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Research on Spatiotemporal Analysis and Prediction of China's Carbon Emissions Based on LSTM Model

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Abstract

Since becoming the world's largest emitting economy in 2014, China's carbon emission issue has become increasingly prominent. In 2020, China's carbon emission intensity decreased by 48.4% compared to 2005, representing a major breakthrough; however, the differences in carbon emissions among provinces and cities have become more apparent. Based on carbon emission data from 30 Chinese provinces and cities from 2000 to 2019, this study employs time series analysis, the Super-SBM model, and cluster analysis to examine carbon emission efficiency, carbon emission intensity, and their characteristics. The results indicate that imbalanced development and insufficient utilization between carbon emissions and energy consumption persist across provinces and cities. While carbon emission efficiency in most provinces and cities has shown a steady annual increase, it remains volatile in a few regions. Accordingly, the following policy recommendations are proposed: (1) Tailor energy-saving and emission reduction targets according to the actual conditions of each province and city; (2) Continuously promote the development of new energy industries and accelerate the research and development of energy-saving and emission reduction technologies.

1. Introduction

Carbon emissions refer to the release of greenhouse gases, which contribute to the greenhouse effect and lead to a rise in global temperatures. The Earth absorbs solar radiation and simultaneously emits heat, primarily in the form of long-wave infrared radiation ranging from 3 to 30 μm. When this radiation enters the atmosphere, it is easily absorbed by gas molecules with large molecular weights and strong polarity. These molecules absorb infrared radiation and prevent heat from escaping, acting as an insulating layer between the Earth and outer space—thus creating the "greenhouse effect" (Mitchell,1989). Carbon emissions have significant environmental and social impacts. Firstly, they exacerbate climate change and increase the frequency of extreme weather events. Secondly, they contribute to rising sea levels, posing threats to coastal ecosystems and communities. Additionally, carbon emissions lead to a loss of biodiversity, undermining the stability of ecosystems and their service functions.

As the world's largest carbon emitter and the second-largest economy, China faces formidable challenges (Liu et al., 2022). On September 22, 2020, China announced its enhanced nationally determined contributions, pledging to peak carbon dioxide emissions by 2030 and strive to achieve carbon neutrality by 2060. China’s Special Envoy for Climate Change, Xie Zhenhua, emphasized that "climate change is not merely an environmental issue but is intricately linked to a nation's economy, society, environment, employment, and other aspects. It is a systemic challenge that requires comprehensive economic and social reforms to achieve these goals." According to the white paper China’s Policies and Actions on Climate Change 2023, China has achieved significant reductions in carbon intensity while sustaining healthy economic and social development. In 2022, China’s carbon dioxide emissions per unit of GDP decreased by over 51% compared to 2005, exceeding the target of a 40% to 45% reduction committed to the international community for 2020. This progress has essentially reversed the rapid growth of carbon dioxide emissions (Solomon et al., 2009).

2. Literature Review

Since carbon emissions gained attention, scholars have conducted extensive research on the topic. At the micro level, one major solution to reducing emissions is to decrease primary energy intensity, which can be achieved by improving energy efficiency (Nam and Jin, 2021). The underlying reason is that industrial carbon dioxide emissions account for a significant proportion of total carbon dioxide emissions, negatively impacting the environment. Market-based trading mechanisms are an important tool for the Chinese government to address environmental pollution, significantly influencing enterprises' carbon technology levels and investments in low-carbon energy (Xuan et al., 2020). However, achieving long-term emission reduction effects requires government regulation of carbon prices and measures such as providing subsidies for emission reduction technologies to guide corporate behavior. Beyond policy effectiveness, urbanization inhibits carbon emissions in the transportation sector, though its effect is weaker than that of energy efficiency (Li et al., 2022). At the macro level, the secondary industry is the primary contributor to China's total emissions, accounting for approximately 88.34% in 2012. Additionally, local governments play a role in mitigating climate change, where better urban design and land use patterns are important factors in reducing greenhouse gases, showing a positive correlation with carbon emissions (Fan et al., 2017; Guadie et al., 2015). International trade also increases carbon emissions and carbon intensity. When carbon emissions are used as outcome-based metrics, corporate environmental performance yields returns (Busch and Hoffmann, 2011).

