ANALYSIS OF THE SPATIOTEMPORAL HETEROGENEITY OF DRIVERS ON PROVINCE-LEVEL SYNERGY OF AIR POLLUTION CONTROL AND CARBON MITIGATION IN CHINA

Man Guo[1,2], Baozhang Chen[2,3], Nicholas Hamm[1*]

[1]School of Geographical Sciences, Faculty of Science and Engineering, University of Nottingham Ningbo China – (man.guo, nicholas.hamm)@nottingham.edu.cn
[2]State Key Laboratory of Resource and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China. – (baozhang.chen)@igsnrr.ac.cn
[3]University of Chinese Academy of Sciences, Beijing, China.

KEY WORDS: Index evaluation system, Coupling coordination degree, Local spatial association, Driving factors, GTWR (Geographically and Temporally Weighted Regression).

ABSTRACT:

Confronting the dual challenges of air pollution control and carbon mitigation, China is seeking a "win-win" pathway to achieve the co-reduction of air pollution and CO_2 emission. In this study, taking 31 provinces in China as research objects, a novel index system, characterized by total emission, emission intensity and emission per capita, was established to evaluate the coupling coordination degree between the air pollution control (AP) subsystem and carbon mitigation (CM) subsystem at the provincial scale from 2013 to 2017. Local Geary's C Index was performed to determine where the coupling coordination was correlated to its neighbour provinces. Considering the discrepancy of the socio-economic status, industrial and energy structure among provinces, Geographically and Temporally Weighted Regression (GTWR) was employed to measure the spatiotemporal heterogeneity of the influences of the driving factors on the coupling coordination degree, aiming to reduce uncertainty in the interpretation of spatial and temporal variability. Results show that: (1) Since the implementation of "Clean Air Action" in 2013, there has been an obvious improving trend of synergistic governance of air pollution control and carbon mitigation. (2) The synergy of air pollution control and carbon mitigation did not achieve good joint governance, locally. (3) The influence of drivers presents significant spatiotemporal heterogeneity among provinces. Generally, the improvement of the coupling coordination is greatly affected by the local energy structure and economic level. This conclusion has propounded practical significance for synergistic governance of air quality improvement and low-carbon development in the context of carbon neutrality achievement.

1. INTRODUCTION

China, as the world's largest carbon emitter with 11,472 Mt, account for 30.9 % of global CO_2 emission in 2021 (Andrew and Peters, 2022). With the responsibility of stabilizing the Earth's climate for sustainable development, China has implemented a series of carbon mitigation policies over the past decades. Generally, CO_2 reduction rely on energy policies such as increasing the share of non-fossil fuel consumption, energy curb, and energy efficiency improvement (Shan et al., 2022). While a decline in the growth rate of carbon emission was observed from 2013 to 2016, there is a clear rebound in 2017 with an 8% increase in coal consumption (Liu et al., 2022). This gives a hint to the Chinese government and authorities that a long-term deeper carbon mitigation plan is required to achieve the NDCs (Nationally Determined Contributions) of carbon neutrality by 2060.

China is also confronted with severe air quality issues, especially $PM_{2.5}$ concentration and ozone pollution (Shi et al., 2021). Therefore, China is now faced with dual challenges, including air pollution control and carbon mitigation. The uniqueness of today's atmospheric environment urges the Chinese government to explore a well-developed policy or governance strategy with aim of achieving a "win-win" situation of air pollutants and CO_2 emissions control (Wu et al., 2022). Identifying the mechanism behind various factors influencing the performance of synergistic governance is the key point to provide valuable suggestions for the further realization of carbon neutrality and air quality improvement in China.

According to the existing literature regarding the evaluation on the co-benefit and co-control performance between air pollution and carbon mitigation, the synergistic effect was analysed from the perspective of comprehensive consideration of the respective relationship between carbon dioxide and air pollutant emission, or building one indicator or parameter to represent the degree of co-benefit or co-control (Dong et al., 2019a; Wu et al., 2022; Yi et al., 2022). In this paper, an index system approach is performed to measure the synergy degree, defined as the coupling coordination degree between two subsystems. A synergistic system involves several dynamics and interactions between components within a single subsystem, as well as between various subsystems within a larger system, which are complex and non-linear (Liu et al., 2021). By employing an index system approach, multiple factors that influence the subsystems can be integrated into a comprehensive indicator that considers a two-way relationship. It could avoid the limitation of the application of the econometric model, which reveals the bidirectional causal relationship between two objects (Xing et al., 2019). The structure and correlation of the AP-CM (Air Pollution Control – Carbon Mitigation) system are shown in Figure 1 with its specific operating rules (Yi et al., 2022). In addition, much existing research investigating the driving factors of CO_2 and air pollution emission does not reflect the discrepancy of the impact from drivers over space and time (Karmellos et al., 2016; Zhang et al., 2016). This study, considering the possibility of the existence of non-stationarity of space and time, identifies whether a location

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specific approach is the appropriate strategy for the realization of effective synergistic governance of air pollution control and carbon mitigation among provinces.

