Eco-Efficiency Measurement and Regional Optimization Strategy of Green Buildings in China Based on Three-Stage Super-Efficiency SBM-DEA Model

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***Abstract*—With the increasing attention of society to sustainable development, green building as an important sustainable building form has attracted much attention. However, the comprehensive assessment of eco-efficiency of green buildings faces many challenges, including the insufficient comprehensive analysis of all stages of the building life cycle and the oversimplification of multidimensional input-output relationships. In addition, the existing methods have subjectivity and uncertainty in data processing and weight allocation, which reduces the reliability of evaluation. To overcome these difficulties, a measurement method based on the three-stage super-efficient data Enveloping analysis (SBM-DEA) model is introduced in this study. By constructing a three-stage super-efficiency SBM-DEA model, the eco-efficiency measurement model of green buildings is established, taking building resources and energy as input and economic and environmental value as output. The results show that after removing the interference of external environment variables and random errors, the measurement results of stage 3 are more reasonable. From 2011 to 2018, the eco-efficiency of green buildings in China showed obvious regional differences, showing a decreasing trend of "the highest in the east (0.884), followed by the central (0.704) and the lowest in the west (0.578)". The innovation of this study lies in the full consideration of timing and dynamics, which provides new theoretical and practical ideas for promoting sustainable development in the field of green building, and is expected to improve the assessment accuracy and reliability in the field of green building.**

***Keywords*—Three stages; data envelopment analysis; super efficiency model; green buildings; ecological efficiency**

I. Introduction

With the continuous warming of global environmental issues and the urgent need for Sustainable Development (SD), Green Buildings (GBS), as a sustainable building model, have gradually become the focus of attention. SD refers to a model of development that meets the needs of the present without compromising the ability of future generations to meet their own needs. At present, the measurement of Green Building Eco-efficiency (GBEE) is particularly important in evaluating its environmental friendliness and resource utilization, especially in the insufficient comprehensive analysis of various stages of the building lifecycle and the simple handling of 3D input-output relationships [1]. GBEE refers to minimizing environmental impact and improving resource efficiency throughout a building's life cycle through sustainable design, efficient use of resources and environmentally friendly technologies. However, the comprehensive evaluation of the comprehensive benefits of green buildings faces many difficulties and challenges. On the one hand, the existing measurement methods are insufficient in the comprehensive analysis of various stages of the building life cycle, and it is difficult to fully reflect the ecological benefits of green buildings at different stages. On the other hand, the existing methods are too simple when dealing with the multi-dimensional input-output relationship, and it is difficult to accurately evaluate the comprehensive ecological efficiency of green buildings. In addition, the existing methods have subjectivity and uncertainty in data processing and weight allocation, which reduces the reliability and credibility of the evaluation results. The Slacks-Based Measure in Data Envelopment Analysis (SBM-DEA) model based on three-stage super-efficiency combines Data Envelopment Analysis (DEA) and Super Efficiency Model (SEM) [2-3], i.e. 3SE-SBM-DEA model, which can more comprehensively and accurately measure the GBEE. The introduction of the 3SE-SBM-DEA model can better grasp the dynamic characteristics of the building lifecycle and more accurately evaluate the ecological benefits of GBS at different stages [4]. Based on this, this study proposes a GBEE measurement and optimization method based on the 3SE-SBM-DEA model. Firstly, by constructing a 3SE-SBM-DEA model with building resources and energy as inputs and economic and environmental values as outputs, a GBEE measurement model is established. Next, based on theoretical logic, the temporal differences in the GBEE from a temporal dimension are analyzed, and the dynamic evolution characteristics through kernel density estimation (KDE) are revealed. The aim of this study is to achieve comprehensive measurement of GBEE and propose corresponding optimization strategies through the method of this 3SE-SBM-DEA model. The innovation of this method lies in fully considering the temporal and dynamic aspects, providing new theoretical and practical ideas for promoting SD in GB. This paper aims to give more scientific and comprehensive basis for GB design and evaluation, and promote the GB field towards a more sustainable direction.

Section I introduces the research background, problems, and solutions of GBEE measurement. Section II provides a review of previous research on GBEE measurement, exploring difficulties and shortcomings in methods. Section III is the method of using the 3SE-SBM-DEA model in GBEE measurement. Section IV designs simulation experiments to verify the effectiveness of the proposed method. Section V summarizes the research methods and analyzes the experimental results, pointing out the shortcomings of the methods and future research directions.

II. RELATED WORKS

The urgent need for global SD has gradually made GBS a mainstream form of construction that emphasizes resource conservation and environmental friendliness. However, to comprehensively evaluate the comprehensive performance of GBS, a single economic indicator is no longer sufficient. Therefore, researchers are gradually paying attention to GBEE measurement, aiming to comprehensively evaluate its sustainability from two aspects: Resource Utilization Efficiency (RUE) and environmental impact. Ishmael et al. addressed the contribution of buildings to climate change by using an intelligent energy building model based on the Internet of Things (IoT) to connect sensors of building equipment using M2M, IoT, and AEP technologies, achieving intelligent monitoring and improving energy efficiency. IoT intelligent building technology has been proven to be crucial in improving energy efficiency [5]. Tavana M et al. adopted a comprehensive DEA and lifecycle assessment approach to address the negative impact of the Construction Industry (CI) on the environment, particularly in material procurement and emissions, to measure the performance of environmentally friendly building materials in GB management. This method provided a scientific evaluation tool for the selection of GB materials [6]. Zhou Y et al. conducted long-term measurements and surveys of resident satisfaction, combined with environmental energy efficiency analysis, to assess the actual performance of the GB. The measured indoor thermal condition did not fully meet the design goals, especially with differences in relative humidity. However, residents had a higher level of satisfaction with IEQ [7]. Petre and other scholars have proposed a method to accurately determine the actual energy consumption of buildings by in-situ measuring the thermal resistance of building components in response to the high energy consumption problem of the CI in global warming. This study provided practical guidance for improving building energy performance and global warming prevention and control [8]. In response to the challenges encountered in implementing green practices in the chemical industry, Sinaga L et al. proposed an evaluation method that combines blockchain building information modeling (BIM) with structural equation model-Partial least squares (SEM-PLS). The research results show that green practices are becoming more and more common in the manufacturing industry and can reduce the adverse impact on the environment, but the adoption of green principles in industry is affected by a variety of factors [9]. Traditional building materials used in the construction industry significantly contribute to air pollution and greenhouse gas emissions, causing considerable environmental damage across Pakistan. Bashir et al., using closed questionnaires, interviews and observations to collect data using planning and random sampling techniques, focused on exploring the feasibility of adopting green building materials in Pakistan's building sector with the aim of mitigating environmental impacts. The results of the study show that factors such as high cost, low market demand and logistical challenges limit people's interest in environmentally friendly materials, with 73% of construction companies in Pakistan not using green building materials [10]. In view of the negative impact of the construction industry on the environment and the problems of resource depletion, emission and biodiversity loss, Kristinayanti W S et al. proposed a method combining local wisdom and green building practices, adopted the PRISMA framework method, and conducted a comprehensive systematic evaluation and qualitative analysis through NVivo software. The research results show that the construction industry needs a sustainable transformation, and combining local wisdom can provide innovative and adaptable solutions to help promote the transformation of construction practices to SD [11].

