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Spatial Heterogeneity and Clustering of County-Level Carbon Emissions in China

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Abstract: At present, China is the world's largest carbon emitter and has also made significant efforts in energy conservation and emission reduction. This study utilized the EDGAR dataset of remote-sensing image inversion to investigate the spatial heterogeneity and clustering patterns of carbon emissions across 2184 counties in China through a data-driven approach. By analyzing the impact of socioeconomic factors on carbon emissions with the Spatial Clustering Autoregressive Panel (SCARP) model, significant regional variations were uncovered. The results reveal significant differences in carbon emission drivers between resource-dependent regions and economically developed areas. For instance, regions with heavy industries, such as Inner Mongolia and Xinjiang, exhibit higher carbon emissions, underscoring the need for policies focused on industrial restructuring and clean energy adoption. In contrast, economically advanced regions such as the Yangtze River Delta and Pearl River Delta show slower emission growth, indicating the potential for further reductions through green technology innovations and energy efficiency improvements. These findings highlight the necessity of regionally tailored carbon reduction strategies, offering policymakers a precise framework to address the specific socioeconomic and industrial characteristics of different regions in China.

Keywords: spatial heterogeneity; spatial clustering; carbon emissions; socioeconomic factors

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1. Introduction

In response to accelerated industrial and urban growth in China, there has been a significant rise in carbon emissions, posing an urgent environmental challenge [1]. At the 2023 National Ecological Conference, the Chinese government emphasized the urgency of adopting greener and low-carbon development strategies to fundamentally address ecological and environmental issues. Balancing the reduction of regional carbon emissions with economic growth poses a substantial challenge for the nation [2]. Given its vast size and varied economic landscape, China shows considerable spatial variation in carbon emissions. These discrepancies are attributable to differences in ecological conditions, industrial setups, energy usage patterns, and regional economic progress [3,4].

In 2024, the Chinese government issued 'Opinions on Strengthening Zoning Control of Ecological Environment', which stressed the need for tailored and precise regional management approaches. This policy highlights the importance of formulating and implementing carbon reduction strategies tailored to the specific conditions of different regions [5]. As fundamental agents of China's economic and industrial transformation, counties play a pivotal role in adopting these mitigation strategies, crucial for fostering low-carbon economic growth and sustainable urbanization [6,7]. While provincial [8–11] and municipal studies [12–14] offer broad insights, county-level studies provide more detailed insights and highlights disparities between counties [15–17]. Therefore, focusing on the county level has become crucial for precise carbon emission control and management. Evaluating the temporal and spatial dynamics and influencing factors of carbon emissions at the county level, especially given the significant spatial variability among counties, is vital for developing targeted energy-saving and emission reduction measures. This will enhance the effectiveness of local-level management and control, thereby improving the overall efficiency of emission reduction strategies.

Carbon emissions are influenced by various factors, including population density, urban form, economic growth, industrial structure, wealth level, and technological progress [15,18,19]. Although the uncertainty of individual factors is significant, systematically revealing these factors and their interactions helps to elucidate the fundamental characteristics of carbon emissions [20,21]. Current research predominantly employs methods such as spatial econometric models [22,23], structural decomposition analysis [24,25], and index decomposition analysis [26,27] to study these influencing factors. Nonetheless, these studies typically presume uniformity across contexts, as exemplified by the spatial autoregressive (SAR) model, which assumes uniform interactions across spatial units and overlooks the effects of regional disparities on carbon emissions. Given the diverse socioeconomic conditions and governance capabilities of different cities, it is essential for governments to design tailored emission reduction strategies that reflect these urban distinctions when directly regulating carbon emissions [28,29]. In conclusion, while existing models have contributed insights into the drivers of carbon emissions, incorporating regional heterogeneity is crucial for devising more scientifically sound and targeted policies.

Empirical studies demonstrate significant regional disparities in the determinants of carbon emissions, largely due to varying economic conditions and resource allocations across regions. Cities have distinct environmental impacts influenced by their unique economic [30]. For instance, the impact of population density on carbon emissions is not uniform. Cities in northern China, characterized by heavier industries and higher population densities, show greater potential for emission reductions through increased urban density compared to their southern counterparts [31]. Additionally, ref. [32] emphasizes that the patterns of economic growth critically shape regional carbon emissions trends. Regions dominated by manufacturing and heavy industries, typically undergoing rapid industrialization and economic development, experience increases in carbon emissions [33]. Ref. [34] points out that regional economic structures and technological capabilities significantly influence the effectiveness of directed technical changes and environmental policies. Furthermore, industrial structure plays a crucial role, with heavy industries in Northeast China contributing to higher emissions, while coastal regions benefit from lower emissions due to their dominance in technology and service sectors [17]. These observations underscore the profound impact of localized energy policies and resource endowments on regional carbon footprints, suggesting that tailored approaches to environmental management and policy-making are essential.

Researchers have utilized the geographically weighted regression (GWR) model to analyze spatial disparities due to its ability to adjust the impact coefficients of various factors according to regional differences [33,35,36]. This model is particularly effective at capturing the nuanced effects that regional variations have on carbon emissions. However, its application is generally confined to smaller areas such as provinces or cities because of its high computational demands and the instability of results over larger or more complex datasets, such as county-level data in China. Additionally, characteristics of carbon emissions, which do not respect geographic boundaries and tend to spread, gradually diminish traditional regional divisions, promoting a freer exchange of factors and products and thereby reducing barriers to spillover effects [37,38]. Despite these strengths, the common practice of visually representing the regression coefficients from the GWR model often does not effectively capture the real spatial dependencies and interactions. While these visualizations make regional disparities easier to understand, they can paradoxically obscure deeper spatial relationships, leading to potential misinterpretations. Moreover, the traditional method of dividing regions into categories such as east, west, north, and south and analyzing each separately tends to simplify the dynamic interactions within and between these regions [10,36,39]. Such categorizations fail to account for the subtle intra-regional variations crucial for precisely evaluating and predicting the effects of environmental policies. A more sophisticated and dynamic approach in spatial analysis is necessary—one that moves beyond simple visual clustering and broad regional categories to reveal the complex patterns inherent in spatial data.

