

Original Research

Spatiotemporal Dynamics and Influencing Mechanisms of Land-Use Carbon Emissions in Counties of Northern Henan, China

Zhigang Li^{✉*}, Yingying Zhao, Yawen Hou, Hongyu Lu, Haidong Li, Yunxing Zhang

School of Architectural and Artistic Design, Henan Polytechnic University, Jiaozuo 454000, China

Received: 13 February 2026

Accepted: 21 August 2026

Abstract

Climate warming driven by greenhouse gas emissions, especially carbon dioxide, severely threatens ecosystems and human societies. Accelerated by urbanization, land-use changes have significantly exacerbated climate change and disrupted carbon dynamics. Counties are key administrative units in China and are crucial for economic growth and achieving carbon neutrality goals. However, systematic research on carbon emission evolution and drivers at this scale remains scarce, hindering targeted low-carbon pathways. This study employs an improved IPCC method to quantify land-use carbon emissions (LUCE) in 37 Northern Henan counties (2000-2020). Using the standard deviational ellipse, Moran's I, and an optimal parameter-based geographical detector, we analyzed spatiotemporal patterns and drivers. The results showed that (1) land transformation primarily involved converting cultivated land to construction land, with the latter increasing by 45.6%. The LUCE distribution exhibited stability, while global Moran's I increased from 0.082 to 0.382, reflecting enhanced "high-high" and "low-low" spatial clustering. (2) Socioeconomic factors were the dominant drivers before 2010, while natural factors gained prominence thereafter. By 2020, natural constraints (especially NDVI) and their interactions with human activities (e.g., NTL) became key determinants, signaling intensified human-nature coupling. (3) Given heterogeneous resources, we propose tailored pathways, including land use optimization, industrial transformation, and regional collaboration. This research establishes a fine-scale methodological framework for identifying complex driving mechanisms, offering scientific evidence for precise spatial planning and differentiated carbon mitigation policies at the county level to promote synergy between regional development and ecological sustainability.

Keywords: Northern Henan, county scale, carbon emissions, driving factors, optimal parameter geographical detector

*e-mail: zhigangli86@hpu.edu.cn

Tel.: +86-196-0391-5643

0009-0008-8303-6960

Introduction

Global climate change poses a critical environmental challenge, threatening human survival and sustainable development through habitat degradation, biodiversity loss, sea level rise, and extreme weather events [1]. Land use/cover change (LUCC) is a major anthropogenic driver of climate change, altering ecosystem structures, processes, and functions, thereby impacting the global carbon cycle [2–4]. Since the Industrial Revolution, rapid LUCC, coupled with fossil fuel combustion and deforestation, has exceeded the regulatory capacity of natural ecosystems, driving unprecedented global warming. As a direct consequence of LUCC, alterations in vegetation ecological quality and landscape patterns are now key determinants of land-use carbon emissions (LUCE), forming a core focus of global environmental assessments [5]. As the world's largest carbon emitter, contributing approximately 27.00% of global carbon dioxide emissions in 2020 [6], China faces significant pressure to achieve synergy between economic development and carbon emission reduction while managing its energy consumption. At the 75th UN General Assembly in 2020, China committed to peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 [7], underscoring the urgency of advancing LUCC-related carbon emission studies to support sustainable development pathways [8].

As a primary driver of anthropogenic carbon emissions, LUCC-related carbon emissions have been extensively studied [9, 10]. Research in this field primarily focuses on three interconnected pillars: (1) the development of robust methods for carbon emission accounting and inventory construction; (2) the analysis of spatiotemporal distribution patterns to identify emission hotspots and trends; and (3) the investigation of the underlying socioeconomic and environmental driving factors to inform effective mitigation policies. Emissions from land use/cover change (LUCC) have been extensively investigated because they constitute a major source of anthropogenic carbon emissions. Existing studies can generally be organized around three closely related strands. First, substantial progress has been made in carbon emission accounting and inventory construction. Bookkeeping models [11, 12], sample inventory methods [13], and IPCC emission factor approaches [14] have become the principal tools for quantifying land-use carbon emissions (LUCE) at different spatial scales. However, despite these methodological advances, the estimation of emissions from construction land remains uncertain in many county-level studies because local energy consumption statistics are often incomplete, which constrains the accuracy of fine-scale carbon inventories. Second, the spatiotemporal patterns of LUCE have become a major research focus, with growing efforts devoted to identifying emission hotspots, center-of-gravity shifts, and interregional disparities [15–17]. Existing studies have revealed marked differences in carbon emissions

among cropland, forestland, grassland, water bodies, unused land, and construction land, because these land-use types exhibit markedly different carbon source–sink effects [18, 19]. In particular, land-use transitions have been recognized as a critical process reshaping regional carbon patterns, as the rapid conversion of ecological land functioning as a carbon sink into urban and construction land can significantly intensify carbon imbalance [20]. Correspondingly, the scope of spatial analysis has gradually expanded from global, national, and provincial assessments to prefecture-level, county-level, and grid-level studies. Recent studies have further combined NTL imagery with energy statistics to estimate county-level carbon emissions, offering a practical solution to data scarcity at small spatial scales [21]. Third, increasing attention has been paid to the driving mechanisms behind LUCE. Current evidence indicates that LUCE is jointly shaped by socioeconomic development and environmental constraints, particularly population size, economic growth, industrial structure, land use composition, topography, temperature, and vegetation cover [22, 23]. To disentangle these interactions, a series of analytical approaches, including LMDI, ESTDA, STIRPAT, GWR, and, more recently, the Optimal Parameter-based Geographical Detector (OPGD), have been widely employed [24, 25]. Nevertheless, existing studies still tend to emphasize socioeconomic drivers, while the coupled effects of natural factors and human activities remain insufficiently explored, especially at the county scale, thereby limiting a more comprehensive understanding of LUCE heterogeneity and the formulation of targeted mitigation policies.

Materials and Methods

Study Area

Northern Henan (34°53'N–36°22'N, 112°01'E–114°45'E) is located in the middle and lower reaches of the Yellow River Basin, covering approximately 23,800 km² (Fig. 1a) and b)). As the core of the Central Plains urban agglomeration, it serves as a strategic hub connecting northern and central China, encompassing major cities including Jiyuan, Jiaozuo, Xinxiang, Anyang, and Hebi (Fig. 1c)). Northern Henan exhibits a stepped topography, sloping from high northwest to low southeast, with diverse landforms such as mountains and hills. Hydrologically, it is traversed by the Yellow River and the Qinhe River, supplemented by the Middle Route of the South-to-North Water Transfer Project, ensuring abundant water resources. The climate is characterized by a temperate monsoon regime. Currently, Northern Henan is undergoing a critical phase of industrial transformation and urban expansion. Significant disparities exist in socio-economic development and ecological conditions among its cities and counties. Land use changes and urbanization

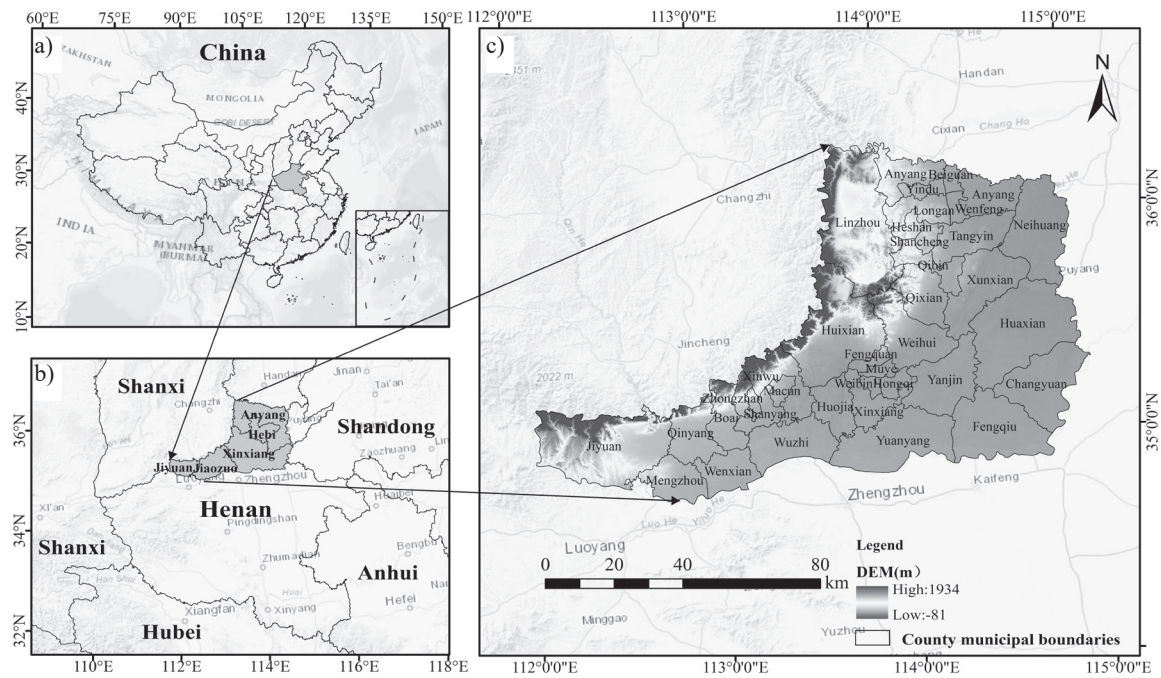


Fig. 1. Map of the study area. a) Location of Henan Province in China. b) Location of the northern Henan region within Henan Province. c) Location of counties and cities in the northern Henan region.

processes have exerted substantial impacts on carbon emissions. This study selects 37 county-level units in Northern Henan as the research scope to systematically investigate the spatiotemporal evolution and driving factors of LUCE, providing theoretical support for Henan Province's "carbon reduction and pollution control" goals and regional low-carbon transition.

