J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 9483--9499

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on resource allocation optimization based on multilevel model in green economy driven by data elements

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ABSTRACT

Green economy is an important factor to measure the quality of economic development. In order to explore the current green economy resource allocation, this paper embeds methods such as DEA-Malmquist model and Tobit regression model into the study of green economy resource allocation, explores the green economy resource allocation efficiency of 30 provinces in China by constructing a multilevel model of green economy resource allocation, and analyzes China's green economy during the period of 2021-2023 through the results of the measurement of the Static, dynamic and level changes of resource allocation efficiency. Tobit regression analysis of the influencing factors of green economy resource allocation efficiency is carried out to optimize the current resource allocation based on the influencing factors. The green economy resource allocation efficiency increases year by year in 2021-2023, and the resource allocation effect improves continuously, with the mean value of the comprehensive efficiency of 0.712, 0.762, and 0.809, respectively. The green economy resource allocation efficiency in Beijing, Shanghai, Jiangsu, and Zhejiang is the highest, and the allocation structure is the most reasonable. Chongqing, Gansu, Qinghai, Ningxia and Xinjiang are less efficient in green economy resource allocation. The per capita GDP and the ratio of education expenditure to GDP have a positive impact on the effect of green economy resource allocation, with an impact of 1.246 and 0.489, respectively.

Keywords: DEA-Malmquist model, Tobit regression, multilevel model, green economy, resource allocation

1. Introduction

As the impacts of global climate change on economy, ecology and society become more and more obvious, people pay more and more attention to sustainable development and environmental protection. Green economy, as a sustainable economic model, has been increasingly emphasized and

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Received 01 February 2024; Revised 20 April 2024; Accepted 10 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-519

widely applied [1]. Green economy refers to the economic form or development model that generates economic, social and environmental benefits due to resource conservation and environmental protection [2-4]. Its basic features are low consumption, low emission, low pollution, high efficiency, high cycle, high carbon sink, which emphasizes the sustainable use of resources and innovation of environmental protection technology, and also solves the contradiction between environmental problems and economic development [5-7]. Green economy has gradually become an important aspect of national and regional strategies and an important trend in global economic development. Green economy involves a wide range of fields, including renewable energy, clean production, circular economy, eco-agriculture, environmentally friendly buildings and emerging environmental protection industries [8-11]. The promotion and development of green economy on a global scale not only creates jobs and improves the quality of life, but also helps to realize the goal of global sustainable development. Green economy follows three key principles: effective utilization of resources, environmental protection, and social justice. Green economy emphasizes the recycling and economical use of resources, reduces energy consumption and material waste, realizes the sustainable use of resources and protects the integrity and diversity of ecosystems, and it pursues the collective benefit in the process of economic development, especially the fair distribution of resources to vulnerable groups and poor areas [12-14].

And the data element is directly related to the innovation ability and economic competitiveness of a country or region. It can directly promote economic growth by catching high production efficiency and promoting product innovation [15]. For example, big data analysis can help enterprises optimize production processes and reduce waste; artificial intelligence algorithms can improve the degree of personalization of services and increase consumer satisfaction. However, the data element is not static, it is affected by a variety of factors, including technological progress, policy environment, market demand, etc. [16]. These factors work together to determine the mechanism of the role of data elements in economic growth. Therefore, it is necessary to optimize the allocation of resources in the green economy driven by data factors.

In order to promote the in-depth development of green economy, this paper constructs a multi-level model of green economy resource allocation. The DEA-BBC model is chosen to construct the green economy resource allocation evaluation model for dynamic and static evaluation. The efficiency of green economy resource allocation is measured by DEA-Malmquist index model. Tobit regression model is utilized to explore the influencing factors of green economy resource allocation. To measure the efficiency of green economy resource allocation in 2021-2023 with 30 provinces in China, and to conduct static, dynamic and level analysis. Six quantifiable indicators are selected to build a Tobit model and regression analysis is conducted. Through the analysis results, targeted optimization suggestions for green economy resource allocation are proposed.

2. Multi-level modeling of resource allocation for a green economy

Multilevel modeling is a statistical technique that uses multiple levels of data to illustrate relationships without using levels. The specific forms can be summarized as multiple regression statistics and structural equation modeling. In this chapter, the DEA model is first used to measure and evaluate the resource allocation efficiency of the green economy, and then the Tobit regression model in multilevel analysis is used to explore the influencing factors of the resource allocation efficiency of the green economy.

2.1. Relevant concepts

2.1.1. Green economy. Green economy is a new mode of economic development, which can ensure the high speed of economic development while the ecological environment is not damaged, so that the society can achieve sustainable development and stable development [17]. The most fundamental principle of green economy is the sustainable development of human society, on the basis of the original economic development model, based on the principle of environmental protection, resource conservation, and the coordinated development of environment and economy as the main line, it is a kind of the most suitable sustainable development mode of human society at this stage.

At this stage, the definition of green economy can be divided into two kinds, one refers to the protection of the environment in economic activities, not to maximize economic benefits as the goal, to consider the environmental losses, and to develop the economy under the premise of protecting the environment, targeting the whole economic development system, especially the industries with serious environmental pollution, such as paper, iron and steel, and chemical industry. Another definition refers to obtaining economic development from the perspective of environmental protection, actively innovating and developing environmental protection technology under the social trend of protecting the environment, developing new energy power generation projects, etc., adapting to the social situation, improving environmental technology and changing the mode of environmental management to obtain more economic benefits.