Overall, despite existing research highlighting the spatial heterogeneity of socioeconomic factors influencing carbon emissions, significant gaps remain, particularly at the county level where intricate heterogeneity is often neglected. This oversight hampers a comprehensive understanding of how these factors differentially impact carbon emissions across finer regional scales. Moreover, while some studies have addressed spatial heterogeneity, few have employed detailed clustering analysis to discern patterns among neighboring regions, limiting the precision and effectiveness of policy interventions. Based on these issues, this study aimed to investigate the heterogeneous impacts of socioeconomic factors on carbon emissions specifically at the county level, employing a data-driven approach to identify clustering patterns in neighboring regions. By focusing on 2184 counties across China, this research seeks to reveal detailed characteristics of carbon emissions and their determinants, providing a robust foundation for crafting targeted carbon reduction policies. Utilizing the Spatial Clustering Autoregressive Panel (SCARP) model, which integrates the SAR model with clustering techniques, this study explored and articulated the spatial heterogeneity and clustering patterns of socioeconomic influences on carbon emissions. Specifically, this research addressed the following pivotal questions:

1. Is there significant spatial heterogeneity in the effects of different socioeconomic factors on carbon emissions at the county level?

2. How can clustering patterns of these impacts in neighboring regions be effectively identified with a data-driven approach?

3. How do these identified clustering patterns compare with existing urban clusters, such as the Chengdu–Chongqing economic circle, Beijing–Tianjin–Hebei, Yangtze River Delta, Pearl River Delta, and the Central Plains?

This study contributes an innovative application of the SCARP model to analyzing county-level carbon emissions across China, providing a clearer view of spatial patterns and regional differences. By combining spatial regression with clustering, the SCARP model allows for a simultaneous analysis of local dependencies and variations in emission drivers, such as industrial structure and population density. Unlike prior studies at the provincial or municipal levels, this research identified specific clusters of counties with similar emission characteristics, supporting the development of more targeted, region-specific carbon reduction policies. These findings offer valuable insights for local governments in designing effective environmental policies and refining frameworks for understanding urban and economic impacts on emissions.

2. Methodology and Data

2.1. Empirical Methodology

2.1.1. Ipat Model and Its Extensions

To accurately quantify the impacts of human activities on the environment, scholars have developed the IPAT (impact, population, affluence, and technology) model [40] and its derivative, the STIRPAT model [20]. The IPAT model posits that environmental pressures are primarily influenced by population, affluence, and technology. The STIRPAT model, as a stochastic extension of IPAT, incorporates more detailed factors, such as specific types of technology and social structures, to more comprehensively quantify these impacts. Additionally, the STIRPAT model is employed to validate nonlinear hypotheses such as the environmental Kuznets curve (EKC), facilitating the decomposition and refinement of related variables. The fundamental expression of the model is as follows:

$$\mathbf{I} = a \times \mathbf{P}^b \times \mathbf{A}^c \times \mathbf{T}^d \times e, \quad (1)$$

where $\mathbf{I}$ represents environmental pressure, while $\mathbf{P}$, $\mathbf{A}$, and $\mathbf{T}$ respectively denote the indices for population, affluence, and technology. The general coefficient is denoted by a, and b, c, and d represent the coefficients for the respective impact factors, with e indicating the error term. In [20], it is noted that sociological and other control variables can be incorporated into the model, provided that these additional factors are conceptually consistent with the multiplicative specification of the model.

This study utilized the STIRPAT model to analyze the determinants of per capita carbon emissions (PCO_2). PCO_2 emissions were selected as the indicator of environmental pressure, with higher values indicating greater pressure. Population density (PD), defined as the number of people per unit area, was used to gauge the population index. To measure the population index, population density (PD) was defined as the number of individuals per unit area. This metric reflects the impact of urbanization and population shifts on carbon emissions due to production and consumption activities. The affluence index comprises local economic output and government fiscal health, as measured by per capita gross domestic product (PGDP) and government general budget expenditures (PFEs), respectively. We also incorporated the second and third powers of PGDP ($PGDP^2$ and $PGDP^3$) to examine the relationship between economic growth and carbon emissions and to evaluate the environmental Kuznets curve (EKC) hypothesis. Technological advancements are crucial for reducing carbon emissions, and a reduction in energy intensity often indicates technological progress. Carbon intensity (CI), representing CO_2 emissions per unit of GDP, serves as a measure of technological efficiency in emission reduction. Additionally, considering that the secondary industry significantly contributes to carbon emissions, the study included an industrial structure index (IS), denoted by the proportion of added value of the secondary industry to GDP, to assess technological and structural advancements.

After defining the scope and core variables of the STIRPAT model, this study extended its analysis to the spatial aspects of carbon emissions. Although the STIRPAT model offers a strong analytical foundation, it lacks the ability to account for spatial correlations. To bridge this gap, we introduced a spatial autoregressive panel (SARP) model, which facilitates the examination of carbon emissions interactions across various regions. In this enhanced model, we integrated traditional STIRPAT factors with a spatial weighting matrix that quantifies the spatial relationships and interactive effects among regions. The adoption of the SARP model enables a comprehensive understanding of both the unique characteristics of carbon emissions in individual regions and the collective impact of regional interactions on the overall pattern of emissions. Such insights are vital for developing targeted and effective regional emission reduction strategies. The SARP model is structured as follows:

$$y_{it} = \delta \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{p=1}^{P} \beta_p x_{itp} + \epsilon_{it}. \tag{2}$$

In this model, y_{it} represents the PCO_2 for district i at time t. The autoregressive coefficient δ quantifies the influence of neighboring regional emissions, factored through the spatial weight matrix W, where w_{ij} denotes the elements of matrix W representing spatial relationships. The variable x_{itp} represents the p-th explanatory variables for district i at time t, for which we selected seven variables: PD, PGDP, $PGDP^2$, $PGDP^3$, PFE, CI, and IS. The coefficient β_p represents the effect of the p-th explanatory variable, capturing its specific impact on carbon emissions. The term ϵ_{it} is the random error component, accounting for unobserved factors affecting emissions. This modeling framework allows us to understand and quantify the spatial and temporal dynamics of carbon emissions across different administrative regions, thereby facilitating targeted environmental policy interventions.

