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Spatiotemporal evolution and driving factors of green energy efficiency in Jiangsu Province: a sustainable development perspective

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With the ongoing global climate change and energy structure transformation, green energy efficiency has become one of the key indicators for achieving sustainable development. This study uses panel data from 13 prefecture-level cities in Jiangsu Province, China, from 2012 to 2022 to explore the spatiotemporal evolution and driving factors of green energy efficiency. The study employs the super-efficiency Slack-Based Measure (SBM) method to measure the green energy efficiency of each region. It uses the Gini coefficient and kernel density estimation methods to analyze the spatiotemporal evolution characteristics of green energy efficiency. Furthermore, based on a fixed effects model, the study delves into the main driving factors influencing green energy efficiency. The results show that green energy efficiency in Jiangsu Province is generally on an upward trend. The Gini coefficients of both the southern and northern regions of Jiangsu have increased, but the gap in green energy efficiency between the two regions has gradually widened. The degree of government intervention and the level of industrialization are unfavorable to the growth of green energy efficiency. In contrast, foreign investment levels, financial development, and urbanization show significant positive effects. Finally, based on the empirical findings, targeted recommendations are provided to promote green energy efficiency, offering important theoretical support and empirical evidence for the country's strategic goals of achieving green and low-carbon development.

KEYWORDS

green energy efficiency, spatiotemporal evolution, driving factors, Jiangsu Province, sustainable development

1 Introduction

With the continuous growth of global energy demand and increasing environmental pressures (Lamnatou et al., 2024), green energy efficiency has become one of the core issues in global energy policy (Belaïd et al., 2023). To achieve carbon peaking and carbon neutrality goals, countries actively promote the innovation and application of green and low-carbon technologies, striving to improve energy efficiency and reduce greenhouse gas emissions (Opazo-Basáez et al., 2024). However, despite the continuous increase in global

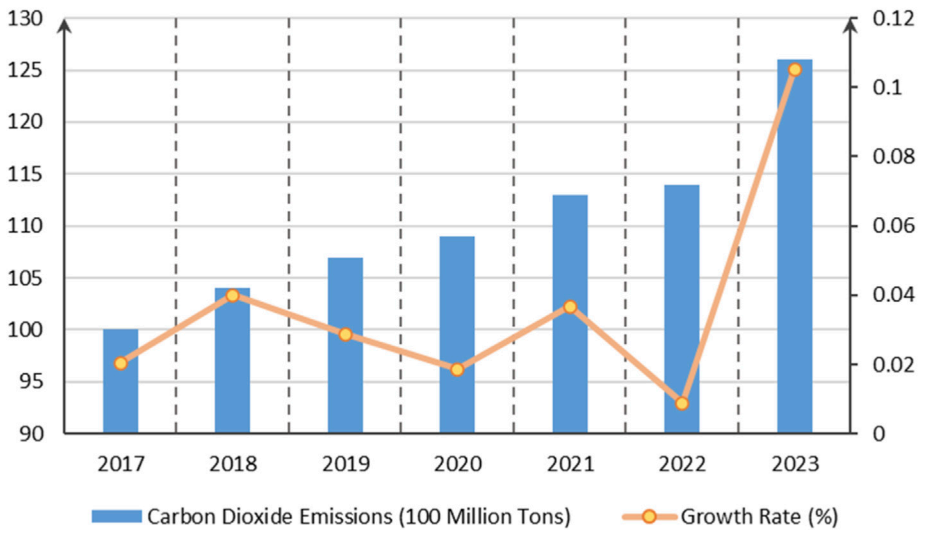

FIGURE 1
Carbon emission trend in China. Source: Mark data network https://www.macrodatas.cn/article/1147472994.

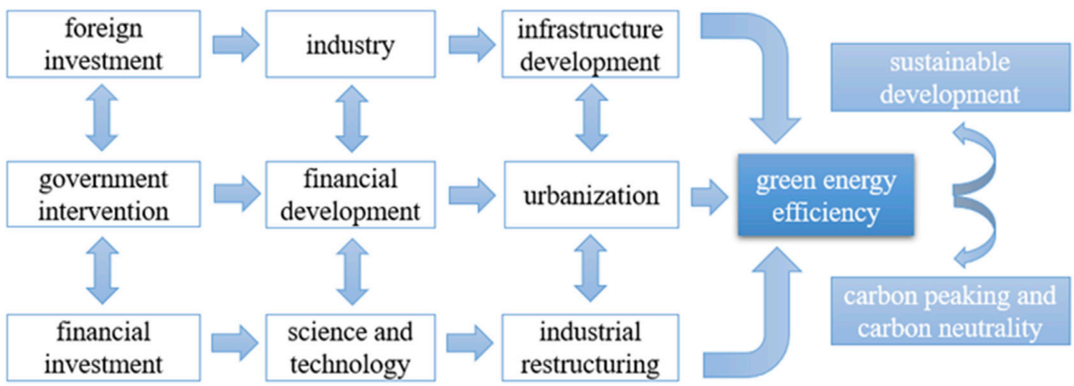

FIGURE 2
Mechanism diagram.

investment and technology in green energy, many countries and regions still face the challenge of slow green energy transition and difficulty improving energy efficiency (Lu and Li, 2024). This is especially true in developing countries, where energy structure adjustment and the implementation of green development policies face numerous challenges (Wang and Shao, 2024). As the largest developing country in the world, China's energy consumption and carbon emissions account for a significant proportion of global total (Zhang et al., 2024), with carbon emissions reaching 12.6 billion tons in 2023 and energy combustion emissions increasing by 5.2%. The carbon emission trend in China is shown in Figure 1. Therefore, the urgency of improving green energy efficiency cannot be ignored. Enhancing green energy efficiency is essential to promote high-quality economic development and a key support for achieving global climate goals (Zeng et al., 2024). As one of China's economically developed provinces, Jiangsu Province faces significant pressure due to its high energy consumption and carbon emissions (Deng et al., 2024). Consequently, the path for improving green energy efficiency in Jiangsu Province is of great reference value for other developing countries. Its achievements in energy structure adjustment, green technology innovation, and policy implementation provide valuable experience for other regions.

