Exploring ecosystem carbon storage change and scenario simulation in the Qiantang River source region of China

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Abstract
To explore the impact of land-use change on carbon storage, this study coupled the InVEST model and the FLUS model to analyse the spatial and temporal characteristics of carbon storage in the Qiantang River source region from 2000 to 2030. The carbon storage in the study area is evaluated which declined rapidly from $166.22 \times 10^6$ t in 2000 to $164.41 \times 10^6$ t in 2020, and the spatial distribution of carbon storage could be characterized by “the northwest and the southwest of region with higher, the east and the centre of the region with lower”. The carbon storage was simulated based on the historical trend development scenario, the food security scenario, and the ecological protection scenario. The carbon storage with the food security scenario could achieve $162.74 \times 10^6$ t in 2030. The carbon storage with the ecological protection scenario had an increase of $62.60$ t/km² compared to the historical natural tendency development. Interestingly, the food security scenario had the smallest carbon loss value which is about $1.39 \times 10^9$, and its net carbon storage value was the largest which is about $3.71 \times 10^9$. The results of this study could provide a scientific reference for the conservation of carbon storage and land use management for climate change and sustainable development. This paper also can lay the foundation for subsequent further studies such as artificial intelligence.

Keywords
carbon storage, FLUS model, InVEST model, simulation, land-use change

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Introduction

Ecosystem carbon storage is important for mitigating climate warming and achieving carbon neutrality.\(^1\) According to the report of the Special Report on Global Warming of 1.5°C in 2018, Land use/cover such as woodland played an important role in achieving the target of raising 1.5°C by enhancing ecosystem function.\(^2\) Maintaining ecosystem balance is an important measure for climate change mitigation and adaptation, as well as a key approach for the implementation of nature-based solutions. To mitigate the effects of climate change on ecosystems, China has taken many actions. The Chinese Academy of Sciences took the lead in launching a project on Carbon Balance Certification and Related Issues in Response to Climate Change (Carbon Special Project), which established the Ecosystem Carbon Sequestration project in 2011. The core of the project was to systematically investigate and observe the carbon storage and sequestration capacity of various ecosystems in China.\(^3–6\) Then, China also renewed its commitment to increase its intended national contributions at the United Nations General Assembly in September 2020. Terrestrial ecosystem carbon storage is an important indicator of the carbon storage services of ecosystems. China also has put forward the goal of striving to peak carbon emissions by 2030 and achieving carbon neutrality by 2060 which is also called the “3060” target. Based on this target, researchers explored new energy and green finance to help achieve carbon neutrality goals.\(^7\) However, due to the impact of human activities and climate change, the capacity of global ecosystem services is decreasing. Therefore, how to increase ecosystem carbon storage is an important issue that needs to be addressed.\(^8\)

The carbon storage function of ecosystems is directly or indirectly affected by land-use change, which is an important driving factor of the carbon cycle in terrestrial ecosystems.\(^9–11\) Land-use change affects carbon emissions and sequestration in the terrestrial ecosystem through changes in land-use type, pattern, intensity, and structure.\(^12\) Recent studies have shown that the increase in cultivated land may have a direct impact on ecosystem services.\(^13,14\) Several studies also found that the increase or decrease in biota population due to land-use change has a direct impact on atmospheric CO\(_2\).\(^15,16\) Therefore, making research on land-use change and carbon sequestration in regional terrestrial ecosystems is particularly important. Several studies set different scenarios like the historical trend development scenario, the Planning scenarios, the ecological protection scenario, and different project scenarios.\(^17,18\) According to the Chinese basic national policy which is “protecting the red line of 1.8 billion acres of cultivated land and the “3060” target, we set the food security scenario and the ecological protection scenario to explore the impact of land-use change on carbon storage.

In terms of carbon storage estimation, carbon storage can be estimated based on the biomass and the carbon content conversion factor through field investigation.\(^19\) The IPCC inventory method is also one of the empirical statistical methods for conducting carbon stock change studies. The IPCC inventory method involves the average soil carbon density and the carbon pool impact factor.\(^20\) But more scholars have applied different models to assess ecosystem carbon sequestration services in several countries or regions. For example, some scholars have used the InVEST model to assess ecosystem carbon sequestration services in Tanzania of Africa, the United States, Minnesota, and
In addition to studies that calculate carbon stocks by land-use type, scholars had also conducted more subdivision studies under each land-use type, for example, assessing the carbon storage using the InVEST model, which subdivided forests more into dense forest, open forest, and scrub forest. Some have used the CASA model which represents the spatial distribution of the demand for carbon sequestration services in vegetation primary habitats each month by the product of photosynthetically active radiation and actual light energy use to calculate the carbon sequestration service supply of the biogenic carbon pool. Some have used the GLO-PEM model which is a model for measuring net primary production(NPP) based on remotely sensed satellite data at a regional scale, to estimate the net primary productivity of vegetation and then to measure the vegetation carbon density of different land-use types. In general, scholars usually use the InVEST model to predict different ecosystem services, which is one of the dominant approaches in current research. Using remote sensing data and geospatial techniques to determine land use/land cover change and estimate carbon pools would make results more accurate and more scholars are studying carbon density in the InVEST model by calculating carbon density for different land-use types in different regions, even down to the precise breakdown of carbon density for different tree species. However, the value of carbon storage which is generated by land-use change over a certain period in the future has been rarely assessed by scholars and few studies used the InVEST model to study the impact of land-use change on carbon storage in terrestrial ecosystems in the Qiantang River Source region. Based on previous studies, this paper estimates the economic value of carbon storage in 2030 and analyses the impact of land-use change on carbon storage, to make the ecosystem carbon storage more complete.

