Spatiotemporal Evolution of Land Use Carbon Emissions and Influencing Factors in Ningxia (Postprint)

Authors: Wang Wei, Shuting Yang, Hai Yunrui

Date: 2025-04-08T16:51:16+00:00

Abstract

Land use change is a key factor influencing carbon emissions, and investigating the spatiotemporal evolution of regional carbon emissions holds significant importance for promoting rational emission reduction. Based on calculated data of land use carbon emissions at two scales—county (district) and 10 km grid—in Ningxia from 1990 to 2020, this study employs trend analysis, spatial autocorrelation analysis, and the GTWR model to examine the spatiotemporal variation characteristics of carbon emissions in Ningxia and their driving factors. The results indicate that: (1) Land use carbon emissions at both scales exhibit an increasing trend over time, with construction land representing the primary source of carbon emissions in Ningxia. (2) Carbon emissions vary across different counties (districts), with Xingqing District and Lingwu City showing the most rapid growth in carbon emissions. (3) Carbon emissions display a spatial distribution pattern of northwestern region > central region > southern region, and grid-scale carbon emissions demonstrate significant spatial autocorrelation, with the agglomeration pattern of carbon emissions intensifying over time. (4) The proportion of construction land and human activity constitute important factors driving the spatiotemporal differentiation of carbon emissions in Ningxia, exerting a significant positive effect with intensifying influence year by year.

Full Text

Preamble

Arid Zone Research Vol. 42 No. 3 Mar. 2025
DOI:10.13866/j.azr.2025.03.14 CSTR:32277.14.AZR.20250314

Spatiotemporal Evolution and Influencing Factors of Land Use Carbon Emissions in Ningxia

WANG Wei, YANG Shuting, HAI Yunrui
(Institute of Agricultural Economy and Information Technology, Ningxia Academy of Agriculture and Forestry Sciences, Yinchuan 750002, Ningxia, China)

Abstract: Land use change is a key factor affecting carbon emissions. Studying the spatiotemporal evolution of regional carbon emissions is of great significance for promoting reasonable emission reduction. Based on measured data of land use carbon emissions in Ningxia at two scales—county (district) and 10 km grid—from 1990 to 2020, this study examines the spatiotemporal variation characteristics and influencing factors of carbon emissions in Ningxia using trend analysis, spatial autocorrelation analysis, and the GTWR model. The results show that: (1) Carbon emissions at both scales show an upward trend in the time series, and construction land is the main source of carbon emissions in Ningxia. (2) There are differences in carbon emissions among different counties (districts), with Xingqing District and Lingwu City showing the most rapid growth. (3) Spatially, carbon emissions exhibit a distribution pattern of northwest region > central region > southern region. Grid-scale carbon emissions have significant spatial autocorrelation, and the agglomeration pattern of carbon emissions strengthens over time. (4) The proportion of construction land and human activities are important factors driving the spatiotemporal differentiation of carbon emissions in Ningxia, which have a significant positive effect and whose impact intensity increases year by year.

Keywords: carbon emissions; spatiotemporal pattern; land use; GTWR; influencing factors; Ningxia

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1.1 Study Area Overview

Ningxia is located in the hinterland of northwestern China, with a temperate continental arid and semi-arid climate characterized by distinct seasons. The total area of the region is 66,400 km^2, with complex terrain that descends stepwise from high in the south to low in the north, and an average elevation exceeding 1000 m. The region extends approximately 450 km from north to south. The southern mountainous areas are humid with abundant rainfall and low temperatures, while the northern region enjoys ample sunlight. Water resources are severely scarce, ranking among the lowest in China, with uneven spatial distribution and high temporal variability. The primary land use types are grassland and cropland.

1.2 Data Sources

The land use dataset used in this study was obtained from the 30 m annual land use dataset of China produced by Wuhan University (http://zenodo.org/record/8176941), with a spatial resolution of 30 m.

Based on Ningxia' s actual conditions and data availability, land use types were consolidated into six categories: cropland, forestland, grassland, water bodies, construction land, and unused land. Statistical data were sourced from the *Ningxia Statistical Yearbook* (1991–2021) and statistical yearbooks of various prefecture-level cities.

