Impact of land use change on carbon storage based on the PLUS-InVEST model: A case study in the urban belt along the Yellow River, China (Postprint)

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Abstract

Terrestrial ecosystems are vital for maintaining equilibrium in the global carbon cycle. Land use and land cover change (LUCC), which is influenced mainly by urbanization and ecological policies,impacts terrestrial ecosystem carbon storage significantly. In this study, spatiotemporal carbon storage changes in the urban belt along the Yellow River in the Ningxia Hui Autonomous Region, China, were estimated through a model that integrated patch-generating land use simulation (PLUS) and integrated valuation of ecosystem services and tradeoffs (InVEST) models from 1993 to 2033. The results revealed that: (1) from 1993 to 2023, the expansion of built-up land and cropland was derived mainly from unused land and grassland, whereas water body and woodland remained relatively stable. Projections to 2033 have indicated that LUCC will continue and be concentrated primarily in the Ningxia Plain; (2) carbon storage increased by a net
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and semi-arid areas. On the basis of these findings, this study provides decision-makers with guidance to optimize ecosystem carbon storage via land use, which plays a key role in developing future land use policies and achieving the " dual carbon" goals.

Full Text

Preamble

J Arid Land (2026) 18(3): 452–476 Impact of land use change on carbon storage based on the PLUS-InVEST model: A case study in the urban belt along the Yellow River, China SHI Hanqi 1,2,3 , DUAN Huan' e 1,2,3* , LI Xuemei 1,2,3 , WANG Guigang 1,2,3 , CHEN Ahui 1,2,3 LIANG Dengrui 1,2,3 1 Faculty of Geomatics, Lanzhou Jiaotong University, Lanzhou 730070, China; National-Local Joint Engineering Research Center of Technologies and Applications for National Geographic State Monitoring, Lanzhou 730070, China; Key Laboratory of Science and Technology in Surveying & Mapping Gansu Province, Lanzhou 730070, China

Abstract

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coordinated urban development for the urban belt as well as for similar arid and semi-arid areas. On the basis of these findings, this study provides decision-makers with guidance to optimize ecosystem carbon storage via land use, which plays a key role in developing future land use policies and achieving the " dual carbon'' goals.

Keywords

carbon storage; land use change; patch-generating land use simulation (PLUS) model; integrated valuation of ecosystem services and tradeoffs (InVEST) model; Moran' s ; ecological protection

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1 Introduction

Since the Industrial Revolution, deforestation, urbanization, and fossil fuel consumption have contributed to significant increases in greenhouse gas (GHG) emissions, which serve as major drivers of global climate change (Lempert, 2021). Consequently, carbon neutrality has become a critical strategic component in the global climate policies implemented by national governments (Roebroek et al., 2024). As a substantial global carbon pool, terrestrial ecosystem has offset approximately one-third of anthropogenic CO emissions in recent decades through biogeochemical processes and has helped regulate climate change (Piao et al., 2022; Xu et al., 2024). Maintaining and enhancing carbon storage mitigates global warming and supports ecosystem stability (Gao et al., 2023). Currently, systematic studies that focus on scientifically optimizing land use planning to improve carbon storage efficiency are limited (Anthony et al., 2024), particularly in arid urban belts characterized by complex mountain–desert–oasis landscapes.

Land use and land cover change (LUCC) primarily influences the spatial distribution of terrestrial ecosystem carbon storage (TECS) (Wang et al., 2024b). By altering ecosystem types, LUCC affects carbon storage in plant biomass and soil through photosynthesis, directly impacting TECS (Lai et al., 2025). Studies demonstrate that LUCC caused a change of 1.32 Pg C in TECS across China from 2000 to 2018 (Chang et al., 2022). Woodland and grassland are key components of terrestrial ecosystem, accounting for nearly 40.00% and 30.00% of TECS, respectively (Bai and Cotrufo, 2022; Liu et al., 2024b). Human activities reduce the area of woodland and grassland, thereby lowering regional carbon storage capacity. In contrast, policies such as unused land reclamation enhance regional carbon storage. In arid areas, water scarcity increases the vulnerability and sensitivity of vegetation and soil carbon pools to LUCC (Tong et al., 2019; Bie and Huang, 2025). The research on the effects of LUCC on carbon storage in arid areas mainly focuses on simple ecosystem and large-scale areas (Bie and Huang, 2025; Han et al., 2025; Kuai et al., 2025). However, it overlooks mountain–desert–oasis urban belts, where complex land use transformations result in unique carbon storage dynamics. Furthermore, studies seldom connect land use policies to TECS changes or determine optimal land use patterns for carbon sequestration. Therefore, quantifying TECS changes resulting from LUCC in arid urban belts will provide policy-makers the direction for enhancing TECS through the optimization of land use patterns.

Currently, methods for estimating carbon storage include sample-plot inventory, model-based analysis, and remote-sensing estimation (Aryal and Ruiz-Corzo, 2020). Scholars consider the sample plot inventory to be the most precise carbon storage assessment method; however, its time-consuming nature and resource demands constrain its large-scale application (Chen et al., 2025). Remote-sensing techniques monitor woodland and soil carbon storage using vegetation spectral reflectance characteristics (Ren et al., 2020). This approach offers an effective solution for large-scale carbon storage assessment, although its accuracy remains limited by ground-based data and scale conversion (Speak et al., 2020). Model-based analyses have gained prominence in carbon storage assessments in recent years. Houghton and Hackler (1999) developed the bookkeeping model to track carbon transfers across terrestrial carbon pools. However, this model fails to account for temporal variations in carbon storage. Process-based ecosystem models, such as the Carnegie–Ames–Stanford Approach (CASA), Century, and Biome BioGeochemical Cycles (Biome–BGC), estimate carbon storage by simulating photosynthesis (Feng et al., 2024; Golchin and Misaghi, 2024; Liu et al., 2025). These methods require substantial data inputs and lack spatial quantification scalability (Wu et al., 2024). Conversely, the integrated valuation of ecosystem services and trade-offs (InVEST) model offers operational simplicity, measurement accuracy, and spatial visualization capabilities, which make it widely applicable in carbon stock

evaluations (Nelson et al., 2009; Shi et al., 2025).

