Article

Urban Analytics and City Science

EPB: Urban Analytics and City Science
0(0) 1–22

DOI: 10.1177/2399808320942777
journals.sagepub.com/home/epb
SAGE

Urban modeling for streets using vector cellular automata: Framework and its application in Beijing

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Abstract
Zones, cells, and parcels have long been regarded as the main units of analysis in urban modeling. However, only limited attention has been paid to street-level urban modeling. The emergence of fine-scale open and new data available from various sources has created substantial opportunities for research on urban modeling at the street level, particularly for modeling the spatiotemporal process of urban phenomena. In this paper, the street is adopted as the spatial unit of an urban model, and a conceptual framework for such modeling based on cellular automata is proposed. The validity of the proposed framework is verified by an empirical application to the urban space within the Fifth Ring Road in Beijing from 2014 to 2018. The results show that the density of points of interest simulated by the cellular automata model for 2018 is basically consistent with the actual distribution according to direct observation, and there is no significant difference in the

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proportion of high, medium, and low points of interest density streets between different ring roads. In addition, the deviation rate and Kappa index are 0.1171 and 0.97, respectively, indicating the proposed model can replicate historical patterns well and predict the transition of points of interest density at the street level. Subsequently, we considered three scenarios, adopting 2018 as the base year and using the proposed model to simulate the distribution of points of interest density in 2022 and the changes in points of interest density from 2018 to 2022. The conceptual framework and empirical application also provide support for urban planning and design based on the integration of linear public space and big data.

Keywords
Applied urban model, street level, cellular automata, big data, Beijing

Introduction

Urban modeling has been applied for several decades and is widely recognized as an effective analytical tool to support urban planning and policy-making (Deal and Schunk, 2004; Eeftens et al., 2013; Hu et al., 2018). The scope of research on traditional urban modeling includes both the macro scale (e.g. cities and zones) and the micro scale (e.g. blocks, parcels, and cells). To respond to the increasing challenges faced by urban development, such as the increasing individualization of society (Wegener, 2011), air and noise pollution (Eeftens et al., 2013; Hadzi-Nikolova et al., 2012), health and energy issues (Jones et al., 2007), crime and safety (Jiang et al., 2018), and an increasing demand for high-quality urban life (Rinner, 2007), the trend in urban modeling is moving toward the micro level. However, modeling urban phenomena at the micro scale continues to face numerous challenges, such as limitations on high-resolution data availability, spatial representation, the speed with which researchers can respond to emerging urban problems, the extent to which a model can be replicated, and how a model can be shared with others (Crooks et al., 2008; Filatova et al., 2013; Wegener, 2011). Previous studies have made efforts to address one or more of these challenges (Crooks et al., 2008; Wegener, 2011). Advances in quantitative methods and emerging big geo-data have created substantial opportunities for quantifying indicators and modeling urban phenomena at the micro level (Hao et al., 2015; Tang and Long, 2019). As key components of urban public space and the built environment, streets have been regarded as important carriers with respect to supporting daily living. Streets are considered to represent a fine spatial scale characterized by directly visible and perceptible spaces in a person's daily life that can significantly affect the physical activities and emotional states of individuals living in urban areas. Urban modeling for streets can potentially enrich the semantics of urban public space, which can help planners and authorities understand the patterns underlying the heterogeneity of such space and reveal the impacts of various factors on public space quality.

The paper is organized into six sections. Following the introduction, this paper reviews typical urban models and studies related to urban modeling for streets in the "Literature review" section. In the "Practical requirements for street-level urban modeling" section, we present the practical requirements for street-level urban modeling. In the "Method for the urban modeling of streets" section, the conceptual framework and modeling design of an urban model for streets are proposed. In the "Empirical application of the model in Beijing" section, an empirical application to an urban space within Beijing's Fifth Ring Road is conducted to verify the feasibility of the proposed framework. The last section provides concluding remarks and discusses potential applications while also noting the study's limitations.

Literature review

Typical urban models

Zones, cells, and parcels have been regarded as the primary units of analysis in urban modeling over the last half century. We have conducted an extensive literature review and the urban models that have appeared since 1964 are listed in Table 1. A large number of urban models have been developed and used in assessing the socioeconomic

Table 1. Typical urban models.

Model name	Modeling unit/scale	Modeling method	Key publication
Alonso's Land Rent Model	City	Location and land rent theory	Alonso (1964)
IRPUD	Zone of urban region	Discrete choice modeling	Wegener (1982)
TRANUS	Subzone of a city	Spatial input–output method	Delabarra et al. (1984) Delabarra and Rickaby (1982)
POLIS	Zone based on census tract	Spatial interaction modeling Discrete choice modeling	Prastacos (1986)
MEPLAN	Zone	Spatial input–output method	Echenique et al. (1990)
CUFM_01	Developable land unit	Model based on allocation rules	Landis (1994)
Metrosim	Zone	Discrete choice modeling	Anas (1994)
MUSSA	Zone	Discrete choice modeling	Martinez (1996)
SLEUTH	Grid cell	Cellular automata	Clarke et al. (1997)
UrbanSim	Multi-scale	Discrete choice modeling Microeconomic modeling	Waddell (2002)
CUFM_02	Grid cell	Model based on allocation rules	Landis and Zhang (1998)
DELTA	Zone	Discrete choice modeling	Simmonds (1999)
ILUTE	Parcel Household	Micro agent interaction modeling	Miller and Salvini (2001)
PECAS	Zone	Spatial interaction modeling Spatial input–output method	Hunt and Abraham (2003)
TLUMIP	Zone	Spatial input–output method	Weidner et al. (2007)
Relu-Tran	Subzone of a metropolitan region	Discrete choice modeling	Anas and Liu (2007)
BUDEM	Grid cell	Cellular automata	Long and Mao (2009)
GeoSOS	Multi-scale	Cellular automata Agent-based modeling	Li et al. (2011)
Agent iCity	Parcel Household	Agent-based modeling	Jjumba and Dragićević (2012)
MATSim	Macro scale	Agent-based modeling	Armas et al. (2016)
FLUS	Multi-scale	Cellular automata	Liu et al. (2017)

