Simulation of Land Use Changes in Jiaodong Peninsular based on the Logistic-CA-Markov Model

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Abstract. Based on Landsat TM/ETM+ images acquired in 2000, 2005, 2010 and 2015 respectively, land use maps of Jiaodong Peninsular were created to analyze the characteristics of land use change. Then the Logistic-CA-Markov model was selected to simulate the spatial-temporal patterns of land use changes in 2010, 2015 and 2020 at 100 m spatial scale and five-year time interval. The results showed that: (1)During the period 2000-2015, areas of farmland decreased continuously, while urban area, rural settlement and independent industrial-mining increased continuously and rapidly; (2) Ten impact factors were chosen as the independent variables of Logistic regression analysis to establish eight logistic regression equations for eight land use types; (3) As the Logistic-CA-Markov model has a good performance in the simulation of land use maps in 2010 and 2015, it was further used to simulate land use change in 2020. (4)The simulation results showed that farmland, forest would decline during 2015 and 2020; Urban area would still increase.

1. Introduction

Land use change is a locally pervasive and globally significant ecological process which has become one of the primary research subjects of global environment change since 1995. It has broad impacts on the environment, such as water scarcity, soil erosion, water quality deterioration and urban heat island effect (Claessens et al, 2009; Tang et al, 2011;). The quantitative structure and spatial pattern of regional land use, as well as their dynamics can markedly affect the sustainability of social and economic development. Therefore, land use change deserves intense study by geographer, economist, planners and policy makers.

Dynamic modeling tools plays an important role in understanding land use change properly and visualizing future land use scenario. Substantial progress has been made in the development of dynamic modeling tools for land use change forecasting over the last decades (Guan et al., 2011; Tayyebi, et al., 2011; Zhang, 2011). One of the most commonly used tools is the Markov model which is applied on the basis of the stochastic nature of land use changes. Markov chain process is suitable to be used in studies of the quantitative changes of regional land use (Bell, 1974). Up to now, Markov chain process has been widely used to simulate land use changes by transition probabilities which can be computed from proportions of past transitions among different land use types. However, early
studies mainly used Markov chain process method to reveal the transfer rate among various land use categories and control temporal change among the land use types (Muller and Middleton, 1994); therefore, it is one of the non-spatial methods.

Subsequently, a combination of Markov chain process and cellular automata techniques has been developed to simulate land use change spatially (Akin et al., 2012; Oguz and Zengin, 2011). For example, Balzter et al. (1998) introduced the spatial dimension into Markov chain by cellular automata technique and tested its effectiveness for spatial-temporal modeling of vegetation dynamics. Jenerette and Wu (2001) proposed a Markov-cellular automata model parameterized by a modified genetic algorithm to simulate the desert landscape transformations caused by urbanization in the central Arizona-Phoenix region, USA. Clark Labs in Clark University (Eastman, 2003) developed CA-Markov model, one of the plug-ins in IDRISI software for land use change modeling which has been widely used in recent years. Peterson et al. (2009) studied the patterns and trends of forested land in the Siberian Baikal region over changing forest management eras by integrating logistic regression and CA-Markov. Mondal and Southworth (2010) evaluated the conservation interventions in the tropical forests of Central India using CA-Markov. What’s more, Markov chain method has been integrated with other dynamic models, such as System dynamic model and Agent-based model. Yang et al. (2012) proposed a simulation model of land use change on the basis of Markov chain, cellular automata and ant colony optimization. Chu et al. (2010) applied the Markov chain model to analyze the stochastic nature of the land use change and calculate the annual land use demand, and then implemented a land use allocation procedure by ANN-CLUE-s and Logistic-CLUE-s.

