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Scenario simulation and landscape pattern dynamic changes of land use in mining area

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ABSTRACT

In this study, we selected 11 townships with severe ground subsidence located in Weishan County as the study area. Based on the interpretation data of Landsat images, the Binary logistic regression model was used to explore the relationship between land use change and the related 7 driving factors at a scale of 60m × 60m. Using the CLUE-S model, combined with Markov model, the simulation of land use under three scenarios—namely, natural development scenario, ecological protection scenario and farmland protection scenario—were explored. Firstly, using land use map in 2005 as input data, we predicted the land use spatial distribution pattern in 2016. By comparing the actual land use map in 2016 with the simulated map of land use pattern in 2016, the prediction accuracy was evaluated based on the Kappa index. Then, after validation, the distribution of land use pattern in 2025 under the three scenarios was simulated. The results showed the following: (1) The driving factors had satisfactory explanatory power for land use changes. The Kappa index was 0.82, which indicated good simulation accuracy of the CLUE-S model. (2) Under the three scenarios, the area of other agricultural land and water body showed an increasing trend; while the area of farmland, urban and rural construction land, subsided land with water accumulation, and tidal wetland showed a decreasing trend, and the area of urban and rural construction land and tidal wetland decreased the fastest. (3) Under the ecological protection scenario, the farmland decreased faster than the other two scenarios, and most of the farmland was converted to ecological land such as garden land and water body. Under the farmland protection scenario, the area of tidal wetland decreased the fastest, followed by urban and rural construction land. We anticipate that our study results will provide useful information for decision-makers and planners to take appropriate land management measures in the mining area.

Introduction

With global environmental changes and deepening research of sustainable development, the study of Land Use/Land Cover Change (LUCC) has attracted more and more attention of the researchers worldwide. The focus of research has also gradually shifted from large scale at territory or regional scale to ecologically fragile areas such as wetland^{1,2}, river basin³⁻⁶ and mining area^{7,8}.

The landscape of mining area is featured mainly by mining and other human production activities. While extensive coal mining boosts regional economy, it also brings significant environmental changes such as severe ground subsidence, land resource destruction, water resource pollution, etc., and often exacerbates the ecosystem fragility in mining area. Land rehabilitation, implying the reclamation of post-mining land subsidence, has complicated intertwined impacts, directly or indirectly, on the structure, composition and function of ecosystem in mining area. The driving force analysis can reveal the evolution law and driving mechanism of regional land use change^{5,9,10}. On this basis, scenario simulation predicts the future trend of land use change¹¹⁻¹³. Scenario simulation results not only provide theoretical foundation for the local government to formulate scientific, plausible and sustainable land use development strategies, but also have great significance for the protection of land resources and the improvement of regional ecological environment.

The research results of domestic and foreign scholars on scenario simulation models of land use showed that single model cannot satisfy both quantitative simulation and spatial pattern analysis simultaneously. Therefore, scenario simulation is gradually changing from using single model to multiple integrated models¹⁴⁻²⁶. Previous studies have suggested that logistic regression model can better reveal the main driving forces and interaction mechanisms of landscape pattern evolution^{11,26-29}. Binary logistic regression model (BLRM) is good for binary dependent variables, while multinomial logistic regression model is more suitable for multivariate dependent variables. Logistic regression model is often used for driving factors analysis of land use change in ecologically fragile areas such as reservoir area^{11,26}, mountainous area²⁹, etc. And it is also mainly used for driving factors analysis of urban landscape pattern evolution^{27,28}. Based on the results of logistic regression analysis, scenario simulation is often carried out. Using the Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model, we can take into account both natural and socio-economic factors, preset multiple scenarios and visualize spatial patterns of land use under different scenarios³⁰⁻³⁶.

In this study, mining area with severe ground subsidence problems was selected as the study area. We used BLRM to analyze the driving forces of land use and landscape pattern evolution in mining area. On this basis, we selected the CLUE-S model and Markov model to simulate and predict the spatial characteristics of land use patterns under different scenarios in the future. We anticipate that our study results will provide theoretical foundation for the optimal allocation and sustainable utilization of land resources in the mining area.

Study Area

Weishan county($34^{\circ}27'N$ to $35^{\circ}20'N$, $116^{\circ}34'E$ to $117^{\circ}24'E$), is located in the southern part of Jining City, Shandong Province. The study area is 120 km long from north to south, 8-30 km wide from west to east. Nansi Lake, the largest freshwater lake in northern China, is located within the study area. Weishan county comprises 3 sub-districts, 10 towns, 2 townships and 1 economic development zone (2014 administrative division), with a total area of 1779.8 km^2 . We selected 11 townships with a total area of 1176.86 km^2 , because this study area has more mines, more severe land subsidence, and is spatially coherent. The geographical location of the study area and the distribution of mining area are shown in Figure 1.

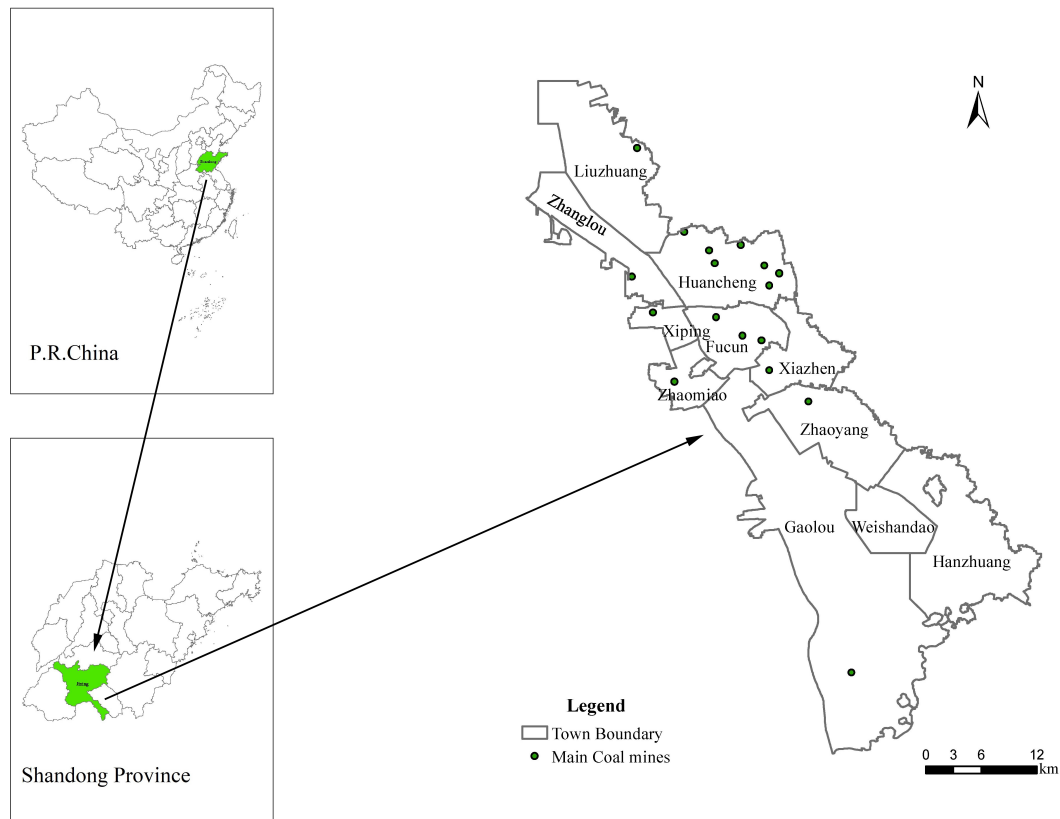


Figure 1. Geographical location and mining area distribution in the research area.

Data and Methods

Data source

Considering factors such as amount of cloud and time intervals of image, four remote sensing images with a spatial resolution of 30 m, including Landsat 5 Thematic Mapper (TM) images for 08-21-2000, 09-04-2005 and 09-18-2010, and Landsat 8 Operational Land Imager (OLI) for 09-02-2016, were obtained from the Geospatial Data Cloud Platform (<http://www.gscloud.cn>). In addition, the digital elevation model (DEM) with a spatial resolution of 30 m was obtained from the website, and the slope classification map was generated based on the DEM data. Other supporting data, such as Weishan County land use data, mine distribution data, general land use planing (2006-2020) and mineral resources planning (2008-2015), Jining City coal mining subsidence land rearrangement planning (2016-2030), were obtained from Weishan Natural Resources and Planning Bureau.

