

Article

Spatio-Temporal Dynamics of Carbon Storage in Rapidly Urbanizing Shenzhen, China: Insights and Predictions

Chunxiao Wang ^{1,2,3,*}, Mingqian Li ¹, Xuefei Wang ¹, Mengting Deng ⁴, Yulian Wu ¹ and Wuyang Hong ^{1,2}

¹ School of Architecture and Urban Planning, Shenzhen University, Shenzhen 518060, China

² State Key Laboratory of Subtropical Building and Urban Science, Shenzhen 518060, China

³ School of Built Environment, University of New South Wales, Sydney 2052, Australia

⁴ Shenzhen Longhua District Development Research Institute, Shenzhen 518000, China

* Correspondence: cxw@szu.edu.cn

Abstract: Rapid urbanization in developing countries leads to significant land-use and land-cover change (LULCC), which contributes to increased carbon dioxide (CO₂) emissions and the degradation of carbon storage. Studying spatio-temporal changes in carbon storage is crucial for guiding sustainable urban development toward carbon neutrality. This study integrates machine-learning random forest algorithm, CA–Markov, and InVEST models to predict carbon storage distribution in Shenzhen, China, under various scenarios. The findings indicate that, over the past two decades, Shenzhen has experienced significant land-use changes. The transformation from high- to low-carbon-density land uses, particularly the conversion of forestland to construction land, is the primary cause of carbon storage loss. Forestland is mainly influenced by natural factors, such as digital elevation model (DEM) and precipitation, while other land-use and land-cover (LULC) types are predominantly affected by socio-economic and demographic factors. By 2030, carbon storage is projected to vary significantly across different development scenarios, with the greatest decline expected under the natural development scenario (NDS) and the least under the ecological priority scenario (EPS). The RF–CA–Markov model outperforms the traditional CA–Markov model in accurately simulating land use, particularly for small and scattered land-use types. Our conclusions can inform future low-carbon city development and land-use optimization.



Citation: Wang, C.; Li, M.; Wang, X.; Deng, M.; Wu, Y.; Hong, W. Spatio-Temporal Dynamics of Carbon Storage in Rapidly Urbanizing Shenzhen, China: Insights and Predictions. *Land* **2024**, *13*, 1566. <https://doi.org/10.3390/land13101566>

Academic Editor: Shaojian Wang

Received: 9 August 2024

Revised: 21 September 2024

Accepted: 24 September 2024

Published: 26 September 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: carbon storage assessment; land-use and land-cover change; random forest; machine learning; multi-scenario simulation of land use

1. Introduction

As stated in the “Sixth Assessment Report of the International Panel on Climate Change” (IPCC), the global surface temperature experienced an increase of 1.1 °C from 2011 to 2020 relative to the period from 1850 to 1900. The sustainable development of human societies is increasingly imperiled by the adverse effects of global warming, which is predominantly attributed to substantial anthropogenic CO₂ emissions [1]. Land use–land cover (LULC) is an indicator to represent natural and economic processes [2]. Over the past 150 years, one-third of global CO₂ emissions have originated from land-use and land-cover change (LULCC), making it a crucial source of emissions of greenhouse gases [3]. The majority of CO₂ emissions resulting from human activities can be absorbed through carbon storage in terrestrial ecosystems. Therefore, enhancing the capacity of these ecosystems to sequester carbon represents one of the most effective strategies for mitigating climate change [4]. LULCC, which is impacted by a variety of natural, social, and economic factors, not only significantly impacts greenhouse gas emissions but also affects soil organic carbon and vegetation carbon storage through land-use category transitions, subsequently influencing the carbon storage function of terrestrial ecosystems [5–7]. Therefore, quantitatively assessing the influence of the LULCC on carbon storage is of paramount importance in mitigating global warming and formulating sustainable urban development strategies.

Currently, field surveys [8], atmospheric inversion [9], and modeling simulations [10] are some of the methods used to assess carbon storage. Field surveys that involve on-site sampling are suitable for small-scale carbon storage investigations, but they are time-consuming and destructive [11]. Atmospheric inversion methods employ the spectral reflectance characteristics of vegetation to calibrate forest biomass, making them ideal for large-scale carbon storage estimates. Nevertheless, this approach is limited by issues of accuracy and inherent errors [12]. With the advancement of remote-sensing technology, the integration of remote-sensing monitoring and relevant models has increasingly become the norm in assessing, simulating, and predicting carbon storage. Modeling simulation methods include the denitrification–decomposition (DNDC) model [13], the forest ecosystem carbon budget model for China (FORCCHN) [14], high-accuracy surface modeling (HASM) [15], and the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model [16], and others. Among these, the InVEST model stands out and is widely used in regional studies because of its simplicity, flexible parameter settings, high accuracy, and unique advantages in assessing the effects of various planning policies on regional carbon storage [17,18].

LULCC models are essential tools for characterizing changes and dynamics in land patterns, and they have always been a core aspect of research in the field of LULCC [19,20]. During the past years, LULCC models have been extensively studied by researchers worldwide, roughly categorized into “top–down” quantitative relationship models and “bottom–up” spatial prediction models. Common quantitative relationship models include the Markov model [21] and the system dynamics model [22], which simulate changes in land-use quantity in an area but do not account for changes in the spatial structure. Among the spatial prediction models, a traditional Cellular Automaton (CA) is undoubtedly among the most widely applied, with powerful simulation capabilities for complex spatial dynamic systems. However, almost no single model can capture all the complex features of LULCC processes and achieve multi-dimensional predictions, such as those related to time and quantity [23]. Therefore, scholars have developed various LULCC coupling models based on CA, such as SLEUTH [24], CLUE-S [25], CA–Markov [26], GeoMod [27], and FLUS [28]. Among these, the CA–Markov model, owing to its benefits in spatial and quantitative simulations, has recently become the most popular method [29–31].

The core of the CA–Markov model is the mining of land-use transition rules according to the drivers. However, the CA–Markov model still cannot handle quantitative factors such as socio-economic factors in the simulation process. Combining other methods to construct LULC conversion rules is a solution to address this deficiency [32]. In earlier research, scholars have often used multi-criteria evaluation (MCE) and logistic regression (LR) to produce maps of land-transition suitability. However, MCE is more subjective and empirical when producing transition-suitability maps, requiring researchers to be more familiar with the study area. Although more objective, the LR requires spatial variables to be linearly uncorrelated; otherwise, they are prone to lower simulation accuracy [33]. In contrast, machine learning recognizes the rules for transitions of land use by repeating the learning of previous empirical data, which are more equipped to handle the nonlinear relationship between driving factors and land use, better capture the transition rules of LULC, and improve the simulation results’ alignment with reality [34]. Commonly used machine-learning methods include artificial neural networks (ANNs), genetic algorithms (GAs), support vector machines (SVMs), random forests (RFs) [35]. Among them, the “black box” mechanism of ANN cannot reflect the impact of various spatial variables on LULCC, and these networks are susceptible to overfitting [36]. GA excels in parameter adaptability and optimization but suffers from high time complexity and a tendency to get stuck in local optima [32]. SVM is generally used for small datasets with few outliers, whereas RF can handle a large number of variables with good interpretability and moderate computational complexity, indicating the contribution of each spatial variable to LULCC [37,38].

In response to the article’s requirements, we propose an algorithm that integrates machine-learning approaches, including the RF and CA–Markov models, to accurately

assess and predict the scale and spatial patterns of future urban LULCC. This integration enables the precise quantification and forecasting of future carbon storage trends, guiding planners to optimize LULC planning structures and enhance carbon storage. It also lays the foundation for low-carbon and high-quality development within the context of stock planning. We specifically investigate the following research questions: (1) How has LULCC affected carbon storage in ecosystems over the past several decades? (2) How will the distribution of future carbon storage change under different development scenarios? (3) What scientific support can we provide for policy formulation to explore ways to rationalize land use and improve carbon storage in regional ecosystems? This study presents a novel model for estimating and forecasting carbon storage in relation to LULCC. By applying various development scenarios, the model simulates the response of carbon storage to different forms of LULCC. This approach aims to enhance and refine predictive methodologies, technical systems, and research content related to land-use and carbon-storage simulations under climate change, thereby offering valuable insights and references for future research in this field.

2. Materials and Methods

2.1. Research Framework

There are three primary components to this study's research framework: analysis of historical LULCC, estimation of historical carbon storage, and multi-scenario simulation of future LULC and carbon storage (Figure 1).

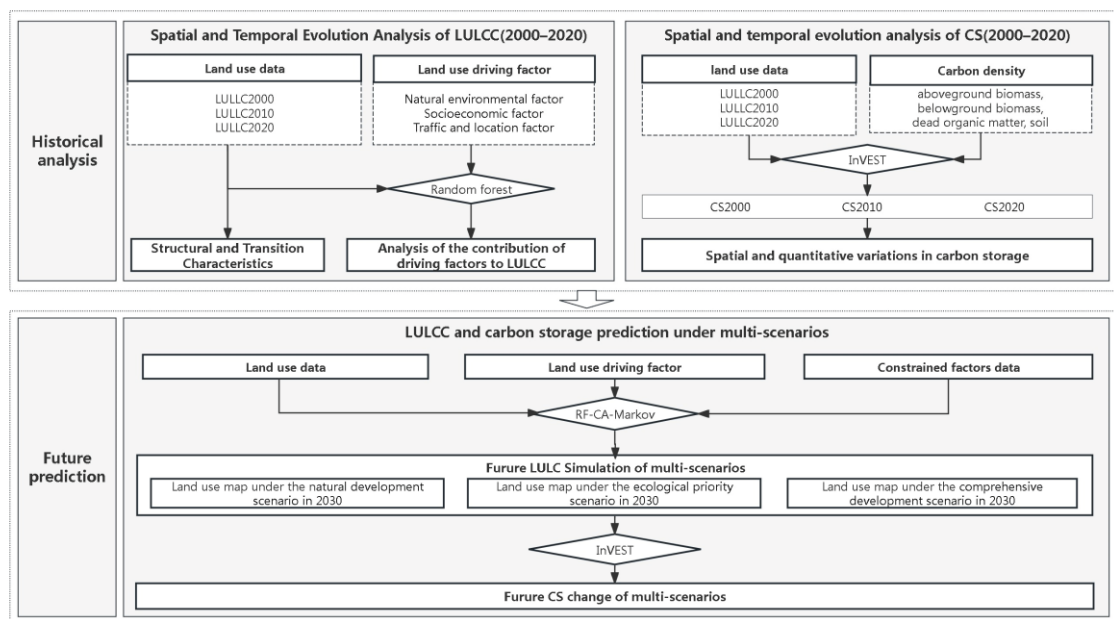


Figure 1. Research framework.

