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Impact of ecological conservation policies on land use and carbon stock in megacities at different stages of development

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A R T I C L E I N F O

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A B S T R A C T

Urban expansion, especially the construction of megacities, increases carbon emissions and adversely affects the carbon storage of terrestrial ecosystems. However, scientific land-use management policies can increase carbon storage. This study takes two megacities at different stages of development, Beijing and Tianjin, as examples to explore the impact of different ecological conservation scenarios on both urban land use and carbon storage to provide recommendations for the construction planning of large cities with low-carbon development as the goal. Furthermore, we coupled the patch-generating land use simulation (PLUS) model with the integrated valuation of ecosystem services and tradeoffs (InVEST) model to simulate land use and carbon storage under a natural development scenario, a planned ecological protection scenario (PEPS), and a policy-based ecological restoration scenario (PERS). From 2000 to 2020, both cities had different degrees of construction land expansion and carbon loss, and Tianjin's dynamic degree of construction land was 0.94% higher than Beijing's, with a carbon loss 183,536.19 Mg higher than Beijing's; this trend of reducing carbon reserves will continue under the natural development scenario (NDS). Under the PEPS and PERS, the carbon stock of both cities increases, and the impact on Tianjin is greater, with an increase of 4.51% and 8.04%, respectively. Under PERS, the carbon stock increases the most, but the dynamic degree of construction land use is negative for both cities. Beijing's carbon stock is 0.40% lower than Tianjin's, which deviates slightly from the trend of urban economic development. Megacities in the rapid development stage can refer to Tianjin, strictly following the ecological protection land planning scope and vigorously implementing ecological restoration policies to effectively increase regional carbon stock. Megacities in the mature stage of development can refer to Beijing, and flexibly implement ecological restoration policies to increase regional carbon stock without affecting the city's economic development.

1. Introduction

Since the industrial revolution, the rise in CO_2 concentration caused by human activities has become an increasingly serious problem. Therefore, 'low carbon' has become a focus of global research in response to the crisis [1]. Carbon stock in terrestrial

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ecosystems is an important component of global carbon stock and a key indicator of ecosystem services [2]. Terrestrial ecosystems regulate climate and increase carbon reserves through forests and other carbon sinks [3], playing a crucial role in maintaining the global carbon cycle [4–6]. Land use change is an important cause of the cyclical processes affecting terrestrial ecosystems, causing changes in carbon sources and sinks, and thus affecting the carbon balance in some regions, even globally [7–9]. Carbon sequestration capacity varies significantly between different land use types. A change in land use type alters the flow of materials and energy cycles on the earth's surface [10], which in turn affects the carbon sequestration capacity of vegetation and soils, thus leading to changes in carbon stock in terrestrial ecosystems [11]. At present, global urbanisation and industrialisation are accelerating, and urban expansion is leading to dramatic land use changes. Large natural ecological areas with high carbon density are gradually being encroached upon

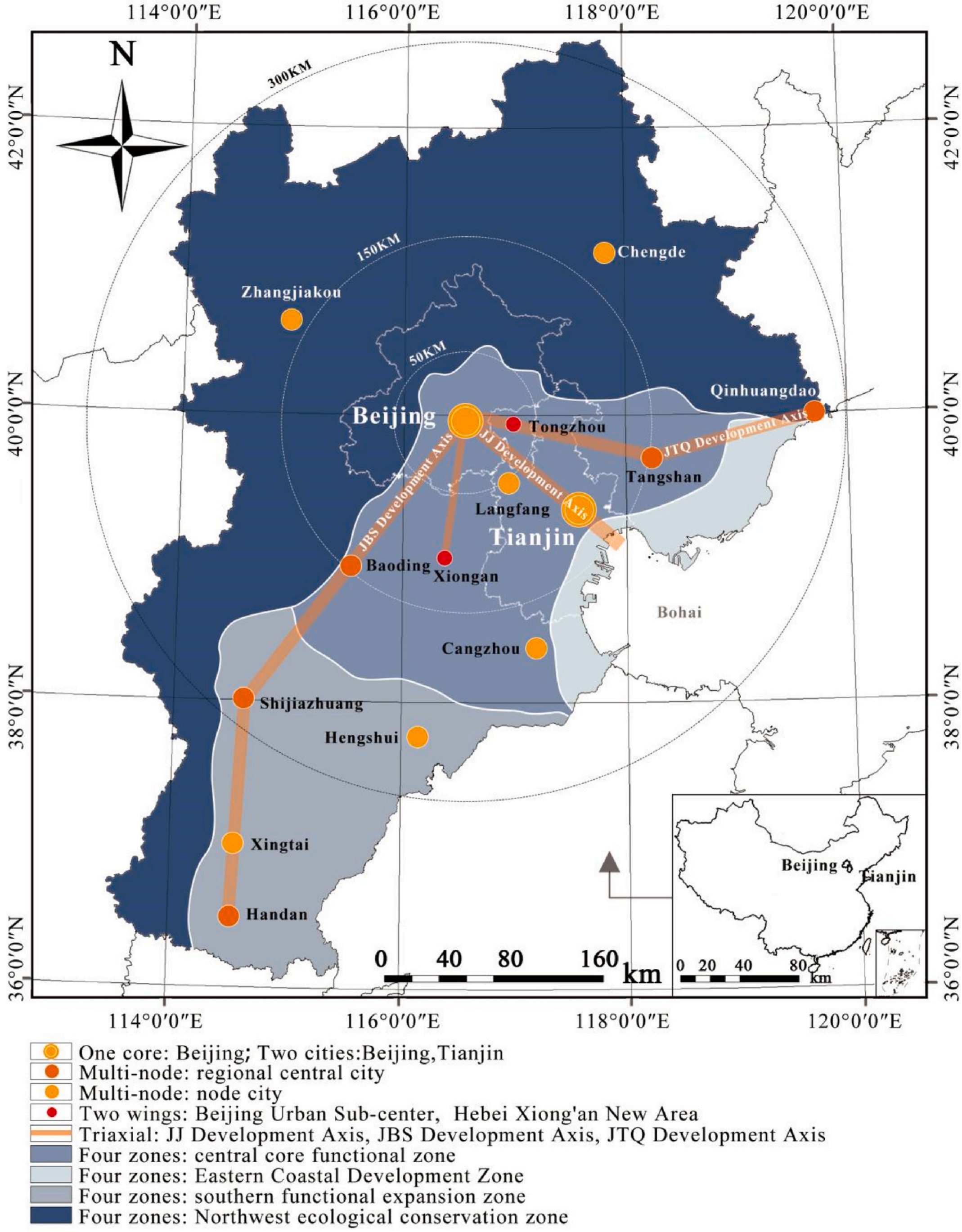

Fig. 1. Study area map.

by cities, altering the carbon stock and balance in these areas and reducing the energy efficiency of carbon sink ecological services. This will continue unless there is intervention [12,13]. Well-planned land-use management practices can re-fix approximately 60–70% of the disturbed carbon [14].

In order to enhance the carbon sink capacity of cities, an in-depth analysis of the impact of land use change on carbon stock is necessary. At present, the main land use change models include Cellular Automata (CA), SLEUTH (Slope-Land use-Exclusion-Urban extent-Transportation-Hill shade model) model, FLUS (Future Land Use Simulation) model, and PLUS (Patch-generating Land Use Simulation) model, among others [15]. The Land Expansion Analysis Strategy (LEAS) and the CA based on Multiple Random Seeds (CARS) modules of the PLUS model are based on a random forest of the planning traffic update mechanism and random seed mechanism within the planning development zone. These take into account the guiding role of land use elements on urban development, and can more accurately analyse the impact of land use evolution on potential ecosystems under different scenarios [16–20]. The InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model has the advantage of being easy to use and fast to run. Furthermore, it has been widely used for ecosystem carbon stock and ecosystem quality assessments [6,21–23].

