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Assessing the impact of temporal dynamics on land-use change modeling

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Abstract

Time is a fundamental dimension in dynamic land-use change modeling. An appropriate treatment of time is essential to realistically simulate landscape dynamics. Current land-use models provide little justification of their treatment of time. As a result, little is known about how the time dimension impacts the spatio-temporal patterns produced by land-use simulation models. This paper reports a first exploration on this issue. It examines the impact of the degree of temporal dynamics on the behavior of an urban growth model which is based on a modified Markov random field and probabilistic cellular automata. Experimental results from this case study suggest that the degree of temporal dynamics does have an important impact on the urban morphology produced by the model. Too much or too little dynamics could both lead to unrealistic patterns. However, the impact seems to vary for processes with different levels of change intensity. In the case of a process with moderate changes, the impact of temporal dynamics is also moderate. For a process with high change rate, the degree of temporal dynamics affects the model output significantly. The implication of these findings is discussed in the context of information accessibility and operational land-use modeling.

Keywords: Time; Land-use change modelling; Cellular automaton; Markov random field

1. Introduction

In recent years, interest in land-use change modeling has grown rapidly. Many of the models in this category were built to simulate the dynamics of landscape change and thus have an explicit time dimension. Although the modeling community has advanced the understanding of many issues in land-use modeling, such as modeling

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theory (Batty & Longley, 1994), model calibration (Clarke, Hoppen, & Gaydos, 1997), and model application (Clarke & Gaydos, 1998), time remains a dimension on which little research has taken place. Little is known about how the treatment of time affects the behavior of a dynamic simulation. Consequently, sparse information is available to guide modelers to implement the time dimension in their models. Yet, an understanding of this issue is important, because the behavior of a dynamic process such as the growth of a city could be significantly affected by small changes in the underlying spatio-temporal structure (O'Sullivan, 2001). It is the intention of this paper to point to this neglected dimension in land-use modeling research. It takes a first step to systematically assess the impact of the degree of temporal dynamics on the spatial pattern produced by an urban growth model. The results, however exploratory and case specific, provide a first look on the issue and hopefully lead toward more research in this hardly explored area.

Following a discussion on time in land-use change modeling, we focus on the examination of two questions: does temporal dynamics have an impact on the behavior of a land-use model? And if so, how does the impact differ for processes with different change rates? We examine these issues using an urban growth model as a case study, and discuss the findings in the context of operational land-use modeling. The paper concludes with a suggestion for future research.

2. Time in dynamic land-use modelling

Dynamic land-use models are built to simulate the evolution of a natural or man-made system. To understand the time dimension of a model, it is helpful to first take a look at the time dimension of the system that the model aims to simulate. Land-use systems are complex systems with multiple change processes. Each change process has its own evolution algorithm and their interconnection may change over the time. In the case of an urban system, three levels of change processes can be identified according to their time scale: slow processes which take 3–5 years or longer to complete and affect the physical structure of a city, e.g. industrial, residential, and transport construction; medium processes such as economic, demographic, and technological changes which affect the usage of the physical structures; and fast processes completed in less than a year, such as mobility of labor, goods, and information (Wegener, 1994). Each of these processes has a unique evolution algorithm. For the most time they are asynchronous in the sense that they don't begin or end at the same time, but every now and then, they can be loosely synchronized (Williams, Messina, Fox, & Fox, 1994). Since all these processes and their interaction contribute to the change of urban land-use, a model has to either simulate the processes explicitly or use a method to summarize their influence.

Thus enter the two approaches in dynamic land-use simulation: process-based and transition-based modeling. Process-based modeling describes the causality between different components in the system explicitly. These models typically contain a number of selected change processes, each of which is implemented by a sub-model (e.g. Waddell, 2002). When operating the model, the sub-models are processed sequentially and exchange information with each other. For the considerations of time, there are at least two places where time treatment becomes important. One is the temporal resolution of each individual process. For example, how often should the demographic transition sub-model be updated? How long does it take to complete a transport construction? The other is the time delay between different sub-models. Examples are: How long does it take before the changes generated by the construction sub-model are perceived by the business location sub-model? When will demographic change start to impact household mobility? From the implementation perspective, if two sub-models are synchronous, which one should be executed first? By letting A proceed first we grant it the priority to access scarce resources like land but it will not know the outcome of B until the next simulation period. On the other hand, although B may get less of the resources it can access the information in the results from A immediately. Some of these problems can be reduced through Monte Carlo simulation by randomizing the order that the sub-models are executed. However, the Monte Carlo approach does not solve the problem completely, because it turns the synchronous process into a sequential one and the two may not be necessarily equivalent.

