Assessment and Estimation of the Spatial and Temporal Evolution of Landscape Patterns and Their Impact on Habitat Quality in Nanchang, China

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Abstract: Assessing and predicting the evolution of habitat quality based on land use change under the process of urbanization is important for establishing a comprehensive ecological planning system and addressing the major challenges of global sustainable development. Here, two different prediction models were used to simulate the land use changes in 2025 based on the land use distribution data of Nanchang city in three periods and integrated into the habitat quality assessment model to specifically evaluate the trends and characteristics of future habitat quality changes, explore the impact of landscape pattern evolution on habitat, and analyze the differences and advantages of the two prediction models. The results show that the overall habitat quality in Nanchang declined significantly during the period 1995–2015. Habitat degradation near cities and in various watersheds is relatively significant. During the period 2015–2025, the landscape pattern and habitat quality of Nanchang will continue to maintain the trend of changes observed between 1995 and 2015, i.e., increasing construction land and decreasing habitat quality, with high pressure on ecological restoration. This study also identified that CA-Markov simulates the quantity of land use better, while FLUS simulates the spatial pattern of land use better. Overall, this study provides a reference for exploring the complex dynamic evolution mechanism of habitats.

Keywords: CA-Markov model; FLUS model; InVEST model; land use change; habitat quality

1. Introduction

China’s urbanization process has been accelerating in recent years, with China’s urbanization rate increasing significantly to 63.89% by 2020 and expected to reach 70% by 2030 [1]. On the one hand, changes in land use/land cover and rapid urban expansion inevitably transform a large amount of ecological land, such as forests, grasslands and waters, into construction land, resulting in the fragmentation of habitats that are suitable for biological survival, which not only affects the changes in ecosystem structure but also influences the content of greenhouse gases in the atmosphere and changes the regional atmospheric chemistry [2]. Then, this destroys ecosystem climate regulation and other service functions, leading to a series of climate change problems, such as ozone layer holes, glacier melting and frequent extreme weather, and the sustainable development of cities is threatened and challenged [3]. On the other hand, climate change, such as global temperature increases, also leads to the degradation of ecosystem functions and habitat fragmentation, thus affecting the quality of ecosystem habitats [4]. According to the results
of the Millennium Ecosystem Assessment published by the United Nations, climate change is already one of the most important factors threatening biodiversity and is expected to have an increasing proportion of its impact in the coming decades, changing the quality of the original habitats to varying degrees. Therefore, assessing and predicting the evolution of habitat quality based on land use change in the process of urbanization is of practical significance for establishing a comprehensive ecological planning system and coping with the great challenge of climate change. Therefore, assessing and predicting the evolution of habitat quality based on land use change under the process of urbanization is of practical importance for establishing a comprehensive ecological planning system and addressing the major challenges of climate change. The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model, developed by Stanford University and the WWF, has been widely used due to its accurate quantification, visualization of results, and low application cost [5,6]. Nelson et al. applied the model to study different land use scenarios in the Willamette Basin, Oregon, North America, and explored the value and spatial distribution of ecosystem services in different scenarios [7]. Loh, Mansoor, D.K. et al. studied the evolution of habitat quality in Ghana and Cote d’Ivoire in different periods, and the authors elaborated on the general situation of habitat quality in these two countries [8]. Kovacs. et al. and Shaw. et al. quantitatively assessed ecosystems in the Minnesota and Sierra Nevada regions of the USA in the form of thematic maps and derived core areas for investment and conservation [9,10].

However, recent studies have generally concentrated on assessing the historical and current habitat quality in the study area, and few have explored future trends in habitat quality. There are many models currently available to estimate future land use variation [11–15], among which the cellular automata (CA)-Markov model integrates the properties of CA model to simulate the evolution of spatial patterns [16] and the superiorities of the Markov model for long-term quantitative estimation [17]; thus, the CA-Markov model has good results for the prediction of spatiotemporal evolution, while the future land use simulation (FLUS) model can better address the complex intertransformation of landscape types occurring under the combined action of natural factors and socio-economic factors, which makes the simulation results match better with real land use conditions [18]. Consequently, the above two prediction models are commonly used in land use simulations. Jenerette et al. applied the CA-Markov model to the vicinity of Phoenix, Arizona, USA, to explore the effects of urbanization and population growth on land-use change [19]. Nouroqilpour et al. used CA-Markov and multicriteria evaluation (MCE) models to estimate landscape variations in oil palm plantations in Kualalangat, Malaysia, and successfully predicted the land-use evolution trend in 2020 [20]. Liang Xun used the FLUS model to predict the urban form of the Pearl River Delta (PRD) area from 2020 to 2050 to establish urban growth boundaries [21]. Taking Hubei Province of China as an example, Wang Xu predicted the ecological spatial distribution of the province in 2035 by using the FLUS model [22]. All the above explorations indicate that CA-Markov and FLUS have good generalizability for the realistic simulation of land use development trends.

