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Retrieving spatial policy parameters from an alternative plan using constrained cellular automata and regionalized sensitivity analysis

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Abstract. In this paper we propose an approach to identify the spatial policy parameters (termed the implementation intensity reflecting planning controls on corresponding spatial constraint) associated with a predefined alternative plan, namely, a predefined-binary urban form. During plan implementation, the alternative plan cannot be fully realized in some cases due to practical urban growth driven by both institutional forces and market incentives, which are comprehensive and complex. Few researchers have investigated spatial policies appropriate for an alternative plan. We aim to propose a novel approach incorporating constrained cellular automata and regionalized sensitivity analysis, a method for global sensitivity analysis to calculate the realization possibility and identify the spatial policy parameters for an alternative plan. This approach is first tested in a virtual space with four predefined urban forms and various point, line, and polygon spatial constraints, with both positive and negative impacts on urban growth. Finally, the approach is also tested in the Beijing Metropolitan Area to identify the required spatial policy parameters for four alternative plans with seven spatial constraints.

Keywords: urban form, spatial plan, cellular automata, regionalized sensitivity analysis, Beijing

1 Introduction

In this paper we propose an approach for identifying the spatial policies associated with a predefined urban form, that is, an alternative plan expected to be realized in the foreseeable future. The spatial policies reflect the implementation intensity of planning controls on corresponding spatial constraints. Recently, urban growth simulations have been studied extensively for simulating future urban form using constrained cellular automata (CA), in which both market incentives and institutional forces (Ward et al, 2000; Wu, 1998) are taken into account. Most spatial constraints in constrained CA are environmental, geographical, and institutional factors. CA modelers also advocate that the simulated urban form can assist planners in drafting an alternative plan (Li and Yeh, 2000). On the other hand, an alternative plan prepared during the plan compilation process is generally prepared by planners with subjective objectives, instead of on the basis of a simulated urban form from a constrained CA model or on other quantitative approaches, we argue that an alternative plan drafted by planners could not be implemented in urban practices if the alternative plan does not properly match urban development conditions defined by spatial constraints. Thus, the required spatial policies reflecting planning controls on spatial constraints need to be identified for developing a feasible alternative plan. This work, which attempts to evaluate whether an alternative plan can be implemented, is the inverse procedure of the conventional urban growth simulation using constrained CA. To date, there have been few investigations of this procedure.

Urban form is associated with many issues. Inappropriate urban forms (eg, sprawled urban forms) may create various negative impacts such as over-consumption of land resources (Kahn, 2000), increased commuting distances and traffic jams (Ewing et al, 2002; Kahn, 2000), decreased provision of affordable housing (Danjelsen et al, 1999), increased urban infrastructure construction costs (Speir and Stephenson, 2002), reduced water supply (Otto et al, 2002), poor neighbourhood interactions (Freeman, 2001), poor public health (Ewing et al, 2003), and increased social inequity (Bullard et al, 1999). However, sustainable strategic urban policies, such as the compact city (Breheny, 1992; Kii and Doi, 2005), smart growth (Shen and Zhang, 2007), and low carbon societies (Remme and Blesl, 2008), focus on sustainable urban forms. Therefore, an appropriate urban form can provide a precondition for a sustainable city. We explore how to realize the desired urban form.

We focus on the quantitative relationship between an alternative plan and the required policy parameters associated with spatial constraints. A spatial constraint (for example, geographical conditions, accessibilities, and amenities) promotes or restrains urban development in an area. A policy parameter is the implementation intensity of planning controls on the corresponding spatial constraint, and is based on opinions of decision makers responsible for the urban development. As a known exogenous variable, we assume the spatial distribution of each spatial constraint to be temporally static. A policy parameter regulates and controls the impact of the corresponding spatial constraint on urban growth. Long et al (2009a) proposed the term 'form scenario analysis' for identification of the optimal policy parameters using a logistic regression approach for four planned forms in the Beijing Metropolitan Area (BMA); this approach uses constrained CA. However, the optimal solution of policy parameters for realizing a predefined alternative plan is not unique. Therefore, we focus on all the possible sets of policy parameters required for realizing an alternative plan.

Methods for identifying the policy parameters for an alternative plan remain unexplored. Our research approach has two aspects. There are numerous authors who discuss methods for measuring urban form using various indices, such as patch numbers, mean patch area, mean patch compactness, edge length, and fractal dimensions. The fractal dimensions is a common metric for evaluating urban form to reflect the complexity of the shape of the urban form across a range of spatial scales (Batty and Longley, 1987; Batty and Xie, 1996; Frenkel and Ashkenazi, 2008). Shen et al (2009) compared land-use patterns between simulated and observed urban forms using the percolation model for validating a CA simulation model. On the other hand, some researchers have investigated the impact of policy parameters on resulting urban form using a scenario analysis approach with traditional land-use models, such as the California Urban Future model (Landis and Zhang, 1998a; 1998b), *What If?* (Klosterman, 1999), and CA-based models (Li and Yeh, 2000; Long et al, 2009b). Therefore, existing studies only consider a single aspect relating policy parameters and urban form, either by simulating the urban form using the policy parameter or by measuring the simulated urban form. In constrained CA-related research the impact of constraints on urban form, a key feature of constrained CA, is the basis for investigating whether an alternative plan can be implemented, and this will be elaborated in this paper prior to policy parameter identification (PPI).

Identifying the appropriate policy parameters for the alternative plan is necessary. Couclelis (2005) argued that little research has been done on future-oriented aspects, such as desired or feared futures, using traditional land-use models. The benefits of identifying policy parameters for an alternative plan are embedded in academic theory (as previously mentioned) and in planning practice. For instance, actual urban growth in China occasionally deviates from the alternative plan. Evaluations of planing implementation performance show that more than 35% of urban development occurs beyond the planned urban form in Beijing (within the sixth ring road, which covers an area of 2273 km^2) (Han et al, 2009) and Guangzhou (Tian and Shen, 2011). Considering these results, local planning authorities lacking policy guidance relating to the planned urban form generally fail to achieve the desired urban form. Given this situation, the urban policies required for the planned urban form are a governmental concern, for which our work has important practical significance.

In section 2 we describe a methodology for PPI. The urban forms generated by various constraints are illustrated in section 3, with evaluations on the impact of constraints on urban form. In section 4 the method for PPI is tested in a virtual space, followed by experiments in the BMA in section 5. In the last section we discuss the PPI method, and then make some concluding remarks.

2 Approach

The main approach of the research reported in this paper is the simulation process based on constrained CA which is repeated using randomly sampled policy parameter sets by regionalized sensitivity analysis (RSA, also called the Hornberger, Spear, and Young algorithm). RSA was developed by Hornberger, Spear, and Young three decades ago (Hornberger and Spear, 1980; Spear and Hornberger, 1980). RSA can be used to explore the uncertainty in modeling a complex system (eg, a water environment system) and analyze the sensitivity of each parameter (Beck, 1987; Spear et al, 1994).

RSA, as a global sensitivity analysis (GSA) approach, can detect each parameter's sensitivity by observing all parameter values in the parameters' entire value space. However, for existing urban CA models, less attention has been paid to RSA compared with the GSA approach. Most sensitivity analyses for urban CA are concerned with the sensitivity of the transition rules, neighbor configurations, and cell size (Kocabas and Dragicevic, 2006; Menard and Marceau, 2005; Yeh and Li, 2006), in which the local sensitivity analysis (LSA) approach is widely applied. LSA is a common approach that changes one factor at a time (OAT) to observe the effect of this variation on the model output. Any observed change in the output is regarded as the contribution of the single factor that was changed (Beck, 1987; Saltelli et al, 2000; 2004; Spear et al, 1994). All other factors remain at their fixed baseline values in OAT. The overall behavior of all factors in constrained CA cannot be identified through the OAT LSA approach. We use the RSA approach to analyze the sensitivity of each parameter to investigate the relationship between policy parameters and a predefined urban form. As the process for retrieving spatial policy parameters, RSA is more feasible for detecting the sensitivity of various parameters in the urban growth models than OAT, which is currently used in LSA.

