Exploring Zoning Scenario Impacts upon Urban Growth Simulations Using a Dynamic Spatial Model

Abstract

Dynamic spatial models are being increasingly used to explore urban changes and evaluate the social and environmental consequences of urban growth. However, inadequate representation of spatial complexity, regional differentiation, and growth management policies can result in urban models with a high overall prediction accuracy but low pixel-matching precision. Correspondingly, improving urban growth prediction accuracy and reliability has become an important area of research in geographic information science and applied urban studies. This work focuses on exploring the potential impacts of zoning on urban growth simulations. Although the coding of land-use types into distinct zones is an important growth management strategy, it has not been adequately addressed in urban modeling practices. In this study, we developed a number of zoning schemes and examined their impacts on urban growth predictions using a cellular automaton-based dynamic spatial model. Using the city of Jinan, a fast-growing large metropolis in China, as the study site, five zoning scenarios were designed: no zoning (S0), zoning based on land-use type (S1), zoning based on urbanized suitability (S2), zoning based on administrative division (S3), and zoning based on development planning subdivision (S4). Under these scenarios, growth was simulated and the respective prediction accuracies and projected patterns were evaluated against observed urban patterns derived from remote sensing. It was found that zoning can affect prediction accuracy and projected urbanized patterns, with the zoning scenarios taking spatial differentiation of planning policies into account (i.e., S2–4) generating better predictions of newly urbanized pixels, better representing urban clustered development, and boosting the level of spatial matching relative to zoning by land-use type (S1). The novelty of this work lies in its design of specific zoning scenarios based on spatial differentiation and growth management policies and in its insight into the impacts of various zoning scenarios on urban growth simulation. These findings indicate opportunities for the more accurate projection of urban pattern growth through the use of dynamic models with appropriately designed zoning scenarios.

Keywords： urban growth simulation; zoning scenarios; cellular automaton models; spatial matching; prediction accuracy

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1. Introduction

The past few decades have witnessed a rapid growth in both the world's urban population and the amount of built-up land, particularly in a number of developing countries. This has led to significant changes in Earth's land surface that threaten the integrity of global ecosystems (Rafiee et al., 2009). For example, although the proportion of people living in cities in China more than tripled between 1978 and 2015, the urban built-up land coverage increased by nearly seven times over the same period (The Yearbook of China's Cities, 2015). Rapid urban land expansion has become the primary form of land-use change in China and has prompted concerns over loss of large areas of high-quality farmland and primary forest, inadvertent climate repercussions, and degradation in the overall quality of life (Ma et al., 2014; Song et al., 2015).

Urban growth is a complex, dynamic process that is driven by multiple biophysical and socio-economic factors (Irwin et al., 2009; Akın et al., 2014; Maimaitijiang et al., 2015; Shafizadeh-Moghadam and Helbich, 2015). Land-use change models can be used to explore urban growth and land-use change dynamics to aid planners and resources managers in understanding land-use changes and their potential socio-ecological consequences under different constraints (Yang and Lo, 2003; Liu et al., 2008). Over the years, various land-use change models have been developed, a number of which are suitable for urban growth simulation,. These include statistical models (e.g., Hu and Lo, 2007), artificial neural network models (e.g., Liu and Seto, 2008), cellular automaton (CA) models (e.g., Clarke et al., 1997; Arsanjani et al., 2013; Chowdhury and Maithani, 2014; Aburas et al., 2016; Ku, 2016), and agent-based models (e.g., Matthews et al., 2007; Valbuena et al., 2010). Whereas statistically-based models are generally static in nature and more appropriate for diagnostic or prescriptive applications, cellular automaton- and agent-based models are dynamic and can be used for exploring future urban development under different constraints (Torrens, 2011).

In this paper, we look primarily at urban cellular automaton models based on their capability for exploring urban dynamics and on their general popularity (Torrens, 2011). Cellular automation models simulate land cover or land use change using a set of rules which regulate cell (pixel) conversions depending on their location, spatial relationships with other cells and various landscape constraints. A well-known example of an urban cellular automata model is the Slope, Land-use, Exclusion, Urban extent, Transportation, and Hillshade (SLEUTH) model, which has been widely applied in urban growth prediction and forecasting (e.g., Clarke et al., 1997; Clarke and Gaydos, 1998; Silva and Clarke, 2002; Herold et al., 2003; Jantz et al., 2003, 2010; Yang and Lo, 2003; Berling-Wolff and Wu, 2004; Al-shalabi et al., 2012; Onsted and Chowdhury, 2014). At the same time, despite their successful track record of application and high overall accuracy, cellular automaton models can suffer from low pixel-matching precision (i.e., low local-scale precision) (Jantz et al., 2003). Thus, improving urban growth prediction accuracy and reliability has become an important area of research in geographic information science and applied urban studies (Torrens, 2011; Brown et al., 2013; Liu and Yang, 2015). Although much progress has been made in developing more technologically sophisticated urban cellular automaton models, there have been some persistent challenges to the applicability of these models in reproducing patterns resembling real cities, driven primarily by limitations on the availability of spatial data at required resolutions and difficulties in representing spatial complexity, regional differentiation, and growth management policies (see Yang and Lo, 2003; Torrens, 2011; Liu and Yang, 2015).

The focus of this paper is the sensitivity of urban growth to development planning policies, which are important in urban growth management but have not been adequately addressed in urban modeling practices (e.g., Clarke et al., 1997; Silva and Clarke, 2002; Berling-Wolff and Wu, 2004; Lahti, 2008; Wu et al., 2009) due to difficulties in incorporating such development policies into the conversion rules used by cellular automaton-based urban models (see Torrens, 2002). One way to address this issue is to use an exclusion layer to indirectly integrate various development policies into the simulation process (e.g., Jantz et al., 2003; Silva et al., 2008; Akın et al., 2014). However, this approach has had only limited success to date because other issues, including spatial complexity and regional differentiation, must be considered along with planning policies (e.g., Goldstein et al., 2004).

Urban planners often use zoning to differentiate land-use types as a method for controlling and guiding the growth and changes in urban land use (Onsted and Chowdhury, 2014). This top-down growth control and management approach has been widely adopted in the developed world and is now being applied in a number of developing countries, including China (Tian and Shen, 2011; Long et al., 2012). In China, all levels of government play very important roles in making urban development policies and in building urban public service facilities and infrastructures. A notable example of this is the establishment of several special economic zones by the central government in the early 1980s as part of the country's economic reforms and policy of opening to the world. These economic zones have profoundly affected urban growth patterns in the country and made it necessary to consider zoning in urban growth modeling.

Several studies have recognized the implications of zoning for urban expansion simulations and have noted how the appropriate use of zoning information can help improve simulation accuracy (Clarke et al., 1997; Onsted and Chowdhury, 2014). In this paper, "zone" is a term used to refer to any subdivision of the landscape and can categorize divisions by land-use type, administrative division, development planning subdivision, etc. Despite its advantages, zoning has rarely been incorporated in urban modeling practices because its ability to significantly affect the modeling outcomes has been generally disregarded or considered too difficult to demonstrate (Onsted and Chowdhury, 2014). For example, in a study by Lahti (2008) the SLEUTH model, a cellular automaton-based dynamic urban model, was successful in capturing bottom-up ecological processes but could not adequately reproduce top-down phenomena due to its difficulty in establishing a connection between bottom-up-oriented conversion rules and top-down urban development policies. In other studies, SLEUTH was found to be incapable of thoroughly capturing the characteristics of urban growth for various administrative divisions even when zoning was taken into account (e.g., Wu et al., 2009). It should be noted that in these previous studies zoning information was generally derived from either large administrative divisions (e.g., Wu et al., 2009) or land-use types (e.g., Berling-Wolff and Wu, 2004; Rafiee et al., 2009; Jantz et al., 2010).

The aim of this study was to explore the potential impacts of zoning on urban growth prediction and forecasting using the SLEUTH cellular automaton-based dynamic spatial model. SLEUTH was selected for the study because of its flexibility, openness, non-linearity, and adaptive ability (Clarke et al., 1997; Clarke and Gaydos, 1998). Using a set of urban growth rules, the SLEUTH model can simulate complex urban growth dynamics. The model can be calibrated using historical urban expansion data to obtain the best possible coefficient combinations. Detailed discussion on model design and implementation procedures can be found in previous studies (e.g., Clarke et al., 1997; Clarke and Gaydos, 1998; Silva and Clarke, 2002; Herold et al., 2003; Yang and Lo, 2003). Because of its rapid growth during the past several decades, the city of Jinan, Shandong Province, China was selected as the study site. Several distinct zoning scenarios based on land-use type, urbanization suitability, administrative division, and development planning subdivision were carefully designed and used to simulate urban growth. Based on the model results, the potential impacts of zoning were examined. Specifically, two questions were addressed: (1) Would zoning affect urban growth prediction accuracy and projected urbanized patterns? and (2) Which zoning scheme would allow the urban growth model to generate more accurate outcomes? The findings of this study provide a valuable reference for addressing zoning information in urban growth simulations and informing future urban planning and zoning policies.

2. Study Area

The study area represents a portion of Jinan, the capital city of Shandong Province in China. Jinan lies between Taishan Mountain to the south and the Yellow River to the north (Figs 1 a, b). The metropolitan area covers 8,117 km^2 and comprises seven districts—Shizhong, Tianqiao, Lixia, Huaiyin, Licheng, Changqing, and Zhangqiu—and three counties—Pingyin, Jiyang, and Shanghe (Fig. 1c). Jinan has experienced rapid growth in its urban population along with an expansion of built-up land from 80.4 km^2 in 1949 to 383.3 km^2 in 2015 (Statistical Year Book of Jinan, 2015). By the end of 2015, the total population of Jinan was 7.13 million, of whom 4.84 million were urban residents. The city of Jinan formulated a primarily top-down regional planning strategy for 1996–2020 with the goal of promoting development toward the east, west, and north but restricting development toward the south owing to the presence of Taishan Mountain. More specific urban development plans were formulated in 2003, including development of a new district, old town renovation, and urban expansion toward both the east and west. As a result, the city of Jinan now comprises a central city and five development planning areas—East Metro, West Metro, Jibei Metro, the airport development zone, and the southern mountain water conservation area (Jinan Municipal Planning Bureau, 2006) (Fig. 1d). Rapid urban expansion in Jinan is closely related to economic development, land-use policies, and physiographic characteristics. Although the southern mountain area, serving as the water recharge area for the numerous springs in Jinan, has been designated a key protected region, the mountain area as a whole has witnessed massive urban expansion, which, in turn, has prompted an even stricter protection and development plan specifically targeting the southern mountain area and the springs in the city. In addition, Jinan has successively implemented a series of urban renewal projects and plans to create new districts. This planning has collectively affected the magnitude and direction of urban growth. In this study, we will specifically target an area of approximately 3,446 km^2 that includes the six districts under the jurisdiction of Jinan and the Jibei metropolitan area in which the government and urban planners have implemented different development policies that can affect future urban development (Fig. 1d).

