TEMPORAL AND SPATIAL EVOLUTION ANALYSIS AND SIMULATION PREDICTION OF CARBON STORAGE IN RESOURCE-BASED CITIES BASED ON INVEST AND CA-MARKOV MODEL: A CASE STUDY OF JIAOZUO CITY, CHINA

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(Received 25th Jan 2025; accepted 22nd Apr 2025)

Abstract. Land use change represents the most significant driver of ecosystem carbon stock dynamics. Investigating the evolutionary characteristics of land use and carbon stocks in Jiaozuo city, China, is crucial for promoting sustainable development and ecological transformation in the region. This study uses the InVEST model to measure carbon stock changes in Jiaozuo City from 1990 to 2020. It also employs the CA-Markov model to simulate 2035 land use under two scenarios: the natural development (NDS) and the ecological priority (EPS), considering various driving factors. The results indicate that: (1) From 1990 to 2020, significant land use changes occurred in Jiaozuo city, predominantly involving the conversion of cropland to forest land, grassland and construction land, with notable expansion of construction land. (2) During this period, Jiaozuo city's carbon storage exhibited a trend of fluctuation, with a total decrease of 1.26 t. The primary factors contributing to this change were the reduction of forest land and the expansion of construction land. (3) By 2035, under the NDS, the continued expansion of construction land is expected to further reduce carbon storage. However, in the EPS, the decline in carbon storage is anticipated to decelerate, with a greater emphasis on the protection of ecological land.
Keywords: *InVEST model, carbon storage, scenario simulation, land use, small-medium cities, ecological protection strategy*

Introduction

Global climate warming, a critical environmental issue, threatens ecological security and the sustainable development of human society. The carbon cycle has thus garnered significant global attention (Zhao et al., 2011). Human activities, particularly urbanization and industrialization, produce large quantities of CO_2, the primary driver of global warming and extreme weather events (Bala et al., 2013; Wei et al., 2020). Following the Paris Agreement in 2015, countries have proposed measures to mitigate climate change, and in September 2020, China set the goal of achieving "carbon peak and carbon neutrality". Consequently, efforts for energy conservation, emission reduction and carbon sequestration are urgent, with enhancing ecosystem carbon storage being key to achieving "carbon neutrality" (Piao et al., 2022a). Terrestrial ecosystems, the largest natural carbon reservoirs, can effectively absorb and store atmospheric CO_2 (Piao et al., 2009). As part of ecosystem services, carbon storage regulates the global carbon cycle balance through material cycles and energy flows, playing a crucial role in mitigating climate change (Sawirdin et al., 2023). Soil, the largest carbon reservoir in terrestrial systems, is significantly impacted by land use changes (Solomon et al., 2018; Xu et al., 2023).

Therefore, studying the impact of land use changes on carbon storage is essential for climate change mitigation.

Terrestrial ecosystems have a pivotal role in carbon emission is suggested to be used and absorption amidst environmental changes. Currently, China's terrestrial ecosystem offsets 7-15% of the country's anthropogenic carbon emissions (Piao et al., 2022b). The carbon cycle is the core process of terrestrial ecosystem dynamics (Piao et al., 2019). Enhancing terrestrial carbon sequestration and improving ecosystem management are vital for mitigating global climate change (Wang et al., 2015). Numerous scholars have researched carbon storage in different regions. Based on a global scale study, Levy et al. (2004) found that land use change was the primary cause of carbon storage alterations from 1700 to 1990. An et al. (2024) and Wen et al. (2023) examined the changes in carbon density in China's terrestrial ecosystems over 30 years, noting significant carbon loss in the southeast coastal region and the Beijing-Tianjin-Hebei region, with a 10% land change resulting in carbon loss of 5907.44×10^4 t, while carbon storage increased in the western region. Jiang et al. (2024) and Wang et al. (2024) assessed the carbon storage mechanisms of different river basins from a vulnerability perspective, revealing the crucial role of forests in carbon storage services. They found that the conversion of forest and grassland was the main driver of carbon storage changes. Wang et al. (2021) concluded that rapid urbanization in Hangzhou led to a 3.93×10^5 t decrease in carbon storage due to the occupation of cropland and wetlands to settlements. Sharma et al. (2019) used multi-temporal satellite data to assess soil carbon storage in half of Rajasthan, India, finding a 3.16Mt of carbon loss from forest conversion to agricultural land between 1993-2014. Patrício et al. (2023) studied land abandonment in northeastern Portugal, assessing soil carbon distribution under different scenarios, and found that agricultural soil had lower carbon storage compared to other land use types. Jiao et al. (2024) analyzed the historical land use and carbon storage evolution in Shanxi Province, incorporating mineral resources driving factors, and predicted a decline in carbon storage under natural development scenarios. Zou et al. (2023) and Wang et al. (2024) analyzed the temporal and spatial changes and driving mechanisms of urban carbon storage in megacities, and found that ecological restoration scenarios can effectively improve regional carbon storage in different scenarios simulated in the future.

The assessment of carbon storage primarily relies on field investigations (Qiu et al., 2020), multi-source remote sensing (Matiza et al., 2023), and model simulations (Xu et al., 2022). Field investigations offer high accuracy and are suitable for small to medium-scale assessments of carbon storage (Rajput et al., 2017), but they require extended sampling periods. Multi-source remote sensing retrieves above-ground biomass from vegetation reflectance in different satellite image bands, thereby quantifying regional carbon storage. This method is intuitive and flexible, making it suitable for large-scale assessments, although its limited wavelength range introduces certain errors (Sun et al., 2020). Model simulations use remote sensing data to estimate regional carbon storage, offering easy of operation and high accuracy, making them widely adopted (Lahiji et al., 2020; He et al., 2023). The InVEST model is commonly used to simulate ecosystem service changes under different land use scenarios due to its simple operation, flexible parameter acquisition, and accurate results (Yang et al., 2019). Scholars often combine InVEST with models like PLUS (Liu et al., 2022; Huang et al., 2023), Markov (Xiang et al., 2022), FLUS (Wang et al., 2023) and CA-Markov (Xia et al., 2018; Liang et al., 2021) to simulate land use changes under different scenarios by setting transformation matrices. The CA-Markov model, comprising Cellular Automata (CA) and Markov chain,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_67536776

simulates complex behaviors through simple transformation rules and is widely used in urban expansion modeling to assist planners and decision-makers in analyzing various future urban development scenarios (Li et al., 2018; Ding et al., 2022). In summary, most current studies focus on large-scale areas such as countries, provinces, and river basins, with relatively few examining carbon storage changes in resource-based cities during their transformation process. However, resource-based cities play a crucial role in social development, and their transformation closely relates to carbon storage. The transformation of resource-based cities not only supports sustainable urban development but also significantly contributes to global carbon emission reduction and climate change mitigation. Therefore, it is necessary to study the relationship between the transformation of typical resource-based cities and carbon storage.

Jiaozuo, known as the "century-old coal city", is a typical resource-based city in central China with abundant mineral resources and a favorable geographical location. It serves as a model for the successful transformation of resource-based cities (Zhao et al., 2021). However, there are relatively few studies on ecosystem carbon storage in Jiaozuo city, making it significant to explore changes in ecosystem carbon sequestration during its transformation for the region’s future development. This study selects Jiaozuo city as the research area, using the CA-Markov and InVEST models to analyze the spatio-temporal evolution of land use and carbon storage from 1990 to 2020, and reveals the change law of land use and carbon storage in different urban development stages. It investigates the influence mechanisms of land use change on carbon storage change. Additionally, the study explores the characteristics of land use and carbon storage in Jiaozuo city under different scenarios (natural development scenario and ecological priority scenario) by 2035, simulating and predicting future years based on driving factors, analyzing the reasons, explored the mechanism of action between carbon storage and different driving factors, and considered how to improve the regional carbon storage capacity. The research results will provide a scientific basis for the future policy planning in optimizing land use structure, maintaining carbon balance and ensuring Jiaozuo city’s sustainable development, offering a reference for other cities undergoing similar transformations.

