

SPATIOTEMPORAL CHANGES IN VEGETATION COVER AND CARBON STORAGE PREDICTION BASED ON THE PLUS-INVEST MODEL: A CASE STUDY OF HENAN PROVINCE, CHINA

ZUO, Z.¹ – FAN, W.^{1*} – YANG, H. Q.¹ – TIAN, L.¹ – ZHAO, H.¹ – FAN, L. L.¹ – DONG, X. M.² – WANG, Q. R.³ – LING, X. M.¹ – YANG, C. H.¹

¹*Henan Academy of Forestry, Zhengzhou 450008, China*

²*Academy of Inventory and Planning, National Forestry and Grassland Administration, Beijing 100714, China*

³*College of Landscape Architecture and Art, Henan Agricultural University, Zhengzhou 450002, China*

**Corresponding author*

e-mail: Hnaf_fanwang@163.com; phone: +86-180-3966-9515

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Abstract. In this study, the spatiotemporal variation in carbon stocks under different vegetation coverages during the period 2001–2020 in Henan Province, China, was evaluated using the InVEST, PLUS, and geodetector models. The vegetation coverage patterns and corresponding carbon stocks were predicted under the three scenarios of natural trend, ecological degradation, and ecological restoration, the results show that: (1) Henan Province's vegetation area has been trending downward over the last 20 years, with losses in grassland, savanna, and farming vegetation. (2) The carbon stocks exhibited a low distribution pattern in the central and eastern parts of the country and a high distribution pattern in the northwest and southeast. The growth of total carbon stocks slowed. (3) The overall carbon stores exhibited a declining pattern throughout the three ecological scenarios. The carbon stocks experienced the least decline under the ecological restoration scenario. (4) Evapotranspiration, altitude, slope, distance from farmland and temperature were the main factors affecting the spatial differentiation of regional carbon stocks. Our results can aid in the sustainable management of ecosystems in Henan Province and provides a scientific basis and research concepts for the effective increase in carbon stocks.

Keywords: *terrestrial ecosystem, vegetation change, climate change, carbon neutrality, Henan province*

Introduction

The massive emission of greenhouse gases such as carbon dioxide is the primary catalyst for global climate change. Subsequently, global climate change is leading to an increase in extreme weather, a decrease in biodiversity, and a rise in sea level, posing an enormous threat to the sustainable development of human society and ecosystems (Box-Steffensmeier et al., 2022). To meet the challenges that global climate change creates, governments worldwide have proposed carbon reduction targets and implementation plans. Specifically, through photosynthesis, respiration, and soil microbial activities, terrestrial ecosystems can absorb approximately 17.7 Gt of CO₂ each year; Terrestrial ecosystems are considered one of the most far-reaching portions of the global carbon cycle and balance (Wen et al., 2024). The land cover type refers to the vegetation, soil, and water body on the land surface. Changes in land cover type directly affect terrestrial ecosystem functions and carbon storage, such as decreases in vegetation coverage, land occupation, or changes in the soil environment (Krause et al., 2022). A judicious evaluation of land cover status and the implementation of effective land protection

measures can optimize the benefits derived from terrestrial ecosystem carbon storage. Consequently, there is considerable interest in studying the repercussions of alterations in land cover on carbon storage (Li et al., 2022b).

Methods for estimating terrestrial ecosystem carbon stocks mainly include the Intergovernmental Panel on Climate Change inventory method. Remote sensing estimation methods (Houghton et al., 1991), quadrat inquiry methods (Zhu et al., 2021) and simulations based on empirical models (Huang et al., 2022) have been used. Among them, the InVEST model has been widely utilized in value estimation studies of ecosystem services due to its simple operation, variable parameters, and high accuracy in the evaluation of large-scale ecosystem services (Lahiji et al., 2020; Ding et al., 2021; Piyathilake et al., 2021; Adelisardou et al., 2022). However, although the existing carbon stock assessments are operable and verifiable, they only reflect the potential carbon storage level of the ecosystem at a certain time and cannot predict the changes in future carbon stocks, and this change is the main basis for formulating emission reduction policies. To further understand the trend of increase or decrease in carbon stocks that may be caused by future land cover change, the CLUE-S, CA-Markov, SLEUTH, GeoSOS-FLUS, and PLUS models combined with the InVEST model can be used to analyze the spatial distribution and trend of carbon stocks under various land use scenarios (Liu et al., 2017; Feng et al., 2020; Babbar et al., 2021; Shao et al., 2023). According to the above land use simulation models, the PLUS model utilizes the transformation analysis strategy and the pattern analysis strategy to predict dynamic changes in land use types at the patch level to investigate the potential driving mechanisms of land use and land cover change (LUCC) (Li et al., 2021a; Wang et al., 2023). Moreover, the PLUS model enables the incorporation of forthcoming spatial policy aspects, hence facilitating a more rigorous and accurate simulation of future LUCC under various policy scenarios; additionally, this model has been widely used. Using the Beijing Municipality, which has high human activity intensity, as the study area, the PLUS model was used to assess the geographical distribution of urban LUCC in Beijing under three scenarios: the natural development, urban expansion, and ecological protection (EP). An optimization simulation was performed on the pattern. Li et al. (2023a) further applied the Markov-PLUS model and the InVEST model to predict and analyze the spatiotemporal distribution characteristics and reaction mechanisms of LUCC and carbon stocks in Liaoning Province under three scenarios in 2050.

At present, most PLUS model studies often analyze land resource functions and the driving mechanisms of LUCC (Gao et al., 2022; Li et al., 2022a). Fewer studies have evaluated the application of carbon stock changes. On the other hand, studies on ecosystem carbon stocks have focused on the size of the carbon stocks, the discussion of the driving factors affecting the change in the carbon stocks has been relatively simple, and studies that systematically compare carbon stocks between different development scenarios are lacking (Fan et al., 2023). Therefore, based on regional carbon stocks and land cover types, different scenario constraints were used to simulate LUCC under multiple scenarios, and geographic detectors were employed to examine the causal mechanisms behind changes in carbon stock, with the aim of determining the most effective strategies for optimizing LUCC under the “dual-carbon” goal. Improving carbon storage has research significance.

In general, China’s terrestrial ecosystem carbon stocks have shown an annual decreasing trend (Xu et al., 2018). Henan Province is an important contributor to China’s grain production and plays a crucial role in the national policy framework for

environmental protection and high-quality growth in the Yellow River Basin. This strategy requires Henan Province to implement effective low-carbon policies in curbing regional carbon emissions and promoting low-carbon land development and utilization (Wang and Lv, 2022). In Henan Province, the planning of landspace ecological restoration and forest construction clearly proposed implementing major decision-making and deployment of carbon peaks and carbon neutrality. Methods to scientifically promote ecological restoration and land greening, enhance the carbon sequestration capacity of the ecosystem are important directions for the future development of Henan Province.

This work employed the InVEST and PLUS models to assess and forecast the carbon stock and spatial pattern attributes of Henan Province from 2001 to 2020, as well as from the future to 2030 and 2060, respectively. Additionally, a geodetector was utilized to identify the primary variables influencing changes in carbon stock. The core problems to be solved in this study include the following: (1) determining the characteristics of spatiotemporal variation in vegetation cover in Henan Province; (2) elucidating the mechanism through which the spatiotemporal evolution of vegetation cover affects carbon stocks in Henan Province; and (3) simulating constraints under different future scenarios. The effect of lower vegetation cover types on provincial carbon stocks is also examined.

Materials and methods

Study area

Henan Province ($E110^{\circ}21'-116^{\circ}39'$, $N31^{\circ}23'-36^{\circ}22'$), located in the second to third ladder of China, across the central China and the middle and lower reaches of the Yellow River (Fig. 1). The total land area is 167,000 kilometers. The Henan Province contains the basins of four major rivers: the Yangtze, Yellow, Huaihe, and Haihe. It serves as the birthplace of the Huaihe River, a crucial water source and the site of the canal head for the middle route of the South-to-North Water Diversion Project. The area features a continental monsoon climate, marked by a transition from the northern subtropical zone to the warm temperate zone. Henan Province, in addition to its significant role in China's ecological pattern, hosts a rich biodiversity. It is encircled by three ecological barriers—the Tongbai-Dabie Mountains, the Funiu Mountains, and the Taihang Mountains—enhancing its ecological significance (Liu et al., 2022).

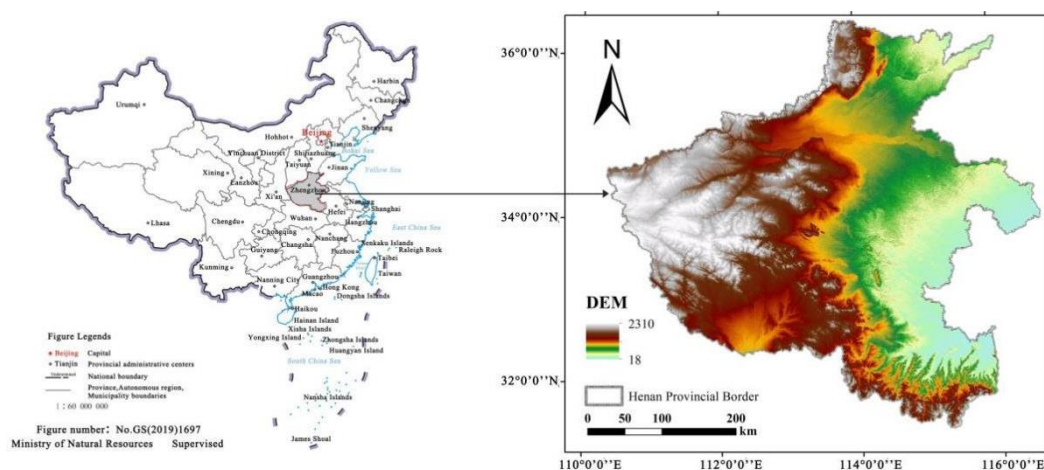


Figure 1. Study area and its terrain

Data sources and preprocessing

Data on vegetation cover types

The 2001, 2010 and 2020 vegetation cover image of Henan Province were obtained from the MODIS data of NASA's Goddard Space Center (<https://ladsweb.modaps.eosdis.nasa.gov/search/>) at a resolution of 500 m. The main vegetation types included deciduous broad-leaved forest, mixed forest, closed shrub forest, forested grassland, savanna, grassland, permanent wetland, farmland, and non-vegetated areas.

