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Multi-scenario Simulation for 2060 and Driving Factors of the Eco-spatial Carbon Sink in the Beibu Gulf Urban Agglomeration, China

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Abstract: Since China announced its goal of becoming carbon-neutral by 2060, carbon neutrality has become a major target in the development of China's urban agglomerations. This study applied the Future Land Use Simulation (FLUS) model to predict the land use pattern of the ecological space of the Beibu Gulf urban agglomeration, in 2060 under ecological priority, agricultural priority and urbanized priority scenarios. The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model was employed to analyse the spatial changes in ecological space carbon storage in each scenario from 2020 to 2060. Then, this study used a Geographically Weighted Regression (GWR) model to determine the main driving factors that influence the changes in land carbon sinking capacity. The results of the study can be summarised as follows: firstly, the agricultural and ecological priority scenarios will achieve balanced urban expansion and environmental protection of resources in an ecological space. The urbanized priority scenario will reduce the carbon sinking capacity. Among the simulation scenarios for 2060, carbon storage in the urbanized priority scenario will decrease by 112.26×10^6 t compared with that for 2020 and the average carbon density will decrease by 0.96 kg/m^2 compared with that for 2020. Carbon storage in the agricultural priority scenario will increase by 84.11×10^6 t, and the average carbon density will decrease by 0.72 kg/m^2. Carbon storage in the ecological priority scenario will increase by 3.03×10^6 t, and the average carbon density will increase by 0.03 kg/m^2. Under the premise that the population of the town will increases continuously, the ecological priority development approach may be a wise choice. Secondly, slope, distance to river and elevation are the most important factors that influence the carbon sink pattern of the ecological space in the Beibu Gulf urban agglomeration, followed by GDP, population density, slope direction and distance to traffic infrastructure. At the same time, urban space expansion is the main cause of the changes of this natural factors. Thirdly, the decreasing trend of ecological space is difficult to reverse, so reasonable land use policy to curb the spatial expansion of cities need to be made.

Keywords: Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model; carbon sink; multi-scenario simulation; ecological space; driving factor; Beibu Gulf urban agglomeration

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1 Introduction

With rapid urbanisation, large-scale socio-economic activities has increased the greenhouse gases release, and enhancing the pressure of the carbon emission in developing countries (Jin and Zhang, 2015; Yu et al., 2022). China is the most populous country in the world, and its economy is developing rapidly. However, the

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impacts of large-scale human activities exceeds carrying capacity of the natural system. The carbon cycle of the earth's surface becomes unbalanced, and the terrestrial and marine ecosystems are damaged. Resource shortage becomes prevalent and the carbon sinking capacity and overall risk resistance capacity are reduced, which has aggravated the global warming (Syvitski et al., 2009; Carter, 2018; Chu et al., 2018; Czech et al., 2020; Geng et al., 2020). The deterioration of the ecological environment and global warming has become one of the most serious environmental problems. As the country with the largest total carbon dioxide emissions in the world (https://edgar.jrc.ec.europa.eu/), China has pledged to 'strive to achieve a carbon peak by 2030 and achieve carbon neutrality by 2060 (hereafter 'Dual-carbon' goal)' (https://www.un.org/zh/ga/75/resolutions.shtml). It is an inevitable choice for China to reduce and control global carbon emission. It is also an urgent requirement to promote low-carbon economic and social transformation, achieve environmental protection and regional development simultaneously. Land forms the basis for human life and industrial, which is the main carrier of carbon emissions and also carbon sinks. Our study incorporated the 'Dual-carbon' goal into the National Spatial planning system and established an ecological space pattern, as well as a production and living style. It is of great significance to create a social and economic system with significant effective emission reduction.

Urban agglomeration is a form of cluster in the mature stage of urban expansion. It puts the built-up environment of individual cities and regional ecological environment into a larger picture. It also provides a variety of ecological services and ecological products in a new balanced carbon dimension (Qin et al., 2022). The 'economy-society-ecological' system shapes different land use and cover changes (Ding et al., 2022), determines the carbon emission/sinking capacity of different land use types and deduces the carbon budget of terrestrial and marine ecosystems. In recent years, the rapid economic and social development and various human activities increased pressure on transportation and living consumption and the construction land is rapid growing. Urbanized space has expanded rapidly, which leads to aggravated changes on the ecological spatial land use pattern. Carbon emissions and ecological pressure also increase substantially. The expansion of urbanized space, industrial production and massive resource development are identified as the main causes of carbon emissions from construction land. Meanwhile, maintaining the scale of the ecological space, reconstructing non-agricultural land and 'Grain for Green' can increase the amount of cropland, forest land and ecological space carbon sink capacities (Wang et al., 2022). Therefore, ecological space can be a conveyor to promote carbon sinks in the ecosystem and restore ecological areas. The Beibu Gulf urban agglomeration should keep the balance of the long-term coordinated and sustainable development of regional urban economic and social development and ecological environment. While the multi-scenario simulation of the ecological space, the land cover changes under various development orientations can be predicted. It is also a scientific and reasonable reference for future ecological space land use management.

Land use simulation based on mathematical models and experiments have developed rapidly in the past two decades. The topics of the simulation models become hot, the predict simulation has experience several developments. Researchers have constructed land use simulation models based on different disciplinary theories (Dai and Ma, 2018), including statistical models, cellular automata (CA) models that emphasise spatial layout and multi-subject models that emphasise developing processes (Feng et al., 2012; Hossein et al., 2017; Bai et al., 2018; Chen et al., 2018; Feng et al., 2018; Yang et al., 2018; Eduardo et al., 2019). With the significant progress of neural network models, their advantages are the approach concerns two pairs relationships (land use patterns-driving forces and natural ecological effects-human activities). Liu et al. (2017) digested the advantages of Artificial Neural Network (ANN), Cellular Automaton (CA) model and Markov chain (or Markov model) and constructed the Future Land Use Simulation (FLUS) model, with an adaptive inertia competition mechanism. The FLUS model can deal with the competition among different land use types, which could display the uncertainty of land change and eliminate the disadvantage that the original CA model cannot directly calculate the number of cellular growths in future decades. Liu et al. (2017) put the model into practise and showed that the FLUS model had a higher simulation accuracy than the traditional Conversion of Land Use and its Effects at Small Region Extent Model (CLUE-S) and ANN-CA models. Currently, the FLUS model mainly focuses on the delineation of urban growth boundaries (Liang et al., 2018) and scenario-based urban-scale flood risk assessment (Lin et al., 2020). Rare simulation studies of land use patterns at the scale of urban agglomerations have been conducted.

Given that the ecological space of urban agglomeration provides the ecosystem functions, the urban expansion will inevitably lead to a series of changes in ecological balance. Moreover, the carbon sinking capacity in the ecological space can accurately reflect the climate change caused by ecological imbalance, which is one of the most important indicators of ecological and environmental benefits. Previous studies on carbon sinks focus on carbon balance (Lin et al., 2016) and the analysis of the relationship between carbon sinks and land use (Zhang et al., 2016; Du, 2020). Few studies on the analysis of the drivers of carbon sink change have been conducted. To estimate the influence of the ecological spatial patterns and their driving mechanisms, this study adopted the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model to measure the carbon sinks of different land use type.

