Spatio-temporal evolution and prediction of carbon storage in Kunming based on PLUS and InVEST models

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Carbon storage is a key ecosystem service of terrestrial environmental systems, which can effectively alleviate regional carbon emissions and is important for achieving carbon neutrality and peaking carbon emissions. We conducted a study in Kunming and analyzed the land utilization data for 2000, 2010, and 2020. We assessed the features of land utilization conversion and forecasted land utilization under three development patterns in 2030 on the basis of the PLUS model. We used the InVEST model to estimate the changes in the trend of carbon storage under three development scenarios in 2000, 2010, 2020, and 2030 and to determine the impact of socio-economic factors and natural factors on carbon storage. The results of the study indicated that (1) Carbon storage is intimately associated with land utilization practices. Carbon storage in Kunming in 2000, 2010, and 2020 was 1.146 × 108 t, 1.139 × 108 t, and 1.120 × 108 t, respectively. During the 20 years, forest land decreased by 142.28 km2, and the decrease in forest land area caused loss of carbon storage. (2) The carbon storage under the trend continuation scenario, Eco-friendly scenario, and comprehensive development scenario in 2030 was predicted to be 1.102 × 108 t, 1.136 × 108 t, and 1.105 × 108 t, respectively, indicating that implementing ecological protection and cultivated land protection measures can facilitate regional ecosystem carbon storage restoring. (3) For the study area, Impervious surfaces and vegetation have the greatest degree of influence on carbon storage. A spatial global and local negative correlation was found between impervious surface coverage and ecosystem carbon storage. A spatial global, and local positive correlation was found between NDVI and ecosystem carbon storage. Therefore, ecological and farmland protection policies need to be strengthened, the expansion of impervious surfaces should be strictly controlled, and vegetation coverage should be improved.

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Abstract

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We conducted a study in Kunming and analyzed the land utilization data for 2000, 2010, and 2020. We assessed the features of land utilization conversion and forecasted land utilization under three development patterns in 2030 on the basis of the PLUS model. We used the InVEST model to estimate the changes in the trend of carbon storage under three development scenarios in 2000, 2010, 2020, and 2030 and to determine the impact of socio-economic factors and natural factors on carbon storage.

The results of the study indicated that (1) Carbon storage is intimately associated with land utilization practices. Carbon storage in Kunming in 2000, 2010, and 2020 was 1.146 × 108 t, 1.139 × 108 t, and 1.120 × 108 t, respectively. During the 20 years, forest land decreased by 142.28 km2, and the decrease in forest land area caused loss of carbon storage. (2) The carbon storage under the trend continuation scenario, Eco-friendly scenario, and comprehensive development scenario in 2030 was predicted to be 1.102 × 108 t, 1.136 × 108 t, and 1.105 × 108 t, respectively, indicating that implementing ecological protection and cultivated land protection measures can facilitate regional ecosystem carbon storage restoring. (3) For the study area, Impervious surfaces and vegetation have the greatest degree of influence on carbon storage. A spatial global and local negative correlation was found between impervious surface coverage and ecosystem carbon storage. A spatial global, and local positive correlation was found between NDVI and ecosystem carbon storage. Therefore, ecological and farmland protection policies

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Introduction

Due to rapid urbanization and industrialization, almost all cities around the world have experienced several climate-related and environmental problems (Cao, 2019; Sarkodie et al., 2020), such as acid rain and the greenhouse effect, which are linked to the increasing intensity of land utilization by humans (Xu et al., 2018). Carbon dioxide strongly influences the climate. Greenhouse gases such as carbon dioxide emitted in unusually large quantities due to human activities are the dominant causes of global warming and aggravate climate instability (Gao et al., 2022; Yang et al., 2022; Zhang et al., 2022). Carbon dioxide can be stored in vegetation and soil, which decreases the atmospheric carbon dioxide content (Dorendorf et al., 2015). The storage of carbon is vital for regulating the climate and is an important ecosystem service function. China is the world's top carbon emitter. At the 75th session of the United Nations General Assembly (2020), China pledged that it will aim to reach the peak of carbon emissions by 2030 and achieve carbon neutrality by 2060 (Chen et al., 2022).

Kunming is a vital city of Yunnan Province in China, and the main population and GDP of Yunnan Province are concentrated in this city. It is the most important center for the economic development of the province and is an essential corridor for economic and cultural communications between China and Southeast Asian countries. Additionally, Kunming has rich forest resources and biodiversity, and thus, is a vital area in the Yangtze River Economic Belt and an Eco-conservation shield in the upstream of the Yangtze River. In October 2021, The 15th Conference of the Parties (COP15) of the UN Convention on Biological Diversity was hosted in Kunming. At the conference, new ideas were presented for conserving worldwide biodiversity. During the 14th five-year plan period of China's national economic and social development, Yunnan Province pledged that it would strive “to become the vanguard of China's ecological civilization construction" as a long-term goal and incorporate the aim to achieve "peaking carbon emissions and carbon neutrality" into the general arrangement of economic development and the establishment of an Eco-civilization. To realize these goals, Yunnan should promote the establishment of an Eco-civilization, which is not only a significant embodiment of Yunnan’s initiative to serve the national developmental strategy, but also an important embodiment of integrating into the national development. Therefore, studying and forecasting the response of land utilization conversions to carbon storage in Kunming can help build a strong ecological security barrier in southwest China and provide theoretical support for reducing regional emissions.

The emission of large amounts of greenhouse gases poses a serious threat to the global climate and environment. Several studies in the field of the ecological environment have estimated regional carbon storage and carbon emissions (Cai and Peng, 2021; Gogoi et al., 2022; Li et al., 2022). Carbon storage is mainly estimated by traditional estimation methods and model methods. Traditional estimation methods, such as the sample inventory (Li et al., 2021) and the ecosystem carbon flux monitoring (Yang et al., 2022), evaluation models include CASA (Tong et al., 2016), Bookkeeping (Kong et al., 2018), InVEST (Zhang et al., 2022a), etc. The traditional estimation method is only suitable for small-area carbon storage research due to its large workload and low efficiency. The InVEST model is broadly applicable to the field of carbon sequestration research (Chen et al., 2021; Wang et al., 2022; Zhang et al., 2022a; Zhao et al., 2022) because it demands a small amount of data, has high speed of operation, and performs convenient space-time visualization. Studying the current space-time characteristics of carbon storage and predicting future variations in land use and carbon storage can help in realizing the 'double carbon' goal. Several researchers have investigated prospective land utilization and carbon storage prediction at different scales. With the FLUS and InVEST models, Shao et al. (2022) predicted the evolution of Beijing's carbon storage in 2035 under natural evolution scenario, population evacuation urban development scenario, and green intensive ecological protection scenario. They also conducted zoning management studies based on spatial autocorrelation models. Li et al. (Li et al., 2020) applied the SEUTH model to estimate the urban growth of Wuhan under different scenarios in 2030 and determined the consequences of urban aprawl on lacal carbon storage in combination with the InVEST model. Using the PLUS and InVEST models, Rukeya et al. (2022) dynamically evaluated the characteristics of land utilization and carbon storage varies in city cluster on the northern slope of Tianshan Mountains under different scenarios from 2000 to 2030. Ding et al. (2022) utilized the PLUS and InVEST models to investigate and predict evolution in land-use and carbon storage around the Hangzhou Bay since 2000 to 2018 and 2018 to 2030.

