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Energy, economy, and climate interactions: Challenges and opportunities, volume II

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Energy, economy, and climate interactions: Challenges and opportunities, volume II

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The influence of the precipitation recycling process on the shift to heavy precipitation over the Tibetan Plateau in the summer

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On the Tibetan Plateau (TP), precipitation intensity has shifted to heavy precipitation due to global warming. However, the influence of the precipitation recycling process on this phenomenon remains unknown. Using the Water Accounting Model-2layers (WAM2layers) model and ERA5 reanalysis, this study investigates the contributions of the precipitation recycling process to precipitation shifts over the TP during 1979–2019. The precipitation shift rate was proposed to quantify this process, and the results reveal that the positive precipitation shift (1.384 mm/41 years) over the TP consists of a positive shift over the western TP (5.666 mm/41 years) and a negative shift (–3.485 mm/41 years) over the eastern TP. Considering the source of moisture, either a local source or a remote source, precipitation was decomposed into internal and external cycles of the precipitation recycling process based on the WAM2layers model. Further analysis indicates that the internal cycle (87.2%) contributes more to the shift than the external cycle (12.8%) over the TP. The contributions of the precipitation recycling ratio (PRR) and precipitation amount to the precipitation shift rate induced by the internal cycle were further investigated. The results indicate that PRR changes contribute more to heavy precipitation over the TP, while precipitation amount changes contribute more to light precipitation. The precipitation recycling process contributes to the shift by increasing atmospheric moisture and increasing (decreasing) the dependency on local evaporation in heavy (light) precipitation. Increased dependence of heavy precipitation on evaporation increases the risk of extreme precipitation, and the government should take preventative actions to mitigate these adverse effects.

KEYWORDS

precipitation recycling process, heavy precipitation, Tibetan plateau, precipitation intensity shift, summer precipitation

1 Introduction

Through the thermal and dynamic effects of high-elevation terrain, the Tibetan Plateau (TP), also known as the "Asian Water Tower" (Immerzeel et al., 2010; Cuo and Zhang, 2017; Immerzeel et al., 2020), greatly affects the water cycle and climate changes over Asia (Xu et al., 2008). Over the past few decades, the TP has experienced enhanced warming (Liu and Chen, 2000; Guo and Wang, 2012; Yan et al., 2020), which has resulted in a number of hydrological changes, such as dramatic lake expansion (Zhang et al., 2017; Brun et al., 2020), glacier melting (Yao et al., 2012; Dehecq et al., 2018; Yao et al., 2022), more intense precipitation (Xiong et al., 2019; Sun et al., 2021), less light precipitation (Ayantobo et al., 2022), and intensified precipitation recycling processes (An et al., 2017; He et al., 2021). The phenomenon of the shift toward heavy precipitation over the TP has been found (Tang et al., 2022) and is anticipated to continue into the foreseeable future as the risk of extreme precipitation rises (Na et al., 2021). According to the Clausius-Clapeyron (C-C) equation, atmospheric warming could raise the total column water vapor (TCWV) (O'Gorman and Muller, 2010; Wang et al., 2017; Nayak and Takemi, 2019), which could enhance the precipitation intensities and transform light precipitation to heavy precipitation. He et al. (2021) investigated the influence of precipitation recycling process on the variation of TCWV by dividing the precipitation recycling process into internal cycle and external cycle, corresponding to the precipitation from local evapotranspiration and the outside of this region, respectively. They found that the internal cycle of precipitation recycling process contributes more to the growth of TCWV than external cycle. The precipitation recycling process was significantly accelerated over the TP between 1979 and 2019, particularly in the western TP, where lake expansion contributes to increased evaporation. On the other hand, there has been a substantial decline in the amount of moisture transported from the Indian Ocean to the eastern TP, resulting in less precipitation. Therefore, how the precipitation recycling process influences the change in precipitation intensity deserves further investigation.

The precipitation recycling ratio (PRR), an indicator of the precipitation recycling process, has been investigated over the TP by different methods (Zhao and Zhou, 2021). For example, Kurita and Yamada. (2008) used isotopic analysis to investigate the PRR for a precipitation event over the central TP and found that the PRR may range from 30% to 80%. However, this method is unrealistic for large areas and long temporal ranges. Therefore, some researchers have used different statistical diagnosed PRR models (dynamic recycling model (DRM) or water accounting model-2layers (WAM2layers)) to investigate the interannual variability of PRR and find the PRR increase over the TP (Zhang, 2020; He et al., 2021), although these methods may ignore the effect of subgrid processes on PRR. The WRF-WVT (water vapor tracers) model may be better for the analysis of subgrid processes due to its high resolution (Gao et al., 2020). However, this tracer model is unsuitable for long periods over the TP due to the computationally intensive nature of high-resolution simulations; hence, statistically diagnosed PRR models are preferable to WRF-WVT simulations.

Due to the effect of different climate systems (Ma et al., 2018), PRR are varied over different parts of TP (Yang et al., 2022). For example, the southern TP and northern TP are affected by the Indian monsoon system and midlatitude westerlies, with PRRs of approximately 11.9% and 12.9%, respectively (Zhang et al., 2019). For the eastern TP, which is influenced by East Asian monsoon system, the PRR is around 10% (Sun and Wang, 2014). For the north east of TP, the PRR is about 5.7%–6.1%, which indicates that the recycled moisture accounted for 5.7%–6.1% of the precipitation (Guo et al., 2022). For the central TP, the PRR may rose to over 80% in August, indicating that most of the precipitation was recycled *via* local evapotranspiration in the summer (Gao et al., 2020). For the whole TP, the PRR is about 23% in the summer (Zhao and Zhou, 2021; Yang et al., 2022) reveal that the PRR should be no more than 40%. Although previous studies investigate PRR sufficiently over different parts of TP, it is unknown the effect of precipitation recycling process to the variations in precipitation intensity and the transition between different precipitation types over different parts of TP under significant hydrological changes. The transition between precipitation types is the transfer of precipitation amount from light to heavy precipitation or from heavy to light precipitation. Ma et al. (2020) indicated that precipitation recycling should not be ignored for extreme precipitation in the summer over the TP. Therefore, how the precipitation recycling process influence the transition of precipitation deserve further investigation.

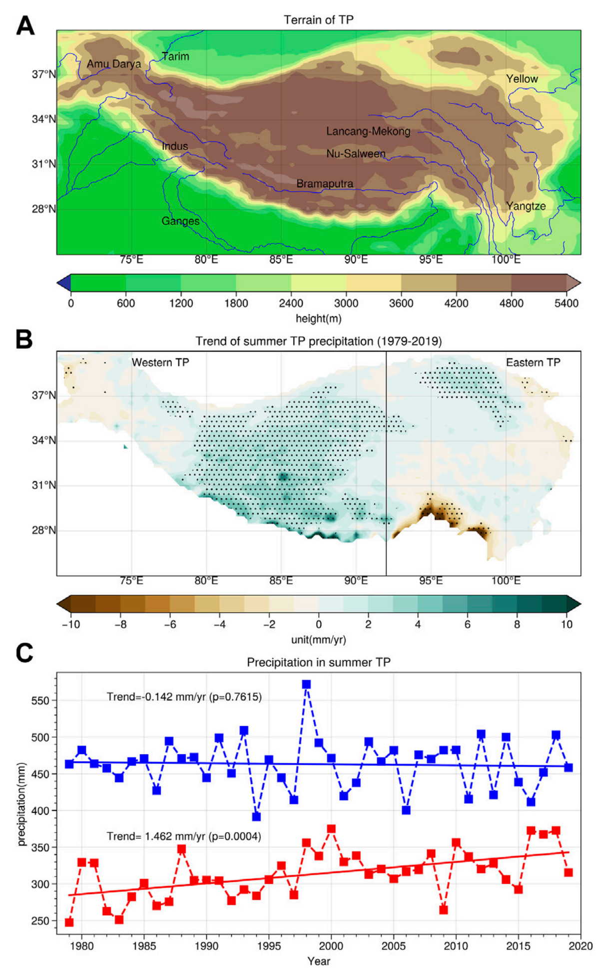

FIGURE 1
The spatial distribution and timeseries of precipitation over the TP and the terrain of the TP. In **(A)** the terrain and major rivers of the TP. In **(B)** the trend map of total precipitation in summer (June to August) over the TP during 1979–2019. The dotted areas indicate statistical significance exceeding 95%. In **(C)** the time series of summer precipitation over the eastern TP (blue lines) and western TP (red lines), which are separated by 92°E.

The following topics are discussed in this study: 1) How can the transition rates between light and heavy precipitation be measured? 2) To what extent does the change in precipitation intensity depend on the internal and external cycles of the precipitation recycling process? 3) Does the change in internal cycles of precipitation depend more on PRR or precipitation amount? 4) Why do light precipitation and heavy precipitation respond differently to the increasing water vapor?

2 Data and methods

2.1 Reanalysis data

This study employed the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA5) dataset, which spans the years 1979–2019 and has a horizontal resolution of 0.25°×0.25°

(Hersbach et al., 2020). The ERA5 single level data and pressure levels data were used as the input to the Water Accounting Model-2layers (WAM2layers) models. The ERA5 single-level data include the 6-hourly surface pressure, total column water vapor and a set of vertically integrated moisture and flux variables (vertically integrated northward/eastward water fluxes in the forms of vapor, liquid, and ice). The hourly precipitation and evapotranspiration from ERA5 single-level data were also used as the input to the WAM2layers models. The ERA5 pressure level data include 6-hourly zonal wind, meridional wind and specific humidity at 16 pressure levels, which include 100, 200, 300, 400, 500, 600, 700, 800, 825, 850, 875, 900, 925, 950, 975, and 1,000 hPa. The surface temperature, convective precipitation and large-scale precipitation are also used to investigate the mechanism of the precipitation shift process. ERA5 has been compared to other reanalysis datasets, such as Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA2) and High Asia Refined analysis version 2 (HARv2) and it has been shown that ERA5 outperforms other reanalysis datasets for long-term trends and can reasonably reflect the summer water vapor characteristics over the TP (He et al., 2021; Yuan et al., 2021). For further information about the selection of ERA5 dataset, please see the description of Figure 1 in He et al. (2021).

2.2 Definition of the shift rate of the precipitation intensity

To evaluate the transition from light to heavy precipitation, a new index was developed to measure the rate of change in precipitation intensity. In this study, a precipitation event is defined as a day with at least 0.1 mm/day of precipitation each day (Sun et al., 2007; Ma et al., 2015). Following previous studies (Shiu et al., 2012; Yu et al., 2022), based on precipitation percentiles at each grid, daily precipitation at each grid over the TP was ranked from light to heavy precipitation for the period 1979–2019. Then, 40 intensity bins are divided by the 0, 2.5th, 5th, 7.5th . . . 97.5th and 100th percentiles of daily precipitation for each individual grid, which represent an intensity interval of precipitation amount. Finally, regionally averaged precipitation histograms were constructed based on 40 intensity bins. The total number of days with precipitation events was used to calculate precipitation frequency, the average precipitation intensity of those events was used to calculate precipitation intensity, and the cumulative precipitation within each intensity interval was used to determine the total precipitation amount for each intensity bin. The slope of the histogram distribution of the precipitation amount trend was used to quantify the rate of intensity shift by least-square linear regression. This rate illustrates the transition from light precipitation to heavy precipitation. A positive slope value indicates a decrease or a relatively smaller increase in light precipitation and an increase in heavy precipitation. The negative value of slope indicates an increase in light precipitation and a decrease in heavy precipitation. Consistent with a previous study (Ma et al., 2017), we classified daily precipitation into three primary categories to make it easier to detect geophysical changes: light precipitation (less than 35%), moderate precipitation (35%–90%), and heavy precipitation (more than 90%). Due to the fixed threshold for these categories of precipitation, this classification may generate some uncertainty, but the basic characteristics of the precipitation trend across 40 intensity bins could support the conclusion.

2.3 Water accounting model-2layers

The WAM2layers model is an updated version of the Water Accounting model, which was developed by van der Ent (Ent et al., 2014). In the original WAM2layers model, the input data are suitable for the European Center for Medium-Range Weather Forecasts interim reanalysis dataset (ERA-Interim), which has a resolution of 1.5°×1.5° (Ent et al., 2014). The time step for the original WAM2layers model is reduced to 15 min to keep the computation stable. However, considering the higher spatial resolution of ERA5, a smaller time step is needed to make the computation stable. Therefore, Xiao and Cui. (2021) modified the original WAM2layers model and reduced the time step to 10 min to fit the ERA5 data. Compared with the original model, we use the modified WAM2layers to calculate the PRR, which is derived from the moisture balance equation for atmospheric water vapor (Eq. 1; Ent et al., 2014).

$$\frac{\partial W}{\partial t} + \frac{\partial Wu}{\partial x} + \frac{\partial Wv}{\partial y} = E - P + \alpha \tag{1}$$

where, as stated by Eq. 2, W represents the precipitable water in an atmospheric column, and u and v represent zonal and meridional winds, respectively. E, P, and α represent the evapotranspiration, precipitation, and residual terms, respectively.

$$W = \frac{1}{g}\int_{100hPa}^{P_s} q\,dp \tag{2}$$

where q represents the specific humidity, g represents the gravitational speed, and p_s represents the surface pressure. The relationship with the moisture from a certain target region is as follows:

$$\frac{\partial W_\Omega}{\partial t} + \frac{\partial W_\Omega u}{\partial x} + \frac{\partial W_\Omega v}{\partial y} = E_\Omega - P_\Omega + \alpha \tag{3}$$

where Ω represents the target source region from which the moisture is evaporated. In addition, the precipitation is separated into two parts: the precipitation that originates in the target region (P_r) and the precipitation that originates from the moisture that is advected into the target region (P_a), which are called internal cycle precipitation and external cycle precipitation, respectively. The contribution of the internal cycle and external cycle was quantified by the ratio of the linear trends of internal cycle precipitation, external cycle precipitation and total precipitation. The PRR (ρ) can be calculated as follows:

$$\rho = \frac{P_r}{P_r + P_a} \tag{4}$$

The WAM2layers model can track the moisture in both forward and backward directions. Using the forward tracking approach, the PRR in each grid was calculated. In this case, the moisture from the target region evaporates E_0 into the atmosphere and is regarded as tagged water in the model. With a mixing ratio of r, the tagged water will mix with precipitable water in the atmosphere. As the model integrates with time, moisture diffuses horizontally and vertically with the wind. When precipitation (P_0) occurs, the moisture from the target region contributes $P_0 \cdot r$ to the precipitation, and the tagged moisture will reduce the $P_0 \cdot r$. This process will continue until no tagged water remains. The PRR on this day was assigned the values corresponding to convective and large-scale precipitation for a specific precipitation day that comprised both types of precipitation.

Because the atmosphere is not fully mixed, which will cause the uncertainty of WAM2layers, especially in regions with strong wind shear (Goessling and Reick, 2013), Ent et al., 2013 showed that the results of WAM2layers are similar to a detailed 3D model (Ent et al., 2013). Both the Euler and Lagrangian methods have uncertainties in moisture tracking, but the WAM2layers can track the real precipitation falling on the ground compared with the Lagrangian methods, which only track the moisture released in the air (Huang and Cui, 2015). Furthermore, WAM2layers can make the "tagged water" conserved (Zhang et al., 2017), which means all evaporated moisture can be tracked forward to the precipitation. In addition, the WAM2layers model has been used in a number of studies to examine wet and dry changes, trace the origin of moisture, and investigate the precipitation recycling process (Zhang et al., 2017; Guo et al., 2019; Zhang et al., 2019; Zhang, 2020; Li et al., 2022). Considering the above characteristics of the WAM2layers, the WAM2layers were suitable for calculating the precipitation recycling ratio (PRR).

2.4 Decomposition of internal precipitation

The internal precipitation can be regarded as the product of precipitation and PRR, as stated by Eq. 5.

$$P_r = \rho * P \tag{5}$$

where P_r represents the internal precipitation, ρ represents the PRR and P represents the precipitation amount. All three variables will change to a certain amount under global warming, which is denoted by Eq. 6.

$$\overline{P_r} + \Delta P_r = (\bar{\rho} + \Delta\rho)(\bar{P} + \Delta P) = \bar{\rho} * \bar{P} + \bar{\rho} * \Delta P + \bar{P} * \Delta\rho + \Delta\rho * \Delta P \tag{6}$$

where the overbar represents the climatology of these three variables and Δ represents the change in these three variables. Eq. 6 minus the climatology of these three variables and ignores the high-order term $\Delta\rho^* \Delta P$, and we can decompose the change in internal precipitation into two parts, as shown in Eq. 7.

$$\Delta P_r = \bar{\rho} * \Delta P + \bar{P} * \Delta\rho \tag{7}$$

where $\bar{\rho}^* \Delta P$ is the precipitation term, which represents the contribution of precipitation amount changes, and $\bar{P}^* \Delta\rho$ is the PRR term, which represents the contribution of PRR changes.

3 Results

3.1 The shift in precipitation intensity

Before examining the variations in precipitation intensity, the slope and trend map of precipitation over the TP were analyzed (Figure 1). Due to geography, the Brahmaputra Grand Canyon in the eastern TP is the principal moisture channel (Figure 1A). However, the trend map indicates that the increasing trend of precipitation over the TP is dominated by the increasing trend over the western TP and Qaidam Basin (Figure 1B). The decrease in precipitation in the eastern TP, particularly over the Brahmaputra Grand Canyon, is associated with the weakening of external water vapor transportation. As described in a recent study (He et al., 2021), the water vapor flux over the southern boundary of the TP exhibits contrasting changes between western and eastern 92°E. Timeseries of precipitation over the western TP and eastern TP suggest that precipitation increases significantly over the western TP at a rate of 1.462 mm/year and decreases insignificantly over the eastern TP at a rate of −0.142 mm/year (Figure 1C). Therefore, this study investigates the effect of the precipitation recycling process on the change in precipitation over the TP, eastern TP and western TP separately.

Based on observations and simulations, a few studies have demonstrated that the intensity of precipitation is shifting from light to heavy precipitation (Na et al., 2021; Tang et al., 2022). Hence, the trends in different intensity bins of precipitation are investigated over the TP, eastern TP and western TP. For the TP and western TP, precipitation intensity shows negative trends for intensity percentile bins below the 35th percentile and positive trends above the 35th percentile (Figures 2A, C). The most significant changes are found for percentiles between the 35th and 90th percentiles over the TP and western TP. For precipitation intensity percentile bins below the 35th percentile, the decreasing trends are significant over the western TP but not significant over the TP. The magnitude of the decreasing trend is much smaller than the increasing trend. For precipitation intensity bins above the 90th percentile, remarkable increasing trends are found over the TP and western TP, albeit they do not reach statistical significance over the TP. Precipitation intensity over the eastern TP increases below the 35th percentile and decreases above the 90th percentile, which is in contrast with the western TP (Figures 2C, E). The most significant increase is found between the 35th and 65th percentiles in the eastern TP. The increasing trends of percentiles below the 35th percentile are close to zero and do not pass the significance test. Over the eastern TP, precipitation decreases obviously above the 90th percentile. For example, heavy precipitation decreases by almost 0.4 mm/year.

To quantify the transition toward heavy precipitation, the rate of change in precipitation intensity was calculated (method details of the calculation of this index are described in Section 2.1). The shift rate for the entire TP is positive, with a rate of 1.384 mm/41 years (Figure 2A). This indicates that the precipitation intensity will transition 1.384 mm from light precipitation to heavy precipitation at the end of the 41-year record. The shift rate over the western TP is similar to that over the whole TP but with larger magnitudes, with rates of 5.666 mm/41 years (Figure 2C). In contrast to the TP and western TP, the eastern TP has a negative shift rate of −3.485 mm/41 years. The negative shift rate implies that heavy precipitation will decline over the eastern TP. Considering the consistent shift rates throughout the entire TP and the western TP, the western TP is more responsible for the shift in precipitation intensity over the TP than the eastern TP.

In this study, light, moderate and heavy precipitation are classified according to the precipitation histogram over the TP to enable discussion about precipitation features. The trends of precipitation amount, frequency, and intensity for light, moderate, and heavy precipitation were examined to better understand the characteristics of the change in precipitation intensity. The frequency of light precipitation is decreasing over the TP, western TP and eastern TP, whereas the frequency of moderate and heavy precipitation is increasing (Figure 2D). This tendency is consistent with the changes in precipitation amount (Figure 2B). The intensities all exhibit an increasing trend except for the eastern TP (Figure 2F), which is primarily caused by the decline in water vapor transfer from the Indian Ocean.

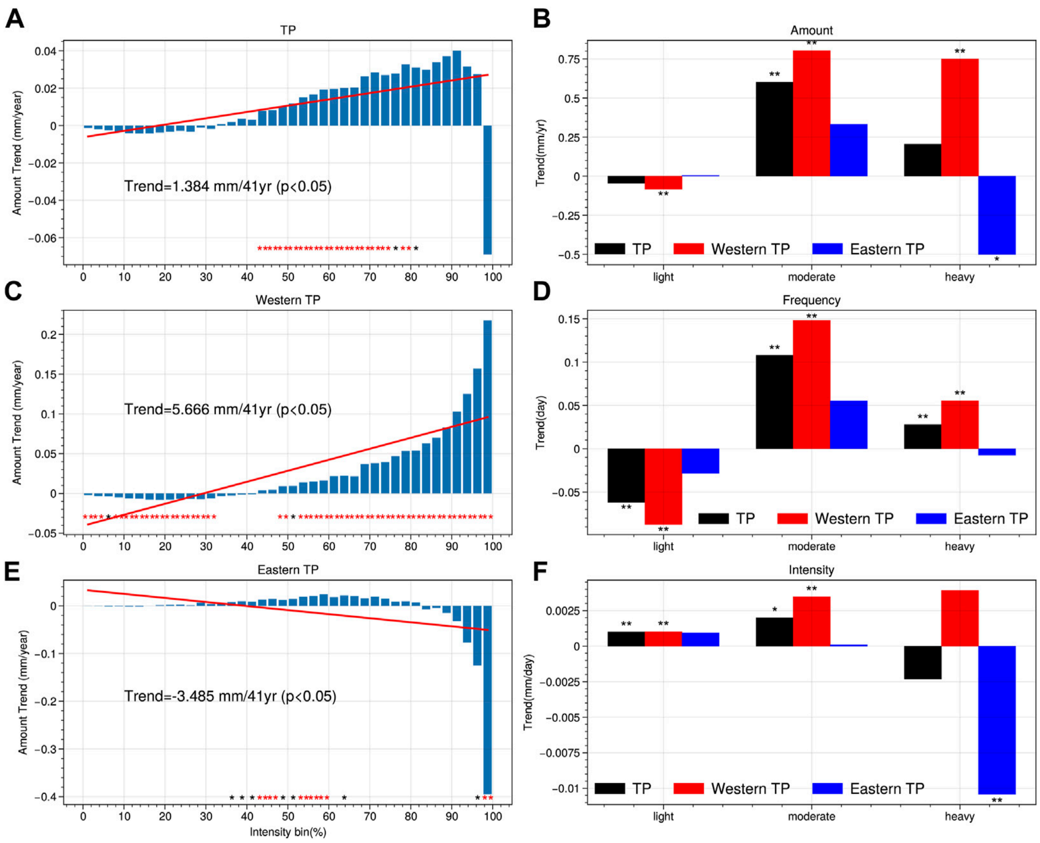

FIGURE 2
Distribution of trends in precipitation percentile intensity bins and precipitation characteristics for different categories of precipitation intensity during the summer of 1979–2019. In **(A,C,E)**, linear trend (blue bars) of precipitation amount in the summer as a function of 40 precipitation percentile intensity bins during 1979–2019 averaged over the TP **(A)**, western TP **(C)**, and eastern TP **(E)**. The red lines indicate the shift rates of precipitation intensity. In **(B,D,F)**, linear trends of the amount **(B)**, frequency **(D)** and intensity **(F)** of light precipitation, moderate precipitation, and heavy precipitation over the TP (black bars), western TP (red bars) and eastern TP (blue bars). The double stars and red stars indicate statistical significance exceeding 95%, and the single star and black star indicate statistical significance exceeding 90%.

3.2 Quantifying the influence of the precipitation recycling process on the precipitation shift

A recent study indicated that the precipitation recycling process has a significant impact on the summertime water vapor over the TP (He et al., 2021). Therefore, the spatial-temporal distribution of total precipitation and the internal and external cycles of the precipitation recycling process for the three types of precipitation were further examined to determine the effect of the precipitation recycling process on the precipitation shift (Figures 3, 4). The results indicate that moderate precipitation and heavy precipitation dominate the precipitation over the western TP and eastern TP and that moderate precipitation contributes more than heavy precipitation (Figure 3). More specifically, the amount of moderate precipitation is approximately 150–250 mm/year and 250–350 mm/year over the western TP and eastern TP, respectively, and the amount of heavy precipitation is approximately 80–140 mm/year and 100–250 mm/year over the western TP and eastern TP, respectively (Figures 3D, E, G, H). Light precipitation contributes no more than 30 mm/year and 45 mm/year over the western TP and eastern TP, respectively (Figures 3A, B).The internal and external cycles both significantly influence the tendency of light precipitation to significantly decrease over the western TP. The internal cycle of precipitation greatly increases the amount of moderate and heavy precipitation over the western TP rather than over the eastern TP. In contrast, the external cycle of precipitation recycling causes a significant increase in moderate and heavy precipitation over the western TP and a substantial decrease over the eastern TP (Figures 3C, F, I; Figures 4G–I). The opposite influence of the external cycle results in a weak and insignificant impact on heavy precipitation over the TP. Further investigation of the spatial distribution of the three types of total precipitation and the internal and external cycles of the precipitation recycling process exhibits consistent results with Figure 3, except for the northern part and southern part of the eastern TP (Figures 4G–I). Specifically, the increase in light precipitation consists of an increase over the southern part of the eastern TP and a decrease over the northern part of the eastern TP (Figure 4A). The internal cycle contributes to a general increase in light precipitation over the eastern TP, and the external cycle contributes to a slight increase in light precipitation over the eastern TP (Figure 3C). For moderate precipitation, internal and external cycles of precipitation both contribute to the increase in moderate precipitation over the eastern TP. The heavy precipitation is opposite to the increase

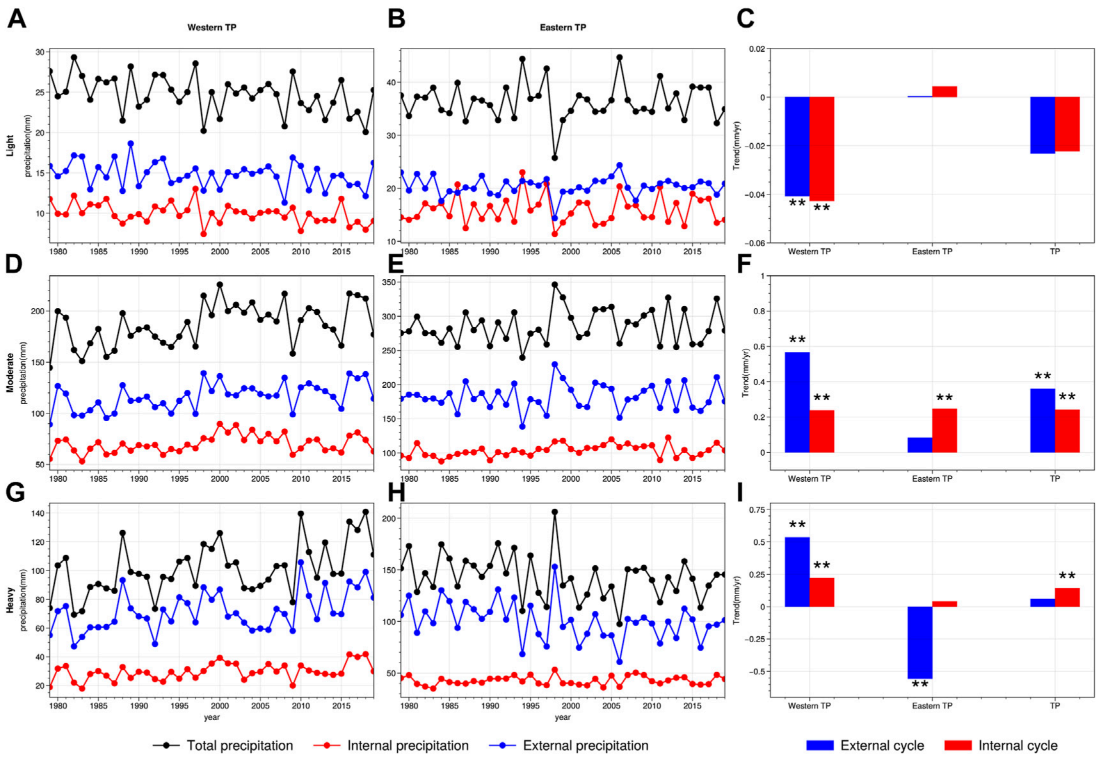

FIGURE 3
Time series of summer (June-August) total precipitation, external cycle precipitation and internal cycle precipitation and its corresponding trend. Black, red, and blue lines represent the total precipitation, internal cycle precipitation and external precipitation, respectively, for light **(A,B)**, moderate **(D,E)** and heavy **(G,H)** precipitation over the western (left column) and eastern (middle column) TP. Blue bars and red bars in **(C,F,I)** represent the trends of the precipitation amount associated with the external cycle and internal cycle over the western TP, eastern TP and TP, respectively. The stars indicate statistical significance exceeding 95%.

in light precipitation, and the decrease in heavy precipitation is composed of an increase over the northern part of the eastern TP and a decrease over the southern part of the eastern TP (Figure 4C). The internal cycle precipitation generally contributes to the increase in heavy precipitation over the eastern TP, but the external cycle exhibits a spatial distribution similar to that of heavy precipitation.

To investigate the change in the internal and external cycles of the precipitation recycling process to the shift in precipitation intensity, the histogram of the trend in internal precipitation and external precipitation is calculated for the TP, western TP and eastern TP (Figure 5). The histogram of internal precipitation and external precipitation is similar to the histogram of total precipitation over the western TP and TP (Figures 5A–D). Both internal precipitation and external precipitation show obvious increasing trends above the 35th percentile, while they decrease below the 35th percentile over the TP and western TP. The magnitude of the decreasing trend is smaller than the magnitude of the increasing trend. However, for the eastern TP, the histograms of internal precipitation and external precipitation show contrasting distributions (Figures 5E, F). The internal precipitation increases across all percentile bins (Figure 5E). However, external precipitation increases slightly below the 80th percentile, which does not exceed the significance test, and decreases above the 80th percentile, especially above the 90th percentile.

Subsequently, to quantify the relative contribution of the internal and external cycles of the precipitation recycling process to the shift in precipitation intensity, the shift rate index is further calculated for the TP, western TP and eastern TP (Figure 5). The contribution was calculated by dividing the shift rate induced by internal and external cycles to the shift rate in total. This result suggests that the shift rate induced by the internal cycle is 1.207 mm/41 years (~87.2%) and contributes more to the shift in precipitation intensity than the external cycle, which shifts at a rate of 0.177 mm/41 years (~12.8%) (Figures 5A, B). Contribution was determined by dividing the shift rate of the internal or external cycle by the shift rate of precipitation. The shift rates of the internal cycle over the western TP and eastern TP show similar TP trends, with rates of 1.725 mm/41 years and 0.745 mm/41 years, respectively. However, the shift rates of the external cycle over the western TP and eastern TP are opposite, with rates of 3.941 mm/41 years and −4.23 mm/41 years, respectively.

Since the map of the precipitation intensity shift rate is more informative and crucial for authorities, the spatial distribution of the shift rate associated with the internal cycle and external cycles are further investigated in Figures 5G, H. The results show that the internal cycle strongly influences the shift in precipitation intensity over the western TP and the Qaidam Basin, while the shift rate generated by the external cycle increases west of the southern boundary but decreases east of the southern boundary (Figures 5G, H). The spatial maps of shift rates are consistent with the changes in light, moderate and heavy precipitation associated with internal cycle precipitation and external cycle precipitation (Figures 4D–I).

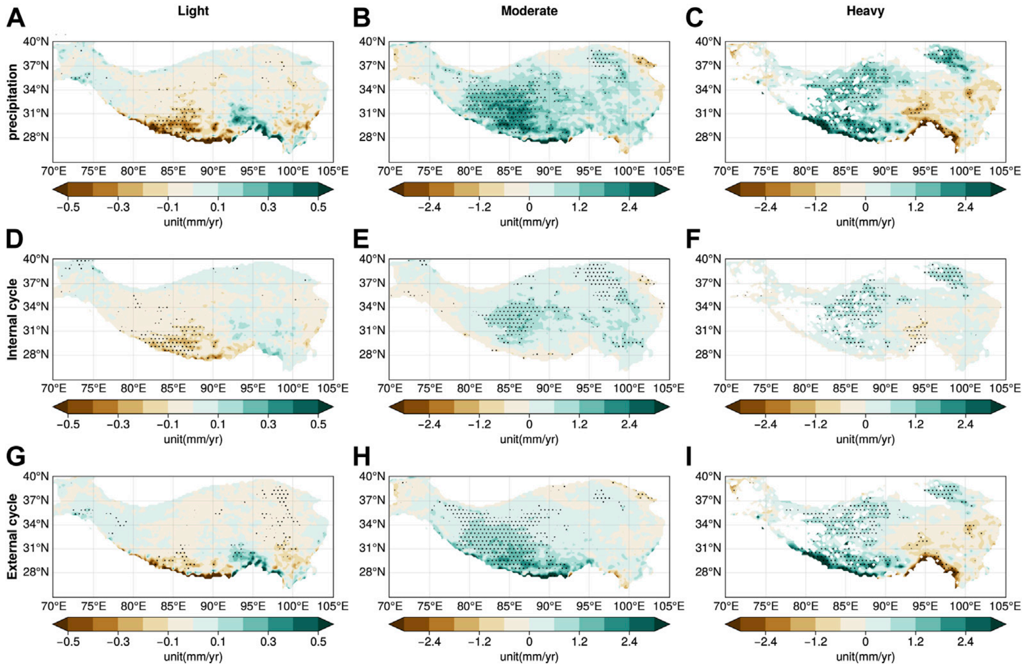

FIGURE 4
The trend map of total precipitation **(A–C)**, precipitation associated with internal **(D–F)** and external **(G–I)** cycles for light (left column), moderate (middle column) and heavy precipitation (right column) over the TP. The dotted areas indicate statistical significance exceeding 95%.

3.3 The dominant factor in the variation in internal precipitation

Considering the non-negligible contribution of internal precipitation to the shift in precipitation over the TP, western TP and eastern TP, the factors that affect the change in internal precipitation are further examined. As Section 2.4 states, the internal precipitation can be decomposed into the PRR term and precipitation term based on Eq. 5. Therefore, it is essential to comprehend the contribution of PRR and precipitation as a function of precipitation intensity to understand the change in internal precipitation under global warming.

The results suggest that the PRR term contributes more to heavy precipitation than to light precipitation (Figures 6, 7). For precipitation percentile bins above the 90th percentile, the PRR term and precipitation term both contribute to the increase in internal precipitation, and the magnitude of the PRR term exceeds the magnitude of the precipitation term over the TP (Figures 6A, B). More specifically, the PRR term contributes much more in the high percentile than in the low percentile, which indicates that the PRR term promotes the increase in heavy precipitation. For precipitation percentile bins between the 35th percentile and 90th percentile, the PRR term and precipitation term exhibit opposite contributions to the increase in internal precipitation over the TP. However, internal precipitation is more affected by the precipitation term since its magnitude is larger than that of the PRR term. For precipitation percentiles below the 35th percentile, both the PRR term and precipitation term cause a decrease in internal precipitation over the TP. For the western TP, the PRR term decreases across all precipitation intensity bins (Figure 7A), and the precipitation term decreases below the 35th percentile bins and increases above the 35th percentile bins (Figure 7B). Considering the magnitude of the PRR term and precipitation term, the precipitation term dominates the change in internal precipitation over the western TP. For the eastern TP, the PRR term increases across all precipitation intensity bins, and the precipitation term increases below the 80th percentile and decreases above the 80th percentile. In summary, the precipitation term dominates the decrease in internal precipitation in light precipitation, while the PRR term dominates the increase in internal precipitation in heavy precipitation over the TP.

3.4 Changes in the precipitation recycling process across precipitation intensity bins

In the summer, the average PRR over the TP is usually lower than 40% (Hua et al., 2015; Guo et al., 2018; Zhao and Zhou, 2021), showing that the internal cycle is far less than the external cycle. Non-etheless, the contribution of the internal cycle to the shift in precipitation intensity is larger than that of the external cycle. Therefore, it is essential to comprehend the variation in PRR as a function of the precipitation intensity to understand how the precipitation recycling process influences the shift.

Because surface temperature and evaporation are directly related to the precipitation recycling process (An et al., 2017), the linear trend of surface temperature and evaporation was evaluated as a function of precipitation intensity bins (Figures 8A, B). The result demonstrates that the surface temperature is increasing across all bins, with light precipitation experiencing the greatest increase. However, evaporation decreases with light precipitation and increases with moderate and heavy precipitation. The smaller increase in temperature during heavy precipitation can be partly explained by the evaporative cooling effect. The results also indicate that the precipitation recycling process weakens

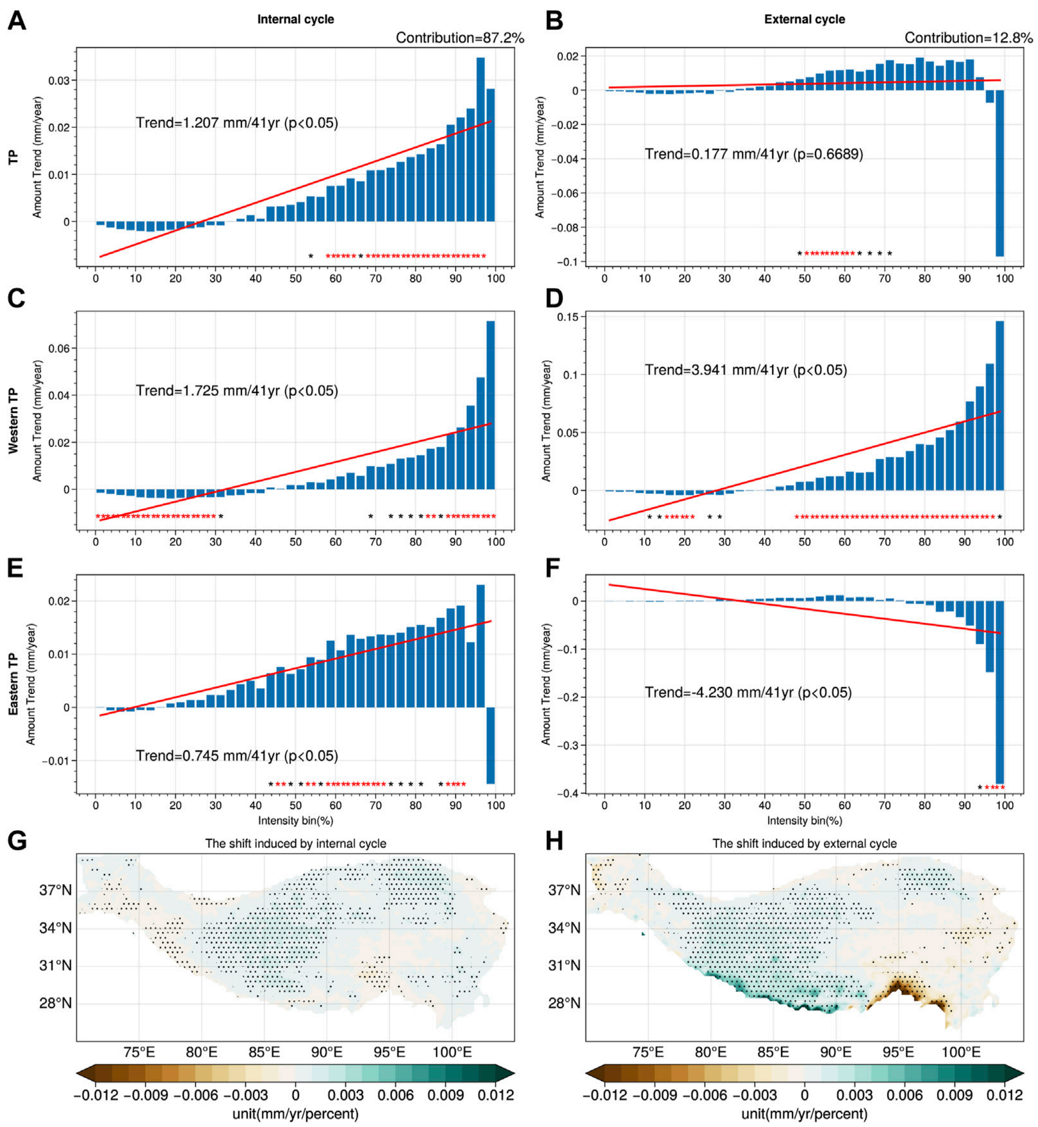

FIGURE 5
Distribution of precipitation trends in precipitation percentile intensity bins of precipitation and the spatial distribution of shift rates during the summer of 1979–2019 averaged over the TP. In **(A–F)**, linear trend (blue bars) in precipitation associated with internal (left column) and external (right column) cycles as a function of 40 precipitation percentile intensity bins over the TP **(A,B)**, western TP **(C,D)**, and eastern TP **(E,F)**. The red lines indicate the shift rates of precipitation intensity. In g and h, the trend map of the shift rate of precipitation intensity induced by the internal **(G)** and external **(H)** cycles on the TP. The dotted areas and red stars indicate statistical significance exceeding 95%. The black stars indicate statistical significance exceeding 90%.

in light precipitation and strengthens in heavy precipitation, as shown in Figure 8C. More specifically, in the climatology of PRR, the climatological mean PRR of light precipitation (~51%) is larger than that of heavy precipitation (~35%), which indicates that the dependence of light precipitation on local evaporation is greater than that of heavy precipitation. However, the trend of PRR for light precipitation is negative, while it is positive for heavy precipitation, indicating that the dependence of light precipitation on local evaporation is decreasing, while the dependence of heavy precipitation is increasing (Figure 8C). Therefore, there exists an issue: why are the responses of light and heavy precipitation in contrast as the precipitation recycling process is strengthened?

To address this issue, convective and large-scale precipitation were separated from precipitation (more information is supplied in Supplementary Text S1). Convective precipitation has a larger PRR than large-scale precipitation and is a strong activator of the precipitation recycling process (Figure 8D). Consequently, Supplementary Figure S1 examines the influence of convective and large-scale precipitation on the shift in precipitation intensity. The results indicate that convective precipitation is more influential than large-scale precipitation on the shift. The trend of PRR for convective and large-scale precipitation over intensity bins (Figure 8D) reveals that convective precipitation has a consistent trend distribution in PRR with total precipitation, whereas large-scale precipitation does not differ significantly across intensity bins. More specifically, the large-scale precipitation PRR decreases across all intensity bins, and the convective precipitation PRR increases in heavy precipitation and decreases in light precipitation. Therefore, the changes in the PRR trend between light precipitation and heavy precipitation are mainly caused by convective precipitation.

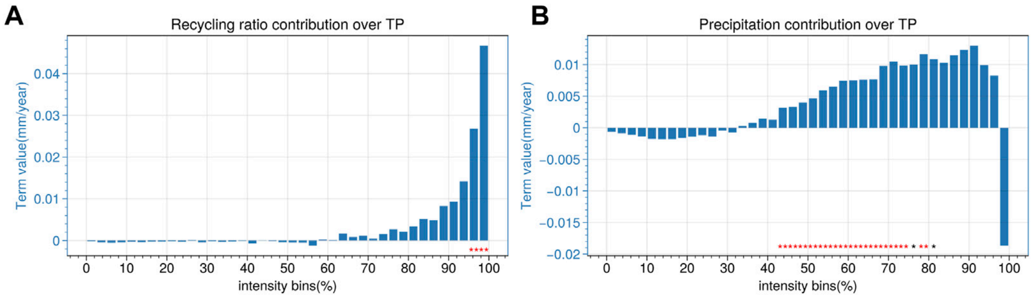

FIGURE 6
Decomposition of internal precipitation trends to the PRR and precipitation over the TP. In **(A,B)** histograms represent the contribution of PRR and precipitation to the internal precipitation over the TP. The red stars and black stars indicate statistical significance exceeding 95% and 90%, respectively.

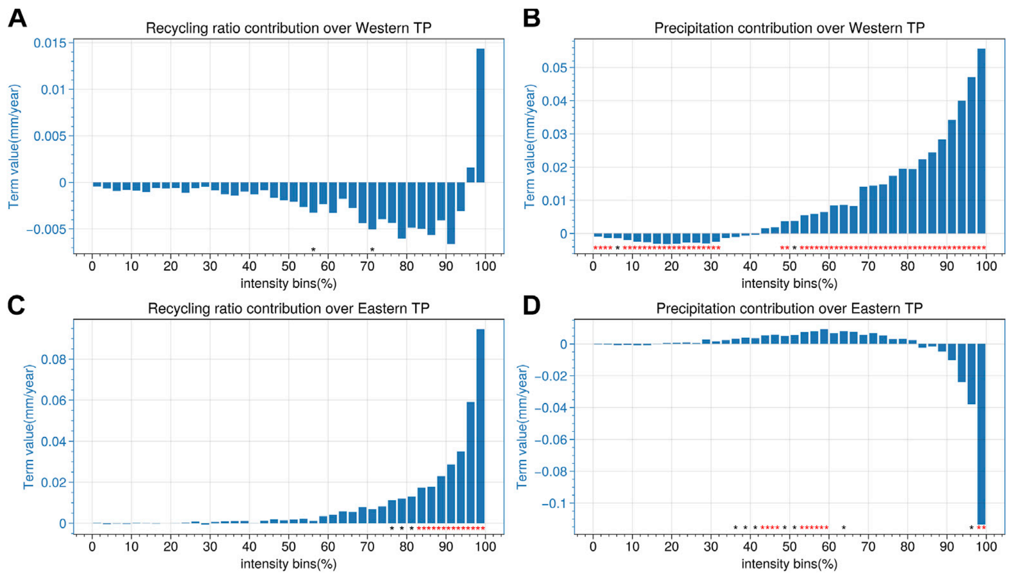

FIGURE 7
Decomposition of internal precipitation trends to the PRR and precipitation over the western TP and eastern TP. Linear trends of internal precipitation associated with PRR **(A,C)** and precipitation **(B,D)** over the western TP **(A,B)** and eastern TP **(C,D)**. The red stars and black stars indicate statistical significance exceeding 95% and 90%, respectively.

4 Discussion

4.1 The mechanism of the precipitation recycling process influencing the shift to heavy precipitation

The mechanism responsible for the precipitation shift over the TP is summarized in the schematic diagram (Figure 8E). Global warming causes an increase in atmospheric moisture and water vapor flux around the TP, which leads to increasing humidity over the TP through the external cycle of the precipitation recycling process. As discussed in (He et al., 2021), the contrast trend between the western TP and eastern TP is positively correlated with the changes in moisture flux at the southern boundary. Moisture flux mainly flowing over the Brahmaputra Grand Canyon brought by the India Summer Monsoon (ISM) has declined (Bingyi, 2005; Zhao and Zhou, 2021). This has reduced the external cycle of heavy precipitation over the eastern TP. Due to the strengthening of the heating source (Xie and Wang, 2019) and the "up-and-over" process (Dong et al., 2016), the moisture flux near the southern boundary of the western TP is increasing (He et al., 2021). In addition, the enhanced warming over the TP has caused glacier melting, lake expansion and increasing evaporation, all of which promote the intensification of the precipitation recycling process. Increasing moisture induced by both the internal and external cycles would help the transition of light precipitation to heavy precipitation, resulting in a decrease in light precipitation and an increase in heavy precipitation.

Because precipitation dominates summer evapotranspiration over the TP (Wang et al., 2018; Ma and Zhang, 2022), decreased light precipitation and increased heavy precipitation would result in a different response to the precipitation recycling process.

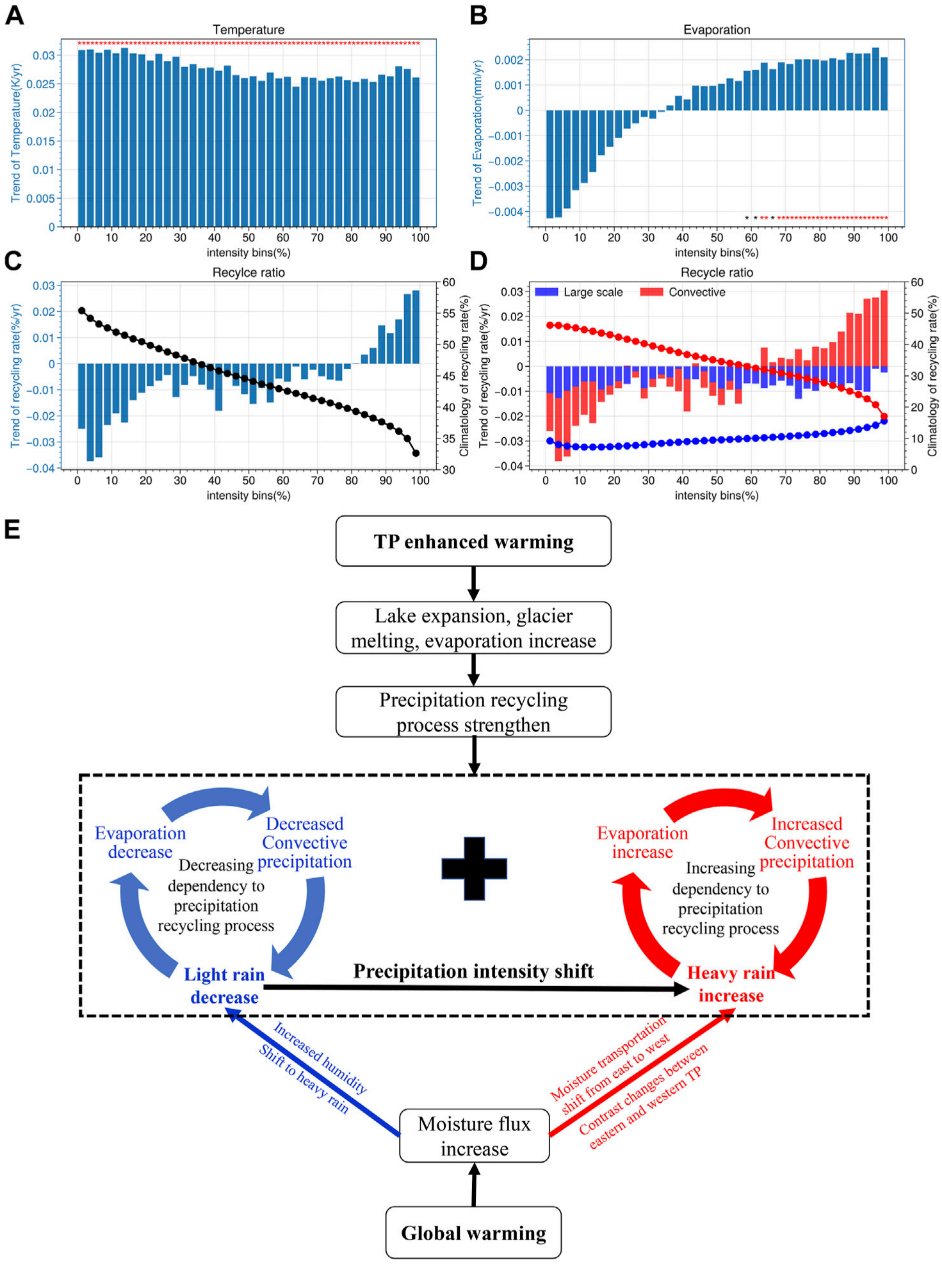

FIGURE 8
Distribution of trends (bars) in precipitation percentile intensity bins of temperature, evaporation, and recycling ratio during the summer of 1979–2019 over the TP and the schematic illustration. Bars show the linear trends of temperature **(A)**, evaporation **(B)**, precipitation recycling ratio **(C)** and precipitation recycling ratio corresponding to convective and large-scale precipitation **(D)**. The black line in figure c shows the climatology of the precipitation recycling ratio. The red line and blue line in d show the climatology of the convective precipitation recycling ratio and large-scale precipitation recycling ratio, respectively. In **(E)** the schematic illustration of how precipitation recycling changes influence the shift of precipitation intensity over the TP. The red stars and black stars indicate statistical significance exceeding 95% and 90%, respectively.

Positive feedback is formed when a decrease in light precipitation leads to a decrease in evapotranspiration, which in turn leads to a decrease in convective precipitation and a further decrease in light precipitation. The decreasing convective precipitation during the aforementioned process also decreases the PRR in light precipitation, thereby decreasing the dependence of light precipitation on local evaporation, despite the intensification of the precipitation recycling process under global warming. The convective precipitation that is enhanced by an increase in evaporation leads to an increase in heavy precipitation, forming positive feedback to increase heavy precipitation. Increasing convective precipitation during heavy precipitation also increases the PRR, indicating that heavy precipitation is increasingly dependent on local evaporation. The contrast changes in PRR between light and heavy precipitation have a positive effect on the shift in precipitation intensity.

Therefore, an intensified precipitation recycling process could facilitate the transition to heavy precipitation by increasing evaporation and adjusting the dependence of light and heavy precipitation on the precipitation recycling process. However, the contrast changes in the external cycle between the eastern and western TP result in a weaker contribution of the external cycle over the TP. Although the internal cycle only amplifies the effect of the external cycle on the shift, its contribution even exceeds that of the external cycle. Further divide the internal precipitation into the PRR term and precipitation term and find that the PRR term contributes more than the precipitation term, especially during heavy precipitation, which heavily amplifies the effect of the external cycle (Figure 6). The TP is projected to warm significantly in the future, which will significantly intensify the internal cycle; consequently, the influence of the internal cycle on the shift is anticipated to increase.

4.2 Implications of the shift in precipitation over the Tibetan Plateau under global warming

The internal cycle and external cycle are important components of the hydrological cycle over the TP. A better understanding of the internal and external cycles over the TP can contribute to the early response to disasters for facilities over the TP. The decrease in light precipitation may contribute to more frequent drought over the TP. It is important to note the amplification effect of the internal cycle, which amplifies heavy precipitation by increasing evaporation over the TP. The amplification of heavy precipitation may also increase the occurrence of extreme precipitation and flood disasters, which could damage the infrastructure over the TP. As internal precipitation amplifies the precipitation shift over the TP, we suggest that the government take measures to mitigate the adverse effects associated with this shift in a warming climate.

5 Conclusion

Due to global warming, the Tibetan Plateau has experienced a shift in precipitation intensity, such as an increase in heavy precipitation and a decrease in light precipitation, in recent decades. To quantify this process and clarify the effect of internal and external cycles of the precipitation recycling process, the concept of the precipitation shift rate was introduced, and the results show that the shift rates over the eastern and western TP are −3.485 mm/41 years and 5.666 mm/41 years, respectively. The impacts of the precipitation recycling process on the shift from light to heavy precipitation were further investigated over the Tibetan Plateau. Both the internal and external cycles have a positive influence on the shift toward heavy precipitation over the western TP, while the internal (external) cycle has a positive (negative) influence on the shift over the eastern TP. The results reveal that the internal (87.2%) and external cycles (12.8%) contribute to the precipitation intensity shift over the TP. The internal precipitation was further decomposed into the PRR term and precipitation term. The variations in internal precipitation were mutually impacted by the PRR term and precipitation term, where the PRR term impacts heavy precipitation more and the precipitation term impacts light precipitation more. The strong impact of the PRR term in heavy precipitation is consistent with the amplified effect of internal precipitation. Therefore, the mechanism of the influence of the precipitation recycling process on the shift was investigated from the perspective of the changes in PRR during light and heavy precipitation. The result reveals that light precipitation has a higher PRR climatology than heavy precipitation, indicating that the dependence of light precipitation on local evapotranspiration is greater than that of heavy precipitation. Under enhanced warming, the PRR increases during heavy precipitation and decreases during light precipitation, which is mostly due to the response of convective precipitation. The results suggest that heavy precipitation is more responsive to the intensified precipitation recycling process than light precipitation. Therefore, the intensified precipitation recycling process generated by the enhanced warming may contribute to the shift of precipitation intensity to heavy precipitation by adjusting the response of PRR. The increasing PRR in heavy precipitation increases the risk of extreme precipitation. This reminds us to pay more attention to the influence of the precipitation recycling process when projecting the changes in extreme precipitation in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author. The ERA5 single level and pressure level data used for the calculation of the precipitation recycling process are available from https://doi.org/10.24381/cds.adbb2d47 and https://doi.org/10.24381/cds.bd0915c6, respectively. Figures are made with Proplot version 0.9.5 (Davis, 2021), available under the MIT license at https://github.com/proplot-dev/proplot. Modified WAM2layers for moisture tracking are licensed under GNU General Public License v2.0 and are available on Github https://github.com/xmingzh/Modified-WAM2layers (Xiao and Cui, 2021).

Author contributions

YH contributes to the conception and design of this study and develops the methodology for analysis. BZ runs WAM2layers, analyzes the results and write the draft. YH reviews the manuscript. YR, BH, YP, SW, and XG discuss the results and contribute to writing the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2023.1078501/full#supplementary-material

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The Belt and Road Initiative and enterprise green innovation: evidence from Chinese manufacturing enterprises

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Building a green silk road is an important path toward implementation of the UN 2030 sustainable development goals. The purpose of the paper is to discuss the sustainable development goals of the "Belt and Road" Initiative (BRI) by evaluating the relationship between the BRI and enterprise green innovation. Employing the technology–organization–environment (TOE) framework to build a theoretical model based on the micro data of Chinese manufacturing enterprises from 2011 to 2018, and using the difference-in-differences method, this paper analyzes the BRI's influence on the green innovation of enterprises. The research results indicate that the BRI has significantly enhanced the level of green innovation in Chinese manufacturing enterprises. This effect is still robust after the analysis of PSM-DID excluding the interference of policies in the same period and heterogeneity analysis. The results of the mechanism analysis show that the percentage of R&D employees, policy support and R&D expenditure can enhance the positive effects of the BRI's influence on enterprise green innovation. The marginal contribution of this paper is to identify the causal relationship between the BRI and green innovation, add a new micro perspective to the research on the relationship between the BRI and sustainable development, and reveal a new micro mechanism.

KEYWORDS

the Belt and Road Initiative, green innovation, manufacturing enterprises, TOE framework, difference-in-differences

1. Introduction

In 2013, Chinese President Xi Jinping proposed "the Belt and Road" Initiative (BRI), which has received great attention from the international community. In 2015, China released the "Vision and Actions on Jointly Building Silk Road Economic Belt and 21st-Century Maritime Silk Road" (hereinafter referred to as "the Vision"), which put forward the concept of "Building a Green Silk Road." In 2017, China introduced the "Guidance on Promoting Green Belt and Road," and building the Green Silk Road has become an important path toward implementation of the UN 2030 sustainable development goals (SDGs). The research literature points out that sustainability has become a major concern for the business community and that companies that are successful in environmentally sustainable projects can obtain greater financial success and social welfare beyond their economic responsibility (Zhu et al., 2019). Studies on the BRI have also paid extensive attention to environmental and sustainable development issues, with the literature discussing sustainable growth, energy consumption and environmental challenges in the "Belt and Road" countries (Rauf et al., 2020), carbon emission reduction in the "Belt and Road" countries (Chen et al., 2021a), and the energy intensity of the BRI and the countries along the" Belt and Road" (Qi et al., 2019). However, there is a lack of research on the relationship between the BRI and sustainable development that considers the enterprise level to discuss the impact of the BRI on green innovation in enterprises, especially manufacturing enterprises.

Green innovation is critical to both organizations and society as an important factor in maintaining environmental stewardship and sustainable development (Aguilera-Caracuel and Ortiz-de-Mandojana, 2013; Zhang et al., 2020; Xu et al., 2021). This importance is reflected in two aspects. On the one hand, in order to face the threat posed by environmental degradation to human society, many organizations and communities have adopted green innovation as a strategy to achieve environmental protection and economic growth (Takalo and Tooranloo, 2021), which is important for both organizations and society in terms of sustainability and economic profitability (Fliaster and Kolloch, 2017). On the other hand, from the perspective of the impact of green innovation on enterprises, green innovation can lead organizations to achieve a sustainable competitive advantage (Hur et al., 2013) and further enhance regional sustainability (Chege and Wang, 2020; Fu et al., 2020; Wang and Yang, 2021; Zhou et al., 2021). The research on corporate green innovation has been conducted from three perspectives as follows: (1) Studies on the factors influencing enterprise green innovation have argued that, as a systemic project, enterprise green innovation requires the creative integration of various internal and external resources. They achieve this through capacity development and capital investment (Lampikoski et al., 2014; Roper and Tapinos, 2016), the technological capabilities of firms (Leyva-de La Hiz et al., 2019; Zhang et al., 2020), firm heterogeneity (Xu et al., 2021), and environmental pressures (Cao and Chen, 2019), which have been identified as the main factors influencing enterprise green innovation. (2) Results of enterprise green innovation. Green innovation in enterprises can reduce energy consumption and pollution (Wang et al., 2017; Albort-Morant et al., 2018), improve resource-use efficiency (Wang et al., 2017), and enhance the environmental sustainability of enterprises (Chu et al., 2018). (3) The impacts of environmental policies on enterprise green innovation, include sustainability performance indicators (Wang and Yang, 2021), carbon trading rights (Chen et al., 2021b; Du et al., 2021), intellectual property rights and government support (Roh et al., 2021), etc.

However, the existing studies lack a comprehensive assessment of the promotion effect of the BRI on green innovation in Chinese manufacturing enterprises. The research gap mainly manifests in three aspects. First, the existing research mainly focuses on the relationship between the BRI and sustainable development from the national level, but there are few studies focusing on green innovation from the enterprise level. Second, existing studies have discussed the impact of policy environment on green innovation of enterprises, but there are few studies on the impact of the BRI on green innovation of enterprises. Third, in the research on the relationship between the BRI and sustainable development, the research focusing on green innovation in manufacturing needs further in-depth discussion.

The focus on green innovation in manufacturing enterprises is based on three main factors: (1) Manufacturing is one of the major causes of industrial waste production and environmental pollution, posing a threat to environmental sustainability, and enhancing the green innovation capacity of manufacturing enterprises is an important strategic tool to ensure environmental sustainability (Wang and Yang, 2021). As the Green Silk Road is an important path toward implementing the UN 2030 Agenda for Sustainable Development, studying the impact of the BRI on green innovation in manufacturing enterprises can provide important theoretical support for the realization of the SDGs of the BRI. Therefore, studying the impact of the BRI on green innovation in manufacturing enterprises can provide important theoretical support for achieving the SDGs of the BRI. (2) Consumers, manufacturers, government departments, and communities are increasingly aware of the importance of sustainability as well as environmental issues, which has created significant social pressure on manufacturing firms (Li et al., 2017), prompting manufacturing firms to incorporate green innovation into their production processes (Gupta and Barua, 2018), and the growing concern for social, economic, and environmental concerns has increased the importance of green innovation in manufacturing firms (Sarkar et al., 2020). (3) Manufacturing is one of the wide-ranging and dynamic industries that are attracting companies to transition toward green innovation (Wang and Yang, 2021). The BRI proposed the concept of supporting major industrial sectors to promote environmental technology innovation, providing an opportunity to study the impact of the BRI on green innovation of manufacturing enterprises.

Thus, this paper poses the following research question: Does the BRI promote green innovation of Chinese manufacturing enterprises? Does this effect have a heterogeneous impact? What is the mechanism of such impact? This paper uses a difference-in-differences approach to analyze the impact of the BRI on green innovation in Chinese manufacturing enterprises, discusses industry heterogeneity and firm ownership heterogeneity, and evaluates the impact of the BRI on green innovation in Chinese manufacturing enterprises based on a technology–organization–environment (TOE) framework (Tornatzky et al., 1990). We analyze the impact of the BRI on green innovation in Chinese manufacturing enterprises in terms of internal technological and organizational factors as well as external environmental factors. The research in this article is timely and necessary. On the one hand, the BRI is believed to enhance the strength and expand the influence of Chinese enterprises in the global economy. This study can add new content to this influence from the perspective of green innovation. On the other hand, this study can also provide valuable information for foreign investors and governments of countries along the BRI.

In the study of the relationship between the BRI and sustainable development, this paper makes marginal contributions in three areas compared to existing studies. (1) This paper extends the analysis to the level of manufacturing enterprises and discusses the impact of the BRI on green innovation in Chinese manufacturing enterprises compared to previous studies that have discussed the environmental impact of the BRI at the national macro level (Qi et al., 2019; Rauf et al., 2020; Chen et al., 2021a). This paper provides a micro perspective at the enterprise level on the relationship between the BRI and sustainable development. (2) This paper uses the method of difference-in-differences to take China's core cities along the "Belt and Road" as the objects to accept exogenous shocks, which is different from previous studies on countries along the "Belt and Road" as the objects to accept exogenous shocks (Du and Zhang, 2018; Yang et al., 2020; Nugent and Lu, 2021). This paper analyzes the intrinsic dynamics of corporate green innovation from the perspective of core cities along China's domestic routes, providing microlevel causal evidence of the relationship between the BRI and sustainable development. (3) This paper analyzes the impact mechanism of the BRI on Chinese manufacturing enterprises based on the TOE framework. Compared with previous studies on environmental issues of the Belt and Road (Qi et al., 2019; Rauf et al., 2020; Chen et al., 2021a), and research on enterprise digital innovation and green process innovation (Dong et al., 2023), this paper analyzes the role of technology, organization and environment at both internal and external levels and reveals the microlevel influence mechanism of the relationship between the BRI and sustainable development. At the same time, at the practical level, the study of these issues can help in the evaluation of the construction effect of the green Belt and Road and provide important theoretical references and decision-making bases for achieving the 2030 SDGs.

2. Theoretical framework

Building the Green Silk Road is an important concept of the BRI. In 2019, China signed a memorandum of understanding with the United Nations Environment Program on building a green Belt and Road and signed cooperation agreements on ecological and environmental protection with more than 30 countries along the route. The construction of the Green Silk Road has become an important path toward implementing the UN 2030 Agenda for Sustainable Development, and more than 100 partners from relevant countries and regions have jointly established the International Alliance for Green Development along the Belt and Road. Studies have found that the BRI reduces carbon emissions (Chen et al., 2021a) and energy intensity (Qi et al., 2019) and promotes sustainable development in the countries along the route (Rauf et al., 2020). Based on this, this paper assesses the promotion effect of the BRI on green innovation in Chinese manufacturing firms and further analyzes its impact mechanism using a TOE framework (Tornatzky et al., 1990).

We first analyze the reasons for the impact of the BRI on the sustainable development of Chinese enterprises, and then analyze the impact mechanism of the BRI on green innovation of Chinese enterprises. The BRI serves as a high-level open platform where various partners can promote the development of an open world economic system by strengthening interregional cooperation (Duan et al., 2018) and thereby allowing Chinese companies to gain value in the international market. The impact of the BRI on the sustainable development of Chinese enterprises can be summarized in the following three outcomes. (1) Resource allocation optimization effect. The BRI promotes the transfer of industries and the restructuring of domestic industries by promoting foreign direct investment in countries along the route; it also optimizes the resource allocation of enterprises in home countries and improves production processes and processing techniques, thus promoting the green transformation and upgrading of enterprises (Yu et al., 2019; Yang and Li, 2021). (2) Achieving economies of scale and improving technical efficiency. As part of a broad international market, the BRI can greatly increase external demand for Chinese products, expand market capacity, achieve economies of scale, and improve production efficiency (Liu and Xin, 2019). (3) Increase competitive pressure and achieve technological progress. While the wide international market brings more room for development for Chinese enterprises, it also imposes higher development requirements for effective survival, i.e., the demand for diversified and high-end products, creating a strong squeezing mechanism for enterprises that want to enter the international market, which needs to prioritize technological innovation and green production to be competitive (Ji et al., 2018).

In order to explain the impact of the above the BRI on the sustainable development of Chinese enterprises, we discuss the impact mechanism of the BRI on green innovation of Chinese enterprises from the perspective of green innovation based on the TOE framework. Tornatzky et al. (1990) developed a TOE framework to describe the factors that influence firms' technological innovation decisions. The technological context reflects the technological infrastructure and capabilities that influence the implementation of a firm's innovation. Technological infrastructure includes a firm's current equipment and technology practices, which are important in innovation decisions because they determine the scope and speed of technological change that can be achieved by a firm (Hue, 2019). Technological capabilities, on the other hand, reflect the expertise and skills needed to effectively utilize the components of technological infrastructure (Aboelmaged, 2014). The literature proposes measuring technological infrastructure and capabilities using the quality of the workforce and the industry sector in which the firm is located, among them, quality of the workforce is measured by the percentage of high-quality employees (Castillejo et al., 2006). In addition, innovation ecosystem theory suggests that high-level talent is a key factor influencing the performance of innovation ecosystems, as the high quality of high-level talent already available can reduce the cost of learning, save the organization's time costs and improve management efficiency (Valkokari, 2015). Based on the above analysis, this study will analyze technological factors from the perspective of innovation talent and measure innovation talent in terms of R&D employees.

The organizational context is concerned with the resources and interactions associated with innovation. Existing studies have discussed the impact of organizational-level factors on innovation from multiple perspectives. Studies from an organizational characteristics perspective have argued that characteristics such as organizational size, organizational ownership structure, and organizational competition affect firm innovation (Hue, 2019; Kinkel et al., 2021). Studies based on the organizational support perspective have found that factors such as organizational support and managerial barriers will also affect firm innovation (Aboelmaged, 2018; Nam et al., 2019). Studies have also combined the TOE framework with absorptive capacity theory to highlight the important role of R&D in innovation (Jantunen, 2005; Liao et al., 2021) and have found that organizational R&D expenditures play an important role in the transformation of science and technology to create new knowledge and enhance innovation capacity (Kim et al., 2020). To manage organizational change for green innovation (Dangelico et al., 2017), firms require expertise in absorptive capacity and sustainability to facilitate the implementation of green innovation (Aboelmaged and Hashem, 2019), and in this sense, R&D is an organizational level that is required for green innovation at the organizational level (Zhang et al., 2020). Therefore, this paper focuses on analyzing the impact of organizational-level factors on green innovation from the perspective of R&D based on the perspective of the TOE framework combined with absorptive capacity theory.

The environmental context reflects the impact of external factors such as competition, stakeholder pressure, and regulatory environment on firm innovation (Tornatzky et al., 1990). The existing literature generally analyzes the impact of environmental factors on firm innovation from two perspectives. On the one hand, the role of factors such as market competition, competitive pressure, customer demand and customer pressure is discussed from the perspective of market stakeholders (Dai et al., 2018; Nam et al., 2019; Qalati et al., 2021). On the other hand, the role of factors such as government laws, environmental protection requirements, and government support are discussed from the perspective of government stakeholders (Aboelmaged, 2018; Chen et al., 2018; Hue, 2019; Nam et al., 2019). It is found that government support for innovation activities conducted by firms through policy support, such as policy leaning and financial subsidies, helps firms break through the resource bottlenecks faced in the process of innovation activities (Hue, 2019). Because this paper focuses on the impact of the BRI on green innovation in manufacturing enterprises, the role of environmental factors is mainly analyzed from the perspective of government support.

According to the TOE framework, firm innovation can be facilitated when internal and external drivers can be effectively established, and one of the key advantages of the TOE framework is its flexible nature, which allows for the categorization of studies that reflect factors that stimulate or hinder firm innovation (Aboelmaged, 2014). Many empirical studies have used the TOE framework as a theoretical basis to examine the adoption of new technologies by firms (Chiu et al., 2017) and the factors influencing innovation (Hue, 2019); environmentally sustainable practices and technological innovation in SMEs (Chege and Wang, 2020); competitive ability and sustainable practices (Aboelmaged, 2018); and climate change, sustainability and economic growth (Ferreira et al., 2020). Therefore, this paper analyzes the influence mechanism of technology–organization–environment factors on the relationship between the BRI and green innovation in manufacturing firms based on the TOE framework, as shown in Figure 1.

3. Research hypothesis

Corporate green innovation refers to innovative activities that contribute to resource conservation and environmental protection in terms of reducing resource and energy consumption, avoiding or reducing pollution emissions, and reducing environmental risks (Castellacci and Lie, 2017). Green innovation can create new opportunities for environmentally friendly practices in firms (Albort-Morant et al., 2018), reduce the pollution rate of firms (Castellacci and Lie, 2017) and save energy (Huang and Li, 2017; Wang et al., 2017). Therefore, green innovation is an important tool that can help societies, organizations, and firms reach environmental sustainability goals, improve economic performance, face the challenges of green and environmental innovation, and play an important role in achieving competitive advantage (Takalo and Tooranloo, 2021).

3.1. BRI and green innovation in manufacturing enterprises

Recent studies have focused on the relationship between the BRI and carbon emission reduction, sustainable development, energy intensity, and green total factor productivity. Country-based studies have found that Chinese outward foreign direct investment (OFDI) helps increase the capacity efficiency of countries along the Belt and Road, thereby reducing their carbon emissions (Chen et al., 2021a). Rauf et al. analyzed the interrelationships among energy consumption, economic growth, population growth, financial development, and carbon emissions in 65 countries along the "Belt and Road" and found that energy consumption, high-tech industries, and economic growth deteriorated environmental quality, while financial and renewable energy consumption had a favorable impact on the environment (Rauf et al., 2020). A study on the relationship between the BRI and energy intensity found that, under the premise of reducing energy intensity, the scale of trade between China and countries along the "Belt and Road" contributes to the convergence rate of energy intensity when the trade threshold is exceeded, and technology effects will accelerate the convergence of energy intensity (Qi et al., 2019). A study at the provincial level in China found that the BRI increased green total factor productivity in the provinces along the route and that technological progress played a major driving role (Liu and Xin, 2019). These studies provide preliminary evidence on the relationship between the "Belt and Road" and green development at the macro level. At the micro level, studies have also begun to discuss the relationship between green innovation of enterprises along the "Belt and Road." Two recent studies have found that firms investing in Belt and Road countries have higher green innovation performance than other firms (Zhu and Sun, 2020; Yang and Li, 2021). Based on the

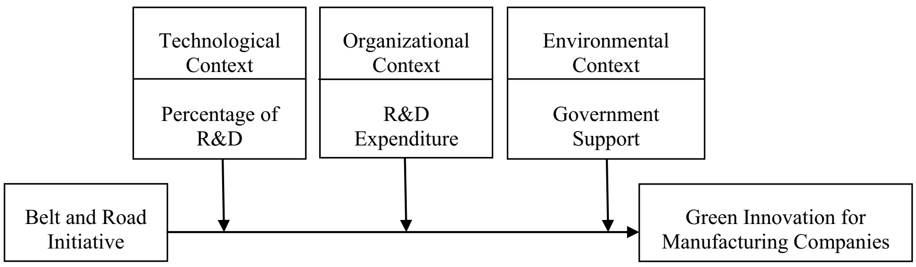

FIGURE 1
Theoretical framework.

above analysis, we believe that the BRI will promote green innovation in Chinese manufacturing enterprises, for which the following hypothesis is proposed.

> *H1*: The BRI will improve the level of green innovation in Chinese manufacturing enterprises.

3.2. Technological factors and green innovation in manufacturing companies

According to the analysis in the theoretical framework section, the quality of the workforce can be a key element in measuring technological infrastructure and capabilities (Castillejo et al., 2006), and in the TOE framework, the technological dimension is crucial for firm innovation because it determines the technological changes that can be made at the firm level (Tornatzky et al., 1990). The value of a technological resource depends to a large extent on the extent to which it works in concert with other technologies being used and facilitates green innovation activities (Zhang et al., 2020). The quality of the workforce as a technological resource affects firm innovation performance (Castillejo et al., 2006), and skilled employees such as R&D staff are an important knowledge resource for the firm because they carry the firm's knowledge and culture to the greatest extent and have the potential to improve the firm's ability to identify, absorb, and manage knowledge and thus promote innovation in the firm (Hue, 2019). Based on the above discussion, we believe that the higher the percentage of R&D employees, the stronger the contribution of the BRI to enterprises green innovation, and we propose the following hypothesis.

> *H2*: The higher the percentage of R&D employees, the stronger the promotion effect of the BRI will be on green innovation in Chinese manufacturing enterprises compared to those with a lower percentage of R&D employees.

3.3. Organizational factors and green innovation in manufacturing companies

This paper discusses the role of organizational factors by combining the TOE framework with absorptive capacity theory (Jantunen, 2005; Liao et al., 2021). According to the TOE framework, organizational capabilities are also an important factor influencing firm innovation (Tornatzky et al., 1990), where innovation capabilities help firms enhance their green innovation (Zhang et al., 2020), while absorptive capacity theory emphasizes R&D importance (Aboelmaged and Hashem, 2019), arguing that R&D is a driving factor that affects firms' innovation capabilities (Kim et al., 2020; Papanastassiou et al., 2020). The impact of R&D on firm innovation in the context of the BRI has also received extensive attention in the literature, and these studies have found that the BRI promotes foreign direct investment in R&D by Chinese firms, which in turn leads to an increase in firm innovation efficiency (Zhao and Fang, 2019). Companies that actively participate in the BRI are able to acquire green technologies for cash through foreign direct investment and cross-border mergers and acquisitions, thus promoting the green R&D capabilities of enterprises (Zhu and Sun, 2020). The BRI enhances the R&D efficiency of enterprises, thus promoting their green upgrading and transformation (Yang and Li, 2021). These studies provide supportive evidence for the relationship between R&D and innovation in the BRI, for which the following hypotheses are proposed.

> *H3*: The stronger the R&D expenditures of firms, the stronger the green innovation effect of the BRI will be on Chinese manufacturing firms compared to the weak R&D expenditures of firms.

3.4. Environmental factors and green innovation in manufacturing companies

This paper assesses the impact of the BRI on green innovation in Chinese manufacturing firms and therefore focuses more on the role of external environmental factors at the governmental level. Environmental factors are the external factors that influence firms' innovation in the TOE framework (Tornatzky et al., 1990), among which government support is one of the external environmental factors that influence firms' innovation (Zhu et al., 2004; Hue, 2019). The focus of cooperation in the BRI involves economic, cultural, political, and transportation areas, which are included in the policy communication, facility connection, trade flow, financial integration, and people-to-people communication proposed in the Vision. The "five links" are the main cooperation elements of the "Belt and Road," among which policy communication is the most basic link and plays a fundamental role (Lu et al., 2021). In China, local governments along the Belt and Road will help enterprises better participate in the construction of the Belt and Road by introducing relevant support policies and improving the local policy environment (Lu et al., 2021). It was found that policy support from local governments along the BRI enhanced the export quality of enterprises in core cities along the BRI (Lu et al., 2021). In addition, government subsidies, as a kind of government-supported institutional arrangement, also play a significant role in enterprises' production and operation (Yu, 2021), based on which we infer that support from local governments will enhance the green innovation level of manufacturing enterprises through the BRI.

> *H4*: The stronger the support from local governments, the stronger the promotion effect of the BRI will be on the green innovation of Chinese manufacturing enterprises.

4. Research design

4.1. Econometric model setting

The main objective of this empirical study is to identify the causal relationship between the BRI and enterprises green innovation. In existing literature, quasi natural experimental design and fsQCA are commonly used methods for identifying causal relationships. For example, the existing research used quasi natural experimental design to discuss the BRI and foreign direct investment (Yu et al., 2019; Nugent and Lu, 2021), there are also literature using the fsQCA method to discuss the issue of digital green innovation in enterprises (Yin and Yu, 2022). This paper uses the research design of quasi natural experiments to identify causal relationships. We use the BRI as a quasi-natural experiment and apply the difference-in-differences method to study the impact of the BRI on green innovation in Chinese manufacturing enterprises. In assessing the effect of the BRI, we choose the year 2014, when the BRI officially appeared in the Government Work Report, as a time of exogenous shocks (Zhu and Sun, 2020). The focus of our analysis is the level of green innovation of Chinese manufacturing firms, so we use the core cities along the Belt and Road in China as the grouping variable. The manufacturing firms located in the core cities along the Belt and Road are in the experimental group, while those located in other cities are in the control group. This research design is consistent with existing literature in terms of selecting grouping variables, the difference is that the existing literature discusses the relationship between the BRI and China's high-quality exports (Lu et al., 2021), while this paper examines the impact of the BRI on green innovation of Chinese manufacturing enterprises.

According to the above design scheme, a two-way fixed effects difference-in-differences model is constructed:

$$GreInv_{it} = \alpha + \beta Dcity_i * post_t + \mu_i + \lambda_t + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

Equation 1 is a two-way fixed effects difference-in-differences model that considers individual fixed effects (μ_i) and time fixed effects (λ_t). In the model, $GreInv_{it}$indicates the green innovation level of enterprises, measured by green patents. $Dcity_i$ is a grouping variable of core cities along the Belt and Road, which takes the value of 1 when the city where the enterprise is located is a core city along the Belt and Road; otherwise, it takes the value of 0. $post_t$ is a dummy variable of the treatment effect period (Zhu and Sun, 2020; Lu et al., 2021). $Dcity_i * post_t$ is a difference-in-differences interaction term used to estimate the micro impact of the BRI. X_{it} is a set of firm-level control variables, and ε_{it} is a random disturbance term. β is the coefficient of the difference-in-differences interaction term that is our focus, and its economic significance is the promotion effect of the BRI on green innovation in manufacturing firms.

4.2. Variables and data

4.2.1. Variables

(1) Corporate green innovation. It is measured by the number of green patents including the number of green invention applications (LnGreInvia), the number of green invention acquisitions (LnGreInvig), and the sum of the number of green invention applications and acquisitions (LnGreInviaig). In the specific analysis of the data, the above three variables were logarithmically transformed, which will be +1 to the number of each green patent and then taking the natural logarithm value.

(2) Variables related to the BRI. In this paper, we construct a difference-in-differences model in two city-year dimensions to identify the micro impacts of the initiative. In the city dimension, we take the 39 core cities along the Belt and Road mentioned in the Vision as the basis; refer to existing studies (Lu et al., 2021); and exclude two cities, "Hong Kong, China" and "Macau, China," which lack data, leaving 37 core cities along the Belt and Road. If an enterprise is located in a core city along the Belt and Road, the value is 1, indicating that the enterprise enters the experimental group; if an enterprise is located in a noncore city along the Belt and Road, the value is 0, indicating that the enterprise enters the control group. In terms of the time dimension, we refer to the existing studies (Zhu and Sun, 2020; Lu et al., 2021) and use 2014, the second year of the BRI, as the starting year when the treatment effect begins to take effect.

(3) Relevant variables for mechanism analysis. In this paper, we apply the TOE framework to analyze the mechanism of the impact of the BRI on green innovation in Chinese manufacturing enterprises, including the technology dimension, measured by the share of R&D personnel (RDpr) (Hue, 2019); the organizational dimension, measured by the logarithm of R&D expenditures (lnRDexp) (Zhang et al., 2020); and the environmental level dimensions, measured by government support (pro_degree) and government grants (govgrants) (Lu et al., 2021; Yu, 2021).

(4) Control variables. Referring to existing studies (Zhu and Sun, 2020; Yang and Li, 2021), the control variable X_{it} is a set of firm-level variables, including total net asset margin (ROAA), operating profit margin (OPR), total asset growth rate (TagrA), operating income growth rate (OrgrA), cash ratio (Cashr), gearing ratio (Alr) Total Assets (Tassets), and Total Operating Income (Toincomes).

4.2.2. Data

The data in this paper are mainly obtained from the China Stock Market & Accounting Research (CSMAR) database and the China Research Data Service Platform (CNRDS). Among them, the basic information of listed companies, financial data and city-level data are obtained from the CSMAR database for the time interval of 2011–2018. The data on green innovation were obtained from the CNRDS Green Patent Database. We first merged the basic information and financial data of listed companies from the CSMAR database into one data file based on the stock codes of listed companies. We then merged the patent data from the CNRDS Green Patent Database, based on the stock codes of listed companies, into the financial data file of listed companies, which became the data file for the analysis of this paper, with a total of 13,424 observations in the data file. In the robustness analysis, city-level data were added.

5. Results

5.1. Baseline regression

The first descriptive statistical analysis was performed for the main variables, as shown in Table 1. The first column in Table 1 shows the names of the variables in the DID model, and the second column shows the meanings of the variables. The first to third rows are the dependent variables in the DID model, and the three measures of green innovation are taken as logarithms; the fourth row is the grouping variables of core cities along the Belt and Road, and the fifth row is the dummy variables of the treatment effect period. The other rows are the variables related to mechanism analysis and control variables.

TABLE 1 Descriptive statistical analysis of the main variables.

Variables	Meaning	Mean	SD	Min	Max
LnGreInvia	Logarithm of the number of green invention applications	0.502	0.908	0	6.810
LnGreInvig	Logarithm of the amount of green inventions obtained	0.242	0.591	0	5.670
LnGreInviaig	Logarithm of the sum of the number of green invention applications and acquisitions	0.597	0.985	0	7.087
Dcity	Core city dummy variables	0.429	0.495	0	1
post	Treatment effect period dummy variables	0.685	0.464	0	1
RDpr	Percentage of R&D staff	8.659103	12.91791	0	94.49
lnRDexp	Logarithm of R&D expenditures	17.50	1.655	6.908	24.62
govgrants	Government grants	3.909e+07	1.363e+08	−4.796e+06	3.985e+09
ROAA	Net profit margin on total assets	0.0395	0.0828	−3.994	0.482
OPR	Operating margin	0.0640	0.452	−25.94	19.16
TagrA	Total assets growth rate	0.234	0.751	−0.928	45.46
OrgrA	Operating income growth rate	0.968	41.66	−5.408	4,500
Cashr	Cash ratio	1.079	3.076	−4.359	167.5
Alr	Gearing ratio	0.391	0.204	0.00708	1.758
lnTassets	Logarithm of total assets	21.87	1.178	17.64	27.39
lnToincomes	Logarithm of total operating income	21.26	1.369	15.51	27.53
Dchangj	Yangtze river economic belt cities dummy variable	0.0853	0.279	0	1
Dprocap	Dummy variables for provincial capital cities or municipalities directly under the central government	0.368	0.482	0	1

In this paper, a difference-in-differences model is constructed to assess the impact of the BRI on green innovation in Chinese manufacturing enterprises. Specifically, the effect of the initiative on green innovation is estimated according to Equation 1, controlling for both individual fixed effects and time fixed effects as well as firm-level and city-level variables; the estimation results are presented in Table 2. The first column of the dependent variable is the number of green inventions applied for, the second column is the number of green inventions obtained, and the third column is the sum of the number of green inventions applied for and obtained. From the results, the BRI has a significant promotion effect at the level of 0.05 ($\beta = 0.0451, p < 0.05$) on the number of applications for green inventions by manufacturing enterprises, a significant promotion effect at the level of 0.1 ($\beta = 0.0269, p < 0.1$), on the number of acquisitions of green inventions, and a significant promotion effect at the level of 0.1 on the number of applications and acquisitions of green inventions by manufacturing enterprises. and a significant contribution effect on the sum of applications and acquisitions of green inventions at the level of 0.05 ($\beta = 0.0512, p < 0.05$). The fourth to sixth columns further control for whether the city where the enterprise is located is a core city in the Yangtze River Economic Belt and whether it is a provincial capital city (or a municipality directly under the central government), and the results remain robust after controlling for city-level variables. The effect on the number of green invention applications and the sum of green invention applications and acquisitions in the manufacturing industry of the BRI remains significant, and the effect on the number of green invention acquisitions is significant at the 0.1 level. From the results of the control variables, the impact of the cash ratio, total assets, gross operating income, and core cities of the Yangtze River Economic Belt on green innovation is significantly positive, while the impact of the total assets growth rate and provincial capital cities (municipalities directly under the central government) on green innovation is negative. From the estimation results of the benchmark model, the "Belt and Road" Initiative does have a catalytic effect on the green innovation level of Chinese manufacturing enterprises, and H1 is supported.

5.2. Parallel trend and placebo test

5.2.1. Parallel trend test

The baseline regression tested the causal effect of the BRI on the green innovation of Chinese manufacturing enterprises, but the validity of the difference-in-differences results must be tested by the parallel trend, so we tested the common trend of the green invention applications of the experimental group and the control group. The results are shown in Figure 2. Before the BRI, the green invention applications of the experimental group and the control group maintained a common growth trend, and after the initiative was proposed, the green invention applications of the experimental group were significantly higher than those of the control group, and the parallel trend test was passed.

TABLE 2 Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnGreInvia	LnGreInvig	LnGreInviaig	LnGreInvia	LnGreInvig	LnGreInviaig
c.Dcity#c.post	0.0451** (0.0207)	0.0269* (0.0152)	0.0512** (0.0210)	0.0478** (0.0208)	0.0255* (0.0153)	0.0533** (0.0210)
ROAA	−0.0770 (0.0745)	−0.1274** (0.0513)	−0.1208 (0.0796)	−0.0808 (0.0746)	−0.1272** (0.0513)	−0.1244 (0.0798)
OPR	−0.0051 (0.0201)	−0.0061 (0.0118)	−0.0120 (0.0232)	−0.0055 (0.0201)	−0.0060 (0.0118)	−0.0123 (0.0232)
TagrA	−0.0357*** (0.0090)	−0.0180*** (0.0040)	−0.0382*** (0.0087)	−0.0357*** (0.0090)	−0.0180*** (0.0040)	−0.0381*** (0.0087)
OrgrA	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)
Cashr	0.0045** (0.0020)	0.0036*** (0.0011)	0.0048** (0.0020)	0.0045** (0.0020)	0.0035*** (0.0011)	0.0048** (0.0020)
Alr	−0.0474 (0.0576)	0.0162 (0.0383)	−0.0406 (0.0582)	−0.0484 (0.0576)	0.0166 (0.0383)	−0.0415 (0.0583)
lnTassets	0.2854*** (0.0261)	0.1223*** (0.0163)	0.3093*** (0.0265)	0.2841*** (0.0261)	0.1228*** (0.0163)	0.3082*** (0.0265)
lnToincomes	0.0423** (0.0193)	−0.0019 (0.0122)	0.0369* (0.0197)	0.0452** (0.0194)	−0.0025 (0.0122)	0.0395** (0.0198)
Dchangj				0.6266*** (0.2393)	0.0314 (0.1207)	0.6093** (0.2556)
Dprocap				−0.2426** (0.1026)	0.0839 (0.0726)	−0.2081* (0.1085)
Constant	−6.6247*** (0.4193)	−2.3968*** (0.2581)	−6.9389*** (0.4166)	−6.6222*** (0.4206)	−2.4281*** (0.2595)	−6.9455*** (0.4183)
Observations	13,424	13,424	13,424	13,424	13,424	13,424
R-squared	0.7446	0.6848	0.7819	0.7447	0.6849	0.7820
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.2.2. Placebo test

As the results of the baseline regression may also be affected by aspects such as omitted variables and random factors, we refer to the methods of existing studies (La Ferrara et al., 2012; Li et al., 2016) by randomly generating the reform time and randomly screening the Belt and Road along the core cities and constructing a randomized experiment at both reform time-city levels to conduct a placebo test. Specifically, randomized experiments were conducted according to the fourth column in Table 2, that is, after controlling for individual fixed effects, time-fixed effects, and firm-level and city-level control variables, to examine the effect of randomly generated reform time-city on firms' green invention filings and to judge the reliability of the findings based on the probabilities of the estimated coefficients of the benchmark regressions obtained from the spurious experiments. We repeat the above placebo test 500 times to enhance the validity of the placebo test and finally plot the distribution of the estimated coefficients of the impact of the BRI on the green innovation of manufacturing enterprises to test whether the level of green innovation of Chinese manufacturing enterprises is also affected by factors other than the BRI. If the estimated coefficients of the impact of the BRI on green innovation are distributed at approximately 0 in the randomized experiment, it indicates that the model setting of Equation 1 does not omit sufficiently important factors, and the estimated results in the baseline regression are indeed due to the BRI. The results of the placebo test are shown in Figure 3, where most of the spurious estimated coefficients are distributed at approximately 0, indicating that the randomly generated combination of reform time and city did not have a significant impact on green innovation, there is no serious problem of omitted variables in the benchmark model setting, and the core findings remain robust.

5.3. Robustness tests

5.3.1. Propensity score matching difference-in-differences model analysis

In the baseline regression analysis, we grouped the firms by whether their cities are core cities along the Belt and Road, which may have advantages in terms of transportation conditions or development strength, making them more likely to enter the experimental group (Lu et al., 2021). Baseline regression may have the problem of sample selection bias. To better select the control group, this paper further employs propensity score matching analysis to test the causal relationship between the BRI and corporate green innovation, all other things being equal.

To match the propensity score, a logit model of whether a city is a core city along the "Belt and Road" is established. The model controls for whether the city is a core city in the Yangtze River Economic Belt, whether it is a provincial capital city or a municipality directly under the central government, the city's GDP, the city's population, the local budget revenue, and the city's total industrial output above the limit. The nearest 1:1 matching is adopted to match the Chinese cities, and then the matched samples are used to estimate the difference-in-differences.

