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Coupling an Ecological Network with Multi-Scenario Land Use Simulation: An Ecological Spatial Constraint Approach

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Abstract: To balance ecological protection and urban development, a land use simulation model that couples an ecological network (EN) and multiple scenarios was developed based on the PLUS model. The simulation of land use in the Qiantang River Basin in 2030 successfully demonstrates the usefulness of the EN-PLUS model. In this model, conventional ecological constraints (nature reserves and water areas) and three different EN levels were taken as restricted conversion areas during the simulation. Then, four ecological constraints were coupled with four simulation scenarios: business as usual (BAU), rapid urban development (RUD), ecological protection (EP), and urban- and ecology-balanced (UEB). Information from the analysis of model simulation results can be used to reduce the potential damage to a range of land cover types. However, this protective effect is not obvious under the RUD scenario due to the impact of significant human disturbance. Furthermore, although EP is the scenario with the least ecological damage at the whole watershed scale, this is not the case for all subbasins. This indicates the existence of a landscape scale effect. Therefore, the best development scenario should be selected by comprehensively weighing the scale effect and the ecological characteristics of each subbasin.

Keywords: land use simulation; ecological land protection; ecological network; multiple scenario; EN-PLUS model

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1. Introduction

Land-use and land-cover (LULC) change is one of the causes of environmental quality changes and reflects the interaction between humans and the environment [1–3]. Human-induced LULC changes (LULCCs), such as urban expansion, industrial construction, and deforestation, have led to food shortages, climate change, and irreversible biodiversity loss, which have aggravated the tension between humans and nature [4–6]. Relevant research shows that the average annual change rate of global land cover in the past 30 years is 0.36%, and it is still accelerating [7]. In addition, the negative impact of humans on the Earth's surface environment will increase by 2–3 times by 2050 compared to the beginning of this century [8,9], so the world will face more severe environmental problems [10]. Therefore, optimizing the LULCC process is of great significance to the sustainable development of the regional economy and environment [11].

The main purpose of land use optimization is to meet the needs of human development to the greatest extent with the least damage to the environment to balance regional development and ecological protection [12]. Regulating the quantity and space of LULCs is an effective way to achieve this goal [13]. The impact of this regulation can be simulated by relevant models. The Markov model [14] and system dynamics (SD) model [15], developed in the early stage of LULCCs modeling research, can predict the quantity of land use, but not its spatial layout [16]. Based on historical land use data, the cellular automata (CA) model can effectively simulate the complex process of LULCCs in space [17,18], which makes up for the deficiency of the Markov model [19]. Therefore, the CA–Markov model, which combines these two models, is widely used in land use simulation [16,19,20]. In recent decades, other models developed based on the CA model have also have also been gradually used, such as the CLUE-S model [21,22], the SLEUTH model [17] and the FLUS model [23]. However, most models ignore the internal competition mechanism and interaction among patches in the process of land use conversion [24]. To solve this problem, Liang et al. [25] developed the patch-generating land use simulation (PLUS) model, which uses the random forest algorithm to obtain the expansion probability of each land use type by retaining the adaptive inertia and roulette mechanism of the FLUS model. This simulation mechanism also makes up for the Markov model's difficulty in simulating changes in ecological land (grassland, woodland, and waters) at the patch level. Therefore, the PLUS model can more accurately reveal the complexity and randomness of future LULCs [26].

At present, protecting ecological land is one of the core factors to be considered in the process of LULCC simulation [27]. Under such constraints, ecological land can be better protected to maintain regional ecosystem services and sustainable development [28,29]. Although some studies have taken ecological red lines [24], construction-forbidden areas [16] and areas with high ecosystem service value [30,31] as ecological constraints, there are still some core issues that deserve further attention. First, the ecological land used in most of the previous studies are independent landscape patches that do not form an interconnected ecosystem in space. Using an ecological network (EN) as an ecological constraint may be an effective way to remedy this deficiency. The EN is a landscape spatial pattern formed by using ecological corridors to organically connect isolated resource patches in an open space [32,33]. Protecting ENs can improve and regulate some specific processes in the ecosystem, which is of great significance to ensure the sustainable acquisition of ecosystem services [34,35]. However, the traditional method of constructing ENs using the minimal cumulative resistance (MCR) model [36] does not allow the constructed ENs be used as an ecological constraint space due to the lack of data on the width and extent of ecological corridors. However, circuit theory developed based on physics and motion ecology [37], can identify the range of corridors by calculating the cumulative resistance [32,38–40].

Second, the LULCCs process includes both spatial and quantitative changes [13]. Therefore, it is necessary to couple the land use demand under different scenarios with different levels of ecological constraints to more comprehensively coordinate the LULCCs process. In this coupling mode, the ecological land used as a spatial constraint must not have fixed layout but should rather be set flexibly according to different simulation scenarios. Different EN levels can be constructed according to different ecological corridor ranges. The quantity of land use in each scenario can be calculated by adjusting the transition probabilities between landscape types in the Markov chain [41].

In addition, current research on land use simulation covers detailed administrative scales, such as provinces [42], urban agglomerations [43] and counties [24]. However, the administrative boundary usually separates the ecological attributes of the region [44]. Although some studies use topographical conditions or hydrological characteristics as the research boundary [45–47], the research is mainly focused on the prediction of climate change, water production, and carbon sinks. As the basic unit coordinating the water and land environment in the complete ecosystem, the watershed is the foundation for building regional ecological security [48]. Therefore, taking the watershed as the research boundary can not only reveal the process of future LULCCs, but also facilitate the coupling of research content and ecological characteristics.

The Qiantang River Basin is the second largest basin in southeastern China and the largest in Zhejiang Province [49]. In the context of rapid urbanization and continuous population growth, the contradiction between people and land in this basin is increasingly prominent. How to balance the contradiction between construction land demand and ecological protection has become a challenge. The simulation of future LULCCs based on quantitative models has become an applicable method for optimizing land use [50]. However, related research in the Qiantang River Basin is still lacking. This study explores land use in the Qiantang River Basin in 2030 by constructing a simulation model (EN-PLUS model) that couples ecological constraints and multiple scenarios. In addition, the characteristics of LULC and landscape patterns in the simulation results were analyzed at the whole basin and subbasin scales. The research method can provide a reference for land optimization under ecological land protection, and can serve as scientific support for sustainable spatial planning and management at the watershed scale.

2. Study Area and Datasets

2.1. Study Area

The Qiantang River Basin flows through the Anhui and Zhejiang provinces, passing through 38 counties, covering an area of more than 50,000 km^2 and including 14 subbasins (Figure 1). The main part (77.45%) of the Qiantang River Basin is located in Zhejiang Province, one of the most economically developed provinces in China, and the overall area of the basin accounts for 2/5 of the province's area [51]. The basin covers rich landforms such as mountains, hills, subbasins, and plains. In recent decades, due to rapid urbanization, unprecedented changes in land use have taken place within the basin, and ecological land has been significantly reduced. In 2020, Zhejiang Province promulgated the Regulations on the Protection and Development of the Qiantang River Basin, which emphasizes the protection of the ecological environment. Therefore, it is crucial and urgent to explore ways to optimize land use and protect ecological land in the Qiantang River Basin for the sustainable development of the region.

