

Article

Spatial Patterns, Drivers, and Spillover Effects of Carbon Footprint Pressure in Chinese Cities

Liyang Feng ^{1,†}, Dongzhe Liang ^{2,3,†}, Li He ^{1,*} and Yanlong Guan ⁴

¹ State Key Laboratory of Hydraulic Engineering Intelligent Construction and Operation, Tianjin University, Tianjin 300350, China

² Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Science and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

³ School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham B15 2TT, UK

⁴ College of Resources and Environment, Fujian Agriculture and Forestry University, Fuzhou 350002, China

* Correspondence: helix111@tju.edu.cn

† These authors contributed equally to this work.

Abstract

Limiting anthropogenic carbon emissions within vegetation carbon sequestration capacity is essential for urban sustainability. However, previous studies frequently neglected spatial dependency among cities, leading to uncertainties in understanding whether local carbon footprint pressure (CFP) is shaped only by local conditions or also by neighboring cities. This study analyzes the spatial patterns of CFP across Chinese cities from 2000 to 2019 and further investigates its driving factors using cross-sectional data for 2019. Spatial analysis methods, an extended STIRPAT model, and spatial econometric models are combined to diagnose the socioeconomic, environmental, and spatial mechanisms of CFP. Results indicate that the mean center of CFP's standard deviation ellipse shifted from northwest to southeast during 2000–2019, reflecting a spatial redistribution of carbon-emission pressure on vegetation carbon sequestration. The 2019 driver analysis shows that carbon-emission intensity, used here as an inverse proxy for technology-related emission efficiency, is the most influential factor: a 1% increase in carbon-emission intensity is associated with an approximate 1.2% increase in local CFP. Affluence, vegetation carbon sequestration, precipitation, temperature, and forest cover also shape CFP distribution patterns. Crucially, the study identifies significant spatial spillover effects: a 1% reduction in the carbon-emission intensity of neighboring cities is associated with at least a 0.8% reduction in local CFP. These findings suggest that CFP is jointly shaped by local socioeconomic development, ecological endowments, and inter-city spatial interactions. The study highlights the need to integrate local emission reduction, carbon-sink protection, and regional collaboration into urban climate governance.

Keywords: spatial spillover effect; carbon footprint pressure; spatial pattern; climate change; dual carbon target

Academic Editor: George F. Baniass

Received: 26 May 2026

Revised: 26 June 2026

Accepted: 3 July 2026

Published: 8 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

In response to climate change, countries worldwide are working to reduce anthropogenic carbon emissions [1,2] and improve vegetation carbon sinks [3]. China is the world's greatest carbon emitter [4], accounting for more than 26% of global emissions [5].

To strengthen the country's self-help contribution, the Chinese government has committed the "Dual Carbon" targets to reaching a carbon peak in 2030 and being carbon neutral by 2060 [6,7]. Cities, as the fundamental unit of policy formation and implementation, play an important role in the commitments [8]. Not only do cities contribute to high carbon emissions [9], but they also destroy and encroach on ecosystems as a result of fast development [10,11], exacerbating the CFP rising [12]. Evidence shows that, from 2001 to 2015, China's CFP increased 9.75 times faster than the global average [13]. Therefore, there is an urgent need to mitigate CFP at the urban scale to improve the Chinese government's ability to fulfill its commitments and provide reference for improving climate policies.

Mitigating the rising CFP demands city-wide cooperation [14,15]. Currently, much research has investigated the potential path to mitigate the rising CFP, e.g., economic structure transformation [16–18], energy structure upgrading [19], ecological environment improvement [7], technical efficiency enhancement [20], population density regulation [21], and urban space optimization [12]. However, past studies have tended to use time series as the primary study object [22], neglecting the spatial dependency, i.e., the link between the cities. As industry and supply networks develop, urban carbon reduction is becoming more sophisticated and under huge strain [23]. There is evidence that industrial transfer has greatly helped carbon reduction and environmental problems in commodity-importing cities [24]. However, this change promotes industrial clusters [25] while tying embodied carbon emissions to commodity export hubs and hastening the creation of impermeable artificial surfaces, resulting in a significant loss of vegetation carbon sinks [26–28]. Between 2000 and 2010, global urban growth cancels out approximately 30% of the net primary productivity (NPP) of the terrestrial environment induced by climate change [29]. Although studies have shown that technological promotion induced by regional spillover of carbon emissions can lead to carbon reductions [30], the loss of vegetation carbon sinks has raised doubt about whether such spatial spillover can mitigate climate change [31,32].

Theoretically, CFP can be understood as the relative pressure of anthropogenic carbon emissions on vegetation carbon sequestration. Therefore, its formation depends on both the emission side and the carbon-sink side. Socioeconomic factors such as economic development, population concentration, and carbon-emission intensity mainly influence the amount of anthropogenic carbon emissions [33], whereas ecological and climatic factors such as vegetation carbon sequestration, precipitation, temperature, and forest coverage affect the capacity of natural systems to absorb carbon. From this perspective, CFP is not only an emission-related indicator but also a coupled socioeconomic–ecological indicator that reflects the balance between human carbon pressure and ecosystem carbon-sink capacity. This theoretical structure also implies that CFP may exhibit spatial dependence. Cities are not isolated units; industrial transfer, technology diffusion, infrastructure connectivity, policy learning, and ecological continuity may transmit carbon-emission pressure or carbon-sink effects across administrative boundaries [34–36]. Therefore, explaining CFP requires not only identifying local drivers but also examining whether neighboring cities influence local CFP through spatial spillover mechanisms.

Methodologically, previous CFP studies have provided important insights into the temporal evolution, decomposition, and decoupling characteristics of carbon-emission pressure. However, these approaches are often insufficient for identifying spatial heterogeneity and inter-city dependence. Because CFP reflects the relative pressure of anthropogenic carbon emissions on vegetation carbon sequestration, its spatial distribution is shaped not only by local socioeconomic activities but also by regional ecological endowments and cross-boundary interactions. Therefore, spatial analytical methods are necessary to identify where CFP is concentrated, how its spatial center changes over time, and whether high- or low-pressure cities tend to cluster geographically. Standard deviation

ellipse analysis is suitable for detecting the directional movement and dispersion of CFP, while hot spot analysis and spatial autocorrelation analysis can reveal statistically significant spatial clusters and local spatial associations. These methods provide a spatial basis for evaluating whether CFP mitigation should be addressed only within individual cities or through broader regional coordination.

In addition, the STIRPAT model [37] provides a useful framework for examining the socioeconomic drivers of environmental pressure because it links anthropogenic environmental impact with population, affluence, and technology. Nevertheless, CFP differs from conventional carbon-emission indicators because it simultaneously reflects carbon emissions and vegetation carbon sequestration. Therefore, relying only on socioeconomic variables may overlook the role of natural conditions in shaping CFP. In this study, the STIRPAT framework is extended by incorporating vegetation carbon sequestration, precipitation, temperature, and forest coverage, which are directly or indirectly related to ecosystem carbon-sink capacity. Furthermore, conventional linear regression cannot adequately account for spatial dependence among cities. Spatial econometric models, including SEM, SLM, and SDM [38], are therefore introduced to identify whether CFP and its drivers exhibit spatial spillover effects. This methodological design allows us to examine not only the local determinants of CFP but also the extent to which neighboring cities influence each other. The purpose of this study is to determine how socioeconomic development, natural endowments, and inter-city spatial interactions influence CFP across Chinese cities. Specifically, this study first identifies the spatial pattern and evolutionary characteristics of city-scale CFP from 2000 to 2019. Second, it extends the STIRPAT model by incorporating natural elements that may affect both anthropogenic carbon emissions and vegetation carbon sequestration. Third, using cross-sectional data for 2019, it integrates the extended STIRPAT model with spatial econometric models to reveal the direct and indirect effects of CFP drivers. The year 2019 is selected because it is the latest year for which all required datasets are consistently available and because it represents the pre-COVID-19 urban socioeconomic and environmental condition, avoiding the potential disturbance caused by the pandemic on emissions, mobility, and economic activities.

Based on the above research gaps and objectives, this study addresses three research questions. First, what are the spatial patterns and evolutionary characteristics of CFP across Chinese cities? Second, can an extended STIRPAT model incorporating both socioeconomic and natural factors better explain inter-city differences in CFP? Third, do CFP and its driving factors exhibit significant spatial spillover effects among cities? Accordingly, this study proposes three research hypotheses. First, CFP in Chinese cities is expected to exhibit significant spatial agglomeration and directional evolution. Second, incorporating natural factors into the STIRPAT framework is expected to improve the explanatory power for CFP compared with socioeconomic variables alone. Third, CFP and its key drivers, especially carbon-emission intensity, are expected to generate significant spatial spillover effects across neighboring cities. The novelty of this study lies in diagnosing the spatial drivers and spillover effects of CFP at the city scale and providing empirical evidence for inter-city collaborative climate governance. This study's marginal contribution is summarized as follows: First, we investigate the spatial pattern and evolution of CFP, which compensates for prior research's neglect of spatial scale. Second, the inclusion of natural elements in STIRPAT that have potential effects on both anthropogenic carbon emissions and vegetation carbon sequestration emphasizes the relevance of regional disparities in resource endowments in mitigating climate change. Finally, the use of spatial econometric models illustrates the direct and indirect effects of driving factors on CFP and provides empirical evidence for interregional collaborative climate governance.

