

Article

Multi-Scenario Simulation of Ecosystem Service Value in Beijing's Green Belts Based on PLUS Model

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Abstract: Urbanization and economic growth have substantially modified the land utilization structure, affecting ecosystem services and their spatial distribution. As a crucial component of Beijing's urban framework, the city's green belts, located at the periphery of its core metropolitan area, play a vital role in supplying urban ecosystem services. They also represent a focal point for land use transformation conflicts, making them an important study area. This research utilizes land utilization data from 2000, 2005, 2010, 2015, and 2020 as the primary dataset. It adopts a modified standard equivalent factor and integrates it with the Patch-Generating Land Use Simulation (PLUS) model to model land utilization in Beijing's green belts for 2035 under three scenarios: the natural development scenario (NDS), ecological protection scenario (EPS) and cultivated protection scenario (CPS). The study aims to analyze and project the spatial and temporal evolution of ecosystem service values (ESVs) in 2035 under different scenarios in the green belts of Beijing. The results indicate that (1) land use in Beijing's green belts is dominated by cropland and construction land. Construction land has expanded significantly since 2000, increasing by 500.78 km², while cropland has decreased by 488.47 km². Woodland, grassland, and water have also seen a reduction. Overall, there is a trend of woodland and water being converted into cropland, with cropland subsequently transitioning into construction land. (2) In the NDS, construction land increases by 91.76 km², while cropland, grassland, and water decrease. In EDS, the growth of construction land decelerates to 22.09 km², the reduction in cropland decelerates, and the conversion of cropland to construction land is limited. Grassland and water remain largely unchanged, and woodland experiences a slight increase. In CPS, the conversion of cropland to construction land is notably reduced, with construction land increasing by 11.97 km², woodland increasing slightly, and grassland and water decreasing slightly. (3) The ESV ranking across scenarios is as follows: EPS 1830.72 mln yuan > CPS 1816.23 mln yuan > NDS 1723.28 mln yuan. Hydrological regulation and climate regulation are the dominant services in all scenarios. ESV in EPS attains the greatest economic gains. This study contributes to understanding the effects of land utilization changes on ESV, offering valuable empirical evidence for sustainable development decision-making in swiftly urbanizing areas.



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Keywords: land use; green belt; PLUS model; driving factors; multi-scenario modeling; ecosystem service values

1. Introduction

Urbanization continues to accelerate globally, driven by the concentration of populations in cities, which fosters the expansion of urban boundaries and infrastructure development. While this process contributes to economic growth and social development, it also results in the encroachment of ecological and agricultural lands [1]. Ecosystem services (ES) form the foundation of the resources and environmental systems that sustain human life and sustainable development [2,3]. Frequent human activities, however, are continually altering the land use/land cover (LULC) patterns, which in turn affect the supply and distribution of these services [4,5].

In recent years, scholars have conducted extensive investigations into ecosystem services from diverse perspectives. Regarding research scope, since Costanza's [6] pioneering global-scale ES valuation in 1997, subsequent studies have progressively refined their focus to regional scales, examining specific ecosystems including forests [7–9], grasslands [10–12], agricultural lands [13,14], wetlands [15–17] and coastal environments [18–20]. The research paradigm has evolved from static assessments of single ecosystems like forests and wetlands to dynamic analyses of complex systems such as urban–rural ecotones. Current research dimensions encompass multiple aspects: quantitative methodologies for ecosystem service evaluation [21–24], the spatiotemporal pattern analysis of ecosystem services [25], and the investigation of service trade-offs and synergies [26]. Methodologically, the application of specialized tools such as the InVEST model [27,28] and SolVES model [29,30] has facilitated significant advancements from basic spatial mapping to sophisticated quantitative assessments. These methodological developments provide crucial insights for understanding the complexity of urban ecosystem services and their multidimensional impacts on human well-being.

International precedents such as the London Metropolitan Green Belt [31,32] and Seoul Green Belt [33,34] demonstrate the perpetual tensions between urban expansion imperatives and ecological conservation in peri-urban transitional zones. Functioning as critical buffer areas between urban and rural landscapes, these greenbelts maintain vital ecological functions while playing important socio-economic roles. This study's selection of the Beijing Greenbelt Area as its research focus addresses both empirical and theoretical imperatives. As China's capital undergoing rapid urbanization, Beijing presents the prototypical urban ecological challenges prevalent among global megacities [35]. The research outcomes possess significant generalizability, offering methodological references for comparable regions worldwide.

The methodological framework of this study involves employing the Patch-Generating Land Use Simulation (PLUS) model for future land use simulation, followed by ecosystem service value (ESV) assessment utilizing the equivalent value factor method. Current spatial simulation models for land use change, including the CA-Markov [36,37], ANN-CA [38], CLUS-S [39], Dyna-CLUE [40], and FLUS [41] models, etc., exhibit limitations in simulating land use patch transformation processes. These models demonstrate insufficient accuracy in ecological condition assessment due to their failure to account for temporal and spatial variations [42]. Compared with alternative models, the PLUS model demonstrates significant advantages by better elucidating the relationship between land use changes and their driving factors, thereby enhancing the precision of regional land use simulations. To address the inherent limitation of the equivalent value method in capturing ESV's spatiotemporal dynamics, Xie [43] enhanced this methodology by integrating the characteristics of China's ecosystems. In this research, we have adopted Xie's improved framework as a theoretical foundation and have further refined the equivalent factor table through the incorporation of Beijing's grain price data and Net Primary Productivity (NPP) data, consequently improving the accuracy of ESV assessment.

2. Materials and Methods

2.1. Study Area

Beijing is the capital of the People's Republic of China. It is located on the northern edge of the North China Plain ($115^{\circ}25'–117^{\circ}35'$ E, $39^{\circ}28'–41^{\circ}05'$ N) and spans a total land area of 1.68×10^4 km². With four distinct seasons, the city has a warm temperate continental monsoon climate. The annual precipitation is 595 mm, with the majority occurring from June to September. Beijing, as the capital city of China and a megacity, features a unique urban planning approach characterized by a “decentralized group approach”. From the outset of urban planning, Beijing's green belts served as an ecological buffer zone between the core urban areas and the surrounding built-up regions. They have also been a focal point for land use conflict during the process of urban development.

The Greenbelt Area of Beijing covers approximately 1220 square kilometers. The First Greenbelt Area, encompassing a policy-defined scope of approximately 310 square kilometers, is designed to safeguard the ecological security framework of the central urban area. The Second Greenbelt Area, covering around 910 square kilometers, extends beyond the First Greenbelt's policy boundary to the outer edge of the Sixth Ring Road. This zone provides extensive green space and serves as a strategic reserve to enhance urban ecological resilience and consolidate the ecological security structure of the plain region. Although the Second Greenbelt Area is delimited based on the urban ecological structure during planning, its implementation is coordinated with township administrative units, leading to a certain degree of policy mismatch. The scope of this study encompasses all township administrative units involved in the relevant planning of the Greenbelt Area, covering an area of 2058.19 km², as shown in Figure 1.

