

Article

Spatio-Temporal Heterogeneity of Regional Carbon Emission Drivers in China: Evidence from an Integrated Random Forest and GTWR Model

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Abstract

Precisely identifying the key drivers of regional carbon emissions and their spatiotemporal heterogeneity is critical for formulating differentiated strategies under China's "Dual Carbon" goals. To address the limitations of traditional models in variable screening and handling non-stationarity, this study constructs an analytical framework that integrates a Random Forest (RF) model for preliminary variable screening, Geographically and Temporally Weighted Regression (GTWR) for spatiotemporal quantification, and the CRITIC method for multidimensional evaluation. Based on panel data from 30 Chinese provinces spanning 2005 to 2023, this study investigates the spatiotemporal evolution of carbon emission drivers. The findings reveal significant regional disparities. In the eastern region, the emission-increasing effect driven by population continues to intensify. Although economic growth shows signs of decoupling from emissions, the emission reduction benefits of industrial upgrading are diminishing. Notably, provinces such as Jiangsu have even experienced a rebound in energy consumption, which is potentially linked to the expansion of digital infrastructure. In the central region, a "pollution haven" effect has emerged due to the relocation of energy-intensive industries. Furthermore, the impacts of population, urbanization, and energy consumption structure exhibit an inverted U-shaped trend, with green urbanization beginning to yield initial emission reductions. In the western region, the suppressive effect of energy intensity on emissions continues to strengthen, particularly around Shaanxi. For northern energy-rich areas, economic growth acts as a prominent driver, while the impact of population displays a clear "positive in the south, negative in the north" spatial pattern. Moreover, northern provinces have successfully leveraged agglomeration effects to achieve emission reductions. Ultimately, these findings provide robust empirical support for constructing a spatially differentiated governance system to facilitate carbon neutrality.

Keywords: carbon emissions; GTWR; RF; spatiotemporal evolution; regional heterogeneity



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1. Introduction

Global climate change has evolved into a critical challenge to human survival and development, with frequent extreme weather events posing profound threats to ecosystem

security and socioeconomic stability [1]. Against this backdrop, advancing global climate governance and fulfilling carbon reduction commitments have become a prevailing consensus within the international community. As a leading developing nation, China has committed to the “Dual Carbon” goals, aiming to peak CO₂ emissions by 2030 and achieve carbon neutrality by 2060. This strategy is not only a vital step in addressing the global climate crisis but also an essential driver for transforming China’s economic structure and achieving high-quality development.

As China advances its “Dual Carbon” strategy [2], critical challenges have emerged due to the significant structural and developmental heterogeneity across its eastern, central, and western regions. Traditional “one-size-fits-all” policies, predicated on national averages, are ill-suited to address these regional divergences, often resulting in policy inefficacy and resource misallocation. Therefore, identifying the key drivers of carbon emissions through a multidimensional spatiotemporal framework is essential for formulating the differentiated and targeted governance strategies required for effective decarbonization.

Extensive research has yielded substantial insights into the identification and underlying mechanisms of carbon emission drivers. Scholars have examined these factors across various scales, ranging from macro-level national and regional analyses to micro-level investigations at the industrial, corporate, and household levels [3]. At the provincial level, studies primarily focus on long-term determinants such as economic development, urbanization, and trade openness. A prevailing consensus identifies economic expansion as the primary catalyst for emission growth in most provinces. Concurrently, urbanization exerts complex, nonlinear impacts driven by agglomeration effects and demographic shifts [4]. Furthermore, comparative analyses indicate that the influence of these factors exhibits significant spatial heterogeneity, largely due to variations in geographical locations and developmental stages across regions.

Methodologically, a diverse array of analytical tools has provided robust frameworks for the quantitative assessment of carbon emission drivers. Notably, the STIRPAT model [5–8] has been widely utilized due to its flexibility in variable expansion, allowing researchers to examine the marginal effects of factors beyond population, affluence, and technology—such as foreign direct investment and environmental regulations. Similarly, the LMDI index decomposition method [9], a classic tool for analyzing fluctuations in total carbon emissions, enables the precise disaggregation and quantification of contribution shares from drivers like energy intensity, industrial structure, and the energy mix. Moreover, with the integration of economic geography, spatial econometric models [10]—including spatial lag and spatial error models—have gained increasing prominence. By capturing spatial spillover effects and strategic interactions between regions, these models effectively address the limitations inherent in traditional econometric approaches.

Empirically, the focus of such research has shifted from single-factor analyses to comprehensive multi-factor frameworks. For instance, Ortega-Ruiz et al. [11] and Ren et al. [12] confirmed that while reliance on fossil fuels remains a core driver of rising emissions, the substitution effect of clean energy exerts a significant mitigating influence. Yang et al. [13] demonstrated that a disproportionately high share of energy-intensive industries exacerbates regional carbon burdens, whereas upgrading industrial structures toward high-end and service-oriented sectors significantly reduces carbon intensity. Furthermore, Zeng et al. [14] emphasized that technological innovation serves as a critical pathway to achieving emission reductions by enhancing energy efficiency and promoting low-carbon processes.

However, existing literature presents four critical limitations hindering precise policy formulation. First, the analysis of driving factors remains oversimplified, often failing to elucidate the underlying mechanisms behind their regional spatiotemporal differentiation [15].

Second, the reliance on traditional global linear models neglects complex nonlinear dynamics and is susceptible to outliers [16–18], potentially compromising robustness. Third, most studies examine temporal evolution or static spatial distribution in isolation, lacking an integrated portrayal of their simultaneous dynamic interplay [19]. Finally, factor importance is typically assessed solely by coefficient magnitude [20], overlooking stability and thus failing to provide a comprehensive and objective evaluation.

To overcome these limitations, this study develops a data-driven analytical framework integrating the RF, GTWR, and CRITIC models based on provincial panel data from 2005 to 2023. This integration leverages the distinct advantages of each method: the RF algorithm's capacity to objectively screen high-dimensional variables without predefined linear constraints, the GTWR model's ability to explore the spatiotemporal heterogeneity of driving mechanisms, and the CRITIC method's strength in objectively evaluating systemic importance based on spatial stability. The research objectives of this study are threefold: (1) to identify the most critical socioeconomic drivers of regional carbon emissions, bridging the gap in nonlinear variable screening; (2) to dynamically quantify the complex, non-stationary spatiotemporal evolution of these drivers across China's Eastern, Central, and Western regions, deepening the understanding of localized emission dynamics; and (3) to comprehensively evaluate the identified multi-scale driving mechanisms via the CRITIC method, providing a scientific foundation for spatially differentiated carbon reduction strategies. The findings of this study not only advance the methodological integration of machine learning and spatial econometrics but also offer practical insights for precise regional governance under China's "Dual Carbon" goals.

2. Materials and Methods

The research procedure follows a systematic three-step outline. First, the Random Forest (RF) algorithm is applied to screen a comprehensive set of initial variables to eliminate redundancy and identify the core drivers of carbon emissions. Second, the selected core variables are input into the Geographically and Temporally Weighted Regression (GTWR) model to quantify their spatiotemporal non-stationary impacts. Third, the CRITIC objective weighting method is utilized to evaluate the importance of these drivers from multiple dimensions (core strength, reliability, and stability), thereby ranking the most critical factors for policy formulation.

2.1. Research Area and Data Sources

This study covers 30 provinces, municipalities, and autonomous regions in China (excluding the Tibet Autonomous Region), with the division into eastern, central, and western regions as shown in Figure 1. The study period spans from 2005 to 2023. During this timeframe, China's industrialization and urbanization advanced rapidly, with significant spatio-temporal heterogeneity emerging across various development dimensions in the eastern, central, and western regions [21–23]. This provides an ideal research area for the GTWR model to investigate the heterogeneous impacts of carbon emission drivers.

Provincial carbon emission data are sourced exclusively from the Emissions Database for Global Atmospheric Research (EDGAR). Other variables come from the China Statistical Yearbook and the China Energy Statistical Yearbook. Missing data points were supplemented using interpolation methods.

