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A Review of Carbon Emissions Research in the Beijing-Tianjin-Hebei Region Based on Nighttime Light Data

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Abstract

With the increasing global attention to climate change and carbon emissions, accurately assessing the characteristics of regional carbon emissions and their driving factors has become a research hot spot. This paper reviews the research progress on carbon emissions in the Beijing-Tianjin-Hebei region based on nighttime light data, analyzes the application status of nighttime light data in carbon emission research, data processing methods, and the extemporization distribution characteristics and driving factors of carbon emissions in the Beijing-Tianjin-Hebei region, aiming to provide references and insights for further in-depth research.

Keywords: Carbon Emissions, Nighttime Light Remote Sensing, DMSP/OLS, Extemporization Distribution.

1. Introduction

Carbon emissions are one of the main factors leading to climate change. The Beijing-Tianjin-Hebei region, as the core economic area in North China, holds significant importance for sustainable regional development in terms of its carbon emission characteristics and driving factors. Nighttime light data, as an emerging source of remote sensing data, can reflect the spatial distribution and intensity of human activities and has been widely used in carbon emission studies. This paper summarizes the application status and main achievements of nighttime light data in the carbon emission research of the Beijing-Tianjin-Hebei region through the collation and analysis of relevant literature.

2. Application Status of Nighttime Light Data in Carbon Emission Research

2.1. Data Sources and Characteristics

Nighttime light data primarily originates from the DMSP/OLS and NPP/VIIRS satellite sensors. The DMSP/OLS data is characterized by its long time series and wide coverage, but it suffers from issues of saturation and discontinuity. The NPP/VIIRS data significantly outperforms DMSP/OLS data in terms of spatial and radiometric resolution, but it faces problems such as data loss and seasonal differences. Scholars both domestically and internationally have proposed various correction and fusion methods in response to these data characteristics to enhance the accuracy and applicability of the data.

2.2. Data Processing Methods

(1) DMSP/OLS Data Processing

Scholars both domestically and internationally have proposed various correction methods to address the saturation and discontinuity issues of DMSP/OLS data. For example, Zhang Mengqi et al. and Lu Xiu et al. established quadratic regression models to systematically correct DMSP/OLS data, significantly improving its continuity and stability. In addition, to make full use of images obtained by multiple sensors in the same year, scholars have proposed multi-sensor intra-annual fusion methods to further enhance the stability and continuity of the data.

Table 1 Parameters of Nighttime Light Data

Parameter Category	DMSP/OLS	NPP/VIIRS
Time Range	1992-2013	2012-Present
Spatial Resolution	2700 meters	740meters
Radiometric Resolution	6-bit（0-63，low dynamic range）	14-bit（0-16383，high dynamic range）
Spectral Range	0.5-0.9μm	0.5-0.9μm
Minimum Detectable Radiance	2.5×10^{-9} W/cm²/sr	5×10^{-10} W/cm²/sr
Overpass Time	Local time around 19:30	Local time around 1:30

Given the poor comparability between different DMSP/OLS data, to reduce the differences in the digital number (DN) values of brightness between different DMSP/OLS data, the correction method proposed by Liu et al. and Cao Ziyang for multi-year and multi-satellite nighttime stable light data was adopted. First, Hegang City in Heilongjiang Province, which has small changes in image DN values and a wide distribution range from 2000 to 2013, was selected as the invariant target area. Second, the data of the F16 satellite in 2007 was used as the reference data to establish a quadratic regression model for each satellite, as shown in the formula below.

$$DN' = C_0 + C_1 \times DN_0 + C_2 \times DN_0^2$$

In the formula, DN_0 and DN' are the brightness values of the pixel before and after correction, respectively, and C_0,C_1, andC_2 are the regression coefficients.

