Research Paper

Ecological risk prediction based on land use simulation under multiple scenarios

A case study of urban agglomeration in central Zhejiang, China

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Abstract

Rapid urban expansion and climate change significantly affect the land-use structure and regional landscape pattern, imparting serious risks to social development, economy, and environment. Ecological risk prediction is a prerequisite for the successful management of resources and the environment to achieve sustainable development. However, ecological risk research lacks suitable methods to predict the ecological risk index and its spatial distribution. Taking the central Zhejiang urban agglomeration, in China, as an example, and drawing from land-use data in 2000 and 2020, this study applies the future land use simulation (FLUS) model to predict the pattern of land use in 2040 under three scenarios: natural development, economic growth, and ecological development. The landscape disturbance and landscape vulnerability indices, measured using the Fragstats software, were applied to calculate the ecological risk index and map its spatial distribution. The results show that, by 2040, the overall landscape ecological risk in the study area will decline under all three scenarios. The largest spatial difference in land-use-induced ecological risk was that under the ecological development scenario; the smallest one was that under the scenario of natural development, adhering to the current development goals. The degree of fragmentation had a significant effect on ecological risk. By simulating the impact of land-use change on ecological risk from 2000 to 2040, this study demonstrates that the land-use change simulation model can predict the change in ecological risk under different spatiotemporal conditions. These predictions provide an important reference for planning and policy adjustments.

Keywords

Landscape ecological risk prediction, Multi-scenario, Urban agglomeration

1. Introduction

With social development, rapid population growth, and the acceleration of urbanization and industrialization, land resources fail to satisfy social demand, and the degree of land-use change gradually accelerates (Peng *et al.*, 2021). The changes in the type and spatiotemporal pattern of land use affect regional natural ecosystems and generate multiple ecological risks (Estoque and Murayama, 2014). Landscape ecological risk assessment, a method to assess the extent of interactions of landscape patterns with ecological processes producing adverse effects through land-use change (Qingpu *et al.*, 2019), is key to the sustainable use of urban land resources and the maintenance of regional ecological security.

Ecological risk assessment has emerged as a natural environmental management tool that permits the quantitative assessment of the ecological effects of land-use change (Peng *et al.*, 2016). Currently, there are two methods for landscape ecological risk assessment: risk sources and sinks, and landscape patterns (Xu *et al.*, 2021). The risk sources and sinks method requires the identification of risk stressors. The entropy weight (Gong, 2012), exposure-response (Liu *et al.*, 2014), and other methods, combined with remote sensing, are used to identify risk sources and risk receptors (Yazhou and Xiaoping, 2015). Due to the differences in the heterogeneity of the land surface and the intensity of natural-environmental and human activity interference, regional landscapes have distinct spatial patterns. The landscape pattern method can efficiently reflect the spatial distribution and changes in ecological impacts, thereby enabling the comprehensive assessment of the potential ecological risk in a region (Zhang *et al.*, 2018). Landscape ecological risk has recently become an important research theme that attracts the attention of many scholars in China and other countries (Peng *et al.*, 2018; Zhang *et al.*, 2020; Peng *et al.*, 2018). However, there is a lack of research on the landscape ecological risk in large cities with a high level of urban development, particularly in regions with a special development orientation. In addition, research on the simulation of landscape ecological risk and the prediction of the evolution of future land-use patterns under different scenarios is also lacking.

In this study, we develop a landscape loss model to predict future landscape ecological risk under different scenarios of land use. The two major objectives of the study are as follows: 1) by taking the central Zhejiang urban agglomeration as a research area, exploring the spatiotemporal pattern of landscape ecological risks in rapidly developing regions; 2) identifying the planning approach suitable for the rational development of land resources in Zhejiang Province. The second part of the study collected data, and the third part explained specific methods. Finally, it provided a theoretical reference basis for optimizing the spatial pattern of land use, improving the ecological resilience of the landscape, and formulating policies for the sustainable development of the region's land use and ecological environment.

