



Regional inequality and driving factors behind low-carbon energy transition in China's provinces

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Abstract

Accelerating the transition of China's energy consumption structure toward low-carbon development is essential for achieving global carbon neutrality goals. As the country with the world's largest share of energy-related emissions, China provides a critical case in which substantial provincial disparities remain. Using panel data from 30 provinces from 2012 to 2022, this study develops an integrated framework combining Geographically and Temporally Weighted Regression (GTWR), eXtreme Gradient Boosting (XGBoost), and SHapley Additive exPlanations (SHAP) to examine the driving mechanisms of low-carbon energy transition from a regional inequality perspective. The results reveal persistent east–west disparities, significant spatial clustering, and clear temporal shifts in the effects of key drivers. Results reveal pronounced spatiotemporal heterogeneity. Green technology innovation consistently showed the strongest positive effect, while industrialization and urban–rural income gaps exerted stronger negative impacts in central and western regions. Government intervention shifted from a negative factor in early years to a positive driver in later years, which reflects the evolving role of policy in steering decarbonization. Moreover, nonlinear threshold effects were identified, such as U-shaped impacts of government intervention and scale-sensitive effects of afforestation. Findings show that China's low-carbon transition is evolving from regional heterogeneity toward policy convergence, yet inequalities remain significant. These results underscore the need for targeted strategies for reducing disparities, including technology diffusion and financial support in less-developed provinces, to ensure a more balanced and equitable energy transition. This study contributes new empirical insights to understanding low-carbon drivers and designing decarbonization policies for ensuring an equitable and coordinated national transition.

Keywords Low-carbon energy consumption · Energy transition · Regional disparities · GTWR · Interpretable machine learning

1 Introduction

The world is currently facing severe challenges from climate change, and low-carbon transition has become a global consensus (Lu et al. 2025). In China, achieving a low-carbon

energy consumption structure is a critical step toward the dual goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 (Liu et al. 2022). For decades, China's coal-dominated energy mix has resulted in high carbon emissions and substantial environmental pressures (Wang et al. 2016; Zhang and Chen 2022; Yan et al. 2022). Worsening environmental degradation and energy security concerns have created an urgent need to accelerate the shift toward a low-carbon energy structure (Xu 2021; Zhang and Kong 2022). The provincial level serves as a key spatial scale for advancing energy transition, yet significant disparities in economic development, resource endowment, and policy enforcement have led to marked regional differences and inequalities in low-carbon energy progress (Ge 2023; Zhong et al. 2024). Some developed provinces have substantially increased the share of clean energy,

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while less-developed regions remain heavily reliant on fossil fuels, making “imbalanced” progress a weak link in the national low-carbon transition. Identifying the mechanisms driving these disparities is essential for formulating region-specific emission reduction policies.

Previous studies have explored various factors influencing the low-carbon transition of energy consumption structures, such as economic development, industrial structure, technological innovation, and policy support (Jiang et al. 2020; Erin Bass and Grøgaard 2021; Bogdanov et al. 2021; Wang et al. 2023b; Li et al. 2023b). However, three critical knowledge gaps remain. First, spatiotemporal heterogeneity is insufficiently addressed. Most existing studies rely on traditional panel regression or econometric models, which implicitly assume uniform effects of driving factors across provinces, overlooking spatial and temporal non-stationarity (Wang et al. 2019; Li et al. 2023a; Xu et al. 2024). In reality, the drivers of low-carbon transition vary across regions and over time, necessitating methods that can capture spatiotemporal heterogeneity (Zhang et al. 2023; Guo and Sun 2025). Second, regional inequality identification has received limited attention. Few studies focus explicitly on inequalities in low-carbon transition across regions, and quantitative assessments of disparities—such as between eastern, central, and western China—are rare. Some policy measures exert uneven impacts across regions (e.g., carbon finance development has a stronger effect in the east), yet systematic analyses of such regional differences remain scarce (Wang and Xie 2025). Third, mechanistic interpretation is insufficient. Traditional statistical models can reveal linear associations but struggle to uncover complex nonlinear mechanisms, threshold effects, and variable interactions. In contrast, machine learning models can capture nonlinear relationships but often function as “black boxes,” making it difficult to explain why and under what conditions factors exert influence (Rudin 2019). This lack of interpretability limits the policy relevance of the findings.

To address these gaps, this study integrates Geographically and Temporally Weighted Regression (GTWR) with the XGBoost gradient boosting decision tree model and SHapley Additive exPlanations (SHAP) to examine the drivers of low-carbon energy consumption structure. More specifically, the first gap concerning insufficient attention to spatiotemporal heterogeneity is addressed through GTWR, which allows regression coefficients to vary across both space and time (Fotheringham et al. 2015). The second gap concerning limited assessment of regional inequality is addressed by quantitatively examining provincial disparities in low-carbon energy transition and comparing their patterns across regions. The third gap concerning insufficient mechanistic interpretation is addressed by combining XGBoost with SHAP, which can capture nonlinear

relationships, marginal contributions, and threshold effects while improving interpretability (Li 2022; Jiang et al. 2025). By combining these methods, the study is able to link spatial inequality identification with both localized linear estimation and interpretable nonlinear analysis.

2 Literature review

The transition of energy consumption from high-carbon to low-carbon sources is essential for achieving sustainable development (Omer 2008; Esseghir and Haouaoui Khouni 2014; Ahmed et al. 2022). The factors influencing low-carbon energy transitions span economic, technological, policy, and social domains (Chen et al. 2014; Shen and Sun 2016; Ding et al. 2018). Economically, development level and industrial restructuring are considered key drivers (Xue et al. 2022; Gyimah et al. 2022). Higher per capita GDP and a growing share of the tertiary sector often lead to improved energy efficiency and reduced carbon intensity per unit of output, facilitating a cleaner energy mix (Qiao et al. 2024). Conversely, high levels of industrialization are typically associated with heavy reliance on coal and other fossil fuels, hindering optimization of the energy structure. Empirical studies frequently confirm that indicators such as industrial share and energy intensity are positively correlated with carbon intensity and negatively correlated with the share of clean energy (Aslam et al. 2021; Su et al. 2022).

Technological progress and innovation have become increasingly important in advancing low-carbon transitions (Maghyereh et al. 2025). Green technological innovation promotes the development and utilization of new energy sources, raising the proportion of renewable energy in the consumption structure, and is a core driver of decarbonization (Cong et al. 2025). Cross-country and regional analyses have found significant positive correlations between low-carbon levels and indicators such as R&D investment and patent outputs (Liao et al. 2023; Maghyereh et al. 2025). Policy and institutional factors also play a decisive role in shaping energy structures. Public expenditure favoring environmental protection and renewable energy projects, energy price reforms, and pilot programs for carbon and energy rights trading can all guide resource allocation toward a cleaner energy mix (Liao et al. 2023). In China, the degree of government intervention is an important measure of policy influence (Su and Tan 2023). In earlier stages, policy emphasis on economic growth sometimes weakened low-carbon objectives, but in recent years, the “dual-carbon” strategy has shifted government efforts toward strongly promoting clean energy development.

Social factors such as demographics and livelihoods are also relevant. Population density influences infrastructure

planning and energy consumption patterns, while urban–rural income disparities affect equitable access to clean energy. Studies have shown that high urban–rural income ratios often indicate limited access to clean energy in rural areas, thereby reducing overall low-carbon levels (Gao et al. 2023; Chen and Sun 2025).

The uneven regional progress of low-carbon energy transitions has drawn increasing attention. Disparities exist not only between developed and developing countries but also among regions within a single country. Indicators such as the Gini coefficient of provincial low-carbon energy levels reveal clear spatial inequalities, reflected both in the absolute level of decarbonization and in the varying impacts of drivers (Wang and Xie 2025). For example, carbon finance and industrial upgrading tend to have stronger effects in eastern China, while the benefits are more limited in the central and western regions due to weaker economic and infrastructural foundations. This suggests that uniform low-carbon policies may yield uneven regional outcomes, underscoring the need to identify local drivers to enable targeted policy design (Tsvetkov 2021; Wang et al. 2022; Jiang et al. 2026). Spatially rooted factors shape diverse regional energy transition pathways, making spatial inequality a central issue in green transitions (Kanger and Sovacool 2022).

Traditional studies often rely on econometric models to analyze the determinants of carbon emissions or energy structure (Li et al. 2023a). The Geographically Weighted Regression (GWR) model, which allows each location to have its own regression coefficients, has been used to explore spatial variations in carbon emission drivers. However, GWR only accounts for spatial heterogeneity, neglecting temporal evolution. The development of GTWR addresses this by incorporating both spatial distance and temporal difference into the weighting scheme, enabling the tracking of temporal changes in factor effects (Fotheringham et al. 2015). Empirical applications have demonstrated GTWR's advantages in capturing spatiotemporal heterogeneity (Zhang et al. 2022, 2023; Wang et al. 2025).

Meanwhile, machine learning methods have gained traction in the energy and carbon emissions fields (Wang et al. 2023a; Cong et al. 2024; Lu et al. 2024; Jiang et al. 2025; Aspiras et al. 2025; Shan et al. 2026). These models can uncover complex nonlinear relationships from large datasets, improving predictive accuracy. However, their lack of transparency makes it difficult to obtain a clear picture of variable effects. To address this, interpretable AI techniques have emerged, with SHAP as a prominent example (Mosca et al. 2022). Based on game theory, SHAP assigns each feature a contribution value to the prediction, providing a consistent measure of feature importance for any machine learning model. As El Bilali and colleagues note, while data-driven machine learning models are objective and efficient,

they often lack physical interpretability; incorporating explanation methods like SHAP can help bridge this gap (Wang et al. 2024). Compared with traditional regression analysis, such approaches can reveal turning points where a variable's impact direction changes and provide precise rankings of variables' relative influence.