Land use simulation data

This study identified 15 driving factors that influence changes in vegetation type and carbon stock, accessed on 19 December 2023. These factors were selected from many categories including topographic, climatic, natural, social, and economic aspects. The distances to woodlands, waters, grasslands, farmlands, towns and roads were measured using the ArcGIS 10.2 Euclidean environment. The normalized difference vegetation index (NDVI) was obtained from the distance analysis tool, and *Table 1* displays the slope, aspect, temperature, and NDVI data. The mentioned factors were sampled into 500m-resolution, which aligns with the resolution of the vegetation coverage type data, and subsequently standardized.

Table 1. Driving factor data and data sources

Type	Number	Name	Sources
Vegetation type data	Y	Vegetation type	The Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center ^a
Topographic Factors	T1	Digital elevation model	Geospatial Data Cloud ^b
	T2	Slope	
	T3	Aspect	
Socioeconomic factor	S1	Distance to farmland	Resource and Environment Science and Data Center ^c
	S2	Distance to city center	OpenStreetMap ^d
	S3	Distance to road	
	S4	Density of population	WorldPop ^e
	S5	Density of Gross Domestic Product	Resource and Environment Science and Data Center ^c
Climatic factors	C1	Temperature	National Qinghai-Tibet Plateau Scientific Data Center
	C2	Precipitation	
	C3	Evapotranspiration	
Natural factors	N1	Normalized Difference Vegetation Index	Resource and Environment Science and Data Center ^c
	N2	Distance to forestland	
	N3	Distance to grassland	
	N4	Distance to river	OpenStreetMap ^d

Note: a to f are the URLs of data sources. <https://ladsweb.modaps.eosdis.nasa.gov/search/>; b. <http://www.gscloud.cn>; c. <https://www.resdc.cn>; d. <https://www.openstreetmap.org/>; e. <https://www.worldpop.org/>; f. <http://data.tpdc.ac.cn/zh-hans/>

Methods

Assessment of carbon storage in various land types using the InVEST Model

The InVEST Model's Carbon Storage and Sequestration module was utilized to compute carbon storage (He et al., 2023). This module divides the carbon storage across the ecosystem into four fundamental carbon pools. The data included the following: (1) aboveground carbon pools; (2) underground carbon pools; (3) soil carbon pools; and (4) dead organic carbon (Liu et al., 2017). The calculation formula is as follows:

$$C_i = C_{i_above} + C_{i_below} + C_{i_soil} + C_{i_dead} \quad (\text{Eq.1})$$

$$C_{total} = \sum_{i=1}^n C_i \times S_i \quad (\text{Eq.2})$$

where in the i -th vegetation type, C_i represents the total carbon density of the soil and biomass, C_{i_above} denotes the carbon density of aboveground organisms, C_{i_below} represents the carbon density of the belowground organisms, C_{i_soil} is the soil carbon density, and C_{i_dead} is the dead organic matter's carbon density. All of the above carbon measurements are in $\text{Mg} \cdot \text{hm}^{-2}$. C_{total} denotes the total carbon storage (Mg), S_i is the total area (hm^2) of vegetation type i , and n is the number of vegetation types.

The carbon density data of each vegetation cover type are shown in Table 2. We collected carbon density data from the 2010 China Terrestrial Ecosystem Carbon Density Dataset (Xu et al., 2019) and related studies (Li, 2019; Shao et al., 2023). Notably, certain carbon density data were not acquired through empirical measurements; therefore, reasonable corrections needed to be applied. Existing studies showed a significant correlation between carbon density and both annual mean temperature/precipitation (Tang et al., 2018).

Table 2. Carbon density of various land use types in Henan Province

Land use type	C_{i_above} ($\text{Mg} \cdot \text{hm}^{-2}$)	C_{i_below} ($\text{Mg} \cdot \text{hm}^{-2}$)	C_{i_soil} ($\text{Mg} \cdot \text{hm}^{-2}$)	C_{i_dead} ($\text{Mg} \cdot \text{hm}^{-2}$)
Deciduous Broadleaf Forests	49.02	24.53	148.60	2.29
Mixed Forests	55.00	27.52	140.24	1.97
Closed Shrublands	29.85	2.01	74.63	2.90
Woody Savannas	19.55	8.02	83.92	1.90
Savannas	9.06	7.15	79.24	0.88
Grasslands	0.67	6.45	75.50	0.07
Permanent Wetlands	3.58	8.63	135.84	0.35
Croplands	19.31	8.30	63.03	1.89
Nonvegetation	0.96	5.16	54.68	0.10

Therefore, in this study, a more versatile carbon density correction formula was chosen to calibrate Henan Province's carbon density based on annual mean temperature/precipitation (Xu et al., 2023). The formula is as follows:

$$K_{BP} = \frac{0.03 \times P' + 14.4}{0.03 \times P'' + 14.4}, K_{BT} = \frac{-0.4 \times T' + 43.0}{-0.4 \times T'' + 43.0}, K_B = \text{Average}(K_{BP}, K_{BT}) \quad (\text{Eq.3})$$

$$K_{SP} = \frac{0.07 \times P' + 79.1}{0.07 \times P'' + 79.1}, K_{ST} = \frac{-3.4 \times T' + 157.7}{-3.4 \times T'' + 157.7}, K_S = \text{Average}(K_{SP}, K_{ST}) \quad (\text{Eq.4})$$

$$K_{DP} = \frac{0.001 \times P' + 0.58}{0.001 \times P'' + 0.58}, K_{DT} = \frac{-0.03 \times T' + 2.03}{-0.03 \times T'' + 2.03}, K_D = \text{Average}(K_{DP}, K_{DT}) \quad (\text{Eq.5})$$

where K_{BP} and K_{BT} are the biomass coefficients expressed by precipitation and temperature, respectively; K_B signifies the final biomass correction factor; K_{SP} and K_{ST} are the soil organic carbon (SOC) coefficients expressed by precipitation and temperature, respectively; K_S represents the final soil organic matter (SOM) correction factor; K_{DP} and K_{DT} are the coefficients of dead organic matter expressed by precipitation and temperature, respectively; K_D represents the final dead organic matter coefficient; P' and P'' represents the precipitation in Henan Province and the whole country (mm); and T' and T'' represents the temperature (°C) in Henan Province and the whole country, respectively.

PLUS-based model

The PLUS model is a raster-based land use simulation model (Liang et al., 2021). Initially, the land expansion analysis method model was employed to sample land type changes over two distinct time periods. Subsequently, the random forest algorithm was applied to understand how these changes correlated with the underlying variables. We used the Cellular Automata model with multiple random seeds to simulate and predict future land types. This involved incorporating pixel values representing different vegetation types, along with the transfer matrix and domain weights for each land use.

According to the requirement of the year boundary rule of the future land demand prediction module of the Markov chain, the annual intervals of the vegetation cover data for the three periods were all 10 years. The Kappa statistic is commonly used to evaluate the models's accuracy in land use simulation. If $Kappa > 0.8$, it indicates that the results are reliable (Huang et al., 2019; Lin et al., 2020). To assess whether the model's accuracy met the study's requirements, vegetation coverage in 2020 was simulated from 2010 data and compared to actual data. The validation results showed that the kappa coefficient of 0.803 and overall accuracy of 90.75%. These values demonstrate a high level of simulation accuracy, suggesting that the research requirements for future vegetation cover simulations in Henan Province may be met.

Land use scenario simulation and parameter setting

Considering the policy demands and the current land spatial planning situation in Henan Province, we used the PLUS model to simulate the vegetation types' distribution under three scenarios: natural trend (NT), ecological degradation (ED) and ecological restoration (ER) in Henan Province in 2030 and 2060. First, basic domain weights were set. Usually, domain weights are established based on the proportion of expansion area for each land use type and can be fine-tuned through experiential adjustments. The calculated values were 0.067 for deciduous broad-leaved forest, 0.038 for mixed forest,

0.002 for closed shrub forest, 0.136 for forested grassland, 0.434 for savanna, 0.110 for grassland, 0.017 for permanent wetland, 0.118 for farmland, and 0.077 for non-vegetated area. Next, the transition matrix was set. In the transition matrix, 0 represented that the transition was not allowed, and 1 represented that the transition could occur. Three different transition matrices could be configured based on varying development scenarios. Finally, parameters for different land use scenarios were set. For the NT scenario, parameters were set assuming that land use demand would remain unaffected by policy changes. We projected land use demand under natural trends using the 2010–2020 land transfer probability. For the ED scenario, there was a likelihood increasing by 30% of grassland converting to forest and wetland. The likelihood of transforming woodland and marsh into different land uses has risen by 40%. The likelihood of transforming arable land and non-vegetation covering regions into different land uses was decreased by 20%. For the ER scenario, the likelihood of arable land converting to other land uses increased by 20%, which of forestland converting to other land uses decreased by 30%. Similarly, the likelihood of grassland converting to other land uses decreased by 10%, and there was a 10% increase in the possibility of non-vegetation land covering land uses other than cropland. In addition, nature reserves were designated restricted areas.