In this study, we analyse the spatiotemporal heterogeneity of the influence of drivers on the synergistic effect of carbon mitigation and air pollutants control from 2013 to 2017 at the provincial scale. This time span coincides with the implementation period of the stringent air pollution prevention and control policy, "Clean Air Action". There are three objectives: (1) To establish an index system to evaluate the spatiotemporal pattern of the synergistic governance performance of air pollution control and carbon mitigation measures among provinces from 2013 to 2017; (2) To reveal the local spatial association of synergy degree at the provincial level from 2013 to 2017; (3) To identify the spatial-temporal heterogeneity of the driving factors influencing the synergistic governance degree at the provincial scale to reduce the uncertainty in the interpretation of spatial and temporal variability.

This study provides a new perspective on the driving factors analysis with the consideration of spatiotemporal heterogeneity, and diversity of the impacts from the drivers. It is conducive to the adoption of different strategies to maximize the co-benefit of synergistic governance of air pollution control and carbon mitigation.

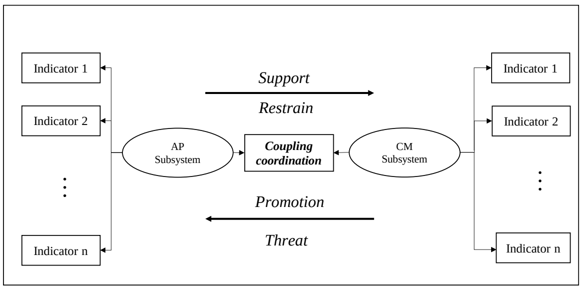

Figure 1. The structure and correlation of the AP-CM system.

2. STUDY AREA AND DATA

2.1 Study area

In this paper, the air pollution and carbon dioxide emission data are acquired from the Multi-resolution Emission Inventory for China Dataset (MEIC), which are developed by Tsinghua University (Zheng et al., 2018). Due to the spatial scope of this dataset, the study area includes 31 provinces in mainland China, except Taiwan, Macau, and Hong Kong. A map of China showing administrative regions
can be found at:
https://en.wikipedia.org/wiki/Template:PRC_provinces_big_imagemap.

2.2 Data source and indicators for AP-CM system assessment

The potential indicators of AP (Air pollution control) and CM (Carbon mitigation) subsystems are listed in Table 1. For each component, the key features such as total emission, emission intensity (emissions per unit of GDP), and emission per capita are selected to represent each subsystem, comprehensively. Therein, features of intensity and per capita take the geographical difference of population and economic development level into account to highlight the spatial discrepancy of coupling coordination degree of the AP-CM system among provinces. All the emission data at the gridded scale are acquired from the MEIC dataset. The dataset derives from the integration of provincial-scale energy statistics (China Energy Statistical Yearbook activity data), and China Power Emissions Database (CPED). It performs a spatial disaggregation to grided scale based on the spatial pattern of population, traffic network, etc. MEIC dataset provides air pollutants and CO_2 emissions with a spatial resolution of 0.25° from 2008 to 2017. Except from that, the socio-economic data and energy statistical data for these 31 provinces are collected from China Statistical Yearbook and Energy Statistical Yearbook from 2013 to 2017.

System	Subsystem	Indicators
AP-CM system	Carbon Mitigation	CO_2 Emission
		CO_2 Intensity
		CO_2 Emission per capita
	Air Pollution Control	CO Emission
		CO Intensity
		CO Emission per capita
		SO_2 Emission
		SO_2 Intensity
		SO_2 Emission per capita
		NOx Emission
		NOx Intensity
		NOx Emission per capita
		$PM_{2.5}$ Emission
		$PM_{2.5}$ Intensity
		$PM_{2.5}$ Emission per capita
		PM_{10} Emission
		PM_{10} Intensity
		PM_{10} Emission per capita

Table 1. Index evaluation system of AP-CM system.

3. METHODOLOGY

3.1 The coupling coordination degree of AP-CM system

A principal component analysis was conducted on all the potential indicators to select the combination of several indicators that are important and can carry the most amount of information to construct the AP subsystem from 2013 to 2017. In this study, we choose the indicators whose contribution is higher than 1/15.

3.1.1 The ordering degree of each subsystem: To get an understanding of the dynamic interaction mechanism of air pollution control and carbon mitigation performance separately, it is significant to identify the weights of these ordinal indicators in each subsystem. Ordering degree is a quantitative criterion for evaluating the combination effect of ordinal indicators (Mu et al., 2022). The ordinal indicators can be used to assess the collaborative development level of each subsystem over time (Dong et al., 2019b; Mu et al., 2022, 2022; Shi et al., 2020). The rank of the score could represent the air pollution control and carbon mitigation level, respectively.