impacts of urban planning or public policies at the macro level, such as the city, zone, or subzone (Wan and Jin, 2014). However, these models are not well suited for addressing micro-level urban processes or small-scale urban problems (Simmonds et al., 2013). With the development of urban modeling algorithms, cellular automata (CA) has become increasingly popular in the field of urban modeling (Kong et al., 2017; Sante et al., 2010). Studies that employ CA to model urban development and land use are abundant in the literature (Almeida et al., 2008; Barredo et al., 2003; Feng and Liu, 2013; Li and Yeh, 2000). Compared with traditional urban models, the CA model adopts a bottom-up simulation process and can capture urban changes in small-scale urban spatial units through simple and flexible transition rules. Although the CA model can effectively simulate rich urban change dynamics at the micro level, most previous CA studies focus on regular grid cells, such as 500 meters by 500 meters (Long and Mao, 2009) or 1 kilometer by 1 kilometer (Liu et al., 2017). In the diverse application of CA modeling, models based on cells on a grid with exact spatial resolution are considered universal. However, the conventional raster-based CA models are sensitive to the size of the grid cells and how they are configured, and thus have limited power to simulate the real world, which has more complex land use layouts and street networks. Vector-based CA models were later developed to simulate the process of urban change with irregular polygons as cells to represent more realistic urban phenomenon (Shen et al., 2009; Stevens and Dragićević, 2007). However, both raster and vector CA models have limitations in incorporating human decision behaviors (Arsanjani et al., 2013). With the development of complexity science and artificial intelligence, agent-based modeling (ABM) has been applied to simulate complex changes in the urban system (Chen et al., 2010). ABM involves the process of adaptation and decision-making of multiple individual agents at the micro level, which better reflects the dynamic relationship between urban changes and the direct or indirect reactions of different agents. The integration of CA models with ABMs has been discussed by various scholars (Hewitt et al., 2014; Li et al., 2011). These urban models tend to simulate urban phenomena at the micro level. However, few attempts have been made to investigate the wider dynamics of the urban system at a finer scale. Streets, as the traffic carrier and a key form of public space in a city, are playing an increasingly important role in urban studies. However, our comprehensive literature review indicates that previous studies on urban modeling have made little effort to link CA-ABM models with finer urban spatial units, such as urban streets.

Studies on street-level urban modeling

In the 1960s, a series of urban research pioneers, represented by Jacobs (1961) and Lefebvre (1962), initiated the discussion of the street space and its social and economic effects. Subsequently, experts in the field of design began paying attention to the spatial characteristics of streets, street design techniques, and how to use streets to improve urban quality and vitality. Whyte (1980), Lynch (1984), Gehl (1987), and Montgomery (1998) made qualitative inductions from different perspectives. Researchers have also investigated quantitative modeling for urban streets in a limited number of studies for a variety of objectives. For example, Penn et al. (1998) proposed a new type of "configurational" road network model, suggesting that the flow of vehicles and pedestrians could be better controlled through configuring the street grid, building height, and street width. Desyllas et al. (2003) quantitatively modeled "natural surveillance" using visibility graph analysis for a traditional street network and a modern university campus, and their model played a significant role in demonstrating the importance of natural surveillance in crime prevention through environmental design. Shen et al. (2009) took the effects of urban planning into account in a vector-based geographic automata model, and focused on simulating the land use patterns on both sides of streets.

During the last 30 years, the space syntax model has been developed to provide important computational support for analyzing spatial relationships within a street network (Hillier and Hanson, 1984; Hillier et al., 1987). Spatial syntax has been applied to pedestrian modeling (Hillier et al., 1993; Koohsari et al., 2016) and street design (Choi et al., 2006; Kim and Sohn, 2002). Space syntax considers the street layout and configuration, focusing on the spatial aspect of streets to estimate where people can move and where facilities can be best located. In relation to street measurement, the space syntax method is primarily used to estimate spatial and socioeconomic characteristics. Space syntax attempts to describe the structure of the street network and to explain human behavior from the perspective of spatial configuration. Most such studies address issues related to the spatial and socioeconomic patterns of streets, but few have linked the method with dynamic changes over time.

The emergence of open and new data available from various sources has created significant opportunities for urban modeling research at the street level, particularly for modeling the spatiotemporal process of urban phenomena. In recent decades, rapid changes in record digitization, network expansion, and society computerization have created a large number of geo-data with dynamic spatiotemporal features relevant to street functions and forms (Glaeser et al., 2018). With the rise of big geo-data, related studies such as those evaluating street characteristics and examining the relationship between street characteristics and urban phenomena are adequate to support further urban modeling of streets (Gan et al., 2018; Long and Liu, 2017). Tang and Long (2019) measured the characteristics of Hutongs, typically representative of historical streets in Beijing, from the perspectives of greenery, openness, enclosure, street wall continuity, cross-sectional proportion, and stay willingness. Other than modeling street characteristics, how people behave on the streets also aroused the research interest of scholars (Potdar and Torrens, 2019; Torrens, 2014). In addition, the emerging big geo-data have created a great opportunity for measuring previously unmeasurable characteristics of streets (Ewing and Handy, 2009) and to examine the previously unclarified relationship between street characteristics and urban phenomena.

Practical requirements for street-level urban modeling

Urban observers and critics have extensively investigated streets in a qualitative and narrative manner. However, limited attention has been paid to street-level urban modeling. On the one hand, because of the laborious, costly, and time-consuming nature of field surveys, it is difficult for researchers to obtain sufficient attribute data on the urban street space for extensive coverage. On the other hand, restricted by the cognitive limitations of the rapid development of urbanization and insufficient attention to the micro environment, researchers often use an urban unit with coarse granularity to represent the street environment, which in reality displays a richer array of connotations. In addition, urban planners or policymakers must address numerous policy/planning goals (e.g. higher GDP, higher employment rate, better air quality, better urban services). As a fundamental urban component, streets influence the quality and vitality of public spaces and the physical activities and psychological perceptions of the people that live in them. One important means to achieve these goals is to plan or design the particular form/characteristics of streets. Developing a comprehensive body of knowledge on streets is becoming increasingly meaningful. Recent advances in quantitative morphological tools, such as space syntax and deep learning, have provided new ways of analyzing street elements. New street data, such as mobile phone traces, points of interest (POIs), and street view pictures, offer novel means to measure streets at a finer scale (Long and Liu, 2017). Street big data are easier to access than traditional geo-data (e.g. land use maps at the parcel level, survey data in gated communities). The rise of big data makes urban modeling for streets feasible (Harvey and Aultman-Hall, 2016).