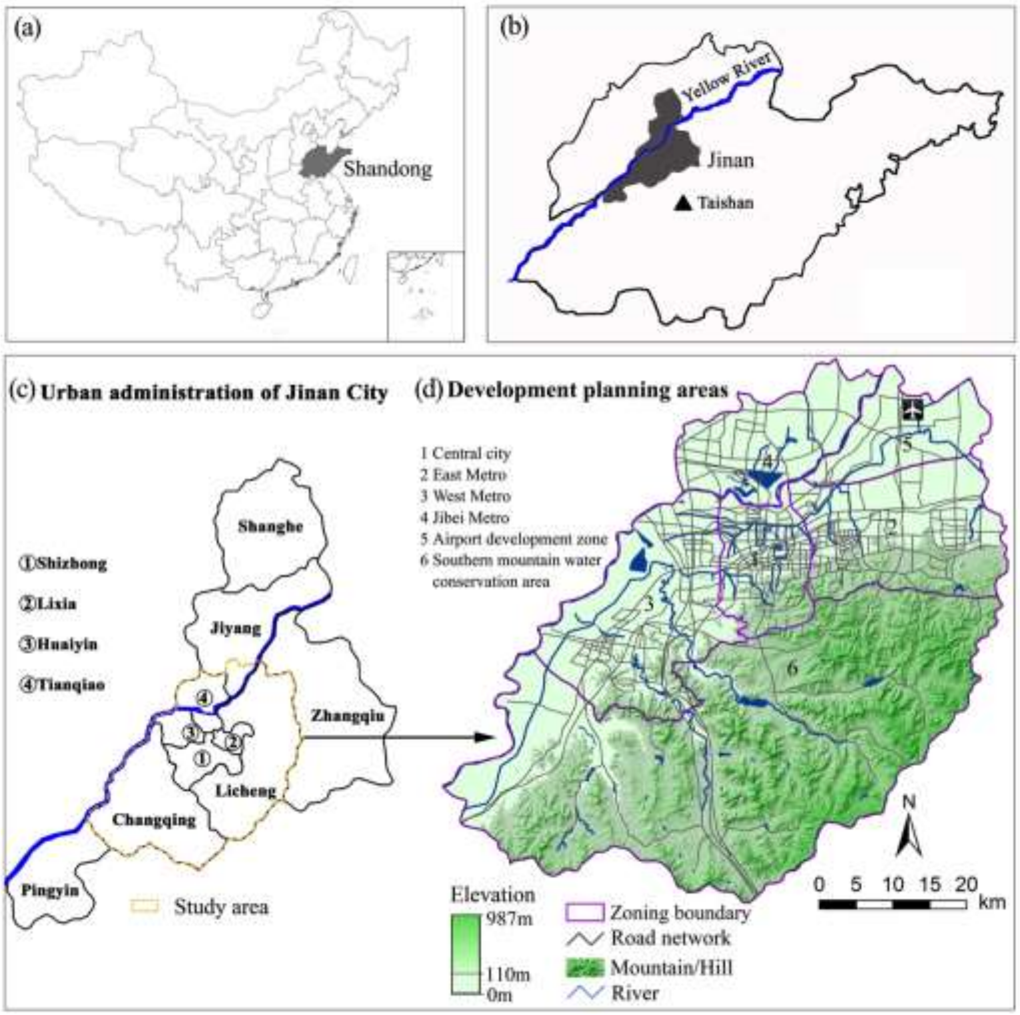

Fig. 1 Location of the study area

3. Research Methods

3.1. Data acquisition and preprocessing

As mentioned earlier, the SLEUTH model was used to explore the impacts of zoning scenarios on urban growth simulations. This process involved the use of several datasets during various stages of model implementation: Landsat Thematic Mapper (TM) images collected in April 1996, July 2001, May 2006, and June 2011; Landsat 8 Operational Land Imager (OLI) images collected in May 2016 (which were used for validation only); topographic maps at 1:50,000; and various urban planning documents from the Jinan five-year development plans (1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2016–2020) and Jinan master plans (2006–2020 and 2016–2020).

Data preprocessing was conducted as follows. First, a geometric correction procedure was applied to the remote sensor images with root mean square (RMS) errors of less than one pixel. In this procedure, the cubic convolution method was used for intensity interpolation between ground control points (GCPs) selected uniformly across the study area. Second, each image was clipped using the study site boundary and a supervised classification method was used to derive an urban extent map from each of the Landsat TM and OLI images (Fig. 2). The overall classification accuracy was found to be 93.2% as determined by error matrices and the Kappa index was found to be 0.91. Finally, a road network dataset comprising an updated road map for each of four different years, i.e., 1996, 2001, 2006, and 2011, was generated by manually digitizing the roads visible in each TM image (Fig. 3).

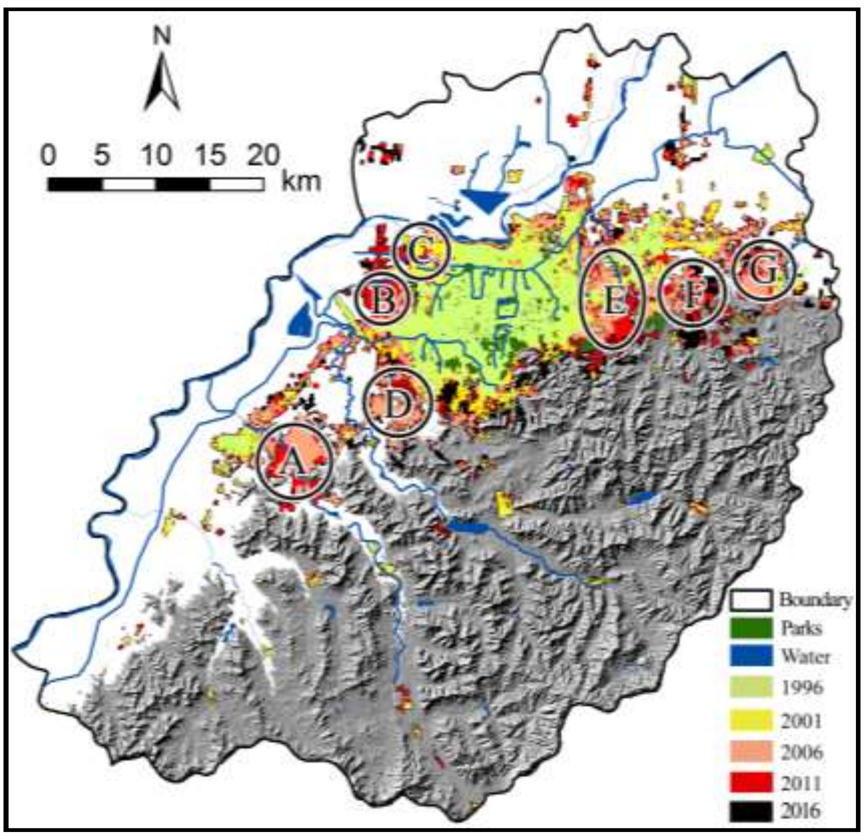

Fig. 2 Spatial growth of urban extent in Jinan from 1996 to 2016. A-G: components of urban growth regions

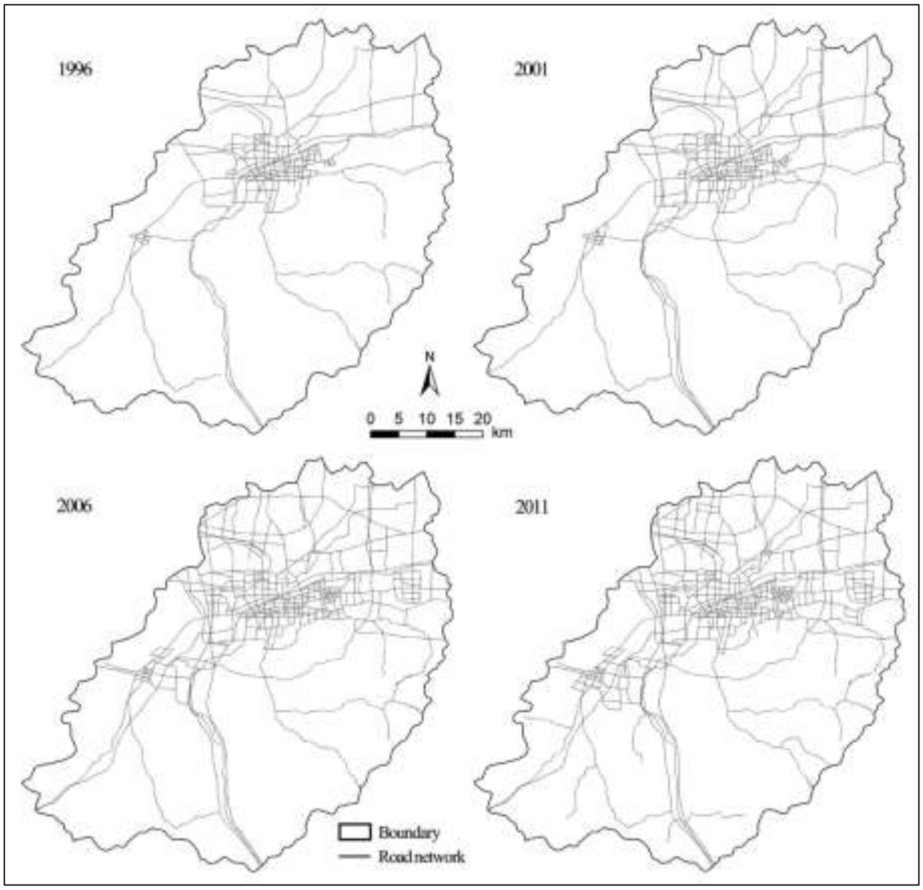

Fig. 3 Road network maps for 1996, 2001, 2006, and 2011

3.2. Model input

To run the SLEUTH 3.0 model, five data layers are required as inputs: urban extent, transportation, slope, hillshade, and an exclusion layer. In this study, the urban extent layer was a binary raster of urban and nonurban land use derived from the TM images (Fig. 2). The roads (transportation) were not weighted following Chaudhuri and Clarke (2013), who found no significant difference in results from road weighting. The slope and hillshade layers were generated from a digital elevation model (DEM) (Fig. 4), with the slope expressed as a percentage representing the ratio of vertical to horizontal change and cells with slopes greater than 100% (out of a possible slope index from 0 to ∞) assigned slope values of 100. The exclusion layer was defined based on specific scenarios discussed in Section 3.3. Finally, as required by the model all data were converted to GIF format with a cell size of 60 m × 60 m.