Firstly, to obtain the ordering degree of indicators in each subsystem, we need to normalize the indicators based on whether the selected indicators have a positive or negative effect on the overall synergistic coupling system (Shi et al., 2020; Yi et al., 2022). The indicators with positive and negative effects follow the equation (1) and (2) respectively.

Indicator with positive effect:

$$X_{ij} = (x_{ij} - x_{ij\,max})/(x_{ij\,max} - x_{ij\,min}), \tag{1}$$

Indicator with negative effect:

$$X_{ij} = (x_{ij\,max} - x_{ij})/(x_{ij\,max} - x_{ij\,min}) \tag{2}$$

Where x_{ij} represents the value of indicator i in province j, and $x_{ij\,min}$ and $x_{ij\,max}$ represent the minimum and maximum value of the indicator i in province j, respectively.

Secondly, the synergy degree of the AP-CM system is the result of the coupling coordination degree of these two subsystems (Dong et al., 2019b; Gan et al., 2020; Liu et al., 2021). For the level of the ordering degree of each subsystem, the weights of each indicator should be assigned to determine which indicators dominate the performance of air pollution control (Mu et al., 2022; Bai et al., 2021). In this study, the entropy weight method, an objective weights assignment strategy was performed to allocate a scheme of weight assignment (Dong et al., 2019b; Yi et al., 2022). To achieve the comparison among provinces, the entropy model is modified in this paper as follows:

Using the entropy weight method to determine the weights for each year is divided into four steps:

(1) To determine the proportion P_{ij}:

$$P_{ij} = \frac{X_{ij}}{\sum_{j=1}^{m} X_{ij}}, \tag{3}$$

Where X_{ij} represent the value of indicator i in province j ($j = 1, 2, \ldots, 31$) after data normalization.

(2) To calculate the information entropy e_i:

$$e_i = \frac{1}{\ln(m)} \sum_{j=1}^{m} P_{ij} \ln(P_{ij}), \tag{4}$$

Where m is the total number of provinces ($m = 31$).

(3) To calculate the entropy redundancy d_i:

$$d_i = 1 - e_i, \tag{5}$$

(4) To calculate the weight w_i:

$$w_{ij} = \frac{d_{ij}}{\sum_{i=1}^{n} d_{ij}}, \tag{6}$$

For a certain indicator i, if its weight is greater than others, it indicates that this indicator has larger contribution in the comprehensive evaluation.

Thirdly, to obtain the level of the ordering degree of these two subsystems of each province, different weights of selected indicators for each year were assigned and summed together through linear weighted regression approach.

$$U_{\theta j} = \sum_{i=1}^{n} w_{ij} X_{ij} \tag{7}$$

Where θ represents each subsystem ($\theta = 1, 2$).

The above steps are performed for each year, respectively. The level of air pollution control and carbon mitigation could be obtained for each province from 2013 to 2017.

3.1.2 Synergy model for AP-CM model: The synergy degree of the compound system determines whether this possible order will be established from disorder. From a dynamic perspective, measuring synergy is reintegrating the ordering degree of each subsystem (Mu et al., 2022).

Given the same importance of air pollution control and carbon mitigation in China from 2013 to 2017, weights (α=0.5, β=0.5) is adopted for each subsystem and the comprehensive synergy degree of AP-CM system can be obtained through the weighted averaging method (Liu et al., 2021; Shi et al., 2020; Yi et al., 2022).

The calculation is divided into two steps:

(1) To calculate the coupling coordination degree of AP and CM subsystems:

$$C_{ij} = \sqrt{\frac{U_{1j} U_{2j}}{(\frac{U_{1j} + U_{2j}}{2})^2}}, \tag{8}$$

Where C_{ij} is the coupling coordination degree of air pollution control and carbon mitigation for each province for each year. U_{1j} and U_{2j} represents the ordering degree of each subsystem in province j.

(2) To calculate the coupling coordination degree of the AP-CM system with consideration of the development level of these subsystems. α =0.5, β =0.5 are used to constrain the same importance of China's atmospheric environment management.

$$T_{ij} = \sum_{i=1}^{2} \alpha_i \times U_i, \tag{9}$$

$$D_{ij} = \sqrt{C_{ij} \times T_{ij}} \tag{10}$$

3.2 Local spatial association of coupling coordination degree of AP-CM system

To identify if the synergy of air pollution control and carbon mitigation has achieved regional joint governance, local spatial association statistic, Geary's c was performed in the whole study area. The calculation formula is shown as below (Geary, 1954):

$$c_i = \sum_{i}^{n} W_{ij} (z_i - z_j)^2 \tag{11}$$

Where W_{ij} is the spatial weight between location i and j. z_i and z_j are the coupling coordination degree of location i and j.