The rapid changes in the city have also resulted in an urgent need for planners and policymakers to perceive and evaluate problems in street space within large-scale urban areas in a more efficient and convenient way. Because street-scale data can be updated per hour, day, or month, urban modeling for streets can be expected to respond to emerging urban challenges in a timely manner. For example, a street-level flood model can be quickly constructed and updated to monitor and diagnose urban rain and flood problems per hour by aggregating urban flood pictures generated through social media and by urban sensor systems. Additionally, urban modeling for streets can provide good support to specific urban planning/policy tasks, such as urban regeneration, historical street conservation, parking pricing policy, and urban poverty detection.

In addition, urban modeling on the street level can integrate land use and transportation systems easier than urban models that focus on areal units. Streets are where urban daily life occurs and the channels that connect origins and destinations. At the micro level, land use and the transportation system can co-exist in a single street unit, and theoretically, it is easier to integrate these two systems within one street unit.

Method for the urban modeling of streets

Conceptual framework

We propose a conceptual framework for a government and public participation cellular automata model for streets (GPCAS) to simulate street situations and their changes (Figure 1). There are three modules in GPCAS: a street measurement module, a street-CA module, and a government and public participation module.

Previous studies on the measurement of street attributes propose various variables, most of which are based on the 5Ds, namely density, diversity, design, distance, and destination accessibility (Ewing and Handy, 2009; Saelens et al., 2003; Yin, 2017). As these studies confirm, the 5Ds are the core paradigm in street measurement. However, these aspects of

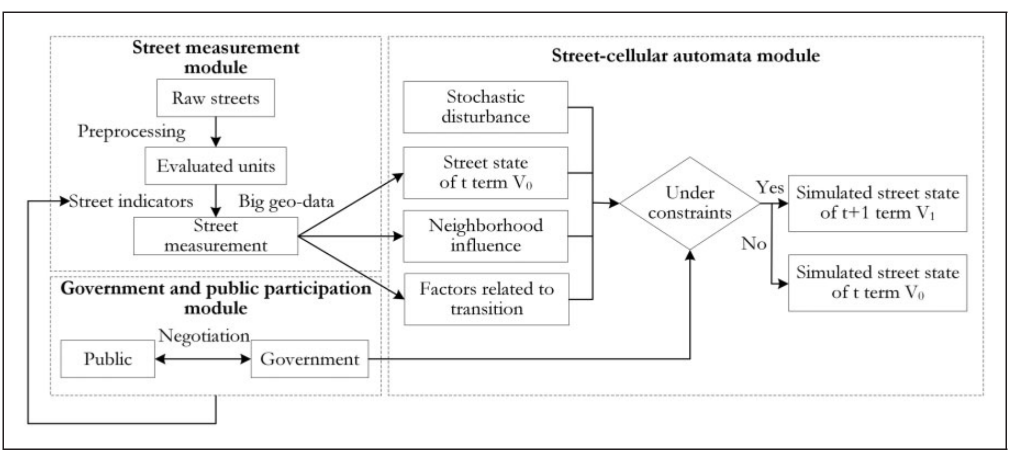

Figure 1. Conceptual framework of urban modeling at the street level.

street measurement do not capture a comprehensive view of the street environment. As important components of the built environment, streets display values across various dimensions, including but not limited to aesthetics, space, traffic, and public health. Based on previous studies on the 5Ds (Cervero and Kockelman, 1997; Ewing and Cervero, 2010; Long and Liu, 2017; Tang and Long, 2019), other indicators, such as vibrancy (Chen et al., 2019), quality (Tang and Long, 2019), traffic (Jiang et al., 2018), and emergency events (Helderop and Grubesic, 2019) are proposed to measure and evaluate street characteristics. Indicators developed according to big geo-data (e.g. POIs, buildings, street view pictures, social media data, mobile phone traces) are presented in Table 2.

Next, based on Feng et al. (2011) and Long and Wu (2017), the conceptual model of the proposed street-CA is expressed as follows

$$V_i^{t+1} = \mathrm{f}\left(V_i^t, Factors,\ Neighbor_i, Constrain, Stoch\right) \tag{1}$$

where V_i^{t+1} and V_i^t are states of street i at time $t+1$ and t, respectively, f is the transition function, $Neighbor_i$ is the neighborhood influence of street i, $Factors$ are the indicators related to the state transition of street i, $Constrain$ is the constrained condition on street state transition, and $Stoch$ is a stochastic disturbance representing accidental errors or urban uncertainty. In the conceptual model, street state, neighborhood influence, and factors related to state transition are outcomes of the street measurement. *Constrain* refers to comprehensive constraints generated by the government.

In the government and public participation module, the government and the public participate in urban modeling by expressing their opinions on the street state transition (Vancheri et al., 2008). Two types of agent are embodied in our proposed urban modeling for streets: the government agent at an upper level and the public agent at a lower level. The decision-making behavior of the government agent is to formulate constraints and determine factors that guide the development direction, scale, and layout of the streets. The public agents exert an effect on the influencing factors by their spatial choice behaviors.

Model design

A CA model is well known for having several basic elements, including cells, cell states, neighbors, constrained conditions, and transition rules. In the proposed model, a street, as a linear geometry, is defined as a cell. The cell state is represented by the street function density, which is proxied as POI density on both sides of the street. Neighbor refers to other streets that are located within a certain buffered space of the target street. The neighborhood effect is calculated as the average POI density of neighbors. The total number of POIs is included in the model as a constrained condition, which controls the number of simulated POIs when the model runs. During the iteration, the model will not stop until it reaches the constrained conditions.

