Ecological Modelling 233 (2012) 11–19

Contents lists available at SciVerse ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata

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ARTICLE INFO

Article history:
Received 28 November 2011
Received in revised form 5 March 2012
Accepted 6 March 2012
Available online 6 April 2012

Keywords:
Land use change
Ant colony optimization
Markov
Cellular automata

ABSTRACT

This paper proposes a spatiotemporal model of land use change based on ant colony optimization (ACO), Markov chain and cellular automata (CA). These three methodologies have previously been used separately or in pairs to simulate land use change. In this paper, we apply them in combination, using ant colony optimization and cellular automata to manage the spatial distribution of land use, and applying Markov chain and cellular automata to manage the total amount of land use coverage. We first describe the principle and implementation of the model. Then a land use map of an experimental area (Changping, a district of Beijing) based on land use maps from 1988 and 1998 is simulated for 2008 using the model. By analyzing with real situation, accuracy of the simulation result manifests that the model is useful for land use change simulation. And compared with the other two models (CA–Markov model and ACO–CA model), the model is more appropriate in predicting both the quantity and spatial distribution of land use change in the study area. Therefore the model proposed by this paper is capable of simulating land use change.

1. Introduction

The simulation of land use change (LUC) is a frequently required but difficult process. LUC simulation is important for a variety of planning and management issues as well as for academic research (Deng et al., 2008). It can help in the assessment of development impacts, the preparation of land use plans and the search for optimal land use patterns, and enable rural and urban planners to provide the public with necessary facilities and services to sustain development (Li and Yeh, 2002). However, LUC is a highly complex spatial dynamic nonlinear system (Verburg et al., 2002). The driving factors and constraint mechanisms of LUC processes are very complex, particularly since natural and human factors may be working at different scales (Lambin et al., 2001).

To date, a variety of methods have been used to model LUC, such as multi-agent systems (Tian et al., 2011; Castella and Verburg, 2007), generalized linear modeling (Rutherford et al., 2008), unbalanced support-vector machines (Huang et al., 2009), and aggregated multivariate regression (Zang and Huang, 2006). In their paper, Du et al. (2010) discuss the advantages and disadvantages of five methods: Markov chains, multivariate statistics, optimization, system dynamics and CLUE (Conversion of Land Use and its Effects model)/CA (cellular automata). For example, Markov chain can predict the amount of land use change, but cannot simulate the change in spatial distribution. Optimization model can provide enough information to support decision-making, but cannot present the dynamic land use change process. To improve the reliability of LUC simulations, a variety of methodologies integrating two or more methods to combine their advantages have been suggested by researchers (Liu and Li, 2007; Qiu and Chen, 2008; Yang and Li, 2007). He et al. (2005) developed the scenarios dynamic simulation model that integrates the advantages of the system dynamic model in scenario simulation and reflection of macrodrivers, as well as the advantage of CA in modeling the spatial pattern of land use. Taking advantage of the capacity of neural networks to cope with erroneous and poor data as well as to capture nonlinear complex features, a CA model based on neural networks was established to simulate LUC (Li and Yeh, 2002). And taking advantage of Markov chain of amount forecast, a CA model based on Markov was established to simulate LUC. The CA–Markov land use change model can be applicable for spatial land use simulation and land use reconstructions, but the "salt-and-pepper" effect of simulation result was inevitable (Wang et al., 2010a,b).

In this paper, we propose a novel method based on the techniques of ant colony optimization (ACO), Markov chain and CA. CA has strong capabilities in simulating the spatiotemporal characteristics of complex systems (Li and Yeh, 2002). It can be used to simulate unexpected behaviors of complex systems that cannot be represented by specific equations. Many studies, such as

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doi:10.1016/j.ecolmodel.2012.03.011

the researches done by Cao et al. (2011) and Luo et al. (2004), have shown the ability of CA for simulating and predicting LUC. The Markov chain is also widely used for the projection of LUC, for example, based on it, Hou et al. (2004) simulated LUC in Hexi Corridor; Risch et al. (2009) predicted long-term development of abandoned subalpine conifer forests in the Swiss National Park; Sang et al. (2011) projected land use spatial pattern of towns and villages. In a Markov chain, the change in an area is summarized by a series of transition probabilities (or a series of transition areas) from one state to another over a specified period of time. These probabilities can be subsequently used to predict land use properties at specific future time points (Muller and Middleton, 1994). ACO reflects a type of swarm intelligence and it is one of the most advanced techniques for approximate optimization (McMullen, 2001). Ant colony systems are very robust to perturbation, meaning that overall dynamics are not easily affected by the failure of one or more agents (Liu and Li, 2007). Additionally, the 'bottom-up' approach adopted in ACO to complete complex tasks through cooperation among agents corresponds well to the structure of CA, making ACO an appropriate tool for the extraction of CA transition rules (Liu et al., 2008; Yu et al., 2011).

The aim of this study was to combine the benefits of ACO, Markov chain and CA, and to integrate them into a spatial framework for LUC simulation. First, ACO and CA were integrated to determine local transition rules of LUC, with the aim of conducting a reasonable local rule discovery process. Then the transition area matrix was predicted by Markov chain analysis with the aim of managing the total amount of LUC. Finally, a future land use map was generated by CA using a combination of the local transition rules and the transition area matrix as simulation rules. We present a case study of the Changping district in Beijing to demonstrate the modeling process and the utility of this model. The paper is organized as follows: Section 2 gives a brief description of the modeling methods and explains the architecture of the ACO–Markov–CA model. Section 3 presents the case study. In Section 4, we offer conclusions and outlooks to the future.