Some studies simulate the changes in regional land use and carbon stock distribution under various ecological conservation or low-carbon development scenarios based on existing policies, conducting comparative analyses [24–27]. Additionally, scholars have simulated the distribution characteristics of regional land use and carbon stocks under different development orientations, such as ecological and economic priority [28,29]. Currently, there are many studies using coupled land use models to simulate and predict regional carbon stocks under different scenarios. However, there are few studies that integrate planning policies to simulate future land use and carbon stock changes in cities at different stages of development, and few that make cross-sectional comparisons. Megacities pay more attention to ecological planning and management, but they face more serious carbon loss problems. In view of the existing research and general trend of urban development [30], their development stages can be mainly divided into mature and potential stages. Beijing and Tianjin are megacities in the Capital Economic Circle of Beijing-Tianjin-Hebei and are low-carbon pilot cities in China [31,32]. Beijing's urban development is already in the late stages of improvement, while Tianjin is at the stage of optimisation and enhancement [33,34]. Both cities have now made public the text of their territorial spatial plans [35,36], which are expected to enhance regional carbon sink capacity through strict planning and management of land use [14]. Therefore, in order to maintain the stability of the urban carbon cycle, it is important to study the relationship between urban land use changes and carbon stock under different projected scenarios, and to compare the differences in carbon stock changes between megacities at different developmental stages.

This paper proposes to use Beijing and Tianjin as a study area, combining the PLUS model and Carbon module of the InVEST model to estimate the carbon stock in 2000, 2010, and 2020. Furthermore, this combined model is used to predict the changes in carbon stock in 2030, comparing different scenarios. Thoroughly analysing the differences in impact of ecological protection policies on carbon stocks of urban ecosystems in different stages of development, and starting from the perspective of ecological protection, this study provides a reference for low-carbon target-oriented urban planning for similar development stages.

2. Research methodology

2.1. Study area

Beijing (115.7 °-117.4 ° E, 39.4 °-41.6 ° N) has a total area of 16,410.54 km^2 and a resident population of over 20 million. Tianjin (116.7 °-118.1 ° E, 38.5 °-40.3 ° N) has a total area of 11,966.45 km^2 and a resident population of over 10 million [37–39]. Beijing and Tianjin both belong to temperate monsoon climate and have similar land surface properties. Both are Chinese municipalities, national central cities, megacities, and low-carbon pilot cities. As a first-tier city, Beijing has entered a mature and stable stage of urbanisation, while Tianjin, a new first-tier city, has a slightly lower gross domestic product per capita than Beijing and still has greater potential for urbanisation. The two cities are the twin cores of the Beijing-Tianjin-Hebei Capital Economic Circle synergistic development, forming the Beijing-Tianjin development axis, which drives regional development (Fig. 1).

2.2. Data sources and pre-processing

Data used for land use simulation in the PLUS model includes land use data, land use driver data, and restriction factor data. According to the model input requirements, aeronautical reconnaissance coverage geographic information system (ArcGIS) 10.7 software was used to reclassify the land use type data into six primary land use types: cultivated land, forest land, grassland, water area, construction land, and unused land. Based on existing research [40,41] and the availability and timeliness of driving factors, 12 significant land use driving factors were selected from natural, traffic, and social aspects: Digital Elevation Model, slope, average annual precipitation, average annual temperature, soil type, distance to railway, distance to expressway, distance to main road, distance to water area, population density, GDP, and distance to municipal government. Furthermore, as different constraints were set according to the differences in prediction scenarios, examples include ecological protection redlines, permanent basic farmland, and water areas. All coordinate data were uniformly post-resampled to 30-m resolution raster images.

2.3. Model design

This study consists of two main processes, the PLUS model to project future land use, and the Carbon module of the InVEST model to estimate carbon stock under different projected scenarios (Fig. 2).

2.4. Multi-scenario land use projections based on the PLUS model

2.4.1. PLUS model

The PLUS model is a raster data patch-level refinement of the land use prediction model that can simulate patch-level land use changes by considering multiple policy-driven land use change triggers [40,42]. The PLUS model has two modules based on the Markov chains: LEAS and CARS.

These Markov modules forecast future land use based on a past land use transfer probabilities matrix with the following equation (Eq. (1)):

$$S_{(t+1)} = p_{ij} S_t \tag{1}$$

where S_t and $S_{(t+1)}$ denote land use at times t and $t+1$, respectively, while P_{ij} denotes the probability matrix of the land use type transfer.

The LEAS module extracts the areas where each type of land use changes; it does this by inputting a two-period land use and land cover, and randomly sampling points for analysis. Furthermore, the random forest algorithm mines land use change patterns through the training data set with the following equation (Eq. (2)):

$$P^d_{i,k(X)} = \frac{\sum_{n=1}^{M} I(h_n(X) = d)}{M} \tag{2}$$

where d takes a value of 0 or 1, a value of 1 indicating a shift from other land-use types to land use types of k, and a value of 0 indicating no transformation. The function X denotes a vector of driving factors, and $h_n(X)$ denotes the type of land use predicted when the decision tree is n. The indicator function of the decision tree is I (.). The function $P^d_{i,(X)}$ is the probability of growth for land type k at spatial unit i.

The CARS model combines multivariate stochastic seed generation with a decreasing threshold mechanism to complete land use simulations with constraints on domain weights and transfer matrices, subject to the law of change mined by the LEAS module. The neighbourhood weights indicate the ease of land use transformation, and the formula is as follows (Eq. (3)):

$$\Omega^t_{i,k} = \frac{con\left(c_i^{t-1} = k\right)}{n \times n - 1} \times w_k \tag{3}$$

where w_k is the domain weight parameter, the expression $n \times n$ is the metacell, and $con(c_i^{t-1} = k)$ is the total number of grid cells occupied by the land class at the end of the metacell iteration. In addition, the domain weight of the momentary land type k at spatial unit i is represented as $\Omega^t_{i,k}$. The domain weights range from [0,1], with larger values indicating a greater spreading capacity.