Geodetectors

We used two detectors: factor and interaction, both of which were implemented using Geodetector (<http://www.gedetector.cn/>). The factor detector is mainly used to determine the spatial variation in carbon stock Y and the explanatory ability of the 15 Factors X , including topography, temperature, and precipitation, on the carbon stock Y , which are expressed by the q value (Wang et al., 2010, 2016). The expression is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (\text{Eq.6})$$

where $h = 1, \dots, L$ is the stratification, i.e., classification or partition, of variable Y or Factor X ; N_h is the number of units in layer h ; N is the number of units in the whole area; σ_h^2 is the variance of the Y value in layer h ; and σ^2 is the variance of the Y value for the whole area. The value range of q was $[0,1]$. A higher value of q represented a greater explanatory power of the factor on the carbon stocks in Henan Province, and vice versa.

An interaction detector was employed to identify the interaction forces among factors affecting carbon stocks in Henan Province, categorizing them into five types, and details are shown in *Table 3*.

Table 3. Rules for interaction detection

Rules	Interaction
$\min(q(X_1), q(X_2)) > q(X_1 \cap X_2)$	Nonlinear reduction
$\min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < \max(q(X_1), q(X_2))$	Single-factor nonlinear reduction
$q(X_1 \cap X_2) > \max(q(X_1), q(X_2))$	Two-factor enhancement
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independent of each other
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Nonlinear enhancement

Results

Spatial variation in vegetation cover

The most widely distributed vegetation type in Henan Province was farmland, accounting for 72.83% on average; the second most distributed vegetation type was deciduous broad-leaved forest, with an average area proportion of 6.85%; the least widely distributed vegetation type was permanent wetland, which accounted for only 0.19% (Table 4). From 2001 to 2020, the areas of forested grassland, grassland and farmland showed decreasing trends of 1,085.75 km², 1,276.00 km² and 1,835.50 km², respectively, accounting for decreases of 0.66%, 0.77% and 1.11%, respectively. The areas of the other vegetation types increased at different magnitudes, with the largest increase occurring in the area of deciduous broad-leaved forest at 1727.75 km², followed by non-vegetation (1545.00 km²) and savanna (344.75 km²). The area of closed shrub forest changed the least, with an increase of only 13.50 km².

Table 4. Changes in the area and dynamics of vegetation during 2001–2020

Vegetation Type	Area/km ²			Area Change and Dynamic Degree during 2001–2020	
	2001	2010	2020	Area/km ²	Dynamic Degree/%
Deciduous Broadleaf Forests	10087.00	12185.75	11814.75	1727.75	17.13
Mixed Forests	1025.00	926.50	1302.50	277.50	27.07
Closed Shrublands	10.75	17.50	24.25	13.50	125.58
Woody Savannas	9229.25	8207.75	8143.50	-1085.75	-11.76
Savannas	10096.00	6666.00	10440.75	344.75	3.41
Grasslands	5246.50	5366.00	3970.50	-1276.00	-24.32
Permanent Wetlands	180.75	301.00	469.50	288.75	159.75
Croplands	120834.25	122444.75	118998.75	-1835.50	-1.52
Nonvegetation	9100.50	9694.75	10645.50	1545.00	16.98

From 2001 to 2020, a total of 19,634.75 km² of land conversion occurred in Henan Province, accounting for 12.00% of the total area of Henan Province (Table 5). The area of vegetation degradation (conversion of vegetation to non-vegetation) was 1602.5 km², and the area of optimal vegetation (conversion of non-vegetation to vegetation) was 57.5 km² (Fig. 2). The vegetation degradation zones were mainly located in Anyang city, Xinxishe city, Hebi city, Luoyang city and Zhengzhou city. Among all the vegetation types, the degraded area of farmland was the largest, accounting for 1318.75 km², which was 82.29% of the degradation zone; it was followed by savanna and grassland, with 10.20% and 5.80%, respectively. The optimal vegetation zones were mainly distributed in northwestern and southeastern Henan Province. The priority vegetation type was permanent wetland, with an area of 28.5 km², accounting for 49.57% of the optimized area, followed by grassland, with an area of 20.50 km², accounting for 35.65% of the optimized area.

Table 5. Vegetation type transfer matrix in Henan Province from 2001 to 2020 (km²)

	Land use type	2020								
		Deciduous broadleaf forests	Mixed forests	Shrublands	Woody savannas	Savannas	Grasslands	Permanent wetlands	Croplands	Non-vegetation
2001	Deciduous broadleaf forests	9380.00	68.25	2.00	458.50	122.00	43.00	0.00	13.25	0.00
	Mixed forests	246.00	716.25	0.25	55.25	4.25	3.00	0.00	0.00	0.00
	Shrublands	2.50	5.25	2.25	0.00	0.75	0.00	0.00	0.00	0.00
	Woody savannas	1731.50	429.50	1.50	5943.25	878.50	137.00	1.00	107.00	0.00
	Savannas	180.00	30.75	3.25	979.25	4615.50	824.25	140.25	3159.25	163.50
	Grasslands	207.25	50.75	14.75	413.50	1394.25	1805.75	90.25	1177.00	93.00
	Permanent wetlands	0.25	1.75	0.00	1.25	1.25	5.00	139.75	4.25	27.25
	Croplands	67.25	0.00	0.25	292.50	3424.25	1132.00	69.75	114529.50	1318.75
	Non-vegetation	0.00	0.00	0.00	0.00	0.00	20.50	28.50	8.50	9043.00

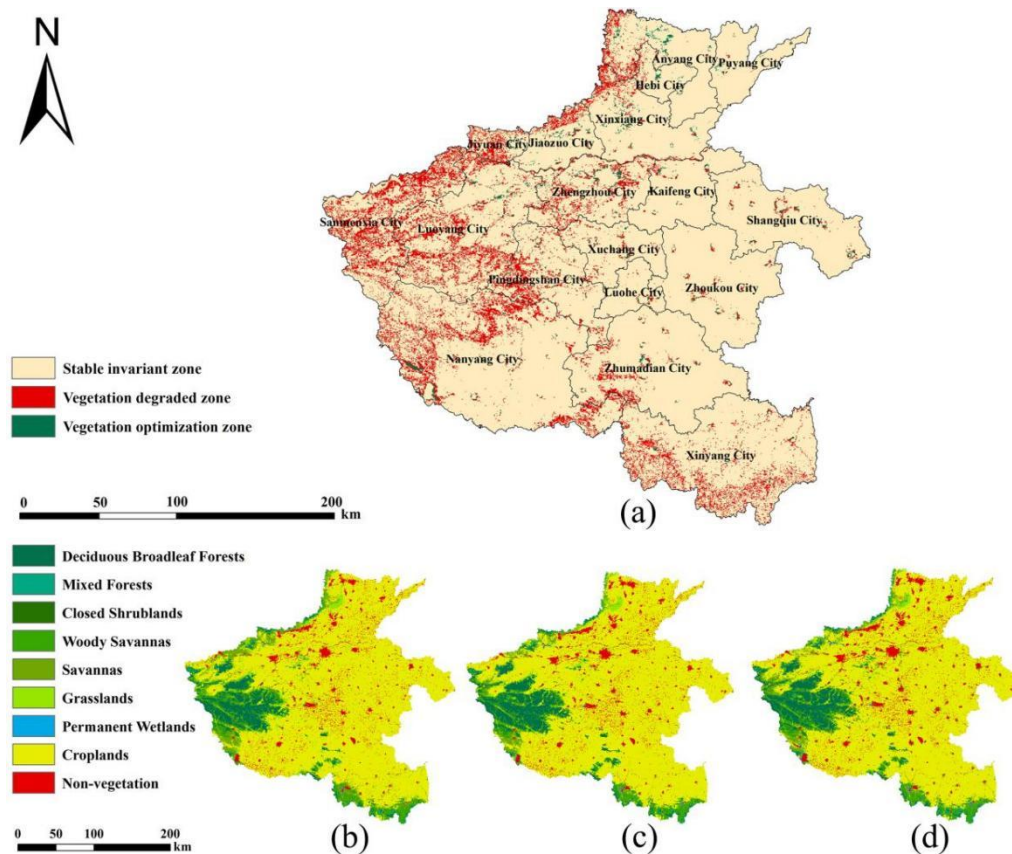


Figure 2. Spatial distribution and changes in vegetable types in Henan Province. (a) 2001-2020; (b) 2001; (c) 2010; (d) 2020

Spatial-temporal variation characteristics of carbon stocks in Henan Province, 2001-2020

Characteristics of the changes in the carbon stocks

The carbon stocks of Henan Province in 2001, 2010 and 2020 were 1,671.02 Tg, 1,692.65 Tg and 1,693.35 Tg, respectively; this showed an overall increase in the carbon stocks but had a slower growth rate; compared with 2001, the amount of carbon storage increased by 22.33 Tg in 2020 (Fig. 3). Soil carbon storage was the main type of carbon storage in Henan Province and accounted for 70.12%, 69.82% and 70.06% of the total carbon storage in 2001, 2010 and 2020, respectively.

During the three study years (2001, 2010 and 2020), farmland had the largest carbon storage amounts of 1117.96 Tg, 1132.86 Tg and 1100.98 Tg, respectively; this accounted for 66.90%, 66.93% and 65.02%, respectively, of the total carbon storage. The carbon storage capacity of the closed shrub forest was the lowest, at only 0.12 Tg, 0.19 Tg and 0.27 Tg during 2001, 2010 and 2020, respectively. Between 2001 and 2020, the carbon storage capacity of forests and grasslands continued to decrease, from 104.64 Tg to 92.33 Tg, for a total reduction of 12.31 Tg. The carbon storage capacity of deciduous broad-leaved forests continued to increase, with a total increase of 38.78 Tg. The carbon stocks of mixed forests and savannas showed a trend of initially decreasing and then increasing.