Materials and methods

Study area

Jiaozuo is located in the northwest of Henan Province, China (34° 49’N-35° 29’N, 112° 43’E-113° 38’E), covering a total area of approximately 4071 square kilometers. The terrain is higher in the north and lower in the south. It borders Jincheng city and Lingchuan County of Shanxi Province along Taihang Mountains to the north and the Yellow River to the south. Jiaozuo administers six counties (including two prefecture level cities) and four districts (including the urban-rural integration demonstration zone). It is one of the core cities of the Central Plains urban agglomeration (*Figure 1*). It is a warm temperate continental monsoon climate with warm, hot and rainy summer and cold and dry winter, the total annual precipitation is 562.7 mm, and the average annual temperature is 15.8℃. In 2020, the GDP was 212.36 billion yuan, with a permanent population of 3.52 million and an urbanization rate of 63.03%. The predominant land use type is cropland, accounting for approximately 62.34%, followed by forest land and grassland at 16.44%, and construction land at 15.95%. As one of the famous coal bases in the country, Jiaozuo has significantly contributed to national and local economic development. However, excessive coal exploitation and urban land expansion have adversely impacted the local land structure and ecological environment. Since the late 1990s, Jiaozuo has transformed from a resource-exhausted city to an ecologically friendly tourist city. This transformation has seen rapid population growth and changes in land use types, which have consequently altered the human settlement environment. In response, Jiaozuo city implemented a series of ecological restoration and environmental improvement measures. Therefore, future development should focus on utilizing land structure changes to stabilize ecosystem carbon storage and maintain ecological security.

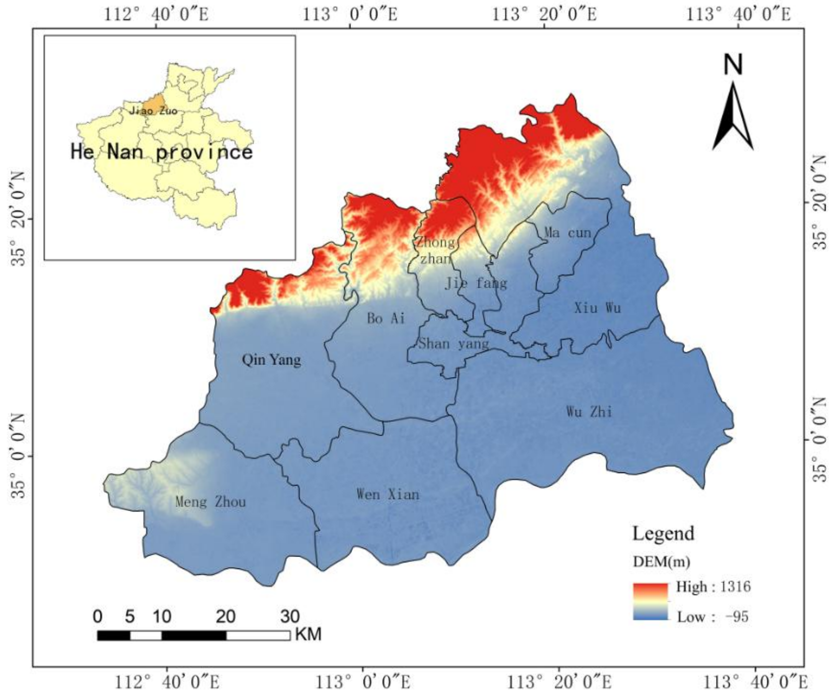

Figure 1. *Jiaozuo city geographical location*

Data sources

The data used in this study include land use data, socio-economic factors (GDP, population density, highways, railways), natural factors (DEM, slope, precipitation, temperature), and resource-based factors (mining areas, key mining and exploration areas) (*Figure 2*). ArcGIS and Origin are used for relevant data processing and visualization mapping. Land use data for 1990, 2000, 2010 and 2020 were sourced from (https://www.gscloud.cn/) and reclassified into seven categories: cropland, forest land, grassland, water areas, construction land, unused land and mining land, the data set is obtained by manual visual interpretation using Landsat remote sensing images of the United States, and the overall accuracy is no less than 85%. DEM data for the study area were obtained from (https://www.gscloud.cn/) with a 30 m×30 m resolution. Slope data were extracted using the surface analysis tool of ArcGIS based on DEM. Annual precipitation and average annual temperature date were sourced from (https://www.geodate.cn/), obtained through annual summative synthesis of monthly precipitation and air temperature datasets (Peng et al., 2019). Population density data were sourced from (https://hub.worldpop.org/), using a random forest redistribution mapping method with 1 km resolution to calculate average population density. GDP data

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DOI: http://dx.doi.org/10.15666/aeer/2304_67536776

were sourced from (https://www.resdc.cn/) with a spatial grid resolution of 1 km, and the average annual GDP can be obtained according to statistics (Zheng et al., 2023). Road date from (https://www.webmap.cn/), mining area date from (http://ngac.org.cn/), and key mining and exploration areas from (https://sgic.net.cn/). All data are uniformly projected to the krasovsky_1940_Albers coordinate system (*Table 1*).

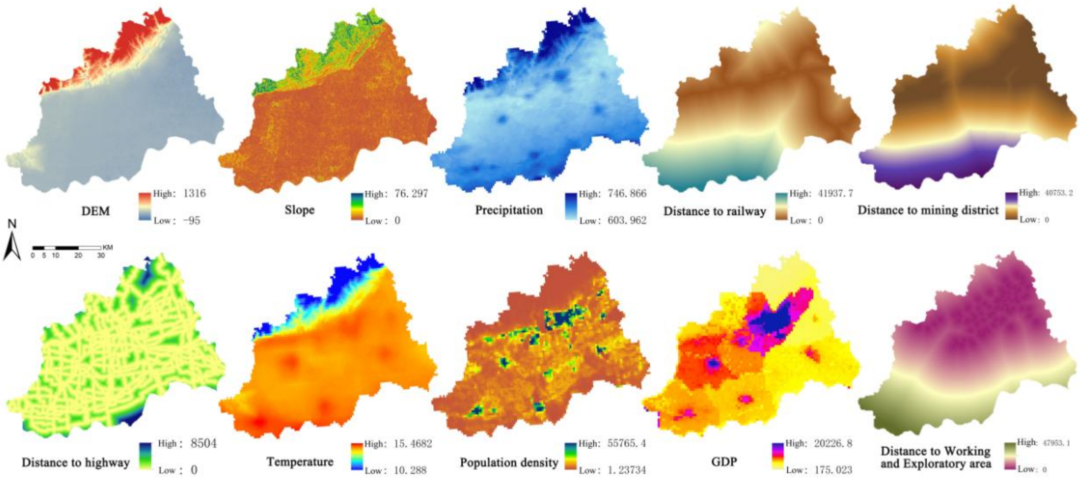

***Figure 2.** Driving factors*

***Table 1.** Data sources and descriptions*

Type	Date	Year	Resolution	Sources
Land use data	Land use	1990, 2000 2010, 2020	30 m	https://www.gscloud.cn/
Natural factor	DEM	2020	30 m	https://www.gscloud.cn/
	Slope	2020	30 m	Extracted according to DEM
	Temperature	2020	1000 m	https://www.geodate.cn/
	Precipitation	2020	1000 m	https://www.geodate.cn/
Social and economic	GDP	2020	1000 m	https://www.resdc.cn/
	Population density	2020	1000 m	https://hub.worldpop.org/
	Highways	2020	1000 m	https://www.webmap.cn/
	Railways	2020	1000 m	https://www.webmap.cn/
Resource-based factor	Mining district	2019	1000 m	http://ngac.org.cn/
	Mining exploration areas	2001	1000 m	https://sgic.net.cn/

Research methods

Land use transfer matrix

Land use transfer matrix is a common method to analyze land use change. In essence, land use transfer matrix uses Markov model to reflect land use change (Luo et al., 2018). Probabilistic analysis and state transition matrix are formed by Markov chain. This model is often used to simulate the state and change trend of land use. Its advantage is that it can simulate the future time according to the land use state at this moment and has the dynamic time evolution ability (Xiang et al., 2022). By calculating the land use transfer

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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matrix of Jiaozuo city in 2020 to predict the land use change in 2035, the formula is as follows:

$$\mathrm{S}_{(t+1)} = \mathrm{S}_t \times \mathrm{P}_{ij} \quad \text{(Eq.1)}$$

$$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \vdots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \quad \text{(Eq.2)}$$

$$0 \le P_{ij} < 1, \sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij} = 1 \quad \text{(Eq.3)}$$

where: P_{ij} represents the transfer probability matrix from class i to class j; St is the state of a certain class in period t; $S_{(t+1)}$ represents the state of land use type at time t+1, which is the predicted result of Markov chain; and n is the number of land use types.

