

Article

Spatio-Temporal Evolution and Multi-Scenario Prediction of Ecosystem Carbon Storage in Chang-Zhu-Tan Urban Agglomeration Based on the FLUS-InVEST Model

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Abstract: Land use/land cover change has a significant indicative effect on the carbon storage of terrestrial ecosystems. We selected Chang-Zhu-Tan urban agglomeration as the research object, coupled FLUS and InVEST models to explore the changes in land use and carbon storage in the region from 2010 to 2020, and predicted their spatiotemporal evolution characteristics under three scenarios in 2035: natural development (S1), ecological development priority (S2) and urban development priority (S3). Spatial autocorrelation was used to analyze the spatial distribution of carbon storage. The results revealed a rapid urban expansion encroaching on cultivated land and forest from 2010 to 2020, resulting in a total urban area of 1957.50 km² by 2020. Carbon storage experienced a total loss of 6.86×10^6 t, primarily between 2010 and 2015. The InVEST model indicated a spatial distribution in a pattern of “low in the middle and high around”, with areas of low carbon storage showing large-scale faceted aggregate distribution by 2035. Under different regional development scenarios, the S3 exhibited the highest carbon storage loss, reaching 150.93×10^6 t. The S1 experienced a decline of 136.30×10^6 t, while the S2 only experienced a reduction of 24.26×10^6 t. The primary driving factor of carbon storage reduction is the conversion of forest and cultivated land into urban areas. It is recommended that the implementation of regional ecological protection policies and the optimization of land use structures effectively minimize the loss of carbon storage.



Citation: Sun, W.; Liu, X. Spatio-Temporal Evolution and Multi-Scenario Prediction of Ecosystem Carbon Storage in Chang-Zhu-Tan Urban Agglomeration Based on the FLUS-InVEST Model. *Sustainability* **2024**, *16*, 7025. <https://doi.org/10.3390/su16167025>

Academic Editor: Irene Petrosillo

Received: 2 April 2024

Revised: 11 August 2024

Accepted: 15 August 2024

Published: 16 August 2024



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Keywords: carbon storage; FLUS model; InVEST model; land use; Chang-Zhu-Tan urban agglomeration

1. Introduction

The carbon pool of terrestrial ecosystems is one of the carbon pools most affected by human activities [1], playing a crucial role in regulating global temperature and mitigating the greenhouse effect [2]. Land use/land cover (LULC) change has become a significant factor in altering regional carbon sources and sinks [3]. Land use (LU) development influences land cover conditions, subsequently impacting terrestrial ecosystem structure and altering the amount of carbon stored in them [4]. Future land use changes could indirectly influence regional carbon storage changes under different development conditions [5]. Exploring the dynamic variations in carbon storage related to regional land use development scenarios can improve the carbon sequestration potential of terrestrial ecosystems, reduce greenhouse gas emissions, and optimize land use structure, thereby contributing to the sustainable development of the region.

In recent years, numerous scholars have undertaken extensive studies on carbon storage within terrestrial ecosystems and the spatio-temporal evolution of such storage based on LULC dynamic changes. In the selection of carbon storage assessment models, the Carbon Storage and Sequestration module of the InVEST model has been widely used in land spatial planning and ecological management due to its user-friendly operation and computational efficiency [6]. Hoque et al. [7] linked the CA-Markov and the InVEST

models to investigate changes in plantation forest cover and carbon storage in central Bangladesh, and the results indicate that alterations in elevation can notably impact the land cover pattern and carbon storage. Mirici et al. [8] precisely simulated the temporal and spatial changes of terrestrial carbon fraction in rural landscapes of the Upper Seyhan Basin from 2014 to 2055 using the InVEST model, revealing that the trend of afforestation has become the main driving force for the significant increase in carbon storage. Overall, these research findings indicate the significant impact of land use/land cover dynamic changes on regional carbon storage.

Although numerous pieces of research have been conducted on the impacts of land use change on ecosystem carbon storage, there are relatively few comprehensive studies examining the impacts of LULC on terrestrial ecosystems using refined simulations. In addition, research on the impacts of LULC on carbon storage has mainly focused on broader scales such as national [9,10], wetland [11,12], and hydrologic basin [13–15], with limited studies conducted on local scales like urban agglomerations. While some scholars have explored the carbon reduction effect of land use transfer and its spatial and temporal differences in Chang-Zhu-Tan urban agglomeration [16], there remains a lack of systematic exploration into the impacts of land use change on the ecosystems of Chang-Zhu-Tan urban agglomeration based on multiple future land use development scenarios. We coupled the FLUS and InVEST models to construct three development scenarios, natural trend development (S1), ecological development priority (S2), and urban development priority (S3), to explore the impact of land use changes on the spatial and temporal evolution of carbon storage in Chang-Zhu-Tan urban agglomeration by 2035. This study aims to provide scientific insights for international research on the effects of regional LULC on variations in ecosystem carbon storage. Especially in areas consistent with subtropical monsoon climatic conditions, we hope to provide a reasonable reference for development strategies related to carbon sequestration, emission reduction, and land use planning.

2. Data Sources and Methods

2.1. Study Area

Chang-Zhu-Tan urban agglomeration is located in the east-central region of Hunan Province (Figure 1), with boundaries of 26°18′–28°41′ N and 111°58′–114°13′ E. It consists of three cities: Changsha, Zhuzhou, and Xiangtan, which are located in the middle and lower reaches of the Xiangjiang River. In addition, it is an important part of the city cluster in the middle reaches of the Yangtze River. The total area of the Chang-Zhu-Tan urban agglomeration is about 28,091 km². The climate is subtropical with monsoon humid. The landform consists mainly of low mountains and hills, with the terrain being lower in the center and higher in the surrounding areas. In 2022, the GDP of Chang-Zhu-Tan has reached two trillion yuan, accounting for 41.7% of the province's total economic output. In recent years, with the advancement of the integrated development of Chang-Zhu-Tan and the acceleration of urbanization and industrialization, the intensity of land development has gradually increased. This is particularly evident in the expansion of urban areas, which has resulted in a more significant loss of carbon storage in this region.

