Land Use Simulation of Qiantang River Basin At Optimal Spatial Scale Based on PLUS Model

Yinan Shi [1, *, †], Pengfei Zhou [2, †]

[1] School of Civil & Environmental Engineering and Geography Science, Ningbo University, Ningbo, China

[2] School of Geography and Tourism, Qufu Normal University, Rizhao, China

* Corresponding Author Email: 206000483@nbu.edu.cn

†These authors contributed equally to this work.

Abstract. The coordinated spatial planning of the nation's territory can be accomplished on the basis of future land use change simulation, and increasing forecast accuracy can aid in properly identifying the trend of these changes. To stimulate the future space distribution in the Qiantang River Basin in a refined manner, this paper selects data on land cover and related influencing factors for the years 2010 and 2020, and screens out the optimal spatial scale by integrating various precision indicators such as Kappa and OA. On this basis, the PLUS model is applied to simulates the regional spatial pattern in 2030. The consequences show that a 30 m cell and a 3×3 neighborhood are the optimal spatial scales for simulating space changes in the region. The simulation results have high accuracy. In the Qiantang River Basin, it is anticipated that by 2030, forest land will predominate over all other land uses, with development land moving further from the city's core. The study believes that in the future, the prediction of land development in the Qiantang River Basin can be improved in terms of stimulation model and accuracy, so as to effectively serve the regional land space planning.

Keywords: Land use change; PLUS model; Qiantang River Basin.

1. Introduction

Land use is the result of the cumulative effects of multiple factors, such as natural environment and social economy. With the acceleration of China's industrialization and urbanization, land use and its spatial pattern changes significantly [1]. A foundation for coordinated spatial planning of the national territory and attaining regional sustainable development will be supplied by investigation of the characteristics and laws governing land cover changes and simulation of future change trends [2]. The Qiantang River, the important rivers in Zhejiang Province, is crucial to preserving the ecological environment of the area and advancing socio-economic progress. The coordination of the relationship between landscape protection and economic advancement in the Qiantang River Basin has come to the forefront recently as a result of the full implementation of the national ecological civilization construction requirements and the "Eight-Eight Strategies".

The theory and methodology of land use change studies have greatly advanced in recent years. Scholars have researched the evolution laws, driving mechanisms, and prediction and simulation at different scales and in different regions [3]. Models currently applied to predict land use evolution include the Simulation models of future land-use change scenarios (GeoSOS-FLUS) model, etc., but those models have deficiencies in exploring the driving forces and in predicting patch-level evolution [4,5]. The Patch-generating Land Use Simulation (PLUS) model integrates a patch-level mining method based on land expansion analysis rules and a cellular automata (CA) model based on multi-type random seed mechanisms and is believed to have better simulation accuracy [6]. Also, prior research has demonstrated that the detailed simulation results are influenced by the spatial scale effect, which includes the size of cells and the type of neighborhood [7]. Therefore, choosing the best geographical scale is crucial to increasing the precision of stimulation.

This paper is relied on the PLUS model, takes the Qiantang River Basin as the research area, and uses the land use data of 2010 and 2020 as the source. Based on comprehensive consideration of the actual situation in the basin, the principles for selecting driving factors, and verification of the model

accuracy, the optimal spatial scale is screened out by integrating Kappa, overall accuracy (OA), and other indicators through the entropy weight method. On this basis, fine simulations are performed to predict the regional space pattern in 2030, which will ensure decision-making for the regional sustainable process.

2. Materials and Methods

2.1. Study Area

Qiantang River, the largest river in Zhejiang Province, has a basin range between 117.62°~121.87°E and 28.17°~30.48°N. In this study, Cities within the basin such as Hangzhou, Quzhou, Jinhua, and Shaoxing (Figure 1) are selected as the study area, which covers 47.2% of Zhejiang Province's total surface area. The basin has a superior natural environment, diverse topography, subtropical monsoon climate, and abundant biological and water resources. The population and economic output in the basin account for one-third of that of Zhejiang Province, making it one of the fastest-growing economic regions in the Yangtze River Delta region of China [8].

