Simulating and forecasting spatio-temporal characteristic of land-use/cover change with numerical model and remote sensing: a case study in Fuxian Lake Basin, China

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ABSTRACT
The land-use/cover (LUC) change (LUCC) in small-scale basins can strongly impact regional environments and developments, and understanding the spatio-temporal characteristics of LUCC is important for sustainable development planning. This study explored the spatio-temporal characteristics of China’s Fuxian Lake Basin in 2017–2067, which may provide decision-making support for ecological and environmental protection measures. Landsat-7 ETM+ and Landsat-8 OLI images combined with a cellular automata–Markov model were used to simulate and forecast LUCC, and expand analysis and reduce analysis methods were applied to explore the spatio-temporal patterns of LUCC in this basin. The results showed that in 2017–2067: (1) arable land, forestland and water would be expected to expand; (2) garden, grassland, building region, road, structure, artificial piling and digging land, and desert and bare surface would contract; (3) the rate of arable land expansion in 2032–2037 and the rate of grassland loss in 2057–2062 would be the largest changes, reaching 1.670 and 0.856 km²/year, respectively and (4) the expansion and contraction of different LUCC classes were closely related to the “Four Retire Three Return” policy implemented by the local government. Therefore, the protection measures for environment should be set in advance according to the forecasting results of this study.

Introduction
Land-use/cover (LUC) change (LUCC) has both direct and indirect impacts on environment as well as regional and global sustainable development, for the continuous evolution and transformation of land surface may result in a number of changes in environmental processes, such as surface run-off, soil erosion and agricultural non-point source pollution (Li, 1996; Ouyang, Skidmore, Toxopeus, & Hao, 2010). Analysing the characteristics of LUCC, exploring its changes at different spatio-temporal scales and predicting its future scenarios are helpful in revealing the processes and mechanisms of regional and global environmental changes under human influences. In addition, LUCC modelling has attracted increasing attention in the context of global climate change (Li, 1996; Wijesekara, Gupta, Valeo, Hasbani, & Qiao, 2012), and it also is particularly useful in watershed research.

Generally, LUCC models include system dynamics model, GeoMod, CLUE-S model, multi-agent model and Markov model (Dawn, Steven, Marco, Matthew, & Peter, 2015; Pontius et al., 2006; Rashmi & Lele, 2010; Verburg, Soepboer, Limpiada, Espaldon, & Sharifa, 2002; Wang, Jin, Du, & Zhou, 2012; Xiao, Wu, Chen, & Hao, 2012); however, none of these models is perfect. GeoMod and CLUE-S models are unsatisfactory in efficiency, and they require the reliance from other auxiliary software. Markov models can quantitatively predict the dynamic changes in landscape patterns; however, they cannot resolve the spatial patterns of landscape change (Balzter & Braun, 1998). In contrast, cellular automata (CA) models can predict the spatial distribution of landscape patterns but cannot predict temporal changes (Cheng, Zhang, & Lv, 2013; Trallia, Attorre, Francesconi, Valenti, & Vitale, 2011). For these reasons, researchers integrate different methods to dynamically model LUCC (Schaldach et al., 2008), for example CA was combined with Markov model to model the spatio-temporal dynamics of LUCC (Adhikari & Southworth, 2012).

The studies of CA–Markov modelling in simulating LUCC are mainly focused on simulation...
accuracy at large or medium scales; however, the sensitivity of this method for smaller regions and the simulation efficiency over a long time still require analysis. Although some studies have concluded that higher spatial resolution input data could result in higher modelling accuracy of the CA–Markov model (Berling et al., 2004), few studies have been carried out over small-scale regions, especially for environmentally fragile basins, and whether the prediction results conform to local government’s policy orientation still needs to be analysed.

