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Analyzing the Spatiotemporal Evolution Features of Habitat Quality and Carbon Storage in Guangzhou Based on the InVEST Model

Qi Zhan, Ruei-Yuan Wang

School of Sciences, Guangdong University of Petrochem Technology (GDUPT), Maoming 525000, China

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***Abstract*— *Habitat quality and carbon storage are key indicators for assessing ecosystem health. Rapid urbanization has significantly altered urban land-use patterns, driving spatiotemporal changes in regional habitat quality and carbon storage. To investigate the spatiotemporal evolution of habitat quality and carbon storage in a megacity undergoing rapid urbanization, this study selects Guangzhou as a representative case study. Using 30 m resolution land-cover data for 2000, 2010, 2020, and 2025, together with ArcGIS spatial analysis techniques and the InVEST model, this study evaluates the spatiotemporal variations in habitat quality and carbon storage. It further summarizes their spatiotemporal evolution over the 25-year period and analyzes the underlying evolutionary patterns and driving mechanisms. The results indicate that: (1) Temporally, habitat quality exhibited a stepwise and continuous decline from 2000 to 2025, while carbon storage decreased steadily, with a cumulative reduction of 3.21%. The conversion of forestland and cropland into built-up land was the primary driver of carbon storage loss and habitat degradation. However, ecological conservation and management measures implemented after 2020 effectively slowed the rate of ecological degradation. (2) Spatially, habitat quality and carbon storage exhibited highly consistent distribution patterns, maintaining a long-term spatial gradient characterized by higher values in the northern mountainous areas and lower values in the southern urbanized areas. The mountainous regions of Conghua and Zengcheng served as core areas with high habitat quality and strong carbon sequestration capacity, whereas the central urban districts and southern plains exhibited relatively low values. In addition, habitat fragmentation in the peri-urban areas of central Guangzhou continued to intensify. (3) Land-cover conversion and residential expansion were the dominant drivers of regional ecological degradation. Implementing zoned ecological conservation and restoration strategies can effectively mitigate the loss of ecological space. Overall, this study provides a scientific basis for territorial spatial ecological restoration planning and sustainable urban development in Guangzhou.*

Keywords*— Habitat quality (HQ); Carbon storage; InVEST model; Land cover; Spatiotemporal evolution; Driving mechanism; Guangzhou.

I. INTRODUCTION

Habitat quality (HQ) is a key indicator for assessing regional ecosystem integrity, biodiversity conservation capacity, and ecosystem service functions. It reflects the impacts of land use and land cover (LULC) change on ecological conditions and thus serves as a fundamental metric for evaluating regional ecological security. A healthy ecological environment underpins sustainable human development by providing essential ecosystem services while enhancing human physical and mental well-being and overall quality of life [1,2]. As China's urbanization enters a stage of high-quality development, megacities have experienced rapid expansion of built-up land and substantial reconfiguration of LULC patterns. These changes have resulted in the continuous loss of natural ecological spaces, intensified habitat fragmentation, and widespread habitat degradation, thereby posing significant challenges to urban ecosystem stability and long-term sustainable development.

In recent years, the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model has become one of the most widely used tools for quantifying habitat quality because of its high modularity, strong spatial interpretability, and open-source reproducibility [3–6]. Applications of the InVEST model now span multiple spatial scales, ranging from county-level administrative units and mountainous regions to urban agglomerations and watershed-based metropolitan clusters, demonstrating its broad applicability in ecological assessment. Nevertheless, several key parameters in the Habitat Quality module—including threat-source weights, habitat suitability scores, habitat sensitivity coefficients, and maximum influence distances—are typically assigned based on expert judgment or values adopted from previous studies. This practice introduces considerable subjectivity and limits the model's ability to capture spatiotemporal heterogeneity, and has therefore been increasingly criticized in recent methodological studies.

Methodologically, the integrated SD/PLUS/FLUS + InVEST + SSP-RCP multi-scenario simulation framework has become the dominant analytical paradigm in recent years. It establishes a closed-loop workflow linking historical simulation (or hindcasting), future scenario projection, and driving-force attribution, while providing strong compatibility for the integrated assessment of habitat quality and carbon storage. Meanwhile, research has gradually shifted from single-service habitat assessments toward multidimensional evaluations that simultaneously examine the trade-offs and synergies among habitat quality, carbon storage, and water yield. Consequently, InVEST-based ecological assessments have evolved from a linear LULC → habitat quality analytical framework to an integrated framework linking LULC and landscape pattern changes → multiple ecosystem services (e.g., habitat quality, carbon storage, and water yield) → trade-off/synergy analysis and driving mechanism attribution. This integrated framework provides comparable, predictive, and scenario-explicit evidence for understanding the ecological consequences of anthropogenic disturbances across urban and regional landscapes [7].

Despite these advances, most existing studies have focused on regional-scale analyses or future scenario simulations, whereas comparatively limited attention has been paid to the long-term spatiotemporal evolution of habitat quality and carbon storage within rapidly urbanizing megacities. Furthermore, the interactions between urban expansion, ecological conservation policies, and ecosystem service dynamics remain insufficiently understood. Addressing these gaps provides the primary motivation for the present study.

As the core city of the Guangdong–Hong Kong–Macao Greater Bay Area (GBA), Guangzhou has undergone rapid industrialization and urbanization since the implementation of China's reform and opening-up policy. Consequently, conflicts between ecological conservation and urban development have become increasingly pronounced. The continuous expansion of built-up land has progressively encroached upon cropland and forests, exerting profound impacts on regional ecosystems [8]. These changes have driven substantial transformations in LULC patterns, with increasing competition between ecological and construction spaces significantly reshaping regional habitat configurations.

Existing studies have primarily focused on the spatial development patterns of the GBA, the spatiotemporal evolution and driving mechanisms of habitat quality, the effects of landscape pattern changes on habitat quality and carbon storage across the Pearl River Delta (PRD), and the influence of urban morphology on habitat quality in

Guangzhou. However, ongoing urbanization continues to generate new ecological challenges, highlighting the need for continuous monitoring and a more comprehensive understanding of the long-term spatiotemporal dynamics of habitat quality in Guangzhou.

Against this background, this study employs four periods of LULC data (2000, 2010, 2020, and 2025) and integrates the InVEST model with ArcGIS spatial analysis techniques to evaluate habitat quality and carbon storage in Guangzhou over the period 2000–2025. By revealing their spatiotemporal evolution patterns, this study aims to provide scientific evidence and theoretical support for ecological governance, territorial spatial planning, and sustainable urban development in Guangzhou.

II. STUDY AREA

Guangzhou is located between 112°57′E–114°03′E and 22°26′N–23°56′N [9] (Figure 1), at the confluence of the Xijiang, Beijiang, and Dongjiang Rivers. As a coastal city facing the Hong Kong and Macao Special Administrative Regions across the Pearl River Estuary, Guangzhou serves as an important hub along the Maritime Silk Road and functions as a key gateway for southern China. It represents a core node within the Guangfo Metropolitan Area, the Guangdong–Hong Kong–Macao Greater Bay Area (GBA), and the Pearl River Delta (PRD) metropolitan regions.

The city is also a critical transportation hub connecting several national railway networks, including the Beijing–Guangzhou, Guangzhou–Shenzhen, Guangzhou–Maoming, and Guangzhou–Meizhou–Shantou railways. In addition, Guangzhou hosts one of the major civil aviation hubs in South China, providing extensive connectivity with other regions across China. The municipality covers an administrative area of 7,434.4 km² [8] and consists of 11 districts: Yuexiu, Liwan, Haizhu, Tianhe, Baiyun, Huangpu, Huadu, Panyu, Nansha, Conghua, and Zengcheng. With a permanent resident population of over 18 million and an urbanization rate of 86.5%, Guangzhou is among the most densely populated and highly urbanized cities in China [10].

