Spatiotemporal Heterogeneity of Regional Decarbonization in China: Forecasting and Differentiated Strategies Based on LSTM and Spatial Econometric Modeling

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Abstract. This study examines the spatiotemporal heterogeneity of decarbonization pathways across China's four major regions (2000–2020) by integrating LSTM forecasting with spatial econometric analysis. Utilizing panel data, three-dimensional visualization, and machine learning, we quantify regional disparities in renewable energy adoption, per capita CO_2 emissions, and industrial efficiency. The results reveal significant disparities: the eastern region exhibits the highest renewable energy consumption(2.05 billion kWh)with moderate emissions(0.061 hundred tons per person),while the northeast shows the lowest renewable energy adoption(0.29 billion kWh)and the highest emissions(0.074 hundred tons per person).LSTM projections(2021–2035)forecast divergent trajectories—renewable energy consumption grows nationally by 24.9%,yet emissions in the west rise sharply(+24.6%)due to industrial inefficiencies, contrasting with moderated growth in the east(+7.7%).Spatial econometrics identifies structural bottlenecks, including seasonal fossil fuel dependence in the northeast and technology diffusion lags in central provinces. The findings underscore the necessity for region-specific strategies: industrial restructuring in energy-intensive western and northeastern regions and cross-regional technology transfer to align decarbonization with China's 2030/2060 climate goals. The methodological integration of machine learning and spatial analysis advances granular policy assessments for heterogeneous energy transitions.

Keywords: Regional Decarbonization, Renewable Energy Consumption, Spatial Econometrics.

1 Introduction

Achieving a sustainable equilibrium between industrial growth, renewable energy adoption, and carbon emission reduction remains a critical challenge for China, par-

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ticularly given its ambitious climate commitments to achieve peak carbon output before 2030 and full carbon neutrality by 2060. [1] The regional disparities in economic structures, energy infrastructure, and policy implementation complicate nationwide decarbonization efforts, necessitating spatially explicit analyses to inform targeted strategies. While existing research has predominantly examined the national-level relationship between renewable energy deployment and emissions reduction.[2], few have addressed the heterogeneous dynamics across China's diverse regions or integrated advanced computational methods to project future trajectories. Existing literature often overlooks the role of industrial inefficiencies and seasonal energy demand in regional decarbonization, resulting in an oversimplified understanding of policy effectiveness (Liu et al.,2021). [3]

Our research bridges these gaps through a multidimensional framework that analyzes spatiotemporal variations in clean energy usage and carbon outputs across China's principal geographic divisions between 2000 and 2020, coupled with predictive modeling. By leveraging panel data, three-dimensional visualization, and long short-term memory (LSTM) networks, we quantify regional disparities in emission decoupling and renewable adoption efficiency. Our approach advances existing methodologies by integrating spatial econometrics with machine learning, thereby enabling a granular assessment of policy outcomes and industrial transformation bottlenecks.

The primary objectives are threefold:(1) to delineate regional heterogeneity in renewable energy-emission linkages, (2) to forecast future trajectories under current policy frameworks, and (3) to propose region-specific decarbonization strategies. Key innovations include the application of LSTM models for emission forecasting and the identification of scale-dependent challenges in high-growth regions. Additionally, we evaluate the relative performance of LSTM against traditional time series models and ensemble methods to highlight its unique advantages in capturing long-term dependencies in carbon emission data.

The paper is structured as follows: Section 2 details data sources, regional classifications, and analytical methods. Section 3 presents empirical findings on spatiotemporal patterns and LSTM projections. This section also includes a comparative analysis of LSTM performance against ARIMA and Random Forest models, providing insights into the strengths and limitations of each approach. Section 4 discusses policy implications and methodological limitations, concluding with recommendations for regionally tailored interventions.

2 Method

2.1 Data Sources and Processing

The analysis employs longitudinal panel data(2000–2020)from China's four principal geographical divisions(Eastern, Central, Western, Northeastern).Core datasets were compiled from the National Bureau of Statistics, the China Carbon Accounting Database, and provincial yearbooks.[4]To standardize measurements and mitigate regional comparability issues, we implemented systematic preprocessing protocols: adjusting per capita real GDP using price indices with 2000 as the base year, aggregating provincial data into four regions based on the National Bureau of Statistics classification standard, addressing sporadic missing values via linear interpolation, and eliminating outliers using the interquartile range(IQR)method to ensure accurate and reliable data analysis. Table 1 shows the detailed division of the four major regions.

Table 1. Regional Classification and Provincial Composition.

