

Article

Spatial–Temporal Difference of Urban Carbon Budget and Carbon Compensation Optimization Partition from the Perspective of Spatial Planning

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Abstract: Spatial planning, recognized as a systematic policy instrument for regional development and governance, plays a crucial role in achieving carbon peak and carbon neutrality. This study establishes a framework for carbon sources/sinks estimation and carbon compensation optimization and conducts empirical research in a representative coal resource-based city. We analyzed the spatial–temporal distribution characteristics of net carbon emissions in Huaibei from 2006 to 2020 using a spatial correlation model and an improved Carnegie–Ames–Stanford approach (CASA). Then, we applied the normalized revealed comparative advantage (NRCA) index and the SOM-K-means clustering model to categorize the carbon pattern into payment, balance, and compensation areas. These areas were further integrated with the “Three-zones and Three-lines” to reclassify nine spatial partition optimization types. Finally, we proposed a targeted emission reduction and sink enhancement optimization scheme. We found that urban carbon emissions and carbon sinks exhibit a significant mismatch, with the net carbon emission intensity reaching 166.76–383.27 t·hm^{−2} from 2006 to 2020, showing a rapid increase followed by stabilization. The high-value area, centered in Xiangshan District, exhibits a circularly decreasing spatial characteristic, gradually extending to the central city of Suixi County. In the optimized payment area, the level of the carbon emission contributive coefficient surpasses the ecological support coefficient (3.92 < ECC < 6.04, 2.09 < ESC < 3.58). The optimized space in the balance area type is primarily situated in mining subsidence areas, leading to a lower overall level (0.42 < ECC < 0.57, 0.49 < ESC < 1.13). The optimized space in the compensation area type (2.24 < ECC < 3.25, 4.59 < ESC < 5.69) requires economic or non-economic compensation from the payment area. The study combines the “Three-zones and Three-lines” with the results of carbon compensation to formulate an urban emission reduction and sink enhancement program, which not only helps to consolidate the theory of low-carbon cities but also effectively promotes the realization of the regional carbon peak goal.

Keywords: carbon budget; carbon compensation; spatial optimization partition; spatial planning; “Three-zones and Three-lines”



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1. Introduction

Since the Industrial Revolution, human activities have markedly elevated carbon dioxide emissions due to extensive fossil fuel consumption and deforestation. Global energy-related CO₂ emissions reached an all-time high of 37.4 Gt in 2023, representing an increase of 410 million tons from 2022 and about three times the level recorded in 1965 [1]. China's carbon emissions from fossil fuels were projected to account for about 32% of total global fossil fuel emissions in 2024, a 0.2% increase compared to the previous year, and the current carbon budget remains highly unbalanced. As a result of global warming and an increase in extreme weather events, these emissions pose a severe threat to the sustainable development of socio-economic and ecological environments [2]. According to the Intergovernmental Panel on Climate Change (IPCC)'s Sixth Assessment Report, the average surface temperature of the world's land and oceans is projected to be approximately 1.5 °C higher than pre-industrial levels by 2040, emphasizing the urgent need for climate change mitigation [3]. As concentrations of population, buildings, transportation, industry, and logistics, cities represent areas most affected by human activities [4], resulting in substantial energy consumption and carbon emissions. Research indicates that about 75% of global carbon emissions originate from urban areas [5,6]. Simultaneously, urban systems are complex, involving natural and artificial processes, both horizontal and vertical, and encompassing economic and social processes. Carbon sources/sinks in cities are complex, diverse, and spatially heterogeneous, significantly impacting the global carbon cycle due to their intensity, efficiency, and flow mechanisms [7,8]. Currently, 127 countries and regions worldwide have set carbon neutrality goals, of which 53 countries, including Switzerland, Italy, and Iceland, have already reached their carbon peak targets. Bhutan and Suriname have successfully achieved carbon neutrality. The United Kingdom, Sweden, France, Denmark, New Zealand, and Hungary have enshrined carbon neutrality in their laws. At the same time, regions and countries such as the European Union, Spain, Chile, and Fiji have also proposed relevant draft legislation. Consequently, achieving emission reduction and sink enhancement has become a strategic focus for ensuring urban sustainable development [9].

In the contemporary era, territorial spatial planning embodies economic, social, cultural, and ecological policies in distinct geographical regions. It directly influences industries, transportation, energy, construction, ecology, and other sectors. Widely recognized, it stands as a systematic policy tool for controlling greenhouse gas emissions [10,11]. In spatial planning addressing global climate change challenges, low-carbon urban construction has increasingly gained attention since 2008 [12,13]. A plethora of quantitative research exists on urban carbon sources/sinks, with a relatively mature accounting method system. However, the majority of research concentrates on macroscopic accounting at the provincial level or larger regional scales, with comparatively fewer studies addressing detailed carbon sources/sinks accounting at the urban scale [14–16]. Regarding optimizing the spatial pattern of carbon sources/sinks, the emphasis often lies on controlling the quantity, size, and structural changes [17,18]. The assessment units are typically county-level administrative units or urban agglomerations combined with main functional area planning [19], and differentiated optimization directions and strategies are proposed based on carbon sources/sinks accounting results [20,21]. Nevertheless, reflecting the spatial characteristics of carbon pattern optimization at the grid scale poses a challenge, making it difficult to translate accounting analysis results into specific spatial planning response strategies [22,23].

The extensive use of remote sensing technology in spatial planning has made carbon sources/sinks estimation methods based on geospatial data a prominent focus. By constructing associated models, statistical carbon sources/sinks are decomposed into spatial

units for estimation [24,25], effectively compensating for incomplete and inconsistent statistical data limitations. Searching for appropriate spatial correlation data becomes crucial for estimating top-down carbon sources/sinks. These data typically include nightlight data, population data, land use data, POI data, and meteorological data [26–29]. Moreover, delineating “Three-zones and Three-lines” in spatial planning can overcome the limitation of restricted main functional areas to the administrative unit level [30]. The “Three-zones” refer to urban space, agricultural space, and ecological space. Urban space is the geographical area primarily dedicated to urban construction and economic development. Agricultural space refers to the land area that supports agricultural production and rural livelihoods. Ecological space encompasses areas with natural attributes, primarily serving the function of providing ecological services or products. By concentrating on more micro-scale units quantitatively, further subdividing the internal space of administrative units, and effectively linking key control parameters, the carbon budget distribution in urban, agricultural, and ecological spaces, which exhibits significant spatial heterogeneity, can be managed [31]. By coordinating the use and combination of various resources within the “Three-zones and Three-lines”, the urban ecosystem’s carbon cycle process and the socio-economic system’s carbon metabolism efficiency can be influenced or even changed [32], optimizing the current carbon pattern.