3 Materials and methods

3.1 Study area and data sources

This study uses 30 provinces in China as the basic spatial units. Energy data were obtained from the China Energy Statistical Yearbook (<https://www.stats.gov.cn>; <https://www.stats.gov.cn/sj/ndsjsj/>) and the China Electric Power Yearbook (<https://www.ccc.org.cn>; <https://www.cepp.sgcc.com.cn>). Fiscal expenditure and investment data were sourced from the China Statistical Yearbook (<https://www.stats.gov.cn>) and the China Finance Yearbook (<https://www.mof.gov.cn>). Environmental data were taken from the China Environmental Statistical Yearbook (Ministry of Ecology and Environment, <https://www.mee.gov.cn>). Green technology innovation data were derived from patent application records of the China National Intellectual Property Administration (<https://www.cnipa.gov.cn>), with patent classifications filtered according to the WIPO IPC Green Inventory (<https://www.wipo.int/classifications/ipc/green-inventory/home>). Figure 1 shows a schematic map of the study area.

The study period was set to 2012–2022 because this is the latest time span for which the provincial-level indicators used in this study can be assembled with relatively consistent statistical calibers across multiple official sources. Data for 2023–2025 were not included because several province-level variables employed in this study had not yet been fully released, or were not yet available in a sufficiently harmonized form across all data sources at the time of data collection.

3.2 Variable description

To systematically assess the driving mechanisms of the Low-Carbon Energy Consumption Index (LECI), this study selected a set of explanatory variables covering economic development, policy orientation, technological innovation, resource availability, and socio-environmental conditions. These variables have strong theoretical foundations and practical representativeness, enabling a comprehensive reflection of both external drivers and internal conditions for low-carbon energy transition.

The LECI is a composite indicator that captures the structural orientation of energy consumption toward low-carbon

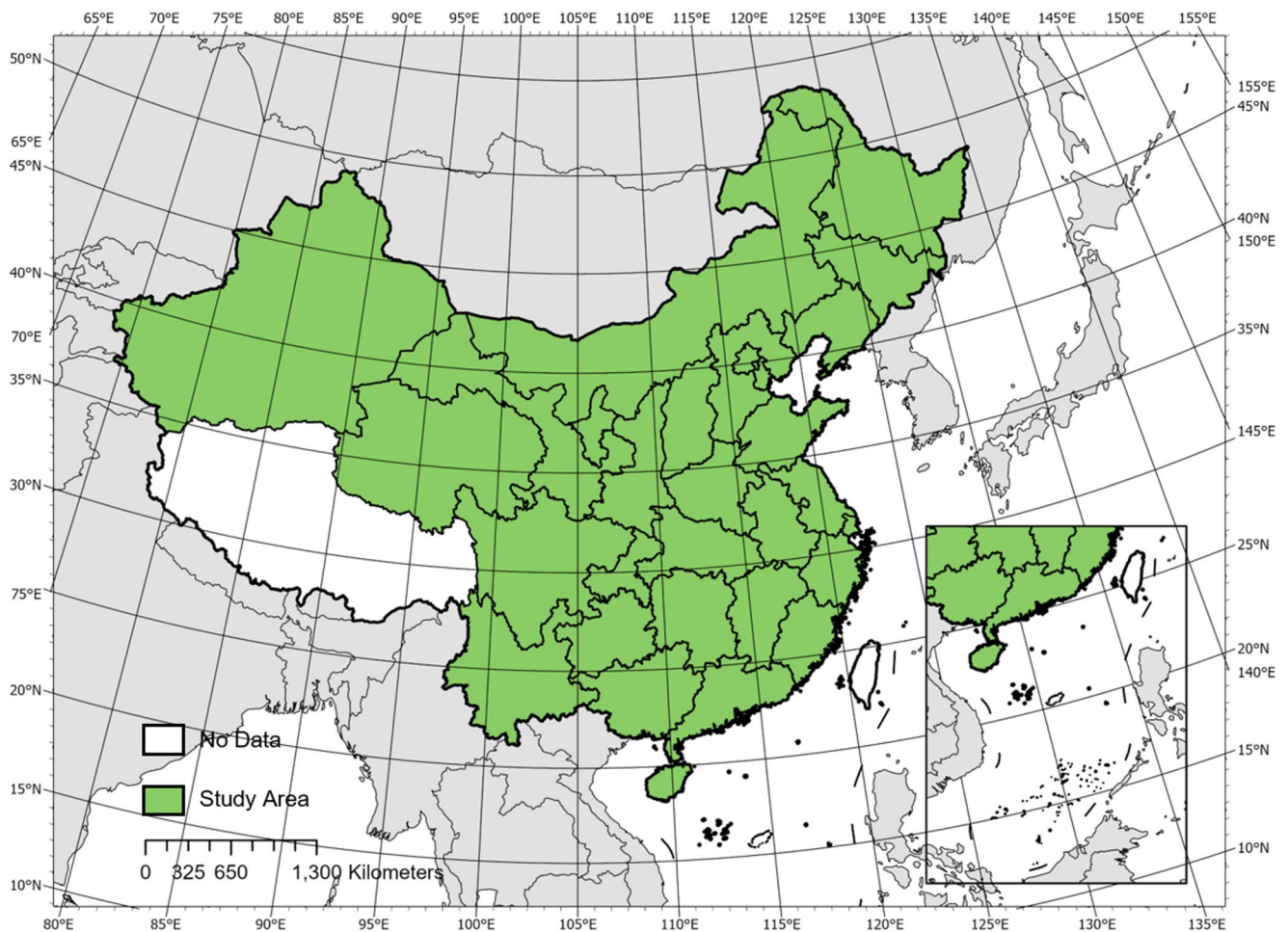


Fig. 1 A schematic map of the study area

sources. It is used to evaluate the environmental friendliness and sustainability of an energy system (Zheng et al. 2011; An et al. 2011). A higher LECI value indicates a cleaner and more low-carbon energy mix. Unlike conventional carbon intensity indicators, which mainly measure carbon emissions per unit of output, the LECI focuses on the composition of energy consumption across energy types. In its construction, the use of arccos transforms cosine similarity into an angular distance, which helps reflect how closely the observed energy mix aligns with benchmark energy structures of different carbon levels and thus better captures the direction of energy transition. The squared terms are part of the vector normalization process, ensuring that the index reflects differences in energy composition rather than scale. Therefore, compared with standard carbon intensity measures, the LECI is more suitable for identifying structural changes in energy consumption and regional disparities in low-carbon energy use.

The LECI is calculated as follows:

$$LECI = \arccos[\cos(\theta_1)]^3 + \arccos[\cos(\theta_2)]^2 + \arccos[\cos(\theta_3)] \quad (1)$$

where α , β , and γ represent the shares of coal, oil and gas, and other energy sources in total energy consumption, respectively; α is coal consumption; β is oil and gas consumption; and γ is other energy consumption. The values are computed as:

$$\cos(\theta_1) = \frac{\alpha}{\alpha^2 + \beta^2 + \gamma^2} \quad (2)$$

$$\cos(\theta_2) = \frac{\beta}{\alpha^2 + \beta^2 + \gamma^2} \quad (3)$$

$$\cos(\theta_3) = \frac{\gamma}{\alpha^2 + \beta^2 + \gamma^2} \quad (4)$$

Other explanatory variables are presented in Table 1.

3.3 Multicollinearity test

Given the multidimensional nature of the selected variables, potential multicollinearity could weaken the explanatory power of regression models. Multicollinearity refers to a high degree of linear correlation among explanatory

Table 1 Variable categories and descriptions

Category	Variable	Abbrev.	Description	Unit
Economic Development	GDP per capita	GDP	Level of regional economic development and per capita wealth	CNY/person
	Industrial structure (tertiary share)	IND	Share of tertiary industry in GDP, reflecting service-sector development	–
	Level of industrialization	LOI	Share of industrial value added in GDP	–
	Urbanization rate	URB	Proportion of urban to total population	–
	Electricity consumption	EC	Regional electricity demand, reflecting economic activity intensity	100 million kWh
	Total energy consumption	TEC	Overall scale of regional energy use and emission pressure	10,000 tce
	Labor force level	LF	Size and educational level of the regional labor supply	–
Fiscal Investment	Govt. expenditure on resource exploration, power & information	LGER	Fiscal support for energy industry and ICT infrastructure	100 million CNY
	Investment in energy industry	IEI	Fixed asset investment in energy infrastructure	100 million CNY
	Govt. expenditure on environmental protection	LGEP	Public spending on pollution control and emission reduction	100 million CNY
	Govt. expenditure on science and technology	LGST	Fiscal support for R&D and innovation activities	100 million CNY
	FAI growth: electricity, heat, gas & water	GRFEP	Investment trend in clean energy infrastructure	%
	FAI growth: scientific research & technical services	GRFST	Investment growth in innovation-related industries	%
	FAI growth: water conservancy, environment & public facilities	GRFWE	Investment dynamics in ecological infrastructure	%
	Degree of government intervention	DGI	Ratio of government fiscal expenditure to GDP	–
Technological Innovation	Green technology innovation	GTI	Number of green patents; reflects regional low-carbon technological capacity	–
	R&D expenditure	RD	Total R&D spending, reflecting research investment intensity	100 million CNY
	Degree of openness	OPL	Ratio of trade/FDI to GDP, reflecting international economic connectivity	–
Natural Resources & Environment	Urban green area	UGA	Urban green infrastructure; microclimate regulation and carbon absorption	10,000 ha
	Total afforestation area	TAA	Annual forest expansion; natural carbon sink component	1,000 ha
	Total water resources	TWR	Regional water supply capacity; indicator of sustainable development conditions	100 million m ³
	Population density	PD	Population distribution density, affecting energy demand and infrastructure	persons/km ²
	Urban-rural income gap	URIG	Ratio of urban to rural per capita income; reflects development equity	–
	Ratio of financial institution loans to GDP	RLG	Financial depth and credit availability for economic activities	–

Note: FAI=fixed asset investment; tce=tonnes of coal equivalent. VIF values were computed on the full candidate set of 24 variables prior to screening. Variables with $VIF \geq 10$ were excluded unless theoretical justification warranted retention; the final model uses 14 retained variables. See the Appendix VIF analysis

variables, which can lead to unstable coefficient estimates and reduced interpretability.