Although studies confirm that LUCC is a dominant driver of TECS change, carbon storage variations across land use trajectories require further investigation (Wang et al., 2024b). This gap necessitates the integration of the InVEST model with land use models. From the perspective of model synergy, the result of land use models serves as one of the essential input variables for the InVEST model. In turn, the InVEST model converts the result of land use models into quantifiable carbon storage values. This integration facilitates the establishment of long-term historical and future carbon storage databases spanning entire ecosystems, offering new insights for future ecological planning (Liang et al., 2021b). The cellular automata (CA)–Markov model (Mohammadyari et al., 2021) is widely used in land use projections, but it fails to consider spatial relationships and multiple factors. The conversion of land use and its effects at small regional extent (CLUE-S) model enhances prediction accuracy by incorporating spatial interactions of natural and anthropogenic factors (Verburg et al., 2002). However, CLUE-S faces limitations in data-scarce areas because it has stringent data requirements (Yu et al., 2023). Building on the future land use simulation (FLUS) model, the patch-generating land use simulation (PLUS) model reveals LUCC causal mechanisms and simulates multi-scenario dynamics through land expansion algorithms (Liang et al., 2021a). Compared with other models, PLUS model achieves higher simulation accuracy (Ma et al., 2025). The research applied PLUS-InVEST integration to explore LUCC-driven carbon storage responses (Liu et al., 2024a; Li et al., 2025b). However, few studies have applied this approach to mountain-desert-oasis urban belts or combined it with a spatial autocorrelation analysis to identify area-specific ecological protection strategies.

The urban belt along the Yellow River in the Ningxia Hui Autonomous Region is the transitional area between central and western China and serves as a crucial ecological barrier, and plays a critical role in carbon accumulation. The Helan Mountains in the urban belt capture atmospheric CO effectively, and the main land uses, such as cropland and grassland, act as important carbon sinks. However, rapid urbanization, infrastructure development, and tourism expansion have resulted in the transformation of natural ecosystems into urban and industrial areas, thus decreasing carbon storage potential. Furthermore, the effectiveness remains uncertain of ecological restoration policies, such as desertification control and land reclamation, in counteracting carbon losses due to urbanization. Additionally, comprehensive research is lacking in exploring the future impacts of LUCC on carbon storage under multiple scenarios. Therefore, evaluating the effects of LUCC on carbon storage is critical for ecological management.

In this context, the study combines the InVEST model, PLUS model, and spatial autocorrelation method to assess the impact of LUCC on carbon storage in this urban belt. The aims of the study are: (1) to clarify the complex patterns of LUCC from 1993 to 2023 and predict the spatial pattern of land use in 2033; (2) to evaluate the impact of LUCC on carbon storage from 1993 to 2033 and explore suitable land use development model; and (3) to reveal the aggregation patterns of carbon storage. This research offers insights for enhancing the ecological environment and adjusting land use planning in the urban belt. In addition, this study contributes to enhancing carbon sequestration potential and promotes a modern society in which humans and nature coexist harmoniously. 2 Materials and methods

2.1 Study area

The urban belt along the Yellow River in the Ningxia Hui Autonomous Region (36°58′-39°22′N, 104°16′-106°58′E) is located in the upper reaches of the Yellow

River Basin (YRB), China, covering an area of 22.00$\times$10 and containing a 397-km stretch of the Yellow River within its boundary (Fig. 1 [Figure 1: see original paper]). The highest elevation of the study area is 3538 m a.s.l. The terrain is complex, with northern mountainous areas, Yinchuan Plain, Weining Plain, and loess hilly area distributed from north to south. The study area has a typical temperate continental climate, with annual

average temperatures spanning from 6.00°C to 11.00°C and annual precipitation ranging from 179.00 to 360.00 mm. Situated in the transitional zone between China' s desert and grassland ecosystems, the dominant land use types of the study area are cropland and grassland. As the demographic and economic center of Ningxia Hui Autonomous Region, this area accommodates 70.00% of the total population and contributes more than 90.00% of the regional gross domestic product (GDP). In recent years, accelerating urbanization and land desertification have heightened the pressure placed on land resource allocation. Therefore, understanding how carbon storage responds to LUCC in this area has practical significance for promoting coordinated ecological and economic development in arid transitional zones.

Overview of the study area. HN, Huinong District; DWK, Dawukou District; PL, Pingluo County; HL, Helan County; XX, Xixia District; XQ, Xingqing District; JF, Jinfeng District; YN, Yongning County; LW, Lingwu City; QTX, Qingtongxia City; LT, Litong District; ZN, Zhongning County; SPT, Shapotou District.