- (1) **Historical LULCC.** Based on historical data, changes in LULC over the past 20 years (2000–2020) were analyzed from both temporal and spatial perspectives. Then, we applied the RF algorithm to investigate the driving mechanisms and potential for future land-use conversion, specifically examining the relative contributions of various driving factors to different land-use categories.
- (2) **Historical carbon storage changes.** To estimate changes in carbon storage, we analyzed the distribution of carbon density and its characteristics over time and space using the InVEST 3.12.0 model.
- (3) **Future LULC and carbon storage prediction.** Land use and carbon storage under different scenarios in 2030, such as the natural development scenario (NDS), ecologi-

cal priority scenario (EPS), and comprehensive development scenario (CDS), were simulated and predicted using the RF-CA-Markov and InVEST models.

2.2. Study Area and Data

The study area is Shenzhen, China, which has emerged as one of the country's fastest-growing cities in recent years (Figure 2). Shenzhen lies in Guangdong Province's southern section in Southern China ($113^{\circ}43'–114^{\circ}38'$ E, $22^{\circ}24'–22^{\circ}52'$ N), with 10 districts and a total area of 1997.47 km². The geography of Shenzhen features low mountains, gentle terraces, and terrace hills, with elevations generally higher in the southeast and lower in the northwest. Its population has grown nearly 60 times over the past 40 years, making it a megacity with over 17 million residents. The degree of LULCC is substantial, with the current land development intensity reaching 50%. Construction land has become the dominant land category in Shenzhen [39]. This rapid encroachment of construction land on ecological areas has negatively impacted carbon storage within ecosystems, hindering the city's pursuit of low-carbon and sustainable development. Consequently, using Shenzhen as a study area to analyze how LULCC affects carbon storage is particularly representative.

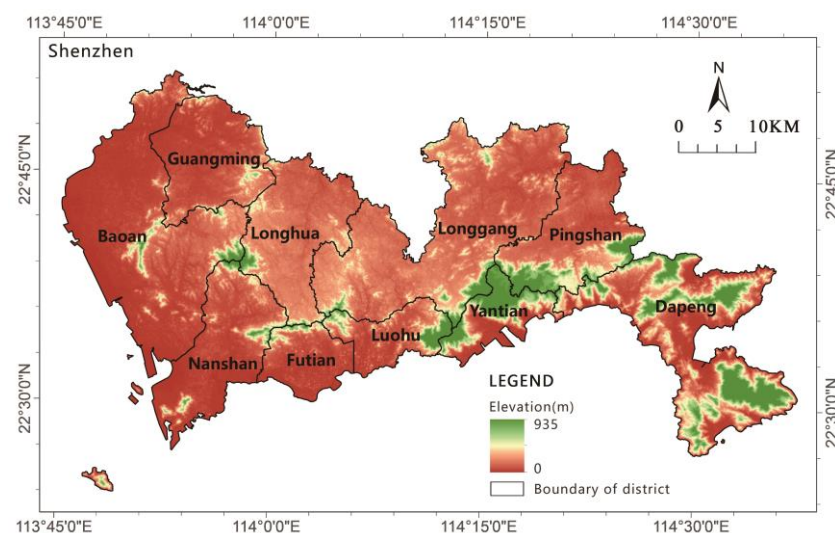


Figure 2. Location of Shenzhen, with elevation.

2.3. Materials

2.3.1. Land-Use Data

The land-use data for the years 2000, 2010, and 2020 used in this study are sourced from the GlobeLand30 global land-cover dataset, with a spatial resolution of 30 m × 30 m. We also reorganized land-use categories into cultivated land, forestland, grassland, waterbodies, and construction land based on the real circumstances to support our research. Land-use change is influenced by a complex interplay of natural, social, economic, and policy factors. In response, this study prioritizes data accessibility and quantifiability while considering the critical factors influencing urban development and relevant policies in the study area. We have meticulously selected five natural environmental driving factors, three socio-economic driving factors, four traffic location factors, and two constraint factors for the land-use simulation. Natural conditions form an important foundation for the formation and development of cities, exerting both direct and indirect influences on urban growth. Socio-economic factors serve as significant drivers of urban expansion, shaping the direction of city sprawl [40]. Additionally, transportation infrastructure shapes urban development and directly influences spatial patterns within cities. To improve the practical applicability of the simulation, this study includes Shenzhen's three zones and three lines, as well as nature reserves, as constraint factors. It contains the specific names, years, and sources of the research data in Table 1. All spatial data were standardized to 30 × 30 m resolution.

Table 1. Sources of research data.

Category	Data	Year	Source
Land-use data	Land use	2000, 2010, 2020	Globallandcover.com, accessed on 15 July 2023
Natural environment data	DEM	2010	Resource and environment science and data center (http://www.resdc.cn/ , accessed on 15 July 2023)
	Slope	2010	Drawn by DEM
	Distance to coastline	2021	The coastline was downloaded from the China Oceanic Information Network (https://www.nmdis.org.cn/ , accessed on 15 July 2023), and plotted by Euclidean distance
	Annual average precipitation	2020	Resource and environment science and data center (http://www.resdc.cn/ , accessed on 15 July 2023)
	Annual average temperature	2020	Resource and environment science and data center (http://www.resdc.cn/ , accessed on 15 July 2023)
Socio-economic data	Population density	2020	Gridded Population of the World, Version 4 (GPWv4) (https://sedac.ciesin.columbia.edu/ , accessed on 15 July 2023)
	GDP	2020	Resource and environment science and data center (http://www.resdc.cn/ , accessed on 15 July 2023)
	Nighttime light data	2020	NPP VIIRS VNL2 (https://eogdata.mines.edu/products/vnl/ , accessed on 15 July 2023)
Traffic location data	Distance to trunk road	2020	Trunk roads were downloaded from primary roads in Openstreetmap (http://www.openstreetmap.org/ , accessed on 15 July 2023), and plotted by Euclidean distance
	Distance to subordinate road	2020	Subordinate roads were downloaded from secondary roads in Openstreetmap (http://www.openstreetmap.org/ , accessed on 15 July 2023), and plotted by Euclidean distance
	Distance to highway/expressway	2020	Highway and expressway were downloaded from Openstreetmap (http://www.openstreetmap.org/ , accessed on 15 July 2023), and plotted by Euclidean distance
	Distance to bus station	2020	The bus stops are taken from the Amap (https://m.amap.com/ , accessed on 15 July 2023), and plotted by Euclidean distance
Constrained factors data	Three zones and three lines	-	Shenzhen Municipal Bureau of Planning and Natural Resources
	Nature reserve	-	China nature reserve standard wood resource sharing platform (http://www.papc.cn/ , accessed on 15 July 2023)

2.3.2. Carbon Density Data

Carbon density provides the fundamental data required for estimating regional carbon storage using the InVEST model. Owing to the long and difficult cycle time for measuring carbon density in the field, as well as the minimal variations in carbon density concerning land-use patterns within the same climatic zone [41], in this study, our carbon density data relied primarily on a literature review, which mainly referenced the aboveground carbon density data of China's terrestrial ecosystem from the 2010s [42], and we combined this with relevant research data from neighboring regions [43–45]. The final data obtained are shown in Table 2.

Table 2. Databases of carbon density of five land-use types in Shenzhen.

Land-Use Type	c_above (t/ha)	c_below (t/ha)	c_dead (t/ha)	c_soil (t/ha)
Cultivated land	13.50	2.70	0.00	30.63
Forestland	18.36	4.95	2.54	44.87
Grassland	1.413	13.53	0.24	9.99
Waterbodies	0.21	0.00	0.00	0.00
Construction land	1.20	0.93	0.00	12.48

2.4. Methods

2.4.1. InVEST Model

According to InVEST's carbon calculation section, the carbon pool of ecosystem carbon storage is mainly divided into the following categories: belowground, aboveground, soil, and dead organic matter. It calculates the total quantity of storage based on the four types of carbon pools associated with each category of land use [46].

$$C_{i-total} = C_{i-above} + C_{i-below} + C_{i-dead} + C_{i-soil} \quad (1)$$

where i is for the i th category of land use, $C_{i-above}$ is for aboveground carbon storage of the i th land-use category, $C_{i-below}$ is for belowground carbon storage of the i th land-use category, C_{i-dead} is for the i th land-use type's dead organic matter carbon storage, C_{i-soil} is for the i th land-use type's soil carbon storage, and $C_{i-total}$ is for the i th land-use type's entire carbon storage.

2.4.2. LULCC Training Based on Improved RF-CA-Markov Model

We proposed an integrated model that combines random forest (RF) algorithm with CA-Markov model to simulate land use and carbon storage according to three development scenarios by 2030 (Figure 3). Specifically, we utilized Python to calculate RF and the IDRISI Selva 17.00 software to run the CA-Markov model. The overall process consists of four main components: RF training, the Markov model, the CA model, and precision validation.

