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The coupling coordination of energy technology and energy allocation efficiency in China: Based on efficiency decomposition modeling

Junjie Zhen[1] · **Yubao Wang**[1,2] · **Huiyuan Pan**[1]

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Abstract

Improving energy efficiency is essential for promoting a more sustainable and resource-efficient economic model. Energy technology and allocation efficiency are critical factors influencing regional energy performance, while the theory of synergistic development provides a novel perspective for advancing energy efficiency. The paper develops a model to decompose energy efficiency and applies a coupled coordination degree (CCD) framework to examine the interaction between technological progress and energy resource allocation across China from 2000 to 2022. The findings reveal that (1) most Chinese provinces maintained a moderate level of coordination in the CCD between energy technology and energy allocation efficiency, while only a few achieved high coordination. (2) Spatial analysis highlights significant regional disparities, largely attributed to the uneven spatial distribution of allocation efficiency. (3) Convergence testing confirms the presence of both σ and β-convergence, suggesting a narrowing of regional gaps in coordination over time. (4) Over time, the primary driver of coupled coordination has shifted from green finance to industrial structure. Interaction analysis indicates that multiple driving forces now collectively foster integrated improvements in energy efficiency. The study concludes by emphasizing the importance of synergistic development in advancing energy performance and proposes policy measures in three areas: the establishment of coordination mechanisms, tailored regional governance, and the refinement of market-based systems.

Keywords Energy technology · Energy allocation efficiency · Energy efficiency · Coupled coordination model · Driver analysis

✉ Junjie Zhen
zhenjunjie@stu.xjtu.edu.cn

[1] School of Economics and Finance, Xi'an Jiaotong University, Xi'an 710061, People's Republic of China

[2] School of Economics and Management, Xinjiang University, Urumqi 830046, People's Republic of China

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1 Introduction

Amid intensifying climate change and persistent global energy challenges, energy efficiency has become a cornerstone of national energy strategies and sustainable development (Gatto, 2023). More and more countries, cities, businesses, and groups have promised to reach net-zero emissions. More than 140 countries, including big polluters like the India, the European Union, and China, have set goals to reach net-zero emissions (Teng & Shen, 2023). Energy transition and sustainable development are pivotal to future economic growth. China, as the biggest producer of carbon pollution in the world, understands that improving energy use and reducing emissions are very important for achieving sustainable growth. Consequently, boosting energy efficiency has become a core goal of China's energy transition strategy aimed at reducing greenhouse gas emissions.

As a developing country, China lags in the development of a modern energy system, facing high overall energy demand and considerable pressure for structural transformation. Empirical evidence from clean energy transitions indicates that enhancing energy efficiency is a practical and effective pathway toward greening the energy structure (Du et al., 2025b). China's efforts in this regard have been both sustained and proactive. Therefore, China's path toward improving energy efficiency offers valuable insights for other countries, particularly developing nations.

Theoretical investigations into energy efficiency primarily concentrate on two core dimensions: energy technology and energy allocation efficiency (Di et al., 2024; Hsieh & Klenow, 2009). Energy technology refers to improvements resulting from advancements in conventional energy production and conversion technologies, as well as breakthroughs in renewable energy. Energy allocation efficiency assesses the optimal distribution of energy resources across sectors to minimize costs and maximize output. According to classical production function theory, improvements in energy efficiency can be attributed to both technological progress and optimized resource allocation (Hsieh & Klenow, 2009; Wimmer & Finger, 2025). Technological progress enhances energy output efficiency by improving production methods and equipment performance. In contrast, resource allocation efficiency indirectly contributes to energy efficiency by optimizing energy use and reducing waste (Hsieh & Klenow, 2009; Jiang et al., 2023). Therefore, at the theoretical level, energy technology and allocation efficiency are interdependent and together determine regional energy efficiency.

Existing literature on the impact of energy technology and allocation efficiency on overall energy performance can generally be divided into the following categories. First, a substantial body of research highlights the pivotal role of energy technology in improving energy efficiency (Naeem et al., 2023; Wang et al., 2024). Technological progress, especially in renewable energy, are essential for improving energy efficiency. Globally, improvements in energy technology can be achieved through multiple approaches, including enhancing conversion efficiency, adopting advanced technologies, and optimizing production processes and management practices. Second, through market mechanisms or policy interventions, energy prices can more accurately reflect their marginal and environmental costs, thereby guiding businesses and consumers toward more efficient energy decisions (Chen et al., 2023). Furthermore, optimizing energy allocation enables more effective utilization of limited resources, supporting economic development while minimizing environmental impacts.

Prior studies have primarily examined the individual effects of either energy technology or energy allocation efficiency on overall energy performance, while paying limited attention to their integrated development (Dhayal et al., 2024a; Guang et al., 2023; Xu & Tan, 2021). While both energy technology and allocation efficiency are critical drivers of energy efficiency, their synergy across regions is crucial to fostering balanced regional development (Wu et al., 2022; Yin & Xu, 2022). Overall, existing research has largely overlooked the role of coordinated development between energy technology and allocation efficiency in enhancing energy efficiency, especially in terms of regional disparities and its influence on balanced growth. The main contributions of this study are summarized as follows:

(1) This research constructs a conceptual model that combines the interactive dynamics between energy technology and allocation efficiency, grounded in an efficiency decomposition approach, thereby filling a critical void in regional studies on energy performance. The study applies a productivity discretization approach to decompose energy efficiency, overcoming the limitations of conventional studies that often consider only one dimension. It highlights the coordinated advancement of both energy technology and energy allocation efficiency.
(2) This study highlights the heterogeneous impact of spatial factors. Adopting a spatial analytical lens, the study investigates the convergence patterns of integrated energy technology and allocation efficiency, employing the geographical detector method to uncover underlying determinants within the Chinese context. The findings provide new empirical evidence to inform global energy development.
(3) This study broadens the analytical focus concerning determinants of the joint advancement of energy technology and allocation efficiency. It investigates both the key drivers specific to China and the interactive effects of multiple influencing variables. Accordingly, this study contributes to the existing literature by adopting a multifactor-driven perspective that more accurately captures the complexity and uncertainty characterizing contemporary energy development.

The structure of the paper is organized as follows: Sect. 2 provides a review of the pertinent literature; Sect. 3 describes the research methods and data sources; Sect. 4 presents the empirical results and analysis; Sect. 5 explores the policy implications; and Sect. 6 offers concluding remarks.

2 Literature review

This section systematically reviews the decomposition of energy efficiency measures, along with related studies on energy technology and energy allocation efficiency. The review is presented below.

2.1 Measurement and decomposition of energy efficiency

Energy efficiency is a central concern in both energy economics and sustainable development, with measurement methods remaining a core topic in related research. According to microeconomic theory, energy efficiency is defined as the ratio of the theoretically minimum energy consumption to the actual energy usage of an economic entity (Huntington, 1994). Researchers typically employ three main approaches to measure energy efficiency: (i) the proportional share method, (ii) parametric methods, and (iii) non-parametric methods (Chang et al., 2015; Du et al., 2025a; Mohsin et al., 2021; Song et al., 2023).

The proportional share approach assesses energy efficiency by analyzing the correlation between energy use and economic output across various regions or time frames. As a commonly adopted and intuitive approach, it defines energy efficiency as the economic or social output generated per unit of energy input. For example, a country's or industry's energy efficiency is often represented by the GDP-to-energy-consumption ratio (Du et al., 2025a). This method has been extensively employed in earlier research, especially for cross-national comparisons of energy performance. Its fundamental advantage lies in the direct quantification of input–output relationships, which enhances both transparency and interpretability.

Aigner et al. (1977) initially proposed a parametric estimation model to integrate multiple influencing factors and improve the precision of energy efficiency assessments. Stochastic frontier analysis (SFA) estimates production efficiency by constructing a stochastic production function that accounts for inputs, outputs, random errors, and inefficiency components. This approach allows researchers to assess the relative efficiency of production units operating below the optimal frontier and to measure energy efficiency by isolating inefficiency from regression residuals. Filippini and Zhang (2016) applied the parametric estimation model to decompose residuals into time-varying, time-invariant, and unit-specific components of energy efficiency.

However, many scholars have noted that parametric estimation models fail to accurately decompose residuals, which limits their practical applicability (Lundgren et al., 2016). Non-parametric models primarily use data envelopment analysis (DEA) to evaluate energy efficiency. The DEA method evaluates energy efficiency by constructing an input-oriented model that applies linear programming to identify the most efficient production frontier without assuming a specific production function.