The models used to mimic futuristic land utilization/land cover mainly include CA-Markov (Song et al., 2022), FLUS (Xie et al., 2022), SD (Zhang et al., 2020b), PLUS (Yang et al., 2022), etc. Among them, the patch-level land use simulation model (PLUS) is a relatively new land utilization/land cover forecast model. By mining various driving factors, using the land expansion analysis strategy (LEAS), the random forest algorithm was used to obtain the development possibility of each category (Liang et al., 2021) to simulate the future changes in land use patches with greater accuracy in different years and different environments. The Markov model has higher accuracy in predicting quantities (Zhao et al., 2022). The integration of the PLUS model with the Markov model allows for better estimation of regional land utilization/land cover at different future development scenarios.

Several studies have predicted the space-time development in regional carbon storage by the model method. Therefore, in this study, we selected Kunming City in Yunnan Province as the study area taking the three-period land use raster dataset and driving factors during 2000 to 2020 as the basis. The goals of this study were as follows: (1) Based on the PLUS model, the land-use pattern under different development patterns in Kunming City in 2030 was predicted, and the land utilization transformation trend since 2000 to 2030 was analyzed. (2) The InVEST model was adopted to assess the time-space distribution and change of carbon storage in Kunming from 2000 to 2030 and determine the influential effect of land using on carbon storage in different periods. (3) The spatial correlation and influencing factors of carbon storage were analyzed to deliver a strong scientific foundation for achieving the goal of peaking carbon emissions and carbon neutralization on a geographical level.

Materials & Methods

Study area

Kunming is directly northeast of central Yunnan Province (102°10' ~ 103°40' E, 24°23' ~ 26°22' N) in the central Yunnan-Guizhou Plateau (Fig. 1) (Fang et al., 2021), is the administrative, commercial, and cultural center of Yunnan Province. The city has seven districts, three counties, one county-level city, and three autonomous regions. In 2021, Kunming had a permanent population of 8.520 million. The land area of Kunming is about 21,011.41 km2, and the elevation of the terrain decreases from north to south. The area has a low latitude highland monsoon climate, affected by the southwest monsoon of the Indian Ocean. The temperature is mild, winters are not very cold, and summers are not very hot, which is why this place is called 'Spring City'. Kunming is positioned in the southwest borderland of China and forms a connection between Southeast Asia and South Asia. It also acts as an overwhelming safe ecological barrier in southwest China. The city aims to become a model city of ecological civilization.

Data sources and preprocessing

The main data used for this research mainly included land utilization data, carbon density, driving factors, and other data. (1) Land utilization data: The land-use data (30 m × 30 m) was obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences. The data were selected in time: 2000, 2010 and 2020, and the geographic coordinate system used was GCS _ WGS _ 1984, which included 25 secondary land types and six primary land types (cultivated land, forest land, grassland, water area, construction land, and unused land). (2) Carbon density: The carbon density varies by land use types. The studies which had similar levels of natural resources (Ke and Tang, 2019) and climatic conditions (Yan et al., 2015; Tang et al., 2019) to that in the study area were selected as references. Then, the data were corrected according to the above-ground carbon density dadaset of the terrestrial ecosystem of China in 2010 and the carbon density dataset of soil in 0 ~ 100 cm of the terrestrial ecosystem of China in 2010. Finally, the carbon density dataset for land utilization categories in Kunming was obtained (Table 1). (3) Driving factors: The driving factor data for future land prediction included physical factors and social factors. The physical factors involved the DEM, slope, annual average rainfall, soil type, annual average temperature, and distance to the water system. The social factors included the GDP, distance to the government office, distance to the highway, distance to the main road (first-class road and second-class road), population density, data source, and resolution, as shown in Table 2. Next, ArcGIS was used to unify the resolution to 30 m × 30 m, and unified the geographic coordinate system to GCS _ WGS _ 1984. (4) Other data: Four Landsat 8 OLI and TIRS images in August 2020 were selected for radiometric calibration, atmospheric correction, splicing, and cropping to obtain remote sensing images of Kunming City, to extract the impervious surface in 2020. NDVI was directly obtained from the vegetation index data MOD13A1.

Methods

The research framework was composed of four stages (Fig. 2). (1) Data preparation and preprocessing. (2) Based on the PLUS model, the land utilization changes under the trend continuation situation, Eco-friendly scenario, and comprehensive development scenario were predicted for 2030. (3) With the InVEST model, the space-time allocation of carbon storage under different development scenarios was evaluated from 2000 to 2030, and the tendency of land use revolution in the study area from 2000 to 2030 was discovered to determine the impact of land utilization variation on carbon sink. (4) The spatial correlation of carbon storage was evaluated using the spatial autocorrelation model, and the influencing factors of carbon storage were analyzed.

Ecosystem carbon storage estimation

In this study, the Carbon Storage and Sequestration module of the InVEST model was used to calculate the carbon storage in Kunming. The basic assumption of this module is that the value of the carbon density of a specific land category is fixed, and the carbon storage of that land type can be acquired by multiplying the value of carbon density with that of the land area (Gong et al., 2022). The carbon storage module in the InVEST model divides the ecosystem carbon storage into four basic carbon pools (Lin et al., 2022), which include the terrestrial biogenic carbon, subsurface biogenic carbon, soil carbon, and dead organic carbon. The sum of the carbon stock of the four carbon pools provides the value for the total carbon storage of the ecosystem in the area, which can be achieved using equations (1) and (2) (Li et al., 2020).

$$C_i = C_{i-above} + C_{i-below} + C_{i-soil} + C_{i-dead} \quad (1)$$

$$C_{tot} = \sum_{i=1}^{n} C_i \times S_i \quad (2)$$

Here, C_i indicates the carbon density of land utilization type i; $C_{i-above}$, $C_{i-below}$, C_{i-soil}, and C_{i-dead} indicate the carbon density of terrestrial biogenic carbon, subsurface biogenic carbon, soil carbon, and dead organic carbon of land use type i, respectively; C_{tot} indicates the total carbon storage in the region; S_i indicates the area of land utilization pattern i; n indicates the total number of land use types.

Future Land Use Prediction and Scenario Setting

(1) PLUS model

In this study, the PLUS model was utilized to forecast land utilization in Kunming under distinct growth scenarios in 2030. The PLUS model is a new land use prediction model proposed by Xun et al. (China University of Geosciences). Compared to other traditional prediction models, it has improved emulation capability and can measure the landscape pattern more precisely (Yang et al., 2022). The PLUS model mainly combines the land expansion analysis strategy (LEAS) and the CA model with multi-type random patch seeds (CARS). The LEAS module is employed to extract the land cover expansion, and then, the random forest classification algorithm is utilized to mine the probability of change and inertia of each land use type (Gao et al., 2022). The CARS module affects the local land contestation process through an self-adaptive coefficient and drives the changes in land utilization intensity to meet the upcoming land use demand. For forecasting the number of prospective land application patches, a Markov model with high simulation accuracy is selected (Sun and Liang, 2021).

(2) Scenario Setting

The development planning and the land use change of Kunming City are affected by many factors. The previous planning of Kunming City started in 2006 and ended in 2020. The next overall planning of land and space in Kunming City started in 2021 and is planned till 2035; 2030 is the intermediate node of the next land and space planning of Kunming City. Additionally, following the implementation outline of "Kunming City building regional international center city (2017–2030)" issued in September 2017, Kunming City will be fully transformed into a regional international center city in southwest China in 2030. Therefore, in this study, we selected 2030 as the prediction year of future land use in Kunming.