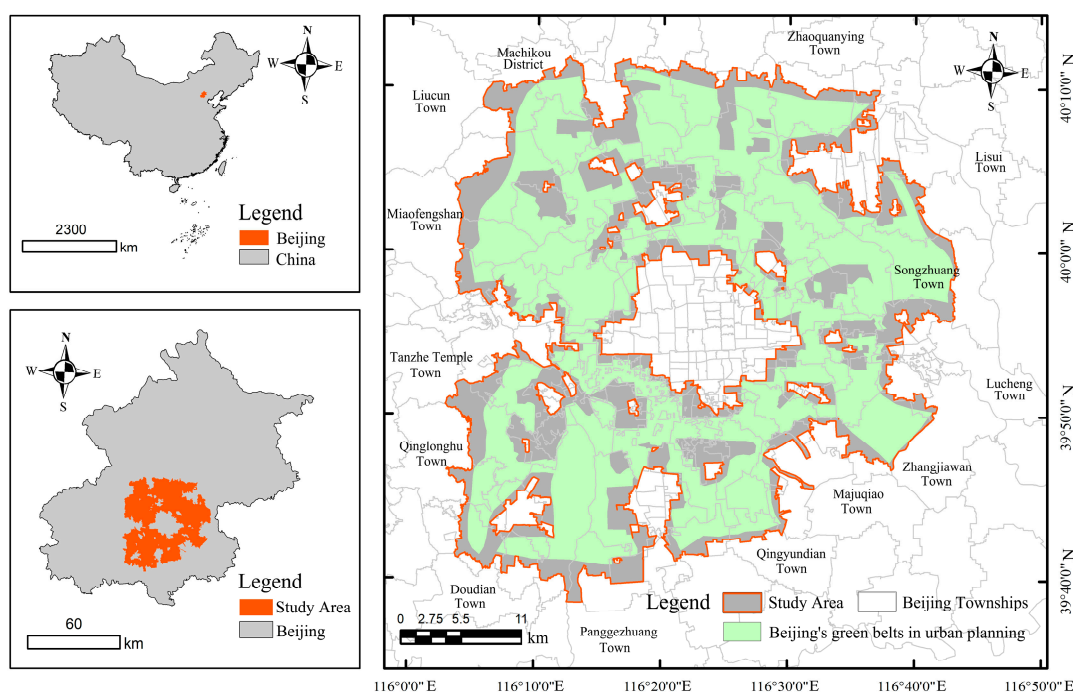


Figure 1. Location and study area.

2.2. Data Sources

The data utilized in this study consist of land use data and driving factors data. The land utilization data were obtained from the China Land Cover Dataset (CLCD), covering five time periods, with a spatial resolution of 30 m: 2000, 2005, 2010, 2015, and 2020. In the selection of driving factors, this paper considered the combined effects of natural, social,

and economic [44] conditions. Thirteen driving factors were chosen (Figure 2) based on the principles of data accessibility, spatial characteristics, and comprehensiveness. The data types and their origins are outlined in Table 1.

Table 1. Data information.

Data	Subdata	Year	Format	Resolution	Institution	Website
Land use data	Land use	2000–2020	Grid	30 m	China Land Cover Dataset (CLCD)	https://zenodo.org/records/12779975 (accessed on 20 December 2024).
Climate and environmental data	Annual precipitation	2022	Grid	1000 m	National Earth System Science Data Center (NESSDC)	http://www.geodata.cn/ (accessed on 20 December 2024).
	Annual temperature	2022	Grid	1000 m	NESSDC	http://www.geodata.cn/ (accessed on 20 December 2024).
	Elevation	2024	Grid	30 m	Geospatial data cloud	https://www.gscloud.cn/ (accessed on 20 December 2024).
	Slop	2024	Grid	30 m	calculated from DEM	/
	Soil type	2018	Shpfile	-	NESSDC	http://www.geodata.cn/ (accessed on 20 December 2024).
	Distance to water	2024	Shpfile	-	Open Street Map (OSM)	https://www.openstreetmap.org/ (accessed on 20 December 2024).
Socio-economic data	GDP	2020	Grid	1000 m	Resources and Environmental Science and Data Center, Chinese Academy of Sciences	https://www.resdc.cn/ (accessed on 20 December 2024).
	Population	2020	Grid	100 m	WorldPop	https://www.worldpop.org/ (accessed on 20 December 2024).
	Railway	2024	Shpfile	-	OSM	https://www.openstreetmap.org/ (accessed on 20 December 2024).
	Motorway	2024	Shpfile	-	OSM	https://www.openstreetmap.org/ (accessed on 20 December 2024).
	Primary road	2024	Shpfile	-	OSM	https://www.openstreetmap.org/ (accessed on 20 December 2024).
	Secondary road	2024	Shpfile	-	OSM	https://www.openstreetmap.org/ (accessed on 20 December 2024).
	Tertiary roads	2024	Shpfile	-	OSM	https://www.openstreetmap.org/ (accessed on 20 December 2024).

