RESEARCH ARTICLE

A coupling model based on spatial characteristics and evolution of terrestrial ecosystem carbon storage: a case study of Hanzhong

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Abstract

Ecosystem carbon storage (ECS) is a critical consideration in reducing the impact of global warming and tackling environmental challenges, positioning it at the forefront of contemporary research. Due to the significant differences in the influence of land usage patterns on ECS in various policy contexts and China's commitment to attaining a carbon-neutral status, a model simulating different scenarios is needed to analyze the spatiotemporal characteristics and evolutionary process of carbon storage in terrestrial ecosystems accurately. To address this challenge, this study established a coupling model of "Geographical analysis -Evolution analysis -Predicting (GEP)" for assessing ecosystem ECS and analyzing its spatial characteristics and evolutionary patterns and projecting the spatial distribution of ECS under various developmental scenarios, which analyzed variations in ECS across different levels of magnitude and delineated the changing areas across a range of varying scenarios in the future additionally. The outcomes suggested that the ECS decreased by 1.17×10^6 t from 1990 to 2020, which pertaining to the utilization transfer of land in the area, whose change in ECS levels with a positive trend. It is predicted that the ECS will grow by 1.15×10^6 t and 1.44×10^6 t, in 2030 and 2060 compared with 2020 within the framework of natural development scenario (NDS), while within the framework of ecological protection scene (EPS), ECS will increase significantly, increasing by 3.06×10^6 t and 4.44×10^6 t. There will be more areas where ECS increases within the framework of EPS, by comparing with the NDS. This study offers a comprehensive analysis of Hanzhong City's carbon storage trends, demonstrating its significant impact on climate change mitigation and serving as a predictive model for similar regions, which underscores the importance of localized carbon management strategies, offering valuable insights for local governments in formulating effective climate adaptation and mitigation policies.

Keywords Terrestrial ECS · Spatial characteristics · Evolution · GEP · PLUS model

Introduction

Ecosystem carbon storage (ECS) denotes the quantity of carbon that is accumulated within diverse natural ecosystems, such as forests, wetlands, grasslands, and oceans (Guddaraddi et al. 2023; Mengist et al. 2023), which holds a crucial position in alleviating the effects of climate change,

supporting biodiversity, and enhancing the ability to cope with environmental challenges by providing a range of ecosystem services that benefit the environment and human society (Gao et al. 2022a; Vicca et al. 2022). Researching and managing ecosystem ECS is critical to sustainable environmental management and climate change efforts (Ruehr et al. 2023). The government of China has pledged to reach the maximum level of carbon dioxide emissions by the year 2030 and to attain a state of carbon neutrality by 2060 (Jiang et al. 2022; Ke et al. 2023). To achieve the "dual carbon" goal requires maintaining the equilibrium of carbon within land-based ecosystems (Ma et al. 2023; Zhang et al. 2023). Enhancing is viewed as a highly environmentally sustainable and economically viable approach to alleviate the greenhouse effect. The huge contribution of forest is the key to attain national objectives of realizing a carbon emission peak and carbon neutrality (Sun et al. 2023). Prior

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studies demonstrate the enhancement in carbon capture in Chinese forests is mainly due to efforts in forest restoration and afforestation (Piao et al. 2022; Zhu et al. 2022), and Shaanxi Province acts as one of the earliest provinces of China to pilot the "grain to green" project (Qian et al. 2019), while the area is an important ECS region in China, which is located in the Qinling Mountains National Key Ecological Functional Zone and has a large number of forest and grassland resources within its region (Liu et al. 2019). How to assess the ECS of terrestrial ecosystems quantitatively, delineate different levels of zoning, and predict future ECS are issues that need to be solved urgently.

Various methodologies have been developed for evaluating ECS, with significant advancements made by scholars in areas such as direct measurement, allometric equations, model simulation, atmospheric, and remote sensing inversion (Nandal et al. 2023). Given the strong correlation among different types of land utilization and ECS (Gong et al. 2023), the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, developed by the Natural Capital Project, has gained popularity. This model assesses the worth of environmental assets and ecological benefits, making it a preferred tool for ECS evaluation (Zhong and Wang 2017; Xiang et al. 2022). These services include carbon storage and sequestration, water regulation, biodiversity conservation, and crop pollination (Nelson et al. 2009). The InVEST model carbon storage simulates the impacts of potential land-use and management scenarios. A model designed to assess the roles of changes in land usage in the ECS offers numerous benefits, including ease of use and adaptable parameters, and fast response speed (Xiang et al. 2022). Certain academics assess the ecosystem carbon storage of land-based ecosystems using the InVEST carbon storage framework. Someone evaluated ecosystem services along the Atlantic coast (Caro et al. 2020). The others evaluated the ECS in Uva Province, Sri Lanka (Piyathilake et al. 2022); There were also some scholars evaluating the spatiotemporal allocation of ECS in Guangdong Province from 1990 to 2020 (Ren et al. 2023). It can be seen that the InVEST model has higher accuracy and wider application in ECS assessment. Despite the advancements in ECS research, there remains a lack of extensive study on ECS within specific areas, notably during the critical "dual carbon" period. Consequently, this research aims to fill this gap by forecasting ECS within this timeframe, thereby offering valuable insights and guidance for the effective implementation of carbon peaking and carbon neutrality policies (Gao et al. 2022c).

Analytical models such as CA-Markov (Zhao et al. 2019), FLUS (Li et al. 2022b), and PLUS (Luan and Liu 2022) have been developed to examine transitions in land usage. Notably, the PLUS model stands out for its exceptional accuracy in forecasting land usage/land cover (LULC) changes

at a patch-scale (Liang et al. 2021; Yu et al. 2023). It has been widely adopted for forecasting future patterns of land utilization, as evidenced by its application in forecasting the landscape dynamics of the Fujian delta by 2050 (Zhang et al. 2022a) and projecting the future of production-living-ecological spaces in Ningbo (Li et al. 2022a). While the PLUS model is renowned for its precision in mapping future land configurations, accurately assessing ecosystem carbon storage (ECS) under various scenarios remains a challenge, highlighting a complex aspect of modern environmental studies.

With the development of spatial technology, GIS and RS are widely used in environmental assessment (Ma et al. 2022), and forest, as the main factor in increasing ECS, greatly influence the achievement of the "double carbon" goal. Hence, we need to research the variations in land usage, the variations in ECS in the past 30 years, and predict the ECS in 2030 and 2060, so as to offer guidance for the for the development of "dual carbon" work in the area. This study built a coupling model named GEP based on geographical analysis, evolution analysis, and predicting and evaluated the historical and future ECS of Hanzhong City where there without previous relevant research under different scenarios. The research contents of this article are shown below: (1) explore the transition in land utilization from 1990 to 2020; (2) evaluate the geographical and chronological spread of carbon reserves by using Moran's I and determine the ECS level zone and analyze its evolution law within the framework of the hierarchical transformation model; (3) divide two scenarios predict ECS changes in 2030 and 2060, delineate zones, and provide recommendations for different zones (Fig. 1). This research framework of "Geographical analysis -Evolution analysis -Predicting (GEP)" provides an approach for analyzing the spatial characteristics and evolutionary process of ECS under different scenarios, offering a practical method for conducting research on global carbon sinks.

Materials and approaches

Research area

Hanzhong City (105.4872°E–108.2803°E, 32.1478°N–33.8794°N) lies in the southwest of Shaanxi Province (Fig. 2). Positioned at the source of the Han River, it serves as a crucial water conservation area for the South-to-North Water Diversion Middle Route Project (Gao et al. 2020). It also plays a significant role in Shaanxi Province's initiative to transfer water from the Han River to the Wei River (Tian et al. 2021). The city is nestled in the western part of the Qinling and Daba Mountains (Zhang et al. 2019). This region falls under the subtropical climate zone.
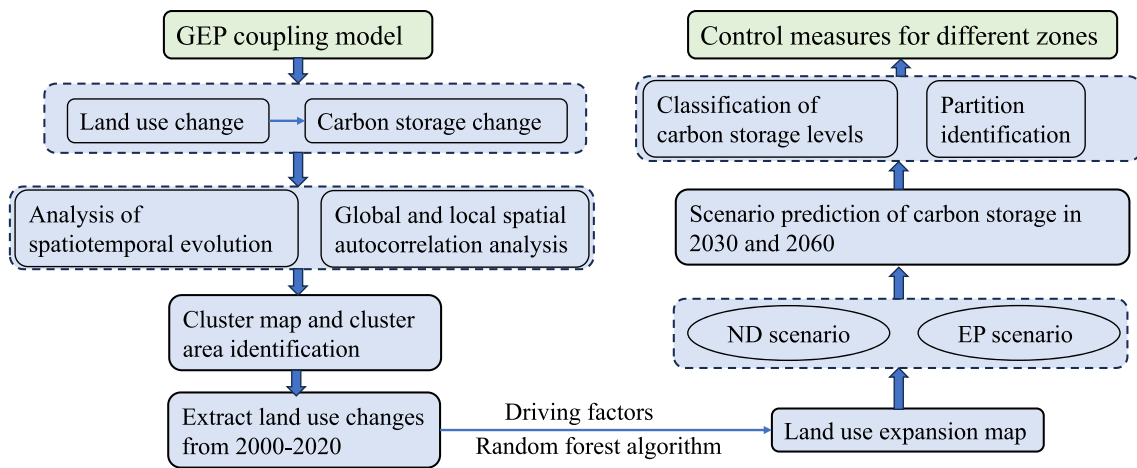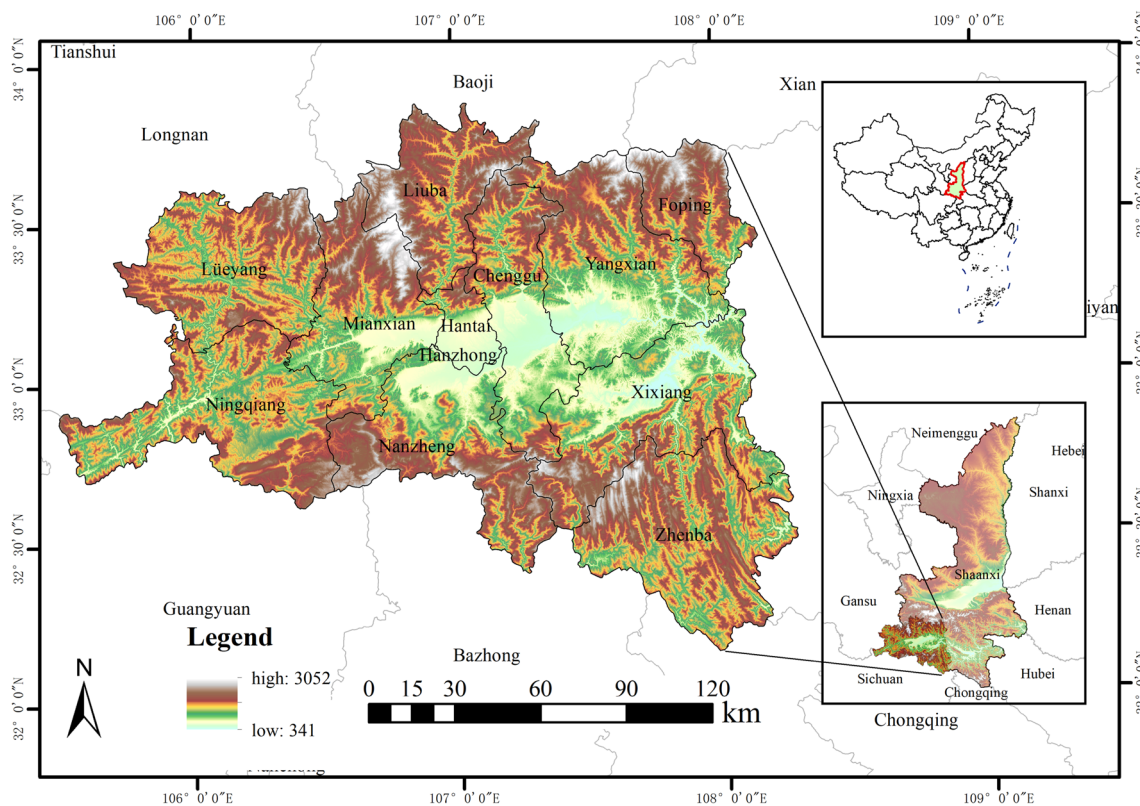
Fig. 1 Research framework diagram