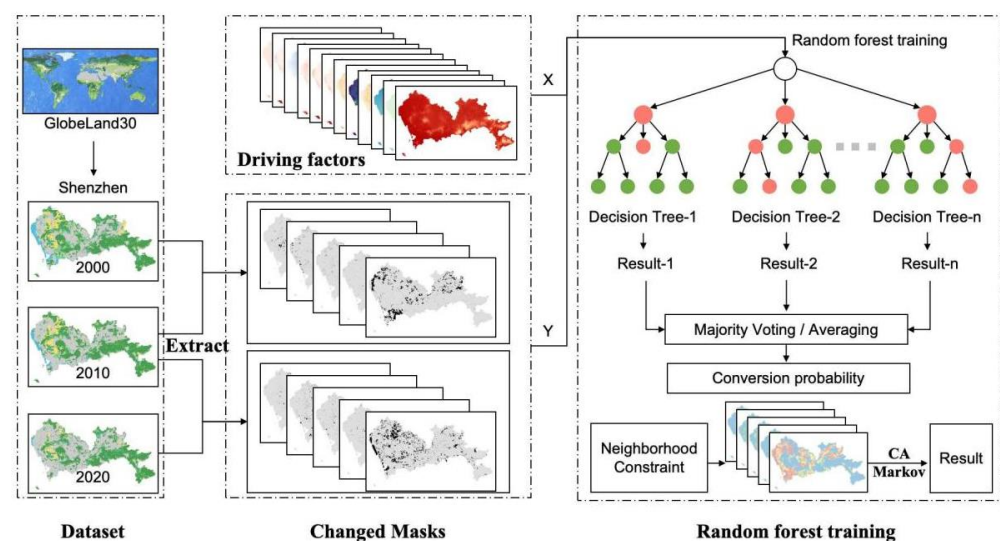


Figure 3. Flowchart of the RF-CA-Markov model.

(1) Random Forest (RF)

Multiple random decision trees make up the RF ensemble-learning method, which uses bagging sampling. It has characteristics such as noise resistance, strong generalization, and the ability to handle land-use classification and prediction problems effectively while avoiding overfitting [47,48]. Specifically, RF classifies training data into multiple random subspaces by performing random sampling with the replacement of training data. It trains individual decision trees in each subspace, yielding random decision trees. By voting on the results of different decision trees, the RF's final output is produced [49].

The training samples for RF consisted of two parts: features (X) and labels (Y). In this study, the sample selection method involved extracting land parcels that experienced LULCC between 2000 and 2010 and between 2010 and 2020. The feature vector of the driving factors for these parcels was used as X for the sample, and the land-use type for the subsequent year was used as Y for the sample. Finally, each decision tree was trained on numerous samples to obtain a nonlinear function that effectively mapped X to Y. In

an RF comprising multiple decision trees, each decision tree can calculate the transition probabilities for each sample for different land-use types as follows:

$$\left[P_{i,1}^k, P_{i,2}^k, \dots, P_{i,G}^k \right] = f^k(D_i) \quad (2)$$

where $P_{i,j}^k$ represents the probability calculated by the k^{th} decision tree, and f^k represents the i^{th} sample transitions to the j^{th} land-use type. G represents all the land-use categories together, and D_i represents the driving factors for the i^{th} sample. Finally, averaging (voting) the results from all K decision trees yields the final transition probability matrix:

$$P_{\text{trans}} = \frac{1}{K} \sum_K \left[P_1^k, P_2^k, \dots, P_G^k \right] \quad (3)$$

where $\left[P_1^k, P_2^k, \dots, P_G^k \right]$ represents the probability matrix calculated separately by the k^{th} decision tree for all Q samples across G land-use types, where $P_{\text{trans}} \in \mathbb{R}^{Q \times G}$.

(2) CA model

Relying on cell space and transformation rules, the cellular automaton (CA) is a dynamic model based on grids that can simulate complex spatial changes. It features discrete time, space, and states. The CA is mainly composed of four parts, which are transition rules, neighborhoods, cell states, and cell. In addition, the states of neighboring cells and transition rules can determine a particular cell's state [37,50,51]. In our study, cells represent each 30×30 m grid, the grid's cell states represent the kind of land use, the neighborhood uses the classic 5×5 Moore neighborhood, and the transition rules are determined using RF. The following formula is applied in this calculation:

$$S_{(t+1)} = f \left[S_{(t)}, N \right] \quad (4)$$

where S is the set of finite and discrete states of cells, f is the transition rules for cell states, N is the neighborhood of each cell at time t , and t and $t+1$ are separate points in time.

(3) Markov model

Based on the current state of the space and transition probabilities between different states, Markov mathematical stochastic models can predict the future development state of the space [52]. As a result, using past land-use data as a guide, we can forecast the land-use demand in 2020 and 2030. The land-use demand for 2020 is derived from the 2000–2010 land-use transfer matrix, and the land-use demand for 2030 is derived from the 2010–2020 land-use transfer matrix. The following formula is applied in this calculation:

$$S_{(t+1)} = P \times S_t \quad (5)$$

where S_{t+1} stands for the status of land use at time $t + 1$, S_t stands for the status of land use at time t , and P stands for the land-use transition matrix.

(4) Precision validation

In this study, we assess the reliability of the RF-CA-Markov model in predicting future LULCC using kappa coefficients. The kappa coefficient evaluates the model's accuracy by comparing the consistency of simulated and actual land use over the same time period. When the $Kappa = 1$, it indicates that the two land-use maps are identical. When $0.75 < Kappa \leq 0.99$, it indicates excellent model performance. When $0.4 < Kappa \leq 0.75$, it suggests good model performance, and when $Kappa \leq 0.4$, it indicates relatively poor model performance [53,54]. The following formula is applied in this calculation:

$$Kappa = \frac{(P_a - P_b)}{(1 - P_b)} \quad (6)$$

where p_a represents the overall classification accuracy, and p_b represents the accidental consistency error theoretical simulation accuracy.

2.4.3. Future Land-Use Simulation under Multi-Scenarios

Different development policies directly influence future urban land-use planning. In our study, we proposed three distinct land-use management scenarios based on the current and future master plan of Shenzhen. Future LULCC was simulated using the RF-CA-Markov model, and future carbon storage was assessed accordingly. The impacts of various policies on land use and carbon storage were analyzed and compared using these scenarios. To determine the land-use demand under different development scenarios, we modified the transition probabilities between various land uses in the Markov model (Table 3).

Table 3. Multi-scenarios development settings.

Scenario Type	Description
Natural development scenario (NDS)	Do not consider any policy constraints on land use and continue the transition probabilities of the original land-use types in 2010–2020 to conduct the land-use simulation.
Ecological priority scenario (EPS)	Taking ecological priority as the principle of development, environmental protection as the primary goal, and limiting the development of urbanization. Based on the ecological protection line, the transition probabilities of three important ecological land-use types, forestland, grassland, and waterbodies, will be adjusted to reduce the area converted to other land-use types, while increasing the transition probabilities of cultivated land and construction land to ecological land.
Comprehensive development scenario (CDS)	In order to meet various conditions such as economic growth, food security, and ecological protection and achieve the city's sustainable development, we will appropriately reduce the rate at which cultivated land, grassland, forestland, and waterbodies are converted to construction land, based on the restrictions of the three zones, three lines, and natural reserves.

3. Results

3.1. Spatial and Temporal Evolution Analysis of LULCC (2000–2020)

3.1.1. Analysis of Spatial Structure and Transition Characteristics of Land-Use Types

Between 2000 and 2020, Shenzhen's land-use types experienced significant changes (Figure 4). In terms of land use, Shenzhen primarily consisted of construction land and forestland. Among these, construction land occupied the dominant position, increasing in proportion to 35.03%, 42.20%, and 50.29% in 2000, 2010, and 2020, respectively. Over the past 20 years, the area of forestland initially increased and then decreased, while the areas of cultivated land, grassland, and waterbodies consistently declined. From 2000 to 2010, the most significant transition was from grassland to construction land. From 2010 to 2020, the most notable transition was from forestland to construction land. Overall, from 2000 to 2020, the predominant land-use shift was toward construction land from the other four types; the most significant change was the conversion of forestland to construction land, followed by cultivated land, grassland, and waterbodies.

Spatially, the majority of the city's construction land has been concentrated in the western, central, and northeastern areas over the past 20 years, steadily expanding. Forestlands were concentrated in the southeastern and central areas, while cultivated land and waterbodies were concentrated in the western areas. Grassland was primarily located in the southwest in 2000; however, by 2020, only a small area remained, and its spatial distribution became more scattered. Owing to the rapid growth of Shenzhen and the persistent shortage of construction land, the western region, which is close to important cities such as Guangzhou and Zhuhai, has experienced significant development driven by economic policies and intercity connections. This has led to the transformation of other land uses in the western region into construction land.

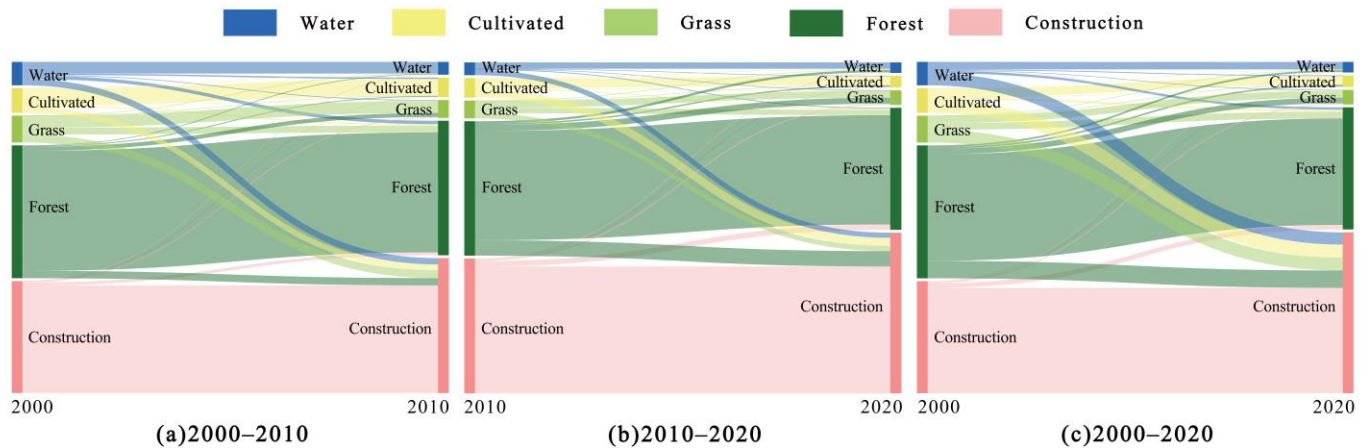


Figure 4. Sankey diagram of land-use area transfer in Shenzhen. Land-use area transfer from 2000 to 2010 (a). Land-use area transfer from 2010 to 2020 (b). Land-use area transfer in Shenzhen from 2000 to 2020 (c).