The models mentioned above have a long history of use and have achieved good results in their respective fields [23–26]. If predictive models and the habitat assessment models can be combined to predict future habitat quality, they will improve the understanding of the complex dynamic evolution mechanism of habitats and provide a reference for the government to implement land and ecological regulation strategies. However, there are few studies on future habitat quality, and most of the studies on future habitat quality simulation apply a single prediction method, lack a reference mechanism, and are unable to verify future land use patterns [27,28]. In this paper, given the abovementioned insufficiencies, two different prediction models (CA-Markov and FLUS) are combined with the habitat assessment model (InVEST). The results of the two prediction models can validate and support each other. Compared with the single-line model combination, this double-line model combination improves the reliability of prediction.
As a large provincial capital city, Nanchang plays an essential role in the Yangtze River economic zone. In recent years, the economic level of Nanchang has rapidly developed in all directions, and a series of problems related to urban expansion have occurred, which may lead to the urban heat island effect, deterioration of the habitat environment and frequent occurrence of extreme weather. Therefore, evaluating and predicting the characteristics of habitat evolution from the perspective of land use evolution is of great significance to maintain the balance of the ecosystem and achieve the goal of sustainable development in Nanchang city. This study took Nanchang city as the research area, two different prediction models (CA-Markov and FLUS) were used to model past, current and future land-use changes, and the InVEST model was introduced to integrate each of these two prediction models into habitat quality modeling to explore the effects of the evolution of landscape patterns on habitats. Specifically, the research can achieve the following three objectives: (1) assess and predict trends and characteristics of habitat quality from the perspective of land use variation; (2) analyze the differences between the two prediction models (CA-Markov and FLUS) and explore their respective advantages; and (3) obtain new information and measures for optimizing landscape patterns and improving habitat quality in Nanchang.

The main contributions of this paper are as follows. In terms of theory, on the one hand, the introduction of habitat evaluative indicators reflecting regional biodiversity allows for a multidimensional and comprehensive analysis of habitats, providing a novel approach and perspective for the diversified development of habitat assessment systems. On the other hand, this study uses the double-line combination of two prediction methods and the habitat assessment model to reduce the uncertainty associated with the model, thus enhancing the reliability of the simulation results. This approach is more reasonable and effective than relying only on a single prediction model. In terms of practical implications, exploring the impact of landscape pattern evolution on habitat can help people to understand the complex mechanisms of habitat quality change to better optimize landscape patterns to improve the current ecological environment and provide a reference for territorial spatial planning and the implementation of ecological control strategies.

2. Materials and Methods
2.1. Study Area

Nanchang (115°27′–116°35′ E, 28°10′–29°11′ N), as the capital of Jiangxi Province, occupies a large area of plains, with relatively flat terrain in the southeast, rolling hills in the northwest, and plains, water bodies, and mountainous hilly terrain, each accounting for approximately one third of the area (Figure 1). The total area of the city is 7402 square kilometers. As a major transportation hub in the central part of China, with transportation running east–west and north–south, and as a major ecological barrier in southern China, Nanchang has undergone rapid population growth and the expansion of construction land. Therefore, maintaining regional ecological security should be the focus of future efforts.

2.2. Data Sources and Processing

The land use data of this research are obtained based on Landsat TM/ETM+ images from the NASA scientific data service platform (https://earthdata.nasa.gov/, accessed on 9 September 2021). The Landsat images with 30 m resolution from July to August in 1995, 2005 and 2015 were preprocessed by cloud mask, atmospheric correction and clipping to form three full coverage images of Nanchang city. By applying the method of combining supervised classification with manual visual interpretation, the land use categories in Nanchang were divided into six categories: cultivated land, forestland, grassland, water area, construction land and unused land. The DEM data come from the geospatial data cloud platform (http://www.gscloud.cn/, accessed on 9 September 2021), and the slope is extracted by using the slope function of ArcGIS. The auxiliary gridded GDP, population density data with 1 km resolution and road data of the corresponding time period are
downloaded from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/, accessed on 9 September 2021).

![Figure 1. The study area.](image)

2.3. Methodology

Based on the data collection and processing, we first analyzed the characteristics of land use dynamics in the study area from 1995 to 2015, applied the InVEST model to determine the habitat quality index, habitat rarity index and habitat degradation index in this time period, and assessed the ecological and environmental conditions of Nanchang in the past 20 years from these three aspects. Second, two different prediction models (CA-Markov and FLUS) are used to simulate the future land use changes in the region to verify and support each other’s simulation results and to compare the differences between the two prediction models and explore their respective advantages. Finally, based on the future land use cover map predicted by the two prediction models, the characteristics and trends of future habitat quality evolution are predicted and evaluated by the InVEST model.

2.3.1. CA-Markov Model

The CA-Markov model is a combination of a temporal prediction model (Markov chain) and a spatially dynamic model (Cellular Automata) with discrete time, space and state [29,30]. The Markov model cannot predict spatial variation, while the CA model has the advantage of simulating the spatiotemporal dynamic development of complex systems; thus, combining the two models could effectively simulate the spatiotemporal changes in land-use patterns [31,32].

A Markov model is first run to obtain the transition matrices (including the transition area, transition probability and a series of auxiliary maps). The land-use status \( S_{(t+1)} \) is forecasted through the status \( S_{(t)} \) at a given moment with a transition probability matrix \( P_{ij} \) in the Markov process. Therefore, the land-use status can be forecasted using the following equation [33]:

\[
S_{(t+1)} = P_{ij} \times S_{(t)},
\]

(1)

In the second step, the CA model is a lattice dynamics model in which spatial interactions and temporal connections are localized and spatiotemporal relationships and morphological conditions are discrete [34,35]; it can be expressed using the following equation [36]:

\[
S_{(t+1)} = f\left(S_{(t)}, N\right),
\]

(2)

where \( S \) represents the set of finite and discrete cellular situations, \( t \) and \( t+1 \) are diverse moments, \( N \) is the cellular neighborhood, and \( f \) is the cellular transition rules.

The suitability image set is generated to define evolutionary rules or criteria based on the MCE model [20], and the state of the metacell at the next moment is determined based
on the suitability image set. Based on the economic and ecological conditions of the study area, eight suitability factors, including elevation, slope, slope direction, distance from road, distance from water, distance from construction land, per capita GDP and population density, are selected to generate transfer suitability images, and finally, the Collection Editor tool is used to package the transfer suitability image set to participate in the later land use change prediction.