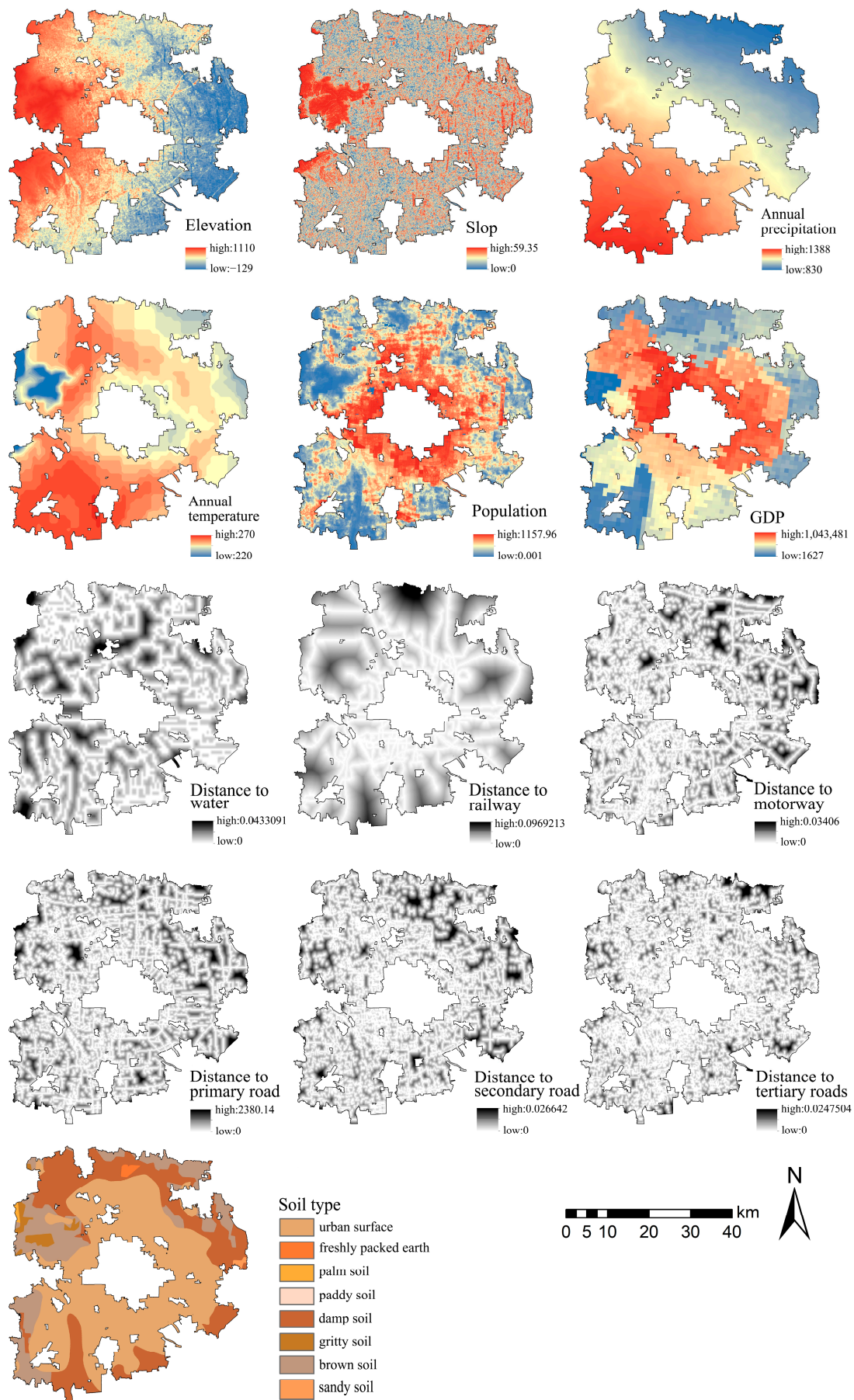


Figure 2. Driving factors.

3. Methodology

The research framework was divided into three parts, as shown in Figure 3. The first part was data preparation, including the CLCD dataset, the data of the 13 driving factors, and the relevant policies on land use in Beijing. The second part was the simulation of land use in Beijing's green belts in 2035 under the NDS, EPS, and CPS, using the PLUS model. The third part involved analyzing and predicting the spatial and temporal evolution of ESV in Beijing's green belts using the modified standard equivalent factor.

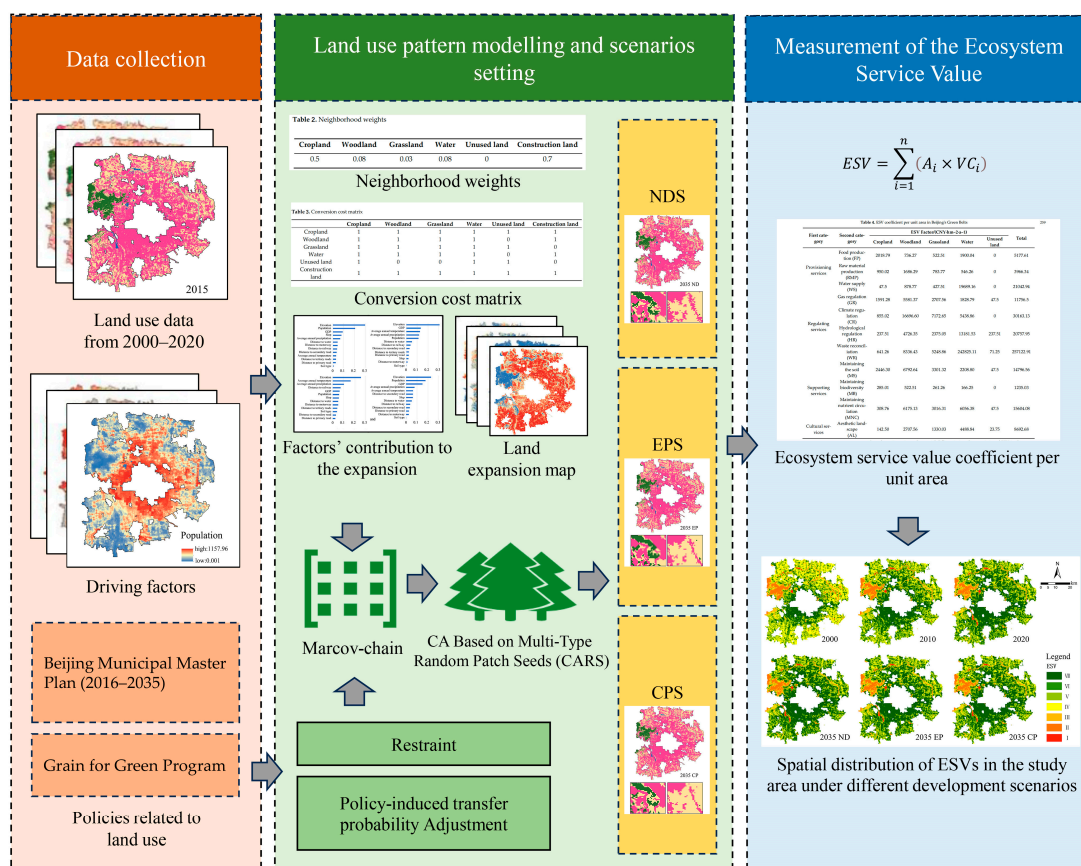


Figure 3. The framework of the study.

3.1. Land Use Change (LUC) Analysis

In this research, the land use transfer matrix approach [45] was employed to present the variations in different land utilization types in the study area between 2000 and 2020, as well as the transitions between these types. The formula used for constructing the transfer matrix is as follows:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \dots & \dots & \dots & \dots \\ S_{n1} & S_{n2} & \dots & S_{nn} \end{bmatrix} \quad (1)$$

In the formula: S_{ij} represents the area of each land use type, i denotes the initial land use type, j is the terminal land use type and n is the number of land use types.

The single land use dynamics (K), which indicate the rate of the quantitative change for a specific land use type within the study area over a given time frame, is expressed using the following formula:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \quad (2)$$

In the formula, K represents the single land use dynamics of a land use type in the study area; U_a and U_b are the areas of the land use type at the beginning and at the end of the study period; and T denotes the number of years between the beginning and the end periods.

3.2. PLUS Model

3.2.1. A Rule-Mining Framework Based on a Land Expansion Analysis Strategy (LEAS)

The LEAS module can investigate the relationship between the expansion among land use types and its driving factors [46,47]. The formula used in this process is as follows:

$$P_{i,k}^d(x) = \frac{\sum_{n=1}^M I(h_x(x) = d)}{M} \quad (3)$$

In the formula, the value of d is 0 or 1, with a value of 1 indicating a shift from other land use types to k land use types, and a value of 0 indicating other shifts; x is a vector consisting of multiple driving factors; $I(\cdot)$ is an indicator function for the set of decision trees; $h_x(x)$ represents the prediction type of the n th decision tree for vector x ; and M denotes the total number of decision trees.