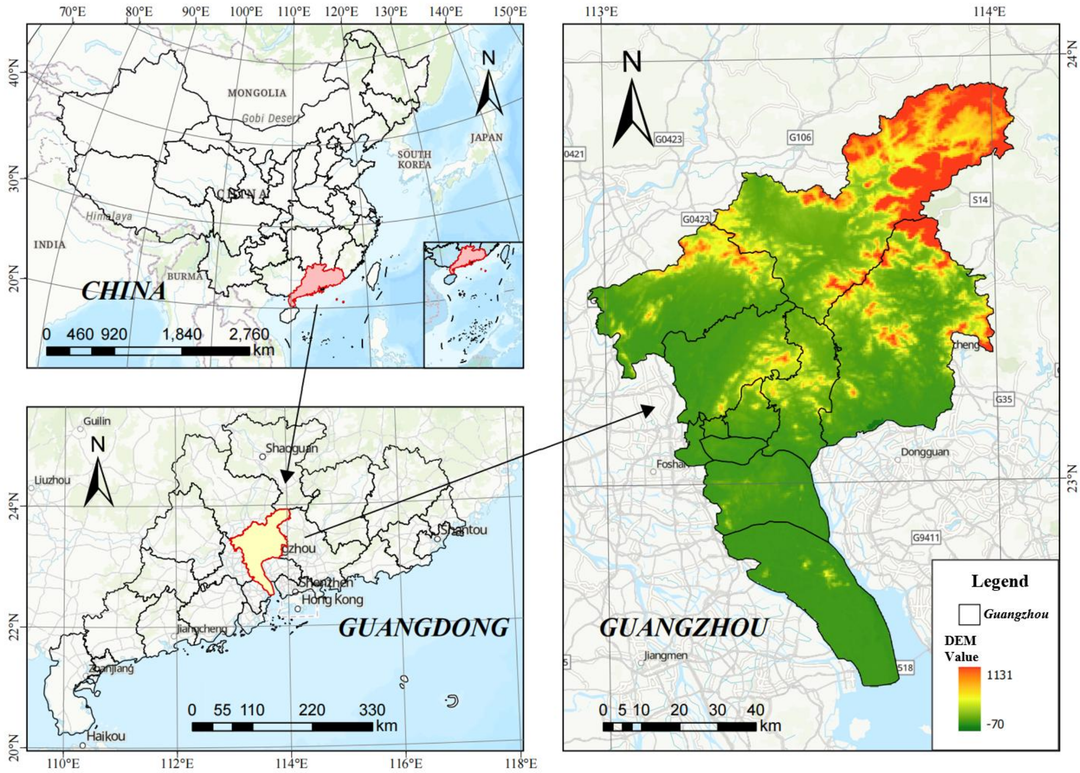

Fig.1 Guangzhou City overview map.

Climatically, Guangzhou is located in a low-latitude region and is strongly influenced by the East Asian monsoon, exhibiting a subtropical monsoon climate characterized by high temperatures, abundant precipitation, ample sunshine, long summers, and short frost-free periods. According to meteorological records, the multi-year mean temperature is approximately 22.0 °C, and the abundant rainfall supports year-round vegetation growth, contributing to Guangzhou's reputation as the "City of Flowers" [9].

Hydrologically, Guangzhou belongs to the Pearl River Basin, with a dense river network, abundant water resources, and an annual surface runoff volume of approximately 203.17 million m^3. Topographically, the city exhibits diverse terrain characteristics, with elevations generally decreasing from the northeast to the southwest. The northern region is dominated by mountainous and hilly landscapes with dense vegetation cover and a forest coverage rate exceeding 42% [8], primarily consisting of subtropical evergreen broad-leaved forests, including Baiyun Mountain and Yuexiu Mountain. The central region is characterized by terraces and low-relief terrain, whereas the southern region mainly consists of the Pearl River alluvial plain with relatively flat topography.

The study area encompasses diverse ecosystem types, including natural forest ecosystems and highly modified urban artificial ecosystems. This ecological heterogeneity makes Guangzhou a representative region for investigating habitat quality changes and carbon storage dynamics under rapid urbanization.

III. MATERIAL SOURCE AND METHOD

3.1 Data Sources and Preprocess

This study utilized four multi-temporal LULC datasets with a spatial resolution of 30 m, corresponding to the years 2000, 2010, 2020, and 2025 (Table 1). The datasets were processed through radiometric calibration, atmospheric correction, mosaicking, and spatial clipping to ensure consistency and accuracy among the multi-temporal LULC products. Based on the classification requirements of the InVEST model and the national land use classification system, the original LULC categories were reclassified into seven major classes: Cropland, Forest, Shrub, Grassland, Water, Bare land, and Built-up land. The original 30-m spatial resolution was preserved throughout the reclassification process. Finally, the LULC datasets were clipped using the administrative boundary vector data of Guangzhou City to generate Guangzhou-specific LULC datasets, which provided reliable input data for subsequent ecosystem service simulations and analyses.

Table 1 Data Source Description.

Data Name	Data Source
2023 DEM	General Bathymetric Chart of the Oceans (GEBCO) (https://www.gebco.net/data and_products/gridded_ bathymetry_data/)
2000-2025 30m LULC	Zenodo platform (https://zenodo.org/records/18180184)
Administrative Division Vector Map	Alibaba Cloud DataV data visualization platform (https://datav.aliyun.com/portal/school/atlas/area_selector)

3.2 Research Methods

This study developed a comprehensive framework integrating multi-source remote sensing and environmental data through data preprocessing, land cover classification, InVEST-based ecosystem service modeling, and spatiotemporal analysis of habitat quality and carbon storage (Figure 2).