In accordance with the historical law of land utilization change in Kunming, along with the development situation and future planning, and assuming that the region can meet the future natural, social, and economic needs, the PLUS model was used to construct three scenarios (Cui et al., 2022; Ding et al., 2021; Zhang and Gu, 2022) for the coming land utilization expansion of Kunming. These scenarios are as follows:

1) Trend continuation scenario (S1). According to the law of land utilization change in Kunming between 2010 and 2020, only the water area can be controlled as the restricted conversion area, and the construction land cannot be transferred to alternative land types. Using the Markov model, the land use types of Kunming in the 2030 trend continuation scenario were predicted.

2) Ecological protection scenario (S2). The Yunnan Province is committed to leading the ecological civilization construction goals, guided by ecological and environmental protection, by limiting the large extension of construction land, increasing the shift of other types of land to woodland and grassland, and reducing the conversion of eco-land to unused land.

3) Comprehensive development scenario (S3). While ensuring economic development, the protection of the ecosystem, substantially reducing the transfer of non-construction land to construction land, and increasing the transfer probability of unused land to ecological land without affecting economic development need to be considered. Since cultivated land is economically important, the conservation policy of cultivated land needs to be considered to strictly control the transformation of cultivated land.

The neighborhood weight reflects the expandability of a certain land utilization type. When the value is closer to 1, the extension capacity of the land utilization type is stronger. Following the law of land utilization conversion in Kunming for the period 2010-2020, and based on the findings of published studies (La et al., 2021), the neighborhood weights of each land utilization type under various scenarios were set by comparing the accuracy of the outcomes of simulation based on different parameters (Table 3).

(3) Verifying the accuracy of the simulation

According to the land use data of Kunming City in 2010, the PLUS model was employed to forecast the results of the land utilization type of Kunming City in 2020. By comparing the simulated results with the real land use data in 2020, the Kappa coefficient of the two sets of data was 0.8638, and the overall accuracy was 90.72%. The simulation accuracy was high, indicating that the model and various parameters might be used for simulating the land use of Kunming City in the future.

Impervious surface extraction

The impervious surface area (ISA) is a typical land cover type and an important indicator for measuring and analyzing city development and the ecology (Xu, 2009). The index method is generally adopted to extract the urban impervious surface. The representative spectral indices include the normalized building index (NDBI), the normalized difference impervious surface index (NDISI), and the enhanced normalized difference impervious surface index (ENDISI) (Duan et al., 2022). ENDISI can better identify shadows of mountains and remains unaffected by terrain factors while identifying impervious surfaces. Kunming City is dominated by mountainous terrain. Selecting this index for extracting information on impervious surfaces can prevent mountain shadows from affecting the extraction accuracy of impervious surfaces. The ENDISI can be calculated using Equation (3).

$$ENDISI = \frac{(2Blue + MIR_2) \div 2 - (NIR + Red + MIR_1)}{(2Blue + MIR_2) \div 2 + (NIR + Red + MIR_1)} \quad (3)$$

Here, Blue, Red, NIR, MIR_1, and MIR_2 are the reflectance of blue, red, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands corresponding to the image.

Before extracting the information on the impervious surface, the normalized water index MNDW (Xu, 2008) needs to be used to mask the large area of water and snow over the study area. The MNDW index can be derived from the Equation (4).

$$MNDWI = \frac{(Green - MIR_1)}{(Green + MIR_1)} \quad (4)$$

Here, Green, MIR_1, and MIR_2 are the reflectance of green, shortwave infrared 1, and shortwave infrared 2 bands corresponding to the image, respectively.

Using ArcGIS, 700 verification points were randomly generated in the working area after masking water and snow. With the data on the impervious surface extracted from the Landsat 8 image in 2020, the land use data and the remote sensing imagery of Kunming City in this period were selected, and the accuracy of the extracted impervious surface was determined by artificial visual interpretation. The Kappa coefficient was 0.7582, and the overall accuracy was 89.86%. It demonstrated that the accuracy of the impervious surface met the requirements of subsequent research.

Results

Land-use change analysis

From the overlay map of the area proportion of land utilization types (Fig. 3), we found that the land in Kunming City during 2000-2020 was mainly forest land, which covered about 45% of the total area studied. Since 2000 to 2020, the total area of forest land, grassland, and cultivated land decreased. The land use transfer matrix from 2000 to 2020 (Table 4) showed that forest land decreased by 142.28 km^2, grassland decreased by 328.95 km^2, and cultivated land decreased by 278.07 km^2 in 20 years. The growth rate of construction land was high; construction land increased by 708.84 km^2, and the area proportion increased from 2.3% to 5.7%. The development process of S1 in 2030 was similar to the trend of 2000–2020. Woodland, grassland, and cultivated land in 2030 decreased by 123.86 km^2, 150.61 km^2, and 197.358 km^2, respectively. However, construction land increased by 451.136 km^2, and water area and unused land remained unchanged. In the S2 scenario, with ecological protection as the leading role, the area of forest land increased by 1.1% and the growth rate of construction land slowed down. In the S3 scenario, where cultivated land conservation policy and economic development were considered, cultivated land and construction land increased by 55.82 km^2 and 209.28 km^2, respectively, while forest land and grassland decreased by 123.96 km^2 and 151.79 km^2, respectively.

The construction land in the four periods was concentrated in the main urban area of Kunming (Wuhua District, Panlong District, Xishan District, Guandu District, and Chenggong District) and the surrounding areas (eastern Anning City, northern Chongming County, and northern Jinning District) (Fig. 4). According to the statistical yearbook of Yunnan Province in 2020, the main urban area of Kunming comprised 63.17% of the population and generated 73.76% of the GDP of the city. A large population and capital flow led to an increase in construction, and ecological land, such as forest land and grassland, decreased considerably. The land utilization types in Luquan County and Xundian County are mainly woodland and grassland, which act as important ecological barriers in Kunming City. The Jiaozi Snow Mountain Nature Reserve is in Luquan County and is an important water conservation ecological reserve in Kunming City. The overall territorial spatial layout of Kunming is: the southern Dianchi Lake basin is the core of economy and population, and the northern mountainous area is the ecological security area.

Analysis of space and time Variation of Ecosystem Carbon Storage

The carbon storage in Kunming in 2000, 2010, and 2020 was 1.146 × 108 t, 1.139 × 108 t, and 1.120 × 108 t, respectively, indicating a continuous decrease, with a total decrease of 2.619 × 106 t in 20 years. The reduction of carbon storage in 2010–2020 was the highest, with a decrease of 1.917 × 106 t. During this period, the economic development and urbanization of Kunming were rapid and the demand for land use was relatively high.