2.1.2. Spatial Clustering Autoregressive Panel Model

Although the SARP model effectively captures the reciprocal impacts of carbon emissions across neighboring regions and elucidates the average effects of key indicators, it is limited in its ability to explore the spatiotemporal heterogeneity of these influencing factors. To address this limitation, recent studies have proposed integrating the STIRPAT model with geographic and temporal weighted regression (GTWR) for a more comprehensive analysis of the diverse determinants of carbon emissions intensity [41]. The GTWR model incorporates both spatial and temporal dimensions, allowing for a more precise examination of the variability in influencing variables over time and across regions. However, this model faces significant challenges, including high computational demands, prolonged convergence times, and reduced accuracy, especially when applied to large-scale regional datasets or in contexts with highly diverse regression coefficients. These issues limit its effectiveness and applicability in extensive spatial analyses.

In response to these challenges, this study employed the SCARP model for its superior efficiency and accuracy in managing large-scale district datasets. Unlike the GTWR model, SCARP streamlines the computational process and enhances the precision of the analysis. SCARP simplifies computational demands by harmonizing regression coefficients within clusters while permitting differentiation among them. This approach leverages geographical proximity to categorize regions, reflecting the spatial clustering tendencies observed in economic activities and carbon emissions. Consequently, SCARP more accurately delineates the variations in carbon emissions across different areas. Such detailed analysis enabled us to identify and quantify regional disparities in carbon emissions more precisely, providing a robust theoretical and empirical foundation for crafting effective regional carbon reduction strategies. The expression for the SCARP model is as follows:

$$y_{it} = \delta \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{p=1}^{P} \beta_{ip} x_{itp} + \epsilon_{it}, \tag{3}$$

$$i = 1, \ldots, N; t = 1, \ldots, T; p = 1, \ldots, P.$$

The first term $\delta \sum_{j=1}^{n} w_{ij} y_{jt}$ represents the spatial autoregressive component, where w_{ij} is the spatial weight matrix and δ is the autoregressive coefficient. This term captures the influence of neighboring regions on region i. The second term $\sum_{p=1}^{P} \beta_{ip} x_{itp}$ represents the impact of independent variables, where β_{ip} is the region-specific regression coefficient for the p-th variable, which varies according to group structure. ϵ_{it} is the error term. To capture the heterogeneous effects of explanatory variables across regions, the model assumes that each regression coefficient β_{ip} is grouped according to the similarities among regions. Specifically, each variable p is associated with K_p groups, where β_{ip} for variable p is defined as follows:

$$\beta_{ip} = \sum_{k_p=1}^{K_p} \alpha_{k_p p} \cdot \mathbb{I}\{i \in G_p^{k_p}\}, \tag{4}$$

Here, $\alpha_{k_p p}$ is the regression coefficient for group k_p for the p-th variable. $G_p^{k_p}$ denotes the set of regions in group k_p for the p-th variable. $\mathbb{I}\{i \in G_p^{k_p}\}$ is an indicator function, equal to 1 if region i belongs to group $G_p^{k_p}$ and 0 otherwise. Each variable $p \in \{1, \ldots, P\}$ is associated with $k_p \in \{1, \ldots, K_p\}$ groups. This grouping structure allows regions within the same group $G_p^{k_p}$ to share the same regression coefficient $\alpha_{k_p p}$, thus reflecting similar characteristics in their response to the p-th explanatory variable. Meanwhile, different groups may have distinct coefficients, capturing the variability in regional impacts. Unlike traditional clustering methods that separate the clustering and regression steps, SCARP follows recent advancements in simultaneous clustering and estimation techniques [42,43]. By estimating group structures and regression coefficients jointly, it ensure consistency between clustering assignments and regression relationships, which mitigates the error propagation commonly seen in sequential methods. While the spatial autoregressive coefficient δ is assumed to be homogeneous across regions, this simplification is technically advantageous, as it reduces model complexity and improves estimation stability [44]. To estimate the model parameters, including the spatial autoregressive coefficient δ and group-specific coefficients $\alpha_{k_p p}$, we employed a maximum likelihood estimation approach. Due to the model's complexity, a regularization method was incorporated to encourage homogeneity within groups, allowing the model to assign regions to clusters based on similar regression patterns. The exact solution procedure can be found in reference [44].

2.2. Data Source and Description

Based on the scope and completeness of the available data, this study selected 2184 districts and counties across 30 provinces, municipalities, and autonomous regions in mainland China as research subjects. Notably, due to data limitations, the Tibet Autonomous Region, Taiwan Province, and the Hong Kong and Macao Special Administrative Regions were not included. The district and county carbon emissions data were sourced from the Emissions Database for Global Atmospheric Research version 8.0 (EDGAR v8.0), which is accessible through EDGAR. Utilizing a bottom-up approach, EDGAR provides high-resolution carbon emissions data with a spatial resolution of $0.1° \times 0.1°$ (approximately 10 km $\times$ 10 km) covering China. This database integrates data from various sources, including energy statistics and emission factors, offering detailed emission information for each sector and country. It is widely used by the international research community for applications ranging from emission estimation and climate policy analysis to the design and evaluation of emission monitoring systems [45]. The grid data were categorized based on geographical administrative regions, resulting in panel data on carbon emissions for the 2184 districts and counties from 2007 to 2021. Socioeconomic variable data primarily came from the China County Statistical Yearbook and the Statistical Bulletin of National Economic and Social Development of the Counties for the years 2007 to 2021, supplemented by the CEInet Statistics Database. Missing data were imputed using the linear interpolation method. As shown in Tables 1 and 2, the mean values and standard deviations of the selected variables varied significantly. Considering the importance of data consistency in models involving lasso regression, the data were standardized to ensure the effectiveness of the model and the reliability of the results.

Table 1. Definition and Calculation Methods of Variables.

Variable Name	Abb.	Unit	Calculation Method
Per Capita Carbon Emissions	PCO_2	Ton/Person	Total Carbon Emissions/Population
Per Capita GDP	PGDP	CNY	GDP / Population
Population Density	PD	Person/km^2	Population/Area
Public Finance Expenditure	PFE	10^4 CNY	—
Industrial Structure	IS	%	Secondary Industry Output / GDP
Carbon Intensity	CI	Ton/10^4 Yuan	Total Carbon Emissions/GDP

Note: Abb., abbreviation.

Table 2. Descriptive Statistics of the explanatory variables.