In contrast to process-based modeling which simulates the causality of each change explicitly, transition-based models use probability or similar terms to summarize the changes happened over an interval. This higher-level description hides the underlying dynamics and generally assumes that the frequency of the changes brought by the processes can be simulated with statistical distributions. An example of such a model is CUF-II (Landis & Zhang, 1998) which uses the discrete choice theory to infer the transition probability between different land uses over a 10-year interval. In transition-based modeling, members (e.g. all patches of land in the region) usually comply with the same evolution rules and are assumed to be synchronous in the sense that they update their states simultaneously. For the consideration of time, the question to be asked is how often the system should be updated and how the updating frequency affects the predicative quality of a model. In the following section, we examine these issues with a case study.

Before we focus on the time dimension of transition-based modeling, the following considerations should be kept in mind. Firstly, although appropriate time treatment will serve to better mimic the behavior of the target land-use system, it does not guarantee the predictive quality of a model. Chaos, along with the problem to measure and represent the components in the target system, can hamper the quality of a model also (Schuster, 1995). This means that even though the time dimension is simulated perfectly in a model, unless the system has powerful attractors to make it a robust system, small randomness can change the results significantly as illustrated in Fig. 1. Consequently, the outputs from the model in different trials may be considerably different from each other. There is no easy way to get around this problem since the conventional approach of using the spatial average from a Monte Carlo simulation is not representative of individual trajectories of the system. Another consideration is that although time is a fundamental dimension in land-use modeling, it is not independent of the other dimensions. For example, in transition-based modeling, when the temporal resolution or the degree of temporal dynamics is

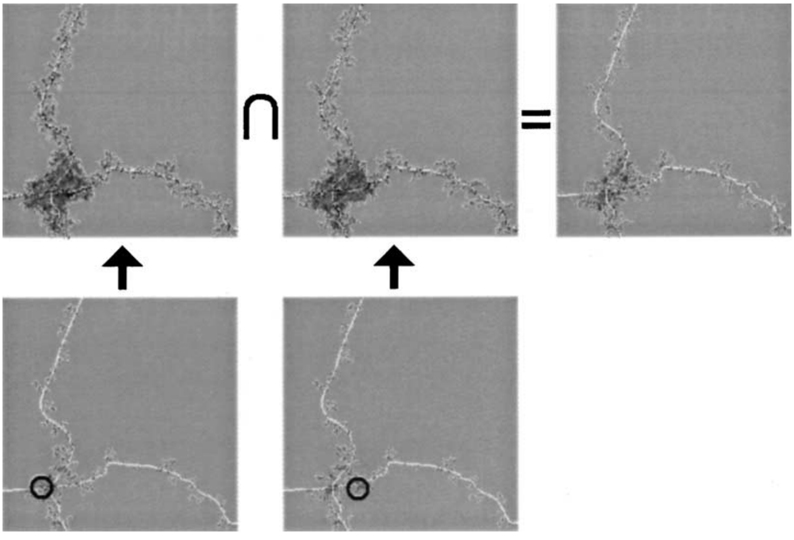

Fig. 1. An example of chaos in model dynamics. The same model is executed with two initial states (bottom) which are nearly identical except for the difference indicated with circle. Although the two results (top) look qualitatively similar, their intersection turns out to be small. This suggests a positive Lyaponov exponent (not measured here)—a commonly used indicator of chaos and unstableness—and thereby a chaotic system.

changed, the method to generate the transition probabilities and their interpretation has to be changed correspondingly. We have more discussion on this issue in the following sections.

We would like to examine the impact of temporal dynamics on the spatial pattern generated from a land-use model. Since the conception of time in a model affects the degree of temporal dynamics directly, a discussion on time conceptualization is necessary. Generally speaking, three types of time exist in transition-based modeling: Duration, discrete, and continuous or event-driven. Duration refers to a significant time interval of 10 or more years (e.g. Landis & Zhang, 1998). A typical duration-based model involves two time steps. In the first step, data associated with the first duration (e.g. from 1975 to 1985) is used to construct and calibrate the model. The other step is to apply the calibrated model to forecast a second duration (e.g. from 1985 to 1995). Notice that in duration-based modeling, only at the end of a duration (e.g. year 1985 or 1995) is the state of the system estimated. The state of the system within a duration (e.g. year 1986 to 1994) remains unknown. Although technically the forecast period of a duration-based model can be beyond one duration, it is usually limited to one duration only, reflecting the general belief that models should only be used to forecast a period no longer than the past interval that the model was calibrated over (Wegener, 1994).

Compared to duration, discrete time enables a much higher degree of dynamics. Discrete time perceives time as a sequence of regularly spaced time steps, each of which is mapped to a time period. A step typically corresponds to a calendar year (e.g. Clarke & Gaydos, 1997; White & Engelen, 1997), though it can be longer (e.g. Berry, Hazen, MacIntyre, & Flamm, 1996) or left undefined (e.g. Wu & Webster, 1998). Discrete time is best exemplified by Cellular automata (CA) which updates its state at each tick of the clock. In models using discrete time, the transition probability is usually based on the initial state only. This is different from that in duration-based models where the transition probabilities are calculated using both the initial and the end state of an interval.