The InVEST model is a relatively mature model for ecosystem service. The research on this model can be abundant in the fields of habitat quality assessment, soil conservation and water supply (Miguel et al., 2018; Abreham et al., 2020; Hu et al., 2020; Li et al., 2021). The carbon storage and terrestrial ecosystem modules can be used to calculate the change in carbon storage, i.e., carbon sequestration. The carbon storage in different scenarios from 2020 to 2060 can be a reference to understand the changes on carbon sinking capacity in the Beibu Gulf urban agglomeration and identify the driving factors for the changes in carbon sinking capacity.

The Beibu Gulf urban agglomeration is a coastal metropolitan area, located in the southern China. It is one of the highly developing urban agglomerations. Satellite data in recent decades showed that the rapid expansion of urbanized space had drastically changed the landscape patterns, eroded agricultural space and ecological space. As a part of regional unit with drastic ecological spatial expansion, the Beibu Gulf urban agglomeration is an ideal area for analysing the land use types and carbon sink development. Both the FLUS and InVEST models have been widely used in their fields individually and have got good results. However, there are few results related to the combination of these two. They rare discuss the spetial distribution of land use types and the development of carbon sink in the future. The researches on driving forces of carbon sinking capacity in a scale of urban agglomerations is relatively lacking (Qin et al., 2022). Therefore, this study focused on the Beibu Gulf urban agglomeration, analysed land use types in 2000, 2010 and 2020. Our study simulated and predicted the spatiotemporal distribution of the landscape patterns in the urban agglomeration in 2060. The study focused on the changes of carbon sink, and found the main driving factors affecting the carbon sinking capacity. It could be a reference for the future ecological spatial and a possible pathway to the regional sustainable development.

2 Materials and Methods

2.1 Study area

The Beibu Gulf urban agglomeration is located in the southern China (Fig. 1); its land area is divided into three parts by the Beibu Gulf, including six prefecture-level cities in Guangxi Zhuang Autonomous Region (i.e., Nanning, Beihai, Qinzhou, Fangchenggang, Yulin and Chongzuo), three prefecture-level cities in Guangdong Province (i.e., Zhanjiang, Maoming and Yangjiang) and six prefecture (county)-level cities in Hainan Province (i.e., Haikou, Danzhou, Dongfang, Chengmai, Lingao and Changjiang). The study area is adjacent to the Guangdong-Hong Kong-Macao Greater Bay Area and Association of Southeast Asian Nations and has subtropical and tropical monsoon climates. With a land area of approximately 116 600 km^2, the Beibu Gulf urban agglomeration is one of the rapidly emerging urban agglomerations in the central and western regions and a strategic sea outlet for the new western land-sea corridor. The rapid economic development in the region in recent years has caused dramatic changes in the landscape pattern and urban expansion, which has brought unprecedented pressure on the ecological environment. To cope with the possible risk of carbon imbalance, the expansion of ecological space in urban agglomerations needs scientific prediction and conservation studies.

2.2 Data

The data sets were divided into five categories, i.e., land use, policy constraints, roads, topography and statistics. The current land use data of the Beibu Gulf urban ag-

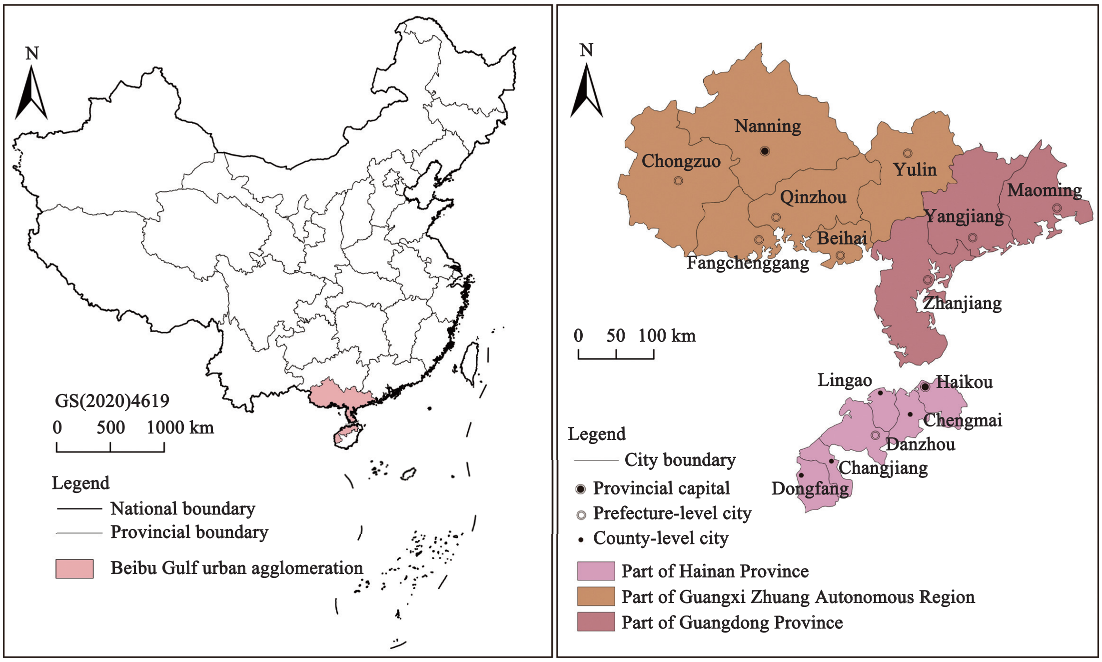

Fig. 1 Location of the Beibu Gulf urban agglomeration in China

glomeration for the years 2000, 2010 and 2020 were obtained from the GlobeLand30 data product. The evaluation of the data accuracy of GlobeLand30 for the years 2000 and 2010 was conducted at Tongji University. A total of 80 maps were extracted from 853 global data, and more than 150 000 test samples were obtained. The Overall Accuracy (OA) of the data was 83.50%, and the kappa coefficient was 0.78. The evaluation of the data accuracy of GlobeLand30 for the year 2020 was conducted at the Academy of Aerospace Information Innovation, Chinese Academy of Sciences. Based on the landscape shape index sampling model, more than 230 000 samples were distributed. The OA of the data is 85.72%, and the kappa coefficient is 0.82. The land use types were divided into six categories, i.e., construction land, cropland, forest land, grassland, water area and unutilised land. According to the national standards and the scientific nature of research, ecological space includes forest land, grassland, water area and unutilised land, which focuses on ecological services.

Indicators that are related to land use pattern changes were selected for analysis according to the current development status of the Beibu Gulf urban agglomeration. The driving factors were selected from both natural conditions and socio-economic aspects. For natural conditions, a total of seven factors (i.e., digital elevation model, slope, slope direction, distance to river, distance to the railroad, distance to the highway and distance to the general road) were selected. Among them, elevation and slope are topographic factors that determine the changes in land use patterns, and traffic accessibility is necessary to attract urban land expansion. For socio-economic aspects, gross domestic product (GDP) data and population density were selected. Moreover, to constrain the simulated expansion, the limiting factors in terms of environmental protection are needed, and six factors (i.e., nature reserves, rivers, important wetlands, mangroves, tropical rainforests and natural forests) were selected. All data sources are listed in Table 1.

2.3 Methods

This study was divided into three parts (Fig. 2), as follows: 1) The Markov model was used to forecast the land demand in 2060, and the FLUS model was used to simulate the development direction of land use patterns under three scenarios, namely, ecological, agricultural and urbanized priority scenarios, in the Beibu Gulf urban agglomeration in 2060. 2) The InVEST model was used to analyse the land carbon storage in the three scenarios from 2020 to 2060. 3) The Geographically Weighted Regression (GWR) model was used to analyse the weight of the driving factors of land use pattern changes and determine the main factors influencing the change in the regional carbon sink pattern.