Another critical dimension of energy efficiency research involves its decomposition into two primary components: (i) energy technology and (ii) energy allocation efficiency (Da-Rocha et al., 2023; Hsieh & Klenow, 2009). Advances in energy technology represent a fundamental driver of energy efficiency. By minimizing the energy required to produce each unit of output, innovation directly contributes to improved efficiency. From the perspective of production function theory, technological advancement typically enables higher output levels without a corresponding increase in energy input. In contrast, energy allocation efficiency concerns the optimal mix of energy with other production factors to maximize output (Hsieh & Klenow, 2009; Wimmer & Finger, 2025).

In contrast to energy technologies, energy distribution efficiency focuses on optimizing the allocation of energy resources to ensure fair and rational distribution among sectors, regions, and users. Distribution efficiency directly impacts the effectiveness of energy resource use and, to some extent, determines whether energy use maximizes social welfare (Singhal & Hobbs, 2023). The energy efficiency decomposition model mainly targets the measurement of energy allocation efficiency, which can be evaluated through three methods: the HK method, the productivity discretization method, and the OP covariance method. The HK method assumes that, absent distortions in energy factors, the marginal returns of energy resources should be equalized across firms (Bartelsman & Doms, 2000; Hsieh & Klenow, 2009; Olley & Pakes, 1996). The productivity discretization method proposes that, without distortions in resource allocation, energy efficiency should be consistent across regions, with more efficient regions outcompeting less efficient ones. The OP covariance method emphasizes the alignment of energy efficiency with regional segmentation; otherwise, further adjustments may be necessary.

2.2 Energy technology and energy allocation efficiency

Advances in energy technology constitute a key driver of energy efficiency, substantially contributing via knowledge spillovers (Chhabra et al., 2023; Shen et al., 2022). Energy technology advances encompass new energy development, conventional energy transformation, and energy transmission and distribution (Ahmad et al., 2022; Shao et al., 2021). Breakthroughs in renewable energy technologies, including solar, wind, and hydro, have diversified the energy structure. Technological advances in conventional energy are equally significant. Innovations in energy transmission and distribution are essential for enhancing regional energy efficiency. The development of smart grids has enhanced the efficiency, stability, and security of power transmission. Smart grids reduce energy losses during transmission and enhance power utilization efficiency through real-time monitoring and grid adjustments (Abdmouleh et al., 2018). Furthermore, the adoption of distributed energy systems enhances flexibility and reliability in energy supply (Zhang et al., 2023).

Energy resource allocation is crucial for enhancing energy efficiency, with numerous studies indicating that optimizing allocation significantly improves energy efficiency (Wei & Zheng, 2020; Yang et al., 2022). According to binary marginal theory, energy allocation efficiency consists of intensive and generalized energy allocation efficiencies (Banerjee & Moll, 2010). Intensive energy allocation efficiency implies that resources flow from energy-efficient to energy-inefficient regions due to regional heterogeneity in energy efficiency. In contrast, generalized energy allocation efficiency suggests that resource allocation is linked to market size, with regions possessing larger markets attracting more resources, thereby enhancing regional energy efficiency (Sun et al., 2020). Studies indicate that energy allocation efficiency significantly influences energy efficiency improvements (Du et al., 2025b; Xu & Tan, 2021). Particularly in developing countries, energy policies—such as energy subsidies and carbon market mechanisms—are frequently formulated to balance energy costs and improve accessibility for low-income groups, thereby contributing to overall social welfare.

In summary, most existing studies concentrate on measuring energy efficiency and analyzing its determinants. Second, the literature largely emphasizes the effects of energy technologies—such as renewables and clean coal utilization—while paying insufficient attention to energy allocation efficiency. Thirdly, existing studies lack a comprehensive examination of both energy technology and energy allocation efficiency, overlooking the critical role of their synergistic development. Therefore, promoting the synergistic development of energy technology and energy allocation efficiency is essential for enhancing energy efficiency. To bridge these research gaps, this paper proposes an integrated analytical framework to assess the coupling and coordination between energy technology and energy allocation efficiency from a synergy perspective, thereby offering novel empirical insights for global energy transitions.

Figure 1 illustrates the research methodology and framework employed in this study.

3 Methods

This section describes the specific models and methods used in this study and details the sample selection as well as data sources for this study.

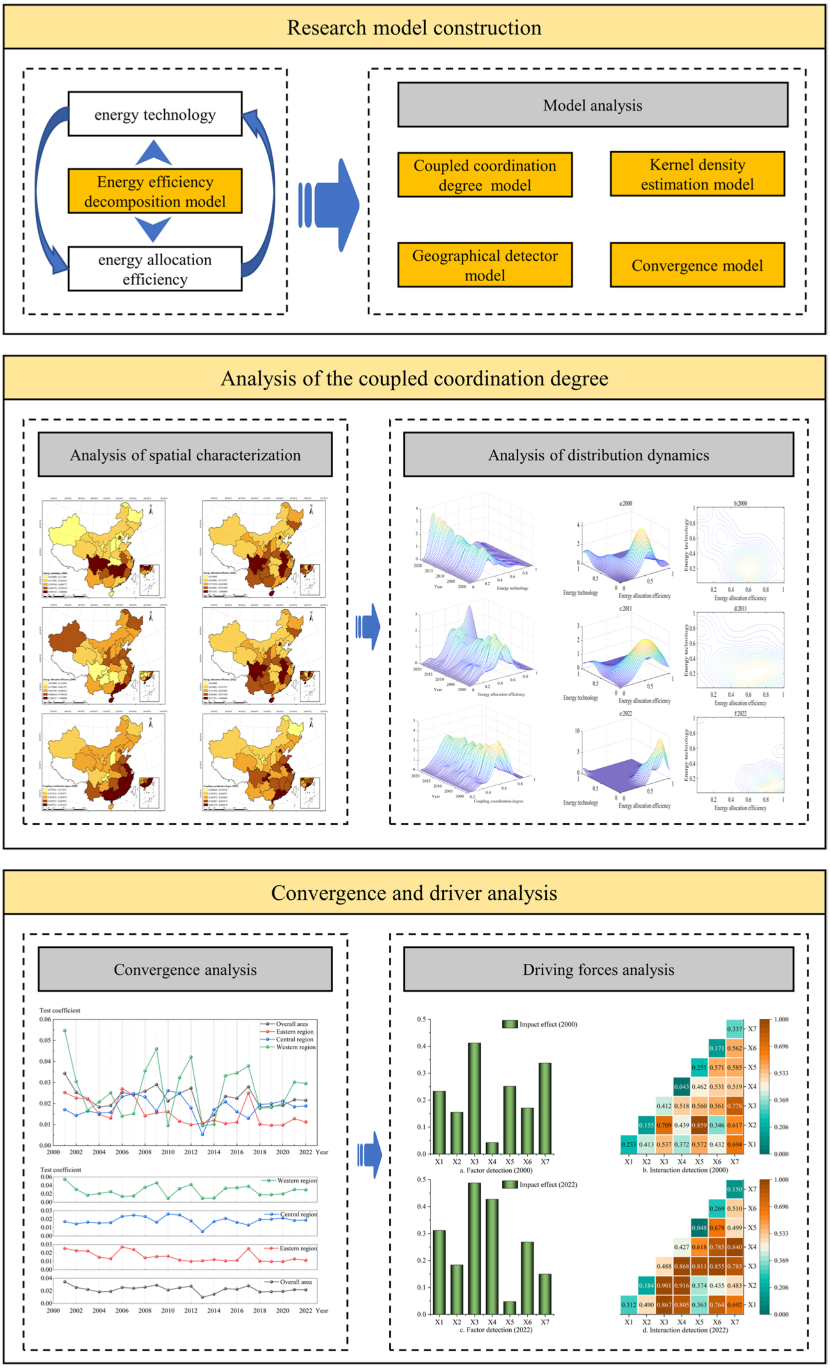


Fig. 1 Research framework and overview

3.1 Measurement and decomposition of energy efficiency

3.1.1 Measurement of energy efficiency

Extensive research has established a robust relationship between energy consumption and regional population dynamics (Okere et al., 2021; Yan et al., 2024). Researchers have demonstrated that nighttime lighting data can provide reliable inverse estimates of regional energy consumption (Liu et al., 2024). In this study, we adopt the method of Chen et al. (2020) to estimate total regional energy consumption using nighttime lighting data.