Before performing PSM-DID estimation, the validity of the matching method was examined by plotting kernel density plots of the *p* value scores of the experimental and control groups before and after matching. From the kernel density plots, it can be seen that the matched control group can better serve as a counterfactual outcome for causal inference for the treatment group. The kernel density plots are shown in Figures 4, 5.

Table 3 reports the results of the propensity score matched difference-in-differences model analysis, controlling for firm-level

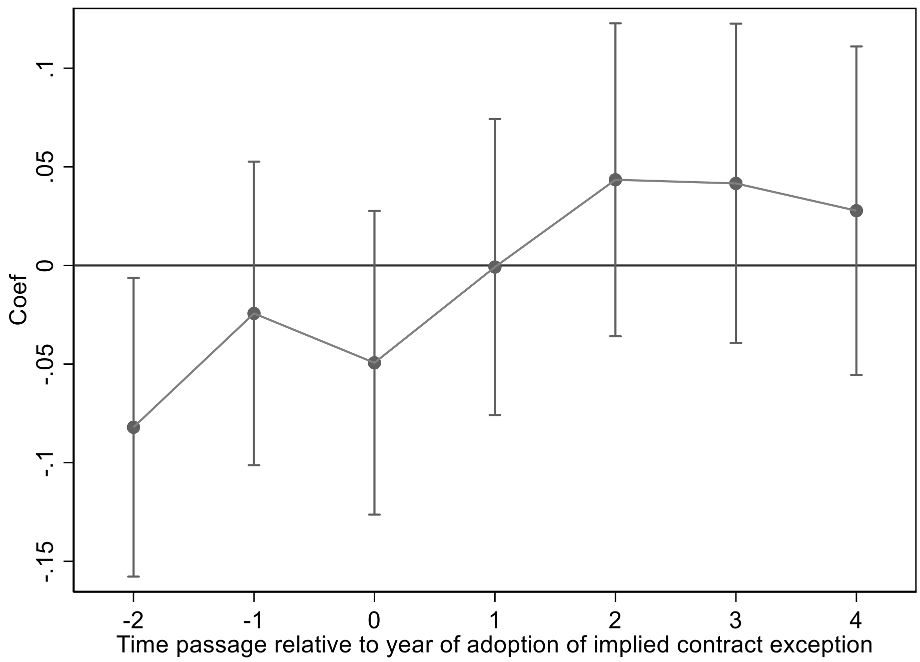

FIGURE 2
Parallel trend test.

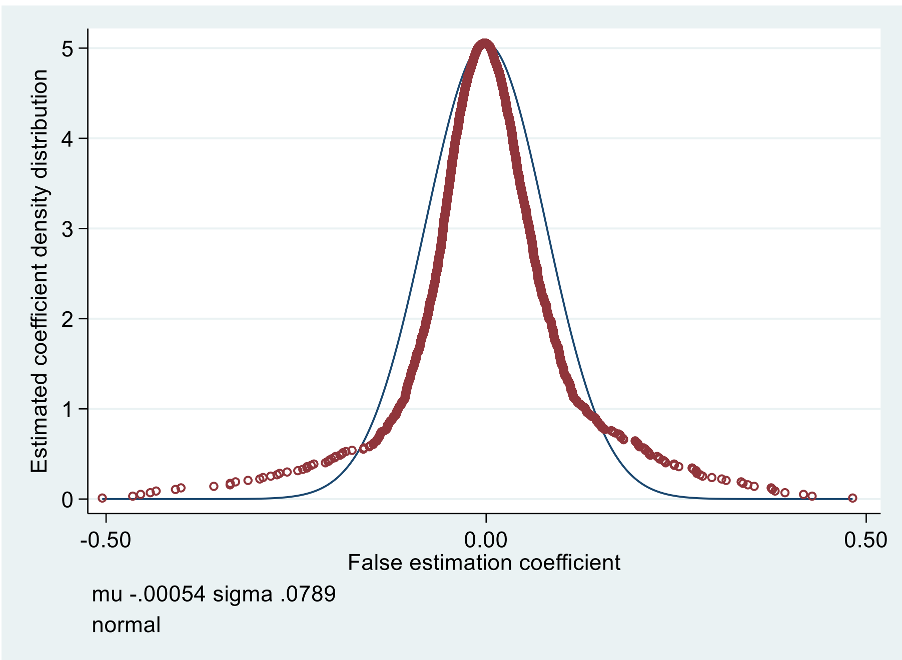

FIGURE 3
Placebo test.

variables in the first column and further controlling for city-level variables in the second column, and the estimation results show that the promotion effect of the BRI on corporate green innovation is significant. In the model controlling only for firm-level variables, the effect of the BRI on green invention applications is significant at the 0.05 level ($\beta = 0.0469, p < 0.05$), the results are still significant at the 0.05 level after controlling for city-level variables ($\beta = 0.0497, p < 0.05$), and the estimation results of the baseline model are still robust.

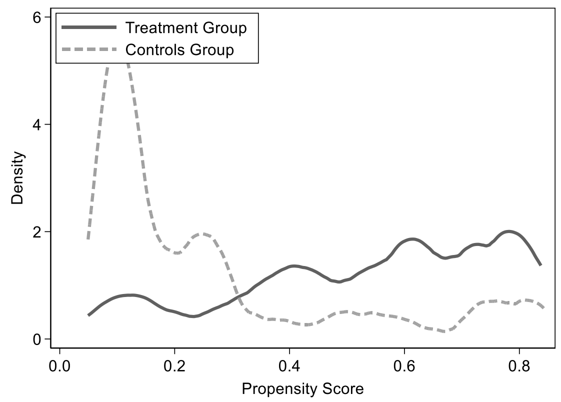

FIGURE 4
p-value fractional Kernel density before matching.

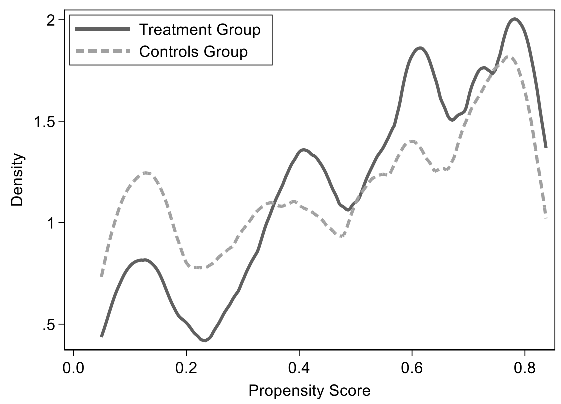

FIGURE 5
P-worthy fractional Kernel density after matching.

5.3.2. Excluding interference from contemporaneous policies

Around the time of the BRI in 2013, there were other policies in China that might affect corporate green innovation. For example, the establishment of the China (Shanghai) Pilot Free Trade Zone in September 2013 and the policy arrangement of expanding the scope of the "VAT reform" pilot in August 2012 will have an impact on enterprise innovation (Liu and Wang, 2018; Wang and Lu, 2019), which may affect the estimation results of the benchmark regression. Therefore, this paper will try to reduce the interference of contemporaneous policies.

(1) Exclude the interference of Shanghai free trade zone

Table 4 reports the effect of the BRI on corporate green innovation after controlling for the Shanghai Free Trade Zone, where Shanghai_after is a dummy variable for the Shanghai Free Trade Zone, which takes the value of 1 for Shanghai after the implementation of the BRI and 0 for Shanghai before. This variable is added to the model as a control variable, representing the effect of controlling for the Shanghai FTA. The first to third columns control for firm-level factors, and the fourth to sixth columns further control for city-level factors. As shown by the results, the effect of the BRI on corporate green innovation is significant after controlling for the effect of the Shanghai Free Trade Zone, and the results of the benchmark regression remain robust.

TABLE 3 PSM-DID estimation results.

Variables	(1)	(2)
	LnGreInvia	LnGreInvia
c.Dcity#c.post	0.0469** (0.0222)	0.0497** (0.0222)
ROAA	−0.0850 (0.0755)	−0.0900 (0.0757)
OPR	−0.0047 (0.0201)	−0.0052 (0.0201)
TagrA	−0.0369*** (0.0092)	−0.0368*** (0.0092)
OrgrA	0.0001 (0.0003)	0.0001 (0.0003)
Cashr	0.0042** (0.0020)	0.0042** (0.0020)
Alr	−0.0407 (0.0606)	−0.0424 (0.0608)
lnTassets	0.2788*** (0.0271)	0.2776*** (0.0271)
lnToincomes	0.0405** (0.0201)	0.0441** (0.0202)
Dchangj		0.7886*** (0.2702)
Dprocap		−0.2440** (0.1039)
Constant	−6.4464*** (0.4396)	−6.4815*** (0.4430)
Observations	12,411	12,411
R-squared	0.7495	0.7497
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

(2) Excluding the interference of the "VAT Reform" policy

Table 5 reports the effect of the BRI on corporate green innovation after controlling for vat_after. Among them, vat_after is the dummy variable of "VAT reform," and the pilot cities of "VAT reform" are taken as 1 after the BRI and 0 before the initiative. This variable is added to the model as a control variable to represent the effect of controlling for the impact of the "VAT reform" policy. The first to third columns control for firm-level factors, and the fourth to sixth columns further control for city-level factors. From the results, we can see that after controlling for the effect of "VAT reform," except for the insignificant effect of the fifth column on the amount of green inventions, the effect of the BRI on the green innovation of enterprises is significant, and the results of the benchmark regression are basically robust.

5.3.3. Heterogeneity test

(1) Heterogeneity of advanced manufacturing and traditional manufacturing

Although the industries analyzed in this paper include only manufacturing industries, 10 major areas are proposed as key development directions according to the plan of the action program of Made in China 2025 to achieve the goal of manufacturing power. Based on Made in China 2025, this paper identifies advanced and traditional manufacturing industries in China's manufacturing sector with reference to the existing literature (Hongjian et al., 2021) and analyzes their heterogeneous impact on the relationship between the BRI and green innovation.

We constructed a heterogeneous DID model for estimation by constructing triple interaction terms in three dimensions: city-industry-year. Table 6 reports the estimation results of the heterogeneous DID model, where tttt is the city-industry-years

TABLE 4 Excluding the impact of the shanghai free trade zone.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnGreInvia	LnGreInvig	LnGreInviaig	LnGreInvia	LnGreInvig	LnGreInviaig
c.Dcity#c.post	0.0443** (0.0218)	0.0388** (0.0161)	0.0579*** (0.0221)	0.0475** (0.0218)	0.0373** (0.0162)	0.0606*** (0.0221)
shanghai_after	0.0058 (0.0444)	−0.0859*** (0.0318)	−0.0491 (0.0453)	0.0022 (0.0445)	−0.0859*** (0.0319)	−0.0527 (0.0454)
ROAA	−0.0769 (0.0745)	−0.1280** (0.0515)	−0.1212 (0.0796)	−0.0808 (0.0746)	−0.1279** (0.0515)	−0.1249 (0.0798)
OPR	−0.0051 (0.0201)	−0.0059 (0.0118)	−0.0119 (0.0232)	−0.0055 (0.0201)	−0.0059 (0.0118)	−0.0122 (0.0232)
TagrA	−0.0358*** (0.0090)	−0.0176*** (0.0041)	−0.0379*** (0.0088)	−0.0357*** (0.0090)	−0.0175*** (0.0041)	−0.0379*** (0.0088)
OrgrA	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)
Cashr	0.0045** (0.0020)	0.0035*** (0.0010)	0.0047** (0.0020)	0.0045** (0.0020)	0.0035*** (0.0010)	0.0048** (0.0020)
Alr	−0.0474 (0.0576)	0.0157 (0.0383)	−0.0410 (0.0582)	−0.0484 (0.0576)	0.0160 (0.0383)	−0.0419 (0.0582)
lnTassets	0.2854*** (0.0261)	0.1218*** (0.0163)	0.3090*** (0.0265)	0.2841*** (0.0261)	0.1222*** (0.0163)	0.3079*** (0.0265)
lnToincomes	0.0423** (0.0193)	−0.0016 (0.0122)	0.0371* (0.0197)	0.0452** (0.0194)	−0.0021 (0.0122)	0.0397** (0.0198)
Dchangj				0.6260*** (0.2398)	0.0566 (0.1127)	0.6247** (0.2505)
Dprocap				−0.2425** (0.1026)	0.0802 (0.0729)	−0.2104* (0.1087)
Constant	−6.6250*** (0.4192)	−2.3923*** (0.2579)	−6.9363*** (0.4163)	−6.6223*** (0.4206)	−2.4254*** (0.2593)	−6.9439*** (0.4181)
Observations	13,424	13,424	13,424	13,424	13,424	13,424
R-squared	0.7446	0.6850	0.7819	0.7447	0.6851	0.7820
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

TABLE 5 Excluding the impact of "VAT reform ".

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnGreInvia	LnGreInvig	LnGreInviaig	LnGreInvia	LnGreUmig	LnGreInviaig
c.Dcity#c.post	0.0428** (0.0208)	0.0261* (0.0153)	0.0490** (0.0211)	0.0456** (0.0209)	0.0235 (0.0209)	0.0512** (0.0212)
vat_after	0.0395* (0.0209)	0.0137 (0.0152)	0.0379* (0.0212)	0.0366* (0.0210)	0.0148 (0.0208)	0.0352* (0.0213)
ROAA	−0.0740 (0.0744)	−0.1264** (0.0513)	−0.1180 (0.0794)	−0.0779 (0.0745)	0.0394 (0.0692)	−0.1217 (0.0797)
OPR	−0.0048 (0.0201)	−0.0059 (0.0118)	−0.0117 (0.0232)	−0.0052 (0.0201)	−0.0212* (0.0127)	−0.0120 (0.0232)
TagrA	−0.0358*** (0.0090)	−0.0180*** (0.0040)	−0.0382*** (0.0087)	−0.0358*** (0.0090)	−0.0280*** (0.0082)	−0.0382*** (0.0087)
OrgrA	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)	0.0001 (0.0003)	0.0003 (0.0003)	0.0001 (0.0003)
Cashr	0.0046** (0.0020)	0.0036*** (0.0011)	0.0049** (0.0020)	0.0047** (0.0020)	0.0051*** (0.0016)	0.0050** (0.0020)
Alr	−0.0487 (0.0575)	0.0158 (0.0383)	−0.0419 (0.0581)	−0.0496 (0.0576)	0.1001* (0.0563)	−0.0427 (0.0582)
lnTassets	0.2852*** (0.0261)	0.1222*** (0.0163)	0.3092*** (0.0265)	0.2840*** (0.0261)	0.2367*** (0.0244)	0.3082*** (0.0265)
lnToincomes	0.0407** (0.0193)	−0.0025 (0.0122)	0.0354* (0.0197)	0.0436** (0.0194)	0.0145 (0.0188)	0.0379* (0.0198)
Dchangj				0.5967** (0.2386)	0.2242 (0.1968)	0.5804** (0.2547)
Dprocap				−0.2339** (0.1021)	0.0936 (0.1076)	−0.1997* (0.1078)
Constant	−6.6042*** (0.4195)	−2.3897*** (0.2581)	−6.9192*** (0.4167)	−6.6024*** (0.4209)	−5.1004*** (0.3985)	−6.9265*** (0.4185)
Observations	13,424	13,424	13,424	13,424	13,424	13,424
R-squared	0.7447	0.6849	0.7820	0.7448	0.7094	0.7821
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

triple interaction term. The coefficients of the triple interaction term are all significant, indicating that the BRI has a more significant effect in promoting green innovation in advanced manufacturing industries than in traditional manufacturing industries. The coefficient of the triple interaction term is significant, which indicates that the BRI promotes green innovation in the advanced manufacturing industry compared with the traditional manufacturing industry.

(2) Heterogeneity of enterprise ownership

In recent years, due to the increasing reform of state-owned enterprises (SOEs), further analysis is needed to determine whether the impact of the BRI on corporate green innovation differs between SOEs and non-SOEs. To this end, we constructed a triple interaction term based on three dimensions, city-ownership-years, and conducted a heterogeneous DID model analysis. Among the three dimensions, enterprise ownership is a dummy variable that takes the value of 1 when it is a state-owned enterprise and 0 otherwise. The estimation results of the heterogeneous DID model are shown in Table 7. Ottt is the city-enterprise ownership-year triple interaction term, and it can be seen from the results that all three interaction terms are significant, indicating that relative to non-SOEs, the BRI has a more significant promotion effect on the green innovation of SOEs.

6. Mechanism analysis

Based on the DID model, we found that the BRI has a significant promotion effect on enterprise green innovation. How does the BRI influence corporate green innovation, and what are the mechanisms of influence? Based on the TOE framework, this section discusses the role of technology, organization and environment at the internal and external levels and analyzes the impact mechanism of the BRI on green innovation in enterprises.

6.1. The role of technical factors

To examine the role of technology factors in the relationship between the BRI and corporate green innovation, we analyze the technology factors of enterprises from the perspective of skilled employees and use the percentage of R&D employees as an indicator of technology factors. We construct a heterogeneous DID model by constructing a triple interaction term with three dimensions: city-skilled employee ratio-years. The estimation results are reported in Table 8, where RNDpr_ttt is the triple interaction term with a significantly positive coefficient. The results show that the promotion effect of the BRI on green innovation is more significant for firms with a higher percentage of R&D employees than for those with a lower percentage of R&D employees, and the results test the role of the technology factor, which is supported by H2.

To further analyze the role of technology factors in the BRI, we conducted a difference-in-differences analysis with the percentage of R&D personnel as the dependent variable, and the results are shown in Table 9 ($\beta = 1.0431, p < 0.01$), indicating that the BRI has strengthened the investment in R&D personnel in core cities, which in turn has enhanced the promotion effect of the initiative on green innovation in manufacturing enterprises.

6.2. The role of R&D expenditures

According to the TOE framework, corporate R&D expenditures will also have an impact on corporate green innovation, so we examine

TABLE 6 Industry heterogeneity.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnGreInvia	LnGreInvig	LnGreInviaig	LnGreInvia	LnGreInvig	LnGreInviaig
ttt	0.1094*** (0.0316)	0.0986*** (0.0232)	0.1301*** (0.0323)	0.1094*** (0.0315)	0.0987*** (0.0232)	0.1302*** (0.0322)
tt	−0.0190 (0.0249)	−0.0310 (0.0190)	−0.0251 (0.0259)	−0.0164 (0.0249)	−0.0327* (0.0190)	−0.0231 (0.0259)
ROAA	−0.0620 (0.0729)	−0.1205** (0.0497)	−0.1055 (0.0768)	−0.0667 (0.0730)	−0.1207** (0.0497)	−0.1101 (0.0770)
OPR	−0.0048 (0.0197)	−0.0057 (0.0116)	−0.0114 (0.0226)	−0.0052 (0.0196)	−0.0056 (0.0115)	−0.0118 (0.0227)
TagrA	−0.0365*** (0.0083)	−0.0181*** (0.0042)	−0.0390*** (0.0080)	−0.0364*** (0.0083)	−0.0180*** (0.0042)	−0.0389*** (0.0080)
OrgrA	−0.0000 (0.0003)	−0.0001 (0.0001)	−0.0000 (0.0003)	−0.0000 (0.0003)	−0.0001 (0.0001)	−0.0000 (0.0003)
Cashr	0.0043** (0.0019)	0.0034*** (0.0010)	0.0046** (0.0020)	0.0043** (0.0020)	0.0033*** (0.0010)	0.0046** (0.0020)
Alr	−0.0635 (0.0580)	0.0069 (0.0385)	−0.0575 (0.0585)	−0.0652 (0.0580)	0.0066 (0.0385)	−0.0591 (0.0585)
lnTassets	0.2797*** (0.0255)	0.1200*** (0.0159)	0.3028*** (0.0259)	0.2784*** (0.0254)	0.1206*** (0.0159)	0.3017*** (0.0258)
lnToincomes	0.0474** (0.0193)	−0.0003 (0.0121)	0.0423** (0.0196)	0.0505*** (0.0193)	−0.0006 (0.0121)	0.0452** (0.0196)
Dchangj				0.7397*** (0.2123)	0.1625 (0.1015)	0.7612*** (0.2162)
Dprocap				−0.2397** (0.1032)	0.0884 (0.0739)	−0.2058* (0.1101)
Constant	−6.6050*** (0.4113)	−2.3783*** (0.2576)	−6.9067*** (0.4083)	−6.6155*** (0.4134)	−2.4299*** (0.2596)	−6.9319*** (0.4108)
Observations	13,423	13,423	13,423	13,423	13,423	13,423
R-squared	0.7465	0.6870	0.7839	0.7467	0.6871	0.7841
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.
$***p<0.01$, $**p<0.05$, $*p<0.1$.

TABLE 7 Business ownership heterogeneity.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnGreInvia	LnGreInvig	LnGreInviaig	LnGreInvia	LnGreInvig	LnGreInviaig
Ottt	0.0764** (0.0354)	0.0922*** (0.0277)	0.0831** (0.0361)	0.0791** (0.0353)	0.0917*** (0.0278)	0.0856** (0.0360)
Ott	0.0226 (0.0230)	−0.0002 (0.0165)	0.0269 (0.0234)	0.0246 (0.0231)	−0.0014 (0.0165)	0.0284 (0.0234)
ROAA	−0.0788 (0.0748)	−0.1301** (0.0517)	−0.1231 (0.0799)	−0.0828 (0.0750)	−0.1300** (0.0517)	−0.1268 (0.0801)
OPR	−0.0051 (0.0201)	−0.0061 (0.0119)	−0.0120 (0.0233)	−0.0055 (0.0201)	−0.0061 (0.0118)	−0.0123 (0.0233)
TagrA	−0.0356*** (0.0090)	−0.0183*** (0.0039)	−0.0380*** (0.0087)	−0.0356*** (0.0090)	−0.0182*** (0.0039)	−0.0380*** (0.0087)
OrgrA	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)	0.0001 (0.0003)	−0.0001 (0.0001)	0.0001 (0.0003)
Cashr	0.0042** (0.0019)	0.0032*** (0.0010)	0.0045** (0.0020)	0.0043** (0.0019)	0.0032*** (0.0010)	0.0045** (0.0020)
Alr	−0.0430 (0.0576)	0.0216 (0.0382)	−0.0360 (0.0581)	−0.0439 (0.0576)	0.0218 (0.0382)	−0.0367 (0.0582)
lnTassets	0.2855*** (0.0262)	0.1226*** (0.0163)	0.3093*** (0.0266)	0.2842*** (0.0262)	0.1231*** (0.0163)	0.3082*** (0.0266)
lnToincomes	0.0431** (0.0194)	−0.0008 (0.0122)	0.0378* (0.0198)	0.0461** (0.0194)	−0.0013 (0.0122)	0.0405** (0.0198)
Dchangj				0.6423*** (0.2371)	0.0495 (0.1175)	0.6260** (0.2530)
Dprocap				−0.2496** (0.1034)	0.0755 (0.0730)	−0.2157** (0.1093)
Constant	−6.6440*** (0.4224)	−2.4282*** (0.2601)	−6.9561*** (0.4194)	−6.6425*** (0.4237)	−2.4586*** (0.2615)	−6.9635*** (0.4211)
Observations	13,349	13,349	13,349	13,349	13,349	13,349
R-squared	0.7440	0.6846	0.7814	0.7442	0.6846	0.7815

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

TABLE 8 The role of R&D staff share.

Variables	(1)	(2)
	LnGreInvia	LnGreInviaig
RNDpr_ttt	0.0925*** (0.0247)	0.1096*** (0.0245)
RNDpr_tt	0.0002 (0.0231)	−0.0031 (0.0232)
ROAA	−0.0771 (0.0744)	−0.1206 (0.0794)
OPR	−0.0055 (0.0199)	−0.0124 (0.0230)
TagrA	−0.0349*** (0.0090)	−0.0372*** (0.0088)
OrgrA	0.0001 (0.0003)	0.0001 (0.0003)
Cashr	0.0047** (0.0020)	0.0050** (0.0021)
Alr	−0.0566 (0.0577)	−0.0514 (0.0582)
lnTassets	0.2823*** (0.0261)	0.3061*** (0.0265)
lnToincomes	0.0448** (0.0193)	0.0391** (0.0197)
Dchangj	0.6359*** (0.2320)	0.6203** (0.2467)
Dprocap	−0.2391** (0.1028)	−0.2040* (0.1087)
Constant	−6.5761*** (0.4208)	−6.8917*** (0.4184)
Observations	13,423	13,423
R-squared	0.7451	0.7824
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

the role of corporate R&D expenditures in the relationship between the BRI and corporate green innovation. We constructed a heterogeneous DID model by constructing a triple interaction term with three dimensions: city-R&D expenditure-years. Table 10 reports the estimation results, where RND_ttt is the triple interaction term and its coefficient is significantly positive. The results show that the promotion effect of the BRI on green innovation is more significant for firms with higher R&D expenditures than for those with lower R&D expenditures, and H3 is supported.

To further analyze the role of organizational factors in the BRI, we conducted a difference-in-differences analysis using R&D expenditure (logarithm) as the dependent variable, and the results are shown in Table 11. The BRI significantly boosted the R&D expenditures of manufacturing enterprises ($\beta=0.0631$, $p<0.05$), suggesting that the BRI has strengthened the R&D expenditures of enterprises in core cities, which in turn has enhanced its impact on the promotion effect of the initiative on green innovation in manufacturing enterprises.

6.3. The role of government support and subsidies

(1) The role of policy support

According to the TOE framework, government support, as an external factor, affects firm innovation. In this paper, we analyze the role of government support in terms of policy support from local governments and government subsidies. In the difference-in-differences model constructed in this paper, whether enterprises participate in Belt and Road construction is grouped by whether their locations are core cities along the Belt and Road route. This grouping plan actually highlights the principle that China will give full play to the comparative advantages of each domestic region to promote the construction of the Belt and Road, as mentioned in the Vision. When considering local advantages, the policy support of local governments for Belt and Road construction will have an

TABLE 9 Impact of the BRI on the share of R&D employees in enterprises.

Variables	RDpr
c.Dcity#c.post	1.0431*** (0.2297)
ROAA	−2.6528*** (0.8574)
OPR	−0.4049** (0.1748)
TagrA	−0.2011** (0.0993)
OrgrA	−0.0087** (0.0039)
Cashr	−0.2730*** (0.0950)
Alr	0.1842 (0.7639)
lnTassets	1.4301*** (0.3060)
lnToincomes	0.6569** (0.2626)
Dchangj	1.8735 (3.3717)
Dprocap	−1.5826 (1.7194)
Constant	−37.1575*** (4.5837)
Observations	13,423
R-squared	0.7627
Firm FE	Yes
Year FE	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 11 Impact of BRI on enterprise R&D expenditure.

Variables	lnRDexp
c.Dcity#c.post	0.0631** (0.0247)
ROAA	−0.0050 (0.1360)
OPR	−0.0633** (0.0258)
TagrA	−0.0544*** (0.0086)
OrgrA	−0.0001 (0.0003)
Cashr	0.0019 (0.0020)
Alr	−0.3926*** (0.0846)
lnTassets	0.4220*** (0.0354)
lnToincomes	0.4785*** (0.0320)
Dchangj	0.8465** (0.4006)
Dprocap	−0.1953 (0.2982)
Constant	−1.5947*** (0.5137)
Observations	12,699
R-squared	0.8918
Firm FE	Yes
Year FE	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 10 The role of R&D expenditures.

Variables	(1)	(2)
	LnGreInvia	LnGreInviaig
RND_ttt	0.2811*** (0.0351)	0.2797*** (0.0350)
RND_tt	−0.0288 (0.0212)	−0.0229 (0.0216)
ROAA	−0.0821 (0.0744)	−0.1258 (0.0787)
OPR	−0.0044 (0.0198)	−0.0112 (0.0230)
TagrA	−0.0335*** (0.0090)	−0.0359*** (0.0088)
OrgrA	0.0001 (0.0003)	0.0001 (0.0003)
Cashr	0.0036** (0.0018)	0.0039** (0.0019)
Alr	−0.0349 (0.0572)	−0.0280 (0.0578)
lnTassets	0.2770*** (0.0257)	0.3012*** (0.0261)
lnToincomes	0.0405** (0.0192)	0.0349* (0.0196)
Dchangj	0.6600*** (0.2253)	0.6424*** (0.2412)
Dprocap	−0.2603** (0.1058)	−0.2257** (0.1115)
Constant	−6.3660*** (0.4110)	−6.6905*** (0.4091)
Observations	13,424	13,424
R-squared	0.7469	0.7839
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

important impact on the effect of the BRI. We refer to the study of Lu et al. (2021) and use the research report of the Belt and Road Data Center of China National Information Center (2016) to group the top 10 provinces in terms of policy support as high. The top 10 provinces in the report are considered to be high policy support provinces while the other provinces are considered to be low policy support provinces, and the triple interaction term of city-policy support-years is constructed to analyze the heterogeneity DID model. The estimated results are shown in Table 12, where pro_ttt is the city-policy support-years triple interaction term with a significantly positive estimated coefficient. The heterogeneous DID model examines the role of policy support at the provincial level and shows that the promotion effect of the BRI on corporate green innovation is marginally significant at the level of 0.1 in provinces with higher policy support compared to provinces with lower policy support.

(2) The role of government subsidies

In addition, we examine the role of government subsidies in the relationship between the BRI and corporate green innovation. We construct a heterogeneous DID model by constructing a triple interaction term with three dimensions: city-government subsidy-years. Table 13 reports the estimation results, where gra_ttt is the triple interaction term with a significant positive coefficient. The results indicate that the promotion effect of the BRI on green innovation is more significant for firms with higher government subsidies than for those with lower government subsidies, and H4 is supported.

To further analyze the role of environmental factors in the BRI, we conducted a difference-in-differences analysis with government subsidies as the dependent variable, and the results are shown in Table 14 ($\beta = 1.1247\text{e}+07, p < 0.01$), indicating that the BRI strengthens the government subsidies of enterprises in core cities, which in turn enhances the promotion effect of the initiative on the green innovation of manufacturing enterprises.

TABLE 12 The role of policy support efforts.

Variables	(1)	(2)
	LnGreInvia	LnGreInviaig
pro_ttt	0.0608* (0.0345)	0.0577 (0.0355)
pro_tt	0.0096 (0.0307)	0.0181 (0.0316)
ROAA	0.0592 (0.0657)	−0.0023 (0.0645)
TagrA	0.0072 (0.0084)	0.0079 (0.0084)
OrgrA	0.0004 (0.0004)	0.0005 (0.0004)
Cashr	0.0025* (0.0015)	0.0026* (0.0015)
Constant	0.4982*** (0.0083)	0.5963*** (0.0084)
Observations	13,424	13,424
R-squared	0.7337	0.7715
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 13 The role of government grants.

Variables	(1)	(2)
	LnGreInvia	LnGreInviaig
gra_ttt	0.1225*** (0.0277)	0.1322*** (0.0277)
gra_tt	0.0139 (0.0212)	0.0174 (0.0216)
ROAA	−0.0825 (0.0751)	−0.1278 (0.0799)
OPR	−0.0058 (0.0200)	−0.0125 (0.0232)
TagrA	−0.0346*** (0.0090)	−0.0367*** (0.0088)
OrgrA	0.0001 (0.0003)	0.0001 (0.0003)
Cashr	0.0044** (0.0020)	0.0047** (0.0020)
Alr	−0.0583 (0.0581)	−0.0481 (0.0586)
lnTassets	0.2815*** (0.0260)	0.3041*** (0.0265)
lnToincomes	0.0474** (0.0194)	0.0416** (0.0198)
Dprocap	−0.2890** (0.1266)	−0.2613** (0.1267)
Constant	−6.5386*** (0.4179)	−6.8257*** (0.4161)
Observations	13,424	13,424
R-squared	0.7462	0.7832
Firm FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7. Conclusion and implications

7.1. Discussion

Through the analysis of DID, this paper finds that the BRI has promoted the green innovation of Chinese manufacturing enterprises, and this result is still robust after the placebo test and robustness test. This result is a strong response to the discussion on the relationship between the BRI and sustainable development in the existing literature (Hu et al., 2023; Zhang et al., 2023). Based on the existing literature on the BRI and renewable energy consumption (Fang et al., 2022), ecological environment (Zhang et al., 2021), sustainable development goals (Senadjki et al., 2022), this paper adds evidence that the BRI promotes green innovation in manufacturing enterprises. The results of heterogeneity analysis show that the BRI plays a stronger role in promoting green innovation in advanced manufacturing industries and state-owned enterprises, and this result can provide a basis for government decision-making. Mechanism analysis is based on the TOE framework, discovering the roles of technology, research and development, and government support. The research results add insightful explanations to existing research on the impact mechanism of green innovation in enterprises (Yin et al., 2022). In addition, the research results of this paper can also provide reference for the development of green innovation in other regions, such as the Pacific Rim region (West and Von Geusau, 2019). In fact, smart specialization in Europe also places great emphasis on the role of policy support in innovation (Balland et al., 2019; Pintar and Scherngell, 2022).

7.2. Conclusion

This paper joins the discussion on the relationship between the BRI and sustainable development by studying the impact of the Initiative on green innovation in Chinese manufacturing enterprises. Based on the core cities along the Belt and Road, we use the difference-in-differences method to identify the causal relationship between the BRI and the green innovation of Chinese manufacturing enterprises and analyze the impact mechanism. Through empirical analysis, we found that (1) the BRI has a significant promotion effect on the green innovation of Chinese manufacturing enterprises. The BRI has significantly increased the number of green invention applications by manufacturing enterprises in core cities along the route, and there is also a significant promotion effect in the total number of green patents (the sum of green invention applications and green inventions obtained), which remains robust after the propensity score matching difference-in-differences analysis, excluding contemporaneous policy interference and heterogeneity analysis. (2) In the benchmark regression, the BRI has a marginally significant impact on the amount of green inventions obtained by enterprises after controlling for the effect of the Shanghai Free Trade Zone in the same period. (3) The results of the heterogeneity test reveal that the BRI has a more significant effect on promoting green innovation in advanced manufacturing enterprises than in traditional manufacturing industries. Compared with nonstate-owned enterprises, the promotion effect of the BRI on the green innovation of state-owned enterprises is more significant. (4) The mechanism analysis shows that the TOE framework explains the impact mechanism of the BRI on green innovation in Chinese manufacturing firms. The BRI has led companies in the core cities to increase their focus on skilled employees, and through the knowledge they bring to the table, the BRI has had an enhanced effect on green innovation in Chinese manufacturing companies. The BRI has prompted enterprises in the core cities to increase their R&D expenditures and enhance their innovation capabilities by strengthening R&D, which has enhanced the green innovation effect of the BRI on Chinese manufacturing enterprises. The BRI has strengthened government support for enterprises by increasing

TABLE 14 Impact of the BRI on government subsidies for enterprises.

Variables	govgrants
c.Dcity#c.post	1.1247e+07*** (3746333.6866)
ROAA	1.3460e+07 (1.2935e+07)
OPR	−2.7104e+06 (1,747,288.3118)
TagrA	−6.2097e+06*** (1,241,305.2326)
OrgrA	19,306.6042 (22,988.1522)
Cashr	155,844.7250 (126,575.5345)
Alr	−2.0970e+07* (1.0760e+07)
lnTassets	4.4382e+07*** (6,522,303.1575)
lnToincomes	−5.4659e+06 (3,887,224.5251)
Dprocap	−3.3426e+06 (3.5821e+07)
Constant	−8.0907e+08*** (9.2210e+07)
Observations	12,802
R-squared	0.6753
Firm FE	Yes
Year FE	Yes

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

subsidies for enterprises, which has enhanced the effect of the BRI in promoting green innovation in Chinese manufacturing enterprises.

7.3. Theoretical contributions

This paper uses a difference-in-differences approach to assess the impact of the BRI on green innovation in Chinese manufacturing enterprises, enriching the study of the relationship between the BRI and sustainable development, with the following major marginal contributions: (1) This paper analyzes the impact of the BRI on the green innovation of Chinese manufacturing enterprises at the level of manufacturing enterprises, providing a new micro perspective on the relationship between the BRI and sustainable development on the basis of the existing macrolevel research. (2) This paper uses the difference-in-differences method to assess the impact of the BRI on the green innovation of Chinese manufacturing enterprises and identifies the causal relationship between the BRI and green innovation by using the core cities of the Belt and Road in China as the recipients of exogenous shocks. (3) Based on the TOE framework, this paper analyzes the impact mechanism of the BRI on the green innovation of Chinese manufacturing enterprises and examines the TOE mechanism at both the internal and external levels, revealing a new micro mechanism for the study of the relationship between the BRI and sustainable development.

7.4. Policy implications

(1) Actively promoting the participation of enterprises and striving to promote green transformation. Manufacturing enterprises can enhance their green innovation level by actively participating in the construction of the Belt and Road. This paper finds that the BRI can significantly improve the green innovation level of manufacturing enterprises in core cities along the route, indicating that participation in Belt and Road construction is an important way to improve the green innovation level of manufacturing enterprises. As important implementers of Belt and Road construction, enterprises should further increase their participation, expand overseas markets, enhance international management capabilities, achieve economies of scale and improve technical efficiency. Manufacturing enterprises in core cities can strengthen green technology exchange and sustainable development cooperation with developed countries along the Belt and Road, absorb advanced production concepts and technologies, and improve green innovation capabilities.

(2) Focusing on the development of advanced manufacturing vigorously promotes the upgrading of state-owned enterprises. Advanced manufacturing enterprises and state-owned enterprises should become an important force in the construction of the Green Silk Road. This paper finds that the BRI can enhance the green innovation level of advanced manufacturing enterprises and state-owned enterprises; therefore, the policy should encourage and support advanced manufacturing enterprises and state-owned enterprises to participate in Belt and Road construction. The current global science and technology innovation has entered a period of unprecedented intensity and activity, and a new phase of scientific and technological revolution and industrial change is reshaping the global innovation map and the global economic structure. By participating in Belt and Road construction, Chinese advanced manufacturing enterprises and state-owned enterprises can more rationally integrate into global industrial and value chains, upgrade their manufacturing processes, optimize their production processes, produce more energy-efficient and high-end products, continuously promote the level of green innovation in their enterprises, and promote the sustainable development process along the Belt and Road.

(3) Continuously improve the innovation mechanism and provide solid talent guarantees. Provide talent guarantees for enterprises' green innovation by improving the innovation mechanism. This paper finds that enterprises with a high proportion of R&D staff have a stronger promotion effect of the BRI on green innovation, so building a high-level R&D workforce is crucial to improve the green innovation capacity of enterprises. First, from the perspective of core cities along the route, the cities should strengthen ecological supervision, refine supervision measures, improve innovation mechanisms and reduce green innovation costs; these cities should recruit high-level talent from overseas and establish an effective talent recruitment mechanism. Second, at the enterprise level, enterprises can start with recruitment, training, incentive and international exchange to vigorously attract innovative talent and improve knowledge reserves to provide human resource guarantees for green innovation and sustainable development.

(4) Improving and optimizing R&D structure and effectively guaranteeing financial support. R&D structure and R&D capital expenditure are the key elements of green innovation. This paper finds that for manufacturing enterprises with strong R&D expenditures, the BRI has a stronger effect on green innovation, so the expenditures of R&D manufacturing enterprises should be enhanced. In terms of the composition of R&D structure, local governments should invest more in R&D and encourage enterprises, universities and other R&D institutions to increase their R&D

expenditures. In addition, R&D distribution structures should be kept rational to avoid resource redundancy and overlap to reduce waste, improve factor utilization, and provide financial security for sustainable development.

(5) Implementing the green concept and strengthening and consolidating policy foundation. The policy support of local governments should be enhanced to provide policy support and economic subsidies for achieving SDGs. This paper finds that provinces with strong local government support have a stronger effect of the BRI in promoting green innovation in manufacturing enterprises; the higher the government subsidies, the stronger the effect of the BRI in promoting green innovation in enterprises. Therefore, the support of local governments should be enhanced. In terms of the development concept, local governments need to adhere to the concept of sustainable development and strive to fully integrate the concept of ecological civilization and green development into economic and trade cooperation. In terms of development and construction, they can support the construction of a number of green industry cooperation demonstration bases, green technology exchange and transfer bases, technology demonstration and promotion bases, science and technology parks and other international green industry cooperation platforms to create a Belt and Road Green supply chain platform. In terms of financial support, they can actively participate in subsidizing manufacturing enterprises' Belt and Road construction. On the one hand, this can provide support to manufacturing enterprises to reduce their negative impact on the environment, and on the other hand, it can also establish an effective green development pattern in Belt and Road construction where ecological and environmental protection and economic and trade cooperation complement each other.

7.5. Limitations and future research directions

This paper also has the following limitations. First, this paper assesses the impact of the BRI on green innovation in Chinese manufacturing enterprises from the perspective of production processes, but the literature also points out that green innovation includes not only innovation in production processes but also in management methods (Horbach et al., 2013), and digital green innovation (Yin and Yu, 2022). Therefore, in the future, the scope of the study can be expanded to include management innovation and digital green innovation to analyze the impact of the BRI on corporate green innovation. Second, this paper focuses on the impact of the BRI on green innovation in Chinese manufacturing enterprises but does not discuss the impact of the BRI on green innovation in the countries along the route, although the impact of the BRI on green innovation in the countries along the route has already been discussed in the literature. Although the impact of the BRI on environmental issues such as carbon emissions has been discussed from the perspective of the countries along the route (Chen et al., 2021a), few studies have focused on green innovation. Future studies can assess the impact of the BRI on green innovation in countries along the route. Third, this paper analyzes the impact of the BRI on the green innovation of manufacturing enterprises using the core cities along the Belt and Road in China as a grouping variable. Although it discusses the heterogeneity of advanced manufacturing and enterprise ownership at the enterprise level, it does not analyze the spatial and temporal heterogeneity at the regional level. Although the heterogeneity between advanced manufacturing and firm ownership was discussed by this paper at the firm level, spatiotemporal heterogeneity was not analyzed at the regional level (Zhou et al., 2021), and future studies could incorporate spatiotemporal heterogeneity into the analysis.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

XC contributed to conceptualization, formal analysis, funding acquisition, methodology, and writing – original draft preparation. FZ contributed to conceptualization, formal analysis, funding acquisition, and writing—original draft preparation. YW and YD contributed to data curation and formal analysis. HZ contributed to conceptualization, formal analysis, and writing–original draft preparation. XH contributed to conceptualization, funding acquisition, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Green economy studies amongst the global climate change challenge between 2016 and 2022: a bibliometric review

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Practical and theoretical advancements have not caught pace with rising scientific researches in the rapidly emerging economy undertaking a shift to a more sustainable and particularly green model. After the UN adopted the 2030 Agenda for Sustainable Development, there has been a surge in interest in the green economy among academics around the world, and the literature on the issue is proliferating. This paper adopts the methodology of bibliometric review and thematic analysis to summarize the relevant literature from 2016 to 2022 on areas related to the theme of green economy. The literature was obtained from the Web of Science database with a total of 1,022 articles. Furthermore, the literature was analyzed using VOSviewer as well as the R language to couple the literature by keywords, country, affiliation, author, and publication. The findings of the current paper show that the green economy has received more academic attention from scholars since 2016. Asia and Europe are leaders in green economy studies. In the context of climate change, future research is anticipated to concentrate on establishing a green economy for global economic growth. This paper makes a substantial contribution to future research on the green economy.

KEYWORDS

green economy, systematic review, policy, sustainability, recycling economy, bibliometric

Introduction

The twenty-first century is defined by rising environmental degradation and depletion of resources, as well as the need to achieve strategic goals for sustainable development, of which the green economy is a crucial component in advancing global economic growth (Jin et al., 2022). This is a unique opportunity to reset national and corporate agendas in the wake of the Environmental, Social, and Governance (ESG) investment boom and the imperative for economic recovery and sustainable growth (Government of Dubai, 2022). Many sustainable development indicators, such as health (Seshaiyer and McNeely, 2020), inequality (Barbier and Burgess, 2020), and education (Anholon et al., 2020), are influenced by the global COVID-19 pandemic (Naidoo and Fisher, 2020). In recent years, the worldwide environment became more devastating, revealing the volatility of the green economy (Gunay et al., 2022), which will have a significant influence on the achievement of sustainable development objectives. In the post-pandemic era, it will be crucial to determine how to designate appropriate legislation and regulations, modify the government's transformation and upgrading, support economic growth, and energetically develop the green economy in order to accomplish UN sustainable development goals (Campbell, 2017; Kronenberg and Fuchs, 2021). This must be driven by a synthesis of academic researches, technologies, and policies (Lee et al., 2022; Metawa et al., 2022). Governments and organizations, under the leadership of the United Nations, have taken action and adopted a variety of policies to achieve the Sustainable Development Goals (Rosati and Faria, 2019). Previous literature studies in the topic of economics tended to summarize and discuss particular green economy concerns (Ferguson, 2015). In numerous past research works, it is argued that the current weak articulation of the green economy agenda does not necessarily imply a future transition to a post-growth society, but Ferguson summarizes and proposes a strategy for reformulating the green economy agenda in a post-growth direction (Bina and La Camera, 2011). The green economy has the potential to achieve what sustainable development cannot and can in some way address the limits of traditional economic growth. Although green economy development is now to some extent similar to the past, it has the potential to m move toward a post-growth society. In the face of global climate change challenges now, where economic development is influenced by environmental factors, only the emergence of a green economy community of practice can truly develop the development potential of a green economy. New technologies such as artificial intelligence, big data, the Internet of Things, and blockchain radically alter how industrial companies capture, generate, and distribute corporate value (Hristov Kalin, 2017; Arenal et al., 2020). Currently, nations throughout the globe may energetically advance the application of the fourth industrial revolution's technology group in the sphere of business innovation and green economy (Wang et al., 2022). In reality, many businesses struggle to properly incorporate the green economy into their operational business models (Sjödin et al., 2021). In the era of digital intelligence, when the function of digital technology is rising, the significance and urgency of this issue are intensifying (Linde et al., 2021). Consequently, it is essential to systematically evaluate and research the relationship between the green economy and business innovation in detail, as well as to thoroughly discuss the mechanism and process of the new generation of green technology that impacts the innovation strategy of global enterprises.

Over the course of the past few years, a large number of scholars have authored academic papers (Loiseau et al., 2016; Georgeson et al., 2017; Mikhno et al., 2021), in an attempt to grasp the impacts of green economy on various global industries and the potential of these industries to reflect the emergence of green digitalization. Most of these articles, however, have only summarized previous research in a somewhat categorized manner, without applying bibliometric-related techniques to it and without considering the issue in a worldwide context. In order to fill in this gap, this study, unlike those previous literature review papers, utilizes a bibliometric analysis technique, which is not influenced by the author's subjective considerations, to analyse the present trends and research tendency of the issue of green economy. Consider that the advancement of technology has been a major contributor to green economy model, the current paper hence particularly attempts to assess the significant themes of prior researches on the subjects of green economy and green finance in order to contribute to the debate involving how major corporations are adopting digital resources to redevelop the operational construct concerning the latest digital advancement. In particular, the purpose of this investigation is to grasp an overall bibliometric understanding to the existing research advancement of green economy and to establish a future research agenda. Some of the following are instances of questions that are pertinent to the bibliometric analysis of green economy: What part has the technology advanced the development of the sustainable and environment-friendly green economy? What does the research agenda for the green economy look like?

In this study, a synthesis of the results of previous research on green economy was first conducted and then the constraints caused by environmental repercussions accordingly. These were the two subjects that generated the greatest conversation in relation to a comprehensive understanding of the green economy and the concerns surrounding environmental preservation. This study drew on the prior work of a combined amount of 1,022 articles about the topic of green economy on environmental issues using a comprehensive selected database. The paper selection procedure as well as the inclusion criteria were further expounded upon throughout the subsequent sections on the research methodology as well as the literature evaluation. Specifically, the organization of this paper is broken down into the following sections. First, the article begins with a summary of the current academic background, which gives an overview of the green economy as well as relevant national policies. In the second part of research methodology, the criteria utilized for selecting the relevant prior literature as well as our full research methodology were explained. The finding section presents the outcomes of this study. Last but not least, the study concludes with a discussion of its theoretical and practical contributions, as well as its limitations and suggestions for further research.

Literature review

According to scholars and a large number of international organizations, the green economy may be characterized as low in carbon emissions, resource-efficient, and socially inclusive (UNEP, 2011). For a significant number of years, one of the primary focal points for economic sustainability has been the application of green economy. A green economy strives to minimize resource depletion and environmental damage, "to generate sustainable, long-term economic growth without causing major environmental damage" (Jacobs, 2012). Meanwhile, the green economy focuses on change, particularly health-improving change. This form of economy prioritizes using renewable energy sources, sustainable transportation, and adequate water, land, and waste management to achieve its goals. Although it is argued such a transition, which emphasizes low-carbon resources, could negatively affect the environment and the local population (Sovacool et al., 2019), businesses everywhere are contemplating changing to adapt to the new paradigm, given the importance attached to the green economy worldwide. The green economy is assumed to have various benefits and therefore vital for creating a sustainable economy and is closely tied to the notion of green growth.

In retrospect, the green economy was originally implemented worldwide in reaction to the global financial crisis and to promote economic recovery (Bina and La Camera, 2011). It has been crucial in attaining the low-carbon transition and sustainable development objectives. As of today, the green economy has had some effect on global policymaking, with Europe and Asia being the most quickly expanding regions (Kaur et al., 2018). For instance, there are a lot of studies that concentrate upon such geographies, such as China (Zhang et al., 2021) and the United Kingdom (Gainsborough, 2018), as well as other emerging nations like Laos (Luukkanen et al., 2019), India (Reddy, 2016), and Cambodia (Vuola et al., 2020).

As was discussed in the preceding section, the primary goal of a green economy is to gradually shift away from the use of traditional energy that are the sources of devastating pollution. Renewable energy sources, such as solar and wind, can help establish a new standard of energy efficiency if they follow the new guiding principles that they have developed (Chenari et al., 2016). It is a terrible thing when certain markets reject the new green economic model and fail to adhere to environmental protection standards for people, animals, and the planet. A substantial portion of expenses are incurred outside of the local market or nation.

Environmental and resource conservation are vital to the development of a green economy. Businesses are supposed to ensure that their economic activities are consistent with the concepts of sustainable development by reducing their environmental effect. In other words, the economic growth does not threaten ecological sustainability. The green economy incorporates precautions to prevent environmental harm from normal financial transactions (Kasayanond, 2019). To connect their operations with sustainable development objectives, enterprises must minimize their ecological impact. This may include establishing sustainable resource management and decreasing air and water pollution. Moreover, corporations must ensure that their actions have no negative impact on the environment, which includes refraining from behaviors that could cause pollution or deplete natural resources.

In addition, there are several benefits of the green economy development. Firstly, the green economy promotes the development of new product markets and the more efficient use of natural resources. It can also solve the energy problem to a certain extent (UNEP, 2012). Currently, many developing countries relying on the import of fossil fuel are heavily influenced by the international situation and pollute the environment. The development of a green economy can reduce the impact of these problems by replacing fossil fuels with green energy (Policy Advisor, 2016). What is more, a green economy aims to achieve sustainable development through the rational use of resources and the regulation of policies that will lead to sustainable development (Smith et al., 2007). All these studies demonstrate that the green economy and environmental protection (for dealing with global climate change) concepts are inextricably intertwined. Green economics apply protections to minimize environmental damage from economic processes, and environmental protection is integral to green economies through fostering efficient and sustainable resource management.

Research methodology

The authors began by conducting an exhaustive research for pertinent publications indexed in Web of Science Index, for instance, the Science Citation Index Expanded (SCI-EXPANDED) and Social Sciences Citation Index (SSCI). Consequently, through searching the Web of Science data, the authors searched the database with the terms of green economy, sustainable development, policy, goal, as well as a review of prior researches. The results included journal articles and proceeding from a variety of conferences. Additionally, we scanned the bibliographies of pertinent review papers. The following criteria were used to screen the papers.

1. Topic = (Green Economy OR Sustainable Development) AND Topic = (Policy) AND Topic = (Goal).
2. Research domains: Sustainability Science; Economics; Environmental Sciences; Environmental Sciences; Ecology; Business Economics.
3. Document Types: Peer-reviewed articles and conference proceedings written in English, which were indexed in Science Citation Index Expanded (SCI-EXPANDED) or Social Sciences Citation Index (SSCI).
4. Web of Science Categories: Environmental Sciences; Green Sustainable Science Technology; Environmental Studies; Economics.

In this article, the research objects utilized to generate the mapping are important indicators linked to the topic of green economy, such as keywords, number of publications, number of citations, nations, and authors of literature. For each article, the authors examined the title, abstract, introduction, or them together to determine that the investigations are pertinent to the current study. Inter-coder dependability was examined throughout such encoding procedure to increase the accuracy and dependability (Clarke and Visser, 2019; Baek et al., 2021). As a result, a total of 1,022 articles were selected after the initial categorization procedure. Specifically, the particular steps can then be broken down into the following phases. First, the target literature was screened from the Web of Science database, with the previously mentioned criteria as the specific research indicator. Second, country analysis was conducted for the published literature. Third, the affiliation of the existing literature was analyzed. Fourth, the journals to which the literature belongs were classified and summarized. Fifth, the number of publications of researchers in the field of green economy was counted. Sixth, using the correlation method of literature coupling, the keyword network mapping was constructed, and the correlation between the countries, authors and references of the literature design was analyzed in detail. Last but not least, the authors used the R language analysis technique to identify the summative analysis to the existing literature. For the acquired literature, this paper adopts a bibliometric-related approach for quantitative research (Farrukh et al., 2020). This method is a combination of three fields: literature, statistics and mathematics, and it analyses the correlation between specific indicators of published scientific results, such as disciplines, journals, regions and countries (Bonilla et al., 2015; Amiguet et al., 2017; Martínez-López et al., 2018).

More specifically, to analyze the existing data, the authors use VOSviewer and R language, two software programs widely used in various fields for their simplicity and efficiency. For literature analysis, coupling analysis is often used, which simply means that the relevance of a research topic is determined by analyzing the citations among published articles (Mora-Valentin et al., 2022). Another alternative to this is to analyze the citations of the existing articles to determine the relevance of the themes' co-relationship (Wang et al., 2013). Both of these two methods are applied in this study to achieve precision with reliability and credibility in the analysis of the acquired literature.

Bibliometric analysis process

Analysis of the published literature

To locate relevant scholarly materials, this article searched the Web of Science database. This section describes the methods used to obtain data from published sources. These particular strategies contain data obtained by two independent reviewers, and we proceed to further investigation to the obtained data. In addition, we explained the Web of Science in terms of the automation technologies used in the procedure. Keyword searches to ensure that no relevant literature on green economy-related policy research is excluded. According to the findings of an information retrieval study conducted using Web of Science, there were 1,022 papers on green economy. A framework analysis of the articles indicates that the number of papers has increased exponentially over the past 9 years, especially from 2016 to 2022. This substantial increase suggests that the study of green economy is gaining increasing growth momentum (see Figure 1).

To be specific, as shown in Figure 2, 1,022 papers were published between 2016 and 2022 with a quick annual growth. In 2016, there were only 22 papers while by the end of 2022, 322

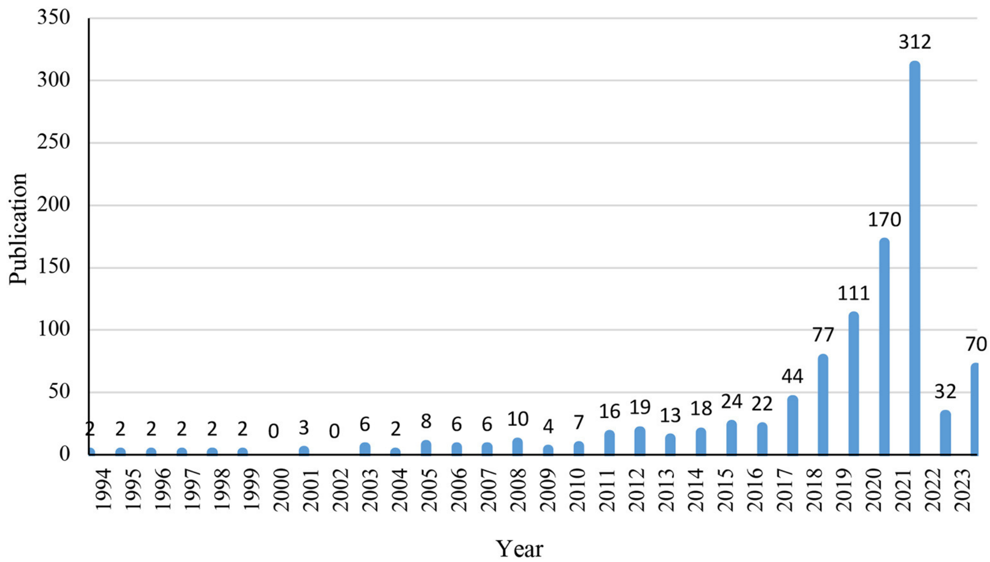

FIGURE 1
The increasing number of articles published on green economy development goals and policies.

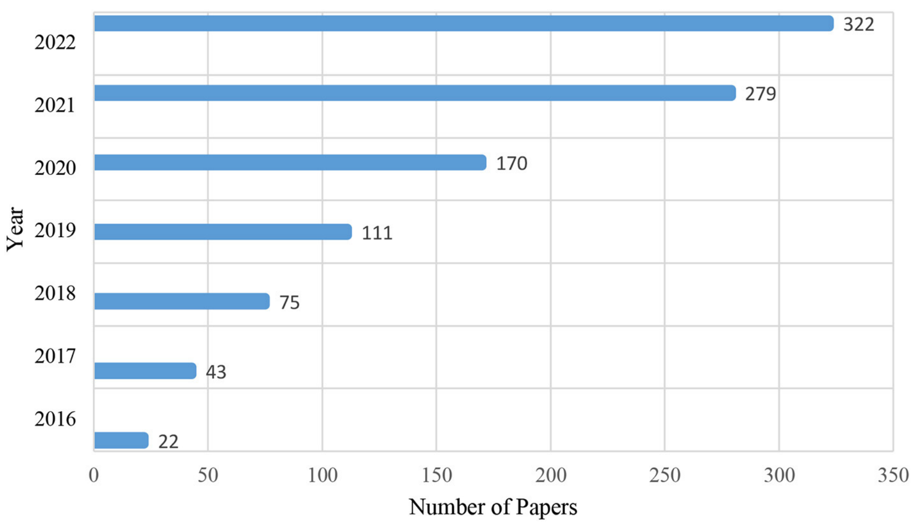

FIGURE 2
Annual publication analysis of green economy issues in published literature.

articles will have been published, a 10-fold increase of 2016. It is assumed that this growth trend will continue.

Analysis of the study area of green economy

Besides the growth in numbers shown before, the study on the green economy has also experienced a geographic expansion worldwide in recent years, as indicated in Table 1. The top 10 nations were selected in terms of the number of papers published worldwide by its scholars from 2016 to 2022. With 353 publications and 5,597 citations, China is far ahead of other countries. This signifies that Chinese scholars have gradually shifted their focus to the green economy, an active response to the green transition policy by the Chinese government Second to China is the United Kingdom. The United States ranks third with 107 articles, subsequently followed by Germany, three Asian countries, Turkey, and Pakistan, India, and three European countries, Italy, Spain, and Netherlands.

TABLE 1 Country analysis.

No	Country	NP	Citations	Citations/paper
1	China	353	5,597	15.86
2	The UK	107	2,843	26.57
3	America	107	2,268	21.20
4	Germany	87	2,563	29.46
5	Turkey	77	3,002	38.99
6	Pakistan	74	1,535	20.74
7	India	67	1,851	27.63
8	Italy	66	1,364	20.67
9	Spain	53	1,511	28.51
10	Netherlands	47	1,461	31.08

Figure 3 depicts the outcomes of the subsequent coupling analysis, which was conducted with VOSviewer analysis software. The quantity of publications is proportional to the diameter of the circle. China, the United Kingdom, and the United States are the top three countries. This conclusion is consistent with the results presented in Table 1.

Since many studies are conducted internationally, it was appropriate to consider the collaboration between scholars in each country. The outcomes of this investigation are demonstrated in Figure 4. China continues to lead the list of countries most inclined to collaborate in research on the trending topic of green economy. It is anticipated that Chinese academics would participate significantly in future studies on the green economy.

Authors' affiliation analysis

The attributing affiliations of the authors of the publication are also an essential component of the bibliometric analysis. Table 2 shows the findings of the authors' affiliation via the VOSviewer analysis. With 32 papers, the Chinese Academy of Sciences was the most prolific institution. With 29 and 28 articles, respectively, Istanbul Gelisim University from Turkey and the University of London from the United Kingdom scored second and third in the list. The significance of Asian research institutions in the study of the green economy is accurately depicted.

Analysis of the volume of publications in relevant journals

Journal analysis is also an integral aspect of our investigation. As shown in Table 3, the authors selected a total of 10 journals that publish high-profile in-depth research on topics connected to the green economy between 2016 and 2022. *Sustainability* is one of the most highly ranked journals on the list. *The Journal of Cleaner Production*, and *Environmental Science and Pollution Research* ranked second and third, respectively, with

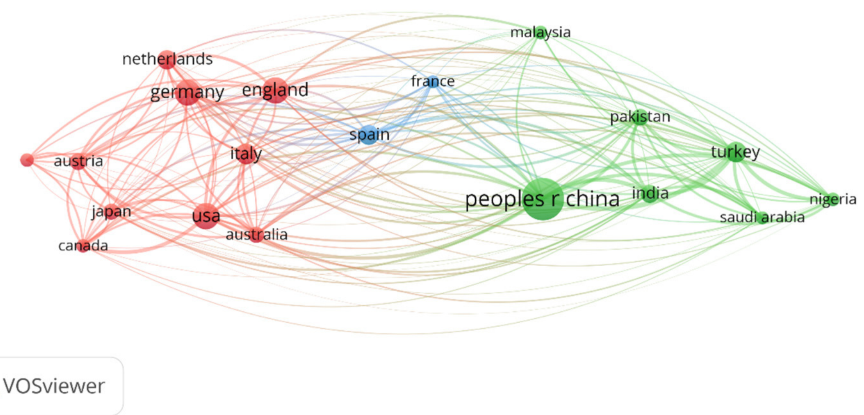

FIGURE 3
Country coupling analysis.

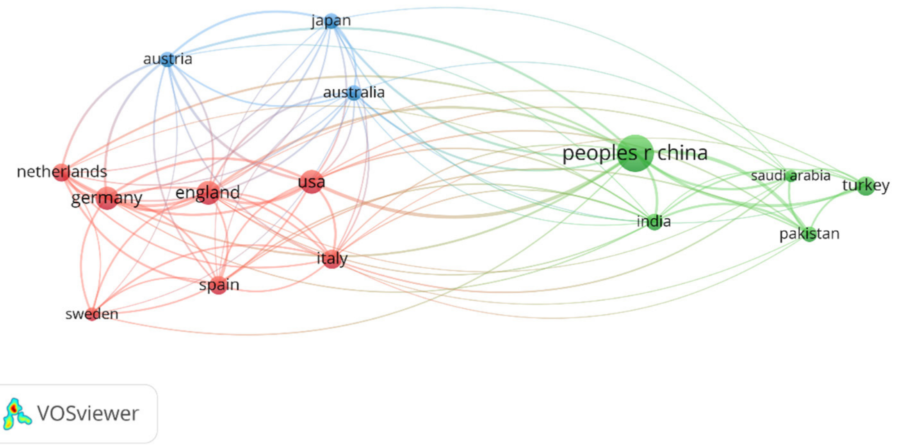

FIGURE 4
National co-authorship analysis.

TABLE 2 Article affiliation analysis.

Universities/institutes	TP	TC
Chinese Academy of Sciences	32	319
Istanbul Gelisim University	29	1,185
University of London	28	653
International Institute for Applied Systems Analysis IIasa	24	580
Goa Institute of Management	20	1,259
Beijing Institute of Technology	19	647
Southern State University	18	634
Tsinghua University	17	752
University College London	17	168
Beijing Normal University	15	246
Potsdam Institut fur klimafolgenforschung (Potsdam Climate Research Center)	15	796
Ulusracht-Kibiris University	15	329
Peking University	14	436
University of Chinese Academy of Sciences CAS	14	117
Utrecht University	14	612

TABLE 3 Journal analysis.

No	Source title	Papers	Citations	C/P
1	Sustainability	188	1,673	8.90
2	Journal of Cleaner Production	124	4,283	34.54
3	Environmental Science and Pollution Research	115	1,801	15.66
4	Energy Policy	48	1,172	24.42
5	Science of the Total Environment	34	1,957	57.56
6	Journal of Environmental Management	28	1,038	37.07
7	Environment Development and Sustainability	26	253	9.73
8	International Journal of Environmental Research and Public Health	25	156	6.24
9	Frontiers in Environmental Science	23	76	3.30
10	Environmental Research Letters	22	458	20.82

124 and 115 articles. *Science of the Total Environment* is the most highly-cited journal, with an average of 57.56 citations per article.

For journal citation research, literature co-citation analysis is frequently employed. Figure 5 illustrates the findings of this analysis. *The Journal of Cleaner Production* is the journal with the highest co-citation frequency, followed by *Sustainability and Environmental Science* and *Pollution Research*, where the high co-citation rate is attributable to a large number of related references.

Analysis of the researchers focusing on the field of green economy

This section contains data pertaining to the green economy researchers with the most publications. Sinha A. is in international spotlight with 21 published articles, as shown in Table 4. With 1,737 citations, Alola A.A. ranked first on the list in terms of citations. With an average of 97.77 citations per article, Bekun F.V. topped the list. Each of the remaining academics has authored a minimum of seven articles.

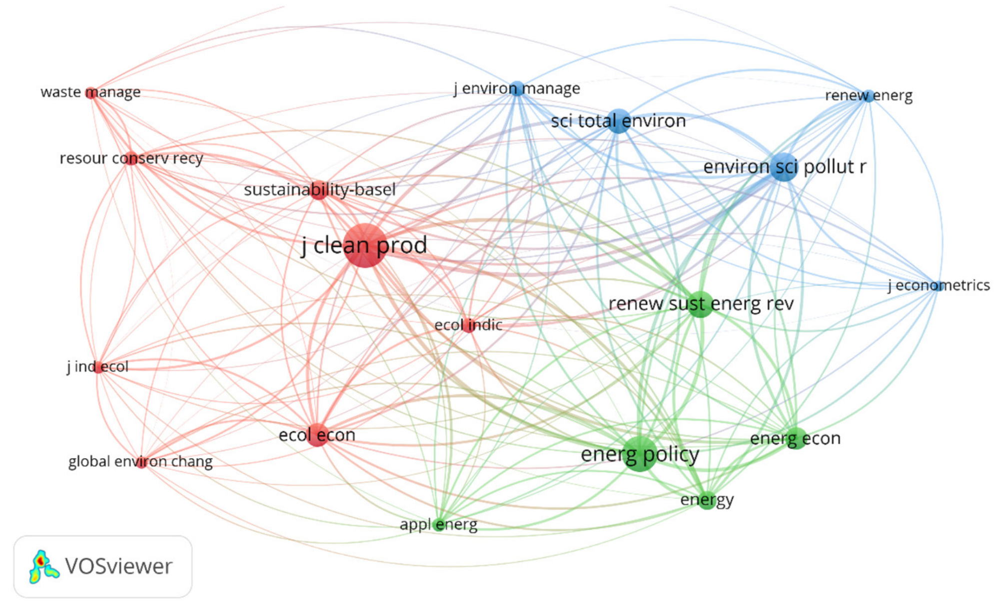

FIGURE 5
Journal co-citation analysis.

TABLE 4 Author analysis.

No	Author	Papers	Citations	C/P
1	Sinha A.	21	1,278	60.86
2	Alola A. A.	19	1,737	91.42
3	Bekun F. V.	13	1,271	97.77
4	Murshed M.	11	417	37.91
5	Schandl H.	10	308	30.8
6	Alvarado R.	9	549	68.63
7	Kirikkaleli D.	8	547	68.38
8	Sharma R.	8	312	39.00
9	Ahmad M.	7	349	49.86
10	Li Y.	7	53	7.57

Literature citation analysis

The number of citations in the selected literature is also a significant indicator when performing a literature review and a crucial criterion for evaluating the quality of a publication. In this part, the top 10 most-cited papers from the Web of Science database were selected based on the search parameters established previously and listed in Table 5. The results suggest that *Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and non-renewable energy in 16-EU countries* is ranked in the first place, which shows its academic significance. The remaining publications have been mentioned at least 156 times, which demonstrates in part their high reference value in the subject of green economy research.

Three-field plot analysis

Among numerous different ways of analysis, the Three-Field Plot Analysis is frequently used to determine the researcher's area of study. This section applies this methodology to the study of the green economy. Figure 6 illustrates the findings of this analysis. On the far left are the names of the researchers, in the center are the most often used terms, and on the right are the countries of the authors. Thus, it is straightforward to associate the researcher with his field of study and nationality. For instance, Liu Y.'s primary research keywords are sustainable development and CO_2 emissions, indicating that he is primarily concerned with sustainable development as a result of CO_2 emissions.

Keyword analysis

This component utilizes the VOSviewer program to perform keyword analysis on the selected documents; the results are displayed in Figure 7. The importance of sustainable development, economic growth, and climate change is evident. This technique is used to map the frequency of keywords in published works. Therefore, future study on the green economy is expected to concentrate on these three terms, which reflect a trend in the field.

Although the keyword analysis references the knowledge content of big data to some extent, it can be utilized to determine future research topics. However, research on the green economy is frequently influenced by a number of uncontrollable circumstances, thus the results of the analysis can serve as a benchmark for particular measurements. Nevertheless, we anticipate that these topics will continue to evolve in the current global situation.

TABLE 5 Literature citation analysis.

Authors	Title	Year	Source title	Number of citations
Bekun F. V., Alola A. A, Sarkodie S. A.	Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and non-renewable energy in 16-EU countries	2019	Science of the Total Environment	572
D'Amato D., Droste N., Allen B., Kettunen M., Lahtinen K., Korhonen J., Leskinen P., Mathies B. D., Toppinen A.	Green, circular, bio economy: A comparative analysis of sustainability avenues	2017	Journal of Cleaner Production	411
Hickel J., Kallis G.	Is Green Growth Possible?	2020	New Political Economy	408
Alola A. A., Bekun F. V., Sarkodie S. A.	Dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on ecological footprint in Europe	2019	Science of the Total Environment	329
van Vuuren D. P., Stehfest E., Gernaat D. E. H. J., Doelman J. C., Van den Berg M., Harmsen M., de Boer H.S., Bouwman L. F., Daioglou V.	Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm	2017	Global Environmental Change—Human and Policy Dimensions	330
Shahbaz M., Balsalobre-Lorente D., Sinha A.	Foreign direct investment-CO_2 emissions nexus in Middle East and North African countries: Importance of biomass energy consumption	2019	Journal of Cleaner Production	285
Schand H., Geschke A., Hatfield-Dodds S., Wiedmann T., Cai Y. Y., West J., Baynes T., Lenzen M., Newth D., Owen A.	Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions	2016	Journal of Cleaner Production	175
Ahmad M., Jiang P., Majeed A., Umar, M., Khan Z., Muhammad S.	The dynamic impact of natural resources, technological innovations and economic growth on ecological footprint: An advanced panel data estimation	2020	Resources Policy	181
Shen Y. J., Su Z. W., Malik M. Y., Umar M., Khan Z. S., Khan M.	Does green investment, financial development and natural resources rent limit carbon emissions? A provincial panel analysis of China	2021	Science of the Total Environment	170
Saidi K., Omri A.	The impact of renewable energy on carbon emissions and economic growth in 15 major renewable energy-consuming countries	2020	Environmental Research	156

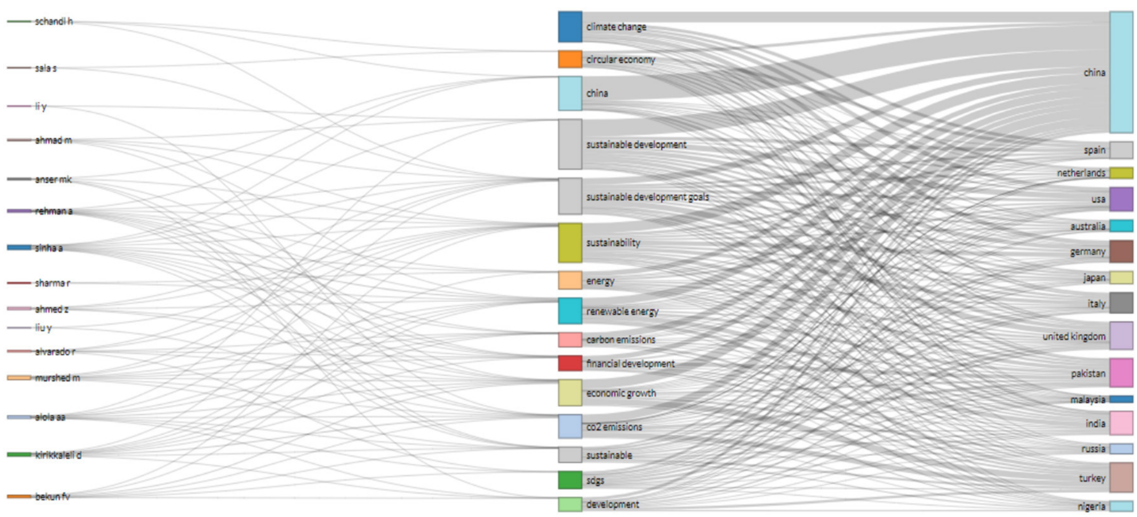

FIGURE 6
Three-field plot analysis.

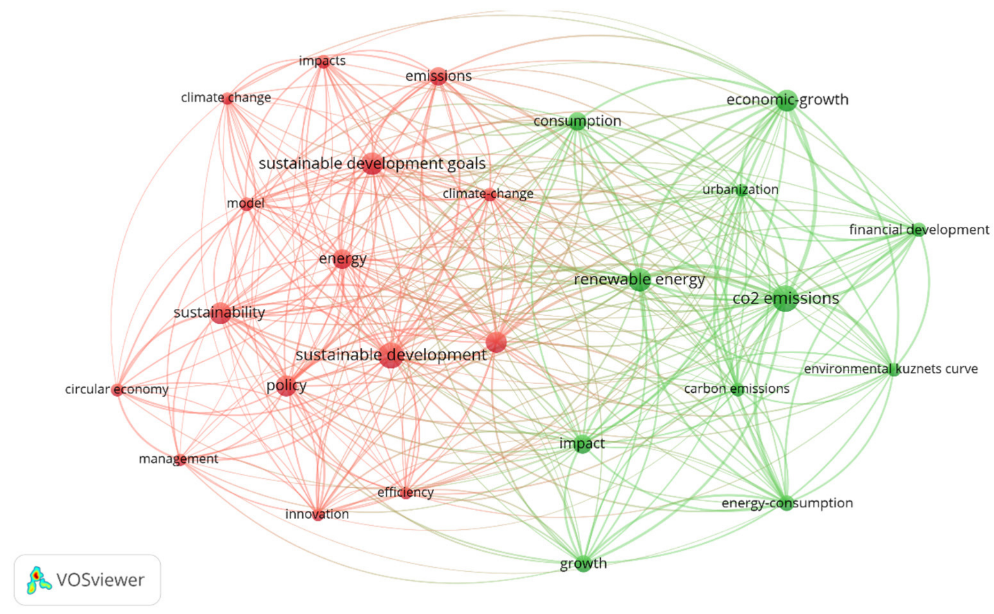

FIGURE 7
Keyword analysis.

Thematic map analysis

This part presents a structured analysis of the selected keywords in the green economy-related literature, drawing a Thematic Map using the bibliophagy data package in R language. The first quadrant of the four-quadrant diagram indicates research fields that are both significant and well-developed. The second quadrant consists of well-developed but less significant research directions. The third quadrant represents insignificant research content, whereas the fourth quadrant represents significant but underdeveloped study areas (Tennekes, 2018). The fourth quadrant represents research fields that are vital but underdeveloped. Figure 8 demonstrates the outcomes. The first quadrant contains the current topical issues, including renewable energy, economic growth, sustainable development, energy transition and other key words.

Niche Themes focuses on the more contemporary and well-established fields of study, including public policy, food shortages, and sustainability factors. The most crucial are the transitions to sustainable development and the shadow economy. The keywords environmental Kuznets curve, environmental regulation, green innovation, poverty alleviation, energy security, sustainable development, and climate change dominate the third quadrant. As a result of climate change, it is evident that research on sustainable development is becoming more centralized and of a broader study interest. The fourth quadrant represents research directions that are not well-developed at present but have a greater scientific value in the future. Green economy, sustainability, circular economy and other contemporary hot topics are included in this quadrant, reflecting the importance of green economy and sustainable development research in the coming period.

Trends in topic selection

Adopting the bibliophagy data package in the R language to construct time windows with literature keywords reveals future research trends. As depicted in Figure 9, energy security is a leading research topic from 2016 to 2018. From 2018 to 2019, the study field is gradually changing toward the establishment of a low-carbon economy to achieve economic growth. Life cycle assessment have been reintroduced and examined bioeconomic issues by 2020. From 2021 onward, policy research on the formation of a green economy to achieve sustainable development goals became an important topic, paving the path for future studies.

Discussion

The development of a green economy can be distinguished into four different forms: green growth, green transformation, green resilience, and green revolution (Death, 2015). Among them, green growth is the most common green economy model in the global context and belongs to a high-quality development model that focuses on the rational use of resources and the reduction of damage to nature (Li et al., 2022). Green resilience is more technical in nature and places greater emphasis on sustainability (Rizzo, 2020). Green transformation and green revolution Green Transformation and Green Revolution are national government policies to promote economic development (Thenkabail, 2010; Lee and Woo, 2020). The green economy as a whole is a series of policies that are designed to promote economic development. As a whole, the green economy is the sum of a number of concepts that encompass the world economy, energy issues, national policies and more. Du et al. (2019) assert that the output of carbon dioxide into the atmosphere, a contributor to

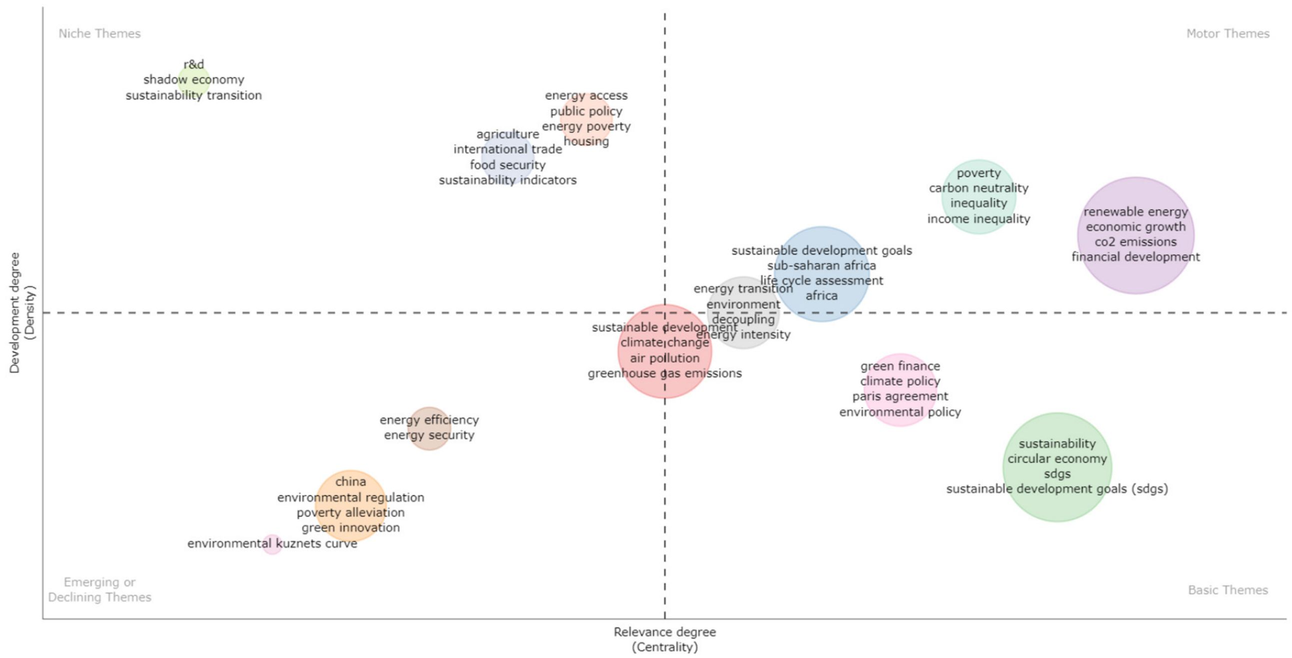

FIGURE 8
Thematic map.

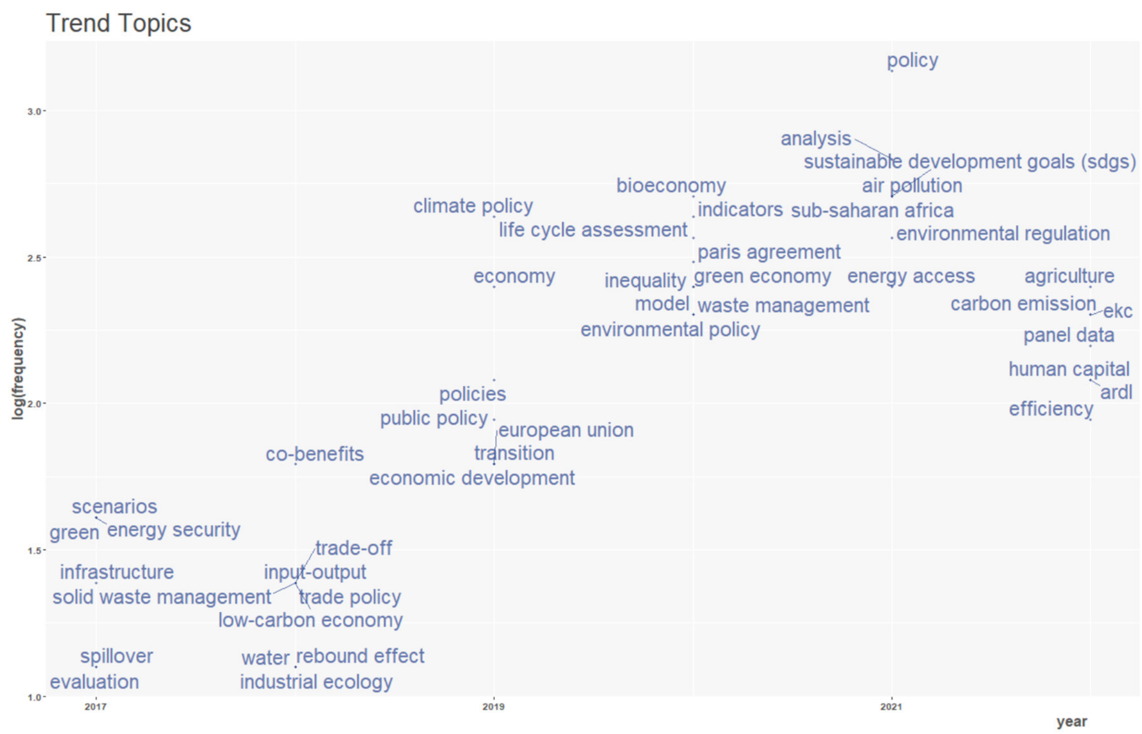

FIGURE 9
Trend topics advancement over the time.

climate change, is reduced by using green technologies such as electric vehicles. In addition, reducing waste and pollution through implementing efficient production and consumption processes adds to environmental protection. Environmental safeguards are also essential for the long-term management of resources. This involves protecting biodiversity, vital to ecosystem health and human quality of life. Moreover, because water is a finite resource, preserving its quality through conservation is essential for maintaining a healthy ecosystem. By protecting the environment, a green economy may ensure that resources are managed responsibly, which is advantageous for both the environment and the economy.

Promoting environmentally friendly ways of transportation is essential to the green economy. Sustainable is any mode of transportation that considers the needs of society, the environment, and the climate, as well as the effects that transportation has on these factors (Björklund, 2011). Since transportation contributes significantly to carbon dioxide emissions and consumes more than 25 per cent of global energy, its environmental effects cannot be overstated (Barceló, 2010). UN Environment Programme (UNEP) asserts that if persons switched to a better and safer mode of transportation, outdoor air pollution-related premature mortality might be reduced (Mahmood, 2011; Levy and Patz, 2015). Electric vehicles are increasingly popular in countries such as the United States and Germany because they reduce air pollution and improve the environment. Due to the increasing number of incentives offered by nations with advanced economies, it is easier for businesses and municipalities to manage the rise in electric vehicle usage.

Environmental protection and a green economy are required for sustainable development. A strategy for sustainable development ensures that present and future generations have access to the resources they need to live happy and productive lives. It considers the needs of the economy, environment, and society. The objective of a green economy is to maximize economic output while decreasing environmental hazards and resource shortages, which include reducing pollution and waste; boosting energy efficiency; promoting renewable energy sources and safeguarding natural resources. In addition, it seeks to promote environmentally responsible economic growth. Renewable energy, energy efficiency, sustainable agriculture, and environmentally friendly transportation are green economic projects.

The development of the green economy plays a decisive role in solving the problem of carbon emissions. In the past, governments favored fossil fuels over the green economy, partly because the green economy sector then was relatively underdeveloped, and partly because of the higher risks and lower returns (Tarkhanova et al., 2020). To achieve the goal of sustainable development, a series of policies must be developed to raise funds for the green economy to thrive.

Theoretical implications

Different from the conventional literature reviews, the current research analyzes a broader number of papers, from various aspects, including geographies, publishing organizations, high-profile journals, authorship, citation frequency, and several other variables. Based on this, the future research trend is predicted, which would be conducive for researchers to define the direction of future research and to facilitate research institutions in conducting research and cooperating with their intended academia. In addition, the current research would be beneficial for national governments to precisely identify countries that are in the forefront of green economy research and then to change their policies accordingly. With the acceleration of global digital and intelligent transformation, the corporate environment is in a state of perpetual flux. It is now necessary for the survival and success of businesses to encourage the integration of new technologies and business to drive business innovation. As green digital technologies are increasingly used in corporate management practices nowadays, green economy, a kind of advanced technology, plays a growing key role in facilitating the business innovation process. The present fast growth of green financing strengthens the prospect of incorporating it into the corporate innovation process. The expansion of sustainable finance has created favorable conditions for an industrial ecosystem that embraces the logic of digital services. Green improvements in product service processes and corporate strategies generate opportunities. Simultaneously, facilitating and supporting enterprise company innovation become more approachable, simple, and collaborative.

Limitations

Despite the fact that this paper has made some contributions, it still has certain limitations. The literature is obtained from the Web of Science database, and there are inevitably important publications that were not counted, which has an influence on the correctness of the analysis. Second, the analytical period for this article is the period between 2016 and 2022, when the green economy is thriving. Therefore, we propose that future research investigate the evolution of the green economy in different eras by comparing the results of studies conducted at different time intervals.

Future research agenda

Future research and analysis on the digital transformation of businesses merits more examination. Topics for research may include the existing and future effects of digital technology, such as artificial intelligence, on digital transformation and business innovation inside enterprises. Based on the theoretical exploration and empirical research conducted, relevant academic achievements can provide practical and effective theoretical guidance and strategies for enterprises to implement digital transformation in the context of the era of digital intelligence enlightenment. In addition, future study subjects may include the role and influence of the COVID-19 pandemic. On the basis of the concepts of digital empowerment and innovation, theoretical debate and empirical study can be conducted on business remodeling, transformation, and upgrading. The relevant academic accomplishments may give useful theoretical advice for conventional firms to implement green innovation using new technologies in the context of the digital economy.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ, XS, and RZ: conceptualization and validation. JZ and XS: data curation, investigation, and writing—review and editing. JZ and RZ: formal analysis, methodology, resources, software, visualization, and writing—original draft. JZ: funding acquisition, project administration, and supervision. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2023.1168437/full#supplementary-material

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Relationship between $PM_{2.5}$ pollution and firms' emissions in Shaanxi Province, China

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The relationship between the high-frequency time series of $PM_{2.5}$ in the atmosphere and the air pollutants emitted by industrial firms is not yet fully understood. This study aimed to identify independent $PM_{2.5}$ clustering regions in Shaanxi Province and to evaluate the spatio-temporal correlations of $PM_{2.5}$ concentrations and pollutant emissions from industrial firms in these regions. To accomplish this, daily data on $PM_{2.5}$ concentrations and air pollutants emitted by industrial firms were analyzed using the K-means spatial clustering method and cross-wavelet transformation. The results show that: 1) $PM_{2.5}$ concentrations in Shaanxi Province can be divided into three independent clustering regions. 2) The lagged impact of industrial emissions on $PM_{2.5}$ concentrations were about 1/4-1/2 period. 3) $PM_{2.5}$ was mainly influenced by particulate matter (PM) emissions from industrial plants during the period of 16–32 days, while nitrogen oxides (NO_x) significantly affected $PM_{2.5}$ concentrations during the period of 32–64 days. 4) Emissions of PM, NO_x, and sulfur dioxide (SO_2) more significantly affect $PM_{2.5}$ concentrations in northern and central Shaanxi, and pollutants emitted by firms in the thermal power generation, utility, and steel industries had more significant effects on $PM_{2.5}$ concentrations than those emitted by the cement manufacturing and electric power industries. During the COVID-19 shutdown, the emissions of firms cannot significantly affect $PM_{2.5}$ concentrations. These findings suggest that emission reduction initiatives should consider industrial, regional, and periodic differences to reduce $PM_{2.5}$ pollution during winter.

KEYWORDS

industrial firms' emissions, $PM_{2.5}$, cross-wavelet method, spatiotemporal clustering, China

1 Introduction

Exposure to high level of fine particulate matter ($PM_{2.5}$) in the atmosphere has been associated with severe adverse effects on human health (Barwick et al., 2017; Zhong et al., 2017; Chen et al., 2018; Liu and Salvo, 2018; Cheung et al., 2020; Fan et al., 2020; He et al., 2020), as well as substantial economic losses (Zhang and Mu, 2018; Sun et al., 2019; Chen et al., 2022; Ito and Zhang, 2020). While efforts have been made to manage $PM_{2.5}$ concentrations in developing countries like China, with notable progress in recent decades (Greenstone et al., 2021), the annual average $PM_{2.5}$ concentrations in China's 339 cities are still expected to exceed the recommended level by the World Health Organization (MEE, 2022; WHO, 2021). Moreover, severe haze pollution remains a common occurrence in many Chinese cities during autumn and winter (Ma et al., 2020; Zhang et al., 2020b).

To effectively reduce ambient $PM_{2.5}$ concentrations, it is crucial to identify the firms that should reduce emissions during periods of heavy pollution as well as during normal times (F. Wang et al., 2019; Zhao et al., 2018; Alari et al., 2021; Frankowski, 2020; Rivera, 2021), for the industrial sector significantly contributes to China's economic growth but also emits a large amount of air pollutants while consuming fossil energy (Choi et al., 2021; MEE, 2020; Zhang et al., 2014). Various studies have analyzed the correlation between $PM_{2.5}$ concentrations and yearly air pollutant emissions using a physicochemical model (Choi et al., 2021; Lu et al., 2021; Wang et al., 2022; Liu et al., 2018b; Zhang et al., 2014; Zhang et al., 2018), likely multiple regression (Zhang et al., 2020), geographically weighted regression model (Wang et al., 2018; Tu et al., 2019) and physicochemical model such as CMAQ (Wang et al., 2022b; Wang et al., 2019b), WRF-Chem (Spiridonov et al., 2019; Azmi et al., 2022; Zhang et al., 2023). Although an increasing body of research begins to concentrate on the interplay between business emissions and air quality (Li et al., 2016; Wu et al., 2023), there has been limited research conducted on the relationship between high-frequency scale (such as a week, day, or even an hour) air pollutant emissions from industrial firms and $PM_{2.5}$ concentrations, which can help the government formulate proper strategies for reducing industrial emissions.

In order to better capture the high-frequency variability of $PM_{2.5}$, some researchers have employed the wavelet analysis technique to identify the temporal patterns of $PM_{2.5}$ changes (Chen et al., 2020; Kapwata et al., 2021; Li et al., 2017; Shi et al., 2014; Sun et al., 2017; Zhao et al., 2009; Zhao et al., 2016). Wavelet analysis has been shown to be effective in studying the periodicity and evolution characteristics of $PM_{2.5}$ concentrations, as well as investigating the influence of natural factors on $PM_{2.5}$ concentrations. Moreover, $PM_{2.5}$ pollution exhibit significant regional variations that often do not align with administrative divisions (Tie et al., 2005; Tie and Cao, 2009; Wang et al., 2011; Zhao et al., 2020), the $PM_{2.5}$ pollution areas must be identify before appropriate mitigation strategies can be established.

To fill the knowledge gap mentioned above, this study selects Shaanxi Province in China as a relatively independent study area to examine the correlation between firms' emissions and $PM_{2.5}$. For the unique topography Guanzhong Plain is one of China's most polluted region for $PM_{2.5}$ (Xu et al., 2018; Li et al., 2022); Southern Shaanxi has a good ecology; Northern Shaanxi has many polluting firms) and diverse types of firms (Miao et al., 2019; Wang et al., 2022c) in Shaanxi Province can provide effective lessons for pollutant management in other regions and countries. We collected a unique daily scale emission data from all continuous emission monitoring system (CEMS) installed firms in Shaanxi Province and air quality monitor site data at county level.