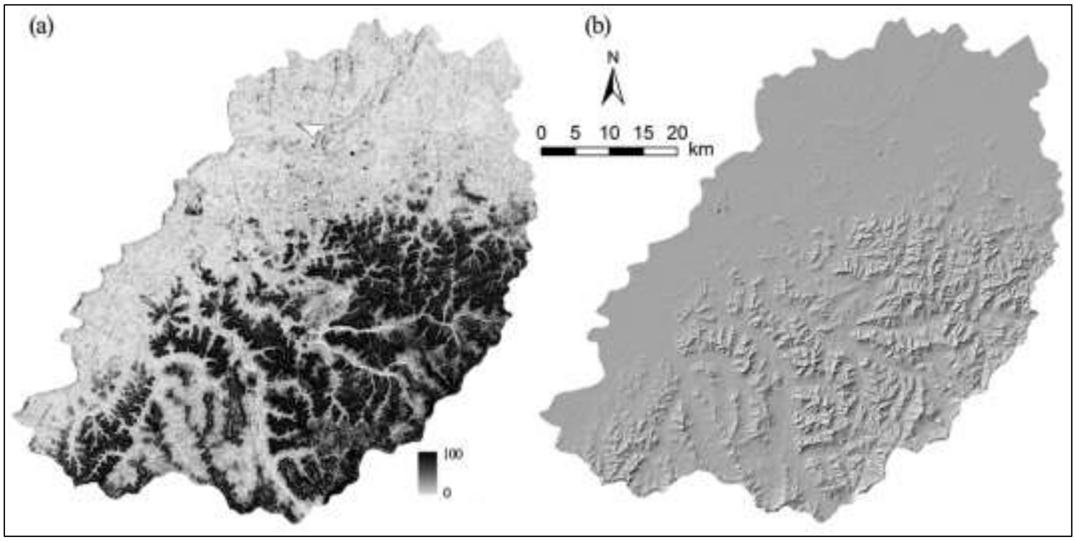

Fig. 4 Two model input layers: slope (a) and hillshade (b)

3.3. Zoning scenarios

The SLEUTH model predicts future urban growth and land cover changes by modifying internal parameters or manipulating the exclusion layer in historical data. In this manner, SLEUTH can be used to support urban planning activities (Clarke et al., 1997, Clarke and Gaydos, 1998; Silva and Clarke, 2002; Jantz et al., 2003, 2010). The ability to relate the exclusion layer to specific land-use or policy constraints based on the integration of geographic information systems with remote sensor data is considered to be another important advantage of the SLEUTH model (Jantz et al., 2003).

In China, the top-down approach has been widely used in urban and regional planning, which can significantly affect urban growth patterns (Long et al., 2012; Tian and Shen, 2011), as is further discussed in the context of Jinan in Section 4.1. To explore the possible impacts of various zoning methods on urban growth simulation, we specifically designed five different zoning scenarios and prepared an exclusion layer for each of them.

3.3.1 Scenario S0: No zoning

Scenario S0 (no zoning) served as a benchmark for examining the potential impacts of specific land-use and development policies on urban growth simulations based on a comparison of its outcomes with those of other scenarios. For S0, an exclusion layer comprising large water bodies and parks (Figs. 2 and 5a) with assigned attribute values of 100 (complete preservation) was created, following the methodology of previous studies (e.g., Silva and Clarke, 2002; Rafiee et al., 2009; Akın et al., 2014).

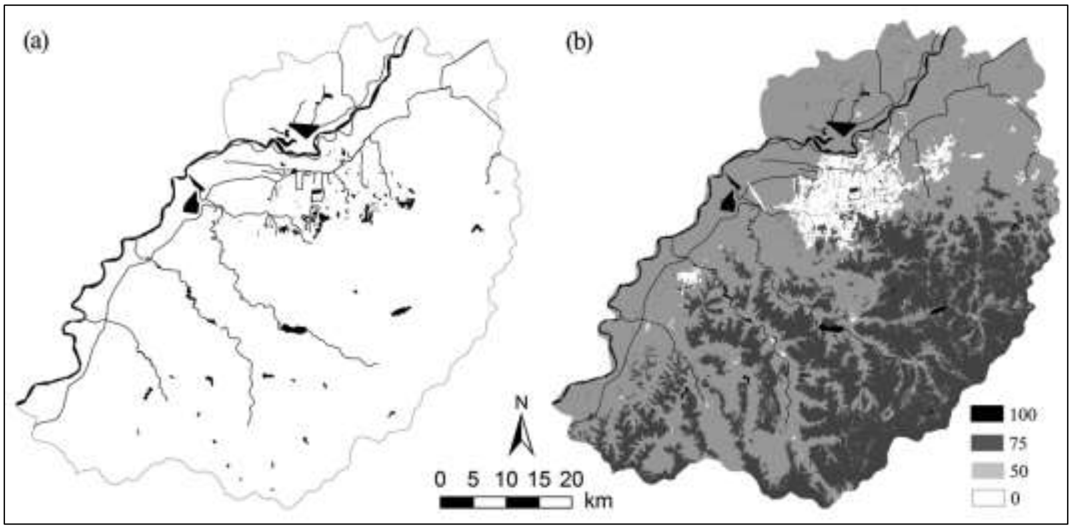

Fig. 5 Exclusion layers used for Scenarios S0 (a) and S1 (b). Note that pixels with the attribute value of 100 represent completely excluded areas

3.3.2 Scenario S1: Zoning based on land-use type

Zoning scenario S1 was designed to address the possible impacts of land-use policies by assigning specific values to different land uses. For example, forest land was assigned a higher value as it is generally more protected. User-defined options have often been used to valuate specific land-use types and design exclusion layers (e.g., Jantz et al., 2003, 2010; Berling-Wolff and Wu, 2004; Rafiee et al., 2009; Akın et al., 2014) even when zoning is not explicitly mentioned. An exclusion layer was also generated as a user-defined option for S1 based on data on land-use in 1996. Under S1, an attribute value of 100 was assigned to large water bodies and parks (as under S0) and values of 75, 50, and 0 were assigned forests, agricultural areas, and areas with no preservation rules, respectively (Fig. 5b). However, the scenario did not consider development policies among different regions or spatial locations within a given land-use type.

3.3.3 Scenario S2: Zoning based on urbanization suitability

Zoning scenario S2 was based on the evaluation of urban growth suitability in terms of both the impacts of land use and urban development policies related to protecting important natural and ecological spaces and regional differentiation of urban growth potential owing to accessibility. This methodology for designing exclusion layers was also used in a number of previous studies regarding smart-growth (e.g., Jantz et al., 2010; Mahiny and Clarke, 2012) or ecologically sustainable development scenarios (e.g., Jantz et al., 2003; Rafiee et al., 2009; Yin et al., 2015).

The exclusion layer under S2 was generated using a multi-factor overlay analysis of eight thematic layers (Table 1), which were assumed to be the primary factors affecting land suitability for urban growth based on situation within the study area and data availability as well as from reference to previous studies (e.g., Mahiny and Clarke, 2012; Yin et al., 2015). The analytical hierarchy process (AHP) method (Saaty, 1980) was used to weight the thematic factors (Table 1). As factor five (proximity to rivers and water bodies) was a constraining factor, the minimum overlay method was specially adapted to combine it with the other seven weighted factors.

Table 1 Data layers used in the multi-factor overlay analysis for urbanized suitability assessment and weights assigned to each of the seven factors

No.	Factor	Weight
1	Slope	0.114
2	Relief	0.114
3	Land use	0.051
4	Forest density	0.052
5	Proximity to rivers and water-bodies	–
6	Accessibility to urban edges	0.223
7	Accessibility to city centers	0.223
8	Accessibility to planned new district centers	0.223

Note: the “proximity to rivers and water bodies” was set as constraining factor

Topographic slope and relief are two important factors affecting urbanized suitability. In this study, areas with slopes greater than 25% and/or reliefs of more than 40 m were considered unsuitable for development and were assigned a value of zero. The values of other areas were linearly fuzzified using a monotonically decreasing trend and normalized to a scale from 0 (least suitable) to 100 (most suitable) (Fig. 6a, b). Fuzzy values for the five land-use categories were defined through a user-defined option. To maintain consistency with the Scenario S1 schema, attribute values of 0, 25, 50, and 100 were assigned to large water bodies and parks, forests, agricultural areas, and areas that were absolutely suitability for urban growth, respectively (Fig. 6c). The normalized difference vegetation index (NDVI) was used to represent forest density, with NDVI values greater than 0.45 assigned a value of 0, indicating an absolutely protected area that should not be used for urban development, and those with NDVIs of less than 0.45 assigned a value of 50 (Fig. 6d).

As a constraint factor, the distances to rivers and water bodies were also weighted through a user-defined option. To protect water resources and riparian vegetation and prevent flood damage to settlements, all rivers and water bodies and their respective buffer zone areas (200 m from the Yellow River and 100 m from all other rivers and water bodies) were assigned a value of zero, indicating restricted areas that were not suitable for urban growth.

