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Analysis of Landscape Pattern Based on the CA-Markov Model

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Abstract: Based on the remote sensing images of Landsat Thematic Mapper (TM), China-Brazil Earth Resources Satellite (CBERS) and Environment and Disaster Monitoring and Forecasting (SSMFDE), this study analyzed the landscape characteristics and spatial pattern of Xi'an City, predicted its future landscape changes and proposed data conversion methods for the landscape pattern prediction. These analyses were by the ENVI, ARCGIS and IDRISI software. The results showed that the study area had a composite landscape matrix consisted of woodland and farmland from 2000 to 2020. The areas of the farmland and grassland will continue to decrease and those of the woodland, construction land, waters and unused land will increase until 2020. The vegetation coverage in the study area would remain high in 2020, corresponding to an excellent ecological environment that would not restrict social and economic development. The difference causes between the simulated landscape pattern with CA-Markov model and the interpreted landscape pattern from remote sensing images were discussed. A major issue needed to be improved for the CA-Markov model was proposed. The data processing and simulating procedures used in this study may significantly streamline the workload and boost efficiency.

Key words: Landscape pattern analysis, CA transition rules, markov chain, CA-markov model

INTRODUCTION

Urbanization is one of the primary consequences of globalization, especially when considering that more than half of the world's population is already settled in urban areas (Kaplan *et al*., 2008). Urban landscape patterns are characterized by dramatic changes, particularly when urbanization undergoes a rapid advancement and artificial landscapes in the cities gradually penetrate into peripheral natural and semi-natural landscapes, which is a notable feature of landscape dynamics during rapid urbanization (Auch *et al*., 2004). Monitoring change brought on by urbanization has already received considerable attention(Arsanjani *et al*., 2012) and the future landscape been a critical concern both to those who study urban dynamics and those who must manage resources and provide services in these rapidly changing environments (Yang and Liu, 2005).

The future landscape pattern can be produced by the model. By using spatial modeling, GIS and remote sensing technologies, a lot of works have been done to understand the patterns, mechanisms and effects of urban growth (Luo and Wei, 2009). Markov model which is based on a transition probability matrix is the earliest of the fitted models and the simplest of stochastic process models. Markov model pays no attention to the influence of neighbor cells and only considers cell states at t1 and t2 (Eastman, 2006), which is mainly used to simulate natural landscape alterations and has been rarely individually used to study urban land use change (Arsanjani *et al*., 2011). However, Cellular Automata (CA) can be used to simulate the spatial variation of the system effectively based on the predefined transition rules (Torrens, 2006; Adhikari and Southworth, 2012) and is most appropriate for incorporating spatial interaction effects and the treatment of temporal dynamics (Arsanjani *et al*., 2012; Hu and Lo, 2007), but it only focus on the simulation of spatial patterning. Due to limitations of each individual modeling technique, a combination of Markov and cellular automata (CA-Markov) approaches has been shown to improve models describing complex patterns (Mondal and Southworth, 2010). The CA-Markov model is a robust approach in the spatial and temporal dynamic modeling of land use changes and can be used to carry out the Spatial-temporal Pattern stimulation (Kamusoko *et al*., 2009; Sang *et al*., 2011; Zhou *et al*., 2012). The potential of the CA-Markov model has been recognized, developed and implemented in different case studies to predict land use and land cover at different scales by some researchers (Guan *et al*., 2011; Adhikari and Southworth, 2012). Based on previous research and the recent trend towards landscape change, this paper analyzed the landscape pattern changes for Xi'an city which were based on the quantity of landscape change characteristics of the structure and spatial pattern as the primary research content. The CA-Markov model

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combined with GIS is selected to predict the future urban landscape patterns of Xi'an City in the paper, which is the scientific basis for its sustainable development and landscape management.