This paper are to make the following contributions to the field: 1) Establish a methodology for identifying $PM_{2.5}$ pollution control areas using spatial clustering techniques; 2) Identify firms and industries with a significant impact on $PM_{2.5}$ pollution areas by utilizing cross-wavelet analysis on high-frequency time scale data; 3) Provide evidence-based support for precisely requiring firms to adopt emission reduction measures during periods of heavy pollution, and effectively reducing socio-economic losses.

The rest of this paper is structured as follows. Part 2 introduces the study area, data, and methodology. Part 3, this study shows cluster and wavelet analysis. In the final part, this paper provides some concluding remarks.

2 Study region, data resource, and methodology

2.1 Study region and data resource

Shaanxi Province, in northwestern China, spans between 105°29′E-111°15′E longitude and 31°42′N-39°35′N latitude, characterized by a complex and diverse terrain. Shaanxi Province, the most affluent among the five northwestern provinces of China, recorded a GDP of 2,980.1 billion RMB in 2021 (National Bureau of Statistics, 2023). The industrial sector played a substantial role, contributing 46.3% to the Shaanxi's GDP. With a diverse industrial landscape encompassing high-end energy and chemical sectors, equipment manufacturing, aerospace, electronic information, and automobile production, Shaanxi Province's industrial firms collectively consumed 92.8 million tonnes of standard coal in 2021. This consumption constituted 68.1% of the total standard coal usage within the province. Such considerable energy consumption consequently led to substantial pollutant emissions. Notably, industrial sources in Shaanxi Province contributed to over 60% of total emissions for both Total Suspended Particulates (TSP) and Sulfur Dioxide (SO_2) pollutants in 2021 (Ministry of Ecology and Environment, 2021).

Shaanxi can be geographically divided into three parts: southern Shaanxi, Guanzhong and northern Shaanxi. Northern Shaanxi, which encompasses the cities of Yulin and Yan'an, is abundant in coal, oil, and natural gas resources and houses several large-scale energy chemical firms, including thermal power, coking, coal chemical, and petrochemical. The Guanzhong plain, comprising cities such as Xi'an, Xianyang, Weinan, Baoji, and Tongchuan, is recognized as one of China's worst air pollution areas in China due to a significant number of thermal power, cement, and steel sectors (Bai et al., 2019). The Southern Shaanxi region, including the cities of Hanzhong, Shangluo, and Ankang, is rich in rare mineral resources, such as molybdenum, rhenium, and mercury, as well as abundant natural resources.

Figure 1 demonstrates the distribution of 169 air quality monitoring stations and 361 firms in Shaanxi Province. Specifically, Guanzhong has 60 air quality monitoring stations and 150 industrial firms, Northern Shaanxi has 59 air quality monitoring stations and 177 industrial firms, while Southern Shaanxi has 50 air quality monitoring stations and 34 industrial firms. Shaanxi's average $PM_{2.5}$ concentrations has decreased from 57 to 43 $\mu g/m^3$ between 2017 and 2020. However, the current concentration remains above the national standard limit of 30 $\mu g/m^3$.

The monitoring data of $PM_{2.5}$ concentrations are from the ambient air quality monitoring stations in Shannxi Province (http://113.140.66.226:8024/sxAQIWeb/pagecity.aspx?cityCode=NjEwMTAw), and meteorological data including wind speed, wind direction, air temperature, air pressure, and humidity are from Shaanxi air quality real-time release system. The research period is from 1 January 2017 to 31 December 2020. The firms'

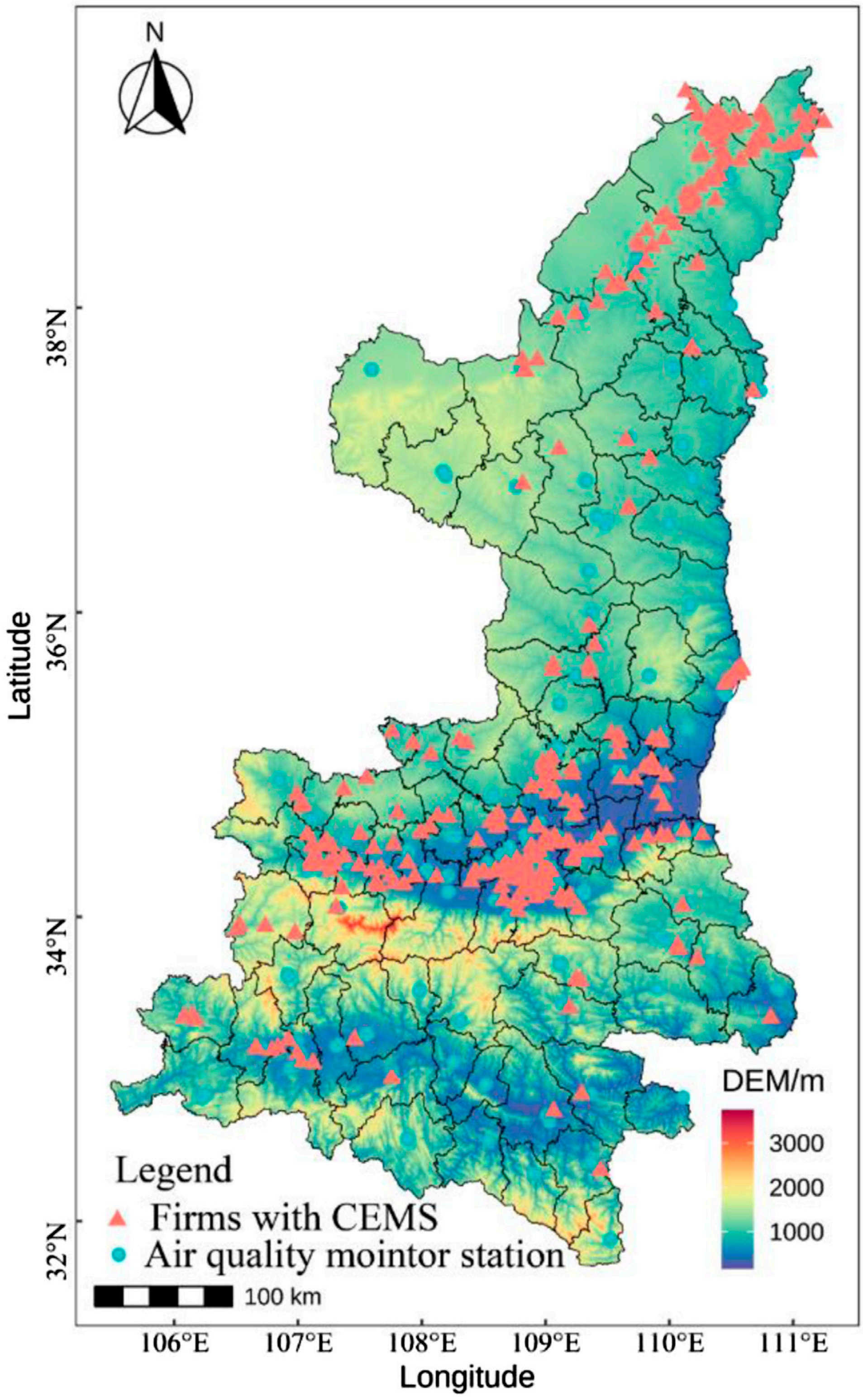

FIGURE 1
Study area of Shaanxi Province.

emissions data come from key pollutant discharge firms' monitoring information release platforms (http://113.140.66.227:9777/envinfo_ps/zdyjbxxpublicity/list), including the three most important pollutants, TSP (total suspended particles), SO_2 (sulfur dioxide) and NOx (nitrogen oxide). The pollutant emissions of the firms installing CEMS exceed 65% of the total pollutant emissions in the region (The State Council, 2007), which basically reflects the regional industrial pollutant emissions.

For air quality monitoring data, we remove outliers in the data and ensure the accuracy of the data by using data from neighbouring air quality monitoring points. For firm emission data, we firstly removed extreme outliers in the firms CEMS data; secondly, we determined whether the firms was in a shutdown state through the firms' flue gas oxygen content, and for missing values in a non-shutdown state, we filled in the pollutant emissions of the firms neighboring time through the missing values to ensure the validity of the data.

2.2 Methodology

2.2.1 Spatiotemporal cluster analysis

$PM_{2.5}$ concentrations exhibits spatial clustering on a daily basis. To identify regions that require targeted control during the study period, daily partitioning results of the clustering process are subjected to correlation clustering analysis. If the external transfer of pollutants is not taken into account, $PM_{2.5}$ concentrations in the identified areas can be reduced by reducing all types of pollutant emissions, such as those from industrial, mobile and non-organized sources. Thiessen polygons are generated from the monitoring stations to ensure the continuity of the identified pollution area and to avoid the limitations imposed by administrative divisions. The resulting clustering categories are consistent with the geographical division, and further refine the control area for $PM_{2.5}$ while smoothing out the boundary of the region.

This paper adopts the K-means clustering method, a fast clustering approach that abstracts clustering units into m-dimensional points and evaluates the similarity between units based on the distance between clustering units (Liu et al., 2018a), to conduct spatial clustering of $PM_{2.5}$:

1) Optional K initial clustering centers: $Z_1(1), Z_2(1), \ldots, Z_k(1)$, 1 is the subsequence of iteration.
2) The rest of the samples are allocated to one of the K cluster centers according to the principle of minimum distance:
$min\{\|X-Z_i(k)\|, i=1, 2, \ldots, K\} = \{\| X-Z_i(k)\|\} = D_j(k)$ (1)

$X \in S_i(k)$,k is the subsequence of iteration; K is the number of cluster centers.

3) Compute the new vector value of each cluster center: Z_j (k+1) j=1, 2, . . . , K

$$Z_j(k+1) = \frac{1}{N_j}\sum_{X\in S_j(k)} X,\ j = 1,2,\ldots,K \tag{2}$$

4) If $Z_j(k+1) \neq Z_j(k)$, return formula (1), classify the pattern samples center by center, and repeat the iterative calculation. If $Z_j(k+1)=Z_j(k)$, algorithm convergence, calculation completes (Wegner et al., 2012).

2.2.2 Wavelet and cross-wavelet analysis

The wavelet transform is a powerful method for the simultaneous analysis of time series in both the time and frequency domains. It involves the use of a variable window function and is generated from mother and child waves through time translation and scaling, as noted by Gao and Zhang (2016) and Mu et al. (2021). This decomposition results in a set of essential functions where increasing the scale is equivalent to decreasing the frequency and sacrificing the time resolution, while reducing the scale and increasing the frequency is equivalent to sacrificing the frequency resolution. By stretching and translational transform, the wavelet function is obtained from the wavelet generator function. The continuous wavelet function is expressed as:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}}\sum_{n'=0}^{N-1} x_{n'}\psi^*\left[\frac{(n'-n)\delta t}{s}\right] \tag{3}$$

where* represents a conjugate complex, N is the total number of the time series, $(\delta_{t/s})/s$ is a factor used for the standardization of wavelet function.

The Morlet wavelet function is commonly used in wavelet analysis as it effectively separates and reconstructs waves of different frequency bands without losing time resolution. This function maintains its shape through frequency shift and has excellent temporal aggregation and high-frequency resolution (Morlet et al., 1982). Therefore, Morlet wavelet function is employed to analyze the periodicity of $PM_{2.5}$ concentrations:

$$\psi_0(t) = \pi^{-1/4}e^{i\omega_0 t}e^{-t^2/2} \tag{4}$$

Where t is time, ω_0 is dimensionless frequency. If ω_0 =6, scale s equals Fourier period. Wavelet power spectrum $|W_n^X(s)|^2$ shows the variation characteristics of the time series on a specific scale and its variation with time. This unbiased and consistent estimation of the real power spectrum of time series is achieved through the use of the full wavelet spectrum (Torrence and Compo, 1998; Torrence and Webster, 1999).

$$\bar{W}^2(s) = \frac{1}{N}\sum_{n=o}^{N-1}|W_n(s)|^2 \tag{5}$$

The boundary effects and errors encountered when handling finite time series are addressed by testing the statistical significance of the wavelet power spectrum using an appropriate equation (Cazelles et al., 2008; Furon et al., 2008; Grinsted et al., 2004; Liu et al., 2018a). Therefore, the test measure display as follows:

$$P_k = \frac{1-\alpha^2}{|1-\alpha e^{-2i\pi k}|^2} \tag{6}$$

Cross-wavelet analysis can compare the frequencies of two-time series X_t and Y_t, and obtain the resonance period and phase of the two sequences in some periods. Cross wavelet spectra of two-time series XWT is $W^{XY} = W^X W^{Y*}$, cross wavelet power is $|W^{XY}|$. The period changes with time, reflected by the cross wavelet power can be visualized by the full spectrum (Veleda et al., 2012). The confidence degree of cross wavelet power can be calculated by the square root of the product of two chi-square distributions. The confidence and correlation coefficient of the two-time series are as follows:

$$D\left(\frac{|W^X{}_n(s)W^{Y*}{}_n(s)|}{\sigma_X\sigma_Y} < P\right) = \frac{Z_v(p)}{v}\sqrt{P^X{}_k P^Y{}_k} \tag{7}$$

$$R^2{}_n(s) = \frac{|S(W^{XY}{}_n(s))|^2}{S(|W^X{}_n(s)|^2)\bullet S(|W^Y{}_n(s)|^2)} \tag{8}$$

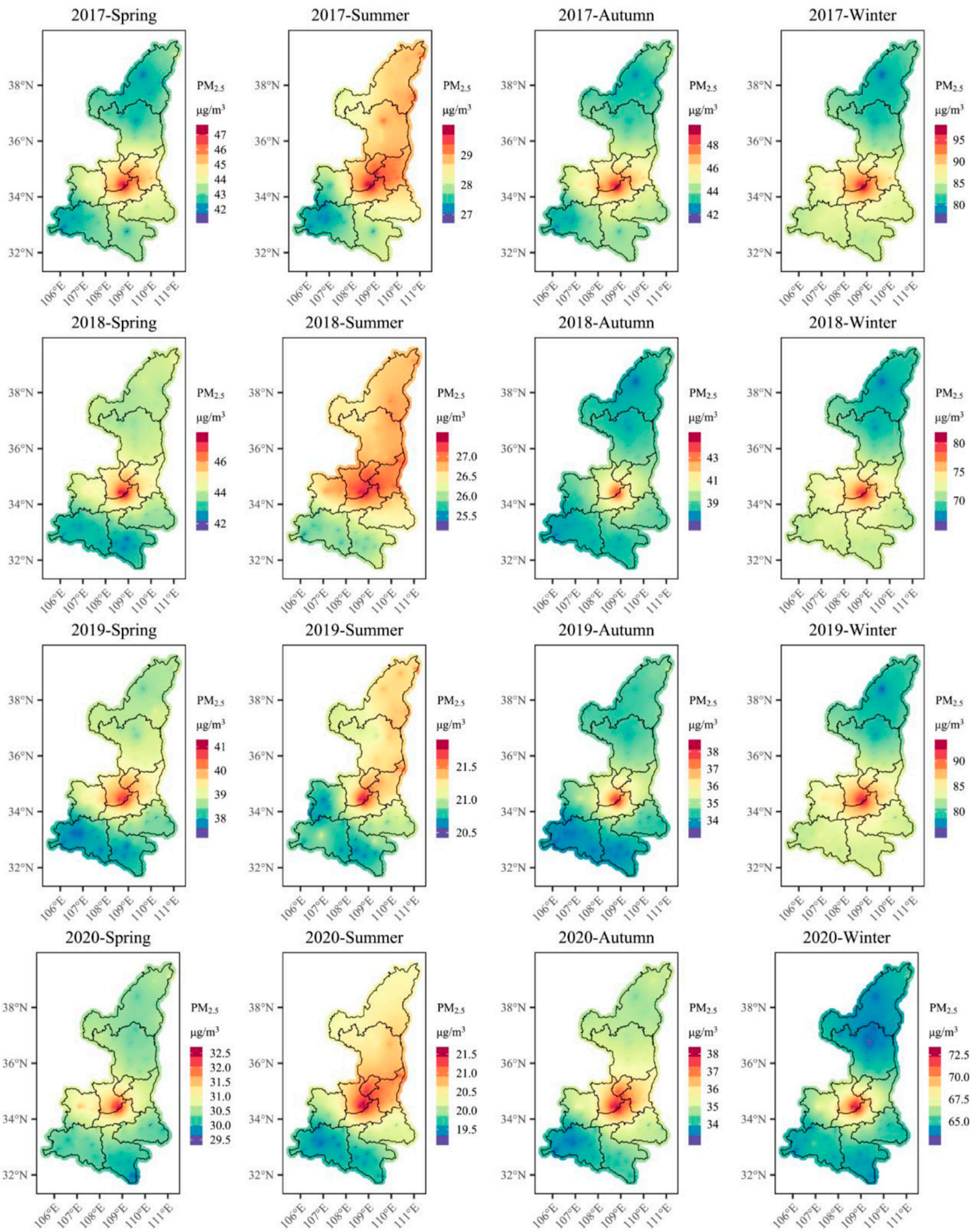

FIGURE 2
Spatiotemporal distribution of $PM_{2.5}$ concentrations.

The phase difference can be transferred to the difference of [-π, π], and its value indicates the lag characteristics of the two sequences (Aguiar-Conraria and Joana Soares, 2011; Addesso et al., 2022). The phase difference formula is as follows:

$$\varphi_{xy} = arctan\left(\frac{\Im\left(W^{XY}{}_{n}(s)\right)}{\Re\left(W^{XY}{}_{n}(s)\right)}\right) \tag{9}$$

3 Results analysis

3.1 Spatiotemporal distribution of $PM_{2.5}$ in study region

The seasonal distribution of $PM_{2.5}$ concentrations in each region is relatively even, with the highest levels in winter and the lowest in summer (Figure 2). During the winter and spring seasons, the $PM_{2.5}$

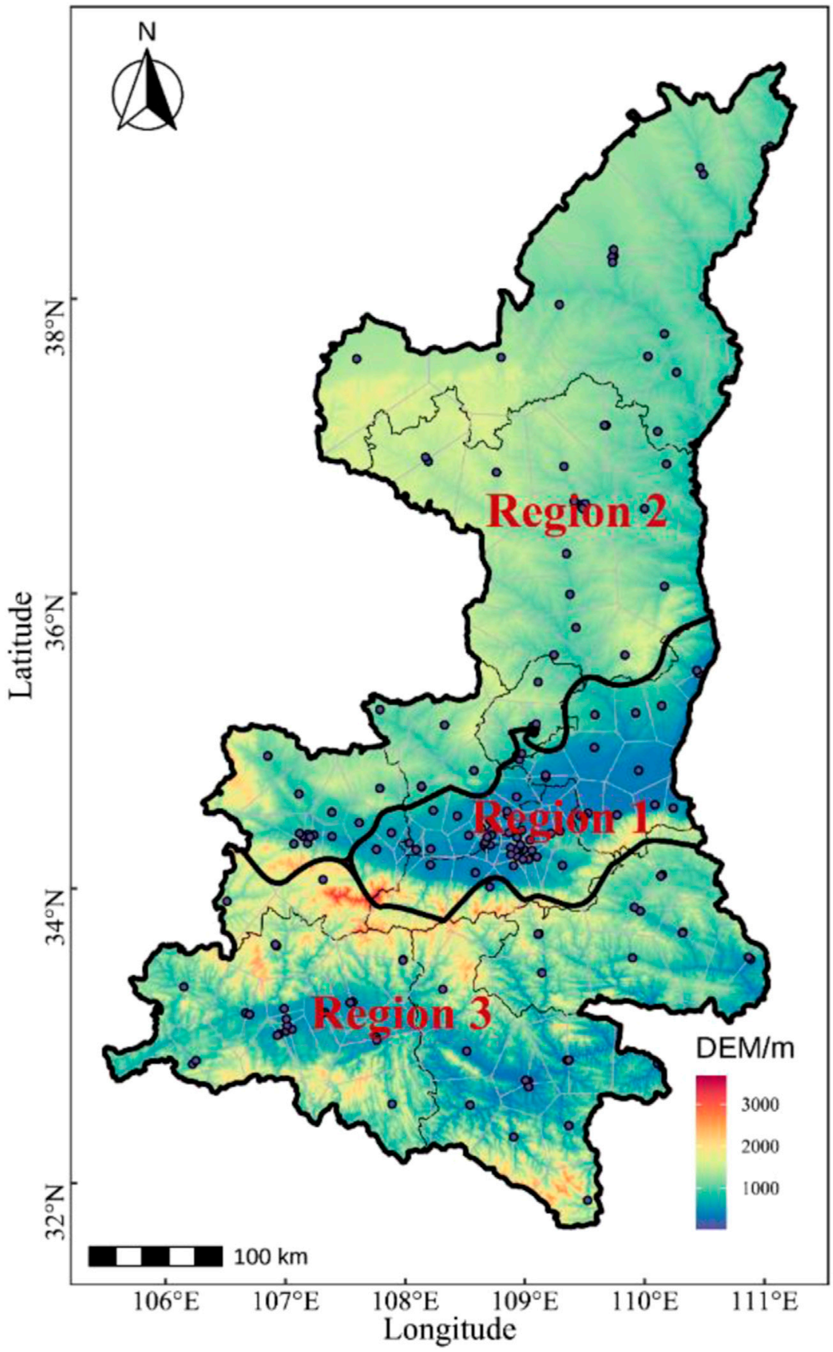

FIGURE 3
Spatial clustering $PM_{2.5}$ in Shaanxi.

concentrations in the three regions display significant variations, ranging from 65 to 95 μg/m³ and 29.5–47 μg/m³, respectively. This indicates that the concentrations during winter are approximately twice as high as those during spring. Conversely, $PM_{2.5}$ concentrations slightly vary among the three regions during the summer and autumn seasons. Moreover, meteorological factors such as temperature, wind speed, and relative humidity significantly promote the diffusion of atmospheric pollutants. In mid-March, the cessation of heating results in a reduction of pollution sources, leading to lower $PM_{2.5}$ concentrations during the spring season than during the winter season.

Annual $PM_{2.5}$ concentrations in the three regions follow the order of Guanzhong > Northern Shaanxi > Southern Shaanxi. Guanzhong is the most economically developed region in Shaanxi Province and has several large coal-fired power plants, cement manufacturers, chemical plants, and metal smelters, which contribute to high $PM_{2.5}$ concentrations. The Guanzhong area's proximity to the Qinling Mountains in the South and the Loess Plateau in the North further hinders airflow movement and pollutant diffusion, thereby intensifying the pollutant concentration (Wang et al., 2015). In Northern Shaanxi, several

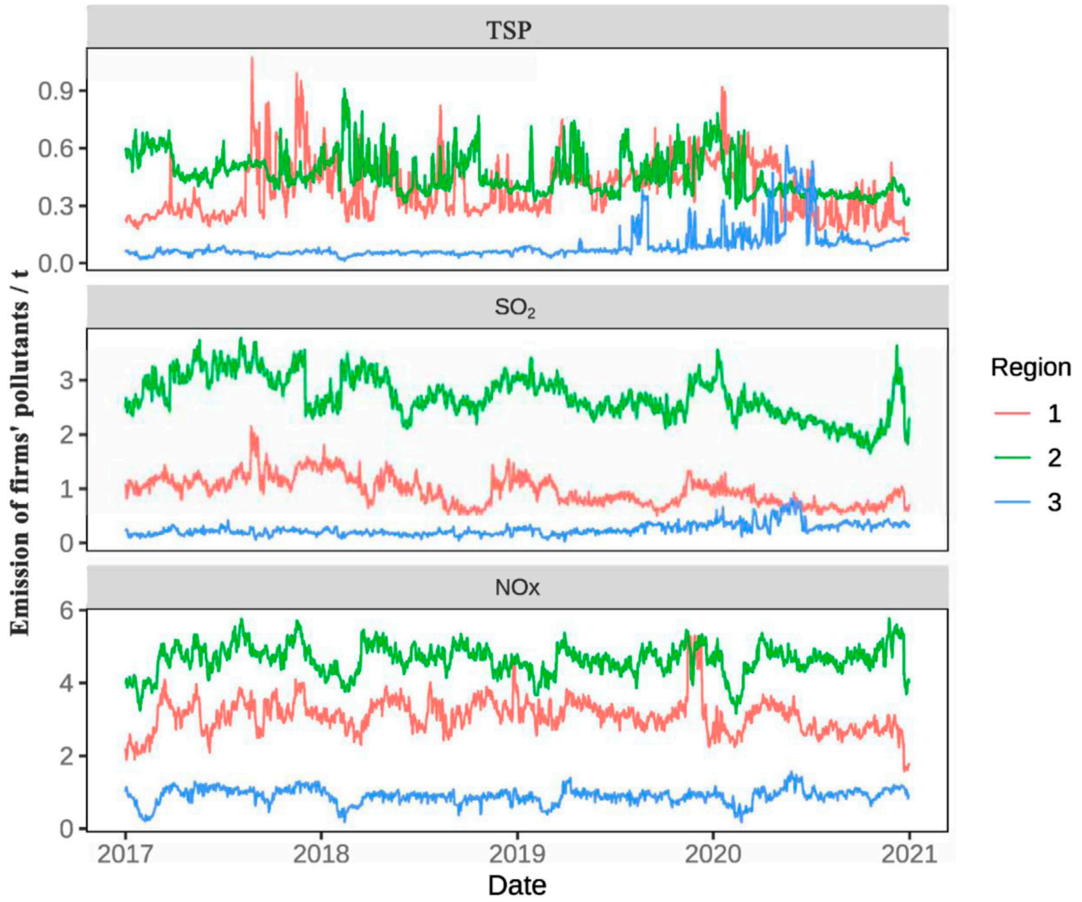

FIGURE 4
Daily variation curves of air pollutants, including TSP, SO_2, and NO_x, emitted by industrial firms from 2017 to 2020.

coal-fired power plants and factories discharge pollutants, and the unique linear canyon terrain in Yan'an City tends to converge local pollutants in the area. Southern Shaanxi primarily relies on natural resources to develop the primary industry, has low urbanization, and has a less prominent contribution of firm emission sources to $PM_{2.5}$ concentrations.

3.2 Clustering results of $PM_{2.5}$ in study region

From Figure 2, it is obvious shows that $PM_{2.5}$ pollution in Shaanxi Province has a significant regional feature, in order to accurately identify each $PM_{2.5}$ pollution region in Shaanxi Province, so as to more accurate identification of the link between pollutant emissions from firms and $PM_{2.5}$ in the air, this part use the $PM_{2.5}$ data of the air monitoring points in the study time period, and the method of spatial clustering to perform spatial clustering. Figure 3 depicts the spatial clustering of air pollution areas in Shaanxi Province. By overlaying the zoning results onto the elevation map of Shaanxi Province, it becomes apparent that delimited regions of $PM_{2.5}$ overlap with the locations of the Guanzhong Plain, Northern Shaanxi, and Southern Shaanxi, suggesting that $PM_{2.5}$ concentrations are influenced by the topography. Three regions were identified based on their coverage area and $PM_{2.5}$ concentration levels. Region 1 covers most of the Guanzhong area, region 2 includes the northern Shaanxi area and a portion of the Guanzhong area, while region 3 comprises the Southern Shaanxi area and a portion of the Guanzhong area. Region 1 had a mean $PM_{2.5}$ of 57.4 μg/m^3, and 335 days per year exceeded 24-h $PM_{2.5}$ thresholds (<75 μg/m^3), representing 20.41% of total days. In Region 2, the mean $PM_{2.5}$ was 40.3 μg/m^3, with 151 days exceeding the 24-h $PM_{2.5}$ benchmark, representing 9.2% of the total number of days. Finally, the mean $PM_{2.5}$ concentration in region 3 was 33.2 μg/m^3, with 79 days exceeding the 24-h $PM_{2.5}$ benchmark, representing 4.81% of the total number of days.

3.3 Air pollutant emissions from industrial firms in study region

The analysis results presented in Figure 4 shows the variations in pollutant emissions among industrial firms in Shaanxi Province. Figure 4 shows that region 1 and region 2 emit about the same amount of TSP pollutants, while region 2 emits a much larger amount of SO_2 and NOx than region 1 and region 3. This emission situation is closely related to the distribution of industries in different regions. This difference was attributed to the lots of

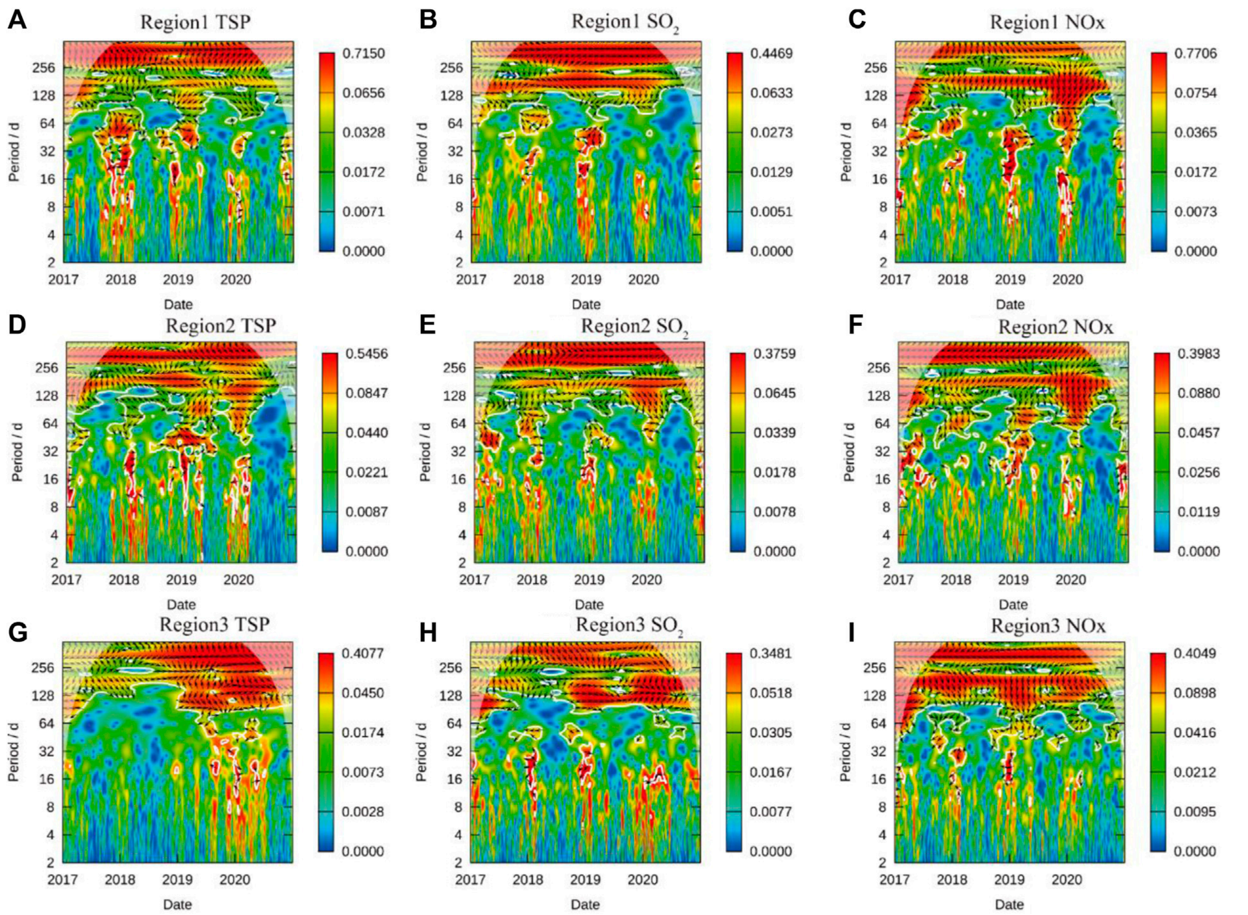

FIGURE 5
Spatiotemporal correlation between $PM_{2.5}$ concentrations and industrial firms' emissions in different regions of $PM_{2.5}$ pollution. Note: region 1 represents Guanzhong, region 2 represents Northern Shaanxi, and region 3 represents Southern Shaanxi. **(A,D,G)** Region 1 TSP, Region 2 TSP, Region 3 TSP; **(B,E,H)** Region 1 SO_2, Region 2 SO_2, Region 3 SO_2; **(C,F I)** Region 1 NOx, Region 2 NOx, Region 3 NOx.

power plants located in region 2, which accounts for 50% of the power plants in Shaanxi Province and contributes to over 70% of total pollutant emissions from power plants. Region 1 is distributed with many processing and manufacturing firms, which mainly emit TSP pollutants, making the emissions of TSP pollutants in region 1 and region 2 similar, although there are significant differences in SO_2 and NOx emissions. Simultaneously, it can be observed that TSP emissions in region 3 saw a notable increase during the COVID-19 period in 2020. In contrast, emissions in regions 1 and 2 experienced a certain degree of decline. There's a reasonable suspicion that regions 1 and 2 redirected a portion of their production capacity to region 3, which may account for this dynamic change.

3.4 Analysis of cross-wavelet in different regions

This part we employ the Morlet wavelet function to conduct a wavelet transform of daily data on TSP, SO_2, and NO_x emissions from industrial firms in three regions of Shaanxi Province from January 2017 to December 2020. The wavelet spectrums of TSP, SO_2, and NO_x are analyzed, with time d as the horizontal axis and time scales as the vertical axis. A wavelet coefficient of 0 signifies a mutation point wherein the correlation coefficient shifts from higher to lower values. The white shadow area in the wavelet spectrum represents the influence cone of the wavelet boundary, while the area enclosed by thick white solid lines indicates that the noise test has passed at a 95% significance level.

Figure 5 shows that the pollutants emitted by industrial firms during the winter prevention period (November to February) in the three regions demonstrate substantial periodicities of 16–64 and 64–128 days, with the impact of contaminants on $PM_{2.5}$ concentrations lagging 1/4-3/8 cycles. The TSP and $PM_{2.5}$ manifest a strong correlation in the 16–32 days range, followed by NO_x and $PM_{2.5}$, while SO_2 and $PM_{2.5}$ exhibit the weakest correlation. These results coincide with the fact that TSP directly influences $PM_{2.5}$ concentrations in the atmosphere, while NOx and SO2 necessitate a chemical reaction to generate nitrate and sulfate and form secondary particles. Simultaneously, the figure shows a notable correlation between pollutant emissions from firm and $PM_{2.5}$ concentrations within short timeframes in both region 1 and region 2. This strong correlation strongly suggests that firms' pollutant emissions play a pivotal role in driving fluctuations in $PM_{2.5}$ concentrations, particularly during the winter months. However, this short-term

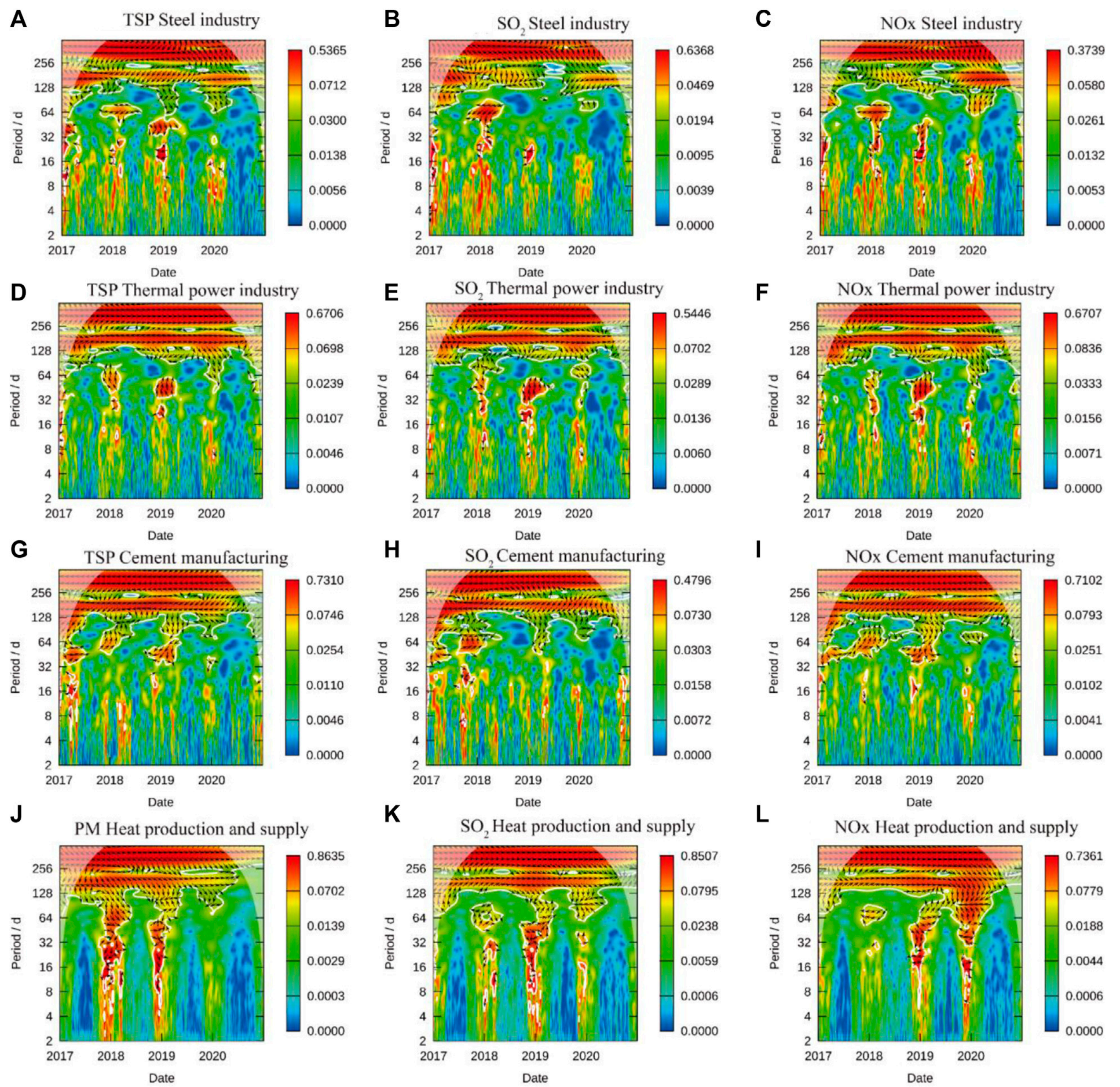

FIGURE 6
Spatiotemporal correlation between $PM_{2.5}$ concentration and the air pollutants emitted by different industrial firms in region1 (Guanzhong). **(A,D,G,J)** TSP steel industry, TSP thermal power industry, TSP cement manufacturing, PM heat production and supply; **(B,E,H,K)** $S0_2$ steel industry, $S0_2$ thermal power industry, $S0_2$ cement manufacturing, $S0_2$ heat production and supply; **(C,F,I,L)** NO_x steel industry, NO_x thermal power industry, NO_x cement manufacturing, NO_x heat production and supply.

influence on $PM_{2.5}$ concentrations as a result of corporate emissions is not evident in region 3.

Figure 5 also shows that the emissions from industrial firms in region 1 strongly resonate with $PM_{2.5}$ from November to February 2017 and 2018. However, during a short period of 32–64 days, the emissions negatively related with $PM_{2.5}$ concentrations, implying that changes in $PM_{2.5}$ concentrations lag behind alterations in TSP emissions from firms. In the winter of 2019, there is a significant correlation between firm emissions and $PM_{2.5}$ concentrations, but no significant correlation is found in the spring of 2020 since industrial emissions reduced during the COVID-19 lockdown, which caused an unprecedented cessation of human activities that affected China's industrial production and pollutant emissions. Therefore, controlling industrial emissions can alleviate $PM_{2.5}$ pollution in Shaanxi.

3.5 Analysis of cross-wavelet in different industries

Using region 1 as an example, the study found a strong correlation between $PM_{2.5}$ concentrations and pollutants emitted by thermal production, supply, and steel industries within a short timeframe of

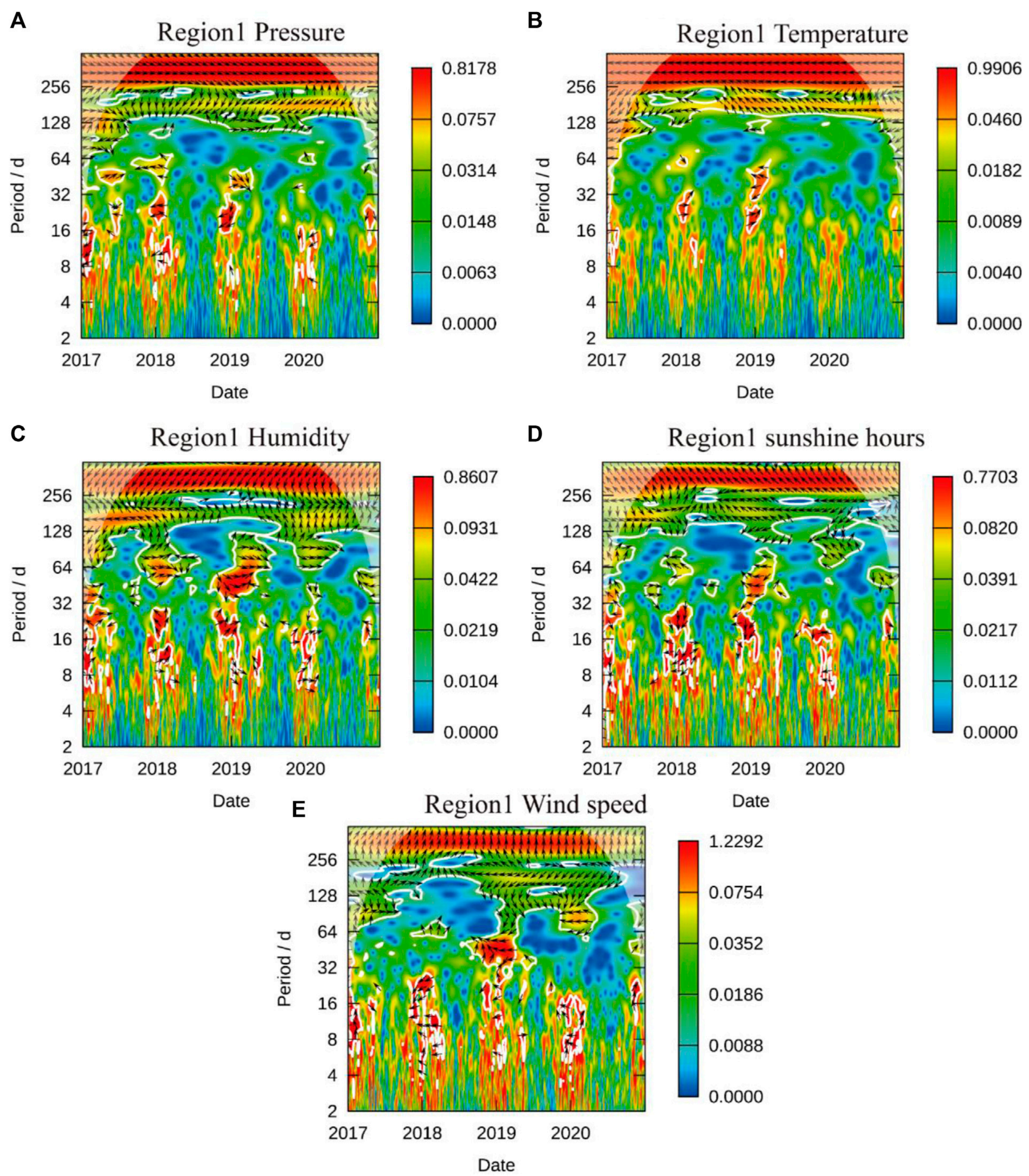

FIGURE 7
Spatiotemporal correlation between $PM_{2.5}$ concentrations and meteorological factors in region 1 (Guanzhong). **(A)** Region 1 pressure, **(B)** Region 1 temperature, **(C)** Region 1 humidity, **(D)** Region 1 sunshine hours, **(E)** Region 1 wind speed.

8–32 days. However, the correlation coefficient displays irregular fluctuations (Figure 6). Conversely, there was a weak correlation between $PM_{2.5}$ and emissions from cement and power sectors. During a medium to long timeframe of 32–64 days, TSP emissions from heat production and supply firms in 2018 and 2019 exhibited correlations with $PM_{2.5}$ concentrations. Moreover, SO_2 positively related $PM_{2.5}$ concentrations in 2018 and 2019, while NO_x and $PM_{2.5}$ displayed positive correlations in 2019 and 2020. Between 2017 and 2019, TSP, SO_2, and NO_x emissions from cement manufacturing firms demonstrated strong positive correlations with $PM_{2.5}$. In contrast, there were weak correlations between $PM_{2.5}$ concentrations and pollutants emitted by firms in the power and iron-steel industries. Within a long timeframe of 64–128 days, the correlation between emissions in the above four industries and $PM_{2.5}$ concentrations gradually weakened, except for significant relationships between $PM_{2.5}$ and NO_x emitted by thermal production and supply firms.

3.6 Spatiotemporal correlation between $PM_{2.5}$ concentrations and meteorological factors

In addition to firms' emissions, meteorological factors are also an important driver of $PM_{2.5}$ concentrations (Jia et al., 2020). This section takes region 1 as an example to further analyse whether meteorology further influences the changes in $PM_{2.5}$ concentrations on basis of emissions from firms. Specifically, the study examines the periodic effects of atmospheric pressure, temperature, humidity, wind speed, and sunshine on $PM_{2.5}$ using time-series data and Morlet cross-wavelet transform analysis. Figure 7 shows that the $PM_{2.5}$ concentration has a negative correlation with atmospheric pressure, humidity, wind speed, and sunshine on an 8–32 days time scale, while no significant correlations are observed with air temperature. In addition, the degree of correlation between $PM_{2.5}$ concentration and wind direction, air pressure, and humidity during the winter defense period in 2017–2018 and 2018–2019 is significantly higher than that in other years. In a certain extent, it can be inferred from Figures 5A–C that a connection exists between the heightened responsiveness of firms' emissions to ambient $PM_{2.5}$ and alterations in meteorological conditions. This dynamic suggests that firms emit comparable levels of pollutants but contribute to more $PM_{2.5}$ pollution, possibly due to changing meteorological factors.

4 Conclusion

This study utilizes data of $PM_{2.5}$ concentrations collected from 169 air quality monitoring stations and 361 industrial firms situated in all county-level cities within Shaanxi Province. The spatial cluster analysis method is used to determine the clustering region of $PM_{2.5}$, while the spatiotemporal correlation between $PM_{2.5}$ concentrations and industrial firm emissions in different smog-contaminated areas is evaluated using the cross-wavelet analysis method.

The findings of this study indicate that the mean $PM_{2.5}$ concentrations in Shaanxi Province decreased from 50.2 to 38.1 μg/m^3 between 2017 and 2020, which can be attributed to the 3-year plan to control haze and improve air quality. The mean $PM_{2.5}$ concentrations in summer and winter were 38.9 μg/m^3 and 77.6 μg/m^3, respectively, with higher concentrations observed during winter. Additionally, the mean $PM_{2.5}$ concentrations in Guanzhong, Northern Shaanxi, and Southern Shaanxi were 57.4, 40.3, and 33.2 μg/m^3, respectively, with Guanzhong having a higher $PM_{2.5}$ concentration than Southern Shaanxi.

The K-means clustering method is employed to cluster daily $PM_{2.5}$ concentrations in winter, and three pollution areas are identified based on ground elevation information and geographical subregions of Shaanxi Province. $PM_{2.5}$ concentrations in the three regions of Shaanxi Province during winter show periodic changes, with pollutants emitted by firms lagging about 1/4-1/2 of the period. In the 16–32 days period, $PM_{2.5}$ concentrations are significantly affected by PM, followed by NO_x and SO_2. NO_x has significantly affected $PM_{2.5}$ concentrations in the 32–64 days period, while in the 64–128 days period, the impact of NO_x and SO_2 on $PM_{2.5}$ concentrations is similar. Industrial firms in regions 1 and 2 significantly affect local $PM_{2.5}$ concentrations, while the impact of industrial firms in region 3 is minor.

We also found during the COVID-19 lockdown, industrial firm emissions, excluding those in the heat production and supply industry, had no significant impact on $PM_{2.5}$ concentrations, indicating that controlling air pollutants emitted from firms can alleviate $PM_{2.5}$ in Shaanxi. Furthermore, pollutants emitted by firms in the thermal production, supply, and steel industries have a greater impact on $PM_{2.5}$ concentrations than those from the cement manufacturing and power industries.

The study findings suggest that the government should focus on reducing and eliminating backward production capacity, strengthening discharge control of thermal power production, supply, and steel-iron industries, and promoting industrial structure optimization and upgrading in Shaanxi Province to reduce $PM_{2.5}$ concentrations during winter. Specifically, for the Guanzhong and northern Shaanxi regions, there is a particular need to control pollutant emissions from firms under unfavourable meteorological conditions in order to effectively mitigate the severe PM2.5 pollution caused by firms' emissions. For the southern Shaanxi region, there is a need to prevent firms in the northern Shaanxi and Guanzhong regions from relocating or relocating some of their production orders to southern Shaanxi.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ: Data curation, Formal Analysis, Methodology, Software, Writing–original draft. LY: Formal Analysis, Writing–original draft. CJ: Visualization, Writing–review and editing. PG: Visualization, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Combination optimization of green energy supply in data center based on simulated annealing particle swarm optimization algorithm

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At present, the high energy consumption of data centers based on grid power supply not only brings huge direct cost of electricity, but also indirectly produces a lot of greenhouse gases, which affects the natural environment. Academia and industry are beginning to introduce clean renewable energy sources such as wind and solar power into data centers to reduce operating costs and environmental damage by building new green data centers. To solve this problem, this study considers the use of waste heat for refrigeration while taking natural gas power generation into account, and introduces wind energy as a green energy source. On the premise of considering the response level of data centers, the two resources are combined and deployed to improve resource utilization and reduce energy consumption costs. Aiming at the instability of wind power generation, a particle swarm energy scheduling optimization algorithm based on simulated annealing algorithm was proposed by combining simulated annealing algorithm and particle swarm optimization algorithm. The research shows that, considering the response level of data centers, the use of natural gas and wind energy as the main energy supply can effectively reduce the overall energy consumption of data centers.

KEYWORDS

data center, simulated annealing algorithm, particle swarm algorithm, green energy consumption, combination optimization

1 Introduction

Data centers can provide resource services and application services such as data computing, storage and exchange, and have become the cornerstone of global economic development. According to the latest data from Synergy Research Group, the total number of large-scale data centers rose to 597 by the end of 2020, doubled the number in 2015. Data center is a building site that provides operating environment for centralized electronic information equipment. It must ensure uninterrupted operation for 8760 h a year, and has the characteristics of large heat dissipation, stable operation, high reliability, and high requirements on air temperature, humidity and cleanliness. Data center requires a large amount of power resources, data centers around the world consumed 200 terawatt hours per year in 2018 (Jones, 2018), which was estimated to account for 1.4% of global power consumption and is expected to reach 5% of global power consumption by 2024 (Avgerinou et al., 2017). The power consumption of data centers is mainly composed of four parts: IT equipment, air conditioning system, lighting system, power supply and distribution system. The energy consumption of IT equipment accounts for about 45%, and that of air conditioning system accounts for about 40% (Gandhi et al., 2012; Vasques et al., 2019). More than 99% of the electricity used to power IT equipment is converted to heat energy. If the excess heat energy is not removed in time, the temperature will rise and result in IT equipment faults or even fires. Therefore, data centers need to be equipped with air conditioning systems to control the device temperature within a certain range. This ensures the stable operation of IT equipment and the optimal performance of the devices in the data center throughout their life cycle. There are a variety of temperature management methods in data centers, such as air cooling (Parolini et al., 2012; Li et al., 2012), water cooling (Xu, 2007), immersion cooling (Yao et al., 2017), etc. Air cooling uses air circulation and air conditioning technology to eliminate the heat generated by data centers. Due to its simplicity and low cost, it has become the most common temperature management method in the data center industry at present.

In order to reduce the consumption of fossil energy in the operation of data centers, enterprises begin to build green data centers, which use renewable energy such as wind and solar energy to supply part or all of the electric energy of data centers, so as to reduce carbon dioxide emissions. However, large-scale data centers are often built in remote areas with wide areas, sparse population and good climate, which are usually rich in solar and wind energy resources. For example, Amazon has built its largest wind farm in Texas, which can produce more than 1 million megawatt hours of energy per year to power its data centers. Green House Data built a wind power plant in Wyoming to power the data center, which can reduce costs and carbon emissions from a global perspective, and has great economic and environmental significance (Goiri Í et al., 2013).

As data volumes proliferate, researchers realize that the advantages of data centers are becoming apparent, so more work is being devoted to the question of how to enhance the energy use of data center networks. Researchers try to use more and more renewable energy equipment to increase new energy to provide energy, and reduce the use of thermal power generation energy (Bi et al., 2016). Li and Hu et al. proposed that energy storage devices could be used to use wind energy in different time domains (Li et al., 2017), and batteries could be used to store solar energy in the daytime and provide power to data centers at night when users are frequently active (Chao et al., 2013; Li et al., 2014), thus reducing carbon emissions of data centers. For data centers equipped with unstable new energy sources such as wind and solar, as well as non-green energy sources such as diesel generators, how to allocate different energy ratios to meet the needs of reliability, environmental protection and economy is a key issue. Kong and Liu proposed Green Planning (Kong et al., 2016), an energy allocation scheme that minimizes the total energy consumption cost and carbon emission cost during the life cycle of data centers. Ren and Wang et al. also proposed an energy allocation scheme that minimizes the total energy consumption cost and limits the total carbon emission during the life cycle of data centers (Ren et al., 2012). Deng and Stewart et al. took carbon emissions generated by energy combustion as part of the application cost from the perspective of application. By studying how to make reasonable and effective resource allocation for data centers with multiple energy sources, they can minimize the use of purchased thermal power from the grid (Deng et al., 2012). Tripathi and Vignesh et al. designed a mixed integer linear programming model for resource planning and total cost minimization of distributed green data centers, it could minimize the cost of server deployment and power usage while minimizing the consumption of renewable energy. The results show that the adoption of green energy can reduce carbon emission and total cost (Tripathi et al., 2017). Deng and Liu et al. studied various types of power supply systems of data centers and designed online control strategies according to the characteristics of different energy sources, so as to reduce the operating costs of power supply systems of data centers (Deng et al., 2013). Ren and Wang et al. took the renewable energy generation, dynamic electricity price and operation cost of energy storage equipment in data centers into account to propose an optimization strategy aiming at minimizing the cost of data centers. Their research results showed that by including renewable energy in the power capacity planning of data centers could minimize the operating cost while reducing the carbon emission of data centers (Ren et al., 2012).

At present, a lot of research work focuses on the design of data centers with green energy as the main power source, and a green computing platform has been built accordingly to further analyze the availability of new energy power supply and the effectiveness of power resource management strategies. Goiri and Bianchini at Rutgers University had been working on new energy data center management in a batch-load environment and proposed the Green Slot parallel batch scheduler, in which the server system was powered by a solar array with grid power as backup power. Green Slot first predicted the solar energy supply based on historical data and weather forecast, and then allocated enough resources for the load to be processed in the future according to forecast information and user information, so as to meet the latest completion time of batch processing tasks and maximize the utilization of new energy (Goiri et al., 2012). Later, the team designed a solar powered data center called Parasol as a research platform. In addition to power grid and solar power system, Parasol was also equipped with backup battery system, air refrigeration unit and air conditioning (Goiri I. et al., 2013). Carroll and Balasubramaniam et al. gave out a dynamic optimization solution of green data service, which took weather, geographical location of data center and other factors affecting the output power of renewable energy into consideration for prediction by using genetic algorithm (Carroll et al., 2011). Zhang and Wang et al. studied how to dynamically allocate service requests among data centers in different geographical locations according to local weather conditions in order to maximize the use of renewable energy (Zhang et al., 2011). Arlitt and Bash et al. put forward the model of "net zero energy data center", which offset the energy consumed in the construction and operation of data center with the utilization of clean energy, and built a prototype system as a test platform (Arlitt et al., 2012).

Distributed energy, represented by natural gas combined cooling and thermal power supply system has high efficiency, cleanliness and reliability due to its characteristics of cascade utilization of energy, which can effectively reduce the primary energy consumption of data centers (Xu and Qu, 2013). At

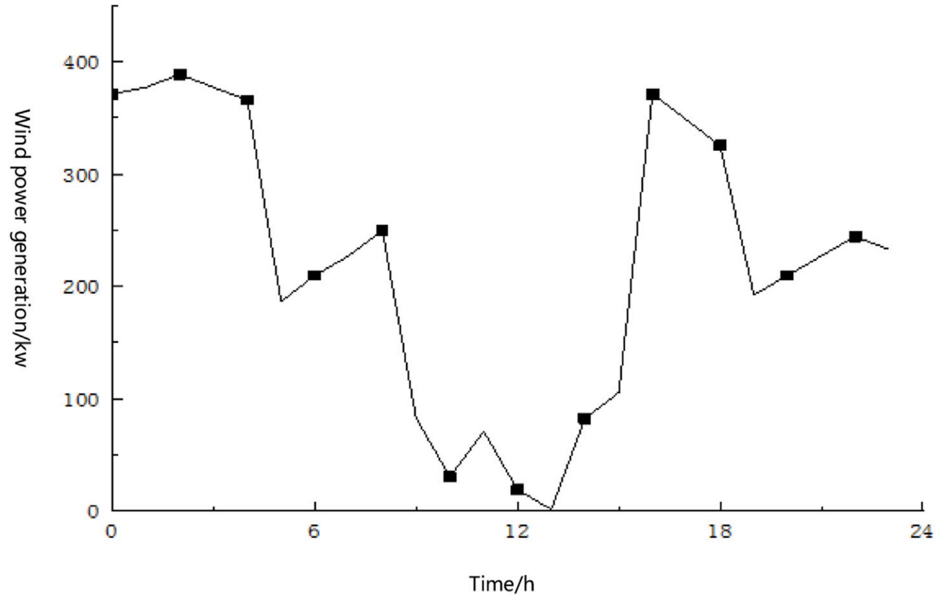

FIGURE 1
Typical daily wind power curve of data center. The wind power at each moment shall not exceed ±10% of the typical value at that moment and add the disturbance value.

present, many studies have proved the feasibility and reliability of using distributed energy system to power data centers. Sevencan and Lindbergh et al. comprehensively analyzes the energy efficiency, economic and environmental characteristics of the combined cooling, thermal and electric power supply system applied in data centers, and the results show that the stable load demand and low electric-cooling ratio of data centers make it a better match with the combined power supply system, and the operation cost can be reduced by 54% (Sevencan et al., 2016). However, due to the limited thermoelectric ratio of the system, it often does not match the dynamic load of the user, resulting in the low utilization rate of the system equipment, poor adaptability and other problems. In order to improve its characteristics, coupled with the deepening of the energy Sustainable Development Goals, the use of renewable energy technologies such as solar and wind power, as well as storage Settings, is also increasing in data centers. However, due to the fluctuation and randomness of renewable energy, instability factors are brought to the planning and operation of cold, hot and electricity combined power supply system (Zheng et al., 2021). Therefore, most studies prefer to adopt complementary ways to power data centers, improve the utilization rate of renewable energy and reduce the consumption of fossil fuels. Sheme et al. demonstrated the possibility of using renewable energy for power supply in data centers at 60° north latitude, and the results showed that natural gas, solar energy and wind power generation could achieve higher economic benefits and better stability through collaboration (Sheme et al., 2018)

The combination of task scheduling algorithm with data center green energy consumption is also a research hotspot in recent years. Tu and Yao et al. adopted load scheduling and alternative energy supply strategies to reduce energy consumption expenses of cloud data centers (Tu et al., 2013; Yao et al., 2014). Kumar and Aujla et al. proposed a green energy sensing task scheduling and classification method based on container technology, which transmit the arrived tasks from multiple devices to the data center and provided enough green available energy. On this basis, a container integration and host specification method based on green energy was proposed (Kumar et al., 2019). Khosravi and Andrew et al. proposed a variety of effective virtual machine layout methods to evaluate the actual performance of virtual machines, and determined the parameters that have the greatest impact on fossil raw materials, green energy consumption, cost and carbon footprint (Khosravi et al., 2017). Li and Qouneh et al. proposed an energy switcher to coordinate the request load and new energy supply by constantly switching between new energy and traditional power grids, so as to maximize the use of new energy (Li et al., 2011). The task scheduler GreenSlot proposed by Goiri and Le et al. which could carry out scientific calculation, and the task scheduler GreenHadoop processing distributed big data both considered the fluctuation of power grid price and solar energy supply (Goiri et al., 2012). And their goal was to achieve green, low-cost task scheduling under the condition of meeting task deadlines. Krioukov and Goebel et al. proposed a supply-following method for task scheduling, so as to balance task load and wind energy supply and realize green data center scheduling (Krioukov et al., 2011). Aksanli and Venkatesh et al. proposed a new energy prediction algorithm, which carried out task scheduling based on the predicted new energy output, so as to improve the utilization rate of new energy (Aksanli et al., 2011). Gmach and Rolia et al. proposed a solution to estimate the power capacity of data centers based on the output of new energy and the requested load. This solution provided the reference basis of the power supply of different sources, so as to achieve the supply and demand balance between new energy and the requested load (Gmach et al., 2010).

TABLE 1 Equipment operating parameter.

Equipment	Efficiency	Cost (RMB/kW)	Output range (kW)
Gas turbine	0.4	0.041	[0,1700]
Lithium Bromide Absorption Chiller	0.95	0.035	[0,1300]
Wind turbine	0.8	0.023	[0,1200]
Electric refrigerator	3	0.050	[0,500]

Through literature review, it can be found that the combination of green energy and data center energy consumption, and the effective scheduling of green energy as a supplement to traditional energy is the hot spot of current research. Particle swarm optimization (PSO) is a representative energy consumption scheduling method for data centers. However, existing researches mainly analyze from the perspective of consumption, and rarely consider the supply optimization of different forms of energy, as well as the combination of data service load allocation and green energy scheduling. Therefore, this paper proposes to consider the coordination of natural gas power generation and wind power generation, and at the same time use the waste heat of natural gas power generation to drive refrigeration, and the dual-objective scheduling model of data center energy consumption under the situation, the simulated annealing particle swarm optimization algorithm is used to solve the model, and the simulation is conducted. The results show that the combination of natural gas and wind power generation, In this way, the overall power consumption of data centers can be reduced without ensuring the service level of data centers.

2 Data center energy conversion model

The data center obtains electricity through natural gas power generation and wind power generation. Considering the instability caused by wind power volume, it needs to charge the battery after the charger rectification and then use the inverter power supply with protection circuit to convert the chemical energy in the battery into alternating current, so as to ensure the stable use. The gas turbine is used to burn natural gas to generate electricity and drive the receiver refrigeration unit to refrigerate, so as to reduce the temperature of the data center.

(1) Gas turbine

Gas turbine is a kind of internal combustion power machinery which uses continuous flow of gas as working medium to drive impeller to rotate at high speed and convert fuel energy into useful work. The air is compressed by the compressor, mixed with light fuel and introduced into the combustion chamber for full combustion to generate high temperature and high-pressure gas, thus driving the rotation of the generator and generating electric energy. The excess high temperature gas is refrigerated by the absorption refrigeration unit to improve the energy utilization rate (Mansourim et al., 2012), and its output power is expressed as:

$$\boldsymbol{P_{GT}} = \boldsymbol{\lambda G_{GT}} \tag{1}$$

G_{GT} and P_{GT} are the input gas power and output electric power of the gas turbine respectively, λ is the energy conversion efficiency.

(2) Absorption refrigeration unit

Absorption refrigeration units refrigerate by absorbing waste heat in gas turbine system, so as to meet the cooling load requirements of data centers. Lithium bromide and water are generally used as catalysts for refrigeration. The lithium bromide absorption chiller can be combined with the gas turbine to use the exhaust steam of the gas turbine as the heating steam of the lithium bromide absorption chiller, which can improve the utilization rate of water steam and meet the requirements of power generation and refrigeration at the same time (Liu and Wang, 2004). Its mathematical model is:

$$\boldsymbol{C_{GC}} = \boldsymbol{\eta} \cdot \boldsymbol{Q_{GT}} \cdot \boldsymbol{\xi} \tag{2}$$

C_{GC} is the cooling capacity of lithium bromide absorption refrigerating machine; η is the recovery rate of waste heat, which is related to room temperature and can reach 0.65 at present. ξ is the refrigeration coefficient of unit; Q_{GT} is waste heat generated by gas turbine, and its value can be expressed as:

$$\boldsymbol{Q_{GT}} = \frac{\boldsymbol{P_{GT}}(1 - \boldsymbol{\lambda} - \boldsymbol{\lambda}_1)}{\boldsymbol{\lambda}} \tag{3}$$

λ_1 is the heat loss coefficient of gas turbine, and the fixed value λ_1=0.03 is usually taken (Misra et al., 2005).

(3) Wind power generation

Wind power as a clean energy source can be used to power data centers. In the process of wind power generation, the fan blade rotates under the thrust action of air inflow, and the low-speed shaft connected to the blade drives the high-speed shaft to rotate through the gearbox, which drives the generator to generate electric energy (Muljadi and Butterfield, 2001). According to Baez theory, the mechanical power captured by the wind turbine from the wind is $P_m = \frac{1}{2}\rho S C_P v_1^3$, where ρ is the air density, the value is $1.25 kg/m^3$ generally, S is the sweep area of the impeller, C_P is the utilization coefficient of wind energy, v_1 is the inlet wind speed of the impeller. The power generation curve of a typical wind day is shown in Figure 1. There is a certain deviation between the wind power value of the data center and the power curve of typical wind power day. Considering the instability of wind power generation, the wind power value at each moment should not exceed ±10% of the typical

TABLE 2 Energy price.

Category	Period		Price (Yuan·kW·h)
Wind power	Normal period		0.667
	Valley period		0.322
Natural gas	peak period	08:00–24:00	0.368
	valley period	00:00–08:00	0.122

value at that moment to add the disturbance value, so as to better simulate its power generation process.

(4) Electric refrigerator

Electric refrigerating machine uses the electric energy generated by gas unit and wind power generation to drive the compression refrigeration unit to refrigerate. The compression refrigeration unit is a refrigeration equipment that converts electric energy consumption into cold energy. By absorbing and compressing the gas in the evaporator, the high temperature and high-pressure gas is transported into the condenser, and the heat is released in the condenser to form high pressure and low temperature gas. The gas is depressed to low temperature and low pressure through the throttle, and finally absorbs excess heat in the evaporator to form cold gas. Its mathematical model is as follows:

$$C_{EC} = \gamma P_{EC} \tag{4}$$

C_{EC} is the output cold power of electric refrigerator, P_{EC} is input power for electric refrigerator, γ is the energy conversion efficiency.

(5) Data center power consumption model

The power consumption of a data center is linearly correlated with the number of active servers in the center (Liu et al., 2022).

$$e_{i,t} = km_{i,t} + \beta, \ \forall i \in I, t \in T \tag{5}$$

T is the set of time nodes; I is the number of data centers set; $e_{i,t}$ is the power consumption of the data center i at time t; k and β are the parameters representing the relationship between data center power consumption and active server, $m_{i,t}$ is the number of active servers in the data center i at time t, the equation is shows as below:

$$m_{i,t} = 0, 1, \ldots, M_i \tag{6}$$

M_i is the total number of servers in the data center.

Server is a device that processes data load, and the time delay of data processing is related to the average service rate and number of servers. Its model can be expressed as:

$$0 < \frac{1}{\mu - \frac{L_{i,t}}{m_{i,t}}} \le D \tag{7}$$

μ is the average service rate of the active server, $L_{i,t}$ is the total data load allocated to data center i at time t; D is the upper limit of time delay for data centers to process data loads.

After sorting out the above formula, the power consumption model of data center can be expressed as follows:

$$\begin{cases} e_{i,t} = km_{i,t} + \beta \\ m_{i,t} \ge \dfrac{L_{i,t}}{\mu - \dfrac{1}{D}} \\ 0 \le m_{i,t} \le M_i, m_{i,t} \in N^* \end{cases} \tag{8}$$

In Eq. 8, although the number of active servers $m_{i,t}$ is a positive integer with unit change, but it can be regarded as a continuous variable in simulation analysis compared with the total number of servers with a large value. Combining the first and second terms of Eq. 8, we can get:

$$\frac{\mu - \frac{1}{D}}{k}(e_{i,t} - \beta) \ge L_{i,t} \tag{9}$$

Combining the first and third items of Eq. 8, we can get:

$$\beta \le e_{i,t} \le kM_{i,t} + \beta \tag{10}$$

To sum up, Eqs 9, 10 are power consumption models of data centers.

3 Economic dispatch model for data center

(1)The upper-layer scheduling model

The upper layer of the optimal scheduling model of energy hub in data center is the energy consumption cost model, whose objective function is the minimum system operation cost, including energy purchase cost and unit operation and maintenance cost. The objective function is:

$$\min C = [c_t^g \cdot G_t^L + (\varepsilon_t^{GT} \cdot P_t^{GT} + \varepsilon_t^{WT} \cdot P_t^{WT} + \varepsilon_t^{GC} \cdot C_t^{GC} + \varepsilon_t^{EC} \cdot C_t^{EC}) + (\tau_t^{ES} \cdot |P_t^{ES}| + \tau_t^{CS} |C_t^{CS}|)] \tag{11}$$

G_t^L is the natural gas power purchased; c_t^g it the price per unit of power purchased natural gas; P_t^{GT}, P_t^{WT}, C_t^{GC}, C_t^{EC} are the output power of gas turbine, the output power of wind turbine, the output cold power of absorption refrigerator and the output cold power of electric refrigerator respectively; ε_t^{GT}, ε_t^{WT}, ε_t^{GC} are operation and maintenance costs of gas turbine, wind turbine, absorption refrigerator and electric refrigerator; P_t^{ES}, C_t^{CS} are the output power of electricity storage and cold storage equipment; τ_t^{ES}, τ_t^{CS} are the operation and maintenance costs of energy storage equipment. The objective function has two constraints.

① Constraints on power balance in system operation

$$P_t^{GT} + P_t^{WT} + P_t^{ES} = Q_t^E + Q_t^{EC} \tag{12}$$

$$C_t^{GC} + C_t^{EC} + C_t^{CS} = Q_t^C \tag{13}$$

Q_t^E, Q_t^{EC}, Q_t^C are the electrical load of IT equipment, electrical load of refrigeration equipment and cooling load demand respectively, among which the electrical load of IT equipment includes basic electrical load and data load.

②The unit output limit

TABLE 3 Data load Simulated.

Time	Data load	Time	Data load	Time	Data load
0	75499	8	71113	16	97043
1	88189	9	70497	17	73808
2	82268	10	77077	18	74948
3	78803	11	74624	19	78892
4	78963	12	96243	20	91461
5	70211	13	76082	21	77660
6	94451	14	61325	22	87657
7	91239	15	72335	23	96880

$$P^{GT}_{t,\min} \le P^{GT}_t \le P^{GT}_{t,\max} \tag{14}$$

$$P^{WT}_{t,\min} \le P^{WT}_t \le P^{WT}_{t,\max} \tag{15}$$

$$C^{GC}_{t,\min} \le C^{GC}_t \le C^{GC}_{t,\max} \tag{16}$$

$$C^{EC}_{t,\min} \le C^{EC}_t \le C^{EC}_{t,\max} \tag{17}$$

$$P^{ES}_{t,\min} \le P^{ES}_t \le P^{ES}_{t,\max} \tag{18}$$

$$C^{CS}_{t,\min} \le C^{CS}_t \le C^{CS}_{t,\max} \tag{19}$$

$$P_{i,t,\min} \le P_{i,t} \le P_{i,t,\max} \tag{20}$$

$P^{GT}_{t,\max}$, $P^{GT}_{t,\min}$ are the upper and lower limits of gas turbine output respectively; $P^{WT}_{t,\max}$, $P^{WT}_{t,\min}$ are the upper and lower limits of wind turbine output; $C^{GC}_{t,\max}$, $C^{GC}_{t,\min}$ are the upper and lower limits of the output of the absorption refrigerator; $C^{EC}_{t,\max}$, $C^{EC}_{t,\min}$ are the upper and lower limits of the electric refrigerator output; $P^{ES}_{t,\max}$, $P^{ES}_{t,\min}$ are the upper and lower limits of the output of the electrical storage equipment; $C^{CS}_{t,\max}$, $C^{CS}_{t,\min}$ are the upper and lower limits of output of cold storage equipment; $P_{i,t,\max}$, $P_{i,t,\min}$ are upper and lower limits of the generator output in center i.

(2) The lower-level scheduling model

The objective function of the lower model is to minimize the total power consumption of data distribution load and the total delay time of data processing.

$$\min G = \omega_1 \cdot \sum_{i\in I} e_{i,t} + \omega_2 \cdot \sum_{i\in I} \frac{L_{i,t}}{\mu - \frac{L_{i,t}}{m_{i,t}}} \tag{21}$$

In the formula, ω_1、ω_2 are the weight coefficients of the two objectives. The constraints of the lower model include the constraint on the number of servers in the data center and the delay constraint. For specific formulas, it can refer to Eqs. 8–10.

(3) Solution Method

According to the characteristics of the model, adaptive simulated annealing particle swarm optimization was used to solve the dual-objective scheduling model. Particle swarm optimization (PSO) algorithm is a swarm intelligence optimization algorithm inspired by the foraging behavior of birds (Kennedy and Eberhart, 1995). This algorithm initializes a set of solutions randomly, and then updates these solutions iteratively to find the optimal solution of the problem within a limited number of iterative steps. The idea of simulated annealing comes from the principle of physical annealing of solid materials. The particles inside will release their internal energy with the gradual decrease of temperature, which gradually makes the particles tend to order. Particle swarm optimization mainly relies on competition and cooperation between groups, so in the initial stage of operation, the algorithm convergence speed is fast, but particle swarm optimization is easy to fall into the local optimal, low precision, which leads to the ability of particle swarm optimization to obtain the global optimal solution is weak. The simulated annealing algorithm has asymptotic convergence. As long as the initial temperature is high enough and the annealing process is slow enough, the algorithm will converge to the global optimal solution with 100% probability in theory. By combining the two methods, the search process selects the probability transform particle flight direction according to the designed simulated annealing, and the central particle leads the particle flight search, so as to avoid the search process falling into the local optimal region, so as to improve the search efficiency and accuracy of the optimal solution, and effectively solve the perturbation problem in reality. The algorithm of the research object in this paper has a small search space, which overcomes the shortcomings of the simulated annealing algorithm which takes a long iteration time to converge to a high-quality approximate optimal solution and has a slow convergence speed. Meanwhile, the asymptotic convergence of the simulated annealing algorithm is consistent with the characteristics of wind power generation, which can better simulate the comprehensive energy consumption change proposed by this model.

In this paper, in the Matlab 2019a language environment, Gurobi solver is used to solve the two-layer model. Combined with the model construction above, the energy scheduling process of data centers is described as follows.

Step 1 : The user requests computing services from the data center.

Step 2 : Data center Calculate the configuration solution based on customer requirements, data center server usage, server distribution, and data center energy consumption cost.

Step 3 : Provide solutions based on user computing requirements, such as response time, transmission speed, and delay time.

Step 4 : Calculate the server resources and energy resources that can be scheduled based on the user's service requirements and input them into the green energy scheduling model of the data center.

Step 5 : The lower layer model aims to calculate the minimum total power consumption of the load and the minimum total delay time. Considering the data service requirements of users and the load distribution of data center servers, the energy consumption requirements are determined and uploaded to the upper layer model.

Step 6 : After receiving the server scheduling policy developed by the lower-layer model, the upper-layer model ensures that the energy consumption policy required by the lower-layer service

TABLE 4 Electrical load and cooling load in 24 h.

Time	Electric load (kW)	Cooling load (kW)	Time	Electric load (kW)	Cooling load (kW)	Time	Electric load (kW)	Cooling load (kW)
0	382.35	1200	8	326.94	1570	16	509.54	1105
1	498.31	1192	9	443.87	1670	17	442.85	1443
2	474.31	1177	10	348.94	1488	18	349.62	1639
3	300.35	1165	11	340.1	1496	19	447.13	1399
4	471.81	1176	12	369.79	1668	20	355.73	1468
5	355.38	1189	13	518.41	1442	21	425.63	1108
6	491.25	1250	14	471.37	1154	22	409.93	1614
7	474.39	1310	15	374.32	1359	23	465.1	1598

has the minimum deviation from the upper-layer energy consumption scheduling plan. After several iterations, the data center energy supply scheduling plan is output when the result meets the requirements.

The pseudo-code of scheduling model is as following:

Algorithm input: particle number M, maximum number of iterations K, maximum and minimum of inertia weight $w_{\max}$, $w_{\min}$, acceleration factor c_1, c_2, temperature attenuation coefficient u.
Algorithm output: global optimal position G_t, $Y(G_t)$.
Generate N particles randomly and initialize the optimal position of individual particles and the global optimal value. Generate initialization position $X_i(0)$, velocity $V_i(0)$ randomly, $Y_i = (G_t^L, P_t^{GT}, P_t^{WT}, C_t^{GC}, C_t^{EC}, P_t^{ES})$, set particle optimal position $Pbest_i = X_i(0)$, global extremum G_{best}.
$n = 0$
$u = 0.95$
$T_k = K/\lg(5)$
While $n < K$
for i =1 to M do
for j =1 to N do
$S_{i,j} = rand \times (P_i - P_j)$
$w_k = w_{\max} - \frac{n}{K} \times \left(1 - \frac{fit(G_{best})}{fit_{mean}}\right)$
$T_k = uT_{k-1}$
$P_{i,n} = \exp\left\{-\frac{fit(Pbest_i) - fit(Pbest_j)}{T_k}\right\}$
$r_{ij} = rand(0,1)$
if $P_{i,n} < r_{ij}$
$V_{i,n+1}^j = w_k V_{i,n}^j + c_1 r_{i,n}^j (P_{i,n}^j - X_{i,n}^j) + c_2 r_{i,n}^j (S_n^j - X_{i,n}^j)$
else
$V_{i,n+1}^j = w_k V_{i,n}^j + c_1 r_{i,n}^j (P_{i,n}^j - X_{i,n}^j) + c_2 r_{i,n}^j (G_n^j - X_{i,n}^j)$
if $-V_{\max}^j < V_{i,n+1}^j < V_{\max}^j$
$X_{i,n+1}^j = X_{i,n}^j + V_{i,n+1}^j$
endfor
calculate $Y(X_{i,n+1}^j)$
if $Y(P_{i,n}) < Y(X_{i,n+1}^j)$
$P_{i,n+1} = P_{i,n}$
else
$P_{i,n+1} = X_{i,n+1}^j$
endfor
find the best $P_{i,n+1}$ from all as G_{n+1}^j
$n = n + 1$
enddo

4 Model simulation

(1) Model parameter setting

In order to verify the effectiveness of the proposed model, the data center of Gansu Province is selected as the simulation example. The data center of this province is rich in wind energy and solar energy resources and convenient in obtaining natural gas, which conforms to the research design of this paper. The dispatching cycle is 24 h a day.

Operating efficiency, maintenance cost, output interval and other parameters of different equipment are different, and these parameters will have an impact on the value of the objective function. Therefore, we use conventional settings for reference and the assignment of relevant parameters is shown in Table 1.

In this study, natural gas power generation and wind power generation are used as energy sources for data centers. The prices of natural gas and wind power generation fluctuate in different periods, as shown in Table 2.

According to the data load assigned to the data center, the power load consumed by the server varies. The 24-h analog data load generated by the whole random system is shown in Table 3, and the basic power load and cooling load are shown in Table 4.

Considering the load distribution of computing demand, this study simulates three data centers to assume computing demand respectively, and data centers provide computing services according to the allocated computing demand. The hardware resources and cooling resources are also different, which leads to different electrical loads consumed by servers, thus affecting the overall energy consumption of data centers. Data center performance parameters and randomly generated 24-h simulated data load values are shown in Table 5.

(2) Simulation result

Assign values to formulas 7 and 8 in accordance with Table 2, Table 3, and assign values to formulas (1)formulas –formulas (4) in

TABLE 5 Performance parameters of different data center.

Parameter	Data center one	Data center two	Data center three
Data load capacity (unit)	[0,45000]	[0,45000]	[0,45000]
β/kW	100	150	200
Mi/unit	1500	1500	1500
k/(kW/unit)	0.4	0.4	0.4
μ/(unit/s)	25	25	25
Db/ms	250	200	150

TABLE 6 Data center load and server allocation. The data before and after "/" in the table are the number of data loads allocated by each data center and the number of servers used respectively.

Time (h)	Data center one	Data center two	Data center three
0	32666/1132	30461/1381	27339/1038
1	32884/1417	32103/1050	26325/1111
2	32109/1348	33141/1446	34841/1472
3	33126/1085	26951/1423	31567/1230
4	33503/1275	35950/1151	34515/1397
5	35918/1343	27846/1229	29634/1173
6	29916/1151	28852/1182	30707/1239
7	32602/1406	26954/1038	27403/1424
8	29145/1098	27349/1477	31910/1421
9	34996/1203	26619/1388	27148/1474
10	30011/1462	27403/1300	31781/1237
11	26142/1252	32571/1388	29264/1459
12	34147/1056	28471/1456	32706/1005
13	26945/1453	26057/1084	29505/1144
14	31654/1196	26166/1431	33431/1201
15	34951/1162	30027/1315	27352/1332
16	33212/1105	35175/1035	34267/1234
17	32468/1378	27862/1471	28606/1453
18	27311/1305	29760/1467	26683/1462
19	26127/1458	31598/1474	31788/1268
20	28733/1007	26110/1308	34973/1446
21	31477/1154	35515/1266	33370/1180
22	32008/1215	32194/1351	32965/1479
23	29411/1353	35545/1013	34685/1201

accordance with Table 1, then substitute them into formula 11 and calculate from the third line of pseudo-code. The corresponding results can be obtained through simulation calculation. After simulation, the data load distribution and the number of servers used in each data center are shown in Table 6.

The purchased power of electricity and gas, the output of all energy conversion equipment and the output of energy storage device are shown in Figure 2, Figure 3, Figure 4.

It can be seen from Figure 2 that due to the stable supply of natural gas, the cost of natural gas fluctuates relatively little

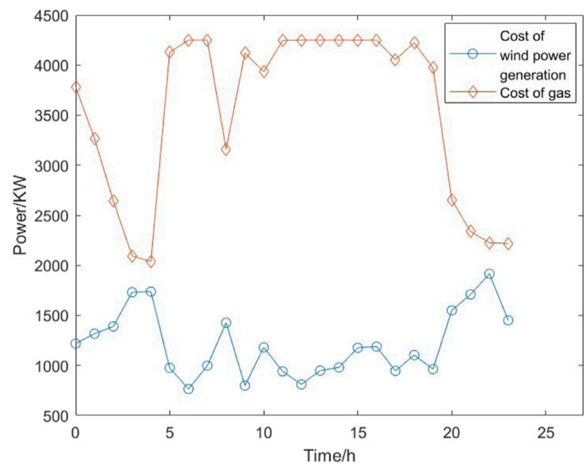

FIGURE 2
Cost of wind power generation and gas.

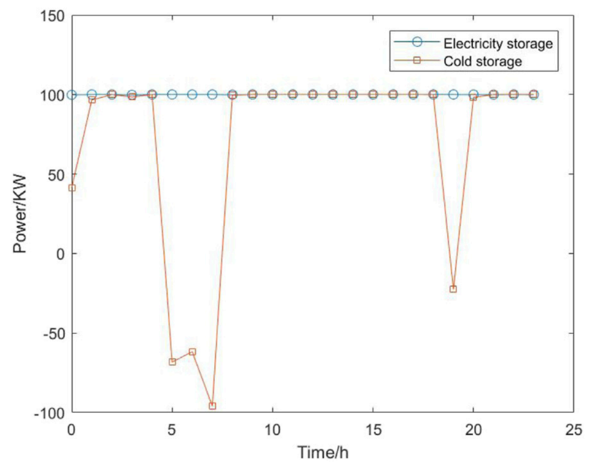

FIGURE 4
Output of electric storage equipment and cold storage equipment.

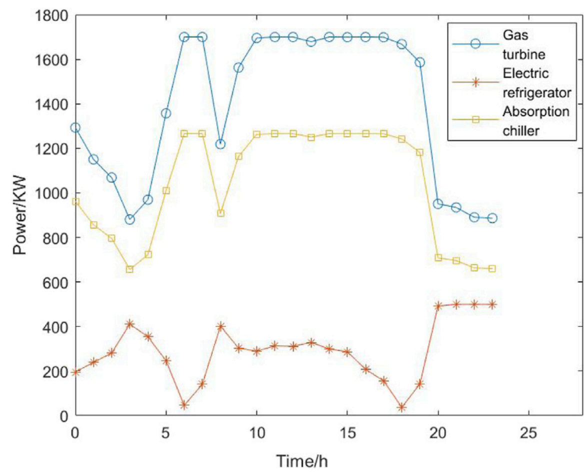

FIGURE 3
Output of energy conversion equipment.

within a day, and there is a stable period of time, while the cost of electric power generation fluctuates to a certain extent due to the disturbance brought by wind instability. In this case, natural gas should be used as the main energy supply mode, and energy storage should be adopted to effectively utilize wind energy, so as to ensure the data center computing service demand and cost requirements.

It can be seen from Figure 3 that output efficiency trends of natural gas power generation and refrigeration are basically similar. Therefore, it is necessary to make full use of natural gas as the main source of power supply and refrigeration for data centers to fully improve energy utilization efficiency. The effect of electric refrigeration has a certain correlation with the cost of electricity. In order to ensure the stability of the effect of electric refrigeration, it is necessary to ensure the stability of natural gas power generation at the same time, and use the stored wind power as an effective supplement when the price of natural gas fluctuates.

It can be seen from Figure 4 that the output level of the electric energy storage device is basically stable, which indicates that the energy of wind power generation can be effectively stored by batteries and continuously and stably output, while the output of the cold storage device fluctuates to a certain extent due to the dual influence of natural gas and electricity.

Although wind power generation has certain instability, the simulation after adding disturbance can find that it can still cooperate with natural gas and purchased electric energy as the energy supply of data centers, which is reflected in the reality that the refrigeration effect formed by it changes with the energy efficiency disturbance. However, the relatively stable natural gas function and the purchase of electric power function can effectively and smoothly input. Ensure the smooth running of the data center. And the main purpose of bringing in wind power is to reduce energy consumption. Meanwhile, by comparing with the author's previous studies, it can be found that under the condition of the same computing power and response speed, this dispatching scheme can reduce the cost by 18.7% compared with the simple use of electricity and 10% compared with the combination of natural gas function and electricity purchase under the condition of guaranteeing the response speed. Therefore, the combination of wind power generation with natural gas and electricity purchase as the energy supply of data centers can not only ensure the service performance requirements of data centers, but also effectively reduce the cost of data centers.

5 Conclusion

Energy saving, cost reduction and carbon emission reduction are the main problems faced by data centers. Researchers begin to introduce clean renewable energy such as wind energy and solar energy into data centers for power supply, and reduce operating costs and environmental damage through the construction of new green data centers. However, in green data centers, the supply of new energy power and the demand for data calculation will each show significant and unrelated fluctuation characteristics over time. Therefore, data centers urgently need efficient scheduling methods to realize the match between load power demand and new energy power supply. In this paper, the computing demand distribution, green energy supply and energy scheduling problems of data centers are studied in combination. Wind power generation and natural gas power generation are used to provide operation and cooling power for data centers. Meanwhile, the waste heat of natural gas is used to drive the refrigeration of lithium bromide absorption refrigerating machine, so as to build the green energy supply and scheduling model and carry out simulation calculation. The results show that the model can effectively satisfy the computing response speed of data centers, ensure the normal operation of data center cooling and equipment, and reduce the cost of data center power by 18.7% compared with traditional energy sources.

Data availability statement

The datasets presented in this article are not readily available. Requests to access the datasets should be directed to: yanglei2512@163.com.

Author contributions

XL: Literature review and theoretical model design. GH: Research concept generation and research fund acquisition. LY: Research thought design and simulation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Revisiting the linkage between green finance and China's sustainable development: evidence from the pilot zones for green finance reform innovations

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Based on the fundamental logic of "green finance – improvement of ecological environment and new kinetic energy of economic development – sustainable development of economy and society", this paper conducts quasi-natural experiments using panel data from 30 provinces and cities in China between 2013 and 2021. It explores the effects of pilot policies of the green finance reform and innovation pilot zone on the sustainable development of the economy and society through a double difference model. The study reveals that the establishment of the green finance reform and innovation pilot zone has a significant promoting effect on the sustainable development of the economy and society. This conclusion remains valid even after conducting a series of robustness tests. In further analysis, it is found that the promotion effect of the green finance reform and innovation pilot zone on sustainable development exhibits some temporal characteristics. It is particularly significant in regions with lower levels of financial development and industrialization but higher levels of technological innovation. Mechanism analysis indicates that the pathways through which the green finance reform and innovation pilot zone facilitates economic and social sustainable development are relatively singular, primarily revolving around the improvement of the ecological environment. The key contribution of this paper lies in demonstrating the crucial role of pilot policies in the field of sustainable economic and social development. Additionally, it offers new insights for strengthening the implementation effectiveness of green finance pilot policies.

KEYWORDS

green finance pilot policy, sustainable development, difference-in-differences model, extended study, pilot zones for green finance reform and innovations

1 Introduction

With the challenge of global climate change, achieving sustainable development in the economy and society has become a crucial issue worldwide. Improving the ecological environment and promoting green development are vital steps towards realizing the harmonious coexistence between humans and nature and enhancing sustainable economic and social development. Green finance, as a financial policy aimed at environmental protection, has emerged with the concept of sustainable development (Sun, 2021). It has gradually become a crucial measure for promoting the green development of the economy and society, significantly impacting the ecological industrial structure, green industrial enterprises, and the construction of ecological civilization. As a representative developing country, China has shifted its economic development mode from extensive to high-quality in recent years, embracing the concept of green development. Green finance plays a vital role in China's sustainable economic and social development. In 2016, the People's Bank of China, along with seven ministries and commissions, issued the Guidance on Building a Green Financial System, making China the first country to promote and establish a green financial system under the central government.

China's green finance sector has experienced significant growth and continuous reform. Extensive efforts have been made to establish a comprehensive green financial system, focusing on top-level design, financial instruments, and policy systems. Notably, pilot policies within green finance have been advancing, with the pilot zones for green finance reform and innovation serving as a notable example. In 2017, the executive meeting of the State Council of China decided to establish eight pilot zones across five provinces and regions, namely Guangdong, Zhejiang, Jiangxi, Guizhou, and Xinjiang. Each pilot zone has its own unique characteristics and development focus, serving as both an innovative regional development model and a benchmark for the nation's green financial progress. These pilot zones represent a stage of further development, incorporating top-down design and bottom-up pilot exploration. This approach facilitates the accumulation of replicable experience in green financial development, provides a platform for promoting comprehensive green development in the economy and society, and accelerates progress towards sustainability. It also contributes to accumulating replicable experience in green financial development, strengthening overall green development in the economy and society, and enhancing sustainability.

Quantitative studies on green finance primarily focus on two aspects. Firstly, they examine the economic benefits of green finance, specifically the impact of its development on economic growth (Ruiz et al., 2016; Muhammad et al., 2022; Yin and Xu, 2022; Zhou et al., 2022; Sheng and Haonan, 2023). Secondly, they investigate the ecological benefits of green finance, particularly its role in improving the ecological environment (Zhu et al., 2020; Ding et al., 2021; Dziwok and Jger, 2021; Ozili, 2021; Tma et al., 2021; Ao et al., 2023; Xu et al., 2023). Some scholars have also examined the influence of green financial development on green technological innovation (Zhang J. et al., 2022; Yang et al., 2023). However, these studies mainly focus on the overall development of green finance and its economic and ecological benefits. Notably, there is limited research on the policy implementation perspective of green finance, which presents an opportunity for further examination in this paper.

China has been implementing pilot zones for green finance reform and innovations for the past five years, making it a typical policy in the field. Evaluating the effectiveness of this policy is essential for future developments and achieving sustainable economic and social growth. This study utilizes panel data from 30 provinces and municipalities in China between 2013 and 2021. By employing a difference-in-differences (DID) model, the paper examines the impact of the establishment of these pilot zones on the sustainable development of the economy and society. The findings of this study contribute to the improvement of green finance's role in promoting sustainable economic and social development.

