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Journal
International Journal of Geographical Information Science, 27(9)

ISSN
1365-8816

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Publication Date
2013-09-01

DOI
10.1080/13658816.2013.787145

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Accepted Version

(Note: Published in *International Journal of Geographical Information Science* Vol. 27, No. 8, pp.1782-1803
The final publication is available at www.tandfonline.com)

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Spatiotemporal Scale Dependency and Other Sensitivities in Dynamic Land Use Change Simulations

Abstract: This study examines how land use change simulation outcomes can vary based on the way the simulation model is applied, attempting to support informed model choices and model applications. This is accomplished through a series of experiments using a hypothetical model that represents the basic logic of various cell-based dynamic land use change modeling environments. In the experiments, consideration is given to the sensitivity of the simulation results with respect to the following four application specifications: 1) the spatial resolution, 2) the temporal resolution, 3) the probability distribution, and 4) the degree of the influence of stochastic factors, under multiple growth scenarios. The experiments show that all four factors, particularly the spatiotemporal resolution and the degree to which stochastic factors are involved, can generate substantial variation in the simulation model outcomes. It is also found that the magnitude of the variation can be affected by changes in regional growth rates and the level of fluctuation, which determine the demand for new development to be allocated over the simulation time horizon.

Keywords: Land Use Change, Simulation Modeling, Scale Dependency, Model Sensitivity, Map Comparison

1. Introduction

Dynamic land use change simulation technology has become more useful and approachable as rapid advancement has been made regarding data availability, computing resources, relevant knowledge bases, and modeling techniques. As a result, land use change simulation models have been increasingly employed not only in academia for scientific research but also in a variety of policy decision-making processes (U.S. Environmental Protection Agency 2000, Verburg et al. 2004, Iacono et al. 2008). Furthermore, in recent years, a broad range of planning organizations and other government agencies have utilized this technology as an essential tool to generate spatially explicit growth forecasts, to conduct impact analysis, and to facilitate participatory planning and visioning projects (Couclelis 2005, Deal and Chakraborty 2010, Kim and Hewings 2011).

As land use change simulation models have been widely applied, a considerable number of studies have synthesized and evaluated these models in many respects, such as regarding their theoretical foundations, modeling strategies, and data requirements (see e.g., Wegener 1994, Briassoulis 2000, Parker 2003, Verburg et al. 2004, Pontius et al. 2008). Recent years have also witnessed increasing recognition of the importance of model application settings and associated model sensitivities (Veldkamp and Lambin 2001, Kok et al. 2001, Veldkamp and Verburg 2004, Verburg 2006, Pontius et al. 2007). For instance, Veldkamp and Fresco (1997) investigate land use patterns in Costa Rica at six different geographical scales and find significant scale dependence from the analysis based on multiple regression models. Drawing on their applications of the CLUE (Conversion of Land Use and its Effects) framework to three study areas (i.e., China, Ecuador and the Atlantic Zone of Costa Rica), Veldkamp et al. (2001) also suggest that spatial resolution of analysis plays a critical role in determining key factors of land use changes. Furthermore, in a study using a cellular automata-based model (i.e., SLEUTH: Slope, Land use, Exclusion, Urban extent, Transportation, Hillshade), Jantz and Goetz (2005) detect substantial variation of the model's ability to simulate dynamic land use change processes with respect to spatial resolution, while some other studies, such as Kok and Veldkamp (2001), report that the influence of spatial extent would be more substantial than that of spatial resolution.

These studies and other previous research have indeed shed lights on the importance of model application settings, particularly spatial scale, in land use change analysis and simulation. To further enhance our understanding of complex model behaviors in various application settings, this study examines how land use change simulation outcomes can vary based on the way these models are applied. More specifically, it develops a simple, hypothetical simulation model that represents the common logic of various dynamic land use change modeling environments and conducts a series of experiments to examine the sensitivities of the simulation results with respect to the following four application details: 1) the spatial resolution, 2) the temporal resolution (i.e., the simulation increment), 3) the probability distribution, and 4) the degree of the influence of stochastic factors, under multiple growth scenarios (high vs. low growth rates and steady vs. fluctuating growth). By doing so, the present study attempts to reveal the pattern of variation in simulation outcomes due to changes in application settings, so as to facilitate more informed and effective use of dynamic land use change simulation technology.

The remainder of this article is organized as follows. Section 2 discusses a series of important choices to be made in developing and applying dynamic land use change models. Then, section 3 provides detailed explanations of the hypothetical model, experimental design, and variation assessment methods used in this study. The experiment results are presented in section 4 and discussed in section 5, followed by a concluding section summarizing the research.

2. Key Choices in Land Use Change Modeling & Simulation

Simulation modeling is a useful scientific methodology that enables one to experiment with and learn about a system of interest (Frigg and Hartmann 2006). It is especially valuable if the system of interest is very complex and, thus, cannot be experimented with in the real world, as is the case for land use change. Although a simulation model is designed to mimic the behavior of a real system, modeling is not a replication of a real system with the same level of complexity. Rather, it is a process of simplifying and describing the core nature of the system under various constraints, such as limited data availability and the costs of model development, and this process always involves a series of choices.

Land use change simulation modeling is not an exception to these rules. For instance, to develop a land use change model, attention needs to be paid to key drivers and/or constraints (e.g., macroeconomic forces, ecological factors, policy influences) of land use change processes. In addition, a particular modeling strategy needs to be selected among various available options to describe the nature of land use change dynamics. One could decide to develop a cellular automata-type model by characterizing land use change as an ecological diffusion process, while others may adopt a microeconomic approach by focusing on land owners' or developers' profit maximization.

The above choices are critical in shaping the overall structure of land use change modeling and simulation. These decisions, however, do not represent all of the choice problems involved. There are many more subsequent details to be decided to put a land use change simulation model into operation. For instance, modelers need to specify the functional forms of individual model formulas, to select explanatory variables, and to consider uncertainty factors, which are essential for many land use simulation tasks. Furthermore, they must decide how to project the future trajectories of key drivers of land use changes. If land use change is modeled as an allocation of increasing demand for urban land uses, it is necessary to estimate the amount of demand for new development in the future. In addition, if transportation conditions are included in the model to reflect the effect of accessibility on land development probabilities, the land use change simulation will require projection of dynamic changes in transportation networks. If possible, one may attempt to endogenize such explanatory variables in the model to better consider reciprocal interactions between land use and the variables, as these interactions are critical in describing the evolution of land use and other key elements of human settlements that are systematically connected to each other (Verburg 2006, Kim and Hewings 2011 and 2012). If it is difficult to fully incorporate the variables into the modeling environment, the projections can be made separately and used as exogenous inputs for the land use change simulation. Different approaches for handling these inputs may generate substantial variation in simulation outcomes.

Another important choice to be made involves the spatiotemporal scale in model applications. As revealed by a considerable number of studies (e.g., Jantz and Goetz 2005, Buyantuyev et al. 2010), model behaviors are often sensitive to the spatial unit of analysis, so the selection of a spatial resolution needs to be made carefully. The temporal resolution (i.e., the time increment in simulation) may also be critical in dynamic land use change simulations where land use change probabilities can rise and fall dramatically over time. It needs to be stressed that these decisions should be made with consideration of the objective of the modeling/simulation, data availability, and many other conditions. Although a finer spatiotemporal resolution may generally be more favorable, a certain scale is not always better than another. An increase in spatiotemporal resolution (i.e., an increase in model complexity), while providing benefits, can require a significant amount of additional costs for data collection, calibration, and simulation.

