Spatial-Temporal Pattern and Influencing Factors of Ecological Efficiency in Zhejiang—Based on Super-SBM Method

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Abstract
The traditional meaning of ecological efficiency generally considers only the ratio of economic output to environmental input. This paper expands the meaning and the evaluation system of ecological efficiency from the perspective of improving people’s livelihoods. Not only are the discharge of wastewater, waste gas, and solid waste included in the undesired output, but the output index also takes full account of the overall development of the economy, innovation, society and the environment from the perspective of high-quality development. Under the assumption of variable returns to scale, a super-efficiency slack-based measure model based on the undesirable output and Malmquist index is introduced to measure the spatial and temporal variation of ecological efficiency of Zhejiang Province in China, and the panel Tobit method is used to study the key factors affecting ecological efficiency. The results include the four following findings: (1) In the past 12 years, the ecological efficiency of Zhejiang Province has steadily increased, except in 2019 and 2020, when seven cities in Zhejiang Province experienced a decline or near stagnation due to the impact of the economic slowdown and the COVID-19 epidemic. (2) The ecological efficiency of Zhejiang demonstrates a severe regional imbalance, showing a high level in the northeast and a low level in the southwest. (3) Malmquist index analysis shows that the improvement of ecological efficiency in Zhejiang Province has shifted from mainly relying on the dual drivers of pure technical efficiency and scale efficiency in the early stage to relying on technological progress in the later stage. (4) Tobit regression analysis shows that industrialization structure, Theil index, and traffic activity have a significant positive effect on ecological efficiency.

Keywords Ecological efficiency · Super-SBM · Unexpected output · Malmquist index · Tobit

1 Introduction
With the rapid growth of the world’s population, a series of problems, such as resource depletion, environmental degradation, and ecological imbalance, have emerged, posing serious threats to the sustainable development of regional economies [1]. How to coordinate the relationship between economic growth, resource conservation, and environmental protection to achieve sustainable development has become a global concern and a great challenge for human beings [2, 3]. Ecological efficiency is an important indicator evaluating how well natural resources meet human needs [4]. It not only reflects sustainable development but also guides humans on how to use resources efficiently in socialized production and maximize their output.

The World Business Council for Sustainable Development defines ecological efficiency and proposes that ecological efficiency should be achieved by providing products or services that can meet human needs and ensure quality of life while reducing the ecological impact and resource intensity of the whole life cycle to a level that the earth can tolerate [5]. China has almost solved the problem of poverty and is shifting from high-speed development to high-quality development [6]. In this process, human needs are moving towards multidimensional development [7]. Therefore, we should not only include the economic output but also include the five dimensions of high-quality development, i.e., innovation, the economy, openness, sharing, and the environment, in the evaluation system.
ecological efficiency evaluation system. In the definition of ecological efficiency in this paper, resource utilization, economic development, scientific and technological development, regional openness, and sharing of output by people are considered to better meet human needs. In contrast, resource consumption and waste pollution need to be limited.

A total of 178 countries and regions around the world signed the Paris Agreement at the United Nations in New York in 2016 to combat the deteriorating global environment. According to the International Energy Agency, global energy-related CO$_2$ emissions increased by 6% to 36.3 billion tons in 2021, reaching the highest point in history (https://www.iea.org/data-and-statistics). Among them, China accounts for 33% of global CO$_2$ emissions. To reduce carbon emissions, Chinese President Xi Jinping proposed at the 75th session of the United Nations General Assembly the goal of “peaking carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060.” One of the most effective measures to reach the goal of carbon neutrality is improving ecological efficiency. It is the only way to reduce carbon emissions effectively without sacrificing people’s living standards.

Zhejiang Province is located on the southeast coast of China, east of the East China Sea, and north of Shanghai and Jiangsu Province. Zhejiang Province has 11 cities: Hangzhou, Ningbo, Wenzhou, Shaoxing, Huzhou, Jiaxing, Jinhua, Quzhou, Zhoushan, Taizhou, and Lishui, as shown in Fig. 1. According to the China Bureau of Statistics (http://www.stats.gov.cn/), Zhejiang, one of the smallest provinces in China, has a land area of 105,600 km$^2$, with only 1.10% of the country’s land and the third-highest per capita disposable income in China in 2020. Carbon emissions in Zhejiang Province ranked 5th in China in 2019. With a reduction of carbon emissions of 56.78% from 2005 to 2019, Zhejiang Province has become a leading province in the practice of low-carbon environmental protection. Choosing the ecological efficiency of Zhejiang Province as the research sample allows us to explore its characteristics of temporal and spatial changes in ecological efficiency and analyze the causes of the province’s ecological efficiency changes. Compared with Beijing, China’s political center, and Shanghai, China’s financial city, Zhejiang Province is more representative of the development model of China’s provinces. The ecological efficiency in Zhejiang Province is of exemplary significance and insight for the improvement of ecological efficiency in the province, throughout China and globally.

Currently, how to improve ecological efficiency has become a key issue in the exploration of sustainable development theory and provides an important methodological reference for the quantitative assessment of regional sustainable development. Therefore, it is necessary to develop a new meaning of ecological efficiency to meet the requirements of high-quality development. The construction of a suitable ecological efficiency model can more objectively evaluate the spatial and temporal changes in ecological efficiency in a region.

The main contributions and innovations of this paper are as follows.

- Traditional studies on ecological efficiency mainly consider the ratio between the size of an economy and its environmental carrying capacity [7]. In this paper, the meaning of ecological efficiency and the evaluation index system of ecological efficiency are expanded to the perspective of improving people’s livelihoods and ecological environment protection. The output system of ecological efficiency
efficiency includes not only economic indicators but also indicators of the other four dimensions of high-quality development: innovation, the environment, sharing, and openness.

- This paper proposes measuring ecological efficiency using the super-efficiency slacks-based measure (Super-SBM) model based on the undesirable output under the assumption of variable returns to scale to overcome the shortcomings of the traditional data envelopment analysis model. At the same time, the emissions of wastewater, waste gas, and solid waste are included in the negative output as undesirable output indicators, which enhances the scientificity of the model results.
- The Malmquist index model based on the assumption of variable returns to scale is adopted, which is more suitable for evaluating the dynamic changes in ecological efficiency. The intrinsic reasons for the changes in ecological efficiency in Zhejiang are further analyzed, and the decomposition of the province’s ecological efficiency is conducted at the level of scale efficiency and technical efficiency.
- In the study of ecological efficiency’s influencing factors, this paper introduces the following indicators that have been previously studied: industrialization structure, urbanization level, and scientific research level. In addition, we innovatively introduced new indicators, such as traffic activity, infrastructure construction, and the Theil index, to systematically analyze the external influencing factors of ecological efficiency.