Table 1 Data source information

Data types	Data content	Data source	Data description
Land use data	2000 2010 2020	GlobeLand30 (http://www.globallandcover.com/)	The spatial resolution is 1 km, and the coordinate system is WGS-84, inputted as the initial condition to verify model accuracy
Restricted conversion data and policy constraint data	Important wetlands distribution map Nature reserve distribution map Mangrove distribution map Tropical rainforest distribution map Natural forest distribution map	ArcGIS Online (https://www.geosceneonline.cn/geoscene/webapps/gallery)	Vector data set, constraints
	Water area	Open Street Map (https://www.openstreetmap.org/)	
Road data	Road network data in 2020	Open Street Map (https://www.openstreetmap.org/)	Vector data set, reflecting traffic drivers
Terrain data	Digital elevation model	NASA ASTER GDEM v2 (https://asterweb.jpl.nasa.gov/)	Raster data set, restricting terrain conditions
Statistical data	National population density data in 2010	World Pop (https://www.worldpop.org/)	Spatial resolution is 1 km, the coordinate system is WGS-84, and the unit is people/km^2
	2010 GDP data of Beibu Gulf cities (counties)	1 km GDP raster data set (http://www.geog.com.cn/EN/Y2014/V69/Is1/41)	Raster data set, reflecting economic drivers

2.3.1 Ecological space simulation

The FLUS model is a scenario simulation prediction model that is used to analyse land use under the effects of natural and human activities. The FLUS model is based on the CA model and introduces a multilayer feed-forward ANN algorithm (i.e., BP-ANN) to enhance the accuracy of the simulation.

The model used Markov chains to forecast the multi-scenario land demand in 2060 based on the current land use data, BP-ANN to deal with the nonlinear problem, and land use data and driving factors to calculate the conversion probability of each land use type combined with the neighbourhood influence factor, adaptive inertia coefficient and conversion cost to obtain the overall conversion probability of the raster. The simulation results were obtained after applying the roulette-based adaptive inertia competition mechanism to solve the uncertainty of different land use types competing with each other.

The BP-ANN algorithm consists of an input layer, several hidden layers and an output layer. In the output layer each neuron represents a certain land use type and its formula is expressed as follows (Liu et al., 2017):

$$sp(p,k,t) = \sum_j w_{j,k} \times \text{sigmoid}\left(net_j(p,t)\right) = \sum_j w_{j,k} \times \frac{1}{1+e^{-net_j(p,t)}} \tag{1}$$

where $sp(p,k,t)$ is the suitability probability of the kth site type at raster p and time t; Σ_j represents the total number of the values which converted from the signal received by neuron j, ranging from 0 to 1; $w_{j,k}$ is the weight of the hidden and output layers; the sigmoid function is the excitation function from the hidden layer to the output layer which can effectively building a connection between neural networks; $net_j(p,t)$ is the signal received by neuron j raster p at time t in the hidden layer. At iteration time t and raster p, the sum of the suitability probabilities $sp(p,k,t)$ for each type of site output by BP-ANN is 1, derived as follows (Liu et al., 2017):

$$\sum_k sp(p,k,t) = 1 \tag{2}$$

The neural network method used to obtain the training samples in this study was random sampling, which was characterised by the number of sampling points for each type of land use varying with the proportion of each category. The number of hidden layers was set to

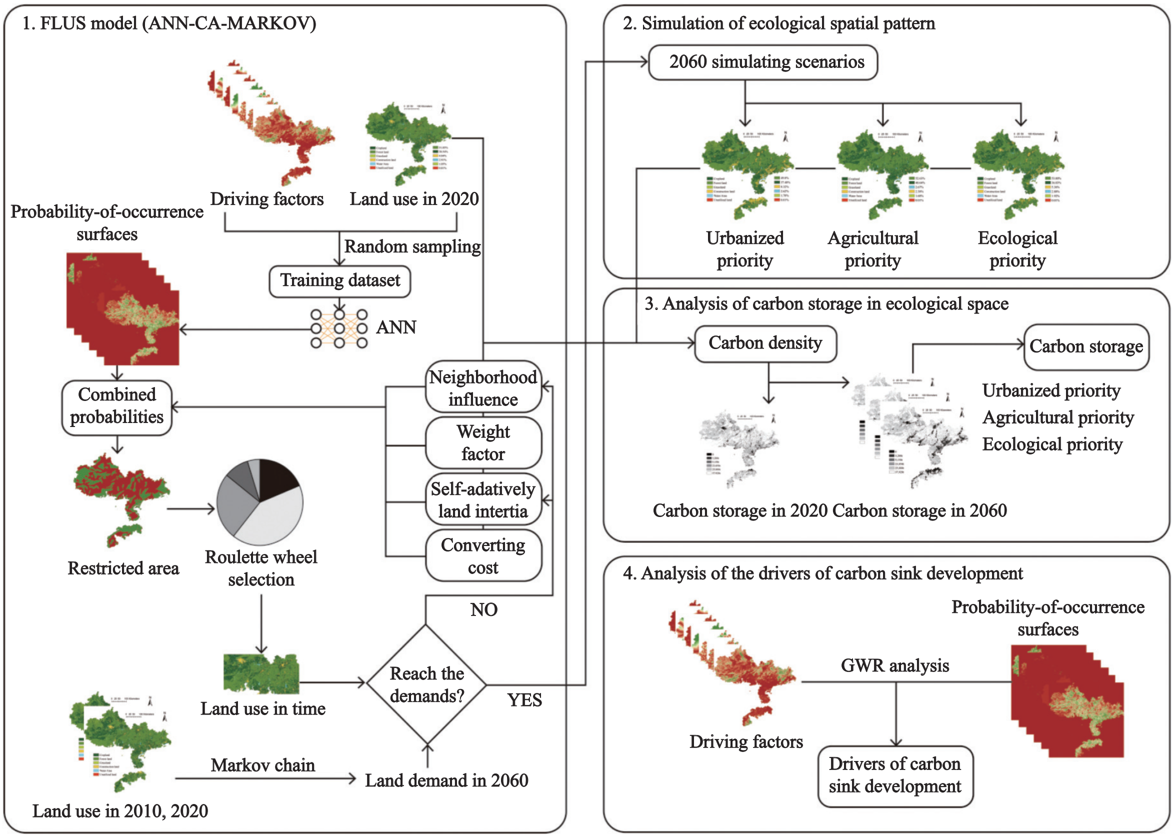

Fig. 2 The study workflow

13 layers. The raster data of land use drivers were normalised and inputted into the BP-ANN model to obtain the suitability probability of each land use category in the study area.

The adaptive inertia coefficient is the core of the adaptive inertia competition mechanism. It is determined by using the current number and demand of each land class and adaptively adjusted in iterations to move the number of land classes toward the target. The adaptive inertia coefficient $Inertia_k^t$ of the kth land class at time t is expressed as follows (Liu et al., 2017):

$$Inertit_k^t = \begin{cases} Inertita_k^{t-1} & \left|D_k^{t-2}\right| \le \left|D_k^{t-1}\right| \\ Inertia_k^{t-1} \times \dfrac{D_k^{t-2}}{D_k^{t-1}} & 0 > D_k^{t-2} > D_k^{t-1} \\ Inertia_k^{t-1} \times \dfrac{D_k^{t-1}}{D_k^{t-2}} & D_k^{t-1} > D_k^{t-2} > 0 \end{cases} \quad (3)$$

where D_k^{t-1} and D_k^{t-2} are the differences between the number of grids and demands for the kth site type at moments $t-1$ and $t-2$, respectively.