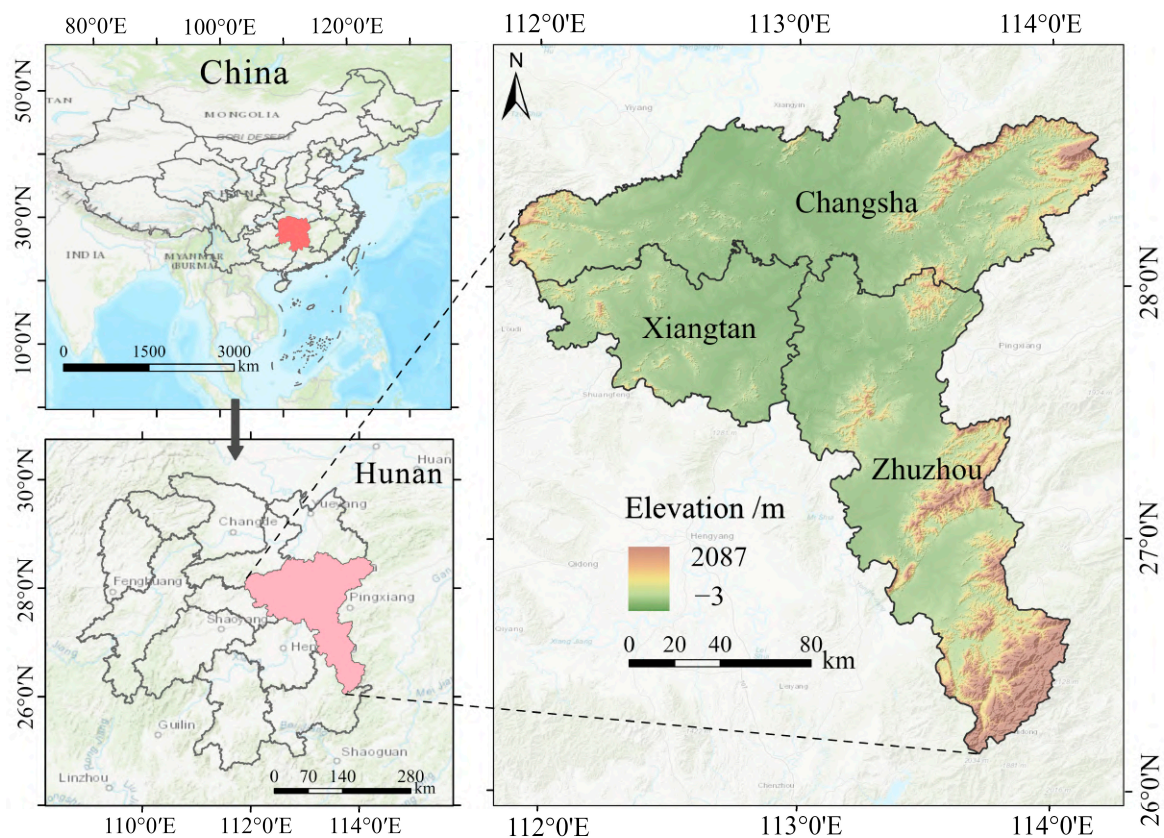


Figure 1. The geographical location of Chang-Zhu-Tan urban agglomeration.

2.2. Data Sources and Processing

The land use data (2010, 2015, and 2020) utilized in this study are from the GLC_FCS30-2020 product produced by Liu's research team [17]. These data were derived from Landsat time series satellite images with a spatial resolution of 30 m and downloaded on the Earth Big Data Science Engineering Data Sharing Service System (<https://data.csearth.cn/>). Furthermore, the land use data were reclassified into five categories: cultivated land, forest, grassland, water bodies, and urban area. The digital elevation model (DEM) was derived from the ASTER GDEM image with a 30 m resolution from the Geospatial Data Cloud (<https://www.gscloud.cn/>), and the slope and slope direction were extracted based on this data. The annual mean precipitation, annual average temperature, GDP, and population grid interpolation data were downloaded from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (<https://www.resdc.cn/>). The railway data and water system vector data were obtained from OpenStreetMap (<https://www.openstreetmap.org/>), and the distances from the railway and water system were calculated by ArcGIS 10.8 Euclidean Distance Tool. The ecological regulation function area was obtained from the Natural Resources Department of Hunan Province. To facilitate the model calculation, all the raster data mentioned above were uniformly processed using the WGS-84 coordinate system, and the resolution was resampled to 100 m × 100 m.

2.3. Methods

2.3.1. Research Framework

This study coupled the FLUS and InVEST models to analyze the impact of land use change on carbon storage (Figure 2). Initially, we combined land use data from 2010 to 2020 with driving factors, restricted areas, and carbon density datasets to analyze the changes in land use and carbon storage during that period. Subsequently, we established multiple land use development scenarios and obtained land use data under multiple scenarios in 2035 using the FLUS model. Finally, the InVEST model was employed to predict the spatial

distribution of carbon storage in 2035 under multiple scenarios, in combination with the land use data simulated by the FLUS model.

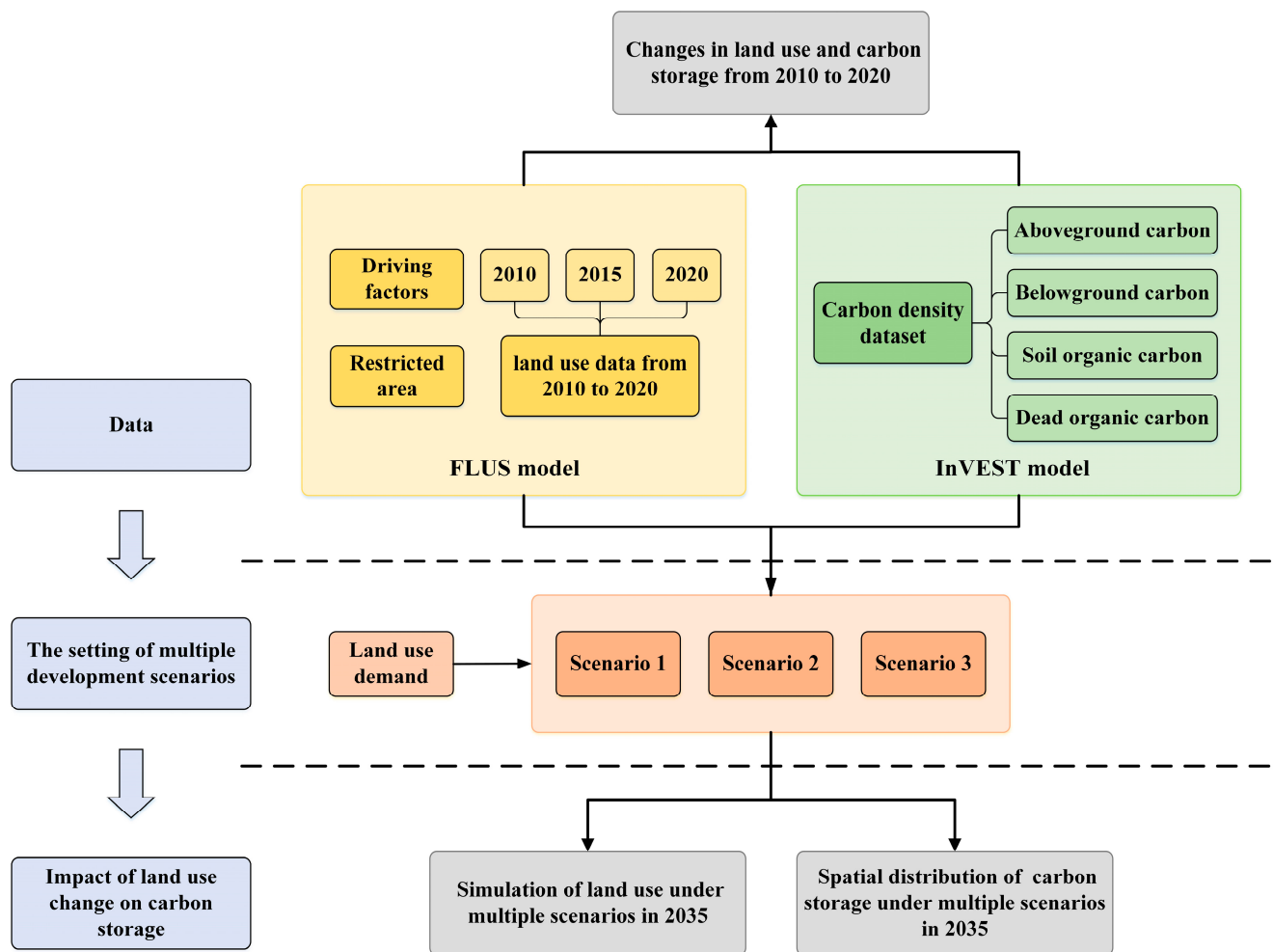


Figure 2. Flowchart of the research.

2.3.2. Carbon Storage Estimation Based on the InVEST Model

The carbon storage of the terrestrial ecosystems in Chang-Zhu-Tan urban agglomeration was calculated using the Carbon Storage and Sequestration module of the InVEST model. This calculation was based on the land use data and carbon density data under three development scenarios from 2010 to 2020 and 2035. The aim was to investigate the impact of LULC on carbon storage under different scenarios. The carbon storage of terrestrial ecosystems is determined by the land use data and carbon density data under the three development scenarios. The carbon storage of terrestrial ecosystems consists of four components: above-ground carbon storage of vegetation (carbon in all active vegetation above the ground), below-ground carbon storage of vegetation (carbon in the active root system of vegetation below the ground), soil organic carbon storage (carbon in the organic matter of the soil), and dead organic matter carbon storage (carbon in the litterfall and dead vegetation), which can be expressed as follows:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (1)$$

where C_{total} is the total carbon storage of terrestrial ecosystems (t/ha); C_{above} is the above-ground carbon storage of vegetation (t/ha); C_{below} is the below-ground carbon storage of vegetation (t/ha); C_{soil} is the soil organic carbon storage (t/ha); C_{dead} is the dead organic matter carbon storage (t/ha). The carbon density data were mainly obtained from existing

research results about subtropical regions [18–21]. Given the difficulty in obtaining dead organic matter carbon density data, thus only the other three carbon density data were taken into consideration [22,23], and we set it to 0. The carbon density data of each land use type in the Chang-Zhu-Tan urban agglomeration are shown in Table 1.