The approach used for estimating policy parameters in CA can be borrowed for identifying the policy parameters of spatial constraints from an alternative plan. This approach is shown as follows:

$$\{X^* \mid F = \mathrm{f}(X, A),\ X^* = X_{\max[\mathrm{GOF}(F_\mathrm{h},\, F)]}\}\ , \tag{1}$$

where f is the simulation mechanism, namely, the transition rule in constrained CA, A is the spatial constraint, X is the policy parameter representing the implementation intensity of planning control on a spatial constraint, F_h is the historically observed urban form, F is the simulated urban form using A and X as inputs into the constrained CA, and X^* is the estimated policy parameter after a calibration process with the maximum goodness-of-fit

(GOF) between F_h and F. The GOF indicators can be the κ value (KAPPA), edge length, and patch size (Clark and Gaydos, 1998; Wu and Webster, 1998).

Each simulated urban form generated by constrained CA is compared with the predefined urban form using κ as the GOF indictor. A benchmark is required to evaluate the degree of matching between the simulated and predefined urban form. If κ is greater than this benchmark, then the specified policy parameters are valid for the predefined urban form, and the simulated and predefined urban forms can be regarded as identical. If κ is less than this benchmark, then the specified policy parameters are invalid. On the basis of a literature review in Liu et al (2008) and our knowledge, two urban forms are significantly similar when their κ value approaches 80%. Therefore, we set the benchmark at 80%. Consequently, all the sampled parameter sets can be classified into two clusters for an alternative plan, namely, valid and invalid.

We introduced the RSA approach into the PPI process using the two clusters to evaluate the sensitivity of each policy parameter. We can generate a valid cluster including all possible policy parameters for a predefined urban form using RSA, rather than only one estimated solution using conventional methodologies, such as logistic regression or genetic algorithm-like approaches. This can be done as follows.

(1) Define the initial distribution of each policy parameter x in X. To reflect the proportional relationship between policy parameters, we assumed that each x is uniformly log-distributed from 10^{-3} to 10^{3}.

(2) Define the benchmark for the GOF indicator. The observed urban form F is compared with the predefined urban form F_d, with κ greater than 80% defined as valid and the urban form accepted; otherwise, invalid and then rejected.

(3) A sample of x as a policy parameter is randomly drawn from the parent probability distribution.

(4) The constrained CA model is run with x to obtain a simulated urban form F.

(5) The κ of the simulated urban form F and predefined form F_d is calculated and evaluated as valid or invalid.

(6) Repeat steps 3 to 5 until the statistical characteristics of κ reach convergence.

(7) Classify F and x into the valid cluster F_B and x_B as well as the invalid cluster F_{NB} and x_{NB}, based on the validation results, where x_B is the identified policy parameter for the predefined urban form F_d.

(8) Assesses the accepted parameter vectors x_B to quantify the parameter uncertainty.

(9) Check the significance s to determine whether the two distributions of x_B and x_{NB} are distinctly separated by the K–S (Kolmogorov–Smirnov) test, using its Z value.

(10) Rank the parameters by their s values to assess the overall sensitivity of each parameter.

The realization possibility of the urban form F can be calculated based on the results of step 7:

$$P = \frac{c_B}{c_B + c_{NB}} 100\% \,, \tag{2}$$

where P is the realization possibility of the predefined urban form F_d, c_B is the counted number of parameter sets for valid form, and c_{NB} is the counted number of parameter sets for invalid forms. This indicator gives the probability of the urban form being realized in a region with existing constraints. $P = 0$ implies that the urban form has no probability of being realized.

3 Investigating the impact of spatial constraints on urban form in a virtual space

3.1 Designing the simulation model

As a principle of CA in urban growth simulation, neighbour effects are key elements. Pure CA considers only neighbor effects and excludes other factors. However, practical urban form is actually affected by various natural, spatial, and institutional constraints, which may reduce the complexity of the simulated urban form caused by neighbor effects. Each spatial constraint corresponds to a spatial policy. These constraints have positive or negative effects (respectively, promoting or restricting urban growth) on future urban form, thus shaping the urban form due to their dynamic interactions with neighbor effects in the simulation process. Whether a given spatial constraint is positive or negative can be determined using data mining approaches, such as logistic regression, principal component analysis, and neural networks, to explore its effect quantitatively (Li and Yeh, 2002; Long et al, 2009b; Wu and Webster, 1998).

In urban growth simulation, urban form emerges as the geometric shape of urban built-up space. The urban form at time $t+1$ can be generated based on the urban form at time t as:

$$F^{t+1} = F^{t} \cup \Omega(P^{t} \mid P^{t} \geqslant P_{\text{threshold}}) \ , \tag{3}$$

where F^{t+1} is the urban form at time $t+1$, F^{t} is the urban form at t, Ω is the entire region, P^{t} is the probability of development in the region at time t, and $P_{\text{threshold}}$ is the development threshold (0–1), above which urban development occurs. The quantity $\Omega(P^{t} \mid P^{t} \geqslant P_{\text{threshold}})$ represents the area where the urban development probability is greater than or equal to the development threshold within the whole region, and this area will be developed from t to $t+1$.

To analyze the interaction between spatial constraints and neighbor effects, spatial constraints are classified into point, line, and polygon types in terms of the geometric shape of the constraint. First, we evaluate the impact of a constraint on urban form without considering the neighbor effect. For point and line constraints, the constrained effect exponentially decays with increasing distance. The development probability varies accordingly with the buffer distance. If a point or line constraint is positive and attracts urban development, the impacted constrained urban form can be expressed as follows:

$$F^{t+1} = F^{t} \cup \left\langle \bigcup_{k=1}^{n} \{\Omega[P_k^t \mid P_k^t = \exp(-\lambda \, \text{dist} a_k^{+}) \geqslant P_{\text{threshold}}]\} \right\rangle \ , \tag{4}$$

where n is the total number of constraints, a_k^{+} is the constraint k, $\text{dist}a_k^{+}$ is the buffer distance to the constraint k, λ is a distance decay coefficient greater than 0 (set at 0.1 in this paper), and P_k^t is the development probability for the constraint k. Within the buffer distance $-(\ln P_{\text{threshold}})/\lambda$ of the positive point or line constraint, k, urban development is completely promoted. For negative points or line constraints, the constrained urban form can be expressed as shown in equation (5):

$$F^{t+1} = F^{t} \cup \left\langle \bigcup_{k=1}^{n} \{\Omega[P_k^t \mid P_k^t = 1 - \exp(-\lambda \, \text{dist} a_k^{-}) \geqslant P_{\text{threshold}}]\} \right\rangle \ , \tag{5}$$

where a_k^{-} is the constraint k and $\text{dist}a_k^{-}$ is the buffer distance to the constraint k. The area within the buffer distance $-(\ln P_{\text{threshold}})/\lambda$ is absolutely forbidden for urban development.

Polygon constraints, as spatial entities, are different from the point or line constraints in constraining urban developments. If a polygon constraint is positive, then P_k^t is assumed to be homogenous within the polygon and 0 outside the shape of the polygon constraint a_k^{+}. Areas within a polygon constraint will be developed when $P_k^t \geqslant P_{\text{threshold}}$, the development threshold. The constrained urban form can then be expressed as follows:

$$F^{t+1} = F^{t} \cup \left\{ \bigcup_{k=1}^{m} [\Omega(P_k^t \mid P_k^t \geqslant P_{\text{threshold}})] \right\} \ , \tag{6}$$

where m is the total number of polygon constraints. Correspondingly, if a polygon constraint is negative, P_k^t is assumed to be 0 within the negative polygon constraint a_k^-, and homogenous outside the polygon. Urban development is absolutely forbidden within the polygon. Areas outside the polygon will be developed provided that $P_k^t \geqslant P_{\mathrm{threshold}}$, the development threshold. The constrained urban form by the negative polygon constraint can also be expressed using equation (6).