Abb.	Sample Size	Minimum	Maximum	Average	Standard Deviation
PCO_2	32,760	0.07	699.32	8.41	19.14
PGDP	32,760	2005.41	622,039.52	38,621.11	38,828.21
PD	32,760	0.13	39,531.94	570.03	2031.87
PFE	32,760	173.36	13,400,000.00	288,916.95	387,816.37
IS	32,760	1.16%	93.87%	41.97%	0.16
CI	32,760	0.01	127.88	2.58	5.07

3. Spatial Heterogeneity Analysis of Carbon Emissions Influencing Factors

3.1. Spatiotemporal Evolution and Regional Differences of Carbon Emissions

From 2007 to 2021, both total carbon emissions and PCO_2 at the county level in China exhibited rapid and sustained growth, while carbon emissions intensity steadily declined (see Figure 1). During this period, total carbon emissions increased from 5.234 billion tons to 8.731 billion tons, representing a 66.81% rise, with an average annual growth rate of 3.72%. Notably, the growth rate was higher at 7.02% annually from 2007 to 2011, but it slowed to 2.43% annually from 2011 to 2021, reflecting the impact of the energy conservation and emission reduction policies introduced in the 12th Five-Year Plan. Similarly, PCO_2 rose from 4.91 tons to 8.31 tons, marking an overall increase of 69.25% and an average annual growth rate of 3.83%. The growth rate of PCO_2 decelerated more significantly after 2014, dropping from 5.62% annually between 2007 and 2014 to 2.07% annually from 2014 to 2021. Meanwhile, carbon emissions intensity experienced a marked reduction, decreasing from 3.12 tons per ten thousand yuan in 2007 to 1.29 tons in 2021, a total reduction of 58.65% with an average annual decline of 6.11%. The incorporation of energy conservation and emission reduction targets into national development plans has played a significant role in reducing carbon emissions intensity.

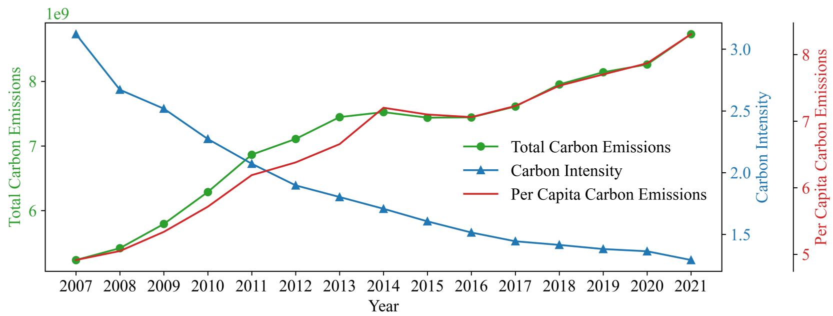

Figure 1. Total carbon emissions (tons), carbon intensity(tons/10^4 CNY), and per capita carbon emissions (ton/person) trends of counties and regions in China from 2007 to 2021.

Figure 2 depicts the spatial distribution of PCO_2 across Chinese counties in 2007, 2012, 2017, and 2021. Over these years, there was a general increase in PCO_2 across the counties, with emissions becoming more evenly distributed. However, significant variations in emissions are evident among the counties, particularly along the Hu Huanyong Line, where a marked contrast was observed: counties to the southeast generally exhibited lower emissions compared to those in the northwest. Regions such as Inner Mongolia, Xinjiang, Qinghai, Shanxi, Shaanxi, and the Northeast, which rely heavily on traditional energy sources such as coal and oil and have carbon-intensive industries, showed higher PCO_2 levels. The increase in emissions in western regions is partly attributed to the relocation of energy-intensive projects from the east and significant population declines, which resulted in a higher PCO_2.

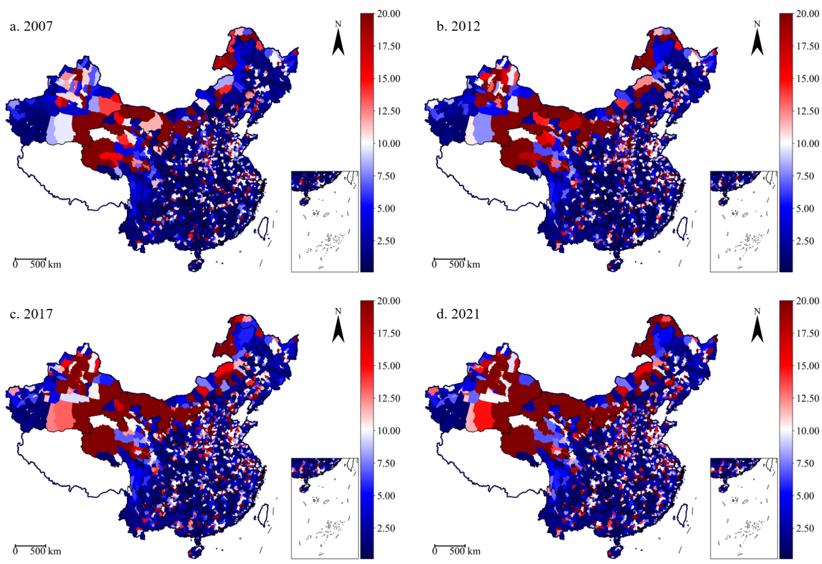

Figure 2. Spatial distribution of PCO_2 in China from 2007 to 2021 (Ton/Person). Note: This imaged was produced based on the standard map service website of the Ministry of Natural Resources of China GS (2019) 1822, with no modification of the base map boundary (the same as below).

In contrast, the coastal city clusters, including the Yangtze River Delta, Pearl River Delta, and Jing-Jin-Ji, did not experience the same increase in PCO_2 as did other high-emission areas. Instead, most of the PCO_2 increases were concentrated in provincial capitals and their surrounding regions. Economic growth and population concentration in these areas have driven up energy demands, further raising PCO_2 levels and creating a distinct core–periphery pattern in regional carbon emissions, as noted by [35]. These economically prosperous areas are increasingly crucial in reducing overall carbon emissions and promoting environmental sustainability in their respective regions.

This study also utilized the global Moran's I index to evaluate the spatial correlation of county-level carbon emissions, as detailed in Table 3. From 2007 to 2021, the global Moran's I index for PCO_2 across Chinese counties consistently remained around 0.2, with a significance level of 1%, highlighting a significant clustering and positive spatial correlation in the distribution of carbon emissions. The index fluctuated between 0.2003 and 0.2333 during this period, confirming the presence of spatial autocorrelation in regional carbon emissions. This finding emphasizes the need to account for both local conditions and the influence of neighboring regions when designing and implementing emission reduction policies.