2. Study area and data

2.1. Study area

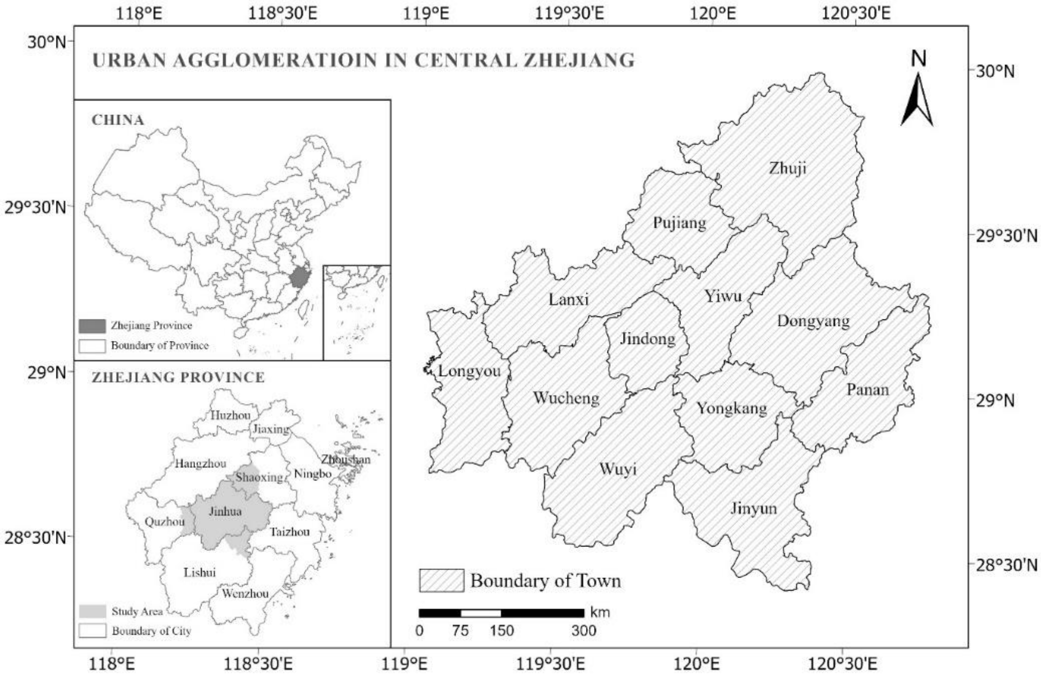

Figure 1. The location map of study area. Source: Authors, 2021.

The central Zhejiang urban agglomeration, with a land area of 15,800 km^2 located in the middle of Zhejiang Province (119°05–120°45 E, 28°35–30°00 N), is the key economic development zone and ecological barrier in the region (Figure 1). It includes twelve county-level units in Jinhua, Shaoxing, Quzhou, and Lishui cities. The central Zhejiang urban agglomeration is a terrain of hilly basins and alluvial plains with mostly flat terrain units and good traffic conditions.

2.2. Data collection

To characterize the changes in land use between 2000 and 2020, we used the GlobeLand30 land use datasets at a spatial resolution of 30 m, obtained from the National Geomatics Center of China (http://www.globeland30.org/). We focused on the seven land-use types generated by data reclassification: cultivated land, forest, shrub, grassland, water, construction land, and unused land. The selected drivers of land-use change included terrain, climate, and socioeconomic factors. Table 1 lists the specific parameters, all of which were acquired from the Chinese Academy of Sciences (http://www.resdc.cn/).

Table 1. Data declaration.