3.1.2. Analysis of the Contribution of Driving Factors to LULCC

The influence of various driving factors on the LULCC over the past 20 years was investigated through the application of RF. In this study, we selected factors of influence from three perspectives to investigate the driving mechanisms of each type of LULCC, including the natural environment, socio-economic factors, and traffic location (Figure 5). Among these factors, nighttime light emerged as the main driving force behind changes in construction land, waterbodies, and grassland, with contribution values exceeding 15% for each. To some extent, nighttime light reflects the level of socio-economic development. Areas with higher nighttime light indicate more frequent human activities and a greater demand for construction land. Conversely, areas with lower nighttime light experience less human influence and often have better ecological environments, along with larger areas of grassland and waterbodies.

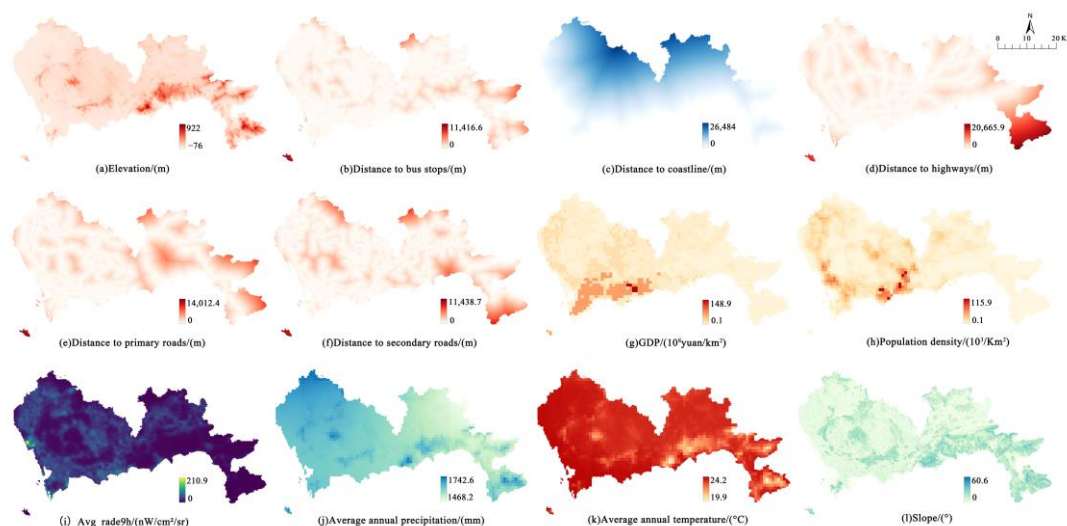


Figure 5. Visualization of driving factors.

Forestland is mainly influenced by the digital elevation model (DEM) and annual average precipitation, as most forested areas are situated in steep terrains that are unsuitable for development, resulting in reduced human disturbance. Moreover, large-scale vegetation contributes to increased atmospheric humidity, thereby enhancing regional precipitation.

Cultivated land is primarily influenced by the distance between subordinate roads (most abundant road type in urban areas) and nighttime light because they are widely

distributed and play a crucial role in connecting different parts of a city, thereby facilitating transportation. The areas around the subordinate roads are predominantly composed of construction land, which is not conducive for crop cultivation. Therefore, cultivated land located farther from the subordinate roads tended to have lower nighttime light.

These findings underscore the complex interplay among various driving factors and LULCC in Shenzhen over the past 20 years. Nighttime light has emerged as a significant driver of urbanization and LULCC, while topography, precipitation, and proximity to road infrastructure also play crucial roles in shaping land-use patterns (Figure 6).

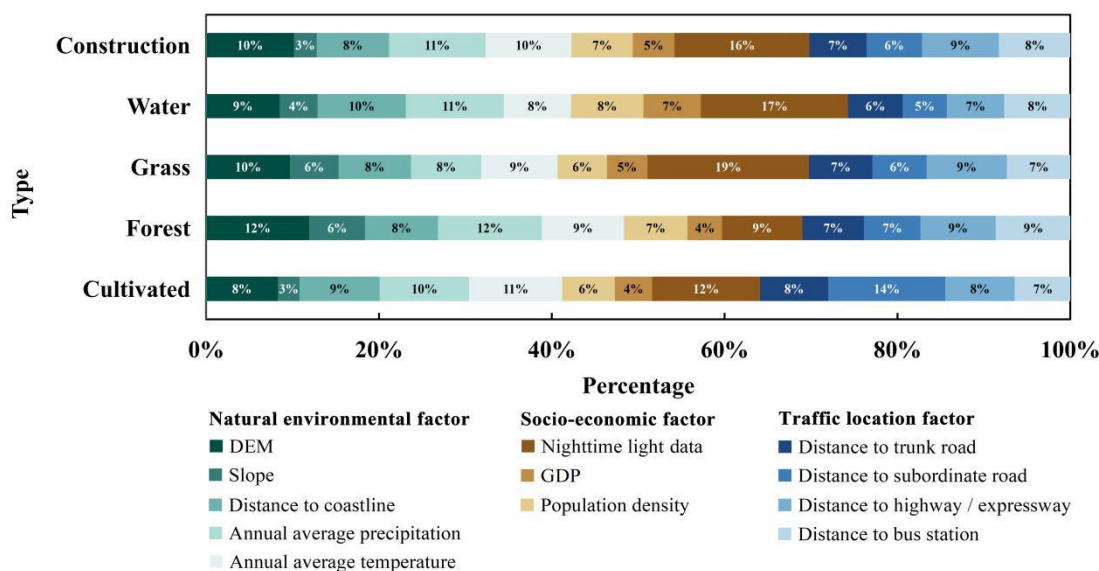


Figure 6. Contributions of various driving factors to each type of land use.

3.2. Spatial and Temporal Evolution Analysis of Carbon Storage (2000–2020)

In terms of quantity, the total carbon storage of Shenzhen in 2000, 2010, and 2020 was 754.85×10^4 t, 754.18×10^4 t, 698.18×10^4 t, respectively. Carbon storage in Shenzhen has declined by 7.51% over the past two decades, with an average annual reduction of 2.83×10^4 t, and a cumulative loss of 56.67×10^4 t. Forestland exhibited the largest decline in carbon storage among all of land-use categories, while construction land showed a continuous increase. Furthermore, the hierarchy of carbon storage according to land-use type is as follows: forestland > construction land > cultivated land > grassland > waterbodies. This indicates that the primary area for carbon storage in the study region is forestland, while construction land, owing to its extensive area, ranks second in total carbon storage for the city. Achieving future carbon storage goals requires a careful balance between forestland and construction land.

Spatially, Shenzhen's carbon storage distribution exhibits a “west low and east high” pattern (Figure 7a). High-density carbon storage areas are located in the southeastern, central-southern, and northwestern parts of the city, including regions such as Wutong Mountain and Malanshan Country Park, which are large mountainous and natural parks with high forest cover. Low-density carbon storage areas are primarily found in the central, northern, and western outskirts, where construction and cultivated lands predominate. These areas have experienced significant human activity and disturbances, resulting in lower levels of carbon storage.

The changes in carbon storage were categorized into three classes: increase, balance, and decrease (Figure 7b). Between 2000 and 2010, there were comparatively minor spatial transformations in carbon storage. However, from 2010 to 2020, there was a noticeable expansion of areas experiencing a decline in carbon storage, primarily in Guangming District, particularly near the boundary with Bao'an District. This decrease can be attributed to the establishment and development of the Guangming New District, which has led to

increased human activities and a significant reduction in carbon storage. A relatively low percentage of locations experienced an increase in carbon storage when examining the overall changes from 2000 to 2020; these locations are mainly situated on the outskirts of the western periphery. Because in the western section of the city, the Guangming and Nanshan Districts are fast urbanizing, and a majority of these places have lowered carbon storage due to a noticeable rise in construction land, which has decreased carbon storage overall.

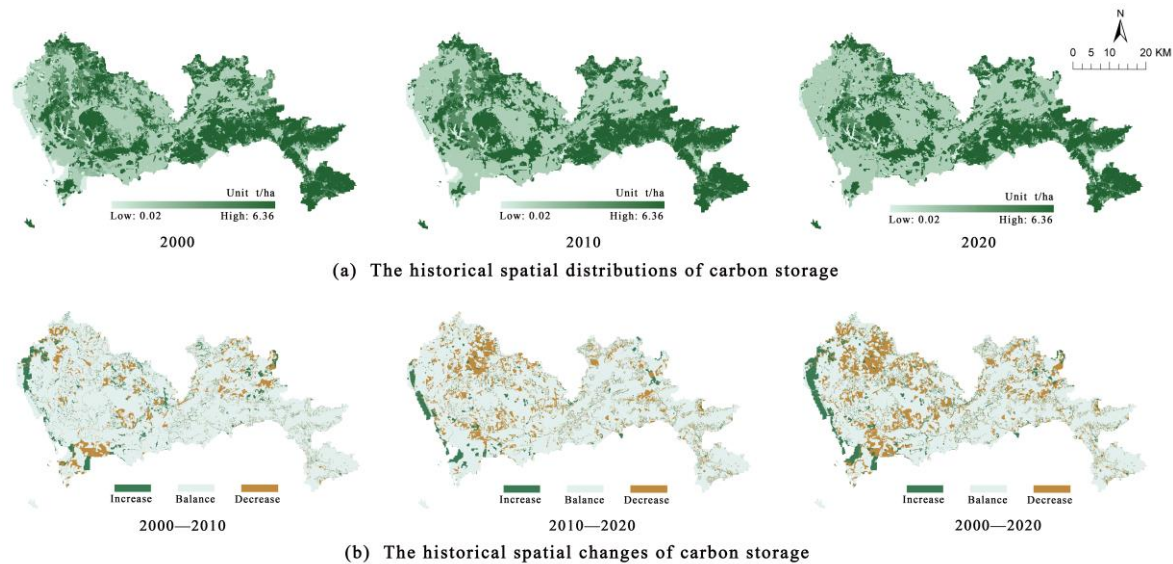


Figure 7. Spatio-temporal characteristics of historical carbon storage (2000–2020). The historical spatial distributions of carbon storage (a) and the historical spatial changes of carbon storage (b).