2. A spatiotemporal model of LUC based on ACO–Markov–CA

2.1. Integration of ACO and CA

CA is a discrete, spatially explicit extended dynamic system characterized by a simple structure (Yang and Li, 2007). It is composed of individual elements, called cells, which evolve in discrete time steps according to a common local transition rules (Wu and Webster, 1998).

Artificial ACO was based on the behavior of ants to find the shortest path when seeking food without the use of visual information (Dorigo et al., 1996). To exchange information about which path should be followed, ants communicate with each other using pheromones which are unique to ants. Pheromones are sensed by moving ants to direct their movement, but they evaporate over time. When the number of ants taking a certain path increases, the amount of pheromones deposited there will also increase, resulting in a higher probability for other ants to also choose this path. In this way, ants can locate the shortest path (Bozdogan and Efe, 2011). This process can be described as a positive feedback loop (Yagmahan, 2011).

When applying ACO to discovery cellular automaton local transition rules, a rule is equivalent to a path; an optimal rule is the shortest path (Li et al., 2011). In this paper, a local transition rule of LUC can be expressed in an IF-THEN form as follows:

$$IF \quad \langle term_1 \quad AND \quad term_2 \quad AND \ldots \rangle \quad THEN \quad \langle Consequence \rangle$$

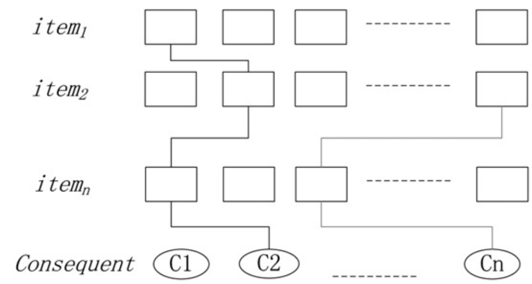

Fig. 1. Routes corresponding to local transition rules derived from ACO–CA model.

where $term_i$ is a conditional item of cellular evolution, $\langle Consequence \rangle$ is the cellular evolutionary result (cellular new state). $term_i$ in a rule is a node of a path. $\langle Consequence \rangle$ in a rule is the destination of a path (Fig. 1).

A flowchart of the ACO algorithm for local transition rule discovery is shown in Fig. 2 (Yu et al., 2011). Discovery of a rule based on ACO can be divided into three stages. First, a rule is constructed. Starting from an empty route, nodes are repeatedly selected and added to the route until complete conditional items are acquired, and then consequence is selected. Second, the rule is pruned. Finally, the pheromone amount on all the routes is updated, which affects rule construction for the next ant (Li et al., 2011).

(a) Rule generation

Ants start from the artificial nest (an empty path). And then choose a value for each node of the path. This process is implemented as a probability function (Eq. (1)). It computes the probability (P_{ij}) that V_{ij} is selected as the value of $item_i$ ($item_i = V_{ij}$), where $item_i$ is the ith item and the jth value of $item_i$.

$$P_{ij} = \frac{\eta_{ij}\tau_{ij}(t)}{\sum_{i=1}^{a}\sum_{j=1}^{b_i}\eta_{ij}\tau_{ij}(t)} \tag{1}$$

where a is the number of nodes; b_i is the number of values of $item_i$; t is the sequence number of the iteration; η_{ij} is the value of a problem-dependent heuristic function for V_{ij}, which is used as the "looking-ahead" characteristic of artificial ants to guide their movements; $\tau_{ij}(t)$ is the amount of pheromone on node V_{ij} at iteration t.

In Eq. (1), η_{ij} is an important parameter. The higher its value, the larger is the chance that the related node is selected by an ant. It plays the role of an indicator of the distance between the nest and food and it guides ants in exploring paths. η_{ij} is specified as Eq. (2).

$$\eta_{ij} = \frac{\max(freqT_{ij}^1, freqT_{ij}^2, \ldots, freqT_{ij}^k)}{T_{ij}} \tag{2}$$

where T_{ij} is the partition containing the cases where $item_i = V_{ij}$, and $freqT_{ij}^k$ is the number of cases in T_{ij} where $Consequence = C_k$. The higher the value of η_{ij}, the higher is the possibility of V_{ij} being selected into the rule as a new node.

Before the ants start to find a path, all V_{ij} are initialized with the same amount of pheromone ($t = 0$). $\tau_{ij}(t)$ is specified in Eq. (3).

$$\tau_{ij}(t=0) = \frac{1}{\sum_{i=1}^{a} b_i} \tag{3}$$

For $t > 0$, $\tau_{ij}(t)$ is specified in Eq. (5).

After the ant has explored all nodes (in other words, the conditional items of the rule has been generated), it will choose the consequence of the rule. The ant selects the consequence that most frequently appears in the training cases covered by the antecedent of the rule.