Green energy efficiency refers to the ratio of economic output and environmental benefits generated by a unit of energy consumption while using green energy. Improving green energy efficiency contributes to energy conservation and environmental protection and promotes the rapid development of the green economy (Song et al., 2024). It is key to solving energy shortages, environmental pollution, and climate change issues. The influence mechanism diagram of green energy efficiency is shown in Figure 2. Academic research on green energy efficiency mainly focuses on its relationship with economic growth and environmental pollution (Chen L. et al., 2024; Zhao et al., 2022), emphasizing the analysis of single factors affecting green energy efficiency and lacking in-depth exploration of its spatiotemporal evolution patterns and regional

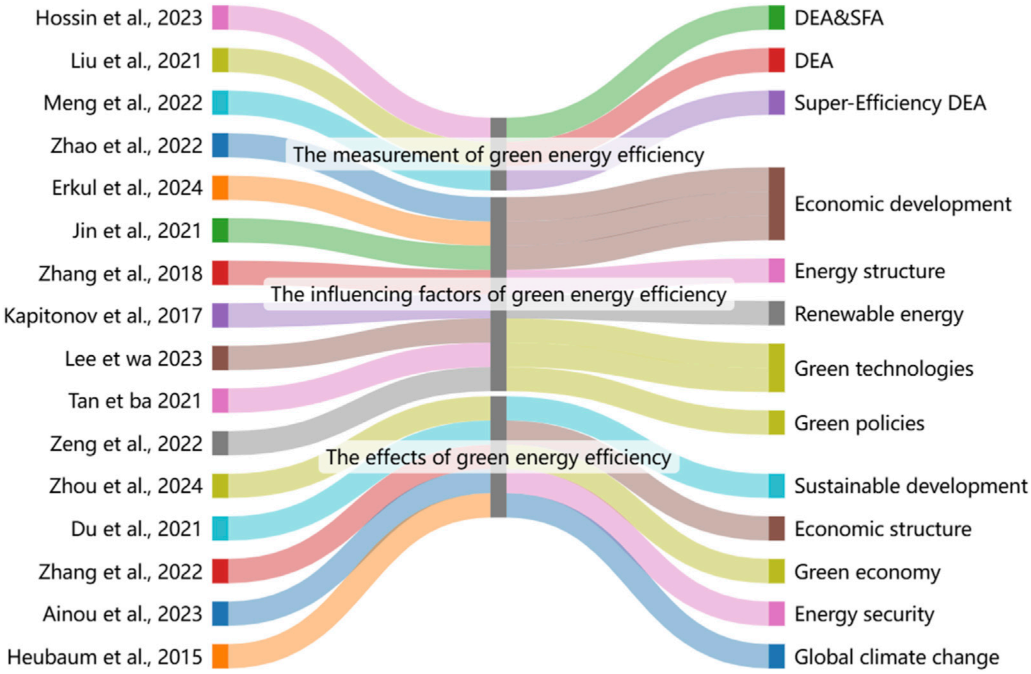

FIGURE 3
Literature review on green energy efficiency.

differences. Therefore, this study aims to systematically analyze the spatiotemporal evolution characteristics of green energy efficiency, explore the regional differences, and reveal the multidimensional driving factors that influence its improvement. It further discusses the pathways to achieving green energy efficiency, providing a valuable reference for the current development of green energy in countries (regions).

This study constructs a green energy efficiency evaluation system, reveals the spatial and temporal evolution trend of green energy efficiency in Jiangsu Province, analyzes its driving mechanism, and puts forward targeted policy recommendations. The contributions of this study are as follows: First, existing literature mainly focuses on exploring single factors affecting green energy efficiency. At the same time, systematic research on its spatiotemporal evolution characteristics and comprehensive driving mechanisms remains insufficient. This study fills the research gap in this field by conducting an in-depth analysis of the dynamic spatiotemporal evolution patterns of green energy efficiency in Jiangsu Province. It deepens the understanding of green energy efficiency from a multidimensional perspective. Second, this study highlights the differentiated characteristics of green energy efficiency across regions and further explores the underlying reasons for this regional heterogeneity, enriching the theoretical exploration of pathways to achieving green energy efficiency. By analyzing regional characteristics and development conditions, this study provides the theoretical basis and empirical support for local governments to formulate differentiated green development policies. Finally, based on the conclusions from the empirical analysis, this study proposes targeted policy recommendations, offering practical insights for other developing countries in implementing green energy policies, while providing guidance for achieving sustainable development goals at the regional level.

The second chapter following this section provides a systematic review of articles related to green energy efficiency. The third chapter introduces the construction of the indicator system and research methods. The fourth chapter presents the empirical analysis, the fifth chapter discussed the empirical results, and the sixth chapter summarizes the research conclusions based on the empirical findings and offers targeted recommendations.

2 Literature review

Research on green energy efficiency mainly focuses on three aspects: the measurement of green energy efficiency, the influencing factors of green energy efficiency, and the effects of green energy efficiency. The literature review diagram is shown in Figure 3.

As an interdisciplinary research area between energy and environmental economics, green energy efficiency has garnered widespread attention. Scholars have employed various methods to measure green energy efficiency, with the most common approaches including Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) (Hossin et al., 2023). DEA is a non-parametric efficiency evaluation method that is widely used in energy efficiency research. By constructing an efficiency frontier, DEA can assess the energy efficiency of various decision-making units (such as different regions, countries, or industries) under specific resource inputs (Liu et al., 2021). The advantage of the DEA method in measuring green energy efficiency lies in its independence from specific production function assumptions, making it suitable for regional comparisons at different stages of development. However, DEA also has the drawback of being overly sensitive to extreme values, especially when data is incomplete. To overcome this issue, scholars often combine variants such as Super-Efficiency DEA or Weighted DEA for further research on green energy efficiency (Meng and Qu, 2022).

In exploring the factors influencing green energy efficiency, existing research has conducted in-depth analyses from multiple dimensions. First, the level of economic development is considered one of the key factors affecting green energy efficiency (Zhao et al., 2022). The impact of economic development on green energy efficiency exhibits different pathways and mechanisms. In some developing countries, economic growth is often accompanied by increased energy consumption and worsened environmental pollution, negatively affecting green energy efficiency (Erkul and Türköz, 2024). However, with the transformation of the economic structure and the application of green technologies, economic development can also promote improving green energy efficiency. Some scholars have further proposed an "inverted U-shaped" relationship, indicating that energy efficiency may decline in the early stages of economic development (Jin et al., 2021). Once a certain level is reached, technological innovation and promoting green policies can enhance energy efficiency. Second, adjusting the energy structure is an important driving factor for green energy efficiency (Zhang et al., 2018). The diversity of the energy structure, especially the proportion of renewable energy, directly affects the efficiency of green energy use. Research by scholars Kapitonov et al. (Kapitonov and Voloshin, 2017) has shown that increasing the share of renewable energy can significantly improve energy utilization efficiency and reduce the use of fossil fuels, thereby lowering carbon emissions. Additionally, the innovation and application of green technologies are key factors in enhancing green energy efficiency (Lee et al., 2023). In particular, breakthroughs in energy conversion and storage technologies, smart grids, and energy management systems can reduce energy consumption and improve production efficiency (Tan et al., 2021). Policy factors also play a crucial role in influencing green energy efficiency (Zeng et al., 2022). Strengthening the implementation of green policies and providing incentive mechanisms can accelerate the promotion and application of green technologies, further improving the efficiency of green energy utilization.

