Improving Urban Simulation Accuracy through Analysis of Control Factors: A Case Study in the City Belt along the Yellow River in Ningxia, China

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Abstract: Spatial heterogeneity of urban expansion and macro-scale influence of socioeconomic development are the two main problems in urban-expansion modelling. In this study, we used the SLEUTH-3r model to simulate urban expansion at a fine scale (30 m) for a large urban agglomeration (22000 km^2) in north-western China. Multiple spatial constraint factors were integrated into the model through Ordinary Least Regression and Binary Logistic Regression to simulate the spatial heterogeneity in urban expansion. A critical parameter—the diffusion multiplier (D_M)—was used to simulate the macro-scale influence of socioeconomic development in the urban model. These two methods have greatly enhanced the ability of the SLEUTH-3r model to simulate urban expansion with high heterogeneity, and adapt to urban growth driven by socioeconomic development and government policy.

1 INTRODUCTION

Urbanization, an unprecedented global phenomenon, has significantly altered natural landscapes and human lives (Zhang et al., 2012). Urban expansion, a significant performance of urbanization, has brought numerous threats to ecosystem, such as loss of natural resources (Delphin et al., 2016), climate change (Singh et al., 2017), and biodiversity decrease (Haase et al., 2012). Therefore, it is critical to predict urban expansion patterns for sustainable development, especially in metropolitan areas, which form the basic unit in future socioeconomic development (Poyil and Misra, 2015).

Urbanization is a dynamic process influenced by geophysical, environmental, demographic, and social factors at multiple scales (Akın et al., 2014). Complicated interactions between these factors, and associated temporal changes lead to spatial and temporal heterogeneity in urban expansion (Li et al., 2017). A number of techniques have been developed to simulate urban expansion, ranging from static models based on gravity theory and optimization mathematics to dynamic models (Berling-Wolff and Wu, 2004). In particular, the cellular automata (CA) model is widely used in urban simulation for its simplicity, flexibility, intuitiveness, and transparency in modeling complex systems (Santé et al., 2010).

However, the CA model often fails to capture the change magnitude of urban expansion driven by political and economic strategies (Qi et al., 2004). Despite its successful application in many cities, the SLEUTH model is also a CA model that fails to consider the macro-scale driving influence of socioeconomic development (Berberoğlu et al., 2016, Chaudhuri and Clarke, 2013). Since urbanization in China is highly driven by government policies, it is essential to integrate these macro-scale control factors into urban model.

The SLEUTH model has been always used to simulate urban land distribution in a single city at coarse resolution (Chaudhuri and Clarke, 2013), but not for large urban agglomerations consisting of several cities with high spatial heterogeneity (Jat et al., 2017). Several approaches have been developed to evaluate the effects of driving forces on urban expansion, such as binary (Haregeweyn et al., 2012), multiple linear (Gao and Li, 2011), and geographically-weighted regressions (Su et al., 2012), analytic hierarchy process (Thapa and Murayama, 2012), and logistic regression (Long et al., 2012). Among them, multiple linear and binary

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regression, both reliable and easy to manipulate, were selected to integrate multiple factors into the SLEUTH model to simulate urban spatial expansion with high heterogeneity (Liu et al., 2014).

To date, most of urban studies in China focused on fast-growing coastal and major interior cities; however, urban growth in inner northwestern China, especially in large urban agglomerations, has not been well described. Our study will help to bridge the gap, as the study area is a large city belt in northwestern China. The main objectives of our study were to: (1) identify factors that control urban expansion, and quantify their impacts, (2) simulate urban expansion with high spatial heterogeneity, and (3) integrate the macro-scale driving influence of socioeconomic development into model to simulate urban expansion with proper magnitude.

2 STUDY AREA AND METHODS

2.1 Study Area

The City Belt along the Yellow River in Ningxia (CBYN), located in northwestern China, is a large urban agglomeration consisting of four cities: Shizuishan, Yinchuan, Wuzhong and Zhongwei (Fig. 1). The study area, with Tengger desert in the west, the Maowusu desert in the east, and the Ulan Buh desert in the north, is one of the core areas of the west Longhair-Lanxin xian economic belt. Since 2000, socioeconomic development in this area has been deliberately enhanced by the government through West Development Project. Gross Domestic Product (GDP) increased from 5045.93 million Yuan in 1990 to 223,550.29 million Yuan in 2013, with an annual growth rate of 188.27%, while population increased at an annual rate of 2.75 %. (Ningxia Statistical Yearbook, 1990-2014). Growing industry and commerce in the urbanized areas provide more work opportunities, and attract population from the rural areas, further promoting urbanization.