MATERIAL AND METHODS

Site description: Xi'an City (E 107°40'-109°49' and N33°39'-34°45') is located in the Guanzhong Plain of Shaanxi Province, which is in the heartland of China. The city has an east-west length of 204 km, a north-south span of 101 km and a total area of 10,108.02 km^2. With an average elevation of 400-450 m, the city boasts a variety of geomorphologic types and features a terrain that is south-high and north-low. The southern part of Xi'an, residing mostly within the northern slope of the middle segment of the Qinling Mountains, is dominated by woodlands, grasslands and unused land and accounts for 54.6% of the city's total area. The northern part of Xi'an is mostly divided into farmlands, parks and urban construction land as well as protected areas containing cultural heritage sites and accounts for 45.4% of the city's total area. Fifty-four rivers flow in the city, with the major ones including Ba River, Chan River, Feng River, Lao River, Hao River and Yu River, along with the passing rivers of Jing and Wei. The total water resources (including the river runoff and groundwater resources) are 3.146×1010 m^3. Featuring a climate of the warm-temperate continental monsoon of East Asia, Xi'an City has a 10°C-based accumulated temperature of 4,400°C, an annual average temperature of 6.4-14.9°C, an average annual precipitation of 537.5-1,028.4 mm, an annual average relative humidity of 70-73% and an annual sunshine duration of 1,983.4-2,267.3 h. The city boasts an urban green coverage of 30.06% and approximately 280 days of good urban environmental and air quality. By the end of 2010, the city had a total residential population of 8.46 million.

Data source and preprocessing: Landscape patterns for 2000, 2004 and 2011 were mapped by using Landsat TM in May 2000, China-Brazil Earth Resources Satellite (CBERS) in May 2004 and Small Satellites for Monitoring/Forecasting Disasters and Environments (SSMFDE) in May 2011. The TM data were obtained courtesy of the University of Maryland, while the latter two data sets were provided by the China Center for Resources Satellite Data and Application. All the images were corrected for sensor and atmospheric calibration errors, resampled to a ground resolution of 30×30 m and projected to Universal Transverse Mercator (UTM) projection in the World Geodetic System 1984 (WGS84) coordinate system with a RMSE of less than 0.5 pixels. The geometric rectification was based on ground control points (GCPs) that were evenly spread over the study area. Nearest neighborhood algorithm was used to resample the images so that the original brightness values of pixels were kept unchanged. Taking into account both the local characteristics and the classification system of China's land uses, the landscapes of the study area were divided into six types: grassland, farmland, woodland, waters, construction land and unused land.

Data processing was supported by the ENVI system (4.7) and the ArcGIS platform (9.3). During this data processing, the 1:100,000 topographic map and the field survey data from the ground truthing were used. The classifications were done using a hybrid approach combining both a supervised (maximum likelihood method) and unsupervised classification using Iterative Self-Organizing Data Analysis Techniques (ISODATA) clustering method. After the interpretation of the three period images, a field inventory, during the summer of 2011, was conducted to check the patch classes and to verify the accuracy of the GIS data: 260 samples were collected. More importantly, errors, especially those produced along the polygon boundaries due to GIS overlay procedures, are eliminated. Afterwards, the "clump" function was used to filter out some small fragments before some patches that were visibly wrong were corrected in a human-computer interactive manner. At this point, the images were ready for the accuracy assessment, which mainly involved Kappa indices to evaluate the precision of the classification results. KAPPA index is the most widely used method for precision assessment, interpretation of aerial image or remote sensing image (Wang *et al*., 2012). The validity of the model results have been evaluated by comparing the KAPPA index of agreement for each category, spatial patterns of land use type and fractal parameter. Our assessment results showed that the overall classification accuracy of the three phases, assessed on the basis of the training sample points collected during field visits of 2011, was 81-83% and the corresponding Kappa index was 0.809-0.829. These data met the requirements of our subsequent analyses. The classification had a low rate of omission and commission errors.