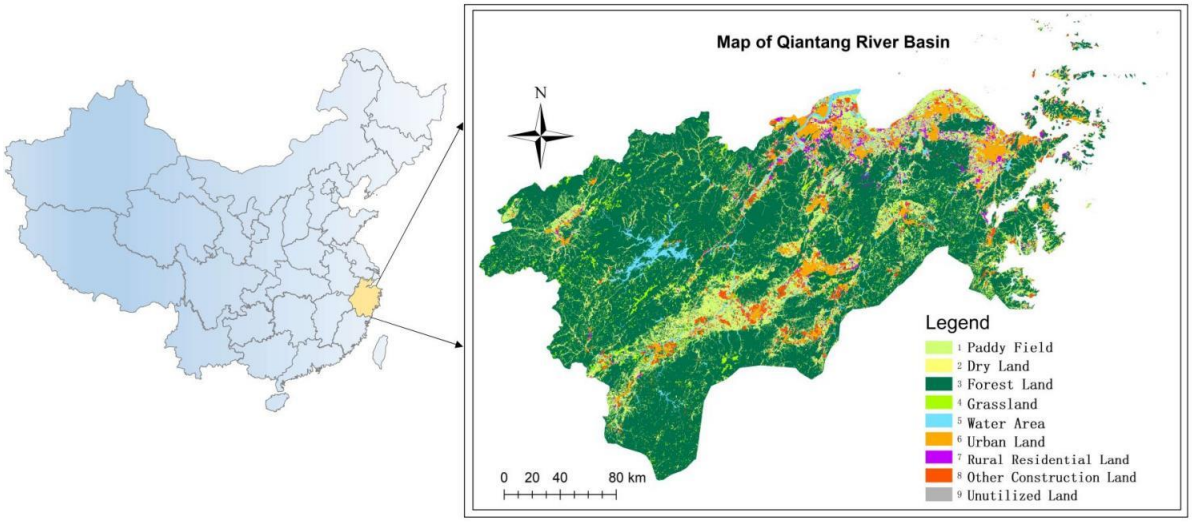


Fig. 1 Diagram of the study area

2.2. Data

The primary types of data used in this investigation are: (1). Land use data and gross domestic product (GDP) grid data are got from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/); (2). Digital Elevation Model (DEM) data comes from the Geospatial Data Cloud (https://www.gscloud.cn/), from which slope data are extracted; (3). Road data and water system data come from OpenStreetMap; (4). Population data for 2010 and 2020 are from the Worldpop population density dataset (http://www.worldpop.org/), which has been matched with the United Nations population estimates; (5). Point of Interest (POI) data are collected through crawling tools using Amap, covering four categories of POI including restaurants, shopping malls, schools, and hospitals in 16 cities within the basin, with a total of 2219, 170, 1737, and 1803 data points, respectively.

3. Methods

The paper derives the influencing drivers from the actual land cover for 2010 and 2020 in the Qiantang River basin, according to the analysis of the research region's space changes during a ten-year period. Under the PLUS model, the study evaluates the simulation precision at various

resolutions and neighborhood sizes, and couples analyze the OA, Kappa, and figure of merit (FOM) index using the entropy weight technique. Thus, the study makes projections for the Qiantang River basin's land usage in 2030 by the obtained optimal spatial scale of simulation. The technical route is shown in Figure 2.