Fig. 2 Location map of Hanzhong City

Shielded by the Qinling Mountains to the north, it is protected from cold currents, resulting in a climate that is both mild and humid (El Kateb et al. 2013).

The area under its jurisdiction is mainly mountainous, making up 75.2% of the entire land area. The Qinling Mountains lie to the north of the research area, while the Micang Mountains of the Daba Mountains are situated to the south. It has natural geographical advantages and is an important forest resource area in Shaanxi Province (Chen and Yao 2022; Su et al. 2023), and the city's forest coverage rate is 63.79%, which is higher than the average forest coverage rate in Shaanxi Province. Lately, as economy develops continuously, the construction land has

continuously expanded, and the city's urban construction land area has reached 59.60 km^2 by 2021.

Data source

The data sources of the research mostly include the aspects below:

1. Land usage type data: sourced from the Resource and Environment Data Center of the Chinese Academy of Sciences. This dataset has a spatial resolution of 30 m, where the original land types have been recategorized into forest land, construction land, cultivated land, water bodies, grassland, and unused land. The dataset includes data for six specific years: 1990, 2000, 2005, 2010, 2015, and 2020 (https://doi.org/10.12078/2018070201).

2. The carbon density data: the cultivated land data and unused land data come from the "2010s China Terrestrial Ecosystem Carbon Density Data Set" collected from journal literature (https://doi.org/10.11922/sciencedb.603.). The carbon density information of the research area, including aboveground carbon density of underground carbon density, vegetation, and soil organic carbon density, were acquired by consulting the data set. The water and construction land data and dead organic matter carbon density data adopt the revised data of research of Wang et al. (2022c). The above-ground carbon density information of forest land comes from the study on above-ground forest biomass in Xi'an (Zhao et al. 2020). The root-shoot ratio of forestland comes from the study of root-shoot ratio of Chinese forests (Guo et al. 2022). The underground carbon density of forest land is obtained from the aboveground carbon density and the root-shoot ratio. The soil organic carbon in forest and grassland comes from the study of

soil organic carbon density in forest on the southern slope of Qinling Mountains. The grassland root-shoot ratio comes from the study of grassland root-shoot ratio (https://doi.org/10.5846/stxb202011202984.). The soil organic carbon in forest and grassland comes from the study of soil organic carbon density in forest on the southern slope of Qinling Mountains (https://doi.org/10.11707/j.1001/7488.20190502.).

3. Driving elements of the PLUS Model required: on basis of the classification criteria of social economy and natural environment, 12 driving element information were selected as training data for the PLUS model (Table 1).

Research methods

InVEST model ECS module

ECS at the plot level is predominantly determined based on the size of four critical carbon reservoirs: aboveground biomass, belowground biomass, soil, and dead organic matter (Paul et al. 2021). Calculate ECS using land use data, according to the following equation:

$$C_{\text{total}} = \sum_{k=1}^{n} A_k \times (C_{\text{above}} + C_{\text{below}} + C_{\text{soil}} + C_{\text{dead}}) \quad (1)$$

where C_{total} represents the total ECS in the research area (unit: t); A_k denotes the area of the kth land kind within the research area; k is from 1 to n; n means the number of land kinds; C_{above}, C_{below}, C_{soil}, and C_{dead} are the aboveground biomass carbon density, underground biomass carbon density, soil organic matter carbon density, and the carbon density of dead organic matter (Wang et al. 2022d), and all of the unit

Table 1 Driver data source table of PLUS model

Data type	Data	Data sources
Socio-economic factors	Population	The Resource and Environment Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/https://doi.org/10.12078/2017121102)
	GDP	
	Railway	OpenStreetMap (https://www.openstreetmap.org/)
	Trunk road	
	Secondary road	
Climate and environmental factors	Soil kind	National Qinghai Tibet Plateau Scientific Data Center (https://data.tpdc.ac.cn/)
	Annual mean temperature	National Tibetan Plateau / Third Pole Environment Data Center. (https://doi.org/10.11888/Meteoro.tpdc.270961)
	Annual mean precipitation	European Centre for Medium-Range Weather Forecasts (https://cds.climate.copernicus.eu/)
	DEM	Geospatial Data Cloud (https://www.gscloud.cn/)
	Water	OpenStreetMap (https://www.openstreetmap.org/)
	NDVI	National Aeronautics and Space Administration (https://www.earthdata.nasa.gov/)
	Night light index	National Earth System Science Data Center (https://www.geodata.cn/main/)

is t/hm^2. Calculate ECS using collected soil carbon density (Table 2).

Geographical and evolution analysis model

Moran's *I* is a statistical measure for assessing the similarity among observed values in spatial data, which is used to identify spatial patterns, such as clustering or dispersion, aiding in the assessment of whether adjacent observations in geographical space are similar, whose range is [−1,1], and the closer the absolute value is to 1, the stronger the corresponding positive or negative correlation (Chai et al. 2023). In this study, the study area was divided into 3 km × 3 km grids to conduct spatial autocorrelation assessment. Moran's *I* was used to clarify the spatial autocorrelation of ECS in the study area, determine whether there is accumulation of carbon storage, and divide it accordingly.

After exploring spatial autocorrelation and aggregation, the obtained ECS spatial distribution is divided into three levels within the framework of the hierarchical transformation model based on the natural breakpoint method and an evolutionary analysis is conducted between different levels (He et al. 2023a; Qi et al. 2023).

Prediction and verification of land usage varies with the PLUS model

On basis of raster image information, the PLUS model adopts a novel land expansion discussion measure and a cellular automaton multiclass random patch seeding (CARS) model on basis of cellular automata (CA) (Liang et al. 2021; Wang et al. 2023c). The LEAS and CARS operations of the PLUS model are completed in the PLUS v1.4 boxed software.

The LEAS module selected 12 driving factors in the study, including factors related to society and the economy, as well as climate and environmental factors. Among them, socioeconomic factors include the population of 2010, the GDP of 2010, the distance to railways, the distance to trunk roads, and the distance to secondary roads; while soil kind, historical annual mean temperature, historical annual precipitation, DEM, night light, and distance to water bodies

and Normalized Difference Vegetation Index are climatic environmental elements (Gao et al. 2022b; Liang et al. 2021; Zhang et al. 2022a).

CARS integrates random seed production and threshold decrease mechanisms. Meanwhile, the automatic production of patches over time and space can be dynamically simulated by the PLUS model, adhering to transition probabilities and constraints (Liang et al. 2021; Xu et al. 2022).

Parameter settings under different development scenarios

Due to the unique geographical location of the research area, two development scenarios are established in this research, which are the natural development scene (NDS) and the ecological protection scene (EPS) (Wang et al. 2023b). Under the framework of NDS, the social development from 2020 to 2030 remains unchanged from the economic development, energy utilization, ecological protection, and land usage policies from 2010 to 2020. Under the framework of EPS, according to the Hanzhong City 14th Five-Year Ecological Environment Protection Plan, the ecological environment protection of "two mountains" (Qinling Mountains and Bashan Mountains) and "two rivers" (Hanjiang River and Jialing River), water and forest land cannot be converted to other land usage kinds. Protect the spatial distribution of existing forests, grasslands, and water bodies unchanged, and strictly limit the change of forests and water bodies into other land use types, reduce the over-development of construction land, and allow the conversion of construction land into forests. In conclusion, protecting the ecological environment for development is the main target.

