Spatiotemporal Evolution Characteristics and Driving Factors of Carbon Emissions in China's Energy Industry

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Abstract. This study focuses on carbon emissions from 2012 to 2021.The main objective is to examine the spatiotemporal evolution characteristics of carbon emissions in China's energy industry and the various driving factors influencing these emissions, as well as to propose emission reduction strategies. The findings reveal that: (1) Energy intensity is the primary positive driving factor for carbon emissions in the energy industry, with spatial spillover effects; (2) The total industrial output value of the energy industry and energy structure are positive driving factors; (3) Environmental regulation is a negative driving factor with spatial spillover effects; (4) Investment structure and investment dependency are negative driving factors without significant spatial spillover effects. Based on these positive and negative driving factors and their spillover effects, the study proposes the following low-carbon emission reduction strategies for China's energy industry: (1) Improve energy utilization efficiency and enhance inter-regional exchange of low-carbon technologies; (2) Optimize the energy consumption structure of the energy industry; (3) Strengthen regulation of emissions in the energy industry and enhance inter-regional cooperation; (4) Reduce the investment proportion in the coal industry and increase investment in clean energy technologies.

Keywords: Energy industry; Carbon emissions; Spatiotemporal evolution; Driving factors

1 Introduction

The report of the 20th National Congress of the Communist Party of China unequivocally highlights that the Chinese economy is presently shifting from high-speed growth to high-quality development. Simultaneously, greenhouse gas emissions resulting from fossil fuel combustion have become a pressing issue that countries around the world need to address[1].In order to reduce carbon emissions, academia has done a lot of research[2].For instance, H Yasmeen (2020)[3] utilized the LMDI method to deeply investigate various factors affecting carbon emissions in Pakistan. Moutinho (2020)[4] using the LMDI method to detect CO2 emissions and their components. Research on the spatial distribution of carbon emissions mainly focuses on global, regional, and national levels, thoroughly analyzing the distribution and temporal changes of carbon emissions across different dimensions. Andersen (2016) [5] studied the net carbon emissions caused by land use changes in Bolivia during 1990-2000 and 2000-2010. Li Z (2022) [6] and colleagues researched the spatial spillover effects of carbon trading on carbon emission reductions. Solaymani (2021)[7] investigated the spatial disparities

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in carbon emissions from the transportation sector across seven major carbon-emitting countries.

The development of the energy industry holds paramount importance for the national economy. While academic research on regional and industrial carbon emissions, including their concepts and influencing factors, is relatively mature, there is a dearth of studies specifically focusing on carbon emissions from the energy industry. Furthermore, empirical research utilizing spatial econometric methods to analyze the influencing factors of industry-specific carbon emissions is also lacking. Therefore, analyzing the spatiotemporal evolution characteristics and driving factors of carbon emissions in China's energy industry is crucial for enhancing the theoretical framework of industrial carbon emissions and exploring practical approaches for carbon emission management in the energy sector.

2 Analysis of the Spatiotemporal Evolution Characteristics of Carbon Emissions in China's Energy Industry

2.1 Sample Selection and Data Sources

According to the industry classifications in the China Statistical Yearbook, the energy industry is divided into four distinct sectors: "Coal Mining and Washing," "Oil and Gas Extraction," "Processing of Petroleum, Coal, and Other Fuels," and "Electricity and Heat Production and Supply." This study gathered data on carbon emissions from the energy sector in 30 provinces, autonomous regions, and municipalities across China, spanning the years 2012 to 2021. The carbon emissions data were sourced from the China Carbon Accounting Database [8][9][10][11][12].

2.2 Model Specification

Global Spatial Autocorrelation.

To investigate the spatial distribution characteristics of carbon emissions in the energy industry, the global autocorrelation Moran's I index was employed. The calculation formula for Moran's I is as follows:

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

Using the spatial weight matrix W_{ij} to represent the spatial adjacency relationships among the 31 provinces, a weight of 1 is assigned if two provinces are adjacent, and 0 otherwise.. The variables x_i and x_j represent the carbon emissions from the energy industry in each province. To quantify the spatial correlation of carbon emissions, an index I, ranging from -1 to 1, is introduced. A positive I indicates a positive spatial correlation of industrial carbon emissions between neighboring provinces, suggesting mutual reinforcement. Conversely, a negative I signifies a negative spatial correlation, indicating that carbon emissions of neighboring provinces may inhibit each other. If I equals 0, it implies no significant spatial correlation.