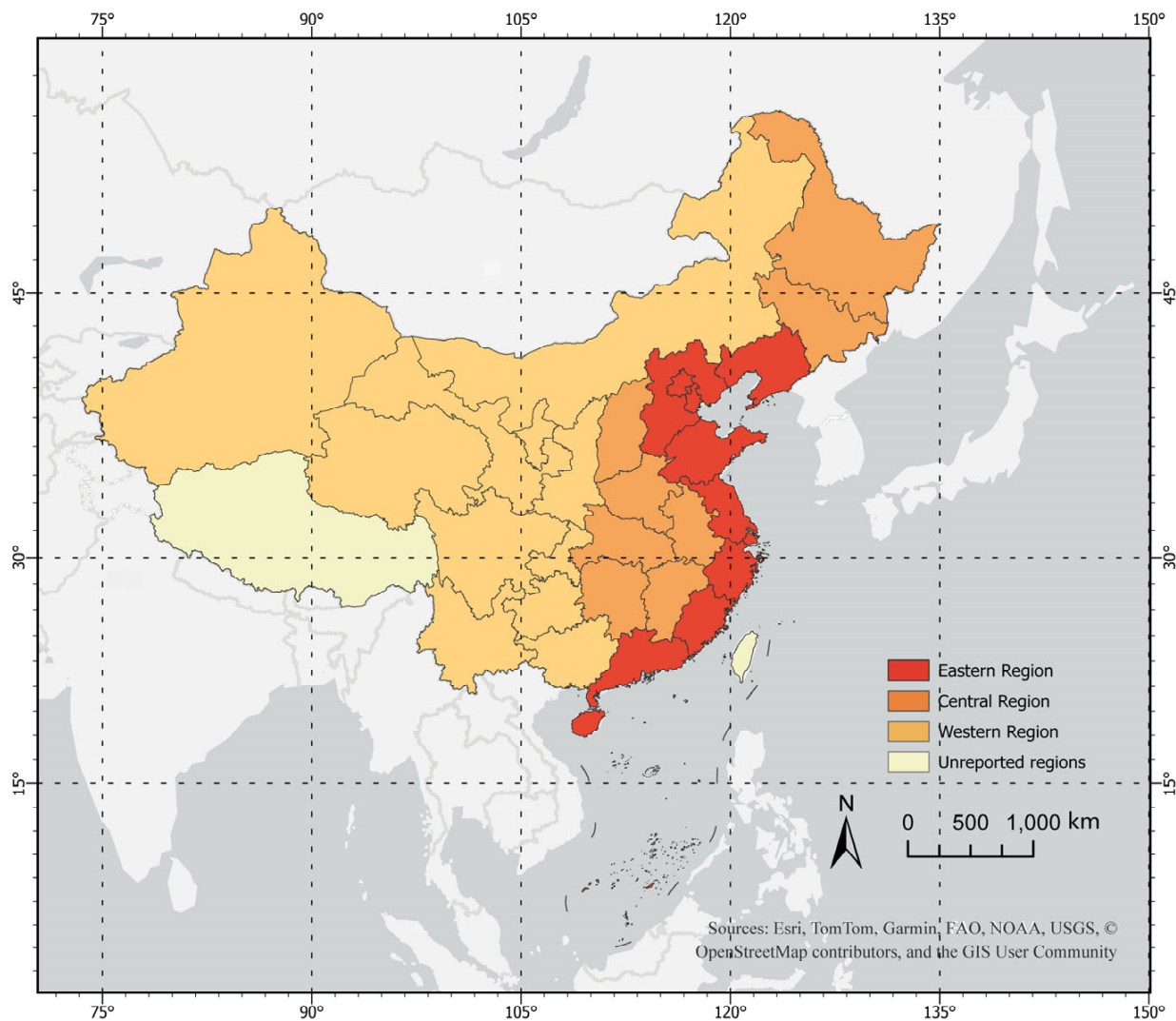


Figure 1. Overview Map of the Study Area.

2.2. Selection and Explanation of Drivers

Drawing on existing literature [24–28], this study selected seven key factors across the social, economic, and resource dimensions to investigate their spatiotemporal evolution and differentiated regional impacts. Within the social dimension, population size acts as a fundamental driver of baseline energy demand (Table 1). The urbanization rate exerts a dual effect: although population concentration increases aggregate consumption, the resulting agglomeration effects can reduce emission intensity through optimized land use and efficient public transportation [24,26]. In the economic domain, per capita GDP reflects development-induced energy requirements, whereas per capita household consumption expenditure influences emissions by altering demand patterns [28]. Regarding resource and structural factors, energy consumption per unit of GDP serves as a reliable proxy for technological efficiency [25], while the energy consumption structure—specifically, the proportion of coal—directly dictates the carbon intensity of energy utilization [27]. Finally, industrial structure upgrading, measured by the ratio of the tertiary to the secondary sector, signifies the broader systemic transition toward low-carbon, high-value-added activities [29].

Table 1. Explanation of Drivers.

Dimension	Influencing Factor	Explanation	Unit
Society	Population	The total number of living individuals within a specific geographic area at a given point in time	Millions
	Urbanization Rate	Urban Population/Total Population	%
Economy	Per capita GDP	Gross domestic product/Population	Yuan (RMB)
	Per Capita Consumption Expenditure of Residents	Total final consumption expenditure on goods and services by resident households over a given period	Yuan (RMB)
Resources	Energy Consumption Per Unit of GDP	Total Energy Consumption/Gross Domestic Product	Tons of Standard Coal Equivalent (tce)/10,000 Yuan
	Energy Consumption Structure	Coal Consumption/Total Energy Consumption	%
	Industrial Structure Upgrading	Tertiary Industry Output Value/Secondary Industry Output Value	Ratio

2.3. Methods

2.3.1. Random Forest Model

The Random Forest (RF) algorithm [30] is an ensemble learning method that integrates multiple decision trees to enhance generalization. Unlike traditional parametric models, RF offers inherent robustness to nonlinear relationships and multicollinearity without relying on strict distributional assumptions, making it ideal for complex socioeconomic analysis. While traditional linear diagnostic tools (such as the Variance Inflation Factor) are commonly used to detect collinearity, they are often insufficient for capturing the complex, nonlinear interactions typical of socioeconomic drivers. Therefore, RF, as a nonparametric ensemble learning method, is employed to robustly evaluate feature importance before spatial regression. Applying the RF algorithm to a concentrated set of macroscopic variables is a well-established approach to bypass strict linear assumptions and capture nonlinear interactions, as demonstrated in recent environmental studies evaluating limited sets of core drivers [31,32]. Specifically, the Permutation Importance mechanism is utilized to quantify feature contributions based on Out-of-Bag (OOB) prediction error fluctuations, expressed as follows:

$$importance(X_j) = \frac{1}{T} \sum_{t=1}^T (OBB^{t(j)} - OBB^t) \quad (1)$$

Here, T denotes the number of decision trees, OBB^t represents the mean squared error of the t -th tree on the original out-of-bag data, and $OBB^{t(j)}$ indicates the mean squared error of the out-of-bag data after randomly permuting the variable X_j within the t -th tree. This metric achieves unbiased estimation and effective ranking of driver contributions by quantifying the marginal impact of variable perturbations on model prediction performance.

2.3.2. Geographically and Temporally Weighted Regression Model

The GTWR model extends the traditional Geographically Weighted Regression (GWR) model by incorporating a temporal dimension, thereby enabling the effective processing and analysis of panel data characterized by spatiotemporal non-stationarity [33]. By constructing a spatiotemporal weight matrix, this model estimates an independent local regression equation for each observation point. This approach effectively reveals the dynamic evolution of variable relationships across different spatial locations and time periods. In this study, the GTWR model is primarily employed to quantify the spatiotemporal impacts of the key driving factors—previously identified through the RF preliminary screening—on regional carbon emissions. The model is expressed as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^p \beta_k(u_i, v_i, t_i) x_{ik} + \varepsilon_i \quad (2)$$

Here, y_i denotes the observed value of the dependent variable at the i -th spatiotemporal observation point, (u_i, v_i, t_i) represents the spatial coordinates (longitude u_i , latitude v_i) and time point t_i of the i -th observation point. $\beta_0(u_i, v_i, t_i)$ is the intercept term. $\beta_k(u_i, v_i, t_i)$ represents the local regression coefficient of the k -th explanatory variable at the i -th observation point, which varies with geographic location and time. x_{ik} denotes the value of the k -th explanatory variable at the i -th observation point. ε_i is the random error term, typically assumed to follow an independent and identically distributed normal distribution.

This study constructs a spatio-temporal weighting matrix based on a Gaussian kernel function with adaptive bandwidth, as expressed by the following formula:

$$w_{ij} = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}^s}{h_s} \right)^2 \right] \times \exp \left[-\frac{1}{2} \left(\frac{d_{ij}^t}{h_t} \right)^2 \right] \quad (3)$$

Here, d_{ij}^s denotes the Euclidean distance between observation points i and j , while d_{ij}^t represents the temporal distance between them. h_s and h_t are bandwidth parameters, signifying spatial bandwidth and temporal bandwidth, respectively.

2.3.3. CRITIC Objective Empowerment Method

The CRITIC method [34] is employed to calculate objective weights by synthesizing two fundamental dimensions: contrast intensity and conflict. Contrast is quantified using standard deviation, where higher dispersion signifies greater discriminative power and, consequently, warrants a higher weight. Conflict is evaluated through correlation coefficients; strong correlations indicate information redundancy, which correspondingly reduces the assigned weight. By integrating these dimensions, the CRITIC method ensures a scientifically rigorous allocation of indicator importance. The calculation proceeds as follows:

$$C_j = \sigma_j \sum_{k=1}^n (1 - r_{jk}) \quad (4)$$

Here, σ_j denotes the standard deviation of the j -th indicator, r_{jk} represents the correlation coefficient between the j -th and k -th indicators, n is the number of evaluations, and C_j indicates the information content of the j -th indicator. A larger C_j value signifies the greater importance of the j -th indicator within the comprehensive evaluation system.

Finally, the information content is normalized to obtain the final objective weight, W_j , for the j -th indicator:

$$W_j = \frac{C_j}{\sum_{j=1}^n C_j} \quad (5)$$

3. Results

3.1. Preliminary Screening Results of Drivers

3.1.1. RF Model Performance Evaluation and Optimal Parameter Determination

To validate the predictive accuracy and robustness of the Random Forest (RF) model, its performance was benchmarked against LASSO and stepwise regression models. A comparative analysis reveals that the RF model significantly outperforms both alternative approaches across all three evaluation metrics (RMSE, R^2 , and MAE) within the eastern, central, and western regions. These findings confirm the model's reliability and its suitability for addressing this complex analytical task. Detailed test results are illustrated in Figure 2.

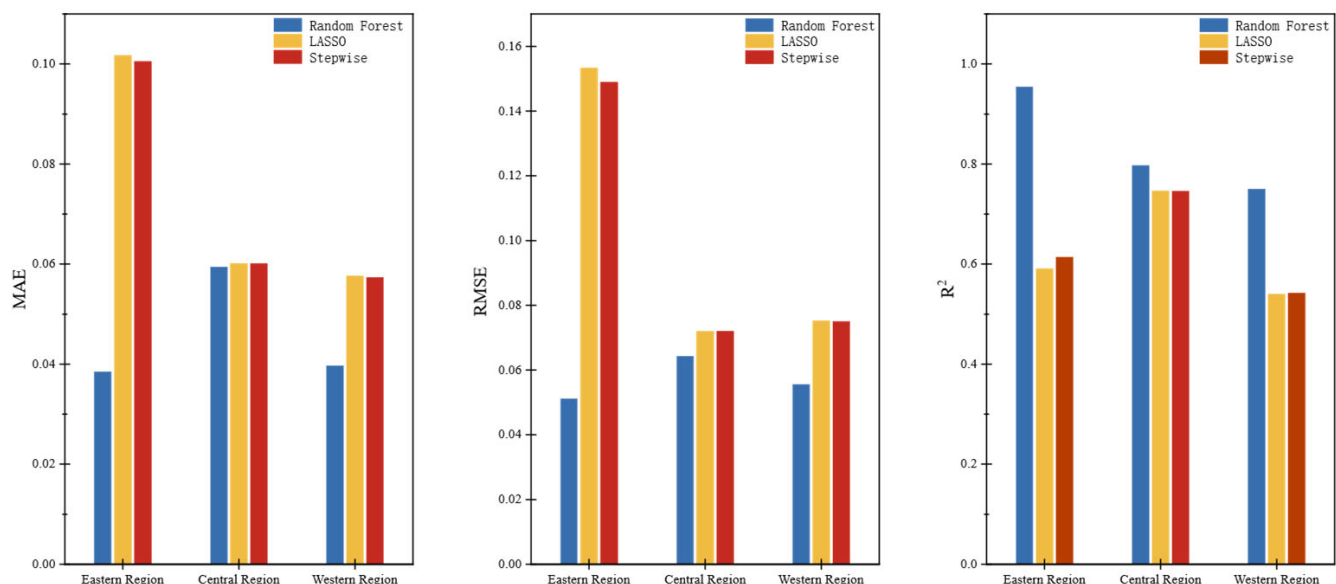


Figure 2. Model Performance Comparison.