2. Methods and Materials

The purpose of this research is to determine the spatial patterns and determinants of city-scale CFP in China. CFP is defined as the ratio of anthropogenic carbon emissions to vegetation carbon sequestration. It represents the extent to which human-induced carbon emissions impose pressure on urban vegetation carbon sinks. A higher CFP indicates greater pressure of anthropogenic carbon emissions on local vegetation carbon sequestration. This study investigates geographical patterns using standard deviation ellipse analysis, hot spot analysis, the Moran index, and local spatial autocorrelation analysis. It further extends the STIRPAT model and integrates it with spatial econometric models to conduct the driver analysis.

CFP reflects the environmental impact of human activities from a carbon emissions perspective, rather than the net-zero carbon emissions. The calculation formula is as follows:

$$CFP = CF/npp \quad (1)$$

where CFP is the ratio of energy-related CO₂ emissions to the carbon sequestration of vegetation; CF is the energy-related CO₂ emissions; and npp denotes the carbon sequestration of vegetation, which is calculated from NPP and represents the dry-matter-fixed CO₂ produced by vegetation.

2.1. Spatial Pattern Characterization

2.1.1. Standard Deviation Ellipse

This study employed the standard deviational ellipse (SDE) to reveal the spatial properties of city-scale CFP, including dispersion, concentration degree, and changing patterns [39]. The SDE employs fundamental parameters such as the mean center, main axes, minor axes, and azimuth to analyze and describe the centrality, dispersion, direction trends, and geometric shape of the CFP's spatial distribution [40]. The SDE area comprises the primary regions in CFP that are spatially dispersed. The minor and main axes represent the directions and scopes of CFP distribution, as well as the degree of their dispersion. When the ellipse is elongated, the dispersion along the major trend becomes more pronounced. A greater distance between the minor and major axes indicates a more apparent polarization in the distribution. The azimuth reveals the predominant direction of CFP dispersion. The mean center, representing the centroid of all cities' CFP in two-dimensional space, indicates the relative locations of CFP and their general evolutionary trajectories over different periods. The calculation formulas are as follows:

$$\bar{X} = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i} \quad (2)$$

$$\bar{Y} = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \quad (3)$$

$$\tan\theta = \frac{\sqrt{(\sum_{i=1}^n w_i^2 \tilde{x}_i^2 - \sum_{i=1}^n w_i^2 \tilde{y}_i^2)^2 + 4(\sum_{i=1}^n w_i^2 \tilde{x}_i \tilde{y}_i)^2}}{2\sum_{i=1}^n w_i^2 \tilde{x}_i \tilde{y}_i} + \frac{\sum_{i=1}^n w_i^2 \tilde{x}_i^2 - \sum_{i=1}^n w_i^2 \tilde{y}_i^2}{2\sum_{i=1}^n w_i^2 \tilde{x}_i \tilde{y}_i} \quad (4)$$

$$\sigma_x = \sqrt{2} \sqrt{\frac{\sum_{i=1}^n (\tilde{x}_i \cos\theta - \tilde{y}_i \sin\theta)^2}{n}} \quad (5)$$

$$\sigma_y = \sqrt{2} \sqrt{\frac{\sum_{i=1}^n (\tilde{x}_i \sin\theta - \tilde{y}_i \cos\theta)^2}{n}} \quad (6)$$

where $\bar{X}$ and $\bar{Y}$ are the transverse and vertical coordinates of the mean center, respectively. w_i is the i -th city's CFP, (x, y) is the geographical coordinates of the center of mass. θ is the azimuth and is defined as a clockwise angle between the true north and the main axes. σ_x and σ_y are the standard deviations along the x -axis and y -axis.

2.1.2. Hot Spot Analysis

Hot spot analysis is utilized to assess the spatial heterogeneity of the CFP at the city scale. Using the Getis-Ord G_i^* statistic, the acquired Z-scores and p -values are calculated, where CFP values serve as weights. This method identifies spatial cluster of high-value areas (hot spots) and low-value areas (cold spots). The calculation formulas are as follows:

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^n w_{i,j}^2 - (\sum_{j=1}^n w_{i,j})^2}{n-1}}} \quad (7)$$

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (8)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (9)$$

where G_i^* indicates that Z is worth scoring. The higher the Z is worth scoring and has statistical significance, the higher the spatial cluster degree of the high-value area (hot spot) is. If the Z-value score is lower and statistically significant, the spatial agglomeration degree of the low-value region (cold spot) is higher.

2.1.3. Global and Local Spatial Autocorrelation Analysis

In this study, the global Moran Index (Global Moran's I), ranging from -1 to 1 , is utilized to quantify the global spatial autocorrelation of city-scale CFP. A value of $I < 0$ indicates a negative spatial correlation, with $I = -1$ representing perfect negative correlation. Conversely, $I > 0$ suggests a positive spatial correlation, increasing towards perfect positive correlation as I approaches 1 . An $I = 0$ indicates no spatial association, with the CFP distributed randomly across space. The formula for Global Moran's I is as follows:

$$I = \frac{n}{V} \times \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (10)$$

$$V = \sum_{i=1}^n \sum_{j=1}^n w_{i,j} \quad (11)$$

where I represents Global Moran's I, n represents the total number of cities, x_i and x_j represent the CFP of cities i and j , respectively, $\bar{x}$ is the average CFP, and $w_{i,j}$ is the standardized spatial weight matrix, which represents the spatial link between cities. The significance of Global Moran's I can be assessed by standardizing Z and p values. If $-1.96 < Z < 1.96$ and $p > 0.05$, Global Moran's I is not significant. The score of Z_I can be calculated as follows:

$$Z_I = \frac{I - E[I]}{\sqrt{VAR[I]}} \quad (12)$$

$$E[I] = -\frac{1}{(n-1)} \quad (13)$$

$$VAR[I] = E[I^2] - E[I]^2 \quad (14)$$

Furthermore, while the global spatial autocorrelation model provides an overall assessment of whether urban CFP is spatially clustered, it does not identify the specific locations of these clusters. To address this limitation, this study employs local spatial autocorrelation analysis to examine the spatial relationships of urban CFP at a more granular level. The local spatial autocorrelation index measures the degree of correlation between each urban CFP value and its neighboring values. The calculation model is as follows:

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n (x_j - \bar{x})}{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (15)$$

where the interpretations of the remaining variables are the same as Equation (10).

All urban CFP could be classified into four classes in the local spatial autocorrelation index, namely, High–High, representing high CFP surrounded by high CFP; Low–Low, representing low CFP surrounded by low CFP; Low–High and High–Low, representing low CFP surrounded by high CFP and high CFP surrounded by low CFP, respectively.

2.2. Drivers Analysis Process

2.2.1. Expanded STIRPAT Model

The STIRPAT model is widely used to reveal the drivers of anthropogenic environmental impact. STIRPAT, a stochastic form of the IPAT equation (Equation (16)), is presented in Equation (17) and may be expanded to meet research needs. By applying logarithms to both sides of the equation, Equation (17) can be transformed into a linear model, Equation (18). In this study, CFP is used as the environmental impact variable in the STIRPAT framework. Population is represented by population density (Pd), and affluence is represented by real GDP per capita (A). The technology-related factor is represented by carbon-emission intensity (T), calculated as anthropogenic carbon emissions per unit of real GDP. It should be noted that T is an inverse proxy for technology-related emission efficiency; a higher T indicates greater carbon emissions per unit of economic output and thus lower emission efficiency, whereas a lower T indicates technological improvement or higher carbon-emission efficiency. Therefore, a positive coefficient of $\ln T$ means that higher carbon-emission intensity increases CFP, while a decrease in T represents improved technology-related emission efficiency and contributes to CFP reduction. Because CFP is jointly shaped by anthropogenic carbon emissions and vegetation carbon sequestration, vegetation carbon sequestration (Cs) is included as a separate explanatory variable. According to relevant research [41–43], we have expanded the STIRPAT model to include temperature (Tem), precipitation (Pre), and forest coverage ($Forest$) as explanatory variables to assess the potential influence of key environmental factors on CFP.

$$I = P \times A \times T \quad (16)$$

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (17)$$

$$\ln I_i = \ln a + b \ln P_i + c \ln A_i + d \ln T_i + \ln e_i \quad (18)$$

$$\ln CFP_i = \ln a + \beta_1 \ln T_i + \beta_2 \ln A_i + \beta_3 \ln Pd_i + \beta_4 \ln Cs_i + \beta_5 \ln Pre_i + \beta_6 \ln Tem_i + \beta_7 Forest_i + \varepsilon_i \quad (19)$$

where I is the environmental impact caused by human activity and represents the CFP in this study. P , A , and T are the effects of population, affluence, and technology, respectively. In Equation (18), a denotes the constant coefficient; b , c , and d reflect the underestimated parameters; and ε is the error term. In Equation (19), CFP_i represents the carbon footprint pressure of city i ; T_i represents carbon-emission intensity, measured as anthropogenic carbon emissions per unit of real GDP; A_i represents real GDP per capita; Pd_i represents population density; Cs_i represents vegetation carbon sequestration; Pre_i and Tem_i represent annual precipitation and annual mean temperature, re-

spectively; $Forest_i$ represents the proportion of forest land; α is the constant term; β_1 – β_7 are estimated coefficients; and ε_i is the error term.