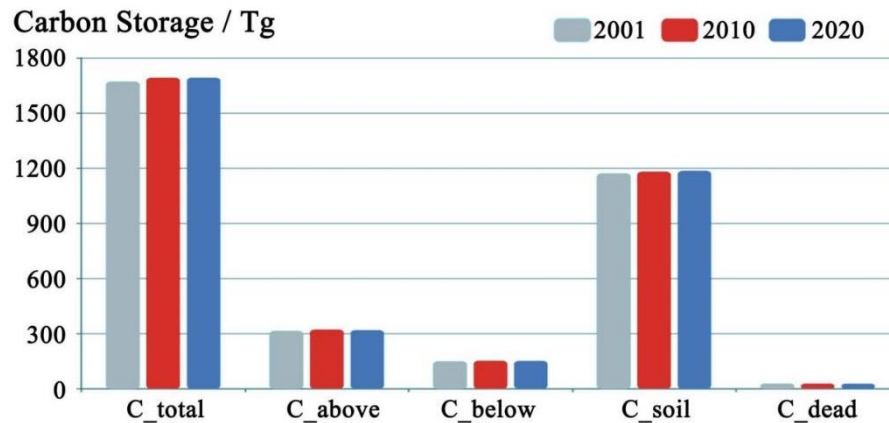


Figure 3. Carbon storage changes in Henan Province during 2001–2020

Spatial variation characteristics of the carbon stocks

From 2001 to 2020, the carbon stocks in Henan Province generally exhibited a distribution pattern in which the stocks were low in the central and eastern regions and high in the northwestern and southeastern regions (*Fig. 4*). Among them, Nanyang city had the largest carbon storage value, with carbon stocks of 294.07 Tg, 301.67 Tg and 297.67 Tg in the three periods. Hebi city had the lowest carbon stocks, with 19.20 Tg, 19.22 Tg and 19.14 Tg, respectively. The cities with increasing carbon stocks included Anyang, Xinxiang, Pingdingshan, Sanmenxia, Zhumadian, Xinyang and Luoyang. Among them, Luoyang city showed the largest increase in carbon stocks, with a net increase of 6.33 Tg. The total values of carbon storage for the remaining cities all decreased by different magnitudes; Shangqiu city experienced the largest reduction in carbon storage, with a total reduction of 0.23 Tg.

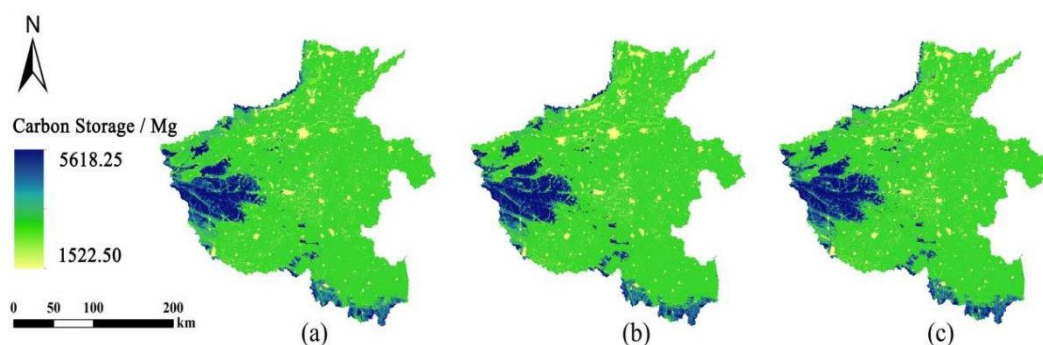


Figure 4. Spatial distribution of the carbon storage in Henan Province during 2001–2020. (a) 2001; (b) 2010; (c) 2020

From 2001 to 2020, the variation in the carbon stocks per unit pixel (500 m×500 m) in the study area ranged from -1420.40 Mg to 1420.40 Mg. The stable zone covered an area of 146.18×10^6 km², accounting for 88.16%, and was distributed continuously in space (*Table 6*). The increase zone (70000-0 Mg) accounted for 4.88% of the total area at 8.10×10^6 km² and was mainly distributed in Sanmenxia city, Jiyuan city and the northwestern city of Puyang city. The decreasing zone (0-70,000 Mg) accounted for

4.87% of the region, with an area of $8.07 \times 10^6 \text{ km}^2$ and was mainly distributed in the mountainous and hilly areas in the west. The significant increase zone ($\geq 70,000 \text{ Mg}$) covered an area of $2.74 \times 10^6 \text{ km}^2$, accounting for 1.65%, and was sporadically distributed in the core area of the mountainous and hilly areas in the west and the transition area between Pingdingshan city and Nanyang city. The zone experiencing a significant decrease ($\leq -70,000 \text{ Mg}$) spanned an area of $0.73 \times 10^6 \text{ km}^2$, accounting for 0.44%, and was distributed in only a small amount of Sanmenxia and Nanyang (Fig. 5).

Table 6. Statistics of the carbon storage changes in Henan Province during 2001–2020

Type of Change	Meaning (Mg)	Area ($\times 10^6 \text{ km}^2$)	Proportion (%)
Significant increase	$\geq 70,000$	2.74	1.65
Increase	70,000-0	8.10	4.88
Stable	0	146.18	88.16
Decrease	0 - -70,000	8.07	4.87
Severe decrease	$\leq -70,000$	0.73	0.44

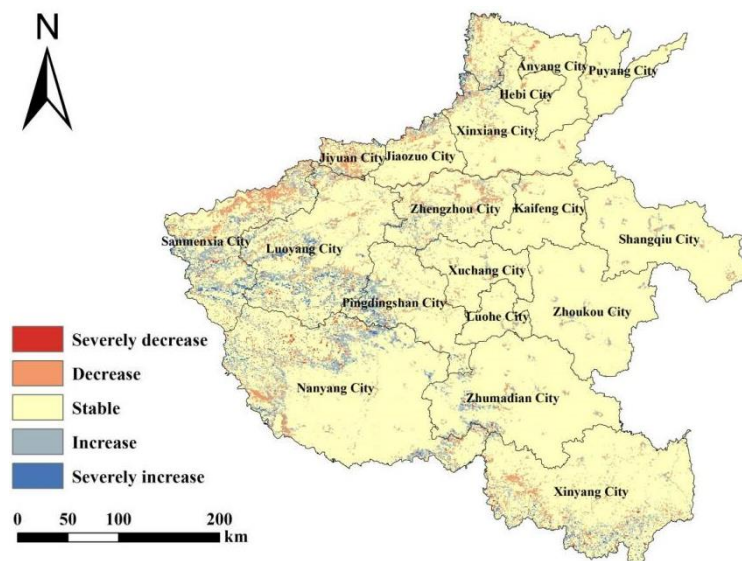


Figure 5. Spatial distribution of the carbon storage changes in Henan Province during 2001–2020

Prediction of the carbon stock changes under different scenarios

Analysis of the vegetation change under different scenarios

The distributions of vegetation types in Henan Province under the three scenarios in 2030 and 2060 are shown in Fig. 6. Under the NT scenario, some vegetation types during 2030–2060 exhibited the same trend as those during 2001–2020. Deciduous broad-leaved forest, forested grassland and savanna gradually increased, farmland decreased, and the non-vegetation area expanded to 14794.75 km^2 . Under the ecological protection scenario, the area of deciduous broad-leaved forest increased significantly, from 11814.75 km^2 in 2020 to 11929.00 km^2 in 2060, an increase of 0.97%. The areas of forested grassland,

savanna and permanent wetland also expanded significantly, by 671.00 km², 6829.00 km² and 227.00 km², respectively, from 2020 to 2060, representing increases of 8.24%, 65.41% and 48.35%, respectively. Because the ecological protection scenario limited the expansion trend of the non-vegetation zones in the ecological protection areas in Henan Province, the increase was 4008.00 km² over the past 40 years. Under the constraints of the ED scenario, compared with that in 2020, the non-vegetated area in the ED scenario increased significantly, by 2060, 4327.75 km², and 40.65%, respectively. In addition, due to the no longer restriction on the expansion of non-vegetation areas, ecological lands such as deciduous broad-leaved forests, mixed forests, grasslands, and permanent wetlands were significantly degraded under the ED scenario, with degradation rates reaching 6.15%, 12.74%, 23.60% and 30.62%, respectively.