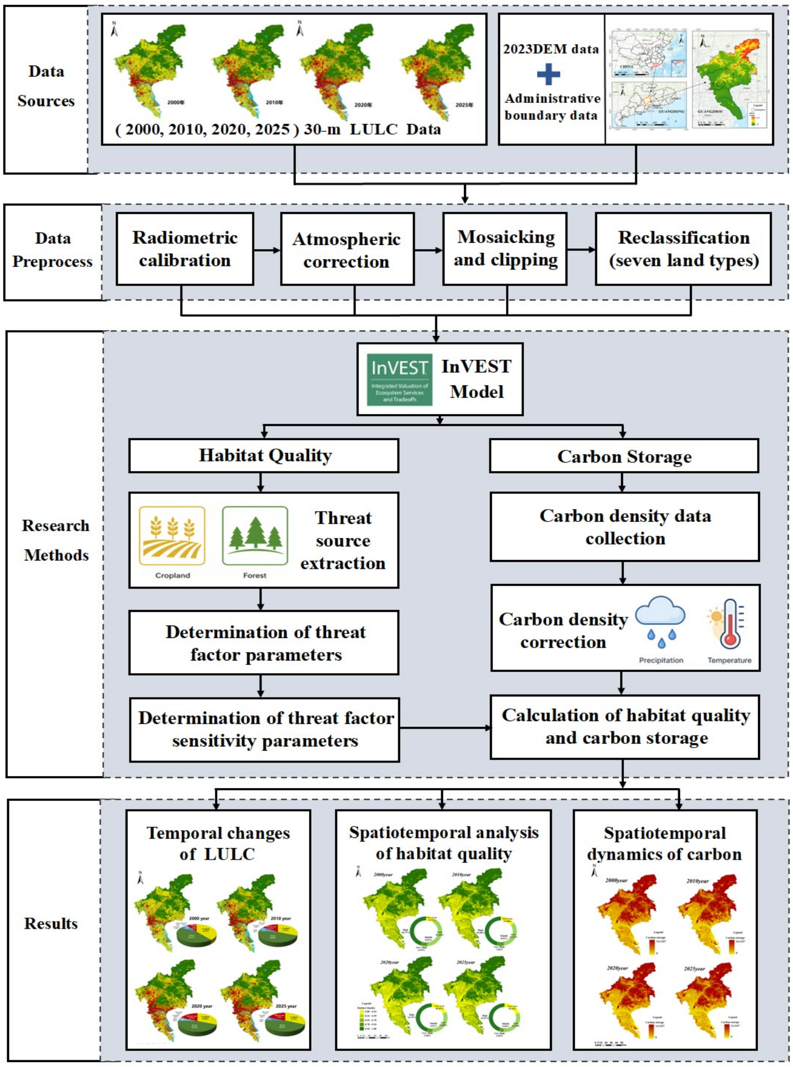

Fig.2. Flowchart of the analytical framework

3.2.1 Habitat Quality Assessment Based on the InVEST Model

(1) Definition and Extraction of Threat Factors

The original LULC data were first imported into the InVEST model, and NoData values were identified and removed during preprocessing. Based on previous studies [6,11,12], built-up land and cropland were selected as the primary threat factors. Cropland was included because agricultural activities and associated human disturbances can increase habitat fragmentation and reduce habitat suitability. The extracted threat factor layers were subsequently normalized to generate threat intensity values ranging from 0 to 1. The resulting spatial distribution indicated that built-up land was primarily concentrated in urban areas with a distinct clustered pattern, whereas cropland exhibited a relatively dispersed yet continuous distribution across the plain regions.

(2) Determination of Threat Factor and Habitat Sensitivity Parameters

Threat factors represent anthropogenic disturbances that exert pressure on ecosystems and consequently reduce habitat quality. In this study, built-up land and cropland were identified as the primary anthropogenic threat factors. The corresponding model parameters, including threat weight, maximum influence distance, decay type, habitat suitability of different LULC types, and their sensitivity to individual threat factors, were determined according to the InVEST User Guide, relevant published studies [13–19], and expert knowledge. The mean parameter values reported in the literature were adopted as the final threat weights and maximum influence distances for the study area.

Different spatial decay functions were assigned to represent the influence range of each threat factor according to its ecological characteristics [6]. Because the intensity of human disturbance associated with built-up land decreases nonlinearly with increasing distance, an exponential decay function was applied. In contrast, the impacts of cropland were assumed to decline gradually with distance; therefore, a linear decay function was adopted. The detailed parameter settings for threat factors, habitat suitability, and habitat sensitivity are presented in Tables 2 and 3.

Table 2 Ecological Threat Factor Parameters.

THREAT	WEIGHT	MAX_DIST /km	DECAY
Cropland	0.60	7	Linear
Built-up Land	1.00	9	Exponential

Table 3 Threat Factor Sensitivity Parameters.

LULC Name	HABITAT	Built-up Land	Cropland
Cropland	0.50	0.35	0.20
Forest	1.00	0.70	0.50
Shrub	0.60	0.50	0.40
Grassland	0.80	0.60	0.35
Water	0.90	0.75	0.50
Bare Land	0.00	0.00	0.00
Built-up Land	0.10	0.01	0.10

(3) Habitat Quality Calculation

The HQ module of the InVEST model was applied to evaluate habitat quality within the study area. Using LULC raster data as the primary input, the model integrates habitat suitability, threat factor weights, and the influence distances of threat factors to quantitatively estimate habitat quality. The habitat quality index ranges from 0 to 1, where higher values indicate greater habitat integrity, stronger ecological stability, and higher biodiversity conservation potential, whereas lower values indicate more severe habitat degradation and weaker ecological functions. The habitat quality model is expressed as Equation (1):

$$Q_{xj} = H_j \times \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right) \quad (1)$$

where Q_{xj} represents the habitat quality index of raster cell x for the j-th LULC type; H_j is the habitat suitability score of the j-th LULC type; D_{xj} denotes the habitat degradation level of raster cell x; z is the scaling constant, which is typically assigned a value of 2.5; and k is the half-saturation constant. Following the recommendations of the InVEST User Guide, the value of k was set to 0.5 in this study. The habitat degradation index D_{xj} is calculated using Equation (2):

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{y_r} \left(\frac{w_r}{\sum_{r=1}^{R} w_r}\right) r_y i_{rxy} \beta_x S_{jr} \quad (2)$$

where R is the total number of threat factors; y is the index of raster cells within the raster layer of threat factor r; y_r denotes the total number of raster cells occupied by threat factor r; w_r represents the weight assigned to threat factor r; r_y is the value of threat factor r at raster cell y; β_x denotes the accessibility of raster cell x; S_{jr} represents the sensitivity of habitat type j to threat factor r; and i_{rxy} represents the relative impact of threat factor r from raster cell y on habitat raster cell x [20].

3.2.2 Carbon Storage Calculation Based on the InVEST Model

(1) Determination and Regional Correction of Carbon Density Values

Considering the regional geographical and environmental characteristics of Guangzhou, this study adopted the six-category carbon density dataset developed by Li Kerang, Xie Xianli, et al. [21,22], which has been widely applied at the national scale in China. However, these carbon density values require regional calibration before being applied to the study area. To improve the accuracy of carbon storage estimation, previous studies conducted in Guangzhou and adjacent regions were systematically reviewed [23-26]. The carbon density values were subsequently calibrated using the correction equations proposed by Alam, Chen Guangshui, et al. [27,28]. The correction equations are expressed as Equations (3)–(5):

$$C_{SP} = 3.3968 \times MAP + 3996.1 \quad (3)$$

$$C_{BP} = 6.798 \times e^{0.0054 \times MAP} \quad (4)$$

$$C_{BT} = 28 \times MAT + 398 \quad (5)$$

where MAP represents the mean annual precipitation (mm); MAT represents the mean annual temperature (°C); C_{SP} represents soil carbon density estimated based on mean annual precipitation; C_{BP} represents vegetation carbon density estimated based on mean annual precipitation; and C_{BT} represents vegetation carbon density estimated based on mean annual temperature.

Based on previous studies, precipitation and temperature were selected as the primary climatic factors for adjusting carbon density values of different land-use types in Guangzhou. The mean annual temperature and precipitation values of Guangzhou and the national average values were substituted into the correction equations, respectively. The ratio between the two estimated carbon density values was then calculated as the regional adjustment coefficient. The adjustment coefficient equations [27,28] are expressed as Equations (6)–(9):

$$K_{BP} = \frac{C_{BP}^1}{C_{BP}^2} \quad (6)$$

$$K_{BT} = \frac{C_{BT}^1}{C_{BT}^2} \quad (7)$$

$$K_B = K_{BP} \times K_{BT} \quad (8)$$

$$K_S = \frac{C_{SP}^1}{C_{SP}^2} \quad (9)$$

where K_{BP} represents the vegetation carbon density adjustment coefficient based on mean annual precipitation; K_{BT} represents the vegetation carbon density adjustment coefficient based on mean annual temperature; K_B represents the integrated vegetation carbon density adjustment coefficient; and K_S represents the soil carbon density adjustment coefficient based on mean annual precipitation. C_{BP}^1 represents the vegetation carbon density in Guangzhou estimated from mean annual precipitation, whereas C_{BT}^2 represents the corresponding national-scale vegetation carbon density. Similarly, C_{BT}^1 and C_{BT}^2 represent vegetation carbon densities estimated from mean annual temperature at the Guangzhou and national scales, respectively. C_{SP}^1 and C_{SP}^2 represent soil carbon densities estimated from mean annual precipitation at the Guangzhou and national scales, respectively.