2.2 Data Collection and Processing

Twelve scenes of Landsat MSS/TM/ETM+/OLI images, covering the study area in 1989, 1999, 2006 and 2016, were used as the primary resource data (involving path/row of 129/33, 129/34 and 130/34). Images were preprocessed in ENVI 5.3, including geographical registration, radiometric calibration and atmospheric correction, and then were exportedinto eCognition 8.7 for an object-based classification. Reference samples were identified in Google Earth and field survey to examine classification accuracy. The Kappa coefficients

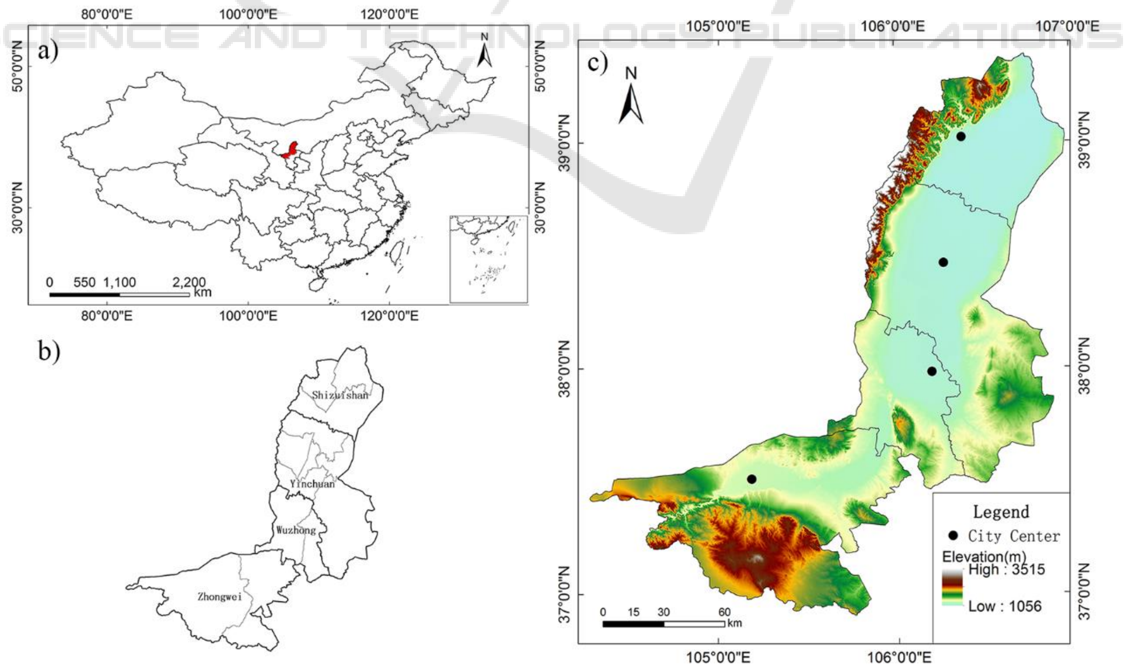

Figure 1: Location and administrative division of the study area—Shizuishan, Yinchuan, Wuzhong and Zhongwei:a) the study area in China; b) the study area in Ningxia Hui Autonomous Region; c) topography and the city center of Shizuishan, Yinchuan, Wuzhong and Zhongwei.

(consistency test between classification results and reference samples) reached 0.93, 0.89, 0.91 and 0.87 in 1989, 1999, 2006 and 2016, respectively, thus the results were reliable.

The ASTER DEM data (version 4.1) (https://search.earthdata.nasa.gov/) was resampled to 30 m in ArcGIS 10.3, and used to generate slope and hillshade layers. Transportation layers were extracted from satellite images and by visual interpretation using Google Earth. All the input layers were resampled for 30 m in ArcGIS 10.3, and then imported into Photoshop CS6 to be exported in GIF format. Socioeconomic data, such as population and GDP, was obtained from Ningxia Statistical Yearbook (1990-2014), compiled by the statistical bureau of Ningxia Hui Autonomous Region and Ningxia Survey Office of National Statistical Bureau, and published by China Statistics Press.

