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Measurement of the New Quality Productive Forces of Computing Power in Chinese Provincial Regions

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ABSTRACT

Computing power has become essential infrastructure for the digital economy and the digital transformation of industries. This study develops an evaluation index system for computing-power-related new quality productive forces from three dimensions: factor productivity, technological productivity, and industrial productivity. The CRITIC method is employed to determine the objective weights of the indicators, while the TOPSIS method is used to measure the development level of computing-power-related new quality productive forces across 31 provincial-level regions in China from 2021 to 2023. Global Moran's I is further applied to examine their spatial correlation. The results indicate that the overall development level increased during the study period, although substantial disparities remained among provinces. Guangdong, Beijing, Zhejiang, Jiangsu, Shanghai, and Shandong were among the leading regions. Development across the three dimensions was unbalanced, with industrial productivity remaining relatively weak. In addition, provincial computing-power-related new quality productive forces exhibited significant positive spatial autocorrelation. Based on these findings, this study recommends optimizing the spatial layout of computing infrastructure, strengthening technological innovation and data utilization, promoting the industrial application of computing resources, and enhancing interregional cooperation.

KEYWORDS

Computing power; New quality productive forces; CRITIC-TOPSIS; Spatial correlation

1. INTRODUCTION

With the rapid advancement of artificial intelligence and other digital technologies, computing power has gradually expanded from the internet sector into transportation, manufacturing, and other industries. As demand for computing resources continues to rise, computing power has become an important foundation for high-quality development in the digital era and a significant indicator of the digital competitiveness of countries and regions. At the same time, the rapid expansion of computing demand has raised concerns regarding electricity consumption and indirect greenhouse gas emissions [1–2]. Data centers currently account for approximately 1%–2% of global electricity consumption, and this share is expected to increase substantially by 2030 [3]. The energy-intensive nature of computing infrastructure therefore presents new challenges for achieving China's carbon peaking and carbon neutrality goals.

The development of computing power is closely related to infrastructure construction, technological progress, data utilization, and industrial applications. Computing resources provide fundamental support for the digital economy, while data circulation, technological innovation, and the expansion

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of application scenarios determine how effectively computing capacity can be transformed into economic and industrial value [4]. Although existing studies have examined computing infrastructure, energy consumption, and green transformation, relatively limited attention has been paid to the systematic measurement of computing-power-related new quality productive forces at the provincial level.

New quality productive forces represent a new form of productivity driven primarily by technological progress and characterized by the transformation and upgrading of traditional industries. Existing studies have investigated new quality productive forces in the fields of energy, agriculture, enterprises, and regional development [5]. The accurate measurement of their development level requires a well-designed indicator system and an appropriate evaluation method.

In terms of indicator construction, previous studies have developed multidimensional evaluation systems based on factors such as human resources, scientific and technological innovation, industrial development, and production methods. For example, Zhao et al. [6] constructed a comprehensive index system based on new-quality human resources, new-quality science and technology, new-quality industries, and new-quality production methods to measure the development of new quality productive forces across Chinese provinces. Chen et al. [7] divided new quality productive forces into factor productivity, technological productivity, and industrial productivity, highlighting the importance of transforming technological achievements into industrial outcomes.

In terms of evaluation methods, existing comprehensive evaluation studies mainly focus on indicator weighting, model selection, and data preprocessing. Common weighting methods include subjective weighting, objective weighting, and combined weighting approaches [8-10]. For the measurement of computing-power-related new quality productive forces, an objective weighting method that captures both indicator variability and information independence can provide a more reliable basis for comparing provincial development levels.

In summary, computing-power-related new quality productive forces have become an important component of regional digital development. However, a systematic evaluation framework that integrates computing infrastructure, technological capacity, and industrial applications remains underdeveloped. To address this gap, this study constructs an evaluation index system from the perspectives of factor productivity, technological productivity, and industrial productivity. The CRITIC-TOPSIS model is then employed to measure the development level of computing-power-related new quality productive forces across 31 Chinese provinces from 2021 to 2023. Finally, global Moran's I is used to examine their spatial correlation. The main contributions of this study are as follows. First, an evaluation index system for computing-power-related new quality productive forces is developed from the three dimensions of factor, technological, and industrial productivity. Second, the CRITIC-TOPSIS method is applied to measure and compare provincial development levels. Third, the spatial correlation characteristics of computing-power-related new quality productive forces are examined.