2.2 Data sources and processing

The data employed in this research included land use data and 15 driving factor datasets (Wu et al., 2024; Table 1). This study collected driving factors from different time periods, nevertheless their timing was as close as possible to that of the latest land use data (Liang et al., 2021a). On the basis of the Land Use Classification of China (GB/T 2010–2017) and regional ecological characteristics, we classified the land cover types into six categories: cropland, woodland, grassland, water body, unused land, and built-up land. The spatial accessibility factors used Euclidean distance to generate the distance raster. Within the dataset employed, land use data and soil type data were categorical variables, whereas the other data were continuous variables. This study resampled these variables to a 30-m resolution using nearest neighbor interpolation and bilinear interpolation methods.

Additionally, all of the data used the World Geodetic System 1984 (WGS84) Albers conic equal-area as their projection coordinate system.

2.3 Methods

In subsequent analyses, the study applied the InVEST model to evaluate the carbon storage affected by LUCC. Additionally, the study introduced the spatial autocorrelation method to

Research data and resources Data type Data name Resolution Source Land use data Land use 1993, 2003, 2013, and Annual land cover datasets and its dynamics in China from 1985 to 2023 Geospatial Data Cloud Natural environmental factors Soil type Resource and Environmental Science Data Annual mean precipitation ational Tibetan Plateau Scientific Data Center Annual mean temperature Resource and Environmental Science Data Socio-economic factors

Population ORNL Land Scan Viewer

Open Street Map Spatial accessibility factors Distance to city center ational Bureau of Statistics of China Note: DEM, digital elevation model; GDP, gross domestic product; ORNL, Oak Ridge National Laboratory.

Flowchart of the research method. PLUS, patch-generating land use simulation; CA, cellular automata; OA, overall accuracy; FOM, figure of merit; InVEST, integrated valuation of ecosystem services and tradeoffs.

explore the aggregation or dispersion of carbon storage.

Carbon storage calculation The InVEST model quantifies carbon storage by combining carbon density values with land use data, which is calculated as in Equations 1 and 2. total above below total total where total is the total carbon density of land use type (Mg C/hm above below , and are the aboveground, belowground, soil, and dead organic matter carbon densities, respectively (Mg C/hm total is the total carbon storage (Mg C); is the area of land cover category); and is the total number of land use types.

Empirical studies have demonstrated significant correlations between carbon density and climatic variables (Tang et al., 2018; Liu et al., 2023b). Therefore, this study selected a carbon density correction formula with enhanced universality and adaptability to similar climatic conditions (Eqs. 3–5) (Xu et al., 2023; Li et al., 2025c). 14.4 , Average 79.1 , Average 0.58 , Average , (5) where are the biomass coefficients determined by precipitation and temperature, respectively; is the final biomass correction coefficient; are the soil coefficients by precipitation and temperature, respectively; is the final soil organic matter correction coefficient; are the dead organic matter coefficients by precipitation and temperature, respectively; is the final dead organic matter correction coefficient; are the precipitation amounts in the urban belt and YRB, respectively (mm); and ' and '' are the temperature values in the urban belt and YRB, respectively (°C).

We corrected carbon density on the basis of relevant research in the YRB (Xu et al., 2023; Wang et al., 2024a). Specifically, the annual mean precipitation (226.54 mm) and temperature (9.93°C) of the urban belt and the YRB (470.13 mm and 6.63°C, respectively) were input into the formula to obtain correction coefficients. Finally, this study calculated the carbon density values of the urban belt by multiplying these correction coefficients by carbon density of the YRB (Table 2).

Land use simulation The PLUS model incorporates a land expansion analysis strategy (LEAS) and a CA model based on multi-type random seeds (CARS) as its two core mechanisms (Liang et al., 2021a). The LEAS module first performs systematic sampling of expansion areas, then applies the Random Forest (RF) to generate land use growth probability surfaces and obtain the relative importance of factors.

The CARS module regulates competition among land use types during simulation using adaptive coefficients, aligning them with future demands. Equations 6 and 7 provide the corresponding calculations.

Carbon density values under different land use types Land use type Aboveground carbon density Belowground carbon density Soil carbon density Dead organic matter carbon density where is the growth probability of land use type at cell is the conversion of other land use types to land use , with a value of 1 meaning that this conversion occurs, and a value of 0 meaning other transitions; integrates all of the driving factors; is an indicator function for the decision tree;) is the land use type predicted by the decision tree for is the aggregate quantity of decision trees; is the overall probability of land use type is a random number within the range of 0–1; is the threshold for new land use patches of type is the future demand effect of land use type , obtained by iterating the quantity-demand gap in year is the neighborhood impacts of land use type in spatial unit , measuring the proportion of adjacent land cover.

The threshold decay mechanism governs land use transition by dually regulating organic and stochastic growth across all land types. We built a roulette wheel based on the overall probabilities of all land use types to determine the land use state in the next iteration. When a new land use type dominates in iterative competition processes, a decreasing threshold is applied to evaluate the selected land use type from the roulette wheel, thereby restricting the excessive expansion of land patches, as shown in Equations 8 and 9.

Step, then Change Nochange where are the differences between the existing amount and future requirement of land use type at the (iterations; Step is the step size of the PLUS model to simulate land use demand; is the total number of decay steps; is the decay factor of , with a range of 1 is a normally distributed random variable with the mean value of 1; and is the transition matrix to specify the conversion potential from land use type (Verburg and Overmars, 2009).

To verify the applicability of the PLUS model in the urban belt, this study simulated land use pattern in 2023 and validated the results against actual data. Model accuracy was evaluated using three indices (Mitsova et al., 2011), with a Kappa coefficient of 0.83, an overall accuracy (OA) of 89.77%, and a figure of merit (FOM) of 0.16. These findings demonstrate that the PLUS model

satisfies the requirements for multi-scenario land use simulation in the urban belt. The supplementary materials list the parameter settings and simulation accuracy for the PLUS model (Table S1; Fig. S1).