3.2.2. Markov-Based Land Use Quantity Projections

The Markov model is a prediction method [48] that estimates the probability of an event occurring based on its initial state and the matrix of state transition probabilities. It predicts the likelihood of various states occurring in the future. The transfer probability P_{ij} at moment n is calculated as follows:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ P_{1n} & P_{2n} & \cdots & P_{nn} \end{bmatrix} \quad (4)$$

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

In the formula, P_{ij} denotes the probability of land use type i converting to land use type j ; n represents the number of land use types; and S_t and S_{t+1} are the states of land use types at moments t and $t + 1$, respectively.

3.2.3. CARS-Based Spatial Modelling of Land Use

The CARS module [49] was also developed based on the CA theory to study LUC spatial simulations. The formula for calculating the overall transition probability $OP_{i,k}^{d-1,t}$ of land use type k is represented as follows:

$$OP_{i,k}^{d-1,t} = P_{i,k}^d \times \Omega_{i,k}^t \times D_k^t \quad (6)$$

In the formula, $P_{i,k}^d$ represents the probability of land use type k growing for the i -th cell; $\Omega_{i,k}^t$ represents the neighborhood effect for cell i ; and D_k^t represents the influence of the future demand for land use type k , expressed as an adaptive driving coefficient that depends on the gap between the current land quantity and the target demand for land use type k at iteration t .

3.2.4. Different Scenario Settings

The design of land use scenarios establishes competitive conditions and defines conversion constraints for land use changes under varying policy frameworks. This is achieved

by adjusting neighborhood weights and land use transition matrices [50]. In multi-scenario simulations, changes in neighborhood weights affect the overall transition probabilities of land use types, while transition matrices impose specific restrictions on the transitions between certain land use categories. This paper is informed by key Chinese land management policies, including the “Beijing Municipal Master Plan (2016–2035)”, the “14th Five-Year Plan” for development, the national policy to prevent the “non-agriculturalization” of cultivated land, and the “Grain for Green” ecological restoration initiative. Based on these guiding frameworks, three distinct land use scenarios were formulated: natural development, ecological priority, and cultivated land protection. The settings for neighborhood weights and land use transition matrices corresponding to these scenarios are detailed in Tables 2 and 3.

Table 2. Neighborhood weights.

Cropland	Woodland	Grassland	Water	Unused Land	Construction Land
0.5	0.08	0.03	0.08	0	0.7

Table 3. Conversion cost matrix.

	Cropland	Woodland	Grassland	Water	Unused Land	Construction Land
Cropland	1	1	1	1	1	1
Woodland	1	1	1	1	0	1
Grassland	1	1	1	1	1	0
Water	1	1	1	1	0	1
Unused land	1	0	0	1	1	0
Construction land	1	1	1	1	1	1

The natural development scenario (NDS) assumes that land use changes proceed in accordance with historical trends, without being directly influenced by specific planning policies. In this scenario, neighborhood weights are derived from historical land use expansion data, and the land use transition matrix is designed without incorporating external interventions or imposing conversion restrictions.

The ecological protection scenario (EPS) prioritizes ecological protection and sustainable development. Under this scenario, the strict enforcement of ecological protection red lines is required, with a focus on gradually expanding ecological spaces, strengthening water conservation measures, and establishing a stable, high-quality ecological security barrier. Specific measures include prohibiting the conversion of forests and grasslands to agricultural land, orchards, or other land uses. The probability of agricultural land transforming into construction land is decreased by 30% [51], while the probability of forest and grassland converting to construction land is reduced by 50%; additionally, the probability of agricultural land and grassland converting to forest is increased by 30%. With a 15-year interval, the land use configuration for 2035 under the ecological priority scenario is predicted based on 2020 data.

The cultivated protection scenario (CPS) is dedicated to ensure national food security by strictly preventing the “non-agriculturalization” and “non-food crop cultivation” of agricultural land. This scenario emphasizes stringent control over the conversion of agricultural land, and aims to guarantee the effective protection of agricultural land. Compared to the natural growth scenario, the probability of agricultural land converting to construction land is reduced by 60% [52]. Using a 15-year interval, the land use configuration under the CPS in 2035 is predicted based on 2020 data.

3.2.5. Accuracy Validation of PLUS Model Results

The validation method involved simulating the land use in 2020 based on 2015 at 5-year intervals, and then calculating the kappa coefficients by comparing the simulation results with the real 2020 land use data. The accuracy evaluation was based on the Kappa coefficient and overall accuracy, where values closer to 1 indicate a higher simulation accuracy. A Kappa coefficient exceeding 0.8 signifies that the simulation accuracy of the model is statistically satisfactory [53]. For the simulation results, the Kappa coefficient was 0.87 and the overall accuracy was 0.94. This shows a strong resemblance between the simulation results for 2020 and the spatial pattern of the modelling results, further validating the model's reliability.

3.3. Measurement of the ESV

In this study, a grid resolution of 300 m × 300 m [54,55] was used as the unit of analysis to quantify the ESV within the study area, employing the equivalent factor method. Originally proposed by Costanza [6] et al., this method was later improved by Xie [43] et al., who derived the equivalent ESV for China. Based on Xie's equivalent values for various land use types, this study further revised the equivalent factor table using findings from relevant research, as well as data on grain prices and the net primary productivity (NPP) specific to Beijing. The revision formulas are provided in Equations (7) and (8), and the calculation formula for ESV is given in Formula (9). The ESV coefficients for the study area are presented in Table 4.

$$E_t = \frac{1}{7} \times \frac{T_t}{X_t} \quad (7)$$

Table 4. ESV coefficient per unit area in Beijing's Green Belts.

First Category	Second Category	ESV Factor/(CNY·hm ^{−2} ·a ^{−1})					Total
		Cropland	Woodland	Grassland	Water	Unused Land	
Provisioning services	Food production (FP)	2018.79	736.27	522.51	1900.04	0	5177.61
	Raw material production (RMP)	950.02	1686.29	783.77	546.26	0	3966.34
	Water supply (WS)	47.5	878.77	427.51	19,689.16	0	21,042.94
Regulating services	Gas regulation (GR)	1591.28	5581.37	2707.56	1828.79	47.5	11,756.5
	Climate regulation (CR)	855.02	16,696.60	7172.65	5438.86	0	30,163.13
	Hydrological regulation (HR)	237.51	4726.35	2375.05	13,181.53	237.51	20,757.95
	Waste reconciliation (WR)	641.26	8336.43	5248.86	242,825.11	71.25	257,122.91
Supporting services	Maintaining the soil (MS)	2446.30	6792.64	3301.32	2208.80	47.5	14,796.56
	Maintaining biodiversity (MB)	285.01	522.51	261.26	166.25	0	1235.03
	Maintaining nutrient circulation (MNC)	308.76	6175.13	3016.31	6056.38	47.5	15,604.08
Cultural services	Aesthetic landscape (AL)	142.50	2707.56	1330.03	4488.84	23.75	8692.68

In the formula, E_t represents the economic value of grain yield per unit area (yuan/hm²); T_t represents the total annual value of grain in the study area (yuan); and X_t represents the annual sown area of grain in the study area (hm²).

$$Q_t = \frac{NPP}{NPP_{mean}} \quad (8)$$

In the formula, Q_t represents the regional difference coefficient in year t , and NPP_{mean} represents the NPP of an average level of natural vegetation in China (t·hm^{−2}·a^{−1}).

$$ESV = \sum_{i=1}^n (A_i \times VC_i) \quad (9)$$

In the formula, A_i represents the area of land use type i and VC_i represents the ecosystem service value per unit area for the i th land use type.