To ensure reliability and robustness, we applied the Variance Inflation Factor (VIF) to diagnose and filter variables (Kalnins And Hill 2023):

$$VIF_i = \frac{1}{1-R_i^2} \tag{5}$$

where VIF_i is the VIF for the i -th variable, and R_i^2 is the coefficient of determination obtained by regressing the i -th variable on all other explanatory variables. Variables with $VIF < 10$ were retained, while those with higher multicollinearity were removed or reconstructed to improve the stability, significance, and interpretability of subsequent GTWR and machine learning models.

3.4 Spatial Autocorrelation Analysis

Before exploring the driving mechanisms of LECI, it is necessary to examine its spatial correlation and clustering characteristics. We employed Global Moran’s I and Local Moran’s I (LISA) to evaluate spatial autocorrelation (Anselin 1995).

The formula for Global Moran’s I is:

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{6}$$

where n is the number of observations, x_i and x_j are the observed values for regions i and j , \bar{x} is the mean, w_{ij} is the spatial weight between i and j , and W is the sum of all spatial weights. Positive I indicates spatial clustering of similar values, negative I suggests dissimilar neighbors, and values near zero imply random spatial patterns.

Local Moran’s I is defined as:

$$I_i = (x_i - \bar{x}) \sum_j w_{ij} (x_j - \bar{x}) \tag{7}$$

It identifies local spatial clusters and outliers, commonly classified into four types: high–high, low–low (positive spatial clusters), and high–low, low–high (spatial outliers or boundary effects).

3.5 Geographically and temporally weighted regression

The GWR model incorporates spatial variation into parameter estimation, allowing for the detection of local non-stationarity (Rogerson and Fotheringham 2008):

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^p \beta_k(\mu_i, v_i) x_{ik} + \epsilon_i \quad (i = 1, 2, 3 \dots n) \tag{8}$$

where y_i is the dependent variable at location i , (μ_i, v_i) are geographic coordinates, β_0, β_k are local intercepts and coefficients, p is the number of explanatory variables, and ϵ_i is the error term.

GTWR extends GWR by adding temporal weights to capture spatiotemporal non-stationarity (Fotheringham et al. 2015):

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^p \beta_k(u_i, v_i, t_i) x_{ik} + \epsilon_i \quad (i = 1, 2, 3 \dots n) \tag{9}$$

The spatiotemporal distance is calculated as:

$$D_{ij} = \sqrt{\gamma [(u_i - u_j)^2 + (v_i - v_j)^2] + \mu (t_i - t_j)^2} \tag{10}$$

$$D_{st} = \gamma D_s + \mu D_t \tag{11}$$

where D_s and D_t represent spatial and temporal distances, γ and μ are scaling parameters for spatial and temporal dimensions.

3.6 Machine learning methods

3.6.1 Machine learning methods

XGBoost is an efficient implementation of the Gradient Boosted Decision Tree (GBDT) framework (Chen And Guestrin 2016). It iteratively builds CART regression trees to fit the negative gradient of the loss function, optimizing:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l \left(y_i, y_i^{(t-1)} + f_t(x_i) \right) + \Omega(f_t) \tag{12}$$

where f_t is the tree added at iteration t , Ω is the regularization term controlling tree complexity and preventing overfitting.

3.6.2 SHAP

In the field of nonlinear relationship modeling, ML algorithms generally demonstrate superior fitting accuracy compared with traditional statistical regression models. This advantage stems from the advanced architectures and flexible activation functions employed by ML algorithms (El Bilali et al. 2023). However, this gain in predictive accuracy often comes at the cost of reduced interpretability relative to statistical models.

SHAP is a post-hoc interpretability method designed for ML models. It quantifies the marginal contribution of each feature to the model output, enabling both global and local interpretation of nonlinear relationships. When a feature is included in the model’s prediction, SHAP measures its effect by evaluating the expected change in the model output. The algorithm considers all possible combinations of

feature values to compute the Shapley value, which represents the average marginal contribution of a feature to the prediction.

By aggregating Shapley values across all features, SHAP provides a global explanation of model behavior. Additionally, SHAP offers local interpretability by computing the Shapley values for individual instances, thereby revealing each feature's contribution to a specific prediction (Wang et al. 2021):

$$\phi_i(f) = \sum_{s \subseteq N \setminus \{i\}} \frac{|s|! \cdot (|N| - |s| - 1)!}{|N|!} [f(S \cup \{i\}) - f(s)] \quad (13)$$

where ϕ_i is the SHAP value for feature i ; N is the set of all features; s is a subset of features excluding i ; and f is the model prediction using only features in s .

SHAP assumes that the model output can be expressed as a linear sum of individual feature contributions:

$$f(x) = \phi_0 + \sum_{i=1}^M \phi_i(x_i) \quad (14)$$

where ϕ_0 is the baseline prediction and ϕ_i is the contribution of feature i .

3.7 Model evaluation

An essential step in model development is validation and performance evaluation. Once the model is built, its predictive quality must be assessed to determine whether it produces reliable results for the intended application. In this study, the predictive models were trained on the training dataset and validated using a test dataset.

To comprehensively evaluate the accuracy and bias between predicted and actual values, we employed multiple performance metrics, including the root mean squared error (RMSE), coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE). MSE quantifies the average squared deviation between predictions and observations, while RMSE, as the square root of MSE, offers a more interpretable measure of error magnitude. The R^2 statistic reflects the proportion of variance in the target variable explained by the model. MAE measures the average absolute deviation between predictions and observations, providing an intuitive representation of prediction accuracy. Collectively, these indicators offer a comprehensive understanding of the model's predictive performance and robustness.

$$RMSE = \sqrt{\sum_{i=1}^N (\hat{y}_i - y_i)^2 / N} \quad (15)$$

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (y_i - \bar{y})^2} \quad (16)$$

$$MAE = \sum_{i=1}^N |\hat{y}_i - y_i| / N \quad (17)$$

$$MSE = \sum_{i=1}^N (\hat{y}_i - y_i)^2 / N \quad (18)$$

where y_i denotes the observed value, \hat{y}_i is the model-predicted value, \bar{y} represents the mean of the observed values, and N is the number of samples in the training or testing stage.

The Akaike Information Criterion (AIC) is a widely used metric for evaluating the quality of regression models, with a smaller value indicating better model fit. The corrected Akaike Information Criterion (AICc) is an adjustment of AIC for small sample sizes and is commonly applied in GTWR model comparisons:

$$AICc = 2k + n \cdot \ln(\sigma^2) + \frac{2k(k+1)}{n-k-1} \quad (19)$$

where k is the number of model parameters and σ^2 is the residual variance.

4 Results

4.1 Spatiotemporal evolution of low-carbon energy consumption

To visualize the spatiotemporal characteristics of the LECI across Chinese provinces, two-dimensional heatmaps were generated for the period 2012–2022, showing east–west (Fig. 2a) and north–south (Fig. 2b) distributions. Darker colors indicate higher levels of low-carbonization. The LECI exhibits pronounced zonal differences and regional heterogeneity in space, alongside a temporal pattern of steady overall improvement and convergence in regional gradients.

In Fig. 2a provinces are arranged by longitude, revealing a clear “high in the east, low in the west” pattern. Eastern provinces such as Jiangsu, Zhejiang, Shandong, Shanghai, and Beijing consistently rank at the top nationally. By 2012, their LECI values had already exceeded 6.2, and by 2022, some provinces, such as Beijing and Zhejiang, surpassed 7.0. Central provinces such as Hunan, Hubei, Jiangxi, and Henan demonstrate stable growth, with a more rapid rise after 2016. Hubei and Jiangxi, for example, surpassed the national average around 2021. Western provinces, including Qinghai, Ningxia, Inner Mongolia, and Xinjiang, maintained relatively low LECI values during 2012–2016, generally between 5.0 and 5.5, but showed an upward trend after 2020.

In Fig. 2b, provinces are arranged by latitude. Northern and central provinces show greater variability, whereas southern provinces display relatively consistent and stable levels. Northern provinces such as Beijing, Inner Mongolia, Liaoning, and Tianjin had comparatively high LECI values

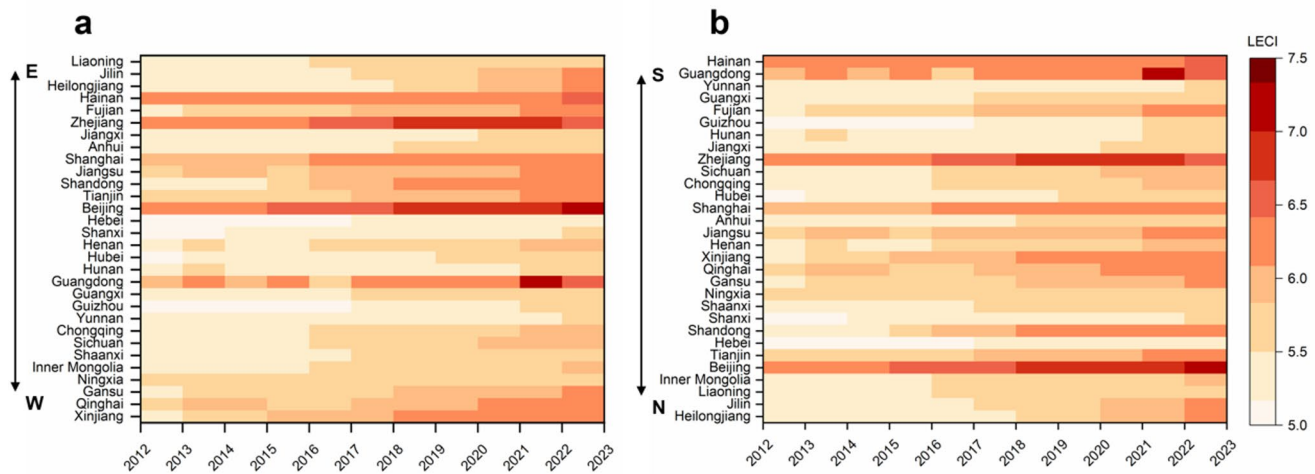


Fig. 2 Two-dimensional heatmaps of LECI from 2012 to 2023, where (a) represents the east–west direction and (b) represents the north–south direction

during the early years, although the three northeastern provinces fluctuated noticeably. Central provinces such as Anhui, Henan, and Shaanxi saw significant improvements after 2016. In the southern coastal region, including Hainan, Guangdong, Guangxi, and Fujian, LECI values were generally high and remained relatively stable over time. Guangdong and Hainan exceeded 7.0 after 2021. Overall, the results indicate that provincial low-carbon energy consumption improved during the study period, while interregional disparities gradually narrowed.