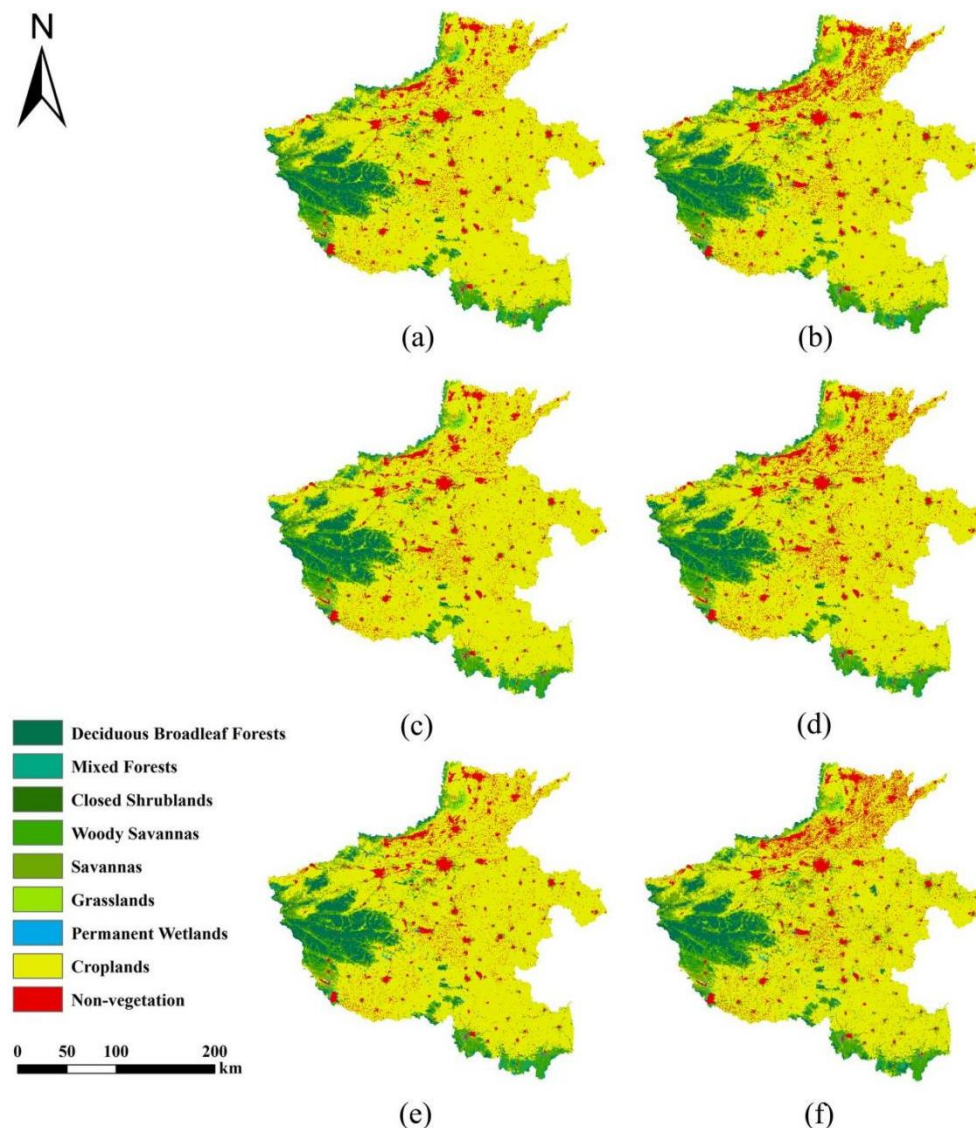


Figure 6. Prediction of the vegetation type distributions in Henan Province under different scenario constraints in 2030 and 2060. (a) NT scenario in 2030; (b) NT scenario in 2060; (c) ED scenario in 2030; (d) ED scenario in 2060; (e) ER development scenario in 2030; (f) ER development scenario in 2060

Analysis of the carbon stock changes under different scenarios

Based on the InVEST model, the distributions of the carbon stocks in 2030 and 2060 were predicted under the three scenarios (Figs. 7, 8 and 9). Compared with those under the 2020 scenario, the total carbon stocks under the three scenarios all exhibited a decreasing trend. Under the NT scenario, the carbon stocks in 2030 and 2060 are 1,689.36 Tg and 1,674.37 Tg, respectively. Under the ER scenario, the decreasing trend in carbon stocks was effectively controlled, and the carbon stocks in 2030 and 2060 were reduced to 0.24 Tg and 11.88 Tg, respectively, with decreasing rates of 0.014% and 0.702%, respectively. Under the ED scenario, the carbon stocks sharply decreased; by 2060, a decrease of 22.50 Tg, or 1.33%, was predicted, mainly due to the large-scale degradation of ecological land caused by the reduction in grassland, permanent wetland and cropland.

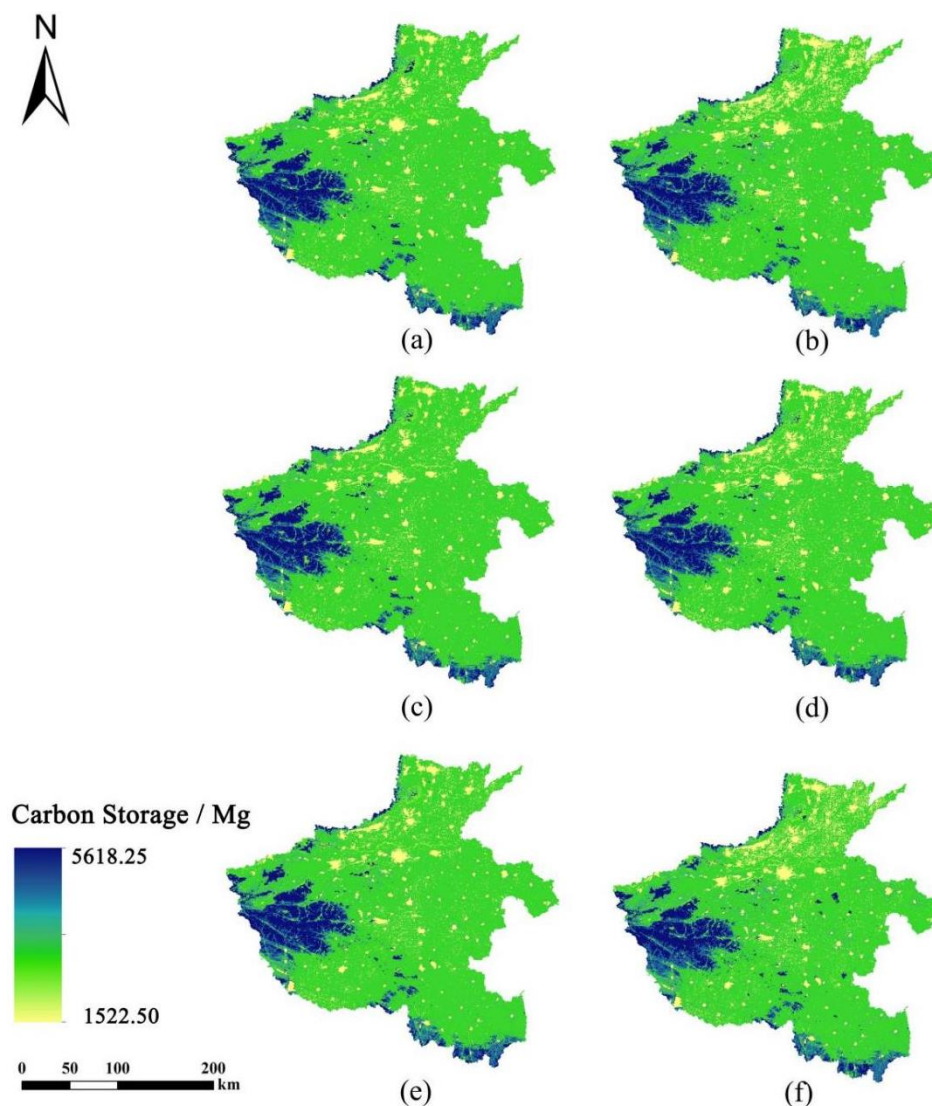


Figure 7. Prediction of the carbon storage distribution in Henan Province under different scenario constraints in 2030 and 2060. (a) NT scenario in 2030; (b) NT scenario in 2060; (c) ED scenario in 2030; (d) ED scenario in 2060; (e) ER development scenario in 2030; (f) ER development scenario in 2060

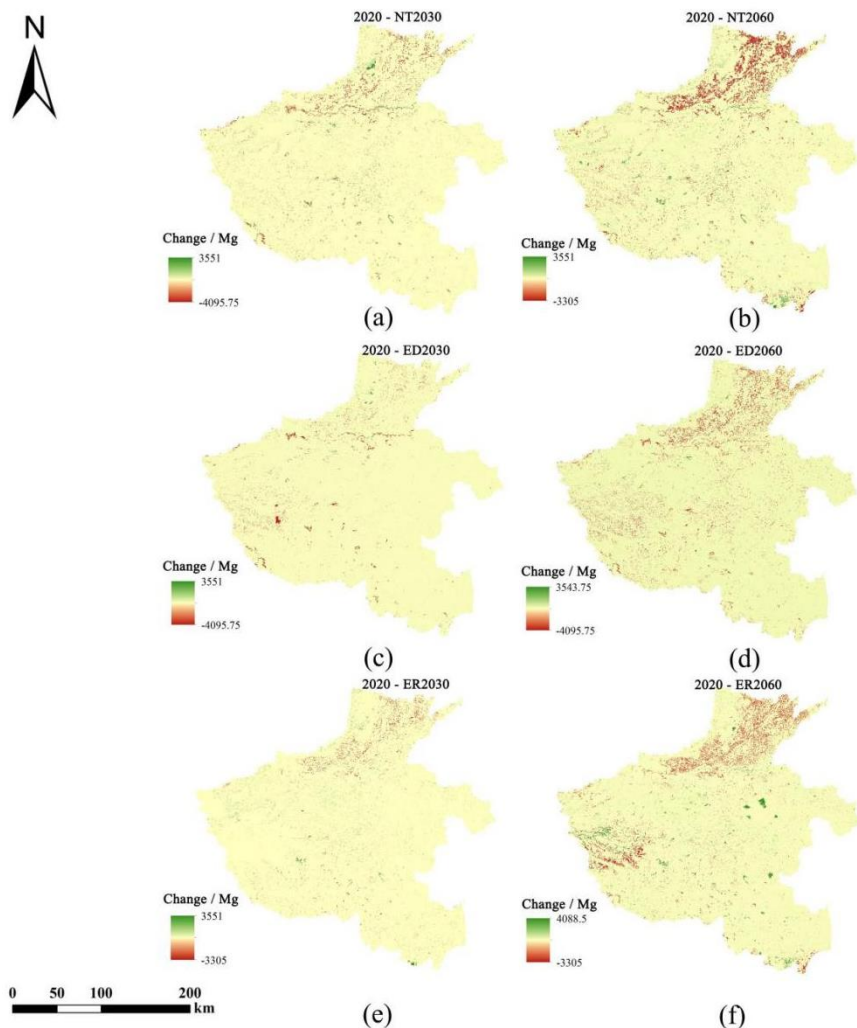


Figure 8. Prediction of the carbon storage change distribution in Henan Province under different scenario constraints in 2030 and 2060. (a) NT scenario in 2030; (b) NT scenario in 2060; (c) ED scenario in 2030; (d) ED scenario in 2060; (e) ER development scenario in 2030; (f) ER development scenario in 2060