In recent years, researchers have studied the prediction of ecosystem carbon sequestration services from a land-use perspective. The future development of cities is influenced by many factors and it is necessary to take scenarios of environmental change into account when modelling future land-use change. Different methods were used to predict land use/land cover demand by conducting scenario analysis. The Shared Socioeconomic Pathways (SSPs) are scenarios proposed by the IPCC according to climate change background and possible future socio-economic conditions. Scholars have conducted the scenario analysis by using the CLUE-S, CA-Markov, and LUSD-urban to predict future land use and further coupled with the InVEST model to assess changes in terrestrial ecosystem carbon storage caused by land-use change under different scenarios. In addition, Chinese scholars have independently developed the SAORES model, which is based on ecological processes and environmental indicators to optimize spatial land use based on the ecosystem.

However, few studies combine remote sensing data with a non-parametric estimation method based on the machine learning method to estimate carbon storage. To address the above-mentioned gap based on previous research. The Markov and FLUS model was used to predict the amount of each land-use type under three scenarios in 2030, and simulate spatial distribution patterns under three scenarios (the historical trend development scenario, the food security scenario, and the ecological protection scenario). Generally, the results of this study provide new insights that could be used to provide decisions regarding land resource allocation and ecological and environmental management in the study area.
Materials and methods

Study area

The study area which is called the Qiantang River source region is in western Zhejiang Province (27°02′N~31°11′N, 118°01′E~123°10′E) and is the source of the Qiantang River. The Qiantang River Source “Shanshui Project” was included in the third group of trial projects to conserve the ecosystems of mountains, forests, farmland, rivers, and lakes in 2018, with a total investment of RMB 18.180866 billion for the pilot project period from 2019 to 2021. The area of the Qiantang River source region is 10,067 km². The study area is an important ecological function area which is the water source in the Yangtze River Delta and an important ecological barrier in East China. The study area involves mainly four counties (cities), including Chun’an County and Jiande City in the northern source of the Qiantang River and Kaihua County and Changshan County in the southern source of the Qiantang River. The climate is subtropical monsoon, with high temperatures, heavy rain in summer, and mild winters. There is average precipitation of 1963 mm and an average annual temperature of 16.2°C. The total population at the end of 2020 was 1,668,200, and the GDP is 94.31 billion yuan. The area of woodland in the region at the end of 2020 will be approximately 7786.60 km², accounting for 78.23% of the total area, and the area of cultivated land will be 1086.15 km², accounting for 10.9% of the total area (Figure 1).

![Figure 1. Location of qiangtang river source region.](image-url)
Data source

The land-use types for 2005, 2010, 2015, and 2020 of Chun’an, Jiande, Kaihua, and Changshan counties were obtained from the Institute of Geographical Sciences and Resources of the Chinese Academy of Sciences (https://www.resdc.cn). The land-use types were classified according to the Chinese Academy of Sciences land use/cover standards, which contained cultivated land, woodland, grassland, water, construction land, and unused land. The meteorological data were obtained from the China Meteorological Data Network (http://data.cma.cn/). Basic geographic data including administrative boundaries of the four counties, roads, railways, rivers, and rural settlements were obtained from the 1:1 million national basic geographic data published by the National Basic Geographic Information Centre (http://www.webmap.cn). The elevation data was obtained from the Geospatial Data Cloud (https://www.gscloud.cn/search), and the slope and aspect data were calculated based on the elevation data. The spatial coordinate system used in this paper is Krasovsky_1940_Albers, with a resolution of 100 m.

Methods

By linking the InVEST and FLUS models, the framework of methodology consisted of three steps. Firstly, setting up different scenarios: Markov chain was used to set three different scenarios (S1, S2, and S3) for 2020–2030 in the Qiantang River source region for land use. The number of land-use types in the study area in 2030 under the three different scenarios was obtained. Secondly, simulation of future land-use distribution: the FLUS model was used to simulate the spatial distribution under the three different project implementation scenarios. Then, we obtained the land-use types of the study area in 2030 under
three different project implementation scenarios. Thirdly, the InVEST model was used to measure the carbon storage of terrestrial ecosystems in the study area in 2000, 2005, 2010, and 2020. Then, the terrestrial ecosystem carbon storage and carbon storage values of the Qiantang River source region in 2030 under three different scenarios were measured (Figure 2).