CA-Markov model

The model is a combination of CA model and Markov chain. CA model, also known as cellular automata, includes four types of elements: cell, cell state, neighborhood and transition rule. It is a dynamic model with discrete time, space and state, and local spatial interaction and temporal causality, and has the ability to simulate the spatio-temporal evolution process of complex systems (Sang et al., 2011).

$$S_{(t+1)} = f\left(S_{(t)}, N\right) \quad \text{(Eq.4)}$$

where: S is a finite, discrete set of cell states; t and t+1 represent different moments; f is the transformation rule; and N represents the neighborhood of the cell.

Scenario setting and accuracy verification

China has committed itself globally to achieving carbon peak by 2030 and carbon neutrality by 2060. Based on this dual carbon target, two scenarios are set to simulate the land use situation in 2035: the natural development scenario (NDS), which simulates the natural evolution process based on the probability of land use transfer between 2010 and 2020, and does not impose restrictions on the direction of transfer of local classes (Schedule 1); ecological priority scenario (EPS), according to the ecological requirements in the Jiaozuo Municipal Territorial Spatial Plan 2021-2035, focuses on the protection of land with ecological functions, prohibits the conversion of forest land and water areas into other land, allows the conversion of grassland into forest land and water areas, and restricts the conversion of construction land and mining land into forest land, grassland and water areas. To achieve the goal of ecological protection (Schedule 2).

Before simulating the future year, land use type transfer probability and adaptive map (MCE) from 2000 to 2010 are obtained by Markov model, which is used to simulate the land use in 2020 and compare with the real year. After accuracy test, kappa value reaches 0.876, indicating high accuracy. Subsequent future years can be simulated.

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InVEST model

The InVEST model, also known as the Ecosystem Services and Tradeoffs Integrated Assessment Model, was developed by Stanford University, the Nature Conservancy and the World Wide Fund for Nature. Carbon storage in the study area was calculated using the carbon storage and sequestration function in the model. The carbon pool in the ecosystem is divided into the following four parts: aboveground biomass carbon, belowground biomass carbon, dead organic matter carbon and soil organic matter carbon. The calculation formula is as follows:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \tag{Eq.5}$$

$$C_{totali} = (C_{abovei} + C_{belowi} + C_{soili} + C_{deadi}) \times A_i \tag{Eq.6}$$

where: C_{total} is the total carbon storage of the ecosystem, including all the biomass, organic matter and litter in the soil layer; C_{above} is the aboveground biomass, mainly plant roots; C_{below} is the belowground biomass; C_{soil} is soil organic matter, which is the organic component in soil; C_{dead} is the dead organic matter, mainly includes litter; A_i represents the total areas of land use type i.

Carbon density correction

The InVEST model requires input carbon density data to calculate carbon storage, and the carbon density of different regions is different due to the influence of climate and soil type. The data of land use carbon density came from previous studies on Henan Province and the Yellow River Basin (Yang et al., 2021; Gai et al., 2024) (Schedule 3). Precipitation and temperature are the main factors that affect carbon storage through changing soil properties. According to Chen et al. (2007) research, there is a significant positive correlation between average annual precipitation and underground carbon, and the carbon density is corrected by referring to relevant studies (Giardina et al., 2001; Alam et al., 2013) (*Table 2*) (*Eq.7-13*).

$$C_{BT} = 28 \times T + 398 \tag{Eq.7}$$

$$C_{SP} = 3.3968 \times P + 3996.1 \tag{Eq.8}$$

$$C_{BP} = 6.7981 \times e^{0.00541P} \tag{Eq.9}$$

where: P is annual precipitation (mm); T is annual mean temperature (°C); C_{SP} is soil carbon density corrected according to precipitation; C_{BP} and C_{BT} are biomass carbon density corrected according to annual precipitation and temperature respectively. The average annual precipitation of Jiaozuo city is 531.63 mm, the average annual temperature is 16.15℃, the average annual temperature of the country is 10.04℃, and the average annual rainfall is 657.36 mm.

By comparing the average annual amount of the whole country with that of Jiaozuo city, the correction coefficient is obtained by multiplied by the reference data to obtain the carbon density of various types in Jiaozuo city.

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$$K_s = \frac{C'_{SP}}{C''_{SP}} \quad \text{(Eq.10)}$$

$$K_B = K_{BT} \times K_{BP} \quad \text{(Eq.11)}$$

$$K_{BP} = \frac{C'_{BP}}{C''_{BP}} \quad \text{(Eq.12)}$$

$$K_{BT} = \frac{C'_{BT}}{C''_{BT}} \quad \text{(Eq.13)}$$

where: K_S is soil carbon density data obtained according to annual precipitation in Jiaozuo and the whole country; K_B is the final modified biomass carbon density; K_{BP} is the revised data of biological carbon density based on precipitation at the regional and national scales of the study; and K_{BT} is the biological carbon density calculated based on the annual average temperature in Jiaozuo city and the national scale.

Table 2. *Revised table of ecosystem carbon density (t/hm²)*

Land Use Type	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	9.79	33.22	83.52	3.43
Forest	17.46	47.71	124.43	6.28
Grass	14.53	35.61	68.18	2.75
Water	0	3.02	0	0
Construction	0	0	63.85	0
Unused	0.54	0	58.12	0
Mining	0	0	62.28	0

Results and analysis

Effects of land use change on carbon storage from 1990 to 2020

The predominant land type in Jiaozuo city is cropland (*Table 3*), accounting for over 60% of the total area, and is widely distributed except for the Taihang Mountains in the northwest. Construction land is the second most common, primarily concentrated in the north and southwest, along rivers and mountains, and accounts for more than 60% of the total area. Forest land constitutes about 13% of the total area, mainly located in the mountainous regions to the northwest. grassland, water areas, and unused land occupy a smaller portion, collectively less than 10%, with grassland mainly found at the junction between plain and mountains and in the southwest corner. Between 1990 to 2020, Jiaozuo city's land use types changed to varying degrees (*Figure 3*), with significant alterations noted in cropland and construction land. Unused land, construction land, and mining land exhibited an increasing trend, with construction land expanding by 199.63 km² (+44.64%), and unused land and mining land increased by 3.2 km² and 67.33 km², respectively. Conversely, water areas decreased by 64.05 km² (-33.55%), forest land by 43.90 km² (-8.23%), grassland by 19.75 km² (-10.04%), and cropland by 142.46 km² (-5.34%). From 1990 to 2020, the total land type change area is 638.26 km², primarily due to transfers between cropland and construction land. The expansion of construction land has led to a reduction in ecological areas such as cropland, forest land and grassland, and some cropland has been developed.