In addition, the 3SE-SBM-DEA combines the advantages of DEA and SEM to assess the relative efficiency of various units. In this model, the projection pursuit method is used to determine the unit's super efficiency boundary, so that an optimal super efficiency frontier can be found under certain constraints. Jiahui et al. utilized the 3SE-SBM-DEA to address the CO2 efficiency issues in the four Chinese major beef-cattle production areas in, and incorporated CO2 into the efficiency calculation framework. External random disturbances had greatly affected the efficiency measurement, and using the 3SE model made the results more in line with reality [12]. Junlong et al. constructed an indicator system to promote the high-quality development of China's shared manufacturing industry and used a 3-phase DEA-Malmquist model to dynamically measure 39 shared manufacturing enterprises from 2018 to 2020. The mean fluctuation of comprehensive/pure/scale efficiency had a significant impact on development efficiency [13]. Radimov N et al. proposed a novel control and optimization strategy for a bidirectional 3-level in vehicle battery charger (OBC) that achieves 80 PLUS titanium efficiency. OBC could change the direction of power flow within a few msec, providing reactive power support for the power grid, with 96.65% peak efficiency and 1% min-total harmonic distortion [14]. Qad et al. measured the relationship between technology industry agglomeration, green innovation, and development quality in the Yangtze River Delta urban agglomeration using superefficient SBM-DEA and improved TOPSIS method. There was a significant spatial connection between these factors, especially in the transformation stage where they mutually promote each other [15].

To sum up, the existing research has made remarkable progress in the field of eco-efficiency measurement of green buildings, but there are still some limitations. For example, although some studies have proposed comprehensive evaluation methods, they are still insufficient in dealing with the dynamic characteristics of the whole life cycle of buildings and the multi-dimensional input-output relationship. In addition, there are subjectivity and uncertainty in data processing and weight allocation in existing studies, which reduces the reliability and applicability of evaluation results. Although some studies try to solve these problems by introducing advanced technical means or improving evaluation models, most studies fail to fully consider regional differences and dynamic evolution characteristics, resulting in the overall assessment of green building eco-efficiency is still insufficient. The DEA method is also adopted as the basic framework in this study. However, the innovation of this study lies in the introduction of the three-stage super-efficiency SBM-DEA model, which can not only evaluate the eco-efficiency of green buildings more comprehensively, but also better deal with data uncertainty and subjectivity by introducing the concepts of super-efficiency and stages. Improve the objectivity and robustness of the evaluation. In addition, this study also combined temporal dimension analysis and kernel density estimation to reveal the dynamic evolution characteristics of green building eco-efficiency, which was rarely involved in previous studies.

The contributions of this research are mainly reflected in the following aspects: First, by constructing a three-stage super-efficiency SBM-DEA model, this research provides a more scientific and comprehensive method for measuring the eco-efficiency of green buildings, which can effectively overcome the limitations of existing methods in data processing and weight allocation. Secondly, this study systematically analyzed the regional differences of eco-efficiency of green buildings in China for the first time, revealing the decreasing trend of "the highest in the east, the second in the central, and the lowest in the west" during 2011-2018, providing a scientific basis for formulating targeted optimization strategies. Finally, based on the measurement results, this study proposed specific optimization strategies to narrow the regional gap and improve the overall ecological efficiency of green buildings across the country.

III. CONSTRUCTION OF 3SE-SBM-DEA MEASUREMENT MODEL

This study first constructs a 3SE-SBM-DEA model, using building resources and energy as inputs and economic and environmental values as outputs, to establish a GBEE measurement model. Next, based on theoretical logic, to analyze the temporal differences of GBEE from the temporal dimension, and to reveal the dynamic evolution characteristics through KDE.

A. Building the GBEE Measurement Model

Eco-efficiency is the efficiency of ecological resources to meet human needs, usually measured by the ratio of output to input [16]. Among them, "output" covers the value of the products and services produced by the enterprise, while "input" includes the resources and energy consumed by the enterprise, as well as the impact on the environment [17]. The mathematical formula related to ecological efficiency is Eq. (1).

$$\text{Eco-e} = \frac{\text{Value of p or s}}{\text{Ei}} \tag{1}$$

In Eq. (1), Eco-e represents ecological efficiency, and Value of p or s represents the value of the product or service. Ei represents environmental impact. GBEE refers to the use of sustainable design, efficient resource utilization, and environmental protection technologies to minimize the impact on the environment during the building lifecycle, increase RUE, and reduce the burden on natural ecosystems [18]. Fig. 1 shows the ecological efficiency evaluation model.