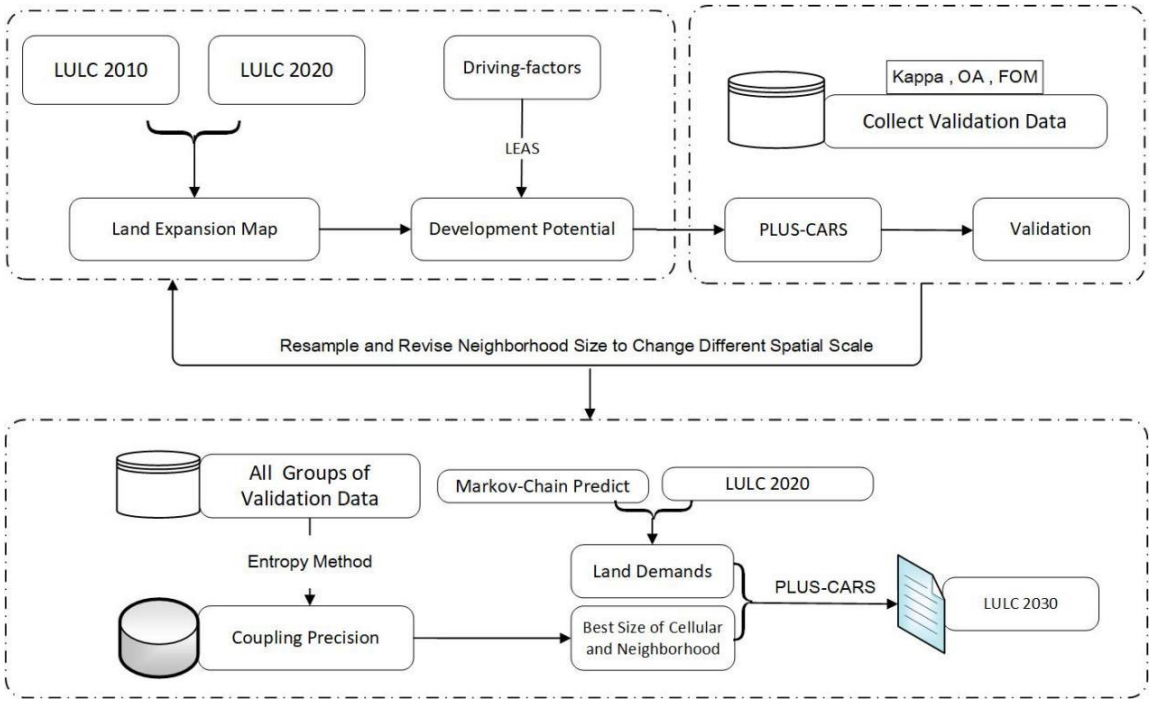


Fig. 2 Technical route of research

3.1. Construction of the Driver Factor Atlas

Based on the various land uses in the study region and drawing on previous research, the factors influencing the evolution of land use are analyzed from four aspects: natural terrain, socio-economy, accessibility, and public services [9]. To improve cellular automata (CA) simulation accuracy, an ArcGIS-based driving factor atlas is constructed. Spatial analysis methods such as buffer zones, raster standardization, and kernel density functions are used to analyze the factors [7]. A total of nine types of quantified driving factor atlas are obtained, including digital elevation model (DEM), slope, aspect, population distribution, GDP distribution, distance from roads and rivers, and kernel densities of three types of points of interest (POI) data: hospitals, schools, and shopping centers.

3.2. PLUS Model

3.2.1 Land Expansion Strategy Analyze

Based on land expansion data and the driving factor atlas, the PLUS model including the LEAS module can explain land use changes effectively, which uses the random forest algorithm [10]. The algorithm can also forecast the likelihood that k different types of land will grow, expressed by the following formula:

$$P_{i,k}^{d}(x) = \frac{\sum_{n=1}^{M} I[h_n(x)=d]}{M} \quad (1)$$

In this equation, k represents land use type; i represents the number of cells; the value of d determines the type of land use conversion. The decision tree's function I is an indicator function.

3.2.2 Markov-Chain Predict

Based on the current information for the space distribution throughout two eras, the Markov chain prediction model can anticipate the future requirement for each form [11]. The calculation formula is as follows:

$$S_{t+1} = S_t \times P_{ij} \quad (2)$$

In this formula, S_t and S_{t+1} means the land status at different time. P_{ij} is the land type transition probability matrix.