In order to investigate the spatial differentiation characteristics of ESV in the green belts of Beijing, the ESV of the study area was divided into 7 classes according to the geometric segmentation method [56] in the ArcGIS 10.8 standard classification system. The value intervals of classes I to VII were [0, 8479), [8479, 28,707), [28,707, 76,963), [76,963, 192,086), [192,086, 466,726), [466,726, 1,121,919), [1,121,919, 2,684,970).

4. Results

4.1. LUC from 2000 to 2020

LUC in Beijing's green belts is predominantly characterized by cropland and construction land (Table 5). Since 2000, significant construction land expansion has been observed, increasing by 500.78 km². Conversely, the cropland area has decreased by 488.47 km², while woodland and grassland have decreased by 9.67 km², 2.37 km², respectively. A substantial amount of cropland has been converted into construction land, with a transfer volume of 497.86 km². Additionally, woodland and water have been converted into cropland, with transfer volumes of 14.52 km², and 5.89 km², respectively. Meanwhile, some cropland has transitioned to woodland and water, with transfer volumes of 6.89 km² and 5.69 km², respectively. Overall, the region exhibits a trend of woodland and water being converted into cropland, and cropland being converted into construction land. In terms of the spatial distribution, construction land is concentrated in the central region, cropland dominates the peripheral areas, and woodland is primarily distributed in the northwestern areas near Beijing's shallow mountainous regions and along the Yongding River (Figure 4). Between 2000 and 2020, construction land in the central urban area expanded significantly, reflecting the ongoing process of urbanization. This expansion of construction land was accompanied by a decrease in cropland, woodland, grassland, and watersheds.

Table 5. Land use area and single land use dynamics.

Land Use Type		Cropland	Woodland	Grassland	Water	Unused Land	Construction Land
Area/km ²	2000	1091.27	124.86	3.48	21.28	0.05	817.26
	2005	885.92	121.26	2.84	18.31	0.03	1029.82
	2010	730.35	123.38	3.61	17.33	0.03	1183.50
	2015	637.85	113.63	1.60	21.62	0.02	1283.47
	2020	602.80	115.18	1.11	21.00	0.05	1318.04
K/%	2000–2005	−3.76	−0.58	−3.65	−2.78	−9.12	5.20
	2005–2010	−3.51	0.35	5.38	−1.08	0.00	2.98
	2010–2015	−2.53	−1.58	−11.14	4.95	−5.16	1.69
	2015–2020	−1.10	0.27	−6.10	−0.57	26.96	0.54
	2000–2020	−2.24	−0.39	−3.40	−0.06	−0.26	3.06

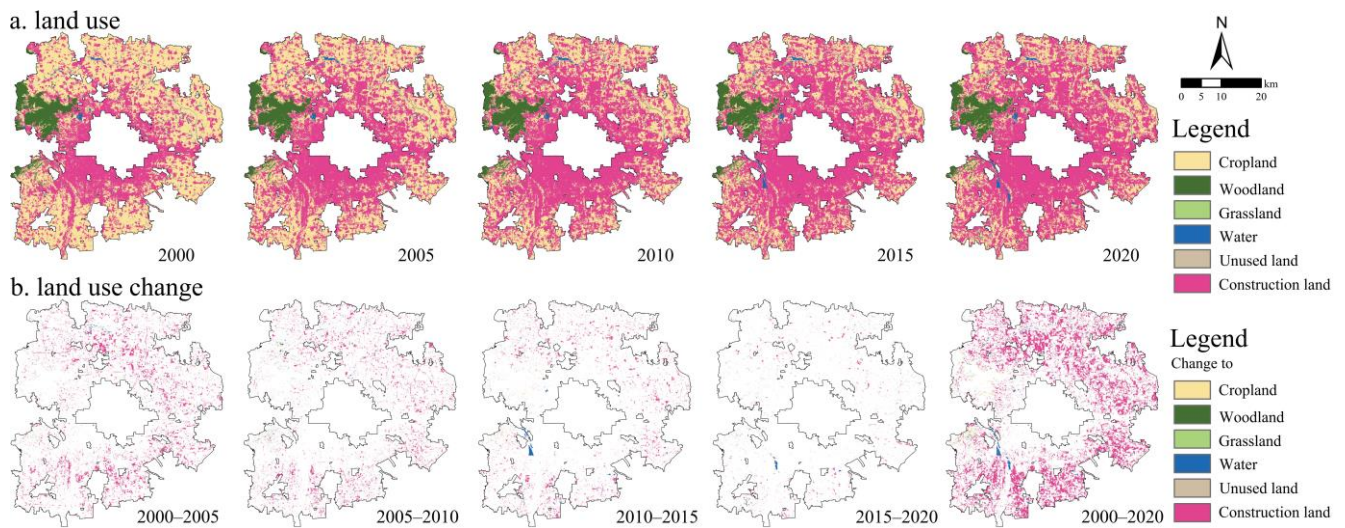


Figure 4. LUC from 2000 to 2020. (a) Land use; (b) Land use change.

4.2. Probability of Expansion of LUC

The contribution of driving factors to the main land cover types (cropland, woodland, water, construction land) and the spatial probabilities of land use development are presented in Figure 5. Significant differences were observed in the contribution of each driving factor to the distribution of various land cover types. For cropland, DEM and POP exhibited the highest explanatory contributions. In contrast, for forest land dynamics, the DEM and average temperature demonstrated the greatest driving contributions. These findings highlight the varying degrees of influence that different drivers exert on the spatial distribution of specific land cover types.

