Digital economy and ecological performance: Evidence from a spatial panel data in China

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The rapid development of information and communication technologies has brought the concept of digital economy into the limelight. Data elements have played a more important role in economic production. As an environmentally friendly economic model, the data factor-driven economy, compared to the traditional one, has low energy consumption and less pollution emissions. Hence, the effect of digital economy development on ecological performance is worth exploring. We measured the digital economy index and the ecological performance index for 30 provinces in China. Furthermore, the relationship between the two was analyzed with the help of a dynamic spatial Durbin model. The results showed the following: 1) closely related to the regional economic foundation, the development level of the digital economy showed obvious spatial characteristics that were high in the eastern region and low in the western region in China. 2) Over time, the pattern of ecological performance in China has changed markedly, showing a high level in the south and a low level in the north. 3) The digital economy showed a significant promoting effect on ecological performance, with a strong externality in space that could have a spillover effect on the surrounding areas. 4) The effect of the digital economy on ecological performance had a significant positive effect, although it lagged behind over time. In addition, the effect has regional heterogeneity and was more obvious in developed regions. Based on these findings, we recommend that the role of ICT in economic activity be strengthened in some developed regions. However, in some developing regions, a balance needs to be struck between digitalization and environmental benefits. At the same time, developed regions should be encouraged to realize economic collaboration with developing regions, with the help of data elements in an effort to narrow the regional gap.

KEYWORDS

digital economy, ecological performance, spatial Durbin model, spatial spillover effect, sustainable development, green economy, ICT, electronic information industry

1 Introduction

After the industrial revolution, the process of global industrialization and urbanization has been accelerating, and the economy has developed rapidly. However, the reason behind the rapid development of the economy is the huge demand for resources. The overexploitation of resources, especially fossil fuel resources, has exacerbated the problem of resource shortages and the deterioration of the ecological environment (Wu et al., 2020; Wang et al., 2022c; Yang et al., 2022a). Currently, grassland degradation and soil erosion are becoming more serious, bringing great negative effects on people's production and life, as are land desertification and other problems. Moreover, excessive energy consumption has caused large emissions of greenhouse gases and has led to the emergence of global extreme climate phenomena. Increasingly frequent natural disasters continue to threaten human settlements and reduce the resilience of cities day-by-day (Yang et al., 2021; Ge et al., 2022; You et al., 2022). Hence, it is necessary to explore the relationship between economic development and the ecological environment to seek future development directions.

Some studies have shown that the improvement of environmental regulation and technical level is conducive to sustainable development and ecological performance. The former can reduce pollution emissions during production to ensure the quality of the ecological environment, and the latter can drive energy efficiency to reduce the consumption of resources (Lorenzoni et al., 2007; Zhu et al., 2014; Zhang et al., 2019; Zhou et al., 2020). More specifically, environmental regulation can effectively prevent economic activities from deteriorating the current ecological situation, which contributes to ecological restoration. Technological advances can improve energy efficiency and reduce pollutant emissions. During this evolution, the same economic output would have consumed fewer resources due to advances in production technology. However, improving the quality of the environment is never such a simple matter. It is a complex system. For developing countries still with a low level of industrialization, including China, simple and rough environmental regulation in such a stage may have a negative influence on industrial agglomeration. This could bring the pollution shelter effect (Copeland and Taylor, 1994; Biswas et al., 2012); that is, as an external constraint on economic activities, the environment will break the production balance of manufacturers in the existing factors of production. In this case, manufacturers have no choice but to adjust their production strategies to face environmental regulation, resulting in an increase in their production cost (Gollop and Roberts, 1983; Gollop and Roberts, 1983). As a result, enterprises have to seek technological breakthroughs to reduce costs.

Although technological progress is more important for these developing countries, not all technological advances can reduce pollution emissions (Adha et al., 2002; Acemoglu et al., 2012;

Anasuya and Narayan, 2022). A new clean technical element is increasingly urgently needed to improve ecological performance and realize the transformation to green and sustainable development. Since the beginning of the 20th century, computer science has been developed continuously, and communication technology has become increasingly mature. Blockchain, artificial intelligence, cloud computing, and the Internet of Things have promoted the transformation of economic development models (Wang et al., 2022b). The digital economy is a new economic form born in this process. As shown in Figure 1, the global trade volume on ICT services has maintained steady growth since 2006. Particularly in Asia, the trade volume increased from $221.37 billion in 2006 to $2010.50 billion in 2019. The trade scale among Africa and Oceania has increased by more than 100% as well (the growth rate of Africa is 105.76% and that of Oceania is 149.69%). This showed that the effect of the digital economy on the global economy was great and obvious.

With information and communication technology, the digital economy takes data or information as key production factors, regulating a series of economic activities such as production or consumption (Miao, 2021). Although data resources are a relatively virtual resource compared to traditional resources such as water and fossil fuel, they can be copied and shared conveniently. Hence, its marginal utility continuously increases while the marginal cost is almost zero. Clearly, data resources are a kind of low cost, high-return factor of production. When data elements participate in economic activities, they can have huge effects on the traditional economic growth style that has high energy consumption and high pollution (Ding et al., 2021). In the digital drive mode, manufacturers are able to use fewer natural resources to generate greater economic benefits and less pollution. This can alleviate the deterioration of the ecological environment and the shortage of resources to a certain extent. Undoubtedly, the digital economy can now be regarded as an important medium to adjust the contradiction between economic development and the ecological environment.

After the entrance of the digital economy into people's vision, the relationship between the digital economy and the ecological environment has become the focus of scholars. Zhou et al. (2021) pointed out that the digital economy has improved the energy consumption structure by optimizing the industrial structure, thus curbing air pollution. This effect was more obvious in developed areas (Zhou et al., 2021). The conclusion of Wu et al. (2022) was similar, and they found that this result could be applied to surrounding regions as well (Wu et al., 2021). Some studies revealed that the digital economy could also promote the level of green innovation in cities to improve cleaner production technology (Wang et al., 2022d; Fang et al., 2022; Wang et al., 2022a). However, some different conclusions have been put forward that the development of the digital economy is not beneficial to the ecological environment in all regions. In those
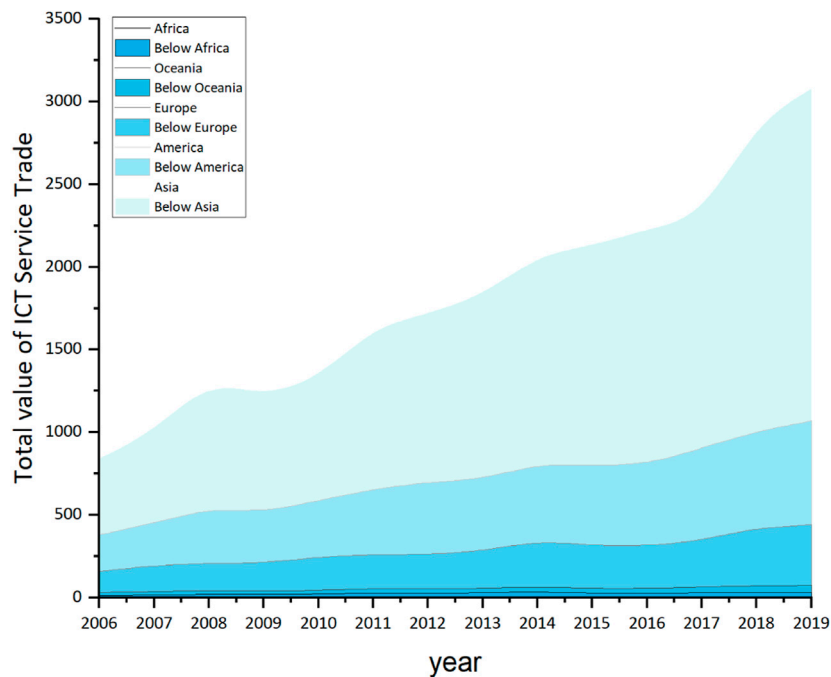
FIGURE 1
2006–2019 trade volume on ICT services in different regions of the world. Note: source from the United Nations Conference on Trade and Development Statistics (UNCTAD stat). Unit: billion USD.

areas that have not yet reached the environmental Kuznets curve (EKC) inflection point, the development of the digital economy has unexpectedly stimulated the demand for electricity in the short term, thus increasing the consumption of fossil fuel resources (Haldar and Sethi (2022); Adha et al., 2022).