2.2.2. Spatial Econometric Model

To address the limitation that the linear model does not account for spatial dependency in regression analysis, this study employed the spatial econometric model based on Equation (19) to investigate the drivers of the CFP spatial pattern. Commonly used spatial econometric models include the Spatial Error Model (SEM), the Spatial Lag Model (SLM), and the Spatial Durbin Model (SDM) [38]. The model is classified as the SEM when the error components exhibit spatial correlated. Its expression is as follows:

$$Y = X\beta + \lambda Wu + \varepsilon, \varepsilon \sim N(0, \delta^2) \quad (20)$$

where Y is the vector $n \times 1$ and represents the explained variable; X is the vector of explanatory variables. It is a $(n \times k)$ matrix if there are k explanatory variables. u is a random error vector; λ is the spatial correlation coefficient between the regression residuals. W is a $(n \times n)$ spatial weight matrix; ε denotes the random error term, which is widely thought to be independent.

When the spatial dependence between the explained variables is critical to the model and results in spatial correlation, it is termed the SLM, also known as a spatial autoregressive model. The formula is as follows:

$$Y = \rho WY + X\beta + \varepsilon, \varepsilon \sim N(0, \delta^2) \quad (21)$$

where ρ represents the coefficient of endogenous interaction effect ($W \times Y$), and its magnitude reflects the degree of spatial diffusion or spatial spillover. If ρ is significant, it indicates that there is a certain spatial dependence between the explained variables.

The SDM is a more general variation in the SEM and SLM that incorporates both endogenous and exogenous interaction effects ($W \times Y$ and $W \times X$). The formula is as follows:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon, \varepsilon \sim N(0, \delta^2) \quad (22)$$

When $\theta = 0$, the SLM model is used and, when $\theta = -\rho\beta$, the SEM model is used. The greater the spatial interaction of explanatory factors is, the more significant θ is. However, θ cannot be used to conclusively determine the presence of spatial spillover effect. The diagonal elements of $(I - \rho W)^{-1}(\beta_k + W\theta_k)$ indicate direct influence, while the non-diagonal elements reveal indirect effect. The significance of these two effects is examined using the method for calculating the partial derivative matrix.

The spatial weight matrix significantly influences the results as a critical coefficient matrix in operations involving SLM, SEM, and SDM. Therefore, the inverse geographic distance matrix and the first-order adjacency matrix are selected as spatial weight matrices for comparison and verification. The inverse distance matrix is defined as the reciprocal of the distance between two cities. Under this specification, cities located closer to each other are assigned larger spatial weights, whereas cities farther apart are assigned smaller spatial weights. The first-order adjacency matrix indicates that only adjacent cities can have interactions.

2.3. Data Sources

This study utilizes multi-source datasets for carbon emissions, vegetation carbon sequestration, socioeconomic conditions, land use, and meteorological variables. Anthropogenic carbon emissions are obtained from the Open-source Data Inventory for Anthro-

genic CO₂, specifically the ODIAC2020b dataset (https://db.cger.nies.go.jp/dataset/ODIAC/DL_odiad2020b.html, accessed on 5 April 2026). Vegetation carbon sequestration is calculated using NASA's net primary productivity product and aggregated to the city scale. Real GDP data are obtained from the gridded real GDP dataset developed by Chen et al. [44]. Population data are obtained from the WorldPop dataset (<https://www.worldpop.org/>, accessed on 5 April 2026). Land-use data are obtained from Yang and Huang [45], and forest coverage is calculated as the proportion of forest land within each city. Meteorological data, including precipitation and temperature, are obtained from the National Tibetan Plateau / Third Pole Environment Data Center (TPDC) (<https://data.tpdc.ac.cn/en/>, accessed on 5 April 2026).

The spatial pattern analysis is conducted for the period 2000–2019 to identify the evolution of CFP. The driver analysis and spatial econometric analysis are conducted using cross-sectional data for 2019. The year 2019 is selected because it is the latest year for which all required variables are consistently available in the datasets used in this study. It also represents the pre-COVID-19 baseline condition, avoiding the potential disturbance caused by the pandemic on carbon emissions, mobility, economic activity, and urban development patterns.

3. Results

3.1. Spatial Characteristics of the Pressure from Carbon Emissions on Vegetational Carbon Sequestration on the City Scale

Vegetation carbon sequestration capability in Chinese cities faces severe pressure from carbon emissions, which range from 0.22 to 118.82, and exhibits substantial spatial agglomeration (Figure 1). The CFP distribution pattern shows a gradient increase from southwest to northeast, with higher CFP concentrations primarily in China's metropolitan agglomeration areas (Figure 1a). CFP hotspots are predominantly concentrated in northwest China at the 1% significance level, while cold spots are primarily found in southwest China at the 10% significance level (Figure 1b). Compared to the year 2000 (Figure S1), the hotspots of CFP have shifted westward, although the overall hotspots pattern remains the same. Standard deviation ellipse analysis indicates that the CFP of Chinese cities is broadly dispersed spatially from northwest to the middle east, with the mean center shifting from northwest to southeast (Figure 1c). Additional relevant parameters can be found in the Supplementary Material, Table S1.

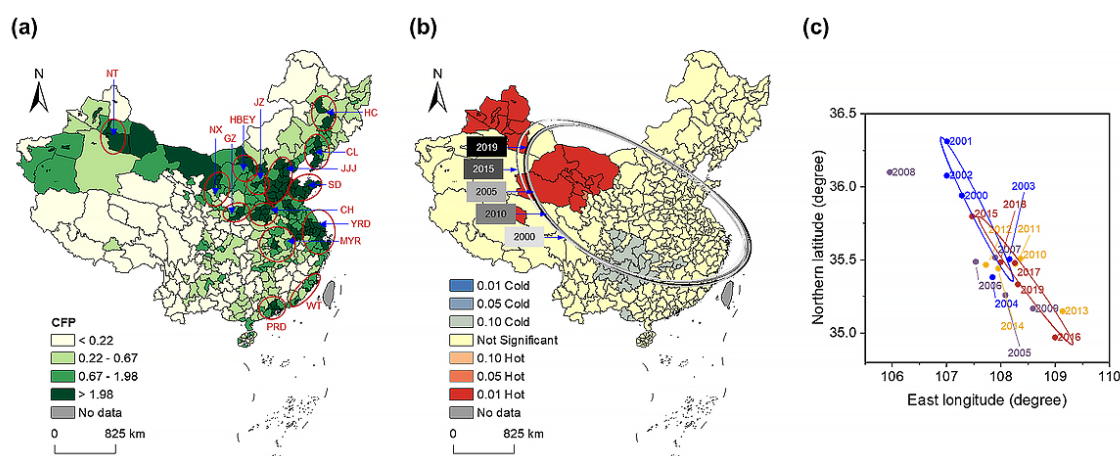


Figure 1. CFP patterns of Chinese cities. (a) Spatial distribution in the year 2019; (b) hot spot distribution in 2019 and standard deviation ellipse for typical years; (c) the spatial shift trend of the mean center of the standard deviation ellipse during the period of the years from 2000 to 2019. In (a), HC,

CL, JJJ, SC, CH, YRD, MYR, WT, PRD, JZ, HBEY, GZ, NX, and NT represent the metropolitan areas of Harbin-Changchun, Central-southern of Liaoning, Jing-Jin-Ji, Shandong Peninsula, Central Henan, Yangtze River Delta, Middle Yangtze River, Western Taiwan Straits, Pearl River Delta, Jinzhong, Hohhot-Baotou-Erdos-Yulin, Guanzhong, Ningxia, and North Slope of Tianshan Mountain, respectively.