Understanding how model simulation outcomes can vary based on the choices described above is essential for producing better model applications. An enhanced understanding of sensitivities can enable the model developers and users to comprehend various advantages and disadvantages of alternative options. It can also support more appropriate use of simulation outputs by recognizing the errors or possible biases involved in the simulation. The following section describes a series of experiments that are conducted to reveal scale dependencies and other sensitivities, attempting to support informed model choices and model applications.

3. Experiments

Do the choices involved in model development and application affect land use change simulation outcomes? What are important factors generating substantial variation? Under what circumstances can the variation be reduced or amplified? This study examines these critical issues by conducting experiments based upon a hypothetical modeling and simulation environment. Specifically, consideration is given to the variation in simulation outcomes due to the changes in four important model application settings: 1) the spatial resolution, 2) the temporal resolution (i.e., the simulation increment), 3) the probability distribution, and 4) the degree of the influence of stochastic factors, under multiple growth scenarios, as explained below.

3.1. Model

The experiments utilize a simple, hypothetical simulation model designed to replicate the essence of various land use change simulation applications, particularly stochastic cellular automata approaches, which have been widely employed for a broad range of land use studies. The hypothetical model uses a grid system with the following binary classification of land uses: 1 indicates developed land cells and 0 undeveloped land areas. Specifically, as demonstrated in figure 1, the grid system is designed such that there is a pre-developed area in the center and undeveloped surrounding hinterlands, where future development (i.e., land use changes) can occur in the simulation. For the baseline simulation experiments, a grid system with dimensions of 36×36 is adopted, while dimensions of 18×18 and 72×72 are also used to test the effects of the spatial resolution on simulation outcomes.

<< Figure 1 about here >>

Figure 1. Initial Setup

Basically, land use changes are characterized here as a demand-driven land development process. This process can be described through two distinct steps: 1) estimation of the aggregated demand for new development and 2) allocation of the demand within the spatially explicit grid system (figure 2). Regarding the first step, for simplicity, the aggregated demand, $D(t)$, is assumed to be determined exogenously, even though regional growth and, thus, the demand for new development would be influenced by the efficiency of internal land use patterns in reality (White and Engelen 2000, Cervero 2001, Kim 2011). As explained in the next sub-section, each exogenous demand structure represents a unique regional growth scenario in the experiments, and multiple hypothetical growth scenarios, including a higher growth rate (i.e., a greater level of new development to be allocated) and a more fluctuating regional growth trajectory as opposed to steady growth, are tested to understand how the model sensitivities can vary under different exogenous conditions.

<< Figure 2 about here >>

Figure 2. Experimental Simulation Procedures

The second step (i.e., the spatial allocation of the demand) is accomplished by considering both deterministic and stochastic factors, similar to many real land use model applications (see, e.g., Wu 2002, De Almeida et al. 2003, Deal and Sun 2006). The deterministic portion indicates the extent to which explanatory variables can describe dynamic land use change processes and can be formulated in terms of the development probability using a logistic function that gives a value between 0 and 1, as follows:

$$\text{IF } i \in \bigcup NG(t) \quad \text{THEN } p_i^t = 0 \quad \text{ELSE } p_i^t = \frac{\exp(z_i^t)}{1+\exp(z_i^t)} \tag{1}$$

$$z_i^t = X_i^t \cdot \beta + \varepsilon \tag{2}$$

where $NG(t)$ indicates No Growth areas that cannot be developed in time *t* due to their current state or other constraints (e.g., pre-developed areas or water); p_i^t is the development probability of cell *i* in time *t*; z_i^t is the cell's raw development score before being converted into the probability; X_i^t and β represent a vector of explanatory variables and the column vector of the associated parameters, respectively; and ε is an error term.

Recent land use change model applications have used a variety of explanatory variables, ranging from each cell's physical, social, and economic conditions to its locational advantages. However, the present hypothetical model assumes no ecological or socioeconomic variation across cells for simplicity. Instead, the model takes into account each cell's proximity to pre-developed areas in the system, which is widely recognized as an important factor in land development in the literature. More specifically, it utilizes a generalized gravity function to calculate the average gravity forces from all pre-developed locations for each cell, as given below.

$$z_i^t = \frac{1}{m_t} \cdot \sum_{j, j \neq i}^{m_t} \ln\left(1 \big/ d_{ij}^{\delta} \right) \tag{3}$$

where j denotes developed cells; m_t indicates the number of existing developed cells in time t; d_{ij} represents the distance between cell i (for which the score is calculated) and the j-th developed cell; and δ is a distance decay rate for the gravity calculation. Figure 3 shows the initial development probability distribution.

<< Figure 3 about here >>

Figure 3. Development Probability

The deterministic portion alone does not fully describe complex patterns of dynamic land use changes in reality. Therefore, land use change models often incorporate stochastic elements by employing the well-known Monte Carlo simulation technique or using random number generators (see e.g., Wu 2002, Li and Yeh 2002, Soares-Filho et al. 2002, Luijten 2003, Almeida et al. 2008). The randomized factor contributes to portraying the real irregularity and probable future land use patterns given the imperfect explanatory power of the deterministic portion, even though the randomness inevitably generates some variation in land use simulation outcomes.

This common characteristic of many land use change simulations (i.e., the inclusion of a stochastic factor) is reflected in the experiments. The present hypothetical model, however, does not simply adopt the Monte Carlo approach or other stochastic features with a fixed range of random values. Instead, it attempts to control the level of the randomized factor relative to the deterministic portion in every simulation practice to examine how land use simulation outcomes are influenced by the degree to which the stochastic factors are involved in the model. More specifically, in each time increment of the experimental simulations, the following procedures are performed to consider the stochastic factors with an appropriate control.

(1) Calculating p_i^t (i.e., the deterministic portion) for individual cells

(2) Computing the mean ($\overline{p}_i^t$) and the standard deviation ($\sigma(p_i^t)$) of the $\{p_i^t\}$ distribution

(3) Generating a set of random numbers $\{r_i^t\}$ based on a normal distribution $N(\alpha \cdot \overline{p}_i^t, \alpha \cdot \sigma(p_i^t))$, where α is a factor introduced to control the relative magnitude of the stochastic factor compared to the deterministic portion

(4) Creating a $\{p_i^t + r_i^t\}$ raster surface by combining the deterministic and stochastic portions

Finally, the demand allocation is completed by identifying specific land cells for new development considering both deterministic and stochastic factors, represented by $\{p_i^t + r_i^t\}$. As mentioned earlier, the amount of new development (i.e., the number of newly developed cells) follows the exogenously determined demand for new development, $D(t)$, in each simulation time increment.

3.2. Land Use Simulation Experiments

The hypothetical model presented in the previous section can be used to simulate dynamic land use changes for a finite simulation time horizon. In this study, the model is first employed to generate a set of baseline land use simulation outcomes with the following detailed simulation setup and a default growth scenario of $D(t) = 4 / year$ in terms of 36×36 cells.