The innovation and contribution of this paper are as follows: Firstly, it adopts a unique research perspective. Unlike existing studies that primarily examine the overall effects (economic or ecological) of green finance development, this paper takes a fresh approach by focusing on the pilot policy of green finance. It evaluates the impact of this pilot policy through its policy effects, thus addressing endogenous problems within the model and providing precise insights into the influence of green finance on sustainable economic and social development. Secondly, it establishes a research mechanism. This paper employs a comprehensive index system to evaluate economic and social sustainable development. It then selects the dimension index of sustainable development as the influencing factor for the green finance pilot policy. This approach eliminates issues of omission, repetition, and lack of economic logic support that may arise from subjective judgments in selecting the action mechanism. Lastly, it offers significant research findings. The analysis of regional heterogeneity and the examination of the action mechanism presented in this paper help explain the distinctive characteristics of pilot policies in China's Green Finance Reform and Innovation Experimental Zone. Furthermore, it verifies the vital role of innovation-driven approaches in fostering the sustainable development of China's economy and society in the present stage.

The remaining sections of this paper are organized as follows: Section 2 provides a comprehensive literature review on the research conducted on green finance and its correlation with sustainable economic development. In Section 3, the model utilized in this study is introduced, and the selection and measurement of variables are explained based on data availability and scientific rigor. Section 4 examines the outcomes of the benchmark regression and robustness tests, shedding light on the impact of the green finance pilot policy. Next, in Section 5, an in-depth exploration is conducted to analyze the mechanism of action. This section delves into the dynamic effects of pilot zones for green finance reform and innovations on both sustainable economic and social development. Finally, Section 6 summarizes the findings presented in this article and provides targeted recommendations and measures.

2 Literature review

Scholars have extensively researched the relationship between green financial development and sustainable economic and social development. Jeucken and Bouma (1999) emphasized the crucial role of financial institutions in promoting sustainable economic development. Other scholars have explored various connections between green finance and sustainability. For instance, Jha and Bakhshi (2019) investigated how green finance development contributes to economic and social sustainability in India. Ronaldo and Suryanto (2022) examined the relationship between green finance development and sustainable development in Indonesian fund villages, highlighting the significance of green finance in fostering sustainability. Afzal et al. (2022) analyzed the positive correlation between green finance and sustainable development across 40 European countries. Wang K. et al. (2022) demonstrated the global impact of green finance on sustainable development. Additionally, Ma et al. (2023) confirmed the positive influence of green finance development on sustainable development in China. The impact mechanism of green finance on sustainable development can be broadly categorized into two aspects: improvement of the ecological environment and optimization of energy structure through the application of renewable energy (Chen et al., 2023).

The development of green finance has been shown to contribute to the sustainable development of the economy and society by aiding in environmental improvement. Bai (2022) argues that green finance can help achieve the goal of "carbon peaking and carbon neutrality" while reducing the impact of climate change. Similarly, Liang and Song (2022) found that green finance in China improves the efficiency of carbon emissions and supports the "double carbon" goal. Wu and Song (2022) highlight the negative impact of green finance on carbon emissions, environmental pollution, and renewable energy. Liu and Xia (2022) emphasize the role of green financing and renewable energy in reducing carbon emissions. Li et al. (2023), using the Delphi method and fuzzy hierarchy analysis, underscore the importance of green finance as a key measure to minimize carbon emissions. Feng and Yang (2023) present results suggesting that green finance development helps reduce carbon emissions. On the topic of sustainable development in developing countries, Hunjra et al. (2023) find that green finance and environmental degradation have opposing effects, with green finance playing a significant positive role. Lastly, Mo et al. (2023) explore sustainable agricultural development and note the contribution of green finance in China by reducing carbon emissions.

The development of green finance and its impact on energy structure and renewable energy have been explored by several studies. Zhang and Wang (2019) found that green finance supports sustainable energy development across various dimensions, such as financial, economic, and environmental domains. Additionally, Sun and Chen (2022) discovered that the development of green finance positively influences the energy consumption structure and contributes to sustainable economic development. The detrimental effects of coal consumption on environmental pollution were highlighted by Wang et al. (2023), who also emphasized the positive impact of renewable energy on improving environmental efficiency and promoting sustainable economic development. Furthermore, Zhou and Li (2022) established a correlation between green finance development, renewable energy utilization, and overall sustainable development in China. However, the effects of these factors were noted to be time-varying and heterogeneous. Carbon emissions reduction was found to be a common outcome of green financial development, renewable energy adoption, and sustainable development, as highlighted by Zhang D. et al. (2022). Furthermore, Zhang J. et al. (2022) demonstrated that investments in green finance and renewable energy help mitigate the adverse effects of climate change by reducing carbon emissions. Xing et al. (2022) identified a negative correlation between green finance and carbon intensity, and they concluded that the utilization of renewable energy is predominantly influenced by policy drivers. Highlighting the channel of renewable energy transition, Lee et al. (2023) emphasized the contribution of green finance to sustainable economic and social development. Lastly, Bei and Wang (2023) argued that renewable energy plays a significant role in achieving sustainable economic and social development.

Several studies have investigated the impact of pilot zones for green finance reform and innovations. Liu and Wang (2023) and Sun et al. (2023) indicated that these pilot policies can promote green technological innovation. Wang et al. (2021) and Zhang et al. (2023) also demonstrated that these pilot zones contribute to regional green development. Huang and Zhang (2021) confirmed the beneficial effect of pilot zones on reducing environmental pollution. From a firm perspective, Chen et al. (2022) and Yan et al. (2022) explored the positive effects of pilot zones on firm performance and investment efficiency. Additionally, there have been studies on low-carbon pilot policies in the realm of green finance, particularly focusing on green technology innovation and low-carbon innovation (Wang J. et al., 2022; Pan et al., 2022; Yang, 2023). However, few scholars have examined the impact of these policies on industrial structure upgrading, energy efficiency, and high-quality economic development (Zheng et al., 2021; Gong et al., 2022; Song et al., 2022). It is necessary to further investigate these aspects to gain a comprehensive understanding of the impact of low-carbon pilot policies.

Existing studies have extensively explored green finance and sustainable development, specifically focusing on the impact of green finance pilot policies. However, these studies have primarily examined the overall development level of green finance. Additionally, research on green finance pilot policies has been skewed towards technological innovation and energy efficiency, neglecting their impact on sustainable economic and social development. Given this context, this paper aims to conduct a quasi-natural experiment to investigate the effects of green financial pilot policies on sustainable economic and social development within the pilot zones for green finance reform and innovations.

3 Methodology

3.1 Model construction

This paper is structured as follows. Firstly, we conduct benchmark regression and robustness tests to verify the impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. These tests also aim to demonstrate the reliability of the benchmark regression results. Secondly, we delve into an extended analysis that primarily addresses the issue of model selection bias. Additionally, we explore the dynamic changes and heterogeneity of the policy effects associated with the pilot zones for green finance reform and innovations. Finally, we analyze the action mechanism and discuss the internal functioning by which the green financial reform and innovation experimental zone influences the sustainable development of the economy and society. Through this analysis, we aim to provide valuable references for further improving the policy effects of the green financial reform and innovation experimental zone.

Pilot zones for green finance reform and innovation have been established in six provincial-level regions in China: Guangdong Province, Xinjiang Uygur Autonomous Region, Jiangxi Province, Zhejiang Province, Guizhou Province, and Gansu Province[1]. This paper utilizes the studies conducted by Fan et al. (2020), Yang et al. (2021), and Martins (2022) to empirically investigate the topic. The investigation primarily employs a difference-in-dfferences (DID) model, with the provincial areas where pilot zones for green finance reform and innovation have been established as the experimental group, while the remaining provincial areas serve as the control group. The model is:

$$Y_{it} = \alpha_0 + \alpha_1 \times Policy\_Time_{it} + \alpha_2 \times X_{it} + \delta_i + \lambda_t + \epsilon_{it} \quad (1)$$

The main explanatory variable in this study is Policy_Time, which is the intersection of two dummy variables: Policy and Time. The variable Policy determines whether a pilot zone for green financial reform and innovation has been established. It takes a value of 1 if such a pilot zone exists at the provincial level, and 0 otherwise. On the other hand, the variable Time represents a time dummy variable indicating the establishment of a pilot zone for green financial reform and innovation. Therefore, the primary focus of this paper is to examine the impact coefficient of Policy_Time. If the impact coefficient is significantly positive, it suggests that the pilot zone for green financial reform and innovation contributes to the enhancement of China's sustainable development. Additionally, X represents the relevant control variables, while δ and λ represent the fixed effects for the different regions and time periods, respectively. The term ϵ represents the random disturbance term. Here, i denotes each provincial and urban area, and t denotes the year.

1 The five provincial-level regions, Guangdong Province, Xinjiang Uygur Autonomous Region, Jiangxi Province, Zhejiang Province, and Guizhou Province, established pilot programs in 2017 and belong to the same batch of pilot zone establishment programs. Gansu Province was established as a pilot zone for green financial reform and innovation in November 2019. Based on the reasonableness of the data during the study, Gansu Province was not included as an experimental group in the benchmark regression.

3.2 Variable selection

The DID model utilizes dummy variables as the core explanatory variables. Consequently, the selection of the variables being explained becomes relatively more crucial. This paper specifically examines the influence of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. It is essential to evaluate and measure the level of sustainable development accurately as it directly impacts the scientific validity of the conclusions. In line with the assessments made by Liao et al. (2020), Lin et al. (2020), and Guo et al. (2022) concerning the level of sustainable development, this study constructs a comprehensive index system to gauge the sustainable development of the economy and society. The comprehensive indicator system used in this study is presented in Table 1.

Compared to a singular level of economic development, sustainable development encompasses not only the progress of the economy and society but also places greater emphasis on their quality. Hence, this paper primarily evaluates the sustainable development of the economy and society across four dimensions: economy, society, population, and environment. In terms of the economy, this study primarily examines the scale, structure, results, and stability of economic and social development. To assess these aspects, the following basic indicators are selected: the ratio of real GDP per capita, the proportion of the tertiary industry to GDP, disposable income per capita, and disposable income per urban and rural residents. Regarding the population, the focus lies on population size, population structure, and urbanization development. Thus, the basic indicators chosen include population density, the proportion of the working-age population, and the proportion of the urban population. As for the environment, the main considerations involve resource stock, environmental management, and environmental conditions. Consequently, the basic indicators consist of the amount of water resources per capita, domestic waste and urban sewage treatment capacity, urban green space area, and green coverage rate. To summarize, the measurement of sustainable development in the economy and society comprises four dimensions with a total of 17 basic indicators.

The sustainable development of the economy and society is influenced by various factors (index system in Table 1). Hence, this paper focuses on four control variables selected from the following aspects: (1) government intervention level (GI), measured by the ratio of general budget expenditure of government departments to the GDP in each region; (2)openness (OP), measured by converting total foreign investment into RMB and calculating its ratio to GDP; (3) employment level (EL), measured by the inverse of the urban registered unemployment rate; and (4) human capital (MC), measured by the number of years of education per capita in each region.

3.3 Comprehensive index measurement

The measurement of comprehensive indicators can be categorized into two methods: subjective and objective weighting. The subjective weighting method mainly relies on the knowledge of

TABLE 1 Indicator system of sustainable development of economy and society.

Dimensional Indicator	Proxy Indicator	Indicator Meaning	Indicator Property
Economic factors	Economic development	Real GDP per capita	Positive
	Industry structure	Share of tertiary sector in GDP	Positive
	Resident income	Disposable income per capita	Positive
	Urban–rural income gap	Per capita disposable income of urban residents/per capita net income of rural residents	Reverse direction
Social factors	Medical insurance participation	Number of medical insurance participants/year-end resident population	Positive
	Unemployment insurance participation	Unemployment insurance participants/year-end resident population	Positive
	Pension insurance participation	Number of pension insurance participants/year-end resident population	Positive
	Injury insurance participation	Number of workers' compensation insurance participants/year-end resident population	Positive
	Maternity insurance coverage	Number of maternity insurance participants/year-end resident population	Positive
Demographic factors	Population density	Year-end resident population/area of urban areas by province	Reverse direction
	Percentage of working age population	Population aged 15–64/total population	Positive
	Urbanization	Urban population/total population	Positive
Environmental factors	Water resources	Water resources per capita	Positive
	Harmless treatment capacity of domestic garbage	Average daily tonnage of household waste disposed of without harm	Positive
	Daily treatment capacity of urban sewage	Average daily municipal wastewater treatment in cubic meters	Positive
	Urban green space area	Amount of urban green space in hectares	Positive
	Greening coverage of built-up areas	Area covered by greenery in built-up areas/area of built-up areas	Positive

experts and scholars with authority in the relevant fields to assign weights to each dimension of the composite indices. The specific process of assigning weights to the indicators of each dimension of sustainable development of economy and society runs as follows.

First, each basic index is averaged, and the correlation and variability of each basic index are retained while eliminating the difference in magnitude and magnitude between each index. The inverse indicators are first taken as the inverse and then averaged:

$$y_{i,t,j} = \frac{x_{i,t,j}}{E(x_{i,t,j})} \tag{2}$$

To explain the notation used in this study, let x represent the original value of the base indicator, E(x) denote the mean value of the base indicator, and y represent the value of the base indicator after averaging. The variables i and t still represent the province (city) and year, while j represents the jth base indicator.

Second, the coefficient of variation for each underlying index can be calculated as:

$$c_j = \frac{sd(y_{i,t,j})}{m_j(y_{i,t,j})} \tag{3}$$

Here, c denotes the coefficient of variation, the corresponding sd denotes standard deviation, and m denotes the mean.

Finally, the coefficients of variation of each base indicator are normalized to obtain the weights of the base indicators:

$$e_j = \frac{c_j}{\sum c_j} \tag{4}$$

$$Y_{i,t} = \sum (y_{i,t,j} \times e_j) \tag{5}$$

Here, e denotes the weight of the base indicator, and Y denotes the composite indicator after cumulative summation; i.e., the sustainable development of economy and society.

3.4 Data sources and preliminary processing

To ensure consistency between the data before and after policy implementation, and considering that the latest relevant data is only available until 2021, this study focuses on the period from 2013 to 2021. The research sample includes 30 provincial regions in China, excluding Tibet, Hong Kong, Macao, and Taiwan due to data availability. The data pertaining to the sustainable development of the economy and society, as well as each control variable, are sourced from the official website of the National Bureau of

Statistics of China and the China Statistical Yearbook from previous years. It should be noted that employment level and human capital are absolute value variables. Given the large range of values for human capital, a logarithmic transformation is applied in this paper. However, the employment level and other relative value variables are retained in their original form.

Table 2 displays the descriptive statistics and grouping results for each main variable studied. The average value for sustainable development of the economy and society is 1.0142. Specifically, the experimental group demonstrates a higher mean value for sustainable development level (1.2781), surpassing both the national average and the control group average. Further analysis reveals that although the experimental group exhibits a lower level of government intervention, its openness to the outside world is also significantly reduced compared to the control group. Moreover, the differences in employment level and human capital between the experimental group and the control group are relatively minor. These findings align with the varying degrees of government intervention and openness across different regions, which can be observed in the context of China's economic and social development. As educational opportunities become increasingly equitable, the regional disparity in human capital gradually diminishes, subsequently leading to a decrease in the gap in employment levels between regions.

4 Analysis of empirical results

4.1 Basic regression

4.1.1 Analysis of baseline regression results

The baseline regressions were conducted using a DID model to examine the impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society, as described earlier in this paper. The results of the benchmark regression are presented in Table 3. Columns (2) to (5) display the regression results with the inclusion of area fixed effects, control variables, squared terms of control variables, and time fixed effects in the preceding columns, respectively. Despite variations in the regression process, all impact coefficients of P_T are greater than zero and statistically significant at the 1% or 5% level. This indicates that the establishment of pilot zones for green finance reform and innovations significantly promote sustainable development. This finding aligns with the conclusions drawn by Wen et al. (2021, 2023) and confirms the positive impact of green development on China's economy and society, as evidenced by the boosting effect on total factor productivity of enterprises through green credit and low-carbon city policies.

Regarding control variables, although the coefficients of government intervention and employment level are not statistically significant, their effects align with expectations. Specifically, as the degree of government intervention and the unemployment rate increase, the level of sustainable development in the economy and society decreases. Additionally, the effects of openness and human capital also align with expectations. Higher levels of openness significantly promote sustainable development in the economy and society, while lower levels of human capital inhibit sustainable development. Only high levels of human capital can further enhance the level of sustainable development in the economy and society.

4.1.2 Parallel trend test

The baseline regression results indicate a significantly positive effect of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. To further validate these findings, this study employs a parallel trend test. To determine the timing of the implementation of the pilot zones for green finance reform and innovations in China, this paper uses 2017 as the benchmark for the time dummy variable. Before 2017, the pilot zones were not established, implying that their policy effect on the sustainable development of the economy and society should not exist within this timeframe. However, from 2017 onwards, the impact of the pilot zones on the sustainable development should become apparent.

Figure 1 displays the results of the parallel trend test. Prior to 2017, the confidence interval for the impact coefficient of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society primarily includes the value 0, despite its incremental nature. This suggests that the impact of establishing these pilot zones is

TABLE 2 Results of descriptive statistics for each variable.

Variable	Variable Symbol	Full Sample		Experimental Group		Control Group	
		Average value	Standard deviation	Average value	Standard deviation	Average value	Standard deviation
Sustainable development of economy and society	SDL	1.0142	0.5317	1.2781	0.5645	0.9615	0.5100
Level of government intervention	GI	0.2629	0.1112	0.2173	0.0533	0.2720	0.1175
Openness	OP	0.7548	3.4157	0.3682	0.3530	0.8321	3.7350
Employment level	EL	3.2070	0.6380	3.0733	0.4649	3.2338	0.6649
Human capital	MC	2.2166	0.0868	2.1767	0.0589	2.2246	0.0894

The human capital variable is logarithmically treated in the above variables.

TABLE 3 Baseline regression results.

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
P_T	0.3863*** (0.1182)	0.1951*** (0.0332)	0.0924*** (0.0257)	0.1088*** (0.0250)	0.0478** (0.0198)
GI			−0.3113 (0.2254)	−0.0358 (0.5438)	−0.0241 (0.4785)
OP			0.0044** (0.0017)	0.0235** (0.0104)	0.0054 (0.0080)
EL			−0.0147 (0.0145)	−0.0396 (0.0790)	−0.0642 (0.0595)
MC			2.6973*** (0.2268)	−21.1834*** (5.4647)	−12.5169*** (4.1828)
GI-squared				−0.6492 (0.6540)	−0.4400 (0.5261)
OP-squared				−0.0005* (0.0002)	−0.0001 (0.0002)
EL-squared				0.0041 (0.0125)	0.0107 (0.0094)
MC-squared				5.3730*** (1.2355)	2.7927*** (0.9557)
Con_	0.9785*** (0.0329)	0.9962*** (0.0074)	−4.8475*** (0.5357)	21.6527*** (6.0554)	15.0198*** (4.6004)
Area fixed	NO	YES	YES	YES	YES
Fixed time	NO	NO	NO	NO	YES
R-squared	0.0445	0.1262	0.5324	0.5781	0.7714

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

not significantly different from zero. In other words, there is no substantial impact of the pilot zones on the sustainable development of the economy and society. However, beginning in 2017, although the confidence interval for the impact coefficient of the pilot zones also includes the value 0, it does not hold true for subsequent years. Furthermore, the impact coefficients for these years are all greater than 0, indicating a potential time lag in the impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. Nevertheless, it is evident that the policy does have an impact, and the establishment of these pilot zones can facilitate considerable improvements in the sustainable development of the economy and society. These test results align with expectations and validate the findings of the baseline regression.

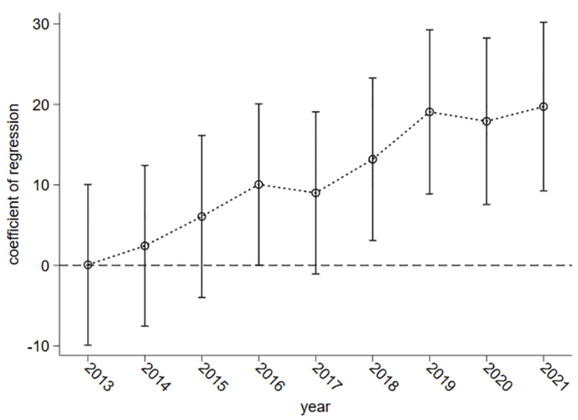

FIGURE 1
Parallel trend test results.

4.2 Robustness tests

4.2.1 Placebo test

The construction of the benchmark model may overlook certain influential factors, thereby introducing bias into the regression results. To address this issue, this paper adopts a double randomized experiment approach, drawing inspiration from Li et al. (2016), to ensure the robustness of the benchmark regression results. The experimental process is as follows: Firstly, a new experimental group is formed by randomly selecting five provincial regions from the full sample, which serves as an extension to the existing experimental group of the benchmark regression model. Secondly, the policy implementation time is set to 2017, and a new policy implementation time frame of 2014–2021 is randomly selected for comparison. However, 2013 is excluded from the selection to ensure a minimum one-year data for policy implementation analysis. Next, a cross-product term is generated through the combination of the new experimental group and the new policy implementation time, and a regression analysis is conducted using the benchmark regression model. This entire process is repeated 500 times, producing a kernel density distribution plot of the new policy effect. By examining the kernel density distribution, it becomes possible to identify any significant influences that might have been disregarded in the benchmark regression model, thereby assessing the robustness of the benchmark regression results.

Figure 2 displays the results of the placebo test conducted in this paper. The kernel density distribution in Figure 2 presents the regression coefficients of the new policy effect (spurious policy effect) after 500 double randomized experiments. These coefficients are uniformly distributed around the approximate value of −0.18, which can be considered as 0. The regression coefficients of the new policy effect exhibit a normal distribution pattern, indicating that the baseline regression model utilized in this paper does not overlook the impact of important influencing factors on the sustainable development of the economy and society. Hence, the baseline regression results demonstrate a certain level of robustness. Furthermore, the establishment of pilot zones for green finance reform and innovations has a positive and credible impact on the sustainable development of the economy and society.

4.2.2 Consideration of the time lag of policy effects

The previous paper's parallel trend test suggests the possibility of a time lag in the impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. This aligns with the reality of economic and social progress, as it takes time for the establishment of such pilot zones and for the policy effects to transmit to the sustainable development of the economy and society. Taking this into account, this paper adopts the approach commonly used by scholars of altering the timing of policy shocks to investigate the future impact of the pilot zone for green financial reform and innovation on the sustainable development of the economy and society. By prioritizing the sustainable development of the economy and society, we can ascertain the time delay in the policy effects of the pilot zone for green financial reform and innovation, while also bolstering the credibility of the conclusions derived from the baseline regression results.

Table 4 presents the regression results obtained by prioritizing the sustainable development of the economy and society. In columns (1) to (3), the regression results reflect the front-loading of the sustainable development of the economy and society by one period. In columns (4) to (6), the regression results demonstrate the front-loading by two periods. It is observed that the positive impact of the pilot zones for green finance reform and innovations on the level of sustainable development remains consistent across different degrees of front-loading. Thus, it continues to promote the sustainable development of the economy and society. This suggests a time lag in the impact of establishing the pilot zones but also underscores their enduring positive influence. These findings further confirm the robustness of the baseline regression results.

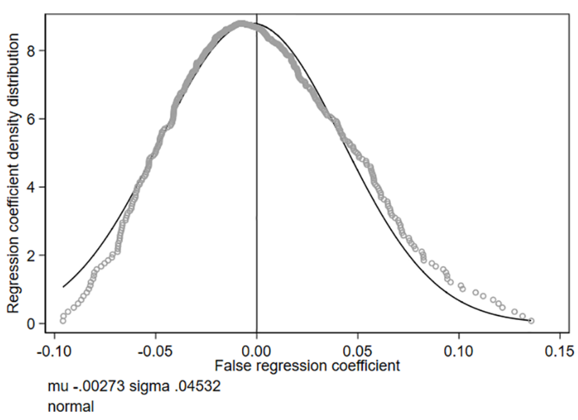

FIGURE 2
Placebo test results.

4.2.3 Consideration of relevant policy interference

As a new financial development model, green finance plays a crucial role in promoting sustainable development in China. The development of green finance in China encompasses various dimensions. For instance, along with the establishment of pilot zones for green finance reform and innovations, certain regions have already taken steps towards carbon emissions trading. Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen became carbon emissions trading pilot regions as early as 2011. In 2016, Fujian also joined as the eighth trading pilot region, launching its carbon trading market. Both the carbon emissions trading pilot policy and the green financial reform and innovation pilot area policy contribute to environmental improvement during the process of sustainable economic and social development. Consequently, they jointly promote the sustainable development of the economy and society. It is worth considering that the implementation of the carbon emissions trading pilot policy may impact the policy implementation effect of the green financial reform and innovation pilot area. In other words, it may influence the green financial reform and innovation pilot area's policy effect on the sustainable development of the economy and society. Therefore, this paper aims to conduct an additional robustness check to examine the potential impact of these policies on the topic at hand.

We have addressed the impact of the pilot carbon trading policy on the baseline regression results by excluding the pilot carbon trading region from the control group. In this paper, Guangdong is included in the experimental group as it became a pilot region for carbon emissions trading in 2011, which predates the research interval of this paper (2013 onwards). Thus, its data are retained in the research sample. The regression results, excluding the influence of the carbon emissions trading pilot policy, are presented in Table 5. In each instance of adding regression conditions, the

TABLE 4 Regression results for different levels of front-loading sustainability.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	SDL_1	SDL_1	SDL_1	SDL_2	SDL_2	SDL_2
P_T	0.1093*** (0.0272)	0.0880*** (0.0248)	0.0429** (0.0195)	0.0924*** (0.0257)	0.1088*** (0.0250)	0.0557*** (0.0208)
GI	0.0181 (0.2752)	−0.0080 (0.6354)	−0.2293 (0.5149)	−0.3113 (0.2254)	−0.0358 (0.5438)	−0.2192 (0.5496)
OP	0.0045* (0.0027)	0.2781*** (0.0399)	0.1023*** (0.0335)	0.0044** (0.0017)	0.0235** (0.0104)	0.2796*** (0.1037)
EL	−0.0241 (0.0184)	−0.1586* (0.0925)	−0.0943 (0.0703)	−0.0147 (0.0145)	−0.0396 (0.0790)	−0.1313 (0.1049)
MC	2.8304*** (0.2690)	−4.2436 (6.1253)	−3.0063 (4.6579)	2.6973*** (0.2268)	−21.1834*** (5.4647)	0.6430 (5.7417)
GI-squared		−0.3736 (0.7411)	−0.1214 (0.5779)		-0.6492 (0.6540)	0.2264 (0.5972)
OP-squared		−0.0078*** (0.0011)	−0.0029*** (0.0010)		−0.0005* (0.0002)	−0.1140** (0.0541)
EL-squared		0.0198 (0.0143)	0.0155 (0.0108)		0.0041 (0.0125)	0.0220 (0.0163)
MC-squared		1.3422 (1.3967)	0.6579 (1.0624)		5.3730*** (1.2355)	−0.0302 (1.3119)
Con_	−5.1683*** (0.6158)	4.0447 (6.7356)	4.5052 (5.1265)	−4.8475*** (0.5357)	21.6527*** (6.0554)	−0.1818 (6.2865)
Area fixed	YES	YES	YES	YES	YES	YES
Fixed time	NO	NO	YES	NO	NO	YES
R-squared	0.4742	0.5969	0.7791	0.5324	0.5781	0.7645

P_T denotes Policy_Time in the model setting. SDL_1 and SDL_2 denote SDL's antecedent one and two periods, respectively. Standard errors are indicated in parentheses. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

coefficient of P_T consistently exceeds the value of 0 and is statistically significant. This indicates that the establishment of the green financial reform and innovation pilot area has a robust positive influence on the sustainable development of the economy and society. Notably, when considering column (5), which comprehensively incorporates regression conditions, and combining these findings with the benchmark regression results in Table 3, we observe that the impact coefficient of P_T in Table 5 is larger after excluding the influence of the carbon emissions trading pilot policy. This implies that the potential impact of the carbon emissions trading pilot policy indeed enhances the implementation of the pilot zones' policy for green finance reform and innovations, while not altering the directional

TABLE 5 Regression results excluding the pilot policy of carbon emissions trading.

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
P_T	0.3900*** (0.1201)	0.1951*** (0.0323)	0.0969*** (0.0253)	0.0998*** (0.0234)	0.0554*** (0.0210)
GI			−0.5435** (0.2469)	−0.7717 (0.5537)	−0.5169 (0.5338)
OP			0.0669*** (0.0209)	0.2503*** (0.0439)	0.0966** (0.0411)
EL			−0.0410** (0.0165)	−0.3981*** (0.1086)	−0.1853* (0.0959)
MC			1.9841*** (0.2629)	−20.1701*** (6.0585)	−11.8463** (5.2501)

(Continued)

TABLE 5 Continued

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
GI-squared				0.0238 (0.6419)	−0.0260 (0.5762)
OP-squared				-0.0539*** (0.0105)	−0.0261*** (0.0095)
EL-squared				0.0551*** (0.0162)	0.0274* (0.0142)
MC-squared				4.9209*** (1.3777)	2.6208** (1.2065)
Con_	0.9748*** (0.0391)	0.9965*** (0.0080)	−3.1277*** (0.6178)	22.3261*** (6.6706)	14.6740** (5.7424)
Area fixed	NO	YES	YES	YES	YES
Fixed time	NO	NO	NO	NO	YES
R-squared	0.0469	0.1553	0.5426	0.6334	0.7510

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

assessment of the benchmark regression's conclusion. In summary, the overall effect is underestimated.

4.2.4 Consideration of the establishment of subsequent pilot zones

In a previous paper, the pilot zones for green finance reform and innovations did not include Gansu, which only became a part of it in 2019. This exclusion may have influenced the baseline regression results. To address this, we have included Gansu in the experimental group in this paper, and the corresponding results are presented in Table 6. The findings align with the outcomes of other robustness tests, indicating that the conclusions from the baseline regression remain unchanged even with the inclusion of Gansu in the experimental group. This reaffirms the significant positive impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society. The test results also demonstrate the robustness of the baseline regression and support the idea that any potential bias in the baseline regression model does not affect the results presented here. Overall, the setting of the baseline regression model is deemed reasonable.

TABLE 6 Regression results considering the establishment of subsequent test areas.

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
P_T	0.3425*** (0.1139)	0.1868*** (0.0310)	0.0739*** (0.0247)	0.0955*** (0.0243)	0.0398** (0.0189)
GI			−0.3111 (0.2273)	-0.0050 (0.5485)	−0.0177 (0.4805)
OP			0.0044** (0.0017)	0.0240** (0.0105)	0.0055 (0.0080)
EL			−0.0149 (0.0146)	−0.0513 (0.0797)	−0.0696 (0.0598)
MC			2.6958*** (0.2323)	−21.9048*** (5.5590)	−12.6677*** (4.2412)
GI-squared				−0.6904 (0.6603)	−0.4455 (0.5290)
OP-squared				−0.0005* (0.0002)	−0.0001 (0.0002)
EL-squared				0.0060 (0.0126)	0.0116 (0.0095)

(Continued)

TABLE 6 Continued

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
MC-squared				5.5303*** (1.2556)	2.8209*** (0.9683)
Con_	0.9800*** (0.0332)	0.9956*** (0.0074)	−4.8424*** (0.5474)	22.4903*** (6.1659)	15.2204*** (4.6681)
Area fixed	NO	YES	YES	YES	YES
Fixed time	NO	NO	NO	NO	YES
R-squared	0.0375	0.1318	0.5248	0.5721	0.7700

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5 Extended research and mechanism analysis

5.1 Extensive research

5.1.1 Baseline regression based on propensity score matching

The issue of unbalanced regional development in China is severe. Consequently, the establishment of pilot zones for green finance reform and innovations may vary between regions, as seen in factors like the level of government intervention and openness in the control variables. Consequently, when applying the DID model, there is a possibility of selection bias in the control group's sample selection. To address this concern, we employ propensity score matching, which can appropriately address the issue. Thus, prior to the baseline regression, this paper pairs the experimental group with the control group, enabling the control group sample to serve as a more suitable reference object and enhancing the rationality of the counterfactual in the DID model.

For propensity score matching, this study utilizes a 1-to-1 nearest-neighbor matching method. The P-value kernel density distributions of the experimental and control groups before and after matching are depicted in Figures 3, 4, respectively. Upon visual observation, it is evident that the P-value kernel density distribution characteristics of the experimental group and the control group differ significantly prior to the propensity score matching. However, after propensity score matching, the discrepancy between the P-value kernel density distribution characteristics of both groups considerably diminishes, thereby indicating the effectiveness of the selected propensity score matching method in this paper.

Table 7 displays the regression results following propensity score matching. Upon considering area fixed effects, control variables, squared terms of control variables, and time fixed effects in succession, it becomes apparent that the impact coefficients of P_T are all positive at the 1% or 5% significance level, albeit with some variation in magnitude. This further supports the notion that the establishment of pilot zones for green finance reform and innovations has a significantly positive effect on both the sustainable development of the economy and society, as well as the overall enhancement of sustainable development in the pilot zone location. In column (5), when comparing these results with the baseline regression results in Table 3, it is evident that the policy effect of the establishment of pilot zones for green finance reform and innovations is even more pronounced after propensity score matching than without it. This suggests that the initial regression results may have underestimated the true impact to some extent. Consistently, this finding aligns with the robustness test, wherein a more suitable control group is selected, mitigating the underestimation and amplifying the actual policy effects resulting from the establishment of pilot zones for green finance reform and innovations.

5.1.2 Dynamics of policy effects

After passing validity and a series of robustness tests, the effect of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society remains consistent. This confirms the rationality of the baseline regression model and the reliability of the results. Additionally, through a time lag test, it is observed that there may be a delay in the impact of these pilot zones on sustainable development. Consequently, this paper further examines the dynamic changes in their effect.

The pilot zones for green finance reform and innovations were implemented in 2017. To further investigate the changes in policy effect over time, this study introduces time dummy variables for

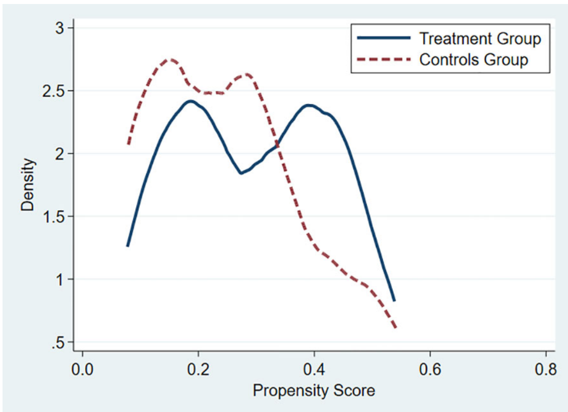

FIGURE 3
Kernel density distribution of P-value before matching.

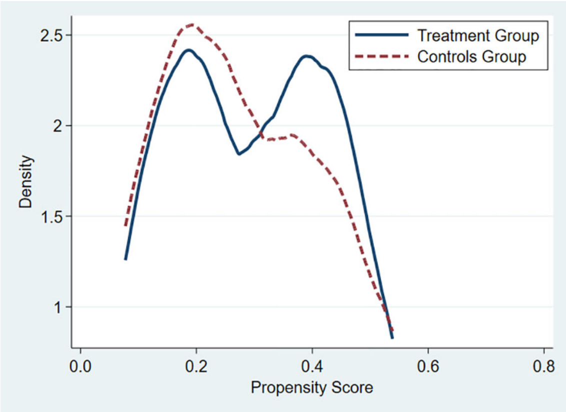

FIGURE 4
Kernel density distribution of P-value after matching.

each year from 2017 to 2021 (e.g., Time_2017 takes the value 1 for the year 2017 and 0 for all other years). By multiplying the dummy variable (Policy) of the experimental group, a key variable reflecting the policy effect across all years is obtained and subsequently subjected to regression analysis.

The results are depicted in Table 8, where it is evident from column (5) that in the initial two years (2017 and 2018) following the establishment of the pilot zones for green finance reform and innovations, there was no significant impact on the sustainable development of the economy and society. It was only in the subsequent years (2019–2021) that the establishment of the pilot zone began to effectively and positively contribute to the sustainable development of the economy and society. This finding further highlights the existence of a time lag in the policy effect of the pilot zone for green financial reform and innovation. Such a delay is closely linked to the time required for setting up the pilot zone and the transmission of policy effects, aligning with the present economic and social development reality.

5.1.3 Heterogeneity analysis of policy effects

This paper aims to analyze the heterogeneous effects of pilot zones for green finance reform and innovations on the sustainable development of the economy and society under different development environments. The study focuses on variables such as the level of financial development, degree of industrialization, and level of technological innovation, which are correlated with sustainable development. For instance, the level of financial development is measured as the financial sector's value added as

TABLE 7 Regression results after propensity score matching.

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
P_T	0.3931*** (0.1212)	0.1920*** (0.0328)	0.0797*** (0.0264)	0.0819*** (0.0230)	0.0566** (0.0231)
GI			−0.0681 (0.4552)	−3.3491*** (1.2066)	−3.3420*** (1.2406)
OP			0.0826*** (0.0316)	0.6234*** (0.0946)	0.4347*** (0.1014)
EL			−0.0619** (0.0251)	-0.3323* (0.1718)	−0.2466 (0.1628)
MC			2.1868*** (0.3599)	−35.6463*** (9.8388)	−27.3875*** (10.2249)
GI-squared				4.4686** (1.9720)	4.1285** (1.9151)
OP-squared				−0.2586*** (0.0427)	−0.1862*** (0.0444)
EL-squared				0.0452* (0.0269)	0.0355 (0.0254)
MC-squared				8.4392*** (2.2479)	6.2988*** (2.3726)
Con_	0.9208*** (0.0304)	0.9507*** (0.0097)	−3.6337*** (0.8549)	39.4472*** (10.7211)	31.4509*** (11.0329)
Area fixed	NO	YES	YES	YES	YES
Fixed time	NO	NO	NO	NO	YES
R-squared	0.1161	0.2063	0.5823	0.7073	0.7657

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8 Changes in policy effects after the establishment of the pilot area.

Variable	(1)	(2)	(3)	(4)	(5)
	SDL	SDL	SDL	SDL	SDL
P_T_2017	0.2635 (0.2390)	0.0723 (0.0541)	0.0403 (0.0410)	0.0452 (0.0392)	−0.0045 (0.0322)
P_T_2018	0.3188 (0.2493)	0.1277** (0.0541)	0.0714* (0.0411)	0.0863** (0.0394)	0.0134 (0.0320)
P_T_2019	0.4084 (0.2532)	0.2172*** (0.0541)	0.1274*** (0.0416)	0.1477*** (0.0399)	0.0788** (0.0321)
P_T_2020	0.4407* (0.2543)	0.2495*** (0.0541)	0.1122*** (0.0424)	0.1361*** (0.0408)	0.0584* (0.0322)
P_T_2021	0.5002* (0.2772)	0.3090*** (0.0541)	0.1264*** (0.0432)	0.1542*** (0.0420)	0.0988*** (0.0326)
GI			−0.3109 (0.2264)	0.0707 (0.5480)	−0.0331 (0.4736)
OP			0.0045*** (0.0017)	0.0241** (0.0103)	0.0059 (0.0079)
EL			−0.0161 (0.0146)	−0.0340 (0.0786)	−0.0618 (0.0589)
MC			2.6006*** (0.2341)	−22.4929*** (5.4590)	−13.5256*** (4.1531)
GI-squared				−0.8031 (0.6574)	−0.4855 (0.5211)
OP-squared				−0.0005* (0.0002)	−0.0001 (0.0002)
EL-squared				0.0030 (0.0124)	0.0099 (0.0093)
MC-squared				5.6406*** (1.2331)	2.9951*** (0.9483)
Con_	0.9785*** (0.0332)	0.9962*** (0.0072)	-4.6292*** (0.5518)	23.2160*** (6.0541)	16.2638*** (4.5714)
Area fixed	NO	YES	YES	YES	YES
Fixed time	NO	NO	NO	NO	YES
R-squared	0.0469	0.1799	0.5408	0.5903	0.7804

P_T denotes Policy_Time in the model setting. P_T_2017 denotes the cross-product term constructed with 2017 as the time of policy occurrence only. Other identical variables have similar meanings. Standard errors are indicated in parentheses. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

a percentage of GDP, while the level of industrialization is expressed as the industry's value added as a percentage of GDP. Additionally, the level of technological innovation is represented by the logarithm of technology market turnover. To effectively examine the effects of green financial reform and innovation pilot zones, this paper utilizes the mean level of development environment as the criterion for grouping. For example, the regions above the mean level of financial development are classified as the high financial development group, while the remaining regions are categorized as the low financial development group. Regression analysis is then performed within each group, followed by a comparison of the policy effects between the groups. It is important to note that although the experimental group in this paper consists of fewer provincial areas, the grouping based on the three development environments enables an effective division.

Table 9 shows the varying impacts of pilot zones for green finance reform and innovations on the sustainable development of the economy and society across different development environments. The findings reveal that the establishment of these pilot zones only yields a significantly positive effect on sustainable development in regions characterized by lower levels of financial development, lesser industrialization, and higher levels of technological innovation. These results are comprehensible as regions with higher levels of financial development and industrialization naturally exhibit relatively advanced sustainable economic and social development. Consequently, the policy effects of pilot zones for green finance reform and innovations are not as prominent in such areas. Moreover, considering that innovation plays a crucial role in driving sustainable development, the effects of these policy measures will also be substantial in regions with higher

TABLE 9 Differences in the policy effects of the establishment of the test area under different relevant factors.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	SDL	SDL	SDL	SDL	SDL	SDL
P_T	0.0312 (0.0459)	0.0470* (0.0244)	0.0141 (0.0245)	0.1099*** (0.0310)	0.1455*** (0.0279)	−0.0168 (0.0253)
GI	1.3566** (0.6535)	−2.3819* (1.2370)	−0.4675 (1.1514)	0.4104 (0.4841)	−1.2411 (0.9939)	−0.5024 (0.6121)
OP	0.0824 (0.0937)	0.0105 (0.0091)	0.2459*** (0.0593)	0.0063 (0.0055)	0.0514 (0.0528)	0.0070 (0.0078)
EL	−0.0464 (0.0710)	−0.2474** (0.1125)	−0.5355*** (0.1674)	−0.0109 (0.0464)	−0.1570** (0.0649)	0.0045 (0.1098)
MC	−10.7419** (4.8718)	−19.6329** (8.3655)	3.2072 (10.7767)	−17.6547*** (3.3080)	−4.8956 (5.4367)	−15.5439** (7.2905)
GI-squared	−1.4441** (0.5963)	2.9665 (1.9802)	−0.0707 (1.8884)	−1.0638** (0.4596)	1.1447 (1.5343)	−0.3501 (0.6033)
OP-squared	−0.0217 (0.0174)	−0.0002 (0.0002)	−0.0507*** (0.0123)	−0.0001 (0.0001)	−0.0200* (0.0107)	−0.0001 (0.0002)
EL-squared	0.0073 (0.0122)	0.0370** (0.0167)	0.0778*** (0.0251)	0.0058 (0.0078)	0.0263** (0.0104)	−0.0014 (0.0169)
MC-squared	2.2301** (1.1042)	4.4881** (1.9260)	−0.7684 (2.4373)	3.9799*** (0.7502)	1.0798 (1.2019)	3.5581** (1.6924)
Con_	13.6316** (5.4039)	23.0876** (9.1069)	−1.3662 (11.8832)	20.1767*** (3.6723)	6.7317 (6.1973)	18.1469** (7.8983)
Area fixed	YES	YES	YES	YES	YES	YES
Fixed time	NO	YES	NO	YES	NO	YES
R-squared	0.9088	0.7474	0.7899	0.8905	0.8727	0.7647
Heterogeneity category	Financial Development_High	Financial Development_Low	Industrialization_High	Industrialization_Low	Technological Innovation_ High	Technological Innovation_ Low

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

levels of technological innovation. Hence, the policy effects of pilot zones for green finance reform and innovations will tend to be more pronounced in regions with greater levels of technological innovation, given the importance of innovation as a driving force for sustainable development.

5.2 Mechanism analysis

During the process of pilot zones for green finance reform and innovation, the sustainable development of the economy and society encompasses various indicators across different dimensions such as economic factors, social factors, demographic factors, and environmental factors. Therefore, this paper aims to analyze the impact of establishing green financial reform and innovation pilot zones on indicators of sustainable economic and social development based on the mechanism research conducted by Li and Wen (2023). Additionally, this paper seeks to explain the policy effects resulting from the establishment of these pilot zones. The above analysis of the mechanism offers several advantages. Firstly, by examining the impact of pilot zones on each dimensional indicator, we can better understand the influence of composite indicators through individual dimensions, which is in line with economic logic. Secondly, exploring the impact of pilot zones on each dimensional indicator allows for a more detailed examination of the policy effects, thereby gaining deeper insights into their overall impact.

Table 10 presents the effects of establishing pilot zones for green finance reform and innovation on the dimensions of sustainable economic and social development. After accounting for regional and time fixed effects, control variables, and their squared terms, it is found that the establishment of these pilot zones does not significantly impact economic, social, and demographic factors in sustainable development. However, there is a notably positive effect on environmental factors. This outcome aligns with the principles of green financial development and supports the concept of green development. Unlike traditional financial industry growth that primarily focuses on economic expansion, green financial development emphasizes improving the quality of the ecological environment and promoting sustainable economic and social progress while maintaining a harmonious coexistence between humans and nature. These findings also shed light on the heterogeneous policy effects of the green financial reform and innovation pilot zones across different developmental environments. Regions with lower levels of financial development

TABLE 10 Impact of the establishment of the pilot area on the dimensional factors of the sustainable development of economy and society.

Variable	(1) Economic Factors	(2) Social Factors	(3) Demographic Factors	(4) Environmental Factors
P_T	0.0128 (0.0097)	−0.0076 (0.0186)	0.0174 (0.0151)	0.1567*** (0.0461)
GI	−0.1815 (0.2344)	0.0122 (0.4502)	−0.5384 (0.3650)	4.6111*** (1.1157)
OP	−0.0018 (0.0039)	−0.0020 (0.0075)	0.0013 (0.0061)	−0.0185 (0.0186)
EL	0.1208*** (0.0292)	0.2571*** (0.0560)	0.1922*** (0.0454)	−0.0620 (0.1388)
MC	−25.2822*** (2.0488)	−18.2543*** (3.9354)	−0.8228 (3.1905)	−7.7829 (9.7538)
GI-squared	−0.2273 (0.2577)	−0.7101 (0.4950)	1.2283*** (0.4013)	−4.8752*** (1.2268)
OP-squared	0.0000 (0.0001)	0.0000 (0.0002)	−0.0001 (0.0001)	0.0002 (0.0004)
EL-squared	−0.0178*** (0.0046)	−0.0371*** (0.0089)	−0.0263*** (0.0072)	0.0133 (0.0220)
MC-squared	5.8397*** (0.4681)	4.3410*** (0.8992)	0.2500 (0.7290)	1.8271 (2.2287)
Con_	28.0621*** (2.2534)	19.5875*** (4.3284)	1.3144 (3.5090)	8.3810 (10.7277)
Area fixed	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES
R-squared	0.9414	0.8899	0.2457	0.5455

P_T indicates Policy_Time in the model setting. Standard errors are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

and industrialization tend to have lower levels of environmental pollution. Consequently, with the support of high technological innovation, the establishment of the pilot zones has a more pronounced positive effect on the ecological environment in these areas.

The regression results in Table 10 also explain the heterogeneous policy effect of the green financial reform and innovation pilot zone across different development environments. It is observed that regions with lower levels of financial development and industrialization tend to have lower levels of environmental pollution. In these areas, supported by higher levels of technological innovation, the establishment of the pilot zone has a more significant positive impact on the ecological environment. Additionally, the results indicate that the channels affecting the sustainable development of the economy and society in the green financial reform and innovation experimental zone are limited, suggesting that there is room for China to further enhance the policy impact of establishing these experimental zones in the future.

6 Conclusions and recommendations

With the transformation of China's main social contradiction and economic development stage, it has become crucial to enhance the sustainable development of the economy and society. In this context, green finance emerges as the primary driver for promoting the green development of the economy and society. This study aims to explore the impact of establishing pilot zones for green finance reform and innovations on the sustainable development of the economy and society in China. To achieve this, a DID model is constructed using sample data from 30 provincial-level regions in China from 2013 to 2021. The findings are refined and supplemented through robustness testing, expansion analysis, and impact mechanism analysis. The results are as follows:

Firstly, the establishment of pilot zones for green finance reform and innovations significantly contributes to the improvement of the sustainable development level of the economy and society. This finding remains consistent after conducting a series of robustness tests, including placebo tests, considering the time lag of policy effects, excluding relevant policy interference, and improving the precision of model settings.

Secondly, the establishment of pilot zones for green finance reform and innovations has a lagging effect on the enhancement of sustainable development in the economy and society. The positive promotion effect of the pilot zones on sustainable development is significant only in areas with lower levels of financial development, lower degrees of industrialization, and higher levels of technological innovation.

Thirdly, the establishment of green financial reform and innovation pilot zones primarily promotes the sustainable development of the economy and society by improving environmental factors, and its influence channel is relatively singular.

Based on the above research findings, several suggestions are put forth to further enhance the sustainable development of the economy and society:

Firstly, the government should carefully summarize the policy experience of the green finance pilot zones, expand the implementation scope of the green financial pilot policies, and continuously promote the green transformation development model. By building upon the practical experience of the pilot zones, increasing the number of green finance pilot areas, and improving the green finance pilot policies and reform and innovation programs, the promotion effects on the sustainable development of the economy and society can be strengthened.

Secondly, the central government should consider the spatial layout of each region, formulate green finance pilot policies according to local conditions, and encourage differentiated development of green finance in each region. The impact of the pilot zones for green finance reform and innovations on sustainable development is currently too singular. Hence, it is necessary to consider factors such as resource endowment, financial development level, industrial development characteristics, and other factors unique to different regions. The one-size-fits-all implementation of green finance pilot policies should be avoided. By implementing differentiated and distinctive regional green financial support initiatives, the impact channels of green finance pilot policies can be expanded, and their implementation effects can truly be realized.

Finally, the authorities should enhance policy support for technological innovation and establish a long-term mechanism for enhancing green technology. Innovation-driven approaches are crucial in leveraging the policy effect in the pilot areas. Therefore, government departments should broaden the scope of policy support, favor green technology innovation, and guide funding towards green technology breakthrough projects and science and technology endeavors with high pollution reduction potential. Moreover, environmental regulations placed on highly polluting and energy-consuming enterprises should be strengthened, compelling these enterprises to undergo technological transformations and process improvements. This will also encourage green innovation across all sectors of the economy and society.

The sustainable development of the economy and society is a long-term and continuous process that requires extensive research. This paper specifically examines the importance of green finance for sustainable development from a policy perspective. However, there are still areas that can be improved. For instance, the specific circumstances of cities, districts, and counties in the research sample were not fully considered due to limited data availability. Additionally, the research methodology did not account for the demonstration effect of green financial policies. The evaluation of policy effectiveness in this paper is based on provincial data, which fails to capture the full impact of environmental policies and only focuses on influential ones like the carbon emission trading policy. In future studies, the spatial effects of green financial policies will be thoroughly explored, highlighting their role in policy implementation. Moreover, the implementation of green finance policies will be analyzed in conjunction with the level of green finance development in different regions, providing a comprehensive understanding of the driving force behind sustainable economic and social development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

GL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Writing – original draft. JL: Funding acquisition, Project administration, Supervision, Writing – review & editing. YS: Conceptualization, Investigation, Methodology, Software, Writing – review & editing. HC: Investigation, Resources, Validation, Visualization, Writing – review & editing. HC: Funding acquisition, Project administration, Supervision, Writing – review & editing.

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Conflict of interest

Author HoC was employed by the Quanzhou Yixing Electrical Engineering Construction Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Environmental pollution liability insurance pilot policy and enterprise green transformation: evidence from Chinese listed corporates

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In the context of dual-carbon, corporate green transformation, a significant measure of the green effect of Environmental Pollution Liability Insurance (EPLI), garners substantial attention in current research. By leveraging the 2008 EPLI pilot policy as an exogenous event, this paper employs a difference-in-difference model to scrutinize the influence of the EPLI pilot on the green transformation of listed companies. We find that: (1) The EPLI pilot actively promotes corporate green transformation. (2) The pilot policy's impact on green transformation is mediated through regional green development and enterprise investment efficiency. (3) The pilot policy manifests asymmetric effects on green transformation, influenced by regional, industrial, and enterprise-specific pollution levels, as well as government environmental concerns. (4) The EPLI pilot policy engenders enduring financial implications and contributes to the governance of information. This study is beneficial to enrich the research on the EPLI system and green transformation of enterprises that provide policy suggestions for improving the green financial system and promoting the green transformation of enterprises.

KEYWORDS

environmental pollution liability insurance, green transition, green insurance, green innovation, environmental regulation

1 Introduction

As a crucial element of green finance, Environmental Pollution Liability Insurance (EPLI) serves as a vital tool for averting environmental risks and mitigating societal pollution. The objective of green finance is to actualize the ecological advancement of society as a whole. It aims to rectify the issue of environmental externalities by redirecting resource allocation and promoting eco-friendly concepts. This, in turn, propels the eco-conscious evolution of microenterprises, leading them to attain their designated objectives (Tolliver et al., 2021). Green innovation stands as a pivotal facet of ecological progress, fostering increased employment opportunities and advancing environmental governance (Kunapatarawong and Martínez-Ros, 2016; Guo et al., 2021). It embodies a pivotal facet of corporate green transformation. For corporations, green innovation yields positive effects on corporate performance, enriching corporate value and competitive advantage, among other benefits (Tang et al., 2018; Tu and Wu, 2021; Hao et al., 2022). Consequently, enterprises are compelled to place significant emphasis on green innovation. They must bolster their green core competencies and uphold an environmentally responsible image to effectively undergo the process of green transformation (Chen, 2008).

EPLI is an insurance that takes the loss caused by a pollution accident to a third party as the subject matter of the corresponding environmental liability by the provisions of the law, and the policyholder can be a sewage disposal enterprise. The policyholder can be a sewage disposal enterprise. The insured enterprise insures the loss caused by the pollution accident in the future and pays the insurance cost to the insurance company at the agreed premium rate according to the provisions of the insurance contract, and the insurance company compensates the corresponding amount according to the provisions of the contract in the event of an environmental accident. EPLI is beneficial to change the existing situation of "enterprises make profits from illegal pollution and everyone pays the bill for environmental damage", which leads to the liability of environmental pollution loss and promotes the standardization and rationalization of China's environmental protection responsibility.

Ralston (1979) developed the pollution loss pricing mechanism of EPLI based on the theory of externalities, marking the inception of EPLI research. In its early stages, studies primarily centered around qualitative analysis. They delved into constructing the EPLI market, exploring the role of EPLI in regulating catastrophic risks and assessing its insurability. These studies also scrutinized the influence of EPLI as a public policy on market functioning. Moreover, they proposed normative solutions for EPLI in the face of availability crises (Katzman, 1988; Brockett et al., 2018). Presently, existing research on EPLI remains rooted in qualitative analysis. The focus largely revolves around identifying drawbacks in EPLI products, summarizing experiences from EPLI pilot programs, and offering policy recommendations for establishing a comprehensive EPLI system (Feng et al., 2014a; Feng et al., 2014b). Given the emergence of governmental policies aimed at mitigating environmental pollution due to accidents, Pu et al. (2017) designed EPLI derivatives. They further validated that these products facilitate underwriting activities for insurance companies, effectively serving EPLI's core purpose as an insurance policy—the function of risk transfer. Notably, EPLI's primary role involves aiding enterprises in minimizing environmental risks. Joint EPLI ventures additionally enhance the suppression of environmental risks across entire industrial alliances (Gao et al., 2018; Wang et al., 2021). Consequently, EPLI's utility lies in enticing enterprises to seek insurance coverage. However, it's crucial to note that only mandatory regulatory policies can compel enterprises to acquire EPLI. Incentive-based regulatory policies, on the other hand, are inadequate for boosting insurance demand (Li et al., 2023).

The literature concerning corporate green transformation primarily centers around the exploration of factors influencing green innovation. Within the realm of macro factors, it has been observed that voluntary and market-based environmental regulations exert a stronger influence on promoting green innovation compared to the impact of command-based environmental regulations (Zhang et al., 2020). Additionally, a range of green financial policies, encompassing regional green financial development, green financial reforms, and green credit policies, contribute favorably to the advancement of corporate green innovation (Huang et al., 2022; Irfan et al., 2022; Wang et al., 2022a). Furthermore, industry synergistic agglomeration and the Belt and Road initiative have been found to have a positive impact on green innovation, whereas local government debt exhibits a negative effect. Interestingly, digital finance emerges as a facilitator for green innovation (Zeng et al., 2021; Chen et al., 2022b; Li et al., 2022; Cao et al., 2023; Ni et al., 2023). Among the micro factors, both corporate governance and quality management show a positive correlation with corporate green innovation. Notably, sources of financing for green innovation encompass both internal and external options. In the context of external financing, the positive effects of government subsidies, equity financing, and debt financing on green innovation sequentially diminish (Amore and Bennedsen, 2016; Li et al., 2018; Xiang et al., 2022). Furthermore, we have to recognize the significance of information innovation and innovation networks for the green transformation of enterprises (Yin and Yu, 2022; Yin et al., 2022b).

Prior research has contended that the EPLI system holds the potential to drive corporate green transformation on a macro scale (Lyu et al., 2022; Shi et al., 2023). However, these studies diverge in their perspectives when examining the micro-level dynamics. Chen et al. (2022a) uncovered that EPLI pilots in China engendered a moral hazard predicament, thereby diminishing firms' motivation to curtail emissions and consequently exacerbating their environmental outcomes. In contrast, Zhu et al. (2023) demonstrated that EPLI pilots contributed to enhancing firms' environmental performance. Moreover, the research by Ning et al. (2023) unveiled a positive correlation between EPLI and firms' green innovation efforts.

Owing to the relatively recent emergence of EPLI in China and the corresponding dearth of available data, research concerning the micro-level effects of EPLI, particularly in terms of its impact on green outcomes, has progressed slowly. In essence, the existing body of research exhibits certain shortcomings, which we elaborate on as follows: Primarily, a significant portion of the studies centered around EPLI remains confined to discussions of institutional enhancements and product design. Few studies delve into the realm of the green financial effects stemming from EPLI (Chen and Xia, 2011; Pu et al., 2017). Secondly, research aimed at understanding corporate green transformation predominantly revolves around the analysis of factors influencing green innovation. This approach often overlooks the critical question of whether corporate green innovation genuinely reflects comprehensive green transformation. Notably, scant attention has been devoted to investigating the interplay between green finance and green innovation (Huang et al., 2022; Irfan et al., 2022). Lastly, the existing body of research concerning the relationship between EPLI and microenterprise green transformation has yielded inconsistent results (Chen et al., 2022a; Zhu et al., 2023). These studies frequently rely on the EPLI-insured list issued by the former Ministry of Environmental Protection (MEP) in 2015–2016. However, this dataset bears notable limitations that hinder its ability to accurately illustrate the green finance impact of EPLI (Ning et al., 2023).

Green development represents a crucial trajectory toward achieving "carbon peaking and carbon neutrality" goals. In this context, green finance emerges as a pivotal instrument within the financial sector, fostering green development. However, the existing green financial market predominantly concentrates on facets like green credit and green bonds. Conversely, the green insurance market's evolution has been relatively brief, characterized by an imperfect framework. To address this, China's financial sector has implemented pilot policies to systematically enhance the green insurance market. The strategic utilization of green insurance in risk management, economic compensation, and social oversight to propel green development, particularly in the micro-enterprise domain, holds both pragmatic implications and theoretical significance. This pertains not only to refining the green insurance system but also to fostering sustainable enterprise development. Against this backdrop and research context, we employ the 2008 EPLI pilot as an exogenous event. We focus on Shanghai and Shenzhen's A-share listed companies, with those within the pilot regions constituting the experimental group, and those outside forming the control group. By employing green innovation as a specific metric for assessing green transformation, we construct a quasi-natural experiment. Employing the difference-in-difference (DID) model, we analyze the influence of the EPLI pilot on enterprises' green innovation, delving into the broader impact on their green transformation. Our study further probes the underlying mechanisms driving this impact, particularly the role of urban green total factor productivity and internal enterprise investment efficiency. Additionally, we investigate potential asymmetries in this effect under the moderating influences of factors such as regional and industry-specific environmental pollution, enterprise environmental protection measures, and governmental environmental concerns. Ultimately, we substantiate the influence of the EPLI pilot on corporate governance. This entails examining the policy's effects on enterprises' environmental protection subsidies, financial risk, bank loans, and information disclosure practices.

This paper's potential research contributions encompass two principal aspects. Firstly, from a research perspective, we accomplish this by investigating the influence of the EPLI pilot on green innovation—an approach that has not been previously explored. Secondly, in terms of research content, we break new ground by utilizing the 2008 EPLI pilot as an exogenous shock to meticulously assess its impact on the green innovation of listed companies. We delve into both the immediate and dynamic effects of the EPLI pilot. Additionally, we delve into the intricate mechanisms underlying the policy's impact on green innovation, unraveling the distinct outcomes resulting from the three dimensions of regional, industrial, and enterprise-level regulation. Lastly, we scrutinize the corporate governance implications of the EPLI pilot policy, thereby making a substantial contribution to the realm of research focused on green financial policies.

The rest of the article is organized as follows: in the second part, the theoretical analysis of the research hypotheses is presented. The third part provides the research design. The fourth part presents and analyzes the main empirical results. In the fifth part of the extended study, we analyze the mechanism of action effect, the moderating effect, and the corporate governance effect of the EPLI pilot policy. The last part summarizes and discusses.

2 Theoretical analysis and research hypotheses

2.1 The role of EPLI

EPLI not only encompasses a broad risk management role but also serves as a mechanism for economic compensation and social management. Within this framework, its social management aspect can effectively enact a form of "subrogated regulation." This facet acts to curtail polluting practices by enterprises, thereby fostering the transition toward green transformation within relevant industries (Zhou and Wang, 2009; Chen and Xia, 2011). Simultaneously, the EPLI system occupies a vital position within the realm of green insurance, operating as a component of green financial policy. Its primary function revolves around channeling financial resources away from polluting sectors and redirecting them towards environmentally sustainable industries. This strategic resource allocation serves to elevate financing costs for polluting industries while reducing financing costs for eco-friendly counterparts. In this manner, it effectively addresses the predicament of environmental externalities (Huang et al., 2022; Irfan et al., 2022; Lin et al., 2023). Furthermore, the EPLI system can be approached as a market-driven environmental regulation, engendering an external regulatory impact on enterprises' environmental conduct. This additional regulatory dimension collaborates with the "subrogation regulation" function, collectively imposing limitations on capital investments by companies. By doing so, it constrains high-pollution practices while incentivizing environmentally responsible behaviors. The outcome is a reduction in environmental risks and an enhancement of overall environmental performance (Lian et al., 2022; Zhu et al., 2023).

2.2 Research hypothesis

Considering the green financial impact and the environmental regulatory role of the EPLI system, we posit that the influence of the EPLI pilot on enterprises' green innovation primarily encompasses four key dimensions:

Firstly, the EPLI pilot performs the essential function of risk transfer through insurance mechanisms, subsequently amplifying the enterprise's internal governance efficacy and propelling green innovation. Following the EPLI pilot, local businesses can offload environmental risks to insurance providers by procuring EPLI coverage. On one hand, this risk transference curtails the enterprise's liability for compensating environmental risks, thus freeing up compensation funds and alleviating constraints on internal cash flow. This enhances the efficiency of internal resource utilization. On the other hand, the EPLI coverage prompts insurance companies to intensify their environmental oversight of the enterprise. This heightened supervision enhances information transparency, diminishes asymmetries in environmental information, guides enterprises toward bolstering environmental performance, mitigates environmental risks, and reduces the likelihood of environmental incidents. Consequently, it upgrades the quality of internal environmental information within the enterprise. This, in turn, augments the efficiency of internal information governance, offering more scientific, objective, and efficient information backing for the enterprise's environmental decision-making. This effect is particularly pronounced for activities such as green innovation and research and development, characterized by heightened risk, prolonged cycles, and gradual effects. As a result, the governance effect of the enterprise's green endeavors is amplified. Hence, the EPLI pilot enriches enterprises' internal governance efficiency in resource utilization and information management while simultaneously furnishing innovative resources and informational support for green innovation initiatives.

Secondly, the EPLI pilot contributes to a more judicious allocation of financial resources within the region, fostering the financing of enterprises' green activities and thus propelling green innovation. Operating as a pivotal component of green finance, the EPLI pilot actively steers financial resources from heavily polluting enterprises towards those championing environmentally conscious initiatives. This strategic reallocation elevates the cost of capital for polluting enterprises while simultaneously reducing the financing burden on environmentally friendly counterparts. Polluting enterprises are compelled to acquire EPLI, thus incurring additional expenditure. Simultaneously, drawing from signaling theory, the acquisition of EPLI implies that enterprises bear elevated environmental risks. This, in turn, may hinder their access to external financing. As a response, these enterprises are prompted to curtail emissions through energy-saving measures, thereby bolstering environmental performance and mitigating external financing constraints. Consequently, green innovation endeavors see a corresponding upsurge. Conversely, for environmentally friendly enterprises, the EPLI pilot fosters a conducive green financing environment. This environment curtails financing costs for environmentally conscious enterprises. Concurrently, these enterprises save on premiums by not purchasing EPLI and are relieved of costs linked to conforming to stringent environmental regulations. In essence, the EPLI pilot's financing constraints on polluting enterprises act as an impetus for innovation aimed at improving their environmental performance. Meanwhile, the "cost savings" realized by environmentally friendly enterprises under the pilot's influence serve to propel their green innovation initiatives.

Thirdly, the subrogation effect and the social management function inherent in the EPLI system yield a form of social governance for enterprises, subsequently driving green innovation initiatives. On one hand, in a bid to forestall adverse selection and moral hazard, insurance companies comprehensively grasp and analyze the environmental information of enterprises before EPLI procurement. This scrutiny extends to continuous monitoring of enterprises' environmental performance throughout the insurance period. The resultant guidance encourages enterprises to amplify their green behaviors while minimizing polluting practices. On the other hand, grounded in signaling theory, EPLI operates as a market signal triggering vigilance from regulators, the public, and investment entities, among other stakeholders. This external oversight proves instrumental in mitigating agency conflicts and harmonizing the divergent goals of enterprises, that seek both profitability and green objectives. Confronted by the pressure of societal supervision, enterprises are compelled to elevate their environmental performance. This dynamic underscores the green governance effect of the EPLI system. In practical terms, this entails a reinforcement of green innovation within corporate endeavors, effectively striking a balance between the pursuit of green transformation and the short-term goals of profitability.

Fourthly, the EPLI pilot imparts the ethos of green development and triggers a shift in the enterprise development paradigm, ultimately fostering green innovation. Serving as a significant institutional framework for sustainable enterprise progress, the pilot EPLI system disseminates the principles of green finance and green development. It draws enterprises' focus toward ESG (environmental, social, and corporate governance) requisites. Concurrently, given the increasing embrace of the green development philosophy by institutional investors, enterprises have begun integrating green transformation and ESG objectives into their overarching strategies. This strategic alignment facilitates their adaptation to evolving social trends. This alignment is manifested in the allocation of corporate resources toward green investments, projects, and industries. Consequently, the enterprises pivot from resource-intensive and polluting endeavors to greener pursuits. Guided by the tenets of green development, these enterprises transition away from their former crude and polluting development models. The result is a continuous enhancement of their environmental performance. In this vein, enterprises channel efforts into green research and development, harnessing the outcomes of green innovation to drive pollution control and green-centric development. Thus, following the EPLI pilot, the influence of the green concept leads enterprises to emphasize green transformation and ESG strategies. This shift drives active participation in green initiatives and augments enterprises' willingness to engage in green innovation.

In summary, the EPLI pilot enhances internal governance, optimizes regional resource distribution, reinforces external oversight, and steers green transformation. As a result, it propels the green innovation of enterprises within the pilot region. On this basis, we present the research hypotheses of this study:

H1: Following the EPLI pilot, the green innovation performance of enterprises in the pilot region improves.

Drawing on the preceding analysis, it becomes evident that EPLI pilots wield influence not only in terms of green governance at the micro-enterprise level but also operate as catalysts for green finance and environmental regulation, thereby fostering local green development (Fan et al., 2022; Li et al., 2023). The impact of EPLI pilots on firms' green innovation predominantly hinges on their capacity to propel green development at the regional scale and to enhance internal governance at the firm level.

The effects of EPLI pilots are as follows: they drive local firms' green innovation by augmenting the green total factor productivity within pilot districts. This enhancement is rooted in the EPLI system pilots' ability to optimize district-level resource utilization, facilitate the transition toward environmentally friendly resource flows, elevate the cost associated with pollution, diminish the expense of environmental protection, and mitigate the adverse ramifications of negative environmental externalities within the districts. Simultaneously, the EPLI pilot imposes penalties on heavily polluting industries, projects, and enterprises, curbing individual enterprises' polluting behaviors. This collective action catalyzes the green upgrading of industries across the entire region, culminating in tangible regional green development. Green total factor productivity (GTFP) stands as a pivotal metric of regional green development, demonstrating a positive correlation with green innovation (Zhao et al., 2022). This relationship emerges from the fact that regional green innovation constitutes a significant component of regional GTFP. Consequently, higher GTFP and elevated efficiency in green innovation output correlate with superior green innovation performance among local enterprises. Therefore, the EPLI pilot serves to facilitate the advancement of local GTFP, subsequently fostering enterprises' green innovation. This underpins the hypothesis regarding the impact mechanism at the regional level proposed in this study:

H2a: The EPLI pilot influences enterprise green innovation performance through the mediation of regional green total factor productivity.

The EPLI pilot contributes to a heightened output of enterprises' green innovation by enhancing investment efficiency within the pilot area. The magnitude of enterprise green output is chiefly influenced by the efficiency of allocating green resources and managing environmental information. Investment efficiency serves as an indicative measure of both resource and information efficiency within enterprises. Consequently, the vigor of enterprise green innovation activities is molded by financing constraints, with investment efficiency holding a pivotal role in shaping the outcomes of green innovation endeavors. EPLI pilots exert a mitigating influence on the agency predicament faced by local enterprises, primarily through their external supervision impact. This external oversight, in turn, enhances the internal governance of enterprises, leading to an amelioration in investment efficiency. Concurrently, the EPLI pilot facilitates the provision of green funding for enterprise-level green initiatives via the mechanism of resource allocation. This infusion of resources fosters improved environmental performance within enterprises, thereby enhancing relations with stakeholders. These stakeholders, in turn, contribute environmental information and offer green resource support for the enterprises' green endeavors. This harmonious synergy serves to augment enterprise investment efficiency, ultimately refining the output of green innovation (Yang et al., 2022). As the EPLI pilot system guides enterprises toward elevating environmental investments to bolster environmental performance, it effectively addresses the issue of underinvestment. This resolution, in turn, yields a positive impact on the efficiency of input and output concerning green innovation. Drawing on the preceding analysis, we posit the following hypothesis regarding the impact mechanism at the firm level:

H2b: Following the EPLI pilot, enterprises' green innovation performance is influenced by the enhancement of investment efficiency.

External pollution serves as a pivotal determinant impacting firms' green innovation, thereby imposing limitations on the efficacy of green finance policies (Wang et al., 2022b). This influence may stem from the capacity of regional pollution to influence resource allocation and exert an impact on micro-firm financing constraints. Similarly, corporate pollution conduct detrimentally affects internal corporate governance, eroding financing capability and casting a negative shadow over corporate green innovation (Amore and Bennedsen, 2016). The government assumes a crucial role in regional pollution management, acting as a principal entity in this realm. Government bodies possess the ability to directly allocate resources for environmental governance, employing environmental regulatory fines to curtail corporate pollution activities. Additionally, they leverage environmental governance investments and environmental protection subsidies to steer enterprises toward energy conservation, emissions reduction, and engagement in green initiatives. This approach indirectly fosters environmental pollution management, thereby influencing enterprises' environmental practices in line with the government's ecological concerns (Farooq et al., 2021). Hence, there will be an asymmetric impact of internal and external environmental pollution and environmental governance on the green micro effects of the EPLI pilot policy. Based on the above analysis, we put forward the hypothesis of moderation effects:

H3: When firms face lower levels of internal and external environmental pollution and higher levels of environmental governance, the EPLI pilot policy has a stronger facilitating effect on firms' green transformation.

3 Methodology

3.1 Sample and data source

Given that the initial cohort of EPLI pilots commenced in 2008, followed by the second cohort in 2012, the research scope of this paper encompasses Chinese Shanghai and Shenzhen A-share listed companies spanning from 2004 to 2011. We adhere to four established research conventions to handle the sample in the following manner: (1) Exclude samples categorized as ST, PT, and *ST during the specified period. (2) Exclude samples that were listed in or after 2004. (3) Omit samples operating in the financial sector. (4) Eliminate samples with missing or anomalous data about key variables. Ultimately, we amassed 10,172 annual sample observations, representing 1,813 listed companies. Among these, there are 2,777 observations for companies within the experimental area and 7,395 observations for companies in the non-experimental group. This winnows the main variables by 1% and 99% (Winsorize) to mitigate the influence of outliers on the regression outcomes.

Enterprise green patent data is sourced from the China Research Data Service Platform (CNRDS). Enterprise financial status, government subsidies, and disclosure appraisal data are procured from Cathay Pacific CSMAR and Vantage Wind databases. Regional environmental and economic data are extracted from the statistical yearbooks of each respective province and region. The frequency of usage of green development-related terms is derived from local government work reports.

3.2 Variables

3.2.1 Explanatory variable

Digital green innovation is one of the important green innovation contents and an important index to measure the green transformation of enterprises, which plays an important role in the digitalization and decarbonization strategy of agricultural high-end equipment manufacturing enterprises (Yin et al., 2022a).

Citing Amore and Bennedsen (2016) and Tang et al. (2018), we employ the count of green patents (referred to as *GI*, calculated as the logarithm of the number of independently filed green patents plus one) as a metric to gauge firms' performance in green innovation. This choice allows us to portray the extent of companies' endeavors towards environmental sustainability. Furthermore, during the robustness assessment, we substitute the count of green patents (*GI*) with the count of green invention patents (abbreviated as *GCI*, calculated by taking the logarithm of the number of independently filed green invention patents plus one) as well as the count of green utility model patents (abbreviated as *GUI*, calculated by taking the logarithm of the number of independently filed green utility model patents plus one). This alteration permits us to delve into the caliber of enterprises' green innovation, adding a layer of depth to our analysis.

3.2.2 Mechanism variables

To elucidate the mechanism behind the impact of the EPLI pilot on enterprises' green transformation, we incorporate specific variables based on the methodologies outlined by Pastor and Lovell (2005) and Richardson (2006). These variables encompass urban green total factor productivity (*GTFP*) at the regional level and over-investment (*OI*) at the enterprise level. These measures serve to quantify the extent of regional green development and the efficiency of enterprises' investment, respectively. The computation of green total factor productivity involves a fusion of an over-efficient SBM model, which takes into consideration undesired outputs, and the Malmquist productivity index. This amalgamation yields a metric for the growth of urban total factor productivity under a global reference data envelopment analysis framework. Concurrently, we gauge underinvestment (*LI*) through an inefficient investment model, which is formulated as follows:

$$I_{i,t} = \alpha_0 + \alpha_1 Q_{i,t-1} + \alpha_2 Leverage_{i,t-1} + \alpha_3 Cash_{i,t-1} + \alpha_4 LAge_{i,t-1} + \alpha_5 Size_{i,t-1} + \alpha_6 SR_{i,t-1} + \alpha_6 I_{i,t-1} + \lambda_t + \eta_j + \varsigma_{i,t-1} \tag{1}$$

In the given context, where *I* signifies new investment (defined as the ratio of cash utilized for procuring fixed assets, intangible assets, and other long-term investments about total assets), *Q* denotes Tobin's Q value (calculated as total market capitalization divided by total assets), Leverage represents the leverage ratio (total liabilities divided by total assets), *Cash* signifies the cash ratio (cash assets divided by total assets), *LAge* stands for the duration since listing, *Size* pertains to the firm's size (logarithmic representation of total assets), and *SR* stands for excess return (annual return accounting for reinvestment of cash dividends—A-share market composite annual return); λ_t symbolizes the time-fixed effect, η_j signifies the industry fixed effect, and ζ represents the residual term. Specifically, when ζ>0, it indicates that the firm is overinvesting, whereas when ζ<0, it signifies that the firm is underinvesting. Derived from the aforementioned inefficient investment model, overinvestment (*LI*) materializes when the residual term (ζ) registers a value below zero.

3.2.3 Moderation variables

According to the above analysis and based on relevant research (Darnall et al., 2008; Hu et al., 2021; Zhang, 2022), we introduce *DPI*, *HPI*, *HERS*, and *DGF* variables to test the impact of the moderating effects of regional environmental pollution, industry pollution, corporate environmental management, and regional government environmental concerns on the benchmark regression. *DPI* represents the regional environmental pollution index, which is obtained by the annual normalization of regional industrial wastewater, exhaust gas, and solid waste. *HPI* is a binary variable for pollution-intensive industries that equals 1 if the firm is in pollution-intensive industries and 0 otherwise. *HERS* is a dummy variable for an environmental management system, which if the enterprise environmental management system disclosure projects[1] are higher than the average value of the annual industry takes the value of 1, otherwise takes the value of 0. *DGF* is the regional government's green development concern that is obtained by normalizing the green development word frequency of the regional government's working report. The green development word frequency is collected manually, and the green development word database is shown in Appendix Table 1.

3.2.4 Control variables

Drawing from prior research (Li et al., 2018; Xiang et al., 2022), we incorporate the subsequent corporate financial characteristic variables and all-encompassing governance variables as control measures: year of establishment (*Age*), firm size (*Size*), leverage (*Leverage*), return on assets (*ROA*), net cash generated from financing activities (*FCF*), Tobin's Q (*Q*, calculated as total market capitalization divided by total assets), *Dual*, and Audit opinion (*Opinion*). The precise symbols and corresponding definitions of these variables are detailed in Table 1.

3.3 Model

To assess the fundamental hypothesis H1, we formulated the subsequent DID panel regression model, drawing insights from

1 The disclosure projects are following: environmental protection management system, environmental protection education and training, environmental protection special action, environmental incident emergency response mechanism, environmental protection honors or awards, "three simultaneous" system.

relevant research (Chen et al., 2022a; Shi et al., 2023; Zhu et al., 2023). This model enables us to delve into the influence of the EPLI pilot on companies' green innovation:

$$GI_{it} = \beta_0 + \beta_1 DID_{it} + \gamma X_{it} + \delta_i + \lambda_t + \epsilon_{it} \quad (2)$$

Where *GI* signifies the dependent variable, specifically the count of green patents. The term *DID* represents the primary independent variable, denoting the DID variable. *DID= Pilot×Policy*, *Pilot* is a dummy that equals 1 if the company is located in the EPLI pilots and 0 otherwise, *Policy* is a dummy that equals 1 if the year is after 2007 and 0 otherwise. The symbol *X* encompasses a collection of control variables, as elaborated in section 3.2.3. The individual fixed effect is captured by δ_i, while λ_t stands for the time-fixed effect. The constant term is represented by β_0, and ϵ accounts for the residual term. Lastly, the coefficient of the DID variable is denoted as β_1.

3.4 Descriptive statistics

Table 2 presents the descriptive statistics for the principal variables. The findings reveal that, on one hand, the median and mean values of the count of green patents (*GI*) are 0.16 and 0, respectively. This suggests that a majority of the sampled firms lack instances of green innovations, with the distribution of green patent counts displaying a right-skewed trend. On the other hand, the average value of the binary group variable (*Pilot*) stands at 0.27, signifying that 27% of the sample represents enterprises in the pilot area, constituting the experimental group. Furthermore, the mean value of the *DID* variable rests at 0.16, indicating that 16% of the sample is influenced by the EPLI policy pilot.

4 Empirical results and discussion

4.1 Parallel trend test

Figure 1 illustrates the temporal trajectory of the average count of green patents for enterprises spanning from 2004 to 2011. The depicted results indicate that during the period preceding the pilot phase, the count of green patents held by zone-based enterprises was essentially comparable to those outside the designated zone. However, following the implementation of the pilot policy, a noticeable contrast emerged. The count of green patents and the growth rate of enterprises situated within the pilot zone surpassed those observed for enterprises in non-pilot zones. These outcomes provide initial corroboration for H1.

TABLE 1 Variable symbols and definitions.

Classification	Variables	Definitions
Explanatory variable	*GI*	The natural logarithm of the number of green patent applications plus 1.
DID variable	*Pilot*	A dummy that equals 1 if the company is located in the EPLI pilots and 0 otherwise.
	Policy	A dummy that equals 1 if the year is after 2007 and 0 otherwise.
	DID	*Pilot×Policy*
Mechanism variables	*GTFP*	Green total factor productivity involves a fusion of an over-efficient SBM model
	LI	Underinvestment through an inefficient investment model
Moderation variables	*DPI*	Regional environmental pollution index, which is obtained by annual normalization of regional industrial wastewater, exhaust gas, and solid waste.
	HPI	A dummy that equals 1 if the if the firm is in pollution-intensive industries and 0 otherwise.
	HERS	A dummy that equals 1 if t the enterprise environmental management system disclosure projects are higher than the average value of the annual industry takes the value of 1 and 0 otherwise.
	DGF	The regional government's green development concern that is obtained by normalizing the green development word frequency of the regional government's working report.
Control variables	*Age*	The natural logarithm of the difference between observation year and establishment year.
	Size	The natural logarithm of total assets.
	Leverage	The ratio of total liabilities to total assets.
	ROA	The ratio of total profits to total assets.
	FCF	The ratio of net cash generated from financing activities to total assets.
	Q	The ratio of total market value to total assets.
	Dual	A dummy that equals 1 if the firm's chairman is the same as its CEO and 0 otherwise.
	Opinion	A dummy that equals 1 the audit opinion is "standard unqualified" and 0 otherwise.

TABLE 2 Descriptive statistics of the main variables.

Variables	N	Max	Median	Min	Mean	S.D.
GI	10172	2.56	0.00	0.00	0.16	0.48
Pilot	10172	1.00	0.00	0.00	0.27	0.45
Policy	10172	1.00	1.00	0.00	0.57	0.50
DID	10172	1.00	0.00	0.00	0.16	0.36
Age	10172	3.30	2.48	1.39	2.46	0.38
Size	10172	6.91	3.05	0.69	3.19	1.18
Leverage	10172	1.41	0.51	0.06	0.51	0.22
ROA	10172	0.23	0.04	−0.28	0.04	0.07
FCF	10172	0.00	0.00	−0.00	−0.00	0.00
Q	10172	7.46	1.41	0.93	1.80	1.10
Dual	10172	1.00	0.00	0.00	0.14	0.35
Opinion	10172	1.00	1.00	0.00	0.94	0.24

4.2 Baseline regression

Table 3 presents the outcomes of the baseline regressions. The initial two columns display regressions conducted without fixed effects, using Ordinary Least Squares (OLS). The subsequent two columns showcase regressions incorporating individual and year-fixed effects (FE). The odd-numbered columns pertain to regressions devoid of control variables, while the even-numbered columns correspond to regressions incorporating control variables. From the regression outcomes, the coefficient estimations for the DID variable (*DID*) amount to 0.097, 0.084, 0.026, and 0.037 in columns (1) through (4). These coefficients exhibit significance at the 5% level for the first three columns and the 1% level for the final column. This underscores that the EPLI pilot exercises a positive influence on the count of green patents held by enterprises. The above regression results collectively endorse the notion that the EPLI pilot policy fosters green innovation among enterprises within the pilot area. Therefore, hypothesis 1 remains substantiated. Following the benchmark regression, a correlation test was executed. The test results affirm that the FE model surpasses the OLS model in performance. Consequently, we consider column (4) as the benchmark for subsequent analysis.

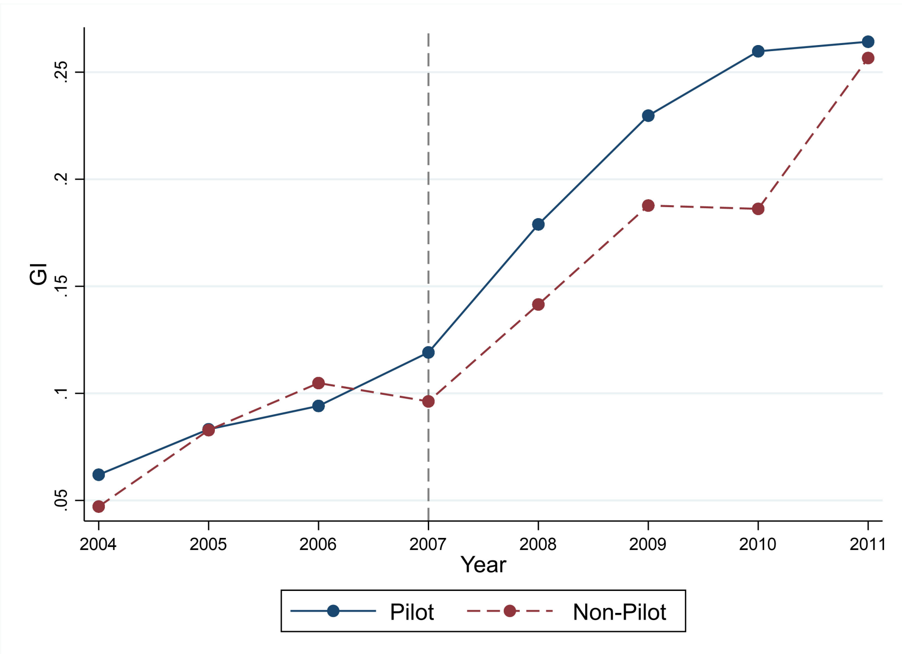

FIGURE 1
Parallel trend test plot. Solid lines represent firms in pilot zones and dashed lines represent firms in non-pilot zones.

TABLE 3 Impact of EPLI pilot on green innovation in firms.

Variables	(1)	(2)	(3)	(4)
	OLS		FE	
	GI	*GI*	*GI*	*GI*
DID	0.097**	0.084**	0.026**	0.037***
	(2.77)	(2.87)	(2.28)	(3.03)
Age		−0.037		0.259***
		(−1.60)		(6.11)
Size		0.095**		0.054*
		(2.48)		(1.99)
Leverage		−0.112**		−0.022
		(−2.68)		(−1.00)
ROA		−0.087		−0.218***
		(−0.59)		(−4.94)
FCF		−18.148		−11.823
		(−1.04)		(−0.66)
Q		0.023***		0.003
		(4.28)		(0.38)
Dual		0.121***		0.016
		(5.66)		(1.57)
Opinion		−0.013		−0.001
		(−0.47)		(−0.09)
Constant	0.140***	−0.055	0.146***	−0.654***
	(3.71)	(−0.45)	(82.27)	(−4.78)
Firm	NO	NO	YES	YES
Year	NO	NO	YES	YES
Observations	10,172	10,172	9,846	9,846
Within R^2	0.00546	0.0578	0.000378	0.00922

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Analyzing the regression results of the control variables reveals the following insights. First, the coefficient estimate for *Age* stands at 0.259 and is significantly positive at the 1% level. This observation suggests that the longer an enterprise has been established, the more pronounced its green innovation performance tends to be. Second, the coefficient estimates for firm size (*Size*) register 0.054 and hold statistical significance at the 10% level. This finding indicates that firm size serves as an indicator of financial robustness, implying that enterprises with greater financial strength tend to exhibit elevated levels of green innovation output. Third, the computed coefficient for Return on Assets (*ROA*) rests at −0.218 and is significantly negative at the 1% level. This highlights that a higher level of profitability is not conducive to green innovation. This phenomenon could arise because heightened profitability often reflects short-term gains for the enterprise. This might, in turn, prompt management to prioritize immediate gains over long-term considerations, thereby hindering the drive toward green innovation.

4.3 Robustness check

Firstly, a non-parametric replacement method is employed for conducting a placebo test. The outcomes of this test are visually depicted in Figure 2. The 95% and 99% quantiles in the placebo test are 0.015 and 0.023 which are both less than 0.037 (in the baseline regression result). Secondly, following the methodology established by Lian et al. (2022), we replace the count of green patents with the counts of green invention patents (*GCI*) and green utility patents (*GUI*). The regression results are showcased in columns (1) and (2) of Table 4. These outcomes indicate that the EPLI pilot possesses a more pronounced positive influence on green invention patents compared to green utility model patents. In essence, the EPLI pilot demonstrates its capacity to significantly foster substantial green transformation within enterprises. Thirdly, leveraging the regression techniques from Hu et al. (2021), Xiang et al. (2022), and Yu et al. (2021), we transform the baseline linear regression into a nonlinear model. This encompassed Poisson regression, negative binomial regression, Tobit regression, and the utilization of two-way fixed effects for both the year and industry. The results of this regression analysis are detailed in Table 4, specifically in columns (3) through (5). Fourthly, we execute a Propensity Matching Score (PSM) approach to create a balanced pairing of samples at a 1:1 ratio between the experimental and non-experimental areas. The paired regression outcomes are displayed in columns (6) and (7) of Table 4. Fifthly, we introduced industry fixed effects, province fixed effects, and provincial economic variables, building upon the benchmark regression, as per the methodologies outlined in Lyu et al. (2022) and Shi et al. (2023). We introduce regional variables including *GNP*, *DFR*, and *DFI*, where *GNP* stands for the growth rate of gross regional product, *DFR* denotes financial development (Growth rate of financial output), and *DFI* signifies fixed-asset investment (Ratio of fixed-asset investment to gross regional product). The results of these regression adjustments are elucidated in Table 5. The robustness tests outlined above consistently corroborate the empirical outcomes established by the benchmark regression, thereby reinforcing the validity of our findings.

5 Extensive research

5.1 Impact mechanism test

Drawing inspiration from Bostwick et al. (2018) and Stuart (2022), we pursued a bifurcated analysis. Firstly, we recalibrated the regressions based on the annual averages of urban green total factor productivity (*GTFP*) at the regional level. This entailed categorizing samples above the mean into the "high green development" group, and those below the mean into the "green development" group. The results of these regressions are presented in columns (1) and (2) of Table 6. From the regression outputs, the coefficient estimations for the DID variable (*DID*) stand at 0.049 and 0.038, both statistically significant at the 5% level. Notably, the coefficient value for the high green development group surpasses that of the low green development group. This indicates that the degree of regional high green development influences the dynamic between the EPLI pilot and local enterprises' green innovations. This insight suggests that the EPLI pilot, by stimulating regional green development, fosters corresponding local enterprises' green innovation. Consequently, hypothesis H2a gains support. Conversely, we classified the sample into underinvestment and non-underinvestment groups based on firm-level underinvestment (*LI*). Within the underinvestment group, the coefficient estimation for the DID variable (*DID*) is 0.003, lacking statistical significance. In contrast, within the non-underinvestment group, the coefficient estimation for the DID variable (*DID*) amounts to 0.005, bearing statistical significance at the 5% level. This implies that the EPLI pilot exclusively influences the green innovation of firms in the non-underinvestment group. This observation signifies that the EPLI pilot rectifies underinvestment among local firms, subsequently catalyzing green innovation. Consequently, hypothesis H2b remains unchallenged.

5.2 Moderation effects analysis

Table 7 presents the regression outcomes concerning the moderating effects. Analysis of these results yields the following conclusions: Firstly, the coefficient estimation for the cross-multiplier of the DID variable and the regional environmental pollution index

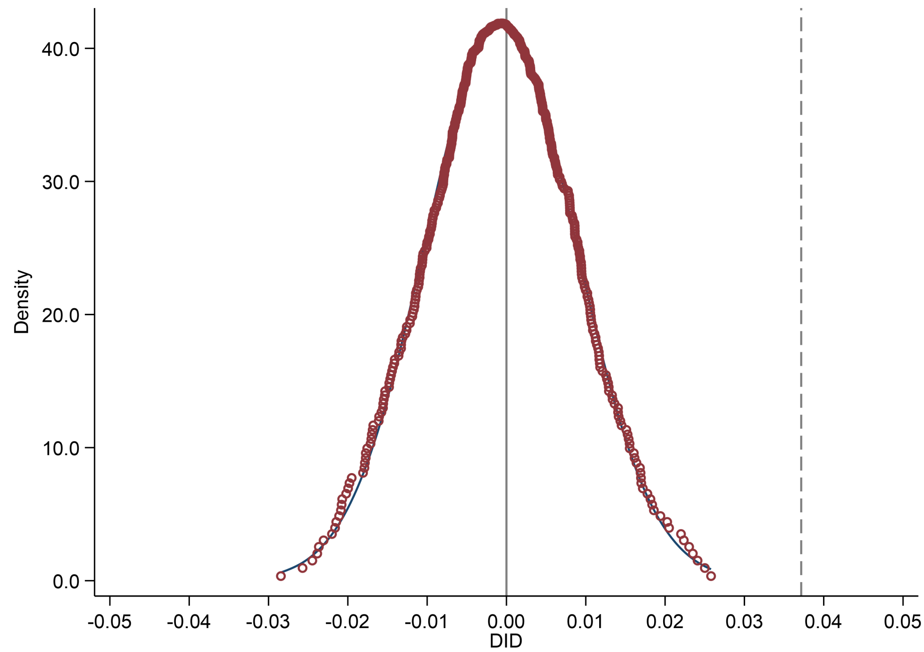

FIGURE 2
Placebo test.