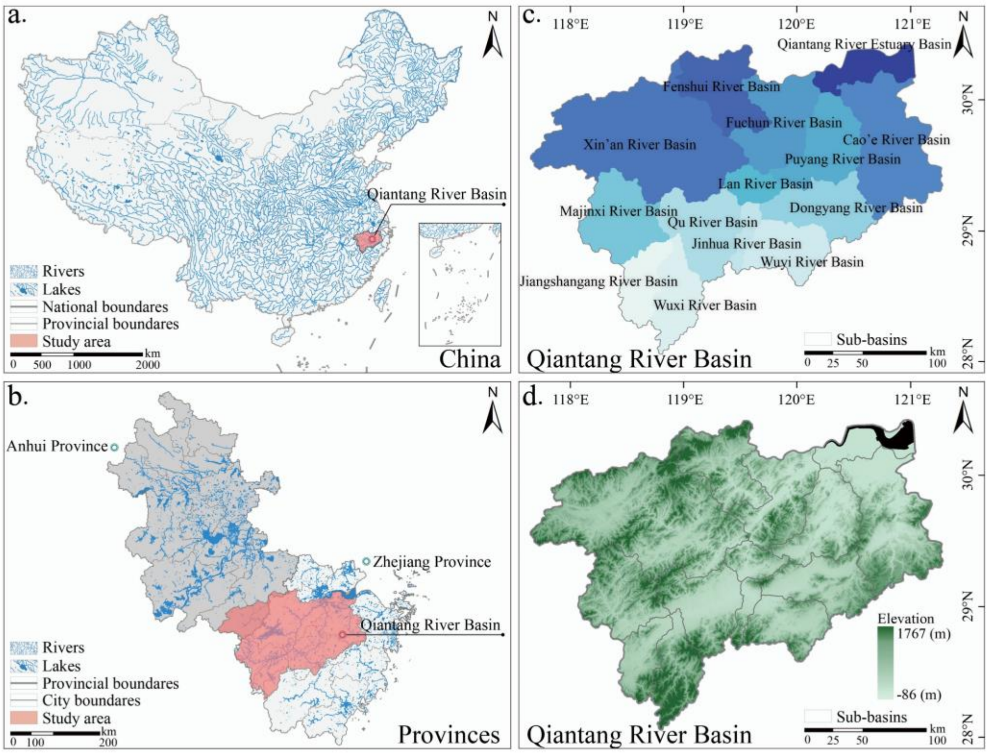

Figure 1. Basic information of the study area: (**a**,**b**) are the locations of the study area in China and provincial scale; (**c**) is the boundary of 14 sub-basins; and (**d**) is the digital elevation model (DEM) of the study area.

2.2. Datasets

According to their function, the data used in this study can be divided into land use data, EN construction data and driving force data (Table 1). Land use data with a resolution of 30 × 30 m in 2010, 2015, and 2020 were used to simulate and verify the land use of the study area in 2030. Land use types are divided into eight categories: cultivated land, woodland, waters, urban construction land, rural construction land, industrial land, grassland, and unused land. We selected elevation, slope, distance from roads of different grades, and the normalized difference vegetation index (NDVI) to calculate the resistance surface required for the construction of ENs. The data for constructing the resistance surface can also be used as the driving force data required for the LULCCs simulation model. We added data on GDP, population density and distance from construction land as driving factors. In addition, we regard the nature reserves in the study area as one of the conventional ecological constraints. Considering the efficiency of data processing, we used the resampling method to unify the resolution of all data to 100 × 100 m [41].

Table 1. Information on the data used in this study.

Data	Year	Resolution	Database Sources	Related Uses
Land use/land cover (LULC)	2010, 2015, 2020	30 × 30 m	Resource and Environment Science and Data Centre of Chinese Academy of Sciences (https://www.resdc.cn) (accessed on 1 January 2022) [52]	LULC simulation (PLUS model) and Resistance factor
DEM	2020	30 × 30 m	Geospatial Data Cloud (http://www.gscloud.cn) (accessed on 1 January 2022) [53]	Resistance factor and driving factor
Slope	2020	30 × 30 m	Calculated from DEM	Resistance factor and driving factor
NDVI	2020	30 × 30 m	National Ecological Science Data Center (http://www.nesdc.org.cn) (accessed on January 2022) [54]	Resistance factor and driving factor
Distance from railway	2020	Vectorgraph	Open Street Map (https://www.openstreetmap.org) (accessed on January 2022) [4]	Resistance factor and driving factor
Distance from highway	2020	Vectorgraph		
Distance from urban road	2020	Vectorgraph		
Distance from rural road	2020	Vectorgraph		
GDP	2015, 2020	1 km × 1 km	Geographical Information Monitoring Cloud Platform (http://www.dsac.cn) (accessed on January 2022) [26]	Driving factor
Population density	2015, 2020	1 km × 1 km		
Distance from urban construction land	2015, 2020	30 × 30 m	Calculated from land use data	Driving factor
Distance from rural construction land	2015, 2020	30 × 30 m	Calculated from land use data	Driving factor
Distance from industrial land	2015, 2020	30 × 30 m	Calculated from land use data	Driving factor
Nature reserve scope	2020	Vectorgraph	Resource and Environment Science and Data Centre of Chinese Academy of Sciences (https://www.resdc.cn) [52]	Spatial constraints

3. Methodology

3.1. Design of the EN-PLUS Model

Based on the PLUS model, this study proposes a land use simulation model with ecological constraints (EN-PLUS), in which the corresponding EN levels are used as ecological constraints in different scenarios. The research framework is shown in Figure 2. The steps mainly include (1) constructing three EN levels through morphological spatial pattern analysis (MSPA), connectivity analysis, and circuit theory; and (2) proposing four simulation scenarios: business as usual (BAU), rapid urban development (RUD), ecological protection (EP), and urban- and ecology-balanced (UEB). Then, traditional ecological constraints (natural reserves and large water areas) were used in all scenarios, and three EN levels were used as ecological constraints for the RUD, EP, and UEB scenarios, respectively. Steps (3) and (4) involve using the EN-PLUS model to simulate the land use in the Qiantang River Basin in 2030 and analyzing the characteristics of LULC and landscape patterns in the simulation results at the whole basin and subbasin scales.

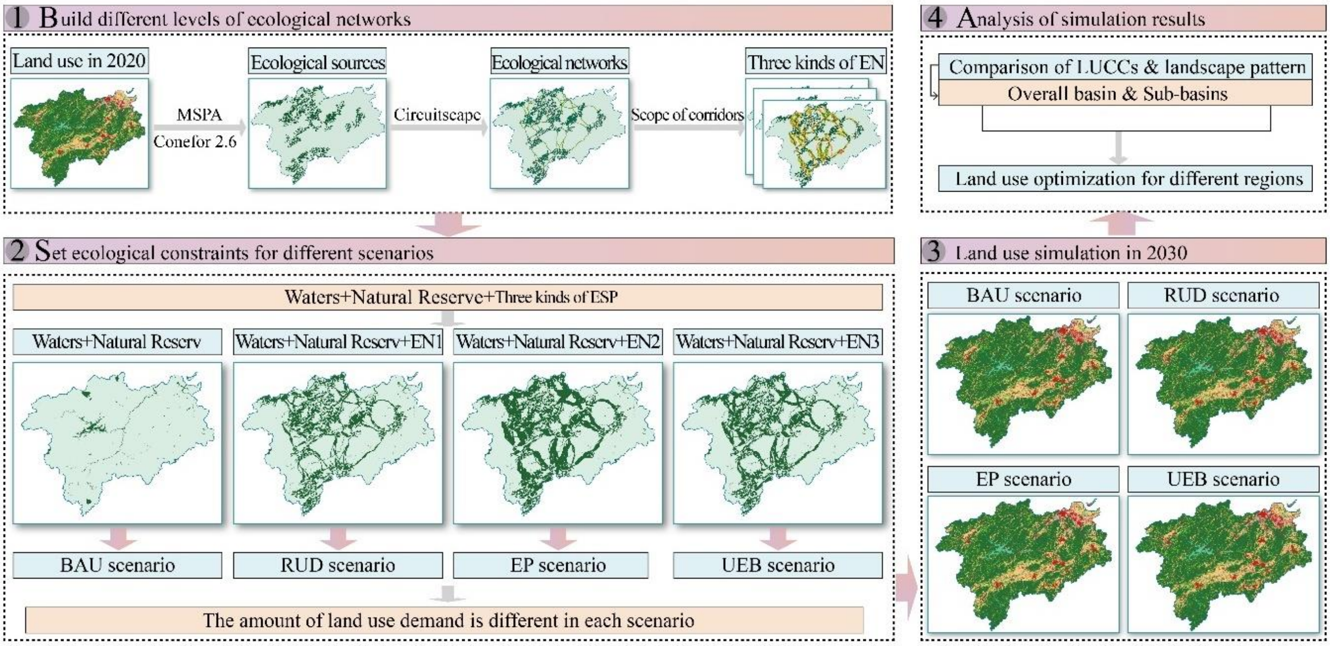

Figure 2. Framework of the EN-PLUS model.