This study primarily used the adjusted carbon density data for Guangzhou reported by Zheng Guibin et al. [23] and Tang Jiahua et al. [29]. The carbon density values corresponding to different LULC types in Guangzhou were summarized and are presented in Table 4.

Table 4 Carbon Density Values of Different LULC Types in Guangzhou (Unit: t/hm²).

LULC Type	Aboveground carbon density	Belowground carbon density	Soil carbon density	Dead organic carbon density
Cropland	13.50	2.70	30.63	0.00
Forest	35.10	7.02	99.00	4.71
Shrub	1.40	6.02	102.60	2.48
Grassland	1.02	4.39	109.80	0.24
Water	0.00	0.00	0.00	0.00
Bare Land	1.22	0.54	29.03	0.16
Built-up Land	1.20	0.93	12.48	0.00

(2) Carbon Storage Calculation

The InVEST model is an open-source ecosystem service assessment tool jointly developed by Stanford University, the World Wide Fund for Nature (WWF), and The Nature Conservancy (TNC) [24]. Its primary function is to quantify and spatially represent the provision of ecosystem services under different LULC change scenarios. The model has been widely applied in ecosystem service evaluation, ecological asset assessment, and spatial conservation planning. In the InVEST Carbon Storage and Sequestration model, LULC types are used as the basic spatial units for carbon storage estimation. Based on the carbon density values of four carbon pools, including aboveground biomass carbon (C_{i_above}), belowground biomass carbon (C_{i_below}), soil organic carbon (C_{i_soil}), and dead organic matter carbon (C_{i_dead}), the total carbon storage of each raster cell is calculated through spatial analysis [30]. The carbon density of each LULC type is calculated using Equation (10):

$$C_i = C_{i\_above} + C_{i\_below} + C_{i\_soil} + C_{i\_dead} \quad (10)$$

where C_i represents the total carbon density of LULC type *i*; C_{i_above} represents the aboveground biomass carbon density of LULC type *i*; C_{i_below} represents the belowground biomass carbon density of LULC type *i*; C_{i_soil} represents the soil organic carbon density of LULC type *i*; and C_{i_dead} represents the dead organic matter carbon density of LULC type *i*.

In this study, the total carbon storage was calculated by summing the carbon storage contributions of all LULC types according to their spatial distributions. The calculation equation is expressed as Equation (11):

$$C_{total} = \sum_{i=1}^{n} C_i \times S_i \quad (11)$$

where C_{total} represents the total carbon storage of the study area; *n* represents the number of LULC types; C_i represents the carbon density of LULC type *i*; and S_i represents the spatial area occupied by LULC type *i*.

IV. RESULTS

4.1 Spatial Pattern Changes in Land Use

As shown in Figure 3, forest and cropland were the dominant land use types in the study area, with their combined area accounting for more than 70% of the total area of Guangzhou across all observation years. This indicates that agricultural and forest ecosystems played important roles in shaping the landscape structure of Guangzhou. From 2000 to 2025, cropland area experienced a substantial decline followed by a slight recovery, whereas forest area exhibited a fluctuating trend, with a slight increase initially followed by a continuous decrease. Specifically, the proportion of cropland decreased sharply from 39.16% to 31.47% between 2000 and 2010. This reduction was substantially greater than the slight increase in forest area during the same period, suggesting that cropland conversion was more pronounced than forest conversion during this stage. Except for cropland, forest, and water bodies, the proportions of the remaining land use types generally increased.

Among all land use categories, built-up land exhibited the most significant expansion, with its proportion increasing continuously from 9.73% in 2000 to 19.42% in 2025. Across different periods, built-up land increased by 5.74 percentage points between 2000 and 2010, representing the period with the fastest urban expansion. From 2010 to 2020, the proportion of built-up land increased by 3.07 percentage points, whereas the increase further declined to 0.88 percentage points during 2020–2025 (Table 5). The decreasing rate of built-up land expansion suggests that strengthened spatial planning and land management policies may have contributed to reducing the conversion of cropland and water bodies into built-up areas during the later period.

Table 5 Proportion of Area for Different Land Use Types in Various Years (Unit: %).

Year	Cropland	Forest	Shrub	Grassland	Water	Bare Land	Built-up Land
2000	39.16	44.17	0.01	0.10	6.83	0.00	9.73
2010	31.47	45.68	0.01	0.15	7.22	0.01	15.47
2020	31.09	44.76	0.01	0.03	5.55	0.02	18.54
2025	31.74	43.87	0.00	0.02	4.93	0.02	19.42