4.2 Spatial autocorrelation and GTWR model performance

To assess the spatial dependence of LECI, Moran's *I* statistics were calculated. The global Moran's *I* for LECI is 0.8254 ($p=0.001$), indicating strong positive spatial autocorrelation. The local Moran's *I* scatterplot (Fig. 3) further shows the coexistence of high–high and low–low clusters, suggesting that provinces with similar low-carbonization levels tend to be spatially concentrated.

Year-by-year Global Moran's *I* statistics for 2012–2022 are reported in Appendix Table C1. The results show that spatial autocorrelation remained positive and statistically significant throughout the study period, while the magnitude of Moran's *I* declined overall, suggesting a gradual weakening of spatial clustering intensity and partial convergence in regional LECI disparities.

Model comparison results are shown in Table 2. OLS produced an R^2 of 0.63 and an AICc of 45.59. GWR improved the model fit substantially, with an R^2 of 0.92 and an AICc of -363.2916 . GTWR also performed well, with an R^2 of 0.89 and the lowest AICc value of -1297.44 . These results

indicate that incorporating spatial and temporal heterogeneity improves the model's explanatory capacity.

4.3 Temporal evolution of GTWR coefficients

To investigate the dynamic influence of each driver over time, boxplots of GTWR regression coefficients for each explanatory variable from 2012 to 2022 were generated (Fig. 4). The medians, ranges, and annual changes of coefficients reveal clear temporal heterogeneity across variables.

Among the explanatory variables, GTI is the only variable with consistently positive and relatively stable coefficients throughout the study period. IEI also remains positive over time. TAA shows positive but fluctuating coefficients, with greater stability after 2015. In contrast, LOI and URIG remain persistently negative, and their negative effects become stronger in later years. LGEP and TWR are also generally negative, although the magnitude of TWR gradually narrows. DGI shows a marked temporal shift, with coefficients changing from negative in the early years to positive in later years. RLG remains positive overall, but its median coefficient declines after 2017. Other fiscal and investment-related variables, such as GRFEP, GRFST, and GRFWE, display relatively weak and unstable coefficient patterns.

4.4 Spatial differentiation of key GTWR drivers

Table 3 ranks variable importance in the GTWR model. GTI has the highest mean absolute coefficient (3.284527), followed by URIG (1.327485), RLG (0.352777), PD (0.17325), and LOI (0.123854). Based on these results, five key drivers—DGI, GTI, LOI, URIG, and RLG—were

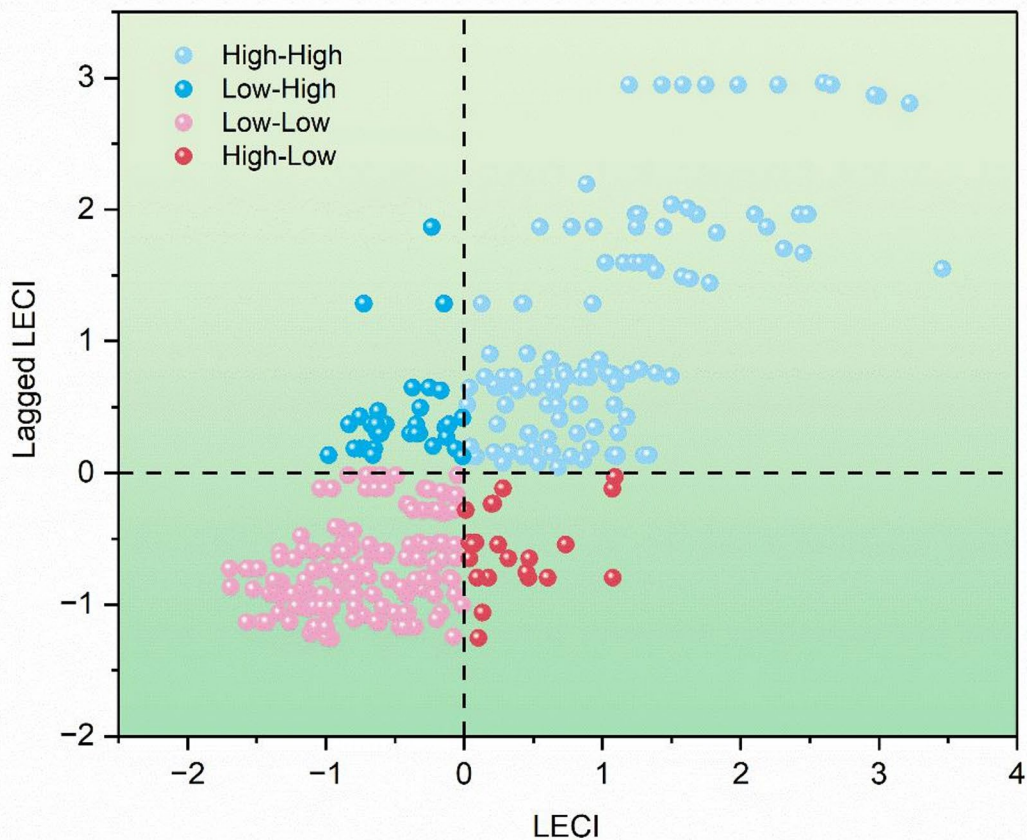


Fig. 3 Local Moran’s I scatter plot, where each point represents a province in a specific year

Table 2 Comparisons of different models

Model	R^2	Adjusted R^2	AICc
OLS	0.63	0.61	45.59
GWR	0.92	0.91	-363.2916
GTWR	0.89	0.88	-1297.44

further examined using spatial coefficient maps for 2012, 2017, and 2022 (see Figs. 5, 6 and 7).

For DGI, positive coefficients were mainly observed in some western provinces in 2012, whereas many central and eastern provinces showed negative coefficients. By 2017, positive coefficients had expanded across central and southeastern provinces, and by 2022, positive impacts were nearly universal. GTI showed strong positive effects in eastern China in 2012, followed by expansion into central and western provinces in 2017, and nationwide strong positive coefficients by 2022. LOI exhibited negative effects throughout the study period, with the strongest negative coefficients initially concentrated in the northwest and later

spreading nationwide. URIG also showed consistently negative effects, initially concentrated in central and western provinces and later expanding into eastern provinces. RLG had positive coefficients mainly in eastern and central provinces in 2012, with the positive influence becoming stronger and more widespread by 2017 and 2022.

Overall, the spatial distributions of these coefficients indicate substantial regional variation in the effects of different drivers, together with an increasing tendency toward broader spatial coverage of several key factors over time.

4.5 XGBoost model performance and SHAP-based importance

To verify the robustness of the drivers identified by GTWR, the XGBoost model was estimated and interpreted using SHAP. The XGBoost model achieved $R^2 = 0.87$, $MSE=0.0267$, $RMSE=0.1635$, and $MAE=0.1250$ on the test set, indicating good predictive performance. The

