SCIENTIFIC OASIS

Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

Improving Higher Education Resource Allocation Efficiency and Its Spatial Correlation for Sustainable Development in China

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ARTICLE INFO

Article history:
Received 29 May 2024
Received in revised form 15 October 2024
Accepted 9 December 2024
Available online 10 December 2024

Keywords:
Higher Education Resource Allocation Efficiency; Three-Stage SBM-DEA; Spatial Correlation; Sustainable Development

ABSTRACT

Amidst global economic integration and the expansion of the knowledge economy, higher education serves as a fundamental pillar of national innovation systems. The strategic importance of its resource allocation efficiency is critical for attaining sustainable development objectives. This study introduces an advanced three-stage super-efficient slacks-based measure (SBM)-data envelopment analysis (DEA) model, incorporating spatial econometric analysis to conduct a multi-dimensional assessment of higher education resource allocation efficiency (HERAE) across 31 Chinese provinces from 2015 to 2022. Unlike the conventional DEA model, this approach innovatively integrates the advantages of the super-efficient SBM model in addressing non-radial relaxation with the Three-stage DEA model's capability to account for environmental variables. It effectively mitigates the shortcomings of prior research that disregards environmental influences and stochastic disturbances. Empirical findings reveal that, after adjusting for environmental variables, the average technical efficiency (TE) and scale efficiency (SE) of higher education resource allocation (HERA) in China declined to 0.553 and 0.659, respectively, whereas pure technical efficiency (PTE) increased to 0.857. This indicates that traditional evaluation techniques tend to overestimate efficiency levels. The overall efficiency in the eastern region (0.739) was significantly greater than in the central (0.689), north-eastern (0.486), and western (0.368) regions. Three principal factors influencing efficiency include the level of regional economic development, governmental support for education, and the extent of social development. Spatial analysis revealed that the global Moran index fluctuated between 0.160 and 0.414 from 2015 to 2021, yet in 2022, it shifted to a non-significant negative correlation due to the pandemic's impact. Consequently, this study suggests policy measures such as establishing a regional coordination framework, strengthening digital governance, and fostering collaboration among educational institutions to support decision-making.

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https://doi.org/ 10.31181/dmame7220241321

1. Introduction

The distribution of educational resources is fundamental to achieving equity in education and serves as a key indicator of the overall health of a country or region's educational system [1-3]. With significant national strategic adjustments and the advancement of the 'Double First-Class' initiative, the status of higher education in China continues to strengthen [4]. Backed by strong national policies, the significance of HERAE has become increasingly pronounced [5,6]. Ensuring the efficient and rational allocation of limited educational resources to maximise their effectiveness and support the long-term growth of education has emerged as a critical issue in educational research. Sustainable development necessitates consideration of both current educational demands and the long-term evolution of resource distribution [7-9]. This approach ensures that the equilibrium of the education system aligns with broader socio-economic progress. Enhancing resource allocation efficiency enables higher education to better address national strategic priorities, nurture innovative talent, and contribute to high-quality economic and social development [10,11].

Accordingly, this study primarily focuses on evaluating HERAE across Chinese provinces and cities, directly linking it to regional educational equity, the overall enhancement of higher education quality, and the effective implementation of the national innovation-driven development strategy. A comprehensive analysis of the current state and challenges of resource distribution across different regions provides a solid foundation for optimising allocation efficiency. This will drive the development of educational resources towards greater efficiency, fairness, and long-term sustainability. Additionally, the study integrates spatial econometric modelling to investigate interregional linkages and collaboration among Chinese provinces and cities. By identifying spatial agglomeration patterns and the potential for regional cooperation, it becomes possible to facilitate the integration and redistribution of educational resources. This approach promotes complementary advantages and synergistic regional development.

The study's findings offer both theoretical insights and practical guidance for policymakers at various levels of government in formulating evidence-based HERA strategies. Furthermore, it establishes a methodological framework for higher education institutions to refine resource management and enhance operational efficiency. By unveiling spatial correlations and the potential for synergistic interregional resource distribution, this research provides a crucial basis for promoting balanced allocation and optimal utilisation of educational resources nationwide. Ultimately, it supports the strategic objectives of modernising education and comprehensively advancing the construction of a modern socialist country.

Numerous scholars have examined the effective utilisation of educational resources, proposing various evaluation methods and perspectives. One study [12] investigated school resource allocation in Spain, concluding that greater autonomy and responsibility in resource distribution enhance efficiency. Another analysis [13] compared educational resource productivity across 35 European nations. A detailed assessment [14] of Taiwan's emerging higher education system determined that dedicated tax funding plays a pivotal role in ensuring institutional sustainability while exhibiting limited effectiveness in reducing systemic disparities across sectors and institutional units. Research [15] analysed the utilisation and productivity changes of higher education resources in China from a provincial perspective, proposing an optimal allocation plan under the condition that total enrolment capacity remains unchanged.

As research on HERAE has progressed, various models have been developed to examine the efficiency of equitable educational resource distribution across regions. One study [16] employed an improved cellular genetic algorithm and adaptive constraint processing technology to construct an input-output evaluation system for innovation and entrepreneurship education resources in universities, significantly enhancing allocation and utilisation efficiency. Another assessment [17] examined the resource distribution of public research universities in the United States from 2005 to 2015 using the SFA model. A separate analysis [18] applied the DEA-Malmquist Tobit model to evaluate the resource allocation efficiency of China's 'Double First-Class' universities, identifying technical efficiency change (EFCH) and technological progress (Tech) as key determinants. Further research [19] highlighted that regional economic development, teaching structure, and international exchange positively influence efficiency, whereas local financial support and policy implementation duration exert negative effects. A multidimensional evaluation framework [20] combining panel data analysis and the Theil entropy coefficient examined the spatiotemporal distribution patterns of preschool education resources in China, revealing substantial regional disparities in human capital development, with pronounced imbalances in less developed areas. Another study [21] applied the Super-SBM model to dynamically evaluate the efficiency of higher education across 30 provinces in mainland China between 2011 and 2020. The empirical findings demonstrated significant technological disparities across Eastern, Central, and Western regions, highlighting that allocative patterns exert differential effects on operational productivity, particularly through the mediating role of resource distribution structures.