3.3. LULCC and Carbon Storage Prediction under Multi-Scenarios

3.3.1. LULCC Simulation (2020–2030)

In order to verify the reliability of the model, land-use data from 2010 and the RF-CA-Markov model are applied to predict the land-use situation for 2020. Compared to the actual land use in 2020, the model produced a kappa coefficient of 0.78, indicating relatively strong performance. Therefore, it is highly credible to utilize this model to simulate land use in Shenzhen for 2030. The spatial distribution characteristics of land use under the three development scenarios showed no significant changes relative to 2020. Although different development scenarios exhibit varying land-use structures, the primary land-use types in the study area remain forestland and construction land (Figure 8).

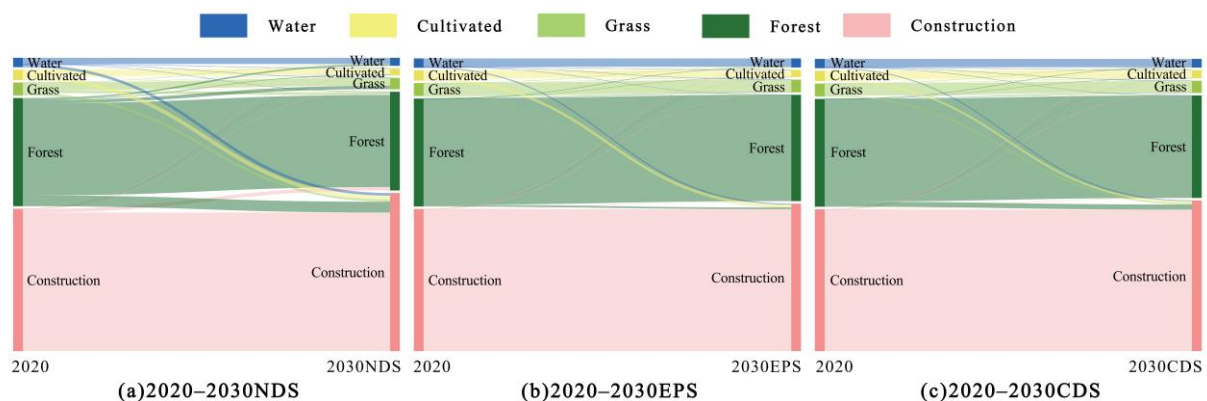


Figure 8. Sankey diagram of land-use area transitions in Shenzhen under multi-scenarios (2020–2030). Land-use area transfer in the NDS (a). Land-use area transfer in the EPS (b). Land-use area transfer in the CDS (c).

In the NDS, land-use transitions are not constrained by policies, and the historical development trend from 2010 to 2020 continues. The most significant increase was observed in construction land. Nevertheless, the areas of grassland, forestland, cultivated land, and waterbodies continued to decline. This decline is evidenced by the extensive degradation of farmland and forests in the research area, driven primarily by the expansion of construction land. In the EPS, forestland, grassland, and waterbodies, as ecological units, are maximally protected, resulting in a stable LULCC. The growth rate of construction land is limited, and the increase of construction land area is the lowest. In the CDS, both ecological and cultivated land are moderately protected. Transitions among various land-use types occur at a slower pace than in the NDS. There is minimal loss of cultivated land, and changes in the areas of construction land and ecological land are more balanced when compared to the NDS and EPS scenarios. These scenarios illustrate the potential impacts of different development policies on land-use patterns and underscore the importance of balancing urban development with ecological preservation and sustainable land-use practices.

3.3.2. Carbon Storage Simulation (2020–2030)

Based on the land-use simulation results for 2030 and the InVEST model, carbon storage projections for Shenzhen under different development scenarios have been derived for that year. In terms of quantity, carbon storage in Shenzhen continues to exhibit a decreasing trend across all three development scenarios from 2020 to 2030. The carbon storage values are projected to be 656.16×10^4 t, 685.21×10^4 t, and 673.62×10^4 t under the NDS, EPS, and CDS, respectively. Compared to 2020, carbon storage under the NDS decreases the most in 2030, reaching 6.02%, followed by the CDS, decreasing by 3.52%. In contrast, the EPS, which prioritizes the protection of ecological land, experiences the smallest reduction in carbon storage at 1.86%.

The spatial distribution patterns of carbon storage under the three development scenarios for 2030 are consistent with the distribution characteristics observed in 2020. High-value areas are primarily located in regions with abundant ecological resources, while low-value areas are predominantly situated in developed regions and areas with high concentrations of waterbodies, and this observation is closely related to land cover (Figure 9a). As illustrated in Figure 9b, the spatial variation of carbon storage in the study area differs significantly across the three scenarios. Among the three development scenarios, the NDS scenario exhibits the most pronounced land-use changes, leading to noticeable fluctuations in carbon storage. Conversely, the EPS scenario imposes stringent restrictions on land-use changes, resulting in more stable carbon storage levels. In the NDS scenario, the substantial reduction in forestland carbon storage accounts for the greatest decline in overall carbon storage. Reduction areas are widespread but primarily concentrated in the western region, with scattered increases in carbon storage observed in the central, northeastern, and northwestern regions. The EPS scenario, characterized by severe constraints on ecological land conversion, results in the smallest decrease in overall carbon storage. In this scenario, cultivated land experiences the most significant reduction in carbon storage, with the decrease concentrated in the northwestern corner, where cultivated land is converted to construction land and waterbodies. Areas of increased carbon storage are primarily found in the western coastal region, where waterbodies are converted to construction land. The CDS scenario shows a decline in carbon storage that is lower than in the NDS scenario but higher than in the EPS scenario. With some protection for cultivated land, the decrease in carbon storage for this land type is the smallest among the scenarios. Reduction areas are mainly located in the northern region, while increases in carbon storage are limited to a small area in the western coastal region. Across all development scenarios, the conversion of cultivated land and forestland significantly contributes to carbon storage loss in the region.

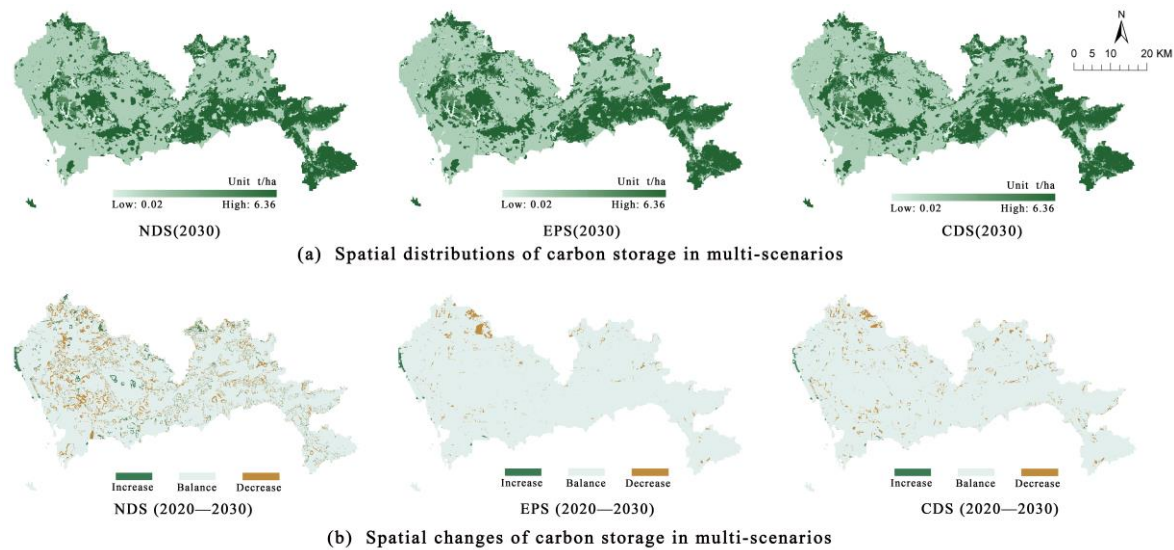


Figure 9. Carbon storage prediction under multi-scenarios (2020–2030). Spatial distributions of carbon storage in multi-scenarios (a) and spatial changes of carbon storage in multi-scenarios (b).

4. Discussion

4.1. LULCC Modeling Based on RF

In this study, we assessed potential changes in land use and carbon storage by 2030 under three development scenarios, utilizing a machine learning approach to develop an RF-CA-Markov model. This innovative method enhances the precision of land-use simulations. Our comparative analysis of the RF-CA-Markov and MCE-CA-Markov models revealed that the accuracy of land-use simulations is significantly improved when combining the RF algorithm with CA-Markov models, particularly for smaller and more fragmented land-use types. As presented in Table 4 and Figure 10, our findings indicate that the RF-CA-Markov model outperformed the MCE-CA-Markov model, achieving a kappa coefficient and overall accuracy that are 0.1 and 6.28% higher, respectively. This difference in accuracy is most pronounced for cultivated land, grassland, and waterbodies. The RF-CA-Markov model demonstrated relatively low gaps in simulation accuracy across various land-use types, with producer and user accuracies for cultivated land, grassland, and waterbodies exceeding 55.00%. In contrast, the overall simulation accuracy of the MCE-CA-Markov model was lower, with only the producer accuracy for grassland surpassing 50% among the three categories. This discrepancy can be attributed to the predominance of forestland and construction land in Shenzhen, as they occupy a significant area and exhibit a relatively concentrated distribution. In contrast, the shares of cultivated land, grassland, and waterbodies are minimal and dispersed, making it challenging for linear regression methods to effectively capture the spatial distribution patterns of these land uses. Low-precision land-use simulations can adversely impact urban planners' decision-making, hindering rational future land-use planning. Therefore, future research should prioritize the use of models with high simulation accuracy to ensure more reliable outcomes.

Table 4. Results of validation of RF-CA-Markov and MCE-CA-Markov models.

RF-CA-Markov		MCE-CA-Markov	
Kappa	0.78	Kappa	0.68
Overall Accuracy	86.70%	Overall Accuracy	80.42%

Table 4. Cont.