The improvement of green energy efficiency has multiple positive effects. First, enhancing green energy efficiency can reduce environmental pollution and resource waste during energy production and consumption, helping countries achieve sustainable development goals (Zhou et al., 2024). Efficient energy use reduces greenhouse gas emissions and mitigates the negative impacts on the ecological environment, providing a safeguard for achieving carbon neutrality goals. Second, improving green energy efficiency can drive the transformation and upgrading of the economic structure (Du et al., 2021). With the continuous maturity of green energy technologies, the rise of green industries provides a new impetus for economic growth. Enhancing green energy efficiency can stimulate the development of green technologies and emerging industries, promoting the growth of the green economy (Zhang et al., 2022b). Third, the improvement of green energy efficiency can also enhance energy security (Ainou et al., 2023). Adjusting the energy structure and increasing the share of green energy, especially local renewable energy, can reduce dependence on external energy resources and strengthen the security and stability of the energy supply. Finally, improving green energy efficiency contributes to fulfilling commitments under international climate agreements, advancing global climate change governance, and promoting global cooperation and win-win outcomes (Heubaum and Biermann, 2015).

As discussed above, existing research on green energy efficiency primarily focuses on efficiency evaluation and analyzing single influencing factors, particularly emphasizing the role of green technologies, policy measures, or economic factors on green energy efficiency. However, there has been insufficient in-depth exploration of the spatiotemporal dynamics and regional differences of green energy efficiency, overlooking the variations and complexities of improvements across different regions and time dimensions. Using panel data from Jiangsu Province, this study employs the super-efficiency SBM model to measure green energy efficiency accurately. Additionally, the Gini coefficient and kernel density model thoroughly analyze the spatiotemporal evolution trends of green energy efficiency. This research fills the gap in existing studies, providing a dynamic and regional analysis framework for green energy efficiency and offering new perspectives and important references for regional sustainable development and the formulation and optimization of regional policies.

3 Research design

3.1 Variable description

This study constructs a green energy efficiency indicator system, as shown in Table 1. Green energy efficiency considers three dimensions: input, expected output, and undesirable output. The input indicators include the number of employees, total energy consumption, and fixed asset investment, comprehensively reflecting the labor input, energy input, and capital investment in green energy utilization at the regional (or industry) level. The expected output indicator is primarily the Gross Domestic Product (GDP) of the region, which is a core measure of economic performance and provides an intuitive reflection of the contribution of energy use to economic growth. The undesirable output indicators include sewage discharge, industrial sulfur dioxide, industrial dust, and industrial smoke emissions. These represent the environmental externalities in the energy consumption process and reveal the negative impact of high-energy and high-pollution industries on the environment.

This study aims to more comprehensively explore the factors influencing green energy efficiency by considering the effects of foreign investment level (FORE), financial development level (FIND), urbanization level (URBAN), government intervention level (GOVER), industrial structure (STRU), technological level (SCIEN), industrialization level (INDU), and infrastructure level (INFRA) on green energy efficiency.

FORE: Introducing foreign investment can effectively promote the dissemination of green technologies and management experience (Castellani et al., 2022), providing local enterprises with opportunities for technological upgrading and management optimization, thereby improving energy utilization efficiency,

TABLE 1 Indicator system construction.

System	Indicator	Meaning
Green energy efficiency	Input indicators	Number of employees (10,000 people)
		Total energy consumption (hundreds of tons of standard coal)
		Fixed asset investment (ten thousand yuan)
	Output indicators	Gross regional product (ten thousand yuan)
	Undesirable output	Sewage discharge (10,000 cubic meters)
		Industrial sulfur dioxide emissions (tons)
		Industrial dust emissions (industrial dust/ton)
		Industrial smoke emissions (tons)
Influencing factors	Foreign investment level	Actual foreign investment/gross regional product (%)
	Financial development level	End-of-year balance of loans and deposits of financial institutions/gross regional product (%)
	Urbanization level	Urban permanent population/total permanent population (%)
	Government intervention level	Government general fiscal expenditure/gross regional product (%)
	Industrial structure	Tertiary industry value-added/gross regional product (%)
	Technological level	Expenditure on science and technology/government general fiscal expenditure (%)
	Industrialization level	Industrial value-added/gross regional product (%)
	Infrastructure level	Per capita road freight volume (square meters per person)

Source: the data of the indicators in Table 1 are from the Statistical Yearbook of Jiangsu Province https://tj.jiangsu.gov.cn/2024/index.htm.

reducing resource waste, and mitigating environmental pollution. As important participants in the international market, foreign-funded enterprises typically place greater emphasis on environmental protection and green production practices. Their high environmental standards and advanced operational models create a positive demonstration effect for local enterprises. Furthermore, foreign investment accelerates the improvement of the green industrial chain and technological innovation, fostering the sustainable development of the green economy and further enhancing regional green energy efficiency. The foreign-investment-driven green transition optimizes resource allocation efficiency and provides crucial support for achieving high-quality regional economic development and ecological environmental protection.

FIND: A well-developed financial system provides adequate and stable funding support for green energy projects (Wang et al., 2022), effectively alleviating the funding bottleneck during the initial stages of the project and creating favorable conditions for the research, development, and application of green technologies. At the same time, the deepening and innovation of financial markets attract more green investment through diversified financing tools, guiding capital toward low-carbon and high-efficiency green industries, thereby achieving optimal resource allocation. The support from the financial system provides a solid foundation for the synergy between green energy and sustainable economic development, serving as an important pillar for driving the green transition and achieving the dual carbon goals.

URBAN: With the continuous advancement of urbanization, the improvement of urban infrastructure and energy utilization efficiency has been significantly enhanced (Chen J. et al., 2024). Higher levels of urbanization are typically accompanied by more mature energy management systems and the widespread application of green technologies. The optimization of energy allocation, production methods, and consumption structures in cities provides strong support for the improvement of green energy efficiency. Urbanization helps promote the adoption of green technologies such as green buildings and smart grids. The agglomeration effect increases the concentration and systematic management of energy use, thereby achieving efficient resource utilization.

GOVER: The government can effectively guide market behavior and enhance the utilization efficiency of green energy by formulating and implementing green energy policies, providing financial incentives, and establishing green funds. Appropriate policy interventions can address market failures and promote optimizing the energy structure and green technology innovation (Malik et al., 2019). However, excessive government intervention, such as large subsidies and price controls, may distort resource allocation and affect the distribution of resources in other key areas.

STRU: Optimizing the industrial structure, particularly by promoting the transformation of high-pollution and high-energy consumption industries, is a key path to improving energy utilization efficiency (Xiong et al., 2019). By accelerating the green transformation of traditional heavy industries and reducing excessive resource consumption, energy intensity can be effectively reduced, promoting more efficient energy use. At the same time, the development of green industries, especially renewable and clean energy sectors, helps improve the overall efficiency of energy production and consumption through technological innovation and industrial upgrading, thereby reducing reliance on fossil fuels.

SCIEN: Technological innovation, particularly breakthroughs in energy conversion, storage, and innovative management, is crucial in improving energy utilization efficiency (Chen et al., 2021). Advances in energy conversion technologies have made the collection and conversion of renewable energy more efficient, while the development of energy storage technologies addresses energy volatility and intermittency issues. Innovative management optimizes the production and consumption processes of energy through precise scheduling. The continuous progress in science and technology drives optimizing the energy structure and green transition, providing essential support for achieving low-carbon economic goals.