Data type	Data content	Unit	Data use
Land use data	Land use type	/	Model base input data
Terrain factors	elevation	m	Driving factor
	slope	1°	Driving factor
	aspect	/	Driving factor
Climate factors	Annual mean temperature	℃	Driving factor
	Annual mean precipitation	mm	Driving factor

Socio-economic factors	distance to highway	m	Driving factor
	distance to railway	m	Driving factor
	population distribution	people/km^2	Driving factor
	GDP distribution	yuan/km^2	Driving factor

3.Methods

3.1. Future land use scenario simulation

The Future Land Use Scenario (FLUS) model, developed by Xiaoping Liu from the traditional meta-cellular automata model (Liu *et al.*, 2017), has an enhanced ability to simulate and predict future land-use patterns. The model primarily comprises two parts: an artificial neural network (ANN)-based probability of occurrence estimation module and a self-adaptive inertia-and-competition cellular automata module. ANNs can simulate multiple driving factors, such as terrain, climate, and socioeconomic factors, and establish their relationship between different land-use types. The self-adaptive inertia-and-competition mechanism cellular automata module is used to deal with the uncertainty and relative complexity of change, to achieve a high-precision simulation of land use/land cover (LULC) change.

The FLUS model included the following operation steps:

a) Setting the driving factors, initial year land use data, cost matrix, and neighborhood weight, to simulate the land use map of the study area in 2020. The cost matrix is the rule of variation among the land use types, which is used to indicate whether the land use types can transform each other or not, without any transformation restriction in the first simulation. The neighborhood weight parameter is the sprawl intensity of the land type. Its threshold value ranges from 0 to 1: the closer the value is to 1, the stronger the sprawl ability of the land type. The total area change reflects the degree of outward sprawl of each land type, which is conceptually fully consistent with the neighborhood weight parameter. Therefore, in this study, we used Fragstats 4.2.1 to calculate the total area change of each LULC type in the central Zhejiang urban agglomeration between 2000 and 2020. We then used Equation 1 to set the neighborhood weight parameters according to the calculation results:

$$X^* = \frac{X - min}{max - min}$$

Equation 1. X is the total area change of each land-use type, and min and max are the minimum and maximum change, respectively.

b) Verification of the model accuracy: the accuracy of the simulation results was verified using the Kappa and FOM coefficients.

c) Land-use demand forecast: the Markov model was used to predict the scale of demand for each land-use type and to obtain the target pixel number of future land use.

d) Resetting the cost matrix, neighborhood factors, and restricted conditions. The LULC map was estimated for the central Zhejiang urban agglomeration in 2040 under the natural development (NDS), ecological development (EDS), and economic growth scenario (EGS). The NDS refers to the actual change in LULC according to the current situation. The EDS takes the nature reserve as the constraint, reduces the conversion rate of cultivated land to construction land by 30%, reduces the conversion rate of other ecological land to construction land by 50%, and increases the expansion capacity of ecological land according to Table 3. The EGS increases the conversion rate of ecological land to cultivated and construction land by 50% and increases the expansion of other land to construction land (Table 4).

Table 2. Total pixel prediction for each land type

	cultivated land	forest	Grass land	shrub	water	constructional land	unused land
2020	5436872	9390762	750103	157828	344341	1594408	543
2040.NDS	4666915	9336470	743473	152760	383662	2391068	511
2040.EDS	4664315	9626646	755148	155703	392553	2070115	513
2040.EGS	5533483	7607477	709552	138123	383444	3292402	513

Table 3. The cost matrix in the ecological development scenario (EDS).

	Cultivated land	Forest	Grass land	Shrub	Water	Constructional land	Unused land
Cultivated land	1	1	1	1	1	1	1
Forest	0	1	1	1	1	0	0
Grass land	0	1	1	1	1	0	0
Shrub	0	1	1	1	1	0	0
Water	0	1	1	1	1	0	0
Constructional land	0	0	0	0	0	1	0
Unused land	1	1	1	1	1	1	1

Table 4. The cost matrix in the economic growth scenario (EGS).