The spatial autocorrelation and clustering of city-scale CFP in China are significant (Figure 2). The Moran index for city-scale CFP was 0.021 ($p < 0.01$) in 2019 (Figure 2a). Spatially (Figure 2b), the Yangtze River Delta, Pearl River Delta, and Urumqi metropolitan areas, along with Shizuishan and Jiayuguan in the northwest, exhibit high-high CFP clusters. In contrast, Zhangye and Haixi are characterized by low-high CFP outliers, and other areas are statistically unimportant. Therefore, spatial effects must be considered in subsequent research.

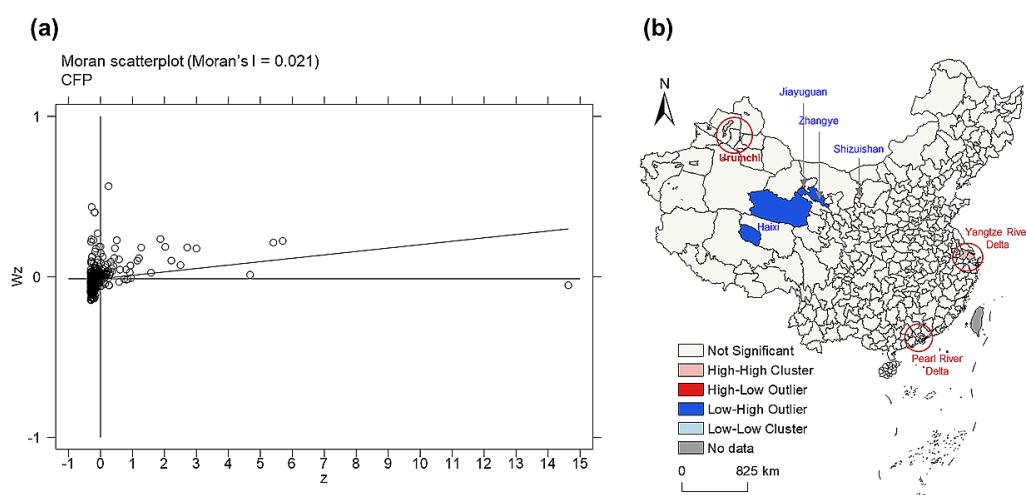


Figure 2. Moran's I (a) and spatial clustering of CFP in Chinese city scale in the year 2019. In (b), the red dashed circles highlight the representative cities and regions discussed in the text, and the gray lines connect the labels to their corresponding locations.

3.2. Preliminary Driver Analysis

Regional disparities in CFP can be more efficiently explained by integrating socioeconomic and natural variables (Table 1). We utilized the ordinary least squares approach to compare the explanatory power of four linear models on CFP in 2019. In Model 1, carbon-emission intensity ($\ln T$) has the largest positive coefficient and is significant at the 1% level. Since T is defined as anthropogenic carbon emissions per unit of real GDP, a higher value of T indicates lower technology-related emission efficiency. Therefore, the positive coefficient should be interpreted as follows: a 1% increase in carbon-emission intensity is associated with a 1.61% increase in CFP. Conversely, a decline in T represents improved technology-related emission efficiency and contributes to CFP reduction.

Affluence also has a positive effect on CFP, suggesting that economically developed cities tend to generate higher carbon-emission pressure when the increase in economic activity is not fully offset by improvements in emission efficiency or carbon-sink capacity. Vegetation carbon sequestration and forest coverage have negative coefficients, which is consistent with the conceptual definition of CFP as the ratio of anthropogenic carbon emissions to vegetation carbon sequestration. Cities with stronger carbon-sink capacity can absorb more carbon and therefore face lower CFP. Precipitation and temperature show positive effects in the combined models. This may reflect the fact that favorable hydro-

thermal conditions are often associated with more intensive socioeconomic activity in many Chinese cities, although these natural factors may also influence vegetation productivity. Population density becomes statistically insignificant after socioeconomic and natural variables are jointly included, indicating that the effect of population concentration may be mediated by economic activity, emission intensity, and ecological conditions.

Overall, the comparison of Models 1–4 supports the need to extend the STIRPAT framework by incorporating natural factors. Model 3 and Model 4 have higher explanatory power than models using only socioeconomic or natural variables, indicating that CFP is jointly shaped by human activities and ecological endowments.

Table 1. Comparison of results from the four linear regression models.

	M1	M2	M3	M4
Constant	22.484 *** (1.597)	−0.643 (0.822)	16.650 *** (1.206)	16.772 *** (1.047)
lnT	1.613 *** (0.104)		1.310 *** (0.074)	1.316 *** (0.067)
lnA	0.842 *** (0.082)		0.821 *** (0.075)	0.827 *** (0.070)
lnPd	−0.097 ** (0.043)		−0.008 (0.041)	
lnCs		−0.475 *** (0.056)	−0.354 *** (0.039)	−0.352 *** (0.038)
lnPre		0.142 (0.112)	0.335 *** (0.081)	0.335 *** (0.080)
lnTem		0.597 *** (0.113)	0.552 *** (0.084)	0.558 *** (0.078)
Forest		−0.038 *** (0.003)	−0.030 *** (0.002)	−0.030 *** (0.002)
R ²	0.597	0.577	0.818	0.818
Adj. R ²	0.594	0.572	0.815	0.815

Notes: ** and *** represent the significance at 5%, and 1% levels, respectively. In the four models, there is no obvious multicollinearity among the variables (see Table S2 in the Supplementary Material). lnT denotes the logarithm of carbon-emission intensity, measured as anthropogenic carbon emissions per unit of real GDP. It is used as an inverse proxy for technology-related emission efficiency. A higher value indicates lower emission efficiency, while a lower value indicates improved emission efficiency.

We also conduct a spatial analysis of the regression residuals, which exhibit a Moran index of 0.097, significant at the 1% level (Figure S2). This suggests that spatial dependence remains in the linear regression results and that spatial econometric models are needed for further analysis of CFP drivers and spillover effects.

3.3. Further Driver Analysis Combined the Extended IPAT Equation and Spatial Econometrics

To investigate the drivers of CFP spatial patterns, the extended STIRPAT equation and spatial econometric models are integrated in this study (Table 2). We first conducted an LM test on the spatial econometric models (Table S3), but the test results did not clearly determine the most appropriate model among SEM, SLM, and SDM. We then examined the spatial autocorrelation of the dependent variable and identified spatial interaction effects (Table S4 and Figure S3). Therefore, maximum likelihood estimation was used to fit the three spatial econometric models. Given the importance of the spatial weight matrix

in spatial econometrics, an inverse geographic distance matrix and a first-order adjacency matrix were constructed for comparison.

Across the spatial econometric specifications, carbon-emission intensity and affluence generally have positive effects on CFP, while vegetation carbon sequestration and forest coverage generally have negative effects. These results are consistent with the theoretical structure of CFP, which is jointly shaped by anthropogenic carbon-emission pressure and vegetation carbon-sink capacity. The significant spatial lag terms of CFP in the SLM and SDM further indicate that the CFP level of neighboring cities is associated with local CFP. Under the first-order adjacency matrix, a 1% increase in neighboring cities' CFP is associated with at least a 0.3% increase in local CFP. This result supports the need to consider spatial dependence when analyzing the drivers of CFP. Table 2 reports the estimation results of SEM, SLM, and SDM under two spatial weight matrices. The results indicate that spatial dependence is an important feature of city-scale CFP. In the SEM, the significant spatial error terms suggest that unobserved factors affecting CFP are spatially correlated. In the SLM, the significant spatial lag terms of CFP indicate that the CFP level of neighboring cities is associated with local CFP. In the SDM, several spatially lagged explanatory variables are statistically significant, suggesting that the drivers of CFP may also operate through spatial spillover channels.

However, the model fit statistics do not uniformly indicate that one model dominates the others under all criteria. For example, under the inverse geographic distance matrix, SEM has a higher log-likelihood than SDM, whereas SDM has a higher Pseudo R^2 . Therefore, we do not claim that SDM uniformly outperforms SEM and SLM. Instead, SEM, SLM, and SDM are treated as complementary spatial econometric specifications [46]. The SDM is further used for effect decomposition because it is a more general specification that includes both the spatial lag of the dependent variable and the spatial lags of explanatory variables. This makes it suitable for estimating direct and indirect effects, which are central to evaluating inter-city spillover mechanisms.

Table 2. Comparison of the estimation results of SEM, SLM and SDM.