In addition, the cell state in the proposed model is not static, but dynamic and changes over time under the impact of the transition rule. Therefore, the transition rule of the simulation contains the time interval, the cell state of the last iteration, the change in each iteration of the cell state, the transition probability, and the stochastic disturbance, which is shown in equation (2). Specifically, (a) the time interval of the iteration can be set to a specific period of time, such as one day, one month, or one year. (b) The change in each iteration refers to the average variation of POI density per time interval from the initial year to the target year. (c) The transition probability is calculated by binary logistic regression based on equations (3) and (4). Equation (3) is used here to identify the transition

Table 2. Main street indicators and data sources.

Aspect	Street indicator	Data source
Density	Population density	Population census
	Road junction density	Mobile phone traces
	Building area density	Location-based services data
		POIs
		Buildings
Diversity	Urban function mix	POIs
	Land use diversity	Land use maps
Design	Street main function	POIs
	Street length	Road networks
	Street width	Buildings
	Pavement material	Land use maps
	Street wall continuity	Street view pictures
	Ratio between average building height and street width	
	Whether the motorized/nonmotorized lane is separate	
	Proportions of each object category, such as buildings, roads, trees, cars, pavement, commercial windows	
Distance	Distance to bus station	POIs
	Distance to subway station	
	Distance to railway station	
	Distance to airport	
Destination accessibility	Distance to city center	POIs
	Distance to central business district	
	Distance to urban subcenters	
	Distance to commercial complex	
Vibrancy	Economic vibrancy	Economic census
		Economic section in travel survey
		Web comments (e.g. Da Zhong Dian Ping)
	Social vibrancy	Location-based services data
		Street view pictures
		Web comments (e.g. Da Zhong Dian Ping)
Quality	Openness	Street view pictures
	Enclosure	
	Willingness to stay	
	Urban informality score	
Traffic	Road class	Travel survey
	Speed limited	Taxi tracing
	Traffic flow	Urban fundamental geographic information system
Emergency event	Urban flood	Public media
	Traffic accident	Social media
		Traffic broadcast

POI: points of interest.

probability and equation (4) is applied to determine the weights of the influencing factors listed in Table 2. Influencing factors, as independent variables, are measured in the initial year, and the dependent variable (either 0 or 1) denotes that the change status of the POI density is either “increasing” or “decreasing” from the initial year to the target year. (d) The stochastic disturbance represents the uncertainty of the urban system, which is a random number ranging from 0.5 to 1.5 to control the speed of actual change in POI density. We can express the relationships as follows

$$V_{t+1} = V_t + V_{change} \times p_i \times Stoch \tag{2}$$

$$p_i = \frac{1}{1 + e^{-s_i}} \tag{3}$$

$$s_i = \text{cont} + w_1 \times X_1 + w_2 \times X_2 + \cdots + w_n \times X_n + w_N \times neighbor_i \tag{4}$$

where V_t is POI density of the last iteration, V_{change} is the average variation of POI density per time interval from the initial year to the target year, p_i is the transition probability, *Stoch* is the stochastic disturbance, s_i is the dependent variable (either 0 or 1), *cont* is the constant, X is the influencing factor, w is the coefficient (weight) of the corresponding influencing factor, and $neighbor_i$ is the neighborhood effect.

To estimate the prediction, scholars frequently report measures that are derived from the overall accuracy and Kappa index (Olmedo et al., 2015; Pontius and Petrova, 2010; Sante et al., 2010; Ye et al., 2018). We use the deviation rate and the Kappa index to evaluate the prediction capability of the proposed model based on the actual and predicted results, both in the target year, which are expressed by the following equations

$$\text{D} = \frac{1}{n}\sum_{1}^{n} \frac{\left| y_i^{predicted} - y_i^{actual} \right|}{y_i^{actual}} \tag{5}$$

$$\text{Kappa} = \frac{(P_o - P_c)}{(P_p - P_c)} \tag{6}$$

where y_i^{actual} is the actual result for street i in the target year, $\text{y}_i^{predicted}$ is the predicted result for street i in the target year, n is the number of streets, P_0 is the observed correct proportion, P_c is the expected correct proportion, and P_p is the absolute correct proportion. A lower deviation rate value indicates strong agreement between the actual and predicted results. The Kappa coefficient ranges from 0 to 1. The value closer to 1 represents higher similarity between the simulation result and the actual result.

Empirical application of the model in Beijing

Study area

The empirical application focuses on an urban area within Beijing’s Fifth Ring Road with a total area of 667 square kilometers (Figure 2). The urban space within the Fifth Ring Road covers the main urban areas of Beijing, including Beijing central business district (CBD), traditional houses, and ordinary residences in the Second Ring Road, where the population

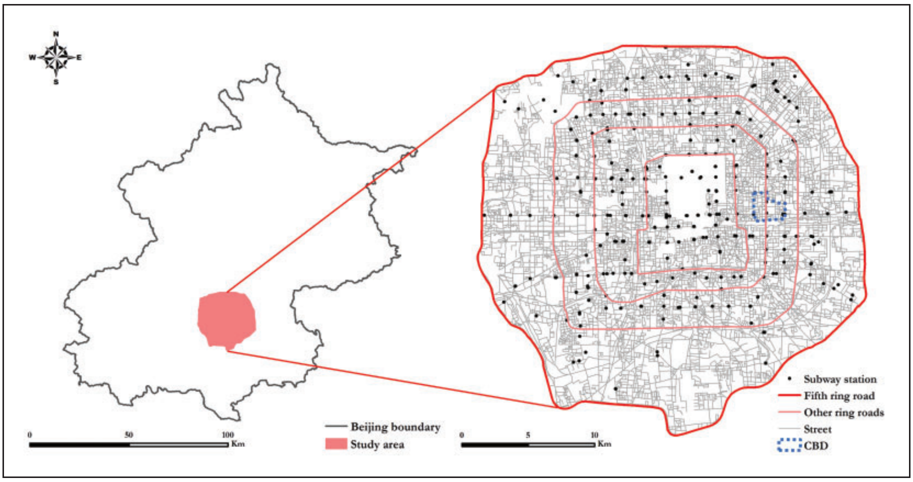

Figure 2. Location of study area. CBD: central business district.

density is relatively high and employment opportunities, cultural activities, and entertainment activities are plentiful.