In urban development practices, an urban form generally results from multiple constraints, rather than a single constraint. Using a multicriteria evaluation approach, the weight of a constraint can be assigned to investigate the effect of the constraints on the urban form. Thus, the urban form affected by multiple spatial constraints can be determined using equation (7):

$$F^{t+1} = F^t \bigcup \Omega[P^t \mid P^t = \mathrm{g}(XA) \geqslant P_{threshold}] \ , \tag{7}$$

where X is the policy parameter reflecting the implementation intensity of each spatial constraint, A is the spatial constraint, and g is the function for calculating the development probability (land-use suitability).

The status transition rule for our proposed constrained CA for urban growth simulation is expressed as follows:

$$\begin{aligned} s^t &= \sum_{k=1}^{m+n} x_k a_k + x_N a_N^t \ , \\ P_g^t &= \frac{1}{1 + \exp - s^t} \ , \\ P^t &= \exp\left[\alpha\left(\frac{P_g^t}{P_{g\,\max}^t} - 1\right)\right] , \\ F^{t+1} &= F^t \bigcup \Omega(P^t \mid P^t \geqslant P_{\mathrm{threshold}}) \ , \end{aligned} \tag{8}$$

where x_k is the policy parameter of spatial constraint a_k; a_N^t, ranging from 0 to 1, is the number of developed cells within the cell's neighborhood (excluding the cell itself) divided by 8 (we use the Moore neighborhood with a 3×3 cell configuration for the constrained CA); x_N is the parameter for the neighbor constraint and is set at 1 and remains static across repeated simulations; x_k varies in the simulation to reflect the proportional relationship between the policy and neighbor parameters in the parameter identification process; s^t is the development suitability at time t; P_g^t is the development potential at time t; $P_{g\,\max}^t$ is the maximum P_g^t across the entire lattice space at iteration t; and α (set at 2 in this paper) is the dispersion parameter, ranging from 1 to 10, which indicates a rigid level of development regulating urban growth speed. In addition, the positive and negative point and line constraints are given effect values using $a_k = \exp(-\lambda\,\mathrm{dist}\,a_k^+)$ and $a_k = 1 - \exp(-\lambda\,\mathrm{dist}\,a_k^-)$ for the positive and negative constraints respectively, to normalize the constraint values to range from 0 to 1. For the positive polygon constraint, the cell's value is set to 1 within the constraint and 0 outside the constraint. For the negative polygon constraint, the cell's value is set to 0 within the constraint and 1 outside the constraint.

We discuss how to retrieve the effects of spatial constraint while considering neighbor impact on urban form to investigate the relationship between spatial policies and urban form. We can evaluate a simulated urban form using the fractal dimension indicator (FDI). The differences between various urban forms can be determined using the FDI. In the following subsections, we conduct several experiments in a virtual space to simulate the urban form, using X as the input for constrained CA. We evaluate the simulated urban form using the FDI and identify the relationship between X and the FDI of the simulated urban form to check the effects of spatial policies on urban form.

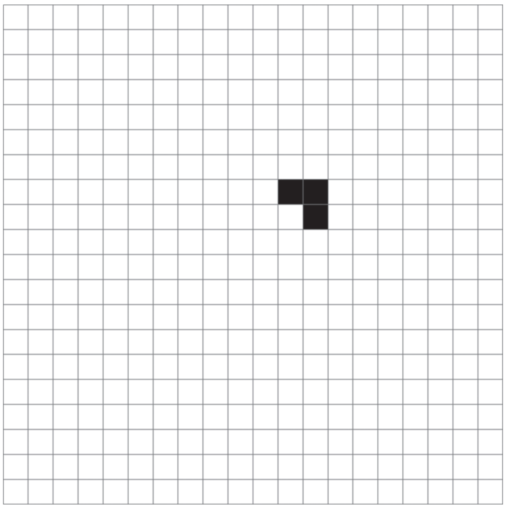
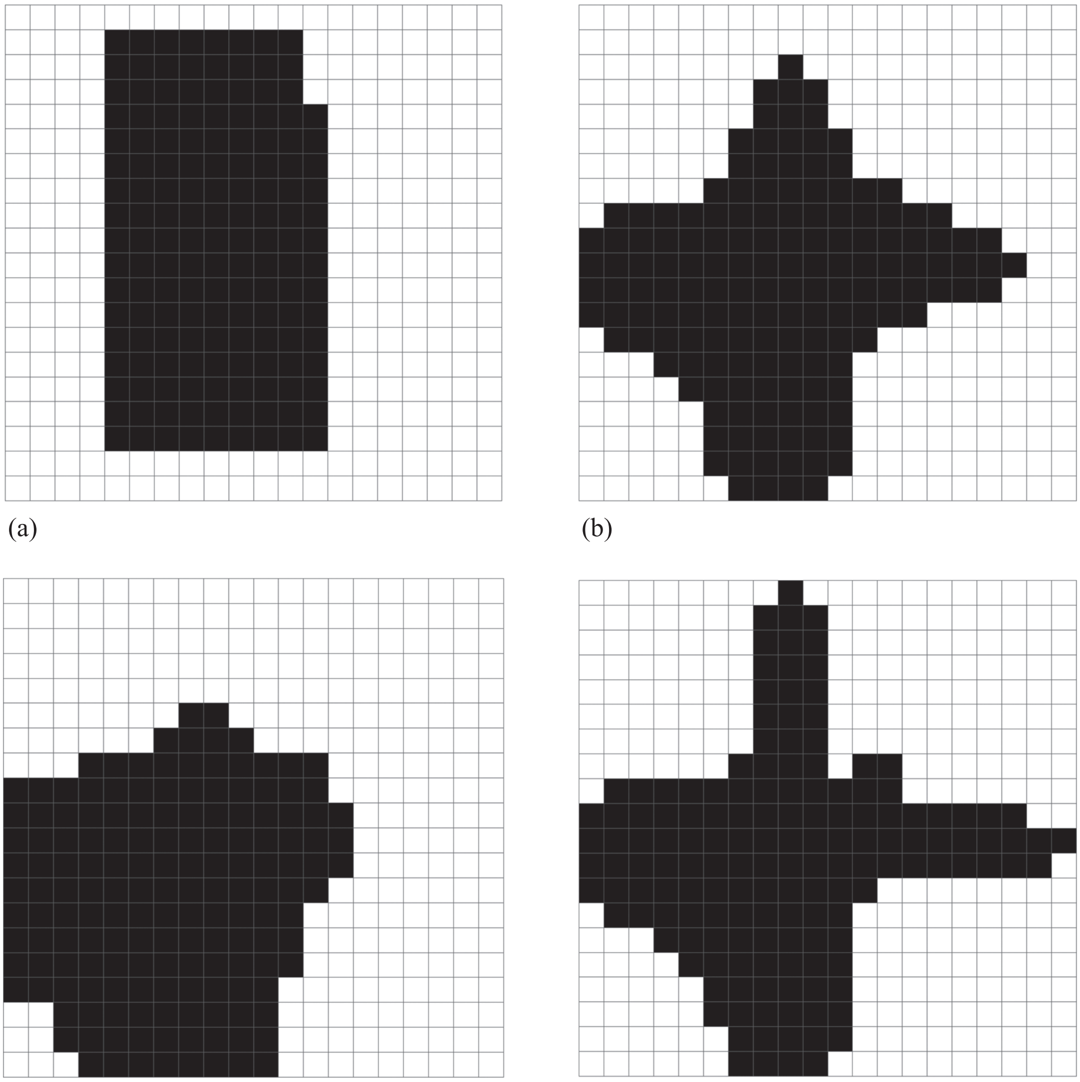


Figure 1. The initial urban form of the virtual space. Cells in black denote development as urban built-up lands. Cells in white denote undeveloped areas.



(a) (b) (c) (d)

Figure 2. Forms 1–4, in (a)–(d), respectively, of predefined urban forms in the virtual space.