Geary's c is designed to identify the local association among georeferenced data by measuring the squared difference from the reference site i, whereas the variogram is used to evaluate the spatial variability across the whole study area. If the trends of the mean, standard deviation, and covariance are dissimilar from place to place, it indicates that the heterogeneity exists among the observations. Getis and Ord (1996) said, "A typical heterogeneity spatial data set would be one containing drift, that is, the occurrence of trends toward high values or low values in certain direction." Hence, local statistics could be used to identify the existence of heterogeneity of spatial georeferenced data. Conversely, it has the capability of identifying whether if the synergy of air pollution control and carbon mitigation present local positive autocorrelation, which indicating the achievement of regional joint synergistic governance (Odongo et al., 2014). Geary's c is between 0 and an undefined value larger than 1. Statistical indicator with small value (less than one) indicates positive spatial autocorrelation (fewer disparities between an observation and its neighbours), whereas statistics with big values (greater than one) indicate negative spatial autocorrelation (Fischer and Wang, 2011).

3.3 Spatiotemporal heterogeneity of drivers on the coupling coordination degree of AP-CM system

GTWR (Geographical and Temporal Weighted Regression) is an extension of GWR (Geographical Weighted Regression) approach. In contrast, GTWR is not only modelling spatial heterogeneous process with the relationship between a response and a set of covariates varying across geographical space, but also considering the temporal non-stationarity (Fotheringham et al., 2015). In this study, considering the spatiotemporal discrepancy of socio-economic development level, emission patterns and local energy and industrial structure, it is of significance to explore whether the influence of each drivers present spatiotemporal heterogeneity. It could provide the valuable information of the mechanism and dynamics of the geographical entities or relationships with the coupling coordination degree. Therefore, in this study, GTWR was chosen to examine and identify the spatiotemporal heterogeneity of the influence of drivers among provinces from 2013 to 2017.

Firstly, OLS (Ordinary Least Squares) regression was performed to identify the potential drivers for the further modelling (Li et al., 2022). Then, it was performed again to model the relationship between the coupling coordination degree of air pollution control and carbon mitigation with potential drivers at a global scale. A multi-collinearity test was used to check the collinearity among potential divers through the variance inflation factor (VIF). BP (Breusch-Pagan) test was performed to identity if homoscedasticity exists in a linear regression with residuals distributed with equal variance of the predictor variable (Liao et al., 2023; Ling et al., 2022). If the null hypothesis is rejected, it means that there may be non-stationarity in the linear regression model. The geostatistical model with consideration of spatial and temporal non-stationarity has the potential possibility to reduce the uncertainty on the explanation of the relationship between the coupling coordination degree and drivers. In this study, GTWR model was used to identity the spatiotemporal heterogeneity of the drivers' impact on the synergy degree of air pollution control and carbon mitigation, as shown in equation (12):

$$y_k = \beta_0(\mu_k, \vartheta_k, t_k) + \sum_{p=1}^{q} \beta_p(\mu_k, \vartheta_k, t_k) x_{kp} + \varepsilon_k \quad (12)$$

Where $\beta_0(\mu_k, \vartheta_k, t_k)$ are the regression intercept; $\beta_p(\mu_k, \vartheta_k, t_k)$ is the regression coefficients of the variable x_{kp} ; μ_k, ϑ_k, t_k are the space-time coordinates of the research unit, representing latitude, longitude and time, respectively; $q = 6$; x_{kp} is the driver; ε_k is the error term for the study unit k.

4. RESULTS

4.1 Spatiotemporal characteristic of the coupling coordination degree of AP-CM system from 2013 to 2017

Based on the PCA result, PM_{10} Emission, $PM_{2.5}$ Emission, CO Emission, PM_{10} Emission per capita, $PM_{2.5}$ Emission per capita, NO_x Emission, PM_{10} Intensity, $PM_{2.5}$ Intensity (order of contribution from largest to smallest) have been used to represent AP subsystem. With the establishment of the index evaluation system and synergy model for the AP-CM system, the coupling coordination degree of air pollution control and carbon mitigation are measured for the 31 provinces in China from 2013 to 2017.

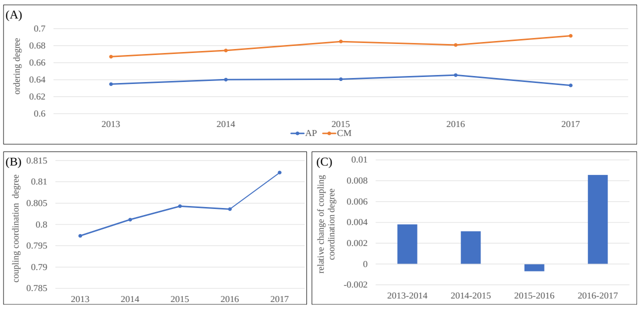

Figure 2. (A) Ordering degree of each subsystem from 2013 to 2017; (B) Coupling coordination degree of AP-CM system from 2013 to 2017; (C) Relative change of the coupling coordination degree.