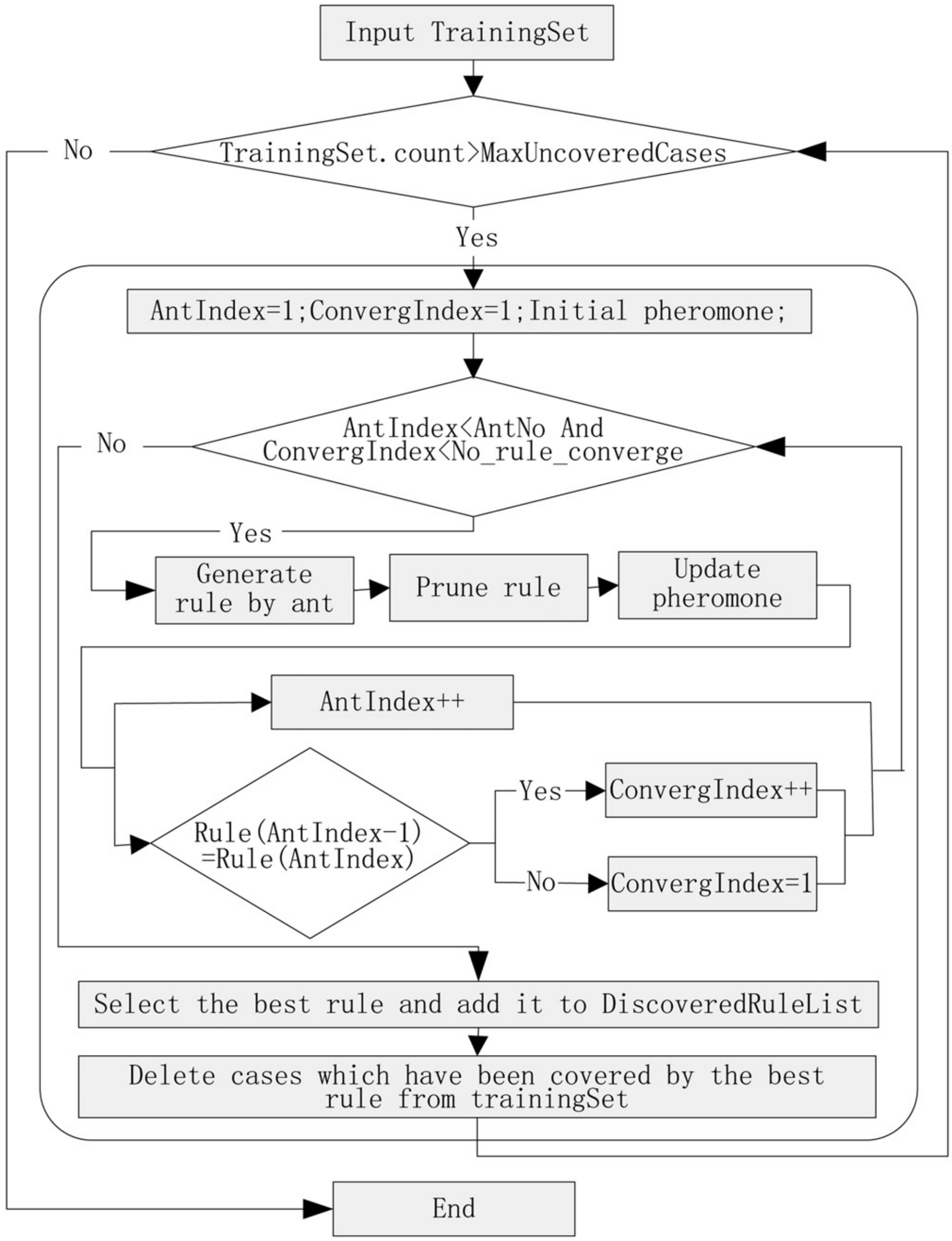

Fig. 2. Workflow of ACO for local transition rules discovery.

(b) Rule pruning

When a rule is generated, all the nodes are selected as a condition of the entire rules, but some nodes may have no or a negative effect on the quality of the rule. Therefore, the rule needs to be pruned by removing one or more nodes to achieve the highest quality. The rule pruning process tries to remove each node of the rule antecedent in turn, and then computes the quality of the rule. After each node in the rule has been tried, the node whose removal most significantly improves the quality of the rule is pruned. The definition of the quality of a rule is given in Eq. (4).

$$Q = \left(\frac{TruePos}{TruePos + FalsePos}\right) + \left(\frac{TrueNeg}{FalsePos + TrueNeg}\right) \tag{4}$$

where Q is the quality of a rule, $0 \le Q \le 1$; *TruePos* (true positive) is the number of training cases in the training set whose antecedent part and consequence part are covered by the rule; *FalsePos* (false positive) is the number of cases whose antecedent part is covered by the rule while the consequence is not covered; *FalseNeg* (false negative) is the number of cases whose antecedent part is not covered by the rule while the consequence is covered; and *TrueNeg* (true negative) is the number of cases in which neither antecedent nor consequence part are covered by the rule.

(c) Pheromone updating

Pheromone updating in the ACO algorithm is designed to simulate the evaporation of ant pheromone. The amount of pheromone on the nodes used by the current rule is updated through the deposition of pheromone by the artificial ants during path exploration. The better the quality of a rule, the more pheromone will be deposited on the path so as to attract more ants to take this

