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Spatially Heterogeneous Response of Carbon Storage to Land Use Changes in Pearl River Delta Urban Agglomeration, China

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Abstract: Carbon storage of terrestrial ecosystems plays a vital role in advancing carbon neutrality. Better understanding of how land use changes affect carbon storage in urban agglomeration will provide valuable guidance for policymakers in developing effective regional conservation policies. Taking the Pearl River Delta Urban Agglomeration (PRDUA) in China as an example, we examined the heterogeneous response of carbon storage to land use changes in 1990–2018 from a combined view of administrative units and physical entities. The results indicate that the primary change in land use was due to the expansion of construction land (5897.16 km^2). The carbon storage in PRDUA decreased from 767.34 Tg C in 1990 to 725.42 Tg C in 2018 with a spatial pattern of high wings and the low middle. The carbon storage loss was largely attributed to construction land expansion (55.74%), followed by forest degradation (54.81%). Changes in carbon storage showed significant divergences in different sized cities and hierarchical boundaries. The coefficients of geographically weighted regression (GWR) reveal that the alteration in carbon storage in Guangzhou City was more responsive to changes in construction land (−0.11) compared to other cities, while that in Shenzhen was mainly affected by the dynamics of forest land (8.32). The change in carbon storage was primarily influenced by the conversion of farmland within urban extent (5.05) and the degradation of forest land in rural areas (5.82). Carbon storage changes were less sensitive to the expansion of construction land in the urban center, urban built-up area, and ex-urban built-up area, with the corresponding GWR coefficients of 0.19, 0.04, and 0.02. This study necessitates the differentiated protection strategies of carbon storage in urban agglomerations.

Keywords: land use change; carbon storage; Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model; hierarchical urban boundaries; Pearl River Delta Urban Agglomeration (PRDUA), China

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1 Introduction

Climate change is a critical and ongoing issue that has caused significant global crises, for example, loss of sea ice, accelerated sea level rise, and extreme weather events such as droughts and precipitation. Urgent action is required to reduce human-caused carbon emissions and promote carbon capture and storage. Terrestrial ecosystems are essential to the global carbon cycle and carbon storage (Yang et al., 2022), and it was estimated that 31% of anthropogenic CO_2 emissions has been absorbed by terrestrial ecosystems during 2010–2019

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(Friedlingstein et al., 2020). To mitigate climate change, 127 countries have proposed or plan to establish targets for terrestrial carbon storage, which would cover 88% of global carbon dioxide emissions. China has also pledged to achieve carbon neutrality by 2060, with increasing terrestrial carbon storage being a crucial step towards meeting this goal (http://www.cikd.org/detail?docId=1538692320059240449).

Land-use change is the second most significant contributor to the rise in global atmospheric carbon levels, trailing only the burning of fossil fuels. Between 1850 and 1998, one-third of human-caused carbon emissions were the result of land-use changes (IPCC, 2022). Despite this, there is a significant opportunity to increase carbon storage on land, which could make a substantial contribution to achieving carbon neutrality (Walker et al., 2022). Different land use processes have varying effects on carbon storage, and understanding the mechanisms behind these effects is crucial to making low-carbon land use decisions (Landman, 2010). Urban expansion, a typical land use process, significantly alters regional carbon storage by influencing the land surface and modifying the structures, processes, and functions of terrestrial ecosystems, as well as the material cycles and energy flows of ecosystems (Lambin et al., 2001; Hutyra et al., 2011). Current studies have mainly indicated a negative linear relationship between carbon storage and land urbanization (Peng et al., 2017). However, land use intensity varies across spatial gradients of urban agglomerations, and will also exert significant spatially heterogeneous impact on carbon storage (Jiang et al., 2017; Ouyang et al., 2021). Therefore, a spatially explicit assessment of carbon storage changes resulting from urban expansion will be essential for making informed and effective urban land use decisions.

The relationship between carbon storage and land use change is scale-dependent, but previous studies have mostly been conducted at administrative units, such as provinces (Wu et al., 2016; Piyathilake et al., 2021; Li et al., 2022b), cities and counties (He et al., 2016; Li et al., 2020; Wang Zhi et al., 2021), and have not adequately revealed the spatially heterogeneous response of carbon storage to land use at physical or functional units of cities (Zhou and Shi, 1995). Physical units are typically delineated based on physical urban entities and can deepen our understanding of urban laws (Xu et al., 2022). Additionally, physical urban units can provide globally comparable delineations of hierarchical urban boundaries, which are a practical basis for addressing global issues such as carbon neutrality (Xu et al., 2021). Urban agglomerations have received increased attention due to their critical roles in high-quality development and urbanization in China (Fang et al., 2016), which emphasizes the need to understand how land use change in urban agglomerations affects regional carbon storage.

To establish the quantitative relationships between land use change and carbon storage, many studies have estimated carbon density and storage in terrestrial ecosystems (Li et al., 2008; Wang et al., 2014; Cheng et al., 2020; Tak and Kakde, 2020; Feng et al., 2021). The field survey of forest resources can provide accurate carbon storage on vegetation and soil through spatial sampling design (Fang et al., 2001; Ni, 2001; Fan et al., 2008), but these methods may not reveal long-term and large-scale responses to climate change and human activities (Piao et al., 2022). To address this, researchers have developed various simulation models like the Carnegie-Ames-Stanford Approach (CASA) model (Xu et al., 2011; He et al., 2017), Biogeochemical model (BGC-ES) (Ooba et al., 2010), and Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model based on Geographic Information System (GIS) technology and mathematical models to estimate regional carbon stocks and analyze land use impacts on carbon storage. In particular, the InVEST model is widely used due to its high data accessibility and spatial explicitness (Zhou et al., 2018), which allows for the spatially explicit analysis of carbon storage response to land use activities (He et al., 2016; Liang et al., 2017; Piyathilake et al., 2021; Adelisardou et al., 2022).

To fill up above-mentioned research gaps, we propose an integrated analysis framework to estimate the changes in carbon storage in the Pearl River Delta Urban Agglomeration (PRDUA) in China from 1990 to 2018, and evaluate the influence of land use changes on carbon storage in terrestrial ecosystems. The PRDUA has experienced the extremely rapid economic development since China's Reforming and Opening Up, leading to high-density land aggregation and urban expansion that pose a threat to terrestrial ecosystems (Feng et al., 2022; Li et al., 2022a). Meanwhile, the PRDUA attaches great significance to the realization of carbon neutrality as the first 'National Demonstration Area of

Forest Urban Agglomeration' in China. Our framework examines spatially heterogeneous changes in carbon storage across urban gradients based on hierarchical urban boundaries, and can assist in policy-making for promoting carbon storage and mitigating climate change in urban agglomerations.

2 Material and Methods

2.1 Study area

The Pearl River Delta Urban Agglomeration (PRDUA) is located in the southern coast and the Pearl River Basin in Guangdong Province of China (Fig. 1). Considering unavailable data of Hong Kong and Macao, this study includes nine mainland cities within the PRDUA, namely Guangzhou, Shenzhen, Zhuhai, Zhongshan, Huizhou, Foshan, Dongguan, Jiangmen, and Zhaoqing (Ning, 2011), covering a total area of 41 698 km^2. These cities fall under four categories of urban classification based on the Chinese Criteria of Urban Classification (https://www.gov.cn): mega-cities (with a resident population of over 10 million), super-cities (with a resident population of 5 million to 10 million), major-cities of type I (with a resident population of 3 million to 5 million) and major-cities of type II (with a resident population of 1 million to 3 million). Specifically, Guangzhou and Shenzhen are mega-cities, Dongguan and Foshan are super-cities, Zhongshan is a major-city of type I, and Zhuhai, Huizhou, Zhaoqing, and Jiangmen are major-cities of type II.