Most existing literature focuses on the driving factors, mechanisms, and decomposition of carbon emissions, while fewer studies analyze the spatiotemporal evolution of carbon emissions from a predictive perspective. Building on an in-depth analysis of the driving factors of carbon emissions, scholars have recently shifted their focus to the spatiotemporal prediction and evolution patterns of carbon emissions to address the lack of long-term dynamic evolution analysis in traditional factor decomposition studies. Relevant literature reveals that the spatiotemporal dynamics of carbon emissions exhibit significant path dependence and spatial spillover effects. Research on China's high-carbon manufacturing industries found that carbon emissions display a distinct "Matthew effect," where historically high-emission regions tend to remain at high levels and form spatial lock-in effects, such as the "high-high" agglomeration areas in the Bohai Bay and North China Plain. This highlights the strong interprovincial correlation of carbon emissions rather than isolated occurrences (Wang et al., 2020). The application of dynamic spatial panel models effectively captures this spatiotemporal interaction, confirming significant temporal inertia and spatial spillover in carbon emissions, indicating that emission changes in one province substantially affect neighboring provinces. Scenario simulation studies from a predictive perspective further reveal the long-term effects and complexity of policy interventions. Theoretical models suggest that policy combinations such as clean technology subsidies and carbon taxes are key to achieving sustainable low-carbon transitions. However, the timing of policy implementation is critical, as delayed action may increase transition costs (Acemoglu et al., 2012). Empirical analysis of China's Emissions Trading Scheme (ETS) pilot programs supports this, showing that the policy significantly suppressed industrial carbon intensity in pilot regions after its launch, with effects strengthening over time. However, significant industry heterogeneity was also observed (Zhou et al., 2020). Emerging technologies such as satellite remote sensing provide new possibilities for tracking emission dynamics at the micro level (Han et al., 2023).

Nevertheless, existing prediction models still face challenges. The "race to the bottom" effect in international trade may undermine regional emission reduction efforts, particularly as foreign investment in manufacturing could temporarily increase local emissions. Meanwhile, the potential emission reduction benefits of industrial structure upgrading have not been fully realized, and its spatial synergistic effects remain relatively limited. Future research needs to integrate more advanced simulation technologies, explore the evolutionary pathways of multi-agent behaviors under the "dual carbon" goals, and strengthen carbon leakage risk assessments from a global value chain perspective to optimize the design and implementation of cross-regional collaborative emission reduction mechanisms (Zhang and Liu, 2022).

3. Model Explanation

3.1 LSTM Model

To reasonably predict carbon emission data for the next seven years, a time series model—the Long Short-Term Memory (LSTM) model—is employed. Currently, the most widely used recurrent neural network architecture in practical applications is the LSTM model proposed by Hochreiter et al. LSTM is a special type of Recurrent Neural Network (RNN) that effectively overcomes the vanishing gradient and exploding gradient problems inherent in traditional RNNs. It significantly outperforms RNNs in tasks involving long-term dependencies, as gradient backpropagation is no longer hindered by vanishing gradients. This allows LSTM to accurately model data with either short-term or long-term dependencies. In simple terms, compared to standard RNNs, LSTM demonstrates superior performance over longer sequences.

3.2 Super-Efficiency SBM Model

Data Envelopment Analysis (DEA) was first proposed by Charne et al. in the United States in 1978. It does not require dimensionless processing of indicators for efficiency analysis and has no strict requirements on sample size, making it widely applicable across various disciplines. However, as traditional DEA models do not account for slack phenomena, Tone proposed the Super-Efficiency Slacks-Based Measure (SBM) model in 2022. This model systematically addresses the issue of slack variables and further enables the ranking of decision-making units (DMUs) with efficiency values greater than 1.

$$minp^* = \frac{\frac{1}{m}\sum_{i=1}^{m} x'/x_{i,k}}{\frac{1}{r+p}\left(\sum_{s=1}^{r_1} y^d y_{s,k}^d + \sum_{q=1}^{r_i} y^u y_{q,k}^u\right)} \qquad (1)$$

s.t.

$$\begin{cases} x' \geqslant \sum_{j=1,\neq k}^{n} x_{i,j}\lambda_j;\, y^d \leqslant \sum_{j=1,\neq k}^{n} y_{s,j}^d\lambda_j;\, y^d \geqslant \sum_{j=1,\neq k}^{n} y_{q,j}^d\lambda_j \\ x' \geqslant xk;\, y^d \leqslant y_d^k;\, y^u \geqslant y_k^u \\ \lambda_j \geqslant 0, i = 1,2,\cdots,m; j = 1,2,\cdots,n; j \neq 0 \\ s = 1,2,\cdots,r; q = 1,2,\cdots,p \end{cases} \qquad (2)$$

4. Empirical Analysis

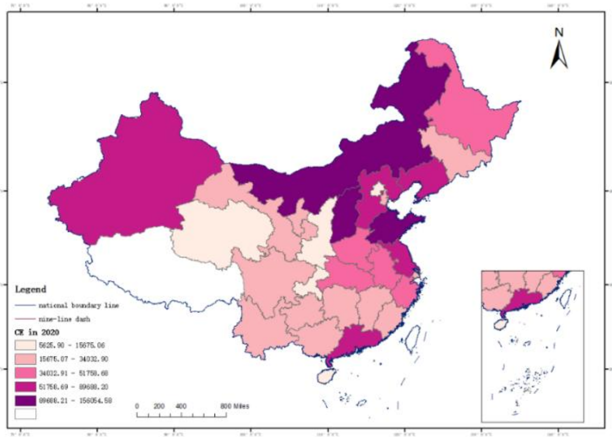
4.1 LSTM Time Series Analysis

This study selects carbon emission data from 30 Chinese provinces and municipalities from 2000 to 2019 as the research subject. The LSTM model is employed to predict carbon emissions for the next seven years, and the results are as follows:

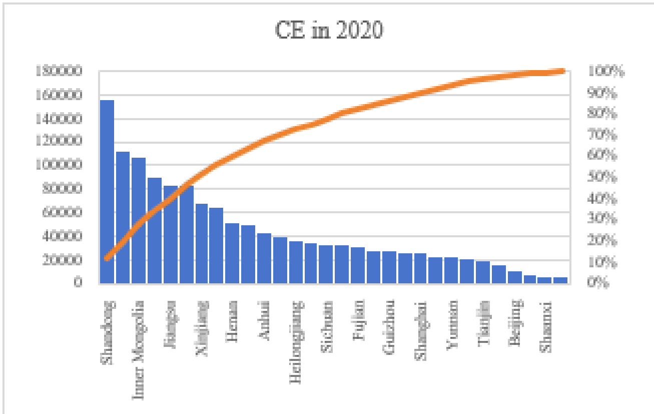
Table 4.1 Predicted Carbon Emission Values and Rankings for 30 Provinces and Municipalities Over the Next Seven Years Using the LSTM Model

Province	2020	2021	2022	2023	2024	2025	2026	Rank
Beijing	11522.18	11646.82	11736.00	11800.25	11846.77	11880.58	11905.21	28
Jiangsu	84340.14	84721.83	85093.00	85454.46	85806.99	86151.27	86487.99	6
Guangdong	65695.94	67324.95	69098.36	71047.79	73213.08	75645.28	78410.94	8
Tianjin	19781.46	19975.53	20141.68	20284.41	20407.37	20513.57	20605.48	25
Zhejiang	50052.44	50446.21	50818.80	51172.33	51508.69	51829.52	52136.28	12
Guangxi	26629.89	26913.43	27188.20	27455.28	27715.64	27970.16	28219.65	21
Hebei	89688.20	86091.14	83531.41	81727.77	80465.88	79587.50	78978.23	7
Anhui	43622.82	44807.73	46077.05	47449.79	48949.17	50604.12	52451.12	13
Hainan	7869.67	8150.98	8432.00	9715.50	9004.29	9301.31	9609.74	29
Shanxi	113204.71	117630.50	122546.05	128082.33	134412.13	141768.05	150469.86	2
Fujian	30963.71	30343.25	29777.59	29264.83	28802.46	28387.54	28016.81	19
Chongqing	15675.06	15881.74	16078.28	16266.02	16446.09	16619.51	16787.15	27
Inner Mongolia	107759.79	110395.99	113232.20	116299.88	119636.58	123287.59	127307.91	4
Jiangxi	28653.53	29946.09	31418.42	33115.69	35097.84	37445.54	40269.00	16
Sichuan	32745.18	32296.18	31897.99	31546.47	31237.41	30966.65	30730.20	18
Liaoning	83964.08	84678.67	85461.45	86322.27	87272.85	88327.36	89503.00	5
Shandong	156054.58	163539.95	11664.94	180582.14	190482.66	201609.52	214276.47	1
Guizhou	28316.13	28654.91	28991.79	29328.21	29665.57	30005.29	30348.81	20
Jilin	23654.95	23347.66	23116.93	22944.36	22815.67	22719.92	22648.78	23
Henan	51758.68	51752.89	51747.63	51742.86	51738.52	51734.58	51731.00	11
Yunnan	22670.61	21578.77	21071.96	20838.09	20730.46	20680.98	20658.26	24
Heilongjiang	36711.94	37147.43	37598.14	38067.19	38558.06	39074.75	39521.93	15
Hubei	40128.51	39431.70	38879.73	38444.36	38102.15	37833.89	37624.05	14
Shaanxi	6368.17	57122.83	58949.65	60868.89	62903.89	62082.15	67436.69	10
Shanghai	26279.43	26001.54	25903.14	25868.35	25856.06	25851.72	25850.19	22
Hunan	32428.45	32860.69	33279.73	33687.65	34086.32	34477.44	34862.60	17
Gansu	20665.78	20255.15	19911.32	19625.19	19388.34	19193.14	19032.84	26
Qinghai	5625.90	5392.41	5211.76	5073.26	4967.83	4888.01	4827.84	30
Ningxia	34032.90	38211.12	43581.61	50720.64	60581.90	74786.69	96079.66	9
Xinjiang	68577.90	78116.48	90328.13	106522.59	128788.27	160388.31	205873.56	3

According to the table above, the top three provinces in terms of carbon emission values over the next seven years are Shandong, Shanxi, and Xinjiang, while the bottom three are Beijing, Hainan, and Qinghai. The specific emission intensity levels are illustrated in the figure below.