Data Sources and Preprocessing

The datasets used in this study include land use, energy-related carbon emissions, and natural and socioeconomic indicators at the county level across Northern Henan Province from 2000 to 2020. These multi-source datasets collectively support the analysis of the spatiotemporal patterns and driving mechanisms of LUCE within a unified spatial framework.

Land use data were obtained from the China Land Cover Dataset (CLCD) [26]. With a spatial resolution of 30 m, the original data were reclassified into six categories: cultivated land, woodland, grassland, water bodies, construction land, and unused land, and aggregated to county-level administrative units. County-level energy-related carbon emissions were estimated by downscaling prefecture-level data from the China Emissions Accounts and Datasets (CEADs) [13], using NTL intensity as a proxy for socioeconomic activity, a method widely applied and validated in previous studies [27, 28]. The downscaling models demonstrated high accuracy, with R^2 values exceeding 0.77 ($p < 0.001$) for all prefecture-level cities (e.g., $R^2 = 0.927$ for Anyang City).

Natural factors comprised NDVI and NPP, derived from NASA's MODIS products (MOD13A3 and MOD17A3, available at <https://search.earthdata.nasa.gov/> and <https://earthexplorer.usgs.gov/>), as well as TEM and ACP obtained from datasets provided by Peng Shouzhang through the National Tibetan Plateau Data Center (<https://data.tpdc.ac.cn/>) [29]. Socioeconomic variables were categorized into social and economic factors. Social factors included permanent population (POP), population density (PD), and urbanization rate (UR). Economic factors consisted of gross domestic product (GDP), industrialization level (IL), per capita GDP (Per GDP), industrial structure (IS), and land use degree index (LUDI). These socioeconomic data were compiled from the China County Statistical Yearbooks and municipal statistical bulletins. NTL data were derived from the validated long-term dataset published by Wu et al. [30], which achieved a 42% reduction in mean relative error compared with traditional methods. All spatial datasets were resampled to a uniform resolution and projected to the WGS 1984 UTM Zone 50N coordinate system (EPSG: 32650) using ArcGIS 10.8 to ensure spatial consistency.

Methodology

This study adopted a systematic, four-stage methodology to quantify and unravel the spatiotemporal dynamics of land-use carbon emissions (LUCE) across the counties of Northern Henan (Fig. 2). The process commenced with data preparation and processing to construct a consistent spatiotemporal dataset.

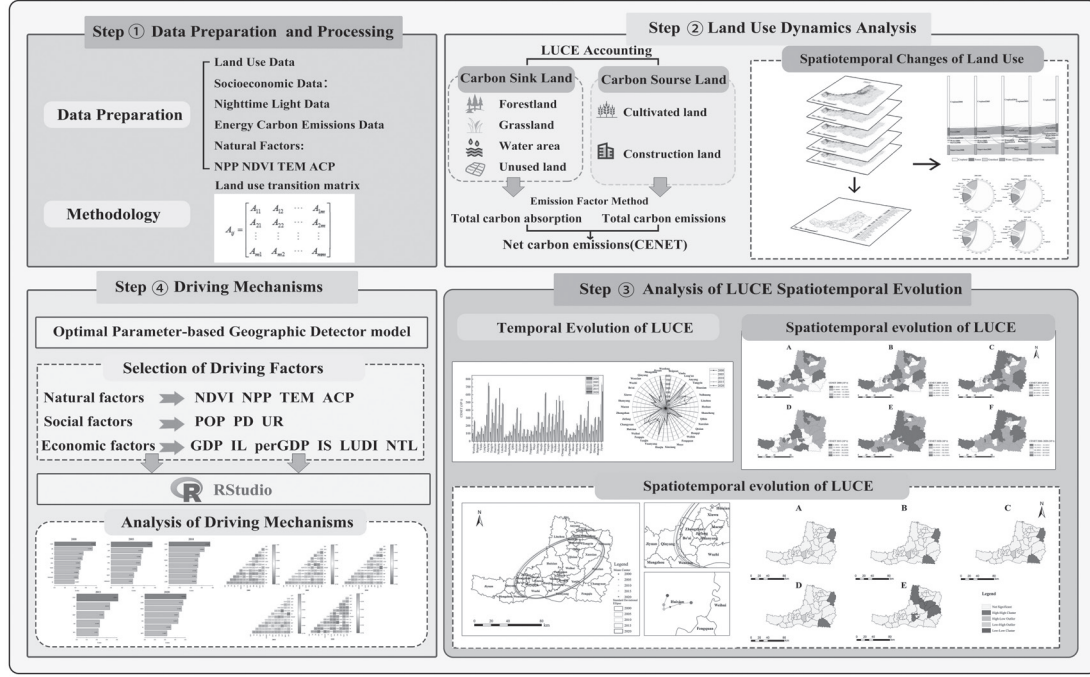


Fig. 2. Analytical framework of this study.

Subsequently, a land use dynamics analysis was conducted to characterize transition patterns. The core of the investigation involved analyzing the spatiotemporal evolution of LUCE, where the Standard Deviatonal Ellipse and Spatial Correlation Index were employed to delineate trajectory shifts and clustering characteristics. Finally, the driving mechanisms were probed using the Optimal Parameter-based Geographical Detector model to identify key determinants and their interactive effects.

Land Use Transition Matrix

The land use transition matrix quantitatively describes the area conversion between different land use types at the beginning and end of a study period through a two-dimensional matrix [31]. It is expressed as shown in Eq. (1):

$$A_{ij} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1m} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mm} \end{bmatrix} \quad (1)$$

Where A_{ij} represents the area (hm^2) converted from the i -th land use type to the j -th land use type, and m represents the total number of land use types.

Carbon Emission Accounting Methods

A county-scale carbon emission accounting model was developed based on the IPCC methodology, incorporating both direct emissions from land use change and indirect emissions from human activities on

the land [32]. The total LUCE, represented as net carbon emissions (CENET), is calculated as shown in Eq. (2):

$$C = C_n + \sum C_m \quad (2)$$

Where C represents CENET, C_n is the carbon emissions from construction land, which carries human production activities and indirectly generates energy-related carbon emissions, and C_m refers to the carbon emissions from the other five land use types.

The carbon emissions from these land use types can be calculated using the IPCC carbon accounting factor method, as shown in Eq. (3):

$$C_m = B_m \times b_m \quad (3)$$

Where B_m represents the area of each land use type (hm^2), and b_m denotes the carbon emission (absorption) coefficient of each land use type. Based on prior research and the actual land use conditions in Northern Henan [19, 22], the coefficients (t/hm^2) for cultivated land, forestland, grassland, water area, and unused land are 0.497, -0.581 , -0.021 , -0.253 , and -0.005 , respectively. Positive values indicate carbon sources, whereas negative values indicate carbon sinks.

Standard Deviatonal Ellipse

The SDE is a spatial statistical technique used to assess the distribution pattern and migration trends of geographic elements [33]. By using the mean center, major axis, minor axis, and azimuth as key parameters, SDE accurately describes the spatial distribution center, direction, and shape of the studied objects, facilitating

the analysis of spatiotemporal variations in carbon emissions [34, 35]. The core parameters are calculated as shown in Eqs. (4)-(7):

Weighted center of gravity:

$$P(\bar{X}, \bar{Y}) = \left[\frac{\sum_{i=1}^n \omega_i x_i}{\sum_{i=1}^n \omega_i}, \frac{\sum_{i=1}^n \omega_i y_i}{\sum_{i=1}^n \omega_i} \right] \quad (4)$$

X-axis standard deviation:

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

Y-axis standard deviation:

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

Azimuth:

$$\tan \theta = \frac{(\sum_{i=1}^n \omega_i \tilde{x}_i^2 - \sum_{i=1}^n \omega_i \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^n \omega_i \tilde{x}_i^2 - \sum_{i=1}^n \omega_i \tilde{y}_i^2)^2 + 4 \sum_{i=1}^n \omega_i^2 \tilde{x}_i^2 \tilde{y}_i^2}}{2 \sum_{i=1}^n \omega_i^2 \tilde{x}_i \tilde{y}_i} \quad (7)$$

Where $P(\bar{X}, \bar{Y})$ denotes the central coordinate of the ellipse; (x_i, y_i) represents the spatial location of the research object; $(\tilde{x}_i, \tilde{y}_i)$ indicates the coordinate deviation of the research object from the mean center; and w_i represents the index weight. In this study, CENET of the Northern Henan region is used as the weight.

Spatial Correlation Index

Spatial autocorrelation analysis was employed to identify clustering patterns in county-level carbon emissions [24, 36]. Global Moran's I was used to evaluate the overall spatial dependence of LUCE across Northern Henan, calculated as shown in Eq. (8):

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (8)$$

Where I denotes the Moran's index, with values greater than 0 indicating positive spatial correlation, values less than 0 indicating negative spatial correlation, and a value of 0 suggesting a random spatial distribution.

Here, n is the total number of counties in Northern Henan; x_i and x_j denote the carbon emissions of counties i and j , respectively; $\bar{x}$ represents the average carbon emissions; and ω_{ij} is the spatial weight matrix.

The local Moran's I was further applied to reveal local spatial associations between individual counties and their neighbors [28]. Local Moran's I is calculated as shown in Eq. (9):

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

This analysis identifies four types of spatial clusters: High-High (HH), Low-Low (LL), High-Low (HL), and Low-High (LH), representing areas of high- or low-emission aggregation or outliers.