As illustrated in Figure 3, the model's performance improves as the number of decision trees increases, evidenced by a steady decline in the out-of-bag (OOB) error. The predictive capability progressively enhances until the forest size reaches 32 trees, at which point the OOB error stabilizes, indicating model convergence. Through automated parameter exploration, the algorithm identified that exactly 34 trees yield the minimum OOB error of 0.0062, ensuring peak predictive accuracy. Consequently, selecting 34 trees dynamically optimizes the model, striking an ideal balance between robust predictive performance and computational efficiency for practical applications.

3.1.2. Preliminary Screening Results of Drivers and Reliability Verification

To ensure analytical robustness, the Random Forest model was independently re-trained 50 times using identical parameters. The frequency with which each variable ranked among the top five was subsequently calculated (Figure 4). The results reveal significant regional heterogeneity in factor stability. Specifically, population size and per capita GDP demonstrate high stability across all regions, whereas urbanization and energy intensity exhibit distinct spatial variations. Notably, while factor stability remains generally consistent in the eastern region, it diverges markedly in the central and western regions.

Based on these iterative tests, variables with a stability frequency exceeding 0.5 were selected as the final key drivers for their respective regions.

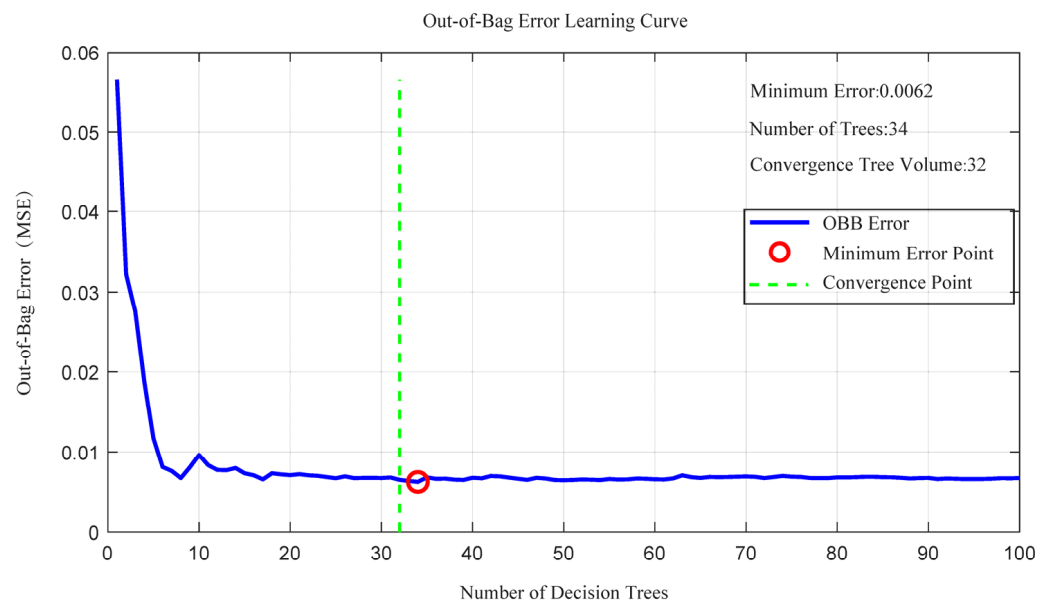


Figure 3. Out-of-Bag Error Learning Curve.

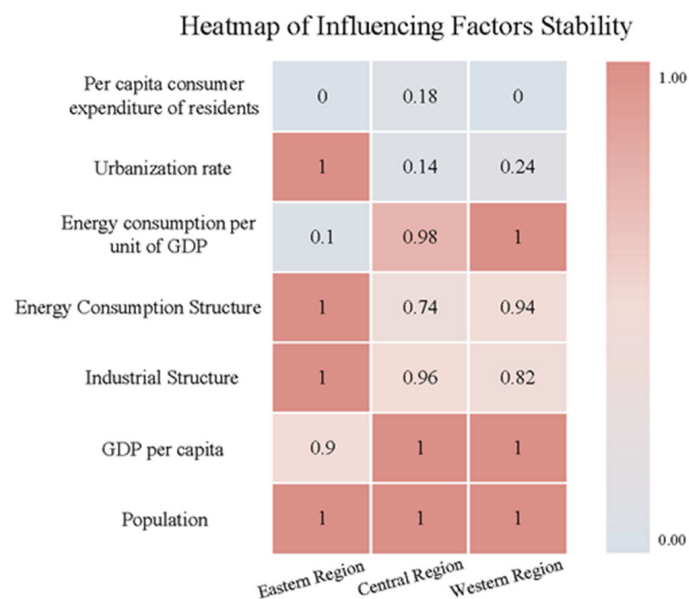


Figure 4. Stability Heatmap of Drivers.

To further validate feature reliability, a shadow feature test was conducted using the incremental out-of-bag (OOB) error as the evaluation metric. Three random noise variables (Shadow 1–3) following a standard normal distribution were introduced as benchmarks. Logically, genuine driving factors must significantly outperform these randomized features in the importance rankings. As illustrated in Figure 5, the shadow features consistently ranked low across all three regions—falling below the eighth position—and failed to penetrate the top five. This substantial margin confirms that the selected factors possess significantly greater predictive power than random noise, thereby verifying the robustness of the feature selection process and effectively ruling out overfitting.

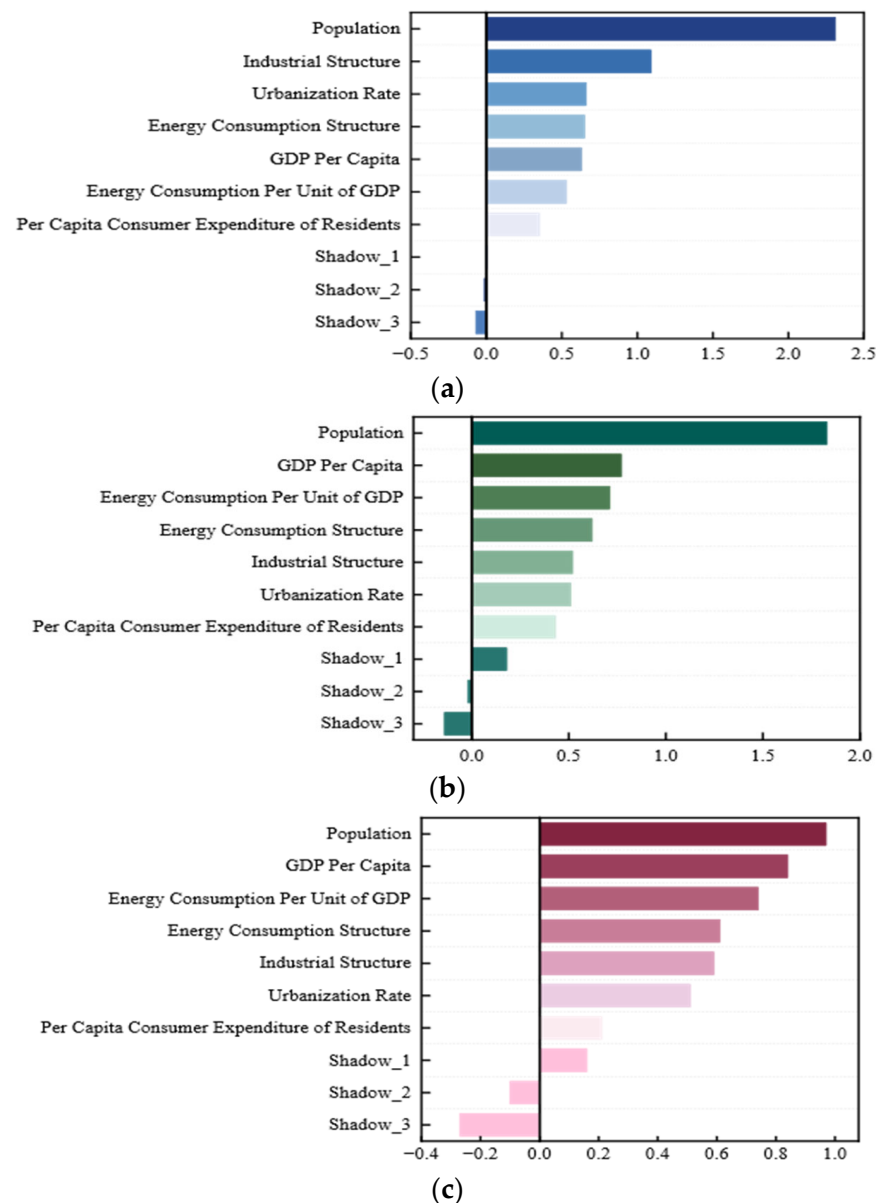


Figure 5. Shadow Inspection Results for Eastern, Central, and Western Regions. (a) Results of the shadow inspection in the eastern region. (b) Results of the shadow inspection in the central region. (c) Results of the shadow inspection in the western region.

Furthermore, to ensure that no critical macro-level drivers were omitted from the initial selection, an extended variable pool including Foreign Direct Investment (FDI) and Environmental Regulation Intensity (ER) was tested. The sensitivity analysis (detailed in Appendix A) confirmed that the original seven variables capture the dominant variations, while the inclusion of additional variables led to model degradation in certain regions.