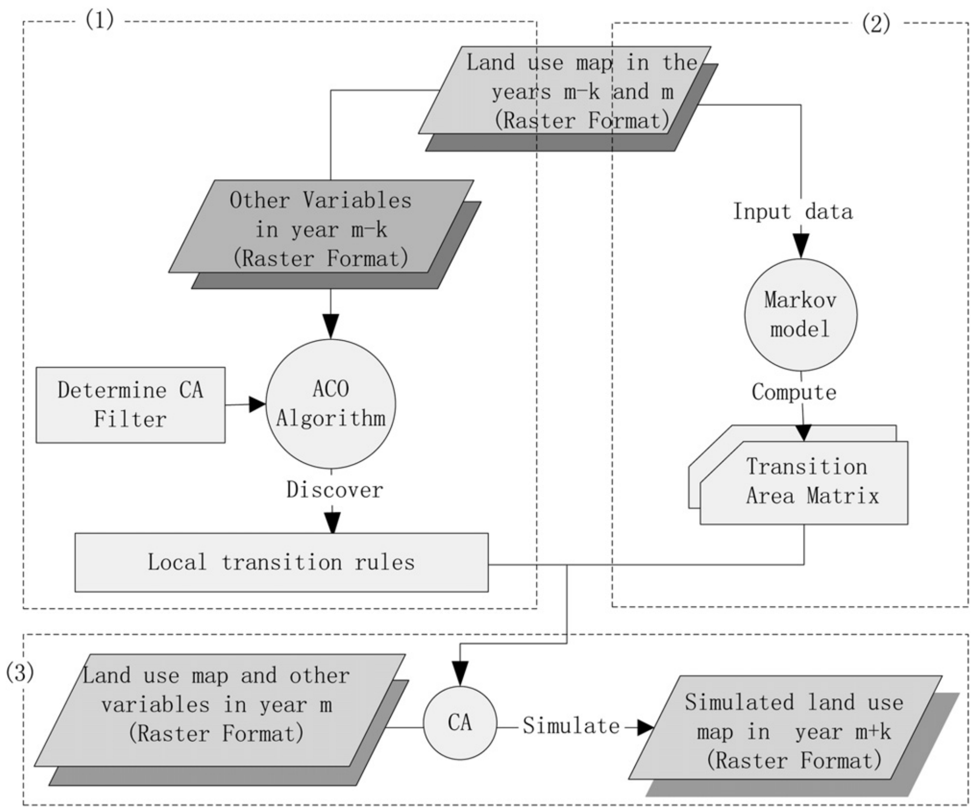

Fig. 3. Implementation of processing architecture of ACO–Markov–CA model.

path. However, pheromone evaporation also needs to be simulated. These two processes are performed according to Eq. (5).

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t-1) + \left(1 - \frac{1}{1+Q}\right)\tau_{ij}(t-1) \tag{5}$$

where ρ is the pheromone evaporation rate which controls how fast the pheromone evaporates from trails; Q is the quality of the rule calculated from Eq. (4); and t is the sequence number of the iteration. Nodes that have not been used by the current rule are subject to pheromone evaporation only. Evaporation occurs according to Eq. (6).

$$\tau_{ij}(t) = \frac{\tau_{ij}(t-1)}{\sum_{i=1}^{a}\sum_{j=1}^{b_i}\tau_{ij}(t-1)} \tag{6}$$

where a is the number of nodes; b_i is the number of values of $item_i$; and t is the sequence number of the iteration. It follows from this equation that the amount of pheromone on unexplored nodes will decrease with time.

2.2. Markov chain

The Markov chain is a discrete random process with the Markov property whereby the probability distribution for the system at the next step and all future steps depends only on the current state of the system and not additionally on the state of the system at previous steps (Guan et al., 2008). It is commonly used in the prediction of geographical characteristics lacking after-effect events and has become an important prediction method in geographical research (Clancy et al., 2010). Markov chain analysis is a convenient tool for modeling land use change when changes in the landscape are difficult to describe, and serves as an indicator of the direction and magnitude of change in the future since it has capabilities of descriptive power and simple trend projection of land use change (Benito et al., 2010; Cabral and Zamyatin, 2009).

In the model proposed by this paper, Markov chain analysis is used to predict the transition area matrix to manage the amount of LUC. And the transition area matrix (denoted by A) for target simulation periods is generated by the MARKOV module in IDRISI Andes (A raster-based spatial analysis software developed by Clark Labs at Clark University. With IDRISI Andes, you can explore, predict, and model impacts on land cover change with the innovative Land Change Modeler facility (IDRISI-Wikipedia, 2012).) The transition area matrix is performed by Eq. (7).

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{7}$$

where A is the transition area matrix, A_{ij} is the sum of areas from the ith state to the jth state during the years from start point to target simulation periods, and n is the number of land use type.

2.3. Integration of ACO, Markov and CA

The core idea behind the ACO–Markov–CA model is trying to absorb the benefits from the time series and spatial predictions of Markov and ACO–CA model, which is embodied in the use of ACO and CA to discover local transition rules to manage the spatial pattern of LUC, and the use of the Markov chain analysis to predict the transition area matrix of LUC in order to control overall LUC amount.

The architecture of the ACO–Markov–CA model is shown in Fig. 3. First, two land use maps from different years are read as two cellular spaces. With some other spatial variables in raster format, ACO is then used to discover the local transition rules between the two maps and build a database of local transition rules and their qualities. At the same time, the Markov chain is used to predict the