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TABLE 4 Robustness test-1.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GCI	*GUI*	*GI*	*GI*	*GI*	*GI*	*GI*
DID	0.035***	0.029**	0.495***	0.360***	0.062***	0.087**	0.044***
	(3.15)	(2.60)	(8.03)	(7.17)	(3.00)	(2.52)	(3.79)
Constant	−0.512***	−0.531***	−3.505***	−5.470***	−0.200**	−0.079	−0.983***
	(56.32)	(−5.70)	(−6.44)	(−14.84)	(−2.06)	(−0.72)	(−3.74)
Controls	YES	YES	YES	YES	YES	YES	YES
Firm	YES	YES	NO	NO	NO	NO	YES
Year	YES	YES	YES	YES	YES	NO	YES
Industry	NO	NO	YES	YES	YES	NO	NO
Observations	9,846	9,846	10,172	10,172	10,172	4,335	3,878
Within/Pseudo R^2	0.000563	0.00814	0.0812	0.143	0.0838	0.0583	0.0123

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(*DID*×*DPI*) stands at 0.026, displaying statistical significance at the 5% level. However, its magnitude is smaller than that of the coefficient value for the DID variable (*DID*) in the baseline regression, with a correspondingly reduced significance level. This suggests that a higher degree of regional environmental pollution weakens the promoting impact of the EPLI pilot on green innovation. In other words, as regional environmental pollution worsens, the efficacy of the EPLI pilot in driving enterprises' green innovation diminishes. Secondly, the coefficient estimation for the cross-multiplication term of the DID variable with the binary variable denoting pollution-intensive industries (*DID*×*HPI*) is −0.006, lacking statistical significance. This signifies that industry-related pollution has eroded the positive influence of the EPLI pilot on enterprises' green innovation. Thirdly, the coefficient estimation for the cross-multiplier of the DID variable and the environmental management system (*DID*×*HERS*) is 0.091, signifying statistical significance at the 1% level. This value surpasses

TABLE 5 Robustness test-2.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GI	*GI*	*GI*	*GI*	*GI*	*GI*	*GI*
DID	0.062***	0.053**	0.037***	0.037***	0.057**	0.053**	0.037***
	(3.00)	(2.52)	(3.03)	(2.97)	(2.16)	(2.53)	(2.96)
GNP				−0.005**	0.004	−0.007**	−0.005**
				(−2.51)	(1.03)	(−2.53)	(−2.50)
DFR				−0.000	−0.000	−0.000	−0.000
				(−0.61)	(−0.36)	(−0.24)	(−0.61)
DFI				0.102	−0.195***	0.192**	0.102
				(1.24)	(−2.70)	(2.15)	(1.24)
Constant	−0.050	0.008	−0.654***	−0.145	−0.341	0.683**	−0.145
	(−0.57)	(0.10)	(−4.78)	(−1.05)	(−0.88)	(2.77)	(−1.05)
Controls	YES	YES	YES	YES	YES	YES	YES
Firm	NO	NO	YES	YES	NO	NO	YES
Year	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	YES	YES	YES
Province	NO	YES	YES	NO	NO	YES	YES
Observations	10,172	10,172	9,846	9,846	10,172	10,172	9,846
Within R^2	0.0521	0.0476	0.00922	0.00962	0.0548	0.0480	0.00962

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6 Impact Mechanism Tests.

Variables	(1)	(2)	(3)	(4)
	External green development mechanism		Internal investment efficiency mechanism	
	High green development	Low green development	Underinvestment	Non-underinvestment
	GI	*GI*	*GI*	*GI*
DID	0.049**	0.038**	0.003	0.050**
	(2.50)	(2.66)	(0.18)	(2.76)
	(−0.05)	(1.34)	(2.18)	(−0.93)
Constant	−0.720***	−0.492**	−0.581***	−0.549**
	(−4.18)	(−2.92)	(−5.18)	(−2.70)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	4,447	5,123	5,278	4,107
Within R^2	0.00877	0.00938	0.00525	0.0102

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables are consistent with model (2).

that of the DID variable in the baseline regression. This implies that a superior environmental management system aligns with more environmentally conscious enterprises, thereby enhancing the effectiveness of the EPLI pilot in promoting green innovation. Fourthly, the coefficient estimation for the cross-multiplier of the DID variable and the government's emphasis on green development (*DID×DGF*) is 0.045, holding statistical significance at the 1% level. Notably, this coefficient value surpasses that of the DID variable (*DID*) in the baseline regression. This underscores that the regional government's environmental priorities amplify the impact of the EPLI pilot in fostering enterprises' green innovation. The above regression results validate hypothesis H3.

TABLE 7 Moderating effects.

Variables	(1)	(2)	(3)	(4)
	GI	*GI*	*GI*	*GI*
DID×DPI	0.026**			
	(2.66)			
DID×HPI		−0.006		
		(−0.34)		
DID×HERS			0.091***	
			(3.89)	
DID×DGF				0.045**
				(2.36)
Constant	−0.638***	−0.610***	−0.617***	−0.642***
	(−4.88)	(−4.89)	(−4.77)	(−4.74)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	9,137	9,137	9,137	9,137
Within R^2	0.00903	0.00850	0.00987	0.00890

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables are consistent with model (2).

5.3 Corporate governance effects of the EPLI pilot policy

In this section, we delve into the corporate governance implications of the EPLI pilot policy. Firstly, government environmental subsidies wield significant influence over firms' environmental behaviors and, in turn, contribute positively to firms' green innovations (Xia et al., 2022). In light of this, we recalibrate the DID regressions by incorporating the environmental subsidy variable (*EPS*). *EPS* equals the ratio of environmental subsidy to total assets. The outcomes of these regressions are displayed in column (1) of Table 8. Upon analyzing the regression results, we find that the coefficient estimations for the DID variable (*DID*) lack statistical significance, indicating that the EPLI pilot has no discernible impact on corporate environmental subsidies. Secondly, green finance policies exert influence over firms' cost of capital, consequently affecting both their financial risk (Tian and Pan, 2022) and green innovation. In consideration of this, we introduce the z-value (*Z*)[2]. The regression outcomes for this scenario are showcased in column (2) of the same table. The results reveal that the coefficient estimations for the DID variable (*DID*) are not statistically significant, indicating that the EPLI pilot does not engender a noticeable impact on corporate financial risk. Thirdly, external financing serves as a pivotal conduit for green innovation. Particularly noteworthy is the influence of the green credit policy, which has accentuated financing constraints for firms with subpar environmental performance, especially in terms of bank loans, thereby restricting external financing avenues (Xiang et al., 2022). To elucidate this, we introduce short-term loans (*Sloan*) and long-term loans (*LLoan*). Columns (3) and (4) showcase the pertinent regression results. Analyzing these outcomes, we ascertain that the coefficient estimation for the DID variable (*DID*) lacks statistical significance in Column (3), yet holds a significant positive value at the 1% level in Column (4). This indicates that the EPLI pilot does not significantly affect firms' access to short-term loans, but it does facilitate their attainment of long-term bank loans. Fourthly, existing research underscores that firms with robust disclosure quality tend to encounter less pronounced financing constraints about their green innovations, compared to firms with inadequate disclosure practices. This dynamic is further accentuated by environmental information disclosure, which bolsters the domain of green finance (Yu et al., 2021). To reflect this, we substitute the count of green patents with the disclosure rating (*IA*). *IA* denotes the evaluation rank of information disclosure of listed companies, which is divided into excellent, good, qualified, and unqualified four grades, *IA* equals respectively 3, 2, 1, and 0. Column (5) in Table 8 illustrates the regression results about the information governance impact of the EPLI pilot. Analyzing these findings, we observe that the coefficient estimation for the DID variable (*DID*) is significantly positive at the 10% level. This signifies that the EPLI pilot policy contributes to diminishing corporate information asymmetry.

2 $Z=1.2X_1+1.4X_2+3.3X_3+0.6X_4+0.999X_5$. X_1 represents the ratio of operating capital to total assets, X_2 stands for the ratio of retained earnings to total assets, X_3 refers to the ratio of EBITDA to total assets, X_4 indicates the ratio of total market capitalization to total liabilities; and X_5 denotes the ratio of operating income to total assets.

To sum up, the EPLI pilot policy yields non-significant effects on government environmental protection subsidies, financial risk, and short-term bank loans. However, it exerts a positive influence on long-term bank loans and disclosure ratings, indicating the presence of a long-term financing effect and an information governance effect stemming from the EPLI pilot.

6 Discussion and conclusion

6.1 Discussion

In this paper, we undertake a comprehensive exploration of the micro-green effects of the EPLI pilot system. Nonetheless, our study does acknowledge two inherent limitations: On one hand, our approach involves constructing a DID model utilizing the EPLI pilot policy to examine its policy effects. However, this methodology may not fully capture the entirety of the green financial effects attributed to EPLI. Based on the previous study, future research could combine the EPLI system with digital green project investment in enterprises and apply it specifically to the new energy-driven construction industry (Dong et al., 2023a).

On the other hand, our study employs green innovation as a sole proxy to gauge enterprises' green transformation. This approach hinges upon identifying substantial green transformation based on the categorization of green patents, which could be considered somewhat one-sided. Considering these limitations, future research endeavors could be directed toward addressing these gaps. Firstly, the focus could shift towards encompassing all insured enterprises, employing premium data to measure the diverse effects of EPLI. Simultaneously, a comprehensive assessment of green transformation could be undertaken from multiple angles, including aspects such as green investment, social responsibility, ESG scores, and environmental information disclosure. This holistic approach could ascertain whether enterprises demonstrate genuine green transformation, while also investigating potential instances of greenwashing behavior from the vantage point of environmental performance. Also, future researchers can analyze the important role of digital technology in industrial structure upgrading in future research by following (Dong et al., 2023b).

6.2 Conclusion

Addressing the unresolved aspects within existing research concerning EPLI and its implications for enterprises' green transformation, this study employs the 2008 EPLI pilot as an exogenous event. By treating enterprises within the pilot area as the experimental group and those outside it as the control group, a quasi-natural experiment is constructed. Green innovation is utilized as a proxy variable for gauging green transformation. Employing the Difference-in-Differences (DID) model, this study scrutinizes the influence of the EPLI on enterprises' green transformation. The outcomes of this study reveal several noteworthy conclusions. Firstly, the EPLI pilot policy demonstrates a fostering effect on enterprises' green innovation. This observation retains its significance even after undergoing a battery of robustness tests. The policy showcases the

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TABLE 8 Corporate governance effects of EPLI pilot policies.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	EPS	*Z*	*SLoan*	*LLoan*	*IT*
DID	0.010	−1.899	0.084	0.016***	0.029*
	(0.67)	(−1.09)	(1.24)	(3.26)	(2.09)
Constant	−0.101	51.112**	−1.572*	−0.082	0.580***
	(−1.53)	(2.31)	(−1.95)	(−1.33)	(3.89)
Controls	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Observations	9,846	9,842	9,846	9,846	9,846
Within R^2	0.00355	0.569	0.572	0.101	0.0181

The values in parentheses are t values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Control variables are consistent with model (2).

potential to drive substantial green transformation among enterprises. Secondly, the EPLI pilot policy positively impacts green innovation by stimulating regional green development and ameliorating firms' underinvestment. Thirdly, regional pollution and industrial pollution act to temper the promotion effect of the EPLI pilot policy on firms' green innovation. Notably, the degree of firms' environmental protection commitment and the environmental concern of local governments wield considerable influence. A higher level of these factors strengthens the positive impact of the EPLI pilot policy on firms' green innovation. Fourthly, the EPLI pilot policy does not significantly influence environmental subsidies, financial risks, or short-term bank loans. Nevertheless, it aids enterprises within the pilot area in securing long-term bank loans and mitigating information asymmetry. Consequently, the EPLI pilot policy manifests both long-term financing implications and information governance effects.

6.3 Managerial implication

For corporate governance, proactive participation in the green insurance market, coupled with deliberate green transformation, is advocated. Particularly relevant for enterprises with significant environmental impact, such as heavy polluters, is the proactive procurement of EPLI to mitigate environmental risks. Simultaneously, these enterprises should undertake deliberate efforts to harness green innovations in their operations, thereby executing effective environmental governance. This not only elevates their environmental performance but also enables their engagement in green activities conducive to green transformation. Such a proactive approach facilitates the optimization of investment efficiency and the attainment of green returns, ultimately guiding enterprises towards a trajectory of sustainable development.

6.4 Practical/social implications

Based on the study's findings, this paper presents two distinct policy implications aimed at enhancing EPLI and propelling enterprises' green transformation for practical/social: on the one hand, there is a call to enhance the enterprise environmental monitoring mechanism to fully leverage the green governance potential of EPLI. Policymakers should establish and refine a comprehensive enterprise environmental monitoring mechanism. This mechanism should incorporate variable rates tailored to individual enterprises' environmental performances. Furthermore, the establishment of an environmental information-sharing platform is recommended. By scientifically determining EPLI rates for diverse enterprises and industries, policymakers can guide these enterprises to actively participate in the green insurance market. This process will result in an optimized allocation of market resources, thereby fostering favorable conditions for the realization of EPLI's green governance potential. On the other hand, a robust emphasis on environmental concern and governance is crucial in facilitating regional green development. Local governments should recalibrate their approach, shifting away from exclusive economic development pursuits. Instead, a stronger emphasis on local green development is advised. This shift involves intensified efforts in regional pollution control, including heightened administrative penalties for polluting practices and increased environmental subsidies for eco-friendly initiatives. These measures serve to steer enterprises towards engaging in green practices that ultimately propel green transformation.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

LH: Writing – original draft, Conceptualization, Formal analysis, Funding acquisition, Project administration. ZL: Data curation, Software, Writing – original draft, Conceptualization, Formal analysis, Methodology, Visualization, Writing – review & editing. PL: Methodology, Supervision, Writing – review & editing, Project administration, Validation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2023.1294160/full#supplementary-material

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A study of the promotion mechanism of digital inclusive finance for the common prosperity of Chinese rural households

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Common prosperity is a social policy goal pursued by the Chinese government and an ideal social status for humanity. On the basis of three theoretical hypotheses, this study involved the analysis of county-level digital inclusive finance data and rural survey data. The Hierarchical Linear Model was employed to empirically analyze the impact and mechanism of digital inclusive finance on the common prosperity of rural households. The results indicate that the county-level digital inclusive finance index, as well as its depth and coverage, can significantly and directly promote common prosperity. Furthermore, it was found that household livelihood strategies are one of the regulatory mechanisms, and digital inclusive finance significantly promotes common prosperity through factors such as opportunities for migrant work, property income, business livelihood models, and agricultural livelihood models. In addition, financing methods are also important adjustment mechanisms, and digital inclusive finance significantly promotes the common prosperity through digital tools and loan availability variables. Our research provides favorable evidence for the cross-level interaction effect of county-level digital inclusive finance on the common prosperity of rural households.

KEYWORDS

Chinese rural households, common prosperity, digital inclusive finance, moderation effect, hierarchical linear model

1 Introduction

Common prosperity is a desirable societal status aspired by humanity. Developed countries do not explicitly use the term "common prosperity," but similar keywords like income inequality (Atkinson, 2016; Alacevich and Anna, 2017), quality of life and wellbeing assessment (OECD, 2012), and subjective wellbeing (Diener et al., 1993) are often included in the discussion of social policy objectives. The 19th National Congress of the Communist Party of China (CPC), held in October 2017, clearly put forward the strategic goal that: "Common prosperity for everyone is basically achieved" by the middle of this Century. Similarly, the Fifth Plenary Session of the 19th Central Committee of the Communist Party of China (CPC) raised the important topic of "Making solid advances toward common prosperity". The 20th National Congress of the Communist Party of China further proposed that: "Chinese-style modernization is a modernization for the common prosperity of all people." In the same vein, the 20th National Congress of the Communist Party of China proposed that "Chinese modernization is the modernization of common prosperity for all people". Common prosperity is an important feature of Chinese-style modernization, emphasizing the prosperity of all people, both in terms of material and spiritual wellbeing. Common prosperity is an essential requirement of Chinese socialism, characterized by all people collectively striving for an increasingly developed and globally leading level of productivity, resulting in the shared experience of a progressively happy and improved life (Liu PL. et al., 2021). Common prosperity encompasses two dimensions: affluence and equitable sharing (Li, 2021). It also includes equal access to opportunities for all members of society (Kakwani et al., 2022). The critical aspect of common prosperity lies in effectively managing the synergistic relationship between equity and efficiency (Xia et al., 2022). On a macro scale, it signifies a state where people enjoy a prosperous life with abundant material resources, spiritual confidence, social harmony, a pleasant environment, and wellbeing (Liu and Wang, 2022). At the household level, meeting people's reasonable needs is a prerequisite for achieving common prosperity for all. In terms of content, common prosperity encompasses income, wealth, health, recreational opportunities, and cultural activities (Liu C. et al., 2022), including addressing subjective well-being disparities (Liu and Zhang, 2023).

However, China still faces significant income disparities and inadequate social security. Yet, implementing reforms that balance efficiency and equity is key to promoting common prosperity (Hong, 2022). Digital financial inclusion refers to a new type of financial model that relies on Internet technologies such as big data and cloud computing and combines financial tools and platforms to provide low-income people with financial services, including credit, payment, deposits, and insurance (Tan et al., 2023). As an inclusive financial system that addresses the financial vulnerabilities of individuals, digital financial inclusion aligns with the ideals and objectives of promoting common prosperity among the people. The Plan for Promoting the Development of Inclusive Finance (2016–2020) issued by China's State Council in 2015 emphasizes that inclusive finance should be based on the principles of "equal opportunity and benefiting people's livelihoods". In 2005, the United Nations introduced the concept of "digital financial inclusion". By integrating technologies such as big data, artificial intelligence, and blockchain, digital financial inclusion allows farmers and low-income groups to access financial services and the resulting economic growth benefits. This provides technological support for achieving common prosperity for the people. The G20 High-Level Principles on Digital Financial Inclusion emphasize that the primary aim of digital financial inclusion is to provide formal financial services to underserved consumer groups like farmers, women, and the poor. These are the "long tail" individuals who have been excluded from the traditional finance system (Beck et al., 2018). The core objectives of digital financial inclusion are "universal" and "inclusive", echoing "common" and "affluent", respectively. On the one hand, "universal" implies a wider audience. Through fragmented scenarios for user credit profiling, digital financial inclusion expands the scope and coverage of financial services (Liu Y. et al., 2021). This, in turn, can provide efficient, convenient, and affordable financial support for disadvantaged groups (Wu et al., 2021). On the other hand, "inclusive" implies benefiting all the people. Digital financial inclusion utilizes digital technology to alleviate information asymmetry, promote national economic growth (Daud and Ahmad, 2023), and allow low-income people to share the dividends of growth through the "trickle-down effect" (Zhang XJ., 2021), thus realizing financial "equal opportunity and benefit people's livelihood" (Zhang JL. et al., 2022).

The existing literature on the impact of digital financial inclusion on rural households' common prosperity is relatively limited. At the macro level, current research predominantly focuses on how digital financial inclusion promotes balanced regional economic growth (Zhang et al., 2019), alleviates regional poverty (Xiong and Huang, 2022; Liu and Liu, 2020), reduces income inequality (Zhou and Chen, 2022), and stimulates rural industrial development (Chen and Wen, 2023), among other issues. At the micro level, existing literature primarily emphasizes digital financial inclusion at the provincial level to promote household income growth (Zhang L., 2021; Zhang and Lu, 2023), increase household employment opportunities (Manyika et al., 2016), and enhance social insurance and educational equity (Pierrakis and Collins, 2013), among other benefits. A few studies have started to examine how digital financial inclusion promotes common prosperity among residents, focusing on aspects such as stimulating entrepreneurship (Zhang JL. et al., 2022), mitigating unequal opportunities (Tian et al., 2022), and encouraging non-farm employment (Chen and Jiang, 2023).

Rural residents are a primary target of digital financial inclusion services, and they are a key group of focus in China's endeavor to construct a society of shared prosperity. This study explores the mechanisms through which digital financial inclusion facilitates rural households' common prosperity. It places particular emphasis on examining how household livelihood strategies and financing instruments moderate the impact of digital financial inclusion. The potential marginal contributions of this study include: (Atkinson, 2016) Distinguishing from existing research that utilizes provincial-level digital financial data, this study matches county-level digital financial inclusion data with farm household data, creating a hierarchical dataset with nested relationships (Alacevich and Anna, 2017). Due to the hierarchical nature of the data, traditional regression methods commonly used in existing studies overlook the nested relationships within the data, potentially leading to bias in parameter estimation. Consequently, this study employs a multilevel model, which is better suited for analyzing data with nested structures by allowing error components at different levels. (OECD, 2012). In the examination of the mechanism of action, this study associates intermediate variables like rural households' livelihood strategies and financing methods with county-level digital financial inclusion. It explores the interactive moderating effect across hierarchical levels to gain a deeper understanding of how digital financial inclusion influences households' common prosperity.

The remainder of the article is organized as follows: Section 2 covers the theoretical analysis and research hypotheses and Section 3 presents the data and methods used. The findings from the study are presented in Section 4, and last but not least, Section 5 presents the conclusions.

2 Theoretical analysis and research hypotheses

2.1 The direct impact of digital inclusive finance on common prosperity

The development of digital inclusive finance is conducive for narrowing regional and urban-rural disparities, promoting inclusive growth in China, and promoting common prosperity (Jing and Deng, 2022; Chen and Jiang, 2023). Provincial digital inclusive finance has significantly increased the *per capita* disposable income of urban and rural residents, and played a mediating role in economic growth and entrepreneurial behavior (Yang WM. et al., 2020). It has also stimulated entrepreneurial vitality and promoted technological innovation to promote regional common prosperity (Yang and Zhang, 2023). In addition, digital inclusive finance at the prefecture level mainly promotes economic growth in various regions by improving the efficiency of regional capital allocation and the level of regional entrepreneurship (Yu et al., 2022). From a multidimensional perspective, the coverage and depth of use of provincial-level digital inclusive finance has effectively promoted regional common prosperity (Liu XY. et al., 2022), while the coverage and depth of use at the prefecture level have a positive effect on common prosperity (Xu and Wu, 2022). Urban level digital inclusive finance can alleviate the uneven opportunities and income disparities faced by residents, thereby promoting overall and shared prosperity of households to a certain extent (Tian et al., 2022). In addition, improving digital infrastructure, popularizing digital tools, and improving individual financial literacy can alleviate the "Matthew effect", thereby improving the quality and efficiency of digital inclusive financial services and promoting common prosperity for families (Zhang JL. et al., 2022). The development of digital inclusive finance can significantly promote the common prosperity of low endowment residents, reflecting the "inclusive" aspect of digital inclusive finance (Chen and Jiang, 2023).

As mentioned in the review, existing research has extensively focused on the relationship between digital inclusive finance and common prosperity, in particular, on the impact of provincial-level digital inclusive finance development on regional common prosperity. However, existing studies lack in-depth examination of how the development of county-level digital inclusive finance affects the common prosperity of rural households. In addition, existing research often matches provincial or municipal financial data with household data, and then uses panel regression methods for empirical analysis. However, such processing methods often overlook the nested relationship between provincial-level data and farmer data, leading to biased regression results. As a result, this article reports findings from a study that sought to understand the construction of a multilevel linear model suitable for processing nested data. Therefore, we propose the following Hypothesis 1.

Hypothesis 1: The county-level digital inclusive finance has a positive impact on the common prosperity of rural households.

2.2 The role of livelihood strategies in the relationship between digital inclusive finance and common prosperity

Existing literature indicates that digital inclusive finance has a positive impact on livelihood activities such as promoting rural households' employment, entrepreneurship, and alleviating financing constraints. In terms of increasing employment opportunities and entrepreneurial capabilities for rural households, Manyika et al. (2016) consider that the widespread application of digital finance in 2025 will create 95 million job opportunities for emerging economies. Fang and Xu (2020) used Chinese household tracking survey data to establish that the development of provincial-level digital inclusive finance has significantly promoted the employment of traditional vulnerable groups, and the impact is inclusive. Du et al. (2020) pointed out that provincial-level digital inclusive finance has significantly promoted the optimization of China's industrial structure, thereby promoting the development of non-agricultural industries in rural areas and promoting farmers to choose non-agricultural employment. Zhang et al. (2021) found that the development of provincial-level digital inclusive finance can increase farmers' ability to access opportunities in the financial ecosystem and improve opportunities for non-agricultural employment. Zhang and Li (2022) found that both the provincial digital inclusive finance total index and sub index increase the probability of part-time rural labor force and pure migrant workers. In addition, Wang et al. (2023) believed that cultivating human capital and enhancing residents' ability to increase income can promote common prosperity.

On the one hand, digital inclusive finance can provide inclusive financial services, which is conducive to increasing social employment opportunities, especially providing more non-agricultural employment opportunities for farmers (Xie et al., 2018). The breadth and depth of digital inclusive finance as an accelerator for financial inclusiveness are beneficial for farmers to obtain employment opportunities (Zhang et al., 2021). With the increase of employment opportunities, the promoting effect of county-level digital inclusive finance on the common prosperity of farmers has been strengthened. This means that the opportunity for families to work outside has a positive moderating effect on the relationship between county-level digital inclusive finance and the common prosperity of farmers.

On the other hand, digital inclusive finance can promote household participation in financial markets, thereby increasing household property income (Zhang and Lu, 2023). With the increase of household property income, the promotion effect of county-level digital inclusive finance on the common prosperity of farmers has been strengthened. In addition, farmers with different livelihood models have varying demands and applications for digital inclusive finance. For households with business and agricultural livelihoods, digital inclusive finance can help them access financing opportunities for business or agricultural production. For working-class households, digital inclusive finance can help increase their access to loan opportunities for living expenses. In other words, family property income and livelihood models have a positive moderating effect on the relationship between county-level digital inclusive finance and common prosperity of farmers. Therefore, we propose the following Hypothesis 2.

Hypothesis 2: Livelihood strategies such as opportunities for rural households to work outside, property income, and business livelihood models play a positive regulatory role in promoting common prosperity through digital inclusive finance.

2.3 The role of financing methods in the relationship between digital inclusive finance and common prosperity of farmers

Existing research has shown that digital inclusive finance can play a positive role in alleviating the constraints of formal and informal credit for farmers, and improving their financial literacy. Wang and Wang (2022) broke through the limitations of spatial regions in provincial-level digital inclusive finance, enhanced the financial willingness of long tail customers, and met the financial needs of different groups. Based on the China Household Finance Survey (CHFS) data, Yang B. et al. (2020) found that the development of provincial-level digital inclusive finance significantly improves the availability of formal credit for rural households and alleviates financial exclusion in rural areas. Fan (2021) pointed out that provincial-level digital inclusive finance has improved farmers' access to formal credit by reducing transaction costs, alleviating information asymmetry, and reducing collateral requirements, especially for low-income households. On the other hand, Zhang YH. et al. (2022) argue that digital inclusive finance alleviates information asymmetry by reducing the cost of human relationships and increasing online shopping behavior, thereby reducing the informal lending needs of farmers. Si (2022) found that county-level digital inclusive finance can help bridge the information and knowledge divide caused by factors such as geography and education level, and improve the financial literacy of farmers.

Digital inclusive finance helps improve the farmers' access to loans (Fan, 2021). With the increase in loan availability, the promoting effect of county-level digital inclusive finance on the common prosperity of farmers is strengthened. As an important digital tool, smartphones can effectively increase the accessibility of online financial services and alleviate "digital exclusion" (Hu et al., 2021). For farmers who own smartphones, the promotion effect of county-level digital inclusive finance on the common prosperity of farmers will be strengthened. In other words, the availability of debt, the digital tools owned by households have a positive moderating effect on the relationship between county-level digital inclusive finance and common prosperity of farmers. Therefore, we propose the following Hypothesis 3.

Hypothesis 3: The availability of digital tools and debt financing methods plays a positive regulatory role in promoting common prosperity through digital inclusive finance.

The above analysis framework is shown in Figure 1.

3 Data and methods

3.1 Data sources

In this study, we investigated the mechanisms through which digital financial inclusion affects common prosperity using data from two different sources. First, we utilized household-level data obtained from a rural survey conducted by our research team in July—August 2020. The survey covered six provinces in China namely: Zhejiang, Jiangxi, Hubei, Hebei, Yunnan, and Guizhou, and employed a stratified sampling technique (Huo and Zhang, 2023). We conducted surveys in the following regions:

(1) Zhejiang Province: Suichang County, Jingning County, Xianju County, Pan'an County, Haishu District, Kecheng District, Jiangshan City, and Yuyao City.
(2) Guizhou Province: Fuquan City, Kaili City, Xiowen County, Taijiang County, and Honghuagang District.
(3) Yunnan Province: Jinghong City, Anning City, Dayaocheng County, and Yiliang County.
(4) Hubei Province: Tianmen City, Yicheng City, Guangshui City, Gongan County, and Badong County.
(5) Jiangxi Province: Wannian County, Xinfeng County, Poyang County, Ruijin City, and Wuning County.
(6) Hebei Province: Sanhe City, Taocheng City, Susong County, Xuanhua District, and Xindu District.

In each county and district, we surveyed approximately 25 households. Finally, we obtained a total dataset of 892 rural households. Specifically, Hubei Province, Jiangxi Province, and Hebei Province, located in the central region of China with average economic development level, include 107, 117, and 130 samples. Yunnan and Guizhou, located in the southwestern region of China with relatively backward economic development involve 133 and 152 samples, respectively. Zhejiang Province, located in the coastal areas of China and with relatively developed economy, involves 253 samples.

In addition, we utilized data from the Peking University Digital Financial Inclusion Index, based on user transaction data from Alipay and known for its high reliability and precision (Guo et al., 2020). This index encompasses data at three levels: provincial, municipal, and county. While previous research mainly relied on provincial and municipal data (Zhang JL. et al., 2022; Tian et al., 2022), this study incorporates county-level data more closely related to rural households ' productive lives. To address endogeneity, we used lagged data from 2019 for the level of digital financial inclusion development and measures of depth of use, coverage breadth, and digitization.

3.2 Indicator selection

3.2.1 Explanatory variable

Explanatory variable: common prosperity. Most studies construct common prosperity indicators from a macro perspective, thus failing to fully capture individual-level variations. A few studies have focused on household or individual common prosperity. For example, Wang and Liu (2022) used the income gap as a measure of rural households ' common prosperity, while Liu XY. et al.

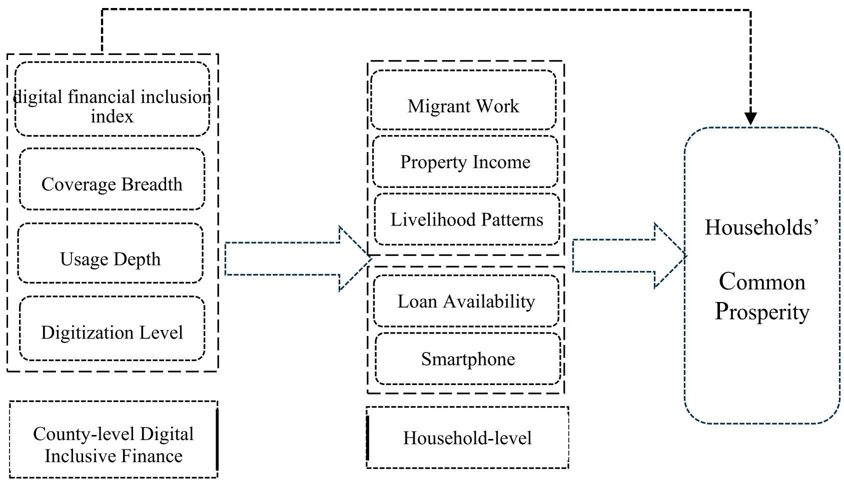

FIGURE 1
The analytical framework.

(2022) assessed it based on multiple dimensions, including income, wealth, education, health, recreation, and culture. Liu et al. assigned binary values (1 or 0) to these dimensions and used the equal-weight method to calculate rural households ' common prosperity. Zhang JL. et al. (2022) constructed a common prosperity index using the equal-weight method, considering material prosperity, spiritual wellbeing, and social sharing as key dimensions.

The concept of common prosperity essentially reflects the conditions for all individuals to lead a better life under socialist principles (Zhang and Wang, 2023). Chen (2022) argues that common prosperity is relative to people's needs, and meeting those needs is a scientifically and human-oriented measure of common prosperity. This study focuses on core aspects of a good life as perceived by rural households, elaborating a common prosperity index comprising eight dimensions: economic wellbeing, healthcare, pension level, education, material life, spiritual fulfillment, community environment, and social engagement. This index is informed by prior research, including works by Tan and Wu (2022) and Zhang and Wang (2023). In particular (refer to Table 1), the economic level indicator reflects the household's economic situation, including whether *per capita* household income exceeds 50% of the *per capita* income and whether the household income satisfaction score exceeds 3. Healthcare indicators reflect family members' health status and eligibility for critical illness insurance. Endowment-level indicators include whether the household has purchased endowment insurance and whether they can provide pensions for elderly family members, reflecting their ability to support the elderly.

Indicators of the level of education reflect children's access to appropriate primary and secondary education and their educational attainment satisfaction level. The material life indicator focuses on the household's possession of key durable goods, such as cars, air conditioning or heating, computers, and the Internet, among other goods, and their subjective evaluation of life satisfaction. Indicators of spiritual life reflect whether the household has opportunities for outbound travel and can enjoy cultural and recreational facilities in the village, as well as "culture to countryside" activities. Community environment indicators reflect socio-ecological conditions, including factors like exposure to water pollution, air pollution, noise pollution, and subjective evaluation of social security status. The social participation indicator reflects the family's engagement in social events such as weddings and funerals of relatives and friends, as well as their relationships with neighbors in terms of mutual assistance.

Given that the equal-weight method overlooks the variations among the indicators, this study draws inspiration from Zhang and Wang (2023) in measuring the rural households' common prosperity index, employing the item response theory method. Since all indicators are binary variables, the two-parameter Logistic model is applied to estimate the potential capacity value Theta, which reflects the rural households' common prosperity status. In the specific application, the Theta value is normalized and transformed into a continuous variable ranging from 0 to 1 (Li, 2020). The function of the two-parameter Logistic model (Luo, 2012) is as follows:

$$P\left(Y_{ij}=1|\theta_i\right)=\frac{\exp\left[\mathrm{a}_j\left(\theta_i-b_j\right)\right]}{1+\exp\left[\mathrm{a}_j\left(\theta_i-b_j\right)\right]} \quad (1)$$

In Eq. 1, the discrimination parameter a_j is the slope of the response function or item characteristic curve. The difficulty parameter b_j represents the ability parameter value of the item characteristic curve when the probability of satisfaction with a certain test item is 50%.

3.2.2 Core explanatory variables

Core explanatory variables: County-level digital financial inclusion index, digital financial inclusion coverage breadth, usage depth, and digitization index. To account for the scale differences between the variable data and to address heteroskedasticity, a logarithmic transformation is applied to the county-level financial inclusion index and its sub-indicators (Zhang and Lu, 2023). To address the issue of endogeneity, this study utilizes the 2019 county-level digital financial inclusion development data with a one-period lag.

TABLE 1 Indicators and Values for Measuring rural households' Common Prosperity.

Variable	Definition	M	SD
Economic wellbeing	If the *per capita* household income is higher than 50% of the *per capita* income of the entire sample = 1, otherwise = 0	0.511	0.500
	If the score of satisfaction with household income is at least 3 = 1, otherwise = 0	0.602	0.489
Healthcare	If the household has purchased critical illness insurance = 1, otherwise = 0	0.961	0.194
	If the health status of family members is rated above 3 = 1, otherwise = 0	0.872	0.334
Pension level	If the household has purchased endowment insurance = 1, otherwise = 0	0.907	0.291
	If the household can pay elders' pensions = 1, otherwise = 0	0.891	0.311
Education	If the child can go to the nearest primary or secondary school = 1, otherwise = 0	0.932	0.253
	If the score of satisfaction with the child's education is at least 3 = 1, otherwise = 0	0.472	0.499
Material life	If the household possesses consumer durables such as cars, air conditioning or heating, computers, internet, etc., = 1; otherwise = 0	0.608	0.488
	If the score of livelihood satisfaction is at least 3 = 1, otherwise = 0	0.489	0.500
Spiritual wellbeing	If the household can travel every year = 1, otherwise = 0	0.686	0.464
	If the village owns cultural and recreational facilities and participates in cultural activities in the countryside = 1, otherwise = 0	0.403	0.490
Community environment	If the score of the community policing is at least 3 = 1, otherwise= 0	0.946	0.226
	If there is no air, water, or noise pollution in the community = 1; otherwise = 0	0.550	0.497
Social engagement	If the household can pay for weddings and funerals of family and friends = 1, otherwise 0	0.963	0.189
	If rural households engage in neighborly assistance = 1, otherwise = 0	0.980	0.141

Moderating variables: rural households' livelihood strategies and financing instruments. The livelihood strategies proposed in this study include property income patterns, migrant work opportunities, and livelihood patterns. First, digital financial inclusion can promote household participation in financial markets, thereby increasing household property income (Zhang and Lu, 2023). In this study, the logarithmic value of property income is chosen as the moderating variable. Secondly, due to the provision of inclusive financial services, digital financial inclusion contributes to the establishment of new enterprises, the expansion of business operation scale, and the creation of more non-agricultural employment opportunities for rural households (Zhang and Li, 2022; Xie et al., 2018). In addition, the breadth and depth of digital financial inclusion, serving as powerful drivers of financial inclusion, can enhance rural youth's access to their financial ecosystems (Zhang et al., 2021). In this study, the proportion of migrant workers is selected as the moderating variable. Thirdly, different livelihood models have different needs and applications for digital financial inclusion, and livelihood models have become an important moderating variable. The livelihood models of rural households referred to in this study are divided into agricultural livelihood model, migrant livelihood model, and business livelihood model (Zhang and Huo, 2022).

On the other hand, the availability of loaning and financing instruments such as smartphone tools are also the moderating variables examined in this study. Studies have shown that household debt, especially non-housing debt, is an important mechanism for digital financial inclusion to improve the livelihood outcomes of rural households (Zhou et al., 2021). As an important digital tool, smartphones can effectively increase the accessibility of online financial services, alleviate "digital exclusion" (Hu et al., 2021), and even promote the investment of rural households in online wealth management products.

3.2.3 Control variables

Control Variables: The common prosperity of households is influenced by various factors, including family characteristics and the characteristics of the household head. In this study, five control variables were selected: the age of the household head, the health status of the household head, the education level of the

TABLE 2 Definition of variables and descriptive statistics.

Definition	Symbol	Meaning and assignment of variables	M	SD
Common prosperity County Level Variables	Y	Measured according to the indicator system in this study	0.649	0.212
Level of digital financial inclusion development	X1	Logarithm of China's digital financial inclusion index from Peking University's digital finance research	5.001	0.104
Coverage breadth	X2	Logarithm of digital financial inclusion coverage breadth	4.774	0.043
Usage depth	X3	Logarithm of digital financial inclusion usage depth	5.000	0.105
Digitization level Households' variables	X4	Logarithm of digital financial inclusion digitization level	4.586	0.062
Agricultural livelihood pattern	V1	If agricultural income comprises more than 50% of total income = 1, otherwise = 0	0.140	0.347
Business livelihood pattern	V2	If business income comprises more than 50% of total income = 1, otherwise = 0	0.113	0.317
Migrant Labor Livelihood Pattern	V3	If wage Income comprises more than 50% of total income = 1, otherwise = 0	0.593	0.492
Family Loans	V4	If the household has home loans, car loans, or education loans = 1, otherwise = 0	0.177	0.382
Family education loans	V5	If the household has loaned for education = 1, otherwise = 0	0.079	0.271
Smartphone	V6	If the household has a smartphone = 1, otherwise = 0	0.925	0.461
Property income	V7	Logarithm of property income	0.664	0.271
Proportion of migrant workers	V8	Proportion of family members engaged in migrant work as a percentage of the total family population	0.448	0.444
Education of the household head	V9	Years of education of the household head	7.499	3.227
Age of the household head	V10	Age of the household head	52.39	15.142
Health of the household head	V11	Self-assessment of the health status of the household head, scale of 1–5	3.795	0.931
Household size	V12	Household population size	3.945	0.512
Household social capital	V13	If the family's social connections include civil servants, employees of public institutions, doctors, etc. = 1, otherwise = 0	0.149	0.356

household head, the household size, and the household's social capital. Definitions and descriptive statistics for each variable can be found in Table 2.

3.3 Model construction

The digital financial inclusion explored in this study uses county-level data, while rural households' common prosperity, livelihood patterns, and household characteristic factors belong to household-level data, and there is a data nesting relationship between the two. For this type of hierarchical data, the hierarchical linear model (HLM) decomposes the changes in the explanatory variables into individual and intergroup changes, which can address the problem of solving the hierarchical effect (James, 1982). Based on the modeling framework proposed by Bryk and Raudenbush (Bryk and Raudenbush, 1992), this study is divided into three steps: First, a null model is constructed to carry out a diagnostic analysis of the cross-tier effects of digital financial inclusion on common prosperity. Second, a random intercept model is constructed to analyze the direct impact of county-level digital financial inclusion on common prosperity. Third, a random intercept model and a random slope model are constructed to analyze the moderating effects of digital financial inclusion at the county level on the variables related to the livelihood strategy category and the means of financing at the household's level affecting' common prosperity. The specific models are described below.

Null model (Eq. 2 and Eq. 3). No explanatory variables are added to the null model, and only a random intercept at the county level is included to test for the presence of a hierarchical structure in the data.

$$\text{Level1:} Y_{ij} = \beta_{0j} + \varepsilon_{ij} \tag{2}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{3}$$

where Y_{ij} is the common prosperity index of the i-th households' common prosperity in the j-th county. β_{0j} is the mean of Y of the j-th second-level unit; ε_{ij} is the variance of Y of the j-th second-level unit; γ_{00} is the total mean of all second-level units, which is a fixed parameter; and μ_{0j} is the random component in the second-level equation.

Random Intercept Models (Eqs 4–6). The random model is based on the zero model by gradually adding explanatory variables, that is digital financial inclusion variables. The intercept terms of explanatory variables of household level vary with different counties, and the random slope of each county is fixed.

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \beta_{k0} X_{kij} + \varepsilon_{ij} \tag{4}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \gamma_{0l} DFI_{lj} + \mu_{0j} \tag{5}$$

$$\text{Overall model}: Y_{ij} = \gamma_{00} + \gamma_{0l} DFI + \beta_{k0} X_{kij} + \mu_{0j} + \varepsilon_{ij} \tag{6}$$

Where β_{k0} is the coefficient of each variable at the farm household level; X_{kij} is the set of farm household characteristic variables; γ_{0l} is the coefficient of county digital financial inclusion variables; DFI_{lj} is the set of county digital financial inclusion characteristic variables; and the meanings of other symbols are consistent with those mentioned earlier.

Random intercept model and random slope models (Eqs 7–9). The random intercept model is designed to take into account the situation that the impact of level 2 digital financial inclusion on common prosperity is changing with the level 1 households' tier variable. This study utilizes random intercept and random slope models to address this issue.

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \beta_{k0} X_{kij} + \varepsilon_{ij} \tag{7}$$

$$\text{Lever 2}: \beta_{0j} = \gamma_{00} + \gamma_{0l} DFI_{lj} + \mu_{0j} \beta_{k0} = \gamma_{k0} + \gamma_{kl} DFI_{lj} + \mu_{kj} \tag{8}$$

$$\text{Overall model}: Y_{ij} = \gamma_{00} + \gamma_{0l} DFI_{lj} + \gamma_{k0} X_{kij} + \gamma_{kl} DFI_{lj} X_{kij} + \left(\mu_{0j} + \mu_{kj} X_{kij} + \varepsilon_{ij}\right) \tag{9}$$

4 Results

4.1 Diagnosis of the cross-level impact of digital financial inclusion on the common prosperity of rural households

The HLM diagnostic model (null model) can verify whether digital financial inclusion has a cross-level impact on rural households' common prosperity. Model 1 in Table 3 provides the results from the null model, with variance estimates of 0.012 and 0.032 for counties (level 2) and households (level 1), respectively, indicating significant differences in common prosperity among counties. The Intraclass Correlation Coefficient (ICC) was further calculated to be 0.273 (ICC = τ20j/(τ20j + δ2ij)), signifying that 27.3% of the overall variation in common prosperity results from county-level factors. The ICC exceeds the diagnostic critical value of 0.059 established by Cohen (1988), and the disparity among the dependent variable groups should not be overlooked. Therefore, a hierarchical linear model should be employed to analyze the mechanism through which digital financial inclusion impacts common prosperity at the county level.

4.2 The direct impact of county-level digital financial inclusion on households' common prosperity

Firstly, a random intercept model is established to incorporate county-level digital financial inclusion and farm household-level characteristic variables separately, to focus on the direct impact effects of digital financial inclusion levels. The random intercept model assumes that the differences in common prosperity all originate from the county level. In Table 3, Models 2-5 are random intercept models that incorporate only county-level digital financial inclusion variables. The results demonstrate that digital financial inclusion, the depth of digital financial inclusion usage, and the level of digitization in digital financial inclusion have a significant positive impact on common prosperity at the 0.05 significance level. This indicates that county-level digital financial inclusion and its two dimensions (depth of usage and digitization level) contribute significantly to the promotion of common prosperity. The development of digital financial inclusion is a significant factor in promoting common prosperity. Hypothesis 1 was partially confirmed with statistical significance. Since the estimated coefficient of cover-age breadth in digital financial inclusion is not significant, it will not be considered in the subsequent models. Additionally, in the random effect part, the variation at the county level decreased from 0.012 to 0.01, resulting in a decrease of 16.7%, indicating that the inclusion of county-level independent variables can enhance the explanatory power of common prosperity.

Models 6–8 in Table 3 indicate that the random intercept model adds characteristic variables of household level. The estimated results of the model show that factors such as the education level and health status of the household head, as well as variables such as family social capital and ownership of smartphones, have significant positive effects on common prosperity. However, the presence of household loans and education loans has a significantly negative impact on common prosperity. The reason is that, due to difficulties in livelihood and daily life, families address their livelihood issues by resorting to loaning, including education loans, and the level of common prosperity among these families is relatively lower. In addition, relatively disadvantaged agricultural livelihood patterns and wage labor livelihood patterns also have a significantly negative impact on common prosperity. This indicates that households primarily engaged in agriculture or wage labor experience relatively lower levels of common prosperity. One possible reason is that, whether engaged in farming or migrating for labor, households' income growth and social security are relatively limited, thereby constraining improvements in family economic wellbeing, material living conditions, and overall quality of life. Furthermore, the between-group variance decreased from 0.032 in Model 1 to 0.027 in Model 8, indicating that the independent variables at the household level explain 15.6% of the variance in household-level common prosperity.

TABLE 3 Regression results of HLM of digital financial inclusion directly affecting to common prosperity.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Level 1: Household Characteristics								
Hh_edu						0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)
Hh_age						0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Hh_health						0.047 * * * (0.007)	0.047 * * * (0.007)	0.047 * * * (0.007)
Family size						−0.000 (0.007)	−0.000 (0.007)	−0.000 (0.007)
Social relation						0.072 * * * (0.017)	0.071 * * * (0.017)	0.071 * * * (0.017)
Loan						−0.048 * * (0.020)	−0.047 * * (0.021)	−0.048 * * (0.020)
Loan_edu						−0.051 * (0.020)	−0.051 * (0.028)	−0.052 * (0.028)
Strategy_1						−0.034 * (0.019)	−0.034 * (0.019)	−0.035 * (0.019)
Strategy_2						0.025 (0.021)	0.025 (0.021)	0.025 (0.021)
Strategy_3						−0.051 * * * (0.016)	−0.051 * * * (0.016)	−0.051 * * * (0.016)
Cellphone						0.042 * (0.023)	0.042 * (0.023)	0.043 * (0.023)
Level 2: County-level digital financial inclusion								
Index		0.702 * * (0.295)				0.554 * * (0.263)		
Coverage breadth			0.363 (0.317)					
Usage depth				0.485 * * * (0.181)			0.362 * * (0.164)	
Digitization					0.967 * * (0.447)			0.802 * * (0.394)
Intercept	0.656 * * * (0.021)	−2.679 * (1.403)	−1.005 (1.449)	−1.768 * * (0.903)	−3.959 * (2.131)	−2.250 * (1.250)	−1.419 * (0.819)	−3.444 * (1.879)
Random effect								
$\tau 2_{0j}$(Intergroup variance)	0.012	0.010	0.012	0.010	0.010	0.008	0.008	0.008
$\sigma 2_{ij}$ (Intra-group variance)	0.032	0.032	0.032	0.032	0.032	0.027	0.027	0.027
ICC	0.273	0.240	0.273	0.238	0.238	0.229	0.229	0.229
Log-likelihood	231.710	234.300	232.353	234.892	233.874	308.365	308.529	308.223
Observation	892	892	892	892	892	892	892	892

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 4 The impact of digital financial inclusion moderating livelihood strategies on common prosperity.

Variable	Model9	Model10	Model11	Model12	Model13	Model14	Model15	Model16	Model17	Model18
Level 1: Houshold Characteristics										
Hh_edu	0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)	0.007 * * * (0.002)	0.007 * * * (0.002)	0.007 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)	0.007 * * * (0.002)	0.008 * * * (0.002)
Hh_age	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)	0.001 (0.000)
Hh_health	0.047 * * * (0.007)	0.047 * * * (0.007)	0.048 * * * (0.007)	0.048 * * * (0.007)	0.048 * * * (0.007)	0.047 * * * (0.007)	0.047 * * * (0.007)	0.048 * * * (0.007)	0.047 * * * (0.007)	0.047 * * * (0.007)
Family size	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)
Social relation	0.073 * * * (0.017)	0.073 * * * (0.017)	0.073 * * * (0.017)	0.073 * * * (0.017)	0.073 * * * (0.017)	0.072 * * * (0.017)	0.069 * * * (0.017)	0.074 * * * (0.017)	0.069 * * * (0.017)	0.070 * * * (0.017)
Loan	−0.048 * * (0.021)	−0.047 * * (0.020)	−0.049 * * (0.020)	−0.049 * * (0.021)	−0.049 * * (0.021)	−0.049 * * (0.021)	0.052 * (0.020)	−0.048 * * (0.020)	−0.51 * (0.020)	−0.053 * * * (0.020)
Loan_edu	−0.048 * (0.028)	−0.049 * (0.028)	−0.050 * (0.028)	−0.051 * (0.028)	−0.051 * (0.028)	−0.053 * (0.028)	−0.048 * * (0.028)	−0.047 * (0.020)	−0.047 * (0.028)	−0.049 * (0.028)
Strategy_1	−0.031 * (0.019)	−0.032 * (0.019)	−0.034 * (0.019)	−0.030 (0.019)	−0.030 (0.019)	−0.032 * (0.019)	−3.611 (2.281)	−0.033 * (0.019)	−2.217 (1.454)	−7.673 * * * (2.459)
Strategy_2	0.026 (0.022)	0.026 (0.021)	0.025 (0.021)	0.023 (0.022)	0.023 (0.022)	0.025 (0.021)	0.023 (0.021)	2.408 * (1.371)	0.023 (0.021)	0.026 (0.021)
Strategy_3	−0.051 * * * (0.017)	−0.052 * * * (0.016)	−0.052 * * * (0.016)	−0.054 * * * (0.017)	−0.054 * * * (0.017)	−0.053 * * * (0.016)	−0.054 * * * (0.016)	−0.050 * * * (0.016)	−0.054 * * * (0.016)	−0.053 * * * (0.016)
Smartphone	0.043 * (0.024)	0.043 * (0.023)	0.044 * (0.023)	0.043 * (0.024)	0.043 * (0.024)	0.045 * (0.023)	0.041 * (0.023)	0.043 * (0.023)	0.041 * (0.023)	0.043 * (0.023)
Property income	0.387 * * * (0.143)	0.255 * * * (0.098)	0.461 * * (0.231)							
Percentage of people working				2.623 * * (1.323)	1.509 * * (0.920)	3.122 (2.194)				
Level 2: County-level digital financial inclusion										
index	0.636 * * (0.266)			0.804 * * (0.284)			0.511 * * (0.267)	0.610 * * * (0.265)		
Usage		0.408 * * (0.166)			0.478 * * (0.174)				0.331 * * (0.167)	
Digitization			0.879 * * (0.397)			1.092 * * (0.433)				0.630 (0.406)
Interaction term										
Index * Property	0.081 * * * (0.030)									
Usage * Property		0.051 * * (0.020)								

(Continued on the following page)

TABLE 4 (*Continued*) The impact of digital financial inclusion moderating livelihood strategies on common prosperity.

Variable	Model9	Model10	Model11	Model12	Model13	Model14	Model15	Model16	Model17	Model18
digitization ∗ property			0.096 ∗ ∗ (0.048)							
Index ∗ work_zb				0.545 ∗ ∗ (0.277)						
Usage ∗ work_zb					0.296 ∗ (0.180)					
Digitization ∗ work_zb						0.648 ∗ ∗ (0.459)				
Index ∗ Strategy_1							0.752 (0.481)			
Index ∗ Strategy_2								0.500 ∗ ∗ (0.288)		
Usage ∗ Strategy_1									0.436 (0.292)	
digitization ∗ Strategy_1										1.601 ∗ ∗ ∗ (0.516)
Intercept	−2.645 ∗ ∗ (1.267)	−1.651 ∗ ∗ (0.829)	−3.813 ∗ ∗ (1.894)	−3.447 ∗ ∗ (1.350)	−2.014 ∗ ∗ (0.873)	−2.250 ∗ (1.250)	−2.033 (1.271)	−2.515 ∗ ∗ (1.263)	−1.254 (0.834)	−2.619 (1.937)
Random effect										
τ20j(Intergroup variance)	0.008	0.008	0.008	0.008	0.007	0.008	0.008	0.008	0.008	0.008
σ2ij j(Intra-group variance)	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
ICC										
Log-likelihood	312.048	311.953	310.233	313.199	312.699	308.365	311.465	309.872	311.436	313.931
Observation	892	892	892	892	892	892	892	892	892	892

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5 Discussion

5.1 The cross-layer interaction mechanism of county-level digital inclusive finance and households' livelihood strategies on common prosperity of rural households

The random intercept and random slope models were further developed to study the interaction between digital financial inclusion development and rural households' livelihood strategies in the county. The focus was on the impact of digital financial inclusion on regulating property income, enhancing opportunities to work outside the home, and livelihood patterns. In Table 4, Models 9–11 represent the regression results of the interaction term with households' property income as the intermediate variable, indicating that the influence of households' property income on promoting households' common prosperity increases with the level of development, depth of usage, and digitization of digital financial inclusion. Hypothesis 2 was partially confirmed with statistical significance. Digital financial inclusion innovates financial products through Internet platforms and explores factors related to financial attributes, which contributes to enhancing residents' property-based income increase (Liu XY. et al., 2022). Models 12–14 represent the regression results of the interaction term with the proportion of households' laborers as an intermediate variable, and the impact of the proportion of laborers on households' common prosperity escalates with the development level of digital financial inclusion. Hypothesis 2 was partially confirmed with statistical significance. Digital financial inclusion increases rural youth's ability to access opportunities in the financial ecosystem and improves the probability of non-farm employment for rural youth (Zhang et al., 2021). Models 15–18 represent the regression results of the interaction term with livelihood mode as the intermediate variable. The results of model 16 indicate that compared to other

TABLE 5 The impact of digital financial inclusion moderating financing means on households' common prosperity.

Variable	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Level 1: Household Characteristics						
Hh_edu	0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)	0.008 * * * (0.002)
Hh_age	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
Hh_health	0.047 * * * (0.007)	0.047 * * * (0.007)	0.048 * * * (0.007)	0.047 * * * (0.007)	0.047 * * * (0.007)	0.047 * * * (0.007)
Family size	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)	−0.000 (0.004)
Social relation	0.072 * * * (0.017)	0.072 * * * (0.017)	0.069 * * * (0.017)	0.071 * * * (0.017)	0.071 * * * (0.017)	0.071 * * * (0.017)
Loan	−0.048 * * (0.020)	−0.049 * * (0.020)	−3.774 * (2.253)	−0.048 * * (0.020)	−0.047 * * (0.020)	−0.048 * * (0.020)
Loan_edu	−1.275 (1.937)	−3.548 (3.105)	−0.057 * * (0.028)	−0.051 * (0.028)	−0.051 * (0.028)	−0.052 * (0.029)
Strategy_1	−0.034 * (0.019)	−0.035 * (0.019)	−0.037 * (0.019)	−0.033 * (0.019)	−0.034 * (0.019)	−0.035 * (0.019)
Strategy_2	0.025 (0.021)	0.025 (0.021)	0.025 (0.021)	0.025 (0.021)	0.025 (0.021)	0.025 (0.022)
Strategy_3	−0.050 * * * (0.016)	−0.050 * * * (0.016)	−0.051 * * * (0.016)	−0.051 * * * (0.016)	−0.051 * * * (0.016)	−0.051 * * * (0.017)
Cellphone	0.042 * (0.023)	0.042 * (0.023)	0.042 * (0.023)	0.043 * (0.023)	0.043 * (0.023)	0.043 * (0.023)
Level 2: County-level digital financial inclusion						
index	0.541 * * (0.265)			0.546 * * (0.263)		
Usage					0.354 * * (0.163)	
digitization		0.761 * (0.395)	0.724 * (0.399)			0.793 * (0.394)
Interaction term						
Index * Loan edu	0.259 (0.409)					
digitization * Loan edu		0.734 (0.632)				
digitization * Loan			0.783 * (0.473)			
Index * cellphone				0.009 * (0.005)		
Usage * cellphone					0.009 * (0.005)	
digitization * cellphone						0.009 * (0.005)
Intercept	−2.185 * (1.261)	−3.245 * (1.888)	−3.069 (1.900)	−2.208 * (1.252)	−1.379 * (0.819)	−3.397 * (1.882)
Random effect						
τ20j(Intergroup variance)	0.008	0.008	0.008	0.008	0.008	0.008
σ2ij j(Intra-group variance)	0.027	0.027	0.027	0.027	0.027	0.028
ICC						
Log-likelihood	308.564	308.895	309.586	308.379	308.559	308.235
Observation	892	892	892	892	892	892

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

households, the common prosperity level of households following the livelihood mode increases with the level of digital financial inclusion. The possible explanation is that digital financial inclusion expands the beneficiary scope of financial services, making it easier for households to access and use financial products, and even providing convenient financing channels for entrepreneurial farmers (Cohen, 1988), which contributes to the realization of common prosperity for these entrepreneurial farmers. Meanwhile, Model 18 shows that the level of common prosperity of households in the agricultural livelihood model increases with the enhancement of digital financial inclusion, which suggests that the improvement in digital financial inclusion also facilitates the utilization of financial products by agricultural production farmers, helping them address financing difficulties and thus enhance their livelihoods. However, the coefficients of the interaction terms of Models 15 and 17 are not significant, indicating that the livelihood mode of labor is not an effective intermediate variable for digital financial inclusion to affect households' common prosperity. Hypothesis 2 was partially confirmed with statistical significance.

5.2 The cross-level interaction mechanism of county-level digital inclusive finance and financing means of households on rural households' common prosperity

Random intercept and random slope models were further developed to study the interaction between digital financial inclusion development and households' means of financing in the county, focusing on the impact of digital financial inclusion in regulating households' loaning, educational loaning and ownership of digital tools (smartphones). In Table 5, none of the interaction term coefficients are significant for the results of Models 19-20 with educational loaning by households as the intermediate variable, indicating that educational loaning is not a valid mediating variable. The results of Model 21, which uses household loaning as an intermediate variable, indicate that the impact of household loaning on common prosperity increases with the degree of digital financial inclusion in the county. Hypothesis 3 was partially confirmed with statistical significance. While digital financial inclusion reduces transaction costs, mitigates information asymmetry, and lowers collateral requirements, among other factors, it increases the likelihood of households' access to formal credit (Fan, 2021). It can particularly reduce the poverty rate among low-income households, thereby contributing to the achievement of common prosperity (Zhou et al., 2021). The results of the interaction terms in Models 22–24, using household ownership of smartphones as an intermediate variable, indicate that the influence of smartphones on common prosperity increases with the level of digital financial inclusion in the county, as well as its depth of usage and digitization. Hypothesis 3 was partially confirmed with statistical significance. The development of digital financial inclusion has led to the popularization of digital financial services, and rural households can conveniently use their smartphones for mobile payments, loan applications, and other financial operations (Yin et al., 2019). This, in turn, helps farmers to alleviate their financing constraints, improves their financial difficulties related to production and livelihood, and enhances the living standards and quality of life for rural households.

6 Conclusion

This article uses the county-level digital inclusive finance index developed by the Digital Finance Research Center of Peking University, and household survey data. It employs the HLM model to empirically examine the direct impact of the digital inclusive finance index and its sub-dimensions on the common prosperity of rural households. It further discusses the regulatory mechanism of household livelihood strategies and financing methods on promoting common prosperity through county-level digital inclusive finance. The main research conclusions are as follows: firstly, the null model indicates that there are significant differences in the common prosperity among different counties. 27.3% of the variation in the common prosperity is caused by county-level digital inclusive finance factors, and the HLM is appropriate. Secondly, the depth and coverage of the county-level digital inclusive finance index and its sub indicators can significantly promote common prosperity. Thirdly, family livelihood strategies are important regulatory mechanisms. With the improvement of the development level of county-level digital inclusive finance, the role of households' property income in promoting common prosperity will become increasingly significant, and the role of migrant work opportunities in promoting common prosperity for rural households will continue to strengthen. In addition, rural households who engage in business and agricultural livelihoods can enjoy more of the common prosperity effect generated by digital inclusive finance. Fourthly, financing methods also play an important regulatory role. With the improvement of county-level digital inclusive finance, the availability of loans and the role of digital tools in promoting common prosperity is becoming increasingly evident.

Based on the above research conclusions, this article proposes the following suggestions. Firstly, it is necessary to strengthen the construction of digital inclusive financial infrastructure in rural areas, and to provide technical support for rural households to deeply utilize digital inclusive finance. On one hand, we should accelerate the construction and upgrading of broadband communication network hardware, and accelerate the promotion and application of big data, cloud computing, and 5G technology (Yang B. et al., 2020). On the other hand, we should promote the popularization of affordable smartphones for rural residents and narrow the gap in external digital resource endowments among residents. Secondly, the development and services of digital inclusive financial products should focus on the key livelihood strategies of rural households. We suggest increasing financial support for rural households' business, entrepreneurship, agricultural production and other business activities. It is also important to strengthen public welfare training on financial knowledge for rural households, and to continuously enrich financial products such as agricultural deposits, wealth management, and insurance, and provide service support for increasing rural households' property income.

Our study provides favorable evidence for the cross-layer interaction effect of county-level digital inclusive finance on the common prosperity. However, the study has some limitations that can be addressed in future studies. Due to the cross-sectional data used, there are significant limitations in inferring causal relationships in this study. Therefore, in future, longitudinal data should be constructed. In addition, this study cannot rule out the possibility of other explanations for the impact of digital inclusive finance on common prosperity, such as differences in financial literacy among rural households. Differences in financial literacy may lead to households' acceptance and application effectiveness of digital inclusive finance, which directly affects households' livelihood decisions and their outcomes. Future research should focus on the internal relationship between regional digital inclusive finance, financial literacy, and the common prosperity of rural households.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://opendata.pku.edu.cn/.

Author contributions

MZ: Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Writing–original draft, Writing–review and editing. TZ: Writing–original draft. ZH: Conceptualization, Data curation, Methodology, Writing–review and editing. PW: Formal Analysis, Validation, Writing–review and editing.

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Conflict of interest

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Publisher's note

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Driving factors analysis and scenario prediction of CO_2 emissions in power industries of key provinces along the Yellow River based on LMDI and BP neural network

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Introduction: Power industry is one of the largest sources of CO_2 emissions in China. The Yellow River Basin plays a supportive role in guaranteeing the effective supply of electricity nationwide, with numerous power generation bases. Understanding the drivers and peak of CO_2 emissions of power industry in the Yellow River Basin is vital for China to fulfill its commitment to reach carbon emissions peak by 2030.

Methods: The Logarithmic Mean Divisia Index (LMDI) model was employed to explore the drivers to the change of CO_2 emissions in power industries of three study areas, including Inner Mongolia Autonomous Regions, Shanxi Province, and Shandong Province in the Yellow River Basin. And Back Propagation (BP) neural network was combined with scenario analysis to empirically predict the trend of the amount of CO_2 emitted by power industry (CEPI) from provincial perspective.

Results: CEPI in Inner Mongolia under the scenarios of a low degree of CO_2 emissions promotion with a medium degree of CO_2 emissions inhibition (LM) and a low degree of CO2 emissions promotion with a high degree of CO_2 emissions inhibition (LH) scenario can reach a peak as early as 2030, with the peak value of 628.32 and 638.12 million tonnes, respectively. Moreover, in Shanxi, only CEPI under a low degree of CO_2 emissions promotion scenarios (LL, LM, LH) can achieve the peak in 2025 ahead of schedule, with amounts of 319.32, 308.07, and 292.45 million tonnes. Regarding Shandong, CEPI under scenarios of a low degree of CO_2 emissions promotion with a high degree of CO_2 emissions inhibition (LH) and a medium degree of CO_2 emissions promotion with a high degree of CO_2 emissions inhibition (MH) could achieve the earliest peak time in 2025, with a peak of 434.6 and 439.36 million tonnes, respectively.

Discussion: The earliest peak time of CEPI in Shandong Province and Shanxi Province is 2025, but the peak of CEPI in Shanxi is smaller than that of Shandong. The peak time of CEPI in Inner Mongolia is relatively late, in 2030, and the peak is larger than that of the other two provinces. The per capita GDP is the most positive driving factor that contributes to the CEPI. Shandong has a strong economy, and its per capita GDP is much higher than Shanxi's. Therefore, even under the same peak time, the CEPI in Shandong is much higher than that of

Shanxi. Inner Mongolia is extensive and sparsely populated, which makes its per capita GDP rank among the top in China. In addition, Inner Mongolia's coal-based power generation structure and high power generation also contribute to its late CO_2 peak time and large CO_2 peak.

KEYWORDS

provincial power industry along the Yellow River, CO_2 emissions peak, Logarithmic Mean Divisia Index, back propagation neural network, scenario prediction

1 Introduction

The negative impact of CO_2 emissions from human activities on the environment is becoming increasingly evident. As the largest emitter of CO_2 emissions in the world, China made a mandatory commitment to the world in 2020 to peak its CO_2 emissions by 2030. Not only the birthplace of Chinese civilization and an essential ecological region in China, the Yellow River Basin, but also is home to many important energy, chemical, and basic industrial bases, with more than half of China's coal reserves (Wu et al., 2023). In 2019, the total consumption of fossil energy and total CO_2 emissions of nine provinces in the Yellow River Basin accounted for 35.1% and 40.5% of China, respectively (Zhao et al., 2022). Therefore, there is no doubt that CO_2 emissions reduction effect of the Yellow River Basin is directly related to the successful achievement of China's CO_2 emission peak target. With the introduction of the significant national development strategy of ecological protection and high-quality development in the Yellow River Basin, accelerating the green and low-carbon development of high-carbon emissions industries in the Yellow River Basin and effectively has become the key to cracking the environmental dilemma and the inevitable way to achieve the goal of CO_2 emissions peaking in the Yellow River Basin. The Yellow River Basin has many coal, wind and photovoltaic power generation bases, which play a supportive role in guaranteeing the effective supply of electricity nationwide (Ma and Zhang, 2020). According to the Statistics of China Electricity Council, as of the end of 2021, the installed power generation capacity of major power companies in the Yellow River Basin is about 180 GW. Among them, the installed capacity of thermal power is 140 GW, accounting for the highest percentage about 77.7%. The installed capacity of hydropower is 14.72 GW, accounting for 8.1%. The installed capacity of wind power is 17.04 GW, accounting for 9.4%. And the installed capacity of solar power is 8.67 GW, accounting for 4.8% (Xia et al., 2022). It is apparently that the large demand for electricity and the electricity production being dominated by coal-fired power generation are the main drivers for the increasing CO_2 emissions in power industry of the Yellow River Basin. Hence, whether or not CO_2 emissions in power industry can peak by 2030 will directly affect the time of total CO_2 emissions peaking in the Yellow River Basin. Meanwhile, considering the significant differences in economic development, resource endowment, fossil energy structure, and power industry development among the provinces in the Yellow River Basin, CO_2 emissions reduction pathways of power industry should be formulated according to diverse situations of different regions.

Numerous institutions and scholars have studied on total CO_2 emissions at national, provincial, and city levels. For example, Ahmed et al. (2022) applied the long short-term method to examine the degree of impact of various factors on CO_2 emissions and predict CO_2 emissions trend in China and India. It concluded that energy consumption has the greatest effect and renewable energy has the smallest impact on CO_2 emissions in both countries. Su and Lee (2020) proposed a cost- effectiveness theoretical model to explore the optimal carbon emissions trajectory and introduced an extended STIRPAT model to predict carbon emissions. The findings showed that China's carbon emissions are likely to peak at an estimated 117.7 $MtCO_2e$ by 2028. Li et al. (2023b) used the random forest model to choose seven predictors from 26 CO_2 emissions influencing indicators and constructed a BP neural network to predict CO_2 emissions under five scenarios. It concluded that China can achieve its carbon peaking on time, reaching 10,434.082 Mt CO_2 emissions in 2030 under the 14th Five-Year Plan scenario. Wang et al. (2022) identified the main influencing carbon factors with the help of Redundancy analysis and Monte Carlo permutation tests and developed a method for determining the status of carbon emissions at provincial level based on score evaluation. The 30 provinces were assigned to four stages, including those with significant reductions, marginal reductions, marginal increases, and significant increases based on the progress toward carbon emissions peak. Lin et al. (2023) combined the SOM (Self-organizing map) neural network method, the decoupling coefficient method and Mann-Kendall test to conduct a cluster analysis and peak carbon trend assessment of cities in underdeveloped western regions of China. The results suggested that western cities are classified into resource-dependent cities, low-carbon buffer cities, economic priority cities, and low-carbon transition cities. Dong and Li (2022) proposed the STIRPAT-IGWO-SVR model to forecast the carbon emissions of Jiangsu Provinces under five scenarios.

Zhang et al. (2021) predicted the urban block carbon emissions of a city in China based on the BP neural network method.

In addition to the above, there are some researches focusing on CO_2 emissions at industry level. Some scholars analyzed the main factors affecting CO_2 emissions of different industries in China, including power industry, transportation industry, logistics industry (Quan et al., 2020; Liu et al., 2021; He et al., 2022). Many researches evaluated the peak situation of CO_2 emissions of different sectors in China, including building, transporting, industrial, agricultural and so forth (Chen et al., 2020; Huo et al., 2021; Li et al., 2023a). For instance, Lu et al. (2020) employed an improved PSO (Particle swarm optimization) algorithm optimized BP neural network model to predict carbon emissions for heavy chemical industry and its sub-sectors from 2017 to 2035. The findings indicates that the carbon emissions in heavy chemical industry will reach peak earlier in 2021 and later in 2026 and the peaking value is in the interval of 9.3-9.5 billion tons. Fang et al. (2022) investigated the Environmental Kuznets Curve hypothesis for eight sectors in China by using regression analysis and Monte Carlo simulation. The results show that CO_2 emissions from agriculture, construction, manufacturing, other industries, and transportation are highly likely to peak by 2030, while emissions from electricity and mining are likely to peak after 2030. Bakay and Agbulut (2021) forecasted the greenhouse emissions of power sector in Turkey using deep learning, support vector machine, and artificial neural network algorithms. Tang et al. (2018) established a National Energy Technology-Power model to assess the impact of advanced technology promotion and fossil energy structure shift on energy consumption and CO_2 emissions in China's power sector from a regional perspective. The result indicated that with the promotion of advanced technology and the development of renewable energy, China's power sector would reach a peak of 3717.99 Mt CO_2 in 2023. Cai et al. (2022) took a power generation enterprise as research subject and explored the pathway for power sector to achieve carbon emissions peak and carbon neutrality under five scenarios, with the help of the LEAP (Low Emission Analysis Platform) model. The results suggest that the carbon emissions in the enterprise is expected to reach a peak in 2023 under the low carbon scenarios and CCUS is the key technology to achieve carbon emissions reduction.

In summary, despite numerous studies on the influencing factors, peak and reduction pathways of CO_2 emissions in various industries, the previous studies focused on CO_2 emissions in power industry mostly at national level, and only a few researches shed light on power industry at provincial or regional level. Consequently, it may be more realistic to explore when and how CO_2 emissions peaks in power industry from the regional perspective, which could provide targeted CO_2 emissions reduction recommendations for policymakers to make decisions.

This paper took power industries in Inner Mongolia Autonomous Region, Shanxi Province, and Shandong Province as research objects, respectively, and measured CO_2 emissions of power industry in each province from 2005 to 2019 based on statistical data. After that, a LMDI decomposition model was used to quantify the contribution of each influencing factor to the change of CO_2 emissions in power industry. Additionally, the accuracy in predicting CO_2 emissions of BP neural network and SVR model was compared with the help of evaluation indexes, and a better model was employed to combine with scenario analysis to predict future CO_2 emissions of power industries in the above three provinces. The main contributions of this work include: 1) CO_2 emissions of power industries in Inner Mongolia Autonomous Region, Shanxi Province, and Shandong Province from 2005 to 2019 are calculated. 2) We use the LMDI method to decompose CO_2 emissions of the power industry and analyze driving factors affecting CO_2 emissions in terms of power generation and power consumption. 3) We compare the prediction accuracy of BP neural network and SVR model regarding CO_2 emissions with the help of evaluation indexes. 4) We set up nine scenarios and apply the trained BP neural network to predict CEPI in three provinces from 2021 to 2035 and analyze their peaking trends.

The structure of this paper is organized as follows. Section 2 introduces the current status of research subjects. Section 3 displayed the methodology and data. The results and related discussions are interpreted in Section 4. Finally, conclusions and policy implications are summarized in Section 5.

2 Case study

Inner Mongolia Autonomous Region, thanks to high-quality coal and wind energy resources endowment, in 2020, the power generation was 581.10 TWh, ranking No.2 in China, and the installed power capacity of the region was 146 GW, including the Wind power installed capacity is 37.85 GW, strongly supporting the National Action Plan for Air Pollution Prevention and Control and clean energy development in China. Furthermore, Inner Mongolia's outgoing electricity was 208.20 TWh in 2020, ranking first among provinces in China, which ensures national energy security and enhances stable energy supply effectively (IMEB, 2022).

Shanxi Province owns three ten million kilowatts of large coal power bases(Northern Shanxi, Central Shanxi, Eastern Shanxi) that are China's focus on the construction (GOSC, 2014). In addition, Shanxi Province ranked among the top ten in China, with a power generation of 339.50 TWh and thermal power generation of 303.25 TWh in 2020 (SXEA, 2023). Therefore, as a traditional energy province, Shanxi Province has large total CO_2 emissions, high CO_2 emissions intensity, and high per capita CO_2 emissions, causing it challenging to accomplish the target of carbon peaking and carbon neutralization.

As one of the "Five Poles" in the development pattern of the Yellow River Basin, Shandong Province has outstanding advantages in economic development and comprehensive strength, contributing to promoting the high quality of central cities and urban clusters along the Yellow River. At the same time, according to the data from the National Bureau of Statistics, in the past decade, Shandong Province has been the largest thermal power generation province in China, which means that the power industry in Shandong Province should be assigned major responsibility for low-carbon transformation and should play a demonstration and leading role in achieving CO_2 emissions reduction of the Yellow River Basin.

In short, these three provinces, as the major thermal power provinces in the Yellow River basin, are the key areas of CO_2 emissions. The CO_2 peaking process of their power industry directly affects the realization of the CO_2 peaking target of the whole basin. Therefore, we choose these three provinces as the research objects of this paper. And the geographical location and elevation of the study area is shown in Figure 1.

3 Methodology and data

3.1 CO_2 emissions measurement

Since it is generally believed that CO_2 emissions from non-fossil energy sources are zero, the amount of CO_2 emitted by power industry (CEPI) calculated in this paper are that from fossil energy sources in the process of thermal power generation. This paper refers to the method provided by the IPCC in 2006 (IPCC, 2006), which is currently more common internationally, to measure CO_2 emissions. As a result of different types of major energy consumption in power industry of each province, the energy types covered in the calculation of CEPI vary from province to province, as shown in Table 1. The specific calculation formulas are shown in Equations 1 and 2:

$$C = \sum_i E_i \cdot NCV_i \cdot CC_i \cdot O_i \cdot \frac{44}{12} \tag{1}$$

$$CI = \frac{C}{H} \tag{2}$$

where C refers to CEPI, i refers to energy type used in thermal power generation; E_i refers to the consumption of energy type i; NCV_i refers to the average low calorific value of energy type i; CC_i refers to the carbon content per unit calorific value of energy type i ; O_i refers to the carbon oxidation rate of energy type i; 44/12 refers to the ratio of carbon dioxide to the carbon molecular weight; CI refers to CO_2 emissions per unit of electricity; H refers to the thermal power generation. The specific values are shown in Table 2.

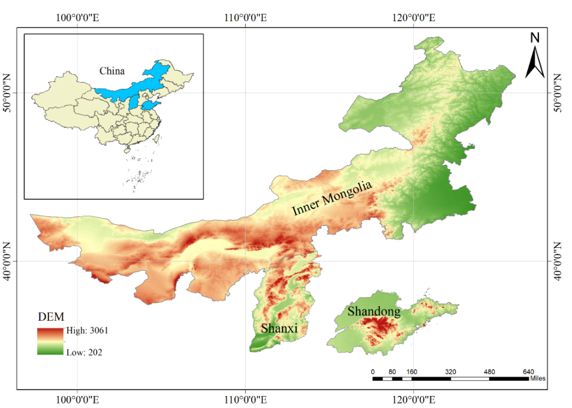

FIGURE 1
Geographical location and elevation of the study area.

3.2 Analysis of influencing factors of CEPI based on the LMDI model

The method of factor decomposition analysis can effectively reflect the degree of contribution of each influencing factor to the change of the target variable at any time. Ang (2004) proposed the LMDI method in 2004, which is widely used in factor decomposition because its advantage of complete decomposition, no residual term, and can handle zero value issues (Luo et al., 2023; Zhang et al., 2023). Accordingly, this paper decomposes the driving forces of CEPI into eight factors: carbon emission coefficient, fossil energy structure, coal consumption for power generation, power generation structure, inter-regional transfer of power, power consumption intensity, GDP per capita, and population to obtain the effect of each factor to the change of CEPI, adopting the extended LMDI method. Specifically, the related equation is as follows:

$$\begin{aligned} C = \sum_i C = \frac{C_i}{F_i} \cdot \frac{F_i}{F} \frac{F}{H} \cdot \frac{H}{E} \cdot \frac{E}{X} \cdot \frac{X}{G} \cdot \frac{G}{P} \cdot P \\ = \sum_i CF_i \cdot CS_i \cdot FH \cdot HE \cdot EX \cdot XG \cdot GP \cdot P \end{aligned} \tag{3}$$

The implications of all the variables in Equation 3 are shown in Table 3.

According to the LMDI model, the change in regional CO_2 emissions from period 0 (base period) to period T (target period) can be decomposed as the sum of the contributions of each driving factor. Since the paper assumed that carbon emission coefficient of each energy type does not change over the time span studied, carbon emission coefficient effect is considered to be zero. The decomposition expressions for the other seven factors are shown in Equations 4–11:

$$\Delta C_{CS_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{CS_i^t}{CS_i^0}\right) \tag{4}$$

$$\Delta C_{FH_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{FH_i^t}{FH_i^0}\right) \tag{5}$$

TABLE 1 The main types of energy consumption of power industries in three provinces.

Provinces	Fossil energy types
Inner Mongolia Autonomous Region	Raw Coal, Cleaned Coal, Other Washed Coal, Briquette, Coal Gangue, Coke Oven Gas, Blast Furnace Gas, Converter Gas, Crude Oil, Diesel, Fuel Oil, Natural Gas
Shanxi province	Raw Coal, Other Washed Coal, Coal Gangue, Coke Oven Gas, Blast Furnace Gas, Converter Gas, Natural Gas
Shandong province	Raw Coal, Cleaned Coal, Other Washed Coal, Briquette, Coke, Coke Oven Gas, Blast Furnace Gas, Converter Gas, Diesel, Fuel Oil, Petroleum Coke, Refinery Gas, Natural Gas

TABLE 2 The value of the coefficient.

Fossil energy Types	NCV_i (KJ/Kg, KJ/m^3)	CC_i (tC/KJ)	O_i (%)
Raw Coal	20908	26.37	0.94
Cleaned Coal	26344	25.41	0.98
Other Washed Coal	8363	25.41	0.98
Briquette	20908	33.56	0.90
Coal Gangue	8363	29.42	0.98
Coke	28435	29.5	0.93
Coke Oven Gas	16726	13.58	0.99
Blast Furnace Gas	3763.44	70.8	0.99
Converter Gas	7945.04	49.6	0.99
Crude Oil	41816	20.1	0.98
Diesel	42652	20.2	0.98
Fuel Oil	41816	21.1	0.98
Petroleum Coke	31947.42	27.5	0.98
Refinery Gas	46055	18.2	0.98
Natural Gas	38932	15.3	0.99

$$\Delta C_{HEt} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{HE_t}{HE_0}\right) \tag{6}$$

$$\Delta C_{EX_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{EX_t}{EX_0}\right) \tag{7}$$

$$\Delta C_{XG_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{XG_t}{XG_0}\right) \tag{8}$$

$$\Delta C_{GP_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{GP_t}{GP_0}\right) \tag{9}$$

$$\Delta C_{P_t} = \sum_i L(C_i^t, C_i^0) \times \ln\left(\frac{P_t}{P_0}\right) \tag{10}$$

$$L(C_i^t, C_i^0) = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \tag{11}$$

3.3 Comparison of BP neural network and SVR model

To obtain the most accurate prediction results of CEPI, this paper adopted BP neural network and SVR model to train and analyze power industry data of each province from 2005 to 2019, respectively. Then, in order to evaluate the prediction ability and accuracy of models intuitively, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are chosen as evaluation indicators to compare the prediction results of two models. The smaller the error indicators, the higher the prediction accuracy and the better the effect of the model. The related equations are shown in Equations 12–14:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{13}$$

$$MAPE = \frac{100\,\%}{n}\sum_{j=1}^{n}\left|\frac{y_j - \hat{y}_j}{y_j}\right| \tag{14}$$

where y_j is the real value, $\hat{y}_j$ is the predicted value, and n is the number of samples.

TABLE 3 Symbolism of each variable in LMDI model.

Variable	Meaning	Unit	Variables	Meaning	Unit
C_i	The amount of CO_2 emitted by energy type $i$in power industry	10^4 tonnes	CF_i	CO_2 emission coefficient of energy type i	tonne/tce
F_i	The amount of standard coal energy type i consumed by thermal power generation	10^4 tce	CS_i	The proportion of energy type $i$in total energy in thermal power generation	%
F	The amount of standard coal energy consumed by thermal power generation	10^4 tce	FH	The amount of standard coal consumed per kWh of power generation	g tce/KWh
H	The amount of thermal power generation	10^8 KWh	HE	The proportion of thermal power generation in power generation	%
E	The amount of total power generation	10^8 KWh	EX	The ratio of power generation to power consumption	%
X	The amount of power consumption	10^8 KWh	XG	Power consumption intensity	KWh/CNY
G	Gross regional product	10^8 CNY	GP	GDP per capita	CNY/people
P	Total population	10^4 people			

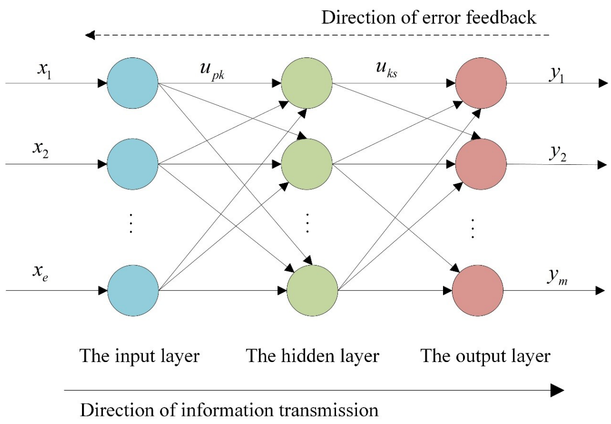

FIGURE 2
Schematic diagram of BP neural network.

3.3.1 BP neural network

BP neural network is a multi-layer feed-forward neural network with backward propagation of error, consisting of three parts: input layer, implicit layer, and output layer (Sun and Huang, 2020). BP neural network is a nonlinear complicated network model with solid stability and autonomy, often used for regression and prediction. It has at least one hidden layer, but it is challenging to determine its node counts. As a result, the ideal node figures are largely determined by experiments while building a neural network. The hidden layer's node numbers typically clearly affect the output solutions to actual issues. Figure 2 shows the structure of a three-layer BP neural network model. The principle is as follows. Suppose there is a set of training samples $\{(X_r, Y_r), r = 1, 2, 3 \cdots, n\}, X_r \in R_n, Y_r \in R_n$, where, $X_r = (X_{r0}, X_{r1}, X_{r2}, \cdots, X_{re})$ is the input value of the sample, $Y_r = (Y_{r0}, Y_{r1}, Y_{r2}, \cdots, Y_{rm})$ is the real value. At the same time, it is assumed that the number of nodes in the input layer is e, the number of nodes in the hidden layer is h, the number of nodes in the output layer is m, the weight and bias of the p node of the input layer to the k node of the hidden layer are u_{pk}, a_k,respectively, and the weight and bias of the k node of the hidden layer to s node of the output layer are u_{ks}, b_k. The output of the hidden layer and output layer are shown in Equations 15 and 16.

$$Z_k = g(\sum_{p=1}^{e} u_{pk}x_{rp} + a_k) \tag{15}$$

$$Z_s = \sum_{k=1}^{m} Z_k u_{ks} + b_k \tag{16}$$

where Z_k is the output of the hidden layer, Z_s is the output of the output layer, and $g(x)$ is the transfer function. The error calculation is defined as Equation 17.

$$E = \frac{1}{2}\sum_{s=1}^{m}(Y_s - Z_s)^2 \tag{17}$$

If E is less than the expected accuracy c, the accuracy requirement is satisfied. Otherwise, error back propagation is required and the calculation process is repeated until the error is within the allowed range or the maximum number of iterations is reached.

In this study, according to BP neural network construction steps, firstly, the data from fifteen samples of each province from 2005 to 2019 are normalized and pre-processed. Secondly, the four selected influencing factors are input variables of the model, and CEPI are output variable. Then, nine samples are randomly selected as training samples, the remaining six samples are chosen as test samples. Simultaneously, "tansig" and "purelin" are selected as the transfer functions of the implicit layer and output layer, respectively, and "trainlm" for the training function. Finally, the model is constructed by the training samples, the accuracy of the model is determined by the test samples, and the number of nodes in the implicit layer is determined by multiple training adjustments, so as to obtain the optimal BP neural network structure.

3.3.2 SVR model

Support vector machine (SVM) is a machine learning method that performs binary data classification in a supervised learning approach. Support vector regression (SVR) is a vital application branch of SVM, which has many strengths, such as solving nonlinear high-dimensional problems with small data size, obtaining the global optimum point in theory, and the computational complexity is independent of the number of sample dimensions, so it is widely used in function approximation and regression prediction. But it is sensitive to outliers and requires careful choice of kernel functions and parameters (Zhang et al., 2022). Its principle is to obtain a regression model on the known sample set to make $f(x)$ and y as close as possible (shown in Figure 3). The sample is shown in Equation 18 and the characteristic function of SVR model is defined as Equation 19:

$$D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_k, y_k), x_k \in R^n, y_k \in R, k = 1, 2, \cdots, n\} \tag{18}$$

$$f(x) = \omega x + b \tag{19}$$

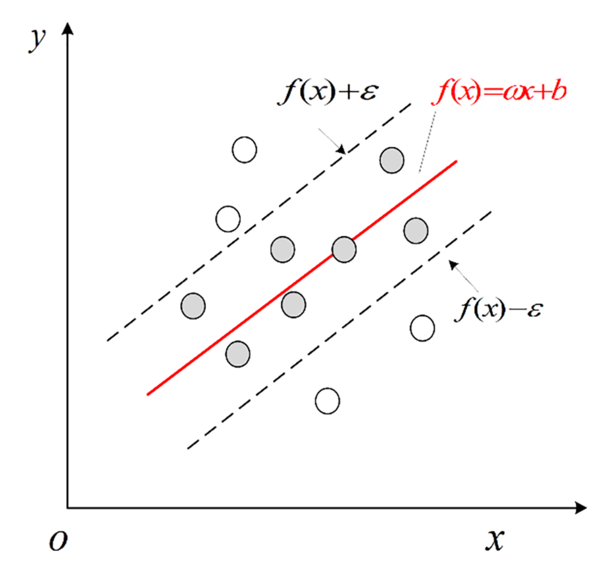

FIGURE 3
Schematic diagram of SVR model.

where x_i is the input value of sample i, y_i is the output value of sample i, and n is the number of samples, ω is the weight, b is the bias. Unlike the general linear model, the SVR model defines the interval ϵ on both sides of the hyperplane and calculates the loss when and only when the absolute value of the gap between $f(x)$ and y is greater than ϵ, while no loss is calculated if it is within the interval band.

The function estimation problem can be transformed into the optimization problem of Equation 20:

$$\begin{gathered}\min_{\omega,b}\frac{1}{2}\|\omega\|^2+C\sum_{k=1}^{n}l_\varepsilon(f(x_i)-y_i)\\ l_\varepsilon(f(x_i)-y_i)=\begin{cases}0 & |f(x_i)-y_i|<\varepsilon\\ |f(x_i)-y_i|-\varepsilon & else\end{cases}\end{gathered} \tag{20}$$

where $\|\omega\|^2$ is the penalty function, C is the penalty factor, and l_ε is the ε-insensitive loss function.

In practical tasks, it is often difficult to directly determine the appropriate ε so that most points are within the interval band, so the relaxation variable ξ_k, ξ_k^* are introduced thereby relaxing the interval requirement of the function and allowing some training samples to fall outside the interval. Therefore, Equation 20 can be transformed into Equation 21:

$$\begin{gathered}\min_{\omega,b}\frac{1}{2}\|\omega\|^2+C\sum_{k=1}^{n}(\xi_k+\xi_k^*)\\ s.t.\begin{cases}y_k-\omega x-b\le\varepsilon+\xi_k\\ \omega x+b-y_k\le\varepsilon+\xi_k^*\\ \xi_k,\xi_k^*\ge 0,k=1,2\cdots,n\end{cases}\end{gathered} \tag{21}$$

By introducing the Lagrange factors α_k,α_k^*, constructing the Lagrange function, and introducing the kernal function, the above optimization problem is transformed into a dual problem, and the decision function is obtained, as shown in Equations 22 and 23:

$$f(x)=\sum_{k=1}^{n}(\alpha_k-\alpha_k^*)K(x_k,x_j)+b \tag{22}$$

$$K(x_k,x_j)=\exp\left(-\frac{\|x_k-x_j\|^2}{2\gamma^2}\right) \tag{23}$$

where $K(x_k,x_j)$ is the kernal function, x_j is the input value of the sample, and γ is the kernal function parameter.

This paper follows the steps of first normalizing the data of power industry in each province, randomly selecting nine training samples and six test samples. Secondly, the radial basis function was selected as the kernel function to process training samples and construct the ϵ-SVR model. Thirdly, we determine the penalty coefficients and kernel parameters applying the method of grid search and cross-validation and simulate the training sample data to obtain the optimal solution of the model. Fourth, the training samples and test samples were substituted into the model to output the fitted values. Finally, we judge the learning and promotion ability of the model by the relevant evaluation indexes, and repeatedly train until the optimal model is obtained.

3.4 Scenario design

According to the decomposition results of the LMDI model, it can be seen that GDP growth is the major factor in increasing CO_2 emissions in all three provinces. Balancing the relationship between economic development and CO_2 emission reduction and integrating the path of achieving CO_2 emissions peak into the overall economic and social development is an important issue facing the realization of green and high-quality economic development. In order to more comprehensively understand the changes in CO_2 emissions under different development rates and emission reduction rates of the power industry in each province, this paper divides the four variables that have a strong influence on CEPI in each province into two types of variables: CO_2 emissions promotion and CO_2 emissions inhibition. Furthermore, three modes of change were set for the two types of variables, respectively, including high degree, medium degree, and low degree. Then, we designed nine different development scenarios of power industry by arranging and combining six modes and set the change rate of relevant influencing factors for a planning period of five years, combining the existing data of the change rate of each influencing factor in previous years. What's more, we regarded the medium degree of CO_2 emissions promotion scenario as the baseline scenario which refers to the development scenario of the power industry in accordance with the existing planning and policies, and set the change rates of low-speed and high-speed accordingly. The CO_2 emissions inhibition scenarios are set in the same way. The definition of nine scenarios of three provinces are shown in Supplementary Tables S1–3, and the specific indicators of three provinces in different scenarios are explained in Supplementary Tables S4–6.