	Cultivated land	Forest	Grass land	Shrub	Water	Constructional land	Unused land
Cultivated land	1	1	1	1	1	1	1
Forest	1	1	1	1	1	1	1
Grass land	1	1	1	1	1	1	1
Shrub	1	1	1	1	1	1	1
Water	1	1	1	1	1	1	1
Constructional land	0	0	0	0	0	1	0
Unused land	1	1	1	1	1	1	1

3.2. Landscape ecological risk assessment

Landscape ecological risk enables the quantification of the possibility and degree of negative ecological effects on the structure and function of the region's ecosystem due to natural change or human activities(Luo *et al.*, 2018). Based on the analysis of the land use characteristics in the study area and landscape ecology and ecological risk assessment theory, we constructed a landscape ecological risk assessment model from the perspective of landscape patterns. The spatial distribution of ecological risk was visualized using ARCGIS Pro2.7.

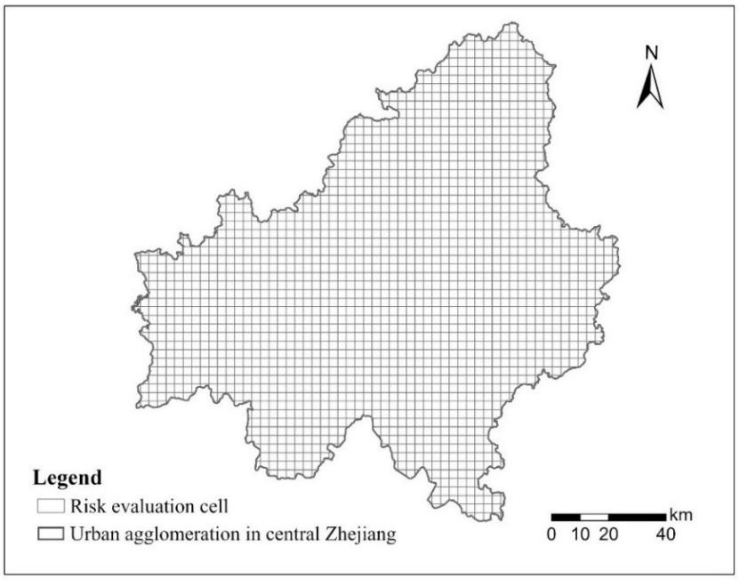

Figure 2. The ecological risk evaluation cells across urban agglomeration in central Zhejiang, China. Source: Authors, 2021.

To spatialize the landscape ecological risk index (ERI), the study area was divided into a 3 × 3 km spatial grid, and 1939 risk evaluation cells were obtained (Figure 2). The ERI of each cell was calculated using a landscape loss model (Zhang et al., 2020) as follows:

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

Equation 2. Where ERI_k is the landscape ecological risk index of the *k*th risk cell; A_{ki} is the total area of the *i*th LULC type in the *k*th risk cell; A_k is the total area of the *k*th risk cell; R_i is the landscape lose index of the *i*th LULC type.

The landscape loss index, R, was calculated from Equation 3:

$$R_i = E_i \times F_i$$

Equation 3. Where R_i is the landscape lose index of the *i*th lnad use type; E_i is the landscape disturbance index of the *i*th LULC type; F_i represents the landscape ecological vulnerability index of the *i*th land use type.

Based on the landscape pattern characteristics of the regional ecosystems, we used the landscape disturbance and landscape vulnerability indices to obtain the landscape loss index. We then constructed an evaluation model of landscape ecological risk that reflected the risk for different LULC types under the influence of the external environment. And the landscape disturbance index, E, was calculated from Equation 4:

$$E_i = aC_i + bS_i + cD_i$$

Equation 4. Ci reflects the changes in landscape ecological processes. Si reflects the degree of separation of different patches in a given landscape type. Di reflects the dominance of patches in different land use types. a, b and c represent the weights of Ci, Si and Di, respectively, and a + b + c = 1.