- Natural development scene: under the scene, Markov chains are adopted to predict the land usage need in 2030 and 2060. The land usage transfer matrix and neighborhood weights remain unchanged from the settings from 2010 to 2020.
- Ecological protection scene: on basis of the natural development scenarios from 2020 to 2030 and 2060, the mutual change between forest and grassland is allowed, and the change of forest and grassland to other land usage kinds is restricted (Sun et al. 2022); the probability of water being transformed into construction land is decreased by 50%, and the possibility of cultivated land being transferred to construction land is reduced by 30% (Wang et al. 2023a). According to the policy of returning cultivated land to forest and grassland, the possibility of transforming cultivated land to forest and grassland is grown by 30%, and the possibility of changing construction land to forest land is increased by 30% and the transition possibility from grassland to forestland increases by 30% (Gu et al. 2022), then change the conversion possibility of every land usage kind, and forecast land

Table 2 Soil carbon density table in Hanzhong City (t/hm^2)

Land-use type	C_{above}	C_{below}	C_{soil}	C_{dead}
Cultivated land	4.87	36.58	78.92	0.74
Forest land	59.2	15.45	125.41	1.95
Grassland	6.24	48.67	122.2	0.46
Water	2.26	11.25	0	0
Construction land	0.72	0	6.37	0
Unused land	0.99	1.2	0	0

Table 3 Land usage neighborhood weights for different land use types

Scenario	Cultivated land	Forest	Grassland	Water	Construction land	Unused land
Natural development	0.9	0.286595	0.028285	0.017608	0.565087	0.01
Ecological protection	0.977060	0.090429	0.9	0.003980	0.063510	0.01

Table 4 Land usage transfer matrix in the context of EPS

Land usage kind	Cultivated land	Forest	Grassland	Water	Construction land	Unused land
Cultivated land	1	1	1	0	1	1
Forest	0	1	1	0	0	0
Grassland	0	1	1	0	0	0
Water	0	0	1	1	0	0
Construction land	0	0	0	0	1	0
Unused land	1	1	1	1	1	1

usage demand and neighborhood weight with Markov chains in 2030 and 2060. In line with the ecological protection scenario's criteria for land use conversion and considering the specific conditions of Hanzhong City, the neighborhood weights for various land usage kinds were established (Table 3). Furthermore, the land usage transfer matrix under the framework of EPS was determined (Table 4), where "1" signifies transferable, and "0" indicates non-transferable.

Result

Research results on land use type transfer

The land usage kinds are mostly forest and grassland, occupying 71.16% of the total. From 1990 to 2020, the overall land usage variations were dominated by forestland, grassland, and construction land. The area of forestland and grassland declined, but the area of construction land grew, which had a negative impact on the increase of ECS. From 1990 to 2020, the land usage kind had been converted from arable land to forest, grassland, and construction land with a larger area of 126.44 km^2, 381.36 km^2, and 130.21 km^2 respectively (Fig. 3). This was related to the transfer of arable land to forest and grassland and the occupation of cultivated land as construction land. The mutual change between forest and grassland was also at a high level, with 133.95 km^2 converted from forest to grassland and 660.46 km^2 converted from grassland to woodland. The major source of construction land expansion was arable land. From 1990 to 2020, the construction land area had grown by 113.51 km^2, and part of the construction land had returned to cultivated land, forest, and grassland, whose area reached 27.9 km^2. The
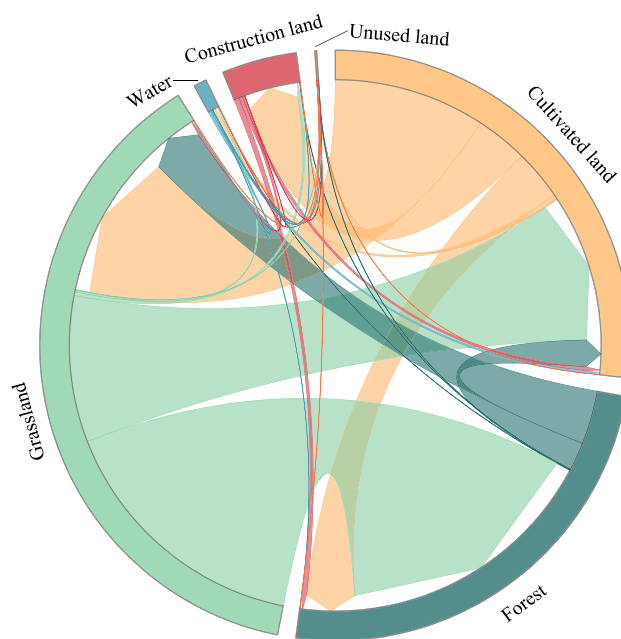

Fig. 3 Transference of land usage kinds from 1990 to 2020

main source of construction land was arable land occupying 91.6% of the grown construction land area. All of these had a greater impact on changes in ECS.

Temporal and spatial variations in ECS

Variations in ECS quantity

It was showed that the total ECS, underground biomass, aboveground biomass, soil organic carbon, and total dead organic matter (Fig. 4). The spatial distribution of ECS obtained by the ECS module of the InVEST model from 1990 to 2020 had occurred a series of changes (Fig. 5).
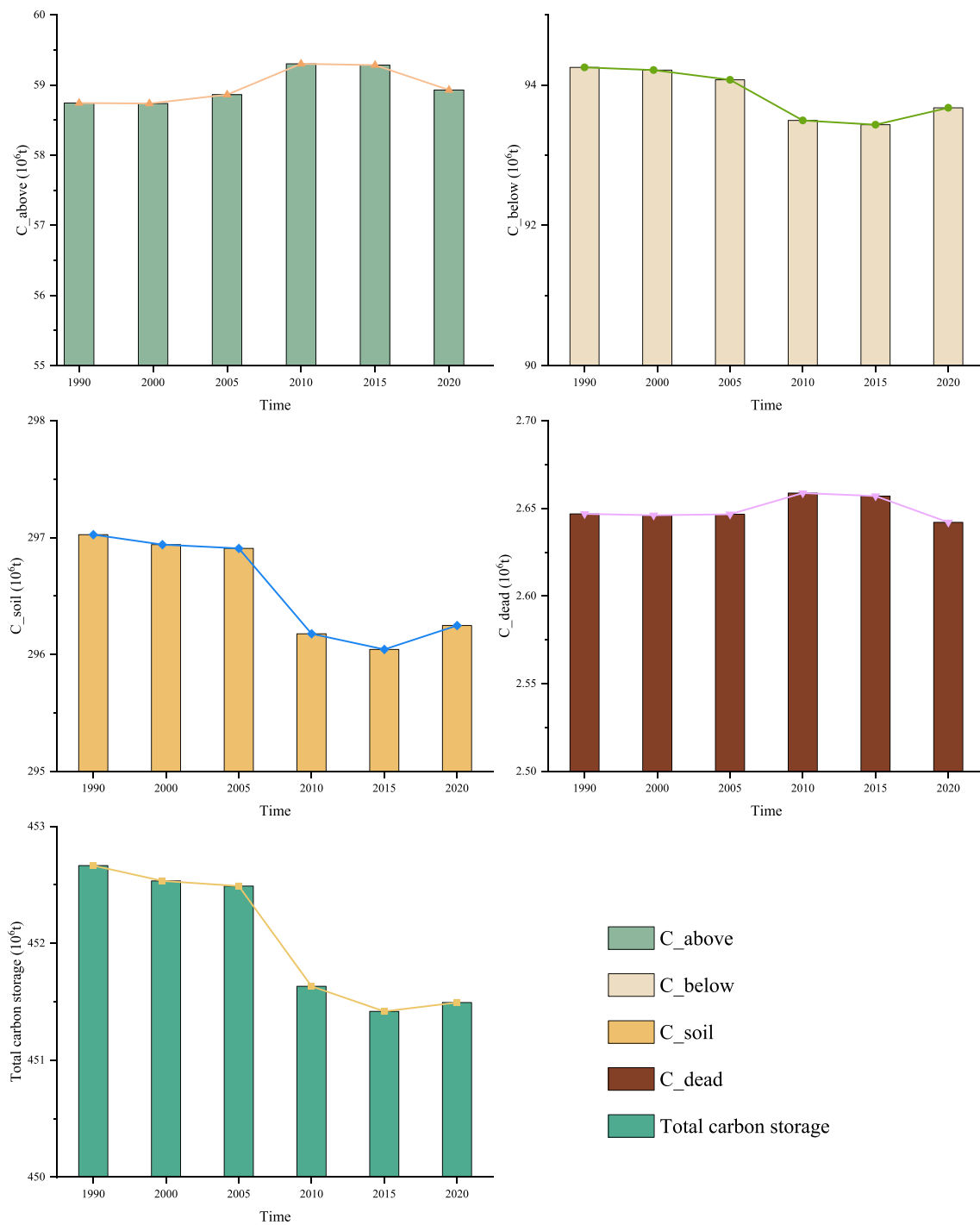
Fig. 4 Annual changes in total ECS in Hanzhong City

The total ECS in 1990 was 452.6650×10^6 t, the total ECS in 2000 was 452.5338×10^6 t, the total ECS in 2005 was 452.4890×10^6 t, the total ECS in 2010 was 451.6323×10^6 t, and the total ECS in 2015 was 451.4173×10^6 t, and the total ECS in 2020 was 451.4929×10^6 t. ECS generally displayed a declining tendency from 1990 to 2020, and increased slightly from 2015 to 2020. The aboveground biomass of

vegetation displayed a total growing tendency from 1990 to 2020, while the aboveground biomass decreased slightly from 2015 to 2020. Since there was a certain proportional relationship between aboveground biomass and underground biomass of vegetation, called the root-to-shoot ratio, the changes in vegetation underground biomass were consistent with the changes in aboveground biomass. Soil organic