Considering severe ground subsidence and seep in the study area, and referring to national standards: *Current Land Use Classification* (GB/T 21010-2017), remote sensing images were interpreted into six land use types: farmland, other

agricultural land, urban and rural construction land, subsided seep area, water area, and tidal wetland. In the process of image interpretation, we used support vector machine (SVM) classification, manual visual interpretation and decision tree classification, hierarchical classification combined with many exponential models, to obtain the 2000, 2005, 2010, 2016 land use type maps (Figure 2). The accuracy of the interpretation results was verified by confusion matrix and kappa coefficient. The kappa coefficients of the four interpretation maps were 0.84, 0.85, 0.82 and 0.86, respectively. The accuracy could meet the needs of further research.

The interpreted land use maps with a resolution of $30\text{m} \times 30\text{m}$ exceed the upper limit of the CLUE-S model data, so the land use maps were resampled to multiple resolution scales including 60 m, 90 m, 120 m, and 150 m to facilitate logistic regression analysis of land use types and driving factors.

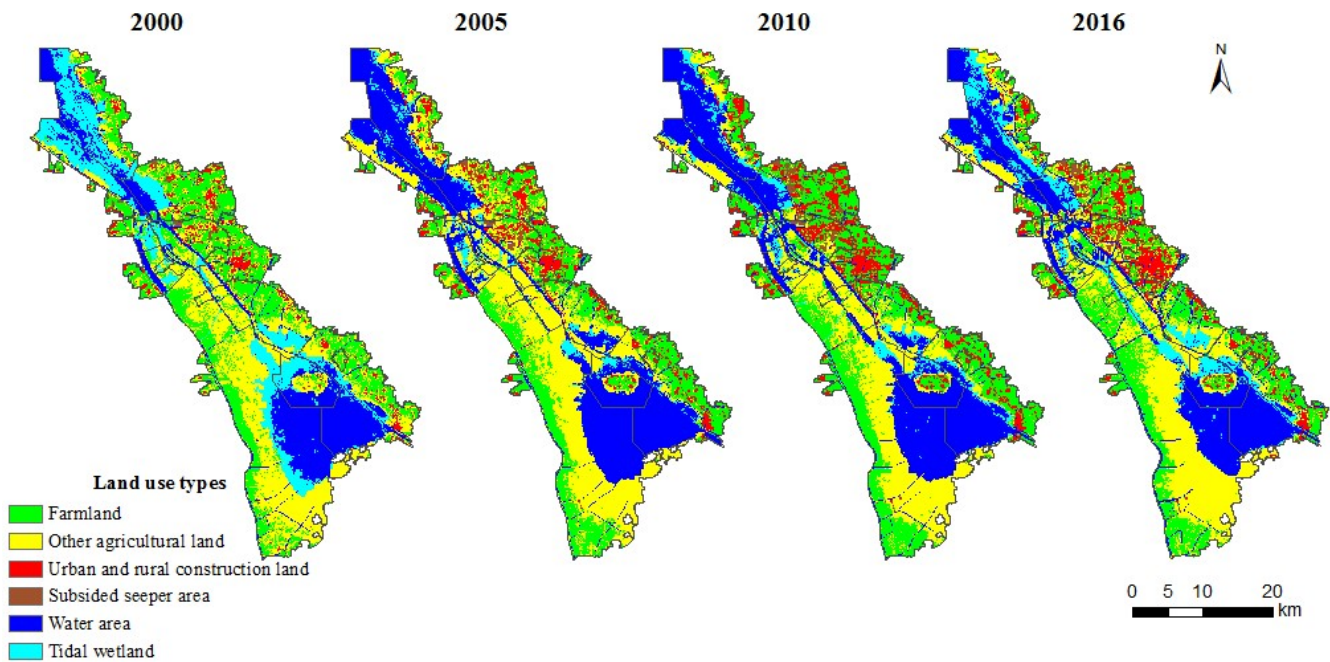


Figure 2. The land use maps of 2000, 2005, 2010 and 2016.

Selection and Processing of Driving Factors

To interpret the relationship between the land use and its driving factors in the mining area, we not only need to identify the driving factors that have greater explanatory power for land use change, but also need to quantitatively describe the relationship between driving factors and land use types.

Considering the accessibility, usability of the data and the actual conditions in the study area, seven driving factors were selected based on the land use map of Weishan County in 2005 and the digital elevation model (DEM) with a spatial resolution of 30 m. The driving factors included: (1) terrain factors, including elevation and slope factors; (2) five accessibility factors, including the nearest distance between each grid pixel and the main roads, the major rivers, the residential area, the major mines, and the ditches. The 30 m grid data of each driving factor were resampled to 60 m, 90 m, 120 m and 150 m respectively.

In this study, the BLRM was used to explore the relationship between land use change and the related 7 driving factors. The receiver operating characteristic (ROC) curve was used to evaluate the accuracy of regression analysis results at different scales. The results showed that using 60 m scale provided more accurate regression analysis results and suffered less loss of land use and driving factor information during resampling. Therefore, we used $60\text{ m} \times 60\text{ m}$ grid cell data to driving forces analysis.

Raster maps of each driving factor at a resolution scale of 60 m are shown in Figure 3.

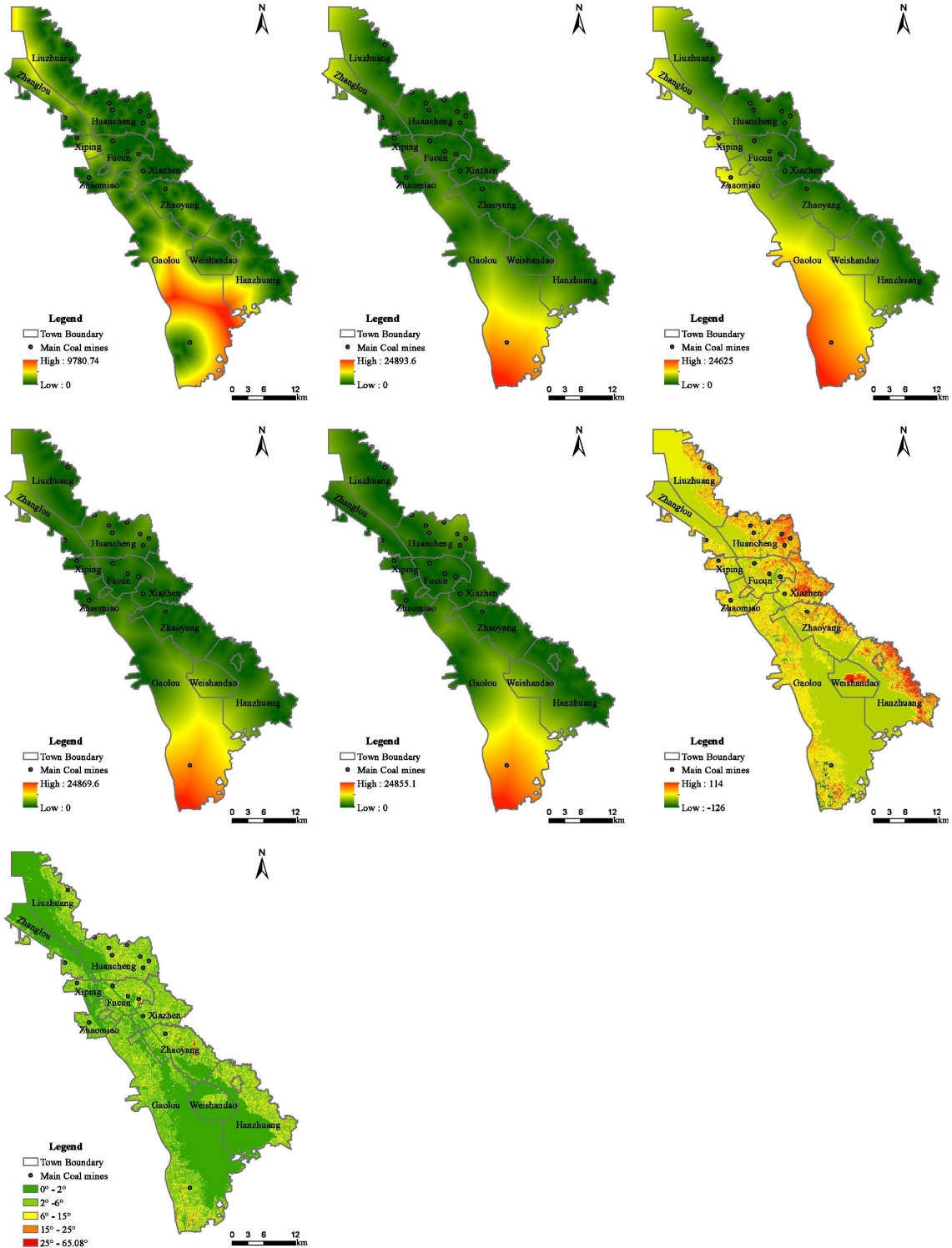


Figure 3. (a) The nearest distance to the residential area; (b) The nearest distance to the major mines; (c) The nearest distance to the main roads; (d) The nearest distance to the major rivers; (e) The nearest distance to the ditches; (f) Elevation; (g) Slope.