The different LULC types of F_i were assigned as follows: unused land = 7, water = 6, shrub = 5, cultivated land = 4, grass land = 3, forest = 2, construction land = 1. After normalization, the vulnerability index for each landscape was obtained.

4. Results and discussion

4.1. Spatiotemporal characteristics of land use changes

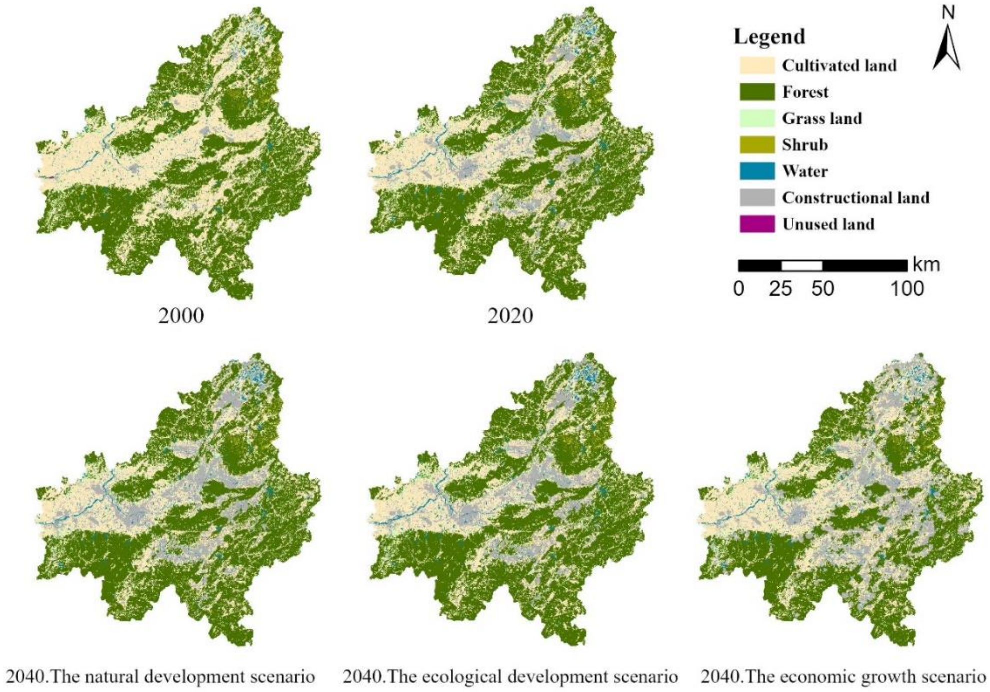

Figure 3. The land use map under different periods. Source: Authors, 2021.

Figure 3 shows the spatial distribution maps of LULC from 2000 to 2020 and the simulation of land use in the central Zhejiang urban agglomeration in 2040. Cultivated land and forests covered most of the study area during the 2000-2040 study period. Construction land was the most variable land-use type from 2000 to 2020, and its distribution expanded from the center of the study region. The spatial pattern analysis identified the structures of Jinhua and Yiwu as the core region. In the NDS, by 2040, the area of construction land and watershed had increased, and that of ecological land and cultivated land had slowly decreased compared with 2020. In the EDS, the area of all types of ecological land increased significantly, the area of construction land increased slowly, and the area of cultivated land decreased. In the EGS, the area of cultivated and construction land increased, and that of forest land decreased significantly.

