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Comparison of Spatialization Process of Carbon Emissions

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Abstract: With the goals of carbon peaking and carbon neutrality, carbon emissions have gradually become a key area of research in environmental science and are of great importance for climate change and sustainable development. Spatialization of carbon data can visually show the differences in emissions between industries and regions. High spatio-temporal resolution data can be used to build a long-time series atlas of carbon emissions, which provides data support for carbon emission monitoring and carbon cycle research. Therefore, starting from the data form and response scale, this paper explains the spatialization process of carbon emissions based on nighttime lighting (NTL) and social statistics data, summarizes the different spatialization methods in different scenarios of carbon emissions change, and analyzes how to spatially visualize carbon emissions at different scales from the perspective of country, province and city. Finally, it discusses the problems encountered in this process and makes suggestions that provide a reference for the efficient implementation of carbon reduction policies.

Keywords: carbon emissions; spatialization; data processing

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1 Introduction

Global climate change has become one of the greatest challenges to human development. The Paris Agreement[1], as a major commitment by countries to address climate change, has become a critical component in building a community with a shared future for humanity[2]. Therefore, accurate measurement of carbon emissions in the research sector will contribute to the implementation of carbon peaking and carbon neutrality goals. As the world's largest carbon emitter[3], China's carbon emissions come mainly from sectors such as electricity[4],

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transportation[5], agriculture[6], construction[7] and industrial production[8]. Carbon data can be used to measure greenhouse gases, such as carbon dioxide, produced by individuals, organisations, or regions during production and consumption processes. Different industries have their corresponding carbon emissions data, and different regional scales also have corresponding carbon data, such as national carbon data list, provincial carbon data list, city carbon data list, and county carbon data list. Different regional scales also have corresponding carbon data, such as national provincial city and county carbon data. Spatialization of carbon emissions data can visually display the differences in carbon emissions across different geographical areas[9], spatial scales[10,11] and industries[12], making it easier for researchers to answer questions from a geographical perspective, such as which regions have the most effective carbon emission reduction and which industries have urgent carbon reduction needs, which is also integrated with multi-source data such as GDP, POI, population, land use, and transportation networks. The spatialization process also involves data transformation issues, such as refining large-scale data to small-scale areas and simulating area-source carbon emissions from point-source carbon data. Clarifying the spatialization mechanism of carbon data will help to formulate feasible carbon emission reduction plans. Therefore, this paper focuses on the spatialization of carbon emissions data, systematically reviews the relevant literature on carbon data processing, summaries the data processing scenarios and corresponding methods involved, and compares carbon emissions data processing in cross-scale application contexts from both technical and application perspectives, so as to provide a reference for the related research involving carbon data processing research.

2 Carbon Emission Data

Carbon emissions are often used as a shorthand for greenhouse gas emissions, and this paper focuses on carbon dioxide emissions. From a societal perspective, carbon emissions data can be obtained from public government data platform, research institutions and corporate organizations. Carbon data includes emission volumes, carbon emission intensity and emission inventories. Emissions data can describe the carbon emissions generated by a certain region, industry or activity, while carbon intensity measures emissions per unit of GDP. Organizations calculate their direct and indirect emissions from different stages of production and daily activities to create a carbon inventory.

From a geoscience perspectives, carbon data collection can be broadly divided into satellite remote sensing and social statistics[13]. Remote sensing satellites provide data on the global distribution data greenhouse gases and terrestrial carbon , with advantages such as stability, wide spatial coverage, and cost-effectiveness. Current remote sensing satellites focusing on carbon gas monitoring include OCO-2, GOSAT, and TanSat. However, these data can be influenced by atmospheric circulation, leading to significant errors when analyzing carbon emissions at smaller scales, such as counties or villages. Research by scholars like Elvidge[14] and Doll[15] has shown a significant correlation between nighttime light intensity and carbon emissions. Commonly used nighttime light remote sensing satellites include the U.S. Soumi NPP and DMSP-OLS and the Luojia-1 satellite led by a team from Wuhan University, as shown in Table 1. As noted by Yu[16], DMSP-OLS data suffer from saturation problems, while NPP-VIIRS provides higher resolution and better imaging. For small-scale studies, nighttime light data from Luojia-1 offers advantages over the other satellites and correlates well with carbon emissions[17]. Nighttime light data provide researchers with comprehensive and continuous carbon emission data, but factors such as regional development, population density, and industrial park distribution can affect the accuracy of carbon emissions derived from these data. Therefore, nighttime light data is often used in conjunction with other data sources. Social statistical data on carbon emissions can be used for large-scale simulations of regional carbon emissions. In GIS, these data can be represented as point data, line data, or polygon data[18].