	Inverse Geographic Distance Matrix			First-Order Adjacency Matrix		
	SEM	SLM	SDM	SEM	SLM	SDM
Constant	18.033 *** (1.159)	16.605 *** (1.009)	18.632 *** (1.237)	16.985 *** (1.154)	15.945 *** (1.063)	14.601 *** (1.237)
$\ln T$	1.242 *** (0.06)	1.264 *** (0.060)	1.195 *** (0.062)	1.293 *** (0.060)	1.198 *** (0.064)	1.201 *** (0.062)
$\ln A$	0.621 *** (0.07)	0.711 *** (0.062)	0.693 *** (0.072)	0.753 *** (0.074)	0.724 *** (0.067)	0.705 *** (0.072)
$\ln Pd$	0.025 (0.029)	0.073 *** (0.026)	0.058 * (0.031)	0.026 (0.029)	0.062 ** (0.029)	0.031 (0.031)
$\ln Cs$	−0.309 *** (0.036)	−0.367 *** (0.034)	−0.369 *** (0.038)	−0.308 *** (0.042)	−0.306 *** (0.036)	−0.372 *** (0.038)
$\ln Pre$	0.010 (0.086)	0.267 *** (0.069)	−0.162 (0.109)	0.247 *** (0.093)	0.251 *** (0.073)	0.421 *** (0.109)
$\ln Tem$	0.503 *** (0.080)	0.612 *** (0.070)	0.453 *** (0.091)	0.519 *** (0.090)	0.481 *** (0.075)	0.392 *** (0.091)
Forest	−0.030 *** (0.002)	−0.022 *** (0.002)	−0.025 *** (0.003)	−0.031 *** (0.003)	−0.024 *** (0.002)	−0.034 *** (0.003)
$W^*\mu$	3.473 *** (0.188)			0.755 *** (0.059)		
W^*CFP		0.949 *** (0.048)	0.930 *** (0.069)		0.300 *** (0.045)	0.600 *** (0.069)

$W^* \ln T$			0.496 (0.430)			−0.283 *** (0.430)
$W^* \ln A$			1.453 ** (0.686)			−0.243 * (0.686)
$W^* \ln Pd$			−0.407 * (0.235)			0.077 (0.235)
$W^* \ln Cs$			1.528 *** (0.429)			0.110 (0.429)
$W^* \ln Pre$			0.555 (0.879)			−0.501 *** (0.879)
$W^* \ln Tem$			0.465 (1.065)			−0.128 (1.065)
$W^* Forest$			0.045 ** (0.020)			0.030 *** (0.020)
Pseudo R^2	0.828	0.858	0.880	0.840	0.838	0.825
Wald test	1744.45 ***	2877.97 ***	3022.92 ***	1246.28 ***	2288.44 ***	2738.41 ***
Log-likelihood	−315.287	−339.817	−321.561	−330.553	−357.805	−337.075

Notes: *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively. $\ln T$ denotes the logarithm of carbon-emission intensity, measured as anthropogenic carbon emissions per unit of real GDP. It is used as an inverse proxy for technology-related emission efficiency. A higher value indicates lower emission efficiency, while a lower value indicates improved emission efficiency.

Although SEM and SLM provide useful evidence on spatial error dependence and spatial dependence in the dependent variable, they cannot fully decompose how explanatory variables in neighboring cities influence local CFP. Therefore, the SDM results are further decomposed into direct and indirect effects (Table 3). The direct effects capture the influence of local explanatory variables on local CFP, while the indirect effects capture the influence of neighboring cities' explanatory variables on local CFP.

Under the inverse geographic distance matrix, carbon-emission intensity, affluence, vegetation carbon sequestration, temperature, and forest coverage have significant direct effects on local CFP, but their indirect effects are not statistically significant. Under the first-order adjacency matrix, most local factors significantly influence local CFP, and the indirect effect of carbon-emission intensity is significant at the 1% level. This means that higher carbon-emission intensity in neighboring cities is associated with higher CFP in the local city. Conversely, a reduction in neighboring cities' carbon-emission intensity, which reflects improved technology-related emission efficiency, can reduce local CFP by at least 0.8%. This result provides empirical evidence for technology-related spatial spillovers.

The theoretical intuition behind this result is that neighboring cities are often connected through industrial chains, labor mobility, infrastructure networks, policy learning, and technology diffusion. Improvements in emission efficiency in one city may therefore influence surrounding cities by promoting cleaner production standards, accelerating low-carbon technology adoption, and encouraging coordinated regional governance. The significance of the first-order adjacency matrix also suggests that such spillovers are more likely to occur among geographically contiguous cities, where economic and policy interactions are stronger. Additionally, the indirect effects of precipitation and the proportion of forest land are significant at the 10% and 5% levels, respectively, demonstrating the spatial agglomeration of these factors (Figure S3).

Table 3. The direct effect and indirect effect of SDM.

	Inverse Geographic Distance Matrix		First-Order Adjacency Matrix	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
$\ln T$	1.259 *** (0.094)	20.122 (21.071)	1.250 *** (0.066)	0.812 *** (0.246)
$\ln A$	0.778 *** (0.103)	26.270 (26.648)	0.726 *** (0.076)	0.336 (0.211)
$\ln Pd$	0.044 (0.033)	−4.420 (4.839)	0.041 (0.032)	0.176 * (0.102)
$\ln Cs$	−0.322 *** (0.059)	14.832 (14.982)	−0.385 *** (0.047)	−0.211 (0.142)
$\ln Pre$	−0.146 (0.106)	5.066 (11.35)	0.392 *** (0.098)	−0.461 * (0.259)
$\ln Tem$	0.489 *** (0.084)	11.101 (16.466)	0.404 *** (0.098)	0.199 (0.246)
<i>Forest</i>	−0.024 *** (0.003)	0.269 (0.361)	−0.032 *** (0.003)	0.018 ** (0.008)

Notes: *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively. $\ln T$ denotes the logarithm of carbon-emission intensity, measured as anthropogenic carbon emissions per unit of real GDP. It is used as an inverse proxy for technology-related emission efficiency. A higher value indicates lower emission efficiency, while a lower value indicates improved emission efficiency.

4. Discussion and Policy Implications

This study explained the spatial pattern of CFP and its drivers. It compensated for previous studies' neglect of this pattern, revealed the role and contribution of natural elements, and clarified the key influence of spatial effects on CFP distribution.

The empirical findings can be interpreted through the coupled structure of CFP. CFP increases when anthropogenic carbon emissions rise faster than vegetation carbon sequestration, and it decreases when emission pressure is reduced or carbon-sink capacity is enhanced. Carbon-emission intensity has the strongest positive effect because it directly reflects the amount of carbon emitted per unit of economic output. Affluence also increases CFP because higher economic output is often associated with greater energy consumption, infrastructure construction, and consumption-related emissions. However, these effects can be moderated by improvements in emission efficiency and ecosystem carbon-sink capacity.

Vegetation carbon sequestration and forest coverage reduce CFP because they strengthen the ability of urban ecosystems to absorb carbon. This finding supports the view that ecological restoration and forest protection are important complements to emission reduction. The spatial spillover results further show that CFP is not only locally generated but also regionally connected. Neighboring cities may influence each other through technology diffusion, industrial transfer, policy imitation, and shared ecological conditions. This provides the theoretical basis for regional collaborative governance.

Higher CFP primarily occurs in metropolitan areas in northern and eastern China, consistent with prior research [13]. Due to their high levels of economic development and urbanization, these locations are major economic and population clusters in China and also hotspots for carbon emissions [47]. We investigated the evolution trend of the spatial pattern of CFP and discovered that the mean center of the spatial standard deviation ellipse shifts from northwest to southeast (Figure 1c), contradicting the findings of the carbon emissions research [48]. This may be linked to significant environmental construction efforts in northwest China [49,50]. Our subsequent regression study supported this, showing that locations with more forest cover had lower CFP (Tables 1 and 2). The spatial trans-

fer of CFP indicates that the main focus of China's response to climate change remains in economically developed areas in the east. On the one hand, these areas should bear greater responsibility for emission reduction [51] due to their high carbon emissions; on the other hand, their favorable hydrothermal conditions enhance the potential for vegetation carbon sequestration [52].

The extended STIRPAT model incorporating natural components can better describe the spatial pattern of CFP. Previous research has mainly concentrated on the role of socio-economic variables in CFP [19] but often disregarded natural elements that directly or indirectly affect both anthropogenic carbon emissions and vegetation carbon sequestration [53]. According to our results, cities with high carbon-emission intensity and high affluence tend to exhibit relatively high CFP. This finding suggests that economic growth alone does not necessarily reduce carbon pressure unless it is accompanied by improvements in emission efficiency and carbon-sink protection. Moreover, we found that regions with favorable hydrothermal conditions tend to have greater CFP, likely because such conditions are also associated with more intensive socioeconomic activity and urban development in many Chinese cities [54]. In contrast, the effect of population density becomes relatively weak after socioeconomic and natural variables are jointly considered. This suggests that CFP is not driven simply by population concentration but by the combined effects of economic activity, emission intensity, and ecological endowments.