**Predicted demand of land use based on markov.** The quantitative demand for land use types in the study area was various under three different scenarios. Therefore, this paper used the Markov model to predict the demand for each land use type under three scenarios: the historical trend development scenario, the food security scenario, and the ecological protection scenario in the Qiantang River source region. To simulate land-use change, the Markov model was applied in the study of land-use change by assuming that the state of the land-use type at \( t + 1 \) was only related to the state of the land-use type at \( t \). The formula was as follows:

\[
S(t+1) = P_{ab} \times S(t)
\]

where \( S_t, S_{t+1} \) for \( t, t+1 \) were the land-use type state matrices for the study area and \( P_{ab} \) denoted the transfer probability matrix for the transformation from type \( a \) to type \( b \).

**Setting scenarios for future land-use types.** According to the research result, that parameter set needs to meet the government goals and needs for economic growth. In the Circular on Printing and Issuing the ‘Three-year Action Plan for the Pilot Project of Ecological Protection and Restoration of Landscape Forest Farmland and Lake Grass in the Source Area of Qiantang River in Zhejiang Province (2019–2021)’ and ‘Measures for the Management of the Pilot Project of Ecological Protection and Restoration of Landscape Forest Farmland and Lake Grass in the Source Area of Qiantang River in Zhejiang Province’, the Government stipulates that the regional forest land ownership reaches more than 1197.2 million mu, forest cover rate maintained at more than 77.05%, cultivated land in the region reached more than 1.2131 million mu, to ensure the safety of Qiantang River south source strategic water area, to ensure the safety of Qiandao Lake and other important drinking water sources. Three scenarios were set for the Qiantang River source region by changing the transfer probabilities for land-use type based on different targets.

1. The historical trend development scenario(S1) is based on the land-use transfer matrix for the Qiantang River source region from 2010 to 2020 and the land-use transfer probability matrix. The number of each land-use type in the Qiantang River source region in 2030 was projected in 10-year steps.
2. The food security scenario(S2) is set according to the Chinese basic national policy of protecting the red line of 1.8 billion acres of cultivated land and fully guaranteeing the total amount of cultivated land, this paper set a food security scenario. To previous research on the Markov process transfer probability correction, the transfer probability of cultivated land to urban was reduced by 50%, and
the transfer probability matrix to woodland, grassland, and water was reduced by 25% in this scenario.

3. The ecological protection scenario (S3) is set with the proposal of the concept of carbon peaking and carbon neutrality. Ecological conservation was gradually becoming an important part of the research. This scenario aimed to protect ecological lands, such as grassland, woodland, and water, which was important for maintaining and improving the ecological environment of the region and protecting regional ecological security. In this scenario, the probability of conversion of woodland, cultivated land, water, and grassland was adjusted so that the probability of conversion of woodland and grassland to construction land was reduced by 50% and the probability of conversion of water to construction land was reduced by 30%. The reduction was added to the probability of conversion of cultivated land to woodland.

**Simulation of spatial-temporal land-use change under three different scenarios.** The FLUS model was a model used to simulate land-use change and future land use scenarios under the influence of human activities and nature. The principle of the model was derived from the theory of Cellular Automata (CA) and had been greatly improved based on the traditional meta-cellular automaton. Firstly, based on the land-use type map of the study area in 2020 and the selected driving factors of land-use change, the ANN-based Probability-of-occurrence Estimation of the FLUS model was used to calculate the probability of suitability of each land-use type in the study area in 2030. Secondly, Self-adaptive inertia and competition mechanism CA in the FLUS model were used to solve the problem of multiple land-use types under the combined effects of nature. Finally, based on this rule and the Markov model, the spatial distribution pattern of land use in 2030 was simulated using the theory of CA.

1. The causes of land-use change were composed of various factors. According to the causes of land-use change and the current situation of the study area,

| Table 1. Data description of driving factors of land-use change. |
|---------------------------------|---------------------------------|----------------|
| **Category** | **Definition** | **Usage** |
| Land use pattern | Land use classification data of 2010 | Model input |
| | land use classification data of 2020 | Precision validation |
| Driving factors | Elevation data | Natural factors for calculating the probability of occurrence |
| | Slopes | |
| | Aspect | |
| | The distance to the railway | |
| | The distance to the river | |
| | The distance to the highway | |
| | The distance to settlements | |
| | Temperature | Climate factors for calculating the probability of occurrence |
| | Precipitation | |
elevation, slope, and slope direction are taken as topographic influences, distance to railways, rivers, roads, and settlements are taken as traffic location influences, and precipitation and temperature were taken as a natural effect in this paper (Table 1).

