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Spatio-temporal Dynamic Simulation of Land use and Ecological Risk in the Yangtze River Delta Urban Agglomeration, China

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Abstract: Rapid urbanization leads to dramatic changes in land use patterns, and the land use/cover change (LUCC) can reflect the spatial impact of urbanization on the ecological environment. Simulating the process of LUCC and predicting the ecological risk future changes can provide supports for urban ecological management. Taking the Yangtze River Delta Urban Agglomeration (YRDUA), China as the study area, four developmental scenarios were set on the basis of the land use data from 2005 to 2015. The temporal land use changes were predicted by the integration of the system dynamic and the future land use simulation (SD-FLUS) model, and the geographically weighted regression (GWR) model was used to identify the spatial heterogeneity and evolution characteristics between ecological risk index (ERI) and socio-economic driving forces. Results showed that: 1) From 2005 to 2015, the expansion of construction land (7670.24 km^2) mainly came from the occupation of cultivated land (7854.22 km^2). The Kappa coefficient of the SD-FLUS model was 0.886, indicating that this model could be used to predict the future land use changes in the YRDUA. 2) Gross domestic production (GDP) and population density (POP) showed a positive effect on the ERI, and the impact of POP exceeded that of GDP. The ERI showed the characteristics of zonal diffusion and a slight upward trend, and the high ecological risk region increased by 6.09%, with the largest increase. 3) Under different developmental scenarios, the land use and ecological risk patterns varied. The construction land is increased by 5.76%, 7.41%, 5.25% and 6.06%, respectively. And the high ecological risk region accounted for 12.71%, 15.06%, 11.89%, and 12.94%, correspondingly. In Scenario D, the structure of land use and ecological risk pattern was better compared with other scenarios considering the needs of rapid economic and ecological protection. This study is helpful to understand the spatio-temporal pattern and demand of land use types, grasp the ecological security pattern of large-scale areas, and provide scientific basis for the territory development of urban agglomeration in the future.

Keywords: urbanization; ecological risk; scenario simulation; geographically weighted regression (GWR); spatial planning

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1 Introduction

Land is the foundation of human survival and development. It is also the medium of interaction between humans and nature. With the rapid urbanization process, the demand for urban space is increasing. The continuous expansion of urban space has led to significant changes in the land use/cover change (LUCC), which affects the structure and function of the urban ecosystem seriously. Understanding rapid LUCC and ecologic-

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al security level in urban agglomerations is vital for urban ecological management and sustainable development (Meneses et al., 2015; Nan et al., 2020; Vadrevu and Ohara, 2020). In fact, the continuing increases in population, urbanization and the accompanying dramatic changes in land use and land cover have significant environmental impacts on ecosystems. Such as land degradation, biodiversity loss, water shortage, and heat island effect (Li et al., 2017a; Bhattachan et al., 2018; Singh and Kalota, 2019; Zhang et al., 2021). These problems have led researchers to focus on the ecological security of urban development (Dong and Xu, 2019; Cao et al., 2020). Assessing the response of the eco-environment to LUCC has become a major research topic in recent years in global change research.

Ecological risk is the likelihood of an ecosystems degraded response to extraneous disturbances, reflecting the negative impacts of human activities and natural environmental changes to the ecosystem (Gong et al., 2015; Depietri, 2020; Mann et al., 2021). Ecological risk assessment refers to the assessment of factors that can generate risks when humans or natural activities affect the ecological environment (Hunsaker et al., 1990; Sajikumar and Remya, 2015). The ecological risk assessment results can be used as an important basis for follow-up work through reasonable measures to reduce the occurrence of risks and protect the ecological environment (Christian et al., 2009; Marhaento et al., 2017; Filonchyk and Hurynovich, 2020). Currently, many types of research on the ecological risk focus on water environment quality assessment (Pešić et al., 2020), landscape ecological risk assessment (Tuholske et al., 2017), and ecological security early-warning (Chen and Wang, 2020). However, although many evaluations of work and methodology studies have been carried out, few researches considering the relationship between LUCC and urban ecological risk (Zhou et al., 2021). How to prevent the threats from land use changes and optimized regional ecological security patterns are the focus of current attention (Li et al., 2020).

The scenario simulation of LUCC plays an important role in urban development because the development of future pattern is full of uncertainty and complexity. Lots of researchers have developed a variety of models to simulate LUCC. These models mainly include two categories: top-down models and bottom-up models (Grimm, 1999). 'Top-down' models have focused on describing the quantitative transfer among different LUCC types at the system level, such as system dynamics (SD), grey prediction (GM) and Markov models (Wang et al., 2012; Rasmussen et al., 2012; Geng et al., 2017). However, these simulated results are only quantitative changes in land use types, and 'top-down' models often lack the ability to simulate the spatial patterns of LUCC. 'Bottom-up' models can predict the spatial patterns of LUCC through simulating the dynamics of all individual units within the system (Castella et al., 2007; Xu et al., 2016a). The most representative model is the cellular automata (CA) model (Itami, 1994). Regrettably, these models have low accuracy in controlling the quantity of land use. Based on this, some researchers have integrated 'top-down' and 'bottom-up' approaches for simulation prediction. The CA-Markov model is the most widely used integrated approach in LUCC simulations (Zhou et al., 2020). In addition, SD-CA and Logistic-CA-Markov models are also included (Siddiqui et al., 2018; Jiao et al., 2019). However, this integrated model could not represent the interconnections between the LUCC and natural and socio-economic factors (Xu et al., 2016a). It's important because LUCC is affected by these factors (Fan et al., 2015). Therefore, an effective LUCC simulation model is still needed to simulate future spatial and temporal changes. The future land use simulation (FLUS) model is a future land use simulation prediction model based on the improved CA principle (Liu et al, 2017). This model has the advantage of incorporated self-adaptive inertia and competition mechanism within the CA model to process the complex competitions and interactions among the different land use types. So, we took the advantages of the SD-FLUS model to simulate LUCC. This model can predict the LUCC from land use types quantity and spatial patterns, which improves the simulation accuracy.

The Yangtze River Delta Urban Agglomeration (YRDUA), China is the largest one of the three major urban agglomerations in China. It is also one of the regions with the highest level of urbanization and the most economically concentrated regions in the country. How to coordinate the relationship between rapid urbanization and ecological risk is essential for building and maintaining regional sustainability. This area is taken as the research object based on the socio-economic data and remote sensing image of the YRDUA. The SD-FLUS model is constructed to predict the land use pattern of the four scenarios in 2025, and the ecological risk pattern is predicted on the basis of the four land use scenarios. The differences in urban development levels will inevitably cause spatial differences in the driving forces, so the geographically weighted regression (GWR) model is well-suited to examining the relationship between ecological risk index (ERI) and urbanization. This research aims to: 1) discover the characteristics of LUCC and ecological risk pattern changes from 2005 to 2015; 2) analyze the spatial heterogeneity and evolution characteristics between ERI and socio-economic driving forces; 3) predict the land use and ecological risk patterns of the YRDUA in 2025 under the four scenarios, and explore the impact of land use changes on the ecological risk pattern under multi-scenario simulation in the YRDUA.

2 Materials and Methods

2.1 Study area

The YRDUA is located in the middle of China, bordering Shandong Province in the north, between 28°80′N–34°27′N and 115°45′E–122°50′E (Fig. 1). As China's economically active, open, and innovative region, the Yangtze River Delta (YRD) achieves strategic significance in the country's modernization and further opening-up. It is mainly composed of 26 central cities in one municipality and three provinces, including Shanghai, Jiangsu Province, Zhejiang Province, and Anhui Province (Luo et al., 2021). In addition, it has a land area of 21.17 × 10^4 km^2, accounting for about 2.2% of China's land area.