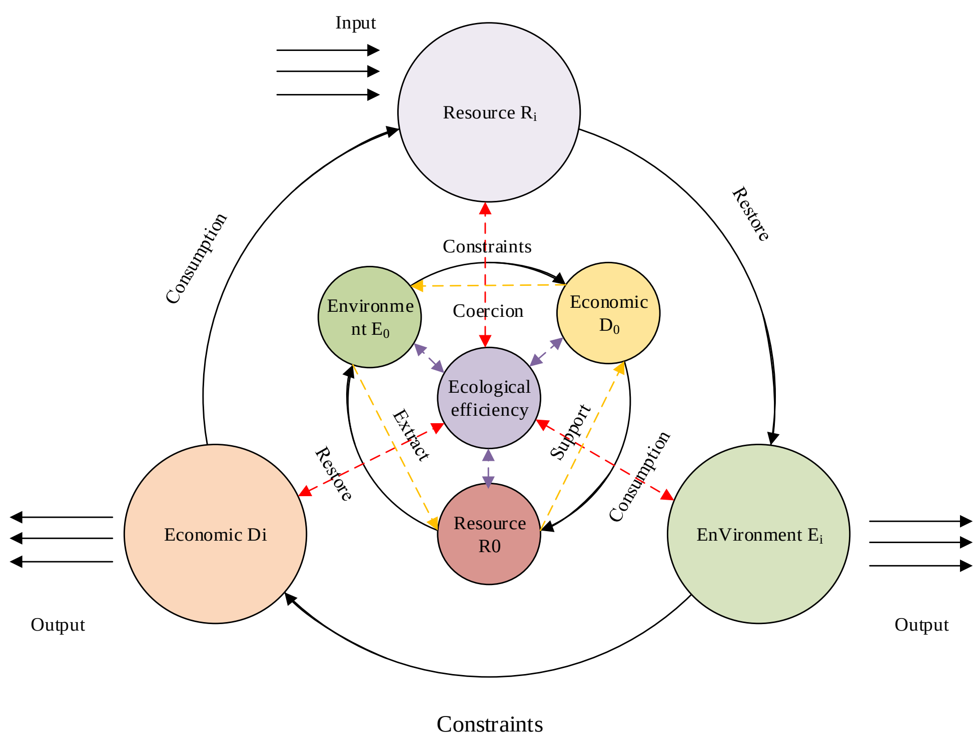


Fig. 1. Ecological efficiency evaluation model.

In Fig. 1, the model mainly revolves around economy, resources, and environment [19]. To evaluate ecological efficiency, it is necessary to first determine key indicators such as energy consumption, material utilization, and water resource utilization. Subsequently, by collecting relevant data from the system, including information on building energy usage, material sources and utilization, water resource management, etc., a comprehensive data foundation is established. Next, a mathematical model is used to quantify the system efficiency. Finally, based on the evaluation results, optimization suggestions are established to lift the Eco-efficiency. To derive the Eco-efficiency calculation formula for buildings based on Eq. (1), as shown in Eq. (2).

$$B\ eco\text{-}e = \frac{Be}{El} \tag{2}$$

In Eq. (2), $B\ eco\text{-}e$ represents the ecological benefits of the building. $B\ eco\text{-}e$ represents the value of the building. El represents environmental load. The GBEE measurement indicator system aims to comprehensively understand the comprehensive ecological benefits of buildings throughout their lifecycle by evaluating their performance in energy utilization, material selection, water resource utilization, environmental impact of design, and indoor environmental quality. Fig. 2 shows the GBEE measurement indicator system.

In Fig. 2, the measurement indicator system of GBEE is mainly divided into two parts: input indicators and output indicators. The investment indicators include capital investment, labor investment, energy investment, land investment, and technology investment. Output indicators include environmental output and economic output. This set of specific parameters is selected to ensure that the eco-efficiency measurement of green buildings based on the three-stage super-efficiency SBM-DEA model can fully and accurately reflect the actual ecological benefits of green buildings, while eliminating the interference of external environment and random errors, and improving the reliability and applicability of the model results. SBM is a distance function based method used to evaluate performance relative to other units, suitable for considering multiple input and output factors, and able to handle different weights and measurement standards. DEA is a non-parametric approach taken to evaluate relative efficiency. DEA does not require prior assumptions about weights or function forms, making it suitable for complex multi input multi output scenarios [20]. Fig. 3 shows the specific process of the 3-stage DEA.

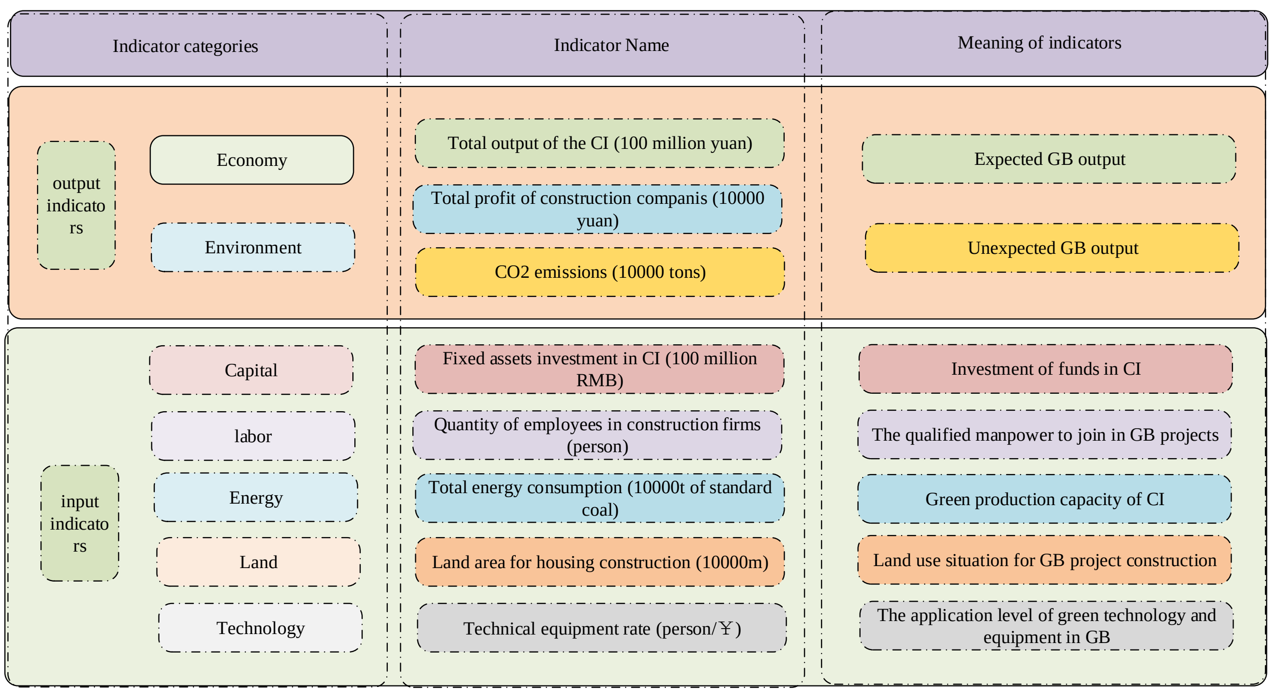


Fig. 2. Index system of GBEE measurement.