3.5 Data source

In this study, various fossil energy consumption data are collected from the Energy Balance Sheet of Inner Mongolia, the Energy Balance Sheet of Shanxi, and the Energy Balance Sheet of Shandong in the China Energy Statistical Yearbook (NBSC, 2005–2019) from 2005 to 2019. The data on the average low calorific value of the fossil energy are from Appendix 4 in the China Energy Statistics Yearbook. Moreover, the data of carbon content per unit calorific value and carbon oxidation rate of fuels are given by Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (NDRC, 2011). The National Bureau of Statistics of China (NBSC, 2019) is the source for the data related to power generation, thermal power generation, and social electricity consumption of the three provinces, and the regional GDP and population data are collected from Inner Mongolia Autonomous Region Statistical Yearbook, Shanxi Statistical Yearbook and Shandong Statistical Yearbook from 2005 to 2019 (IMBS, 2005–2019; SXBS, 2005–2019; SDBS, 2005–2019). At the same time, to eliminate the influence of the price index, we selected 2005 as the base period to calculate China's GDP data.

4 Results and analysis

4.1 CO_2 emission measurement results

CO_2 emissions and CO_2 emissions intensity in power industries from three provinces were measured based on Equations 1 and 2, and the results are shown in Figure 4. It can be seen that CEPI in all three provinces showed a growth trend during 2005-2019, in which CEPI in Inner Mongolia Autonomous Region grew from 119.34 to 518.20 million tonnes, with a rapid annual growth rate of 22.28%, and CEPI in Shanxi province rose from 122.56 to 263.61 million tonnes at an average annual growth rate of 7.67%. CEPI in Shandong Province increased from 199.89 to 434.87 million tonnes with the annual growth rate of 7.84%. Contrary to the increasing trend of CO_2 emissions, CO_2 emissions intensity presented a declining trend in the past fifteen years. From 2005 to 2019, CO_2 emissions intensity of power industry in Inner Mongolia Autonomous Region fluctuated but decreased from 1145.05 to 1128.94 g/KWh. For Shanxi Province, the power industry had a decline from 948.86 to 934.05 g/KWh in CO_2 emissions intensity. Moreover, CO_2 emissions intensity of power industry in Shandong Provinces was down to 787.12 g/KWh in 2019, a decrease of 24.81% compared with that in 2005.

4.2 LMDI decomposition results of CO_2 emissions

The annual contribution value of each factor to CEPI in each province were calculated, as displayed in Supplementary Tables S7–9. And then they were summed to obtain the cumulative contribution rate of each factor, as shown in Figure 5. CEPI in Inner Mongolia increased by 398.86 million tonnes from 2005 to 2019. During this period, the GDP per capita of Inner Mongolia increased at an average rate of 21.13%, which caused 414.59 million tonnes growth in CEPI. This was the major positive driving force, contributing to 103.95% of CO_2 growth. The power consumption intensity increased from 1895.74 to 2473.20 gtce/KWh, thus exhibiting a positive effect (ΔC = 83.76 million tonnes) on CEPI. The change of fossil energy structure has accounted for an increase of 3.93 million tonnes on the growth of CEPI. Also indicated, was that the power generation structure effect was the main negative effect (ΔC = −46.78 million tonnes) on change of CEPI, followed by inter-regional transfer of power effect (ΔC = −27.98 million tonnes). The proportion of thermal power generation in total power generation decreased from 98.64% to 83.86% in the past years. Correspondingly, the power generation structure effect reflected a significant negative effect that suppressed 11.72% of CEPI. The coal consumption for thermal power generation has a negative effect (ΔC = −25.14 million tonnes), and the population had no obvious effect (ΔC = −3.52 million tonnes) on the change of CEPI.

By calculation, it can be clearly seen that CEPI of Shanxi Province increased by 2.15 times, with a total increase of 141.05 million tonnes. During the whole study period, economic effect, inter-regional transfer of power effect, and population effect collectively drove the increase of CEPI by 216.20 million tonnes (196.71, 14.23 and 5.26 million tonnes, respectively). On the other

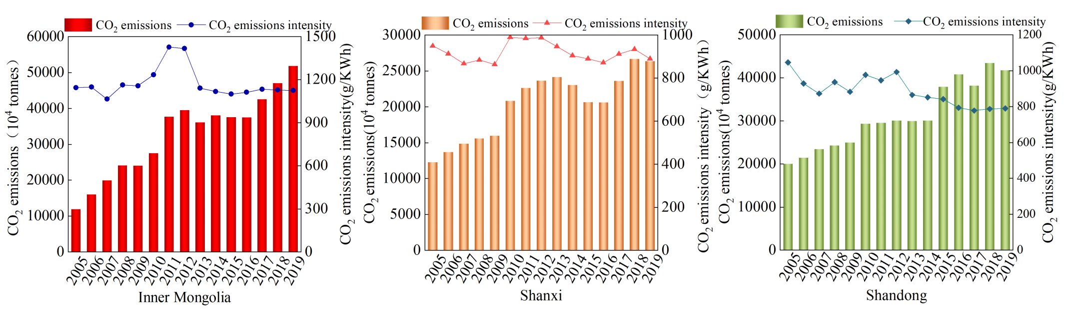

FIGURE 4
CO_2 emissions and CO_2 emissions intensity of power industry in three provinces.

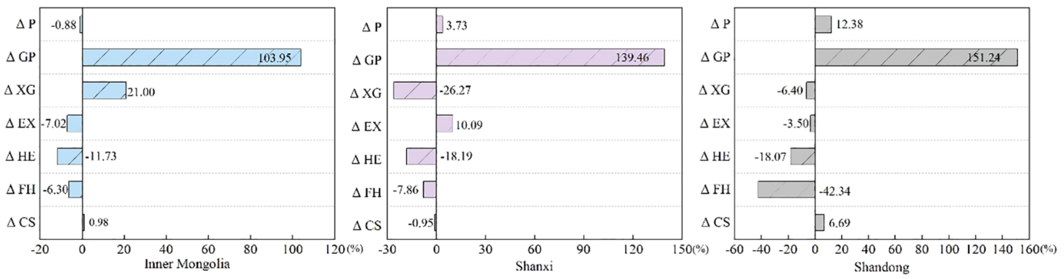

FIGURE 5
Cumulative contribution rate of each factor of CEPI change from 2005 to 2019 in three provinces.

hand, the change of power consumption intensity, power generation structure, coal consumption for power generation, and fossil energy structure jointly offset 75.15 million tonnes of CEPI growths (−37.05, −25.67, −11.09, and −1.35 million tonnes, respectively). Obviously, from Figure 5, the GDP per capita growth from 12158.34 CNY to 32683.10 CNY was the most dominant factor in the increment of CEPI, leading to 139.46% growth in CEPI. As the ratio of power generation to power consumption growing from 1.39 to 1.49, the effect of inter-regional transfer of power became the other key cause of CEPI increase, pulling 10.09% of CEPI growth. The contribution rate of the population effect was patently weaker than the other two factors, with only 3.73%. In respect to the power consumption intensity effect, in the whole period, it reduced from 2318.98 to 1979.29 KWh/CNY, thus showing inhibitory effects on CEPI, with −26.27% of the ΔC. In the meantime, because of the decline in the ratio of thermal power generation to power generation, 18.19% of CEPI growth was inhibited. The coal consumption for power generation exhibited a negative effect on CEPI that explains −7.86% of the total change of CEPI, and the fossil energy structure had a subtle effect on CEPI, with a contribution rate of −0.95%.

With regard to Shandong Province, the whole growth of CEPI in 2019 enlarged by 1.09 times (217.98 million tonnes) compared with that in 2005. As depicted in Figure 5, the changes of CEPI were mainly influenced by four factors, which are economic effect, population effect, coal consumption for power generation effect, and power generation structure effect. Among them, the growth of GDP per capita from 15947.51 to 53412.05 CNY played a particularly prominent role in driving the increase of CEPI (329.67 million tonnes), equaling to 151.24% of ΔC throughout the study period in total. And the rise of population promoted 26.98 million tonnes CEPI increase, accounting for 12.38% of ΔC. In the matter of coal consumption for power generation, in the entire period, it decreased from 393.40 to 269.04 gtce/KWh, bringing about a reduction of 92.30 million tonnes in CEPI, amounting to −42.34% of ΔC. The power generation structure was conducive to CO_2 emissions reduction owing to the decrease of the ratio of thermal power generation to power generation, thus avoiding 39.39 million tonnes of CEPI. Apart from the above factors, the change of fossil energy structure also became a positive driving force resulting in a total increase of 14.58 million tonnes CEPI, amounting to 6.69% of ΔC. The decline of power consumption intensity and inter-regional transfer of power collectively reduced CEPI by 21.57 million tonnes, with the equivalent to −6.40%, −3.50% of ΔC, respectively.

4.3 Selection result of the prediction model

Based on the preliminarily analyze in Section 4.2, four factors that have a greater impact on CEPI were selected as input variables for models in this paper, among which the factors selected for Inner Mongolia Autonomous Region are power generation structure, inter-regional transfer of power, power consumption intensity and GDP per capita, for Shanxi Province are power generation structure, inter-regional transfer of power, power consumption intensity and GDP per capita, and for Shandong Province are coal consumption for power generation, power generation structure, GDP per capita and population. Meantime, CEPI of each province are taken as the output variable. According to the above, we perform a fitting experiment comparison between BP neural network and SVR model, of which 60% of the samples are used for training and 40% are used for testing.

The optimal computational results of BP neural network and SVR model are selected for comparative analysis, as shown in Table 4 and Figure 6. Apparently, for Inner Mongolia Autonomous Region, although the accuracy of SVR model in the training period is slightly higher than that of BP neural network, the error indicators in the testing period is much larger than BP neural network. In a comprehensive view, BP neural network is more suitable than SVR model. Nonetheless, for Shanxi Province and Shandong Province, the error indicators of BP neural network are obviously smaller than that of SVR model. In addition, the prediction accuracy of SVR model is closely related to the selection of parameters. Parameter adjustment requires constant trial and error to complete, which leads to a lot of work and is prone to overfitting or poor prediction. In contrast, BP neural network can update the rules and continuously adjust the weight and threshold parameters in the neural network according to the preset parameters. In short, compared with SVR model, BP neural network in this paper has higher accuracy and superiority which can better predict the arrival of CO_2 emissions peak in power industries of three provinces.

TABLE 4 Comparison of CEPI prediction error indicators between BP neural network and SVR model.

Error indicators		Inner Mongolia Autonomous Region		Shanxi Province		Shandong Province	
		BP neural network	SVR	BP neural network	SVR	BP neural network	SVR
Training Set	RMSE	3170.57	2252.24	884.61	941.56	1603.80	2079.90
	MAE	1601.57	1345.18	405.67	529.22	1317.75	1489.93
	MAPE(%)	4.85	3.66	1.68	2.76	3.96	4.24
Test Set	RMSE	2022.94	2746.53	1088.34	1026.66	1394.91	2323.04
	MAE	1478.51	2598.59	722.76	855.13	1029.47	1805.20
	MAPE(%)	3.82	7.93	4.16	5.05	3.29	5.27

4.4 CO_2 peak prediction results

By putting the normalized influencing factors data from different scenarios into the trained BP neural network for prediction, CEPI change trend of each province from 2021 to 2035 under the nine scenarios was obtained. The predicted results are displayed in Figure 7. It can be seen from the predicted results that there is a significant difference in the trend of CEPI in each province from 2021 to 2035 under nine scenarios.

As indicated in Figure 7 and Table 5, the total CEPI of Inner Mongolia Autonomous Region under nine scenarios, in descending order, are HL > HM > HH > ML > MM > MH > LL> LM > LH. Among them, CEPI under LM and LH scenarios will peak earliest, reaching its peak in 2030 and equaling to 638.12 and 628.32 million tonnes, respectively. Then, under MH scenario, CEPI will achieve a peak at 652.81million tonnes in 2031. After that, CEPI will peak in 2032 under LL scenario, with an amount of 649.63 million tonnes. Finally, in the MM scenario, CEPI will peak in 2034, with a peak of 658.23 million tonnes, while CEPI in the three CO_2 emissions inhibition scenarios with high-speed growth of CO_2 emissions promotion factors (HL, HM and HH) and ML scenario show an upward trend in CO_2 emissions, none of which peak before 2035. And in 2035, CEPI under them will reach 668.28, 666.82, 664.61, and 664.47 million tonnes, respectively.

In respect of Shanxi Province, the total CEPI under nine scenarios, in descending order, are HL > HM > HH > ML > MM > MH > LL> LM> LH. Under the three scenarios with low-speed growth (LL, LM, LH), CEPI will peak in 2025, with a peak of 319.32,

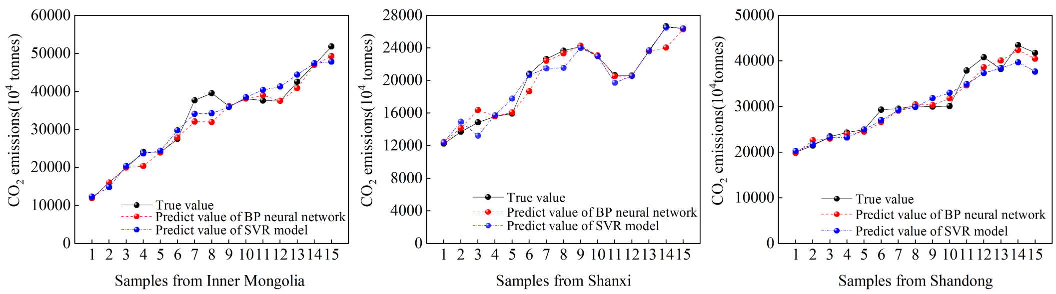

FIGURE 6
Comparison of BP neural network and SVR model prediction results in three provinces.

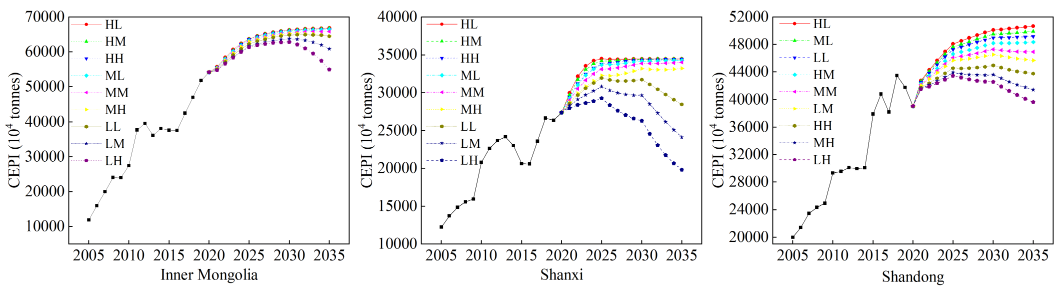

FIGURE 7
Prediction of CEPI in three provinces under nine scenarios.

TABLE 5 The peak year and level of CEPI of three provinces in different scenarios.

Provinces	Scenarios	LL	LM	LS	MW	MM	MS	HW	HM	HS
Inner Mongolia Autonomous Region	Peak year	2032	2030	2030	/	2034	2031	/	/	/
	Emission (million tonnes CO_2)	649.75	638.12	628.32	/	658.23	652.81	/	/	/
Shanxi Province	Peak year	2025	2025	2025	/	/	/	/	/	/
	Emission (1 million tonnes CO_2)	319.32	308.07	292.45	/	/	/	/	/	/
Shandong Province	Peak year	/	2030	2025	/	2030	2025	/	/	2030
	Emission (million tonnes CO_2)	/	465.44	434.60	/	472.83	439.36	/	/	449.75

308.07, and 292.45 million tonnes, respectively, which will realize the goal of China's total CO_2 peak in 2030 ahead of schedule. Nevertheless, CEPI under other six scenarios (HL, HM, HH, ML, MM, MH) will not peak and exhibit an increasing trend year by year, accounting for 344.52, 344.49, 344.39, 342.86, 340.71, 332.03 million tonnes of CEPI in 2035.

Unlike two provinces mentioned above, Figure 7 reveals that CEPI of Shandong Provinces under different scenarios, in descending order, are HL > ML > LL > HM > MM > LM > HH > MH > LH. CEPI under LH scenario and MH scenario will achieve its peak in 2025, followed by CEPI under HH, LM, and MM scenarios which will reach a peak in 2030, with a peak of 434.60, 439.3, 448.75, 465.44, and 472.83 million tonnes, respectively. However, under the three emissions growth scenarios with low degree of CO_2 emissions inhibition (HL, ML, LL) and HM scenario, by 2035, the total CEPI shows a continuous growth trend and does not peak. Among them, the fastest growth in CO_2 emissions is HL scenario, followed by ML, LL, and HM scenarios, with CEPI of 506.98, 499.0, 492.08, and 483.85 million tonnes by 2035, respectively.

The decomposition result of the LMDI model proves that the growth of GDP per capita and power consumption intensity are the main reasons for the increase of CEPI of Inner Mongolia Autonomous Region. Nowadays, Inner Mongolia's economy is in the stage of high-speed development, with a wide area and abundant resources, which leads to the high GDP per capita. At the same time, due to the heavy industrial structure, industry, especially high energy-consuming fossil energy extraction industry accounts for a relatively large share of power consumption structure. Besides, the backward technology of industrial capacity gives rise to the low efficiency of power consumption in the production process, resulting in the waste of electricity resources, thus causing high power consumption intensity and promoting the growth of CEPI. For another, the factors that inhibit CEPI are mainly power generation structure and inter-regional transfer of power. As a substantial national energy base, Inner Mongolia Autonomous Region is gradually intensifying the transformation of energy supply to green and low-carbon under the premise of doing a good job in supplying traditional fossil energy, and striving to take a lead in building a new power system with new energy as the mainstay, so that the proportion of thermal power generation in total power generation is decreasing year by year. Inter-regional transfer of power represents the regional shift of power. As a significant province of power generation, Inner Mongolia Autonomous Region's demand for its power consumption side is increasing while it is delivering electricity to other provinces. And the trend of clean end-use energy consumption is accelerating, thus curbing the increase of CEPI. The prediction results of CEPI in Inner Mongolia visually suggest that when such factors as power consumption intensity and GDP per capita increases at a high rate, no matter how to optimize CO_2 emissions inhibition factors such as power production structure and inter-regional transfer of power, the peak of CEPI cannot be achieved in 2035. Besides, when the CO_2 emissions promotion factors increase at a medium rate, and the future power generation structure continues to achieve certain optimizations and adjustments to reach a medium or high reduction rate of decline, CEPI can reach the peak by 2035, but cannot by 2030. When the economy and power consumption intensity in a certain range of low-speed growth, only the CO_2 emissions inhibition degree of thermal power share and inter-regional transfer of power to medium or high can ensure that CEPI in Inner Mongolia can complete the goal of peaking in 2030.

For Shanxi Province, the main factors leading to the increase in CEPI are the growing economic development level and inter-regional transfer of power, among which the growth of GDP per capita is the biggest driver of CEPI because the accelerated industrialization and urbanization will undoubtedly be accompanied by large consumption of energy and CO_2 emissions. Being considered as a national coal base, power transmission base, and hub for west-east and north-south power transmission, Shanxi Province's outbound power supply is growing year by year. Although it has secured the national energy and power supply, Shanxi Province pay the price of generating more CO_2 emissions in the process of power generation. What is more, reducing the intensity of electricity consumption and the share of thermal power generation in total power generation is an effective way to diminish CEPI. Though thermal power generation is still the main power source in Shanxi Province, with the in-depth implementation of development strategies such as technological reform and energy revolution, the capacity of new energy generation will gradually appear in the future and the efficiency of electricity consumption will also be further improved. Similar to Inner Mongolia, the impact of CO_2 emissions promotion factors on CEPI is stronger than that of CO_2 emissions inhibition factors in Shanxi Province. When CO_2 emissions promotion factors grow at medium or high rates, even through a series of initiatives such as increasing the adjustment of power supply structure on the power generation side, enlarging the installed capacity of new energy generation to ensure that the share of thermal power generation decreases at a higher rate, and improving the efficiency of end-use electricity on the demand side, CEPI remains in a growth trend year by year without peaking by 2035. Whereas, when the growth rate of CO_2 emissions promotion factors is low, CEPI under all three CO_2 emissions inhibition scenarios in Shanxi Province will be able to achieve carbon peaking in 2025.

The leading factors affecting CEPI in Shandong province are coal consumption for power generation, power generation structure, GDP per capita, and population. Similar to the above two provinces, GDP per capita is the factor that contributes most to CEPI. The difference is that the yearly increase in the number of populations, with considerably stimulating demand for abundant materials and energy, has become the second major factor in the increase of CEPI. Despite the fact that the population growth rate in Shandong Province in recent years is slow and the aging problem is relatively severe, the population will be stimulated to grow and continue to play a critical part in CEPI in the future, considering the supporting measures related to "three children policy" will be further improved. Concerning the CO_2 emissions inhibition factors, establishing the coal power units clean and efficient to reduce coal consumption for power generation can significantly suppress the increase of CEPI, followed by the optimization of the power generation structure.

In addition, CEPI in Shandong Province is generally higher under low degree of CO_2 emissions inhibition scenarios, followed by the differences in CEPI caused by economic development and population growth factors, which indicates that the inhibiting effect of CO_2 emissions inhibition factors on CEPI is stronger than the driving effect of CO_2 emissions promotion factors in the future period. It is noteworthy that this is not consistent with the conclusion that the GDP per capita has the most significant impact on CEPI obtained with the LMDI model above. It may attribute to the fact that as the economic development of Shandong Province enters a new normal stage, the government departments pay much more attention to energy conservation and CO_2 emissions reduction, thus promoting the upgrading and transformation of power generation structure and the continuous research and development of low-carbon technologies for power. Hence, the economic growth and CO_2 emissions are gradually decoupled, which represents that economic growth is no longer at the cost of resource consumption and environmental damage and the relationship between economic growth and CO_2 emissions increase is no longer close (Li et al., 2022).

In terms of the low degree of CO_2 emissions inhibition, if the power generation structure is adjusted slightly and the use of fossil energy cannot achieve clean and efficient enough resulting in the CO_2 emissions reduction is less, it is hard to achieve the peak target by 2035 even by controlling the population and economic growth rate. Under the medium degree of CO_2 emissions inhibition scenarios, the proportion of thermal power generation in the total power generation decreases at a faster rate and the effective improvement of fossil fuel power generation can remarkably suppress CEPI when the population and economy in the low and medium-speed growth rate, with the peak of CEPI reaching at 2030. In addition, it is observed that CEPI under the high degree of CO_2 emissions inhibition scenarios can peak at 2030 regardless of the growth rate of the economy and population, which means that although economic growth has the greatest impact on CEPI, it will be able to peak earlier if CO_2 emissions reduction technologies achieve breakthroughs on the existing basis.

In general, the earliest peak time of CEPI in Shandong Province and Shanxi Province is 2025, but the peak of CEPI in Shanxi is smaller than that of Shandong. The peak time of CEPI in Inner Mongolia is relatively late, in 2030, and the peak is larger than that of the other two provinces. Shandong has a strong economy, and its per capita GDP is much higher than Shanxi's. Therefore, as the main factor for the increase in CO_2 emissions, even under the same peak time, the CEPI in Shandong is much higher than that of Shanxi. Inner Mongolia is extensive and sparsely populated, which makes its per capita GDP rank among the top in China. In addition, Inner Mongolia's coal-based power generation structure and high power generation also contribute to its late CO_2 peak time and large CO_2 peak.

5 Conclusions and policy implications

5.1 Conclusions

This paper selected Inner Mongolia Autonomous Region, Shandong Province, and Shanxi Province as representative provinces of Yellow River Basin, respectively, and measured CEPI of three provinces separately using relevant data on energy consumption of power industry from 2005 to 2019. Then an extended LMDI model was utilized to decompose different effects to understand the contribution value of each factor to CEPI in three provinces. Additionally, this study selected BP neural network with higher accuracy to make muti-scenario forecasts for CEPI peaking of three provinces from 2021 to 2035 after comparing with SVR model. Finally, we draw the following conclusions.

Firstly, according to the extended LMDI model results in all three provinces, GDP per capita is the most positive driving factor that contributes to CEPI. Furthermore, the main factor that leads to CEPI growth in Inner Mongolia Autonomous Region is power consumption intensity, and fossil energy structure has a more negligible positive effect. The factors that inhibit CEPI are, in order of magnitude, the power generation structure, the inter-regional transfer of power, coal consumption for power generation, and population. For Shanxi Province, apart from GDP per capita, the key factors that result in the increment of CEPI are inter-regional transfer of power and population. Besides, power consumption intensity and power generation structure have a negative effect on the increase of CEPI. In contrast, coal consumption for power generation and fossil energy structure play a less inhibiting role. In Shandong province's power industry, the population is second only to GDP per capita in promoting CO_2 emissions, and fossil energy structure also positively influenced it. On the other hand, the coal consumption for power generation is the primary factor inhibiting the increase of CEPI, followed by the power generation structure effect. And the effects of power consumption intensity and inter-regional transfer of power on suppressing CEPI are dramatically weaker than other factors.

Secondly, the prediction results under nine different scenarios reveal that for the power industries in Inner Mongolia Autonomous Region and Shanxi Province, CO_2 emissions are generally higher under the high degree of CO_2 emissions promotion scenarios, followed by the difference due to the rate change of emission inhibition factors. Only CEPI under LM and LH scenarios in Inner Mongolia Autonomous Region can meet the requirement of peaking in 2030. CEPI in Shanxi Province under the low degree of CO_2 emissions promotion scenarios can peak in 2025, while the rest of the scenarios do not peak. CEPI in Shandong Province under the low degree of CO_2 emissions inhibition scenarios are generally higher, followed by differences in CEPI caused by the fast or slow growth rate of GDP per capita and population. Meanwhile, under MM, HH, and LM scenarios, CEPI can peak in 2030, while in the LH and MH scenarios, the power industry can achieve CO_2 emissions peak carbon in 2025 early.

5.2 Policy implications

In view of CEPI influencing factors and CEPI prediction results of three provinces provided in this paper, combined with the development of three provinces and the Yellow River Basin, this paper proposes the following policy recommendations.

Firstly, optimize the power generation structure. The decrease in the proportion of thermal power generation in total power generation is the main factor inhibiting the growth of CEPI in all three provinces, so it is indispensable for CO_2 emission reduction in power industry to optimize and adjust the power generation structure dominated by thermal power generation. Inner Mongolia Autonomous Region can rely on its rich renewable energy sources, such as photovoltaic and wind energy, to increase the installed capacity of new energy sources. At the same time, enhance the capacity of renewable energy consumption by actively improving transmission and distribution pricing policies and boosting market-oriented transactions thus reducing the occurrence of wind abandonment as much as possible. Shanxi Province can promote the development of renewable energy power generation by steadily accomplishing the construction of ten million kilowatt level wind power base and photovoltaic runner bases in coal mining subsidence areas. As for Shandong province, it can give full play to its advantages of the sea and actively accelerate to build offshore wind power bases. Meanwhile, building land-based wind power and other renewable energy per local conditions is equally significant. Besides, the “other provincial electricity into Shandong Province” strategy should continue implementing to strengthen power cooperation with energy-rich areas. For example, it can actively strive for the “electricity from Gansu Province into Shandong Province” new channel construction to increase renewable energy delivery.

Secondly, reduce the intensity of electricity consumption and enhance the efficiency of electricity consumption. For one thing, industrial electricity consumption is still the main driving force behind total electricity consumption. In 2019, the industrial electricity consumption of each province accounted for more than 70% of the total electricity consumption in the whole society, respectively. Accordingly, the electricity utilization efficiency of key electricity-consuming industries needs to be urgently improved. Given the fact above, government departments should establish incentive and restraint mechanisms to reflect electricity trading and CO_2 emissions reduction costs in the composition of electricity prices, with price instruments used comprehensively. Moreover, it is essential for authorities to strictly forbid the implementation of electricity price preferences for high energy-consuming and high-emission industries to promote energy saving and efficiency of enterprises, thus reducing CO_2 emissions. For another thing, with the improvement of living standards, the proportion of residential household electricity consumption in total electricity consumption is also increasing yearly. Consequently, the provinces can take measures to continue improving the residential tier electricity price policy and actively increase the publicity of energy saving and electricity saving so that the awareness of low carbon and energy saving is deeply rooted in the people.

Last but not least, lower the energy consumption intensity of coal power and facilitate the clean and efficient utilization of coal. The empirical results demonstrate that the coal consumption for power supply is the most important factor that inhibits the increase of CEPI of Shandong Province, so it should further promote the “three changes” to unite, including transformation of coal power energy saving and carbon reduction, flexibility transformation and heat supply transformation. Furthermore, it deserves more attention that eliminating and shutting down unprofitable and backward coal power generation steadily to promote the cleanliness of coal power, with investment in the development of CCS technology and its infrastructure construction simultaneously. The government should also increase financial and monetary policy support to solve the problem of high costs and lack of effective return mechanisms for unit transformation and flexibility investment to enterprises. In the end, it is vital to recognize that coal power is still the first major support power source of the power system in a period of time, which means energy-saving transformation should not be eager for quick success and instant benefit. We need to promote the clean and efficient use of coal and advance the energy revolution reasonably under the premise of safeguarding economic development.

Although this study analyzes the main influencing factors of CO_2 emissions from the power sector in the three provinces of the Yellow River Basin and simulates CO_2 emission scenarios in the future, it still has some limitations. In this paper, only the main influencing factors of CO_2 emissions in the power industry are selected for the prediction of CO_2 peaking, and other minor influencing factors are not included, which may cause some deviations in the results. Furthermore, the study area of this paper only includes three typical provinces in the Yellow River basin, and the CO_2 emissions of the power industry in the other six provinces are also worthy of further study.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

CW: Writing – review & editing, Methodology, Validation. SS: Writing – original draft. YC: Methodology, Writing – review & editing. SX: Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2024.1362541/full#supplementary-material

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ISSA-enhanced GRU-Transformer: integrating sports wisdom into the frontier exploration of carbon emission prediction

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Introduction: Carbon neutrality has become a key strategy to combat global climate change. However, current methods for predicting carbon emissions are limited and require the development of more effective strategies to meet this challenge. This is especially true in the field of sports and competitions, where the energy intensity of major events and activities means that time series data is crucial for predicting related carbon emissions, as it can detail the emission patterns over a period of time.

Method: In this study, we introduce an artificial intelligence-based method aimed at improving the accuracy and reliability of carbon emission predictions. Specifically, our model integrates an Improved Mahjong Search Algorithm (ISSA) and GRU-Transformer technology, designed to efficiently process and analyze the complex time series data generated by sporting events. These technological components help to capture and parse carbon emission data more accurately.

Results: Experimental results have demonstrated the efficiency of our model, which underwent a comprehensive evaluation involving multiple datasets and was benchmarked against competing models. Our model outperformed others across various performance metrics, including lower RMSE and MAE values and higher R2 scores. This underscores the significant potential of our model in enhancing the accuracy of carbon emission predictions.

Discussion: By introducing this new AI-based method for predicting carbon emissions, this study not only provides more accurate data support for optimizing and implementing carbon neutrality measures in the sports field but also improves the accuracy of time series data predictions. This enables a deeper understanding of carbon emission trends associated with sports activities. It contributes to the development of more effective mitigation strategies, making a significant contribution to global efforts to reduce carbon emissions.

KEYWORDS

sustainable development, carbon neutrality, time-series data, ISSA, GRU-transformer

1 Introduction

In the contemporary context, achieving carbon neutrality stands out as a pivotal goal in combatting global climate change. This term denotes the attainment of a state where carbon emissions are balanced or even surpassed by efforts involving removal, reduction, or compensation strategies.The significance of this concept is self-evident, as climate change has profound impacts on the Earth's environment, society, and economy (Moshari et al., 2023; Keshavarzzadeh et al., 2023). However, achieving carbon neutrality is not an easy task and is accompanied by a series of challenges. One of these challenges lies in the widespread and diverse sources of global carbon emissions, making the tracking, monitoring, and reduction of emissions complex and challenging. Another challenge is ensuring the long-term sustainability of carbon neutrality measures to maintain a state of net-zero carbon emissions. These challenges necessitate innovative approaches for resolution (Zhao et al., 2022; Wu et al., 2022). With the rapid advancement of deep learning technology, researchers have begun to apply it to the field of carbon neutrality. Deep learning is a machine learning technique that mimics the neural network structures of the human brain to process complex data, exhibiting exceptional pattern recognition capabilities (Wang et al., 2021; Yu, 2023). This has made deep learning a powerful tool for exploring solutions to carbon neutrality. Currently, researchers have been utilizing deep learning in various domains to advance carbon neutrality research (Zahedi et al., 2022a; Zahedi et al., 2022b). These domains include monitoring and management of carbon emissions sources, improvements in carbon capture and storage technologies, and optimization of carbon offset projects, among others (Somu et al., 2021). Among the numerous applications of deep learning, time series forecasting holds particular importance in carbon neutrality research. Time series data provides valuable information regarding carbon emissions, energy consumption, weather changes, and more. By analyzing and forecasting this time series data, researchers can gain a better understanding of the effectiveness of carbon neutrality measures and optimize their strategies. For instance, through time series forecasting, one can more accurately predict future energy demands, thus optimizing energy production and distribution while reducing carbon emissions (Amasyali and El-Gohary, 2018; Feng et al., 2023). Additionally, time series analysis can aid in monitoring and predicting weather changes to enhance the efficiency of renewable energy utilization. Therefore, time series forecasting plays an indispensable role in carbon neutrality research, providing robust support for achieving the goal of net-zero carbon emissions (Wang et al., 2021; Yu, 2023).

In recent years, researchers have actively explored various time series forecasting models to address challenges in the field of carbon neutrality. One such model is the ARIMA (Autoregressive Integrated Moving Average) model, a classic method that combines the concepts of autoregression (AR) and moving averages (MA). Widely applied in numerous carbon neutrality studies, especially for predicting carbon emission trends, the ARIMA model, however, has limitations in dealing with nonlinear relationships and complex seasonal variations, leading to potential inaccuracies in practical carbon neutrality scenarios (Sun and Ren, 2021). Additionally, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) models are two other extensively used models in time series forecasting. These models possess the ability to capture long-term dependencies and are suitable for handling nonlinear and non-stationary time series data. However, due to their complexity, computational expenses, and the often substantial amount of data required, their application in certain carbon neutrality research contexts can be challenging (Shen et al., 2022). On another front, the Transformer model is emerging as a notable contender in the field of time series forecasting. Built on a self-attention mechanism, it can capture relationships between different time steps in a sequence, providing a better understanding of temporal and seasonal variations. Despite its excellent performance in handling time series data, the Transformer model may face challenges in certain carbon neutrality studies, particularly those with high data requirements (Chen et al., 2022).

Based on the aforementioned limitations, this study introduces a comprehensive model that combines ISSA and GRU-Transformer to address the shortcomings of previous models. Leveraging the strengths of the Transformer encoding layers and the GRU model, this model achieves more accurate carbon emission predictions and conducts in-depth exploration of factors influencing carbon neutrality. Firstly, the model utilizes the Transformer encoding layers as feature extractors, delving into various influencing factors in the carbon neutrality process. Subsequently, the extracted features are prepared for the prediction task through a fully connected layer. The model incorporates two layers of GRU models to enhance learning capacity. Secondly, the output of the GRU model is fitted through a fully connected layer to realize predictions of carbon emissions. The optimization process employs the improved Sparrow Search Algorithm, adjusting hyperparameters to enhance model performance and training efficiency.

- This study introduces a time series forecasting approach based on a combination of ISSA and the GRU-Transformer model to enhance the accuracy of carbon emission predictions. By integrating the encoding layers of the Transformer with the GRU model, the model can better capture the temporal and seasonal patterns in carbon emission data, resulting in more precise carbon emission forecasts. This contribution is of paramount importance in guiding the development and implementation of carbon neutrality strategies.
- The research further explores the application of the ISSA method to gain a deeper understanding of the crucial influencing factors during the carbon neutrality process. Through the analysis of timeseries data, we can identify factors related to carbon emissions and incorporate them into the model's considerations. This approach provides a more comprehensive perspective, aiding in revealing dynamic relationships underlying carbon neutrality and offering decision-makers additional insights to optimize emission reduction strategies.

- Additionally, this study introduces an enhanced Sparrow Search Algorithm to optimize the hyperparameters of the GRU-Transformer model. This optimization process enhances the model's performance and makes it more versatile, allowing it to adapt to various datasets and problem scenarios. The application of this algorithm contributes to improved model efficiency and applicability.

2 Method

This article proposes a combined model based on ISSA and GRU-Transformer. Firstly, the encoding layers of the Transformer are used as feature extractors to deeply explore the influencing factors of carbon neutrality. Relevant features associated with these influencing factors are expressed and extracted to obtain the most significant features from the training data. Subsequently, the extracted features are passed through a fully connected layer, followed by the use of two layers of GRU models for prediction, which significantly enhances the model's learning capacity compared to a single-layer GRU. Finally, a single fully connected layer is used to fit the predicted values, achieving predictions of carbon emissions.

Building upon this foundation, an improved Sparrow Search Algorithm is introduced to optimize the GRU-Transformer model. Hyperparameters such as learning rate, batch size, and hidden layer node count within the model are optimized using this algorithm. Figure 1 illustrates the process: Firstly, the original carbon emission data is input into the GRU-Transformer prediction model, with the input layer node count, output layer node count, and other non-ISSA optimized parameters pre-set. Parameters for the ISSA model are determined, including maximum iteration count (epoch), dimensionality (d), threshold (ST), and warning value R2. Subsequently, ISSA is employed to optimize the learning rate, batch size, and hidden layer node count within the GRU-Transformer prediction model. Fitness of the sparrow individuals is calculated, and their best positions are updated accordingly. If the best position is achieved, the algorithm concludes; otherwise, the new position is updated as the best position. Finally, the hyperparameters obtained through ISSA optimization are input into the GRU-Transformer prediction model for forecasting, and the model's performance is assessed by comparing the error between the actual and predicted values.

2.1 GRU-Transformer model

The GRU-Transformer model is a powerful deep learning architecture widely applied in domains such as time series forecasting and natural language processing (Chen et al., 2022). As shown in Figure 2, the overall structure of this model integrates both the GRU (Gated Recurrent Unit) network and the Transformer network to efficiently model sequences and extract features. The roles and structures of the GRU network and the Transformer network within this model will be separately explained below.

2.1.1 GRU model

GRU (Gated Recurrent Unit) is a variant of recurrent neural networks (RNNs) known for its strong sequence modeling capabilities (Lv et al., 2023; Yang et al., 2022). In the GRU-Transformer model, the GRU network plays a crucial role in handling short-term dependencies within sequential data. As shown in Figure 3, it introduces essential mechanisms, including update gates and reset gates, to effectively control information flow while mitigating the common gradient vanishing issue associated with standard RNNs. The update gate is represented by a sigmoid activation function and selectively determines which information from the previous time step should be propagated to the current time step. Similarly, the reset gate, also controlled by a sigmoid function, determines which information should be discarded (Liu

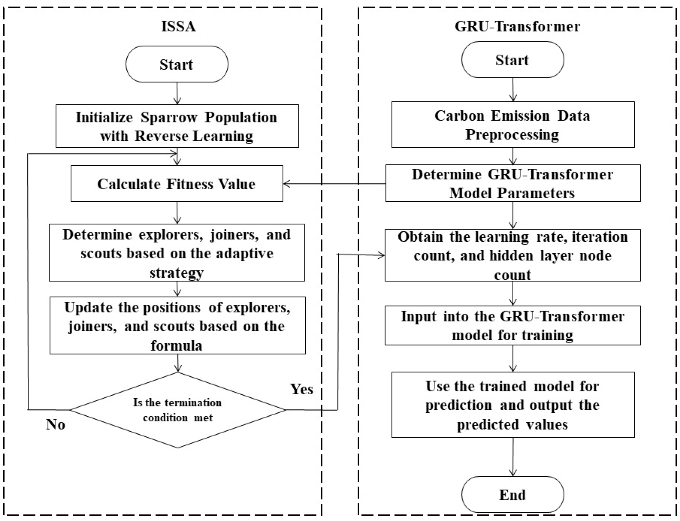

FIGURE 1
Overall flow chart of the model.

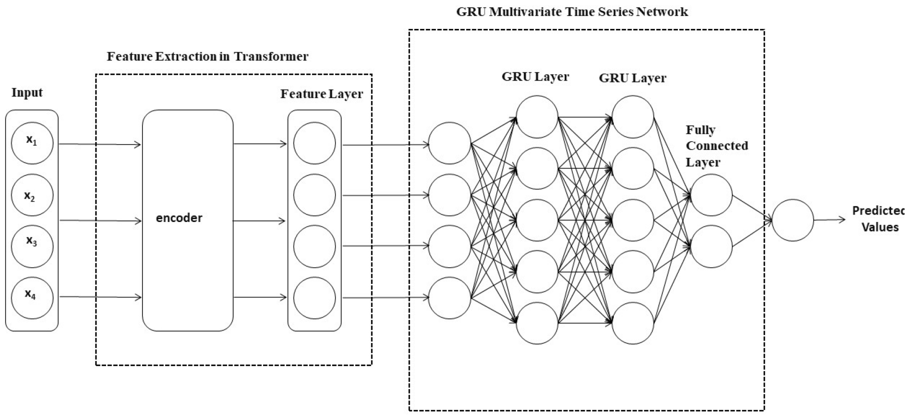

FIGURE 2
Flow chart of the GRU-Transformer model.

et al., 2023). These gates collaborate to capture and propagate relevant temporal patterns, making the GRU network adept at understanding dynamic changes and patterns in the data, particularly suitable for time series analysis. Below are the key reasoning steps for GRU:

Equation (1) can be used to quantify and assess the extent to which carbon-neutral actions taken at each time step contribute to the reduction of greenhouse gas emissions. This can help the sport community to develop more effective carbon neutral strategies to reduce the impact of sport on climate change.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (1)$$

where: z_t: Output of the Update Gate. σ: Sigmoid activation function. W_z: Weight matrix of the Update Gate. h_{t-1}: Previous time step's hidden state. x_t: Input at the current time step.

Equation (2) is a GRU update rule. It works by updating the hidden state of the current time step based on the hidden state of the previous time step and the inputs of the current time step, thus enabling modelling and prediction of sequence data. For example, time series data is used in sports to predict the performance of athletes. By collecting athletes' training, physical state, game results, etc., and then using recurrent neural networks to learn the patterns and trends of these data, the performance of the athlete at future time steps can eventually be predicted.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (2)$$

where: r_t: Output of the Reset Gate. σ: Sigmoid activation function. W_r: Weight matrix of the Reset Gate. h_{t-1}: Previous time step's hidden state. x_t: Input at the current time step.

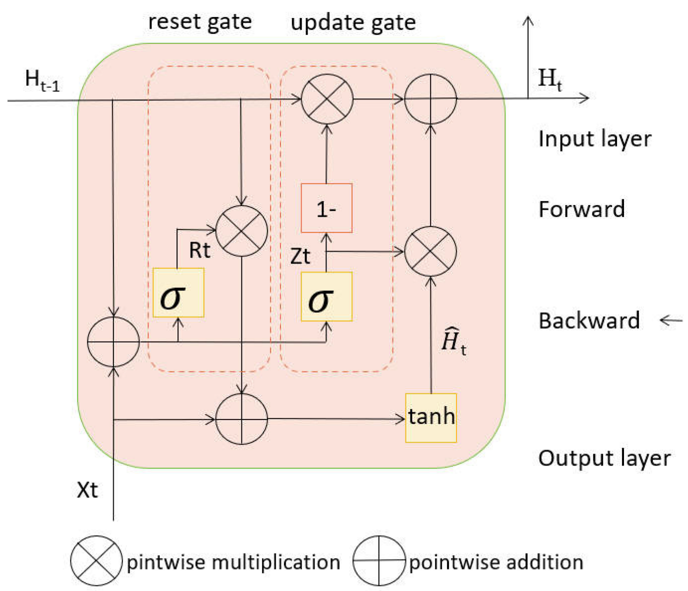

FIGURE 3
Flow chart of the GRU model.

Equation (3) allows us to better understand and assess the impact of actions taken in carbon neutral and sport on reducing carbon emissions and promoting sustainable development.

$$\tilde{h}t = \tanh(W \cdot [r_t \odot ht - 1, x_t]) \tag{3}$$

where: $\tilde{h}_t$: Candidate hidden state. tanh: Hyperbolic tangent activation function. W: Weight matrix used to calculate the candidate hidden state. r_t: Output of the Reset Gate. h_{t-1}: Previous time step's hidden state. x_t: Input at the current time step.

In the field of carbon neutrality and sport, Equation (4) is more effective in updating and maintaining the state of the model, leading to a better understanding and assessment of the impact of different actions on carbon emissions and sport performance.

$$h_t = (1 - z_t) \odot h_{t-}1 + z_t \odot \tilde{h}_t \tag{4}$$

where: h_t: Current time step's hidden state. z_t: Output of the Update Gate. $\tilde{h}_t$: Candidate hidden state. h_{t-1}: Previous time step's hidden state.

2.1.2 Transformer model

The Transformer is a neural network architecture based on self-attention mechanisms, particularly adept at handling long-range dependencies and parallelized computation (Oyando et al., 2023; Zhang et al., 2023). In the GRU-Transformer model, the Transformer network is employed to extract long-term dependencies and global associations within sequence data. Its encoder layers enable the model to autonomously learn crucial relationships between different time steps within the sequence, without relying on traditional sliding window approaches. As illustrated in Figure 4, the Transformer's self-attention mechanism assists the model in adaptively focusing on critical features, thereby enhancing sequence modeling performance.

Here, we introduce the key mathematical principles of the Transformer model:

Equation (5) represents the Multi-Head Attention mechanism, which is an extension of the Self-Attention mechanism for learning the dependencies between positions in an input sequence. We can apply the Multi-Head Attention mechanism to the need or concern for carbon neutral and sports related information.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h) W^O \tag{5}$$

where: MultiHead(Q,K,V): Output of multi-head attention. head$_i$: Individual attention head. W^O: Weight matrix for the output projection.

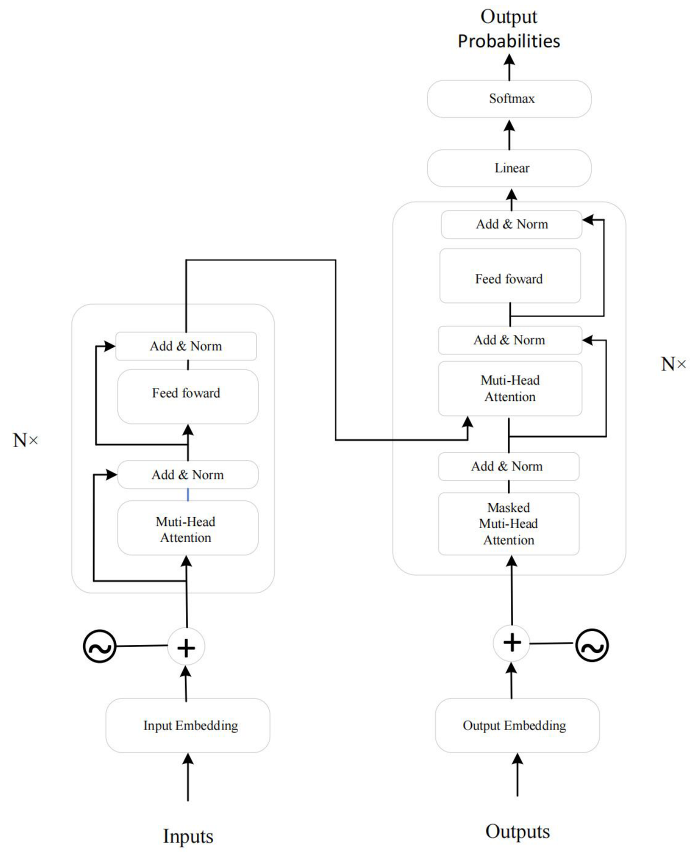

FIGURE 4
The Transformer model architecture. Left: Encoder with N = 6 identical layers, each containing two sub-layers - a multi-head self-attention mechanism and a position-wise fully connected feed-forward network. Right: Decoder with N = 6 identical layers, including the two sub-layers from each encoder layer and an additional sub-layer performing multi-head attention over the encoder stack's output.

$$\mathrm{PositionwiseFFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2 \tag{6}$$

In Equation (6), PositionwiseFFN(x): Output of the position-wise feed-forward network. W_1, b_1, W_2, b_2: Weight matrices and bias terms.

$$\mathrm{LayerNorm}(x) = \frac{x-\mu}{\sigma} \tag{7}$$

In Equation (7), LayerNorm(x): Layer normalization of x. μ: Mean of x. σ: Standard deviation of x.

2.2 ISSA

Nature inspires solutions to complex problems, with collective behaviors in bird flocks and insect swarms offering valuable insights. The Sparrow Search Algorithm (SSA), inspired by sparrow foraging patterns, addresses optimization challenges. However, SSA's limited communication among group members hinders solution quality. In this paper, we enhance SSA by introducing reverse learning, Levy flight, and adaptive learning strategies to improve convergence speed and solution quality.

2.2.1 Levy flight strategy

By employing the Levy flight strategy to update individual parameters in the formula, we enhance the algorithm's global optimization capabilities, thus preventing the Sparrow Search Algorithm from getting trapped in local optima.

$$\sigma = \frac{\gamma(1+\tau)\cdot\sin(\frac{\pi\cdot\tau}{2})}{\gamma(\frac{1+\tau}{2})\cdot\tau\cdot 2^{\frac{\tau-1}{2}}} \tag{8}$$

$$s = \frac{\partial}{|v|^{\frac{1}{\tau}}} \tag{9}$$

$$P_{i,j}^{t+1} = m\cdot\mathrm{step}\cdot s\cdot(P_{i,j}^{t} - P_{best,j}^{t}) \tag{10}$$

In Equations (8–10) γ represents the gamma function, and τ is a hyperparameter, which is set to 1 in this paper. δ and v follow normal distributions $N(0,\sigma^2)$ and $N(0,1)$, respectively. Here, m represents a random number, and s represents the step size, which is set to 0.001. $P_{best,j}$ denotes the value of the globally best position in dimension j from the previous iteration.

2.2.2 Adaptive learning strategy

During the SSA search process, some individuals in the population may become trapped in local optima, and their positions remain unchanged over several consecutive iterations (Sun et al., 2022). These individuals are considered to lack search capability and should be updated in subsequent search processes to enhance convergence speed and accuracy. We have improved SSA using the Equation (11):

$$\mathrm{fit}(X_i) = \begin{cases} \left(\frac{1}{1+f(X_i)}\right), & f(X_i) \geq 0 \\ 1+|f(X_i)|, & f(X_i) < 0 \end{cases} \tag{11}$$

where: $f(X_i)$ represents the objective function of the minimization problem. When a sparrow's fitness is greater than 0.9, it will be considered as a discoverer. When the sparrow's fitness value is greater than 0.7 and less than 0.9, the sparrow will be considered as a joiner. It will immediately leave its current position and approach the best discoverer. When the sparrow's fitness value is less than 0.7, the sparrow will become a joiner but will not approach the best discoverer.

3 Experiment

3.1 Datasets

To comprehensively validate our model, this experiment utilizes four distinct datasets: MLCO2 dataset, GCA dataset, GHGI dataset, and CCKP dataset.

MLCO2 (Mauna Loa Carbon Dioxide): This dataset is based on atmospheric carbon dioxide concentration data collected at the Mauna Loa Observatory in Hawaii and is one of the crucial datasets in climate science. It records global atmospheric carbon dioxide concentrations since 1958, making it widely used for researching climate change and greenhouse gas emissions (Tveter, 2020).

GCA (Global Carbon Atlas): The GCA is a comprehensive global carbon dataset that provides detailed information on global carbon dioxide emissions and absorption. It includes carbon emission data from various sources, including energy production, transportation, industry, and land-use changes (Franzen and Mader, 2019).

GHGI (Greenhouse Gas Inventory): GHGI is an international greenhouse gas inventory compiled and published by governments and international organizations. It encompasses various greenhouse gas emission data, such as carbon dioxide, methane, and nitrous oxide, categorized by sources and industries (Shi et al., 2021).

CCKP (Climate Change Knowledge Portal): The CCKP is a data platform provided by the World Bank, which aggregates various data related to climate change, greenhouse gas emissions, and adaptation measures. It includes data from various countries, covering climate indicators, risk assessments, and adaptability data (Leal Filho et al., 2023).

3.2 Experimental environment

This article's experimental platform server configuration is shown in Table 1.

3.3 Experimental details

3.3.1 Step 1: Data preprocessing

- Data Cleaning: In this step, we thoroughly cleaned the raw data. Regarding the handling of missing values, if the missing values in a column exceed 10%, we choose to remove the entire column; otherwise, we fill the missing values with the mean of that column.

TABLE 1 Experiment environment.

Component	Description
Operating System	Windows 11
CPU	Intel Core i9-9900K CPU @ 3.60GHz
GPU	NVIDIA RTX3090 Graphics Cards (2 units) with CUDA Cores
Memory	32GB
Python Version	3.9.18
Matplotlib Version	3.3.4
CUDA Version	11.3
NumPy Version	1.26.1
Torch Version	1.8.0

- Data Standardization: To ensure data consistency and comparability, we standardized all data features. This involves transforming numerical features into a form with a mean of 0 and a standard deviation of 1. This process helps eliminate scale-related issues that may arise during the modeling process.
- The dataset is divided into three subsets: the training set, validation set, and test set. Specifically, approximately 70% of the data sample is allocated to the training set, 15% to the validation set, and the remaining 15% to the test set. After removing missing data, the final dataset selection resulted in 63,788 data samples for the MLCO2 dataset, 72,345 for the GCA dataset, 56,920 for the GHGI dataset, and 67,213 for the CCKP dataset. The specific dataset distribution is shown in Table 2:

3.3.2 Step 2: Model training

- Begin by preprocessing the carbon emission data and feeding it into the GRU-Transformer prediction model. Set the model's input layer nodes, output layer nodes, and other parameters that don't require optimization via ISSA in advance. Determine key parameters for the ISSA model, such as the maximum iteration count (epoch), dimension (d), threshold (ST), and warning value (R2).
- Apply the ISSA algorithm to optimize hyperparameters within the GRU-Transformer prediction model, including learning rate, batch size, and hidden layer node count. Calculate the fitness of each sparrow and subsequently update their best positions. Inject these optimized hyperparameters into the GRUTransformer prediction model, compute corresponding fitness values, and assess whether there is a need to update the best positions. The algorithm will terminate if the best positions are achieved; otherwise, new positions will replace the best.
- Input the finely tuned hyperparameters, obtained through ISSA optimization, into the GRU-Transformer prediction model for forecasting. Evaluate the model's performance by comparing errors between actual and predicted values.

TABLE 2 Dataset splitting.

Dataset	Initial Samples	Training Set	Validation Set	Test Set
MLCO2	63,788	44,651	9,589	9,548
GCA	72,345	50,641	10,867	10,837
GHGI	56,920	39,844	8,548	8,528
CCKP	67,213	47,049	10,065	10,099

3.3.3 Step 3: Model evaluation

- Model Performance Metrics: In this step, the evaluation of the developed model is conducted through the application of various performance metrics. These metrics include but are not limited to Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R2) statistics. These metrics provide a comprehensive overview of how well the model performs in predicting carbon emissions. The chosen metrics help in assessing the accuracy, precision, and reliability of the model's predictions.
- Cross-Validation: Cross-validation is an essential technique employed to validate the model's performance and assess its generalization capabilities. In this step, the dataset is divided into multiple subsets or folds. The model is trained on a portion of the data and tested on another. This process is repeated multiple times, with different subsets serving as both training and testing data. The results from each iteration are then averaged to provide a more robust evaluation of the model's performance. Cross-validation helps to mitigate overfitting and ensures that the model can make accurate predictions on unseen data, enhancing its reliability and applicability.

Below, we will introduce the evaluation metrics used in this study:

Equation (12): Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{12}$$

where: n is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value.

Equation (13): Symmetric Mean Absolute Percentage Error (SMAPE):

$$\mathrm{SMAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2} \times 100 \tag{13}$$

where: n is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value.

Equation (14): Coefficient of Determination (R-squared, R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{14}$$

where: n is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value. $\bar{y}$ is the mean of the actual values.

Equation (15): Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

where: n is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value.

Equation (16): Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{|y_i|} \times 100 \tag{16}$$

where: n is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value.

3.4 Experimental results and analysis

Table 3 provides a comprehensive comparison of various models on the MLCO2, GCA, GHGI, and CCKP datasets across different performance indicators. Among all evaluated models, our approach consistently outperforms others across multiple metrics. Specifically, on the MLCO2, GCA, GHGI, and CCKP datasets, our model demonstrates significant advantages in terms of RMSE, MAE, SMAPE, and R2. In comparison to competing models such as BIGRU-Transformer, GRU-Transformer, CNN-GRU, Attention-GRU, SSAGRU-Transformer, and SSA-CNN-GRU, our approach achieves lower RMSE and MAE values, as well as higher R2 scores. This underscores the universality and reliability of our method, indicating that our model exhibits higher accuracy and reliability in carbon-related prediction tasks.

As shown in Table 4, we conducted a detailed comparison of performance metrics for different models on multiple datasets. Specifically, our model outperforms competitors consistently in terms of parameter count and computational complexity on MLCO2, GCA, GHGI, and CCKP datasets. For instance, on the MLCO2 dataset, our model exhibits a significant advantage, with only 416.45 million parameters and a computational complexity of 55.28 billion floating-point operations (Flops), much lower than other models.

The design of our model structure takes into account the characteristics of the tasks it handles. Through the customization of the GRU-Transformer, we targetedly simplified the model structure, retaining only the essential components for the task and avoiding unnecessary complexity. Our model exclusively utilizes the encoder part of the Transformer structure, omitting the decoder. Since the decoder, in sequence generation, needs to consider previously generated parts, it is typically more complex than the encoder. Omitting the decoder contributes to reducing computational complexity, enhancing inference speed, especially in scenarios where inference efficiency is crucial. We implemented the Information Separation and Self-Attention (ISSA) mechanism to achieve effective fusion of information. This mechanism maintains model performance while more efficiently processing information, reducing the amount of information representation required in the parameter space. This method of information fusion contributes to lowering the model's parameter count.

3.5 Ablation experiments

In Table 5, we conducted experiments by removing the ISSA module to validate its effectiveness. For instance, on the MLCO2 dataset, our model outperformed SSA, PSO, QPSO, and WOA in terms of RMSE. Specifically, our model achieved a reduction of

TABLE 3 Comparison of different models in different indicators comes from the MLCO2 dataset, GCA dataset, GHGI dataset, and CCKP dataset.

Model	Datasets															
	MLCO2 (Fveter, 2020)				GCA (Franzen and Mader, 2019)				GHGI (Shi et al., 2023)				CCKP (Leal Filho et al., 2023)			
	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2
BIGRU-Transformer (Sheng et al., 2023)	133.29	117.47	0.68	0.86	138.66	102.26	0.78	0.83	129.91	132.08	0.82	0.87	134.44	119.12	0.68	0.88
GRU-Transformer (Lv et al., 2023)	137.28	111.67	0.63	0.87	134.17	100.12	0.72	0.87	123.35	121.84	0.94	0.87	133.73	134.77	0.64	0.87
CNN-GRU (Elmaz et al., 2021)	139.03	110.74	0.63	0.88	138.52	92.48	0.62	0.85	134.22	111.26	0.93	0.86	134.77	118.92	0.61	0.86
Attention-GRU (Yang et al., 2022)	138.16	113.24	0.68	0.85	127.76	93.78	0.66	0.83	135.88	122.94	0.95	0.85	130.73	122.93	0.62	0.84
SSA-GRU-Transformer (Wang et al., 2021)	136.90	113.29	0.62	0.88	127.46	110.33	0.65	0.82	149.88	132.78	0.84	0.84	132.78	129.88	0.64	0.88
SSA-CNN-GRU (Tang and Li, 2022)	134.48	110.53	0.69	0.89	129.19	91.60	0.64	0.89	143.4	112.27	0.6	0.85	138.07	128.59	0.68	0.89
Ours	113.23	89.12	0.60	0.91	118.2	85.12	0.59	0.91	115.2	104.12	0.65	0.89	115.2	94.12	0.58	0.90

TABLE 4 The comparison of different models in different indicators comes from the MLCO2 dataset, GCA dataset, GHGI dataset, and CCKP dataset.

Method	Datasets							
	MLCO2 (Tveter, 2020)		GCA (Franzen and Mader, 2019)		GHGI (Shi et al., 2021)		CCKP (Leal Filho et al., 2023)	
	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)
BIGRU-Transformer (Sheng et al., 2023)	545.47	64.65	463.46	58.22	488.83	67.18	513.15	43.53
GRU-Transformer (Lv et al., 2023)	456.78	66.52	450.44	69.27	572.58	66.37	519.76	47.58
CNN-GRU (Elmaz et al., 2021)	596.65	58.33	488.09	63.92	423.83	68.90	589.14	63.11
Attention-GRU (Yang et al., 2022)	455.06	77.36	468.67	65.23	451.20	65.25	457.94	68.75
SSA-GRU-Transformer (Wang et al., 2021)	523.03	68.85	499.87	63.21	432.91	71.55	683.71	47.42
SSA-CNN-GRU (Tang and Li, 2022)	588.36	56.58	445.16	55.06	426.75	50.55	685.36	73.04
Ours	416.45	55.28	425.5	44.25	419.33	65.32	542.45	40.56

approximately 10.16 in RMSE compared to SSA, about 13.05 compared to PSO, roughly 11.1 compared to QPSO, and approximately 15.93 compared to WOA. Similarly, on the GCA, GHGI, and CCKP datasets, our model demonstrated superior performance in various performance metrics.

The main reason for this significant performance advantage lies in the introduction of the Levy Flight strategy by ISSA. By employing a random step-length movement, ISSA enables the algorithm to explore the search space more extensively. Compared to SSA, PSO, QPSO, and WOA, ISSA possesses enhanced global search capabilities, effectively avoiding being trapped in local optima. Furthermore, ISSA enhances inter-individual information interaction and integration through information separation and self-attention mechanisms. Compared to other algorithms, ISSA maximizes the utilization of internal information within the group, thereby improving the algorithm's adaptability to complex problems. On the other hand, ISSA introduces an adaptive learning strategy, facilitating timely updates for individuals trapped in local optima to accelerate convergence speed. Compared to other methods, ISSA demonstrates dynamic individual adjustment capabilities, enhancing the accuracy of solutions. These series of experimental results indicate that the introduction of the ISSA module has a significantly positive impact on algorithm performance, showcasing outstanding performance across multiple datasets.

In Table 6, we conducted further experiments involving the removal of the GRU module, revealing significant advantages of our GRU model over competing models (LSTM, BILSTM, RNN, BIGRU) across four datasets (MLCO2, GCA, GHGI, CCKP) in terms of RMSE, MAE, SMAPE, and R2. For instance, on the MLCO2 dataset, our GRU model demonstrated outstanding performance in RMSE. Compared to LSTM, BILSTM, RNN, and BIGRU, our model achieved reductions of approximately 20.08, 13.97, 22.1, and 15.93, respectively.

This notable performance advantage can be attributed to the relatively lightweight design of the GRU module, featuring fewer parameters and higher computational efficiency. The gate mechanism in the GRU module provides increased flexibility, enabling better capture of long-term dependencies in sequences and consequently enhancing sequence modeling performance. Additionally, the GRU module's efficient information processing contributes to improved learning and representation of sequence features. Finally, the design of the GRU module facilitates the capturing of patterns in the data during the training process, enhancing the model's generalization performance. The effective

TABLE 5 Ablation experiments on the ISSA module come from the MLCO2 dataset, GCA dataset, GHGI dataset, and CCKP dataset.

Model	Datasets															
	MLCO2				GCA				GHGI				CCKP			
	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2
SSA	123.39	97.47	0.65	0.88	118.66	92.26	0.79	0.83	129.91	122.08	0.82	0.87	116.44	115.12	0.68	0.87
PSO	127.28	91.67	0.64	0.87	124.17	90.12	0.73	0.87	123.35	121.84	0.85	0.87	118.73	124.77	0.64	0.87
QPSO	125.33	90.74	0.62	0.86	128.52	92.48	0.65	0.85	134.22	111.26	0.81	0.86	116.77	115.92	0.61	0.85
WOA	128.16	93.24	0.69	0.85	127.76	95.78	0.64	0.83	135.88	122.94	0.65	0.85	120.73	128.93	0.62	0.84
Ours	113.23	89.12	0.60	0.91	118.20	85.12	0.59	0.91	115.2	104.12	0.65	0.89	115.2	94.12	0.58	0.90

TABLE 6 Ablation experiments on the GRU module come from the MLCO2 dataset, GCA dataset, GHGI dataset, and CCKP dataset.

Model	Datasets															
	MLCO2				GCA				GHGI				CCKP			
	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2	RMSE	MAE	SMAPE	R2
LSTM	133.31	93.47	0.74	0.89	128.66	92.24	0.78	0.87	139.91	132.08	0.88	0.86	118.44	115.12	0.63	0.89
BILSTM	127.20	93.67	0.74	0.88	134.17	90.11	0.77	0.86	133.35	131.84	0.82	0.85	118.73	124.77	0.74	0.88
RNN	135.33	94.74	0.72	0.87	138.52	92.49	0.75	0.88	124.22	121.26	0.83	0.84	116.77	115.92	0.68	0.88
BIGRU	128.16	94.24	0.79	0.86	137.76	95.77	0.65	0.89	125.88	132.94	0.64	0.88	125.73	128.93	0.82	0.85
Ours	113.23	89.12	0.60	0.91	118.20	85.12	0.59	0.91	115.20	104.12	0.65	0.89	115.2	94.12	0.58	0.90

modeling of sequential data by our GRU model enables more accurate predictions across multiple datasets.

4 Conclusion

In this study, we proposed an approach based on the combination of ISSA and GRU-Transformer models for time series prediction in the field of carbon neutrality. Through experiments, we conducted a thorough evaluation of the model on multiple datasets and compared its performance with competing models. The experimental results show that our model excels in various performance metrics, including lower RMSE and MAE values, as well as higher R2 scores. This indicates the potential and application prospects of our model in the carbon neutrality domain.

Despite achieving satisfactory results in time series prediction tasks, there are still some shortcomings in our model. Firstly, the robustness of our model in handling extreme cases needs improvement. In certain situations, such as sudden events or anomalies, the model's performance may degrade. Secondly, the training and optimization of the model still require significant computational resources and time, limiting its scalability and applicability. Therefore, future work needs to address these issues, further enhance the model's robustness, and optimize the training and tuning processes to make it more practical and scalable.

Looking ahead, carbon neutrality remains a crucial strategy in addressing global climate change. Our research provides a novel deep learning-based time series prediction method for the carbon neutrality domain, offering a powerful tool for better understanding and optimizing carbon neutrality measures. Future work can explore further applications of the model, including monitoring and management of carbon emissions sources, improvements in carbon capture and storage technologies, and optimization of carbon offset projects, among others. Additionally, further research and performance enhancements can be pursued to meet the requirements of different fields and applications. The combination model based on ISSA and GRU-Transformer presented in this study offers a new approach to time series prediction in the carbon neutrality domain, achieving a series of encouraging results. Despite the challenges and limitations, this research lays a solid foundation for future exploration and innovation in the carbon neutrality field, promising to provide more powerful tools and support for addressing global climate change issues.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding authors.

Author contributions

WJ: Investigation, Writing – review & editing. CL: Conceptualization, Writing – review & editing. QQ: Methodology, Writing – review & editing. ZW: Formal Analysis, Writing – original draft. LH: Project administration, Writing – original draft. ZX: Project administration, Writing – review & editing. BZ: Resources, Writing – original draft. JH: Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The spatial effect of integrated economy on carbon emissions in the era of big data: a case study of China

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The digital economy has the characteristics of resource conservation, which can solve China's high carbon emissions problems. The digital economy can quickly integrate with the real economy, forming an integrated economy. However, it is still unclear whether an integrated economy can effectively reduce carbon emissions and achieve China's 'dual carbon goals'. Therefore, this study takes 30 provinces in China as the research object, constructs the integration economy index system through the statistical data from 2011-2021, and explores the spatial effect of the impact of the integration economy on carbon emissions by using principal component analysis, coupled coordination model and spatial econometric model. The research results are as follows. (1) From 2011 to 2021, the comprehensive economy showed a trend of increasing yearly (from 0.667 to 0.828), and carbon emissions showed a slow decrease (from 0.026 to 0.017). (2) Due to the infiltration of China's economic development from the eastern to the western, the spatial distribution of the integrated economy shows a decreasing trend from east to west. The spatial distribution of carbon emissions may be related to China's industrial layout of heavy industry in the northern, and light industry in the southern, showing a trend of low in the south and high in the north. (3) The integrated economy can significantly reduce carbon emissions (the coefficients of influence, -0.146), and the reduction effect will be more obvious if spatial spillover effects are taken into account (-0.305). (4) The eastern coast, the middle reaches of the Yangtze River, and the middle reaches of the Yellow River economic zones all increase carbon emissions at a certain level of significance (0.065, 0.148, and 3.890). The Northeast, South Coastal and Southwest economic zones significantly reduce carbon emissions (-0.220, -0.092, and -0.308). The results of the Northern Coast and Northwest are not significant (-0.022 and 0.095). (5) China should tailor regional economic development policies, such as strengthening investment in digital infrastructure in the Northwest Economic Zone and fully leveraging the spatial spillover effects of integrated economy in the Northeast, Southern Coastal, and Southwest Economic Zones to reduce carbon emissions.

KEYWORDS

integrated economy, carbon emissions, digital economy, real economy, spatial effect, China

1 Introduction

In recent years, climate issues have become increasingly severe (Yuan et al., 2024), with frequent occurrences of extreme weather phenomena such as air pollution, haze pollution, and rising temperatures (Tian et al., 2022). According to the International Energy Agency (IEA), China has had the highest global carbon emissions since 2007 (Cheng et al., 2018).In response to concerns from the international community about China's willingness to contribute and share obligations towards global climate change goals, China and the United States signed the Sino-US Joint Declaration on Climate Change in 2014 (Gao et al., 2021; Xu et al., 2024).In 2021, the Central Committee of the Communist Party of China and the State Council issued the *Action Plan for Carbon Peak before 2030*, incorporating 'carbon peak and carbon neutrality' into the overall economic and social development, advocating for accelerating the green transformation of production and lifestyle, and ensuring the timely achievement of the 'carbon peak' goal before 2030 (Zhao et al., 2022; Feng et al., 2024).

In the era of big data, the integrated economy is the focus point for countries to seize the leading position in global strategy and has become an inevitable choice to solve the problem of carbon emissions (Shi and Sun, 2023; Sun et al., 2024). Integrated economy refers to the integration of the digital economy and real economy. The digital economy is the leading force in the current world technological revolution and industrial transformation, and many countries regard it as the new driving force for restructuring national core competitiveness (Wang et al., 2023). The real economy is the foundation of a country, the source of wealth, and the soul of industry, and is the strategic core of economic development for all countries (Cheng et al., 2023). With the vigorous development of digital technology, 'integrated economy' has become a new development model and concept (Liu et al., 2024).

In 2020, the Global Climate Action Summit released the Index Climate Action Road map, which proposed implementing 'digital' solutions in physical industries that can help reduce global carbon emissions by up to 15% (Feng et al., 2023a; Feng et al., 2023b). It can be seen that the integration of 'digital technology' and physical industries, namely the integrated economy, plays a sustained and powerful role in the process of carbon reduction (Lopes de Sousa Jabbour et al., 2022; Sun et al., 2024). To achieve economic leadership and reduce pollution, countries have issued strategic plans to promote the development of integrated economies (Granados and Gupta, 2013; Xu et al., 2018), such as the United States issuing the National Strategic Plan for Advanced Manufacturing (Fatima et al., 2020), Germany issuing The High Technology Strategy 2025 (Klippert et al., 2020), and the United Kingdom implementing the Extraordinary Export Plan. Made in China 2025 (Xu et al., 2017) also proposes carbon reduction measures to promote China's green and low-carbon development through intelligent manufacturing and an integrated economy (Wang et al., 2020). However, China is a vast country, and the status of the integrated economy and carbon emission is different in different regions. Studying the spatial effect of an integrated economy on carbon emission is of great theoretical and practical significance for realizing the coordinated development of the economy.

Based on this, this paper takes 30 provinces in China (excluding Hong Kong Special Administrative Region, Macao Special Administrative Region, Taiwan, and Tibet Autonomous Region due to difficulties in data acquisition) as the research object, uses panel data from 2011 to 2021 to construct a measurement system for the development level of the digital economy and the real economy, and applies the empirical method to analyze the spatial effect of the integrated economy on carbon emissions. We attempt to explore the following issues: (1) What is the current situation of China's integrated economy and carbon emissions? (2) What is the impact of an integrated economy on carbon emissions? (3) What is the spatial effect of the impact of an integrated economy on carbon emissions? (4) What policies should be increased to promote green and coordinated development across China's regions to jointly achieve the dual-carbon goal? So, the research content of this article mainly includes the following aspects. Firstly, this article uses *Principal Component Analysis (PCA)* to separately measure the results of the subsystems of the digital economy and the real economy. Based on the results of the digital economy and the real economy, a *coupled coordination model* is used to integrate the results of the two subsystems to calculate the integrated economy. Secondly, based on comprehensive economic and carbon emission data, the *Natural Breaks Classification* method using software such as *QGIS* is used to analyze its time evolution and spatial distribution trend. Thirdly, we use *Moran's index* to analyze the spatial autocorrelation of integrated economy and carbon emission levels. Fourthly, we use spatial econometric models to examine the impact of an integrated economy on carbon emissions and decompose its spatial effects. Fifthly, we classify the Chinese region into eight major economic zones and once again use spatial econometric models to analyze the heterogeneity of the impact of the integrated economy on carbon emissions in each region. Finally, based on the results, targeted policy recommendations are proposed to lay the foundation for achieving the 'dual carbon goals'.

The main contributions of this article are reflected in the following aspects. Firstly, the existing research gap lies in the fact that few scholars have measured the integrated economy. However, as an important form of economy, the integrated economy is different from the traditional real economy and digital economy. This article constructs a coupled coordination model based on the two subsystems of the integrated economy, the digital economy and the real economy, to accurately measure the level of China's integrated economy, filling the gap in existing research that lacks measurement of the integrated economy. Secondly, existing studies rarely mention the impact of an integrated economy on carbon emissions, and more tend to discuss the impact of a digital economy on carbon emissions. As a new form of economy, an integrated economy requires the penetration and unification of the digital economy and the real economy. This article incorporates the integration economy and carbon emissions into the same theoretical framework, analyzes the relationship between the two, and fills the gap in research on the relationship between the integration economy and carbon emissions. Finally, few scholars have considered the spatial heterogeneity of the impact of an integrated economy on carbon emissions. China, the subject of the study, is a vast country with a wide range of landmasses, and inter-regional development is bound to have differences. Our study of the spatial heterogeneity of the impact of the integrated economy on carbon emissions from the perspective of the eight economic zones has certain policy implications for the development of the integrated economy in China's provinces according to local conditions.

2 Literature review and analysis of theoretical mechanisms

2.1 Literature review

This paper divides the previous studies into three parts, integration economy-related studies, carbon emission-related studies, and studies on the relationship between integration economy and carbon emission.

Firstly, there are fewer studies on the converging economy, mainly focusing on exploring the intrinsic coordination mechanism between the subsystems of the converging economy, i.e., the digital economy and the real economy, as well as the current development situation (Sun et al., 2024). The digital economy promotes the development of China's real economy through industrial digitization and digital industrialization, with industrial structure optimization and upgrading as the intermediary (Hong and Ren, 2023). The impact of the digital economy on the real economy presents an inverted U-shaped feature, with a crowding-out effect in the eastern part of China and a promoting effect in the western part and the real economy (Jiang and Sun, 2020; Xu et al., 2021). At present, the integrated economy is showing a decreasing trend in the east, middle, and west, with problems such as insufficient integration depth, lack of key technologies, and lax market supervision (Zhang et al., 2022b). It is urgent to strengthen investment in technological innovation and digital infrastructure construction, create high-level manufacturing industries, and improve and strengthen digital governance to promote the deep integration of the digital economy and the real economy (Liu et al., 2022a).

Secondly, the research direction of carbon emissions mainly focuses on three aspects: the current status of carbon emissions (Xu et al., 2019), carbon peak prediction (Wang and Feng, 2024), and the influencing factors of carbon emissions (Tong, 2020; Xu, 2023). Firstly, the analysis of the current status of carbon emissions focuses on industries with high carbon concentration, regions with high carbon emissions, the carbon emissions of a certain region under China's 2030 carbon peak target, and the carbon emissions tracking of a specific location or factory (Li et al., 2016; Ahmadi et al., 2019). Secondly, regarding the research on carbon peak prediction, most of the previous researchers used big data models and scenario analysis methods to predict the future growth of carbon emissions. And the results show that most of the provinces and cities in China can achieve the goal of a carbon peak by 2030, and only individual regions, such as Hubao, Eyu and Elm, have difficulties in achieving a carbon peak (Zhang et al., 2022b; Dai et al., 2022). Finally, according to existing research, public policy factors such as carbon emission trading pilot programs and low-carbon city pilot policies (Zhao et al., 2022), industrial structure factors such as energy structure and industrial robots (Meng et al., 2018; Li and Zhou, 2021; Jiang et al., 2023), and macro technological factors such as outward direct investment, population aggregation, digital economy development (Zhao and Zhu, 2022; Liu et al., 2023), and technological innovation will all have an impact on carbon emissions, carbon intensity, or efficiency (Chen et al., 2023; Zha et al., 2023).

Thirdly, there is currently limited research on the relationship between integrated economy and carbon emissions. Most of the related research focuses on the impact of the digital economy, a subsystem of the integrated economy, on carbon emissions (Wu et al., 2022). Most studies suggest that the digital economy can improve carbon emission efficiency by reducing energy consumption (Jiang et al., 2023). The rationalization (advanced) of the industrial structure undermines (enhances) to some extent the carbon-emission efficiency-enhancing effect of the digital economy (Zhang et al., 2022a; Chang et al., 2023). The carbon reduction effect of the digital economy varies in different regions of China (Zhang et al., 2022a). The paths for the digital economy to reduce regional carbon emission intensity or enhance carbon emission efficiency mainly include increasing digital infrastructure and formulating policy guidance based on regional characteristics (Feng et al., 2023a; Feng et al., 2023b; Tang and Yang, 2023).

In summary, existing studies focus on the role of the digital economy or industrial development in reducing carbon emissions, but few scholars have scientifically measured the level of development of the convergence economy, and fewer studies consider its carbon reduction effect from the perspective of the integrated economy. Therefore, the main contributions of this article are reflected in the following aspects. Firstly, using reasonable methods and indicator systems to measure the integrated economy can fill the gap in the measurement of the integrated economy in the existing literature. Secondly, the innovative incorporation of integrated economy and carbon emissions into the same theoretical framework has deepened the theoretical research on low-carbon economy. Finally, analyze the current situation and inherent relationship between integrated economy and carbon emissions from a spatial perspective, and deepen relevant research in spatial economics.

2.2 Theoretical mechanisms

The integrated economy is a large economic system constructed by the digital economy subsystem and the real economy subsystem (Jiang et al., 2023). The process of integrating internal subsystems is essentially a process of mutual influence and mutual promotion, in which industrial digitization and digital industrialization are achieved (Hong and Ren, 2023). Therefore, industrial digitization and digital industrialization are external manifestations of an integrated economy. Digital industrialization refers to the continuous expansion of digital technology industries such as the Internet, big data, and cloud computing to form an industrial scale, manifested as the materialization of the digital economy (Peng et al., 2023). Industrial digitization refers to the application of digital technology to achieve intelligent manufacturing in the process of physical industry development, manifested as the digitization of the real economy (Yi et al., 2023). The integrated economy can effectively reduce carbon emissions, mainly through the multiplier effect of the digital economy and the efficiency effect of the real economy.

On the one hand, the digital economy has natural green and energy-saving characteristics, with a virtual and networked nature, which can realize low-carbon growth (Sun et al., 2024). The development of the digital economy has expanded the industrial cornerstone of the real economy, changed traditional business models, and injected green and low-carbon elements into the development of the real economy (Jiang and Sun, 2020). Firstly, the development of the digital economy has promoted the growth of digital industries such as the Internet and cloud platforms that rely on data elements. These digital industries are based on new digital facilities, driven by innovation, and have natural high-tech attributes. Knowledge and innovation spillovers together constitute the multiplier effect of numbers. In the development of the digital industry, through digital diffusion, green creation can be achieved and regional industrial carbon emissions can be reduced. Secondly, in the era of big data, people's product needs have completely changed. Through mining and analyzing data elements, some green and low-carbon needs have been deeply explored, guiding green innovation in enterprises. Modern enterprises have begun to be guided by consumer green demands, breaking away from the traditional value creation model of product research and development as the core.

On the other hand, using digital technology in the real economy can fully leverage the efficiency effect of innovative technology, accelerating the transformation and upgrading of the real industrial structure towards low-carbon and environmentally friendly green industries (Liu et al., 2023). The real economy provides a source of data elements for the digital economy, increasing the demand for digital technology in the real industry, driving digital technology innovation, improving innovation efficiency, and achieving regional carbon emissions reduction (Shi and Sun, 2023). Firstly, the major industries of the real economy involve various aspects of social life and are the main sources of carbon emissions. User characteristics, individual needs, unknown risks, etc. can be accurately analyzed and predicted through digital technology, reducing unnecessary carbon pollution and waste. Secondly, the integration of the physical industry and the digital economy can improve enterprise productivity, reduce unnecessary carbon emissions in the product manufacturing process, bring more value to the physical industry, and force enterprises to continuously engage in green innovation and achieve low-carbon development.

According to the theory of unbalanced growth, the path of economic development is full of obstacles and bottlenecks, such as shortages of technology, equipment, and products, and factor endowments (Qi et al., 2013). The current state and path of development, and policy orientations are not the same in different regions, so the phenomenon of imbalance is presented regionally, and therefore imbalance is the norm (Liu et al., 2022b). At the current stage of development in China, there are still some policies, resources, and factors that are biased, resulting in spatial differences in the integration economy and carbon emission levels. According to the theory of spatial economics, the integrated economy has both multiplier effects and efficiency effects. From a spatial perspective, there must be spatial spillover effects, that is, the integrated economy in the local area can affect the development of the integrated economy and other economic variables in the surrounding areas. According to the theory of externalities, carbon emissions are an important pollutant in the climate environment, and environmental pollution is bound to accumulate maliciously in the region, affecting the ecology and economy of the local and surrounding areas. In summary, the spatial performance of the integrated economy and carbon emissions will inevitably exhibit spatial agglomeration effects, and the impact of the integrated economy on carbon emissions has a certain spatial spillover effect.

3 Methods and data

3.1 Variable selection and data sources

3.1.1 Variable selection

3.1.1.1 Integrated economy

Referring to relevant research, this paper uses the coupling coordination model to measure the level of Integrated economy (*IE*) (Zhang et al., 2022). We divide *IE* into digital economy (*DE*) and real economy (*RE*) subsystems, establish index systems, and use principal component analysis (*PCA*) to independently calculate the comprehensive values of the two subsystems. Considering the availability of data, we refer to (Zhao et al., 2020) and measure the development level of the digital economy from the aspects of internet development and digital finance development. We measure the level of development of the real economy from three aspects: the scale and structure of the real economy and its future development. The specific indicators and attributes are shown in Table 1.

3.1.1.2 Carbon emissions

In this paper, carbon intensity (The Amount of carbon emissions/GDP) is used as a proxy variable for carbon emissions respectively. This paper uses apparent carbon emissions to measure the amount of regional carbon emissions. Data on carbon emission quantities are from China Emission Accounts and Datasets (CEADs) (Shan et al., 2016, 2018, 2020; Guan et al., 2021).

3.1.1.3 Other variables

According to the requirements of China's high-quality development: innovation, coordination, green, openness, and sharing, this paper selects eight control variables, as shown in Table 2. (1) Innovation. Scientific and technological innovation to guide industrial innovation and accelerate the realization of green transformation. Talent is the fundamental source of realizing green innovation. So, technology innovation intensity (*TI*) and innovative talents (*IT*) are the control variables associated with innovation. (2) Coordination. Regional coordination will accelerate the rate of inter-regional capital, technology, and talent flow, injecting capital vitality into the research and development of industrial carbon reduction technology. So, regional coordination (*RC*) and industry coordination (*IH*) are the control variables associated with coordination. (3) Green.

TABLE 1 Index measurement system of the digital economy and the real economy.

Subsystems	First-level indicators	Second-level indicators	Definition	Weights	Attribute
Digital Economy (*DE*)	Internet development	Internet penetration	Number of Internet broadband access users	0.196	+
		Practitioners	Number of employees in the computer services and software industry	0.200	+
		Industry output	Postal, telecommunications business volume	0.193	+
		Mobile subscription	Number of mobile phone users per 100 people	0.190	+
	Digital finance	Digital inclusive finance	China Digital Inclusive Finance Index	0.221	+
Real Economy (*RE*)	Industry scale	Output value	Gross real economic output	0.156	+
		Investment	Fixed investment	0.137	+
		Consumption	Total retail sales of social	0.156	+
		Import and export	Total import and export of goods	0.144	+
		Public income and expenditure	General fiscal revenue	0.156	+
			General fiscal expenditure	0.145	+
	Industry Structure	Non-agricultural employees	The proportion of non-agricultural employees	0.037	+
	Development potential	Industrial science and technology input intensity	Industrial R & D input above designated size/profit	0.069	+

Gross real economic output refers to GDP except finance and real estate industry, and '+' refers to the positive index.

The increase in green governance capacity will accelerate the research and development of digital green technology and solve the problem of high pollution and high energy consumption of heavy physical industry. So, green governance capability (*GG*) is the control variable associated with green. (4) Open. The diversification of capital can stimulate the vitality of enterprises to learn and introduce advanced carbon reduction technologies from abroad, and foreign investment will also inject new momentum into the development of domestic industries. So, foreign investment intensity (*FI*) and traffic-developed degree (*TD*) are the control variables associated with openness. (5) Sharing. Well-developed transportation is the basis for realizing the rapid circulation of physical industries. The Internet is the link of modern industrial connection and the basis for the development of the digital economy, which is of great significance to the green manufacturing of enterprises. Social consumption capacity is the embodiment of the purchasing power of the society, which pushes the industry to elaborate research and development of a more green and low-carbon, in order to provide green products and services. So, internet development level (*ID*) is the control variable associated with sharing. Among them, *TI*, *FI*, *TD*, and *ID* indicators are calculated by the entropy method, and the other indicators are logarithmically processed on the original data.

3.1.2 Data sources

This paper uses a sample of 30 provincial administrative units in China (excluding China's Hong Kong Special Administrative Region, Macao Special Administrative Region, Taiwan, and Tibet Autonomous Region, which has a lot of missing values) to conduct empirical analysis for the years 2011-2021. Data from the Chinese Research Data Services Platform (CNRDS) data service platform, Easy Professional Superior (EPS) database, China Carbon Accounting Database (CEADs), China Statistical Yearbook (2012-2022), China Energy Statistics Yearbook (2012-2022), China Information Industry Yearbook (2012-2022), Peking University Digital Inclusive Finance Index (2011-2021) Index Report, China E-Commerce Report (2011-2021), provincial statistical yearbooks and government work reports, etc., where missing values are filled in using linear interpolation.

3.2 Research method

The steps to use the method in this article are as follows: (1) Firstly, this article uses *Principal Component Analysis (PCA)* to separately measure the results of the subsystems of the digital economy and the real economy. (2) Secondly, based on the results of the digital economy and the real economy, a *coupled coordination model* is used to integrate the results of the two subsystems to calculate the integrated economy. (3) Thirdly, based on comprehensive economic and carbon emission data, the *Natural Breaks Classification* method using software such as *QGIS* is used to analyze its spatial distribution trend. (4) Fourthly, use *Moran's index* to analyze the spatial autocorrelation of integrated economy and carbon emission levels. (5) Fifthly, use spatial econometric models to examine the impact of an integrated

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TABLE 2 Control variable description table.

Indicator	Indicator description	Attribute
Technology innovation intensity (TI)	Technology expenditure/Regional fiscal revenue	+
	Patent Number	+
Innovative talents (IT)	Number of college students per 100,000	+
Regional coordination (RC)	Regional per capita GDP/National per capita GDP	+
Industry coordination (IH)	The tertiary industry output value/ Secondary industry output value	+
Green governance capability (GG)	Industrial pollution treatment investment	+
Foreign investment intensity (FI)	Foreign registered capital	+
	Total Foreign Investment	+
Traffic developed degree (TD)	Passenger capacity	+
	Cargo carrying capacity	+
Internet development level (ID)	Cable length/Provincial area	+
	Number of Internet access ports	+

' + ' refers to the positive index.

economy on carbon emissions and decompose its spatial effects. (6) Sixth, classify the Chinese region into eight major economic zones and once again use spatial econometric models to analyze the heterogeneity of the impact of the integrated economy on carbon emissions in each region. *PCA* and *Coupled Coordination Model* are used to measure the integrated economy in section 3.2.1. The *Natural Breaks Classification* is used to classify integrated economies and carbon emissions in section 3.2.2. *Moran's index* is used to test spatial correlation in section 3.2.3. The determination of spatial econometric models is in section 3.2.4. The classification of the eight major economic zones is in section 3.3.5.

3.2.1 Measurement models of the core indicator

3.2.1.1 PCA

Using the principal component analysis method to measure the development level of *DE* and *RE* subsystems can avoid the subjectivity of human empowerment and has certain reliability. The specific steps are as follows.

a. Construct the matrix according to the selection of each subsystem index. If there are n samples and p indices, then the original matrix x of size n × p can be formed as shown in Equation 1.

$$x = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix} = (x_1, x_2, \cdots, x_p) \tag{1}$$

b. The original matrix is standardized to obtain a standardized matrix X as shown in Equations 2–4.

$$X_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \tag{2}$$

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}, S_j = \sqrt{\frac{\sum_{i=1}^{n}(X_{ij} - \bar{X}_j)^2}{n-1}} \tag{3}$$

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1p} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{np} \end{bmatrix} = (X_1, X_2, \cdots, X_p) \tag{4}$$

c. Calculate the covariance matrix of the normalized sample as shown in Equations 5, 6.

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1p} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{np} \end{bmatrix} = (r_1, r_2, \cdots, r_p) \tag{5}$$

$$r_{ij} = \frac{1}{n-1}\sum_{k=1}^{n}(X_{ki} - \bar{X}_i)(X_{kj} - \bar{X}_j) \tag{6}$$

d. Calculate the eigenvalue λ and eigenvalue vector a of R where R is a positive semidefinite matrix, eigenvalue $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$ as shown in Equation 7.

$$a_1 = \begin{bmatrix} a_{11} \\ a_{21} \\ \cdots \\ a_{p1} \end{bmatrix}, a_2 = \begin{bmatrix} a_{12} \\ a_{22} \\ \cdots \\ a_{p2} \end{bmatrix}, \cdots, a_1 = \begin{bmatrix} a_{1p} \\ a_{2p} \\ \cdots \\ a_{pp} \end{bmatrix} \tag{7}$$

e. The principal component contribution rate c and the cumulative contribution rate s are calculated shown in Equation 8, and the *i-th* principal component corresponding to the eigenvalues with a cumulative contribution rate of more than 80% is extracted. The index calculation result is Y_i shown in Equation 9.

$$c = \frac{\lambda_i}{\sum_{k=1}^{p}\lambda_k}, s = \frac{\sum_{k=1}^{i}\lambda_k}{\sum_{k=1}^{p}\lambda_k}, (i = 1, 2, \cdots, p) \tag{8}$$

$$Y_i = a_{1i}X_1 + a_{2i}X_2 + \cdots + a_{Pi}X_P \tag{9}$$

3.2.1.2 The coupling coordination model

The coupling coordination degree model can measure the dependence and correlation between multiple subsystems to analyze the coordinated development level between subsystems, not only considering the overall coordination but also paying attention to the development of subsystems (Shao et al., 2016). This paper uses the coupling coordination model to calculate *IE*. The steps are as follows:

a. The maximum and minimum normalization processing is performed on the principal component calculation results of DE and RE subsystem (the 0 value in the calculation result is translated, and the translation unit is 0.1). Both DE and RE system indicators are positive indicators, so the formula is as shown in Equation 10.

$$Z_{itj} = \frac{(Y_{itj} - \min_{Y_j})}{(\max_{Y_j} - \min_{Y_j})} \quad (10)$$

where i,t,j refer to the region, year and index, respectively, j=1 refers to DE, j=2 refers to RE, Z_{itj} refers to the value of the normalized t year j index in region i, Y_{itj} refers to the value of the t year j index in region i, and $\max_{Y_j}$ and $\min_{Y_j}$ refer to the maximum and minimum values of the j index, respectively.

b. According to the calculation results, the comprehensive coordination index T_{ti} is calculated. DE_{ti} is Y_{it1} and RE_{ti} is Y_{it2}. The calculation formula is as shown in Equation 11.

$$T_{ti} = \alpha * DE_{ti} + \beta * RE_{ti} \quad (11)$$

α and β are coefficients of development and take 0.5 here.

c. Calculate the coupling level of the digital economy and real economy C_{ti}. The calculation formula is as shown in Equation 12.

$$C_{ti} = 2 * \frac{\sqrt{DE_{ti} * RE_{ti}}}{(DE_{ti} + RE_{ti})} \quad (12)$$

d. Calculate the coupling coordination degree, that is, IE. The calculation formula is as shown in Equation 13.

$$IE_{ti} = \sqrt{C_{ti} * T_{ti}} \quad (13)$$

e. According to the value range of the coupling coordination degree, it is divided into 10 grades by referring to, as shown in Table 3:

3.2.2 Natural breaks classification

This article uses *QGIS* software to draw a spatial distribution map of *IE* and *CE* in China, and the classification principle of the map is based on natural breaks classification. The natural breaks classification refers to a method of determining the segmentation structure based on the characteristics of the data itself. This method is commonly used for segmented analysis of time series or signal data, to identify turning points or structural changes in the data, thereby dividing it into different paragraphs or categories. The basic idea of natural breakpoint classification is to use the inherent properties of data to determine the optimal segmentation structure by detecting inflection or mutation points in the data. These inflection points or mutation points are called 'natural breaks', at which the properties of the data may undergo significant changes. By identifying these natural breakpoints, data can be divided into different paragraphs and further analyzed or processed for each paragraph. The natural breaks classification method can avoid the subjectivity of manual classification and classify data reasonably through machine clustering algorithms. This can reduce human bias and improve the objectivity and accuracy of classification results. This also helps to reveal the potential structure and patterns of data and improve the depth and accuracy of data analysis. To clarify the spatial distribution status of *IE* and *CE* in the 30 provinces studied in this article, the natural classification algorithm configured in *QGIS* software was used to divide the research data into three categories.