INDU: High levels of industrialization are often associated with higher energy consumption (Sumaira and Siddique, 2023). However, through technological upgrades and industrial optimization, improvements in energy efficiency can be achieved. Nonetheless, during the industrialization process, industries' high dependence on fossil fuels significantly reduces the proportion of green energy, thereby affecting energy efficiency enhancement.

INFRA: Well-developed infrastructure supports the effective utilization of green energy and enhances the efficiency of energy transmission and distribution (Khoshnava et al., 2020). Additionally, constructing infrastructure such as green transportation and smart grids helps optimize the energy usage structure, improving overall energy efficiency. Improving infrastructure is a fundamental condition for achieving the efficient use of green energy.

3.2 Model construction

3.2.1 The super-efficiency SBM

The Super-Efficiency SBM (Slacks-Based Measure) model is an efficiency measurement method based on slack variables and is an important extension of the DEA (Data Envelopment Analysis) model (Zhong et al., 2021). It considers the proportional relationship between inputs and outputs and incorporates slack variables for both input and output insufficiency into the model. This allows it to effectively address the issue in traditional DEA models where high-efficiency decision-making units cannot be distinguished when the efficiency value is 1, enabling ranking decision units with higher efficiency. This study applies logarithmic transformation to the raw data to avoid the impact of objective data factors on the empirical results. It uses the Super-Efficiency SBM model to calculate the green energy efficiency in Jiangsu Province. Let $x \in R^m, y^d \in R^{p^1}, y^u \in R^{p^2}$, where *m* represents the number of input indicators, p_1 represents the number of output indicators, and p_2 represents the number of undesirable output indicators.

$$X = [x_1, x_2, \cdots, x_n] \in R^{m\times n}$$
$$Y^d = \left[y_1{}^d, y_2{}^d, \cdots, y_n{}^d\right] \in R^{p_1\times n}$$
$$Y^u = \left[y_1{}^u, y_2{}^u, \cdots, y_n{}^u\right] \in R^{p_2\times n}$$

The construction of the Super-Efficiency SBM model is shown in Formula 1.

$$\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\left(s_i{}^- / s_{ik}\right)}{1 - \frac{1}{p_1 + p_2}\left(\sum_{r=1}^{p_1}\frac{s_r{}^+}{y_{ik}{}^d} + \sum_{t=1}^{p_2}\frac{s_t{}^{u^-}}{y_{tk}{}^u}\right)} \tag{1}$$

$$s.t.\begin{cases} \sum\limits_{j=1,\neq k}^{n} x_{ij}\gamma_j - s_i{}^- \leq x_{ik} \\ \sum\limits_{j=1,\neq k}^{n} y_{rj}{}^d\gamma_j + s_r{}^+ \leq y_{ik}{}^d \\ \sum\limits_{j=1,\neq k}^{n} y_{tj}{}^u\gamma_j - s_t{}^{u-} \leq y_{ik}{}^u \\ 1 - \dfrac{1}{p_1 + p_2}\left(\sum\limits_{r=1}^{p_1}\dfrac{s_r{}^+}{y_{ik}{}^d} + \sum\limits_{t=1}^{p_2}\dfrac{s_t{}^{u^-}}{y_{tk}{}^u}\right) > 0 \\ \gamma_j, s_r{}^+, s_r{}^- \geq 0 \\ i = 1, \cdots, m \\ r = 1, \cdots, p_1 \\ t = 1, \cdots, p_2 \\ j = 1, \cdots, n(j \neq k) \end{cases}$$

In this model, X, Y^d, Y^u represent the input, desired output, and undesirable output variables, respectively. ρ denotes the efficiency value. $s_i{}^-, s_r{}^+, s_t{}^{u^-}$ represent the input slack variables, desired output slack variables, and undesirable output slack variables, respectively. i, r, t represent the input, desired output, and undesirable output, while j, k represent the decision-making unit and the evaluated unit, respectively. An efficiency value greater than 1 indicates that the decision-making unit performs excellently within its category, whereas an efficiency value less than 1 indicates the presence of room for improvement.

3.2.2 Gini coefficient

Compared to the traditional Gini coefficient, the Dagum Gini coefficient decomposition model not only distinguishes between intra-group inequality and inter-group inequality but also considers the overlapping inequality caused by group overlap, providing a more detailed analysis of the distribution structure (Zhang et al., 2022a). The decomposition formula for the Dagum Gini coefficientis is shown in Formula 2.

$$G = G^w + G^b + G^o \tag{2}$$

In this formula, G^w represents the intra-group inequality contribution, indicating the inequality in income distribution within each group; G^b represents the inter-group inequality contribution, reflecting the inequality caused by differences in the average income between different groups; G^o represents the overlapping inequality contribution, measuring the impact of the overlapping portion of income distribution across groups on overall inequality.

3.2.3 Kernel density estimation

Kernel density estimation is used as a non-parametric method to estimate a random variable's probability density function (Jones, 1993). Unlike parametric methods, kernel density estimation does not require prior assumptions about the data distribution, offering greater

TABLE 2 Descriptive statistics.

Variable	N	Mean	sd	p50	Min	Max
GEE	143	0.737	0.119	0.686	0.596	1.007
FORE	143	2.441	0.802	2.352	1.347	5.373
FIND	143	0.312	0.307	0.201	0.063	1.607
URBAN	143	0.679	0.086	0.662	0.510	0.870
GOVER	143	0.123	0.030	0.113	0.082	0.203
STRU	143	0.471	0.049	0.470	0.380	0.628
SCIEN	143	0.036	0.016	0.031	0.015	0.096
INDU	143	0.386	0.056	0.388	0.241	0.504
INFRA	143	17.70	7.085	17.77	4.888	39.36

flexibility. It is widely used in economic distribution characteristic analysis. In this study, to explore the distribution characteristics of green energy efficiency in Jiangsu Province, the specific kernel density estimation model formula is shown in Formulas 3, 4.

$$f(x) = \frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x\text{-}x_j}{h}\right) \tag{3}$$

$$K(x) = \left(\frac{1}{\sqrt{2p}}\right)\exp\left(-\frac{x^2}{2}\right) \tag{4}$$

In this formula, $f(x)$ represents the estimated density at point x, n is the sample size, h is the bandwidth parameter that determines the degree of smoothing, and $K(x)$ is the kernel function.