2.1.2. Resource allocation. Resource is a generic term for factors of production such as human, material and financial resources required for productive activities or available in the region. Resources include natural resources such as wind, light, land, water, etc., as well as social resources such as human resources, technology, information, etc. At the same time, resources can also be divided into tangible and intangible resources, intangible resources refers to the production activities required in technology, information and other resources, is not directly converted into physical value of the resources, is through the role of tangible resources, production activities and thus converted into an entity with value, so the object of resource allocation should be directly converted into a physical entity of tangible resources. Resource allocation is to achieve the goal of production activities, the limited production factors in the distribution of tangible resources, so that the use of the least resources to obtain the maximum value of benefits [18]. Through rational resource allocation, enterprises can effectively utilize limited resources to create more value, but also to ensure the balance of supply and demand of resources required for production activities.

2.2. Green economy resource allocation efficiency evaluation model construction

2.2.1. Indicator system downscaling. In order to simplify the model construction and accelerate the calculation process while guaranteeing the accuracy, this study adopts principal component analysis (PCA) to downsize the output indicators. The application of this method helps to estimate resource allocation efficiency quickly and accurately with a small sample size.

Dimensionality reduction using PCA not only reduces the computational load, but also improves the explanatory power and accuracy of the model. These downscaled indicators synthesize information from the original multiple output indicators, while reducing unnecessary complexity while retaining the core information of the dataset [19]. These new indicators can be directly used in the construction of the DEA model, thus providing a streamlined and effective method when evaluating the resource allocation efficiency of the green economy. The specific ideas are as follows:

1) Data preparation: collect the original dataset $X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix}$, if there are n evaluation objects, where x_{ij} is a variable indicating the value of the j th indicator corresponding to the i th evaluation object.

Since PCA is affected by the scale of variables, data preprocessing is required. Each indicator value a_{ij} is transformed into a standardized indicator to obtain a standardized data sample X_{std}, which is calculated as follows:

$$X_{std} = \frac{X - \mu}{\sigma} \tag{1}$$

In the formula:

$$\mu = \frac{1}{n}\sum_{i-1}^{n} X_i, \sigma = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(X_i - \mu)^2} \tag{2}$$

2) Calculation of covariance matrix: the covariance matrix is calculated based on the standardized data. This step is to understand the relationship between the variables. The covariance formula is as follows:

$$C = \frac{1}{n-1}\sum_{k=1}^{n}(X_{ki} - \overline{X}_i)(X_{kj} - \overline{X}_j) = \frac{1}{n-1}\sum_{k=1}^{n} X_{ki}X_{kj} \tag{3}$$

3) Calculate the eigenvalues and eigenvectors of the covariance matrix: eigendecomposition of the covariance matrix C is performed to obtain the eigenvalues λ_i and corresponding eigenvectors Eigenvalues v_i denote the contribution to the variance of each principal component, while the eigenvectors define the direction of the principal components. For eigenvalue λ, according to the definition of eigenvalue, there exists a non-zero vector v such that:

$$C_x v = \lambda u \tag{4}$$

Since the covariance matrix of the data is a semi-positive definite matrix. For the selected k eigenvalue, we require the eigenvalue $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$, transforming Eq. (4) into Eq:

$$(C - \lambda\, I)u = 0 \tag{5}$$

Where I is the unit matrix, $(C - \lambda I) = 0$ solve the eigenvalues of the matrix λ, for each eigenvalue, bring it into (4) can be solved corresponding to the eigenvector v, each eigenvalue corresponds to a set of eigenvectors, the vectors are orthogonal to each other.

4) Determine the principal components: Determine the main principal components based on the eigenvalues, and rank them according to the size of the eigenvalues. The larger the eigenvalues are, the more important the corresponding eigenvectors are in describing the variability of the dataset, and these eigenvectors constitute the new base of the data.

The cumulative contribution ratio of each eigenvalue is then calculated to determine how many principal components are needed to satisfactorily describe the variability of the data set. The cumulative contribution rate formula is given below:

$$a_i = \frac{\sum_{k=1}^{i}\lambda_k}{\sum_{k=1}^{p}\lambda_k}\ (i = 1,1,\ldots,m) \tag{6}$$

The general rule in common use is to take the m principal component corresponding to the eigenvalue with a cumulative contribution of more than 85%.

2.2.2. Static resource allocation efficiency evaluation model. The traditional data envelopment analysis (DEA) model measures the static relative efficiency of different decision-making units in the same period of time, and through the DEA model [20], we can identify which decision-making units (DMUs) are effective and which are ineffective, and further analyze the causes of inefficiency of ineffective DMUs. In Data Envelopment Analysis (DEA), CCR and BCC models are two basic models for assessing the relative efficiency of decision-making units (DMUs). The difference between these two models mainly lies in the difference in the assumptions about the rewards of scale.

Assuming that there are k region (decision unit), each region has m inputs and n outputs for green economy resource allocation, x_{ij} is the amount of i inputs for the jth region $(r=1,2,...,k)$. y_{rj} is the amount of r outputs corresponding to the jth region $(r=1,2,...,k)$. v_i is the weight of the ith input $(i=1,2,...,m)$. u_r is the weight of the rth output. $(i=1,2,...,n)$.

