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The Forecast of Beijing Habitat Quality Dynamics Considering the Government Land Use Planning and the City's Spatial Heterogeneity

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Abstract: The evaluation of the habitat quality dynamics is important to conservation management and sustainable development. Forecasting future habitat quality changes depends on reliable projections of future land uses that align with government's future land-use planning. Additionally, the spatial heterogeneity problem cannot be dismissed in spatial modelling and the uneven distribution of urban development should be considered in the land use simulation and prediction. To address these issues, we established a bidirectional framework: from the top-down side, we impose land use and land cover (LULC) quantity constraints considering the goals of government land use planning; from the bottom-up side, we adopt zoning methods to consider the spatial heterogeneity of land use transition rules for improving the accuracy of land use prediction. We applied this approach to project habitat quality of Beijing in 2035 under different development scenarios. Firstly, we constructed multiple future scenarios (natural development, ND; economic development, ED; ecological protection, EP; livable city, LC) and computed the quantities of various land uses under those scenarios. Secondly, we addressed the spatial heterogeneity issue by adopting the zoning methods to improve the land use simulation accuracy of the PLUS model. Finally, based on the predicted LULC data, we analyzed the future habitat quality patterns in Beijing under different scenarios using InVEST model. We found that the zoning method can improve the simulation accuracy of LULC. Furthermore, significant spatial differences can be found in the habitat quality under different land use scenarios, which represent various government land use strategies. Among the four scenarios, the LC scenario is the most conducive one due to its ability to achieve a good balance between economic and ecological benefits. This study provides evidence for justifying the feasibility of Beijing's development plan to become a livable city.

Keywords: LULC prediction; habitat quality; livable city; government planning; spatial heterogeneity

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1. Introduction

Forecasting future habitat quality changes can facilitate strategic planning to balance the needs of ecosystem conservation and socioeconomic development [1–4]. And the habitat quality dynamics of Beijing in 2035 are important to the sustainable development of this megacity. Beijing Municipal Government proposes a goal that builds Beijing into an "international first-class harmonious and livable city" by 2035 requires a forest coverage rate of 45%, an ecological land scale of 75%, a population of less than 23 million, and a construction land scale of 2760 km^2. To achieve this goal, the habitat quality dynamics in Beijing need to be explored by simulating future land use, a key determinant both in ecological and economic development [5–7]. Many studies utilized multi-scenario simulation to achieve reliable prediction of future land use [8,9]. Through multi-scenario simulation, evaluation, comparison, and selection among different development pathways can be explicitly presented. The Markov chain, Grey model, and linear interpolation quantitative models are widely adopted to establish demand for land use and are capable of 'top-down' prediction of land demand [10,11]. However, the current study set the future scenarios subjectively without considering future government planning [12–15]. The multi-objective programming (MOP) model can address well the influence of government planning on land use changes and has good potential in scenario design [16]. Therefore, this study collected government planning data to set the overall land-use amount constraints quantitatively and gathered statistical data to build scenarios suitable for characterizing future regional development.

The above 'top-down' prediction by setting the total land use demand should be coupled with a 'bottom-up' prediction of land use, which can contribute to spatial land use simulation from cell to zoning area automatically. At present, the mainstream land use simulation models include Cellular Automata (CA) [17,18], CLUE-S [19], Future Land Use Simulation (FLUS) [20,21], and Patch-generating Land Use Simulation (PLUS) [22]. PLUS model takes the inherent nonlinear relationship in the change of LULC patches into account and can lead to higher accuracy of LULC simulation [23]. Mining land use transition rules is an important part of the PLUS model, and solving the spatial heterogeneity in land use conversion rules will help improve the simulation accuracy of land use, and thus improve the prediction quality of predicting future habitats [8,24–26]. Spatial heterogeneity is a geographical phenomenon that should not be ignored in LULC simulation for characterizing the inconsistency of development level and expansion rate of urban areas in different subregions [27]. Another challenge is that the interaction of LULC does not follow the same change function: the expansion rate of urban areas may be very high in some regions with booming economies or populations, but it may be relatively slow in developed or underdeveloped regions [28]. Therefore, using the same LULC transition rule and ignoring its spatial heterogeneity throughout the study area can be biased across different sub-regions and can result in poor performance in terms of LULC simulation accuracy [29,30]. This affects the spatial distribution pattern of LULC [31], thus affecting the accuracy of habitat quality assessment. To solve these problems, the partition method is adopted to solve the problem of spatial heterogeneity of land use transition rules to improve the accuracy of LULC prediction.

To fulfill our work, a regional habitat quality assessment framework is presented under different future development modes, which integrates future scenario setting modules, land use simulation modules, and habitat quality assessment modules. We then applied this framework to assess the habitat dynamics under different scenarios in Beijing City. Specifically, the objectives of this study are threefold. First, we considered the spatial heterogeneity of transition rules to improve the accuracy of LULC prediction. Second, we consider the future land use change under four scenarios that are built up using MOP methods to integrate statistical data and government planning data to ensure their reliability. Third, we evaluate the future habitat quality changes in Beijing under different scenarios with the LULC map derived from the former step. The framework proposed in this study is conducive to regional sustainable development in the future.

2. Materials and Methods

2.1. Study Area

Beijing is located between 115°25′–117°30′ E and 39°28′–41°05′ N, with a total area of about 160,000 square kilometers (Figure 1). Beijing has a typical temperate monsoon climate, with hot and rainy summers and cold and dry winters [32]. Beijing includes four functional zones, namely the Capital Core Functional Area (CCFA), including Dongcheng, and Xicheng districts, the Urban Function Extension Area (UFEA) including Haidian, Chaoyang, Fengtai, Shijingshan districts, the Urban Development New Area (UDNA) including Changping, Daxing, Tongzhou, and Shunyi districts, as well as the Ecological

Conservation Area (ECA) which include Mentougou, Fangshan, Huairou, Pinggu, Yanqing, and Miyun districts.