3.2. Analysis of Key Factors Affecting Carbon Emissions

3.2.1. GTWR Model Performance Comparison and Robustness Testing

To validate model superiority, both the pooled OLS global model and the standard Fixed Effects (FE) panel model were used as benchmarks and compared against GTWR. As detailed in Table 2, the GTWR model yielded significantly lower AICc values than both baselines, indicating a superior trade-off between goodness-of-fit and complexity consistent with the literature [35]. Notably, while the FE model achieved a moderate fit in the Eastern region, it yielded negative R^2 values in the Central and Western regions. This phenomenon

typically indicates the presence of severe unobserved spatial heterogeneity, suggesting that imposing a single global coefficient distorts local realities. The GTWR model successfully overcomes this limitation by allowing coefficients to vary across space and time. Crucially, compared to the traditional OLS, GTWR enhanced fitting performance by 21.2%, 42.3%, and 85.4% in the Eastern, Central, and Western regions, respectively. These substantial gains confirm that the spatiotemporal weighting matrix in GTWR is entirely necessary to capture the profound non-stationarity in the highly heterogeneous Central and Western regions, far exceeding the capabilities of standard panel econometrics.

Table 2. Model Performance Evaluation.

Region	Model	R ²	Adjust R ²	AICc	MSE
Eastern Region	OLS	0.8030	0.7981	−872.42	0.0145
	FE	0.4719	0.3613	1.87	0.0389
	GTWR	0.9732	0.9725	−1246.94	0.0020
Central Region	OLS	0.6711	0.6598	−748.33	0.0067
	FE	−2.2115	−3.1096	101.82	0.0654
	GTWR	0.9551	0.9536	−1006.22	0.0009
Western Region	OLS	0.5272	0.5156	−1078.02	0.0054
	FE	−1.3759	−1.8731	−72.41	0.0272
	GTWR	0.9776	0.9770	−1673.24	0.0003

To ensure the reliability of the model, Moran’s I index is employed to conduct spatial autocorrelation testing, thereby determining whether the model adequately accounts for the spatial dependence of the dependent variable. Its formula is as follows:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2} \quad (6)$$

Furthermore, residuals were tested for spatial autocorrelation to detect potential specification errors [36]. As detailed in Table 3, results for all three regions yielded *p*-values exceeding 0.05 [37], indicating a statistically insignificant spatial clustering. This confirms that the GTWR model has adequately captured spatial dependencies and possesses a reasonable configuration without requiring further adjustment.

Table 3. Residual Space Autocorrelation Test.

Region	Moran’s I	Z-Value	<i>p</i> -Value
Eastern Region	0.0019	0.0967	0.9230
Central Region	0.0316	0.4678	0.6399
Western Region	−0.0675	−0.9020	0.3671

Finally, bandwidth sensitivity tests were conducted by adjusting the optimal spatio-temporal bandwidth within $\pm 20\%$ to verify result stability. As presented in Table 4, the resulting variation in R² remained consistently below 0.05. This minimal fluctuation confirms that the model is highly insensitive to parameter selection, thereby validating the robustness of the spatio-temporal analysis outcomes [38].

Furthermore, prior to interpreting the spatial coefficients, a comprehensive Local Condition Number analysis was conducted to ensure the GTWR models were not compromised by local multicollinearity. The diagnostic revealed that the mean local condition numbers for the Eastern, Central, and Western regions are 28.05, 16.99, and 19.40, respectively. Because the average condition numbers across all regional models are strictly below the

conventional critical threshold of 30, the models are fundamentally robust. Although a minor proportion of localized spatiotemporal points exhibit condition numbers exceeding 30 (27.75% in the East, 9.21% in the Central, and 13.40% in the West) due to localized data homogeneity, the regional averages indicate that the overarching coefficient surfaces remain highly stable. This diagnostic confirms the robustness of the spatial regression results against severe local multicollinearity.

Table 4. Bandwidth Sensitivity Analysis.

Region	Bandwidth $\times$ 0.8	Bandwidth $\times$ 1.0	Bandwidth $\times$ 1.2	Average Stability Index
Eastern Region	0.9843	0.9732	0.9604	0.0080
Central Region	0.9743	0.9551	0.9288	0.0160
Western Region	0.9922	0.9776	0.9510	0.0140

3.2.2. Key Drivers Importance Evaluation

Unlike other studies that rely on a single metric to measure the magnitude of drivers, which often leads to inconsistent evaluation results, this research employs three indicators—core strength, reliability, and stability—to comprehensively assess the importance of drivers. Core strength is measured using the median absolute value of standardized regression coefficients [39]; reliability is assessed by calculating the significance level of each regression coefficient via *t*-tests and computing the ratio of significant coefficients [40]; stability is represented using the interquartile range (IQR) [41]. Unlike standard global regressions, GTWR generates spatially varying coefficients. Relying solely on their mean magnitude can be misleading for macro-policy formulation. A high-magnitude but low-stability driver indicates extreme spatial volatility, posing high trial-and-error risks for regional policy implementation. Therefore, to identify robust and universally actionable policy levers rather than factors with strong but highly localized impacts, the CRITIC method was employed to calculate the objective weights for these three indicators. This yielded the comprehensive importance scores for each regional influencing factor, identifying the top three most influential factors for the eastern, central, and western regions. The weights for the core strength, reliability, and stability indicators, along with the comprehensive importance scores for each regional influencing factor, are shown in Figure 6.

In the Eastern region (Figure 6b), Population (0.737), GDP per capita (0.523), and Industrial Structure (0.366) emerge as the top three drivers. Population exhibits the highest dominance (Strength = 1, Reliability = 1), identifying it as the absolute core driver, though its moderate spatial stability (0.405) reflects uneven agglomeration effects across provinces. GDP per capita follows with the highest stability score (1.0), suggesting that economic development exerts a uniform and widespread pressure on emissions across the region. In contrast, Industrial Structure maintains a balanced but subordinate influence, indicating that structural upgrading has not yet overtaken scale effects (population and economy) as a primary driver.

For the Central region (Figure 6c), Population (0.832) remains the primary driver with exceptional intensity and reliability. Notably, Urbanization Rate (0.729) ranks second with balanced high scores across all metrics, confirming that rapid urbanization acts as the steady engine of emissions in this region. Crucially, while Energy Consumption Structure (0.445) shows weaker direct intensity, it exhibits exceptional spatial stability. This characteristic reflects a pronounced “carbon lock-in” effect, implying that high coal dependence is a pervasive and rigid feature across central provinces, making structural adjustment particularly challenging.

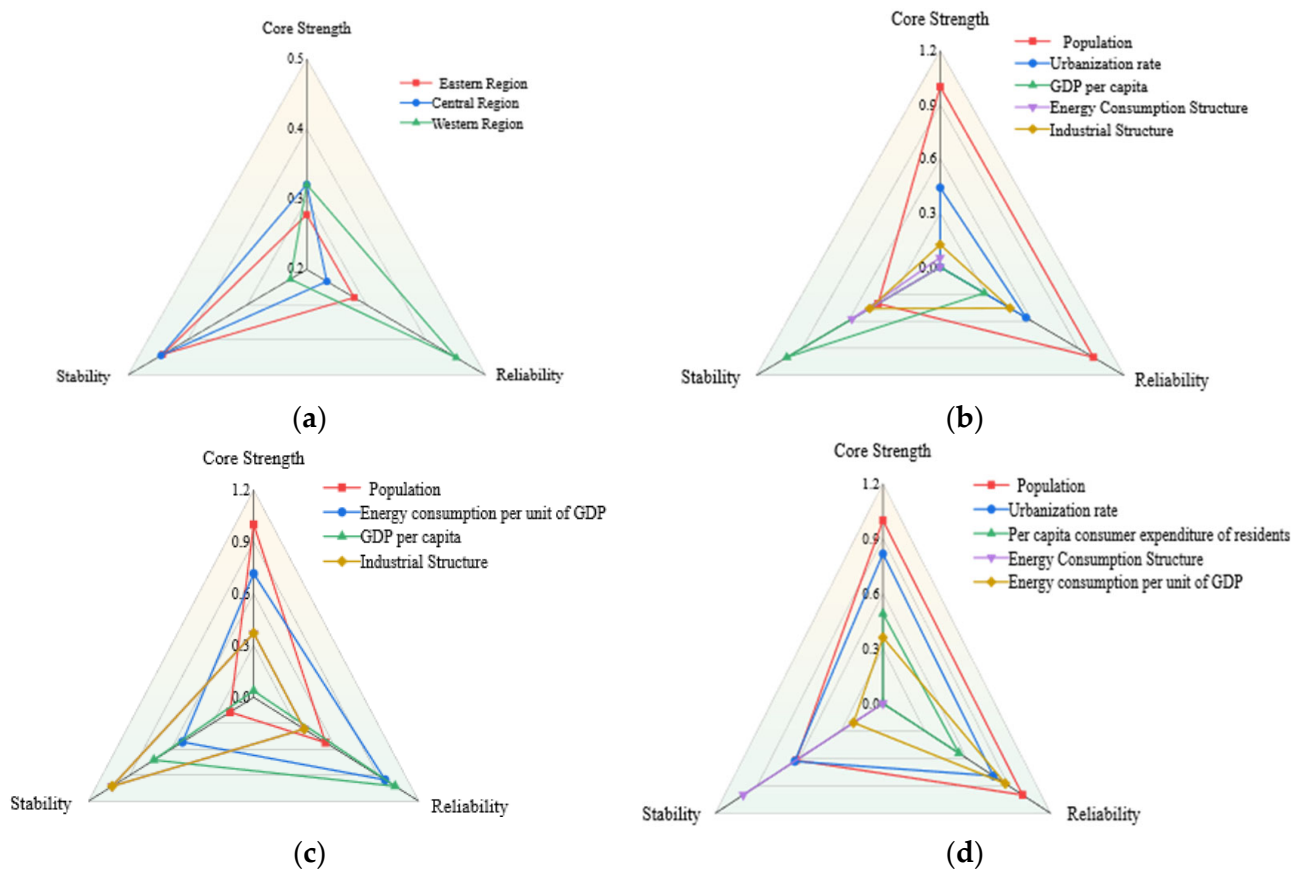


Figure 6. Comprehensive Scores for Regional Evaluation Indicator Weights and Key Factors' Importance. (a) represents the calculated weights for regional evaluation indicators; (b) denotes the importance scores for drivers in the eastern region; (c) denotes the importance scores for drivers in the central region; (d) denotes the importance scores for drivers in the western region.

