



OPEN Integrating land use simulation and carbon assessment for sustainable urban planning in Fuzhou metropolitan area using PLUS and InVEST models

Qiuyi Zhang^{1,2,3✉}, Ronghui Huang¹, Changhua Zhu¹, Liyun Huang^{1,3✉} & Di Yang^{4✉}

In the pursuit of sustainable urban planning, integrating land use simulation with carbon storage assessment is crucial for achieving the “dual carbon” goals. This study focuses on the Fuzhou Metropolitan Area, utilizing land use data from 2000, 2010, and 2020. By establishing three future development scenarios—natural, urban, and dual-carbon target scenarios—based on the “Fuzhou Metropolitan Area Development Plan,” this research employs the Patch-generating Land Use Simulation (PLUS) and the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) models. The analysis reveals that from 2000 to 2020, the areas of cultivated land, forest land, grassland, and water bodies decreased, while construction land and bare land increased. Notably, the nighttime lighting factor significantly impacts land use changes, with elevation playing a crucial role in changes to water bodies and bare land. Under natural and urban development scenarios, carbon storage exhibits a downward trend, whereas the dual-carbon target scenario limits construction land expansion and reverses this trend, resulting in increased carbon storage. Based on these insights, this study proposes a three-stage urban planning strategy: strengthening carbon assessment in the early stages, fostering cross-departmental collaboration during implementation, and ensuring dynamic monitoring and adaptive adjustments in the later stages. This approach aims to harmonize urban development with ecological conservation, thereby maximizing economic and ecological benefits and supporting the achievement of the “dual carbon” policy goals.

Keywords PLUS model, InVEST model, Land use simulation, Land use change, Carbon storage, Fuzhou metropolitan area

Within the global carbon cycle, land use/cover change (LUCC) stands out as a critical factor, with land use pattern alterations significantly impacting carbon storage^{1–4}. Since China's reform and opening up, its urbanization has been marked by extensive economic growth and intensive population aggregation. This has spurred a continuous expansion of urban land use and conversions between different land use types. The dominant extensive development paradigm has led to a considerable reduction in cultivated and forest land, resulting in increased carbon dioxide emissions and decreased carbon storage⁵. As a key driver of terrestrial carbon cycling, land use type transitions are often associated with significant changes in carbon flux, directly influencing the functional characteristics and spatial patterns of carbon cycling. Research indicates that the expansion of urban construction land can accelerate regional carbon loss. Conversely, ecological conservation measures can enhance ecosystem carbon sequestration capabilities^{6,7}. “Reach a peak in carbon emissions before 2030” and “Become carbon neutral before 2060” have become significant strategic goals for promoting high-quality development in China^{8,9}. Therefore, analyzing the relationship between land use change and carbon storage, and scientifically

¹College of Architecture and Urban Planning, Fujian University of Technology, Fuzhou 350118, China. ²Key Laboratory of Monitoring, Evaluation and Early Warning of Territorial Spatial Planning Implementation, Ministry of Natural Resources (LMEE), Chongqing 401147, China. ³Technology Innovation Center for Monitoring and Restoration Engineering of Ecological Fragile Zone in Southeast China, Ministry of Natural Resources, Fuzhou 350001, China. ⁴Key Laboratory of Ecology and Energy Saving Study of Dense Habitat, Ministry of Education, Shanghai 200092, China. ✉email: zhangqy@fjut.edu.cn; 16397562@qq.com; 2533129073@qq.com

assessing the changes in future land use patterns and carbon storage, are of great importance for China to achieve the “dual carbon” goals.

At present, extensive research has been conducted on land use simulation to accurately and scientifically predict changes in land use patterns. Various models have been widely used, including the Future Land Use Simulation (FLUS) model^{10–14}, the System Dynamic (SD) model^{15–17}, the Conversion of Land Use and its Effect at Small Regional Extent (CLUE-S) model^{18–20}, the Cellular Automata (CA)-Markov model^{21–24} and so on. The Evolutionary Algorithm (EA) and FLUS model was constructed by coupling it with the evolutionary algorithm, using Guilin as a case study to analyze the model's improvement effects. Three development scenarios—natural development, farmland conservation, and ecological priority—were set up to simulate and predict land use changes in Guilin²⁵. The SD and FLUS models were coupled to simulate land use changes in the China-Pakistan Economic Corridor, providing methodological support for its sustainable development²⁶. The CLUE-S model was used to simulate the future land use pattern of Huainan City and predict the spatial distribution of various land use types in the study area for the years 2028, 2034, and 2040²⁷. Land use changes under three development scenarios in the Loess Plateau from 2020 to 2050 were simulated based on improved Markov and CA models²⁸. Although these models are effective in simulating land use changes and are widely applied in land spatial planning and land policy formulation, they lack flexibility when dealing with multi-class land use patch changes and multi-period concepts²⁹. The PLUS model, a novel approach to land use change simulation, is designed to investigate the drivers behind land expansion and shifts in landscape patterns. It also enables the simulation of alterations across various land use patches. This model stands out from its counterparts by offering enhanced simulation precision and generating more realistic landscape representations³⁰. The carbon storage module of the InVEST model directly assesses carbon storage changes caused by different land uses, characterized by easy access to driving factor data, simple operation, and high accuracy^{31,32}. In recent years, the InVEST model has been employed by many researchers to study ecosystem services. For example, the carbon storage of the ecosystem in Jinan was estimated using the InVEST model, and its changing characteristics were analyzed, revealing achievements in greening and conservation³³. Two carbon sequestration assessment methods—biomass and the InVEST model—were applied to estimate carbon storage and carbon density within the Luqiao District of Taizhou City, comparing carbon sequestration levels among different townships in the county, providing a basis for ecological conservation and resource development and utilization³⁴. To sum up, the InVEST and PLUS models exhibit strong performance in evaluating carbon storage and simulating as well as forecasting land use changes.

Some recent studies have combined the PLUS and InVEST models to simulate the spatiotemporal evolution of land use patterns and carbon storage at the levels of urban agglomerations^{35,36}, provinces^{37–39}, cities^{40–42}, and watersheds⁴³. However, there is a relative scarcity of research focusing on the metropolitan area level. The Fuzhou metropolitan area, as a key driver of high-quality development in Fujian Province, is crucial for implementing national strategies on regional coordinated development and leading integrated development across the Taiwan Straits. Despite its importance, research on land use simulation in the Fuzhou metropolitan area is notably lacking⁴⁴. Moreover, the “Fuzhou Metropolitan Area Development Plan” emphasizes integrating “peak carbon dioxide emissions” and “carbon neutrality” goals into the broader framework of ecological civilization construction, highlighting the significance of carbon storage in this context.

In view of this, this study utilizes land use data from the Fuzhou Metropolitan Area for the years 2000, 2010, and 2020. By integrating the PLUS and InVEST models, the study aims to forecast the spatiotemporal dynamics of land use and carbon storage changes within the region. The findings are intended to offer theoretical insights that could support the ecological civilization initiatives in the Fuzhou Metropolitan Area, contributing to informed decision-making and sustainable urban planning.

Study area and data collecting

Overview of the study area

The Fuzhou Metropolitan Area is located in the southeast coastal region of China, in the northeastern part of Fujian Province. Centered around Fuzhou, the capital of Fujian Province (see Fig. 1), this study covers four cities and one district, with a total land area of 33,000 square kilometers, accounting for 21.5% of Fujian Province. In 2020, the permanent resident population was about 13 million, representing 33.5% of Fujian Province, and the regional GDP was approximately 1.5 trillion yuan, constituting 34.5% of Fujian Province. As the second national-level metropolitan area approved by China, the Fuzhou Metropolitan Area plays a significant role in the coordinated economic development of the region. As a core area of the 21st Century Maritime Silk Road, it holds great potential for comprehensive development⁴⁴.

Data source and processing

The data involved in this study include land use data, natural environment data, socio-economic data, transportation location data, and policy planning data. Among them, the land use data consist of remote sensing monitoring data from 2000, 2010, and 2020. There is a total of 16 driving factors for land use simulation. To eliminate the interference of negative values, the nighttime light data with negative values are set to 0, and normalization processing is carried out to eliminate the impact of abnormal data. All driving factor raster data are resampled to a resolution of 30 m, and their row and column numbers are unified. The WGS_1984_Albers coordinate system is adopted as the spatial reference. For specific data sources, years, and other relevant information, please refer to Table 1.