The YRDUA terrain is mainly composed of plains, low hills, waters, mountains, islands, and basins. The highest elevation is found in the south, whereas the lowest one is in the north. The elevation ranges from −92 m to 1738 m. The annual average temperature range is from 15.6℃ to 18.1℃, and the annual precipitation range is from 704 mm to 1734 mm (He, 2019). As of 2018, the population of the 26 cities in the YRDUA reached 154 million, and the average urbanization rate was 67.38%. In the same year, the average total GDP was 17 800 billion yuan and achieved an increase of 12 700 billion yuan (RMB) over 2017 with a growth rate of 7.14%, which was higher than the national aver-

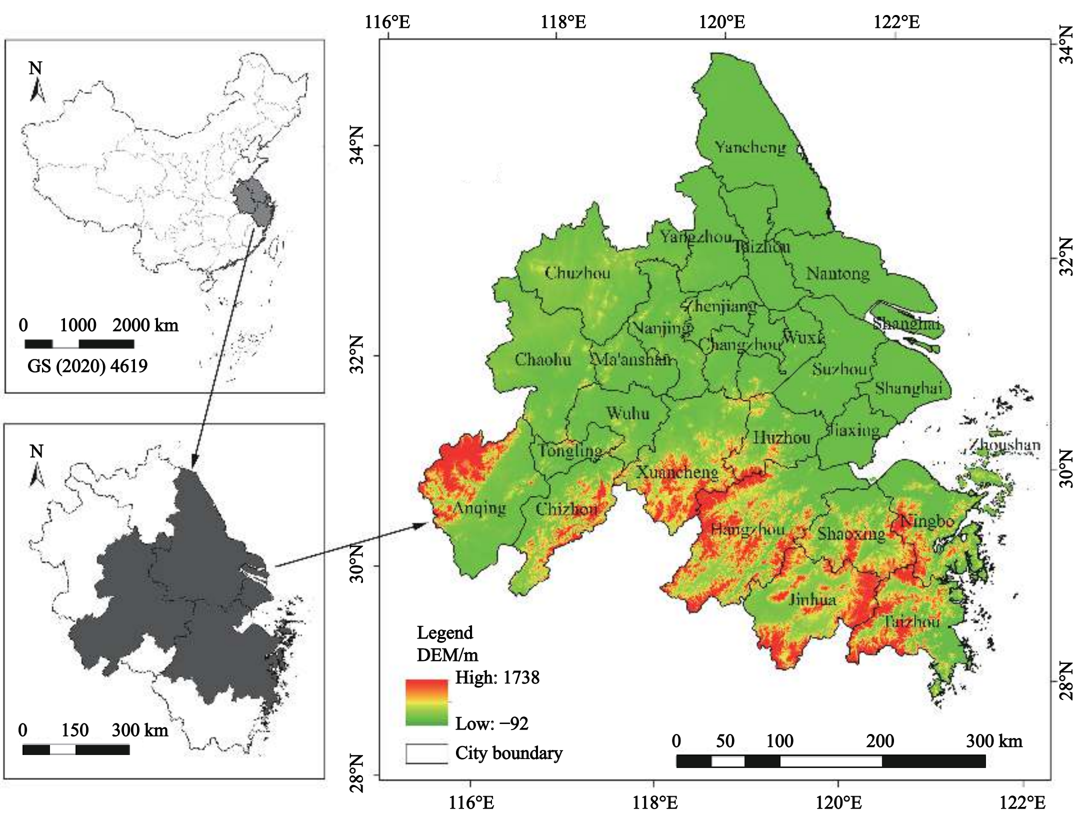

Fig. 1 Geographical location of the Yangtze River Delta Urban Agglomeration (YRDUA) in China

age GDP growth rate of 6.6% (Luo et al., 2021).

2.2 Data source

1) LUCC maps of the YRDUA region from 2005, 2010 and 2015 were downloaded from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/) with a resolution of 30 m and the YRDUA was clipped. To increase calculation speed, the spatial resolution was resampled to 100 m. The land use types are classified into six types, namely, cultivated land, forest land, grassland, water area, construction land, and unused land. 2) A digital elevation model with a spatial resolution of 30 m was used in the study area (http://www.gis-cloud.cn/). 3) The 1000 m × 1000 m grid data of GDP, population density (POP), and soil organic matter content were downloaded from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). 4) Road information was obtained from the China National Geographic Information Center (http://ngcc.sbsm.gov.cn), and the distance indicators were calculated on the basis of ArcGIS. 5) The annual average temperature data were obtained from National Meteorological Science Data Center (http://data.cma.cn). 6) The socio-economic statistics data were acquired from the regional statistics yearbook of the study area from 2006 to 2016 (http://www.stats.gov.cn/tjsj/ndsj/).

2.3 Methods

The study was conducted by using a four-step method: 1) integrating the SD model and FLUS model to simulate LUCC; 2) designing four scenarios representing future development levels; 3) establishing the ERI; 4) spatial regression analysis between ERI and urbanization. The following sections give details on each of these steps.

2.3.1 Simulation model of LUCC (SD-FLUS model)

(1) Dynamic simulation model of land use type quantity: SD Model

The SD model is an effective approach for modeling the nonlinear behavior of complex systems over time by using stocks, flows, internal feedback loops, and time delays (Coyle, 1997). This model is widely used to represent the socio-economic driving forces and complex systems (Lauf et al., 2012). Moreover, it can provide the results of land use demand projection for the FLUS model (Liu et al., 2017). The developed SD model includes population sub-model, economy sub-model, environment sub-model, and land use sub-model. This model contains 7 exogenous variables, 8 state variables, 36 auxiliary variables, and 57 mathematical equations. The SD model (Fig. 2) was carried out using the Vensim PLE 7.3.5 program. The time step of the SD model was 1 year. In addition, the SD model was parameterized using the official statistical and LUCC data from 2005 to 2015.

(2) Spatio-temporal simulation model of LUCC: FLUS Model

The FLUS model is a future land use simulation prediction model based on the improved CA principle (Liu et al, 2017). This model has the advantage of incorporated self-adaptive inertia and competition mechanism within the CA model to process the complex competitions and

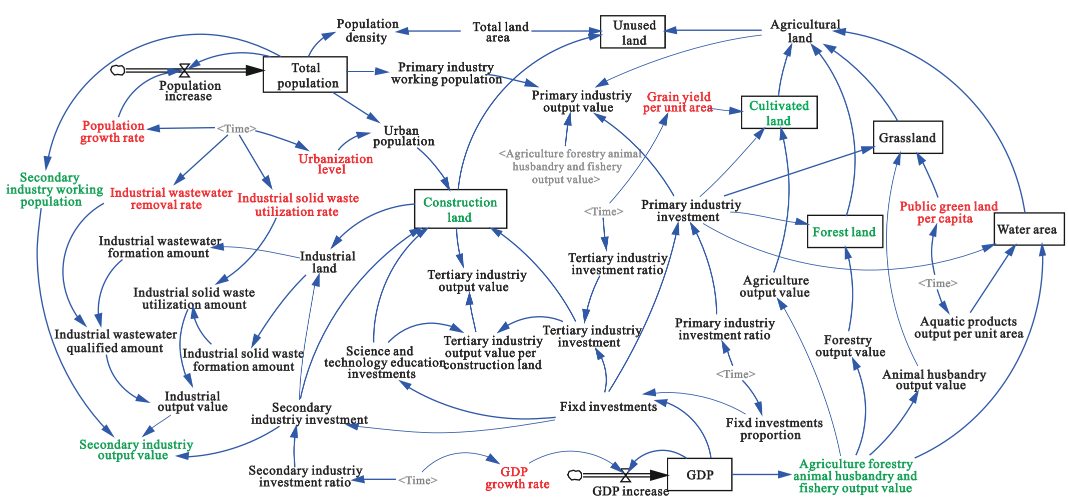

Fig. 2 Structure of the SD model. Variables in red indicated the exogenous variable of the model, which varied in different scenarios. Variables in green are arbitrarily selected indicators from the model that are used for accuracy verification

interactions among different land use types. The principle of the FLUS model is as follows. Firstly, the development suitability probability of land use types is calculated by using the data of each driving factor based on ANN. Secondly, a cellular automata module based on adaptive inertia mechanism is constructed, which is composed of development suitability probability and neighborhood factor, inertia coefficient and conversion cost. Finally, the future land use is simulated based on the adaptive inertial competition mechanism of roulette selection.