3.3.3 CARS Module

The CARS module contains a cellular automata (CA) model constructed using multi-class random patch seeds. Considering the probability of land expansion and the total future pixel quantity, this module can simulate space usage demands using random seeds. The CA model's reliability is affected by transformation rules, cell size, neighborhood size, and neighborhood shape [12]. This study employs a single-variable method to consider the simulation accuracy of CA under different combinations of spatial scales and select the optimal spatial scale for prediction.

3.3. Accuracy Verification

The Kappa coefficient can effectively verify the correctness of the prediction model, and both the OA coefficient (the overall accuracy of the image simulation before and after) and the FoM coefficient commonly have the same effect. Combining the two can enhance the scientific basis for simulation accuracy. The measurement algorithm is as drawn:

$$Kappa = \frac{P-P_e}{1-P_e} \quad (3)$$

3.4. Entropy Weight Method

The entropy weight method is used to obtain the coupling value of the simulation accuracy evaluation, and the optimal spatial scale is selected to speculate the future alteration in the research region while also accounting for the variable level differences of the OA, Kappa coefficient, and FOM index. The relevant calculation methods are as follows:

$$Y_{ij} = \frac{X_{ij}-\min(X^i)}{\max(X^i)-\min(X^i)} \quad (4)$$

$$P_{ij} = \frac{Y_{ij}}{\sum_1^n Y_n} \quad (5)$$

$$E_{ij} = -\frac{1}{lnN}\sum_1^n P_{ij} \quad (6)$$

$$W_i = \frac{1-E_i}{k-\sum E_i} \quad (7)$$

$$Y' = \sum_1^n (X_i)(W_i) \quad (8)$$

In these formulas, Y' refers to the coupling accuracy.

4. Results

4.1. Characteristics of Land Use Change

To investigate the characteristics and patterns of land management change in the region, the land cover area transfer matrix for 2010-2020 in the basin is produced using the thematic data from the multi-period land use remote sensing monitoring dataset of China. (Table 1).

Table 1. 2010-2020 Land Use Transition Matrix unit: square kilometer(km^2)

2010 / 2020	Paddy field	Dry land	Forest land	Grass land	Water area	Urban land	Rural residential land	Other construction land	Unutilized land
Paddy field	10455.66	164.91	685.39	14.96	67.07	281.64	253.60	316.93	1.86
Dry land	60.28	1723.76	134.23	4.95	10.06	55.15	34.30	57.83	1.11
Forest land	363.01	130.60	37506.60	89.78	45.44	33.11	37.44	167.59	16.38
Grass land	16.47	4.91	86.53	1419.62	3.72	1.48	2.53	15.72	2.60
Water area	38.32	10.08	42.61	2.27	1499.02	7.18	5.51	22.49	1.02
Urban land	20.52	3.42	9.64	0.63	3.49	1413.52	4.92	4.61	0.02
Rural residential land	94.28	12.18	25.03	1.09	5.39	23.22	1145.85	10.57	0.25
Other construction land	39.88	13.02	18.07	1.59	10.54	34.00	8.18	689.68	0.29
Unutilized land	1.39	9.62	95.17	2.00	10.93	4.36	6.08	22.22	130.80

From 2010 to 2020, all nine space types underwent varying degrees of transformation. With an extent of 685.39 km^2 , the conversion in land use from paddy fields to forest lands was the greatest. The second largest transfer occurred from forest lands to paddy fields, with an area of 363.01 km^2, a total of up to 0.9% of the transfer area from forest lands. From these two indicators, it is evident that there was more activity in the mutual exchange involving paddy fields and forest tracts. In comparison to change to other land use types (1460.77 km^2), urban land converted from them covered 1853.67 km2, a substantially bigger area. Among them, the largest area of conversion to urban land was from paddy fields, which was approximately 281.64 km^2, composing 15.2% of the total area of conversion to urban land. Additionally, dry lands, forest lands, and other construction lands were transformed into urban land. At the same time, some paddy fields were turned into rural homesites and other construction lands, with areas of 253.60 km^2 and 316.93 km^2, respectively, and 167.59 km^2 of forest lands were switched to other construction lands. Moreover, unutilized land, with 154.33 km^2, had the smallest amount of changeover, the large portion of which was reverted to forest land.