Previous studies on the spatial distribution of the carbon budget have been relatively simplistic and lack a systematic understanding. Moreover, they have failed to optimize the partition of different functional areas within cities based on the intrinsic relationship between the current carbon budget and the human–environment system. As a result, they struggle to translate the outcomes of accounting analyses into actionable spatial planning strategies, rendering their application to territorial spatial planning impractical. This study centers on urban carbon pattern accounting and spatial partition optimization, contributing to the “carbon peaking and carbon neutrality” goal of territorial spatial planning. Selecting the typical resource-based city of Huaibei as a case study area for empirical analysis, the research aims are as follows: (1) Construct an urban carbon sources/sinks accounting framework based on spatial correlation models and remote sensing estimation models and analyze the spatial and temporal characteristics of net carbon emissions in the case area. (2) Choose relevant indicators to construct a carbon compensation partition methodology and divide the carbon pattern into different types. (3) Formulate an optimization plan for different spatial partition types by using the “Three-zones and Three-lines” data and combining the results of the carbon compensation partition. This research helps the development and refinement of other cities with similar backgrounds. Simultaneously, it provides a theoretical basis for the targeting of emission reduction and sink enhancement, the overall layout, and the allocation of elements in the planning practice, and provides a new direction for the conceptualization of spatial planning programs.

2. Materials and Methods

2.1. Study Area

Huaibei City is located in the northeastern part of Anhui Province, China, spanning from 116°24′ to 117°03′ E and 33°16′ to 34°10′ N. It comprises four county-level administrative units: Xiangshan, Lieshan, Duji, and Suixi (Figure 1). It falls within the warm-temperate and semi-humid monsoon climate zone, characterized by an annual average total solar radiation of 124.5 kCa·m^{−2}, an average surface temperature of approximately 14.8 °C, and an average annual precipitation of about 831.5 mm. The terrain slopes from the northwest to the southeast, with the small presence of low mountains in the northeast. Most of the area is a vast plain, reaching its highest elevation at about 331 m. Additionally, Huaibei is one of the 14 large-scale coal bases prioritized for development in China and is classified as

a typical coal resource-based city. The mining area possesses diverse resource reserves totaling 8.04 billion tons, constituting 17.63% of the coal resource reserves in Anhui Province. In the industrial structure, the secondary industry, primarily composed of energy and raw materials industries, holds an overwhelmingly dominant proportion. The first and third industries lag relatively behind. Specifically, the mining industry exhibits a high location entropy value, reaching 7.6. Huaibei excessively relies on the coal-fired electricity and coal chemical industries, leading to the pronounced issue of high carbon emissions. Simultaneously, this reliance gives rise to a series of ecological and environmental problems, including severe atmospheric pollution due to the exceeding of greenhouse gas emissions standards, continuous expansion of mining subsidence areas, severe geological disasters resulting from vegetation destruction, intensified surface water pollution coupled with excessive groundwater utilization, and decreased productivity from changes in soil structure.

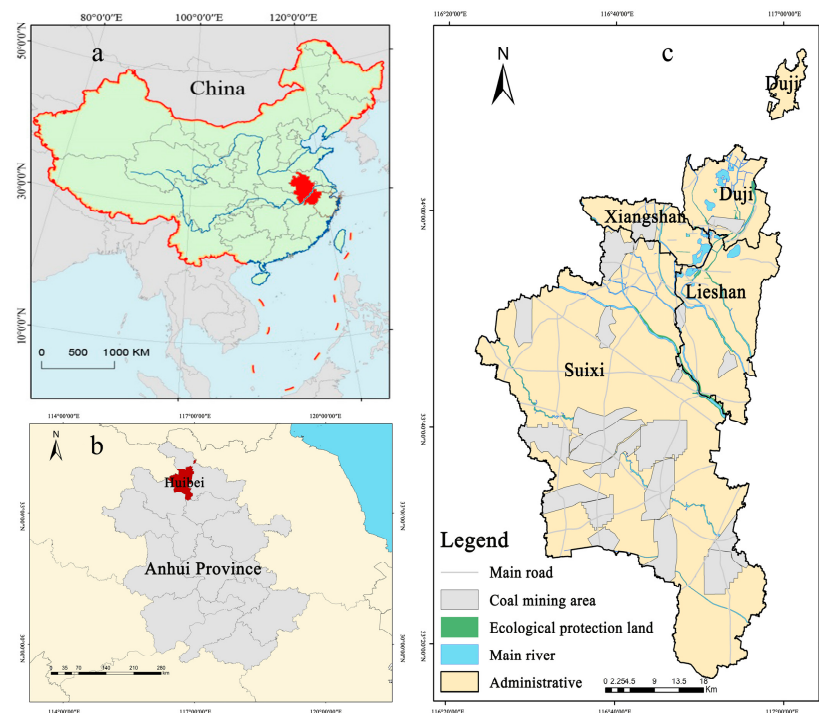


Figure 1. Location of Huaibei City (c), Anhui Province (b), China (a).

2.2. Data Source

The data involved in this study mainly included statistical, remote sensing, meteorological, socio-economic, and vector data. Table 1 shows the primary data types and their accuracies. Given that the Huaibei Statistical Yearbook commenced in 2006, our study encompassed the period from 2006 to 2020. Instances of missing yearly data were addressed by substituting them with approximate years.

Statistical data quantified industrial, agricultural, commercial, transportation, and residential carbon emissions. The associated spatial data for each sector comprised population density data (<https://www.worldpop.org/>), POI data (extracted from Gaode maps), land use type data, and road network data (<https://www.openstreetmap.org/>; accessed on 20 November 2024). These datasets calculate weighted densities, generating high-resolution carbon emission datasets. Remote sensing data and meteorological data were used to produce carbon sink datasets. Notably, MODIS13Q1 was employed, a synthesized dataset with an 8-day temporal resolution (<https://ladsweb.modaps.eosdis.nasa.gov/>; accessed on 20 November 2024). A total of 96 remote sensing images from 2006 to 2020 were downloaded, and NDVI bands were spliced, cropped, and extracted using the MRT

tool. Land cover type data (<https://ladsweb.modaps.eosdis.nasa.gov/>; accessed on 20 November 2024) were categorized into coniferous forests, broad-leaved forests, shrubs, grasslands, farmlands, deserts, water bodies, and unvegetated areas based on the International Geosphere-Biosphere Program (IGBP). Additionally, the spatial distribution of monthly mean temperature, monthly total precipitation, and monthly total solar radiation was determined through the kriging interpolation of meteorol data (<https://data.cma.cn/>; accessed on 20 November 2024). GDP determined the economic contributive coefficient of carbon emissions (<https://www.resdc.cn/>; accessed on 20 November 2024). The “Three-zones and Three-lines” data from the Anhui Urban and Rural Planning and Design Institute was utilized to optimize carbon compensation partitions.