Logistic Regression Analysis of Land Use Types and Driving Factors

BLRM is often used for regression analysis of explanatory binary variables. The presence and absence of a certain type of land use in a specific area is set as 1 and 0, respectively, which is characteristic for binary variable. Therefore, we used BLRM to

82 calculate the probability (P) of various land use types in a specific spatial location, and its mathematical expression is:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X \quad (1)$$

83 Where $\frac{P}{1-P}$ is the 'odds ratio' of an event, abbreviated as Ω , which represents the odds that an outcome will occur given a
84 particular condition compared to the odds of the outcome occurring in the absence of that condition; β_0 is a constant; β_1 is the
85 correlation coefficient of an explaining variable and an explained variable. Making mathematical transformation of the above
86 formula, we get: $\Omega = \left(\frac{P}{1-P}\right) = e^{\beta_0 + \beta_1 X}$.

87 Regression analysis using BLRM, we divided the study area into many grid cells. Taking each land use type as the explained
88 variable, and the driving factor causing land use change as the explanatory variable, we calculated the odds ratio of each land
89 use type in a specific spatial location, and analyzed the relationship between each land use type and the driving factors. The
90 calculating formula is:

$$\text{Logit}P = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \quad (2)$$

91 Making mathematical transformation of the above formula, we get:

$$P_i = \frac{e^{(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i})}}{1 + e^{(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i})}} \quad (3)$$

92 Where: P_i is the probability of a certain land use type i in a grid cell, $X_{1,i} \sim X_{n,i}$ are the driving factors of land use type i , β_0
93 is the constant, $\beta_n \sim \beta_n$ are the correlation coefficients of each driving factor and land use type i .

94 The relationship between each land use type and the driving factors was obtained using BLRM^{11,29}. The β coefficients
95 (listed in Table 1), derived from the logistic regression equation, were used as input parameters for the CLUE-S model. Table 1
96 shows that the distance to residential area was the main driving factor for the change of urban and rural construction land, and
97 there was obvious negative correlation between them, which suggested the probability of construction land occurrence was
98 relatively less in areas far away from the residential area. There was a significant negative correlation between subsided seep
99 area and the distance from mines, main rivers, and roads, suggesting that the probability of subsidence water area occurrence
100 increased around mines, rivers and main roads. The distance to river was a negative explanatory variable for other agricultural
101 land, suggesting that areas far away from major rivers would show smaller probability of other agricultural land. In particular,
102 aquaculture land is one of the land use types of other agricultural land, aquaculture land area would drop significantly as the
103 distance to river increased. The distances to major ditches and roads were significant negative explanatory variables for water
104 area and tidal wetland.

Explanatory variable	Farmland	Other agricultural land	Urban and rural construction land	Subsided seep area	Water area	Tidal wetland
The distance to residential area	-0.974	0.136	-3.282	1.197	1.564	0.562
The distance to mines	-	0.316	-1.112	-5.813	-0.419	1.274
The distance to roads	0.894	-0.101	-0.216	-0.833	-1.221	-0.603
The distance to rivers	-1.769	-0.738	-	-1.562	3.396	-
The distance to ditches	1.588	0.655	0.207	0.481	-3.337	-2.287
Elevation	-0.19	0.045	0.044	0.571	0.214	0.225
Slope	-0.136	0.104	-0.057	-	0.051	0.275
Constant	-0.009	-1.284	-5.483	-8.94	-1.779	-4.237

Table 1. Regression coefficient (β) of each land use type and driving factors.

105 The receiver operating characteristic (ROC) was used to evaluate the accuracy of regression analysis results. As shown in
106 Figure 4, except for other agricultural land, the values of ROC of other land use types were above 0.70, which suggested the

selected driving factors could better simulate the spatial pattern of land use. The probability distribution of the simulated land use types was consistent with that of the actual land use types.

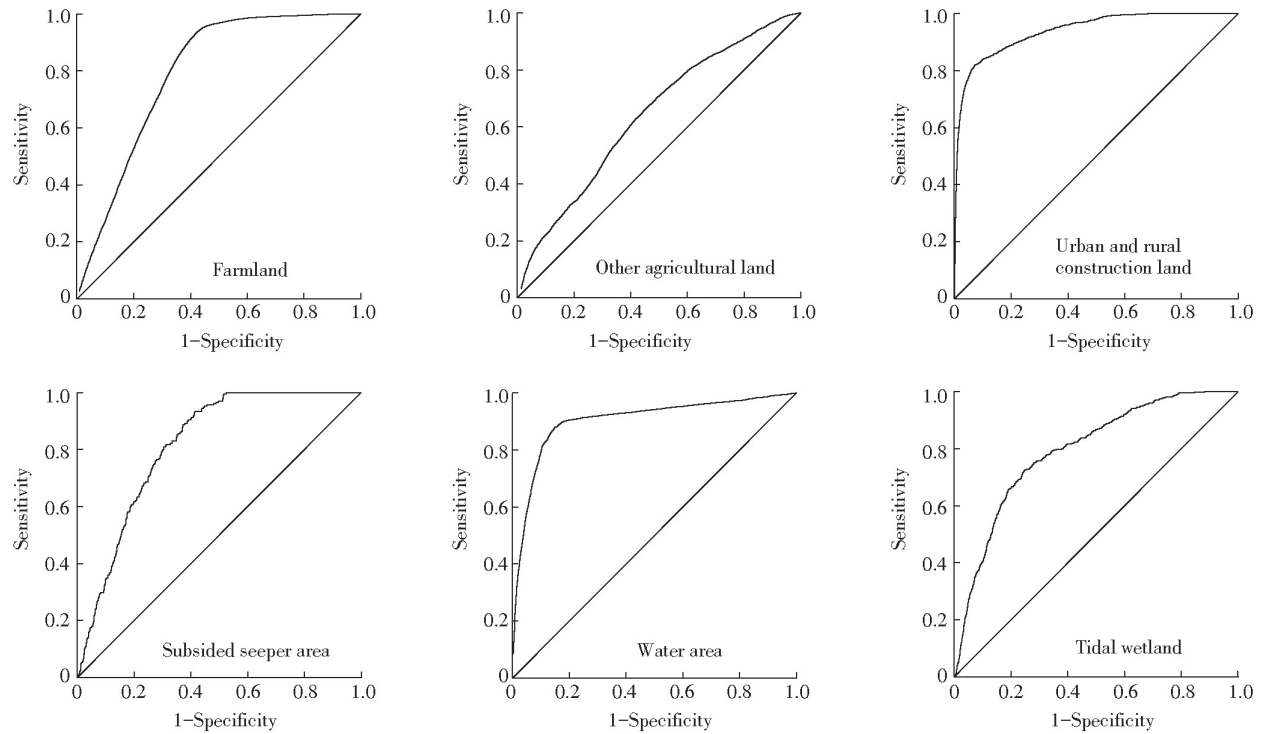


Figure 4. ROC curves for regression analysis of land use type and driver factors.

CLUE-S simulation and accuracy validation

Before using the CLUE-S model for scenario simulation, the prediction accuracy needs to be verified. Based on the data of land use pattern in 2005, the map of land use types in 2016 was predicted. The modeling accuracy was evaluated based on the Kappa index by comparing the actual land use map in 2016 with the simulated in 2016. On the basis of the accuracy verification of the model, the spatial distribution of land use in 2025 under different scenarios was simulated and predicted.