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Table 3. *Proportion of land use types*

Year	Cropland	Forest	Grass	Water	Construction	Unused	Mining
1990	65.86%	13.15%	4.85%	4.71%	11.03%	0.03%	0.37%
2000	66.68%	13.16%	4.89%	2.46%	12.33%	0.08%	0.40%
2010	63.80%	12.11%	4.28%	3.23%	14.93%	0.08%	1.57%
2020	62.34%	12.07%	4.37%	3.13%	15.95%	0.11%	2.03%

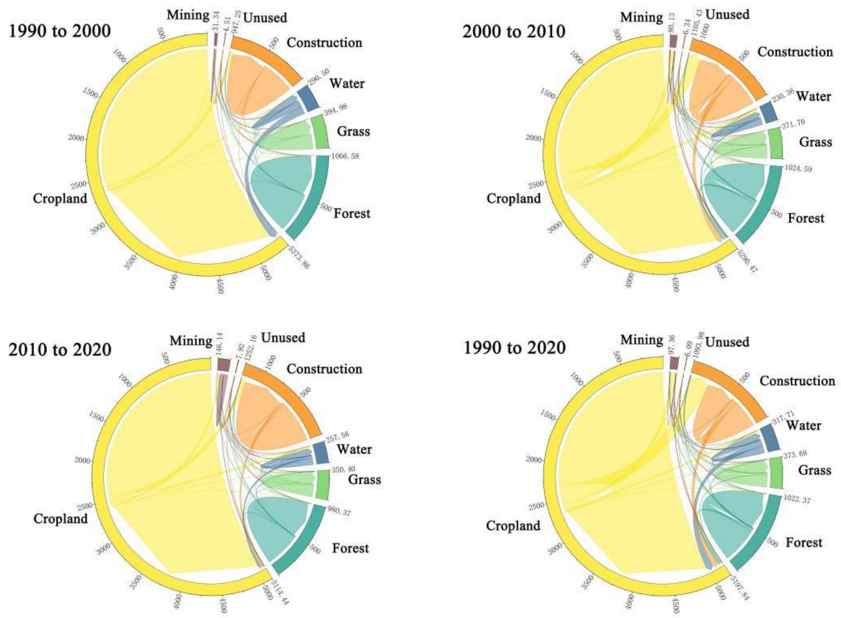

Figure 3. *String map of land use transfer from 1990 to 2020*

Spatially, due to variations in topography, slope, and regional development, significant differences in land use type changes are observed in Jiaozuo city (*Figure 4*). The reduction in forest land is mainly concentrated in the western part of Taihang Mountains and Boai County in the city's center. In the northwest, grassland at the boundary between the Taihang Mountains and the plain has been converted to cropland. The Yellow River, passing through the south of Jiaozuo city, has seen a reduction in water areas due to climate and environmental changes. The decrease in cropland is primarily in the urban center, while mining land is chiefly near the mountains. Economic development and the expansion of construction land have continuously reduced cropland from 1990 to 2020. The figures indicate a significant increase in construction land, mainly in the northwest along the mountains.

Based on the carbon storage module of InVEST model, the carbon reserves of Jiaozuo city for the years 1990, 2000, 2010 and 2020 were 50.54×10^6 t, 51.33×10^6 t, 49.66×10^6 t and 49.28×10^6 t, respectively. Overall, from 1990 to 2020, carbon storage in Jiaozuo city initially increased and then decreased, resulting in an overall reduction of 1.26×10^6 t. Specifically, carbon storage increased by 0.79×10^6 t between 1990 and 2000, decreased by 1.67×10^6 t between 2000 and 2010, and further decreased by 0.38×10^6 t between 2010 and 2020. *Figure 5* shows that the spatial distribution pattern of carbon storage in Jiaozuo city remained relatively consistent across all periods. High-carbon storage areas were

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primarily concentrated in the Taihang Mountains in the north, which benefit from favorable precipitation and high vegetation coverage, resulting in a carbon density is greater than 17.62 t/km². These areas are predominantly covered by forest land and grassland, which possess strong carbon retention capabilities. Conversely, low-carbon storage areas were mainly located in the central region and major cities and towns, with a carbon density of less than 5.75 t/km². These areas experience frequent human activity, significant interference with nature, and are primarily used for cultivation, leading to poor carbon fixation capabilities. Therefore, the distribution of carbon reserves in Jiaozuo city is closely related to land use type, with higher carbon reserves in forest land and grassland, and lower reserves in construction and cropland areas.

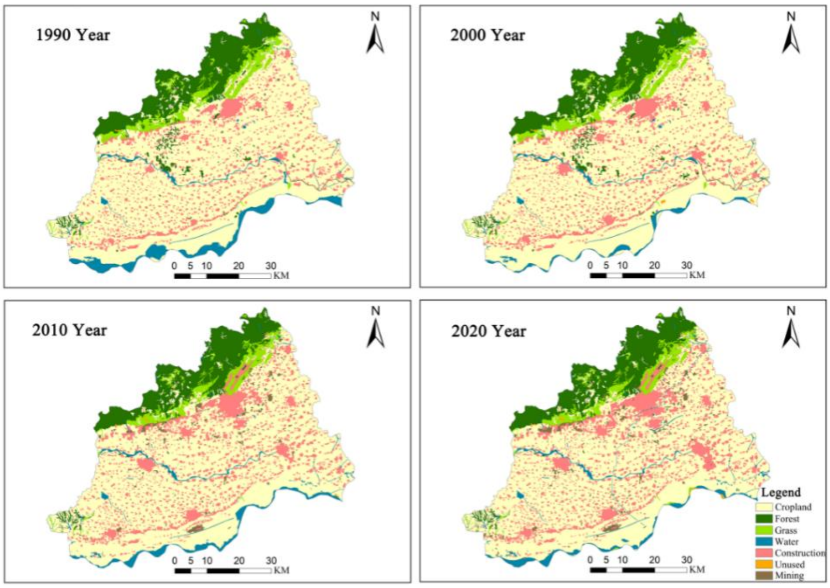

Figure 4. *Land use changes in Jiaozuo city from 1990 to 2020*

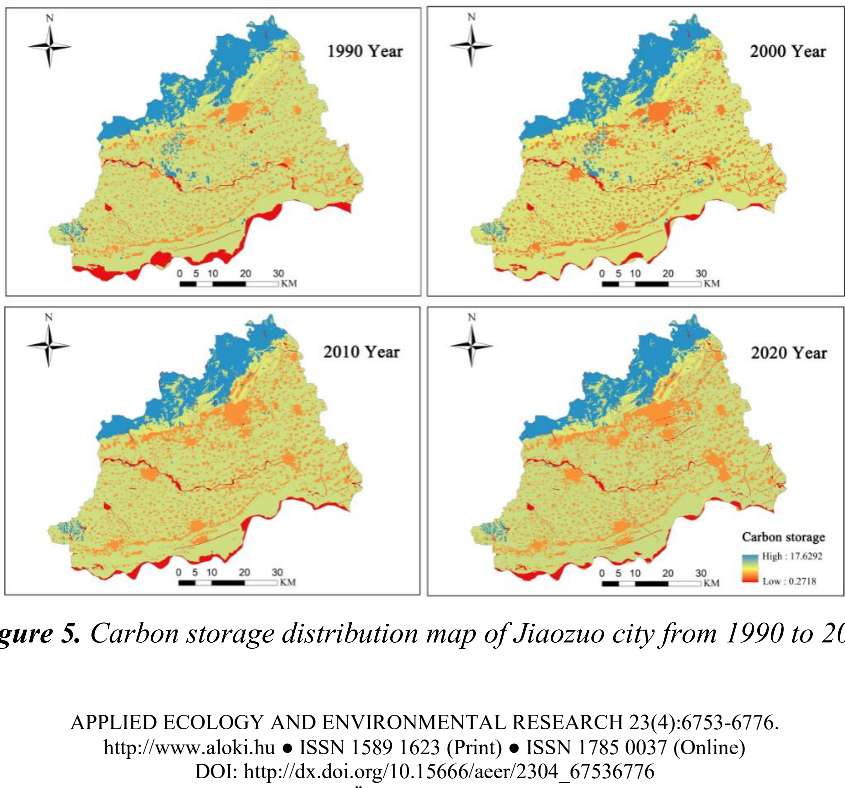

Figure 5. *Carbon storage distribution map of Jiaozuo city from 1990 to 2020*

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Figure 6 illustrates the dynamic changes in carbon storage caused by different land types in Jiaozuo city from 1990 to 2020. Based on the changes in carbon storage in the grid unit, the spatial change pattern of carbon storage is categorized into "carbon source", "carbon balance" and "carbon sink". Over the past 30 years, the increase in carbon storage was mainly concentrated in the north and southeast regions, primarily due to the conversion of parts of the Yellow River into cropland, thereby enhancing carbon sequestration capacity. The reduction in carbon storage was concentrated in Boai County and Wuzhi County in the west, where grassland was transformed into cropland, weaking carbon sequestration capacity, and urban expansion encroached on existing cropland. It is evident that areas with increased carbon storage include forest land, grassland and cropland, while areas with decreased carbon storage include water areas and construction land (*Figure 6*). The differing carbon sequestration capacities of various land types result in varying impacts of area changes on carbon storage. The conversion of water areas and construction land into cropland covers areas of 89.18 km² and 70.46 km², respectively, leading to corresponding increases in carbon storage by 1.13×10^6 t and 0.47×10^6 t. The primary cause carbon storage from 1990 to 2020 is increase in construction land areas. Over the 30-year period, construction land increased by 276.74 km², resulting in a decrease in carbon storage by 1.8×10^6 t. The remaining reduction is due to the conversion of cropland into water areas, forest land and grassland into other land types (*Table 4*).