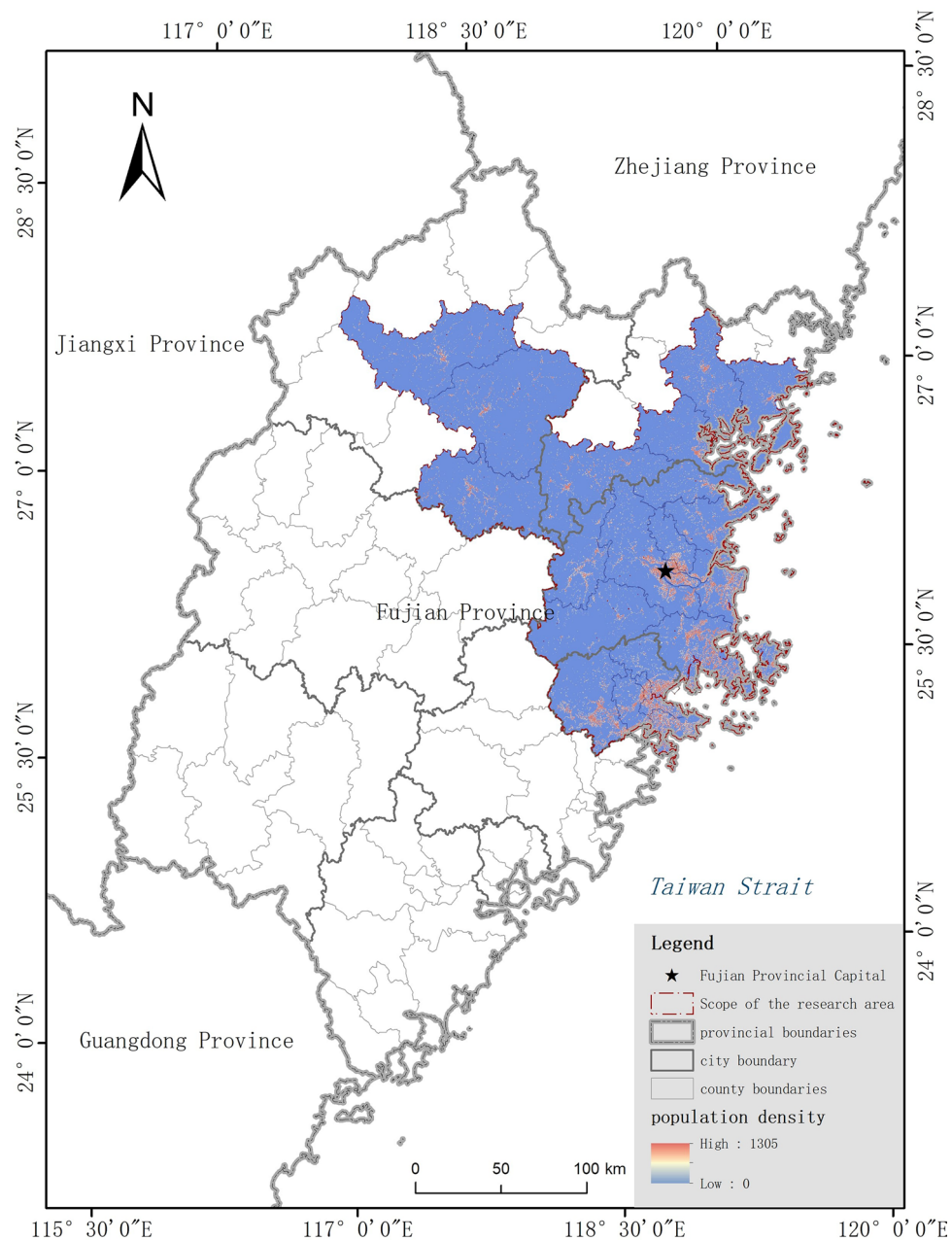


Fig. 1. The Location of Fuzhou Metropolitan Area in Fujian Province, China. Note: This map is made based on the standard map with the approval number of GS (2019) 1822 downloaded from the website of the China Surveying, Mapping and Geographic Information Standard Map Service of the Map Technology Review Center of the Ministry of Natural Resources of China (<http://bzdt.ch.mnr.gov.cn/>) and was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>) without modifying the map boundary.

Research methodology

This study outlines a research framework (Fig. 2) utilizing multi-phase land use data in conjunction with the PLUS and InVEST models. Initially, the study simulates the distribution of land use patches under three distinct scenarios: natural development, urban development, and development aligned with dual-carbon targets. Subsequently, leveraging carbon storage densities reported in prior research, the study employs the InVEST model's carbon storage module to estimate and analyze the total carbon storage and its dynamic changes in the Fuzhou Metropolitan Area across these scenarios. Ultimately, the study offers recommendations for future land use planning and spatial policy development, informed by the simulation outcomes.

PLUS model Building and validation

The PLUS model is employed to simulate future land use in the Fuzhou Metropolitan Area, incorporating the Land Expansion Analysis Strategy (LEAS) model and the Cellular Automaton (CA) model based on the multi-

| Data type | Data name | Data year | Data source | Resolution |
|-------------------------|--|----------------|---|------------|
| Land Use | Land Use Types of Fuzhou Metropolitan Area in 2000, 2010, and 2020 | 2000/2010/2020 | Center for Resource and Environmental Science and Data, Chinese Academy of Sciences ⁴⁵ | 30 m |
| Natural Environment | DEM (Digital Elevation Model) | 2020 | Geospatial Data Cloud | 30 m |
| | Slope | 2020 | Extraction Based on DEM | 30 m |
| | Annual Average Temperature | 2020 | Resource and Environment Data Cloud Platform | 1 km |
| | Annual Average Precipitation | 2020 | Resource and Environment Data Cloud Platform | 1 km |
| | Soil Type | 1995 | Resource and Environment Data Cloud Platform | 1 km |
| | Distance from Water System | 2020 | Resource and Environment Data Cloud Platform | / |
| Socio-economic | Nighttime Light Data | 2020 | Resource and Environment Data Cloud Platform | 1 km |
| | Population Density | 2019 | Resource and Environment Data Cloud Platform | 1 km |
| | GDP | 2019 | Resource and Environment Data Cloud Platform | 1 km |
| Transportation Location | Distance from Railway Station | 2020 | OpenStreetMap | / |
| | Distance from Railway | 2020 | OpenStreetMap | / |
| | Distance from Expressway | 2020 | OpenStreetMap | / |
| | Distance from National Highway | 2020 | OpenStreetMap | / |
| | Distance from Provincial Highway | 2020 | OpenStreetMap | / |
| | Distance from County Road | 2020 | OpenStreetMap | / |
| Policy Planning | 《Development Plan for Fuzhou Metropolitan Area》 | 2021 | National Development and Reform Commission | / |

Table 1. Research data information.

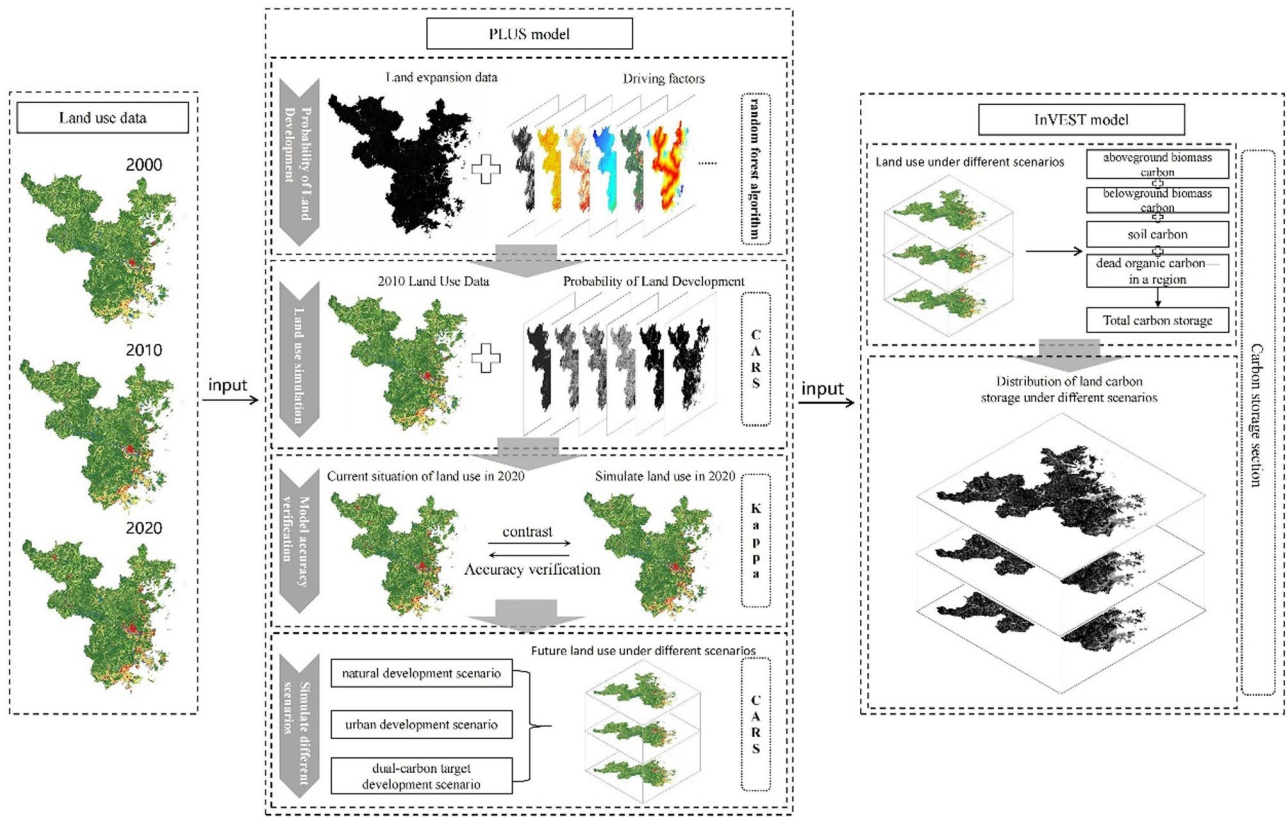


Fig. 2. The framework of the research.