3.2 Predefined urban forms and spatial constraints in the virtual space

The virtual space has 400 100 m × 100 m cells (figure 1). The virtual space is 2 km wide and 2 km long. Three cells are developed in the initial urban form of this virtual space, and we aim to develop 150 cells in the future. Assuming we need 100 m^2 of urban land per person, 100 people will occupy one cell. After development, there will be 15 000 people living in the virtual space in the future.

We set four predefined urban form (forms 1, 2, 3, and 4, figure 2), which are intended as alternative spatial structures of urban forms in the virtual space. The four urban forms, which vary greatly from each other, are used as various future images of the virtual space for urban growth simulation with single and multiple constraints.

For spatial constraints in the virtual space, we consider two point constraints (PP and NP), two-line constraints (PL and NL), and four polygon constraints (PG1, PG2, NG1, and NG2) based on the polygon areas (PG1 and NG1 are for small polygons, and PG2 and NG2 are for large polygons). Table 1 lists all these constraints in the virtual space, together with their detailed descriptions. The spatial distributions of the constraints are shown in table 2 in the next subsection.

Table 1. Inventory of constraints and their detailed descriptions.

Geometry type	Constraint type	Name	Descriptions
Point	positive	PP	promoting urban growth, such as town centers, subway stations, and public service centers
	negative	NP	restricting urban growth, such as geological disaster sites, pollution sources, solid waste and wastewater treatment facilities, and other NIMBY (not-in-my-backyard) facilities
Line	positive	PL	promoting urban growth, such as road networks and rivers
	negative	NL	restricting urban growth, such as high-voltage power lines and seismological fault lines
Polygon	positive	PG1	promoting urban growth, such as officially planned areas and special policy zones
		PG2	
	negative	NG1	restricting urban growth, such as ecologically protected areas and steep areas
		NG2	

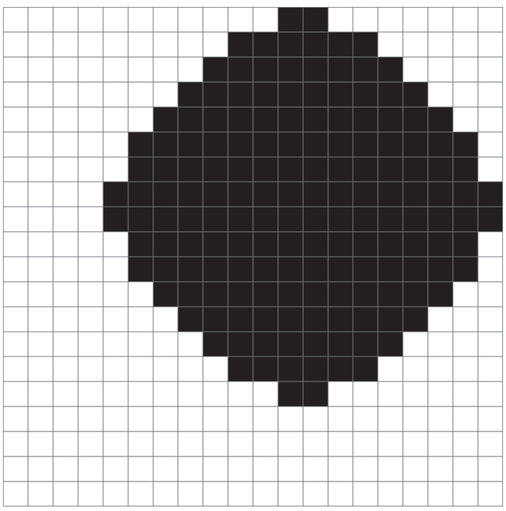


Figure 3. The simulated urban form with no constraint in the virtual space.

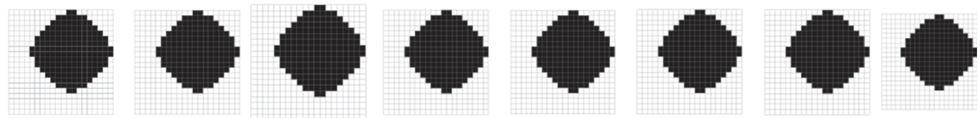
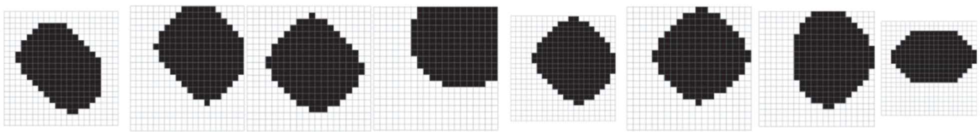
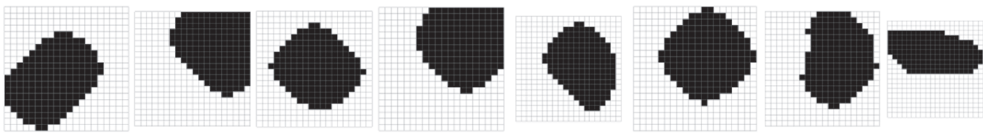
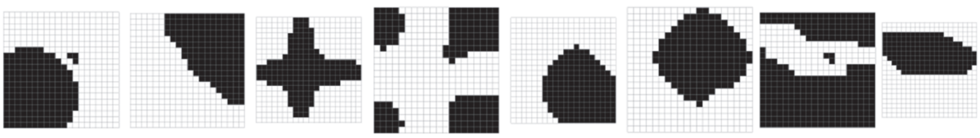
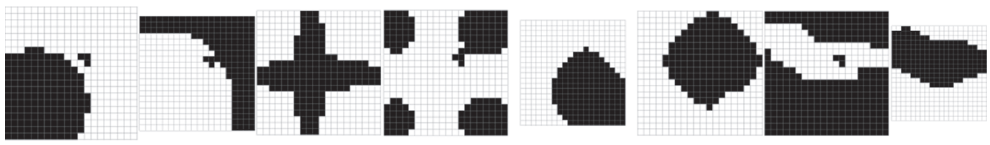
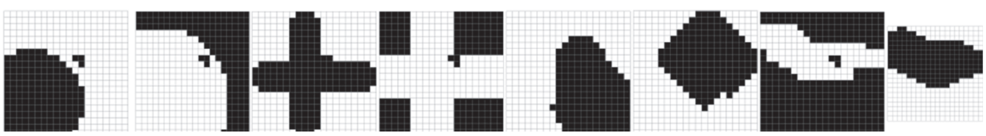
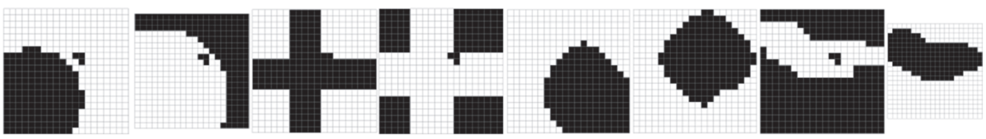
3.3 Urban growth simulations using distinguished spatial constraints

In the virtual space, we conduct two types of experiments: one without constraints and the other considering a single constraint to investigate the constraint's impact on the simulated urban form. In the no-constraint experiment, the CA is pure CA. The development suitability in equation (8) can then be expressed as $s^t = x_N a^t_N = a^t_N$ (sections 3.1, where x_N is set to 1). The simulated urban form of pure CA with no constraint contains only one patch around the initially developed cells (figure 3).

Table 2. Simulation results of various single constraint tests in the virtual space.

Point constraints Line constraints Polygon constraints

(small) (large)

β	
0.001	
0.01	
0.1	
1	
10	
100	
1000	

Note: In some urban forms with constraint PG2, the number of developed cells exceeded 150 because of the number of promoted cells for PG2 exceeded 200.

[a] See subsection 3.2 and table 1 for details.

We run eight single-constraint tests for the eight constraints using constrained CA. In the constrained CA, the simulation process runs considering the dynamic interactions between the neighbor and the constraint. The neighbor effect is the main driving force of urban growth, whereas the constraint affects the process. The proportion between the constraint and the neighbor parameter is a key factor influencing the simulated form. Therefore, to test the impact of the single constraint on the simulated urban form, we keep changing the proportion between the single policy parameter and the neighbor parameter using $\beta = x/x_N$, where x is the policy parameter of constraint, x_N is the parameter of the neighbor effect (set at 1), and β reflects the impact of the single constraint in contrast to the neighbor effect. To identify the effect of the constraint on the simulated urban form, we set β at 10^{-3}, 10^{-2}, 10^{-1}, 10^{0}, 10^{1}, 10^{2}, and 10^{3}, while obeying the log–uniform distribution as described in section 2.

The simulated results of various experiments using constrained CA ($P_{\text{threshold}}$ is set at 0.999) with different β values are shown in table 2. From the simulated urban forms, we can conclude that the single constraint can change the simulated urban form, and β has a significant effect on the simulated urban form.