3.2. Constructing the Ecological Network

The process based on "ecological source identification–resistance surface construction–ecological corridor extraction" has become the basic paradigm for constructing ENs [4,55]. The detailed process is as follows.

3.2.1. Identifying of Ecological Sources

The ecological source is the starting point of ecological flow operation, and is the key area to maintain the stability of the ecosystem [32,56]. The selection of ecological sources based on MSPA can identify areas that play an key role in landscape connectivity at the pixel level [57,58] and has been widely used [40]. First, the Guidos Toolbox software was used to perform MSPA on the reclassified land use data (Figure 3a). Then, Conefor 2.6 software was used to analyze the importance of patches in the core area. According to the analysis results, we selected 39 patches with a dPC greater than 1 and an area greater than 5 km^2 as the ecological source [59,60]. Patch importance was calculated using the following formula:

$$dPC = \frac{P - P'}{P} \times 100\% \tag{1}$$

where dPC represents the impact of removing a patch on the regional landscape connectivity, and the greater the value is, the more important the patch is [4]; P is the probability that the patches can be connected; and P' is the connectivity probability after removing a certain patch.

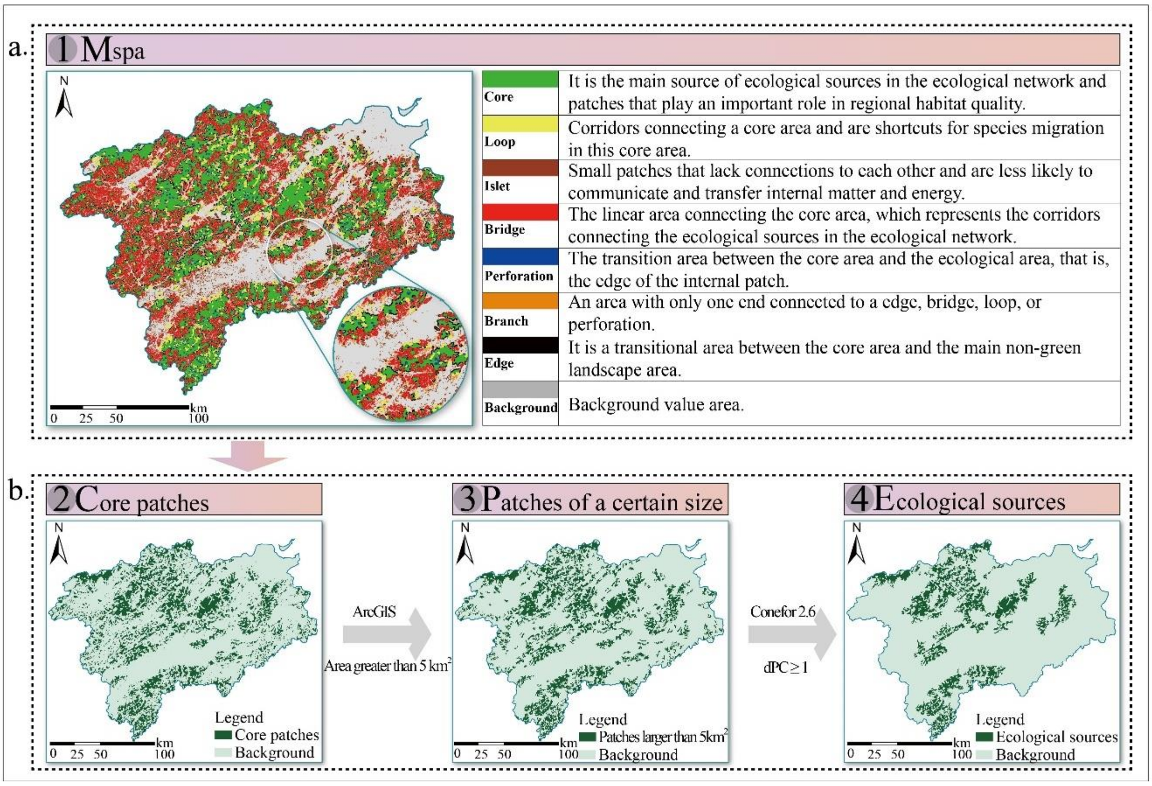

Figure 3. Process of ecological source selection: MSPA (**a**) and connectivity analysis (**b**).

3.2.2. Mapping the Ecological Resistance Surface and Identifying the Ecological Corridor

The ecological resistance surface represents the disturbance species encounter during horizontal movement [61]. This study selected nine resistance factors (Table S1) and used ArcGIS 10.8 to superimposed them to obtain the resistance [60,62]. The weight of each factor was determined by spatial principal component analysis (SPCA). The calculation formula is as follows, and the detailed process is shown in Section S2 of the Supplementary Materials.

$$RV = \sum_{k=1}^{m} a_{ik} w_k = \sum_{k=1}^{m} \frac{a_{ij} F_k}{\sum_{p=1}^{m} F_k} \tag{2}$$

where RV and w_k are the resistance values of the i-th grid and the weight of the k-th resistance factor, respectively; a_{ik} is the k-th resistance factor of the i-th grid; and F_k is the common factor variance of the k-th resistance factor.

Ecological corridors are linear spaces that connect ecological sources and are the main paths for biological migration and material flow [63,64]. This study uses circuit theory to extract ecological corridors and their extents [65]. Circuit theory uses the random walk characteristics of electrons to simulate the diffusion of species in the landscape [65,66] calculated as follows:

$$I = V/R_{eff} \tag{3}$$

where I is the current, V is the voltage between ecological sources, and R_{eff} is the effective resistance, which reflects the degree of isolation between ecological sources. The higher the value of R_{eff} is, the more difficult it is for species to move.

Ecological sources and resistance surfaces were imported into the Linkage Mapper module of Circuitscape 4.0 software to identify ecological corridors. The resistance surface construction and ecological corridor identification processes are shown in Figure 4.

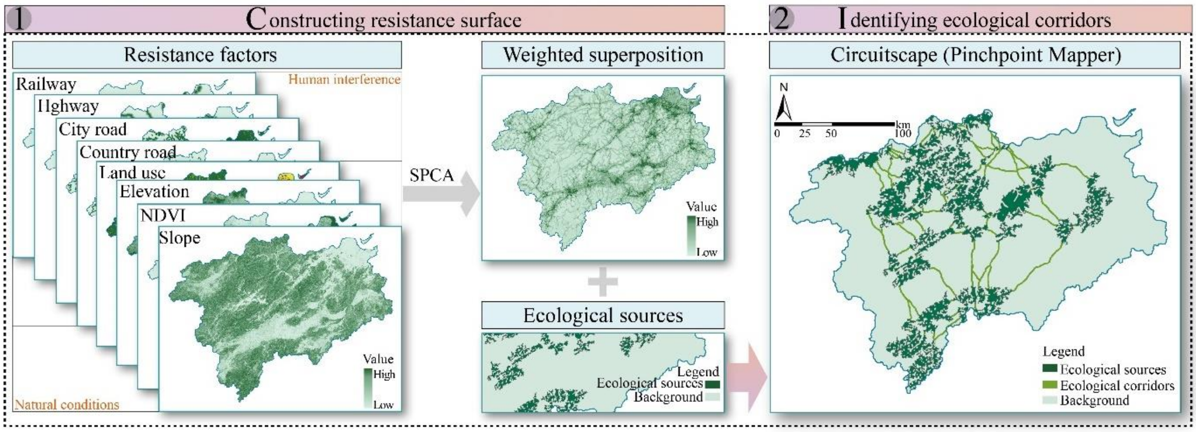

Figure 4. The construction of resistance surface and the extraction of ecological corridor.