The Western region (Figure 6d) presents a unique pattern driven by efficiency rather than scale. Energy Consumption per Unit of GDP (0.734) achieves the highest score, characterized by high reliability (0.914), highlighting that technological efficiency is the most critical determinant of emissions in the West. Population ranks third with a distinctive profile: maximum core strength (1.0) but zero stability (0.0). This extreme variance corroborates the “South-Positive, North-Negative” spatial differentiation identified in the GTWR analysis, indicating that population acts as a strong driver in some western provinces while serving as a reducer in others.

In summary, the factors that significantly influence carbon emissions vary across China's eastern, central, and western regions. Tailored carbon reduction policies should be formulated based on each region's specific drivers to enhance the effectiveness of coordinated regional emission reduction governance.

3.2.3. Spatial and Temporal Evolution of Key Drivers

The temporal evolution of driving factors exhibits distinct regional characteristics. In the Eastern region (Figure 7), population concentration has solidified as a dominant and intensifying driver, with its impact coefficient steadily climbing from 0.244 in 2005 to 0.429 in 2023, while 90.9% of samples exhibited a sustained positive effect. This reflects the rigid energy demand associated with population agglomeration. Conversely, economic growth (per capita GDP) validates the Environmental Kuznets Curve (EKC): its impact trajectory shifted from an initial rise (0.019 to 0.175) to a decline (−0.063) after 2015, signaling that advanced provinces have entered a phase of “absolute decoupling.” However,

a concerning trend emerges in industrial structure upgrading: while the impact remains generally negative, its reduction benefit is noticeably diminishing as the coefficient rose from -0.251 to -0.027 . The significant increase in the proportion of positive effects (from 27.3% to 45.5%) suggests that the indiscriminate expansion of energy-intensive services is eroding the traditional environmental dividend.

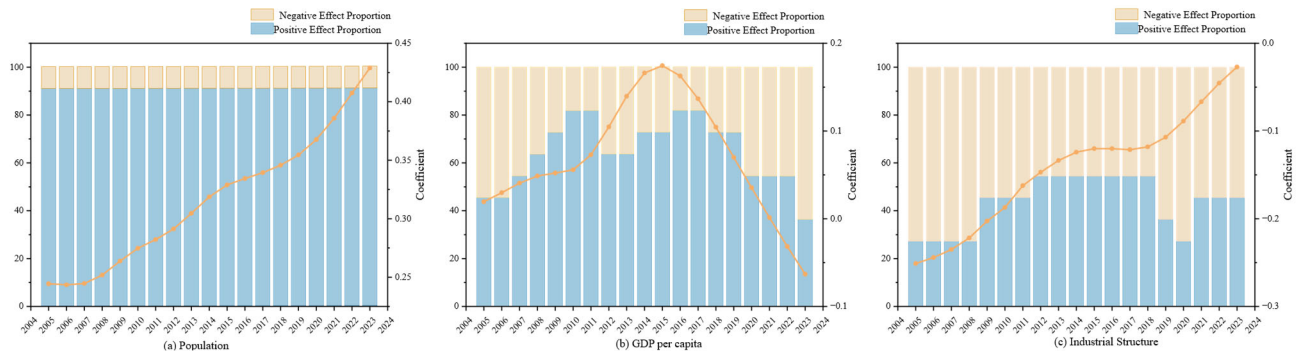


Figure 7. The Temporal Evolution of Drivers in the Eastern Region.

Moving to the Central region (Figure 8), the influence of demographic and structural factors follows a notable “inverted U-shaped” trajectory. Specifically, the population impact coefficient peaked in 2012, with the proportion of positive effects stabilizing at 75.0%, indicating a weakening driving force. Similarly, the urbanization coefficient, which maintained a 100% positive driving effect before 2016, began to decline and shift toward negative values (a 12.5% negative effect emerged post-2017). This reversal reflects the strategic pivot from resource-intensive expansion to quality-focused “New Urbanization.” Concurrently, the energy consumption structure exhibits high volatility; although its coefficient peaked at 0.097 in 2014, a recent downward trend indicates that the substitution effect of non-fossil energy is beginning to materialize in provinces rich in clean energy resources.

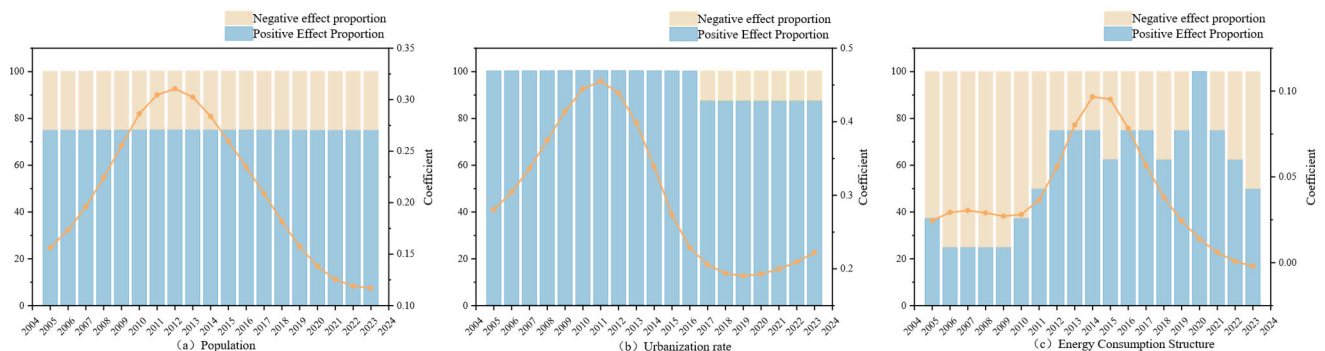


Figure 8. The Temporal Evolution of Drivers in the Central Region.

In contrast, the unique structure of factors influencing carbon emissions in Western regions (Figure 9) is notable. The impact of energy consumption per unit of GDP has maintained a dominant negative effect, although its suppression magnitude fluctuated during the initial industrialization phase (2005–2017) as rapid capacity expansion partially offset efficiency gains. Recently, this negative effect has stabilized, indicating that the accumulation of low-carbon technologies is effectively curbing emissions. Simultaneously, economic growth (per capita GDP) has solidified as a robust positive driver, with its coefficient turning consistently positive after 2014 and continuing to rise. This indicates that, unlike the Eastern region, the West’s development remains heavily coupled with carbon emissions. Conversely, population exerts a sustained negative impact, with the proportion of negative effects stabilizing at 54.5%. However, the intensity of this reduction

effect is diminishing, as evidenced by the coefficient narrowing from -0.056 to -0.005 . This suggests that while centralized infrastructure in sparsely populated areas improves per capita energy efficiency, the marginal benefits of this “agglomeration reduction effect” are gradually weakening.

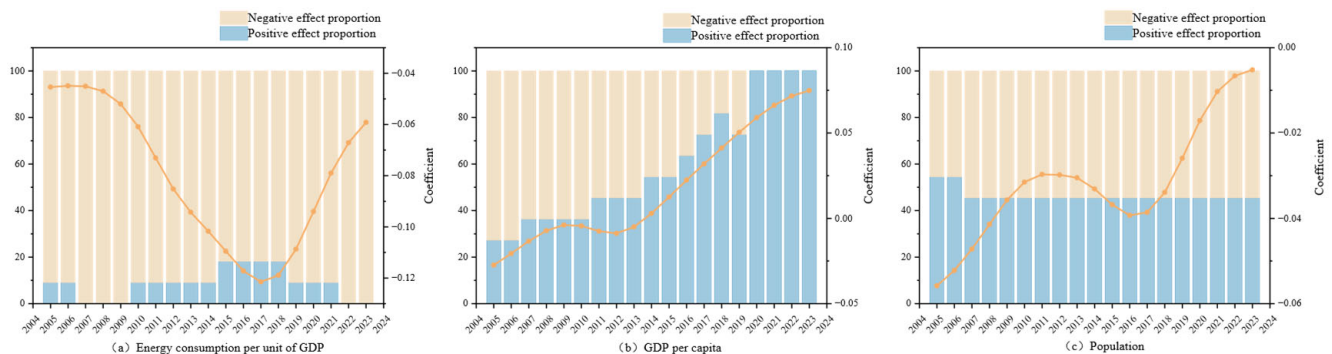


Figure 9. The Temporal Evolution of Drivers in the Western Region.

In the Eastern region (Figure 10), the population driver exhibits a persistent “North-High, South-Low” divide. High-value clusters remained concentrated in the Bohai Rim (Beijing-Tianjin-Hebei and Shandong) throughout the period. Notably, Liaoning Province presented a unique case of “negative population growth with non-declining emissions,” attributed to rigid centralized heating demands that do not decrease linearly with population shrinkage. In contrast, southern provinces like Guangdong maintained lower impact levels due to cleaner energy habits. GDP per capita witnessed a policy-driven reversal: while Beijing and Tianjin acted as positive drivers in 2014, their coefficients turned significantly negative by 2023. This decoupling is largely credited to the 2018 “Blue Sky Defense” Action Plan, which mandated the closure of scattered polluting enterprises. However, industrial structure reveals a divergent trend: while northern cities achieved emission reductions through service sector transformation by 2023, the Yangtze River Delta (e.g., Jiangsu) shifted from a negative to a positive driver. This anomaly might potentially indicate that the energy-intensive nature of new digital infrastructure (e.g., data centers) is beginning to offset the environmental benefits traditionally associated with the tertiary sector. However, since a direct proxy for the digital economy was not included in our model, this remains a speculative hypothesis requiring further empirical investigation.

In the central region (Figure 11), the population influence reached its zenith in 2014, with high-value clusters in Shanxi and Henan, but universally declined by 2023 to levels below 2005, indicating a widespread weakening of the demographic driver. In contrast, the Northeast provinces (Jilin and Heilongjiang) exhibited consistently weak or negative population effects. Urbanization remained a robust positive driver for most provinces, yet Anhui emerged as a distinct outlier: its coefficient turned negative in the later period. This shift is structurally attributed to its integration into the YRD, where it replaced traditional models by sharing low-carbon technologies and implementing intensive renewal within the Hefei metropolitan area. A striking reversal occurred in the energy consumption structure: traditional coal bases like Shanxi shifted from strong positive drivers to negative by 2023, validating the “Energy Revolution Strategy.” Conversely, inland provinces receiving industrial transfers, like Jiangxi and Hubei, experienced an industrial energy surge due to manufacturing relocations. Clean energy sources could not meet demand, increasing coal’s share.