The efficiency of resource allocation in universities exhibits significant spatial heterogeneity, influenced by various contextual factors such as historical legacies, geographical constraints, and socio-economic disparities, which manifest both across regions and within administrative units. Furthermore, as higher education institutions in China rely heavily on government financial support while lacking effective efficiency assessment mechanisms, some institutions fail to fully utilise allocated funds, leading to financial stagnation and even waste. This issue exacerbates the imbalance in educational resource distribution and constrains overall improvements in education quality. Therefore, optimising resource allocation, maintaining a reasonable input-output ratio, and maximising resource utilisation have become urgent priorities. To address these challenges, this study introduces an innovative hybrid modelling framework that integrates the strengths of three-stage DEA and super-efficient SBM methodologies, overcoming key limitations of traditional efficiency assessment techniques. By incorporating stochastic frontier analysis, this model enhances the existing three-stage approach through improved treatment of environmental variables and non-radial inefficiencies. Applying this refined framework to national-level panel data on higher education resource allocation, the study systematically evaluates efficiency patterns at the provincial level. Additionally, a spatial econometric analysis using the Moran index identifies regional clusters, revealing considerable spatial heterogeneity in innovation factor allocation efficiency across China's administrative divisions.

2. Research Design and Data Sources

2.1 Three-Stage DEA Model

Stage 1: In the first stage, a non-radial and non-oriented super-efficient SBM-DEA model based on slack variables is employed. This approach provides a more comprehensive and intuitive reflection of HERAE across various provinces in China. The detailed construction of this model is as follows:

$$\min \rho = 1 + \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}} \tag{1}$$

s.t. $\mathrm{s.t}\ x_{ik} \geq \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - S_i^-$

$y_{rk} \geq \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j$

$S_i^- \geq 0; \lambda_j \geq 0$

$i = 1,2,\cdots,m; r = 1,2\cdots,v$

$$j = 1,2 \cdots, n(j \neq k) \tag{2}$$

Where, ρ represents the HERAE. When, ρ≥1 indicates that the decision-making unit (DMU) is in an effective state, and the larger the efficiency value, the higher the education resource allocation efficiency in colleges and universities. When ρ<1, the DMU is in an inefficient state. m and v are the quantities of inputs and outputs, respectively. S_i^- represents the slack and redundant variables of the input of HERA. x_{ik} represents the input of HERA in i of Province k. x_{ij} represents the input of HERA in i of Province j. y_{rj} represents the output of HERA in r of province j. This is because the super-efficient SBM-DEA model is used to compute other decision-making units as a reference set for the evaluated DMUs, $j \neq k$. λ_j is the weight variable.

Stage 2: The first-stage efficiency measurement does not account for managerial inefficiencies, random disturbances, or environmental factors. To address these limitations, the second stage employs the Stochastic Frontier Analysis (SFA) model to capture these missing influences. Specifically, the SFA model adjusts the slack variables obtained for each city in the first stage. Additionally, environmental variables are incorporated as explanatory variables to distinguish the effects of environmental conditions, random shocks, and managerial inefficiencies. The SFA model, a crucial component of the three-stage DEA framework, is detailed below:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni}; i = 1,2 \cdots, I; n = 1,2, \cdots, N \tag{3}$$

S_{ni} denotes the relaxation value associated with the DMU. Z_i is the environment variable, and β_n represents the environment variable coefficient. $v_{ni} + \mu_{ni}$ is the mixture error term. v_{ni} is the random disturbance, and μ_{ni} represents managerial inefficiency. Where $v \sim N(0, \sigma_v^2)$ denotes the random error term, which captures the impact of random disturbances on the input slack variables. μ represents management inefficiency, indicating the impact of management-related factors on input slack variables.

This study follows the research approach of [22], formulating the management inefficiency model as a cost function. The specific expression of this model is as follows:

$$E[u_{ni}|v_{ni} + u_{ni}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\frac{\varepsilon\lambda}{\sigma}\right)}{\phi\left(\frac{\varepsilon\lambda}{\sigma}\right)} + \frac{\varepsilon\lambda}{\sigma}\right] \tag{4}$$

$$\begin{cases} \lambda = \dfrac{\sigma_u}{\sigma_v} \\ \varepsilon = u + v \\ \sigma^2 = \sigma_u^2 + \sigma_v^2 \end{cases} \tag{5}$$

Where, φ and ϕ denote the density and distribution functions of the standard normal distribution, respectively. The formula of the random disturbances value model is as follows:

$$E[v_{ni}|v_{ni} + u_{ni}] = S_{ni} - Z_i\beta_n - E[u_{ni}|v_{ni} + u_{ni}] \tag{6}$$

SFA regression aims to neutralise the effects of environmental factors and random disturbances on efficiency measurement, thereby standardising the external environment for all DMUs. The formula for this adjustment is presented below:

$$X_{ni}^A = X_{ni} + \left[max\left(f\left(Z_i; \hat{\beta}_n\right)\right) - f\left(Z_i; \hat{\beta}_n\right)\right] + [max(v_{ni}) - v_{ni}] \tag{7}$$

X_{ni}^A is the adjusted input; X_{ni} is the input before the adjustment; $\left[max\left(f\left(Z_i; \hat{\beta}_n\right)\right) - f\left(Z_i; \hat{\beta}_n\right)\right]$ is to adjust external environmental factors; $[max(v_{ni}) - v_{ni}]$ is placing all DMUs under the same level of luck.

Stage 3: Following the adjustment of input variables in the second stage, new input variables are derived by isolating environmental variables and managerial inefficiency factors. The super-efficient SBM-DEA model is then reapplied to measure efficiency. The calculated efficiency is TE, which can be further decomposed into PTE and SE.

2.2 Moran Index Model

The Moran index model is a statistical approach for assessing spatial autocorrelation, which refers to the correlation between geographically proximate locations. This study utilises both the Global Moran's index and Local Moran's index to conduct a spatial autocorrelation analysis of HERAE across provinces. The specific formula is presented in the literature [23].