Accessibility to urban edges, urban centers, and planned new district centers are important driving factors for urban growth (Hansen, 1959; Geurs and Van Wee, 2004). In this case, accessibility can be defined as “the ease with which any land-use activity can be reached from a location using a particular transport system” (Dalvi and Martin, 1976), which can be easily calculated using the cost-distance method by any GIS software package such as ArcGIS (e.g., Kong et al., 2012). In this study, travel speed was defined as 40 km per hour and cost-distance as 15 min/10 km along all types of road in the road network. Areas with no roads were defined as walking networks and assigned cost values according to three categories: rivers and water, 1,000; mountains, 500; and others, 120. Three different levels of accessibility were also identified. If an area’s accessibility to urban edges or planned new district centers was less than 10 min and that to urban centers was less than 30 min, it was assigned 100 to indicate highest suitability. Similarly, if the urban edge/planned new district center and urban center accessibilities were within 10–30 and 30–60 min, respectively, the accessibility values were linearly fuzzified using a monotonically decreasing trend and normalized to 25–100. Accessibilities to urban edges and planned new district centers urban centers greater than 30 and 60 min, respectively, resulted in an assigned value of 25 (low suitability) (Fig. 7a, b, c).

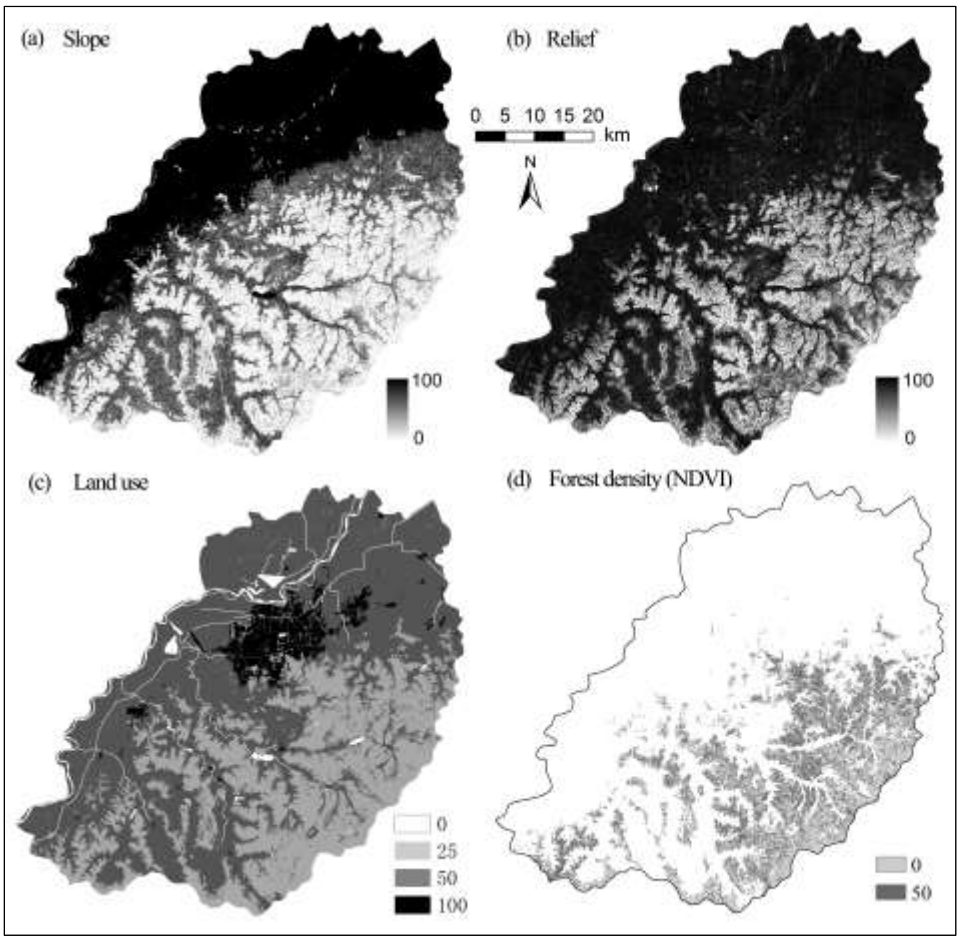

Fig. 6 Four factors used in multi-factor overlay analysis for urbanized suitability assessment

To yield an urbanized suitability map, an overlay operation was used to sum the weighted factors. As the highest suitability corresponded to the lowest value in the excluded layer, the values of urbanized suitability were, therefore, reversed with respect to the values in Scenario S1 (Fig. 7d).

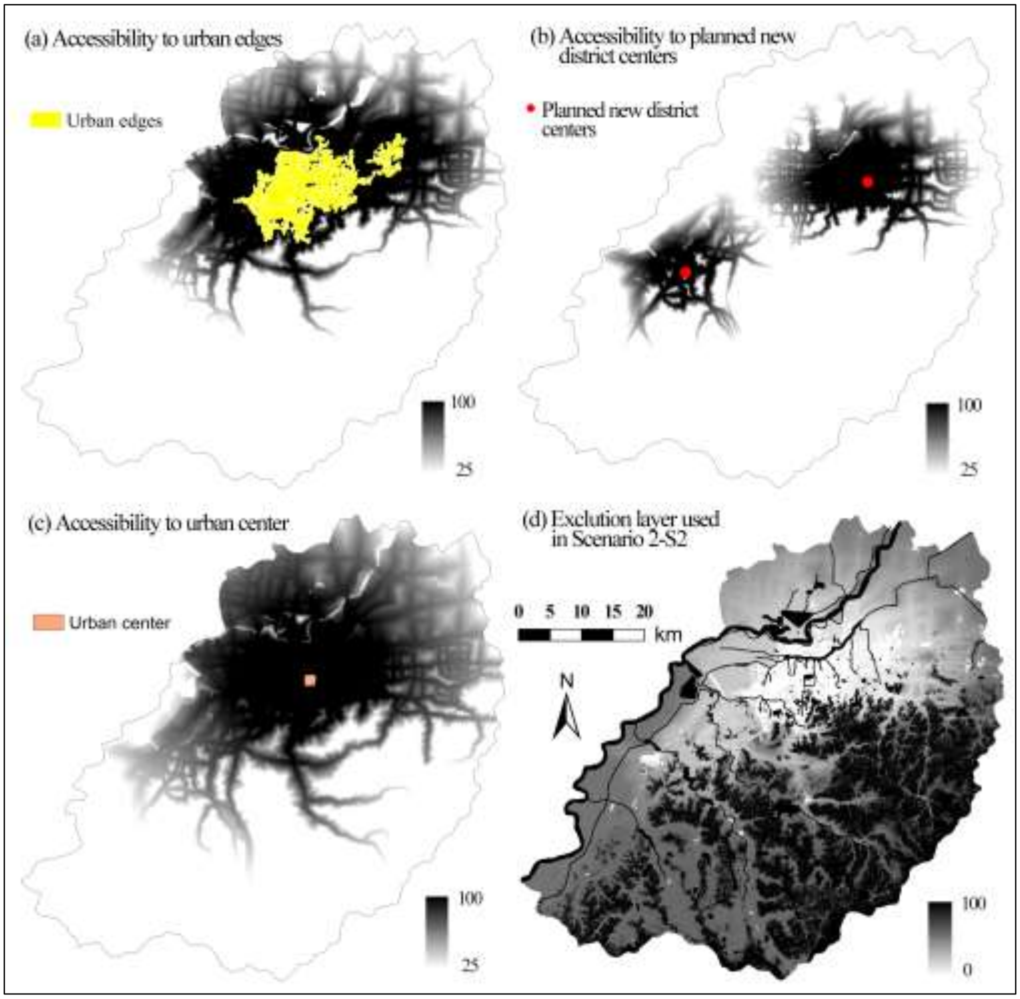

Fig. 7 Accessibility factors used in multi-factor overlay analysis for urbanized suitability assessment and the exclusion layer used in Scenario S2

3.3.4 Scenario S3: Zoning based on administrative division

Zoning scenario S3 was used to assess urbanized suitability and the potential impacts of development policies on different administrative divisions. Different top-down development policies can result in different urban growth patterns (Yu and Ng, 2007); in this study, a development policy impact coefficient layer was created to represent such impacts, and the exclusion layer in Scenario S3 was derived by combining the urbanized suitability layer derived for Scenario S2 with this policy impact coefficient layer.

The study area was first subdivided based on the present administrative divisions. As some administrative divisions in downtown Jinan had already become completely urbanized and were mostly adjacent to each another, these divisions were grouped into one division, resulting in a study area comprising sixty divisions (Fig. 8a). To create the development policy impact coefficient layer, the respective policies related to the expansion of urban land use were first categorized. The primarily executive urban and regional development policies in Jinan are listed in Table 2. These policies were then divided into four different levels (national, provincial, municipal, district or below) and assigned the user-defined values of 1.45, 1.30, 1.15, and 1.00, respectively (Table 2). Finally, urban growth areas were classified and assigned zoning values by policy level to create the development policy impact coefficient layer. Using this layer, the development policies in different administrative divisions could be evaluated with respect to specific policy level (Fig. 8a).

A policy-restricted urban growth suitability layer for Scenario S3 was generated by multiplying the urbanization suitability layer values for Scenario S2 with those of the respective administrative division-based development policy impact coefficient layer areas (with all of the resulting values larger than 100 set to 100). The values in the resulting layer were then reversed to generate the final exclusion layer for Scenario S3 (Fig. 8b).