The kappa coefficient can check the consistency between simulation results and observation data as a whole and is widely used in studies on the accuracy of land use change simulations, which can be expressed by the following formula [37,38]:

\[
Kappa = \frac{(P_o - P_c)}{(P_p - P_c)},
\]

where \(P_o\) denotes the probability of correct prediction; \(P_c\) denotes the probability of correct prediction in the random case; and \(P_p\) denotes the probability of correct prediction under ideal classification. The Kappa coefficient for 2015 was 0.86, as calculated by IDRISI software, indicating that the model had a good prediction effect, and the prediction results were credible. Based on this result, this study further simulated the land use in 2025 in the study area.

2.3.2. FLUS Model

The FLUS (future land use simulation) model mainly includes three major components: ANN-based probability-of-occurrence estimation [39], self-adaptive inertia and competition mechanism, and Markov chain. This is a land-use simulation model based on the probability of occurrence and land competition mechanism. The formula is expressed as follows [18]:

\[
TPS_{k,t}^{l} = p(k, t, l) \times \Omega_{k,t}^{l} \times Inertia^{l} \times (1 - sc_{c \rightarrow t}),
\]

where \(TPS_{k,t}^{l}\) is the total probability of conversion of raster \(k\) to land category \(t\) at moment \(l\); \(p(k, t, l)\) is the probability of suitability of land category \(t\) on raster \(k\) at moment \(l\); \(\Omega_{k,t}^{l}\) is the meta-neighborhood influence factor; \(Inertia^{l}\) is the adaptive inertia coefficient of land category \(t\) at moment \(l\); \(sc_{c \rightarrow t}\) is the cost required to convert land use category \(c\) to category \(t\); and \(1 - sc_{c \rightarrow t}\) is the ease of land category conversion.

After obtaining suitability probabilities, the roulette selection mechanism is used to simulate the future evolution characteristics of land use [40]. The future demand for each land use category is obtained through expert empirical methods or other land type quantity forecasting methods [21]. In this study, we obtained land use demand data for each year from 2015–2025 by expert empirical methods and Markov chains. The following driving factors are selected: elevation, slope, slope direction, distance to road, distance to water, distance to construction land, regional gross domestic product (GDP) and population density.

The precision validation module in FLUS software estimated that the Kappa coefficient for 2015 was 0.90, which confirms that the model has a good prediction effect and reliable prediction results. On this basis, the simulation of the evolution of land patterns in the study area in 2025 was further carried out.

2.3.3. Establishment of Habitat Evaluative Indicators

The habitat quality module of the InVEST model habitat quality evaluation is based on land use/cover information and biodiversity stressors and thus assesses the function of biodiversity maintenance [41]. The module assumes areas with better habitat quality have better biodiversity and that a decrease in habitat extent and habitat quality indicates a decrease in biodiversity in the area. By analyzing the impact of ecological threat factors related to human activities on land use, the degree of habitat degradation (degradation), habitat quality (habitat quality) and habitat rarity (habitat rarity) are evaluated in general.
(1) Habitat Degradation Index

The value of the habitat degradation index represents the impact level of threat factors on habitat and, thus, the potential for habitat destruction and the degradation of habitat quality. The habitat degradation index takes values from 0 to 1; the closer the value is to 1, the greater the potential damage caused by the threat source to the regional habitat and the more detrimental the maintenance of biodiversity [42]. The habitat degradation index is calculated by the following equation:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left( \frac{w_r}{\sum_{r=1}^{R} w_r} \right) r_y i_{rxy} \beta_x S_{jr}$$

(5)

where $D_{xj}$ is the habitat degradation index; $R$ is the total number of threat factors; $w_r$ is the weight; the number of grids in the threat factor $r$ is $Y_r$; $r_y$ is the threat factor $r$ in grid $y$; $\beta_x$ denotes the accessibility of the threat source to grid $x$ under the protection of society and law; $S_{jr}$ is the sensitivity of land use type $j$ to threat $r$; and $i_{rxy}$ is the threat effect of threat factor $r$ in grid $y$ on the habitat in grid $x$.

(2) Habitat Rarity Index

The habitat rarity index refers to the degree of fragmentation and ecological stability of the habitat patches in a region. The higher the habitat rarity index is, the more unstable the ecological structure and function of the area and the greater the possibility of ecological environment damage [43]. The lower the habitat rarity index, the more stable the ecosystem, and the material and energy cycles are not easily broken. Habitat scarcity is calculated by the equation:

$$R_x = \sum_{x=1}^{X} \sigma_{xj} R_j$$

(6)

where $R_x$ is the habitat rarity index; $R_j$ is the discriminant index of land use category $j$ of the raster cell; and $\sigma_{xj}$ indicates whether the current land cover category of raster cell $x$ is $j$. If yes, then $\sigma_{xj}=1$; if not, then $\sigma_{xj}=0$.

(3) Habitat Quality Index

Habitat quality refers to the ability of an ecosystem to provide suitable conditions for the survival of individual organisms and populations. In the grid layer, the habitat quality index changes continuously from 0 to 1. The closer the value is to 1, the more favorable the maintenance of biodiversity [44]. The specific calculation equation is as follows:

$$Q_{xj} = H_j \left[ 1 - \left( \frac{D_{xj}^2}{D_{xj}^2 + k^2} \right) \right]$$

(7)

where $Q_{xj}$ represents the habitat quality of grid $x$ in land cover category $j$; $H_j$ denotes the habitat suitability of land cover category $j$; and $k$ is the half-saturation factor, whose value is equal to half the resolution size of the raster cell.

(4) Parameter requirement analysis of the InVEST model

The main parameters required to run the InVEST model include the weights and effective distances of the threat factors as well as the suitability and sensitivity of the habitat for each threat factor.