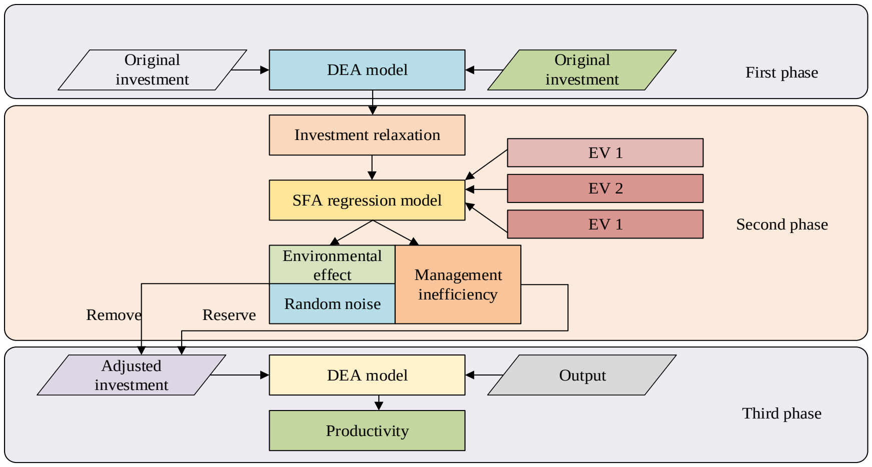


Fig. 3. Specific process of the three-stage DEA.

In Fig. 3, the first phase of constructing the three-stage DEA is the construction of the SBM model. The 2nd phase is to construct a stochastic frontier model. The third stage is based on the foundation of stages one and two, to obtain more accurate measurement values that reflect the GBEE levels of all DEAs [21]. Specifically, the first step is to construct an ultra efficient SBM model. This study adopted an input-oriented model to test the initial efficiency of GBEE. The improved super-efficient SBM model is obtained by optimizing the objective function based on relaxation variables. The process is shown in Eq. (3).

$$\rho = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}_r^a}{y_r^a}+\sum_{j=1}^{s_2}\frac{\bar{y}_j^b}{y_{j0}^b}\right)}$$
$$\text{s.t.}\begin{cases} x_0 = X\lambda + S^-, \quad y_0^a = Y^a\lambda - S^a, \quad y_0^b = Y^b\lambda - S^b \\ \bar{x} \ge \sum_{j=1,\neq 0}^{n}\lambda_j x_j, \quad \bar{y}^a \le \sum_{j=1,\neq 0}^{n}\lambda_j y_j^a, \quad \bar{y}^b \le \sum_{j=1,\neq 0}^{n}\lambda_j y_j^b \\ \bar{x} \ge x_0, \quad \bar{y}^a \le y_0^a, \quad \bar{y}^b \ge y_0^b \\ \sum_{j=1,\neq 0}^{n}\lambda_j = 1, \quad S^- \ge 0, \quad S^a \ge 0, \quad S^b \ge 0, \quad \bar{y}^g \ge 0, \quad \lambda \ge 0 \end{cases} \tag{3}$$

In Eq. (3), m represents the number of input indicators. n represents Decision-making Unit (DMU). x represents the input item. λ and ρ represent weight vectors and objective function values, respectively. y_a and y_b represent expected and unexpected output items, respectively, with S_1 and S_2 as the number of indicators. S^- is the input, S^a is , expected output, and S^b is the unexpected output. After constructing the SBM, a random frontier model is then constructed [22]. By measuring GBEE, the original efficiency data and relaxation variable of each DMU can be obtained. The process function model is Eq. (4).

$$S_{ni} = f\left(Z_i;\beta^n\right) + v_{ni} + \mu_{ni} \quad ;i=1,2,\ldots,I;n=1,2,\ldots,N \tag{4}$$

In Eq. (4), i and n represent the number of DMUs and the input items, respectively. S_{ni} represents the input relaxation value (IRV) of n of the i -th DMU. Z_i represents P Environmental Variables (EVs). β^n represents the estimated parameter of i . $f\left(Z_i;\beta^n\right)$ represents the impact of external EV on the IRV. $v_{ni}+\mu_{ni}$ is the mixed-error, where v_{ni} is the Random Error (RE). To eliminate the influence of external EVs and REs, homogeneous adjustments are made to each input quantity. The specific adjustment method can refer to Eq. (5).

$$X_{ni}^A = X_{ni} + \left[\max f\left(Z_i;\hat{\beta}^n\right) - f\left(Z_i;\hat{\beta}^n\right)\right] + \left[\max\left(v_{ni}\right) - v_{ni}\right] \tag{5}$$

In Eq. (5), this study homogenized the input of each DMU and obtained the adjusted input value X_{ni}^A. By maximizing $\max f\left(Z_i;\hat{\beta}^n\right) - f\left(Z_i;\hat{\beta}^n\right)$, this study adjusts the external environment to the same state. Among them, $\max f\left(Z_i;\hat{\beta}^n\right)$ is the benchmark adjusted by other DMUs, indicating the worst environmental conditions. This adjustment takes into account both good and bad conditions, and increases or decreases investment. To adjust the RE to the same state through $\max\left(v_{ni}\right) - v_{ni}$, ensuring that all DMUs are in the similar external EV and RE status.

B. GBEE Based on Temporal Dimension

After establishing a scientific measurement index system, this study further analyzes the temporal changes of GBEE through the temporal dimension based on national, regional, and inter provincial differences, and uses KDE to reveal its dynamic evolution characteristics [23]. On the spatial dimension, the spatial distribution pattern of GBEE is visualized, and the spatial agglomeration and transition characteristics of GBEE in various provinces and cities through spatial auto-correlation (SAC) analysis are revealed. The specific technical road-map is Fig. 4.

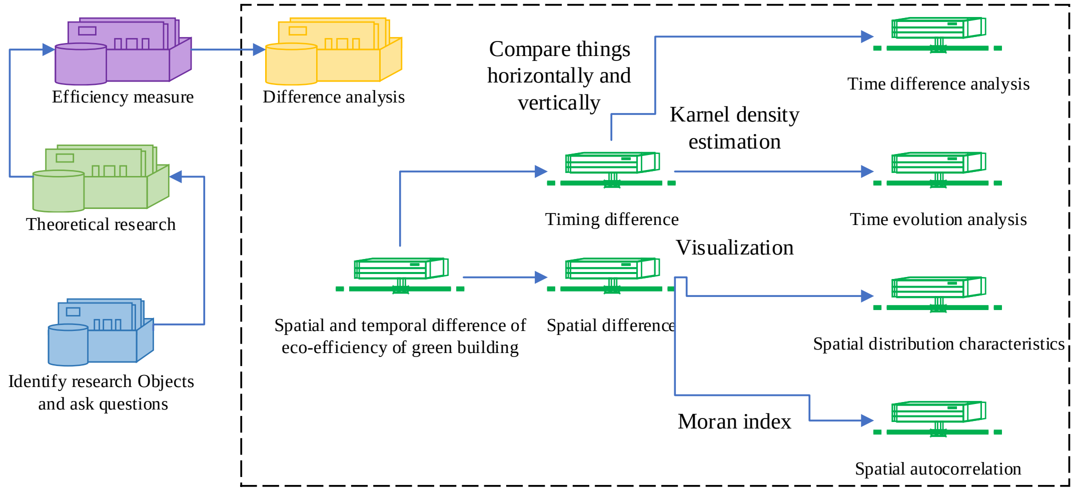


Fig. 4. Technology road-map.