CA-markov model: GIS can be used to define initial conditions, to parameterize the CA-Markov model, to calculate transition matrixes and to determine the neighborhood rules (Aitkenhead and Aalders, 2009). The specific procedures are illustrated below:

- First: Generation of the area transition matrices of the landscape patterns and the images of conditional probability. The derived shapefile vector graphs of the landscape types were converted into the vector format of the IDRISI software. Subsequently, the vector property table was opened to apply the vector-to-grid conversion function to produce unit grids of 30 m×30 m before the Markov model was employed to generate the area transition matrices and transition probability of the landscape types along with the appropriate images of the transition matrices. The transition areas matrix is a text file that records the number of pixels that are expected to change from each landscape type to each other landscape type over the specified number of time units
- Second: Establishment of the CA transition rules. These rules are the core of the CA model and determine its dynamic transitional processes. For each landscape unit, the transitional direction and quantity among individual types are pertinent to its regional and natural conditions. The degree of correlation was used as a transitional rule to suggest the transition likelihood for each landscape type. The likelihood of each landscape type undergoing changes in a grid cell can be calculated with the Eq:

$$TR_i = I_i+|D_i|+V_i \quad (1)$$

where, TR_i is the transitional suitability of the cell, i is the landscape type, I_i or D_i is the increased or reduced area, respectively, of the landscape type i, $I_i+|D_i|$ is the base transitional capacity of the landscape type i and V_i is the quantitative difference between the landscape types of two phases, used for modifying the base transitional capacity. The derived Tr_i value was subjected to normalization at the scale of 255 before being used in the simulation computation of the CA-Markov model:

- Third: Selection of the filter. According to the neighboring cells, the status of a grid cell was changed using the weighting factor determined by the filter. In an iterative process the CA-Markov model uses the transition probability maps for each land cover to establish the inherent suitability of each pixel for each land cover type but contiguity filter down-weights the suitability of pixels far from existing areas of that class (as of that iteration), thus giving preference to contiguous suitable areas. A filter of 5×5 was used such that each grid cell was at the center of a 5×5 matrix of cells (Fig. 1). The matrix has a significant impact on the status change of the central cell

0		1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Fig. 1: 5×5 mean contiguity filter applied in CA markove model

- Fourth: Simulation. The starting time and the number of cycles were determined before the simulation was performed. The study takes the year 2004 as a starting point. The number of CA iterations is selected at 20 in order to simulate the landscape spatial pattern for the study area in 2020
- Fifth: Generation of the results. The predicted landscape thematic maps were compared with the actual landscape map of 2011, upon which the Kappa index and the modified Lee-Sallee shape index were used to perform the accuracy test before the final results were produced

RESULTS AND DISSCUSSION

Prediction of the landscape patterns: To use the CA-Markov model in the IDRISI software to simulate landscape patterns, the first step is the generation of a Markov model-based area transition matrix for the landscape. The Markov model was used herein to generate the area transition matrices of 2000-2004 and it was also used as the transition rules. The year 2000 was set as the starting point of the prediction, from which the CA-Markov model was employed to simulate the landscape patterns of the study area in 2011 and 2020 (Fig. 2), with ten iterations. Subsequently, the Kappa index and the amended Lee-Sallee shape index were recruited to compare the simulation results and the observed landscape results for 2011 and thereby determine the accuracy of the prediction and the similarity between the simulated results and observed patterns. The Kappa index was 0.76 and the Lee-Sallee index was 0.65,