In summary, most of the current studies have aimed to investigate the influence of the digital economy on energy consumption and environmental pollution. However, few studies have been concerned about the relationship between the digital economy and ecological performance. In fact, resource constraints and environmental protection are two major issues faced by the Chinese government at the same time (Lan et al., 2012). Energy consumption is related to China's economic growth, while pollution control is related to China's ecological environment (Shakib et al., 2022). Obviously, especially for China, which has not completed the industrialization process, this is a complex problem (Wang et al., 2022; Wang et al., 2022c). Thus, based on the studies mentioned earlier, this article focused on the dynamic spatial relationship between the digital economy and ecological performance. The following work was carried out: 1) a set of evaluation systems of the digital economy was designed, and then the development level of the digital economy in 30 provinces in China during the period 2013–2019 was quantified. 2) The super-SBM model was used to calculate the ecological performance level of various regions in China from 2013 to 2019. 3) The spatial

distribution patterns of the digital economy and ecological performance were summarized. 4) Based on the obtained results, the spatial influence of the digital economy on ecological performance was finally examined.

The contribution of this study was mainly reflected in the following aspects: 1) this study designed a set of index systems to evaluate the digital economy from the three dimensions of digital industrialization, industrial digitalization, and information facilities, providing a set of scientific calculation methods for related research. 2) The investigation of the influence of the digital economy on ecological performance, combined with the discussion of its spatial spillover effect from the perspective of spatial economics, confirmed the role of the digital economy in building an environmentally friendly society. 3) According to the level of economic development, China was divided into eastern regions and central and western regions for discussion. In fact, this was also in line with the actual situation of most developing countries: not all regions had a good digital economy foundation. The results of the heterogeneity analysis also provided empirical evidence for many other developing countries.

The article is structured as follows: the relevant literature, theoretical analysis, and hypotheses are given in Section 2. In Section 3, the measurement system of the digital economy index and ecological performance index was constructed, and the results were calculated. The construction of the regression model and the data sources are displayed in Section 4. The role of the digital

economy on ecological performance is empirically tested in Section 5, with the discussion of the time lag, regional heterogeneity, and endogeneity. Further discussion, conclusions, and policy recommendations are given in Sections 6, 7.

2 Literature review and research hypothesis

2.1 Digital economy

The concept of the digital economy was first proposed by Don (2022). At that time, he used it to refer to the various new economic relationships that emerged after the advent of Internet technology. Since then, with the development of Internet technology, the digital economy has gradually attracted widespread attention from the academic community. Lane (1999) pointed out that the widespread growth of e-commerce, new competitive strategies, and changes in organizational structure were precisely caused by the digital economy. Driven by the combination of information, computing, and communication, the digital economy was considered to have a great influence on the Internet industry.

However, some scholars believe that the essence of the digital economy is digital trade in goods and services and view it as a new economic model derived from the traditional economic model, Teo (2001); Kim (2006) gave a broader definition: the economic development model is driven by information and communication technology. He pointed out that the digital economy could effectively improve the organizational form of enterprises and the cooperation efficiency of various departments (Balcerzak and Pietrzak, 2017). In addition, Mentsiev et al. (2019) thought that the digital economy was a commercial and trade activity based on the Internet. E-commerce is a representative form of the digital economy. Most scholars believe that the digital economy has benefited from the development of information technology. It could promote production and consumption through the replication and sharing of data elements; Li et al. (2021); Li and Liu (2021); Miao (2021) proposed that the digital economy was a collection of industrial digitization and digital industrialization, including the transformation and upgrading of traditional industries by data elements and new industries derived from digital technology (Miao, 2021). In addition, studies have shown that the digital economy has a significant positive impact on environmental quality, sustainable economic development, and the health of the population (Lange et al., 2020; Wu et al., 2022; Wang et al., 2022d).

2.2 Ecological performance

With increasingly serious environmental problems, people have attempted to use fewer resources to produce more profits.

"Ecological performance" is often used to measure the relationship between resources and benefits to evaluate the use efficiency of natural resources. The concept of "ecological performance" was first proposed by Bruce and Rupert (1983). They aimed to create a more reasonable evaluation index system and calculation model to measure the benefits produced by the use of natural resources. For a long time, many scholars all over the world have had a heated discussion on this concept that used four ecological performance indicators to quantify the influence of the use of natural resources on the ecological environment (Whitford et al., 2001). Mickwitz et al. (2006) proposed that ecological performance, as a ratio between economic benefits and resource consumption, could be used to detect the changes in ecological situations in a region (Mickwitz et al., 2006).

With the deepening of research in this field, the index selection and calculation method of ecological performance have been gradually improved using the superefficient data envelopment analysis (DEA) model to measure the ecological performance of Chinese cities. The results showed that there was an N-shaped relationship between resource consumption and ecological performance (Bai et al., 2017; Biswas and Farzanegan, 2012). Estimated ecological performance from different perspectives and measured resource use efficiency in the context of urban development (Chen et al., 2020; Copeland and Taylor, 1994). To calculate the ecological performance, China's ecological footprint was taken as the sample. Using the empirical method of a dynamic panel regression model, they revealed that the improvement of resource utilization efficiency would have a positive effect on ecological performance (Dong et al., 2020). Although the selection of ecological performance evaluation indicators in the existing results was different, the research methods and models were relatively similar.

2.3 H1: The digital economy can effectively improve ecological performance

Research on the digital economy and ecological performance by scholars in various fields can be divided into two areas, the effects of the digital economy on resource saving and the digital economy on pollution reduction. On the one hand, it is argued that the development of the digital economy has increased the level of production technology, which has led to a reduction in energy consumption. Specifically, the digitalization of production processes enables manufacturers to better manage consumables including energy and production materials. Computer science and technology can help planning departments allocate these resources more rationally and avoid waste in production activities. In addition to the production sector, digital technology can also affect the distribution sector. With the help of Internet technology, the efficiency of logistics has been

FIGURE 2
Mechanisms of the digital economy to ecological performance.
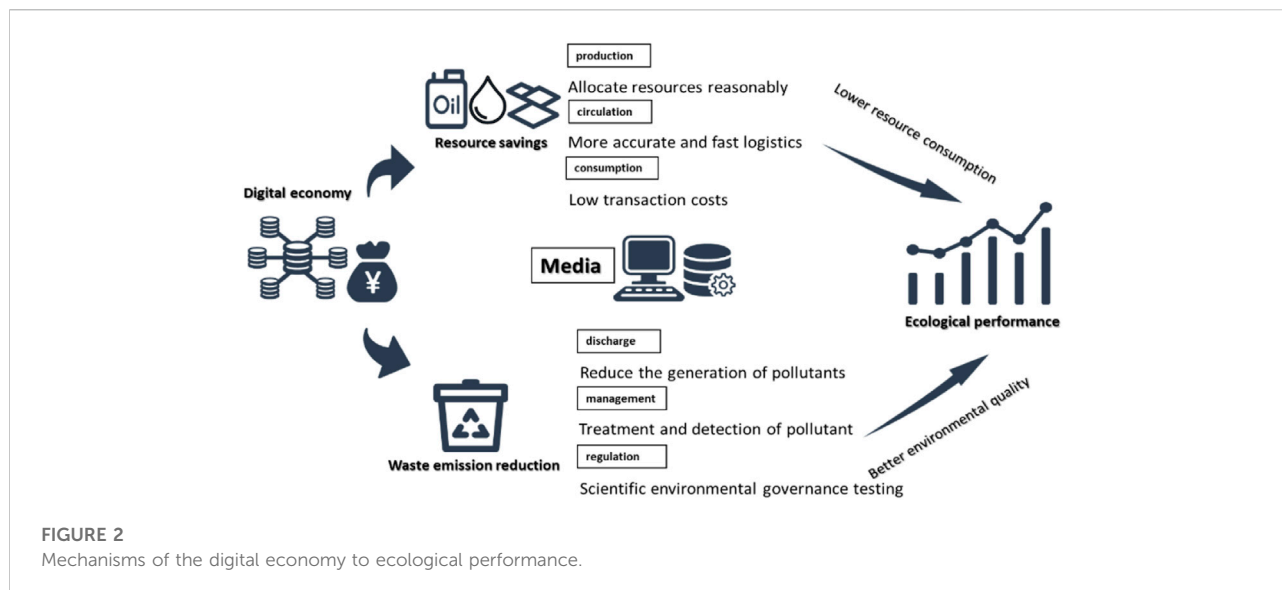
greatly improved. Transactions between buyers and sellers have become much easier. This has stimulated market consumption to a large extent. Unlike traditional distribution and sales activities, the data element acts as the medium for completing these transactions, and its costs are almost negligible. In other words, the resources previously spent on this part of the consumption have been saved. At the same time, digitalization has highlighted the role of communication technology in economic activity. Some unnecessary commuting and gatherings are replaced by electronic communication, reducing the energy consumption of economic collaboration activities. This shows that the development of the digital economy can be effective in saving resources and improving energy efficiency (Zhong et al., 2021).