In Fig. 4, the spatiotemporal differences of GBEE are divided into temporal differences and spatial differences. Kernel density estimation is a non-parametric statistical method utilized to estimate the shape of the probability density function. This method involves placing kernel functions (KerF) around each data-point and then overlaying these functions to form an estimate of the overall probability density. The specific expression is Eq. (6).

$$f(x)=\frac{1}{Nh}\sum_{i=1}^{N}K\left(\frac{X_i-\bar{x}}{h}\right) \tag{6}$$

In Eq. (6), bandwidth h is an important parameter. The set of observation samples is represented by N, and the values of independent and identically distributed observation samples are represented by X_i. x represents the input item. The K is a weighted or smooth transformation function. The mathematical formula that needs to meet the conditions is Eq. (7).

$$\begin{cases}\lim\limits_{x\to\infty}K(x)\cdot x=0\\ K(x)\geq 0 \quad \int_{-\infty}^{+\infty}K(x)dx=1\\ \sup K(x)<+\infty \quad \int_{-\infty}^{+\infty}K^2(x)dx<+\infty\end{cases} \tag{7}$$

KerFs generally include trigonometric KerFs, quadrilateral KerFs, and Gaussian KerFs. This study chose to use Gaussian density KerF, as shown in Eq. (8).

$$K(x)=\frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}} \tag{8}$$

Building a spatial weight matrix is a commonly used task in spatial analysis, which is used to describe the degree of correlation between adjacent regions in geographic space. Construct a binary symmetric spatial matrix W_{n*n} of n*n to represent the spatial adjacency relationship between n positions. The matrix is specifically expressed as Eq. (9).

$$W_{n\times n}=\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n}\\ w_{21} & w_{22} & \cdots & w_{2n}\\ \cdots & \cdots & \cdots & \cdots\\ w_{n1} & w_{n2} & \cdots & w_{nn}\end{bmatrix} \tag{9}$$

In Eq. (9), $W_{i\times j}$ represents the proximity relationship between region i and j. This study uses the spatial weight matrix under the geographical distance standard, as expressed in Eq. (10).

$$w_{ij}=\begin{cases}1, & \text{The distance between region i and j is<d}\\ 0, & \text{others}\end{cases} \tag{10}$$

Global SAC is a method taken to analyze the spatial correlation between geographic units in an entire region or system. It mainly focuses on the global distribution pattern of variables within the entire region to reveal spatial clustering or dispersion trends. This study uses a geographic distance spatial weight matrix and uses the global Moran's I index (MII) for measurement, as shown in Eq. (11).

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \tag{11}$$

In Eq. (11), n is the amount of provinces and cities. x_i and x_j represent the GBEE values of province and city i and j. $\bar{x}$ and S^2 represent the mean and variance of GBEE in each province and city. Further to adopt the Z-score normal distribution hypothesis to verify the accuracy of MII. Its expression is Eq. (12).

$$Z(I)=\frac{I-E(I)}{\sqrt{\mathrm{VAR}(I)}} \tag{12}$$

In Eq. (12), $E(I)$ is the expected value. $\mathrm{VAR}(I)$

represents the expected variance. The specific expression of $E(I)$ is Eq. (13).

$$E(I) = -\frac{1}{n-1} \tag{13}$$

Local SAC is usually measured by Local Moran's I. This paper uses local MII and Moran scatter plot to evaluate the local distribution characteristics of GBEE, as shown in Eq. (14).

$$I_i = \frac{\left(x_i - \bar{x}\right)}{S^2} \sum_{j=1}^{n} W_{ij}\left(x_j - \bar{x}\right) \tag{14}$$

The spatial lag model is adopted to spatial data analysis. It considers spatial correlation, which is commonly used to describe the interactions and dependencies between spatial data, as shown in Eq. (15).

$$Y = \rho WY + X\beta + \mu \tag{15}$$

The relationship between GBEE Y and the influencing factor matrix X was studied in Eq. (15). Considering spatial interaction, spatial auto-regressive coefficient ρ and spatial weight matrix are introduced. The RE is represented by μ, while the spatial lag term WY reflects the influence of adjacent regions.

As a comprehensive efficiency evaluation method, the core assumptions of 3SE-SBM-DEA model mainly include the following points: First, the model assumes that there is a clear linear relationship between input and output, that is, under given technical conditions, the increase of input will lead to the increase of output in a certain proportional relationship. Secondly, the 3SE-SBM-DEA model assumes that the effects of external environment variables and random errors on efficiency are independent and can be separated and adjusted by appropriate statistical methods. In addition, the model also assumes that the data is accurate and complete, that is, the input and output data can truly reflect the actual operation of green buildings. Finally, the model assumes that each DMU is homogeneous in terms of technical conditions and production functions, that is, all evaluated green building projects are comparable at the technical level.

IV. Performance Analysis and Validation of the GBEE Measurement Model

This study first analyzes the statistical characteristics of the sample data and the assumption of homogeneity of measurement indicators, confirming the applicability of the measurement model. Subsequently, using indicator data, the GBEE in China is measured, and the efficiency levels and variation differences of Stage One and Stage Three at the national, regional, and inter provincial levels are compared and analyzed.

A. GBEE Analysis

This study uses panel data on input-output and EVs from 2011 to 2018, selecting 30 provinces in China as research subjects, with the aim of calculating the GBEE of each province and city. To better analyze its regional differences, the research area is segmented into eastern, central, and western regions. Table I presents the statistical results.

According to Table I, through statistical analysis of the collected data, it is found that the SD and range among individual indicators are huge, showing a significant difference, and the input-output situation also shows a significant difference. Before conducting the GBEE measurement, the measurement model requires that the input and output items meet the assumption of homogeneity, that is, the principle that "as the input increases, the output does not decrease.". To verify this hypothesis, this study conducts Pearson correlation tests between input indicators and output indicators using SPSS 20.0 software. Table II shows the test results.

In Table II, && is significantly correlated at the 1% level (bilateral). In Table II, the correlation coefficients are all positive and have all passed the bilateral test at the 1%, indicating that the input and output variables satisfy the principle of homogeneity assumption. This study further adopts the super efficiency SBM model and uses MAXDEA software to run GBEE input-output data, obtaining the GBEE levels of each province and city without considering the influence of external EVs and REs. The specific results are shown in Fig. 5.