$\Omega_{p,k}^t$ is the neighbourhood influence factor of raster p at time t that reflects the interaction between different land use types and different land units within the neighbourhood; its equation is expressed as follows (Liu et al., 2017):

$$\Omega_{p,k}^t = \frac{\sum\limits_{N\times N} \mathrm{con}(c_p^{t-1} = k)}{N \times N - 1} \times w_k \quad (4)$$

where $\sum_{N\times N} \mathrm{con}(c_p^{t-1} = k)$ is the raster number of the kth land use type at the end of the previous iteration in the Moore neighbourhood window of $N \times N$ and w_k is the weight of neighbourhood effect of each land use type, ranging from 0 to 1. In this study, $N = 3$, and the number of CA iterations was 300. Based on previous studies and the land characteristics, the strongest expansion capability of construction land and the weakest expansion capability of forest land were set to 1 and 0.01, respectively. Because of the activities from both human and nature, the expansion capability of unutilised land is moderate; thus, its weight was set to 0.5. After the comparison, the w_k parameters were ranked from largest to smallest, i.e., construction land, unutilised land, water area, grassland, cropland and forest land. The details are listed in Table 2.

The conversion cost indicates the difficulty of con-

Table 2 Neighbourhood effect weight of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model

Land use type	Construction land	Unutilised land	Water area	Grassland	Cropland	Forest land
Neighbourhood effect weight	1.00	0.50	0.40	0.30	0.20	0.01

verting the current land use type to the target land use type. Conversion costs reflect the inherent nature of land use without considering the variable effects of technological progress, policies and human activities (https://geosimulation.cn/FLUS.html). For three different development scenarios, three conversion costs need to be set, the details of which are shown in Table 3. The principle of the conversion is as follows: except for some land use types, high-grade land can not be converted into low-grade land. The ranking results based on the ecological benefits of each land use type in the ecological priority scenario are forest land, water area, grassland, unutilised land, cropland and construction land. Meanwhile, the ranking results based on the urban expansion needs in the urbanized priority scenario are construction land, cropland, forest land, grassland, water area and unutilised land. In the agricultural priority scenario, all land use types, except for construction land, can be converted into cropland, and the others are similar to the urbanized priority scenario.

The probability of conversion of each raster p to k was calculated using the BP-ANN model, and iterations were performed using the CA model to assign each land use type to the raster. The equation for the overall conversion probability $Tp^{t}_{p,k}$ of raster p to land use type k at moment t is expressed as follows (Liu et al., 2017):

$$Tp^{t}_{p,k} = sp(p,k,t) \times \Omega^{t}_{p,k} \times Inertia^{t}_{p,k} \times (1 - sc_{c \to k}) \tag{5}$$

where $sc_{c \to k}$ is the conversion cost of land use types c to k and $(1 - sc_{c \to k})$ is the ease of converting occurrence.

To ensure the validity of the model, this study used the kappa coefficient, OA and FoM index to test the accuracy, which is verified by collecting historical data for simulation. The model simulation accuracy is acceptable when kappa ≥ 0.7 (Kaviari et al., 2019). The closer the OA is to 1, the higher the simulation accuracy. The FoM index is affected by the simulation duration, with the increase in the FoM index of less than 0.01 each year as the standard level.

2.3.2 *Driving factor analysis*

The GWR model is a regression analysis model with spatial dimension, which can be used in the field of land use change scenario prediction. GWR analysis can be used to determine the influence weights of each independent variable, understand which independent variables mainly affect the dependent variable and judge the degree of influence of the independent variable on the dependent variable according to the weight of the independent variable. In this study, because carbon sink change is related to land use type change, the model selected the driver data with the probability of suitability of each land use type for the study of land use change drivers, the analysis of the relationship between drivers and land pattern and the discovery of the main drivers of carbon sink change. The GWR model is expressed as follows (Zhang et al., 2021):

$$y_i = \beta_0(u_i, v_i) + \sum_{i=1}^{k} \beta_i(u_i, v_i) x_{ik} + \varepsilon_i \tag{6}$$

where u_i and v_i are the location coordinates of point i,

Table 3 Conversion cost matrix of the InVEST model

Land use types	Urbanized priority						Agricultural priority						Ecological priority					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
A	1	0	0	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1
B	1	1	0	1	0	0	1	1	1	0	0	1	0	1	0	0	0	0
C	1	0	1	1	0	0	1	1	1	1	1	1	0	1	1	0	1	0
D	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0
E	1	1	1	1	1	0	1	0	1	0	1	1	0	0	0	0	1	0
F	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Notes: A, B, C, D, E and F denote cropland, forest land, grassland, construction land, water area and unutilised land, respectively, 1 means convertible, 0 means non-convertible. The determination of 1 and 0 refers to the relevant experience of the existing research (Li, 2018) and FLUS website user manual (https://geosimulation.cn/FLUS.html), and the conversion cost of each land use is determined according to the local expert experience and urban planners. The rows in the table represent future land use types, and the columns represent current land use types

$\beta_0(u_i,v_i)$ is the regression coefficient, ε is the residual, x is the independent variable and y is the dependent variable. The results show that the goodness-of-fit R^2 of factors is a parameter that reflects the degree of influence of factors, which can be used to explain the influence of the drivers of carbon sink pattern changes.

2.3.3 Carbon storage change analysis

The InVEST model was developed by the US Natural Capital Project to enable the quantitative assessment and spatial visualisation of ecosystem services. The model consists of marine, freshwater and terrestrial ecosystem modules. Users can input data and parameters into the modules to obtain the results according to their needs. As land managers need to make choices about where to protect or develop, these assessment modules are ideal for supporting decisions about ecosystem services.

The module used is the carbon storage section located in the terrestrial ecosystem module, and the carbon storage module is based on carbon density. The principle is that the InVEST model uses land use or coverage categories, timber harvest, harvest product degradation rate and carbon storages of four carbon pools to estimate the carbon storages and carbon sequestration in a period. The four carbon pools include above-ground biomass, below-ground biomass, soil organic matter and dead organic matter. The formula is expressed as follows (Yang et al., 2021):

$$C_i = C_{\text{above}} + C_{\text{below}} + C_{\text{soil}} + C_{\text{dead}} \tag{7}$$

where C_i is the carbon density of land use type i and C_{above}, C_{below}, C_{soil} and C_{dead} are the above-ground biological carbon density, below-ground biological carbon density, carbon density of soil organic matter, and carbon density of dead organic matter, respectively. In this study, the sum of the carbon storages of different land use types was calculated according to the research needs of ecological space and the carbon density values of land use type T_c. The equations are expressed as follows (Wu et al., 2020):

$$T_i = C_i \times A_i \tag{8}$$

$$T_c = \sum_{i=1}^{n} T_i \tag{9}$$

where T_c is the total carbon storage, T_i is the carbon storage of land use type i (there are n land use types in the region), C_i refers to the carbon density of land use type i and A_i is the acreage of land use type i. The total carbon storage and the carbon storage of different land use types in 30 years can be obtained by subtracting the carbon storage calculation results from different scenarios in 2020 and 2060, through which the change in carbon sink distribution can be understood.