2.3 Overview of the SLEUTH Model

The SLEUTH model (Clarke et al., 1997) is designed to simulate urban growth and land use change. The name includes the first letters of the input layers: slope, land cover, excluded, urban, transportation, and hillshade. The model simulates urban expansion with four rules: spontaneous growth that simulates the random urbanization, new spreading center growth that establishes new urban centers, edge growth and road influenced growth. The model behavior are controlled by five growth coefficients (diffusion, breed, spread, road gravity, and slope) that range from 0 to 100, indicating the relative contribution of each growth types for whole urban growth. Moreover, self-modification is applied to better predict rapid or depressed urban growth. Model calibration allows users to obtain parameters describing past urban expansion, while prediction helps forecast urban growth and land use change under different scenarios.

Due to the large amounts of input data, we selected the 3r-version of the SLEUTH model (SLEUTH-3r) for our study; it has more efficient utility of computer memory and higher simulation accuracy of dispersed settlements (Jantz et al., 2010). Two new accuracy parameters—area fractional difference (AFD) and clusters fractional difference (CFD)—were designed in SLEUTH-3r model to compare urban pixels and clusters between simulated and real maps. Besides that, Lee-Sallee metric, the shape index of spatial fit between actual urban map and predicted one, has also been used in our study to examine the simulation accuracy.

2.4 Simulating Spatial Heterogeneity

To address spatial heterogeneity in urban expansion, we first established a suitability system of factors driving urban growth from past studies (details in 2.4.1 below). Second, we detected the spatial relationships between factors and urban expansion through the Ordinary Least Square (OLS) regression model in ArcGIS 10.3 (details in 2.4.2 below). Finally, suitability for urban expansion was calculated and mapped through Binary Logistic Regression with weighted factors derived from the former step (details in 2.4.3 below). Then the suitability map was transformed into the excluded layer for the SLEUTH-3r model.

2.4.1 Suitability-Factor System

Different types of explanatory variables have been identified (Gao and Li, 2011, Su et al., 2012), and categorized based on physical conditions, ecological protection, and socio-economic development (Table 1). Ecological factors are protected from urban expansion and are assigned value of 100 in the excluded layer. Slope factor is not included in the system, as it is already in SLEUTH-3r model. All variables were first normalized into the range of 0-1 to eliminate the effect of magnitude. Based on correlation analysis, multicollinearity did not exist among the explanatory variables in the subsequent regression analysis.

Table 1: Factors influencing urban development.

Type	Factor	Code
Physical	Elevation	X_E
	Geomorphic type	X_M
Ecological	Water areas	X_W
	National natural reserves	X_N
Socio-economic	Growth rate of GDP	X_G
	Growth rate of population	X_P
	Distance to city centers	X_{D1}
	Distance to county centers	X_{D2}

2.4.2 Weights Estimation

OLS, which could minimize the sum of squared vertical distance between observed variables and simulation values (Gao and Li, 2011), was used to explore the relationships between urban expansion and its driving factors, as follows:

$$Z=C+\sum_n w_i X_i +er \tag{1}$$

Where Z was the dependent variable, C was the constant parameter; w_i was the parameter of independent variable X_i; er was the error term.

Because non-urbanized area greatly surpassed urbanized area in CBYN, we randomly selected 5,000 points in each area, with a distance between each point > 300 m to minimize the impacts of spatial autocorrelation. The “extract multi values to points” tool in ArcGIS 10.3 was used to obtain the values of driving parameters and urban expansion (0 for non-urbanized area and 1 for urbanized area) at each point. They were then used to establish the OLS model in ArcGIS 10.3.

2.4.3 Generating Suitability Maps

If the probability of a cell suitable for urbanization followed the logistic curve described in Eq. (2), the possibility of a cell being urbanized was estimated with Eq. (3):

$$\ln\frac{p_i}{1-p_i}=C+\sum_{i=1}^{n} w_i X_i \tag{2}$$

$$p_i=\frac{1}{1+\exp(-C-\sum_n w_i X_i)} \tag{3}$$

Where p_i was the probability of a cell becoming urbanized, X_i was the driving factor for urban expansion, w_i was the coefficient of each factor derived from OLS, and C was a constant.