The unified spatial reference format for the research data was WGS_1984_UTM_zone_50N, and the administrative boundary data of Huaibei City were used for mask extraction. Considering that the geospatial data used in the study have spatial resolutions of 1 km and 100 m, the 1 km resolution failed to adequately capture the spatial heterogeneity of carbon emission intensity and carbon sink distribution at the micro-scale. In contrast, the 100 m resolution is more suitable for urban-scale studies, as it enables more accurate carbon compensation partition and policy implementation, balancing both accuracy and practicality.

Table 1. Data type, name, and accuracy.

Type	Name	Accuracy
Remote sensing data	MODIS13Q1	2005–2020, 250 m
	Land cover type	2005–2020, 500 m
Meteorological data	Temperature, precipitation, and solar radiation	2005–2020
Socio-economic data	GDP	2005–2019, 1 km
	Population density	2005–2020, 30 m
Vector data	POI	2005–2020
	Land use types	—
	Road network	2010–2020
	“Three-zones and Three-lines”	—
Statistics data	Energy consumption	2006–2020
	Low heating value, heating value carbon content, and oxygen content of consumption	—

2.3. Methods

Figure 2 summarizes the procedural steps for net carbon emission estimation and compensation partition. The following sections provide a detailed description of the implementation steps. After identifying and determining the elements of the carbon budget and expenditure at the urban scale, we developed a spatial correlation model and an improved Carnegie–Ames–Stanford Approach (CASA) model to account for carbon emissions and carbon sinks in Huaibei City, respectively. Based on the socio-economic data and the results of the carbon budget, the normalized revealed comparative advantage (NRCA) index was formulated, and the SOM-K-means clustering model was used to perform carbon compensation partition, which was divided into payment areas, balance areas, and compensation zones. Combined with the urban, agricultural, and ecological space, we reconstructed nine types of optimized carbon compensation partition and proposed differentiated emission reduction and sink enhancement strategies.

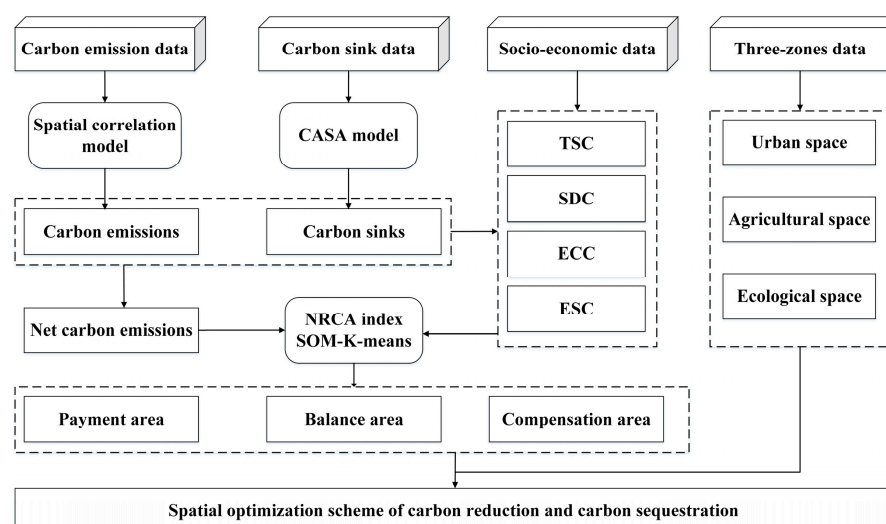


Figure 2. Research framework.

2.3.1. Calculation of Carbon Emissions and Carbon Sinks

The total carbon emissions in the industrial, agricultural, transportation, commercial, and residential sectors were computed based on human activities' energy consumption and carbon emission coefficients. Corresponding spatial data for each sector were filtered to construct the correlation model. The carbon emissions for each sector were then decomposed to the raster pixel scale using the top-down weighted density mapping method, and the spatial distribution of the total carbon emissions was generated at a 100 m resolution from 2006 to 2020. The main formulas for calculating total carbon emissions by sector and carbon emissions at the raster pixel scale are shown in Equations (1) and (2). The spatial data for the industrial sector included industrial land types and POI, with industrial land categorized into Class I, Class 2, and Class 3 industrial land. The spatial data for the agricultural sector comprised agricultural land, and the weighted density was generated based on the density of agricultural land. The spatial data for the transportation sector included road networks, classified into main roads, primary roads, secondary roads, tertiary roads, and ordinary roads, with weights assigned according to a ratio of 5:4:3:2:1. The spatial data for the commercial sector included commercial land and POI, further classified into wholesale and retail, accommodation and dining, and other service industries. The spatial data for the residential sector encompassed residential land and population density, with the weighted density derived from the product of the two.

$$E_{s,i} = \sum_{k=1}^n M_{k,i} \times NCV_k \times CEF_k \times COF_K \times 44/12 \quad (1)$$

$$E_{s,i,j} = \frac{P_{s,i,j}}{SumP_{s,i}} \times E_{s,i} \quad (2)$$

where $E_{s,i}$ is the carbon emissions generated in sector j in year i ; K is the energy type; n is the number of energy types; M is the physical amount of energy consumption; NCV is the average low-level heating value of the energy; CEF is the carbon content per unit of calorific value; COF is the rate of carbon oxidation; and $44/12$ is the coefficient for the conversion of elemental carbon to carbon dioxide. $E_{s,i,j}$ is the carbon emission intensity of pixel j in sector s in year i ; $P_{s,i,j}$ is the weighted density of pixel j in sector s in year i ; and $SumP_{s,i}$ is the total weighted density in sector s in year i .