Firstly, for the ordering degree of each subsystem, an improvement was observed in both subsystems from 2013 to 2015. Whereas there was an opposite trend from 2015 to 2017 for the AP and CM subsystem. The ordering degree of the CM subsystem slightly decreases in 2016, then increases to 0.6916 in 2017. In addition, as shown in Figure 2B, the degree of coupling coordination of the AP-CM system at the national scale is slightly increasing from 2013 to 2017 (degree: 0.79732 – 0.81216), but a slight decrease in the coupling coordination degree was observed from 2015 to 2016.

Secondly, the spatial distribution of the coupling coordination degree of air pollution control and carbon mitigation is present in Figure 3. Based on the division scheme from (Shi et al., 2020), the coupling coordination degree is categorized into four types: basic coordination (0.40-0.50), primary coordination (0.50-0.60), moderate coordination (0.60–0.80), quality coordination (0.80-1.0) (Shi et al., 2020). From 2013 to 2017, with the implementation of "Clean Air Action", the provinces in the middle and southern areas present better performance of synergistic governance than other areas. The coupling coordination degree of Inner Mongolia drops from primary coordination to basic coordination in 2017. And there is a dramatic improvement in the performance of the synergistic governance of air pollution control and carbon mitigation in Hebei, Henan, and Anhui Provinces. The rank of the coupling coordination degree at the provincial scale is shown in Figure 4A. The top five provinces with better performance are Tibet, Beijing, Shanghai, Hainan, and Tianjin.

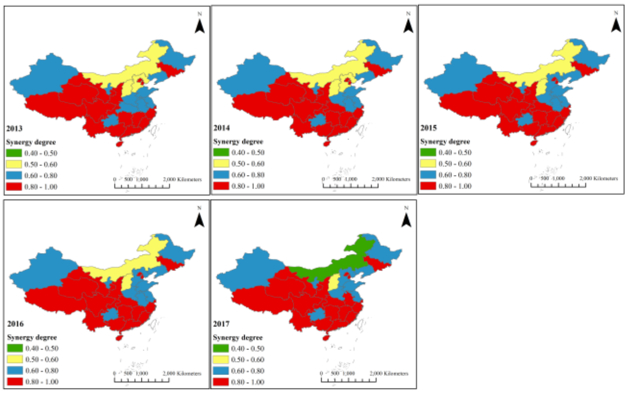

Figure 3. Spatial distribution of the coupling coordination degree.

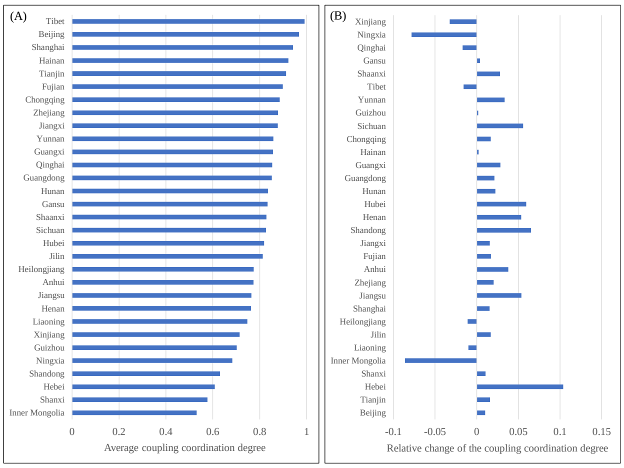

Figure 4. (A) The coupling coordination degree of air pollution control and carbon mitigation for the 31 provinces during 2013 – 2017; (B) Relative change of the coupling coordination degree from 2013 to 2017.

Thirdly, Figure 4B presents the relative change of the coupling coordination degree for the 31 provinces from 2013 to 2017. Although some provinces present lower coupling coordination over the years, they have shown relatively large improvement in synergistic governance of air pollution control and carbon mitigation from 2013 to 2017. The top five provinces with improvement over the years are: Hebei (relative change: 0.10383) > Shandong (relative change: 0.06527) > Hubei (relative change: 0.05955) > Sichuan (relative change: 0.05578) > Jiangsu (relative change: 0.05358).

4.2 Spatial association of the coupling coordination degree at local scale

The spatial association at the provincial scale is shown in Figure 5. The local Geary's c is used to detect the clustering of similar coupling coordination degree in the spatial distribution. High - High means the high value of coupling coordination degree is surrounded by the areas with a similarly high value. Whereas Low - Low indicates there is a lower coupling coordination degree in the spatial distribution in the specific local area.

In terms of the spatial pattern of local spatial autocorrelation of the coupling coordination degree of air pollution control and carbon mitigation, it is obvious that from 2013 and 2017, there is a locally positive autocorrelation in Guangxi and Sichuan Province with the attribution of High – High classification. Shanxi and Hebei Provinces present a local cluster of poor performance of synergistic governance in 2013, and 2014 - 2015, respectively. Heilongjiang Province shows a clear positive autocorrelation with a similar higher value of the coupling coordination degree with surrounding provinces in 2013 and 2014. Subsequently, Heilongjiang Provinces and Inner Mongolia entered a Low – Low positive spatial autocorrelation pattern. And Xinjiang shows a negative spatial autocorrelation over the years.