The PRDUA boasts a subtropical monsoon climate, thriving tropical vegetation, and a dense water network. With a plain in the central region and hills, mountains, and islands in the marginal areas, the region has unique geographic advantages that have facilitated rapid economic development and urbanization, making it one of the developed regions in China and one of the demonstration areas for high-quality development in the Chinese 14th Five-Year Plan. Meanwhile, the PRDUA is the first national forest city cluster with the significant ecological values and abundant carbon storage in China (Yu et al., 2018; Li et al., 2022a). Thus, it is of great significance to examine the spatial and temporal patterns of carbon storage in response to land use changes for high-quality development and realization of the dual carbon goals.

Based on the study of Xu et al. (2021), the hierarchical urban boundaries of the PRDUA can be identified as urban extent (UE), urban built-up area (UB), and urban dense center (UC) (Fig. 1). Besides, urban open space (UOS), urban water (UW), and ex-urban built-up area (EB) were also extracted. Specifically, UE refers to the maximum area of an independent urban settlement, which is composed of urbanized patches (impervious surface above a certain local density) and their surrounding or adjacent open spaces. UB denotes the agglomeration of all artificial impervious surfaces with UE. UC is the high-density center of impervious surface that needs to exceed a certain area (more than

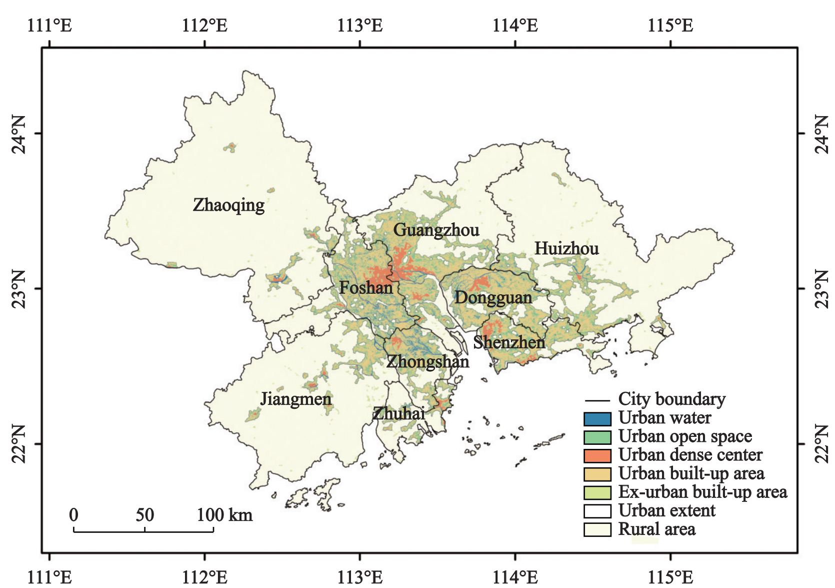

Fig. 1 Location of Pearl River Delta Urban Agglomeration (PRDUA), China

50 km^2 or 10% of UB's area). EB refers to urban patches that are far from other urban settlements and are too small to constitute a separate urban settlement. UOS denotes to land surface in the city completely or basically not covered by artificial structures, including green areas and bare ground and so on. UW refers to water areas in the city (Xu et al., 2021). And then, rural area (RA) was defined as the non-urban areas to further investigate the urban-rural differences in carbon storage changes, referring to the area within the administrative boundary and outside the UE.

2.2 Data source

The data used in this work included land use maps and hierarchical urban boundary data. The land use maps were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn). To analyze land use change and estimate carbon storage, a time series of land use maps at 1990, 2000, 2005, 2010, 2015 and 2018 with a spatial resolution of 30 m × 30 m were downloaded and recategorized into six land use types: arable land, forest, grassland, water, construction land, and unused land. The overall accuracy of the land-use data classification assessed via field survey was reported to be higher than 94.30% (Yang and Huang, 2021).

The hierarchical urban boundary data at 2018 were collected from the study of Xu et al. (2021), and used to examine the heterogeneous response of carbon storage to land use changes. The boundary data were generated using the Landsat Thematic Mapper (TM) images at a spatial resolution of 30 m according to the concept of physical urban entity. The overall accuracy and compatibility to various urban experiments of these data have been thoroughly examined in the existing studies (Xu et al., 2021; 2022).

2.3 Methods

To analyze heterogeneous response of carbon storage to land use changes within urban agglomeration, we proposed an analysis framework based on the integration of land use dynamic degree analysis, InVEST model, and geographically weighted regression (GWR) approach. The framework consists of three steps. At the first step, we calculate land use dynamic degree based on a time series of land use maps. The second step estimates the carbon storage of terrestrial ecosystem in PRDUA using the InVEST model. At the final step, spatially heterogeneous effects of land use changes on carbon storage are examined using GWR approach, and a comparative analysis is performed between the outcomes of GWR and those of ordinary least squares (OLS).

2.3.1 Calculating land use dynamic degree

Land use dynamic degree depicts the rate of land use change over a time period (Liu et al., 2003). In this study, land use dynamic degree (K) was used to indicate the changes of a certain land use type, which can be calculated as follows:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \qquad (1)$$

where U_a, U_b represents the area of a certain land use type at the beginning and the ending of a time period, respectively, and T denotes the time interval of a certain period.

2.3.2 Estimating carbon storage using InVEST model

The carbon storage in the PRDUA was estimated using the InVEST model, which has been proven effective to link carbon storage to land use data at large scale (Polasky et al., 2011). In this model, the carbon storage of each land use type was determined by above ground carbon density (AGCD), below ground carbon density (BGCD), soil organic carbon density (SOCD), and dead organic carbon density (DOCD) (Turner et al., 1995). Based on the land use maps and the parameters of carbon density, the regional carbon storage can be estimated as follows:

$$C_{i,l} = A \times \left(D^{l}_{\mathrm{AGC}} + D^{l}_{\mathrm{BGC}} + D^{l}_{\mathrm{SOC}} + D^{l}_{\mathrm{DOC}} \right) \qquad (2)$$

where, $C_{i,l}$ represents the carbon storage of cell i with land use type l. A represents the area of grid cell. D^{l}_{AGC}, D^{l}_{BGC}, D^{l}_{SOC}, D^{l}_{DOC} represent the aboveground carbon density, belowground carbon density, soil organic carbon density and dead organic carbon density for land use type l, respectively.

Then, the total change of carbon storage (ΔC) for the whole region can be calculated as:

$$\Delta C = \sum \left(C^{t_1}_{i,l} - C^{t_2}_{i,m} \right) \qquad (3)$$

where $C^{t_1}_{i,l}$, $C^{t_2}_{i,m}$ represent the carbon storage in grid cell i with land use type l and m at the time t_1 and t_2, respectively.