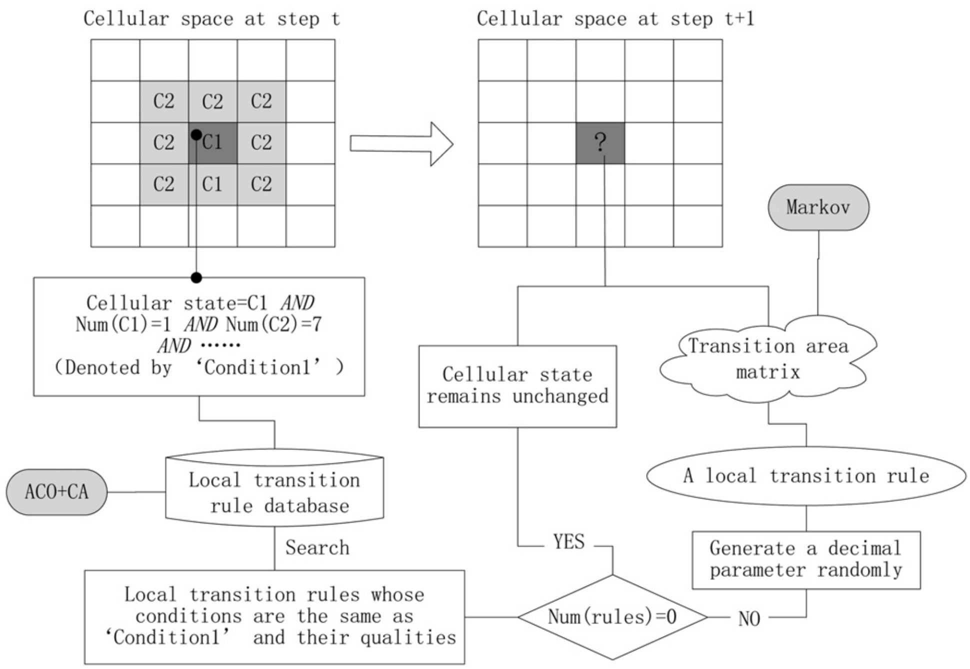

Fig. 4. Implementation of the process for integrating local transition rules with the transition area matrix into a rule for the CA model.

LUC transition area matrix. Finally, the database and the transition area matrix are integrated into the CA model to simulate future land use patterns with the most recent available land use map and the maps of some spatial variables as initial data.

The key functionality of the ACO–Markov–CA model is the integration of the local transition rules discovered by ACO with the transition area matrix to generate the rule for the CA model. The following approach is used: in each simulation loop, the states of each cell's neighbors are scanned (the CA filter used in this process must be identical to that used in discovering local transition rules based on ACO and CA) to form the condition of a local transition rule denoted by *Condition1*. Then those rules whose conditions are equal to *Condition1* are selected from the local transition rule database, and their qualities (the values of *Q*), denoted by *QR*, are recorded. Then a random decimal parameter between 0 and 1 is generated. The random number and *QR* are used to determine the simulation result of one cell based on roulette-wheel selection. This process is repeated until the simulated result is sufficiently close to the transition area matrix (Fig. 4).

As shown in Fig. 3, the implementation of the model can be divided into three parts. As mentioned in Section 2.2, the part (2) was implemented by using the IDRISI Andes MARKOV module. For the implementation of parts (1) and (3), based on the theory described above, two tools called ACO–CA-Miner tool and simulation tool were developed using Microsoft C#.NET (a multi-paradigm programming language encompassing strong typing, imperative, declarative, functional, generic, object-oriented, and component-oriented programming disciplines. It was developed by Microsoft within its .NET initiative (C_Sharp-Wikipedia, 2012)) and ESRI ArcGIS Engine development components (a collection of GIS components and developer resources that can be embedded, allowing you to add dynamic mapping and GIS capabilities to existing applications or build new custom mapping applications (ArcGIS Engine-Esri)).

According to the principle of ACO–Markov–CA model, the simulation process can be divided into three stages. First, the local transition rules should be discovered by the ACO–CA-Miner tool. Second, the predicted transition area matrix is generated using the MARKOV module in IDRISI. Finally, the future land use map can be simulated by the simulation tool.

3. Case study

To demonstrate the feasibility of the model proposed in this paper, a case study was conducted to predict land use change in the Changping district, Beijing, China. This district was selected as a study area because of its land use complexity and data availability. As of the end of 2010, the study area covers an area of approximately 1352 km^2, and includes 10 towns. As some of its edges comprise outer borders of the area of Beijing, Changping is a rapidly growing area. While developing rapidly in economy, land use changed dramatically under the common influence of human environmental system. For example, paddy land gradually reduced; ecological land use of closed forest land, artificial pasture, natural reserve and forest park increased drastically (Wang et al., 2010a). Land use changes in Changping are complex.

3.1. Data source

The data used in this case study to provide actual urban areas include three land use maps generated from the classification of Landsat TM5 images, acquired during the summers of 1988, 1998 and 2008 at the spatial resolution of 30 m. Each land use map is treated as a cellular space with each pixel representing a cell. Thus, each cell represents an area of 30 m × 30 m = 900 m^2. The maps contain five land use/land cover classes: forest (FL), cultivated land (CuL), construction land (CoL), water (WL) and other unused land

Table 1
Changes in land use area in Changping, 1988–1998.

	FL	CuL	CoL	WL	OUL
1988 (km^2)	671.93	313.38	121.34	2.87	242.48
1998 (km^2)	680.81	367.28	206.46	5.83	91.62
Changed area (km^2)	8.88	53.9	85.11	2.96	−150.85
Change ratio (%)	1.32	17.2	70.14	103.09	−62.21

Table 2
Spatial variables used for the conditional items of local transition rules.