- Spatial resolution: 36×36
- Temporal resolution: 2 year increments for a 20-years simulation time horizon (i.e., t=2,4,…18,20)
- Probability distribution: $\delta = 1$
- Stochastic factor: $\alpha = 1$

With the above baseline setting, the model is run 50 times to observe the variation in simulation outcomes arising from the same setting (hereafter, single-setting variation). Basically, this single-setting variation originates from the stochastic factor involved in the model. However, the magnitude of the variation can also be influenced by other factors that shape the dynamics of land use changes in the simulation. For this reason, even if the stochastic factor holds constant, the single-setting variation can differ in different application settings.

Then, in addition to the baseline, land use simulations are conducted with eight other settings to examine how the model simulation outcomes are influenced by changes in spatiotemporal resolution and other application details. Table 1 presents all of the settings tested in this study, along with the application specifications. Again, in each setup, the model simulations are conducted 50 times to observe the single-setting variation in each setting.

<< Table 1 about here >>

Table 1. Experimental Settings

Finally, to examine how the variation in simulation outcomes can be affected by external conditions, particularly the regional demand growth trend, three additional growth scenarios are tested in this study. The growth scenarios (in terms of 36×36 cells) include

- Default: Constant level of the demand for new development at the rate of $D(t) = 4\theta$ where θ indicates the time increment in simulation (e.g., 1 year, 2 years, and 4 years) – i.e., even distribution of the total 80 cells over the simulation time horizon[1]
- Fluctuation: Fluctuating level of the demand with the same total amount as in the Default scenario – i.e., $D(t) = 8\theta, 0, 8\theta, 0, \ldots$
- High Growth: Constant level of the demand for new development at the rate of $D(t) = 8\theta$ – i.e., even distribution of the total 160 cells over the simulation time horizon
- High Growth & Fluctuation: Fluctuating level of the demand with the same total amount as in the High Growth scenario – i.e., $D(t) = 16\theta, 0, 16\theta, 0, \ldots$

In summary, nine different simulation settings (i.e., one baseline and eight alternative setups) are tested under four different growth scenarios. The total number of model runs is 1,800, i.e., 9 (settings) × 4 (growth scenarios) × 50 (model runs). The following section explains how the

[1] In order to be consistent, the number of cells is adjusted depending on the spatial scale used in the experiments. For instance, in the case of the 72×72 scale (i.e., Setting 2. High Resolution), $D(t)$ is set to 16/year (i.e., even distribution of the total 320 cells), which is equivalent to four 36×36 cells per year.

many land use change simulation outcomes are compared with each other to identify meaningful results from the experiments.

3.3. Evaluation Methodology – Comparisons and Variation Measurements

To systematically assess how the simulation outcomes (i.e., 1,800 maps) differ based on the model application settings, an evaluation strategy along with appropriate measurements is required.[2] In this study, the outcome assessment is accomplished from the following two different perspectives: 1) evaluation of the single-setting variation in each group of 50 simulation outcomes based on the same simulation setting and 2) evaluation of the cross-setting variation across 36 setups (9 settings × 4 growth scenarios).

3.3.1. Single-setting Variation

To measure single-setting variation, this study employs some map comparison methods. The most comprehensive approach for accomplishing this task would be to compare all 50 maps from a simulation setup with each other to determine the single-setting variation. However, this would require an overly large number of comparisons (i.e., 1,225 pairs of the maps given 50 simulation outputs) and would not add substantial value with respect to enhancing the interpretation of the experimental results. Therefore, to achieve greater efficiency, this study identifies a basis map in which the external demand for new development is met by the cells that are most frequently selected in the 50 maps, and then compares all 50 simulation outcome maps with this basis map.

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[2] In fact, map comparisons and the identification of differences have long been placed at the center of the spatial modeling and GIS literature (see e.g., Pontius 2000, Power et al. 2001, Hagen 2003, Hagen-Zanker 2006, Pontius and Cheuk 2006, White 2006, Remmel 2009, Ruiz et al. 2012).

For instance, in the case of the baseline simulation, a basis map is derived from the 50 simulation outcomes produced under the baseline setting, as illustrated in figure 4. Then, each of the 50 maps is compared with the basis map (i.e., 50 comparisons, as opposed to 1,225 comparisons), and the differences between each map and the basis map are quantified. The logic of this approach is similar to that of the variance calculation in statistics that measures the gap between each observation and the mean and then synthesizes the gaps. The basis map is something like the mean value that helps identify the variation in the simulation outcomes.

<< Figure 4 about here >>

Figure 4. Basis Map Development

A remaining issue is how to quantify the differences between the basis map and individual land use change simulation outcomes. To perform this quantification, the simplest, most straightforward method is to conduct a cell-by-cell comparison that checks the match between each pair of corresponding cells in the two maps and calculating the percentage of the cell matches (*CM*), as shown below (p. 976, Kuhnert et al. 2005).

$$CM = \frac{N_{id}}{N} \tag{4}$$

where N_{id} and N represent the number of identical (i.e., matched) cells between the two maps and the total number of cells, respectively.

Another useful metric is the *figure of merit* that has recently gained popularity in the field of geographical studies (see e.g., Pontius et al. 2007, 2008, and 2011). This index, which can range between 0 and 1, focuses on the cells that are predicted to experience changes in their status (i.e., land use conversion), while the cell matches (i.e., *CM*) considers the entire group of cells in quantifying the level of correspondence between two maps. In other words, the figure of merit prevents analysts from ending up with a high value of correspondence simply due to a large number of cells with no change (i.e., persistence) in their study areas. More specifically, the figure of merit indicator (*FM*) can be expressed, as shown below.

$$FM = \frac{M_{1\cap 2}}{M_{1\cup 2}} \tag{5}$$

where $M_{1\cap 2}$ represents the number of cells that are projected to be newly developed according to both maps, while $M_{1\cup 2}$ indicates the number of cells that are chosen for new development in either the first or the second map.

The figure of merit index is useful, but it is another type of cell-by-cell comparison and, thus, cannot capture the similarity between two maps in terms of the overall land use patterns, which are critical in land use simulation practices. Pattern-wise comparison is needed to determine if two simulation outputs fundamentally differ from each other. This can be accomplished by employing landscape structure metrics (see e.g., Turner et al. 1989; Mas et al. 2012) or by applying a moving or expanding window method (see e.g., Pontius et al. 2004; Kuhnert et al. 2005). This study adopts a moving window approach presented in Costanza (1989) to complement the cell-by-cell comparison statistics. The moving window index (*MWI*), which quantifies the pattern-wise similarity in a single value, is defined as follows.

$$MWI = \frac{\sum_{w} WM_{w} \cdot e^{-(w-1)}}{\sum_{w} e^{-(w-1)}} \tag{6}$$

$$WM_{w} = 1 - \frac{1}{S_{w}} \sum_{s=1}^{S_{w}} \frac{\sum_{l} \left| m1_{l} - m2_{l} \right|}{2 \cdot w^{2}} \tag{7}$$

where w is the window size in terms of the cell numbers (e.g., 1 cell × 1 cell, …, n cell × n cell); S_w indicates the total number of the windows required to cover the spatial extent of the maps compared (e.g., $S_w = n^2$ when w is 1 cell × 1 cell, whereas $S_w = 1$ when w is n cell × n cell); and $m1_l$ and $m2_l$ represent the number of cells with an l-type land use within each window in the first and the second maps, respectively.