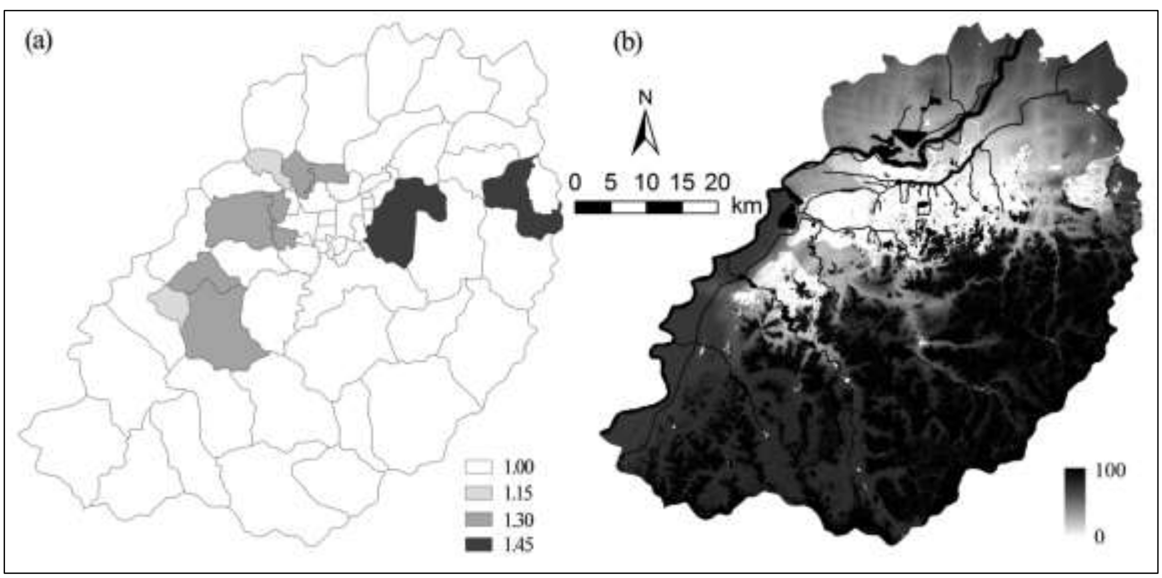

Fig. 8 Administrative division-based development policy impact coefficient layer (a) and exclusion layer used in Scenario S3 (b). Note that pixels with attribute values of 100 represent completely excluded areas

Table 2 List of major urban and regional development policies for Jinan since 1996 and their respective policy levels

No.	Policy	Policy makers	Policy level	Weighted value
1	Jinan high and new technology industrial development zone (1991–-)	Shandong provincial government (National level)	National	1.45
2	Jinan Economic Development Zone (1999–)	Shandong provincial government (Provincial level)	Provincial	1.30
3	Jinan ninth five-year development plan (1996–2000)	Jinan development and reform commission, Jinan Municipal government	Municipal	1.15
4	Jinan master planning (1996–2010)	Jinan municipal planning bureau	Municipal	1.15
5	Jinan big changes in five years (1997–2002)	Shandong provincial government Jinan municipal government	Provincial	1.30
6	Jinan tenth five-year development plan (2001–2005)	Jinan development and reform commission, Jinan Municipal government	Municipal	1.15
7	Jinan master planning (2006–2020)	Jinan municipal planning bureau	Municipal	1.15
8	Jinan eleventh five-year development plan (2006–2010)	Jinan development and reform commission, Jinan Municipal government	Municipal	
9	Jinan twelfth five-year development plan (2011–2015)	Jinan development and reform commission, Jinan Municipal government	Municipal	1.15
10	The main function zoning in Shandong province (2013)	Shandong provincial government Shandong provincial development and reform commission	Provincial	1.30
11	Jinan thirteenth five-year development plan (2016-2020)	Jinan development and reform commission, Jinan Municipal government	Municipal	1.15
12	Jinan master planning (2016–2020)	Jinan municipal planning bureau	Municipal	1.15
13	The ecological protection red line planning in Shandong province (2016–2020)	Shandong provincial government Environmental protection bureau of Shandong Province	Provincial	1.30

*Note: A series of district or below level policies were published in the past few years and have been weighted as “1” for this study.

3.3.5 Scenario S4: Zoning based on development planning subdivision

Zoning scenario S4 was developed as an extension of Scenario S2 to reflect the potential impacts of development policies on different planning subdivisions (functional groups). A detailed planning scheme (Jinan Municipal Planning Bureau, 2006) defines six major functional areas in Jinan, namely, the central area, the East Metro district, the West Metro district, the Jibei Metro district, the airport development zone, and the southern mountain ecological conservation district (Fig. 1d). The scheme also specifies eighty-four functional groups (Fig. 9a). Scenario S4 incorporates subdivisions additional to those in Scenario S3, particularly in the urban development planning area, i.e., the East Metro, West Metro, and Jibei Metro districts (Fig. 8a, Fig. 9a). The same data processing procedure used in Scenario S3 was used to create S4, with the generation of a functional group-based development policy impact coefficient layer (Fig. 9a) followed by the generation of an exclusion layer (Fig. 9 b).

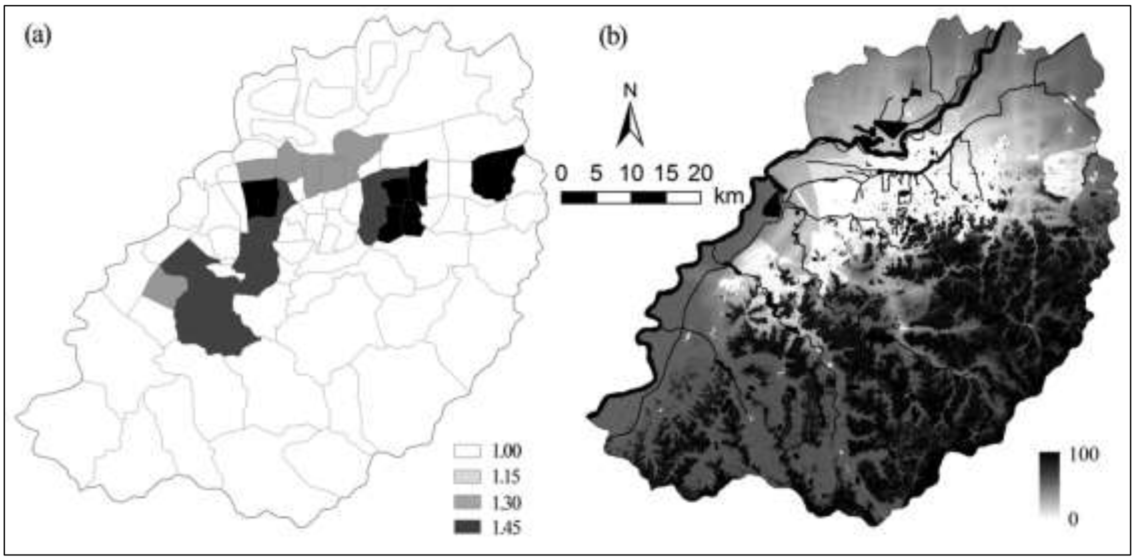

Fig. 9 Functional group-based development policy impact coefficient layer (a) and exclusion layer used in Scenario S4 (b). Note that pixels with attribute values of 100 represent completely excluded areas

3.4. Model calibration

Urban model calibration is carried out to obtain sets of parameters that can be used to accurately reproduce historical urban growth, which in turn enables the simulation of future urban growth in support of land-use planning activities (Dietzel and Clarke, 2007; Akın et al., 2014). The success of model simulation depends significantly on the calibration process (Silva and Clarke, 2002). In this study, a brute-force Monte Carlo method was used for model calibration in a three-step process of coarse, fine, and final calibration. The set of growth coefficients obtained in each step was used as input for the calibration in the next step, which progressively narrowed the range of each parameter. Each calibration involved several Monte Carlo experiments. Although comparison of experimental results such as these with data generated from remotely sensed images can generate series of statistics to quantify simulation accuracy, there remain controversies over which indices can best characterize the accuracy of a model (Clarke et al., 1997; Silva and Clarke, 2002; Herold et al., 2003; Jantz et al., 2003; Onsted and Chowdhury, 2014). Here, the Optimal SLEUTH Metric (OSM), representing the product of seven metrics—Compare, Pop, Edges, Cluster, Slope, Xmean, and Ymean—was used for model calibration (Table 3). The selection of metrics was largely based on the research conducted by Dietzel and Clarke (2007), who found that these metrics are weakly correlated and can be used to quantify model simulation accuracy.

Table 3 Description of metrics used for evaluation of the calibration results (Dietzel and Clarke, 2007).

Metric name	Description
Compare	Comparison of modeled final urban extent to real final urban extent
Pop	r^2 Population: Least-squares regression score of modeled urbanization compared with actual urbanization for control years
Edges	Edge r^2: Least-squares regression score for modeled urban edge count compared with actual urban edge count for control years
Cluster	R^2 cluster: Least-squares regression score of modeled urban clustering compared with known urban clustering for control years
Slope	Average slope r^2: Least-squares regression of average slope of modeled urbanized cells compared with average slope of known urban cells for control years
Xmean	X- r^2; Center of gravity [X]: Least-squares regression of average X values for modeled urbanized cells compared with average X values of known urban cells for control years
Ymean	Y- r^2; Center of gravity [Y]: Least-squares regression of average Y values for modeled urbanized cells compared with average Y values of known urban cells for control years
OSM	Optimal SLEUTH Metric, the product of the preceding seven indices

The 1996 data were used as the initial layers, while the existing urban extents of 2001, 2006, and 2011 were used for model calibration. Coefficient calibration was carried out under the five designed scenarios using their respective exclusion layers. During the coarse and fine calibration steps, data were resampled into 240 m × 240 m and 120 m × 120 m pixels using five and seven Monte Carlo iterations, respectively. The OSM was calculated in each phase of the model calibration, with the results with the ten highest OSM values selected to determine the optimum combination of the five coefficients for narrowing down the coefficient range, thereby generating five new coefficient ranges. In the final calibration, nine Monte Carlo iterations were performed to extract the five optimum coefficient combinations with the highest OSM values, after which the command "Derive" was executed with a step length of one. One hundred Monte Carlo iterations were used to generate the five final coefficients.

The final calibrated coefficients were then used to initialize the prediction module and generate a simulated urban development probability map for 2011. The urbanization thresholds on the probability maps under the respective scenarios were set based on the fact that the urban land use had increased by 285.89 km^2 during 1996–2011, so any cells with probabilities greater than this threshold value were considered to be the urban areas. To quantify the model simulation accuracy, a comparative analysis between the simulated and remote sensing-derived 2011 urban extent was performed on a pixel scale.