This study simulates the future land use changes under multi-scenario in the YRDUA based on the SD-FLUS model. First, the SD model was used to estimate the demand for land use under different scenarios based on socio-economic statistics and LUCC data. Second, the FLUS model was used to obtain the overall suitability conversion probability of various land use types and then the simulation results of LUCC was obtained considering various natural and human factors, such as terrain, climate, population, soil, and transportation. Third, the present and future LUCC and ecological risk patterns were simulated and analyzed on the basis of model verification.

(3) Model validation

The SD model is verified by calculating the degree of deviation between the simulated value and the true value. Six indicators (variables in green from Fig. 2) were randomly selected for model verification. According to the relation error analysis, the relation error of model was within ±5%. The result showed that the model conforms to the historical behavior and has validation (Ladevèze and Chamoin, 2011; Geng et al., 2017). The processed data of 2005, 2010, and 2015 are imported into the FLUS model, and the simulated LUCC map of 2015 was compared with the actual one, which had a calculated Kappa value of 0.886. Therefore, the parameters set by this model can express the land expansion of YRDUA. The SD-FLUS model has certain precision and can achieve the research purpose.

2.3.2 Multi-scenario setting of future LUCC

Scenario analysis has emerged over the past half-century as a methodology for analyzing deeply uncertain, long-run future sustainability pathways for complex social-ecological systems to support strategic decision-making (Kates et al., 2001; Swart et al., 2004). Scenario simulation is an effective tool for predicting the dynamic trend of land and conducting long-term sustainability evaluation (Bryan et al., 2016). In the YRDUA, a new rapid development period is going to occur soon based on the state plan for the integrated regional development of the YRD. The land use simulation is clearly necessary for future decision-making. Future development has uncertainty because different socio-economic and ecological environments have varying impacts on land use changes.

On the basis of previous researches (Xu et al., 2016a; Liu et al., 2017; Jiao et al., 2019), four development scenarios of inertial development, rapid economy development, ecological protection and coordinated development were designed, which representing different ecological environments and socio-economic development levels for 2025, respectively. The multi-scenario setting is carried out from two aspects, namely, the setting of land use quantity and the setting of land use conversion mechanism. According to the adjustment of population, economy, policy, ecological environment, and the land use area in the SD model, different scenarios are built up. In addition, neighborhood factors and land conversion costs are set for different scenarios in the FLUS model.

(1) The setting of land use quantity

Scenario A or inertial development. This Scenario is constructed to find the projected future land use trends without the impact of policy regime and other factors. Based on the development trend from 2005 to 2015, the values from 2016 to 2025 are fitted. The values of the 7 exogenous variables all change dynamically. Scenario A represents the arithmetic mean of their values (Table 1).

Scenario B or rapid economic development. In this scenario, the economic development is given priority, with the highest GDP growth rate, population growth rate, and urbanization rate. The setting of these parameters refers to the long-term goals of the Yangtze River Delta Urban Agglomeration Development Plan (2016), the ‘National Economic and Social Development Plan’ of each province, and the overall planning of major cities such as Shanghai, Nanjing, Suzhou and other cities in 2025. In addition, in order to meet the population demand, the grain yield per unit area is set as the maximum value of Scenario A, and the other three parameters remain unchanged (Table 1).

Scenario C or ecological protection. Green development and ecological environment protection are the

Table 1 Four scenarios with different variable values in SD model

Parameters	Scenario A	Scenario B	Scenario C	Scenario D
GDP growth rate/%	5.23	10.16	5.23	7.70
Population growth rate/%	4.13	7.32	4.13	5.73
Urbanization level/%	69.30	75.77	61.99	68.88
Industrial wastewater removal rate/%	97.01	87.60	100	93.80
Industrial solid waste utilization rate/%	99.05	94.91	100	97.46
Grain yield per unit area/(t/km^2)	259.445	270.49	247.36	258.37
Public green land per capita/(m^2/person)	7.38	5.28	8.55	6.91

foundation based on the plan for building a demonstration area in the YRD on ecologically friendly development. Therefore, under the condition of strictly controlling pollutant discharge, the industrial wastewater removal rate and industrial solid waste utilization rate are set to maintain 100%. And the per capita green area should be increased as far as possible, so it is set as the maximum value of Scenario A. In addition, we strictly control GDP and population growth and set them as the average of Scenario A, and the urbanization rate remains the same as the base year (Table 1).

Scenario D or coordinated development. This scenario focuses on coordinated rapid development and ecological environmental protection, and tries to protect the environment while developing, so as to take the road of sustainable development. The factors of economy and ecological protection are all taken into account. Therefore, we simulate the Scenario B and C simultaneously, and set the parameters to the average of the above scenario (Table 1).

(2) The setting of land use conversion mechanism

Different land use types have different neighborhood effects. According to the experience of existing research (Liu et al., 2017; Liang et al., 2018), the expansion capacity of land use types is defined as construction land > unused land > water area > grassland > cultivated land > forest land. According to the characteristics of multi-scenario, different neighborhood factors are set (Table 2(a)). Among them, the neighborhood factor ranges from 0 to 1. The larger the neighborhood factor,

Table 2 Neighborhood factors and land conversion costs setting

(a) Neighborhood factor parameters

Land use types	Scenario A	Scenario B	Scenario C	Scenario D
Cultivated land	0.6	0.5	0.5	0.6
Forest land	0.3	0.1	0.7	0.4
Grassland	0.4	0.3	0.5	0.4
Water area	0.5	0.4	0.6	0.5
Construction land	0.7	1	0.5	0.7
Unused land	0.6	0.6	0.6	0.6

(b) Conversion cost matrix

Land use types	Scenario A						Scenario B						Scenario C						Scenario D					
	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f
a	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	0	1	1	0	1	0	0
b	1	1	0	0	1	0	1	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0
c	0	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0
d	1	0	0	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	0
e	1	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1	0	1	0	0	0	1	0
f	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	0	0	0	0	1	1

Notes: a, b, c, d, e, and f represent cultivated land, forest land, grassland, water area, construction land, and unused land, respectively the stronger the expansion type of the land use types. The conversion cost matrix is used to indicate whether the current land use types can be converted. The four different scenarios correspond to four different land conversion cost matrices (Table 2(b)), where 0 means no conversion and 1 means can be converted.

Taking Scenario B as an example, the expansion capacity of construction land was the strongest in this scenario, and the neighborhood factor was set as 1. Affected by human demand for food, the expansion capacity of cultivated land was secondary. The expansion capacity of other land use types was assigned in the above order. In addition, in the context of green ecological integration in the YRD, water resources protection was very important. Therefore, except for the water area, all other land types were set to be converted to construction land in Scenario B.

2.3.3 ERI of LUCC

In order to describe the relationship between land use types and comprehensive regional ecological risks, the land use ERI is established. Specifically, the proportion of land use types in the study area is used to construct the ERI. Land use types are transformed into spatialized ecological risk variables through sampling methods.

To express the regional heterogeneity of land use ecological risk spatially, the study area was divided into 10 km × 10 km units (Zhang et al., 2018). The total of 2446 risk cells were generated, and the ERI was calculated in each unit. Among them, the results of ERI were assigned to the central pixel of the evaluation area. The calculation formula of the land use ERI is expressed as follows:

$$ERI = \sum_{i=1}^{m} \frac{A_i W_i}{A} \tag{1}$$

where ERI is the land use ERI, i is the land use type, m is the total number of land use types, A_i is the area of land type i in a risk community, W_i is the weight of the ecological risk intensity of land type i, and A is the total area of land use in a risk community. By combining the expert consultation methods and previous research results (Xu et al., 2016b; Zhang et al., 2018; Zhang et al., 2020b), the ecological risk intensity weights of each land use type are presented as 0.32 for cultivated land, 0.12 for forest land, 0.16 for grassland, 0.53 for water area, 0.85 for construction land, and 0.82 for unused land.