2. CONSTRUCTION OF THE EVALUATION INDEX SYSTEM

Following the underlying logic of new quality productive forces, namely, the innovative allocation of production factors, technological breakthroughs, and deep industrial transformation, this study constructs an evaluation index system from three dimensions: factor productivity, technological productivity, and industrial productivity. Factor productivity reflects the basic resources and infrastructure required for computing development. Technological productivity captures data utilization, digital governance, and technological innovation. Industrial productivity measures the application of computing resources and the transformation of technological achievements into industrial value.

2.1. Evaluation Index System for Computing-Power-Related New Quality Productive Forces

The development of computing power depends on computing capacity, storage capacity, network transmission capacity, and other forms of digital infrastructure. It is also closely associated with data circulation, technological innovation, and industrial applications. Accordingly, this study constructs an evaluation index system from three dimensions.

The factor productivity dimension measures the infrastructure and resource base supporting computing development. The technological productivity dimension reflects the utilization of data elements, digital governance capacity, and innovation performance. The industrial productivity dimension captures the level of digital application and the transformation of computing-related achievements into industrial development. The specific indicators are presented in Table 1.

Table 1. Evaluation index system for computing-power-related new quality productive forces

Target	criteria	Indicator	Code
Computing Power New Quality Productive Forces	Factor Productivity	Optical Cable Line Length	C11
		Storage Capacity Scale	C12
		Computing Power Scale	C13
		Computing Facility Density	C14
	Technology Productivity	Rack Utilization Rate	C21
		Data Openness Forest Index	C22
		Digital Government Development Index	C23
		Market Environment	C24
	Industrial Productivity	Digitalization Level	C31
		Future Industry Level	C32
		E-commerce Sales	C33
		Strategic Emerging Industry Structure	C34

3. EVALUATION METHODOLOGY

3.1. Comprehensive Evaluation Model

3.1.1. CRITIC Method

The CRITIC method, or, determines objective indicator weights based on the statistical characteristics of the data. It considers both the contrast intensity and the conflict between indicators.

Contrast intensity is generally measured by the standard deviation of an indicator. A larger standard deviation indicates greater differences among the evaluated regions and therefore more information provided by the indicator. Conflict is assessed using the correlation coefficients between indicators. When an indicator has a lower correlation with other indicators, the information it provides is considered more independent. By incorporating both dimensions, the CRITIC method can reduce the subjectivity associated with traditional weighting procedures.

The CRITIC (Criteria Importance Through Intercriteria Correlation) method determines objective weights by considering both the variation of each indicator and its correlation with other indicators. Let n denote the number of evaluated regions and m the number of indicators. The original data matrix is:

$$X = (x_{ij})_{n\times m} \tag{1}$$

Where x_{ij} is the value of indicator j for region i. To eliminate differences in measurement units, positive indicators are normalized as follows:

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

For negative indicators, normalization is performed using:

$$z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{3}$$

Where z_{ij} is the normalized value of indicator; $\max(x_j)$ and $\min(x_j)$ are its maximum and minimum values among the evaluated regions.

The contrast intensity of indicator j is measured by its standard deviation:

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(z_{ij} - \bar{z}_j)^2} \tag{4}$$

Here, $\bar{z}_j$ is the mean normalized value of indicator j. Let r_{jk} denote the correlation coefficient between indicators j and k. The information content of indicator j is calculated as:

$$C_j = \sigma_j \sum_{k=1}^{m}(1 - r_{jk}) \tag{5}$$

A larger C_j indicates that the indicator provides more distinguishing information. Its objective weight is:

$$w_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{6}$$

3.1.2. TOPSIS Method

After obtaining the objective weights, the TOPSIS method is applied to evaluate the development level of computing-power-related new quality productive forces across 31 provincial-level regions in China.