1.3.1 Land Use Carbon Emission Estimation

The carbon emission coefficient method was employed to calculate annual carbon emissions from five land use types: cropland, forestland, grassland, water bodies, and unused land. Based on reference [31], the carbon emission coefficients for these land use types were determined as 0.253, -0.445, -0.021, -0.025, and -0.005 $t \cdot hm^{-2}$, respectively. Due to the lack of fossil energy emission statistics at the county (district) level in Ningxia, carbon emissions from construction land were estimated using the product of energy consumption per unit GDP and the sum of secondary and tertiary industry output values [32]. The calculation formulas are as follows:

$$E = \sum_{i=1}^{n} S_i \times V_i$$

where:
- E is the total carbon emission (10^4 t)
- S_i and V_i are the area (hm^2) and carbon emission coefficient ($t \cdot hm^{-2}$) of the i-th land use type, respectively
- n is the number of land use types

$$C = T \times K \times \frac{G_2 + G_3}{G}$$

where:
- C is the carbon emission from construction land (10^4 t)
- T is total energy consumption (10^4 t standard coal)
- G is gross domestic product (10^4 yuan)
- G_2 and G_3 are the output values of secondary and tertiary industries (10^4 yuan), respectively
- K is the carbon emission coefficient for coal consumption, valued at 2.4567

1.3.2 Change Trend Analysis

To further reveal the temporal change trend of carbon emissions in Ningxia, a univariate linear regression model was used to calculate the slope of carbon emission changes based on the obtained emission data for study units from 1990 to 2020, simulating the interannual variation trend of carbon emissions. The formula is as follows:

$$\text{Slope} = \frac{n \times \sum_{i=1}^{n} x_i E_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} E_i}{n \times \sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}$$

where:
- Slope is the regression slope
- n is the total number of years
- x_i is the i-th year
- E_i is the carbon emission in the i-th year

The standard deviation classification method was used to classify the carbon emission growth trends .

1.3.3 Geographically and Temporally Weighted Regression (GTWR)

The GTWR model introduces spatial data into regression parameters for local regression statistics, considering spatial heterogeneity to improve model estimation accuracy. Using 10 km × 10 km grids as the unit scale for regression analysis, the model calculates regression coefficients of influencing factors to explore the relationship between carbon emission spatial distribution and various dominant factors.

1.3.4 Selection of Influencing Factors

Based on the actual conditions of the study area and data availability, ten influencing factors (Table 2) were initially selected to analyze the influencing factors of land use carbon emissions in Ningxia from natural and socioeconomic perspectives. Among them, the Terrain Relief Index (TR) was calculated using 30 m resolution DEM data for Ningxia in 2020. Data for Normalized Difference Vegetation Index (NDVI), vegetation coverage (FVC), and annual net primary productivity (NPP) for 2020 were missing, while data for other influencing factors covered the period 1990-2020. The random forest model was used to rank the importance of influencing factors for three periods (1990-2000, 2000-2010, 2010-2020), identifying the dominant driving factors of land use carbon emissions in different periods.

2.1.1 Temporal Changes in Carbon Emissions by Land Use Type

Analysis of carbon emission trends in Ningxia shows that the total land use carbon emissions exhibited a 逐年递增 trend, increasing from 444.84$×10^{4}$ t in 1990 to 4937.31$×10^{4}$ t in 2020, with an average annual growth rate of 12.53%. Construction land, as the main source of carbon emissions in Ningxia, showed a consistent trend with total carbon emissions, with its contribution rate to total emissions increasing annually. Carbon emissions from cropland fluctuated with changes in cropland area (Table 3) but remained basically stable, contributing a small and declining share to total emissions. The total carbon sink showed an overall increasing trend during the study period, with grassland carbon sinks accounting for 64.19% of the total and contributing the most. Carbon absorption by forestland continued to grow, while carbon absorption by water bodies and unused land showed no significant changes.

2.1.2 Temporal Changes in County-Level Land Use Carbon Emissions

County-level land use carbon emissions in Ningxia generally followed the same pattern as the autonomous region, but differences among counties led to varying change patterns. Before 2000, carbon emissions in Xiji County, Pengyang County, and Haiyuan County were dominated by cropland, with cropland contributing over 61.85% of emissions. After 2000, carbon emissions from all counties increased substantially, with construction land gradually becoming the main carbon source. By 2020, all counties were dominated by construction land carbon emissions. Net carbon absorption in Xixia District, Helan County, Pingluo County, Longde County, and Jingyuan County was dominated by forestland, while other counties were dominated by grassland. Lingwu City showed the largest change in net carbon emissions, increasing from 13.19$×10^{4}$ t in 1990 to 710.50$×10^{4}$ t in 2020, an increase of 697.31$×10^{4}$ t. Xingqing District ranked second with an increase of 666.51$×10^{4}$ t. Jingyuan County had the smallest increase in net carbon emissions over the 30-year period.