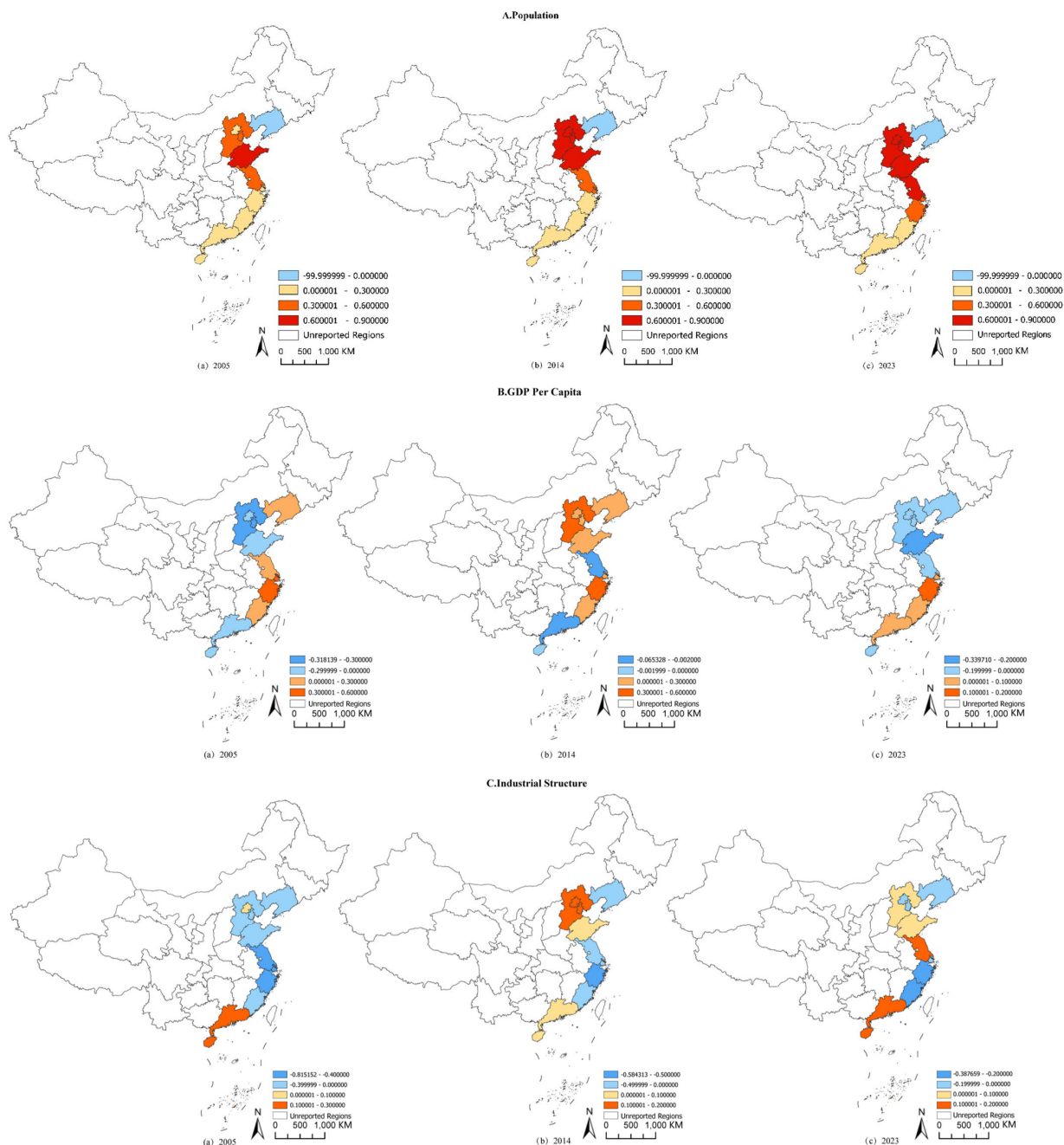


Figure 10. Spatial Evolution of Drivers in the Eastern Region.

The western region (Figure 12) presents the most complex spatial heterogeneity. The impact of population maintained a distinct “positive in the south, negative in the north” spatial divide. To empirically substantiate this divergence, we conducted a targeted sub-analysis using specific provincial data from representative provinces: Xinjiang in the north and Guangxi in the south (Table 5). The mechanisms driving this spatial divergence differ fundamentally. In the southern part of the western region (e.g., Guangxi), population growth translates directly into a demographic dividend for industrialization. As shown in Table 5, the share of employment in the secondary sector experienced significant growth (from 12.0% to 25.9%), reflecting its role in absorbing labor-intensive manufacturing transferred from eastern China (e.g., the Pearl River Delta). Here, population agglomeration expands the industrial labor force, directly driving up carbon emissions. Conversely, in the northern part of the western region (e.g., Xinjiang), population agglomeration exerts a significant emission-suppressing effect. First, the transition from a dispersed to a con-

centrated population enables the efficient sharing of urban infrastructure, most notably centralized heating. As Table 5 illustrates, the centralized heating area in Xinjiang surged from 19,162 to 38,598 hectares between 2010 and 2020. This expansion effectively substitutes inefficient, high-emission decentralized heating methods (such as the direct combustion of wood and raw coal) with centralized and cleaner energy utilization, thereby significantly reducing the per capita carbon footprint. Second, alongside demographic concentration, the employment structure has fundamentally shifted. The growing workforce has been predominantly absorbed by the tertiary sector (which expanded from 23.9% to 53.6%) rather than heavy manufacturing (which slightly declined from 15.5% to 14.3%). Thus, through the dual mechanisms of infrastructure sharing and service-sector expansion, population agglomeration in the north effectively improves energy efficiency and suppresses regional carbon emissions.

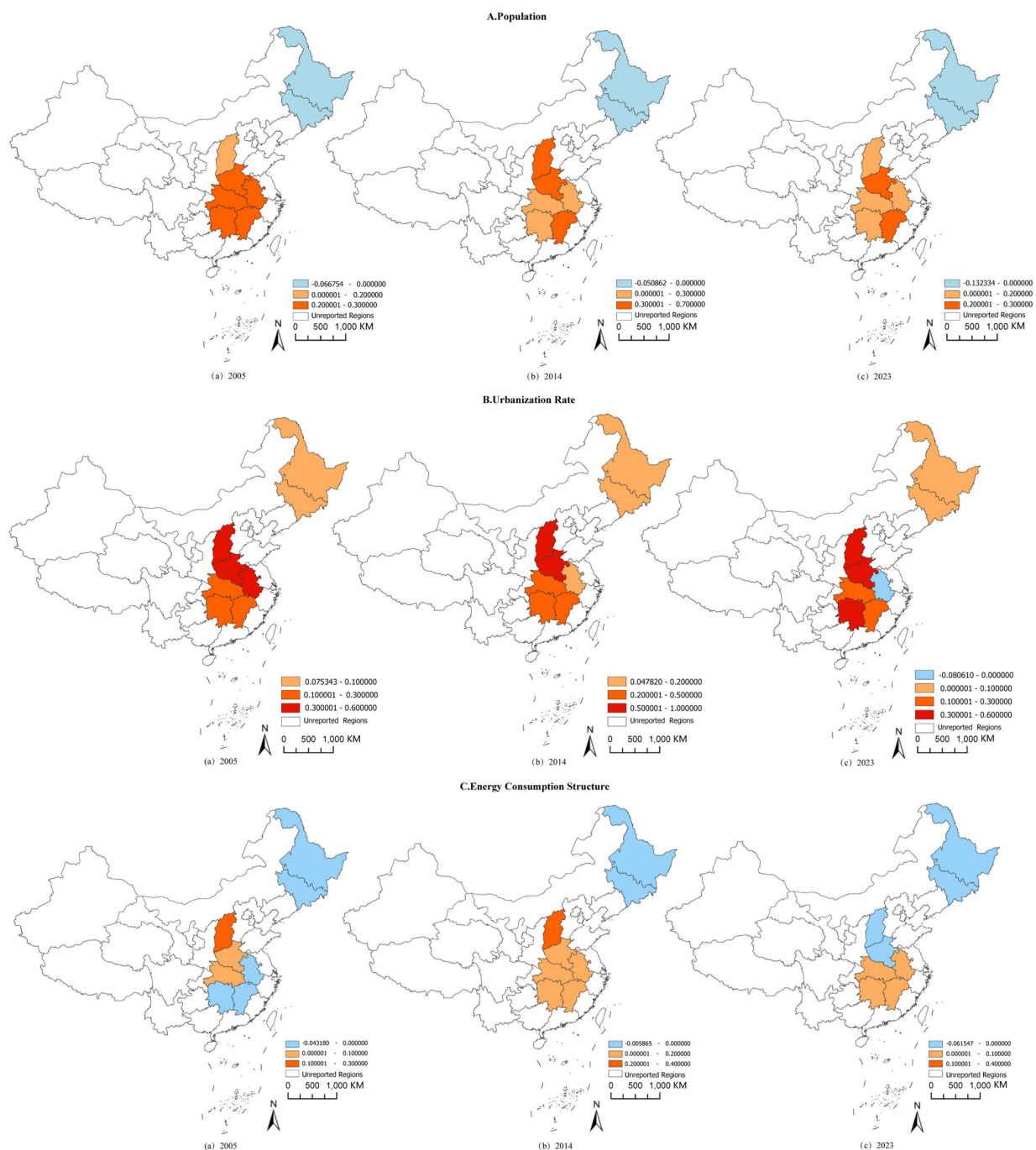


Figure 11. Spatial Evolution of Drivers in the Central Region.