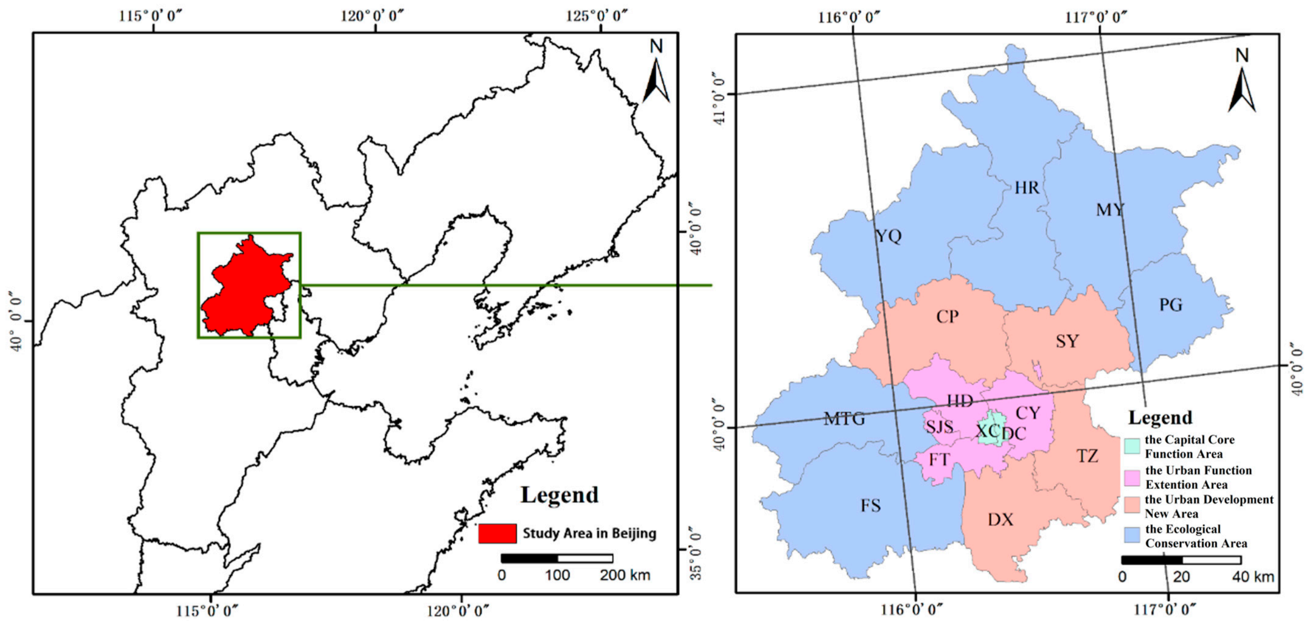

Figure 1. The location of the study area.

Beijing has experienced rapid urbanization. The increase in urban land use has brought great pressure on ecosystems. The decline of ecosystem functions in some regions has become the bottleneck of sustainable economic and social development [33]. To build Beijing into a world-class livable city and the implementation of the Fourteenth Five-Year Plan for Beijing's National Economic and Social Development and the Outline of the Long-term Goals for 2035 by the governments, Beijing's urban development has ushered in new opportunities and its ecological environment will also face new challenges. To improve the quality of residents' life, Beijing has put forward the goal of building a "world-class livable city". According to this goal, setting a livable city scenario, simulating the land use change in Beijing, and evaluating its potential impact on the ecological environment can lay a foundation for optimizing land uses and improving habitat quality.

2.2. Data Sources

Government planning data for Beijing in 2035 comes from the Beijing Land and Space Ecological Restoration Plan (2021–2035), the Beijing Urban Master Plan (2035), and the 14th Five-Year Plan for Beijing's National Economic and Social Development and the Outline of the 2035 Vision Goals. The statistical data is from Beijing Statistical Yearbook (2011–2020).

Geographical data are gathered according to the research purpose and regional landscape characteristics are grouped into 6 categories: cultivated land, forest, grassland, water body, construction land, and others. The change in LULC is affected by many social, economic, and natural factors [34,35], and this is why we obtained a variety of driving factors related to the LULC changes from the natural and socio-economic aspects. Table 1 lists the spatial data used in this study.

All data are preprocessed through projection transformation, Euclidean distance, resampling, and clipping. The data is converted to grid data with the same projection coordinate system, with a spatial resolution of 30 m.

Table 1. Data source.

Category	Data	Resolution	Data Resource
Land	Land Cover	30 m	https://www.resdc.cn/, accessed on 6 June 2021.
Socioeconomic Factors	Population GDP	1000 m	https://www.resdc.cn/, accessed on 10 June 2021.
	Proximity to railway Proximity to highway Proximity to road Proximity to District Proximity to Towns	30 m	https://www.webmap.cn/, accessed on 2 July 2021.
Nature Factors	DEM Slope	90 m	http://www.gscloud.cn/, accessed on 26 May 2021.
	Annual Mean Temperature Annual Precipitation Soil type	1000 m	https://www.resdc.cn/, accessed on 26 May 2021.
	Proximity to open water	30 m	https://www.webmap.cn/, accessed on 26 May 2021.

2.3. Methodology

The framework for the prediction of habitat quality based on LULC includes three parts (Figure 2). In the part of setting scenarios and quantity demand planning, we designed four future development scenarios and calculated the quantity requirements for each scenario using Markov and MOP models. Then, the PLUS model is adopted to simulate the spatial distribution of LULC in these scenarios. Finally, we use the simulated LULC data to analyze the temporal and spatial dynamics of habitat quality under each scenario using InVEST model.

2.3.1. Setting Future Development Scenario and Quantity of Land Demand

Scenario Definitions

To evaluate the changing pattern of land use and habitat quality in Beijing from the perspective of environmental protection and economic policy changes, this study set up four scenarios.

The natural development (ND) scenario is set based on the current trend of LULC changes. In the ND scenario, the land development status maintains the current trend and is not affected by anything. We use the Markov model to calculate the area of each LULC type in 2035, according to the transfer probability matrix of LULC from 2015 to 2020.

The economic development (ED) scenario is featured by rapid economic development. In the ED scenario, the economic development of cities is at the cost of certain ecological environment development. Therefore, we increased the transfer probability of cultivated land, forest land, grassland, and water to construction land by 20% compared to that in the ND scenario. Similarly, we reduced the transfer probability of construction land to cultivated land, forest land, grassland and water by 20%.