The organization of the paper is as follows: Section 2 introduces the meaning of ecological efficiency and related quantitative analysis methods proposed by scholars. Section 3 introduces the mathematical models adopted in this paper, including the SBM model, undesirable output Super-SBM model, Malmquist Index, and Tobit model. In Sect. 4, the definition of ecological efficiency is extended, and the ecological efficiency evaluation index system is constructed. In Sect. 5, the temporal and spatial variations in ecological efficiency are measured and decomposed in Zhejiang Province, the influencing factors affecting ecological efficiency are further studied, and the empirical results are analyzed. The whole paper is summarized in Sect. 6, which analyzes the limitations of our work and expresses the expectations of future research.

2 Literature Review

2.1 The Meaning of Ecological Efficiency

The concept of ecological efficiency was first used by the Canadian Scientific Committee in the 1970s and was reiterated by the World Union for Conservation of Natural Resources in the 1980s, but neither provided a clear definition of the concept of ecological efficiency [8]. Schaltegger and Sturm first proposed the concept of ecological efficiency and gave a clear definition as the ratio of increased value to increased environmental loads [7]. In 1992, the World Business Council for Sustainable Development (WBCSD) cited the concept of ecological efficiency in economic activities from an economic perspective [5].

In earlier studies, ecological efficiency was used to measure economic activities and environmental impacts [9, 10]. Later, different scholars developed and refined the study of ecological efficiency from their perspectives [11, 12]. Schaltegger and Burritt considered that ecological efficiency is the ratio between expected economic return and environmental impact, which is generally accepted by scholars at present [13]. Some scholars have extended the concept of ecological efficiency with the advancement of related research. Picazo-Tadeo et al. consider ecological efficiency as the ability to create more goods and services with less impact on the environment and consume fewer natural resources, thus involving both economic and ecological issues [14]. Stepien et al. define the concept of ecological efficiency as the ability to achieve a quantitative economic result with minimum environmental degradation [15].

In general, scholars agree that ecological efficiency is a value that considers both the environment and resources with economic value and service output. The fundamental purpose of promoting ecological efficiency is to obtain more material output with minimum resource and environmental losses.

2.2 Correlation Quantitative Analysis Method

The earliest study on quantifying the concept of ecological efficiency was by the World Business Council for Sustainable Development (WBCSD) using the definition proposed by the Organization for Economic Cooperation and Development (OECD) as a basis for calculating ecological efficiency [16]. Since then, various methods of quantification studies have been gradually developed.

In terms of the quantitative measurement methods of ecological efficiency, there are measurement methods according to different evaluation scales and purposes. The ecological efficiency measurement methods include the ratio method [17], comprehensive index method [18], material flow analysis [19], energy value analysis [20], and so on.

The ratio method is the ratio of selected socioeconomic indicators to environmental indicators [21]. The comprehensive index method calculates the comprehensive ecological efficiency value by weighting the ecological efficiency indexes [18, 22]. The material flow analysis method is an analytical tool that quantifies the flow of a specific substance in a specific system at a given spatial and temporal scale.
The current most common method to study ecological efficiency is data envelopment analysis (DEA) [25, 26]. DEA and its family are described below.

### 2.2.1 The DEA Model and Its Family

The main advantage of the DEA models is that they overcome the subjective weighting problem of the ratio method and have been more widely used [3, 27, 28]. The most common DEA models are the CCR (Charnes, Cooper, and Rhodes model) and BBC (Banker, Charnes, and Cooper model) [29, 30], which differ in whether they assume variable returns to scale (VRS). The CCR model assumes that the decision-making unit (DMU) is under the assumption of constant returns to scale and is used to measure comprehensive efficiency. The BBC model assumes that the DMU is in a variable returns to scale and is used to measure pure technical efficiency and scale efficiency [31].

In the traditional DEA methods of CCR and BBC, there are multiple decision-making units (DMUs) with an efficiency value of 1, which cannot effectively distinguish the merits of DMUs. The super-efficiency DEA model constructed by Andersen and Petersen [32] covers this gap and achieves complete ranking among decision units. Moreover, in the traditional DEA model, the measurement error due to the slack variable problem and the radial problem is neglected, resulting in inaccurate measurement results. Tone proposed a nonradial, nonoriented SBM model based on slack variables to solve this problem [33]. Since then, Tone also proposed a Super-SBM model in conjunction with the super-efficiency DEA model, which remedies the shortcoming of the SBM model that cannot achieve a complete ranking of DMUs [34]. Recently, some scholars have used the improved Super-SBM DEA method to measure the ecological efficiency of regions [35, 36]. However, undesirable outputs are not considered in most of the articles.

### 2.2.2 Malmquist Index

The DEA method is used to measure the efficiency value at a certain point in time and is a method for calculating static efficiency, which is not conducive to long-term comparison. When the decision unit uses panel data, the Malmquist index model is needed for a more in-depth analysis of the spatial and temporal evolution trends of the efficiency. The method was proposed by Malmquist [37] and later combined with the DEA model by Fare et al. [38]; it gradually developed into a method that can be used to analyze the dynamic efficiency of DMUs. Zhang et al. calculated Chinese cities’ total factor energy efficiency based on the Malmquist index model [20]. However, some studies use the Malmquist index model under the assumption of constant returns to scale, which does not capture the real changes in DMUs [38]. To solve this problem, Ray et al. considered the Malmquist index decomposition method based on the assumption of VRS, which decomposes the technical efficiency reflecting the real changes of the DMUs [39]. In this paper, we will use the Malmquist index model based on the assumption of VRS, which is more suitable for evaluating the dynamic changes in ecological efficiency.

### 2.2.3 Influencing Factors Analysis Method

The DEA method and Malmquist index model measure the efficiency of the DMUs, and the two methods do not obtain the key factors affecting the DMUs [20, 35]. Therefore, to make more targeted recommendations and suggestions with guidance for the DMUs, an effective influence factor analysis method is needed for analysis. Common analysis methods include the least-square method [40], stochastic frontier method [41], Lasso method [42, 43], robust penalized extreme learning machine regression [44], and physics-informed statistical learning method [45]. However, the efficiency value measured by the DEA method has a lower limit, and using traditional analysis methods is likely to cause serious bias. Therefore, some scholars use the Tobit method for analysis [46, 47], which is a restricted dependent variable regression method [48]. The Tobit regression method is also more commonly used in the field of efficiency evaluation research [49, 50].

Many scholars at different levels have proven many factors affecting ecological efficiency. For example, Wang et al. introduced regulatory factors and resource misallocation factors to identify the key elements that affect ecological efficiency [51]. Wu and Ma showed that regional GDP per capita and easterly geographic location positively affect ecological efficiency, while the industrial structure and population density negatively affect ecological efficiency [52]. Han et al. used an improved comprehensive measurement method of ecological efficiency and found that industrial upgrading significantly improved ecological efficiency in a Chinese province [53].