2. The weight of the neighbourhood was used to reflect the interactions between different site types and different site units within the neighbourhood. In this paper, a $3 \times 3$ Moore neighbourhood model was chosen to calculate this parameter as follows:\(^4^3\)

$$\Omega'_{p,k} = \sum_{3 \times 3 \text{con}(c^t_{p-1} = k)} \times w_k$$

where $\text{con}(c^t_{p-1} = k)$ denoted the total number of cells occupied by site type $k$ at the last iteration $t-1$; $w_k$ denoted the neighbourhood factor parameter of each site type; $\Omega'_{p,k}$ defined as the neighbourhood influence factor of $p$ cells at time $t$.

The neighbourhood factor parameter ranged from 0 to 1, which meant the closer to 1, the stronger the expansion capacity of the land type. Referring to the experience of existing studies and considering the characteristics of the land in the study area, the expansion capacity of the land-use types was defined as construction land > unused land > water area > grassland > cultivated land > woodland. The expansion capacity of construction land was the strongest due to human factors, and the expansion capacity of forest land was the weakest. Considering the combined effect of natural and human activities, the expansion capacity of unused land was moderate, and its parameter value was set at a moderate level (Table 2).

3. Model validation can be used to test the simulations and adjust parameters to ensure that the model can be applied to the simulation of land-use change in the study area. In this paper, the Kappa coefficient is used to verify the simulation accuracy of the FLUS model. Both the Kappa coefficients range from 0 to 1. The closer the value is to 1, the better the simulation accuracy is, and the opposite is the worse. Generally, when $Kappa > 0.5$, the model simulation accuracy is poor; when $0.5 < Kappa \leq 0.75$, the model simulation accuracy is average; when $0.75 < Kappa \leq 1$, the model simulation accuracy is high.

**Calculating the demand and value of carbon storage.** The InVEST model, jointly developed by Stanford University, WWF, and The Nature Conservancy, was a free open-source model primarily used for ecosystem services assessment.

| Table 2. Neighbourhood factor parameters. |
|------------------------------------------|
| Land-use type | Construction land | Unused land | Water | Grassland | Cultivated land | Woodland |
|---------------|--------------------|-------------|-------|-----------|-----------------|----------|
| Weight of neighbourhood | 1 | 0.4 | 0.4 | 0.3 | 0.01 | 0.09 |
1. The InVEST was a library-based alternative approach to carbon stock estimation, based on the current status of land use classification, and used four carbon pools such as above-ground carbon storage, below-ground root carbon storage, soil carbon storage, and dead organic matter carbon storage to calculate the total carbon storage and spatial distribution of a region. Its basic equation for carbon stock was:

\[ C_{\text{tot}} = C_{\text{above}} + C_{\text{below}} + C_{\text{soil}} + C_{\text{dead}} \]  

Where \( C_{\text{tot}} \) was the total regional carbon stock; \( C_{\text{above}} \) was the above-ground carbon stock; \( C_{\text{below}} \) was the below-ground root carbon stock; \( C_{\text{soil}} \) was the soil carbon stock; \( C_{\text{dead}} \) was the dead organic matter carbon stock.

Many studies had shown that many factors such as temperature, precipitation, and topography can affect the carbon density of each land-use type in different ways. The average annual precipitation had a significant positive effect on biomass carbon density as well as soil carbon density, while the average annual temperature had a smaller effect on carbon density. In this paper, through literature reading, the carbon density of each land use was selected and determined according to the region. Because the Qiantang River source region is in western Zhejiang Province and Qianjiangyuan national park is in the Qiantang River source region, the natural condition such as temperature, precipitation, and topography in the research area is similar to those of these places. Therefore, the result of carbon density was selected by this paper (Table 3).

2. The economic valuation of carbon storage in terrestrial ecosystems was calculated by the InVEST model. It is calculated as follows:

\[ \text{value}_{-x} = V \cdot \frac{\text{sequest}_x}{\text{yr}_{\text{fut}} - \text{yr}_{\text{cur}}} \sum_{t=0}^{\text{yr}_{\text{fut}} - \text{yr}_{\text{cur}}} \frac{1}{(1 + \frac{r}{100})^{t}} \left(1 + \frac{c}{100}\right)^{t} \]  

Where \( \text{value}_{-x} \) denoted the economic value of the carbon storage of the carbon sequestration grid in the future land-use change scenario, and \( x \) denoted the carbon sequestration grid; \( V \) denoted the value of each ton of carbon.