In this study, energy consumption (E) is defined as the dependent variable within the estimation model, while the aggregated grayscale values of rasterized nighttime lights (DN) serve as the independent variable. The variables were fitted using known provincial-level energy consumption data and three correlation models: exponential, logarithmic, and linear. A comparison of the goodness of fit among the three models shows that the linear correlation model provides the best fit. The results of the comparison between the three fitting models are presented in Appendix A.

$$E_{it} = k_t DN_{it} \tag{1}$$

E_{it} denotes the total energy consumption of province i in year t. DN_{it} refers to the aggregated rasterized nighttime light gray values within province i during the same year. The parameter k_t represents the fitting coefficient for year t. To obtain these values, ArcGIS 10.7 was utilized to compute the total DN for each prefecture-level city in China. Subsequently, the total energy consumption E for each city was estimated indirectly by applying the fitting coefficients derived from Eq. (1).

The energy efficiency (EE) of each prefecture-level municipality is calculated using the energy consumption data, as derived from Eq. (2).

$$EE = \frac{E}{GDP} \tag{2}$$

where E represents the energy consumption of each municipality and GDP denotes the gross domestic product of each municipality.

3.1.2 Decomposition of energy efficiency

This study identifies energy technology progress and energy factor allocation efficiency as the primary drivers of energy efficiency growth (Brandt et al., 2012; Da-Rocha et al., 2023; Hsieh & Klenow, 2009). Referring to Da-Rocha et al. (2023) and Olley and Pakes (1996), this study examines the coupled and coordinated development of energy technology progress and energy factor allocation efficiency by decomposing energy efficiency into these two components, as presented in Eq. (3).

$$EE_i = \sum\nolimits_{c=1}^{n_c} s_{ci} EE_c \tag{3}$$

EE_i indicates the energy efficiency of province i, while EE_c corresponds to the energy efficiency of each prefecture-level city within that province. The variable s_{ci} represents the proportional share of city c in province i, and n_c denotes the total number of cities in province i.

Equation (3) can be further derived as Eq. (4).

$$EE_i = \overline{EE_i} + \sum\nolimits_{c=1}^{n_c} \left(s_{ci} - \overline{s_i}\right)\left(EE_c - \overline{EE_i}\right) = \overline{EE_i} + n_c Cov\left(s_{ci}, EE_c\right) \tag{4}$$

where $\overline{EE_i}$ represents the average energy efficiency of province i and $Cov\left(s_{ci}, EE_c\right)$ denotes the covariance of s_{ci} and EE_c. For simplification, Eq. (4) can be further expressed as Eq. (5).

$$EE_i = \overline{EE_i} + \sum\nolimits_{c=1}^{n_c} s_{ci}\left(EE_c - \overline{EE_i}\right) \tag{5}$$

According to Eq. (5), energy efficiency can be decomposed into two components: energy technology progress and energy allocation efficiency. Where $\overline{EE_i}$ represents the level of energy technology progress, while $\sum\nolimits_{c=1}^{n_c} s_{ci}\left(EE_c - \overline{EE_i}\right)$ denotes the energy allocation efficiency.

3.2 The coupled coordination degree (CCD) model

Referring to Wang and Tan (2021), ET and EAF represent energy technology progress and energy allocation efficiency, respectively, which can be measured using the energy efficiency decomposition model. C denotes the degree of coupling, T signifies the coordination index, and D refers to the CCD of regional energy technology progress and energy allocation efficiency. This study posits that energy technology progress is equally important to energy allocation efficiency, thus setting $\alpha = \beta = 0.5$.

$$C = \left\{ \frac{ET \times EAF}{\left[\frac{1}{2}(ET + EAF)\right]^2} \right\}^{\frac{1}{2}} \tag{6}$$

$$T = \alpha ET + \beta EAF \tag{7}$$

$$D = \sqrt{C \times T} \tag{8}$$

Referring to Wu et al. (2025) and Jiang et al. (2022), this study classifies the CCD values into four distinct intervals, as presented in Table 1.

3.3 Kernel density estimation model

This study employs a nonparametric kernel density estimation model to analyze the dynamic evolution of variables, effectively capturing their distributional characteristics and temporal patterns. The model relies on data samples for inference, requires minimal assumptions about the overall distribution, and can adapt to various shapes of probability density functions,

Table 1 Classification of CCD

CCD	$0 < D \leq 0.4$	$0.4 < D \leq 0.5$	$0.5 < D \leq 0.7$	$0.7 < D \leq 1$
Coupling type	No coordination	Low degree of coordination	Moderate coordination	High coordination

thereby accurately reflecting the data's actual characteristics (Sang et al., 2024). The specific model settings are as follows:

$$f(D) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{D_i - \overline{D}}{h}\right) \tag{9}$$

where $f(D)$ represents the density function, D_i indicates the CCD level of energy technology and energy allocation efficiency in province i, $\overline{D}$ denotes the mean value of D_i, n refers to the number of samples, h indicates the bandwidth, which is selected according to standard practices in this study, and $K(\cdot)$ represents the kernel function, with the Gaussian kernel function utilized for the calculations in this paper.

3.4 Convergence model

3.4.1 Spatial σ convergence

The traditional σ-convergence model, as presented in Eq. (10), directly reflects the trends in variable differences between regions, is suitable for time series analysis, and allows for the observation of long-term convergence patterns. However, this model fails to account for spatial variability among variables, which complicates the generalization of research findings to a spatial context.

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{i,t} - \overline{x_t}\right)^2} \tag{10}$$

This paper extends the traditional σ-convergence model by incorporating spatial correlation, resulting in the spatial σ-convergence model. In contrast to the traditional model, the spatial σ-convergence model incorporates regional spatial weights in its formulation and estimation, leading to results that more accurately reflect regional conditions (Nie & Lee, 2023). Drawing on Rey and Dev (2006) and Wang et al. (2023), the spatial error model (SEM) is constructed, as detailed in Eq. (11).

$$y = \beta X + \rho W u + \varepsilon, \varepsilon \sim N\left(0, \sigma^2\right) \tag{11}$$

We combine the spatial error model with the σ-convergence model to establish the spatial σ-convergence model, as presented in Eq. (12).

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(D_{i,t} - \overline{D_t}\right)^2} \bullet (E - \rho W)^{-1} \bullet \left(E - \rho W^T\right)^{-1} \tag{12}$$

E is a unit vector; D represents the CCD level of energy technology and energy allocation efficiency. Other variables correspond to those defined in Eq. (10) and (11). The parameter σ_t denotes the spatial convergence coefficient of the CCD in year t. A decrease in σ_t over successive years indicates the presence of spatial σ-convergence of the CCD.

3.4.2 Absolute spatial β convergence

The σ-convergence model represents the degree of dispersion in CCD levels across regions over time, while β-convergence examines the relationship between the growth rate of CCD levels and their initial values. The traditional β-convergence model is presented in Eq. (13).

$$Ln\left(\frac{x_{i,t+1}}{x_{i,t}}\right) = \alpha + \beta Ln\left(x_{i,t}\right) + \varepsilon_{i,t} \tag{13}$$

This study extends the methodologies of Han et al. (2018) and Cheng et al. (2020) by integrating spatial correlation into the conventional β-convergence framework, thereby constructing an absolute β-convergence model. Equation (14) applies the spatial autoregressive (SAR) model, whereas Eq. (15) employs the spatial error model (SEM).

$$Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) = \alpha + \beta Ln\left(D_{i,t}\right) + \rho \sum_{j=1,j\neq i}^{n} W_{i,t} Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) + \omega_i + \tau_t + \varepsilon_{i,t} \tag{14}$$

$$Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) = \alpha + \beta Ln\left(D_{i,t}\right) + \rho \sum_{j=1,j\neq i}^{n} W_{i,t} u_{i,t} + \omega_i + \tau_t + \varepsilon_{i,t} \tag{15}$$

where $Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right)$ represents the growth rate of the CCD level, W denotes the spatial weight matrix, ω_i and τ_t denote the individual and time fixed effects, respectively. The coefficient β represents the spatial absolute convergence parameter.