Additionally, the spillover effect coefficient calculated in our model was 0.0530, suggesting a modest yet significant interaction in carbon emissions between neighboring regions. While the impact was not strong, this result indicates that carbon reduction efforts in one region may still exert some influence on adjacent areas. This finding supports the importance of cross-regional cooperation in carbon reduction strategies. Although this study modeled the spillover effect as homogeneous to simplify analysis, future research could investigate heterogeneous spillover effects to understand how these interactions vary across different regions, potentially providing further insights for targeted regional policies.

Table 3. Global spatial autocorrelation test of county PCO_2 from 2007 to 2021.

Year	Moran's I	Year	Moran's I	Year	Moran's I
2007	0.2098 ***	2012	0.2173 ***	2017	0.2219 ***
2008	0.2207 ***	2013	0.2238 ***	2018	0.2247 ***
2009	0.2149 ***	2014	0.2095 ***	2019	0.2008 ***
2010	0.2333 ***	2015	0.2227 ***	2020	0.2039 ***
2011	0.2176 ***	2016	0.2303 ***	2021	0.2023 ***

Note: *** is significant at levels of 0.01.

3.2. Spatial Heterogeneity Analysis of the Impact of the Influencing Factors on Carbon Emissions

3.2.1. Spatial Heterogeneity Analysis of the Impact of Population on Carbon Emissions

This section explores the spatial heterogeneity of the impact of PD on PCO_2. According to [46], there is a negative correlation between PD trends and PCO_2. However, these trends vary significantly across different regions due to factors such as energy infrastructure, industry distribution, transport modes, and urban planning. Figure 3a illustrates the PD across Chinese counties in 2021, with the Hu Line highlighting stark regional variations. The eastern regions exhibited high PD, driven by advanced industrialization and urbanization. Central counties, despite being less industrialized, maintained relatively high densities due to robust agricultural activities and substantial demographic bases. In contrast, the western parts of China, including the mountainous areas of the Sichuan–Chongqing region, were characterized by lower densities. These lower densities were influenced by challenging natural environments and limited economic development, which constrain population growth and economic opportunities. This distinct spatial distribution underscores the varied development strategies and resource utilization across regions and reflects the challenges China faces in striving for balanced regional development.

Figure 3b illustrates how regional PD influences PCO_2 within China, revealing distinct regional variations. For the northern areas above the Yellow River, including Xinjiang, Inner Mongolia, Gansu, Qinghai, and southern Shaanxi, the positive regression coefficients indicate that PD directly correlates with carbon emissions. These areas, although sparsely populated, have economies that focus on resource extraction and heavy industries, which are inherently energy intensive. Even small increases in population can significantly elevate carbon emissions, reflecting the substantial impact of industrial and energy sector characteristics on emissions.

In contrast, coastal regions such as Jiangsu, Zhejiang, and Fujian, as well as adjacent inland areas, also exhibit a positive relationship between density and emissions. Here, high density enhances industrial activity and energy demands, leading to increased carbon emissions. However, the Jing-Jin-Ji region and Central and Southern China showed a negative correlation, indicating advanced urban planning and improved energy efficiency. Particularly in the Jing-Jin-Ji region, China's political and cultural hub, intensive sustainable development measures such as the promotion of new energy vehicles, public transport enhancements, and energy mix optimization are prevalent. These strategies consolidate population and resources, improve energy allocation and usage, and reduce incremental emission costs through economies of scale, as documented by [19]. Consequently, higher population density in this region resulted in more efficient utilization of energy resources and a reduction in emissions at the county level.

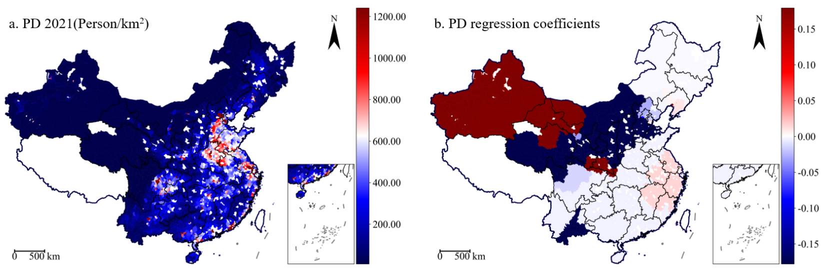

Figure 3. Spatial distribution of PD and its impact on carbon emissions.

3.2.2. Spatial Heterogeneity Analysis of the Impact of Economic on Carbon Emissions

Figure 4a illustrates the spatial distribution of PGDP across Chinese counties in 2021, highlighting significant geographical disparities that reflect the varying levels of economic development, industrial structures, and energy usage across different regions. In the coastal eastern provinces such as Guangdong, Fujian, Jiangsu, Zhejiang, and Shanghai, high levels of industrialization and urbanization, coupled with the prominence of service and high-tech industries, significantly enhanced PGDP. Economic activities in these regions have not only displayed considerable diversity but have also increasingly embraced more efficient and sustainable low-carbon industrial models. Conversely, certain counties in eastern Xinjiang and Inner Mongolia, despite their low population densities, have achieved higher PGDP primarily due to the abundant presence of mineral and energy resources, such as coal, oil, and natural gas. This reflects an economic model that is heavily reliant on resource extraction and energy-intensive industries. While this model does stimulate economic growth, it also leads to substantial energy consumption and high carbon emissions. Despite the specific advantages in natural resources, the central and western regions of China generally exhibit lower PGDP compared to the coastal east. This disparity is partly due to the dependence of these areas on natural resources and heavy industries. Additionally, the economic activities in these regions are not only less intensive but also smaller in scale, contributing to their relatively lower PGDP.