Another aspect is the mechanism of the impact of the digital economy on pollution reduction. From the production side, the development of the digital economy can effectively alleviate the problem of information asymmetry. This has led to greater mobility of technological factors and promoted cooperation and innovation in production technology (Jaffe et al., 2002; Yang et al., 2022b). This means that manufacturers will be more productive and the pollution emissions from the production process will be reduced. Specifically, manufacturers can use platforms such as the Internet to quickly exchange technical issues, form stable cooperation, and expand the added value of their goods. According to the Porter hypothesis, manufacturers can invest this capital in research and development. This will lead to more improved and cleaner production techniques (Wang et al., 2022e). Similarly, in the process of digitalization, environmental regulation has given rise to many new forms. For example, with the help of Internet of Things (IoT) technology, it is possible to monitor the situation regarding the generation and treatment of pollutants in

real time. The production department can use its feedback to adjust the scale of production. This technology can also be used in the collection and analysis of environmental monitoring data, using cloud computing to quickly access environmental pollution data in the area (Chen et al., 2022). On this basis, the environmental quality and pollutant emissions are analyzed. This helps the government curb the excessive emissions of some enterprises in a timely manner. We speculate that the development of the digital economy can curb pollution emissions.

Figure 2 shows the possible impact of the digital economy on ecological performance more clearly. Therefore, we believe that the digital economy is closely related to both resource conservation and ecological quality and propose H1 in this regard: The digital economy can effectively improve ecological performance.

2.4 H2: There is a spatial spillover effect of digital economy on ecological performance

There is a significant feature in data elements, that is, strong liquidity. When different production departments work together, data elements can be transferred with little time, thus improving the efficiency of information exchange. As shown in Figure 2, another key point is that the transmission of data elements is not limited by geographical distance. The digital economy forms spatial spillovers through three channels. The first channel is the use effect. For example, the digital economy can drive the construction of information and communication service facilities in surrounding areas (Shahnazi and Dehghan Shabani, 2019). The second channel relates with derivatives of

FIGURE 3
Spatial effect mechanism of resource consumption.
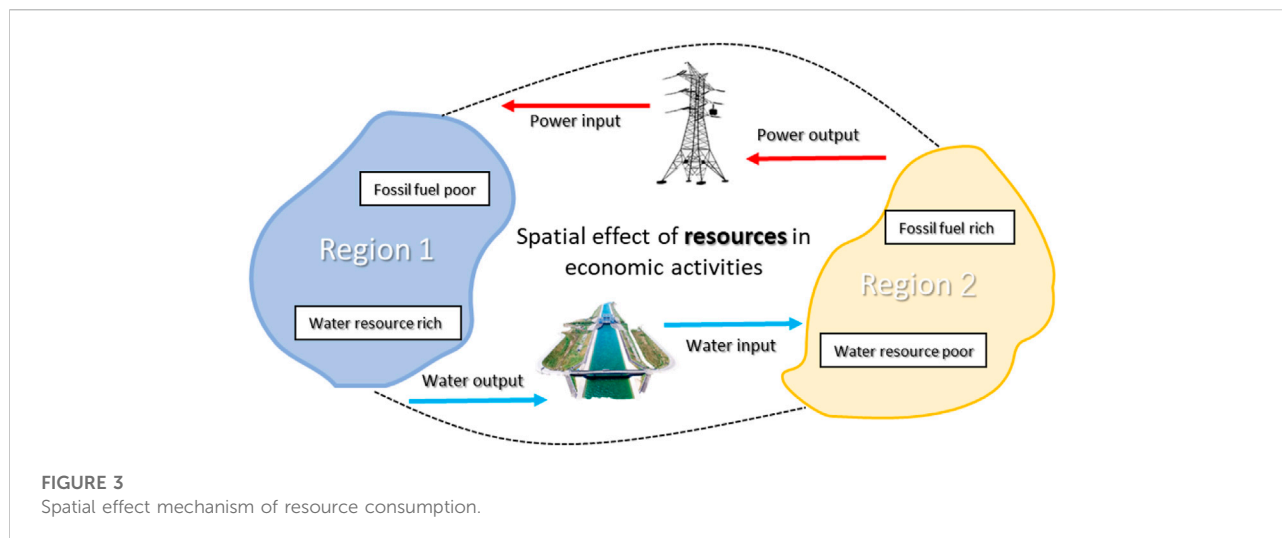
the digital economy that have an effect on relevant developments in various regions. These effects are known as substitution effects, which replace physical goods with virtual goods. Virtual mobile, e-commerce, e-government, e-shopping, remote work, e-banking, e-commerce, virtual education, and virtual conferencing are all alternative forms (Jorgenson 2001; Toffel and Horvath 2004; Schmidt and Kløverpris 2009). The last channel is cost-effective. The cost of data transmission, processing, computing, and storage continues to decline as digital technologies continuously evolve (Goldfarb and Tucker, 2019). Therefore, driven by the digital economy, the possibility of data elements being transferred to other regions is also greatly increased.

As shown in Figure 3, as the level of production cooperation improves, interregional cooperation becomes the mainstream form of regional economic development. Projects such as natural gas transmission from west to east China, the West–East electricity transmission project and the South-to-North Water Diversion are typical cases of cross-border cooperation in resources.

However, the difference in the technological level and resource distribution among regions causes a certain gap in the industrial structure and economic development level. Consequently, regional economic cooperation has also brought some unexpected environmental problems. Most intuitively, the wastewater generated by the upstream plant is likely to cause diffuse pollution to other areas downstream. Undoubtedly, it increases the sewage treatment cost in the downstream area. In addition, some factories have been relocated to the edge of the city under the consideration of the cost of environmental restoration. Their exhaust gas may diffuse with the atmosphere and eventually form cross-border pollution with other pollutants in the air (so called the spatial agglomeration effect of environmental pollution) (Sun et al., 2020; Sun et al., 2022). Figure 4 depicts the spatial effects of environmental pollution.

Similarly, we propose H2: there is a spatial spillover effect of the digital economy on ecological performance.

3 Measurement of digital economy and ecological performance

3.1 Digital economy index

At present, several indicators have been proposed to measure the development of the digital economy. Li et al. (2021), referring to the standards issued by the Ministry of Industry and Information Technology of China and Tencent Research Institute, constructed a set of evaluation systems from three levels: digital talent, digital infrastructure, and digital industry value (Li et al., 2021). In addition, some indicators that consider the development level of the Internet and digital finance have also been put forward in several studies. However, there is no widely used indicator to measure the development of the digital economy. Consequently, a scientific, objective, and comprehensive digital economy index measurement system was certainly needed. Based on these studies, the digital economy was divided into three parts: "information infrastructure," "digital industrialization level," and "industrial digitization level."

Among the three parts, the information infrastructure is viewed as the basis of the development of the digital economy. It mainly included the length of optical cable lines, the number of mobile Internet users, and the number of 4G users. These selected indicators could objectively reflect the scale of demand for information and communication services and the activity of the digital economy in the region. The development of industries such as e-commerce, software business, and software products, formed by using information technology, is the performance of digital industrialization. Hence, indices such as the number and sales of e-commerce enterprises,
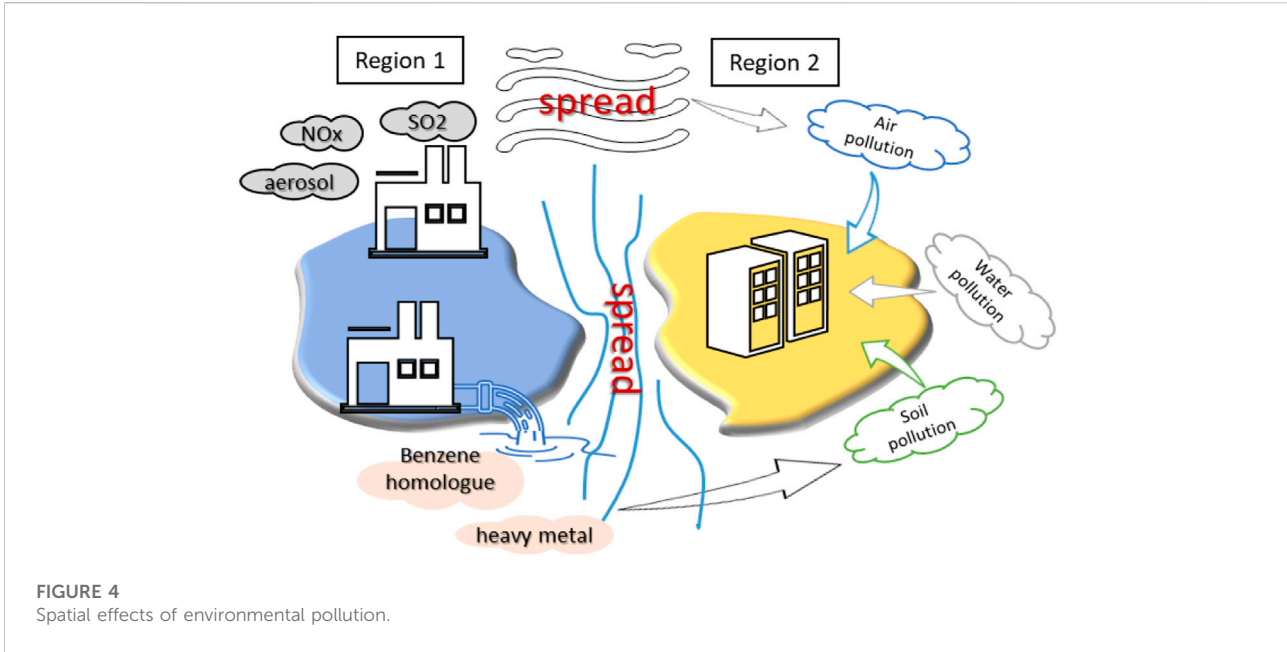
FIGURE 4
Spatial effects of environmental pollution.