3.4.3 Conditional spatial β convergence

Absolute β-convergence presumes structural homogeneity among regions, representing an idealized case. This study addresses regional structural heterogeneity by integrating relevant influencing variables. Based on the framework proposed by Guo and Luo (2021), the conditional β-convergence model is formulated as follows:

$$Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) = \alpha + \beta Ln\left(D_{i,t}\right) + \rho \sum_{j=1,j\neq i}^{n} W_{i,t} Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) + \delta X_{i,t}^{(k)} + \omega_i + \tau_t + \varepsilon_{i,t} \tag{16}$$

$$Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) = \alpha + \beta Ln\left(D_{i,t}\right) + \rho \sum_{j=1,j\neq i}^{n} W_{i,t} Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) + \delta X_{i,t}^{(k)} + \omega_i + \tau_t + \varepsilon_{i,t} \tag{17}$$

$$\begin{aligned} Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) =& \alpha + \beta Ln\left(D_{i,t}\right) + \delta X_{i,t}^{(k)} + \theta \sum_{j=1,j\neq i}^{n} W_{i,j} Ln\left(D_{i,t}\right) \\ &+ \rho \sum_{j=1,j\neq i}^{n} W_{i,j} Ln\left(\frac{D_{i,t+1}}{D_{i,t}}\right) + \gamma \sum_{j=1,j\neq i}^{n} W_{i,j} X_{i,t}^{(k)} + \omega_i + \tau_t + \varepsilon_{i,t} \end{aligned} \tag{18}$$

where Eq. (16) is the equation setting for SEM, Eq. (17) is the equation setting for SAR, and Eq. (18) is the equation setting for SDM. $X_{i,t}^{(k)}$ denotes a set of control variables affecting the CCD level, while other variables retain their previously defined meanings. The coefficient β represents conditional spatial convergence, and a negative indicates the presence of conditional β-convergence.

3.5 Geographical detector model

The geographical detector model identifies spatial differentiation among dominant drivers and their interactions, thereby uncovering the driving forces behind geographic phenomena (Wang et al., 2016). The model infers from data samples without assuming an underlying distribution, making it well-suited for multidimensional analysis and capable of handling complex data structures. Moreover, it can detect the combined influence of two interacting factors on a dependent variable, a task that traditional statistical methods often fail to address.

This study utilizes the factor detector and interaction detector within the geographical detector model to examine the drivers of energy technology and energy allocation efficiency at the CCD level. The specific model setup is presented in Eq. (19).

$$q = 1 - \frac{SSW}{SST} = 1 - \frac{\sum_{n=1}^{n} N_n \sigma_n^2}{N\sigma^2} \tag{19}$$

where n represents the number of subregions in the spatial whole; N is the total number of spatial units in the spatial whole; N_n is the number of samples in the subregion n; σ_n represents the variance in the subregion n; and σ represents the total variance in the subregion n. The variable q represents the driving force of an influencing factor on CCD levels, with a range between 0 and 1.

3.6 Sample selection and data sources

This study analyzes Chinese provinces from 2000 to 2022, focusing on the CCD level of energy technology and energy resource allocation. Energy consumption statistics were derived from provincial statistical yearbooks, nighttime light intensity data were obtained from NOAA's National Geophysical Data Center (NGDC), and regional GDP data were collected from the National Bureau of Statistics of China (NBSC).

To control for the effects of other relevant factors, this study follows the methodology of Tanaka and Managi (2021) and Teng and Shen (2023) by incorporating the following control variables: (1) economic development level, proxied by per capita GDP; (2) population size, measured by total regional population; (3) degree of marketization, reflected by the marketization index; (4) industrial composition, represented by the ratio of secondary to tertiary sector output; (5) environmental regulation intensity, quantified as the proportion of completed investment in industrial pollution control relative to industrial value added; (6) capital scale, denoted by regional capital stock; and (7) green finance, assessed via the regional green finance index. All data were obtained from the China Economic Database (CEIC). Descriptive statistics are provided in Appendix B.

4 Results and discussion

Based on empirical results, this section first uncovers fundamental patterns by systematically measuring the coupling coordination degree of energy technology and energy distribution efficiency. It then integrates spatial characterization with the analysis of distribution dynamics to develop a multidimensional research framework. Finally, it elucidates the driving factors behind regional differences.

4.1 Analysis of the CCD of energy technology and efficiency of energy distribution

Table 2 presents the CCD results of energy technology and resource allocation across Chinese provinces. Most provinces show moderate harmonization between energy technology and allocation efficiency, with a few achieving a high level of coordination. In 2000, Jiangsu, Zhejiang, and Fujian demonstrated strong coupling and harmonization between energy technology and resource allocation, while Shanxi and Chongqing remained uncoordinated. By 2022, Beijing, Jiangsu, Guangdong, and Chongqing had achieved high coordination between energy technology and resource allocation, whereas Heilongjiang, Shanghai, and Ningxia remained uncoordinated.

Further analysis reveals that Shanghai, as an economically developed region in China, experiences high energy demand but has limited local energy resources, with its energy supply largely dependent on external sources. This dependency impacts the efficiency and flexibility of energy allocation. Heilongjiang's energy system remains predominantly dependent on conventional energy sources, with a relatively low share of new and renewable energy. This disparity restricts the region's progress in energy transformation, technological upgrading, and sustainable development. Although Ningxia is making rapid progress in China's new energy sector, the intermittent and unstable nature of new energy poses challenges for energy allocation. The development of energy storage technology lags behind, making it challenging to effectively address issues related to new energy consumption and stable supply, thereby limiting the efficiency of regional energy allocation.

Overall, from 2000 to 2022, most provinces in China exhibited a declining trend in the CCD of energy technology and resource allocation. However, a few provinces, including Beijing, Tianjin, Shanxi, Guangdong, Chongqing, and Sichuan, displayed an increasing trend. These CCD results highlight considerable opportunities to enhance the integrated development of energy technology and resource allocation across China. Advancing such coordination constitutes a feasible approach to further improving national energy efficiency.

Research has demonstrated that promoting the synergistic development of energy technology and energy allocation efficiency is crucial. On one hand, technological advances can offer more efficient means of resource allocation (Jiakui et al., 2023). For instance, the application of smart grids and energy storage technologies can optimize energy distribution and utilization. On the other hand, rational resource allocation can stimulate technological innovations and create market opportunities, forming a virtuous cycle (Dhayal et al., 2023).

4.2 Analysis of spatial characterization

Figure 2a and b show that in 2000, China's energy technology exhibited significant spatial clustering, with higher levels concentrated mainly in the southern regions, reflecting a pronounced imbalance in regional development. By 2022, following over twenty years of development, the spatial pattern of energy technology had transformed into a“multi-center” spatial development pattern.

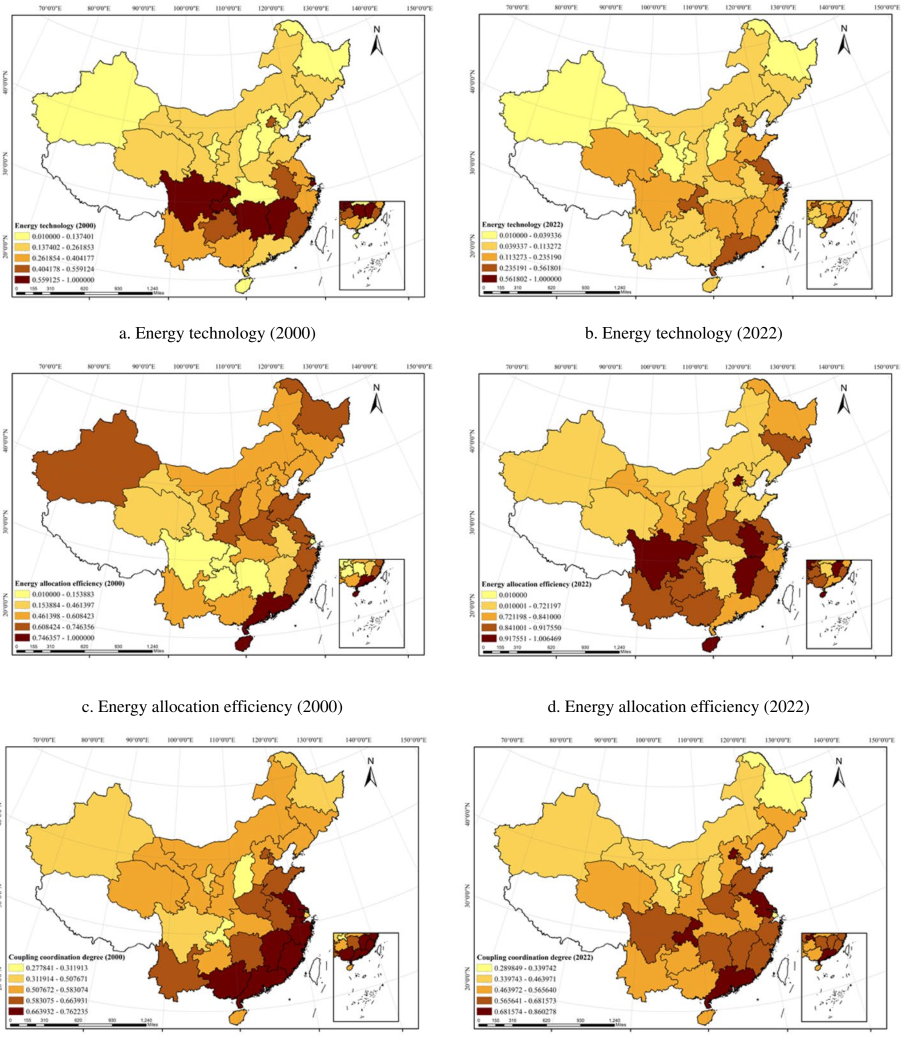
Figure 2c and d illustrate the spatial patterns of energy allocation efficiency across China in 2000 and 2022. Overall, energy allocation efficiency in China exhibits significant spatial disparities. In 2000, high levels of energy allocation efficiency were predominantly found in eastern coastal provinces, whereas the southwestern areas showed