4.2. Analysis of Driving Factors of Land Use Change

The comprehensive impact of numerous variables has led to changes in land management. Using the LEAS module, each driving factor's involvement is assessed. The driving force estimate for the extension of each type is given utilizing generated contribution estimates of each driving factor (Figure 3).

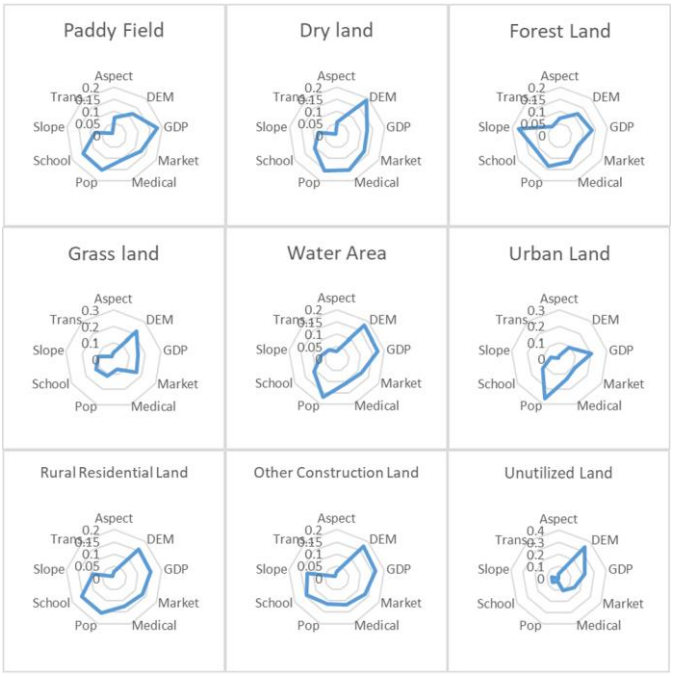


Fig. 3 Contribution of driving factors

*DEM represents elevation elements, Trans represents transportation elements, GDP represents socioeconomic elements, and Pop represents population elements.

The factors that have the greatest impact on changes in paddy fields are GDP, population distribution, and school location, while the distance from highways and railways has little effect on it. Dry land, grass land, and water areas are strongly affected by the DEM and are also affected to some extent by population and socio-economic development factors. The slope has the strongest influence on the expansion of forest land, while other driving factors also have a significant effect on forest land. The main drivers of the expansion of urban land are population and GDP. This indicates that population growth fundamentally promotes the urbanization and leads to the steadily growth of city land, which is distributed in regions with relatively good socio-economic conditions. Multiple dynamic factors have a considerable impact on changes in rural residential land and other construction lands. The DEM has a significant effect on the unutilized land, while GDP and the location of shopping malls also promote it.

4.3. Optimal Spatial Scale Screening for Land Use Change Simulation

This paper employed the PLUS model and selected cell size and neighborhood size as variables that affect the space scale effect in order to take into account the scale sensitivity of specific components. Twelve various spatial scales are employed to carry out enhanced prediction tests on land use change using a data source with a 30 m pixel size, and sets the cell size interval to 30 m, with neighborhood sizes of 3×3, 5×5, and 7×7. For evaluating the simulation's correctness, the simulated results for 2020 are compared to the actual scenario, and coupling indicators are calculated (Table 2).

