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Sub-District Level Spatiotemporal Changes of Carbon Storage and Driving Factor Analysis: A Case Study in Beijing

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Abstract: Analyzing the current trends and causes of carbon storage changes and accurately predicting future land use and carbon storage changes under different climate scenarios is crucial for regional land use decision-making and carbon management. This study focuses on Beijing as its study area and introduces a framework that combines the Markov model, the Patch-based Land Use Simulation (PLUS) model, and the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model to assess carbon storage at the sub-district level. This framework allows for a systematic analysis of land use and carbon storage spatiotemporal evolution in Beijing from 2000 to 2020, including the influence of driving factors on carbon storage. Moreover, it enables the simulation and prediction of land use and carbon storage changes in Beijing from 2025 to 2040 under various scenarios. The results show the following: (1) From 2000 to 2020, the overall land use change in Beijing showed a trend of "Significant decrease in cropland area; Forest increase gradually; Shrub and grassland area increase first and then decrease; Decrease and then increase in water; Impervious expands in a large scale". (2) From 2000 to 2020, the carbon storage in Beijing showed a "decrease-increase" fluctuation, with an overall decrease of 1.3 Tg. In future carbon storage prediction, the ecological protection scenario will contribute to achieving the goals of carbon peak and carbon neutrality. (3) Among the various driving factors, slope has the strongest impact on the overall carbon storage in Beijing, followed by Human Activity Intensity (HAI) and Nighttime Light Data (NTL). In the analysis of carbon storage in the built-up areas, it was found that HAI and DEM (Digital Elevation Model) have the strongest effect, followed by NTL and Fractional Vegetation Cover (FVC). The findings from this study offer valuable insights for the sustainable advancement of ecological conservation and urban development in Beijing.

Keywords: carbon storage; land use; Markov–PLUS model; GTWR; Sen + MK

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1. Introduction

Currently, the greenhouse effect caused by factors such as carbon emissions has become one of the major issues affecting human survival and economic development [1]. According to the 2023 Carbon Emissions Report released by the International Energy Agency (IEA), global energy-related carbon dioxide emissions increased by 1.1% in 2023, rising by 410 million tons to a total of 37.4 billion tons, of which China's carbon emissions accounted for 12.6 billion tons [2]. Carbon within terrestrial ecosystems constitutes a significant component of global carbon storage; terrestrial carbon storage plays a crucial role in mitigating

atmospheric carbon dioxide concentrations and alleviating global climate change [3,4]. Previous research has demonstrated that land use patterns and soil organic carbon pools are fundamental determinants of carbon storage capacity in terrestrial ecosystems [5]. The conversion of land use types in different periods significantly affected the change of carbon storage. From 1990 to 2020, the plantation area in China almost doubled, and the aboveground carbon storage increased from 675.6 ± 12.5 Tg C to 1873.1 ± 16.2 Tg C [6,7]. As land use patterns shift due to social and economic development, simulating and predicting associated changes in carbon storage can inform the sustainable management of land resources and promote carbon storage within the region [8].

In recent years, scholars have extensively studied carbon storage changes in various land use systems in the world's terrestrial ecosystems [9–11]. However, we found that existing studies on carbon storage changes have largely focused on large-scale important ecological conservation areas, river basins, wetlands, and coastal regions, which are ecologically fragile. In contrast, research on urban scales is relatively scarce, particularly when it comes to mega-cities [12]. The role of mega-cities in the economic and social development of a country, as well as in assessing urban carbon storage and addressing the climate crisis, is crucial [13]. The choice of scale is significant for analyzing carbon storage changes in cities. Existing studies have mainly focused on the provincial [14] and municipal [15,16] scales to estimate carbon storage, providing references for increasing carbon storage and improving climate change in cities. However, due to the complex spatial structure of cities, there are significant differences in carbon storage trends in different regions within the same city [17]. To address this issue, adopting sub-district as the fundamental analytical unit presents a viable methodological approach. Sub-district, as the basic planning unit of the urban system, offers a novel approach for analyzing carbon storage dynamics. It has clear and stable geographical and administrative boundaries, facilitating data collection [18]. The research findings at the sub-district level serve as a micro-foundation for the overall urban analysis. By aggregating carbon storage change data of each sub-district, the spatial distribution pattern of urban carbon storage change can be obtained, and significant change areas can be pinpointed, providing precise target area positioning for urban planning strategies [19,20]. Moreover, studies have shown that studying multiple sub-districts over different time sequences helps observe the evolution trends of different urban areas, which aids in understanding the dynamic relationship between urban development and environmental change [21]. Thus, a sub-district level was adopted in this study to quantify carbon storage capacity and investigate the driving factors, covering spatial and temporal dimensions and providing a comprehensive framework for understanding urban carbon dynamics at a fine scale.

Land cover change is a tangible example of how human civilization and environment are intertwined. It is closely related to ecological environment and urban spatial planning, so the transition between land cover affects the change of carbon storage. Therefore, the change in carbon storage caused by LUCC (Land Use and Cover Change) in terrestrial ecosystems has become a prominent topic for researchers at home and abroad [22]. Coupling multiple models to analyze the change on carbon storage is currently the main method for revealing the current status and future trends of regional carbon storage. The methods and models used for simulating and calculating carbon storage include plot inventories [23,24], remote sensing estimation [25,26], and model estimation [27,28]. While plot inventories offer clear estimations and ease of operation, their limited spatial representativeness and small sample sizes restrict their ability to accurately capture the link between long-term temporal and large-scale spatial variations in carbon storage driven by natural and anthropogenic factors [29]. Remote sensing estimation is also widely used for estimating terrestrial ecosystem carbon storage. However, since remote sensing can only

monitor aboveground areas, the carbon storage calculated using remote sensing methods is limited to aboveground carbon storage and cannot accurately reflect the overall level of carbon storage [30]. Model-based estimation approaches have gained widespread recognition in carbon storage research due to their minimal data requirements and robust analytical capabilities. These methodologies demonstrate high accuracy in assessment outcomes and exhibit remarkable adaptability across various spatial scales in regional carbon storage dynamics studies [31–33]. Among them, the InVEST model is easy to handle and has the advantages of low data requirements, fast computation time, and the ability to visualize the spatial distribution and dynamic changes of carbon storage. It enables more convenient and efficient observation of the spatiotemporal distribution and dynamic changes of carbon storage over long time periods [34–36]. Accordingly, this study employs the InVEST model in conjunction with land use data to quantify carbon storage.

Some studies have predicted carbon storage [37–40] in some areas by using the InVEST model assessment. However, it is difficult to provide carbon storage simulations for specific scenarios or complex situations using the InVEST model alone. Therefore, it is necessary to couple the InVEST model to the land use simulation model to enable the analysis of the relationship between land use and carbon storage from a spatial and temporal perspective. Using multi-scenario simulation to predict future trajectories of ecological risk and carbon storage is critical for providing informed decision support for regional land use management. Various complex modeling approaches for land use change prediction have been developed and validated, some of which with frameworks that are particularly influential in the field. Among them, the PLUS model can more accurately capture the spatiotemporal evolution of various land use patches [41,42]. Currently, with accelerated urban development and the emergence of a series of related policies, future land use may be influenced by various factors. The integration of the PLUS model with the Markov model enables land use prediction under multiple scenarios [43,44]. Thus, studying the Markov–PLUS–InVEST model allows for dynamic quantitative analysis of carbon storage from a visual perspective, improving the accuracy of land use and carbon storage forecasts. Furthermore, the application of this method to sub-district level facilitates a more comprehensive exploration of the relationship between fine-scale land use change and carbon storage, providing insights into future trends in regional carbon storage.

More and more studies are no longer limited to a single aspect of land use change but are exploring the mechanisms between land use change and ecological indicators such as precipitation, temperature, and carbon storage. Analyzing long-term carbon storage changes and revealing their underlying causes can provide clearer information for improving carbon storage in the study area. In exploring carbon storage changes, most studies primarily analyze the numerical changes in carbon storage, lacking spatial perspectives. However, the Sen + Mann–Kendall (Sen + MK) method can effectively address these issues [45,46]. The Sen + MK method exhibits high accuracy and can capture the spatiotemporal trends of carbon storage at the sub-district level through analyzing carbon storage changes in different years. The Geographically and Temporally Weighted Regression (GTWR) analyzes the relationship between carbon storage and driving factors at the level of individual sub-district, explaining the spatial heterogeneity of the driving factors [47,48]. Additionally, we utilize the Random Forest (RF) model to explore the importance of each factor on overall carbon storage. Compared to previous methods, RF exhibits higher accuracy and better investigates the impacts of various factors on carbon storage [49]. Therefore, conducting research based on the Sen + MK method to reveal the spatiotemporal changes in carbon storage at the sub-district level, and using GTWR and RF to analyze the impacts of factors on carbon storage, can provide a detailed understanding

of the relationship between land use types, socioeconomic factors, and carbon storage. This study is of great significance for future policy-making and spatial planning.

Situated in the temperate zone with diverse land types, Beijing stores a significant amount of carbon, playing a crucial role in regional and global carbon cycling and energy flow [50]. At the same time, rapid urbanization and construction development in Beijing have led to continuous changes in land use types [51]. This study aims to explore the underlying factors of land use change and carbon storage in Beijing. On this basis, this would entail simulating the future development scenarios under the Beijing land use pattern that may trend, and estimating the corresponding carbon storage change results. Therefore, this study analyzed the characteristics of land use and carbon storage during the 2000–2020 period using the Markov–PLUS–InVEST modeling framework. Moreover, the spatial distribution pattern of carbon storage was analyzed by the method of Sen + MK, and the mechanisms of land use change and socioeconomic factors on carbon storage were revealed using the GTWR and RF models. Finally, the changes in carbon storage were predicted through different scenarios of land use types (natural development scenario (ND), economic development scenario (ED), and ecological protection scenario (EP)) from 2025 to 2040. The empirical results provide evidence-based support for optimizing land use allocation strategies in Beijing. Furthermore, this study established a standardized analytical paradigm that provides transferable implications for similar urban environments across China.

This study makes a quantitative attribution of carbon storage changes in Beijing and their driving factors at the level of individual sub-district. The contributions of this study include the following:

(1) It estimates and investigates the spatiotemporal changes in carbon storage in Beijing from 2000 to 2020;
(2) It identifies and quantifies the key factors influencing the spatiotemporal changes in carbon storage;
(3) It quantitatively reveals the scale differences and spatial heterogeneity of the impacts of these key driving factors on carbon storage;
(4) It predicts the carbon storage situation in Beijing from 2025 to 2040 under different scenarios.

2. Study Area and Data

2.1. Study Area

Beijing is the capital of China, located in north China, with a total area of 16,410 km^2 (Figure 1). In topography, the area is dominated by mountainous terrain (62%), with a clear elevation gradient descending from northwest to southeast. By the end of 2020, the forest coverage rate was about 50% of the total administrative area, with a population of 21.893 million. Rapid expansion of urban impervious areas, reduction of barren land, and shrinkage of ecological land will inevitably lead to changes in carbon storage and carbon density. The study area was the whole administrative area of Beijing. By analyzing the impact of different policy scenarios on the future land use transformation and carbon storage in Beijing, as well as the prediction of the future development trajectory, it is possible to promote a more synergistic relationship between urban agglomeration development and ecological and environmental protection.