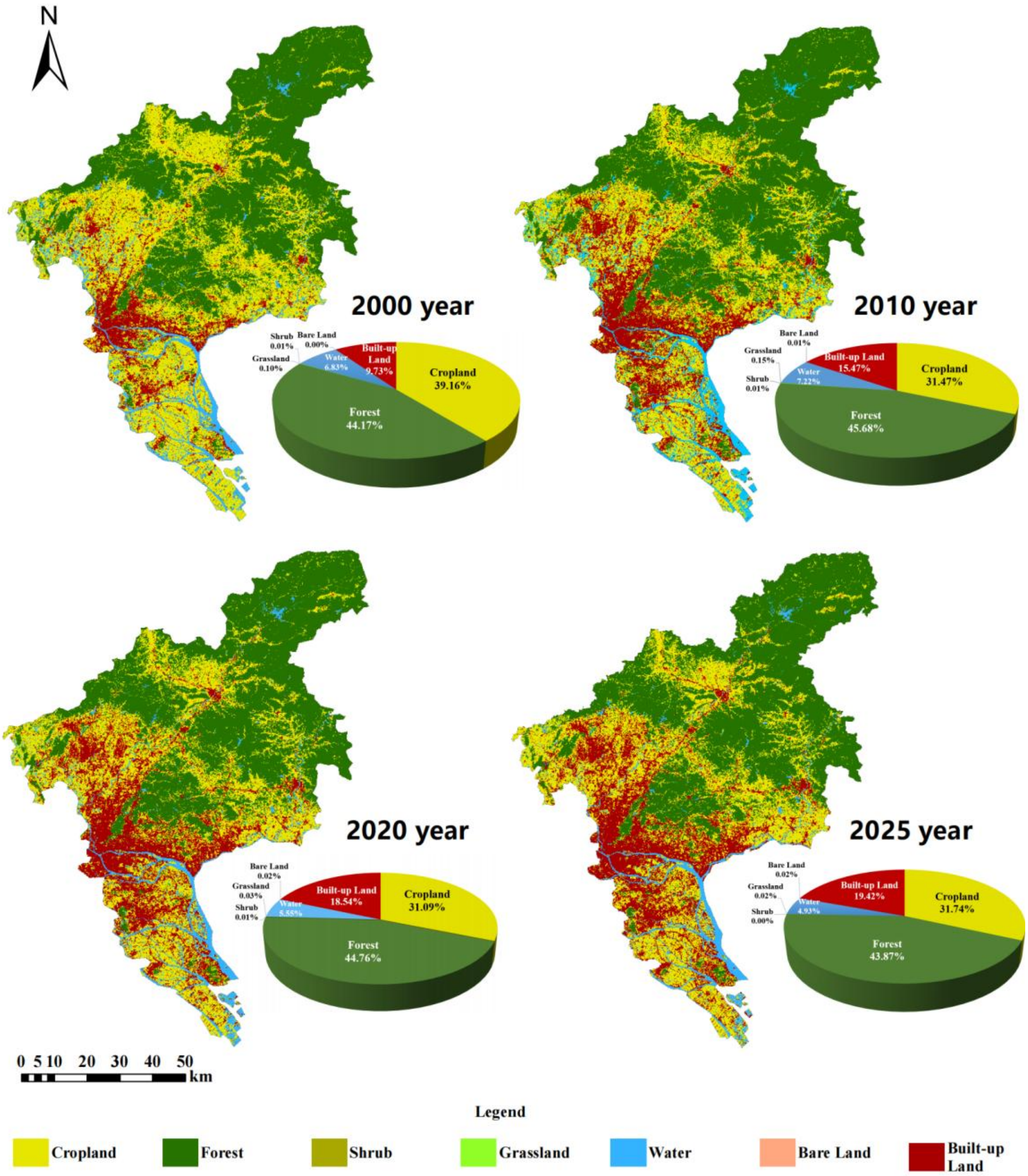

Fig.2 Spatial distribution of land use in Guangzhou City in 2020 and 2025.

4.2 Spatiotemporal Variation in Habitat Quality

The habitat quality index ranges from 0 to 1, with higher values indicating better habitat integrity and ecological conditions. Habitat quality in Guangzhou during 2020–2025 was evaluated using the InVEST model. Based on the Natural Breaks (Jenks) classification method, habitat quality was categorized into five levels: Very Low (0–0.24), Low (0.24–0.55), Middle (0.55–0.78), High (0.78–0.93), and Very High (0.93–1.00).

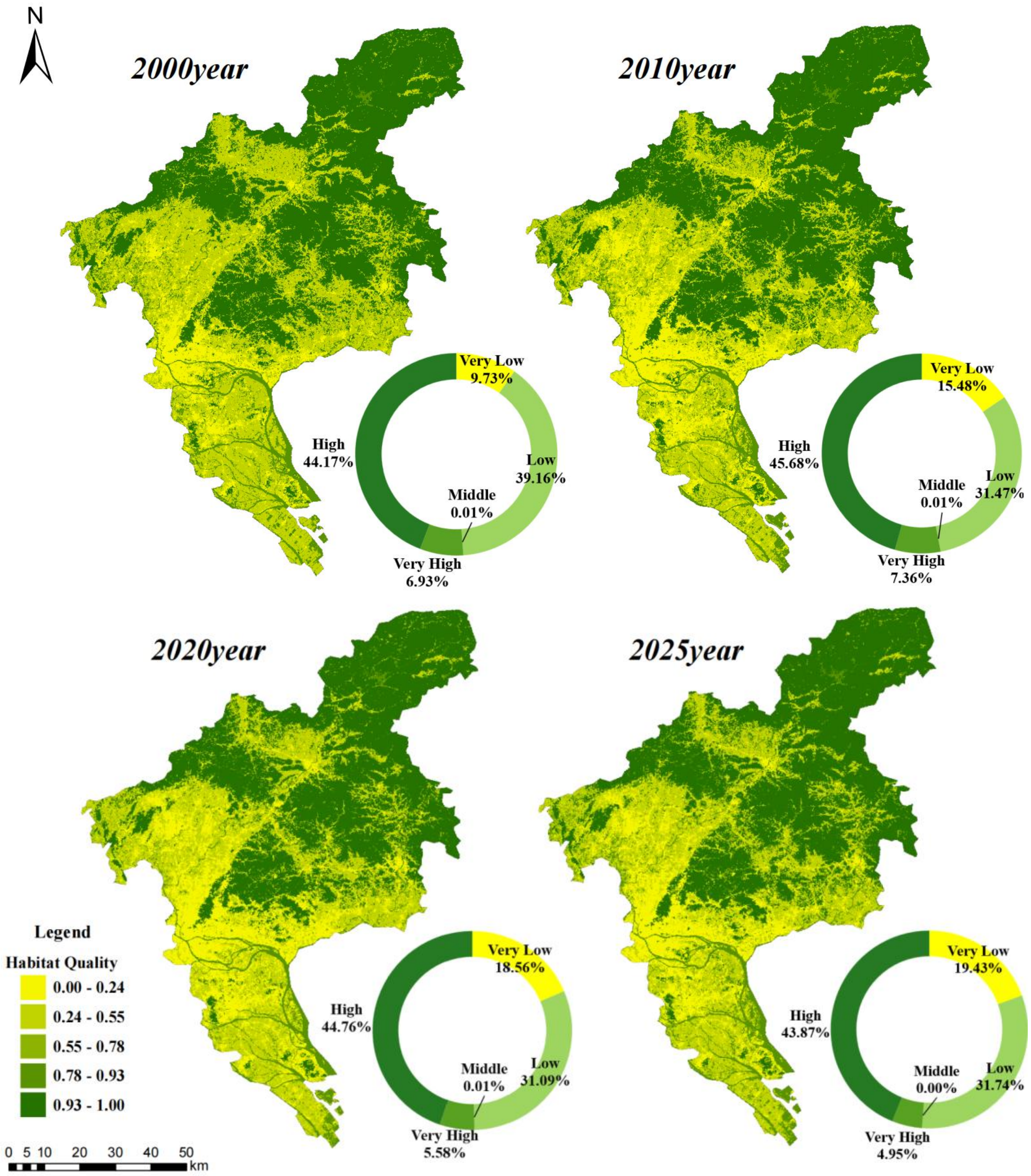

Fig.3 Spatial distribution of habitat quality in Guangzhou City during four periods.

In terms of spatial distribution, habitat quality exhibited a distinct north–south spatial gradient. Forest areas in the mountainous regions of northern and northeastern Guangzhou generally exhibited habitat quality values exceeding 0.78, corresponding to the High and Very High categories. In contrast, plain areas and urban built-up regions in the south, southeast, and west mainly exhibited habitat quality values below 0.55, corresponding to the Low and Very Low categories. From 2000 to 2025, areas with Low and Very Low habitat quality gradually expanded outward from the central built-up areas toward the eastern, northern, and southern regions. The spatial distribution of high-quality habitat patches remained relatively stable, with only slight shrinkage occurring in marginal areas (Figure 4).

Table 6 presents the proportions and spatial extents of different habitat quality categories in Guangzhou during four periods from 2000 to 2025. As shown in Table 6, the proportion of areas classified as Low habitat quality increased continuously, rising from 9.73% in 2000 to 19.43% in 2025, representing a cumulative increase of 9.70 percentage points over the 25-year period. Correspondingly, the area expanded from 698.184 km² to 1391.897 km², representing the largest expansion among all habitat quality categories.

The proportion of areas classified as Very Low habitat quality remained relatively high; however, despite a slight increase in spatial extent between 2020 and 2025, it generally exhibited a declining trend throughout the study period. The proportion of Middle habitat quality remained relatively low and showed limited variation during the study period. Areas with High habitat quality exhibited a fluctuating pattern, initially increasing and subsequently declining, with the proportion decreasing slightly from 44.17% in 2000 to 43.87% in 2025, corresponding to a reduction of 0.30 percentage points. The corresponding area decreased from 3167.923 km² to 3142.071 km². Similarly, the proportion of areas classified as Very High habitat quality showed a fluctuating trend, increasing from 6.93% in 2000 to 7.36% in 2010, followed by a decline to 4.95% in 2025. The corresponding area decreased from 496.938 km² to 354.351 km².