In 2030, carbon storage is predicted to be 1.102 × 108 t in the S1, and the loss of ecosystem carbon stock is greater. The ecosystem carbon storage might decrease by 1.818 × 106 t compared to that in 2020. In 2030, carbon storage is predicted to be 1.136 × 108 t in the S2 scenario, which is 1.601 × 106 t higher than that in 2020, indicating that ecological protection can restore ecosystem carbon storage in Kunming. Finally, carbon storage in the S3 is predicted to be 1.105 × 108 t in 2030, and the ecosystem carbon storage might decrease by 1.479 × 106 t compared to that in 2020, which is less than the carbon loss in the S1. As shown in Fig. 5, the terrestrial biogenic carbon, subsurface biogenic carbon, dead organic carbon, and soil carbon in the S2 scenario in 2030 are predicted to be higher than those in the S1 and S3 scenarios. The soil carbon gap was found to be the largest, which was 1.539 × 106 t and 1.250 × 106 t higher than the soil carbon in the S1 and S3 scenarios, respectively. The terrestrial biogenic carbon storage, belowground carbon storage, and dead organic carbon storage in the S1 and S3 scenarios were similar, while the soil carbon storage in S3 was higher than that in S1, which was consistent with the changes in total carbon storage.

The overall content of ecosystem carbon stock in Kunming is high, showing a 'north high, south low' distribution (Fig. 6 and 7). Carbon storage is mainly distributed in Luquan County, Xundian County, and Yiliang County on the east and west of the research area, while the main urban area of Kunming City in the south of the study area is highly urbanized and has lesser quantities of stored carbon. From 2000 to 2030, the change in the spatial layout of carbon storage in Kunming was mainly found to occur in the main urban area of Kunming. On the basis of our findings using the S1 scenario, from 2000 to 2030, due to rapid urbanization, the construction land in the main urban area expanded remarkably, resulting in the loss of regional ecosystem carbon storage every year. Under the ecological protection-oriented development of the S2 scenario, in 2030, the carbon stock in the main urban area of Kunming increased compared to that in 2020. When considering the cultivated land conservation policy, eco-friendly policy, and economic development, carbon storage in the main urban area of Kunming was lower than that in 2020, but the reduction range was narrower than that in the S1 scenario. The results showed that carbon sequestration in the main urban area of Kunming can strongly affect the change in the ecosystem carbon storage in the whole city.

Effects of Land-Use Conversion on Carbon Storage

Land utilization/land cover significantly affects vegetation cover and biomass and is also the primary purpose for the distribution and change of carbon sequestration in regional terrestrial ecosystems (Zhang et al., 2022b). The dynamic changes in carbon stock induced by the changes in main land use types in Kunming from 2000 to 2030 are shown in Fig. 8. From 2000 to 2030, according to the S1 scenario, carbon storage decreased mainly because of the shift from forest land and grassland to other land use types. Although the policy of returning farmland to forest has partly promoted the transfer of cultivated land to forest land, expansion of construction land encroaches forest land, leading in a sharp decrease in the ecosystem carbon reserve. Under the S2 scenario, in 2030, the increase in ecological lands, such as forest land and grassland, was predicted to be the key reason for the increase in carbon sequestration. Under the S3 comprehensive development scenario, in 2030, the cultivated land conservation policy was found to promote the increase in cultivated land carbon storage, while the forest land and grassland carbon stock decreased. The carbon density of forest land and grassland was higher than that of cultivated land, resulting in a decrease in the overall ecosystem carbon storage. The outcomes suggested that the conversion in land utilization type is consistent with the changes in the ecosystem carbon stock, and land use/land cover directly affects ecosystem carbon sequestration.

Spatial Correlation Analysis of Ecosystem Carbon Storage

Spatial correlation is segmented into spatial global autocorrelation and spatial local autocorrelation (Luo et al., 2022). In this study, Moran's I index was employed to represent the spatial global autocorrelation of ecosystem carbon storage in Kunming (Xiong et al., 2021) and Getis-Ord Gi * was employed to measure the spatial local autocorrelation (Zhang et al., 2020a).

In this study, Kunming was divided into a 2 km × 2 km grid, and the carbon storage data in the three development scenarios for 2000–2020 and 2030 were linked to the grid. Based on this scale, the spatial correlation of carbon stock in Kunming was analyzed.

Regarding global autocorrelation, the spatial Moran's I values of carbon storage in Kunming were 0.5583 in 2000, 0.5546 in 2010, 0.5635 in 2020, 0.5900 in 2030 S1, 0.5672 in 2030 S2, and 0.5763 in 2030 S3, respectively (all values were greater than 0), indicating a significant spatial global autocorrelation in carbon storage in Kunming. For local autocorrelation, the results of the carbon storage hotspot analysis under the three development scenarios in Kunming from 2000 to 2030 are shown in Fig. 9. From 2000 to 2020, the area designated as the hotspot of carbon stock in Kunming reduced, while the area considered to be a coldspot increased. Except for the northeast of Dongchuan District, the coldspot area in other areas, especially in the main urban area of Kunming, increased. In the last 20 years, the hotspots of carbon stock in the research area were scattered in the northwestern, western, central, and eastern regions, including the east and west sides of Luquan County, Xishan District, the western part of Chongming County, the northern part of Yiliang County, and the eastern part of Guandu District. Carbon storage was not only higher in these areas but high-value areas of carbon sequestration were also gathered in these areas, primarily situated in zones with less construction land, excellent plant coverage, and more ecological land. The coldspot area was mostly distributed in the northeastern, central, and southern locations of Kunming, i.e., the northeastern part of Dongchuan District, the eastern part of Chongming County, the eastern part of Yiliang County, the northern and western parts of Shilin County, and the central part of the main urban area of Kunming City. These areas underwent rapid land development, had complex topography and geomorphology, and fragmented distribution of ecological land, forming an area with low carbon storage. In the S1 scenario, in 2030, the coldspot area in the main urban areas of Anning City and Kunming City increased. The coldspot area in the S2 scenario was slightly smaller compared to 2020 in the main urban area. The coldspot area in the S3 scenario, in 2030, was similar to that in 2020, indicating that the eco-friendly and cultivated land protection policies were beneficial to moderate the loss of ecosystem carbon sequestration in Kunming City.

Research on Driving Factors of Ecosystem Carbon Storage

Correlation between Ecosystem Carbon Storage and Impact Factors

Based on the spatial-temporal allocation and variation of carbon stock in Kunming, in this study, we performed correlation analysis (Chen et al., 2022; Zhang et al., 2022) to determine the effects of natural factors and socio-economic factors on carbon storage. Taking the data on impact factors and carbon storage in 2020 as an example, the data were set to a grid of 2 km × 2 km according to the study area using the grid method. In total, 5,153 grid points were generated. The impact factors included impervious surface coverage, GDP, population density, altitude, NDVI, and annual average precipitation.

The results of Pearson's correlation coefficient analysis between carbon storage and various influencing factors in Kunming are shown in Table 5. Carbon storage was moderately negative correlated with impervious surface coverage, weakly negatively correlated with GDP and population density, strongly positively correlated with NDVI, and weakly positively correlated with altitude and annual rainfall. The results showed that at a grid scale of 2 km × 2 km, impervious surface and vegetation had the greatest impact on carbon storage in Kunming, and carbon storage was negatively correlated with impervious surface coverage and positively correlated with NDVI.

Bivariate spatial autocorrelation analysis of carbon storage and the influencing factors

Depending on the results of Pearson's correlation analysis, two indicators that had the strongest relevance with the carbon storage of the ecosystem in Kunming were selected, i.e., impervious surface coverage and NDVI, and bivariate spatial autocorrelation analyses were performed between the two indicators and carbon storage data. The bivariate global spatial autocorrelation is represented by the bivariate 'Moran's I index. The bivariate 'Moran's I index of impervious surface coverage and ecosystem carbon storage was –0.379. The negative value of 'Moran's I index indicated a global negative correlation between impervious surface coverage and ecosystem carbon storage. The bivariate 'Moran's I index of NDVI and ecosystem carbon storage was 0.450. The positive value of 'Moran's I index indicated that there was a global positive correlation between NDVI and ecosystem carbon storage.