Responding to the lack of focus on spatial dependence in earlier research, we utilized spatial econometric models based on the extended STIRPAT framework to investigate the mechanisms associated with CFP. Our findings reveal considerable spatial spillover effects of CFP, implying that responses to carbon-emission pressure should emphasize interregional coordination [55]. Further examination shows that the direct and indirect impacts of explanatory factors vary under the two spatial weight matrices. Under the first-order adjacency matrix, carbon-emission intensity has both strong direct and indirect effects on CFP. This implies that reducing CFP in a local city depends not only on its own emission-efficiency improvement but also on the carbon-emission intensity of neighboring cities. In geographically contiguous areas, low-carbon technology diffusion, coordinated industrial upgrading, and policy learning may help reduce regional carbon-emission pressure. Precipitation and forest coverage also exhibit indirect effects under the first-order adjacency matrix, indicating that contiguous places often share similar ecological and climatic conditions. Conversely, the statistical insignificance of several indirect environmental effects under the inverse geographic distance matrix underscores the importance of considering regional resource endowments and spatial proximity when formulating responses to CFP [56].

Technical innovation [57] and ecological development [58] are important drivers of CFP mitigation. However, regions with high CFP are often highly urbanized and economically developed [59], where further improvements in carbon-emission efficiency may become more difficult and land available for green-space expansion may be constrained [60]. As a result, reducing CFP requires an integrated strategy rather than isolated local action. Authorities should promote inter-regional collaborative development by leveraging emission-efficiency improvements, ecological restoration, and coordinated industrial policies in nearby regions. This strategy can reduce the pressure of local anthropogenic carbon emissions on vegetation carbon sequestration. Simultaneously, ensuring fairness requires the development and improvement of carbon trading markets, which can help reduce the burden on regions overloaded with CFP through virtual trade and interregional compensation mechanisms. Such approaches may also promote inter-regional income equality and help avoid environmentally damaging industrialization pathways.

Several limitations should be acknowledged when interpreting the findings of this study. First, CFP was calculated using multi-source gridded datasets, including carbon-

emission, vegetation carbon sequestration, socioeconomic, land-use, and meteorological data. Although these datasets are widely used in urban-scale environmental studies, uncertainties may remain due to spatial resolution, data harmonization, and cross-source consistency. Second, this study focuses on Chinese cities during 2000–2019. Therefore, the findings should be interpreted primarily within the context of China's urbanization process, ecological restoration policies, and regional development patterns. Extrapolating the conclusions to other countries or global urban systems requires caution because urban development stages, industrial structures, ecological conditions, and governance systems may differ substantially. Third, the driver analysis is based on cross-sectional data for 2019. Although this year provides a consistent pre-COVID-19 baseline, the results should be interpreted as cross-sectional associations rather than long-term dynamic causal relationships. Future research could further employ panel spatial econometric models or causal identification strategies to examine the temporal dynamics and causal mechanisms of CFP drivers.

5. Conclusions

This study investigates the spatial patterns, driving factors, and spatial spillover effects of CFP across Chinese cities. The spatial pattern analysis covers the period from 2000 to 2019, while the driver analysis and spatial econometric analysis are conducted using cross-sectional data for 2019. By integrating spatial pattern analysis, an extended STIRPAT model, and spatial econometric models, this study provides evidence that CFP mitigation should be understood not only as a local urban issue but also as a regional collaborative governance challenge.

The empirical findings respond directly to the research hypotheses proposed in the Introduction. First, CFP in Chinese cities exhibits clear spatial agglomeration and directional evolution. High CFP values are mainly concentrated in major metropolitan areas and economically developed regions, while low CFP values are more frequently observed in areas with relatively stronger vegetation carbon-sink capacity. The standard deviation ellipse analysis further shows that the mean center of CFP shifted from northwest to southeast during the study period, indicating a spatial redistribution of carbon-emission pressure on vegetation carbon sequestration. The significant Moran's *I* and local spatial clustering results confirm that CFP is not randomly distributed across cities but instead shows statistically significant spatial dependence.

Second, the results show that the extended STIRPAT model incorporating both socioeconomic and natural factors provides stronger explanatory power for inter-city CFP differences than models using only one group of variables. Carbon-emission intensity is identified as the most important factor affecting CFP, followed by affluence. Vegetation carbon sequestration, precipitation, temperature, and forest coverage also play important roles in shaping CFP distribution. These findings indicate that CFP is jointly determined by human activities and ecological conditions. Therefore, mitigation strategies should not focus only on reducing anthropogenic carbon emissions but should also consider the protection and enhancement of vegetation carbon sinks.

Third, the spatial econometric results reveal significant spatial spillover effects of CFP and its drivers. In particular, the indirect effect of carbon-emission intensity is statistically significant, suggesting that reductions in neighboring cities' carbon-emission intensity, which reflect improvements in technology-related emission efficiency, can contribute to reducing local CFP. This finding highlights the importance of inter-city cooperation, technology diffusion, and regional coordination in CFP mitigation. The results suggest that isolated city-level policies may be insufficient, especially in highly connected urban agglomerations where emissions, industrial activities, population movement, and ecological impacts extend beyond administrative boundaries.

The practical implications of this study are relevant to several stakeholder groups. For national policymakers, the findings suggest that CFP mitigation should be incorporated into regional climate governance frameworks, rather than relying only on individual city-level emission-reduction targets. Differentiated responsibilities should be designed according to regional development stages, carbon-emission intensity, and vegetation carbon-sink capacity. For municipal governments, the results emphasize the need to improve carbon-emission efficiency, protect ecological land, enhance urban vegetation carbon sinks, and coordinate mitigation policies with neighboring cities. For regional planning authorities, the evidence of spatial spillover effects supports the establishment of collaborative governance mechanisms across metropolitan areas and urban agglomerations. For enterprises and industrial parks, the results indicate that low-carbon technology diffusion, cleaner production, and coordinated industrial upgrading can generate benefits beyond local administrative boundaries. For researchers, this study demonstrates the value of combining CFP accounting, extended STIRPAT modeling, and spatial econometric analysis to examine the coupled socioeconomic–ecological mechanisms behind urban carbon pressure.

Overall, this study shows that reducing CFP requires an integrated approach that combines local emission reduction, ecological carbon-sink protection, technological improvement, and regional collaboration. Strengthening cross-city cooperation can reduce the pressure of anthropogenic carbon emissions on vegetation carbon sequestration and contribute to China’s dual carbon targets and broader sustainable development goals.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18146984/s1>, Figure S1: CFP’s hotspot distribution in 2000; Figure S2: Moran’s I (a) and spatial clustering (b) of M4’s standard deviation; Figure S3: Local autocorrelation of explanatory variables; Table S1: The parameters of standard deviation ellipse analysis from 2000 to 2019; Table S2: The variance inflation factor of the explanatory variable; Table S3: Results of the Lagrange Multiplier (LM) test; Table S4: Global autocorrelation of explanatory variables.

Author Contributions: Conceptualization, L.F. and D.L.; methodology, L.F. and D.L.; validation, L.F. and D.L.; formal analysis, L.F. and D.L.; investigation, L.F. and D.L.; resources, L.H.; data curation, L.F. and Y.G.; writing—original draft preparation, L.F. and D.L.; writing—review and editing, L.F., D.L., L.H., and Y.G.; visualization, Y.G. and L.F.; supervision, L.H.; project administration, L.H.; funding acquisition, L.H. and D.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (72394403, 42477508); the Postdoctoral Fellowship Program of CPSF (GZC20241689); and the CAS Interdisciplinary Innovation Team (JCTD-2019-04).

Data Availability Statement: The original contributions presented in this study are included in the article/Supplementary Materials. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Campbell-Lendrum, D.; Neville, T.; Schweizer, C.; Neira, M. Climate change and health: Three grand challenges. *Nat. Med.* **2023**, *29*, 1631–1638. <https://doi.org/10.1038/s41591-023-02438-w>.
2. Daehn, K.; Basuhi, R.; Gregory, J.; Berlinger, M.; Somjit, V.; Olivetti, E.A. Innovations to decarbonize materials industries. *Nat. Rev. Mater.* **2022**, *7*, 275–294. <https://doi.org/10.1038/s41578-021-00376-y>.