Model parameters

In the model, we exclude the streets within historical protected areas from our sample because the development within these areas is highly restricted by policies and laws. The iteration time interval is set to one month. Considering that walking speed is 1.1 meters per second (Almodfer et al., 2017), the maximum distance that a person can travel on foot in one and half minutes is approximately 100 meters. Therefore, the streets within a 100-meter buffer zone from the centerline of the target street are selected as neighbors. The initial year is set to 2014 while the target year is 2018. The independent variables used in the logistic regression are all quantified using 2014 data. The binary dependent variable (either 0 or 1) is determined based on the changes of POI density from 2014 to 2018, where 0 indicates an increase in POI density and 1 indicates a decrease. Historical data are shown in Table 3.

The regression results for 2014–2018 are provided in Table 4. In the logistic regression, the Nagelkerke R-squared can be used to measure the fraction of the total variation in the dependent variable that is explained by the independent variable. However, this coefficient of determination is usually not as high as that in linear regression. In addition, the overall percentage is adopted to describe the accuracy of the prediction by comparing the actual classification results with the predicted classification results. The Nagelkerke R-squared and overall percentage of logistic regression in the paper are presented in Table 4. As shown in the table, the coefficient of building area density is the largest, and accordingly, the transition probability will increase with the increased density of buildings. The variables of the distance category are negatively correlated with the transition probability, indicating that the increase in distance has a negative effect on transition probability.

Model evaluation

Considering the influence of stochastic disturbance in the simulation process, we simulated the change 30 times continuously and calculated the average value as the result of the final simulation. To further examine the accuracy of the CA model, a null model was established.

Table 3. Historical data from 2014 to 2018.

Data	Year	Maximum	Minimum	Average	Source
POI density (number/km^2)	2014 2018	9000.00 26,620.00	0.00 0.00	469.00 1360	POIs derived from Gaode Map
Neighborhood effect (number/km^2)	2014	5033.00	0.00	465.00	
Distance to subway station (m)	2014	6295.86	0.00	1011.45	
Distance to bus station (m)	2014	1400.77	0.00	142.37	
Building area density (km^2/km^2)	2014	26.33	0.00	2.03	Building footprints derived from Baidu Map
Distance to CBD (m)	2014	22,425.35	55.65	10,498.34	Land use map
Street length (m)	2014	2948.73	70.00	250.02	Road network derived from Gaode Map
Street width (m)	2014	78.00	2.00	35.64	
Road junction density (number/km^2)	2014	578.00	3.00	188.00	
Data	Year			Value	Source
Number of streets	2014			15,942	Road network derived from Gaode Map
Number of POIs	2014 2018			186,747 558,226	POIs derived Gaode Map
Constrained total number of POIs	2018			558,226	

CBD: central business district; POI: points of interest.

Table 4. Variables in the logistic regression equation for 2014–2018 (B is the regression coefficient).

Variable	B	Standard error (SE)	p	Exp(B)
Street length	0.001514	0.000	0.000	1.002
Street width	0.014939	0.002	0.000	1.015
Road junction density	0.000105	0.000	0.820	1.000
Building area density	0.838204	0.047	0.000	2.312
Distance to CBD	−0.000024	0.000	0.002	1.000
Distance to subway station	−0.000059	0.000	0.160	1.000
Distance to bus station	−0.000338	0.000	0.144	1.000
Neighborhood effect	−0.000945	0.000	0.000	1.000
Constant	1.687570	0.170	0.000	5.406
Nagelkerke R-squared	0.127			
Overall percentage	95%			

CBD: central business district; SE: standard error.

Specifically, we calculated the average number of POIs that increases or decreases from 2014 to 2018 and then assigned this value to the corresponding street to predict the POI density in 2018 based on 2014. In this paper, four methods based on both actual POI density and predicted results in 2018 were applied to validate the performance of our proposed CA model.

1. Direct observation. The actual POI density in 2018 was divided into three categories (low, medium, and high) by using the natural breaks method. According to the range values of the three categories, the CA result and the null model result in 2018 were assigned to the corresponding categories (Figure 3). The actual POI density and the predicted result from the CA model are generally consistent in terms of spatial distribution, while the result of the null model simulation is substantially different with respect to high POI density distribution.
2. Density proportion comparison. We calculated the proportion of the actual value and the simulated values in the high, medium, and low POI densities between different ring roads in 2018 (Figure 4). As shown in the figure, the proportion of the actual result and the CA simulation result for the three categories is similar.
3. Deviation rate. The deviation rates of the CA model and the null model were calculated by using actual POI density in 2018 and the predicted results in 2018 (Table 5).