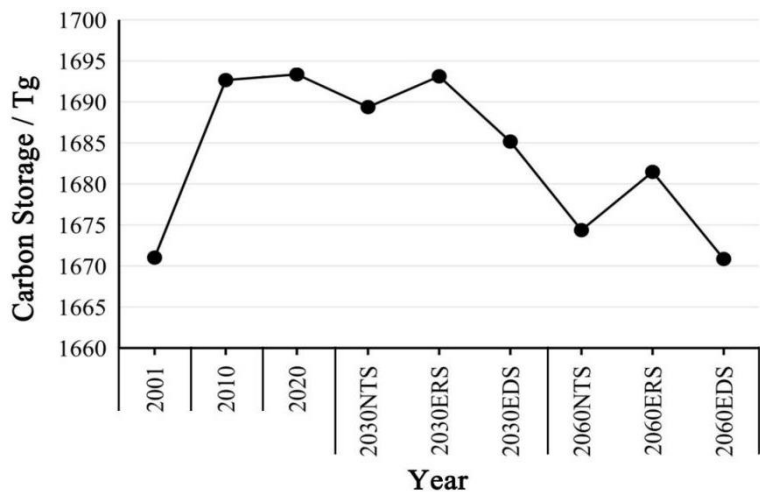


Figure 9. Carbon storage fluctuations in Henan Province from 2001 to 2060

Driving factors of the carbon stock changes in Henan Province

Dominant univariate analysis

As shown in Fig. 10, among the single-factor driving factors, evapotranspiration had the greatest contribution to the change in the carbon stocks in Henan Province, with an average q value of 0.69; this was the leading factor affecting the spatial differentiation of carbon stocks. The average q values of the altitude, slope, distance from farmland and temperature on carbon storage were 0.60, 0.49, 0.49 and 0.50, respectively; these were the primary variables that affected how regional carbon stores differed spatially. With an average q value of 0.43, climatic variables had the most effect on changes in the carbon stocks in Henan Province among all factor types. Topographic factors came in second with an average q value of 0.36. In general, the natural causes have little ability to explain variations in the carbon reserves. Furthermore, there was an annual tendency of growing influence for each factor on the changes in the carbon stocks in Henan Province.

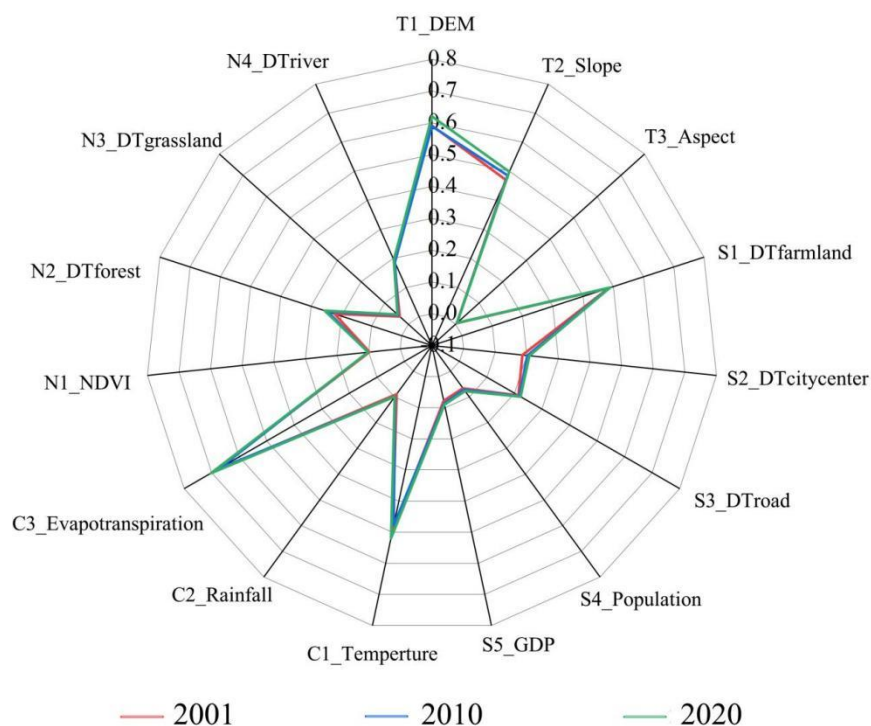


Figure 10. Assessing the influence of various individual factors on the changes in carbon storage in Henan Province from 2001 to 2020

Factor analysis of dominant interactions

An interaction detector was used to validate the enhancement relationship of the pairwise interactions among the 15 factors on the carbon stocks (Fig. 11). During 2001-2020, the interactions of the driving factors of the carbon stock changes in Henan Province all increased nonlinearly. Although the effects of some factors on the carbon stocks were weak (e.g., the q value of rainfall is less than 0.1), they could significantly enhance their explanatory power when they interacted with the other factors. Among them, the interaction explanatory powers of evapotranspiration and precipitation were the highest, reaching 0.77, 0.76 and 0.78. The interaction explanatory powers of

evapotranspiration and the NDVI were 0.76, 0.76 and 0.78. The q values for the interaction between evapotranspiration and the other factors were all greater than 0.70, indicating strong explanatory power. In addition, the interaction explanatory powers of the altitude, slope, and distance from farmland with other factors all exceeded 0.50, revealing a nonlinear enhancement effect.

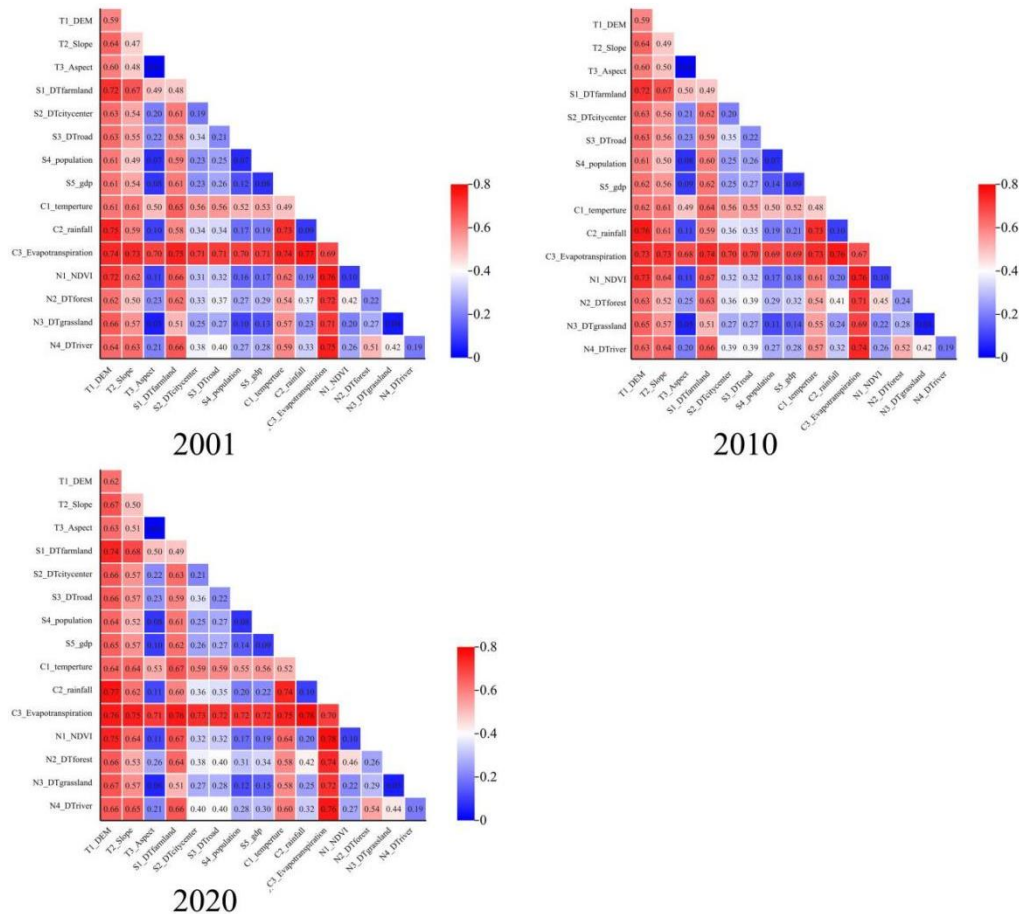


Figure 11. Primary influential factors impacting the alterations in carbon storage between the years 2001, 2010 and 2020. A redder color in the figure indicates stronger interactive explanatory power on carbon stocks

Discussion

Effect of the vegetation cover on the carbon stocks in Henan

Exploring the driving mechanism of the effect of vegetation cover on carbon storage has always been a popular research area in related fields because the carbon storage of terrestrial ecosystems is mainly affected by vegetation cover (Yu et al., 2013; Wang et al., 2021). The results showed that the carbon density of the deciduous broad-leaved forest and the mixed forest was the highest, which was equivalent to 3.69 times that of the non-vegetated area. Different vegetation cover types have different carbon density characteristics; therefore, there are spatiotemporal differences in the total amount of the carbon stocks in the different regions. The high-value carbon storage areas are mainly concentrated in the Dabie Mountains in the southern region, the mountainous and hilly

areas in the western region and the Taihang Mountains in the northern region. These mountainous areas are dominated by forests and have a strong carbon sequestration capacity. Although urbanization inevitably leads to a sharp expansion of nonvegetation areas, under the ER scenario, land use in the ecological protection areas in Henan Province is strictly constrained, and deciduous broad-leaved forests are predicted to increase from 11814.75 km² in 2020 to 11929 km² in 2060.; this represents an increase of 0.97%. These results show that an increase in the area of land types with high carbon density, such as forests, can effectively inhibit the negative impact of urban expansion in Henan Province on the carbon stocks.