Table 1. Carbon density for each land use type in the study area.

Land Use Type	C _{above} /(t/ha)	C _{below} /(t/ha)	C _{soil} /(t/ha)	C _{dead} /(t/ha)	C _{total} /(t/ha)
Cultivated land	27.9	94.6	108.4	0.0	230.9
Forest	50.5	151.8	213.2	0.0	415.5
Grassland	22.8	86.5	99.9	0.0	209.2
Water bodies	22.4	79.0	0.0	0.0	101.4
Urban area	12.5	56.7	110.8	0.0	180.0

2.3.3. FLUS Model

The Future Land Use Simulation Model (FLUS) combines the advantages of System Dynamics (SD) and Cellular Automata (CA). By introducing the roulette selection mechanism and Artificial Neural Network (ANN) model, it can effectively deal with and predict the complexity and uncertainty of mutual transformation between various land use types under the influence of the human-land relationship [24]. Compared with traditional models, the FLUS model can achieve high-precision simulation of future land use changes under multiple scenarios. The specific steps of land use simulation are as follows:

(1) Suitability probability calculation based on ANN. An artificial neural network consists of hidden layers, input layers, and output layers, and the layers are interconnected by neurons in the form of a network [25] with the following formula:

$$sp(p, k, t) = \sum_j \omega_{j,k} \times \text{sigmoid}\{net_j(p, t)\} = \frac{\sum_j \omega_{j,k}}{1 + e^{-net_j(p, t)}} \quad (2)$$

In the formula, $sp(p, k, t)$ is the suitability probability of the k th land use appearing at time t cell p ; $\omega_{j,k}$ is the weight between the hidden layer and the output layer; $net_j(p, t)$ is the input layer signal received by the hidden layer neuron j at training time t and cell p ; $\text{sigmoid}()$ is the activation function from the hidden layer to the output layer. The sum of the suitability probabilities of each land use type is constant to 1, on the iteration time t and cell p , the formula as is given:

$$\sum_k sp(p, k, t) = 1 \quad (3)$$

(2) Adaptive inertia coefficient calculation. Based on the demand for land use in the future scenario and the actual quantity of each type of land use, the inertia of each kind of land use is automatically adjusted through multiple iterations so that the quantity of each land use develops towards the set target, thus realizing the simulation of the spatial distribution of land use in a specific future scenario [26]. The formula for calculating the adaptive inertia coefficient is as follows:

$$Inertia_k^t = \begin{cases} Inertia_k^{t-1} & \text{if } |D_k^{t-1}| \leq |D_k^{t-2}| \\ Inertia_k^{t-1} \times \frac{D_k^{t-2}}{D_k^{t-1}} & \text{if } D_k^{t-1} < D_k^{t-2} < 0 \\ Inertia_k^{t-1} \times \frac{D_k^{t-1}}{D_k^{t-2}} & \text{if } 0 < D_k^{t-2} < D_k^{t-1} \end{cases} \quad (4)$$

In the formula, $Inertia_k^t$ is the adaptive inertia coefficient of the k th land use type at the moment t ; D_k^{t-1} and D_k^{t-2} are the difference between the demand and the current allocation of the k th land use type at the moment $t - 1$ and $t - 2$, respectively.

(3) Comprehensive probability calculation of land use conversion. In the iterative process of the cellular automata, combining the suitability probability, adaptive inertia

coefficient, neighborhood weight, and conversion cost, different land use types are assigned to each tuple lattice grid, and the integrated probability of tuple p to be converted from the initial land use type to the target land use type k at the moment of iteration t is calculated, and its expression is as follows:

$$TProb_{p,k}^t = sp(p, k, t) \times \Omega_{p,k}^t \times Inertia_k^t \times (1 - sc_{c \rightarrow k}) \quad (5)$$

where $TProb_{p,k}^t$ is the integrated probability that cell p is converted from the initial land type to the target type k at moment t ; $sc_{c \rightarrow k}$ denotes the conversion cost of converting from land use type c to type k ; $(1 - sc_{c \rightarrow k})$ denotes the difficulty of occurring the conversion; $\Omega_{p,k}^t$ is the neighborhood effect, which reflects the influence of the land use types around the cell on the type of the central cell [27], and is formulated as follows:

$$\Omega_{p,k}^t = \frac{\sum_{N \times N} con(c_p^{t-1} = k)}{N \times N - 1} \times \omega_k \quad (6)$$

In the formula, $\Omega_{p,k}^t$ is the neighborhood weight of k th land use type on cell p at the t th iteration; $\sum_{N \times N} con(c_p^{t-1} = k)$ is the total number of grids occupied by land use type k in the $N \times N$ Moore window at the last iteration $t - 1$, and we took $N = 3$; ω_k is the weight of the neighborhood between different land use types, and its value is directly proportional to the expansion capacity of the land use type.

2.3.4. FLUS Model Parameters Setting

(1) Land use change driving factors selection. The key factor in selecting driving factors is the availability of data, which determines the smooth operation of the FLUS model. Considering the accessibility of various data types in the study area, nine factors were selected as the driving factors of land use change. For the natural environment driving factors, we selected elevation, aspect, slope, annual average temperature, and precipitation, which are less difficult to obtain and of higher quality compared to field investigation data such as soil type and lithology. Moreover, given that LULC change is a complex process influenced by various factors, it is necessary to consider socio-economic and transportation factors to enhance the precision of land use change simulation. The socio-economic driving factors include GDP and population density, while the transportation driving factors include the distances from the water system and railway, which reflect changes in urban areas. All the driving factors underwent normalized processing and were utilized in the FLUS model (Figure 3).

(2) Neighborhood weight setting. This study employed the trial-and-error method to calculate the neighborhood weights [28]. Firstly, the suitability probability data of LULC in 2010 was calculated using the ANN module of the FLUS model, based on the 2010 LULC data alongside nine driving factors. Secondly, the suitability probability data were inputted into the CA module. Following the setting of parameters such as neighborhood weights, the LULC simulation data for 2020 was obtained. These data were then verified with the actual LULC data for 2020 using Kappa accuracy. The neighborhood weights with higher accuracy were eventually obtained after several exploratory experiments (Table 2). Neighborhood weight ranges from 0 to 1, with values closer to 1, indicating a greater ability of land use types to expand into others. Therefore, it is crucial in land use modeling and effectively represents the expansion potential of different land use types.

Table 2. Neighborhood weights of land use.

Land Use Type	Cultivated Land	Forest	Grassland	Water Bodies	Urban Area
Neighborhood weight	0.15	0.01	0.3	0.4	0.98

Notes: Neighborhood weight ranges from 0 to 1, where values closer to 1 suggest a higher capability for the current land use to expand into other types.