To test the significance of Moran's I, we use the Z-value, which can be calculated as follows:

$$z = \frac{1-E(1)}{\sqrt{Var(1)}} \tag{2}$$

$$E(I) = \frac{1}{(N-1)} \tag{3}$$

where:E(I) represents the expected value of Moran's I under the null hypothesis of no spatial autocorrelation,Var(I) denotes the variance of Moran's I.

Local Spatial Autocorrelation.

Local spatial autocorrelation analysis offers an effective approach to gauge the level of carbon emission clustering within each province. Employing the Local Indicators of Spatial Association (LISA) cluster map provides an alternative means to assess the clustering of carbon emissions within each province, four types of carbon emission clusters can be visually identified: High-High (HH), High-Low (HL), Low-High (LH), and Low-Low (LL). The HH and LL categories reveal a strong mutual correlation in carbon emissions between a province and its neighboring provinces, indicating dense or sparse clusters of energy industry carbon emissions. In contrast, the LH and HL types indicate negative spatial correlation, where high carbon emission provinces are surrounded by low carbon emission provinces, or vice versa.

2.3 Spatial Autocorrelation Analysis

Global Spatial Autocorrelation Analysis of Carbon Emissions in China's Energy Industry.

It can be observed from Table 1 that since 2012, the total carbon emissions from the energy industry in China's provinces have demonstrated a notable positive spatial correlation. This conclusion is derived from the changes in Moran's I value and Z-score. Specifically, these two indicators initially show a slow increase followed by a rapid decline. Referring to 2015 as a pivotal moment, the intensity and significance of spatial clustering progressively rose and subsequently declined. By the end of the study period, the degree and significance of spatial clustering had weakened compared to the initial phase.

The total carbon emissions of China's energy industry display noteworthy clustering in spatial distribution. However, throughout the study period, this clustering experienced a dynamic process of first strengthening and then weakening. Ultimately, the intensity of spatial clustering has significantly decreased compared to the initial phase.

Table 1. Moran's I and Z Values for Total Carbon Emissions from the Energy Industry

Year	Moran'sI	Z-value	P-value
2012	0.1369	2.8978	0.0058
2013	0.132	2.8566	0.0033
2014	0.1168	2.7332	0.0013
2015	0.1517	3.0353	0.0005
2016	0.1417	2.9565	0.0006
2017	0.1229	2.7972	0.0053
2018	0.108	2.6654	0.0061
2019	0.0828	2.4605	0.0291
2020	0.06	2.2751	0.0232
2021	0.0397	2.1106	0.0256

Local Spatial Autocorrelation Analysis of Carbon Emissions in China's Energy Industry.

To explore this issue more deeply, local spatial autocorrelation analysis methods are employed to supplement and enrich the details of the global analysis. The results are shown in Fig.1.

The carbon emissions of the provincial energy industry in China exhibit unique spatial distribution characteristics. The provinces in East China, such as Shandong, Beijing, Tianjin, Anhui, and Henan in Central China, form High-High (HH) carbon emission clusters. These regions are known for their developed heavy industries or rich resources, necessitating large-scale production of primary industrial products. In contrast, High-Low (HL) clusters are scattered across provinces like Xinjiang and Guangdong, without forming contiguous areas. Low-High (LH) clusters briefly appeared in 2012, observed only in Anhui and Shanghai. On the other hand, Low-Low (LL) clusters are consistently found in provinces such as Qinghai, Sichuan, Chongqing, and Yunnan. These regions have carbon emission growth rates and increments below the national average, indicating relatively lower carbon emission pressure.