(2) NPP/VIIRS Data Processing

To address the issues of background noise and seasonal differences in NPP/VIIRS data, Li Mingfeng et al. and Li Xueping et al. proposed correction methods based on multi-temporal data. Through convolution operations and maximum entropy threshold adaptive filtering, abnormal noise pixels were eliminated, significantly improving the fitting ability of the data. In addition, to reduce the impact of seasonal differences, scholars have proposed annual image synthesis methods. By selecting data from specific months for synthesis, the integrity and consistency of the data were improved.

(3) Data Fusion

To fully leverage the advantages of both DMSP/OLS and NPP/VIIRS data, scholars both domestically and internationally have proposed various data fusion methods. For example, by establishing a nonlinear regression model to fit DMSP/OLS data with NPP/VIIRS data, a long time-series nighttime light dataset was constructed. This method not only improves the spatiotemporal resolution of the data but also provides reliable data support for long-term carbon emission monitoring.

For the years 2000-2007, data from two different sensors existed for the same year. To make full use of the images obtained by multiple sensors in the same year and ensure the stability and continuity of the nighttime light image data, the method proposed by Lu Xiu et al. was referenced to correct the images obtained by different sensors in the same year. The formula is as follows:

$$DN_{(n,i)} = \begin{cases} 0 & DN^{a}_{(n,i)} = 0 \text{ and } DN^{b}_{(n,i)} = 0 \\ \dfrac{DN^{a}_{(n,i)} + DN^{b}_{(n,i)}}{2} & \text{other} \end{cases}$$

In the formula, n=2000，2001，…，2007；$DN^{a}_{(n,i)}$，$DN^{b}_{(n,i)}$represent the brightness values of the pixels obtained by the two different sensors after correction, respectively; i represents the brightness value of the pixel in year$DN_{(n,i)}$after correction. When theDN values of both sensors are 0, the area is considered to be a no-light area.

3. Spatiotemporal Distribution Characteristics of Carbon Emissions in the Beijing-Tianjin-Hebei Region

3.1. Spatiotemporal Distribution Characteristics

Based on the calibrated nighttime light data, the spatiotemporal distribution characteristics of carbon emissions in the Beijing-Tianjin-Hebei region show significant spatiotemporal differentiation. Beijing and Tianjin, as core cities, have seen their high-intensity light areas expand outward year by year, forming a clear belt-like integration trend. In addition, the light intensity of secondary central cities such as Shijiazhuang and Tangshan has also increased significantly, indicating the continuous enhancement of their economic importance. However, regional coordinated development still faces gradient barriers, and some remote areas, such as Yu County in Zhangjiakou, Chicheng, and Fengning in Chengdu, have long maintained low brightness levels.

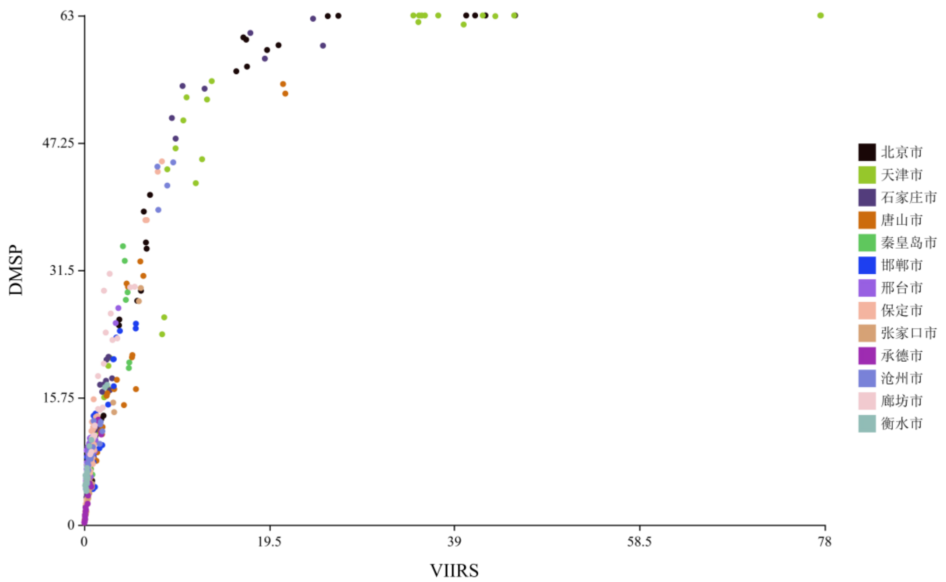

Figure 1 Nonlinear Relationship Characterization between DMSP and VIIRS Nighttime Light Data