TOPSIS ranks evaluation objects according to their relative closeness to the positive and negative ideal solutions. Specifically, the optimal alternative should be as close as possible to the positive ideal solution and as far as possible from the negative ideal solution. This approach allows the relative performance of different provinces to be assessed using a unified framework.

Suppose an evaluation problem has n criteria $X_j(j = 1,2,\cdots,n)$ and m alternatives, and let the ideal solution—after normalizing and weighting the attribute values—be A^+, where $A^+ = (z_1^+, z_2^+, \cdots z_n^+)^T$. Using Euclidean distance for measurement, the distance between the normalized attribute values $A_i(i = 1,2,\cdots,m)$ of any alternative and the ideal solution A^+ is:

$$S_i^+ = \sqrt{\sum_{j=1}^{m}(z_{ij} - z_j^+)}, i = 1,2,\cdots,m \tag{7}$$

Where z_{ij} is the normalized weighted value of the i alternative relative to the j criterion.

Similarly, the distance between any solution and the negative ideal solution can be defined as A^-, where $A^- = (z_1^-, z_2^-, \cdots z_n^-)^T$, so that:

$$S_i^- = \sqrt{\sum_{j=1}^{m} (z_{ij} - z_j^-)}, i = 1, 2, \cdots, m \tag{8}$$

The relative proximity of a solution's A_i to the ideal solution A^+ is:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \cdots, m \tag{9}$$

3.2. Moran's I

Moran's I is used to measure the spatial correlation of regional data. It includes global Moran's I and local Moran's I. Global Moran's I reflects the overall spatial clustering pattern of observations across the entire study area.

When global Moran's I is greater than zero, regions with similar values tend to be spatially adjacent, indicating positive spatial autocorrelation. A value below zero indicates negative spatial autocorrelation, meaning that regions with relatively high and low values tend to be adjacent. When Moran's I is close to zero, the spatial distribution is approximately random and spatial dependence is weak.

3.3. Data Sources

Considering the consistency of provincial administrative units and the availability of relevant computing-power statistics, this study uses panel data from 31 provincial-level regions in China, excluding Hong Kong, Macao, and Taiwan, for the period from 2021 to 2023. The data are collected from the China Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, provincial statistical yearbooks, and other publicly available statistical sources. A small number of missing observations are filled using linear interpolation.

4. RESULTS AND DISCUSSION

4.1. Indicator Weighting Results

Figure 1 presents the weights of the indicators used to evaluate computing-power-related new quality productive forces. The weighting results provide a basis for identifying the relative strengths and weaknesses of regional computing development. Improving computing-power-related new quality productive forces requires not only the expansion of infrastructure and resource capacity but also improvements in data utilization, technological innovation, and industrial application. The effective integration of these aspects is essential for transforming computing resources into practical economic and industrial outcomes.

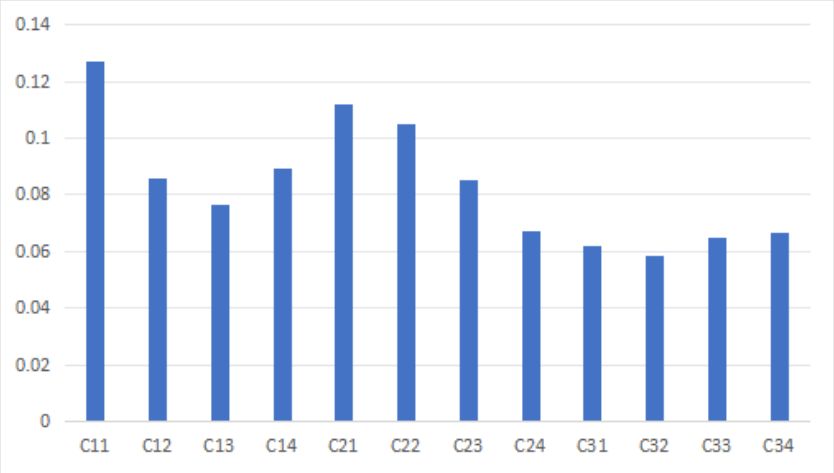


Figure 1. Indicator weights of computing-power-related new quality productive forces

4.2. Measurement Results

Based on the indicator weights, the TOPSIS method is applied to calculate the comprehensive development level of computing-power-related new quality productive forces across Chinese provinces. The results are shown in Figure 2.