The transfer matrix is set to define whether conversion can occur between different types of sites, with 1 meaning that conversion is possible and 0 meaning that conversion is restricted, using the following formula (Eq. (4)):

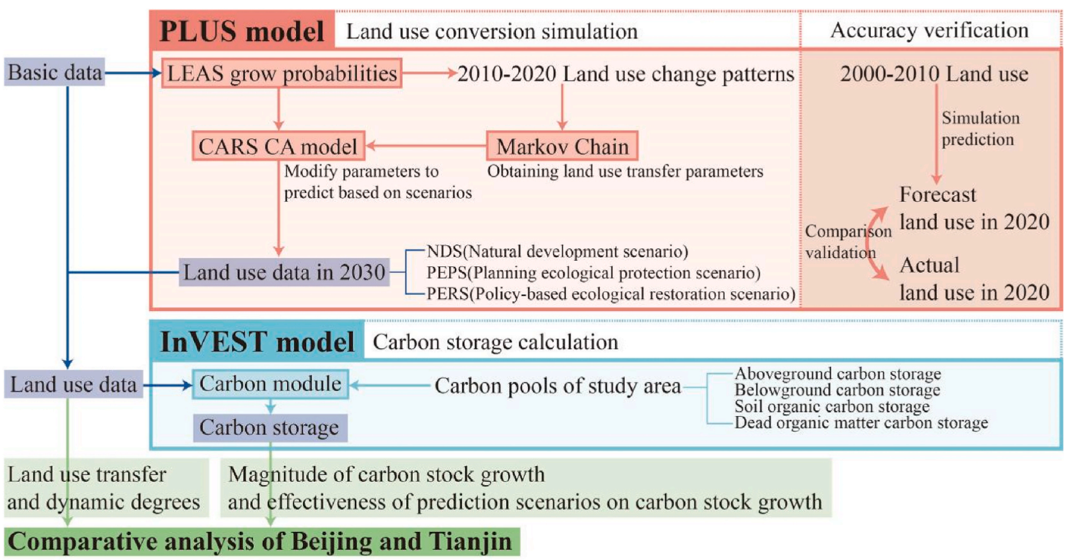

Fig. 2. Research framework diagram.

$$\begin{cases} P_{i,c}^{d=1} > \tau, TM_{k,c} = 1 & Change \\ P_{i,c}^{d=1} \le \tau, TM_{k,c} = 0 & No\ change \end{cases} \tau = \delta^{l} \times R_1 \tag{4}$$

where $P_{i,k}^{d}$ is the suitability probability of land type k at spatial unit i. The elements of the transition matrix are represented by $TM_{k,c}$, which defines whether the land type k can be shifted to c. The variable δ, which varies between 0 and 1, is the attenuation coefficient of the attenuation threshold τ. The variable R_1 is normally distributed with a mean of 1.

This paper verifies the simulation results by the Kappa coefficient, which ranges from 0 to 1. The closer the Kappa coefficient is to 1, the higher the model's accuracy. Furthermore, the simulation consistency is good when $0.6 < \text{Kappa} \le 0.8$. The equation for Kappa is (Eq. (5)):

$$Kappa = \frac{P_0 - P_c}{P_p - P_c} \tag{5}$$

where P_0 is the scale at which the simulation results agree with the reference map. The function P_c is the ratio of correct simulations in the random case of the model, while P_p is the ratio of correct simulations in the ideal case.

2.4.2. Prediction scenarios and parameter setting

High carbon stock in natural ecological areas greatly influences the maintenance of carbon balance of cities. Furthermore, the influence of natural ecological areas must be fully considered when carrying out land use change simulations. In this study, three land transformation scenarios, namely the natural development scenario (NDS), planned ecological protection scenario (PEPS), and policy-based ecological restoration scenario (PERS), were set up to simulate the land use evolution results under different management policies by modifying the transfer probability of different types of land, neighbourhood weighting parameters, and the scope of restricted development areas.

The NDS is a simulation of land use projections based on the land conversion trend from 2010 to 2020, without considering the impact of any planning policy restrictions on land change. The PEPS was set regarding the territorial spatial plans of the two cities. Furthermore, with ecological protection as the main objective, the red lines for ecological protection and permanent basic agricultural land were defined to restrict the scope. The PERS refers to *the Regulations on Returning Farmland to Forests issued by the State Council* [43] and *the Opinions of the General Office of the State Council on Encouraging and* Supporting *Social Capital Participation in Ecological Protection and Restoration* [44], which combine ecological protection with ecological restoration policies, such as the integrated protection and restoration of mountains, water, forests, fields, lakes, and grasses, as well as other ecological restoration policies such as returning farmland to forests and grasses in order to increase ecological management efforts. Finally, according to the characteristics of different development scenarios, model parameters were set to import model calculations (Table 1; Table 2).

2.4.3. Land use dynamic degree

The simulated urban land use dynamics were defined using the change in the number of land use types over a certain period of time with the following equations (Eq. (6,7)) [45].

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{6}$$

$$LC = \frac{\sum_{i=1}^{n} \Delta LU_{i-j}}{2\sum_{i=1}^{n} LU_i} \times \frac{1}{T} \times 100\% \tag{7}$$

In the first equation, K is the dynamic degree of a particular type of land use. The variables U_a and U_b represent the area of a particular land use type at the beginning and end of period T, respectively. In the second equation, LC represents the combined land use dynamics, where LU_i is the initial area of land use type i, and ΔLU_{i-j} is the area of land converted from land use type i to a different land use type j.

Table 1
PLUS model simulated 2030 multi-scenario land neighbourhood weights.

Development scenarios	Cultivated land	Forest land	Grassland	Water area	Construction land	Unused land
Natural development scenarios	0.291	0.286	0.059	0.084	0.268	0.012
Planned ecological conservation scenarios	0.291	0.296	0.069	0.084	0.248	0.012
Policy-based ecological restoration scenarios	0.231	0.326	0.099	0.084	0.248	0.012

Table 2
Multi-scenario for parameter settings in land use transfer matrix.

Development scenarios		Cultivated land	Forest land	Grassland	Water area	Construction land	Unused land
Natural development scenarios	Cultivated land	1	1	1	1	1	1
	Forest land	1	1	1	1	1	1
	Grassland	1	1	1	1	1	1
	Water area	0	0	0	1	0	0
	Construction land	0	0	0	0	1	0
	Unused land	1	1	1	1	1	1
Planned ecological conservation scenarios	Cultivated land	1	1	1	0	0	0
	Forest land	1	1	1	0	0	0
	Grassland	1	1	1	0	0	0
	Water area	0	0	0	1	0	0
	Construction land	0	0	0	0	1	0
	Unused land	1	1	1	1	1	1
Policy-based ecological restoration scenarios	Cultivated land	1	1	1	0	0	0
	Forest land	0	1	0	0	0	0
	Grassland	1	1	1	0	0	0
	Water area	0	1	1	1	0	0
	Construction land	0	1	0	0	1	0
	Unused land	1	1	1	1	1	1

2.5. InVEST model for estimating carbon stock

2.5.1. InVEST model

The Carbon module in the InVEST model analyses the distribution of carbon stock in the region under this land type. It uses a map of land cover types in the region, as well as the carbon stock in the four carbon pools (above-ground biomass, below-ground biomass, soil, dead organic matter), and is calculated as follows (Eq. (8)):

$$C_{i\_total} = C_{i\_above} + C_{i\_below} + C_{i\_soil} + C_{i\_dead} \tag{8}$$

where i is the i th land use type, C_{i_total} is the total carbon stock in the area, C_{i_above} is the above-ground biomass, including the carbon stock of all surviving plant material above the soil, such as tree trunks and bark, C_{i_below} is the carbon stock of the subsurface biomass, including the living root fraction of plants, C_{i_soil} is the carbon stock of soil organic matter from 0 to 100 cm depth, and C_{i_dead} is the carbon stock of dead organic matter, including dead branches and leaves.

2.5.2. Carbon pool setting

Carbon density data were obtained from *the Chinese Terrestrial Ecosystem Carbon Density Dataset (the 2010s)* at the National Ecosystem Science Data Center (http://www.cern.ac.cn) [46], the Web of Science (https://www.webofscience.com), and China Knowledge Network (http://www.cnki.net) using "carbon density" and "carbon stock" as keywords to search for literature on ecosystem carbon stock surveys published since 2000 [14,47–51]. Data were selected according to the following principles: 1) carbon density data sampled from the study area and adjacent regions were preferred; 2) if there were still gaps in the data, national carbon density data were used, which were corrected using climatic conditions in the study area and across the country.