2.3 Index System Construction

The fundamental objective of optimising educational resource allocation is to maximise educational output while minimising resource input, thereby enhancing overall resource utilisation efficiency. Evaluating the efficiency of educational resources in universities serves this purpose by measuring changes in efficiency concerning educational input and research output. Accordingly, this study develops an efficiency evaluation index system based on system thinking, providing a more comprehensive and scientific assessment of universities' input-output efficiency.

2.3.1 Input Index

This study considers the actual development of higher education across China's provinces and cities, drawing on data availability and existing literature on HERA. Focusing on three key aspects—human input, financial input, and material input—it selects the number of research and development personnel, research expenditure, and library collections as the three input indicators.

2.3.2 Output Index

In developing the output index system, this study places particular emphasis on scientific research achievements and social services. Scientific research serves as both a critical indicator of universities' core competitiveness and a key measure of educational quality. The social service dimension reflects universities' capacity to apply research outcomes to real-world production and daily life, thereby indicating the practical value of their scientific contributions. Accordingly, this study selects the number of published papers and patent copyrights to represent scientific research achievements, while actual income from technology transfer is used to measure the level of social services.

2.3.3 Environmental Index

Existing literature on HERAE has largely overlooked environmental variables, leading to measurement errors in efficiency values. This study incorporates environmental variables, selecting indicators from three key perspectives: regional economic environment, government financial support, and degree of social development.

Regional Economic Environment – Per capita GDP is used to reflect regional economic development, serving as a key metric for assessing economic prosperity, living standards, and financial capacity. Higher per capita GDP enables local governments to allocate greater resources to higher education, including increased investment, improved facilities, and talent attraction. Conversely, regions with lower per capita GDP face financial constraints that may hinder higher education development. Thus, regional economic conditions significantly influence HERAE as a critical external factor.

Government Financial Support – The government plays a crucial role in shaping HERA, primarily through financial allocations. Government funding not only determines the overall availability of higher education resources but also influences their distribution across universities and regions, thereby affecting the trajectory and pace of higher education development. To capture this impact, this study selects the ratio of general public budget education expenditure to total public budget expenditure as an indicator of government financial support.

Degree of Social Development – The urbanisation rate is chosen to represent social development, reflecting the pace and extent of urbanisation. Higher urbanisation levels are typically associated with superior infrastructure, a more developed service sector, and higher living standards, all of which contribute to a conducive external environment for higher education. The selected indicators are presented in Table 1.

Table 1
HERAE Evaluation Index System

Type	Primary index	Secondary index	Unit
Input Index (x)	Human Input	Number of Scientific Research and Development Personnel (x_1)	Person-Year
	Financial Input	Scientific Research Expenditure (x_2)	10,000 Yuan
	Material Input	Library Collection (x_3)	10,000 Volumes
Output Index (y)	Research Achievements	Number of Published Papers (y_1)	Piece
		Number of Patent Copyrights (y_2)	Piece
	Social Services	Actual Income from Technology Transfer (y_3)	1000 Yuan
Environmental Index	Regional Economic Environment	Per Capita GDP	Yuan
	Government Financial Support	Education Expenditure as a Proportion of Total Public Expenditure	%
	Degree of Social Development	Urbanization Rate	%

2.4 Data Source and Regional Division

This study analyses HERAE across various provinces in China using panel data from 2015 to 2022. Due to data limitations, Hong Kong, Macao, and Taiwan are excluded from the analysis. To better capture regional characteristics, the 31 provinces are categorised into four distinct regions (see Figure 1). The sample data and variables are primarily sourced from the Compilation of Scientific and Technological Statistics of Colleges and Universities, the China Education Statistical Yearbook, the China Statistical Yearbook, and reports from provincial and municipal statistical bureaus.

Fig.1. Four Regions

2.5 Data Check

Before applying the three-stage DEA model to assess HERAE across China's provinces, it is essential to ensure a positive correlation between input and output indices. Ignoring this correlation may lead to biased evaluation results. Therefore, this study employs Pearson correlation analysis to examine the relationships among the three selected input and output indices. The test results are presented in Table 2. The results in Table 2 indicate a significant positive correlation between the three input and three output indicators, with all correlations passing the 1% significance test. This finding confirms the hypothesis that, within the DEA model, an increase in input indices corresponds to a rise in output indices. Furthermore, it validates the reliability of the HERAE evaluation index system developed in this study, demonstrating its effectiveness in assessing HERAE.

Table 2
Correlation test of the Input-Output Index of Higher Education in China

Index	x_1	x_2	x_3	y_1	y_2	y_3
x_1	1					
x_2	0.867***	1				
x_3	0.835***	0.622***	1			
y_1	0.904***	0.912***	0.735***	1		
y_2	0.712***	0.604***	0.746***	0.627***	1	
y_3	0.705***	0.779***	0.537***	0.826***	0.462***	1

Note: *** indicates significance at a 1% level.

3. Empirical Analysis

3.1 Analysis of Super-Efficient SBM-DEA Results

3.1.1 Analysis of the First Stage of Super-Efficient SBM-DEA Results

In the absence of environmental factors and random interference, this study employs MAXDEA software to evaluate HERAE in China from 2015 to 2022. The results obtained from the super-efficiency SBM-DEA model in the first stage (as presented in Table 3) provide only the average values of each index for reference. The findings indicate that, prior to adjustment, the TE, PTE, and SE of higher education resource allocation were 0.678, 0.818, and 0.888, respectively, suggesting that an optimal state has not yet been achieved. Notably, only seven regions—Beijing, Shanghai, Jiangsu, Zhejiang, Henan, Chongqing, and Xinjiang—recorded a TE of 1 or higher, signifying that these provinces have reached the optimal technical level with a more efficient allocation of educational resources. In contrast, TE in other regions remained below the standard, highlighting the need for further improvements in HERA.