Jiaodong Peninsular lies in the east of Shandong Province, which is also the largest peninsula in China. Jiaodong Peninsular is the key areas to lead the economy progress of Shandong Province where land use change dramatically. In this paper, Jiaodong Peninsular, China is selected as the case study area. Based on Landsat TM/ETM+ images acquired in 2000, 2005, 2010 and 2015 respectively, land use maps of Jiaodong Peninsular are created to analyze the characteristics of land use change. Then the Logistic-CA-Markov model is selected to simulate the spatial-temporal patterns of land use changes in 2010, 2015 and 2020 at 100 m spatial scale and five-year time interval.

2. Study Area and Data Processing

2.1 Study Area

Jiaodong Peninsular, which includes the whole cities of Yantai, Qingdao, and Weihai, is located in North China between the range of 119° 30′ E – 122° 42′ E and 35° 35′ N – 38° 23′ N as shown in Figure 1, with an total area of approximately 30800 km². The coastline of Jiaodong Peninsular extends about 1700 km along the East China Sea coast. It is one of the regions in China with most rapid land use changes in the past decades.

Figure 1. Location of Jiaodong Peninsular.
2.2 Data Acquisition and Processing

The land use of Jiaodong Peninsular is classified into eight types: farmland, forest, grassland, water body, urban area, rural settlement, independent industrial and mining land (independent industrial-mining) and unused land. Land use maps are created based on Landsat TM/ETM+ images acquired in 2000, 2005, 2010 and 2015 respectively. The detailed processing procedure is as follows: Firstly, remote sensing images are geometrically rectified using topographical maps with 1:50 000 scale. Then, on-screen visual interpretation technique is used to delineate land use boundaries in ArcGIS 10.2 environment. The land use maps are stored as vector format spatial data in ArcGIS 10.2 with the spatial accuracy reaching up to 1: 100 000 scale which would be the original input data of the Spatial-Markov model. Thirdly, vector format land use maps in 2000, 2005, 2010 and 2015 are converted into raster format land use maps with spatial resolution of 100 m × 100 m and the generated raster format land use maps will be used as input data by the CA-Markov model. Finally, a binary categorical raster format image is created for each type of land use which would be taken as dependent variables by Logistic regression analysis.

Ten factors were chosen as the independent variables of the Logistic regression analysis, and they were compiled into Arc/Info Grid data format with spatial resolution of 100 m × 100 m. Then, each of them was normalized between 0 and 255. The detailed list of these variables was shown in Table 1.

Table 1. Variables used in the logistic regression model.

| Variable name          | Description                                           |
|------------------------|-------------------------------------------------------|
| Highway distance       | Distance to nearest highway                           |
| Road distance          | Distance to nearest road                               |
| Rail distance          | Distance to nearest rail                              |
| River distance         | Distance to nearest river                              |
| Shore distance         | Distance to nearest shore                              |
| Rain                   | Average yearly precipitation                          |
| Temperature            | Average yearly temperature                            |
| Urban distance         | Distance to 2005 urban use                            |
| Elevation              | USGS digital elevation models, resampled to 100 m × 100 m cell sizes |
| Slope                  | A slope layer derived from the USGS digital elevation model data |

3. Methods

3.1 Land Use Dynamic Degree

Land use dynamic degree refers to the changed amounts of land use change over a certain period of time in a certain study area, which is calculated as follows: (Xiao et al, 2006)

\[ K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \] (1)

where \( U_a \) and \( U_b \) represent the area of a certain land use type at the beginning and end of the research period, respectively; \( K \) donates the dynamic degree of a single land use type.

3.2. Markov Chain Process

Markov chain process is a special random moving from one state to another state at each time step with non-aftereffect property (Guan et al., 2011). On the basis of the nature of Markov chain process and the definition of conditional probability, the prediction of land use change is as follows:

\[ S(t+1) = S(t) \times P \] (2)

Where \( S(t) \) and \( S(t+1) \) mean the row vectors at time step \( t \) and time step \( t+1 \); \( P \) refers to the transition probability matrix for prior time interval, which is calculated as follows:
Where $p_{ij}$ indicates the transition probability from land use type $i$ to $j$.