The Kappa index was 0.829, which indicated satisfactory accuracy and suggested that the model could be used to simulate the land use change in the future under different scenarios.

Scenario setting of future land use simulation

Due to the continuous population growth and mineral exploitation in the study area, the land resources, especially farmland resources, have become increasingly scarce and the environment has been deteriorating. Based on the simulation and validated results during 2005-2016, we defined three scenarios—namely natural development scenario, ecological protection scenario, and farmland protection scenario—to predict land use spatial patterns for 2025.

(1) Natural development scenario

In this scenario, the land use demand of the study area was basically not restricted by policies in near future. We assumed that the change rate of each land use type in the near future was consistent with the change trend from 2005 to 2016. Using Markov model to obtain the area transition probability matrix of each year from 2017 to 2025, and taking the proportion of each land use type area in the total study area in 2005 as the initial state matrix, the area of each land use type in 2025 under the natural development scenario was predicted.

Based on the characteristics and trend of the land use change from 2005 to 2016, after appropriately adjusting the transition probability matrix of different land use types, we predicted the demands of each land use type in 2025 under ecological protection scenario and farmland protection scenario using Markov model^{37,38}.

(2) Ecological protection scenario

This scenario emphasizes protecting the ecological environment, restricting the conversion of the land use types that have more regulatory effects on the ecosystem, such as tidal wetland and water area, to other land use types. Garden land, woodland,

grassland, and aquaculture land, belong to other agricultural land, which have regulatory effects on the local ecosystem, so their conversion to other land use types should be restricted as well.

(3) Farmland protection scenario

According to the guidelines of “the general land use planning in Weishan County (2006-2020)”, we should maximize the potential use of current construction land, implement intensive and economical utilization of construction land, and use less or not use farmland to economical construction, so as to ensure the dynamic balance of total farmland amount and the regional food supply security. Therefore, in the farmland protection scenario, the conversion from farmland to other land use types should be restricted. The projected land use demands for 2025 under the three different scenarios are shown in Table 2.

Table 2. Areas of land use types in 2025 under different scenarios (hm^2)

Scenarios	Land use types					
	Farmland	Other agricultural land	Urban and rural construction land	Subsided seep area	Water area	Tidal wetland
Natural development scenario	25907.39	41817.72	6642.7	1119.64	39199.37	2995.01
Ecological protection scenario	24535.92	42839.93	6385.32	1020.68	39362.02	3537.96
Farmland protection scenario	28074.34	40163.25	6449.67	1099.93	38918.11	2976.55

Results

Prediction of spatial distribution of future land use under different scenarios

The demands of each land use type under three different scenarios were input into the CLUE-S model. Meanwhile, according to the land use change in the study area from 2000 to 2016, the conversion elasticity values of each land use type in the future land use scenario simulation were preliminarily determined. During the simulation, by comparing the simulation results with the set scenarios, the conversion elasticity values were repeatedly adjusted. Finally, the conversion elasticity coefficient values of each land use type under three different scenarios were determined as shown in Table 3.

Table 3. The ELAS of land use types under different scenarios.

Land use types	Natural development scenario	Ecological protection scenario	Farmland protection scenario
Farmland	0.7	0.7	0.8
Other agricultural land	0.5	0.6	0.5
Urban and rural construction land	0.9	0.9	0.9
Subsided seep area	0.6	0.5	0.6
Water area	0.6	0.7	0.6
Tidal wetland	0.55	0.6	0.5

The BLRM was established and validated to explore the relationship between driving factors and land use types. Using the selected 7 driving factors and land use data in 2016 as input data for simulation, the spatial distribution of each land use type in 2025 under three different scenarios were predicted after fine-tuning configuration of model parameters. The prediction results are shown in Table 4 and Figure 5.

Landscape pattern characteristics in the future

As shown in Table 4 and Figure 5, other agricultural land and water area increased under the three scenarios. It showed that ecological land, such as other agricultural land and water area, which play an important role in regulating the regional

Table 4. Dynamic change of land use types under different scenarios from 2017 to 2025.

Land use Types	Natural development scenario		Ecological protection scenario		Farmland protection scenario	
	Area change (hm^2)	Single dynamics (%)	Area change (hm^2)	Single dynamics (%)	Area change (hm^2)	Single dynamics (%)
Farmland	-2801.25	-1.95	-4172.49	-2.91	-629.73	-0.44
Other agricultural land	5515.83	3.04	6548.31	3.61	3867.03	2.13
Urban and rural construction land	-3168.18	-6.46	-3434.58	-7.01	-3370.5	-6.88
Subsided seep area	-65.61	-1.12	-166.05	-2.84	-85.05	-1.46
Water area	7817.13	4.98	7978.77	5.08	7528.41	4.79
Tidal wetland	-7302.15	-14.2	-6758.19	-13.14	-7314.39	-14.23

ecological environment, has attracted more and more attention from 2017 to 2025. Farmland, urban and rural construction land, subsided seep area and tidal wetland showed a shrinking trend. And the single dynamic degree of tidal wetland and urban and rural construction land were the largest, -14.23% and -7.01% respectively. There are several possible explanations for the observed quick shrinkage of urban and rural construction land and tidal wetland. First of all, with the gradually increased utilization of tidal wetland and other unused land, some tidal wetland could be developed into aquaculture land or artificial wetland, which is also consistent with the current change trend of tidal wetland. Secondly, under the proposing of intensive and economical utilization of construction land, some abandoned industrial and mining land could be gradually reclaimed into usable garden land, forest land and other agricultural land. The single dynamic degree of farmland was the greatest in the ecological protection scenario. The result indicated that under this scenario, farmland decreased faster than the other two scenarios. This accelerated reduction of farmland area was probably due to the implementation of “Grain for Green Project” and “Grain for water Project”, and other ecological environmental protection measures. During 2017-2025, the area of projected subsided seep also gradually reduced because of the advancement of land reclamation and the improvement of technology.

To further analyze the dynamic land use change in 2025, the simulated land use maps in three different scenarios and land use map in 2016 were subjected to raster calculation. The results are shown in Figure 6.

(1) Natural development scenario

As shown in Figure 6 and Table 4, under the natural development scenario, some farmland concentrated in the east of Wanglou Village of Gaolou Township and surrounding areas, was projected to be converted to garden land or other agricultural land in 2025, due to its natural geological characteristics or adjustment of agricultural structure. Other farmland, located in the tributaries of Weishan Lake and surrounding areas southern to the secondary dam, was projected to be converted to water body, due to rainfall and resulting lake water level rise. The area of construction land in the south of Xiazhen Street and the north of Zhaoyang Street was projected to decrease, and it was mainly transferred into other agricultural land. Fucun Street has severe land subsidence and is close to lake. After reclamation, some of the subsided land with water accumulation was projected to be converted to water area. Tidal wetland was mostly predicted to be converted to other agricultural land or water area. Specifically, the large areas of tidal wetland, located in the east bank of Zhaoyang Lake and the north bank of Weishan Lake, were projected to be converted to water area, and a large area of tidal wetland in the north of Liuzhuang Town was projected to be converted to other agricultural land.

(2) Ecological protection scenario

In the ecological protection scenario, the change of land use types was similar to those in the natural development scenario. Urban and rural construction land and tidal wetland decreased the fastest. A large area of construction land in the east of Xiazhen Street and the middle of Zhaomiao Township was projected to be converted to other land. In this scenario, the reduction of construction land was faster than that in the other two scenarios, with -7.01% changing rate and total area reduction of 3434.58 hm^2 . The tidal wetland was mostly to be converted to water body. In addition, the reduction of farmland was also faster in this scenario as compared with the other two scenarios, with an estimated changing rate of -2.91% and a total area reduction of 4172.49 hm^2 . The farmland was mainly converted to more ecological land types such as garden land and water area, due to the implementation of “Grain for Green Project” and “Grain for water Project”. The subsided land with water accumulation also had a faster conversion rate in this scenario and was mostly to be converted to water area.