A third conception of time, namely the continuous (Resinik, 1992) or event-driven time (Langran, 1992; Pequet & Duan, 1995) views time as a continuous flow only to be broken by changes. Changes are triggered by discrete events that may happen at any time. Continuous time completely dissolves the boundary between time steps and thus displays a full range of dynamics. The idea of continuous time for land-use change modeling was hinted at by Wegener, Feidrich, and Vannahame (1986), but was never implemented because it would require data such as a perfect record of land transaction history.

This paper examines the impact of temporal dynamics on transition-based land-use change modeling. We present a simulation where the implementation of the time dimension is based on both the discrete and continuous conception of time. Before the design of the simulation is presented, we give a conceptual discussion on why temporal dynamics can have an impact on the land-use patterns generated by a model.

3. Land-use dynamics: a path-dependent process

A fundamental insight in land-use change modeling is that the macro-scale pattern is a result of interactions among micro-level system components over time. Different conceptions of time affect how often the interactions are simulated by a model and thus have an impact on the spatial pattern generated. When discrete time is used, changes within one time-step are assumed to happen simultaneously and do not interact with each other. In the case of continuous time, changes are assumed to arrive one after another, and the current change may influence the succeeding ones. Consider the following example. In a homogenous area of farmland (Fig. 2), five

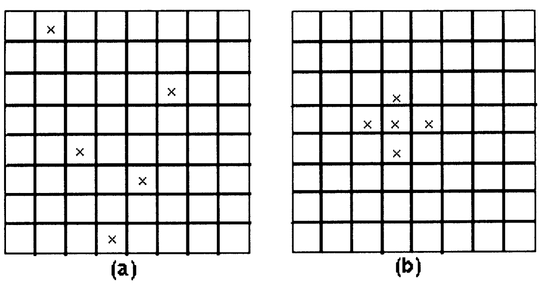

Fig. 2. Results of a model by using different conceptions of time: (a) discrete time with 1-year resolution; (b) continuous time.

cells are to be converted to meet the projected housing demand. A model is built to determine the location of the five developments. If the model uses discrete time with a resolution of 1 year, all five conversions are assumed to happen simultaneously, and the five cells are selected based on their initial suitability for housing. Since the initial landscape is homogenous, the five cells are selected randomly, displaying a pattern such as that in Fig. 2a. On the other hand, if continuous time is applied, and assuming no two conversions happen simultaneously, the model progresses in five steps. At each step, it picks up the currently most suitable cell for development, propagates the change to other cells and updates their suitability for development. The first cell is randomly selected, as in the case of discrete time. Under the assumption that residential developments tend to cluster, cells adjacent to the selected one now have a higher suitability for housing than other cells. So the second conversion is likely to happen in the neighborhood of the first cell. The second conversion in turn propagates a series of changes on the suitability of other cells and the process goes on. By the time all allocations are completed, the spatial pattern is more likely to be clustered (Fig. 2b) than randomly distributed (Fig. 2a).

The above example illustrates that for a same model, different temporal dynamics form different paths leading to different outcomes. For a specific study site, there exists only one historical path of land-use change. The task of dynamic land-use modeling is to reconstruct this unknown path so that by following it, the land-use history can be simulated and the future can be forecasted with confidence. Since the degree of temporal dynamics affects the path, a natural question to ask is how much temporal dynamics is appropriate. Furthermore, under what circumstances are different degrees of temporal dynamics functionally equivalent in the sense that they produce similar patterns? In the following section, a numerical simulation is conducted to explore these issues.

As aforementioned, in transition-based land-use modeling, time and transition probability are closely related to each other. For a specific land-use model, the method to calculate transition probability is fixed and thus not all conceptions of time are applicable. Since discrete and continuous time are more often used in dynamic land-use modeling, they are explored in the following experiment which examines the impact of temporal resolution on the behavior of an urban growth model.

4. Simulation framework

We use a transition-based land-use model to simulate the evolution of urban settlement pattern. The model uses a probabilistic cellular automaton with global interaction (as opposed to finite-neighborhood) and an update function similar to a Markov random field. The basic logic behind the model is the equilibrium between supply and demand, i.e. the projected land-use demand is satisfied by supplying suitable lands. Like the models reported by Landis and Zhang (1998) and White and Engelen (1997), our model consists of three subsystems: (1) a module to project future land-use demand; (2) a module to estimate the suitability of a site for a land use; and (3) a spatial allocation module to allocate suitable sites to meet the projected demand. Subsystem (1) is described in Section 4.1 and 4.4. Subsystem (2) is addressed in Section 4.3, and subsystem (3) can be found in Section 4.2. A thorough description of the model is beyond the scope of the paper. In the following sections, we present a general overview. Readers interested in more theoretical and technical details are referred to two papers: Andersson, Rasmussen, and White (in press), and Andersson, Lindgren, Rasmussen, and White (2002).