3.2.3. Three Types of ENs Serving as Ecologically Constrained Space

Only when the corridor has a certain width or extent can it be used as an ecological constraint. Therefore, in circuit theory, we identify the corridor range according to the threshold value of the accumulated resistance [38]. Taking into account the corridor width requirements for biological flow [4,67] and the proportion of EN area in the study area [68], we extracted the ecological corridors when the cumulative resistance was 5000, 11,000, and 19,000 to construct the bottom-line EN (BEN), satisfactory EN (SEN) and ideal EN (IEN) (Figure 5).

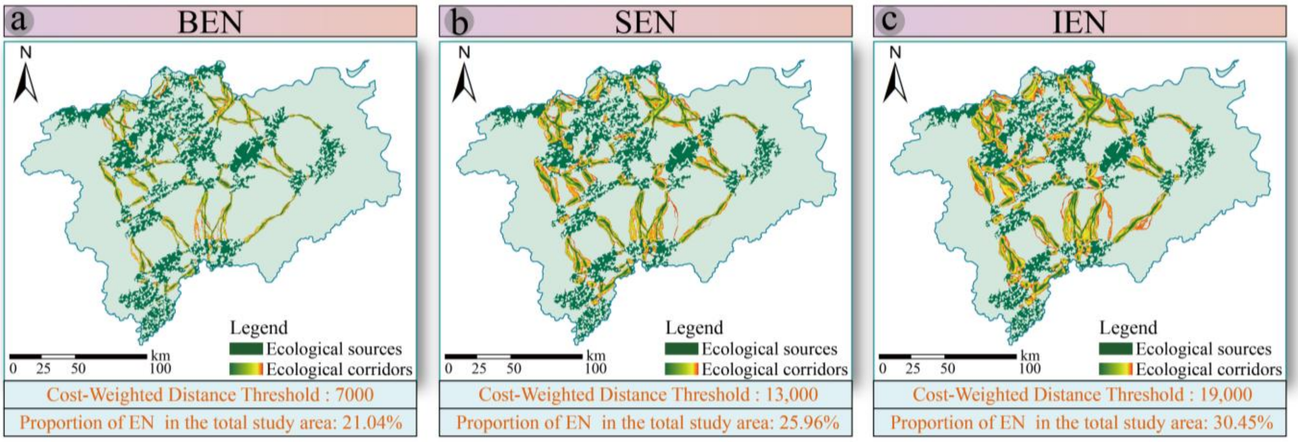

Figure 5. Three types of ENs.

3.3. Four Scenarios for Regional Development

To explore the multiple possibilities of LULCCs in the future, we set up four regional development scenarios: business as usual (BAU), rapid urban development (RUD), ecological protection (EP), and urban- and ecology-balanced (UEB). We used Markov chains to calculate the probability of transitions between landscapes during the period 2010–2020. Then, referring to related research [26,41], we reset the transition probability between landscapes according to the characteristics of the different scenarios, as follows:

1. BAU scenario: In this scenario, the trend of land use change is consistent with that in the past 10 years.
2. RUD scenario: In this scenario, the scale of urban expansion and the intensity of human development are greater than before. Therefore, the probability of converting nonconstruction land into urban construction land increases by 20%, and the probability of converting it into rural construction land and industrial land increases by 10%. The probability of converting construction land to other land use is reduced by 30%, and the probability of converting rural construction land to the other two types of construction land is increased by 20%.

3. EP scenario: This scenario emphasizes protecting the environment and reducing urban expansion. Therefore, the probability of converting cultivated land and woodland into construction land is reduced by 30%. The probability of converting waters, grassland, and unused land into construction land is reduced by 20%. In addition, the probability of converting construction land into cultivated land, woodland, and grassland is increased by 20%, and the probability of converting rural construction land into other construction land types is decreased by 20%.
4. UEB scenario: This scenario requires the coordination of ecological protection and urban development. In terms of ecological protection, the probability of converting cultivated land and woodland into construction land is reduced by 15% and the probability of converting waters and grassland into construction land is reduced by 10%. In terms of urban development, the expansion probability of rural construction land in the RUD scenario is reserved. In addition, the probability of converting construction land into other land is decreased by 15%, and the probability of converting unused land into construction land is increased by 10%.

Considering the protection of large-scale waters and nature reserves, this study set them as restricted conversion areas in all scenarios. The ecologically restricted areas in each scenario are shown in Figure 6. In addition, considering that urban construction land is difficult to convert into other land, and this type of conversion is excluded [24].

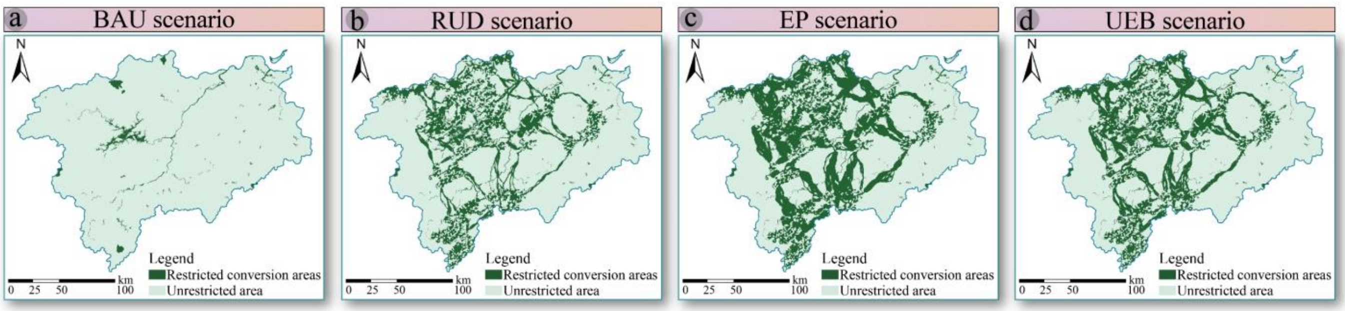

Figure 6. Ecologically restricted areas in each scenario.

3.4. Land Use Simulation Model—PLUS

PLUS is a land use simulation model based on the land expansion analysis strategy (LEAS) and CA based on multiple random seeds (CARS) [25,69,70]. In the simulation process, the expansion part of the two-phase land use data was analyzed through the random forest algorithm in the LEAS module to obtain the development probability of various land types. Then, based on the random seed generation and threshold decrement mechanisms in the CARS model, the automatic generation of patches was simulated under the constraints of developmental probability.

3.4.1. PLUS Model Settings—Driving Factors Required for the LEAS Module

This study selected 12 driving factors in terms of natural conditions (elevation, slope, and vegetation cover), economic development (GDP), and human disturbance (distance from roads of different grades), as shown in Figure S1.

3.4.2. PLUS Model Settings—Cost Matrix and Neighborhood Weight Required for the CARS Module

The cost matrix represents whether the land can be converted between different types. A value of 1 means that it can be converted; 0 means otherwise [25]. The cost matrix in the BAU scenario is determined based on the land use transfer matrix from 2010 to 2020 [41], while in the other three scenarios, the conversion of construction land into other land types is restricted (Table S3).

The neighborhood weight represents the expansion ability of each landscape type, and its value is between 0 and 1; the larger the value is, the stronger the ability. In this study, according to the research method of Wang et al. [71], the area changed by each land type from 2010 to 2020 was normalized and used as the neighbor weights. To avoid the occurrence of 0 and 1 values, we set the normalization range to between 0.1 and 0.9 (Table 2).

Table 2. Weight of the neighborhood.