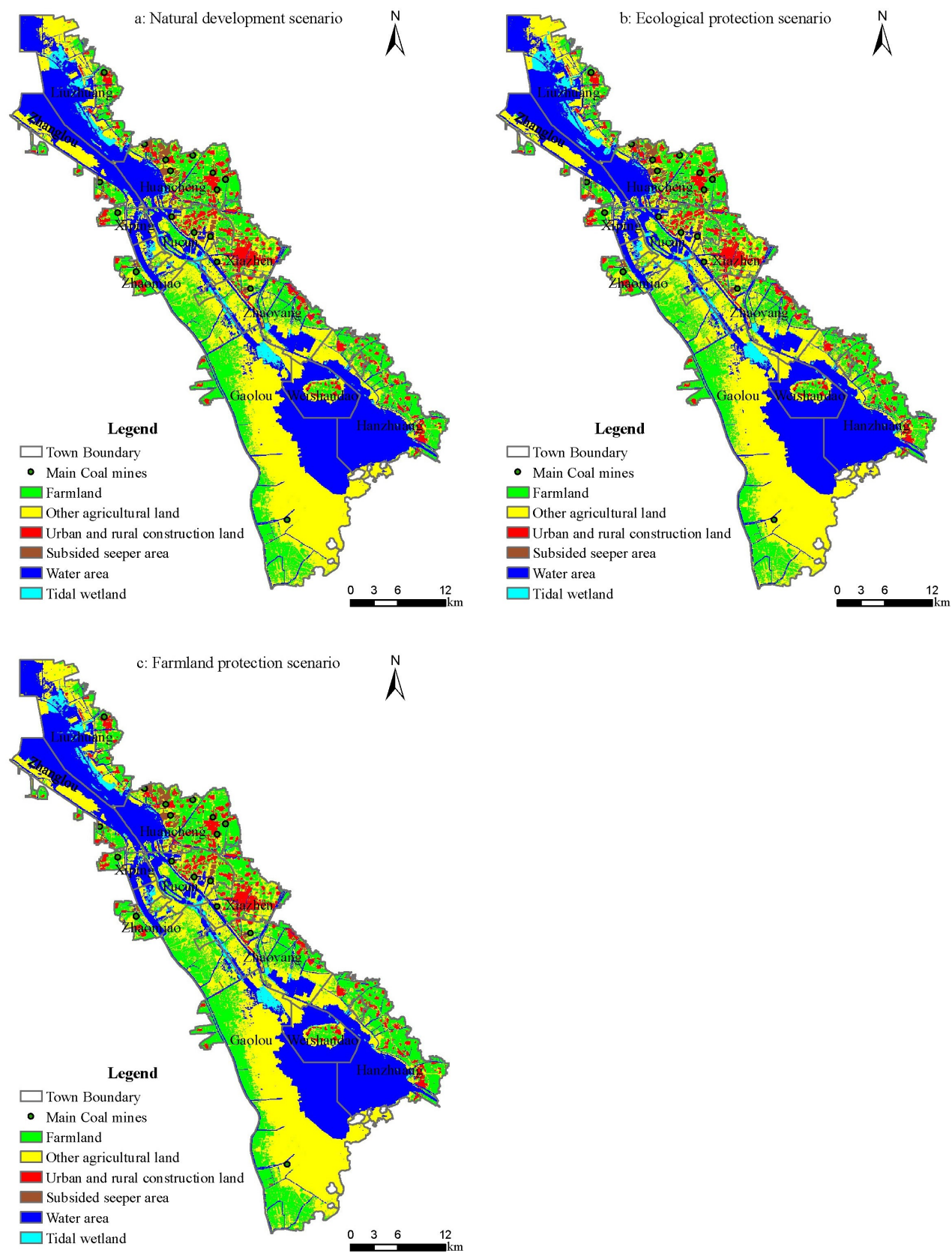


Figure 5. Land use simulation maps in 2025 under different scenarios.

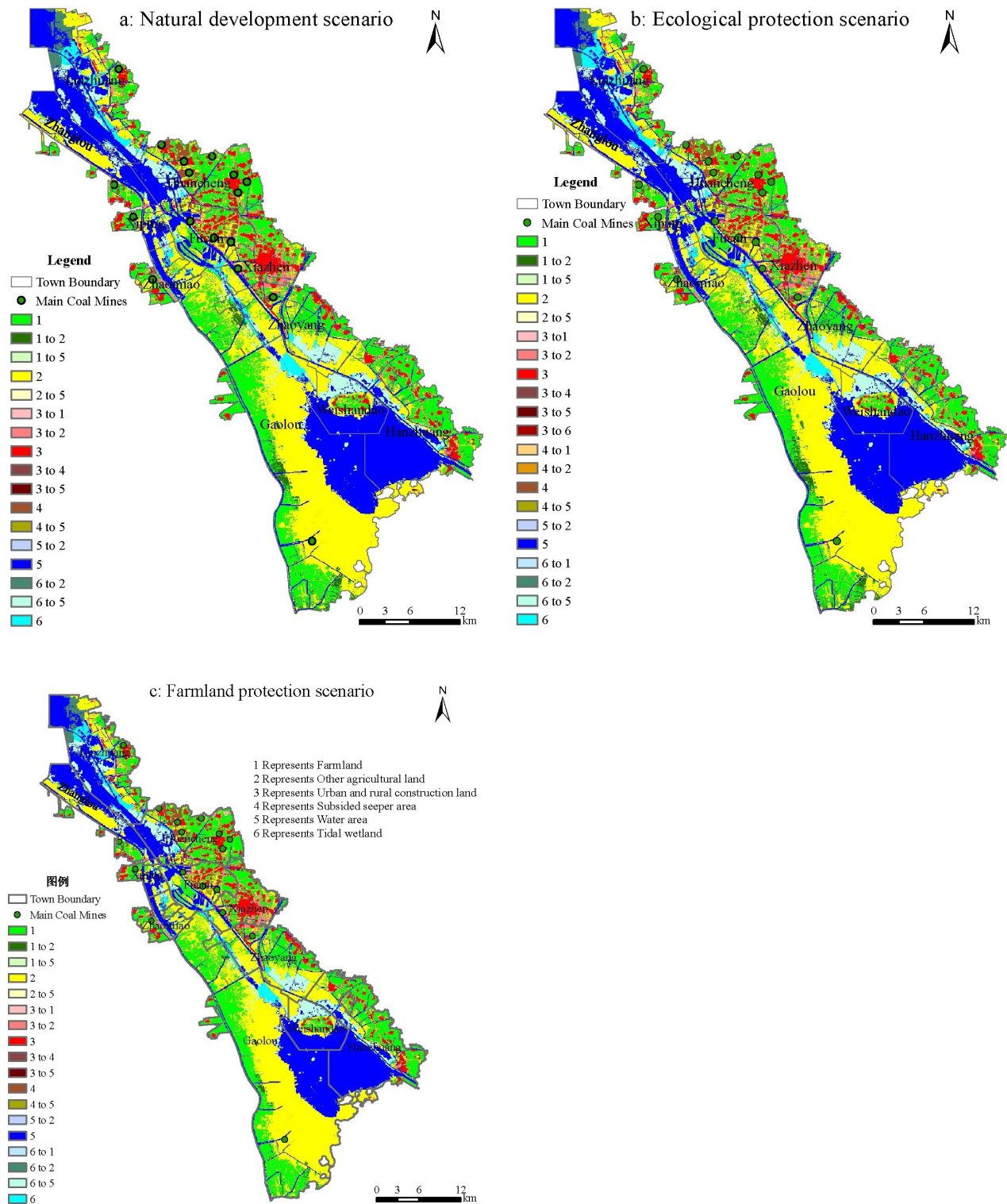


Figure 6. Land use changes under different scenarios from 2017 to 2025.

(3) Farmland protection scenario

In this scenario, the reduction rate of farmland dropped significantly, with a small changing rate of -0.44% and a total area reduction of 629.73 hm^2 . And in the northeast of Huancheng Town, some of the construction land was projected to be converted to farmland, which contributed to the farmland preservation. Both urban and rural construction land and tidal

wetland showed deceasing trends, which are similar to those in the natural development scenario and the ecological protection scenario. However, the tidal wetland was projected to have the fastest changing rate in this scenario. A small proportion of tidal wetland located in the northern part of Huancheng Town was projected to be converted to farmland. Due to the effective farmland preservation measures, the changes of garden land and other agricultural land were significantly less in this scenario as compared with the other two scenarios. The change of water area in this scenario was similar to that and slightly slower than that in the natural development scenario, but significantly different from that in the ecological protection scenario. The subsided land with water accumulation changed in a similar decreasing trend in the three scenarios.

