SIMULATION OF ECOLOGICAL RISK IN BEIJING USING MOP-PLUS MODEL

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ABSTRACT:

The accelerated urbanisation, threatening the integrity of ecological environment. The lack of future simulation in ecological risk assessment in current studies. Especially in metropolis, to address this problem, this study uses the Multiple objective programming (MOP) and the improved patch-generating land use simulation (PLUS) models to simulate land use in Beijing in 2035 under the Natural Development (ND) scenario and the Liveable City (LC) scenario; the changes in land types and land transfers under different scenarios are analysed. In addition, a landscape ecological risk assessment method was applied to analyse the ecological risks caused by land use in each scenario. The study found that, in general, the dominant trend of land use change in Beijing is the shift from construction land to ecological land. The spatial pattern of ecological risk is polarized from east to west, and the conversion of a large amount of built-up land to arable land or grassland, and the high vulnerability of arable land and grassland to human destruction, are the reasons for the continuous increase in ecological risk in Beijing. The area of construction land in the LC scenario is closer to the planned area than in the ND scenario, and the ecological risks faced by the LC scenario are slightly lower than those of the ND scenario. Therefore, it is reasonable to use the LC scenario to simulate the land use situation in Beijing in 2035.

1. INTRODUCTION

Ecological risks caused by the interactions between ecological environment and complex human activities, threaten the harmony of human-earth relations and healthy ecosystem development(Depietri, 2020; Wang et al., 2019). Ecological risks index (ERI) , influenced by the LULC ,can be effectively measured and assessed in terms of the impacts of human activities or natural hazards on regional ecosystems(Chen and Liu, 2014). As both the probability of risk occurrence (level of disturbance) and potential damage (level of vulnerability) are taken into account(Liang et al., 2022), ERI has become an important tool for analysing and revealing the spatial and temporal characteristics of landscape ecological risk(Ji et al., 2021; Jiang et al., 2020). However, most of the existing studies on landscape ecological risk assessment are based on the assessment of historical data(Ai et al., 2022; Karimian et al., 2022; Mo et al., 2017; Zhang et al., 2022). It is important to simulate the patterns of predicting future ecological risks.

Existing models, such as CA-Markov, FLUS(Chen et al., 2021; Guo et al., 2021; Liang et al., 2018; Liu et al., 2017), CLUE-S(Wang et al., 2018), are widely adopted in LULC studies. However, these models have the disadvantage of being difficult to represent the underlying drivers of land-use change and unable to capture the evolution of multiple land-use patches in space and time(Liang et al., 2021). Furthermore, the drivers behind the dynamics of land-type shifts and their impact on the expected change cannot be illustrated (Meentemeyer et al., 2013). Therefore, to reveal the spatial and temporal evolution of ecological risks in cities, more advanced prediction models are expected to reveal the potential drivers of change in multiple landscape types and simulates the patch-level evolution of landscape types(Liang et al., 2021). Among these models, PLUS can predict the land use structure, so as to promote high-quality economic and social development in urban areas in the future. Moreover, this model has higher simulation accuracy than other models(Deng and Quan, 2022). In this study, we try to simulate and predict the dynamic trends of landscape ecological risks in urban cities by adopting advanced tools to quantitatively assess changes in ecological risk distribution.

Most of the current studies focus on under-urbanised cities, which still have a lot of room for urbanisation in the coming period. However, for cities like Beijing, which are highly urbanised, in order to achieve the goal of building an international first-class liveable city, population decongestion, vacating building sites and increasing greenery will be used to achieve the goal, and it will be a challenge to reconcile urbanisation and ecology to predict the future development scenario(Yujie et al., 2022). Thus, we try to use MOP model to find the balance point between economic and ecological benefits in urban development. PLUS model is used to predict land use demand and spatial distribution patterns under two development scenarios (ND Scenario and LC Scenario) at the urban level, and the ERI model is used to quantitatively assess changes in ecological risk distribution under different scenarios.

To optimise the national land space and provide scientific support for the formulation of strategic decisions on the metropolis Beijing, this research aims to solve the following objectives: (1) integrate statistical data and land use variables using the MOP model and simulate changes in land use demand between 2015 and 2035 under different scenarios; (2) more accurately predict the spatial distribution of land use using the PLUS model; (3) assess the future distribution of ecological risks in the study area at landscape scale and analyse the changes in ecological risks under different scenarios. The results from this study are

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expected to provide scientific support development of land use policies to adapt to the social development goal in the new era.

2. MATERIALS AND METHODS

2.1 Study Area

Beijing is located between 115°25′-117°30′ East longitude and 39°28′-41°05′ North latitude, with a total area of about 160,000 square kilometres. It is situated in the northern part of the North China Plain, with the TaiHang Mountains and Yan Mountains to the west and north respectively. The topography of Beijing is high in the northwest and low in the southeast, with an average altitude of 43.5 metres above sea level. Beijing has a typical temperate monsoon climate, with hot and rainy summers and cold and dry winters. As one of the most urbanised regions in China, Beijing has already experienced and suffered the consequences of a rough and tumble approach to develop. In order to combat the negative effects of urbanisation, Beijing, unlike many cities, has set the goal of building a 'liveable city'. Based on this objective, a liveable city scenario is developed to simulate land use changes in Beijing and assess their potential ecological impacts, which can provide a basis for optimising land use patterns and reducing future ecological risks.