3.5. Model predictions and validation

The model predictions based on the exclusion layers under Scenarios S1–S4 were validated against the 2011 urban land-use map (Fig. 10) (under Scenario S0, the exclusion layer remained unchanged from that in the actual map). Using the 2011 urban extent, exclusion layers, slope gradients, hill shading, and 2011 and 2030 roadway networks as initial input data, 100 Monte Carlo iterations were performed in the model's prediction mode. The method described in Section 3.4 was then used to obtain urban growth simulation results for 2016 and 2040 under the five specified scenarios. The thresholds (88% for S0, 30% for S1, 75% for S2, and 85% for S3 and S4) used in the urbanization probability maps for these scenarios were the same as those in the model calibration stage and were used to reconstruct the urban extent in 2016 and 2040. To examine the zoning scenario impacts, the predicted 2016 maps under the respective scenarios were compared with the 2016 urban extent map derived by remote sensing.

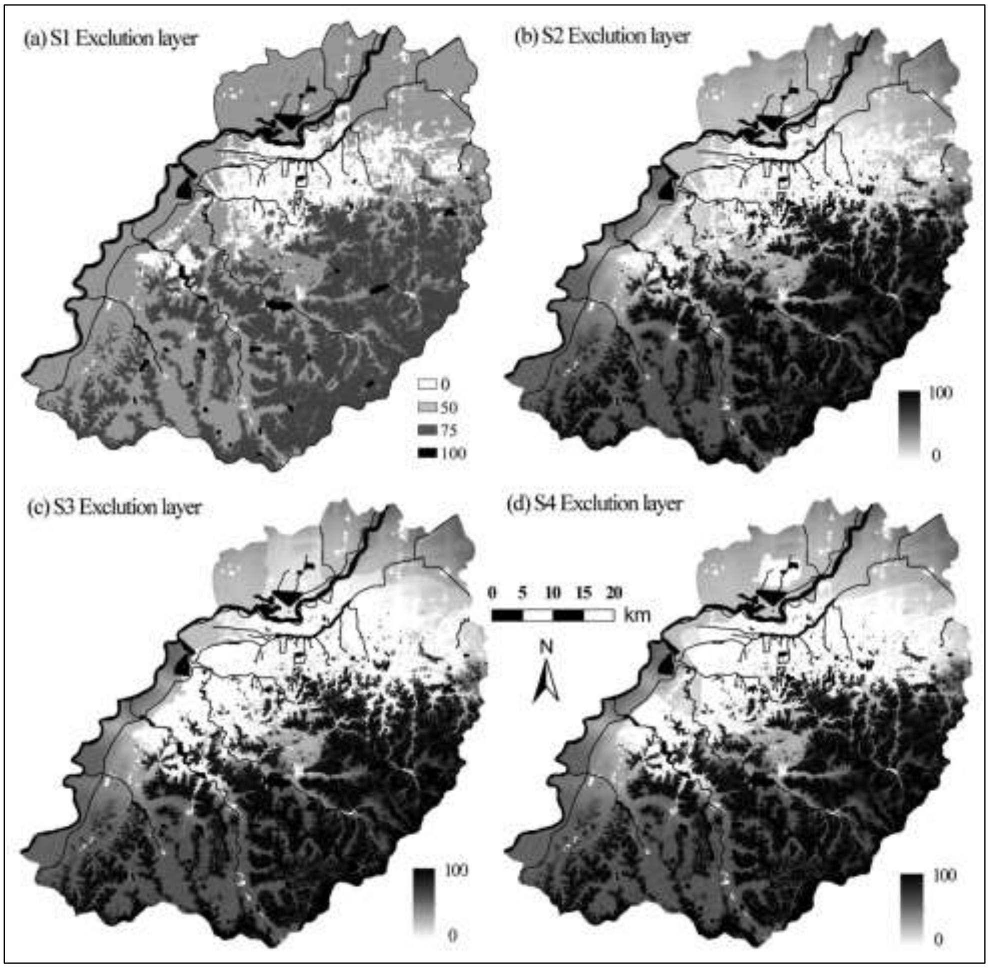

Fig. 10 Exclusion layers used for simulations under Scenarios 1–4. Note that pixels with attribute values of 100 represent completely excluded areas

4. Results

4.1. Historical urban growth during 1996–2016

The urban extent in the study area grew rapidly from 1996 to 2016 (Fig. 2). During 1996–2001, the urban expansion primarily involved sprawling and infilling (new growth occurring through infilling of free spaces within the developed area) growth at the urban edges. Note that there was nearly no growth in the urban center, primarily because of the implementation of the "Great Changes of Jinan in Five Years" policy (1997–2002) that aimed to enhance the old town and improve the city center environment (Jinan Municipal Planning Bureau, 1997). During 2001–2006, the rapid urban growth primarily occurred in the centers and edges of the new urban areas. For example, in Fig. 2 regions A, D, F, and G exhibit generally spread patterns of these new growth centers, whereas B, C, and E show typical edge-growing patterns. These regions all correspond to the functional groups identified in the Development Plans for the East Metro and West Metro districts since 2003. During 2006–2016, urban growth again comprised primarily edge sprawling and infilling in the newly developed district centers (A–G). These newly developed urban centers saw a rapid development of road networks and accessibility as a result of policy support. The historical urban growth progress appears to be closely related to the development policies. The 2011–2030 Jinan master plan specified the promotion of development in the East Metro and West Metro districts, the Jibei Metro area, and the airport development district; these areas are likely to be the primary urban growth areas, and the new planning policies are likely to induce a resumed period of rapid urban growth in Jinan.

4.2. Model calibration results under different scenarios

The data in Table 4 show that each of the seven calibration metrics for the five scenarios is above 0.79, indicating an overall satisfactory simulation performance. The OSM metrics from Scenarios S0 to S4 gradually increase, indicating an improving overall simulation performance, although the improvements among S2, S3, and S4 are all quite limited. The Xmean and Ymean metrics of Scenarios S2, S3, and S4 are significantly higher than those for S0 and S1, indicating better performance in simulating the final urban spatial distribution. The Cluster and Edge metrics increase from Scenarios S0 to S4, indicating that the urban cluster and edge development are also well simulated. The variations seen in the calibration metrics suggest that zoning can affect overall simulation accuracy.

Table 4 Summary of calibration metrics for different scenarios

Scenarios	**Calibration metrics**							
	Compare	Pop	Edges	Cluster	Slope	Xmean	Ymean	OSM
S0	0.8183	0.9426	0.8807	0.8790	0.9664	0.8144	0.8105	0.3809
S1	0.8174	0.9368	0.8807	0.8807	0.9413	0.8815	0.7933	0.3916
S2	0.8018	0.9219	0.9100	0.9089	0.9108	0.8766	0.9982	0.4872
S3	0.8184	0.9192	0.9147	0.9139	0.9278	0.9009	0.9280	0.4877
S4	0.8342	0.9194	0.9175	0.9126	0.9250	0.9017	0.9181	0.4957

The final calibration coefficients differ significantly among the five scenarios (Table 5). Each of the diffusion coefficient values exceeds 98, indicating a clear spontaneous growth pattern. The breed coefficient for Scenario S0 is 48, as compared to 90 and 96 for Scenarios S3 and S4, and 100 for Scenarios S1 and S2, respectively. This indicates that zoning affected the simulation results in terms of growth of new urban centers. Each of the spread values is greater than 85, indicating that the simulations all accurately captured edge growth. The slope coefficient value in Scenario S0 is 21 but is 1 for the other four scenarios, suggesting that slope had a limited impact on urban growth, which is potentially partially attributable to the fact that, during 1996–2011 most urban growth occurred in low slope areas or because the impact of terrain had been considered in generating the exclusion layers. The road gravity coefficient values are all larger than 56, indicating that the road network significantly affected urban growth. However, the values gradually decrease from Scenarios S0 to S4, suggesting that zoning weakened road-influenced urban growth.

Table 5 Final coefficients for respective scenarios

Scenarios	Diffusion	Breed	Spread	Slope	Road gravity
S0	98	48	95	21	90
S1	100	100	85	1	89
S2	100	100	100	1	85
S3	100	90	100	1	61

S4	100	96	100	1	56

Table 6 Accuracy assessments of 2011 predictions under different scenarios

Scenarios		Nonurban	Urban	New urban	Overall accuracy (%)
	Status as of 2011	826200	131060	79414	–
S0	Modeled pixels	826708	130552	78906	–
	Number of correct pixels	775769	80137	28491	89.41
	Producer accuracy (%)	93.89	61.15	35. 88	–
	User accuracy (%)	93.84	61.38	36.11	–
S1	Modeled pixels	826419	130841	79195	–
	Number of correct pixels	774356	78956	27310	89.14
	Producer accuracy (%)	93.73	60.24	34.39	–
	User accuracy (%)	93.70	60.34	34.48	–
S2	Modeled pixels	821302	135958	84312	–
	Number of correct pixels	781716	91490	39844	89.90
	Producer accuracy (%)	94.62	69.81	50.17	–
	User accuracy (%)	95.18	67.29	47.26	–
S3	Modeled pixels	826853	130407	78761	–
	Number of correct pixels	789028	93156	41510	92.16
	Producer accuracy (%)	95.50	71.08	52.27	–
	User accuracy (%)	95. 43	71.43	52.70	–
S4	Modeled pixels	825639	131621	79975	–
	Number of correct pixels	789553	93990	42344	92.19
	Producer accuracy (%)	95.56	71.72	53.32	–
	User accuracy (%)	95.63	71.41	52.95	–

Comparative analysis at the pixel level between the simulated 2011 urban extent and the urban extent derived from remote sensing reveals overall accuracies of above 89% for all scenarios, with a small but persistent increase from Scenarios S0 to S4 (except for Scenario S1) (Table 6). The results indicate that the model performed better under zoning scenarios S2, S3, and S4 than under the non-zoning (S0) or simplified zoning (S1) scenarios. Except for Scenario S1, the producer accuracy increases by 10.57% from S0 to S4, with the user accuracy following a similar trend. However, the simulation accuracy for predicting newly urbanized pixels between 1996 and 2011 increases by only about 17% from S0 to S4, suggesting that the zoning scheme based on land-use type (S1) barely helped to improve the simulation accuracy, although the other three zoning schemes (S2–S4) did help boost the model's capability in this regard. Nevertheless, it was still quite difficult to accurately model newly urbanized areas.