2.1.3 Change Trends in Land Use Carbon Emissions at Different Scales

The slope method was used to analyze land use carbon emission trends at both scales (Figure 4). At the county scale, Xingqing District and Lingwu City showed the most rapid growth, with slope values of 13.19 and 10.64, respectively, classified as rapid growth type. Helan County was classified as relatively rapid growth type, and Xixia District as medium growth type. Five counties (districts), including Jinfeng District, Dawukou District, Huinong District, and Yuanzhou District, were classified as relatively slow growth type, with slope values between 0.61 and 4.01. Three counties (districts) were classified as slow growth type, with slope values between -4.01 and 0.61. At the grid scale, carbon emission trends were divided into rapid growth type and medium growth type. Litong District showed relatively slow growth overall, but internal grids exhibited both medium and relatively rapid growth patterns.

2.2.1 Evolution of Carbon Emission Spatial Patterns

Using the natural breaks method, total carbon emissions in Ningxia were divided into five levels. Four temporal cross-sections of land use carbon emission spatial distribution maps were generated (Figure 5). At the county scale, carbon emission growth types showed a spatial distribution pattern of high in the northwest and low in the southeast. The northwest region experienced the most rapid carbon emission growth over the past 30 years. This area is located in the Ningxia Yellow River Economic Zone urban belt, with booming economic and industrial development and huge energy consumption, resulting in high carbon emission growth levels. The central and southern regions lagged in development, with less obvious carbon emission change trends. At the grid scale, carbon emission change trends were largely consistent with the county scale, with differences existing between regions. Helan County, Lingwu City, and Pingluo County showed significant spatial heterogeneity in carbon emission growth trends within counties. High and severe carbon emission areas were concentrated in Yinchuan’ s municipal districts and surrounding areas, while moderate carbon emission areas were mainly distributed along the Yellow River urban belt and Yuanzhou District (the seat of Guyuan City). Light and low carbon emission areas were primarily located in southern Ningxia. Due to extensive construction land area and high energy consumption, Xingqing District consistently ranked first in land use carbon emissions, accounting for over 10% of Ningxia’ s total carbon emissions. Lingwu City showed the most significant change in carbon emission levels, transitioning from light to severe emissions over 30 years. Longde County and Jingyuan County transitioned from low carbon emission areas in 1990 to carbon absorption areas in 2020. These areas are important ecological function zones in Ningxia, rich in forest and grassland resources with high vegetation coverage and strong carbon sequestration capacity. Severe and high carbon emission areas were concentrated in Yinchuan’ s municipal districts and surrounding areas, while moderate carbon emission areas were mainly distributed along the Yellow River urban belt and Yuanzhou District. Ningxia’s carbon emissions showed a trend of clustering toward municipal districts and surrounding areas (economic and industrial centers), consistent with the changing trend of carbon emission growth rates mentioned above. At the grid scale, the spatial distribution showed that low carbon emission areas gradually decreased while high carbon emission areas continuously expanded, with emission intensity gradually increasing. High and severe carbon emission areas were mainly concentrated in the centers of counties (districts), while moderate carbon emission areas were concentrated in the peripheries of counties (districts). Different grids within counties showed differences in carbon emission intensity levels, with overall changes consistent with county-level carbon emission intensity changes. Spatially, high and severe carbon emission areas expanded outward from urban construction land centers, steadily converting adjacent low carbon emission areas to severe carbon emission areas at a stable rate, which aligns well with the concentrated distribution and expansion trend of regional construction land.