Fuxian Lake is one of the most important supply areas for freshwater in Yunnan Province, China. As a typical representative of environmentally fragile plateau lake, the LUCC in its watershed greatly affects water quality and environment. Local government and land management departments need to understand the spatio-temporal characteristics and driving factors of LUCC as well as to simulate the LUCC over the next half century for improving environmental sustainability in this basin. To achieve this goal, this study employed a CA–Markov model and remote sensing data to forecast the spatial–temporal features of LUCC in Fuxian Lake Basin from 2017 to 2067: (1) to apply a framework for modelling the future spatio-temporal changes of LUC effectively, (2) to detect the structural characteristics of expansion patterns and (3) to analyse the driving factors of LUCC. It is hoped that the results of this study may provide adequate and helpful suggestions for protecting the ecology of this watershed.

Materials and methods

Study area

Fuxian Lake Basin (24°21’28”–24°38’00”N, 102°49’12”–102°57’26”E), with a total run-off area of about 675 km², is located in the northern Yuxi City of Yunnan Province in China (Figure 1). The lake is the second deepest freshwater lake in China, and it covers an area of 211 km² with the maximum water depth of 155 m. This basin is an important resource for sustainable social and economic development in Yunnan Province and also provides water resources for the pan-pearl river delta region (Li, Jin, Zhou, Wang, & Peng, 2017). Due to environmental shifts and human activities, the LUC in the Fuxian Lake Basin has changed dramatically, drawing increasing attention to LUCC modelling. The accurate simulation and analysis of spatial–temporal LUCC trends can provide some basic information and scientific evidence for the sustainable development of this basin ecosystem.

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Data and preprocessing

Landsat-7 ETM+ (20 February 2007, 20 January 2012) and Landsat-8 OLI (25 January 2017) multi-spectral images covering the study area were downloaded from the USGS Global Visualization Viewer
(GloVis, [https://glovis.usgs.gov/](https://glovis.usgs.gov/)). These images have 30 m resolution multispectral bands and one 15 m resolution panchromatic band. The Landsat-7 ETM+ images in 2007 and 2012 were used for model calibration, and the Landsat-8 OLI image of 2017 was applied for model validation. Auxiliary data included a 30 m resolution digital elevation model (DEM), digital vector data (roads, drainage, transportation and residential objects updated in 2017) at scale 1:10,000, planning data for Fuxian Lake protection and development from the administration of Fuxian Lake protection and LUC classification validation data. A topographic map along with previous LUC maps from 2007 to 2012 were included in the classification validation data. The GPS observations from field surveys were obtained on 25 January 2017 using a handheld GPS. A total of 508 GPS points were collected, and they were evenly distributed considering different LUC types, including arable land (68 points), forestland (70 points), garden (50 points), grassland (65 points), building region (50 points), roads (40 points), structure (45 points), artificial piling and digging land (40 points), desert and bare surface (40 points) and water (40 points).

All images were subjected to geometric correction, image enhancement and strip processing. The Landsat 30 m spatial resolution multispectral bands were fused with the 15 m panchromatic band using Gram–Schmidt fusion method, which can improve the spatial resolution of multispectral bands and retain the spectral information of source imagery ([Li, Liu., Wang, & Wang, 2004; Yang, Wu, et al., 2017]). A Quick Unbiased Efficient Statistical Tree – classification algorithm (Duan, Deng, & Deng, 2016; Wu, Pan., Peng, & Huang, 2012) – was used to extract LUC classes from images. All pixels were classified into 10 classes, including arable land, forestland, garden, grassland, building region, roads, structure, artificial piling and digging land, desert and bare surface and water, considering the “Contents and Indices of the First National Geographic Survey in Yunnan” and the limited spatial resolution of Landsat images. The classification accuracy for the Landsat-8 OLI image in 2017 was assessed by GPS observations. The classified land-use maps in 2007 and 2012 were compared with the topographic map and previous land-use maps. The LUC data for the three study periods were stored in vector format for further analysis.

The slope and aspect data over the study area were derived from a 30-m DEM, and a suitability map for each land-use class in the study area was generated considering elevation, roads, drainage, transportation, resident population and census data (such as administrative boundaries, core area and protected area).