According to the review of relevant literature [6,28,42–45], reference to the application examples in the InVEST User’s Guide [46], expert consultation and analysis of field survey for Nanchang area, the region has higher population, arable land and villages and towns, human activity disturbance has a greater impact on the change of landscape pattern in the study area, construction land and agricultural land reflect the threat of human activity to habitat, while traffic roads also have an impact on the evolution of habitat with the modification of the surface by human activity. The habitat quality evolution of the
agricultural land, rural residential land, urban land, other construction land, highway and railroad, which have more population activities and greater influence on ecological landscape, were selected as threat factors, and the influence distance and weight of each threat factor (Table 1) and the suitability and sensitivity of each landscape type (Table 2) were assigned.

Table 1. Attributes of threat data.

| Threat Factor                  | Maximum Distance | Weight | Spatial Decay Type |
|-------------------------------|------------------|--------|-------------------|
| Farmland                      | 1.5              | 0.6    | Linear            |
| Rural Resident Land           | 2.5              | 0.4    | Exponential       |
| Urban Land                    | 6                | 0.8    | Exponential       |
| Other Construction Land       | 4                | 0.5    | Exponential       |
| Highway                       | 6                | 0.6    | Linear            |
| Railway                       | 5                | 0.3    | Linear            |

Table 2. Sensitivity of land-use types to each threat.

| Landscape Types               | Habitat Suitability | Farmland | Rural Resident Land | Urban Land | Other Construction Land | Highway | Railway |
|-------------------------------|---------------------|----------|---------------------|------------|-------------------------|---------|---------|
| Farmland                      | 0.4                 | 0        | 0.35                | 0.5        | 0.3                     | 0.5     | 0.5     |
| Woodland                      | 1                   | 0.8      | 0.85                | 1          | 0.8                     | 0.9     | 0.8     |
| Grassland                     | 0.6                 | 0.5      | 0.35                | 0.6        | 0.5                     | 0.7     | 0.7     |
| Waters                        | 1                   | 0.7      | 0.75                | 0.9        | 0.9                     | 0.75    | 0.6     |
| Construction Land             | 0                   | 0        | 0                   | 0          | 0                       | 0       | 0       |
| Unutilized Land               | 0                   | 0        | 0                   | 0          | 0                       | 0       | 0       |

3. Results

3.1. Land Use and Its Transfer Changes in the Study Area

Woodland, farmland and waters are the major land categories in Nanchang city, accounting for 70% of the total area, of which 50% is farmland (Figure 2). The land-use pattern changed considerably between 1995 and 2015, with the greatest changes occurring in farmland and construction land. The area change of each land type was mainly reflected in the decreases in farmland, woodland and grassland each year. Among them, farmland has been decreasing at a rate of 0.2% per year, with a total reduction of 293,550 ha, and the pressure on farmland has been increasing. Woodland and grassland also showed declines, with more moderate rates of reduction. The area of construction land has increased each year, with a growth rate of 96.44% and an overall increase in area of 2,951,500 ha in the past 20 years, which reflects the increasing demand for the expansion of construction land under the background of an increasing level of urbanization, an increase in population pressure and continuous economic development. The rate of decline in unused land was more moderate. A slight increase is observed in the water area (Figure 3).

As shown in Table 3, from 1995 to 2005, the most transferred land type in the study area was farmland, with a net transfer of 58,403 ha, shifting mainly to 32,878 ha of waters and 47,612 ha of construction land, with the transfer of farmland being influenced by the return of farmland to lakes and the expansion of urban construction land. The next largest land type transferred out was woodland, with a net transfer of 17,475 ha, and the majority transferred to farmland (4202 ha) and construction land (14,291 ha), indicating that the clearance of woodland for farmland and construction land expansion still occurs. The land types that significantly increased were water (16,657 ha) and construction land (59,513 ha), with the increase in water mainly coming from farmland (32,878 ha), reflecting the achievements of returning farmland to lakes. At the same time, the most transferred
land type was construction land, with 69.9% of the transferred construction land coming from farmland, indicating that the main land type occupied by urban expansion is still farmland. The areas of grassland and unused land did not change much.

![Spatial distribution patterns of landscape types in 1995, 2005, and 2015.](image)

**Figure 2.** Spatial distribution patterns of landscape types in 1995, 2005, and 2015.

![Land-use area of the first classes in 1995, 2005, and 2015.](image)

**Figure 3.** Land-use area of the first classes in 1995, 2005, and 2015.

From 2005 to 2010, farmland was still the most transferred land type, and its area continued to decrease by 35,344 ha, with the rate of reduction tending to be smaller and the main shifts to construction land (46,976 ha), followed by water (11,669 ha) and woodland (9873 ha); additionally, the conversion of farmland and the conversion of grassland largely offset one another. The decrease in woodland also tended to be smaller, with a reduction of 8894 ha and the main shifts to farmland (15,815 ha) and unused land (6519 ha). The area of grassland decreased slightly. The waters were significantly different from the previous period, from a net transfer of 32,878 ha to a net transfer of 1823 ha, mainly due to the shrinkage of Poyang Lake and the transfer of water out to unused land. The construction land continued to increase, with a net transfer of 5,699,300 ha, but the growth rate was lower than that of the previous period. Farmland was still an important source of construction land, with a net transfer of 46,977 ha of farmland to construction land. The net transfer of unused land was 2605 ha, with a clear interconversion between and water.
Table 3. Land use transfer matrix in the study area (ha).