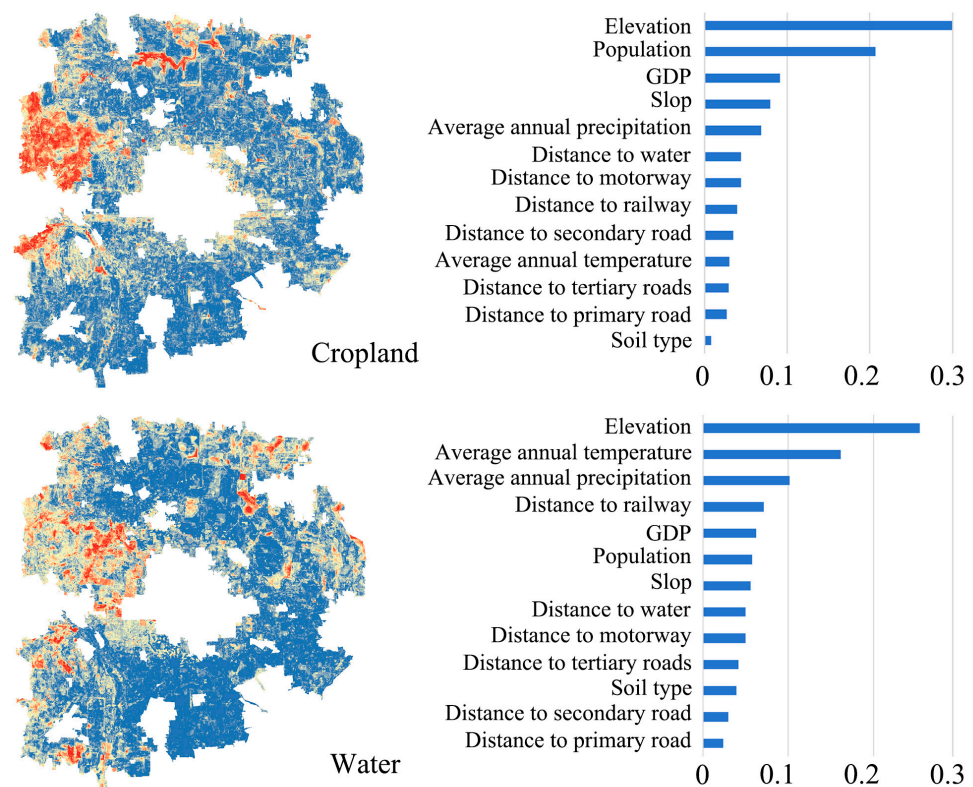


Figure 5. Cont.

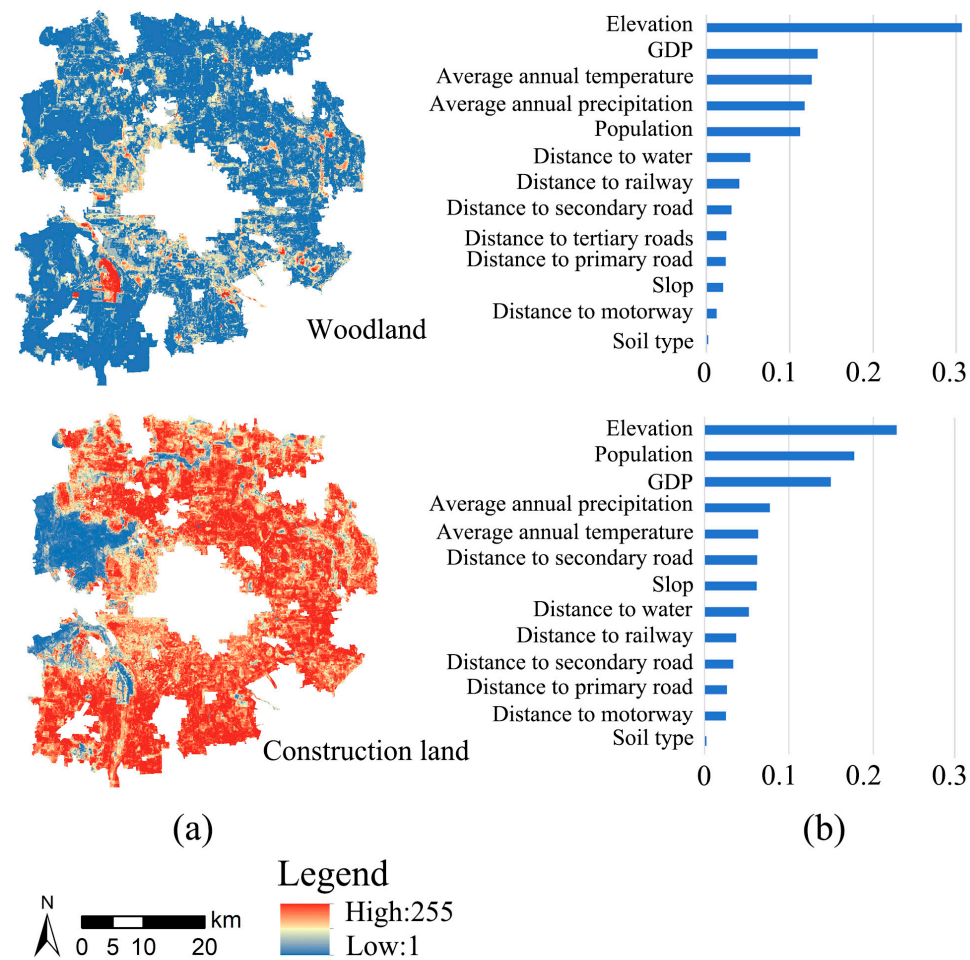


Figure 5. (a) Atlas of expansion probability; (b) Contribution of drivers to expansion.

4.3. LUC Simulation Results for Different Scenarios in 2035

Figure 6 illustrates the spatial distribution of projected land use types for 2035. Table 6 presents the corresponding quantitative data, including the area and the percentage change relative to the baseline year 2020, demonstrating notable shifts and trends in land use dynamics.

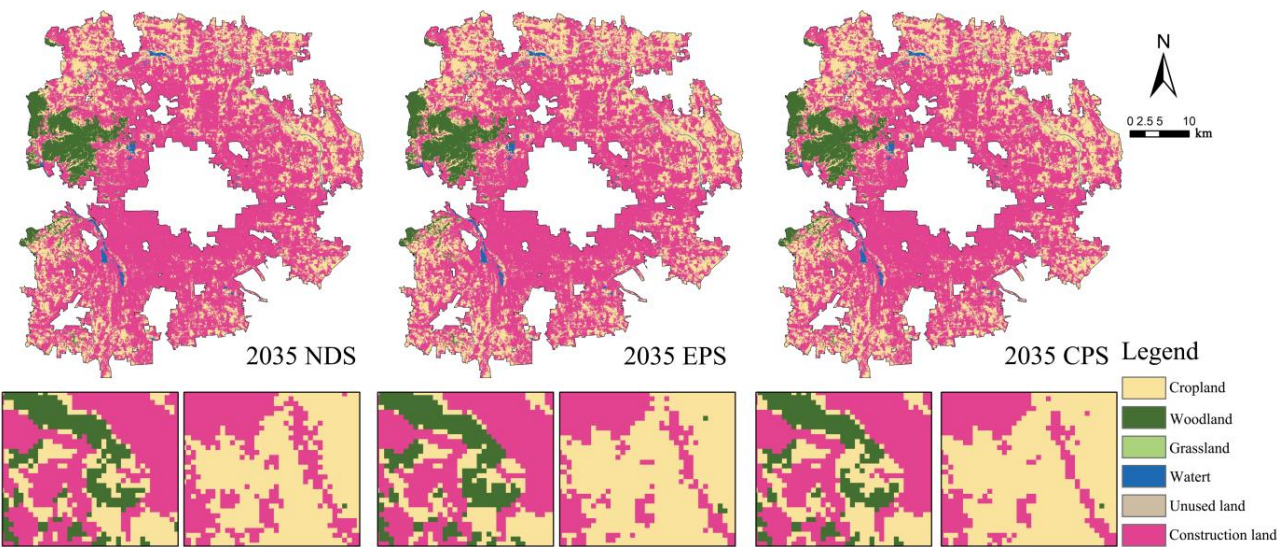


Figure 6. Simulation of spatial distribution of land use under different scenarios in 2035.