TABLE 1 Digital economy index system.

Criterion layer	Index layer	Weight
Information infrastructure	Length of optical cable lines	0.1125
	Number of mobile Internet users	0.0667
	Number of 4G users	0.0913
Digital industrialization level	Total assets of the electronic information manufacturing industry	0.0789
	Number of e-commerce enterprises	0.0514
	Sales of e-commerce enterprises	0.1371
	Software business income	0.1181
	Software product income	0.0987
Industrial digitization level	Expenditure on technology introduction	0.1025
	Expenditure on technology improvement	0.0417
	Number of computers per 100 people	0.0697
	Number of websites per 100 enterprises	0.0314

software business income, software product income, and the total assets of the electronic information manufacturing industry were taken into consideration here. For the last part, industrial digitization refers to the utilization level of digital technology by enterprises. The expenditures on technology introduction, technology improvement, computers per 100 people, and websites per 100 enterprises were selected to quantify the level of digitization in this part. The specific indicators are shown in Table 1, and the relatively objective entropy method was selected for the determination of weight (Li et al., 2021).

The specific calculation for the entropy method is as follows:

Calculate the characteristic proportion degree in the ith year under the jth index:

$$P_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{n} x_{ij}}, \ (i = 1, 2, 3 \cdots n; j = 1, 2, 3 \cdots m) \quad (1)$$

Calculate the entropy of the jth index:

$$e_j = -k \sum_{i=1}^{n} P_{ij} \ln(P_{ij}), \ (j = 1, 2, 3 \cdots m), \ (0 \leq e_j < 1) \quad (2)$$

Coefficient of difference calculation:

$$d_j = 1 - e_j \quad (3)$$

Determine the weight of evaluation index:

$$\omega_j = \frac{d_j}{\sum\limits_{j=1}^{m} d_j}, \ (j = 1, 2, 3 \cdots m) \quad (4)$$

Three representative years: 2013, 2016, and 2019 were chosen in this article (Figure 5):

The results of the digital economy index calculation show that there are significant spatial differences in the development of the digital economy across provinces, with significant local clustering characteristics, such as the Yangtze River Delta region and the Pearl River Delta region. The Yangtze River Delta and Pearl River Delta regions are mostly in the red zone, which indicates a high level of digital economy development in these regions. However, the western (north-western) region is in the blue zone, where the level of digital economy development is relatively low, especially in Xinjiang and Qinghai provinces. In terms of time, the overall differences in the development of the digital economy in the provinces have narrowed, and in terms of the speed of development, the central region is the fastest, followed by the western region, with a gradual convergence of characteristics between regions. It is worth noting that the level of digital economy development in each region has grown in tandem with economic development. By 2019, the blue areas decreased while the orange areas continued to increase, which indicates a gradual increase in the level of digital economy development in these regions. Some regions, Beijing, Shanghai, and Guangdong, still maintain a high level of digital economy development. Overall, China's digital economy is gradually showing relative spatial stability, and there are some ups and downs in the development of the digital economy in some regions. However, overall, the development of the digital economy is gradually improving in all provinces.

3.2 Ecological performance index

There are a number of approaches to measuring ecological performance, and we have compared these approaches, as shown in Table 2:

In the current study, the calculation of the eco-performance index can be broadly divided into two categories, the ratio method and the input–output model method (Dyckhoff and Allen, 2001; Dahlström and Ekins, 2005). In contrast, scholars prefer input–output modeling approaches, such as DEA, to evaluate ecological performance (Ge et al., 2022). There are two traditional forms of DEA models, CCR and BCC, which are unable to measure the full range of undesirable output. Compared to traditional DEA models, the SBM model has the advantage of successfully addressing the neglect of slack variables in the process of efficiency evaluation by radial models. The SBM model is a model that allows both desirable output and undesirable output to be considered. However, the result of the SBM model cannot be greater than 1. As a result, Anderson and Petersen (1993) integrated a new model, the super efficiency model (DEA-SEM), based on a modification of

FIGURE 5
Digital economy index of each province for 2013 **(A)**, 2016 **(B)**, and 2019 **(C)**.
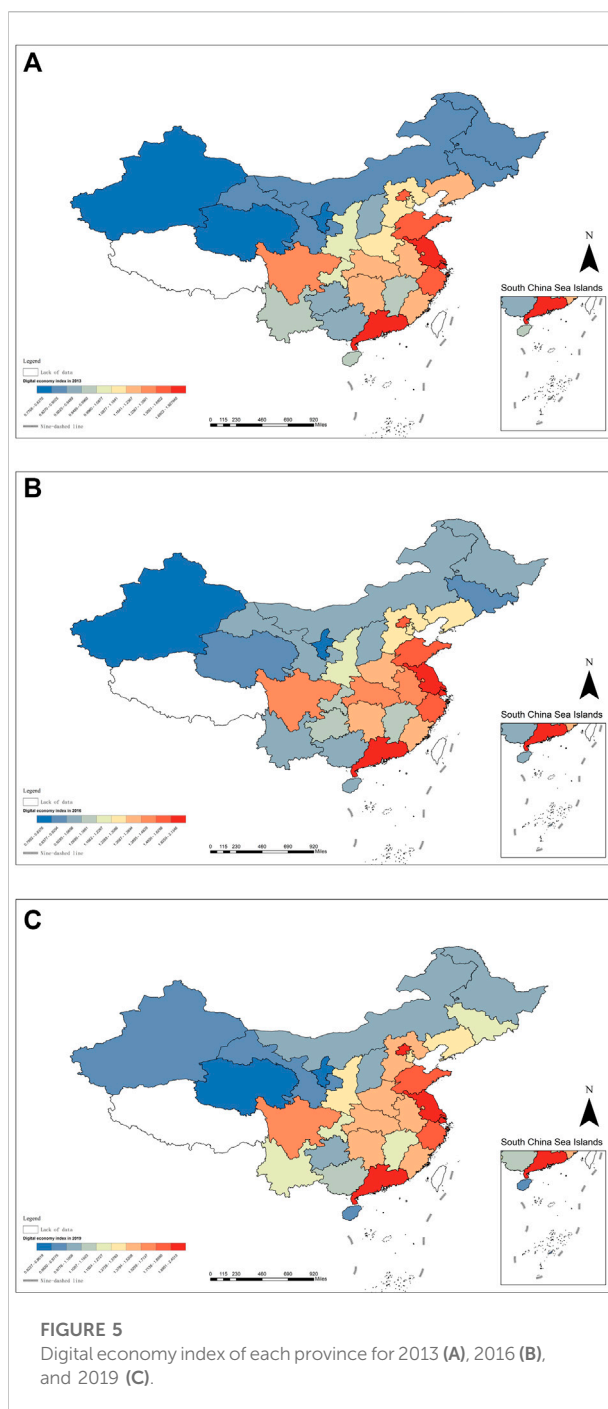
the traditional DEA model. In this method, the efficiency value can be greater than one to better distinguish its efficiency. The Super-SBM model is a combination of the super efficiency and SBM models. Among these submodels, the Super-SBM method considers both undesirable output and super efficiency and is considered a more appropriate method. Therefore, a set of measurement systems of ecological performance was built based on the Super-SBM method,

TABLE 2 Relevant measurement methods of ecological performance.

Model	Interpretation	Reference
Ratio method	Numerator is economic benefits and the denominator is resource consumption	Remer and Nieto (1995)
		Dahlström and Ekins (2005)
56DEA (CCR/BBC)	Base model for DEA, a special linear programming model	Li et al. (2021)
DEA-SEM	On the basis of DEA, the model can be calculated with results greater than 1.	Andersen and Petersen (1993)
		Tone (2001)
DEA-SBM	On the basis of the DEA, undesirable outputs are considered.	Lee (2021)
Super-SBM	Combines features of both the SBM model and the DEA-SEM.	Ge et al. (2022)

TABLE 3 Ecological performance index calculation system.