Conclusion and discussion

Conclusion

(1) Under the three scenarios, the area of other agricultural land and water body which have regulatory effect on regional ecosystem showed an increasing trend; while the area of farmland, urban and rural construction land, subsided seep area, and tidal wetland showed a decreasing trend, and the area of urban and rural construction land and tidal wetland decreased the fastest from 2017 to 2025. Under the ecological protection scenario, the decrease of farmland was faster than that in the other two scenarios. The projected area of subsided land with water accumulation also reduced gradually because of the advancement of reclamation.

(2) Under the natural development scenario, some farmland concentrated in the east of Wanglou Village of Gaolou Township and surrounding areas, was projected to be converted to garden land or other agricultural land. Some farmland, located in the tributaries of Weishan Lake and surrounding areas southern to the secondary dam, was projected to be converted to water body. Fucun Street has severe land subsidence and is close to lake. After reclamation, some of the subsided land with water accumulation converted to water body. Tidal wetland was mostly converted to other agricultural land or water body. The construction land was mainly converted to other agricultural land.

(3) Under the ecological protection scenario, the changes of land use types were similar to the natural development scenario, but the change speed was faster than the other two scenarios. Among all land use types, urban and rural construction land decreased the fastest. Farmland also decreased rapidly, and most of it converted to more ecological land such as garden land and water body. Under the farmland protection scenario, the tidal wetland decreased the fastest, followed by urban and rural construction land. Some construction land was projected to be converted to farmland, so that farmland would be effectively protected.

Discussion

In this study, the application of the CLUE-S model, combined with Markov model and BLRM, suggests that this method can reveal the driving factors of land use change at a scale of 60m × 60m, and can effectively simulate the multi scenario of land use in the future. The results can guide the government to make more reasonable allocation of land resources in the mining area. In near future, in order to ensure the regional food supply security, Weishan's government should enforce the management of farmland resources, especially high quality cultivated field, control the increase of construction land and implement the intensive and economical use of construction land. Meanwhile, the ecological land use types, such as other agricultural land, water body and tidal wetland, should maintain a balanced proportion in the mining area. And the subsided land with water accumulation should be effectively reclaimed using appropriate technologies, in order to ensure the sustainable utilization of land resources and improve the ecological environment in the mining area.

However, due to the limitation of data acquisition, we should need to further improve the comprehensiveness of driving factors. Therefore, we should need to incorporate policies, measures, as well as other human factors in future research to better analyze the driving forces of land use dynamic changes.

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Author contributions statement

Dr. Xiaoyan Chang conceived and designed the experiments, and guided the fundamental concept to the co-author. Dr. Kanglin Cong and Ms. Xiaojun Liu performed the experiments and analyzed the data. Dr. Xiaoyan Chang wrote the main manuscript text. Dr. Feng Zhang reviewed the manuscript and put forward suggestions for revision.

Additional information

Competing interests

The authors declare no competing interests.

Figures

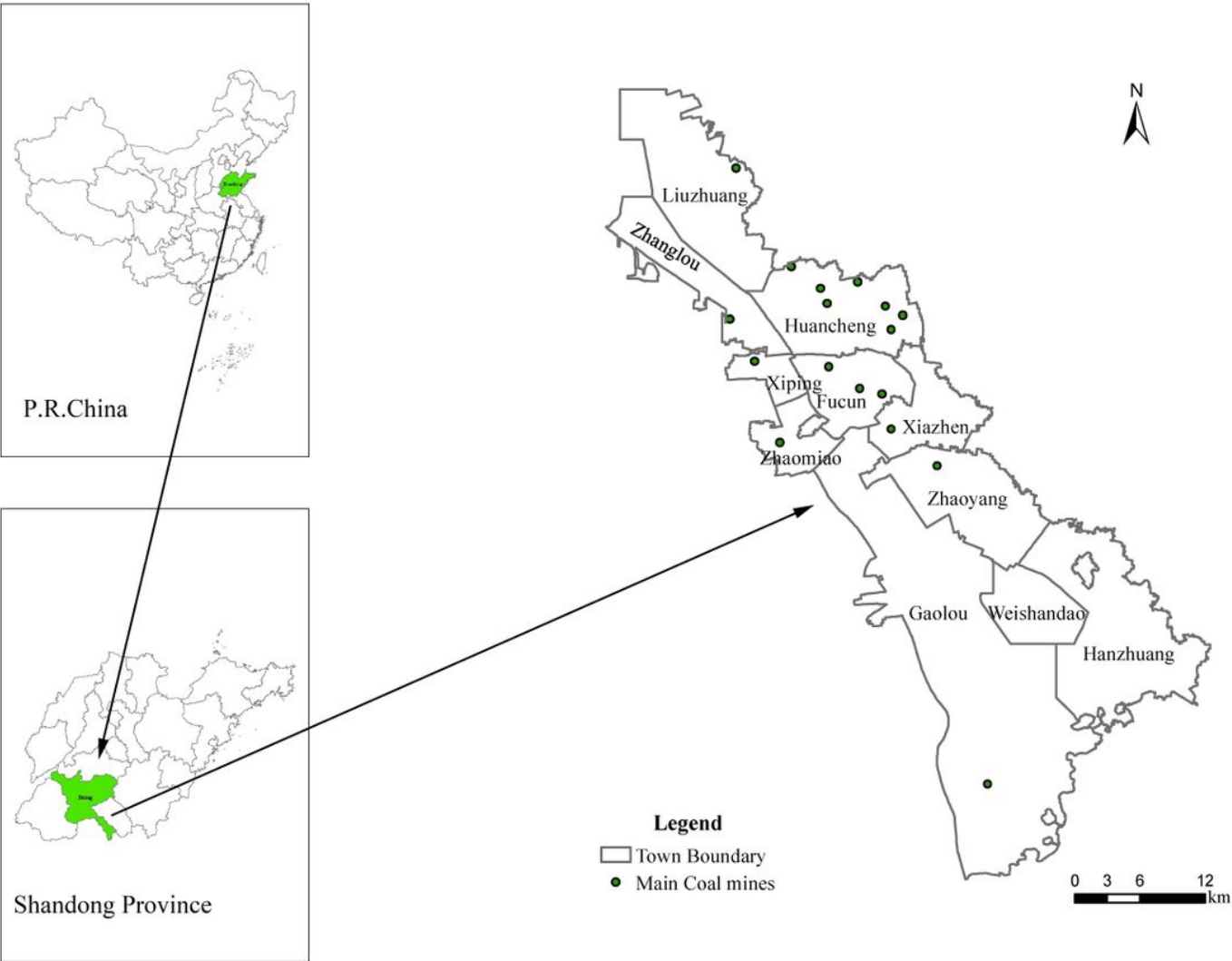


Figure 1

Geographical location and mining area distribution in the research area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