3.2.4 Fixed effects model

Fixed effects modeling is a central method used in panel data analysis to control for unobservable heterogeneity (Breuer and DeHaan, 2024). The central role of this method is to eliminate the endogeneity problem arising from the correlation of individual or time effects with explanatory variables and to improve the consistency of causal effect estimates. Compared with the mixed OLS or random effects model, the fixed effects model is more suitable for analyzing non-experimental panel data, especially when the explanatory variables are correlated with the inherent characteristics of individuals, and it can effectively separate the true associations among variables. Therefore, in this study, the dependent variable is GEE, and the independent variables are FORE, FIND, URBAN, GOVER, STRU, SCIEN, INDU, and INFRA. A fixed effects model is constructed with the specificformula is shown in Formula 5.

$$GEE = \beta_0 + \beta_1 X_{it} + id_i + year_t + \varepsilon \tag{5}$$

In this model, id_i represents the individual fixed effects, $year_t$ represents the time fixed effects, β_0, β_1 are the parameters to be estimated, ε is the random error term, and X_{it} is the matrix of independent variables.

4 Empirical analysis

According to the descriptive statistics in Table 2, the minimum value of GEE in Jiangsu Province is 0.596, and the maximum is 1.007, indicating specific differences in GEE across regions. Variables such as FORE and FIND show significant regional differences, with foreign investment unevenly distributed across regions and developed areas attracting significantly more foreign capital. Financial resources also exhibit considerable distribution disparities within the province. In addition, urbanization is more advanced in developed areas, while some regions still require further progress. The regional imbalances in GOVER and STRU are still prominent. Therefore, there are significant differences in GEE and its influencing factors across different regions of Jiangsu Province. Policies should focus on regional differentiated development, strengthening technical support and resource optimization in low-efficiency areas, and promoting green development.

4.1 Spatiotemporal characteristics of green energy efficiency

The measurement results of GEE in Jiangsu Province are shown in Table 3, and the trend of GEE in Jiangsu Province is illustrated in Figure 4. The trend chart shows that, overall, between 2012 and 2022, the GEE in Jiangsu Province exhibited a fluctuating upward trend. However, there were significant differences across regions and years. On the provincial average level, the green energy efficiency 2012 was 0.660, increasing to 0.873 by 2022, an improvement of 0.213. This indicates that Jiangsu Province has made significant progress in green development, with a marked improvement in green energy utilization efficiency. However, this increase was not evenly linear but instead exhibited phased characteristics. A decline in efficiency occurred between 2016 and 2017, which may be related to factors such as industrial structure adjustments, technological application bottlenecks, or uneven policy implementation in some regions during this period (Kong et al., 2023).

From a regional perspective, the economically developed southern Jiangsu region (such as Nanjing, Wuxi, and Suzhou) has significantly improved GEE. Wuxi's GEE increased steadily from 0.653 in 2012 to 1.004 in 2022, making it one of the most efficient areas. This reflects its substantial technological innovation, energy structure optimization, and policy implementation advantages (Liang et al., 2021). Nanjing showed a similar trend, with its efficiency rising from 0.621 in 2012 to 1.001 in 2022. Changzhou reached its peak green energy efficiency value of 1.004 in 2021. However, the northern Jiangsu region (such as Suqian, Huai'an, and Lianyungang) generally exhibited lower green energy efficiency (Huang et al., 2015). Lianyungang's efficiency remained below the critical value of 1 throughout the analysis period, rising slowly from 0.656 in 2012 to 0.782 in 2022. While showing some progress, the overall improvement was relatively limited, suggesting potential shortcomings in green energy technology adoption, industrial structure optimization, and policy support in northern Jiangsu.

In addition, from 2012 to 2022, Jiangsu Province's GEE exhibited significant fluctuations. The average efficiency value reached 0.873 in 2022, marking a high point over the decade, which could be attributed to the implementation of energy-saving and emission-reduction policies or breakthroughs in technological innovation across the province during that year. However, the overall GEE values in Jiangsu showed periodic

TABLE 3 Green energy efficiency of Jiangsu Province.

Province	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Nanjing	0.621	0.654	0.625	0.686	0.867	0.729	0.656	0.749	0.641	0.750	1.001
Wuxi	0.624	0.653	0.629	0.688	0.943	0.656	0.632	0.776	0.642	0.790	1.004
Xuzhou	0.611	0.677	0.640	0.693	1.002	0.661	0.632	0.803	0.651	0.878	1.003
Changzhou	0.633	0.707	0.645	0.719	0.650	0.644	0.642	0.819	0.674	1.004	0.780
Suzhou	0.655	0.723	0.654	1.001	0.625	0.642	0.646	0.877	0.686	1.002	0.738
Nantong	0.661	0.727	0.654	0.698	0.596	0.645	0.668	0.827	0.944	0.834	0.786
Lianyungang	0.656	0.741	0.670	0.678	0.599	0.652	0.673	0.852	0.703	0.778	0.782
Huai'an	0.659	0.782	0.666	0.660	0.604	0.657	0.687	1.000	0.704	0.806	0.826
Yancheng	0.649	1.004	0.671	0.676	0.627	0.669	0.624	0.688	0.661	0.795	0.808
Yangzhou	0.661	0.642	0.647	0.708	0.647	0.664	0.701	0.661	0.652	0.878	0.833
Zhenjiang	0.741	1.005	0.657	0.758	0.679	0.679	0.976	0.633	0.659	0.869	0.772
Taizhou	0.702	0.618	0.667	0.799	0.691	0.957	1.003	0.624	0.688	0.826	1.007
Suqian	0.702	0.620	0.685	0.822	0.716	0.663	1.001	0.635	0.717	0.890	1.004
Average	0.660	0.735	0.655	0.737	0.711	0.686	0.734	0.765	0.694	0.854	0.873