### 3 Mathematical Models

#### 3.1 Undesirable Output SBM Model

In the traditional DEA model, the measurement error caused by the slack variable problem and the radial problem is neglected, resulting in inaccurate measurement results [36]. Tone proposed a nonradial, nonoriented SBM model based on slack variables to solve this problem [33]. Considering
the existence of undesirable output indicators such as solid waste emissions, exhaust gas emissions, and wastewater emissions in the ecological efficiency input-output system, the SBM model that can handle undesirable outputs is developed as follows:

\[
\rho = \min \left( 1 - \frac{1}{m} \sum_{i=1}^{m} (s^{-}_i/x_{ik}) \right) \frac{1 + \frac{p_1}{1+p_2} \left( \sum_{j=1}^{p_1} s^d_j / y^d_{jk} + \sum_{q=1}^{p_2} s^{ud}_q / y^{ud}_{qk} \right)}{1 + \frac{1}{p_1+p_2} \left( \sum_{j=1}^{p_1} s^d_j / y^d_{jk} + \sum_{q=1}^{p_2} s^{ud}_q / y^{ud}_{qk} \right)}
\]

s.t.  \( x_{ik} = \sum_{r=1}^{n} x_{ir} \lambda_r + s^-_i, i = 1, 2, \ldots, m; \)
\( y^d_{jk} = \sum_{r=1}^{n} y_{jr} \lambda_r - s^d_j, j = 1, 2, \ldots, p_1; \)
\( y^{ud}_{qk} = \sum_{r=1}^{n} y^{ud}_{qr} \lambda_r + s^{ud}_q, q = 1, 2, \ldots, p_2; \)
\( \sum_{r=1}^{n} \lambda_r = 1; \)
\( s^-_i, s^d_j, s^{ud}_q, \lambda_r \geq 0, \forall i, j, q, r. \)

In the above, \( n \) is the number of DMUs; \( m \) is the number of inputs; \( x_{ik} (i = 1, 2, \ldots, m) \) denotes the \( i \)th input of the \( k \)th DMU; \( d \) represents desirable outputs; \( ud \) represents undesirable output; \( p_1 \) is the number of desirable outputs; \( p_2 \) is the number of undesirable outputs; \( y^d_{jk} (j = 1, 2, \ldots, p_1) \) denotes the \( j \)th desirable output of the DMU; \( y^{ud}_{qk} (q = 1, 2, \ldots, p_2) \) denotes the \( q \)th undesirable output of the DMU; \( s^d_j \) is the slack variable for the \( j \)th desirable output, representing the shortage of desirable outputs. \( s^-_i \) is the \( i \)th input residual variable, which represents the excess of input; \( s^{ud}_q \) is the \( q \)th residual variable of undesirable output, which represents the excess of undesirable output; \( \lambda_r (\geq 0) \) is the weight; and \( \sum_{r=1}^{n} \lambda_r = 1 \) represents the consideration of the VRS assumption. The objective function \( \rho \) ranges from [0,1]. If and only if \( \rho = 1, s^- = s^d = s^{ud} = 0 \), DMU is the effective decision unit of SBM. Otherwise, the DMU is inefficient, and the input or output needs to be improved.

### 3.2 Undesirable Output Super-SBM Model

Tone proposed a super-efficient SBM model to remedy the SBM model’s deficiency in being unable to achieve complete ordering of DMUs [34]. When the Super-SBM is evaluated, it is necessary to use the SBM model to identify effective DMUs [54]. When the DMU is effective, the Super-SBM is further used to calculate the efficiency value. The Super-SBM model considering undesirable conditions is given as

\[
\rho^* = \min \left( 1 - \frac{1}{m} \sum_{i=1}^{m} (\tilde{x}_i/x_{ik}) \right) \frac{1}{p_1+p_2} \left( \sum_{j=1}^{p_1} y^d_j / y^d_{jk} + \sum_{q=1}^{p_2} y^{ud}_q / y^{ud}_{qk} \right)
\]

s.t.  \( \tilde{x}_i \geq \sum_{r=1 \neq k}^{n} x_{ir} \lambda_r, i = 1, 2, \ldots, m; \)
\( \tilde{y}^d_j \leq \sum_{r=1 \neq k}^{n} y_{jr} \lambda_r, j = 1, 2, \ldots, p_1; \)
\( \tilde{y}^{ud}_q \geq \sum_{r=1 \neq k}^{n} y^{ud}_{qr} \lambda_r, q = 1, 2, \ldots, p_2; \)
\( \sum_{r=1 \neq k}^{n} \lambda_r = 1; \lambda_r \geq 0, \forall r, r \neq k, \tilde{y}^d_j \geq 0, \forall j. \)

In the above, \( \rho^* \) is the objective function of the model, which represents the efficiency value of Super-SBM. The other symbols are defined as in Eq. (1). For effective DMUs (\( \rho = 1 \)), the Super-SBM model recalculates their production fronts nudged. For ineffective DMUs (\( \rho < 1 \)), their production fronts do not change, and the results are consistent with the SBM model.

### 3.3 Malmquist Index Model

The Malmquist index was originally proposed by Malmquist, and the DEA-Malmquist theory was then developed to portray the dynamic changes in relative efficiency [55]. The change in technical efficiency from period \( t \) to period \( t+1 \) under technical conditions is in the current period \( t \) is denoted by:

\[
M' = \frac{D' (x^{t+1}, y^{t+1})}{D' (x^t, y^t)}.
\]

In the above, \( D' (x', y') \) is a distance function that denotes the distance from the current period DMU to the hyperplane of the production possibility set. The change in technical efficiency from the current period \( t \) to the period \( t + 1 \) under the technical conditions of the current period \( t + 1 \) is expressed as

\[
M'_{t+1} = \frac{D'_{t+1} (x^{t+1}, y^{t+1})}{D'_{t+1} (x^t, y^t)}.
\]

The Malmquist index uses the geometric mean of Eqs. (3) and (4) to calculate the change in productivity:
If the latent variable is less than or equal to 0.