	Spatial variable	Short name
Physical attribute	Cellular initial state	IS
Distance-based variables	Distance from the cell to the major urban areas	Dist(MU)
	Distance from the cell to the closest town areas	Dist(CT)
	Distance from the cell to the closest road	Dist(CR)
	Distance from the cell to the closet railway	Dist(CW)
Neighborhood conditions	Amount of cells used as forest	Num(FL)
	Amount of cells used as cultivated land	Num(CuL)
	Amount of cells used as construction land	Num(CoL)
	Amount of cells whose states are water	Num(WL)
	Amount of cells used as other unused land	Num(OUL)

Table 3
Part of the local transition rules derived by ACO and CA.[a]

No.	IS	Distance-based variables				Neighborhood conditions					Consequence	Q
		Dist(MU)	Dist(CT)	Dist(CR)	Dist(CW)	Num(FL)	Num(CuL)	Num(CoL)	Num(WL)	Num(OUL)		
1	FL	≥416	–	–	–	48	–	–	–	–	FL	0.917
2	FL	–	≥203	–	–	≥34	–	–	–	–	FL	0.842
3	FL	–	≥76	≤168	–	–	≥3	–	–	–	CuL	0.816
4	FL	–		≤181	–	–	–	≥1	–	≥3	CuL	0.727
5	FL	–	≤257	–	–	–	–	≥33	–	–	CoL	0.564
6	CuL	–	≥46	–	–	–	≥25	–	–	–	CuL	0.831
7	CuL	–	–	≤177	–	>9	–	≥2	–	–	CuL	0.622
8	CuL	–	≤269	–	–	–	–	≥24	–	–	CoL	0.593
9	OUL	–	≥94	≤116	–	≥1	–	–	–	–	CuL	0.838
10	OUL	≥198	≥76	–	–	≥1	–	–	–	–	FL	0.759

[a] "–" indicates that the number of cells of this kind in the neighborhood is not evaluated, but the sum of each cellular neighborhood cells does not exceed 48.

(OUL). The two maps for 1988 and 1998 were used to capture the transition rule and historical development trends. The 2008 map was used to test the simulation.

The land use maps for 1988 and 1998 are shown in Fig. 5. Changes in the land use types are clearly visible over the 10 year period. Using the CROSSTAB model in IDRISI, the changes in land use area can be obtained (see Table 1). In 1988, the main types of land use in Changping were FL, CuL and OUL, which account for 90.81% of the total. In 1998, the main types of land use were FL, OUL and CoL. From 1988 to 1998, there were small changes in total FL area, and CuL increased by 17.2%. Another obvious trend is the expansion of CoL, driven by economic development.

In this paper, a total of ten spatial variables were used for the conditional items of local transition rules. Table 2 lists the details of the spatial variables. They include a series of distance-based variables, neighborhood functions and physical attributes, which can derived from remote sensing and GIS data. Studies, such as those done by White and Engelen (1993) and Wu and Webster (1998), have shown that these variables are closely related to the probability of land use changes.

To derive the distance-based variables, traffic data, urban area and town area (GIS format) in 1988 and 1998 were prepared, and the Euclidean Distance function of ArcMap (ArcInfo) was used to obtain the Euclidean distance raster map for the distance-based variables.

3.2. Simulation process

With the two starting land use maps (1988 and 1998), 76 local transition rules was yielded, part of which are listed in Table 3. As an example, the first rule in Table 3 can be expressed in the following form:

IF
Cellular initial state = FL *AND* Distance from the cell to the major urban areas ≥416 *AND* Amount of cells used as forest = 48
THEN
Cellular evolutionary result = FL. The quality of this rule is 0.917.

There is one explain that the filter used in this study is a standard 7 × 7 contiguity filter. Of course, other kinds of contiguity filter can be defined, but in the former research the problem has been pointed out that a combination of small cell size and small neighborhood size generated improper expressions of the land use transitions (Pan et al., 2010).

Applied the 1988 and 1998 maps (using a proportional error of 0.15), the predicted transition area matrix of land use types during 1998–2008 was yielded (Table 4). With the above local transition rules database, the transition area matrix, the land use map and the raster map representing the value of the distance-based variables in 1998, the simulated land use map in 2008 was generated.

3.3. Simulation result

The simulated land use map is shown in Fig. 6(a), and the simulated areas made count by categories are listed in Table 5. In order to analysis the simulated result, it should be compared with the actual one. Actual land use map is shown in Fig. 6(b), and the areas made count by categories are also listed in Table 5.

Visual comparison indicates that the simulated land use map is similar with the actual one, especially the south of and the north of

Table 4
Transition area matrix of land use types in Changping, 1998–2008 (unit: km^2).

1998	2008				
	FL	CuL	CoL	WL	OUL
FL	632.26	39.32	3.56	1.69	3.98
CuL	18.27	283.53	61.03	0.41	4.04
CoL	17.48	14.11	168.07	0.82	5.97
WL	0.24	0.54	0.53	4.49	0.03
OUL	13.9	39.76	14.04	0.38	23.54

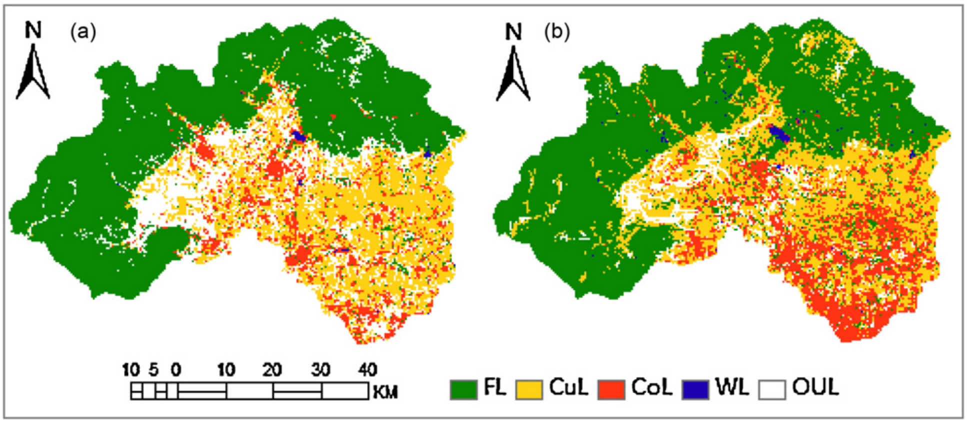

Fig. 5. Land use maps (a) 1988 land use map; (b) 1998 land use map. Land use maps generated from the classification of Landsat TM5 images, acquired during the summers of 1988 and 1998 at the spatial resolution of 30 m. FL – forest, CuL – cultivated land, CoL – constructive land, WL – water.