This paper integrates DMSP/OLS and VIIRS nighttime light data to construct a long time-series dataset. The specific method is as follows: First, the overlapping period of DMSP and VIIRS sensor data from 2012 to 2013 is selected for cross-calibration.

At the county-level spatial scale, the annual average stable light brightness values (DN values) of DMSP and the annual average radiance values ($nW \cdot cm^{-2} \cdot sr^{-1}$) of VIIRS after noise reduction treatment are extracted as paired samples. Based on the R language (v4.4.3) statistical computing platform, with VIIRS radiance values as the independent variable (X) and DMSP DN values as the dependent variable (Y), the optimal fitting equation is determined through statistical significance testing. This calibration model is finally applied to the reconstruction of the 2000-2020 nighttime light time series, achieving the conversion of VIIRS data to DMSP through inverse calibration, thereby constructing a nighttime light dataset with spatiotemporal continuity.

3.2. Driving Factor Analysis

The geographical detector model has been widely used in the analysis of driving factors of carbon emissions. Studies have shown that carbon emissions in the Beijing-Tianjin-Hebei region are mainly influenced by factors such as the level of economic development, industrial structure, and energy consumption. For example, Beijing and Tianjin have a high proportion of the tertiary industry, resulting in relatively lower carbon emission intensity. In contrast, Hebei has a higher proportion of the secondary industry, leading to higher carbon emission intensity. Additionally, the implementation of regional coordinated development strategies has also significantly impacted the distribution of carbon emissions. For instance, after the establishment of the Xiong'an New Area, its light brightness increased significantly, reflecting infrastructure construction and economic development driven by policy.

4. Research Prospects

Despite the progress made in the study of carbon emissions in the Beijing-Tianjin-Hebei region based on nighttime light data, there are still some shortcomings. For example, the accuracy of data and the applicability of methods need to be further improved, and the technology for fusing multiple data sources needs to be perfected. Future research should focus on the following aspects:

4.1. Data Accuracy Enhancement

Further optimize the correction and fusion methods of nighttime light data to improve the spatiotemporal resolution and accuracy of the data. At the same time, integrate other data sources (such as meteorological data, population data, etc.) to build a more comprehensive carbon emission monitoring dataset. For example, by incorporating meteorological data, the impact of climate change on carbon emissions can be assessed more accurately; by incorporating population data, the impact of population movement on carbon emissions can be assessed more accurately.

4.2. Dynamic Change Research

Strengthen the monitoring and analysis of the dynamic changes in carbon emissions, explore the driving mechanisms of these changes, and provide scientific basis for policy-making. For example, by analyzing carbon emission data from different time periods, high and low emission areas can be identified, thereby providing targeted suggestions for policy-making.

4.3. Detailed Discussion of Future Research Directions

(1) Data Accuracy Enhancement

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(3) Multi-Source Data Fusion

Explore the deep integration of nighttime light data with other data sources (such as ground monitoring data, satellite remote sensing data, etc.) to improve the accuracy and reliability of carbon emission monitoring. For example, by combining ground monitoring data, the actual impact of carbon emissions can be assessed more accurately; by combining satellite remote sensing data, the spatial distribution of carbon emissions can be assessed more comprehensively.

5. Conclusion

The study of carbon emissions in the Beijing-Tianjin-Hebei region based on nighttime light data has made significant progress in data processing, analysis of spatiotemporal distribution characteristics, and identification of driving factors. However, further optimization of data processing methods, improvement of data accuracy and applicability, and deepening of multi-source data fusion technology are still needed to better serve the low-carbon development and sustainable development of the Beijing-Tianjin-Hebei region.

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