4.2. Landscape pattern and landscape loss index

The landscape index in 2040 for each land-use scenario (Table 6) was obtained through Fragstats 4.2.1 and the statistical analysis function of Excel 2019. From 2000 to 2040, the disturbance index of ecological land decreased. From 2020 to 2040, the landscape ecological risk index (ERI) decreased by 6.6% under the NDS, 5.6% under the EDS, and 6.3% under the EGS. The overall analysis revealed that, by 2040, the ERI will decrease. The ecological risk decreases the most under the NDS. Table 6 shows that, among the seven land-use types, the contribution of the ERI was the largest for cultivated land and forest and the smallest for unused land. This indicates that the occupation and fragmentation of cultivated land and forest have the greatest potential impact on the ecological environment and socioeconomic development of the central Zhejiang urban agglomeration. The degree of landscape loss under the three scenarios was EGS > NDS > EDS. The maximum landscape loss under the EGS was due to the significant increase in forest separation and fragmentation. Under the EGS, the spatial distribution characteristics changed from a high-lumpiness, centralized distribution to a random, scattered distribution. When the EGS was disturbed by the external environment, the ecological loss was greater than that in the other scenarios. The landscape ecological risk under the three scenarios was EDS > EGS > NDS. Although the ecological land area increased under the EDS, the patches of this area were difficult to expand, and fragmentation was extremely high due to the constraint of the city clusters in central Zhejiang. These conditions led to an increase in ecological risk under the EDS.

Table 5. Indexes of landscape patterns of urban agglomeration in central Zhejiang from 2000 to 2040.

Landscape Type	Time	Disturbance index (E_i)	Vulnerability index (F_i)	Lose index	ERI	Contribution rate
Cultivated land	2020	0.5988	0.1429	0.0855	0.026311	45.06%
	2040.NDS	0.5763	0.1429	0.0823	0.021739	39.88%
	2040.EDS	0.5742	0.1429	0.0820	0.021686	39.33%
	2040.EGS	0.5979	0.1429	0.0854	0.026742	48.89%
Forest	2020	0.6794	0.0714	0.0485	0.025786	44.16%
	2040.NDS	0.6754	0.0714	0.0482	0.025484	46.75%
	2040.EDS	0.6789	0.0714	0.0485	0.026414	47.91%
	2040.EGS	0.6422	0.0714	0.0459	0.019768	36.14%
Grass land	2020	0.4598	0.1071	0.0493	0.00209	3.58%
	2040.NDS	0.4595	0.1071	0.0492	0.002071	3.80%
	2040.EDS	0.4570	0.1071	0.0490	0.002092	3.79%
	2040.EGS	0.4580	0.1071	0.0491	0.001970	3.60%
Shrub	2020	0.4365	0.1786	0.0779	0.000696	1.19%
	2040.NDS	0.4363	0.1786	0.0779	0.000673	1.24%
	2040.EDS	0.4365	0.1786	0.0779	0.000687	1.25%
	2040.EGS	0.4358	0.1786	0.0778	0.000608	1.11%
Water	2020	0.4571	0.2143	0.098	0.001908	3.27%
	2040.NDS	0.4554	0.2143	0.0976	0.002110	3.87%
	2040.EDS	0.4547	0.2143	0.0974	0.002164	3.93%
	2040.EGS	0.4572	0.2143	0.0980	0.002126	3.89%
Constructional land	2020	0.4943	0.0357	0.0177	0.001592	2.73%
	2040.NDS	0.5042	0.0357	0.0180	0.002436	4.47%
	2040.EDS	0.4998	0.0357	0.0178	0.002091	3.79%
	2040.EGS	0.5230	0.0357	0.0187	0.003479	6.36%
Unused land	2020	0.4593	0.25	0.1148	0.000004	0.01%
	2040.NDS	0.4577	0.2500	0.1144	0.000003	0.01%
	2040.EDS	0.4573	0.2500	0.1143	0.000003	0.01%
	2040.EGS	0.4555	0.2500	0.1139	0.000003	0.01%

4.3. Spatiotemporal variations of landscape ecological risk

Using the natural discontinuity grading method, the calculated landscape ecological risk index in the central Zhejiang urban agglomeration was divided into five grades: lowest-risk (ERI ⩽ 0.0496), lower-risk (0.0496 < ERI ⩽ 0.0596), middle-risk (0.0596 < ERI ⩽ 0.0636), higher-risk (0.0636 < ERI ⩽ 0.0736), and highest-risk (ERI > 0.0736) areas. The ordinary Kriging interpolation method was applied to obtain the spatial distribution of ecological risk in the central Zhejiang urban agglomeration using the ArcGIS pro2.7 platform. The spatial distribution of the ERI is shown in Figure 4. From 2000 to 2040, the ERI decreased.