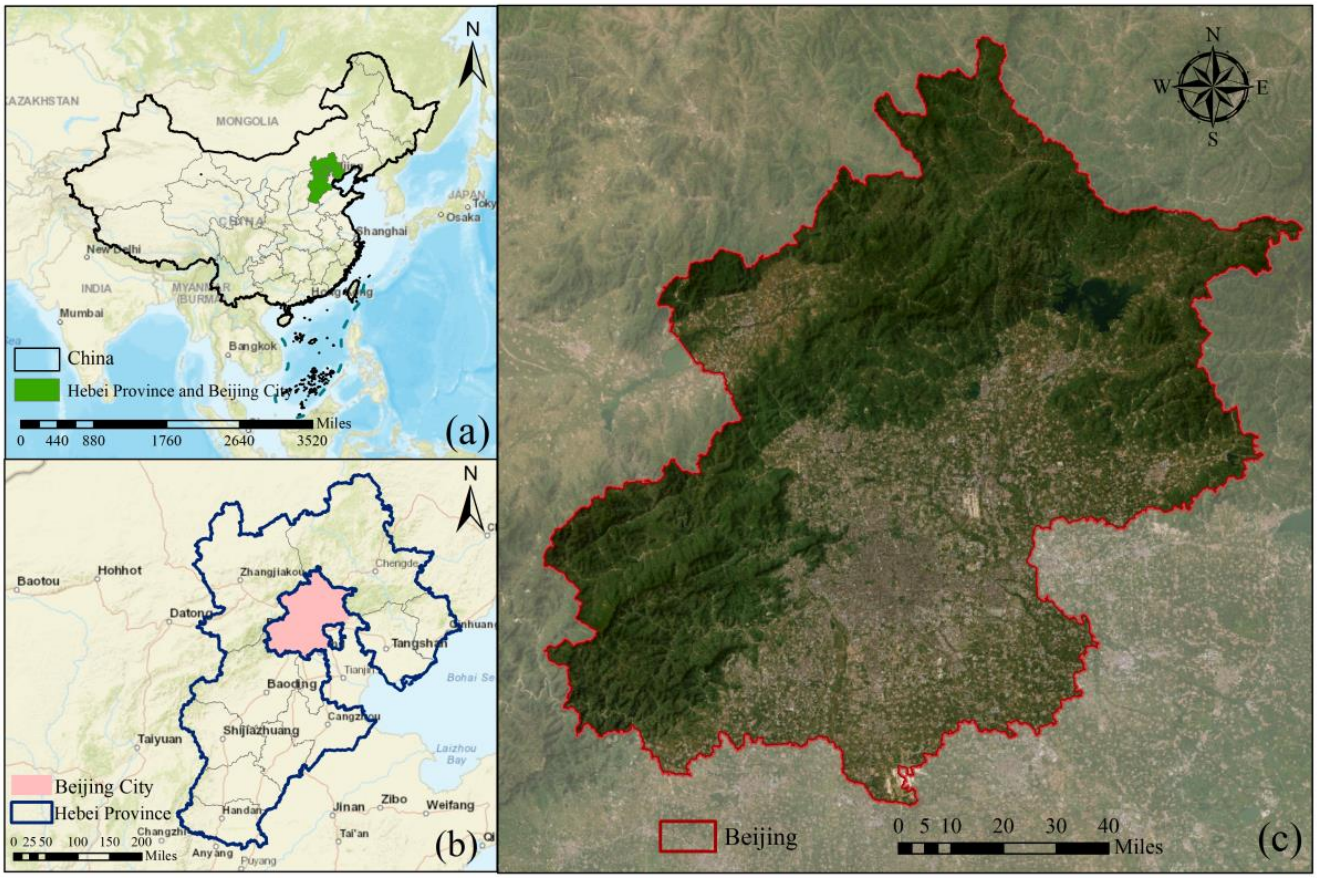


Figure 1. Location of the study area. Hebei–Beijing location map (**a**), Beijing location map (**b**), and remote sensing image of Beijing (**c**).

2.2. Data

2.2.1. Land Use Data

The land use data of Beijing in 2000, 2005, 2010, 2015, and 2020 come from the national 30 m time series land use data (China Land Cover Dataset, CLCD) released by Wuhan University (https://zenodo.org/records/5816591#.ZAWM3BVBy5c/, accessed on 1 July 2023). The land use data of the study area are divided into nine types: cropland, forest, shrub, grassland, water, snow/ice, barren, impervious, and wetland.

2.2.2. Data of Driving Factors

Eleven driving factors were selected for analysis of carbon storage changes in Beijing, guided by the principles of data availability, timeliness, and factor significance (as shown in Table 1). PM2.5 can affect carbon storage by affecting vegetation growth [43,51], and relevant studies demonstrated that it can be used as a comprehensive indicator reflecting the impact of human activities on carbon storage [29,30,52]. For NTL data, it is an intuitive representation of urbanization and the intensity of human activity. In this study, the intensity and distribution of night lights can well reflect the level of economic development, population density, and infrastructure construction in different regions [52–54].

The data come from the Resource and Environmental Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 1 July 2023). This study takes the sub-district as the unit of analysis. The unit vector data come from the National Catalogue Service For Geographic Information (https://www.webmap.cn/, accessed on 22 July 2023). The data of each driving factor are collected into the sub-district for the analysis of the drivers of subsequent carbon storage changes.

Table 1. Driving factors analyzed in this study.

	Driving Factors	Definitions	Resolution
Natural Factors	The annual average temperature (TEM)	Reflects the temperature which influences vegetation growth	1000 m
	The annual average precipitation (PREP)	Reflects the precipitation which influences vegetation growth	1000 m
	Digital Elevation Model (DEM)	Reflects the ground elevation information which affects vegetation distribution	30 m
	Slope	Reflects the ground inclination which affects vegetation distribution	30 m
	Normalized Difference Vegetation Index (NDVI)	Reflects the vegetation coverage and growth status	30 m
	Particulate Matter 2.5 (PM2.5)	Reflects the level of fine granularity in the air	1000 m
	Nighttime Light Data (NTL)	Reflect the characteristics of the urban night light intensity	1000 m
	Fractional Vegetation Cover (FVC)	Describes the density or growth of vegetation	100 m
Socioeconomic Factors	Population (POP)	Reflects the population data	1000 m
	Gross Domestic Product (GDP)	Reflects the economic situation	1000 m
	Human Activity Intensity (HAI)	Characterizes the degree of utilization, modification, and exploitation of the land surface layer by human activities	30 m

3. Methods

As shown in Figure 2, in order to achieve the objectives of this study, the research framework consists of four steps:

(1) Calculation of carbon storage: The InVEST model is introduced to calculate the carbon storage in Beijing by using carbon density data and land use categories for each year.
(2) Analysis of carbon storage changes: The spatiotemporal changes in carbon storage are analyzed using the Sen + MK model to explore variations across sub-districts, while the standard deviation ellipse is applied to examine the overall trend of carbon storage changes in Beijing.
(3) Analysis of driving factors: The RF method is used to calculate the impact of natural socioeconomic factors on the overall carbon storage in Beijing, while the GTWR method is used to analyze the factors influencing carbon storage within each sub-district.
(4) Future carbon storage prediction: The future carbon storage is predicted by using the Markov–PLUS–InVEST model to conduct multi-scenario forecasts for the period from 2025 to 2040.

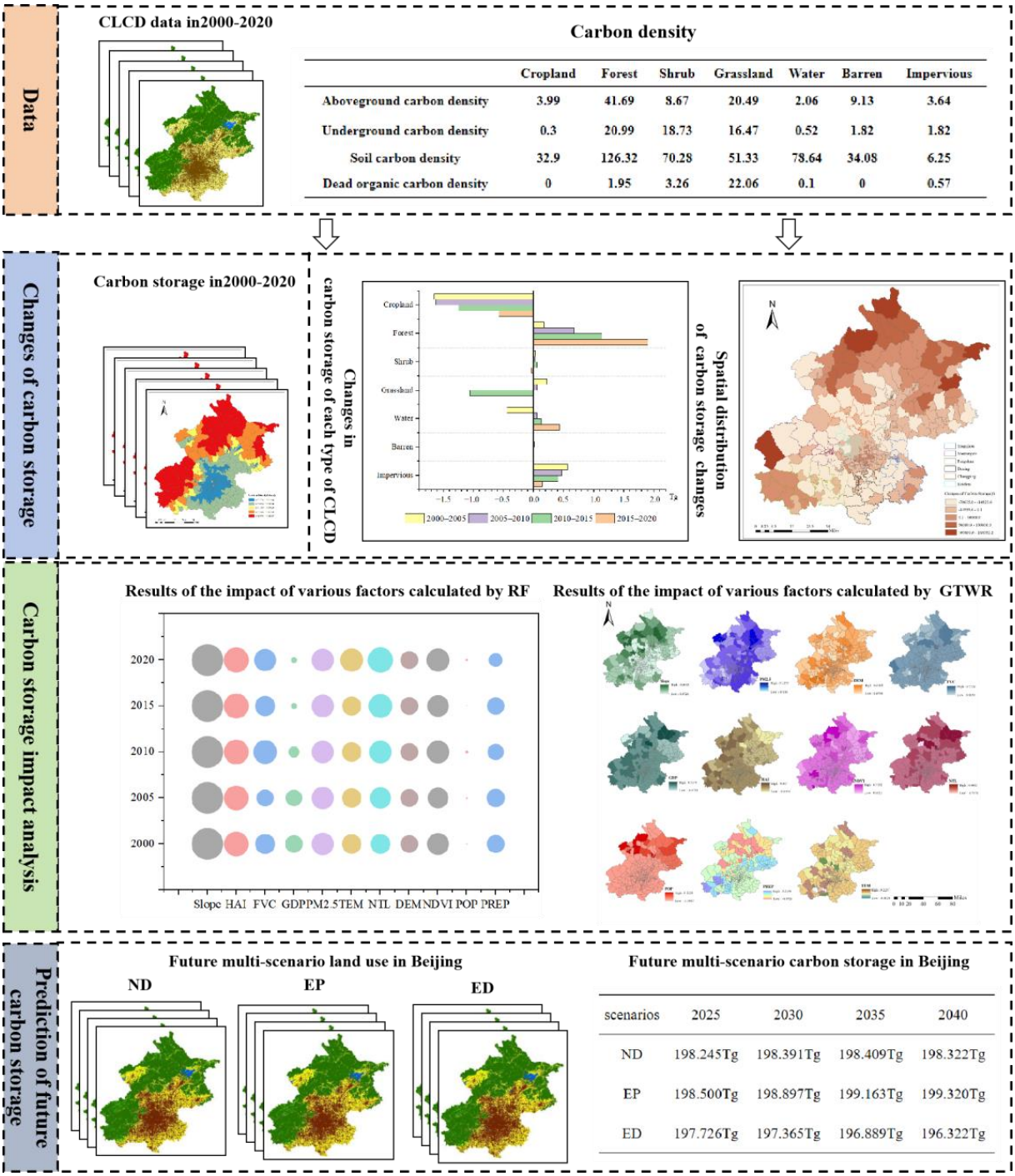


Figure 2. Flowchart of this study.