The bivariate LISA cluster map of impervious surface coverage and carbon storage of the ecosystem in Kunming, which reflects the local agglomeration characteristics of the two in space, is shown in Fig. 10a. The impervious surface coverage and carbon storage of the ecosystem showed opposite values of the two-pole agglomeration characteristics in space, which mainly were high-low agglomeration and low-high agglomeration, i.e., carbon stock in the area with low impervious surface coverage was higher, and carbon stock in the area with high impervious surface coverage was lower. The bivariate LISA clustering results of NDVI and ecosystem carbon storage in Kunming (Fig. 10b) showed that NDVI and ecosystem carbon storage had a similar value for the polar agglomeration characteristics in space, mainly high-high agglomeration and low-low agglomeration. Thus, the regional ecosystem carbon storage with higher vegetation coverage was higher, and the regional ecosystem carbon storage with lower value coverage was lower. These results suggested a local negative correlation between impervious surface coverage and ecosystem carbon storage and a local positive correlation between NDVI and ecosystem carbon storage.

Discussion

Contribution of Land Use Driving Factors

Social and natural factors mainly drive land use change (Gong et al., 2022). Social factors include population density, GDP, distance to road, distance to the government office, etc. Natural factors include terrain factors, such as slope and elevation, and climatic factors, such as mean annual rainfall and mean annual temperature. In this study, 11 driving factors of social economy and climate were selected to forecast land utilization in 2030, and the contribution of each driving factor was evaluated (Table 6). A higher contribution of a factor indicated a greater impact of the driving factor on local land use evolution.

The driving factors with the highest contribution to cultivated land were GDP (0.166), DEM (0.111), and population density (0.104). Cultivated land expansion is inextricably linked to population and economic development because rapid population and economic growth will lead to greater food demand (Liao et al., 2021). Climatic conditions were different at different altitudes. Agricultural farming was closely related to climatic conditions, and thus, cultivated lands were generally distributed in low-altitude suitable farming areas. The driving factors with the highest contribution to forest land were DEM (0.183), population density (0.125), and slope (0.117). The altitude and slope were important topographic factors affecting vegetation growth. Generally, areas that have a small slope and are at a low altitude are more suitable for the growth of vegetation. Areas with a higher population density have less forest land area, and population density partly limits the expansion of forest land. The driving factors with the highest contribution to grassland were GDP (0.133), population density (0.117), and distance to the water system (0.104). The GDP and population density restricted grassland expansion, while the water system promoted grassland expansion. The area closer to the water system was more prone to grassland expansion. The driving factors with the highest contribution to construction land were population density (0.154), GDP (0.143), and the mean annual temperature (0.122). A greater population density and a higher GDP were associated with a greater demand for and more expansion of construction land. The mean annual temperature affected the development of construction land by changing the population density. The driving factors with the highest contribution to the unused land were DEM (0.306), the mena annual temperature (0.199), and the mean annual rainfall (0.156). The climate in high-altitude areas is harsh, and the perennial temperature is low, which is unfavorable for vegetation growth and human habitation.

Suggestions on Carbon Sink Function Restoration and Governance

The period from 2000 to 2020 was an important stage of economic development in Kunming. In the last 20 years, the gross domestic product increased from 6,262.853 million yuan to 67,337.909 million yuan, the population increased from 4.8094 million to 8.463 million, and the construction land expanded from 484.21 km^2 to 1193.05 km^2. The area of forest land and grassland decreased considerably, resulting in a decline in ecosystem carbon storage in Kunming in the last 20 years. Based on the predictions of the trend continuation scene, ecological protection scene, and comprehensive development scenario, taking timely measures to protect the ecosystem is necessary to reduce the loss of carbon reserves. According to the "14th Five-Year Plan for National Economic and Social Development of Yunnan Province and the Outline of the Visionary Goals for the Year 2035", Yunnan Province focused on "making new progress in the building of eco-civilization by 2025, and building the vanguard of China's ecological civilization by 2035". Responding climate change and achieving carbon peak and carbon neutrality are also necessary for future development. Kunming needs to incorporate the dual-carbon goal into the overall future development and foster comprehensive greener shift in environmental development.

Based on the distribution of carbon sink in Kunming from 2000 to 2030 (Fig. 5), Luquan County, Xundian County, and Dongchuan District in the north and Yiliang County and Shilin

County in the southeast were found to be the essential sources of carbon storage in Kunming. The luquan mountain area takes up 98.4% of the whole area of the county, and the forest coverage rate is around 55.4%. Based on these advantages, forestry development and ecological green development can be organically combined. Focusing on the positioning of the ecological containment function area of Kunming, Luquan County, Xundian County, and Dongchuan District need to strengthen ecological conservation construction and develop the Jiaozi Snow Mountain Nature Reserve as an important water source conservation area and ecological protection guard not only in Kunming but also the middle and upper reaches of the Yangtze River. These areas should build a strong ecological security defense line in the north of Kunming. As an 'ecological civilization county of Yunnan Province', Shilin County should lead the construction of the national ecological civilization and help Yunnan in achieving its target of 'double carbon'. Considering that the tourism industry is important in Shilin County, eco-tourism should be promoted to construct an ecological civilization. Yiliang County has an abundance of forest resources and species diversity. The forest coverage rate of the county is 46.2%. Yiliang County can utilize its resource advantages, strengthen the protection of forest resources based on the current condition of forestry resources, simultaneously develop an ecological civilization and forestry economy, and build an ecological security barrier with Shilin County in the southeast of Kunming. Period 2000 to 2030, the carbon storage in the main urban area of Kunming City, especially in the Dianchi Lake Basin, was found to decrease every year. Promoting the ecological management of the Dianchi Lake Basin is imperative for the development of Kunming City. The main urban area of Kunming City is located in the red line of water conservation and eco-protection of plateau lakes and the upper reaches of the Niulan River. Thus, its resource advantages need to be fully utilized to drive holistic and sustainable development of the plateau lake basin. It is also necessary to improve the 'three lines and three zones' delineation standards, strictly control the wetland parks and basic farmlands delineated in the Dianchi Lake Basin, rationally conduct land and space planning, and enhance the efficiency of land resources utilization. The ways to satisfy the requirements of urban expansion during accelerated evolution and perform ecological protection need to be determined urgently for developing Kunming City. Solving this problem is also the key to achieve the dual carbon goals and the establishment of eco-civilization in Yunnan Province.

Research prospect

With the PLUS and InVEST models, the space-time changes in carbon storage in Kunming City were predicted and evaluated, and the influence of land utilization conversion on carbon stock was analyzed. The correlation between impervious surface coverage and vegetation index and regional ecosystem carbon storage was analyzed. The findings provided new ideas for sustainable development in the future. However, this study had some limitations. First, the carbon storage calculation module of the InVEST model had certain shortcomings. Carbon stock in the ecosystem is affected by many factors. The InVEST model considered land use change as the only factor affecting carbon storage and ignored the effect of climate, topography, hydrology, and other conditions. Additionally, the model also ignored the impact of interannual changes in carbon density. Second, only 11 driving factors were considered when using the PLUS model for future land cover; however, the actual land utilization evolution is affected by a large number of physical and human factors. In future studies, the measured data might be used to determine the dynamic carbon density. Besides land use, other influencing factors might be considered to comprehensively evaluate the regional ecosystem carbon storage. While performing land-use simulations, we should select as many driving factors as possible to predict future requirement of land utilization and improve the prediction accuracy of future land utilization patterns.