TABLE I. DESCRIPTIVE STATISTICAL RESULTS OF SAMPLE DATA

Variable	Minimum	Mean	Maximum	SD	Sample
Housing construction land area	738	39362	249176	47499	240
Employees in construction company	54847	1604115	8110275	1785021	240
Total energy consumption	14	126	354	1785021	240
Rate of technical equipment	728	14354	91231	9978	240
Carbon emission	562	13178	52901	11055	240
Gross output of CI	52	1211	6717	1302	240
Investment in fixed assets in the CI	0.09	131	1136	201	240
Total profits of construction enterprises	64449	2093927	11617738	2070219	240

TABLE II. PEARSON CORRELATION TEST BETWEEN INPUT AND OUTPUT VARIABLES

Type	Index	Construction Enterprise Number of Employees	House Construction Land Area	Investment in Fixed Assets in CI	Energy Consumption Gross Amount	Technology Equipment Rate
Gross output value of CI	Significance (bilateral)	0.000	0.000	0.003	0.001	0.001
	Pearson correlation	0.948&&	0.974&&	0.626&&	0.566&&	0.603&&
Gross profit	Significance (bilateral)	0.000	0.000	0.003	0.001	0.002
	Pearson correlation	0.924&&	0.922&&	0.601&&	0.555&&	0.525&&
Carbon emission	Significance (bilateral)	0.000	0.000	0.002	0.004	0.001
	Pearson correlation	0.887&&	0.816&&	0.667&&	0.511&&	0.755&&

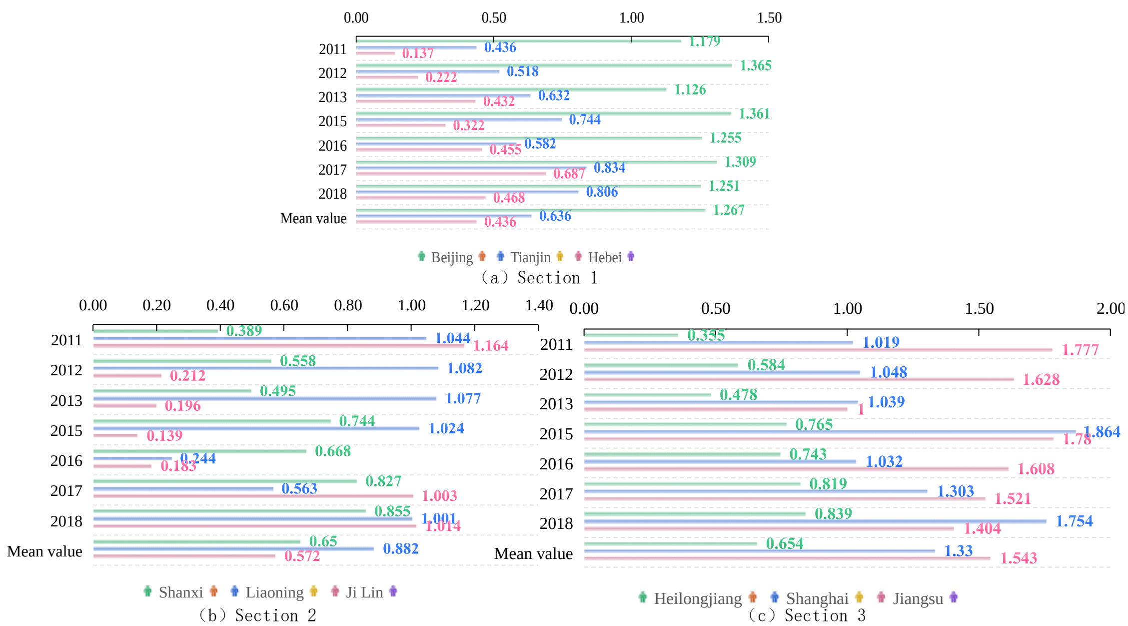


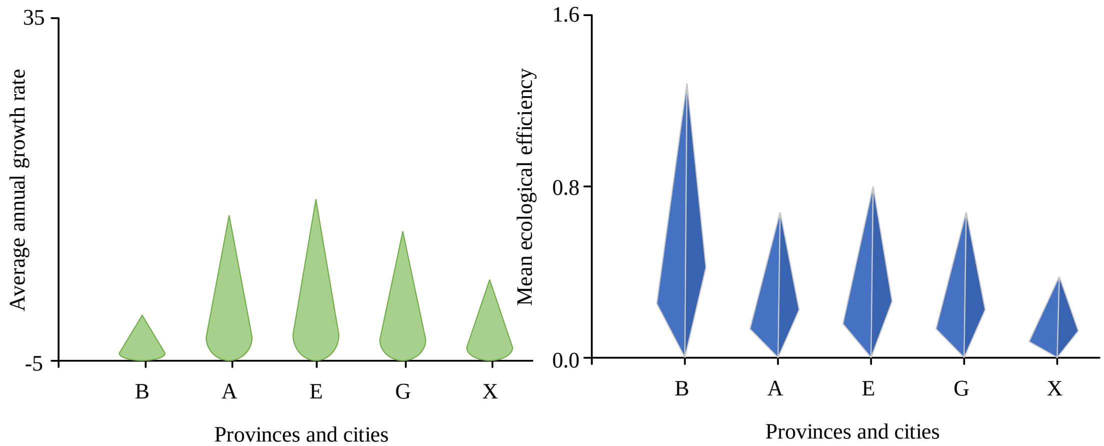
Fig. 5. Eco-efficiency level of green buildings.

Fig. 5 (a) shows the GBEE levels in provinces and cities B, T, and H. Annual Growth Rate (AGR) is used to describe the average annual growth of an indicator in a specific period of time. Fig. 5 (b) shows the GBEE levels in S, L, and J provinces. Fig. 5 (c) shows the GBEE levels of provinces and cities A, C, and D. Fig. 5 shows that from 2011 to 2018, China's GBEE showed a good development trend, with an overall average efficiency increasing trend, with an average AGR of 4.71%. After 2015, ecological efficiency achieved sustained and steady growth, reaching a peak of 0.916 in 2018, with an average AGR of 14.5%. The average and AGR of GBEE in some provinces and cities in China are shown in Fig. 6.

Fig. 6 (a) shows the AGR, and Fig. 6 (b) shows the Mean Ecological Efficiency (MEE). There are obvious discrepancies in GBEE among provinces. The MEE of province and city A is below 0.7, with an average AGR of 13.07%. Provinces and cities such as E show fluctuating fluctuations, with no significant increase or decrease trend. Fig. 7 shows the comparison of the MEE and average AGR of GBEE among different regions in China.