The study region has recently received increased investment in urban infrastructure and environmental management. The development of services and advanced manufacturing and the optimization of industrial structures for economic growth have been accompanied by improved environmental management. In terms of the spatial distribution of ecological risk, the highest-risk and higher-risk areas have gradually shifted to the edge of the central Zhejiang urban agglomeration, shrank into smaller areas, and continued to decline. Among the three scenarios, the EGS not only had the largest areas of the lowest risk grade but also an overall higher risk grade. The NDS, which followed the current development goals, resulted in a relatively acceptable ecological risk compared with the other two scenarios.

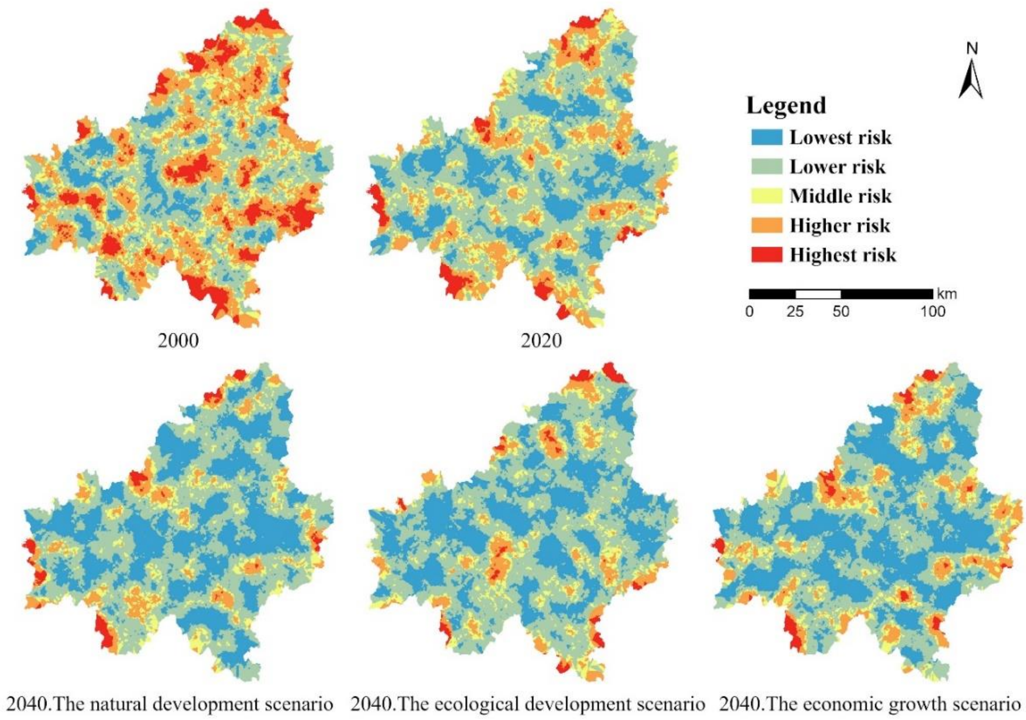

Figure 4. The spatial distribution of landscape ecological risk under different periods. Source: Authors, 2021.

Figure 5 shows the total area of each grade of ecological risk in the central Zhejiang urban agglomeration in 2000, 2020, and 2040 according to each scenario. The areas of lowest- and lower-risk generally expanded from 2000 to 2040, whereas those of the highest and higher risk decreased. Among the three scenarios, the EGS had the highest proportion of highest- and higher-risk areas (2.2% and 11.9%, respectively). The EDS had the highest proportion of lower-risk areas (48.7%) and a proportion of lowest-risk areas lower than that under the NDS (30.9 and 35.6%, respectively).