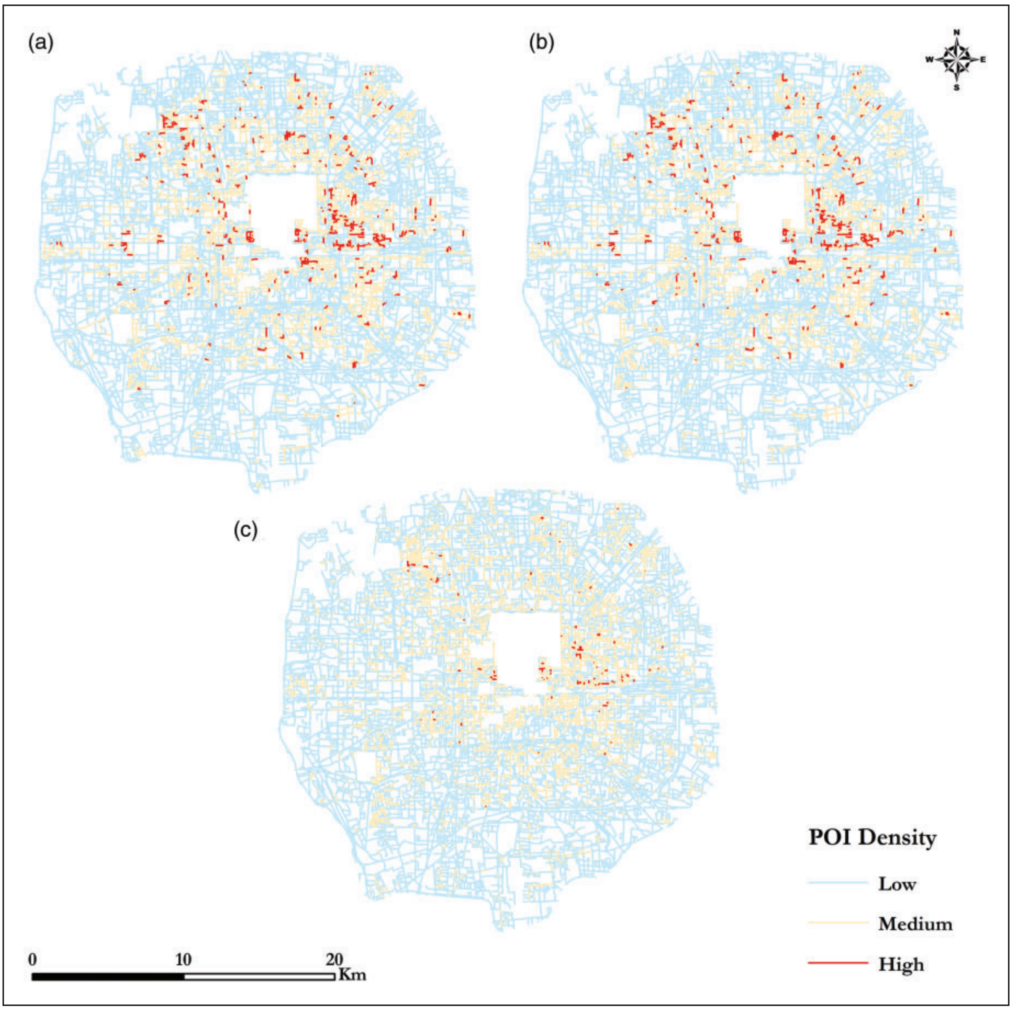

Figure 3. POI density categorized by the same classification criterion in 2018. (a) Actual result, (b) CA result, and (c) null model result. POI: points of interest.

The deviation rate of the CA model is closer to 0, which is significantly smaller than that of the null model (2.0931). For the CA model, the proportion of the number of streets in the three deviation rate ranges of 0.01, 0.05, and 0.1 is much higher than that of the null model.

4. Kappa index. Based on actual POI density and the predicted results both in 2018, we marked the values of low, medium, and high POI density as 1, 2, and 3 and then calculated the Kappa index of the CA model and the null model using SPSS software (Table 5). The Kappa index of the CA model is closer to 1 than that of the null model, indicating higher similarity between the actual result and the simulated result of the CA model.

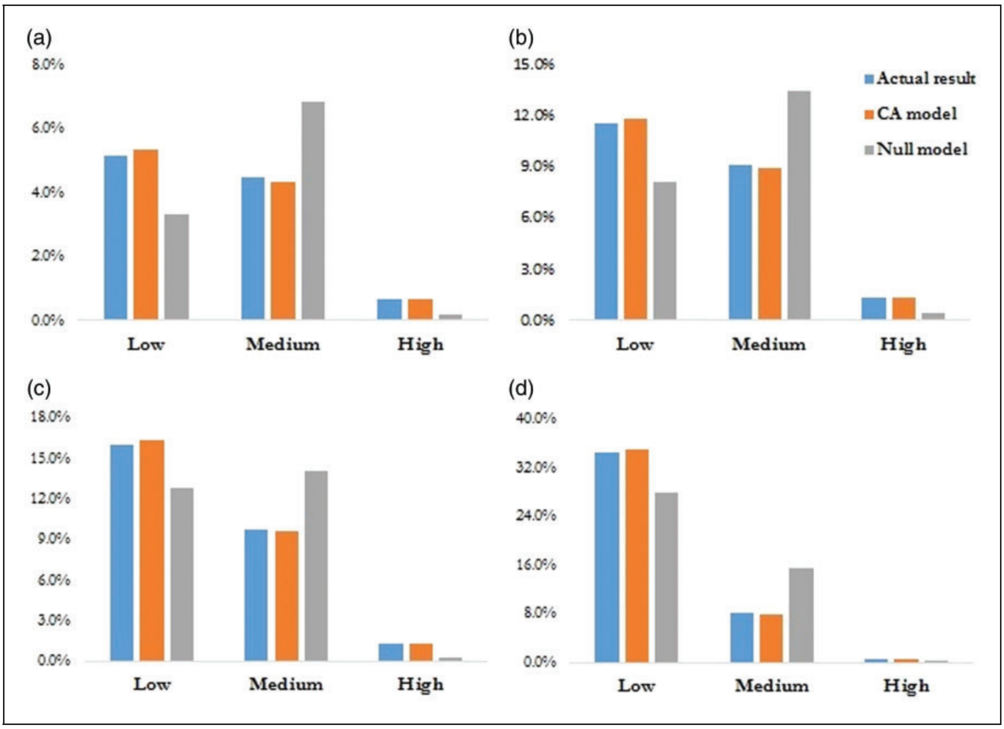

Figure 4. Proportion of three types of POI density for actual and simulated results between different ring roads in 2018. (a) Within the Second Ring Road, (b) between the Second and Third Ring Road, (c) between the Third and Fourth Ring Road, and (d) between the Fourth and Fifth Ring Road. CA: cellular automata.

Table 5. Deviation rate and Kappa index of CA model and null model.

		CA model	Null model
Deviation rate	Overall	0.1171	2.0931
	Proportion of $\leq$ 0.01	15.77%	2.48%
	Proportion of $\leq$ 0.05	74.99%	7.15%
	Proportion of $\leq$ 0.1	93.07%	12.54%
Kappa index		0.97	0.38

CA: cellular automata.

Table 6. Parameters of the three scenarios.