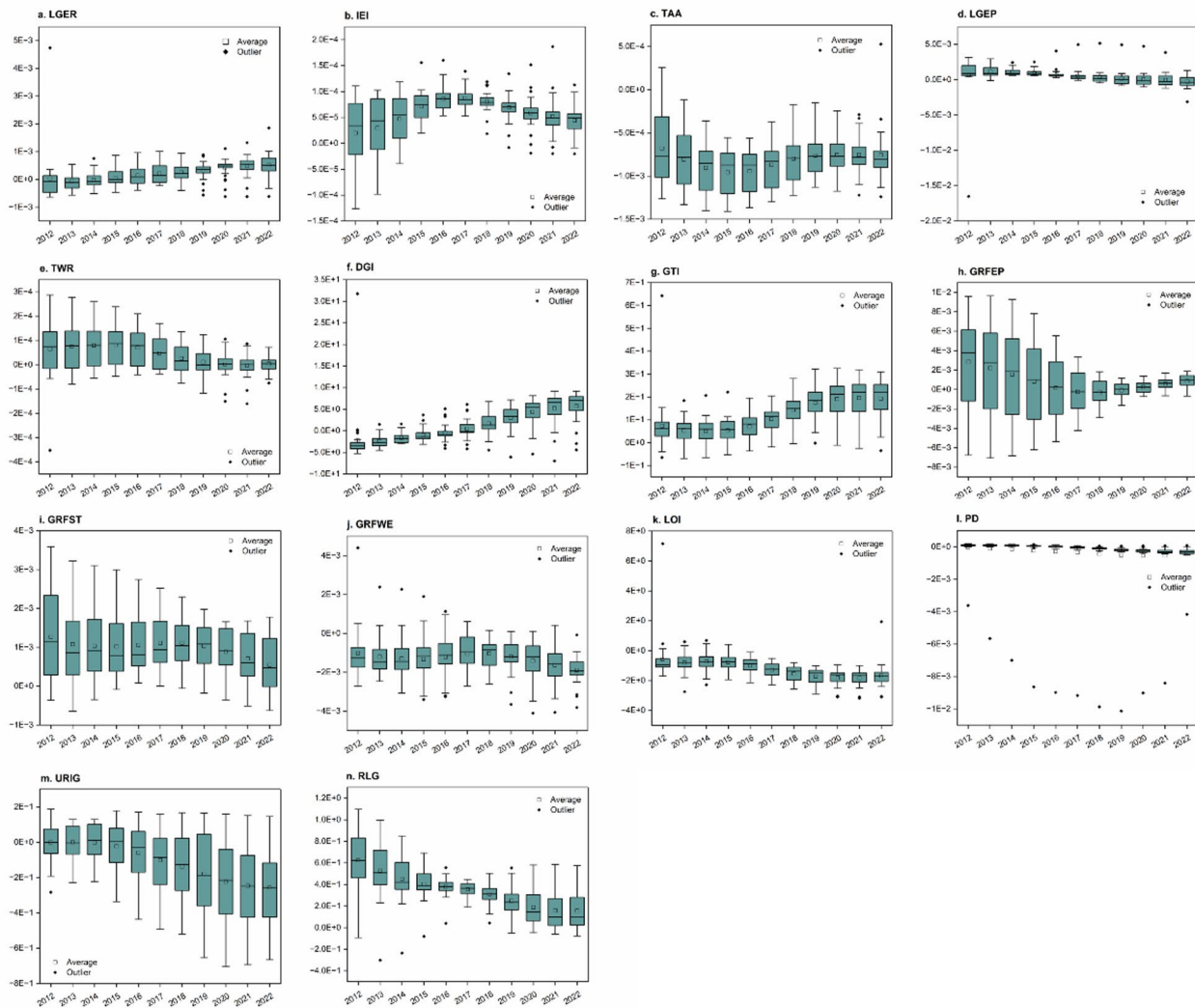


Fig. 4 Boxplots of regression coefficients for each variable from 2012 to 2022

Pearson correlation heatmap further shows that most variables have low pairwise correlations, with only a few moderate correlations (see Fig. 8).

Figure 9 shows the SHAP results, which rank GTI as the most important variable, with a mean SHAP contribution of about 27.4% of the total. RLG accounts for 14.1%, while TAA and IEI each contribute about 10%. PD contributes about 4.6%. DGI and GRFST have relatively low average contributions, but their SHAP values are notable for some observations. LOI and URIG have comparatively smaller global contributions, but their SHAP values are concentrated in the negative range. Variables such as LGER, GRFEP, GRFWE, and LGEP contribute less than 2.5%.

4.6 Nonlinear effects of key variables

SHAP dependence plots were used to further examine nonlinear effects of representative variables (Fig. 10). The results reveal heterogeneous response patterns across variables. DGI exhibits a U-shaped relationship. RLG shows a clear positive relationship, with contributions increasing as the variable rises. URIG displays a stronger negative marginal effect when the urban–rural income ratio exceeds 2.4. GTI shows a pronounced nonlinear positive effect, with SHAP values rising sharply when GTI exceeds 5. TAA displays an inverted pattern, with positive effects at smaller values and negative effects after afforestation exceeds approximately 200,000 hectares. IEI shifts from negative effects at very low levels to positive and stable effects at higher levels. PD shows a stepwise pattern, with relatively higher positive contributions in low-density provinces and reduced SHAP

Table 3 Importance ranking of variables in the GTWR model

Name	mean_abs.	std_coef
GTI	3.284527	4.190852
URIG	1.327485	0.870061
RLG	0.352777	0.225035
PD	0.17325	0.204457
LOI	0.123854	0.094787
GRFWE	0.002305	0.003172
GRFST	0.001397	0.001012
GRFEP	0.001045	0.000843
DGI	0.000867	0.001357
TWR	0.000822	0.000287
LGEP	0.000394	0.001438
LGER	0.000367	0.000469
IEI	6.69E-05	4.43E-05
TAA	6.57E-05	8.23E-05

Note: "mean_abs." refers to the mean absolute value of the estimated coefficients across repeated model runs, reflecting the overall magnitude of each variable's effect regardless of direction. "std_coef" refers to the standard deviation of the estimated coefficients, indicating the stability and variability of the coefficient estimates across runs. A larger mean_abs. suggests a stronger overall contribution, whereas a larger std_coef suggests less stable estimates

values in high-density provinces. LOI exhibits a relatively flat curve with a generally weak but negative tendency. R^2 represents the coefficient of determination, which measures the goodness of fit of the model.

4.7 Comparison between GTWR and XGBoost-SHAP

The results of GTWR and XGBoost-SHAP are broadly consistent in identifying major drivers. GTI, RLG, and PD emerge as important positive drivers in both approaches. GTI ranks first in both models, with the highest mean absolute coefficient in GTWR and the highest SHAP contribution in XGBoost. RLG is also ranked among the leading positive drivers in both methods. PD has a moderate but positive contribution in both frameworks.

Differences also appear across methods. URIG ranks second in GTWR but has a lower global contribution in SHAP, although both approaches indicate a negative effect. LOI is ranked fifth in GTWR and has relatively low SHAP importance, while remaining negative in both models. By contrast, TAA and IEI rank very low in GTWR but contribute substantially in SHAP, indicating that their effects