Table 1 Commonly used nighttime light remote sensing satellites

Satellite name	Country	Acquisition Pathway	Launch year		Data products	Spatial resolution	Data characteristics
DMSP-OLS	USA	NOAA	DMSP 5D-3F15	1999	Annual composite stable light data (1992–2013)	–1000 m	Widely used, the resulting product remains one of the most widely applied nighttime light remote sensing datasets to date. However, affected by sensor limitations, the maximum brightness of the light signal is capped at 63, leading to data saturation issues. This poses challenges for long-term series analysis and issues like the "blooming effect" on the light boundary
			DMSP 5D-3F16	2001			
			DMSP 5D-3F17	2006			
			DMSP 5D-3F18	2009			
NPP-VIIRS	USA	NOAA	2011		Annual composite data (2015, 2016) Monthly composite data (April 2012 to present)	–500 m	Compared to DMSP-OLS, it offers higher spatial resolution and better imaging effects, which are beneficial for studying finer regional scales. However, the short temporal resolution hasn't fully addressed issues like removing abnormal light signals and background noise
					Nighttime original data (January 19, 2012 to present)	–750 m	
Luojia-1	China	Luojia-1 official website	2018		Original data (produced from June 2018)	–130 m	Higher spatial resolution than DMSP-OLS and NPP-VIIRS. Ideally, it can complete global nighttime light remote sensing data collection within 15 days

3 Spatial Processing of Carbon Emission Data

The study of carbon emissions and its temporal and spatial changes is of great significance for China's development. The spatialization of carbon emissions data can be seen as a process of making abstract data more concrete. Whether using remote sensing data to infer regional carbon emissions or simulating them based on point, line, and polygon data, spatial proxy parameters are often selected to better achieve data spatialization. In this process, classic geographic theories such as Tobler's First Law of Geography, spatial spillover effects, and spatial interpolation are widely used to help explain the spatio-temporal variations in carbon emission intensity.

3.1 Carbon Emission Spatialization Analysis Based on Nighttime Light Data

Nighttime light remote sensing satellites can detect urban lighting. Shi *et al.*[19] noted that the pixel DN values of nighttime light data are positively correlated with CO_2 emissions at the corresponding locations, so nighttime light data can evaluate regional carbon emissions at the grid level. Different satellites also have their own advantages. For example, NPP-VIIRS offers higher resolution and better timeliness than DMSP-OLS data, but DMSP-OLS data have a longer time span, allowing for deeper time-series research. The DMSP-OLS-like nighttime light remote sensing dataset for China is published by Shi's team from Southwest University, and its accuracy in evaluating social indicators has been validated as superior to these two types of data[20]. In practical applications of carbon emission spatialization, nighttime light data are often combined with energy data and population density data. Zhang *et al.*[17] spatialized carbon emissions in Xi'an using nighttime light data and energy statistics as the basis, with population data as a weighting factor. Wei *et al.*[21] used nighttime light data and population data to simulate carbon emissions across China.

The general process of spatialising carbon emissions based on nighttime light data includes the following steps: (a) obtaining and pre-processing nighttime light data for the study area according to the research scale; (b) integrating population density, energy consumption, and land use data to build a model that produces spatialized carbon emissions; (c) data validation; (d) result analysis. In step (c), nighttime light data and carbon emission statistics are often used to construct estimation models, and the model with the best fit is selected to establish the relationship between the two. Alternatively, the Root Mean Square Error (RMSE) and Mean Relative Error (MRE) can be obtained by comparing the estimated carbon emissions for a particular industry with the total carbon emissions of that industry, thus assessing data accuracy and exploring regional carbon emissions. There are also studies[22] that verify the accuracy of the data by comparing it with the carbon emissions assigned by the International Carbon Database. Related research[23] shows that when establishing a mathematical relationship between energy consumption and nighttime light, linear relationships have a relatively optimal fit. When constructing models for estimating polynomial functions, higher-order polynomials tend to provide better fits[17]. The R^2 values of the fitting formulae often range from 0.6 to 1[24–27], or $p < 0.01$[28], indicating good accuracy of the data results.