type Cellular Automaton with Random Seeds (CARS)³⁰. Firstly, the LEAS module inputs the land use data of two periods, extracts the land use expansion data over the years, and simultaneously inputs the driving factor data. The random forest algorithm is then used to obtain the relationship between land expansion and driving factors for different types of land use, thereby obtaining the development probability of various land use types and the contribution of driving factors to land use type changes⁴⁶. Secondly, in the CARS module, parameters

| Land Type | Simulated area (km ²) | Actual area (km ²) | Error (km ²) | Relative error(%) |
|-------------------|-----------------------------------|--------------------------------|--------------------------|-------------------|
| Cultivated Land | 6095.89 | 6065.07 | 30.82 | 0.51 |
| Forest Land | 19789.38 | 19662.43 | 126.95 | 0.64 |
| Grassland | 4596.63 | 4686.22 | 89.59 | 1.95 |
| Water Area | 908.55 | 816.07 | 92.48 | 10.18 |
| Construction Land | 1260.31 | 1373.23 | 112.92 | 8.96 |
| Bare Land | 23.57 | 27.96 | 4.39 | 18.65 |

Table 2. Actual and simulated land use in 2020.

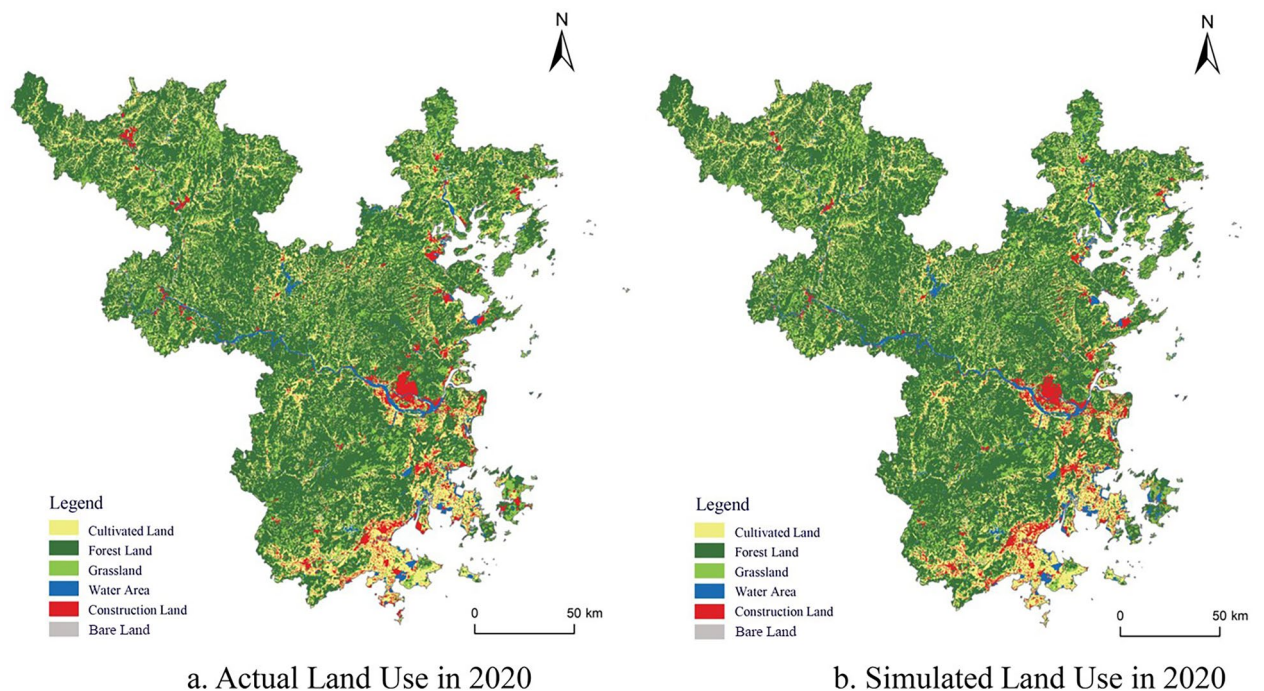


Fig. 3. Actual and simulated land use in 2020. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

such as neighborhood weights and transition rules are set. The neighborhood weights are determined based on the ratio of land expansion area to total regional area⁴⁷ and the transition rules are set based on previous research results³¹. Then, the land use situation in 2020 is simulated, and the accuracy of the simulated land use is verified against the current land use situation.

The Kappa coefficient is an index that takes into account both mapping accuracy and user accuracy. It is used to evaluate the consistency between predicted data and actual monitoring results and is one of the commonly used methods for measuring validation accuracy³⁰. The formula for calculating the Kappa coefficient is:

$$Kappa = \frac{P_a - P_b}{1 - P_b} \quad (1)$$

where P_a represents the proportion of grids that are correctly simulated in reality, and P_b represents the proportion of grids that are correctly simulated according to the prediction. The Kappa coefficient ranges from 0 to 1, with higher values indicating greater simulation accuracy.

The actual and simulated land use in 2020 are shown in Table 2; Fig. 3. the Kappa coefficient obtained is 0.89, indicating that the simulation prediction has high accuracy and strong applicability, and can well simulate the land use changes in the Fuzhou metropolitan area.

The carbon storage module of the invest model

The InVEST model calculates the carbon storage of four basic types—aboveground biomass carbon, belowground biomass carbon, soil carbon, and dead organic carbon—in a region. It does this by setting the carbon density values for different land use types within the study area and then computing the total carbon storage across the area³¹. The formula for calculating total carbon storage is:

| Land Use Type | Aboveground Carbon Density | Belowground Carbon Density | Soil Carbon Density | Dead Organic Carbon Density |
|-------------------|----------------------------|----------------------------|---------------------|-----------------------------|
| Cultivated Land | 0.21 | 0.12 | 0.96 | 0.02 |
| Forest Land | 0.41 | 0.07 | 1.42 | 0.03 |
| Grassland | 0.20 | 0.19 | 1.27 | 0.03 |
| Water Area | 0.00 | 0.00 | 0.92 | 0.00 |
| Construction Land | 0.00 | 0.00 | 0.83 | 0.00 |
| Bare Land | 0.27 | 0.05 | 0.84 | 0.02 |

Table 3. Carbon density of each land use type (unit: 10⁴t/km²).

| Development scenario | Cultivated land | Forest land | Grassland | Water area | Construction land | Bare land |
|---|-----------------|-------------|-----------|------------|-------------------|-----------|
| Natural Development Scenario | 0.2648 | 0.1328 | 0.0301 | 0.0722 | 0.4952 | 0.0048 |
| Urban Development Scenario | 0.2654 | 0.1370 | 0.0353 | 0.0623 | 0.4965 | 0.0035 |
| Dual-Carbon Target Development Scenario | 0.2990 | 0.1792 | 0.1075 | 0.0935 | 0.3146 | 0.0062 |

Table 4. Domain weights of land use types under different development scenarios.

$$C_i = C_{above} + C_{below} + C_{soil} + C_{dead} \tag{2}$$

$$C_{total} = \sum_{i=1}^n A_i C_i \tag{3}$$

In the formula: C_i represents the carbon density of various land use types, C_{above} represents the aboveground carbon density, C_{below} represents the underground carbon density, C_{soil} represents the soil carbon density, and C_{dead} represents the dead organic carbon density. C_{total} represents the carbon storage of terrestrial ecosystems, A_i represents the area of Type i of Land Use, and n represents the number of land use types.

This article refers to the revised carbon density data, adapted for the regional characteristics of Fujian Province³⁷. The carbon density data of various types are shown in Table 3:

Settings of different land use scenarios and domain weights

This study uses the “Fuzhou Metropolitan Area Development Plan” as a guiding framework and proposes three land development scenarios: natural development, urban development, and dual-carbon target development. The land use transitions for each scenario are detailed in Appendix Table A.1.