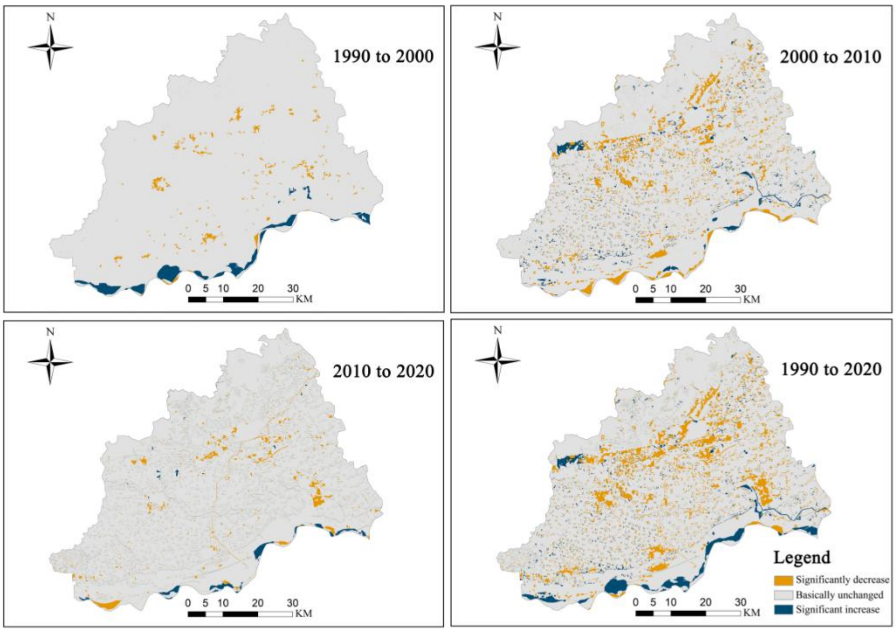

***Figure 6.** Carbon storage change map of Jiaozuo city from 1990 to 2020*

Effects of future land use change on carbon storage

Under the NDS, cropland and forest land are projected to decrease, while other land types are increase from 2020 to 2035. Specifically, cropland is anticipated to decrease by 299.36 km² and forest land by 54.57 km². Conversely, grassland, water areas, and construction land are expected to increase by 28.78 km², 70.77 km², 155.70 km², respectively. Unused land and mining land are projected to increase by 2.59 km² and 96.09 km², respectively. The decline in cropland is the most significant, at 11.84%,

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whereas construction land is set to increase by 24.07%, in line with trends observed over the past 30 years. In terms of land conversion, cropland is primarily converted to construction land, with smaller portions converted to water areas and grassland. The conversion of forest land to cropland, grassland, and construction land is basically equal, with a minor portion converted to water areas. Only a small fraction of grassland is converted to construction land (*Table 5*) (*Eq.1-3*). Spatially, the increase in grassland is mainly concentrated in the Taihang Mountains in the northwest, while construction land in Jiefang District, Zhongzhan District and Wuzhi County shows an expansion trend. Therefore, it is evident that land use changes are primarily occurring in the northwest and north of Jiaozuo (*Figure 7*).

Table 4. *Dynamic changes of land use and carbon stock from 1990 to 2035*

Land Use Type	Transfer	Change of area (km²)	Change in Carbon storage ($\times10^6$Mg C)	Change of area (km²)	Change in Carbon storage ($\times10^6$Mg C)	Change of area (km²)	Change in Carbon storage ($\times10^6$Mg C)
Cropland	Forest	4.17	0.03	0	0	0.99	0.01
	Grass	4.34	-0.004	0	0	8.03	-0.01
	Water	28.02	-0.36	71.96	-0.91	71.29	-0.90
	Construction	262.96	-1.74	134.43	-0.89	144.68	-0.96
	Unused	1.03	-0.01	0	0	0	0
	Mining	64.75	-0.44	107.19	-0.73	0	0
Forest	Cropland	36.68	-0.24	13.71	-0.09	2.61	-0.02
	Grass	6.33	-0.05	32.36	-0.24	3.29	-0.02
	Water	1.49	-0.03	1.97	-0.04	2.22	-0.04
	Construction	4.68	-0.06	1.97	-0.03	0.93	-0.01
	Unused	0.13	-0.002	0.01	-0.0001	0.01	-0.0001
	Mining	2.93	-0.04	4.55	-0.06	0.002	-0.00002
Grass	Cropland	17.59	0.02	0.32	0.0003	1.73	0.002
	Forest	3.70	0.03	0	0	1.23	0.01
	Water	1.45	-0.02	0	0	0.03	-0.0003
	Construction	3.35	-0.02	2.82	-0.02	3.47	-0.02
	Unused	1.59	-0.01	0	0	0.08	-0.0005
	Mining	6.47	-0.04	1.87	-0.01	0	0
Water	Cropland	89.18	1.13	0.03	0.0004	0.11	0.001
	Forest	0.26	0.01	0	0	0.003	0.0001
	Grass	2.75	0.03	1.39	0.02	0.36	0.004
	Construction	2.80	0.02	0	0	0.002	0.00001
	Unused	1.00	0.01	2.78	0.02	2.76	0.02
	Mining	1.15	0.01	0	0	0	0
Construction	Cropland	70.46	0.47	0	0	10.64	0.07
	Forest	0.19	0.002	0	0	0.05	0.001
	Grass	0.84	0.005	0	0	0.40	0.002
	Water	1.77	-0.01	1.05	-0.01	0.45	-0.003
	Mining	3.85	-0.001	0	0	0	0
Unused	Cropland	0.49	0.004	0.15	0.001	0.16	0.001
	Forest	0.02	0.0003	0	0	0	0
	Grass	0.03	0.0002	0.04	0.0003	0.01	0.0001
Mining	Cropland	8.40	0.06	0	0	0.41	0.003
	Forest	0.01	0.0001	0	0	0.04	0.001
	Grass	0.11	0.001	0	0	0.02	0.0001
	Water	0.34	-0.002	0	0	0.04	-0.0003
	Construction	2.96	0.0005	17.52	0.003	17.62	0.003

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Table 5. *Land use transfer matrix from 2020 to 2035 (km^2)*