3.2 Carbon Emission Spatialization Analysis Based on Social Statistics Data

Spatial interpolation can be applied to original carbon emission point data obtained from social statistics. Combined with methods such as cluster analysis and hot spot analysis, this approach helps to identify high and low carbon emission areas and understand the spatial distribution characteristics and driving factors of carbon emissions. Spatial interpolation methods include inverse distance weighting (IDW), Thiessen polygons, trend surface, and kriging. Kriging interpolation is often used to process carbon data to smallscales such as counties, while inverse distance weighting is commonly used for provincial and city data, as shown in Table 2. It should be noted that inverse distance weighting is very sensitive to the choice of weighting function, and if the data are unevenly distributed, abnormal results may occur. The interpolation result is sensitive to extreme values, and the variance of the predicted value cannot be estimated. Therefore, the interpolation effect of this method is better when the known points are evenly distributed. Kriging, a geostatistical method, calculates the weights of each measured point through the semi-variogram function, allowing for adjustable model parameters that can be set according to the nature of the regionalized variables. At the same time, the error and accuracy of the results can be dictated, which is suitable for the factors with correlation of the regionalized variables. In reviewing the literature, the use of traditional simple interpolation methods is more common in domestic studies than in international research. Some scholars believe that relying solely on traditional interpolation methods to obtain grids may lead to large errors. Therefore, they modify the parameters of traditional methods[41] or establish new models[38] to convert point data into area data. Cross-validation of results obtained by different methods in different study areas is necessary to ensure accuracy.

When collecting raw carbon emissions data based on social statistics, researchers often use either a top-down or bottom-up approach to construct spatialized carbon emissions datasets, as shown in Figure 1. In the former, the total carbon emissions are divided into grid units according to the weight ratio of population, regional development level and other factors. This method has a wide range of applications and is of great value for regions with few carbon emissions data (Figure 2a). The latter is a grid construction method integrated

Table 2 Application of interpolation methods in domestic and international data processing

Reference	Research area	Research method	Content
Yan (2018)[29]	Huailai County	Kriging	Spatial distribution of land carbon emissions in Huailai County
Su *et al*. (2011)[30]	Shaanxi Province	IDW	Analyzed the spatial differences and variations in carbon emissions across different regions in Shaanxi Province
Guo *et al*. (2016) [31]	Jiangsu Province	Kriging	Interpolated the total carbon emissions of each county
Kong (2018)[32]	Lanzhou City	IDW	Spatial distribution of industrial carbon emissions in Lanzhou City
Yuan *et al*.(2021)[33]	Jinan City	Kriging	Spatial distribution characteristics of transportation carbon emissions in Jinan City
Rong *et al*. (2018)[34]	Kaifeng City	IDW	Visualization of the spatial distribution of daily carbon emissions in Kaifeng City
Wu (2016)[35]	China	IDW	Modeled the spatial distribution of total carbon emissions in China from 1990 to 2012
Huang *et al*. (2015)[36]	Wuhan City	Kriging	Trend prediction of household carbon emissions in Wuhan City
Mohit *et al*. (2006)[37]	India	G-SMILE	A statistical model using grid data to achieve the required resolution for carbon emission distribution
Sanayanbi *et al*. (2017)[38]	India	IDW and Kriging	Studied the spatial distribution of ET_0 in India, comparing the precision of inverse distance weighting with Kriging methods
Vahid *et al*. (2024)[39]	Australia	Linear Interpolation	Explored the precision of carbon emission distribution, using this method to supplement missing data for carbon emission estimation
Marko *et al*. (2023)[40]	Belgrade	Bilinear Interpolation	Established a bilinear interpolation model for estimating vehicle tailpipe emissions

with the idea of aggregation. The principle is to collect carbon emission information of different departments in the research area, grid them and then overlap them to form a comprehensive grid map, as shown in Figure 2. Compared with the former approach, the bottom-up method is more complex and requires more raw data to support carbon emission calculations for different sectors, but it provides higher accuracy with relatively smaller errors[43].