Net ecosystem productivity (NEP) is a crucial ecosystem indicator, calculated as the disparity between net primary productivity (NPP) and the carbon consumed by soil

microbial respiration. It quantitatively represents the carbon sink capacity of urban ecosystems [33,34]. Initially, we assessed the NPP using the improved CASA model [35]. Then, we established the regression model of temperature and precipitation to estimate the spatial distribution of soil microbial respiration consumption. These distributions were then overlaid to derive the spatial distribution of carbon sinks in Huaibei spanning 2006 to 2020. The formulas are as follows [36].

$$NEP(x, t) = NPP(x, t) - R_H(x, t) \quad (3)$$

$$NPP(x, t) = APAR(x, t) \times \varepsilon(x, t) \quad (4)$$

$$APAR(x, t) = SOL(x, t) \times FPAR(x, t) \times 0.5 \quad (5)$$

$$\varepsilon(x, t) = \varepsilon_{max} \times T(x, t) \times W(x, t) \quad (6)$$

where $NEP(x, t)$ is the net ecosystem productivity of pixel x in month t ($\text{gC} \cdot \text{m}^{-2}$); $NPP(x, t)$ is the net primary productivity of image x in month t ($\text{gC} \cdot \text{m}^{-2}$); $R_H(x, t)$ is the respiratory consumption of soil microorganisms by image x in month t ($\text{gC} \cdot \text{m}^{-2}$); $APAR(x, t)$ is the photosynthetically active radiation absorbed by image x in month t ($\text{MJ} \cdot \text{m}^{-2}$); $\varepsilon(x, t)$ is the light energy conversion rate of image x in month t ($\text{gC} \cdot \text{MJ}^{-1}$); $SOL(x, t)$ is the total solar radiation of image x in month t ($\text{MJ} \cdot \text{m}^{-2}$); $FPAR(x, t)$ is the photosynthetically active radiation uptake ratio (%) of image x in month t ; ε_{max} is the maximum light energy conversion rate; $T(x, t)$ is the temperature stress coefficient of image x in month t ; $W(x, t)$ is the moisture stress coefficient of image x in month t ; and $R(x, t)$ is the total precipitation (mm) of image x in month t .

2.3.2. Carbon Compensation Partition Method

Adopting the four-dimensional framework developed by Xia and Yang (2022) [37], we assert that various factors, including nature, socio-economy, and spatial development degree, may influence carbon budgets. We comprehensively examined indicators such as the total scale of carbon emissions (TSC), the spatial development coefficient (SDC), the economic contributive coefficient (ECC), and the ecological support coefficient (ESC). Specifically, the SDC refers to the proportion of construction land area within the evaluation unit, serving as an indicator characterizing the spatial structural attributes of carbon budgets. The ECC and ESC represent socio-economic and ecological environmental attributes, respectively, with their calculation formulas below.

$$ECC = \frac{G_i / G}{E_i / E} \quad (7)$$

$$ESC = \frac{CA_i / CA}{E_i / E} \quad (8)$$

where G_i and C represent the GDP of unit i and Huaibei, respectively; E_i and E represent the carbon emissions of unit i and Huaibei, respectively; and CA_i and CA represent the carbon sinks of unit i and Huaibei, respectively.

Utilizing the NRCA index and clustering model, the carbon budgets were categorized into three types: payment area, balance area, and compensation area.

1. NRCA Index

The NRCA index is typically employed to assess whether a specific product in a region holds a comparative advantage. It is now extensively utilized to determine the spatial

advantage function [38,39], which, in this study, was applied to identify the advantageous attributes of carbon budgets. The calculation formula is as follows:

$$NRCA_j^i = X_j^i / X - X_j X^i / XX \quad (9)$$

where $NRCA_j^i$ represents the value of the NRCA index for attribute j in unit i . If $NRCA_j^i > 0$, it indicates a comparative advantage. On the contrary, If $NRCA_j^i < 0$, it indicates a lack of comparative advantage; X_j^i represents the indicator value for attribute j in unit i ; X_j represents the total value of attribute j ; X^i represents the total indicator value for all attributes in unit i ; and X represents the overall total value for all attributes and units.

2. SOM-K-means Clustering Model

Self-Organization Mapping (SOM) is an unsupervised competitive neural network introduced by Kohonen (1982) [40]. It can map intricate nonlinear relationships from high-dimensional features to low-dimensional relationships while preserving topological similarity. The K-means clustering algorithm is an iteratively solved method for clustering analysis, capable of categorizing and organizing data with similar features in a dataset. The SOM-K-means clustering model was employed to classify the NRCA index for each indicator, thereby categorizing the type of carbon compensation partition. Initially, SOM was utilized to cluster the data, determining the number of categories and centroids for each category. The results of this initial clustering were then input into the K-means algorithm, yielding the final clustering results.

3. Results

3.1. Spatial–Temporal Characteristics of Net Carbon Emissions

In terms of time series changes, the average net carbon emission intensities in 2006, 2010, 2015, and 2020 were $166.76 \text{ t} \cdot \text{hm}^{-2}$, $298.63 \text{ t} \cdot \text{hm}^{-2}$, $453.94 \text{ t} \cdot \text{hm}^{-2}$, and $383.27 \text{ t} \cdot \text{hm}^{-2}$, respectively. This exhibits a trend of rapid increase followed by a slight decrease. Statistics on the proportion of carbon sources/sinks in different administrative districts can be found in Table 2. These reveal that from 2006 to 2020, the proportion of carbon source areas has significantly increased, while the proportion of carbon sink areas has decreased significantly, both in the municipality and districts. Particularly noteworthy is the area of carbon sources in Lieshan District, which increased from 99 km^2 in 2006 to 250 km^2 in 2020. The proportion of carbon sources in Lieshan District increased from 25.79% to 64.75%, marking a 2.51 times increase. When comparing the proportion of carbon source/sink areas in different jurisdictions, the order of carbon sources is Xiangshan District, Duji District, Suixi County, and Lieshan District, in descending order. The order of carbon sinks is Lieshan District, Suixi County, Duji District, and Xiangshan District, in descending order.

Table 2. Carbon sources/sinks statistics in Huaibei (unit: km^2 ; %).

Year	Types	Huaibei		Xiangshan		Duji		Lieshan		Suixi	
		Area	Ratio	Area	Ratio	Area	Ratio	Area	Ratio	Area	Ratio
2006	Carbon source	1418	51.76	128	90.69	187	81.81	99	25.79	1004	50.57
	Carbon sink	1326	48.24	13	9.31	42	18.19	299	74.21	981	49.43
2010	Carbon source	1514	55.24	129	91.53	194	84.75	197	51.00	994	50.08
	Carbon sink	1227	44.76	12	8.47	35	15.25	189	49.00	991	49.92
2015	Carbon source	2275	83.02	130	92.05	207	90.62	367	95.09	1571	79.15
	Carbon sink	466	16.98	11	7.95	22	9.38	19	4.91	414	20.95
2020	Carbon source	1999	72.95	135	95.85	196	85.85	250	64.75	1417	71.42
	Carbon sink	742	27.05	6	4.15	33	14.15	136	35.25	568	28.58