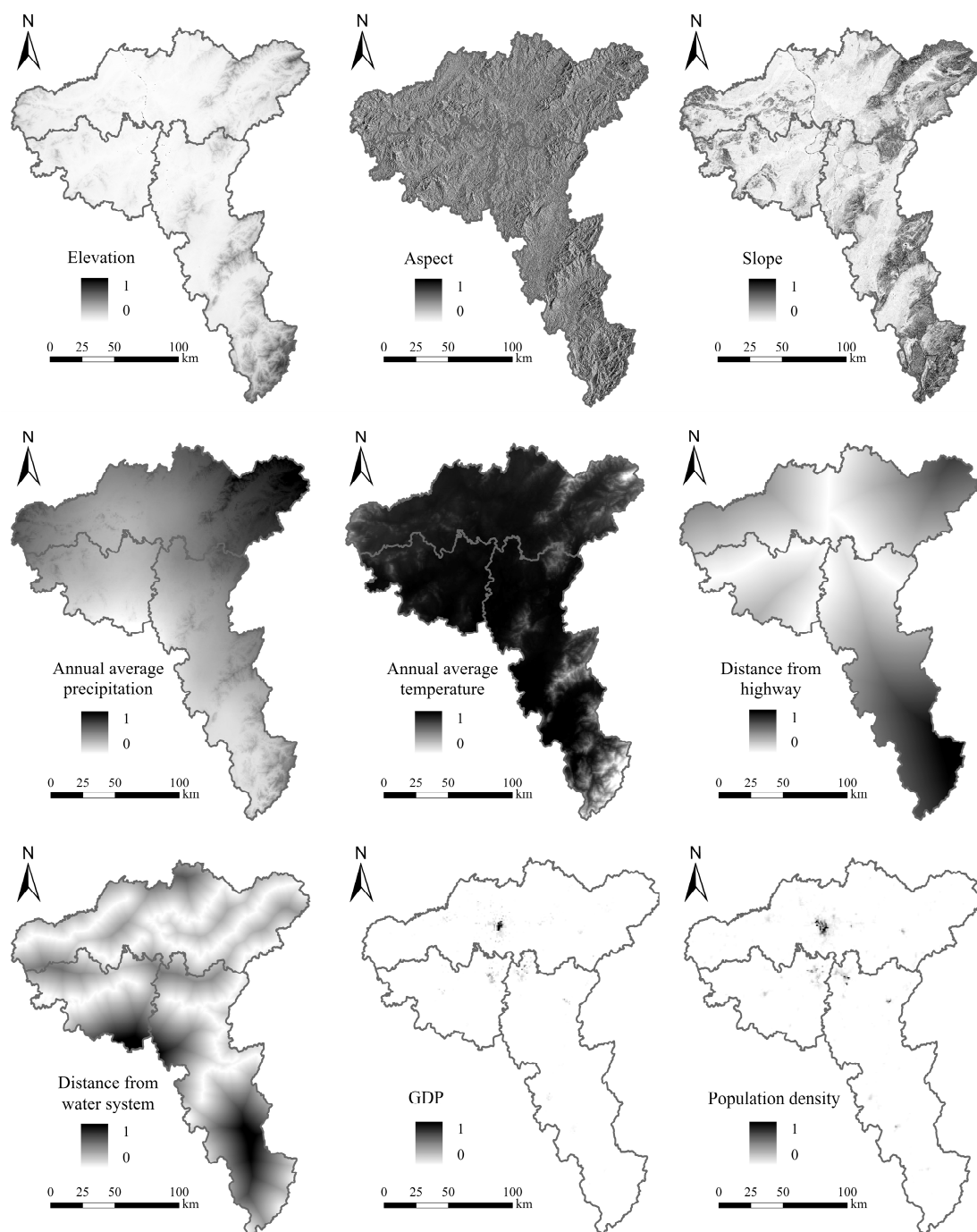


Figure 3. Spatial distribution of each driving factor.

(3) Transfer cost matrix setting. Transfer cost, a crucial factor influencing land use change, denotes the level of difficulty in converting the current land use type to other types. A value of 1 indicates that the current land use can be converted to the target land use type, while 0 indicates that it cannot be converted. We combined the development policies of the Chang-Zhu-Tan region and formulated the land use transfer cost matrix under three different land use development scenarios (Table 3). Among them, under the natural trend development (S1), no imposed restrictions were set, allowing mutual conversion between all land use types except urban areas. Since forest carbon sequestration is an effective means to reduce atmospheric CO₂ concentration [29], we set the ecological development priority (S2) and referred to the relevant regulations outlined in the *Three-Year Action Plan for the Integration and Development of Chang-Zhu-Tan (2023–2025)*, to increase the vegetation

coverage in the study area. The ecological regulation function areas within the Chang-Zhu-Tan region were reclassified to 0, such as soil and water conservation function areas, as the restricted area of the FLUS model and the input data for the CA module. Furthermore, prohibits the conversion of forests to other land use types. Under the urban development priority (S3), restricting the conversion among cultivated land, forest, and water bodies contributes to the outward expansion of urban areas and promotes regional urbanization.

Table 3. Transfer cost matrix of different land use types under multiple scenarios.

Land Use Type	S1					S2					S3				
	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E
Cultivated land	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1
Forest	1	1	1	1	1	0	1	0	0	0	1	1	1	0	1
Grassland	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1
Water bodies	1	1	1	1	1	0	1	1	1	0	1	1	0	1	1
Urban area	0	0	0	0	1	0	1	0	0	1	0	0	0	0	1

Notes: A: cultivated land; B: forest; C: grassland; D: water bodies; E: urban area; 1: the two land use types can be converted; 0: the two land use types cannot be converted.

(4) Accuracy assessment. Based on the suitability probability data of land use in 2010, the predicted land use data in 2020 were obtained through CA simulation, and the actual land use data in 2020 were utilized for testing. We used overall accuracy and the Kappa coefficient to assess the simulation accuracy of the FLUS model. The overall accuracy of the simulation results was obtained to be 0.88, and the Kappa coefficient was 0.79, which was greater than 0.75. This indicates that the simulation of the FLUS model is of great quality and has a high level of credibility.

2.3.5. Land Use Dynamic Degree

Single land use dynamic degree is used to measure the land use changes in time from 2010 to 2020 in the Chang-Zhu-Tan area, and the main characteristics of land use changes are obtained by analyzing the land use dynamic degree in each period. The formula of single land use dynamic degree is as follows:

$$O = \frac{U_i - U_j}{U_i} \times \frac{1}{T} \times 100\% \quad (7)$$

In the formula, O is the dynamic degree of a certain land use type in the study period; U_i and U_j are the area occupied by this land use type at the beginning and the end of the study; T is the length of the study period.

2.3.6. Spatial Autocorrelation Analysis Based on GIS

Spatial autocorrelation analysis refers to the correlation of the same variable in different spatial locations, which helps to indicate the degree of similarity among different geographic areas [30], including global spatial autocorrelation and local spatial autocorrelation. We selected the global Moran's I index and the local Moran's I index for spatial autocorrelation analysis to explore the degree of clustering between spatial cells and their adjacent cells.

3. Results and Discussion

3.1. Analysis of Land Use Change in Chang-Zhu-Tan Urban Agglomeration

To effectively illustrate the flow direction of land use changes, the Sankey diagram was used to visualize the transformation process of each land use type from 2010 to 2020 (Figure 4). It reveals a distinct mutual flow relationship between cultivated land and forests during this period. Furthermore, there is a large number of cultivated land and forest flow to urban areas, contributing to a rapid increase in urban area.