As shown in Figure 4, the relationship between PGDP and PCO^2 in China exhibits a clear nonlinear pattern across different regions. Initially, the regression coefficients for PGDP are uniformly positive, with the highest values in the northwest, followed by northern and eastern China, indicating that economic growth in underdeveloped, labor-intensive, and infrastructure-driven areas has led to increased energy consumption and substantial carbon emissions. However, as these economies have progressed, regional environmental awareness and rising living standards have promoted a transition toward clean energy and energy-saving technologies, which have gradually reduced emissions. In regions dominated by energy-intensive industries, such as Xinjiang, Ningxia, and Inner Mongolia, economic growth is closely linked to high emissions due to heavy reliance on fossil fuels, especially coal and petroleum. At a more advanced stage, as indicated by the generally negative coefficients for $PGDP^2$, the growth rate of emissions begins to slow in most regions, reflecting the benefits of technological innovation, improved energy efficiency, and sustainable development policies. In the northeaster provinces and eastern Inner Mongolia, however, positive $PGDP^2$ coefficients indicate continued high emissions growth due to economic inertia in traditional heavy industries and resource extraction. Finally, as economic development reaches even higher levels, the cubic coefficients ($PGDP^3$) are positive across all regions, signaling a new acceleration in emissions driven by increased consumption and demand for high-carbon products at higher income levels. This effect is especially pronounced in the Sichuan–Chongqing area and western Yunnan, where high energy consumption and emissions characterize advanced economic stages. Meanwhile, the relatively smaller positive $PGDP^3$ coefficients in the northeast and in eastern Inner Mongolia suggest a moderated pace of emissions growth, highlighting some success in energy efficiency improvements and policy interventions. Overall, these results reveal a nonlinear relationship between PGDP and PCO_2, characterized by an initial rise in emissions with economic growth, a deceleration as energy efficiency improves, and a renewed increase at advanced economic stages due to lifestyle changes and consumption demands.

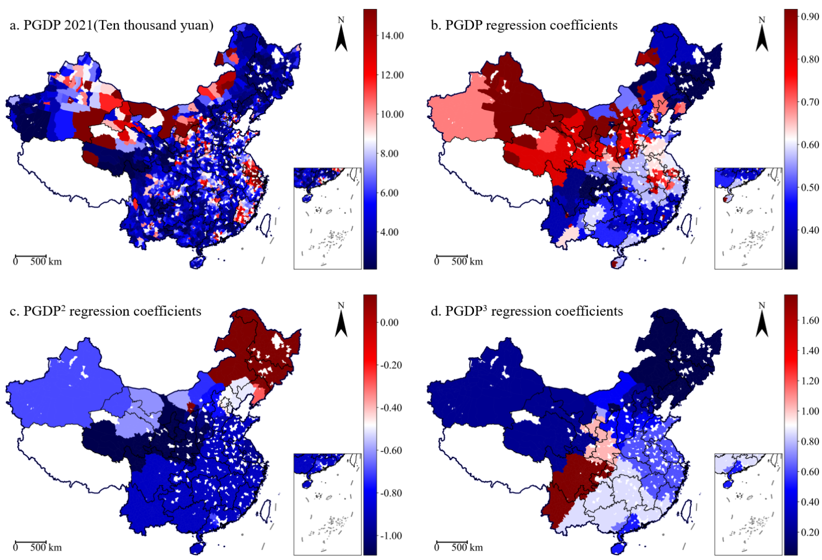

Figure 4. Spatial distribution of PGDP and its impact on carbon emissions.

Figure 5a illustrates the spatial distribution of PFE across Chinese counties in 2021, revealing higher expenditures in the eastern regions compared to the western ones and greater budget allocations in the southern regions than in the northern ones. The Jiangsu–Zhejiang–Shanghai region exhibits the highest expenditures, while the northwest has the lowest. Extensive investments in fixed assets have expanded urban infrastructure, such as buildings, roads, and pipelines, thereby altering urban spatial patterns and increasing energy consumption and carbon emissions. Investments in sectors such as low-carbon industries, new energy, and public transportation have contributed to optimizing industrial structures and reducing carbon emissions intensity. Additionally, expenditures in areas such as education, healthcare, and social security have indirectly curbed carbon emissions growth by promoting environmental awareness and sustainable lifestyles among residents. For one, government spending on environmental protection, clean energy, and energy-saving initiatives directly reduces carbon emissions. On the other hand, these investments indirectly influence carbon emissions by shaping industrial structures, infrastructure development, and consumption patterns.

Figure 5b highlights the significant regional variations in the impact of general public budget expenditures on carbon emissions, which are closely tied to the economic and industrial characteristics of each area. In regions where PFE had a negative impact on PCO_2, such as Xinjiang, northeastern provinces and eastern Inner Mongolia, Jiangsu–Zhejiang, Henan, Sichuan, and western Yunnan, PFE was generally directed toward green energy projects, renewable resources, and sustainable infrastructure. For instance, in Xinjiang and Northeast China, PFE was increasingly channeled into renewable energy sources such as wind and solar, effectively reducing emissions despite the areas' historical reliance on high-carbon industries. Similarly, Jiangsu–Zhejiang prioritized high-tech industries, energy-efficient infrastructure, and technological innovation, which have driven successful emissions reductions. Additionally, Sichuan and western Yunnan focused on ecosystem protection due to their unique geographical conditions, including mountainous terrain that limits industrial activities, which contributed to the negative correlation between PFE and PCO_2. In contrast, regions where PFE had a positive impact on PCO_2, such as Qinghai, Gansu, Shaanxi, Shanxi, Ningxia, western Inner Mongolia, Guizhou, Guangxi, Hubei, and eastern Yunnan, often directed fiscal spending towards traditional infrastructure projects supporting resource extraction, mining, and heavy industry. For example, Qinghai, Shanxi, and Ningxia's fiscal priorities align with resource extraction, particularly coal and mineral mining, which resulted in high energy consumption and significant carbon emissions, reinforcing the positive PFE impact on PCO_2. In eastern Yunnan, fiscal spending was similarly directed toward agricultural and industrial development, which heightened emissions levels.

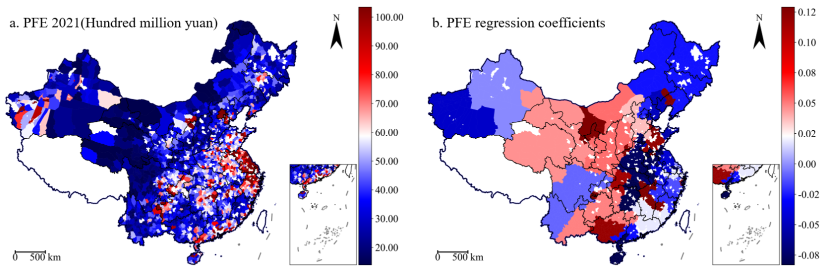

Figure 5. Spatial distribution of PFE and its impact on carbon emissions.