Optimal Parameter-based Geographic Detector (OPGD)

The optimal parameter-based geographical detector (OPGD) was used to explore the driving factors behind the spatial heterogeneity of LUCE [32]. The OPGD improves upon the standard Geographical Detector [37, 38] by incorporating optimal discretization methods for spatial data classification, thereby enhancing the evaluation of factor explanatory power. The factor detector quantifies a factor's explanatory power using the q-statistic, as shown in Eq. (10):

$$q_{x,y} = 1 - \frac{\sum_{h=1}^L n_h \sigma_h^2}{n \sigma^2} \quad (10)$$

Where $q_{x,y}$ denotes the explanatory power of variable x on CENET y , ranging from 0 to 1; h represents the stratum of the selected explanatory variable; n_h and σ_h are the sample size and variance of stratum h , respectively; and n and σ^2 are the total sample size and variance.

The interaction detector evaluates whether the combined influence of two factors strengthens or weakens the explanation of CENET by comparing the q-values of individual and interacting factors (Table 1). In this study, CENET serves as the response variable, with 13 explanatory variables considered (Table 2). All OPGD analyses were performed using the GD package in RStudio.

Table 1. Interaction modes between the independent and dependent variables.

Interaction Types	Interaction Criteria
Nonlinear-weakening	$q(X1 \cap X2) < \min(q(X1), q(X2))$
Univariate-weakening	$\min(q(X1), q(X2)) < q(X1 \cap X2) < \max(q(X1), q(X2))$
Bivariate-enhancement	$q(X1 \cap X2) > \max(q(X1), q(X2))$
Independent	$q(X1 \cap X2) = q(X1) + q(X2)$
Nonlinear-enhancement	$q(X1 \cap X2) > q(X1) + q(X2)$

Table 2. Variables used in the OPGD analysis.

Variable Type	Variable	Data type	Description	Unit
Independent Variable	Net carbon emissions (CENET)	Raster	Carbon emissions from energy and land use minus carbon absorption by land types	Mt
Natural factors	Normalized difference vegetation index (NDVI)	Raster	Indicator of vegetation growth status	0-1
	Net primary productivity (NPP)	Raster	Annual mean total primary productivity	KgC·/(m ² ·a)
	Temperature (TEM)	Raster	Annual average temperature at the county scale	°C
	Annual cumulative precipitation (ACP)	Raster	Annual cumulative precipitation at the county scale	mm
Social factors	Permanent population (POP)	Csv	Resident population from statistical yearbooks	10,000 people
	Population density (PD)	Csv	Population concentration per unit area	persons/km ²
	Urbanization rate (UR)	Csv	Ratio of urban population to year-end resident population	%
Economic factors	GDP	Csv	Gross domestic product at the county scale	10,000 CNY
	Industrialization level (IL)	Csv	Industrial value added at the county scale	10,000 CNY
	Per GDP	Csv	County-level GDP divided by resident population	10,000 CNY
	Industrial structure (IS)	Csv	Proportion of secondary industry in GDP	%
	Land use degree index (LUDI)	Csv	Ratio of construction land to total area	%
	Nighttime light index (NTL)	Raster	Proxy for human economic activity using nighttime light data	nw/(cm ² ·sr)

Results

Spatiotemporal Changes of Land Use in Northern Henan

From 2000 to 2020, land use in Northern Henan underwent substantial transformations driven by urbanization, with marked variations in area dynamics across land use categories (Fig. 3(a-e)). Construction land expanded from 3186.04 km² to 4629.04 km², with its proportion rising from 13.46% to 19.56% and a growth rate of 45.3%, calculated from 45.29%. In contrast, cropland decreased by 1325.15 km², reducing its proportion by 5.60% from 71.62% to 66.02%. Throughout the period, construction land consistently increased while cropland steadily declined, with both exhibiting a phased pattern of initial acceleration from 2000 to 2010 followed by deceleration from 2010 to 2020.

Land use transfer analysis from 2000 to 2020 revealed that a total of 23,662.301 km² of land underwent type conversions in Northern Henan (Fig. 3f) and g)). The expansion of construction land was predominantly driven by the conversion of cropland, with 1429.67 km² transformed, accounting for 30.88% of the total cropland outflow. Construction land exhibited a net inflow of 1443.00 km², with an inflow of 4629.04 km² and an outflow of 3186.04 km², primarily sourced from cropland. Forest land, water bodies, and unused land recorded net inflows, whereas cropland and grassland experienced net outflows. For forest land, water bodies,

and unused land, the inflow exceeded the outflow, while cropland and grassland exhibited greater outflow than inflow.

Spatially, construction land expanded outward from urban centers at the county level, while forest land and grassland, key carbon sinks, remained concentrated in the northwestern mountainous and hilly regions. Land use transitions displayed pronounced spatial heterogeneity: central and southeastern areas were dominated by inflows to construction land, whereas the northwest featured conversions favoring forest land and grassland.

Spatiotemporal Evolution of LUCE in Northern Henan

Analysis of the Temporal Evolution Characteristics of LUCE

Table 3 presents CENET in Northern Henan from 2000 to 2020. Net carbon emissions increased from 4744.05 to 15285.56 ten thousand tons, with an average annual growth rate of 4.73%, showing a pattern of rapid increase followed by stabilization. Construction land, driven by human activities, was the dominant carbon source, contributing 98.31% to 99.35% of total CENET, with emissions rising from 4659.83 to 15223.06 ten thousand tons. In contrast, cropland emissions gradually declined from 84.22 to 77.64 ten thousand tons.

Forest land was the primary carbon sink, with its carbon sequestration capacity increasing from 0.16 to

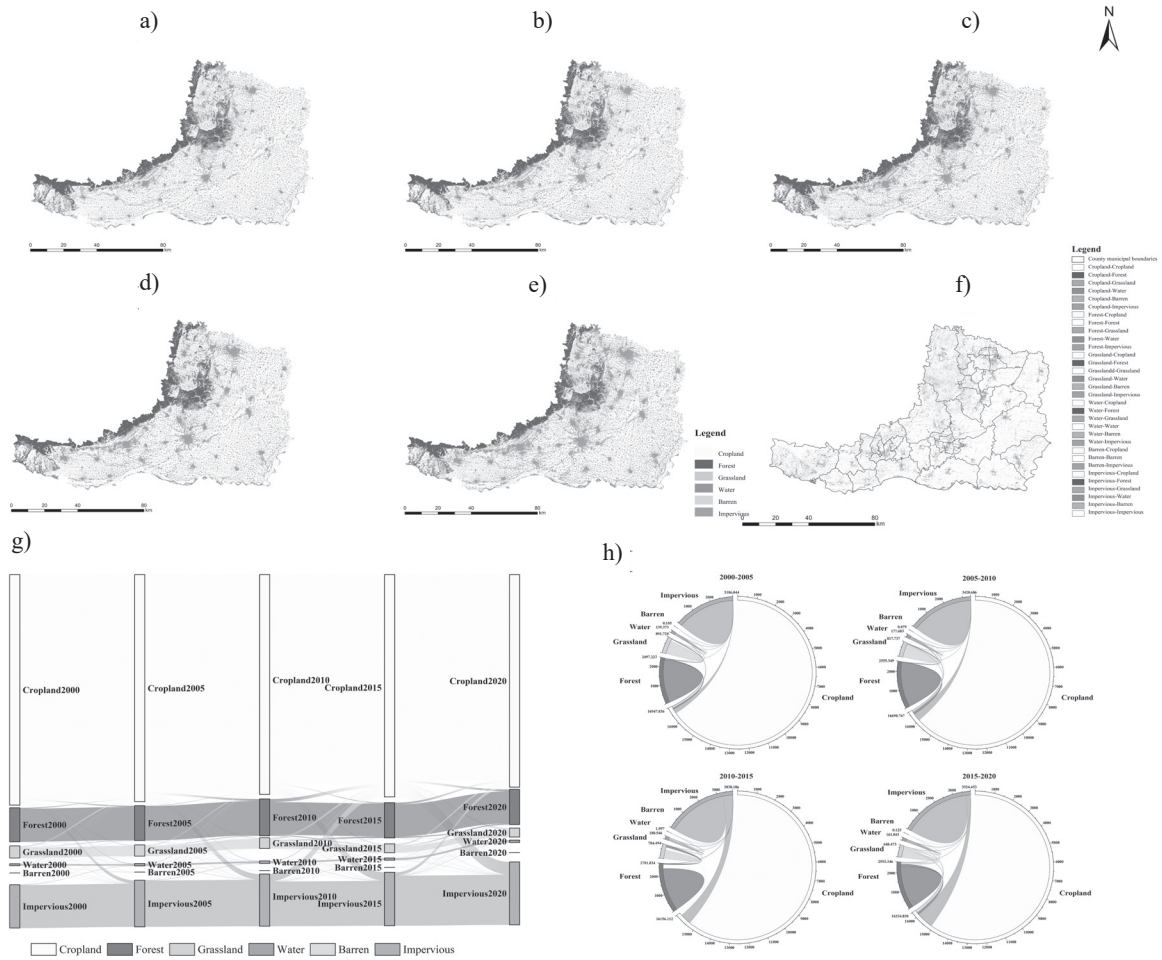


Fig. 3. Spatiotemporal evolution and transition of land use in Northern Henan from 2000 to 2020. (a-e) Spatial distribution of land use types: a) year 2000, b) year 2005, c) year 2010, d) year 2015, and e) year 2020; f) Sankey diagram of land use transitions; g) Chord diagram of the land use transfer matrix.

15.07 ten thousand tons from 2010 to 2015, accounting for 98.80% of total carbon sequestration by 2020. Grassland and water-body carbon sinks remained relatively stable, while unused land contributed negligibly to carbon sequestration.