Year	Type	Cropland	Forest	Grass	Water	Construction	Unused	Mining
1990-2020	Cropland	2304.89	4.17	4.34	28.02	262.96	1.03	64.75
	Forest	36.68	480.89	6.33	1.49	4.68	0.13	2.93
	Grass	17.59	3.70	162.57	1.45	3.35	1.59	6.47
	Water	89.18	0.26	2.75	93.75	2.80	0.99	1.15
	Construction	70.46	0.19	0.84	1.77	370.07	0	3.85
	Unused	0.49	0.02	0.03	0	0	0.90	0
	Mining	8.40	0.01	0.11	0.34	2.96	0	3.20
2020-2035 (NDS)	Cropland	2214.12	0	0	71.96	134.43	0	107.19
	Forest	13.71	434.66	32.36	1.97	1.97	0.01	4.55
	Grass	0.32	0	171.95	0	2.82	0	1.87
	Water	0.03	0	1.39	122.63	0	2.78	0
	Construction	0	0	0	1.05	645.76	0	0
	Unused	0.15	0	0.04	0	0	4.45	0
	Mining	0	0	0	0	17.52	0	64.82
2020-2035 (EPS)	Cropland	2302.70	0.99	8.03	71.29	144.68	0	0
	Forest	2.61	480.18	3.29	2.22	0.93	0.01	0.002
	Grass	1.73	1.23	170.43	0.03	3.47	0.08	0
	Water	0.11	0.003	0.36	123.60	0.002	2.76	0
	Construction	10.64	0.05	0.40	0.45	635.28	0	0
	Unused	0.16	0	0.01	0	0	4.47	0
	Mining	0.41	0.04	0.02	0.04	17.62	0	64.21

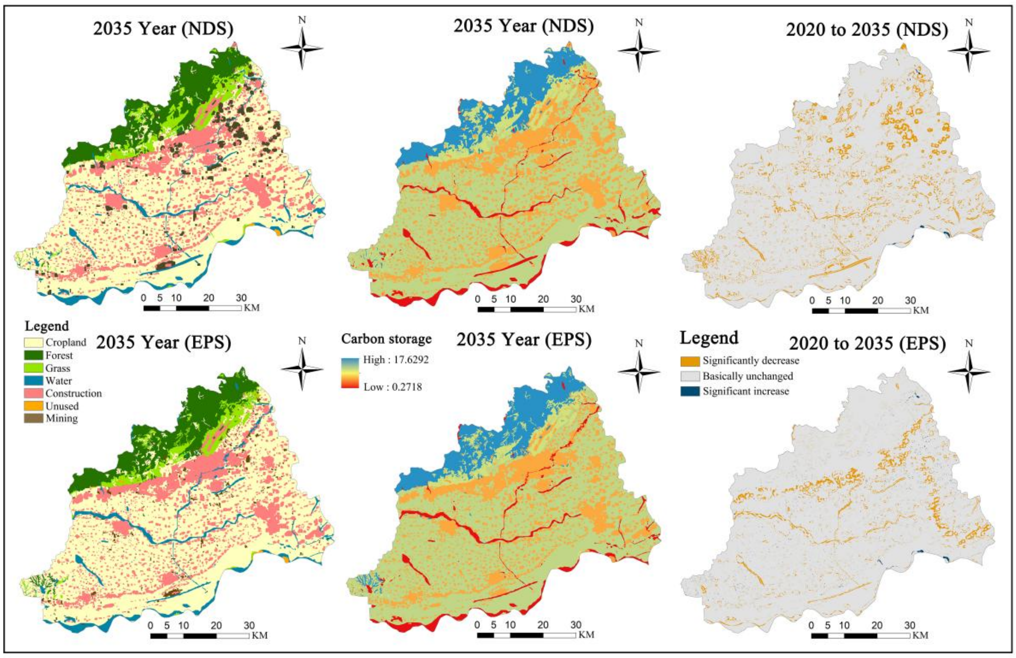

Figure 7. *Changes in land use and carbon stocks under different scenarios in 2035*

Compared to the NDS, land use changes under the EPS differ. Although construction land continues to increase, the decrease in forest land is significantly less, at only 6.75 km². Cropland decreases by 209.33 km², and mining land decreases by 18.14 km². Grassland and unused land increase by 5.57 km² and 2.67 km², respectively, while the water areas

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increased by 70.79 km². Forest land and grassland are protected, and the smaller increase in grassland compared to the natural scenario is due to the conversion of forest land to grassland and vice versa (*Figure 7*).

Under the NDS, it is predicted that the carbon reserve of Jiaozuo city will be 46.30×10^6 t in 2035, representing an overall decrease of 2.98×10^6 t (*Table 6*). The conversion of cropland, forest land, and grassland to construction land, as well as the expansion of construction land and mining land, leads to a significant decline in carbon stocks. Spatially, global carbon storage generally declines and is evenly distributed throughout the country, with a slight increase in the northwest. The decrease in carbon storage gradually diminishes from the urban center to the periphery (*Figure 7*). Under the EPS, the carbon storage of Jiaozuo city is 47.41×10^6 t, shoeing a downward trend but with a slower decline of 1.87×10^6 t compared to the NDS. In terms of spatial distribution, there is almost no significant decrease in forest land and grassland in the north, and carbon storage in some areas increases, indicating effective protection. The significant decrease is primarily concentrated along the railway line, closely related to the expansion of construction land along the road (*Figure 7*).

Table 6. *Different types of carbon stocks from 1990 to 2035 ($\times10^6$t)*

Year	Cropland	Forest	Grass	Water	Construction	Unused	Mining
1990	34.7	10.44	2.38	0.06	2.86	0.01	0.09
2000	35.14	10.45	2.4	0.03	3.19	0.02	0.1
2010	33.62	9.62	2.1	0.04	3.87	0.02	0.4
2020	32.85	9.58	2.14	0.04	4.13	0.03	0.51
2035 (NDS)	28.96	8.51	2.49	0.06	5.12	0.04	1.11
2035 (EPS)	30.13	9.45	2.21	0.06	5.12	0.04	0.4

A dynamic comparison of the two scenarios to 2035 shows that under the NDS, changes in carbon stocks due to land use change are primarily attributed to increases in land for construction and mining, and decreases in forest land. Specifically, 156.74 km² of land was converted to construction land, resulting in a decrease of 0.93×10^6 t of carbon storage. The total transfer of forest land was 54.57 km², causing a reduction of 0.46×10^6 t in carbon storage. The conversion of cropland to water areas and mining land was 71.96 km² and 107.19 km², respectively, leading to a total reduction of 1.64×10^6 t in carbon storage. Compared to the NDS, the reduction of carbon stocks under the EPS is somewhat mitigated, primarily because there was almost no conversion of forest land to other land types. The conversion of grassland to cropland and forest land was 2.96 km², resulting in an increase of 0.012×10^6 t in carbon stocks by, while the area of construction land converted to cropland was 10.64 km², leading to an increase of 0.07×10^6 t in carbon storage (*Table 4*). It is evident that changes in forest land and construction land have the greatest impact on carbon storage. Under the EPS, the expansion of construction and mining land is effectively controlled, and ecological land such as forest land and grassland is also protected.

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Analysis of the driving force of the spatiotemporal differences in carbon storage in Jiaozuo city

Origin2022 was used to analyze the correlation between carbon storage and various driving factors (*Figure 8*), and 1000 random, evenly distributed sampling points were generated in ArcGIS. The variables extracted at these points included carbon storage, elevation (DEM), slope, GDP, population density (POP), average annual precipitation (PRE), average annual temperature (TEM), distance to railways (DTR), distance to highways (DTH), distance to mining areas (DTM), distance to mining and exploration areas (DTME). The results showed that, except for DTR and DTME, the significance level between other factors and carbon storage was greater than 99.9% ($p \leq 0.001$). Based on the R^2 values, the relationships between different factors and carbon storage are categorized as follows: $R^2=0$ indicates a compatibility relationship, $R^2 < 0$ indicates a tradeoff relationship, and $R^2 > 0$ indicates a synergy relationship (Chen et al., 2016; Yang et al., 2022).