TABLE 3 *IE* grade division.

Value ranges	Grade standard	Value ranges	Grade standard
(0,0.1]	Extreme disorder (B1)	(0.5,0.6]	Reluctant integration (A1)
(0.1,0.2]	Serious disorder (B2)	(0.6,0.7]	Primary integration (A2)
(0.2,0.3]	Moderate disorder (B3)	(0.7,0.8]	Moderate integration (A3)
(0.3,0.4]	Mild disorder (B4)	(0.8,0.9]	Good integration (A4)
(0.4,0.5]	On the verge of disorder (B5)	(0.9,1]	Best integration (A5)

3.2.3 Spatial autocorrelation test method

We intend to use a spatial econometric model for regression analysis. Considering the possible spatial dependence and autocorrelation of *IE* and *CE*, we use *Global Moran's I* to test the spatial autocorrelation of *IE* as shown in Equation 14 and *CE* as shown in Equation 15. The calculation formula is as follows:

$$I_{IE} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(IE_i - \overline{IE})(IE_j - \overline{IE})}{S_{IE}{}^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (14)$$

$$I_{CE} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(CE_i - \overline{CE})(CE_j - \overline{CE})}{S_{CE}{}^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (15)$$

where n represents the number of research objects, I is Moran's I, S^2 is the variance, $S_{IE}{}^2 = \frac{\sum_{i=1}^{n}(IE_i - \overline{IE})^2}{n}$, $S_{CE}{}^2 = \frac{\sum_{i=1}^{n}(CE_i - \overline{CE})^2}{n}$, $\overline{IE}$ is the mean of IE, $\overline{CE}$ is the mean of CE and w_{ij} is the spatial weight matrix.

To increase the accuracy of the analysis, this paper adopts a nested weights matrix by an inverse-distance-based spatial weights matrix and an economic-based weights matrix (Case et al., 1993).

$$w = \varphi w_1 + (1 - \varphi) w_2,$$

$$w_1 = \begin{cases} 1/d_{ij}, i \text{ and } j \text{ have a common boundary} \\ 0, i \text{ and } j \text{ have no common boundary or } i = j \end{cases},$$

$$w_2 = \begin{cases} 1/|\bar{X}_i - \bar{X}_j|, i \neq j \\ 0, \ i = j \end{cases}.$$

Refer to Zhang et al. (2022c), φ=0.5,

$\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$ is the sum of all spatial weights. The value range of I is [-1,1], I>0 represents spatial positive correlation, I<0 represents spatial negative correlation, The closer $|I|$ is to 1, the stronger the spatial autocorrelation is.

3.2.4 Spatial econometric model

The spatial econometric model is different from the traditional econometric model, as it can consider spatial factors and reduce the estimation error. Traditional spatial econometric models include the spatial autoregressive model (*SAR*) as shown in Equation 16, spatial error model (*SEM*) as shown in Equation 17, and spatial Durbin model (*SDM*) as shown in Equation 18. The specific expressions are as follows:

$$SAR: CE_{it} = \beta_0 + \sum_{k=1}^{K} \alpha_k X_{ikt} + \rho WCE_{it} + \delta_{it} \tag{16}$$

$$SEM: CE_{it} = \beta_0 + \sum_{k=1}^{K} \alpha_k X_{ikt} + \varepsilon_{it}, \varepsilon_{it} = \lambda W \varepsilon_{it} + \mu_{it} \tag{17}$$

$$SDM: CE_{it} = \beta_0 + \sum_{k=1}^{K} \alpha_k X_{ikt} + \rho WCE_{it} + \varepsilon_{it} \tag{18}$$

where i is area, t is time, k is the influencing factor(*IE* and 8 control variables are included), β_0 is a constant term, α_k is the regression coefficient of the k-th influencing factor, X_{ikt} is the k-th influencing factor at time t in region i, ρ and λ are the spatial autoregressive coefficients, W is the n $\times$ 1-order spatial weight matrix, and δ_{it}, ϵ_{it} and μ_{it} are random error terms.

To determine which spatial econometric model to use, the Lagrange Multiplier Test (LM test) is carried out in this paper. The test results show that the statistic of Robust-LM in the two columns of Spatial error and Spatial lag rejects the null hypothesis at the significance level of 0.01, indicating that there are both error and lag effects, and the *SDM* model is selected. Subsequently, the Hausman test was used to determine whether the random effect model or the fixed effect model was used. The results show that the null hypothesis is rejected at the significance level of 0.01, that is, the fixed effect model is adopted. All test results are shown in Table 4.

3.2.5 The division of the eight major economic zones

To further analyze the regional heterogeneity of the carbon emission reduction effect of the integrated economy, we divide China (mainly refers to China's inland areas excluding Hong Kong, Macao, Taiwan, and other places) into eight groups according to the eight economic zones in *the Strategy and Policy for Coordinated Regional Development* of the Development Research Center of the State Council. Figure 1 shows the distribution of China's eight economic zones.

According to Figure 1, the northern coastal comprehensive economic zone includes Beijing, Tianjin, Hebei and Shandong provinces. The Northeast Comprehensive Economic Zone includes Liaoning, Jilin and Heilongjiang provinces. The eastern coastal comprehensive economic zone includes Shanghai, Jiangsu and Zhejiang provinces. The southern coastal economic zone includes Fujian, Guangdong and Hainan provinces. The comprehensive economic zone in the middle reaches of the Yangtze River includes Hubei, Hunan, Jiangxi, and Anhui provinces. The southwest comprehensive economic zone includes Yunnan, Guizhou, Sichuan, Chongqing, and Guangxi provinces. The comprehensive economic zone of the middle reaches of the Yellow River includes Shaanxi, Shanxi, Henan, and Inner Mongolia provinces. The Northwest Comprehensive Economic Zone includes Gansu, Qinghai, Ningxia, Tibet, and Xinjiang provinces. It is worth noting that when dividing the region, Tibet belongs to the Northwest Comprehensive Economic Zone. However, due to the difficulty of counting data for Tibet, only the other four provinces in the Northwest Comprehensive Economic Zone are counted in this paper.

TABLE 4 Model test process and results.

Test		Statistic	selection
LM	Spatial error(R-LM)	19.085***	Spatial Durbin
	Spatial lag(R-LM)	20.846***	
Hausman	chi-square	34.730***	Fixed Effect
The final application model		SDM with fixed effect	

*** indicate that the statistics are significant at the significance level of 0.01. The values in the table retain the last three decimal places, the same below.

4 Results

4.1 Measurement results of the integrated economy

According to the coupling coordination model, the results of the *IE* in China from 2011 to 2021 are shown in Table 5.

The grade of *IE* in the 30 provinces of China continued to rise from 2011 to 2021, and the overall transformation from primary integration (A2) to good integration (A4) and the integration status was good in recent years. In 2011, most provinces were in a state of primary integration (A2, 41.9%) and moderate integration (A3, 22.6%). In 2021, most provinces were in a state of moderate integration (22.6%) and good integration (45.2%). Guangdong has been at a high level of integration for a long time. Beijing, Jiangsu, Zhejiang, and other head provinces are second only to Guangdong. It is worth noting that the DRID in Hainan, Qinghai, Ningxia, and Tibet has been in a state of imbalance or low integration, showing a significant gap with the integration of other provinces.

4.2 The time evolution and spatial distribution of *IE* and *CE*

4.2.1 Trends in time evolution

The national average time evolution of *IE* and *CE* from 2011 to 2021 is shown in Figure 2. It can be seen from Figure 2 that *IE* shows a growth trend, and *CE* shows a general downward trend. It can be seen that China has a significant implementation effect on the integration of the digital economy and real economy and the promotion of low-carbon emission reduction policies. With the development of digital technology, physical industry manufacturing began to shift to the intelligent trend, and the development of the integrated economy is bound to show an upward trend. However, after 2019, due to the impact of the epidemic, the overall pace of economic development has slowed down, which has caused a certain impact on both the physical industry and the digital

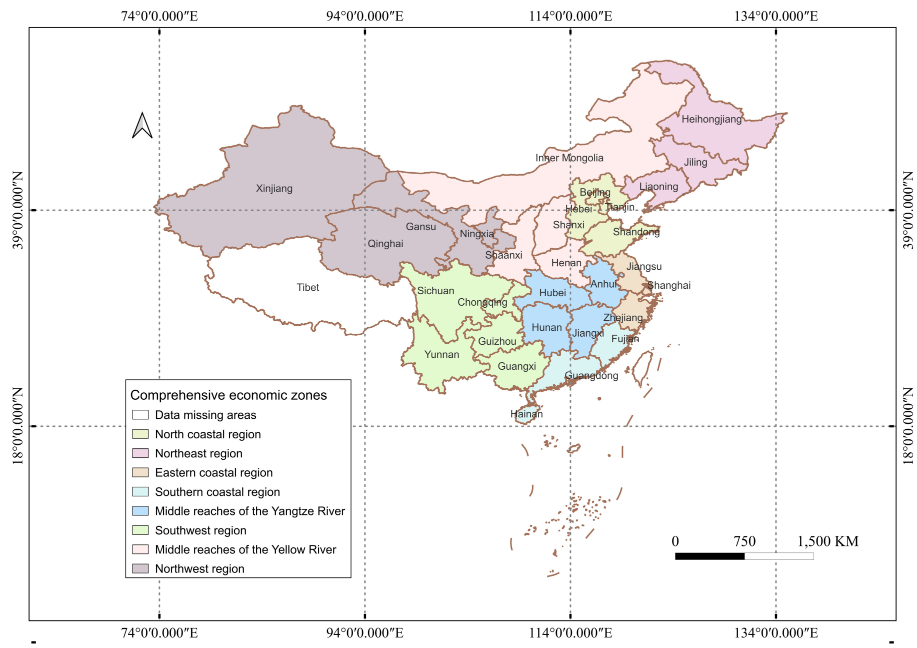

FIGURE 1
Distribution of China's eight economic zones.

TABLE 5 The level of *IE* in China from 2011 to 2021.

Province	2011	2013	2015	2017	2019	2021	Changes in *IE*'s grade
Mean	0.655	0.750	0.780	0.800	0.843	0.817	A2→A4
Beijing	0.813	0.866	0.892	0.907	0.930	0.923	A4→A5
Tianjin	0.685	0.744	0.772	0.785	0.817	0.816	A2→A4
Hebei	0.719	0.802	0.826	0.846	0.891	0.878	A3→A4
Shandong	0.781	0.862	0.890	0.908	0.936	0.922	A3→A5
Liaoning	0.754	0.829	0.829	0.829	0.856	0.829	A3→A4
Jilin	0.638	0.734	0.759	0.774	0.791	0.748	A2→A3
Heilongjiang	0.640	0.733	0.757	0.773	0.802	0.769	A2→A3
Shanghai	0.791	0.850	0.871	0.889	0.926	0.939	A3→A5
Jiangsu	0.822	0.893	0.918	0.934	0.971	0.960	A4→A5
Zhejiang	0.819	0.878	0.908	0.929	0.962	0.958	A4→A5
Fujian	0.747	0.820	0.843	0.863	0.897	0.883	A3→A4
Guangdong	0.863	0.929	0.952	0.973	1.000	0.988	A4→A5
Hainan	0.490	0.610	0.642	0.671	0.721	0.688	B5→A2
Jiangxi	0.612	0.728	0.771	0.792	0.846	0.839	A2→A4
Hubei	0.705	0.791	0.825	0.843	0.891	0.864	A3→A4
Hunan	0.676	0.772	0.802	0.824	0.880	0.864	A2→A4
Anhui	0.656	0.760	0.796	0.820	0.878	0.865	A2→A4
Guangxi	0.633	0.726	0.770	0.791	0.846	0.814	A2→A4

(Continued)

TABLE 5 Continued

Province	2011	2013	2015	2017	2019	2021	Changes in *IE*'s grade
Chongqing	0.650	0.750	0.788	0.809	0.855	0.834	A2→A4
Sichuan	0.713	0.811	0.845	0.867	0.916	0.889	A3→A4
Guizhou	0.551	0.693	0.739	0.767	0.824	0.783	A1→A3
Shaanxi	0.690	0.772	0.803	0.823	0.870	0.839	A2→A4
Henan	0.691	0.807	0.841	0.867	0.914	0.895	A2→A4
Shanxi	0.656	0.747	0.772	0.777	0.822	0.806	A2→A4
Inner Mongolia	0.668	0.755	0.766	0.776	0.815	0.777	A2→A3
Gansu	0.530	0.665	0.704	0.716	0.766	0.704	A1→A3
Qinghai	0.385	0.526	0.568	0.576	0.628	0.572	B4→A1
Ningxia	0.430	0.554	0.596	0.629	0.665	0.625	B5→A2
Tibet	0.316	0.412	0.452	0.506	0.576	0.484	B4→B5
Xinjiang	0.577	0.700	0.721	0.739	0.802	0.765	A1→A3

Due to the limited space, this paper only gives the calculation results of some years.

industry. Therefore, the development of an integrated economy has a little downward trend. In recent years, President Xi Jinping has put forward the green development concept of 'green mountains are golden mountains' and the dual-carbon goal of 'achieving carbon peak by 2030 and carbon neutrality by 2060', which has made people more concerned about green development and reducing carbon emissions. Carbon emissions have begun to show a downward trend year by year. However, due to China's large population and industrial base, energy consumption is still high all year round, and the downward trend is not obvious.

4.2.2 Spatial distribution and evolutionary trends

In order to clarify the evolution trend of the spatial distribution of *IE* and *CE*, the spatial distribution maps of *IE* and *CE* in 2011 and 2021 are drawn respectively, as shown in Figures 3–6. In this paper, the relevant maps are drawn by QGIS software, and the classification principle of drawing is based on Python's natural breaks classification.

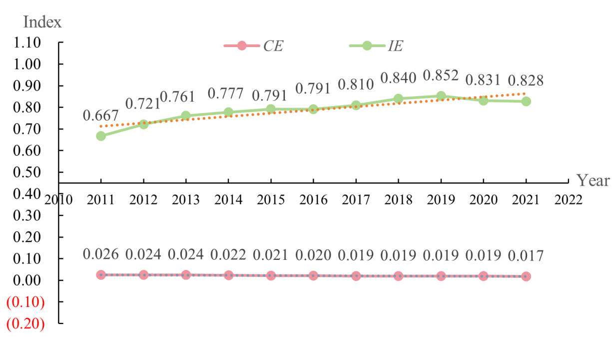

FIGURE 2
Time evolution trend of *IE* and *CE* from 2011 to 2021. The red font is a negative value.

Figures 3 and 4 show the spatial distribution of *IE* in 2011 and 2021. From Figures 3 and 4, it can be seen that, firstly, the regions with high *IE* values in 2011 are mainly concentrated in the eastern coastal provinces, while Qinghai, Gansu, Ningxia, Guizhou, and Hainan have low *IE* values, and most of the central regions have medium *IE* values. It can be seen that in 2011, *IE* had just started and had not yet been popularized nationwide, and the eastern region had been ahead of other regions in realizing the integration of the digital economy with the real economy. Second, in 2021, the *IE* dominant regions started to penetrate the interior, and Henan, like many coastal cities, had a high level of *IE*. The three western poor regions of Qinghai, Gansu, and Ningxia have relatively low *IE*, and most central provinces still have medium *IE* levels. Finally, according to the categorized data in the legend, it can be seen that from 2011 to 2021, the level of *IE* in each province has been increasing and the inter-provincial gap has been narrowing. In short, the spatial distribution of *IE* shows a trend of 'decreasing from east to west', with regional differences decreasing with the evolution of time.

Figures 5 and 6 show the spatial distribution of *CE* from 2011 to 2021. According to Figures 5 and 6, firstly, the *CE* in 2011 shows a polarization trend of low in the south and high in the north, and regions with high *CE* account for the majority of the country. Ningxia and Shanxi may have a higher *CE* than the rest of the country because of the development of heavy-polluting industries such as coal, iron, and steel. Secondly, by 2021, the *CE* low-level areas in 30 provinces will be far more than the medium-level areas, and only Shanxi Province has a long-term high *CE* due to the development of coal and mineral resources. Finally, from 2011 to 2021, *CE* decreased to a certain extent, and the low-emission area expanded significantly, indicating that the carbon emission reduction policy has achieved some success. Overall, China's *CE* shows a distribution of 'low in the south and high in the north', with low-carbon areas continuing to spread from south to north.

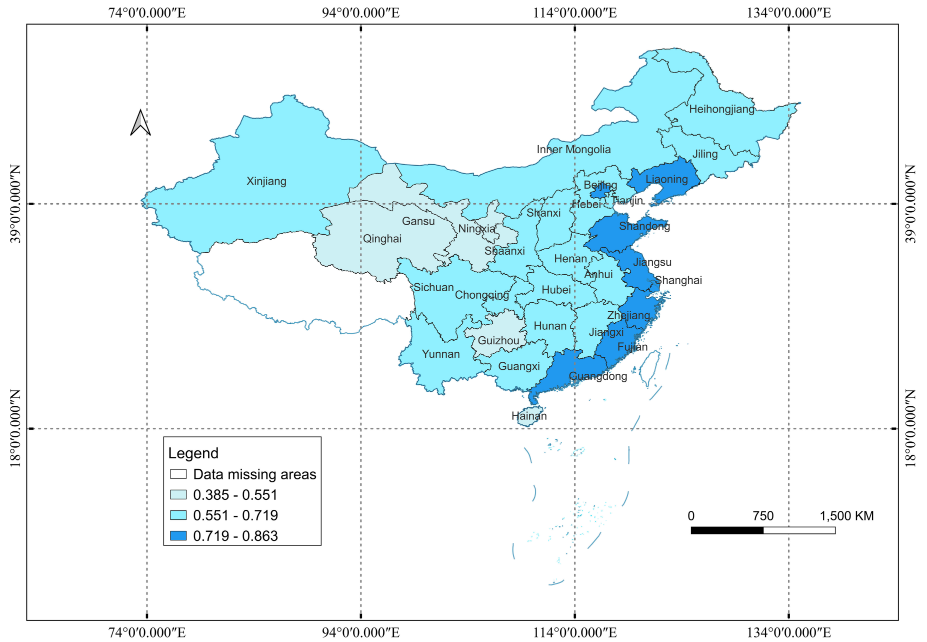

FIGURE 3
The spatial distribution of *IE* in 2011.

4.3 Spatial autocorrelation of *IE* and *CE*

4.3.1 Global spatial autocorrelation

Figure 7 shows the evolution of spatial correlation between *IE* and *CE* from 2011 to 2021.

First of all, it can be seen from Figure 7 that *IE* has strong spatial autocorrelation, that is, places with strong *IE* tend to gather positively, and vice versa. Secondly, except for 2013 to 2015 (in 2013-2015, *CE* was negatively correlated but the results were not significant and not statistically significant), *CE* has a positive and significant spatial correlation, which indicates that *CE* has 'good neighbors' or 'beggar neighbors'. Finally, the spatial correlation of *IE* is much higher than that of *CE*, indicating that the economic effect is more likely to form spatial agglomeration than the environmental effect.

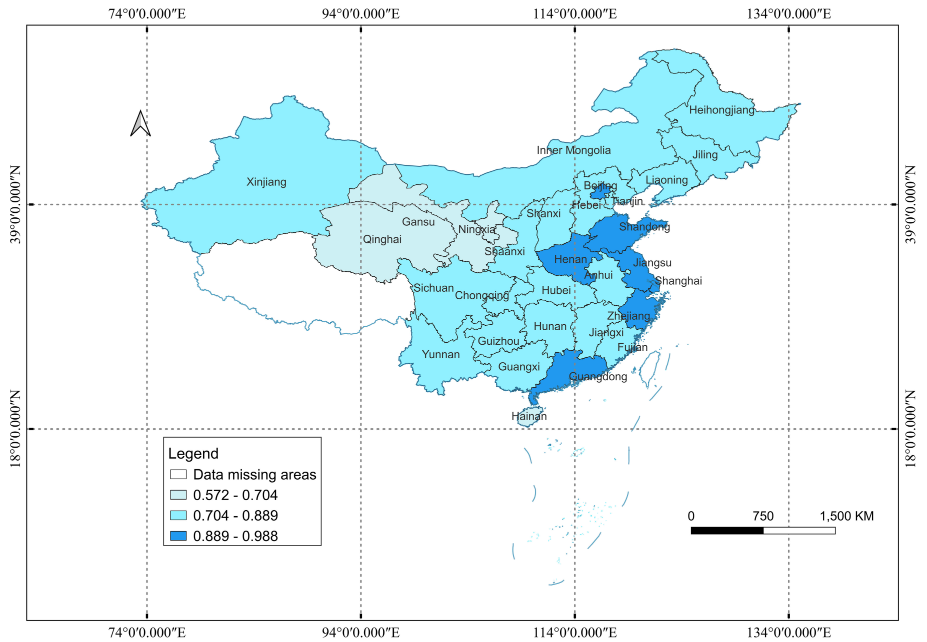

FIGURE 4
The spatial distribution of *IE* in 2021.

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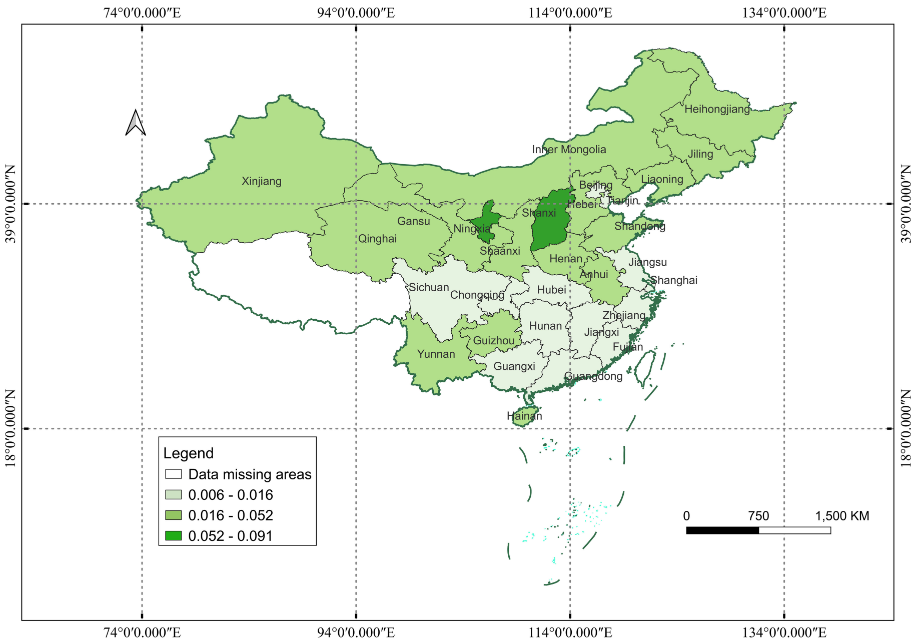

FIGURE 5
The spatial distribution of *CE* in 2011.

4.3.2 Local spatial correlation

The local Moran's I index is the key to accurately capturing the heterogeneity of local spatial elements, reflecting the correlation between the value of an attribute in a region and neighboring regions (He et al., 2023). In this paper, the Moran index scatter plots of *IE* and *CE* from 2011 to 2021 are drawn to describe the local spatial correlation. Due to space limitations, only the Moran scatter plots of 2011 and 2021 are shown, as shown in Figures 8, 9.

According to Figure 8, we can see that the *IE* of 30 provinces is mainly concentrated in the first and third quadrants from 2011 to 2021, indicating that 'good neighbors' and 'beggar neighbors' coexist. This two-way agglomeration may lead to the emergence

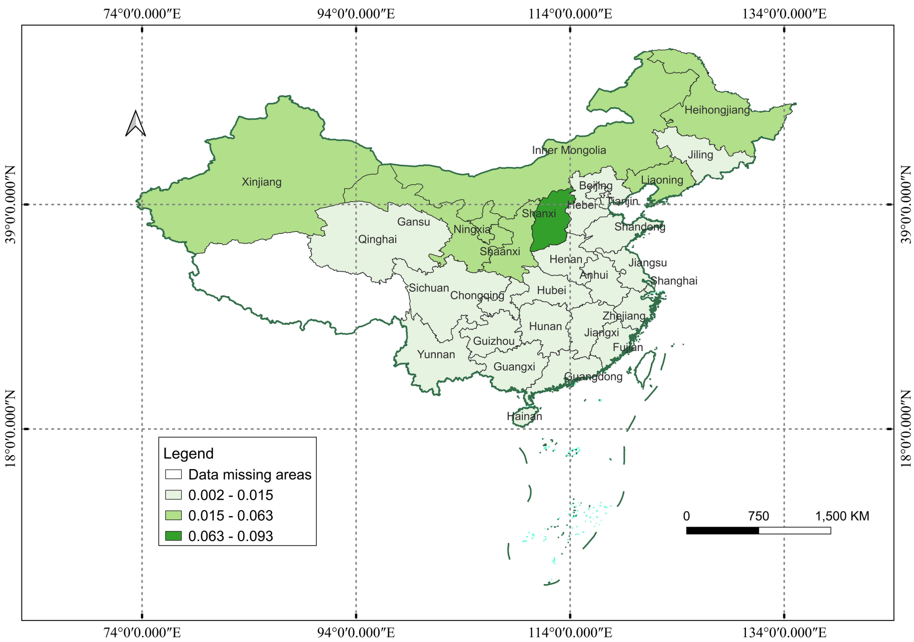

FIGURE 6
The spatial distribution of *CE* in 2021.

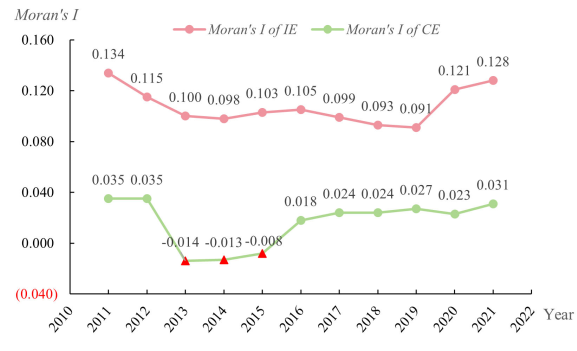

FIGURE 7
Moran's I of *IE* and *CE* from 2011 to 2021. The red triangles in the figure are marked as insignificant results, and the others are significant at the significance level of 0.01 or 0.1. The red font is a negative value.

of a gap. It can be seen from Figure 9 that the Moran scatter plot of 30 provinces in China in 2011 is mainly concentrated in the second and third quadrants, and the third quadrant is more, indicating that mixed agglomeration and 'low-low agglomeration' coexist, and the agglomeration of places with lower carbon emissions is more obvious. The Moran scatterplot of China's 30 provinces in 2021 is mainly concentrated in the third quadrant, significantly more than in 2011, indicating that the carbon emission situation has eased in the past 10 years, and the low-carbon emission areas have increased and continued to gather.

4.4 The spatial effect of *IE* on *CE*

4.4.1 Spatial econometric model results

4.4.1.1 Spatial modeling regression results

The measurement results of *SDM* with fixed time are shown in Table 6. According to Table 6, first of all, the spatial autoregressive coefficient is -0.383, which is significant at the significance level of 0.05, indicating that the more concentrated the regions with large carbon emissions, the more conducive to centralized governance and the easier it is to reduce carbon emission intensity. Secondly, *IE* can significantly inhibit *CE*, and the coefficients are -0.146 and -0.305 without considering and considering the spatial effect of the spatial matrix, respectively. It can be seen that *IE* has a stronger inhibitory effect on *CE* when considering spatial spillover. Finally, under the consideration of the spatial matrix, the control variables such as *TI*, *RC*, *GG*, etc. have a significant reduction effect on *CE*.

4.4.1.2 Spatial Spillover Effect Decomposition

To further analyze the spatial effect of *IE* on *CE*, the spatial spillover effect is decomposed, and the results are shown in Table 7. It can be seen from Table 7 that the direct and spatial effects of *IE* on *CE* are significant, and the indirect inhibitory effect on *CE* is stronger than the direct effect.

4.4.2 Robustness test

The robustness test of this paper is divided into two categories: First, the robustness test of the model. On the one hand, according to the model selection process in Table 4 in section 3.2.4, it can be determined that the model selected in this paper is appropriate. On the other hand, to further determine the credibility of the conclusions, the SDM model with both OLS and individual time fixed is selected for testing in this paper. Second, the robustness test of the spatial matrix. In this paper, the economic distance matrix is used for the test. The above test results are shown in Table 8. According to Table 6, it can be seen that *IE* has a significant reduction effect on *CE* (all at the 0.01 level of significance), indicating that the previous test results are robust.

4.5 Regional heterogeneity analysis

Spatial econometric regression of the data for the eight integrated economic zones based on the selected time-fixed SDM model described above is shown in Table 9. *IE* in the North Coastal Economic Zone all had a reducing effect on CE, but the results were not significant. The Northeast Economic Zone, the Southern

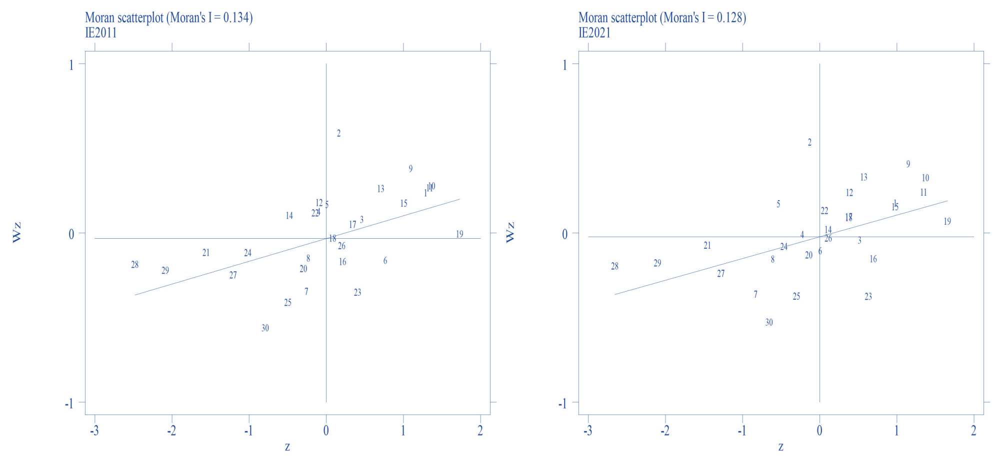

FIGURE 8
Moran scatterplot of *IE* in 2011 and 2021.

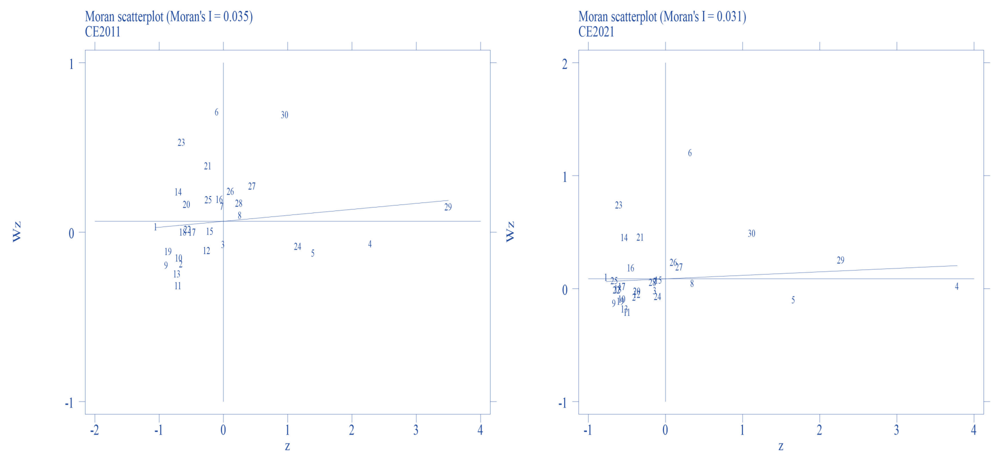

FIGURE 9
Moran scatterplot of *CE* in 2011 and 2021.

TABLE 6 Model measurement results.

variable	coefficient	standard error	Z	p
IE	-0.146***	0.023	-6.410	0.000
TI	-0.006	0.013	-0.500	0.619
IT	0.0183***	0.006	2.920	0.003
RC	-0.001	0.004	-0.220	0.829
IH	-0.000	0.003	-0.100	0.923
GG	0.0108***	0.001	8.280	0.000
FI	0.0180	0.014	1.320	0.187
TD	-0.009	0.011	-0.820	0.411
ID	-0.017	0.017	-1.040	0.296
W**IE*	-0.305**	0.130	-2.350	0.019
W**TI*	-0.242***	0.076	-3.170	0.002
W**IT*	0.221***	0.038	5.780	0.000
W**RC*	-0.081***	0.030	-2.740	0.006
W**IH*	-0.010	0.023	-0.440	0.658
W**GG*	-0.016**	0.008	-2.090	0.037
W**FI*	0.130	0.102	1.280	0.202
W**TD*	0.075	0.060	1.250	0.213
W**ID*	0.401***	0.097	4.120	0.000
ρ	-0.383**	0.157	-2.440	0.015
N	330			
R^2	0.119			
Log-L	926.5552			

*, **, *** indicate that the statistics are significant at the significance levels of 0.1,0.05 and 0.01, respectively.

Coastal Economic Zone, and the Southwest Economic Zone *IE* have significant decreasing effects on *CE* (coefficients of -0.220, -0.092, and -0.308), and the decreasing effects are even stronger when spatial effects are taken into account (-0.344, -0.118, and -0.724). The Eastern Coastal Economic Zone and the Middle Yangtze River Economic Zone *IE* have a significant contributing effect on *CE*. However, it is not significant when spatial effects are considered. The middle reaches of the Yellow River economic zone *IE* have a significant contribution to *CE* (3.890), which is stronger when spatial effects are considered (11.668). The Northwest Economic Zone *IE* has a facilitating effect on *CE* when spatial effects are considered (1.947). In addition, different control variables have different effects in different regions.

5 Discussion

5.1 Discussion of results

The main contributions of this article are reflected in the following aspects. Firstly, using reasonable methods and indicator systems to measure the integrated economy can fill the gap in the measurement of the integrated economy in the existing literature. Secondly, the innovative incorporation of integrated economy and carbon emissions into the same theoretical framework has deepened the theoretical research on low-carbon economy. Finally, analyze the current situation and inherent relationship between integrated economy and carbon emissions from a spatial perspective, and deepen relevant research in spatial economics. Therefore, for the discussion of the test results this paper will develop 3 aspects. (1) An in-depth discussion of the measured results of the integrated economy and carbon emissions, which includes a discussion of the temporal evolution, spatial distribution, and spatial correlation of *IE* and *CE*. (2) In-depth discussion of the test results of the impact of an integrated economy on carbon

TABLE 7 Spatial spillover effect decomposition results.

variable	Direct	Indirect	Total
IE	-0.140***(0.023)	-0.180*(0.093)	-0.320***(0.096)
TI	-0.002(0.012)	-0.183***(0.061)	-0.185***(0.066)
IT	0.014**(0.006)	0.161***(0.029)	0.175***(0.031)
RC	0.009(0.004)	-0.062***(0.020)	-0.061***(0.021)
IH	-0.000(0.003)	-0.007(0.018)	-0.007(0.018)
GG	0.011***(0.001)	-0.016***(0.006)	-0.005(0.006)
FI	0.016(0.013)	0.093(0.077)	0.109(0.081)
TD	-0.011(0.010)	0.061(0.048)	0.050(0.046)
ID	-0.026(0.016)	0.306***(0.078)	0.280***(0.082)

*, **, *** indicate that the statistics are significant at the significance levels of 0.1,0.05 and 0.01, respectively. The numbers in parentheses are standard errors. The same is below.

emissions. (3) In-depth discussion of the regional heterogeneity of the impact of the integrated economy on carbon emissions in the eight economic regions.

5.1.1 In-depth discussion of measurement results

In this section, the results of the *IE* and *CE* measurements are discussed, which are mainly divided into the discussion of the results of the *IE* measured by the coupled coordination model, the evolutionary characteristics of the *IE* and *CE*, and the spatial autocorrelation of *IE* and *CE*.

5.1.1.1 Measurement results of the integrated economy

Table 5 shows the measurement results of the integrated economy. Firstly, the *IE* grades of China's 30 provinces show an upward trend during the study period, and the overall shift from A2 to A4 is realized, which is consistent with the findings of (Zhang et al., 2022). This indicates that China's economy still maintains a high level of growth, and *IE* formed by the coupling and coordination of the digital economy and the real economy has become a new type of economic form. This is related to China's policy move since 2015 to focus on the real economy and vigorously develop the digital economy. This paper constructs an indicator system to measure the development level of the real economy from three aspects: scale, structure, and development potential, which is different from the measurement of the real economy by scholars such as (Zhang et al., 2022; Shi and Sun, 2023), and has certain innovation and application value. Secondly, the level of *IE* varies among the 30 provinces in the country. Guangdong has been highly integrated for a long time. The headline provinces of Beijing, Jiangsu, and Zhejiang are second only to Guangdong. Notably, the *IE* of Hainan, Qinghai, Ningxia, and Tibet have been in an unbalanced or low integration state, with a large gap between their integration levels and those of other provinces. Differences in regional development are related to China's policy preferences. China's economic development started in the eastern coastal region and penetrated from the east to the west (Chen, 2022). Thus Guangdong, Beijing, Jiangsu, and Zhejiang have higher levels of integrated economic development than Qinghai, Ningxia, and Tibet in the west. This reveals that China should make full use of the penetration effect of the eastern region in policy formulation to reduce regional differences.

5.1.1.2 The time evolution and spatial distribution of *IE* and *CE*

Figure 2 shows the change in national mean time for *IE* and *CE* from 2011 to 2021. From Figure 2, it can be seen that *IE* shows an increasing trend (decreasing after 2019) and *CE* shows a slow decreasing trend in general. The fluctuation of *IE* in 2019 is related to the impact of the new crown epidemic on the development of the real economy (Takyi et al., 2023). As China's national attention to carbon reduction and emission reduction continues to increase, and policy pilots continue to grow, carbon emissions will also show a significant downward trend (Feng et al., 2024). However, given China's large energy consumption base, carbon emissions will only decline slowly.

Figures 3 and 4 show the spatial distribution of *IE* in 2011 and 2021. Comparing the two figures, it can be found that: firstly, from 2011 to 2021, the level of *IE* in each province has been increasing, and the inter-provincial gap has been decreasing. This suggests that China's policy initiatives for *IE* have achieved some success, and the digital economy can effectively reduce regional disparities (Zhou et al., 2023), which is consistent with the findings of (Zhang et al., 2022). The spatial distribution of *IE* shows the trend of "decreasing from the east to the west", and regional disparities are reduced over time, which is similar to the results of the study of (Wu et al., 2023). This is related to China's long-standing policy bias, where all of China's eastern coastal cities are developed cities, the western region is economically backward, and environmental and geographic factors are strong impediments to the development of the economy, so the regional distribution of most economic forms shows a decreasing trend from east to west. The results of this paper reveal the spatial evolution trend of *IE*, effectively proving the

TABLE 8 Results of the robustness test.

	Model replacement				Spatial matrix replacement	
	OLS		SDM (both fixed)			
IE	-0.086***	-0.107***	-0.105***	-0.060***	-0.054***	-0.101***
Cons/ρ	0.088***	-0.062	-0.216	-0.223	-13.116***	-11.206***
N	330	330	330	330	330	330
R^2	0.187	0.344	0.173	0.037	0.323	0.525
Controls	No	Yes	No	Yes	No	Yes

*** indicate that the statistics are significant at the significance level of 0.01.

TABLE 9 The spatial econometric regression results of the eight comprehensive economic zones.

variable	Northern coastal	Northeast	Eastern coastal	Southern coastal	Middle reaches of the Yangtze River	Southwest	Middle reaches of the Yellow River	Northwest
IE	-0.022	-0.220***	0.065*	-0.092***	0.148***	-0.308***	3.890***	0.095
TI	-0.005	0.097***	0.005	0.001	-0.043***	-0.027	0.099	0.147**
IT	-0.002	0.040***	0.022***	-0.0122	-0.029***	-0.004	-0.202***	-0.044***
RC	-0.000	0.001	0.095***	0.044***	-0.000	0.041***	0.036	-0.041***
IH	0.000	0.011***	0.011**	0.012***	0.002	0.011**	-0.067***	0.034**
GG	0.001	-0.002**	0.005***	0.001	0.002***	-0.002	0.018**	0.004
FI	-0.016**	0.134***	-0.064*	-0.012***	-0.097**	0.0169	-23.548***	-0.212
TD	0.005**	-0.002	0.005	0.009***	-0.004	0.020	-0.117	-0.166***
ID	0.030***	-0.101***	0.062***	-0.039***	-0.110***	-0.026	-0.141	-0.010
W**IE*	-0.073	-0.344***	0.036	-0.118***	0.104	-0.724***	11.668***	1.947***
W**TI*	-0.027	0.152***	0.005	-0.006	-0.059***	-0.144**	-0.001	0.064
W**IT*	0.000	0.062***	0.049***	-0.024	-0.064***	0.070**	-0.467***	-0.084
W**RC*	0.029	0.025**	0.188***	0.098***	0.034**	0.199***	0.254**	-0.094**
W**IH*	0.012	0.024***	0.003	0.038***	0.0169	0.046**	-0.159***	0.035
W**GG*	0.003	-0.004**	0.009***	0.002**	0.004**	0.001	0.051**	0.022**
W**FI*	-0.163***	0.114	-0.057	-0.024***	-0.468***	-0.136	-65.247***	-3.399
W**TD*	0.021***	-0.011	0.011	0.010**	-0.037**	0.046	-0.307	-0.234***
W**ID*	0.109***	-0.273***	0.139***	-0.050**	-0.320***	-0.056	-0.296	-0.212
ρ	-0.122	-0.110	0.128	-0.043	-0.335	-0.138	-0.256	-0.230
N	330	330	330	330	330	330	330	330
R^2	0.579	0.226	0.605	0.350	0.458	0.351	0.025	0.139
Log-L	290.531	226.660	271.457	248.790	274.706	297.551	196.551	181.496

*, **, *** indicate that the statistics are significant at the significance levels of 0.1,0.05 and 0.01, respectively.

important role of the digital economy in narrowing regional gaps and promoting high-quality development.

Figures 5 and 6 show the spatial distribution of *CE* in China from 2011 to 2021. The comparison shows that the national distribution of China's *CE* has changed from polarization (i.e., the gap between *CE* in the north and south regions was large in 2011) to a trend of concentration and diffusion (i.e., a smaller gap between *CE* in the north and south in 2021, with regional agglomeration). 2011, China's industrial layout was that the north was dominated by heavy industry, the south was dominated by light industry and service industry, and the north's carbon emissions were higher. In 2011, China's industrial layout was dominated by heavy industries in the north and light industries and services in the south, with higher carbon emissions in the north. By 2021, after 10 years of industrial transformation and the application of decarbonization technologies, carbon emissions in the north will be lower, and thus the gap between the north and the south of *CE* will be gradually narrowed. The results of this study are similar to (Wang et al., 2014), but this paper reveals the trend and characteristics of *CE*, which is a reference value for understanding the current situation of *CE* in China's provinces.

5.1.1.3 Spatial autocorrelation of *IE* and *CE*

Figure 7 plots the trend of the global *Moran's index* of *IE* from 2011 to 2021. First, *IE* has strong spatial autocorrelation (i.e., places with strong *IE* tend to be positively clustered and vice versa), which is consistent with the findings of (Zhang et al., 2022). *IE* belongs to the new economic form, which has strong industrial agglomeration characteristics. Relevant industries will cluster to give full play to the scale advantage of the industry, such as the Internet industry cluster, which can make full use of the infrastructure advantage and knowledge spillover effect in the space. Second, the CE all have significant positive spatial correlations (except for 2013-2015), indicating that carbon emissions also have spatial agglomeration characteristics. Because energy consumption is closely related to industrial layout, high-carbon emission industries tend to cluster to give full play to the scale effect of the industry. This is similar to the findings of (Zhang et al., 2024). Finally, the spatial correlation of IE is much higher than that of CE, indicating that economic effects are more likely to form spatial agglomeration than environmental effects, which is because economic activities are more affected by distance, while environmental pollution is more likely to spread.

This study reveals the important role of economic effects in regional agglomeration theory and also proves that environmental pollution can form regional agglomeration in the diffusion to surrounding areas, enriching relevant theoretical research.

Figures 8, 9 shows the localized Moran's index results for *IE* and *CE* in 2011 and 2021. It can be seen that from 2011 to 2021, the *IE* of the 30 provinces is mainly concentrated in the first and third quadrants. This is because regions with higher *IE* levels will have a diffusion effect on their neighbors, promoting *IE* in the surrounding provinces and forming 'high - high agglomeration', while places with lower *IE* levels are not led by the leading provinces and it is difficult for them to leap forward in the hierarchy, thus forming 'low - low agglomeration'. The 'low-low agglomeration' is formed. This is consistent with the findings of (Zhang et al., 2022). However, this study finds that this two-way agglomeration may lead to the widening of the East-West regional gap and exacerbate the Matthew effect, and it is expected that 'low-low agglomeration' can be reduced through effective policy instruments. The Moran scatterplot of *CE* for 30 provinces in China in 2011 is mainly concentrated in the second and third quadrants, and there are more in the third quadrant. This suggests that 'mixed agglomeration' and 'low-low agglomeration' co-existed in 2011, and the agglomeration is more obvious in places with lower carbon emissions. In 2021, the Moran scatterplot of China's 30 provinces mainly concentrates in the third quadrant and most of them are southern cities, and the number of low-carbon emission areas increases and continues to be agglomerated. This is related to the implementation of low-carbon pilot policies (Feng et al., 2024). Unlike previous spatial agglomeration analyses of carbon emissions, the study in this paper can effectively demonstrate the impact of policy preferences on carbon emissions, for example, taking developed coastal cities (Zhejiang, Shanghai, Jiangsu, etc.) as the pilot areas for low-carbon policies can effectively reduce carbon emissions in the local area and neighboring regions.

5.1.2 In-depth discussion of the impact of *IE* on *CE*

5.1.2.1 Spatial modeling regression results

The results of the spatial effect test of *IE* on *CE* are shown in Table 6. Firstly, the spatial autoregressive coefficient is negative and significant. This indicates that the more concentrated the area with large carbon emissions is, the more favorable it is for centralized management, and the easier it is to reduce the intensity of carbon emissions. Second, *IE* has an obvious inhibitory effect on *CE*, and the inhibitory effect is stronger when considering the spatial spillover effect. It can be seen that *IE* can give full play to the clean production characteristics of the digital economy and green the real economy, which is similar to the findings of (Wu et al., 2023). The impacts of *IE* have spatial spillovers, i.e. the development of local IE can effectively reduce carbon emissions in neighboring areas. Unlike previous studies, this paper focuses on exploring the carbon reduction effect of *IE* from a spatial perspective, aiming to propose feasible regional policies. Finally, the control variables such as *TI*, *RC*, and *GG* have a significant reduction effect on CE when the spatial matrix is considered (the influence coefficients are -0.242, -0.081, and -0.016, respectively). This is an important finding of this paper that is different from other studies. Therefore, policymakers should fully consider the coordination and linkage among technological innovation, regional coordination, green development policies, and *IE* to help reduce carbon emissions.

5.1.2.2 Spatial Spillover Effect Decomposition

The decomposition results of the spatial spillover effects are shown in Table 7. From Table 7, it can be seen that the direct and spatial effects of *IE* on *CE* are both significant, and the indirect inhibition effect on *CE* is stronger than the direct effect. It shows that *IE* in this region and adjacent areas will reduce *CE*, and *IE* in adjacent areas has a stronger effect. The development of *IE* in this region will have a demonstration effect on *IE* in neighboring areas, prompting neighboring areas to vigorously promote *IE*, thereby reducing *CE* in neighboring areas. The results of the study can inform the formulation of regional development policies.

5.1.3 In-depth discussion of regional heterogeneity

Spatial econometric regression of the data for the eight integrated economic zones based on the selected time-fixed SDM model described above is shown in Table 9. Table 9 shows that, firstly, the *IE* of the three regions of the Northeast, the Southern Coastal Region, and the Southwest Comprehensive Economic Zone can significantly reduce *CE* (similar to the results of Shi and Sun, 2023), and the carbon emission reduction effect is stronger after considering the spatial spillover effect. This is because the Northeast Economic Zone is an old industrial base with a larger carbon emission base, and *IE* has a stronger carbon emission reduction effect in the region. The southern coastal economic zone has a more developed digital economy, which has a double carbon reduction effect. The Southwest Comprehensive Economic Zone has a stronger carbon sink capacity, which can promote the *IE* effect to a large extent. Secondly, the *IE* to *CE* enhancement effect is obvious in the Middle reaches of the Yangtze River Comprehensive Economic Zone and the Middle reaches of the Yellow River Comprehensive Economic Zone, which may be related to the fact that the current comprehensive economies of these two regions are dominated by high-carbon manufacturing and supplemented by digital intelligent manufacturing. It is worth noting that, considering the spatial effect, the enhancement effect of *IE* on *CE* is more obvious in the Middle Yellow River Comprehensive Economic Zone. Finally, the effect of *IE* on *CE* in the North Coastal Integrated Economic Zone is negative and insignificant, which may be due to the inconsistent development of the internal provinces. The *IE* of the East Coast Comprehensive Economic Zone has an increasing effect on *CE*, but the effect is not strong, and the effect is not significant when spatial spillover effects are considered. Considering the spatial effect, the *IE* of the Greater Northwest Comprehensive Economic Zone can significantly increase *CE*, which may be due to the imperfect construction of digital infrastructure in the Northwest. The results of the study prove that the effects of *IE* on *CE* impacts in China's eight economic regions are different, and not all regions have a lowering effect of *IE* on *CE*. This reveals that we should formulate policies according to the characteristics of regional development to avoid the enhancing effect of *IE* on *CE*. In addition, different control variables have different effects in different regions, which also makes the eight economic zones *IE* have different effects on *CE*, and the result has important implications for the harmonization of different regional policies.

5.2 Policy implications

Based on these findings and discussion, this paper offers the following policy implications. These policy insights, combined with regional development characteristics and the findings of this paper, can provide a reference for policymakers to effectively reduce carbon emissions and achieve green and high-quality development.

(1) Continuously strengthening investment in digital infrastructure. Accelerating the construction of new digital infrastructure such as 5G, data centers, artificial intelligence, the Internet of Things and the industrial Internet in all provinces, especially in the western provinces, so as to build a firm foundation of integration for the development of an integrated economy and promote the interconnection of the digital economy and the real economy. The real economy will be transformed and upgraded through intelligent and collaborative new modes of production, and the divide in the development of the convergence economy will be reduced with the help of the digital economy dividend.

(2) Give full play to the spatial spillover effect of the integrated economy to reduce carbon emissions. First, the development advantages of the head provinces, such as Beijing, Shanghai, and Jiangsu, should be promoted to establish 'demonstration zones' for the integration and development of the digital economy and the real economy, so as to form a diffusion effect and drive the development of the surrounding regions with the center. Secondly, the central region should fully cooperate with the east, fully absorb the overflow from the east, and realize a new situation of regional green development. Finally, the disadvantaged western provinces should make full use of the role of the 'One Belt and One Road' and 'Western Development' strategies to reduce the spatial spillover effect of the disadvantaged regions and embark on the road of ecological protection and green development based on their resource endowments and environmental characteristics.

(3) 'Tailor-made' regional economic development policies. Differentiated macroeconomic control policies have been implemented by the actual situation of the economic zones, and different high-quality development policies have been focused on promoting integrated economic development and carbon emission reduction. On the one hand, encourage the construction of a digital economy in the Northeast, Southern Coastal, and Southwest Comprehensive Economic Zones, to promote industrial integration through the development of a digital economy and realize the effective reduction of carbon emissions. On the other hand, strengthen the development of industrial modernization in the middle reaches of the Yangtze River and the middle reaches of the Yellow River comprehensive economic zones, reduce the proportion of high-energy-consuming industries in the integration economy, and reduce carbon emissions within the economic zones. In addition, regional economic development strategies under the global framework are formulated to reduce the overall differences in the integrated economy.

5.3 Research limitations

Taking China as the research object, this study analyzes the spatial impact effect of the integration economy on carbon emissions using data from 30 provinces from 2011 to 2021. However, this study has certain limitations in terms of variable selection, data collection, and research object, which need to be improved and refined in subsequent studies. First, this study examined the spatial impact of the integration economy on carbon emissions at the national level, but it lacked the consideration of intermediate action mechanisms. Future studies should analyze in depth the intrinsic mechanisms through which the integration economy acts on carbon emissions. Second, due to the limitation of data availability, the relevant calculation results may not accurately represent the variables. Therefore, future research should start with data to enhance the accuracy and completeness of variable measurement. Finally, based on eight comprehensive economic zones, this study analyzed the regional heterogeneity of the impact of *IE* on *CE* based on provincial data but did not consider the city, county, and district levels. Subsequent studies could focus on specific regions such as the city and county levels.

6 Conclusions

This paper takes 30 inland provinces in China (Hong Kong Special Administrative Region, Macao Special Administrative Region, Taiwan, and Tibet Autonomous Region are excluded from the study due to data acquisition problems) as the research subjects. Based on the panel data from 2011 to 2021, this paper analyzes the spatial characteristics of the impact of the integrated economy on carbon emissions by using principal component analysis, coupled coordination degree model, Moran index, and spatial econometrics. The contributions of this article are reflected in the following aspects. Firstly, using reasonable methods and indicator systems to measure the integrated economy can fill the gap in the measurement of the integrated economy in the existing literature. Secondly, the innovative incorporation of integrated economy and carbon emissions into the same theoretical framework has deepened the theoretical research on low-carbon economy. Finally, analyze the current situation and inherent relationship between integrated economy and carbon emissions from a spatial perspective, and deepen relevant research in spatial economics. The main conclusions of the study are as follows.

(1) Characterizing the spatial and temporal evolution of the integrated economy and carbon emissions. Over the study period, the integrated economy showed a yearly increase while carbon emissions showed a yearly decrease. The spatial distribution of *IE* shows a trend of 'decreasing from east to west', with regional differences decreasing with the evolution of time. China's *CE* shows a distribution of 'low in the south and high in the north', with low-carbon areas continuing to spread from south to north.

(2) Analyzing the spatial correlation between the integrated economy and carbon emissions. From the global perspective of China, both integrated economy and carbon emissions have significant positive spatial correlations. From the local perspective, an integrated economy is mainly characterized by 'high-high agglomeration' and 'low-low agglomeration',

while carbon emissions are characterized by 'low-low agglomeration'.

(3) Exploring the spatial impact effects of an integrated economy on carbon emissions. Using the time-fixed SDM model, it is found that the integrated economy has a significant negative effect on carbon emissions, and the negative effect is even stronger when spatial spillover effects are considered, and the result still holds under multiple robustness tests. This suggests that the integrated economy has a strong spatial effect and can effectively reduce carbon emissions in China.

(4) Discussing the spatial heterogeneity of the impact of the integrated economy on carbon emissions. The impact of an integrated economy on carbon emissions varies from one integrated economic zone to another. The integrated economy of the three regions of the Northeast, the Southern Coastal Region, and the Southwest Comprehensive Economic Zone can significantly reduce carbon emissions. The integrated economy to carbon emissions enhancement effect is obvious in the Middle reaches of the Yangtze River Comprehensive Economic Zone and the Middle reaches of the Yellow River Comprehensive Economic Zone. The effect of an integrated economy on carbon emissions in the North Coastal Integrated Economic Zone is negative and insignificant. The integrated economy of the East Coast Comprehensive Economic Zone has an increasing effect on carbon emissions, but the effect is not strong.

(5) Providing insights for policy development. First, investment in digital infrastructure should be continuously strengthened. Accelerate the construction of new digital infrastructure in all provinces, especially in the western provinces, and promote the interconnection of the digital economy with the real economy. Second, give full play to the spatial spillover effect of the integrated economy to reduce carbon emissions. Promote the development advantages of headline provinces such as Beijing, Shanghai, and Jiangsu, and establish "demonstration zones" for the integrated development of the digital economy and the real economy, so that the center can drive the development of the surrounding areas. Finally, 'tailor-made' regional economic development policies. Implement differentiated macro-control policies based on the actual situation of economic zones, and implement different high-quality development policies around promoting integrated economic development and carbon emission reduction.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

YW: Funding acquisition, Methodology, Resources, Supervision, Writing – review & editing. QK: Conceptualization, Data curation, Methodology, Resources, Validation, Writing – original draft, Writing – review & editing. SL: Data curation, Methodology, Writing – review & editing, Funding acquisition.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2024.1374724/full#supplementary-material

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Efficiency improvement of wastewater treatment plants under the background of "double carbon": a case study in Jiujiang city, China

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Wastewater treatment plants (WWTPs) play a crucial role in modern urban water environmental protection. However, they face challenges related to high operational costs and carbon emissions. This study focused on addressing these issues through an analysis of four urban WWTPs in Jiujiang city, China. The study involved comparing the size and processes of the plants, evaluating influent and effluent water quality, assessing energy consumption and chemical usage, and calculating both direct and indirect carbon emissions. The results demonstrated that the high operational costs and increased carbon emissions in these WWTPs were primarily attributed to low hydraulic loadings, low influent concentration, and high energy and chemical consumption. In response, three targeted scenarios were proposed to enhance the efficiency of the WWTPs and reduce carbon emissions. These scenarios involved adjusting the amount of wastewater imported into the WWTPs to meet the designed capacity, optimizing operating costs, or combining both approaches. Among the scenarios, Scenario 3 emerged as the most effective in terms of improving efficiency and reducing carbon emissions. The operational costs for WWTPs could be reduced in the range of 0.42–1.04 RMB/m^3, representing a reduction rate of 35%–57%. Additionally, carbon emissions could be lowered from 15.02 to 598.85 gCO_2e/m^3, corresponding to a reduction of 2.91%–41.38%. Although Scenario 2 exhibited a lower carbon emission reduction of 14.8–316.33 gCO_2e/m^3, it was identified as the most feasible and easily implementable high-efficiency solution at present, with a reduction in operational costs ranging from 0.43 to 1.31 RMB/m^3. To achieve zero energy consumption and zero carbon emissions in wastewater treatment in the future, it is recommended to undertake additional measures, such as enhancing dosing system accuracy, implementing tail gas collection, adopting photovoltaic power generation, implementing carbon sequestration techniques, and exploring wastewater heat source recycling.

These findings provide valuable insights for optimizing the operational efficiency of urban WWTPs, reducing carbon emissions, and promoting sustainable wastewater treatment practices in Jiujiang city, China.

KEYWORDS

wastewater treatment plant, efficiency improvement, carbon reduction, influent concentration, carbon emissions, operating cost

1 Introduction

In response to the urgent global climate change problem, the United Nations convened a historic signing ceremony for the Paris Agreement in New York, USA, on 22 April 2016. Over 170 countries participated in this event, emphasizing their commitment to address climate change (Paris Agreement, 2015). China, recognizing the significance of this issue, formally acceded to the Paris Agreement on 3rd September of the same year and established its own national autonomous contribution target. This target aimed to reduce carbon dioxide emissions per unit of gross domestic product by 40%–45% by 2020 and by 60%–65% by 2030 when compared with the 2005 levels, showcasing China's commitment as a responsible major nation (Zhang, 2016). In 2020, China further demonstrated its dedication to climate change mitigation by presenting two key proposals during the United Nations General Assembly. The first proposal focused on achieving a "carbon peak," which signifies reaching a point where national greenhouse gas emissions cease to rise and gradually decline. The second proposal aimed for "carbon neutrality," which involves implementing emission reduction measures to reduce anthropogenic greenhouse gas emissions and ultimately achieve a balance between emissions and natural absorption (Zhao et al., 2022). These initiatives highlight China's proactive approach to tackling climate change and its determination to contribute to global efforts in mitigating the impacts of greenhouse gas emissions. By aligning its goals with the Paris Agreement and setting ambitious targets, China plays a significant role in addressing climate change and fostering sustainable development on a global scale.

In line with China's strong commitment to "carbon peaking and carbon neutrality" goals, the wastewater treatment industry must actively contribute to addressing climate change and reducing carbon emissions. Globally, the wastewater treatment sector ranks among the top 10 carbon-emitting industries, with greenhouse gas emissions from the treatment process accounting for 1.6% of the world's total emissions (Jegatheesan et al., 2009; Gu et al., 2023). As urbanization continues to expand and the scale of wastewater collection and treatment increases, greenhouse gas emissions from the industry have steadily risen. Between 2005 and 2020, the rise in global emissions of nitrous oxide (N_2O) and methane (CH_4) from wastewater treatment is estimated at 13% and 20%, respectively (Paustian et al., 2001; Gupta et al., 2012).

The growth of the wastewater treatment industry in China exemplifies this trend. In 1978, China had only 37 urban

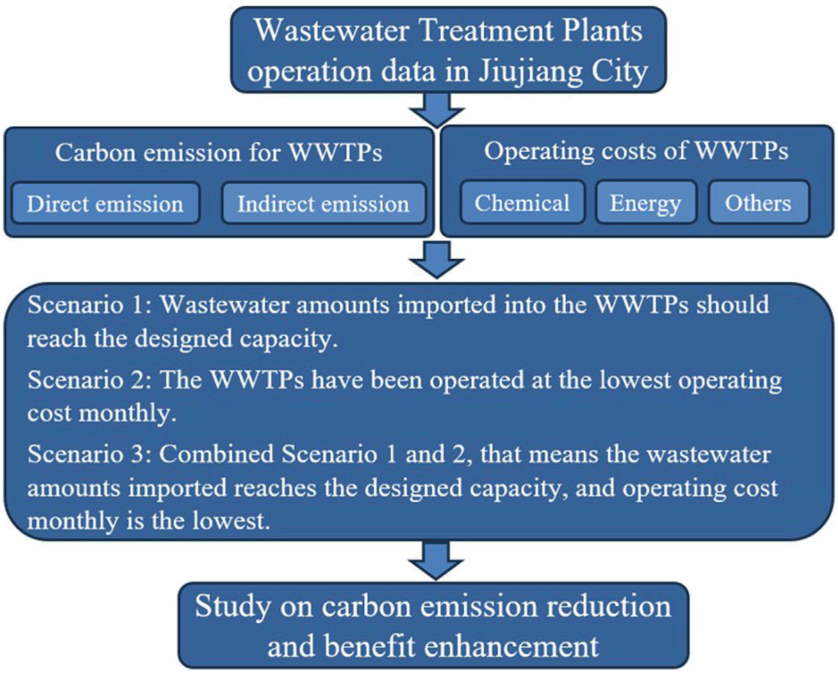

FIGURE 1
The technical roadmap.

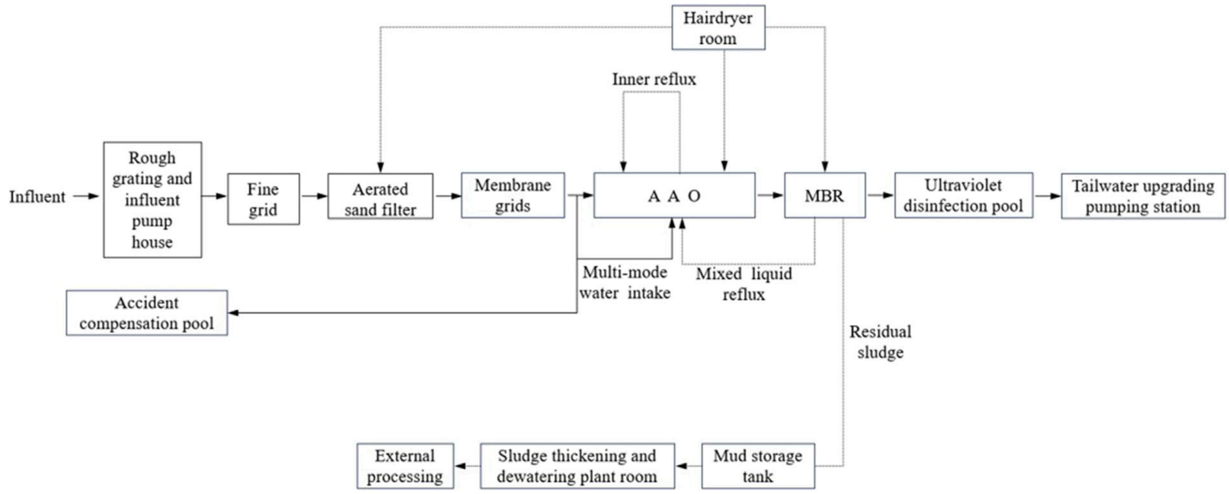

FIGURE 2
Process Flow for WWTP A.

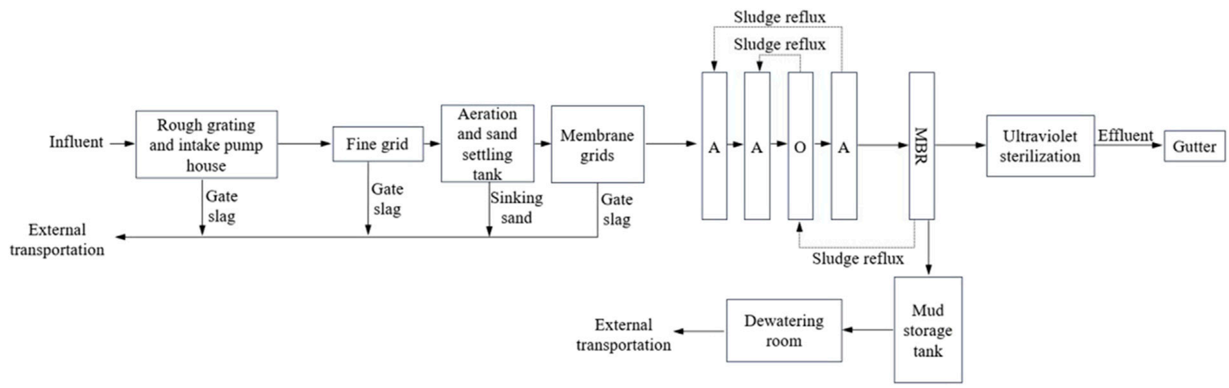

FIGURE 3
Process Flow for WWTP B.

wastewater treatment plants (WWTPs). However, by 2019, this number had surged to 4,140, representing an astounding growth rate of 2,836% (Kitano et al., 2023). The total annual greenhouse gas emissions from these plants in China has exceeded 39.84 million tons, with a national daily wastewater treatment capacity of 178.63 million tons (Xiaoshan et al., 2007). These emissions contribute to an intensified greenhouse effect, leading to rising global temperatures, elevated sea levels, and disruptions in ecosystems, which include a rise in more frequent and severe extreme weather events (Zickfeld et al., 2017).

Recent reports highlight the urgency of addressing climate change. The World Meteorological Organization (WMO) states that Latin America and the Caribbean have experienced an average warming of 0.2°C per decade over the past 30 years, while the snowpack of glaciers in the central Andes has nearly disappeared (Bodin et al., 2010; Vergara et al., 2013). The WMO's State of the Global Climate report indicates a 66% probability of the global near-surface annual mean temperature temporarily exceeding pre-industrial levels by 1.5°C in at least 1 year between 2023 and 2027 (Deben et al., 2013). In light of these increasingly severe climatic changes and global warming trends, reducing carbon emissions has become an urgent task for the entire global community.

Given this context, it is imperative for the wastewater treatment industry to actively contribute to carbon emission reduction efforts, aligning with China's goals and global initiatives. By implementing sustainable practices and adopting innovative technologies, the industry can play a pivotal role in mitigating climate change and fostering a more sustainable future.

Furthermore, it is important to acknowledge that wastewater treatment is a highly energy-intensive process. Studies have shown that in Europe, wastewater collection and treatment account for approximately 1% of global electricity consumption (Yang et al., 2021). WWTPs collectively contribute to over 20% of global electricity consumption (Longo et al., 2016). This poses a significant challenge for the wastewater treatment industry,

TABLE 1 Effluent wastewater quality and pollutant removal rates for waste water treatment plants (WWTPs).

Norm	Plant A		Plant B		Plant C		Plant D		Standard Class A, Level 1 (mg/L)
	Wastewater concentration	Removal rate (%)	Wastewater concentration	Removal rate (%)	Wastewater concentration	Removal rate (%)	Wastewater concentration	Removal rate (%)	
BOD_5	2.49	96.9	0.92	98.6	1.12	98.8	1.07	98.2	10
SS	0.19	99.9	0.27	99.9	4.80	96.2	4.29	93.9	10
COD	9.81	94.0	8.98	93.7	9.05	95.0	9.23	94.0	50
NH_3-N	0.05	99.8	0.12	99.4	0.07	99.5	0.28	98.4	5
TN	10.36	68.3	10.52	60.5	7.15	74.2	9.71	61.4	15
TP	0.14	96.0	0.39	83.4	0.08	96.9	0.24	90.4	0.5

particularly in terms of cost, as operating expenses constitute a substantial portion. These costs encompass energy consumption, material usage, and labor-related expenses (Abuhasel et al., 2021). The United Nations General Assembly had recognized sustainable development as the pivotal aspect of environmental protection and socioeconomic progress back in 2005. However, many WWTPs still consume excessive energy during wastewater treatment, resulting in noticeable waste management and financial constraints. Strengthened legal frameworks and environmental regulations have driven continuous upgrades in wastewater treatment processes, further increasing operational costs (Maktabifard et al., 2018). These factors significantly impact the sustainable development of WWTPs, making it crucial to focus on reducing energy consumption and operational costs.

Currently, microbial electrochemical technologies have gained popularity as a means of recovering energy from waste streams through bioreactors. Examples include microbial electrolysis cells for electromethanogenesis (Pawar et al., 2022), microbial electrolysis cells with non-platinum catalysts and binders in cathodes (Son et al., 2021), microbial desalination cells (Zahid et al., 2022), and the valorization of CO_2 into value-added products through microbial electrosynthesis and electro-fermentation technologies (Quraishi et al., 2021). However, this article proposes a novel perspective that can significantly reduce costs and achieve sustainable development. It conducts a comprehensive analysis of carbon emissions and economic efficiency within four major urban WWTPs in Jiujiang city, China. The analysis employs methods recommended in the "2019 IPCC Guidelines for National Greenhouse Gas Inventory" to calculate generated carbon emissions. Additionally, it takes into account the chemical consumption of each WWTP and the unit prices of consumables to calculate the economic benefits and carbon reduction amounts under different scenarios. Finally, the article proposes recommendations for improving the operational efficiency of WWTPs in a dual-carbon context, as illustrated in Figure 1.

2 Material and methods

2.1 Overview of WWTPs

2.1.1 Size and combined processes

This study chose four representative WWTPs in Jiujiang city, denoted as A, B, C, and D. Plant A caters to a population of approximately 150,000, with a total daily processing capacity of 30,000 m^3. Plant B serves approximately 100,000 residents and has a total daily processing capacity of 15,000 m^3. Plant C accommodates approximately 120,000 inhabitants and possesses a total daily processing capacity of 30,000 m^3. Plant D, the largest among them, serves a population of roughly 300,000 and operates with a total daily processing capacity of 70,000 m^3. The process flows for these plants are shown in Figures 2–5.

In accordance with the emission standards of pollutants for municipal wastewater treatment plants in China (GB 18918-2002), all four WWTPs fall under the category of medium-sized treatment plants. Furthermore, the effluent quality from each WWTP complies with the standard Class A, Level 1, as shown in Figure 6.

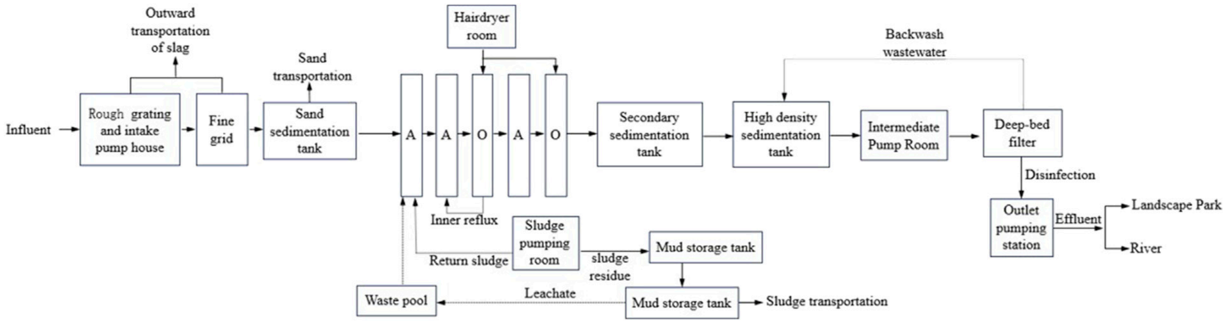

FIGURE 4
Process Flow for WWTP C.

TABLE 2 Energy consumption and treatment capacity of each waste water treatment plant (WWTP).

WWTP	Designed capacity (m^3/d)	Actual capacity (m^3/d)	Load factor (%)	Electricity consumption per unit of wastewater (kWh/m^3)	Scale
A	30,000	8,946	29.8	0.81	Medium
B	15,000	8,551	57.0	0.88	Medium
C	30,000	18,578	61.9	0.66	Medium
D	70,000	65,577	93.7	0.24	Medium

TABLE 3 Consumption of chemicals by waste water treatment plants (WWTPs).

Form	Plant A	Plant B	Plant C	Plant D
	Dosage per unit of wastewater (g/m^3)			
Tap water	2,481.64	2,901.64	2,624.17	1,910.57
CH_3COONa	335.10	148.60	59.92	37.44
PAC	90.50	30.32	59.25	46.73
PAM	0.77	1.19	0.36	0.90
NaClO	20.70	22.77	3.94	9.41
Magnetic particle	—	—	—	0.67

2.1.2 Effluent concentration and pollutant removal rates

Table 1 presents the effluent wastewater quality and pollutant removal rates for the four selected WWTPs. Minimal variation in wastewater quality exists among the plants. The average effluent concentrations for biological oxygen demand over 5 days (BOD_5), suspended solids (SS), chemical oxygen demand (COD), ammonia nitrogen (NH_3-N), total nitrogen (TN), and total phosphorus (TP) at all four plants are 1.4, 2.39, 9.27, 0.13, 9.44, and 0.21 mg/L, respectively. The average removal rates for these pollutants are 98.1%, 97.5%, 94.2%, 99.3%, 66.1%, and 91.7%, respectively. With the exception of TN, the removal rates for all other pollutants exceed 90%. Although TN exhibits a lower average removal rate, the effluent concentrations meet the standard Class A, Level 1 in China.

In terms of the overall pollutant removal rates, nationwide urban WWTPs in China achieve BOD_5, SS, COD, NH_3-N, TN, and TP removal rates of 94.2%, 95.1%, 90.6%, 97.3%, 70.7%, and 92.3%, respectively (Hu, 2021). Comparatively, the selected WWTPs demonstrate higher BOD_5, SS, and COD removal rates than the national average. However, the TN removal rates for Plants A, B, and D are 2.4%, 10.2%, and 9% lower than the national average, respectively. Similarly, the TP removal rates for Plants B and D are 8.9% and 1.9% lower than the national average, respectively. Despite these slightly lower TN and TP removal rates, the overall removal efficiency for other pollutants remains quite good.

2.1.3 Characteristics of influent wastewater

The design influent concentrations of BOD_5, SS, COD, NH_3-N, TN, and TP for each WWTP were initially set at 140, 200, 300, 30, 40, and 4 mg/L, respectively, according to the design standards. However, the actual influent concentrations of BOD_5, SS, COD, NH_3-N, TN, and TP for each plant were approximately 53.29%, 82.1%, 53.48%, 63.93%, 70.1%, and 68.75% of these design values, respectively. These findings, as illustrated in Figure 6, indicate consistently low influent concentrations at the four urban WWTPs.

The influent BOD_5/COD ratio is a widely used biochemical index in wastewater treatment, serving as an indicator of wastewater's biochemical properties and reflecting the degree of microbial degradation of organic matter and nutrients, thereby influencing pollutant removal effectiveness (Al-Sulaiman et al., 2018). In most cases, an influent BOD_5/COD ratio between 0.4 and 0.6 is considered favorable for biochemical processes (Xu et al., 2022). The statistical analysis of influent BOD_5/COD ratios across various provinces reveals that the majority fall within this range. For instance, Qinghai, Chongqing, and Tibet exhibit the highest influent BOD_5/COD values, reaching 0.52, 0.51, and 0.51, respectively. Conversely, Zhejiang, Fujian, and Hunan display the lowest influent BOD_5/COD ratios, with values of 0.38, 0.38, and 0.40, respectively. Among the four WWTPs (Plants A, B, C, and D), all exhibit influent BOD_5/COD ratios higher than 0.4. Specifically, these ratios are 0.49, 0.47, 0.50, and 0.40, respectively, as depicted in Figure 7. This indicates favorable biochemical conditions in all four WWTPs.

The influent COD/TN ratio primarily reflects the relative content of carbon and nitrogen sources in wastewater, providing insights into the nutrient balance for heterotrophic bacteria (Pan et al., 2020). A low COD/TN ratio suggests an excess of the nitrogen source component and an insufficient carbon source, hindering the growth of heterotrophic bacteria and reducing treatment efficacy. Conversely, a high COD/TN ratio indicates an excess of carbon source and insufficient nitrogen source, resulting in excessive sludge formation and biochemical challenges (Sun et al., 2016). Research indicates that the optimal COD/TN ratio falls within the range of 8–12 (Fernández-Arévalo et al., 2017). When the COD/TN ratio is close to 11, TN removal rates can reach 93.48% and TP removal rates approach 100% (Zhang et al., 2016). Among the four WWTPs, Plant C demonstrates the highest COD/TN ratio at 6.55, although it still falls below the optimal ratio, as depicted in Figure 8. A nationwide assessment of urban WWTPs in China reveals COD/TN ratios ranging from 4.8 to 8.7 (Hu, 2021), consistently below the optimal range. This prevalent issue results in insufficient carbon sources during denitrification processes, reducing the effectiveness of nitrogen and phosphorus removal (Figures 7, 8).

2.1.4 Energy consumption and chemical usage

The loading rates of urban WWTPs in key cities across the country have reached an average of 102.8%, with Hohhot notably reaching as high as 152% (Xu et al., 2022). However, the wastewater hydraulic loads of Plants A, B, and C are comparatively low. Notably, Plant A has a loading rate of only 29.8%, creating a scenario analogous to a substantial vehicle with minimal cargo capacity, as depicted in Table 2. Furthermore, when considering the “China Urban Construction Statistical Yearbook” and Chinese national statistics, it becomes evident that the annual average unit wastewater consumption of electricity for 5,389 WWTPs nationwide is 0.48 kWh/m^3. Approximately 80% of these WWTPs have a unit wastewater consumption of electricity lower than 0.61 kWh/m^3, and 50% achieve values below 0.36 kWh/m^3 (Hu et al., 2021). However, among the four WWTPs examined, only Plant D exhibits unit wastewater consumption of electricity lower than 0.36 kWh/m^3. The remaining three plants have higher levels of electricity consumption, surpassing more than 80% of the WWTPs included in the statistics.

On an international scale, WWTPs in China contribute significantly to urban energy consumption. For instance, in Germany, WWTPs account for approximately 20% of the total urban energy consumption, with electricity consumption being a dominant factor (Racoviceanu et al., 2007; Wang et al., 2016). In the United States, the electricity consumption of wastewater treatment accounts for 0.6% of the nation’s annual electricity consumption (Gu et al., 2017), with an average electricity consumption for wastewater treatment units of approximately 0.52 kWh/m^3 (Yeshi et al., 2013). Notably, countries like the Netherlands, the United States, and Australia maintain lower levels of electricity consumption in the range of 0.36–0.45 kWh/m^3. By contrast, countries such as the United Kingdom, Switzerland, Spain, Germany, and Singapore have higher levels ranging from 0.52 to 0.67 kWh/m^3 (Hernández-Sancho et al., 2011). It is important to highlight that the electricity consumption of WWTPs in these countries is generally lower than that of Plants A, B, and C.

In terms of chemical consumption, Table 3 presents the average daily tap water consumption ranging from 22.21 to 123.50 m^3, with unit wastewater consumption ranging from 1,910.57 to 2,901.64 g/m^3. The order of unit wastewater consumption from the highest to lowest is as follows: Plant B > Plant C > Plant A > Plant D. Similarly, the average daily dosage of chemicals, such as CH_3COONa, PAC, PAM, and NaClO, is provided. Regarding CH_3COONa consumption, to compare it uniformly in terms of COD equivalent, the median value of CH_3COONa dosing for WWTPs nationwide in China is 16.9 gCOD/m^3, with approximately 95% of WWTPs consuming less than 115 gCOD/m^3 of carbon sources per unit of wastewater and 50% consuming less than 18.9 gCOD/m^3 (Hu et al., 2021). Given the conversion rate of 1 g CH_3COONa to COD equivalent (approximately 0.78 g COD/g CH_3COONa), the unit wastewater dosages for Plants A, B, C, and D are 261.38, 115.91, 46.74, and 29.20 gCOD/m^3, respectively. These values exceed half of the carbon source consumption values of WWTPs nationwide. Additionally, the nationwide median value for PAC dosing is 6.7 g/m^3, with unit wastewater consumption primarily falling within the range of 1–22 g/m^3 (which accounts for approximately 90% of the total). Although Plant B has the lowest consumption among Plants A, B, C, and D (30.32 g/m^3), it still exceeds 90% of the national consumption in WWTPs.

2.2 Carbon emissions from WWTPs

The carbon emissions from WWTPs can be divided into two main components. The first component refers to direct emissions during the biochemical treatment process, which primarily include the release of greenhouse gases such as CH_4 generated during the removal of COD, methane produced during sludge treatment, and N_2O resulting from the removal of TN (Lv et al., 2022).

The second component involves indirect emissions generated during plant operations, mainly originating from the energy consumption of the wastewater treatment process. This encompasses carbon dioxide emissions implicitly associated with purchased electricity, carbon dioxide emissions resulting from the addition of chemicals during wastewater treatment, and carbon dioxide emissions produced during equipment operation and sludge treatment through the combustion of fossil fuels (Demir et al., 2019).

In this study, we calculated the carbon emissions for each WWTP by considering three greenhouse gases: CO_2, CH_4, and N_2O. To assess their contribution to global warming, we utilized the global warming potential (GWP) values provided by the Intergovernmental Panel on Climate

Change (IPCC). The GWP represents a basis for comparing the global warming impact of different gases, with CO_2 assigned a GWP of 1. The GWP values for other greenhouse gases are quantified in relation to CO_2 (Table 4), enabling us to calculate the equivalent emissions of these gases by multiplying their actual emissions by their respective GWP values (Koutsou et al., 2018).

TABLE 4 IPCC global warming trend values.

Name	Radiation efficiency	GWP
CO_2	1.4×10^{-5}	1
CH_4	3.7×10^{-4}	25
N_2O	3.03×10^{-3}	298

2.2.1 Direct carbon emissions

2.2.1.1 Carbon emissions from TN removal

$$\mathbf{E_1 = Q \times (TN_i\text{-}TN_e) \times 10^{-6} \times EF_{N_2O} \times C_{N_2O/N_2} \times GWP_{N_2O},} \quad (1)$$

where E_1 is the removal of TN produced by N_2O converted to carbon dioxide equivalent annual emissions, tCO_2eq/a; Q is the annual treatment volume of wastewater, m^3/a; TN_i is the average annual influent concentration of TN, gCO_2e/m^3; TNe is the average annual effluent concentration of TN, gCO_2e/m^3; EF_{N2O} is the amount of nitrogen in the wastewater per unit mass of ammonia that can be converted to nitrous oxide, tN_2O -N/tN; $C_{N2O/N2}$ is the ratio of the molecular weight of N_2O/N_2, 44/28; and GWP_{N2O} is the global warming potential value of N_2O, which takes the value of 298.

2.2.1.2 Carbon emissions from COD removal

$$\mathbf{E_2 = \left[\left(Q \times (COD_i\text{-}COD_e) \times 10^{-6}\text{-}SG \times \rho_s\right) \cdot EF_{CH_4}\text{-}W_{CH_4} \right] \times GWP_{CH_4},} \quad (2)$$

$$\mathbf{SG = Q_a \times EF_S \times D \times 10^{-4},} \quad (3)$$

$$\mathbf{EF_{CH4} = B_0 \times MCF,} \quad (4)$$

where E_2 denotes the removal of COD in wastewater produced by CH_4 converted to carbon dioxide equivalent emissions per year, tCO_2eq/a; Q denotes the annual treatment of wastewater, m^3/a; COD_i denotes the COD of the average annual concentration of influents, gCO_2e/m^3; CODe denotes the COD of the average annual concentration of effluents, gCO_2e/m^3; SG denotes the annual generation of urban WWTP sludge dry matter, t/a; ρ_s is the content of organic matter in the sludge dry matter, tCOD/t; WCH_4 is the annual recovery of CH_4, tCH_4/a; the WWTPs are zero; EF_{CH4} is the CH_4 emission factor, $tCH_4/tCOD$; GWP_{CH4} is the CH_4 GWP value and takes the value of 25; Q_a is the daily treatment of urban wastewater, m^3/d; EFs is the daily processing EFs for the daily treatment of wastewater produced by the sludge dry mass, t/(10,000 m^3d); D denotes the annual operation of the WWTP days, d/a; EF_{CH4} denotes the CH_4 emission factor, $tCH_4/tCOD$; MCF denotes the CH_4 correction factor and takes the value of 0.15; and B denotes the maximum CH_4 generation potential and takes the value of 0.25 $tCH_4/tCOD$.

2.2.1.3 Carbon emissions from sludge treatment

$$\mathbf{E_3 = SR \times \beta_S \times DOC_f \times MCF \times F \times C_{CH_4/C} \times GWP_{CH_4},} \quad (5)$$

$$\mathbf{SR = SG\text{-}SE,} \quad (6)$$

where E_3 is the annual emission of CH_4 converted to the carbon dioxide equivalent from sludge removal in the municipal WWTP, tCO_2eq/a; SR is the annual amount of dry sludge in the WWTP, t/a; SG is the amount of dry sludge generated in the municipal WWTP, t/a; SE is the mass of dry sludge transported outside the boundary of the municipal WWTP, t/a; semi-finish is the organic matter content in the dry sludge of the municipal WWTP sludge dry matter content of organic matter, tC/t; DOC_f is the ratio of degradable organic carbon in sludge dry matter and takes the value of 50%; MCF is the CH_4 correction factor and takes the value of 1 for completely anaerobic and the value of 0 for completely aerobic; F is the ratio of CH_4-producing carbon in the degradable organic carbon and takes the value of 50%; $C_{CH4/C}$ is the ratio of the molecular weight of CH_4/C and takes the value of 16/12; and the parameter β_S is assigned a value of 0.1 tC/t.

TABLE 5 Chemical emission factors.

Chemical	Emission factor ($kgCO_2$/kg chemical)
CH_3COONa	1.07
PAC	1.62
PAM	2.1
NaClO	1.4

2.2.2 Indirect carbon emission

2.2.2.1 Carbon emissions from energy consumption

$$\mathbf{E_4 = EH \times EF_{CO_2} \times GWP_{CO_2},} \quad (7)$$

where E_4 is the CO_2 emission equivalent generated by the annual consumption of electricity for the operation of wastewater treatment equipment, tCO_2eq/a; EH is the annual electricity consumption for the operation of wastewater treatment equipment, MWh/a; EF_{CO2} is the CO_2 emission factor for electricity, tCO_2/MWh, and according to the results of the baseline emission factor of the Chinese regional power grid of the emission reduction program in the year 2019, Jiujiang city's emission factor is taken as 0.8587; and GWP_{CO2} is the CO_2 global warming potential value and takes the value of 1.

2.2.2.2 Carbon emissions from chemical usage

$$\mathbf{E_5 = \Sigma Y_i \times EF_{CO_2,i} \times GWP_{CO_2} \times 10^{-3},} \quad (8)$$

where E_5 is the CO_2 emission equivalent produced by the chemicals added in the wastewater treatment process of the urban WWTP, tCO_2eq/a; Y_i is the consumption of the *j*-th type of chemicals added

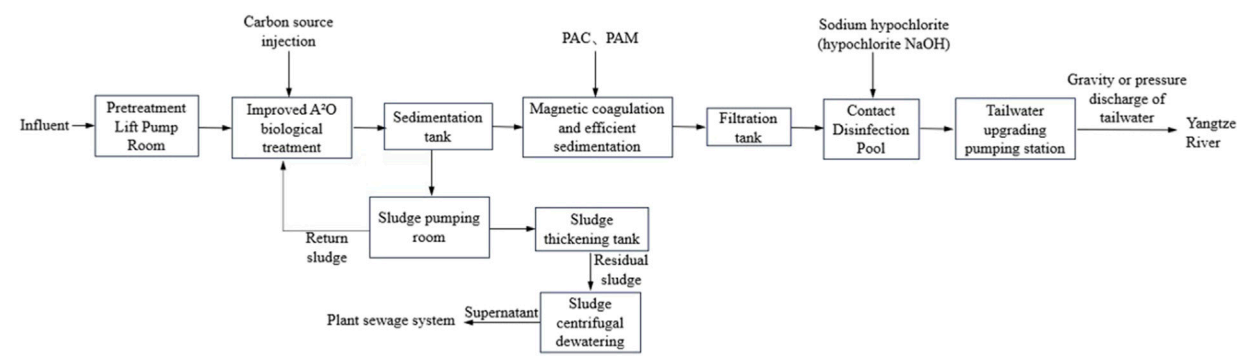

FIGURE 5
Process Flow for WWTP D.

in the domestic wastewater treatment process, kg; and $EF_{CO2,i}$ is the CO_2 emission factor consumed by the *j*-th type of chemicals used in the wastewater treatment, $kgCO_2/kg$ of chemicals, as shown in Table 5.

2.3 Scenarios for the efficiency improvement of the WWTPs

To enhance the efficiency of WWTPs and reduce carbon emissions, this study proposes three distinct scenarios for research. Each scenario focuses on removal rates, carbon emission reduction, and cost optimization. Subsequently, we calculate the carbon emission generated under each scenario and analyze the effects of emission reduction. The objective is to derive the lowest operating cost while maintaining low carbon emission and meeting WWTP emission standards.