3. Kooperman, G.J.; Chen, Y.; Hoffman, F.M.; Koven, C.D.; Lindsay, K.; Pritchard, M.S.; Swann, A.L.S.; Randerson, J.T. Forest response to rising CO₂ drives zonally asymmetric rainfall change over tropical land. *Nat. Clim. Change* **2018**, *8*, 434–440. <https://doi.org/10.1038/s41558-018-0144-7>.
4. Yang, Y.; Qu, S.; Cai, B.; Liang, S.; Wang, Z.; Wang, J.; Xu, M. Mapping global carbon footprint in China. *Nat. Commun.* **2020**, *11*, 6–13. <https://doi.org/10.1038/s41467-020-15883-9>.
5. Olhoff, A.; Christensen, J.M. Emissions Gap Report 2019. United Nations Environment Programme. 2019. Available online: <https://www.unenvironment.org/resources/emissions-gap-report-2019> (accessed on 5 April 2026).
6. Normile, D. China's bold climate pledge earns praise-but is it feasible? *Science* **2020**, *370*, 17–18. <https://doi.org/10.1126/science.370.6512.17>.
7. Xiao, H.; Duan, Z.; Zhou, Y.; Zhang, N.; Shan, Y.; Lin, X.; Liu, G. CO₂ emission patterns in shrinking and growing cities: A case study of Northeast China and the Yangtze River Delta. *Appl. Energy* **2019**, *251*, 113384. <https://doi.org/10.1016/j.apenergy.2019.113384>.
8. Hsu, A.; Tan, J.; Ng, Y.M.; Toh, W.; Vanda, R.; Goyal, N. Performance determinants show European cities are delivering on climate mitigation. *Nat. Clim. Change* **2020**, *10*, 1015–1022. <https://doi.org/10.1038/s41558-020-0879-9>.
9. Pan, H.; Page, J.; Shi, R.; Cong, C.; Cai, Z.; Barthel, S.; Thollander, P.; Colding, J.; Kalantari, Z. Contribution of prioritized urban nature-based solutions allocation to carbon neutrality. *Nat. Clim. Change* **2023**, *13*, 862–870. <https://doi.org/10.1038/s41558-023-01737-x>.
10. Liao, Z.; Zhang, L. Spatio-temporal evolution and future simulation of urban agglomeration expansion in the Guangdong–Hongkong–Macau Greater Bay Area. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 468. <https://doi.org/10.1057/s41599-023-01968-5>.
11. Li, G.; Fang, C.; Li, Y.; Wang, Z.; Sun, S.; He, S.; Qi, W.; Bao, C.; Ma, H.; Fan, Y.; et al. Global impacts of future urban expansion on terrestrial vertebrate diversity. *Nat. Commun.* **2022**, *13*, 1628. <https://doi.org/10.1038/s41467-022-29324-2>.
12. Liang, D.; Lu, H.; Guan, Y.; Feng, L.; Chen, Y.; He, L. Further mitigating carbon footprint pressure in urban agglomeration by enhancing the spatial clustering. *J. Environ. Manag.* **2023**, *326*, 116715. <https://doi.org/10.1016/j.jenvman.2022.116715>.
13. Chen, J.; Fan, W.; Li, D.; Liu, X.; Song, M. Driving factors of global carbon footprint pressure: Based on vegetation carbon sequestration. *Appl. Energy* **2020**, *267*, 114914. <https://doi.org/10.1016/j.apenergy.2020.114914>.
14. Glaeser, E.L.; Kahn, M.E. The greenness of cities: Carbon dioxide emissions and urban development. *J. Urban Econ.* **2010**, *67*, 404–418. <https://doi.org/10.1016/j.jue.2009.11.006>.
15. Xia, C.; Zheng, H.; Meng, J.; Shan, Y.; Liang, X.; Li, J.; Yin, Z.; Chen, M.; Du, P.; Wang, C. Outsourced carbon mitigation efforts of Chinese cities from 2012 to 2017. *Nat. Cities* **2024**, *1*, 480–488. <https://doi.org/10.1038/s44284-024-00088-8>.
16. Gingrich, S.; Kušková, P.; Steinberger, J.K. Long-term changes in CO₂ emissions in Austria and Czechoslovakia-Identifying the drivers of environmental pressures. *Energy Policy* **2011**, *39*, 535–543. <https://doi.org/10.1016/j.enpol.2010.10.006>.
17. Li, R.; Wang, Q.; Liu, Y.; Jiang, R. Per-capita carbon emissions in 147 countries: The effect of economic, energy, social, and trade structural changes. *Sustain. Prod. Consum.* **2021**, *27*, 1149–1164. <https://doi.org/10.1016/j.spc.2021.02.031>.
18. Semieniuk, G.; Taylor, L.; Rezai, A.; Foley, D.K. Plausible energy demand patterns in a growing global economy with climate policy. *Nat. Clim. Change* **2021**, *11*, 313–318. <https://doi.org/10.1038/s41558-020-00975-7>.
19. Liang, D.; Lu, H.; Guan, Y.; Feng, L. Drivers for decoupling carbon footprint pressure from economic growth in China's provinces. *Geogr. Sustain.* **2022**, *3*, 258–267. <https://doi.org/10.1016/j.geosus.2022.08.003>.
20. Huang, Y.; Yu, Q.; Wang, R. Driving factors and decoupling effect of carbon footprint pressure in China: Based on net primary production. *Technol. Forecast. Soc. Change* **2021**, *167*, 120722. <https://doi.org/10.1016/j.techfore.2021.120722>.
21. Álvarez-Berrios, N.L.; Parés-Ramos, I.K.; Aide, T.M. Contrasting patterns of urban expansion in Colombia, Ecuador, Peru, and Bolivia between 1992 and 2009. *Ambio* **2013**, *42*, 29–40. <https://doi.org/10.1007/s13280-012-0344-8>.
22. Fan, W.; Huang, S.; Yu, Y.; Xu, Y.; Cheng, S. Decomposition and decoupling analysis of carbon footprint pressure in China's cities. *J. Clean. Prod.* **2022**, *372*, 133792. <https://doi.org/10.1016/j.jclepro.2022.133792>.
23. Ramaswami, A.; Tong, K.; Fang, A.; Lal, R.M.; Nagpure, A.S.; Li, Y.; Yu, H.; Jiang, D.; Russell, A.G.; Shi, L.; et al. Urban cross-sector actions for carbon mitigation with local health co-benefits in China. *Nat. Clim. Change* **2017**, *7*, 736–742. <https://doi.org/10.1038/nclimate3373>.
24. Zheng, X.; Wang, R.; He, Q. A city-scale decomposition and decoupling analysis of carbon dioxide emissions: A case study of China. *J. Clean. Prod.* **2019**, *238*, 117824. <https://doi.org/10.1016/j.jclepro.2019.117824>.
25. Chontanawat, J.; Wiboonchutikula, P.; Buddhivanich, A. An LMDI decomposition analysis of carbon emissions in the Thai manufacturing sector. *Energy Rep.* **2020**, *6*, 705–710. <https://doi.org/10.1016/j.egyr.2019.09.053>.
26. Armstrong, G. Urban Regeneration in Australia: Policies, Processes and Projects of Contemporary Urban Change. *Urban Policy Res.* **2020**, *38*, 369–370. <https://doi.org/10.1080/08111146.2020.1801138>.