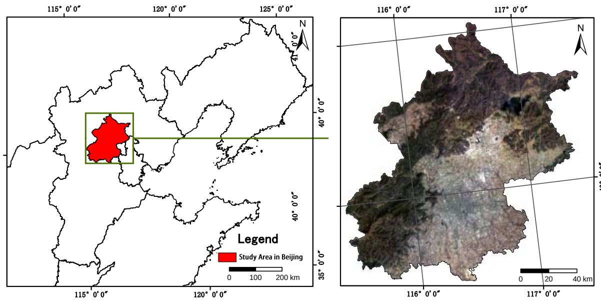

Figure 1. Location of the study area.

2.2 Data and Processing

The land use types were classified into six categories based on the purpose of the study and the characteristics of the regional landscape: arable land, forest, grassland, water bodies, built-up land and other land. Details of the spatial data used in this study and how they were obtained are listed in Table 1.

All data were subjected to a series of data pre-processing in ArcGIS such as projection transformation, Euclidean distance, resampling and cropping to convert the data to raster data with the same projection coordinate system and a spatial resolution of 30 m.

Table 1. The spatial driving factors of the land use change in this study.

Category	Data	Orginal Resolution	Data Resource
Land	Land Cover	30m	https://www.resdc.cn/
Socioeconomic Factors	Population	1000m	https://www.resdc.cn/
	GDP		
	Proximity to railway	30m	https://www.webmap.cn/
	Proximity to highway		
	Proximity to road		
	Proximity to District		
	Proximity to Towns		
Nature Factors	DEM	90m	http://www.gscloud.cn/
	Slope		
	Annual Mean Temperature	1000m	https://www.resdc.cn/
	Annual Precipitation		
	Soil type		
	Proximity to open water	30m	https://www.webmap.cn/

2.3 Methods

2.3.1 MOP: MOP is a dynamic multi-objective planning method that finds ways to optimise land use under a variety of constraints imposed by different scenarios, which is capable of optimising the area of one or more land classes. It also takes into account the uncertainty of these constraints. As a result, an accurate model of how land use is distributed in space can be better developed. The objective of this study is to find a sustainable land use approach using MOP by using objective functions, constraints and parameters.

In the optimisation of urban land use structure, consideration of economic or ecological benefits alone often leads to uncoordinated and unsustainable urban development. Therefore, in this study, the MOP model was constructed on Lingo18 to optimise the land use structure of Beijing in 2035 from the perspective of maximising both economic and ecological benefits, in conjunction with the land structure optimisation objectives designed in the 14th Five-Year Plan for National Economic and Social Development of Beijing and the Outline of Vision 2035. In this study, two objective functions were set for economic and ecological benefits respectively.

$$F_1(x) = \max(\sum_{i=1}^{6} Eco_i \times x_i)$$
$$F_2(x) = \max(\sum_{i=1}^{6} Esv_i \times x_i) \quad (1)$$

where F_1 and F_2 are economic value and ecological value functions respectively; Eco_i and Esv_i are economic value and ecological value coefficients respectively, representing the economic output and ecosystem service value per unit area of the i-th land use type. x_i is the area of the i-th land use type.

For the calculation of economic benefits, this study refers to the method of some scholars (Jiang et al., 2022)and takes the gross value of agriculture, forestry, animal husbandry and fishery in the Beijing Statistical Yearbook as the economic benefits of arable land, forest land, grassland and water bodies respectively, the gross value of secondary and tertiary industries as the economic benefits of construction land, and the economic benefits of unused land as 0. Using 2020 as the base year, the economic benefits of each type of land were calculated separately. The economic benefits per unit area are calculated separately for each type of feature. The economic benefits of arable land, forest land, grassland, water bodies and construction land were calculated as 294, 131, 360, 97 and 1014 million yuan/km^2 respectively.

$$F_1(x) = 294x_1 + 131x_2 + 360x_3 + 97x_4 + 101400x_5 + 0x_6 \quad (2)$$

Current ecological benefits are mainly estimated using value quantities and quantified in monetary terms. This paper draws on previous research(Zhao, 2020) to establish the ecological benefits of various types of features.

$$F_2(x) = 1368x_1 + 24083x_2 + 1614x_3 + 15292x_4 + 0x_5 + 11x_6 \quad (3)$$

The LULC situation in Beijing in 2035 is constrained according to the 14th Five-Year Plan for National Economic and Social Development of Beijing and the outline of Vision 2035 and other relevant plans, and the constrained situation is shown in Table 2.

Table 2. Constraints on the objective function for the 2035 LC scenario.

constraint condition	Description
$\sum_{i=1}^{6} x_i = S$	**Total area constraint:** The total area of all land use types shall be equal to the total area of Beijing
$0.46x_1 + x_2 + 0.49x_3 \geq 45\% \times S$	**Forest control rate constraint:** According to the objectives in the policy, Beijing is required to achieve a forest coverage rate of 45%. Calculate the share of forest coverage according to "ecological green equivalent". In the land system, the land use types that meet the green equivalent include farmland, forest land and grassland, with coefficients of 0.46, 1.00 and 0.49 respectively.
$200 \times (x_1 + x_2 + x_3) + 5800x_5 \leq 23000000$	**Demographic constraints:** The outline of goals requires that the population of Beijing be controlled within 23 million by 2030. Referring to the research of some scholars(Liang, 2017), the population density of construction land and ecological land in Beijing is 5800 people /km^2 and 200 people /km^2 respectively(Zhao, 2020)
$x_1 + x_2 + x_3 + x_4 \geq S \times 75\%$	**Ecological land constraints:** The policy requires that the scale of ecological land in Beijing by 2035 should reach more than 75%
$3543.14 \leq x_1 \leq 3841.57$ $7482.06 \leq x_2 \leq 7989.07$ $1255.07 \leq x_3 \leq 1616.30$ $422.39 \leq x_4 \leq 581.89$	**Cultivated land/Forest /Grassland/Waterbody area constraint:** The area of these features should not be lower than 2020, nor higher than the corresponding maximum area in economic or ecological benefits.
$2637.46 \leq x_5 \leq 2760$	**Built land area constraint:** The area of built land shall not be higher than the 2760 km^2 required in the policy, and shall not be lower than the minimum area corresponding to the highest economic or ecological benefits
$0 \leq x_6 \leq 29.08$	**Unused land area constraint:** As the "regulator" of land optimization, unused land can balance the area of various types of features, so the largest unused land area is taken as the upper limit