2.3.1 Scenario 1: wastewater amounts imported into the WWTPs should reach the designed capacity

Since the influent flow rate at each WWTP is less than the designed capacity, all equipment within the plants operate at normal power, resulting in the phenomenon of "using a sledgehammer to crack a nut." This leads to higher energy consumption per unit of wastewater. In Scenario 1, with the assumption that the influent flow rate reaches the designed wastewater flow, the energy consumption per unit of water is recalculated by each WWTP, and the cost of energy consumption per unit of wastewater is calculated based on the local electricity tariff, as shown in formulas (9) and (10). The unit chemical consumption per unit wastewater remains constant, and the cost of chemical consumption per unit wastewater is calculated based on the local chemical price, as shown in formula (11). Combining the costs of energy consumption and chemical consumption per unit wastewater results in the operational cost, as indicated in formula (12). In this scenario, energy consumption can be significantly reduced, leading to a reduction in indirect carbon emission, which positively contributes to carbon reduction.

$$\mathbf{p_1} = \frac{\sum_{1}^{12} \textbf{Electricity consumption per month}}{\sum_{1}^{12} \textbf{Volume of wastewater designed to be treated per month}}, \tag{9}$$

$$\mathbf{w_1} = \boldsymbol{\alpha} \mathbf{p_1}, \tag{10}$$

$$\mathbf{w_2} = \boldsymbol{\beta_1 r_1 + \beta_2 r_2 + \beta_3 r_3 + \beta_4 r_4 + \beta_5 r_5 + \beta_6 \gamma_6 + \beta_7 r_7}, \tag{11}$$

$$\mathbf{oc_1} = \mathbf{w_1 + w_2}. \tag{12}$$

In the equations, P_1 represents the energy consumption per unit of wastewater when the influent flow rate reaches the designed wastewater flow, with the units kWh/m^3; α represents the electricity tariff; W_1 denotes the cost of energy consumption per unit of wastewater; γ_1 to γ_7, respectively, represent the consumption of PAM, water, NaClO, coal, PAC, CH_3COONa, and electricity per unit of wastewater, while β_1 to β7 correspond to the unit prices of these chemicals; W_2 represents the cost of chemical consumption per unit of wastewater; and operating cost OC_1 indicates the operational cost per unit of wastewater in Scenario 1. The units for all these costs are RMB/m^3.

2.3.2 Scenario 2: the WWTPs have been operated at the lowest OC_2 monthly

To break free from the current situation of high standards, high costs, and high emissions, a path for wastewater discharge that is both in line with urban WWTP pollutant discharge standards and economically low carbon is explored. We comprehensively analyze the monthly average effluent concentration, unit wastewater operation cost, and pollutant removal rate for each WWTP in 2022. By means of monthly average OC_2, we select the month with the lowest OC_2 and analyze whether its pollutant removal rate meets the standard. If it does not meet the standard, we select the OC for the second-lowest month, and so on, until we obtain the minimum OC_2 that complies with the emission standard. We then use this month as a benchmark, with equipment operation modes and the dosage of chemicals of the other months consistent with those of this month, reducing the OC_2. In this scenario, it significantly reduces the OC_2, implying reduced energy consumption and chemical consumption, and a substantial

TABLE 6 Summary of carbon emissions (CEs) per unit of wastewater.

Waste water treatment plant (WWTP)	Direct emission				Proportion of total CE (%)	Indirect emissions			Proportion of total CE (%)	Total CE (gCO_2e/m^3)
	Chemical oxygen demand (COD) (gCO_2e/m^3)	Sludge (gCO_2e/m^3)	Ammonia nitrogen (TN) (gCO_2e/m^3)	Total (gCO_2e/m^3)		Energy consumption (gCO_2e/m^3)	Chemical consumption (gCO_2e/m^3)	Total (gCO_2e/m^3)		
A	148.65	17.62	34.49	200.75	13.87	696.70	549.75	1,246.45	86.13%	1,447.20
B	127.35	15.97	24.89	168.20	14.39	758.09	242.34	1,000.42	85.61%	1,168.63
C	165.35	20.94	31.71	218.00	22.87	568.85	166.36	735.21	77.13%	953.21
D	139.06	18.23	23.86	181.15	35.21	202.51	130.84	333.35	64.79%	514.50

reduction in indirect carbon emissions, thereby achieving energy savings and emission reduction. This approach allowed us to explore a viable path for wastewater treatment that balances the requirement for pollutant removal, economic efficiency, and low carbon emission.

2.3.3 Scenario 3: combined Scenarios 1 and 2, which means that the wastewater amounts imported reach the designed capacity, and lowest monthly OC_3

By combining Scenarios 1 and 2, under the premise of the wastewater volume reaching the designed value, the unit wastewater electricity consumption obtained from Scenario 1 and the chemical consumption obtained from the month with the lowest operating cost in Scenario 2 are selected by each WWTP. By combining these two factors, energy consumption and chemical usage are minimized, resulting in the optimal OC_3. In this scenario, reducing indirect emissions to the lowest extent and maximizing carbon emission reduction.

3 Results and discussions

3.1 Carbon emission comparison of the present and the scenarios

3.1.1 Present carbon emissions

The calculation of carbon emissions for the four WWTPs in 2022 involves the utilization of Eqs 1–8. When analyzing the annual carbon emissions, it becomes evident that the volume of wastewater treatment plays a dominant role in determining the total carbon emissions, surpassing any impact arising from changes in the concentration of incoming and outgoing wastewater quality. Consequently, the total carbon emissions are ranked as follows: Plant D > Plant C > Plant A > Plant B.

When considering carbon emissions per unit of wastewater, the results indicate the following order: Plant A > Plant B > Plant C > Plant D, as detailed in Table 6. Notably, indirect emissions constitute the majority of the carbon emissions for each plant. Among these, Plant A stands out with indirect emissions accounting for a substantial 86.13% of the total emissions, while direct emissions make up only 13.87% of the total.

The carbon emissions per unit of wastewater at a WWTP in Zhengzhou city were calculated to be 1,060 gCO_2e/m^3 (Yu et al., 2020), indicating similarities with those of Plant B in Zhengzhou city. The WWTP processes in Zhengzhou city resemble those of Plant B, although they handle more wastewater and achieve higher pollutant removal rates per unit of wastewater. However, the energy consumption and chemical consumption per unit of wastewater are lower than those of Plant B. The difference in carbon emissions can be attributed to the higher influent concentration in Zhengzhou city's WWTP, resulting in greater direct carbon emissions per unit of wastewater.

By contrast, the carbon emissions per unit of wastewater at a WWTP in Canada were calculated to be 390 gCO_2e/m^3 (Shahabadi et al., 2010), which is lower than the values observed in this study. This discrepancy arises because the study only accounted for the direct emissions from the biochemical treatment portion of the

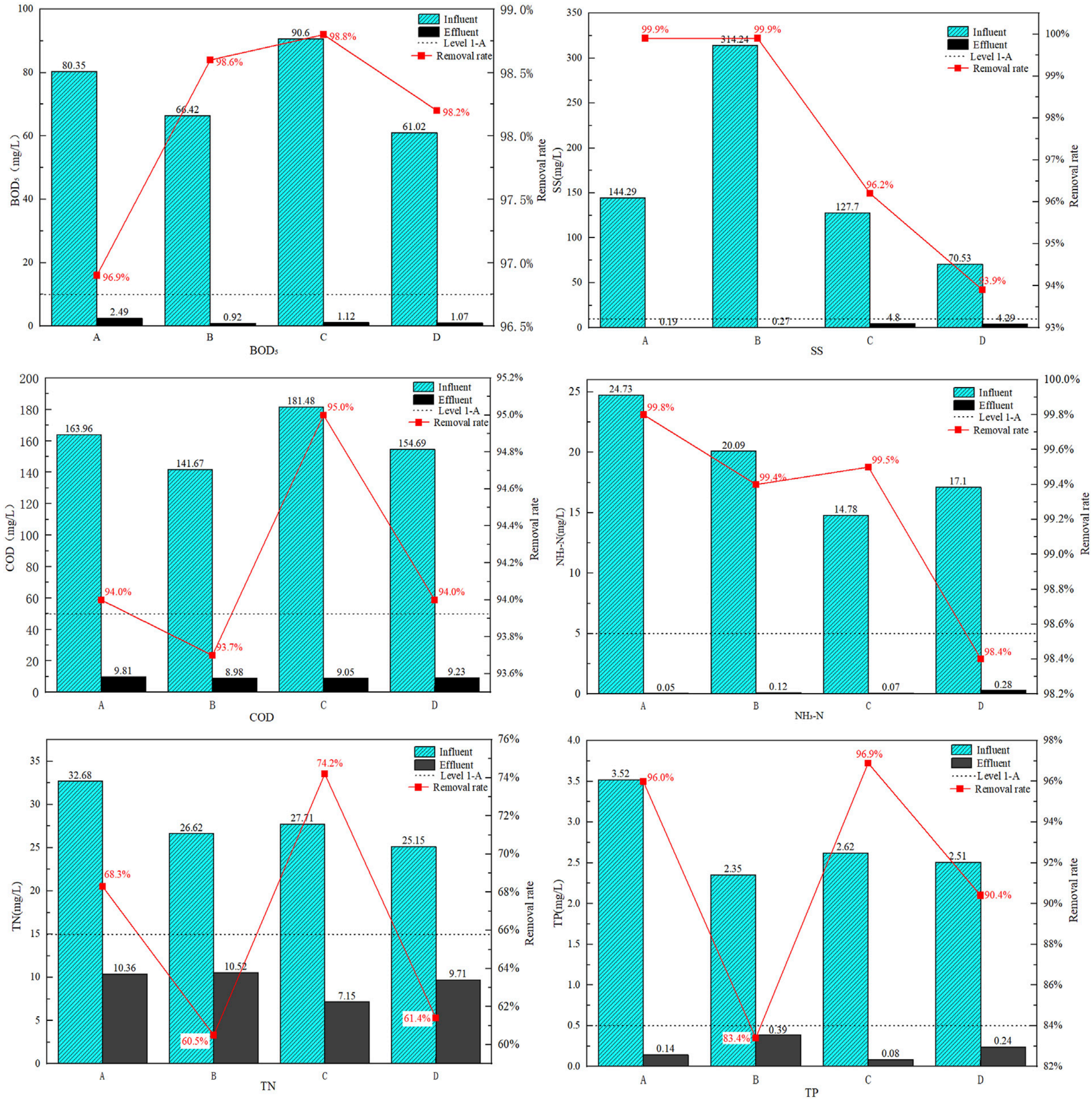

FIGURE 6
Concentration of wastewater and pollutant removal rates for WWTPs.

WWTP, neglecting the indirect emissions encompassing energy and chemical consumption.

Another noteworthy case is a WWTP in Shenzhen, where the carbon emissions per unit of wastewater were 430 gCO_2e/m^3 (Song et al., 2015), which are lower than the values in this study. However, this difference can be attributed to the exclusion of carbon emissions related to sludge treatment in the study by Song et al.

The carbon emissions per unit of wastewater for 50 small-scale WWTPs in India and the United Kingdom yielded a value of 3,040 gCO_2e/m^3 (Singh et al., 2016), which is significantly higher than the values observed for the four large WWTPs. This discrepancy arises from the inclusion of energy consumption, encompassing both electricity and fuel consumption. Lower fuel efficiency led to higher consumption, coupled with a larger fuel carbon emission factor, resulting in elevated carbon emissions. By contrast, the analysis of the four WWTPs considered only electricity consumption.

Lastly, the carbon emissions per unit of wastewater volume for a WWTP in the northern region yielded a value of 950 gCO_2e/m^3 (Xie et al., 2012), which is close to that of Plant C. Although its wastewater treatment capacity and pollutant removal per unit of wastewater exceeded those of Plant C, energy consumption and chemical consumption per unit of wastewater were lower. It is important to note that in all these cases, direct carbon emissions exceeded indirect carbon

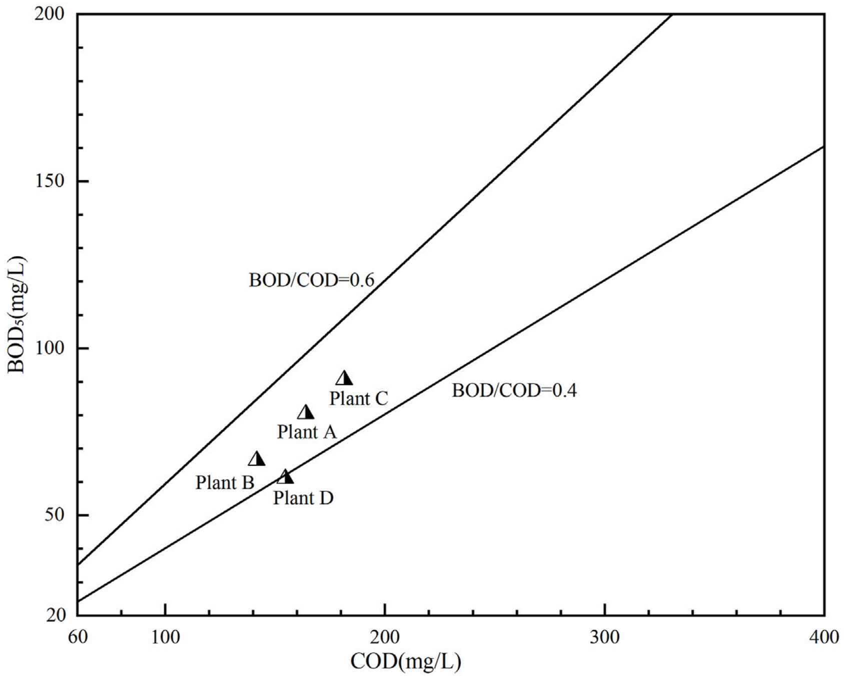

FIGURE 7
Characteristic of BOD5/COD in imported wastewater for WWTPs.

emissions, indicating excessive indirect carbon emissions from WWTPs in Jiujiang city.

In terms of carbon emission composition, Plants A, B, and C exhibited the following hierarchy: energy > chemical > COD > TN > sludge. However, Plant D displayed a slightly different pattern: energy > COD > chemical > TN > sludge. Across all WWTPs, energy consumption accounted for the majority of carbon emissions, followed by chemical consumption, COD, TN, and sludge, which contributed the least to carbon emissions.

When analyzing individual plant-level carbon emissions (Figure 9), it becomes evident that carbon emissions per unit of wastewater produced are primarily influenced by energy consumption and chemical consumption, while carbon emissions from COD, sludge, and TN remain relatively consistent. Notably, there were significant variations among the plants, with Plant D recording the lowest carbon emissions and Plant A exhibiting the highest. Specifically, the carbon emissions per unit of wastewater for Plant C, Plant B, and Plant A were 2.81 times, 3.74 times, and 3.44 times that of Plant D, respectively. Furthermore, carbon emissions per unit of wastewater from chemical consumption were 1.27 times, 1.85 times, and 4.2 times greater than that of Plant D. In total, the cumulative carbon emissions per unit of wastewater for Plant C, Plant B, and Plant A were 1.85 times, 2.27 times, and 2.81 times that of Plant D (Figure 9).

Considering the different processes employed, Plants A, B, C, and D utilize the following technologies, respectively: AAO + MBR, AAOA + MBR, AAOAO + coagulation precipitation filtration (CPF), and AAO + CPF. The carbon emissions decrease sequentially based on these technologies. A previous study on WWTPs in the Yangtze River mainstream basin, employing various technologies, reported carbon emission intensities ranging from 3,776 g/m^3 to 9,559 g/m^3 (Fu et al., 2022). Among these, the AAO + MBR combination process exhibited the highest carbon emission intensity due to its elevated electricity consumption, while the oxidation ditch (OD) + CPF process demonstrated the lowest carbon emission intensity.

Although Jiujiang city falls within the Yangtze River mainstream basin, Plant A's carbon emissions significantly exceed those of WWTPs employing similar technologies. Plants B and C, which utilize currently unaccounted technology combinations, also exhibit higher carbon emissions than WWTPs using similar processes (AAOA + MBR and AAOAO + CPF). However, the carbon emissions of Plant D are comparable to those of WWTPs utilizing the same technology combination. This outcome can be attributed to the high levels of indirect carbon emissions from Plants A, B, and C, which impede the efficient operation of WWTPs. Increased energy consumption leads to lower electrical efficiency, while the low influent concentration in the WWTPs results in an insufficient carbon source, leading to higher chemical consumption. To address these issues, it is advisable to increase the influent concentration to enhance energy efficiency and reduce per-unit wastewater chemical consumption.

3.1.2 Carbon emissions of the scenarios

Three different scenarios are presented to demonstrate the efficiency improvements of WWTPs and propose a cost-effective, easily implementable low-carbon approach. In Scenario 1, the focus is on reducing carbon emissions related to energy consumption. In Scenario 2 and Scenario 3, reductions in both energy-related and chemical consumption–related carbon emissions are considered.

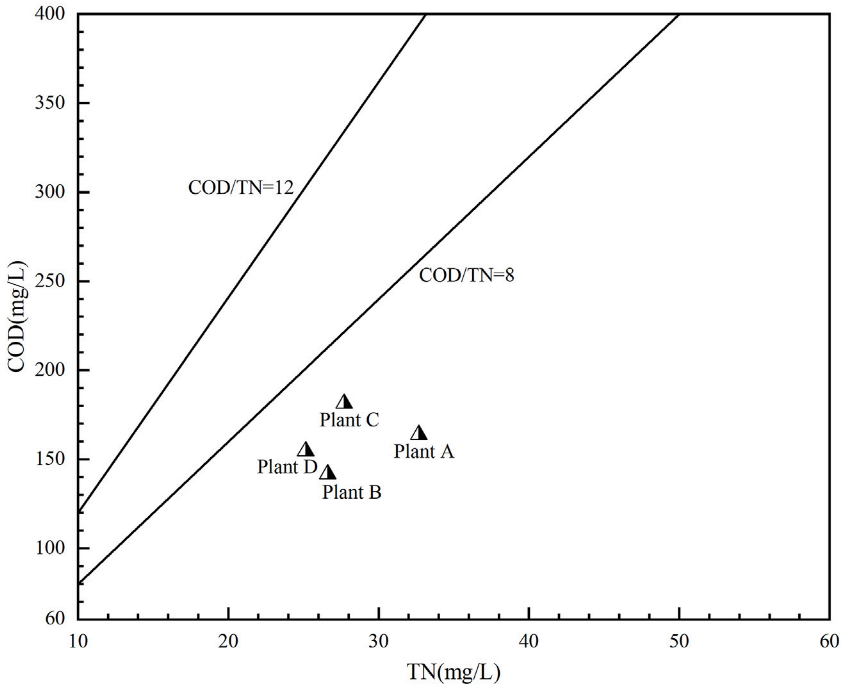

FIGURE 8
Characteristic of COD/TN in imported wastewater for WWTPs.

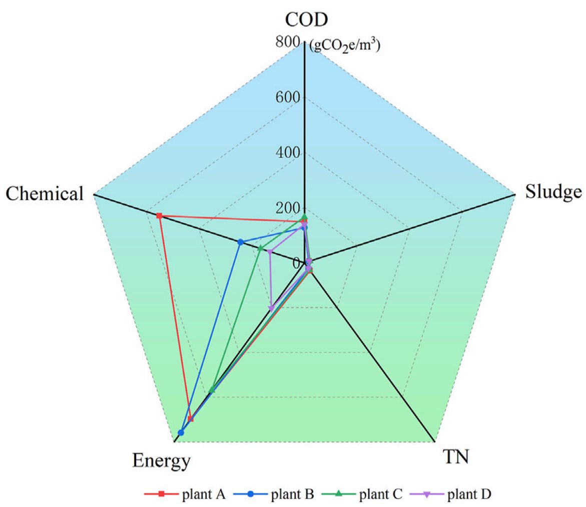

FIGURE 9
Carbon emissions per unit wastewater of WWTPs.

Figure 10 illustrates the carbon emission compositions for the four WWTPs and the carbon reduction effects of the three scenarios. The carbon emission reduction results for 2022 under each scenario are as follows:

(1) Scenario 1: The energy consumption reductions for Plant A, Plant B, Plant C, and Plant D are 0.57, 0.38, 0.25, and 0.02 kWh/m^3, respectively. The corresponding carbon emission reductions from energy consumption, calculated using formula (7), are 489, 325, 217, and 15 gCO_2e/m^3, respectively. Based on the designed wastewater inflow, the carbon emission reductions for 2022 are estimated to be 5,354.55, 1,779.38, 2,376.15, and 383.25 tCO_2e/a, respectively.

(2) Scenario 2: The carbon emission reductions from energy consumption for Plants A, B, C, and D are 134.56, 219.29, 29.92, and 14.78 gCO_2e/m^3, respectively. The carbon emission reductions from chemical consumption, calculated using formula (8), are 109.85, 97.04, 96.22, and 0.02 gCO_2e/m^3, respectively. The total carbon emission reductions are 244.41, 316.33, 126.14, and 14.8 gCO_2e/m^3, respectively. Considering the actual wastewater inflow, the carbon emission reductions for 2022 are projected to be 798.66, 988.41, 854.76, and 349.20 tCO_2e/a, respectively.

(3) Scenario 3: The energy consumption carbon emission reductions for Plants A, B, C, and D are the same as in Scenario 1. The carbon emission reductions from chemical consumption remain the same as in Scenario 2. The total carbon emission reductions are 598.85, 422.04, 313.22, and 15.02 gCO_2e/m^3, respectively. Based on the designed wastewater inflow, the carbon emission reductions for 2022 are projected to be 6,557.41, 2,310.67, 3,429.76, and 383.76 tCO_2e/a, respectively (Figure 10).

In addition to the methods employed in this study, various measures can be implemented to achieve a reduction in carbon emissions. These include exhaust gas collection, photovoltaic power generation, carbon sequestration by green plants, and wastewater reuse. For example, the implementation of an automatic control system for dissolved oxygen can lead to

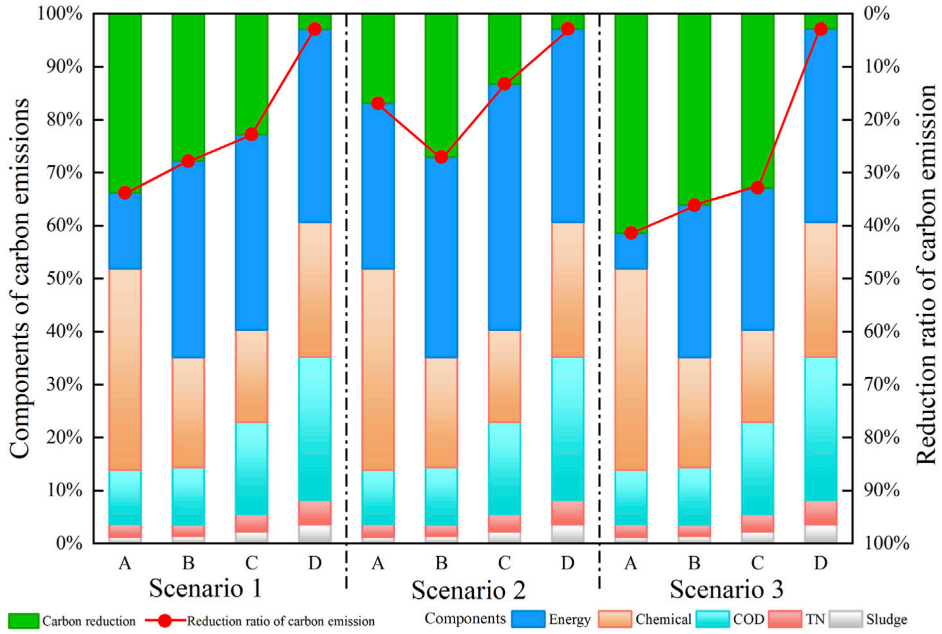

FIGURE 10
Carbon emission composition of the three scenarios for WWTPs.

energy savings ranging from 10% to 25% (Nana, 2013). A study on 31 WWTPs in China demonstrated that photovoltaic projects at WWTPs can reduce carbon emissions by 10%–40% (Chen, 2022). The Jinamar WWTP in the Canary Islands of Spain incorporated energy recovery, photovoltaic, wind energy, and hydropower generation, resulting in zero energy consumption and zero carbon emissions annually (Del et al., 2020). These examples highlight the possibility of achieving zero carbon emissions.

3.2 Operating costs comparison of the present and the scenarios

3.2.1 Present operating costs

The operating costs discussed in this article for WWTPs include expenses related to energy consumption and chemical usage, such as electricity, tap water, CH_3COONa, PAC, PAM, coal, and NaClO. Labor costs and other miscellaneous expenses were not considered in the analysis at this stage. The data on energy and chemical consumption for the year 2022 from four prominent WWTPs were collected, and the unit electricity rates and chemical prices were determined based on the prevailing local market conditions. For consistency, we used a water equivalent where 1 ton is considered equivalent to 1 m^3. Through detailed calculations, the monthly operating costs for each plant were derived, as shown in Figure 11.

The operating costs for WWTPs A, B, C, and D ranged from 1.31 to 2.33, 0.77 to 1.59, 0.6 to 2.19, and 0.43 to 0.78 RMB/m^3, respectively. The mean values for these WWTPs were 1.78, 1.18, 1.05, and 0.66 RMB/m^3, respectively. In a case study of an urban WWTP in Nanchang, the operating cost before an upgrade was 0.75 RMB/m^3, which decreased to 0.6 RMB/m^3 after the upgrade (Zhao et al., 2023), similar to the operating cost of Plant D. According to research, the operating cost of a semi-underground WWTP in China is 0.7 RMB/m^3 (Kong et al., 2021). Xie et al. (2017) conducted a study on a domestic WWTP in a town in Beihai, determining the operating cost to be 0.62 RMB/m^3. Tan et al. (2015) calculated the average operating cost for 227 WWTPs across China's eastern, central, and western regions to be approximately 0.8 RMB/m^3. The operating costs for urban WWTPs mentioned in these studies typically range from 0.6 to 0.9 RMB/m^3, which include labor expenses. Notably, the four major WWTPs, excluding labor costs, exhibited operating costs exceeding 0.9 RMB/m^3. Therefore, Plants A, B, and C have relatively high operating costs.

The composition of operating costs reveals that a significant portion of the expenses are attributed to electricity, CH_3COONa, PAC, coal, and NaClO, while the costs associated with tap water and PAM relatively constitute a smaller share. The study shows that electricity consumption in China amounts to approximately 0.24 RMB/m^3 (Miyoshi et al., 2018). However, the cost of electricity consumption per unit of wastewater, calculated based on the national average unit wastewater consumption, amounts to approximately 0.32 RMB/m^3. The electricity consumption costs for Plants A, B, and C exceed the aforementioned values, standing at 0.55, 0.6, and 0.44 RMB/m^3, respectively. Notably, Plant D has the lowest electricity consumption cost, which is 0.16 RMB/m^3. The variation in electricity consumption and chemical usage primarily arises from the differences between Plant D and Plants A, B, and C. While Plant D exhibits lower power and chemical consumption, Plants A, B, and C demonstrate higher consumption of electricity and CH_3COONa, which contributes to an overall increase in unit wastewater costs. The underlying reason for this issue is that the volume and concentration of influent wastewater do not meet the designed requirements, resulting in a situation similar to that of an

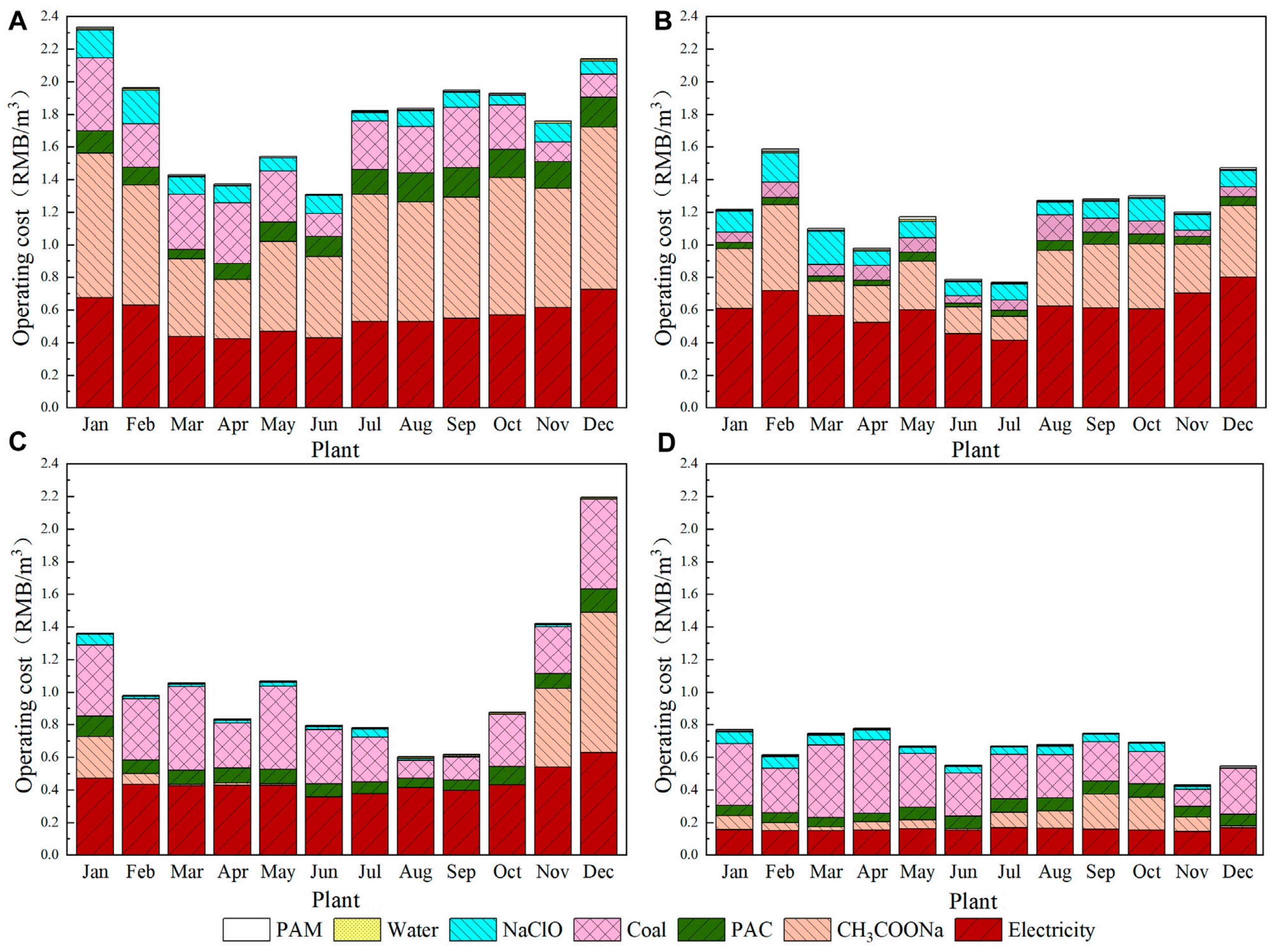

FIGURE 11
Operating costs per unit of wastewater for WWTPs.

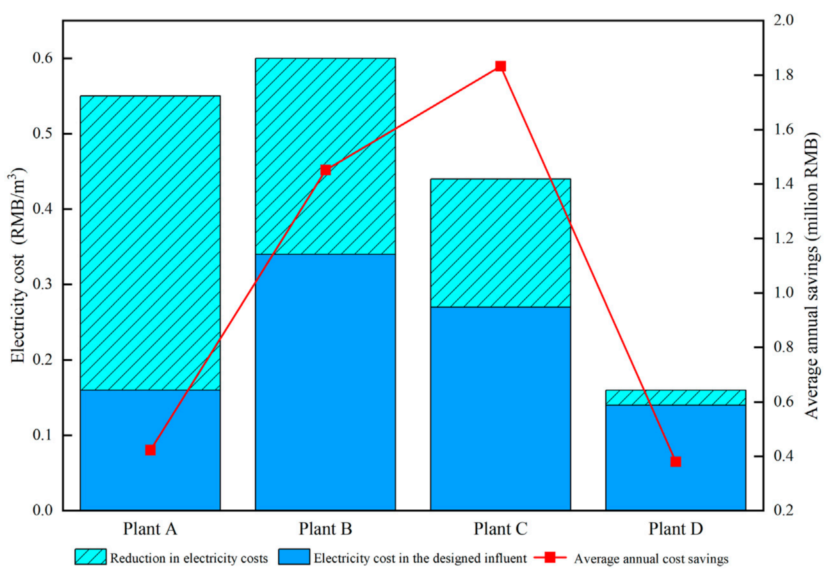

FIGURE 12
Electricity consumption per unit of wastewater for WWTPs.

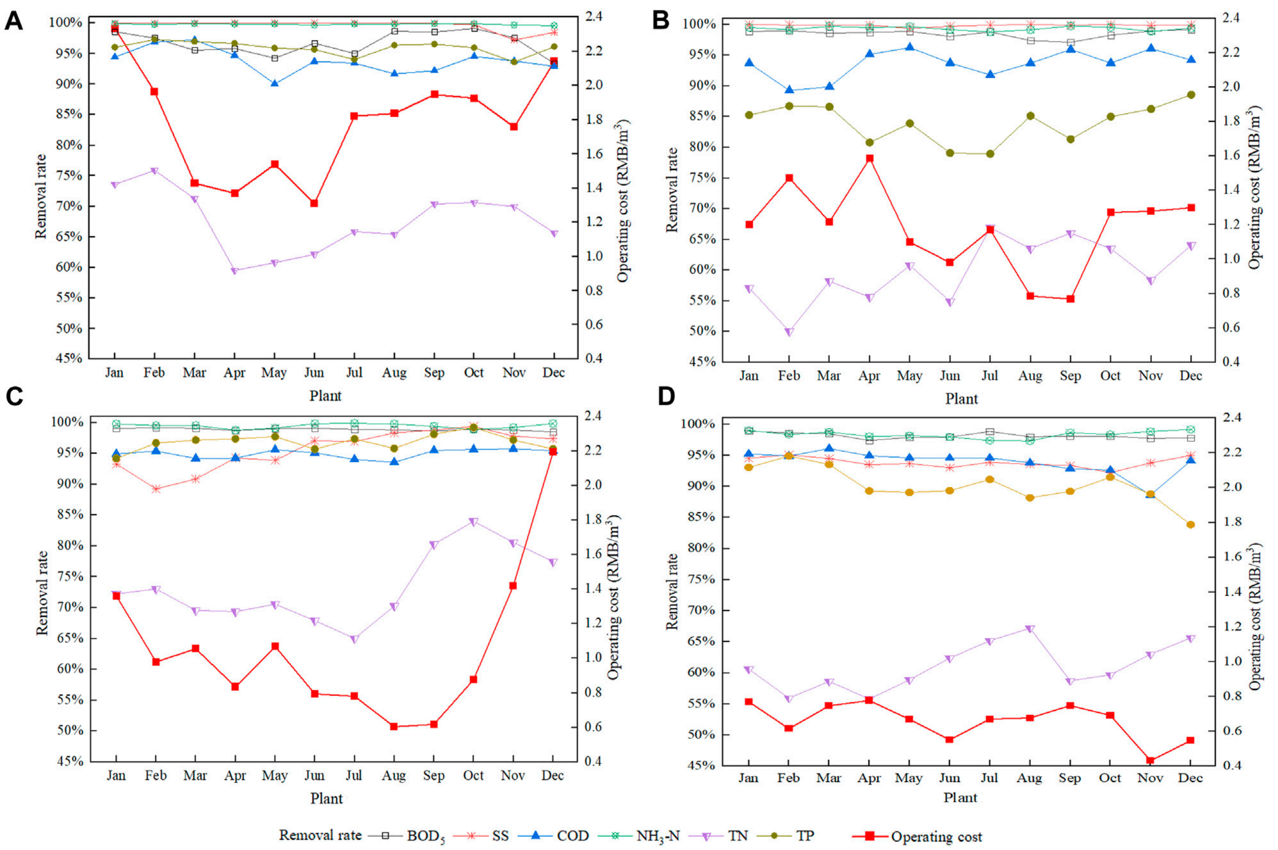

FIGURE 13
Removal rates and operating costs of WWTPs.

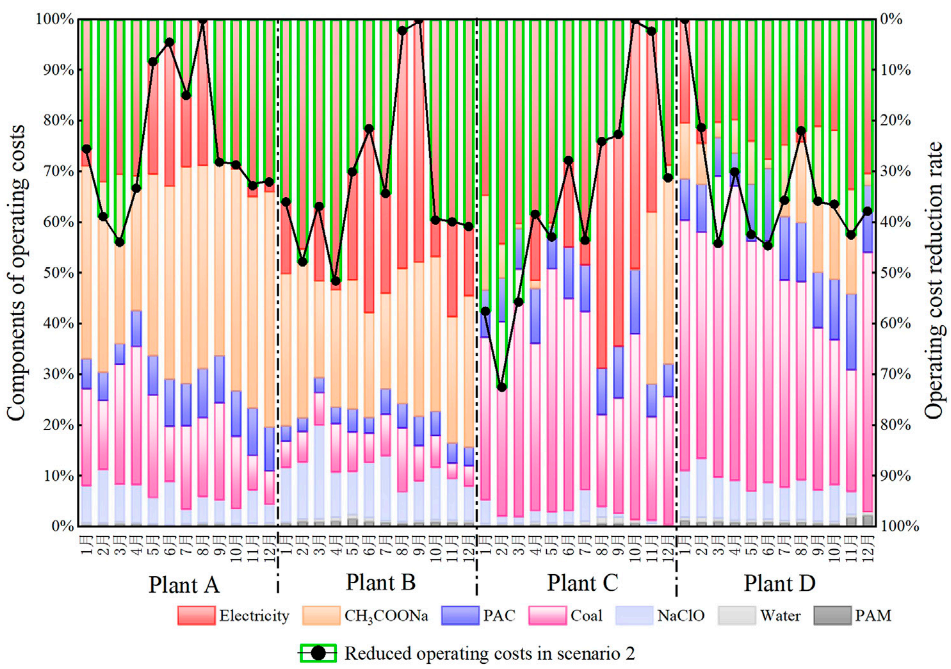

FIGURE 14
Composition of operating costs per unit of wastewater and benefit improvement for WWTPs in Jiujiang City in 2022.

overloaded system. Consequently, the unit wastewater power consumption remains elevated. Additionally, in the biochemical reaction process, there is an insufficient supply of carbon sources, necessitating the addition of a substantial quantity of carbon sources.

3.2.2 Operating costs of the scenarios

Scenario 1: The calculated results demonstrate that the operating costs (OC_1) per unit of wastewater volume for Plant A, Plant B, Plant C, and Plant D, based on their designed wastewater treatment capacity, are 1.39, 0.91, 0.88, and 0.64 RMB/m^3, respectively. Among these costs, electricity consumption accounts for 0.16, 0.34, 0.27, and 0.14 RMB/m^3, respectively. The year-on-year cost reductions are 0.39, 0.26, 0.17, and 0.02 RMB/m^3, respectively. As illustrated in Figure 12, the reduction percentages in unit wastewater operating costs (OC_1) are 22%, 23%, 16%, and 3%, respectively. In this scenario, when the wastewater inflow reaches the designed capacity, annual cost savings for each plant can amount to 4.23 million, 1.45 million, 1.83 million, and 0.38 million RMB, respectively (Figure 12).

Scenario 2: The months with the lowest operational costs for Plants A, B, C, and D are June, September, August, and November, respectively. During these months, the pollutant removal efficiencies met the Class A, Level 1, emission standards of pollutants for municipal wastewater treatment plants in China (GB 18918-2002) at the specified rates. For example, in Plant A, the BOD_5, SS, COD, NH_3-N, TN, and TP removal efficiencies in June were 1.13 times, 1.08 times, 1.37 times, 1.31 times, 1.34 times, and 1.14 times that of the Class A, Level 1 standard, respectively. Similar trends were observed in the other plants during their respective optimal operating months. As shown in Figure 13, the months with the lowest operational costs resulted in favorable pollutant removal efficiencies and cost-effectiveness for all plants. The outlet wastewater concentrations and removal rates for each plant generally fall within the upper–middle range. Additionally, there was minimal fluctuation in influent concentrations each month, and the influent concentrations of pollutants in the month with the lowest operating cost (OC_2) typically fall near the median concentrations of each pollutant across various months. The composition of OC_2 per unit of wastewater volume and the improvement in cost-effectiveness for 2022 are shown in Figures 13, 14.

In Plant A, if operating conditions similar to those in June are maintained, such as electricity consumption, wastewater inflow, and chemical dosage, the minimum OC_2 is calculated as 1.31 RMB/m^3. The actual monthly average OC_2 is reduced by 0.47 RMB/m^3 when compared with the same period of the past year, indicating a reduction ratio of 26%. With the same wastewater inflow, Plant A is expected to save 1.26 million RMB in the next year. Plant B, operating under September conditions, achieves a minimum OC_2 of 0.77 RMB/m^3. The actual monthly average OC_2 is reduced by 0.41 RMB/m^3 when compared with the same period of the past year, representing a reduction ratio of 35%. With the same wastewater inflow, Plant B anticipates saving 1.28 million RMB in the next year. Operating under August conditions, Plant C achieves a minimum OC_2 of 0.60 RMB/m^3. The actual monthly average OC_2 is reduced by 0.45 RMB/m^3 when compared with the same period of the past year, reflecting a reduction ratio of 43%. With the same wastewater inflow, Plant C is projected to save 3.05 million RMB in the next year. Finally, operating under November conditions, Plant D attains a minimum OC_2 calculated at 0.43 RMB/m^3. The actual monthly average OC_2 is reduced by 0.23 RMB/m^3 year-on-year, representing a reduction ratio of 35%. With the same wastewater inflow, Plant D is expected to save 5.43 million RMB in the following year (Figure 14).

Scenario 3: For Plant A, the optimal OC_3 is 1.04 RMB/m^3, and the actual monthly average OC_3 is reduced by 0.74 RMB/m^3 year-on-year, resulting in a reduction ratio of 42%. The designed wastewater inflow will lead to a savings of 8.13 million RMB in the next year. Plant B's optimal OC_3 is 0.72 RMB/m^3, and the actual monthly average OC_3 is 0.45 RMB/m^3 lower than that during the same period of the past year, representing a reduction ratio of 38%. The designed wastewater inflow will result in savings of 2.82 million RMB in the next year. Plant C's optimal OC_3 is 0.45 RMB/m^3, and the actual monthly average OC_3 is reduced by 0.60 RMB/m^3 when compared with the same period of the past year, marking a reduction ratio of 57%. With the designed wastewater inflow, Plant C is projected to save 6.48 million RMB in the next year. Finally, for Plant D, the optimal OC_3 is 0.43 RMB/m^3, and the actual monthly average OC_3 is reduced by 0.43 RMB/m^3 when compared with the same period of the past year, representing a reduction ratio of 35%. The designed wastewater inflow will result in a savings of 5.91 million RMB in the following year.

If further reduction in operating costs is desired, a series of improvement measures can be adopted. For instance, Gaona et al. (2023) achieved a reduction in operating costs of 41%–47% through the nitrite pathway, although this led to increased N_2O emissions.

4 Conclusion and recommendations

(1) Through an analysis of four typical urban WWTPs in Jiujiang city, China, it was found that the four WWTPs have common features, such as low influent concentrations and effluent water quality meeting discharge standards, with pollutant removal rates higher than the national average for all pollutants except TN. Furthermore, the BOD_5/COD values for influents ranged between 0.4 and 0.6, whereas the COD/TN values were less than 8, indicating that although the wastewater is good to biodegrade, it has insufficient carbon sources in the treatment processes. In terms of energy consumption, Plant D exhibited electricity consumption lower than 0.36 kWh/m^3, which is below 50% that of WWTPs in China, whereas the other three WWTPs had electricity consumption exceeding 0.61 kWh/m^3, surpassing 80% that of WWTPs. For chemical consumption, the four WWTPs showed a higher usage of CH_3COONa and PAC than the national average, with Plant A significantly exceeding 90% of WWTPs.

(2) Concerning the carbon emissions per unit wastewater treatment, it was observed that Plant A > Plant B > Plant C > Plant D have values of 1,447.20, 1,168.63, 953.21, and 514.50 g CO_2e/m^3, respectively. Plants A, B, and C have higher carbon emissions mainly due to the excessively high indirect emissions resulting from energy and chemical consumption. The proportions of indirect emissions for Plants A, B, C, and D were 86.13%, 85.61%, 77.13%, and 64.79%, respectively. In addition, the

operational costs for Plants A, B, C, and D were 1.78, 1.18, 1.05, and 0.66 RMB/m^3, respectively, excluding labor costs. Regarding the composition of operational costs, electricity and CH_3COONa costs contributed to a significant portion.

(3) The improvement efficiency for the four WWTPs was researched under three scenarios accordingly. In Scenario 1, the operational costs for Plants A, B, C, and D could be reduced from 3.03% to 22.88%. In comparison, the operational costs were reduced to 1.31, 0.77, 0.60, and 0.43 RMB/m^3, resulting in cost savings of 1.26, 1.28, 3.05, and 5.43 million RMB/year in Scenario 2 and 1.04, 0.72, 0.45, and 0.42 RMB/m^3 in Scenario 3, respectively, which help save costs by 8.13, 2.82, 6.48, and 5.91 million RMB/year, respectively. The results show that for the four WWTPs, carbon emissions were reduced by 489, 325, 217, and 15 gCO_2e/m^3 in Scenario 1; 244.41, 316.33, 126.14, and 14.8 gCO_2e/m^3 in Scenario 2; and 598.85, 422.04, 313.22, and 15.02 gCO_2e/m^3 in Scenario 3, respectively. The carbon emission reduction ranged from 2.87% to 27.07% in Scenario 2, i.e., lower than those of the other scenarios, due to energy consumption being a critical factor. Combining the operational cost analysis, Scenario 2 is the most efficient solution to improve the efficiency of WWTPs at present. It is hoped that more actions such as dosing system accuracy enhancement, tail gas collection, photovoltaic power generation, carbon sequestration, and wastewater heat source recycling are carried out to achieve zero energy consumption and zero carbon emission in the WWTPs in future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding authors.

Author contributions

RT: data curation, formal analysis, investigation, methodology, writing–original draft, and writing–review and editing. YH: data curation, methodology, project administration, resources, visualization, and writing–review and editing. EH: data curation, funding acquisition, supervision, visualization, and writing–review and editing. HL: formal analysis, investigation, and writing–review and editing. DW: funding acquisition and writing–review and editing. PL: investigation, visualization, and writing–review and editing.

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Conflict of interest

Authors EH and DW were employed by China Three Gorges Corporation. Authors EH and DW were employed by Yangtze Ecology and Environment Corporation Limited.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Research on the impact of FDI and environmental regulation on the industrial structure upgrading in the Yellow River Basin

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Introductions: Since the reform and opening up, the inflow of foreign direct investment (FDI) has provided a steady stream of capital, technology, talent and other resources for the development of the Yellow River basin, while caused problems such as environmental pollution, ecological fragility and industrial structure upgrading difficulties to some extent. Environmental regulation is a pivotal initiative to achieve mutual harmony between ecological environment and economic development, which could enhance the quality of the introduction of FDI and accelerate the green transformation of the development mode.

Methods: Based on urban panel data from 2006–2019, this study empirically examined the impact of FDI and environmental regulation on industrial structure upgrading in the Yellow River Basin. Moreover, taking environmental regulation as a threshold variable, a panel threshold model was established to further explore the role of environmental regulation in the impact of FDI on industrial structure upgrading in the Yellow River Basin.

Results: (1) The relationship between FDI and industrial structure upgrading in the Yellow River Basin is not a simple linear relationship, but an inverted "U"-shaped relationship that rises first and then falls, and the results of this inverted "U"-shaped relationship are still robust after replacing key indicators. (2) The environmental regulation policy has a driving effect on the upgrading of industrial structure in the Yellow River Basin. (3) Environmental regulation has a positive role in the influence of FDI on the industrial structure upgrading in the Yellow River basin, and the positive role increases gradually as the intensity of environmental regulation increases moderately, but if the intensity of environmental regulation is too high, it will have a negative impact on the upgrading of industrial structure in the Yellow River basin to some extent.

Discussion: In the future, policymakers should make reasonable and effective use of FDI and improve the quality of FDI; reasonably formulate environmental regulation policies; coordinate the intensity of FDI and environmental regulation; thus, bring into play the promotion effect of FDI and environmental regulation on industrial structure upgrading, and then realize the win-win of ecological protection and high-quality economic development in the Yellow River Basin.

KEYWORDS

FDI, environmental regulation, industrial structure upgrading, Yellow River Basin, empirical analysis

1 Introduction

As the mother river of the Chinese nation, the Yellow River is an important ecological barrier and economic zone in China. Since the reform and opening up, foreign direct investment (FDI) has become an important force for the economic development of the Yellow River basin, where the amount of foreign capital actually used maintains an upward trend as a whole since 2009 and it tends to be stabilized at ¥290 billion in recent years. FDI has provided a steady stream of capital, technology, talent and other resources for the development of the Yellow River basin, which could not only promote the scientific and technological innovation capacity, but also boost the high-quality economic development (Feng et al., 2019; Wang and Liu, 2019; Zhang, 2021).

However, FDI also has the potential to lead to serious environmental issues (Yu et al., 2021). A considerable amount of FDI has been concentrated in the "high energy consumption, high pollution, low output" of the secondary industry, resulting in environmental pollution, ecological fragility and industrial structure upgrading difficulties, which has become a crucial factor limiting the quality of economic development of the Yellow River Basin. Precisely because of this, on 18 September 2019, President Xi Jinping chaired and addressed a symposium in Zhengzhou, stressing that the protection of the Yellow River is critical to the great rejuvenation and sustainable development of the Chinese nation, and ecological conservation and high-quality development of the Yellow River Basin is a major national strategy.

Not only that, on 8 October 2021, the Communist Party of China Central Committee and the State Council have jointly issued an outline document on the ecological protection and high-quality development of the Yellow River basin, which requires the cities along the Yellow River to plan the development of industries and others based on their water resource capacities. Immediately following, on October 22, President Xi Jinping pointed out that provinces and regions along the Yellow River should implement the strategic plan for the high-quality development, and unswervingly follow the modernization path of ecological priority and green development.

Environmental regulation involves the government's oversight and control of the actions of enterprises and individuals in relation to environmental conservation and resource management, and its implementation depend on the enforcement of laws, policies, and standards (Feng et al., 2024). It needs to be emphasized that environmental regulation is an essential measure for the government to realize mutual coordination between ecological environment and economic development.

In particular, environmental regulation can attract "new entrants" to join the green technology market and launch more green innovations (Yan et al., 2024), which could enhance the quality of the introduction of FDI and accelerate the green transformation of the development mode. Moreover, it has been suggested that the technology spillover effect of FDI is significant under the constraint of environmental regulation (Zou and Chen, 2022).

Hence, when studies refer to FDI and industrial structure upgrading of the Yellow River Basin, it is essential to take the environmental regulation into account. In this case, it is significant to deal with the inherent relationship between FDI, environmental regulation and industrial structure upgrading to fulfill ecological protection and high-quality economic development in the Yellow River Basin. Specifically, the detailed tasks of this study are: (a) respectively search for the relationship between FDI/environmental regulation and industrial structure upgrading in the Yellow River Basin; (b) explore the role of environmental regulation in the impact of FDI on industrial structure upgrading in the Yellow River Basin in depth.

The rest of the paper is organized as follows (as shown in Figure 1). The second section reviews the literature relevant to this study. The theoretical analysis and research hypotheses are presented in the third section. The fourth section describes the variables, data sources, and models. The fifth part is the empirical analysis of this paper, including benchmark regression analysis, heterogeneity analysis, robustness test, and threshold effect test. The sixth, seventh and eighth parts give the research conclusions, countermeasure suggestions and research prospects, respectively.

2 Literature review

In recent years, studies on the impact of FDI on the industrial structure upgrading have been conducted widely. With respect to those researches, the mainstream views of the impact of FDI could be broadly divided into two types: the "pollution haven" hypothesis and the "pollution halo" hypothesis (Feng et al., 2019). On one hand, a vast majority of scholars believe that the inflow of foreign capital can ameliorate the rationalization of industrial structure by providing capital, technology spillover and promoting the flow of production factors, which in turn promotes the upgrading of industrial structure in the host country. Tang et al. (2019) concluded empirically that FDI spillovers have a positive effect on local technological upgrading in nearby and neighboring cities. Yu and Han (2019) conducted an empirical analysis based on VAR model and the results showed the positive impact of foreign direct investment on industrial structure upgrading in Jiangsu province. Wang et al. (2020) introduced spatial autocorrelation analysis method and spatial panel econometric model by constructing a weight matrix of economic distance to prove that FDI is a key driving factor for industrial structure upgrading in China. Wu and Liu. (2021) used the spatial Durbin model to indicate that FDI has positive direct and indirect effects on industrial structure upgrading. Xu (2021) found that the industrial competition brought by FDI has a positive impact on the upgrading and progress of China's industrial structure.

On the other hand, a few scholars argue that the inflow of foreign capital will introduce high pollution and high emission industries. This may make the host country enterprises too dependent on foreign capital instead of pursuing high value-added industries, which is detrimental to the technological research and development of local enterprises and thus hinders the upgrading of the industrial structure of the host country. Li et al. (2021) adopted exploratory spatial data analysis methods to prove the conclusion that FDI can enhance the rationalization of industrial structure, however, to a certain extent, it hampers the upgrading of industrial structure.

The relationship between environmental regulation and industrial structure upgrading is currently viewed as facilitation, inhibition and indeterminacy in academic circles. Wu et al. (2019) took Chinese provincial manufacturing industries as the survey object and found that environmental regulations have

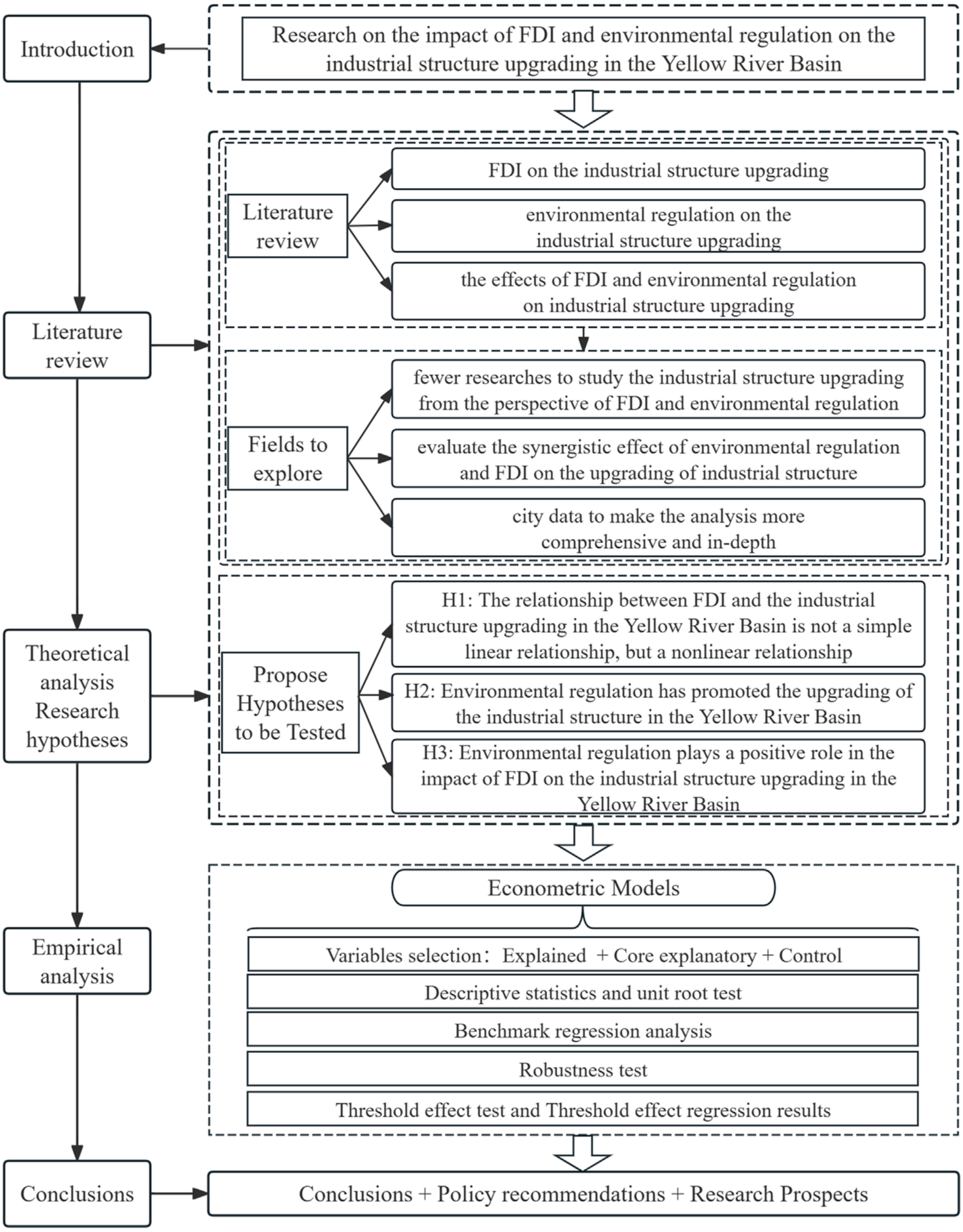

FIGURE 1
Research framework.

a suppressive effect on the industrial structure upgrading of China's manufacturing industry. Chen and Qian (2020) pointed out that adjusting the environmental regulation policy is effective facilitator in enhancing industrial structure upgrading, which in turn promotes the high-quality development of the regional economy. Chen et al. (2020) proved that various types of marine environmental regulations have a positive U-shaped relationship with the transfer of polluting industries and industrial structure upgrading. Wang et al. (2020) noted that formal environmental regulations have an inverted "U" shaped direct impact on industrial upgrading and a positive impact on industrial upgrading through technological innovation strategies. Song et al. (2021) held the view that there are regional differences in the impact of environmental regulation on industrial structure upgrading. Under the western sample, there is a negative relationship between environmental regulation and industrial structure upgrading while there is a positive relationship under the national sample and the eastern sample. Zhou et al. (2021) based on a spatial econometric approach to demonstrate that the stringency of environmental regulation helps to optimize the industrial structure. By exploring three major economic zones in China, Guan et al. (2022b) believed that environmental regulation has a dampening effect on industrial structure rationalization, but effectively promotes industrial structure upgrading. Wang et al. (2022b) argued that command-based environmental regulation and market-based environmental regulation can motivate firms to engage in green technology innovation, which is an efficient technique to promote green economic development. Yin et al. (2022b) used the mediating effects and threshold models, and reported that industrial upgrading in the central and western regions is impeded by environmental regulations.

Some scholars have also started to study the effects of FDI and environmental regulation on industrial structure upgrading. Qiu et al. (2021) asserted that strict environmental regulatory policies can effectively raise the entry barrier of FDI into China, improve the quality of FDI, and enhance the technological absorption capacity of enterprises. Wang et al. (2022a) found that there is a partial mediating effect of FDI in the process of various types of environmental regulations affecting industrial upgrading. Xie et al. (2021) concluded that there is a single threshold of FDI between environmental regulation and industrial structural upgrading by testing the threshold effect. Feng and Liang (2022) found that the moderating effect of environmental regulation is partially and conditionally established. However, Yin et al. (2022a) studied 30 Chinese provinces and argued that environmental regulations impede the spillover and capital accumulation effects of FDI, and curb technological progress to some extent.

Through literature combing, the existing studies provide insights into the role of FDI and environmental regulation in industrial structure upgrading. Both FDI and environmental regulation will have an impact on the upgrading of industrial structure, but unconditional openness and non-strict environmental regulation will have a negative direct effect on economic development (Feng et al., 2019; Zhang et al., 2022). Nevertheless, there are still some fields to explore. Firstly, it is found that there are fewer researches to study the industrial structure upgrading from the perspective of FDI and environmental regulation at the same time, and the literature that takes the Yellow River Basin as the study area is even scarcer. Secondly, this study made the initial effort to evaluate the synergistic effect of environmental regulation and FDI on the upgrading of industrial structure, which bridges the gap between theory and practice by providing a profound vision of spatial econometrics. Finally, this study utilized a panel data of the Yellow River Basin from 2006–2019 rather than provincial data, which makes the analysis more comprehensive and thorough.

Therefore, this study focused on the Yellow River Basin, examined the impact on industrial structure upgrading from the perspective of FDI and environmental regulation, and added the interaction between the two to explore the role of environmental regulation in the impact of FDI on industrial structure upgrading. The panel threshold model was further established to analyze the impact of FDI on the industrial structure upgrading in the Yellow River Basin under different environmental regulatory intensities. This would provide a reference for the coordination and cooperation of FDI and environmental regulation in the Yellow River Basin to promote the industrial structure upgrading.

3 Theoretical analysis and research hypotheses

3.1 FDI and industrial structure upgrading

FDI is an external force for upgrading industrial structure (Cheng et al., 2022). The introduction of FDI in the Yellow River Basin has played a momentous role in its economic development and has become an essential driving force for the industrial structure upgrading in the Yellow River Basin (Water Resources Department of Henan Province, 2021). On one hand, the introduction of foreign capital could provide enterprises with advanced technology and management experience, reduce the production cost of enterprises, boost their production efficiency, and promote the transformation of industries from low value-added to high value-added, which indirectly promotes the industrial structure upgrading of the Yellow River Basin, and form the “pollution halo” (Feng et al., 2019; Zou and Chen, 2022). However, the technology spillover of FDI will also be restricted by domestic technological level, innovation capability and human resources, which may affect the effect of FDI (Feng et al., 2019). On the other hand, the scale of FDI flowing into the tertiary industry in the Yellow River Basin has gradually multiplied, providing financial support for the development of the tertiary industry in the Yellow River Basin (Zhang, 2021), but the entry threshold for the tertiary industry is relatively high, which may affect the pulling role of the FDI in the third industry of the Yellow River Basin.

However, the introduction of FDI also has some negative effects. The excessive introduction of FDI may make the Yellow River Basin enterprises over-reliant on foreign capital, while ignoring the amelioration of their own innovation capabilities and production efficiency. At the same time, it is also possible to introduce some low-quality FDI, such as polluting FDI, which not only causes environmental pollution, but also hinders the economic development, and form the “pollution haven” (Feng et al., 2019). Therefore, the following hypothesis one was put forward.

Hypothesis 1: The relationship between FDI and the industrial structure upgrading in the Yellow River Basin is not a simple linear relationship, but a nonlinear relationship.

3.2 Environmental regulation and industrial structure upgrading

With the gradual aggravation of environmental pollution problems, environmental regulation is of great significance in improving the quality of ecological environment. Environmental regulation can force and guide enterprises to consider environmental factors in their investment and emissions trading, promote the transformation of enterprises from high energy consumption and pollution to low-carbon environmental protection, accelerate the transformation and upgrading of industrial structure (Feng et al., 2024). In addition, with the implementation of environmental regulation policies, the living environment has been greatly ameliorated, the public’s awareness of environmental protection is gradually increased, and the public’s demand for “green products” is also gradually on the rise, so that enterprises can produce a wider variety of green products to meet consumer demand, thus promoting industrial restructuring (Chen and Qian, 2020; Liao and Shi, 2018; Du et al., 2021).

With the implementation of China's environmental regulation policies and the popularization of environmental protection concepts in recent years, this study believes that, environmental regulation has promoted the industrial structure upgrading in the Yellow River Basin as a whole, so hypothesis two was proposed.

Hypothesis 2: Environmental regulation has promoted the upgrading of the industrial structure in the Yellow River Basin.

3.3 FDI, environmental regulation and industrial structure upgrading

Since FDI affects the industrial structure of the Yellow River Basin, it also causes environmental pollution, so the implementation of environmental regulation policies can enhance the entry threshold of FDI, refine the quality of FDI, and reduce the introduction of polluting FDI. Most of the synergistic effects of environmental regulation and FDI on urban innovation are significantly positive, implying that the "Porter hypothesis" is established in China when the inflow of FDI cooperated with the implementation of environmental regulation properly (Feng et al., 2019). Environmental regulation can crowd out investment in polluting technology innovation, allow FDI to flow into the technology innovation market, incentivize potential entrants who have identified the green technology market opportunity, and thus promote the upgrading of industrial structure (Yan et al., 2024).

At the same time, the augmentation in environmental regulation costs will also make some foreign-invested enterprises with serious pollution turn to industries with lower environmental regulation intensity, while the tertiary industry has relatively low environmental regulation costs due to its low energy consumption and less pollution. Therefore, it is speculated that environmental regulation has promoted the role of FDI in industrial structure upgrading of the Yellow River Basin to a certain extent. Based on this, hypothesis three was formulated.

Hypothesis 3: Environmental regulation plays a positive role in the impact of FDI on the industrial structure upgrading in the Yellow River Basin.

4 Research design

4.1 Variables selection

4.1.1 Explained variable

Industrial structure upgrading (U) was introduced to denote the explained variable. Referring to the method proposed by Du et al. (2021), this study measured the industrial structure upgrading from the perspective of industrial structure advancement, and conducted theoretical as well as empirical research on this basis. The ratio of the added value of the tertiary industry to the secondary industry was adopted to measure the industrial structure advancement.

4.1.2 Core explanatory variables

In this study, FDI and environmental regulation were selected as the core explanatory variables. Based on the research thoughts of Shi et al. (2022), FDI was expressed by the ratio of the actual use of FDI in each city to the GDP of the year, and adjusted by the average annual exchange rate of the year. Environmental regulation means that the government regulates and manages the behavior of enterprises and individuals through laws, policies, and standards, so to achieve the goal of coordinated development of environment and economy (Feng et al., 2024).

Since the intensity of environmental regulation could not be directly obtained and is limited by data availability in the Yellow River Basin, this study drew on the practice of Meng and Shao. (2020), selected the emission data of industrial sulfur dioxide, industrial wastewater and industrial smoke (powder) dust to construct a comprehensive index of environmental pollution, and utilized its reciprocal to measure the degree of environmental regulation, expressed as ER, which is shown in the formula Eq. 1:

$$ER_{jt} = \frac{1}{E_{jt}} = \frac{1}{\left(\sum_{i=1}^{3} X_{i,jt}/y_{jt}\right)/3} \tag{1}$$

which $X_{i,jt}$ represents the ratio of pollutant discharge amount i in city j in year t to the total emission amount of pollutant i in the country in year t, and y_{jt} represents the ratio of the total industrial output value of city j in year t to the total industrial output value of the country in year t. E_{jt} is the comprehensive index of environmental pollution in city j in year t, The smaller the value, the stronger the intensity of environmental regulation; the larger the value, the weaker the intensity of environmental regulation.

4.1.3 Control variables

In this study, economic development level (EDL), degree of government intervention (GI), higher education level (HEL) and marketization level (ML) were chosen as the control variables. The economy is a critical driving force for the industrial structure upgrading. Referring to the practice of Guan et al. (2022a), this study selected the *per capita* GDP of the cities in the Yellow River Basin to represent the economic development level.

Moreover, the government could promote the industrial transformation and upgrading through financial and policy means. However, improper government control may also bring pressure to enterprises, restrict the market function to allocate resources, and is not conducive to the optimization and upgrading of the industrial structure. Therefore, drawing on the treatment of variable in Li and Ding. (2018), this study selected the ratio of the government fiscal revenue to the regional GDP of the cities in the Yellow River Basin in the current year to represent the degree of government intervention.

In addition, human capital is a valued factor affecting economic growth and industrial structure upgrading. With reference to the research thoughts of Zhu and Liu. (2020), this study adopted the ratio of the number of students in higher education of various cities in the Yellow River Basin to the resident population in the region to measure the higher education level.

Furthermore, the higher the marketization level, the more efficient the flow of resources, which is more conducive to the industrial structure upgrading. Therefore, referring to the treatment of variable in Zhang and Qin. (2018), marketization level was expressed as "1-(local fiscal expenditure/GDP)".

4.2 Model design

In order to test the impact of FDI on the industrial structure upgrading and whether environmental regulation would affect the effect of FDI on the industrial structure upgrading in the Yellow River Basin, the interaction term FE was hereby added. At the same time, based on the previous analysis, it can be seen that there may be a nonlinear relationship between FDI and industrial structure upgrading, so the quadratic term of FDI was added to the benchmark regression model. Therefore, the benchmark regression model was established as follows in formula Eq. 2:

$$\ln U_{it} = \beta_0 + \beta_1 \ln FDI_{it} + \beta_2 (\ln FDI_{it})^2 + \beta_3 \ln ER_{it} + \beta_4 FE + \beta_j \sum control_{it} + \varepsilon_{it} \quad (2)$$

among them, i represents each city in the Yellow River Basin, t denotes each year, β_0 is a constant term, ε_{it} represents a random disturbance term, U_{it} is the industrial structure upgrading, ER_{it} denotes the environmental regulation, and $control_{it}$ represents a set of control variables, including the economic development level (EDL), the degree of government intervention (GI), the higher education level (HEL), and the marketization level (ML).

At the same time, in order to further explore the positive influence of environmental regulation on FDI and the industrial structure upgrading in the Yellow River Basin, this study introduced environmental regulation as a threshold variable to construct a following threshold panel model Eq. 3 to clarify its positive impact under different intensities.

$$\begin{aligned} \ln U_{it} = {} & \varphi_0 + \varphi_1 \ln FDI_{it}(\ln ER_{it} \le \gamma) + \varphi_2 \ln FDI_{it}(\ln ER_{it} > \gamma) \\ & + \varphi_3 F^* E(\ln ER_{it} \le \gamma) + \varphi_4 F^* E(\ln ER_{it} \ge \gamma) \\ & + \varphi_j \sum control_{it} + \varepsilon_{it} \end{aligned} \quad (3)$$

which φ_0 is the constant term, γ represents the threshold value of environmental regulation.

4.3 Study area setting and data sources

According to the "Hohhot-Baotou-Erdos-Yulin City Cluster Development Plan," "Guanzhong Plain City Cluster Development Plan," "Central Plain City Cluster Development Plan," "Lanzhou-Xining City Cluster Development Plan" and the city cluster development plans of various provinces and cities, the Yellow River Basin was set as seven city clusters, namely, the Hohhot-Baotou-Erdos-Yulin City Cluster, City Cluster along the Yellow River in Ningxia, and Lanzhou-Xining City Cluster in the upper reaches, Guanzhong Plain City Cluster, Jinzhong City Cluster, and Central Plain City Cluster in the middle reaches, as well as Shandong Peninsula City Cluster in the lower reaches. Among them, as the data of autonomous prefectures in Lanzhou-Xining City Cluster was not available, and Haidong City, Wuzhong City, Zhongwei City, Tianshui City, Dingxi City, Baiyin City, Jiyuan City and Yangling Demonstration Zone have serious data shortages, they were excluded from the study area.

Thus, in this study, 53 cities in the Yellow River Basin were selected. All the data were collected from the "China Statistical Yearbook," "China Urban Construction Statistical Yearbook" and "China Environmental Statistical Yearbook" from 2006 to 2019. Partial missing data were filled by linear interpolation. Specially, the following calculation was conducted based on Stata 16.0 software.

4.4 Descriptive statistics and unit root test

In particular, this study introduced the logarithm of all variables into the model to reduce the heteroscedasticity problem in model setting. Table 1 describes the mean value, standard deviation, minimum value, median value and maximum value of each variable.

In addition, 14 years of data collected by this study belong to the short panel data. However, due to the time-series nature of panel data, nonstationary time series would lead to the phenomenon of "pseudo regression." Therefore, HT test was introduced into this study to test the stationarity of each variable, and the results are shown in Table 2. It can be seen that some variables in the original series failed the stationarity test, but the first-order difference series were all significant at the 1% significance level, which was expressed as a first-order single integer.

5 Empirical analysis

5.1 Benchmark regression analysis

From the Hausman test results (as shown in Table 3), the p-value of 0.0097 is less than the significance level of 0.05, the null hypothesis of the fixed effect model could be accepted. It can be concluded that the fixed effects regression method should be utilized for the panel data in this study. Therefore, the fixed effects model was introduced to empirically analyze the relationship between FDI and the industrial structure upgrading in the Yellow River Basin.

At the same time, this study performed stepwise regression to improve the robustness, and the regression results based on the fixed effects model are shown in Table 4.

It can be seen from models (1) to (7) that the coefficient of FDI primary term is significantly negative. As for FDI quadratic term, the coefficient in model (2) is negative but not significant, while in models (3) to (7), it is significantly negative. The results indicated that the relationship between FDI and the industrial structure upgrading in the Yellow River Basin is not a simple linear relationship, but an inverted "U"-shaped relationship that firstly rises and then falls. That is to say, the proportion of FDI in GDP is not the more the better, but within a suitable range, FDI could promote the industrial structure upgrading in the Yellow River Basin, otherwise it would be counter-productive, which verifies the Hypothesis 1.

In addition, it can be seen from the benchmark regression results (as illustrated in Table 3) that the current FDI in the Yellow River Basin is at the right end of the inverted "U"-shaped curve. In other words, the large proportion of FDI in GDP hampers the industrial

TABLE 1 Descriptive statistics.

Variable	Sample size	Mean value	Standard deviation	Minimum value	Median value	Maximum value
lnU	742	−.3263028	.4425957	−1.671056	−.3194326	.9114966
lnFDI	742	−4.49823	1.219242	−9.211221	−4.326281	−1.08761
lnER	742	.1003504	1.106484	−4.205263	.202896	2.647152
lnEDL	742	10.4947	.6586391	8.476371	10.53562	12.16495
lnGI	742	−2.708564	.3501431	−3.794952	−2.683311	−1.730207
lnHEL	742	−4.379065	1.123383	−7.931242	−4.492064	5.065858
lnML	742	−.1730123	.0945311	−.7792926	−.1504496	−.0435896

TABLE 2 Unit root test results.

lnU	−1.6545 * *	D_ lnU	−23.5531 * * *
lnFDI	−10.3056 * * *	D_ lnFDI	−34.0437 * * *
lnER	−3.7404 * * *	D_ lnER	−39.2317 * * *
lnEDL	1.5545	D_ lnEDL	−17.6185 * * *
lnGI	−0.2520	D_ lnGI	−25.4698 * * *
lnHEL	−27.0897 * * *	D_ lnHEL	−57.0950 * * *
lnML	−1.8787 * *	D_ lnML	−30.9874 * * *

D_ means the first-order difference. *,* * and * * * represent significance at the 10%, 5% and 1% levels, respectively (similarly hereinafter).

TABLE 3 Fixed effects and random effects regression results.

Variable	Fixed effects	Random effects
lnFDI	−.2101937	−.1994592
$(\ln FDI)^2$	−.0193382	−.0186776
LnER	.1601582	.1380704
F ∗ E	.0390483	.0339894
lnEDL	.1671074	.1526516
LnGI	.0335328	.0539746
lnHEL	.0503762	.0785607
lnML	−1.869141	−1.785496
constant term	−2.628635	−2.248151
F value	28.83	
Prob>chi2 = 0.0097		

structure upgrading in the Yellow River Basin to a certain extent. The reason may be that the proper introduction of foreign capital, that is, the low proportion of FDI in GDP, could reduce the production cost of enterprises, encourage them to carry out technological innovation, and promote the industrial structure upgrading in the Yellow River Basin. However, the introduction of foreign capital may also cause environmental pollution. When attracting more foreign capital and accounting for a large proportion of GDP, not only foreign technology and management experience but also foreign capital of uneven quality is introduced. Poor quality technical experience and human resources hinder the industrial structure upgrading. At the same time, it would also make enterprises overly dependent on foreign capital, ignoring their own productivity and technological innovation, thereby curbing the industrial structure upgrading.

The coefficient of environmental regulation is positive, which is significant at the 5% significance level in models (3) to (6), and 1% significance level in model (7), indicating that environmental regulation has promoted the industrial structure upgrading in the Yellow River Basin. Although this finding is different from the positive "U"-shaped conclusion of the existing studies, it is consistent with the later conclusion that the two are positively related, and to a certain extent verifies the Porter hypothesis. That is, environmental regulation could force enterprises to carry out technological innovation, which in turn could promote the entire industry upgrading, verifies the Hypothesis 2.

The reason may be that in recent years, the environmental regulation policies of the Yellow River Basin have burdened enterprises with more environmental governance costs, and the profit rate has fallen, which forced enterprises to carry out technological innovation. In the end, the compensation brought by enterprises' technological innovation made up for the cost of environmental regulation. The environmental regulation policy of the Yellow River Basin has played a positive role in the industrial structure upgrading.

The coefficient of interaction term (FE) between FDI and environmental regulation is positive and passed the significance test, which shows that environmental regulation could promote the effect of FDI on the industrial structure upgrading of the Yellow River Basin. That is to say, environmental regulation has a positive role in promoting the impact of FDI on the industrial structure upgrading, which verifies the Hypothesis 3.

Among the control variables, the regression coefficient of economic development level is significantly positive, indicating that

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TABLE 4 Stepwise regression results of fixed effects model.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
LnFDI	−.0394872*** (−2.65)	−.1387748** (−2.23)	−.1838754*** (−2.79)	−.1578243*** (−2.88)	−.1851086*** (−3.35)	−.1817009*** (−3.31)	−.2101937*** (-3.96)
$(\ln FDI)^2$	–	−.0095448 (−1.64)	−.0147129** (−3.01)	−.0175865*** (−3.40)	−.0171865*** (−3.34)	−.0193382*** (-3.89)	
LnER	–	–	.1439248** (2.56)	.108464** (2.32)	.1211644** (2.59)	.118883** (2.56)	.1601582*** (3.54)
F*E	–	–	.0347824*** (2.95)	.0345308*** (3.53)	.0366158*** (3.75)	.0355222*** (3.66)	.0390483*** (4.17)
LnEDL	–	–	–	.3414867*** (17.52)	.2922212*** (11.23)	.2628986*** (9.53)	.1671074*** (5.63)
LnGI	–	–	–	–	.1542044*** (2.84)	.1537742*** (2.85)	.0335328 (0.61)
LnHEL	–	–	–	–	–	0641452*** (3.06)	.0503762** (2.48)
LnML	–	–	–	–	–	–	−1.869141*** (−7.27)
_cons	−.5039251*** (−7.44)	−.7432444*** (−4.63)	−.8439151*** (−4.98)	−4.289201*** (−17.73)	−3.433637*** (−8.91)	−2.839443*** (−6.61)	−2.628635*** (−6.33)
R^2	0.0101	0.0140	0.0270	0.3284	0.3362	0.3452	0.3923
N	742	742	742	742	742	742	742

The corresponding t values are in parentheses (similarly hereinafter).

the economic development in the Yellow River Basin has promoted the industrial structure upgrading, thus proving that the economy is a critical driving force for the industrial structure upgrading. The higher the economic development level, the stronger the promotion effect on the industrial structure upgrading in the Yellow River Basin. In addition, the economic development level reflects people's wealth creation ability, and high wealth creation ability also means people's high consumption level. The higher the consumption level, the better the development of the tertiary industry. Meanwhile, enterprises would also innovate to produce more high value-added products, thereby promoting the industrial structure upgrading in the Yellow River Basin.

The coefficient of degree of government intervention is significantly positive at the significance level of 1% in both models (5) and (6), indicating that government intervention has a positive effect on the industrial structure upgrading in the Yellow River Basin. Moderate government intervention could provide financial support and policy support for the transformation of enterprises, ultimately promoting the industrial structure upgrading in the Yellow River Basin. The regression coefficient of higher education level is significantly positive. In other words, higher education has cultivated high-tech talents, and the human capital delivered to the society has caused the agglomeration of other production factors, which has promoted the technological innovation of enterprises, and has a positive promotion effect on the industrial structure upgrading in the Yellow River Basin. The coefficient of marketization level is significantly negative at the significance level of 1%. The possible reasons are that the government has less intervention in the market and enterprises, and the market self-regulation in the Yellow River Basin is flawed. There may be problems such as improper resources allocation and unequal social distribution, affect the sustainable growth of economy in the Yellow River Basin, which is not conducive to the industrial structure upgrading.

5.2 Robustness test

In order to confirm the robustness of the benchmark regression results, this paper adopts the method of replacing key indicators to conduct robustness test. Referring to the practices of Ji et al. (2022), the industrial structure hierarchy coefficient including the primary industry, the secondary industry and the tertiary industry is used as a measure of the upgrading of the industrial structure. The measurement formula of the new industrial structure upgrading is shown in Eq. 4:

$$U = \sum_{i=1}^{3} x_i \times i \tag{4}$$

which x_i represents the proportion of the output value of the i industry to the total output value; i denotes the corresponding weight assigned to each industry, $i = 1, 2, 3$.

The robustness test results are shown in Table 5. It can be seen that after replacing the key indicators, the coefficients of the primary and secondary terms of FDI are still significantly negative, indicating that the relationship between FDI and the upgrading of the industrial structure in the Yellow River Basin is still the inverted "U"-shaped relationship verified above; other environmental regulation coefficients are significantly positive, which is consistent with the previous research results that environmental regulation has a promoting effect on the upgrading of the industrial structure in the Yellow River Basin; the coefficient of interaction between FDI and environmental regulation is significantly positive, which is consistent with the previous research results; the coefficients of each control variable have changed slightly, However, neither the sign direction nor the significance has changed. It can be seen that the results of the previous empirical analysis are robust.

5.3 Threshold effect test

Table 6 shows the estimated results of the threshold effect test. The F statistic of the single threshold of environmental regulation is 47.68, which is significant at the 1% significance level and passed the single threshold test; the F statistic of the double threshold is 28.68, which passed the 5% significance level test. This shows that there is a double threshold effect of environmental regulation in the impact of FDI on the upgrading of the industrial structure in the Yellow River Basin. The environmental regulation thresholds are 1.7176 and −1.7148, respectively.

From the regression results of the threshold effect in Table 7, it can be seen that the double threshold of environmental regulation divides the intensity of environmental regulation into three ranges: low (lnER≤−1.7148), medium (−1.7148<lnER≤1.1716) and high (lnER> 1.1716). When the intensity of environmental regulation is in the lower intensity range, the regression coefficient of FDI and the regression coefficient of the interaction term of FDI and environmental regulation are all significantly negative, which are −0.1199222 and −0.0243728, respectively; when the intensity of environmental regulation crosses the first threshold, When it is in the medium intensity range, the regression coefficient of the FDI term is not significant, indicating that the inhibitory effect of FDI on industrial structure upgrading is not obvious at this time, and the regression coefficient of the interaction term rises to 0.0233899, which is significant at the level of 1%; When the double threshold is in the higher intensity range, the coefficient of FDI is significantly positive at 0.0851813, while the coefficient of the interaction term is negative. It can be seen that in the process of gradually increasing the intensity of environmental regulation, the FDI regression coefficient changed from negative to positive and gradually increased, indicating that environmental regulation has a positive role in promoting the impact of FDI on the upgrading of the industrial structure in the Yellow River Basin, which further verifies the Hypothesis 3; the interaction term coefficient changes from negative to positive when the intensity of environmental regulation crosses the first threshold, indicating that this positive promoting effect is gradually enhanced, and when the intensity of environmental regulation crosses the second threshold, the interaction term coefficient becomes negative, that is, although under the intensity of environmental regulation, FDI can promote the upgrading of the industrial structure in the Yellow River Basin. However, if the environmental regulation intensity is too high, it may also lead to excessive production costs of enterprises, which in turn has a negative impact on the upgrading of the industrial structure in the Yellow River Basin to a certain extent.

TABLE 5 Robustness test results.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (6)
LnFDI	−.0187893 * * (−2.30)	−.0145553 * * * (−2.61)	−.0172628 * * * (−3.06)	−.0170766 * * * (−3.03)	−.0182195 * * * (−3.24)
$(lnFDI)^2$	−.0014955 * * (−1.95)	−.0016288 * * * (−3.10)	−.0018326 * * * (−3.47)	−.0018107 * * * (−3.43)	−.001897 * * * (−3.60)
LnER	.0240493 * * * (3.45)	.018286 * * * (3.83)	.0195463 * * * (4.09)	.0194217 * * * (4.07)	.0210773 * * * (4.41)
F ∗ E	.0042369 * * * (2.90)	.004196 * * * (4.20)	.0044029 * * * (4.42)	.0043432 * * * (4.36)	.0044846 * * * (4.52)
lnEDL	–	.0555007 * * * (27.90)	.0506119 * * * (19.06)	.0490098 * * * (17.32)	.0451675 * * * (14.37)
LnGI	–	–	.0153022 * * * (2.76)	.0152787 * * * (2.76)	.0104557 * (1.81)
lnHEL	–	–	–	.0035047 (1.63)	.0029525 (1.37)
lnML	–	–	–	–	−.0749728 * * * (−2.75)
_cons	.770281 * * * (36.66)	.2103301 * * * (8.52)	.2952305 * * * (7.50)	.3276959 * * * (7.44)	.3361515 * * * (7.65)
R^2	0.0246	0.5438	0.5488	0.5506	0.5555
N	742	742	742	742	742

TABLE 6 Threshold effect test and estimation results.

Threshold variable	Threshold number	F statistic	1% threshold	5% threshold	10% threshold	Estimated threshold
LnER	single threshold	47.68 * * *	49.4336	37.0145	31.8310	1.1716
	double threshold	28.68 * *	30.8965	27.1047	22.7699	−1.7148
	triple threshold	13.50	73.5477	54.9519	47.8159	1.9258

TABLE 7 Threshold effect regression results.

Environmental regulation range	lnFDI	F * E
lnER≤-1.7148	−.1199222 * * * (−4.98)	−.0243728 * * (−2.58)
−1.7148<lnER≤1.1716	−.0030318 (−0.25)	.0233899 * * * (5.37)
lnER>1.1716	.0851813 * * (2.06)	−.0704012 * * (−2.57)
_cons	−2.172846 * * * (−5.41)	−2.172846 * * * (−5.41)
control variable	yes	Yes
n	742	742
R^2	0.4455	0.4455

6 Conclusion

The industrial structure upgrading is a prominent prerequisite for achieving high-quality development. To achieve high-quality economic development in the Yellow River Basin, it is necessary to optimize the industrial structure and realize green development. This study selected the panel data of 53 cities in the Yellow River Basin from 2006 to 2019, and empirically analyzed the relationship between FDI, environmental regulation and industrial structure upgrading in the Yellow River Basin, and obtained the following research conclusions.

1) The relationship between FDI and the industrial structure upgrading in the Yellow River Basin is not a simple linear relationship, but an inverted "U"-shaped relationship that firstly rises and then falls. This shows that as the proportion of FDI in GDP gradually enlarges, FDI would firstly promote the industrial structure upgrading in the Yellow River Basin, while it reaches a certain level, FDI would have a negative effect on the industrial structure upgrading. Moreover, the finding of this inverted "U"-shaped relationship is still stable after the replacement of key indicators.
2) Environmental regulation policies have a role in promoting the industrial structure upgrading in the Yellow River Basin, that is, they could force enterprises to carry out technological innovation, raise productivity and profit margins, make up for the cost of sewage and pollution control, and then promote the transformation and upgrading of the entire industry in the Yellow River Basin. To a certain extent, the "Porter Hypothesis" has been verified, and this is in line with the research results of Yan et al. (2024)

3) Environmental regulation has a positive contribution in promoting the impact of FDI on the industrial structure upgrading in the Yellow River Basin, and with the moderate increment in the intensity of environmental regulation, the positive effect is gradually enhanced. However, if the intensity of environmental regulation is too high, it may also result in excessive production costs, which will be detrimental to the industrial structure upgrading in the Yellow River Basin to a certain extent. These are consistent with the findings of Feng and Liang (2022), who figured out that the moderating role of environmental regulation is partially and conditionally established.

To be specific, the environmental regulation thresholds are 1.1716 and −1.7148, respectively. In the process of increasing the intensity of environmental regulation and crossing the value of −1.7148, the negative impact of FDI on the impact coefficient in the Yellow River Basin is constantly weakening. When the first threshold value of 1.1716 is crossed, the coefficient of FDI on the industrial structure upgrading changes from negative to positive. This represents that environmental regulation has a positively facilitating effect on the impact of FDI on the industrial structure upgrading in the Yellow River Basin, which verifies the thesis of Feng et al. (2019) on the synergistic effect of environmental regulation and FDI.

At the same time, with the moderate rise in the intensity of environmental regulation, the positive role also gradually increases. With the gradual strengthening of the intensity of environmental regulation, the cross-term coefficient of FDI and environmental regulation firstly turns from negative to positive, and then from positive to negative, suggesting that if the intensity of environmental regulation is too strong, the interaction between FDI and environmental regulation would restrict the industrial structure upgrading in the Yellow River Basin. This finding further extends the study of Feng et al. (2019), which bridges the gap between theory and practice by providing a profound vision of spatial econometrics.

(4) The economic development level, degree of government intervention and higher education level have a significant role in promoting the industrial structure upgrading, and the marketization level has a negative impact on the industrial structure upgrading in the Yellow River Basin. A higher level of economic development reflects a higher standard of living. With the amelioration of living standards, people's consumption needs are more and more diversified, which is conducive to the transformation and upgrading of enterprises to meet people's diversified consumption needs, thereby promoting the development of the tertiary industry, and this is similar to the research results of Guan et al. (2022b). The government can create a good environment for industrial structure upgrading and provide financial and policy support for the development of enterprises, which is in line with the findings of (Li et al., 2021; Zhang et al., 2022). Therefore, the government's moderate intervention could drive the industrial structure upgrading. Higher education can cultivate high-quality talents with scientific skills and innovation capabilities, and this is consistent with the research results of (Zhu and Liu, 2020; Zhang, 2021). Human capital can spur the aggregation of other capitals, and is also a valued factor affecting the industrial structure upgrading and economic growth. The marketization level has a negative effect on the industrial structure upgrading, which is similar to the findings of Zhang and Qin, (2018). The market in the Yellow River Basin may have problems such as improper allocation of resources and unequal distribution, which affects the development of enterprises and thus stunts the industrial structure upgrading in the Yellow River Basin.

7 Policy recommendations

Based on the above research conclusions, this study put forward the following policy recommendations.

1) Introduce FDI reasonably and effectively to raise the quality of FDI. On one hand, the government should set up a reasonable scale of investment introduction, strengthen the management of FDI introduction, raise the entry threshold of FDI, control the proportion of FDI in GDP, and give full play to the role of FDI in promoting the industrial structure upgrading in the Yellow River Basin. On the other hand, enterprises should give full play to their subjective initiative, bring productivity gains and innovation capacity from their own perspective, avoid over-reliance on FDI, and make full use of the technological spillover effect of FDI to reinforce their own technological innovation capacity. The FDI technology spillover effect should be fully utilized to improve their own technological innovation capabilities.
2) Rationally formulate environmental regulation policies and give full play to the role of environmental regulation in promoting the industrial structure upgrading in the Yellow River Basin. The government should formulate appropriate environmental regulation policies based on regional differences. It should complete the legal system for environmental regulation, constrain the production activities of enterprises, strictly implement supervision and control, increase investment in environmental pollution control, and limit emissions of pollutants such as sulfur dioxide, industrial wastewater and industrial dust.
3) Coordinate the intensity of FDI and environmental regulation, and organically combine the two to promote the industrial structure upgrading in the Yellow River Basin. Strictly implement environmental regulation policies, attract more high-quality, low-emission, and low-pollution FDI industries, maximize the proactive role of environmental regulation between FDI and the industrial structure upgrading in the Yellow River Basin, and realize the win-win for the introduction of high-quality FDI and ecological environmental protection.
4) Create a favorable environment for industrial structure upgrading. The economic development level, degree of government intervention and higher education level all have a significant role in promoting the industrial structure upgrading in the Yellow River Basin. Consequently, the government should promote the industrial structure upgrading by improving the level of economic development, appropriately intervening in the production and operation activities of enterprises, and vigorously cultivating higher

education talents. At the same time, the role of the market should be better brought into play, the rational allocation of resources should be realized, and the inhibitory effect on the industrial structure upgrading should be alleviated.

8 Research prospects

Though the effectiveness of environmental regulation, FDI and its interaction term on the industrial structure upgrading was preliminarily investigated in this study, some limitations remain and in-depth studies are still needed. (1) Industrial structure upgrading includes two aspects: industrial structure advancement and industrial structure rationalization. In this study, industrial structure advancement represents the upgrading of industrial structure, and the content of industrial structure rationalization should be appropriately added in the later stage to further strengthen the persuasive of this study. (2) Concentrated on the whole Yellow River basin, this study explored the impact of environmental regulation and FDI on the upgrading of industrial structure, without considering the regional spatial heterogeneity. (3) Limited by the availability and stability of data, the method of measuring environmental specifications could be further optimized, and a more scientific and effective index system should be built in the future and calculated by comprehensive index method.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

JY: Writing–original draft, Writing–review and editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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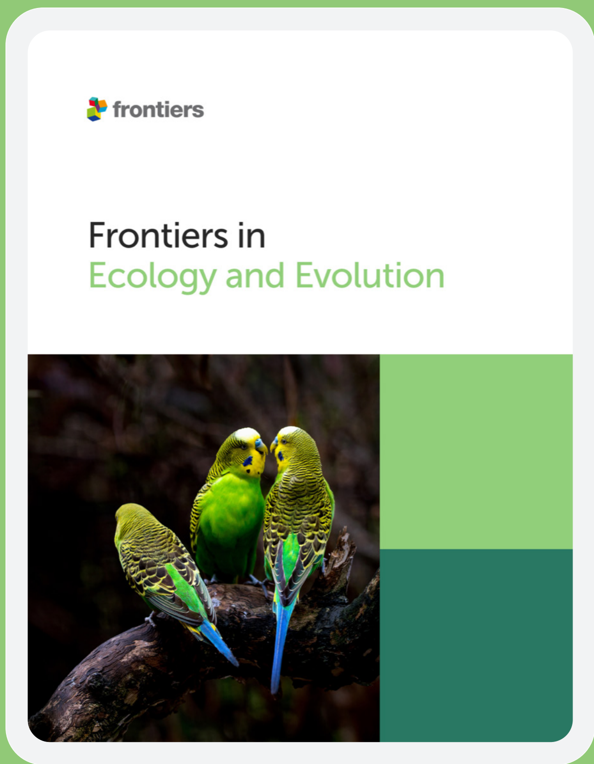

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