3.4 Measuring simulated urban forms

The FDI is used to evaluate the simulated urban forms and is defined as $[2(\ln 0.25p_{ij})]/\ln a_{ij}$, where p_{ij} is the perimeter (m) of patch ij, and a_{ij} is the area (m^2) of patch ij. An FDI greater than 1 for a 2-dimensional patch indicates a departure from Euclidean geometry (ie, an increase in shape complexity). An FDI close to 1 represents simple shapes, such as circles or squares. An FDI close to 2 represents shapes with highly convoluted, plane-filling perimeters.

The simulated form without any constraint has an FDI of 1.0873. The FDI results for the eight simulations with single constraint are plotted in figure 4, which shows that the policy parameter of the single constraint changes the shape of the simulated form. The calculated FDIs generally range from 1 to 1.24. When β is 0.001, the FDIs for all tests are identical, indicating that the effect of the constraint can be ignored compared with the neighbor effect. In this condition, constrained CA is identical to a pure CA model. For β between 0.001 and 0.01, the FDI decreases with increasing β, which indicates that the effect of the constraint increases and the effect of the neighbor decreases. The effects of the constraint and the neighbor are the same when $\beta = 1$, and the FDI varies depending on the type of constraint. The neighbor effect can be ignored compared with the effect of the constraint when $\beta = 100$. The FDI values remain stable when $\beta > 100$ for most constraints. The resulted urban form

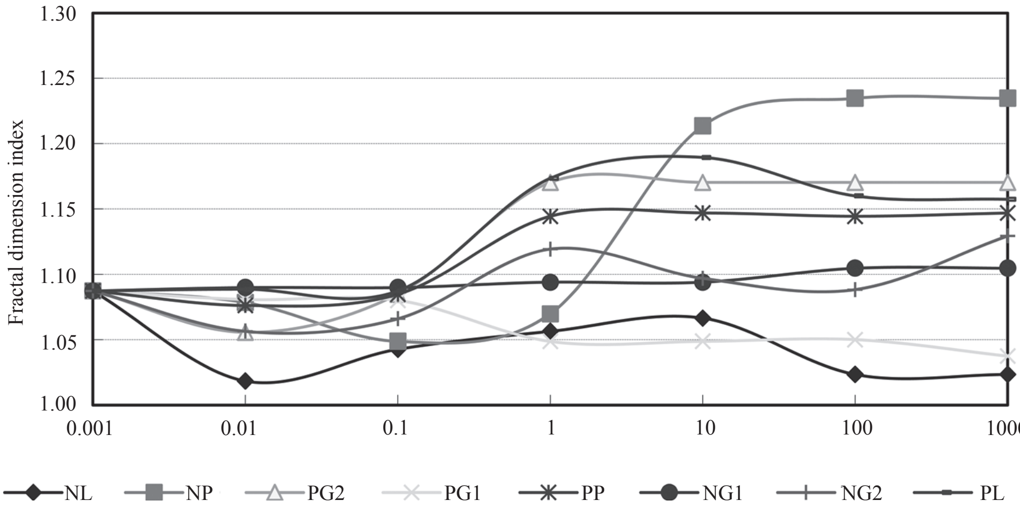


Figure 4. Fractal dimension index-β curve for the virtual space. (See table 1 for definitions.)

by pure CA ($\beta = 0.001$) has a medial FDI compared with that of urban forms in other tests ($\beta \geqslant 0.01$), indicating that the urban form by pure CA is not the most complex in terms of shape.

We can conclude that different spatial constraints have various impacts on urban growth. Theoretically, there are many solutions of policy parameters for an alternative plan. The methodology for retrieving policy parameters from a predefined urban form is described in section 4.

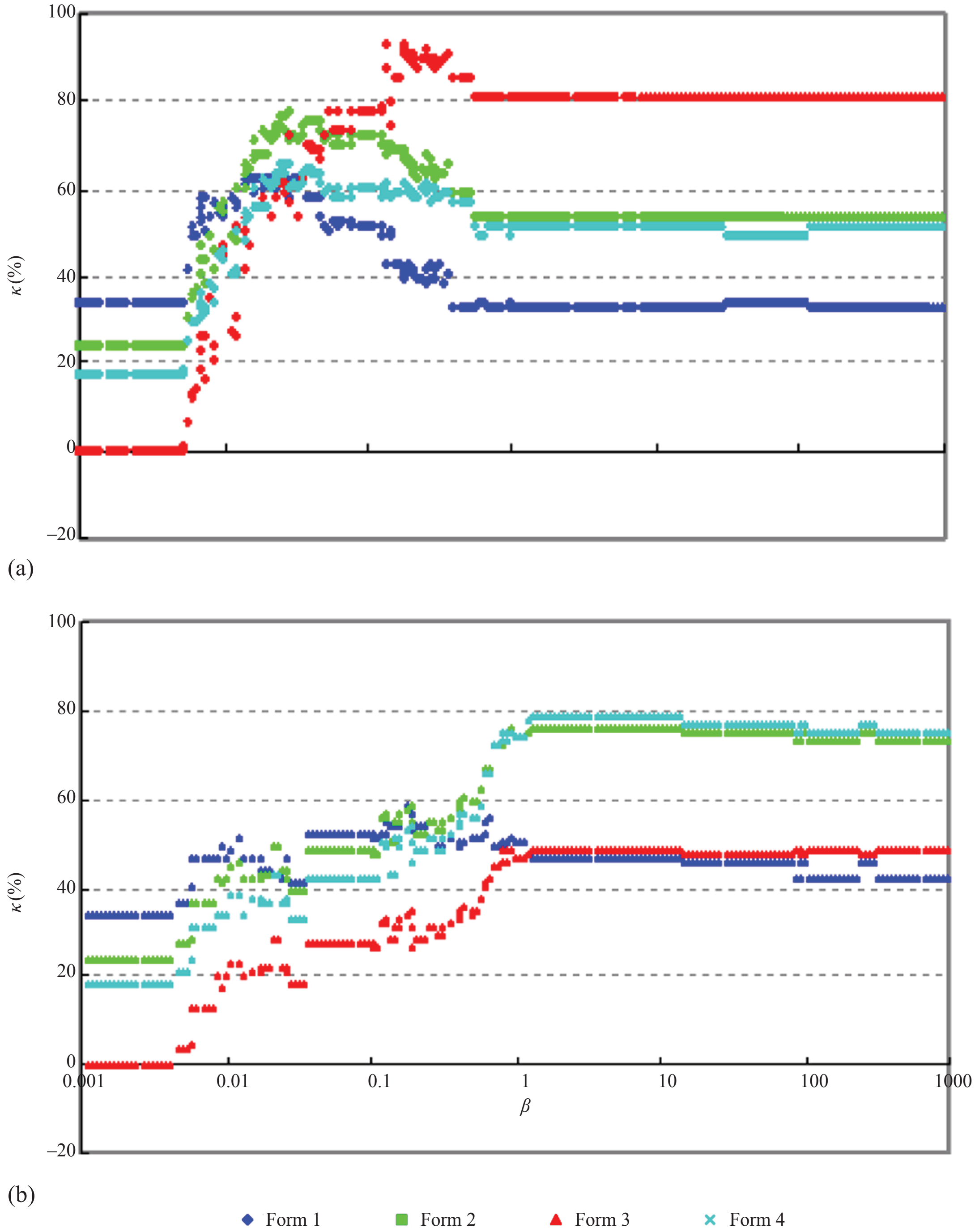


Figure 5. [In color online.] Scatter plots of κ and β for (a) positive point constraint and (b) positive line constraint in the virtual space.

4 Policy parameter identification for predefined urban forms in the virtual space

Four predefined urban forms are selected to identify policy parameters meeting the 80% κ restriction based on a constraint's quantitative effect on the simulated urban form. Two conditions are tested in the virtual space: a single constraint and two combined constraints.