Scenario setup of PLUS model The Territorial Spatial Plan of the Ningxia Hui Autonomous Region (2021–2035) includes several core policies that provide key guidance for setting the multi-scenario parameters in this study.

Specifically, the plan stabilizes the high-quality grain production base in the Yinchuan Plain, strengthens the ecological security barrier function of the Helan Mountains while promoting ecological protection in the YRB, and guides the integrated development of the urban belt to establish a core engine for high-quality development in Northwest China. On the basis of these policies, this study ultimately constructs four scenarios: natural development, cropland protection, ecological protection, and urban development (Li et al., 2025a). This study determined the corresponding land use transfer cost matrices for these scenarios on the basis of their specific objectives and relevant studies (Lin et al., 2024; Wu et al., 2024; Lai et al., 2025). The matrices serve as the core constraint for the PLUS model simulation to reflect the differentiated policy orientations of each scenario (Table S2).

The settings for future land use scenarios are outlined below. Natural development scenario (NDS): land use demand in 2033 was projected by following the trends from 1993 to 2023 (Liang et al., 2021a). This study designated the Yellow River Corridor (YRC) as a restricted conversion zone. Cropland protection scenario (CPS): we adjusted the transition probabilities as follows: a 30.00% decrease in cropland conversion to built-up land, a 20.00% decrease in cropland conversion to grassland/water body, and a 60.00% increase in unused land conversion to cropland.

Spatial constraints prioritized the protection of stable cropland, high-quality cropland, and YRC conservation zones. Ecological protection scenario (EPS): we strengthened regional ecological protection to alleviate the ecological damage arising from urbanization and land development with conversions of woodland, grassland, and water body to built-up land (Lai et al., 2025). This study suppressed the land conversion rates in the following ways: 50.00% for woodland/water body conversion to built-up land, 20.00% for grassland conversion to built-up land, and 15.00% for cropland conversion to built-up land. We also decreased the probability of woodland shifts to grassland by 30.00% while increasing the probabilities of positive ecological transitions: 50.00% for built-up land/grassland/unused land conversion to woodland, 30.00% for built-up land/unused land conversion to grassland, and 20.00% for unused land conversion to water body. This study designated ecological reserves and YRC areas as conversion-prohibited zones. Urban development scenario (UDS): we modulated the transition rates as follows: a 30.00% increase in cropland conversion to built-up land, a 20.00% increase in woodland/grassland conversion to built-up land, a 30.00% decrease in built-up land transition to noncropland, and a 20.00% increase in unused land transformation to built-up land.

Monte Carlo method for uncertainty quantification The Monte Carlo method, also called the probabilistic statistical method, is rooted in probability theory. It approximates predicted values by conducting mathematical statistical experiments and simulating the distribution probabilities of random variables (García-Alonso et al., 2012). Its basic framework involves four key steps: (1) assuming that variable follows a specific probability distribution; (2) generating sample values through random sampling: first producing random numbers within the [0, 1] interval, then combining them with original data to create random sequences that follow the designated distribution (sample values); (3) identifying and selecting statistical indicators, including percentiles, mean, standard deviation, and coefficient of variation; and (4) deriving estimated values of statistics from the arithmetic mean of statistics, and further approximating both predicted values and their uncertainty ranges (Huang et al., 2020).

Spatial autocorrelation Spatial autocorrelation was employed to quantify the carbon storage aggregation or dispersion degree. Global Moran's assesses overall clustering patterns, and local Moran' s detects specific

clustering and outliers. The analyses utilized Euclidean distance with inverse distance weighting to account for spatial proximity, using a 2-km threshold for weight matrix construction. To ensure comparability, we standardized Global Moran's using Z scores. To assess the significance of Moran's , we performed 999 permutations, and applied false discovery rate (FDR) correction to adjust the value. To mitigate edge effect biases, we extended the spatial neighborhood on the basis of defined distance threshold along the urban belt boundaries. Equations 10 and 11 present the formulas for the global and local Moran' s indices, respectively. where is the global Moran' s index, with values spanning [-1, 1]; is the sum of the spatial weight matrix; ' is the number of regions of the study object space; is the spatial weighting coefficient between areas are the carbon storage of areas , respectively (Mg is the mean carbon storage across all areas (Mg C); is the local Moran' s index for a specific area ; and is the variance in carbon storage across areas (Mg C).

3.1 LUCC dynamics in urban belt

3.1.1 Contribution of driving factors in LUCC Using RF classification, we systematically quantified the impacts of driving factors on LUCC (Fig. 3 [Figure 3: see original paper]). DEM had a pervasive influence across all land use types. For cropland conversion, distance to city center (DCC; 10.25%) and temperature (11.85%) were identified as primary determinants. In contrast, soil type predominantly controlled woodland and unused land dynamics by 43.34% and 11.55%, respectively. DCC mainly influenced grassland and water body transitions by 9.90% and 13.07%, respectively. Built-up land expansion was correlated strongly with population density (10.07%). The analysis demonstrated that socio-economic factors, Contribution of driving factors in land use and land cover change (LUCC). DEM, digital elevation model; GDP, gross domestic product.

particularly urban/road proximity, emerged as key drivers of built-up land expansion. Spatial accessibility factors were strongly influenced by infrastructure planning and consequently exerted certain effects on LUCC.