The carbon density for each land use type is the key parameter of the InVEST model, and was estimated based on the existing literatures (Table S1). Carbon densities in these studies were obtained from direct field measurements or estimation using a common carbon density method for vegetation and soils relating to the vegetation types (Fang et al., 2001; Ni, 2001; Wang et al., 2001; Chuai et al., 2013), which have been validated and applied in numerous studies in China.

2.3.3 Analyzing response of carbon storage to land use changes

The influencing factors of carbon storage vary across space and over time (Sun et al., 2022). Geographically weighted regression (GWR) is an effective model to explain the spatially heterogeneous relationship of carbon storage and its influencing factors (Lin et al., 2018). In GWR, the heterogeneous relationship can be represented as the varying regression coefficients determined by locations (Brunsdon et al., 1996), which can be expressed in the following:

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{p} \beta_k(u_i,v_i)\, x_{ik} + \varepsilon_i \quad (4)$$

where (u_i,v_i) is the coordinate of the ith grid cell. x_{ik} represents the kth independent variable (k = 1, 2, 3, …, p) (i.e., a certain influencing factor) of carbon storage at the ith grid cell.

β_0 is regression constant. $\beta_k(u_i,v_i)$ is the kth regression parameter at the ith grid cell, which is a function of geographic location; ε_i is the random error of the ith cell, which satisfies the basic assumptions of null hypothesis, homoskedasticity, and mutual independence.

In GWR, the carbon storage change was considered as the dependent variable, land use dynamic degree of each land use type, i.e., construction land, forest, grassland, arable land, water area, and unused land were regarded as the explanatory variables. Among them, the dynamic degree of unused land was excluded from the regression analysis due to that its Koenker (*BP*) is not statistically significant. Specifically, k_0 is the intercept, k_1 denotes the regression coefficient of construction land, k_2 represents the coefficient of forest, k_3 signifies the coefficient of grassland, k_4 represents the coefficient of arable land, k_5 refers to the coefficient of water areas. The GWR utilizes the locally weighted least square method to estimate the regression parameters.

In this study, the GWR was performed in ArcGIS10.2, Gaussian kernel function was used to construct the spatial weight matrix, and the optimal bandwidth was selected using the Corrected Akaike information criterion index (*AICc*). Then, GWR was compared with the Ordinary least squares (OLS).

3 Results and Analyses

3.1 Land use changes

Fig. 2 and Table 1 show that forest land was the largest

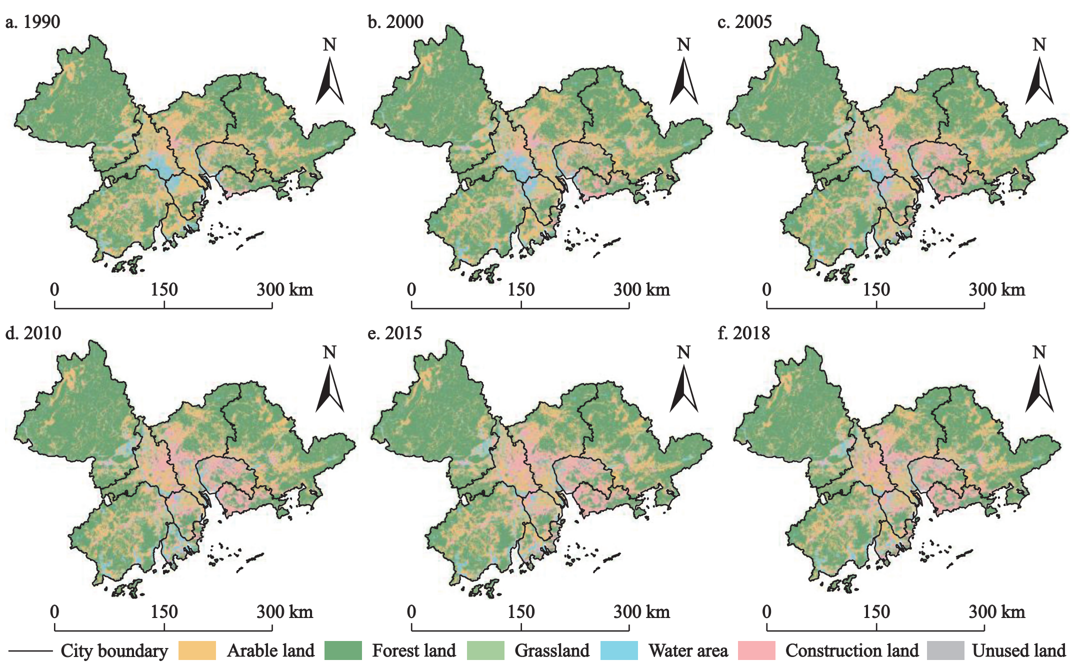

Fig. 2 Land use patterns of the PRDUA, China from 1990 to 2018

Table 1 Land use area and dynamic degrees in the Pearl River Delta Urban Agglomeration (PRDUA), China from 1990 to 2018

Types	Land use area / km^2						Land use dynamic degrees / %				
	1990	2000	2005	2010	2015	2018	1990–2000	2000–2005	2005–2010	2010–2015	2015–2018
Arable land	18675.30	16969.98	15407.05	14840.56	14765.13	14576.02	–0.91	–1.84	–0.74	–0.10	–0.43
Forest land	35840.74	35507.86	35060.62	34827.73	34453.71	34397.93	0.09	–0.25	–0.13	–0.21	–0.05
Grassland	1318.96	1265.15	1180.98	1125.37	1291.43	1292.82	–0.41	–1.33	–0.94	2.95	0.04
Water area	4594.81	5180.25	5042.26	4929.90	4531.47	4511.08	1.27	–0.53	–0.45	–1.62	–0.15
Construction land	3502.14	5055.60	7293.26	8431.06	9127.29	9399.30	4.44	8.85	3.12	1.65	0.99
Unused land	28.84	28.30	22.93	13.80	13.09	10.02	–0.19	–3.80	–7.96	–1.03	–7.82

land use type, accounting for over 50% of the total area of the PRDUA from 1990 to 2018, followed by arable land and construction land, which accounted for over 32% in total. During this period, construction land increased by 5897.16 km^2, with the greatest land use dynamic degree of 6.01%. The dynamic degree of construction land reached up to 8.85% from 2000 to 2005 and slowed down significantly from 2005 to 2018 as the urbanization process became less land-dependent. Arable land decreased by 4099.28 km^2 (–0.78%) from 1990 to 2018, reaching its peak decline during 2000–2005 (–1.84%). Forest land decreased by 1442.81 km^2 (–0.14%) in northern Shenzhen and northeastern Dongguan, mainly converted into arable land (2231.51 km^2) and construction land (1348.43 km^2). Water area and grassland showed similar trends of rising and then falling, decreased by 83.73 km^2 and 26.14 km^2, respectively, during the same period.

