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Critical role of temporal contexts in evaluating urban cellular automata models

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ABSTRACT

Cellular automata (CA)-based models have been extensively used in urban expansion modeling because of their simplicity, flexibility and intuitiveness. Previous studies on CA-based urban growth modeling have mainly focused on the process of spatial allocation of increased urban lands; however, the temporal contexts during the simulation have not been properly explored. In this study, we examined the influence of temporal contexts of initial seeds (i.e. urban extent maps), transition rules, and urban demands (i.e. urban areas) on the CA-based urban growth modeling in Beijing, China, over a long period of 1984–2013. Comparison of the annual model outputs with the time series data of annual urban extent maps from satellite observations revealed that the overall accuracy of urban growth modeling decreased by approximately 12%, with an increase in iterations from 1984–2013. By contrast, the value of the figure of merit (FoM) increased to 26.57%. The continuous change of FoM during the modeling suggests a "spin-up" effect, a rapid increase in FoM at the beginning of modeling, of CA-based urban growth models, and this effect is primarily attributed to the neighborhood component in CA. The effect of temporal contexts reflected by components of initial seeds and urban demands in CA-based urban growth models have considerable impacts on the model performance, i.e. the FoM increased by 7% when using actual urban demands during each iteration instead of the commonly used linear growth during the modeling period. Hence, we suggest that more efforts regarding the temporal contexts in CA-based modeling are required, to better understand error propagation and uncertainty assessment.

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Initial seeds; urban demands; transition rules; annual change; neighborhood

1. Introduction

Cellular automata (CA) models are discrete and grid-based dynamic systems that can generate complicated global patterns in space and time through local interactions (Batty, Xie, and Sun 1999; Batty and Fotheringham 1989; Li et al. 2016). CA models have been extensively used for urban growth modeling because of their simplicity, flexibility, and intuitiveness (Santé et al. 2010). The pioneering work of Tobler (1970) on simulating urban growth in Detroit using a geographic CA model has led to CA-based urban growth models (hereafter called urban CA models) being extensively used for simulating the urban expansion process in many cities and regions worldwide, such as the Pearl River Delta (Liu et al. 2017; Li, Liu, and Yu 2014; Li and Yeh 2002), Beijing (He et al. 2008; Li, Liu, and Gong 2015b), Shanghai (Han et al. 2009; Feng and Tong 2018), Greater Wuhan Area (Wang et al. 2013; Xia and Zhang 2021), Phoenix (Berling-Wolff and Wu 2004), Atlanta (Hu and Lo 2007) and Sydney (Liu and Phinn 2003). Urban CA models can simulate the complicated process of urban land evolution by introducing a bottom-up approach with spatially explicit transition rules (or conversion probabilities) (Li and Gong 2016). Supported by additional spatial constraints, urban CA models are capable of simulating the evolution process of urban landscapes through local interactions of neighboring pixels (Kocabas and Dragicevic 2006; Couclelis 1987; Zhang and Wang 2021). Consequently, they have become predominant tools for various urban studies.

Many studies focusing on improving the transition rules in urban CA models have been conducted over the past few decades. Initially, the transition rules of

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urban CA models are defined as a set of explicit "if-then" rules, which determine the status of a potential pixel that is expected to be developed as urban in the future. Representative examples of this category include the SLEUTH (Clarke, Hoppen, and Gaydos 1997) and Fuzzy-CA (Liu and Phinn 2003) models. However, the "if-then" rules were modified using a synthesized probability to delineate the complex urban expansion process in a quantitative manner (Batty 2009; Chen et al. 2020). Many urban CA models have been developed using a probability-based mechanism to date, including the Logistic-CA model (Wu 2002; Feng and Tong 2018), constrained CA model (White and Engelen 1993), artificial neural network (ANN)-CA (Pijanowski et al. 2002; Omrani, Tayyebi, and Pijanowski 2017), and Patch-CA (Li et al. 2017; Liu et al. 2014). Although these models have been developed for different applications, they are primarily used for allocating urban demands to suitable locations in a spatially explicit manner. The typically adopted transition rules are a quantitative expression of suitability for urban development, considering different factors related to the urban expansion process (for example, terrain, traffic, and location), similar to the general framework of land use/cover change modeling (Verburg and Overmars 2009; Sohl and Sayler 2008).

The urban expansion process is associated with diverse urban landscape patterns in different phases, specifically in rapidly developing regions (Liu and Phinn 2003; Batty and Torrens 2005). It is crucial to improve the capacity of transition rules in characterizing urban expansion patterns in different phases, which is oversimplified as static drivers during the modeling process in most cases, e.g. Wu (2002); Li and Yeh (2004); Li, Liu, and Gong (2015b). In fact, the driving forces related to urban growth may change during the modeling process (Yeh and Li 2006; Li, Liu, and Yu 2014). Consequently, the urban landscape (for example, aggregated or diffused) changes at different urbanization stages (Li et al. 2017). However, few attempts have been made to explore the influence of these temporal issues during the modeling (Kocabas and Dragicevic 2006; García et al. 2011).