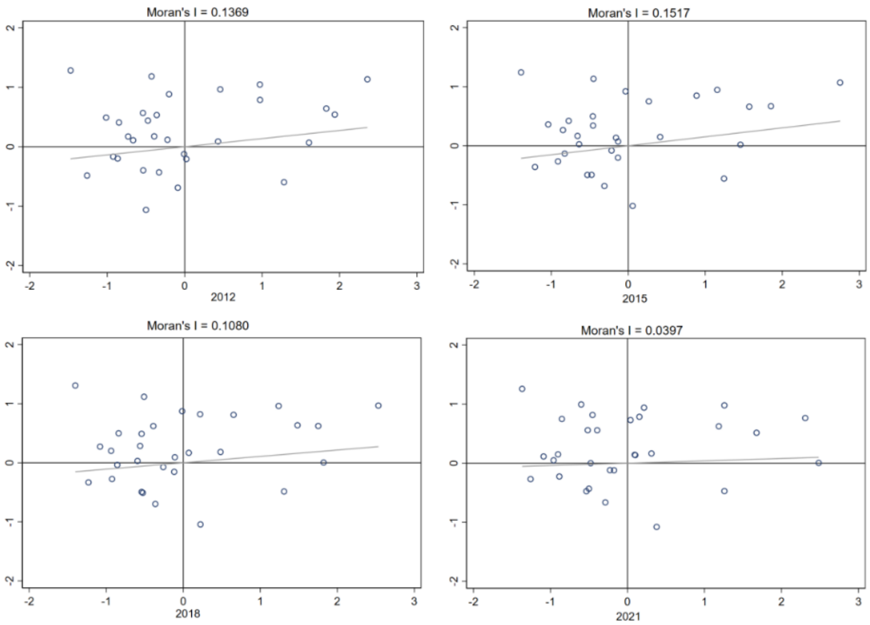

Fig. 1. Moran's I Scatter Plot of Provincial Total Carbon Emissions in the Energy Industry

Overall, the spatial distribution of carbon emissions in China's energy industry shows clear regional disparities. From a global perspective, the spatial clustering of total carbon emissions in the energy industry has gradually decreased. Notably, provinces with significant clustering characteristics are mainly concentrated in the HH and LL types. This indicates that, within the total carbon emissions of China's energy industry, the spatial clustering of high carbon emission types is more pronounced.

3 Empirical Analysis of the Driving Factors of Carbon Emissions in China's Energy Industry.

3.1 Selection of Indicators and Data Sources.

The Logarithmic Mean Divisia Index (LMDI) method, widely used in various fields for analyzing energy consumption and emissions, is employed in this study to analyze the factors driving carbon emissions in the energy industry. Based on Ang B W's LMDI factor decomposition method, we derive the decomposition formula for carbon emissions in the energy industry (Equation 4).

$$C = \sum_{ij} C_{ij} = \sum_{ij} \frac{C_{ij}}{E_{ij}} \times \frac{E_{ij}}{E_j} \times \frac{E_j}{G_j} \times \frac{G_j}{EI_j} \times \frac{EI_j}{EI} \times \frac{EI}{G} \times G = \sum_{ij} CE_{ij} \times EM_{ij} \times EG_j \times GEI_j \times EIM_j \times EIG_j \times G \quad (4)$$

The variables are explained in Table 2:

Table 2. LMDI Decomposition Model Variables for Energy Industry Carbon Emissions

Variable	Explanation	Variable	Explanation
C	Carbon emissions in the energy industry	CE	Carbon emission coefficient
i	Type of energy used in the energy industry	EM	Energy composition
j	Energy sector	EG	Energy intensity
E	Energy consumption	GEI	Energy technology
G	Industrial output	EIM	Investment structure
EI	Fixed investment in energy industry	EIG	Investment reliance

The carbon emission data utilized in this study are sourced from the China Emission Accounts and Datasets (CEADS), focusing solely on emissions generated from energy consumption. According to the 3E theory, there is a close interaction between energy, economy, and environment, indicating a significant relationship between energy consumption, industrial output, fixed investment, and carbon emissions. Therefore, these indicators, or the derived influencing factors, are considered as internal factors affecting carbon emissions in the energy industry.

Given the high pollution characteristics of the energy industry, environmental regulation is selected as an external influencing factor. Numerous academic studies have explored the impact of environmental regulations on carbon emissions, with many concluding that such regulations significantly affect the emissions of industrial enterprises. Therefore, this study incorporates environmental regulation as an external factor from both industrial and spatial perspectives, in addition to the internal influencing factors mentioned above.

In summary, seven indicators are selected as explanatory variables for carbon emissions: carbon emission coefficient (CE), energy structure (EM), energy intensity (EG), investment structure (EIM), investment dependence (EIG), total industrial output of the energy industry (G), and environmental regulation (ER). The details are provided in Table 3.