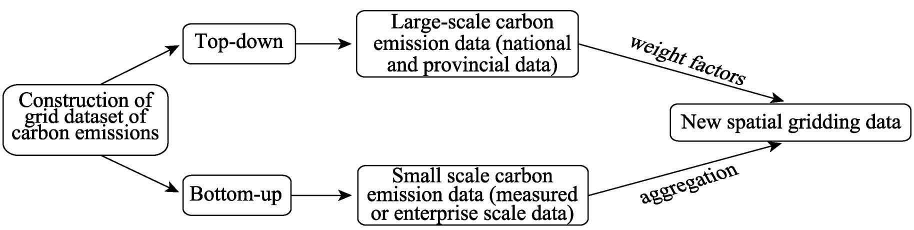

Figure 1 Technical road map of top-down and bottom-up

The spatial grid method can further refine the spatial distribution of carbon emissions data, allowing visualization at specific spatial resolutions and creating a spatially continuous carbon emissions dataset. This allows more detailed analysis of regional carbon emission patterns. Spatially allocating carbon emissions in small areas requires taking into account various factors such as population density, traffic flow and land use , and setting appropriate weighting coefficients to simulate a carbon emission distribution grid that closely reflects reality. This process can take a top-down approach (Figure 2b), where carbon emissions data are distributed by downscaling to produce spatial distribution maps of regional energy consumption. This method typically integrates GIS with one or more cross-referenced datasets, such as POI , population density, traffic flow, land use, and nighttime light data, to allocate emissions to grids. For example, Wang *et al*.[44] utilized a series of spatial proxy data to develop a gridded inventory that reflects the spatial patterns of carbon emissions in Hangzhou.

3.3 Differences and Connections between Spatialization of Carbon Emissions Based on Nighttime Light Data and Social Statistics Data

The differences between the two are as follows: (a) In terms of data sources, nighttime light data is primarily obtained through remote sensing techniques that capture surface illumination at night, while social statistics data is derived from socio-economic indicators. (b) The former performs better in areas with dense energy consumption and economic activities, while the latter has more potential to reflect carbon emissions in rural and other less developed regions. (c) Nighttime light data can help researchers quickly identify areas with a relatively higher intensity of economic activity, whereas social statistics data focus more on identifying specific emission sources.

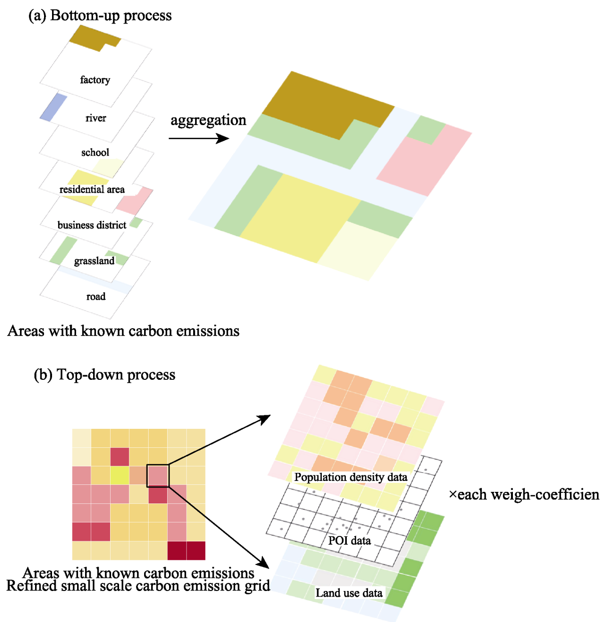

Figure 2 Spatialization of carbon emissions based on nighttime light data and social statistics data

4 Application Scenarios of Carbon Emission Spatialization from a Technical Perspective

In economic research, line or bar graphs are often used to present the temporal and spatial trends of regional carbon emissions[45]. However, from a geoscientific perspective, it is somewhat counterintuitive to represent changes in carbon emissions only with numerical values, and geographical base maps are usually used to depict specific information such as changes in carbon emissions. Scholars, at home and abroad have conducted extensive research on the spatial differentiation of carbon emissions, influencing factors, change mechanisms, and driving factors at different scales, such as national, provincial and regional, using nighttime light data.