The ecological protection (EP) scenario is featured by the implementation of strict environmental protection. In the EP scenario, the development of the ecological environment needs to sacrifice economic interests. In this scenario, we reduced the transfer probability of cultivated land, forest land, grassland and water to construction land to by 10% compared to that in the ND scenario. Similarly, we increased the transfer probability of construction land to cultivated land, forest land, grassland and water by 15%.

The livable city scenario (LC) is set according to the 2035 urban development goals of Beijing. In the LC scenario, we have affiliated the planning data of future urban development, and set the objective function of MOP constrained by the balance of economic and ecological benefits.

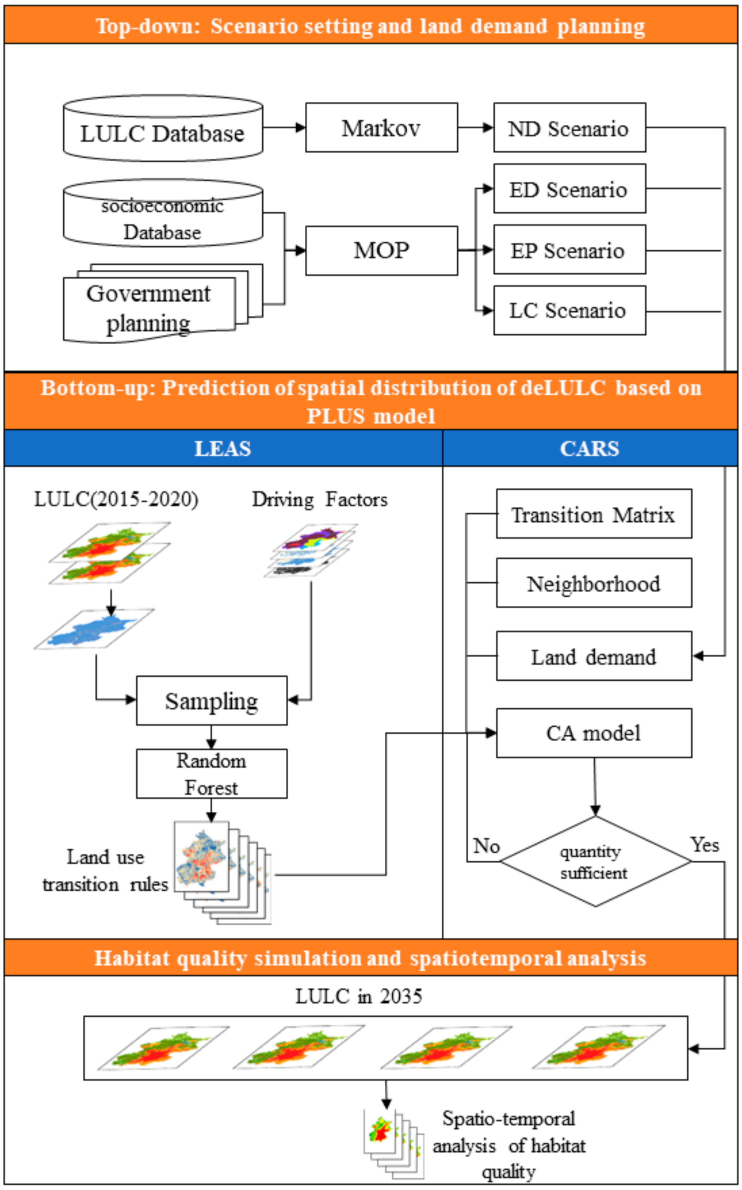

Figure 2. Flowchart of data processing for the forecast of habitat quality dynamics.

Multi-Objective Programming

The MOP model is an important branch of mathematical programming, which can be flexibly incorporated into various ecological or macroeconomic policies. It optimizes the quantitative structure of land use/cover data based on objective rules and data. MOP consists of two parts: (1) the objective function, which refers to the mathematical expression of model optimization objective and is expressed as a function of decision variables; (2) the constraint condition, which specifies the value range of the decision variable under the objective function and is represented by a set of equations or inequalities about the decision variable [36,37]. The MOP model can be expressed by the below formula:

$$\text{unction\_F}_k(X) = \sum_{i=1}^{n} K_i X_i, (k = 1, 2, \cdots, r) \tag{1}$$

$$\text{s.t.} = \begin{cases} \sum\limits_{i=1}^{n} C_{ij} X_i = (\leq, \geq) d_i, (j = 1, 2, \cdots, m) \\ X_i \geq 0, (i = 1, 2, \cdots, n) \end{cases} \tag{2}$$

where r is the number of objective functions; function_$F_k(X)$ represents the objective function; X_i is the ith decision variable, K_i is the coefficient of the ith decision variable in the objective function; C_{ij} represents the coefficient corresponding to the decision variable in the j constraint; d_i is the constraint value.

① Objective function

To balance the coordinated development of economy and ecology in urban planning, and pursue the maximization of total benefits. This study constructed an objective function from both economic and ecological perspectives, using the following method:

$$\max\{F_1(x), F_2(x)\} \tag{3}$$

$$F_1(x) = \max\left(\sum_{i=1}^{6} Eco_i \times x_i\right) \tag{4}$$

$$F_2(x) = \max\left(\sum_{i=1}^{6} Esv_i \times x_i\right) \tag{5}$$

where $F_1(x)$ is the economic benefit, $F_2(x)$ stands for ecological benefits, Eco_i is the economic benefit per unit area, Esv_i is the ecological benefit per unit area, x_i represents cultivated land, forest, grassland, water, built-up land, and unused land respectively.

For economic benefits, the gross production value of agriculture, forestry, animal husbandry, and fishery is taken as the economic benefits of cultivated land, forest land, grassland, and water body respectively. The economic benefits of construction land are replaced by the GDP of the secondary and tertiary industries. According to the statistical yearbook, the economic benefits of various ground features are represented by the ratio of the gross product of various ground features to the area, respectively 294, 131, 360, 97, 101,400, and 0 (unit: 10^4 yuan/km^2).

For ecological benefits, this paper uses the "China's terrestrial ecosystem unit area ecological service value coefficient table" constructed by Xie et al. [38] and Zhao [39] research to quantify the monetary value based on the current year's grain value. The ecological benefits of each category are 1368, 24,083, 1614, 15,292, 0, and 11 (unit: 10^4 yuan/km^2).