3.1. Carbon Storage Estimation Based on InVEST Model

The present study adopts the InVEST model for the quantification of carbon storage. This model employs a methodology that estimates carbon storage through the assignment of carbon density values to distinct land use categories [55]. The fundamental algorithm of the InVEST model for carbon storage assessment employs a constant carbon density coefficient for each land use classification. The total carbon storage is derived through the summation of products between land-specific carbon density param and their respective spatial coverage.

$$C_{all} = S_i \times (C_{above} + C_{below} + C_{soil} + C_{dead}) \quad (1)$$

where C_{all} represents the total carbon storage of the ecosystem (t); i is a certain land type, S_i is the area of a certain land use type (ha); C_{above},C_{below},C_{soil}, and C_{dead} represent the aboveground biological carbon density, underground carbon density, soil carbon density, and dead organic carbon density, respectively.

While the static carbon density models focus on the basic framework of relatively stable factors such as land use type and soil texture, the dynamic carbon density models focus on dynamic factors such as biological growth processes and the effects of climate change. The carbon density database developed for this study mainly utilizes the measured data from the existing literature, namely, static carbon density data. However, data from field surveys conducted within the Beijing study area are prioritized. For data that lack reference literature, the missing values are supplemented based on literature data from neighboring areas [56]. As shown in Table 2, if there are still gaps, the carbon density correction formula proposed by Alam et al. [57] and the carbon density data of six national land types obtained from Li et al. [58] are used for correction, obtaining the carbon density values corresponding to different parts of different land types in the study area. The formulas are as follows:

$$C_{BP} = 6.789 \times e^{0.0054 \times MAP} \quad (2)$$

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

$$K_{BP} = \frac{C_{BP1}}{C_{BP2}} \quad (4)$$

$$K_{SP} = \frac{C_{SP1}}{C_{SP2}} \quad (5)$$

where MAP represents the average annual precipitation, C_{BP} is the corrected biomass carbon density, C_{SP} is the corrected soil carbon density, K_{BP} denotes the biomass carbon density precipitation factor correction coefficient, and K_{SP} represents the soil carbon density precipitation factor correction coefficient.

Table 2. Carbon density of different land use types in Beijing (t/ha).

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Aboveground carbon density	3.99	41.69	8.67	20.49	2.06	9.13	3.64
Underground carbon density	0.3	20.99	18.73	16.47	0.52	1.82	1.82
Soil carbon density	32.9	126.32	70.28	51.33	78.64	34.08	6.25
Dead organic carbon density	0	1.95	3.26	22.06	0.1	0	0.57

3.2. Analysis of Carbon Storage Changes Based on Sen + MK Model

Existing studies on changes in carbon storage have focused more on the overall changes, with little attention paid to changes at the sub-district level, which can lead to inconsistent results in different regions. Therefore, this study uses the Sen + MK method to analyze changes in carbon storage at the sub-district level in Beijing from 2000 to 2020, and uses the standard deviation ellipse method to analyze the overall trend of carbon storage changes in Beijing.

The integrated Sen + MK methodology enables the analysis of carbon storage dynamics at the sub-district level. The Sen slope estimator is mainly used to calculate the median slope of time series data. When analyzing the dynamics of carbon storage, we will have a series of data points regarding the change in carbon storage over time [45,46]. The Sen method describes the changing trend of the data by calculating the median slope of the sequence formed by these data points. However, it lacks the ability to assess the significance of the trend. On the other hand, the Mann–Kendall test has solved this problem quite well. It can provide a statistical significance assessment of the time trend, which just

complements the deficiency of the Sen slope estimator [47]. It can tell us whether the observed changing trend of the carbon storage dynamics is statistically significant [48]. The formula for calculating the Sen trend gauge is as follows:

$$\beta = \text{meadian}\frac{x_j - x_i}{j - i}(1 < i < j < n) \tag{6}$$

In the formula, n represents the number of years of study, that is, n = 20; x_i represents the carbon storage value of the i-th year; β is the trend degree—when β < 0, it indicates a decreasing trend of carbon storage over time, and when β > 0, it indicates an increasing trend of carbon storage over time.

The Mann–Kendall trend is calculated using the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \tag{7}$$

where

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, x_j - x_i > 0 \\ 0, x_j - x_i = 0 \\ -1, x_j - x_i < 0 \end{cases} \tag{8}$$

The selection of the appropriate test statistic for significance testing varies depending on the length of the time series. We analyzed the 20-year trends, calculated as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{VAR(S)}}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{\text{VAR(S)}}}, S < 0 \end{cases} \tag{9}$$

where, $\text{VAR(S)} = (n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5))/18$; n represents the total number of data points. m denotes the number of distinct groups of repeated data within the sequence, while t_i indicates the width of each group, or the number of consecutive, identical data points within the i-th group of repeated data. When $|Z| \leq Z_{1-\frac{\alpha}{2}}$, the null hypothesis is accepted, indicating that the trend is not significant; if $|Z| > Z_{1-\frac{\alpha}{2}}$, the null hypothesis is rejected, indicating that the trend is significant.

3.3. Geographically and Temporally Weighted Regression Model

Natural, socioeconomic, and geographic variables interact in a complex manner, posing methodological challenges in determining the main drivers of carbon storage dynamics. These factors have multiple collinearity and spatial heterogeneity, which requires complex analysis methods to distinguish key determinants, and it is still a key issue to understand their specific effects on sub-district carbon storage, such as the difference of specific factors in different regions. Quantifying the relationship between the two is important for the comprehensive analysis of the spatial and temporal changes of carbon storage; so, in this study, GTWR analysis is used to evaluate the influence of each factor on the change of carbon storage in Beijing. The formula is as follows [59]:

$$\gamma_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \tag{10}$$

where γ_i represents the dependent variable for the i-th sample area. X_{ik} denotes the observed value of the k-th explanatory variable in the i-th sample area. (u_i, v_i, t_i) represents the spatiotemporal coordinates of the i-th sample area. $\beta_0(u_i, v_i, t_i)$ and $\beta_k(u_i, v_i, t_i)$ repre-

sent the spatiotemporal intercept for the i-th sample area and the regression coefficient of the k-th explanatory variable in the i-th sample area, respectively. $\beta > 0$ indicates a positive correlation between the explanatory variable and the dependent variable, while a negative value indicates a negative correlation. ε_i represents the random disturbance term.

3.4. Markov–PLUS Model

In the current era of rapid economic development, in order to achieve the goals of increasing carbon storage and reducing carbon emissions, measures should be formulated considering different development scenarios [60]. The PLUS model offers robust capabilities in simulating and quantifying the influence of driving factors on land use change; its integration with the Markov model enables scenario-based forecasting of land use dynamics.

The PLUS model is a fine-grained land use prediction model that considers policy-driven guidance based on the FLUS model [61]. The model utilizes two key modules: the Land Expansion Analysis Strategy (LEAS) and the Cellular Automata model based on Random Seed (CARS), each contributing to its overall functionality. LEAS converts the mining of land class conversion rules in various regions into a binary classification problem. The model builds on two existing land use data for different periods that will represent the area of each land use change by extracting late land use statistics for a given change state in the image element. The association between types of land management patterns and several drivers was then investigated by a Random Forest algorithm. The study found that different land use types will produce change rules, showing the development potential of each type [62]. PLUS will automatically generate simulated plaque results due to limited developmental potential. Previous results found that [63,64] the PLUS model can dynamically combine existing spatial and geographical factors to analyze land use change and further obtain simulation results of the spatial distribution of land use with high accuracy.

In this study, we first simulated 2020 using the land use data from 2010 and 2015 to ensure the accuracy of the experimental results. Then, the Markov–PLUS model was used to predict land use in three scenarios in Beijing from 2025 to 2040. These three scenarios are ND, ED, and EP. The ND scenario assumes that land use changes in Beijing mainly follow current trends and patterns, and that there is no large-scale human intervention policy or plan to intentionally guide the transition of land use in a specific direction. In the ED scenario, it is assumed that land use changes in Beijing are mainly driven by economic development goals. The EP scenario assumes that Beijing attaches great importance to ecological and environmental protection, with the protection and restoration of ecosystems as the primary task [65,66].

As shown in Table 3, referring to relevant literature methods, the neighborhood factor weights are the percentage of each land use type to total area data from 2000 to 2020. Tables 4–6 represent the conversion rules between the different land use types. When one land use type can be converted into another, the corresponding value in the matrix is 1; otherwise, it is 0 [52,65–67]. The matrix transformations in the three different contexts are as follows:

Table 3. Neighborhood factor weight.

Gentle	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Neighborhood weight	0.2419	0.4795	0.0037	0.0333	0.0075	0.0001	0.2340

Table 4. Land use transfer matrix for ND scenario.

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Cropland	1	1	1	1	1	1	1
Forest	1	1	1	1	0	1	1
Shrub	1	1	1	1	1	1	1
Grassland	1	1	1	1	1	1	1
Water	0	0	1	1	1	0	0
Barren	1	1	1	1	1	1	1
Impervious	1	1	1	1	0	1	1

Table 5. Land use transfer matrix for EP scenario.

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Cropland	1	1	1	1	0	0	1
Forest	1	1	1	1	0	1	1
Shrub	1	1	1	1	1	1	1
Grassland	1	1	1	1	1	1	1
Water	1	0	1	0	1	0	0
Barren	1	1	1	1	1	1	1
Impervious	0	0	1	1	1	0	1

Table 6. Land use transfer matrix for ED scenario.

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Cropland	1	0	1	1	0	0	1
Forest	1	1	1	1	0	0	1
Shrub	1	1	1	1	1	1	1
Grassland	1	1	1	1	1	1	1
Water	1	0	1	1	1	1	1
Barren	1	1	1	1	1	1	1
Impervious	0	0	0	0	0	0	1

4. Results

4.1. Spatiotemporal Changes of Land Use in Beijing

As shown in Figure 3 and Tables 7 and 8, based on the land use distribution map and land use type area table for Beijing from 2000 to 2020, it can be observed that the main land use type in Beijing is forest. It is located in the northwest region of Beijing, with an area that has increased from 7809.65 km^2 in 2000 to 8012.90 km^2 in 2020. In 2020, the forest accounted for 48.9% of the total area. The central part is mainly impervious, and the areas of cropland and barren are gradually decreasing, with a decrease of 24.5% and 45.1% respectively. The reduction in the area of these two regions illustrates the inevitable encroachment of urban areas on agricultural land during development. In 2020, the area of impervious increased significantly, reaching 3580.63 km^2, with a growth rate of 56.8% compared to the previous year. The area occupied by shrubs increased from 0.19% of the total area to 0.34% over a period of 20 years. The distribution of grassland, on the other hand, became more scattered and decreased by 35.5% compared to the original baseline. In the northeastern region, there is a relatively prominent lake. The proportion of its total area increased from 201.07 km^2 in 2000 to 222.25 km^2 in 2020, indicating a strong emphasis on the protection of water resources during urbanization development. The proportion of barren and shrubs is relatively small, and their changes during the study period are not very significant. Based on the above analysis, there are significant differences in land

use changes in different areas of Beijing. Currently, there is a relatively high proportion of forest and cropland, while the proportion of Impervious is continuously increasing.