(1) Natural Development Scenario: This scenario is based on the land use change patterns observed in the Fuzhou Metropolitan Area from 2000 to 2020. It assumes no influence from planning policies on land use changes. The land use demand from 2020 to 2030 is projected using Markov Chain transition probabilities from 2010 to 2020, forecasting the land use situation in the Fuzhou Metropolitan Area for 2030.

(2) Urban Development Scenario: In this scenario, the likelihood of converting agricultural, forest, and grasslands to urban construction land is increased by 20%. Conversely, the probability of converting urban construction land back to forest, grassland, water bodies, or bare land is decreased by 20%. This scenario aims to predict the land use situation in the Fuzhou Metropolitan Area by 2030 under an urban development focus.

(3) Dual-Carbon Target Development Scenario: Aligned with the “Fuzhou Metropolitan Area Development Plan,” this scenario emphasizes the construction of a model area for ecological conservation, supporting the achievement of dual-carbon goals. Given the higher carbon densities of agricultural, forest, and grasslands, this scenario reduces the probability of converting forest and grasslands to urban construction land by 60% and agricultural land to urban construction land by 40%. It also increases the probability of converting agricultural and grasslands to forestland by 30%, projecting the land use situation in the Fuzhou Metropolitan Area for 2030 under a dual-carbon strategy.

The domain weight of land use types is used to represent the probability of conversion between different land use types. The value of domain weight ranges from 0 to 1, with a higher value indicating a greater probability of land type conversion and vice versa. The proportion of expansion area based on land use type to total land expansion determine the domain weight of each land use type based on the rate³⁰. See Table 4 for the parameter settings of domain weights.

Results and discussion
Analysis of land use evolution characteristics

Changes in land use area from 2000 to 2020

The area and proportion of each land use types in the Fuzhou metropolitan area from 2000 to 2020 is shown in Table 5. Forest land was the predominant land type during this period. Following China’s nationwide policy of converting farmland back to forests initiated in 1999, Fujian Province actively implemented this policy, leading to an increase in forest land area from 2000 to 2010. However, as urbanization progressed in Fujian Province, the demand for urban and rural construction land grew, causing some forest land to be converted to construction land and resulting in a decrease in forest land area from 2010 to 2020. Meanwhile, the areas of arable land and

| Land type | 2000 | | 2010 | | 2020 | |
|-------------------|-------------------------|------------|------------------------|------------|------------------------|------------|
| | Area (km ²) | Proportion | Area(km ²) | Proportion | Area(km ²) | Proportion |
| Cultivated Land | 6539.64 | 20.03% | 6293.94 | 19.26% | 6065.07 | 18.58% |
| Forest Land | 19684.09 | 60.31% | 19773.75 | 60.52% | 19662.43 | 60.24% |
| Grassland | 4904.34 | 15.04% | 4718.30 | 14.44% | 4686.22 | 14.37% |
| Water Area | 846.21 | 2.61% | 892.99 | 2.73% | 816.07 | 2.52% |
| Construction Land | 631.13 | 1.93% | 970.41 | 2.97% | 1373.23 | 4.21% |
| Bare Land | 25.55 | 0.08% | 24.95 | 0.08% | 27.96 | 0.09% |

Table 5. Area and proportion of each land use types in the Fuzhou metropolitan area from 2000 to 2020 (unit/km²).

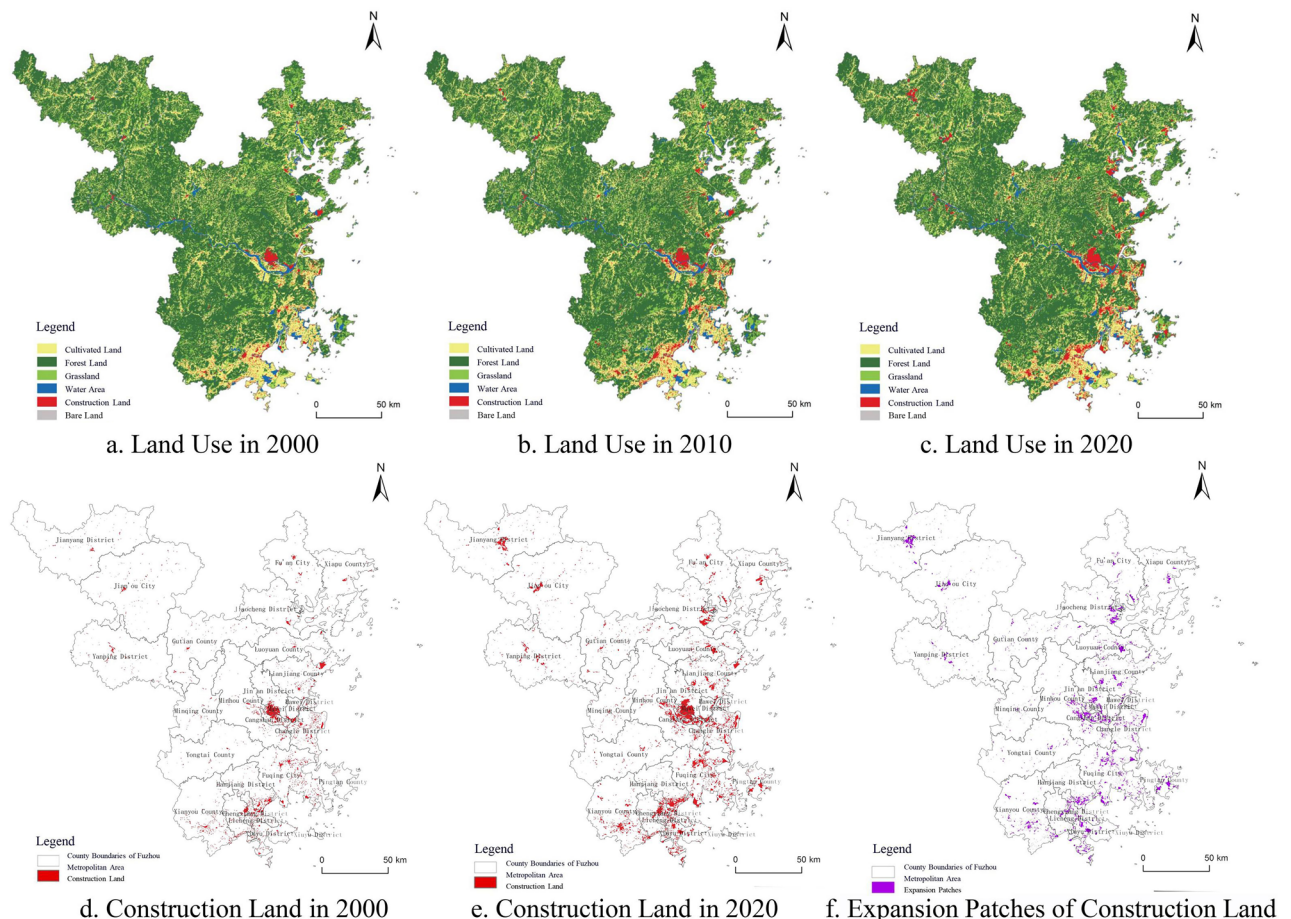


Fig. 4. Land use types and expansion of construction land in different periods. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

grassland showed a declining trend, while construction land continued to expand from 2000 to 2020, increasing by approximately 743 km² over 20 years, which accounts for a 2.3% increase.

The land use types and expansion of construction land from 2000 to 2020 are shown in Fig. 4. Cultivated land is generally distributed in a scattered pattern, with a clustered distribution in coastal areas. Construction land is primarily concentrated in the coastal and main urban area of Fuzhou, with the top five districts/counties experiencing the highest expansion ratio of construction land being Cangshan District, Jianyang District, Changle District, Chengxiang District, and Luoyuan County. This expansion trend aligns with the development pattern of “one core, three centers, two belts, and three bay areas” as outlined in the “Fuzhou Urban Circle Development Plan,” which are located at key nodes in the spatial pattern (see Fig. 5).