| Period | Landscape Types | Farmland | Woodland | Grassland | Waters | Construction Land | Unutilized Land | Transfer Out | Net Transfer Out |
|--------|-----------------|----------|----------|-----------|--------|------------------|----------------|-------------|------------------|
| 1995–2005 | Farmland | 305,959 | 1238 | 916 | 32,878 | 47,612 | 1166 | 83,811 | 58,403 |
|          | Woodland | 4202 | 99,495 | 334 | 1423 | 14,291 | 54 | 20,304 | 17,475 |
|          | Grassland | 310 | 662 | 7227 | 444 | 603 | 0 | 2019 | 656 |
|          | Waters | 14,146 | 778 | 112 | 93,473 | 5588 | 1261 | 21,885 | −16,657 |
|          | Construction land | 3551 | 82 | 1 | 2118 | 43,069 | 2837 | 8589 | −59,513 |
|          | Unutilized land | 3200 | 69 | 0 | 1679 | 8 | 26,124 | 4956 | −362 |
|          | Transfer in | 25,408 | 2829 | 1363 | 38,542 | 68,102 | 5318 | |
| 2005–2015 | Farmland | 318,526 | 9873 | 659 | 11,669 | 46,976 | 43 | 69,220 | 35,344 |
|          | Woodland | 15,814 | 93,681 | 642 | 463 | 6518 | 6 | 23,443 | 8893 |
|          | Grassland | 805 | 1714 | 4921 | 93 | 49 | 0 | 2661 | 781 |
|          | Waters | 9033 | 2631 | 98 | 86,935 | 3368 | 9548 | 24,678 | 1022 |
|          | Construction land | 8169 | 331 | 46 | 4179 | 47,333 | 32 | 12,756 | −44,235 |
|          | Unutilized land | 54 | 1 | 434 | 6453 | 81 | 25,352 | 7025 | −2604 |
|          | Transfer in | 33,876 | 14,550 | 1879 | 22,857 | 56,992 | 9629 | |

3.2. Analysis of Habitat Degradation

The value of the habitat degradation index represents the impact level of threat factors on habitat and, thus, the potential for habitat destruction and the degradation of habitat quality. The habitat degradation index takes values from 0 to 1; the closer the value is to 1, the greater the potential damage caused by the threat source to the regional habitat and the more detrimental the maintenance of biodiversity.

As shown in Figure 4, the maximum values of the habitat degradation index at each time point were 0.1411, 0.1422 and 0.1473, respectively, with a gradual increasing trend from 1995 to 2015. The areas with a high degree of habitat degradation were around the city and in various watersheds, indicating that their habitats had high degradation potential. The expansion of cities has resulted in the conversion of farmland and other land types around cities into construction land, which causes the most serious damage to the ecological environment. The ecosystem around the watershed is vulnerable to external disturbance, and the level of habitat degradation is significant. In addition, habitat degradation at the junction of the plain and Meiling is very prominent, presenting almost a linear trend. The areas with a low degree of habitat degradation were located in the Poyang Lake area in the northeastern portion of Nanchang city, where the corresponding land types were mainly water and mudflat swamps, and the land types were relatively singular and less disturbed by humans; thus, the habitat quality was not significantly degraded. Generally, the urbanization of Nanchang city developed rapidly from 1995 to 2015, which led to the increasing trend of habitat degradation.

![Figure 4](image-url) Spatial distribution pattern of the habitat degradation index in 1995, 2005, and 2015.
3.3. Analysis of Habitat Rarity

The habitat rarity index refers to the degree of fragmentation and ecological stability of the habitat patches in a region. The higher the habitat rarity index, the more unstable the ecological structure and function of the area are, and the greater the possibility of ecological environment damage. The lower the habitat rarity index, the more stable the ecosystem, and the material and energy cycles are not easily broken.

The minimum value of the habitat rarity index in Nanchang decreased from $-0.6888$ to $-0.9644$ (Figure 5), and the maximum value increased from $0.0663$ to $0.2094$ in both periods, indicating that the range of the habitat rarity index in the study area expanded; i.e., the stability of landscape patches became more variable. A comparative analysis of Figure 5 and the land use types in Nanchang showed that the red area in Figure 5 indicates the highest habitat rarity index, and the land-use type is mainly farmland. Due to the expansion of construction land, the farmland was relatively more damaged and became more fragmented and less stable. The woodland landscape (orange) in the western and southeastern parts of the study area had a high habitat rarity, which may be due to the influence of the surrounding construction land as well as human factors; in addition, the landscape integrity of the woodland suffered some disturbances, and the woodland cover tended to be unstable. The land use types with low habitat rarity (blue) were mainly construction land and water. Moreover, the habitat rarity of unutilized land, such as the mudflats and marshes of Poyang Lake in the northeastern part of the study area, changed from medium (yellow) to low (blue), and the decrease in the habitat rarity index in this area reflected the effectiveness of ecological restoration and the construction of the Poyang Lake Nature Reserve in recent years. There is an urgent need for governments and ecological managers to take certain initiatives to enhance the regulation and protection of farmland, woodland, and grassland to prevent further habitat degradation.

![Figure 5](image.jpg)

**Figure 5.** Spatial distribution pattern of the habitat rarity index in 1995–2005 and 2005–2015.

3.4. Analysis of Habitat Quality

To further investigate the influence of land-use change on habitat quality in the study area, the results of the habitat quality index calculations for the three periods were classified into five levels: low (0–0.2), relatively low (0.2–0.3), medium (0.3–0.4), relatively high (0.4–0.8) and high (0.8–1) (Table 4), and the habitat quality area and its percentage of each level in the three periods were calculated (Table 5, Figure 6). The results showed the following:

1. In terms of temporal change, the proportion of low-grade habitats has been increasing over 20 years, while the proportion of relatively low-grade habitats has been decreasing over 20 years; however, both types of habitat have changed more in the last 10 years than in the first 10 years. The proportion of medium-grade habitats decreased significantly and then increased slightly, showing an overall decreasing trend. The proportion of relatively high-grade habitat also showed a decreasing trend. The proportion of high-grade habitat experienced a slight fluctuation of increasing
and then decreasing, with no significant overall change. The above changes represent a process of transition from relatively high-grade, middle-grade and relatively low-grade habitats to low-grade habitats, and the habitat quality is in the process of being degraded. Finally, the degradation was more serious in the first 10 years than in the last 10 years.