2.3.2 PLUS: The PLUS model is a future land use change simulation model that integrates a rule-mining framework based on a land expansion analysis strategy (LEAS) and a CA based on multi-type random patch seeds (CARS). The rule mining method of the LEAS module extracts the portion of each type of land use expansion between the two periods of land use change, and uses the random forest algorithm to mine the factors of each type of land use expansion and driver one by one to obtain the development probability of each type of land use and the contribution of the driver to the expansion of each type of land use in that time period. The CARS model combines random seed generation and a decreasing value mechanism to allow for the automatic generation of spatio-temporal dynamic simulations of patches within the constraints of development probabilities.

2.3.3 LULC Accuracy Verification: The 2020 LULC data for the study area was compared with the contemporaneous LULC data simulated based on the PLUS model to calculate the Kappa coefficient and the overall accuracy (OA). The closer are these two values to 1, the higher the accuracy of the simulation; values greater than 0.8 indicate that the accuracy of the model is satisfactory(Shi et al., 2022). The simulated LULC Kappa coefficients for 2020 in this paper are 0.841 and the overall accuracy is 0.891 respectively, indicating that the simulation results have a high degree of confidence.

2.4 Scenario Setting

Two different development scenarios of potential land use change are proposed in this study, namely ND Scenario and LC mentioned in the 14th Five-Year Plan of Beijing. The principles and objectives of the design scenarios are as follows:

2.4.1 ND Scenario: The scenario assumes that past trends in land use change will continue. As the Markov model is a model of purely mathematical significance, it is used by many scholars to represent a scenario of natural development of the LULC(An et al., 2022; Linjuan Li et al., 2022). Therefore, this paper calculates the land demand for the 2035 ND scenario based on the Markov chain transfer transfer probabilities for the period 2015-2020.

2.4.2 LC Scenario: In reality it is difficult for a single scenario of maximum ecological or economic benefits to occur, so the future development of Beijing does not necessarily need to be modelled using a single scenario, and trade-offs between economic and ecological benefits need to be made to find the most appropriate development model for the region. To this end, this study combines socio-economic data on Beijing and plans for the future development of the city to propose a Liveable City Scenario that provides a new perspective on the future development of Beijing. In order to realise the LC Scenario, land use benefits need to be maximised both in terms of economic and ecological benefits in order to achieve an optimal state of urban development.

$$\text{LC Scenario} = \max\{F_1(x), F_2(x)\} \tag{4}$$

2.5 Ecological Risk Index

①Division of landscape ecological risk evaluation units. Using ArcGIS, the LULC data of Beijing was gridded by 5km×5km, and Beijing was divided into 753 evaluation units; Fragstats 4.2 software was used to calculate the ecological risk index value of each evaluation unit, which was used as the ecological risk value of the central point of the sample site. The ecological risk index of each evaluation unit was calculated using Fragstats 4.2 software. ② From the perspective of landscape pattern, the landscape ecological risk index was constructed based on existing research results(Wang et al., 2021; Zhang et al., 2022). The calculation formula is.

$$ERI_k = \sum_{i=1}^{n} \frac{A_{ki}}{A_k} R_i \tag{5}$$

where ERI_k denotes the ecological risk index of the landscape within the kth evaluation unit, A_{ki} denotes the area of landscape type i within the kth evaluation; A_k is the area of the kth evaluation unit and R_i is the landscape loss index of landscape type i.

$$\begin{gathered} R_i = \sqrt{S_i \times F_i} \\ S_i = aC_i + bN_i + cD_i \end{gathered} \tag{6}$$

where S_i is the landscape disturbance index, which is constructed by the landscape fragmentation degree C_i, landscape separation degree S_i and landscape dominance degree D_i. a, b and c are the weights of each landscape index, and a+b+c=1, which are assigned as 0.5, 0.3 and 0.2 respectively according to the existing research results and the actual situation; F_i is the landscape fragility index, which is combined with the existing research results(Ran et al., 2022), and the fragility index (F_i) values of each landscape are normalized to 0.19, 0.10, 0.14, 0.24, 0.05 and

0.29 respectively. ③ Exploratory spatial data analysis. The ArcGIS geostatistical analysis module was used to spatially interpolate the LULC data using the kriging method for the sample site centroid data and to classify the landscape ecological risk levels into five categories: lower, lower, medium, higher and higher using the natural interruption point method with 2020 as the base year.

2.6 Technical Route

The technical route for this study is shown in Figure 2.