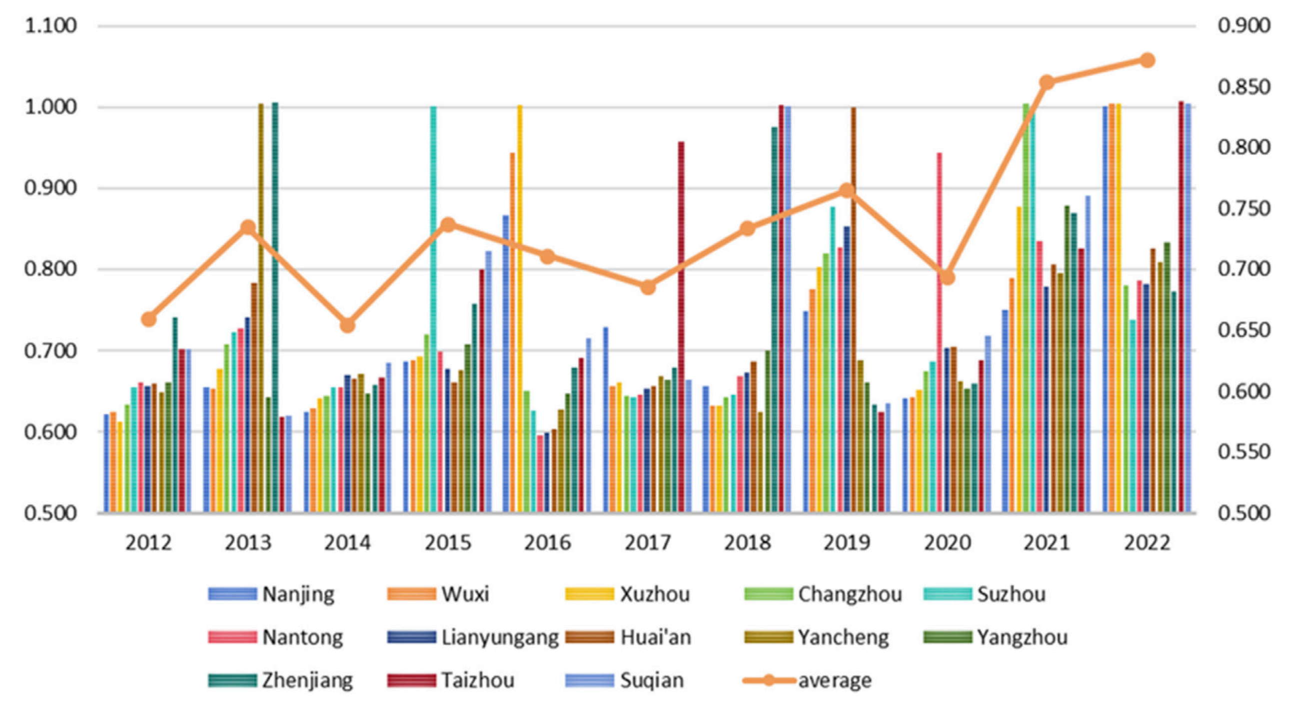

FIGURE 4
Trend of green energy efficiency in Jiangsu Province.

declines in 2014 and 2016, reflecting short-term adjustments in energy utilization in certain regions. The decline in efficiency observed in 2020 may have been influenced by external economic conditions, notably the outbreak of the COVID-19 pandemic (Liu et al., 2020), which disrupted the operation of Jiangsu's economic and energy systems.

4.2 Analysis of spatial agglomeration characteristics of green energy efficiency

According to Table 4, which presents the Dagum Gini coefficient and its decomposition results, the overall Gini coefficient for GEE in Jiangsu Province showed fluctuations from 2012 to 2022. The total

TABLE 4 Dagum Gini coefficient and its decomposition results.

Year	Total	Intra	Inter	Density	Sunan	Subei	Sunan-Subei
2012	0.029	0.013	0.003	0.013	0.033	0.022	0.033
2013	0.085	0.044	0.007	0.034	0.083	0.083	0.087
2014	0.014	0.006	0.007	0.001	0.011	0.011	0.018
2015	0.057	0.026	0.017	0.014	0.073	0.040	0.065
2016	0.094	0.045	0.023	0.026	0.091	0.085	0.102
2017	0.044	0.023	0.009	0.011	0.025	0.051	0.043
2018	0.093	0.048	0.012	0.032	0.079	0.096	0.095
2019	0.080	0.042	0.003	0.035	0.058	0.089	0.079
2020	0.045	0.023	0.019	0.003	0.015	0.055	0.046
2021	0.048	0.020	0.013	0.015	0.065	0.027	0.060
2022	0.065	0.032	0.006	0.027	0.071	0.058	0.069

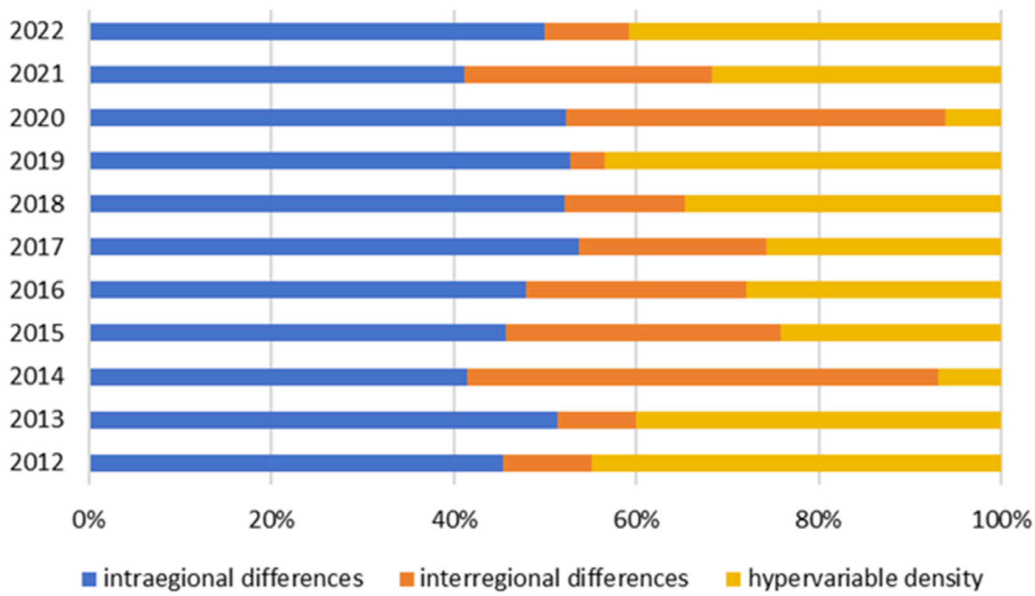

FIGURE 5
Trend of contribution rates.

value increased from 0.029 in 2012 to 0.065 in 2022, indicating an expansion in the degree of inequality in GEE across the province.

From the perspective of within-group contributions, the Gini coefficients within the southern Jiangsu (Sunan) and northern Jiangsu (Subei) regions have increased. In contrast, the disparity between the two regions has persisted. The within-group Gini coefficient for Sunan rose from 0.022 in 2012 to 0.058 in 2022, indicating a gradual intensification of inequality in green energy efficiency within the region. Meanwhile, the within-group Gini coefficient for Subei increased significantly, from 0.033 in 2012 to 0.069 in 2022, reflecting further widening disparities in green energy efficiency within the northern region. The between-group difference between Sunan and Subei grew from 0.033 to 0.069, highlighting the increasing divergence in green development between the two regions.

The decomposition results of the Gini coefficient for green energy efficiency in Jiangsu Province reveal the dynamic changes in the contributions of intra-regional differences, inter-regional differences, and hypervariable density to overall inequality across different years, as shown in Figure 5.