4.1. Basic dynamics

Formally, the model updates its state iteratively. For each iteration, the simulation can be summarized as follows:

$$S(t+1) = S(t) + A(t) \tag{1}$$

where $S(t)$ is the global system state at time $t.A(t)$ represents the birth process at time t, i.e. the process to allocate suitable sites to meet the projected land-use demand. This defines a traditional evolutionary dynamics with the addition of the cells most fit for a land use within the population.

4.2. Lattice and land-use transition probability

We represent land as a two-dimensional (2-D) grid divided into $N = n \times n$ cells which are equal square patches of land. Each cell corresponds to an area of homogenous land use. There are C types of land uses. For each cell, its suitability for each land use depends on two factors: (1) the intrinsic characteristics of the cell itself, such as topographic slope and current land use; and (2) the aggregate effect of the cells in its neighborhood. Let $E_a(x)$ denotes the suitability of land use a for cell x. To determine which cells are to be allocated to meet the demand for land use a at each update, the suitabilities are transferred into transition probabilities through the following normalization process:

$$p_a(x) = \frac{F(E_a(x))}{\sum_{x=1}^{N} F(E_a(x))} \tag{2}$$

where F is a Maxwell-Boltzmann transformation defined by

$$F(E_a(x)) = \mathrm{e}^{-\beta E_a(x)} \tag{3}$$

and β is a free parameter specified by the user. Eq. (2) suggests that the conversion of a cell is determined by global optimality. This means that even though a cell is more suitable for land use a than land use b, i.e. $E_a(x) > E_b(x)$, it may still be converted to land use b if the demand for land use b is not satisfied and this cell has higher suitability than the other cells left.

4.3. Land use potential and the meanfield model

The heart of Eq. (3) is the calculation of $E_a(x)$, which is determined by the aforementioned two local factors. In particular, the neighborhood effect is the key to obtaining $E_a(x)$. Classic Markov random fields as well as cellular automata take only a finite neighborhood into account (e.g. the eight nearest neighbors). However, in the real world, land-use influences can exist across a hierarchy of scales as exemplified by central place theory (Christaller, 1966). To capture the cross-scale interaction in a computationally efficient way, the meanfield model from statistical physics is borrowed and explained as follows (Fig. 3)

The fundamental lattice with N lattice points is referred to as the level-0 grid and is the grid with the highest resolution. Grids at higher levels l of aggregation have cells that are aggregates of progressively larger concentric portions of the level-0 grid. Thus, a l-level cell has contribution from 3^2 times as many level-0 cells as a 1-level cell. These recursive levels are illustrated in Fig. 2. Starting from the most coarse-grained, or aggregated, level L where the whole lattice is aggregated, 3^2 new sub-grids are generated for each recursion and thus $N = (3^2)^L$ and $L = \frac{1}{2}\log_3 N$. This indicates $\frac{1}{2}\log_3 N$ recursive lattice averaging operations are needed for the update of each site. L then defines the depth of the lattice.

The suitability of site x for land use a can be simulated as follows:

$$E_a(x) = \sum_{l=0}^{L}\sum_{b=1}^{C} I_{ab}^{(l)} c_b^{(l)}(x) \tag{4}$$

where $I_{ab}^{(l)}$ expresses the cost associated with the change from land use a to land use b. It is calculated by

$$I_{ab}^{(l)} = d^{(l)} A_{ab}^{(l)} \tag{5}$$

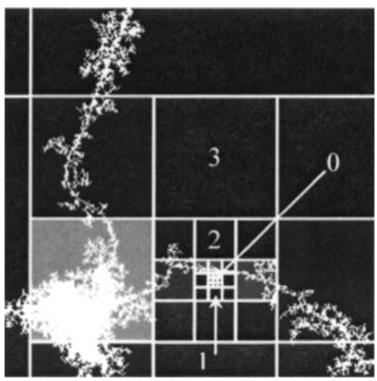

Fig. 3. The multilevel lattice representation (meanfield) is here illustrated by showing how the center cell perceives its surroundings at different levels.

In Eq. (5), $d^{(l)}$ is an exponential decay function describing the decreasing interaction between different scales (l). $A_{ab}^{(l)}$ is the affinity term describing the attraction between land use a and land use b at scale l. A negative value means the two land uses tend to be spatially close to each other. For example, residential land use may not prefer mega-commercial land use in its immediate neighborhood but would like to have it within a specific distance. The corresponding affinity term is thus positive at a lower scale (e.g. $l=1$ or 2) but become negative at a higher scale (e.g. $l=3$ or 4). $A_{ab}^{(l)}$ is determined by the user.