From 2000 to 2020, total carbon emissions in Northern Henan increased by 227.98%, rising from 4744.05 to 15285.56 ten thousand tons, with a pattern of rapid increase from 2000 to 2010, a slight decline from

2010 to 2015, and a moderate rise from 2015 to 2020. By 2020, all five prefecture-level cities exhibited negative growth rates in emissions: Jiyuan, -17.01%; Xinxiang, -5.23%; Jiaozuo, -4.41%; Anyang, -3.85%; and Hebi, -1.13%. County-level analysis revealed significant spatial differentiation, with Jiyuan, Neihuang, and Weihui showing the largest emission increases, while Heshan and Changyuan experienced notable declines by 2020 (Fig. 4).

Table 3. CENET in Northern Henan from 2000 to 2020 (Unit: 10,000 tons).

Year	Carbon Source Land Use			Carbon Sink Land Use					CENET
	Cropland	Construction land	Total Emissions	Forest	Grassland	Water	Barren	Total Absorption	
2000	84.22	4659.83	4744.05	-0.15	0.00	0.00	0.00	-0.15	4743.90
2005	82.95	7504.91	7587.85	-0.15	0.00	0.00	0.00	-0.15	7587.70
2010	80.29	12487.09	12567.37	-0.16	0.00	0.00	0.00	-0.16	12567.22
2015	81.19	12487.09	12568.27	-15.07	-0.14	-0.04	0.00	-15.25	12553.03
2020	77.64	15223.06	15300.69	-14.96	-0.14	-0.05	0.00	-15.14	15285.56

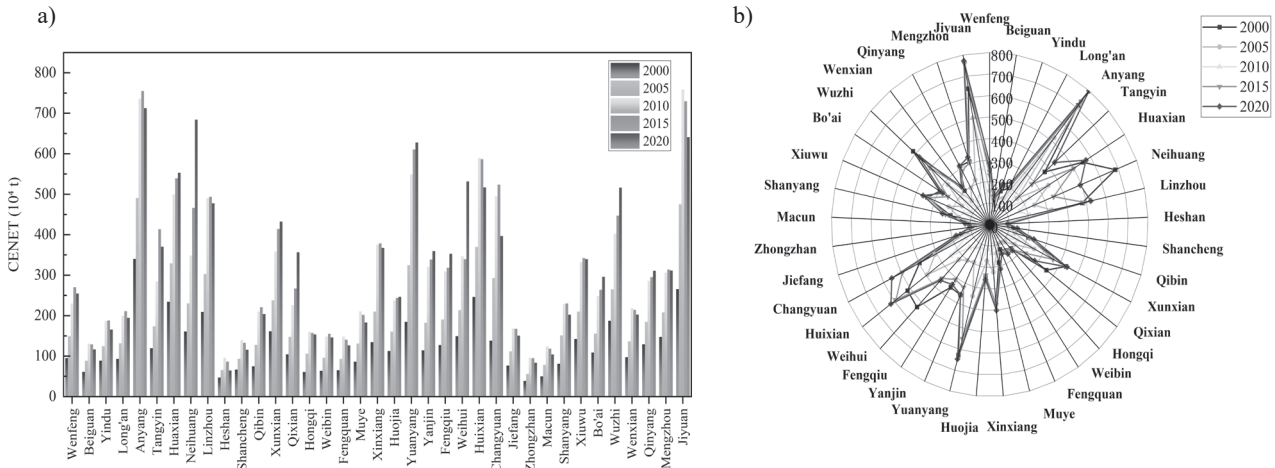


Fig. 4. The trend of LUCE in various districts and counties of Northern Henan from 2000 to 2020: a) Bar chart; b) Radar chart.

Analysis of the Spatial Evolution Characteristics of LUCE

(1) Spatial evolution of LUCE at the county level in Northern Henan

The spatial evolution of LUCE in Northern Henan showed distinct phased characteristics from 2000 to 2020. In 2000, low-emission zones dominated the region, with high-emission areas emerging in scattered locations. Between 2005 and 2015, high-emission zones expanded, forming contiguous patches, particularly in central and eastern counties such as Anyang and Xinxian, establishing a spatial gradient. From 2015 to 2020, high-emission areas became concentrated in central districts of major cities, including Muye, Weibin, and Hongqi in Xinxian City, where emissions from peripheral counties increased. Meanwhile, the northwest region, rich in forest and grassland, saw a rise in low-emission zones, contributing to a spatial pattern of

higher emissions in the center and lower emissions in the northwest. Overall, the carbon emission distribution evolved from dispersion to aggregation with increased differentiation (Fig. 5).

(2) Spatial pattern evolution analysis

The spatial analysis using the SDE method revealed (Fig. 6, Table 4) that the spatial distribution pattern of county-level LUCE in Northern Henan from 2000 to 2020 exhibited high stability, with no significant centroid shifts or drastic elliptical morphological changes. The major axis of the SDE was consistently oriented along the southwest-northeast direction, and the centroid remained stable near Huixian City (113.85° - 113.90° E, 35.46° - 35.48° N). Specifically, the SDE area decreased by 1.25%, the perimeter decreased by 0.68%, and the major and minor semi-axis lengths contracted by 0.4 km and 0.35 km, respectively. The analysis indicated a weak centripetal aggregation trend of carbon emissions along the major axis, with emissions further

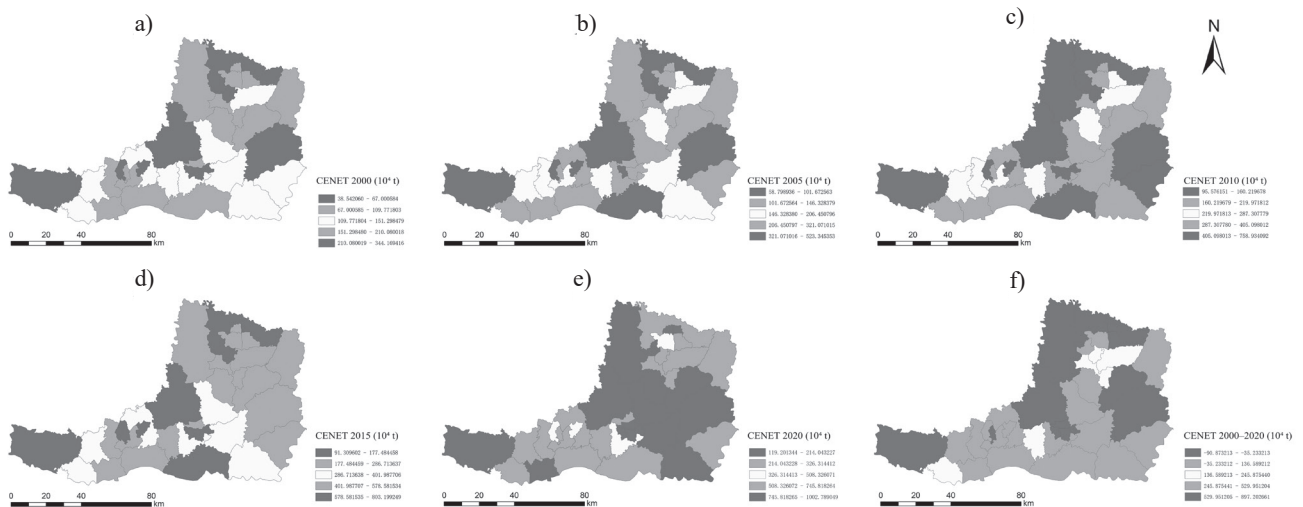


Fig. 5. Spatial distribution of CENET at the county level in Northern Henan from 2000 to 2020: a) year 2000, b) year 2005, c) year 2010, d) year 2015, e) year 2020.

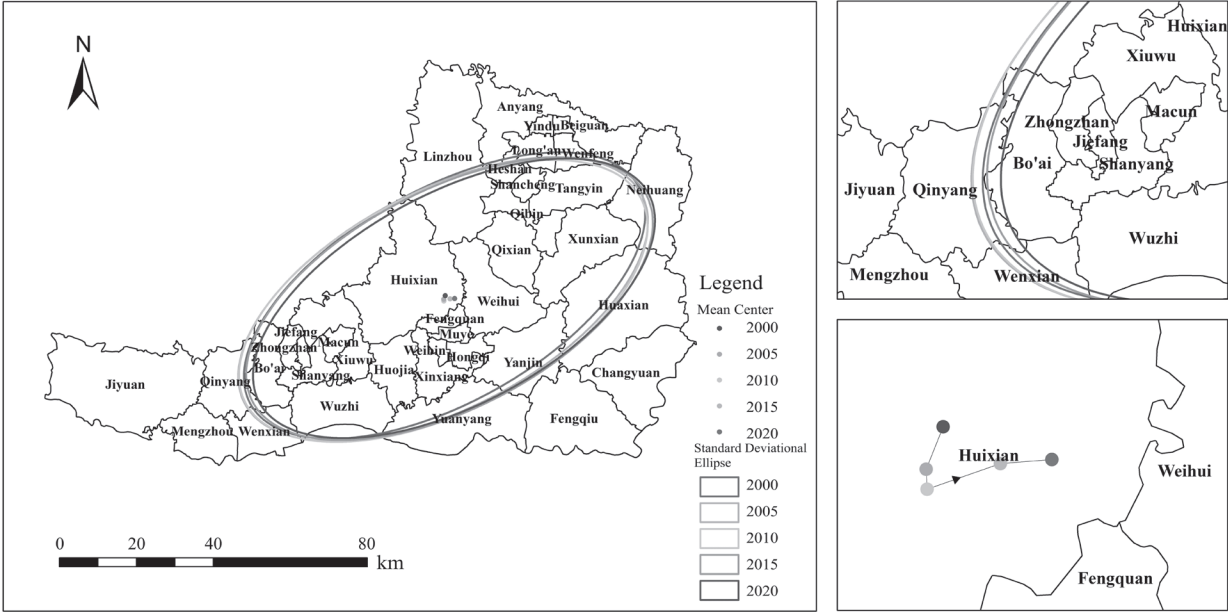


Fig. 6. The SDE of LUCE at the county level in Northern Henan from 2000 to 2020.

concentrating toward the centroid from the southwest to the northeast.