Fig. 5 Spatial distribution map of ECS
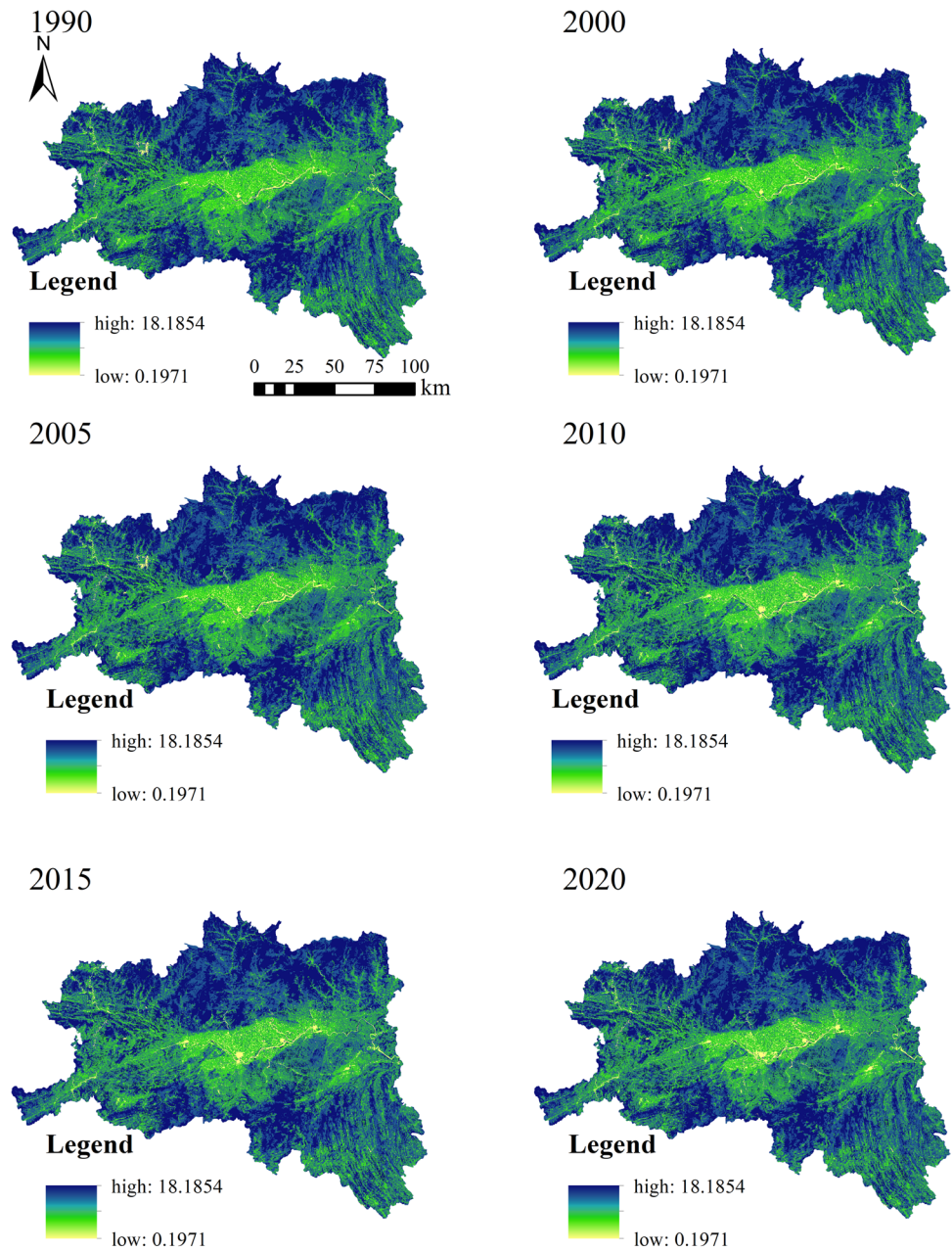
carbon occupied the overwhelming majority of the total carbon reserves. Soil organic carbon gradually decreased from 1990 to 2015, while the total soil organic carbon increased slightly from 2015 to 2020.

Spatial changes in ECS in the study area

High ECS areas were allocated in the north and south, mainly forest and grassland, accounting for 74.4% of total ECS (Fig. 5). The central location was a low-ECS area, occupying 25.6% of the total ECS. The high ECS area in the northern part of the research area included all of Liuba County, etc. To the south that was the Bashan Mountains,

the land usage kinds were mostly forest and grassland. It was a significant carbon sink area and also contains huge ECS. The high ECS area in southern area included most area of Ningqiang County, etc. The center was located in the Hanzhong Basin plain area and was the political and economic center, so it had lower ECS. The Loess Plateau, land desertification, and Hanzhong urban agglomeration in northern Shaanxi had resulted in lower carbon sinks. The ECS of Shaanxi Province was mainly in southern area of Shaanxi, and the ECS accounted for 15.0% of the total region's ECS, making it an important ECS area (Wang et al. 2022c).

Spatial autocorrelation analysis of ECS from 1990 to 2020 was performed by creating spatial weight matrix

of adjacency effect, and the Moran's *I* were obtained as 0.75905, 0.76037, 0.76214, 0.76511, 0.76669, and 0.75831 respectively (Gong et al. 2023), indicating that the distribution of ECS showed a high positive association with the geographical location of the research area and the spatial distribution is clustered (Fig. 5). High-high

ECS areas were allocated in a small part of the north and south from the LISA cluster map in 2020 (Fig. 6), where the Qinling Mountains and Daba Mountains located in and there was a large distribution of forests, accounting for 21.31% of the total area. While low-low ECS areas were allocated in the central part that was the Hanzhong
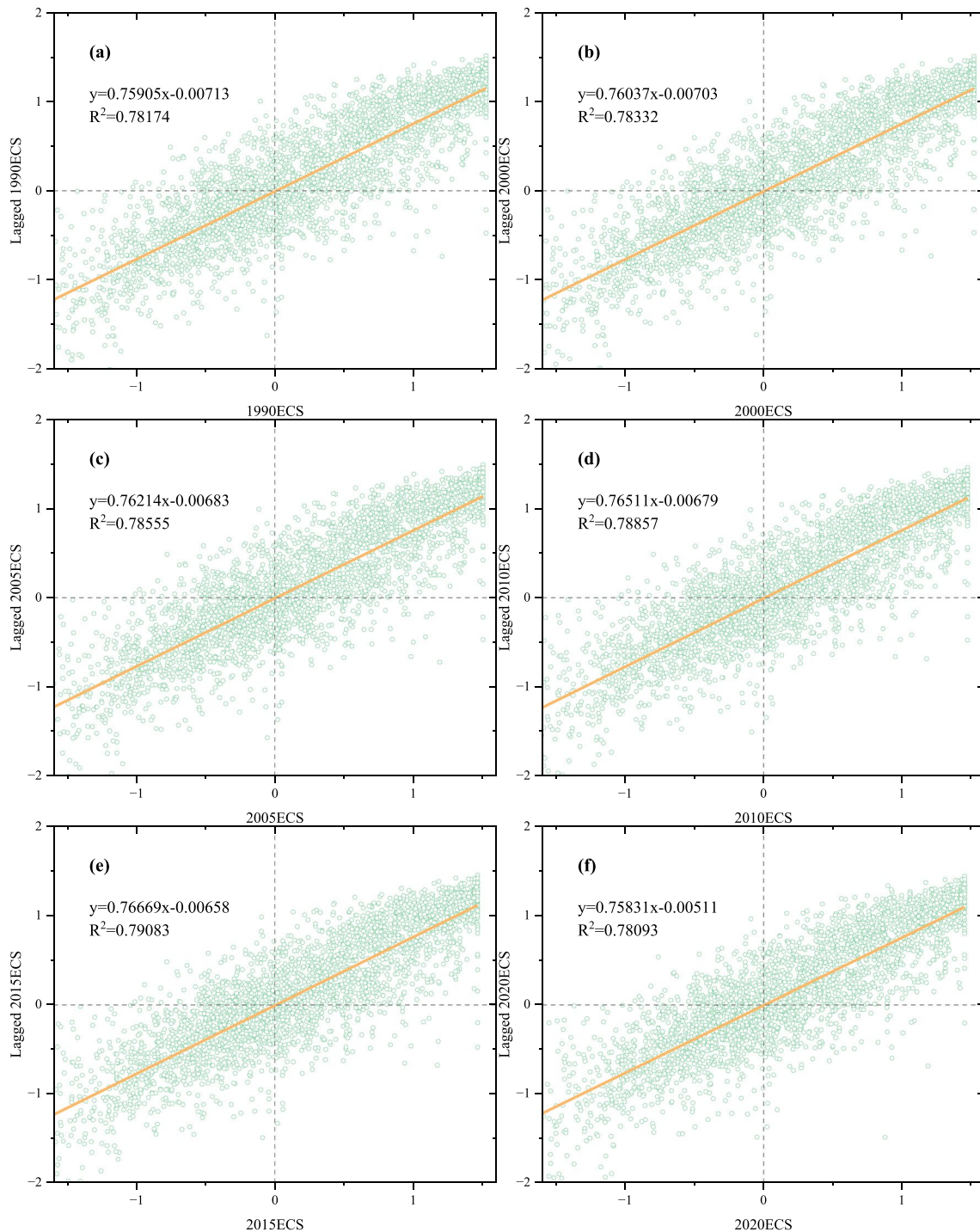

Fig. 6 Moran scatter plot t of ECS from 1990 to 2020

Plain area, which was an area where humans gathered, and agriculture and industry were relatively developed, accounting for 13.70%. The location of high-low area in a small part of the south and north of the low-low area was found, showing the characteristics of discrete distribution (Fig. 7).
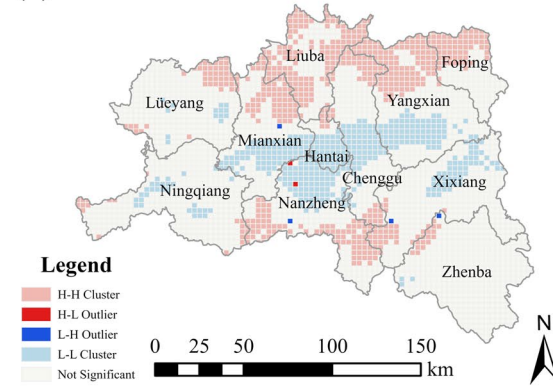
Changes in ECS in counties and districts of the area