The other term in Eq. (4) is $c_b^{(l)}(x)$, which refers to the number of grid cells (c) with land use b in the level-l neighborhood of cell x. It is calculated recursively as follows. Starting at level 0, we define $c_a^{(0)}(i,j)$ as the count of cells with land use a at location (i, j)

$$c_a^{(0)}(i,j) = \begin{cases} 1 \text{ iff landuse} = a \\ 0 \text{ otherwise} \end{cases} \tag{6}$$

Then

$$c_a^{(l)}(i,j) = \sum_{k=-1}^{1} \sum_{m=-1}^{1} c_a^{(0)}(i+k, j+m) \tag{7}$$

defines the count of cells with land use a at level 1. By induction, it is seen that

$$c_a^{(l)}(i,j) = \sum_{k=-1}^{1} \sum_{m=-1}^{1} c_a^{(l-1)}\left(i+k3^{l-1}, j+m3^{l-1}\right) \tag{8}$$

expresses the number of cells that have land use a at level l defined from the cells at level l-1. Compared to direct calculation, this recursive method reduced the computational cost of $c_b^{(l)}$ significantly.

4.4. Varying temporal dynamics

The basic logic behind our transition-based model is the equilibrium between supply and demand. To operate the model, the demand factor has to be determined first. This is implemented with a statistical model.

With respect to the land use history of an area, it is reasonable to assume that the history consists of homogenous intervals. A homogeneous interval refers to a time period in which changes happen at a stationary rate, i.e. the intensity of the change is roughly constant. A homogeneous Poisson process, which is usually used in connection with continuous Markov chains (Resnick, 1992), is employed to simulate the arrival of the changes (Fig. 4).

Suppose the two snapshots represent the starting and the ending state of a homogeneous process, and are time-stamped as T_1 and T_2 respectively. Let

$\Delta T = T_2 - T_1$. The overall quantity of the changes for each category (e.g. the addition of residential land use) can be obtained by differencing the two snapshots. Let ΔN_k denote the change in class k. This is the projected demand for land use k for the interval between T_1 and T_2. These ΔN_k changes happened according to a homogeneous Poisson process $\{T_k\}_{k \geqslant 1}$ of intensity $\lambda_k > 0$. The arrival of the ith change is time stamped as T_k^i (Fig. 5).

For each Poisson process k, the rate λ_k is estimated by

$$\lambda_k = \Delta N_k / \Delta T \tag{9}$$

We generate random numbers under a Poisson distribution for each land use, and order them to determine a sequence. The number of events happened between T_i and T_{i+1} is considered as the land-use demand during the interval. The spatial allocation process is then conducted by allocating sites whose probability of change is proportional to its suitability to convert to the land use in demand.

5. Findings and discussion

Two questions were examined with the proposed simulation. The first is whether temporal dynamics has an impact on the behavior of the model, and the other is how such impact, if it exists, differs for processes with different degrees of change intensity. To answer these questions, we experimented with two processes with moderate and intense change rates respectively. The models were calibrated with 1-year resolution. A varying degree of temporal dynamics was experimented and the results are shown in Figs. 6 and 7. In particular, Figs. 6c and 7e are considered as the reference patterns since they are obtained with 1-year resolution. The goodness of other images is measured by their similarity to the reference pattern. To measure similarity, a difference map is created which shows the cell-to-cell difference between two maps and is interpreted visually. Although this method is not quantitative, it

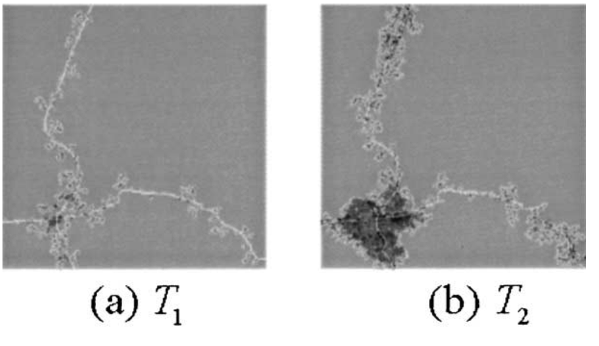

Fig. 4. Two snapshots of the landscape: (a) the initial state of the simulation, and (b) the ending state of the simulation.

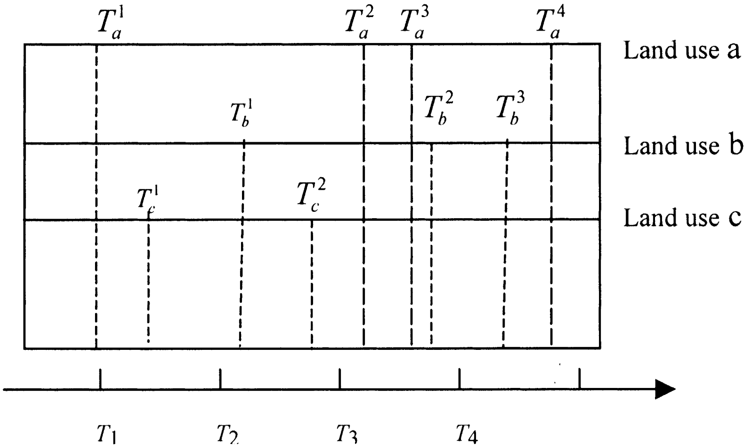

Fig. 5. The continuous time model which simulates the demand for each land use in a time interval. T_1, T_2, T_3, T_4 mark the beginning of an interval. T_i^j (e.g. T_a^2) registers the time when the *j*th change to land use i happened. The changes to each land-use category (e.g. a, b, c) follow a homogenous Poisson distribution. The demand for each land use in each interval is determined by counting the number of changes to each land use within the interval. For example, for the interval of (T_3, T_4), the demand for land use *a* is 2, because both T_a^2 and T_a^3 fall into it. Similarly, the demand for land use *b* is 1 and 0 for land use *c*.

can be more comprehensive and robust than using spatial metrics because human brain is known to have better ability to synthesize information than computers.