Table 2. Accuracy verification experiment under single variable

Number	Cell size(m)	Neighborhood sizes	Kappa	OA	FoM	Accuracy Evaluation Coupling Index Y’
1	30	3	0.8683	0.9311	0.0937	0.6827
2	30	5	0.8657	0.9297	0.0905	0.6804
3	30	7	0.8664	0.9300	0.0871	0.6798
4	60	3	0.8611	0.9274	0.0792	0.6748
5	60	5	0.8616	0.9277	0.0746	0.6739
6	60	7	0.8617	0.9277	0.0727	0.6734
7	90	3	0.8595	0.9264	0.0690	0.6711
8	90	5	0.8595	0.9264	0.0665	0.6705
9	90	7	0.8595	0.9264	0.0659	0.6703
10	120	3	0.8584	0.9259	0.0565	0.6672
11	120	5	0.8593	0.9264	0.0529	0.6667
12	120	7	0.8602	0.9268	0.0523	0.6671

According to Table 2, all of the predicted results under different combinations of cell size and neighborhood size have high accuracy. However, when contrasting the data from Group 1 to Group 12, the magnitude differences in the three accuracy evaluation indicators are disparate. To choose the best spatial scale combination, the coupling index Y' based on the entropy weighting method is introduced. Comparing the results, the optimal spatial scale combination is determined to be a cell size of 30m and a neighborhood size of 3×3, with a coupling index of 0.6827 for accuracy evaluation. At the same time, from the experiment data, it has been shown that when cell size grows, the simulation accuracy decreases, while the influence of the neighborhood size on the accuracy cannot be determined. For example, for a cell size of 120m, the simulation accuracy of the 7×7 neighborhood size is higher than that of the 5×5 neighborhood size.

4.4. Land Use Simulation Results at the Optimal Spatial Scale

A Markov chain prediction model is applied to anticipate the land demand in 2030 according to the land use transition probability matrix for the Qiantang River Basin between 2010 and 2020 (Table 3). In respect of land cover quantity, the land amount for forest, urban land, and other construction land will all witness an upward trend in 2030. Among them, the number of forest land grows continuously and remains the largest, even though the growth rate of construction land is rather high. In contrast, the land demand for paddy fields, dry land, grass land, and unutilized land will decline.

Using the 2020 Qiantang River Basin land use type data as a benchmark and combining the predicted future land amount by the Markov, the fine-scale simulations of the Qiantang River Basin land use in 2030 are obtained at the optimal spatial scale by the PLUS (Figure 4). By 2030, there is still an uneven state in the way that different land use types are dispersed in space. While forest land has the widest distribution in the basin due to the influence of terrain, agricultural land such as paddy fields and dry land are allocated in the coastal plain and river areas. Construction land such as urban land is scattered in block shapes around cities. In terms of spatial development, construction land shows a tendency of expanding from the city center to the surrounding areas, and correspondingly, the number of agricultural lands such as paddy fields around the town has dropped. In short, future changes in the Qiantang River Basin's land use pattern will mostly involve the transmutation of arable and unutilized land to forest and construction land.

Table 3. Prediction of Land Use Demand Based on Markov Model Unit: number of pixels

	Paddy field	Dry land	Forest land	Grass land	Water area	Urban land	Rural residential land	Other construction land	Unutilized land
2010	13602262	2312973	42655505	1726205	1809448	1623077	1464300	905837	313953
2020	12322018	2302772	42892527	1707664	1839645	2059629	1664898	1452929	171478
2030	11277596	2284777	43022347	1690142	1864040	2476810	1816819	1875374	105655