Table 3
The Average Value of HERAE

Area	First Stage			Third Stage		
	TE	PTE	SE	TE	PTE	SE
Beijing	1.155	1.232	0.937	1.148	1.215	0.944
Tianjin	0.368	0.377	0.975	0.352	0.447	0.793
Hebei	0.401	0.438	0.913	0.460	0.579	0.791
Shanxi	0.613	0.627	0.978	0.490	0.810	0.617
Inner Mongolia	0.534	0.554	0.953	0.097	0.749	0.153
Liaoning	0.540	0.555	0.968	0.592	0.631	0.941
Jilin	0.605	0.626	0.964	0.617	0.754	0.814
Heilongjiang	0.335	0.341	0.978	0.250	0.370	0.824
Shanghai	1.083	1.087	0.996	1.069	1.090	0.981
Jiangsu	1.086	1.414	0.768	1.119	1.403	0.808
Zhejiang	1.086	1.090	0.996	1.099	1.118	0.983
Anhui	0.410	0.422	0.967	0.449	0.480	0.941
Fujian	0.474	0.475	0.997	0.529	0.560	0.949
Jiangxi	0.619	0.634	0.976	0.545	0.888	0.638
Shandong	0.648	0.865	0.763	0.837	0.950	0.887
Henan	1.257	1.296	0.970	1.152	1.177	0.979
Area	First Stage			Third Stage		
	TE	PTE	SE	TE	PTE	SE
Hubei	0.629	0.822	0.796	0.795	0.867	0.925
Hunan	0.526	0.681	0.799	0.703	0.769	0.928
Guangdong	0.601	0.651	0.922	0.734	0.750	0.977

Guangxi	0.487	0.556	0.913	0.309	0.597	0.557
Hainan	0.219	0.267	0.703	0.046	0.984	0.060
Chongqing	1.143	1.151	0.992	1.045	1.151	0.905
Sichuan	0.962	1.092	0.879	1.060	1.083	0.980
Guizhou	0.977	0.987	0.989	0.212	0.979	0.229
Yunnan	0.119	0.134	0.898	0.081	0.279	0.383
Tibet	0.054	2.461	0.022	0.005	1.084	0.005
Shaanxi	0.942	0.945	0.996	0.912	1.019	0.894
Gansu	0.505	0.588	0.905	0.144	0.740	0.250
Qinghai	0.975	1.151	0.884	0.003	1.079	0.003
Ningxia	0.482	0.656	0.737	0.076	0.891	0.092
Xinjiang	1.173	1.190	0.986	0.199	1.073	0.183
Mean	0.678	0.818	0.888	0.553	0.857	0.659

3.1.2 The Second Stage of SFA Analysis

In the first stage, HERAE was influenced by environmental factors, random disturbances, and managerial inefficiencies, leading to inaccuracies in the results. To mitigate these effects, the second stage employed the SFA model for analysis. The input slack variables obtained from the first stage were used as explanatory variables in the SFA model, while regional economic environment, government financial support, and degree of social development were incorporated as explanatory variables. Data processing was conducted using Frontier 4.1 software (as presented in Table 4).

Table 4
Results of SFA Regression Analysis in the Second Stage

Variable	Number of Scientific Research and Development Personnel	Scientific Research Expenditure	Library Collection
Constant term	-5604.566***	-1260895.400***	-460.092***
Regional economic environment	-0.030**	-1.781***	-0.016***
Government financial support	9273.317***	1323196.000***	4251.770***
Degree of social development	84.455**	15715.774***	9.890***
σ^2	16705293.000***	518613470000.000***	1449457.200***
γ	0.801***	0.561***	0.333***
LR	154.844***	59.951***	18.386***

Note: **, and *** respectively indicate significant at 5%, and 1% significance levels

The results of the SFA regression analysis in Table 4 indicate that the LR values for all three environmental variables were statistically significant at the 1% level. This confirms the presence of inefficiency terms in the model, validating the necessity of using the SFA model to isolate environmental variables. Additionally, the γ values of the explained variables were all below 1 and statistically significant at the 1% level, demonstrating that managerial inefficiency plays a substantial role in the redundancy variables and is a primary influencing factor. The specific findings related to environmental variables are as follows:

1. Regional Economic Environment: Measured using per capita GDP, the analysis reveals that the regression coefficients of per capita GDP on the relaxation variables for the number of scientific research and development personnel, scientific research expenditure, and library collections were all negative and statistically significant at the 5% and 1% levels. This suggests that an increase in per capita GDP reduces redundancy in these input indicators, thereby enhancing HERAE. Economic growth contributes to higher fiscal revenues and resource availability, facilitating better allocation of educational resources, improving educational quality and efficiency, and ultimately strengthening HERAE.

2. Government Financial Support: The findings indicate that the intensity of government financial

support is positively correlated with the slack variables of the three input indicators, with all relationships significant at the 1% level. This implies that excessive government investment in higher education may lead to greater redundancy in resource allocation, reducing efficiency. The inefficiency stems from insufficient management and oversight of financial investments, potentially leading to ineffective utilisation of funds. In certain regions, a focus on infrastructure development at the expense of educational quality, along with weak regulatory mechanisms, exacerbates inefficiencies. If government funding is not optimally allocated and effectively utilised, resource wastage and diminished allocation efficiency may result. Addressing this issue requires the establishment of a robust financial management system for education, optimisation of input structures, and enhanced efficiency monitoring to ensure that investments genuinely contribute to improved education quality and equity.

3. Degree of Social Development: The urbanisation rate, used as an indicator of social development, was found to be positively correlated with the slack variables of the three input indicators, with all correlations significant at the 1% level. This suggests that higher urbanisation rates contribute to increased input redundancy, thereby negatively affecting HERAE. Several factors may explain this, including the spatial redistribution of educational resources, imbalances in institutional distribution, and mismatches between population migration and resource availability. Further contributing factors include misalignment between education inputs and outputs, inadequacies in policy adaptation to resource allocation demands, and disparities in resource matching and education quality. To address these challenges, policymakers must develop a comprehensive understanding of the dynamics of educational resource allocation within the context of China's urbanisation process.