Analysis of Spatial Agglomeration Characteristics

Global Spatial Autocorrelation

Table 5 presents global Moran's *I* for county-level LUCE in Northern Henan from 2000 to 2020. All years showed Moran's *I* values greater than 0, with a significant positive correlation in 2020 (Moran's *I* = 0.382, Z-score = 4.020, *p*=0.000) at the 95% confidence level, indicating spatial clustering of high-

and low-emission counties. The Moran's *I* increased from 0.082 in 2000 to 0.382 in 2020, suggesting increasingly strong positive spatial correlation over time, with counties exhibiting high or low carbon emissions increasingly clustering together.

Local Spatial Autocorrelation

The spatial heterogeneity of LUCE in Northern Henan was analyzed using local Moran's *I* (Fig. 7). This approach identified distinct clustering patterns over the study period. In 2020, Xinxiang, Weinan, and Muye formed High-High (HH) clusters, indicating high-emission areas with significant influence on neighboring

Table 4. Parameters of the SDE for county-level LUCE in Northern Henan from 2000 to 2020.

Year	Perimeter (km)	Area (km ²)	X-coordinate (°)	Y-coordinate (°)	Major axis (km)	Minor axis (km)	Orientation angle (°)	Flattening ratio (%)
2000	446.66	13051.22	113.85	35.48	98.43	41.87	65.93	0.57
2005	452.02	13474.53	113.85	35.47	99.64	42.70	67.40	0.57
2010	450.54	13487.17	113.85	35.46	99.06	42.98	67.91	0.57
2015	449.50	13391.32	113.88	35.47	98.87	42.77	67.53	0.57
2020	443.63	12888.74	113.90	35.47	98.03	41.52	67.00	0.58

Table 5. Global Moran's *I* of LUCE in Northern Henan (2000-2020).

YEAR	2000	2005	2010	2015	2020
Moran's <i>I</i>	0.082	0.066	0.064	0.108	0.382
Z-Score	1.107	0.946	0.920	1.338	4.020
p-Value	0.268	0.344	0.357	0.181	0.000



Fig. 7. Evolution of LUCE cluster types in Northern Henan: a) year 2000, b) year 2005, c) year 2010, d) year 2015, e) year 2020.

regions. Huojia consistently exhibited Low-High (LH) clusters from 2000 to 2020, reflecting a persistent pattern where low-emission counties adjoin high-emission ones. Low-Low (LL) clusters expanded over time, starting with Neihuang and Fengqiu and expanding by 2020 to include Linzhou, Qixian, and Changyuan, signifying an increasing expanse of low-carbon regions.

Analysis of Driving Factors Using Geo-detector

Independent Influences of Single Factors

Geo-detector analysis identified key drivers of LUCE in Northern Henan from 2000 to 2020. The results showed temporal variation in driving factors, with social factors (POP, UR, PD) as primary drivers throughout the period (Fig. 8(a-e) and Table 6).

In 2000, POP ($q = 0.787^{***}$) and UR ($q = 0.727^{***}$) were dominant, reflecting the impact of population growth and urbanization; in 2005, UR ($q = 0.577^{***}$) remained significant, while NDVI ($q = 0.326$) and IS ($q = 0.203$) showed reduced influence; in 2010, GDP ($q = 0.647^{***}$) emerged as a primary driver, while IL ($q = 0.502$) showed declining explanatory power; in 2020, NTL ($q = 0.815^{***}$) emerged as the primary indicator, alongside the increased influence of LUDI ($q = 0.753^{**}$) and NDVI ($q = 0.720^{***}$).

Temporal evolution analysis revealed three key trends: the average q -value of social factors decreased from 0.659 to 0.493, indicating a 25.2% reduction in their explanatory power; the explanatory power of economic factors increased slightly from 0.448 to 0.469, a 4.7% rise driven primarily by GDP growth and land-use intensity (LUDI); the influence of natural factors increased from 0.285 to 0.375, a 31.3% rise, with NDVI

($q = 0.720^{*}$) and NPP showing strengthened constraints on carbon emissions. This shift highlights a transition from socioeconomic to ecologically constrained drivers, supporting low-carbon goals.

Interaction Effects between Two Factors

Interaction detection revealed that two-factor interactions predominantly exhibited enhancement or nonlinear enhancement effects, with no independent or weakening relationships observed (Fig. 8(f-j)). In 2000 and 2005, both enhancement and nonlinear enhancement were dominant, while from 2010 to 2020, enhancement effects prevailed.

From 2000 to 2005, social and economic factors dominated, with the interactions GDP $\cap$ UR ($q = 0.944$) and PD $\cap$ UR ($q = 0.914$) in 2000, and UR $\cap$ TEM ($q = 0.930$) and NDVI $\cap$ Per GDP ($q = 0.886$) in 2005. During 2010–2020, the interactions among economic, land use, and ecological factors became prominent, including NDVI $\cap$ TEM ($q = 0.905$) in 2010, PD $\cap$ ACP ($q = 0.962$) in 2015, and in 2020 NTL $\cap$ IS ($q = 0.990$) and NDVI $\cap$ LUDI ($q = 0.940$), indicating strengthened interactive effects.

Further analysis was conducted on data spanning from 2000 to 2020, identifying instances where individual factors had no significant effect ($p > 0.05$) or ($q < 0.3$), yet demonstrated a notable increase in explanatory power following interactions (Table 7). The findings revealed a pronounced synergistic impact of economic factors (e.g., GDP, Per GDP) and natural and social factors (e.g., TEM, ACP, NDVI, NPP) on carbon emissions, surpassing the cumulative effect of single factors. In 2000, the interaction between GDP and TEM exhibited a substantial 68.26% increase

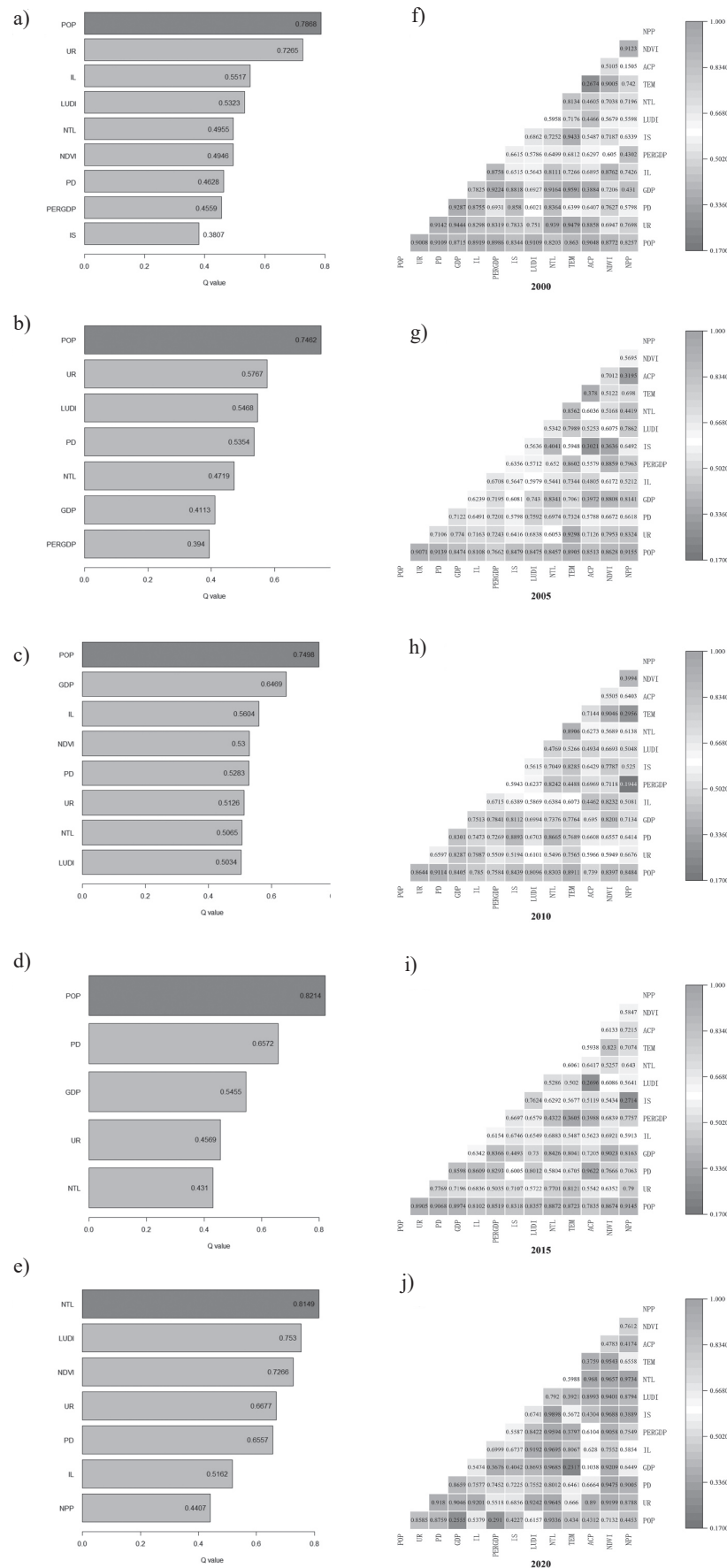


Fig. 8. Independent influences and interaction effects of driving factors on LUCE. Left column (a-e): q-values of individual driving factors in a) 2000, b) 2005, c) 2010, d) 2015, and e) 2020.