3.2.3. Spatial Heterogeneity Analysis of the Impact of Technology on Carbon Emissions

Figure 6a illustrates the spatial distribution of IS across Chinese counties in 2021. Nationally, the secondary industry accounted for over 40% of the economic output in most counties, although significant regional variations were present. Counties with a high proportion of secondary industry were predominantly located in regions such as Inner Mongolia, Ningxia, Shanxi, and eastern Xinjiang, where the economy is heavily dependent on energy resources such as oil, coal, natural gas, wind, and solar energy and is dominated by extraction and processing industries. In contrast, coastal provinces in the east, such as Jiangsu, Zhejiang, and Guangdong, exhibit high levels of economic development, industrialization, and a diverse industrial structure, often leading the nation. The northeastern region, a traditional heavy industrial base, is experiencing a decline in the economic contribution of its secondary industry due to resource depletion, overcapacity, and aging infrastructure, with these effects being particularly pronounced in areas where resources have been exhausted. Conversely, regions such as Yunnan, Guizhou, and Guangxi, which had lower IS indices, are focused on developing tourism, specialty agriculture, and biomedicine. Their complex topography and limited transportation infrastructure constrain industrial development, influencing their economic structure.

Figure 6b demonstrates how the diversity in IS affects PCO_2, leading to varied clustering patterns across different regions. In northern areas such as Xinjiang, Inner Mongolia, and Gansu, which heavily rely on natural resources, the regression coefficients are generally negative. These regions benefit from favorable natural conditions, making them well-suited for the development of renewable energy industries, such as wind and solar power. This transition has reduced their dependence on traditional fossil fuels. The experiences of these regions underscore how emerging energy sectors can effectively drive regional economic growth while reducing carbon emissions. In contrast, coastal regions in the east, such as Zhejiang, Fujian, and Jiangsu, exhibited positive regression coefficients, indicating that while their economic advancement and industrial density fuel economic growth, they also contribute to higher carbon emissions. Central and southwestern regions, including Hubei, Sichuan, and Yunnan, displayed a mix of significantly positive and negative coefficients, reflecting inconsistencies in their industrialization processes and environmental policy implementation. Notably, even though the secondary industry structure in the Yunnan–Guizhou area was less dominant, it significantly impacted carbon emissions due to its concentration in high-pollution sectors. These regions must prioritize environmental improvements and technological advancements in resource extraction industries, as well as strengthen the development and enforcement of environmental policies, to mitigate carbon emissions and promote sustainable development.

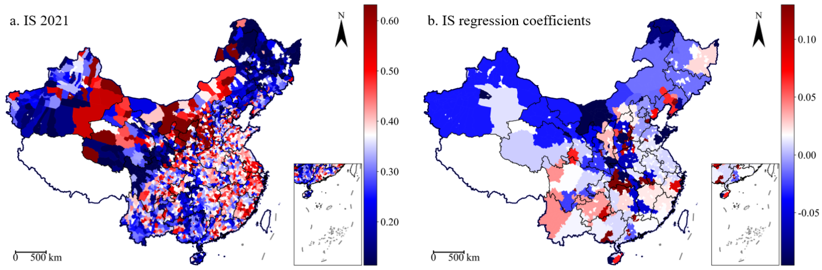

Figure 6. Spatial distribution of IS and its impact on carbon emissions.

Figure 7a depicts the spatial distribution of CI across Chinese counties in 2021, revealing pronounced differences between the northern and southern regions. Southern cities generally displayed higher CI and notably lower PCO_2 compared to their northern counterparts. This disparity stems from the energy structure in the northern regions, which are heavily reliant on coal and its byproducts. The colder winter temperatures in the north further increase the consumption of fossil fuels for heating, thereby leading to higher PCO_2 levels. Conversely, cities in eastern China maintained a leading position in CI nationwide, closely followed by cities in the central region. However, cities in the northeast and western regions experienced a significant decline in CI, with continued deterioration. The primary factors include the transformation and upgrading of industrial structures in eastern cities, which have embraced emerging digital industries and modern services that are more environmentally friendly and emit less carbon. Additionally, the relocation of labor-intensive and high-energy-consuming industries to other regions has contributed to this trend. Notably, cities in the Chengdu–Chongqing area have shown significant improvements in CI, establishing them as leaders in low-carbon development among western cities.

As shown in Figure 7b, regions such as Inner Mongolia, eastern Xinjiang, northern Qinghai, Ningxia, and Shanxi exhibited higher regression coefficients, reflecting that despite technological advancements, these regions, which are heavily dependent on high carbon-emitting industries, still have high carbon emissions per unit of GDP. Similarly, regions such as the Jiangsu–Zhejiang–Shanghai area, although technologically advanced and economically developed, had significant overall carbon emissions due to their industrial density and high economic output. In contrast, regions such as Guangdong, Fujian, and those in the southwestern and central areas exhibited smaller coefficients, indicating substantial progress in advancing a green, low-carbon economy. This is particularly evident in their adoption of new energy sources and energy-saving technologies. Additionally, the smaller coefficients in the northeastern provinces suggest that economic transformations and industrial upgrades are reducing reliance on traditional heavy industries.

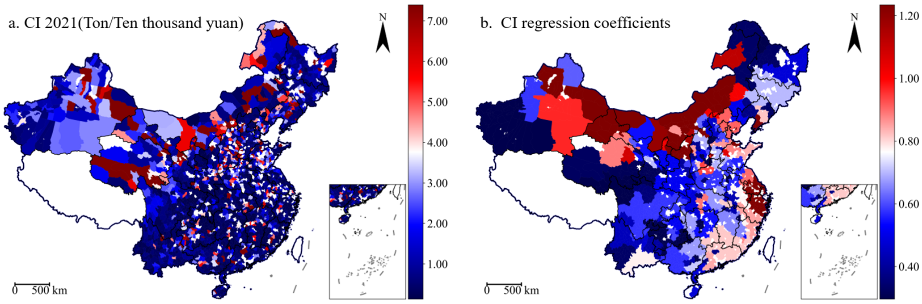

Figure 7. Spatial distribution of CI and its impact on carbon emissions.