The author of [56] decomposes the Malmquist index into the technical progress index, pure technical efficiency change, and scale efficiency change. The author of [56] studies a Malmquist index model based on the constant returns to scale assumption, but this paper uses Ray’s [39] Malmquist change, and scale efficiency change. The author of [56] studies an Malmquist index model to measure ecological efficiency based on VRS. Its total factor productivity decomposition equation is:

\[
M(x_i, y_i, x_i^{t+1}, y_i^{t+1}) = (M' \times M^{t+1})^{1/2} = \left[ \frac{D_i'(x_i^{t+1}, y_i^{t+1})}{D_i'(x_i, y_i)} \times \frac{D_i^{t+1}(x_i^{t+1}, y_i^{t+1})}{D_i^{t+1}(x_i, y_i)} \right]^{1/2}.
\]

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\]

In the above, \(x_i, y_i\) denotes the inputs and outs of DMU \(k\) in period \(t\). \(D_i'(x_i, y_i)\) is a distance function, which is denoted as the distance of DMU \(k\) from period \(t\) to the hyper-plane of the set of production possibilities in period \(t\). \(v\): Variable returns to scale. \(c\): Constant returns to scale. \(TC, EC, PECH, SECH, TFP\) are the technology progress index, changes in technical efficiency, pure technical efficiency, scale efficiency, and total factor productivity, respectively. If TFP>1, total factor productivity has increased and decreased if it is less than 1. If PECH>1, the pure technical efficiency increases and decreases if it is less than 1. If TFP>1, the total factor productivity has a positive impact on the rate of change of TFP; otherwise, technical progress has a negative impact on it. SECH>1 indicates that DMU is getting closer to the optimal efficiency for scale.

### 3.4 Tobit Model with Random Effects

The Tobit regression model is also known as the restricted dependent variable model, which is the econometric model established by Tobin [57]. Considering that ecological efficiency is a value greater than or equal to 0, a direct regression of the model using traditional linear methods may result in a negative fitted value. Moreover, the efficiency values are discrete distributed data with lower bounds, and their parameter estimates would be seriously biased if the least-square method were applied. This paper uses the Tobit regression model to estimate influencing factors using a great likelihood estimation. The Tobit model is as follows:

\[
y_i = \beta x_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2)
\]

In the above, \(x_i\) is the vector of independent variables; \(\beta\) is the coefficient vector; \(\epsilon\) is the error satisfying the normal distribution; and \(y_i\) takes the value of \(y_i^*\) if the latent variable is less than or equal to 0. Otherwise, \(y_i\) will truncate at 0 if the latent variable is less than or equal to 0.

When \(y_i = 0\),

\[
P(y_i = 0 \mid x_i) = P(y_i^* \leq 0 \mid x_i) = P(u_i < -x_i^' \beta \mid x_i)
= P(u_i / \sigma < -x_i^' \beta / \sigma \mid x_i) = \Phi(-x_i^' \beta / \sigma).
\]

When \(y_i > 0\),

\[
P(y_i > 0 \mid x_i) = P(y_i^* > 0 \mid x_i) = 1 - P(u_i \leq -x_i^' \beta \mid x_i)
= 1 - P(u_i / \sigma \leq -x_i^' \beta / \sigma \mid x_i) = \Phi(x_i^' \beta / \sigma).
\]

Its probability density function is

\[
f(y_i \mid x_i) = \left[ \Phi(-x_i^' \beta / \sigma) \right]^{y_i} \left[ 1 - \Phi(-x_i^' \beta / \sigma) \right]^{1-y_i}.
\]

In the above, \(I_o\) is an indicator function of \(y_i = 0\) and \(I_+\) is an indicator function of \(y_i > 0\). \(\Phi(\cdot)\) is the standard normal distribution function, and \(\phi(\cdot)\) is the density function of the standard normal distribution. Its log-likelihood function is:

\[
L = \sum_{i=1}^{n} [I_o \ln(\Phi(-x_i^' \beta / \sigma)) + I_+ \ln(1 - \phi(y_i^* - x_i^' \beta / \sigma))].
\]

Finally, the parameters \(\beta\) and \(a\) are found by taking the maximum value of \(\ln L\).
4 The Evaluation System of Ecological Efficiency

4.1 A New Meaning of Ecological Efficiency

The traditional meaning of ecological efficiency generally considers only the ratio of economic output to environmental input [7], which is more suitable for evaluating the ecological efficiency of less developed regions because survival is the priority problem that needs to be solved. As China’s economy has shifted from the stage of high-speed growth to high-quality development, the output system of ecological efficiency should no longer be considered only in terms of economic output but should also consider a broader understanding of high-quality development that includes innovation, the economy, environmental protection, openness, and sharing.

This paper expands the meaning of ecological efficiency and the evaluation index system of ecological efficiency from the perspective of improving people’s livelihoods. Ecological efficiency should be defined not only from the perspective of the ecological environment and economy simply but also from multiple dimensions, such as technology and social development, opening, sharing, and the environment. The process of ecological efficiency evaluation is based on basic input, energy input, and capital input; it attempts to maximize economic development, openness, innovation development, and sharing development and to minimize wastewater, waste gas, and solid waste (undesirable output).

Innovation represents a region’s ability to lead in all aspects of development through science and technology and represents its potential to improve people’s living standards through higher output per input value. An increase in absolute GDP will bring a certain degree of improvement in people’s living standards, which is a common output indicator. Unlike GDP, residents’ disposable income is an indicator of how much social wealth is actually distributed to the people. The openness level evaluates a region’s ability to integrate into the global industrial chain, and people in open areas can more easily accept new ideas and increase their life satisfaction. Resource consumption and damage to the environment need to be accounted for in environmental costs as a negative output in terms of ecological efficiency.

4.2 Ecological Efficiency Evaluation System Based on the Input-Output Perspective

4.2.1 Input and Output Indicators of Ecological Efficiency

Based on the definition of ecological efficiency, the relationship between ecological efficiency and indicators such as resources, environment, capital, human resources, innovation, and economic development is analyzed. An ecological efficiency evaluation system is established according to the correlation and inner regularity among the indicators. The design of indicators follows the principles of systematical, dynamics, typical representativeness, comparability, and quantification. The selection of indicators should be calculated among provinces. The measurement of indicators must be consistent, micro, and can be collected in the authoritative Yearbook. Ecological efficiency input indicators include basic input, energy input, and capital input, while output indicators include innovation, the economy, openness, sharing, and the environment. The details are shown in Table 1.

Quantification of Input Indicators  The ecological pressure will increase with the increasing usage of basic inputs. Thus, the basic input measurement must include the basic factors of production, employment, and land resources, which are measured by the number of people employed and land area in this paper. As overall resources are limited, traditional energy consumption has a certain impact on the ecological environment. Thus, the input indicators should include the energy input, which is measured by energy consumption and water consumption in this paper. Moreover, the capital inputs in socialized mass production should be considered, which are measured by local fiscal expenditure.