**CA–Markov model developing**

1. **Markov model**

The Markov model not only explains the quantification of conversion states between the LUC types but also can reveal the transfer rate among different LUC types (Sang, Zhang, Yang, Zhu, & Yun, 2011).
In Markov model, LUC types correspond to “possible states”, and the area or proportion of mutual conversion between LUC types is “state transition probability”. Land-use change was predicted using following formula (Gong, Yuan, Fan, & Stott, 2015; Guo & Zhang, 2009; Miller & Childers, 2004):

\[ S(t+1) = P_{ij} \times S(t) \]  

(1)

where \( S(t+1) \) and \( S(t) \) represent the respective land-use states at moments \( t+1 \) and \( t \); \( P_{ij} \) is the state transition probability.

\[
P_{ij} = \begin{bmatrix}
P_{11}, P_{12}, ..., P_{1n} \\
P_{21}, P_{22}, ..., P_{2n} \\
... & ... & ... \\
P_{n1}, P_{n2}, ..., P_{nn}
\end{bmatrix}; \text{ } \mu_{0} \leq P_{ij} < 1 \text{ and } \\
\sum_{i=1}^{n} P_{ij} = 1, (i, j = 1, 2, 3, ..., n)
\]  

(2)

(2) CA

CA underlies the dynamics of change events based on the concept of proximity, and the regions closer to existing areas of the same class are more likely to change to a different class (Memarian, Balasundram, Talib, Sung, & Sood, 2012). A cellular automaton is an entity that independently varies its condition based on its previous state (according to a Markov transition rule) and the state of adjacent pixels. CA can be represented by the following models:

\[ S_{t}(t+1) = f(S(t), N) \]  

(3)

where \( S \) is the collection of cellular discrete and finite states, \( N \) represents cell neighbourhood, \( t \) and \( t+1 \) represent two different moments and \( f \) represents the transformation rule between cell states.

(3) CA–Markov model

CA–Markov model is a combination of CA and Markov chain, which adds an element of spatial and the knowledge of likely spatial distribution of transitions to Markov chain analysis. Markov model focuses on quantitatively predicting dynamic changes of land-use pattern but lacks skill at dealing with the spatial patterns of land-use change and also do not know the various types of land-use changes in spatial extents. CA model has the ability to predict the transitions among any number of categories (Robert, Pontius, & Jeffrey, 2005; Yang, Su, Chen, Xie, & Ge, 2016). Combining the advantages of CA theory and the temporal forecasting abilities of Markov model, a CA–Markov model performs better at modelling LUCCs in both temporal and spatial dimensions. IDRISI software developed by the Clark Labs at Clark University is one of the best platforms to conduct CA–Markov modelling, and it was applied in this study. The CA–Markov model in IDRISI integrates the functions of cellular automaton filter and Markov processes, using conversion tables and conditional probability of the conversion map to predict the states of land-use changes, and it may be better to carry out land-use change simulations (Sang et al., 2011). Carrying out CA–Markov modelling using IDRISI involves two techniques: Markov chain analysis and CA (Araya & Cabral, 2010; Yeh & Li, 2006).

**LUC forecasting and accuracy assessment for 2017**

(1) Calculating transition matrix

The Markov chain in IDRISI software was applied to calculate land-use transition matrix. The LUC maps in 2007 and 2012 were overlaid, and the time interval between the two maps was set to be 5 years with a 5-year forward prediction time. After several tests, the error ratio was set to 0.10 and the transition probability matrix for land use and the transition area matrix for land change were calculated.