Figs. 6a and 7a represent the simulation with maximum degree of temporal dynamics. In these simulations, changes happened sequentially. Every single change propagates an influence to the land use of its neighbors and thus affects where the subsequent changes happen. Figs. 6f and 7i describe the other extreme situation where the least temporal dynamics is involved. In these simulations, all changes happened simultaneously with no interaction between each other. The other figures correspond to varying temporal resolution. The finer the resolution is, the more often the system updates its state and thus displays a higher degree of temporal dynamics. From the analysis of Figs. 6 and 7, we report the following findings:

1. Not surprisingly, the degree of temporal dynamics or the granularity of the time dimension does have an impact on the spatial pattern generated from the model. This is illustrated by the visible difference between Figs. 6a and 6f, or 7a and 7i. In both processes, as the degree of temporal dynamics decreases, the edges of existing clusters get smoother and smoother, and the system demonstrates a self-reinforcing behavior. (Andersson, Rasmussen, & White, in press). This is especially distinct in Figs. 6e and 7h. The reason is because as temporal resolution gets coarser, more additions are introduced in each update. Since in our model, sites close to existing land-use clusters have higher suitability for a land use than the sites with no development in their neighborhood, the edge cells get allocated first. This is what happened in Fig. 6f. If the boundaries are filled, the locations for excessive developments

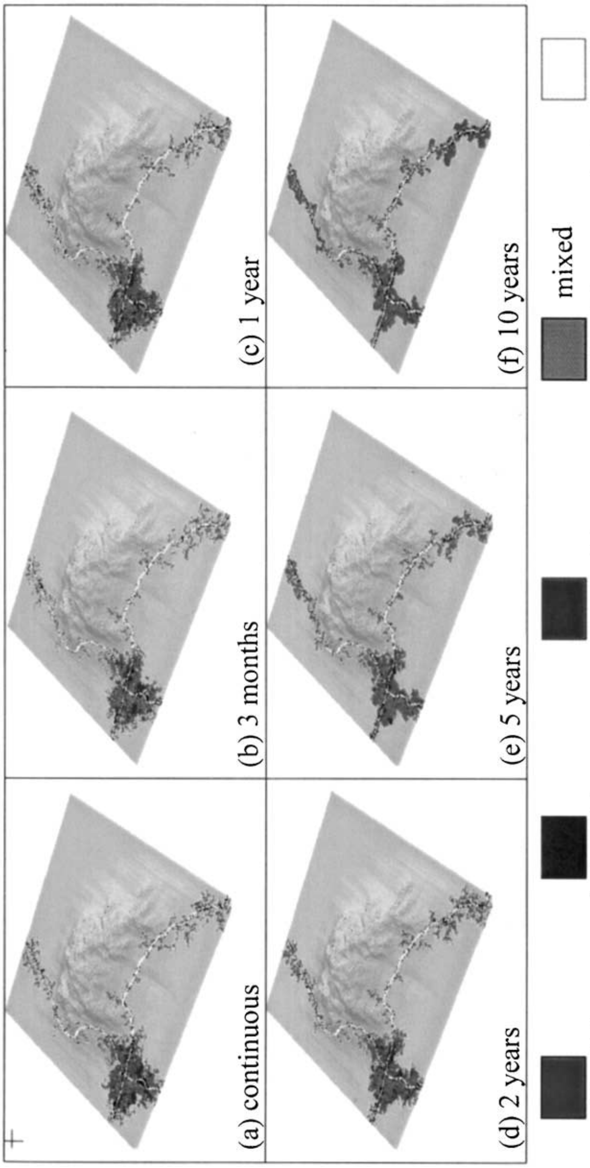

Fig. 6. Impact of temporal resolution on a process with moderate change rate.