LUCC dynamics from 1993 to 2023 From 1993 to 2023, significant land conversion was documented among grassland, cropland, unused land, and built-up land (Fig. 4 [Figure 4: see original paper]). Over this period, cropland and built-up land increased by 1070.06 and 825.97 km , respectively, whereas unused land and grassland decreased by 1226.70 and 708.61 km , respectively. Woodland and water body changed slightly, increasing by 5.82 and 33.46 km , respectively (Fig. 5 [Figure 5: see original paper]). The initial decade (from 1993 to 2003) featured a 703.80 km decrease in unused land, with 89.23% of the area transitioning to grassland. From 2003 to 2013, economic development drove the conversion of cropland (208.32 km) and grassland (168.15 km to built-up land. From 2013 to 2023, grassland decreased by 743.07 km , with conversions primarily to cropland and unused land. Built-up land expanded by 188.52 km The geospatial analysis revealed that cropland and built-up land expanded across all of the study phases (Fig. 5). Urban economic growth and demographic pressure drove built-up land expansion through conversions of cropland, grassland, and unused land, forming high-density clusters in the Shizuishan and Yinchuan cities. Cropland expansion was concentrated in the Ningxia Plain, primarily through conversions of grassland and unused land. Unused land decreases were concentrated along the ecological transition zones of Shapotou District and Lingwu City.

LUCC dynamics from 2023 to 2033

2033. Under NDS, grassland and water body decreased by 408.50 and 18.95 km

, respectively, Land use transformation. (a), 1993-2003; (b), 2003-2013; (c), 2013-2023; (d), 1993-2023.

Distribution and areas of land use in 1993 (a), 2003 (b), 2013 (c) and 2023 (d) while cropland, woodland, unused land, and built-up land increased by 161.10, 1.15, 147.03, and 118.17 km , respectively. Among all categories, built-up land had the highest expansion rate (10.78%). Land transitions under this scenario aligned with historical trends observed from 1993 to 2023. Geospatial analysis revealed distinct patterns: cropland expansion was concentrated in the Yellow River irrigation zones, and urban growth was clustered in the Ningxia Plain, particularly in Yinchuan City.

CPS exhibited expansion in cropland, woodland, built-up land, and unused land, whereas compared with the baseline conditions in 2023, grassland and water body showed persistent contraction. The cropland area increased most significantly (223.02 km). Grassland decreased by 317.71 km , representing the most severe decrease among all land categories. This decrease resulted primarily from conversion to cropland.

EPS exhibited progressive expansion in cropland, woodland, and built-up land, whereas grassland, water body, and unused land showed sustained contraction relative to the baseline conditions in 2023. Within this framework, grassland loss decelerated by 74.59 km , indicating a significant slowdown compared with the NDS. LUCC analysis revealed the preferential conversion of agriculturally suitable grassland ecosystems to cropland. This coordinated transition aligned with regional agricultural intensification strategies. Enhanced remediation measures limited built-up land expansion rates while improving conservation efficacy in key

Distribution and areas of land use under four scenarios in 2033. (a), NDS (natural development scenario); (b), CPS (cropland protection scenario); (c), EPS (ecological protection scenario); (d), UDS (urban development scenario). ecosystems.

UDS exhibited accelerated urbanization, with built-up land expansion of 131.58 km , primarily through grassland conversion. Geospatial analysis indicated that built-up land expansion was concentrated along the Yellow River irrigation zones, with Yinchuan City exhibiting the most pronounced growth. 3.2 Carbon storage evolution in urban belt 3.2.1 Carbon storage evolution from 1993 to 2023 TECS in the urban belt increased from 130.04$×10*MgCin*1993*to*135.06×10*MgCin*2023, *yieldinganetaccumulationof*5.01×10*MgCoverthreedecades*
*specificanalysisrevealedthatthemaximumincreaseoccurredfrom*1993*to*2003(3.19×10*MgC*, *representingagr*
Mg C (0.30%) from 2013 to 2023. Carbon storage in urban belt exhibited significant spatial heterogeneity (Fig. 8 [Figure 8: see original paper]). The highest values clustered in the Yellow River irrigation zones and Helan Mountains, where high-carbon-density cropland and woodland ecosystems dominate. Lower values appeared in urban and desert-edge areas, particularly near the Shapotou District and Lingwu City transition zones, where sparse vegetation led to decreased carbon density.

Carbon storage changes were classified into increase, stable, and decrease phases on the basis of grid-level temporal variations (Fig. 9 [Figure 9: see original paper]). From 1993 to 2023, most of the areas exhibited an

Land use transformation under four scenarios from 2023 to 2033. (a), NDS; (b), CPS; (c), EPS; (d), UDS. increase in carbon storage. However, Jinfeng District (0.12%), Xixia District (0.42%) and Zhongning County (1.44%) shifted from initial increases to net losses. The most pronounced growth occurred in Huinong District (9.03%) and Pingluo County (9.25%). From 1993 to 2003, Litong District experienced a decrease (0.92%), while Qingtongxia City experienced a substantial increase (6.71%). From 2003 to 2013, a significant decrease occurred in Dawukou District (9.63%) alongside a net increase in Huinong District (6.30%). From 2013 to 2023, Dawukou District reversed to a positive trend (7.70%), while Qingtongxia City (4.51%) and Zhongning County (3.49%) experienced pronounced declines. Areas with sustained decreases in carbon storage (e.g., Jinfeng District and Zhongning County) were associated with accelerated urban encroachment into ecologically sensitive areas. In contrast, sustained increases in Lingwu City, Xingqing District, and Pingluo County corresponded to conversions of unused land to ecological land.