The changes in ECS were more obvious from 2005 to 2010 and from 2015 to 2020 (Fig. 8). From 2005 to 2010, ECS in most counties showed a decrease, and Lueyang County and Foping County showed an increase. The increase in Lueyang County was larger, at 262,000 tons. The ECS in Xixiang County and Yang County decreased significantly, 235,800 t and 211,800 t respectively, accounting for 38.91% of the
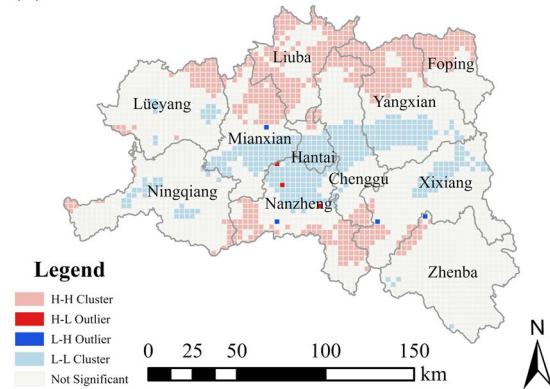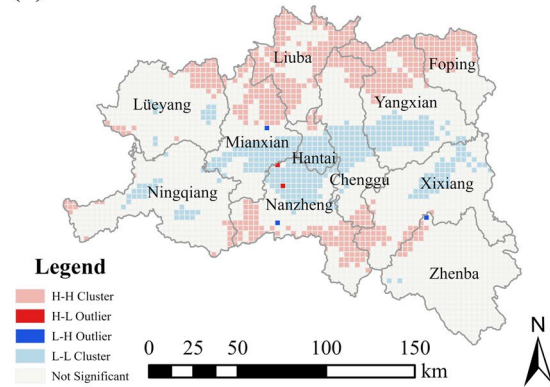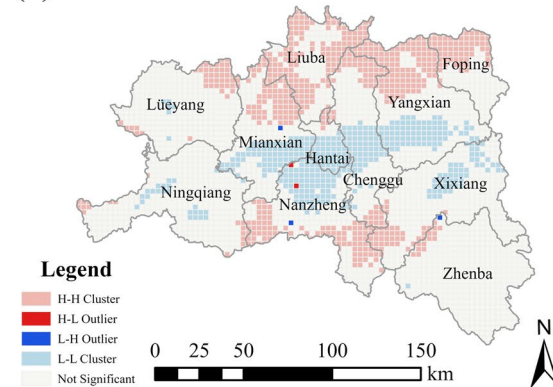

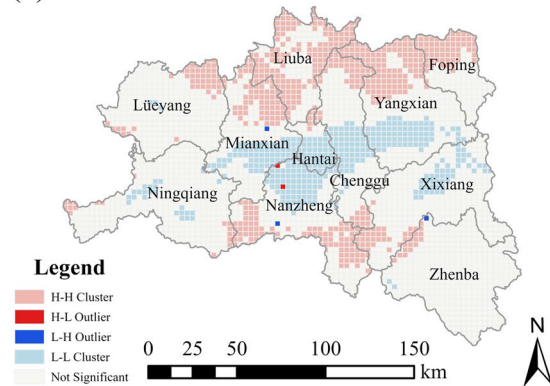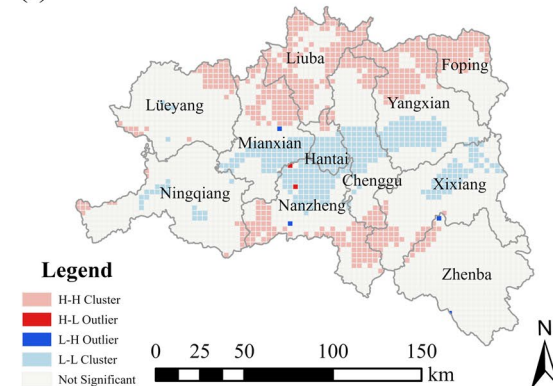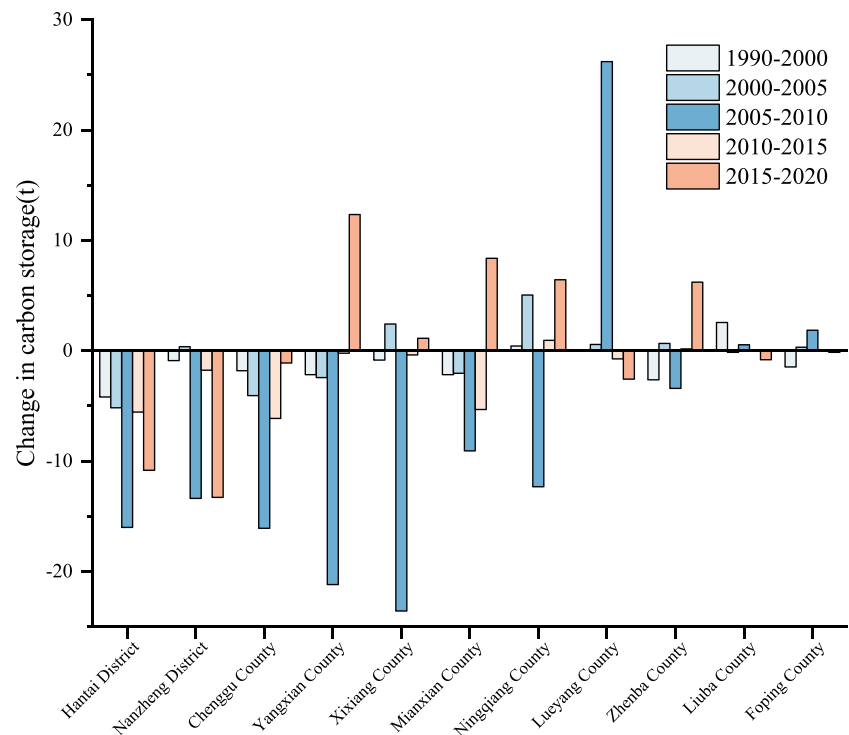**Fig. 7** LISA spatial clustering chart of ECS from 1990 to 2020

Fig. 8 Changes in ECS over time in various counties and districts

ECS reduction. From 2015 to 2020, the ECS of Hantai District and Nanzheng District showed a large decrease, and Yangxian county, et.al showed a large increase, while the ECS of other counties showed less changes. Hantai District and Nanzheng District were located in the Hanzhong Plain, and their construction land areas had increased significantly, reaching 10.07 km^2 and 7.72 km^2 respectively. Yangxian County, on the other hand, experienced a larger increase in ECS due to an increase in grassland area of 20.33 km^2.

Changes in ECS levels from 1990 to 2020

The spatial allocation of ECS in the research area from 1990 to 2020 was divided into low ECS areas, medium storage areas, and high ECS areas, and the ECS distribution levels are defined as three levels: I, II, and III respectively using natural breakpoint classification (NBC) (Wu et al. 2021).

- Level I areas were mainly human activity areas and waters and some unused land, accounting for a small area.
- Level II areas were medium ECS areas, which were mainly grassland, cultivated land, and a small number of human activity areas. They also played a significant role in ecosystem carbon sinks. As China have strengthened the protection of ecosystems, some of these areas would be converted into high ECS areas and urban expansion would occupy cultivated land and grassland, leading to the reduction of medium ECS areas.

- Level III areas, forests were mainly distributed, and taking 2020 as an example, the high ECS area was a national key protected area with a large amount of forest resources distributed. It was an important area for carbon sinks in Shaanxi Province, China, in terms of ecosystem carbon sinks, the area played a key role in realizing carbon neutralizing targets.

Between 1990 and 2020, the three levels of ECS distribution areas had basically remained unchanged (Fig. 9). Level I areas, that was, lower ECS areas accounted for a smaller proportion, about 1.4% of the total area. Level II areas occupied about 68.6% of the entire area, it was the main ECS distribution area, and level III areas accounted for approximately 30.0%. This result was due to that there were vast forests and grassland resources in the north and south mountains, and relatively few human active areas. From 1990 to 2020, level II areas had shown a slight downward trend, which might be related to the occupation of arable land by converting cultivated land to forest and grassland, while level III areas had shown a slight upward trend.

Between 1990 and 2000, the land use changes during this period were negligible; therefore, the changes in ECS levels were small, and there were only changes in a small number of areas. For example, the changed area from level II area to level I area was only about 10 km^2.

As China's policies including returning cultivated land to forest and developing the western region are adopted, the ECS level had changed significantly from 2000 to
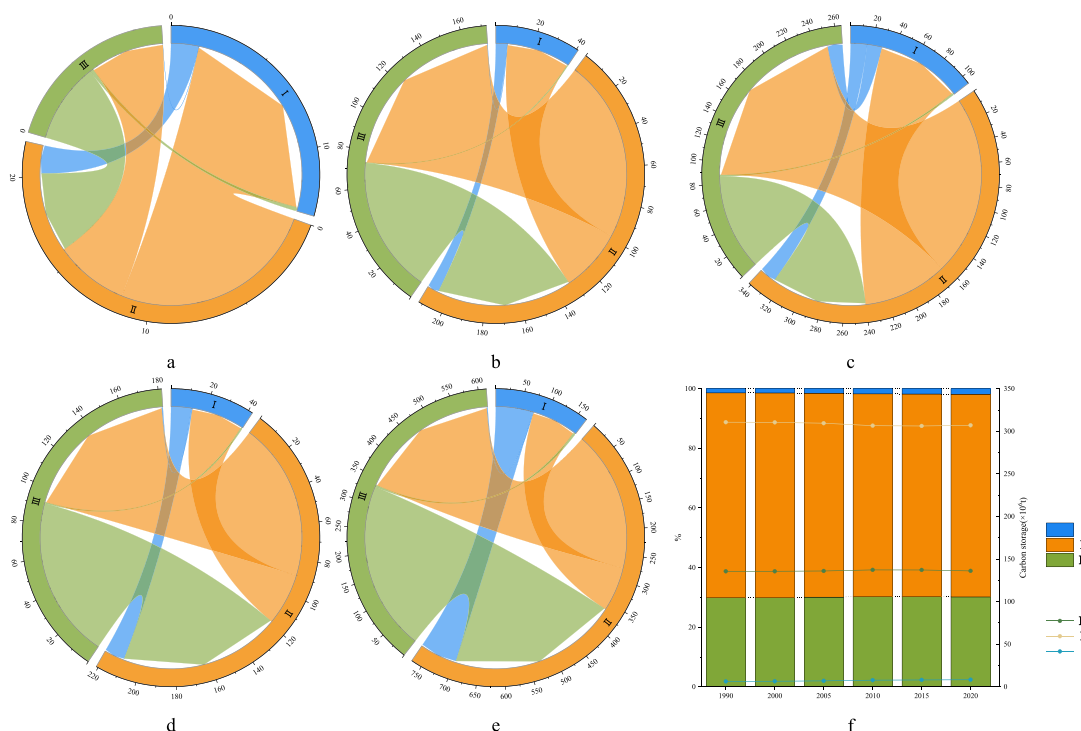
Fig. 9 1990–2020 ECS grade evolution and total change in the research are as follows: (**a**) 1990–2000; (**b**) 2000–2005; (**c**) 2005–2010; (**d**) 2010–1015; (**e**) 2015–2020; (**f**) the proportion of each grade and the change in ECS in each year