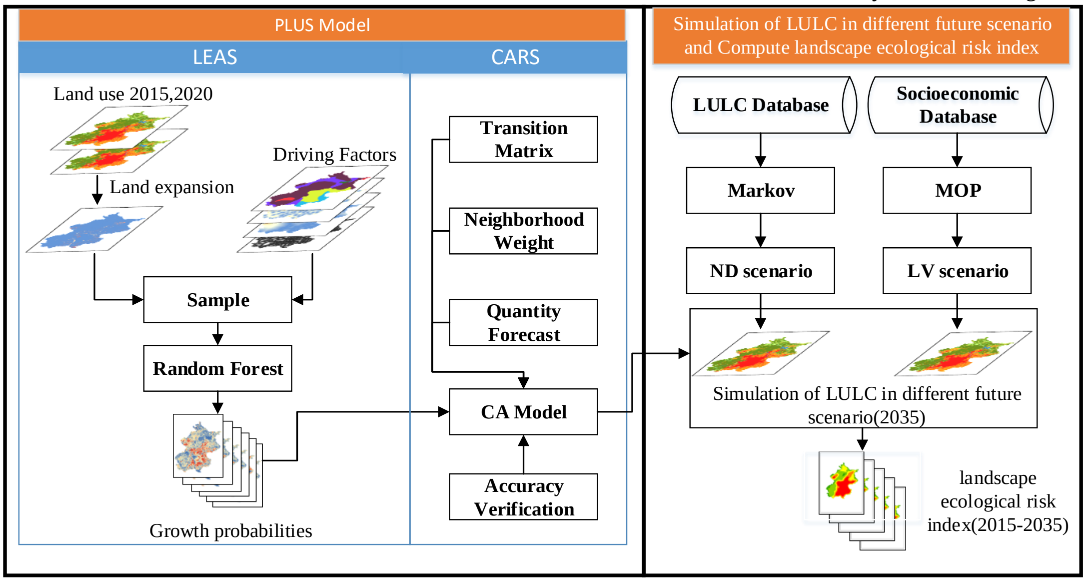

Figure 2. Technical flow chart.

3. RESULTS AND ANALYSIS

3.1 LULC Simulation under Multi-Scenarios

3.1.1 Spatial-Temporal Land Use Changes in Beijing

We applied the PLUS model to simulate the spatial distribution of land use in Beijing under different scenarios in 2035 (Figure 3), and calculated the area of each type of feature and the area of each type of land use for the historical and future periods (Table 3). In general, as shown in Figure 3, ecological land in Beijing is concentrated in the north-west and the areas affected by human activities are concentrated in the south-west. During the period 2015-2020, the land use types in the urban agglomeration are mainly forests, accounting for more than 40% of the entire area, followed by agricultural land, built land and grassland. Water body and unused land make up only a small part of the study area. The areas of agricultural land, forest land, grassland and water body show an increase, by 33.81 km^2, 180.18 km^2, 145.17 km^2 and 94.08 km^2 respectively. The area of built land is shrinking, from 4028.5 km^2 to 3560.23 km^2, indicating that Beijing's ecological protection efforts are effective in 2015-2020.

In both scenarios of the 2035 land use simulation, as shown in Figure3(c) and Figure3(d), the ND Scenario and LC Scenario still maintain the trend that the area of agricultural land, forest land, grassland and water bodies show an increase and the area of built land decreases. In the ND Scenario 2035, compared to 2000, the areas of agricultural land, forest land, grassland and water body show an increase of 177.27 km^2 ,512.34 km^2 ,60.61 km^2 and 160.28 km^2 respectively, while the built land decreases by 922.774 km^2. In the LC Scenario, compared to 2000, the area of agricultural land, forest land, grassland and water body increased by 145.05km^2, 405.49km^2, 94.14km^2 and 160.72km^2 respectively; while the built land decreased by 805.28km2. This is due to the fact that in the government's plan, the size of the built-up land in Beijing in 2035 is explicitly mentioned, making the ND Scenario This is due to the fact that the government has explicitly mentioned the size of the built-up land in 2035, which makes the ND Scenario significantly more urban than the LC Scenario.

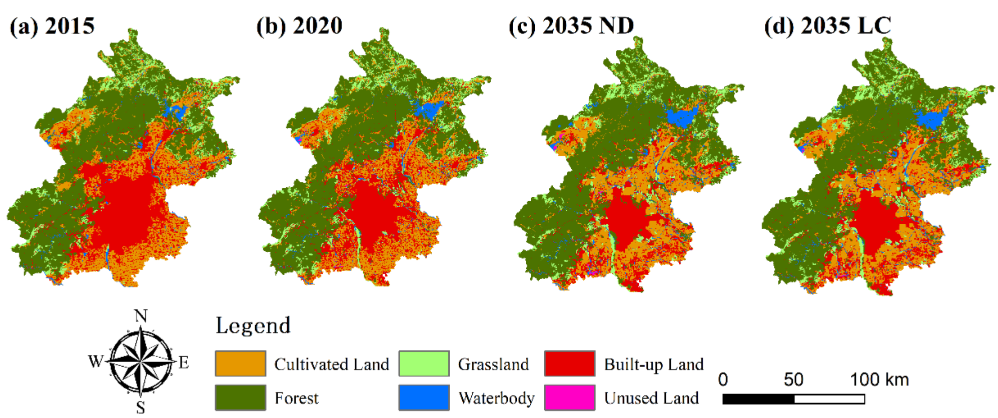

Figure 3. Land use:(a) year 2015; (b) year 2020 and simulation results in 2035: (c) ND Scenario; (d) LC Scenario.