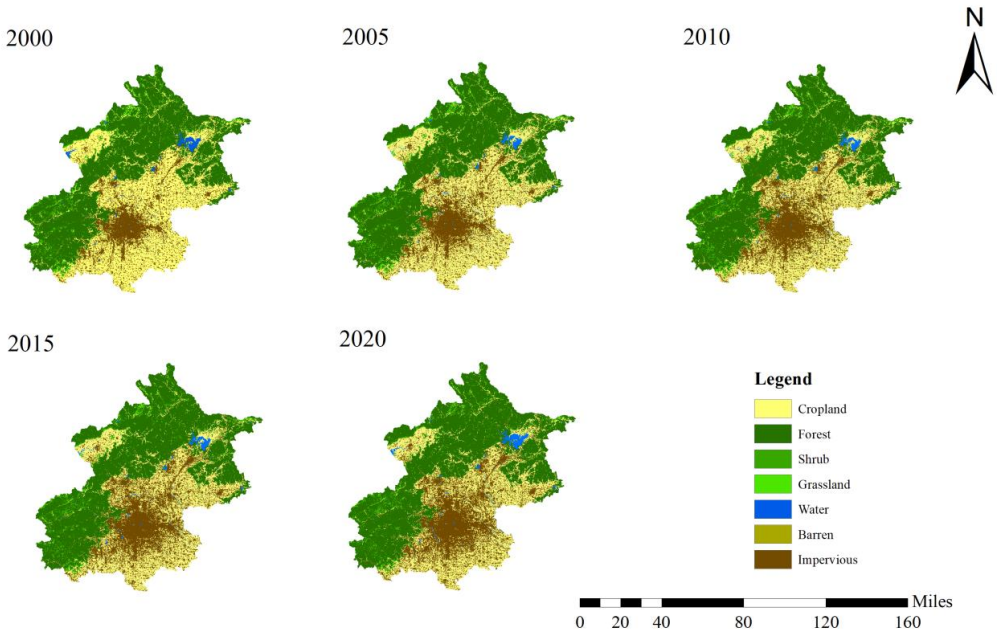


Figure 3. Land use map of Beijing from 2000 to 2020.

Table 7. Land use area in Beijing from 2000 to 2020 (km^2).

	2000	2005	2010	2015	2020
Cropland	5574.613	5129.764	4692.399	4357.222	4201.587
Forest	7809.649	7818.788	7853.788	7913.307	8012.893
Shrub	30.968	41.872	46.949	69.530	55.514
Grassland	486.710	506.343	511.799	415.592	314.001
Water	201.074	146.142	153.498	169.008	222.254
Barren	0.946	0.626	0.902	0.690	0.521
Impervious	2283.471	2743.890	3128.079	3461.823	3580.633

Table 8. Proportion of land use area in Beijing occupied from 2000 to 2020.

	2000	2005	2010	2015	2020
Cropland	34.00%	31.3%	28.63%	26.59%	25.64%
Forest	47.7%	47.71%	47.93%	48.29%	48.90%
Shrub	0.19%	0.25%	0.29%	0.42%	0.34%
Grassland	2.97%	3.09%	3.12%	2.54%	1.91%
Water	1.23%	0.89%	0.94%	1.03%	1.36%
Barren	0.01%	0.01%	0.01%	0.01%	0.01%
Impervious	13.93%	16.74%	19.09%	21.13%	21.85%

According to Figure 4, it can be seen that from 2000 to 2010, most of the cropland was converted to impervious, and the forest area increased less. The shrub increased by nearly 50% after the conversion of various land uses, and the area of impervious increased the most. Compared with the previous ten years, the decrease in the amount of cropland from 2010 to 2020 gradually decreased. At the same time, the rate of impervious expansion decreased. Water shows an increasing trend, mainly from farmland and barren. The area of grassland decreased year by year, mainly converted to forest. As the capital of China, Beijing carries the central functions of economy, culture, politics, and other aspects. During

2000–2020, the active urbanization strategy promoted the continuous expansion of urban space. The redistribution and construction of functional areas in urban planning, such as the construction of central business district and science and technology parks, guide the transformation of land use from agricultural and ecological land to construction land. With the improvement of the importance of ecological environment, Beijing has issued a series of policies on forest resources protection and greening. For example, a compensation mechanism for ecological forest in mountainous areas has been implemented to encourage farmers to participate in forest protection and afforestation activities. At the same time, the promotion of the "Green Beijing" strategy makes urban greening become an important part of urban construction.

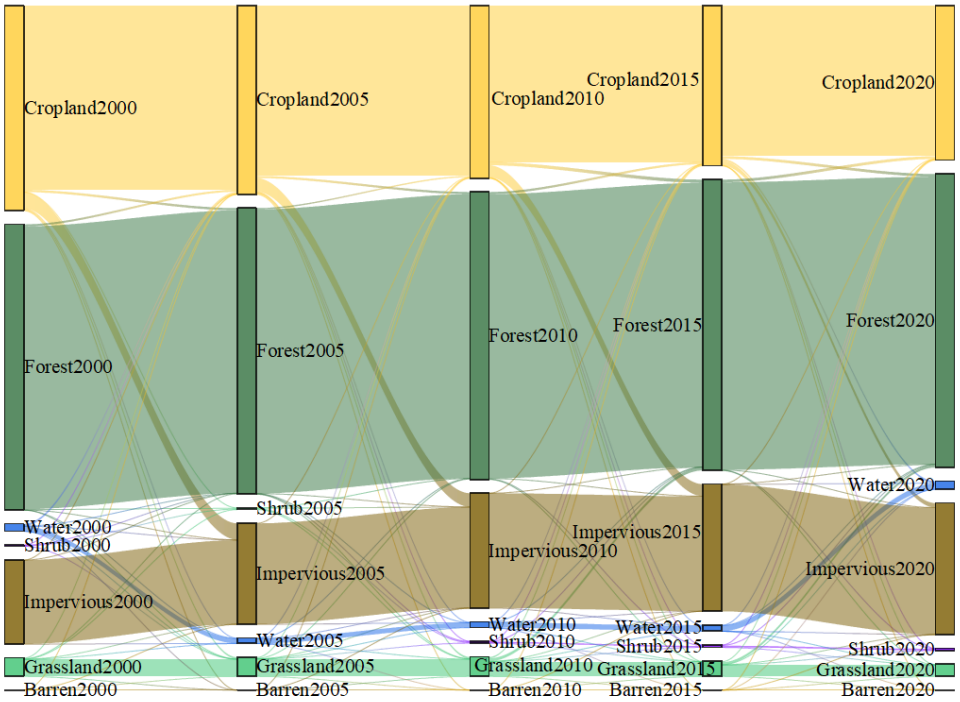


Figure 4. Conversion between various land use types in Beijing from 2000 to 2020.

4.2. Spatiotemporal Variation Characteristics of Carbon Storage in Beijing

4.2.1. Temporal Change Characteristics of Carbon Storage in Beijing

As shown in Figure 5, in 20 years from 2000 to 2020, the carbon storage in Beijing generally decreased. The carbon storage in Beijing was 179.76 Tg, 178.64 Tg, 178.29 Tg, 177.71 Tg, and 178.46 Tg in the years 2000, 2005, 2010, 2015, and 2020, respectively. From 2000 to 2015, there was a decreasing trend with a cumulative loss of 2.05 Tg. The most significant decrease occurred between 2000 and 2005, with a decrease of 0.62%. From 2015 to 2020, the carbon storage gradually increased with an increase of 0.42%. This may be due to Beijing reaching a certain level of economic development during this period, leading the government to pay more attention to ecological sustainability and formulate a series of environmental protection policies.

As shown in Figure 6, in the process of carbon storage simulation, the carbon density of different land use types is fixed, so the change in carbon storage is mainly influenced by the increase or decrease in the area of different land use types. The contributions of different land use types to carbon storage are as follows: forest > cropland > impervious > grassland > water > shrub > barren. Cropland and forest are the main carbon reservoirs and also the land use types that have caused significant changes in carbon storage in Beijing over the past 20 years.

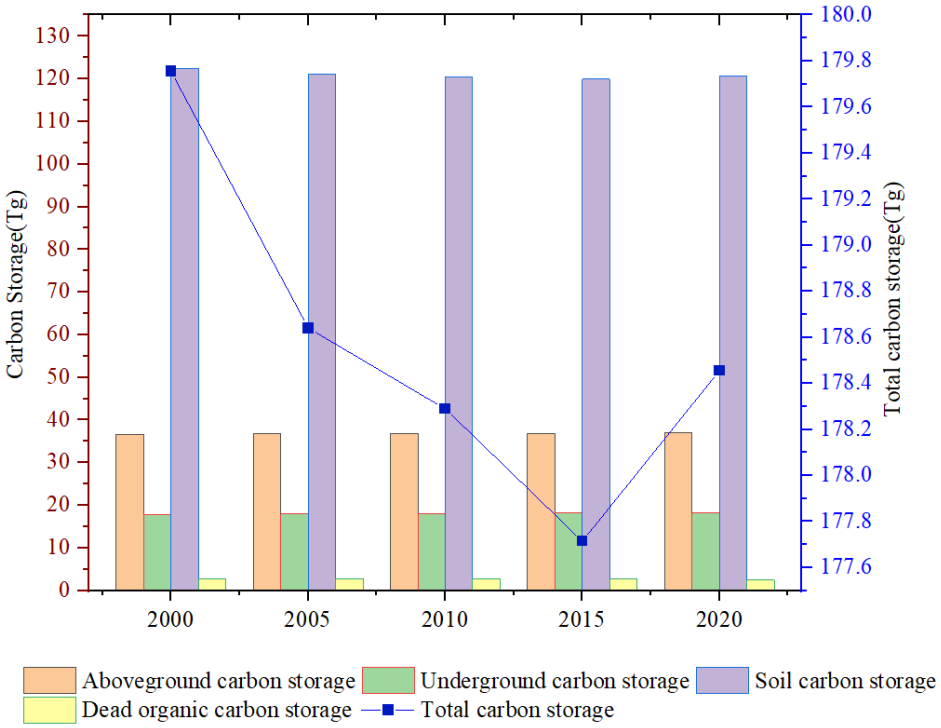


Figure 5. Changes in the amount of various carbon storage and the total carbon storage in Beijing from 2000 to 2020.

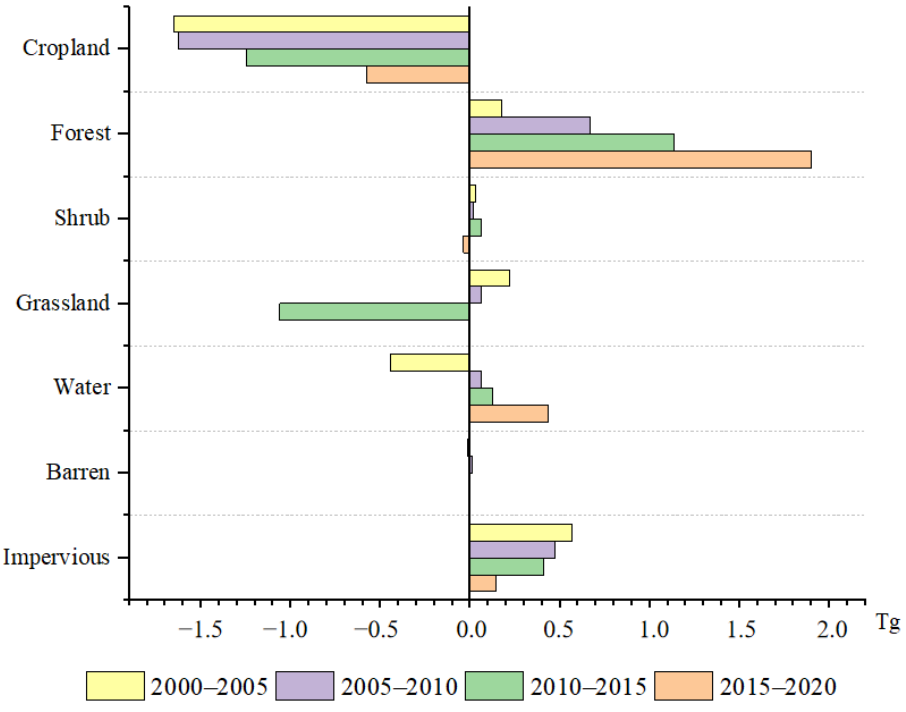


Figure 6. Changes in carbon storage in various regions of Beijing, 2000–2020.