② Constraint conditions

According to the planning data of Beijing, we set constraints for the total area, forest coverage, population, ecological land vacancy rate, and the area of various land features. The specific constraints are as follows:

(1) Total area constraint

From the perspective of keeping the total land area unchanged, the total land area S is set by the formula below:

$$\sum_{i=1}^{6} x_i = S \tag{6}$$

(2) Forest coverage constraints

According to the policy planning, the forest coverage rate in Beijing is required to reach 45% of the total area, and the share of the forest coverage rate is calculated according to the "ecological green equivalent". In the land system, the types of land use conforming to "green equivalent" include farmland, forest land, and grassland, with coefficients of 0.46, 1.00, and 0.49 respectively [40]. Therefore, the constraints of forest coverage are:

$$0.46x_1 + x_2 + 0.49x_3 \geq 45\% \times S \tag{7}$$

(3) Population constraints

According to the policy planning, the population of Beijing in 2035 is required to be less than 23 million. According to Liang [41], the population density of ecological land is 200 people/km^2, and the population density of construction land is 5800 people/km^2. The population constraints are:

$$200 \times (x_1 + x_2 + x_3) + 5800x_5 \le 23,000,000 \tag{8}$$

(4) Constraints on ecological land use

According to the policy requirements, the area of ecological land in Beijing reaches 75% of the total area, namely:

$$x_1 + x_2 + x_3 + x_4 \ge \mathrm{S} \times 75\% \tag{9}$$

(5) Area constraint of cultivated land/forest land/grassland/water body/unused land

We take the area of cultivated land/forest land/grassland/water body under ED and EP scenarios as the upper and lower limits respectively, to achieve the restriction on the area of various surface features:

$$3437.49 \le x_1 \le 3600.03 \tag{10}$$

$$7979.10 \le x_2 \le 8010.38 \tag{11}$$

$$1595.05 \le x_3 \le 1621.03 \tag{12}$$

$$569.97 \le x_4 \le 588.40 \tag{13}$$

$$29.07 \le x_6 \le 29.13 \tag{14}$$

(6) Constraint on construction land area

It is stipulated in the policy that the construction land in Beijing will be restricted to 2760 km^2 in 2035. Therefore, the constraint of construction land area is set as:

$$x_5 = 2760 \tag{15}$$

2.3.2. Land Use Simulation

PLUS model integrates a rule training framework based on a land expansion analysis strategy (LEAS) and a CA based on multi-type random patch seeds (CARS) [22]. LEAS can explore the driving factors, and use random forest classification to obtain the applicable probability of various types of LULC expansion. CARS retains the advantages of adaptive inertial competition and roulette competition mechanism of the FLUS model and adds an innovative multi-type random patch seeding mechanism based on threshold reduction. In general, the PLUS model is more helpful to understand the internal mechanism of LULC changes from the perspective of complex mechanisms [36] and it helps in the acquisition of higher simulation accuracy.

In addition, the transition rules of land use are also an important factor affecting the simulation accuracy. Due to the uneven expansion of built-up land, the same transition rules are insufficient in simulating the spatial pattern of LULC in the entire region. Therefore, in this study, the conversion rules of land use in each region were excavated based on the functional areas of Beijing.

2.3.3. Habitat Quality Assessment

We used the Habitat Quality module in the InVEST model to evaluate the habitat quality in Beijing. The InVEST model is widely used for ecological environment quality assessment at various regional scales. The advantage of the InVEST model is that it ignores detailed data on species and summarizes the relationship between species and habitats at a higher level. It requires fewer data, allows for visualization of evaluation results, and can clarify habitat quality scores and degree of degradation.

According to the actual situation of the study area and in alignment with relevant literature [42,43], cultivated land, construction land, and unused land are selected as factors threatening habitat quality. The relative weight, maximum impact distance, spatial decline category and habitat suitability of each category to threat factors are presented in Tables 2 and 3.

Table 2. Threat source, its weight, and maximum influence distance.

Threat Factor	Weight	Maximum Impact Distance/km	Decay Type
Cultivated land	0.6	8	linear
Built-up land	0.9	10	exponential
Unused land	0.2	4	linear

Table 3. Habitat suitability and its relative sensitivity to threats.

Land Use Type	Habitat Suitability	Threat Factors		
		Cultivated Land	Built-Up Land	Unused Land
Cultivated land	0.4	0.1	0.7	0.5
Forest	1	1	0.8	0.5
Grassland	0.8	0.7	0.85	0.6
Water	0.9	0.5	0.4	0.2
Built-up land	0	0	0	0
Unused land	0.3	0.6	0.4	0.1

3. Results

3.1. Transition Rules and Accuracy Verification of LULC

Extracting transition rules for LULC is an important component of the PLUS model. However, due to the different degrees of urbanization, the transition rules for LULC changes in different regions are inconsistent. Different urban functional areas in Beijing show different levels of urbanization. Then, we have selected the percentage of built-up land in Beijing in 2015 and the rate of change in built-up land from 2015 to 2020 as two indicators to characterize the differences in the degree of urbanization (Figure 3). Because the coverage of built-up land can reflect the level of urban development, the rate of change in built-up land reflects the speed of future urban development in different regions. CCFA has a very high proportion of construction land, and its rate of change is almost zero. UFEA has a relatively high proportion of construction land, but the rate of change is low. Although UDNA and ECA have different proportions and rates of change of construction land, both exhibit a low coverage-high change pattern. Therefore, when simulating LULC, it is necessary to consider the difference in urbanization degree and use different rules to improve the simulation accuracy. At the same time, due to the small area of CCFA and its construction land, we have merged the area of CCFA into UFEA.