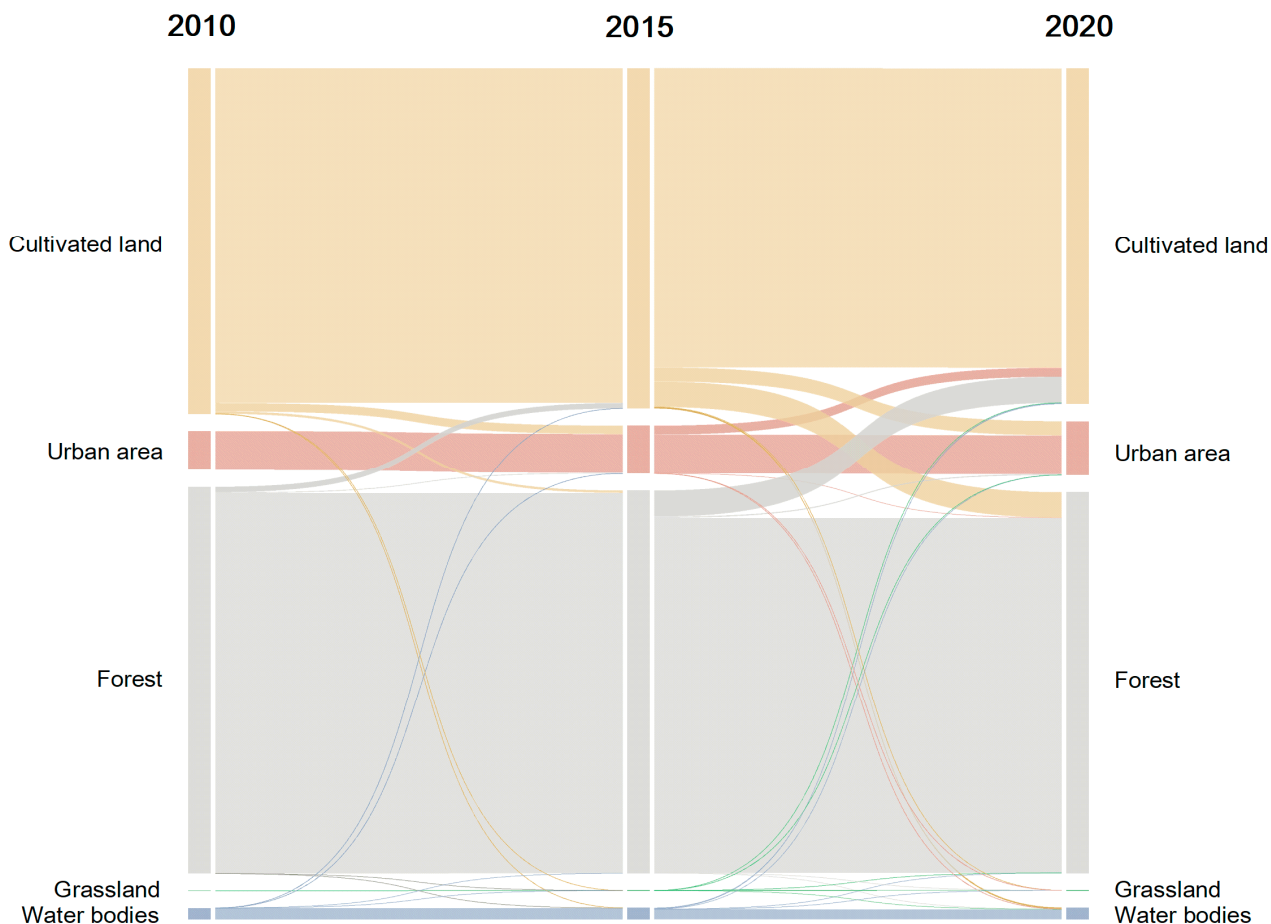


Figure 4. Conversion of each land use type from 2010 to 2020.

Table 4 illustrates the changes in the dynamic degree of each land use type in the study area from 2010 to 2020, which indicates that from 2010 to 2015, the dynamic degree of cultivated land in the Chang-Zhu-Tan area was -0.32% from the total cultivated land area, resulting in a decrease of 199.33 km^2 . The dynamic degree of the forest was -0.21% of the total forest area, ranking second only to cultivated land, with a decrease in the area of 143.29 km^2 . Due to the drastic expansion of the urban area, its dynamic degree was as high as 4.69% of the total urban area, with an increase in area of 331.08 km^2 . From 2015 to 2020, influenced by regional environmental protection policies, the dynamic degree of cultivated land, forest, and grassland all increased, especially grassland increased to 12.22% from the total grassland area, indicating that the expansion of the urban area to other land use was weakened. The overall land use change from 2010 to 2020 indicates a decrease in the area of cultivated land and forest and an increase in the area of water bodies, grasslands, and urban areas. The most notable change was observed in the urban area, which increased by 546.75 km^2 . The percentage of urban areas grew from 5.02% in 2010 to 6.97% in 2020. The land use change in the Chang-Zhu-Tan urban agglomeration is primarily driven by a significant increase in urban areas, with cultivated land and forest being the main targets for expansion.

The FLUS model is utilized to obtain the spatial distribution of land use in the Chang-Zhu-Tan urban agglomeration under multiple scenarios in 2035. Figure 5 shows that all the scenarios exhibit similar land use patterns. Among them, the S1 and the S3 show a higher degree of similarity. The area of cultivated land under each scenario is the same, and forest accounts for the largest proportion of the total area, with 46.75% , 48.64% , and 46.92% under the S1, S2, and S3, respectively. Most of the forests are distributed in the eastern and southern parts of Chang-Zhu-Tan urban agglomeration, where the altitude is high. Cultivated land is primarily located in the plain areas of the western part of the

urban agglomeration, as well as in the Xiangjiang River basin and its surrounding areas. The urban area is mainly concentrated in the metropolitan area of the central and northern parts of the urban agglomeration (such as Kaifu, Furong, and Yuhua districts in Changsha, Yuhu and Yetang districts in Xiangtan, and Lusong, Tianyuan, and Shifeng districts in Zhuzhou) and the central urban areas of the counties, with a few distributed in strips along the traffic lines.

Table 4. Changes in the area and dynamic degrees of each land use type from 2010 to 2020.

Land Use Type	2010–2015		2015–2020		2010–2020	
	Change Area/km ²	Dynamic Degree/%	Change Area/km ²	Dynamic Degree/%	Change Area/km ²	Dynamic Degree/%
Cultivated land	−199.33	−0.32	−166.32	−0.27	−365.65	−0.29
Forest	−143.29	−0.21	−60.09	−0.09	−203.38	−0.15
Grassland	0.01	1.18	0.11	12.22	0.12	7.06
Water bodies	11.53	0.57	6.87	0.33	18.40	0.45
Urban area	331.08	4.69	215.67	2.48	546.75	3.88

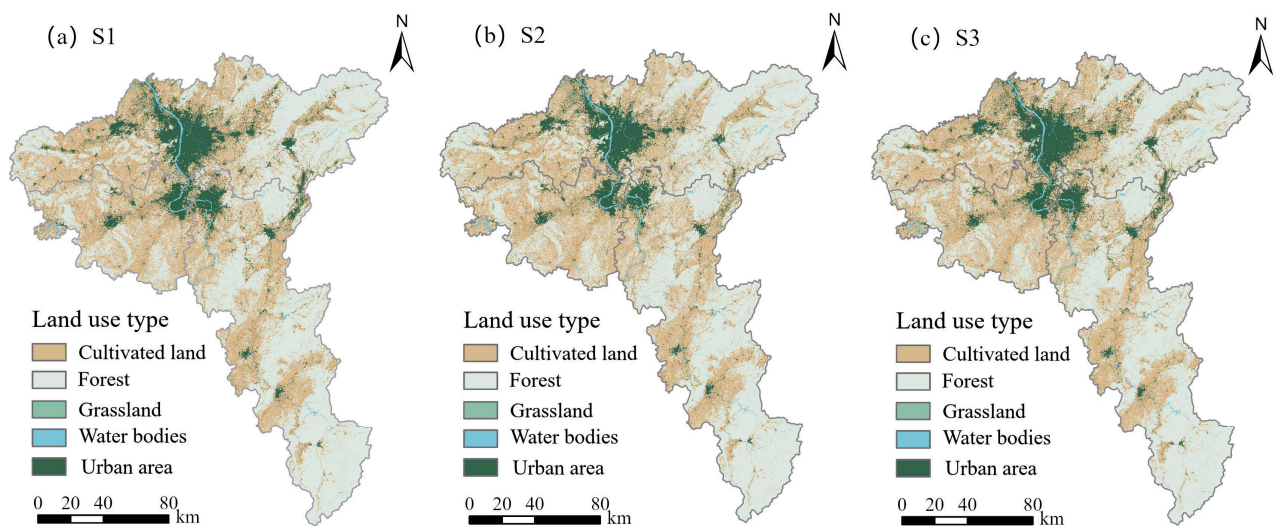


Figure 5. Spatial distribution of land use in 2035 under future land use development scenarios.