### Table 3. Carbon densities of different land-use types in the Qiantang River source region.

| Land-use type       | \( C_{\text{above}} \) | \( C_{\text{below}} \) | \( C_{\text{soil}} \) | \( C_{\text{dead}} \) |
|---------------------|-------------------------|------------------------|-----------------------|-----------------------|
| Cultivated land     | 14.47                   | 37.08                  | 99.45                 | 13                    |
| Woodland            | 31.92                   | 6.38                   | 146.82                | 2.96                  |
| Grassland           | 2.75                    | 7.37                   | 44.03                 | 4.07                  |
| Water               | 0                       | 0                      | 0                     | 0                     |
| Construction land   | 0                       | 0                      | 0                     | 0                     |
| Unused land         | 0.13                    | 0                      | 3.14                  | 0                     |
sequestered ($); $r$ denoted the market discount rate (%), reflecting society's preference for current returns rather than a greater preference for future returns; $c$ denoted the annual rate of change in the value of each ton of carbon sequestered (%); $yr_{\text{cur}}$ denoted for terrestrial ecosystem carbon storage under the current land use scenario. In this paper, it was the Qiantang River source regional ecosystem carbon storage in 2020; $yr_{\text{fut}}$ indicated the terrestrial ecosystem carbon storage used to calculate the future land-use scenario. It was the ecosystem carbon storage of the Qiantang River source region in 2030. The $\text{sequest}$ represented the amount of carbon storage or loss in each grid under current and future land-use scenarios.

The research showed that the social cost of carbon emissions in China was approximately 24 $/t$ with an interannual rate of change in the social cost of carbon emissions of 0.55. Based on the Asian Development Bank's assessment of the discount rate for the carbon storage market, the economic value market discount rate was determined to be 11% in this study.

**Results**

*Prediction of land use demand based on the Markov model*

We use the Markov model to predict the amount of each land-use type under three different scenarios which are based on the probability matrix of land use in 2010–2020 and the current land use in the Qiantang River source region in 2020 (Table 4). The area of woodland, grassland, and cultivated land decreased slightly from 7834.59 km$^2$ to 7785.34 km$^2$, 431.33 km$^2$ to 413.27 km$^2$, and 1159.22 km$^2$ to 1110.45 km$^2$ respectively, while the area of water increased slightly from 526.25 km$^2$ to 532.85 km$^2$. The area of construction land increased from 41.05 km$^2$ to 151.44 km$^2$, of which 60.49 km$^2$ of arable land and 47.4 km$^2$ of woodland were converted into construction land, becoming the main source of the increase in construction land. However, the reduction of woodland and cultivated land will inevitably affect the ecological security of the Qiantang River source region. Therefore, it’s important to simulate future land use to guide the government towards scientific planning.

The demand for land use under three different scenarios is predicted by the probability of conversion according to the ways which are presented in the method. Under the food security scenario, the largest area is cultivated land (1100.27 km$^2$), under the ecological protection scenario, the largest area is woodland (7777.26 km$^2$), grassland (412.85 km$^2$), and water (536.98 km$^2$), and under the historical trend development scenario, the largest amount of land is construction land (248.04 km$^2$). The area of construction land under the historical trend development scenario increased by 73.36 km$^2$ and 36.66 km$^2$ respectively compared with the food security scenario and ecological protection scenario. Compared to 2020, the area of cultivated land, woodland, grassland, and unused land will decrease under three scenarios. The area of water and construction will increase under three scenarios. The amount of unused land in the Qiantang River source region is predicted to
decrease after the conversion of some of the unused land to forest and grassland in 2020 (Table 5).

**Simulation of the spatial distribution of land use based on the FLUS model**

Based on the land use of 2020 and the nine selected driving factors (Figure 3), the FLUS model was used to simulate the land-use scenario in 2020. After the Kappa accuracy test of the FLUS model, the Kappa index was 0.94 which indicates that the model simulation accuracy is believable.

The predicted demand for land use which was output by the Markov model was loaded into the FLUS model and the spatial-temporal change of land use under the three scenarios in 2030 was simulated. Under the historical inertia development scenario, there is a significant increase in construction land and most of it expands outwards in line with the original distribution of construction land. The food security scenario and the ecological security scenario show an increase in construction land, but the expansion is less extensive compared to the historical development scenario. Most of the increase in construction land is converted from woodland and grassland, which reduces the quality of the ecological environment in the study area (Figure 4).
Evaluation of changes in carbon storage

The current and future land use were input into InVEST model, and the carbon storage from 2000 to 2020 was assessed. It can be seen from the Figure 5 that the distribution of carbon storage in the study area is related to the type of land use, with water in yellow, which represents the lower carbon storage, and the grassland as well as the cultivated land in green, which has more carbon storage than the water. As woodland is the main land-use type in the Qiantang source region, most of the blue is the carbon storage of woodland and it has more carbon storage. It is obvious that the large increase in construction land and the decrease in the water, cultivated land, and woodland. The carbon storage is reduced, and the spatial change of carbon storage in the grassland is not obvious because the area of the grassland changes slightly (Figure 5).