(a)



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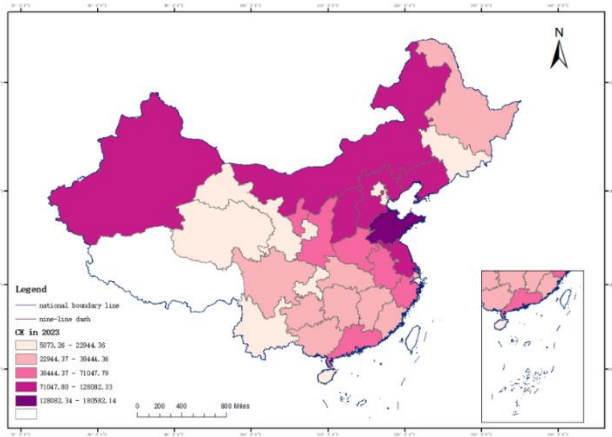

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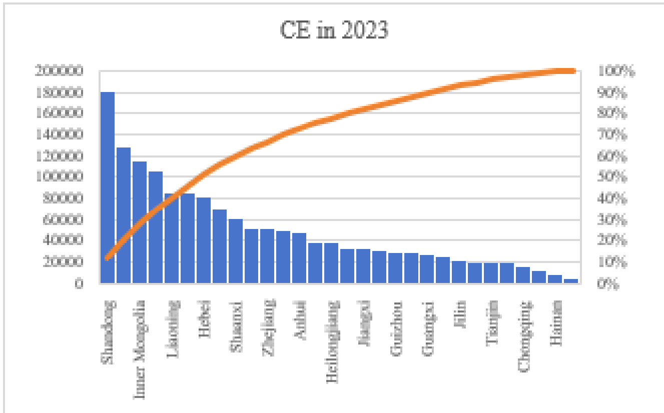

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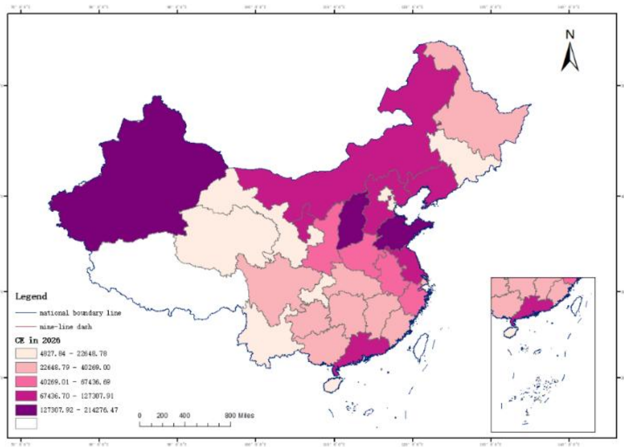

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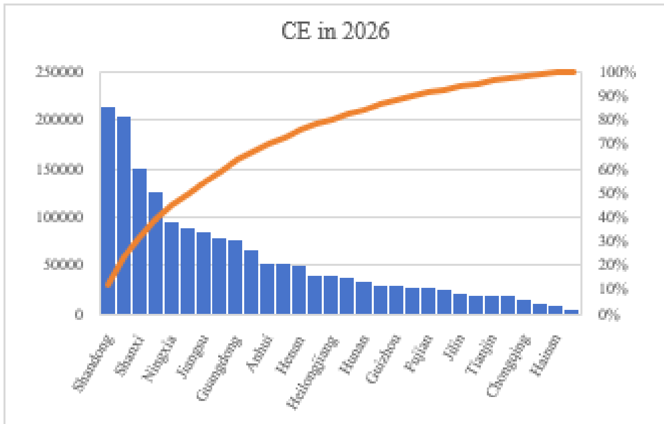

(f)

Figure 4.1 Carbon Emission Intensity by Province in China for 2020, 2023, and 2026

Note: This figure is based on the standard map from the Standard Map Service System of the Ministry of Natural Resources of the People's Republic of China (Approval Map Number: GS (2022) No. 1873). The base map has not been modified.

4.2 Analysis of Carbon Emission Efficiency

This study employs the Super-SBM model with undesirable outputs to comprehensively measure two input and two output indicators. The input and output indicators are shown in the table below:

Table 4.2 Input and Output Indicators of the Super-SBM Model with Undesirable Outputs

Variable Type	Variable Name	Unit	Explanation
Input Indicators	Population Size	Persons	Annual total population
	Energy Consumption	10,000 tons	Annual energy consumption
Output Indicators	Regional GDP	10,000 yuan	Actual GDP
	Carbon Emissions	Tons	Annual carbon emissions

The measurement results of the Super-SBM model are as follows:

Table 4.3 Carbon Emission Efficiency Values and Rankings Measured by the Super-SBM Model