(2) Creating suitability maps

A suitability map was created based on the regulations for compiling overall land-use planning at county level, the relevant provisions from the Food and Agriculture Organization of the United Nations land evaluation program and existing data on LUC for Fuxian Lake Basin. Transition rules were generated using multi-criteria evaluation (MCE) and fuzzy membership function suitability maps for each simulated land-cover class (Clercq & Wulf, 2007; Eastman, Jin, & Ak, 1995). The core of CA is its rules for evolution, which are defined by MCE, and the suitability maps were generated by the COLLETION EDIT module in IDRISI (Poska, Sepp, Veski, & Koppel, 2008). Suitability maps provided the status of each cell for the next time step. At the same time, in order to improve simulating accuracy in the basin, suitability maps were improved based on constraints, such as current land use and distance, combined the impacts of other factors (roads, towns, water bodies, slope, gradient, building region and areas where development is limited) on LUC types. Those factors were then combined to generate a single suitability map based on certain weights that were calculated using analytic hierarchy process method (Author, Kazemi, & Haghhyghy, 2014; Bozdag, Yayuz, & Gunay, 2016; Halil, Ayse, & Bulet, 2013; Pramanik, 2016).

(3) Forecasting and accuracy assessment

The LUC classification results in 2007 and 2012 were used as initial conditions. The land-use transition probability matrix, land change transition area matrix and suitability map were added to model, which set the number of CA iterations to be 10 and the CA filter type to be standard 5 × 5 contiguity type. The forward prediction time interval was set to 5 years and LUC was modelled for 2017. Kappa coefficient was selected as assessment standard for LUC modelling results (Patil &
results

Data preprocessing and LUCC forecasting results for 2017

The Kappa coefficients for classification accuracy in 2007, 2012 and 2017 were 0.86, 0.87 and 0.89, respectively, which met the requirements of the study. The values for suitability map were standardized to [0, 1] as CA transition parameters, in which higher values indicate greater suitability. The suitability maps for each land-use class in the study area are shown in Figure 3. The simulated LUC map in 2017 was validated using the classification map of the same year. The Kappa coefficient of 2017 modelling result was 0.89, which satisfied the study criteria for the effectiveness of this method.

LUCC forecasting and analysis results in 2022–2067

LUCC simulating and forecasting results in 2022–2067

Using the same methods, LUCC was simulated from 2022 to 2067 (Figure 4). In order to facilitate further statistical analysis, the simulation results of 2017 are also shown in Figure 4.

As seen in Figure 4, LUC types did not have large changes between 2017 and 2067, with each type of LUC having only small changes. Only slight differences were observed from the north and northeast in the Fuxian Lake Basin, in which arable land increased and building region decreased. It did not appear that the areas of building region and roads would increase over time, while forestland area was expected to decrease. The LUCC simulation and forecasting results were transformed into vector layers to calculate the area of each class for quantitative analysis (Table 1).

General increasing or decreasing trends for all classes were relatively stable, except for garden and artificial piling and digging land (Table 1). Arable land, forestland and water increased with time, while garden, grassland, building region, roads, structure, artificial piling and digging land, and desert and bare surface decreased from 2017 to 2067. The respective areas of arable land, forestland and water increased from 138.98, 199.10 and 185.63 km² in 2017 to 210.74, 201.42 and 196.13 km² in 2067, with cumulative increases of 71.76, 2.32 and 10.5 km² (Figure 5(a)). On the other hand, the respective areas of garden, grassland, building region, roads, structure, artificial piling and digging land, and desert and bare surface decreased from 8.45, 78.28, 16.82, 7.60, 13.12, 13.09 and 14.43 km² in 2017 to 0.83, 40.31, 8.81, 2.45, 3.64, 0.04 and 11.13 km², with cumulative decreases of 7.62, 31.97, 8.01, 5.15, 9.50, 13.05 and 3.30 km² (Figure 5(b)), respectively. Based
on the above statistics, a significant expansion is expected in arable land area (71.76 km²) from 2017 to 2067. The contractions of building region, grassland, and artificial piling and digging land from 2017 to 2067 are also expected, with respective reductions of 8.01, 31.97 and 13.05 km², respectively. The reductions in desert and bare surface, and artificial piling and digging land, can benefit the environment in the basin, but the impacts of expansion of arable land and the loss of garden and grassland are negative, meaning that effective preventative and protective measures should be adopted.

Figure 3. Transition suitability maps for different LUC types generated using MCE, (a) arable land, (b) forestland, (c) garden, (d) grassland, (e) building region, (f) roads, (g) structure, (h) artificial piling and digging land, (i) desert and bare surface and (j) water.