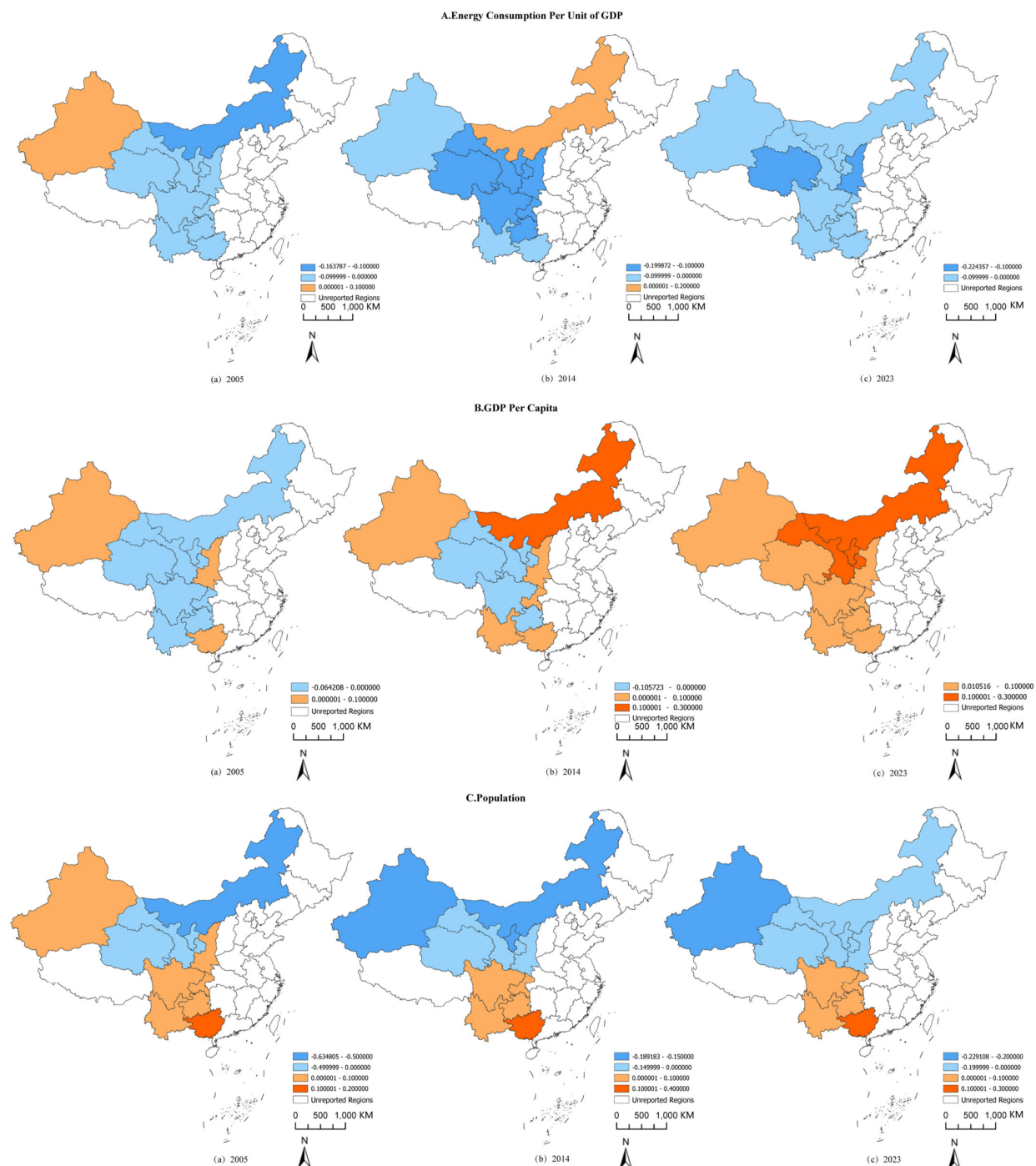


Figure 12. Spatial Evolution of Drivers in the Western Region.

Table 5. Comparison of employment structure and urbanization drivers between Xinjiang and Guangxi.

Province	Secondary Industry Emp. (2005–2023)	Tertiary Industry Emp. (2005–2023)	Centralized Heating Area (2010–2020)
Xinjiang	15.5–14.3%	23.9–53.6%	19,162–38,598 Hectares
Guangxi	12.0–25.9%	31.8–41.3%	Non-heating zone

The data for the share of secondary and tertiary industry employment are sourced from the China Statistical Yearbook, while the centralized heating area data are obtained from provincial statistical bureaus. Based on data availability, the growth trend of the centralized heating area is represented by data from 2010 to 2020.

The influence of per capita GDP transitioned from a marginal or negative impact in 2005—when most cities exhibited minimal correlation between economic development and emissions—to a universally positive driver by 2023. This shift was most pronounced in energy-rich northern provinces (e.g., Inner Mongolia and Gansu), highlighting the coupling of economic growth and high carbon emissions as the economic returns from energy-intensive industries are realized. Furthermore, energy intensity (energy consumption per unit of GDP), a key proxy for technological efficiency, exhibited a negative correlation across all western provinces in 2005, with the exception of a slight positive value in Xinjiang. However, by 2014, the coefficient for Inner Mongolia turned positive, likely due to the commissioning of large-scale coal chemical projects in 2012, before reverting to a negative value by 2023. Meanwhile, Shaanxi consistently maintained the strongest negative correlation; although the province reduced its energy intensity through technological and industrial upgrades, the emission-increasing scale effect continued to outpace the technological reduction effect. Conversely, Xinjiang exhibited minimal fluctuation, as its energy supply and demand dynamics are heavily regulated by China’s national “West-to-East Power Transmission” strategy.

In summary, the spatial patterns and driving mechanisms of carbon emissions across regions have undergone significant changes in response to socioeconomic development and policy adjustments, exhibiting both regional differentiation and temporal dynamics.

4. Discussion

4.1. Results Analysis

This study investigates the driving factors behind regional carbon emissions in China. Utilizing an integrated RF-GTWR-CRITIC framework, it assesses the primary determinants and their evolutionary trajectories from both spatial and temporal perspectives. The findings reveal significant spatiotemporal heterogeneity in these emission drivers, which is closely intertwined with regional disparities in economic development stages, population distribution, and energy utilization patterns.

In the eastern region, the evolutionary trajectories of key factors are broadly consistent with classical development theory, yet they also expose emerging constraints on structural upgrading. Population size exerts a persistently strong, positive effect on emissions, corroborating the findings of Han et al. [42]. As the primary destination for inter-regional migration, the east faces cumulative emission pressures from housing, transportation, and daily energy demands driven by population inflows [43]. Spatially, these high-impact areas are concentrated in the Bohai Rim (e.g., the Beijing–Tianjin–Hebei region and Shandong), whereas southern provinces like Guangdong exhibit comparatively weaker population effects. This north–south divergence partly reflects the inelastic heating demand in northern provinces, which cannot be scaled down proportionally with population changes. Conversely, the coefficient for per capita GDP shifts from positive to negative, substantiating the Environmental Kuznets Curve (EKC) hypothesis within the developed eastern provinces [44]. Shandong and the Beijing–Tianjin–Hebei region exhibit significantly negative coefficients; this trend can be attributed to stringent environmental regulations and the policy-driven eradication of scattered and heavily polluting enterprises since 2018, thereby facilitating a relative decoupling of economic growth from carbon emissions. However, the emission-reducing effect of industrial upgrading is attenuating, deviating from the anticipated linear “structural dividend.” While municipalities like Beijing and Tianjin have advanced the low-carbon transformation of their service sectors through targeted relocation and upgrading policies, the core area of the Yangtze River Delta, represented by Jiangsu, has experienced a paradoxical reversal in the industrial upgrading coefficient, moving from negative to positive. This anomaly suggests that the energy-intensive nature

of emerging digital infrastructure (e.g., data centers and 5G base stations) may be offsetting the environmental benefits traditionally associated with the tertiary sector. Nevertheless, because a direct proxy for the digital economy was not incorporated into our model, this remains a speculative hypothesis that warrants further empirical investigation.

In the central region, the main feature is the nonlinear impact of urbanization. The carbon emission impact coefficients display an inverted U-shaped pattern, consistent with the view that urbanization has threshold effects on the environment [45]. In the early stage, extensive land expansion and traditional infrastructure investment generated pronounced “carbon lock-in.” After the inflection point, the focus gradually shifted from scale expansion to quality improvement. Under the combined influence of the “New Urbanization” strategy and the “dual carbon” targets, some central provinces began adopting a more intensive, intelligent, and green urbanization model that mitigates additional emissions from population concentration. The spatial contrast between provinces illustrates this transition: Anhui’s urbanization coefficient has turned negative, reflecting its integration into the Yangtze River Delta, strengthened cross-regional environmental cooperation, and uptake of mature low-carbon technologies, whereas Henan and parts of Shanxi still rely heavily on land expansion and infrastructure-led growth, showing strong path dependence and continued carbon lock-in. The evolution of the energy structure coefficient in the central region reveals a clear “pollution refuge” effect. Traditional coal bases such as Shanxi have reduced emissions through energy structure optimization under the energy revolution. Meanwhile, Anhui, Jiangxi, and Hubei, which have received transfers of energy-intensive industries, experienced a shift in their energy structure coefficients from negative to positive. This phenomenon is strongly supported by specific national industrial transfer policies. Notably, the establishment of the ‘Wanjiang City Belt Industrial Transfer Demonstration Zone’ in Anhui—the first national-level demonstration zone of its kind—and the designation of National Demonstration Zones for Undertaking Industrial Transfer in Jiangxi and Hubei, have institutionalized the relocation of mature, often energy-intensive manufacturing sectors from the eastern coastal areas (such as the Yangtze River Delta) to the central hinterland. Consequently, this systematic industrial relocation has significantly driven up industrial energy demand in these receiving provinces, and in the absence of sufficient clean energy supply, coal use has rebounded [46]. The central region thus faces a tangible risk that its progress in energy-structure greening may stall or even regress during the industrial transfer process. At the same time, the gradual weakening of demographic effects suggests that the region is slowly shedding the emission pressure associated with past population growth.