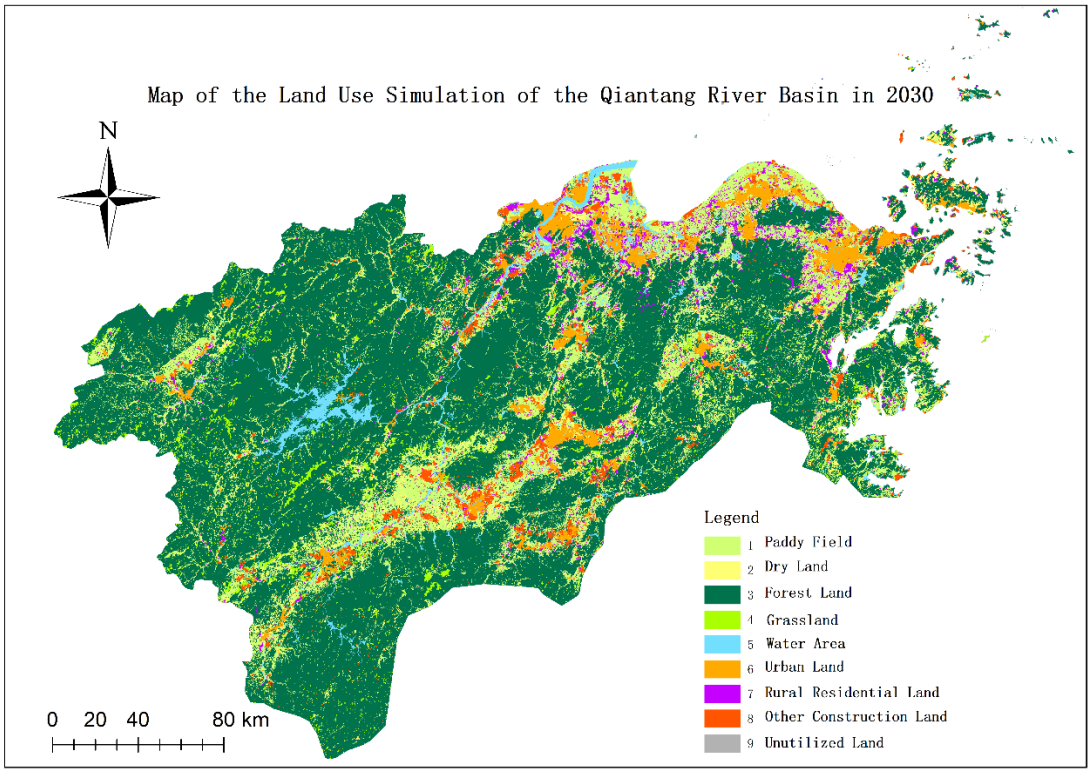


Fig. 4 Simulation results of land use in the Qiantang River Basin in 2030

5. Discussion

According to the land cover status in 2021 and 2020, it is discovered that while the occupation of construction land was expanding, the forest land was also steadily increasing. This indicates that the basin has achieved a relatively good balance between ecological protection and economic development in land use. Active conversion of unutilized land into forest land and paddy fields into forests demonstrates the efficiency of land control and spatial conservation in Zhejiang Province. The comprehensive development of land production and ecological functions has been realized through farmland consolidation and ecosystem restoration [13]. Secondly, the development of agricultural land adjacent to urban regions is primarily responsible for the extension of urban land and other building land, reflecting the general trend of expanding land usage in support of urbanization. Besides, the efficiency of urban land consolidation and the protection of agricultural land are needed to give further attention [14].

The potential space situation with in Qiantang River Basin can serve as a guide for regional land use development by taking into account the laws of land use shift and driving forces. However, the

study still has several flaws. Because of the long-time horizon, the data in terms of land usage can be enlarged, which may have an impact on prediction precision. When analyzing land expansion strategies, the preprocessing of the original driving factors data and the analysis of driving force results need to be improved. The repeatability of the single variable experiments using the PLUS model is large, and the set of variables is limited. Therefore, so as to increase the reliability of proposed development of land studies' predictions, it is still necessary to enhance simulation techniques.