Although several studies have been conducted to explore the effect of temporal dynamics on urban growth modeling (Abolhasani and Taleai 2020; Wang et al. 2019; Li, Liu, and Yu 2014; Chaudhuri and Clarke 2014; Kim 2013; Liu and Andersson 2004), most have focused only on the influence of the time interval during the modeling. For example, Abolhasani and Taleai (2020) used two different time intervals (i.e. 10-years and a sequence of 1-year time steps) to examine the effect of temporal dynamics on urban growth modeling. Li, Liu, and Yu (2014) also explored the influence of different time steps (i.e. yearly, seasonal, and monthly) in their modeling of urban growth in Guangzhou (China). Further, Kim (2013) experimented with urban expansion modeling using different temporal resolutions (that is, 1-, 2-, and 4-years). These studies demonstrated that the degree of temporal dynamics (i.e. time steps) can considerably impact the modeled results. However, most studies were conducted using limited validation data (for example, one epoch), without a comprehensive examination of error generation and propagation using actual observations. Moreover, other components that are relevant to the temporal contexts (for example, change of transition rules, selection of initial seeds, – the urban extent map before modeling, or asynchronous urban demands) in urban CA models have always been neglected in these studies.

The temporal contexts of certain components (for example, transition rules, initial seeds, or urban demands) in urban CA models must be comprehensively examined for model assessment (Santé et al. 2010). First, the initial seeds are always subjectively selected in most studies, depending on the available multi-temporal land use/cover maps (Chen et al. 2002; Li and Yeh 2004; He et al. 2006). Essentially, the initial seeds are closely related to two factors that are important to the modeling performance: (1) spatial distribution of urban extent, and (2) temporal span of modeling, when compared to the urban map in the target year (i.e. the end year of modeling). The temporal contexts involved in the initial seeds deserve attention because different initial seeds would result in different accuracies, although the target year of modeling was the same. Second, urban demands might change over time, representing an asynchronous urban area increase during each iteration. Urban demands are typically estimated using empirical relationships between population and urban areas or other complicated approaches, such as system dynamics (He et al. 2013, 2005; Han et al. 2009). Following the determination of the urban demands, the increment of urban areas over each iteration (for example, per year) is usually linearly allocated, without considering the temporally uneven development (Li and Yeh 2004; Liu et al. 2008; Linard, Tatem, and Gilbert 2013). Third, the transition rules calibrated from different historical periods are different, and they would further impact the pathway of urban development in the modeling. However, impacts caused by transition rules on model performance have not been well explored, i.e. the transition rules would affect the error generation and propagation during the modeling (Yeh and Li 2006; Li, Liu, and Yu 2014).

Thus, to better understand the impacts of temporal contexts (i.e. the selection of initial seeds, asynchronous urban demands over iteration, and sensitivity of transition rules calibrated from different periods) in urban CA models, we developed a framework for evaluating the roles of these three components in the urban CA model. We selected Beijing City (a megacity in China) as our study area because of its rapid urban expansion over the past three decades and evaluated the modeling performance using long-term (30-year) annual urban extent maps from remotely sensed observations (Sexton et al. 2013; Li, Gong, and Liang 2015a; Li et al. 2018). We aim to improve our understanding of the impact of temporal contexts in urban CA models. The remainder of our paper is organized as follows: Section 2 introduces the study area and datasets; Section 3 describes the urban CA model and the evaluation schemes; Section 4 presents the results and discussion, Section 5 presents the conclusions.

2. Study area and datasets

We chose Beijing City as our study area to examine the influence of temporal contexts in urban CA models (Figure 1). The population in Beijing has doubled over the past three decades, reaching 21.54 million in 2019 (Li, Gong, and Liang 2015a). This rapid population growth has induced a dramatic expansion of urban areas. Consequently, concerns about the sustainability of urban expansion in Beijing have extensively discussed (Chen et al. 2002; Wu et al. 2006; Hu et al. 2016). Therefore, Beijing City is a good case for evaluating urban expansion with a span of almost 30 years.

We used a spatiotemporally consistent dataset of the annual urban extent for Beijing from 1984–2013 as our primary data source for the evaluation of the model (Li, Gong, and Liang 2015a). This dataset was processed using the temporal consistency check algorithm, and it follows the logic of urban development (i.e. from non-urban to urban consistently). The quality of this dataset is well controlled (the mean overall accuracy of annual results is approximately 95%), and the training samples used for classification were carefully collected with visual interpretation each year. Therefore, this dataset can serve as actual observations of the urban extent from satellite observations.

In addition, we also collected nine spatial proxies to derive the transition rules in urban CA models (Figure 2), including locational factors (i.e. distances to Tiananmen Square and central districts), traffic networks (i.e. distances to primary roads, secondary