27. Bai, X.; Dawson, R.J.; Ürge-Vorsatz, D.; Delgado, G.C.; Salisu Barau, A.; Dhakal, S.; Dodman, D.; Leonardsen, L.; Masson-Delmotte, V.; Roberts, D.C.; et al. Six research priorities for cities and climate change. *Nature* **2018**, *555*, 23–25. <https://doi.org/10.1038/d41586-018-02409-z>.
28. Liu, Z.; Fang, C.; Sun, B.; Liao, X. Governance matters: Urban expansion, environmental regulation, and PM2.5 pollution. *Sci. Total Environ.* **2023**, *876*, 162788. <https://doi.org/10.1016/j.scitotenv.2023.162788>.
29. Liu, X.; Pei, F.; Wen, Y.; Li, X.; Wang, S.; Wu, C.; Cai, Y.; Wu, J.; Chen, J.; Feng, K.; et al. Global urban expansion offsets climate-driven increases in terrestrial net primary productivity. *Nat. Commun.* **2019**, *10*, 5558. <https://doi.org/10.1038/s41467-019-13462-1>.
30. Wu, Y.; Al-duais, Z.A.M.; Peng, B. Towards a low-carbon society: Spatial distribution, characteristics and implications of digital economy and carbon emissions decoupling. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 761. <https://doi.org/10.1057/s41599-023-02233-5>.
31. Järvi, L.; Havu, M.; Ward, H.C.; Bellucco, V.; McFadden, J.P.; Toivonen, T.; Heikinheimo, V.; Kolari, P.; Riikonen, A.; Grimmond, C.S.B. Spatial Modeling of Local-Scale Biogenic and Anthropogenic Carbon Dioxide Emissions in Helsinki. *J. Geophys. Res. Atmos.* **2019**, *124*, 8363–8384. <https://doi.org/10.1029/2018JD029576>.
32. Yang, S.; Zhu, S.; Deng, G.; Li, H. Study on Influencing Factors and Spatial Effects of Carbon Emissions Based on Logarithmic Mean Divisia Index Model: A Case Study of Hunan Province. *Sustainability* **2022**, *14*, 15868. <https://doi.org/10.3390/su142315868>.
33. Skeie, R.B.; Hodnebrog, Ø.; Myhre, G. Trends in atmospheric methane concentrations since 1990 were driven and modified by anthropogenic emissions. *Commun. Earth Environ.* **2023**, *4*, 317. <https://doi.org/10.1038/s43247-023-00969-1>.
34. Huang, X.; Srikrishnan, V.; Lamontagne, J.; Keller, K.; Peng, W. Effects of global climate mitigation on regional air quality and health. *Nat. Sustain.* **2023**, *6*, 1054–1066. <https://doi.org/10.1038/s41893-023-01133-5>.
35. Wang, C.; Song, J.; Shi, D.; Reyna, J.L.; Horsey, H.; Feron, S.; Zhou, Y.; Ouyang, Z.; Li, Y.; Jackson, R.B. Impacts of climate change, population growth, and power sector decarbonization on urban building energy use. *Nat. Commun.* **2023**, *14*, 1–16. <https://doi.org/10.1038/s41467-023-41458-5>.
36. Wu, C.; Coffield, S.R.; Goulden, M.L.; Randerson, J.T.; Trugman, A.T.; Anderegg, W.R.L. Uncertainty in US forest carbon storage potential due to climate risks. *Nat. Geosci.* **2023**, *16*, 422–429. <https://doi.org/10.1038/s41561-023-01166-7>.
37. Dietz, T.; Rosa, E.A. Effects of population and affluence on CO₂ emissions. *Proc. Natl. Acad. Sci. USA* **1997**, *94*, 175–179. <https://doi.org/10.1073/pnas.94.1.175>.
38. Paul Elhorst, J.; Fréret, S. Evidence of political yardstick competition in france using a two-regime spatial durbin model with fixed effects. *J. Reg. Sci.* **2009**, *49*, 931–951. <https://doi.org/10.1111/j.1467-9787.2009.00613.x>.
39. Lefever, D.W. Measuring Geographic Concentration by Means of the Standard Deviational Ellipse. *Am. J. Sociol.* **1926**, *32*, 88–94. <https://doi.org/10.1086/214027>.
40. Fraley, C.; Raftery, A.E. Model-Based Clustering, Discriminant Analysis, and Density Estimation. *J. Am. Stat. Assoc.* **2002**, *97*, 611–631. <https://doi.org/10.1198/016214502760047131>.
41. Algunaibet, I.M.; Guillén-Gosálbez, G. Life cycle burden-shifting in energy systems designed to minimize greenhouse gas emissions: Novel analytical method and application to the United States. *J. Clean. Prod.* **2019**, *229*, 886–901. <https://doi.org/10.1016/j.jclepro.2019.04.276>.
42. Tian, Y.; Xie, D.; Li, T.; Li, J.; Zhang, Y.; Jing, H.; Zhong, D.; Wang, G. Achieving Chinese Carbon Neutrality Based on Water–Temperature–Radiation–Land Coupling Use. *Front. Environ. Sci.* **2021**, *9*, 740665. <https://doi.org/10.3389/fenvs.2021.740665>.
43. Yilanci, V.; Ulucak, R.; Yaoqi Zhang, V.A. The role of affluence, urbanization, and human capital for sustainable forest management in China: Robust findings from a new method of Fourier cointegration. *Sustain. Dev.* **2022**, *31*, 812–824. <https://doi.org/10.1002/sd.2421>.
44. Chen, J.; Gao, M.; Cheng, S.; Hou, W.; Song, M.; Liu, X.; Liu, Y. Global 1 km × 1 km gridded revised real gross domestic product and electricity consumption during 1992–2019 based on calibrated nighttime light data. *Sci. Data* **2022**, *9*, 202. <https://doi.org/10.1038/s41597-022-01322-5>.
45. Yang, J.; Huang, X. The 30m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. <https://doi.org/10.5194/essd-13-3907-2021>.
46. Berndt, E.R.; Savin, N.E. Conflict among Criteria for Testing Hypotheses in the Multivariate Linear Regression Model. *Econometrica* **1977**, *45*, 1263–1277. <https://doi.org/10.2307/1914072>.
47. Shang, H.; Yin, H. Dynamic simulation research on urban green transformation under the target of carbon emission reduction: The example of Shanghai 1–16. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 754. <https://doi.org/10.1057/s41599-023-02283-9>.
48. Zeng, S.; Yi, C. A study of the potential for peak carbon dioxide emissions in metropolitan areas: The case of China. *Environ. Monit. Assess.* **2023**, *195*, 787. <https://doi.org/10.1007/s10661-023-11371-x>.

49. Jiang, W.; Fu, B.; Gao, G.; Lv, Y.; Wang, C.; Sun, S.; Wang, K.; Schüler, S.; Shu, Z. Exploring spatial-temporal driving factors for changes in multiple ecosystem services and their relationships in West Liao River Basin, China. *Sci. Total Environ.* **2023**, *904*, 166716. <https://doi.org/10.1016/j.scitotenv.2023.166716>.
50. Wang, Z.; Fu, B.; Wu, X.; Li, Y.; Feng, Y.; Wang, S.; Wei, F.; Zhang, L. Vegetation resilience does not increase consistently with greening in China's Loess Plateau. *Commun. Earth Environ.* **2023**, *4*, 336. <https://doi.org/10.1038/s43247-023-01000-3>.
51. Sasse, J.P.; Trutnevyte, E. A low-carbon electricity sector in Europe risks sustaining regional inequalities in benefits and vulnerabilities. *Nat. Commun.* **2023**, *14*, 2205. <https://doi.org/10.1038/s41467-023-37946-3>.
52. Spohn, M.; Bagchi, S.; Biederman, L.A.; Borer, E.T.; Bråthen, K.A.; Bugalho, M.N.; Caldeira, M.C.; Catford, J.A.; Collins, S.L.; Eisenhauer, N.; et al. The positive effect of plant diversity on soil carbon depends on climate. *Nat. Commun.* **2023**, *14*, 6624. <https://doi.org/10.1038/s41467-023-42340-0>.
53. Harper, A.B.; Powell, T.; Cox, P.M.; House, J.; Huntingford, C.; Lenton, T.M.; Sitch, S.; Burke, E.; Chadburn, S.E.; Collins, W.J.; et al. Land-use emissions play a critical role in land-based mitigation for Paris climate targets. *Nat. Commun.* **2018**, *9*, 2938. <https://doi.org/10.1038/s41467-018-05340-z>.
54. Feng, C.; Ye, G.; Zeng, J.; Zeng, J.; Jiang, Q.; He, L.; Zhang, Y.; Xu, Z. Sustainably developing global blue carbon for climate change mitigation and economic benefits through international cooperation. *Nat. Commun.* **2023**, *14*, 6144. <https://doi.org/10.1038/s41467-023-41870-x>.
55. Han, D.; Yu, D.; Qiu, J. Assessing coupling interactions in a safe and just operating space for regional sustainability. *Nat. Commun.* **2023**, *14*, 1369. <https://doi.org/10.1038/s41467-023-37073-z>.
56. Guy, J.; Shears, E.; Meckling, J. National models of climate governance among major emitters. *Nat. Clim. Change* **2023**, *13*, 189–195. <https://doi.org/10.1038/s41558-022-01589-x>.
57. Huo, J.; Meng, J.; Zheng, H.; Parikh, P.; Guan, D. Achieving decent living standards in emerging economies challenges national mitigation goals for CO₂ emissions. *Nat. Commun.* **2023**, *14*, 6342. <https://doi.org/10.1038/s41467-023-42079-8>.
58. Duncanson, L.; Liang, M.; Leitold, V.; Armston, J.; Krishna Moorthy, S.M.; Dubayah, R.; Costedoat, S.; Enquist, B.J.; Fatoyinbo, L.; Goetz, S.J.; et al. The effectiveness of global protected areas for climate change mitigation. *Nat. Commun.* **2023**, *14*, 2908. <https://doi.org/10.1038/s41467-023-38073-9>.
59. Li, L.; Zhang, Y.; Zhou, T.; Wang, K.; Wang, C.; Wang, T.; Yuan, L.; An, K.; Zhou, C.; Lü, G. Mitigation of China's carbon neutrality to global warming. *Nat. Commun.* **2022**, *13*, 5315. <https://doi.org/10.1038/s41467-022-33047-9>.
60. Friedlingstein, P.; Allen, M.; Canadell, J.G.; Peters, G.P.; Seneviratne, S.I. The global tree restoration potential. *Science* **2019**, *366*, 76–79. <https://doi.org/10.1126/science.aay8060>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.