LULC Type	Cultiv	Wood	Waters	Urban Constr	Rural Constr	Indust	Grass	Unused
Weight	0.1000	0.4439	0.4520	0.8018	0.6823	0.9000	0.5906	0.5671

3.5. Landscape Pattern Analysis of Each Scenario

Landscape patterns are the structure, number, and spatial distribution of landscape components, which reflect the effects of ecological processes at different scales [72]. To compare the simulation results of the EN-PLUS model under different scenarios, this study selected the landscape pattern indices from the aspects of landscape fragmentation (number of patches: NP, landscape division index: DIVISION), diversity (Shannon diversity index: SHDI, Shannon evenness index: SHEI), and dispersion (patch cohesion index: COHESION, contagion index: CONTAG) for analysis [13,73]. The analysis of landscape pattern indices was performed in Fragstats4.2, and their ecological meanings are listed in Table S4.

4. Results

4.1. Validation

We simulated the land use in the Qiantang River Basin in 2020 under the BAU scenario using the land use data of 2010 and 2015 and compared it with the actual data to verify the accuracy of the model settings (Figure 7). The results show that all construction land types and woodland are in good agreement with the actual situation, and the Kappa coefficients are all above 90%. In addition, in the simulation process, we adopted the ecological constraints in the BAU scenario (large-scale waters and natural reserve area), so the accuracy of the waters is high and the kappa coefficient is 95%. The verification results at the overall landscape level show that the kappa coefficient is 93%, which indicates that the simulation accuracy is ideal and can meet the research needs [24,74].

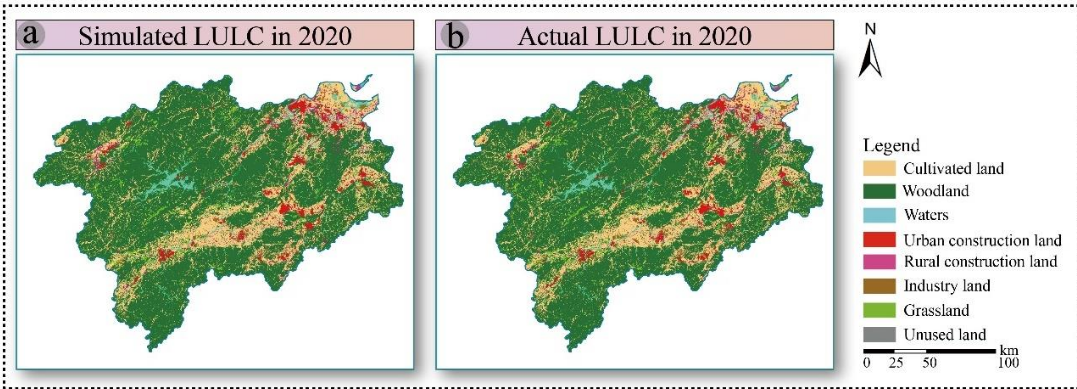

Figure 7. Comparison of simulated (**a**) and actual LULC (**b**) in 2020.

4.2. Land Use Quantity and Layout in Each Scenario

4.2.1. Analysis at the Whole Basin Scale

The EN-PLUS model was used to simulate the land use of the Qiantang River Basin in 2030, and the results are shown in Figure 8a. As shown in Table 3, compared with 2020, there are obvious differences in the degree of land use change in each scenario. The most obvious changes are in urban construction land and industrial land. The average annual growth rates of urban construction land were 2.34% (BAU scenario), 2.83% (RUD scenario), 1.87% (EP scenario), and 2.18% (UEB scenario). Industrial land shows the same trend as urban construction land. However, rural construction land experiences the fastest growth under the BAU scenario, which is different from the result obtained using the Markov chain, which calculated that its growth was the fastest under the RUD scenario. Although we tried to make the simulation results match the preset scenario by adjusting the patch generation threshold and expansion coefficient by referring to the method of Liu, Liu, Wang, and Liu [41], this did not work. This may be due to the PLUS model introducing the analysis of competition within patches, which resulted in the expansion ability of rural construction land being weakened by other landscape types under the RUD scenario, so its amount was less than the preset value, but the deviation was <5%. The simulation mechanism of the PLUS model makes the simulation results more in line with the actual situation [52].

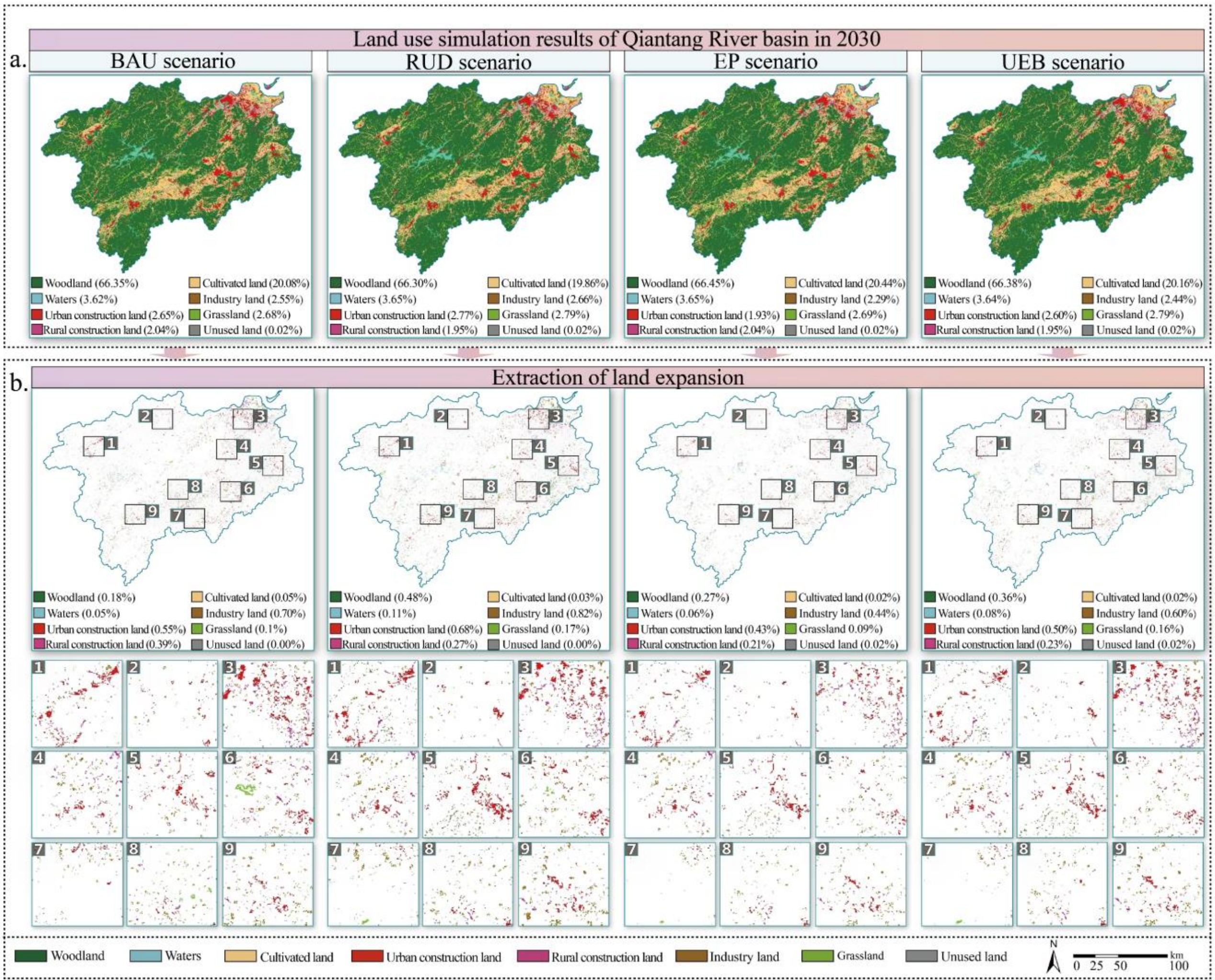

Figure 8. The results of the multi scenario simulation (**a**) and the analysis of the expansion region (**b**).

Table 3. LULCCs in each scenario in 2030 (compared with 2020).