RF-CA-Markov			MCE-CA-Markov		
Producer's Accuracy	Cultivated land	64.87%	Producer's Accuracy	Cultivated land	71.59%
	Forestland	88.03%		Forestland	86.24%
	Grassland	56.46%		Grassland	52.54%
	Waterbodies	62.95%		Waterbodies	38.40%
	Construction land	91.49%		Construction land	81.93%
User's Accuracy	Cultivated land	64.51%	User's Accuracy	Cultivated land	49.20%
	Forestland	88.22%		Forestland	82.04%
	Grassland	55.62%		Grassland	34.15%
	Waterbodies	61.10%		Waterbodies	48.60%
	Construction land	91.68%		Construction land	91.80%

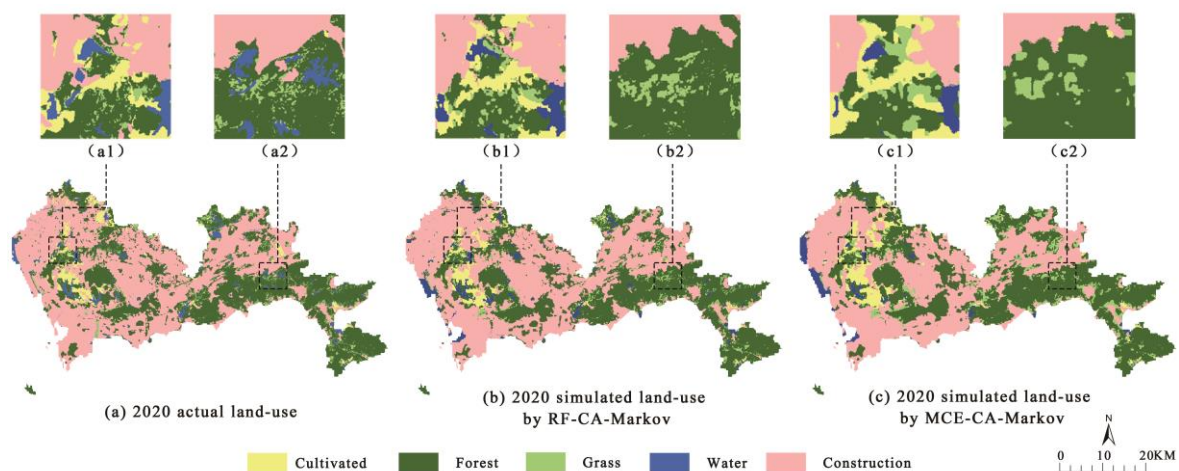


Figure 10. Comparison between the 2020 actual land use (a), 2020 simulated land use by RF-CA-Markov (b), and 2020 simulated land use by MCE-CA-Markov (c). The RF-CA-Markov has a better performance in regard to improving the accuracy of land-use simulations, especially for small and scattered land-use types. (a1–c2) represent regions of detailed magnification.

4.2. Impacts of LULCC on Carbon Storage

According to our research, the two primary ways that the LULCC affects carbon storage are through spatial layout and total quantity. First, we found that there is a strong similarity between the spatial distribution of carbon storage and land-use in Shenzhen during the period 2000–2020, with the majority regions of high carbon storage clustered in the eastern region rich in vegetation resources. And the western region, which has an abundance of waterbodies and development sites, is where the low carbon storage regions are mostly found. The medium carbon storage regions coincided with distribution pattern of cultivated land. Furthermore, significant changes in land-use types have resulted in substantial fluctuations in carbon storage.

In exploring the impact of LULCC on carbon storage, the conclusions of this study align with those found by other scholars. The findings indicate that the transition between high-carbon-density land and low-carbon-density land is the primary driver of changes in carbon storage. In particular, the transition from forestland to construction land has shown that, in line with previous researchers' findings, the major increases and decreases in carbon storage originate from the shifts between land uses with strong and weak capacities for storing carbon [55,56]. At the same time, we also found that, among the four types of carbon pools, the soil carbon pool is the most important one, and the changes between different land uses will lead to great fluctuations of the soil carbon pool. In the terrestrial ecosystem, the capacity of the soil carbon pool can determine the size of total carbon storage to the greatest extent [57]. In addition, when exploring the deeper driving factors

of LULCC, compared to previous studies, we also found that construction land, grassland, and waterbodies are greatly influenced by nighttime light data, indicating that these types of land use are mainly affected by the level of socio-economic development and human-activity interference. In contrast, cultivated land is mainly affected by the distance between ancillary roads and nighttime lights, usually located in areas with larger distances. The above two points prove that the main driving force of LULCC is socio-economic and population factors [58]. While forestland is greatly influenced by natural factors such as DEM and annual precipitation, which correlate closely with the high altitude, sufficient sunlight, and high humidity of the forestland, this is beneficial to the photosynthetic carbon fixation function of plants. However, this aspect is less frequently addressed in prior studies [59,60].

How can we adjust the land-use structure to mitigate the decline of carbon storage during future urban development? Our multi-scenario forecasting model reveals that the conversion of cultivated land and forestland is a significant driver of carbon storage loss in the region. The balance of land-use proportions among forestland, cultivated land, and construction land directly affects total urban carbon storage (Figure 11). Under the three development scenarios, carbon storage in construction land continues to increase due to ongoing expansion; conversely, carbon storage in the other four land-use types shows a declining trend, with the most substantial reductions observed in forestland and cultivated land (Figure 11a). In the ecological protection scenario, stringent preservation of ecological spaces results in the smallest loss of carbon storage. In contrast, the comprehensive development scenario, which imposes only moderate conversion restrictions on forestland and cultivated land, achieves a carbon storage level that is 17.46×10^4 t higher than in the natural development scenario. This finding suggests that future development plans should prioritize the maintenance of forest and cultivated land ecosystems while minimizing their degradation due to construction land development to effectively mitigate carbon storage loss. Figure 11b illustrates that, in all three development scenarios, forestland serves as the core carbon reservoir, with its carbon storage proportion exceeding 70%, the highest among land-use types. This is followed by construction land, cultivated land, grassland, and waterbodies. Although construction land is not classified as a high-carbon-density land-use type, its expansion, driven by urban development trends, remains a dominant factor.

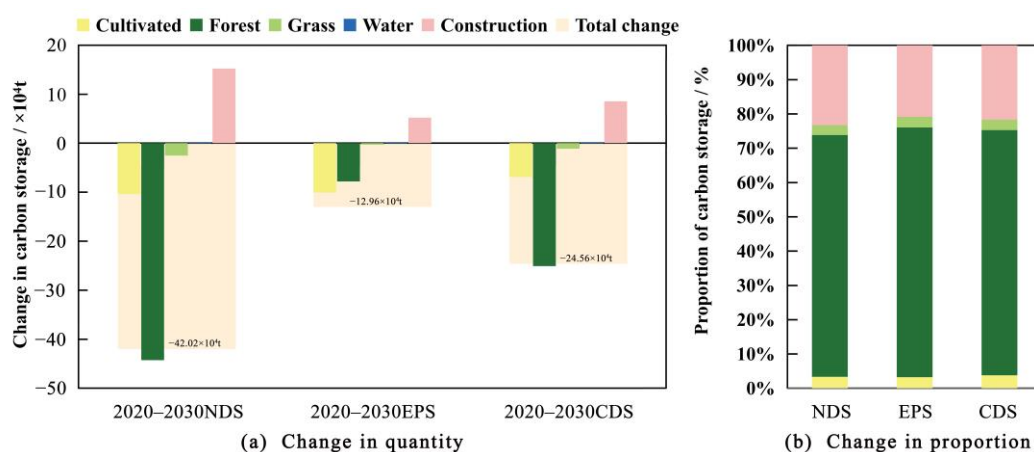


Figure 11. The change of carbon storage of land use in Shenzhen under a multi-scenario simulation in 2030. Changes in carbon storage quantities across different land-use types (a) and changes in the proportion of carbon storage across different land-use types (b).

4.3. Policy Proposal

In this study, the unregulated expansion of construction land and its encroachment on ecological land are identified as the primary causes of the rapid decline in urban carbon storage. Consequently, we propose several policy recommendations aimed at maximizing

the carbon sequestration benefits of Shenzhen, which can be optimized in the following two aspects:

In terms of construction land management, firstly, it is essential to moderately control the expansion rate of construction land and focus on refined management practices to promote intensive development. Secondly, if development is necessary due to urban strategic planning, more detailed carbon sequestration-capacity monitoring of land-use types should be conducted, prioritizing the development on land spaces with relatively weaker carbon sequestration capabilities. Lastly, the carbon sequestration potential of construction land can be further explored by fully utilizing its three-dimensional spatial potential. This includes employing building materials with enhanced carbon sequestration properties and expanding areas of three-dimensional greening to improve the carbon sequestration capacity of construction land, thereby bolstering the city's future carbon sequestration abilities.

Regarding the management of ecological land, firstly, it is essential to strengthen the protection of high-density land-use types, such as forest land, cultivated land, and grassland. For instance, formulating forest-conservation plans is crucial. Given the significant impact of human activities on grasslands and cultivated land, it is imperative to enhance policies for the protection of cultivated land and promote ecological restoration projects for grasslands to effectively mitigate adverse human interference. Secondly, the carbon sequestration functions of various ecosystems should be improved through scientific approaches. Relevant studies have indicated that reasonable and effective farming practices can enhance soil carbon storage in cultivated land [61]. Additionally, the carbon sequestration capacity of forest land can be improved by optimizing tree species and age composition [59]. Lastly, ecological networks and corridors should be established to connect isolated ecological spaces, particularly to enhance the interconnectivity of small ecological spaces within construction land. This approach ensures that the ecological land area does not decrease but only increases, thereby comprehensively improving the spatial quality of ecological land and enhancing its carbon storage function.

5. Conclusions

In order to combat global warming and achieve “carbon neutrality,” it is important to study the evolutionary trends in carbon storage and the effect of land use on it. In this study, we constructed a RF-CA-Markov model combined with the InVEST model to analyze the spatio-temporal changes in land use and carbon storage in Shenzhen City from 2000 to 2020. We also explored how land use and carbon storage might change in accordance with the NDS, EPS, and CDS for 2030. The study reveals the responsiveness of carbon storage to changes in land use.