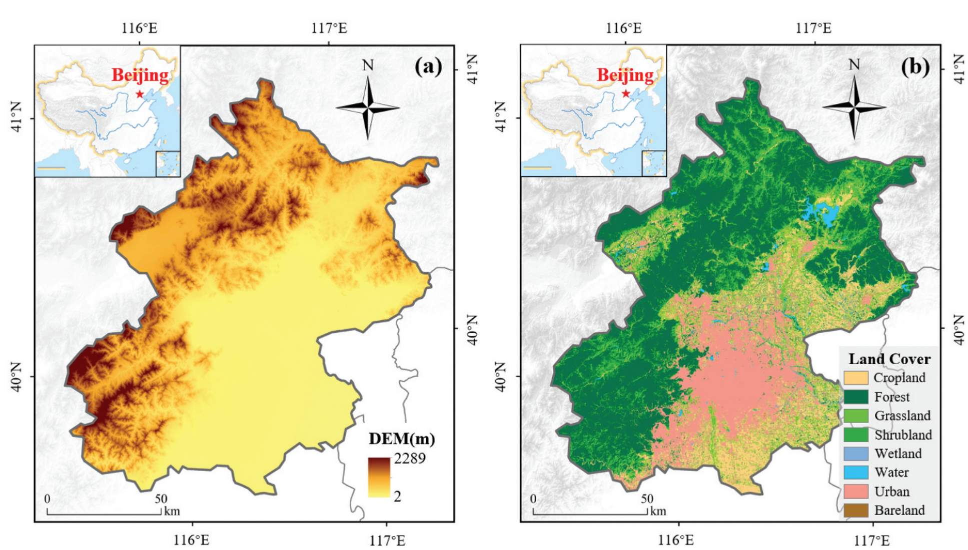

Figure 1. The study area of Beijing city, China. (a) Terrain and (b) land cover map (2010) (Gong et al. 2013).

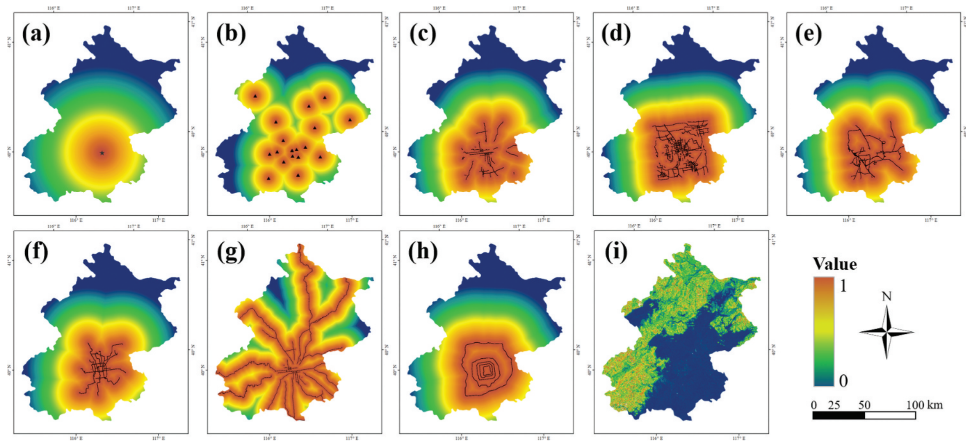

Figure 2. Spatial proxies of the distances to (*a*) Tiananmen Square; (*b*) central districts; (*c*) primary roads; (*d*) secondary roads; (*e*) railways; (*f*) subways; (*g*) highways; (*h*) rings. (*i*) Spatial proxy of the slope. Black dots in (a-b) are Tiananmen Square and central districts in Beijing, while black lines in (c-h) are different traffic networks.

roads, railways, subways and highways), and terrain (i.e. slope) (Chen et al. 2014; Li et al. 2013). These spatial proxies were derived from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn) and OpenStreetMap (http://www.openstreetmap.org/), and they were normalized before the modeling. Furthermore, a land cover map derived from Gong et al. (2013) was used as a specific land constraint in our study, that is, forest and water were regarded as unsuitable land for urban development (Chen et al. 2014).

3. Methodology

3.1 Logistic-CA model

We adopted the widely used logistic regression (LR) model for extracting the transition rules of urban CA models because of its generality and ease of implementation (Wu 2002). The LR model can be formulated as follows (Eqs. 1–2):

$$p_{ij}^{g} = \frac{\exp(z_{ij})}{1+\exp(z_{ij})} = \frac{1}{1+exp(-z_{ij})} \tag{1}$$

$$z_{ij} = b_0 + \sum_k b_k x_{ij}^k \tag{2}$$

where p_{ij}^{g} is the calculated suitability value (or transition rules in most CA models) for cell $[i,j]$, b_0 and b_k are the constant term and derived coefficient (or weight) for each variable x_k(i.e. d_TianAnMen, d_District, d_RoadPrimary, d_RoadSecondary, d_Railway, d_SubWay, d_Highway, d_Ringway and slope) (Figure 2), respectively, and z_{ij} is the linear regressed value for cell $[i,j]$. The output of the LR model is a suitability surface, where each pixel indicates the possibility of being developed as urban land considering aspects of location, traffic, and terrain.

The three other components in the logistic-CA model are: neighborhood, stochastic perturbation, and land constraints. At first, we used the Moore neighborhood as the neighborhood configuration with a sensitivity analysis of its window size (Kocabas and Dragicevic 2006; Shafizadeh-Moghadam et al. 2017) (Eq.3).

$$\Omega_{ij} = \frac{\sum_{w\times w} con(S_{ij} = urban)}{w\times w - 1} \tag{3}$$

where Ω_{ij} is the neighborhood density for cell $[i,j]$, S_{ij} is the land cover status of cell $[i,j]$, which returns 1 if the type is urban, and w is the window size, which was determined after the sensitivity analysis.

Second, stochastic perturbation was used to represent the impacts of unknown or unconsidered factors (for example, policies) during the modeling, as described by White and Engelen (1993) (Eq. 4).

$$RA_{ij} = 1 + (-\ln\lambda)^{\alpha} \tag{4}$$

where RA_{ij} represents the degree of stochastic disturbance of cell $[i,j]$, λ is a random value from 0 to 1, and α is a parameter representing the degree of stochasticity.