In sum, the single-setting variation in the land use simulation outcomes is assessed in this study by conducting map comparisons between the basis map for each application setting and individual simulation outcomes with the three following indicators: 1) the rate of the cell matches (*CM*), 2) the figure of merit indicator (*FM*), and 3) a moving window index (*MWI*).

3.3.2. Cross-setting Variation

Second, to assess the variation in the land use change simulation outcomes due to the changes in the settings, multiple basis maps that represent individual simulation setups are compared. More specifically, under each growth scenario, the basis map from the baseline setup is compared with the basis maps for the remaining eight alternative settings, which are listed in table 1. Again, the map comparison results are quantified by utilizing the three indicators *CM*, *FM*, and *MWI*, as explained above.

Regarding the investigation of cross-setting variation, this study considers one additional issue: how the variation between two basis maps differs based on the number of model runs used to derive the basis maps. It is hypothesized that the cross-setting variation is mitigated as the number of model runs increases. To test this hypothesis, the basis maps are derived from five different sets of model runs (i.e., the first 10 model runs, first 20 model runs, first 30 model runs, first 40 model runs, and the total of 50 model runs) for each setting under each growth scenario, and comparisons are then made.

4. Results

4.1. Single-setting variation

As explained in the previous section, the model is run with a wide range of simulation settings, and the simulation outputs are then systematically compared to examine how the model outcomes can vary based on the way the model is applied. This section presents the experimental results and the single-setting and cross-setting variation analysis outcomes. Table 2 summarizes the single-setting variation analysis results.

<< Table 2 about here >>

Table 2. Single-setting Variation Analysis Result

The mean and standard deviation in the table are descriptive statistics for the 50 different values of the three indicators from the comparisons between the basis map and the 50 simulation outcomes for each setting (for example, see figure 5 for the 50 *CM* values from the baseline under the default growth scenario that result in a mean of 0.949 and a standard deviation of 0.006).

<< Figure 5 about here >>

Figure 5. *CM* Distribution of the 50 Simulations

The analysis results first suggest that the simulation outcomes vary significantly, even if they come from an identical application setup. For instance, in the case of the baseline under the default scenario, simulation outcomes exhibit 94.9% of cells matched with the basis map on average. This indicates a substantial magnitude of variation (i.e., only approximately 47 cells showing accordance, out of 80 newly developed cells in a simulation), which is also highlighted by the *FM* value, 0.419.

Admittedly, this single-setting variation can mainly be attributed to the randomized factor involved in the simulation model. The higher accordance under the small random setup (e.g., *CM*: 0.971 under the default scenario) and the lower accordance in the large random case (e.g., *CM*: 0.921 under the default scenario) clearly demonstrate this fact. However, it should be stressed that the single-setting variation can also be influenced by other specifications once a randomized factor is included. More specifically, even if the level of the randomized factor remains fixed, relatively larger variation in the simulation outputs is found with (i) a lower spatial resolution, (ii) a more aggregated temporal scale (i.e., a larger simulation increment), and (iii) more evenly distributed development scores. In particular, when a higher spatial resolution is implemented for the simulation, the variation can be substantially reduced. Under the default growth scenario, the *CM* value is 0.968 for the higher spatial resolution setting, while the baseline setting presents a *CM* value of 0.949.

All of the observed patterns appear to be consistent with the expectations. For example, under the settings with lower spatial and temporal resolution levels, the model simulation has to treat a larger chunk of the demand for new development together rather than allocating smaller pieces separately. As a result, the simulation outcomes tend to lean to one side and, thus, involve a greater degree of single-setting variation. In the case of a setting with more evenly distributed development scores, the stochastic model simulation outcomes are less likely to be identical (i.e., large single-setting variation), as many alternative undeveloped cells can be picked in every round of allocation, as they exhibit similar development probability levels.

The results of the analysis also suggest that the variation in the model simulation outcomes can be significantly influenced by the external demand to be allocated. In particular, the fluctuating growth scenarios present much smaller values of all three indicators (i.e., *CM*, *FM*, and *MWI*) which imply higher levels of single-setting variation. The increasing variation in fluctuation is not surprising, as the fluctuation has an effect in the simulation similar to the lower temporal resolution, which generates a higher level of the single-setting variation, as mentioned above. The effects of a change in growth rates, however, are mixed. While the high growth scenarios generate smaller values of *CM* and *MWI* similar to the fluctuating growth scenarios (i.e., a higher level of variation in terms of *CM* and *MWI*), the *FM* values derived from these scenarios turn out to be greater than those from the default scenario (i.e., a lower variation level in terms of *FM*). This suggests that the influence of demand growth rates on the variation is indeterminate, although a change in the external demand trajectory does modify land use simulation outcomes. There is no reason that an increase in the demand growth rate should result in a larger degree of variation. The variation can either increase or decrease in response to a change in the growth rate, while the fluctuation tends to increase the variation, as found in this study.

4.2. Cross-setting Variation

The cross-setting variation is also analyzed by comparing the baseline's basis map with those from other settings. Table 4 presents the cross-setting variation analysis results when the basis maps are derived from the first 10 simulation outcomes in each simulation setting. Table 5 shows the analysis results using the basis maps from the total of 50 simulation runs. As explained in section 3.3.2., investigation of the cross-setting variation with different numbers of model runs could aid in checking whether the variation can be mitigated by increasing the number of model runs.

<< Tables 3 and 4 about here >>

Table 3. Cross-setting Variation Analysis Result (First 10 Model Runs)

Table 4. Cross-setting Variation Analysis Result (50 Model Runs)

Above all, table 3 clearly shows that the model application specifications do matter. In this case, the simulation outcomes systematically differ across all of the four tested aspects, i.e., 1) the spatial resolution, 2) the temporal resolution, 3) the probability distribution, and 4) the degree of the influence of stochastic factors. In detail, the rate of cell matches (i.e., *CM*) ranges from 0.91 to 0.98, with median 0.96 which indicates that approximately 55 cells show accordance, out of 80 newly developed cells. Furthermore, the fluctuation scenarios are again found to involve generally higher levels of cross-setting variation, as in the case of the single-setting variation.

Regarding the relationship between the cross-setting variation and the number of model runs, the results suggest that the difference between the two basis maps can be mitigated as the number of model runs increases. As an example, figure 6 shows how *CM* under the default scenario varies based on the number of model runs. The generally higher values of the accordance statistics observed in table 4, with 50 model runs, compared to table 3, based on 10 simulations, also support this finding.

<< Figure 6 about here >>

Figure 6. *CM* between the Basis Maps by Number of Model Runs

5. Discussion of Results

Among others, the results of this study show that land use change simulation outcomes can vary within and across application settings, and that the variation in simulation outcomes can be influenced not only by the randomized factor but also by other specifications in the model application. Table 5 presents a set of t-tests conducted to check the statistical implications of the resultant gaps from the experiments with 50 model runs for each setting. As shown in the table, the gaps between the means of the baseline and other settings are substantial in most cases.

<< Tables 5 about here >>

Table 5. T-statistics of the Gaps between the Means of Each Setting and the Baseline

It also needs to be stressed that the simulated land use patterns and their variation can differ significantly based on the overall growth trends (represented by the four growth scenarios in the experiments), even if there are no changes in the allocation settings. This finding suggests that regional growth forecasting and demand estimation largely shape the detailed land use simulation outcomes. Given that macro growth forecasts and aggregate demand estimations are critical, land use modelers may need to pay more attention to the quality of population and macroeconomic forecasts, rather than focusing only on demand allocation, assuming that regional growth forecasting is outside the scope of their analysis.