Parameter		Trend development	CBD-based development	TOD promotion
Weight of influencing factor	Street length	0.001514	0.001514	0.001514
	Street width	0.014939	0.014939	0.014939
	Road junction density	0.000105	0.000105	0.000105
	Building area density	0.838204	0.838204	0.838204
	Distance to CBD	−0.000024	**−0.000100**	−0.000024
	Distance to subway station	−0.000059	−0.000059	**−0.000100**
	Distance to bus station	−0.000338	−0.000338	−0.000338
	Neighborhood effect	−0.000945	−0.000945	−0.000945
Initial year of simulation		2018		
Target year of simulation		2022		
Constrained total number of POIs in 2022		929,705		

CBD: central business district; POI: points of interest; TOD: transit-oriented development.
Note: The bold weights are increased compared to the weights of variables in the logistic regression from 2014 to 2018, while others keep the same weights for the variables between 2014 and 2018.

Therefore, based on the verification of the four qualitative and quantitative methods, the proposed model enables better replication of the historical laws to predict the transition of POI density at the street level.

Future prediction based on three scenarios

Adopting 2018 as the initial year and 2022 as the target year, three scenarios were considered to simulate the change of POI density, including (1) the trend development scenario. This scenario is generated based on the assumption that the trend of change in POIs from 2018 to 2022 stays the same as that between 2014 and 2018. Therefore, the weights of the variables do not change. (2) The CBD-based development scenario. The influencing intensity of CBD as a key feature is strengthened. Therefore, the weight of distance to CBD is increased to −0.0001 while the others remain the same. (3) The transit-oriented development (TOD) promotion scenario. The influencing intensity of the subway station as a key feature is strengthened. Therefore, the weight of the distance to a subway station is increased to −0.0001 while the weights of other variables are fixed. In addition, we assumed that the change in the number of POIs from 2018 to 2022 is consistent with the change pattern from 2014 to 2018. Thus, the total number of POIs in 2022 is 929,705. The parameters of the three scenarios are presented in Table 6.

Using the validated model, we predicted the POI density of streets in 2022 based on the three scenarios (Figure 5). We calculated the number of three types of street within 500 meters of the CBD and a subway station in the different scenarios. Compared with the trend development scenario, with the increase in the influence weight of the CBD and the subway station, the number of streets with high POI density increases from 33 to 36 within 500 meters of the CBD, while the number of streets with high POI density increases rapidly

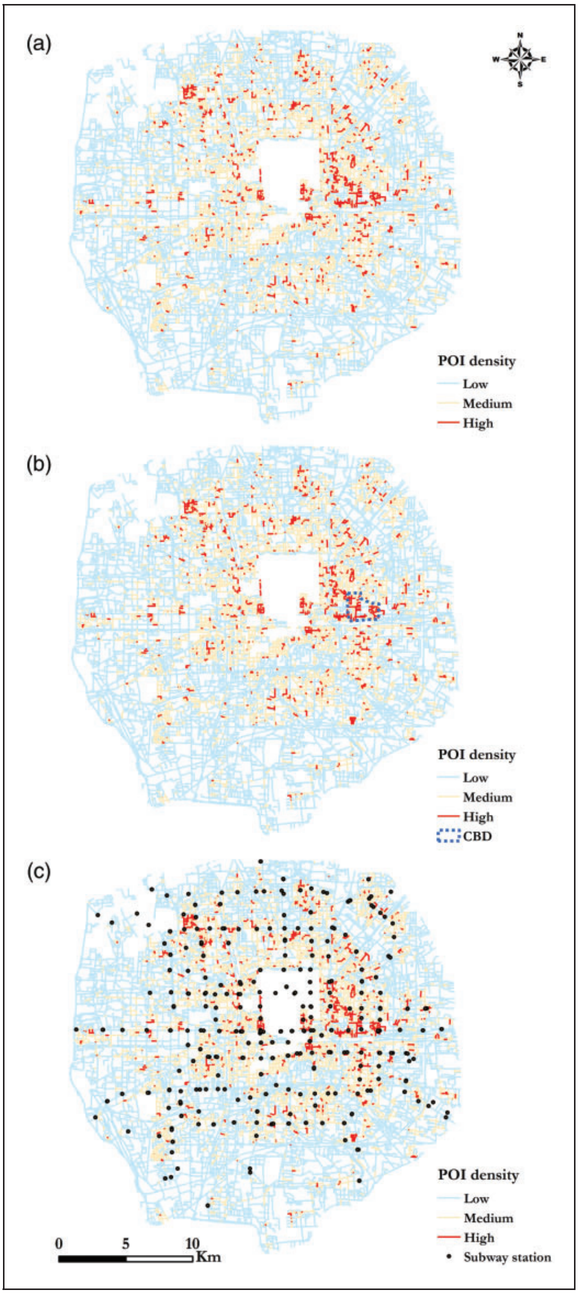

Figure 5. POI density categorized by the same classification criterion in 2022. (a) Trend development, (b) CBD-based development, and (c) TOD promotion. CBD: central business district; POI: points of interest.