4.1 Research Subjects

Estimation of land use carbon emissions typically involves socio-economic data, fossil fuel consumption, remote sensing data of land cover and nighttime light DN values, combined with spatial statistical analysis, geographic detectors, or geographically weighted regression methods. For example, Niu *et al*.[46] studied carbon emissions from land use and influencing factors in the Changsha Zhuzhou Xiangtan area, using nighttime light brightness values and energy consumption to build equations with an R^2 greater than 0.85. Su *et al*.[47] found a strong correlation between carbon emissions from energy consumption and nighttime light index in Shanxi Province, with an R^2 of 0.991,4. Grid methods are often used to divide regions, which helps to highlight regional differences in carbon emissions. Wang *et al*.[48] used the area of different land types multiplied by corresponding carbon emission coefficients to construct a regional grid and found an increasing trend in carbon emissions in the Nansi Lake Basin. Some studies also incorporate time series data to investigate the temporal and spatial differentiation within regions. For instance, Deng *et al*.[49] used remote sensing imagery and socio-economic data from different years to reveal the temporal and spatial evolution and driving factors of carbon emissions from land use in Wuhan. Liu *et al*.[50] constructed a fitting model based on nighttime light data and statistical data from 2012 to 2021 to depict the spatio-temporal evolution of carbon emissions in seven eastern provinces and cities. In short, when exploring carbon emissions from land use, a fitting equation is often constructed to reflect the fitting degree between remote sensing data and regional carbon emissions, usually $R^2 > 0.8$. The accuracy of the data used in this study is lower than that use in the study of changes in carbon emissions from land use within provinces, cities or counties. The former usually gives different colors to different large areas in the form of spatial results, while the latter can reflect regional emission hot spots more finely.

The agriculture, energy and transport sectors have made important contributions to China's rapid economic development,but are also significant sources of carbon dioxide emissions. Agricultural research often uses data on crop area and crop type to estimate carbon emission intensity. For example, Cui *et al*.[51] used crop planting area data and exploratory spatial data analysis to visualize agricultural carbon emissions in Hebei Province. In the energy sector, the focus is on the temporal and spatial evolution characteristics. Hao *et al*.[52] simulated energy carbon emissions in combination with nighttime lighting data and statistical data and found that carbon emissions in most regions changed little. In the transportation sector, studies have examined carbon emission distribution patterns based on different road networks, such as Dai *et al*.[53] who visualized carbon emissions in Shandong Province's expressway network. Others have studied carbon emissions from motor vehicles, such as Wang *et al*.[54] who obtained a high accurate inventory of vehicle carbon emissions based on traffic statistics. Different sectors have different data characteristics. Spatialization research in the agricultural sector and data from the energy sector are often area-based; data from the transport sector may be tripe or area-based, depending on the environment, specifications, and power sources of the vehicles used.

4.2 Spatial Scope

With the continuous deepening of research, carbon emission grid data has evolved from annual data to near-real-time daily data[55], and the spatial resolution has improved from 1º × 1º[56] and 0.25º × 0.25º resolution datasets to 0.1º × 0.1º grids[57]. In studies investigating the spatial distribution of national carbon emissions, existing research often uses provinces as the basic unit, starting from a national perspective to study the spatial distribution of carbon emissions in the energy consumption sector. Nighttime light data and population data are typically used as a basis, and spatial interpolation methods are employed to fill missing values, distributing carbon emissions to grid scales[58]. Wang[59] integrated population, GDP, and nighttime light data, combined with correlation and regression analysis, to construct a cross-scale spatial model of China's carbon emissions. At the provincial scale, counties are often used as the smallest unit to study the spatial patterns of carbon emissions. Studies also construct highly fitting equations to reveal the spatial variation patterns of carbon emissions within regions. Gu et al.[60] constructed a function representing energy consumption carbon emissions based on nighttime light pixel values, and then used emission inventories to calculate and simulate the energy consumption carbon emissions in Henan Province. Xie *et al*.[61] constructed a spatial distribution map of greenhouse gas emissions on a 200 m × 200 m grid and explored the differences in greenhouse gas emission levels in the study area. Current regional-scale research mainly involves regions such as the Lanxi urban agglomeration[62], the Harbin Changcheng urban agglomeration[63], and the Yangtze River Economic

Belt[64]. Yang *et al.*[65] used a bottom-up method to calculate pollutant emissions and show the spatial distribution of air pollutants in the Pearl River Delta region. Research institutes at city level require higher data accuracy and often use social statistical data such as population density, POI, and GDP, as well as related remote sensing data. Combined with carbon emission measurement methods such as “top-down” and “bottom-up”, they rely on GIS platforms to obtain spatial distribution of carbon emissions in different industry backgrounds. For instance, Li *et al.*[66] proposed a method for establishing a high spatial resolution carbon emission inventory at the city level, and established a 1 km × 1 km carbon emission inventory for Yingkou City.