Quantification of Output Indicators  There are many forms of output in human society. Based on the perspective of high-quality development, the output system of ecological efficiency should be considered not only in terms of economic volume but also in terms of other aspects of high-quality
development of human society, such as innovation, the environment, sharing, and openness, and each aspect should be selected with certain representative indicators. The number of granted patents is used to measure the level of innovation. Gross domestic product is used to measure the level of economic development. The total import-export value is used to measure the level of openness. Total residents’ disposable income is used to measure the level of sharing. Emissions of the three wastes cause damage to the ecological environment. The emissions of three wastes, including wastewater, gas, and solid waste, are considered undesirable outputs. The higher the emissions, the lower the ecological efficiency.

### 4.2.2 Factors Influencing Ecological Efficiency

Scholars have analyzed various influencing factors on ecological efficiency, including industrial structure, urbanization level, and scientific research level [59, 60]. Since good infrastructure development, a small gap between rich and poor and frequent transportation may have an impact on ecological efficiency, this paper considers the following six influencing factors: industrialization structure, urbanization level, scientific research level, traffic activity, infrastructure construction, and regional income disparities. The six indicators constitute the influencing factors of ecological efficiency, as shown in Fig. 2.

- **Industrialization structure**: A reasonable industrial structure is not only helpful for economic and social development but also promotes the improvement of people’s material and cultural life. In this paper, the proportion of the tertiary industry is chosen to measure the industrialization structure.
- **Urbanization level**: The level of urbanization is an important indicator of population structure. Urbanization is to some extent conducive to the promotion of urban development, but excessive urbanization may result in the overloading of cities. In this paper, the urbanization rate is chosen to measure the urbanization level.
- **Scientific research level**: Innovation is the first driving force leading to high-quality development, and is an important driver of improved ecological efficiency. The increase in innovation mainly relies on the level of science and technology. In this paper, the proportion of the regional population working in R&D is selected to measure the level of scientific development.
- **Theil index**: The Theil index is used to measure the gap between urban and rural disposable incomes. It is an important indicator to measure the level of regional coordination. The Theil index is a cost indicator; that is, the smaller the indicator value, the better the degree of coordination. It is calculated using the following formula:

\[
T(z,t) = \sum_{i=1}^{2} \left( \frac{DI_i(z,t)}{DI(z,t)} \right) \ln \left( \frac{DI_i(z,t)/DI(z,t)}{P_i(z,t)/P(z,t)} \right).
\]

In the above, \(T(z,t)\) represents the Theil index of region \(z\) in year \(t\), \(DI_i(z,t)\) represents the total income and total population in year \(t\) in region \(z\), respectively. \(i = 1\) and \(i = 2\) represent urban and rural areas, respectively.
- **Traffic activity**: Residents of a region travel more and are involved in more frequent commerce, which may have some impact on ecological efficiency. Traffic activity is expressed by (the total number of passengers of land, sea, and air divided by population).
- **Infrastructure construction**: Better infrastructure construction in a region may have a beneficial impact on ecological efficiency. Infrastructure construction is expressed by highway mileage divided by land area.

According to the analysis above, this paper uses ecological efficiency as the explanatory variable and industrialization structure, urbanization level, scientific research level,
transportation activity, and infrastructure construction as explanatory variables, as shown in Table 2.

5 Empirical Results and Analysis

5.1 Data Preprocessing

To make the study more scientific, all representative indicators were obtained from government agencies. The data of each indicator from 2009 to 2020 were obtained from Zhejiang Provincial Bureau of Statistics (http://tjj.zj.gov.cn/), Zhejiang Provincial Department of Science and Technology (http://kjt.zj.gov.cn/), and Zhejiang Provincial Department of Ecology and Environment (http://sthjt.zj.gov.cn/). Due to the difference in government or statistical caliber, the data on the population working in R&D were missing in 2009, which were obtained by the linear fitting method in this paper.

The number of DMUs should be more than the multiplication of the number of input and output indicators.

Table 2 Influencing factors and descriptions

| Variable being explained | Explanatory variables | Specific indicators | Indicators’ description |
|--------------------------|-----------------------|---------------------|-------------------------|
| Ecological efficiency    |                       |                     |                         |
| Influencing Factors      | Industrialization structure | Proportion of the tertiary industry | Gross GDP of third industry/GDP |
|                          | Urbanization level     | Urbanization rate   | Urban population / total population |
|                          | Scientific research level | Proportion of R&D people | The number of R&D people/population |
|                          | Traffic activity       | Passenger volume per unit population | Total number of land, sea, and air passengers/population |
|                          | Infrastructure construction | Highway mileage per unit area | Highway mileage/land area |
|                          | Regional income disparities | Theil index | Formula 15 |

Fig. 2 Ecological efficiency evaluation system and its influencing factors
Moreover, the number of DMUs should not be less than three times the number of input and output indicators [61], which is shown in formula (16).

\[ n \geq \max\{p \times m, 3(P + m)\} \]  

In the above, \( m \) is the number of input indicators, \( p \) is the number of output indicators, and \( n \) is the total number of DMUs. Each of the 11 cities in Zhejiang Province was treated as a DMU for each year from 2009 to 2020 to make horizontal and vertical comparisons under a unified scale. A total of 132 DMUs are combined to satisfy the basic requirements of DMUs.

### 5.2 Ecological Efficiency Based on the Super-SBM Model

First, the ecological efficiency of 11 cities in Zhejiang Province from 2009 to 2020 was measured by the SBM model using MATLAB programming to identify the effective DMUs. Then, the undesirable output Super-SBM model is used under the assumption of VRS to calculate ecological efficiency, and the results are shown in Table 3. When using the Super-SBM evaluation, for those DMUs with an efficiency evaluation value of 1, the Super-SBM model recalculates its production frontier nudge. For DMUs with an efficiency value less than 1, their production frontier does not change, and the results are consistent with the SBM model.

The overall ecological efficiency of 11 cities in Zhejiang Province has increased steadily over time. However, there are significant differences between the ecological efficiency of cities, and the gap between advanced cities and backward cities is increasing. It is worth noting that Hangzhou, the provincial capital city, has the largest increase in ecological efficiency and ranks first in the province after 2020. Zoushan, Jiaxing, and Ningbo are the top cities in terms of ecological efficiency, which are located in northern and eastern Zhejiang. The ecological efficiency of Lishui and Quzhou was at the bottom level, located mainly in the western part of the province. The ecological efficiency of Jinhua and other cities in the middle of Zhejiang Province is in the middle range.

In Fig. 3, the lower limit of the efficiency value of the eleven cities was approximately 0.2 from 2008 to 2018, which showed an increasing trend year by year. Lishui and Quzhou are at the lower limits of the efficiency value every year. The upper limit of the annual efficiency value is above 1, and the highest value is 1.14. According to the median, the overall trend is upward, and the improvement is increasing. The box width increases annually, indicating that the efficiency distribution is relatively discrete, and the differences between cities are more differentiated. In addition, the figure shows that there are abnormal data from 2009 to 2017, which illustrates that Zhoushan’s ecological efficiency is far ahead in these years.