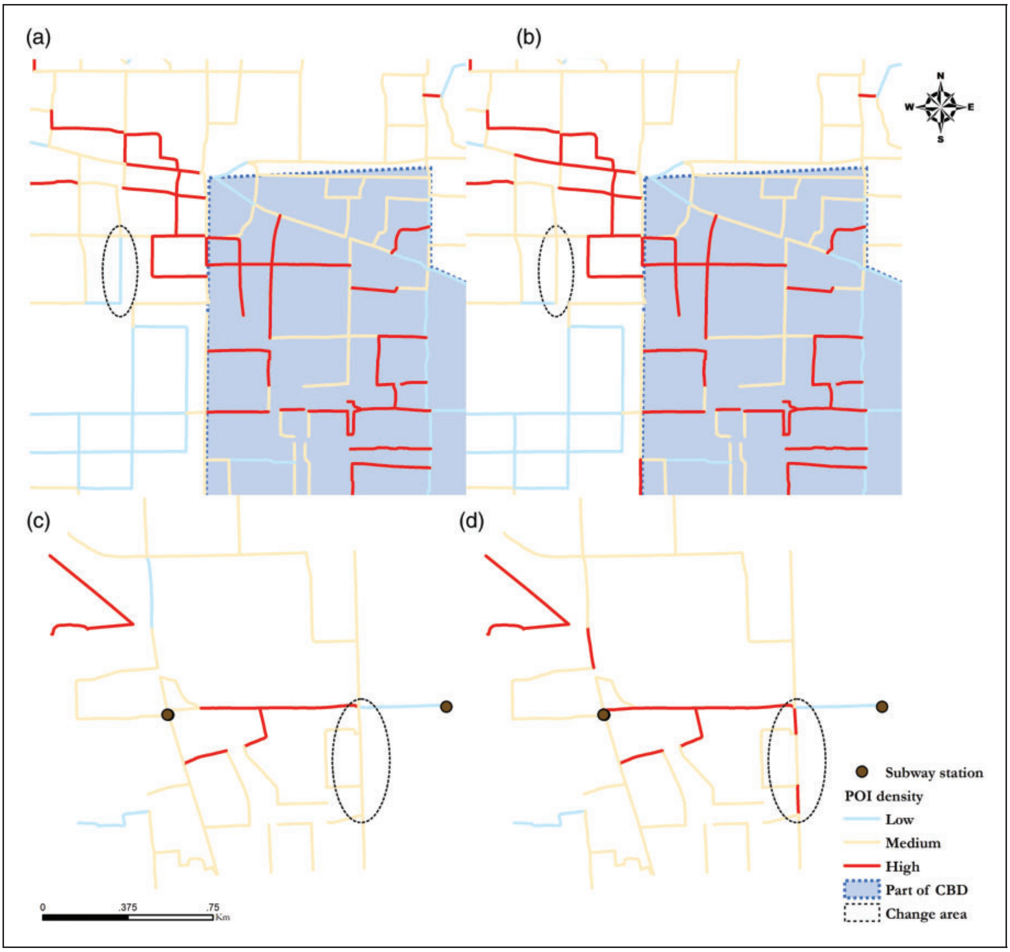

Figure 6. POI density of certain streets close to the CBD and two subway stations. (a) Streets close to CBD in the trend development scenario, (b) streets close to CBD in the CBD-based development scenario, (c) streets close to a subway station in the trend development scenario, and (d) streets close to a subway station in the TOD promotion scenario. CBD: central business district; POI: points of interest.

within 500 meters of the subway station (from 700 to 742). In addition, a small sample area was selected to compare changes in POI density (Figure 6). As shown in the figure, the POI density of certain streets close to the CBD and a subway station increases because of the increase in the weight of the CBD and the subway station.

Conclusions and discussion

Concluding remarks

In this paper, we reviewed the applied urban models that are typically applied and found that CA-based modeling for streets was less studied in the literature. Then, we proposed a conceptual framework for urban modeling at the street level based on CA and verified the validity of the proposed framework by running the model with empirical data for Beijing. Four methods, including direct observation, density proportion comparison, deviation rate, and Kappa index, were applied for validation of the proposed model using actual POI density and predicted results, both in 2018. We found that the distribution of the simulated POI density is basically the same as the actual distribution, that the street proportion of three types of POI density displays no obvious difference, that the deviation rate is close to 0, and the Kappa coefficient is closer to 1. These outcomes indicate good agreement between the actual results and the predicted results of the CA model. The prediction results are consistent with the true values, which encouraged us to predict using three additional scenarios. We adopted 2018 as the initial year and used the proposed model to simulate the distribution of POI density in 2022 and the change in POI density from 2018 to 2022. The results reveal that the number of streets with high POI density increases with an increase in the influence of distance to the CBD and a subway station.

Potential applications

Compared with previous urban models, the street-CA model focuses on street scale and takes it as units of analysis, which reflects more realistic urban phenomenon, especially for public spaces. This model is available for supporting actual refined urban projects, especially urban renovation, urban micro-regeneration, community building, etc., helping explain which factors have an impact on street function, thus contributing to a more targeted and efficient solution to improve the overall development of street space. It should also respond better to policy-making related to streets, since it can integrate and evaluate the impacts of macro policies and specific planning schemes on urban street space, and simulate multiple schemes reflecting various space development strategies. For urban planners and designers, the model plays an important role in assessing the development potential of streets under different scenarios.

Academic contributions

Based on classical theories of complex systems, a conceptual framework is constructed for urban modeling at the street level that can be widely applied. The street considered as a linear geometry is adopted as the spatial unit of the proposed CA-based urban model compared to vector polygons in previous studies, whereby the model's validity is verified through an empirical application to urban space within Beijing's Fifth Ring Road. The spatial characteristics of a city on a fine scale could be reflected through street-level urban modeling as opposed to models reflecting coarse spatial granularity. The street-scale CA model has undoubtedly contributed to the fineness of urban modeling at the linear scale, thus filling the gap in the current research. In addition, the proposed model and its application provide empirical evidence for capturing features of urban change dynamics by using emerging sources of big geo-data, which will strongly support the simulation of planning decisions and multi-scenario comparison. The conceptual framework and empirical application also provide support for urban planning and design based on the integration of linear public space and big data.

Potential limitations and future research

In our model, only the total number of POIs is considered as the constrained condition. In future studies, more constraint factors should be introduced into the proposed model to simulate POI density change, such as urban-planning management policies. In addition, an agent-based model could be added to simulate urban agents for various activities based on different urban policy scenarios. Relevant indicators of the space syntax model will also be taken into account in future studies. Other big data such as street view images and human activity records using location-based services can capture spatial information with a lower cost and larger spatial coverage. Therefore, these data can be used to represent street functions and be combined with our model for the validation of CA urban modeling in future studies.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: We are grateful for the financial support of the National Science and Technology Major Project of the Ministry of Science and Technology of China (No. 2017ZX07103-002) and the National Natural Science Foundation of China (Nos. 51778319 and 71834005). We will share the code and data used in this paper online at the Beijing City Lab's website (https://www.beijingcitylab.com/projects-1/52-modeling-streets/).

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