Right column (f-j): q-values of two-factor interactions in f) 2000, g) 2005, h) 2010, i) 2015, and j) 2020, showing enhancement effects.

Table 6. Driving factors and their significance.

		2000	2005	2010	2015	2020
		q-value	q-value	q-value	q-value	q-value
Social factors	POP	0.787***	0.746***	0.7498***	0.821***	0.154
	UR	0.727***	0.577***	0.5126**	0.457**	0.668***
	PD	0.463**	0.535***	0.5283**	0.657***	0.656***
Economic factors	GDP	0.268	0.411**	0.6469***	0.545***	0.167
	IL	0.552**	0.422	0.5019	0.468	0.516**
	Per GDP	0.456*	0.394*	0.2257	0.261	0.239
	IS	0.381*	0.203	0.3537*	0.240	0.322
	LUDI	0.532*	0.547**	0.5034*	0.507*	0.753**
	NTL	0.496*	0.472*	0.5065**	0.431*	0.815***
Natural factors	TEM	0.302	0.337	0.3314	0.283	0.169
	ACP	0.135	0.228	0.2942	0.333	0.168
	NDVI	0.495*	0.326	0.53**	0.507*	0.720***
	NPP	0.209	0.306	0.2222	0.271	0.441

Notes: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

compared to the combined impact of the individual factors. Between 2005 and 2015, the interplay between ecosystems and human activities steadily intensified, with the explanatory power of the interaction between Per GDP and NPP rising by 45.90% in 2015, indicating a reinforced constraint effect of vegetation carbon sequestration on carbon emissions at higher income levels due to economic model enhancements. In 2020, the collaborative enhancements of Per GDP with ACP and POP with TEM stood at 34.20% and 33.97%, respectively. These results show that even if a single factor has no significant effect, such factors can serve as pivotal drivers of carbon emissions through their interactions, elucidating the intricate mechanisms governing the dynamic interplay of natural and socio-economic factors on carbon emissions.

Further analysis of 2000-2020 data identified interactions where single factors ($q < 0.3$ or $p > 0.10$) showed significant explanatory power increases (Table 7). Notable enhancements included GDP $\cap$ TEM increasing by 68.26% in 2000, Per GDP $\cap$ NPP by 45.90% in 2015, and in 2020, Per GDP $\cap$ ACP by 49.88% and POP $\cap$ TEM by 34.20% over single-factor effects. These findings highlight that interactions between economic (e.g., GDP, Per GDP), natural (e.g., TEM, ACP, NDVI, NPP), and social factors enhance carbon emission drivers beyond individual contributions, revealing complex dynamic mechanisms.

Discussion

Spatiotemporal Pattern of LUCE in Northern Henan

From 2000 to 2020, Northern Henan exhibited a pronounced urbanization-driven transition in land use, primarily characterized by the conversion of cultivated land to construction land. This shift, reflecting the encroachment on farmland resources caused by population agglomeration and industrial expansion under rapid urbanization [39, 40], is consistent with national trends during this period [41]. A representative example is Jiyuan City, where construction land expanded from 98.7 km² to 156.3 km² during this period. As a national demonstration zone for integrated urban-rural development, Jiyuan has experienced accelerated industrial restructuring and urbanization, highlighting the close association between construction land expansion and urban spatial change, which is consistent with recent studies emphasizing the environmental significance of urban spatial reconfiguration and social infrastructure development.

Overall, total carbon emissions in Northern Henan showed a significant increase from 2000 to 2020, a trend consistent with national patterns and those observed in the Yellow River Basin [42]. However, since approximately 2015, the regional growth rate of LUCE has slowed considerably, with several cities even exhibiting negative growth. For instance, Jiaozuo experienced a decline of 4.41% by 2020, while emissions in Hongqi District of Xinxiang stabilized post-2015.

Table 7. Significant changes in interactive explanatory power from 2000 to 2020.

	Rank	Two-factor interaction (X1∩X2)	q(X1) + q(X2)	Interactive q-value	Enhancement compared with q(X1) + q(X2)
2000	1	GDP∩TEM	0.570	0.959	68.26%
	2	TEM∩IS	0.683	0.943	38.11%
	3	TEM∩NPP	0.511	0.742	45.21%
	4	GDP∩IS	0.649	0.882	35.87%
	5	GDP∩Per GDP	0.724	0.922	27.40%
	6	GDP∩PD	0.731	0.929	27.05%
	7	NPP∩NDVI	0.704	0.912	29.59%
	8	GDP∩NTL	0.764	0.916	19.95%
	9	TEM∩NDVI	0.797	0.901	12.99%
2005	1	NPP∩IS	0.509	0.649	27.52%
	2	NDVI∩Per GDP	0.72	0.886	23.01%
	3	TEM∩Per GDP	0.731	0.86	17.69%
	4	NPP∩GDP	0.718	0.814	13.43%
2010	1	Per GDP∩ACP	0.52	0.697	34.05%
	2	ACP∩NPP	0.516	0.64	23.99%
	3	TEM∩ACP	0.626	0.714	14.19%
2015	1	Per GDP∩NPP	0.532	0.776	45.90%
	2	Per GDP∩IS	0.501	0.67	33.80%
	3	TEM∩NPP	0.553	0.707	27.80%
	4	NPP∩ACP	0.603	0.722	19.60%
2020	1	Per GDP∩ACP	0.407	0.61	49.88%
	2	POP∩TEM	0.323	0.434	34.20%
	3	POP∩ACP	0.322	0.431	33.97%
	4	IS∩TEM	0.492	0.567	15.33%
	5	TEM∩ACP	0.337	0.376	11.44%

This deceleration likely reflects the early effects of national strategies such as the Beautiful China Initiative and supply-side structural reforms, which have helped curb emission growth through industrial upgrading and efficiency gains.

Spatially, the distribution of LUCE demonstrated strong path dependence and notable stability over the two-decade study period. The standard deviational ellipse (SDE) showed minimal variation, with a coefficient of variation below 2.5%. The SDE area and perimeter decreased only marginally by 1.25% and 0.68%, respectively, from 2000 to 2020, indicating limited spatial dispersion. This spatial persistence stands in sharp contrast to the dynamic restructuring seen in rapidly industrializing coastal regions like the Yangtze River Delta [43]. Two mechanisms likely explain this difference: the topographic constraints imposed by the eastern Taihang Mountains

and the “high-carbon lock-in” effect within the established Anyang–Xinxiang industrial corridor. Local spatial autocorrelation (LISA) analysis revealed weaker emission agglomeration in Northern Henan compared with China’s more developed regions, reflecting its incomplete industrialization and delayed structural transformation. Limited spillover effects from high-emission counties further restrained the spatial diffusion of emissions. In 2020, high-high (HH) clusters were primarily located in industrialized zones such as Xinxiang and Weibin District, driven by secondary industries and strategic emerging sectors. In contrast, low-low (LL) clusters were concentrated in Linzhou, Qi County, and Qibin District, where the ecological functions of the Taihang Mountains and more diversified land-use patterns contributed to lower emission intensities. These spatial patterns collectively underscore the pronounced heterogeneity

in regional development stages and the underlying driving mechanisms of LUCE across Northern Henan.

Temporal Variation and Interaction Detection of Driving Factors

The dominant drivers of LUCE in Northern Henan underwent a distinct transition from socioeconomic dominance before 2010 to a synergistic interplay between natural and socioeconomic factors thereafter, as revealed by OPGD analysis. This evolutionary pattern aligns with findings from other industrializing regions [44, 45], underscoring common trajectories in carbon emission driving mechanisms during economic transformation.

During 2000–2010, GDP, urbanization rate (UR), and population density (PD) emerged as primary drivers, reflecting the characteristic “population-land-industry” coupling typical of rapid urbanization phases [46, 47]. The period 2010–2015 marked a critical transition, characterized by significantly strengthened interactions between natural and socioeconomic variables, especially NDVI and temperature. This shift indicates an emerging synergy between land use intensity, economic development, and ecological constraints. By 2020, this co-evolution culminated in powerful interactions, notably between nighttime light (NTL) and NDVI ($q = 0.940$), suggesting that economically active regions are navigating increasingly complex trade-offs between development imperatives and ecological boundaries, consistent with observations in comparable regions [48].

This temporal evolution, particularly the inflection point around 2010–2015, corresponds with the implementation of transformative national policies. Initiatives including the Beautiful China Initiative and supply-side structural reforms have demonstrably promoted industrial restructuring and energy efficiency improvements. Consequently, the influence of individual socioeconomic factors has been progressively moderated, while natural system constraints and their interactions with anthropogenic activities have become increasingly determinative in shaping regional LUCE trajectories, signaling a transition toward ecologically bounded development pathways.

Suggestions for Differentiated Control of County Carbon Emissions

Building on the spatiotemporal patterns and driving factors identified above, we propose differentiated optimization strategies across three dimensions: land use structure, industrial transformation, and regional governance coordination.

Land Use Structure Optimization

Based on the findings that identify construction land and cropland as the primary carbon sources and forest land as the core carbon sink, land use policies

should focus on rebalancing the carbon source-sink landscape. On the source side, it is essential to strictly contain the disorderly expansion of construction land by delineating and enforcing urban development boundaries at the county level, a measure that aligns with the latest territorial spatial planning mandates [49]. This approach should be complemented by systematic ecological restoration and comprehensive management of abandoned mining and industrial sites, aiming to convert legacy carbon sources into functional carbon sinks, particularly in counties with extensive brownfields.