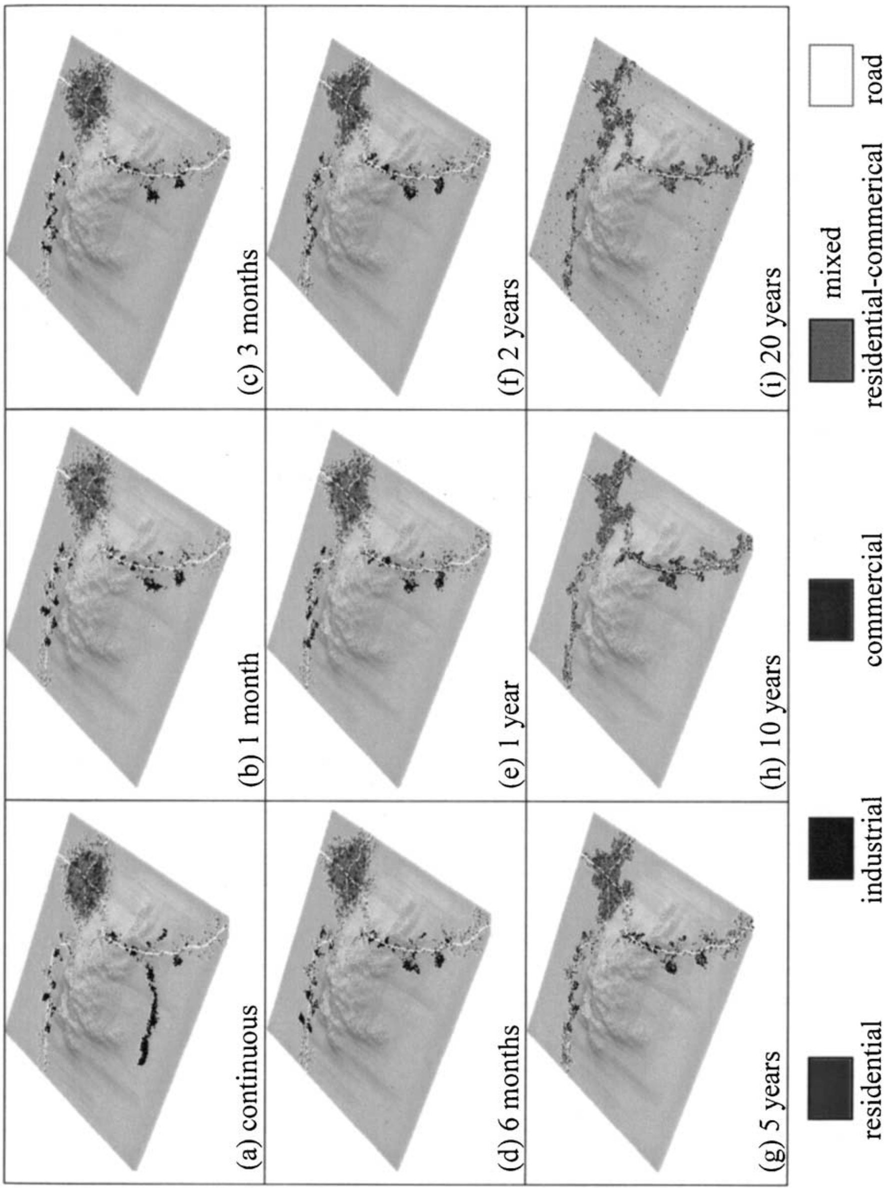

Fig. 7. Impact of temporal resolution on a process with intense change rate.

have to be selected more randomly because the suitabilities of the rest of the cells are nearly equal, resulting in the pattern in Fig. 7i. A calculation of the fractal dimension of Fig. 7i indicates that it does not have the fractal property which urban systems are well known to exhibit. This finding together with our experience with operational models (e.g. Clarke & Gaydos, 1998) suggest that credible urban patterns can only be produced by models that are either dynamic, or alternatively, contains a prior information which is the result of a dynamic process.

2. As mentioned previously, temporal dynamics and model parameters can both affect the spatial pattern output from a model. In both experiments, the parameters was tuned with a temporal resolution of one year and thus may not be optimal for other resolutions. However, previous research (Anderson et al., in press) suggests that the model is not very sensitive to the change of the parameters. In fact, in both simulations there is an interval (e.g. from 5b to 5d, from 6c to 6f) where the outcomes are quite similar to each other. This confirms that the model is not very sensitive to the parameters—at least within a range of temporal resolutions—because otherwise the patterns generated using other temporal resolutions would not be similar to that obtained with 1-year resolution. Using deductive reasoning, if model parameter does not seem the major source of variations among the patters in Figs. 6 and 7, temporal dynamics is likely the cause. In fact, the spurious behaviors such as that in Fig. 7a seems to originate from fundamental effects of the amount of changes introduced per time unit, which in turn is determined by the system update frequency.
3. Although both simulations confirm that temporal dynamics indeed have an impact on the behavior of a model, the impact seems to differ for the two processes. For the process with moderate change intensity (Fig. 6), the variation between different images is less dramatic than that in the process of intense change rate. In Fig. 7, when continuous time is applied (Fig. 7a), a string of industrial land uses lined up around the foot of the hill, forming a rather unexpected pattern which is significantly different from that in 7e. However, when the temporal resolution is changed to 1 month, the industrial string disappeared immediately and the resulted pattern bears more similarity to the reference map in 7e. Compared with the process with low change intensity, the difference between Fig. 7a and 7b is much more significant than that between Fig. 6a and 6b. Similarly, the difference between 6e and 6f is more significant than that between 7h and 7i. Overall, the variation among images in Fig. 6 is less than that in Fig. 7, suggesting that the impact of temporal dynamics on the process with moderate change intensity is less dramatic than on the process with intense change intensity.