2.3.4 Regression analysis

The GWR model is an improvement of the Ordinary Least Squares (OLS) model, which allows parameters to be estimated locally (Foody, 2003; Zhang et al., 2020a). The GWR model supports the parameter estimation of the local variation between independent and dependent variables and can reflect the spatial heterogeneity of parameters, which causes the relationships between the variables to vary with location (Yang et al., 2018; Dadashpoor et al., 2019). The GWR model is expressed as follows (Fotheringham et al., 1998):

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ki} + \varepsilon_i \tag{2}$$

where y_i represents the land use ERI, i is the sample point, x_{ki} represents the socio-economic driving forces factors, u_i and v_i are the spatial coordinates of i, β_0 (u_i, v_i) is the intercept at the location k, β_k (u_i, v_i) is the local estimated coefficient of the independent variable, k is the grid cell involved in the analysis, p is the total number of grid cells, and ε_i is the error term.

In this study, we used the GWR model to analyze the spatial heterogeneity and evolution characteristics between ERI and socio-economic driving forces. The GDP and POP are the representative socio-economic factors (Li et al., 2017b; Kefalas et al., 2019). Thus, the GDP and POP were used as the explanatory variables, and the ERI was used as the dependent variable. The GWR analysis was performed using the GWR tools in ArcGIS10.4. In the GWR model, two types of kernel functions exist: the fixed and the adaptive kernels. The fixed-kernel bandwidth was selected because of the grid data used in this study, for which the density of sampling points in the space is uniform. The bandwidth methods included the Akaike information criterion (AIC) or cross-validation (CV), and the AIC approach considered the differences in the freedom degree of different models compared with the CV method. Therefore, we used the AIC method to determine the optimal bandwidth.

3 Results

3.1 Changes in land use patterns

From 2005–2015, the land use structure of the YRDUA had undergone significant spatial changes (Fig. 3). The

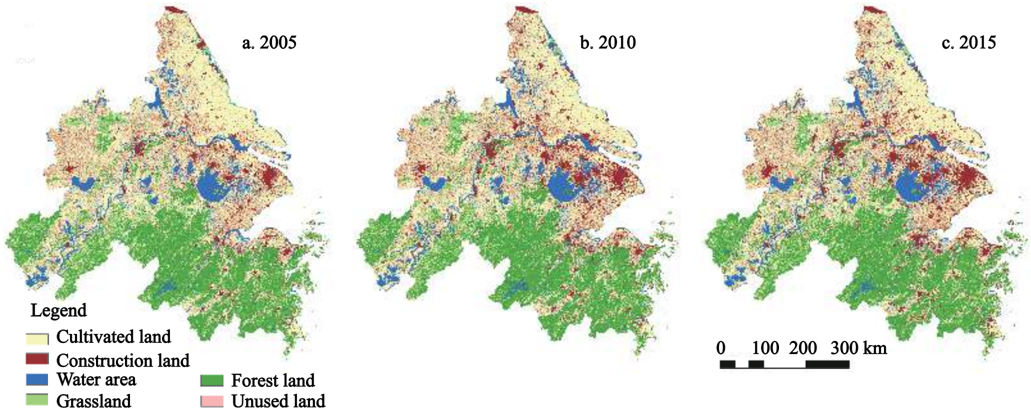

Fig. 3 Land use classification map of the Yangtze River Delta Urban Agglomeration (YRDUA) in 2005, 2010 and 2015

cities located in the lower-and-middle sections of the Yangtze River experienced the most rapid expansion of construction land. Cultivated land had the widest distribution and largest area in the YRD and showed a decreasing trend with time. The distribution of forest land was related to the terrain, and it was mainly distributed in the high-altitude areas of the southern Anhui Province and the northern Zhejiang Province. Water area was mainly concentrated in the Taihu Lake Basin. The unused land with the smallest area was mainly distributed around the YRDUA.

The land use changes in YRDUA were analyzed from two time periods of 2005–2010 and 2010–2015. The land use transfer matrix was shown in Table 3. Construction land expanded rapidly, from 18 856.23 km^2 in 2005 to 24 141.79 km^2 in 2010 to 26 526.47 km^2 in 2015, with a net increase of 7670.24 km^2 and a substantial increment of 40.68%. The increase in construction land was mostly at the expense of cultivated land. The area converted from cultivated land into other land types was 6824.02 km^2 and 3394.29 km^2, accounting for 71.72% and 65.60% of land use change areas over the two stages, respectively. This result indicated that the construction land continually occupied cultivated land, which led to the continuous decrease in cultivated land. In addition, the implementation of policies, such as 'returning farmland to forests, returning farmland to the lake' also reduced cultivated land. The total area of forest land and grassland over the two stages decreased by 392.43 km^2 and 358.24 km^2, respectively. At the same time, the total water area increased by 776.10 km^2. Overall, the main changes in the YRDUA included construction land that grew continuously and cultivated land that decreased correspondingly. Changes in other land types were relatively unobvious, and no significant difference was observed in spatial distribution.

3.2 Spatio-temporal changes of ERI pattern

To explore the spatial structure of the land use ERI in the YRDUA, we fitted the optimal model parameters according to the spherical function of the semi-variation model and used the ordinary Kriging method to calculate the ERI of every grid element in the study area in 2005, 2010 and 2015. Referring to the classification criteria in Table 4, the ecological risk distribution in the YRDUA was obtained (Fig. 4).

Fig. 4 shows that the spatial distribution pattern of ERI was extremely uneven in the YRDUA in 2005, 2010 and 2015. The ERI had evident north-south differences with the characteristics of circle diffusion. In 2005, the overall ecological risk pattern of the YRDUA presented a high situation in the central region, including Shanghai, Suzhou, Wuxi, Changzhou, and Nanjing; and a low situation in the southern region, mainly located in inter-provincial fringe cities with high altitude. The high risk region in 2010 was connected near the Taihu Lake Basin, and a new high risk region appeared in Hefei, Anhui in comparison with that in 2005. At the end of 2015, the spatial distribution of various risk regions remained stable, and only some high risk regions expanded slightly on the original basis.

The change of the ERI pattern of the YRDUA was shown in Table 5. With the continuous advancement of urbanization, the ecological risk level of the YRDUA had increased to a certain level in 2005–2015. The area of high risk region and medium-high risk region increased rapidly, from 43 157.71 km^2 to 61 427.27 km^2, and the proportion of total land area rose from 20.76%

Table 3 Transfer matrix of land use types in the Yangtze River Delta Urban Agglomeration (YRDUA) from 2005 to 2015 (km^2)

(a) Transfer matrix from 2005 to 2010

Year	Land use types	2005						
		Cultivated land	Forest land	Grassland	Water area	Construction land	Unused land	Class total area in 2010
2010	Cultivated land	101202.12	352.55	55.88	248.42	562.52	0.17	102421.66
	Forest land	363.01	56393.63	50.67	16.29	36.72	1.55	56861.87
	Grassland	35.55	83.55	6906.13	11.91	31.65	0.3	7069.09
	Water area	737.34	29.09	196.67	16002.21	277.67	0.45	17243.43
	Construction land	5627.59	262.72	92.68	246.47	17910.92	1.41	24141.79
	Unused land	60.53	33.28	60.48	1.38	36.75	29.87	222.29
	Class total area in 2005	108026.14	57154.82	7362.51	16526.68	18856.23	33.75	

(b) Transfer matrix from 2010 to 2015

Year	Land use types	2010						
		Cultivated land	Forest land	Grassland	Water area	Construction land	Unused land	Class total area in 2015
2015	Cultivated land	99027.37	345.79	43.39	227.72	517.41	10.24	100171.92
	Forest land	357.06	56274.22	71.29	20.03	38.37	1.42	56762.39
	Grassland	34.87	56.83	6895.35	12.12	5.01	0.09	7004.27
	Water area	348.35	27.32	16.41	16859.32	34.71	16.67	17302.78
	Construction land	2652.66	154.47	41.29	123.97	23545.01	9.07	26526.47
	Unused land	1.35	3.24	1.36	0.27	1.28	184.8	192.3
	Class total area in 2010	102421.66	56861.87	7069.09	17243.43	24141.79	222.29	

Table 4 Criterion of ecological risk index (ERI) classification in the Yangtze River Delta Urban Agglomeration (YRDUA)