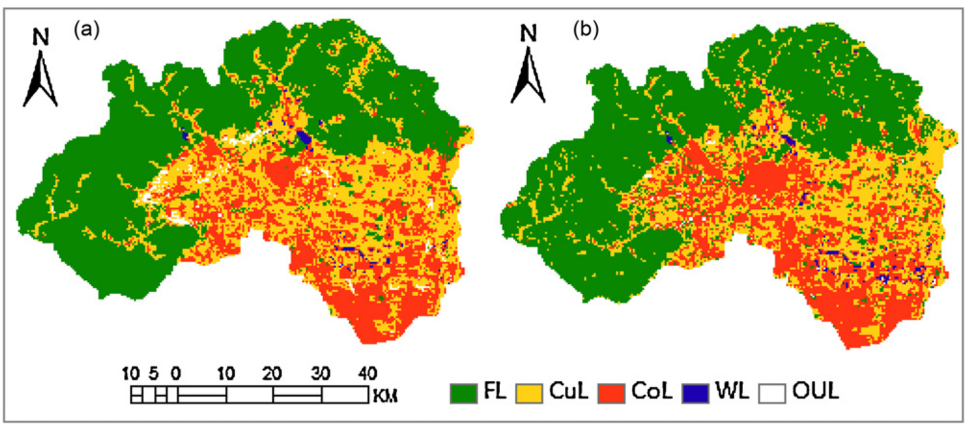

Fig. 6. Land use maps (a) simulated land use in 2008; (b) actual land use in 2008 (generated from the classification of Landsat TM5, acquired during the summers of 2008 at the spatial resolution of 30 m). FL – forest, CuL – cultivated land, CoL – constructive land, WL – water.

Changping. And both maps show that the urban land development was mainly distributed around urban centers in 1998. The main deviation is located in the center area, and obviously there is more other unused land and less construction land in the simulated map.

Following preliminary analysis by visual comparison, the accuracy of the simulation results was analyzed quantitatively. In this process, the CROSSTAB model in IDRISI was used again to compare the simulation results and the actual land use map cell by cell. The results of the cross-tabulation analysis, including error rate (computed by the actual area and the deviation between simulation area and actual area, and used to evaluate the quantitative accuracy) and accuracy (computed by the actual area and right part of the simulation area, and used to evaluate the spatial accuracy), are shown in Table 5.

In terms of the quantitative accuracy, the best agreement is shown in forest, where the actual area is 666.75 km^2, while the corresponding simulated area is 673.17 km^2. Error rates for forest and cultivated land are particularly low at 0.010 and 0.077, respectively. Error rates for construction land and water are 0.182 and 0.174 respectively, which are little higher than that of forest and cultivated land. From the numbers, we can see that the model is effectively to predict area change of land use in the future. In terms of the spatial accuracy, accuracy of forest, cultivated land and construction land are 84.99%, 65.28% and 58.49% respectively, which means that great part of spatial locations of forest, cultivated land and construction land in simulated map are right. And the overall accuracy is 72.93%. Therefore, the model can be used to forecast the spatial distribution of land use in the future.

Table 5
Comparison of accuracy for simulated area of ACO–Markov–CA model and actual area.

	Simulated area (km^2)	Actual area (km^2)	Error rate	Accuracy (%)
FL	673.17	666.75	0.010	84.99
CuL	381.32	354.01	0.077	65.28
CoL	258.49	316.11	−0.182	58.49
WL	8.86	10.73	−0.174	29.62
OUL	30.15	4.39	5.862	2.55

From the accuracy of both quantity and spatial distribution, the simulation results of forest and cultivated land better than the other three land use types. And the most high error rate and low accuracy are both for other unused land, 5.862 and 2.55% respectively. Because the land use map for 2008 was simulated assuming the continuation of trends and dynamics of urban development from 1988 to 1998, we can conclude that the changes of forest and cultivated land are steady, yet the expansion rate of urban area was great than the pace from 1988 to 1998, which leads to deviations in the quantity and spatial distribution of construction land and other unused land especially in the center of the map.

3.4. Model validation and comparison

3.4.1. Comparison with CA–Markov model

In order to validate the ACO–Markov–CA model, a comparative study was carried out by using CA–Markov model. CA–Markov

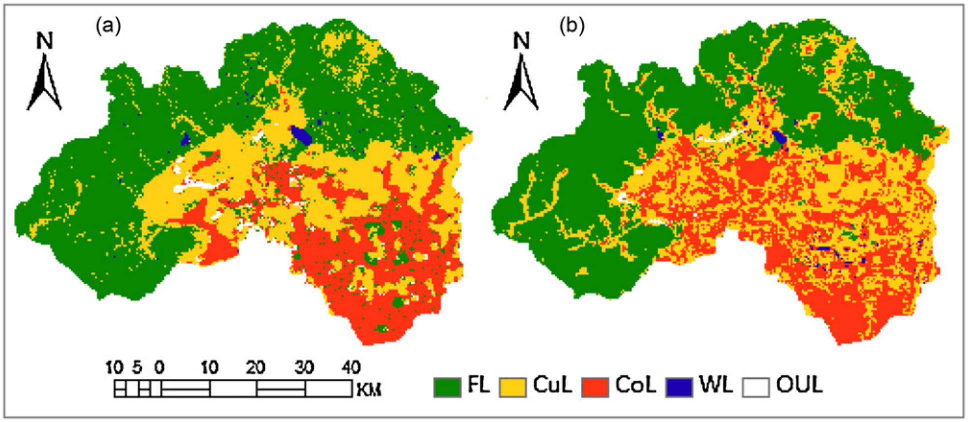

Fig. 7. Simulated land use maps in 2008 (a) using CA–Markov model; (b) using ACO–CA model. FL – forest, CuL – cultivated land, CoL – constructive land, WL – water.