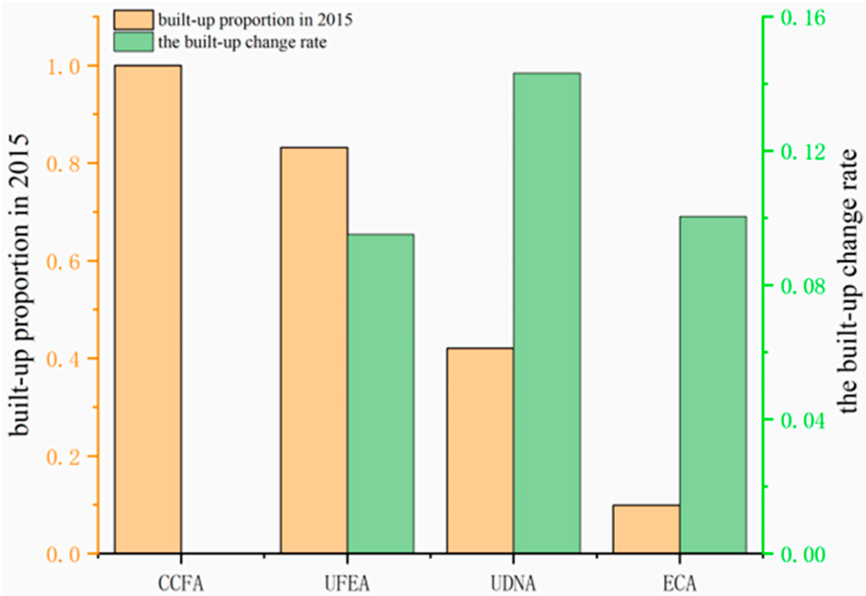

Figure 3. The percentage of built-up land in Beijing in 2015 and the rate of change in built-up land from 2015 to 2020.

To verify the rationality of the zoning strategy, we used the PLUS model to simulate the land use in 2020, with 2015 as the starting year and 2020 as the ending year. To simulate land use by adopting the PLUS model, the parameters that need to be set include "patch generate", "expansion coefficient", and "neighborhood size", which represent the degree of difficulty for land use type conversion, the degree of generating new patches, and the range of effect, respectively. In this study, the parameters were adjusted and set through an iterative procedure which tested different combinations of the parameters for achieving the best simulation accuracy as measured by the kappa and FOM indicators. The simulation results of zoning and non-zoning are compared with the real 2020 land use map, and the simulation accuracy was evaluated with Kappa, overall accuracy, and FOM coefficients. The accuracy evaluation results are as Table 4.

Table 4. Accuracy evaluation.

Index	Kappa	OA	FOM
Non-zoning	0.8418	87.2%	0.0596
Zoning	0.8633	89.7%	0.0636

The Kappa, OA, and FOM indicators show that the method with consideration of zoning improved the simulation accuracy as compared with the results without considering the zoning. The difference is most evident in FOM, with an increase of 6.7%. Therefore, the simulation accuracy using the partition method is better than that of the non-partition approach.

3.2. Spatiotemporal Evolution of LULC

By setting four different scenarios, the number of various land cover features is input into the PLUS model, and we obtain the area of various ground features in 2035 (Table 5) and the spatial distribution of future LULC (Figure 4). From 2015 to 2035, cultivated land and built-up land showed a decreasing trend. In particular, the change in built-up land was the most significant. Compared with 2020, the change in built-up land was particularly significant. The area of built-up land decreased by 26.01, 21.59, 28.28, and 22.48% respectively. Forestland, grassland, and water bodies showed an increasing trend, and the area of these three types of ground objects increased the most significantly under the ED scenario, increasing by 7.05, 29.16, and 39.30%, respectively.

Table 5. The area of LULC in Beijing under different scenarios in the future.

Type	History		2035			
	2015	**2020**	**ND**	**ED**	**EP**	**LC**
Cultivated land	3630.47	3664.3	3545.22	3437.49	3600.03	3437.49
Forest	7302.65	7482.83	7999.39	7979.1	8010.38	7981.05
Grassland	1109.91	1255.08	1611.75	1595.05	1621.03	1611.75
Water	328.31	422.39	582.59	569.97	588.4	582.59
Built-up land	4028.5	3560.23	2634.12	2791.52	2553.24	2760
Unused land	1.68	16.71	29.11	29.07	29.13	29.07