From the analysis of spatial differences, the upper limit of ecological efficiency of each city is ranked from high to low in the following order: Ningbo, Hangzhou, Wenzhou, Zhoushan, Jiaxing, Jinhua, Shaoxing, Taizhou, Huzhou, Lishui, and Quzhou. The median ecological efficiency of each city can be ranked from high to low as follows: Hangzhou, Ningbo, Jiaxing, Shaoxing, Jinhua, Wenzhou, Taizhou, Huzhou, Quzhou, and Lishui. The difference between the two ranks indicates that the ecological efficiency of cities experienced either significant or little progress in 12 years of development. Zhoushan, which ranked almost steadily first before 2018, experienced a decline and was overtaken by four cities in 2020, falling to 5th place. Hangzhou, the city with the largest increase in ecological efficiency, increased by 204% from 2009 to 2020. In addition, Zhoushan, Lishui, and Quzhou have the smallest data dispersion, and the ecological efficiency did not improve significantly from 2009 to 2020. Affected by the new coronavirus epidemic and economic slowdown, some cities experienced a rare year-to-year decline in ecological efficiency in 2019 and 2020, for which Zhoushan and Quzhou had the most significant decline.

| City      | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|-----------|------|------|------|------|------|------|------|------|------|------|------|------|
| Zhoushan  | 1.00 | 1.00 | 1.00 | 1.02 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.08 | 1.04 | 1.02 |
| Hangzhou  | 0.21 | 0.28 | 0.36 | 0.39 | 0.45 | 0.52 | 0.61 | 0.70 | 1.01 | 0.97 | 1.01 | 1.14 |
| Ningbo    | 0.24 | 0.32 | 0.38 | 0.44 | 0.48 | 0.48 | 0.57 | 0.67 | 0.68 | 0.75 | 1.19 | 1.09 |
| Jiaxing   | 0.17 | 0.25 | 0.28 | 0.33 | 0.37 | 0.41 | 0.44 | 0.48 | 0.57 | 0.71 | 0.70 | 1.04 |
| Wenzhou   | 0.14 | 0.17 | 0.20 | 0.22 | 0.25 | 0.27 | 0.34 | 0.38 | 0.41 | 0.64 | 1.03 | 1.05 |
| Shaoxing  | 0.19 | 0.21 | 0.23 | 0.27 | 0.31 | 0.34 | 0.41 | 0.45 | 0.45 | 0.59 | 0.55 | 0.65 |
| Jinhua    | 0.13 | 0.16 | 0.18 | 0.23 | 0.27 | 0.30 | 0.35 | 0.40 | 0.42 | 0.49 | 0.63 | 1.00 |
| Taizhou   | 0.15 | 0.19 | 0.21 | 0.24 | 0.25 | 0.28 | 0.35 | 0.38 | 0.40 | 0.49 | 0.50 | 0.59 |
| Huzhou    | 0.13 | 0.17 | 0.20 | 0.22 | 0.24 | 0.27 | 0.31 | 0.36 | 0.36 | 0.43 | 0.43 | 0.48 |
| Quzhou    | 0.05 | 0.08 | 0.09 | 0.12 | 0.14 | 0.15 | 0.17 | 0.16 | 0.20 | 0.21 | 0.22 | 0.19 |
| Lishui    | 0.05 | 0.07 | 0.09 | 0.10 | 0.12 | 0.13 | 0.15 | 0.16 | 0.18 | 0.17 | 0.17 | 0.24 |
5.3 Spatiotemporal Evolution Analysis Based on the Malmquist Index

The Malmquist index model under the assumption of VRS was used to measure the dynamic ecological efficiency of 11 cities in Zhejiang Province from 2009 to 2020 using DEAP software. The total factor productivity (TFP) of ecological efficiency and its decomposition in Zhejiang Province from 2009 to 2020 are shown in Table 4.

According to the results shown in Table 4, the TFP of Zhejiang Province is greater than 1 for most of the years, indicating that the general trend of ecological efficiency in Zhejiang Province is developing in a positive direction. From the decomposition of TFP, TECH is basically in the same direction as the change in TFP, which indicates that total factor productivity in Zhejiang Province benefits from technological progress. Currently, technology improvement has played a positive role in ecological efficiency in Zhejiang Province. Nearly half of the technical efficiency EC is less than 1 in each year, which indicates that there is still some room for technical efficiency improvement.

EC can be decomposed into PECH and SECH. In 2009–2014, SECH and PECH’s mean values are mostly greater than 1, indicating that the improvement of technical efficiency depends on the two-way drive of pure technical efficiency and scale efficiency. In 2014–2018, PECH and SECH oscillated around 1. Both SECH and PECH are less than 1 in 2018–2020, with mean values of 0.944 and 0.994, respectively, indicating that the improvement of technical efficiency no longer depends on pure technical efficiency and scale efficiency but on technological progress.

To further explore the causes of the change in the Malmquist index of ecological efficiency in each city, the total factor productivities of 11 cities in Zhejiang Province are decomposed
in Table 5, which is helpful to understand the changing pattern of ecological efficiency in the spatial dimension.

Seven of the 11 cities have a TFP greater than 1, indicating that the ecological efficiency of these cities is developing in a positive direction, with Ningbo and Hangzhou showing the most significant improvement in ecological efficiency, reaching 1.067 and 1.054, respectively. However, from the decomposition of TFP, some regions reveal deficiencies. Among them, the EC of Huzhou, Shaoxing, Wenzhou, Taizhou, Quzhou, and Lishui are all less than 1, indicating that the technical efficiency of these six regions lags and is not sufficient to support the improvement of ecological efficiency. From the analysis of technical progress, only Lishui and Quzhou are less than 1. Moreover, the technical efficiency of these two cities is also less than 1, which makes them the bottom of ecological efficiency in Zhejiang Province for a long time.

EC reflects the strengths and weaknesses of management methods and management structures and the correctness or incorrectness of decision-making. EC can be decomposed into SECH and PECH. According to Table 5, the main reason for EC being less than 1 in six cities is the lack of pure technical efficiency.

### 5.4 Results of Panel Tobit Regression Analysis

Based on the panel Tobit model, using Stata software, regression analysis is performed on the panel data of 11 cities in Zhejiang Province from 2009 to 2020, and the regression results are shown in Table 6. Considering that the Tobit model with unconditional fixed effects is biased, the panel Tobit model with random effects will be used in this paper.