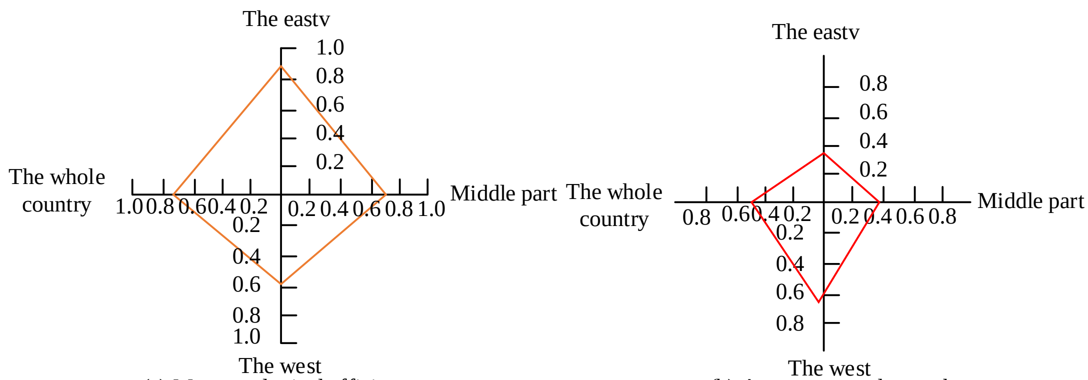
Fig. 7 (a) is the MEE, and Fig. 7 (b) shows the AGR. Between 2011 and 2018, China's GBEE showed significant regional differences, with the highest in the East (0.884), followed by the central (0.704), and the lowest in the West (0.578). Fig. 8 shows the trend of changes in the mean GBEE across different regions.

Fig. 8 (a) shows the eastern and central regions, while Fig. 8 (b) shows the national and western regions. Fig. 8 shows that the GBEE in the East showed fluctuating patterns from 2011 to 2018, consistently higher than the national average, with no significant increase or decrease trend. In contrast, the efficiency curve in the central region shows a similar development trend to the national average curve, with an overall low growth rate. Although the three major regions reached their peak efficiency in 2018, the average AGR in the West reached 6.99%, which is 48.84% and 41.33% higher than that in the East and Center, respectively.



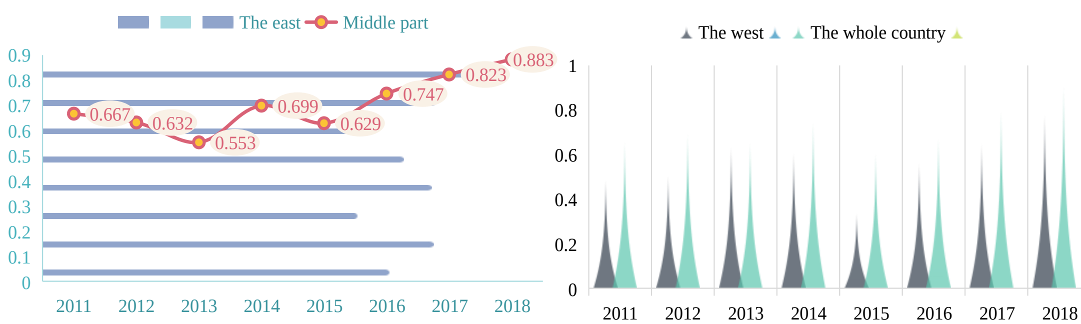
(a) Average annual growth rate (b) Mean ecological efficiency

Fig. 6. MEE and average AGR of GBEE in China.



(a) Mean ecological efficiency (b) Average annual growth rate

Fig. 7. Comparison of MEE and average AGR of GBEE in different Chinese regions.



(a) The east and Middle part (b) The west And The whole country

Fig. 8. Variation trend of mean value of GBEE in each region.

B. *Performance Verification Based on the 3SE-SBM-DEA Model*

After the SFA regression analysis in stage two, it is found that there are significant differences in the impact of external environmental differences and GB investment factors among provinces and cities, which in turn have a significant impact on GBEE. To eliminate these impacts, adjustments are made to the input variables to ensure that each province and city are compared under the equal external EV and RE. The final GBEE is obtained by using the SBM model and MAXDEA software for efficiency analysis. The GBEE mean measurement results for Stage 1 and Stage 3 are shown in Fig. 9.

Fig. 9 (a) and Fig. 9 (b) show the results of the first and third stages. By comparing Fig. 9 (a) and 9 (b), the MEE of the three stages is lower than that of the first stage, except for 2015 and 2016. Fig. 10 further illustrates the comparison of GBEE mean values.

Fig. 10 (a) shows the results of the first stage, and Fig. 10 (b) shows the results of the third stage. After excluding the external EVs and REs influences, GBEE still maintains a pattern of "greater in the east than in the central and greater in the west", but the regional gap has widened. The efficiency in the East outperforms than the national average, while that in the Center and West has decreased. From 2011 to 2018, there is a slight decrease in the national average GBEE, indicating that there is still significant room for improvement in GBEE.

In order to verify the robustness of the eco-efficiency measurement results of green buildings based on the three-stage super-efficiency SBM-DEA model under different conditions, sensitivity analysis was conducted. By adjusting the key parameters of the model, the influence of these changes on the eco-efficiency of green buildings was analyzed, so as to evaluate the robustness of the model results. The details are shown in Table III.

In Table III, the eco-efficiency measurement results of green buildings show good robustness under different conditions. When the weight adjustment of input-output index is ±10%, the mean eco-efficiency of eastern, central and western regions decreases by 0.008, 0.006 and 0.008 respectively, and the mean eco-efficiency of the whole country decreases by 0.005. This indicates that weight adjustment has a certain impact on the measurement results of eco-efficiency, but the overall change range is small, indicating that the model is less sensitive to weight. When the adjustment amplitude of the influence of external environmental variables is ±15%, the mean eco-efficiency of eastern, central and western regions increases by 0.008, 0.008 and 0.008 respectively, and the national mean eco-efficiency increases by 0.008. This indicates that external environmental variables have a significant impact on the eco-efficiency measurement results, but the adjusted results still maintain the original regional difference pattern, that is, "East > central > west". When the random error adjustment amplitude is ±20%, the mean eco-efficiency in eastern, central and western regions decreases by 0.004, 0.004 and 0.004 respectively, and the national mean eco-efficiency decreases by 0.003. The adjustment of random error has relatively little effect on the eco-efficiency measurement results, which further verifies the robustness of the model results.