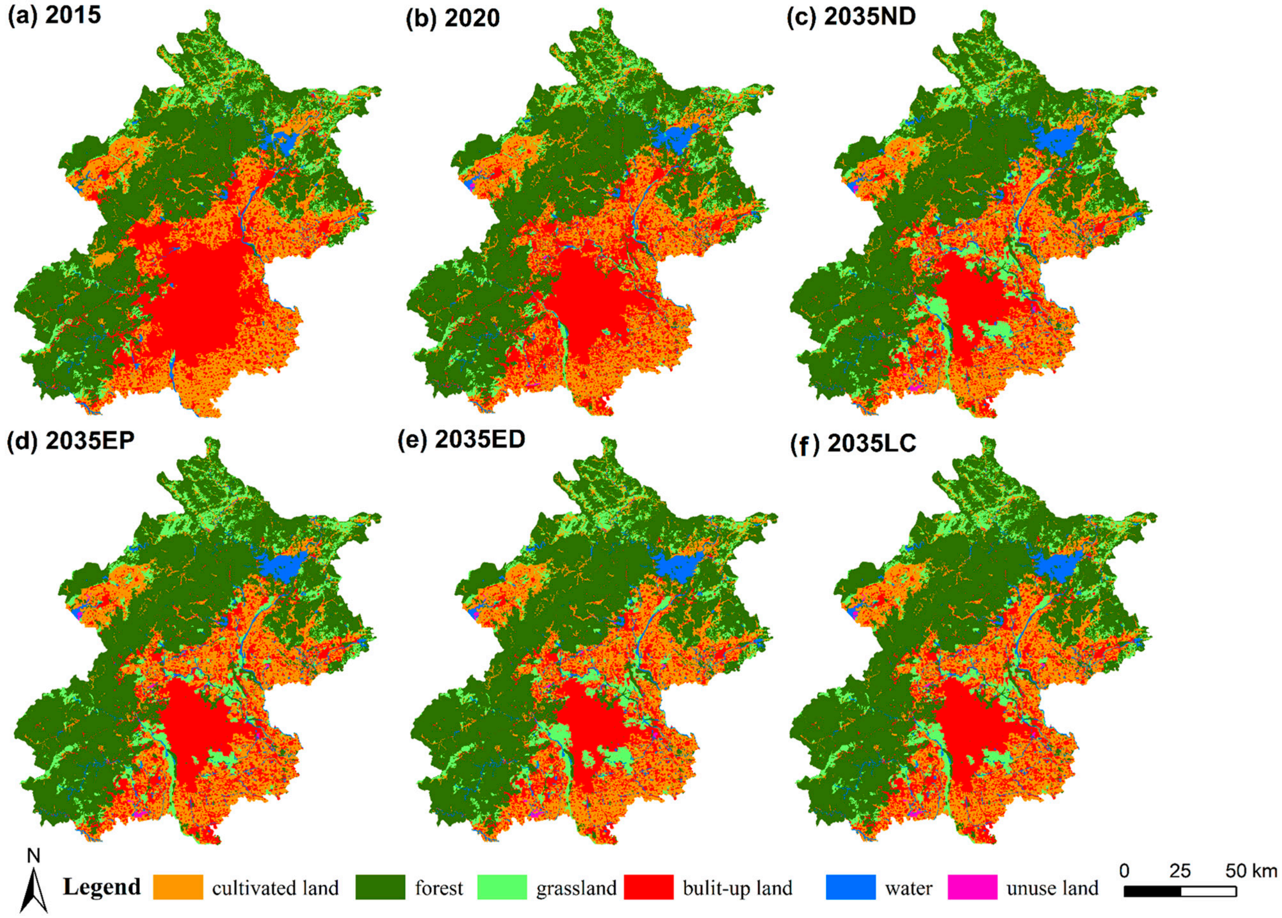

Figure 4. Prediction results of land use distribution patterns in different scenarios.

3.3. Temporal Variations in Habitat Quality

3.3.1. Temporal Variations in Habitat Quality

From 2015 to 2035, the habitat quality in Beijing has shown a trend of improvement (Table 6). The average habitat quality of the whole study area increased from 0.459 in 2015 to 0.506–0.511 in 2035. Comparison of habitat quality under different scenarios in 2035 shows that the average value of habitat quality in EP scenario (0.511) is the highest. The average value of habitat quality in LC scenario is slightly lower than that in EP, while the average value of habitat quality in the ED scenario is the worst. This means that in the process of urban development, environmental protection factors have been considered, which can improve the quality of urban habitat.

Table 6. The mean value of habitat quality.

Time	2015	2020	2035 ND	2035 ED	2035 EP	2035 LC
Mean	0.459	0.461	0.508	0.506	0.511	0.510

3.3.2. Spatiotemporal Evolution of Habitat Quality

To compare and explain the impact of land use change on habitat quality in Beijing under different scenarios, we classified the habitat quality index values between 2015–2020 into five intervals: 0–0.16, 0.16–0.45, 0.45–0.69, 0.69–0.88, 0.88–1. Those intervals were generated using the natural breakpoint classification method based on the habitat quality result in 2020 (Figure 5), which correspond to excellent, good, medium, poor, and poor. The area of each quality level was presented in Table 7.

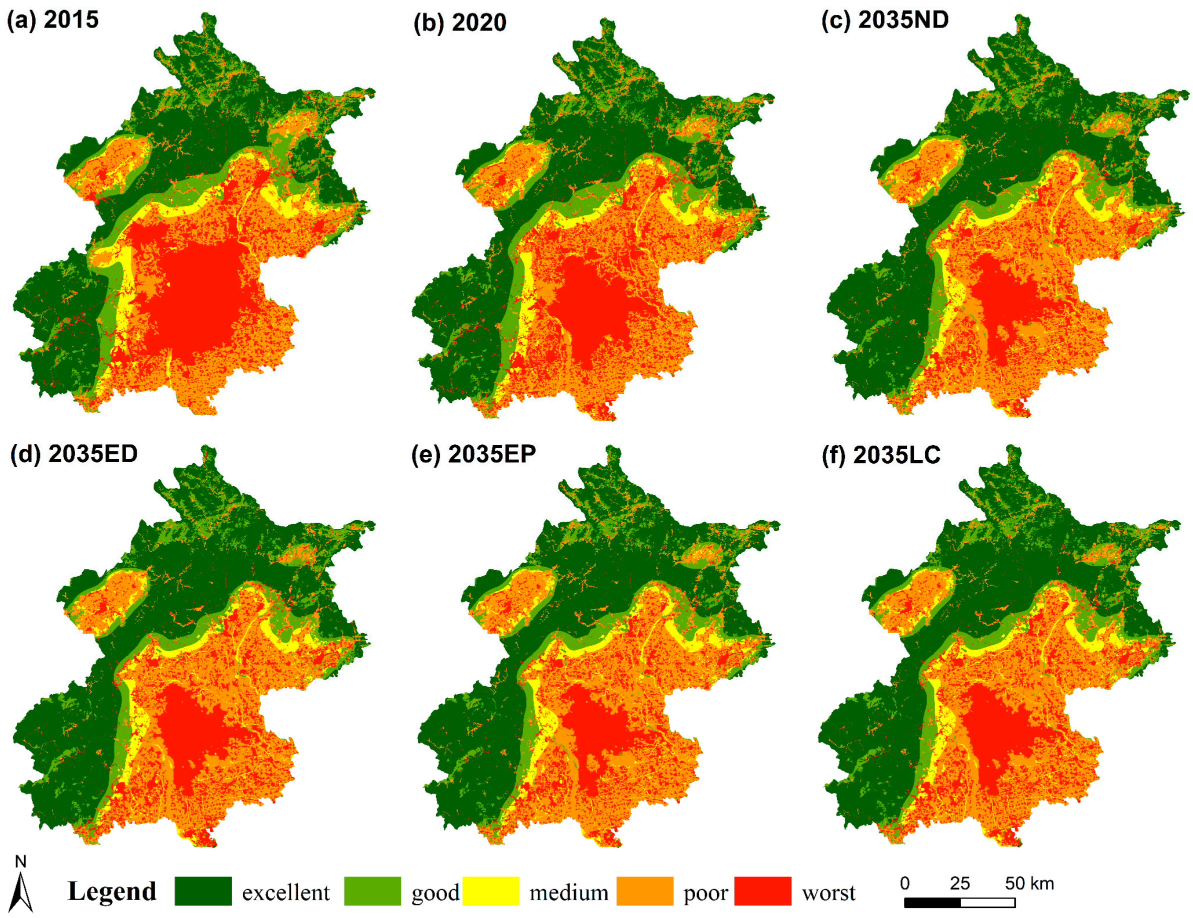

Figure 5. Spatial distribution of habitat quality in Beijing from 2015 to 2035.

Table 7. Area of each grade of habitat quality.