As shown in Fig. 3, land use changes varied among nine cities in the PRDUA from 1990 to 2018. The mega-city Guangzhou, super-cities Dongguan and Foshan, and Zhongshan (major-city of type I) had similar trends, with the highest dynamic degree of construction land during 2000–2005. During this time, the dynamic degree of construction land in Zhongshan was 19.23%, while that in Dongguan (14.17%) and Foshan (12.54%) followed. Among them, forest land in Guangzhou was better protected, decreasing only by 2.12%, while the dynamic degree of grassland in Dongguan, Foshan and Zhongshan from 2010 to 2018 was even positive. In contrast, Shenzhen, another mega-city, has been rapidly expanding its construction land area, with evident land use dynamics from 2015 to 2018 (1.35%). Zhuhai, a major-city of type II, had the highest construction land expansion rate of 18.07% between 1990 and 2000, with negative degrees for all other land use types. Other major-cities of type II, e.g., Huizhou, Jiangmen and Zhaoqing, had relatively stable land use change, with a slow expansion rate of construction land and a decreased area of arable land between 1990 and 2018. Huizhou showed a high rate of construction land expansion (7.26%) in 2000–2005.

The land use changes exhibited considerable diversity within different types of urban boundaries (Table 2). From 1990 to 2018, the land use dynamic degree of construction land within UOS was the highest (9.49), which was over three times that of RA (3.01). Ecological regions within UC, such as arable land, forest land and grasslands, suffered a greater loss compared to those within other boundaries such as UB and UE. Conversely, the grassland within RA increased from 1990 to 2018 (0.87), and most of the converted construction land was from unused land.

3.2 Carbon storage changes

The carbon storage estimated by the InVEST model in this study was validated by field samples proposed in the existing studies (Wang et al., 2008; Yang and Guan, 2008; Zhou et al., 2019). The relative error (RE) of carbon storage was less than 15%, indicating the applicability of our results (Table 3).

The carbon storage in the PRDUA exhibited a spatial pattern of high wings and the low middle from 1990 to 2018 (Fig. 4). However, the areas with low carbon storage in the PRDUA showed a constant expansion trend. Based on the calculations of this study, the total carbon storage significantly declined from 767.34 to 725.42 Tg C at a rate of 5.46% during the period of 1990–2018, along with the annual loss of carbon storage slowed down from 0.41% to 0.03% (Fig. 5).

The changes in carbon storage of different sized cities showed significant diversity (Fig. 6). The mega-cit-

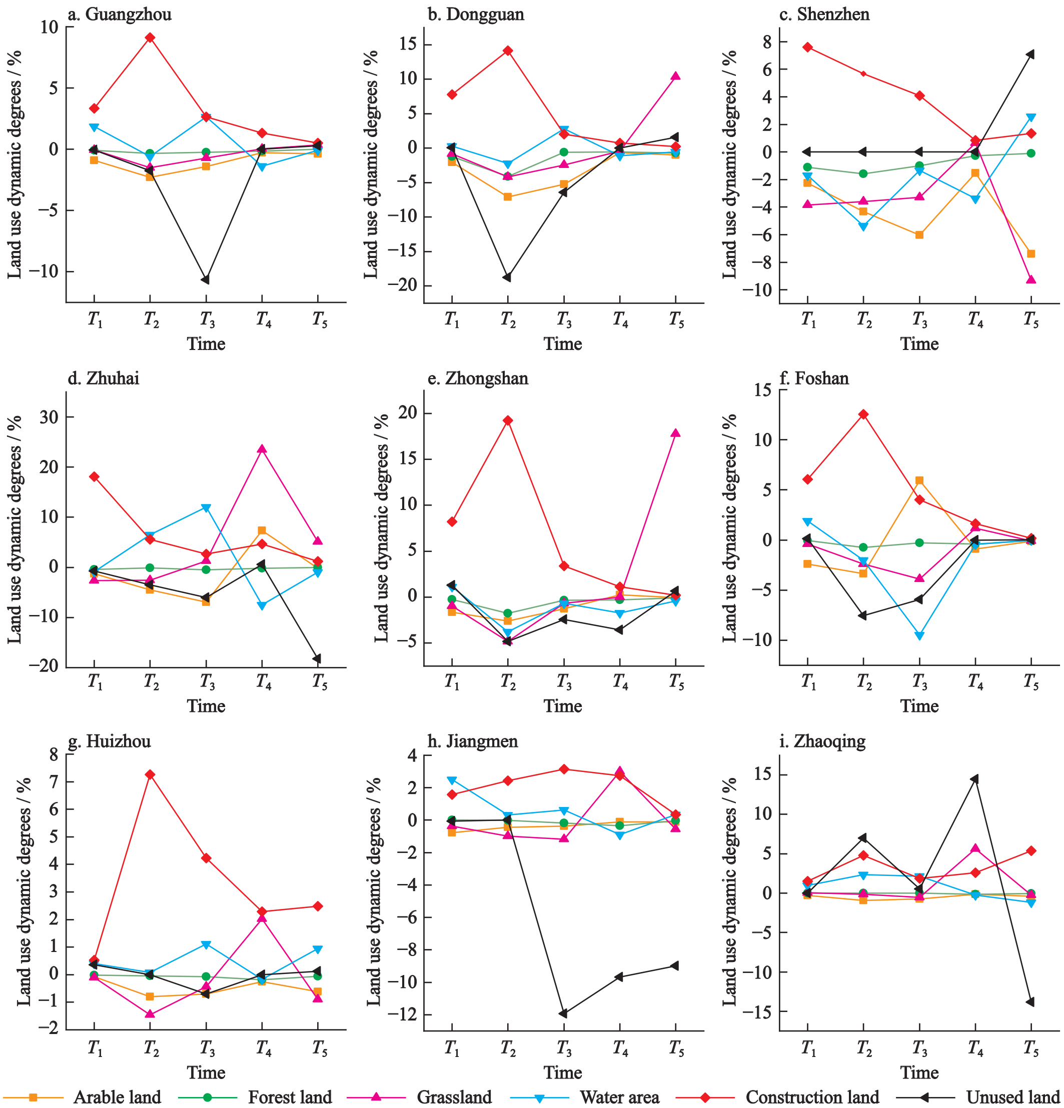

Fig. 3 Land use dynamics degrees of different cities in the PRDUA, China from 1990 to 2018

Table 2 Land use dynamics degrees within different types of urban boundaries in the PRDUA, China from 1990 to 2018 / %

Areas	Arable land	Forest land	Grassland	Water area	Construction land	Unused land
UE	–1.68	–1.38	–1.80	–1.38	7.25	–2.54
UB	–2.22	–2.31	–2.56	–2.24	6.95	–2.80
UC	–3.45	–3.40	–3.57	–2.95	3.26	–3.57
EB	–1.38	–2.00	–1.10	0.10	4.04	–0.39
UOS	–0.71	–0.50	–0.73	–1.26	9.49	–2.04
UW	–0.81	–1.00	–1.34	–0.12	6.24	–1.93
RA	–0.30	–0.04	0.27	0.87	3.01	–2.26

Notes: UE represents urban extent, UB represents urban built-up area, UC represents urban dense center, UOS represents urban open space, UW represents urban water, EB represents ex-urban built-up area, and RA represents rural area

ies experienced a continuous decrease in carbon storage. Guangzhou has the largest carbon storage loss from 97.08 Tg C in 1990 to 88.63 Tg C in 2018, while Shenzhen decreased by 4.71 Tg C. Unlikely, different patterns of carbon storage loss can be observed in super-cities. Compared with the two mega-cities, Dongguan