Another important finding is that the variation can be mitigated by increasing the number of model runs, as demonstrated in figure 6. This point is important, as it shows how model users can better deal with the variation in simulation outcomes involved in most stochastic dynamic land use change simulation models. Given the variation, it is apparent that focusing on a single model simulation outcome is not desirable. It would be better to recognize a wide range of possible futures represented by a large number of simulation outcomes. In fact, to some extent, the variation is an intended outcome of the model, which seeks to describe the possible irregularity and path dependence in land use changes in reality. Using one or a few simulation outputs based on a single baseline growth scenario must represent an under-utilization of the land use change simulation model. An attempt needs to be made to thoroughly understand a variety of possible land use patterns in the future through extensive scenario analyses, as have been performed in some recent studies, such as those of Li and Liu (2008), Robinson and Brown (2009), and Houet et al. (2010). Policy decision making and planning practices also should consider many different possibilities that can take place in a study area with a more extensive use of models and scenario planning approaches in order to attain more robust planning and policy decision-making (Chakraborty et al. 2011).

6. Conclusion

Understanding complex model behaviors in various application settings is crucial to improving the quality of land use simulation models and promoting more effective use of these promising tools. To enhance the understanding of the model behaviors, this study examines how dynamic land use change model outcomes can vary based on simulation settings with an emphasis on four key aspects: 1) the spatial resolution, 2) the temporal resolution, 3) the probability distribution, and 4) the degree of the influence of stochastic factors, under multiple growth scenarios. This is accomplished through a set of experiments using a hypothetical simulation environment that represents the basic logic of the cell-based dynamic land use change models employed for various empirical studies on land use dynamics and in making many policy decisions.

The experiments show that the simulation outcomes are substantially influenced not only by changes in the influence of stochastic factors but also by the determination of spatiotemporal scales and the probability distribution. More specifically, higher levels of variation are found under lower spatiotemporal resolution levels and more evenly distributed probability distributions. In addition, the cross-setting variation analysis shows that land use simulation models can generate different outputs if one of the four factors is set up differently. Furthermore, the results of the experiments reveal that macro growth forecasts are critical in dynamic land use change simulation, not only because they provide control totals to be allocated but also because they can affect detailed patterns of land use change simulation outcomes.

Future research to test the model sensitivities with the use of a more complex simulation environment will be extremely valuable, as it can help us grasp how the variation pattern examined in this study is determined in a more specific context and what other factors are involved in shaping the model sensitivities. Such research endeavors can lead to more successful implementation of the simulation modeling technology, which in turn can enhance our understanding of the dynamics and complexity of land use changes.

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Table 1. Experimental Settings

Category	Setting	Spatial Resolution	Temporal Resolution	Probability Distribution	Stochastic Factor
Baseline	1. Baseline	36×36	10 × 2-year increment	$\delta = 1$	$\alpha = 1$
Spatial Resolution	2. Low Resolution	18×18	10 × 2-year increment	$\delta = 1$	$\alpha = 1$
	3. High Resolution	72×72	10 × 2-year increment	$\delta = 1$	$\alpha = 1$
Temporal Resolution	4. Less Frequent	36×36	5 × 4-year increment	$\delta = 1$	$\alpha = 1$
	5. More Frequent	36×36	20 × 1-year increment	$\delta = 1$	$\alpha = 1$
Probability Distribution Conditions	6. More Evenly Distributed	36×36	10 × 2-year increment	$\delta = 0.5$	$\alpha = 1$
	7. Less Evenly Distributed	36×36	10 × 2-year increment	$\delta = 2$	$\alpha = 1$
Extent of the Influence of Randomness	8. Small Random Involved	36×36	10 × 2-year increment	$\delta = 1$	$\alpha = 0.5$
	9. Large Random Involved	36×36	10 × 2-year increment	$\delta = 1$	$\alpha = 2$

Table 2. Single-setting Variation Analysis Result

Growth Scenario	Setting	Rate of the Cell Matches (*CM*)		Figure of Merit (*FM*)		Moving Window Index (*MWI*)	
		Mean	SD	Mean	SD	Mean	SD
Default Scenario	1. Baseline	0.949	0.006	0.419	0.049	0.964	0.004
	2. Low Res.	0.946	0.010	0.395	0.080	0.962	0.007
	3. High Res.	0.968	0.005	0.586	0.047	0.977	0.003
	4. Less Freq.	0.944	0.005	0.380	0.040	0.961	0.004
	5. More Freq.	0.952	0.005	0.445	0.046	0.966	0.004
	6. More Ev. Dist.	0.949	0.004	0.418	0.037	0.964	0.003
	7. Less Ev. Dist.	0.951	0.005	0.432	0.044	0.965	0.004
	8. Small Random	0.971	0.005	0.623	0.053	0.980	0.004
	9. Large Random	0.921	0.007	0.222	0.040	0.944	0.005
Fluctuation Scenario	1. Baseline	0.943	0.005	0.372	0.039	0.960	0.004
	2. Low Res.	0.930	0.012	0.282	0.083	0.951	0.009
	3. High Res.	0.966	0.005	0.567	0.048	0.976	0.003
	4. Less Freq.	0.922	0.008	0.226	0.048	0.945	0.006
	5. More Freq.	0.944	0.006	0.376	0.043	0.960	0.004
	6. More Ev. Dist.	0.941	0.006	0.358	0.042	0.959	0.004
	7. Less Ev. Dist.	0.943	0.006	0.372	0.045	0.960	0.004
	8. Small Random	0.968	0.004	0.591	0.038	0.977	0.003
	9. Large Random	0.911	0.006	0.162	0.032	0.937	0.004
High Growth Scenario	1. Baseline	0.921	0.006	0.518	0.029	0.944	0.004
	2. Low Res.	0.916	0.013	0.494	0.059	0.940	0.009
	3. High Res.	0.956	0.005	0.697	0.030	0.969	0.004
	4. Less Freq.	0.914	0.007	0.486	0.031	0.939	0.005
	5. More Freq.	0.927	0.007	0.544	0.031	0.948	0.005
	6. More Ev. Dist.	0.920	0.005	0.511	0.024	0.943	0.004
	7. Less Ev. Dist.	0.926	0.007	0.538	0.033	0.947	0.005
	8. Small Random	0.958	0.005	0.710	0.030	0.970	0.004
	9. Large Random	0.866	0.009	0.296	0.031	0.905	0.006
High Growth & Fluctuation Scenario	1. Baseline	0.912	0.009	0.476	0.038	0.938	0.006
	2. Low Res.	0.903	0.012	0.436	0.051	0.931	0.009
	3. High Res.	0.950	0.005	0.662	0.027	0.964	0.003
	4. Less Freq.	0.877	0.008	0.335	0.029	0.913	0.006
	5. More Freq.	0.920	0.008	0.511	0.037	0.943	0.006
	6. More Ev. Dist.	0.910	0.007	0.466	0.032	0.936	0.005
	7. Less Ev. Dist.	0.917	0.006	0.499	0.028	0.942	0.004
	8. Small Random	0.954	0.005	0.684	0.028	0.967	0.004
	9. Large Random	0.855	0.009	0.262	0.028	0.898	0.006