3.2. Spatial and Temporal Evolution of Carbon Storage from 2010 to 2020

Figure 6 illustrates the spatial distribution of carbon storage in Chang-Zhu-Tan urban agglomeration in 2010, 2015, and 2020, as well as the spatial variation of carbon storage from 2010 to 2020 calculated by the InVEST model. The distribution of carbon storage exhibits significant spatial heterogeneity, characterized by a pattern of “low in the middle and high around” (Figure 6a,c). During the study period, the carbon storage in the Chang-Zhu-Tan area was 8911.23×10^5 t in 2010, decreased to 8866.43×10^5 t in 2015, and further dropped to 8842.61×10^5 t in 2020. The low-value areas of the carbon storage were distributed in clusters in the urban centers of the three cities, with some areas showing scattered distribution and a tendency to spread out year by year. As the urbanization level of the low-value areas is high, the predominant land use type is urban area, influenced by human activities and characterized by low vegetation coverage, leading to low levels of carbon storage. High-value areas were mostly located in forests and cultivated areas with dense vegetation coverage and great forest economic benefits. In addition, the eastern and southern parts of the urban agglomeration have higher elevations and relatively rugged terrain. This, to a certain extent, restricts the expansion of the urban area into forests and cultivated land, as well as human production activities. Consequently, these areas have a higher potential for carbon sequestration.

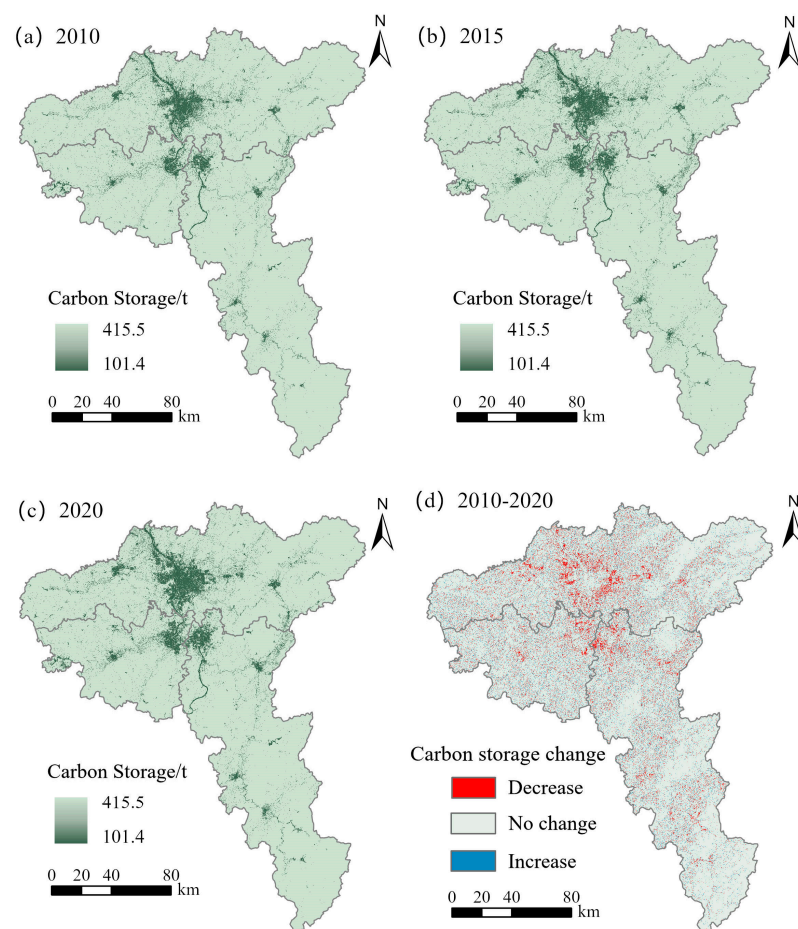


Figure 6. Spatial distribution and changes in carbon storage from 2010 to 2020.

The areas of carbon storage changes showed spatial characteristics of continuous aggregation and scattered distribution (Figure 6d). During the study period, 88.52% of the area of carbon storage remained unchanged, mainly concentrated in the forest in the eastern and southern parts of the study area, with flaked aggregation distribution. The areas with increasing carbon storage only accounted for 4.50% of the total area, with the scattered distribution. The areas with decreasing carbon storage accounted for about 6.98% of the total area. Among these, the areas with significant decreases in carbon storage were mainly clustered in the urban area in the north–central part of the study area. The reason for this is that the urbanization of the study area accelerated from 2010 to 2015. The expansion of the city scale and the increase in urban area led to a significant decrease in carbon storage in the municipal districts and their surrounding areas. Since the 19th National Congress in 2017, Hunan Province has aimed to advance high-quality economic development. Consequently, the economy of the Chang-Zhu-Tan region has transitioned from rapid growth to high-quality development. This shift has led to a deceleration in the expansion of the low-value areas of carbon storage from 2015 to 2020.

3.3. Relationship between Land Use Change and Carbon Storage under Multi-Scenarios

3.3.1. Impact of Future Land Use Change on Carbon Storage under Multi-Scenarios

Figures 7 and 8 depict the spatial distribution of carbon storage under multiple scenarios and changes in carbon storage distribution from 2020 to 2035, as predicted by the InVEST model. These figures are analyzed in conjunction with the statistics of LULC and carbon storage under the three scenarios in 2035 (Table 5). In general, the spatial distribution pattern of carbon storage under the three scenarios in 2035 shows minimal variation, with no significant changes compared to 2020. The spatial pattern of “low in the

middle and high around” remains consistent. Specifically, the areas experiencing a decrease in carbon storage from 2020 to 2035 under the three scenarios are primarily located in the expanding urban areas. These areas are concentrated and consistently spread across the metropolitan regions of Chang-Zhu-Tan urban agglomeration and their surrounding zones, with a few sporadic distributions in villages and towns characterized by lower levels of urbanization. The areas with essentially unchanged carbon storage are mainly distributed in regions consisting of wide ranges of forest and cultivated land. The areas with increasing carbon storage are scattered.

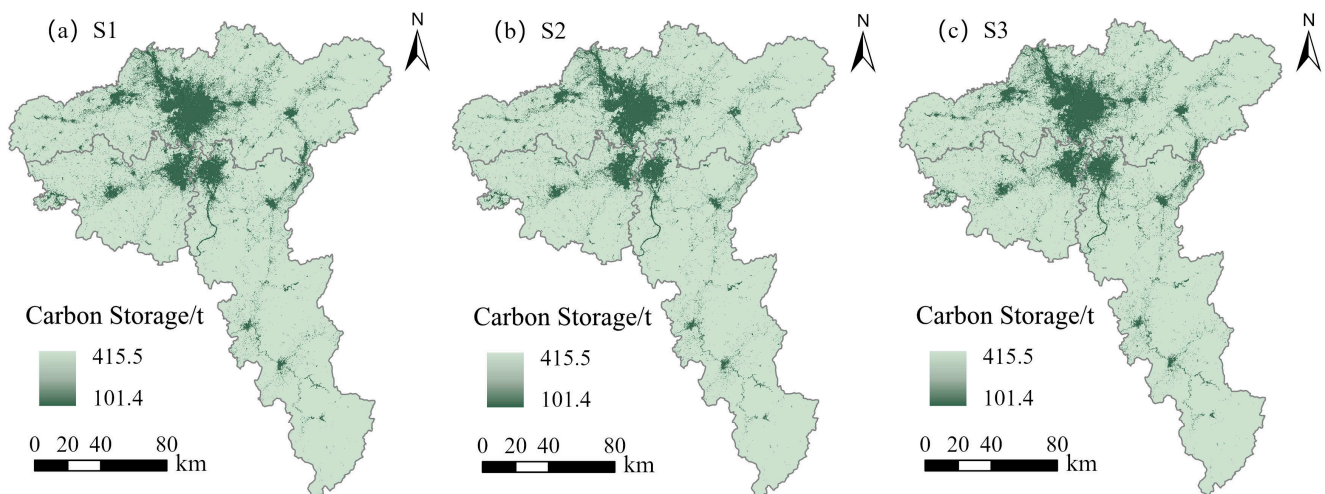


Figure 7. Spatial distribution of carbon storage in 2035 under multiple scenarios.