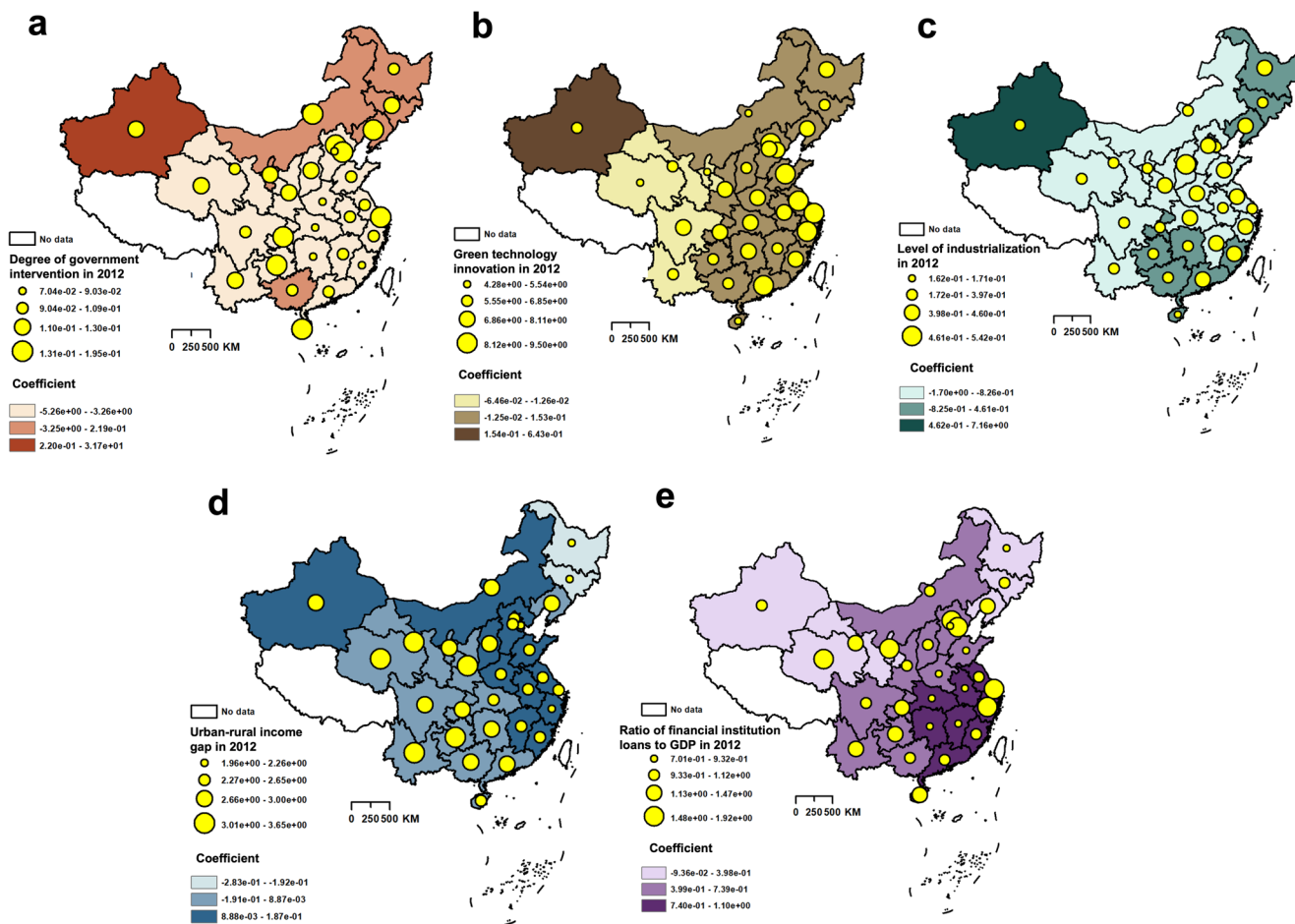


Fig. 5 Spatial distribution of regression coefficients for each variable in 2012

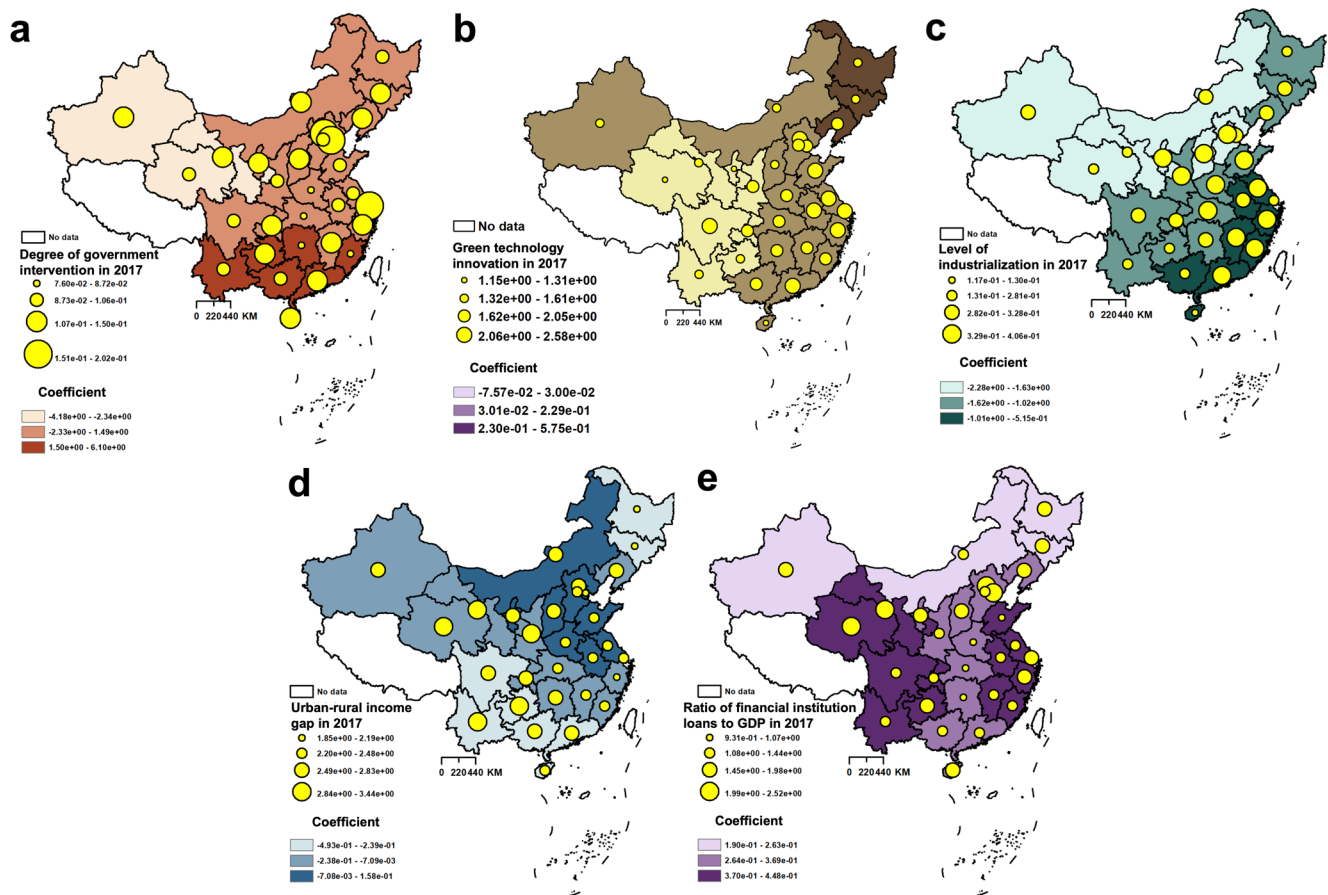


Fig. 6 Spatial distribution of regression coefficients for each variable in 2017

are more prominent in the nonlinear framework. DGI also shows limited average importance in GTWR but displays visible SHAP effects in specific observations, while GTWR additionally captures its strong temporal variation.

4.8 Robustness check

To ensure that the core findings are not an artifact of the LECI construction method, a robustness check was conducted by replacing LECI with the share of non-fossil energy in total electricity generation (NFES) as the dependent variable. NFES is a widely adopted, directly observable indicator of clean energy transition and serves as a more conventional benchmark against which the LECI-based results can be validated. Provincial NFES values were constructed using data from the China Electric Power Yearbook, calculated as the combined output of hydropower, nuclear, wind, and solar generation divided by total electricity generation for each province-year observation over 2012–2022.

The GTWR model was re-estimated with NFES as the dependent variable using identical explanatory variables, spatial coordinates, and bandwidth parameters ($\lambda=100$, $k=80$). The model achieved an R^2 of 0.950 and an adjusted

R^2 of 0.882, confirming strong model fit. The results provide substantial support for the robustness of the key conclusions drawn from the LECI-based analysis. Specifically, GTI retained a consistently positive and strengthening effect from 2015 onwards; LOI maintained a negative effect throughout the entire period; and URIG exhibited a persistent and deepening negative impact, fully consistent with the original findings. DGI also showed a predominantly negative directional pattern under NFES, with signs of gradual moderation toward the end of the study period, mirroring the temporal shift observed in the LECI model.

One notable divergence was observed for RLG, which showed a positive effect in the LECI model but a largely negative effect in the NFES model. This discrepancy is interpretable and does not undermine the overall conclusions. RLG captures the ratio of financial institution loans to GDP—a measure of credit availability and financial deepening. In the context of energy consumption structure (LECI), higher financial activity facilitates household and industrial access to cleaner energy technologies, thereby promoting low-carbon consumption patterns. In contrast, NFES reflects the generation-side composition of the electricity system, which is more directly shaped by large-scale

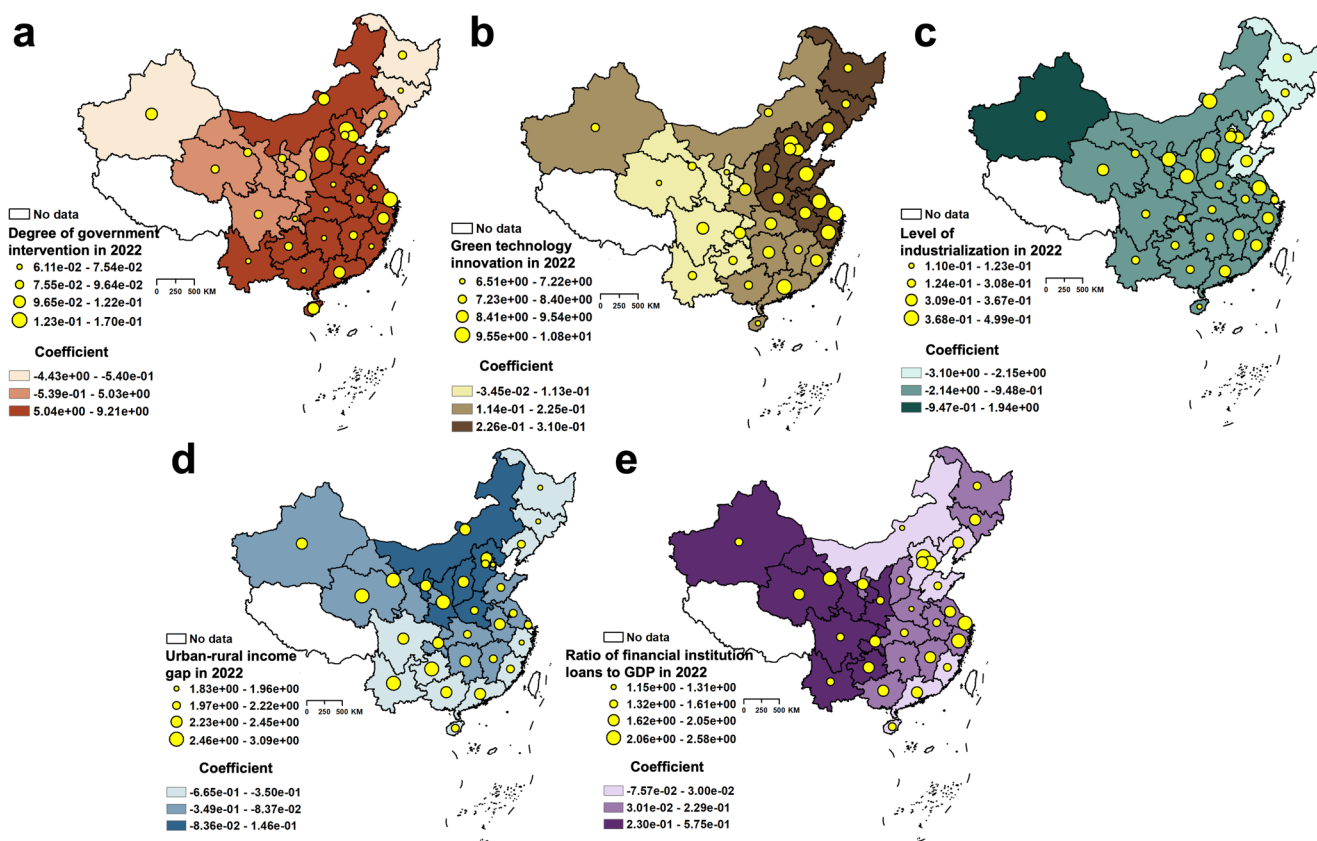


Fig. 7 Spatial distribution of regression coefficients for each variable in 2022

capital investment in renewable capacity and grid infrastructure rather than by general credit conditions. The divergence thus reflects the inherently different dimensions of energy transition captured by the two indicators, rather than an inconsistency in the underlying mechanism. Overall, the robustness check confirms that the principal conclusions of this study—particularly regarding the dominant role of GTI, the structural constraint of LOI, and the equity barrier of URIG—are not sensitive to the choice of dependent variable.

5 Discussions

5.1 Persistent regional inequality: institutional and structural explanations

China's provincial LECI improved steadily from 2012 to 2022, yet the east–west gap has not closed. This persistence cannot be explained by investment gaps alone. Two structural mechanisms deserve attention.

First, China's inter-provincial electricity trade system creates a statistical artifact that inflates eastern LECI values. Western provinces such as Qinghai, Sichuan, and Xinjiang generate large volumes of hydropower and wind power

that are transmitted eastward through ultra-high-voltage lines. The receiving provinces record the electricity as part of their consumption mix, raising their apparent low-carbon share, while the exporting provinces remain locked in heavy industrial energy use domestically. China's national ETS covers approximately 4.5 Gt CO₂ from the power sector alone, yet it does not resolve the misalignment between where clean power is generated and where it is consumed (International Energy Agency (IEA) 2022). Addressing this requires reforms to how renewable energy consumption is attributed across provincial boundaries.

Second, fiscal decentralization constrains local government capacity to enforce clean energy standards in less-developed provinces. Provincial officials' performance evaluations historically emphasized GDP growth, which biased public expenditure toward conventional industrial infrastructure. Low-carbon energy transition is increasing but shows uneven spatial distribution, and its effectiveness in reducing urban–rural energy inequality varies significantly by region, partly because local institutional capacity determines how effectively national mandates translate into local action (Sun et al. 2024). The persistent “low–low” spatial clusters in Moran's I reflect not only economic backwardness but also institutionally embedded path dependence in governance and energy system design.