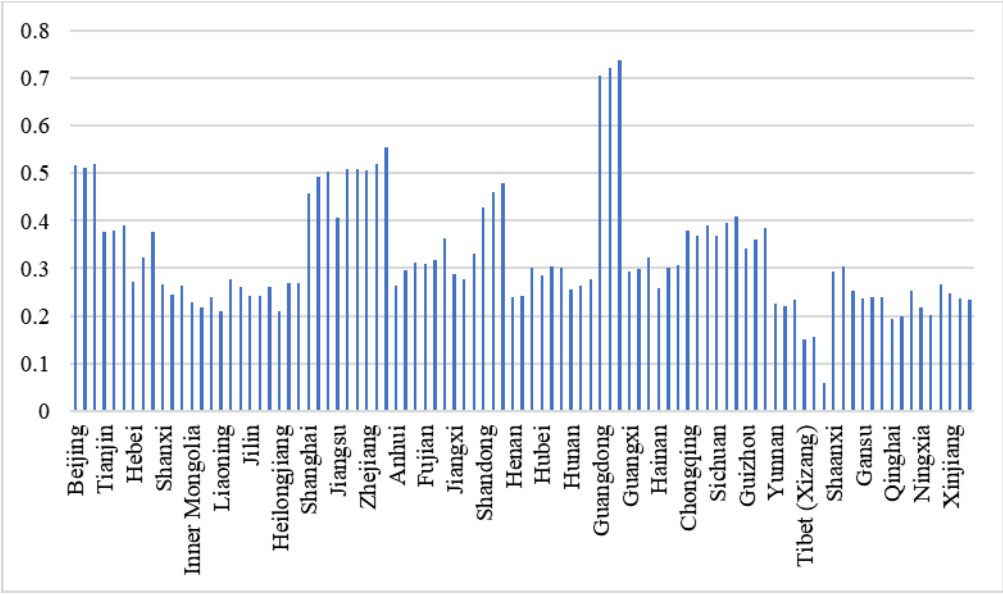


Figure 2. Development level of computing-power-related new quality productive forces

Figure 2 illustrates the development levels of computing-power-related new quality productive forces across Chinese provinces. Considerable regional disparities can be observed. Guangdong, Beijing, Zhejiang, Jiangsu, Shanghai, and Shandong rank among the leading regions. The performance of individual provinces varies across factor productivity, technological productivity, and industrial productivity, indicating that the development of computing power depends not only on infrastructure construction but also on data utilization, technological innovation, and industrial transformation capacity.

The three-dimensional evaluation framework helps each region identify its development advantages and weaknesses. In particular, the transformation of computing resources into industrial applications remains an important area for improvement in many provinces.

4.3. Spatial Correlation

Based on the comprehensive evaluation results for each province, this study introduces an economic-geographical nested matrix and applies global Moran's I to examine the spatial correlation of computing-power-related new quality productive forces. The results are reported in Table 2.

Table 2. Global Moran's I test results

Time	Computing-Power New Quality Productive Forces
2021	0.104***
2022	0.109***
2023	0.103**

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The results in Table 2 show that global Moran's I remained positive and statistically significant from 2021 to 2023. This finding indicates that computing-power-related new quality productive forces exhibited significant positive spatial autocorrelation across Chinese provinces. In other words, provinces with similar development levels tended to be geographically clustered.

Therefore, improving local computing capacity should be accompanied by greater attention to cross-regional resource allocation, technological exchange, and industrial cooperation. Regions with relatively advanced computing development can play a stronger role in supporting and stimulating the development of regions with comparatively weaker capacity.