Table 6 Proportion of Area for Each Habitat Quality Level by Year (Unit: %)

Year	Very Low (%)	Low (%)	Middle (%)	High (%)	Very High (%)
2000	9.7342	39.1646	0.0053	6.9284	44.1676
2010	15.4410	31.4736	0.0051	7.3638	45.6765
2020	18.5564	31.0940	0.0060	5.5830	44.7606
2025	19.4343	31.7423	0.0048	4.9476	43.8710

Based on the calculated proportions of different habitat quality categories, the results showed that the proportions of areas classified as Low and Very Low habitat quality increased continuously during the study period. In contrast, areas classified as Middle, High, and Very High habitat quality generally exhibited slight declining trends. However, the spatial extent of High habitat quality areas in the northern forest regions remained relatively stable, consistent with the overall stability of habitat quality in Guangzhou.

To further characterize the spatial variation in habitat quality, zonal statistics were conducted using administrative districts as spatial analysis units to calculate the mean habitat quality value of each unit. The results revealed clear spatial differentiation in average habitat quality among the administrative districts of Guangzhou from 2000 to 2025 (Figure 5).

Overall, habitat quality exhibited a clear spatial gradient, with higher values mainly distributed in mountainous and ecological conservation areas and lower values concentrated in highly urbanized central regions. Specifically, the northern districts of Conghua and Zengcheng were dominated by mountainous forest ecosystems, where habitat quality remained relatively high and stable throughout the study period. In contrast, transitional urban districts such as Huadu and Huangpu experienced rapid urban development, accompanied by gradual declines in habitat quality. The Baiyun, Nansha, and Panyu districts, which represent important urban expansion areas, exhibited pronounced habitat degradation characteristics associated with intensive land development activities. Meanwhile, the central urban districts, including Yuexiu, Tianhe, Haizhu, and Liwan, were characterized by high-density built-up land, and habitat quality remained relatively low due to the limited distribution of natural habitats.

From a temporal perspective, habitat quality in Guangzhou exhibited an overall slight declining trend from 2000 to 2025, with considerable spatial heterogeneity in temporal variations among different regions. During the rapid urbanization period from 2000 to 2010, built-up land expanded substantially, accompanied by notable declines in habitat quality in peri-urban and southern regions. From 2020 to 2025, the decreasing trend of habitat quality weakened considerably, while slight improvements were observed in some central urban areas. These changes coincided with increased attention to urban ecological restoration and green space enhancement. However, habitat degradation remained evident in peri-urban expansion areas, which exhibited relatively high ecological vulnerability.

In summary, the spatial distribution of habitat quality in Guangzhou reflected a distinct contrast between mountainous ecological zones and highly urbanized areas. A clear gradient was observed between regions with relatively intact ecological conditions and areas characterized by intensive human development.

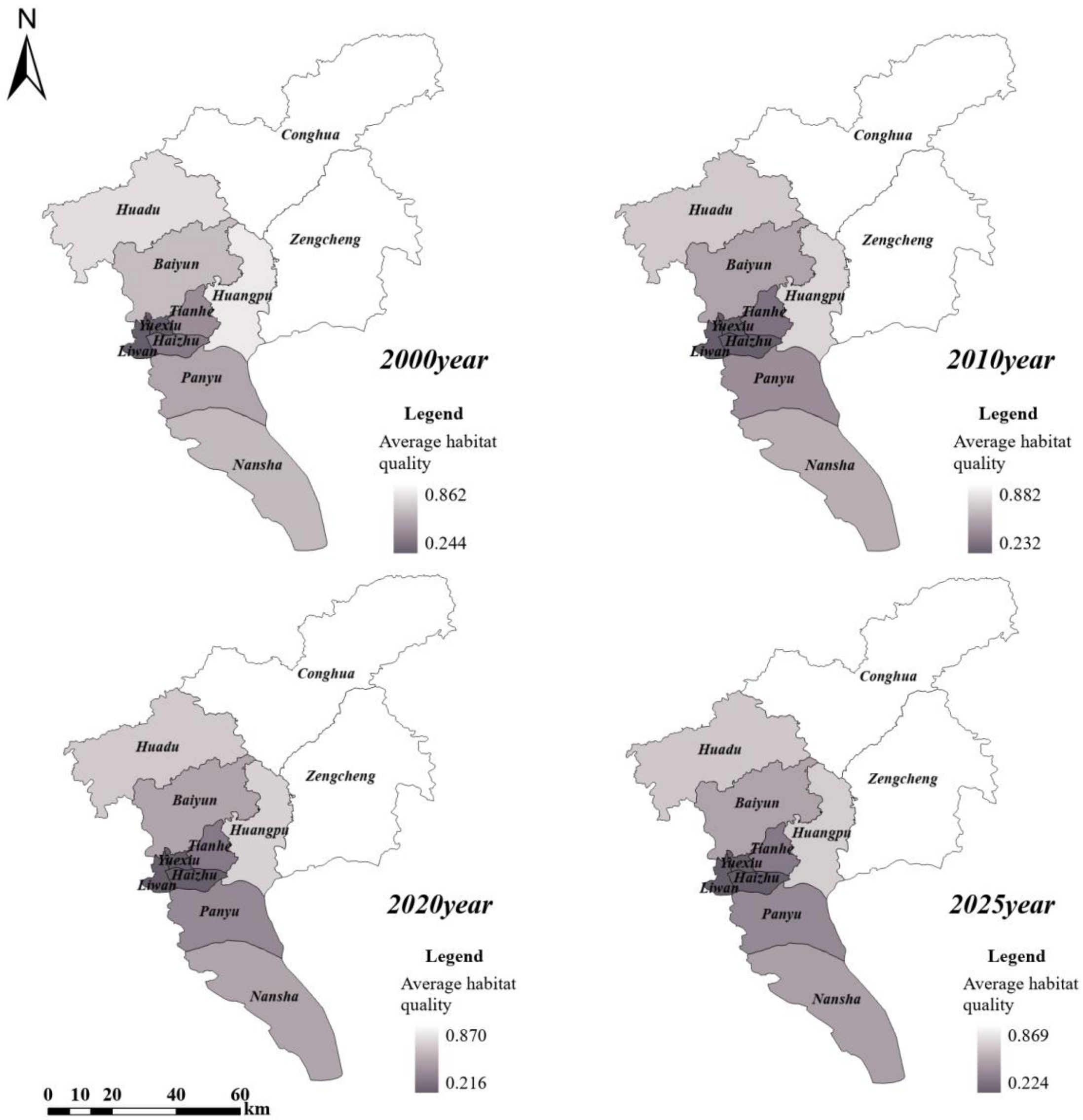

Fig.4 Spatial distribution of average habitat quality in different districts from 2000 to 2025.

4.3 Spatiotemporal Variation in Carbon Storage

Carbon storage in Guangzhou during 2000–2025 was estimated using the InVEST model. In terms of spatial distribution, the spatial patterns of carbon storage in 2000, 2010, 2020, and 2025 were generally consistent, showing a distinct gradient characterized by higher values in the northern region and lower values in the southern region (Figure 6). The overall spatial distribution of carbon storage exhibited a similar pattern to habitat quality. Areas with low carbon storage were mainly associated with water bodies and built-up land, whereas areas with high carbon storage were predominantly distributed in forest regions.

The high-carbon storage areas were mainly located in the mountainous forest regions of Conghua and Zengcheng districts in northern Guangzhou, as well as Huadu District. In these areas, forest areas formed continuous patches with high vegetation coverage and substantial carbon storage. The spatial distribution of high-carbon storage areas remained relatively stable throughout the study period. These regions consistently exhibited the highest carbon storage levels in Guangzhou, corresponding to extensive forest coverage and dense vegetation. The maximum carbon storage per unit area reached 13.1247 t/ha.