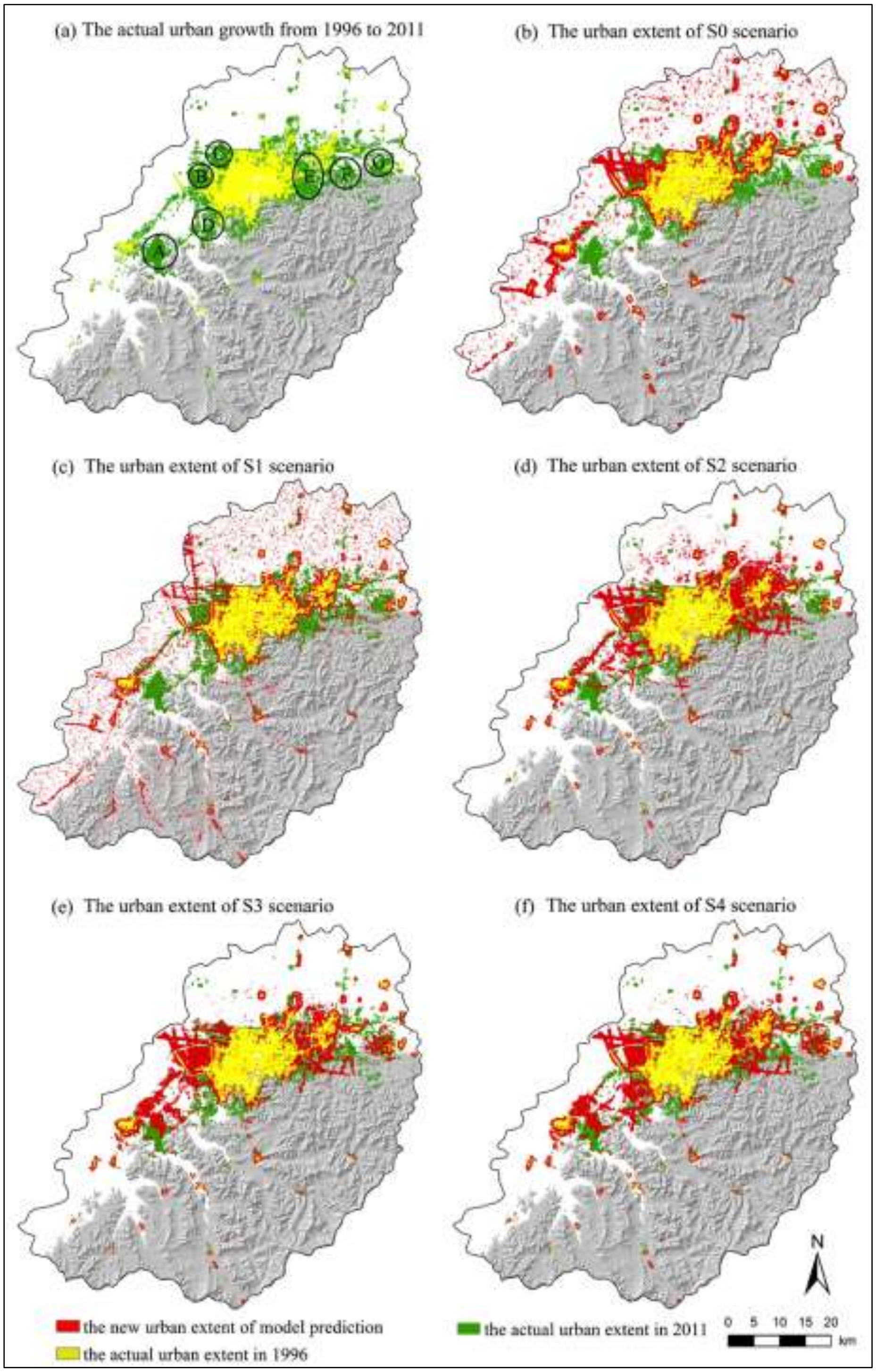

Fig. 11 Existing (a) and simulated (b-f) urban extents in 2011 under different scenarios.

Further comparison of the simulated and remote sensing-derived 2011 urban extent (Fig. 11) reveals that, under Scenarios S0 and S1, the model performed well in projecting urban growth along edges and roads but not very well in predicting clustered growth (Fig. 11b, c). This suggests that when zoning is not considered or is represented in a simplified manner (as in Scenario S1), it is difficult to accurately reproduce the clustered growth that can be spurred by urban development policies or strategies. Even though spatial growth along urban edges and roads remains the dominant pattern under zoning scenarios S2–S4, clustered growth and newly urbanized centers begins to rise in varied patterns across Regions A–G (Fig. 11d-f). For example, the clustered growth in Regions A, C, and G under Scenario S2 was much smaller than under Scenarios S3 and S4. Compared with the other scenarios, S3 and S4 yielded the most extensive clustered growth, closely matching the urban growth patterns revealed by remote sensing. This suggests that appropriate zoning schemes can help improve model performance in projecting the clustered urban growth that can be spurred by development policies and strategies.

4.3. Urban growth predictions under different zoning scenarios

Two snapshots (2016 and 2040) of predicted urban growth were generated and the remote sensing-derived and modeled urban extents of 2016 were compared to examine the impacts of zoning scenario on urban growth simulation accuracy. The 2016 simulation accuracies obtained using the selected metrics for the respective scenarios (Table 7) follow trends similar to those of 2011 (Table 6). Specifically, identical to the 2011 results a high level of overall accuracy (universally greater than 96%) was achieved by using the calibrated SLEUTH model to predict the urban growth in 2016 under each scenario. Except for Scenario S1, the overall accuracy gradually increased from Scenarios S0 to S4 (Table 7), suggesting that the model performed better under the latter three zoning scenarios than under the non-zoning (S0) or simplified (S1) zoning scenarios. The producer and user accuracies of the simulated non-urban and urbanized areas for 2016 were all higher than those for 2011 but lower for the simulated newly urbanized area (Tables 6, 7). A comparison of the 2011 and 2016 newly urbanized pixels (Fig. 12) reveals a decrease from 79,414 to 14,862 pixels over this period with a corresponding reduction in the number of clustered growth areas. The lower accuracy for the newly urbanized areas suggests that the simulation was more difficult for such areas than for other (non-urban and urban) areas. These results indicate that some newly urbanized areas developed primarily in conjunction with the implementation of urban planning policies, although the decrease in the impacts of zoning on projected urban growth might have contributed to the observed reduced producer and user accuracies.

Table 7 Assessment of the accuracy of 2016 predictions under different scenarios

Scenarios		Nonurban	Urban	New urban	Overall accuracy (%)
	Status as of 2016	811338	145922	14862	–
S0	Modeled pixels	817204	140056	8996	–
	Number of correct pixels	804080	132798	1738	97.87
	Producer accuracy (%)	99.11	91.01	11.69	–
	User accuracy (%)	98.39	94.81	19.32	–
S1	Modeled pixels	798999	158261	27201	–
	Number of correct pixels	788527	135450	4390	96.52
	Producer accuracy (%)	97.19	92.82	29.54	–
	User accuracy (%)	98.69	85.59	16.14	–
S2	Modeled pixels	804314	152946	21886	–
	Number of correct pixels	793864	135172	4112	97.05
	Producer accuracy	97.85	92.63	27.67	–
	User accuracy (%)	98.70	88.38	18.79	–
S3	Modeled pixels (%)	806193	151067	20007	–
	Number of correct pixels	795489	135218	4158	97.23
	Producer accuracy (%)	98.05	92.66	27.98	–
	User accuracy (%)	98.67	89.51	20.78	–
S4	Modeled pixels	806413	150847	19787	–
	Number of correct pixels	795702	135211	4151	97.25
	Producer accuracy (%)	98.07	92.66	27.93	–
	User accuracy (%)	98.67	89.63	20.98	–

The predicted urban extent for 2040 indicates that the simulated urban growth under Scenario S0 is primarily characterized by edge and infilling development (Fig. 12b), reflecting the patterns observed during the calibration stage. The model output map shows that the urban growth within Regions A–F, H, and I comprised primarily edge growth without significant clustered growth (Fig. 12b). This result might be related to the fact that the state of a cell within the SLEUTH model depends significantly on the state of its neighboring cells; thus, an existing urban cell will tend to expand outward rapidly, but the spread of new growth center tend to be slower (Akın et al., 2014; Jantz et al., 2003, 2010). Scenario S1 also shows an obvious edge growth pattern (Fig. 12c), which indicates that the model still cannot capture future clustered growth caused by regional differentiation of urban development policies despite the consideration of land-use type-based zoning.

The clustered growth in Zones A, B, F, and G under Scenarios S2, S3, S4 was significantly greater than under S0 and S1 (Fig. 12), indicating that the model is able to incorporate zoning information into urban development and differentiate urban growth within various zones accordingly. Relative to the other four scenarios, S4 produced the most clustered growth in Zone H (the center of the Jibei Metro area) (Fig. 12f), suggesting that zoning based on development planning can help effectively project clustered development stimulated by urban development policies and strategies.

The data in Fig. 13 indicate that the urban area is predicted to grow quickly during 2011–2040 under all five scenarios, with Scenario S0 producing among the fastest urban growth. Under this scenario, the urbanized area increases by 451 km^2 at an annual growth rate of 2.34%. By comparison, Scenario S4 produces the least urban growth, with an urbanized area increasing by only 377 km^2 at an annual growth rate of 2.05%. The projected urban growth areas under Scenarios S1–S3 are all slightly larger than under Scenario S4 and differ significantly from S4 during 2012–2020. This indicates that Scenario S0, which does not incorporate any zoning scheme, projects a higher rate of urbanization than Scenarios S1–S4. These findings suggest that designing specific zoning scenarios based on spatial differentiation and growth management policies can help not only in revealing the impacts of different zoning scenarios on urban growth simulation results but also improve performance in predicting future urban growth.