Figure 3 shows the spatial distribution of net carbon emission intensity for the years 2006, 2010, 2015, and 2020. Since the primary contribution to net carbon emission intensity originates from carbon emissions in the industrial sector, its spatial distribution is consistent with the spatial characteristics of carbon emission intensity. Within the main urban area, high-value regions exhibit a spatial pattern centered around the Xiangshan District, depicting a concentric and decreasing trend from the inner to outer circles. In Suixi County, the spatial characteristics transition from an initially punctate distribution to a dispersed distribution in patches. The contribution of the net carbon emission intensity mainly comes from the energy consumption component, and the total carbon emissions in Huaibei City increased rapidly from 2006 to 2014, rising by 267.41%. The growth rate of the total carbon emissions slowed after 2014, showing a stable and fluctuating trend. Analyzing the development trend of total net carbon emissions in Huaibei City, the influence of policy is evident. Ecological security was incorporated into the national security system for the first time in 2014, becoming a crucial component of national security. In response to national pilot initiatives for low-carbon cities and climate-adapted cities, the “Work Program for Energy Conservation and Emission Reduction in Huaibei City (13th Five-Year Plan)”, the “Work Program for Greenhouse Gas Control in Huaibei City (13th Five-Year Plan)”, and the “Pilot Construction of Low-Carbon Cities in Huaibei City Action Plan (2017–2020)”, among other documents, have focused on optimizing industrial and energy structures, reducing energy consumption, and cutting carbon dioxide emissions per unit of GDP. These efforts have resulted in significant progress in promoting the transformation and development of resource-oriented cities, striving to create a landscape eco-city conducive to living, working, and visiting.

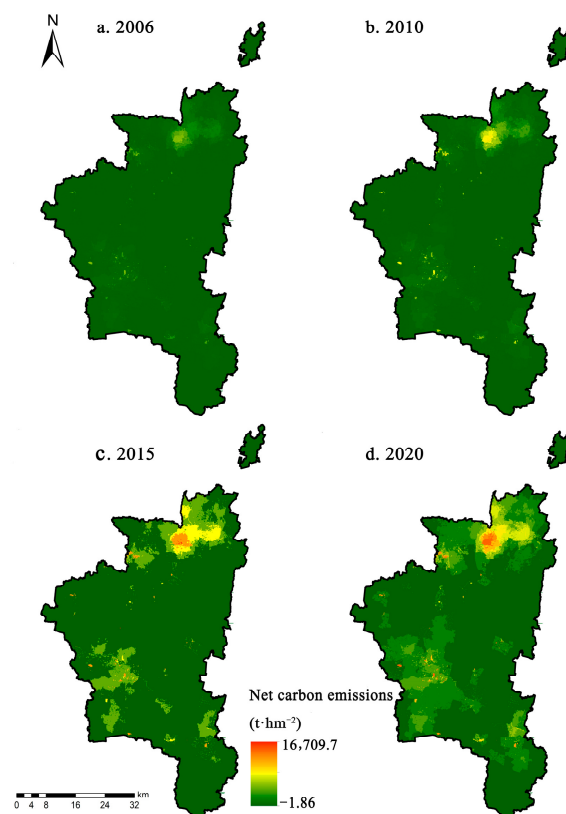


Figure 3. Spatial distribution of net carbon emissions.

Figure 4 plots the distribution center of gravity and standard deviation ellipse of net carbon emission intensity. This visualization allows for an understanding of the evolutionary trend of the primary spatial distribution range of net carbon emission intensity.

Regarding the center of gravity of the distribution, it generally remains in the northeastern direction and gradually shifts southwestward from Xiangshan District to Suixi County. The parameters of the standard deviation ellipse calculation results (Table 3) indicate that the shape and direction of the standard deviation ellipse for the distribution remained relatively stable, with rotation angles maintained in the northeast direction. The semi-minor axis, semi-major axis, and area of the standard deviation ellipse exhibit a pattern of increase followed by a decrease, reflecting an overall evolutionary trend of gradual increase. The results suggest that the distribution of areas with high net carbon emission intensity values is becoming more decentralized.

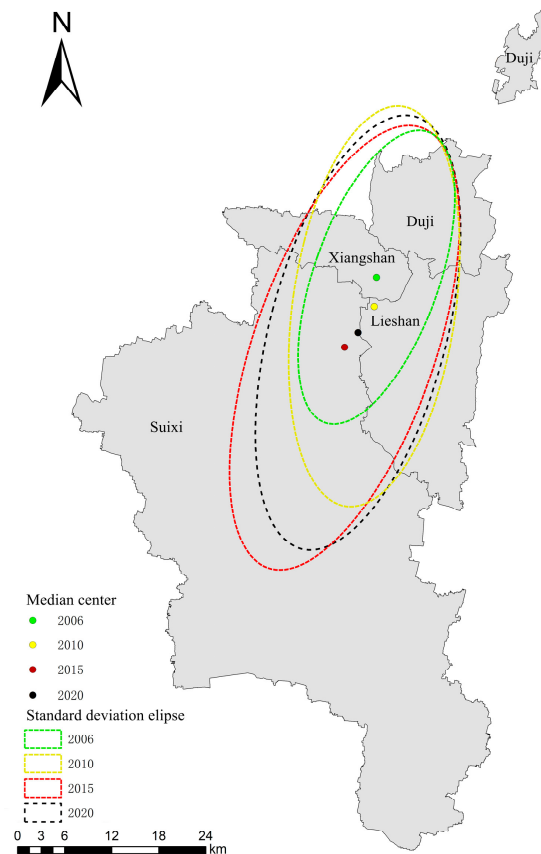


Figure 4. Elliptical distribution of standard deviation of net carbon emission intensity.

Table 3. Standard deviation ellipse parameters of net carbon emission intensity.

Year	Area (km ²)	Semi-Minor Axis (km)	Semi-Major Axis (km)	Rotation Angle (°)
2006	493.39	7.98	19.69	19.50
2010	843.02	10.39	25.81	8.02
2015	1081.59	11.55	29.78	19.18
2020	1011.93	11.26	28.58	14.65

3.2. Carbon Compensation Spatial Partition

Figure 5 shows the NRCA indices for the TSC, SDC, ECC, and ESC. Specifically, the advantage zones of the TSC are concentrated in the main and central urban areas of Suixi County, with administrative units exemplified by Gaoyue Street (59.61) and Hancun Town (54.30). These areas necessitate focused efforts on energy conservation and emission reduction. The disadvantage zones of the SDC, represented by administrative units such as Shuangduiji Town (−107.75) and Gurao Town (−103.87), indicate low energy–economic output efficiency and issues related to an extensive economic development model which

needs to prioritize improving energy utilization efficiency. The disadvantage zones of the ESC—represented by administrative units including Qugou Town (−87.18), Sandikou Street (−68.65), and Quyang Street (−53.93), all situated within the Xiangshan District—are characterized by relatively scarce carbon sink resources.