Third, certain specific types such as water or forest were regarded as land constraints ($Land_{ij}$) owing their stability and the low probability of being converted into urban land in practice (Eq. 5).

$$Land_{ij} = \begin{cases} 0, if\left(S_{ij} = waterorforest\right) \\ 1, otherwise \end{cases} \quad (5)$$

Finally, these components and constraints were synthesized as a finial probability of development P_{ij}^{d} (Kocabas and Dragicevic 2006) (Eq-6).

$$P_{ij}^{d} = p_{ij}^{g} \times \Omega_{ij} \times RA_{ij} \times Land_{ij} \quad (6)$$

Thus, during each iteration, the potential cells (i.e. non-urban and non-constrained land) were sorted, and only a certain number (i.e. urban demand) of cells that were ranked ahead were considered for development (Chen et al. 2002; Linard, Tatem, and Gilbert 2013; Li, Liu, and Yu 2014). Furthermore, there are only two classes (i.e. urban and non-urban) in our modeling of urban development. More details of the Logistic-CA model can be found in (Li, Liu, and Yu 2014).

3.2 Evaluation scheme

We developed an evaluation framework for temporal contexts in the urban CA models (Figure 3). The workflow of urban growth modeling consists of two subcomponents (Figure 3a): urban demands and spatial allocation. In contrast to the commonly used evaluation scheme that only focuses on the target year of T_N, we examined the impact of temporal contexts during the modeling using continuous urban extent maps derived from remotely sensed observations (see the dashed box in Figure 3a). Further, we considered four factors related to the temporal contexts in the modeling (Figure 3b), namely initial seeds, transition rules, demand processing, and model assessment. The details of each component are given in the following sections.

(1) In this study, we set the target year of modeling to 2013. Three different starting years (1984, 1994, and 2004) were used with modeling at intervals of 30, 20, and 10 years, respectively. For each period, transition rules acquired from the corresponding periods were used. Considering the initial seed of 2004 as an example, we used the transition rules calibrated from the period 2004–2013. Thereafter, the annual increment of urban land derived from the urban extent maps was used as the urban demand in the modeling. Subsequently, the annual model outputs from the urban CA model were compared with the annual urban extent data from remote sensing.

(2) We derived the transition rules using training samples in the corresponding period (i.e. persistent and changed during the modeling period). The sample locations were fixed over different periods (1984–2013, 1994–2013, and 2004–2013) when extracting transition rules, to avoid possible biases caused by their spatial locations (Li, Liu, and Yu 2014). Specifically, we first randomly generated samples over changed (i.e. from non-urban to urban) and persistent regions to derive the transition rules for the period of 1984–2013. Subsequently, the transition rules were derived for the period 1994–2013; however, the urbanized samples within the period 1984–1994 were excluded. Similar processing was performed for the period 2004–2013. Adequate samples were collected to ensure that the number of collected samples was greater than 1000 in

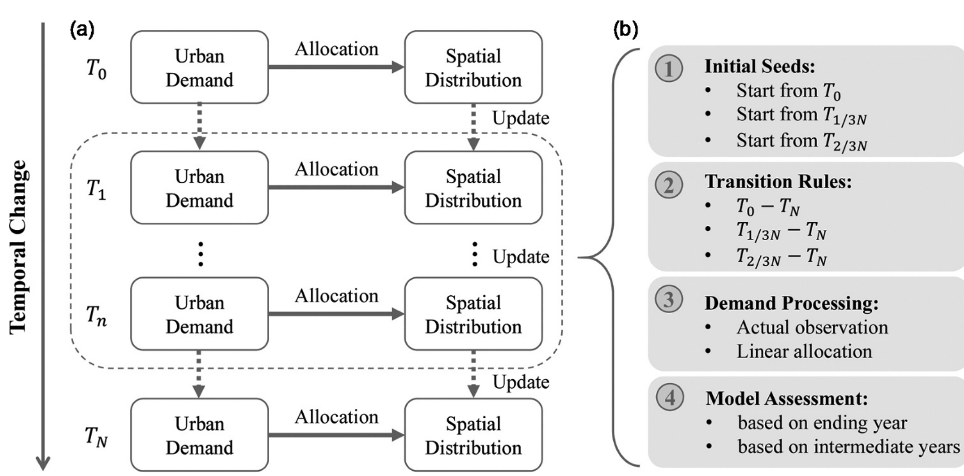

Figure 3. Proposed evaluation framework of the impact of temporal contexts in urban CA modeling. (a) Schematic of the urban CA models and (b) related components considered in this study.

each period. The obtained transition rules from different periods were evaluated using the receiver operating characteristic (ROC) approach (Hosmer, Lemeshow, and Sturdivant 2013).

(3) We compared the impacts of urban demands using two different schemes: the equal increments over years and actual increments obtained from annual urban extent maps. For the first scheme, the total increment of urban areas within a particular period was linearly divided for each year, which is a method that has been extensively used in other studies (Li and Yeh 2004). However, for the second scheme, we used the actual urban increment from remotely sensed images because urban growth is temporally uneven. Consequently, we compared the model performance using these two schemes to explore the influence of urban demands on model performance.

(4) We investigated the error generation and propagation during the modeling process using annual and continuous urban extent maps. The traditional assessment of urban CA models was made through map comparison between the modeled and observed urban extent maps for the target year (i.e. 2013 in our case) (Foody 2004). In addition, we implemented an annual assessment using continuous urban extent maps during each iteration. Furthermore, we included the typically used indicators for map comparison, i.e. the overall accuracy (OA), kappa coefficient, and figure of merit (FoM) (Pontius et al. 2007; Xia et al. 2020).