Table 2 CCD evaluation results and overall trends

Provinces	Coupled coordination degree (2000)	Coupling type	Coupled coordination degree (2022)	Coupling type	Overall trend
Beijing	0.650	Moderate coordination	0.860	High coordination	↑
Tianjin	0.623	Moderate coordination	0.646	Moderate coordination	↑
Hebei	0.538	Moderate coordination	0.531	Moderate coordination	↓
Shanxi	0.278	No coordination	0.418	Low degree of coordination	↑
Inner Mongolia	0.549	Moderate coordination	0.464	Low degree of coordination	↓
Liaoning	0.583	Moderate coordination	0.527	Moderate coordination	↓
Jilin	0.576	Moderate coordination	0.492	Low degree of coordination	↓
Heilongjiang	0.508	Moderate coordination	0.340	No coordination	↓
Shanghai	0.490	Low degree of coordination	0.317	No coordination	↓
Jiangsu	0.713	High coordination	0.707	High coordination	↓
Zhejiang	0.716	High coordination	0.643	Moderate coordination	↓
Anhui	0.664	Moderate coordination	0.566	Moderate coordination	↓
Fujian	0.762	High coordination	0.682	Moderate coordination	↓
Jiangxi	0.675	Moderate coordination	0.626	Moderate coordination	↓
Shandong	0.621	Moderate coordination	0.617	Moderate coordination	↓
Henan	0.621	Moderate coordination	0.605	Moderate coordination	↓
Hubei	0.657	Moderate coordination	0.633	Moderate coordination	↓
Hunan	0.615	Moderate coordination	0.609	Moderate coordination	↓
Guangdong	0.680	Moderate coordination	0.729	High coordination	↑
Guangxi	0.681	Moderate coordination	0.481	Low degree of coordination	↓
Hainan	0.572	Moderate coordination	0.559	Moderate coordination	↓
Chongqing	0.312	No coordination	0.714	High coordination	↑
Sichuan	0.403	Low degree of coordination	0.635	Moderate coordination	↑
Guizhou	0.527	Moderate coordination	0.515	Moderate coordination	↓
Yunnan	0.637	Moderate coordination	0.498	Low degree of coordination	↓

Table 2 (continued)

Provinces	Coupled coordination degree (2000)	Coupling type	Coupled coordination degree (2022)	Coupling type	Overall trend
Shaanxi	0.582	Moderate coordination	0.530	Moderate coordination	↓
Gansu	0.564	Moderate coordination	0.418	Low degree of coordination	↓
Qinghai	0.548	Moderate coordination	0.536	Moderate coordination	↓
Ningxia	0.463	Low degree of coordination	0.290	No coordination	↓
Xinjiang	0.478	Low degree of coordination	0.410	Low degree of coordination	↓
Average	0.576	Moderate coordination	0.553	Moderate coordination	↓



a. Energy technology (2000)

b. Energy technology (2022)

c. Energy allocation efficiency (2000)

d. Energy allocation efficiency (2022)

e. Coupled coordination degree (2000)

f. Coupled coordination degree (2022)

Fig. 2 Spatial distribution of energy technologies, energy allocation efficiency and coupled coordination degree

comparatively low efficiency. By 2022, notable improvements were observed in the southern and eastern coastal areas. However, northern provinces remained substantially less efficient compared to their southern counterparts.

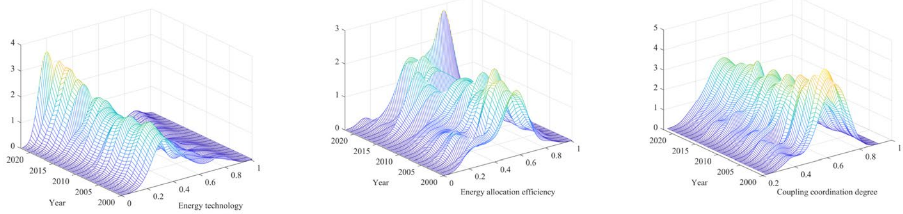
Figure 2e and f reveal a pronounced spatial imbalance in the coupled and coordinated development of energy technology and energy allocation efficiency. In 2000, eastern coastal provinces exhibited a substantially greater degree of coupling and coordination compared to other regions. By 2022, regions with higher coupling and coordination were predominantly concentrated in the southern and eastern areas. Overall, the coupling of energy technology and energy allocation efficiency across regions in China remains unbalanced, with considerable variability in the spatial distribution of CCD.

4.3 Analysis of distribution dynamics

Figure 3 presents the kernel density distributions of energy technology, energy allocation efficiency, and CCD, facilitating a deeper analysis of the distribution trends, shapes, and polarization characteristics of these variables. The primary peak of the kernel density distribution for energy technology has increased significantly over time, indicating a reduction in the overall gap in energy technology levels. Energy allocation efficiency exhibits a multi-peak distribution, indicating an overall bifurcation trend. The kernel density distribution of CCD remains relatively stable but continues to exhibit a potential risk of polarization. Regarding changes in the curve's center, the distribution centers of energy technology and CCD are relatively stable, suggesting no significant improvement in these areas overall. The center of energy allocation efficiency shows noticeable fluctuations, reflecting a lack of stable growth in recent years, with considerable uncertainty regarding future changes.

Since the trajectory of the CCD is determined by the interplay between energy technology and energy allocation efficiency, this study proceeds to examine how their joint distribution has evolved over time. Figure 4 displays the joint distribution curves of energy technology and allocation efficiency for the representative years 2000, 2011, and 2022.

Figure 4 reveals distinct bimodal characteristics in the joint distribution of energy technology and energy allocation efficiency in 2000 and 2011. These bimodal peaks indicate that most regions were clustered around different combinations of energy technology and energy allocation efficiency levels. Specifically, between 2000 and 2011, energy technology remained relatively stable, while energy allocation efficiency exhibited increasing concentration. This indicates that despite stable energy technology levels, there were significant regional differences in energy allocation efficiency. These disparities may result from variations in economic development, industrial structure, energy policies, and technological advancement across regions (Dhayal et al., 2024b). For instance, economically developed regions may possess more advanced energy technologies and efficient allocation systems, whereas less developed regions often encounter technological lags and inefficient resource distribution.



a. Energy technology b. Energy allocation efficiency c. Coupled coordination degree

Fig. 3 Distribution dynamics of energy technologies, energy allocation efficiency and coupled coordination degree