Intra-regional differences have consistently been the primary source of green energy efficiency inequality in Jiangsu, accounting for a significant proportion of the total Gini coefficient. In 2012, the contribution rate of intra-regional differences was 45.4%, the highest among the components, indicating a pronounced disparity in green energy efficiency within regions in Jiangsu. This rate peaked at 53.7% in 2017 before slightly declining, but it remained high in 2022,

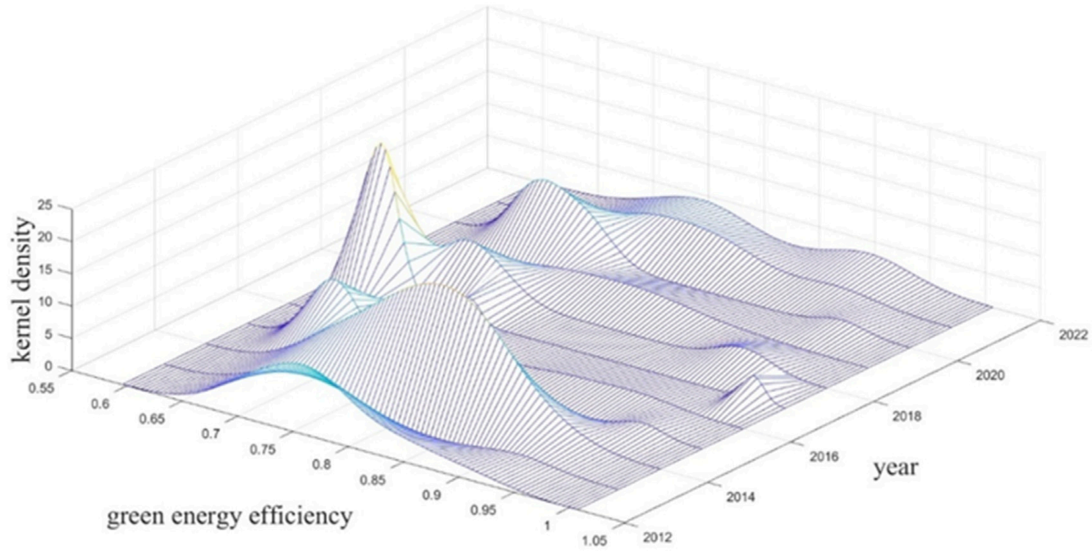

FIGURE 6
Kernel density distribution of green energy efficiency.

highlighting that intra-regional inequality remains a key governance focus. The contribution of inter-regional differences to inequality has exhibited fluctuations. In 2012, the inter-regional contribution rate was 9.7%, reaching a peak of 51.7% in 2014 before gradually declining to 9.2% in 2022. This indicates that the efficiency gap between the Sunan and Subei regions experienced considerable variation but has improved compared to 2012, possibly due to the coordinated advancement of green policies across the province and technology diffusion. Hypervariable density also shows inevitable fluctuations, decreasing from 0.449 in 2012 to 0.409 in 2022, with its contribution rate remaining generally stable but still noteworthy. Suggesting that while inter-regional differences have improved, the overlapping and differentiation of green energy efficiency across regions persist, continuing to influence overall inequality.

4.3 Dynamic evolution analysis of regional differences in green energy efficiency

The kernel density distribution map of GEE in Jiangsu Province, as shown in Figure 6, demonstrates significant dynamic evolution characteristics between 2012 and 2022, reflecting the overall trend of change and regional distribution features of GEE in the region. Firstly, the overall peak of the kernel density distribution gradually shifts to the right, indicating a steady improvement in green energy efficiency levels across Jiangsu Province. This highlights the positive outcomes of green development and energy transition efforts, which may be attributed to Jiangsu's remarkable advancements in technological innovation, energy structure optimization, and policy implementation (Ma et al., 2023).

From the perspective of distribution patterns, the kernel density distribution in 2012 displayed a relatively concentrated unimodal shape, reflecting minor differences in green energy efficiency and relatively balanced performance across regions at that time. However, over time, the distribution gradually evolved into a multimodal pattern. Particularly after 2016, multiple density peaks emerged, indicating a growing disparity in green energy efficiency between regions. This phenomenon suggests uneven progress among regions regarding technological advancement, industrial structure optimization, and policy implementation. Furthermore, the 2022 kernel density distribution shows a significant increase in density within the high-efficiency range, indicating that some regions have reached a high level of green energy efficiency. However, a "long-tail" phenomenon remains in the low-efficiency range, suggesting that a few regions still have substantial room to improve green energy efficiency. These differences are likely closely related to regional economic development levels, the adoption rate of green technologies, and the intensity of policy implementation (Huang et al., 2015).

Therefore, Jiangsu Province has achieved significant overall progress in GEE, but regional heterogeneity has gradually intensified. In the future, differentiated policy designs should be implemented to further support low-efficiency areas, strengthen the promotion of green technologies (Feng et al., 2022), and optimize energy structures (Wu et al., 2021), thereby achieving coordinated regional development and an overall improvement in efficiency.

4.4 Analysis of factors influencing green energy efficiency

According to the regression results of the fixed effects model presented in Table 5, FORE, FIND, URBAN, and STRU exhibit a significant positive impact on green energy efficiency, with all variables achieving a 1% significance level. Advanced technologies, management practices, and stringent green production requirements introduced by foreign-funded enterprises have significantly improved the green energy efficiency in Jiangsu Province. Foreign direct investment has contributed to optimizing the energy structure and driving the development of local green industries (Wang and Jiayu,

TABLE 5 Baseline regression results.

Variables	GEE	GEE	GEE	GEE	GEE	GEE	GEE	GEE
FORE	3.829***							
	(2.842)							
FIND		0.128***						
		(4.480)						
URBAN			1.087***					
			(5.502)					
GOVER				−2.232***				
				(-2.687)				
STRU					1.021***			
					(2.979)			
SCIEN						2.734*		
						(1.769)		
INDU							−1.129***	
							(-5.328)	
INFRA								0.004**
								(2.113)
Fix effect	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.490***	0.126	−0.178	0.974***	0.123	0.582***	1.091***	0.634***
	(7.319)	(0.913)	(-1.063)	(9.884)	(0.602)	(6.611)	(14.400)	(11.505)
N	143	143	143	143	143	143	143	143

2019), thereby playing an active role in enhancing energy utilization efficiency. Improving the financial system provides ample funding for green energy projects (Sun and Chen, 2022), promoting the innovation and application of green technologies. Consequently, the effective operation of financial markets can channel capital into high-efficiency green industries, thereby improving energy efficiency. Additionally, the urbanization process, characterized by the enhancement of infrastructure and energy utilization efficiency, has positively affected green development (Yang et al., 2016). Urbanization often involves implementing efficient energy management systems and the widespread adoption of green technologies, thereby driving improvements in energy efficiency. Optimizing the industrial structure, mainly by reducing the share of high-pollution, high-energy-consuming industries and fostering the development of green economic sectors, has also effectively enhanced energy utilization efficiency.

The regression coefficients for SCIEN and INFRA are 2.734 and 0.004, respectively. SCIEN is significant at the 10% level, while INFRA is significant at the 5% level. Therefore, SCIEN has a significant positive impact on green energy efficiency. Technological progress, especially in the application of energy technologies and energy-saving and emission-reduction technologies, serves as a core driving force for improving green energy efficiency (Peng et al., 2022). Through technological innovation, energy consumption and environmental pollution can be significantly reduced. Improvements in INFRA contribute positively to green energy efficiency. Well-developed infrastructure, particularly green transportation and smart grids, provides strong support for the efficient utilization of energy.