2.3.4 Methods for obtaining carbon density

Because of the difficulty of carbon density measurement, carbon storage was analysed using the carbon density table for land use types derived from existing studies (Table 4). The soil carbon density table of China refers to the carbon density data from the National Ecological Science Data Center (https://www.cnern.org.cn/) and some results of other studies (Chen et al., 2002; Li et al., 2004; Xie et al., 2004; Chuai et al., 2013; Liu et al., 2019).

Given that this study needed to obtain the carbon density data for the Beibu Gulf urban agglomeration, which was affected by climate and soil, more accurate carbon density needed to be calculated (Fu et al., 2019). Related studies have shown that both biomass carbon density and soil carbon density in China were positively correlated with annual precipitation and weakly correlated with annual mean temperature (Raich and Nadelhoffer, 1989; Chen et al., 2007) (Table 5). Therefore, the relationship between annual precipitation and soil organic matter carbon density was corrected using the existing equation (Alam et al., 2013):

$$C_{PS} = 3.3968P + 3996.1 \tag{10}$$

where C_{PS} is the soil carbon density obtained from annual precipitation in g/cm^2 and P is the annual precipitation in mm. The annual precipitation of Zhanjiang, a city in the central part of the Beibu Gulf urban agglomeration, was 1999.4 mm in 2018, and the national average annual precipitation was 671.1 mm in 2018. The soil carbon density of the Beibu Gulf urban agglomeration and the entire country was obtained by substituting the values into the equation. The ratio of carbon density

Table 4 Soil carbon density of different land use types in the Beibu Gulf urban agglomeration, China

Land use type	Cropland	Forest land	Grassland	Construction land	Water area	unutilised land
Density / (t/ha)	108.4	158.8	99.9	0	0	21.6

Table 5 Ratio of below-ground to above-ground biomass carbon density for different land use types in the Beibu Gulf urban agglomeration

Land use type	Cropland	Forest land	Grassland	Construction land	Unutilised land
Ratio	0.66	0.20	1.20	0.20	0.20

between them is the correction factor, and the product of the national carbon density data and the correction factor is the carbon density data of the Beibu Gulf urban agglomeration.

$$K_{PS} = \frac{C'_{PS}}{C''_{PS}} \tag{11}$$

where K_{PS} is the soil carbon density correction factor and C'_{PS} and C_{PS}'' are the soil carbon density obtained based on the annual precipitation at the scale of the Beibu Gulf urban agglomeration and the nation, respectively. According to existing studies, the carbon density between different land use types can be converted by the following equations (Xi et al., 2013; Ke and Tang, 2019):

(1) Construction land: 100% of total = 21% of biomass + 79% of soil organic matter,

(2) Cropland/forest land/grassland/unutilised land: 100% of total = 26% of biomass + 72% of soil organic matter + 2% of dead organic matter.

Then, the carbon density of the Beibu Gulf urban agglomeration was calculated (Table 6).

3 Results

3.1 Simulation of the development trend of ecological spatial patterns

3.1.1 Model operation and results

The FLUS model was used to simulate the land use changes under different scenarios of the Beibu Gulf urban agglomeration in 2060 to observe the changes in ecological space. Restricted areas were added to all scenarios because of the need to restrict development in policy-protected areas, such as nature reserves, ecological wetlands, natural forests, mangroves, tropical rainforests and watersheds. The results of the simulation based on the development priority of land use types under different scenarios are shown in Fig. 3. Results show that the ecological space of the Beibu Gulf urban agglomeration is widely distributed, covering more than half of the total land area. In general, the expansion of ecological space in the Beibu Gulf urban agglomeration in 2060 tends to expand under the ecological priority and agricultural priority scenario; in contrast, it tends to shrink under the urbanized priority scenario. The areas with high variability in each scenario are mainly in the urban fringe. The detailed changes are shown in Table 7.

3.1.2 Urbanized priority scenario

In the urbanized priority scenario, construction land is the dominant land use type to develop. In the 2060 projection, the proportion of urbanized space represented by construction land will increase from 4.84% to 8.31%, whereas the proportion of agricultural space represented by cropland will decrease from 38.54% to 37.48% and the proportion of ecological space represented by the other five types of land will decrease from 56.62% to 54.20%. The aforementioned changes reflect that the expansion of construction land under the priority orientation of urbanized areas will squeez the agricultural and ecological spaces, and the ecological quality will be reduced as a result.

Table 6 Carbon density of different land use types in the Beibu Gulf urban agglomeration, China / (t/ha)

Land use type	Above-ground biomass	Underground biomass	Soil organic matter	Dead organic matter
Cropland	40.5	26.8	186.3	5.2
Forest land	82.2	16.4	273.0	7.6
Grassland	28.2	33.8	171.7	4.8
Construction land	5.6	1.1	25.3*	0
Water area	0	0	0	0
Unutilised land	11.2	2.2	37.1	1.0

Note: * means data from Xi et al. (2013)

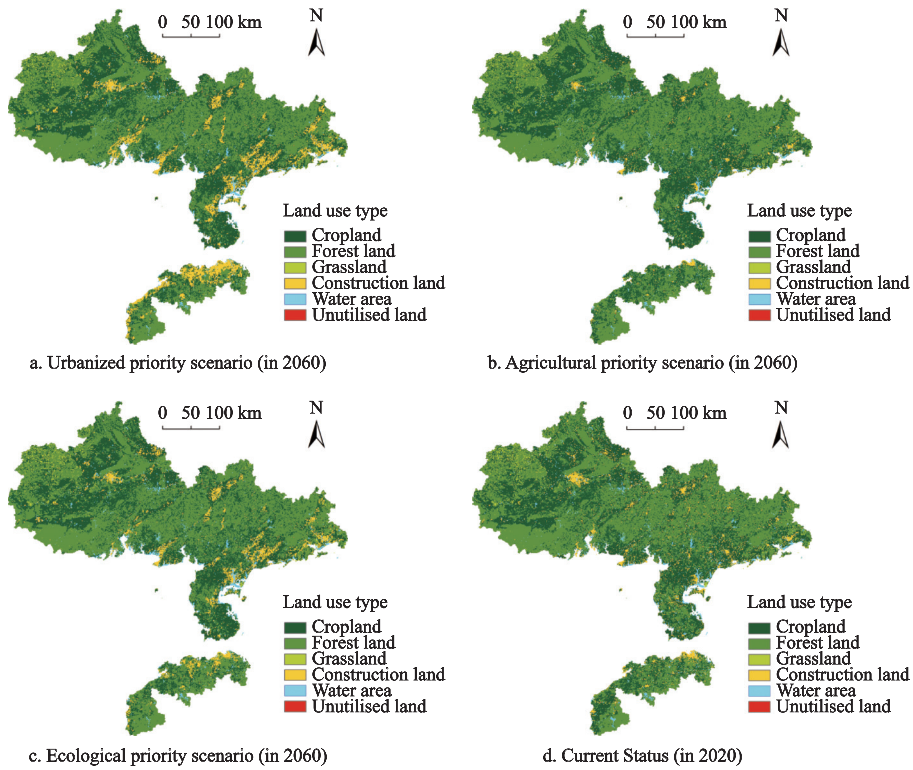

Fig. 3 Simulation results of the urbanized, agricultural and ecological priority scenarios in 2060 in the Beibu Gulf urban agglomeration, China