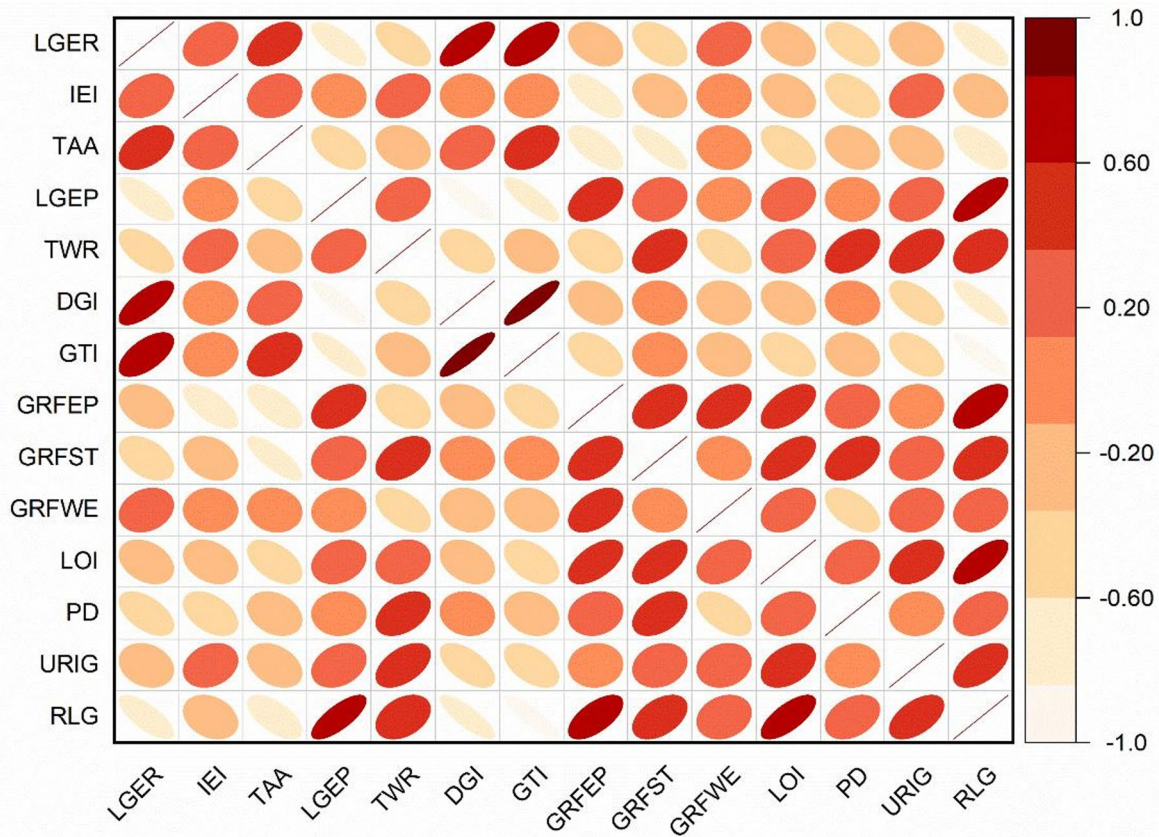


Fig. 8 Correlation matrix of the variables

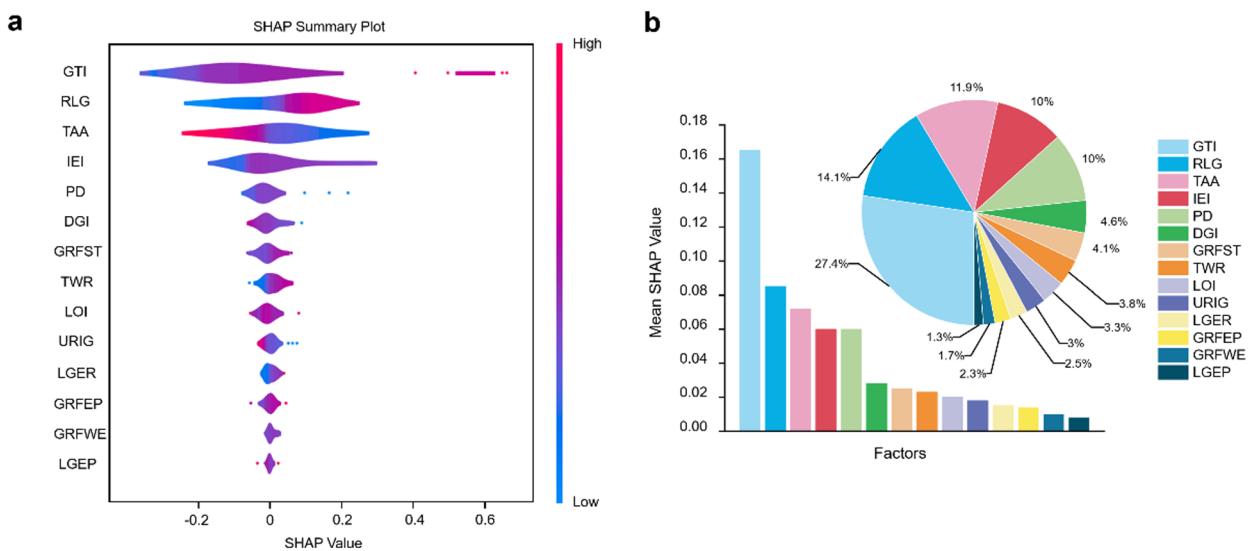


Fig. 9 SHAP results: (a) SHAP summary plot; (b) mean SHAP values of each variable

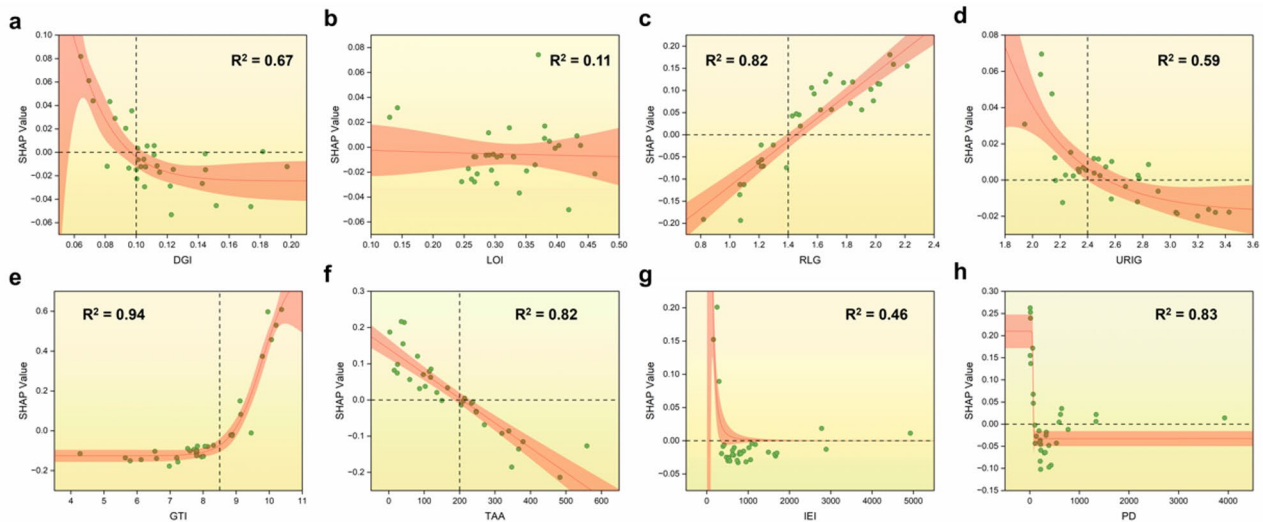


Fig. 10 Partial dependence plots of key influencing factors identified by machine learning and GTWR

5.2 Green technology innovation: threshold effects and spatial diffusion

GTI is the dominant driver in both GTWR and XGBoost-SHAP, and this convergence across methods with fundamentally different assumptions strengthens the finding considerably. The result is broadly consistent with Maghyreh et al. (Maghyreh et al. 2025), who find that green innovation drives energy transition investments, and with Liao et al. (Liao et al. 2023), who confirm positive GTI effects on renewable energy transition across OECD economies. Our study extends these findings to China's provincial context and adds two dimensions absent from the prior literature.

First, the SHAP dependence plot reveals a nonlinear threshold: GTI's positive effect on LECI becomes pronounced only when GTI exceeds approximately 5 patent units. Below this threshold, marginal increases in green patents produce limited structural change. This pattern is consistent with the absorptive capacity hypothesis: innovation generates energy structure effects only after a minimum technological base is established. Renewable energy innovation in China shows distinct spatial differences, being high in the east and south and low in the west and north, exhibiting spatial locking and path-dependence (Ma et al. 2023). For provinces below the threshold—predominantly in central and western China—incremental increases in green patent counts will not automatically translate into cleaner energy mixes. Policy should therefore target R&D infrastructure investment and personnel training to raise the absorptive floor, rather than expecting patent quantity alone to drive change.

Second, GTWR captures the spatial diffusion of GTI effects over time, from eastern coastal provinces toward the

interior. When a province achieves breakthroughs in new energy fields, surrounding provinces are inspired to adopt similar technologies and strategies through knowledge spillovers, supply chain integration, and policy learning (Jiang et al. 2024). This diffusion mechanism implies that supporting innovation leaders in eastern provinces can generate downstream benefits for lagging regions, but the magnitude of spillover depends critically on the absorptive capacity of receiving provinces.

A point of apparent inconsistency with (Liao et al. 2023) is that Liao et al. find green innovation effects on ecological sustainability mediated by industrialization, while our results show LOI as a negative driver independent of GTI. This reflects the different outcome variables: Liao et al. examine ecological sustainability broadly, whereas we focus specifically on the energy consumption structure. In a heavily industrialized province, green innovation may improve energy efficiency at the firm level without shifting the overall energy mix away from coal—explaining why LOI remains robustly negative even after controlling for GTI.