In contrast, low-carbon storage areas were concentrated in Tianhe, Liwan, Haizhu, and Yuexiu districts in the central urban area, as well as Panyu and Nansha districts in the south. These areas were primarily characterized by built-up land, water bodies, and cropland, with relatively limited vegetation coverage and carbon storage values approaching zero.

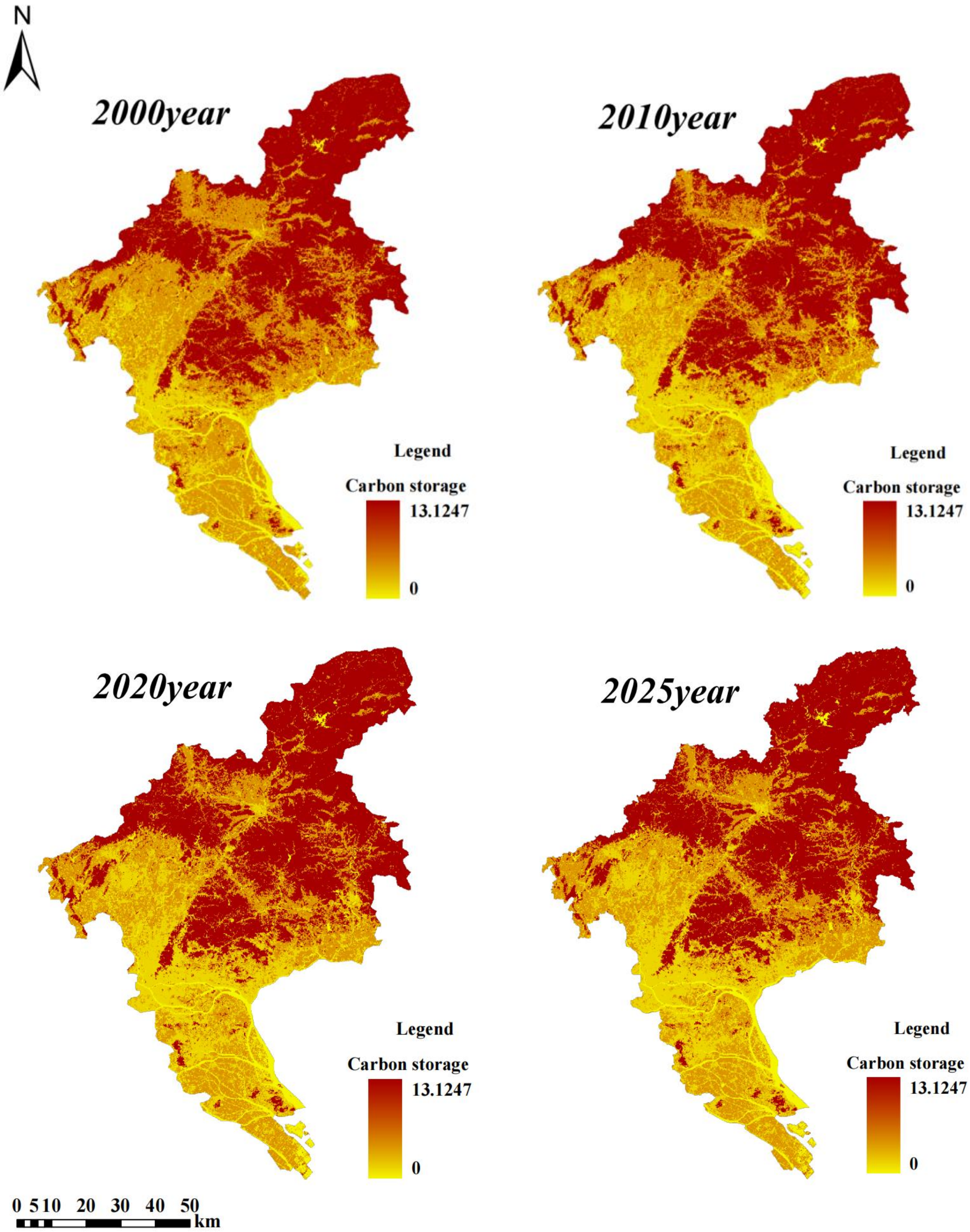

Fig.5 Spatial distribution of carbon storage in Guangzhou City from 2000 to 2025.

From 2000 to 2025, carbon storage exhibited a distinct north–south spatial differentiation pattern. During the initial stage of urban expansion from 2000 to 2010, carbon storage in the northern mountainous areas (Conghua and Zengcheng districts) remained relatively stable, whereas decreases were mainly observed in peri-urban areas, including Huadu, Baiyun, Huangpu, and Panyu districts.

From 2010 to 2020, carbon storage within ecological land areas in Baiyun, Huadu, Huangpu, and Panyu districts increased, resulting in a partial recovery of regional carbon storage. Subsequently, carbon storage in Guangzhou remained relatively stable from 2020 to 2025, with a reduced rate of decline compared with previous periods.

Regarding temporal variations, the total carbon storage values in Guangzhou in 2000, 2010, 2020, and 2025 were 60.46×10^6 t, 60.09×10^6 t, 59.24×10^6 t, and 58.52×10^6 t, respectively. Overall, carbon storage exhibited a continuous declining trend from 2000 to 2025, with a total loss of 1.94

× 10^6 t, corresponding to a decrease of 3.21%. During different periods, the magnitude of carbon storage decline varied. From 2000 to 2010, carbon storage decreased by 0.60%. The decline rate increased to 1.42% during 2010–2020, followed by a reduction to 1.21% during 2020–2025.

The carbon storage contributions of different land use types followed the order: Forest > Cropland > Built-up land > Grassland > Shrub > Bare land > Water bodies. Forest and cropland were the dominant contributors to carbon storage in Guangzhou, jointly accounting for more than 90% of the total carbon storage during all study periods. In contrast, water bodies contributed negligibly to total carbon storage. Because water bodies in LULC datasets primarily represent surface water rather than carbon-rich aquatic sediments, their assigned carbon density values are generally low in InVEST-based carbon storage assessments. Therefore, following previous studies, the carbon density of water bodies was set to zero in this study, resulting in a negligible contribution of water bodies to total carbon storage (Figure 7 and Table 7).

Table 7 Proportion of Carbon Storage by Land Use Type in Different Years (Unit: %)

Year	Cropland	Forest	Shrub	Grassland	Water	Bare Land	Built-up Land
2000	21.76	76.41	0.01	0.14	0.00	0.00	1.69
2010	17.59	79.50	0.01	0.20	0.00	0.00	2.70
2020	17.63	79.03	0.01	0.05	0.00	0.01	3.28
2025	18.19	78.30	0.01	0.03	0.00	0.01	3.47

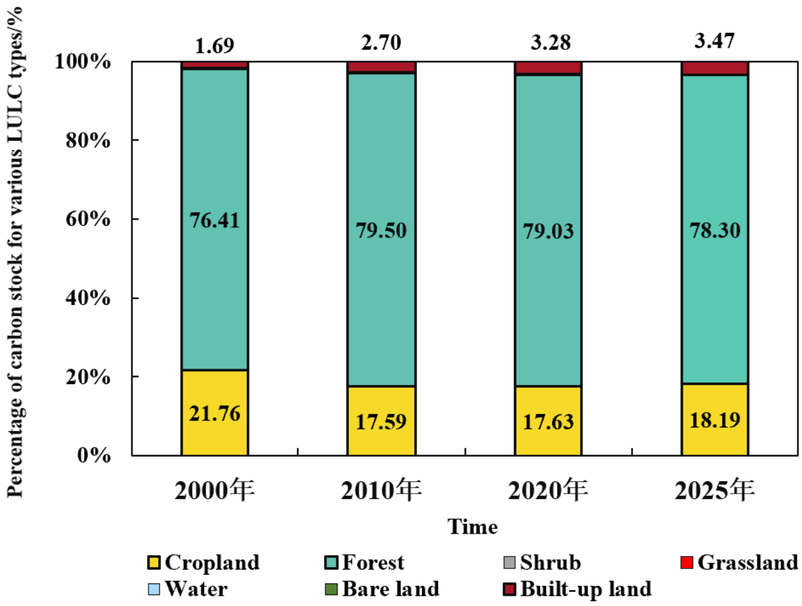

Fig.6 Proportion of carbon storage by land use types in Guangzhou City from 2000 to 2025.