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Beijing	0.20	0.17	0.30	0.29	0.45	0.21	0.45	0.26	0.93	0.65	0.63
Tianjin	0.15	0.43	0.37	0.23	0.23	0.45	0.25	0.26	0.82	0.63	0.66
Hebei	0.47	0.43	0.33	0.28	0.28	0.15	0.21	0.18	0.71	0.35	0.32
Shanxi	0.26	0.22	0.17	0.10	0.33	0.25	0.29	0.28	0.45	0.39	0.38
Inner Mongolia	0.27	0.23	0.16	0.15	0.34	0.31	0.31	0.34	0.58	0.47	0.42
Liaoning	0.45	0.17	0.35	0.36	0.23	0.18	0.18	0.22	0.50	0.39	0.32
Jilin	0.32	0.29	0.21	0.20	0.11	0.37	0.41	0.44	0.21	0.20	0.49
Heilongjiang	0.39	0.41	0.46	0.27	0.16	0.13	0.47	0.15	0.28	0.26	0.20
Shanghai	0.30	0.46	0.34	0.34	0.57	0.55	0.38	0.64	0.91	0.87	0.60
Jiangsu	0.33	0.28	0.14	0.14	0.50	0.43	0.41	0.51	0.90	0.88	0.68
Zhejiang	0.39	0.27	0.13	0.33	0.42	0.59	0.37	0.79	0.71	0.72	0.57
Anhui	0.34	0.23	0.18	0.27	0.31	0.44	0.27	0.21	0.17	0.27	0.14
Fujian	0.21	0.13	0.18	0.16	0.18	0.42	0.16	0.55	0.32	0.52	0.28
Jiangxi	0.21	0.11	0.09	0.14	0.08	0.12	0.15	0.15	0.14	0.13	0.12
Shandong	0.35	0.13	0.11	0.28	0.27	0.39	0.19	0.57	0.47	0.34	0.34
Henan	0.43	0.23	0.21	0.30	0.43	0.21	0.34	0.27	0.26	0.16	0.19
Hubei	0.47	0.17	0.16	0.10	0.23	0.29	0.25	0.36	0.40	0.17	0.36
Hunan	0.33	0.12	0.11	0.16	0.13	0.16	0.20	0.28	0.32	0.13	0.18

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Guangdong	0.51	0.13	0.12	0.31	0.54	0.65	0.38	0.73	0.80	0.50	0.66
Guangxi	0.22	0.08	0.08	0.10	0.18	0.10	0.14	0.11	0.13	0.19	0.13
Hainan	0.11	0.08	0.11	0.12	0.14	0.14	0.18	0.25	0.14	0.23	0.28
Chongqing	0.32	0.13	0.28	0.12	0.10	0.32	0.13	0.34	0.42	0.23	0.36
Sichuan	0.32	0.10	0.30	0.15	0.17	0.15	0.21	0.23	0.69	0.12	0.54
Guizhou	0.18	0.09	0.14	0.11	0.18	0.18	0.21	0.19	0.38	0.15	0.32
Yunnan	0.20	0.13	0.20	0.17	0.28	0.30	0.31	0.28	0.49	0.25	0.15
Shaanxi	0.25	0.14	0.19	0.18	0.27	0.30	0.30	0.29	0.20	0.22	0.17
Gansu	0.19	0.10	0.14	0.15	0.20	0.22	0.30	0.31	0.36	0.18	0.31
Qinghai	0.14	0.08	0.09	0.10	0.15	0.18	0.14	0.15	0.22	0.16	0.21
Ningxia	0.13	0.07	0.07	0.07	0.09	0.10	0.09	0.10	0.21	0.10	0.14
Xinjiang	0.26	0.16	0.18	0.18	0.34	0.30	0.32	0.33	0.15	0.18	0.48

Continuation of the Table.

Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean	Rank
Beijing	0.37	0.48	0.60	1.22	0.58	1.62	0.88	7.64	1.90	0.99	8
Tianjin	0.54	0.83	0.96	1.86	1.02	1.61	1.29	6.44	2.01	1.05	7
Hebei	0.27	0.41	0.50	1.30	0.40	1.35	0.65	6.81	1.16	0.83	11
Shanxi	0.37	0.42	0.47	0.63	0.41	0.58	0.40	2.34	0.55	0.46	19
Inner Mongolia	0.44	0.48	0.58	1.02	0.41	0.65	0.45	3.23	0.84	0.58	16
Liaoning	0.42	0.48	0.99	1.50	0.86	1.14	0.75	4.48	1.22	0.76	13
Jilin	0.21	0.24	0.52	0.72	0.54	0.70	0.37	2.65	0.81	0.50	18
Heilongjiang	0.44	0.47	0.65	0.92	0.66	0.86	0.65	3.23	0.92	0.60	15
Shanghai	0.91	0.78	1.07	1.55	1.28	1.72	1.33	5.10	2.02	1.08	6
Jiangsu	0.90	0.91	1.17	2.45	1.46	1.80	1.25	9.86	1.99	1.35	5
Zhejiang	1.35	0.69	20.09	1.31	1.64	1.25	2.72	5.42	2.94	2.14	1

Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean	Rank
Anhui	0.64	0.32	4.44	0.65	0.92	0.67	1.21	2.70	1.30	0.79	12
Fujian	1.08	0.39	13.36	0.97	1.41	1.01	2.30	3.42	2.58	1.48	3
Jiangxi	0.45	0.16	1.61	0.57	0.63	0.54	0.79	1.11	0.97	0.41	21
Shandong	1.23	0.69	10.48	1.53	1.62	1.65	2.73	5.12	2.29	1.54	2
Henan	0.39	0.39	5.59	0.90	0.94	0.96	1.78	2.63	1.31	0.90	9
Hubei	0.60	0.47	5.12	0.83	0.80	0.95	1.33	2.61	1.43	0.86	10
Hunan	0.46	0.37	2.57	0.66	0.54	0.67	1.02	2.05	1.14	0.58	17
Guangdong	0.86	0.46	5.51	1.65	1.40	1.53	2.36	6.31	2.51	1.40	4
Guangxi	0.30	0.15	1.01	0.55	0.48	0.52	0.73	1.60	0.64	0.37	22
Hainan	0.35	0.38	0.47	0.20	0.19	0.46	0.24	0.89	0.23	0.26	26
Chongqing	0.32	0.84	0.92	0.70	0.34	0.84	0.52	1.46	0.52	0.46	20
Sichuan	0.44	1.27	1.97	0.85	0.45	1.16	0.87	2.41	0.86	0.66	14
Guizhou	0.29	0.52	0.34	0.16	0.14	0.26	0.21	0.49	0.17	0.23	28
Yunnan	0.14	0.35	0.72	0.37	0.37	0.57	0.53	0.95	0.45	0.36	23
Shaanxi	0.17	0.37	0.64	0.26	0.25	0.36	0.36	0.85	0.28	0.30	25
Gansu	0.31	0.19	0.31	0.15	0.15	0.19	0.21	0.35	0.55	0.24	27
Qinghai	0.21	0.41	0.19	0.32	0.34	0.40	0.46	0.41	0.31	0.23	29
Ningxia	0.14	0.20	0.30	0.17	0.19	0.20	0.23	0.30	0.19	0.15	30
Xinjiang	0.36	0.49	0.57	0.40	0.43	0.44	0.50	0.65	0.40	0.36	24

Under the assumption of constant returns to scale, the Super-SBM model with undesirable outputs measured higher carbon emission efficiency in the following provinces: Zhejiang, Shandong, Fujian, Guangdong, and Jiangsu. These provinces are generally characterized by high levels of modernization and urbanization, with well-developed clean energy systems and circular economy practices, which aligns with the actual situation.

4.3 Analysis of Carbon Emission Characteristics Classification

Based on spatiotemporal cluster analysis, the provinces can be divided into four clusters:

Table 4.4 Classification of Carbon Emission Characteristics in Chinese Provinces and Municipalities

Cluster	Provinces

Cluster	Provinces
0	Zhejiang, Guizhou, Shanxi, Jiangsu, Shandong, Guangdong
1	Jiangxi, Fujian, Hubei, Sichuan, Guangxi, Anhui, Shanghai, Hunan, Yunnan
2	Ningxia, Henan, Liaoning, Hebei, Xinjiang, Inner Mongolia
3	Gansu, Heilongjiang, Chongqing, Hainan, Shaanxi, Beijing, Jilin, Tianjin, Qinghai

The measurement data from the cluster analysis are as follows:

Table 4.5 Cluster Analysis Measurement Values

Indicator	Cluster 0	Cluster 1	Cluster 2	Cluster 3
year_mean	2010.05	2010.18	2014.13	2007.80
year_std	5.61	5.75	3.54	5.54
CE_mean	449,781,977.51	356,601,042.43	821,945,301.23	154,719,110.28
CE_std	289,984,177.31	146,379,327.85	264,368,072.96	82,563,061.71
CE/real_gdp_mean	12.61	2.95	2.57	4.05
CE/realGDP_std	4.14	1.28	1.10	1.96
CE/nominalGDP_mean	8.64	2.42	1.84	3.30
CE/nominal_gdp_std	4.14	1.24	0.88	1.88
population_mean	23,972,054.79	61,038,663.37	91,276,610.17	26,779,813.91
population_std	11,583,240.41	18,348,243.53	16,620,321.96	13,401,587.51