5.3 Government intervention: a policy-driven transition

The shift in DGI coefficients from negative to positive is among the most theoretically significant findings. It reflects a genuine change in the orientation of Chinese fiscal governance, traceable to specific policy milestones. Before 2015, provincial government expenditure was disproportionately directed toward conventional industrial infrastructure, and environmental regulation was frequently subordinated to growth targets in cadre evaluation systems. The Paris

Agreement in December 2015 initiated a normative shift, but the critical turning point was institutional. Carbon emissions trading pilots had operated in seven provinces and cities since 2013 (Beijing, Shanghai, Tianjin, Guangdong, Hubei, Chongqing, and Fujian). In July 2021, the National Carbon Emission Trading Market was launched for online trading, becoming the largest carbon trading market in the world in terms of greenhouse gas emissions covered (Zhang et al. 2025). China's announcement of the dual-carbon goals at the United Nations General Assembly in September 2020 elevated climate targets to the highest level of national political commitment. China's 14th Five-Year Plan presents an opportunity to link long-term climate goals with short-to-medium-term social and economic development plans, embedding renewable energy targets into provincial planning requirements for the first time (Hepburn et al. 2021).

The SHAP dependence plot adds a critical nuance: DGI shows a U-shaped relationship with LECI. At moderate intervention levels ($DGI \approx 0.1-0.3$), the effect remains negative, suggesting that partial intervention distorts market signals without achieving structural change. Only at high intervention intensity ($DGI > 0.3$) does a strongly positive effect emerge. This threshold pattern is consistent with the policy credibility literature: ambiguous or incremental government signals can delay private clean energy investment by increasing uncertainty, while decisive and sustained commitments trigger investment cascades. The practical implication is that half-measures in provincial clean energy governance may be worse than no intervention, as they impose costs without delivering structural transformation.

5.4 Industrialization and urban–rural inequality: structural barriers

The persistent negative effects of LOI and URIG reveal the structural barriers behind regional inequality. Regarding LOI, the contribution of industrial structure upgrading to China's carbon peak target is estimated to exceed that of energy structure transformation by a factor of three. Industrial structure upgrading contributes 456.3% to China's carbon peak, whereas the contribution from the low-carbon transition of energy structures is 143.2% (Yang et al. 2024). In this context, the deepening negative LOI coefficients observed in GTWR—from approximately -1.5 in 2012 to below -9 in several provinces by 2022—are consistent with a sectoral lock-in effect rather than simple industrial growth. Provinces with persistent high industrial shares are not only dependent on fossil fuels for current production; they have accumulated stranded-asset risks that make energy restructuring economically and politically costly.

Regarding URIG, low-carbon energy transition is effective in reducing urban–rural energy inequality, but only

under conditions where energy service accessibility is available (Sun et al. 2024). The SHAP analysis reveals that the negative effect of URIG intensifies when the urban–rural income ratio exceeds 2.4, which defines a threshold beyond which income disparities begin to actively suppress clean energy adoption rather than merely failing to promote it. Urban residents benefit from favorable energy policies and abundant infrastructure, while rural residents in remote areas are often overlooked by energy policymakers and remain at the lower end of the energy ladder (Xiao et al. 2024). This finding reinforces that low-carbon transition is a distributional question, not only a technological one: provinces with wide income gaps face a socially embedded barrier that infrastructure investment alone cannot overcome.

The discrepancy between GTWR and XGBoost-SHAP in the importance of IEI also merits explanation. In GTWR, IEI's mean absolute coefficient is among the lowest (6.69×10^{-5}), suggesting limited average spatial effect. Yet SHAP assigns IEI approximately 10% of total contribution. This divergence arises because GTWR estimates locally linear effects, which average out IEI's contribution across heterogeneous spatial contexts. XGBoost captures the nonlinear structure: IEI's effect is negligible at low investment levels, transitions sharply positive in the medium range, and stabilizes at higher levels. This threshold behavior—consistent with economies of scale in clean energy infrastructure—is invisible to local linear regression. The finding implies that energy industry investment only generates energy structure benefits above a minimum scale threshold, which has direct relevance for targeting investment in lagging provinces.

5.5 Green finance: from quantity to quality

RLG is a positive driver in both models, and GTWR shows its spatial footprint expanding from eastern provinces toward the interior over time. Green finance development has a positive role in promoting low-carbon energy structure transformation, and this influence exhibits significant spatial spillover, exhibiting local and neighborhood reciprocity (Wan et al. 2023). However, the declining median GTWR coefficient after 2017 signals a transition in the nature of green finance's role. As access to credit expanded nationally under the 14th Five-Year Plan, the marginal effect of finance quantity diminished. This is consistent with the growing body of evidence suggesting that China's green bond market, despite being the largest globally by issuance volume, continues to finance projects with substantial transition-risk exposure rather than genuinely low-carbon activities. The implication is that the policy priority should shift from expanding the scale of green lending to improving its targeting: directing credit specifically toward renewable energy

capacity in lagging provinces, with stricter additionality criteria.

5.6 Policy implications

For eastern provinces, the priority is deepening green innovation spillovers and improving the quality of green finance. Specifically, technology transfer programs targeting provinces below the GTI threshold of 5 should be designed around concrete mechanisms—joint R&D platforms, patent licensing schemes, and inter-provincial technical assistance—rather than general knowledge diffusion initiatives.

For central and western provinces, investment should target raising absorptive capacity in green technology rather than simply scaling patent counts. SHAP results show that TAA's positive effect reverses above approximately 200,000 hectares of annual afforestation, suggesting diminishing returns and possible land-use conflicts at large scales. Provincial afforestation programs should therefore be calibrated to stay within productive ranges rather than maximizing area coverage.

For high-URIG provinces, narrowing urban–rural income disparities should be treated as a prerequisite for clean energy transition, not an incidental social policy objective. The SHAP threshold at URIG=2.4 provides a concrete benchmark: provinces exceeding this ratio should receive targeted clean energy subsidies for rural households—structured to reduce both upfront technology costs and ongoing energy expenditures—as part of their transition pathway, not as a separate welfare program.

For high-LOI provinces, carbon market coverage should be extended to energy-intensive industrial sectors beyond the power sector, and ETS allowance benchmarks should be tightened to internalize the costs of industrial lock-in. The national ETS currently covers only the power sector; expanding to steel, cement, and chemicals—planned for 2027—is essential for making industrial restructuring economically rational in provinces where LOI remains persistently high.

These findings also carry implications beyond China. The core challenge documented here—that uniform national policies produce spatially uneven outcomes due to divergent innovation capacity, industrial structures, and income conditions—is common to large, regionally heterogeneous economies undergoing energy transition. In developing economies with substantial regional inequalities, aggressive or uniform climate actions may exacerbate inequity and induce economic losses that undermine national pledges (Yu et al. 2023). The threshold effects identified through SHAP analysis—on GTI, URIG, and DGI—offer a replicable methodology for calibrating differentiated transition policies in other federal or multi-regional contexts, such as

India, Brazil, and Indonesia. More broadly, the finding that income inequality actively suppresses clean energy adoption beyond a quantifiable threshold reinforces the case, relevant across developing economies, for treating distributional equity as an integral condition for effective energy transition rather than a secondary concern.

6 Conclusion

6.1 Main conclusions

Based on panel data from 30 Chinese provinces over 2012–2022, this study draws three main conclusions. First, provincial LECI improved steadily but regional disparities persist. The east–west gap has narrowed rather than closed, with spatial autocorrelation remaining significant throughout the period, reflecting structurally embedded differences in institutional capacity, industrial base, and infrastructure. Second, GTWR reveals marked spatiotemporal heterogeneity in driver effects. GTI is the most stable and powerful positive driver nationwide. URIG and LOI exert persistent negative effects, deepening over time. DGI shifted from negative to positive following the introduction of the dual-carbon policy framework, demonstrating the steering effect of sustained policy commitment. RLG shows a positive but weakening marginal effect, indicating a transition from quantity to quality in green finance allocation. Third, XGBoost-SHAP confirms the main drivers and uncovers nonlinear threshold effects invisible to linear models—including a U-shaped DGI relationship, scale-dependent TAA effects, and an investment threshold for IEI—enriching understanding of how driver effects vary across value ranges.

These findings carry broader relevance for other economies undertaking energy transitions. The evidence that uniform national policies systematically underperform in lagging regions—owing to divergent innovation capacity, industrial lock-in, and income inequality—applies to any large, regionally heterogeneous country. The threshold effects identified through SHAP provide a quantitative basis for calibrating differentiated policies, a methodology transferable beyond China. More broadly, the results reinforce that achieving an equitable energy transition requires simultaneous attention to technology diffusion, industrial restructuring, and distributive fairness, rather than treating these as sequential priorities.

6.2 Limitations and future research

This study has three limitations. First, the provincial scale and 2012–2022 window constrain the findings; key variables such as energy prices, carbon abatement costs, and

institutional quality indicators are absent. Finer spatial resolution and an extended time series would strengthen subsequent analyses.

Second, potential endogeneity warrants attention. GTI and DGI are likely subject to reverse causality: provinces with more advanced low-carbon energy structures may attract greater green innovation investment and stronger policy commitment, rather than being driven by them. Similarly, RLG may reflect endogenous financial deepening in regions already undergoing structural transformation. The GTWR and XGBoost frameworks employed here do not correct for endogeneity, and the estimated effects should therefore be interpreted as associations rather than causal relationships. Future research could address this through instrumental variable approaches or quasi-natural experiments—for example, exploiting the staggered rollout of China's carbon trading pilots as an exogenous source of variation in DGI, or using upstream patent citations as an instrument for GTI.

Third, the findings are grounded in the Chinese context; their transferability to other economies with different institutional arrangements and resource endowments requires cross-country validation.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

Declaration of generative AI and AI-assisted technologies in the writing process During the preparation of this work, the authors utilized GPT-5 to improve the English language presentation. After employing this service, the authors carefully reviewed and revised the content as necessary, and take full responsibility for the content of the published article.

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