2. In terms of spatial pattern, the change in the spatial pattern in Nanchang had a certain amount of regularity. The area with high habitat quality accounted for a small proportion and was mainly distributed in Meiling in northwestern Nanchang, Poyang Lake in the northeast, and Junshan Lake and Qinglan Lake in the southeast. The famous Meiling National Forest Park is located in Meiling, and this zone is mainly woodland, rich in biodiversity, with little human activity and a high degree of ecological protection; thus, the habitat quality of this zone is high. Poyang Lake, Junshan Lake and Qinglan Lake have the ecological function of maintaining the biodiversity of the wetland landscape and replenishing groundwater. The habitat quality in this area is also relatively high under the protection of the local government. Areas of low habitat quality were mainly located in the Honggutan, East Lake, West Lake and Qingshan Lake districts on both sides of the Ganjiang River in central Nanchang, which are the central urban areas of Nanchang; these areas have rapid economic development, commercial development, rapid expansion of construction land, massive occupation of farmland resources and serious disturbances by human activities, resulting in poor habitat quality in this area. Areas of relatively low habitat quality were concentrated in most of the plain areas, where the land type is mainly farmland. These regions also have concentrations of rural settlements, and human activity is frequent; thus, ecological damage has occurred.

Table 4. Classification value of habitat quality.

| Grade          | Value Range | Description        |
|---------------|-------------|--------------------|
| Low           | 0.0–0.2     | Poor habitat quality|
| Relatively low| 0.2–0.3     | Relatively poor habitat quality|
| Medium        | 0.3–0.4     | Medium habitat quality|
| Relatively high| 0.4–0.8    | Relatively high habitat quality|
| High          | 0.8–1       | High habitat quality|

Table 5. Area and percentage of habitat quality at all grades (10^4 ha, %).

| Grade            | 1995 | 1995 Percentage | 2005 | 2005 Percentage | 2015 | 2015 Percentage |
|------------------|------|----------------|------|----------------|------|----------------|
| Low              | 6.1491 | 8.56          | 8.3151 | 11.57          | 9.2899 | 12.93          |
| Relatively low   | 39.5481 | 55.05        | 37.4760 | 52.16          | 37.1181 | 51.66          |
| Medium           | 2.2179  | 3.09          | 1.5215  | 2.12           | 1.7134  | 2.38           |
| Relatively high  | 0.9609  | 1.34          | 0.9260  | 1.29           | 0.7484  | 1.04           |
| High             | 22.9699 | 31.97         | 23.6073 | 32.86          | 22.9761 | 31.98          |

3.5. Comparison of Land Use Pattern Projections

Both the CA-Markov model and the FLUS model found that the simulated land use category in Nanchang in 2025 (Figure 7) is dominated by farmland, woodland land and water bodies, with these three types together accounting for more than 79% of the study area. In 2025, there were differences in the area of different land types simulated by the two models (Figure 8), but the characteristics of future land use change were similar. From 2015 to 2025, the area of construction land continued to increase significantly, and the area of watershed and unutilized land increased slightly, with construction land increasing by 4% compared to 2015, and the situation of construction land expansion was serious. The area of other land types decreased compared with 2015, including farmland, which decreased...
by at least 20,000 ha, reflecting the pressure on farmland conservation, while the areas of woodland and grassland both shrank to different degrees. These changes are mainly due to the impact of urban expansion. The differences in the spatial distribution by the two simulated models are reflected in the following two regions.

![Figure 6. Spatial distribution pattern of habitat quality in 1995, 2005, and 2015.](image)

One region is located in the Poyang Lake area in the northeastern part of the study area, and the grassland and water bodies predicted by the above two models differ significantly in quantity and spatial distribution. Compared with the distribution in 2015, the grassland in 2025 predicted by the CA-Markov model is significantly larger, and the watershed area is smaller, while the grassland and watershed areas predicted by the FLUS model change little. In recent years, many sand mining vessels have entered Poyang Lake and carried out sand mining operations due to the increased crackdown on sand mining in the Yangtze River and the interest driven by the high price of natural sand. Sand mining has caused the riverbed to be dug deeper and the volume of the river channel to be enlarged continuously, resulting in a drop in the water level, a reduction in water, and the exposure and expansion of grassy patches [47]. Hence, the prediction of FLUS in this area is error, and the CA-Markov model performs better in this region.

The other region is the Meiling area, located in the northwestern part of the study area, where the two models predict a significant difference in the area of construction land. CA-Markov predicts a significant expansion of construction land in 2025 compared to 2015, while FLUS predicts a smaller change in construction land. The region is located in Meiling National Forest Park, and the land use type is mainly woodland, which is a pivotal ecological security barrier in Nanchang and is protected by the government and ecological managers. The area is less likely to be developed for building land, so the prediction of the CA-Markov model is biased in this area, and the FLUS model performs better in this region. In general, the two models are well applied overall, but there are still deviations and shortcomings in individual regions.

3.6. Prediction of Habitat Quality

The future land use cover maps simulated by the two prediction models in Section 3.5 were input into the InVEST model, and the parameters were set according to Section 2.3.3 to obtain the spatial distribution patterns of habitat quality in 2025 predicted by CA-Markov and FLUS.