Thereafter, we implemented a primary parameter scheme for (1) time step (or iteration), (2) α in stochastic perturbation, and (3) window size w of the neighborhood configuration, in addition to the specific settings related to the temporal contexts in the modeling. The time step was annual, and the coefficient α was set as 1 (Li, Liu, and Yu 2014), where for the neighborhood size, we performed a sensitivity analysis using different sizes before the modeling. In addition, considering the uncertainty caused by stochastic perturbation, we implemented a repeated running scheme ten times, following which the mean accuracy was calculated for comparison and analysis when evaluating the model performance.

4. Results and discussion

4.1 Sensitivity analysis of the neighborhood size

Prior to the modeling, we implemented a sensitivity analysis of the neighborhood size using different sizes (see Table 1), and found that when w was greater than 5, the increments of both OA and FoM were not noticeable, and they plateaued when the window size exceeded 5. Hence, we set the w to 5 in our study.

Table 1. Sensitivity analyses of window size w in the neighborhood.

w	3×3	5×5	7×7	9×9	11×11
OA (%)	88.04	88.23	88.52	88.73	88.86
FoM (%)	30.66	34.52	34.34	34.47	33.72

4.2 Influence of transition rules

The calibration process was performed for three periods: 1984–2013, 1994–2013, and 2004–2013. The coefficients (or weights) of the spatial proxies adopted are listed in Table 2. The indicator of the area under the curve (AUCs) from the ROC approach is approximately 0.85, indicating a good overall performance with regard to the derived transition rules (Hu and Lo 2007; Hosmer, Lemeshow, and Sturdivant 2013). However, the main drivers of urban development differ from the three sets of transition rules. For the periods 1984–2013 and 1994–2013, apart from the constant term, proxies of slope and distance to subway play critical roles in urban expansion with relatively high weights. However, the absolute values of slope and distance to the subway decreased from 0.93 (1984–2013) to 0.66 (2004–2013) and from 1.16 (1994–2013) to 0.45 (2004–2013), respectively.

Subsequently, we compared the calibrated transition rules (called suitability surface) from different periods in a pair-based manner (Figure 4). Although the absolute biases among these surfaces were relatively low, their overall patterns were different. For the urban core regions, the suitability surfaces acquired from 1984–2013 and 1994–2013 were similar (see black ellipses in Figure 4a). However, biases in urban

Table 2. Calibrated coefficients of the logistic regression model from different periods.

Spatial Proxies	1984–2013	1994–2013	2004–2013
Constant Term	0.90	0.80	0.66
d_TianAnMen	−0.64	−0.44	−0.54
d_District	0.05	0.21	0.31
d_RoadPrimary	−0.12	−0.01	−0.15
d_RoadSecondary	0.27	0.24	−0.35
d_RailWay	0.07	0.19	0.38
d_Subway	−0.98	−1.16	−0.45
d_Highway	−0.23	−0.28	−0.23
d_Ringway	0.54	0.27	0.25
slope	−0.93	−0.83	−0.66
AUC	0.85	0.85	0.84

Note: p-values of these weights are all < 0.001.

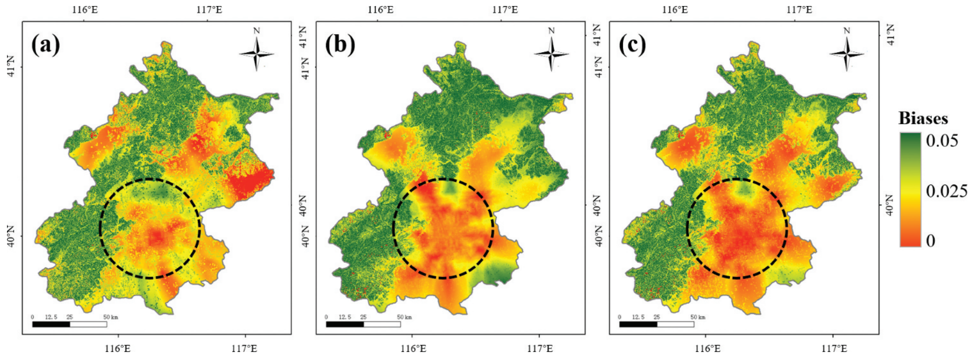

Figure 4. Pair-based comparison (absolute biases) of obtained suitability surfaces from different periods. (a) 1984–2013 and 1994–2013; (b) 1994–2013 and 2004–2013; (c) 1984–2013 and 2004–2013.

fringe areas, specifically the south-easterly part of Beijing, were more distinctive when comparing the suitability surface of 2004–2013 to those derived from the two earlier periods (Figure 4b and Figure 4c). Although the biases caused by the different periods are not significant in the LR model, the obtained spatial patterns of the suitability surface were notably different. Consequently, these suitability surfaces would influence the pathway of urban development; for example, the acquired suitability surfaces from two earlier periods (1984–2013 and 1994–2013) are similar but distinctively different compared to that from the last period (2004–2013) (Figure 4).

The impact of the transition rules derived from the different periods is relatively limited. To highlight the influence of transition rules acquired from different periods, we used the urban map of 2004 as the initial seed (i.e. to reduce possible error propagation if started from earlier years) and the annual urban increment derived from urban extent maps. The model performance in the target year (2013), using different transition rules, is presented in Table 3. Overall, their differences are not considerable; for example, the *OA*, *Kappa*, and *FoM* are approximately the same. In addition, their accuracies are consistent with the results reflected by AUCs (Table 2), i.e. the performance slightly decreased when using transition rules from the period 1984–2013 instead of 2004–2013.