1) CCR model. The premise assumption of the DEA-CCR model is constant returns to scale [21], in addition to convexity, conicity, inefficiency, and minimality assumptions, and the set of production possibilities T that satisfy these assumptions is:

$$T=\left\{(x,y)\mid \sum_{j=1}^{n} x_j\,\lambda_j \le x, \sum_{j=1}^{n} y_j\,\lambda_j \ge 0, \lambda_j \ge 0, j=1,2,\dots,n\right\} \tag{7}$$

The efficiency evaluation index for each region is:

$$h_j=\frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}=\frac{u_r Y_j^T}{v_i X_j^T} \tag{8}$$

The CCR model is the ability to have maximized outputs given inputs, and the data model for evaluating the efficiency of Region j is:

$$\max \frac{u_r Y_j^T}{v_i X_j^T}$$
$$s.t.\begin{cases} h_j=\dfrac{u_r Y_j^T}{v_i X_j^T} \le 1, j=1,2,\dots,k \\ v_i \ge 0, i=1,2,\dots,m \\ u_r \ge 0, r=1,2,\dots,n \end{cases} \tag{9}$$

The model is in the form of nonlinear programming, so it is transformed into a linear programming form as:

$$\max u_r Y_j^T$$
$$s.t.\begin{cases} u_r Y_j^T - v_i X_j^T \le 0 \\ v_i X_j^T = 1 \\ v_i \ge 0, i=1,2,\dots,m \\ u_r \ge 0, r=1,2,\dots,n \end{cases} \tag{10}$$

Since the decision variables of the dyadic model include efficiency values, model (10) is transformed into dyadic form as follows:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{z=1}^{n} \lambda_i x_{zi} \leq \theta x_{zi} \\ \sum_{z=1}^{n} \lambda_i y_{zr} \leq y_{jr} \\ \lambda_i \geq 0 \\ i=1,2,\ldots,m; r=1,2,\ldots,n; j=1,2,\ldots,k \end{cases} \tag{11}$$

In the dyadic form of the DEA-CCR model, λ represents the linear combination coefficients of the county and city, and the parameter θ is the efficiency value, which ranges from 0 to 1. When θ_0 =1, the county or city is DEA efficient. When θ_0 < 1, the county or city is DEA ineffective.

2) BBC model. The DEA-BBC model is premised on the assumption of variable returns to scale, and it differs from the CCR model by the addition of Equation Constraint $\sum \lambda = 1$, whose dyadic model is:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{z=1}^{n} \lambda_i x_{zi} \leq \theta x_{zi} \\ \sum_{z=1}^{n} \lambda_i y_{zr} \leq y_{jr} \\ \sum_{z=1}^{n} \lambda_i = 1 \\ \lambda_i \geq 0 \\ i=1,2,\ldots,m; r=1,2,\ldots,n; j=1,2,\ldots,k \end{cases} \tag{12}$$

2.2.3. Dynamic resource allocation efficiency evaluation model. The DEA-Malmquist index model is a method used to assess the relative efficiency change of decision-making units (DMUs) over time [22]. With the change of time conditions, the external environment in which the decision-making unit is located may change, including changes in market demand, technological progress, policies and regulations, etc. At this time, the traditional DEA model (CCR model, BCC model) is usually static, i.e., it evaluates the decision-making unit at a specific point of time, and in the face of face-plate data, such a model may not be able to adequately take into account the time-variation brought by the When facing face-to-face data, this model may not be able to fully consider the impact of time change, resulting in the evaluation results are not accurate enough. Combining the Malmquist index with the DEA model can be used to measure the efficiency change (EC) and technical progress (TC) at different points in time.

Suppose there are k regions (decision units), each with m inputs and n outputs in period t, $x_j^t = (x_{1j}^t, x_{2j}^t, \ldots, x_{mj}^t)^T$ being the inputs in period t for region j. $y_j^t = (y_{1j}^t, y_{2j}^t, \ldots, y_{nj}^t)^T$ is the amount of outputs in the jth region in the tth period and x_j^t, y_j^t are all positive, $t = 1, 2, \ldots, T$.

1) Malmquist index. Under the conditions of the base period, the distance function of the decision-making unit (DMU) is $D^0(x, y), (x^t, y^t)$ in period t then $D^t(x^t, y^t)$, in period $t+1$ then $D^t + 1(x^t, y^t); (x^{t+1}, y^{t+1})$ in period t then $D^t(x^{t+1}, y^{t+1})$, and in period $t+1$ then $D^t + 1(x^{t+1}, y^{t+1})$.

Based on the condition of period t, the equation of technical efficiency from period t to period $t+1$ is:

$$M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \tag{13}$$

Based on the $t+1$-phase condition, the formula for technical efficiency from t to $t+1$ phases is:

$$M^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \tag{14}$$

The change in efficiency between the two periods is obtained by calculating the geometric mean of the two indices, i.e., the total factor productivity index:

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{M^t \times M^{t+1}} = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}} \tag{15}$$

2) Decomposition of the Malmquist Index. The Malmquist index can be further decomposed into a composite technical efficiency change index (EFFCH) as well as a technical progress index (TECH), and this decomposition helps to understand the different sources of efficiency changes, i.e., whether they are due to changes in the management efficiency of the decision-making units (DMUs) themselves, or due to changes in the industry as a whole, or in the level of technology. The decomposition steps are as follows:

$$\begin{aligned} M(x^t, y^t, x^{t+1}, y^{t+1}) &= \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \cdot \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}} \\ &= \mathrm{EFFCH} \cdot \mathrm{TECH} \end{aligned} \tag{16}$$

Therefore:

$$EFFCH = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \tag{17}$$

$$TECH = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}} \tag{18}$$

If EC is greater than 1, it indicates an increase in efficiency. If EC is less than 1, it indicates a decrease in efficiency. If TC is greater than 1, it indicates technological progress. If TC is less than 1, it indicates technological regression.