In Rstudio, the SOM-K-means algorithm was employed to divide Huaibei into fifteen payment areas, nine balance areas, and six compensation areas. Table 4 shows the average values of the NRCA indices for the different types of regions. Payment areas exhibit high levels of economic development, with the TSC at a moderate level. A significant characteristic is the presence of regions with a severe mismatch in NRCA indices between their ECC and ESC, with values of 45.35 and −33.44, respectively. These areas are primarily located in Lieshan District, Xiangshan District, and Duji District and require payment mechanisms to mitigate adverse external effects on the ecological environment. The NRCA indices for ECC and ESC in balance areas are relatively stable, with values of −34.95 and −19.65, respectively, while the NRCA value for the TSC is higher than in payment areas. These areas are mainly situated at the junction of Lieshan District, Xiangshan District, and Duji District, for which neither payment nor compensation is required. Compensation areas have smaller average NRCA values for both the TSC and ECC than payment areas, but their mean value of ESC is the highest. These areas are primarily located on the periphery of Suixi County and require economic or non-economic compensation.

Table 4. Each NRCA index in different carbon compensation partition types.

Type	TSC	SDC	ECC	ESC
Payment area	−10.64	−1.27	45.35	−33.44
Balance area	34.20	20.40	−34.95	−19.65
Compensation area	−21.16	−27.00	−76.04	124.21

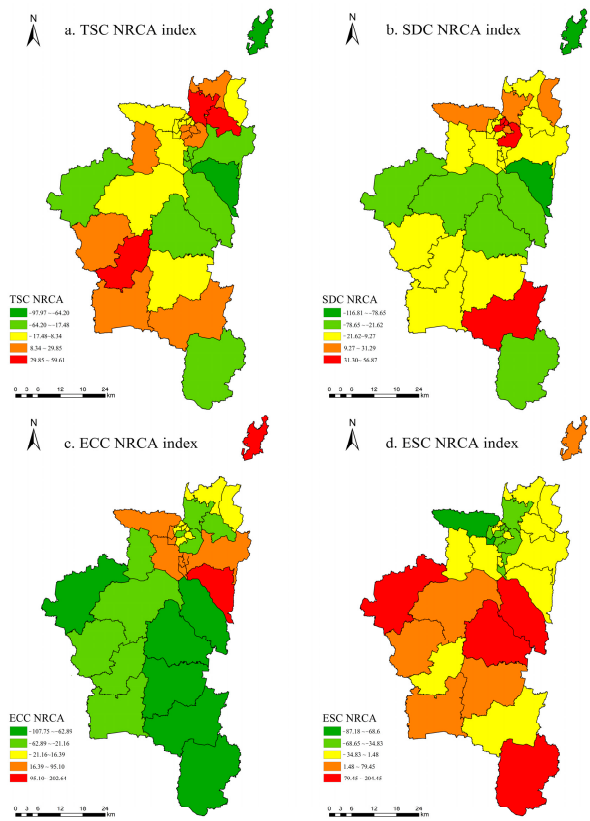


Figure 5. Spatial distribution of each NRCA index.

Leveraging the theoretical framework of carbon compensation partition optimization, the payment areas, balance areas, and compensation areas were overlaid with urban, agricultural, and ecological space. The carbon pattern was restructured into nine types, namely Payment area–Urban Space (PU), Payment area–Agricultural Space (PA), Payment area–Ecological Space (PE), Balance area–Urban Space (BU), Balance area–Agricultural Space (BA), Balance area–Ecological Space (BE), Compensation area–Urban Space (CU), Compensation area–Agricultural Space (CA), and Compensation area–Ecological Space (CE). Figure 6 shows the distribution of the optimized zones for each type.

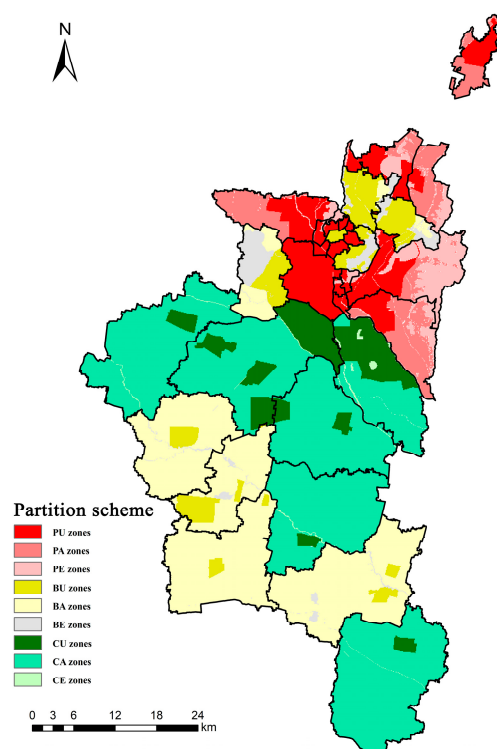


Figure 6. Spatial distribution of carbon compensation optimization partition.

PU zones are mainly located in the traditional industrial space of the main urban areas. While the region boasts a well-developed economy and a high or relatively high degree of industrialization, the available carbon sink resources are insufficient to offset its carbon emissions fully ($ECC = 3.92$, $ESC = 2.09$). The region should optimize industrial and energy structures, implement low-carbon intelligent transportation, construct energy-efficient buildings, and pursue other measures to mitigate urban carbon emissions. The overarching development goal is to move towards a “high-tech, high value-added, low-pollution, low-energy consumption” direction. It is crucial to systematically implement greening projects and systems to increase carbon sinks in built-up areas, thereby advancing the construction of green carbon sink capacity. PA zones are mainly in the Lieshan, Xiangshan, and Duji Districts. Despite favorable basic conditions for agricultural development in these areas, they face significant interference from human activities ($ECC = 6.04$, $ESC = 3.58$). In the ongoing modernization of agriculture, the ecological degradation resulting from excessive urbanization and industrialization will be mitigated by optimizing spatial layouts in urban and rural areas. Additionally, measures will be implemented to control agricultural practices that harm the ecosystem. PE zones are mainly located in the ecological conservation area of Lieshan District, boasting high biodiversity, environmental quality, and aesthetic value in its green landscape ($ECC = 3.96$, $ESC = 2.36$).

Nevertheless, it faces a challenge in establishing an effective connection with Xiangshan Park in the northwest, diminishing its service function to the city center. A synergistic approach should be adopted by integrating the ecological corridor design of the blue landscape, thereby enhancing connectivity between the main city's northwest and southeast landscape functions.