4.1 Single constraint and neighbor effect

For a single constraint, the suitability from equation (8) is calculated using $s^t = \beta a_1 + a_N^t$, where a_1 is the single constraint. We consider constraints PP and PL as single constraints in this paper. The simulated urban forms are then generated using constrained CA. Figure 5(a) shows whether the urban forms stimulated using the constraint PP can fit into the four predefined forms in terms of κ. Only form 3 can be achieved by the single constraint PP when its β value ranges from 0.1–0.6 ($P = 66.0\%$). The other three forms cannot be achieved with PP regardless of the β value ($P = 0$). Similarly, figure 5(b) shows that for PL, no valid β value can be identified for any of the four forms ($P = 0$). However, both plots in figure 5 show that for $\beta < 0.01$ or $\beta > 1$, a relatively steady κ value is achieved for all predefined forms. Thus, κ is sensitive when β is between 0.01 and 1, where the constraint's effect becomes larger and closer to the neighbor effect. When β is greater than 1, the constraint effect becomes the dominant factor during simulations. For PP or PL, the Monte Carlo approach is effective for identifying available parameters for predefined urban forms in the virtual space.

4.2 Two combined constraints and policy implications

We now understand the interaction between the effects of the single constraint and a neighbor. In this subsection, we test the effects of two combined constraints by simultaneously adjusting the parameter of each constraint. To demonstrate how the parameters of the combined constraints are retrieved, we use two constraints in the computer simulations: PP and PL.

In this test, the suitability of equation (8) is calculated using $s^t = x_1 a_1 + x_2 a_2 + a_N^t$, where x_1 and x_2 are the policy parameters for PP (a_1) and PL (a_2), respectively. Both are simultaneously adjusted using the RSA approach for 500 times to allow the simulation results to reach convergence. The PPI results for the four predefined forms vary (figure 6). For form 1, no parameter pair is valid, indicating that this urban form cannot be achieved with the combined PP and PL constraints. If form 1 is set as the planned urban form, then practical urban spatial development will deviate from the planned urban form within the context of current development policies. For the other three urban forms, valid parameter pairs can be applied to realize the corresponding urban form. Form 3 has the greatest realization possibility (46.4%).

The numerous parameter pairs demonstrate that the relevant spatial constraints required for realizing the predefined urban form have elasticity. Thus we investigate the sensitivity of the policy parameters on urban form to identify further policy implications for decision makers concerning urban planning compilation and implementation. As no parameters are identified for form 1, an RSA for form 1 is not available. For the other three urban forms, we separately conduct an RSA for parameters x_1 and x_2 using the proposed RSA approach. The RSA results are shown in table 3. For form 2 and form 4, x_2 is more sensitive than x_1. For form 3, however, the RSA result is reversed, which indicates that sensitivity value is partially dependent on the predefined urban form. Of the three valid forms, x_1 for form 3 and x_2 for form 4 are the most sensitive parameters, which suggest that minor changes in the policy parameter will lead to large differences between the generated urban form and the corresponding predefined urban form.

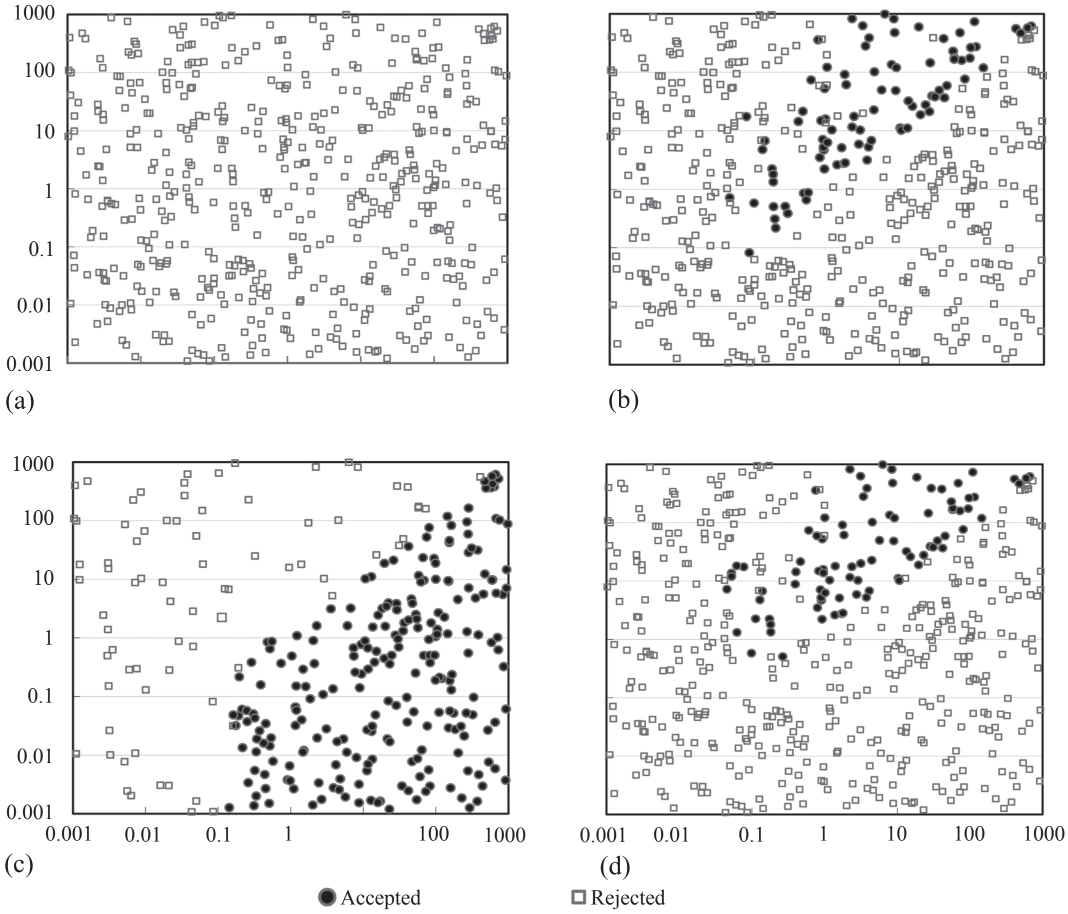


Figure 6. Scatter plots of policy parameters identified for two combined constraints in the virtual space, when the x axis is x_1, y axis is x_2 and 'accepted indicates' $\kappa \geqslant 80\%$. (a) Form 1, possibility of the urban form $P = 0\%$; (b) form 2, $P = 17.8\%$; (c) form 3, $P = 46.4\%$; (d) form 4, $P = 17.8\%$.

Table 3. RSA results for four forms in the virtual space.

Sensitivity	Form 1	Form 2	Form 3	Form 4
x_1	na	3.169	7.762	2.872
x_2	na	4.161	4.066	5.080

Note: All are significant (2-tailed) at the 0.001 level; na—not applicable.

5 Policy parameter identification for alternative plans for the BMA

The PPI process above can be applied as a case study in the BMA with an area of 16 410 km^2 located in northern China. The BMA has experienced a period of rapid urbanization in terms of both GDP and population since the Reform and Opening Policy was initially advocated in 1978 by the central government of the People's Republic of China (PRC). Consequently, the alternative plan for the BMA has been challenged by this rapid urban growth.