Category	Primary index	Secondary index	Index interpretation
Investment	Resource consumption	Energy consumption	Fossil fuel consumption
		Land resource consumption	Residential land and industrial land
		Water consumption	Industrial water consumption
Desirable output	Ecological environment	Forest resources	Forest area per capita
		Wetland resources	Wetland area per capita
		Water resources	Water resources per capita
		Economic level	Per capita GDP
Undesirable output	Environmental pollution	Wastewater emissions	Industrial wastewater emissions
		Exhaust emissions	Industrial waste gas emissions
		Solid waste emissions	Emission of industrial solid waste

according to researchers (Dong et al., 2020; Ge et al., 2022). The inputs, desirable and undesirable outputs used here are given in Table 3. The specific calculation for the DEA-SBM model is as follows:

Suppose there is a set, D (DMU), composed of n decision units, with three sets of vectors defined as $x \in R^m$, $y^d \in R^a$, and $y^u \in R^b$, where m is m input elements, a is the number of desirable output types and b is the number of undesirable output types.

Then, there are matrices $X = [x_1, \cdots, x_n] \in R^{m \times n}$, $Y^d = [y_1^d, \cdots, y_n^d] \in R^{a \times n}$, $Y^u = [y_1^u, \cdots, y_n^u] \in R^{b \times n}$

$$\rho = \min \frac{1 - m^{-1} \sum_{i=1}^m \frac{D_i}{x_{i0}}}{1 + \frac{1}{a+b} \left(\sum_{r=1}^a \frac{D_r^d}{y_{r0}^d} + \sum_{h=1}^b \frac{D_h^u}{y_{h0}^u} \right)} \quad (5)$$

$$s.t. \begin{cases} x_0 = x\lambda + D^- \\ y_0^d = Y^d \lambda + D^d \\ y_0^u = Y^u \lambda + D^u \\ D^- \geq 0, D^d \geq 0, D^u \geq 0, \lambda \geq 0 \end{cases} \quad (6)$$

where λ is the weight variable, D^- is the slack variable of input, D^d is the slack variable of desirable outputs, and D^u is the slack variable of undesirable outputs.
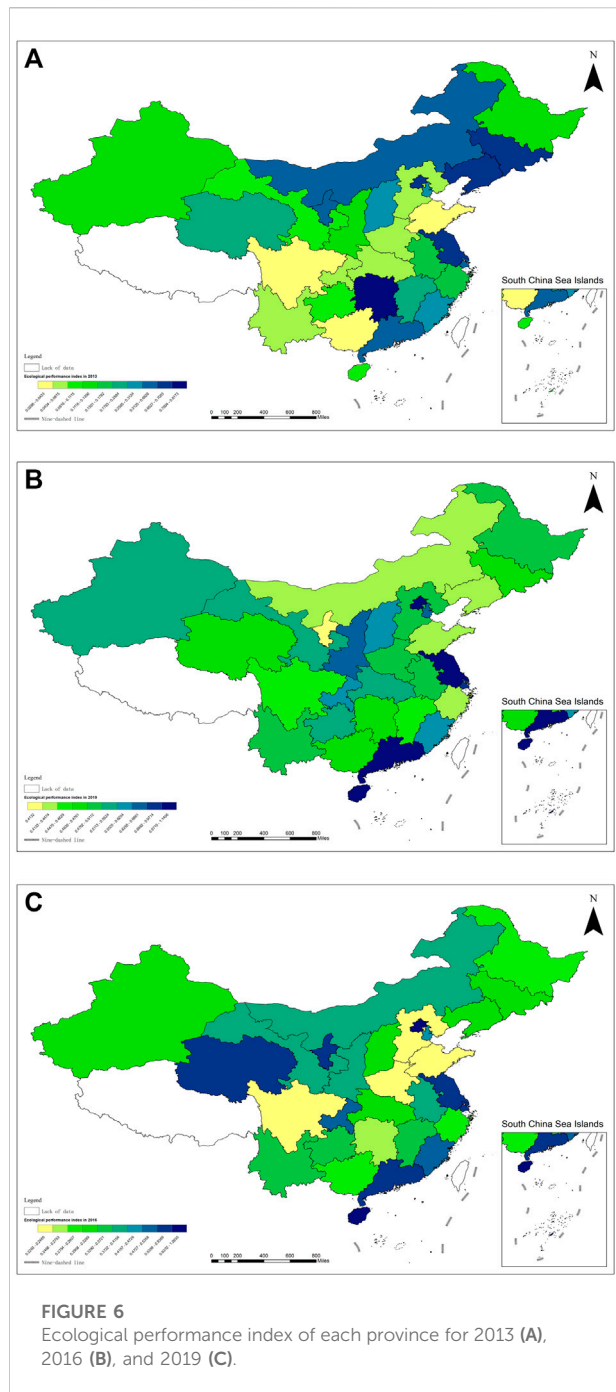
Then the super efficiency SBM model with undesirable outputs is constructed as follows:

$$\varphi = \min \frac{1 + m^{-1} \sum_{i=1}^m \frac{\bar{x}}{x_{ik}}}{1 - \frac{1}{a+b} \left(\sum_{r=1}^a \frac{\bar{y}^d}{y_{rk}^d} + \sum_{h=1}^b \frac{\bar{y}^u}{y_{hk}^u} \right)} \quad (7)$$

$$s.t. \begin{cases} \bar{x} \geq x_{ij} \lambda_j \\ \bar{y}^d \leq \sum_{j=1,\neq k}^n y_{rj}^d \lambda_j \\ \bar{y}^u \geq \sum_{j=1,\neq k}^n y_{sj}^u \lambda_j \\ i = 1, \cdots, m; r = 1, \cdots, a; s = 1, \cdots, b \end{cases} \quad (8)$$

If the result is less than 1, it means efficiency regression. If the result is greater than 1, efficiency is progressive.

Among the input indicators, the consumption of three major resources is mainly energy consumption, land resource consumption, and water resource consumption. In terms of expected output, we use the three indicators of forest resources, water resources and wetland resources to measure them. However, to better describe the synergistic relationship between these resources and the economy, we have included per capita GDP on the original basis to reflect the effect of resource consumption on the economy (Sun and Loh, 2019; Sun et al., 2020). In addition, in the unexpected output, we use the three indicators of industrial wastewater, industrial waste gas, and industrial waste (Wang et al., 2020; Wu and Zhang, 2021). Similarly, we select three representative years: 2013, 2016, and 2019 (Figure 6).

FIGURE 6
Ecological performance index of each province for 2013 **(A)**, 2016 **(B)**, and 2019 **(C)**.

4 Data and methodology

4.1 Basic econometric model specification

To investigate the effect of the digital economy on ecological performance, a benchmark regression model was constructed, with the following equation:

$$ep_{it} = \beta_0 + \beta_1 \ln de_{it} + \beta_2 C_{it} + \mu_i + \varepsilon_{it} \tag{9}$$

where i is the individual, t is the time, ep represents the ecological performance, and $\ln de$ stands for the natural logarithm of the digital economy index. C_{it} is a series of control variables that may affect ecological performance except for the digital economy. β is the coefficient of each variable, and ε_{it} is the stochastic disturbance term. μ_i and v_t represent the individual effect and time effect, respectively.

4.2 Spatial econometric model specification

According to Hypothesis 2 (H2 in Section 2.4), the digital economy may have spatial spillover effects on the ecological performance of surrounding areas due to its strong spatial externalities. However, traditional econometric models mainly consider analyzing the effects of independent variables on themselves and do not consider spatial interaction effects, which may lead to estimation errors (Moshiri and Cameron, 2000). It is therefore necessary to develop a spatial model. In spatial econometrics, common models are the spatial error model (SEM), the spatial lagged model (SLM), and the spatial Durbin model (SDM) (Wu et al., 2021; Liu et al., 2022). In these models, SEM is unable to account for spatial spillover effects (Yildirim and Mert Kantar, 2020). Whereas the direct effect of SLM is equal to the spillover effect, and the coefficient estimates may be biased. The SDM, on the other hand, not only provides a more comprehensive measure but also takes into account the bias of the model estimates at the same time. More importantly, it considers both the spillover effects of the independent variables on the dependent variables in the surrounding area and reveals the impact that the independent variables in the surrounding area have on their own dependent variables (Tang et al., 2022). However, spatial econometric models are not without their limitations. For example, there is a high degree of subjectivity, and the choice of spatial matrix depends entirely on the author. In particular, the economic matrix, with regard to the choice of economic variables within it, determines the distances of each geographical unit (unlike the neighborhood matrix and the geographical distance matrix). The distances of the economic matrix are variable, which makes it difficult to derive a general pattern of results and makes it necessary to take more factors into account in the interpretation of the results. Nevertheless, SDM is still the most widely used model. Hence, Eq. 2 could be given based on SDM to investigate the spatial spillover effect of the digital economy on ecological performance.

$$ep_{it} = \beta_0 \ln de_{it} + \rho \sum_{i=1}^{n} w_{ij} ep_{it} + \varphi_0 + \beta_1 C_{it} + \eta \sum_{i=1}^{n} w_{ij} \ln de_{it}$$
$$+ \lambda \sum_{i=1}^{n} w_{ij} C_{it} + \mu_i + \epsilon_{it} \tag{10}$$

TABLE 4 Descriptive statistics of each variable.