	BAU Scenario		RUD Scenario		EP Scenario		UEP Scenario	
LULC	**Area (km^2)**	**Rate (%)**	**Area (km^2)**	**Rate (%)**	**Area (km^2)**	**Rate (%)**	**Area (km^2)**	**Rate (%)**
Cultiv	−486.76	−4.65	−592.52	−5.67	−304.01	−2.91	−444.34	−4.25
Wood	−143.16	−0.43	−167.18	−0.51	−96.99	−0.29	−127.97	−0.39
Waters	−67.80	−3.63	−56.38	−3.02	−56.33	−3.12	−58.23	−3.21
Urban	271.85	26.08	335.94	32.23	212.73	20.41	250.49	24.03
Rural	118.49	13.24	72.62	8.11	64.20	7.17	75.81	8.47
Indust	335.95	36.03	386.85	41.49	270.36	22.24	280.14	30.05
Grass	−28.42	2.09	20.89	1.53	−26.86	1.97	24.30	1.78
Unused	−0.15	1.39	−0.22	2.04	−0.1	0.93	−0.2	1.85

We calculated the growth rate of all construction land types, including urban construction land, rural construction land, and industrial land, and the results show that it increased by 25.31%, 27.72%, 16.88%, and 21.13% in the BAU, RUD, EP, and UEB scenarios, respectively. This trend is completely in line with our preset scenarios. The expansion of construction land is mainly concentrated in several central urban areas in the northwest of the Qiantang River Basin. From the nine samples we selected according to the location of the central urban area, ENs effectively protected the ecological spaces in some regions (Figure 8b). For example, under the EP and UEB scenarios, sample 7 has very little expansion of construction land. This ecological constraint is also valid in the RUD scenario with the largest urban construction intensity.

In terms of ecological land, the degree of decline in woodland in each scenario was RUD > BAU > UEB > EP, which is consistent with our preset scenario. We also counted the changes in the total area of ecological land, including water, woodland, and grassland, and the results showed that their areas decreased by 239.38 km^2 (BAU scenario), 202.67 km^2 (RUD scenario), 180.18 km^2 (EP scenario), and 161.90 km^2 (UEB scenario). The UEB scenario replaces the EP scenario as the one with the least reduction in ecological land. By comparing the deviations between the simulation results and the presets scenario, we found that this is mainly because, under the UEB scenario, part of the expansion probability of rural construction land is transferred to water and grassland, while the expansion capacity of grassland under the EP scenario is reduced. This indicates that the use of EN as an ecological constraint affecting the expansion probability of landscape patches.

In summary, although the simulation results of a few landscape types in some scenarios are not exactly the same as our presuppositions, the overall matching degree is still high. Based on the analysis of the results, the constraints set in the EN-PLUS model effectively control the expansion of construction land and improve the protection of ecological land.

4.2.2. Analysis at the Subbasins Scale

To reveal the characteristics of LULCCs in different regions, the analysis was carried out at the scale of 14 subbasins of the Qiantang River Basin. As shown in Figure 9, the characteristics of land use composition and change in different subbasins are significantly different. In terms of land composition, ecological land (woodland, water, and grassland) is the dominant type in most subbasins, and its average proportion under the four scenarios at the whole basin scale is 72.75%. However, the proportion of ecological land in the Qiantang River Estuary subbasin is only 42.72%, which is mainly due to the high construction and development intensity in this subbasin. The average proportion of construction land under the four scenarios in this basin is 23.86%, which is higher than that in the whole Qiantang River Basin (6.97%).

In terms of the degree of LULCCs, the Qiantang River Estuary subbasin (1.64%) and Puyang River subbasin (1.41%) had the largest average decline in ecological land under the four scenarios. This indicates that it is very urgent for these regions to formulate future ecological compensation plans in the context of high urbanization rates. In addition, the ecological land in the Majinxi River subbasin increased by 0.36%, which indicates that the improvement in the expansion capacity of ecological land under the UEB scenario that we found in the previous analysis mainly occurred in this watershed. The subbasins with the fastest average growth in construction land were the Fengshui River subbasin (40.04%) and Lanjiang River subbasin (39.90%). However, since the current construction land in these subbasins is relatively small, even after rapid growth, the average proportion of construction land is only 1.90% and 2.44%, respectively. The subbasins with the lowest average growth rates of construction land are the Fuchun River subbasin (18.98%) and Dongyang River subbasin (17.24%). This is mainly because these two watersheds have been relatively intensively developed and the available land for urban expansion is limited under ecological constraints.

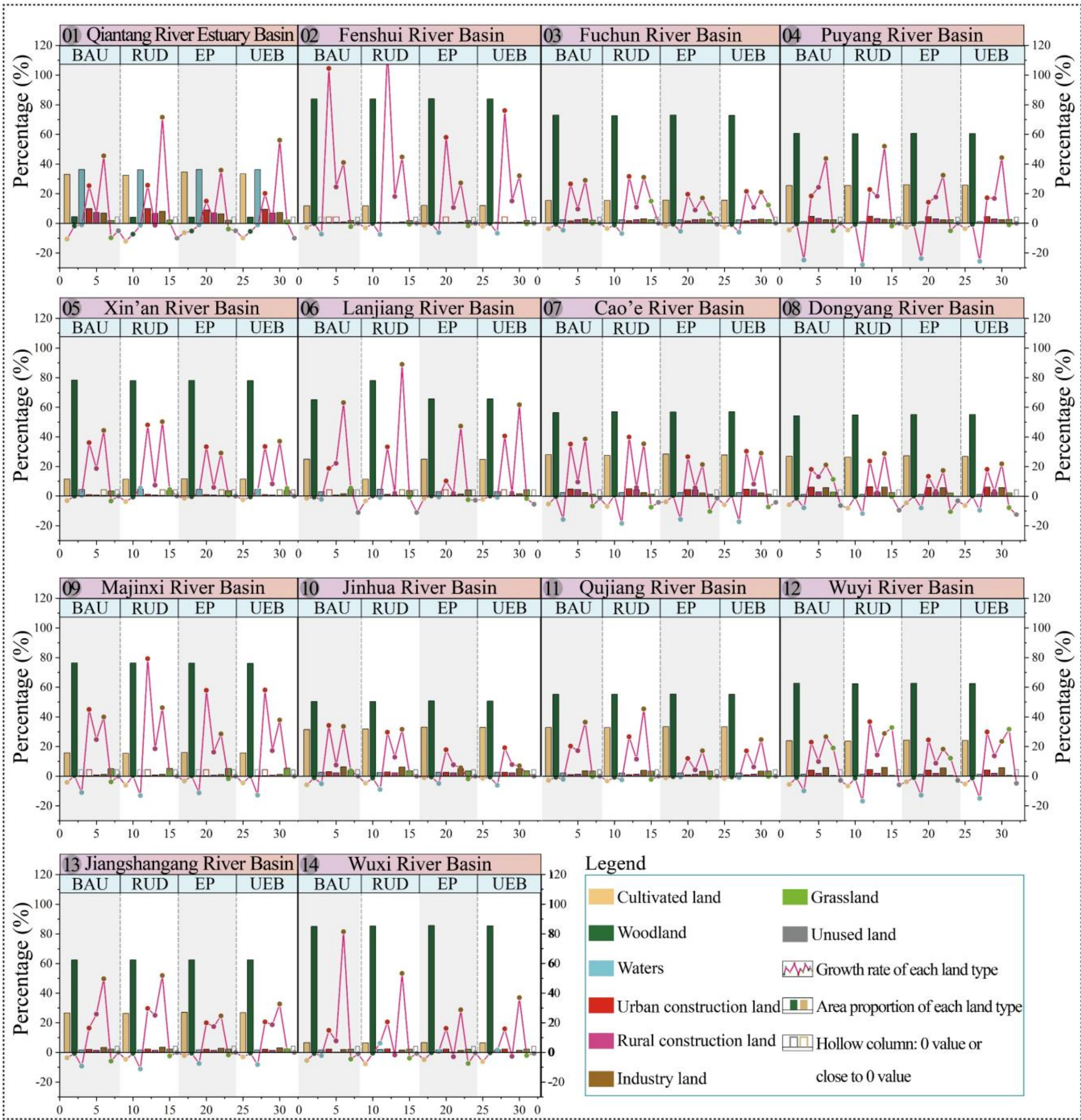

Figure 9. Land composition and change degree of each subbasin in different scenarios.