The above findings provide some insight in the implementation of time in operational land-use modeling. As stated previously, the history of land-use development is composed of periods whose within-period change rate is relatively stationary but the cross-period change rate is significantly different. Existing models do not differentiate these periods. Usually the same temporal resolution is applied throughout the time span that the model is designed to simulate. The findings reported in this paper suggest they should be treated differently. For periods with low change rate, since the impact of temporal resolution is moderate, a coarse experiment could be sufficient to determine a resolution to produce the target pattern. On the other hand, if it is a period where significant changes have happened, it is worthwhile to experiment with a few different temporal resolutions to determine which one captures the spatial pattern best. In calibration terms, a fine calibration is necessary for periods with intense changes. This separation of different periods has empirical meanings because it directs the limited computing power to places with more impact on the model behavior. Although computing technologies have been improved significantly in recent years, computational cost remains a bottleneck when calibrating a dynamic land-use model especially in environments with limited access to cutting-edge technology (Silva & Clarke, 2002). The findings reported here provide guidance in designing the calibration strategy and is thus worthwhile considering.

So far, we have discussed the simulation results from the model implementation perspective. Another way to interpret its implication is from the information accessibility perspective. The simulations in Figs. 6 and 7 assume that changes within an update happened simultaneously. However, whether the changes are synchronous or asynchronous is not the heart of the problem, it is the interaction between them, i.e. the propagation of the information to other decision makers that the land use of one site has been changed, that ultimately lead to the patterns in Figs. 6 and 7. When a change happens, it affects the suitability of cells in its neighborhood. If the time resolution is fine, more of the future additions will perceive the change and weigh it into their decision. Cumulatively, this increases the tendency of the system to generate self-reinforcing behavior. In the case of continuous time, all decision makers acquire the most up-to-date information. In the case of 1-year resolution, the decisions are made based on the information from last year. In the extreme case of 10-year resolution, it is equivalent to say that all information available to the decision maker is a decade old. Without access to the up-to-date information of the whole region, the decision makers are forced to utilize local information only. Consequently, the decisions made are different from those based on full knowledge of what is happening. As we enter information society, it can be expected that in the future, information delay will be reduced significantly. How will the increased information accessibility affect human decision making on land use and consequently the urban morphology is an interesting issue to speculate. Up to date, many discussions on cities in information society are from transportation perspective (Sui, 1998), e.g. the impact of telecommuting on trip generation or reduction, etc. Since reduced information delay introduces more randomness into the system which can give rise to chaotic behavior, we wonder whether the urban morphology in information society will still be similar to what we see today. On the other hand, unless there is no information delay, the continuous time model would not be applicable. Instead, coarser time granularity will work better because it accommodates information delay which does exist in the real world.

6. Summary and recommendations for future research

In this paper, we reported a first exploration on the impact of the degree of temporal dynamics on land-use change modeling. Two issues were examined: does temporal dynamics have an impact on the behavior of a model? And how? To answer these questions, a model based on modified Markov random field was built to simulate the change of urban settlement pattern. An experiment is conducted with two processes of moderate and intense change rate respectively. The results show that too fine or too coarse temporal resolution could both lead to spurious patterns. For the process with intense change rate, the impact of temporal resolution seems to be more dramatic than that on the process with moderate change rate. The implications of these findings were then discussed in the context of operational land-use change modeling and information accessibility.

Although the research reported here presented a first effort in this hardly explored field, we have to admit that time in dynamic land-use change modeling is an enormously difficult issue. Many questions remain untouched. For example, the research conducted in this paper is based on transition-based models only. The impact of time treatment on process-based models has not been explored. Section 2 discussed some time-related concerns for this type of model and suggested many research opportunities. Even within transition-based modeling, many questions still exist. For example, when a coarse temporal resolution is applied, more developments are assumed to happen within an update. In which order should the additions be made and how does the order affect the behavior of a model? As we pointed out in Section 2 for process-based modeling, if one type of land-use demand consistently gets satisfied first, it will have more local information than the others and the resulted pattern may be biased. How to solve the problem and in particular, whether randomization forms a sufficient solution is yet to be examined.

Insofar, our discussion of time has been based on the notion of "Newtonian time" which perceives time as only a device to register change as it happens (Couclelis & Liu, 2000). The other notion of time, namely "real time," has not been studied in land-use modeling. In contrast to "Newtonian time," "Real time" considers time as a determinant of events and thus has an impact on model prediction. How does this epistemological difference affect model construction is yet another research opportunity. Meanwhile, since time and other dimensions of a land-use model are closely related to each other, what is the covariance like between time and other dimensions? The more we think about it, the more we have to confess how little we understand. With this paper, we hope to establish the grounds by which more research can be conducted to further our understanding of time.

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