3.3 CA-Markov Model
As a dynamic and spatial explicit model, a cellular automaton is composed of a discrete time step, a space of discrete cells, a neighborhood, and transition rules. Cells can change their states in discrete time steps. Generally, the change of a cell is related to its neighborhood and the corresponding transition rules which can be constructed by the logistic regression model (LR), multi-criteria evaluation (MCE), ANNs, and so on. In the CA-Markov model, which is a package in IDRISI software developed by Clarke labs at Clark University, the temporal dynamics among different land use types are controlled by the Markov chain, while CA model controls the spatial dynamics based on local rules which are determined by the transition potential maps. The IDRISI’s CA-Markov model is used in this paper for land use simulation.

3.4 Logistic Regression Method
The logistic regression method was selected to construct transition rules for CA-Markov in this study. The basic forms of logistic regression are given below:

$$
\log \left( \frac{P_i}{1-P_i} \right) = a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n
$$

(4)

Where $x_1, x_2, \ldots, x_n$ refer to explanatory variables; The parameter $a$ indicates the intercept of the regression curve; The parameters $b_1, b_2, \ldots, b_n$ are the regression coefficients to be calculated; $P_i$ indicates the probability of the occurrence of the corresponding land use category; In this study, the relationship between the presence/absence of each land use type and driving factors is identified by binary logistic regression model.

3.5 Logistic-CA-Markov Model
The Logistic regression model and the IDRISI’s CA-Markov are integrated together in this study. The detailed process was as follows: Firstly, based on land use maps in 2000 and 2005, the Markov chain method is applied to predict the transition area matrix from 2005 to 2010 and 2010 to 2015. Secondly, the transition rules are established by the Logistic regression method. Eight logistic regression equations were established for eight land use types respectively by computing the coefficients for the independent variables. Thirdly, to simulate land use pattern in 2010 and 2015, the time point of 2005 is set as the starting point while the CA iterations are set as 5 and 10. Meanwhile, the transition matrix and transition potential maps were loaded into the model.

3.6 Kappa Coefficient
Kappa coefficient is a widely used measure for chance-corrected nominal scale agreement between two images. It is generally considered that kappa > 0.8 means excellent simulation effect, 0.6 to 0.8 means good simulation effect, 0.2 to 0.4 means poor simulation effect, 0 to 0.2 means poor simulation effect.

4. Results and Discussion

4.1 Land Use Changes
Land use structures of Jiaodong Peninsula in 2000, 2005, 2010 and 2015 are shown in Table 2. Farmland dominated the study area covering over 54% of the study area, however areas of farmland...
decreased those years. The rate of decline increased during 2000 and 2010 and then slowed during 2010 and 2015. The secondary land use type was grassland covering over 13% of the study area which also decreased during 2000 and 2015. Forest was the third land use type which occupied over 10% of the study area. With acceleration of industrialization and urbanization process in Jiaodong Peninsula, areas of urban area increased dramatically over these time periods from 1014 km$^2$ to 1978 km$^2$, while the change rate of urban area slowed down over the period. Areas of rural settlement and independent industrial-mining rised up during 2000 and 2010, but declined in 2015.

| Land use type                  | Area (km$^2$) | Percentage (%) | Land use dynamic degree (%) |
|-------------------------------|---------------|----------------|----------------------------|
| Farmland                      | 18071         | 59.31          | -0.49                      |
| Forest                        | 3314          | 10.88          | -0.10                      |
| Grassland                     | 4332          | 14.22          | -0.18                      |
| Water body                    | 1033          | 3.39           | 0.11                       |
| Urban area                    | 1014          | 3.33           | 0.81                       |
| Rural settlement              | 1805          | 5.92           | 4.71                       |
| Independent industrial-mining | 821           | 2.69           | 1.03                       |
| Unused land                   | 80            | 0.26           | -45.44                     |