In addition, the regression coefficients for GOVER and INDU are −2.232 and −1.129, respectively, both significant at the 1% level. This negative impact indicates that excessive government intervention may hinder the effective functioning of market mechanisms (Lin and Zhou, 2021), thereby suppressing the improvement of green energy efficiency. If the formulation and implementation of policies lack scientific rigor and flexibility, they may reduce resource allocation efficiency and negatively affect green development. Moreover, the reliance on traditional high-energy-consuming industries during industrialization weakens green energy efficiency enhancement. Therefore, it is crucial to accelerate the green transformation of high-energy-consuming industries during the industrialization process.

5 Discussion

This study provides innovative insights into the regional disparities, influencing factors, and trends in GEE. First, the finding that GEE in Jiangsu Province shows an overall upward trend while significant regional disparities persist highlights the reality of unbalanced regional development. This provides a theoretical foundation for the regional implementation of green energy policies, particularly in offering guidance on how differentiated policies can promote regional coordination and development. Second, the observed increase in GEE inequality across Jiangsu Province from 2012 to 2022 further underscores the challenges of regional differences in the green energy transition. This trend is likely linked to variations in the intensity of government policy implementation, the progress of industrial structure adjustment, and changes in external economic environments (Wei et al., 2020). Finally, the empirical analysis reveals that GOVER and INDU negatively impact GEE. This innovative conclusion challenges the conventional view that government policies and industrialization processes are inherently favorable for energy efficiency. Instead, it points out that improper policy implementation and industrial structure adjustments can constrain improvements in energy efficiency during the green energy transition. Therefore, balancing the relationship between government policies, industrial structures, and technological innovation becomes crucial to further enhancing GEE. In addition, fossil fuels still dominate global energy demand (Biswas et al., 2024), and improving the green energy efficiency of fossil fuels plays a pivotal role in improving the environment.

6 Conclusion and implications

Based on the empirical analysis, the following conclusions can be drawn: First, the overall GEE in Jiangsu Province shows an upward trend, but still has a large room for improvement. Second, the level of inequality in GEE across Jiangsu Province increased between 2012 and 2022, with the southern Jiangsu region generally outperforming the northern Jiangsu region. Finally, FORE, FIND, URBAN, STRU, SCIEN, and INFRA have significant positive impacts on GEE, while GOVER and INDU exhibit significant negative impacts on GEE. Based on the above summary, this study proposes the following policy implications:

Firstly, strengthen technological innovation and infrastructure synergy to release the growth potential of GEE. It is found that the overall GEE in Jiangsu Province shows a fluctuating upward trend, and as of 2022, the green value of GEE in most cities in Jiangsu Province has not reached the critical value of 1. Therefore, it is recommended to further improve the overall efficiency by strengthening technological innovation, policy support and optimizing resource allocation, relying on universities and research institutes in Nanjing and Suzhou, focusing on breaking through the bottleneck areas of high-efficiency photovoltaic materials, smart grids, scheduling algorithms and hydrogen energy storage technologies; and simultaneously promoting the construction of energy Internet infrastructure. Synchronously promoting the construction of energy Internet infrastructure, building new regional integrated energy hubs in central and northern Suzhou, and realizing the optimal allocation of wind and light resources across the region through the ultra-high-voltage transmission network to form a virtuous cycle of technological iteration and efficiency improvement.

Secondly, the establishment of regional compensation and factor flow mechanism, cracking the North-South efficiency imbalance dilemma. Gini coefficient and kernel density empirical results show that regional differences in GEE are obvious, in order to alleviate the structural contradiction of the widening gap between the GEE of southern Jiangsu and northern Jiangsu, it is necessary to adopt a policy adjustment mechanism, set up a provincial green energy coordinated development fund, levy ecological adjustment tax on it according to the intensity of carbon emissions in the region, and use the special funds for the construction of distributed photovoltaic power stations and biomass energy projects, so as to achieve the purpose of alleviating the regional differences and enhancing the GEE. In addition, improve the cross-regional energy right trading market, allowing enterprises in southern Jiangsu to complete the emission reduction target by purchasing green power quotas in northern Jiangsu, forming a market-based ecological compensation path.

Finally, optimize the combination of policy tools and construct a regulation system of positive incentives and negative constraints. Through the analysis of GEE influencing factors, it can be seen that FORE, FIND, etc. have a significant positive impact on GEE, while GOVER and INDU show negative effects, therefore, based on the two-way effect characteristics of influencing factors, we should expand the list of foreign investment access, develop green financial innovation tools, and adhere to the development of new urbanization, which will help to improve the GEE of the city. The level of industrialization should be included in the ecological civilization assessment system, and the government intervention mode should be reformed to reduce the distorting effect of administrative means on the market mechanism.

Despite the aforementioned policies providing comprehensive guidance and support for enhancing GEE, several challenges remain in the implementation process. First, there are inherent difficulties in advancing green technology innovation (Söderholm, 2020). While the government has established dedicated funds to support green energy technology research and development, innovation in high-tech fields often requires long cycles and significant financial investment, with high barriers to achieving technological breakthroughs. Second, improving market mechanisms is hindered by regional disparities and an underdeveloped financial system. The differing levels of economic development and energy demand across regions make it difficult for a single green financial policy to address the needs of all areas (Yang et al., 2024). In particular, underdeveloped regions in Jiangsu Province face challenges due to underdeveloped capital markets, making it harder to attract green financial investments. Finally, enhancing and optimizing public infrastructure faces dual challenges of investment and technology. Infrastructure construction requires substantial upfront investment and long-term maintenance (Greer, 2020). In less developed regions, the promotion of distributed renewable energy systems is further constrained by the lack of technological dissemination, cost barriers, and limited execution capacity of local governments. To address these challenges, further efforts are needed to refine mechanism design, strengthen technological innovation, and foster regional collaboration, while promoting the deepening of green financial systems and optimizing infrastructure development.

7 Limitations and prospects

This study systematically analyzed the spatial-temporal evolution and driving factors of green energy efficiency in

Jiangsu Province. However, the research primarily relied on macro-level statistical data and did not fully consider the heterogeneity at the micro-enterprise level in the calculation of green energy efficiency. This limitation may reduce the specificity and effectiveness of the policy recommendations in practical implementation. Future research could incorporate enterprise-level data and case studies to explore the distribution and determinants of green energy efficiency at the micro level. Additionally, the research perspective could be further expanded by integrating green energy efficiency studies into the multi-level policy coordination and industrial chain restructuring under the carbon neutrality goal. Such an approach would facilitate the development of more actionable policy recommendations, providing more precise and systematic theoretical support for comprehensively improving green energy efficiency in Jiangsu Province. Despite these limitations, this study's analysis of the spatial-temporal evolution and influencing factors of green energy efficiency enriches the existing literature. It offers valuable insights for regional low-carbon development.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

XZ: Writing–original draft. HW: Writing–review and editing, Software. SJ: Conceptualization, 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.

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