Table 3 Comparison of carbon storage estimation

Area		Carbon storage / Tg C		Relative error / %	References
		Our results	Previous study		
PRDUA	Forest	526.28 (1990)	485.70 (1989)	8.35	(Yang and Guan, 2008)
PRDUA	AGC + BGC + SOC	622.42 (2015)	714.14 (2015)	14.74	(Zhou et al., 2019)
Guangzhou	Forest	5.46 (1990)	5.92 (1990)	7.77	(Wang et al., 2008)

Note: The values in parentheses indicate the year of which the carbon storage was measured

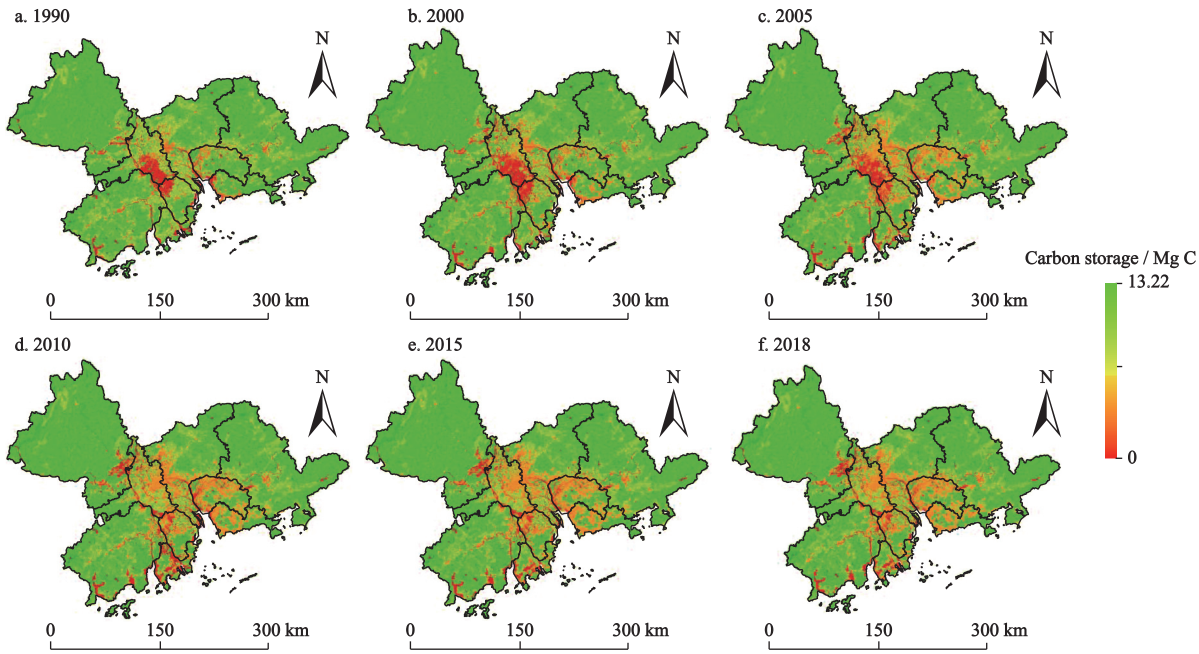

Fig. 4 Spatial distribution of carbon storage in the PRDUA, China from 1990 to 2018

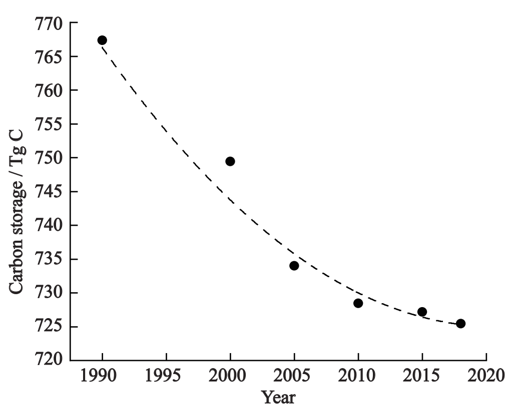

Fig. 5 Carbon storage changes in the PRDUA, China from 1990 to 2018

presented a similar trend but a larger loss rate of 28.19%. From 2000 to 2010, the loss of carbon storage (5.23 Tg C) accounted for 63.23% of the total loss in Dongguan. In contrast, Foshan exhibited an evident fluctuation of carbon storage. The carbon storage firstly continuously decreased by 5.57 Tg C from 1990 to 2005 and then increased by 3.98 Tg C from 2005 to 2018. The carbon storage of major-cities of type I showed a U-shaped trend, with a minimum value in 2010, and the total carbon loss in the entire study period was 2.15 Tg C. Major-cities of type II exhibited a steady decrease in carbon storage, especially during the period of 2000–2010. Specifically, Zhuhai had a trend of carbon storage similar to Zhongshan; Zhaoqing and Huizhou experienced a slow decline of carbon storage from 2000 to 2015 and a fast decline then after. Jiangmen showed a continuous decrease in carbon storage by 5.35 Tg C with a similar trend to mega-cities.

The PRDUA presents a significantly spatial heterogeneity of carbon storage in different areas covered by hierarchical urban boundaries (Fig. 7). During 1990–2018, the decrease in carbon storage within UE reached up to 29.98 Tg C, accounting for 71.52% of the total carbon loss in the PRDUA, and that in RA occupied 28.48%