3.1.3 Analysis of the Third Stage of Super-Efficient SBM-DEA Results

The SFA regression results effectively eliminated environmental factors and random disturbances. The adjusted input variables were then recalculated using the super-efficient SBM-DEA model, while retaining the original output variables from the first stage. This allowed for a more refined assessment of HERAE in the third stage (see Table 3). The efficiency results obtained from this stage were more scientifically robust, reasonable, and reflective of actual conditions compared to those from the first stage. In the initial analysis, seven regions were identified as efficient. Following the adjustments in the second stage, these regions remained efficient in the third stage. However, a notable change was observed in Xinjiang, which lost its previously efficient status after the second-stage adjustments. Conversely, Sichuan, which did not meet the efficiency threshold in the first stage, achieved an efficient status after adjustments. This indicates that, following refinements, HERAE in seven regions—Beijing, Shanghai, Jiangsu, Zhejiang, Henan, Chongqing, and the newly added Sichuan—can be considered the most reasonable and effective.

3.1.4 The Average Value of Efficiency Before and After Adjustment from 2015 to 2022

As illustrated in Figure 2, the mean values of TE, PTE, and SE for China's HERA from 2015 to 2022 exhibited a discernible trend of change, demonstrating an overall upward trajectory before and after adjusting for environmental factors and random disturbances. In the third stage, TE and SE mean values showed a yearly decline, whereas the PTE mean experienced a slight increase. This suggests that failing to account for external environmental factors and random disturbances may lead to an overestimation of China's HERAE, particularly in terms of SE. The adjusted PTE mean consistently exceeded the SE mean across all years, indicating that, compared to PTE, low SE is a more critical constraint on HERAE in China.

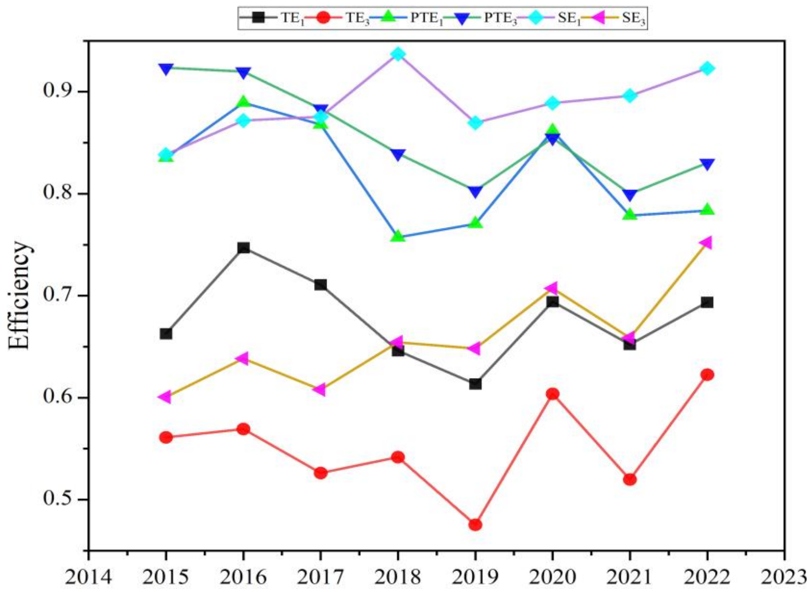

Fig.2. Trends in Average Value of Efficiency Before and After Adjustments. 1 Indicates Before Adjustment (The First Stage), and 3 Indicates After Adjustment (The Third Stage).

As depicted in Figure 2, the mean PTE in the third stage experienced a significant decline following its peak in 2017, whereas the mean SE exhibited a rapid increase after a marked decrease in 2018. This trend can be attributed primarily to a series of higher education reform policies introduced by the Chinese government in 2017, which enhanced the management and quality control of universities while improving teaching and research standards. Consequently, the mean PTE showed an initial rise in 2017. The implementation of a new education evaluation system subsequently led to adjustments and optimisations in resource allocation, causing a notable decline in the mean PTE in 2018. However, as the policy took effect, the mean PTE gradually rebounded from 2019 onwards. Additionally, since 2018, structural adjustments and optimisations have been undertaken to integrate and reform universities that did not meet the required standards. This restructuring temporarily reduced the scale of HERA, leading to a sharp drop in the mean SE in 2018. Nonetheless, with the completion of these reforms, the mean SE has exhibited a steady recovery since 2019.

3.1.5 TE Analysis of HERA in Each Province

In the third stage, the average TE of HERA declined across provinces (see Figure 3). A particularly pronounced decrease was observed in regions such as Xinjiang, Ningxia, Qinghai, Guizhou, and Gansu. This underscores the limitations of the traditional DEA model, which does not consider external environmental factors and random disturbances, leading to an overestimation of TE levels in provincial HERA assessments. Despite these adjustments, the overall TE of HERA remained relatively high, with particularly strong performance in the western region. In the third stage, several provinces remained at the relative technological frontier, with Beijing, Shanghai, Jiangsu, and Zhejiang achieving the highest TE. This indicates that HERAE in these regions is consistently high and less influenced by external environmental factors and random disturbances. Conversely, regions such as Tibet and Qinghai experienced significant declines in TE, suggesting that their previous efficiency was largely dependent on external conditions and policy support. Once these factors were accounted for, their true allocative efficiency proved to be considerably lower. For instance, TE in Beijing declined from 1.155 to 1.148, while in Shanghai, it decreased from 1.083 to 1.069. These minor reductions suggest that these provinces maintain strong efficiency levels even after adjustment. In contrast, Tibet's TE plummeted from 0.054 to 0.005, and Qinghai's from 0.975 to 0.003, highlighting the extreme reliance of these regions on policy support for maintaining efficiency. Additionally, provinces such as Henan, Hubei, and Shandong sustained high TE after adjustment, indicating strengths in resource management and technological integration. However, provinces like Hebei, Shanxi, and Inner Mongolia exhibited significant declines in TE, potentially reflecting inefficiencies in resource allocation and management practices.