Table 3. Cross-setting Variation Analysis Result (First 10 Model Runs)

Growth Scenario	Baseline vs.	Rate of the Cell Matches (*CM*)	Figure of Merit (*FM*)	Moving Window Index (*MWI*)
Default Scenario	2. Low Res.	0.955	0.468	0.968
	3. High Res.	0.978	0.702	0.985
	4. Less Freq.	0.968	0.584	0.977
	5. More Freq.	0.975	0.667	0.983
	6. More Ev. Dist.	0.969	0.600	0.978
	7. Less Ev. Dist.	0.972	0.633	0.980
	8. Small Random	0.980	0.720	0.986
	9. Large Random	0.952	0.441	0.966
Fluctuation Scenario	2. Low Res.	0.963	0.538	0.974
	3. High Res.	0.977	0.684	0.984
	4. Less Freq.	0.963	0.538	0.974
	5. More Freq.	0.971	0.616	0.979
	6. More Ev. Dist.	0.968	0.584	0.977
	7. Less Ev. Dist.	0.971	0.616	0.979
	8. Small Random	0.977	0.684	0.984
	9. Large Random	0.952	0.441	0.966
High Growth Scenario	2. Low Res.	0.952	0.675	0.966
	3. High Res.	0.965	0.749	0.975
	4. Less Freq.	0.958	0.711	0.971
	5. More Freq.	0.957	0.702	0.969
	6. More Ev. Dist.	0.957	0.702	0.969
	7. Less Ev. Dist.	0.951	0.667	0.965
	8. Small Random	0.960	0.720	0.972
	9. Large Random	0.918	0.502	0.942
High Growth & Fluctuation Scenario	2. Low Res.	0.949	0.658	0.964
	3. High Res.	0.955	0.693	0.968
	4. Less Freq.	0.943	0.624	0.960
	5. More Freq.	0.948	0.649	0.963
	6. More Ev. Dist.	0.946	0.641	0.962
	7. Less Ev. Dist.	0.960	0.720	0.972
	8. Small Random	0.954	0.684	0.967
	9. Large Random	0.912	0.475	0.938

Table 4. Cross-setting Variation Analysis Result (50 Model Runs)

Growth Scenario	Baseline vs.	Rate of the Cell Matches (*CM*)	Figure of Merit (*FM*)	Moving Window Index (*MWI*)
Default Scenario	2. Low Res.	0.977	0.684	0.984
	3. High Res.	0.986	0.798	0.990
	4. Less Freq.	0.983	0.758	0.988
	5. More Freq.	0.989	0.839	0.992
	6. More Ev. Dist.	0.988	0.818	0.991
	7. Less Ev. Dist.	0.989	0.839	0.992
	8. Small Random	0.992	0.882	0.995
	9. Large Random	0.977	0.684	0.984
Fluctuation Scenario	2. Low Res.	0.972	0.633	0.980
	3. High Res.	0.992	0.882	0.995
	4. Less Freq.	0.988	0.818	0.991
	5. More Freq.	0.981	0.739	0.987
	6. More Ev. Dist.	0.981	0.739	0.987
	7. Less Ev. Dist.	0.991	0.860	0.993
	8. Small Random	0.989	0.839	0.992
	9. Large Random	0.980	0.720	0.986
High Growth Scenario	2. Low Res.	0.965	0.749	0.975
	3. High Res.	0.985	0.882	0.989
	4. Less Freq.	0.977	0.829	0.984
	5. More Freq.	0.981	0.860	0.987
	6. More Ev. Dist.	0.978	0.839	0.985
	7. Less Ev. Dist.	0.978	0.839	0.985
	8. Small Random	0.986	0.893	0.990
	9. Large Random	0.968	0.768	0.977
High Growth & Fluctuation Scenario	2. Low Res.	0.971	0.788	0.979
	3. High Res.	0.974	0.808	0.981
	4. Less Freq.	0.974	0.808	0.981
	5. More Freq.	0.977	0.829	0.984
	6. More Ev. Dist.	0.981	0.860	0.987
	7. Less Ev. Dist.	0.980	0.850	0.986
	8. Small Random	0.986	0.893	0.990
	9. Large Random	0.963	0.739	0.974

Table 5. T-statistics of the Gaps between the Means of Each Setting and the Baseline

Growth Scenario	Baseline vs.	Rate of the Cell Matches (*CM*)	Figure of Merit (*FM*)	Moving Window Index (*MWI*)
Default Scenario	2. Low Res.	2.03 *	1.81	2.03 *
	3. High Res.	17.15 ***	17.43 ***	17.14 ***
	4. Less Freq.	4.34 ***	4.39 ***	4.34 ***
	5. More Freq.	2.74 **	2.73 **	2.74 **
	6. More Ev. Dist.	0.09	0.17	0.08
	7. Less Ev. Dist.	1.39	1.36	1.39
	8. Small Random	19.71 ***	20.02 ***	19.71 ***
	9. Large Random	22.30 ***	22.19 ***	22.22 ***
Fluctuation Scenario	2. Low Res.	6.98 ***	6.94 ***	6.98 ***
	3. High Res.	22.56 ***	22.28 ***	22.55 ***
	4. Less Freq.	16.18 ***	16.82 ***	16.16 ***
	5. More Freq.	0.49	0.52	0.49
	6. More Ev. Dist.	1.80	1.75	1.80
	7. Less Ev. Dist.	0.03	0.02	0.03
	8. Small Random	28.10 ***	28.68 ***	28.10 ***
	9. Large Random	29.80 ***	29.60 ***	29.73 ***
High Growth Scenario	2. Low Res.	2.80 **	2.63 **	2.80 **
	3. High Res.	30.46 ***	30.53 ***	30.44 ***
	4. Less Freq.	5.42 ***	5.40 ***	5.42 ***
	5. More Freq.	4.23 ***	4.27 ***	4.23 ***
	6. More Ev. Dist.	1.29	1.32	1.29
	7. Less Ev. Dist.	3.26 **	3.27 **	3.25 **
	8. Small Random	32.25 ***	32.58 ***	32.22 ***
	9. Large Random	36.03 ***	37.19 ***	35.95 ***
High Growth & Fluctuation Scenario	2. Low Res.	4.52 ***	4.48 ***	4.52 ***
	3. High Res.	26.98 ***	28.32 ***	27.00 ***
	4. Less Freq.	21.23 ***	21.10 ***	21.21 ***
	5. More Freq.	4.63 ***	4.62 ***	4.62 ***
	6. More Ev. Dist.	1.47	1.51	1.48
	7. Less Ev. Dist.	3.43 ***	3.39 **	3.44 ***
	8. Small Random	29.64 ***	31.24 ***	29.66 ***
	9. Large Random	32.80 ***	32.22 ***	32.76 ***

*** 0.1% level significance | ** 1% level significance | * 5%level significance

$$t = \frac{\bar{x}_{setting} - \bar{x}_{baseline}}{\sqrt{\frac{{s'_{setting}}^2 + {s'_{baseline}}^2}{n}}}$$

where $\bar{x}$ and s' represent the mean and standard deviation of a particular setting, and n is the number of samples (i.e., the number of simulation runs in each setting, which is 50)