In addition, the threat of farmland reclamation to carbon stocks also warrants attention (Lyu et al., 2023). To ensure food supply and agricultural development, changes in the regional vegetation type are often the result of the occupation of farmland by construction land caused by urbanization. Under China's strict arable land protection policy, other ecological lands, such as forests and grasslands, have further encroached into farmland. Although the carbon density of cropland is not low, it is not at the same level as that of forestland and wetland. The positioning of Henan's ecosystem as a "major grain-producing area" has caused an unbalanced trend in Henan's ecosystem, which is facing enormous pressure from increased carbon availability. Against this background, promoting the transformation of low-carbon density vegetation types to high-carbon density vegetation types is an effective way to solve the carbon increase problem (Wang et al., 2017).

Relationships between the carbon stocks and government policies

Policies are crucial in facilitating the advancement of regional economic growth and the restoration of ecological balance (Wen et al., 2022; Cai et al., 2023). Socioeconomic development policies need to pursue economic benefits but also cannot neglect the enormous pressure and challenges they may cause to protect ecosystems. Therefore, it is crucial to embrace proactive ecological protection and restoration policies, as these measures can significantly contribute to the restoration of stability and integrity within ecosystems, consequently enhancing regional carbon stocks (Li et al., 2021b). Over the last two decades, there has been a gradual recovery in ecosystem carbon stocks in Henan Province. This recovery is predominantly attributed to the ongoing expansion of deciduous broad-leaved forest, wetland areas, and mixed forest, with increments of 1727.75 km², 288.75 km², and 277.50 km², respectively. The resulting carbon storage gain is 42.30 Tg. These results are intricately linked to the efficient execution of a range of environmental conservation measures. We can also find examples of this from other studies, Li et al. (2023b) found that the afforestation project in Liaoning Province resulted in a net increase of 851.84 km² in forestland area. This increase in forestland area also led to a corresponding increase in carbon stocks of 20.44 Tg (Li et al., 2021a). Muñoz-Rojas et al. (2011) reported that the 17.24 Tg increase in carbon storage in Andalusia was largely due to its afforestation policy. Therefore, sustainable ecosystem management and a significant increase in carbon stocks can be accomplished by developing scientific ecological strategies to preserve and restore natural ecosystems.

Measures and suggestions for carbon management

With the socioeconomic development and population increase, the land use in Henan Province is facing multiple challenges, including the advancement of urbanization, maintenance of food security, and protection of the ecological environment. To address

these challenges, we propose a series of land use policy recommendations to increase the carbon stocks and achieve the sustainable use of land.

1. In the process of urbanization, the boundaries of urban construction and development should be rationally planned to balance the relationship between urban expansion and ecological protection. Carbon storage can be effectively increased by restoring severely degraded vegetation zones and implementing vegetation reconstruction. The analysis of the 2001–2020 land type transfer matrix showed that a total of 57.50 km² of non-vegetation area in Henan Province was optimized for wetland, grassland and farmland, and the corresponding increase in carbon storage reached 0.32 Tg. Therefore, when planning urban boundaries, permanent basic farmland needs to be ensured to not be occupied. Moreover, the construction of artificial grasslands should be promoted to restore degraded grasslands, and an increase in grasslands should be promoted through measures such as grazing fallow and grass fencing. This helps to increase the carbon density of the land and achieve the growth of the carbon stocks.
2. The establishment of an ecological protection red line is the key to protecting the ecological environment. While promoting urbanization, the principle of ecological red lines needs to be followed to ensure the integrity of ecological protection areas (Yang et al., 2023). Through the establishment of the concept of ecological red lines, the protection and restoration of important ecological barriers, patches, and corridors can effectively increase regional carbon stocks. Therefore, for important ecosystems such as forests, wetlands and grasslands, we need to strengthen their protection and management to ensure their role as carbon sinks. Ecological protection measures not only promote the healthy development of ecosystems but also increase soil carbon storage.
3. The promotion of the construction of new urban spaces is also critical to improving land carbon stocks. In the process of urbanization, the expansion of construction land needs to be strictly controlled, and the destruction of land carbon sinks by the disorderly expansion of urban space needs to be avoided through scientific planning and policy measures. The intensive use of construction land is key, and we need to shift from “incremental development” to “mining the potential stock” to save more arable land and ecological land. Moreover, the area of urban green spaces needs to increase, and the carbon sink function of urban green spaces needs to be improved through the construction of green infrastructure to support the sustainable development of cities.

The formulation and implementation of these measures and suggestions need to be tailored to the local conditions and account for Henan Province’s geographic characteristics, resource status, population density and other factors to ensure the feasibility and effectiveness of the policies. Through the implementation of these suggestions, we hope that in the future, the carbon storage level in Henan Province will increase, the sustainable use of land can be achieved, and contributions can be made to healthy economic and social development and continuous improvement of the ecological environment.

Limitations

The carbon density values presented in this study were not obtained through direct measurements but were obtained by adjusting the results from previous studies to meteorological data (Xiang et al., 2022). In addition, due to limitations in the use of the InVEST model, the carbon density data in this model are based on fixed assumptions. In

reality, the carbon density value will change under the influence of various factors, such as environmental change and human activities (Li et al., 2023b). Notably, the InVEST model is based mainly on large-scale land use change and does not consider the seasonal variation in carbon density within a given land use type or for different types of carbon loss. Therefore, future studies should focus on the field measurements and consider the carbon density changes within the land use types to validate and improve these carbon density values, thereby further increasing the accuracy of the estimates; the carbon density changes especially applies to the increases or decreases in carbon due to seasonal changes in the land use and cover and the vegetation age.

Conclusions

In elucidating the influence of spatiotemporal variations in vegetation cover on carbon stocks in Henan Province spanning the years 2001 to 2020, three models were employed. The InVEST model facilitated the estimation of carbon stocks in the province, the PLUS model explored carbon stock alterations under diverse scenarios, and the geodetector model provides the contribution of driving factors to changes in carbon storage. By employing these models, the primary drivers behind changes in carbon stocks were identified. The key findings are outlined as follows:

1. From 2001 to 2020, the vegetation area in Henan Province generally exhibited a trend of initially decreasing and then increasing. The degraded vegetation was mainly farmland, savanna, and grassland, and farmland had the largest degraded area accounting for 82.29% of the degradation zone. A total of 57.5 km² of non-vegetation area was optimized as wetland, grassland and cropland.
2. The 2001–2020 carbon stock distribution pattern was low in the central and eastern regions and high in the northwestern and southeastern regions. The overall growth showed a slowing trend, with a net increase of 6.33 Tg. The area of severely reduced carbon stocks was 2.74×10^6 km², accounting for 1.65%. The area of substantial increase in carbon stocks was 0.73×10^6 km², accounting for 0.44%.
3. In 2030 and 2060, under the constraints of the ER scenario, the reduction in carbon stocks was the lowest, at 0.24 Tg and 11.88 Tg, respectively, with magnitudes of reduction of 0.014% and 0.702%, respectively. Under the ED scenario, carbon stocks were predicted to show the largest reduction, decreasing by 22.50 Tg by 2060; this is equivalent to a decrease of 1.33%.
4. Evapotranspiration, altitude, slope, distance from farmland and temperature were the main factors affecting the spatial differentiation of regional carbon stocks. The interaction between the driving factors and the changes in carbon stocks was mainly reflected in a nonlinear enhancement, and the explanatory power of the interaction between evapotranspiration and precipitation was the highest among the three stages. In addition, the interaction effects of the altitude, slope, and distance from farmland with other factors was also strongly influenced by the changes in the carbon stocks.

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REFERENCES

- [1] Adelisardou, F., Zhao, W., Chow, R., Mederly, P., Minkina, T., Schou, J. S. (2022): Spatiotemporal change detection of carbon storage and sequestration in an arid ecosystem by integrating Google Earth Engine and InVEST (the Jiroft plain, Iran). – *International Journal of Environmental Science and Technology* 19(7): 5929-5944.
- [2] Babbar, D., Areendran, G., Sahana, M., Sarma, K., Raj, K., Sivadas, A. (2021): Assessment and prediction of carbon sequestration using Markov chain and InVEST model in Sariska Tiger Reserve, India. – *Journal of Cleaner Production* 278: 123333.
- [3] Box-Steffensmeier, J. M., Burgess, J., Corbetta, M., Crawford, K., Duflo, E., Fogarty, L., Gopnik, A., Hanafi, S., Herrero, M., Hong, Y. Y., Kameyama, Y., Lee, T. M. C., Leung, G. M., Nagin, D. S., Nobre, A. C., Nordentoft, M., Okbay, A., Perfors, A., Rival, L. M., Sugimoto, C. R., Tungodden, B., Wagner, C. (2022): The future of human behaviour research. – *Nature Human Behaviour* 6(1): 15-24.
- [4] Cai, Q., Wang, G., Wen, X., Zhang, X., Zhou, Z. (2023): Perceived effectiveness and responsibilities of the forest biological disasters control system of China: a perspective of government administrators. – *Forests* 14(1): 6.
- [5] Ding, Q., Chen, Y., Bu, L., Ye, Y. (2021): Multi-scenario analysis of habitat quality in the Yellow River delta by coupling FLUS with InVEST model. – *International Journal of Environmental Research and Public Health* 18(5): 2389.
- [6] Fan, L., Cai, T., Wen, Q., Han, J., Wang, S., Wang, J., Yin, C. (2023): Scenario simulation of land use change and carbon storage response in Henan Province, China: 1990–2050. – *Ecological Indicators* 154: 110660.
- [7] Feng, Y., Chen, S., Tong, X., Lei, Z., Gao, C., Wang, J. (2020): Modeling changes in China's 2000–2030 carbon stock caused by land use change. – *Journal of Cleaner Production* 252: 119659.
- [8] Gao, L., Tao, F., Liu, R., Wang, Z., Leng, H., Zhou, T. (2022): Multi-scenario simulation and ecological risk analysis of land use based on the PLUS model: a case study of Nanjing. – *Sustainable Cities and Society* 85: 104055.
- [9] He, Y., Ma, J., Zhang, C., Yang, H. (2023): Spatio-temporal evolution and prediction of carbon storage in Guilin based on FLUS and InVEST models. – *Remote Sensing* 15(5): 1445.
- [10] Houghton, R. A., Skole, D. L., Lefkowitz, D. S. (1991): Changes in the landscape of Latin America between 1850 and 1985 II. Net release of CO₂ to the atmosphere. – *Forest Ecology and Management* 38(3-4): 173-199.
- [11] Huang, D., Huang, J., Liu, T. (2019): Delimiting urban growth boundaries using the CLUE-S model with village administrative boundaries. – *Land Use Policy* 82: 422-435.
- [12] Huang, C., Zhang, C., Li, H. (2022): Assessment of the impact of rubber plantation expansion on regional carbon storage based on time series remote sensing and the InVEST model. – *Remote Sensing* 14(24): 6234.
- [13] Krause, A., Papastefanou, P., Gregor, K., Layritz, L. S., Zang, C. S., Buras, A., Li, X., Xiao, J., Rammig, A. (2022): Quantifying the impacts of land cover change on gross primary productivity globally. – *Scientific Reports* 12(1): 18398.
- [14] Lahiji, R. N., Dinan, N. M., Liaghati, H., Ghaffarzadeh, H., Vafaeinejad, A. (2020): Scenario-based estimation of catchment carbon storage: linking multi-objective land allocation with InVEST model in a mixed agriculture-forest landscape. – *Frontiers of Earth Science* 14(3): 637-646.
- [15] Li, H. (2019): The evaluation on ecological effects of the project of returning farmland to forest in Liaoning Province, based on remote sensing and InVEST model. – Ph.D. Thesis, Jilin University. Changchun, China.
- [16] Li, C., Wu, Y., Gao, B., Zheng, K., Wu, Y., Li, C. (2021a): Multi-scenario simulation of ecosystem service value for optimization of land use in the Sichuan-Yunnan ecological barrier, China. – *Ecological Indicators* 132: 108328.