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Table 3. LULC change in the study area during different periods (km^2).

LULC Type	2015	2020	2035ND	2035LC
Cultivated land	3630.47	3664.30	3841.57	3809.34
Forest	7302.65	7482.83	7995.17	7888.33
Grassland	1109.91	1255.08	1315.69	1349.22
Waterbody	328.31	422.39	582.66	583.11
Built-up land	4028.50	3560.23	2637.46	2754.95
Unused Land	1.68	16.71	29.13	16.71

3.1.2 Land use conversion relationship

In addition, the transfer relationships and areas of various features were calculated for the period 2015-2035 (Table4, Figure4). Under historical conditions, Figure5 shows that the most significant conversion of building land to other land types was observed, with 458.91km^2, 96.26km^2, 121.22km^2 and 56.62km^2 being transferred from built-up land to agricultural land, forest land, grassland and water bodies respectively; however, only 224km^2, 25.69km^2, 6.59km^2 and 12.1km^2 were transferred from other land types to building land. For building land, the outflow is greater than the inflow, and building land is the main source of increase in ecological land area, especially for agricultural land area. Once again, this shows that Beijing's ecological conservation efforts in 2015-2020 are effective.

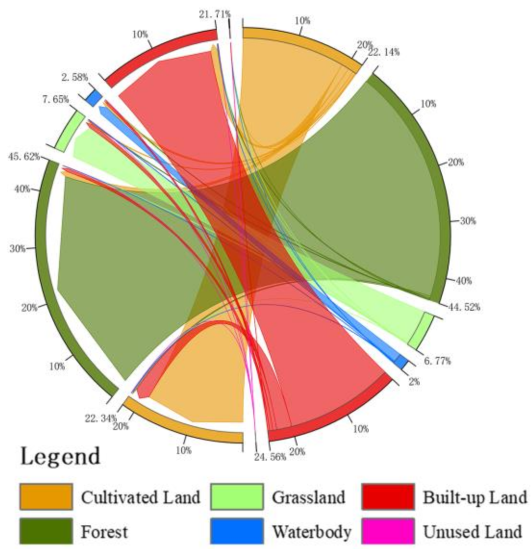

Figure 4. The relationship between land use conversion in 2015-2020(The beginning of the arrow indicates the land proportion in the baseline year, and the arrow points to the land proportion in the target year).

For the period 2020-2035, this study counts the relationship of land use transfer between ND Scenario and LC Scenario between 2020 and 2035 respectively. The trend of shifting from built land to ecological land use continues during this period. In the ND Scenario, Table5 shows that the conversion of built land to agricultural land, forest land, grassland and water body is 1061.43km^2, 207.31km^2, 120.03km^2 and 23.15km^2. However, the other land types only transfer 454.19km^2, 26.22km^2, 11.54km^2 and 0.44km^2 to building land. In the LC Scenario, Table6 shows that built land was converted to agricultural land, forest land, grassland and water bodies by 1061.43km^2, 207.31km^2, 120.03km^2 and 23.15km^2 respectively. Other land types were only transferred to built-up land by 454.19km^2, 26.22km^2, 11.54km^2 and 0.44km^2. The increase in the area of woodland was also a more obvious factor of change during this period. In addition to the conversion of built land to woodland, grassland and cropland were also converted to woodland to varying degrees. in ND Scenario, Figure5(a) shows that about 1.74% and 1.44% of grassland and cropland were converted to woodland, and 1.26% of the conversion of built-up land to woodland. In the LC Scenario, Figure5(b) shows that about 1.49% and 1.13% of grassland and cropland were converted to woodland and 0.91% of built-up land was converted to woodland. This indicates that cropland and grassland are the main sources of increase in woodland area.

Table 4. Conversion of Land Types from 2020 to 2035 (km^2).

	Cultivated Land	Forest	Grass -land	Water-body	Built-up Land	Unused Land
Cultivated Land	3126.00	164.80	27.80	79.84	224.0	8.05
Forest	54.06	7178.41	24.37	19.63	25.69	0.50
Grass-land	7.71	29.42	1062.17	4.01	6.59	0.02
Water-body	16.85	13.91	19.52	262.29	12.10	3.64
Built-up Land	458.91	96.26	121.22	56.62	3291.69	3.80
Unused Land	0.77	0.03	0.01	0.001	0.17	0.70

Table 5. Conversion of Land Types from 2020 to 2035 ND scenario (km^2).

	Cultivated Land	Forest	Grass-land	Water-body	Built-up Land	Unused Land
Cultivated Land	2711.74	235.97	185.26	65.89	454.19	11.17
Forest	42.93	7264.60	86.43	62.71	26.22	0.13
Grassland	24.27	285.88	923.22	10.13	11.54	0.03
Waterbody	1.14	0.73	0.35	419.75	0.44	0.03
Built-up Land	1061.43	207.31	120.03	23.15	2145.01	3.32
Unused Land	0.06	0.68	0.41	1.06	0.06	14.45

Table 6. Conversion of Land Types from 2020 to 2035 LC scenario (km^2).