Table 3. Comparison of modeled results in 2013 using transition rules calibrated from different periods during the modeling period of 2004–2013.

Transition rules calibrated from	OA (%)	Kappa	FoM (%)
1984–2013	92.62	0.74	20.74
1994–2013	92.61	0.74	20.73
2004–2013	92.59	0.74	20.64

4.3 Influence of initial seeds

We adopted different initial seeds (1984, 1994, and 2004) as our starting years for modeling. Subsequently, transition rules obtained from the corresponding periods (for example, rules that calibrated from 1984–2013 were used for the initial seed of 1984), and the actual urban increments from annual urban extent maps were used to mitigate possible biases caused by these two components. Table 4 shows the accuracy of the target year (2013) using different initial seeds. The initial year 2004, which is closer to the target year (2013), exhibited relatively good performance in terms of OA and Kappa, i.e. their accuracies increased by 4.37% (OA) and 0.16 (Kappa) when changing the initial year from 1984 to 2004. However, the result of *FoM* suggests an opposite trend, i.e. the *FoM* slightly decreased from 26.57% to 20.64%.

The comparison of continuous changes for all the intermediate years (Figure 5) shows a similar trend to that shown in Table 4. For example, the OA decreases and the *FoM* increases when the initial seed is closer to the target year (see Figure 5), suggesting that errors accumulate during the modeling process. Considering 1984 as an example of the initial seed, when the modeling year reached 1995, the accumulated error was approximately 4% compared to the observations (Figs. 5a-Figure 2). This trend is also confirmed by Figs. 5a-Figure 3 when the continuous

Table 4. Comparison of modeled results in 2013 using different initial seeds.

Initial seeds	OA (%)	Kappa	FoM (%)
1984	88.22	0.58	26.57
1994	89.98	0.64	24.58
2004	92.59	0.74	20.64

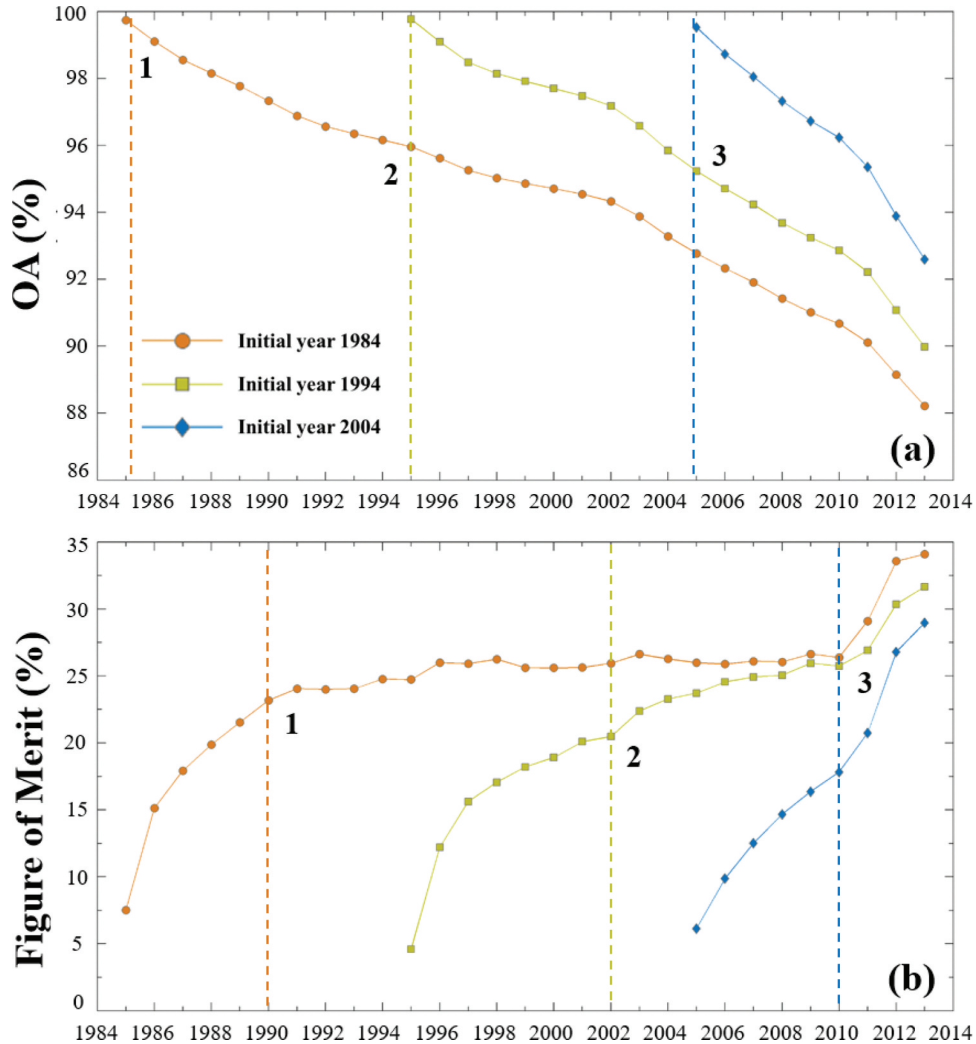

Figure 5. Continuous accuracy changes during the modeling using different initial seeds. Change of (a) OA and (b) figure of merit (FoM). Numbers in (a) and (b) represent error accumulation reflected by OA and the spin-up effect reflected by FoM during the modeling, respectively.