model has been widely used in simulating land use change and urban development, for example, Hou et al. (2004) simulated LUC in Hexi Corridor based on CA–Markov model, Yang et al. (2007) simulated LUC in Guangzhou based on CA–Markov model, Wang et al. (2010a) simulated LUC in Changping district based on CA–Markov model. This model has been implemented by CA_MARKOV module in IDRISI Andes. Sang et al. (2011) introduce the application of CA_MARKOV module in his paper explicitly. Applied CA_MARKOV module to simulate the land use change in the study area, the simulated map is shown in Fig. 7(a).

The first impression of the simulated map by CA–Markov model is that the construction lands and cultivated lands are more concentrative. On the other hand the "salt and pepper" of the cultivated land and the forest is as serious problem. That is because CA–Markov model only uses the conditional probability images generated by Markov module in IDRISI Andes to restrict spatial distribution, and ignores the effect of various spatial variables on land use. The ACO–Markov–CA model obviously overcomes the shortcoming and improves the spatial accuracy. We can easily see that, the spatial accuracy of the simulated land use map by CA–Markov model is lower than the simulated map by the ACO–Markov–CA model.

3.4.2. *Comparison with ACO–CA model*

Finally, the simulated result of ACO–Markov–CA model was compared with ACO–CA model. As described in the paper written by Liu and Li (2007), ACO–CA model shows higher accuracy in simulating complex geographical system. The spatial variables as local transition rules used in ACO–CA model are the same as those used in the ACO–Markov–CA model. Applied ACO–CA model to simulate the land use change in the study area, the simulated map is shown in Fig. 7(b).

It is difficult to compare the simulation results of ACO–Markov–CA and ACO–CA model by visual comparison, so they were compared quantitatively. The simulated land use areas, error rates and accuracy of ACO–CA model are listed by categories in Table 6. In terms of quantitative accuracy, the simulated forest area and cultivated land area of ACO–CA model are 632.57 km^2 and 418.85 km^2 respectively, the simulated forest area and cultivated land area of ACO–Markov–CA model is closer to actual area than ACO–CA model. The simulated areas of other land use type of ACO–CA model is closer to actual area than ACO–Markov–CA model, but the deviation area of other land use type of the two models are small values. In terms of the spatial accuracy of ACO–CA model, accuracy of forest and cultivated land are 80.13% and 60.46% respectively, which are lower than those of ACO–Markov–CA model. And the overall accuracy of simulated result generated by ACO–CA model is 69.65%, which is lower than the ACO–Markov–CA model. We can see that overall the accuracy of ACO–Markov–CA model is higher than ACO–CA model in this case study.

Table 6
Simulation result of ACO–CA model for Changping.

	Simulated area (km^2)	Error rate	Accuracy (%)
FL	632.57	−0.051	80.13
CuL	418.85	0.183	60.46
CoL	264.12	−0.164	59.98
WL	9.35	−0.129	32.92
OUL	27.12	5.172	5.19

The above comparisons demonstrate the advantage of ACO–Markov–CA model in managing the total amount of land use coverage and the spatial distribution of land use change. On the whole, the model proposed by this paper has much better simulation performance, and can predict future land use patterns objectively and accurately.

4. Conclusions

This paper has introduced a new model integrating ACO, Markov and CA models for the simulation of land use change. On the one hand, this model integrates ACO with CA to discover local transition rules that manage the spatial distribution of land use while taking into account both the natural and the social environment. ACO is good at solving this kind of hard combinatorial optimization problems, and shows great performance with the "ill-structured" problems (Dorigo et al., 1996). On the other hand, rules got by ACO are not expressed in mathematical formulae and more easily comprehended by people, so can describe the complex relationships in a more convenient and precise way. On the other hand, the model also employs Markov chain analysis to manage the total amount of land use change, absorbs the advantage of Markov chain of long-term forecast. Therefore, the model must be useful for land use change simulation.

The model has been successfully applied to the simulation of a fast-growing region in the capital of China, using data from satellite images. Compared with the real situation of study area, the experimental results indicated that the accuracy of the simulation in predicting both the quantity and spatial distribution of land use changes is sufficient to be of help to planners and policy makers. Specifically, it can help understand land use problems associated with the current trend of urban development. Further comparisons with other two models (CA–Markov and ACO–CA) also indicate that the proposed method shows high accuracy of amount and spatial distribution in simulating land use change. It seems that the transition area matrix generated by Markov chain help ACO–Markov–CA model control the amount of land use change well, and the local transition rules generated by ACO help ACO–Markov–CA model control the spatial distribution of land use change well.

Limitations of this model include the restriction of local transition rules to the effect of the quantity of land use while ignoring the effect of the spatial distribution. Additionally, human decision-making is lacking in the model. These areas should be addressed in further research.

Acknowledgment

This research was supported by the National Public Benefit Research Foundation of China (No. 20101018).

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