The model equations for the relationships between biomass carbon density, soil carbon density, and precipitation [52], and the model equation for the relationship between biomass carbon density and mean annual temperature are given as follows (Eqs. (9) and (10)) [53,54]:

$$C_{SP} = 3.3968 \times MAP + 3996.1\left(R^2 = 0.11\right) \tag{9}$$

$$C_{BP} = 6.798e^{0.0054 \times MAP}\left(R^2 = 0.70\right) \tag{10}$$

$$C_{BT} = 28 \times MAT + 398\left(R^2 = 0.47, P < 0.01\right) \tag{11}$$

where C_{SP} is the soil carbon density (Mg/ha) obtained from annual precipitation, C_{BP} is the biomass carbon density (Mg/ha) obtained from annual precipitation, C_{BT} is the biomass carbon density based on mean annual air temperature, MAP is the average annual precipitation (mm), and MAT is the mean annual air temperature (°C).

The annual mean temperature and annual precipitation for the Beijing-Tianjin region and the whole country were substituted into the equations above. From 2000 to 2020, the average annual temperatures at the national scale and in the Beijing-Tianjin region were 10.25 °C and 13.80 °C, respectively. The annual precipitation was 664.00 mm and 552.70 mm, respectively [55,56]. The final carbon intensity correction equation is as follows (Eq. (12)–(15)):

$$K_{BP} = \frac{C'_{BP}}{C''_{BP}} \tag{12}$$

$$K_{BT} = \frac{C'_{BT}}{C''_{BT}} \tag{13}$$

$$K_B = K_{BP} \times K_{BT} = \frac{C'_{BP}}{C''_{BP}} \times \frac{C'_{BP}}{C''_{BP}} \tag{14}$$

$$K_S = \frac{C''_{SP}}{C'_{SP}} \tag{15}$$

where K_{BP} and K_{BT} denote the correction coefficients for precipitation and temperature on biomass carbon density, respectively, and K_B and K_S represent the correction coefficients for biomass carbon density and soil organic carbon density, respectively. Furthermore, C'_{BP} and C''_{BP} represent the carbon density obtained from the annual mean temperature in the Beijing-Tianjin region and in China, respectively, and C'_{SP} and C''_{SP} represent the soil carbon density data obtained from the annual mean temperature in the Beijing-Tianjin region and in China, respectively.

The reference data were collated to summarise the carbon density data for the different land types (Table 3).

2.5.3. Analysis of carbon stock changes

To compare the average carbon stock change of the land system in two cities at different times and under different simulated scenarios, the carbon stock increase of PEPS and PERS was subtracted from the carbon stock increase of NDS to obtain the net carbon stock increase of the two scenarios. This was used as to measure the influence of the two scenarios on carbon stock changes in the two cities. The formulas for these calculations are (Eq. (16) and (17)):

$$CR_{NDS/PEPS/PERS} = \frac{C_{NDS/PEPS/PERS} - C_{2020}}{C_{2020}} \tag{16}$$

$$CGE_{PEPS/PERS} = CR_{PEPS/PERS} - CR_{NDS} \tag{17}$$

where C_{2020} is the carbon stock in 2020, $C_{NDS/PEPS/PERS}$ is the amount of carbon stock in the three scenarios, $CR_{NDS/PEPS/PERS}$ is the simulated carbon stock growth in 2030 for the three scenarios, and $CGE_{PEPS/PERS}$ is the effectiveness of the impact of the PEPS or the PERS on carbon stock growth.

3. Results and analysis

3.1. Land use change

3.1.1. Spatial and temporal land use change characteristics

In the PLUS model, land use data from 2000 to 2010 were used as the basis for simulating land use in 2020. When compared with the actual 2020 land use dataset, the overall accuracy reached 85.231%, and the Kappa coefficient was 0.769, proving that the PLUS model is highly accurate in simulating the evolution of land use in this study.

ArcGIS was used to calculate the land use transfer and dynamic degree of each type of land use between 2000 and 2020 (Figs. 3–5; Table 4). A single-dynamic degree can indicate the efficiency of the increase or decrease of a certain land use type. Furthermore, a comprehensive dynamic degree can indicate the total land transfer. The results show that, over the 20-year period, Beijing had the highest proportion of forested land area, at over 45%, and Tianjin had the highest proportion of cultivated land area, at over 49%. The area of cultivated land in both cities decreased year by year, while construction area rose year by year. From 2000 to 2020, Tianjin had the largest dynamic degree towards construction land, at 3.87%, which was higher than that of Beijing's (2.83%). Beijing had the highest dynamic degree towards unused land, at 55.44%. However, both cities had the lowest dynamic degree towards forest land,

Table 3
InVEST model carbon pool table (Mg of C/ha).

Type of land use	C_{i_above}	C_{i_below}	C_{i_soil}	C_{i_dead}	References
Cultivated land	4.28	0	84.63	0	[14,46,49]
Forest land	38.07	10.41	136.39	18.03	[46,50,51]
Grassland	1.32	12.75	79.17	0.71	[46,50,51]
Water area	1.82	0.67	85.37	1.24	[46,50,51]
Construction land	4.41	2.21	1.67	0	[48,49]
Unused land	0	0	0	0	[47]

Note: Data from the same author were chosen when possible to increase data reliability and to avoid the excessive variations in carbon density data that comes from using different sources.

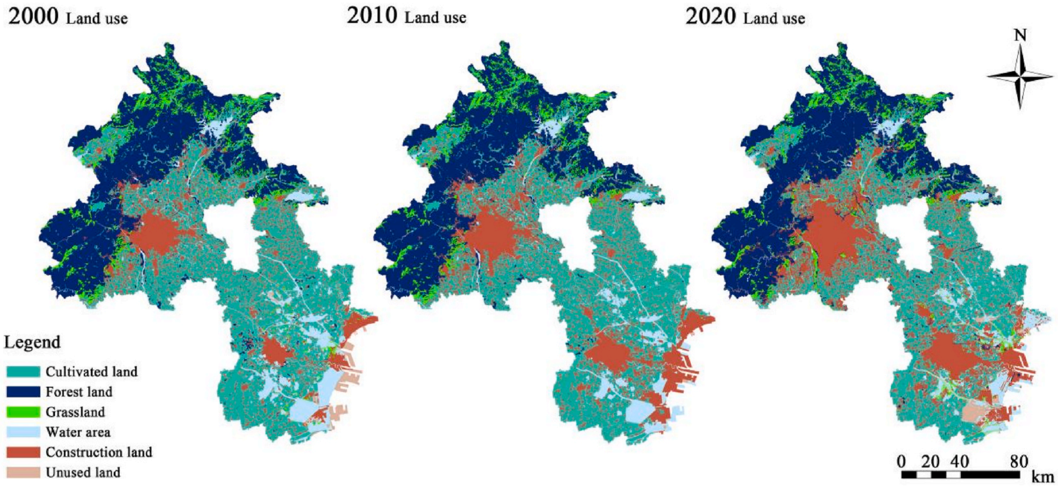

Fig. 3. 2000–2020 land use map.