BU zones are mainly located in the peripheral region of the traditional industrial spaces and the mining subsidence area of Suixi County ($ECC = 0.44$, $ESC = 0.54$). There is potential to moderately enhance urbanization efforts, facilitating the establishment of a green, low-carbon, and circular industrial system. Proactive measures should be implemented to advance ecological restoration and governance in villages impacted by coal mining subsidence, like establishing ecological and humanistic spaces to augment the carbon absorption capacity in these areas. BA zones are mainly located in the mining collapse area southwest of Suixi County ($ECC = 0.57$, $ESC = 1.13$). Through artificial means such as land reclamation and biological restoration, efforts can improve soil, vegetation, and water conditions. Continuing initiatives such as reclamation, aquaculture, and the ecological management of water systems can be implemented to enhance ecological economic value. BE zones are mainly located in the western part of Xiangshan District and the surrounding urban space areas in Suixi County. The ecological environment is fragile and sensitive, with a relatively low capacity for resource and environmental carrying ($ECC = 0.42$, $ESC = 0.49$). It is essential to control development intensity, rigorously manage various development activities, and adhere to point-based development. BE zones should have reasonable control over the scale of tourist facility construction, ensuring that the stability and relative integrity of the ecosystem are not compromised.

CU zones are mainly located in the central region of Suixi County ($ECC = 2.69$, $ESC = 5.13$). It is advisable to moderately enlarge the development space for modern service industries and strategic emerging industries. Strategies should be actively pursued, including promoting industrial structural transformation and expediting the relocation of vital functions from the main urban area to this region. CA zones are mainly located in the northern and southeastern parts of Suixi County, boasting excellent agricultural production conditions and a robust carbon sink capacity in their ecosystem ($ECC = 2.24$, $ESC = 4.59$). Emphasis should be placed on improving the per-unit production capacity of agricultural products. This objective can be realized by expanding the agricultural product industry chain, elevating the added value and depth of processing for agricultural products, and fostering the establishment of specialty agricultural product areas. CE zones are mainly located in the ecological conservation space of Suixi County, characterized by favorable natural ecological conditions and abundant carbon sink resources ($ECC = 3.25$, $ESC = 5.69$). It is essential to convert ecological advantages into economic strengths and establish a modern ecological industrial system.

4. Discussion

4.1. Comparison of Carbon Emission and Carbon Sink Results

To validate the precision of our carbon emissions, they were initially compared with carbon emission data from the Multi-Resolution Emission Inventory for China (MEIC) model. The MEIC model encompasses emission data from 1990 to 2018, covering 10 major air pollutants and greenhouse gases. The CO_2 emissions are categorized by sectors/industries, including electric power, industry, civil, transportation, and agriculture [41,42]. The MEIC model indicates that Huaibei City's total carbon emissions in 2015 ranged from 10,000 to 20,000 million tons, markedly exceeding those of neighboring cities. The comparison results align closely with this study's total carbon emissions, estimated through statistical data accounting and falling within the same order of magnitude. For

a more detailed analysis of carbon emission spatial accuracy, the 2020 emission intensity data based on nightlight was generated for comparison. The distribution range of emission intensities derived from nightlight data is broader, constituting 91.39% of the total, with values ranging from 0 to $172.10 \times 10^4 \text{ t} \cdot \text{km}^{-2}$. In contrast, the distribution range of carbon emission intensities based on spatial modeling is 12.41% narrower than that of nightlight data. The highest carbon emission intensity value is significantly greater than that observed data in this study, which is attributable to the saturation issue in nightlight data elements. An examination of the scatter plot for carbon emission intensity produced by both methods reveals a spillover effect from nightlight, causing some pixels to exhibit high brightness values in areas with weak brightness due to surrounding bright light influences (Figure 7a). This results in elevated carbon emission intensity values at specific sample points. Consequently, the carbon emission intensity data generated based on correlation vector data boasts higher spatial resolution and more realistically portrays the spatial distribution of urban carbon emission sources, accurately identifying high-value areas of urban carbon emissions.

Concerning the precision assessment of carbon sinks, the estimated results were compared with the MODIS MCD17A3H NPP product for 2000–2020. A total of 2732 sample points were selected, and a linear regression was performed using the multi-year averages of the two NPP products. Figure 7b shows the comparison results of the two NPP products, indicating a significant correlation between them ($R^2 = 0.755$, $p < 0.01$) [36]. In summary, the net carbon emission estimation results are considered reliable in terms of both total quantity and spatial distribution. The high precision of the assessment effectively reflects the actual conditions in the region.

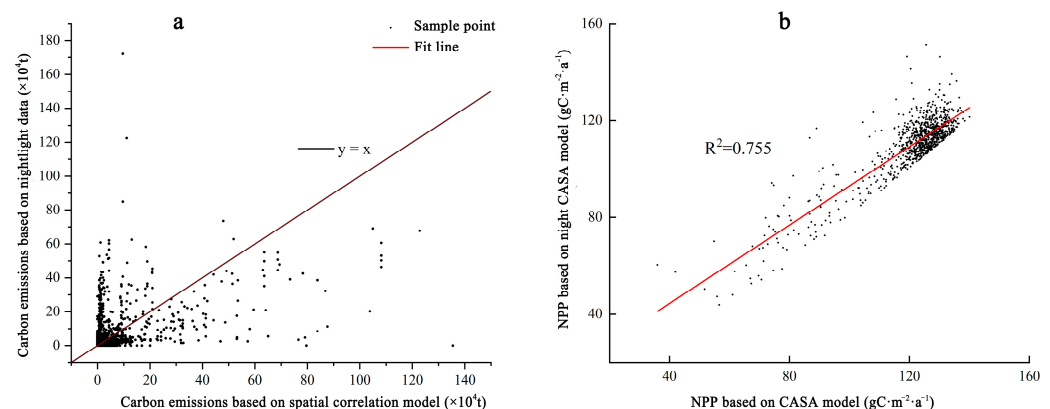


Figure 7. Scatter plot of carbon emissions (a) and carbon sinks (b) results.

4.2. Limitations and Improvements

(1) There was uncertainty in our net carbon emission and carbon sink estimates. The uncertainty in the results of carbon emissions accounting primarily stems from the carbon emission coefficients, statistical data parameters, the precision of associated spatial data, and the absence of genuine and reliable measured carbon emission data. The total carbon emissions for each sector rely on a top-down accounting method, incorporating default values from the IPCC or empirical coefficients derived from relevant studies for certain factors. Moreover, the absence of some statistical data introduces errors in determining relevant parameters. For instance, in the carbon emission accounting for the transportation sector, the default vehicle energy consumption type is gasoline. In addition, the current associated spatial data only includes basic information such as location, name, and type. More detailed attribute information, such as industrial enterprise output values, building age and height for residential land, and road traffic flow, is missing and challenging to obtain. These gaps in the data could be supplemented with field surveys and ongoing

research. By combining field surveys with continuously enriched statistical data, the weighted density accuracy can be enhanced.