5. CONCLUSION

Using panel data from 31 Chinese provinces from 2021 to 2023, this study constructs an evaluation index system for computing-power-related new quality productive forces. The CRITIC-TOPSIS model is employed to measure provincial development levels, and global Moran's I is used to examine their spatial correlation. The main conclusions are as follows.

(1) The overall level of computing-power-related new quality productive forces increased during the study period. Nevertheless, substantial differences remained among provinces, with Guangdong, Beijing, Zhejiang, Jiangsu, Shanghai, and Shandong exhibiting relatively high development levels.

(2) Development across factor productivity, technological productivity, and industrial productivity was uneven. Industrial productivity was comparatively weak, indicating that the transformation of computing resources into industrial applications and economic outcomes still requires improvement.

(3) Computing-power-related new quality productive forces showed significant positive spatial autocorrelation across Chinese provinces. This suggests that provincial development is not independent and that spatial spillovers and regional clustering may exist.

Based on these findings, the following policy recommendations are proposed.

(1) The spatial layout of computing infrastructure should be optimized. Infrastructure planning should take into account regional resource endowments, industrial demand, and existing development conditions in order to improve utilization efficiency and avoid redundant construction.

(2) Technological innovation and the utilization of data elements should be strengthened. Improvements are needed in data circulation, data governance, and application mechanisms so that infrastructure, technological capabilities, and market demand can be more effectively connected.

(3) The integration of computing power with the real economy should be promoted. More application scenarios should be developed in manufacturing, transportation, finance, public services, and other sectors to enhance the industrial conversion of computing resources. At the same time, interregional

cooperation and resource sharing should be strengthened, allowing regions with more advanced computing capabilities to support provinces with relatively weaker development foundations.

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REFERENCES

[1] Wang, Y., Lin, J., Han, Y., et al. (2025). Comprehensive evaluation of all-element flexibility resources in data centers: considering synergistic benefits of computing, electricity, and heat. Applied Energy, 399, 126442.

[2] Alnori, A., Djemame, K., & Alsenani, Y. (2024). Agnostic energy consumption models for heterogeneous GPUs in cloud computing. Applied Sciences, 14(6), 2385. https://doi.org/10.3390/app14062385

[3] Zhou, Y., Wei, F., Li, S., et al. (2025). Data center load modeling through optimal energy consumption characteristics: A path to simultaneously enhance energy efficiency and demand response quality. Applied Energy, 393, 126095.

[4] Lee, C., Fang, Y., Quan, S., et al. (2024). Leveraging the power of artificial intelligence toward the energy transition: The key role of the digital economy. Energy Economics, 135, 107654.

[5] Yuan, B., Gu, R., Wang, P., et al. (2025). How does new quality productive forces affect green total factor energy efficiency in China? Consider the threshold effect of artificial intelligence. Sustainability, 17(15), 7012.

[6] Zhao, H., Li, C., Yang, Z., et al. (2025). How can new quality productivity decrease carbon emission intensity? Evidence from 30 provincial regions in China. Energy, 136487.

[7] Chen, H., Niu, D., & Gao, Y. (2025). Research on the impact of energy transition policies on green total factor productivity of Chinese high-energy-consuming enterprises. Energy, 319, 135066. https://doi.org/10.1016/j.energy.2025.135066

[8] Yang, L., Tianwei, M., & Fang, T. (2025). Research on the influence mechanism of digital transformation on the development of new quality productive forces in manufacturing enterprises–Based on the spatial perspective. SAGE Open, 15(4), 21582440251377433.

[9] Wu, H., Yang, H., & Yan, J. (2025). Level measurement, regional difference decomposition and dynamic evolution of China's agricultural new quality productive forces. Journal of Nonlinear and Convex Analysis, 26(6), 1887–1898.

[10] Li, W., Dong, F., & Ji, Z. (2021). Research on coordination level and influencing factors spatial heterogeneity of China's urban CO2 emissions. Sustainable Cities and Society, 75, 103323.