Level	ERI	Features
Low risk region	<0.2	The ecosystem is quite stable, and its anti-risk ability is very strong
Medium-low risk region	0.2–0.3	The ecosystem is relatively stable, and its anti-risk ability is relatively strong
Medium risk region	0.3–0.4	The ecosystem is moderately stable, and its anti-risk ability is moderately strong
Medium-high risk region	0.4–0.5	The ecosystem is relatively unstable, and its anti-risk ability is relatively weak
High risk region	>0.5	The ecosystem is unstable, and its anti-risk ability is weak

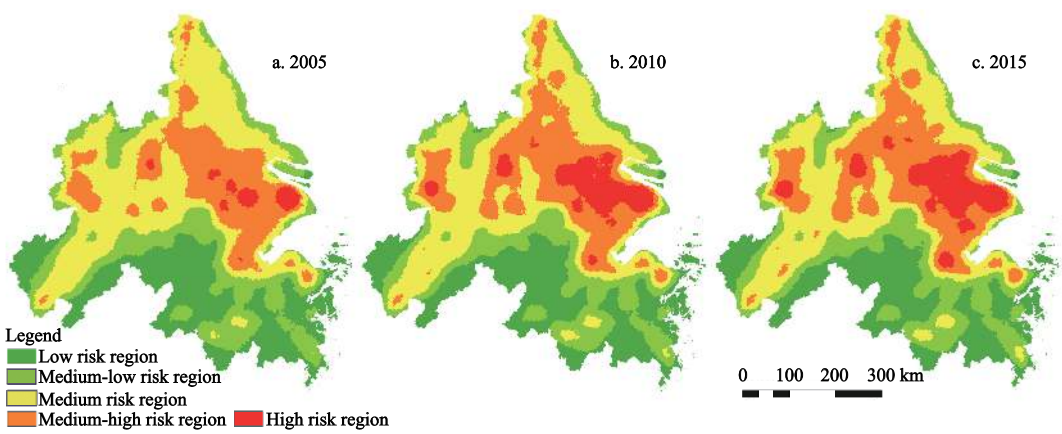

Fig. 4 Distribution of land use eclogical risk index (ERI) of the Yangtze River Delta Urban Agglomeration (YRDUA) in 2005, 2010 and 2015

Table 5 Criterion of ecological risk classification in the Yangtze River Delta Urban Agglomeration (YRDUA)

Ecological risk grade	2005		2010		2015	
	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%
Low risk region	47241.66	22.71	45335.45	21.80	43750.43	21.04
Medium-low risk region	46325.90	22.27	44446.65	21.37	43455.22	20.89
Medium risk region	71257.99	34.26	61277.57	29.46	59350.34	28.54
Medium-high risk region	39095.60	18.81	42984.29	20.67	44695.54	21.49
High risk Region	4062.11	1.95	13939.30	6.70	16731.73	8.04

to 29.53%. Among them, the growth in the high risk region was the most significant with an area increase of 12 669.62 km^2, and the proportion was four times than the original. The proportion of low risk region and medium-low risk region decreased slightly and the proportion of medium risk region dropped significantly, from 34.26% to 28.54%.

3.3 Relationship change between ERI and socio-economic driving forces

The GWR model produces adjusted R^2, coefficient, and residual of each grid, which can clearly express the fitting effect in different locations and thus identify spatial heterogeneity (Li et al., 2017b). We used the ERI values in 2005, 2010 and 2015 as the dependent variables, and the GDP and POP in the corresponding years as the independent variables when building the GWR model. The adjusted R^2 of the GWR model in 2005, 2010 and 2015 reached 0.73, 0.76 and 0.72, respectively. This result demonstrated that GDP and POP could explain most of the ecological risk situation from 2005 to 2015.

The regression coefficients of GDP and POP were counted in Table 6. It could be seen that GDP and POP had different positive and negative effects on ERI, and the proportion of positive and negative effects vary. In general, the socio-economic factors (GDP and POP) had a mostly positive correlation with the ERI. GDP and POP increased continually because of the development of social economy and the expansion of urban space, thereby resulting in the continuous increase in construction land and the gradual decrease in other land types. As a result, the ERI of land use increased, and the degree of ecological risk strengthened.

The spatial distribution of coefficients between socio-economic factors and ERI were shown in Fig. 5. It could be seen the driving forces of urbanization on ecological risk patterns changed with the variation of spatial position. From a spatial perspective, the response degree of ERI to GDP and POP was clearly high in the southwest and north of the YRDUA and relatively lower in the fringe. From 2005 to 2015, the proportion of positive correlation coefficient of GDP increased from 83.11% to 86.01% and then decreased to 83.86%. The result indicated that the positive drive of GDP increased first and then decreased, over the two stages. In comparison, the proportion of positive correlation coefficient of POP had been increasing, and the range of the impact was further enhanced. In 2010, with the increased urbanization in the YRDUA, the POP became larger, thereby causing the positive driving range of GDP and POP to gradually spread outward, and the regression coefficient in the peripheral region was higher than that of central cities. In 2015, with the balanced development of the region, the impact of GDP on ecological risk tended to be balanced. In terms of space, the positive correlation coefficient of GDP on ecological risk was more concentrated, and the proportion of grid with higher coefficients reduced. At the same time, the positive influence of POP on ERI expanded from the center to the

Table 6 Regression coefficient ratio of GDP and POP of 2005, 2010 and 2015 in the Yangtze River Delta Urban Agglomeration (YRDUA)

Regression coefficients	2005		2010		2015	
	GDP/%	POP/%	GDP/%	POP/%	GDP/%	POP/%
Positive regression coefficients ratio	83.11	83.96	86.01	84.68	83.86	87.90
Negative regression coefficientratio	16.89	16.04	13.99	15.32	16.14	12.10

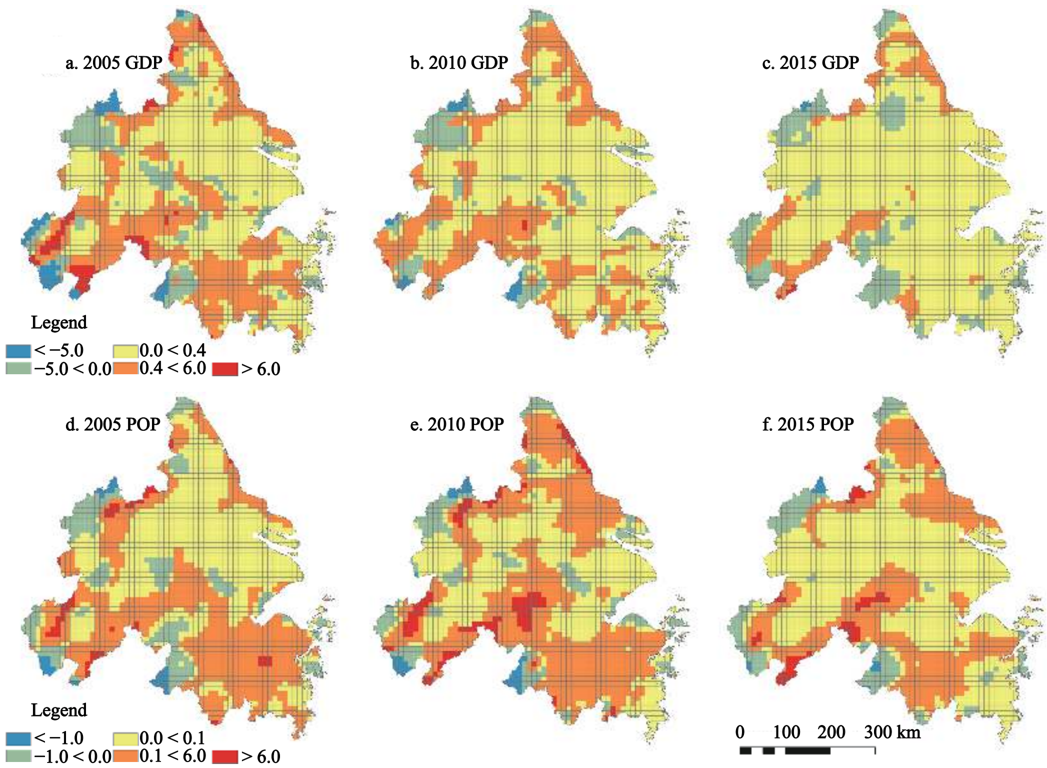

Fig. 5 Spatial patterns of correlation coefficients between ERI and socio-economic driving forces: GDP and POP in 2005, 2010 and 2015 in the Yangtze River Delta Urban Agglomeration (YRDUA)

edge. Especially, with the increased urbanization in Nanjing, Suzhou and Jiaxing, the POP impact on ERI changed from a negative driving force to a positive one. In general, urbanization had a positive impact on the land use ERI in the YRDUA, and the impact of POP on ecological risk was more significant than that of GDP.