From 2000 to 2020, the overall fluctuation trend of carbon storage in cropland and grassland in the Beijing region decreased, with the largest decrease observed in cropland and the largest increase in forest. The carbon storage in cropland has been continuously decreasing, but at a slower pace. In contrast, the carbon storage in forest and impervious has been continuously increasing, particularly during the period from 2015 to 2020, when there was a significant growth in forest carbon storage. From the perspective of carbon

storage changes in different land use types, different land use types exert distinct impacts on carbon storage dynamics. In Beijing, forests, cropland, and impervious surfaces are the dominant land use categories driving significant carbon storage changes over time, collectively accounting for 87.3% of total changes in the past two decades. Notably, the expansion of forests and impervious surfaces has far outpaced the decline in cropland, positioning these two land use types as the primary drivers of increased carbon storage in the region.

4.2.2. Spatial Distribution and Change Characteristics of Carbon Storage in Beijing

Figure 7 illustrates that the spatial distribution of carbon storage in Beijing exhibits significant heterogeneity and a strong correlation with land use change. From 2000 to 2020, the carbon storage areas in Beijing were mainly located in the northern and western regions, which have higher elevation and vegetation coverage. Regions exhibiting low carbon storage values are primarily located in the central urban area of Beijing, where impervious surfaces dominate and vegetation coverage is minimal.

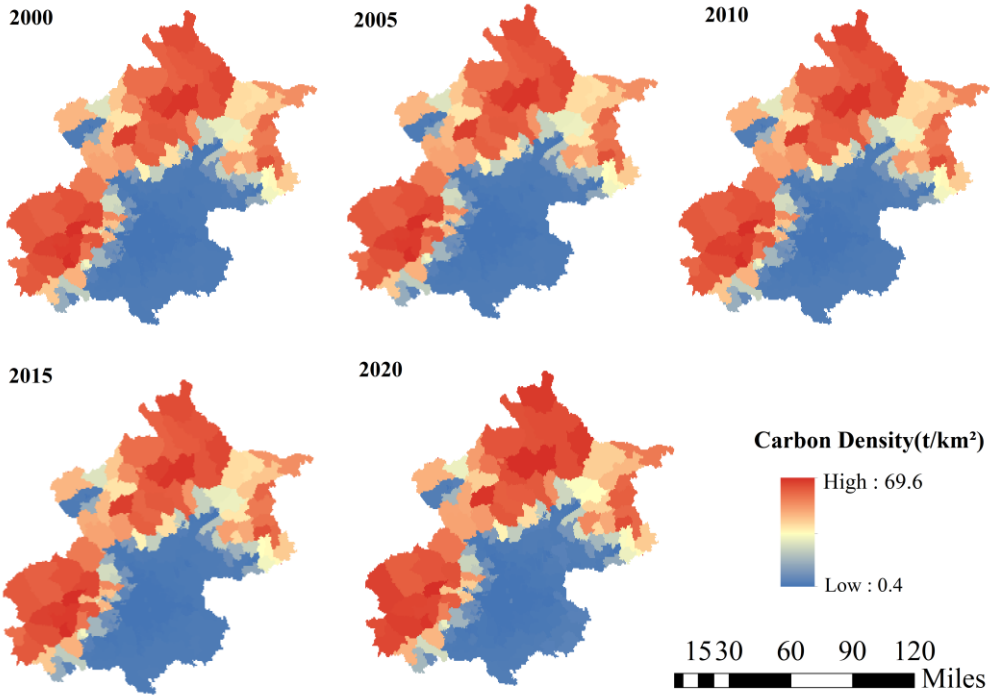


Figure 7. Spatial distribution of carbon density in Beijing from 2000 to 2020.

Using the standard deviation ellipse method, the spatial distribution and centroid migration of carbon storage in Beijing's sub-districts can be further studied. With the modification of the ellipse's major axis, a consistent "from south to north" pattern in spatial distribution is observed, as shown in Figure 8. Along the major axis, carbon storage in Beijing decreased from 179.76 Tg in 2000 to 178.46 Tg in 2020, indicating a trend of carbon storage from south to north in Beijing. One possible explanation is that as the capital and economic and cultural center of China, Beijing has developed rapidly in the past twenty years but has overlooked ecological protection. As a result, the overall change in carbon storage has shifted towards the northwestern region, while the carbon storage in the southeastern urban development center has decreased. The change in the minor axis compared to the central axis is more significant, expanding from 144.809 km to 145.703 km, indicating a clear centrifugal distribution of sub-district carbon storage.

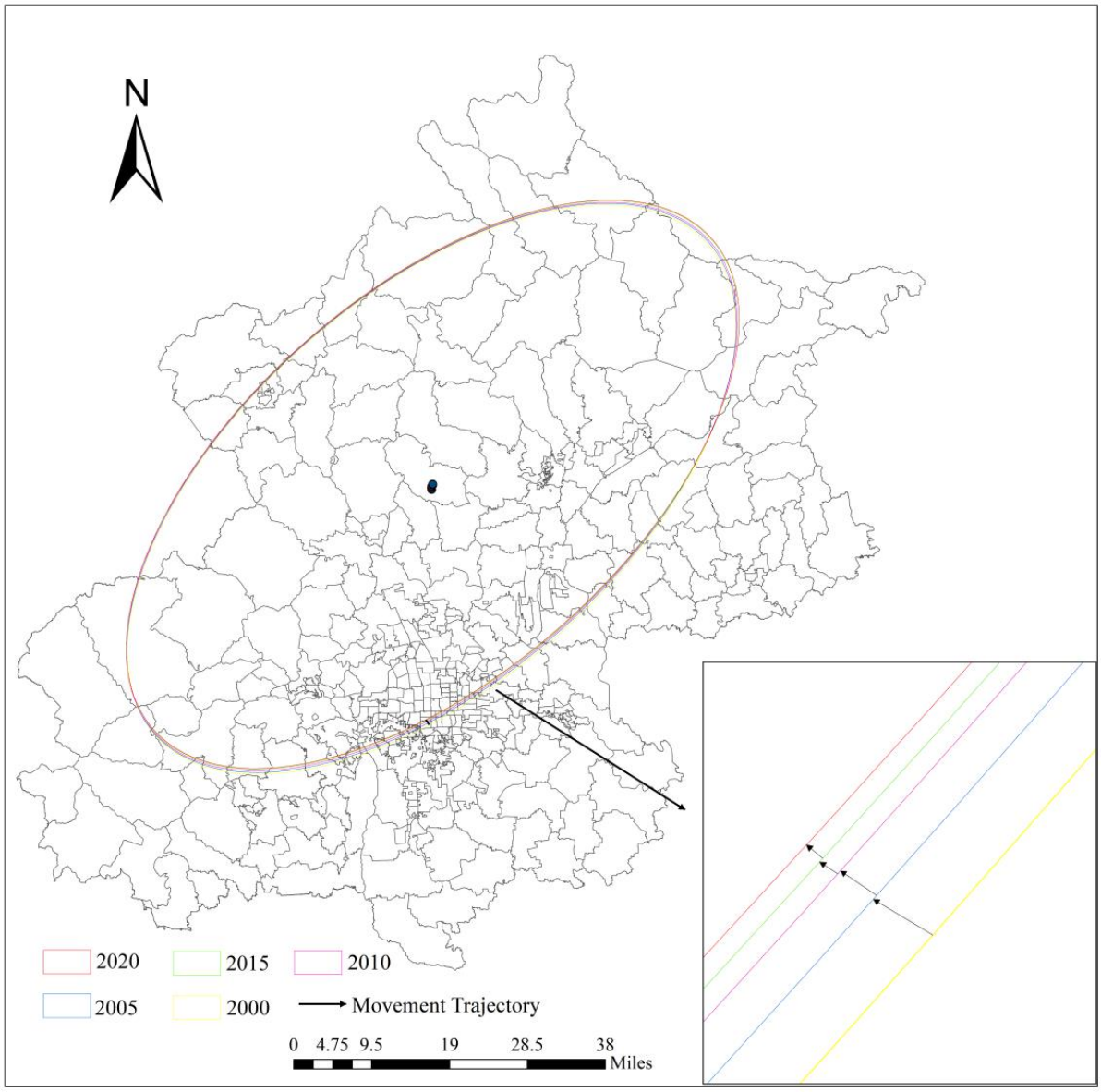


Figure 8. Standard deviation ellipse result. The change in the middle point represents the shift in the center of gravity of the carbon storage.

The Sen + MK significance test was conducted to study the sub-district level carbon storage in Beijing. The study found that from 2000 to 2020, areas with a Sen trend coefficient <0 accounted for 75.62% of the total number of sub-districts in Beijing, indicating an overall decreasing trend in carbon storage. According to the Mann–Kendall significance test results, the carbon storage trend was classified into nine categories: extremely significant increase, significant increase, slightly significant increase, no significant increase, no significant reduction, slightly significant reduction, significant reduction, extremely significant reduction, and no change. From Table 9, it can be observed that based on the significance test, the proportion of areas in Beijing with a decreasing trend in carbon storage is much higher than the proportion with an increasing trend, accounting for 70.34% and 25.46%, respectively.

As shown in Figure 9, the distribution of carbon storage reduction in Beijing is concentrated in the southern region, spreading from the city center to the surrounding areas, with the degree of reduction gradually strengthening, which is related to urban construction and urban development. The distribution of carbon storage increase is concentrated in the northern forest areas of Beijing. In addition, there is no significant increase in the city center

of Beijing, which also confirms that Beijing has been focusing on environmental protection in recent years and the ecological environment is developing in a positive direction.

Table 9. Results of Sen trend of carbon storage change in Beijing.