Though different scenarios have different objectives, the spatial analysis shows that woodland is still the main land-use type in the Qiantang River source region, with the
most carbon storage in woodland. The spatial distribution of carbon storage in the Qiantang River source area is low carbon storage in the middle and high carbon storage in the surrounding area. The low-carbon storage areas in the 2030 historical trend scenario and the 2030 ecological security scenario are significantly larger than the low-carbon storage areas in the 2030 food security scenario (Figure 6). It can be seen from Table 3 that the carbon storage per square kilometre of each land use is woodland > cultivated land > grassland > unused land > water > construction land. By comparing the simulated land use/land cover with the carbon storage distribution, it is found that the low-carbon storage area is the construction land and water area. This indicates that the results are consistent with the carbon density of land use types per square kilometre in Table 3. The area of construction land and water area under the historical trend development and ecological protection scenarios is larger than the area of construction land and water area under the food security scenario, which leads to the fact that the low-carbon storage area under the historical trend development and ecological protection scenarios is significantly larger than that under food security scenario (Table 3). The area of forest land, cultivated land, grassland, and other carbon-rich regions in the historical trend development scenario is smaller than that in the food security scenario, and the area of construction land in the historical trend development scenario is larger than that in the food security scenario. Therefore, the total carbon storage in the historical trend development scenario is smaller than that in the food security scenario. Although the forest area under the ecological protection scenario is larger than that under the food security scenario, the construction land area under the ecological protection scenario
is larger than that under the food security scenario, thus the total carbon storage under the ecological protection scenario is less than that under the food security scenario.

The carbon storage in the Qiantang River source region declined rapidly from $166.216 \times 10^6$ t to $164.414 \times 10^6$ t from 2000 to 2020. The most carbon storage in 2030 is the food security scenario (S2) and the number of these in S3 is larger than in S1. The average carbon density in the Qiantang River source area also changes with the change in carbon storage, and there is a decreasing trend in the average carbon density from 2000 to 2020. The average carbon intensity in the Qiantang River source region in 2030 also varies with the scenario targets. In general, the food security scenario has the highest mean carbon density, and the ecological protection scenario has a 62.60 t/km² increase in mean carbon density compared to the historical natural tendency development (Figure 7).

The most obvious is that the carbon storage of water and construction land is lowest from 2000 to 2020. Because the area of cultivated land is 2.7 times larger than the area of grassland, the carbon storage of cultivated land is larger than that of grassland. The
carbon storage of cultivated land and woodland is the most abundant in 2005, respectively reaching $19.01 \times 10^6$ t and $147.35 \times 10^6$ t. Moreover, the carbon storage of cultivated land gradually decreases from 2005. The carbon storage of grassland also changes with the change of grassland area every year, with the highest carbon storage in 2000 up to $2.51 \times 10^6$ t and the lowest in 2015 at $2.14 \times 10^6$ t. At the same time, the carbon storage of unused land gradually decreases from 2000 to 2020, from 693 t to 526 t. In terms of the stimulated carbon storage, the amount of this is $1.67 \times 10^6$ t lower than 2020 in the 2030 historical trend natural development scenario, $1.05 \times 10^6$ t lower than 2020 in the ecological protection scenario, and 39.38 t lower than 2020 in the food security scenario (Table 6, Figure 8).

The future valuation of carbon storage under three different scenarios

As a nationally important ecological function area and an important ecological barrier for the Yangtze River Delta as well as East China, the economic value of carbon storage in the Qiantang River source region is gradually becoming an important part of the ecosystem studies conducted. In the historical trend natural development scenario, the economic value of carbon storage is $2.69 \times 10^9$ and the value of carbon losses is $2.81 \times 10^9$, resulting in a net carbon storage value of $2.66 \times 10^9$. In the food security scenario, the economic value of carbon storage is $2.71 \times 10^9$ and the value of carbon losses is $1.39 \times 10^9$, resulting in a net carbon storage value of $2.70 \times 10^9$. In the ecological conservation scenario, the economic value of carbon storage is $2.70 \times 10^9$ and the value of carbon losses are $3.71 \times 10^9$, resulting in a net carbon storage value of $2.66 \times 10^9$. Under all three scenarios, the food security scenario has the smallest carbon loss value,
and its net carbon storage value is also the largest. Because of land-use change, the net value of carbon storage is $2.66 \times 10^9$, $2.69 \times 10^9$, and $2.66 \times 10^9$ under the three scenarios in the Qiantang source region on average (Table 7).