Table 3. Variable Descriptions and Types

Variable Type	Variable Name	Code	Description
Dependent	Carbon Emissions	C	/
Explanatory	Carbon Emission Coefficient	CE	Ratio of carbon emissions to consumption
Explanatory	Energy Structure	EM	Share of coal in the total energy consumption
Explanatory	Energy Intensity	EG	Ratio of total energy consumption to total output value
Explanatory	Investment Structure	EIM	Ratio of fixed assets in the coal industry to total fixed assets of the energy industry
Explanatory	Investment Dependence	EIG	Ratio of total fixed investment in the energy industry to the total output value of the industry
Explanatory	Total Output Value of Energy Industry	G	/
Explanatory	Environmental Regulation	ER	Ratio of operating costs of wastewater and waste gas treatment facilities to total output value

Data on carbon emissions in the energy sector is obtained from the China Carbon Accounting Database. Data on energy consumption is sourced from the China Statistical Yearbook and the China Energy Statistical Yearbook for the years 2013 to 2022. Data related to environmental regulation is sourced from the Environmental Statistics Yearbook. The China Industrial Statistical Yearbook (2013-2022) provides information on fixed asset investment and total industrial output value for the energy sector. Missing fixed asset data is supplemented from provincial statistical yearbooks, with some values averaged over the past three years. The total industrial output value is calculated by adding the main business income to the year-end value of finished products and then subtracting the beginning-of-year value of finished products.

3.2 Model Setup

Spatial econometric models are currently classified into three main categories: SAR (Spatial Auto-regressive Model), SEM (Spatial Error Model), and SDM (Spatial Durbin Model).

The SAR model is formulated as follows:

$$y = \lambda Wy + X\beta + \varepsilon \tag{5}$$

To explain the potential influence of unobserved interference factors in neighboring regions on carbon emissions, the SEM introduces spatial error components, formulated as follows:

$$\begin{cases} y = X\beta + \delta \\ \delta = \lambda W\varepsilon + \mu \\ \varepsilon \sim N(0, \delta^2) \end{cases} \tag{6}$$

λ is the spatial error coefficient, assessing the degree of interaction in carbon emissions across space.

The SDM integrates multiple influencing factors and the spatial lag effect of carbon emissions into a comprehensive model to offer a deeper and more thorough understanding of the spatial relationships among variables. The mathematical form of the SDM is:

$$y = \rho Wy + X\beta + WX\delta + \varepsilon \quad (7)$$

In the above equations, the carbon emissions are denoted by y, and their influencing factors by X. The spatial weight is represented by W. The coefficients λ and β are to be estimated, while is ε the random error term. To eliminate heteroscedasticity and reduce data volatility, the spatial models are constructed as shown.

$$lnC_{it} = \rho WlnC_{it} + \beta_1 lnCE_{it} + \beta_1 WlnCE_{it} + \beta_2 lnEM_{it} + \beta_2 WlnEM_{it} + \beta_3 lnEG_{it} + \beta_3 WlnEG_{it} + \beta_4 lnEIM_{it} + \beta_4 WlnEIM_{it} + \beta_5 lnEIG_{it} + \beta_5 WlnEIG_{it} + \beta_6 lnG_{it} + \beta_6 WlnG_{it} + \beta_7 lnER_{it} + \beta_7 WlnER_{it} + \varepsilon_{it} \quad (8)$$

3.3 Empirical Analysis

Examining panel data of various variables using the LM test method and a robust enhanced LM test tool.

Table 4. LM Test Results

LM Test	Test Result	P-Value
R-LM (error)	492.028	0.062
LM (error)	574.503	0.035
R-LM (lag)	38.409	0.026
LM (lag)	5.604	0.003

The results from Table 4 indicate that the LM (Lag), LM (Error), Robust LM (Lag), and Robust LM (Error) statistics all pass the significance level tests. Indicates significant spatial correlation in provinces' energy industry carbon emissions Therefore, employing spatial econometric models for the empirical analysis is more appropriate. Due to the presence of spatial lag and spatial error terms, the Spatial Durbin Model (SDM), which integrates these factors, is deemed appropriate.

To validate the effectiveness of the spatial model, the study utilizes panel data and incorporates a spatial adjacency weight matrix. LR tests and Wald tests are conducted under the SDM, SAR, and SEM models. The outcomes of these examinations are showcased in Table 5. The data indicate that when using the spatial adjacency weight matrix, the R^2 values of the SDM surpass those of the SEM and SAR models. This confirms the appropriateness of the SDM for analyzing carbon emissions in China's energy industry.

Table 5. Model Comparison and Validation

	SDM	SAR	SEM
R2	0.9467	0.9397	0.8892
LR	180.3***	230.3***	420.6***
Wald	196.7***	240.8***	369.3***

In order to decide between a random effects model and a fixed effects model, we set the null hypothesis as selecting the random effects model and conducted the Hausman test. The results are displayed in Table 6.