Time	2015	2020	2035 ND	2035 ED	2035 EP	2035 LC
Worst	4048.22	3575.15	2639.45	2795.09	2558.24	2753.90
Poor	3918.53	4152.92	4539.96	4492.89	4156.57	4359.54
Medium	897.79	825.16	913.90	847.31	932.70	882.96
Good	2270.08	2175.44	1956.58	1936.36	2002.68	1993.33
Excellent	5270.24	5676.05	6354.82	6330.09	6451.65	6414.97

The habitat quality in the western part of Beijing is higher than in the east. This is because Yanqing District is isolated from the main urban area. A patch of poor habitat quality has formed in the northeast. The habitat quality value in areas with intensive human production and living activities is relatively low, mainly in areas with poor and worst levels. In the west and northwest, due to the large area of forest coverage, the quality of habitat is high. The area of excellent habitat quality is projected to increase. In 2035, the largest area of excellent habitat is in the EP scenario, and the smallest area is in the ED scenario. The results show that the reduction of construction land and the increase of natural surface contribute to the improvement of habitat quality.

To study the change in habitat quality, we subtracted the habitat quality map in the later study period (2035) from the previous study period (2015) to obtain the habitat quality change map of Beijing from 2015 to 2035 (Figure 6) and calculated the changing area (Figure 7). Most of the habitat quality in Beijing has not changed, and the improved areas are mainly concentrated in the surrounding areas of the urban center, which is caused by the transformation from built-up land to grassland. The regional distribution of deterioration is scattered. The scenario with the largest habitat quality improvement is the EP scenario, and the area that exhibited habitat quality improvement from 2020 to 2035 accounts for 19.3% of the total. The second is the 2035 LC scenario, with the proportion of improved areas reaching 18.5%. This shows that ecological protection can improve the quality of habitats.

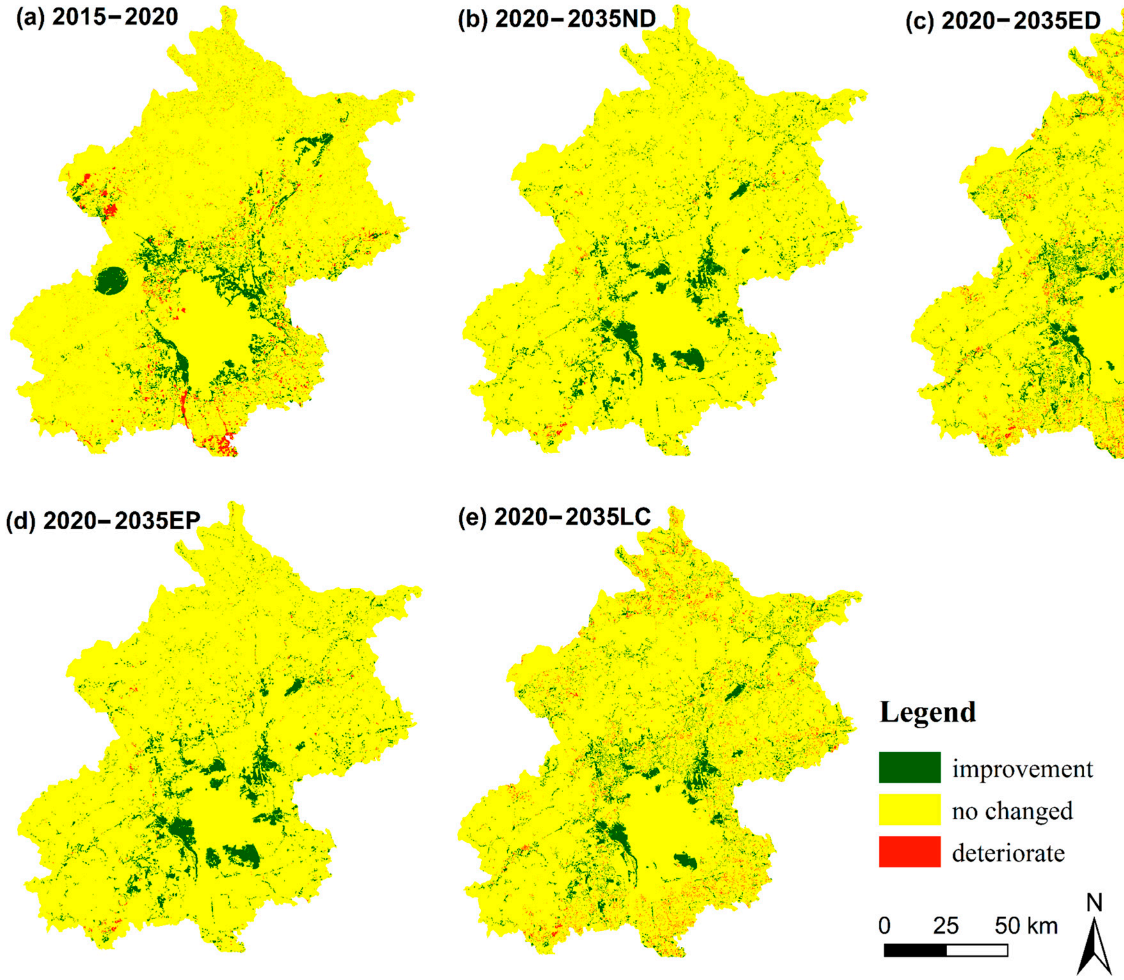

Figure 6. Changes in habitat quality in Beijing.

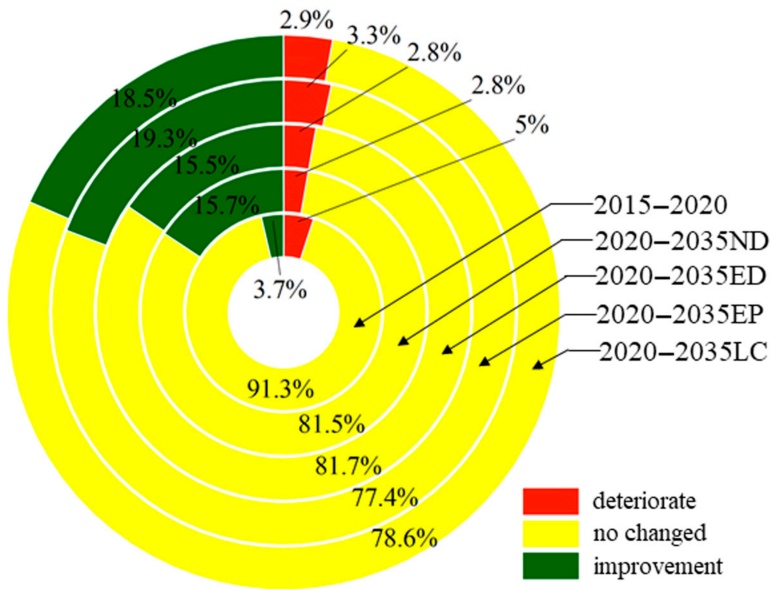

Figure 7. The proportion of land that experienced different types of habitat quality change under four future development scenarios.