Region	Provinces Included
Eastern region	Beijing; Tianjin; Hebei; Shanghai; Jiangsu; Zhejiang; Fujian; Shandong; Guangdong; Hainan
Central region	Shanxi; Anhui; Jiangxi; Henan; Hubei; Hunan
Western region	Inner Mongolia; Guangxi; Chongqing; Sichuan; Guizhou; Yunnan; Xizang; Shaanxi; Gansu; Qinghai; Ningxia Hui; Xinjiang Uyghur
North-east region	Liaoning; Jilin; Heilongjiang

2.2 Research Design

This study integrates big data analytics, descriptive statistics, and econometric methods to investigate the equilibrium among industrial sustainability, economic growth, and emission reduction in China. The research framework comprises the following steps: constructing three-dimensional visualization models to elucidate relationships among regional renewable energy consumption, per capita emissions, and temporal trends. Predictive modeling techniques leveraging machine learning were further implemented to project prospective trends in clean energy utilization and carbon output dynamics.

2.3 Analytical Methods

Three-Dimensional Visualization. Three-dimensional scatterplots were generated using Python's Matplotlib library to visualize the relationships between renewable energy consumption (x-axis), time (y-axis), and per capita CO_2 emissions (z-axis) across various regions.

Machine Learning Forecasting Model. We implemented a recurrent neural network architecture based on long short-term memory (LSTM) to project future trends in sustainable energy utilization and carbon emission dynamics.[5] The structural configuration of this predictive model is detailed below:

(1) Forget Gate: The forget gate output$f_t$regulates information retention from the prior cell stateC_{t-1}.This operation is parameterized by learnable weights$W_f$and biases$b_f$that jointly determine historical feature preservation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

(2) Input Gate: The input gate produces i_t, which modulates the integration of current input x_t into the memory cell. The associated parameters W_i and b_i govern this selective retention process:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i$$

(3) Candidate Cell State: A provisional cell state $\widetilde{C}_t$ is generated through nonlinear transformations of the input data, encapsulated by parameters W_c and b_c. This intermediate state encodes potential updates to the system memory:

$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

(4) Cell State: The memory cell C_t undergoes dynamic updates by combining historical information retention and fresh input assimilation. This composite operation leverages outputs from both forget and input gates:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t$$

(5) Output Gate: The output gate computes o_t to control information exposure from the updated cell state to the hidden state h_t, with parameters W_o and b_o shaping this regulatory mechanism:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

(6) Hidden State: The resultant hidden state h_t serves as both the temporal output and the carrier of sequential dependencies to subsequent time steps:

$$h_t = o_t * \tan h(C_t)$$

Our comparative analysis revealed that, although LSTM models excelled in capturing intricate non-linear trends, they exhibited greater sensitivity to input features. On the other hand, ARIMA models demonstrated superior performance in short-term forecasting, especially in regions with more stable emission patterns. Random Forests exhibited robust performance across various regional datasets but lacked LSTM's capability to capture long-term dependencies.

3 Results

3.1 Descriptive Statistics and Spatiotemporal Patterns

A systematic quantification of selected indicators is provided in Table 2, encompassing data from all four administrative regions in China across two decades (2000–2020). The eastern region exhibited the highest mean renewable energy consumption (2.05 billion kWh) but moderate per capita CO_2 emissions (0.061 hundred tons/person). Conversely, the northeastern region showed the lowest renewable energy adoption (0.29 billion kWh) coupled with the highest emissions (0.074 hundred tons/person).

Regional disparities are further evidenced by standard deviations, with the western provinces displaying the greatest variability in both energy and emission metrics (0.608 and 0.025, respectively).

Table 2. Descriptive statistics of key variables (2000-2020).

Statistic	Region	Renewable Energy (10^8 kWh)	Per Capita CO_2 (10^2 tons/person)
Mean	Eastern	2.054	0.061
	Central	0.801	0.048
	Western	1.084	0.059
	Northeastern	0.288	0.074
Std.Dev.	Eastern	0.934	0.017
	Central	0.364	0.016
	Western	0.608	0.025
	Northeastern	0.092	0.023

The 3D visualization (Figure 1) reveals distinct spatiotemporal trajectories:

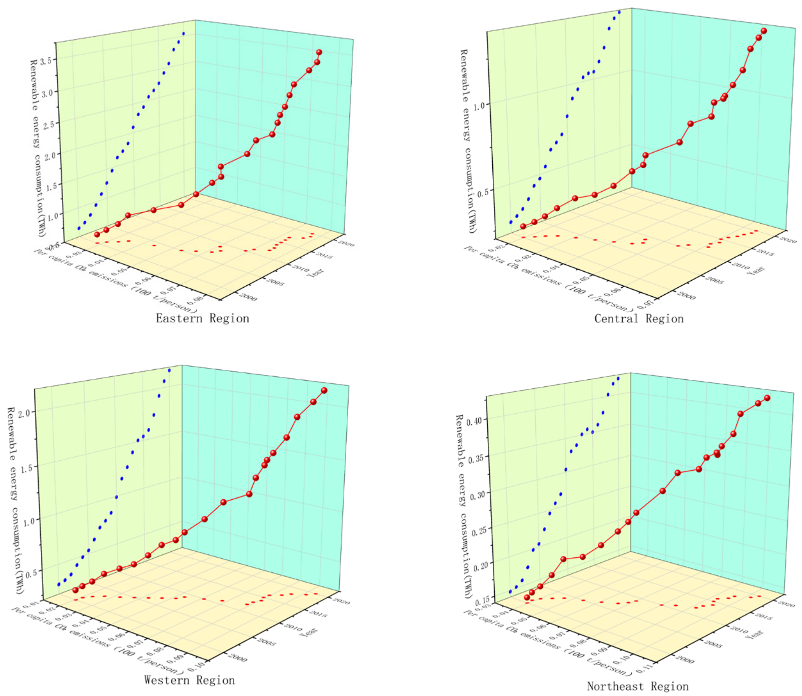

Fig. 1. A 3D model of renewable energy consumption, CO_2 emissions per capita and time (2000-2020) in four regions.