Whether the alternative plans in the BMA master plan (2004–20) are valid for the current policy context is an issue of concern for local decision makers in Beijing. For this study, we set four alternative plans for the BMA (figure 7). Alternative A is the plan approved by the State Council of PRC in 2005 featuring the prevention of excessive sprawl in the central city and the promotion of the development of new towns. Urban planners at the Beijing Institute of City Planning prepared alternative A, and most of these planners had a background in

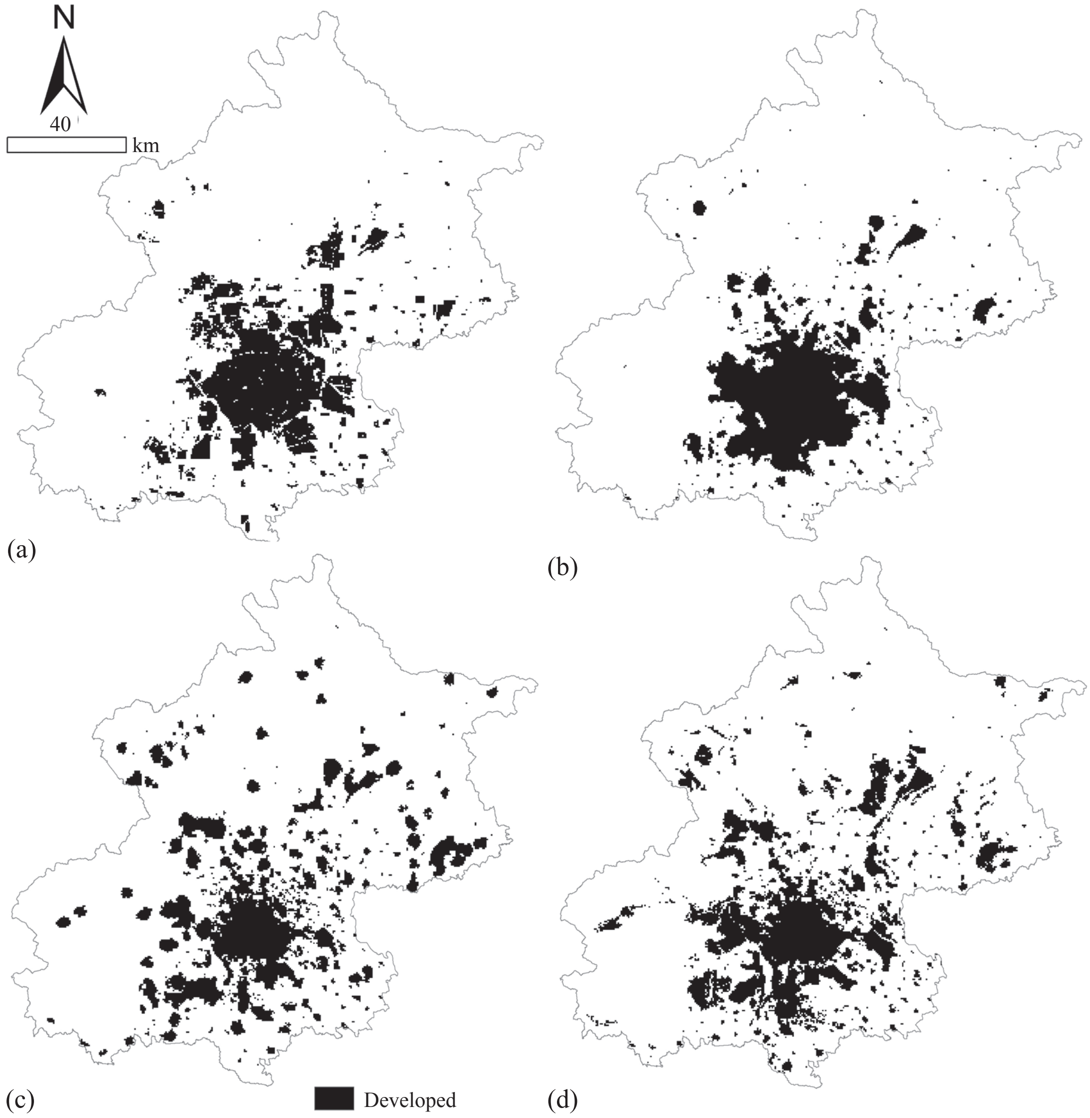


Figure 7. Four alternative plans for the Beijing Metropolitan Area: (a) alternative A; (b) alternative B; (c) alternative C; (d) alternative D.

architecture instead of geography or economics. Alternative A lacked sufficient quantitative analysis in the preparation process. Alternatives B, C, and D are artificially set by us. Alternative B is a sprawling scenario, where developments in the central city are promoted and developments in new towns are controlled. Alternative C is a grape-cluster scenario that promotes development along the transport corridors and round small towns. Alternative D is a sustainable scenario with less encroachment into ecological spaces, resulting in a more dispersed urban form.

In the BMA, there are seven spatial constraints as driving forces of urban growth, including five locational constraints and two institutional constraints (table 4). The distribution of the spatial constraints, together with the BMA urban form in 2006, is shown in figure 8.

Policy implications for decision makers can be drawn from the PPI results for the four alternatives in the BMA (table 5) including several perspectives. First, each pair of identified policy parameters is available for decision makers to either design a proper development pathway for the future or adjust the current policies. Second, alternative A is invalid under the current policy context ($P = 0$), indicating that the approved plan for the BMA will not

Table 4. Spatial constraints and relevant policies in constrained cellular automata for the Beijing Metropolitan area.

Name[a]	Description	Value range	Data source	Policy implications
Locational constraints				
a_1	Tiananmen Square	0–1	derived from GIS dataset	central city developments
a_2	new city	0–1	derived from GIS dataset	new city developments
a_3	town	0–1	derived from GIS dataset	small town developments
a_4	river	0–1	derived from GIS dataset	developments along rivers
a_5	road network	0–1	interpreted from TM image of 2006-11-01	developments along transport corridors
Institutional constraints				
a_6	development-forbidden zone	{0, 1}	Beijing Municipal Planning Committee (2007)[b]	ecological protection and geological disaster prevention
a_7	suitability for agriculture developments	0–1	Beijing Planning Commission (1988)	high-quality farmland protection

[a] See figure 8.
[b] Refer to Long et al (2011) for details of the approach for generating this spatial constraint.

Table 5. Descriptive table of valid variables for the three valid alternative plans for Beijing Metropolitan Area.

Name	Valid parameter sets	Possibility, P (%)	Minimum	Maximum	Mean	Standard deviation
Alternative B						
x_1	305	61.0	0.011	98.617	30.215	28.928
x_2			0.010	41.068	3.626	6.66
x_3			0.011	14.588	0.730	1.600
x_4			0.010	53.106	2.760	6.658
x_5			0.010	17.248	1.207	2.508
x_6			0.010	47.064	3.319	6.642
x_7			0.010	16.740	1.214	2.265
κ			80.027	91.671	82.492	1.921
Alternative C						
x_1	258	51.6	0.010	86.744	6.681	12.025
x_2			0.010	43.076	4.835	7.391
x_3			1.111	99.855	32.160	28.975
x_4			0.010	83.237	8.599	15.735
x_5			0.010	77.594	3.726	8.163
x_6			0.014	92.885	10.203	15.277
x_7			0.010	27.362	1.444	3.424
κ			80.023	88.940	81.896	1.558
Alternative D						
x_1	4	0.8	0.014	1.791	0.461	0.887
x_2			0.059	2.682	0.926	1.236
x_3			0.013	2.076	0.774	0.965
x_4			0.068	6.143	3.466	2.661
x_5			0.098	1.202	0.479	0.507
x_6			1.433	9.703	3.661	4.031
x_7			0.550	4.313	1.618	1.803
κ			80.135	81.216	80.824	0.486