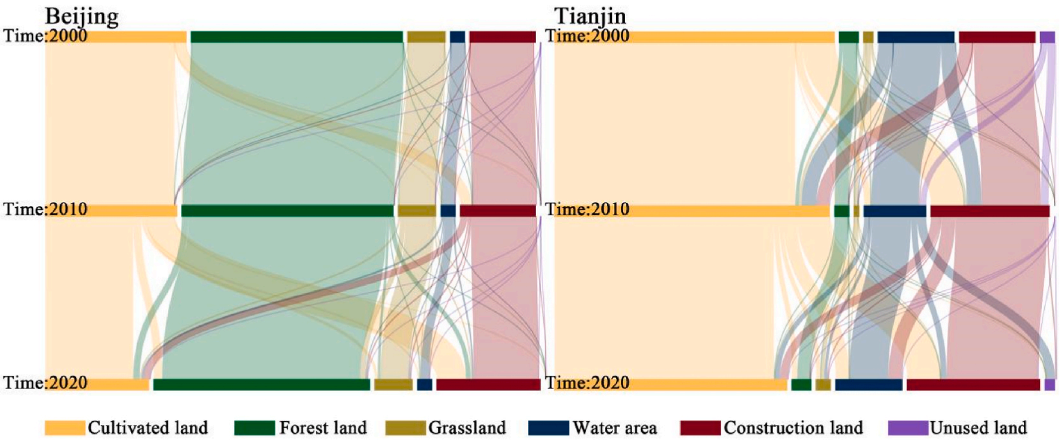

Fig. 4. 2000–2020 sandy chart of land use transfers.

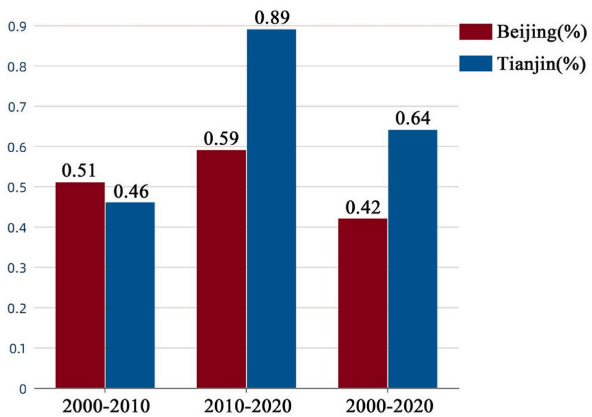

Fig. 5. 2000–2020 land use comprehensive dynamic degree.

indicating that forest land had the least amount of land transfer. The comprehensive dynamic degree of land use in Beijing between 2000 and 2010 was 0.51% higher than that in Tianjin. The comprehensive dynamic degree between 2000 and 2020 was higher in Tianjin, at 0.64%. However, both cities had the highest comprehensive dynamic degree in 2010–2020, accounting for the largest

Table 4
2000–2020 land use dynamics degree by category.

Type of land use	2000–2010 Single-dynamic degree (%)		2010–2020 Single-dynamic degree (%)		2000–2020 Single-dynamic degree (%)	
	Beijing	Tianjin	Beijing	Tianjin	Beijing	Tianjin
Cultivated land	−0.78	−0.15	−1.91	−4.53	−1.27	−0.83
Forest land	−0.01	−2.47	0.07	3.51	0.03	0.09
Grassland	0	−5.57	−0.32	20.53	−0.16	1.74
Water area	−0.48	−1.99	−1.33	0.82	−0.87	−0.66
Construction land	1.85	5.95	3.39	1.12	2.93	3.87
Unused land	−1.43	−9.60	130.99	176.37	55.44	−1.26

amount of land transfer in this decade.

3.1.2. Spatial and temporal land use change characteristics under multiple scenarios

Statistics on land use distribution and transfer under the three scenarios in 2030 (Figs. 6–8; Table 5) show that the proportion of construction land in Beijing will continue to rise to 24.11%, while in Tianjin it will rise to 30.61% under the NDS, with approximately 19,725 ha of cultivated land converted to construction land in Beijing and 5366 ha of cultivated land converted to construction land in Tianjin. Under the NDS, Tianjin's comprehensive dynamic degree is 0.37%, which is higher than that of Beijing (0.36%). Under the PEPS, the comprehensive dynamic degree of land use in Beijing is 0.22%, and that of Tianjin is 0.13%. The comprehensive dynamic degree of Beijing under the PERS is 0.61%, much higher than that of Tianjin at 0.26%, indicating that both the PEPS and PERS have a greater impact on land use transfer efficiency in Beijing. Furthermore, under the PEPS, the forest dynamic degree of Tianjin is 1.49% and that of Beijing is 0.48%; under the PERS, the dynamic degree of forest land in Tianjin is 5.66%, approximately four times that of Beijing, indicating that the forest land area in Tianjin grows faster under the both scenarios.

3.2. Carbon stock changes

3.2.1. Spatial and temporal characteristics of carbon stock

The carbon stock distribution and carbon density changes from 2000 to 2020 (Fig. 9; Table 6) show that the carbon stock of both Beijing and Tianjin decreased year by year during the 20-year period, with carbon stock decreasing by 10, 348, 471.54 Mg and 10, 532, 007.73 Mg, respectively, and carbon density decreasing by 6.31 Mg/ha and 8.80 Mg/ha, respectively. The carbon loss in Tianjin from 2000 to 2020 was greater than that in Beijing, probably because Tianjin was in a phase of rapid urban development during this period, resulting in higher carbon loss due to both faster urban construction and greater demand for land development as compared to Beijing, which was relatively mature in terms of urbanisation.

3.2.2. Spatial and temporal variability of carbon stock under multiple scenarios

The carbon stock distribution (Fig. 10) and changes (Fig. 11) under each scenario in 2030 were obtained. Furthermore, the growth rate of carbon stock under the three scenarios, and the effectiveness of PEPS and PERS on carbon stock growth were calculated (Fig. 12). The results show that the NDS scenario has the lowest carbon stock, with a negative growth trend relative to 2020. Beijing has a larger carbon stock, which is 200, 898, 879.96 Mg, while Tianjin has a carbon stock of 79, 497, 538.14 Mg. The carbon density of Beijing is 122.421 Mg/ha, which is 55.987 Mg/ha higher than that of Tianjin. The PEPS has a carbon stock of 206, 886, 898.49 Mg in

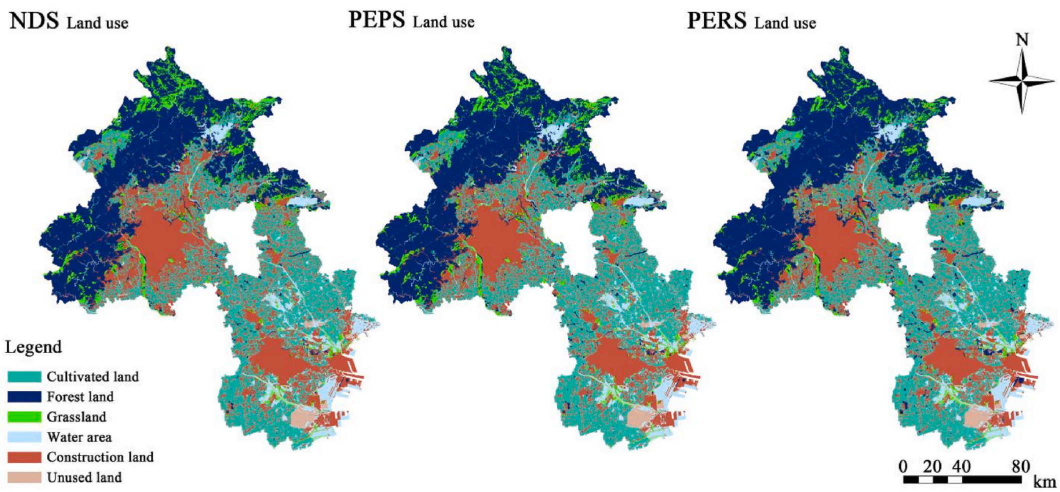

Fig. 6. Modelled 2030 land use map.