The three-dimensional visualization illustrates the spatiotemporal patterns of renewable energy consumption, per capita carbon dioxide emissions, and temporal dynamics across the four regions in China. The central region demonstrates moderate adoption of renewable energy and a gradual decrease in per capita carbon dioxide emissions, indicating a stepwise decarbonization consistent with policy timelines. In contrast, the western region has a higher utilization rate of renewable energy, yet carbon dioxide emissions remain elevated, reflecting inefficiencies in industrial transformation. The northeastern region exhibits cyclical fluctuations in both indicators, potentially due to seasonal energy demand and the reliance of heating systems on fossil fuels. Notably, the eastern region achieves the strongest negative correlation between renewable energy consumption and carbon dioxide emissions reduction, reflecting advanced technological integration and a diversified energy mix. [6] Temporal trends reveal an acceleration in renewable energy adoption in all regions after 2010. However, differences in emission trajectories highlight the heterogeneity in policy implementation and infrastructure readiness. These findings underscore the critical role of regional industrial structures and governance frameworks in balancing renewable energy expansion with emission reduction targets.

3.2 Machine Learning Projections

Figure 2 shows the LSTM model's projections of renewable energy consumption and CO_2 emissions (2021-2030).

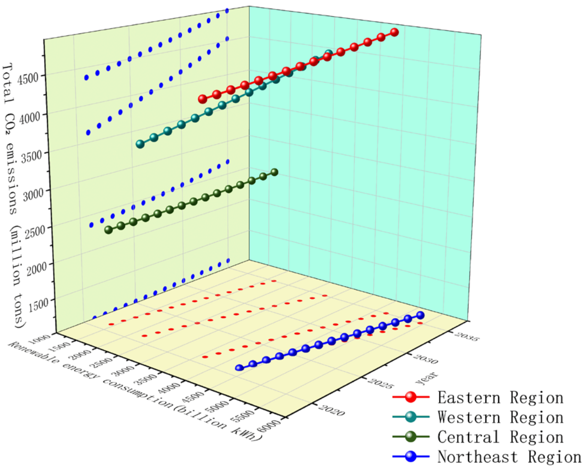

Fig. 2. LSTM forecast Results (2021-2030).

The LSTM-based projections from 2021 to 2035 reveal distinct regional trajectories in renewable energy consumption and CO_2 emissions across China. Nationwide, renewable energy consumption exhibits a steady annual growth, with an aggregate increase of 24.9%over the 15-year period. This growth is primarily driven by the northeastern region (5433.59 billion kWh in 2035 vs.4346.15 billion kWh in 2021, +25.0%) and the eastern region (+29.6%). Conversely, CO_2 emissions display heterogeneous patterns. In the northeast, emissions remain relatively stable (+11.2%), while the western region shows a pronounced upward trend (+24.6%), potentially linked to sustained utilization of carbon-intensive energy infrastructure in manufacturing sectors. The central and eastern regions demonstrate moderated emission growth (+13.9%and+7.7%, respectively), suggesting partial decoupling between economic activity and carbon intensity through renewable integration. Notably, the eastern region achieves the highest absolute renewable consumption (4716.34 billion kWh by 2035) yet maintains the largest emission volumes (4934.39 million tons), highlighting scale-dependent challenges in decarbonization. These spatially differentiated outcomes underscore the necessity for region-specific policy frameworks to effectively balance renewable adoption and emission mitigation.

4 Conclusion

This study reveals distinct spatiotemporal patterns in renewable energy adoption and CO_2 emissions across China's regions, challenging uniform decarbonization assumptions. Eastern China's inverse renewable-emission relationship aligns with technological convergence theories [7], while western regions' persistent emissions despite renewable growth highlight overlooked industrial inefficiencies. Northeastern cyclicality underscores seasonal demand impacts, contrasting linear decarbonization models [8]. Methodological limitations include provincial aggregation bias and LSTM feature sensitivity, suggesting future integration of spatial econometrics and hybrid ML frameworks (e.g., LSTM-ARIMA) [9]. The study underscores the necessity of formulating region-specific policies and accentuates the significance of selecting models tailored to distinct regional characteristics and data availability. Future research should prioritize the development of more robust hybrid models capable of adapting to the diverse spatiotemporal patterns observed across various regions in China.

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