Analysis on land use conversion

As shown in Table 6, the land use types mainly converted out in Fuzhou Metropolitan Area from 2000 to 2020 are cultivated land, forestland, and grassland, with converted-out areas of 786.56 km², 712.27 km², and 568.15 km²

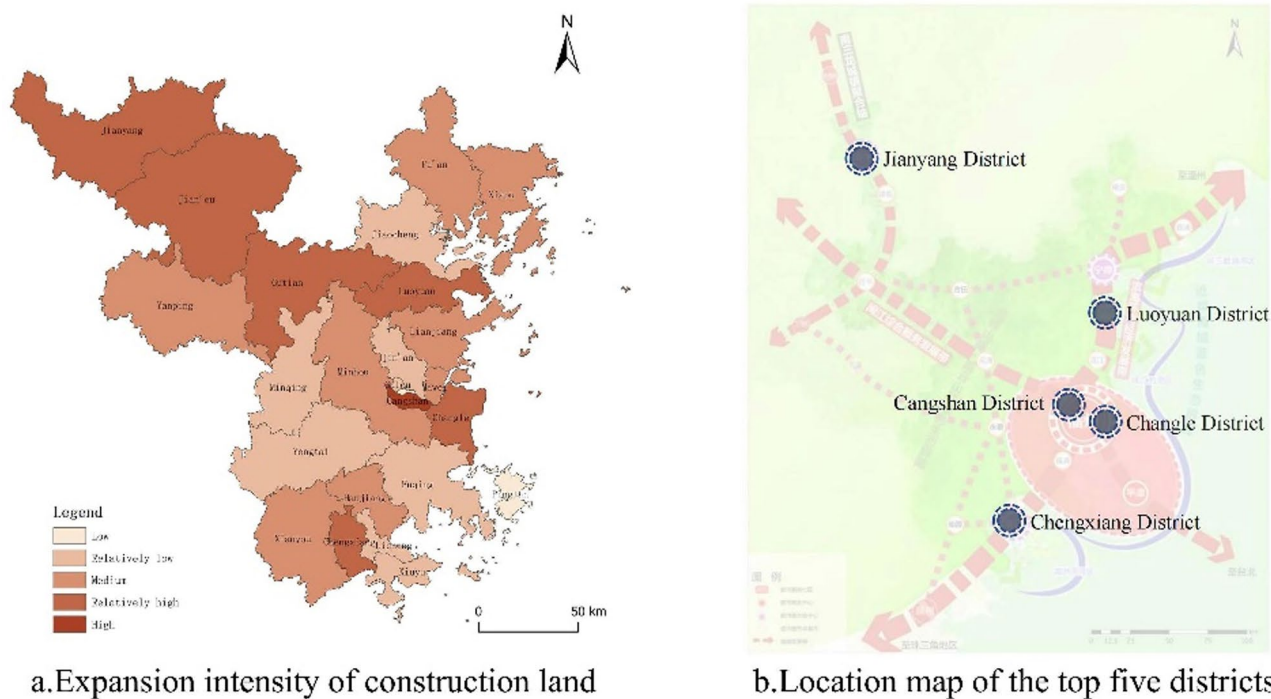


Fig. 5. Spatial pattern of land use expansion in the Fuzhou metropolitan area. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

| Land use type | | 2020 | | | | | | Transfer-out volume | Transfer-out rate |
|---------------|---------------------|-----------------|-------------|------------|------------|-------------------|-----------|---------------------|-------------------|
| | | Cultivated land | Forest land | Grassl-and | Water area | Construction land | Bare land | | |
| 2000 | Cultivated Land | 5753.08 | 226.92 | 56.92 | 54.97 | 447.42 | 0.33 | 786.56 | 12.03% |
| | Forest Land | 226.15 | 18971.82 | 274.09 | 33.04 | 177.54 | 1.45 | 712.27 | 3.62% |
| | Grassland | 41.45 | 444.24 | 4336.18 | 7.57 | 74.44 | 0.45 | 568.15 | 11.58% |
| | Water Area | 24.35 | 11.21 | 15.27 | 709.02 | 84.32 | 2.05 | 137.2 | 16.21% |
| | Construction Land | 19.74 | 6.32 | 3.27 | 11.23 | 589.43 | 1.13 | 41.69 | 6.61% |
| | Bare Land | 0.29 | 1.92 | 0.49 | 0.23 | 0.08 | 22.55 | 3.01 | 11.75% |
| | Transfer-out Volume | 311.98 | 690.61 | 350.04 | 107.04 | 783.8 | 5.41 | 2248.88 | |
| | Transfer-out Rate | 5.14% | 3.51% | 7.47% | 13.12% | 57.08% | 19.35% | | |

Table 6. Land use transfer matrix from 2000 to 2020 (unit/km²).

respectively. The main land use types converted in were construction land and forest land, with respective areas of 783.80 km² and 690.61 km². With the rapid economic growth of the Fuzhou Metropolitan Area, significant portions of cultivated land and forest land were transformed into construction land. Due to the implantation of the concept of ecological civilization and the active implementation of the policy of returning farmland to forestland⁴⁸, the converted-in and converted-out areas of forestland from 2000 to 2020 are roughly the same.

To better illustrate the dynamics of land use changes, we refer to Fig. 6, a Sankey map of land use area transfer, which visually represents the flow and conversion of different land use types from 2000 to 2020. The land use types with the highest conversion rates were construction land and bare land, indicating a significant tendency for other land use types to shift towards these categories. Similarly, water bodies and cultivated land exhibited the highest transfer rates, highlighting their relatively unstable structures and susceptibility to conversion into other land types. This visualization underscores the primary drivers of land use changes in the Fuzhou Metropolitan Area. The growing demand for construction land, driven by the region's role as a key economic development zone in Fujian Province, is evident in the expansion of construction land at the expense of other land types. However, the complex geographical environment, including natural barriers such as mountain peaks, has constrained the speed and direction of urban expansion. Additionally, stringent protection policies for important ecological functional areas and nature reserves have limited development in ecologically sensitive regions like mountainous areas. Given the limited availability of land resources, farmland and water bodies, which are predominantly located in plains and relatively easier to develop, have become significant sources for the expansion of construction land. This pattern is clearly reflected in Fig. 5, where the substantial conversion of

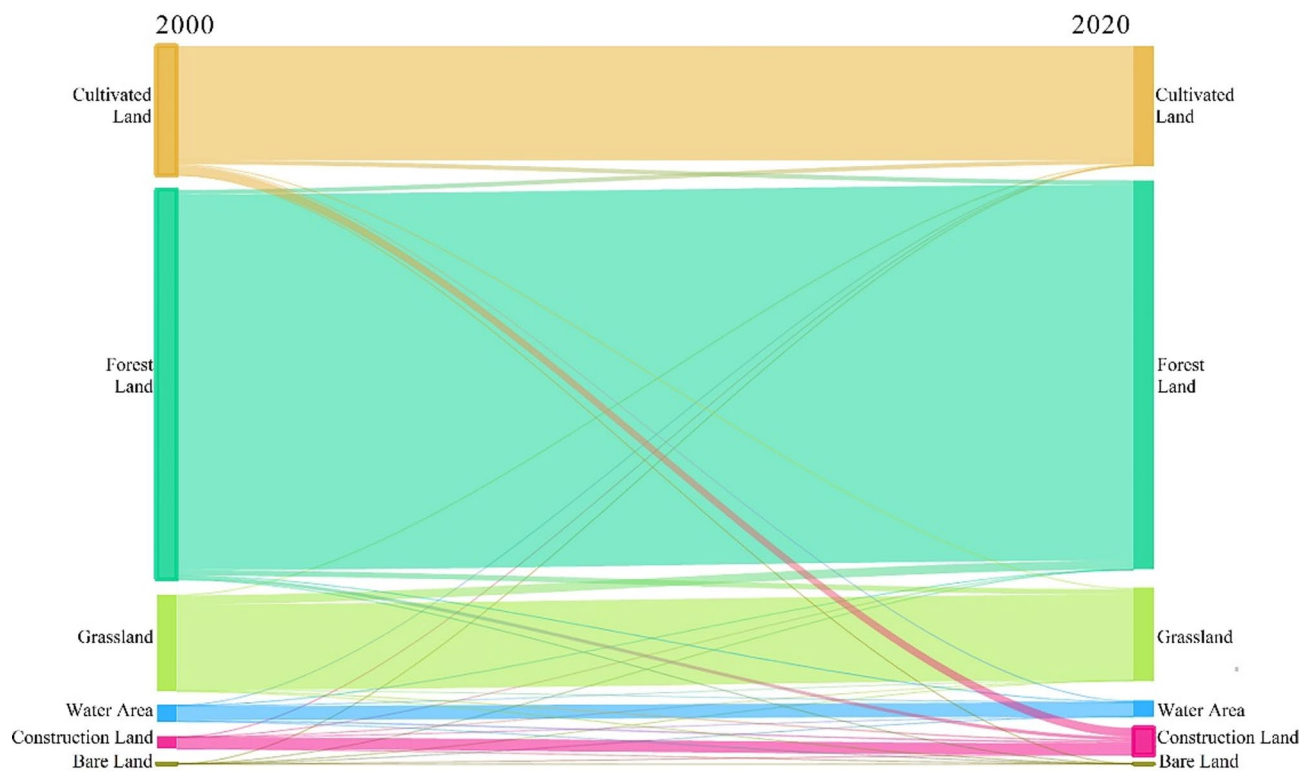


Fig. 6. Sankey map of land use area transfer.

farmland and water bodies into construction land is a dominant feature of the land use changes over the study period.