	Cultivated Land	Forest	Grass-land	Water-body	Built-up Land	Unused Land
Cultivated Land	2775.59	184.79	202.29	87.52	414.01	0.02
Forest	38.96	7309.65	74.21	37.55	22.64	0.007
Grassland	24.36	244.61	961.90	13.83	10.36	0.006
Waterbody	1.13	0.69	0.38	419.77	0.44	0.01
Built-up Land	969.30	148.58	110.44	24.41	2307.49	0.01
Unused Land	0.01	0.004	0.007	0.03	0.001	16.66

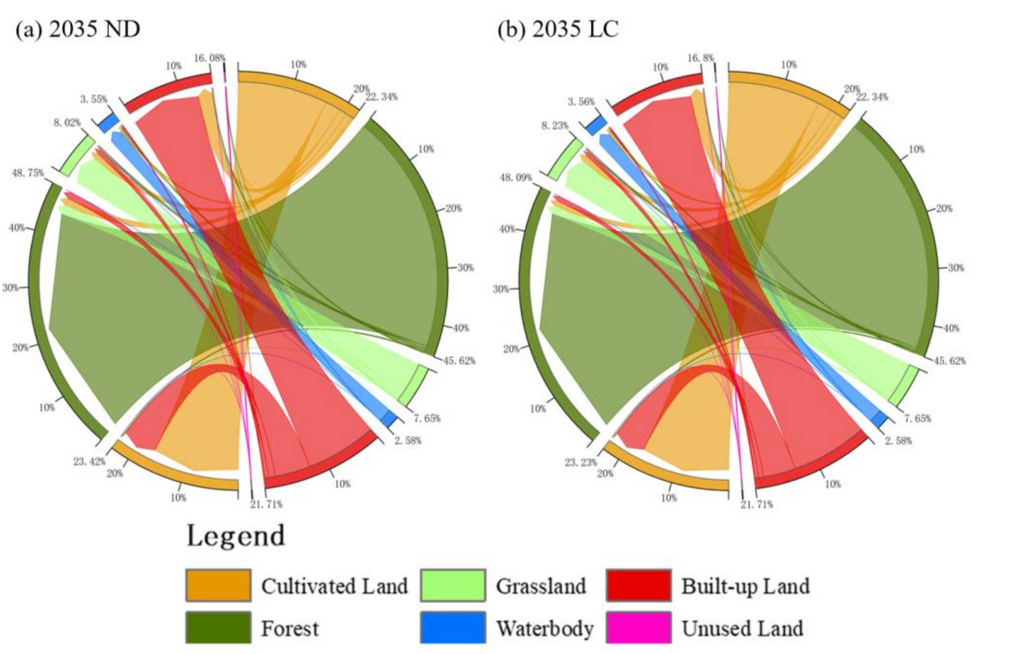

Figure 5. The relationship between land use conversion in 2020-2035 ((a) represents 2020–2035 ND Scenario, (b) represents 2020–2035 LC Scenario. The beginning of the arrow indicates the land proportion in the baseline year, and the arrow points to the land proportion in the target year).

3.2 Spatial and Temporal Changes in the Supply of ERI under Different Scenarios

Based on the future land use raster data simulated by the PLUS model, we assess the ecological risk of the landscape in Beijing. From the spatial pattern (Figure6), there is a clear east-west polarised structure of landscape ecological risk in Beijing. Areas of higher ecological risk are concentrated in the north and south-east of the city, increasing over time and gradually shifting from dispersion to aggregation. In contrast, lower ecological risk and low ecological risk areas are mainly located in the centre and west of the city, and show a decreasing trend. Meanwhile, Figure7 shows that the proportion of areas at higher and higher ecological risk increases each year, with 27%, 36.3%, 48% and 46.8% for the two scenarios from 2015 to 2035, respectively. The area at low and lower ecological risk decreases each year to 48.5%, 37.6%, 31.3% and 31.8% respectively.

Table 7. Area and change of each level of landscape ecological risk.

Time	Lower	Low	Medium	High	Higher
2015	2243.83	5709.11	4020.48	3073.04	1358.48
2020	1465.52	4606.02	4239.38	3686.29	2184.70
2035ND	1160.33	3970.23	3399.44	2805.27	5069.68
2035LC	1203.97	4016.27	3499.40	2937.59	4747.75
2015-2020	-778.31	-1103.09	218.90	613.25	826.22
2020-2035ND	-305.19	-635.79	-839.94	-881.02	2884.98
2020-2035LC	-261.55	-589.75	-739.98	-748.70	2563.05