2.3. Tobit regression model

The DEA-Malmquist index model can better measure the efficiency of green economy resource allocation, but the model only examines the influence of the input-output factor of green economy resource allocation and does not consider the influence of other factors. However, in reality, in addition to the input-output indicators mentioned above, the efficiency of green economy resource allocation may also be affected by uncontrollable factors such as economy, population and system. Therefore, based on the DEA-Malmquist index model to measure the resource allocation efficiency of the green economy in each region of China, the Tobit model can be used to further analyze the main internal and external factors affecting the resource allocation efficiency of the green economy in China.

The Tobit model, also known as the restricted dependent variable model, is applicable to the situation where the explanatory variables are restricted data or truncated data, and its basic structure is as follows (19):

$$Y_{it} = \begin{cases} 0, & Y_{it} \leq 0 \\ \alpha + \beta X_{it} + \mu_{it}, & Y_{it} > 0 \end{cases} \tag{19}$$

Where Y_{it} is the explanatory variable (i is the specific province and city, t is the year), and X_{it} is the explanatory variable, i.e., the internal and external factors that have an impact on the resource allocation efficiency of the green economy. α is the intercept term, β is the estimated parameter, when the parameter is positive, it indicates that the factor has a positive impact on the resource allocation efficiency of green economy, and vice versa, the impact is negative. μ_{it} is the random perturbation term.

3. Empirical analysis

3.1. Results of green economy resource allocation efficiency measurements

3.1.1. Static analysis. In order to gain an in-depth understanding of the static situation of resource allocation in China's green economy, this paper adopts the panel data of 30 provincial-level administrative regions in China (excluding Hong Kong, Macao, Taiwan, and Tibet) for the 3-year period of 2021-2023, and applies the DEA-BCC model in the DEAP2.1 software to measure the efficiency of China's resource allocation in the green economy, and the results of the measurements are shown in Table 1, in which, IE, PTE and SE are integrated efficiency, pure technical efficiency and scale efficiency, respectively.

From Table 1, it can be found that in recent years, China's provinces have made remarkable progress in the allocation of green economy resources, and the comprehensive efficiency has shown a rising trend. Specifically, the average values of the comprehensive efficiency of green economy resource allocation in China's provinces in 2021-2023 are 0.712, 0.762, and 0.809, respectively. This data shows that over time, the efficiency of China's provinces in green economy resource allocation has improved, and the structure of resource allocation has increasingly tended to be more fair and reasonable. Among them, Beijing, Shanghai, Jiangsu, and Zhejiang are leading the way with their comprehensive efficiency values consistently at 1, reaching DEA effectiveness. The provinces of Guangdong, Tianjin and Shaanxi also follow, with average integrated efficiency values of 0.952, 0.922 and 0.904 respectively. These provinces also perform well in resource allocation, but there is still some room for improvement relative to the four aforementioned places. However, there are also some provinces that have greater problems in resource allocation. For example, Chongqing, Gansu, Qinghai, Ningxia, and Xinjiang have lower values of integrated efficiency, 0.687, 0.625, 0.574, 0.578, and 0.640, respectively. The average value of integrated efficiency of these provinces is lower than 0.7, which indicates that they are less efficient in resource allocation for the green economy and are unable to make full use of various resources.

Table 1. 2021-2023 China green economy resource allocation efficiency

	2021			2022			2023		
	IE	PTE	SE	IE	PTE	SE	IE	PTE	SE
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.831	0.934	0.890	0.864	0.932	0.927	0.922	1.000	0.922
Hebei	0.743	0.826	0.899	0.960	1.000	0.960	0.898	0.985	0.912
Shanxi	0.796	0.873	0.912	0.848	0.900	0.942	0.904	0.927	0.975
Inner Mongolia	0.457	0.701	0.652	0.509	0.732	0.696	0.607	0.797	0.761
Liaoning	0.701	0.803	0.873	0.743	0.826	0.899	0.830	0.886	0.937
Jilin	0.712	0.806	0.883	0.783	0.847	0.925	0.808	0.867	0.932
Heilongjiang	0.743	0.833	0.892	0.795	0.850	0.935	0.837	0.889	0.941
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	0.733	0.889	0.824	0.765	0.904	0.846	0.849	0.963	0.882
Fujian	0.694	0.879	0.790	0.748	0.921	0.812	0.824	0.945	0.872
Jiangxi	0.689	0.824	0.836	0.736	0.863	0.853	0.790	0.881	0.897
Shandong	0.676	0.820	0.824	0.716	0.852	0.840	0.751	0.876	0.857
Henan	0.664	0.813	0.817	0.707	0.846	0.836	0.736	0.863	0.853
Hubei	0.685	0.826	0.829	0.758	0.874	0.867	0.797	0.899	0.887
Hunan	0.708	0.836	0.847	0.779	0.889	0.876	0.869	0.943	0.922
Guangdong	0.901	1.000	0.89	0.950	1.000	0.922	0.952	1.000	0.952
Guangxi	0.639	0.793	0.806	0.691	0.836	0.827	0.754	0.877	0.860
Hainan	0.686	0.827	0.830	0.714	0.850	0.840	0.790	0.899	0.879
Chongqing	0.577	0.794	0.727	0.626	0.816	0.767	0.687	0.877	0.783
Sichuan	0.719	0.862	0.834	0.786	0.883	0.890	0.872	0.923	0.945
Guizhou	0.642	0.800	0.802	0.698	0.839	0.832	0.722	0.845	0.855
Yunnan	0.654	0.853	0.767	0.692	0.876	0.790	0.768	0.921	0.834
Shaanxi	0.776	0.863	0.899	0.836	0.897	0.932	0.879	0.916	0.960
Gansu	0.475	0.763	0.622	0.534	0.800	0.667	0.625	0.827	0.756
Qinghai	0.474	0.753	0.630	0.521	0.793	0.657	0.574	0.831	0.691
Ningxia	0.435	0.730	0.596	0.511	0.781	0.654	0.578	0.790	0.732
Xinjiang	0.562	0.763	0.737	0.604	0.783	0.772	0.640	0.807	0.793
Mean	0.712	0.849	0.830	0.762	0.880	0.859	0.809	0.908	0.886