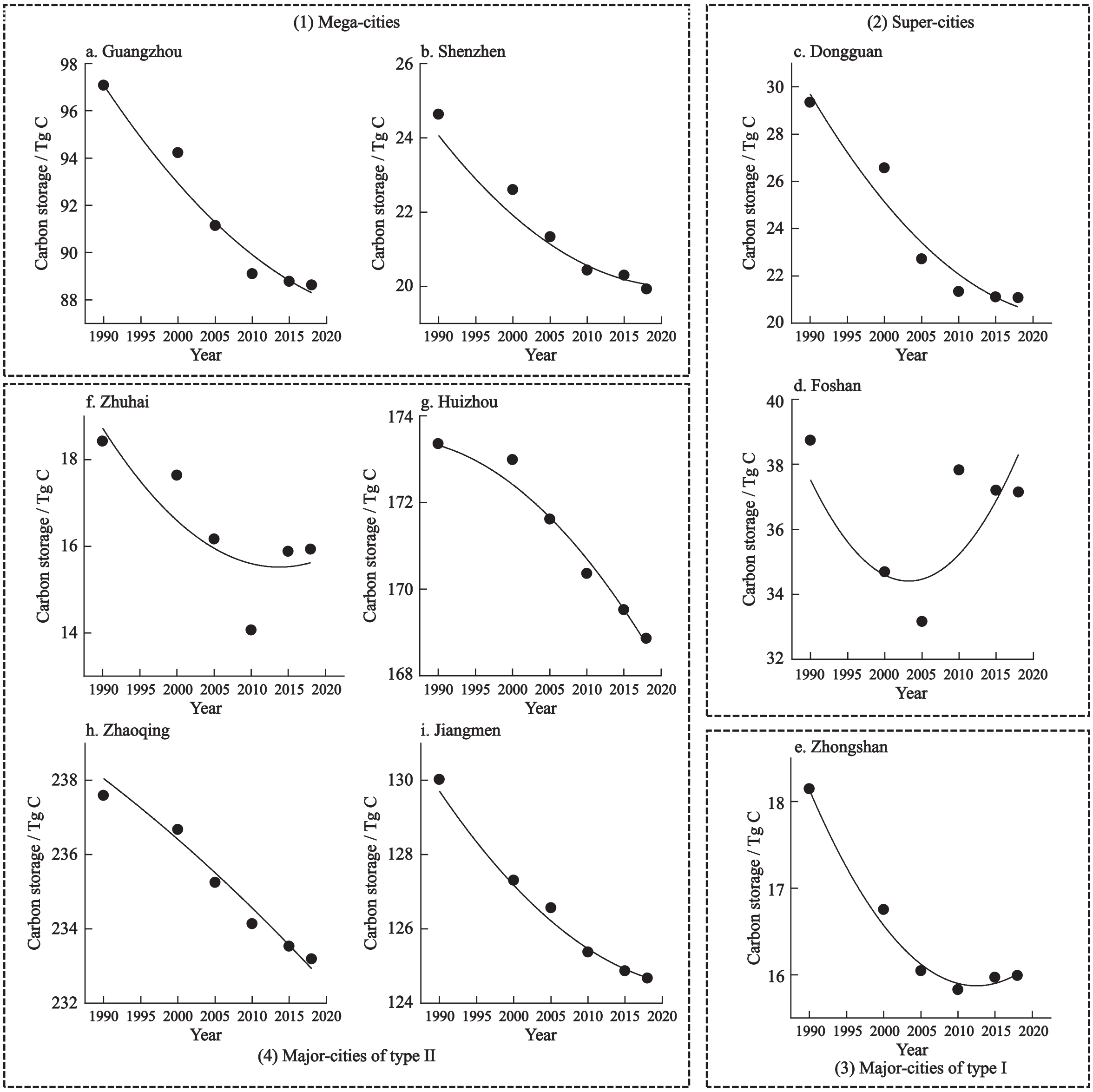

Fig. 6 Carbon storage changes in different cities of PRDUA, China from 1990 to 2018

(–11.94 Tg C). Specifically, UB experienced the maximum loss of carbon storage within UE (–22.80 Tg C, 54.40%), followed by UOS (–4.04 Tg C, 9.65%) and UC (–2.57 Tg C, 6.12%).

3.3 Heterogeneous response of carbon storage to land use changes

The results demonstrated a negative correlation of carbon storage changes with the land use dynamic degree of construction land and water areas, while a positive correlation with the land use dynamic degree of arable land, forest land and grassland. As shown in Table 4, the loss of carbon storage in the PRDUA was mainly due to the expansion of construction land, accounting for 55.74% of the total carbon loss caused by land use change. Most increase of construction land (96.63%) were from the occupation of arable land, forest and water areas. Forest degradation caused 54.81% decrease of carbon storage, second only to the influence of the expansion of construction land. As a result, carbon storage experienced a significant loss. Almost a half of arable land (5122.36 km^2, 49.48%) was converted into construction land, which caused 173.92 Pg C loss of carbon storage. Notably, a small portion of arable land was converted into water area, which caused remarkable carbon storage loss of 105. 41 Pg C. Those land use conversions to forest and grassland with higher carbon density have promoted carbon storage of 52.68 Pg C

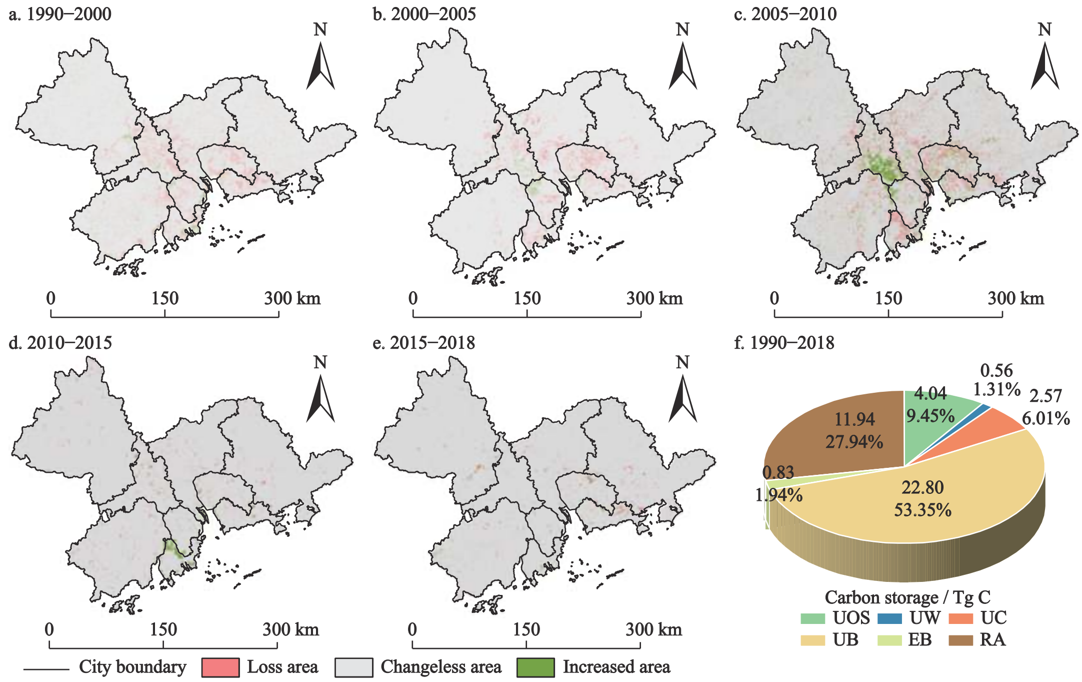

Fig. 7 Carbon storage changes (a to e), and carbon storage and its percentage (f) within different areas in the PRDUA, China from 1990 to 2018. UE represents urban extent, UB represents urban built-up area, UC represents urban dense center, UOS represents urban open space, UW represents urban water, EB represents ex-urban built-up area, and RA represents rural area

Table 4 Main causes of carbon storage changes in the PRDUA, China from 1990–2018

Causes	Types of land use change	Area / km^2	Carbon storage change / Pg C	Percentage / %
Construction land expansion	Arable land → construction land	2534.57	–173.92	55.74
	Forest → construction land	1348.43	–139.40	
	Water → construction land	903.38	39.26	
	Grassland → construction land	148.28	–11.69	
Forest degradation	Forest → construction land	1348.43	–139.40	54.81
	Forest → arable land	2231.51	–77.56	
	Forest → water area	363.74	–53.41	
	Forest → grassland	431.69	–10.58	
Farmland conversion	Arable land → construction land	2534.57	–173.92	43.95
	Arable land → water area	940.5	–105.41	
	Arable land → forest	1515.51	52.68	
	Arable land → grassland	130.82	1.33	

and 1.33 Pg C, which reminds us to highlight the vegetation conservation while implementing the stringent protection of arable land.