Table 6. Hausman Test for Spatial Models

Test Value	P-Value
48.92	0.001

The Hausman test results indicate that at the 1% significance level, we reject the applicability of the random effects model, reinforcing the decision to use the fixed effects Spatial Durbin Model (SDM) for empirical analysis.

The fixed effects SDM in regression analysis finds: Energy intensity significantly increases carbon emissions, dominating their rise (Table 7).Whenever energy intensity increases by 1%, the carbon emissions of the energy industry increase by 1.336%. Yet, the spatial lag term's regression coefficient (-0.054) passes the significance test. It implies carbon emissions have a spatial spillover effect in nearby regions. The total output of the energy sector correlates positively with carbon emissions; for every 1% rise in output, carbon emissions increase by 0.336%. However, the coefficient for the lag term is -0.054, indicating a somewhat weak negative impact on the carbon emissions of neighboring regions. However, given a p-value of 0.085, this impact lacks statistical significance. Investment structure and environmental regulations exhibit significant negative impacts on carbon emissions in China’s energy industry. The spatial lag term coefficient for environmental regulations is negative and significant at the 1% level, suggesting that strengthening environmental regulations can significantly reduce local carbon emissions..

Table 7. Regression Results of the Spatial Durbin Model for Factors Influencing Carbon Emissions

Variable	Coefficient	P-Value	Variable	Coefficient	P-Value
lnEG	1.336	0.000	W*lnEM	-0.401	1.016
lnEM	0.288	0.000	W*lnCE	0.121	0.067
lnG	0.194	0.000	W*lnEIM	0.213	4.806
lnCE	0.036	0.007	W*lnEG	-0.054	1.086
lnEIG	-0.002	0.320	W*lnG	-0.004	0.085
lnEIM	-0.089	0.000	W*lnEIG	-0.025	2.370
lnER	-0.077	0.031	W*lnER	-0.054	0.038
ρ	0.715		Sigma2_e	0.004	
Log_L	385.493		R^2	0.5502	

When handling spatial data, the spatial lag term of the Spatial Durbin Model (SDM) may not fully capture the mutual influence of neighboring regions, potentially leading to biased point estimates. To comprehensively explore both direct and indirect effects of one region on the carbon emissions of adjacent areas, a more detailed decomposition of the Spatial Durbin Model is warranted. The specific decomposition results are depicted in Table 8. It is evident that an increase in energy intensity significantly boosts carbon emissions in China's energy industry, with impacts extending both directly and indirectly. The direct effect coefficient of total energy industry output on carbon emissions stands at 0.219, while the indirect effect coefficient is 1.106, albeit not significant. Environmental regulations notably curb local energy industry carbon emissions, although their indirect effect slightly elevates neighboring region emissions by -0.007%. This phenomenon might relate to the relocation of high-emission industries from developed cities to nearby areas. Conversely, investment structure exerts a significant direct impact on carbon emissions. Despite an indirect effect coefficient of -0.203 for investment structure, its significance remains insignificant. The energy consumption structure manifests both direct and indirect positive influences on carbon emissions. Although the indirect effect coefficient reaches 0.356, it lacks statistical significance, indicating a limited spatial spillover effect of energy structure on carbon emissions and leaving the specific impact on neighboring region emissions uncertain.

Table 8. Decomposition Results of the Spatial Durbin Model

Variable	Direct Effect	Indirect Effect	Total Effect
lnCE	0.036	0.129	0.128*
lnEM	0.288***	0.356	1.110**
lnEG	1.336***	0.374***	1.595***
lnEIM	-0.012***	-0.203***	-0.008
lnEIG	-0.004**	-0.091***	-0.095***
lnG	0.219***	1.106	1.325**
LnER	-0.081**	-0.007**	0.058**
lnGDP	0.554***	0.956***	1.510***

To ensure the timeliness and applicability of the model, this paper will use alternative spatial weight matrices and models for robustness tests. According to the analysis in Table 9, the Spatial Durbin Model (SDM) shows consistency in the direction of the regression coefficients and stability in the significance level when applying geographical distance and economic distance weight matrices. This indicates that the SDM model can effectively adapt to different types of spatial weights. Meanwhile, the results of the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM) also show consistency in the direction of the explanatory variables and similarity in the significance levels, further validating the robustness of the SDM model estimates.