Analysis of driving factors for changes in land use layout

The Land Expansion Analysis Strategy (LEAS) module of the PLUS model was applied to quantify the contributions of 15 driving factors to land use type conversions in the Fuzhou Metropolitan Area between 2000 and 2020. Statistical validation using root mean square error (RMSE) confirmed the robustness of the results, with values as follows: cultivated land (0.145), forest land (0.161), grassland (0.135), water areas (0.051), construction land (0.093), and bare land (0.013). The average error of 9.97% further underscores the scientific reliability of the analysis.

The Sankey diagram (see Fig. 7) provides a comprehensive view of the contribution of various driving factors to land use changes in the Fuzhou Metropolitan Area from 2000 to 2020. For more detailed information on the specific data changes, please refer to Table A.2 in the appendix. Elevation and nighttime lighting emerge as the primary driving factors. Elevation significantly influences water bodies and bare land, contributing 20.97% and 40.03%, respectively, reflecting how natural conditions constrain land use. Nighttime lighting shows a high contribution to changes in cultivated land, forest land, grassland, and construction land, especially construction land at 27.28%, highlighting human activities as a key driver of land use change. Notably, nighttime lighting contributes 15.49% to forest land changes, likely linked to the “Grain for Green” policy. Average precipitation also plays a substantial role in cultivated land changes, with a contribution rate of 11.88%.

Other factors like distance from water, slope, and soil type have varied impacts. Distance from water notably affects water body changes at 12.55% but has minimal influence on bare land. Slope significantly impacts forest land and grassland changes at 10.82% and 10.07%, respectively, possibly due to its effects on soil erosion and water retention. Population density and GDP, while having lower overall contributions, still influence cultivated and construction land changes. Transportation-related factors show relatively low impacts but still affect forest and construction land changes, with distance from provincial highways contributing 6.40% and 5.78% to forest and construction land changes, respectively.

The Sankey diagram (Fig. 7) visually reinforces these findings by illustrating the complex interactions and relative influences of these driving factors on different land use types. Together, these results emphasize the interplay of human activities and natural conditions in shaping land use dynamics in the region.

Prediction of land use change under different scenarios

The Markov Chain module of the PLUS model was used to predict land use data for 2030, and the CARS module was employed to simulate land use in the Fuzhou Metropolitan Area under three scenarios: natural development, urban development, and dual-carbon target development (Table 7).

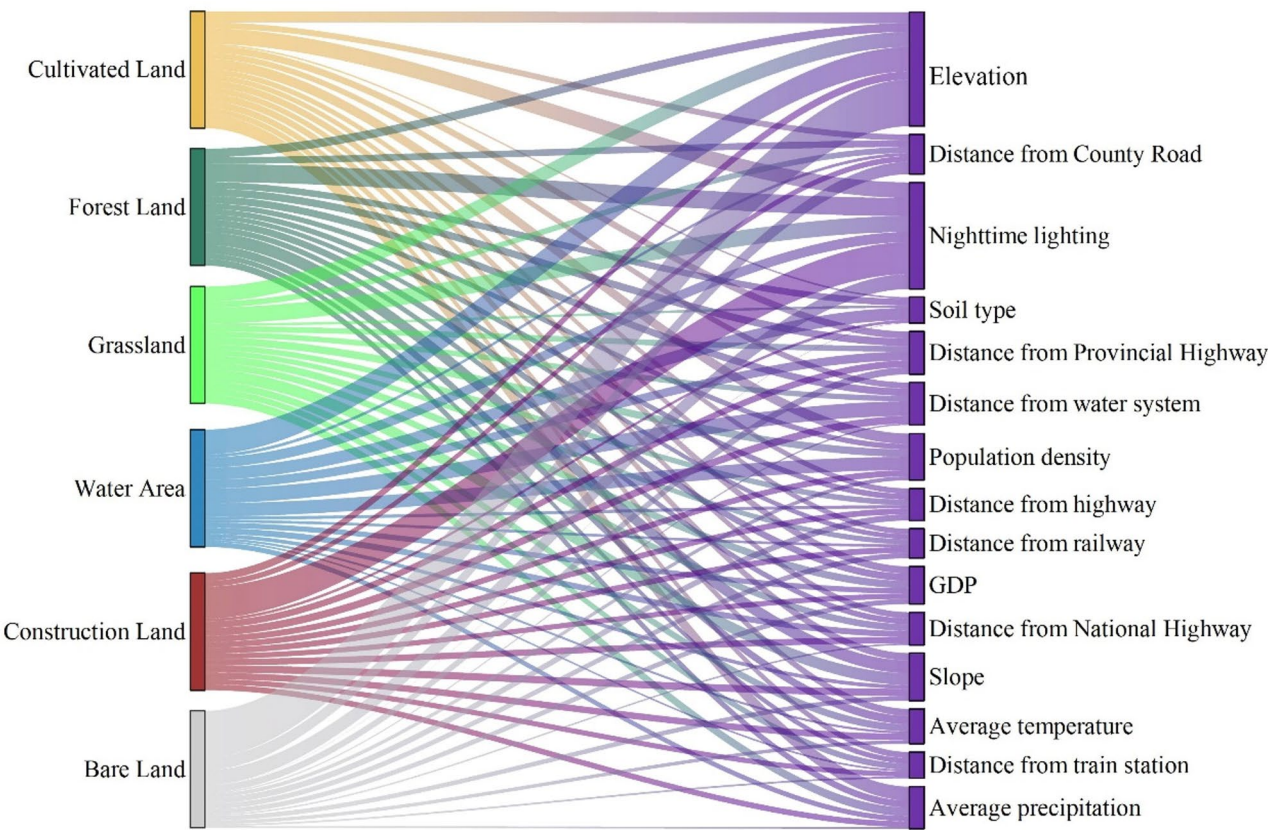


Fig. 7. Sankey map of driving factor contributions to land use changes.

| Development scenario | Cultivated land | Forest land | Grassland | Water area | Construction land | Bare land |
|---|-----------------|-------------|-----------|------------|-------------------|-----------|
| Natural Development Scenario | 5873.52 | 19588.67 | 4670.37 | 769.92 | 1736.97 | 19.18 |
| Urban Development Scenario | 5827.02 | 19549.28 | 4660.51 | 766.39 | 1824.04 | 31.40 |
| Dual-Carbon Target Development Scenario | 5997.86 | 19774.22 | 4648.79 | 843.54 | 1369.22 | 25.01 |

Table 7. Land use area under different development scenarios (unit/km²).

Under the natural development scenario, there is a significant expansion of construction land, with substantial decreases in the areas of cultivated land and forest land. Specifically, the area of cultivated land decreases by 191.55 km² forest land by 73.76 km² grassland by 15.85 km² and water areas by 46.15 km². In contrast, the area of construction land increases by 363.74 km² and bare land decreases by 8.78 km².

The urban development scenario shows a similar overall trend to the natural development scenario, with decreases in the areas of cultivated land, forest land, grassland, and water bodies, by 238.05 km², 113.15 km², 25.71 km² and 49.68 km² respectively. Meanwhile, the areas of construction land and bare land increase, by 450.81 km² and 3.44 km² respectively.

Under the dual-carbon target development scenario, the areas of forest land and water bodies show an expansion trend, with the most significant increase in forest land, by 111.79 km² and water areas by 27.47 km². The areas of cultivated land, grassland, construction land, and bare land show a downward trend, decreasing by 67.21 km², 37.43 km², 4.01 km² and 2.95 km² respectively. The spatial distribution of each land use type is shown in Fig. 8.

Assessment of carbon stock change characteristics

Spatial variation characteristics of carbon stock from 2000 to 2020

The land use data for 2000, 2010, and 2020 were input into the carbon storage module of the InVEST model, and the carbon storage was calculated in combination with the carbon density data of various land types. The carbon storage amounts were 562.48 million tons, 561.06 million tons, and 558.02 million tons, respectively (Table 8), showing an overall downward trend with a total reduction of 4.46 million tons over 20 years.

The spatial distribution of carbon storage in the Fuzhou Metropolitan Area from 2000 to 2020 is illustrated in Fig. 9 below.