Table 6. Prediction of land use structure under different scenarios.

Year	Index	Cropland	Woodland	Grassland	Water	Unused Land	Construction Land
2020	Area/km ²	602.80	115.18	1.11	21.00	0.05	1318.04
2035 NDS	Area/km ² change	510.33	117.69	0.53	19.79	0.05	1409.80
		−92.47	2.51	−0.58	−1.21	0.00	91.76
2035 EPS	Area/km ² change	578.54	117.63	0.83	21.00	0.05	1340.13
		−24.26	2.45	−0.28	0.00	0.00	22.09
2035 CPS	Area/km ² change	590.23	116.54	0.82	20.54	0.05	1330.01
		−12.57	1.36	−0.29	−0.47	0.00	11.97

In NDS, land use changes are projected to continue along the trends observed between 2015 and 2020. Construction land is expected to expand by 91.76 km², primarily in the northern part of Haidian District, the eastern part of Chaoyang District, the northwestern part of Daxing District, and the northeastern part of Fangshan District. Meanwhile, cropland is projected to decrease by 92.47 km². Grassland and water bodies are also anticipated to decrease by 0.58 km² and 1.21 km², respectively.

In EPS, the expansion of construction land will slow down, and the decrease in cultivated land will decelerate. The rate at which cultivated land is converted into construction land will diminish. Grassland and water bodies are expected to remain largely unchanged, while woodland will experience a slight increase. Specifically, construction land will expand by 22.09 km², cultivated land will decrease by 24.26 km², and forestland will increase by 2.45 km². Furthermore, 0.7 km² of grassland and 0.42 km² of water bodies will be converted into woodland. Land use conversions from cropland, grassland and water will occur in the eastern Fangshan District, the eastern Mentougou District, and the western Haidian District.

In CPS, the conversion of cropland to construction land will decrease significantly. Construction land will increase by 11.97 km², while cropland will decrease by 12.57 km². Woodland will experience a slight increase of 1.36 km², and both grassland and water bodies will decrease slightly, by 0.29 km² and 0.47 km², respectively.

4.4. ESV Simulation Results for Different Scenarios

Figure 7 and Table 7 illustrate the ESV of Beijing in different years (2000, 2010, 2020), along with projections for 2035 under the NDS, EPS, and CPS in 2035.

Table 7. ESV for each ecological service type under multi-scenario modeling/million yuan.

First Category	Second Category	2000	2010	2020	2035		
					NDS	EPS	CPS
Provisioning services	FP	233.72	160.01	134.22	115.48	129.60	131.68
	RMP	126.16	91.42	77.92	69.45	76.18	76.91
	WS	58.20	48.59	54.38	51.75	54.56	53.52
Regulating services	GR	248.17	189.23	164.35	150.66	162.37	162.95
	CR	315.85	280.46	256.07	251.28	259.44	256.81
	HR	113.81	99.36	96.70	93.96	97.73	96.37
	WR	692.63	572.40	645.19	611.67	646.67	634.20
Supporting services	MS	357.62	267.49	230.71	209.33	227.06	228.36
	MB	38.07	27.64	23.58	21.04	23.06	23.27
	MNC	124.73	110.32	102.79	100.58	104.12	102.88
Cultural services	AL	59.37	52.07	49.35	48.09	49.92	49.29
Total		2368.35	1899.00	1835.26	1723.28	1830.72	1816.23

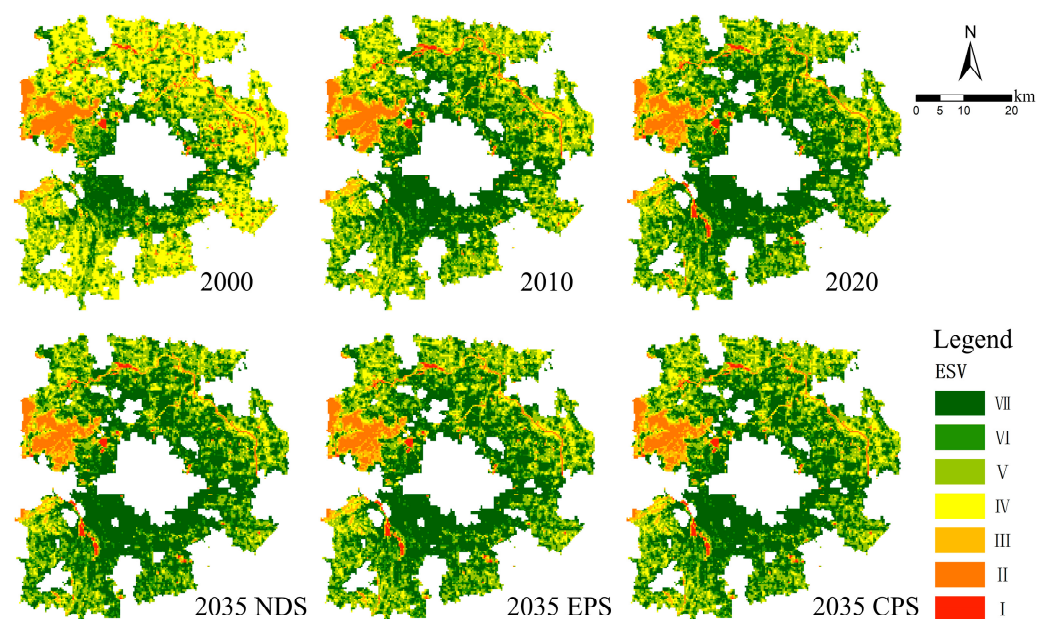


Figure 7. ESV simulation results.

In terms of provisioning services, the value of FP, RMP and WS have all decline between 2000 and 2020. For example, the value of FP will decline from CNY 233.72 million in 2000 to CNY 134.22 million in 2020. Under the projected scenarios for 2035, these values are expected to differ, with the NDS showing the lowest values, and the EPS indicating relatively higher values.

In regulating services, the values of GR, CR, HR, and WR are also projected to exhibit a downward trend. Among these, WR maintains the highest value, with the most significant differences anticipated across the forecasted scenarios for 2035. Specifically, under EPS, the value of WR is projected to reach CNY 646.67 million, but under the NDS, it is forecasted to be only CNY 611.67 million.

For supporting services, the values associated with MS, MB and MNC have also declined. For instance, the value of MS was CNY 357.62 million in 2000, decreasing to CNY 230.71 million by 2020. When considering the projected scenarios for 2035, these values are expected to vary according to different development scenarios. However, the overall magnitude of change is likely to be relatively small.

The aesthetic landscape value within cultural services has also exhibited a downward trend, dropping from CNY 59.37 million in 2000 to CNY 49.35 million in 2020. For the projected scenarios in 2035, the differences in these values across various development scenarios are expected to be relatively small.