Conclusions

Based on the data on land use and driving factors from 2000 to 2020, the PLUS and InVEST models were used to monitor and study the time-space dynamics of land and ecosystem carbon storage in Kunming from 2000 to 2030. The findings illustrated the following: (1) From 2000 to 2020, the land-use types in Kunming were mainly forest land. The total area of forest land, grassland, and cultivated land decreased, and construction land increased. In the S1, the construction land was predicted to expand greatly in 2030. In the S2, the forest land area was predicted to increase greatly. In the S3, the cultivated land area was predicted to increase, the construction land was predicted to increase moderately, and the forest land and grassland were predicted to decrease slightly. (2) The carbon storage in Kunming showed a distribution pattern of 'high in the north and low in the south'. The carbon storage of the ecosystem in 2000, 2010, and 2020 was found to be 1.146 × 108 t, 1.139 × 108 t, and 1.120 × 108 t, respectively, suggesting a continuous decrease. The carbon storage in 2030 was predicted to be 1.102 × 108 t in S1, 1.136 × 108 t in S2, and 1.105 × 108 t in S3. (3) A significant spatial autocorrelation of carbon storage was found in Kunming City. In the local space, the ecosystem carbon storage in Kunming City from 2000 to 2020 was mainly characterized by the expansion of the coldspot area. In 2030, the coldspot area was predicted to increase in the S1 scenario, slightly decrease in the S2 scenario, and be similar to 2020 in the S3 scenario. (4) A global and local negative correlation was found between impervious surface coverage and ecosystem carbon storage, and a global and local positive correlation was found between NDVI and ecosystem carbon storage.

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Table 1(on next page)

Carbon density database of land use types in Kunming.

Table 1

Carbon density database of land use types in Kunming.

Land use	Aboveground carbon density	Underground carbon density	Soil carbon density	Carbon density of dead organic matter
Cultivated land	1.31	0.73	11.65	0
Forest land	40.41	10.45	42.75	2.62
Grassland	2.55	8.31	15.1	0.85
Water area	0	0	0	0
Construction land	0	0	0	0
Unused land	0	0	4.2	0

Table 2(on next page)

Driving factors and data sources.

Table 2

Driving factors and data sources.

Data Type	Data Name	Resolution/m	Data Source
Social factors	GDP	1000	Resource and Environment Science and Data Center, Chinese Academy of Sciences（https: //www.resdc.cn/）
	Population density	1000	
	Distance to government office	30	
	Distance to main road	30	Openstreetmap（https: //www. openstreetmap.org/）
	Distance to highway	30	
Physical factors	Elevation	30	Geospatial Data Cloud Official Website（https/ /www.gscloud.cn/）
	Slope	30	
	Distance to water system	30	Resource and Environment Science and Data Center, Chinese Academy of Sciences（https: //www.resdc.cn/）
	mean annual temperature	1000	
	mean annual rainfall	1000	
	Soil type	1000	

Table 3 (on next page)

Neighborhood weights of simulation scenarios.

Table 3

Neighborhood weights of simulation scenarios.

Scenarios	Cultivated land	Forest	Grassland	Water body	Construction land	Unused land
Trend continuation	0.50	0.77	0.50	0.58	0.83	0.50
Ecological protection	0.50	0.82	0.75	0.58	0.70	0.60
Comprehensive development	0.50	0.77	0.75	0.58	0.77	0.60

Table 4(on next page)

Land utilization transfer matrix of Kunming from 2000 to 2020.

Table 4

Land utilization transfer matrix of Kunming from 2000 to 2020.

2020								
Land use		Cultivated land	Forest land	Grassland	Water area	Construction land	Unused land	Total
	Cultivated land	3426.40	218.07	196.14	25.74	387.23	0.80	4254.38
	Forest land	230.43	8765.48	441.07	40.69	119.74	1.79	9599.20
	Grassland	268.31	456.62	5154.64	19.52	236.11	6.52	6141.72
2000	Water area	17.92	4.07	6.27	420.81	24.26	0.32	473.65
	Construction land	32.26	11.51	10.47	4.20	425.58	0.19	484.21
	Unused land	0.99	1.17	4.18	0.51	0.13	60.91	67.89
	Total	3976.31	9456.92	5812.77	511.47	1193.05	70.53	21021.05

Table 5(on next page)

Pearson correlation coefficient between carbon storage and impact factors in Kunming.

Table 5

Pearson correlation coefficient between carbon storage and impact factors in Kunming.

Impact factors	Impervious surface percentage	GDP	Population density	Elevation	NDVI	Average annual rainfall
carbon storage	-0.530	-0.2	-0.215	0.339	0.689	0.225

Table 6(on next page)

Contribution of driving factors of land use.

Table 6

Contribution of driving factors of land use.

Driving factors	Land use					
	Cultivated land	Forest land	Grassland	Water area	Construction land	Unutilized land
DEM	0.111	0.183	0.1	0.136	0.085	0.111
GDP	0.166	0.091	0.133	0.187	0.143	0.166
Distance to government	0.093	0.091	0.104	0.022	0.104	0.093
Distance to highway	0.091	0.075	0.092	0.028	0.089	0.091
Population density	0.104	0.125	0.117	0.168	0.154	0.104
Average annual rainfall	0.089	0.081	0.089	0.069	0.111	0.089
Distance to main road	0.089	0.063	0.08	0.017	0.063	0.089
Distance to water system	0.079	0.071	0.104	0.097	0.069	0.079
Slope	0.078	0.117	0.084	0.2	0.096	0.078
Soil type	0.022	0.018	0.015	0.046	0.023	0.022
mean annual temperature	0.079	0.084	0.083	0.031	0.122	0.079

Figure 1

Study area.

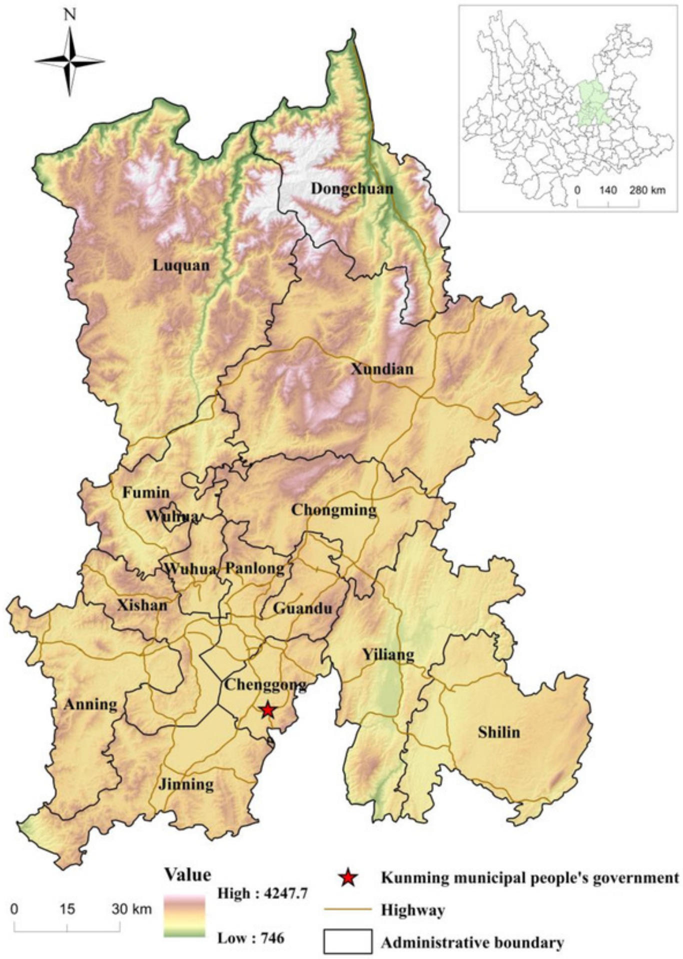

Fig.1. Study area.