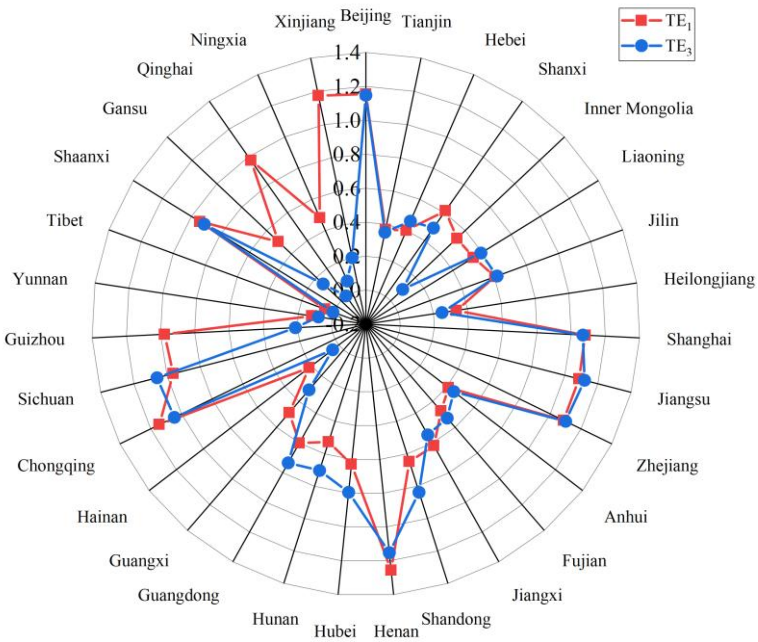

Fig.1. Comparison of TE Before and After Adjustment

3.1.6 PTE Analysis of HERA in Each Province

Before adjusting for external factors, HERA's PTE means varied across provinces, generally lower. By the third stage, the mean PTE rose, but the increase differed (see Figure 4).

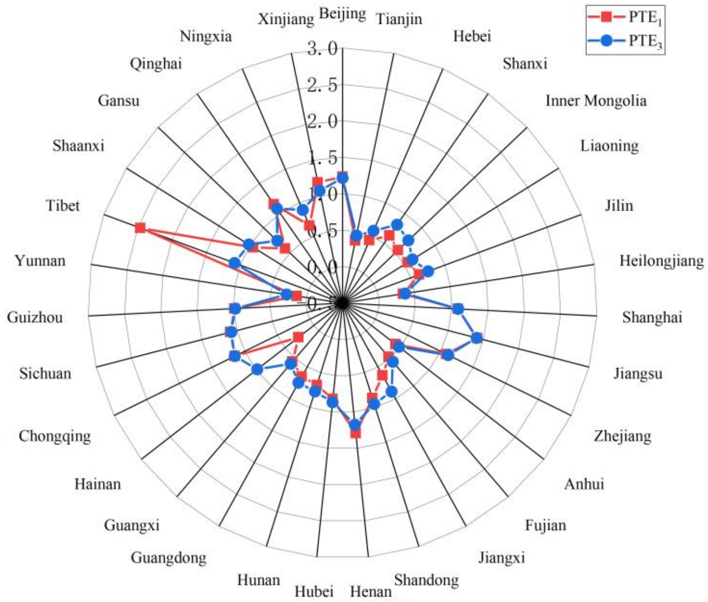

Fig.4. Comparison of PTE Before and After Adjustment

More provinces achieved PTE validity compared to TE. Initially, Beijing, Tianjin, Shanghai, Shandong, Guangdong, Sichuan, Chongqing, and Shaanxi reached technical validity. After adjustment, Hebei, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Hunan, Guangxi, Guizhou, Yunnan, and Tibet also achieved PTE effectiveness. Notably, Beijing, Shanghai, Jiangsu, and Zhejiang maintained high PTE levels post-adjustment, highlighting their technological and managerial advantages. Conversely, Tibet and Qinghai's PTE remained low, indicating HERA shortcomings. Provinces like Henan, Hubei, and Shandong saw PTE increases, likely due to recent education reforms and resource investments. Inner Mongolia and Liaoning improved but remained below average, suggesting significant room for HERA enhancement.

3.1.7 SE Analysis of HERA in Each Province

After adjusting for external factors, the mean SE of HERA decreased in each province (see Figure 5). Initially, Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong, and Shandong achieved scale efficiency. By the third stage, Hebei, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Hunan, Guangxi, Guizhou, Yunnan, and Tibet also reached technical effectiveness. While some provinces, like Beijing (0.999), Shanghai (0.993), and Jiangsu (0.997), did not achieve full technical efficiency, their values were high. Over 70% of provinces had SE above average. Figure 5 shows minimal differences among north-eastern, eastern, and central provinces, but greater variation in the west. For example, Tibet's SE was 0.005, Qinghai 0.003, and Ningxia 0.092. Overall, SE in eastern and central regions was high with small inter-provincial gaps, indicating reasonable resource allocation. However, most western provinces had low SE, well below average, highlighting the need for better resource allocation and improved efficiency in higher education.