β	Z	Trend Characteristics	Number	Percentage/%
β > 0	2.58 < Z	Extremely significant increase	4	1.05
	1.96 < Z ≤ 2.58	Significant increase	7	1.84
	1.65 < Z ≤ 1.96	Slightly significant increase	25	6.56
	Z ≤ 1.65	No significant increase	61	16.01
β = 0	Z	No change	16	4.20
β < 0	Z ≤ 1.65	No significant reduction	182	47.77
	1.65 < Z ≤ 1.96	Slightly significant reduction	44	11.55
	1.96 < Z ≤ 2.58	Significant reduction	40	10.50
	2.58 < Z	Extremely significant reduction	2	0.52

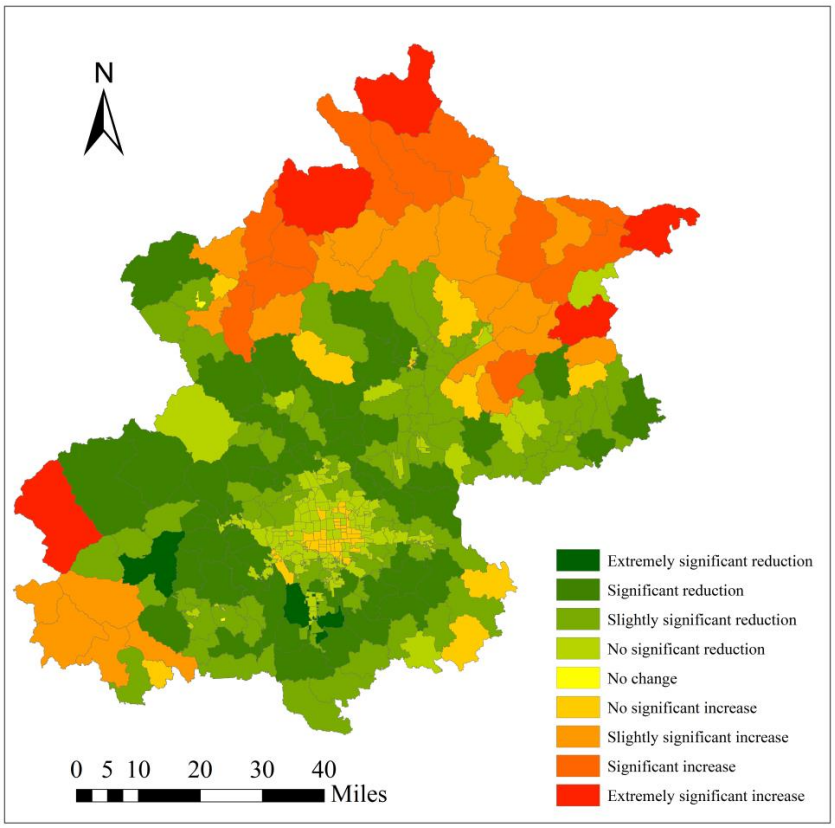


Figure 9. Results of carbon storage changes of different sub-districts using the Sen + MK model.

4.3. Quantitative Attribution of Spatiotemporal Differentiation of Carbon Storage in Beijing

This study selects eleven driving factors to analyze the changes in carbon storage of Beijing from 2000 to 2020. This study employs an RF model to assess the overall carbon storage in Beijing, as illustrated in Table 10 and Figure 10. The analysis reveals that the eleven natural and socioeconomic factors considered exert a significant influence on the distribution of carbon storage across the region. Examining static carbon storage data reveals significant disparities in the explanatory power of various factors for spatial differentiation, with notable differences observed across different years. Among them, slope has the highest explanatory power for the spatial differentiation of carbon storage among various factors, followed by HAI, NTL, PM2.5, NDVI, FVC, TEM, DEM, PREP, and GDP. POP has the weakest explanatory power.

Table 10. Analysis of driving factors of spatiotemporal differentiation of overall carbon storage in Beijing.

Factors\Year	2000	2005	2010	2015	2020
Slope	0.765	0.766	0.766	0.766	0.764
HAI	−0.596	−0.598	−0.599	−0.606	−0.607
FVC	0.487	0.409	0.575	0.49	0.537
GDP	0.424	0.398	0.269	−0.145	−0.147
PM2.5	−0.542	−0.544	−0.545	−0.547	−0.547
TEM	−0.475	−0.47	−0.474	−0.463	−0.56
NTL	−0.483	−0.516	−0.546	−0.579	−0.611
DEM	0.43	0.432	0.433	0.433	0.433
NDVI	0.531	0.5	0.552	0.523	0.558
POP	0.029	0.043	0.076	0.021	0.055
PREP	−0.437	−0.445	−0.399	−0.424	−0.334

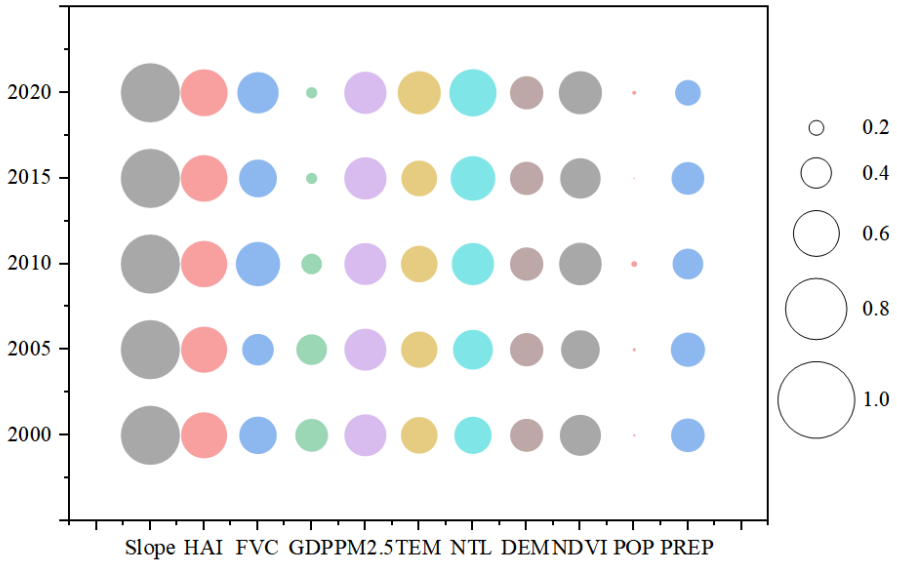


Figure 10. Result of the factors' impact on overall carbon storage in Beijing.

From the dynamic perspective of different years, the explanatory power of different factors for the spatial differentiation of carbon storage changes over time. However, the main explanatory factors are basically consistent. From 2000 to 2020, slope emerged as the dominant factor, exhibiting a strong positive correlation with carbon storage. FVC and DEM also positively correlate with carbon storage, while TEM, PREP, HAI, PM2.5, and NTL show negative associations. Notably, slope, FVC, and DEM play key roles in determining land use patterns, with mountainous regions displaying higher vegetation coverage and carbon storage in Beijing. TEM and PREP determine the water and thermal conditions of the study area, affecting the photosynthesis of vegetation. HAI, PM2.5, and NTL determine the level of urbanization and human impact, reflecting the urban economic situation to some extent. The higher the level of urbanization, the higher the land use rate and the proportion of construction land, resulting in lower vegetation coverage and lower carbon storage values. GDP showed a positive correlation with carbon storage from 2000 to 2010, but continued to show a negative correlation after 2015. The impact of POP on carbon storage is not significant. In addition, the impact of HAI, FVC, and NTL on carbon storage has been continuously increasing with time.

At the same time, due to the presence of mountains and forests in the northwestern part of Beijing, there are deviations in the results of carbon storage influenced by factors to a certain extent. At the same time, in order to study the relationship between urban

development and carbon storage, this study analyzes the correlation between 11 factors and carbon storage in the built-up areas of Beijing by RF model. The results are shown in Table 11 and Figure 11; there are significant differences in the impact of carbon storage and factors between the built-up areas of Beijing and the overall carbon storage and factor impact of Beijing (Table 9 and Figure 10). Within the built-up area, DEM, HAI, and NTL have a significant impact on carbon storage, followed by slope, NDVI, and PM2.5. The impact of POP on carbon storage is noticeably increasing. HAI reflects the negative impact of human activities on carbon storage, while NTL indirectly reflects the improvement in urban economic development and also has a negative impact on carbon storage. NDVI and FVC reflect the land use situation within the urban built-up area, and the correlation between the two and carbon storage demonstrates the city's efforts in environmental protection and sustainable development in recent years.

Table 11. Analysis of driving factors of spatiotemporal differentiation of carbon storage in the built-up areas of Beijing.

Factors\Year	2000	2005	2010	2015	2020
Slope	0.698	0.737	0.739	0.739	0.737
HAI	−0.755	−0.756	−0.764	−0.778	−0.775
FVC	0.571	0.439	0.648	0.522	0.587
GDP	−0.318	0.329	0.329	−0.426	−0.423
PM2.5	−0.483	−0.483	−0.485	−0.489	−0.491
TEM	−0.686	−0.825	−0.819	−0.837	−0.697
NTL	−0.81	−0.604	−0.675	−0.772	−0.831
DEM	0.82	0.842	0.843	0.843	0.841
NDVI	0.605	0.562	0.623	0.561	0.621
POP	0.289	0.321	0.186	0.215	0.272
PREP	−0.28	−0.352	−0.394	−0.43	−0.309

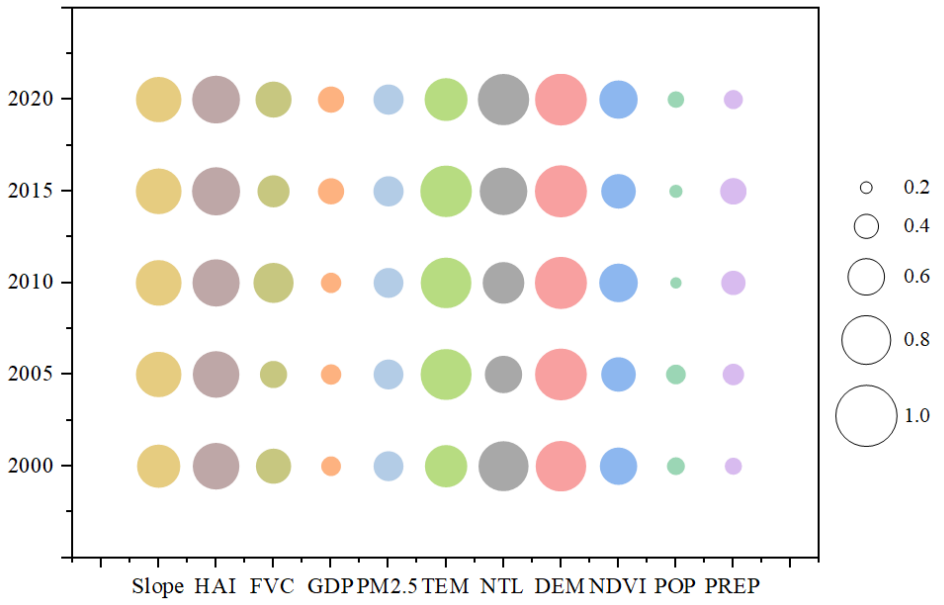


Figure 11. Result of the factors' impact on carbon storage in the built-up areas of Beijing.

This study employs the GTWR model to quantify the contribution of various driving factors to carbon storage across sub-districts during the study period, mapping their spatiotemporal variations (Figure 12). In the sub-district level, PM2.5, HAI, and NTL have the greatest impact on carbon storage in Beijing, and they all have a negative effect. In terms of regional distribution, the factors that have a major impact on the central area of Beijing

are GDP, HAI, and NTL, while the factors that have a major impact on the surrounding areas include slope, DEM, FVC, and NDVI, and they have a positive effect. Economic growth factors have significantly suppressed carbon storage. The primary drivers of this decrease in carbon storage are likely the ongoing expansion of built-up areas, the growth of industrial and manufacturing activities, and the rising energy demand. Areas with less influence from population size include two types: one category comprises sub-districts with small populations and relatively underdeveloped economies, resulting in a less significant impact on carbon storage; the other comprises areas with a large population size but a high degree of concentration, where population concentration effectively improves energy utilization efficiency and increases carbon storage.