Figure 2

Research framework.

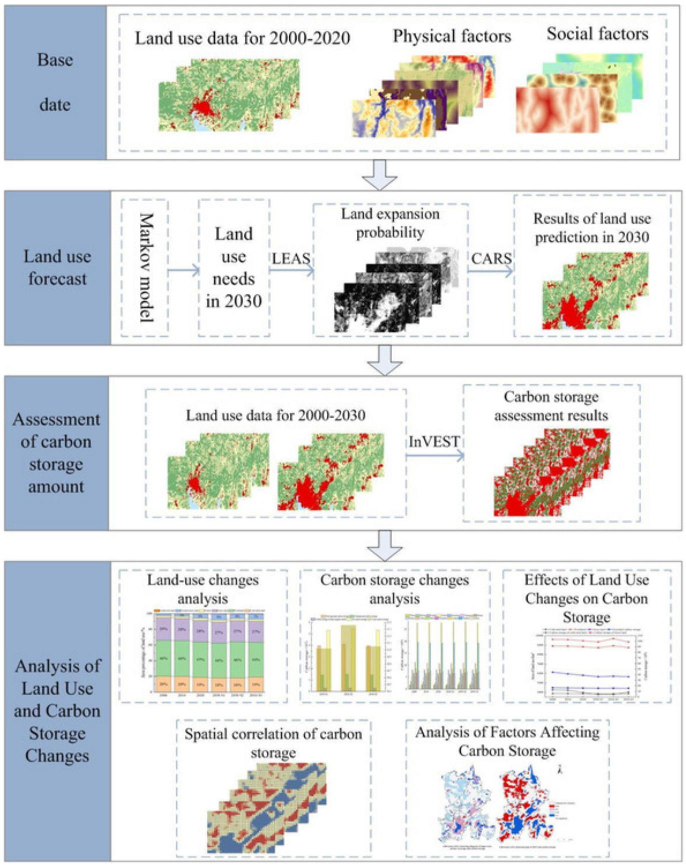

Fig.2. Research framework.

Figure 3

The overlay map of the area proportion of land utilization in Kunming from 2000 to 2030.

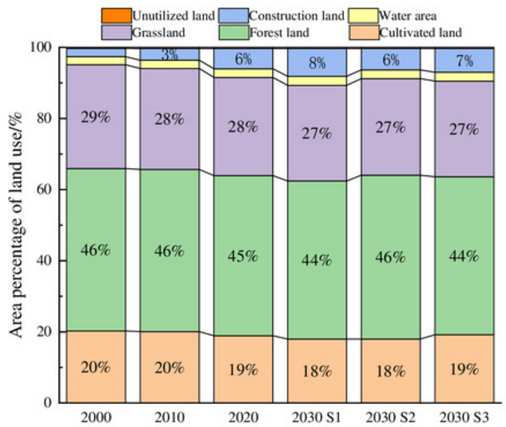

Fig.3. The overlay map of the area proportion of land utilization in Kunming from 2000 to 2030.

Figure 4

Land use changes in Kunming from 2000 to 2030.

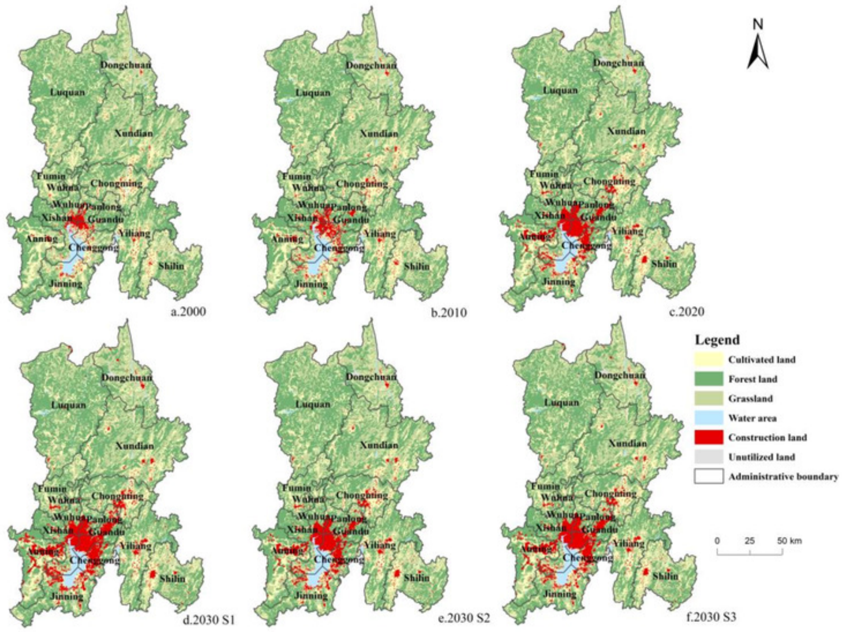

Fig.4. Land use changes in Kunming from 2000 to 2030.

Figure 5

Changes of carbon stock in Kunming under three development scenarios in 2030.

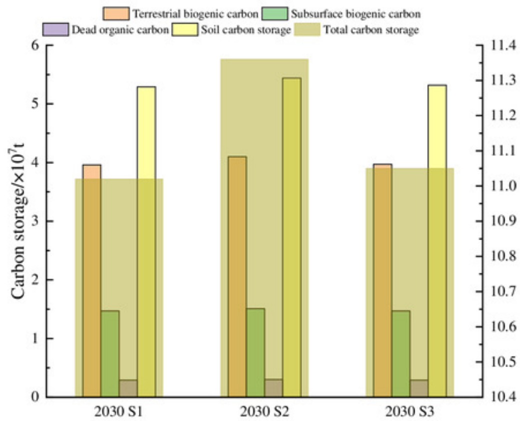

Fig.5. Changes of carbon stock in Kunming under three development scenarios in 2030.

Figure 6

Changes in carbon storage in Kunming from 2000 to 2030.

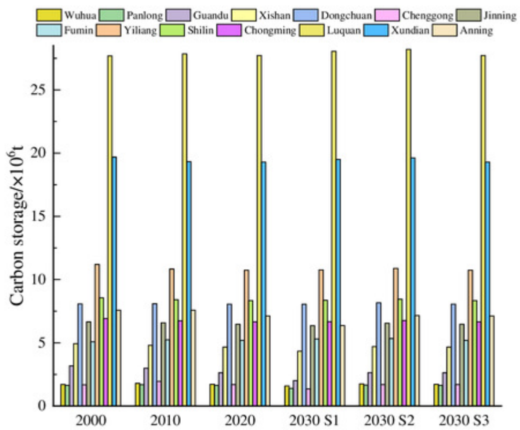

Fig.6. Changes in carbon storage in Kunming from 2000 to 2030.