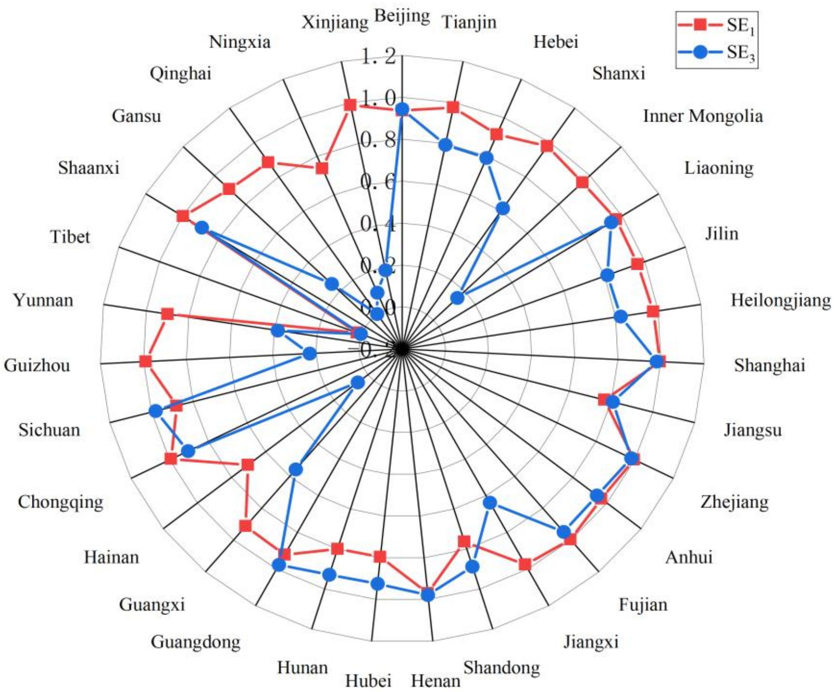

Fig.5. Comparison of SE Before and After Adjustment

3.1.8 Regional Distribution Characteristics of HERAE

As shown in Table 5, significant changes in regional HERAE values were observed in the third stage. TE and SE declined across all regions after adjustment, except for a slight increase in TE in the Eastern and Central regions. This suggests that, once external environmental factors and random disturbances were accounted for, HERAE was negatively impacted, leading to an overall decline in efficiency. However, the increase in PTE in the Northeast, Central, and Western regions indicates that, after adjustment, the level of educational technology in these areas improved. By the third stage, TE in the Central region (0.689) surpassed that of the Northeast (0.486) and Western (0.368) regions, suggesting that TE in the Western region was previously overestimated, while the Central region demonstrated relatively high true efficiency. The Eastern region maintained the highest TE, both before (0.712) and after (0.739) adjustment, underscoring its advantages in resource allocation and technological capabilities. The Northeast region exhibited the lowest PTE, increasing from 0.507 pre-adjustment to 0.585 post-adjustment, yet remaining lower than other regions. This indicates a need for technological advancements in the Northeast to enhance resource utilisation efficiency. Meanwhile, the Western region recorded the lowest SE, declining sharply from 0.836 to 0.407 after adjustment. This highlights the necessity for optimising higher education resource utilisation, improving operational models, and establishing a more balanced supply structure within the higher education system in the Western region.

Table 5
HERAE in Our Country by Region

Area	First Stage			Third Stage		
	TE	PTE	SE	TE	PTE	SE
Northeast Region	0.493	0.507	0.970	0.486	0.585	0.860
Eastern Region	0.712	0.790	0.897	0.739	0.910	0.817
Central Region	0.676	0.747	0.914	0.689	0.832	0.838
Western Region	0.711	0.992	0.836	0.368	0.907	0.407

3.2 Moran Index Model Results

3.2.1 Global Moran Index Model Results

Building on the preceding analysis of HERAE in China, there is a possibility of spatial correlation among different regions. Thus, examining the spatial distribution of efficiency is crucial for understanding the internal dynamics of HERAE from a broader spatial perspective. The corresponding results are presented in Table 6. According to Table 6, the HERAE global Moran index was greater than 0 from 2015 to 2021, passing significance tests at the 5% level, indicating positive spatial correlation and strong agglomeration. However, in 2022, the Moran index dropped to -0.038 with a P-value of 0.475, failing the significance test and suggesting weak or even negative spatial correlation. This shift may be linked to the COVID-19 pandemic, which disrupted university operations, caused financial strain, and hindered resource allocation, weakening spatial ties. The highest Moran index was in 2015 (0.414), showing the strongest spatial correlation, while 2019 (0.160) and 2020 (0.200) saw weaker but still significant correlations. Overall, HERAE exhibited positive spatial significance from 2015 to 2021, but the trend shifted notably in 2022. Moving forward, promoting regional coordination and enhancing HERA resilience is crucial to address external challenges. Further research into the causes of these spatial changes is needed to optimise HERA effectively.

Table 6
Global Moran Index Results

Year	Global Moran's *I*	Z	P
2015	0.414***	3.796	0.001
2016	0.275***	2.584	0.007
2017	0.315***	2.951	0.002
2018	0.311***	2.828	0.003
2019	0.160**	1.715	0.042
2020	0.200**	2.114	0.019
2021	0.301***	2.747	0.003
2022	-0.038	0.014	0.475

3.2.2 Local Moran Index Model Results

The Global Moran's Index indicates the overall spatial clustering characteristics of HERAE in China but does not capture the spatial interconnections between provinces. To address this, the study utilised the Local Moran's I index to examine provincial-level spatial relationships. Since the Global Moran's Index for 2022 was not statistically significant, LISA cluster analysis was not conducted for that year. Consequently, the selected years for analysis were 2015, 2017, 2019, and 2021. The LISA clustering diagram illustrating local spatial autocorrelation is presented in Figure 6.