First, dependent variables were analyzed for correlation to avoid multicollinearity. From the correlation analysis, it can be seen that the Pearson correlation coefficients of the scientific research level (proportion of the population working in R&D) and urbanization level and Theil index are as high as 0.76 and 0.78, respectively. To avoid the generation of multicollinearity, we remove the scientific research level in the Tobit regression model. The remaining five variables were regressed on ecological efficiency in the Tobit regression model. The results are shown in Table 6.

The regression results of the Tobit model in Table 6 show a chi-square statistic of 52.1 with a significance level of 1%, indicating that the variables have high explanatory power for the explanatory variables. Among them, industrialization structure, Theil index, and traffic activity are significantly positively correlated with ecological efficiency. The urbanization level and infrastructure construction are not significantly correlated with ecological efficiency.

The regression coefficient of industrialization structure on ecological efficiency is 0.008 and is significant at the 10%, which indicates that the increase in the share of the tertiary industry positively influences the improvement of ecological efficiency in Zhejiang Province. The main

| Year     | EC   | TECH | PECH | SECH  | TFP  |
|----------|------|------|------|-------|------|
| 2009–2010| 1.02 | 0.996| 1.003| 1.018 | 1.016|
| 2010–2011| 1.019| 1.028| 1.026| 0.993 | 1.047|
| 2011–2012| 1    | 1.031| 0.994| 1.006 | 1.031|
| 2012–2013| 1.011| 0.941| 1.018| 0.994 | 0.951|
| 2013–2014| 1.013| 0.994| 0.988| 1.025 | 1.008|
| 2014–2015| 0.972| 1.001| 0.97  | 1.002 | 0.973|
| 2015–2016| 0.984| 0.994| 1.003| 0.981 | 0.979|
| 2016–2017| 1.016| 0.976| 0.979| 1.038 | 0.992|
| 2017–2018| 1.006| 1.02 | 1.032| 0.975 | 1.026|
| 2018–2019| 0.976| 1.119| 0.984| 0.992 | 1.092|
| 2019–2020| 0.899| 1.13 | 0.903| 0.995 | 1.016|
| mean value| 0.992| 1.019| 0.99  | 1.002 | 1.011|

**Table 5** Total factor productivity and its decomposition of 11 cities

| Area          | EC   | TECH | PECH | SECH  | TFP  |
|---------------|------|------|------|-------|------|
| Hangzhou      | 1    | 1.054| 1    | 1     | 1.054|
| Jiaying       | 1    | 1.062| 1    | 1.062 |      |
| Huzhou        | 0.994| 1.001| 0.994| 1.001 | 0.995|
| Ningbo        | 1    | 1.067| 1    | 1.067 |      |
| Zhejiang      | 1    | 1.006| 1    | 1.006 |      |
| Shaoxing      | 0.995| 1.013| 0.996| 0.999 | 1.008|
| Wenzhou       | 0.995| 1.027| 0.974| 1.022 | 1.022|
| Taizhou       | 0.986| 1.011| 0.983| 1.003 | 0.997|
| Lishui        | 0.979| 0.975| 0.978| 1.001 | 0.954|
| Jinhua        | 1.002| 1.009| 1.015| 0.987 | 1.011|
| Quzhou        | 0.96  | 0.993| 0.955| 1.006 | 0.954|

EC reflects the strengths and weaknesses of management methods and management structures and the correctness or incorrectness of decision-making. EC can be decomposed into SECH and PECH. According to Table 5, the main reason for EC being less than 1 in six cities is the lack of pure technical efficiency.

**Table 6** Tobit model regression results

| Explaining variable | Coefficient | Standard deviation | Z value | P value |
|---------------------|-------------|--------------------|---------|---------|
| Urbanization level  | 0.008       | 0.004              | 1.63    | 0.103   |
| Industrialization structure | 0.008 | 0.004         | 1.89    | 0.059*  |
| Theil index         | 0.010       | 0.002              | 5.1     | 0.000***|
| Infrastructure construction | 0.014 | 0.019       | 0.72    | 0.475   |
| Traffic activity    | 0.333       | 0.125              | 2.68    | 0.007***|

LR chi2(5) = 52.1 Prob > chi2 = 0.000

* ** denote 1%, 5%, 10% significant levels, respectively. Scientific research level has been removed because of multicollinearity
reason is that an increase in the proportion of the tertiary industry contributes to the region gradually changing from an industry-dominated economy to a service-dominated economy. A service-dominated economy is conducive to achieving greater economic output and social benefits with less energy consumption and environmental costs.

The regression coefficient of the Theil index on ecological efficiency is 0.01, which passes the 1% significance level test, indicating that the Theil index has a significant positive effect on ecological efficiency. As an indicator of income disparity or inequality between regions, it takes a value between 0 and 1. The larger the Theil index, the greater the income gap within the city. Since the difference in rural per capita income in Zhejiang cities is not obvious, they are all at a low level. A larger Theil index means that income, GDP, and other output indicators in the richer areas of the city will be significantly improved, which can improve the ecological efficiency to a certain extent.

The regression coefficient of traffic activity on ecological efficiency was 0.333, which passed the 5% significance level test. This indicates that traffic activity has a positive effect on ecological efficiency. Traffic activity refers to the number of times each person in the region uses sea, air, and road transportation annually. On the one hand, high traffic activity means a developed service industry such as tourism. On the other hand, high traffic activity means frequent trade and commerce transactions. In regions with high traffic activity, output indicators such as economic output, income, and foreign trade volume will be enhanced to some degree, which helps improve ecological efficiency.

The regression coefficient of the urbanization level on ecological efficiency is 0.008, but it does not pass the significance level test of 10%. On the one hand, urbanization is conducive to promoting economic development and bringing into effect the scale efficiency of the economy to a certain extent, which is conducive to increased output and, hence, ecological efficiency. On the other hand, urbanization that is excessive and that takes place too quickly may place a significant load on cities, as shown by the rapid rate of urbanization, the excessive size of cities, and the overpopulation of cities in a short time, inevitably leading to mass unemployment, a tight supply of fresh water and energy, environmental degradation, etc., which hinders the improvement of ecological efficiency. Therefore, the impact of urbanization on ecological efficiency needs to be further studied.

The regression coefficient of infrastructure construction on ecological efficiency is 0.014, which does not pass the significance test and may be related to government transfer payments. Because the construction of roads in Zhejiang Province is government-led, the density of roads in Zhejiang Province depends more on topography and geographical location. Thus, the relationship between the density of roads and ecological efficiency is not significant.

6 Summary and Future Work

6.1 Summary

1. Overall, the mean value of ecological efficiency in Zhejiang Province increased steadily by 245% from 0.224 to 0.772 from 2009 to 2020. Among these cities, the ecological efficiency was below 0.4 before 2011, except for Zhoushan, but six cities exceeded 1 by 2020.