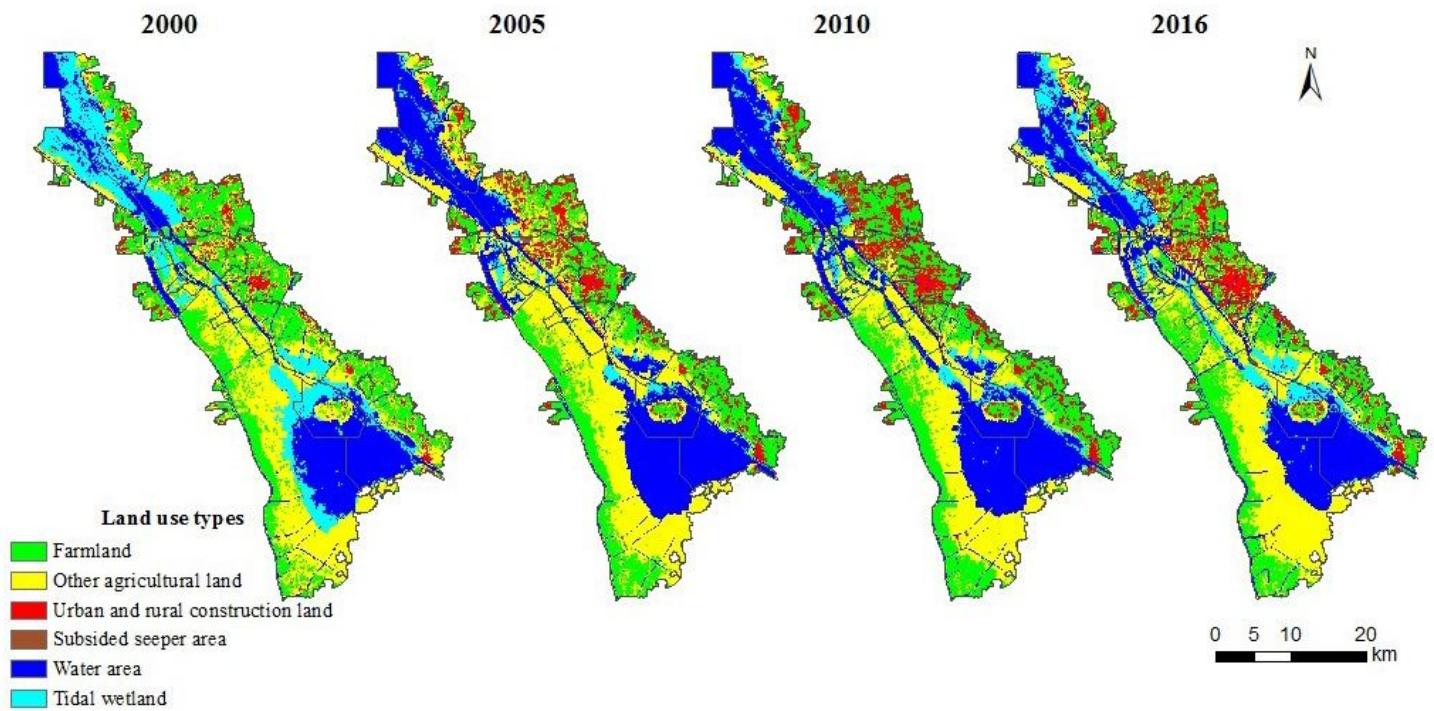


Figure 2

The land use maps of 2000, 2005, 2010 and 2016. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

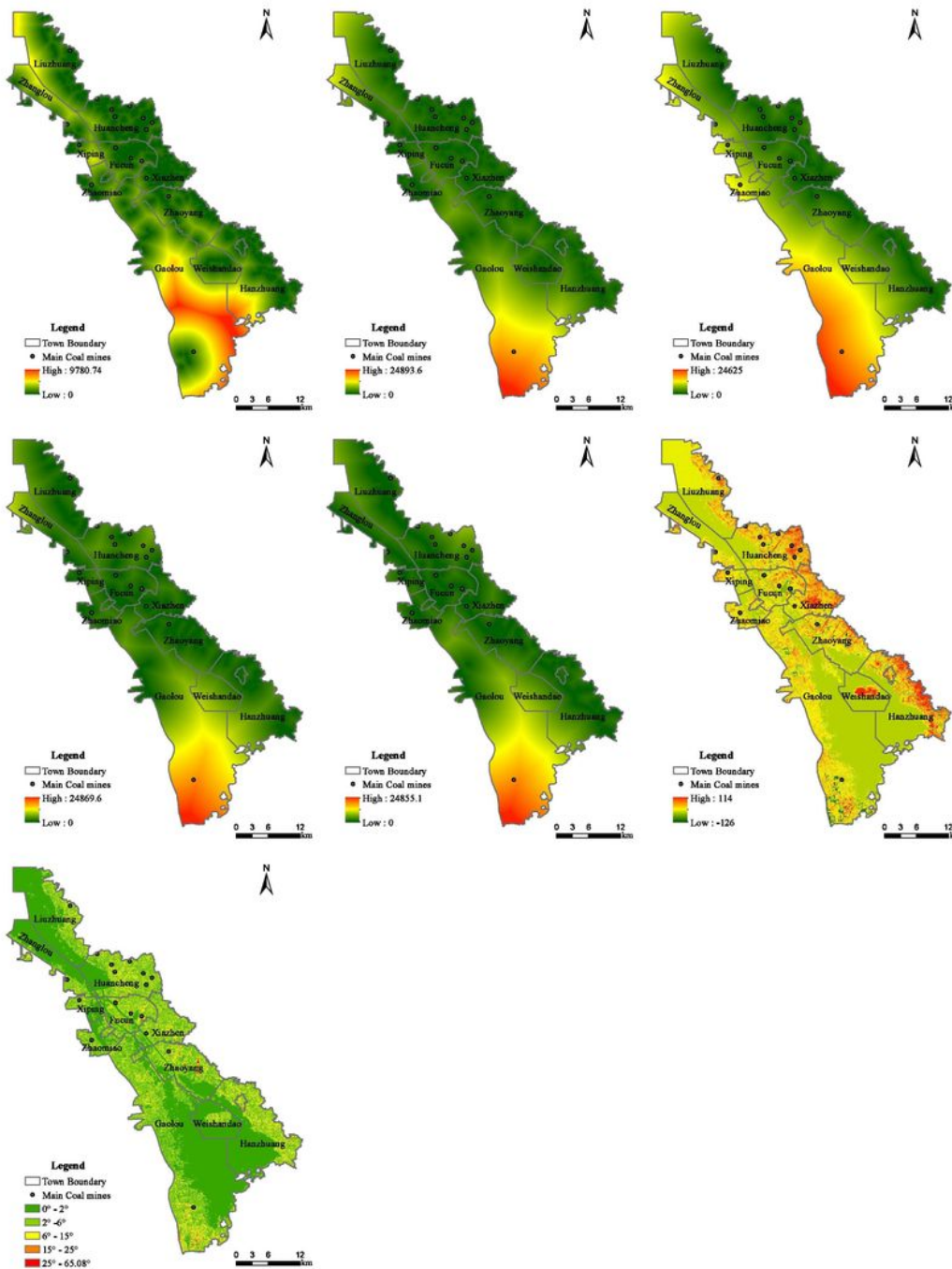


Figure 3

(a) The nearest distance to the residential area; (b) The nearest distance to the major mines; (c) The nearest distance to the main roads; (d) The nearest distance to the major rivers; (e) The nearest distance to the ditches; (f) Elevation; (g) Slope. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research

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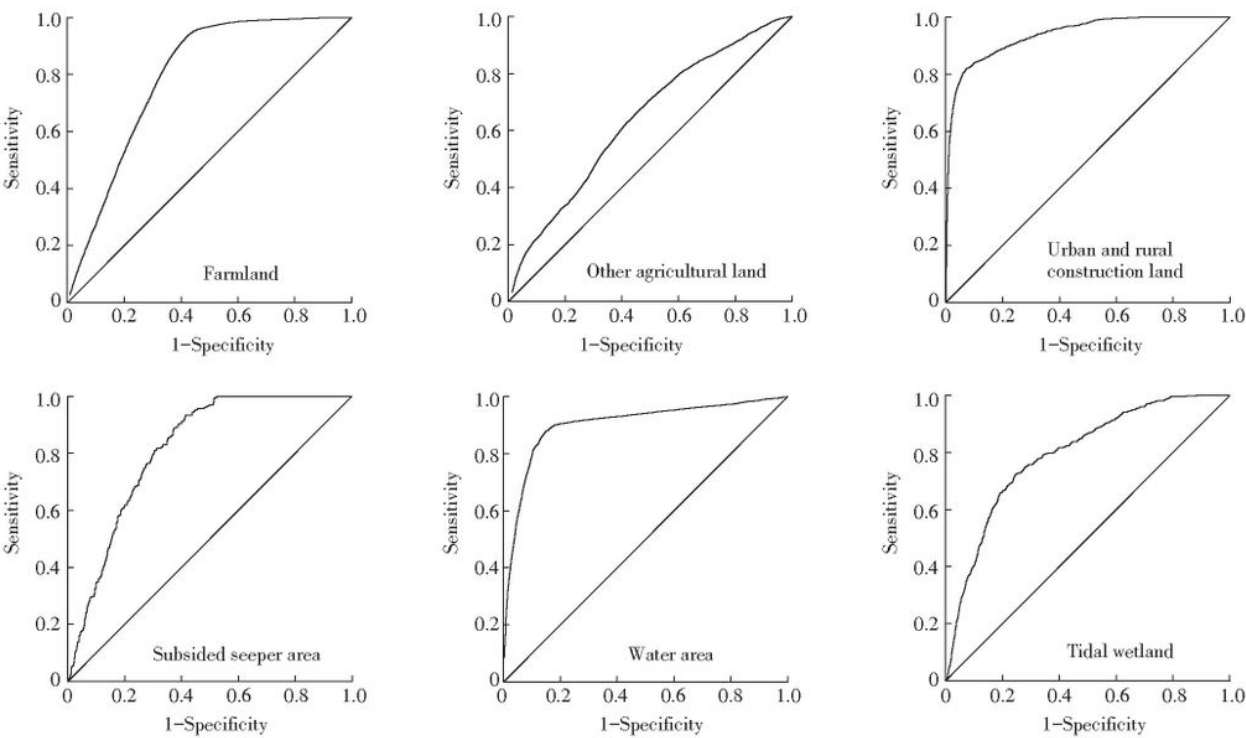


Figure 4

ROC curves for regression analysis of land use type and driver factors.