3.1.2. Dynamic analysis. Based on panel data for the three-year period 2021-2023, this study explores the overall efficiency of resource allocation in China's green economy from a dynamic perspective using the DEA-Malmquist index model in DEAP2.1 software. In assessing the changes of total factor productivity (TFP), it is necessary to focus on two core indicators: the index of technical efficiency change (effch) and the index of technical progress (techch). At the same time, the technical efficiency change index (techch) can be further subdivided into pure technical efficiency change (pech) and scale efficiency change (sech), which can help to more precisely analyze the nuances of each region at the efficiency level, and China's TFP index of resource allocation efficiency in the green economy for the period of 2021-2023 and its decomposition index are shown in Table 2.

As can be seen from Table 2, the total factor productivity of China's green economy in 2021-2023 has shown an upward trend. This is manifested by the fact that during the period of 2021-2022, the index of technical progress efficiency and the change in pure technical efficiency are both greater than 1, which means that these two indexes play a positive role in promoting the improvement of total factor productivity. However, the index of change in technical efficiency and the index of change in scale efficiency are less than 1, indicating that these two indicators contribute less to the improvement of total factor productivity. Specifically, the technical efficiency change index showed a decline of 5.8%, while the technical progress efficiency index realized an increase of 0.3%. Meanwhile, pure technical efficiency increased by 1.4%, but scale efficiency decreased by 1.7%. Overall, total factor productivity decreased by 0.2%. This shows that the reason for the poor performance of resource allocation efficiency in China's green economy in 2021-2022 is mainly attributed to the decline in the index of technical efficiency change. Into 2022-2023, it can be seen that the technical efficiency index, technical progress efficiency index, pure technical efficiency and scale efficiency have all increased. In particular, the technical progress efficiency index has risen by 7.8%, which is the main reason for the increase in the efficiency of resource allocation in the green economy during this period. This means that, while maintaining the current level in all places, the capacity of the relevant personnel has been enhanced and equipment has been supplemented, thus driving the increase in technical progress efficiency. However, it is also important to note that the scale efficiency only showed an increase of 1.5%, which is a small improvement compared to other indicators. Therefore, in the process of improving the efficiency of resource allocation in the green economy in the future, it is necessary to pay attention to and focus on improving scale efficiency.

Table 2. 2021-2023 green economy resource allocation efficiency TFP and decomposition index

Year	effch	techch	pech	sech	TFP
2021-2022	0.942	1.003	1.014	0.983	0.998
2022-2023	1.041	1.078	1.032	1.015	1.090
Mean	0.992	1.041	1.023	0.999	1.044

3.1.3. Level changes. In this study, the green economy input and output indicators of Chinese provinces for the period of 2021-2023 were further measured and organized using the DEA-Malmquist index model in the DEAP2.1 software with 30 Chinese provinces as the research object. The technical efficiency change index, technical progress index and total factor productivity of each province are shown in Table 3.

According to the data in Table 3, it can be found that in 2021-2023, China's green economy shows a vigorous development. At this stage, the total number of provinces with total factor productivity not lower than 1 is 28, occupying 93.3% of the total number of provinces, and the only provinces with Malmquist index lower than 1 are Gansu and Ningxia.

Table 3. China green economy resource allocation efficiency TFP

Province	effch	techch	TFP	Province	effch	techch	TFP
Beijing	1.189	1.072	1.286	Hubei	1.000	1.026	1.026
Tianjin	1.000	1.000	1.000	Hunan	1.044	1.032	1.038
Hebei	1.025	1.005	1.031	Guangdong	1.000	1.131	1.131
Shanxi	1.033	1.005	1.039	Guangxi	1.000	1.025	1.025
Inner Mongolia	1.014	1.011	1.027	Hainan	1.006	1.025	1.032
Liaoning	1.011	1.003	1.015	Chongqing	1.024	1.023	1.050
Jilin	1.008	1.001	1.010	Sichuan	1.033	1.021	1.060
Heilongjiang	1.013	1.006	1.020	Guizhou	1.005	1.008	1.015
Shanghai	1.187	1.068	1.275	Yunnan	1.014	1.012	1.028
Jiangsu	1.178	1.048	1.234	Shaanxi	1.023	1.034	1.058
Zhejiang	1.182	1.064	1.271	Gansu	0.990	1.002	0.996
Anhui	1.000	1.015	1.015	Qinghai	1.025	1.028	1.055
Fujian	1.004	1.020	1.025	Ningxia	1.000	0.998	0.998
Jiangxi	1.031	1.003	1.035	Xinjiang	1.000	1.016	1.016
Shandong	1.007	1.007	1.013	Mean	1.035	1.024	1.062
Henan	1.014	1.010	1.025				