Figure 4. Simulation and forecasting maps of LUCC from 2017 to 2067.
Spatial–temporal pattern analysis results

Based on LUCC trends in 2017–2067, arable land, forestland and water areas are expected to increase, while garden, grassland, building region, roads, structure, artificial digging pile, and desert and bare surface will decrease (Figure 6). In Figure 6, the expansion and contraction trends were divided into four groups: (1) arable land rapidly expanded, (2) forestland and water slowly expanded, (3) grassland rapidly contracted and (4) garden building region, roads, structure, artificial digging pile, and desert and bare surface slowly contracted. Generally, arable

Table 1. Different LUC class areas in 2017–2067.

| Land-use/cover classes unit (km²) | 2017 | 2022 | 2027 | 2032 | 2037 | 2042 | 2047 | 2052 | 2057 | 2062 | 2067 |
|----------------------------------|------|------|------|------|------|------|------|------|------|------|------|
| Arable land                      | 138.98 | 147.29 | 149.1 | 155.67 | 164.02 | 172.31 | 180.61 | 188.96 | 196.67 | 203.63 | 210.74 |
| Garden                           | 8.45 | 7.62 | 7.55 | 6.78 | 5.92 | 5.07 | 4.23 | 3.39 | 2.53 | 1.69 | 0.83 |
| Forestland                       | 199.10 | 199.37 | 199.91 | 199.94 | 200.19 | 200.46 | 200.72 | 200.98 | 201.15 | 201.23 | 201.42 |
| Grassland                        | 78.28 | 74.08 | 73.63 | 69.88 | 65.67 | 61.47 | 57.27 | 53.06 | 48.79 | 44.51 | 40.31 |
| Building region                  | 16.82 | 15.90 | 15.85 | 14.96 | 14.10 | 13.25 | 12.39 | 11.51 | 10.58 | 9.71 | 8.81 |
| Roads                            | 7.60 | 7.05 | 6.99 | 6.44 | 5.88 | 5.33 | 4.76 | 4.19 | 3.58 | 3.02 | 2.45 |
| Structure                        | 13.12 | 12.18 | 11.50 | 11.24 | 10.29 | 9.34 | 8.39 | 7.43 | 6.39 | 5.17 | 3.64 |
| Artificial piling and digging land | 13.09 | 11.14 | 10.33 | 8.86 | 6.90 | 4.95 | 3.01 | 1.07 | 0.12 | 0.07 | 0.04 |
| Desert and bare surface          | 14.43 | 14.07 | 13.82 | 13.71 | 13.35 | 12.98 | 12.61 | 12.24 | 11.87 | 11.50 | 11.13 |
| Water                            | 185.63 | 186.80 | 186.82 | 188.02 | 189.18 | 190.34 | 191.51 | 192.67 | 193.82 | 194.97 | 196.13 |
| Total                            | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 | 675.50 |

Figure 5. Quantitative analyses of LUCC in 2017–2067, (a) arable land, forestland and water, (b) garden, grassland, building region, roads, structure, artificial piling and digging land, and desert and bare surface.

Figure 6. Simulation and forecasting trend chart for LUCC, (a) and (c) expansion trends; (b) and (d) contraction trends.
land expansion and grassland loss were the largest changes through time.

Using Equations 4 and 5 and the information from Table 1, the LUCC change rates from 2017 to 2067 were derived (Table 2). Considering the classes that expanded in range, the maximum change rates of arable land, forestland and water were 1.670, 0.108 and 0.240 km²/year, respectively. Among the classes that contracted, the maximum change rates for garden, grassland, building region, roads, structure, artificial digging pile, and desert and bare surface were −0.172, −0.856, −0.186, −0.114, −0.306, −0.392 and −0.074 km²/year, respectively. The maximum change rates for both expansion and contraction occurred between the intervals of 2032–2037, 2037–2042, 2052–2057 and 2062–2067, and the rate of expansion for arable land and the rate of contraction for grassland were the highest, at 1.670 and −0.856 km²/year, respectively. Therefore, prevention and control measures could be made in advance according to the maximum and minimum LUCC change rates during the years singled out above.