The spatial and temporal variation characteristics of habitat quality in Nanchang in 2025 simulated by the CA-Markov and FLUS combined with the InVEST model are basically consistent with those in the previous period. From the spatial pattern (Figure 9), there is an overall pattern of high habitat quality in the Meiling belt in the northwest and in the Poyang Lake area in the northeast, a dense lake network in the southeast, and a gradual decrease in habitat quality toward the central area. From the temporal variation (Table 6), the combination of the CA-Markov and InVEST models predicts an average habitat quality index of 0.4236 in 2025, and the combination of the FLUS and InVEST models predicts an average habitat quality index of 0.4359 in 2025. Compared with the values in 2015, the two
averages in 2025 decreased by 0.0209 and 0.0086, respectively, suggesting that in the context of the continuous expansion of construction land, the habitat quality of Nanchang City in 2025 will further decline. Although the percentages of future habitat quality predicted by the combination of the two models differed slightly for different classes, the trends in habitat quality were consistent with those observed in 2015 (Table 6). By 2025, the percentage of high-grade and higher-grade habitats continues to decrease, shifting mainly to low-grade and mid-grade habitats. Areas with low-grade habitats are mostly construction land, and habitat quality in these areas declines further. Although the percentage of relatively low-grade habitats in 2025 is lower than that in 2015, the percentage of low-grade habitats increases significantly, with an area increase of at least 4%. The above phenomenon reflects that the habitat quality in the region is expected to deteriorate significantly from 2015 to 2025, mainly due to the significant expansion of land use types with poor habitat suitability, such as construction land and unutilized land, and the decreases in the areas of woodland and grassland with good habitat suitability during that period.

Figure 7. Spatial distribution patterns of land-use types in 2025 projected by CA-Markov and FLUS.

Figure 8. Percentage of each land-use type in 2025 projected by CA-Markov and FLUS.
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Figure 9. Spatial distribution patterns of habitat quality in 2025 projected by CA-Markov and FLUS.

Table 6. Changes in area and percentage of different classes of habitat quality in 2015–2025 (10^4 ha, %).

| Grade            | 2015 Area | 2015 Percentage | 2025 by CA-Markov Area | 2025 by CA-Markov Percentage | 2025 by CA-Markov Area | 2025 by CA-Markov Percentage |
|------------------|-----------|-----------------|------------------------|-------------------------------|------------------------|-------------------------------|
| Low              | 9.2899    | 12.93           | 14.1289                | 19.67                         | 12.2113                | 17.00                         |
| Relatively low   | 37.1181   | 51.66           | 33.5012                | 46.63                         | 34.4019                | 47.88                         |
| Medium           | 1.7134    | 2.38            | 1.7451                 | 2.43                          | 2.1673                 | 3.02                          |
| Relatively high  | 0.7484    | 1.04            | 0.6250                 | 0.87                          | 0.6750                 | 0.94                          |
| High             | 22.9761   | 31.98           | 21.8461                | 30.41                         | 22.3909                | 31.17                         |

4. Discussion

4.1. Analysis of the Causes of Changes in Habitat Quality

With the accelerated urbanization of Nanchang, issues such as increased population and town expansion can cause a certain amount of damage to the regional ecological environment, and the protection of the ecological environment must not be neglected in the pursuit of social and economic development. The prediction and evaluation of landscape patterns and habitat quality are important tools for optimizing regional landscape patterns and maintaining regional ecological security, which fits with the results of other case studies listed in the first section [5–10]. In this paper, two different prediction models (CA-Markov and FLUS) are used to model historical, present and future land use variations, and the InVEST model is introduced to integrate each of these two prediction models into habitat quality modeling to explore the effects of the evolution of landscape patterns on habitats. This study found a significant decline in habitat quality in Nanchang during 1995–2025.

From a land use perspective, the main variations in Nanchang were the high rate of expansion of construction land and the significant reductions in woodland, grassland and water areas with high habitat suitability. The area of construction land, which is a source of habitat quality threat, increased dramatically during the research period, especially around the central urban areas represented by the Honggutan, East Lake, West Lake and Qingshan Lake districts on both sides of the Ganjiang River. Furthermore, the abovementioned areas have continuously encroached on woodlands, waters and grasslands with high habitat suitability, thus expanding the area and impact of the threat source and leading to a continuous decline in the habitat quality of the study area. These findings coincide with those of other case studies indicating that urban expansion is the primary cause of habitat quality decline [48,49].

From a topographical perspective, the landform of Nanchang city is mainly plain, with a wider water area and a large number of hills and low hills. The Ganjiang River and the Fujiang River flow through Nanchang from south to north. The study area also has the famous Gan-Fu Plain with relatively flat topography, and the only hilly area in the
study area is in Meiling National Forest Park in the northwest. In terms of topography, it is less difficult to develop construction land, and the area is prone to unrestricted sprawl, while hilly areas have always maintained a high habitat quality due to the low impact of human activity.

From the spatial distribution of habitat quality, the areas with a habitat quality index above 0.8 were mainly distributed in Meiling in the northwest, Poyang Lake in the northeast, the watersheds of Ganjiang River and Fuxiang River running through the study area, and Junshan Lake and Qinglan Lake in the southeast; specifically, the areas with a high index included Meiling National Forest Park, which is dominated by woodlands and rich in biodiversity, and Poyang Lake, Junshan Lake and Qinglan Lake, which are important wetland areas in Nanchang with a superior natural environment. At the same time, the government has paid great attention to the ecological protection of these areas, and as a result, they have a high habitat quality. The increase in ecological land, such as woodland and water, can offset the negative effects of urbanization [50].

In the pursuit of socioeconomic development in Nanchang, if the existing land-use pattern is not changed, the dramatic increase in construction land and the decreases in woodland and grassland, such as industrialization and urbanization acceleration, will lead to a continued decline in the overall habitat quality. By 2025, the proportion of low-grade habitats in Nanchang will rise significantly, with an increase of at least 4% in area, and most of the low-grade habitat areas will be construction land. The government should strengthen the risk monitoring and the assessment of these areas to avoid habitat deterioration as much as possible.