Variable type	Symbol	Mean	Std. dev	Minimum	Maximum
Explained variable	*Ep*	0.427	0.255	0.027	1.104
Explanatory variable	ln*de*	1.270	0.372	0.711	2.451
Control variable	*Ur*	0.587	0.116	0.378	0.896
	ln*do*	6.710	1.343	3.401	9.880
	Is	0.424	0.082	0.162	0.573
	ln*id*	10.17	1.363	6.219	13.176
	ln*pcg*	10.885	0.410	10.04	12.009

TABLE 5 Global Moran index of digital economy and ecological performance (2013–2019).

Matrix		W_1		W_2		W_3	
Variable		*Lnde*	*ep*	*lnde*	*Ep*	*Lnde*	*ep*
Year	2013	0.121*** (2.956)	0.226** (2.218)	0.296** (2.472)	0.230*** (2.657)	0.152*** (2.717)	0.118** (2.220)
	2014	0.126*** (3.033)	0.222** (2.071)	0.234*** (3.336)	0.267** (2.101)	0.138*** (2.937)	0.119*** (2.727)
	2015	0.118** (2.057)	0.223*** (3.224)	0.240** (2.232)	0.228*** (2.884)	0.143*** (3.210)	0.108** (2.111)
	2016	0.126*** (2.681)	0.217*** (3.023)	0.327*** (2.612)	0.266*** (2.995)	0.128*** (3.210)	0.106** (2.015)
	2017	0.146*** (3.329)	0.212*** (2.998)	0.335*** (2.793)	0.287*** (3.231)	0.139*** (3.349)	0.121** (2.188)
	2018	0.136** (2.015)	0.209*** (3.017)	0.252*** (3.087)	0.270*** (3.146)	0.131** (1.999)	0.137** (2.136)
	2019	0.123* (1.928)	0.188* (1.957)	0.325*** (2.791)	0.245** (2.099)	0.125*** (2.166)	0.131* (1.835)

Note:* denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%. Z statistics in parentheses.

In addition to the variables mentioned in Section 4.1, ρ, η, and λ denote the spatial regression coefficients of the sample observations. ϕ_0 is the constant term, and w_{ij} is the spatial weight matrix.

To ensure the accuracy of the results, it is necessary to select the appropriate spatial weight matrix before spatial regression analysis. In this study, three common matrices, the geographical adjacency matrix, inverse-distance weight matrix, and economic distance weight matrix, were chosen. The geographic adjacency matrix was used for regression estimation, and the inverse-distance weight matrix was introduced because resource consumption and environmental pollution might form diffusion or agglomeration effects in space. Ultimately, since there might be a large correlation between the development level of the digital economy and the level of the regional economy, the economic distance weight matrix was taken into consideration as well.

In different matrices, $w_{i,j}$ in Eq. 2 has different assignments:

(1) In the ground adjacency matrix (W_1), spatial correlation is related to the existence of a common edge. If space adjacent regions i and j have a common border, then $w_{i,j}$ is 1; otherwise, it is 0:

$$w_{ij} = \begin{cases} 1 \ , \ if \ i \neq j \ and \ neighboring \\ 0 \ , \ if \ i \neq j \ and \ not-neighboring \\ 0 \ , \ if \ i = j \end{cases} \quad (11)$$

(2) In the inverse-distance weight matrix (W_2), the spatial correlation decreases with increasing distance.

$$w_{ij} = \begin{cases} \left(d_{ij}\right)^{-1} \ , \ if \ i \neq j \\ 0 \qquad \ , \ otherwise \end{cases} \quad (12)$$

where d_{ij} is the geographic distance between region i and region j.

(3) In the economic distance weight matrix (W_3), the closer the economic level of the two regions is, the greater the spatial correlation is, and vice versa. Its equation is as follows:

$$w_{ij} = \begin{cases} \left|E_i - E_j\right|^{-1} \ , \ if \ i \neq j \\ 0 \qquad \quad \ , \ otherwise \end{cases} \quad (13)$$

where E_i and E_j are the per capita GDP of region i and region j, respectively.

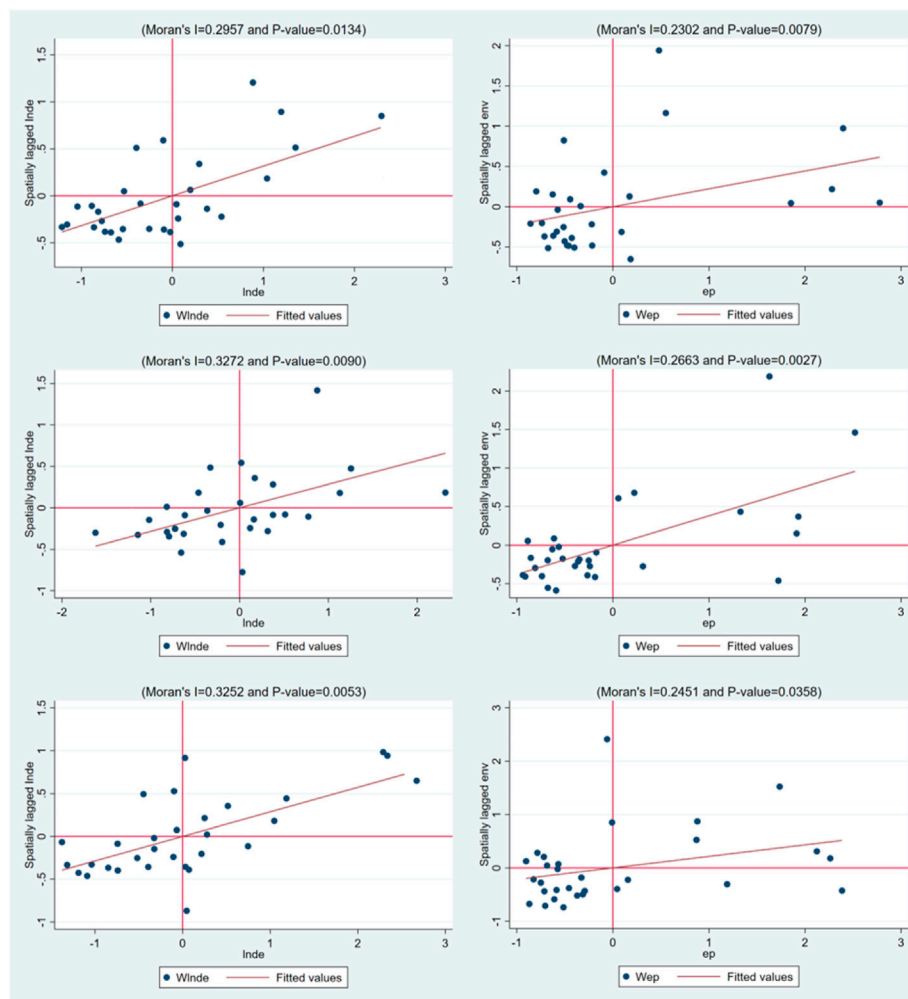Other factors that might affect ecological performance were also considered here:

FIGURE 7
Moran scatter of *ep* and *Inde* in 2013, 2016, and 2019. Note: the variable on the left is the digital economy, and the variable on the right is ecological performance. From top to bottom, the years of each picture are 2013, 2016, and 2019.

a) Urbanization rate (UR): the urbanization process itself may lead to a large amount of resource consumption demand. However, it can also promote the development of industrialization and realize cleaner industrial production (Sadorsky, 2013) to improve environmental quality. The proportion of the urban population in the total population was introduced to measure UR.

b) Degree of openness (DO): opening to the outside world can attract some advanced energy-saving and emission reduction technologies for more "green production" (He (2006)) (Jie, 2007), which may have a positive effect on ecological performance. DO was measured by the logarithm of local FDI.

c) Industrial structure (IS): the industrial sector is the most important source of pollution emissions. Consequently, the greater the ratio of the secondary industry in the structure is, the greater the pollution emission is (Shao et al., 2011), and ecological performance will decrease. IS was measured by the ratio of industrial added value to GDP.

d) Innovation degree (ID): invention patents can reflect the level of production technology and then reflect the efficiency of resource utilization (Zhou et al., 2021), which would have a positive effect on ecological performance. The logarithm of the number of patent licenses was selected to measure the level of ID.

e) Per capita GDP (PCG): digital technology innovation would enhance the progress of ecological performance and be related to the level of economic development. As a result, the logarithm of per capita GDP was taken into account (Shao et al., 2011) to evaluate the degree of PCG.

Under the constraints of data availability, to ensure the reliability, accuracy, and results, this study was based on a balanced panel dataset of 30 provinces in mainland China observed over 2013–2019. The statistical data were derived from China's authoritative database, including CSMAR and ESTDA. The missing data were supplied through the China Environmental Yearbook and China Statistical Yearbook. The descriptive statistics of each variable are shown in Table 4.