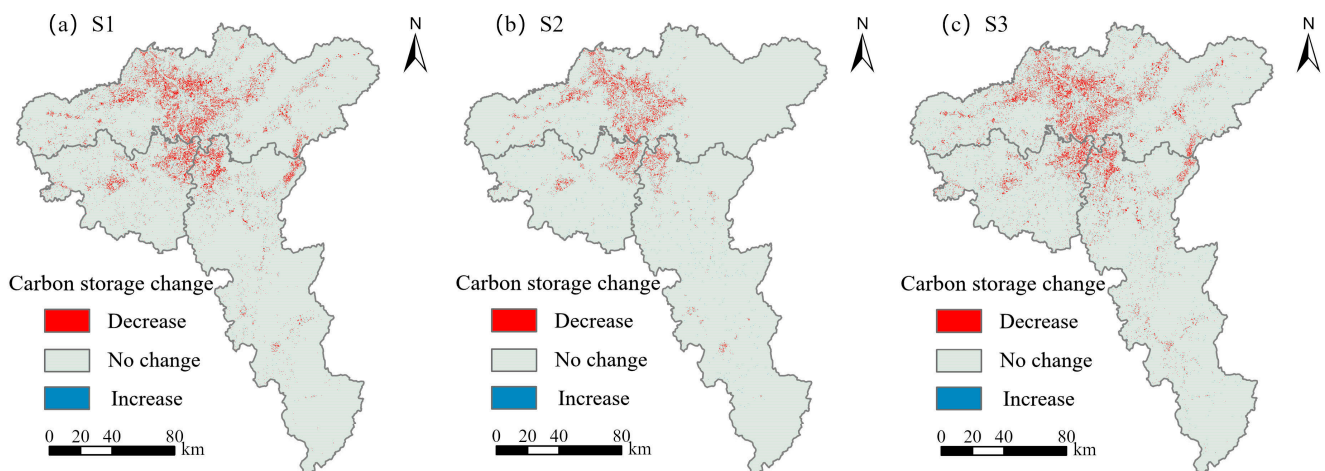


Figure 8. Changes in the spatial distribution of carbon storage from 2020 to 2035.

In S1, the areas with low values of carbon storage expand in a scattered pattern centered on the low-value areas in 2020 (Figures 7a and 8a). This scenario is not affected by regional development policies, and the changes in the area of each type of land use in 2035 follow the same trend as that of 2010–2020. Cultivated land decreases the most, followed by forest, and the carbon storage decreases by 135.81×10^5 t and 189.61×10^5 t, respectively. The most significant change occurs in the urban area, which increases by 1058.72 km^2 , primarily due to the conversion of cultivated land and forest.

In S2, the Chang-Zhu-Tan urban agglomeration vigorously implements actions for ecological environment protection and enhances the ecological value of the green-core area by supplementing forest areas. The area of forest under this scenario is the largest, with carbon storage reaching 5672.80×10^5 t, accounting for 64.33% of the total carbon storage.

In addition, the area of forest increased by 25.23 km² from 2020 to 2035, marking the only scenario with a positive growth in forest area. The restriction on converting forests to other land types results in a significant reduction in the expansible area of the urban areas, which is 47.1% lower than that of S1, and the area of carbon storage reduction decreased significantly (Figures 7b and 8b).

In S3, the forest area reduction decreased by 9.3% compared to S1. The area of water bodies shrank more significantly, while the changes in cultivated land, grassland, and urban area were approximately the same as in S1. The decrease in carbon storage under this scenario is the largest, with a reduction of 150.90×10^5 t compared to 2020. The area experiencing a reduction in carbon storage is mainly distributed in the expanding urban area (Figures 7c and 8c).

In summary, the simulation results for carbon storage under S1 and S3 are generally less different. Even without the intervention of regional development policies, the urban area and its surrounding areas in the north-central part of the urban agglomeration still exhibit a development trend where the urban area expands into cultivated land and forest. This expansion affects terrestrial ecosystems, exacerbating the loss of carbon storage. In S2, the ecological protection policy effectively controls the expansion rate of urban areas, leading to a significant reduction in carbon storage loss. In comparison, the large-scale expansion of urban areas into forests and cultivated land is the main cause of carbon storage loss, which is consistent with the studies by Geng et al. [31].

Table 5. Land use change and carbon storage under multiple scenarios in 2035.

Scenario	Data Type	Land Use Type				
		Cultivated Land	Forest	Grassland	Water Bodies	Urban Area
2020	carbon storage/ 10^5 t	2784.69	5662.32	0.06	43.19	352.35
S1	change area/km ²	−588.19	−502.94	0.07	32.48	1058.72
	carbon storage/ 10^5 t	2684.88	5472.71	0.05	41.75	542.92
S2	change area/km ²	−588.19	25.23	0.07	3.24	559.79
	carbon storage/ 10^5 t	2684.88	5672.80	0.05	43.51	453.11
S3	change area/km ²	−588.19	−456.33	0.07	−14.13	1058.72
	carbon storage/ 10^5 t	2684.88	5453.35	0.05	46.48	542.92

3.3.2. Spatial Autocorrelation Analysis of Carbon Storage under Multi-Scenarios

Based on the spatial distribution of carbon storage in the study area in 2035, the global Moran index is used to analyze the spatial autocorrelation (Table 6). The z-score is significantly greater than 2.58, leading to the rejection of the null hypothesis that carbon storage is spatially distributed as a stochastic process. Positive global Moran's I indicates a positive spatial correlation in the distribution of carbon storage in the Chang-Zhu-Tan area.

Table 6. Global spatial autocorrelation analysis of carbon storage under multiple scenarios in 2035.

Scenario	Global Moran' I	p Value	Z Score
S1	0.480	0.000	56.09
S2	0.456	0.000	53.28
S3	0.480	0.000	56.05

The local spatial autocorrelation analysis of the carbon storage distribution in Chang-Zhu-Tan urban agglomeration in 2035 under each scenario was further conducted using the ArcGIS clustering and outlier analysis tool (Anselin Local Moran's I). From the Local Indicators of Spatial Association (LISA) cluster analysis (Figure 9), it can be seen that the spatial distribution of carbon storage under the three scenarios exhibits clear aggregation characteristics. Particularly, S1 and S3 demonstrate a higher degree of similarity. Low-value

carbon storage aggregation areas are concentrated in the metropolitan area in the north-central part of the urban agglomeration, and a few are scattered in the main urban areas of counties. This indicates that the carbon storage of each city district in the metropolitan area is low and spatially aggregated. The high carbon storage aggregation areas are more scattered, mainly in the mountainous areas at the edge of the urban agglomeration. These areas include the eastern part of Youxian County, Chaling County, Yiling County, and the northeastern part of Liuyang City.