3.3. Clustering Analysis of Influence Factors on Carbon Emissions

This study provides a detailed analysis of the clustering patterns in how various factors influence carbon emissions, revealing distinctions that differ from traditional geographic or economic divisions. Despite the extensive coverage and diverse industrial structure of the Chengdu–Chongqing Economic Zone, rapid economic growth and accelerated urbanization in core cities such as Chengdu have led to increased population density and carbon emissions, highlighting an imbalance in economic development and resource allocation compared to other parts of the region. Although the Beijing–Tianjin–Hebei area serves as the political and economic center of northern China, its population density is negatively correlated with PCO_2, reflecting the effectiveness of environmental policies and urban planning.

In the Yangtze River Delta, despite close economic ties, significant differences in PGDP and CI between Shanghai and its neighboring Jiangsu provinces reveal variations in economic activity and levels of industrialization. These internal disparities indicate considerable differences in the intensity of economic activity and industrialization among cities within the region, suggesting a need for more localized carbon emissions policy formulation. Conversely, in the highly industrialized Pearl River Delta region, there was a positive correlation between PD and PCO_2, indicating that despite intensive industrial activity, carbon management strategies may require further optimization to effectively address the challenges posed by ongoing urban expansion and industrial growth.

Furthermore, the study identified the three northeastern provinces and Eastern Inner Mongolia as forming a distinct cluster. Within the framework of the Northeast Revitalization Strategy, national policies have placed particular emphasis on strengthening the economic and industrial integration of the eastern Inner Mongolian region with the three northeastern provinces. This policy direction not only fosters similarities in economic structures among these regions—especially in the development of heavy industry and energy extraction—but also influences their carbon emissions patterns. The further integration of eastern Inner Mongolia with the three northeastern provinces on the basis of heavy industry exhibits a significant clustering pattern in carbon emissions data, indicating a synchronization of industrial activities and corresponding carbon emissions strategies.

Meanwhile, Yunnan is divided into two clusters, east and west, primarily due to differences in environmental resources and economic development. Eastern Yunnan is relatively developed, being closer to major economic hubs such as Kunming, while western Yunnan is more reliant on traditional agriculture and tourism, with potentially stricter environmental protection policies. This differentiation could lead to distinct energy consumption patterns and carbon emissions behaviors, necessitating specific regional policies to address the diverse environmental and economic challenges.

These clustering results effectively reflect the direct influence of national policies on the directions of regional economic and environmental development. They also highlight the policy context and practical considerations of economic integration that must be taken into account when formulating regional carbon emissions reduction strategies. These analyses not only uncover significant differences in carbon emissions across regions but also underscore the importance of developing targeted, region-specific environmental policies. They provide a scientific foundation for local governments in shaping environmental policies, thereby supporting the promotion of healthy economic development and environmental sustainability within these regions.

4. Conclusions

The study provides comprehensive insights into the spatial heterogeneity of carbon emissions across China's counties by employing the SCARP model. This detailed analysis addresses the key questions posed in the introduction, delivering nuanced results that can guide targeted policy-making:

First, the analysis revealed significant spatial heterogeneity in the factors influencing carbon emissions across Chinese counties. In the northern resource-rich areas, including Xinjiang and Inner Mongolia, a positive correlation existed between population density and carbon emissions, primarily driven by heavy industries and energy extraction sectors. Conversely, in developed coastal regions such as Jing-Jin-Ji, higher population density was associated with reduced carbon intensity, reflecting the impact of advanced urban planning and improved energy efficiency. These findings indicate that socioeconomic influences on carbon emissions vary markedly across regions, validating the need for tailored, region-specific carbon management strategies.

Second, the application of the SCARP model facilitated the identification of distinct clustering patterns among counties with similar emission characteristics. Key clusters included a high-emission, resource-intensive cluster in the northwest (e.g., Xinjiang and western Inner Mongolia), a mixed agricultural-industrial cluster in central and southwestern provinces (e.g., Hubei and Sichuan), and a low-emission, technology-driven cluster along the eastern coast (e.g., the Yangtze River Delta). One notable cluster included eastern Inner Mongolia and the three northeastern provinces (Heilongjiang, Jilin, and Liaoning), which were grouped together due to their reliance on heavy industry and shared industrial characteristics. This cluster reflects the impact of the Northeast Revitalization Strategy, which has fostered similarities in economic structure and industrial reliance, leading to a higher carbon intensity compared to other regions. Each cluster reflects distinct economic and industrial profiles, providing a data-driven basis for designing adaptive regional carbon reduction policies. The identification of these clusters highlights how similar socioeconomic factors drive emissions in neighboring areas, informing localized intervention approaches.

Lastly, by comparing these identified clusters with traditional urban and economic agglomerations, the study uncovered important distinctions. For example, the Chengdu–Chongqing economic circle displayed a core–periphery emission pattern, with central cities such as Chengdu and Chongqing exhibiting higher emissions compared to surrounding areas, emphasizing the need for targeted emission controls in core urban zones. In the Yangtze River Delta, internal industrial differences, such as those between Shanghai's service sector and Jiangsu's manufacturing industry, suggest opportunities for further optimization within advanced clusters. Similarly, in the Jing-Jin-Ji area, while Beijing maintained low emission levels, nearby industrial cities such as Tianjin and parts of Hebei exhibited higher emissions, underscoring the need for differentiated policy approaches within this agglomeration.

Based on these findings, we recommend implementing tailored carbon reduction policies that address the specific characteristics of each region. In resource-dependent areas such as Xinjiang and Inner Mongolia, policies should prioritize the development of renewable energy infrastructure and incentivize cleaner industrial restructuring to reduce carbon intensity. In economically advanced regions such as the Yangtze and Pearl River Deltas, advancing green technologies, supporting innovation in low-carbon solutions, and improving energy-efficient urban infrastructure are essential to sustaining growth while curbing emissions. High-emission clusters in Central and Southwest China, including Sichuan and Hubei, would benefit from stricter emissions controls in core industrial zones and support for economic diversification through cleaner industries. Additionally, high-density regions such as Jing-Jin-Ji require enhanced urban planning policies, including energy-efficient infrastructure and expanded public transportation, to reduce per capita emissions effectively. These region-specific approaches will enable China to balance economic growth with sustainable development and advance its environmental targets.

In conclusion, the findings advocate for precision-targeted carbon reduction strategies tailored to the unique socioeconomic and industrial characteristics of each cluster. By emphasizing spatial heterogeneity and leveraging clustering analysis, this study provides actionable insights to support China's broader sustainability goals, enhancing the effectiveness of carbon management policies across diverse regional contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	directory of open access journals
TLA	three-letter acronym
LD	linear dichroism

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