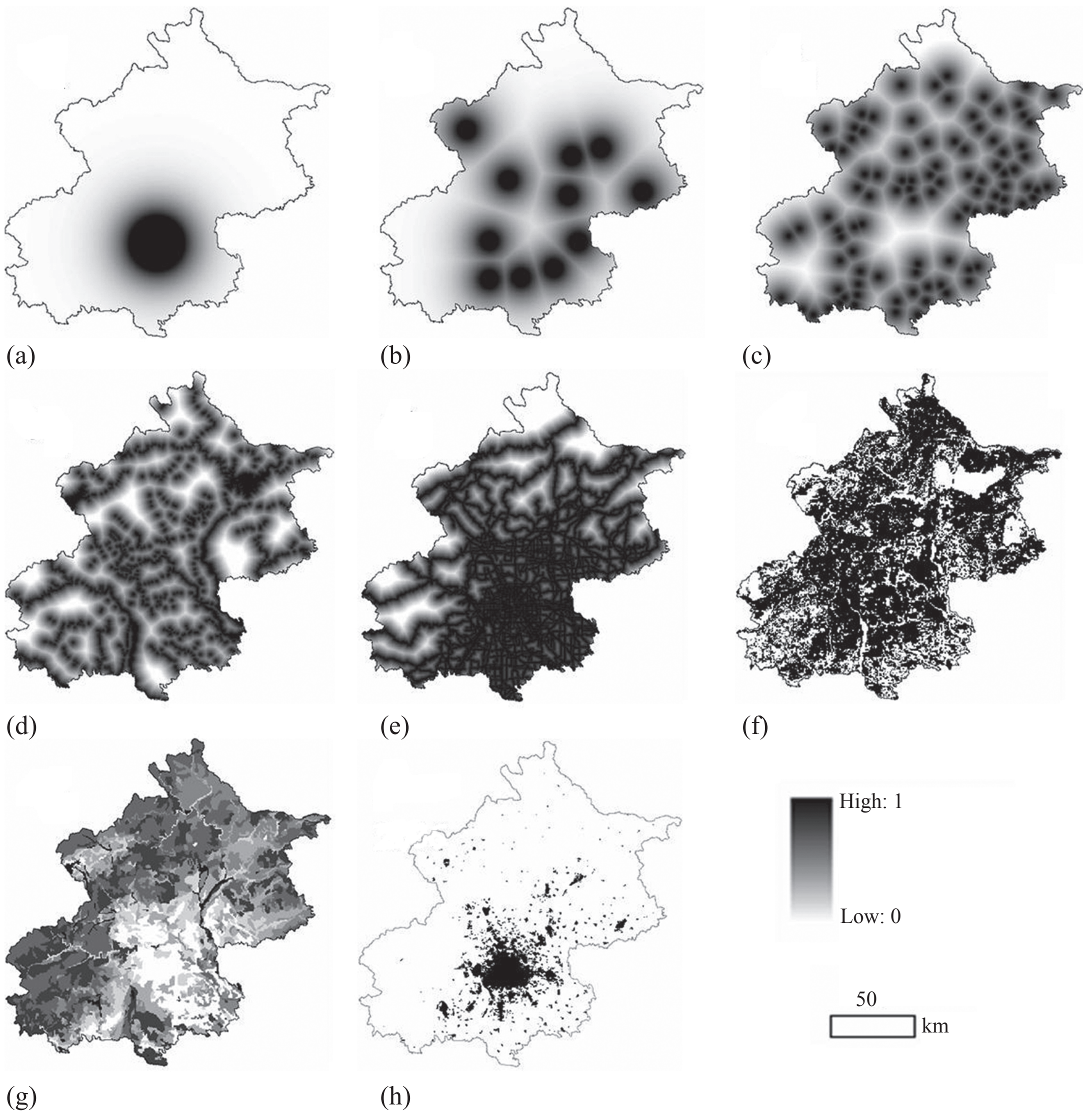


Figure 8. (a)–(g) Show spatial constraint a_1–a_7 (see table 4) and (h) shows the urban form in 2006 in the Beijing Metropolitan Area. Black represents 1, white represents 0, and gray represents a value between 0 and 1.

be realized in the future unless the policy context (namely constraints) is changed. Either the plan or spatial constraints should be adjusted to guarantee the realization of the master plan. The other three alternatives are valid and can be realized. Alternative B has the highest realization possibility indicator (P) and therefore, has the greatest probability of being realized. Alternative D has the least P-value although it is valid, indicating that its probability of being realized is very limited because of the existing constraints. Third, the policy parameters with the highest κ value (eg, 91.671% for alternative B) are the best development pathways for achieving the corresponding alternative. The policy parameters with the lowest κ value can be used to avoid undesirable developments. Finally, the policy parameters can be compared between alternatives to understand further deferences in the required policies to achieve the corresponding alternative. Therefore, this PPI work is useful for planning practice.

A sensitivity analysis is also conducted for the alternative plans in the BMA using the RSA approach. The results are shown in table 6. The sensitivities of different policy parameters vary for different alternative forms. For alternatives B and D, parameter x_1 is

Table 6. Regionalized sensitivity analysis results for the three valid alternative plans in the Beijing Metropolitan Area. Bold face indicates the most sensitive parameter. Values in parentheses are p-values.

Alternative	x_1	x_2	x_3	x_4	x_5	x_6	x_7
B	**7.771**	3.183	6.778	3.281	5.291	2.224	4.838
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
C	1.472	2.617	**8.246**	1.359	2.801	5.089	4.616
	(0.026)	(0.000)	(0.000)	(0.050)	(0.000)	(0.000)	(0.000)
D	**1.351**	0.857	0.930	0.747	0.984	1.117	0.866
	(0.052)	(0.455)	(0.353)	(0.631)	(0.287)	(0.165)	(0.441)

the most sensitive, whereas x_3 is the most sensitive parameter for alternative C. For policy parameters with higher sensitivities, a greater degree of attention should be applied to the corresponding policy implementation intensity in planning practice. Small variations in these sensitive conditions could lead to large changes in the κ value, causing the future urban form to deviate from the alternative plan. Therefore, in planning practice, more attention should be paid to these highly sensitive policies to ensure the implementation of the alternative plan.

6 Conclusions and discussion

In this research, we aimed to capture what is needed in terms of urban policies (referred to as policy parameters) to ensure that urban forms resulting from urban growth match predefined plans made by planners. To achieve this purpose, we conducted a three-part study. First, we investigated the relationships between positive and negative point, line, and polygon constraints and the resulting urban form using a constrained CA model with simulations of urban growth in a virtual space. The FDI, as a landscape metric, was used to evaluate simulated urban forms quantitatively. The relationships between FDI and corresponding policy parameters were tested, allowing us to detect indigenous behaviors of the constrained CA model (eg, the balance between neighbor and constraint effects). Second, we successfully calculated possibilities and identified policy parameters for urban forms in both the virtual space and the BMA using a Monte Carlo-based RSA approach. The results can provide policy implications for decision makers to design appropriate development pathways for alternative plans and eliminate planned alternatives that are unachievable in theory. Third, GSA, as a by-product of the PPI process, was conducted for the constrained CA model in the virtual space and in the BMA, respectively. The policy implications for planning practice can also be identified from the GSA results. GSA was also proven to be an alternative attempt for evaluating the behavior of constrained CA, in addition to existing LSA.

The novelty of our work lies in our attempt to link theory and behavior of constrained CA by investigating how spatial constraints act as driving forces of urban growth. We did this by quantifying the resulting urban form as a landscape metric and constraint influences as policy parameters. This is a new attempt using a CA application to identify how well the desired urban form of the future conforms to spatial constraints, rather than a conventional urban growth simulation using constrained CA. How the urban form is impacted by spatial constraints, as the nature of constrained CA, was preliminarily explored in our work. In addition, the GSA approach was first introduced into constrained CA as an alternative to LSA for testing the CA model behavior.

In addition to the theoretical value, our work has significance in planning practice. Our approach can be used as a tool for evaluating the spatial plan compiled by planners as follows. First, the proposed realization possibility indicator (P) for an alternative plan can be regarded as a key evaluation result. This shows the realization possibility of a plan and can alert planners or officers in advance when compiling a plan. This tool can assist planners to design a better layout based on the evaluation results, and is not discussed in existing urban planning evaluation literature. Second, for a valid plan, required policies can be identified as development pathways to guide decision makers in implementing the compiled urban plan. Third, this approach can be applied for evaluating conformity between a spatial plan drafted by planners and corresponding specialized plans in terms of spatial constraints proposed by different departments of local government during the urban planning compilation process, such as hazard-sensitive areas proposed by the geological department and farmland conservation planning proposed by the agriculture department.

Several aspects need further exploration. We set $\kappa = 80\%$ as the benchmark for accepting or rejecting policy parameters for the predefined urban form on the basis of our experience. In the future, we will use the κ value as the acceptance probability by introducing the generalized likelihood uncertainty estimation (GLUE) (Saltelli and Scott, 1997) as an alternative approach for GSA, instead of the RSA approach used here. This is to overcome our subjective setting of the 80% benchmark although it is based on empirical researches and our experience. In addition, policy parameters may be spatially heterogeneous, which should also be considered in further work. It will be difficult but important to develop an urban CA model with distributed parameters, as this, too, remains unexplored.

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