Response of carbon storage to land use changes showed heterogeneity among different cities in the PRDUA (Fig. 8). According to the calculations of this study, carbon storage change in Guangzhou had more sensitivity to the dynamics of construction land (–0.11) than other cities, while that in Shenzhen was mainly affected by the dynamics of forest land (8.32). The land use dynamic degree of grassland and water area mostly threatened the carbon storage changes in Foshan (2.65, –2.21, respectively), but posed the least threat in Zhuhai (0.07, –0.18, respectively) and Zhaoqing (0.19, 0.09 respectively). The most threat to carbon storage in Jiangmen, Zhongshan, and Dongguan was loss of arable land (6.43, 4.80, 5.70, respectively). The maximum coefficient in Huizhou was dynamics of forest land (6.38).

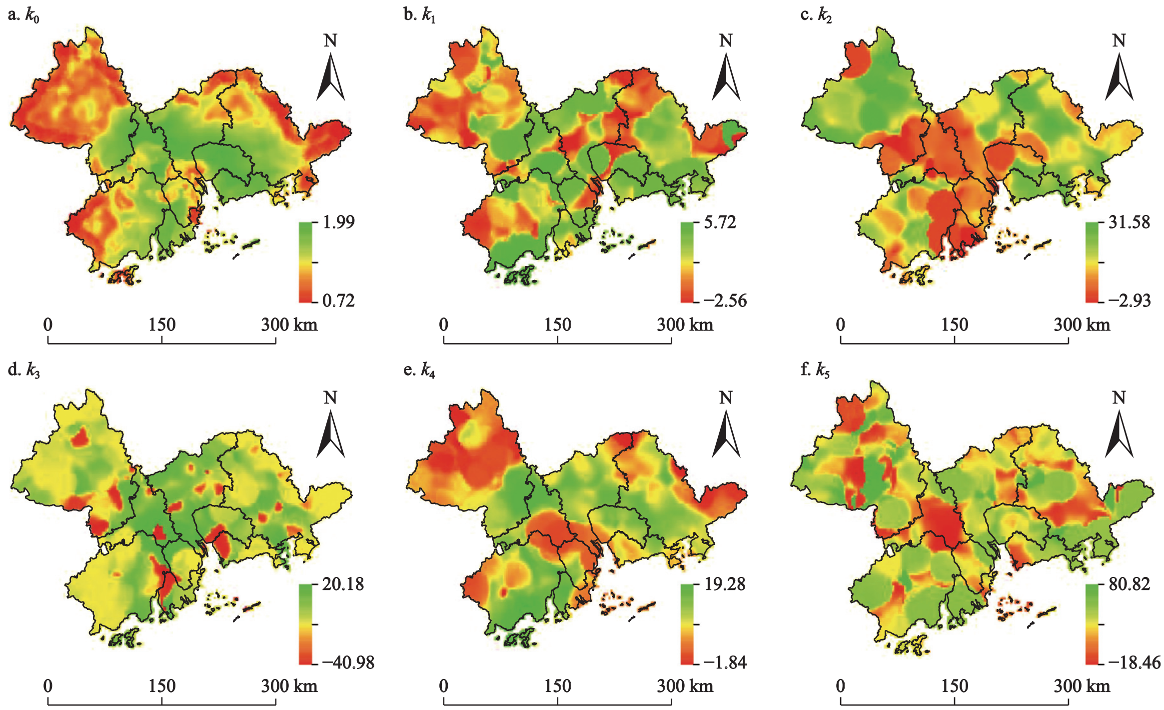

Fig. 8 Geographically weighted regression (GWR) coefficients of different independent variables. k_0 is the intercept, k_1, k_2, k_3, k_4, k_5 denotes the regression coefficient of construction land, forest, grassland, arable land, water areas, respectively

Table 5 Geographically weighted regression (GWR) coefficients within different areas in the PRDUA, China from 1990 to 2018

Areas	k_0	k_1	k_2	k_3	k_4	k_5
UE	1.16	–0.05	2.71	1.69	5.05	–0.81
UOS	1.12	–0.04	3.07	1.48	5.30	–0.80
UW	1.13	–0.04	1.41	2.17	4.26	–1.38
UC	1.26	–0.19	1.46	1.91	4.28	–0.62
UB	1.17	–0.04	2.78	1.72	5.05	–0.76
EB	0.95	–0.02	4.01	1.18	5.70	–0.46
RA	0.90	–0.05	5.82	0.42	4.06	–0.12

Notes: k_0 is the intercept, k_1, k_2, k_3, k_4, k_5 denotes the regression coefficient of construction land, forest, grassland, arable land, water areas, respectively

As shown in Table 5, the changes in carbon storage in UE were mainly affected by the dynamics of arable land, while those in RA were mostly caused by forest land conversions. Within UE, land use changes within different types of urban boundaries had different impacts on the loss of carbon storage. With the increase of impervious surface density, the sensitivity of carbon storage to construction land change also increased. The land use dynamic degree of construction land had the maximum influence on carbon storage in UC, with the GWR coefficient of almost 10 times as much as that in EB. Similarly, the land use dynamics of arable land and forest mostly threatened the carbon storage in EB, but posed the least threat in UW. Notably, the changes in grassland and water areas had the maximum influence on carbon storage in UW but the minimum influence in EB, which were opposite compared with other land use types.

4 Discussion

4.1 The influences of land use changes on carbon storage

Land urbanization has a direct impact on ecosystem services (Peng et al., 2017). We found that land use changes in the PRDUA were dominated by conversion from ecological areas to construction land, and the expansion of construction land corresponded to regional social and economic development, which were consistent with the study of Lin et al. (2022). Our results indicated a total decrease of the overall carbon storage in the PRDUA by 41.92 Tg C from 1990 to 2018, and 60.45% of which was due to land use changes (Fig. 5, Table 4). The spatial distribution and variation of carbon storage in Guangdong Province were similar to the findings of Wu et al. (2016). Considering that approximate a half of unrealized potential carbon storage exist in AGB and

BGB globally (Walker et al., 2022), the loss of forest land and arable land will exert great negative impact on carbon storage (Wang S J et al., 2021). As the major carbon pool in the PRDUA, forest land played a key role in the carbon storage conservation (Table 4). The conversions of forest land to construction land and arable land have caused remarkable loss of carbon storage, which were mainly concentrated in the southern Guangzhou-Dongguan and Northern Shenzhen. Besides, the loss of arable land with high carbon density also led to the reduction of carbon storage, which were mainly distributed along the Pearl River. At the same time, urban expansion has caused significant decrease of carbon storage in Guangdong Province (Wu et al., 2016; Zhou et al., 2019; Lin et al., 2022). Notably, the construction of the national forest city cluster in the PRDUA had effectively improved carbon storage. From 1990 to 2018, Nanshan Park, Xiaonanshan Park, Lianhua Mountain Park, and Bijia Mountain Park in Shenzhen have supplemented a large area of forest land, which benefited the carbon storage promotion and the ecological civilization of the PRDUA (Fig. 4). Our results better understood how land use change affected regional carbon storage, and suggested that carbon storage could be promoted through enhanced land use management (Walker et al., 2022). The relative error (RE) was adopted to compare the results of InVEST model and filed sample (Table 3), which promoted the accuracy of carbon storage estimation (Houghton, 2003).