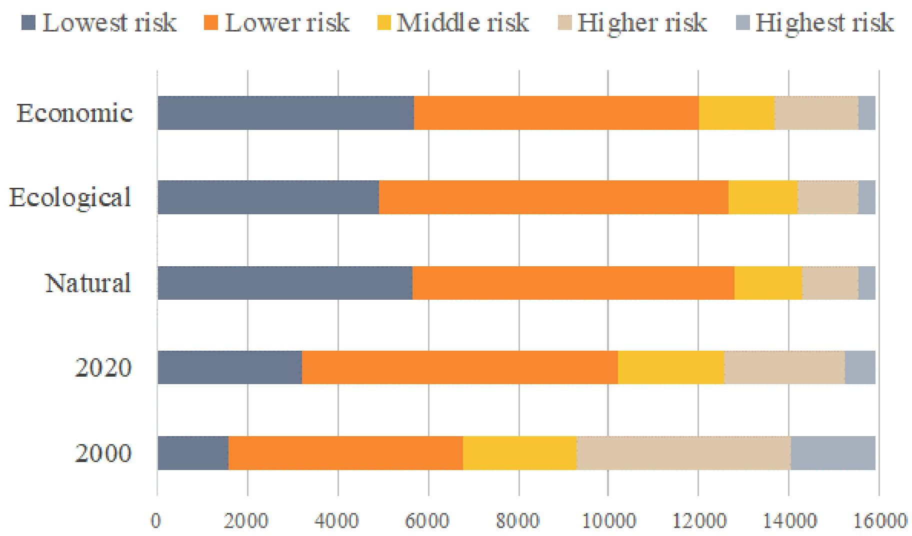

Figure 5. The area of ecological risk levels in each scenario

5. Conclusion

This study simulated the future landscape ecological risk in 2040, assessed the ERI, and discussed the landscape ecological risk responses to future land-use patterns in the central Zhejiang urban agglomeration under three scenarios of land use (natural development, ecological development, economic growth).

The growth rate of construction land was the fastest during 2000–2020. Cultivated land and forest had the greatest impact on the loss index, which affected the landscape ecological risk. The overall landscape ecological risk in the study area declined under all three scenarios. The lowest ecological loss and the greatest decrease in ecological risk were under the natural development scenario. This phenomenon indicated that, in the urban agglomeration of central Zhejiang, development consistent with the current policy that pays equal attention to the ecology and economy is the optimal route.

Land-use change in the study area led to the changes in the landscape pattern. The area of ecological land can be effectively protected by restricting the expansion of construction land under an ecological development scenario. However, the increase in the total number of patches and the deepening of fragmentation would lead to a higher ERI. In the ecological development scenario, ecological land increased; however, the ecological risk also increased due to the high degree of fragmentation. This indicates that the cost of ecological protection in the study area is extremely high, as the study area is vulnerable to interference from the external environment. Therefore, future development should pay attention to the connectivity of ecological land.

Based on these results, the rational allocation of land resources is particularly important. The blind pursuit of both ecological areas and economic development is not scientifically justified. The central region of the urban agglomeration should adhere to the plan of developing ecological land and construction land in patches, forming a focused, pearl-like landscape that will drive the development of western Zhejiang Province. Marginal areas such as Longyou, Wuyi, Zhuji, and Jinyun are the key areas of ecological risk control in the future.

The ecological risk value obtained in this study is based on the landscape pattern index as an indicator of the relative landscape ecological risk in the central Zhejiang urban agglomeration. The scenario simulation is flexible: the use of multi-temporal landscape structure data combined with spatial statistics can quantify the relative landscape ecological risk in the study area and reveal the spatial distribution and dynamic change of future ecological risk. These insights can guide urban planning strategies.

6. References

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