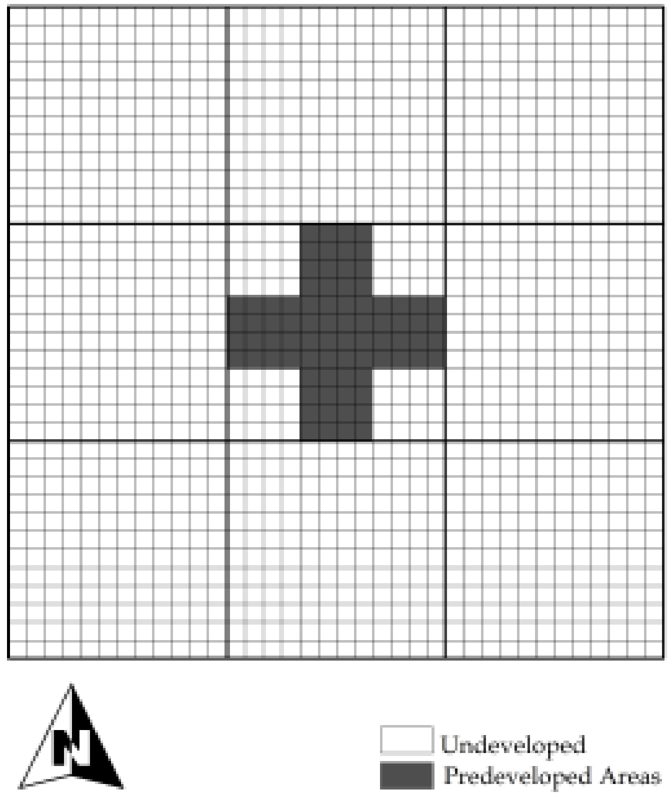


Figure 1. Initial Setup

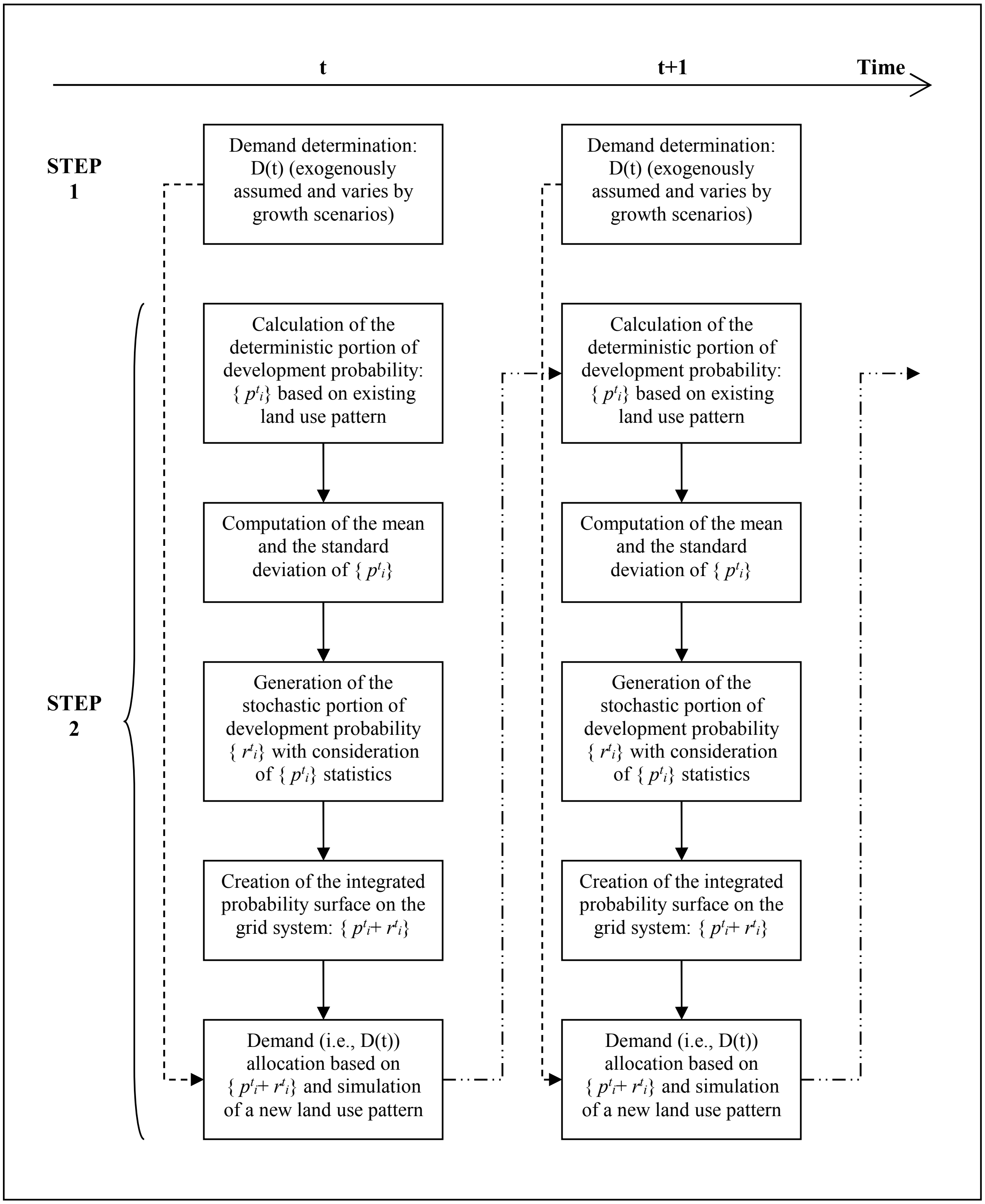
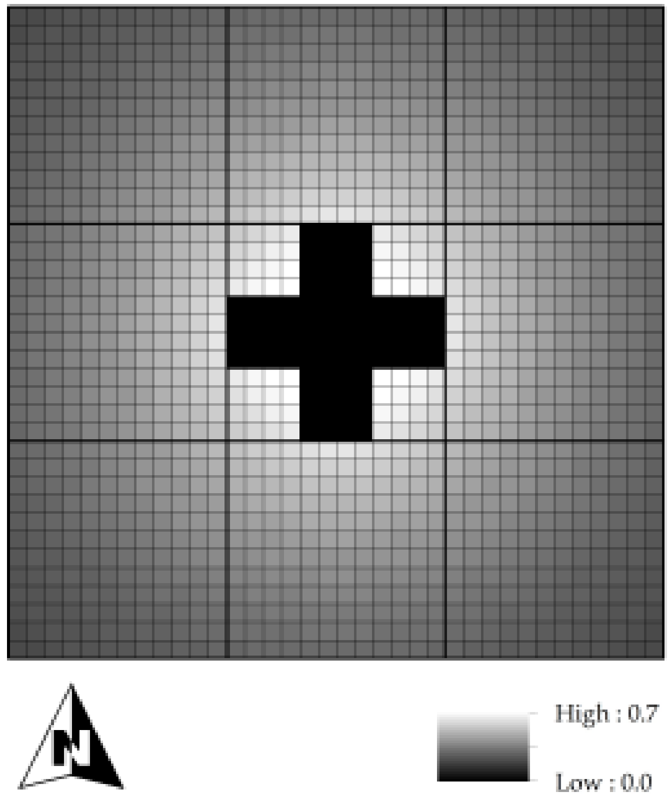