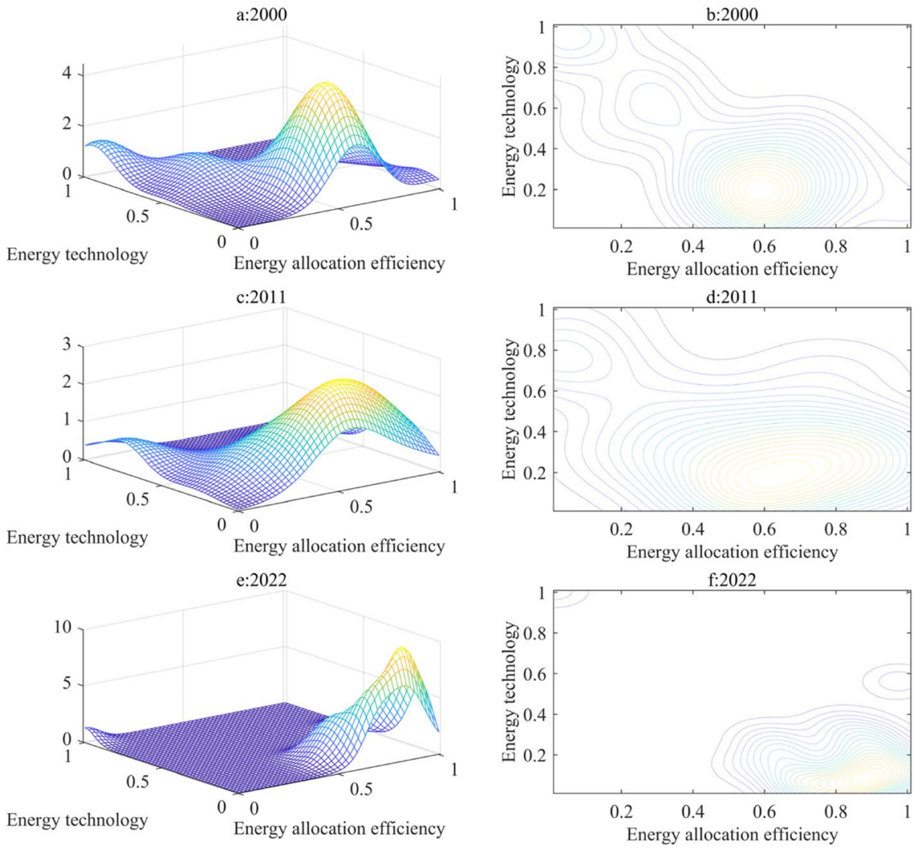


Fig. 4 Joint distribution of energy technologies and energy allocation efficiency

4.4 Convergence analysis

4.4.1 σ convergence

The σ-convergence analysis reveals a reduction in regional disparities of CCD, as evidenced by the decreasing standard deviation over time. To overcome limitations of traditional σ-convergence approaches, this study accounts for spatial interdependence among regions by employing a spatial error model to assess the spatial convergence of CCD.

Figures 5 and 6 illustrate the spatial convergence patterns of the CCD at both the national and regional levels—specifically, the eastern, central, and western regions of China. Nationally, the continuous decline in the σ-convergence coefficient suggests a narrowing gap in the coordinated evolution of energy technology and allocation efficiency. At the regional level, the σ-convergence coefficients decline in the western and eastern regions, whereas no evidence of σ-convergence is observed in the central region.

These differences arise from variations in regional energy roles and the extent of policy support (Gielen et al., 2019). The western region, characterized by its role as a key energy supplier, is endowed with abundant natural resources and receives considerable public investment in energy infrastructure. These advantages have promoted the advancement

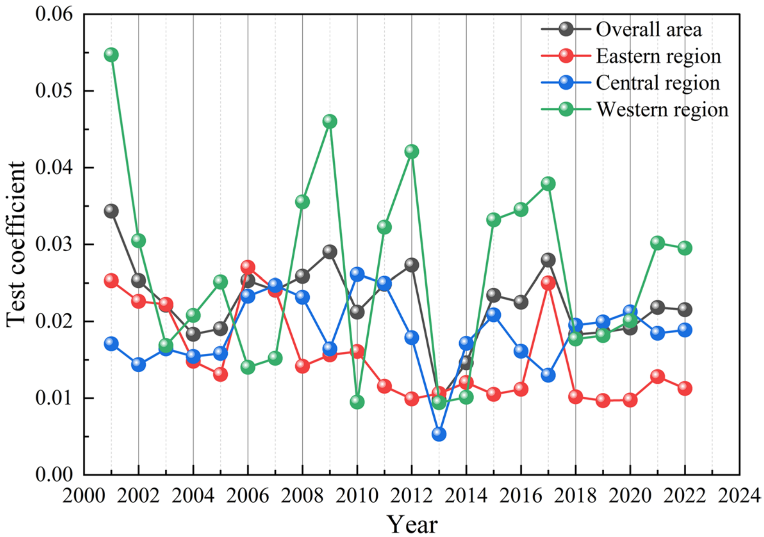


Fig. 5 Coupled coordination degree spatial σ convergence across regions in China: overall trends

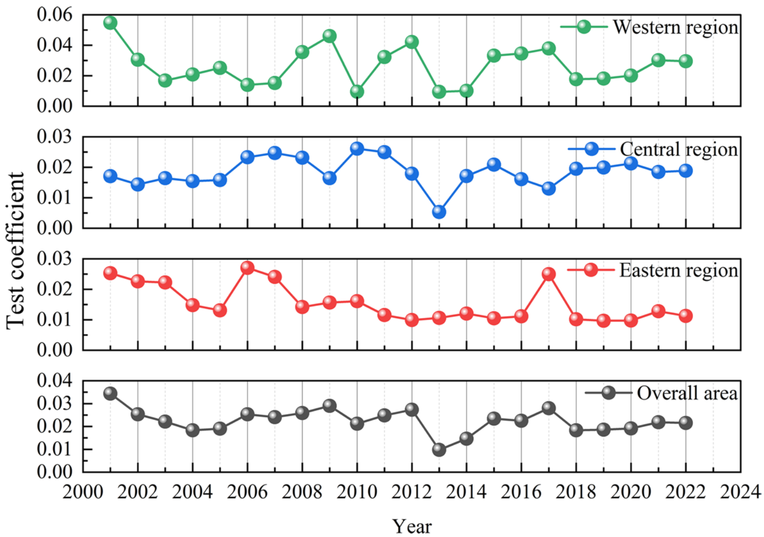


Fig. 6 Coupled coordination degree spatial σ convergence across regions in China: regional comparison

and implementation of energy technologies, substantially improving energy allocation efficiency. The eastern region, as a primary energy consumer, possesses a developed economy and strong capacity for technological innovation, enabling it to rapidly absorb and adopt advanced energy technologies, thereby enhancing energy utilization and allocation efficiency.

In contrast, the central region's weak energy infrastructure and limited renewable energy capacity are key barriers to integrating energy technology and allocation efficiency.

(Islam et al., 2022). The central region lags behind in energy production, consumption, and technology application, compounded by insufficient policy support and investment, resulting in substantial challenges during the energy transition. Additionally, the region's industrial landscape remains dominated by conventional, energy-intensive sectors, resulting in a strong reliance on energy inputs and hindering progress in improving allocation efficiency.

4.4.2 Absolute β convergence

This study examines the absolute β-convergence of CCD using OLS, SEM, and SAR models. To ensure robustness, data from 2020 onwards—potentially affected by the COVID-19 pandemic—were excluded. Column (1) in Table 3 presents the absolute β-convergence results obtained from the OLS model without accounting for spatial effects. The significantly negative β coefficient (− 0.338) indicates a clear tendency toward absolute convergence in CCD. Columns (2) and (3) show the results from the SEM and SAR models that incorporate spatial effects. Significantly negative coefficients further confirm the existence of spatial absolute β-convergence, aligning with the OLS findings and reinforcing the robustness of the results. This consistency persists even when data from after 2020 are excluded.

From an economic perspective, this convergence trend carries important implications for energy policy formulation. First, it implies that effective policy interventions and resource allocation can promote coordinated improvements in energy technology and allocation efficiency, thereby narrowing regional disparities. Second, the robustness of the spatial effect highlights the importance of accounting for interregional interactions in policy design to avoid potential spillover effects from one region to others. Moreover, this convergence trend can enhance overall energy utilization efficiency and support sustainable energy development.