3.2. Analysis of factors affecting resource allocation efficiency in the green economy

In the previous section, an evaluation study of the resource allocation efficiency of green economy was conducted, and in order to explore the influencing factors of the resource allocation efficiency of green economy, a series of indicators were selected and the corresponding data of 30 provinces from 2021 to 2023 were collected in this section. Quantitative research is conducted through Tobit regression analysis to assess the extent of the role of each influencing factor on the resource allocation efficiency of the green economy, and the results are analyzed in detail.

By reviewing the literature on the analysis of influencing factors on the allocation efficiency of green economic resources and taking into account the actual situation of the industry, six quantifiable external factors were selected from the perspectives of the level of economic development, urbanization, financial support and education level of each place, and three quantifiable factors were selected for analysis from the perspective of green economic resources; the six factors were the level of regional production per capita, the proportion of the urban population to the resident population, the proportion of local financial allocations to green economy, the proportion of education expenditure to GDP, the number of green economy employees per 1,000 population, and the proportion of green economy-type institutions. The selected indicators are summarized in table 4.

Table 4. Indicators of factors affecting the efficiency of green economy resource allocation

Influencing factor	Indicator	Variable	Unit
Economic development	Per capita regional GDP	F1	yuan/person
Degree of urbanization	The proportion of urban population in permanent population	F2	%
Financial support	The proportion of green economy in local financial funds	F3	%
Related talent	The number of green economic people in each thousand people	F4	person
Education level	The number of education in GDP	F5	%
Green economy infrastructure	The proportion of green economy institutions	F6	%

3.2.1. Data sources and processing. The initial statistics used in this subsection corresponds to the efficiency evaluation in the previous section, and the data collection scope is 30 provinces in China in 2021-2023, and the data of some indexes are obtained after calculation through statistical summarization, and the display of some of the data is shown in Table 5.

Table 5. Factors affecting the efficiency of green economy resource allocation in 2023

Region	F1	F2	F3	F4	F5	F6
Beijing	187392	0.89	4.53	1.35	0.05	0.13
Tianjin	113546	0.83	6.52	1.06	0.05	0.06
Hebei	54021	0.60	5.64	0.75	0.07	0.05
Shanxi	65354	0.62	8.28	0.72	0.07	0.07
Inner Mongolia	87568	0.66	11.15	0.98	0.05	0.17
Liaoning	64759	0.72	3.96	0.61	0.05	0.11
Jilin	54865	0.64	9.48	0.73	0.07	0.14
Heilongjiang	46784	0.67	7.81	0.55	0.07	0.13
Shanghai	175120	0.90	4.97	0.54	0.05	0.12
Jiangsu	138026	0.76	5.82	0.54	0.04	0.17
Zhejiang	113645	0.75	8.32	0.72	0.05	0.10
Anhui	69684	0.62	6.57	0.54	0.05	0.10
Fujian	118346	0.72	5.94	0.63	0.04	0.06
Jiangxi	65758	0.63	11.58	0.47	0.08	0.08
Shandong	81264	0.66	5.01	0.64	0.05	0.06
Henan	58146	0.58	7.02	0.63	0.06	0.07
Hubei	86178	0.68	6.28	0.52	0.05	0.07
Hunan	68752	0.62	6.31	0.62	0.05	0.16
Guangdong	98244	0.78	7.04	0.47	0.06	0.11
Guangxi	49865	0.56	8.05	0.55	0.09	0.11
Hainan	63758	0.63	10.07	0.45	0.10	0.19
Chongqing	87266	0.74	6.29	0.78	0.06	0.15
Sichuan	64523	0.59	6.97	0.86	0.06	0.06
Guizhou	48596	0.56	6.32	0.57	0.010	0.09
Yunnan	57425	0.54	8.03	0.53	0.08	0.09
Shaanxi	75843	0.67	8.74	0.61	0.06	0.09
Gansu	38957	0.56	9.38	0.84	0.11	0.08
Qinghai	56742	0.64	9.08	0.82	0.11	0.08
Ningxia	63168	0.71	7.42	064	0.08	0.10
Xinjiang	62744	0.60	5.16	0.55	0.09	0.08

3.2.2. Tobit regression analysis of influencing factors. Since the Tobit regression model is suitable for solving the problem of "deleting/restricted explanatory variables", and the efficiency evaluation results obtained from the BCC model are "fault" data of "0~1", the comprehensive efficiency measured by the BCC model is taken as the dependent variable, and the indicators of influencing factors are taken as the independent variables after min-max standardization treatment. Therefore, the comprehensive efficiency in the BCC model is taken as the dependent variable, and the indicators of influencing factors are taken as independent variables, and after min-max standardization, the Tobit model is used to analyze the influencing factors of resource allocation efficiency in green economy.