Based on the data in the tables above, it can be observed that Cluster 0, including provinces such as Zhejiang and Jiangsu, exhibits high carbon emissions, high GDP, low carbon emission intensity, a large population, and significant usage of both fossil and non-fossil energy. These provinces demonstrate high consumption of both types of energy, strong economic development, and relatively low carbon emissions. Cluster 1, including provinces such as Jiangxi and Fujian, shows low carbon emissions, low GDP, high carbon emission intensity, a small population, high fossil energy usage, and low non-fossil energy usage. These provinces have low carbon emissions and economic development levels but high carbon emission intensity, with fossil energy dominating their energy structure. Cluster 2, including provinces such as Ningxia and Henan, displays medium carbon emissions, low GDP, the highest carbon emission intensity, a small population, high fossil energy usage, and low non-fossil energy usage. These provinces have moderate carbon emissions, low economic development levels, the highest carbon emission intensity, and an unbalanced energy structure. Cluster 3, including provinces such as Beijing and Heilongjiang, features medium carbon emissions, medium GDP, low carbon emission intensity, a large population, high fossil energy usage, and high non-fossil energy usage. These provinces have moderate economic development and carbon emissions, low carbon emission intensity, and a relatively balanced energy structure.

4.4 Characteristics of Carbon Emissions and Their Causes

The fundamental basis for natural geographical zoning involves conducting zoning work based on scientific foundations, integrating historical, ethnic, and other dimensions, and adhering to relevant zoning principles. The general principles of geographical zoning include: the combination of zonality and non-zonality principles, the emphasis on primary factors and comprehensive analysis, the principle of relative consistency, the genetic principle, and the principle of regional contiguity. These principles are not independent but rather interconnected, mutually integrated, and complementary. As early as 1949, China divided its regions into different zones. Due to data limitations, the Tibet Autonomous Region, Taiwan Province, Hong Kong Special Administrative Region, and Macao Special Administrative Region are not included in this zoning.

Table 4.6 Regional Division of Chinese Provinces and Municipalities

Region	Provinces and Municipalities
North China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia Autonomous Region
Northeast China	Liaoning, Jilin, Heilongjiang
East China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Central and South China	Henan, Hubei, Hunan, Guangdong, Guangxi Zhuang Autonomous Region, Hainan
Southwest China	Sichuan, Guizhou, Yunnan, Tibet Autonomous Region, Chongqing
Northwest China	Shaanxi, Gansu, Qinghai, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region

In terms of industrial structure analysis, the industrial structure here is determined by the proportion of primary energy and secondary energy. Primary energy refers to natural energy, which exists in nature, such as coal, crude oil, natural gas, and hydropower. Secondary energy refers to energy products processed and converted from primary energy, such as electricity, gas, steam, and various petroleum products. The classification of primary and secondary energy is as follows:

Table 4.7 Energy Classification

Grade	Name
Primary Energy	Coal, Crude Oil, Natural Gas
Secondary Energy	Coke, Gasoline, Kerosene, Diesel, Fuel Oil

Table 4.8 Industrial Structure Distribution

Province	2000	2019

	Primary Energy Share	Secondary Energy Share	Primary Energy Share	Secondary Energy Share
Beijing	80.94%	19.06%	68.89%	31.11%
Tianjin	85.43%	14.57%	79.76%	20.24%
Hebei	89.01%	10.99%	75.81%	24.19%
Shanxi	90.65%	9.35%	94.02%	5.98%
Inner Mongolia	93.02%	6.98%	93.91%	6.09%
Liaoning	89.91%	10.09%	84.11%	15.89%
Jilin	92.70%	7.30%	88.93%	11.07%
Heilongjiang	89.78%	10.22%	92.61%	7.39%
Shanghai	78.74%	21.26%	72.36%	27.64%
Jiangsu	89.76%	10.24%	80.86%	19.14%
Zhejiang	86.75%	13.25%	89.69%	10.31%
Anhui	88.74%	11.26%	87.59%	12.41%
Fujian	84.01%	15.99%	83.83%	16.17%
Jiangxi	87.33%	12.67%	84.40%	15.60%
Shandong	88.62%	11.38%	88.01%	11.99%
Henan	92.42%	7.58%	86.67%	13.33%
Hubei	85.82%	14.18%	82.60%	17.40%
Hunan	86.41%	13.59%	82.22%	17.78%
Guangdong	77.78%	22.22%	82.34%	17.66%
Guangxi	85.66%	14.34%	84.04%	15.96%
Hainan	68.72%	31.28%	89.14%	10.86%
Chongqing	91.13%	8.87%	83.08%	16.92%
Sichuan	87.25%	12.75%	76.84%	23.16%
Guizhou	93.53%	6.47%	90.42%	9.58%

Yunnan	84.29%	15.71%	78.62%	21.38%
Shaanxi	88.59%	11.41%	94.14%	5.86%
Gansu	88.65%	11.35%	89.32%	10.68%
Qinghai	91.46%	8.54%	82.46%	17.54%
Ningxia	93.13%	6.87%	94.08%	5.92%
Xinjiang	90.74%	9.26%	93.27%	6.73%