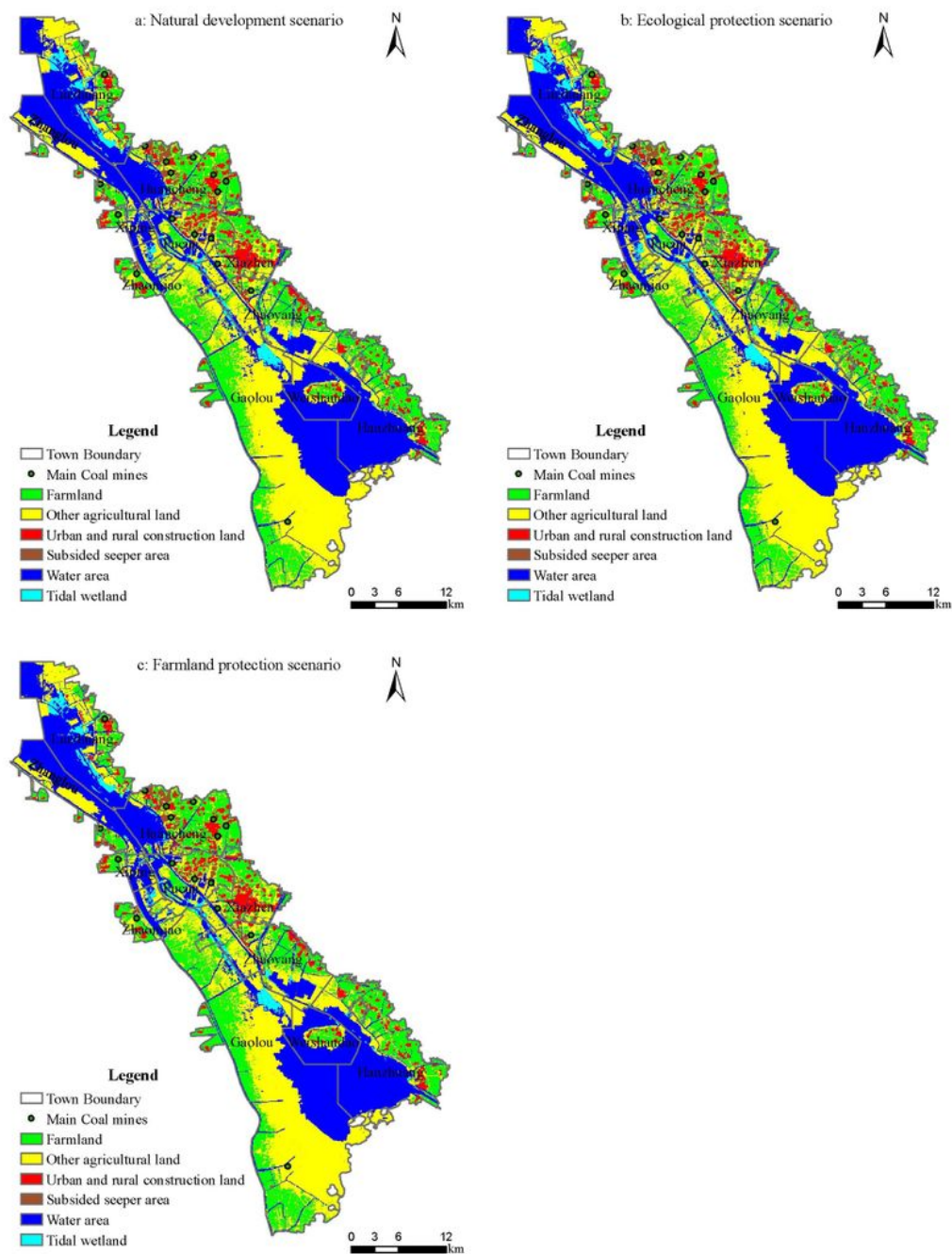


Figure 5

Land use simulation maps in 2025 under different scenarios. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

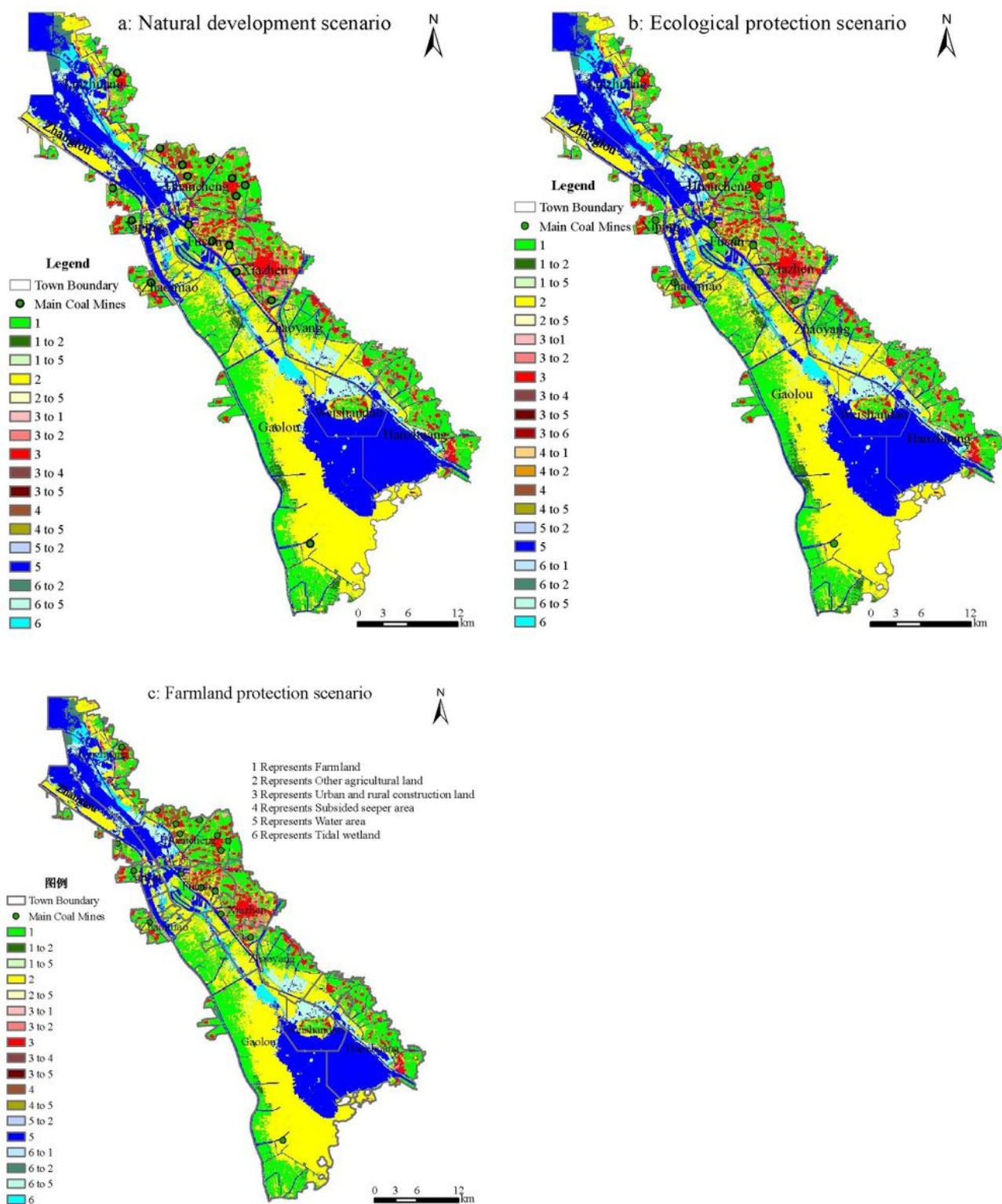


Figure 6

Land use changes under different scenarios from 2017 to 2025. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.