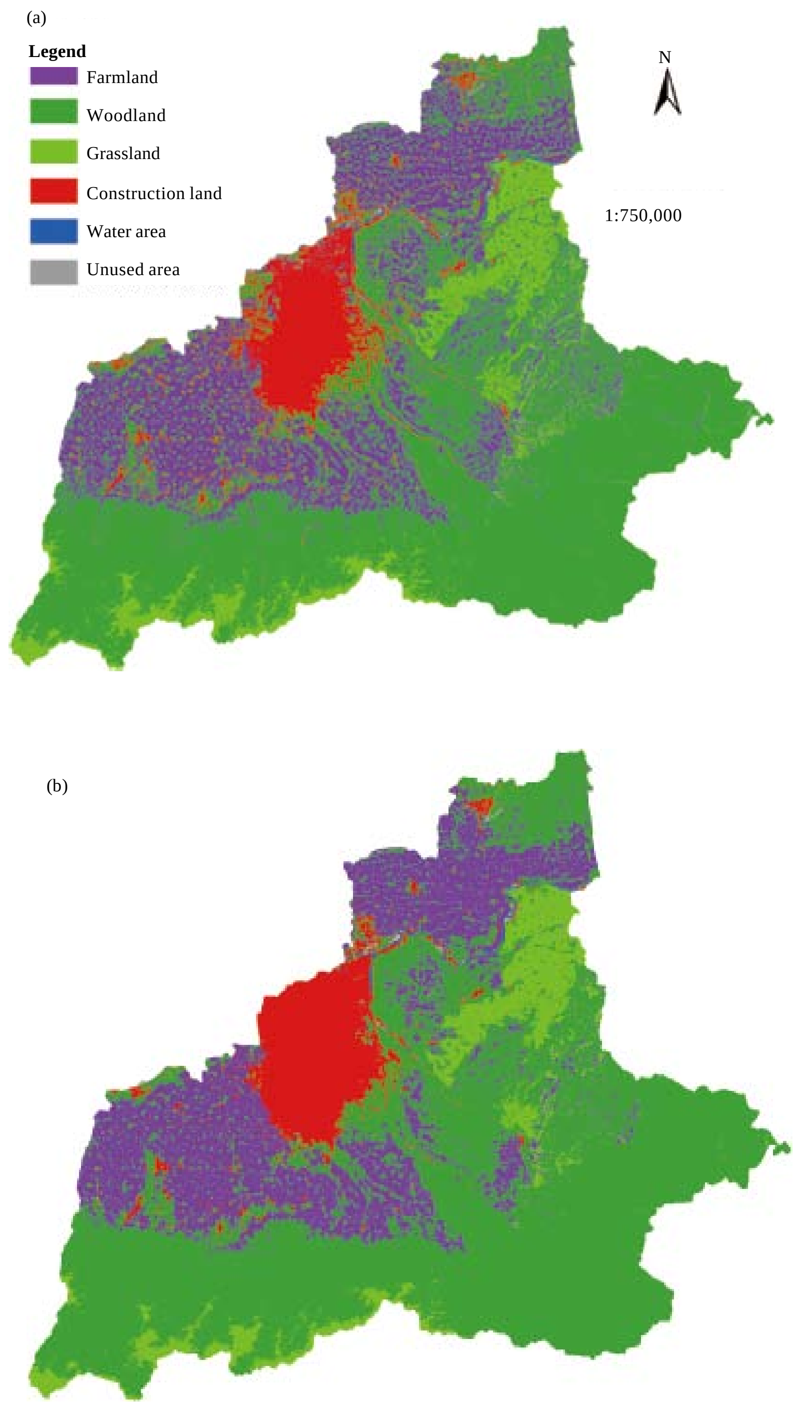

Fig. 2(a-b): Forecasted landscape pattern in the study area, (a) 2011 and (b) 2020

indicating that the accuracy of the model had decent precision and met the research requirements. Hence, the simulated results from this model can satisfactorily capture the reality.

The largest part of the study area was woodland followed by farmland from 2000 to 2011. The background of the study area was a composite landscape matrix dominated by woodland and farmland and embedded with patches or corridors of grassland, waters, construction land and unused land. Importantly, the augmented connectivity of the woodland landscape is crucial for stabilizing regional landscapes. Based on the results of 2000, 2004 and 2011, the predicted landscape patterns of 2011 and 2020 were produced with CA-Markov model. According to the prediction results, all of the landscape types will undergo considerable changes by 2020, such that the areas of the farmland and grassland will continue to decrease and those of the woodland, construction land, waters and unused land will increase (Fig. 2). On the one hand, the farmland and grassland would slip from 14.73 and 11.63% in 2011 to 13.94 and 8.75%, respectively, in 2020. On the other hand, the woodland, construction land and waters would increase to 59.46, 16.54 and 0.48%, respectively. According to the changes of the study area from 2000 to 2011, the predictions for the farmland, grassland, woodland, construction land and waters matched the actual trends. In contrast, the unused land is a back-up resource for a city's development, which diminishes and even disappears as urbanization intensifies and the city expands. Hence, its predicted increase in area was not in agreement with the actual development. Such an inconsistency might be attributed to the models and the transition matrix employed. Based on the spatial pattern, the elevated proportion of the construction land was mainly reflected by the increased built-up area of Xi'an City, manifesting an outward expansion from its original base. The result was related to the models, the starting point of the prediction and the transition matrix being employed herein. According to the prediction, the vegetation coverage in the study area would remain high in 2020, corresponding to an excellent ecological environment that would not restrict social and economic development. Nevertheless, the actual vegetation coverage and environmental quality in 2020 may be below the predicted value due to issues involving the skyrocketing population and construction land.