2.2.2 Spatial Autocorrelation Analysis of Land Use Carbon Emissions

Global autocorrelation analysis was conducted on carbon emissions at the 10 km grid scale. The results showed that carbon emissions at the grid scale in Ningxia had extremely significant spatial autocorrelation. During the study period, the global Moran’ s I index showed an upward trend, with the degree of spatial autocorrelation gradually strengthening, indicating that the agglomeration pattern of carbon emissions strengthened over time and differences in carbon emissions among regions gradually increased . To further reveal local spatial agglomeration characteristics, local Moran’ s I was calculated for four periods. The transformation of cold and hot spots of carbon emissions at the grid scale in Ningxia was relatively obvious. Hot spots gradually gathered in the northern part of the study area, while cold spots expanded from both sides toward the southern direction. After 2000, hot spots in Qingtongxia City gradually disappeared, concentrating instead toward Yinchuan’ s municipal districts and Shizuishan City. Cold spots in Hongsibu District gradually disappeared, with cold spot areas in the southern part of the study area expanding northward. After 2010, hot spots gathered at the junction of Qingtongxia City, Lingwu City, and Litong District, while linking with hot spots in Yinchuan’ s municipal districts. Cold spots continued to expand northward along Shapotou, Haiyuan, and Xiji counties.

2.3.1 Importance of Carbon Emission Influencing Factors

Different factors have different effects on land use carbon emissions, and their impacts vary across different stages. To avoid multicollinearity problems caused by multiple factors, the random forest model was used to analyze the importance of ten influencing factors, using the IncMSE method as the importance measure. Larger values indicate more important influencing factors (Figure 7). The relative importance value of CLP (construction land proportion) was the highest, making it the dominant factor for analyzing the spatiotemporal heterogeneity between various factors and carbon emissions using the GTWR model.

3 Discussion and Policy Implications

The contradictions between socioeconomic development and ecological environmental protection continue to emerge in Ningxia. Against the backdrop of high-quality development of new productive forces, achieving the “dual carbon” goals depends not only on reducing carbon emissions but also on comprehensively improving the carbon sink capacity of ecosystems. Based on the above conclusions, the policy implications are as follows: (1) For high carbon emission areas, optimize land use structure, control the total amount and development intensity of construction land, and improve land use efficiency. For light and low carbon emission areas, reduce human occupation of natural ecological spaces and comprehensively strengthen ecological environmental protection. (2) Coordinate the control of total energy consumption within the carrying capacity of resources and the environment. Based on the region' s abundant energy resources, leverage the advantages of comprehensive development of coal, wind, solar, and other energy sources to reduce dependence on fossil fuels. (3) Focus on increasing vegetation and greening, and promote integrated protection and comprehensive management of mountains, rivers, forests, farmlands, lakes, grasslands, and deserts to enhance regional carbon sink capacity, while fully considering water resource carrying capacity.

This study measured the spatiotemporal evolution characteristics and influencing factors of carbon emissions in Ningxia at two spatial scales over the past 30 years, clarifying that construction land expansion and human activities are important driving factors for carbon emission growth in Ningxia. The research results have certain reference value. The study used the energy carbon emission coefficient published by the IPCC to estimate carbon emissions, ignoring carbon emissions from agricultural activities, human respiration, and residential energy consumption, which may affect the rationality of carbon emission estimation to some extent. Future research can conduct in-depth studies on carbon emission coefficients for different land use types in Ningxia through field surveys and remote sensing monitoring.

4 Conclusions

(1) From 1990 to 2020, the total land use carbon emissions in Ningxia showed a continuous growth trend, increasing slowly before 2000 and rapidly after 2000. Carbon emissions from construction land were consistent with the trend of total carbon emissions and were the main source of total emissions. This finding is consistent with research results by Jia Keli [16,26], Wang Yajuan [27], and Zheng Yongchao [28]. After 2000, the development of secondary industry became an important pillar of Ningxia' s economic growth, with industrial energy consumption rising sharply, directly leading to rapid growth in carbon emissions.

(2) During the study period, carbon emissions in various counties (districts) continued to grow with significant spatial distribution differences, showing a pattern of northwest region > central region > southern region. At the grid scale, the area of high carbon emission zones expanded and emission intensity gradually increased, while the area of low carbon emission zones decreased over time. Different grids within counties (districts) showed spatial differences in carbon emission intensity levels, with overall changes consistent across the two scales. Grid-scale carbon emissions showed significant spatial autocorrelation, with the agglomeration pattern strengthening over time.

(3) The influencing factors of land use carbon emissions in Ningxia showed obvious spatial heterogeneity. Construction land expansion and human activities had significant positive effects on carbon emission growth, with

land use structure change being the most important factor driving carbon emission increase.

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Note: Figure translations are in progress. See original paper for figures.