3.4 Future change in LUCC under multi-scenario

The simulation results of the land use pattern in the YRDUA in 2025 under four scenarios were shown in Fig. 6. The construction land was increased by 5.76%, 7.41%, 5.25% and 6.06%, respectively. The expansion of construction land was mainly concentrated in Shanghai, Suzhou, Wuxi, Changzhou, Nanjing and Hefei. At the same time, the expansion of construction land had reduced cultivated land. Both forest land and grassland were in a slightly decreasing trend. The water area modestly increased and maintained at around 0.05% under the four scenarios. The unused land changed slightly.

In Scenario A, given the same development trend used in the simulation, the basic pattern of land use in 2025 is consistent with that in 2015. The cultivated land is still the main type of land use in the YRDUA, accounting for 46.29%, and most transferred cultivated land is converted to construction land, which accounts for 15.18%. In Scenario B, the rapid development of the social economy has led to an increase for construction land. The expansion rate of construction land has accelerated, accounting for 16.83%. In Scenario C, ecology and greenness are the prerequisites for development. The development of cultivated land and grassland is protected, accounting for 46.29% and 3.39%, respectively. The expansion rate of construction land is decreased, accounting for 14.67%, which is 0.51% and 2.16% lower than Scenarios A and B, respectively. In Scenario D, the cultivated land accounts for 45.58% which can meet the basic requirement of human beings, and the pattern of cultivated land is similar to the spatial distribution of Scenario A (45.91%). The area of forest land and unused land remain stable, and the proportion of grassland is also consistent with Scenarios A and B. In addition, the proportion of water area is consistent with Scenarios B and C. Construction land has a relatively reasonable expansion, and the area ratio (15.48%) is between the three aforementioned scenarios.

3.5 Multi-scenario simulation of ERI pattern

The land use simulation results in 2025 vary under the

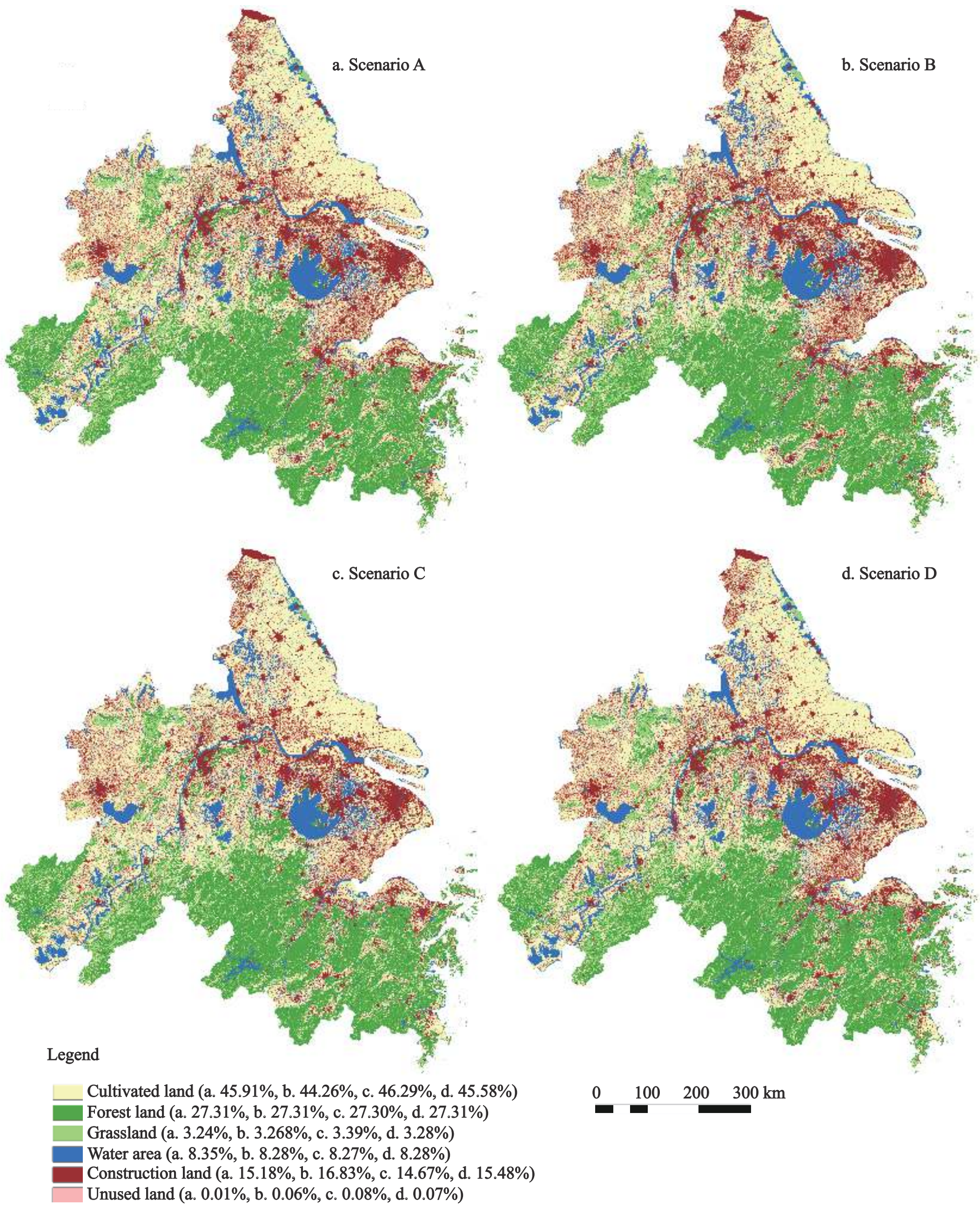

Fig. 6 Simulated LUCC map of 2025 under four scenarios in the Yangtze River Delta Urban Agglomeration (YRDUA)

four different development scenarios, thereby causing major changes in the ERI pattern. According to the classification method (Table 4), the simulated land use ecological risk map of 2025 under different development scenarios are obtained (Fig. 7).

In terms of spatial layout, the degree of land use ecological risk differs significantly under various development scenarios. Scenario A continues the trend of 2015, and only the high risk region has changed significantly. Compared with that in 2015, the high risk region in Scenario A continues to spread outward from cities near the Taihu Lake, which connects Yangzhou and Zhenjiang forming a whole high risk region. The medium-high risk region distributed around the high risk region continually expands outward, which in turn leads to a reduction of medium risk region. The low risk region and medium-low risk region decrease slightly. Scenario B takes the rapid economic development as a demand, thereby resulting in a significant increase and a wide coverage in the high risk region. The ecological risk level is positively correlated with the social economy. The more economically developed a region is, the great-