We compared the average habitat quality of various functional zones in Beijing in 2035 (Table 8) and found the value habitat quality in CCFA is 0.150 under different scenarios. This is because all land in this region is built-up land area. So the habitat quality will not change. In UFEA and UDNA, the highest habitat quality is in the EP scenario, followed by ND and LC scenarios, and the lowest is in the ED scenario. In ECA, the highest habitat quality is in the EP scenario, followed by LC and EP scenarios, and the lowest is in the ED scenario. Overall, the habitat quality gradually increases from the central urban area to the outside, and the average habitat quality ranging from low to high is CCFA, UFEA, UDNA, and ECA.

Table 8. Mean habitat quality of different functional zones in Beijing.

Scenarios	CCFA	UFEA	UDNA	ECA
2035 ND	0.150	0.168	0.238	0.664
2035 ED	0.150	0.156	0.232	0.662
2035 EP	0.150	0.171	0.243	0.672
2035 LC	0.150	0.163	0.236	0.671

4. Discussion

The habitat quality dynamics of Beijing in 2035 are important to the conservation management and sustainable development of this megacity. To fulfill this objective, we established a bidirectional framework, which contains two models (the quantitative model and the spatial model, adopting constraints from the "top-down" and the "bottom-up" respectively). Setting reasonable scenarios is the key toward achieving "top-down" optimization. The methods of scenario setting include modifying the land transfer probability matrix, adjusting the cost matrix, and resetting the development law. In this study, ND, NP, and EP scenarios are realized by setting the land transfer probability. In the study of Gao [37] and Zhou [44], the MOP method has successfully balanced economic benefits, ecological benefits, and other objectives. According to the requirements of building a first-class livable city put forward in the "Fourteenth Five-Year Plan for National Economic and Social Development of Beijing and the Outline of the Long-term Goals for 2035", the forest coverage rate reaches 45%, the ecological land area reaches 75%, the population is controlled below 23 million, and the built-up land area is 2760 km^2. Based on these conditions, we apply the MOP method to the construction of the LC scenario in Beijing in the 2035 LC scenario, under which the forest coverage rate reached 63.1%, the area of ecological land accounted for 82.9%, the population was 18.644 million, and the area of built-up land was 2760 km^2. These results indicate that the future land development plan is achievable, though more constraints should be added to more accurately set the development scenarios of future cities in future research.

The spatial heterogeneity in the LULC simulation results is mainly determined by the land use transition rules. The land use transition rules caused by the imbalance of urban development are established by the “bottom-up” optimization as economically developed or populous areas are more likely to be converted into construction land, while those in developed or underdeveloped areas are less likely to be converted. Common partitioning methods include using existing administrative boundaries and K-means clustering. However, using existing administrative boundaries is subjective, while the performance of K-means clustering decreases when faced with high-dimensional and sparse input data because it is based on Euclidean distance space partitioning [31]. More advanced methods can automatically and effectively discover land use transition rules, such as a Self-Organizing Map (SOFM), which has the characteristics of self-organization and competitive learning to conduct spatial partitioning [45,46]. This study confirms that the partition method can improve the simulation accuracy of the PLUS model. Future research may apply this approach in other regions to further examine the spatial heterogeneity in the pattern of habitat quality changes.

To justify Beijing’s development plan in 2035 to become a livable city, the best development of the LC scenario is completed among the four scenarios. From the perspective of economic and ecological benefits, the LC scenario is designed based on the government’s planning data and takes into account the coordinated development of the economy and ecology, and the sum of economic and ecological benefits is higher than the other three scenarios (LC: 49,389.93, ED: 49,097.76, ND: 47,883.65, EP: 47,110.02 (unit: 10^4 yuan)), which make it the urban development scenario of the highest performance in balancing the ecological conservation and economic development. From the perspective of construction land, the construction land area in the LC scenario is close to the natural development construction land in the ND scenario, which suggests the LC scenario can be realized. From the perspective of habitat quality, the LC scenario is second only to the EP scenario and higher than ND and ED scenarios. Considering comprehensively, the LC scenario is the most favorable development model for Beijing in 2035. To achieve more sustainable development, more constraints, such as climate and low-carbon objectives can be included in future analysis.

5. Conclusions

To achieve high-quality LULC prediction and evaluate the spatial and temporal pattern of habitat quality of Beijing in 2035, the overall land demand and land use structure are optimized in our study by adopting the bidirectional framework which contains two main parts: the “top-down” and “bottom-up” designs. For the “top-down” design, we set four development scenarios to satisfy the constraint conditions to achieve land demand quantitatively. Among the four scenarios, the LC scenario is the most reasonable one for its pursuit of maximum benefits of ecological and economic development. We highlighted the LC scenario in our analysis because LC was built in accordance with the 2035 development strategy plan of Beijing, which has become a guideline plan for the future development of Beijing. For the “bottom-up” design, we use urban functional areas as the zoning units to improve the simulation accuracy of LULC. The city’s spatial heterogeneity is considered by adopting the zoning function to improve the performance of the LULC forecasting model and improve the simulation accuracy of the PLUS model. Results show that the simulation accuracy with zoning is higher than that of non-zoning. In the habitat quality of each scenario in 2035, improvements can be observed in EP and LC scenarios, and slight deterioration can be observed in ED scenarios, while the highest deterioration occurred in the ND scenario. These findings provide helpful guidance for reliable projection of future habitat quality at the landscape scale and offer useful information to justify Beijing's development plan for becoming a livable city.

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