TABLE III. SENSITIVITY ANALYSIS RESULT

Parameter adjustment type	**Adjustment range**	**Average ecological efficiency in eastern China**	**Average ecological efficiency in central region**	**Average ecological efficiency in western China**	**Average national ecological efficiency**
Reference model	/	0.884	0.704	0.578	0.723
Input-output index weight adjustment	±10%	0.876	0.698	0.570	0.718
External environment variables affect adjustment	±15%	0.892	0.712	0.586	0.731
Random error adjustment	±20%	0.880	0.700	0.574	0.720

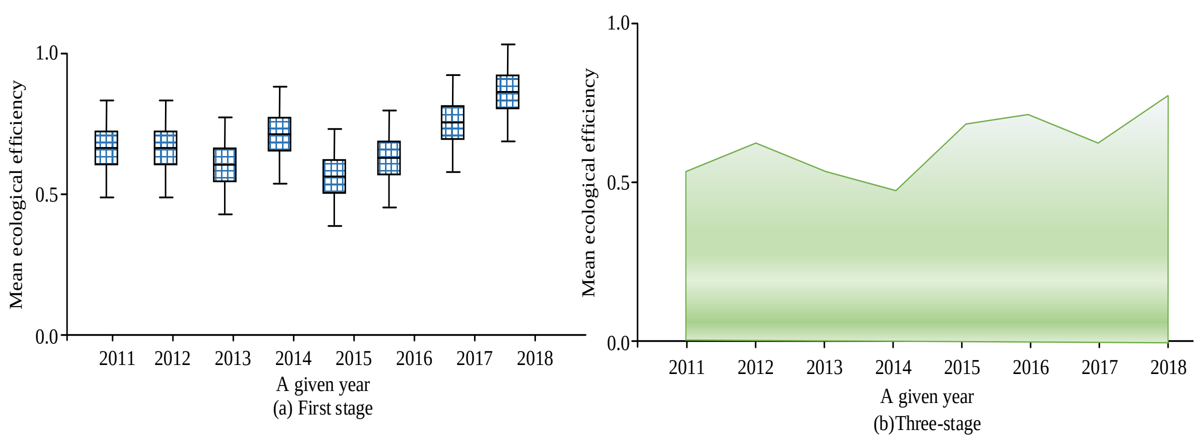


Fig. 9. Average measurement results of GBEE in stage 1 and stage 3.

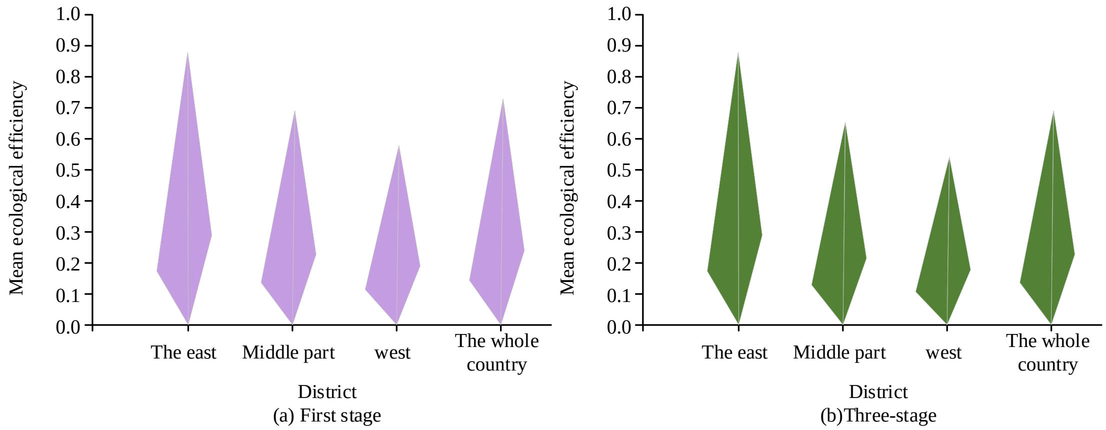


Fig. 10. Comparison of mean GBEE.

V. Optimization Strategy Discussion

The results showed that the eco-efficiency of green buildings in China showed obvious regional differences during 2011-2018, with the highest efficiency in the eastern region, followed by the central region and the lowest in the western region. The formation of regional differences is closely related to various factors such as economic development level, technological input, policy support and resource endowment. Therefore, according to the characteristics of different regions, the following optimization strategies are proposed in order to narrow the regional gap and improve the overall ecological efficiency of green buildings in the country. For the eastern region, although its green building ecological efficiency is at a high level, there is still room for further improvement. The eastern region has a relatively high level of economic development and relatively abundant technology and capital, so it should focus on strengthening the innovation and application of green building technology. The eco-efficiency of green buildings in the central region is at a medium level, and its optimization strategy should focus on the combination of technology introduction and talent training. The central region has certain advantages in terms of resources and market, but it is relatively short of technology and talents. Therefore, we should actively introduce advanced green building technology and management experience in the eastern region, and promote the popularization and application of green building technology in the central region through technical cooperation and project demonstration. The eco-efficiency of green buildings in western China is relatively low, and its optimization strategy should focus on solving the problems of weak infrastructure and shortage of funds. The economic development of the western region is relatively backward, and the infrastructure construction is insufficient. We should increase the investment in the construction of green building infrastructure and improve the basic conditions for the development of green building. The government should increase financial support for green building projects in the western region through financial transfer payments and special funds. At the same time, the western region should give full play to its own resource advantages, develop green buildings according to local conditions, increase the application proportion of renewable energy in buildings, and reduce the dependence on traditional energy.

VI. Conclusion

The continuous attention of society to SD has attracted attention to GBS as a key form of sustainable building. To comprehensively evaluate the comprehensive benefits of GBS, the focus is gradually shifting towards their ecological efficiency. In this context, this study constructed a measurement method based on the 3SE-SBM-DEA model, with building resources and energy as inputs and economic and environmental values as outputs, and established the GBEE measurement model. The results showed that from 2011 to 2018, China's GBEE saw overall growth with an average AGR of 4.71%. From 2011 to 2015, there was an M-shaped oscillation, reaching the lowest value of 0.611. After excluding the influence of external EVs and REs, the measuring data of stage three were more reasonable. From 2011 to 2018, China's GBEE showed a decreasing trend, with the highest in the East (0.884), the sequential Center (0.704), and the lowest in the West (0.578). The efficiency in the eastern area was higher than the national average, while the efficiency in the central and western areas has decreased. This study has made progress in GBEE measurement and optimization methods, but there are limitations to the data, uncertainty in model parameter selection, and important factors that have not been considered. Future research should focus on expanding the sample range, improving model parameter selection methods, improving data quality and reliability, and comprehensively considering more factors to promote the development of this field.

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Competing Interests

The author(s) declare none.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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