Both nighttime light-based and social statistics-based methods can spatialize carbon emission intensity at national, provincial, and municipal scales. When selecting data, it is important to clarify the research scope and topic in order to select appropriate resolution data. Large spatial resolutions are often required to study macroscopic distributional characteristics. When studying emission details at the city or smaller scale, higher resolution data are usually selected to construct grids of sizes such as 1km × 1km or 200m × 200m. If the original data resolution is too low to reflect differences in distribution of carbon emissions between regions, top-down methods based on social statistics can be used to achieve more accurate results.

5 Discussion

5.1 Suggestions

First, there is often a lack of validation accuracy in regression modelling. When studying regional carbon emissions based on nighttime light data, a common approach is to estimate emissions using regression modelling. However, many researchers overlook the validation of regression accuracy when analyzing spatial and temporal scales. Simple regression only quantifies the relationship between data on temporal or spatial scales, without considering the combined effects of multiple factors. The scientific community generally agrees that using statistical data to estimate carbon emissions is more comprehensive. Some scientists have also questioned the results of studies that rely solely on nighttime light data for small-scale regions[52]. Meanwhile, other research suggests that constructing models to reverse-engineer the relationship between light intensity and carbon emissions is a crucial direction for future carbon accounting methods[67]. Therefore, models that couple nighttime light with other factors should be developed and validated by comparison.

Second, the top-down approach often lacks spatial information in the carbon emissions data used. When grid-mapping carbon emissions for large regions, data for smaller areas may be overly smoothed, failing to reflect local variations in emissions. Conversely, while the bottom-up approach offers higher accuracy, it requires more extensive raw data accumulation. In cases where statistical data are incomplete or imprecise, combining both top-down and bottom-up methods, supplemented by spatial interpolation, can adjust the values within spatial grids, resulting in more accurate carbon emission maps.

Thirdly, current research often overlooks the differences in the principles behind different spatial interpolation methods and directly chooses a particular method to simulate missing data. However, choosing the wrong interpolation method in different research contexts can lead to discrepancies between predicted and actual values, resulting in significant errors in simulated spatial carbon emission results. This discrepancy is particularly pronounced when studying the spatial distribution of carbon emissions at the county level or smaller scales. Therefore, in such cases, the choice of spatial interpolation methods is crucial, and multi-source data should be integrated with cross-validation to achieve the highest degree of fit for spatial prediction surfaces of carbon emissions.

Finally, carbon dioxide emissions and transfers are strongly influenced by spatial and geographical factors. As for different issues, it is essential to consider the impact of human-environment relationships, geographical elements, terrain or climatic conditions on the study factors. Investigating the effects of different factors on the transfer of carbon emission and constructing targeted spatial distribution models will help to simulate high-precision real-time monitoring networks for carbon emissions, improve the understanding and management of air quality issues, and promote air pollution control and emission reduction measures. When interpolating carbon emissions at small scales, different emission scenarios should be considered to minimize errors due to differences in building types. At larger scales, integration of data from multiple sources can reduce errors and uncertainties caused by low resolution.

5.2 Outlook

First, more research should be done on small or micro-scale carbon emissions. Compared to larger regions, smaller scales such as villages and campuses have greater potential to reduce emissions and can serve as pioneers in exploring innovative emission reduction technologies and models. Therefore, future research should explore the differences in the distribution of carbon emissions within small scales and between regions. An accurate understanding of the spatial flow of carbon emissions can enable more targeted point-to-point emission reduction strategies and provide scientific evidence for governments to formulate more targeted reduction policies based on local conditions.

Second, the presentation of carbon emissions on maps needs to be refined. Most current studies use administrative regions at the provincial or municipal level as the unit of analysis, with entire regions being coloured according to sectoral or industrial emissions. However, this approach does not effectively represent the specific locations of industries or sectors within the administrative region. Grid-based approaches can more accurately capture the spatial distribution and trends of carbon emissions, highlighting the gradient changes in emission intensity within the area. However, few studies have used this refined grid-based approach. Therefore, future research on regional carbon emissions should place greater emphasis on the detailed distribution of study objects on maps and the detailed representation of how emissions decrease with increasing distance from the source.

Author Contributions

Xue, B. and Gang, S. conceived the overall design of the study. Zhou, Y. L. drafted the manuscript. Zhou, Y. L. and Xu, Y. T. conducted data and literature collection and analysis. Xiao, X. and Li, J. Z. revised the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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