The western region exhibits the most distinctive pattern, with several drivers deviating from conventional expectations. First, the population effect shows a “positive in the south, negative in the north” pattern that contrasts with the homogeneity assumption of traditional STIRPAT formulations. Population growth in southern provinces such as Guangxi and Yunnan significantly increases emissions, reflecting the combined pressures of taking over labor-intensive industries from the Pearl River Delta and redundant infrastructure construction in complex terrain. In contrast, northern provinces such as Inner Mongolia and Xinjiang exhibit a net suppressing effect of population growth on emissions. This is related to sparse settlement patterns and recent large-scale ecological resettlement and poverty-alleviation relocation. By concentrating previously scattered rural populations that relied on inefficient biomass or raw coal, these policies make centralized heating, upgraded power grids, and public transport economically viable, improving energy-service efficiency and generating per capita emission reductions [47]. Benefiting from latecomer advantages and strong national support, many Western cities can also directly adopt more stringent building standards, clean energy technologies, and planning concepts

than those used in the early development phase of the East, producing a “concentrated emission reduction” effect during urbanization. Furthermore, our sub-analysis clarifies the divergent impacts of population agglomeration in the western region. Rather than uniformly increasing emissions, the environmental impact of population growth depends heavily on local industrial and infrastructural contexts. In the southern West (e.g., Guangxi), population growth is closely tied to the expansion of energy-intensive manufacturing, which directly drives up emissions. In contrast, in the northern West (e.g., Xinjiang), population agglomeration facilitates the sharing of centralized heating infrastructure and aligns with a shift toward service-sector employment, thereby improving overall energy efficiency and suppressing emissions.

Second, the trajectory of the energy-consumption-per-GDP coefficient reflects a fierce competition between technological progress and scale expansion. This provides empirical evidence of a strong macro-level rebound effect in Western industrialization. In provinces such as Shaanxi, technological upgrading has indeed reduced energy intensity. However, the rapid expansion of coal-chemical and heavy manufacturing capacity has completely offset these efficiency gains. To quantify this, we utilized the ratio of the latest GTWR coefficients (2023) as a proxy for the macroeconomic rebound percentage. By evaluating the coefficient magnitudes, the positive driving force of economic scale (per capita GDP coefficient of approximately 0.0749) significantly outpaces the negative suppressing force of energy intensity (energy intensity coefficient of -0.0592). Calculated via the absolute ratio of these two coefficients, the rebound percentage reaches approximately 126.5 percent. This strictly indicates a severe ‘backfire’ effect: the emission reductions expected from efficiency gains are fully absorbed and exceeded by capacity expansion, confirming why total regional emissions continue to rise despite structural improvements. Third, the effect of per capita GDP in the West has shifted from slightly negative to clearly positive. By 2023, the per capita GDP coefficients are positive across all western provinces, with the strongest impacts in energy-rich northern regions such as Inner Mongolia, Ningxia, and Gansu. Under the strategy of “Advancing the Development of Western Regions in the New Era,” these provinces are in a phase of concentrated release of resource dividends. Unlike the East, where decoupling is supported by a shift toward services, northwest growth remains heavily dependent on upstream fossil-based industries (coal mining, nonferrous metallurgy, and petrochemicals), making increments in GDP closely tied to intensive fossil fuel consumption.

The nuanced findings of this study are largely attributable to the integrated RF-GTWR-CRITIC analytical framework. By moving beyond the global average coefficients produced by traditional econometric models, this approach effectively captures the underlying spatiotemporal heterogeneity that is often obscured [48]. Specifically, identifying the exact spatial inflection points of urbanization and quantifying the regional rebound effects of economic expansion provides concrete empirical evidence for the necessity of localized, rather than uniform, climate governance.

In summary, this study reveals the drivers of carbon emissions in China, highlighting regional and temporal variability. These findings emphasize the need for customized strategies under the dual carbon goals, taking into account regional differences.

4.2. Policy Recommendations

Based on the above analysis, differentiated and targeted emission reduction strategies should be formulated for factors affecting different regions, avoiding a one-size-fits-all approach.

In the eastern region, the continuously strengthening positive driving effect of population scale necessitates a shift toward targeted consumption-side management. Specifically, for provinces with population coefficients consistently exceeding 0.6 (such as the

Beijing-Tianjin-Hebei region), relying solely on production-side emission reductions is insufficient. In these high-coefficient areas, local governments must rigorously implement consumption-side management measures—such as establishing pilot low-carbon communities and enforcing personal carbon accounts—to curb rigid demand stemming from population concentration. Furthermore, for provinces where industrial structure coefficients have shifted from negative to positive drivers (e.g., Jiangsu), stricter access standards should be established for new digital infrastructure (such as data centers and 5G base stations). Mandatory requirements for rigorous power usage effectiveness (PUE) metrics and renewable energy consumption ratios must be enforced to prevent new carbon pressures arising from digital economic growth.

In the central region, policy differentiation should be guided by the inflection points of the urbanization and energy structure coefficients. First, regarding urbanization, in provinces where the urbanization coefficient remains strongly positive, local governments must mandate the implementation of green building standards and low-carbon transportation systems in all new urban development projects [49]. Conversely, in provinces where the urbanization coefficient has crossed the inflection point and turned negative (such as Anhui), the policy focus must shift away from land expansion and redirect resources toward low-carbon retrofitting of the existing urban stock and smart energy management. Second, to address the ‘pollution refuge’ effect, for specific provinces where the energy consumption structure coefficient has shifted from a negative to a positive driver (e.g., exceeding 0.05, such as Jiangxi and Hubei), authorities must establish strict quantitative green thresholds for accepting industrial transfers from the East. Projects must be evaluated against strict carbon emission intensity limits before approval. Simultaneously, these provinces should leverage the geographical advantages of clean energy bases in central China to accelerate the construction of a multi-energy complementary supply system integrating wind, solar, hydro, thermal, and storage resources [50], thereby systematically reducing the proportion of coal in the energy structure.

In the western region, interventions must be tailored to the unique coefficient disparities and spatial divides. First, addressing the severe Rebound Effect, for provinces where the positive driving coefficient of per capita GDP significantly exceeds the absolute value of the negative energy intensity coefficient, simple efficiency incentives are inadequate. These specific provinces must enforce strict, rigid constraints on total energy consumption (a ‘Cap’ mechanism) while deepening the East–West collaboration mechanism [51]. By introducing advanced industrial energy-saving technologies from the eastern regions under a total consumption cap, policymakers can ensure that technological gains translate into absolute emission reductions rather than being diluted by new capacity expansion. Second, given the bifurcated demographic impacts, policies must be highly spatially differentiated. For southern western provinces where the population coefficient remains positive (such as Guangxi), policies should focus on decoupling population growth from labor-intensive, high-carbon manufacturing. In contrast, for northern provinces where the population coefficient is decisively negative (e.g., falling below 0.0, such as Xinjiang and Inner Mongolia), local planning should actively leverage the ‘agglomeration emission reduction effect’ by further consolidating scattered settlements and expanding centralized clean heating and public transport networks.

4.3. Limitations

Although this study offers valuable insights, several limitations remain. First, the analysis relies on provincial-level macro data. Future research utilizing higher-resolution data at the city or even county level could more precisely capture regional heterogeneity. Second, the selection of the seven influential factors for this study was predicated upon

extant literature and the availability of data. Future research may consider incorporating additional dimensions, such as green technology innovation investment, foreign direct investment (FDI), and the intensity of local environmental regulations. Additionally, while the GTWR addresses spatio-temporal heterogeneity, it does not fully reveal the interactions among factors. Further research should explore the synergistic or antagonistic interactions among drivers using methods like geographical detectors. Moreover, future studies could expand the spatial scope to city or county levels to capture even finer regional heterogeneity and formulate micro-level reduction pathways.

5. Conclusions

This study builds an analytical framework integrating “RF screening—spatial GTWR quantification—CRITIC comprehensive evaluation” using a panel dataset covering 30 Chinese provinces from 2005 to 2023. The key conclusions are summarized as follows:

1. The integration of machine-learning-based variable screening and spatiotemporal regression effectively reveals regional heterogeneity obscured by traditional econometric models. Key drivers identified through RF screening demonstrate significantly greater explanatory power in the GTWR model compared to global OLS estimations. This approach successfully overcomes the estimation bias of “global averaging,” precisely capturing the non-stationary characteristics of carbon emission drivers and providing a reliable methodological foundation for localized analysis.
2. The driving mechanisms of carbon emissions exhibit profound spatial non-stationarity, characterized by distinct regional disparities. In the eastern region, population (a strengthening promoter), per capita GDP (an inverted U-shaped pattern), and industrial structure upgrading (a diminishing suppressor) are the primary drivers. In the central region, urbanization, population, and energy structure are key, all exhibiting an inverted U-shaped relationship with emissions. In the western region, the inhibitory effect of population diminishes, per capita GDP shifts from a suppressor to a positive driver, and the emission-reduction effect of energy intensity initially strengthens before weakening. These specific coefficient trajectories offer actionable insights: central policymakers can allocate differentiated carbon quotas, local governments can design targeted regulations, and investors can align green technologies with regional transition trends.
3. The key drivers exhibit complex nonlinear characteristics, revealing counterintuitive phenomena that diverge from conventional understanding. First, the trajectory of energy intensity in the West indicates a macroeconomic rebound effect, where improving technological efficiency alone cannot independently offset the emissions from overall capacity expansion. Second, an “agglomeration emission reduction effect” is observed in northern Western provinces (e.g., Inner Mongolia and Xinjiang), challenging the assumption that population growth inevitably increases emissions; rather, these areas have achieved reductions through intensive urbanization. Finally, the phenomenon of increased emissions resulting from industrial upgrading in certain eastern digital economy hubs (e.g., Jiangsu) highlights a potential risk warranting future study: the rapid expansion of energy-intensive data centers during digital transformation may offset the traditional emission reduction benefits of the service sector.

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Appendix A. Sensitivity Analysis of Expanded Variable Pool

Appendix A.1. Additional Variables Description

FDI: Actual utilized foreign direct investment/GDP (%), sourced from China Statistical Yearbook

Environmental Regulation Intensity(ER): Industrial pollution treatment investment/industrial output value (%), sourced from China Environment Statistical Yearbook

Appendix A.2. GTWR Model Performance Comparison

As shown in Table A1, after forcibly incorporating the new variable in the central region, the model’s AICc deteriorated (from −1006 to −946), and the original key variable (urbanization rate) was pushed out of the model. To ensure the stability of the spatial regression model and the optimal information criterion, the main text retains the initial 7-variable benchmark model.

Table A1. Model Performance Comparison in the Central Region.

Model	Included Variables	AICc	R ²	Note
Original Baseline	7 core variables	−1006.22	0.9551	Optimal parsimony and stability
Expanded Model	9 variables (Original + FDI + ER)	−946.38	0.9335	Displacement of Urbanization Rate; Model degradation

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