Table 7 Proportion of ecological space composition type status in 2020 and simulation in 2060 in the Beibu Gulf urban agglomeration, China

	Forest land / km^2	Grassland /km^2	Water area / km^2	Unutilised land / km^2	Total ecological space / km^2	Proportion / %
Status in 2020	60667	2162	3401	11	66241	56.62
Urbanized priority in 2060	58260	2080	3061	7	63408	54.20
Agricultural priority in 2060	61576	1968	3119	7	66670	56.98
Ecological priority in 2060	62010	2241	3373	7	67631	57.81

The most affected areas are the urban fringe, where the agricultural and ecological spaces around towns are eroded; the coastal cities of Guangdong and Hainan provinces have the most obvious changes in urbanized space. In the simulation, the urbanized space expansion of Nanning, the provincial capital city of Guangxi, is small, whereas the large cities of Guangdong and Hainan expand more. Therefore, the over-expansion of urbanized space in most cities under the urbanized priority scenario requires construction control to prevent ecological imbalance.

3.1.3 Agricultural priority scenario

In the agricultural priority scenario, urban agglomeration development is oriented to the expansion of cropland. This scenario increases the probability of conversion of land use types (other than construction land) to cropland and the cost of converting cropland to other land use types. In the scenario projections for 2060, the percentage of agricultural space represented by cropland will increase from 38.54% to 40.64%, while urbanized space will decrease from 4.84% to 2.38% and ecological space will increase from 56.62% to 56.98%. The agricultural space and ecological space are well protected. However, urbanized space is encroached upon under the agricultural priority scenario, and urban expansion is limited. The land use types in urban fringe areas are more variable, with cropland encroaching on the dominant urbanized space.

3.1.4 Ecological priority scenario

In the ecological priority scenario, ecological conservation becomes the development objective and everything is done with ecological protection in mind, which increases the conversion cost of ecological space land use type to other land use types. In the scenario projections for 2060, the proportion of ecological space will increase from 56.62% to 57.81% and that of urbanized space will increase from 4.84% to 5.36%, whereas that of agricultural space will decrease from 38.54% to 36.83%. Ecological space is protected in this scenario, and the expanding urbanized space mainly decreases the agricultural space. The main areas in which these changes occurred are the Beibu Gulf coast and Yulin. However, ecological space still does not increase substantially, indicating that ecological space shows irreversible characteristics after destruction under urbanisation. Thus, sustainable development can be achieved based on urban agglomeration only by limiting encroachment on ecological spaces.

3.2 Analysis of carbon storage in ecological space

3.2.1 Simulation of future carbon storage changes

In the multi-scenario projections for 2060, the carbon storage under different scenarios changs with the change in land use patterns. As shown in Table 8, the carbon storages in 2060 under the urbanized priority scenario are significantly lower than those in the agricultural and ecological priority scenarios, and carbon storage in the urbanized priority scenario will decrease more compared with the two other scenarios between 2020 and 2060. Moreover, only the urbanized priority scenario shows a decrease in carbon density in 2060 compared with 2020 for the three scenarios in the Beibu Gulf urban agglomeration, whereas all other scenarios show an increase from 2020.

As shown in Fig. 4 and Table 9, the distribution of carbon storage in 2060 in the Beibu Gulf urban agglomeration is generally similar under each simulation scenario in terms of spatial distribution, with the high carbon storage areas distributed widely. In the urbanized priority scenario, Lingao, Chengmai and Haikou are the cities where the average carbon density decreased more severely, whereas all other cities, except for Dongfang and Nanning, experience a decline because of the rapid spatial expansion of towns, which leads to a decrease in carbon sinking capacity. In the agricultural priority scenario, the carbon density of all cities increases because the carbon sinking capacity of agricultural space is maintained, exhibiting only a slight decrease. In the ecological priority scenario, the carbon density of Beihai, Fangchenggang, Chongzuo, Maoming, Zhanjiang and Yangjiang decreases slightly, the carbon density of other cities increases slightly and the preservation of ecological space stabilizes the regional carbon sinking capacity.

3.2.2 Analysis on the drivers of carbon sink development

Because the changes in land use patterns determine the spatial patterns of carbon sink changes in urban agglomerations, the advancement of urbanisation would reduce the regional carbon sinking capacity. Thus, the regression analysis of the drivers of the change in land use pattern using the GWR model can help determine the driving mechanism of the changes in carbon sink pattern and the degree of influence of each driver on the changes in carbon sink pattern. The influence coefficients of driving factors of land use types change fitted by GWR model are shown in Table 10. The driving factors that have the most significant influence on the changes in forest land are the elevation and slope factors. Secondly, in the GWR of each subdivision, the

Table 8 Carbon storage, average density and changes in the urbanized, agricultural, and ecological priority scenarios in the Beibu Gulf urban agglomeration, China

	Carbon storage / 10^9 t	Carbon storage in 2020–2060 / 10^6 t	Average carbon density / (kg/m^2)	Change in average carbon density in 2020–2060 / (kg/m^2)
Status in 2020	3.54	–	30.23	–
Urbanized priority	3.43	−112.26	29.27	−0.96
Agricultural priority	3.62	84.11	30.95	0.72
Ecological priority	3.54	3.03	30.26	0.03

Notes: '–' in the first row represents the carbon storage in 2020 alone which is no change value, so it is no data. Except the first one, the other three values in the second column represent carbon storage in 2060 for urbanized priority, agricultural priority and ecological priority

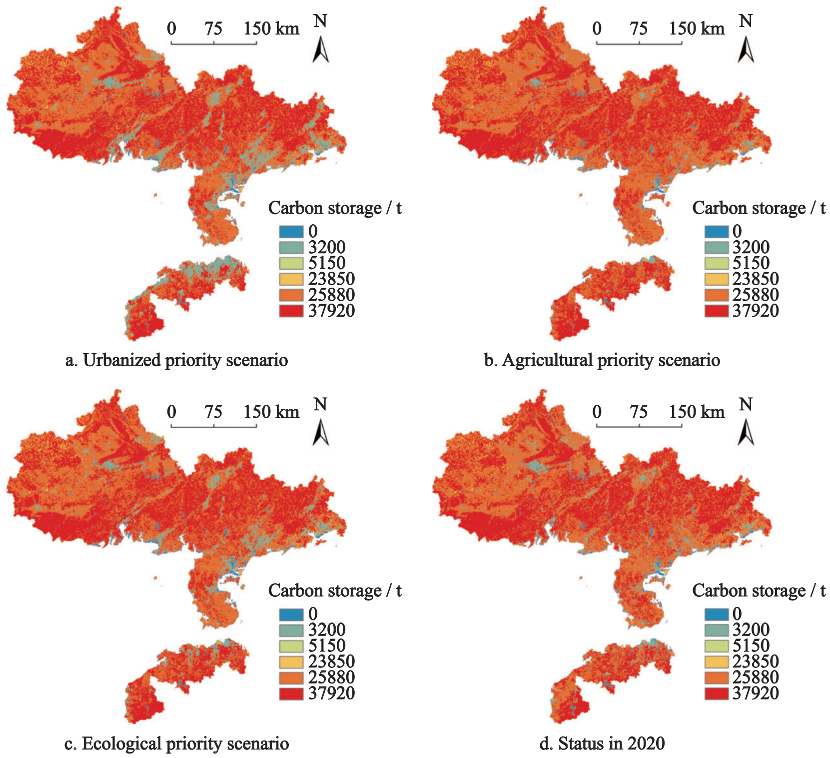

Fig. 4 Carbon storage distribution in the Beibu Gulf urban agglomeration of China in 2060 under the urbanized, agricultural, and ecological priority scenarios