On the sink side, strengthening forest carbon sequestration is crucial. Special attention should be paid to the Taihang Mountains in the northwestern part of Henan Province, which serves as an ecological transition zone and a key area for ecological restoration. Owing to its complex topography and long-term human disturbance, vegetation cover in this region is relatively unstable. In some areas, the degradation of forest and grassland vegetation, coupled with the simplification of community structure, has resulted in weak carbon sink capacity and compromised ecosystem stability [50]. Therefore, in these critical areas, structural optimization of forest stands and vegetation restoration emphasizing native tree species, through measures such as optimizing stand spatial arrangement and implementing targeted afforestation in zones with high restoration potential, are essential for enhancing carbon sequestration and strengthening the resilience and stability of the regional ecosystem [51, 52].

Industrial Structure Optimization

The analysis identified economic factors, particularly GDP, industrialization level (IL), and industrial structure (IS), as the primary drivers of LUCE throughout the study period. Given the resource-dependent nature of most counties in Northern Henan, optimizing industrial structure is a critical pathway toward reducing carbon emissions [53, 54]. County-specific strategies should be developed in accordance with emission intensity and developmental stage.

For high-emission industrial counties (e.g., Wenfeng, Beiguan), policy priorities should emphasize industrial restructuring, adoption of clean transportation systems, promotion of renewable and low-carbon energy, and application of best available technologies. These efforts need to be supported by performance-based regulatory standards and green financing instruments. As the industrial core of the Anyang–Xinxiang corridor, these areas require deep technological upgrading to overcome entrenched high-carbon lock-in effects.

For low-emission but rapidly growing counties (e.g., Huojia), the focus should be on fostering low-carbon development through the cultivation of green manufacturing and modern producer services, as well as the advancement of eco-agriculture. Strict spatial-planning controls are also essential to prevent

the emergence of carbon-intensive industries. Leveraging their relatively clean industrial base, these counties can pursue sustainable growth while maintaining low-emission levels.

For low-emission and slow-growth counties (e.g., Zhongzhan), priorities include the gradual phase-out of inefficient coal-based energy systems, enhancement of energy efficiency in public and industrial sectors, and facilitation of technology transfer to improve productivity without increasing emissions. Such transitional regions require targeted policy and financial support to stimulate economic revitalization while avoiding the recurrence of high-carbon development patterns.

Coordinated Governance Framework

Spatial analysis reveals that carbon emissions in Northern Henan exhibit a dispersed clustering pattern compared to more developed regions, indicating limited spillover effects and regional synergy. To address this fragmented spatial structure, a coordinated inter-county governance framework is needed. Drawing on China's regional coordination strategies and successful models such as the Yangtze River Delta Ecological Green Integration Demonstration Zone, we propose a collaborative mechanism centered on industrial synergy, policy coordination, and multi-stakeholder participation.

In High-High clusters, such as Xinxiang, Weibin, and Muye, which function as regional carbon emission hotspots, joint carbon intensity control mechanisms and industrial synergy networks should be established. These can facilitate resource recycling, by-product exchange, and the diffusion of low-carbon technologies. Cross-jurisdictional coordination is essential in these areas to maximize mitigation outcomes.

In Low-Low clusters, including Linzhou, Qi County, and Qibin, horizontal ecological compensation mechanisms should be strengthened. High-emission counties are encouraged to provide financial or technical support for forest conservation, ecological restoration, and carbon sink enhancement in these low-emitting regions.

In Low-High transitional zones, such as Huojia, cross-boundary land use regulation and shared emission monitoring systems should be implemented. These measures can help mitigate spillover risks from adjacent high-emission areas while supporting balanced low-carbon development. Careful governance is required in these regions to maintain their low-emission status without hindering development opportunities.

Research Limitations and Prospects

This study systematically analyzed the spatiotemporal patterns and driving mechanisms of LUCE at the county level in Northern Henan, providing evidence to inform the formulation of differentiated

carbon mitigation strategies. However, this study still has certain limitations: county-scale carbon emission data are estimated based on land-use data, and the study area's natural and socioeconomic conditions are relatively complex; the analysis does not include forward-looking LUCE simulations. Future work should integrate multi-source data (e.g., high-resolution remote sensing, energy and industrial statistics, firm-level inventories) to build a more detailed accounting model and calibrate emission coefficients suited to Northern Henan; conduct a fuller assessment of driving factors using complementary methods (SDEM, LMDI, STIRPAT) and model fusion to improve stability; and develop scenario-based LUCE simulations and forecasts that link land-use change with socio-ecological drivers and include uncertainty analysis, providing a stronger theoretical basis for effective carbon-reduction policies and Henan Province's carbon-neutrality pathway.

Conclusions

This study employed the carbon emission coefficient method, SDE, Moran's I, and OPGD to examine county-level LUCE in Northern Henan from 2000 to 2020, providing a scientific basis for differentiated low-carbon strategies. The main conclusions are as follows:

(1) LUCE in Northern Henan exhibited a consistent growth pattern over the studied period, with the center of gravity of carbon emissions showing high stability, as the SDE analysis revealed no significant centroid shifts or drastic elliptical morphological changes. Global and local spatial autocorrelation in the distribution of carbon emissions gradually intensified and became statistically significant over time. By 2020, the H-H cluster areas were mainly concentrated in counties with intensive industrial activities, such as Xinxiang County, while the L-L cluster areas were grouped in counties dominated by ecological functions, such as Linzhou. These patterns reveal that different land use types have significantly varying impacts on carbon emissions.

(2) The influencing factors of LUCE evolved from socioeconomic dominance (2000-2010) to

a natural-socioeconomic co-driven pattern post-2010. Socioeconomic factors, including GDP, UR, and PD, were key from 2000 to 2010. After 2010, the influence of NDVI, TEM, and NPP increased, with the 2020 NTL-NDVI interaction ($q = 0.940$) highlighting a dynamic balance between economic activity and ecological constraints.

(3) Considering the unique characteristics of LUCE in Northern Henan, marked by spatial discontinuity and reliance on industrial development paths, it is necessary to address the dual constraints of the geographic environment and industrial structure through differentiated emission reduction strategies. These strategies encompass land use optimization, industrial structure optimization, and a coordinated governance framework.

Acknowledgments

Funding: The study was supported by the Planning Projects of Philosophy and Social Sciences in Henan (Grant No. 2023BYS007) and the Henan Key Scientific Research Program of Colleges and Universities (Grant No. 24B220001).

AI Usage Disclosure Statement

No AI tool was used in the research design, data collection, data processing, data analysis, result interpretation, or conclusion development of this study. DeepSeek (<https://www.deepseek.com/>) was used only for language polishing during manuscript revision, and all revisions were carefully checked and approved by the authors.

Conflict of Interest

The authors declare no conflict of interest.

References

- WUDU K., ABEGAZ A., AYELE L., YBABE M. The impacts of climate change on biodiversity loss and its remedial measures using a nature-based conservation approach: a global perspective. *Biodiversity and Conservation*, **32** (12), 3681, **2023**.
- AUSTIN A.T., ZANNE A.E. Whether in life or in death: fresh perspectives on how plants affect biogeochemical cycling. *Journal of Ecology*, **103** (6), 1367, **2015**.
- BHAN M., GINGRICH S., ROUX N., NOË J.L., KASTNER T., MATEJ S., SCHWARZMÜLLER F., ERB K.H. Quantifying and attributing land use-induced carbon emissions to biomass consumption: a critical assessment of existing approaches. *Journal of Environmental Management*, **286**, 112228, **2021**.
- ZHOU Y., CHEN M.X., TANG Z.P., MEI Z.A. Urbanization, land use change, and carbon emissions: quantitative assessments for city-level carbon emissions in the Beijing-Tianjin-Hebei region. *Sustainable Cities and Society*, **66**, 102701, **2021**.
- PENG X., TANG R., LI J., TANG H., GUO Z. Spatiotemporal dynamics of landscape pattern and vegetation ecological quality in Sanjiangyuan National Park. *Sustainability*, **17** (1), 373, **2025**.
- LIU Z., DENG Z., HE G., WANG H., ZHANG X., LIN J., QI Y., LIANG X. Challenges and opportunities for carbon neutrality in China. *Nature Reviews Earth & Environment*, **3** (2), 141, **2022**.
- WEI Y.M., CHEN K., KANG J.N., CHEN W., WANG X.Y., ZHANG X.Y. Policy and management of carbon peaking and carbon neutrality: A literature review. *Engineering*, **14**, 52, **2022**.
- SHAHBAZ M., PATEL N., DU A.M., AHMAD S. From black to green: quantifying the impact of economic growth, resource management, and green technologies on CO₂ emissions. *Journal of Environmental Management*, **360**, 121091, **2024**.
- PIAO S., HE Y., WANG X., CHEN F. Estimation of China's terrestrial ecosystem carbon sink: methods, progress and prospects. *Science China Earth Sciences*, **65** (4), 641, **2022**.
- QIN Z.C., ZHU Y.K., CANADELL J.G., CHEN M., LI T.T., MISHRA U., YUAN W.P. Global spatially explicit carbon emissions from land-use change over the past six decades (1961-2020). *One Earth*, **7** (5), 835, **2024**.
- CHOI S.E., HONG S.G., SONG C.L., KIM J., KIM W., HA R., LEE W.K. Construction of land-use change matrix and estimation of greenhouse gas inventory focusing on settlements in South Korea. *Carbon Balance and Management*, **18** (1), 4, **2023**.
- HONG C.P., BURNEY J.A., PONGRATZ J., NABEL J., MUELLER N.D., JACKSON R.B., DAVIS S.J. Global and regional drivers of land-use emissions in 1961-2017. *Nature*, **589** (7843), 554, **2021**.
- CHEN J.D., GAO M., CHENG S.L., HOU W.X., SONG M.L., LIU X., LIU Y., SHAN Y.L. County-level CO₂ emissions and sequestration in China during 1997-2017. *Scientific Data*, **7** (1), 391, **2020**.
- LIU J.L., PENG K.L., ZUO C.C., LI Q. Spatiotemporal variation of land-use carbon emissions and its implications for low-carbon and ecological civilization strategies: evidence from the Xiamen-Zhangzhou-Quanzhou metropolitan circle, China. *Sustainable Cities and Society*, **86**, 104083, **2022**.
- GUI D.W., HE H.G., LIU C.M., HAN S.S. Spatio-temporal dynamic evolution of carbon emissions from land use change in Guangdong Province, China, 2000-2020. *Ecological Indicators*, **156**, 111131, **2023**.
- YANG Y.J., LI H.Y. Monitoring spatiotemporal characteristics of land-use carbon emissions and their driving mechanisms in the Yellow River Delta: a grid-scale analysis. *Environmental Research*, **214** (Pt 4), 114151, **2022**.
- YE C.Y., MING T. Land use carbon emissions estimation and carbon emissions control strategy effect scenario simulation in Zhejiang Province. *Heliyon*, **9** (11), e20783, **2023**.
- KANG T.T., WANG H., HE Z.Y., LIU Z.Y., REN Y., ZHAO P.J. The effects of urban land use on energy-related CO₂ emissions in China. *Science of the Total Environment*, **870**, 161873, **2023**.
- XIAO D.Y., NIU H.P., GUO J., ZHAO S.X., FAN L.X. Carbon storage change analysis and emission reduction suggestions under land use transition: a case study of Henan Province, China. *International Journal of Environmental Research and Public Health*, **18** (4), 1844, **2021**.
- PENG X., XU D., BAI T., LI J., ZHU K. Staunch defender of COP27: a 20-year journey of land revegetation projects in China. *Land Degradation & Development*, **36** (5), 1677, **2025**.
- LIU Y., LIU W., QIU P., ZHOU J., PANG L. Spatiotemporal evolution and correlation analysis of carbon emissions in the nine provinces along the Yellow River since the 21st century using nighttime light data. *Land*, **12** (7), 1469, **2023**.
- SUN H., LIANG H.M., CHANG X.L., CUI Q.C., TAO Y. Land use patterns, carbon emission, and spatial association in China. *Economic Geography*, **35** (3), 154, **2015**. [In Chinese]
- YANG S.J., WEN L.J., ZHANG A.L. The spatiotemporal response of land-use carbon emissions to climate change. *Ecological Indicators*, **170**, 112893, **2025**.