To further explore land use change characteristics, GIS overlap analysis was used to statistic land use transition areas from 2000 to 2005, 2005 to 2010, 2010 to 2015. From 2000 to 2005, the area of land use change was 648.37 km$^2$, accounting for 2.13% of the total area. The top three types of land use transition were from farmland to urban area, from farmland to rural area and from rural area to urban area, accounting for 35.41%, 18.08% and 8.76% of the total transfer area, respectively. From 2005 to 2010, the change characteristics tended to be complex, as the area of land use transition had increased significantly, which was 1508.72 km$^2$, accounting for 4.95% of the study area. In specific, the proportion of farmland to urban area was 42.87%. In addition, 103.03 km$^2$ of farmland was converted into grassland, while the grassland flowed to rural settlement, farmland, independent industrial and mining land. During 2010 to 2015, the area of land use change was 846.27 km$^2$, the main land use transition type was rural settlement to urban area, account for 15.98% of the total land use change areas. The secondary land use transition type was independent industrial and mining land to urban area. Besides, 250.56 km$^2$ of farmland was converted to urban area, rural settlement, independent industrial and mining land.

4.2 Impact Factors of Land Use Change

In this paper, based on Binary Logistic Regression, eight logistic regression equations were established for eight land use type respectively by computing the coefficients for ten independent variables. The fitness of every model was assessed by computing the relative operating characteristic (ROC) values. The ROC value for each equation was greater than 0.7, which demonstrated that independent variables were well correlated with the corresponding dependent variable.

4.3 Land Use Change Simulation

To simulate land use pattern in 2010 and 2015, the time point of 2005 was set as the starting point while the CA iterations was set as 5 and 10 respectively. Meanwhile, the transition matrix and transition potential maps were loaded into the model. The inherent suitability for each land use type was established in each pixel by transition potential maps. Besides, the $5 \times 5$ contiguity filter was adopted to set each cell’s neighborhood and weight the suitability of areas close to each existing land use type higher for the establishment of that land use type.

The simulated maps of land use in 2010 and 2015 were compared with the observed map in 2010 and 2015 respectively so as to evaluate the performance of CA-Markov model. Furthermore, Kappa
coefficient was chosen to assess the simulation. The results showed that kappa coefficient for 2010 and
2015 were 0.9575 and 0.9041 respectively. That was to say Logistic-CA-Markov model achieved good
simulation in this case.

Therefore, based on Logistic-CA-Markov model, land use map in 2020 was also simulated.
According to the simulation results(Figure 2 and Table 3), areas of farmland and forest will continue to
fall, urban area will expand consistently. Areas of rural settlement and independent industrial-mining
will decrease. Area of water body will stay stable.

Figure 2. Simulated Land Use Maps in 2020.

Table 3. The Simulation Result of Land Use 2020 (km²).

| Farmland | Forest | Grassland | Water body | Urban area | Rural settlement | Independent industrial-mining | Unused land |
|----------|--------|-----------|------------|------------|-----------------|-------------------------------|-------------|
| 16387    | 3249   | 4179      | 1052       | 2289       | 2070            | 983                           | 261         |

5. Conclusions

During 2000 and 2015, farmland dominated the study area covering over 54% of the study area,
however areas of farmland decreased those years. The secondary land use type was grassland which
also decreased during 2000 and 2015. Areas of urban area increased dramatically over these time
periods Areas of rural settlement and independent industrial-mining raised up during 2000 and 2010,
but declined in 2015.

Based on Logistic-CA-Markov model, land use maps in 2010 and 2015 were simulated. The result
showed that Logistic-CA-Markov model had a good performance in the simulation of land use maps
in 2010 and 2015, therefore it was further used to simulate land use change in 2020.

The simulation results showed that farmland, forest would decline during 2015 and 2020; Urban
area would still increase.

The study on the historical and future land use change and its impact factors in Jiaodong Peninsula
can provide data support for the study of social economy and ecological problems caused by land use
change. On the other hand, this study can provide important reference information for land use
planning of government departments.

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