It has been pointed out that urban scale and urban expansion modes have a significant effect on urban land use patterns. The filling model of urban expansion may occupy a large proportion of ecological land if the urban scale grows rapidly (Yu et al., 2018). Further, ecological response to urban development showed notable spatial heterogeneity in different types of cities (Huang et al., 2020; Yang et al., 2020). The long-term time series evaluation of carbon storage in the PRDUA verified these conclusions to some extent and demonstrated three types of carbon storage changes in nine cities (Fig. 6): 1) the rapid expansion of construction land mainly encroached on arable land and forest land, resulting in the decline of carbon storage in the mega-cities such as Guangzhou and Shenzhen, and the super-city Dongguan; 2) From 2000 to 2015, medium-sized cities adjacent to the Pearl River system, such as Foshan, Zhongshan and Zhuhai, experienced significant conversions of water areas into urban construction land and arable land (Wu et al., 2016). Consequently, the changes of carbon storage in the three cities at this stage were evident. 3) Huizhou, Zhaoqing and Jiangmen, three major-cities of type II located in the periphery of the PRDUA, experienced different rates of decline in carbon storage from 1990 to 2018. Before the year of 2000, carbon storage had only a slight decline due to the small urban scales and slow expansion of these cities, but turned to a significant decline after 2000 because of booming economic development (Wu et al., 2016).

4.2 Informing land use decisions

Regional land use decisions should incorporate spatial heterogeneity of land use patterns and its effects (Omernik and Griffith, 2014; Schirpke et al., 2020). The results of this study indicated different magnitudes of linear correlation between carbon storage changes and land use dynamic degrees (Fig. 8, Table 5). The findings demonstrated that the relationship between land use change and carbon storage varied among cities and across spatial gradients of urban agglomerations. Previous studies had shown similar findings across the urban hierarchy (Sun et al., 2022) or along an urban-rural gradient (Larondelle and Haase, 2013). From the coupled view of administrative units and physical cities, our results can provide more accurate information on carbon storage in different hierarchies of urban space and support regional planning.

From an administrative perspective, different levels of cities showed varying responses to land-use changes, with carbon storage differing (Fig. 8). Mega-cities and super-cities had significant variation in carbon storage with land use dynamics, highlighting the need for strict monitoring and control measures of land use activities. For example, such as limiting disorderly expansion of construction land in Guangzhou, developing forest land in Shenzhen, protecting grassland and water in Foshan, and increasing arable land in Dongguan are needed. In contrast, major-cities of type II, such as Zhuhai and Huizhou, had relatively stable carbon storage despite land use changes, and could prioritize sustainable and green development. Cities with sensitive carbon storage to land-use changes should adopt innovative land use technologies to balance development requirements with carbon storage protection (Cheng et al., 2022). Our results also indicated that rapidly urbanizing areas on the Chinese coast exhibited significant carbon storage changes, as also observed in Zhu et al. (2022).

From the view of physical entities of cities, the relationship between land use change and carbon storage varied across the spatial gradient of urban agglomerations (Table 5). Within UC, the rapid expansion of construction land has threatened carbon storage and controlling its continuous growth is necessary. Additionally, as impervious surface density decreases, green spaces positively impact carbon storage in UB. Therefore, protecting urban green spaces is key to promoting carbon storage (Bonilla-Bedoya et al., 2020; Dangulla et al., 2021). The results also showed that forest land, grassland, and water areas exerted a positive impact on carbon storage within UE. However, due to the scarcity of ecological land within urban areas, compact green city centers with high-density land use and efficient green infrastructure may contribute to more sustainable development than large ecological land patches (Stott et al., 2015; Tappert et al., 2018). Within the EB, promoting urbanization while ensuring the quantity and quality of arable land is a major challenge for carbon storage conservation. In rural areas, large-scale forest land management is crucial for carbon storage conservation in the entire urban agglomeration (Sun et al., 2022).

4.3 Limitations and future works

This study investigated the heterogeneous response of carbon storage change to land use in the PRDUA from the perspective of administrative units and physical cities. However, there are some limitations. Firstly, land use is an interactive process between humans and the environment. We used hierarchical urban boundaries to explore the spatial heterogeneity of carbon storage within different physical entities of cities and further considered the different effects of socioeconomic development of cities on carbon storage among administrative units. In the future, integrating both types of boundaries may provide more spatially explicit ecosystem management strategies; Secondly, the InVEST model was used to evaluate carbon storage due to the unavailable long-term and large-scaled monitoring data of carbon density (Houghton and Hackler, 1999; Houghton, 2003). The parameters of carbon density in the InVEST were fixed based on the direct field measurements (Fang et al., 2001; Ni, 2001; Wang et al., 2001; Chuai et al., 2013). Although these parameters have been validated in previous studies, field survey is still required to improve the estimation accuracy of carbon storage; Thirdly, our study revealed how carbon storage respond to land use changes in the PRDUA from 1990 to 2018 at different sizes of cities and hierarchical boundaries within physical cities. The scale effect should be further explored to deepen our understanding of the influencing mechanism.

5 Conclusions

Based on the land use data from 1990 to 2018, we took the Pearl River Delta as a case and used the InVEST model to explore the impact of land use changes on carbon storage across spatial gradients of the urban agglomeration. Different from previous studies, this work analyzed the changes in carbon storage and their influencing factors within hierarchical urban boundaries from the perspective of physical cities. Our findings are more applicable to decision making of regional development of urban agglomerations.

We found that construction land expansion was the main land use change in the PRDUA, with the area increase of 5897.16 km^2 and land use dynamic degree of 6.01%. Carbon storage in the PRDUA exhibited a spatial pattern of high wings and the low middle and decreased by 41.92 Tg C from 1990 to 2018, which mainly caused by construction land expansion (55.74%) and forest degradation (54.81%). According to the coefficients of GWR, we found remarkable heterogeneity of carbon storage changes in different sized cities and hierarchical urban boundaries. Among different cities, carbon storage in mega-cities and super-cities varied greater with land use change, for example, construction land in Guangzhou had a regression coefficient of –1.11 and forest land in Shenzhen had a coefficient of 8.32. Within different types of urban boundaries, carbon storage was mainly affected by farmland conversion within urban extent (5.05) and forest land degradation in rural areas (5.82). In addition, coefficients of construction land's dynamic degree in UC (0.19), UB (0.04) and EB (0.02) dropped with the decrease of impervious surface density, which means the sensitivity of carbon storage changes to the expansion of construction land gradually decreased. In future, the fragmentation and expansion of construction land should be controlled, and more precise ecological land protection policies should be implemented within the hierarchical boundaries of cities.

Appendix

Table S1 Carbon intensity for each land use type in the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model

Land use types	AGCD	BGCD	SOCD	DOCD	Sources
Arable land	17.55	11.59	80.70	2.24	(Fang et al., 2001; Ni, 2001; Wang et al., 2001; Chuai et al., 2013)
Forest land	31.83	6.37	105.7	2.94	(Fang et al., 2001; Ni, 2001; Chuai et al., 2013)
Grassland	14.45	17.35	88.06	2.45	(Fan et al., 2008; Chuai et al., 2013)
Water	0	0	0	0	(Zhang et al., 2012)
Construction land	7.61	1.52	34.33	0	(Ni, 2001; Zhang et al., 2017)
Unused land	10.36	2.07	34.42	0.96	(Ni, 2001; Zhang et al., 2017)

Notes: AGCD represents above ground carbon density, BGCD represents below ground carbon density, SOCD represents soil organic carbon density, and DOCD represents dead organic carbon density

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