4.3 Spatiotemporal heterogeneity of driving factors on the coupling coordination degree

4.3.1 Selection of the main driving factors: To reveal the mechanism of the dynamic evolution characteristics of the coupling coordination degree of air pollution control and carbon mitigation in China from 2013 to 2017, this study uses OLS and GTWR to conduct a comparative analysis for the influence of driving factors. Air pollutants and CO_2 emission are influenced by local emission pattern, economic status, energy and industrial structure. Hence, we assume these factors are the potential drivers of the coupling coordination degree between air pollution control and carbon mitigation. Hence, we collected relevant socio-economic and energy statistics and grouped them into four sets of factors. They are: (1) Investment: investment in exhaust gas treatment; (2) Industrial structure: regional GDP of the primary industry, regional GDP of the secondary industry, regional GDP of the tertiary industry, GDP proportion of primary industry, GDP proportion of secondary industry, GDP proportion of tertiary industry, GDP index of primary industry, GDP index of secondary industry, GDP index of tertiary industry; (3) Energy structure: energy consumption, coal consumption, crude oil consumption, natural gas consumption, electricity consumption, energy intensity; (4) Economic level: regional GDP, GDP per capita, GDP index.

OLS regression analysis was performed to determine the statistically significant variables for the global explanation of the relationship between the coupling coordination degree and potential driving factors. After the screening, the variables that have a significant impact are investment in GDP per capita (X1), energy consumption (X2), coal consumption (X3), crude oil consumption (X4), natural gas consumption (X5) and energy intensity (X6). OLS regression is performed between the coupling coordination degree and the selected drivers. The result shows that these six variables could explain 90.39% variation in the coupling coordination degree of air pollution control and carbon mitigation at a global scale from 2013 to 2017.

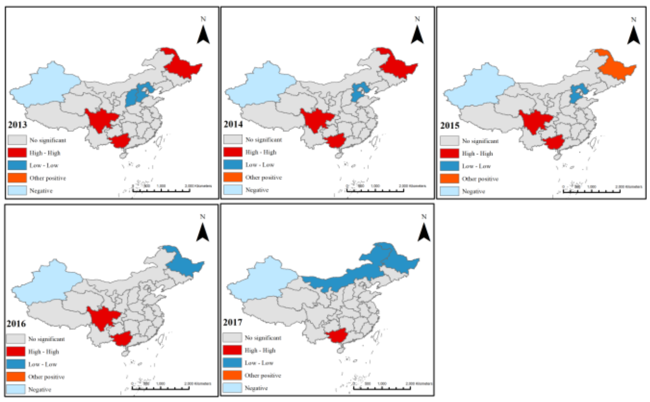

Figure 5. Local Geary's c for the coupling coordination degree at provincial scale.

The variance inflation factor (VIF) results show that except for X2 (energy consumption), there is no significant collinearity among the other five variables. Therefore, these other five drivers (including X1, X3, X4, X5, X6) are reasonable to explain the results of OLS analysis and can also be used as potential dependent variables for further GTWR modelling. In addition, the Breusch – Pagan test results shows that the relationship between coupling coordination degree and potential drivers presents spatial heteroscedasticity. Therefore, OLS regression analysis at a global scale is not appropriate to be used. In contrast, it is more reasonable to use GTWR to identify the impact of driving factors.

4.3.2 Spatiotemporal characteristic of the impact of driving factors: The GTWR model has a R^2 = 91.62% and the AICc = -605.1, compared to 90.19% and -588.9 for OLS. This means that GTWR fits the data better, although the mean predictive ability of the two models is similar. The regression coefficients of the GTWR model are non-stationary in time and space. Hence, GTWR reveals the spatial and temporal differences in the impact of drivers on the coupling coordination degree among provinces from 2013 to 2017. See also Hamm et al. (2015).

Table 2 shows the time evolution characteristic of these five driving factors at the national scale over these five years. Generally, GDP per capita, crude oil consumption, and natural gas consumption are the dominant factors in the improvement of provincial-level coupling coordination degree of air pollution control and carbon mitigation. Whereas coal consumption and energy intensity led to the decline of synergistic governance performance with the fluctuating regression coefficients.

Year	X1	X3	X4	X5	X6
2013	0.004	-0.092	0.005	0.013	-0.040
2014	0.007	-0.099	0.004	0.012	-0.039
2015	0.008	-0.088	0.004	0.012	-0.037
2016	0.009	-0.084	0.003	0.011	-0.041
2017	0.003	-0.082	0.006	0.012	-0.047

Table 2. The mean of the regression coefficients for each driving factor from 2013 to 2017.