2005, evolving from level II areas to level I and level III areas with areas of 34.0 km^2 and 98.4 km^2 respectively and the area that evolved from level III area to level II area was 73.3km^2. Between 2005 and 2010, a discernible shift occurred in the ECS classification of various areas. Specifically, 34.0 km^2 of level II zones advanced to level I, while another 98.4 km^2 was downgraded to level III. Concurrently, an expanse of 73.3 km^2 transitioned from level III to level II. As the decade progressed, the pattern of change became more pronounced. In the span leading up to 2010, level II areas yielded 76.9 km^2 to level I and relinquished 163.5 km^2 to level III. Conversely, level III areas saw a reduction, with 86.7 km^2 elevating to level II status. The interval from 2010 to 2015 marked a continuation of this trend, albeit at a modified pace. Level I welcomed 29.3 km^2 from level II, and level III incorporated an additional 89.2 km^2 from the same. Interestingly, level II zones recovered slightly by absorbing 91.0 km^2 from level III. In the final 5-year period leading up to 2020, the transformations intensified. A considerable 87.6 km^2 of level II territory ascended to level I, and a significant surge saw 276.0 km^2 relegated to level III, highlighting a dynamic landscape of ECS capabilities across the regions. Overall, from 1990 to 2020, the distribution area of ECS levels had varied greatly, and the areas that had evolved from level II areas to level I and level III areas were 165.2 km^2 and 316.4 km^2 respectively. The areas that had evolved from

level III areas to level II areas were 273.3 km^2. Overall, the ECS showed a better trend.

Prediction of ECS in 2030 and 2060

Contribution of various influencing factors in the PLUS model

The study predicts future land usage spatial distribution on basis of the PLUS model, using land usage information in 2010 and 2020 as the basis for model prediction. The LEAS module selects 12 driving elements and obtains the land usage development potential map through the random forest algorithm. The root means square errors of the prediction of arable land, forest land, grassland, water, construction land, and unused land are 0.1489, 0.1098, 0.1577, 0.0245, 0.0403, and 0.0077. For the expansion of cultivated land, elevation, night light index, and GDP have the greatest contribution, accounting for 35.8% of the total contribution; for forest land expansion, elevation and precipitation have the greatest contribution, accounting for 27.2% of the total contribution, which are closely related to the growth of forests (Fig. 10). Elevation, population density, and distance to trunk road are the main contributing elements to grassland expansion, accounting for 34.7% of the contribution factors to grassland expansion. Elevation is the main contributing factors to water body expansion, accounting for 32.9% of

Fig. 10 Contribution diagram of driving factors for land use expansion
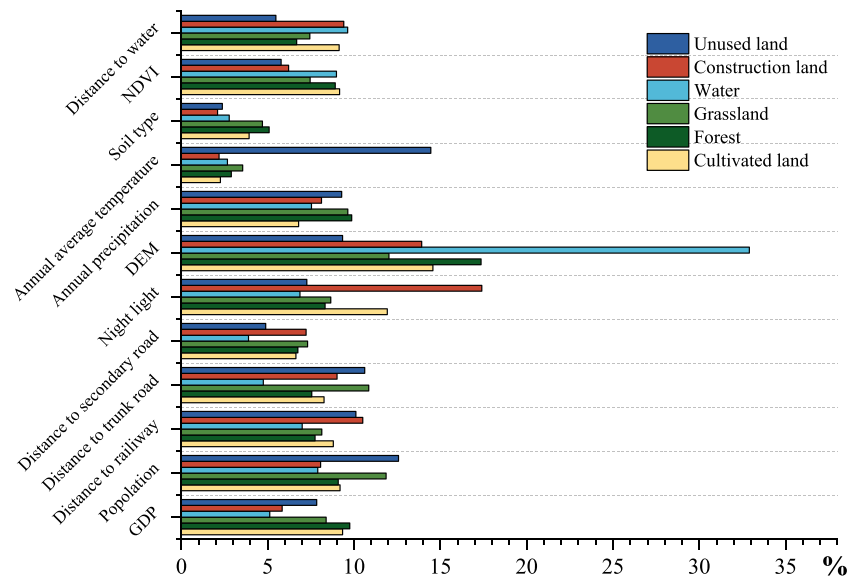
the total contribution, which is consistent with the facts. The major contributing elements to the expansion of construction land are night light index, elevation, and distance to railway, accounting for 41.8% of the overall development contribution. The night light index represents the density of human activity areas, thus having a significant impact on the expansion of construction land. The elements that have the greatest influence on the overall land use transfer are elevation, population density, distance to railway, and GDP.

Prediction precision of PLUS model

The land usage allocation in 2020 under the framework of NDS was predicted with the PLUS model, and by comparing with the land usage data in 2020 of the CAS in the PLUS v1.4 boxed software, the Kappa parameter of the model was obtained to be 0.88, and the total precision is 0.92. When the Kappa parameter is above 0.75, we consider the precision of the model to be higher (Jescovitch et al. 2021). This shows that the PLUS model in this research has high model precision and can be employed to forecast future land usage changes. There are some slight differences between the detailed drawings forecast by the PLUS model and the actual land usage map (Fig. 11).

Spatial distribution of ECS predictions for 2030 and 2060

The PLUS prediction model in the study has high prediction precision and can be adopted to forecast future ECS. According to the forecast outcomes, in 2030, under the framework of NDS, the total ECS will be 452.6475×10^6 t, and under the framework of EPS, the total ECS will be 454.5506×10^6 t. Under the framework of NDS in 2060, the ECS will reach 452.7730×10^6 t, and under the framework of EPS, the ECS

will reach 455.9290×10^6 t. Under the framework of NDS in 2030, ECS will grow by 1.1546×10^6 t compared with 2020, while the ECS under the framework of EPS will have 3.0577×10^6 t more total terrestrial ECS than the NDS. In 2060, under the framework of NDS, ECS will increase by 1.4361×10^6 t compared with 2030, while the ECS under the framework of EPS will have a total ECS that is 4.4361×10^6 t above the NDS. The prediction results of ECS show that under two development scenes (NDS and EPS) in 2030 and 2060, ECS will show growth changes, which plays a positive role in the achievement of the "double carbon" objective. Under the framework of the EPS, the increase in ECS is much greater than the NDS. The future development path should coordinate the development of economy and ecological environment protection, and make ecological protection a priority for future development.

The CARS module of the PLUS model obtained the land usage distribution maps in 2030 and 2060, and the ECS module of the InVEST model was adopted to obtain the spatial distribution maps of ECS for the two development scenarios (Fig. 12). The ECS prediction map under two development scenarios in 2030 and 2060 divides each pixel point according to its value using the Jenks method and divides it into a low ECS area ($0 \le C_{cell} \le 1.2159$), a medium ECS area ($1.2159 < C_{cell} \le 10.8999$), and a high ECS area ($10.8999 < C_{cell}$), and the unit is ton (Fig. 13). Under the two prediction scenes, the high ECS areas in 2030 and 2060 are distributed in the forest and grassland regions in the north and south, including northern Lueyang County. Medium ECS area is located in the central, western, and eastern regions, including southern Lueyang County and southern Mianxian County. The low ECS areas are distributed in the central human activity region, including Hantai District.