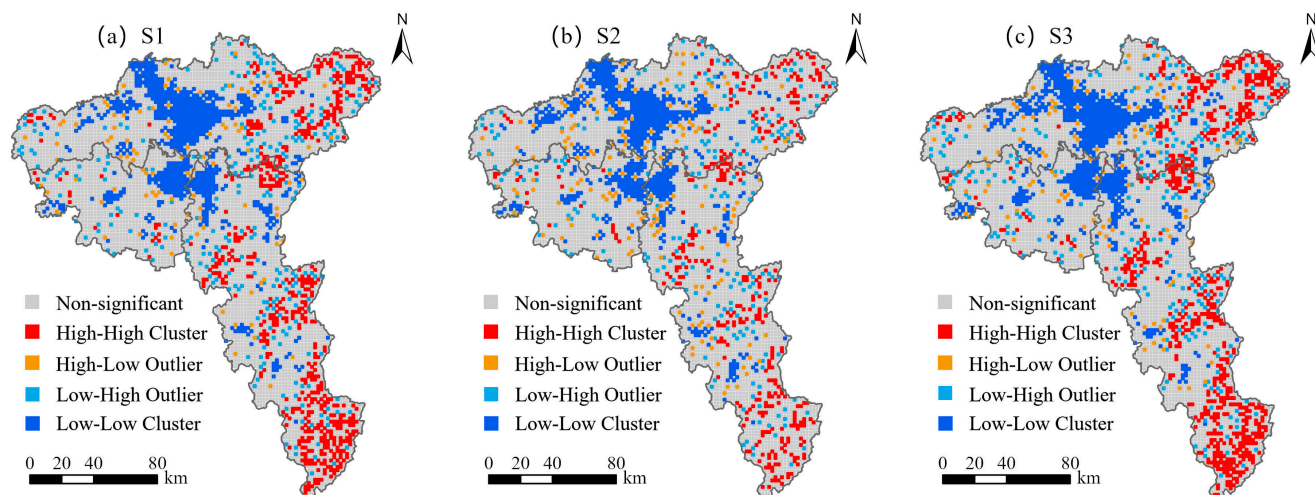


Figure 9. LISA cluster of carbon storage in 2035 under future land use development scenarios.

In addition, by combining the spatial distribution of land use in the Chang-Zhu-Tan region under the three scenarios in 2035 (Figure 5), it is evident that the spatial aggregation characteristics of carbon storage are closely related to the spatial distribution of land use. The high-high cluster areas of carbon storage are primarily distributed in forests and cultivated land with dense vegetation coverage or high ecological value. The low-low cluster areas are mainly concentrated in urban areas with a high degree of land development and frequent human activities, such as the north-central metropolitan area and its neighboring towns. The low-high outlier area is a region characterized by low values surrounded by high values, indicating a spatial outlier of low values that may be due to the influence of local forest growth. The high-low outlier area is a region that exhibits high values surrounded by low values, indicating a spatial outlier of high values, which could be related to frequent human activities. Most of the non-significant areas consist of high land use mixing.

3.4. Limitations

(1) The intensity of human activities has weakened after 2020 due to the influence of the COVID-19 pandemic. Various land use types exhibit varying degrees of response, which was not considered in the model. In addition, land use types such as forests and grasslands are notably impacted by climate change. The number of natural environment-driving factors in this study is relatively limited, and the data collection period varies, potentially resulting in a bias in the simulation outcomes;

(2) Owing to external factors such as environmental conditions and weather, satellite images are frequently obscured by clouds, consequently impacting the precision of interpreting target features [32]. Improving the cloud removal algorithm can enhance the accuracy of satellite images, thereby reducing error with the actual value. Furthermore, achieving precise image classification requires data with high spectral and spatial resolution that may not be obtainable from a single satellite sensor [33]. Thus, fusing data from different sensors to achieve higher temporal and spatial resolutions can efficiently improve the precision of image classification [34];

(3) In recent years, the InVEST model has been widely applied in evaluating carbon storage and related studies. Nonetheless, the model itself still has some limitations. Since the InVEST model focuses on the carbon density difference between different land use types, neglecting future climate variations and carbon sequestration capacity differences within the same type of land use may reduce the accuracy of future carbon storage predictions [35]. Besides, there is a lack of field investigation data regarding the carbon density of various land use types in the Chang-Zhu-Tan urban agglomeration, and discrepancies persist between the carbon density data we utilized and the actual values. Hence, future research should identify the investigation and measurement of carbon density data while making appropriate corrections to enhance the accuracy and scientific validity of carbon storage estimation results.

4. Conclusions and Advice

4.1. Conclusions

We integrated the FLUS and InVEST models to forecast the trend of land use change and the spatial distribution of carbon storage under the S1, S2, and S3 scenarios in 2035. This study conducted a comprehensive evaluation of the current status of land use change and carbon storage in the Chang-Zhu-Tan urban agglomeration from 2010 to 2020. The conclusions are outlined as follows:

(1) Throughout the research period, the predominant characteristic of land use change in the Chang-Zhu-Tan urban agglomeration is the substantial expansion of urban areas. This expansion primarily encroached upon cultivated land and forests. Between 2010 and 2020, the transformation of urban areas into cultivated land and forests occurred rapidly, leading to a 138.8% growth, equivalent to an increase of 546.75 km². The dynamic degree of urban area was notably high at 3.88%. Conversely, the area of cultivated land decreased by 365.65 km², and the forest area decreased by 203.38 km². After 2015, due to policy interventions, constraints were placed on urban development expansion, leading to increased conservation of cultivated land, forests, and grasslands. Urban areas decreased by 2.48%; consequently, the capacity for expansion into other land types diminished;

(2) The distribution of carbon storage in the Chang-Zhu-Tan urban agglomeration is spatially heterogeneous. Low-value areas of carbon storage are predominantly clustered in the central and northern metropolitan areas, while regions with high value are mostly scattered in cultivated land and forests with dense vegetation coverage. In addition, LULC has a significant impact on the change in carbon storage. The significant decrease in carbon storage from 2010 to 2015 is closely linked to the rapid expansion of urban areas during that period. However, the implementation of appropriate regional development policies aided in alleviating the decline in carbon storage from 2015 to 2020;

(3) The forecast for 2035 suggests that the Chang-Zhu-Tan area will follow a development pattern similar to that of the S3 under the S1. The expansion of urban areas with low carbon storage into cultivated land and forests with high carbon storage will continue, resulting in a reduction of 13.63×10^6 t in carbon storage. In contrast, in the S2, carbon storage will only decrease by 2.42×10^6 t compared to the 2020 levels. This indicates that the implementation of ecological protection measures can effectively mitigate the loss of carbon storage. In the S3, an imbalanced land use structure will lead to an increase in the loss of carbon storage, reaching 15.09×10^6 t.

4.2. Advice

Considering the variations in land use and carbon storage under the three future scenarios, to achieve sustainable development in the region, it is essential for the Chang-Zhu-Tan urban agglomeration to strategically plan for future development by optimizing the land use structure, segmenting developments, and focusing on ecological restoration. To optimize the land use structure and prevent the conversion of high carbon storage ecosystems such as forests and cultivated land into low carbon storage urban areas, it is advisable to rationally plan cultivated land and forests, promote sustainable forestry

management, and implement scientific agricultural techniques. The suggested actions aim to augment the soil organic carbon accumulation and enhance the overall carbon storage capacity of the region. As predicted by the InVEST model, the development trend of the study area in the S1 is closely consistent with that of the S3. Thus, it is crucial to clearly define the intensity of development and functional zoning of key regions such as urban areas and county centers. Furthermore, reasonably limiting land development intensity is necessary, which is consistent with the research results of Verstegen et al. [36].

Compared with other terrestrial ecosystems, forest ecosystems show the highest productivity [37], which indicates the necessity of promoting ecological protection and green projects in urban and rural planning by reducing emissions from deforestation and forest degradation caused by human activities, improving and protecting forest carbon storage to promote ecological restoration and achieve sustainable forest management [38].

Overall, the future development of the Chang-Zhu-Tan region should prioritize sustainable development of society, economy, and ecology, addressing areas such as land use structure and ecological and environmental protection, guiding the formulation of comprehensive future development policies.

Author Contributions: X.L. designed the research, supervised and revised the manuscript; W.S. performed the research, carried out data analysis, and wrote and revised the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Project of Hunan Provincial Department of Education, China, grant number 23A0353.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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