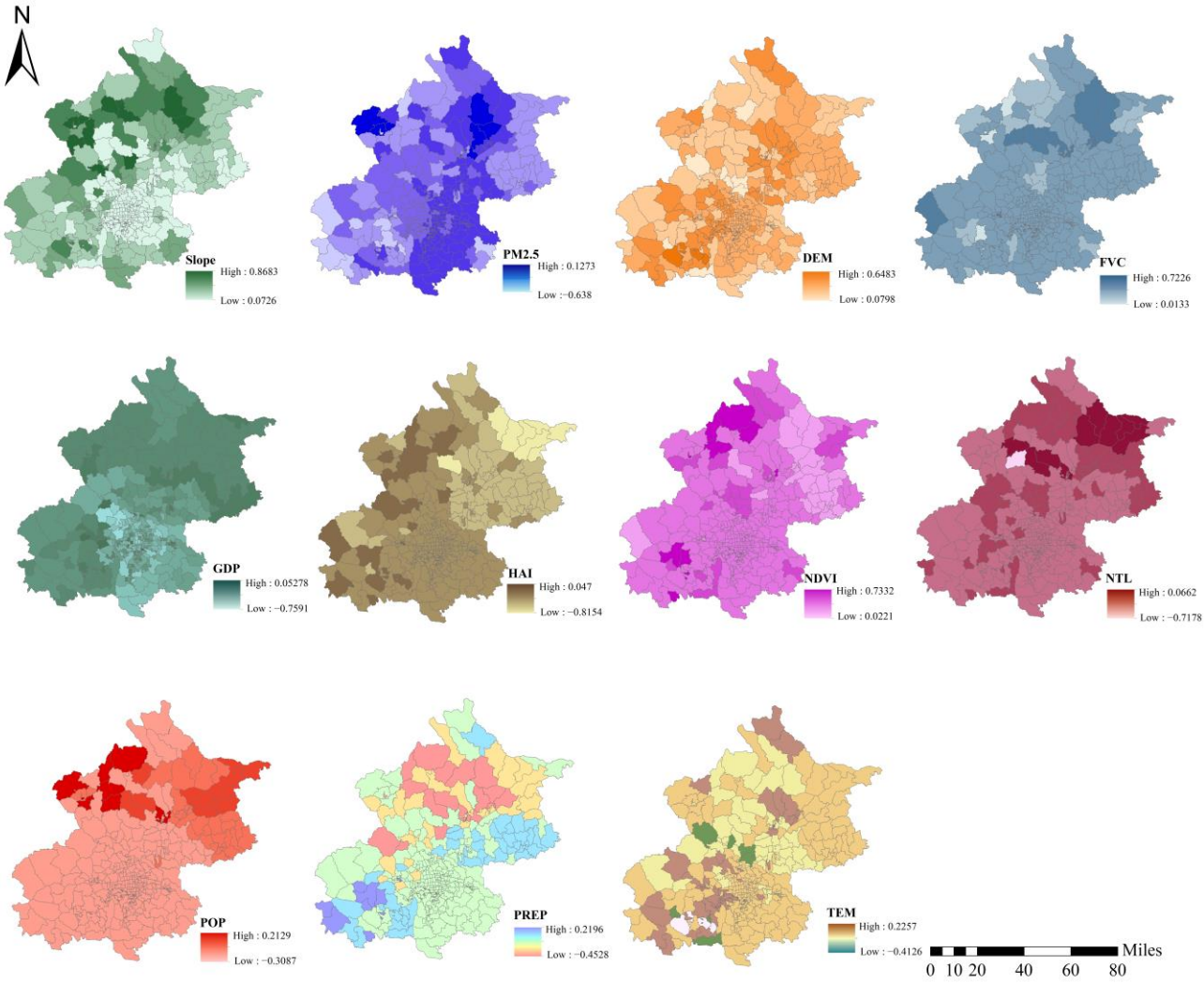


Figure 12. Result of the factors' impact on carbon storage in Beijing by GTWR.

4.4. Prediction of Land Use and Carbon Storage in Beijing Form 2025 to 2040

Based on the Markov–PLUS model, the three land use scenarios in the Beijing area from 2025 to 2040 were simulated. Carbon storage was calculated accordingly, as shown in Tables 12–14. There were significant differences in land class changes under different scenarios, which would have different impacts on the study area. Under the natural development scenario, each land use type was allowed to evolve freely, with land class transitions following historical patterns. However, this scenario did not incorporate the specific conditions of the study area. Under the urban development scenario, the urban area expanded rapidly outward; although the economic level of the city further improved,

it would threaten cropland and grassland. In the long term, it is not conducive to the development of the city. In the ecological conservation scenario, efforts were made to protect valuable forest, grassland, and water areas, while reducing encroachment on cropland, leading to some positive improvements in the ecosystem.

Table 12. Land use in Beijing from 2025 to 2040 in the ND scenarios.

	2025/km^2	**2030/km^2**	**2035/km^2**	**2040/km^2**
Cropland	4507.891	4355.883	4212.755	4078.376
Forest	8931.983	8973.390	9001.201	9018.201
Shrub	60.085	54.495	50.260	47.040
Grassland	295.500	240.357	198.052	165.522
Water	301.334	349.642	393.013	431.915
Barren	0.532	0.436	0.360	0.299
Impervious	4109.307	4232.430	4350.991	4465.279

Table 13. Land use in Beijing from 2025 to 2040 in the EP scenarios.

	2025/km^2	**2030/km^2**	**2035/km^2**	**2040/km^2**
Cropland	4514.774	4369.946	4234.140	4107.112
Forest	8938.870	8988.198	9024.672	9050.849
Shrub	60.304	54.948	50.935	47.912
Grassland	302.386	252.261	213.585	183.649
Water	308.054	362.496	411.466	455.476
Barren	0.688	0.710	0.725	0.739
Impervious	4081.557	4178.077	4271.116	4360.906

Table 14. Land use in Beijing from 2025 to 2040 in the ED scenarios.

	2025/km^2	**2030/km^2**	**2035/km^2**	**2040/km^2**
Cropland	4494.489	4328.435	4170.934	4022.088
Forest	8918.689	8944.998	8956.463	8956.295
Shrub	59.945	54.076	49.523	45.993
Grassland	282.224	217.558	168.514	131.303
Water	284.357	317.024	345.986	371.608
Barren	0.457	0.326	0.236	0.172
Impervious	4166.515	4344.310	4515.128	4679.383

As shown in Figure 13 and Table 15, in the ND scenarios, the future distribution of land use will continue to increase on the basis of the past, and the area of impervious will continue to increase, while the area of cropland will decrease. The distribution of carbon density is similar to that of the previous 20 years. The carbon density is higher in the northwest mountainous area and lower in the southeast. In the ED scenario, the carbon storage in Beijing has shown a decreasing trend, and the expansion of impervious has spread along the riverside and the outskirts of the city. This indicates that if the extensive development with a single focus on economic development continues, the urban built-up area will continue to expand, encroaching on ecological land within the region, leading to an imbalanced land use structure and threatening regional ecological security, thereby exacerbating land use conflicts. In the EP scenario, the carbon storage in Beijing has increased rapidly, and land use has been significantly mitigated. The mitigating effect of land use in the sustainable development scenario is better than the other two scenarios, which indicates that in areas with complex human–environment relationships, blindly pursuing economic development will only worsen land use conflicts and damage the regional ecological environment. It is necessary to plan economic development and construction areas as well as ecological protection areas rationally, and adhere to the strategy of coordinating and synchronizing ecological protection and economic development.

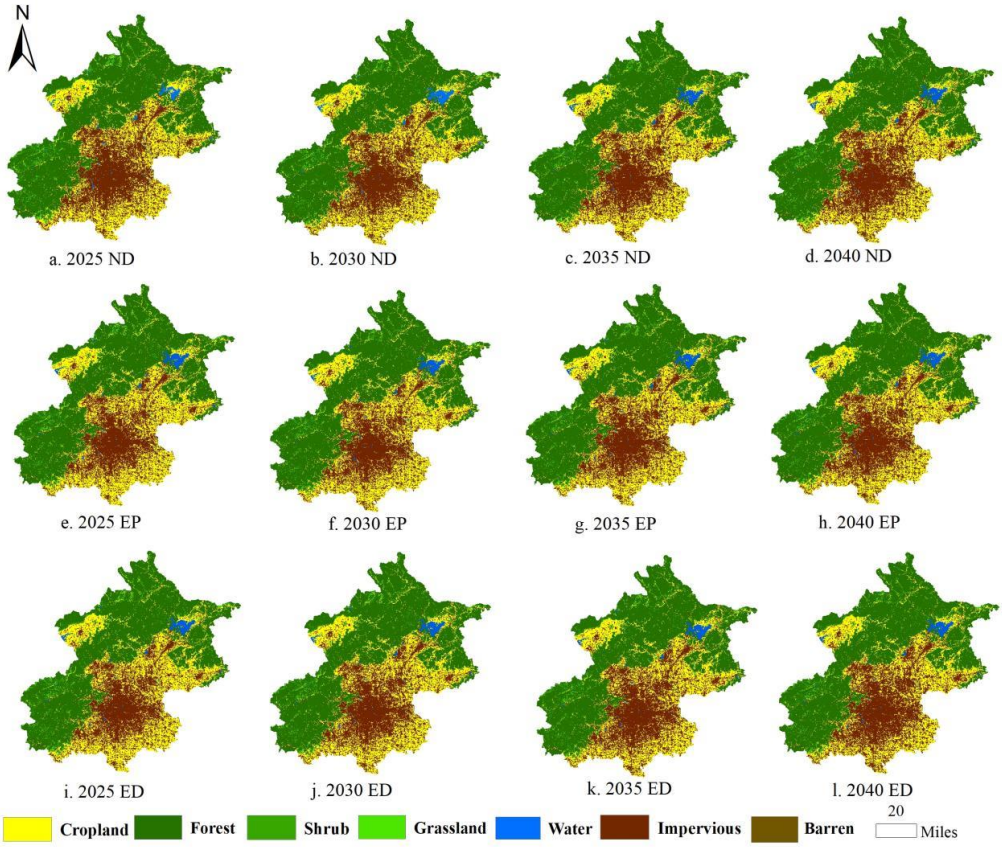


Figure 13. Spatial distribution prediction under three scenarios of land use in Beijing in 2025–2040.

Table 15. Carbon storage in Beijing from 2025 to 2040 in three scenarios.

Scenarios	2025	2030	2035	2040
ND	198.245 Tg	198.391 Tg	198.409 Tg	198.322 Tg
EP	198.500 Tg	198.897 Tg	199.163 Tg	199.320 Tg
ED	197.726 Tg	197.365 Tg	196.889 Tg	196.322 Tg

In view of the prediction results, we found that the reduction in carbon storage in Beijing is concentrated in the southern region, spreading from the city center to the surrounding areas, and the reduction degree is gradually increasing, which is related to urban construction and urban development. The distribution of increased carbon storage is mainly concentrated in the northern forest area of Beijing. In addition, there is no significant increase in Beijing center, which also confirms that Beijing has been paying attention to environmental protection in recent years, and the ecological environment is developing in a positive direction. At the same time, under the EP scenarios, efforts are made to protect the precious forests, grasslands, and waters, while reducing the erosion of farmland, so as to bring some positive improvements to the ecosystem. Therefore, in terms of urban planning, it can be considered to increase the green area in the south of Beijing, improve the vegetation coverage rate by establishing urban parks and green corridors, and thus enhance the carbon sink function, adjust the type of land use, reduce the proportion of industrial or commercial land with high carbon emission, and increase the proportion of ecological land.