Discussion

Significance and uncertainty of LUCC simulation and forecasting

Simulating and forecasting the spatio-temporal characteristics of LUCC in advance is very important for sustainable development and planning, because it can provide scientific evidence for decision-making on regional land-use planning and environmental protection. The LUCC simulation and forecasting obtained satisfactory result (Kappa = 0.89). According to Foody (2002), the Kappa coefficient of more than 0.80 met the accuracy requirement of land-cover change evaluation, and a Kappa value of 0.85 indicated “very good accuracy” (Monserud & Leemans, 1992; Zhang et al., 2010). Therefore, the Kappa accuracy threshold set to 85% was reasonable in this study.

The LUCC trends between 2017 and 2067 were clearly visible through the simulation. Based on simulation results, it is implied that the expansion and contraction of different LUC classes can have different effects on the environment of the basin: for example the rapid expansion of arable land and rapid contraction of grassland may lead to ecological imbalances, causing regional water issues, soil erosion and grassland degradation.

Although the LUCC forecasting results in 2017–2016 were obtained, only the simulation accuracy in 2017 was validated, while other simulation results in 2022–2067 could not be verified. Therefore, it is worthwhile to discuss whether there exist uncertainties during modelling. Unfortunately, there is no effective method to verify future prediction results, and we do not fully consider the socio-economic parameters due to its variability, so our LUCC simulation results are based on ideal state. Fortunately, our forecasting results are highly consistent with the local government’s policy orientation, which supports and confirms the credibility of simulation results. The future works should be carried out to propose a suitable evaluating method for future forecasting result and try to use the socio-economic parameters for a reliable result.

| Land use/cover change rate | Arable land | Garden | Forestland | Grassland | Building region | Roads | Structure | Artificial piling and digging land | Desert and bare surface | Water |
|----------------------------|------------|--------|------------|-----------|----------------|-------|----------|---------------------------------|-----------------------|-------|
| 2017–2022                  | 1.662      | 0.166  | 0.054      | −0.840    | −0.184         | −0.110| −0.188   | −0.390                          | −0.072                | 0.234 |
| 2022–2027                  | 0.362      | 0.014  | 0.108      | −0.090    | −0.010         | −0.012| −0.136   | −0.162                          | −0.050                | 0.004 |
| 2027–2032                  | 1.314      | 0.154  | 0.006      | −0.750    | −0.178         | −0.110| −0.052   | −0.294                          | −0.022                | 0.240 |
| 2032–2037                  | 1.670      | 0.172  | 0.050      | −0.842    | −0.172         | −0.112| −0.190   | −0.392                          | −0.072                | 0.232 |
| 2037–2042                  | 1.658      | 0.170  | 0.054      | −0.840    | −0.170         | −0.110| −0.190   | −0.390                          | −0.074                | 0.232 |
| 2042–2047                  | 1.660      | 0.168  | 0.052      | −0.840    | −0.172         | −0.114| −0.190   | −0.388                          | −0.074                | 0.234 |
| 2047–2052                  | 1.670      | 0.168  | 0.052      | −0.842    | −0.176         | −0.114| −0.192   | −0.388                          | −0.074                | 0.232 |
| 2052–2057                  | 1.542      | 0.172  | 0.034      | −0.854    | −0.186         | −0.122| −0.208   | −0.190                          | −0.074                | 0.230 |
| 2057–2062                  | 1.392      | 0.168  | 0.016      | −0.856    | −0.174         | −0.112| −0.244   | −0.010                          | −0.074                | 0.230 |
| 2062–2067                  | 1.422      | 0.172  | 0.038      | −0.840    | −0.180         | −0.114| −0.306   | −0.006                          | −0.074                | 0.232 |
| Max.                       | 1.670      | 0.172  | 0.108      | −0.856    | −0.186         | −0.114| −0.306   | −0.392                          | −0.074                | 0.240 |
| Min.                       | 0.362      | 0.014  | 0.006      | −0.090    | −0.010         | −0.012| −0.052   | −0.006                          | −0.022                | 0.004 |
policy. “Three Return” involves returning lakes, forestland and wetlands, and it is expected to increase water and forestland. LUC types less affected by human activities will be restored and protected through “Three Return” policy. “Four Retire Three Return” policy will play significant role in the land-use and ecological protection of small-scale basins. All current construction and development activities, including villages, businesses and institutions, should be gradually phased out. Environmental restoration should be enhanced with better use of space after the removal of construction, with active promotion of wetland forest protection and the like.