Figure 7

Spatial distribution of carbon storage in Kunming from 2000 to 2030.

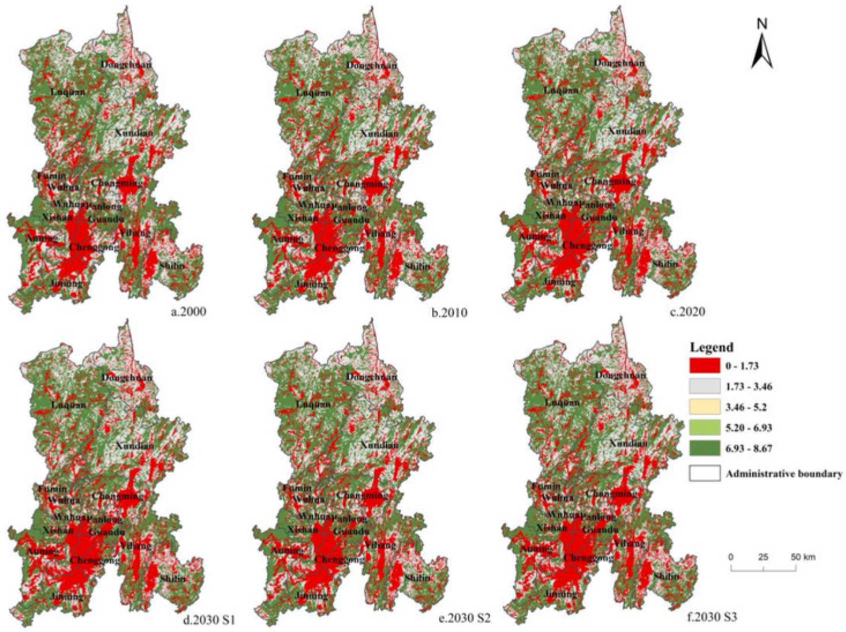

Fig.7. Spatial distribution of carbon storage in Kunming from 2000 to 2030.

Figure 8

Changes of main land types and carbon storage in Kunming from 2000 to 2030.

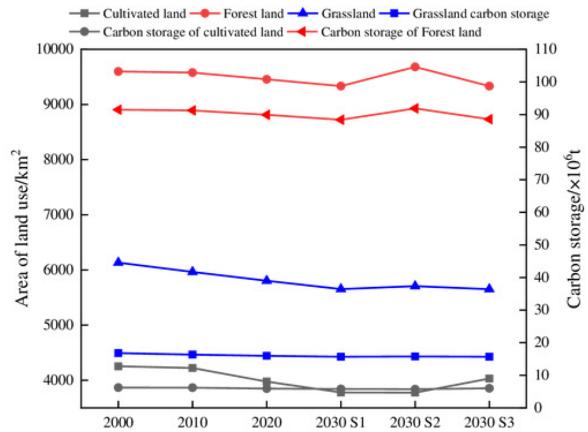

Fig.8. Changes of main land types and carbon storage in Kunming from 2000 to 2030.

Figure 9

Getis-Ord Gi * analysis of carbon storage in Kunming from 2000 to 2030.

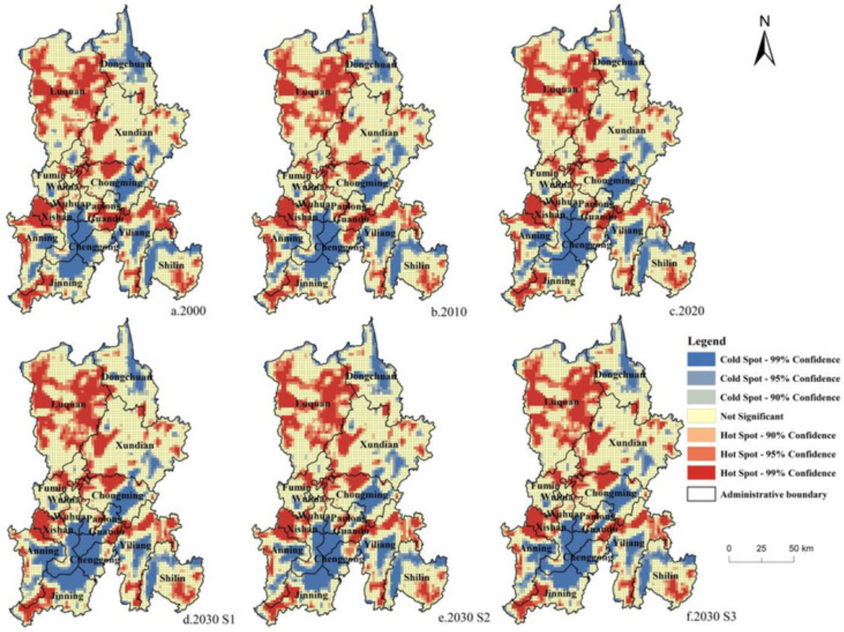

Fig.9. Getis-Ord Gi * analysis of carbon storage in Kunming from 2000 to 2030.

Figure 10

Bivariate LISA cluster map of carbon storage and influencing factors in Kunming.

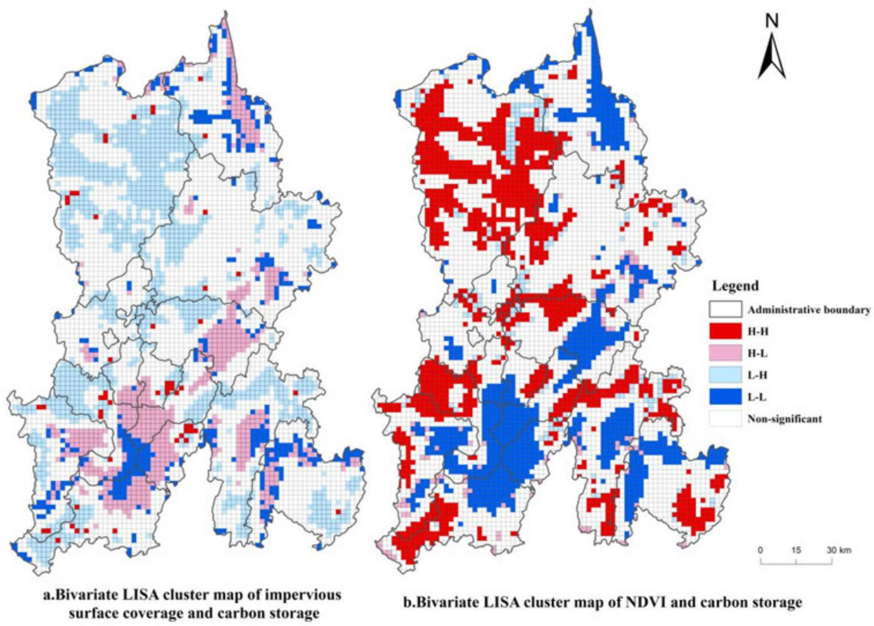

Fig.10. Bivariate LISA cluster map of carbon storage and influencing factors in Kunming.