Additionally, the significantly positive spatial autoregressive coefficient (ρ) indicates that a province's CCD positively affects neighboring regions. These results suggest that, over time, regional CCD levels tend to converge toward a stable equilibrium even without external conditions or targeted policy interventions. Furthermore, the significant positive

Table 3 Estimation of absolute β convergence for coupled coordination degree

	Full Sample			Excluding COVID19 impact samples		
	OLS	SEM	SAR	OLS	SEM	SAR
	(1)	(2)	(3)	(4)	(5)	(6)
β	−0.338***	−0.350***	−0.332***	−0.391***	−0.401***	−0.385***
		(0.029)	(0.028)	(0.034)	(0.033)	(0.032)
lambda		0.256***			0.246***	
		(0.054)			(0.058)	
ρ			0.206***			0.196***
			(0.053)			(0.057)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	660	660	660	570	570	570
R^2	0.268	0.033	0.033	0.283	0.034	0.033

spatial spillover effect of CCD underscores the importance of fostering interregional cooperation in energy technology and resource allocation to facilitate innovation and knowledge transfer, thereby enhancing energy efficiency across regions.

4.4.3 Conditional β convergence

Absolute β-convergence represents the result of a convergence analysis that excludes the impact of additional variables. However, significant disparities exist in regional economic development conditions. Consequently, this study performs a conditional β-convergence test by incorporating control variables potentially affecting the CCD. To ensure robustness, data from 2020 onwards—potentially affected by the COVID-19 pandemic—were excluded, and the results are reported in Table 4.

Table 4 presents the conditional β-convergence results. Utilizing various spatial econometric specifications, the estimated absolute β-convergence parameters for China's CCD remain uniformly negative and are statistically significant at the 1% level, leading to rejection of the null hypothesis. This implies that, holding other factors constant, regions with lower initial CCD levels grow more rapidly, gradually converging with regions that have higher CCD levels. After excluding the post-COVID-19 samples, the results remained consistent with those derived from the full sample.

The findings of this study hold significant theoretical and practical value. First, the results of conditional β-convergence suggest that the interregional gap in energy technology and allocation efficiency is not static, but can be progressively narrowed through policy guidance and technological advancements. This provides a theoretical foundation for formulating a coordinated regional development strategy, particularly in regions with significant disparities in energy resource endowments in China, where balanced interregional development can be effectively promoted by optimizing resource allocation and technological innovation (Islam et al., 2022). Second, regions with lower initial coupling

Table 4 Estimates of conditional space β convergence for coupled coordination degree

	Full Sample			Remove COVID19 impact samples		
	SEM	SAR	SDM	SEM	SAR	SDM
	(1)	(2)	(3)	(4)	(5)	6)
β	−0.356***	−0.344***	−0.375***	−0.408***	−0.397***	−0.427***
	(0.029)	(0.028)	(0.030)	(0.033)	(0.032)	(0.034)
lambda	0.233***			0.223***		
	(0.057)			(0.061)		
ρ		0.197***	0.385***		0.187***	0.360***
		(0.053)	(0.047)		(0.057)	(0.052)
control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	660	660	660	570	570	570
R^2	0.032	0.020	0.047	0.049	0.036	0.057

ρ denotes spatial autoregressive coefficient; lambda denotes spatial error coefficient. The values in parentheses are standard errors; ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively harmonization exhibit faster growth, highlighting the potential for technological catch-up and improvements in resource allocation efficiency in latecomer regions.

4.5 Driving forces of regional CCD differences

In this research, the geographical detector approach is utilized to assess how each of the factors—economic development (X1), population scale (X2), degree of marketization (X3), composition of industries (X4), environmental governance (X5), capital stock (X6), and green financial instruments (X7)—as well as their interactions, contribute to spatial heterogeneity in regional CCD.

Figures 7a and 7c present the detection results for the individual influencing factors. The results indicate that, in 2000, marketization level and green finance were the primary drivers of spatial differentiation in CCD, whereas the industrial structure had a relatively minor impact. By 2022, marketization level and industrial structure emerged as the main drivers of spatial differentiation in CCD, while environmental regulation played a comparatively smaller role. A notable shift occurred between 2000 and 2022, during which the primary driver of CCD in China transitioned from green finance to industrial structure.

Advancing energy technologies demands considerable capital input and entails high uncertainty, thereby requiring reliable financial backing in the early phases. In this context, green financial mechanisms were instrumental in supporting the initial coupling and

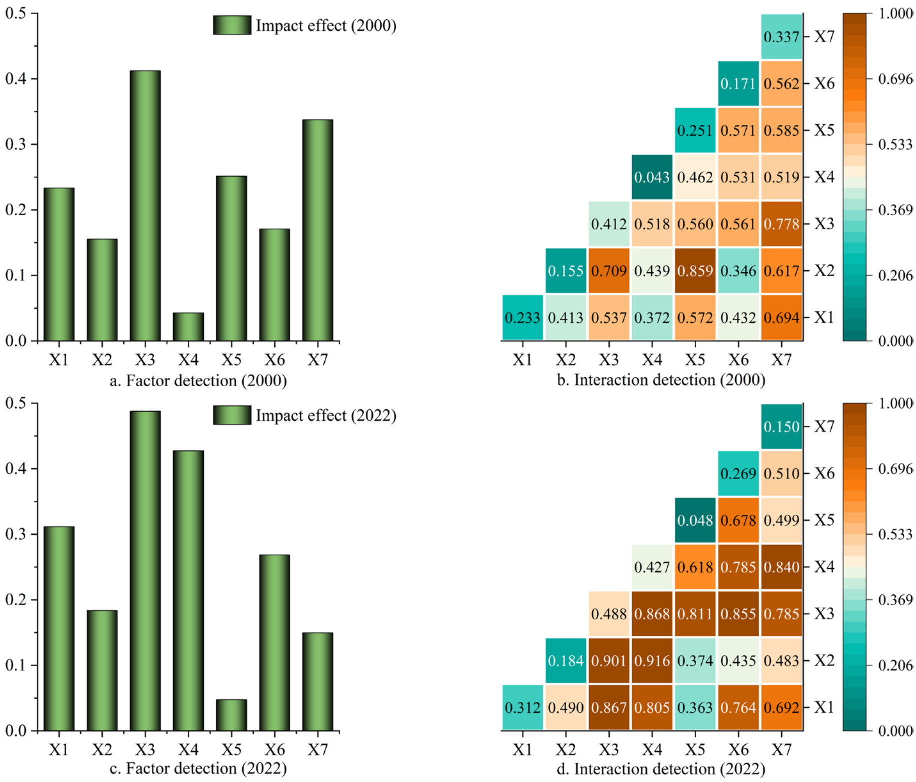


Fig. 7 Results of factor detection and interaction detection of coupled coordination degree drive forces

coordination between technological innovation in energy and the efficiency of energy distribution in China. As energy technology advances, energy allocation efficiency has become the primary barrier to the development of CCD. This makes an industrial structure that supports clean and green practices essential for improving energy allocation efficiency. Consequently, the industrial structure has become the primary driving force behind the current coupled and coordinated development of energy technology and energy allocation efficiency in China.

Figures 7b and 7d present the results of the interaction effect tests for various drivers. In the year 2000, the combined influence of population magnitude and regulatory stringency on the synergy between energy innovation and allocation efficiency reached its peak, recording an interaction value of 0.859. This finding underscores the strong synergy between China's population size and its environmental regulation policies. Therefore, policy formulation in the early stages of energy development should incorporate effective environmental regulation, considering China's substantial population. By 2022, the interaction factors influencing the coupled and coordinated development of energy technology and energy allocation efficiency became more diverse. For instance, the interaction effect between population size and industrial structure was about 0.916, while that between population size and marketization level reached approximately 0.901. Additionally, significant interactions were observed between marketization level and other variables.

These diverse interaction effects indicate that the coupled and coordinated development of energy technology and energy allocation efficiency is influenced by multiple factors. The dynamic adjustment of the industrial structure directly determines the type, scale, and distribution characteristics of energy demand. However, as the industrial structure transforms towards higher-end, diversified, and greener sectors, the rise of new industries has increased the flexibility and adaptability requirements for energy technologies, thereby promoting improvements in energy allocation efficiency. Market-oriented reform has optimized energy resource allocation through the introduction of competition mechanisms and price signals, enabling the innovation and application of energy technologies to more effectively respond to market demand fluctuations.