Table 9 Average carbon density of cities under three scenarios and changes in the Beibu Gulf urban agglomeration, China / (kg/m^2)

Priority scenario		Nanning	Fangchenggang	Qinzhou	Beihai	Chongzuo	Yulin	Maoming	Zhanjiang	Yangjiang	Haikou	Danzhou	Dongfang	Chengmai	Lingao	Changjiang
Urbanized priority	Density	29.45	33.08	31.41	24.79	31.29	31.67	29.18	24.78	28.55	22.68	27.70	30.56	26.09	19.23	31.32
	Difference	0.04	−0.89	−0.75	−1.95	−0.15	−0.40	−1.19	−1.65	−2.17	−4.22	−2.23	0.85	−5.12	−10.23	−0.57
Agricultural priority	Density	30.24	34.08	32.62	26.84	31.57	32.82	31.01	27.12	31.21	29.83	30.93	33.24	32.70	30.78	34.24
	Difference	0.83	0.11	0.46	0.10	0.13	0.75	0.64	0.69	0.49	2.93	1.00	3.53	1.49	1.32	2.35
Ecological priority	Density	29.75	33.94	32.35	25.55	31.44	32.19	29.88	25.77	30.01	28.71	30.44	32.56	31.45	26.86	34.17
	Difference	0.34	−0.03	0.19	−1.19	0.00	0.12	−0.49	−0.66	−0.71	1.81	0.51	2.85	0.24	−2.60	2.28
Density in 2020		29.41	33.97	32.16	26.74	31.44	32.07	30.37	26.43	30.72	26.90	29.93	29.71	31.21	29.46	31.89

Table 10 The influence coefficients of driving factors of land use changes fitted by GWR model in the Beibu Gulf urban agglomeration, China

Land use type	Elevation	GDP	Population density	Slope direction	Slope	Distance to the highway	Distance to the railroad	Distance to river	Distance to the general road
Cropland	0.33	0.29	0.29	0.27	0.31	0.27	0.26	0.29	0.33
Forest land	0.34	0.32	0.32	0.30	0.34	0.28	0.28	0.30	0.33
Grassland	0.15	0.13	0.13	0.13	0.14	0.14	0.13	0.16	0.15
Water area	0.10	0.11	0.12	0.10	0.08	0.09	0.09	0.11	0.11
Construction area	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.10	0.08
Unutilised land	0.12	0.09	0.10	0.09	0.09	0.10	0.10	0.12	0.11

elevation and distance to the general road factors are more influential on the change in cropland, and the distance to river factor is more influential on grassland. The population density factor is more influential on the change in the water area, and the distance to river factor is more influential on construction land. For the unutilised land, elevation and distance to river factors are more important factors. Therefore, the main drivers of the change in ecological spatial carbon sink patterns are elevation, slope and distance to river.

4 Discussion

4.1 Performances of FLUS model and InVEST model

According to the above numerical results of Kappa coefficient, OA and FoM indicators, it is shown that the FLUS model has high accuracy and estimation value in the simulation of the development trend of land use change according to its adaptive inertia competition mechanism. Previous studies have shown that different land use conversion costs can be constructed from land range, land transferring degree and land transferring speed. Then put forward countermeasures and suggestions according to the natural development, ecological protection and economic priority efficiency goals (Lin et al., 2019; Liu et al., 2019; Chen, 2020; Song, 2020). Compared with ANN, CA model and Markov chain, FLUS model can connect the driving factors with land use change and reduce the impact of the errors in land use conversion under long time series (Liu et al., 2017). This enables more precise consideration of the parameters of different development possibilities. In this study, land use multi-scenario simulations of a long term and a large scale is carried out, to serve as a baseline for subsequent carbon storage development simulations.

There are many factors affecting land carbon sinking capacity, so the measurement of driving factors and related studies are also various. Compared to Varying Permeability model (Wang, 2019), Carbon Fix model (Han, 2017), Remote Sensing and Geographic Information System technology (Pan, 2017), InVEST model based on the distributed algorithm which provides a new technical way to access quantification and value of ecosystem services under various land use conditions. In this study, the carbon density of different land use types and the average density of each city in the Beibu Gulf urban agglomeration during 2020–2060 are obtained by using the carbon storage calculation module of InVEST model. In this way, the change of large-scale regional carbon storage simulations is analysed.

4.2 Future feasibility of combining FLUS-InVEST model with computer simulation technology

The change of land use types under different development directions can be predicted by multi-scenario simulations of carbon sink changes. The FLUS-InVEST model can handle all parameters accurately and effectively deal with the dynamics and complexity of this study. However, the methods of this study have some limitations, which comes from the accuracy of FLUS-InVEST. The accuracy problem caused by the empirical value problem and the simplification of the result by InVEST algorithm (the carbon storage module considers the static transformation while ignoring the carbon cycle and dynamic transformation between different carbon pools. Simplification of the carbon cycle algorithm leads to the assumption that the carbon sink development linearly in a certain period of time, and is not close enough to the actual situation). But the overall error is acceptable (Liu et al., 2017).

With the continuous development and improvement of computer simulation technology, the computer simulation prediction model has gone through several iterations. At present, except the limitation of improving accuracy of simulation, FLUS space simulation model has relative stability. At present, the PLUS model supporting the contribution rate analysis of driving factors has been available, which can support the high precision simulation of large high-performance computers (Liang et al., 2021). But its disadvantage is that the compatibility with the computer system is not good enough. If the compatibility problem is solved after version iteration, the relevant simulation research can be further improved and then the sensitivity of large-scale model simulation prediction can be improved.

4.3 The necessity of multi-scale spatial planning responses under multi-scenario simulations

4.3.1 Countermeasures to the carbon sink problem of the Beibu Gulf urban agglomeration

For the cities in Guangxi, due to the rapid economic development in Nanning, urban construction land is easy to expand, and the carbon sinking capacity is weak. According to the study results, the average carbon density of Nanning from 2000 to 2020 decreased by 1.23 kg/m^2. According to Table 5, the acceleration of carbon loss is more reflected in urbanized space expansion. Therefore, Nanning should strictly adhere to the ecological protection red line, so as to ensure there is enough ecological space provides enough capacity to neutralize the carbon emission generated by the city. Strictly restricting and guiding the balanced industrial and ecological development of the city, and consciously grouping urbanized areas can reduce the environmental deterioration caused by the expansion of construction land. In the coastal zone, Qinzhou and Fangchenggang have strong carbon sinking capacity, with carbon storage of 3.42×10^8 t and 2.01×10^8 t in 2020. Therefore, these two cities should ensure a reasonable population density to prevent excessive development of coastal zones from affecting the normal operation of land-sea interface carbon sinking capacity. The carbon sink capacity of Beihai is weak, and the carbon storage in 2020 was 8.81×10^7 t. In urban construction, the overall carbon sink capacity will be improved by means of returning farmland to forest. The results show that the carbon sinking capacity of Chongzuo and Yulin are greatly affected by the slope due to the mountainous terrain. Therefore, it is necessary to prevent the soil erosion and rocky desertification resulted from deforestation. The above two cities have relatively high total carbon storage and strong carbon sinking capacity, so they should play more roles in ecological conservation.