5 Empirical results and discussions

5.1 Regression model results and discussions

Before spatial regression, the test of the spatial correlation is necessary. Spatial statistical analysis of the Moran index was mainly adopted in this article. The global Moran index (Moran's I) can describe the overall spatial correlation of variables, which is between −1 and 1. When the result is greater than 0, it means a positive correlation, and vice versa. Table 5 shows the results of the global Moran index of $lnde$ and ep, which were all positive. Except for 2019's ep in W_3 (passing the significance test at the 10% level), the $lnde$ and ep in the three spatial weight adjacency matrices all passed the significance test at the 5% level. This indicated that there was a positive correlation between the digital economy and ecological performance in space. To more intuitively show the spatial relationship between the samples, we drew Moran scatter plots in 2013, 2016, and 2019 under the W2 matrix, as shown in Figure 7.

As a comprehensive spatial econometric model, SDM can obtain a more refined spatial spillover relationship between variables through total effect decomposition, which is conducive to the accurate analysis of the actual situation. The LM test was adopted to judge whether the panel data are applicable to SDM, and the results rejected the original hypothesis at the 1% level. Furthermore, the results of the Wald test showed that SDM could not be simplified to SEM and SLM. Column (1) in Table 6 displays the regression results of the basic econometric model, and its measurement results were used to analyze H1. Columns (2)–(4) show the regression results of the SDM combined with three spatial weight matrices. Similarly, its measurement results were used to discuss H2.

Based on the aforementioned results, first, regardless of whether spatial effects were considered, the influence coefficient of the digital economy on ecological performance was positive and significant at the 1% level. Among them, the regression coefficient considering the spatial effect was higher. This showed that some real effects would be ignored without considering the spatial correlation of the digital economy, and the positive effect of the digital economy on ecological performance would consequently be underestimated. From the

regression results of the three different matrices, the regression coefficient is approximately 0.4, which indicates that the estimation result is relatively robust. This suggests that the development of the digital economy can improve the level of ecological performance. This also means that the digital economy can offer higher environmental benefits in exchange for lower energy costs.

Second, from the perspective of the spatial spillover effect, the development of the digital economy could promote the development of local ecological performance in both geographically and economically adjacent areas. This showed that the digital economy had very strong and positive externalities. According to the regression coefficient, one of the geographic distance matrices was highest, showing that the spatial transmission of this effect depended more on geographical distance. This indicated that the digital economy and ecological performance were more relevant in the geographical matrix, which was in line with the results in Table 4. Therefore, the spillover effects of the digital economy continue to diminish as distance decays. This could well explain the apparent disparity between the eastern and central-western regions. This shows that the digital economy still has one of the characteristics of economic activity, the agglomeration effect.

Finally, in terms of the results of the control variables, UR had a significant negative effect on ecological performance in models (1)–(4). This showed that the growth of the urban population stimulated regional resource consumption and intensified pollution emissions. It also had a significant spillover effect in space. In contrast, almost all ISs, IDs, and PCGs had significant positive effects with a forward overflow in space as well. In addition, the degree of DO did not pass the significance test, so we would not discuss it further.

Since the spatial Durbin model takes into account the explained variables and explanatory variables in different geographical units, it will produce a spatial lag and cause some errors in the estimation results. We need to decompose the regression coefficient into direct effects, indirect effects, and total effects (Li et al., 2016) (Shahnazi and Dehghan Shabani, 2019). Table 7 shows the effect decomposition results of core variables under three matrices.

The results from Table 7 demonstrated that the digital economy actually had a significant direct effect on ecological performance. In the three matrices, both the total effect and the direct effect showed positive and significant results, while the significance of the indirect effect was relatively poor. The coefficient of the direct effect was significantly higher than that of the indirect effect, which indicated that the digital economy had a greater effect on itself. Meanwhile, it could be found that the direct effects of results obtained by decomposition and its coefficients were not equivalent. This might be caused by the existence of feedback between regions due to the correlation of the digital economy.

TABLE 6 Regression results.

| Variable | Non-spatial | SDM | | |
	(1)	(2) W_1	(3) W_2	(4) W_3
Lnde	0.338*** (0.104)	0.438*** (0.102)	0.391*** (0.102)	0.405*** (0.106)
Ur	−0.222* (0.130)	−0.517* (0.273)	−0.532*** (0.168)	−0.633*** (0.242)
lndo	−0.005 (0.035)	−0.015 (0.027)	−0.012 (0.033)	−0.009 (0.034)
is	0.831*** (0.211)	0.288* (0.155)	0.256* (0.154)	0.416 (0.293)
lnid	0.058** (0.028)	0.070** (0.027)	0.059** (0.027)	0.062** (0.029)
lnpcg	0.353*** (0.093)	0.196* (0.102)	0.172* (0.102)	0.252** (0.118)
$W \times$ lnde		0.395** (0.168)	0.759*** (0.206)	0.397*** (0.125)
$W \times ur$		−1.108* (0.645)	−3.385** (1.369)	−1.493** (0.702)
$W \times$ lndo		0.045 (0.074)	−0.100 (0.156)	0.060 (0.086)
$W \times is$		0.908*** (0.319)	1.672** (0.793)	1.431*** (0.484)
$W \times$ lnid		0.191 (0.139)	0.220* (0.120)	0.181* (0.105)
$W \times$ lnpcg		0.294** (0.144)	0.639** (0.271)	0.524** (0.230)
rho		0.275*** (0.085)	0.292*** (0.072)	0.173*** (0.064)
C	2.807*** (0.834)			
Year	YES	YES	YES	YES
Province	YES	YES	YES	YES
N	210	210	210	210
R^2	0.4520	0.4233	0.4497	0.4480

Note: Standard error in parentheses. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%, similarly, hereinafter.

TABLE 7 Estimated results of total, direct, and indirect effects.

Type	(1) W_1	(2) W_2	(3) W_3
Total effect	0.540*** (0.173)	0.885** (0.381)	0.597*** (0.199)
Direct effect	0.437*** (0.107)	0.582*** (0.104)	0.405*** (0.108)
Indirect effect	0.103 (0.084)	0.303* (0.171)	0.192* (0.098)

Note: Standard error in parentheses. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%, similarly, hereinafter.

5.2 Lag effect analysis

The previous section verified that the digital economy had a positive impact on ecological performance. As an informal economy, the digital economy has a continuous impact on ecological performance. Considering the lag in the construction of digital economy infrastructure and the upgrading of communication technology services, it was necessary to further analyze whether the influence of the digital economy on ecological performance lagged behind. Referring to the work of Li et al. (2016), a dynamic Durbin model was built for the lag of the digital economy in 1 phase, followed by regression (Li and Wu, 2016). Table 8 shows the regression results.

$$ep_{it} = \beta_0 \ln de_{i,t-1} + \rho \sum_{i=1}^{n} w_{ij} ep_{it} + \varphi_0 + \beta_1 C_{it} + \eta \sum_{i=1}^{n} w_{ij} \ln de_{it-1}$$
$$+ \lambda \sum_{i=1}^{n} w_{ij} C_{it} + \mu_i + \epsilon_{it}$$

$$(14)$$

According to Table 8, the positive effect of the digital economy on ecological performance was significant and lagged behind. This conclusion was applicable to all three spatial matrices, indicating that the estimation results were robust. Similarly, it was also true in the spatial spillover effect, that is, the positive effect of the digital economy on the ecological performance of surrounding areas also lagged behind. The development of the digital economy is closely related to the progress of Internet technology and the development of the information and communication industry. However, the research and development of Internet technology requires a certain process. Similarly, the growth of the scale of the information and communication industry is relatively slow. Therefore, the digital economy itself has strong development inertia. At least, from the samples from 2013 to 2019, the positive effect of the rapid development of the digital economy on the development of an environmentally friendly society was obvious.

TABLE 8 Regression results of the lag effect.

Variable	(1) W_1	(2) W_2	(3) W_3
lnde_{t-1}	0.385*** (0.116)	0.346*** (0.111)	0.362*** (0.118)
$W \times$ lnde_{t-1}	0.282*** (0.092)	0.149*** (0.042)	0.190* (0.101)
Year	YES	YES	YES
Province	YES	YES	YES
N	180	180	180
R^2	0.4999	0.5304	0.5112

Note: Standard error in parentheses. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%, similarly, hereinafter.

5.3 Regional heterogeneity analysis

Like most developing countries in the world, China's development also had very obvious regional characteristics. In China, the development of coastal areas was better than that of inland areas. Correspondingly, the development of the digital economy was highly correlated with the regional economic level, which could be proven by the results in Figure 5 that some regions with a high index were distributed in eastern China. Thus, it was important to discuss the heterogeneity of the digital economy on ecological performance in different regions. In this section, the heterogeneity between developed and developing regions in the same region is further examined, with a comparison between more developed eastern regions and less developed central and western regions. The eastern region included ten provinces, including Hebei, Beijing, and Tianjin, while the central and western regions included 20 provinces other than Tibet. The statistical caliber of Taiwan, Hong Kong, and Macao was different from that of other provinces, and there was a large lack of data in Tibet, so they were not discussed in the heterogeneity analysis.