The results indicate that, over the past 20 years, significant changes in land use have occurred, primarily characterized by the conversion of forestland to construction land. Concurrently, carbon storage has exhibited a declining trend in quantity, attributed to this conversion of forestland to construction land, particularly concentrated in regions undergoing rapid urbanization. Multi-scenario simulations of land-use and carbon storage in 2030 indicate that, with further urban land development, carbon storage will continue to decline. However, enhanced protection of ecological land significantly mitigates the rate of carbon storage decline. Finally, the study found that the RF-CA-Markov model, optimized with random forest, effectively extracts rules governing land-use transitions with high accuracy, thereby enhancing the simulation precision of land-use dynamics. Based on these conclusions, it is evident that future planning and design should continuously strengthen control over urban development expansion, enhancing land-use intensification, optimizing the ecological security framework, and protecting the integrity of ecosystems. Ultimately, this approach will fully leverage the role of high-quality forested areas as carbon sinks. Moreover, the importance of driving factors calculated by the random forest algorithm indicates a close correlation between the expansion of various land uses and the intensity of

human activity. Therefore, in future planning, it is crucial to consider population dynamics as a significant factor to incorporate into strategic planning and design.

This study acknowledges several limitations in data acquisition and model application. First, while the InVEST model selected for this research is appropriate for the study area's scale and designed to estimate carbon storage based on large-scale land-use changes, it has inherent limitations. The model simplifies the carbon cycle by assuming that carbon density remains constant over time and does not account for variations in carbon sequestration capacity among different vegetation types. Additionally, it overlooks key indicators critical for carbon sequestration, such as photosynthetic rates and soil microbial activity. Second, although the RF-CA-Markov is an improved land-use simulation model, it still fails to capture the complexity of real-world LULCC, particularly the effects of hard-to-measure policy factors, such as transportation, population dynamics, and development zone planning, which can directly influence assessments of carbon storage. In future studies, the accuracy of carbon storage estimates could be enhanced by incorporating field research data. To increase the scientific validity of land-use modeling and improve the precision of carbon storage assessments, policy considerations such as transportation, population dynamics, and development zone planning should be integrated into the driving factor system. Although the models we used have certain limitations, we have noticed that other scholars also employ similar methods. Our approach can still reveal the impact of land-use changes on carbon storage [62–64].

Author Contributions: Conceptualization, C.W. and M.D.; methodology, C.W.; software, M.L. and M.D.; formal analysis, C.W. and X.W.; data curation, M.L. and X.W.; writing—original draft preparation, C.W.; writing—review and editing, C.W., M.L., X.W., M.D., Y.W. and W.H.; visualization, M.L., M.D., Y.W. and X.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by THE GUANGDONG BASIC AND APPLIED BASIC RESEARCH FOUNDATION, grant number 2024A1515010507; and the SHENZHEN BASIC RESEARCH PROJECT, grant number JCYJ20220531101010021.

Data Availability Statement: Data will be made available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Chen, M.X.; Xian, Y.; Wang, P.L.; Ding, Z.J. Climate change and multi-dimensional sustainable urbanization. *J. Geogr. Sci.* **2021**, *31*, 1328–1348. [\[CrossRef\]](#)
2. Chowdhury, M.S. Comparison of accuracy and reliability of random forest, support vector machine, artificial neural network and maximum likelihood method in land use/cover classification of urban setting. *Environ. Chall.* **2024**, *14*, 100800. [\[CrossRef\]](#)
3. Ding, W.; Chang, N.; Zhang, G.; Kang, J.; Yi, X.; Zhang, J.; Zhang, J.; Wang, L.; Li, H. Soil organic carbon changes in China's croplands: A newly estimation based on DNDC model. *Sci. Total Environ.* **2023**, *905*, 167107. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Dybala, K.E.; Steger, K.; Walsh, R.G.; Smart, D.R.; Gardali, T.; Seavy, N.E. Optimizing carbon storage and biodiversity co-benefits in reforested riparian zones. *J. Appl. Ecol.* **2019**, *56*, 343–353. [\[CrossRef\]](#)
5. Eglinton, T.I.; Galy, V.V.; Hemingway, J.D.; Feng, X.J.; Bao, H.Y.; Blattmann, T.M.; Dickens, A.F.; Gies, H.; Giosan, L.; Haghipour, N.; et al. Climate control on terrestrial biospheric carbon turnover. *Proc. Natl. Acad. Sci. USA* **2021**, *118*, e2011585118. [\[CrossRef\]](#)
6. Fu, F.; Deng, S.M.; Wu, D.; Liu, W.W.; Bai, Z.H. Research on the spatiotemporal evolution of land use landscape pattern in a county area based on CA-Markov model. *Sustain. Cities Soc.* **2022**, *80*, 103760. [\[CrossRef\]](#)
7. Fu, H.Z.; Waltman, L.; Oppenheimer, M.; Yohe, G. A large-scale bibliometric analysis of global climate change research between 2001 and 2018. *Clim. Chang.* **2022**, *170*, 36. [\[CrossRef\]](#)
8. Fu, K.; Chen, L.; Yu, X.; Jia, G. How has carbon storage changed in the Yili-Tianshan region over the past three decades and into the future? What has driven it to change? *Sci. Total Environ.* **2024**, *945*, 174005. [\[CrossRef\]](#)
9. Fu, X.; Wang, X.H.; Yang, Y.J. Deriving suitability factors for CA-Markov land use simulation model based on local historical data. *J. Environ. Manag.* **2018**, *206*, 10–19. [\[CrossRef\]](#)
10. Gounaridis, D.; Chorianopoulos, I.; Symeonakis, E.; Koukoulas, S. A Random Forest-Cellular Automata modelling approach to explore future land use/cover change in Attica (Greece), under different socio-economic realities and scales. *Sci. Total Environ.* **2019**, *646*, 320–335. [\[CrossRef\]](#)
11. Han, M.G.; Zhu, B. Changes in soil greenhouse gas fluxes by land use change from primary forest. *Glob. Chang. Biol.* **2020**, *26*, 2656–2667. [\[CrossRef\]](#) [\[PubMed\]](#)

12. Hao, L.N.; He, S.; Zhou, J.L.; Zhao, Q.; Lu, X. Prediction of the landscape pattern of the Yancheng Coastal Wetland, China, based on XGBoost and the MCE-CA-Markov model. *Ecol. Indic.* **2022**, *145*, 109735. [\[CrossRef\]](#)
13. Kafy, A.A.; Saha, M.; Fattah, M.A.; Rahman, M.T.; Dutti, B.M.; Rahaman, Z.A.; Bakshi, A.; Kalaivani, S.; Nafiz Rahaman, S.; Sattar, G.S. Integrating forest cover change and carbon storage dynamics: Leveraging Google Earth Engine and InVEST model to inform conservation in hilly regions. *Ecol. Indic.* **2023**, *152*, 110374. [\[CrossRef\]](#)
14. Kundu, S.; Khare, D.; Mondal, A. Past, present and future land use changes and their impact on water balance. *J. Environ. Manag.* **2017**, *197*, 582–596. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Li, W.; Ciais, P.; Peng, S.S.; Yue, C.; Wang, Y.L.; Thurner, M.; Saatchi, S.S.; Arneeth, A.; Avitabile, V.; Carvalhais, N.; et al. Land-use and land-cover change carbon emissions between 1901 and 2012 constrained by biomass observations. *Biogeosciences* **2017**, *14*, 5053–5067. [\[CrossRef\]](#)
16. Liang, X.; Guan, Q.F.; Clarke, K.C.; Liu, S.S.; Wang, B.Y.; Yao, Y. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, e101569. [\[CrossRef\]](#)
17. Liang, X.; Liu, X.P.; Li, X.; Chen, Y.M.; Tian, H.; Yao, Y. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landsc. Urban Plan.* **2018**, *177*, 47–63. [\[CrossRef\]](#)
18. Liao, G.T.; He, P.; Gao, X.S.; Lin, Z.Y.; Huang, C.Y.; Zhou, W.; Deng, O.P.; Xu, C.H.; Deng, L.J. Land use optimization of rural production-living-ecological space at different scales based on the BP-ANN and CLUE-S models. *Ecol. Indic.* **2022**, *137*, 108710. [\[CrossRef\]](#)
19. Lin, J.Y.; He, P.T.; Yang, L.; He, X.Y.; Lu, S.Y.; Liu, D.Y. Predicting future urban waterlogging-prone areas by coupling the maximum entropy and FLUS model. *Sustain. Cities Soc.* **2022**, *80*, 103812. [\[CrossRef\]](#)
20. Lindén, L.; Riikonen, A.; Setälä, H.; Yli-Pelkonen, V. Quantifying carbon stocks in urban parks under cold climate conditions. *Urban For. Urban Green.* **2020**, *49*, 126633. [\[CrossRef\]](#)
21. Piao, S.L.; He, Y.; Wang, X.H.; Chen, F.H. Estimation of China's terrestrial ecosystem carbon sink: Methods, progress and prospects. *Sci. China-Earth Sci.* **2022**, *65*, 641–651. [\[CrossRef\]](#)
22. Robinson, D.T.; Di Vittorio, A.; Alexander, P.; Arneeth, A.; Barton, C.M.; Brown, D.G.; Kettner, A.; Lemmen, C.; O'Neill, B.C.; Janssen, M.; et al. Modelling feedbacks between human and natural processes in the land system. *Earth Syst. Dyn.* **2018**, *9*, 895–914. [\[CrossRef\]](#)
23. Santé, I.; García, A.M.; Miranda, D.; Crecente, R. Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landsc. Urban Plan.* **2010**, *96*, 108–122. [\[CrossRef\]](#)
24. Saxena, A.; Jat, M.K. Land suitability and urban growth modeling: Development of SLEUTH-Suitability. *Comput. Environ. Urban Syst.* **2020**, *81*, 101475. [\[CrossRef\]](#)
25. Tepe, E.; Safikhani, A. Spatio-temporal modeling of parcel-level land-use changes using machine learning methods. *Sustain. Cities Soc.* **2023**, *90*, 104390. [\[CrossRef\]](#)
26. Wang, J.Y.; Bretz, M.; Dewan, M.; Delavar, M.A. Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Sci. Total Environ.* **2022**, *822*, 153559. [\[CrossRef\]](#)
27. Wei, G.; Zhang, C.; Li, Q.; Wang, H.; Wang, R.; Zhang, Y.; Yuan, Y. An evaluation of topsoil carbon storage in Chinese deserts. *Sci. Total Environ.* **2023**, *872*, 162284. [\[CrossRef\]](#)
28. Wu, Q.; Wang, L.; Wang, T.; Ruan, Z.; Du, P. Spatial-temporal evolution analysis of multi-scenario land use and carbon storage based on PLUS-InVEST model: A case study in Dalian, China. *Ecol. Indic.* **2024**, *166*, 112448. [\[CrossRef\]](#)
29. Wu, X.; Pan, J.; Zhu, X. Optimizing the ecological source area identification method and building ecological corridor using a genetic algorithm: A case study in Weihe River Basin, NW China. *Ecol. Inform.* **2024**, *80*, 102519. [\[CrossRef\]](#)
30. Xiong, N.; Lu, H.; Yang, X.; Wang, J.; Yue, D. Spatial characteristics and multifactorial driving analysis of fly-tipping bulky waste in Beijing based on the random forest model. *J. Clean. Prod.* **2022**, *363*, 132534. [\[CrossRef\]](#)
31. Xiong, Q.L.; Xiao, Y.; Halmy, M.; Pan, K.W.; Dakhil, M.A.; Zhang, L.; Li, T.; Liang, P.H. A blessing for the Yangtze River: Optimization of Chinese regional policy planning for water yield and purification in the Three Gorges Reservoir Area. *Environ. Sci. Pollut. Res.* **2020**, *27*, 7040–7052. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Xu, T.T.; Gao, J.; Coco, G. Simulation of urban expansion via integrating artificial neural network with Markov chain—Cellular automata. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 1960–1983. [\[CrossRef\]](#)
33. Yang, D.; Luan, W.X.; Li, Y.; Zhang, Z.C.; Tian, C. Multi-scenario simulation of land use and land cover based on shared socioeconomic pathways: The case of coastal special economic zones in China. *J. Environ. Manag.* **2023**, *335*, 117536. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Ye, L.; Zhao, S.; Yang, H.; Chuai, X.; Zhai, L. Urban land use simulation and carbon-related driving factors analysis based on RF-CA in Shanghai, China. *Ecol. Indic.* **2024**, *166*, 112555. [\[CrossRef\]](#)
35. Zafar, Z.; Zubair, M.; Zha, Y.; Mehmood, M.S.; Rehman, A.; Fahd, S.; Nadeem, A.A. Predictive modeling of regional carbon storage dynamics in response to land use/land cover changes: An InVEST-based analysis. *Ecol. Inform.* **2024**, *82*, 102701. [\[CrossRef\]](#)
36. Zhao, J.F.; Liu, D.S.; Cao, Y.; Zhang, L.J.; Peng, H.W.; Wang, K.L.; Xie, H.F.; Wang, C.Z. An integrated remote sensing and model approach for assessing forest carbon fluxes in China. *Sci. Total Environ.* **2022**, *811*, 152480. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Zhou, L.; Dang, X.; Sun, Q.; Wang, S. Multi-scenario simulation of urban land change in Shanghai by random forest and CA-Markov model. *Sustain. Cities Soc.* **2020**, *55*, 102045. [\[CrossRef\]](#)