2. A stagnant economy and the COVID-19 epidemic had a significant impact on ecological efficiency. Ecological efficiency continued to rise in every city in Zhejiang Province before 2018, but showed a declining trend in four cities and was flat in two cities in 2019 because the growth of economic output was weak. In 2020, ecological efficiency still declined in two cities, which may be due to the impact of the epidemic.

3. Geographical location has a strong influence on ecological efficiency. It can be concluded through empirical analysis that coastal areas have significantly higher ecological efficiency rates than inland hilly areas. There is a significant imbalance of ecological efficiency within Zhejiang Province, and the ecological efficiency decreases from northeast to southwest. The ecological efficiency of Hangzhou, Zhoushan, and Ningbo is high and is mainly concentrated in northern and eastern Zhejiang. The ecological efficiency of Lishui and Quzhou is low and is mainly concentrated in southwestern Zhejiang.

4. The improvement of ecological efficiency in Zhejiang Province is attributed to technological progress, scientific management, and a reasonable policy system. The change in technical efficiency mainly relies on the twoway drive of pure technical efficiency and scale efficiency from 2009 to 2014. The period from 2015 to 2018 belonged to the transition stage of ecological efficiency. There was a decline in pure technical efficiency and scale efficiency, and the improvement of ecological efficiency mainly relied on technical progress from 2019 to 2020.

5. Seven cities in Zhejiang Province have achieved an acceptable level of performance of ecological efficiency. Ningbo and Hangzhou have the most significant improvement in ecological efficiency. In contrast, Huzhou, Shaoxing, Wenzhou, Taizhou, Quzhou, and Lishui are six cities that are lagging in ecological efficiency. Lishui and Quzhou's ecological efficiency has long been the lowest in Zhejiang Province because their technical progress and technical efficiency are both less than 1. Since the scale efficiency of the two cities is greater than 1 in the last two years,
they belong to the few cities that have improved ecology efficiency by increasing inputs.

6. Industrialization structure, the Theil index, and traffic activity are significantly positively correlated with ecological efficiency. The relationship between urbanization level and ecological efficiency, as well as infrastructure construction and ecological efficiency, needs to be further explored. The traffic activity of 11 cities in Zhejiang Province decreased, the optimization of industrialization structure slowed down, and the technical efficiency decreased in 2020 (source: http://tjj.zj.gov.cn/) because of the COVID-19 epidemic, which triggered a slowdown or even a decrease in the growth rate of some output indicators, leading to a decrease in ecological efficiency in some cities.

6.2 Conclusions

The following four countermeasures and recommendations are put forward based on the results of the empirical analysis.

1. The main effective way to improve ecological efficiency in Zhejiang Province is to improve the level of technology rather than relying on scale investment. It is difficult to develop ecological efficiency by expanding the input scale in the future in most cities of the province. Technological progress has played a positive role in the improvement of ecological efficiency, and the lack of technical efficiency in some regions is mainly reflected in outdated management and policies. Regions lagging in ecological efficiency should enhance technological exchange and rely on talent, management, and policy formulation to promote the technology level and narrow the gap with developed regions. Unlike other cities, Lishui and Quzhou can still increase the scale of input, relying on scale efficiency to promote ecological efficiency.

2. Improving ecological efficiency requires further optimization of industrial institutions. Zhejiang Province should achieve industrial restructuring, from high consumption and high pollution to resource-saving economic growth and construct a modern and innovative development pattern. On the one hand, Zhejiang Province should improve its environmental protection regulations and gradually eliminate high input, high consumption, high emissions and high pollution industries. On the other hand, Zhejiang Province should upgrade and transform its traditional industries to increase the added value of products and achieve environmental protection. First, the proportion of the cultural and creative sector, tourism and leisure, financial services, the health industry, advertising and media, the fashion industry, and other service industries in GDP should be increased. Second, high-tech industries such as the information industry, high-end equipment manufacturing, and 5G should be further developed to increase the proportion of low-pollution and high value-added products.

3. Traffic activity and openness should be further improved to enhance ecological efficiency. Through the popularization of vaccines, the restrictions on people's travel due to COVID-19 will be reduced, and regional traffic and production activities will be enhanced. Due to China's COVID-19 quarantine policy, the total number of land, sea, and air passengers has dropped sharply, severely affecting tourism, logistics, and production [62]. To improve ecological efficiency, China needs to be open enough to support logistics, production and trade. Openness not only includes the increase in import and export trade volume but also includes the openness of tourism, education, ideas and scientific & technological exchanges. A more open China can interact with the rest of the world and draw on each other's strengths, which is conducive to protecting the earth on which mankind depends [63].

4. Seek the best balance between the level of urbanization and green development. Urbanization of a certain scale gives full play to the agglomeration mechanism of urban development, strengthens the driving role of cities and towns in regional economic development, and is conducive to the development of mass production, the improvement of modern conveniences, and the popularization of high-quality education [64]. However, after urbanization has developed to a certain extent, simple urbanization will bring about a series of problems, such as overcrowding, water pollution, solid waste pollution, and a decline in air quality [65]. At present, the urbanization of Zhejiang Province no longer has the function of significantly improving ecological efficiency, so it is necessary to slow down the urbanization process and seek the best balance between the level of urbanization and green development.

6.3 Future Research

Against the international background of carbon emission reduction, how to solve the problems of ecological protection and human social development will continue to be hot topics for scholars. Research on ecological efficiency can solve the problem of sustainable development of human society. There is no doubt that a better index design, evaluation model, influencing factors, and comparative study of typical regions will drive the improvement of ecological efficiency in human society to satisfy the growing human pursuit of material and spiritual well-being in a favorable ecological environment.

First, the research on some issues is not in-depth enough due to the limitations of data availability. The incompleteness
of statistical work limits the richness and completeness of the ecological efficiency evaluation system in this paper. Ecological efficiency output and input indicators are designed on the premise of data accessibility in this paper.

Moreover, it is suggested that future research be conducted at the national level to study the spatial and temporal differences and patterns and identify corresponding countermeasures to improve ecological efficiency. Second, the research methods can be enriched. For example, multiple models can be used to measure the ecological efficiency of a uniform evaluation system. It is valuable to explore the impact of different methods on the evaluation value of ecological efficiency through a comparative study.

Finally, more than 10 variables were explored in the selection of influencing factors before research, and 6 variables were finally selected for the analysis. The influencing factors can be expanded to include education, culture, geographical location, climate, and other aspects, which will further enrich research in this area.

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Code Availability Matlab code is available by authors (Email: 31911058@stu.zucc.edu.cn). Other code is available in DEAP and STATA.

Declarations

Conflict of Interest The authors declare no competing interests.

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