**Discussion**

*Carbon storage loss due to land-use change*

The terrestrial ecosystem is the world’s largest carbon pool. The distribution of carbon storage in the Qiantang River source region is related to the type of land use. Because the woodland is the main land-use type in the Qiantang source region, most of the blue is the carbon storage of woodland and it has more carbon storage. Due to economic development, humans convert carbon-rich land-use types such as woodland and cultivated land to construction land. The area of construction land increased from 41.05 km² to 151.44 km², of which 60.49 km² of cultivated land and 47.40 km² of forest land were...
| Year       | 2000   | 2005   | 2010   | 2015   | 2020   | S1     | S2     | S3     |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|
| Cultivated land | 1901.12 | 1901.17 | 1873.88 | 1844.44 | 1821.14 | 1730.02 | 1804.44 | 1730.04 |
| Woodland   | 14735.30 | 14735.49 | 14689.48 | 14691.95 | 14642.67 | 14565.74 | 14622.02 | 14627.48 |
| Grassland  | 251.12  | 237.61  | 241.75  | 214.08  | 240.61  | 238.55  | 237.94  | 240.36  |
| Unused land| 0.07   | 0.06   | 0.06   | 0.05   | 0.05   | 0.05   | 0.05   | 0.05   |
| Water      | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| Construction land | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
converted into construction land from 2000 to 2020 (Table 8). And at the same time, the carbon storage in the Qiantang River source region declined rapidly from $166.22 \times 10^6$ t to $164.41 \times 10^6$ t from 2000 to 2020 (Figure 7). Similar results can be found in other studies. Some scholars also found that carbon storage has also experienced heavy losses, with the occupation of cultivated land. The other studies found that carbon storage experienced heavy losses due to land-use change. For example, carbon densities in the five municipal districts decreased from 1986 to 2011 due to the rapid expansion of urban land, which encroached on areas previously dominated by green open spaces. The results show that the impact of land-use change on ecosystem carbon storage should be fully considered in land use planning and urban planning. The government can take reasonable planning policies to enhance the carbon sequestration services of the ecosystem, thereby increasing the carbon storage of the ecosystem.

**Integrating ecosystem services into land-use planning**

Different scenarios often result in various impacts on ecosystem services. The fact also can be reinforced by our study. Under the S1 and S2 and S3, carbon storage loss varies a lot in the Qiantang River source region from 2020 to 2030. Therefore, it is important to integrate ecosystem services into land-use planning. Several studies have been conducted. Some scholars optimized the projected land-use structure to increase terrestrial ecosystem carbon storage and simulated its spatial distribution using the CLUE-S model. Some analysed the effects on carbon emissions by land-use changes and optimized land-use patterns based on the prediction which was used to calculate the carbon storage and planning model. There are significant differences in carbon storage between different land-use types, and the same land-use type also differs greatly in terms of carbon emissions and sequestration due to different management measures. In this paper, we can draw a result that the high or low carbon sequestration capacity of the Qiantang River Source region is closely related to land-use change, and woodland is the most carbon-rich land type in the ecosystem. Therefore, in terms of the protection of ecosystems, the function of carbon storage can be further enhanced by optimizing the structure of land use or by improving land use management measures, enhancing natural resource management, and ecological restoration.

**Table 7.** The economic value of carbon storage under three different scenarios in the qiantang river source area in 2030.

| Scenario | Carbon storage ($10^5$ t) | Value of carbon ($10^4$ $) | Value of carbon losses ($10^4$ $) | The net value of carbon ($10^4$ $) | The net value of average land carbon storage ($$/km^2$) |
|----------|---------------------------|-----------------------------|-----------------------------------|----------------------------------|-----------------------------------------------------|
| S1       | 1627.40                   | 269076.58                   | -2812.45                          | 266264.13                       | 266397.86                                           |
| S2       | 1640.20                   | 271193.57                   | -1393.96                          | 269799.61                       | 269935.11                                           |
| S3       | 1633.65                   | 270110.87                   | -3711.67                          | 266399.20                       | 266533.00                                           |
| 2000                | Construction land | Unused land | Woodland | Water  | Cultivated land | Grassland | sum   |
|---------------------|-------------------|-------------|----------|--------|----------------|-----------|-------|
| Construction land   | 35.56             | 0.00        | 1.40     | 0.17   | 3.83           | 0.11      | 41.07 |
| Unused land         | 0.09              | 1.31        | 0.38     | 0.00   | 0.01           | 0.33      | 2.12  |
| Woodland            | 47.40             | 0.26        | 7606.54  | 24.8   | 114.41         | 41.18     | 7834.59 |
| Water               | 3.13              | 0.00        | 20.61    | 498.32 | 3.77           | 0.82      | 526.65 |
| Cultivated land     | 60.49             | 0.00        | 100.48   | 8.64   | 981.47         | 8.14      | 1159.22 |
| Grassland           | 4.77              | 0.06        | 55.93    | 0.92   | 6.96           | 362.69    | 431.33 |
| sum                 | 151.44            | 1.63        | 7785.34  | 532.85 | 1110.45        | 413.27    | 9994.98 |
There are two main ways to achieve the goal of carbon neutrality: one is to reduce carbon emissions, and the other is to increase carbon storage. The former takes the “source” as a starting point to reduce carbon emissions. The latter is considered from the “storage” point of view, using reasonable and effective measures to fix more carbon in terrestrial ecosystems.\textsuperscript{12} Therefore, integrating ecosystem services into land-use planning is an important way to achieve carbon neutrality through the “storage” point of view. From the perspective of land use structure optimization, the main ways to increase carbon storage are to increase the proportion of woodland, appropriately adjust the proportion of cultivated land, grassland, and construction land, and pay attention to the carbon storage function of grassland and wetland, strictly control the excessive conversion of grassland and woodland into construction land, and pay attention to the protection of regional space with high carbon storage. It is necessary to focus on the protection of national forest parks in the Qiantang River source region. In territorial spatial planning, the government needs to establish a carbon storage impact assessment system, carbon storage loss compensation mechanism, or carbon storage spatial compensation mechanism.