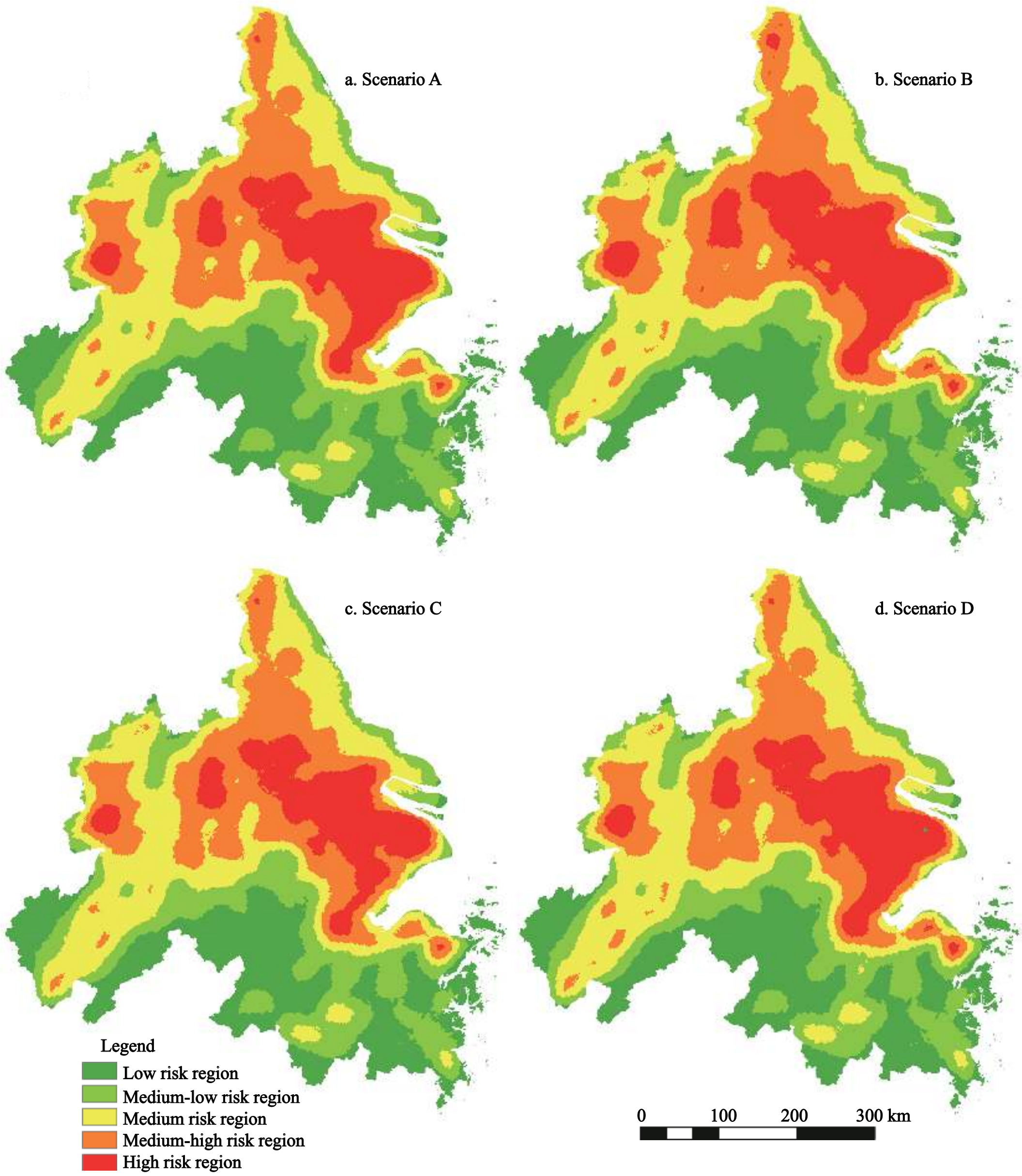

Fig. 7 Simulated land use ecological risk map of 2025 under different development scenarios in the Yangtze River Delta Urban Agglomeration (YRDUA)

er the ERI will be. In Scenario C, the low risk region has increased and concentrated in the marginal area of the YRDUA. The high risk region has the smallest outward expansion among all the scenarios, whereas other types of ecological risks have also changed slightly. Scenario D considers the coordination of economic and ecological development, and its ecological risk level is in the middle of all scenarios. In addition, a low risk region with a small area first appeared in Shanghai.

In terms of quantitative trends, Table 7 and Fig. 8 show the area ratios of different grades of the land use ecological risks in 2025 under four scenarios. From 2005 to 2015, the low risk region, medium-low risk region, and medium risk region are in a downward trend, while medium-high risk region and high risk region are increasing. Regardless of whether it is decreasing or increasing, the slope of the change is gradually decreasing. After joining the multi-scenario development, the medium-low risk region and the medium risk region are consistent with the past trends and continued to decline. The area decreases the least in Scenario C, which is 1329.48 km^2 and 6775.32 km^2, respectively, and declines the most in Scenario B, which is 2294.42 km^2 and 12 94.23 km^2, respectively. With the rapid development

Table 7 Area ratio of different grade of land use ecological risk of the Yangtze River Delta Urban Agglomeration (YRDUA) in 2025

Ecological risk grade	Scenario A		Scenario B		Scenario C		Scenario D	
	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%
Low risk region	44289.97	21.30	43295.44	20.82	44470.52	21.38	43614.83	20.97
Medium-low risk region	41685.46	20.04	40505.80	19.48	42125.74	20.25	41395.40	19.90
Medium risk region	50978.48	24.51	47256.11	22.72	52575.02	25.28	51063.57	24.55
Medium-high risk region	44597.23	21.44	45596.34	21.92	44084.37	21.20	45002.79	21.64
High risk region	26432.12	12.71	31329.57	15.06	24727.61	11.89	26906.67	12.94

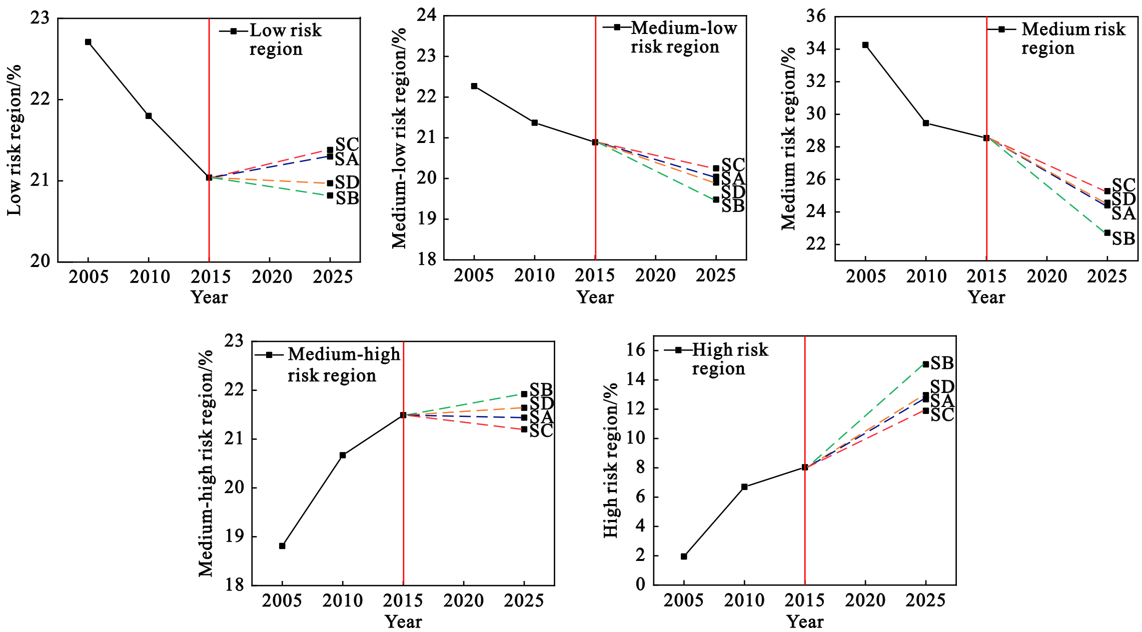

Fig. 8 Simulated land use ecological risk map of 2025 under different development scenarios in the Yangtze River Delta Urban Agglomeration (YRDUA). SA, SB, SC and SD represent Scenario A, Scenario B, Scenario C and Scenario D, respectively

of social economy and the acceleration of urbanization, the high risk region continues to increase. It has the highest proportion under Scenario B, accounting for 15.06% with an increase of 7.02% over 2015. And it has the lowest proportion under Scenario C, accounting for 11.89% with an increase of 3.85% over 2015. Besides, Scenario D is basically consistent with the low risk region and medium-high risk region in 2015, which accounting for 20.97% and 21.64%, respectively. The other ecological risk regions under Scenario D are in the middle of the four scenarios.