6. Conclusion

In evaluating the characteristics and patterns of land use shifts across the region, this study considers the finest cellular automata for modeling spatial scales and simulates future land development in the research region. The ensuing conclusions are reached: (1) Between 2010 and 2020, the Qiantang River Basin's land cover underwent some change, while the current dominant land use sort is forest land. Also, there is an active conversion between forest land and paddy fields, and various types of building land principally have been changed from paddy fields. With regard to driving forces for land use, different types of land use have different expansion drivers. (2) The study applies the entropy weight method to extensively evaluate OA, Kappa coefficient, and FOM index, so that the coupling index procured can illustrate the simulation accuracy more synthetically. Through the experiment using a single-variable method, it is found that the optimal spatial scale combination of the Qiantang River Basin's land use simulation is 30 m cells and a 3x3 neighborhood. Based on this, the simulation of Qiantang River Basin's land use in 2020 is loaded. Its OA of 0.9311 and the Kappa of 0.8683 can be considered to have a high simulation accuracy. (3) Given the results of the thorough data analysis of anticipated modifications to land cover, forest land would keep governing the region's land use by 2030. The amount of different land types has various trends. Different land uses are distributed unevenly, and the fragmentation of land around cities will expand.

References

[1] Tang W Y. Analysis of land use change and its driving factors in Jiangsu and Zhejiang [J]. Anhui Agricultural Science Bulletin,2021, 27(14):118-122.

[2] Wu H, Wu X, Wang W, Lin A Q, Song D X, Gao C. Analysis and simulation of spatio-temporal evolution of land use in the Yangtze River Economic Belt since 2000. Journal of Central China Normal University(Nat. sci.),2019,53(05):692-702.

[3] Bai S Y, Chen L M, Wang L, Li H P. Study of land use/cover change—present and prospect [J]. Journal of Anhui Agricultural Sciences, 2010,38(30):17003-17005+17016.

[4] Chen L T, Cai H S, Zhang T, Zhang X L, Zeng H. Land use multi-scenario simulation analysis of Rao River Basin based on Markov-FLUS model. Acra Ecological Sinica,2022,42(10):3947-3958.

[5] Liang X, Liu X P, Chen G L, et al. Coupling fuzzy clustering and cellular automata based on local maxima of development potential to model urban emergence and expansion in economic development zones [J]. International Journal of Geographical Information Science，2020,34(10):1930-1952.

[6] Wu D, Zhu W K, Zhang Y, Huang C Q, Li J. Evolution analysis of carbon stock in Chengdu-Chongqing economic zone based on PLUS model and InVEST model[J]. Ecology and Environmental Monitoring of Three Gorges,2022,7(2):85-96.

[7] Li Y, Lin A Q, Wu H, Wu X, Cen L Y, Liu H, Jiang Z M. Refined simulation of urban land use change with emphasis on spatial scale effect[J]. Acta Geographica Sinica,2022,77(11):2738-2756.

[8] Su S L. Spatio-temporal responses of watershed ecosystems to urbanization[D]. Zhejiang University,2013.

[9] Liu J Y, Zhang Z X, Xu X L, et al. Spatial pattern and driving force analysis of land use change in China in the early 21st century[J]. Acta Geographica Sinica,2009,64(12):1411-1420.

[10] Wang J N, Zhang Z. Land use change and simulation analysis on the northern margin of Qaidam based on Markov-PLUS model[J]. Journal of Northwest Forestry University,2022,37(03):139-148+179.

[11] Wang H N, Wang Z C, Hai M M. Simulation Analysis of Land Use Change in Shandong Province Based on PLUS Model[J]. Territory & Natural Resources Study,2022(06):1-8.

[12] Wu H N, Zhou L, Shi W Z, et al. Scale Sensitivity Analysis of Cellular Automata Simulation Process of Land Use Change Based on Orthogonal Experimental Design[J]. Scientia Geographica Sinica,2013,33(10):1252-1258.

[13] Qiu D, Gu J. Evaluation of sustainable land use in the process of urbanization——Taking Zhejiang Province as an example[J]. NanFang ZiRan ZiYuan,2021,No.225(08):33-39.

[14] Mei S Y, Qiao G M, Zhou Q, Cheng Y. Evolution of Urban and Rural Land Use Efficiency and Coupling Relationship in Zhejiang Province[J]. Bulletin Of Soil And Water Conservation, 2020,40(04):295-302+2.