Although the remote sensing data sources used in the carbon sink assessment are relatively reliable, they are influenced by various interpolated pixels, interpolation methods, data accuracy, and classification standards [43]. These factors may result in differences between the NPP estimation results and those of other related studies. In the future, establishing vegetation monitoring stations in urban areas can provide abundant and continuous measured data for urban ecosystem carbon cycle studies and regional model simulation studies, which can help accurately assess carbon dynamics' spatial and temporal patterns in urban ecosystems.

(2) There were limitations in the latest data updates. Carbon emission and sink accounting were conducted at five-year intervals, and the limited access to multi-source geospatial data and statistical information resulted in the latest carbon partition optimization study concluding in 2020. However, the global and national climate agendas have shifted significantly in recent years, with policy priorities increasingly focusing on carbon neutrality, sustainable development, and the green energy transition. Particularly in resource-based cities, stricter emissions regulations, the rapid adoption of renewable energy technologies, and changes in industrial practices may have influenced carbon emission patterns post-2020. While the 2006–2020 period reflects the region's actual carbon emissions and sinks, it may not fully capture the latest trends and changes. To improve the accuracy and relevance of future studies, updated data will be incorporated in subsequent analyses, enhancing the carbon peaking strategy for Huaibei City.

(3) The implementation of carbon compensation partition optimization. When selecting key indicators for the advantage index analysis, only factors such as TSC, SDC, ECC, and ESC were considered to construct the theoretical framework for the carbon compensation partition. However, the synergistic reduction in carbon emissions in compensation is influenced by per capita carbon emissions level, industrial structure, technological innovation, and more. It is essential to enrich and enhance the theoretical framework of regional carbon compensation and conduct the division of carbon compensation partition more scientifically and reasonably. Additionally, the study combines the results of "Three-zones and Three-lines" and carbon compensation partition and proposes corresponding optimization schemes. However, the study lacks a quantification-based evaluation of the applicability of these optimization schemes. In subsequent research, the Bayesian network model, multi-objective optimization, multi-criteria decision-making, logistic regression, and other methods can be integrated to focus on changes in carbon sources/sinks regarding quantity, scale structure, and spatial configuration, which will further evaluate the effectiveness of emission reduction and sink enhancement.

4.3. Application in Territorial Spatial Planning

Territorial spatial planning is categorized into master planning, detailed planning, and special planning, and the results of this research can be applied to the municipal spatial planning system with multi-level implementation. The master plan focuses on forming a low-carbon spatial pattern and overall strategic deployment. Based on the results of the high-precision carbon emissions and sink accounting, it identifies key issues in low-carbon development related to natural resources, socio-economics, and spatial development, considering local conditions. It also outlines significant development trends, clarifying key areas and regions. The formulated target systems include total carbon emissions, carbon dioxide per unit of GDP, energy consumption per unit of GDP, and carbon dioxide emissions per capita. Based on the optimization results of carbon compensation partition, the phased and categorical control of urban, agricultural, and ecological spaces is specified.

Detailed planning is oriented toward land use control, where urban space is constrained by the carbon emission intensity of land use to promote carbon source control. Measures include improving the layout of various public service facilities, constructing energy-efficient buildings, establishing an effective public transportation network and pedestrian infrastructure, and developing a “blue-green network” of urban public space to enhance carbon sinks. Agricultural and ecological spaces primarily focus on increasing carbon sinks and should adhere to “mountains, water, forests, fields, lakes, and grasses” as a community of life. Ecosystem protection and restoration should be carried out, and mechanisms for realizing the value of carbon sinks should be explored through land remediation, particularly in the case of a city that requires comprehensive remediation of mining areas and subsidence zones.

Specialized planning breaks down key areas and defines specific pathways. In Huaibei City, there are issues such as excessive industrial carbon emissions, rapid growth of carbon emissions from transportation, an irrational energy structure, and severe ecosystem degradation. Industrial, transportation, energy, and ecological planning should be developed to define these specific pathways. A trend of gradual diffusion and distribution is observed based on the spatial distribution of net carbon emission intensity. Industrial planning can integrate the current industrial distribution status with the development direction of industrial structure adjustment, proposing a multi-center agglomeration spatial layout model. In transportation planning, the development of green public transportation should be prioritized, forming a public transportation system with rail transit and rapid transit as the backbone, conventional buses as the primary mode, and taxis as the auxiliary. Energy planning should optimize the energy structure and vigorously promote clean energy sources in residential and industrial areas, such as solar, biomass, and wind energy. The ecological plan should include the division of restoration zones, such as ecological conservation areas, ecological service areas, ecological restoration core zones, and comprehensive control areas, with differentiated ecological restoration strategies for each.

5. Conclusions

This study centers on the “carbon peak and carbon neutrality” target orientation for territorial spatial planning, emphasizing urban carbon pattern accounting and spatial partition optimization. Huaibei, a typical resource-based city, is the case study area for empirical analysis. The following conclusions were drawn.

(1) Net carbon emission estimates reveal a varied spatial pattern of net carbon emission intensity in Huaibei, with high-value areas gradually spreading. The proportions of carbon sources/sinks differ across different jurisdictions, with the main city exhibiting a spatial characteristic of decreasing intensity from its inner to outer circles and Suixi County transitioning from point-like distribution to piecewise distribution.

(2) Based on NRCA index values of key indicators, carbon compensation partition results employed a SOM-K-means clustering partitioning model to categorize Huaibei into fifteen payment zones, nine balancing zones, and six compensation zones. The payment-type areas are primarily concentrated in the central urban districts, while the balance-type areas are mainly situated at the interface between the central urban areas and Suixi County. The compensation-type areas are mainly located in the peripheral regions of Suixi County.

(3) Combining “Three-zones and Three-lines” with carbon compensation partition, nine types of carbon compensation partition were reconstructed, proposing a spatial optimization plan for differentiated emission reduction and sink enhancement in functional areas. For the various zones within the payment-type areas, efforts should focus on enhancing the decongestion function to reduce carbon emissions, strictly prohibiting agricultural activities that harm the ecosystem, and strengthening ecosystem connectivity. Development

intensity should be carefully regulated in the balance-type areas, with particular emphasis on the ecological restoration of mining subsidence regions. Designated spaces should be developed in the compensated areas for emerging industries, modern agriculture, and ecological industry systems.

The research framework proposed in this paper demonstrates notable applicability and flexibility, making it suitable for application in other resource-based cities. For non-resource cities, the results of the carbon compensation partition can be integrated with the “Three-zones and Three-lines” approach to develop emission reduction and sink enhancement strategies. However, these strategies must be tailored to each city’s industrial structure, energy consumption patterns, green space distribution, and other contextual factors. Future research could include cross-regional comparative studies to explore differences in optimized carbon compensation partitions. Additionally, the dynamic relationship between carbon emission reduction and socio-economic development should be further examined to identify the optimal pathway for fostering high-quality regional development.

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