Carbon storage evolution from 2023 to 2033 Figures 10 and 11 depict projected carbon storage levels and their variations. Under NDS, carbon storage was projected to be 134.46$\times 10MgC, indicatingadecreaseof 0.60\times 10MgC (0.44\times 10C, indicatingadecreaseof 0.21\times 10. Mg C (0.31%).

To quantify uncertainties in carbon storage changes across scenarios, we conducted a Monte Carlo simulation with 1000 iterations using a uniform distribution, with detailed results shown in Table S3. Relative perturbations of $±$5.00% and $±$10.00% were applied respectively to two key parameters affecting carbon storage: carbon density and land use conversion probability, ensuring

Spatial distribution of carbon storage in 1993 (a), 2003 (b), 2013 (c), and 2023 (d). (a1)-(a3), (b1)-(b3), (c1)-(c3), and (d1)-(d3) represent the spatial distribution of carbon storage in zones 1, 2, and 3 in 1993, 2003, 2013, and 2023, respectively. that the perturbation ranges are reasonable and conservative. Results showed that for each scenario, the 50 percentile and mean values were closely aligned. The standard deviation increased with the magnitude of carbon storage change, and the coefficient of variation remained stable within 5.80%–7.60%.

Except for EPS, NDS, CPS, and UDS resulted in carbon storage losses. In contrast, EPS showed superior carbon accumulation. This result was achieved by enhancing the conversion of unused land to woodland/cropland and restricting the conversion of cropland to unused land and built-up land. The spatial distribution pattern remained consistent from 1993 to 2023 (Fig. 10 [Figure 10: see original paper]).

High carbon storage areas clustered in the Yellow River irrigated zones and Ningxia Plain, characterized by grassland–cropland–woodland ecosystems. Low-carbon storage areas occurred in desert areas of Shapotou District and irrigation fringe zones, characterized by unused and built-up land.

Spatiotemporal changes of carbon storage from 1993 to 2023. (a), 1993-2003; (b), 2003-2013; (c), 2013-2023; (d), 1993-2023. The bar chart denotes the county-level percentage change in carbon storage. (0.75%). Conversely, carbon storage increased in Jinfeng District (0.20%). In contrast to the southern areas, the northern areas, such as Shizuishan and Yinchuan cities, demonstrated relatively stable carbon sequestration. Under CPS, carbon storage increased in northern urban belt, with the most significant increase in Jinfeng District (0.32%). However, carbon storage decreased in southern areas, particularly in Zhongning County (0.58%). Under EPS, carbon storage increased across all study areas. These increases resulted from ecological protection measures, which helped protect high-carbon-density ecosystems. Under UDS, only Pingluo County showed increases in carbon storage (0.05%), whereas all of the other areas experienced decreases. The most significant decreases occurred in Zhongning County (0.77%) and Shapotou District (0.47%).

Changes in northern urban belt were relatively moderate, whereas southern areas experienced more pronounced declines. Overall, across all four scenarios, carbon storage distribution in urban belt showed marked spatial aggregation in northern areas. This pattern resulted from the concentration of woodland and cropland in the north. In contrast, southern areas, characterized by more unused land and severe grassland degradation, experienced more significant decreases in carbon storage.

Influence of LUCC on carbon storage Compared with 1993, all scenarios projected carbon storage accumulation in 2033 (Table 3).

Under NDS, total land use conversion reached 6091.76 km , increasing carbon storage by 4.41$×10MgC.Conversionsofgrasslandtocropland(1652.74kmand0.68×10MgC),unusedlandtocro
Mg C higher than that of NDS through restricting the conversion of cropland to other land types. Under EPS, the greatest

Spatial distribution of carbon storage in 2033. (a), NDS; (b), CPS; (c), EPS; (d), UDS. (a1)-(a3), (b1)-(b3), (c1)-(c3), and (d1)-(d3) represent the spatial distribution of carbon storage in zones 1, 2, and 3 for NDS, CPS, EPS, and UDS, respectively. carbon storage increase occurred (5.19$×10MgC)throughstrengthenedecologicallandprotection.UnderUDS,carbonstorageincreasedby4.60×1
uplandadjacenttoextensiveunusedland(Fig.5).ComparedwithNDS,UDSfeaturedmorebuilt−
uplandexpansiontounusedland,adding10,280MgCofcarbonstorage.Additionally,comparedwithNDS,urban
Mg C to carbon storage. Overall, grassland, unused land, and cropland were key land use categories influencing carbon storage changes, and EPS was the most conducive scenario for enhancing future carbon storage capacity. 3.3 Spatial autocorrelation analysis of carbon storage The global spatial autocorrelation analysis showed that the Moran’ s values for 1993, 2003, 2013, and 2023 were 0.805, 0.783, 0.741, and 0.710, respectively. For the four scenarios, the values

Spatiotemporal changes of carbon storage from 2023 to 2033. (a), NDS; (b), CPS; (c), EPS; (d), UDS.

The bar chart denotes the county-level percentage change in carbon storage. were 0.760, 0.759, 0.762, and 0.760 under NDS, CPS, EPS, and UDS, respectively, all of which were significant statistically (<0.01). These results demonstrated that carbon storage exhibited remarkable aggregation characteristics.

The region exhibited a dominant spatial aggregation of high-high (H-H) and low-low (L-L) clusters (Fig. 12 [Figure 12: see original paper]). The H-H clusters occurred in strips along the Ningxia Plain and Helan Mountains. The flat terrain and concentrated water sources facilitated carbon storage accumulation. The implementation of policies such as the Three-North Shelterbelt Forest program have protected woodland and cropland effectively. This protection enhanced the regional carbon sequestration potential. The L-L clusters were concentrated along the Tengger Desert margins and urbanized areas, which are predominantly composed of unused and built-up land. Urban expansion occupied some ecological land, and the arid and desertified geological features of the Tengger Desert weakened the natural carbon storage capacity of these areas. However, the L-L clustering extent decreased due to the implementation of ecological protection project.