The decline in carbon storage associated with cropland was the primary contributor to the overall reduction in Guangzhou's total carbon storage, with cropland carbon storage decreasing by 19.07% (equivalent to 2.5086 million t) from 2000 to 2025. Carbon storage in grassland also exhibited a continuous declining trend. Forest carbon storage showed a fluctuating pattern, increasing from 2000 to 2010 and subsequently declining continuously, resulting in a cumulative reduction of 0.82% (equivalent to 0.3770 million t) over the 25-year study period.

In contrast, carbon storage in built-up land increased by 1.0119 million t during the study period. Although carbon storage in bare land also increased, its contribution to total carbon storage remained negligible due to its limited spatial proportion. Overall, the changes in carbon storage among different LULC types indicated that cropland and forest ecosystems were the primary sources of carbon storage loss in Guangzhou, whereas increases in built-up land contributed only marginally to the overall carbon balance.

V. CONCLUSIONS

5.1 Main Conclusions

Based on 30 m-resolution land cover datasets from 2000, 2010, 2020, and 2025, this study integrated ArcGIS spatial analysis techniques and the InVEST model to investigate the spatiotemporal dynamics of habitat quality and carbon storage in Guangzhou over the past 25 years. The main conclusions are summarized as follows:

(1) Regarding temporal evolution, habitat quality exhibited a gradual declining trend with distinct stage characteristics, whereas carbon storage showed a continuous decrease during the study period. From 2000 to 2025, the proportion of areas with Low habitat quality increased from 9.73% to 19.43%, while High habitat quality remained relatively stable, indicating that habitat degradation was mainly concentrated in highly urbanized and expansion areas. Habitat degradation was more pronounced during 2000–2020, corresponding to rapid urban expansion and increased land conversion pressure. After 2020, the rate of habitat degradation slowed, coinciding with enhanced ecological restoration and urban greening initiatives.

During the same period, carbon storage in Guangzhou declined continuously, decreasing from 60.46 million t in 2000 to 58.52 million t in 2025, representing a total loss of 1.94 million t (3.21%). The greatest decline occurred during 2010–2020, followed by a slower decreasing trend after 2020. Forest and cropland remained the dominant contributors to regional carbon storage, accounting for more than 90% of the total carbon storage throughout the study period. The conversion of cropland to built-up land represented the dominant land-use transition associated with carbon storage loss. Carbon storage in cropland decreased substantially, whereas forest carbon storage exhibited a fluctuating pattern with an initial increase followed by a gradual decline. In contrast, carbon storage associated with built-up land increased continuously during the study period.

(2) Spatially, habitat quality and carbon storage exhibited highly consistent spatial distribution patterns, characterized by higher values in the north and lower values in the south, with better ecological conditions in mountainous regions and poorer conditions in highly urbanized areas.

The spatial distributions of habitat quality and carbon storage in Guangzhou showed strong spatial consistency. High-value areas of both indicators were mainly concentrated in the northern mountainous regions of Conghua and Zengcheng, where continuous forest patches, high vegetation coverage, and relatively limited human disturbance supported important ecological conservation and carbon storage functions. In contrast, low-value areas were primarily distributed in the central urban districts (Yuexiu, Tianhe, Haizhu, and Liwan) and southern regions such as Panyu and Nansha, where intensive land development and limited vegetation coverage were associated with lower habitat quality and carbon storage.

Transitional urban areas, including Huadu, Baiyun, Huangpu, and Panyu, exhibited intermediate ecological conditions. The expansion of built-up land and associated land-use changes contributed to increasing ecological fragmentation and declines in habitat quality and carbon storage. Low habitat quality and low carbon storage areas gradually expanded from central urban regions toward surrounding suburban areas, whereas high-value ecological areas in the northern mountainous regions remained relatively stable. Overall, the spatial structure of ecological barrier areas showed limited change during the study period. Clear spatial differences existed among administrative districts, with northern mountainous areas maintaining higher ecosystem service functions and central urban areas exhibiting persistent ecological constraints.

(3) Regarding driving mechanisms, land-use conversion and built-up land expansion were identified as the primary factors associated with ecological degradation, whereas ecological conservation and restoration measures contributed to mitigating ecological decline.

The conversion of forest and cropland into built-up land represented the dominant land-use transition associated with habitat quality degradation and carbon storage loss in Guangzhou from 2000 to 2025. Cropland and built-up land, as major anthropogenic disturbance sources, exerted substantial pressures on surrounding ecological areas, leading to reductions in habitat integrity and vegetation carbon storage.

Ecological protection measures, including northern forest conservation, peri-urban ecological restoration, and permanent basic farmland protection, helped maintain high-

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quality ecological spaces and slowed regional carbon storage loss. However, ecological pressures associated with continued urban expansion and land-use transformation remained evident in peri-urban and southern coastal development areas. These regions represent important targets for future ecological management and spatial optimization.

5.2 Management Implications

Based on the differentiated ecological characteristics of Guangzhou, including the "northern mountainous areas, central peri-urban zones, and southern plains," differentiated ecological management strategies should be implemented by integrating the spatiotemporal variations in habitat quality and carbon storage.

In the northern regions of Conghua and Zengcheng, strict ecological conservation boundaries should be maintained in mountainous areas, and the expansion of development activities into forest core areas should be effectively controlled. Meanwhile, ecological public welfare forest protection and ecological compensation mechanisms should be further strengthened to restore degraded forest ecosystems, maintain biodiversity, and enhance regional carbon storage capacity.

In the central peri-urban areas of Baiyun, Huadu, and Huangpu, fragmented ecological land should be integrated to establish ecological buffer zones connecting northern mountainous ecosystems with southern urban areas. Unregulated expansion of urban development boundaries should be controlled, while the restoration of abandoned land, inefficiently used land, and degraded mining areas should be promoted to reduce habitat fragmentation and improve ecological connectivity.

In the central urban districts and southern areas of Panyu and Nansha, the conversion of cropland and wetland areas into new construction land should be strictly controlled. Ecological corridors should be developed based on the Pearl River water system to enhance regional ecological connectivity. Meanwhile, ecological agriculture should be promoted to reduce agricultural ecological pressures while improving urban green space carbon storage capacity and habitat suitability.

Furthermore, an ecological dynamic monitoring system should be established by integrating remote sensing data with the InVEST model. The assessment results of habitat quality and carbon storage should be incorporated into territorial spatial planning and urban renewal decision-making processes. Through long-term differentiated management strategies, including northern ecological conservation, central ecological connectivity enhancement, and southern ecological quality improvement, a more sustainable balance between urban development and ecological protection can be achieved.

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