5. Research Findings and Policy Recommendations

5.1 Research Findings

Reducing carbon emissions is a crucial component of promoting green and high-quality urban development. This study first selected panel data from 30 Chinese provinces and municipalities from 2000 to 2020 and used an LSTM model to predict carbon emissions in these regions for the next seven years. Next, an evaluation index system for carbon emissions was constructed, and the super-efficiency SBM model with undesirable outputs was employed to calculate carbon emission efficiency values. Data from multiple databases, including the China Economic Network and the China City Statistical Yearbook, were used to analyze the relationship between energy consumption structure and carbon emission intensity through a clustering model. Finally, the characteristics and causes of carbon emissions were summarized. The main findings of the study are as follows:

(1) There remains an imbalance between carbon emissions and energy consumption across provinces and municipalities, along with issues of underutilization. Most provinces and municipalities exhibit high carbon emissions due to their industrialization needs, while advancements in urban modernization have led to significant improvements in energy-saving and emission-reduction technologies, thereby enhancing energy utilization efficiency. However, some provinces and municipalities have made slow progress in optimizing their energy consumption structures, remaining overly reliant on traditional high-carbon energy sources. For instance, the proportion of primary energy sources such as coal has not significantly decreased over the past two decades, resulting in persistently high carbon emissions. Additionally, some regions lack effective policy guidance and financial support for the promotion and application of energy-saving and emission-reduction technologies, making it difficult to widely adopt advanced energy utilization technologies. Furthermore, regional development disparities have, to some extent, hindered overall improvements in energy utilization efficiency. Economically developed regions often have more resources to invest in research, development, and the adoption of energy-saving technologies, while less developed areas face greater challenges in reducing carbon emissions and improving energy efficiency due to financial and technological constraints.

(2) Carbon emission efficiency has steadily increased year by year in most provinces and municipalities, though it remains volatile in a few regions. A significant number of provinces and municipalities have achieved sustained and stable progress in controlling and optimizing carbon emissions. These regions have implemented a series of effective measures, such as actively promoting the use of clean energy, upgrading high-energy-consumption and high-emission industries, improving energy utilization efficiency, and strengthening supervision and policy

guidance for energy conservation and emission reduction. By vigorously developing renewable energy sources like solar and wind power, these regions have gradually optimized their energy structures, thereby reducing carbon emissions per unit of GDP. Some provinces and municipalities have also reduced energy consumption and carbon emissions in industrial processes through technological innovations and improvements in production workflows.

However, a few provinces and municipalities have not yet established a stable trend of improvement in carbon emission efficiency, exhibiting uncertainty and fluctuations. Possible reasons include difficulties in adjusting local industrial structures, high reliance on traditional high-carbon emission industries, challenges in achieving fundamental transformations in the short term, insufficient implementation of energy-saving and emission-reduction policies, lack of effective regulatory mechanisms and incentive measures, or impacts from external economic conditions and fluctuations in energy prices, leading to volatility in carbon emission efficiency.

5.2 Policy Recommendations

(1) Tailor energy-saving and emission-reduction targets to the specific conditions of each province and municipality. The current carbon emission status of provinces and municipalities can be categorized into high-emission, medium-emission, and low-emission regions. High-emission provinces such as Inner Mongolia, Shanxi, and Hebei exhibit high levels of carbon emissions and emission intensity, primarily due to their coal-dominated energy structures. Economically developed regions like Shandong, Jiangsu, and Guangdong have high carbon emissions but relatively low emission intensity, indicating higher energy utilization efficiency. Medium-emission provinces such as Sichuan, Henan, and Zhejiang have moderate levels of carbon emissions and emission intensity. These regions can achieve emission reduction targets by further optimizing their energy structures and improving energy efficiency. Low-emission provinces include municipalities like Beijing, Shanghai, and Tianjin, as well as provinces like Hainan, which have low carbon emissions and emission intensity. These areas have a solid foundation for advancing low-carbon economic development and green growth.

(2) Continuously promote the development of the new energy industry and accelerate the research and development of energy-saving and emission-reduction technologies. Increase financial investment in the new energy sector, encourage technological innovation among enterprises, and enhance the core competitiveness of the industry. Strengthen collaboration between industry, academia, and research institutions to facilitate the rapid transformation and application of scientific research achievements. Gradually optimize and upgrade the energy structure, reduce reliance on traditional fossil fuels, and inject strong momentum into sustainable development. Enhance the construction of new energy infrastructure, optimize power grid layout, and improve the capacity for integrating new energy sources. Establish a robust evaluation system for energy-saving and emission-reduction technologies to scientifically assess and screen new technologies, ensuring their reliability and effectiveness. Emphasize the protection of intellectual property rights, encourage enterprises and research institutions to actively apply for patents, and safeguard the legitimate rights and interests of innovative achievements. Strengthen public education and awareness campaigns to improve public understanding of new energy and energy conservation, fostering a societal atmosphere of collective participation.

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