As shown in Table 9, the regression coefficient of the digital economy was significantly positive in both the eastern region and the central and western regions. However, the coefficients of the eastern region were slightly higher than those of the central and western regions, which indicated that the digital economy had a higher marginal contribution to ecological performance in regions with a higher level of economic development. This illustrated that the positive role of the digital economy in promoting ecological performance was more obvious in developed regions. From the perspective of the spatial spillover effect, the coefficient and significance of the eastern region were also better than those of the central and western regions. This suggests that in areas where the digital economy is less developed, their impact on ecological performance is limited. The digital economy is unable to create agglomeration effects to reduce resource consumption or curb pollution emissions. This also reflects the heterogeneity of the digital economy on the regional ecological environment. Only when the development of

the digital economy reaches a certain threshold it will be able to exert a positive effect on ecological performance.

5.4 Robustness test

To solve the possible endogenous problems in the model, appropriate instrumental variables were required for the core explanatory variable, namely, the digital economy. The instrumental variables needed to meet the exogenous and correlation requirements at the same time. Based on the practice of Zhou et al. (2021), the logarithm of post and telecommunications business volume (lnpt) were selected as the explanatory variable and instrumental variable of the digital economy (Andersen and Petersen, 1993). On the one hand, the post and telecommunications business could reflect the local information and communication infrastructure level. On the other hand, the influence of the use of traditional telecommunications tools, such as fixed-line telephones, on economic development should meet the exclusivity. With the continuous development of the digital economy, the frequency of traditional communication showed a downward trend, which could be regarded as a suitable tool variable. Considering that the robustness test is to examine the rationality of the core explanatory variables, the spatial effect was excluded from the consideration. The results are given in Table 10.

For the test of the null hypothesis of insufficient identification of instrumental variables, the LM statistic p value was 0, which rejected the null hypothesis. Meanwhile, in the Wald test, the F statistic was 194.935, indicating that there was no problem with weak instrumental variables. The coefficient and significance did not change significantly after considering endogeneity, showing that the effect of the digital economy on ecological performance was still robust.

6 Discussion

Obviously, the results we obtained are very similar to many related studies, again all proving that the digital economy (or ICT, Internet, etc.) is an environmentally friendly economy (Ren et al. (2021); Wang et al., 2022) (Gollop and Roberts, 1983; Zhou et al., 2020; Wang et al., 2022a). However, our results also differ in some interesting ways from some related studies, most notably from the EKC curve, which suggests that economic development and environmental pollution should follow an "inverted U-shape." Therefore, further discussion of this study is needed. In this study, ecological performance is not the same as environmental pollution or resource consumption. It combines considerations of both. As the calculation process of the Super-SBM model is a black box, it is not possible to specify the reasons for the changes in the ecological performance index. It is clear from the SBM data that all expected outputs gradually

TABLE 9 Regression results of the lag effect.

Variable	Eastern region			Central and western region		
	(1) W_1	(2) W_2	(3) W_3	(1) W_1	(2) W_2	(3) W_3
lnde	0.423*** (0.101)	0.405** (0.178)	0.329*** (0.089)	0.271* (0.153)	0.289* (0.161)	0.339** (0.137)
$W \times$ lnde	0.312*** (0.070)	0.903*** (0.272)	0.296** (0.123)	0.189* (0.101)	0.216 (0.150)	0.406* (0.213)
Control	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES
N	70	70	70	140	140	140
R^2	0.5407	0.5173	0.4998	0.4261	0.4017	0.4322

Note: Standard error in parentheses. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%, similarly, hereinafter.

TABLE 10 2SLS test results.

Variable	Phase 1	Phase 2
lnde		0.310*** (0.076)
lnpt	0.360*** (0.047)	
Control	YES	YES
Year	YES	YES
Province	YES	YES
LM statistic	50.773 (0.000)	
Wald F statistic	194.935 [16.38]	
N	210	210
R^2	0.5109	0.4261

Note: Standard error in parentheses. * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%, similarly, hereinafter.

increase. In this case, if resource consumption decreases while environmental pollution increases, it is clear that ecological performance decreases. However, if resource consumption and environmental pollution are reduced at the same time, changes in ecological performance will be determined by production technology factors, and the digital economy is a new type of factor in this category. The different relationships between ecological performance and economic development derived from this study are therefore justified because ecological performance and environmental pollution are measured in different ways.

Indeed, the measurement of the digital economy is likewise a possible limitation in the study. As it is a novel concept, much of the data were missing until 2013. We are unable to judge the impact of the digital economy on ecological performance prior to 2013. In addition, although we divided the different samples in our heterogeneity test, we came to different conclusions. However, it is important to note that these regions are in reality fully bordered, meaning that the spillover benefits of the digital economy in the east also affect the central region.

Therefore, we may be overestimating the positive effect of the digital economy on ecological performance in developing regions.

7 Conclusion and policy recommendations

7.1 Conclusion

In this study, we measured the level of the digital economy and the level of ecological performance in 30 Chinese provinces. We found that, overall, China's eastern regions have higher levels of digital economy development, which is in line with the true picture of China's economic development. Unlike the digital economy, the level of ecological performance increased more in the southern regions of China over the period from 2013 to 2019. In 2019, ecological performance was high in the southern regions and low in the northern regions. Furthermore, we analyzed the impact of the digital economy on ecological performance. We found that the digital economy has a positive effect on ecological performance overall and has a strong spatial externality. This finding holds for changing the geographical weight matrix, which indicates that the results are generalizable. Dynamically, the positive effect of the digital economy on ecological performance has a lag, suggesting that the digital economy has certain inertia of influence on ecological performance. By region, this result is better in the eastern region (higher regression coefficient). In contrast, it is relatively weaker in the central and western regions.

The aforementioned results suggest that the digital economy played an important role in improving energy efficiency and reducing pollution during the period 2013–2019. With the rapid flow of data elements, a strong network effect can be created, thus contributing to the improvement of the ecological performance of the surrounding areas. The higher level of development of the digital economy in the eastern region has a more significant

impact on ecological performance. This provides strong empirical evidence for the potential of the digital economy in the central and western regions. In other words, when the digital economy in the western region rises to a certain level, the improvement in ecological performance will also be more pronounced.

7.2 Policy recommendations

From the aforementioned results and analysis, we offer the following policy recommendations: 1) for regions with a more developed digital economy, the digitization process needs to be realized as soon as possible to transform the traditional economic model into a new digital economic model. Specifically, the government should focus on the role that e-commerce, especially cross-border e-commerce, plays in trade. Subsidies should be provided to relevant enterprises according to existing policies to reduce the pressure on their development. At the same time, the government needs to breakdown some rigid policies to provide a better trade environment for enterprises. In addition, the government can facilitate the digital transformation of enterprises through different standards of environmental regulation. For companies involved in the data and information industry, the standards are relaxed. For some traditional enterprises, the standards are maintained intact or can even be raised. This can be a good way to exploit the positive effects of the digital economy on the ecological environment and thus improve the environmental quality of the region (Abbass et al., 2022). 2) However, for some regions where the development of the digital economy is relatively weak, it is necessary to balance the relationship between digital transformation and economic production. Until a certain level of economic production is reached, the marginal benefits of digitalization on ecological performance are not high; therefore, a large number of factors of production should not be invested in the digital transformation process. Local governments need to make judgments in this decision-making process in the context of the actual situation. This is because the energy consumption resulting from the digital economy can easily cause ecological pressure overload. Therefore, prior to a full digital transformation, pilot developments can be carried out in regions with a relatively good economic base. For these regions, the most direct way is to directly import mature enterprises and technologies from developed eastern regions (Shakib et al., 2022). 3) The last point is that the digital economy has strong spatial externalities, which suggests that the development of the digital economy in developed regions can have a driving effect on neighboring regions. Considering the extremely low cost of data factors, some economic collaboration between different regions can be achieved through the digital economy, thus effectively reducing the cost of building a digital economy in less developed regions. In addition, governments in all regions should be aware of the spillover effects of pollution. When faced with some pollution that may cause spillover, joint efforts should be made to combat it as much as possible. In the process of gradually narrowing the regional digital economy gap, it is also important to prevent harm to the ecological environment of the surrounding areas (Murshed et al., 2022).

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

XS, HZ, and JY contributed to the work equally, and should be regarded as co-first authors. All authors contributed to the study conception and design. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. 1. XS is responsible for overall conception and article writing 2. HZ is responsible for calculation of the regression model and article writing 3. JY is responsible for results analysis and article writing 4. ZW is responsible for data collection and language quality assurance 5. TH is responsible for literature collection 6. JL is responsible for improvement and calculation of the DEA model.

Funding

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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