5 Policy implications

Based on the empirical results, this paper proposes targeted policy guidance across three strategic dimensions: establishing integrated coordination mechanisms, implementing regionally tailored governance, and enhancing the market framework. The detailed measures are outlined below:

5.1 Optimizing regional energy allocation efficiency and cross-regional synergies

The study finds that most Chinese provinces exhibit a moderate level of harmonization in the CCD between energy technology and energy allocation efficiency, with only a few provinces achieving high harmonization. A pronounced imbalance exists in the coupling of these factors, and the uneven spatial distribution of energy allocation efficiency contributes to regional CCD disparities. Future efforts to enhance regional energy efficiency in China should primarily target improvements in energy allocation efficiency. Currently, energy allocation efficiency significantly lags behind advancements in energy technology, impeding their coordinated development.

To address this, priority should be given to accelerating infrastructure development for regional energy allocation, strengthening energy transmission and distribution networks, and improving transportation efficiency between major energy-producing and consuming areas by establishing inter-provincial and inter-regional energy transmission corridors.

5.2 Developing differentiated regional energy development policies

The study confirms that provinces with advanced energy technology in China are predominantly located in the southern region, reflecting uneven regional development in energy technology. Concurrently, energy allocation efficiency exhibits pronounced spatial imbalance. Therefore, bolstering policy assistance for resource-constrained areas is essential to fostering integrated progress in energy innovation and allocation across territorial divisions. Tailored energy policies should be formulated according to the specific energy endowments of each region. Directing green finance instruments—including green lending and bond issuance—toward energy-scarce regions may effectively reduce capital barriers for energy-related investments. Additionally, implementing differentiated dual-control measures on energy consumption can provide targeted policy relief to these regions, incentivizing improvements in energy efficiency aligned with their developmental contexts.

Additionally, a regional energy internet can be developed with the aid of advanced information technology to achieve the interconnection and synergistic operation of different energy systems within the region. This platform enables optimization across energy production, transmission, storage, and consumption, thereby improving the system's overall efficiency and flexibility. Additionally, it supports the growth of distributed energy resources while strengthening the reliability and security of the regional energy supply.

5.3 Focusing on the development of regional energy marketization

The findings highlight that optimizing the allocation of energy resources is central to improving China's aggregate energy performance. Interaction analysis indicates that various elements—including demographic scale and industrial composition—collectively contribute to the synchronized advancement of energy efficiency, while market liberalization is simultaneously shaped by these underlying drivers. Hence, promoting energy marketization serves as an institutional foundation for further enhancing energy efficiency. Optimizing energy resource allocation requires establishing an open, competitive, and well-regulated energy market system. Key measures include deepening market-oriented reforms in the electricity and natural gas sectors, removing industry barriers, fostering diverse market participation, and encouraging energy prices that accurately reflect supply–demand dynamics and environmental externalities. To promote synergistic interregional energy development, it is crucial to create a regional energy cooperation mechanism that facilitates complementarity and collaboration between energy-rich and energy-deficient regions.

Finally, enhancing policy incentive mechanisms is essential to foster the integration of new and traditional energy sources. Improving the initial distribution of carbon allowances can enhance the interlinkage among carbon trading, green power transactions, and certificate mechanisms, gradually shifting away from dependence on compulsory punitive approaches. Additionally, supportive regulations and market-based incentives should motivate legacy energy firms to collaborate with renewable energy enterprises, thereby facilitating energy mix optimization and accelerating the sector's ecological transition.

6 Conclusion

This study constructs a decomposition model that separates energy efficiency into two components: energy technology efficiency and energy allocation efficiency. Additionally, a CCD model is applied to evaluate the coupling coordination between these two efficiencies across 30 Chinese provinces during the period 2000–2022. The dynamic distribution, convergence, and drivers of the coupled coordination between energy technology and energy allocation efficiency are further analyzed using kernel density estimation, convergence models, and the geographical detector model. The study presents the following conclusions:

(1) Between 2000 and 2022, most Chinese provinces maintained a moderate level of coordination between energy technology and energy allocation efficiency, with only a few provinces reaching high coordination levels. The overall trend in CCD across provinces is declining, although a minority exhibit growth. Spatial analysis reveals that inter-regional energy technology and energy allocation efficiency in China have not achieved balanced coupling and coordinated development, leading to a pronounced spatial imbalance. Specifically, energy technology in various provinces exhibits a "polycentric" spatial development pattern, with Beijing, Jiangsu, Guangdong, and Chongqing emerging as centers for energy technology development in China. Conversely, energy allocation efficiency displays a "strong south–weak north" pattern, which largely accounts for the spatial variation in CCD.
(2) The σ-convergence coefficient of the CCD levels for energy technology and energy allocation efficiency in China has been gradually declining, suggesting that the differences in coordinated development between these areas are narrowing. Regional breakdowns show declining σ-convergence in the eastern and western zones, whereas the central region has yet to demonstrate convergence. Negative values in both absolute and conditional β-convergence coefficients for China's coordinated development suggest that, holding other factors constant, provinces starting from lower CCD bases experience faster growth, progressively narrowing the gap with higher-level counterparts. As a result, regional inequalities in coordinated development are expected to stabilize and diminish over the long term.
(3) The driver detection results based on the geographical detector model indicate that in 2000, marketization and green finance were the primary drivers of spatial divergence in CCD, while the industrial structure had a relatively minor role. By 2022, marketization and industrial structure emerged as the main drivers of spatial divergence, with environmental regulation playing a diminished role. In summary, the leading factor driving the integrated advancement of energy technology and allocation efficiency transitioned from green finance toward industrial restructuring. Furthermore, interaction analyses indicate that in 2000, the synergy between demographic scale and environmental regulation exerted the strongest influence on the joint progression of energy innovation and allocation efficiency. However, by 2022, the interaction factors influencing this development became more diverse, with the combined interaction of multiple factors emerging as the primary driving force.

Nonetheless, certain limitations are inherent in this research. Firstly, the analysis centers on the coordinated advancement of energy technology and allocation efficiency, employing the proportional share approach for assessing regional energy efficiency due to its ease of application and interpretability. Future research could explore the use of parametric and nonparametric methods for this purpose. Secondly, although an innovative framework is presented to examine the coupled coordination between energy technology and allocation efficiency, the model presumes these subsystems operate independently. Future research should integrate additional economic and social systems to enhance and broaden this framework. Finally, the convergence analysis here emphasizes spatial factors and indicator convergence but neglects regional equity considerations. Future investigations could integrate convergence assessments with inequality metrics, such as the Gini coefficient and Taylor's index, to provide a more comprehensive understanding of regional disparities and convergence patterns.

Appendix A

Comparison of different model fitting effects (R^2)

Table 5 Comparison of different model fitting effects (R^2)

Year	Exponential model	Logarithmic model	Linear model
2000	0.644	0.785	0.890
2001	0.640	0.803	0.877
2002	0.657	0.782	0.913
2003	0.653	0.777	0.911
2004	0.656	0.772	0.917
2005	0.664	0.752	0.936
2006	0.655	0.750	0.933
2007	0.665	0.750	0.932
2008	0.674	0.753	0.925
2009	0.681	0.755	0.930
2010	0.708	0.756	0.933
2011	0.696	0.764	0.921
2012	0.726	0.770	0.934
2013	0.732	0.780	0.943
2014	0.702	0.785	0.933
2015	0.708	0.768	0.937
2016	0.703	0.766	0.931
2017	0.714	0.771	0.948
2018	0.708	0.776	0.945
2019	0.708	0.779	0.941
2020	0.714	0.769	0.942
2021	0.724	0.770	0.950
2022	0.801	0.732	0.873

Appendix B

Variable descriptions

Table 6 Comparison of different model fitting effects (R^2)

Variable	Obs	Mean	Std. dev	Min	Max
CCD	690	0.572	0.132	0.224	0.918
Economic development	690	10,251.760	5568.867	2743.874	30,595.700
Population size	690	4464.651	2738.815	518.000	12,684.000
Marketization level	690	7.182	2.153	2.243	12.864
Industrial structure	690	0.970	0.314	0.189	1.930
Environmental regulation	690	0.004	0.004	0.000	0.029
Capital scale	690	32,744.050	34,105.270	597.390	195,848.000
Green finance	690	0.424	0.115	0.186	0.683

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Authors contributions Junjie Zhen: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing.

Yubao Wang: Formal analysis, Funding acquisition, Writing – review & editing.

Huiyuan Pan: Project administration, Software, Writing – review & editing.

Data availability Data will be made available on request.

Declarations

Competing interest The authors declare that they have no competing financial interests for personal relationship that could have appeared to influence the work reported in this paper.

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