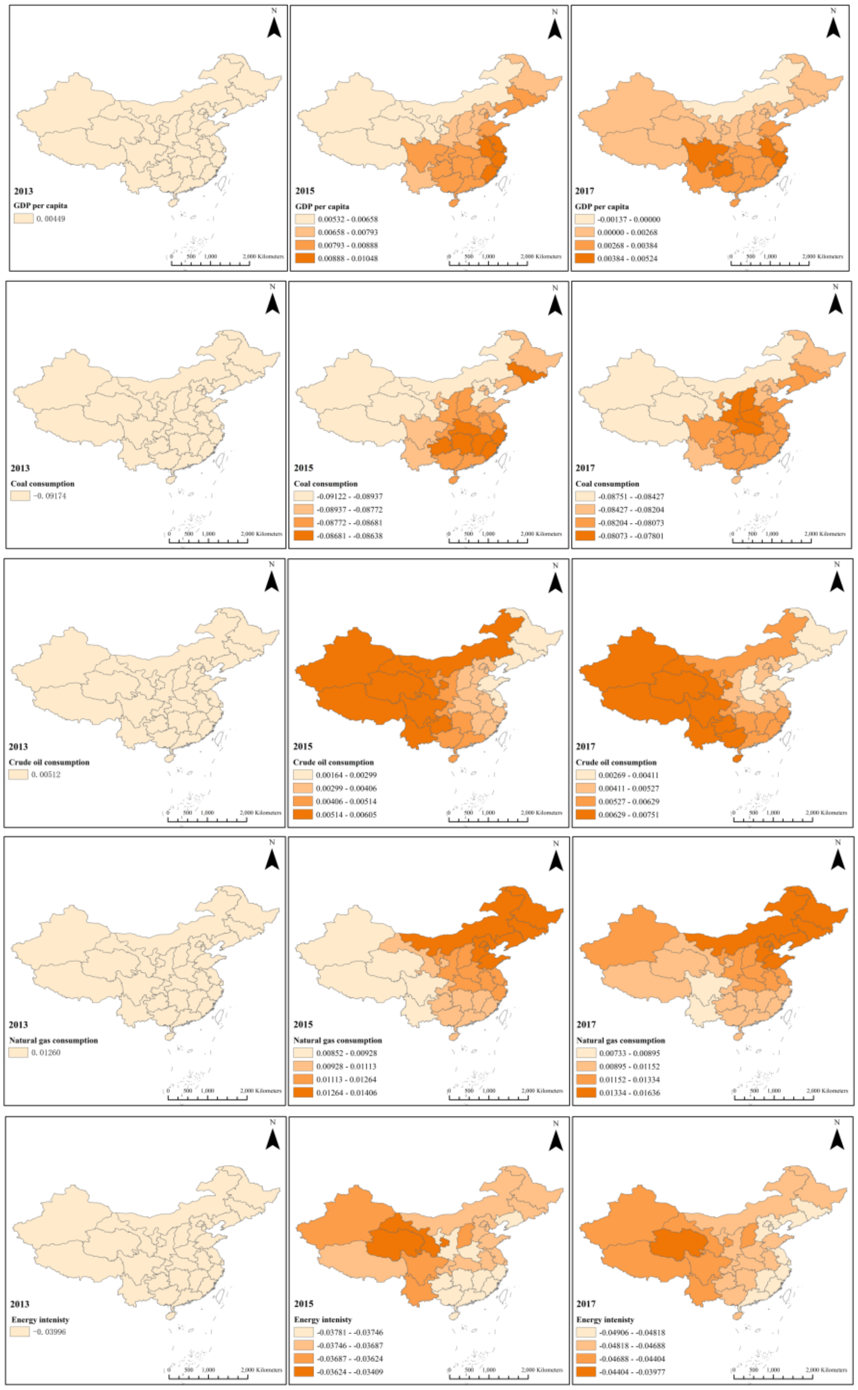

Figure 6. Spatial distribution of the regression coefficients of five drivers in 2013, 2015 and 2017.

The GTWR model can determine the regression coefficients of the influences of five drivers on the provincial-level coupling coordination degree over space and time. The visualization of the spatiotemporal pattern of each driver is shown in Figure 6.

As shown in Figure 6, the magnitude of the regression coefficient of GDP per capita presents an increasing trend from 2013 to 2015, but a decrease from 2015 to 2017. In contrast, the provinces in the southern and south-eastern areas show a relatively strong positive relationship between GDP per capita and the coupling coordination degree of air pollution control and carbon mitigation, especially in Anhui and Zhejiang Provinces. In 2015, the improvement effect is mainly presented in the eastern coastal provinces, like Zhejiang, Jiangsu and Fujian Provinces. It indicates that the positive impact from the local economic level is more significant in these provinces and eastern areas with well economic development. Whereas, in 2017, the dramatic improvement effect is located in Sichuan, Guizhou, Anhui, and Zhejiang Provinces. But there is an inhibition effect of GDP per capita on the synergistic governance in Inner Mongolia in 2017.