Grassland-dominated areas showed no significant clustering. However, ecological protection policies promoted the recovery of grassland and carbon accumulation. In general, the carbon storage clustering patterns were closely associated with land use policies, regional geographic features, and anthropogenic activities.

4 Discussion

4.1 Spatiotemporal variation characteristics of land use From 1993 to 2023, built-up land and cropland expanded steadily, primarily at the expense of unused land and grassland. These observations align with the results of Lin et al. (2024). From 1993 to 2003, the ecological environment in Ningxia Hui Autonomous Region improved substantially because of the adoption of windbreak and sand-fixation and wasteland reclamation

Carbon storage variations induced by land use transitions from 1993 to 2033 -158,842.47 -150,679.30 -155,208.78 -149,891.98 -417,032.76 -412,872.26 -441,454.30 -430,335.89 -56,710.73 -55,096.68 -50,376.98 -55,184.16 -563,938.31 -545,934.43 -542,077.13 -566,581.89 -40,472.78 -13,203.31 -38,772.71 677,514.32 686,594.68 648,958.70 639,146.00 70,681.06 41,955.00 28,042.61 67,050.25 -326,092.03 -333,683.41 -333,433.73 -330,332.34 844.35 -3,981,545.67 -3,733,591.73 -3,354,587.62 3,757,538.82 -342,236.12 -278,730.10 -260,065.69 -337,033.59 540,688.78 555,298.01 544,915.77 544,459.83 113,612.25 100,050.27 95,038.99 100,900.08 109,829.15 110,808.66 101,152.53 112,126.54 1,809,271.46 1,828,421.45 1,719,877.15 1,694,878.93 6,497,592.53 6,562,985.44 6,740,423.82 6,626,848.36 494,361.31 460,806.95 478,788.65 504,641.12 12,809.36 10,545.81 14,144.21 -31,575.66 -30,870.42 -33,784.00 -31,796.49 Total 4,413,120.22 4,804,690.63 5,191,443.11 4,595,961.54 Note: A, cropland; B, woodland; C, grassland; d, water body; E, unused land; F, built-up land. ’ ‘-’ ’ indicates a decrease in carbon storage. measures. As a result, unused land decreased, particularly in the Shapotou District, while grassland and cropland areas expanded (Li and Xu, 2019). Li et al. (2016) also reported this trend.

In 2003, Ningxia Hui Autonomous Region implemented a comprehensive ban on grazing and fenced breeding measures, which contributed to grassland ecosystem protection (Li et al., 2021).

Large-scale ecological migration in 2011 (Li et al., 2024) increased significantly the population size and socioeconomic activity in this area (Lyu et al., 2019), particularly in Shizuishan and Yinchuan cities. This growth heightened the demand for built-up land, decreasing grassland area directly. The National Land Use Master Plan emphasized the need to limit the conversion of high-quality cropland for construction purposes. Thus, the cropland area in the Ningxia Plain increased continuously. The implementation of ‘ Approval of the Ningxia Hui Autonomous Region Forest Protection and Utilization Plan (2010-2020)’ ’ in 2013 emphasized forest protection, leading to increased forest cover in the Helan Mountains. Additionally, Ningxia Territorial Spatial Planning highlighted the protection of the Ningxia plain, which led to an increase in the areas of cropland. Ecological restoration efforts gradually reduced unused land in Shapotou District.

Multi-scenario predictions of land use indicate that the expansion of built-up land will continue to be the dominant trend (Lin et al., 2024). The main driver of this trend is the sustained demand for urban space driven by regional socioeconomic development (Wang and Wang, 2017).

Spatial autocorrelation analysis of carbon storage. (a), 1993; (b), 2003; (c), 2013; (d), 2023; (e), NDS; (f), CPS; (g), EPS; (h), UDS.

Predictions also show a moderate increase in cropland and woodland within the study area, largely due to long-term national policies focused on protecting high-quality cropland and ecologically sensitive areas (Hu et al., 2024). These policies have effectively supported regional ecosystem restoration and stabilized cropland resources over the past three decades. As a major land cover type in the urban belt, grassland is extensively distributed on the peripheries of cropland and built-up land, making it more vulnerable to conversion (Li et al., 2025a). Although unused land is expected to increase, its growth rate will slow due to the ecological restoration efforts and occupation by built-up land (Li and Xu, 2019; Song et al., 2021). 4.2 Effects of land use change on spatiotemporal carbon storage dynamics LUCC primarily influences the terrestrial carbon accumulation (Tang et al., 2018). Globally, grassland stores 525–634 Pg C (Liu et al., 2023a), representing the second largest carbon pool among global carbon reserves. As a typical arid area in the upper YRB, the urban belt features grassland (nearly 60.00% of the total area) and cropland (nearly 30.00%). Consequently, changes in these land covers influence regional carbon stock dynamics significantly.

Temporally, carbon storage tends to increase overall as growth rates decrease (Lin et al., 2024).

From 1993 to 2003, windbreak forest, sand fixation, and ecological restoration projects increased the vegetation cover of unused and sandy land, increasing carbon storage (Zang et al., 2025).

Furthermore, the construction of hydraulic engineering and irrigation systems facilitated high-carbon-density cropland expansion into unused land, improving carbon sequestration.