change of *FoM* shows an opposite trend, as it is slightly increasing during the modeling process. In addition, the change in *FoM* is not consistent during the modeling, as it increased rapidly at the beginning and then slowly plateaued (see Figs. 5b-Figure 1 and Figs. 5b-Figure 2), which is distinctive for the scheme with the initial seed of 2004 (Figs. 5b-Figure 3). This fast increment in *FoM* at an earlier time can be regarded as a "spin-up" phenomenon in urban CA models (Figs. 5b-Figure 1 and Figs. 5b-Figure 2), and the temporal span (or iteration) of the "spin-up" process is approximately 5–7 years in our study (see dashed lines in Figure 5). In addition, there is a new increment in *FoM* around 2010 in these modeling schemes. This phenomenon is probably related to the role of neighborhood in urban CA models. The proposed "spin-up" process is essentially related to the role of the neighborhood in CA models. First, the *FoM* increased quickly because many new urban cells developed around the initial urban extent. This expansion pattern can be captured well by the neighborhood and the calibrated suitability surface. With the increase in modeling iterations, errors accumulated during the modeling process, resulting in a weakened suitability surface and a relatively stable level of *FoM*. Around 2010, we observed a rapid increment in *FoM* (Figs. 5b-Figure 3), which is probably due to the aggregated urban lands within the period of 2010–2013. Based on the remotely sensed urban extent maps, the mean increment of the urban area is approximately 200 ha per year during that period (2010–2013) (Li, Gong, and Liang 2015a). Such an

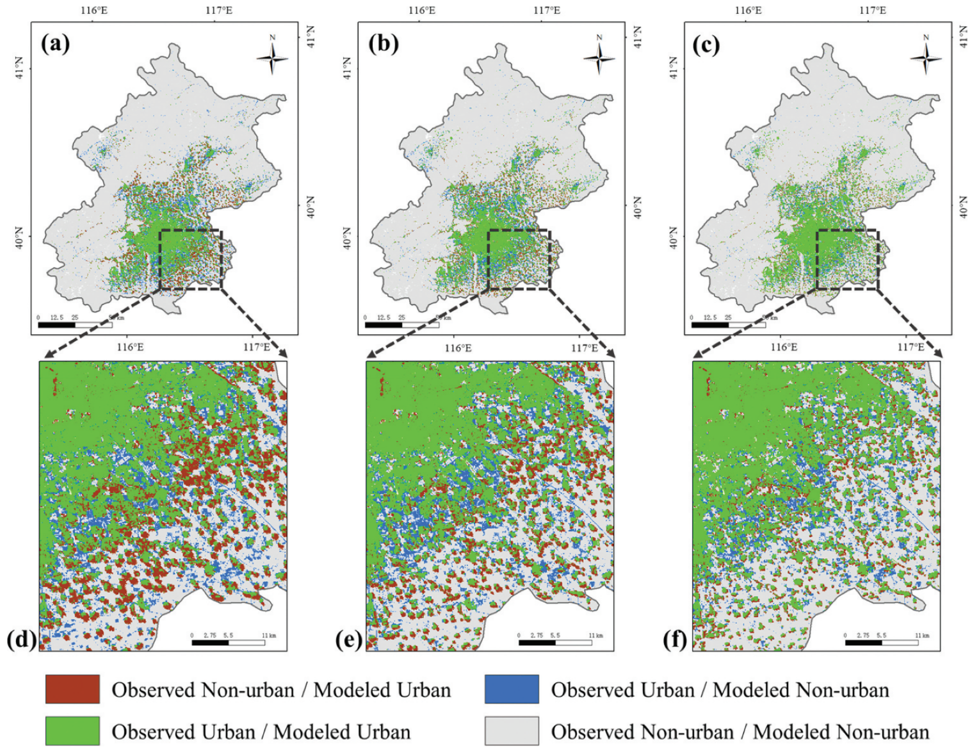

Figure 6. Agreements of modeled urban extent (2013) based on different initial seeds of (a) 1984, (b) 1994, and (c) 2004. (d), (e), (f) are enlarged views of (a), (b), (c), respectively.

aggressive expansion pattern in urban areas can be reflected well using the neighborhood component. As illustrated in Figure 6, the agreement between modeled and observed urban maps using the initial seed of 2004 (OA: 92.59%) is higher than the other two initial years (i.e. 1984 with OA of 88.22% and 1994 with OA of 89.98%).

4.4 Influence of urban demands

There is an evident difference in model performance when using different urban demand schemes. Table 5 lists the accuracy assessment of the target year (2013) using two different schemes. In terms of OA and Kappa, the improvements were almost the same. However, for *FoM*, the increments were 7.55, 7.22, and 3.5% for the periods 1984–2013, 1994–2013, and 2004–2013, respectively, when an actual urban demand scheme was adopted for each iteration (i.e. per year). In addition, if the modeling period covers a longer temporal span, the influence of urban demands among different years is more distinctive, with the highest improvement occurring from 1984 to 2013.