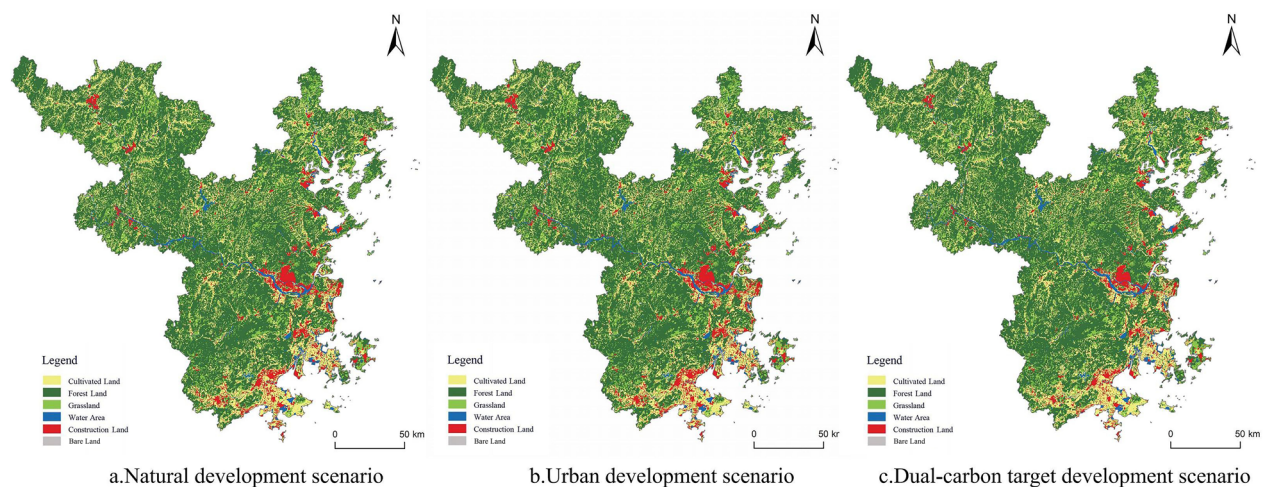


Fig. 8. The 2030 Land Use Forecast under Different Development Scenarios. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

| Land type | 2000 | | 2010 | | 2020 | | 2000–2020 Total Change |
|-------------------|----------------|------------|----------------|------------|----------------|------------|---------------------------|
| | Carbon Storage | Proportion | Carbon Storage | Proportion | Carbon Storage | Proportion | |
| Cultivated Land | 86.26 | 15.34% | 83.02 | 14.80% | 80.00 | 14.34% | -6.26 |
| Forest Land | 380.24 | 67.60% | 381.97 | 68.08% | 379.82 | 68.07% | -0.42 |
| Grassland | 82.71 | 14.70% | 79.57 | 14.18% | 79.03 | 14.16% | -3.68 |
| Water Area | 7.74 | 1.38% | 8.17 | 1.46% | 7.47 | 1.34% | -0.27 |
| Construction Land | 5.23 | 0.93% | 8.03 | 1.43% | 11.37 | 2.04% | 6.14 |
| Bare Land | 0.30 | 0.05% | 0.30 | 0.05% | 0.33 | 0.06% | 0.03 |
| Total | 562.48 | 100% | 561.06 | 100% | 558.02 | 100% | -4.46 |

Table 8. Changes in carbon storage from 2000 to 2020 (unit/ 10^6 t).

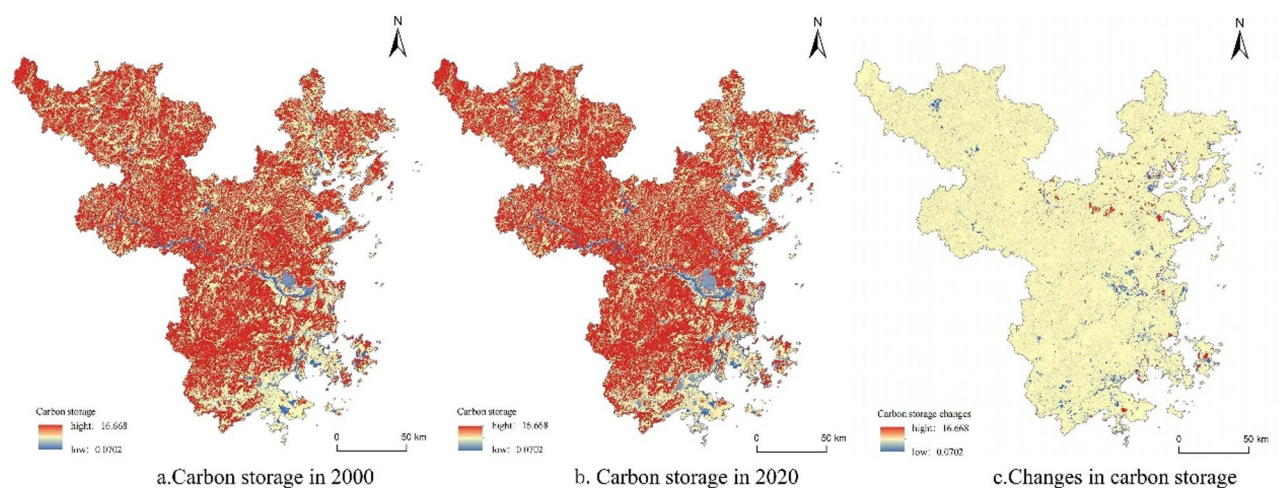


Fig. 9. Changes in carbon storage from 2000 to 2020. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

As depicted in the figure, carbon loss is predominantly concentrated in the coastal areas, the main urban area of Fuzhou, and the northwestern region. This pattern is attributed to the expansion of construction land, which has encroached upon and replaced significant portions of cultivated land and forest land, thereby reducing their carbon storage capacity. Conversely, carbon sequestration is predominantly observed in the northeastern and southeastern regions. Here, substantial areas of cultivated land and grassland have been reclassified as forest

land over the past two decades. Given that forest land inherently possesses a higher carbon density compared to cultivated land and grassland, this land use transition has resulted in increased carbon storage within these regions.

Carbon stock changes under different scenarios

Using the carbon storage module of the InVEST model, the land use raster data for 2030 under multiple scenarios were input, resulting in carbon storage amounts of 556.29 million tons, 555.56 million tons, and 558.86 million tons, respectively (Table 9). Under the natural development and urban development scenarios, carbon storage decreased by 1.73 million tons and 2.46 million tons, respectively, while under the dual-carbon target development scenario, carbon storage increased by 0.84 million tons.

Under the natural development scenario, maintaining the current land development model would result in a reduction of 1.73 million tons of carbon stock compared to 2020, continuing the downward trend from 2000 to 2020. There are only a few carbon sequestration areas, and the areas of cultivated land and forest land have significantly declined, indicating that this development scenario is not conducive to food and ecological security. Carbon losses mainly occur in coastal areas and main urban area of Fuzhou, consistent with the trend of construction land expansion.

Under the urban development scenario, the downward trend of carbon stock is more significant than that of the natural development scenario, with a reduction of 2.46 million tons compared to 2020. The carbon sequestration areas continue to decrease, while the carbon loss areas increase compared to the natural development scenario, resulting in patches of carbon loss. This shows that human activities can accelerate the destruction of ecological resources.

Under the dual-carbon target development scenario, due to the increased conservation of cultivated land, forest land, and grassland, the overall carbon stock has increased by 0.84 million tons compared to 2020, resulting in a larger area of carbon sequestration regions than carbon loss regions. This indicates that under this development scenario, it can effectively mitigate the trends of construction land expansion and the reduction of forest and cultivated land areas. However, it is not conducive to the economic development of the Fuzhou metropolitan area. Therefore, a combination of ecological conservation and urban development should be considered to find the optimal solution. The spatial distribution of carbon storage in the Fuzhou Metropolitan Area under different scenarios in 2030 is shown in Fig. 10.

Discussion

Spatiotemporal responses of land use and carbon storage and key driving factor analysis

This study reveals the interaction between land use changes and carbon storage in the Fuzhou Metropolitan Area. The expansion of construction land from 2000 to 2020, which caused a loss of forest and cultivated land, was the main driver of a 4.46 million-ton carbon storage decrease. This aligns with Huang et al.’s³⁷ findings on carbon storage in Fujian Province. Notably, carbon loss was more pronounced in coastal areas and the core zone of the metropolitan area, highlighting the negative impact of urbanization on ecological land fragmentation. Multi-scenario simulations further indicate that carbon storage continued to decline under natural and urban development scenarios. In contrast, the dual-carbon target scenario, which incorporates ecological conservation, increased carbon storage by 0.84 million tons. This underscores the sensitivity of ecosystem services to land use policies and echoes mechanisms identified in previous studies^{29,32}.

The analysis of driving factors reveals that the nighttime light index is the most significant contributor to the expansion of construction land. This confirms that human activities are the primary driver of land use changes in the Fuzhou Metropolitan Area. Additionally, the dominant role of elevation in changes to water bodies and bare land highlights the rigid constraints of natural conditions on ecological land use, underscoring Fuzhou’s unique coastal and hilly terrain.