Overall, farmland in Beijing has demonstrated a downward trend from 2000 to 2020. In the projected scenarios for 2035, these values will vary depending on the chosen development scenarios. However, in general, the ESV will be relatively higher under the EP development scenario. This indicates that while promoting economic and social development, prioritizing ecological environmental protection plays a crucial role in enhancing the ESV.

5. Discussion

5.1. Comparison with Previous Studies

The rapid urbanization of Beijing's greenbelt areas has triggered significant land use transitions and ecosystem service degradation over the past two decades. Our findings revealed a pronounced shift from ecological and agricultural land such as forests, water

bodies, and croplands to urban construction, aligning with global patterns of peri-urban land conversion under urban sprawl pressures [57]. Notably, the net loss of 488.47 km² of cropland and 497.86 km² of cropland-to-construction conversion between 2000 and 2020 underscore the dominance of economic development priorities, reflecting China's broader urbanization trajectory [58]. The divergent contributions of driving factors, including DEM, population and temperature, to land cover changes highlight the complexity of urbanization processes. The prominent role of DEM in shaping the distribution of croplands and forests aligns with previous findings from Wuhan [59]. In our study, the distance to roads exhibited a relatively low contribution to land use transitions, diverging from observations in Wuhan's urban context. This discrepancy can be attributed to Wuhan's implementation of a transit-oriented development (TOD) strategy, emphasizing transportation corridors along metro lines and major highways, whereas Beijing's central urban area follows a monocentric outward expansion pattern characterized by radial development from its historical core. Meanwhile, population emerged as a key driver of cropland conversion, reinforcing the role of population growth in land use conflicts—a phenomenon well documented in the rapidly developing Chongqing [60] region. Scenario analyses revealed stark contrasts in ESV trajectories. The natural development scenario's 91.76 km² construction land gain and associated ESV decline exemplified the environmental costs of unregulated urban growth. In contrast, the EPS's moderated land conversion and partial ESV recovery demonstrated the viability of targeted conservation policies. These results resonate with analogous studies [42].

5.2. Discussion on Land Use and Ecological Conservation Policies

The study revealed that from 2000 to 2020, approximately 497.86 km² of cropland underwent conversion into construction land. This rapid transformation underscores the urgent need for land use policy optimization. Future urban development strategies should prioritize brownfield redevelopment over cropland encroachment. Implementation approaches could include land consolidation and intensive utilization strategies, specifically through spatial optimization measures such as green space restoration, industrial structure adjustment, old village renovation, and illegal structure demolition to achieve construction land conservation.

Under the EPS, the research demonstrated significantly enhanced ESV, with the hydrological regulation value reaching CNY 646.67 million compared to 611.67 million under NDS. This divergence emphasizes the necessity of proactive ecological conservation measures. A “negative list” system could be established to restrict construction activities in ecologically sensitive zones, particularly critical forest–water interface areas near mountainous regions and the Yongding River watershed. Expanding protected areas along northwestern riparian corridors would facilitate wetland rehabilitation and urban green space expansion, thereby enhancing the capacity of climate regulation and biodiversity conservation to offset the 1.21 km² water body loss projected under natural development patterns.

The quantitative analysis of ESV revealed substantial losses: grain production declined by 49% and the soil retention capacity decreased by 35% between 2000 and 2020. These outcomes emphasize the imperative of integrating ESV assessments into urban and regional planning processes. It is recommended that ESV metrics be adopted to quantify cross-regional ecological responsibilities, ensuring compensation mechanisms where beneficiaries compensate ecosystem service providers. Predictive models utilizing drivers such as DEM and population data should be developed to provide early warnings of detrimental land use conversions. Furthermore, establishing an interdepartmental committee—encompassing agricultural, ecological, and urban planning authorities—would align policies with the

Sustainable Development Goals and ensure the transparent management of trade-offs between construction demands and ESV preservation.

5.3. Limitations

This research has some constraints. In research utilizing multi-source data, the simulation accuracy was constrained by the driving factor data limitations imposed by data providers. Future investigations could employ updated, higher-precision data with unified temporal consistency for prediction, which would significantly enhance the forecasting accuracy. Moreover, the three scenario configurations adopted in this research may not comprehensively capture the potential impacts of future policy changes, suggesting that subsequent studies could establish additional policy scenarios for comparative analysis. Additionally, future research might also integrate more advanced methodologies, such as the GMOP [61] approach, to refine the mathematical modeling of policy elements' influence on land use scenarios, which might yield more precise predictive outcomes.

6. Conclusions

This study utilized data from 2000 to 2020, adopted revised standard equivalent factors, and integrated the PLUS model to simulate land use in Beijing's Green Belt Area under three scenarios—NDS, EPS, and CPS—for the year 2035. The analysis focused on predicting the spatiotemporal evolution of ESV under these scenarios.

The study shows that from 2000 to 2020, land use in Beijing's Green Belt Area was dominated by cropland and construction land. Construction land expanded significantly, increasing by 500.78 km², while cultivated land decreased by 488.47 km². Additionally, woodland, grassland, and water bodies also declined. The overall trend indicated the conversion of woodland and water bodies into cropland, and subsequently, the transformation of cropland to construction land. By 2035, under the NDS, construction land is projected to increase by 91.76 km², accompanied by decreases in cropland, grassland, and water bodies. In contrast, under the EPS, the growth of construction land is expected to slow down, with an increase of 22.09 km². The decrease in cropland will also decelerate, and the rate of conversion from cropland to construction land will decrease. Grassland and water bodies are anticipated to remain largely unchanged, while woodland will experience a slight increase. Similarly, under the CPS, the conversion of cropland to construction land will decrease significantly, resulting in an increase in construction land of 11.97 km². Woodland will increase, while grassland and water bodies will decrease slightly. In terms of ecosystem service assessment, the projected ESV for 2035 is CNY 1830.72 million under the EPS, exceeding CNY 1816.23 million for the CPS and CNY 1723.28 million for the NDS. Among the individual ESV components, WR and CR will remain dominant. The EPS demonstrates the potential to achieve higher economic benefits in terms of ESV.

The innovations of this study are mainly reflected in the following aspects: First, it focuses on the Beijing Green Separation Area, a representative region of land use conflict. By collecting and analyzing land use data at five time points (2000, 2005, 2010, 2015, and 2020), the study constructed a detailed temporal basis for land use change, providing a robust foundation for understanding long-term trends and transitions. Thirteen key driving factors were selected by comprehensively considering both natural and socio-economic dimensions, allowing for an in-depth analysis of the intrinsic driving forces and likelihood of land use transformation. Secondly, the study integrates the PLUS model, a cutting-edge tool in land use simulation. By designing scenarios for NDS, EPS, and CPS, it simulated the land use status of the Green Separation Area in 2035 under different policy orientations. These simulations offer a scientific basis for effective land management and policy formulation. Finally, the study enhances the accuracy of ESV, by using the equivalent

value factor method of Xie as the theoretical basis. The equivalence factor table was revised using Beijing-specific data, such as its food price and NPP, thereby improving the precision of the valuation.

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