\textbf{The application of the ml model in the carbon storage}

This paper coupled the FLUS and InVEST models for carbon storage in terrestrial ecosystems under different scenarios and achieves good results. However, there are still two points for discussion as follows. Although the InVEST model has been widely used worldwide in the assessment of carbon storage in terrestrial ecosystems. Because of its simplicity, high speed, and wide applicability, it has contributed to the progress of research on ecosystem carbon storage change. However, the InVEST model also has some limitations. The carbon cycle principle of the InVEST model is too simplified. Although this paper uses carbon density coefficients of the area which may have similar natural conditions to the study area, there is still some uncertainty in the model results. And then, in terms of scenario sets for future land-use change, the scenarios in this paper focus on the amount of land use, and the projection of the number of land-use types under three different scenarios is mainly based on the historical trend of land-use change. As a result, the scenario setting and the projection of the number of land-use types under different future scenarios ignore the role of the local government in socio-economic policies and land-use change in this paper. This has led to the neglect of the constraints and interventions of local governments on future land-use changes in terms of socio-economic and land use planning policies.

Future studies, on the one hand, can be conducted by making up for limitations. The validity of the carbon density values should be verified through field research and continuous monitoring of the sample sites in the study area for many years so that the results of the InVEST model can be more accurate. In terms of simulation in future land-use types, future research can focus on how to integrate the national or local development processes of natural and social systems in the study area, and set up more realistic and policy-oriented land use development scenarios.

On the other hand, research can combine remote sensing and artificial intelligence to calculate carbon storage accurately. Simulation of land use/land cover has attracted much
attention in recent years, as it is a complex issue involving physical, environmental, and socio-economic factors. Machine learning models (ML models) can be solved via the use of programming languages such as Python, which can improve the simulation capabilities of the machine learning models. ML model applications commonly used in land use applications can be divided into two categories, one using only ML models, such as (1) artificial neural networks (neural networks), (3) decision trees (DT), (4) support vector machines (SVM), (5) land transformation models (LTM) and genetic algorithms (genetic algorithms), and the other being dynamic models, such as coupling ML models with CA, LR and FR models to improve the simulation accuracy of the models.62 This paper mainly uses the FLUS model which is based on an artificial neural network (ANN) and CA model to forecast land use. Others have even compared the ANN model with other types of statistical models such as LR, FR, and MCE in generating suitability maps.63 Studies also had been carried out to assess ecosystem carbon storage on a regional or global scale based on different remote sensing data in recent years. Xu used the Landsat TM remote sensing data and integrates NDVI, IND53, and GNDVI into a BP neural network to predict forest carbon storage of Kaihua County.64 The BP neural was used are now also widely used in different research areas like the electrical resistivity distribution and Mechanical Engineering.65,66 Combining remote sensing data with sample plot survey data to build a carbon storage inversion model, or a non-parametric estimation method based on machine learning method to estimate forest carbon storage, which can have good development and application prospects.67 Therefore, this paper will use the FLUS model which is based on an ANN, and the InVEST model to predict ecosystem carbon storage in the Qiantang River source region in 2030, which can provide a case study for how machine learning can be combined with other models for further analysis of ecosystem services.

**Conclusion**

We linked the FLUS and InVEST models to assess the effects of land-use change on carbon storage in the Qiantang River source region. Firstly, the spatial distribution of carbon storage is characterized by “the northwest and the southwest of region with higher, the east and the centre of region lower”. Secondly, the high or low carbon sequestration capacity of the Qiantang River Source is closely related to land-use change. The contribution of woodland, cultivated land, grassland, unused land, construction land, and water to carbon storage in the study area decreases in order. Under three different scenarios, the S2 can better achieve the carbon storage target of the study area, and S1 predicts a decrease in carbon stock in 2030 compared to the carbon storage of 2020; the S2 has the highest average carbon density, and the S3 has an increase of 62.60 t/km² compared to the historical natural tendency development. Finally, the net value of carbon storage would be respectively $2.66 \times 10^9$, $2.70 \times 10^9$, and $2.66 \times 10^9$ in three different scenarios. Generally, these results of this study can guide the construction of a city for sustainable development in the study area, as well as a scientific reference for the conservation of carbon storage resources and land use management.
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