38. Zhou, W.; Li, H.R.; Xie, L.J.; Nie, X.M.; Wang, Z.; Du, Z.P.; Yue, T.X. Remote sensing inversion of grassland aboveground biomass based on high accuracy surface modeling. *Ecol. Indic.* **2021**, *121*, 107215. [\[CrossRef\]](#)
39. Cheng, J.; Chen, M.; Tang, S. Shenzhen—A typical benchmark of Chinese rapid urbanization miracle. *Cities* **2023**, *140*, 104421. [\[CrossRef\]](#)
40. Liu, X.; Li, Y.; Zhang, S.; Niu, Q. Spatiotemporal patterns, driving mechanism, and multi-scenario simulation of urban expansion in Min Delta Region, China. *Ecol. Indic.* **2024**, *158*, 111312. [\[CrossRef\]](#)
41. Zhou, J.; Zhao, Y.; Huang, P.; Zhao, X.; Feng, W.; Li, Q.; Xue, D.; Dou, J.; Shi, W.; Wei, W.; et al. Impacts of ecological restoration projects on the ecosystem carbon storage of inland river basin in arid area, China. *Ecol. Indic.* **2020**, *118*, 106803. [\[CrossRef\]](#)
42. Xu, L.; He, N.; Yu, G. A dataset of carbon density in Chinese terrestrial ecosystems (2010s). *Sci. Data Bank* **2018**, *4*. [\[CrossRef\]](#)
43. Lint, Y.M.; Wu, D.F. Spatial correlation and prediction of land use carbon storage based on the InVEST-PLUS model: A case study in Guangdong Province. *China Environ. Sci.* **2022**, *42*, 4827–4839.
44. Zhu, Z.Q.; Ma, X.; Hu, H. Spatio-temporal evolution and prediction of ecosystem carbon stocks in Guangzhou City by coupling FLUS-InVEST models. *Bull. Soil Water Conserv.* **2021**, *41*, 222–229.
45. Juanyu, W.; Yilei, Z.; Weikang, J. Spatio-temporal evolution of ecosystem carbon storage in guangdong-Hong Kong-Macao greater bay area. *Landsc. Archit.* **2020**, *27*, 57–63.
46. Zhang, Z.; Jiang, W.; Peng, K.; Wu, Z.; Ling, Z.; Li, Z. Assessment of the impact of wetland changes on carbon storage in coastal urban agglomerations from 1990 to 2035 in support of SDG15. 1. *Sci. Total Environ.* **2023**, *877*, 162824. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Sheykhou, M.; Mahdianpari, M.; Ghanbari, H.; Mohammadimanesh, F.; Ghamisi, P.; Homayouni, S. Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 6308–6325. [\[CrossRef\]](#)
48. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
49. Ho, T.K. The random subspace method for constructing decision forests. *IEEE Trans. Pattern Anal. Mach. Intell.* **1998**, *20*, 832–844.
50. Ghosh, S.; Chatterjee, N.D.; Dinda, S. Urban ecological security assessment and forecasting using integrated DEMATEL-ANP and CA-Markov models: A case study on Kolkata Metropolitan Area, India. *Sustain. Cities Soc.* **2021**, *68*, 102773. [\[CrossRef\]](#)
51. Zhang, Z.; Hu, B.; Jiang, W.; Qiu, H. Identification and scenario prediction of degree of wetland damage in Guangxi based on the CA-Markov model. *Ecol. Indic.* **2021**, *127*, 107764. [\[CrossRef\]](#)
52. Mokarram, M.; Pourghasemi, H.R.; Hu, M.; Zhang, H. Determining and forecasting drought susceptibility in southwestern Iran using multi-criteria decision-making (MCDM) coupled with CA-Markov model. *Sci. Total Environ.* **2021**, *781*, 146703. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Beyene, E.; Minale, A.S. Modeling urban land use dynamics using Markov-chain and cellular automata in Gondar City, Northwest Ethiopia. *Chin. J. Popul. Resour. Environ.* **2023**, *21*, 111–120. [\[CrossRef\]](#)
54. El Haj, F.A.; Ouadif, L.; Akhssas, A. Simulating and predicting future land-use/land cover trends using CA-Markov and LCM models. *Case Stud. Chem. Environ. Eng.* **2023**, *7*, 100342. [\[CrossRef\]](#)
55. Liu, Q.; Yang, D.; Cao, L.; Anderson, B. Assessment and prediction of carbon storage based on land use/land cover dynamics in the tropics: A case study of hainan island, China. *Land* **2022**, *11*, 244. [\[CrossRef\]](#)
56. Zhu, G.; Qiu, D.; Zhang, Z.; Sang, L.; Liu, Y.; Wang, L.; Zhao, K.; Ma, H.; Xu, Y.; Wan, Q. Land-use changes lead to a decrease in carbon storage in arid region, China. *Ecol. Indic.* **2021**, *127*, 107770. [\[CrossRef\]](#)
57. Sahu, C.; Mishra, R.; Basti, S. Land-use change affects carbon storage and lability in tropical soil of India. *Geoderma Reg.* **2023**, *32*, e00621. [\[CrossRef\]](#)
58. Setiawan, O.; Rahayu, A.A.D.; Samawandana, G.; Tata, H.L.; Dharmawan, I.W.S.; Rachmat, H.H.; Suharti, S.; Windyoningrum, A.; Khotimah, H. Unraveling land use land cover change, their driving factors, and implication on carbon storage through an integrated modelling approach. *Egypt. J. Remote Sens. Space Sci.* **2024**, *27*, 615–627. [\[CrossRef\]](#)
59. Liu, J.; Yan, Q.; Zhang, M. Ecosystem carbon storage considering combined environmental and land-use changes in the future and pathways to carbon neutrality in developed regions. *Sci. Total Environ.* **2023**, *903*, 166204. [\[CrossRef\]](#)
60. Wang, N.; Chen, X.; Zhang, Z.; Pang, J. Spatiotemporal dynamics and driving factors of county-level carbon storage in the Loess Plateau: A case study in Qingcheng County, China. *Ecol. Indic.* **2022**, *144*, 109460. [\[CrossRef\]](#)
61. Yu, Z.; Lu, C.; Cao, P.; Tian, H. Long-term terrestrial carbon dynamics in the Midwestern United States during 1850–2015: Roles of land use and cover change and agricultural management. *Glob. Chang. Biol.* **2018**, *24*, 2673–2690. [\[CrossRef\]](#) [\[PubMed\]](#)
62. Wu, W.; Xu, L.; Zheng, H.; Zhang, X. How much carbon storage will the ecological space leave in a rapid urbanization area? Scenario analysis from Beijing-Tianjin-Hebei Urban Agglomeration. *Resour. Conserv. Recycl.* **2023**, *189*, 106774. [\[CrossRef\]](#)
63. Nie, X.; Lu, B.; Chen, Z.; Yang, Y.; Chen, S.; Chen, Z.; Wang, H. Increase or decrease? Integrating the CLUMondo and InVEST models to assess the impact of the implementation of the Major Function Oriented Zone planning on carbon storage. *Ecol. Indic.* **2020**, *118*, 106708. [\[CrossRef\]](#)
64. Zhao, M.; He, Z.; Du, J.; Chen, L.; Lin, P.; Fang, S. Assessing the effects of ecological engineering on carbon storage by linking the CA-Markov and InVEST models. *Ecol. Indic.* **2019**, *98*, 29–38. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.