The following model is constructed first:

$$Y_{it} = \beta X_{it} + \mu_i + \varepsilon_{it} \tag{20}$$

where Y_{it} represents the value of the comprehensive efficiency of green economy resource allocation in each region in 2021-2023, i is each region, t represents the year, μ_i is the individual heterogeneous effect that does not change over time and is not related to the explanatory variables, ε_{it} is the random variable that changes over time and individually, and X_{it} represents the external factors that have an impact on the efficiency of green economy resource allocation in each region, including the level of regional production per capita, the proportion of the urban population to the 6 indicates the external factors that affect the resource allocation efficiency of green economy in each place, including the level of regional production per capita, the proportion of urban population to resident population, the proportion of local financial allocations to green economy, the proportion of education expenditure to GDP, the number of green economy employees per 1,000 population, and the proportion of green economy-type organizations.

Tobit regression analysis of the comprehensive efficiency of resource allocation in the green economy with the six influencing factors selected in the previous section was conducted using the panel data of 30 provinces in 2021-2023, and the regression results are shown in Table 6. The results of the likelihood ratio chi-square test of the model show a significance p-value of 0.000***, which presents significance at the level of 0.01 and rejects the original hypothesis, thus the model is valid.

The formula for the model is:

$$Integrated\ efficiency = 0.842 + 1.246F_1 - 0.243F_2 - 0.215F_3 - 0.605F_4 + 0.489F_5 - 0.204F_6 \tag{21}$$

The significant P-values of GDP per capita, degree of urbanization, proportion of local financial allocations to the green economy, number of green economy employees per 1,000 population, proportion of education expenditure to GDP, and proportion of institutions in the green economy category are all less than 0.01, and are meaningful at the level of 0.01. Among them, the impact coefficient of GDP per capita is positive 1.246, indicating that the increase of GDP per capita positively contributes to the improvement of the comprehensive efficiency of resource allocation in green economy. The impact coefficient of the ratio of education expenditure to GDP is positive 0.489, indicating that the level of education is positively related to the comprehensive efficiency. And the impact coefficients of the degree of urbanization, the proportion of local financial allocations to the green economy, the number of green economy employees per 1,000 population, and the proportion of green economy-type institutions are all negative, indicating that the larger the value of these indicators, the lower the efficiency of green economy resource allocation. Among them, the higher the degree of urbanization, the lower the efficiency of green economy resource allocation.

Table 6. Tobit regression of factors influencing resource allocation efficiency of green economy

Variable	Regression coefficient	SD	t	p	95%CI	
					Upper	Lower
Constant	0.842	0.052	20.165	0.000***	0.946	0.795
F1	1.246	0.142	9.015	0.000***	1.508	0.978
F2	-0.243	0.093	-2.715	0.005***	-0.064	-0.412
F3	-0.215	0.081	-2.648	0.007***	-0.055	-0.362
F4	-0.605	0.097	-6.578	0.000***	-0.422	-0.789
F5	0.489	0.066	-6.524	0.000***	0.602	0.362
F6	-0.204	0.078	-2.841	0.008***	-0.065	-0.346

When analyzing the factors affecting the resource allocation efficiency of the green economy, it was found that the level of regional production per capita, the proportion of urban population in the resident population, the proportion of local financial allocations to the green economy, the proportion of education expenditure in GDP, the number of green economy employees per 1,000 population, and the proportion of green economy institutions are the key factors affecting the resource allocation efficiency of the green economy. From the level of economic development, in the process of allocating resources to the green economy, it is necessary to focus on the development of other industries at the same time, so as to improve the level of the economy and core competitiveness, and with the development of the economy, it is possible to increase the investment in infrastructure, so as to promote the sustainable development of the green economy. From the perspective of professionals, should increase the investment in resource management personnel training, cultivate more excellent talents, help rational and scientific planning and management, and promote the full utilization of input resources. From the perspective of the degree of urbanization and the proportion of green economy institutions, each region should rationally plan the layout of institutions according to its own actual situation. From the perspective of financial support, each region should pay attention to increase the green economy financial allocations and other aspects of support, at the same time, each region should actively increase the publicity of the green economy.

4. Conclusion

This paper utilizes DEA-BBC model, DEA-Malmquist model and Tobit regression model to construct a multilevel model of green economy resource allocation. By evaluating and regressing the efficiency of green economy resource allocation in 30 provinces in China, it explores the influencing factors and optimizes the existing allocation methods.

1) The average values of comprehensive efficiency of resource allocation in China's green economy in 2021-2023 are 0.712, 0.762 and 0.809, respectively; the efficiency of resource allocation in the green economy is improving year by year, and the structure of resource allocation is becoming more and more fair and reasonable. Among them, Beijing, Shanghai, Jiangsu, and Zhejiang are far ahead, with comprehensive efficiency values consistently at 1. Provinces such as Guangdong, Tianjin, and Shaanxi also follow, with average comprehensive efficiency values exceeding 0.9. Chongqing, Gansu, Qinghai, Ningxia, and Xinjiang have comprehensive efficiency values below 0.7, and the resource allocation efficiency of the green economy is relatively low. 2021-2023, China's green economy develops rapidly. In this stage, the total number of provinces with total factor productivity not lower than 1 is 28, and the only provinces with Malmquist index lower than 1 are Gansu and Ningxia.

2) Among the six influencing factors, namely the level of regional production per capita, the ratio of urban population to resident population, the proportion of local financial allocations to the green economy, the proportion of education expenditure to GDP, the number of green economy employees per 1,000 population, and the proportion of institutions in the category of the green economy, the influence coefficients of the per capita regional GDP and the proportion of education expenditure to GDP are positive, at 1.246 and 0.489 respectively.