4 Discussion

4.1 Comparison of urbanization impact on ERI

In the process of rapid urbanization, land use change directly leads to different land use structure of risk communities, which affects the entire ERI. In this study, POP and GDP are used to represent urbanization, and their explanatory ability and degree of influence are different. In general, the impact of POP on ecological risk is more significant than that of GDP. As we know, urban development in China is driven by population growth. The size of the population reflects the intensity of human activities and interference directly. The population size directly affects the area of urban construction land, which in turn affects the ERI. Highly correlated with population density, GDP can indirectly affect ecological risk patterns. The result is essentially the same as the others in previously published research (Li et al., 2017b).

In the middle part of the YRDUA, GDP and POP have a positive impact on the ERI. Especially in the high risk region, GDP and POP account for a high proportion that increases along with time. With the development of GDP and POP, people's living demand for construction land is also increasing. Construction land constantly occupies cultivated land. At the same time, the demand of population grain makes the cultivated land expand to forest land and grassland, which lead to the increase of ERI and the expansion of high ecological risk region. Whether the future land use layout is reasonable or not, it is directly related to the ecological risk pattern of the region.

4.2 Simulation model and scenario setting

LUCC is influenced by many factors, including natural, social and economic variables (Jiao et al., 2019). The quantity and spatial pattern of land use types are necessary for LUCC simulation. Most previous studies use mathematical or statistical methods (e.g., Markov chain) to predict LUCC magnitudes (Arsanjani et al., 2013; Han et al., 2015), but it has been proved that these model could not demonstrate the effects of various socio-economic factors on LUCC, which resulting misestimating the LUCC magnitudes (Xu et al., 2016a). For example, according to the Markov model simulation (Table 8), the magnitude of water will increase considerably comparing with the actual area in 2015. Obviously, it is not in compliance with the fact. In addition, Table 8 shows that the simulated results of the SD model has lower error rates than the Markov model, and the simulated error rates are less than 1.0% in absolute value. The SD model obtains a result closer to the actual amount because it includes comprehensive factors, including social, economic, policy and planning factors. The FLUS model can simulate the land use dynamics in a more realistic manner due to the use of the self-adaptive inertia and competition mechanism (Liu et al., 2017). So, we integrates the SD model and FLUS model to simulate LUCC, the kappa value of simulation results is 0.886 and the overall accuracy is 0.924. Based on the above research, the SD-FLUS model can be applied to simulate the spatial and quantitative dynamics of urban expansion in the YRDUA.

In order to depict different development strategies, we design four scenarios, which considering socio-economic developments and ecological protection. The multi-scenario setting includes the setting of exogenous variables in the SD model, and the setting of development adaptability probability, neighborhood factor and land conversion cost in the FLUS model. In the SD model, we select seven socio-economic and ecological environment variables in the subsystem. The variable data are all from the statistical yearbook, and the model has passed the accuracy verification. In the FLUS model, twelve natural geography and socio-economic factors are selected to calculate the development suitability probability based on the ANN model, and then neighborhood factors and land conversion costs are set for different scenarios according to planning constraints and environmental constraints. In future research, the LUCC simulation model will be improved by adding big data and artificial intelligence algorithms. In terms of data, the data directly representing human activities (such as mobile phone signaling, social media, transportation, *etc.*) are incorporated into simulation model.

4.3 Analysis of LUCC impact on ecological risk pattern under multi-scenario simulation

The ecological risk pattern and its changes reflect the comprehensive impact of nature, human factors, and ecological processes on the ecosystem to a certain extent (Depietri, 2020). Under the four development scenarios, urban construction land always tends to expand outward. Especially under Scenario B, the construction land expands with the fastest rate, and the proportion of high risk regions has increased from 8.04% in 2015 to

Table 8 Comparison of the simulation results between SD and Markov model

Land use types	Actual area/km^2	SD model		Markov model	
		Simulated area/km^2	Relative error/%	Simulated value/km^2	Relative error/%
Cultivated land	99503.37	98677.10	–0.83	96617.24	–2.90
Forest land	56619.2	56558.80	–0.11	56418.56	–0.35
Grassland	7055.96	7005.47	–0.72	6851.87	–2.89
Water area	17434.28	17540.7	0.61	18105.47	3.84
Construction land	27175.66	27429.7	0.93	29591.32	8.89

15.06% in 2025. In Scenario A, cultivated land and water area have become the most protected land use type. In Scenario C, the cultivated land and grassland decrease the least. Moreover, the low-speed expansion of construction land directly forms the best ecological risk pattern. However, this goal is difficult to achieve because of various social needs. In contrast, Scenario D coordinates the rapid economy and the ecological environment and relieves the pressure on the ecological environment caused by the expansion of construction land. The high risk regions under this scenario accounted for only 12.94%.

By comparing the four development scenarios set, we find that Scenario D is more in line with urban development needs and current national policies and guidelines. The GDP development target and population growth rate under Scenario D can not only meet the needs of rapid urbanization in the region, but also have less impact on the environment to a certain extent. However, under this scenario, the high risk regions in YRDUA significantly increase and show a flaky distribution, spreading from the development belt along the river to the interior. Among them, the high risk regions have been distributed in patches in Shanghai and Suzhou-Wuxi-Changzhou metropolitan areas, while the Nanjing metropolitan area has not yet been connected. It is not difficult to find that even under the coordinated development scenario, urbanization expansion occupies other land types, which is bound to increase ecological risks in the region. For the Shanghai metropolitan area and the Suzhou-Wuxi-Changzhou metropolitan area experiencing economy developed earlier, focusing on the ecological transformation after rapid urbanization is crucial. While for the current development of Nanjing metropolitan area, it is necessary to learn from previous experience to develop unused land efficiently and improve the efficiency of land intensive use under the principle of not destroying useful arable land and ecological land. This will help reduce ecological risk and play an early warning role, avoiding the path of first destruction and then protection.

In short, due to the different development backgrounds and objectives, policy makers need to weigh the relationship between economic development and ecological protection in urban and regional development planning. They should not only plan overall development, but also formulate scientific strategies according to local conditions. In view of the current impact of LUCC on the ecological risk pattern, the future development strategy of the YRDUA can be guided by differentiated policies from the perspective of regional coordination, such as implementing strict ecological protection strategies, formulating rationalized economic and social development goals and giving priority to economic development in underdeveloped areas.

5 Conclusions

This paper mainly studies the LUCC simulation based on SD-FLUS model under multi-scenario in the YRDUA and its impact on urban ecological risk patterns.

(1) The greatest impact on LUCC from urbanization was construction land expansion (7670.24 km^2) and cultivated land degradation (7854.22 km^2) during 2005–2015. The ecological risk pattern of land use varies from north to south, showing apparent circle diffusion characteristics. The ERI generally showed an upward trend, which was due to urbanization intensified the development of construction land.

(2) Socio-economic and human activities had changed the ecological risk pattern in the YRDUA because of rapid urbanization. The relationship between socio-economic driving factors and ecological risk patterns had significant spatial heterogeneity. GDP and POP had a positive effect on the ERI during 2005–2015, and the impact of POP gradually exceeded GDP.

(3) Construction land and ERI increased in various degrees under different scenarios. In Scenario B, construction land expanded the fastest (16.83%), and high ecological risk accounted for the highest proportion (15.06%). In Scenario C, the ecological risk pattern was the best, with the high risk region accounting for 11.89%. In Scenario D, the construction land (32 94.50 km^2) expanded moderately, and the high risk region accounted for 12.94%. Considering the needs of rapid economic and ecological protection, the structure of land use and ecological risk pattern under Scenario D was the best, which could be recommended for the coming decade.

The SD-FLUS model is highly effective in representing the impacts of natural and socio-economic factors, and it can be used for LUCC simulation with high precision. The evaluation of urban ecological risk from the perspective of the spatio-temporal dynamics of LUCC can provide a practical way to describe its ecological risk pattern. In addition, the multi-scenario simulation of land use and its ecological risk is helpful for decision-makers to make reasonable development strategies.

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