The continuous changes in OA and *FoM* reveal different processes of error generation and propagation during the modeling. The change in modeling accuracy for the two periods (1984–2013) and (1994–2013) are shown in Figure 7. We excluded the period of 2004–2013 because the differences between these two demand schemes were subtle (Table 5). In general, the curves derived from the actual annual demand are above the linear ones in terms of the OA and*FoM*. In addition, the gaps in *FoM* caused by the demand scheme are considerable; for example, the maximum gaps occur from 1996 to 2004 (Figure 7c), which is uneven in terms of the annual increment of urban areas, i.e. actual observations show a range from 280 ha to 1,039 ha, whereas the

Table 5. Comparison of modeled results in 2013 using different schemes of annual urban demand.

Period 1984–2013	OA (%)	Kappa	FoM (%)
Actual Demand	88.22	0.58	26.57
Linear Demand	87.68	0.57	19.02
Period 1994–2013	OA (%)	Kappa	FoM (%)
Actual Demand	89.98	0.64	24.58
Linear Demand	89.63	0.64	17.36
Period 2004–2013	OA (%)	Kappa	FoM (%)
Actual Demand	92.59	0.74	20.64
Linear Demand	92.59	0.74	17.14

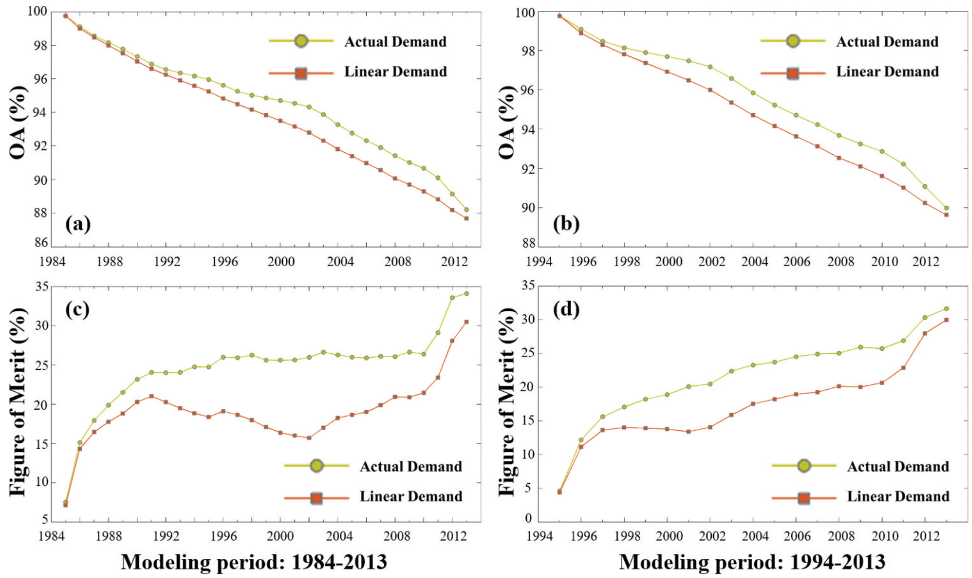

Figure 7. Continuous accuracy changes during the modeling using different urban demand schemes. (a) Change of overall accuracy (OA) in modeling period 1984–2013, (b) change of figure of merit (FoM) in modeling period 1984–2013, (c) change of OA in modeling period 1994–2013, and (d) change of FoM in modeling period 1994–2013.

increment in the linear scheme is consistent at 760 ha. In addition, the impacts of urban demands are more considerable in the middle than those at the margin in the modeling, specifically for the case shown in Figure 7b. This is because when the modeling year is close to 2013, there is a noticeable aggregation of urban lands, which can be well captured by the neighborhood. Overall, the maximum *FoM* around the target year (2013) was approximately 35%. Although this indicator is not as high as the OA, it is common and acceptable when compared to other similar studies, for example, 27–28% in Pontius et al. (2007), 21% in Pontius et al. (2008), and 16.79% and 25.81% for the patch – and cell-based logistic CA models in Chen et al. (2014), respectively.

5. Conclusions

We explored the influence of temporal contexts in urban CA models using continuous and long-term (30 years) records of urban extent maps in Beijing, China. Different components in the urban CA model, including the initial seed, transition rules, and urban demand, were comprehensively compared and analyzed. Using the continuous observations to validate the intermediate output of the urban CA model, we revealed the process of error generation and propagation during modeling.

The OA decreased along with modeling while *FoM* slightly increased but was limited to less than 35%. Both the initial seed and annual demand play crucial roles in the model performance; for example, the actual annual increment of urban areas increased by 7% in terms of *FoM* when compared to the linear demand. Further, a shorter modeling interval always exhibited a relatively high performance with reduced errors. The change in *FoM* reveals the role of the neighborhood, and indicates that the contribution of the persistent transition rules is reduced during the modeling.

Our results demonstrated the crucial role of temporal contexts in urban CA models, which show great potential for future model development. For example, the transition rules specified by different urbanization stages can be further explored to support long-term modeling, which is closely related to the influence of temporal contexts. In addition, the prediction of urban demand is essential to the final modeled results (Li et al. 2019), which deserves attention in the development of urban CA models in the future. Furthermore, greater efforts are required to develop efficient methods that can generate temporally consistent annual urban extent time series data with good qualities, such as transfer learning of training samples to extend them in space and time (Wei et al. 2021), or continuous time series analysis to identify multiple change events (Li et al. 2018; Gong et al.

2020).

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability statement

The data that support the findings of this study are openly available in figShare at https://figshare.com/s/2caaf120fe03d41fe642.

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