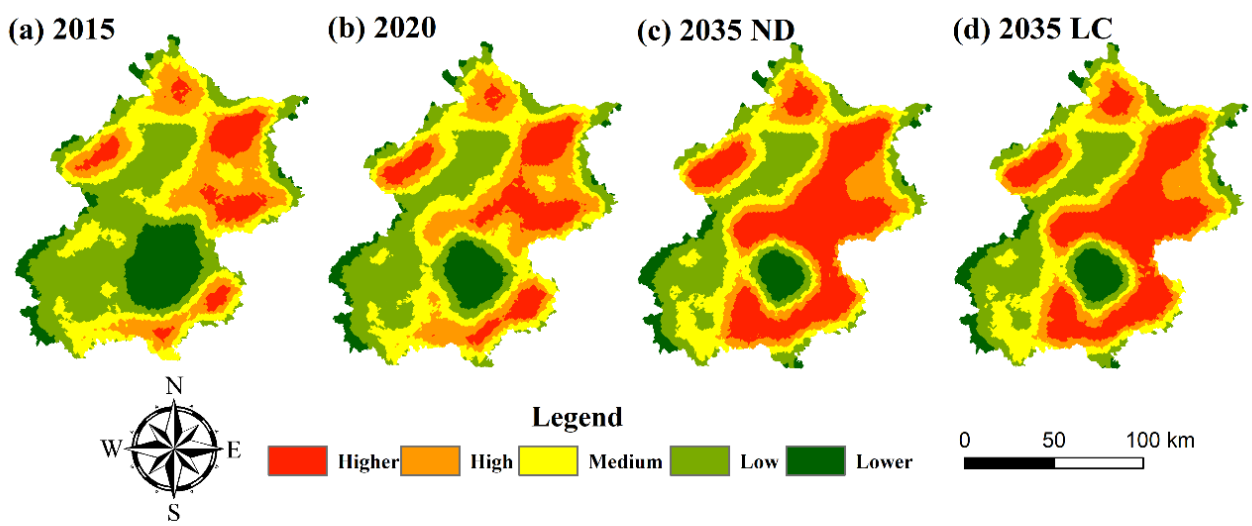

Figure 6. Spatial distribution of landscape ecological risk(a) year 2015; (b) year 2020 and simulation results

Between 2015-2020, the higher and higher ecological risk levels increased by 826.22km2 and 613.25km^2, while the area of lower and lower ecological risk was decreasing by 778.31km^2 and 1103.09km^2, respectively, and the ecological risk of the landscape increased in this period. Between 2020 and 2035, the most significant change in higher ecological risk is observed, with ND Scenario and LC Scenario increasing in higher ecological risk by 2884.98km^2 and 2563.05km^2 respectively, while the area at lower ecological risk decreases by 235.34km^2 and 205.29km^2 respectively. In comparison, LC Scenario faces slightly lower ecological risk than ND Scenario.

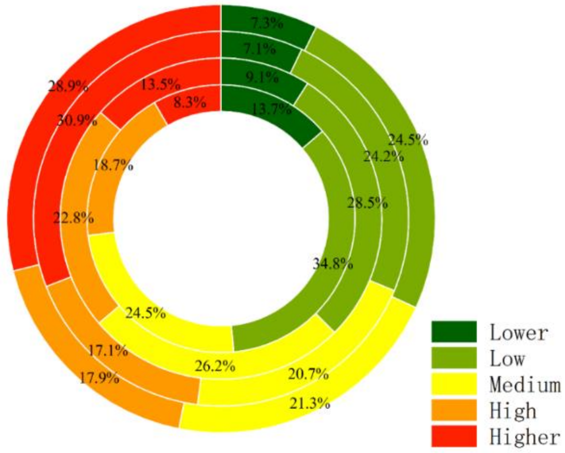

Figure 7. Area proportion of each level of landscape ecological risk(From the inner ring to the outer ring in the order of 2015, 2020, 2035 ND Scenario, 2035 LC Scenario).

4. CONCLUSIONS AND DISCUSSIONS

4.1 Conclusions

In this study, we proposed a new development scenario for a liveable city for optimising the future land use structure of Beijing based on planning documents for urban development. This work also explores the spatial and temporal changes in landscape ecological risk patterns in large cities from the perspective of land-use change. The findings from this study are as follows:

1. The main feature of LULC change in Beijing in the future is the transformation of construction land to surrounding ecological land. The mountainous area in the northwest of Beijing is dominated by ecological land. The area of urbanization mainly occurs in the southeast plain area, and the scope of built-up land in the main urban area is greatly reduced. In 2035, the built-up land area under LC scenario is closer to the policy requirements than that under ND scenario. It shows that the future land use situation of Beijing simulated by the LC scenario is reasonable.
2. By comparing the spatial pattern of LULC and ecological risk, we find that there is a high correlation between them. The built-up land mainly shows lower ecological risk, the forest shows lower ecological risk, and the grassland and cultivated land show higher and higher ecological risk. The built-up land is distributed intensively, and it is difficult for human activities to cause further damage to the construction land. Therefore, the urban center is faced with lower ecological risks. In contrast, cultivated land and grassland are extremely vulnerable to human activities, which leads to higher ecological risks of cultivated land and grassland. Therefore, it leads to the spatial pattern of dual polarization.
3. The increase of ecological risk is caused by the change of grassland, cultivated land and built-up land. Specifically, the increase of grassland and cultivated land area leads to the increase of areas with higher ecological risks. The reduction of built-up land has led to the reduction of the area with low ecological risks.

4.2 Discussions

4.2.1 Drivers of Urban Development

Cities are complex megasystems and the choice of LULC drivers has focused on static factors in society, economy and nature. However, many studies have shown that dynamic factors such as policy planning, the daily activities of residents and the regional industrial structure also have a significant impact on land use change. As a world-class tourist city, the daily activities of tourists and local residents will affect the transportation, commercial sites and other factors. These factors also affect the changes in LULC (Yujie et al., 2022). In the following research, we use the Point of Interest (POI) data of residents' daily dynamic activities to improve the accuracy of the prediction model.

4.2.2 Scenarios for the Future of the City

In the study, we constructed the ND scenario that is not affected by any factors, and the LC scenario that represents the balanced development of economic and ecological benefits. However, urban development is not limited to the two scenarios in this paper. Future climate scenarios, SDG goals, etc. can be used to build future urban development scenarios. In addition, this study only predicts the LULC in 2030, which is difficult to reflect the long-term change of LULC. In the following research, LULC should be predicted in the short, medium and long term to meet the need for urban planners to formulate land use policies in different periods.

4.2.3 Limits of Ecological Risk

Due to the difficulty of data collection, this study only considers the changes of LULC caused by human activities. However, the change of ecological risk is also affected by other factors, such as the expansion of road network, terrain, meteorological changes, geological disasters and other natural factors.(Mo et al., 2017). This will contribute to a better understanding of the impact of human activities on ecological risk. Therefore, an integrated evaluation of ecological risk from a multi-risk source perspective is necessary in the future.