Additionally, the implementation of the " Grain for Green' ' program further increased woodland area, increasing carbon stocks (Ma et al., 2024). Ding et al. (2023) demonstrated that grassland carbon storage in Ningxia Hui Autonomous Region became more pronounced as precipitation increased. However, rapid urbanization from 2003 to 2013 caused the expansion of built-up land, increasing the risk of carbon storage decline (Anindita et al., 2022). During this period, grassland

grazing bans and ecological compensation programs mitigated degradation to unused land, sustaining carbon storage growth. From 2013 to 2023, while urbanization continued to accelerate, carbon storage increased through ecological protection measures, particularly in the Helan Mountains. The ecological protection red line project and spatial planning reforms helped maintain high carbon density in the area. However, rapid urbanization in the Ningxia Plain has occupied surrounding grassland and threatened carbon storage stability.

Carbon storage exhibited distinct regional variations. The Helan Mountains maintained high carbon storage stability due to the limited human disturbance (Li et al., 2022). The Ningxia Plain experienced rapid urban expansion because of its flat terrain and sufficient water resources. This expansion encroached on cropland and grassland, especially in Shizuishan and Yinchuan cities, where urbanization disrupted ecological land and decreased carbon storage stability (Bu et al., 2019). In contrast, desertification-affected areas such as Shapotou District and Nature Reserve of the Lingwu City had sparse vegetative cover, resulting in lower carbon storage (Gao et al., 2019).

However, ecological protection measures converted large portions of unused and sandy land into conservation areas, increasing regional carbon storage.

Future scenario projections, the increased carbon storage under EPS provides a framework for enhancing regional carbon reserves. In high-carbon-density areas such as the Helan Mountains, enhancing ecological protection and reducing anthropogenic interference is crucial. In the rapidly urbanizing Ningxia Plain, built-up land expansion requires control to limit ecological land encroachment. Additionally, sandy lands need to protect sand-fixing plants, and arable unused lands require ecological reclamation to increase vegetation cover. Collectively, these measures promote coordinated eco-economic development (Roy et al., 2023; Ran et al., 2024).

4.3 Limitations and prospects

Although this study explored LUCC and carbon storage changes by integrating various models, it has several limitations. Firstly, the carbon density data were obtained through climatic modification of historical data. However, these data may not fully reflect the specific conditions of urban belt. Secondly, the land use classification was relatively generalized and lacked detailed stratification. This limitation may have overlooked variations in carbon storage across different vegetation succession stages and differences in carbon density among subclasses. Additionally, the coupled PLUS–InVEST framework did not incorporate certain key drivers, such as sudden natural disasters, which could limit the comprehensive characterization of carbon storage.

Future studies should focus on validating carbon density values through high-resolution remote sensing or field measurements, thereby enhancing the accuracy of carbon storage calculations.

Moreover, research could consider subclass differentiation for grasslands. For instance, grassland could be stratified into low, moderate, and high coverage subtypes, which would further capture variations in vegetation cover and associated carbon storage capacities. Furthermore, future land use simulations should incorporate regional natural disaster risks and climate change factors.

Such adjustments would enable simulations to more accurately estimate carbon storage and capture land use dynamics.

5 Conclusions

This study employed a PLUS-InVEST spatial autocorrelation framework to evaluate and project the effects of LUCC on carbon storage. The key findings showed that carbon storage in urban belt increased from 130.04$×10*MgCin*1993*to*135.06×10*MgCin*2023, *representinganoverallincreaseof*5.01×10*MgC*.*Restoration*
carbon—*densitylandpromotedcarbonaccumulation*.*Conversely*, *convertinggrasslandintolow*—
carbon—*densitylandreducedcarbonaccumulation*.*RegionalheterogeneityrevealedthatHuinongDistrictandPi*

in carbon storage through grassland conservation. Spatial autocorrelation analysis revealed H–H clusters occurred in the Ningxia Plain and Helan Mountains, areas covered predominantly by woodland and cropland. Conversely, L–L clusters concentrated in desert margins and urbanized areas, where built-up and unused land mainly distributed. These findings underscore the spatial variability of carbon storage across different land use types. Therefore, land use planning in urban belt should prioritize the protection of ecological areas, and limit the expansion of built-up land to safeguard potential carbon storage areas. Balancing ecological conservation with economic development will promote the realization of carbon neutrality goals in similar urban belt areas.

Conflict of interest LI Xuemei is a Young Editorial Board member of Journal of Arid Land and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Zang J, Li Q, Yu Q, et al. 2025. Study on the relationship between topological characteristics of vegetation ecospatial network

Appendix

Table S1 Parameter settings of the PLUS model Regression tree Sampling rate (%) Patch generation threshold Expansion coefficient Percentage of seed (%) Note: PLUS, patch-generating land use simulation.

Fig. S1 Spatial pattern of actual (a) and simulated (b) land use distribution in 2023 Table S2 Land use transfer matrix Note: NDS, natural development scenario; CPS, cropland protection scenario; EPS, ecological protection scenario; UDS, urban development scenario; A, cropland; B, woodland; C, grassland; D, water body; E, unused land; F, built-up land; " 1' ' represents the alterable state of the land type; " 0' ' represents the unalterable state of the land type.

Table S3 Carbon storage change uncertainty analysis in 2033 Scenario percentile Mg C) percentile Mg C) percentile Mg C) Coefficient variation (%) Standard deviation Mg C) Mg C) Number of iterations

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

Source: ChinaXiv —Machine translation. Verify with original.