- [17] Li, Q., Shi, X., Wu, Q. (2021b): Effects of protection and restoration on reducing ecological vulnerability. – *Science of the Total Environment* 761: 143180.
- [18] Li, X., Fu, J., Jiang, D., Lin, G., Cao, C. (2022a): Land use optimization in Ningbo City with a coupled GA and PLUS model. – *Journal of Cleaner Production* 375: 134004.
- [19] Li, Y., Brando, P. M., Morton, D. C., Lawrence, D. M., Yang, H., Randerson, J. T. (2022b): Deforestation-induced climate change reduces carbon storage in remaining tropical forests. – *Nature Communications* 13(1): 1964.
- [20] Li, P., Chen, J., Li, Y., Wu, W. (2023a): Using the InVEST-PLUS model to predict and analyze the pattern of ecosystem carbon storage in Liaoning Province, China. – *Remote Sensing* 15(16): 4050.
- [21] Li, X., Li, F., Wang, D., Hou, J., Wang, Z., Cao, R., Yang, W. (2023b): Zonal patterns and driving factors of soil organic carbon density in Zhejiang Province, China. – *Geoderma Regional* 34: e00679.
- [22] Liang, X., Guan, Q., Clarke, K. C., Liu, S., Wang, B., Yao, Y. (2021): Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: a case study in Wuhan, China. – *Computers, Environment and Urban Systems* 85: 101569.
- [23] Lin, W., Sun, Y., Nijhuis, S., Wang, Z. (2020): Scenario-based flood risk assessment for urbanizing deltas using future land-use simulation (FLUS): Guangzhou Metropolitan Area as a case study. – *Science of the Total Environment* 739: 139899.
- [24] Liu, J., Zhang, G., Zhuang, Z., Cheng, Q., Gao, Y., Chen, T., Huang, Q., Xu, L., Chen, D. (2017): A new perspective for urban development boundary delineation based on SLEUTH-InVEST model. – *Habitat International* 70: 13-23.
- [25] Liu, Y., Wu, K., Cao, H. (2022): Land-use change and its driving factors in Henan Province from 1995 to 2015. – *Arabian Journal of Geosciences* 15(3): 247.
- [26] Lyu, L., Zhu, J., Long, H., Liao, K., Fan, Y., Wang, J. (2023): Effects of farmland use transition on soil organic carbon in dry farming areas. – *Environment, Development and Sustainability*. doi: 10.1007/s10668-023-02998-4.
- [27] Muñoz-Rojas, M., de la Rosa, D., Zavala, L. M., Jordan, A., Anaya-Romero, M. (2011): Changes in land cover and vegetation carbon stocks in Andalusia, Southern Spain (1956-2007). – *Science of the Total Environment* 409(14): 2796-2806.
- [28] Piyathilake, I. D. U. H., Udayakumara, E. P. N., Ranaweera, L. V., Gunatilake, S. K. (2021): Modeling predictive assessment of carbon storage using InVEST model in Uva Province, Sri Lanka. – *Modeling Earth Systems and Environment* 8(2): 2213-2223.
- [29] Shao, Z., Chen, C., Liu, Y., Cao, J., Liao, G., Lin, Z. (2023): Impact of land use change on carbon storage based on FLUS-InVEST model: a case study of Chengdu–Chongqing urban agglomeration, China. – *Land* 12(8): 1531.
- [30] Tang, X., Zhao, X., Bai, Y., Tang, Z., Wang, W., Zhao, Y., Wan, H., Xie, Z., Shi, X., Wu, B., Wang, G., Yan, J., Ma, K., Du, S., Li, S., Han, S., Ma, Y., Hu, H., He, N., Yang, Y., Han, W., He, H., Yu, G., Fang, J., Zhou, G. (2018): Carbon pools in China's terrestrial ecosystems: new estimates based on an intensive field survey. – *Proceedings of the National Academy of Sciences of the United States of America* 115(16): 4021-4026.
- [31] Wang, J. F., Li, X. H., Christakos, G., Liao, Y. L., Zhang, T., Gu, X., Zheng, X. Y. (2010): Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. – *International Journal of Geographical Information Science* 24(1): 107-127.
- [32] Wang, J. F., Zhang, T. L., Fu, B. J. (2016): A measure of spatial stratified heterogeneity. – *Ecological Indicators* 67: 250-256.
- [33] Wang, Y. F., Liu, L., Shangguan, Z. P. (2017): Carbon storage and carbon sequestration potential under the Grain for Green Program in Henan Province, China. – *Ecological Engineering* 100: 147-156.

- [34] Wang, L. X., Gao, J. X., Shen, W. M., Shi, Y. L., Zhang, H. W. (2021): Carbon storage in vegetation and soil in Chinese ecosystems estimated by carbon transfer rate method. – *Ecosphere* 12(1): e03341.
- [35] Wang, Z., Lv, D. (2022): Analysis of agricultural CO₂ emissions in Henan Province, China, based on EKC and decoupling. – *Sustainability* 14(3): 1931.
- [36] Wang, Z., Guo, M., Zhang, D., Chen, R., Xi, C., Yang, H. (2023): Coupling the calibrated globalland30 data and modified PLUS model for multi-scenario land use simulation and landscape ecological risk assessment. – *Remote Sensing* 15(21): 5186.
- [37] Wen, X., Gu, T., Qi, H., Zhang, F. (2022): Incineration or pulverization? Evolutionary game model of management of nematode-infected pine wood in China in the carbon neutrality context. – *Frontiers in Environmental Science* 10: 1041357.
- [38] Wen, X., Hong, Y., Zhong, J., Li, L., Ma, Q., Hu, X., Han, X., Guo, W., Huang, Y., Zhang, F. (2024): Assessing the impact of pine wilt disease on aboveground carbon storage in planted *Pinus massoniana* Lamb. forests via remote sensing. – *Science of the Total Environment* 914: 169906.
- [39] Xiang, S., Wang, Y., Deng, H., Yang, C., Wang, Z., Gao, M. (2022): Response and multi-scenario prediction of carbon storage to land use/cover change in the main urban area of Chongqing, China. – *Ecological Indicators* 142: 109205.
- [40] Xu, L., Yu, G., He, N., Wang, Q., Gao, Y., Wen, D., Li, S., Niu, S., Ge, J. (2018): Carbon storage in China's terrestrial ecosystems: a synthesis. – *Scientific Reports* 8(1): 2806.
- [41] Xu, L., He, N., Yu, G. (2019): A dataset of carbon density in Chinese terrestrial ecosystems (2010s). – *China Scientific Data* 4: 90-96.
- [42] Xu, C., Zhang, Q., Yu, Q., Wang, J., Wang, F., Qiu, S., Ai, M., Zhao, J. (2023): Effects of land use/cover change on carbon storage between 2000 and 2040 in the Yellow River Basin, China. – *Ecological Indicators* 151: 110345.
- [43] Yang, Y., Lu, Y., Fu, B., Wu, X., Wang, S., Wu, T. (2023): The potential for carbon sequestration by afforestation can be limited in dryland river basins under the pressure of high human activity. – *Science of the Total Environment* 858(Pt 2): 159817.
- [44] Yu, P., Li, Q., Jia, H., Zheng, W., Wang, M., Zhou, D. (2013): Carbon stocks and storage potential as affected by vegetation in the Songnen grassland of northeast China. – *Quaternary International* 306: 114-120.
- [45] Zhu, G., Qiu, D., Zhang, Z., Sang, L., Liu, Y., Wang, L., Zhao, K., Ma, H., Xu, Y., Wan, Q. (2021): Land-use changes lead to a decrease in carbon storage in arid region, China. – *Ecological Indicators* 127: 107770.