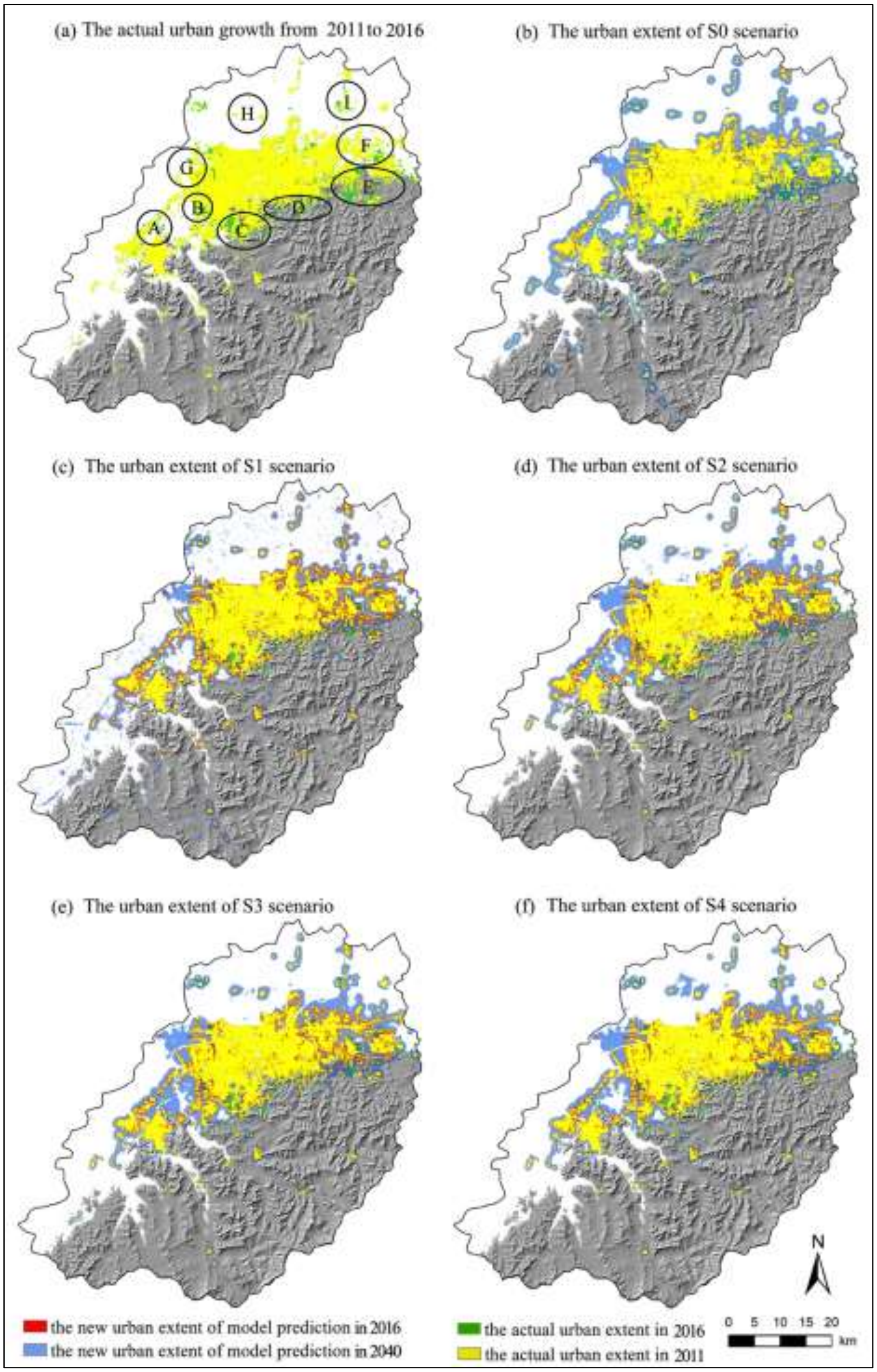

Fig. 12 Simulated urban extents in 2016 and 2040 under different scenario s: (a) actual and (b-f)

modeled urban growth.

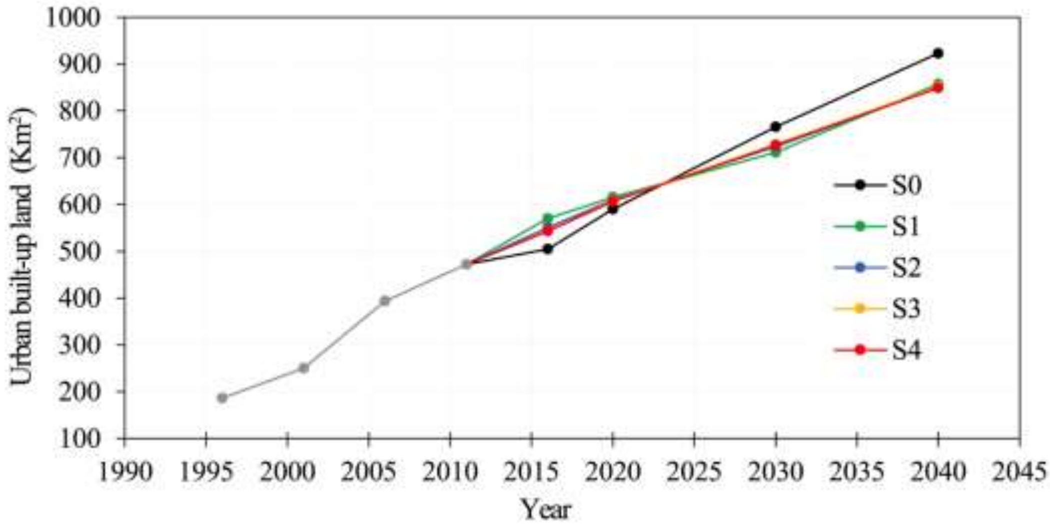

Fig. 13 Growth of urban built-up land during 2011–2040 under the five scenarios

5. Discussion and Conclusions

In this study, the city of Jinan, China was used as a case study to demonstrate the potential impacts of planning policies and strategies on urban growth prediction patterns and accuracy using a cellular-automaton-based urban growth model. To date, it has been difficult to integrate planning policies into the conversion rules used by the SLEUTH model (Torrens, 2011), and many case studies have indicated that this model could not effectively characterize the potential impacts of urban development policies on urban land use (Clarke et al., 1997; Silva and Clarke, 2002; Lahti, 2008; Wu et al., 2009). However, we found that using an appropriate method to incorporate zoning can help improve simulation accuracy and therefore the capability of simulating the effects of urban development policies (Chaudhuri and Clarke, 2013; Akın et al., 2014; Onsted and Chowdhury, 2014).

Four zoning scenarios (S1–S4,) as well as a scenario that did not include zoning (S0), were developed through the generation of different types of exclusion layers. The SLEUTH 3.0 model was used to simulate urban growth in 2011, 2016, and 2040 under various scenarios and the results were assessed at the pixel level. The main conclusions are as follows. (1) At the pixel level, overall accuracy is not quite meaningful in representing model accuracy; instead, producer or user accuracy of newly urbanized pixels might be more appropriate. (2) Incorporating planning policies into zoning information can help improve the prediction accuracy of newly urbanized pixels, better represent clustered development, and boost the level of spatial matching, while zoning based on land-use type does not offer such improvements. (3) Compared with the no-zoning scenario (S0), the scenario in which zoning was based on development planning subdivisions (S4) generated the largest improvement in the prediction accuracy, followed by scenarios S3, S2, and S1. Using the city of Jinan as a case study, the study demonstrated that more detailed (i.e., more finely divided) zoning, particularly in areas with high probability of urban growth, can yield more accurate predictions. The scenarios taking into account the spatial differentiation of development planning policies (S2–S4) generated better predictions than the scenario considering land-use type only (S1), as the former scenarios incorporated more finely divided zoning schemes. In a summary, incorporating zoning information based on spatial differentiation and growth management policies can help improve simulation accuracy and spatial matching degree, thus allowing the more accurate projection of urbanizing patterns through the use of appropriately designed zoning schemes.

Although a number of previous studies examined the impacts of zoning on simulation accuracy (e.g., White and Engelen, 1993; Berling-Wolff and Wu, 2004; Onsted and Chowdhury, 2014), the potential impact of different zoning schemes on simulation accuracy has not been thoroughly investigated. For example, Berling-Wolff and Wu (2004) considered agricultural land to be a separate category in simulating the urban landscape dynamics of the city of Phoenix in the United States in an approach similar to that used in other studies that did not consider zoning information (Jantz et al., 2003, 2010; Rafiee et al., 2009; Akın et al., 2014). Models in which various protection levels (or conversion probabilities) were assigned to different land-use types based on urban development policies have proven capable of capturing the spatial consequence of urban development policies. Onsted and Chowdhury (2014) considered three types of zoning, i.e., developmental, interim, and agricultural zoning, using various zoning assignment methods and evaluated the model accuracy variation in terms of the amounts or rates of urban growth under different assignment methods using the OSM metric. Unlike these previous studies, this study explored the impacts of several zoning schemes based on land-use type, urbanized suitability, administrative division, and planning subdivision (functional groups), with the prediction accuracy evaluated at the pixel level using the OSM metric. Our findings should be useful in improving the performance of urban growth predictions through the use of appropriately designed zoning scenarios.

However, several issues may require further attention. First, an alternative weighting method might help better capture the zoning information within a model, as the demand on urban land use in different areas often varies (Goldstein et al., 2004) and land-use change can be significantly influenced by local land-use policies. Under Scenarios S3 and S4, the development policy impact coefficient layer was used to indicate the impact of development policies on regional differences in urban growth using a user-defined option. However, the relationship among different levels of development policy is usually difficult to quantify precisely, and therefore the values of policies at various levels requires further testing. Second, further research is required on choosing an appropriate zoning scale, as this can significantly affect the simulation outcome. A study conducted by Wu et al. (2009) on the Shenyang Metropolitan area found that the SLUETH model did not perform well when modeling a zoning scheme with large administrative districts (~700 km^2). In our study, the use of more detailed zoning schemes in conjunction with development policy, such as the schemes in Scenarios S3 and S4 based on administrative districts (av. 57.43 km^2) and development functions (av. 41.02 km^2), respectively, helped boost the simulation accuracy. Similarly, the scheme used for S2 featuring more detailed zoning granularity but not considering spatial differences in development policy yielded moderate simulation accuracy. Thus, further research is needed to examine the development policy effects of scale on simulation accuracy through the application of measurable weighting methods under various zoning schemes.

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Table list

Figure list