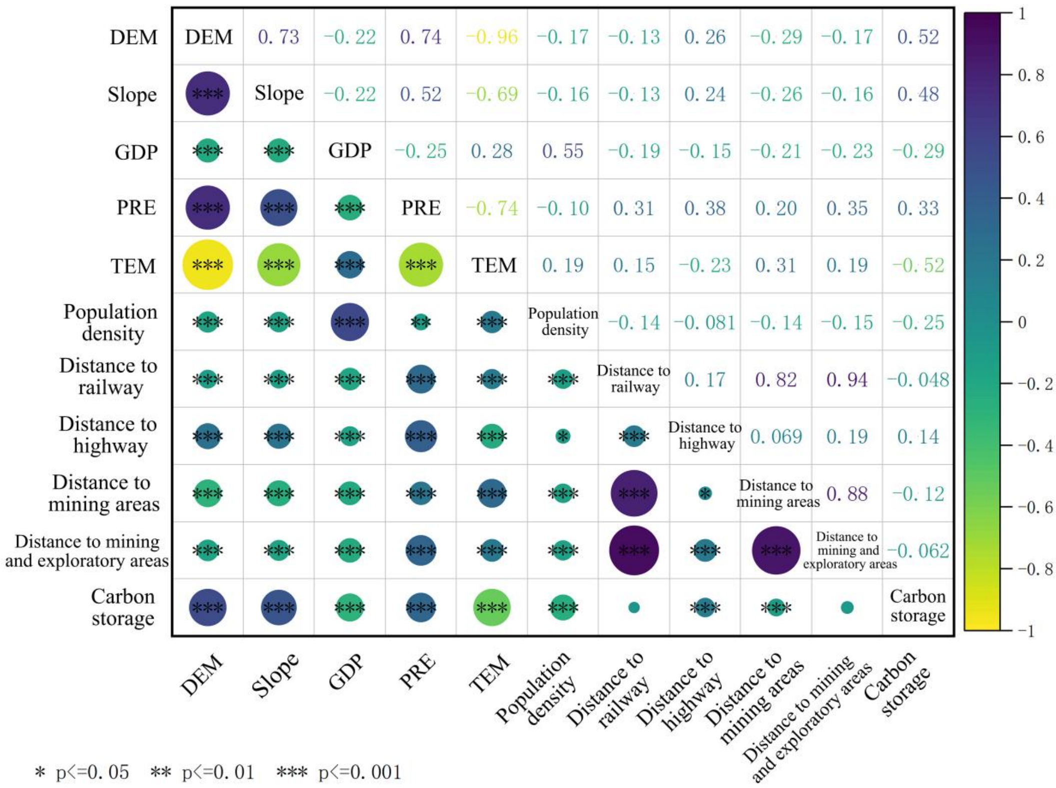

Figure 8. *Heat map of correlation analysis between driving factors and carbon storage*

Natural factors

The correlation coefficient (R^2) between carbon storage and DEM and slope in Jiaozuo city is 0.52 and 0.48, respectively. Elevation and slope directly influence land use types and, consequently, carbon storage. cropland is predominantly found in areas with flat terrain and gentle slopes, while forest land and grassland are primarily located in regions with higher elevations and steeper slopes, which are less affected by human activities and more conducive to vegetation growth. These three land types possess strong carbon sequestration capacities. As elevation and slope increase, the proportion of forest land

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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and grassland increases, leading to higher carbon storage. Thus, elevation and slope have a synergistic relationship with carbon storage. The correlation coefficient (R^2) for PRE is 0.33, indicating a synergistic relationship with carbon storage. There is a positive correlation between precipitation and carbon storage in the northern mountainous area of Jiaozuo city, which is rich in vegetation, predominantly forest land and grassland, and has a high carbon sequestration capacity. The correlation coefficient (R^2) for TEM is -0.52. Apart from the northern mountain area, the highest temperatures are observed in the urban center, followed by the surrounding construction land and cropland. This indicates a significant negative correlation between temperature and carbon storage, demonstrating a trade-off relationship.

Socio-economic factors

The correlation coefficients R^2 for DTR and DTH are -0.048 and 0.14 respectively, while for GDP and POP they are -0.29 and -0.25. Generally, GDP and POP reflect the economic development level of a region. Areas with high GDP are typically urban, characterized by extensive construction land and high population density. Although DTR shows no significant correlation with carbon storage, areas near railways tend to have more construction land and lower carbon storage, indicating a tradeoff relationship. In Jiaozuo, highways are widely and uniformly distributed, mostly built along towns, whereas areas far from highways are predominantly forest land and grassland, less affected by human activities. Overall, there is a positive correlation with carbon storage, with a correlation coefficient of 0.14, indicating a synergistic relationship with a minor influence.

Resource-based factors

The correlation coefficients R^2 of DTM and DTME are -0.12 and -0.062, respectively. Due to the presence of minerals in the mining areas, the carbon reserves are relatively high. However, as these minerals are depleted, the carbon reserves will diminish. Consequently, the DTM shows a weak negative correlation with the carbon reserves. Mining and exploration areas suggest the presence of both mined and unmined mineral resources. In terms of overall land use distribution in Jiaozuo city, areas distant from mining and exploration areas are mainly construction land and cropland, both with poor carbon storage capacity. Although there is no significant relationship with carbon storage, a slight mutual restriction and tradeoff relationship exists in the correlation.

Discussion

This study not only analyzed the temporal and spatial evolution characteristics of land use and carbon storage in Jiaozuo city, but also selected various factors from natural, social, and resource perspectives to explore the contribution of land use patterns and the driving mechanisms of carbon storage. Additionally, it predicted future changes in carbon storage under different scenarios. This section will combine the current development status of Jiaozuo city with an in-depth analysis of the research findings and compare them with related studies from other cities.

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Spatiotemporal evolution of land use and carbon storage in Jiaozuo city

Human activity is the primary driving factor behind changes in land use patterns (Qiu et al., 2019). From 1990 to 2020, Jiaozuo city experienced significant land use changes. The areas of cropland, forest land, grassland and water areas all decreased, with the most substantial reduction occurring in cropland, while construction land expanded significantly, increasing to half of its initial annual area. The main transformations among land types occurred between cropland, forest land, grassland and construction land, consistent with Li et al. (2022) research findings, reflecting the implementation of economic development and ecological restoration policies in the region in the past 30 years. Land use changes lead to fluctuations in ecosystem carbon stocks, affecting atmospheric CO_2 levels. The expansion of construction land dramatically reduces ecological land, converting "carbon sink area" into "carbon source area", resulting in a decline in carbon storage (Wang et al., 2022). Although carbon storage in the study area has been declining over time, it increased from 1990 to 2000. This is because, in the early stages of urbanization in China, productivity levels were low, the development and expansion of construction land were limited, and the mutual conversion of various land types could still maintain the carbon balance of the ecosystem. The conversion of forest land into cropland and grassland, and cropland into construction land, are the main reasons for the decline in carbon storage, which is consistent with the previous research results (Li et al., 2023). Li et al. (2022) simulated and predicted the land use patterns and carbon storage in Yunnan Province, discovering that when forest land was converted to other uses, significant carbon release occurred from most above-ground biomass and plant roots. From 2000 to 2020, Jiaozuo city implemented several environmental policies, such as the "Ecological environment Protection Plan" and the "Jiaozuo City Beishan Ecological Environment Protection Regulations", which rationally adjusted the land structure and achieved economic transformation. The implementation of these policies has been crucial for transforming land use and the balancing carbon storage in the region. Protecting forest and grassland and moderately controlling the expansion of construction land will be conducive to the region’s sustainable development.

Driving mechanism of carbon storage by different factors

Based on the analysis of the contribution degree of each driving factor to land use and its correlation with carbon storage, the contribution of different factors to different regions of land use was studied. The results indicate that DEM has the greatest influence on grassland and mining land. Areas with high elevation and steep slopes have lower levels of human exploitation, dense vegetation, and rich mineral resources. PRE and TEM have the highest contribution to cropland, as they are the decisive conditions for crop growth and soil fertility maintenance. Therefore, agricultural land should be selected in areas with sufficient precipitation. PRE and DEM are the most significant factors for water areas and construction land. Rivers typically flow to low-lying areas, and precipitation directly affects river water levels. Construction land is predominantly located in low-lying regions. Slope has the greatest impact on unused land (*Figure 9*). It is evident that both social and natural factors are the main drivers of land use change, consistent with Gong et al. (2022) research findings. Ecological land and cropland, such as forest land and grassland, have strong carbon storage capacities. Population growth and economic development increase the demand for residential land and agricultural land, altering land use structure and affecting carbon storage changes, while climate conditions

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directly influence plant survival and distribution. Therefore, social and natural factors should be comprehensively considered in land use policy formulation and planning to achieve sustainable use of land resources.