In terms of the influence of energy structure, coal consumption is a dominant driver for the decrease of the coupling coordination degree at the provincial scale. The magnitude of the negative regression coefficient of coal consumption does not change a lot. It indicates that after the implementation of "Clean Air Action", coal consumption still has a strong inhibition effect on the synergistic governance improvement, especially for the western and northern provinces such as Xinjiang, Tibet, Inner Mongolia, Gansu, and Qinghai Provinces. In contrast, there is a relatively lower inhibition effect of coal consumption in Shanxi, Shaanxi, Henan, and Hubei Provinces in 2017. In addition, from 2013 to 2017, the increasing share of crude oil consumption presents an improvement effect on the increasing coupling coordination degree of air pollution control and carbon mitigation. Compared with the eastern provinces, western provinces present a dramatic impact from the structural shift of crude oil consumption in the energy consumption structure. But the contribution to Shanxi, Henan, Shandong, and northeastern provinces is limited. Moreover, the increasing share of natural gas is the other significant driver for the improvement of the synergistic governance of air pollution control and carbon mitigation from 2013 to 2017. In contrast, provinces in the northern, north-eastern, and eastern areas present a good performance of synergistic governance improvement affected by the increasing share of natural gas consumption in the local energy structure. In contrast, Sichuan and Yunnan Provinces show less influence from the benefit of natural gas consumption. There is a dramatic improvement effect to Inner Mongolia, north-eastern provinces, Shandong, and Jing-Jin-Ji Region. Given these areas strongly rely on fossil-fuel combustion for residential living and transportation, it indicates that during the implementation of "Clean Air Action", the energy structure adjustment of more share of natural gas is an effective abatement measure for the synergistic governance of air pollution and carbon emission reduction.

In terms of energy intensity, it is obvious that it presents a relatively strong inhibition effect to the south-eastern and eastern provinces in 2015 and 2017. respectively. Based on the magnitude and direction of the regression coefficient, it indicates that energy intensity is the key driver for the decreasing of the coupling coordination degree of air pollution control and carbon mitigation at the provincial scale over these five years. Increasing energy efficiency and the development of the low-consuming industry has the potential to improve synergistic governance, especially for the whole eastern area of China.

5. DISCUSSION AND CONCLUSION

This study provides a novel index evaluation system and a new attempt of the driving factors analysis on the coupling coordination degree of air pollution control and carbon mitigation, while reducing the uncertainty in the interpretation of temporal and spatial variability of drivers' influences.

As the spatial distribution of synergy degree among provinces suggested, the proposed novel index evaluation system with the consideration of local differences in emission features, socio-economic status has the capability of distinguishing the performance of synergistic governance between air pollution control and carbon mitigation in China. Although coupling coordination degree has significantly improved nationally, there are dynamic transition among provinces over years. Compared with the provinces relying on heavy industry with energy-intensive consumption (such as Inner Mongolia, Shanxi, and Shandong Provinces), eastern provinces with well socio-economic development and service-oriented economic structures present a better performance of synergistic governance of air pollution control and carbon mitigation (such as Beijing and Shanghai). It indicates that the abatement measures of the "Clean Air Action" involving energy structure adjustment and industrial structure update are closely related to the co-reduction of air pollution and CO_2 emission. But the poor performance of local joint synergistic governance and dynamic transition of the coupling coordination degree implies that the targeted measures still need to be identified and improved under the comprehensive consideration among local and trans-local capacity, knowledge, and functionality.

In this study, GTWR can reduce the uncertainty in the interpretation of the spatiotemporal heterogeneity of driving factors' impacts on synergistic governance performance. Locally, the energy structure adjustment with the increasing share of non-fossil-fuel, clear energy promotion, energy efficiency improvement, as well as industrial structure adjustment with more low energy-consuming industries are still the effective pathways to improve the synergistic governance of air pollution control and carbon mitigation. But the increase in the local economic level presents a limited improvement effect on the coupling coordination degree year by year. The "one-fit-all" approach is not appropriate to deal with the current atmospheric environmental issue in China. Different synergistic governance strategies should be adhered to by each province. The targeted energy dispatch, wide usage of clean and green energy, and cross-local diversified economic intervention are the potential effective pathways for further synergistic governance of deeper carbon mitigation and air pollution control locally.

For this study, there are several limitations and shortcomings: (1) From the perspective of the construction of the subsystem evaluation system, different choices mean different definitions of "coordinated governance of air pollutants and carbon emission reduction". This study mainly focuses on emissions characteristics. (2) Considering the data incompleteness of local energy statistics, the differences in accounting methods, emission scope, and spatial downscaling methods to establish the CO_2 inventory, data quality problem inevitably exists. Data uncertainty is propagated throughout the data analysis process. For further research, we could downscale the spatial scale of research from the provincial scale to the city or county scale. The decentralized strategy of synergistic governance between air pollution control and carbon mitigation could narrow down the regional difference. But it is largely constrained by data availability for air pollution and CO_2 emission.

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