Table 9. Regression Results of SDM and SAR Models Under Various Weight Matrices

Variable	Geographical Distance	Economic Distance
	SDM	SEM
lnCE	0.53*** (21.06)	0.617*** (21.96)
lnEM	0.133*** (24.26)	0.176** (25.19)
lnEG	0.098** (8.57)	0.108** (9.39)
lnEIM	-0.016** (17.76)	-0.207** (17.29)
lnEIG	-0.00198	-0.00145
lnG	0.194** (14.79)	0.194** (14.89)
LnER	0.077** (2.16)	0.055* (1.76)
lnGDP	0.533*** (24.26)	0.576*** (25.19)

In summary, energy intensity is the primary driving factor, exerting a positive effect and demonstrating spatial spillover effects. The energy consumption structure and the total output value of the energy industry also act as positive driving factors, but they do not exhibit significant spatial spillover effects. Environmental regulation, on the other hand, is a negative driving factor and shows spatial spillover effects. Both investment structure and investment dependency negatively impact carbon emissions in the energy industry, and neither displays spatial spillover effects..

4 Conclusion

Based on an integrated spatiotemporal perspective. The theoretical and empirical analysis leads to the following conclusions:(1) China's energy industry carbon emissions exhibit significant spatial autocorrelation. Compared to the national average, provinces with lower and higher carbon emissions show a "first concentrated, then dispersed" spatial distribution pattern.(2) Energy intensity is the primary driving factor of carbon emissions in China's energy industry, significantly promoting carbon emissions and showing spatial spillover effects.The energy consumption structure and the gross output value of the energy industry are positive driving factors. Local environmental regulation is a negative driving factor with spatial spillover effects.The investment structure and investment dependence in the energy industry are negative driving factors for carbon emissions.Based on the above conclusions, the following recommendations are proposed:(1) Improve Energy Utilization Efficiency. (2) Optimize Energy Consumption Structure.(3) Strengthen Environmental Regulation and Regional Cooperation. (4) Optimize Energy Industry Investment Structure.

References

[1] Cui Jie, Zhang Ning, Wang Wenjing, et al. Analysis and Prospect of the development trend of China's energy and coal industry [j]. coal economy research, 2023,43 (12): 50-55.doi:10.13202/j.cnki.cer.2023.12.007

[2] renhongyang, duruolan, xieguilin, et al. Research status of influencing factors and identification methods of carbon emissions in China [j]. environmental engineering, 2023,41 (10): 195-203+244.doi:10.13205/j.hjgc.2023.10.023.

[3] Yasmeen H, Wang Y, Zameer H, et al. Decomposing factors affecting CO2 emissions in Pakistan: insights from LMDI decomposition approach[J]. Environmental Science and Pollution Research, 2020, 27: 3113-3123.

[4] Moutinho V, Madaleno M, Inglesi-Lotz R, et al. Factors affecting CO2 emissions in top countries on renewable energies: a LMDI decomposition application[J]. Renewable and Sustainable Energy Reviews, 2020, 90: 605-622.

[5] Andersen L E, Doyle A S,del Granado S, et al. Net Carbon Emissions from Deforestation in Bolivia during 1990-2000 and 2000-2010: Results from a carbon bookkeeping model[J]. PloS one, 2016, 11(3): e0151241.

[6] Li Z, Wang J. Spatial spillover effect of carbon emission trading on carbon emission reduction: Empirical data from pilot regions in China[J]. Energy, 2022, 251: 123906.

[7] Solaymani S.CO2 emissions patterns in 7 top carbon emitter economies:The case of transport sector[J].Energy, 2021, 168:989-1001.

[8] Shan et al. (2018) "China CO2 emission accounts 1997-2015. Scientific Data", https://www.nature.com/articles/sdata2017201;

[9] Shan et al. (2020) "China CO2 emission accounts 2016-2017. Scientific Data", https://www.nature.com/articles/s41597-020-0393-y;

[10] Guan et al. (2021) "Assessment to China's recent emission pattern shifts. Earth's Future", https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021EF002241;

[11] Shan et al. (2016) "New provincial CO2 emission inventories in China based on apparent energy consumption data and updated emission factors. Applied Energy", https://www.sciencedirect.com/science/article/abs/pii/S0306261916303932.
[12] Xu et al. (2024) "China carbon emission accounts 2020-2021. Applied Energy", https://www.sciencedirect.com/science/article/pii/S0306261924002204#ac0005.