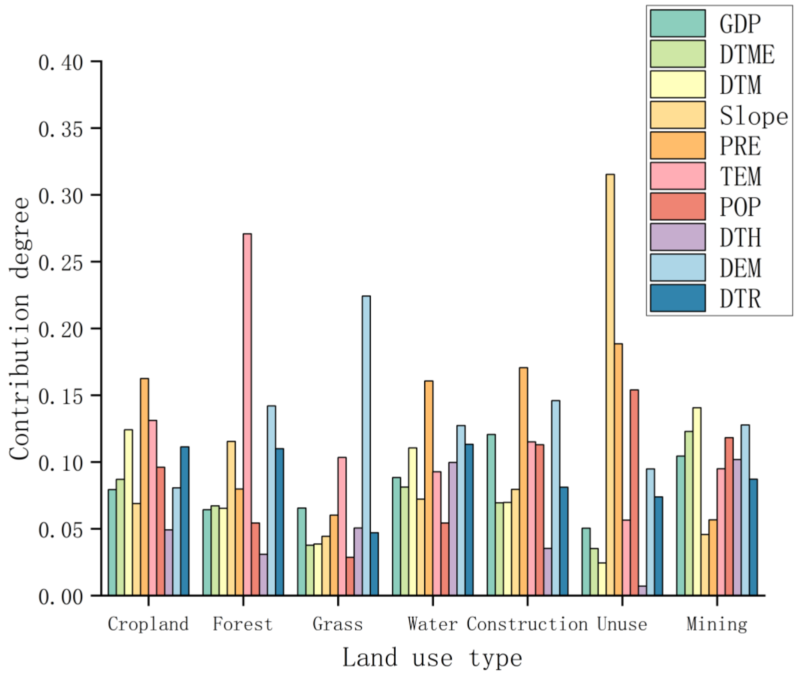

Figure 9. *Contribution degree of each driving factor to land use*

Suggestions for the optimization of future land use patterns

Based on previous data and prediction results, the primary cause for the decline in ecosystem carbon storage in Jiaozuo city is the expansion of construction land and the reduction of ecological lands such as forest land and grassland. From a developmental necessity standpoint, optimizing productivity and meeting human needs make it challenging to curb urbanization trends, resulting in difficulties in maintaining carbon balance and a continuous decrease in carbon storage in the Jiaozuo region. Densely populated, compact urban areas are key for coordinated development and carbon balance. The government and decision-makers can revitalize existing land and reduce new construction land through renewal and partial reconstruction. Promoting green and low-carbon urban development models, increasing green spaces such as parks and shelterbelts at city edges, improving land use efficiency, preventing urban sprawl, and increasing carbon storage are essential. Establishing a robust ecological monitoring and evaluation system to regularly assess and adjust urban ecological and environmental protection measures based on findings is crucial. Land use patterns primarily drive changes in carbon stocks, and the heterogeneity in their spatial and temporal distribution suggests that different measures should be adopted.

From an ecological importance perspective, Jiaozuo city should aim for low-carbon, green, sustainable development. The extensive cropland in Jiaozuo city has high carbon storage value. Measures such as conservation tillage and organic matter restoration should be implemented according to the permanent basic farmland red line defined by the state to improve farmland fertility and carbon content. The northern mountainous area, with its

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large expanse of high carbon grassland and forest land, has significant ecological advantages and serves as an important carbon sink in Jiaozuo. The government should strictly protect ecologically sensitive and vulnerable areas, ensure that the ecological background remains undamaged, and fully leverage local resource advantages to achieve sustainable resource use and maximize ecological and economic benefits.

Limitations and prospects

In the selection of influencing factors, only socio-economic and natural and resource factors were considered, while the inpact of relevant policies was neglected. Policies play a crucial role in land use change, and incorporating them into the adaptive atlas of decision-making can yield more accurate future simulations. The carbon density sources referenced in this paper are based on other relevant studies, showing variability across different years and geographic locations. To enhance the simulation accuracy of land use patterns predicted by the CA-Markov model, coupling it with other models in the future is recommended.

Conclusions

By integrating the CA-Markov and InVEST models, this paper quantitatively analyzes land use and carbon storage in Jiaozuo city from 1990 to 2020. It predicts changes in land use and carbon storage by 2035 under two scenarios: NDS and EPS, and discusses the impact of land use changes on carbon storage. The conclusions are as follows:

(1) From 1990 to 2020, the primary feature of land use change in Jiaozuo city has been the conversion of cropland into forest land, grassland, and construction land, with the cropland area decreasing from 65.84% to 62.34%. Notably, construction land expanded significantly, increasing from 11.03% to 15.95%. forest land was mainly converted into cropland, and grassland was mainly converted from forest land. Carbon storage initially increased and then decreased, showing an overall declining trend. High carbon value areas were concentrated in forest land and grassland at higher elevations in the north. However, the increase in carbon storage was scattered regionally, particularly in the south, where the conversion of some water areas to cropland led to an increase in carbon storage.

(2) Using the CA-Markov model to predict land use and carbon storage under different scenarios for 2035, carbon storage shows a downward trend under both scenarios. Under the NDS, the areas of cropland and forest land in Jiaozuo city decrease compared to 2020, mainly converting into construction land and grassland. Under the EPS, the cropland area still decreases, but the reduction in forest land slows significantly compared to the NDS, and the expansion of construction land is also somewhat controlled. Although carbon stocks decline overall under both scenarios, forest land and grassland are effectively protected under ecological priority, mitigating the reduction in carbon stocks.

(3) From 2020 to 2035, changes in land use significantly impact carbon stocks. Under the NDS, the expansion area of construction land increases by 24.07%, and the spatial change in carbon storage is evident. In the EPS, forest land and grassland are protected, effectively alleviating the trend of carbon storage reduction, indicating that the implementing ecological policies can help promote carbon sequestration in the region. Moving forward, guidance by low-carbon goals and leading ecological restoration efforts should continue.

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Acknowledgements. This research was funded by Humanities and Social Sciences Foundation of Henan Polytechnic University (GSKY2024-35); the Young Backbone Teacher Foundation of Henan Polytechnic University (2022XQG-05); the Philosophy and Social Science Planning Project of Henan Province, China (2023BYS007, 2024CYS034).

Conflict of interest. The authors declare that they have no conflicts of interest.

Data availability. The data used to support the findings of this study are available from the corresponding author upon request.

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APPENDIX

Schedule 1. *Land transfer Settings for natural development scenario*

NDS	Cropland	Forest	Grass	Water	Construction	Unused	Mining
Cropland	1	1	1	1	1	0	1
Forest	1	1	1	0	1	0	1
Grass	1	1	1	0	1	0	1
Water	0	0	0	1	0	1	0
Construction	1	0	1	0	1	0	0
Unused	1	1	1	1	1	1	1
Mining	1	1	1	0	1	0	1

Schedule 2. *Land transfer Settings for ecological priority scenario*

EDS	Cropland	Forest	Grass	Water	Construction	Unused	Mining
Cropland	1	1	1	1	1	0	1
Forest	0	1	0	0	0	0	0
Grass	0	1	1	1	0	0	0
Water	0	0	0	1	0	0	0
Construction	1	0	0	0	1	0	0
Unused	1	1	1	1	1	1	1
Mining	1	1	1	1	1	0	1

0 indicates that the class cannot be converted to other types, and 1 indicates that the class can be converted to other types

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DOI: http://dx.doi.org/10.15666/aeer/2304_67536776

Schedule 3. *Table of ecosystem carbon density (t/hm²)*

Land Use Type	C_{above}	C_{below}	C_{soil}	C_{dead}
Cropland	15.44	52.39	89.67	5.41
Forest	27.53	75.24	133.59	9.91
Grass	22.92	56.15	73.20	4.34
Water	0	4.77	0	0
Construction	0	0	68.55	0
Unused	0.39	0	62.40	0
Mining	0	0	66.86	0

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