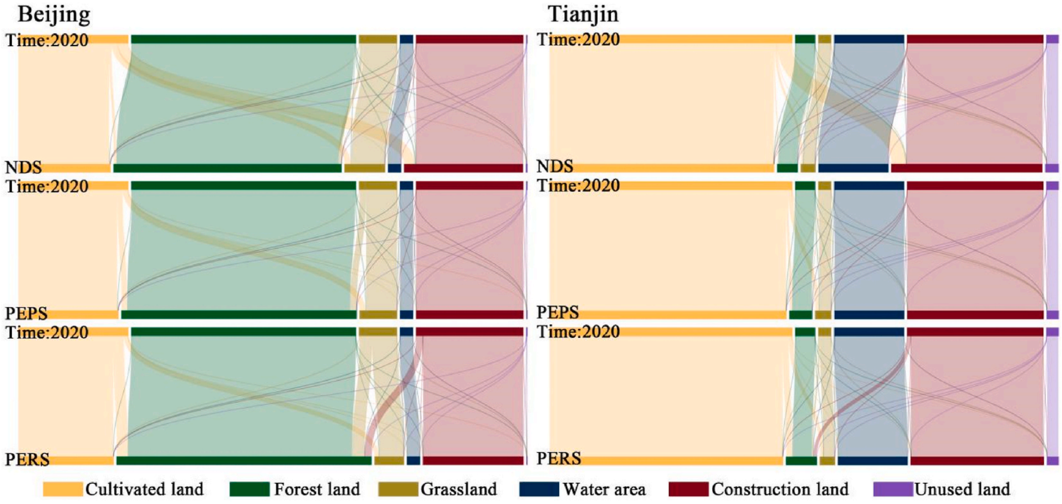

Fig. 7. 2020–2030 sandy chart for land use transfer.

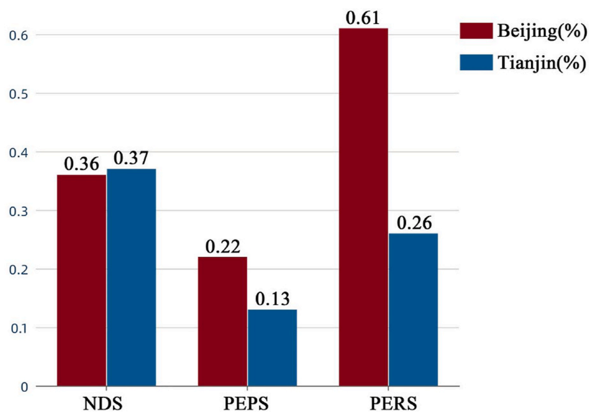

Fig. 8. 2020–2030 land use comprehensive dynamic degree.

Table 5
2020–2030 land use dynamic degrees.

Type of land use	Natural development scenarios Single-dynamic degrees (%)		Planned ecological conservation scenarios Single-dynamic degrees (%)		Policy-based ecological restoration scenarios Single-dynamic degrees (%)	
	Beijing	Tianjin	Beijing	Tianjin	Beijing	Tianjin
Cultivated land	−1.63	−0.75	−0.92	−0.24	−1.34	−0.39
Forest land	0.15	0.45	0.48	1.49	1.35	5.66
Grassland	0.67	1.26	−0.14	2.49	−2.29	1.55
Water area	0	0	0	0	0	0
Construction land	1.10	1.09	0.01	0.01	−0.62	−0.22
Unused land	5.24	0.77	−1.90	−0.29	−3.16	−0.54

Beijing, and 83, 208, 306.71 Mg in Tianjin. The carbon density of Beijing is 126.07 Mg/ha, which is 56.535 Mg/ha higher than that of Tianjin. Beijing's carbon stock increases by 2.00%, which is 0.93% higher than that of Tianjin. In the PERS, the carbon stock of Beijing is 216, 004, 904.01 Mg, while that of Tianjin is 86, 119, 579.4 Mg. The carbon density of Beijing is 131.626 Mg/ha, which is 59.658 Mg/ha higher than that of Tianjin. The growth rate of carbon stock in Beijing is approximately 6.50%, which is 1.89% higher than that of Tianjin. The effect of the PEPS and PERS on carbon stock growth in Tianjin is more effective than that in Beijing, indicating that the ecological protection and restoration strategy is more helpful in enhancing carbon stock in Tianjin. This is likely because Tianjin has less forested land and a larger proportion of construction land with a lower carbon intensity, which loses more carbon under the natural development scenario. Because the ecological protection and restoration policy has greatly increased the proportion of forest land area in Tianjin, it has had an outsized impact on its carbon stock.

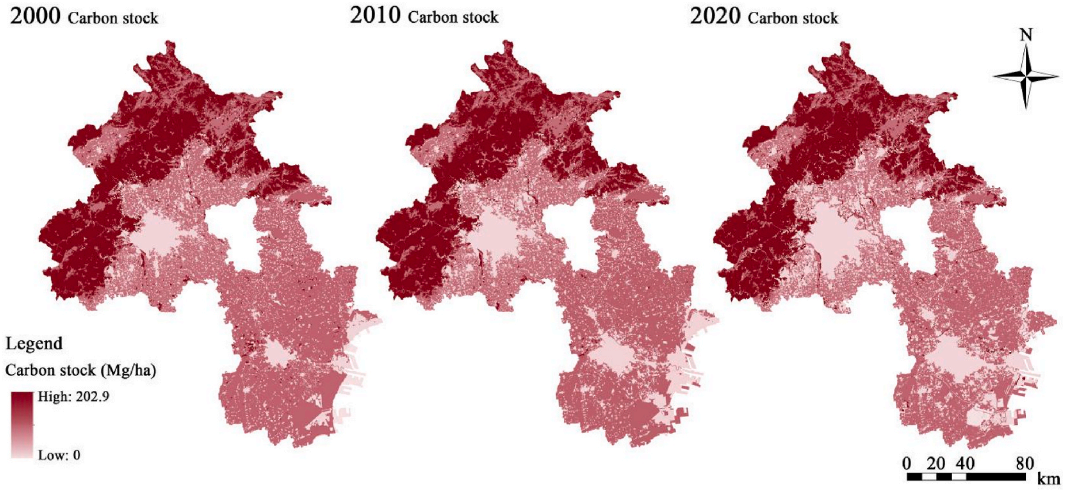

Fig. 9. 2000–2020 carbon stock distribution.

Table 6
2000–2020 carbon stock and carbon intensity.