For cities in Guangdong Province, Zhanjiang, Maoming and Yangjiang have similar geographical conditions. Among them, Leizhou Peninsula in Zhanjiang has gentle land and relatively more cropland, which is easier to form the spreading trend of cropland. According to the analysis results, the carbon density of Zhanjiang is lower than the average carbon density of Beibu Gulf urban agglomeration. While Maoming tends to form an oblique urban sponge belt along the terrain. Both of Zhanjiang and Maoming need scientific guidance in the initial stage, so that they can prevent the expansion of towns and farmland from forming impervious water areas and agricultural belts, resulting in the imbalance of carbon sinking capacity.

For the cities in Hainan Province, the carbon storage of Haikou decreased by 6.92×10^6 t during 2010–2020, and the trend of urban spatial diffusion with Haikou as the center will have a negative impact on the ecological space of the coastline and surrounding areas. In the future development, scientific zoning is needed to form clusters to achieve regional carbon balance. Some cities in the west of Hainan have gentle terrain and are suitable for farming. Therefore, it is necessary to prevent the loss of carbon sinking capacity caused by the shrinking ecological space.

The study shows that in the future urban agglomeration planning and construction, the influencing factors of elevation, slope, population density and distance from the water system should be mainly considered. In order to prevent soil erosion and dynamic adjustment of river water volume, the future planning should control urban population density and the number of settlements.

4.3.2 Changing trends of enhance carbon sink strategies in urban agglomeration

At the same time that the ecological restoration of the territorial space is in full swing, the ‘Dual-carbon’ policy emerges at the historic moment, elevating the carbon sink to a whole concept of the territorial space (Chen et al., 2022). Enhancing carbon sinks has the effect of reversing ecosystem degradation and needs to be widely integrated into natural resource management frameworks and sustainable development strategies (Ding et al., 2022). In 2022, the Implementation Plan for the 14th Five-Year Plan for the Construction of the Beibu Gulf urban agglomeration (http://www.gov.cn/zhengce/zhengceku/2022-04/08/content_5684015.htm) was issued. Certain measures have been taken to strengthen the zoning of the terrestrial and marine ecological environment, improve the carbon sinking capacity of natural ecosystems, and construct a benign mode of urban construction and operation, as well as production and life style. Forming a green and low-carbon society has become the focus of national sustainable development. Therefore, it is more necessary to build a complete monitoring, evaluation system and dynamic governance system of urban agglomeration carbon sinking capacity in the future.

In terms of technology control, it is necessary to increase the planting density of plants with high carbon sinking capacity. By increasing vegetation with high carbon sinking capacity per unit area as the target to enhance the carbon sink absorption intensity, combined with ecological restoration technology, restore carbon function in some areas, a high-density and high-quality forest carbon pool could be built (Xu and Jiang, 2015).

In terms of planning and development, this paper combines the development situation of carbon sink land as a base map, and based on the three types of spatial carbon sink development principle of 'production, life and ecology' of urban agglomeration, brings together the land and sea elements and carbon circulation efficiency of urban agglomeration, and orderly adjusts and optimizes the land use type and structure.

In terms of social distribution, a redistribution system of carbon source and carbon sink resources should be created. It is necessary to implement human activity control, positive and negative distribution list, corresponding reward and punishment mechanism within the carbon sinking capacity monitoring system. This will help resolve the structural contradiction between economic development and environmental protection in urban agglomerations and ensure the rational implementation of regional low-carbon development.

5 Conclusions

Under the situation that the processes of carbon peaking and carbon neutrality are accelerating and the importance of carbon neutrality is becoming increasingly prominent, many cities within the Beibu Gulf urban agglomerations have successively carried out carbon sink enhancement work. The study made a detailed quantitative analysis of the development characteristics of land and carbon sink in Beibu Gulf urban agglomeration, identified the main driving factors that affect the development of carbon sink in urban agglomeration, and constructed the spatial planning response system of carbon sink security pattern and ecological restoration in urban agglomeration. It is an important task to ensure the integrity of ecosystem and protect the safety of carbon sink land in each individual city. In this study, the FLUS model, InVEST model, GWR model, spatial statistical analysis and other methods were used to simulate and predict the spatial distribution of carbon storage in 2060 under three different pre-set scenarios: urbanized priority, agricultural priority and ecological priority. And the main driving factors affecting the development of carbon sinks were identified, so they provide a reference for the future 'urbanized-agricultural-ecological' spatial expansion path of Beibu Gulf urban agglomeration. Our study lays the foundation for future policy development and implementation in the region.

The carbon sinking capacity of urban agglomerations, which has a significant influence on regional climate, is strongly affected by land use changes. Based on the land use data for the years 2000, 2010 and 2020, the land use changes and carbon sink patterns of the Beibu Gulf urban agglomeration under the urban, agricultural and ecological priority scenarios for 2060 were simulated, and the factors driving the changes in carbon sink patterns were explored. Among the simulation scenarios for 2060, carbon storage in the urbanized priority scenario will decrease by 112.26×10^6 t compared with that for 2020, and the average carbon density will decrease by 0.96 kg/m^2. The urbanized priority scenario is the fastest declining carbon density scenario for cities and counties in the Beibu Gulf urban agglomeration. If the expansion of urban construction land is not strictly restricted, the ecological environment and carbon sink function of urban agglomerations will be significantly damaged. Carbon storage in the agricultural priority scenario will increase by 84.11×10^6 t compared with that for 2020, and the average carbon density will decrease by 0.72 kg/m^2. The ecological priority scenario is similar to the agricultural priority scenario, with carbon storage will increase by 3.03×10^6 t compared with that for 2020, and the average carbon density will increase by 0.03 kg/m^2. According to the carbon neutrality target in the report on the work of the government and the urbanisation requirements of agglomeration, adopting an approach that pay attention to agricultural and ecological development can balance the urban expansion with the need for resource and environmental protection of the ecological space. Under the premise that the population continues to go into the town, the ecological priority development approach may be a wise choice. Besides, the driving factors of carbon sink pattern development in the Beibu Gulf urban agglomeration were explored from a spatial perspective using the GWR model, and the relationships and mechanisms among carbon sink, land and driving factors were understood. Slope, distance to river and elevation are the most influential variables and most important drivers of the changes in land use patterns and carbon sink patterns in the region. While elevation, slope, population density and distance to river are the main drivers of ecological space, carbon sink patterns. Moreover, the expansion of urbanized space crowding out ecological space is the main cause of changes in the ecological space carbon sink. Studies have shown that ecological spaces experience different degrees and scales of shrinkage, and that damage is almost irreversible. According to the spatiotemporal situation of land use change and carbon sink under the expected three types of scenarios, the spatial planning response and habitat restoration logic in line with the regional characteristics of the Beibu Bay urban agglomeration are proposed. From the technical control, our study needs to build a monitoring and evaluation system and dynamic governance system for the carbon sinking capacity of urban agglomerations. From the perspective of planning and development and social distribution, our study needs to guide ecological spatial planning, create practical solutions for increasing sinks, provide considerable contributions to the exploration of regional land and spatial planning to enhance carbon sink, and connect the spatial planning system to effectively implement the requirements of carbon peak and carbon neutrality.

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