Fig. 11 Actual and predicted land use maps of PLUS model; (**a**) the land use map from the Resource and Environment Data Center of the Chinese Academy of Sciences; (**b**) land use predicted by PLUS Model
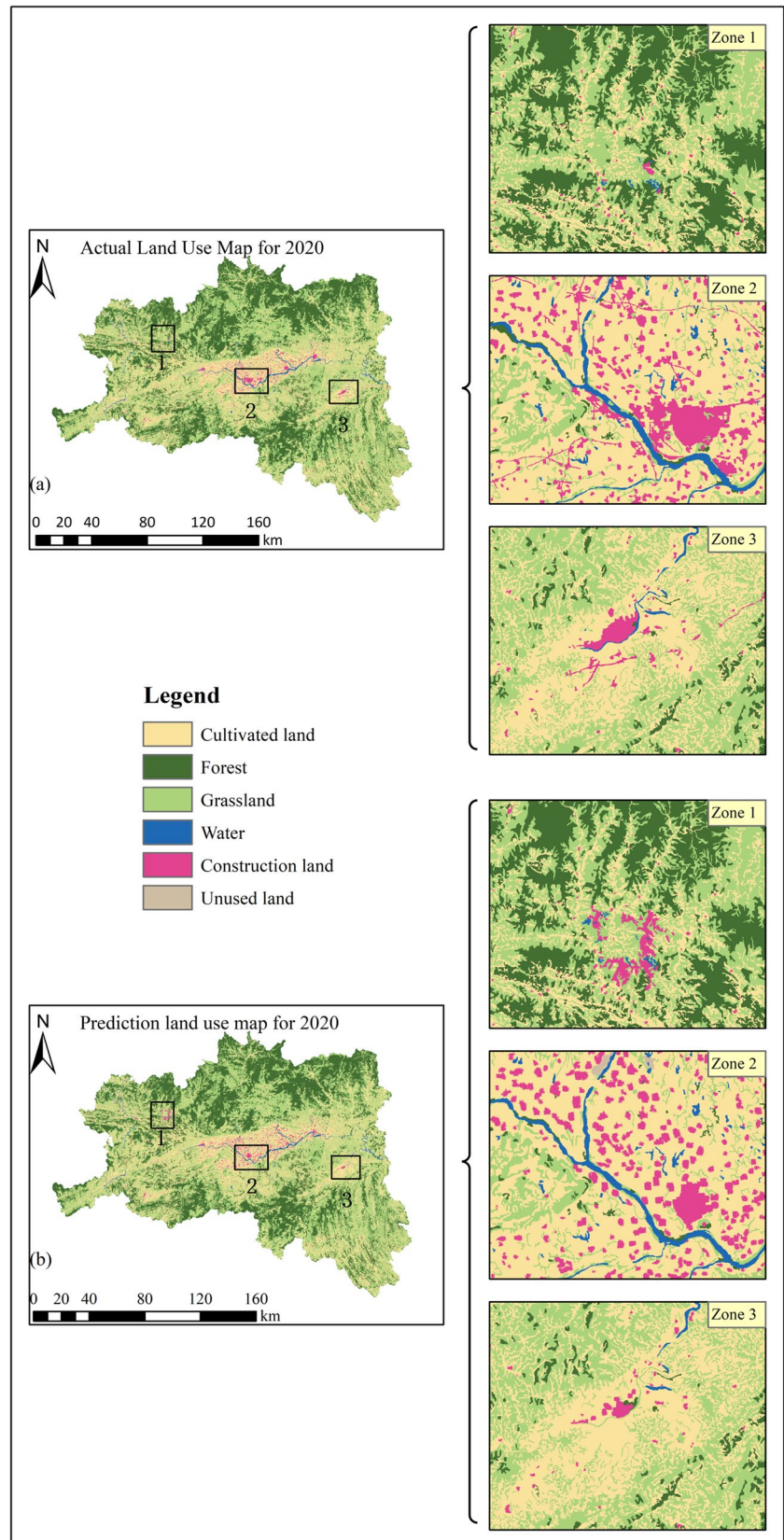
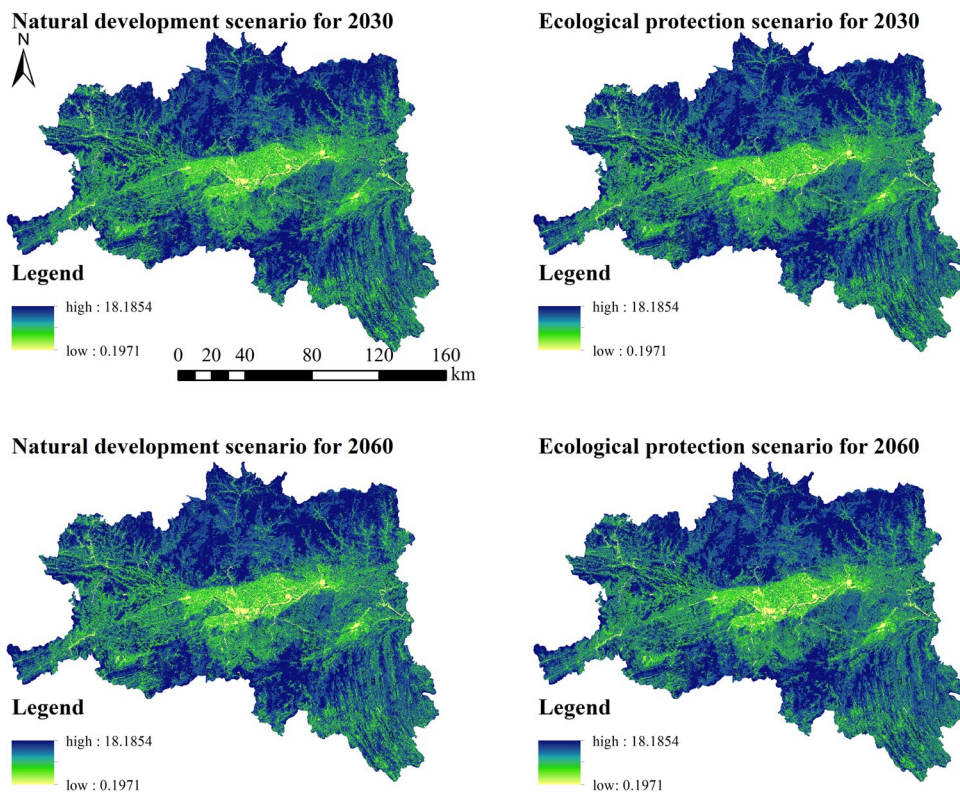**Fig. 12** Spatial distribution map of predicted ECS in the research area in 2030 and 2060

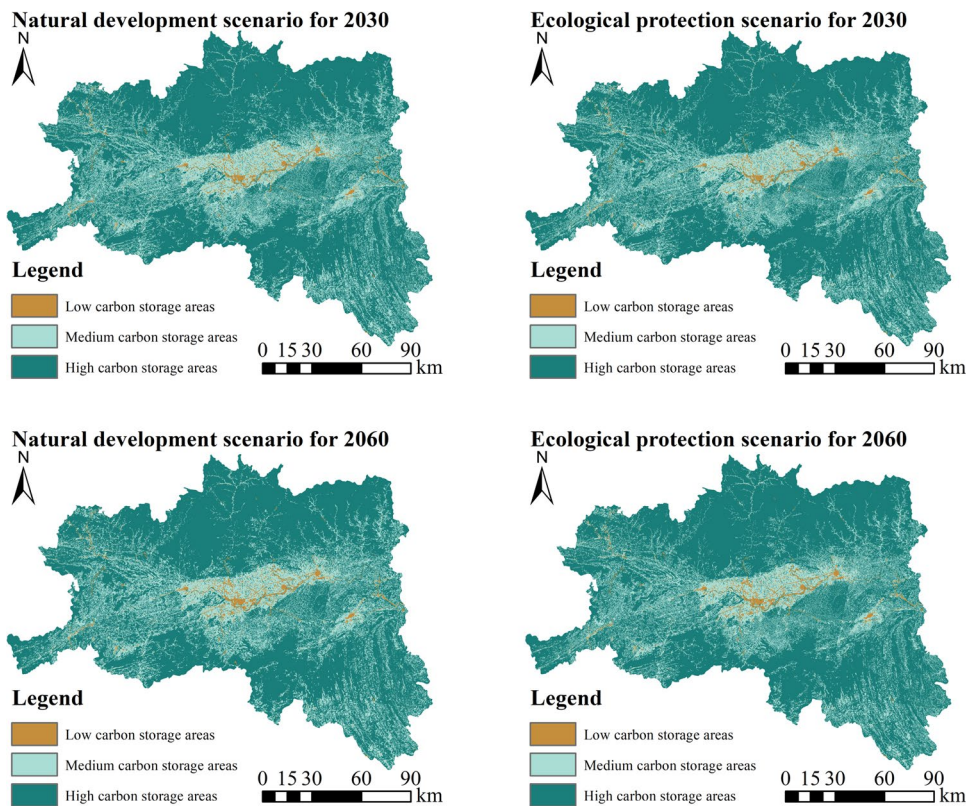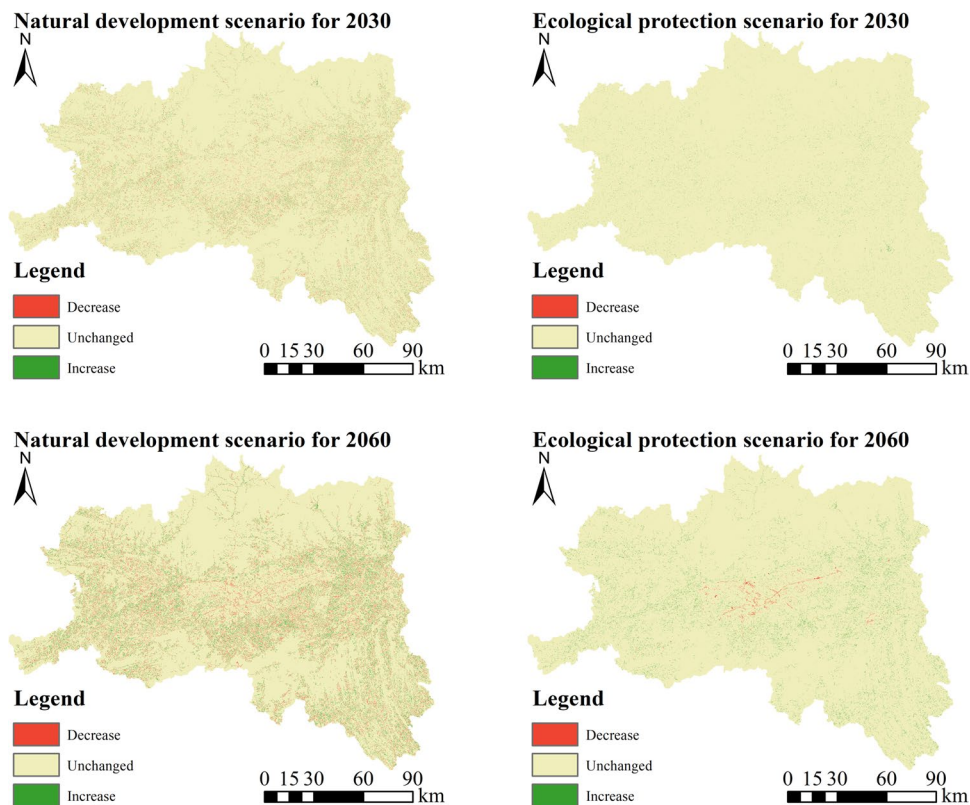**Fig. 13** Partition maps of ECS prediction under different scenarios

Fig. 14 Changes in ECS prediction for 2030 and 2060

Natural development scenario for 2030

Ecological protection scenario for 2030

Natural development scenario for 2060

Ecological protection scenario for 2060

Compared with the ECS in 2020, under the framework of NDS, the ECS will decline in a large region in 2030, with a reduction area of 595.26 km^2, distributed in the central area (Fig. 14). While under the framework of EPS, the area of ECS increase is 321.76 km^2, which is distributed in the human activity area in the center. Because of the optimization of land usage in the ecological protection scene, the ECS increases (Ren et al. 2023). Compared with 2020, in 2060, under the framework of NDS, ECS will also decrease in a large area, with a reduced area of 1231.42 km^2, mostly allocated in the central Hanzhong Plain area. Under the framework of EPS, the research area's ECS increased significantly, with an increase area of 759.01 km^2, allocated in the central, western, and eastern parts of the area. These areas contain a lot of arable land and construction land, which are of human activity areas (Wei et al. 2023). Due to in the ecological protection scenario, the protection of forest and grassland and the restriction of the expansion of construction land into forest and grassland will lead to a larger area of ECS increase (Yang et al. 2023).