5. Discussion

5.1. Compared with Relevant Studies

This study elucidates the spatial distribution of carbon storage in Beijing and contributes to the sustainable development of future carbon storage strategies. Future land use scenarios were simulated using a combined PLUS and Markov model. To evaluate the accuracy of the simulated land use relative to actual conditions in 2020, this research employs the Kappa coefficient, FOM value, and overall accuracy metrics. The results show that the simulation accuracy is high, and the PLUS model can support the simulation of different future land use scenarios in the study area. Compared to other related studies, this study analyzed the changes in carbon storage at the sub-district level and introduced the Sen + MK model to conduct spatial analysis. Compared to the other studies using larger-scale analysis units, the results at the sub-district level can be used as a microscopic basis for the overall urban analysis. By summarizing the changing data of carbon storage in each partition, the spatial distribution pattern of urban carbon storage changes can be obtained, and the significant changing areas can be determined, so as to provide precise target area positioning for urban planning strategies. The Sen + MK model, compared to other models, offers more robust support for measures aimed at enhancing urban carbon storage by capturing changes at finer spatial units. Recognizing that carbon storage dynamics are influenced by multiple factors, this study integrated the RF and GTWR models to establish the relationships between natural and socioeconomic factors and carbon storage. These models enabled the quantitative identification and clarification of the factors driving the spatiotemporal changes in carbon storage from multiple perspectives, effectively demonstrating that these changes result from a combination of diverse influences.

The analysis reveals a decreasing-then-increasing trend in Beijing's carbon storage from 2000 to 2020, with urban impervious expansion exerting a significant impact. These findings align with results from several previous studies [68–71]. The research by He et al. [68] found that carbon storage of Beijing–Tianjin–Hebei showed a decreasing–increasing trend from 1990 to 2020, which is similar to the results of the corresponding years in this study. Ke and Tang [69] identified the coupled processes of urban expansion and cultivated land protection as a primary driver of declining ecosystem carbon storage. This finding aligns with the observed changes in carbon storage within this study, which were primarily driven by increases in impervious surfaces and forest areas. Meanwhile, this study also found that the most influential factor on the overall carbon storage of Beijing is slope, while the most influential factors on the carbon storage of built-up areas in Beijing are DEM, HAI, and NTL. This aligns with the findings of Li et al. [70], who identified DEM and human activities as the primary drivers shaping the spatial pattern of ecosystem carbon storage in the Loess Plateau region.

In addition, this study has different conclusions from other studies. While Zhu et al. [72] found that changes in farmland and grassland exerted the greatest influence on urban carbon storage, our study indicates that impervious surfaces and forests are the primary drivers of carbon storage change. This is because economic development in Beijing has led to a continuous conversion of forest areas to impervious surfaces, while the study area is a coastal region where the main land changes are forests and grasslands being converted to farmland. This study found that at the sub-district level, PM2.5, HAI, and NTL have the greatest impact on carbon storage in Beijing, and they all have a negative effect. In contrast to our results, Xiang et al. [73] found that at the 200 m grid scale, the factors with the greatest impact on the main urban area of Chongqing are GDP, population, and construction land expansion. The reason for this may be the significant reduction in arable land and significant increase in construction land in the main urban area of Chongqing in

the next 15 years, as the city is in a state where economic development is the main task. Also, different research units will have different results.

5.2. Limitations of This Study

This study used the InVEST model to quantify carbon storage. The model used a method for estimating carbon storage by assigning carbon density values to different land use categories [37]. The carbon density database developed for this study mainly utilizes measurements from the available literature. However, data from field surveys conducted within the Beijing research field were prioritized. For data lacking references, the missing values, such as static carbon density values, were added according to literature data from adjacent regions [38].

The carbon density data used in this study have a certain degree of literature comprehensiveness. However, carbon density should be dynamic data rather than a constant value [74]. We found that similar studies of carbon storage also used constant carbon density data [12,20,75,76]. Although there may be some differences between the estimated results and the actual results, it is still meaningful to reveal the factors affecting carbon storage changes. Despite the use of static carbon density data in this study, we are also fully aware of its limitations as well as the potential advantages of combining dynamic data. The static carbon density model mainly focuses on the basic framework of relatively stable factors such as land use type and soil texture, while the dynamic carbon density model mainly focuses on the dynamic factors such as the biological growth process and the influence of climate change [77]. Through a specific coupling mechanism, the dynamic model can be corrected and supplemented on the basis of the static model, and the advantages of the two data types are fully utilized to realize the optimization and accuracy of carbon storage calculation.

On the other hand, based on the principles of data availability, timeliness, and factor significance, for this study, 11 driving factors were selected to analyze the changes of carbon storage in Beijing, including natural factors and socioeconomic factors. The number of socioeconomic factors selected in this study is relatively small, which is a limitation. But in terms of socioeconomic factors, population and GDP are the most core factors, which can reflect the relationship between carbon storage and socioeconomic factors to some extent [54,77]. In related studies, the choice of socioeconomic factors was also these several factors. For instance, Niu et al. [54] used a new model to explain spatial variation in regional carbon storage, arguing that GDP has a significant effect on changes in carbon storage. Future studies should dig deeper into relevant data to incorporate other important socioeconomic factors, such as industrial structure, and analyze their relationship with changes in carbon storage.

Moreover, we have some limitations in predicting future carbon storage using the Markov–PLUS model. The future land use change is mainly based on the transition probability of land use types in the past time period [78–80]. This method relies too much on historical data and does not fully consider the impact of external policy changes, technological innovation, unexpected major events, and other factors on land use. In the land use system, there may be some trend reversal or a new equilibrium state in the long term [52,81]. Since forecasting methods do not timely reflect changes in external drivers, policy-makers who rely solely on such forecasts may develop land use policies that lag behind the actual situation.

5.3. Impact of Driving Factor Selection on Carbon Storage Changes

From a natural and socioeconomic perspective, this study selected eleven factors to reveal the impact of each driving factor on the spatiotemporal changes in carbon storage

in Beijing. It provides insights into the relationships between various factors and carbon storage changes. Chen et al. [53] studied the spatiotemporal dynamics behind the changes in carbon storage in the Daxing District of Beijing, China. Niu et al. [54] used a new model to explain the spatial variation of regional carbon storage, and believed that urbanization and ecological environment indicators had a significant impact on the change of carbon storage. According to the published literature, the change of carbon storage is affected by multiple factors [82]. For example, Li et al. [83] discussed the best path and scenario for carbon neutrality in Shanghai, and found that the use of energy and human activities are the biggest factors, and the ecological protection scenario can help achieve the goal of carbon neutrality. Han et al. [84] analyzed the relationship between carbon storage and influencing factors in different cities such as Shanghai, Tokyo, London, and Paris, and found that human activities have a great impact on urban carbon storage. Of course, there are other conclusions that differ from the results of this study. For example, Pan and Pan [85] analyzed the carbon storage drivers of Hong Kong, China and found that economic factors had the greatest influence on carbon storage. The main factors affecting carbon neutralization vary in different types of cities. To sum up, many scholars' research results and the results of this study effectively confirm that carbon storage is a complex and multidimensional ecosystem property; its dynamic change is influenced by multiple factors: the transformation of land use mode, the fluctuation of natural conditions, and the difference of soil type are key factors that cannot be ignored. In particular, this study focused on Beijing, a region with highly urban characteristics, revealing the profound impact of the urbanization process on carbon storage mechanisms, which is an important feature that distinguishes it from other study areas. These results show that we can analyze the trend and influencing factors of Beijing's carbon storage, which can be used as a reference for other cities to optimize the development path, better coordinate the relationship between economic development and ecological protection, and contribute to the realization of global carbon emission reduction goals.

5.4. Explore the Universality of This Study

This research is of great significance in practical applications of Beijing. For the Beijing area, this research framework can systematically analyze the spatiotemporal evolution patterns of land use and carbon storage from 2000 to 2020, providing detailed data basis and scientific decision-making references for urban planning and land resource management in Beijing. For example, policy-makers may focus on areas with high carbon storage and significant susceptibility to land use changes by implementing stringent development restrictions or protective measures. Simulating and predicting the changes of land use and carbon storage in Beijing under different scenarios from 2025 to 2040 is of important significance for Beijing to formulate long-term climate change response strategies and ecological environment protection plans. The simulation results of different scenarios can help policy-makers evaluate in advance the consequences of carbon storage changes under different policy orientations and development models, thereby formulating more forward-looking, adaptable, and sustainable strategic plans, such as determining future urban greening goals and formulating carbon emission control policies, to ensure the realization of ecological security and sustainable development goals in the process of economic and social development in Beijing. At the same time, it also provides practical experience and demonstration cases for other similar cities or regions in climate change response and land resource management.

From the perspective of research methods, different types of cities are facing the need to study carbon storage changes. These cities can use the provided methodology to screen out the drivers of carbon storage change that are applicable to their local areas based on their

actual conditions. In terms of the conclusions, although Beijing has its unique geographical, political, economic, and social characteristics, the influencing mechanism of some common factors can provide references for other cities. The Beijing study could provide a different idea for other cities, especially in areas with rapid urbanization. For example, some emerging cities in developing countries can learn from our research on impervious surfaces and forests when conducting large-scale infrastructure construction and land development to explore how to optimize land use in the process of urban development to achieve better carbon storage effects.

6. Conclusions

In this study, the spatiotemporal evolution of carbon storage in Beijing and its driving factors was analyzed from 2000 to 2020 at the sub-district level, and the land use and carbon storage from 2025 to 2040 were predicted. The specific conclusions are as follows:

(1) From 2000 to 2020, Beijing land use experienced significant changes: cropland was mainly transformed into forest land, grassland, and impervious, reflecting the effect of "grain for green" and built land expansion policy. Carbon storage showed a trend of decreasing first and then increasing, but the overall increase was large, spatially higher in the northwest and lower in the southeast.

(2) Slope is the main factor affecting carbon storage in Beijing, with both HAI and NTL having negative effects. Within the built-up area, HAI and DEM had the greatest effects on carbon storage. At the sub-district level, PM2.5, HAI, and NTL had the largest comprehensive impact on Beijing's carbon storage, and all had negative effects.

(3) Based on future projections, the EP scenario will support carbon peak and neutralization targets, ecological policy playing a key role in strengthening carbon storage throughout the region. In the future, ecological protection with a low-carbon focus should continue to take the lead.

The results have a multifaceted support for achieving carbon neutrality in Beijing. Through the analysis of the changes of carbon storage at the sub-district level in Beijing and the determination of the driving factors, the regions with great carbon sink potential can be accurately identified, and these areas can be taken as the objects of key protection and ecological restoration to further improve their carbon sink capacity. In addition, the conclusion on the relationship between land use transformation and carbon storage in this study can provide scientific basis for urban planning departments to formulate land use planning and guide the city to develop into low-carbon and green spatial layout.

In future work, we will integrate dynamic and static carbon density data while also considering the impact of other important socioeconomic factors, such as industrial structure. At the same time, we will also integrate machine learning or satellite-based remote sensing for real-time monitoring of carbon storage.

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