4.2. Comparison and Suitability Analysis of the CA-Markov and FLUS

In general, the future land use distributions predicted by CA-Markov and FLUS have a high consistency, with a few differences in the edges of the land types. The edges of the land type patches predicted by CA-Markov are smoother, especially for construction land with more intense expansion, and the land type shapes are distributed in clusters, mainly due to the more aggressive simulation mechanism. The edges of the land type patches predicted by FLUS are more fragmented, and the land type shapes are more irregular, thereby portraying the spatial morphological evolution of land use more precisely.

In terms of quantitative land-use change, CA-Markov predicts a more radical evolution of the landscape pattern than FLUS. In particular, the growth rate of construction land and the shrinkage rates of woodland and grassland increase significantly, which is more in line with the observed situation of land use evolution in Nanchang. In terms of spatial land-use change, the kappa coefficient of CA-Markov was lower than that of FLUS, proving that the simulation results of FLUS in this study are better than those of CA-Markov in terms of spatial pattern. Through comparison, this paper finds that CA-Markov is better at predicting land use quantities, while FLUS is closer to the real land use pattern in terms of spatial morphology and overall structure. The CA-Markov model is more suitable when focusing on the prediction of quantitative land-use changes, especially for construction land, and the FLUS model is relatively more suitable when putting particular emphasis on the spatial morphology and overall structure of land use.

By conducting spatial and quantitative comparisons, the prediction results of the two models are mutually supported and indirectly verified, and the above findings provide a more accurate reference for land use simulation for different needs. In practical applications, the corresponding models should be selected according to specific requirements and purposes to achieve better simulation results.

4.3. Implications

The implications of this paper can be described from both theoretical and practical aspects. In terms of theory, on the one hand, the introduction of habitat evaluative indicators reflecting regional biodiversity provides a novel approach and perspective for the diversification of habitat assessment systems. On the other hand, the method of this study
is more reasonable and effective than the traditional single-line model combination of a single prediction method and the habitat assessment model. Although this study provides some references for helping to understand the complex dynamic evolution mechanism of habitats under global urbanization and provides a guide for habitat assessment and prediction in other areas with rapid urbanization, there are still some shortcomings. There are many models currently available to estimate future land-use variation, such as the gray model, logistic regression model, conversion of land-use and its effects (CLUE)-S model and composite models based on CA. [11–15]. All of these models are now widely used in the field, yet we did not study whether there are some models with higher simulation accuracy available. Exploring whether higher precision models are available will be a direction for future improvement and effort. Since the evolution of land use patterns is a complex process influenced not only by the geographical conditions of the region but also by human interventions such as land use policies, it will be essential to explore the role of policy interventions on the evolution of land types to improve the prediction accuracy [51]. In addition, the InVEST model only considers the influence of threat factors on habitats within the study area, while habitats at the edge of the study area are also influenced by other threat factors outside the study area boundary, which might make the assessment results inaccurate. In the future, attention should be given to collecting data on threat factors at the edge of the study area [27]. These shortcomings provide a direction for future theoretical development.

In terms of practice, by studying the impact of land use evolution on habitat quality in Nanchang city, we obtained the following measures that are crucial for optimizing the landscape pattern of Nanchang city and maintaining regional ecological security: (1) The dramatic expansion of construction land is the primary cause for the decline in habitat quality, and the scale of construction land should be managed to avoid the disorderly expansion of urban construction land. (2) The reduction in the area of ecological land, such as woodland and grassland, can also directly lead to a decrease in habitat quality, so it is necessary to set up a forest manager system; implement the zoning management of woodland, grassland and other types of land with high habitat suitability; and establish a system of responsibility for resource targets in ecological barrier areas [52]. (3) From the perspective of habitat degradation, habitat degradation is especially obvious near the city and around the watershed. On the basis of controlling the scale of construction land, it is also crucial to strengthen watershed protection to achieve the goal of ecological security [53]. The above measures are of practical significance for territorial development plans and the construction of ecological security. In the future, the impact of land use/land cover changes on ecological and environmental quality should be fully considered, a constraint mechanism between environmental protection and economic development should be established, and scientific decisions and reasonable planning should be made for rapidly urbanizing areas to promote the win-win development of the social economy and ecological protection.

5. Conclusions

Evaluating and predicting the spatial and temporal evolution of habitat quality under land-use change provides a scientific reference for carrying out ecological conservation and sustainable development. In this paper, two different prediction models (CA-Markov and FLUS) were used to simulate past, current and future land use changes based on the land use distribution data of Nanchang city in three periods of 1995, 2005 and 2015, and the InVEST model was introduced to integrate each of these two prediction models into habitat quality modeling to analyze the effects of the spatial and temporal evolution of landscape patterns on habitats. The results indicate that the habitat quality of the study area is expected to decline significantly from 1995 to 2025, and low-grade habitats will continue to increase. By 2025, the percentage of high-grade and relatively high-grade habitats continues to decrease, shifting mainly to low-grade and middle-grade habitats. Areas with low-grade habitats are mostly construction land. With accelerated industrialization and urbanization, the high rate of expansion of land types with low habitat suitability, such as construction
land, will in turn interfere with areas with high habitat quality, such as woodlands, water bodies and grasslands, resulting in the expansion of the scale and sphere of influence of threat sources, greater landscape fragmentation and reduced stability, which will cause a continuous decline in habitat quality in Nanchang city. This study also identified that the future land use distributions predicted by the CA-Markov and FLUS models have a high consistency, with a few differences in the edges of the land types.

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