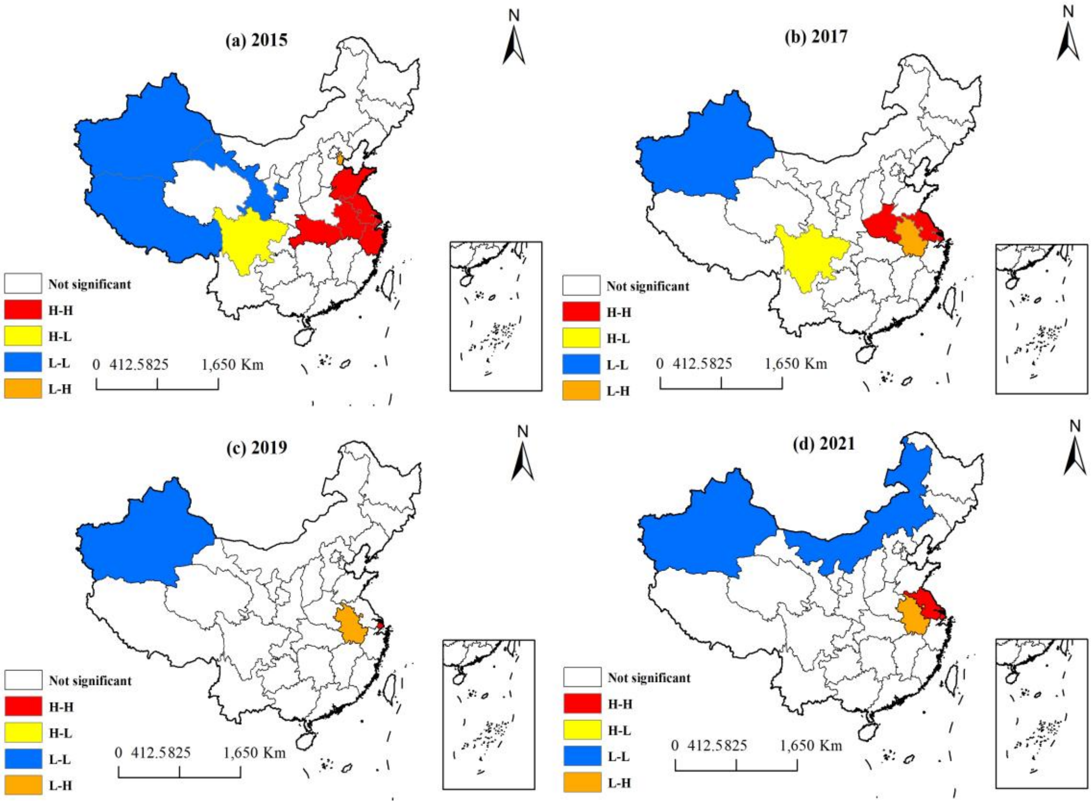

Fig.6. LISA Cluster Diagram

The local autocorrelation of HERAE in China primarily featured H-H and L-L agglomerations, though local autocorrelation was generally weak, as shown in Figure 6. Between 2015 and 2021, the number of provinces with spatial agglomeration fluctuated, with 11, 6, 3, and 5 provinces showing agglomeration in 2015, 2017, 2019, and 2021, respectively. Only 20% of provinces exhibited LISA spatial agglomeration annually. H-H agglomerations were concentrated in eastern coastal provinces like Shandong, Jiangsu, Shanghai, Zhejiang, Anhui, and Hubei, reflecting strong positive spatial autocorrelation due to their developed economies and abundant educational resources. Jiangsu and Shanghai consistently appeared in H-H agglomerations, highlighting their sustained HERA advantages. Sichuan was the only province with H-L agglomeration in 2015 and 2017, indicating better resource allocation than its neighbours but still room for improvement.

Western regions, including Xinjiang, Tibet, Gansu, and Inner Mongolia, were primarily L-L agglomerations, reflecting low HERAE and negative spatial autocorrelation due to resource scarcity. Xinjiang remained in L-L agglomeration for years, indicating a long-term issue, while Inner Mongolia joined in 2021. Tianjin showed L-H agglomeration in 2015, suggesting poorer resource allocation compared to neighbours but with some foundation. Anhui consistently displayed L-H agglomeration from 2017 to 2021, indicating lower efficiency but comparative advantages over neighbouring provinces. Overall, the eastern regions demonstrate strong HERAE, while the western regions lag, underscoring the need for improved resource allocation and efficiency in these areas.

4. Conclusions and Suggestions

4.1 Conclusions

The study establishes a scientifically sound index system and employs a three-stage DEA model and Moran index model to evaluate HERAE across 31 Chinese provinces from 2015 to 2022. Key findings include:

1. Unadjusted HERAE Trends: From 2015 to 2022, China's HERAE fluctuated, with some provinces achieving efficiency without accounting for external factors.

2. Impact of External Factors: After adjusting for environmental and random influences, factors like regional economic conditions, government financial support, and social development significantly affect input variables. This highlights the need for improved management, resource allocation, and standardized development by both governments and universities to enhance HERAE.

3. Regional Efficiency Disparities: In the third stage, the Eastern region has the highest average TE for higher education systems, surpassing the Northeast, Central, and Western regions. The Central region slightly outperforms the Northeast and Western regions. The Northeast has the lowest PTE mean, while the Western region has the lowest SE mean.

4. Spatial Imbalance: HERAE's spatial distribution is uneven, with the Eastern region showing H-H agglomeration (high efficiency clusters) and the Western region exhibiting L-L agglomeration (low efficiency clusters), reflecting significant regional disparities.

These findings underscore the need for targeted policies to address regional imbalances and improve HERAE, particularly in the Northeast and Western regions.

4.2 Suggestions

Although higher education serves as a cornerstone for fostering an innovative nation, fluctuations in the efficiency of educational resource allocation are to be expected. However, the pronounced regional disparities in efficiency necessitate urgent attention.

1. Optimising Resource Allocation

The government should allocate educational resources in alignment with the economic development levels and educational needs of different regions. In economically disadvantaged areas, increased investment is essential to promote a more equitable distribution of resources. For provinces demonstrating substantial efficiency improvements, their successful education reform strategies should be systematically evaluated and applied on a broader scale. Conversely, provinces with limited efficiency gains must conduct in-depth analyses of their challenges and implement targeted reforms.

2. Leveraging Advanced Technologies

Higher education institutions should be encouraged to integrate big data, AI, and advanced digital technologies into their management systems. These tools can facilitate modern education governance and enhance the precision and efficiency of resource allocation.

3. Enhancing Regional Collaboration

Strengthening the exchange and collaboration of educational resources between the Eastern and Western regions is crucial. This can be achieved by establishing trans-regional cooperation initiatives, promoting resource-sharing mechanisms, and fostering mutual learning to advance educational equity. For low-efficiency cluster areas, particularly in the western region, further policy support and resource investment are necessary to improve local HERA. Financial support and faculty development for universities in western China should be expanded. Furthermore, inter-university collaboration should be promoted through resource-sharing initiatives and strategic partnerships that leverage complementary strengths. These measures will contribute to the sustainable development of higher education, laying a strong foundation for educational modernisation and the establishment of a globally competitive education system.

Data Availability Statement

The data that underpinned the conclusions of this study are available upon request from the corresponding author.

Conflicts of Interest

The author posits that he possesses no conflicts of interest.

Acknowledgment

This research was funded by Henan Province Soft Science Research Project (No. 232400410354).

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