Figure 2. Experimental Simulation Procedures



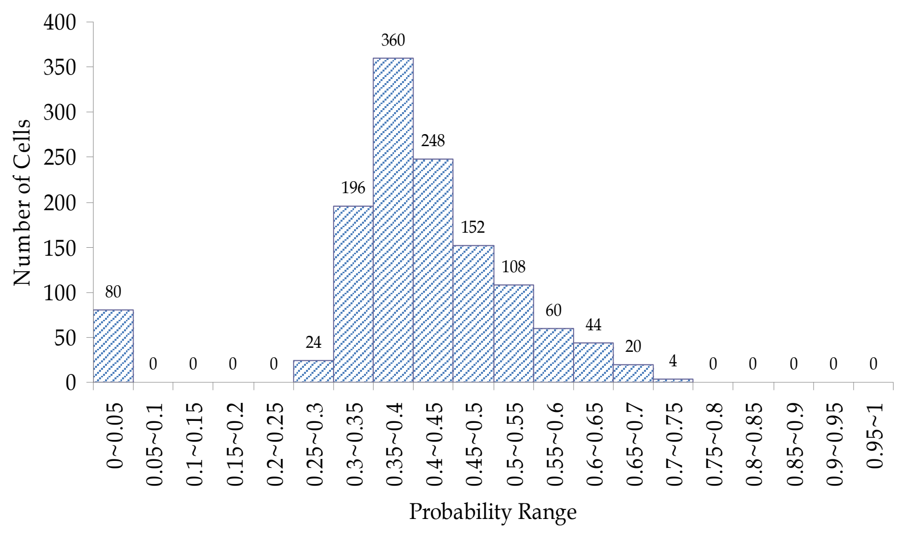
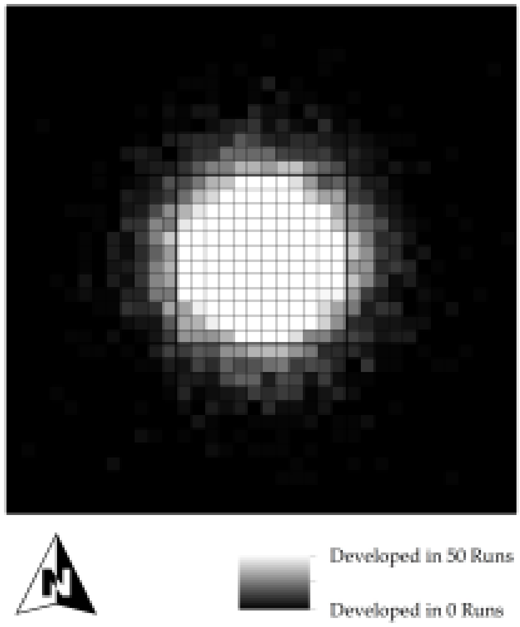
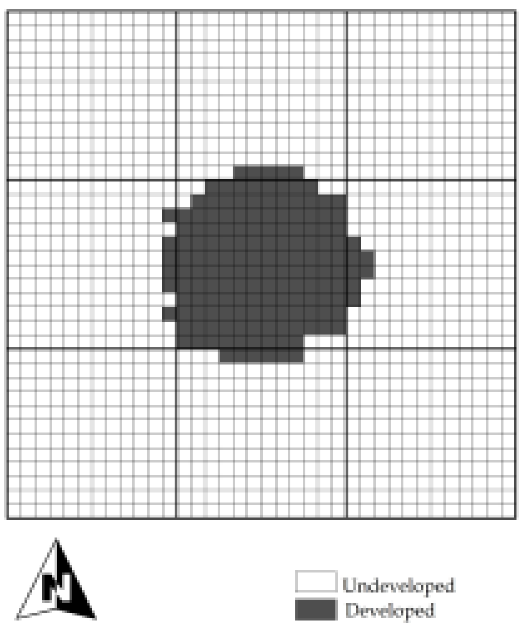


Figure 3. Development Probability



<< Aggregation of 50 Simulations >>



<< Basis Map >>

Figure 4. Basis Map Development

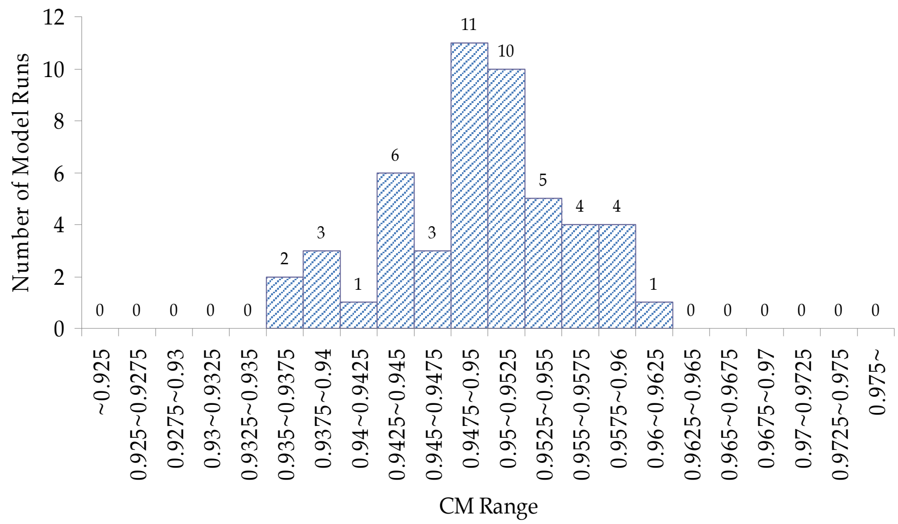


Figure 5. *CM* Distribution of the 50 Simulations

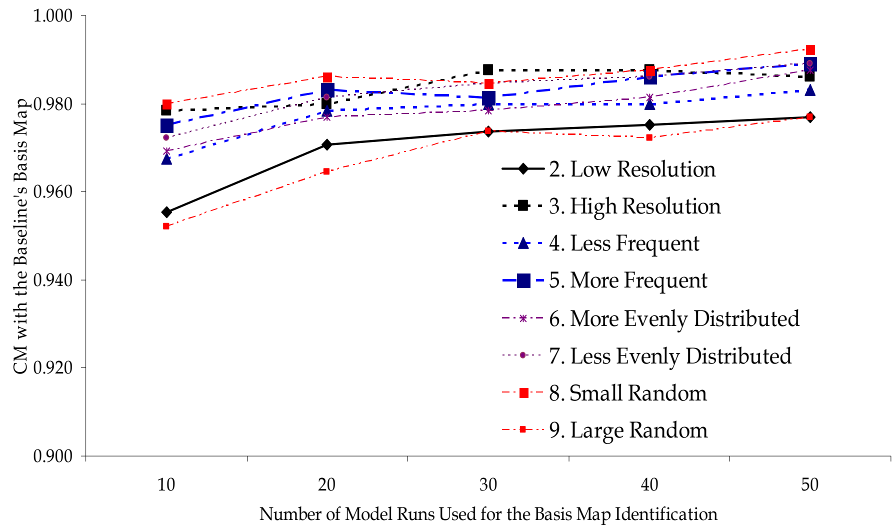


Figure 6. *CM* between the Basis Maps by Number of Model Runs