Year	Carbon stock (Mg)		Carbon density (Mg/ha)	
	Beijing	Tianjin	Beijing	Tianjin
2000	213,170,852.66	92,858,473.93	129.899	77.599
2010	209,712,373.86	85,889,702.53	127.791	71.775
2020	202,822,381.12	82,326,466.2	123.593	68.798

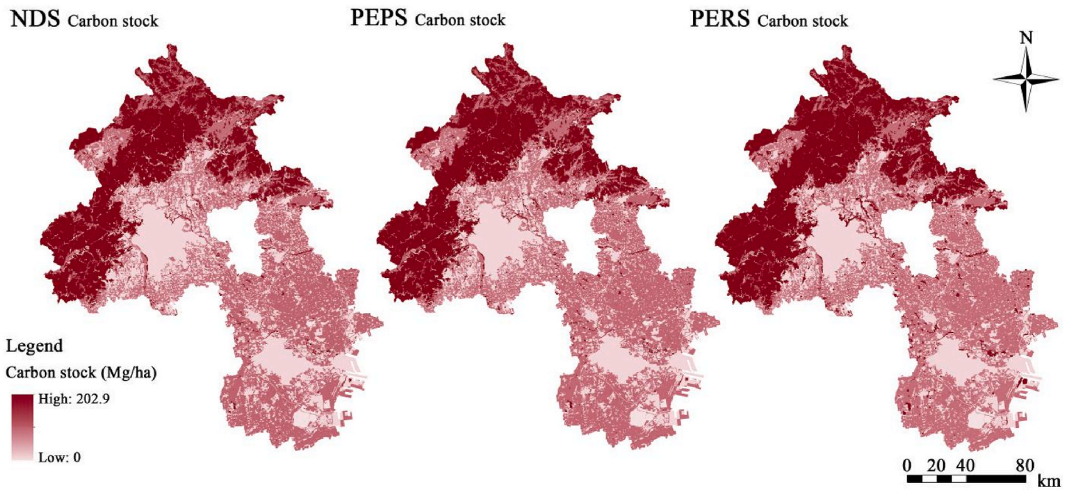

Fig. 10. 2030 carbon stock distribution.

3.3. *Impact of ecological conservation policies on land use and carbon stock changes*

3.3.1. *Impact of ecological conservation policies on land use changes*

In the PEPS, the comprehensive dynamic degree of land use in Beijing is the lowest, 0.14% lower than that of NDS and 0.39% lower than that of PERS. In the PEPS, the comprehensive dynamic degree of land use in Tianjin is 0.24% lower than that of NDS and 0.13% lower than that of PERS (Fig. 8). Both cities have the smallest degree of land use change in the PEPS, indicating that there is less land transfer in this scenario. This may be because ecological conservation and restoration are strictly implemented based on the land planning boundary in the PEPS, leading to the smallest comprehensive dynamic degree. In the PEPS, the dynamic degree of forest land in Beijing is 0.48%, which is 0.33% higher than that of NDS and 0.52% lower than that of PERS. In the PEPS, the dynamic degree of

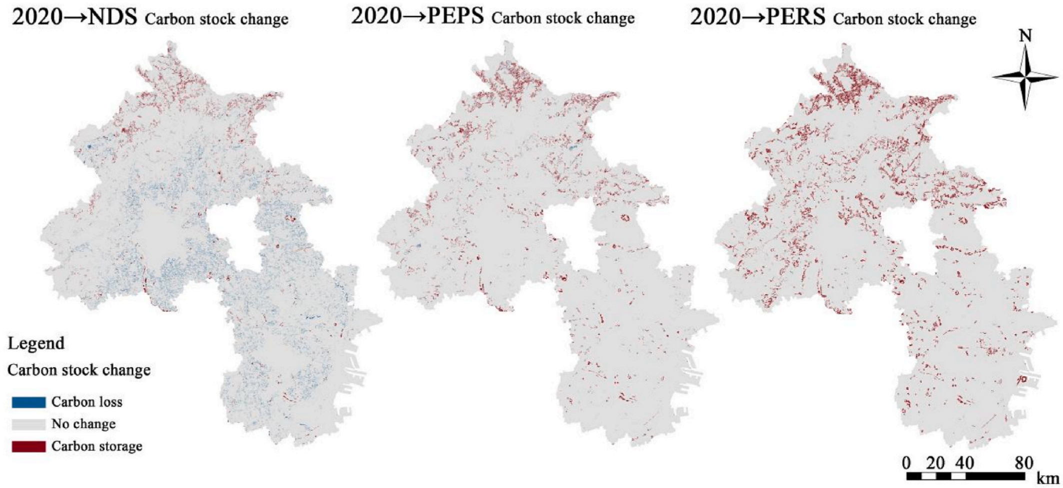

Fig. 11. 2020–2030 spatial changes in carbon stock.

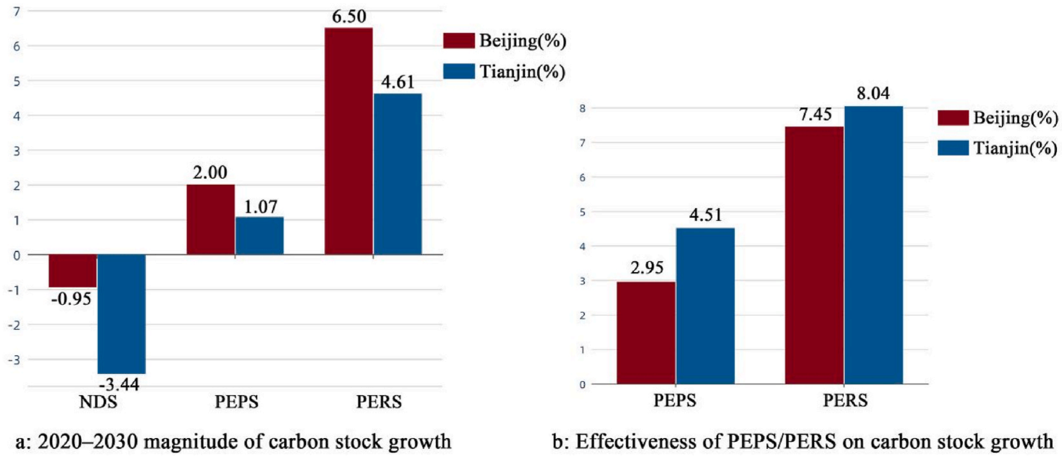

Fig. 12. A) 2020–2030 magnitude of carbon stock growth, b) effectiveness of PEPS/PERS on carbon stock growth.

forest land in Tianjin is 1.04% higher than that of NDS and 4.17% lower than that of PERS (Table 5). Both cities have the highest dynamic degree of forest land in the PERS, indicating that the increase in forest land area is the largest for PERS. This may be because PERS strives to implement a series of ecological restoration policies based on the PEPS, and increases the intensity of ecological restoration, effectively increasing the area of forest land.

3.3.2. *Impact of ecological conservation policies on carbon stock changes*

In the PEPS, the carbon stock growth rate of Beijing is 2.00%, which is 2.95% higher than that of NDS and 4.50% lower than that of PERS. In the PEPS, the carbon stock growth rate of Tianjin is 1.07%, which is 4.51% higher than that of NDS and 3.54% lower than that of PERS (Fig. 12). In the NDS, both cities have negative growth rates in carbon stock, while in the PEPS and PERS, both cities have positive growth rates, indicating that the implementation of ecological conservation policies has a positive effect on regional carbon storage. In the PERS, the carbon stock growth rates of Beijing and Tianjin are the highest, at 6.50% and 4.61%, respectively, indicating that more aggressive ecological conservation and restoration policies can more effectively increase carbon storage. The impact of the PERS on the carbon stock growth of Beijing and Tianjin is 7.45% and 8.04%, respectively, which is approximately 1.5–2.5 times that of the PEPS scenario (Fig. 12). This indicates that the PERS can more effectively increase the carbon stock of the two cities, and that increasing the effectiveness of ecological restoration policies while adhering to the ecological conservation red line can more effectively increase carbon storage.