Discussion

Practical analysis of coupling ECS model analysis in environmental management

In this study, the integration of the InVEST model with geographic evolutionary analysis and the PLUS model marks a significant methodological advancement in simulating land use changes and assessing ECS capabilities within environmental management frameworks (Wang et al. 2022d). The combination of these models utilizes the precision of the InVEST model in obtaining detailed carbon density information and its analysis of spatial characteristics and evolutionary processes. At the same time, it benefits from the simplicity and high accuracy of the PLUS model, enhancing our predictive capabilities regarding land use changes (He et al. 2023b; Zarandian et al. 2023). This synergistic effect signifies a pioneering step

in simulating land use changes and evaluating ECS within the scope of environmental management. We applied this integrated approach to Hanzhong City, providing a practical case study. The city can tackle its unique challenges in land use and environmental management by referencing the model suggested. This case study demonstrates the model's effectiveness in real world scenarios, showing its practical applicability and potential scalability in similar urban environments, which underscores the importance of localized carbon management strategies, offering valuable insights for local governments in formulating effective climate adaptation and mitigation policies. This study extends beyond Hanzhong City, offering global applicability. Considering various urban densities, climatic conditions, and ecological diversities, the versatility of the integrated model is evident in its potential to adapt to diverse urban settings globally (Shao et al. 2023). The model provides a scalable framework for planning and managing ECS in different urban environments (Guo et al. 2024). Quantitatively, there is an increase in the accuracy of predictions related to land use changes and carbon sequestration. Qualitatively, the model contributes to a better understanding of decision-making processes, assisting policymakers and stakeholders in developing more effective environmental strategies (Li et al. 2023a). The results of this study have significant implications for environmental policy at both local and global levels (Fernandes et al. 2020). The insights derived could lead to more informed policy decisions, emphasizing sustainable development and conservation, and could inspire new initiatives aimed at environmental stewardship and sustainable urban planning. While the integration of the models marks a significant step forward, there are challenges and limitations inherent in this approach (Tao et al. 2023). Future research should focus on refining these models, exploring additional integrations, and expanding their application to diverse urban environments globally to further validate and enhance their efficacy.

Analysis of changes in historical ECS

Land use change directly determines the change in ECS. High ECS is distributed in areas with lush vegetation and good ecological environment, while low ECS areas are located in ecologically fragile areas (He et al. 2023a, b; Li et al. 2023b; Wei et al. 2023). From 1990 to 2020, with the continuous economic growth and urban expansion, the construction land continued to increase (Liu and Xin 2022). The main source of conversion of construction land in the research area was cultivated land, accounting for 91.6% of the source, which was related to the research area's economic growth and ecological protection policies in the past 30 years (Wei et al. 2023; Zhang et al. 2022b). The north and

south of the research region were covered by large areas of forest and grassland, which were restricted areas for human activities, while the central part was the Hanzhong Plain, which was the center of human activities (Yang et al. 2022). As Shaanxi Province continued to promote the Qinling Mountains protection policy, and the research region was located at the southern foot of the Qinling Mountains, with the Daba Mountains southern, and there were few human activities (Li et al. 2022c). Therefore, as construction land expands, less construction land being converted from forest and grassland had been resulted in. Shaanxi Province is the earliest pilot province in the country to convert farmland into forests, and with the execution of the natural forest resource protection policy (Ding and Yao 2022), the area of arable land in the region had declined (Wang and Gong 2022), while the area of forest and grassland had grown, which was beneficial to the area's ECS increasing. In 2020, forest land increased by 7.3% compared with 1990, while the grassland area decreased by 4.6%, while due to the advancement of ecological projects in Shaanxi Province, the main source of forest land expansion was grassland (Zou et al. 2022). From the ECS variations in the research region in the past 30 years, it could be seen that with high ECS correlated with regions of dense vegetation and robust ecological environments (Ning et al. 2021). This aligns with and builds upon previous studies by offering a detailed exploration of land use transformations in Hanzhong and their implications for ECS over a 30-year timeline (Li et al. 2022a). While corroborating general trends identified in earlier research, this study also uncovers the nuanced effects of urban expansion and ecological conservation policies on ECS within this specific urban context (Wang et al. 2022b). The detailed analysis underscores the importance of continuous ecological conservation efforts and highlights the potential impacts of urban planning decisions on the region's ecological sustainability. By offering localized yet globally relevant insights into ECS dynamics, the study contributes to the broader discourse on sustainable urban development and ecological conservation.

Some suggestions of terrestrial ECS in the research region

The essence of carbon storage prediction lies in its ability to inform tailored management strategies for different forecasted zones, a concept which warrants further elaboration. For the areas with high ECS in the ecological protection scenario of the prediction results (Fig. 13), the focus would be on preserving and enhancing the existing ecological assets. This would involve stringent conservation efforts, such as the enforcement of strict regulations against land degradation activities, along with proactive measures like reforestation or the restoration of degraded lands to their natural

state (Wang et al. 2022b). These areas, being critical carbon sinks, require a heightened level of protection to maintain and possibly increase their carbon sequestration potential (Huang et al. 2021). In contrast, areas with moderate carbon storage might necessitate a different set of actions. These regions could benefit from balanced approaches that combine conservation with sustainable land use. Strategies could include controlled afforestation, selective logging practices that ensure regeneration (Fu et al. 2022), and the integration of sustainable agricultural practices that help maintain or moderately increase carbon storage without compromising the land's usability for human purposes (Ding et al. 2022). For areas with low carbon storage, which is generally an area of human activity, the approach shifts towards transforming these regions into more efficient carbon sinks. This could be realized by adopting innovative land use planning with carbon sequestration as a central goal, coupled with the implementation of energy-saving and emission-reduction strategies in construction zones, and the development of renewable energy sources (Cheng et al. 2022). Urban planning, for instance, can integrate green spaces effectively, promoting urban forestry and rooftop gardens, which not only enhance the esthetic appeal of the city but also contribute to carbon storage (Raihan et al. 2022). For areas with increased ECS in the ecological protection scenario (Fig. 14), policies should be implemented to protect forest and grassland, limit the change of forest and grassland to other land usage kinds, and keep the carbon sink capacity of forests and grassland (Pan et al. 2023). For areas with reduced ECS, the expansion of construction land into this area should be restricted and forest, grassland, and cultivated land should be protected (Wang et al. 2022a).

Research prospect analysis

This study conducted a quantitative analysis of the area's ECS from a land use perspective, and provided reference opinions for the implementation of the area's "dual carbon" policy. The global relevance of the findings lies in the demonstration of how urban areas, through strategic planning and policy implementation, can effectively manage and improve their ECS, contributing to global climate change mitigation efforts. However, this approach had limitations, including its simplified representation of carbon cycling and its reliance on linear projections for carbon sequestration changes (Tao et al. 2023). Future research directions should focus on overcoming its limitations by incorporating more complex representations of carbon cycling and predictions of non-linear changes. Moreover, there was a lack of information on the impact of ecological protection projects executed over the past 30 years, such as the conversion of farmland to forest project. Future ECS research can embark on the viewpoint of ecological engineering and

detail the impact of ecological protection projects on the changes in ECS in the research area (Wang et al. 2022b), and provide specific opinions on the research area's future carbon sink policy from the viewpoint of ecological protection engineering (Gu et al. 2022). Two different prediction scenes were set up in this research, namely the NDS and the EPS, but the parameter settings of these two scenarios are still quite different from the actual future development (Sun et al. 2022). Therefore, combining local policies and future development planning to set a more realistic future land usage demand and setting the parameters of the PLUS model more reasonably are the research directions for future ECS prediction (Ren et al. 2023). Since the ECS module of the InVEST model uses the average carbon density of the first-level classification of each land usage kind, the research results will deviate from the actual ECS to a certain extent (Li and Zhu 2022). The land use remote sensing data used has a resolution of 30 m, providing high resolution, but due to the limitations of remote sensing and the particularity of the study area being in a mountainous region, this data still cannot accurately reflect the actual land use changes. Other data such as socio-economic, climate, and carbon density data are derived from national data interpolations, so there may be deviations from actual data. Future ECS research should focus on finely classifying the vegetation growing in each land use, developing more accurate above-ground and underground biomass models of forest trees and herbaceous plants, and soil carbon density models, and finely classifying land use types, using two-level classification to optimize ECS calculations (Ding and Yao 2022). Integrating tree and vegetation growth equations to transform the assessment of carbon storage from a static to a dynamic process represents a future research direction (Zhao et al. 2022).

Conclusion

This study analyzed the land usage transfer, adopted the coupling model GEP to calculate and explore the historical ECS and analyzed its geographical spatial characteristics and evolutionary patterns, and predicted the ECS in 2030 and 2060 on the framework of the NDS and EPS, and obtains the following conclusions:

1. The land usage transfer from 1990 to 2020 was mostly a growth in construction land and a decline in forestland and grassland areas, which had an adverse impact on ECS.

2. The region area is an important carbon reservoir in Shaanxi Province. High ECS areas were distributed in northern and southern areas where there are forest and grassland areas, while low ECS areas were distributed in the central human activity area. Overall, the ECS

showed a better trend from 1990 to 2020 on an evolutionary perspective, which was related to economic and urban development policies.

3. The PLUS model was employed to forecast future land usage, whose Kappa coefficient is 0.88, had high prediction accuracy.

4. Under the framework of NDS in 2030, ECS increases slowly compared with 2020, while under the framework of EPS, the ECS increases more. Under the framework of NDS in 2060, ECS will increase less than in 2030, while under the framework of EPS, ECS will grow significantly. Therefore, the future development should focus on ecological protection, focusing on protecting the Qinba Mountains, optimizing land use layout, restricting the change of forest and grassland to other land usage kinds, and restricting the occupation of forest and grassland by human activities.

Author contribution Bing Yuan is the main contributor to the manuscript, a major participant in the research, and the writer of the manuscript. Kang Hou controls the overall direction of the research and manuscript, providing funding support. Yaxin Li participated in data collection and research content, while Pengcheng Sun provided methodological support.

Data availability Not applicable.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Competing interests The authors declare no competing interests.

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