Difference cause of the landscape patterns: The simulation results derived from the CA-Markov model of 2011 and 2020 would likely be different from the actual interpreted values (of the 2011 remote sensing data) and the future development in 2020. The following might be deviating factors. First, the transition matrix derived using the Markov model had starting and terminating points of 2000 and 2004 and thus represented the transition matrix of the individual landscape types for the period of 2000-2004. The landscape changes during this period might be less significant than those of the 2004-2011 period, resulting in differences between the simulated areas of the landscape types and the corresponding interpreted values. This difference might be especially true for the simulated results for 2020 because some grand developmental plans, such as the Development Plan of the Guanzhong-Tianshui Economic Zone, International Metropolitan Plan, Xi'an-Xianyang New District Plan, northward migration of the municipal government seat and reconstruction of the villages in the city, are being implemented. Theoretically, adopting the transition matrix of 2004-2011 may generate more reliable results. Adoption of this matrix was practically impossible because the study area did not harbor any unused land that caused inconsistency in the landscape types between 2004 and 2011 and the Markov model in the IDRISI software requires matched landscape types between two phases to construct a transition matrix. This problem was certainly a major issue that demands improvements for the simulation using this software. The second deviating factor is that the interpretation accuracy of the remote sensing images may influence the prediction based on these images to a certain degree. The brightness of each pixel in a remote sensing image is a comprehensive depiction of the total material reflection within a given area. Because some pixels are mixed pixels composed of multiple landscape types, they may be subject to incorrect classification, leading to errors in the proportions of individual landscape types (Han and Chang, 2004). If the study had chosen the remote sensing images with higher resolutions, such as those of Quickbird, SPOT and IKONOS, the interpretation accuracy of the results might have been higher and the area of the grid cells might have been smaller. Consequently, the reliability of the simulated results might have been enhanced. The third factor is the series of intrinsic modeling uncertainties in the CA-Markov model, which are associated with many elements defining a CA model (e.g., neighboring area, size of grid cells, calculation time and transition rules). Although the simulated results had considerable differences from the actual development, they might still serve as a reference for the development of the study area. In addition, the IDRISI software is recommended here for simulation. Specifically, its input and output functions are directly used to convert shapefiles to vector files in the IDRISI format. Subsequently, the vector property table was opened using the database workshop to apply the 'create idrisi raster image' function to produce the grid files, a procedure that significantly streamlines the workload and boosts efficiency.

CONCLUSION

Based on the landscape maps (2000, 2004 and 2011), the CA-Markov model that combines the Markov chain analysis and CA models successfully simulated landscape changes in Xi'an in 2020. The simulated result can reliably capture the future evolution of the landscapes. The number and spatial distribution of the area is analyzed and the overall results are satisfactory: the six landscape types will maintain their changes in the direction and rates of change basically.

This study represents an important contribution to landscape pattern modeling as shown by the CA-Markov model. The model only considers the surrounding natural environment of the cellular, there is no consideration for the social environment, which is playing a decisive role in landscape dynamics changes. At the same time, the Markov model requires the same number of landscape types between two phases to construct a transition matrix, which was certainly a major issue that demands be improved for the model. As a result, the human decision-making model for the simulation is still a weakness which needs further study. The data processing and simulation procedures used in this study significantly streamline the workload and boost efficiency.

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