4. Discussion

The carbon stock of terrestrial ecosystems, which plays a major role in the global carbon cycle system, is influenced by the carbon intensity of different land use types [9,57,58]. Land use changes that have a large impact on carbon stock can be summarised as the expansion of urban construction land and the encroachment of ecological land [6], due to the large carbon emissions from construction land and the carbon sink effect of ecological areas that can store more carbon. This shows that the conservation and restoration policies of eco-regions are important for increasing carbon storage.

The effectiveness of ecological protection policies on urban carbon stock varies between cities because of their different development profiles. In addition, as highly urbanised megacities, Beijing and Tianjin are at different stages of development, with Beijing as the capital city urbanising faster than Tianjin from 2000 to 2010. Beijing gradually moved into a later stage of urban development and improvement from 2010 to 2020. Beijing issued over 15,000 ecological protection-related regulations and policies during this period (Beijing Municipal People's Government http://www.beijing.gov.cn/). Furthermore, it promulgated and implemented *the Beijing Urban Master Plan (2016–2035)*, which specified development restriction areas such as the ecological protection red line and the scope of basic cultivated land, effectively curbing the progress of urban expansion. Meanwhile, Tianjin, which still has great urbanisation potential, has accelerated its urbanisation process, with more than 5000 ecological protection-related regulations and policies (Tianjin Municipal People's Government https://www.tj.gov.cn/). The lower level of ecological protection and the faster rate of urban expansion in Tianjin leads to a higher level of carbon loss than that in Beijing. The results of this paper are consistent with previously published literature [59–62] (Table 7).

The PERS practices ecological restoration policies based on the PEPS. Compared to the strictly controlled, planning-based ecological protection red line, its policy implementation is more flexible, and in practice, it is difficult to realise the idealised ecological restoration scenario. The large population and large carbon emissions of megacities require more effective carbon sequestration strategies. Considering the negative impact of land use change on carbon stock of terrestrial ecosystems, as well as the contribution of natural ecological areas to carbon stock, it seems clear that natural ecological areas should be preserved as much as possible as cities grow. Given that the effectiveness of the PERS on carbon stock growth is approximately 1.5–2.5 times that of the PEPS, which is even more significant, the government should also increase the implementation of ecological protection and restoration policies, including the policy of returning farmland to forest and grass [43]. To effectively increase the carbon stock, this should be done while adhering to strict land use planning policies to alleviate ecological pressure on large cities through measures such as grass storage balance and the greening of construction land [25].

This study still has some limitations. Land use data comes from remote sensing satellite image interpretation. Satellite data has varied in accuracy over the years, and the subjectivity of manually interpreting and correcting land use types can also lead to a level of uncertainty in the results. In addition, the InVEST model calculates carbon stock based on land use type data, ignoring the influence of factors such as land transfer, temperature and humidity changes, as well as plant status on carbon stock [62]. In subsequent studies, the accuracy of land use simulations and carbon stock calculations can be increased by doing the following: clarifying land use types in conjunction with field visits, classifying land use types more finely, shortening the simulation year interval, and calculating carbon density under different temperature and humidity environments. In addition, this study only selects Beijing and Tianjin as representatives of super-large cities in different stages, which is somewhat one-sided. In subsequent studies, more detailed and comprehensive classifications will be made for urban development stages, and more cities will be sampled for comparative studies.

5. Conclusion

Taking Beijing and Tianjin as examples, this study couples the PLUS model and the InVEST model to simulate NDS, PEPS, and PERS, and analyses the effects of these three scenarios on land use and carbon storage in megacities at different stages of development.

The results showed that both Beijing and Tianjin had different degrees of urban expansion encroaching on ecological areas during 2000–2020. The dynamic rate of construction land in Tianjin was 3.87%, which was 0.94% higher than that of Beijing. The comprehensive dynamic rate in Tianjin was 0.64%, which was 0.22% higher than that of Beijing. Both cities experienced varying

Table 7
Related research summary.

Research results	Reason	References	Similarities	Differences
The impact of the PEPS and PERS on the carbon stock increase in faster expanding Tianjin is greater	PEPS and PERS effectively curbed the expansion of construction land.	[59]	Under the ecological protection scenario, the green area increases, and the construction land decreases.	The prediction of the ecological protection scenario is more reasonable than that of the historical trend scenario.
	The restriction of construction land is conducive to the increase of carbon stock.	[60]	Green areas contribute significantly to carbon storage, and the expansion of construction land is the main reason for the decrease in carbon storage.	The Ecological Priority (EP) scenario only slightly slows down the rate of decrease in carbon storage.
Under the PERS, the growth rate of urban carbon stock is much higher than that under the PEPS	The PERS has a greater ecological restoration effort, with a larger increase in forest area, and a higher growth rate of carbon stock.	[61]	The increase in carbon storage is mainly attributed to the expansion of forest area.	The relationship between carbon storage and environmental changes was analyzed.
		[62]	Land use types with high carbon density (such as wetlands, forests, and grasslands) should be protected.	The carbon loss caused by the expansion of cultivated land is equivalent to or greater than the loss caused by urban expansion.

degrees of carbon loss over a 20-year period, with Tianjin experiencing more severe carbon loss. Tianjin's carbon stock reduction was 183,536.19 Mg more than what occurred in Beijing, and its carbon density reduction was 2.49 Mg/ha greater. Under the NDS, construction land in both cities will continue to expand and carbon stock will be reduced to varying degrees, with comprehensive land use dynamics in Beijing expected to be 0.01% lower than that in Tianjin. Additionally, carbon stocks are predicted to be 2.49% lower in Beijing than in Tianjin.

Under the PEPS and PERS, the expansion of construction land in both cities is restricted and the dynamic rate of construction land is lower than that of the NDS, while the increase in carbon stock is higher than that of the NDS. Under the PEPS, the comprehensive land use dynamics in Beijing is 0.09% higher than that in Tianjin. The growth of carbon stock in Beijing is 0.93% higher than that in Tianjin. Additionally, the effectiveness of the PEPS on the growth of carbon stock in Beijing is 1.56% lower than that in Tianjin. Under the PERS, the comprehensive dynamic degree is 0.35% higher in Beijing than in Tianjin. Moreover, the carbon stock increase in Beijing is 1.89% higher than that in Tianjin. Additionally, the effectiveness of the PERS on the growth of carbon stock in Beijing is 0.59% lower than that in Tianjin. Under the PERS, the increase in carbon stock in both cities is higher, and the impact on the growth of carbon stock in both cities is also greater.

Under the PERS, there is a greater emphasis on ecological restoration, resulting in a larger increase in carbon storage, but also a large-scale reduction in urban construction land, which is somewhat different from the trend of urban economic development. In particular, the PERS has a greater impact on megacities like Beijing, which are in a mature and well-developed stage. Both scenarios have a greater impact on the growth of carbon stock in megacities with greater development potential, such as Tianjin. Additionally, megacities in the rapid development stage can refer to this conclusion and vigorously implement ecological restoration policies, while strictly following the ecological protection land planning scope to increase regional carbon stock effectively. Furthermore, megacities in the mature and perfect development stage can flexibly implement ecological restoration policies to increase regional carbon stock without affecting the economic development of the city.

Author contribution statement

Ning Zou: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Chang Wang: Analyzed and interpreted the data; Wrote the paper.

Siyuan Wang: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Yunyuan Li: Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e18814.

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