Funding

This work was supported by the National Social Science Fundation of China (Grant No. [24BTQ069]).

References

[1] Mentes, M. (2023). Sustainable development economy and the development of green economy in the European Union. Energy, Sustainability and Society, 13(1), 1-18.

[2] Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. Research Policy, 51, 103948.

[3] Mikhno, I., Koval, V., Shvets, G., Garmatiuk, O., & Tamošiūnienė, R. (2021). Green Economy in Sustainable Development and Improvement of Resource Efficiency. Central European Business Review, 2021(1), 99-113.

[4] Zhao, P. J., Zeng, L. E., Lu, H. Y., Zhou, Y., Hu, H. Y., & Wei, X. Y. (2020). Green economic efficiency and its influencing factors in China from 2008 to 2017: Based on the super-SBM model with undesirable outputs and spatial Dubin model. The Science of the Total Environment, 741, 140026-140026.

[5] Honcharuk, I., Tokarchuk, D., Gontaruk, Y., & Kolomiiets, T. (2024). Production and Use of Biogas and Biomethane from Waste for Climate Neutrality and Development of Green Economy. Journal of Ecological

Engineering, 25(2), 20-32.

[6] Cao, L. (2023). How green finance reduces CO 2 emissions for green economic recovery: empirical evidence from E7 economies. Environmental Science & Pollution Research, 30(2).

[7] Budimansyah, B., Kuswanto, A., & Supriyaningsih, O. (2023). Green Economic System as Environmental Protection: Case Study in Pt. Pertamina Geothermal Energy Indonesia. ADVANCES IN BUSINESS RESEARCH INTERNATIONAL JOURNAL, 9(2), 64-77.

[8] Liu, W., Liu, M., Liu, T., Li, Y., & Hao, Y. (2022). Does a Recycling Carbon Tax with Technological Progress in Clean Electricity Drive the Green Economy. Environmental Impact Assessment by Green Processes, 19, 25.

[9] He, L., Zhang, L., Zhong, Z., Wang, D., & Wang, F. (2019). Green credit, renewable energy investment and green economy development: Empirical analysis based on 150 listed companies of China. Journal of Cleaner Production, 208, 363-372.

[10] Arsawan, I. W. E., Koval, V., Suhartanto, D., Hariyanti, N. K. D., Polishchuk, N., & Bondar, V. (2023). Circular economy practices in SMEs: aligning model of green economic incentives and environmental commitment. International Journal of Productivity and Performance Management, 73(3), 775-793.

[11] Bergius, M., Benjaminsen, T. A., & Widgren, M. (2018). Green economy, Scandinavian investments and agricultural modernization in Tanzania. The Journal of Peasant Studies, 45(4), 825-852.

[12] Zhang, D., Mohsin, M., Rasheed, A. K., Chang, Y., & Taghizadeh-Hesary, F. (2021). Public spending and green economic growth in BRI region: Mediating role of green finance. Energy Policy, 153(C).

[13] Altenburg, T., & Rodrik, D. (2017). GREEN INDUSTRIAL POLICY: ACCELERATING STRUCTURAL CHANGE TOWARDS WEALTHY GREEN ECONOMIES. Green Industrial Policy.

[14] Wu, M., Wu, J., & Zang, C. (2021). A comprehensive evaluation of the eco-carrying capacity and green economy in the Guangdong-Hong Kong-Macao Greater Bay Area, China. Journal of Cleaner Production, 281, 124945.

[15] Hao, X., Li, Y., Ren, S., Wu, H., & Hao, Y. (2022). The role of digitalization on green economic growth: Does industrial structure optimization and green innovation matter?. Journal of Environmental Management, 325(Pt A), 116504-116504.

[16] Zhou, X., Tang, X., & Zhang, R. (2020). Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China. Environmental Science & Pollution Research, 27(16).

[17] F Tursunov. (2024). Assessment of the influence of the green economy on sustainable development: bibliometric approach. IOP Conference Series: Earth and Environmental Science(1),012033-012033.

[18] Xiaoyue Xiao,Keyi Shen,Xinyue Zheng,Dan Wu,Tong Pei,Xin Hao Lin & Xuehui Meng. (2024). Resource allocation efficiency in 68 county-level traditional Chinese medicine hospitals in China: a data envelopment analysis. BMJ open(10),e088462.

[19] Adele E Cave,Frances M De Blasio,Dennis H Chang,Gerald W Münch & Genevieve Z Steiner Lim. (2024). Eyes-open and eyes-closed EEG of older adults with subjective cognitive impairment versus healthy controls: A frequency principal components analysis study. Brain research149399.

[20] Ying Liu,Lanxian Mai,Feng Huang & Zhiyu Zeng. (2024). Regional healthcare resource allocation and decision-making: Evaluating the effectiveness of the three-stage super-efficiency DEA model. Heliyon(23),e40312-e40312.

[21] Zhou Pengfei,Yang Siyuan,Wu Xiaohang & Shen Yang. (2022). Calculation of regional agricultural production efficiency and empirical analysis of its influencing factors-based on DEA-CCR model and Tobit model. Journal of Computational Methods in Sciences and Engineering(1),109-122.

[22] Guiju Liu & Xiu Li. (2024). Evaluation of Urban Innovation Efficiency in Shandong Province Based on DEA-Malmquist Model. Academic Journal of Business & Management(7).