From the perspective of the role of ecological constraints, the growth rate of construction land in 11 subbasins was RUD > BAU > UEB > EP. However, in the Cao'e River, Jinhua River, and Wuxi River subbasins, the highest growth rate of construction land was under the BAU scenario, which is mainly due to the higher growth rate of rural construction land in this scenario. Compared with the RUD scenario, the growth rate of construction land under the EP scenario dropped by an average of 13.61%. In addition, focusing the analysis on the growth rate of urban construction land, which has the greatest impact on the environment, the results show that there were 10 subbasins with the trend RUD > BAU > UEB > EP. However, in the Lanjiang River, Jiangshangang River, and Majinxi River subbasins, the trend was RUD > UEB > BAU > EP. The reason for this difference is in line with our analysis in Section 4.2.1. In conclusion, the EN-PLUS model, we constructed can effectively control the scale and degree of future LULCCs.

4.3. Scenario Comparison Using the Landscape Pattern Index

We analyzed the landscape pattern of the Qiantang River and its subbasins in terms of fragmentation, aggregation, and diversity. As shown in Figure 10, in terms of fragmentation, the NP index under the different scenarios was mainly RUD > BAU > UEB > EP, which is in line with our preconceived assumptions. However, the lowest NP index values in the three subbasins appeared under the BAU scenario, indicating that the current number of patches in these areas is increasing at a slower rate, and there may be a natural and coherent process of ecological patch merging. The other three scenarios we set may disrupt this process and thus lead to an increase in the NP value in these regions. The trend in the NP value in the Jinhua River subbasin was BAU > RUD > EP > UEB, which is consistent with the change trend in construction land in this subbasin that we found in Section 4.2.1. Changes in the DIVISION index showed that the landscape separation in most of the regions was the largest under the BAU scenario, which indicated that the ecological constraints we set played a significant role in improving ecology.

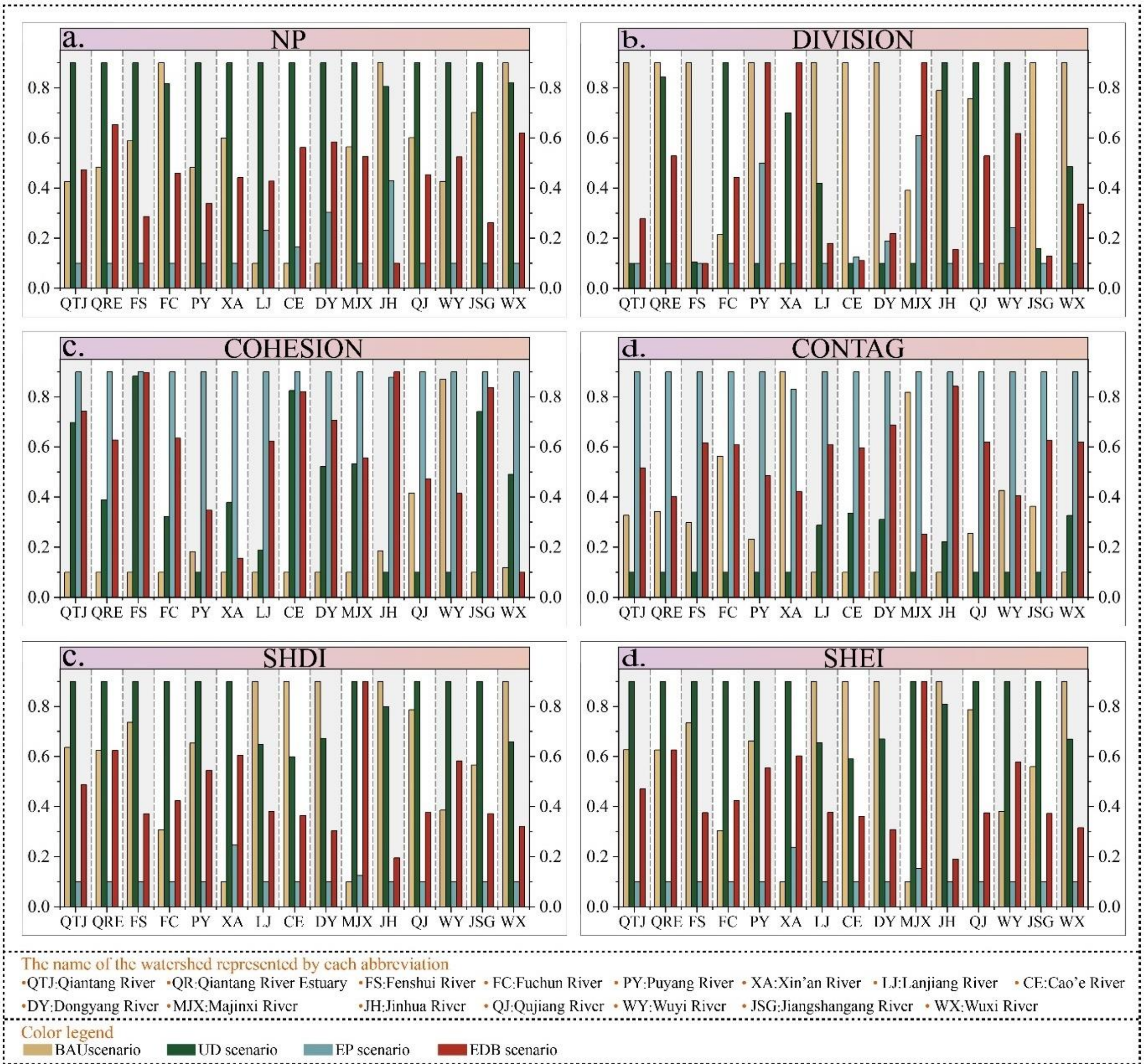

Figure 10. Landscape pattern change of Qiantang River and its sub-basins in different scenarios.

In terms of landscape aggregation, on the whole, the COHESION index under the other three scenarios was higher than that under the BAU scenario. This is due to the fact that LULCCs occurs in a more clustered space under the constraints of EN, which helps increase the connectivity between patches. This is also confirmed from the overall change trend in the CONTAG index. However, in the Xin'an River subbasin, the performance of the CONTAG and COHESION indices was not consistent, and the highest CONTAG value appeared under the BAU scenario. This indicates that, although the current landscape patch aggregation in this watershed is low, the distribution of patches of the same landscape type is relatively concentrated. However, the ecological constraints we set may destroy the spatial continuity of the original landscape evolution to a certain extent, so the concentration of expanded construction land in this subbasin needs to be improved.

In terms of the landscape diversity index, the trend in the SHDI value in most regions was RUD > BAU > UEB > EP, which indicated that landscape heterogeneity was positively correlated with the degree of human disturbance. However, there are five subbasins with a maximum SHDI value under the BAU scenario, because the construction land in some subbasins (Cao'e River, Jinhua River, and Wuxi River subbasins) increases the most under this scenario. In addition, in the Lanjiang River and Dongyang River subbasins, this phenomenon may be caused by the disorderly development of the current construction land.

In conclusion, the ecological constraints we set effectively slowed the degree of landscape pattern destruction, but not in all scenarios and regions. Especially under RUD scenarios with high development intensity, this protective effect is not considerable.

5. Discussion

5.1. Matching Degree between the EN-PLUS Model and the Preset Scenarios

LULCCs are influenced by a combination of natural conditions, economic development, and policy regulation [13]. It is difficult for any model to fully accurately simulate this complex process. Section 4.2 shows the deviation between the results of our simulations and the calculations of the Markov chain. As shown in Table 4, the deviation is mainly caused by the increase in patch expansion probability in water areas and the decrease in rural construction land and grassland. However, the deviation is approximately 5%, which has little impact on the overall trend. As this deviation occurs, on the one hand, the PLUS model considers the competition mechanism between patches, which makes the transition conditions between patches more accurate, so it is difficult to simply change the results by adjusting the model parameters. On the other hand, this may be due to the difficulty in quantifying the impact of social and economic factors on LULCCs in the model [13]. Therefore, there may be a slight inconsistency between the transition probabilities adjusted in the Markov chain and those determined in the PLUS model using random forests and roulette. Finally, the EN area used as the restricted conversion zone in this study is relatively large, which may also have a certain impact on the simulation results.