24. SONG Y.Z., WANG J.F., GE Y., XU C.D. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. *GIScience & Remote Sensing*, **57** (5), 593, **2020**.
25. XU D., PENG X., TANG Q., SONG Y. Urbanization's role in shaping ornamental tree diversity: a remote sensing- and future scenario-based perspective. *GIScience & Remote Sensing*, **62** (1), 2557050, **2025**.
26. YANG J., HUANG X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth System Science Data*, **13** (8), 3907, **2021**.
27. MO H., WANG S. Spatio-temporal evolution and spatial effect mechanism of carbon emission at county level in the Yellow River Basin. *Scientia Geographica Sinica*, **41** (8), 1324, **2021** [In Chinese].
28. HUANG H., JIA J., ZHANG Z. Spatiotemporal pattern evolution and influencing factors of land-use carbon emissions in counties, Jiangxi Province. *Acta Ecologica Sinica*, **43** (20), 8390, **2023** [In Chinese].
29. PENG S.Z., DING Y.X., LIU W.Z., LI Z. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017. *Earth System Science Data*, **11** (4), 1931, **2019**.
30. WU Y.Z., SHI K.F., CHEN Z.Q., LIU S.R., CHANG Z.J. Developing improved time-series DMSP-OLS-like data (1992-2019) in China by integrating DMSP-OLS and SNPP-VIIRS. *IEEE Transactions on Geoscience and Remote Sensing*, **60**, 4007714, **2022**.
31. CHEN J., ZHANG J., LI J., LI S. Spatiotemporal pattern of carbon emissions and its driving factors in the Beijing-Tianjin-Hebei region. *Acta Ecologica Sinica*, **44** (6), 2270, **2024** [In Chinese].
32. LI X., LIU Z., LI S., LI Y., WANG W. Urban land carbon emission and carbon emission intensity prediction based on patch-generating land use simulation model and grid with multiple scenarios in Tianjin. *Land*, **12** (12), 2160, **2023**.
33. GONG J. Clarifying the standard deviational ellipse. *Geographical Analysis*, **34** (2), 155, **2002**.
34. DU Q., ZHOU J., PAN T., SUN Q., WU M. Relationship of carbon emissions and economic growth in China's construction industry. *Journal of Cleaner Production*, **220**, 99, **2019**.
35. YANG D., LUAN W.X., QIAO L., PRATAMA M. Modeling and spatio-temporal analysis of city-level carbon emissions based on nighttime light satellite imagery. *Applied Energy*, **268**, 114696, **2020**.
36. YANG L.Y., JI X., LI M., YANG P.W., JIANG W., CHEN L.Y., YANG C.J., SUN C.Z., LI Y.G. A comprehensive framework for assessing the spatial drivers of flood disasters using an optimal parameter-based geographical detector-machine learning coupled model. *Geoscience Frontiers*, **15** (6), 101889, **2024**.
37. WANG J.F., XU C.D. Geodetector: principle and prospective. *Acta Geographica Sinica*, **72** (1), 116, **2017** [In Chinese].
38. WANG J.F., ZHANG T.L., FU B.J. A measure of spatial stratified heterogeneity. *Ecological Indicators*, **67**, 250, **2016**.
39. CAO W., ZHOU W., WU T., WANG X.C., XU J.H. Spatial-temporal characteristics of cultivated land use eco-efficiency under carbon constraints and its relationship with landscape pattern dynamics. *Ecological Indicators*, **141**, 109140, **2022**.
40. ZHOU Y.R., CHEN T.Q., FENG Z., WU K.N. Identifying the contradiction between cultivated land fragmentation and construction land expansion from the perspective of urban-rural differences. *Ecological Informatics*, **71**, 101826, **2022**.
41. WANG C.Q., IBRAHIM H., WU F.H., CHANG W.T. Spatial and temporal evolution patterns and spatial spillover effects of carbon emissions in China in the context of the digital economy. *Journal of Environmental Management*, **373**, 123811, **2025**.
42. LIU C., HU S., WU S., SONG J., LI H. County-level land use carbon emissions in China: spatiotemporal patterns and impact factors. *Sustainable Cities and Society*, **105**, 105304, **2024**.
43. XU J.H., LI Y.Y., HU F., WANG L., WANG K., MA W.H., RUAN N., JIANG W.Z. Spatio-temporal variation of carbon emission intensity and spatial heterogeneity of influencing factors in the Yangtze River Delta. *Atmosphere*, **14** (1), 163, **2023**.
44. XU J. Study on spatiotemporal distribution characteristics and driving factors of carbon emission in Anhui Province. *Scientific Reports*, **13** (1), 14400, **2023**.
45. WU J.H., LI K.Q. Analysis of spatial and temporal evolution and driving factors of carbon emission in Shandong Province: based on the perspective of land use. *Environmental Sciences Europe*, **36**, 171, **2024**.
46. DAI F.Y., ZHAN M.J., CHEN X.J., YANG X.L., OUYANG P. Spatiotemporal evolution and driving factors of land use carbon emissions in Jiangxi Province, China. *Forests*, **15** (10), 1825, **2024**.
47. RONG T.Q., QIN M.Z., ZHANG P.Y., CHANG Y.H., LIU Z.Y., ZHANG Z.F. Spatiotemporal evolution of land use carbon emissions and multi-scenario simulation in the future based on the carbon emission fair model and PLUS model. *Environmental Technology & Innovation*, **38**, 104087, **2025**.
48. GUO Q.R., LAI X.T., JIA Y.H., WEI F.L. Spatiotemporal pattern and driving factors of carbon emissions in Guangxi based on geographic detectors. *Sustainability*, **15** (21), 15477, **2023**.
49. FU H., PENG Y., ZHENG L., LIU Q., ZHOU L., ZHANG Y., KONG R., TURVEY C.G. Heterogeneous choice in WTP and WTA for renting land use rights in rural China: choice experiments from the field. *Land Use Policy*, **119**, 106123, **2022**.
50. CHEN Y., WANG X.P., ZHEN N., ZHANG G., GUO Y.J., I Z., REN H.T. Practice of ecological protection and restoration of mountain-river-forest-farmland-lake-grassland based on connotation of ecosystem service theory: taking the pilot project of South-Taihang Area in Henan Province as an example. *Journal of Environmental Engineering Technology*, **11** (4), 701, **2021** [In Chinese].
51. QU Q., JIAN S., CHEN A., XIAO C. Investigating the dynamic change and driving force of vegetation carbon sink in Taihang Mountain, China. *Land*, **13** (9), 1348, **2024**.
52. GUO H.C., HE S., JING H.T., YAN G.D., LI H. Evaluation of the impacts of change in land use/cover on carbon storage in multiple scenarios in the Taihang Mountains, China. *Sustainability*, **15** (19), 14244, **2023**.
53. XIE Y., ZHANG H., CHEN Y. The impact of double carbon goals on industrial structure in a region of China. *Computers & Industrial Engineering*, **184**, 109574, **2023**.
54. ZHANG F., DENG X., PHILLIPS F., FANG C., WANG C. Impacts of industrial structure and technical progress on carbon emission intensity: evidence from 281 cities in China. *Technological Forecasting and Social Change*, **154**, 119949, **2020**.