Spatial optimization strategies and response mechanisms in urban planning

Under the dual pressures of urbanization and ecological conservation, the Fuzhou Metropolitan Area urgently needs to establish a multi-dimensional spatial optimization strategy system. First, a coupled “ecological matrix–urban clusters” spatial pattern should be constructed. By leveraging the Minjiang River ecological corridor and the Jiufeng-Daiyun Mountain ecological barrier, rigid ecological protection redlines defined by higher-level planning must be implemented. Areas of forest expansion under dual-carbon targets should be designated

| Land type | 2020 | Natural development scenario | | Urban development scenario | | Dual-carbon target development scenario | |
|-------------------|----------------|------------------------------|-----------|----------------------------|-----------|---|-----------|
| | Carbon storage | Carbon storage | Variation | Carbon storage | Variation | Carbon storage | Variation |
| Cultivated Land | 80.00 | 77.48 | -2.52 | 76.86 | -3.14 | 79.12 | -0.88 |
| Forest Land | 379.82 | 378.39 | -1.43 | 377.63 | -2.19 | 381.98 | 2.16 |
| Grassland | 79.03 | 78.76 | -0.27 | 78.59 | -0.44 | 78.40 | -0.63 |
| Water Area | 7.47 | 7.05 | -0.42 | 7.01 | -0.46 | 7.72 | 0.25 |
| Construction Land | 11.37 | 14.38 | 3.01 | 15.10 | 3.73 | 11.34 | -0.03 |
| Bare Land | 0.33 | 0.23 | -0.10 | 0.37 | 0.04 | 0.30 | -0.03 |
| Total | 558.02 | 556.29 | -1.73 | 555.56 | -2.46 | 558.86 | 0.84 |

Table 9. Carbon storage prediction for 2030 under different development scenarios(unit/10⁶t).

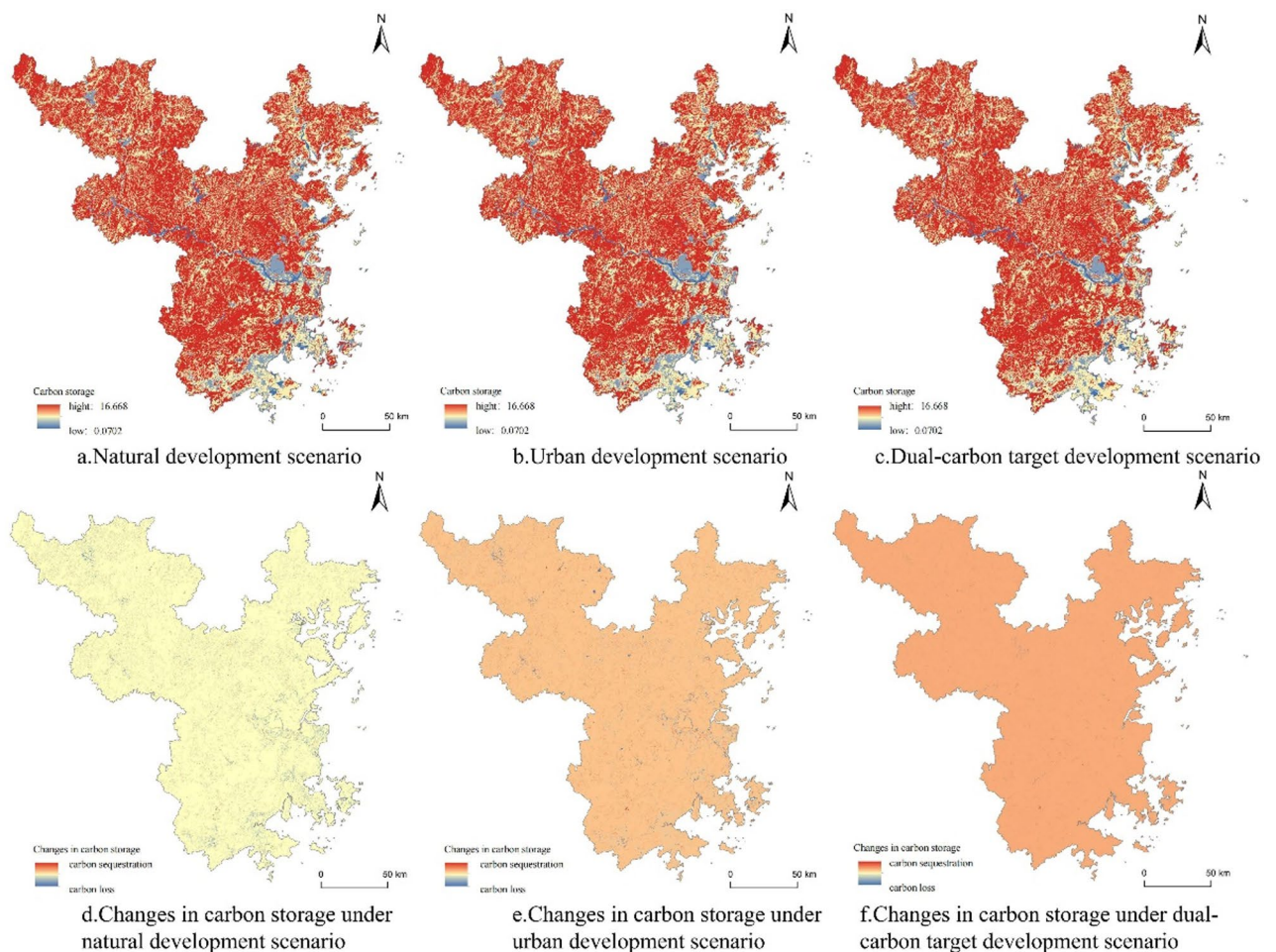


Fig. 10. Carbon storage and changes under different development scenarios. The figure was generated by ArcGIS 10.7 (<https://www.esri.com/zh-cn/arcgis/products/arcgis-desktop/overview>).

as permanent ecological reserves, with hierarchical zoning controls. Second, given the cross-administrative characteristics of the metropolitan area, it is recommended to establish a Minjiang River Basin Ecological Compensation Alliance. Market-based mechanisms, such as construction land quota trading and carbon sink trading, should balance the interests between ecological conservation zones and development areas. Additionally, the implementation pathway of “planning transmission–public participation” needs refinement. Simulation results should be translated into binding indicators for territorial spatial planning, embedding carbon storage unit management requirements into regulatory detailed planning. A community ecological credit system could incentivize public participation in ecological space stewardship, forming a sustainable development framework led by the government, regulated by the market, and supported by society.

To achieve synergistic development between dual-carbon goals and urbanization, future urban planning must optimize strategies across the entire “formulation–implementation–supervision” process. First, strengthen carbon assessment mechanisms during the planning formulation stage by quantifying the carbon balance effects of different schemes, ensuring low-carbon principles are integrated upfront into spatial layouts and land-use decisions. Second, establish cross-departmental collaboration mechanisms to promote data sharing and policy coordination among planning, ecological, and energy authorities, aligning land-use adjustments with multi-domain strategies such as energy transition and ecological conservation. Finally, develop dynamic monitoring and adaptive adjustment frameworks, leveraging real-time data to track key indicators like carbon storage and construction land expansion, enabling timely refinements to address uncertainties. This pathway—through a “source control–process coordination–dynamic feedback” closed-loop management system—provides a scientific foundation for high-density metropolitan areas to pursue low-carbon resilient development.

Conclusions

This study integrates the PLUS and InVEST models to assess land use and carbon storage changes in the Fuzhou Metropolitan Area, offering a scientific approach for related evaluations. The findings reveal that rapid urbanization has led to the conversion of cultivated land and forest land into construction land, resulting in a net loss of 4.46 million tons of carbon storage from 2000 to 2020. However, the dual-carbon target development scenario effectively curbs the expansion of construction land and reverses the downward trend of carbon

storage. This scenario underscores the importance of balancing urban development with ecological protection to achieve sustainable growth. The study also highlights the significant impact of human activities, particularly urban expansion, on land use changes and carbon storage dynamics. By proposing a multi-dimensional spatial optimization strategy and a closed-loop management framework, this research provides practical references for future urban and land use planning in high-density metropolitan areas.

Despite these contributions, the study has some limitations. The consideration of policy-driven factors, such as adjustments in industrial layout and the sudden impacts of disaster events, is insufficient. These factors could be incorporated into future models to enhance the dynamism and realism of the scenarios. Additionally, the carbon density data rely on regional research correction values, which may introduce local biases. Future research could optimize parameter accuracy through field monitoring and high-resolution remote sensing inversion, thereby deepening decision support for the optimization of territorial space.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Q.Z.: conceptualization, validation, formal analysis, funding acquisition, writing—original draft. R.H.: conceptualization, validation, data curation, writing—review and editing. L.H., and C.Z.: data curation, investigation, resources. D.Y.: methodology, validation, supervision, formal analysis, writing—review and editing.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Q.Z., L.H. or D.Y.

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