Table 4. The difference between the results simulated by PLUS model and the Markov chain model.

	BAU Scenario		UD Scenario		EP Scenario		UEB Scenario	
LULC	Area (km^2)	Rate (%)	Area (km^2)	Rate (%)	Area (km^2)	Rate (%)	Area (km^2)	Rate (%)
Waters	52.05	2.98	71.08	4.08	53.72	3.06	63.80	3.65
Rural	-	-	−71.08	−6.84	-	-	−63.80	−6.17
Grass	−52.07	−3.76	-	-	−53.71	−3.87	-	-

5.2. Land Use Optimization Modeling Oriented to Ecological Land Protection

Protecting ecological land is one of the basic principles for optimizing land use [1]. The EN-PLUS model we constructed coupled EN with multiscenario simulations to protect the land space that plays a key role in ecological processes within the region. The simulation results show that the area of ecological land in the scenarios with the EN as an ecological constraint (RUD, EP, and UED) increases by 15.34%, 24.73%, and 32.37%, respectively, compared with the scenario without this constraint (BAU) (Section 4.2.1). The results of the landscape pattern analysis show that the degree of damage to the landscape pattern is the lowest under EP and UEB scenarios in most areas (Section 4.2.2). These results are consistent with those of some studies using ecological land as spatial constraints [16,75,76]. However, compared with the conventional ecological constraints (nature reserves, water areas, large forest patches) used in other studies, the ecological constraints we set are closer to a complete ecosystem due to the connection function of ecological corridors.

In addition, most relevant studies only simulate two scenarios according to whether ecological constraints are applied. This is helpful to verify the role of ecological constraints for land use optimization, but does not consider the multiple possibilities of future LULCCs. Therefore, in this study, different EN levels were coupled with the corresponding development scenarios, which improved the simulation process to a certain extent. The simulation results demonstrate that this simulation mechanism can bring some new discoveries to research. For example, the study found that although the reduction in ecological land under the RUD scenario was smaller than that under the BAU scenario, the overall landscape pattern damage was still the most serious under the RUD scenario, which proves the limited protection effect of ENs (Section 4.3). Although multiscenario simulation is the mainstream research method at present, it mainly focuses on land use prediction (conventional ecological constraints) [77], ecosystem service value [78], and ecological risk [79,80] simulation. Therefore, this study broadens the research scope of the multiscenario simulation to some extent.

5.3. Scale Dependence of Simulation Results

From Section 4.2.2 and 4.2, it can be seen that the characteristics of LULCCs and landscape pattern in a few subbasins are not consistent with the overall Qiantang River Basin. This is due to the existence of the landscape scale effect, which dictates that ecological characteristics and impact mechanisms at a certain research scale may not be applicable at other scales [81,82]. Research on scale effects is meaningful for improving the operability of research results, because pure large-scale research is only suitable for macromanagement and planning, and conclusions at smaller scales can be better matched with administrative management [83]. For example, we found that the increase in construction land under the BAU scenario was higher than that under the RUD scenario in the three subbasins, which indicated that the constraints we set to protect ecological land were not effective in these regions. Therefore, different regions have their own most suitable development scenarios, but to coordinate the overall economic development planning of the Qiantang River Basin, some subbasins cannot be fully developed according to the scenario with minimal ecological sacrifice. In this case, we can choose areas with low ecological sensitivity to prioritize economic development. For example, in the Wuxi River subbasin, the difference in landscape pattern between the RUD and EP scenarios is relatively small, so the future development of this area can be planned based on the RUD scenario.

In addition, the scale effects of landscape patterns can be combined with the conservation objectives of subbasins. For example, there is a relatively high proportion of woodland in the Xin'an River subbasin, and the Qiandao Lake subbasin, the largest lake in the Qiantang River Basin, is located in this subbasin, so protecting habitat quality in this subbasin is particularly important. Related studies suggest that habitat quality is inversely associated with the SHDI in this region [84]. Therefore, BAU may be an appropriate development scenario for this subbasin, although the degree of landscape fragmentation in this scenario is not the lowest.

In conclusion, revealing the landscape scale effect on the multiscenario simulation results will help us formulate more detailed land use and ecological governance strategies for each region. At present, research on scale effects mainly focuses on land use evolution [83,85] and ecological function evaluation [82,86]. Therefore, our study enriches the research on the scale effect to some extent.

5.4. Limitations and Future Research Directions

Based on anti-planning thinking, the EN-PLUS model can simultaneously coordinate the space and quantity of LULCCs, which plays a prominent role in balancing regional development and ecological protection. Theoretically, the model is applicable to the research of land use and management in the urban planning discipline, and helps alleviate the problem of ecological pattern destruction during urban development. In addition, the optimization of ecological functions can also be incorporated into the model. For example, the evaluation of ecosystem services, ecological sensitivity, and landscape stability can be incorporated into the process of selecting ecological land. In the process of scenario setting, more quantitative models can be combined, such as system dynamics (SD) or gray multiobjective optimization (GMOP) models, which can provide more diverse attempts to calculate the amount of land use in different scenarios [78].

However, some uncertainties and limitations also exist in our study. First, even under the ecological protection policy, LULCCs in ENs are inevitable, so adopting an evaluation method for zoning ENs may solve this problem to a certain extent. Second, we only used landscape pattern indices to analyze the simulation results, and more landscape ecological features should be evaluated. Third, when analyzing the scale effect, we only considered the spatial scale effect and did not incorporate the time scale effect by simulating and analyzing multiyear land use. Finally, we use the resampling method to unify the resolution of all data to 100 × 100 m, which may lead to the loss of some information in the data and bring a certain uncertainty to the results.

6. Conclusions

The EN-PLUS model was proposed, which takes different EN levels as ecological constraints and couples them with a multiscenario simulation of LULC. The model was used to simulate land use in the Qiantang River Basin in 2030 under four scenarios, and the land use change and landscape pattern characteristics of the simulation results were analyzed at the scale of the whole basin and subbasins. The conclusions are as follows:

1. The four ecological constraints in the EN-PLUS model play different roles in the protection of ecological land. This protective effect is more pronounced under the EP and UEB scenarios, while under the RUD scenario, the extent of ecological pattern destruction is still greater than that under the BAU scenario due to excessive human disturbance.
2. The simulation results showed obvious landscape scale effects at subbasins scale.
3. Although the damage to the landscape pattern is generally lower under the EP scenario, it is not the best development scenario for all subbasins. The scale effect and the regional ecological characteristics should be comprehensively considered to select the best regional development scenario.

The EN-PLUS model provides a reference for the ecological protection and sustainable development of the Qiantang River Basin and its subbasins by introducing the EN as the goal of ecological land protection in simulations of future land use. Future research can incorporate this research framework into ecological governance and land planning policy formulation in a more objective way by integrating policy drivers and more diverse evaluation methods of ecological functions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs14236099/s1, Figure S1. Three types of ecological networks. Table S1. Classification and assignment of resistance factors. Table S2. Principal component load matrix, cumulative contribution rate, and weight of each factor. Table S3. Cost matrix for each scenario. Table S4. Description of selected landscape indices. Table S5. Abbreviations and their meanings. Reference [87] is cited in the supplementary materials

Author Contributions: W.N. and B.X. designed the study and methodology. F.Y., S.M., N.H. and B.L. extracted and compiled the data. Z.B. analyzed the data with the help of R.W., Y.S. and W.L. All authors contributed to the article and approved the submitted version. All authors have read and agreed to the published version of the manuscript.

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