**Available measures for future LUCC management**

**Management and control measures**

The LUC types of Fuxian Lake Basin are expected to change rapidly in 2017–2067. Most impacts resulted from these changes will be positive, such as the expansions for forestland and water, losses for building region, roads, structure, artificial piling and digging land, and desert and bare surface. However, the increase of arable land and the reduction of grassland have negative impacts for this basin. Therefore, the control measures for limiting irrational arable land expansion and grassland reduction should be done. Examples of this include promoting Grain for Green Project policy which helped returning arable land to forest or grassland (Li, Jing, & Sun, 2008; Cao, Chen, & Yu, 2009), cultivation of cash crops on arable land as a form of economic compensation for farmers, minimizing human impacts by limiting the number of farmers, tourists and grazing livestock; delimiting the ecological red line according to Multiple Planning Integration policy (Lin, Fan, Wen, Liu, & Li, 2016; Liu & Wang, 2016; Yan, Chen, & Xia, 2017). In addition, shallow dredging should be implemented to improve the basin environment and ensure the recovery of indigenous species and biodiversity. Comprehensive reform of management system should be promoted in Fuxian Lake Basin. Unified trusteeship can break down the obstacles of protection and development. For example, turning the basin into an independent administrative unit cannot only solve the multi-management problem but also can ensure the effectiveness of management. Public–private–partnership mode should be used to urge enterprises to fulfil responsibilities of basin environmental protection, and invest in environmental protection projects, such as relocation of surrounding villages, landscape renovation, greening and wetland construction. Attracting social capital participates in projects to optimize the allocation of land resources. Policies support need strive, such as integrating resources and shantytown reconstruction, accelerating the implementation of “Four Retire Three Return” measures and ecological migration. Control measures aim at the sustainable growth of arable land, preventing loss of grassland and protecting water quality.

**Predictive measures**

In light of the expansion and contraction of different LUC types, which could lead to environmental imbalances, the simulation and forecasting results can be used to set up different monitoring sites in advance. Outreach and education activities both inside and outside the region could promote the importance of the protection of Fuxian Lake Basin for today’s and future generations.

**Conclusion**

In this study, a CA–Markov model combining with remote sensing data was applied to simulate and forecast the spatial–temporal characteristics of LUCC in the Fuxian Lake Basin over the next half century (2017–2067). We also proposed the EA and RA analysis methods to quantify expansion and contraction of LUC types through time and developed some potential environmental protection measures. The CA–Markov model obtained satisfactory accuracy in LUCC simulation, and the Kappa accuracy for 2017 was 0.89. The dynamic spatio-temporal characteristic changes of the study area showed that from 2017 to 2067, arable land, forestland and water areas would expand, while garden, grassland, building region, roads, structure, artificial piling and digging land, and desert and bare surface areas would contract. The rate of expansion for arable land between 2032 and 2037 and the rate of contraction for grassland between 2057 and 2062 would be the largest changes, reaching 1.670 and 0.856 km²/year, respectively. The expansions for forestland and water, losses for building region, roads, structure, artificial piling and digging land, and desert and bare surface will be positive, while the increase of arable land and reduction of grassland are the negative results for Fuxian Lake Basin. The expansion and contraction of different LUC classes would be closely related to the “Four Retire Three Return” policy implemented by the local government.

**Disclosure statement**

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