REFERENCES

Ai, J. et al., 2022. Assessing the dynamic landscape ecological risk and its driving forces in an island city based on optimal spatial scales: Haitan Island, China. *Ecological Indicators*, 137: 108771.

An, X. et al., 2022. Spatial and temporal evolution of carbon stocks in Dongting Lake wetlands based on remote sensing data. *Geocarto international*, ahead-of-print(ahead-of-print): 1-27.

Chen, G. et al., 2021. Future "local climate zone" spatial change simulation in Greater Bay Area under the shared socioeconomic pathways and ecological control line. *Building and Environment*, 203: 108077.

Chen, Q. and Liu, J., 2014. Development process and perspective on ecological risk assessment. *Acta Ecologica Sinica*, 34(5): 239-245.

Deng, Z. and Quan, B., 2022. Intensity Characteristics and Multi-Scenario Projection of Land Use and Land Cover Change in

Hengyang, China. *International Journal of Environmental Research and Public Health*, 19(14): 84-91.

Depietri, Y., 2020. The social – ecological dimension of vulnerability and risk to natural hazards. *Sustainability Science*, 15(2): 587-604.

Guo, H., Cai, Y., Yang, Z., Zhu, Z. and Ouyang, Y., 2021. Dynamic simulation of coastal wetlands for Guangdong-Hong Kong-Macao Greater Bay area based on multi-temporal Landsat images and FLUS model. *Ecological Indicators*, 125: 107559.

Ji, Y., Bai, Z. and Hui, J., 2021. Landscape Ecological Risk Assessment Based on LUCC — A Case Study of Chaoyang County, China. *Forests*, 12(9): 1157.

Jiang, S., Meng, J. and Zhu, L., 2020. Spatial and temporal analyses of potential land use conflict under the constraints of water resources in the middle reaches of the Heihe River. *Land Use Policy*, 97: 104773.

Jiang X., Duan H., Liao J., 2022. A multi-model-based simulation of land use scenarios in the midstream of the Heihe River in Ganlingao. *Journal of Agricultural Machinery*: 1-17.

Karimian, H., Zou, W., Chen, Y., Xia, J. and Wang, Z., 2022. Landscape ecological risk assessment and driving factor analysis in Dongjiang river watershed. *Chemosphere*, 307: 135835.

Liang, T. et al., 2022. Land-Use Transformation and Landscape Ecological Risk Assessment in the Three Gorges Reservoir Region Based on the "Production–Living–Ecological Space" Perspective. *Land*, 11(8): 12-34.

Liang, X. et al., 2018. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landscape and urban planning*, 177: 47-63.

Liang, X. et al., 2021. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. Computers, *Environment and Urban Systems*, 85: 101569.

Linjuan Li, Z. et al., 2022. A static and dynamic coupling approach for maintaining ecological networks connectivity in rapid urbanization contexts. *Journal of cleaner production*, 369.

Liu, X. et al., 2017. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, 168: 94-116.

Meentemeyer, R.K. et al., 2013. FUTURES: Multilevel Simulations of Emerging Urban-Rural Landscape Structure Using a Stochastic Patch-Growing Algorithm. *Annals of the Association of American Geographers*, 103(4): 785-807.

Mo, W., Wang, Y., Zhang, Y. and Zhuang, D., 2017. Impacts of road network expansion on landscape ecological risk in a megacity, China: A case study of Beijing. *Science of The Total Environment*, 574: 1000-1011.

Ran, P. et al., 2022. Exploring changes in landscape ecological risk in the Yangtze River Economic Belt from a spatiotemporal perspective. *Ecological Indicators*, 137: 108744.

Shi, M. et al., 2022. Cropland Expansion Mitigates the Supply and Demand Deficit for Carbon Sequestration Service under Different Scenarios in the Future — The Case of Xinjiang. *Agriculture (Basel)*, 12(1182): 1182.

Wang, H. et al., 2021. Spatial-temporal pattern analysis of landscape ecological risk assessment based on land use/land cover change in Baishuijiang National nature reserve in Gansu Province, China. *Ecological Indicators*, 124: 107454.

Wang, J., Zhou, W., Pickett, S.T.A., Yu, W. and Li, W., 2019. A multiscale analysis of urbanization effects on ecosystem services supply in an urban megaregion. *Science of The Total Environment*, 662: 824-833.

Wang, Y., Li, X., Zhang, Q., Li, J. and Zhou, X., 2018. Projections of future land use changes: Multiple scenarios-based impacts analysis on ecosystem services for Wuhan city, China. *Ecological Indicators*, 94: 430-445.

Yujie, L., Jinlian, S., Yaomin, Z. and Xiankai, H., 2022. The Evolution Pattern and Simulation of Land Use in the Beijing Municipal Administrative Center (Tongzhou District). *Journal of Resources and Ecology*, 13(2).

Zhang, D., Jing, P., Sun, P., Ren, H. and Ai, Z., 2022. The non-significant correlation between landscape ecological risk and ecosystem services in Xi'an Metropolitan Area, China. *Ecological Indicators*, 141: 109-118.

Zhang, S. et al., 2022. Landscape ecological risk projection based on the PLUS model under the localized shared socioeconomic pathways in the Fujian Delta region. *Ecological Indicators*, 136: 108642.