2.5 Socioeconomic Factors in the Model

In SLEUTH-3r model, spontaneous urban growth was the foundation of other growth types, and mainly determined by a diffusion multiplier (D_M), diffusion coefficient (D_C), and the size of input images (Jantz et al., 2010). Thus D_M could generally determine the simulation magnitude of urban growth in model, and allowed the integration of socioeconomic development into the model.

The D_M value was 0.005 in the original version, and 0.015 in the 3r version of the SLEUTH model, and neither could generate enough urban growth (AFD ranging from -0.847 to -0.06). Thus, the first problem was obtaining an appropriate D_M. As discussed above, D_M was related to simulation magnitude, so we explored the relationship between D_M and simulation magnitude of urban area and cluster (AFD and CFD) to find appropriate D_M.

We selected the annual growth rates of GDP and population as the representatives for socioeconomic development, and generated an indicator (SE) using factor analysis in SPSS 22.0. Then we explored the relationship between SE and D_M through regression analysis in SPSS 22.0, to use D_M representing different socioeconomic development conditions.

3 RESULTS

3.1 Urban Expansion Suitability Map

Multiple linear regression analysis processed in SPSS 22.0 had the same results as OLS in ArcGIS 10.2 (Eq. (4)). The six factors had different effects on urban expansion, indicated by the coefficients of each factor. And the influence of geophysical factors was greater than that of socioeconomic factors. The regression model was as follows (Eq. (4)):

$$\ln\left(\frac{p_i}{1-p_i}\right)=1.53-1.32\times X_E-0.4\times X_M-0.51\times X_{D1}-0.53\times X_{D2}+0.05\times X_G+0.02\times X_P \tag{4}$$

Where p_i was the urbanization probability of each cell.

Based on binary logistic regression, a probability map for urban suitability was generated (Fig. 2a). Then, we converted it to an excluded layer that contained areas ranging from unsuitable for urbanized (value=100) to suitable (value=0) in SLEUTH-3r model using the “map algebra” tool in ArcGIS 10.3 (Fig. 2b). The transformation equation was as follows (Eq. (8)):

$$R_E=(\frac{MAX(R_{suit})-R_{suit}}{MAX(R_{suit})-MIN(R_{suit})})\times 100] \tag{5}$$

Where R_E and R_{suit} were the raster maps of excluded layer and suitability map, respectively.

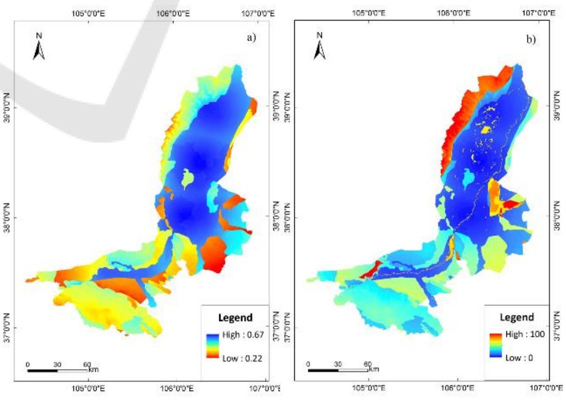

Figure 2: Suitability map for urbanization probability (a) and excluded map for SLEUTH-3r model (b).

3.2 Determination of D_M

We explored the relationships between AFD/CFD and D_M in the calibration mode of the model with the five growth coefficients ranging from 0 to 100 and an increment of 50. We found that the minimum values of AFD and CFD were almost the same (-0.847 and -0.73) under different D_M, while the maximum value increased with an increase in D_M. The relationships between the maximum values of AFD/CFD and D_M were established through regression analysis in SPSS 22.0. The equations and simulated curves were as follows (Eq (6) with R^2 of 0.975, Eq (7) with R^2 of 0.997, and Fig. 3)):

$$AFD_{max}=3.323+0.79\times\ln(D_M) \quad (6)$$

$$CFD_{max}=2.69+202.67\times D_M-188.45\times D_M^2+71.49\times D_M^3 \quad (7)$$

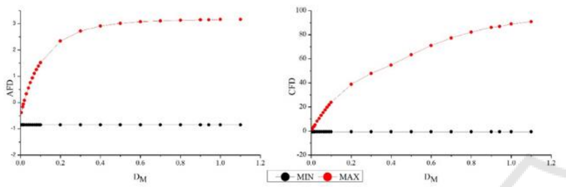

Figure 3: Maximum and minimum values of AFD and CFD over increasing D_M.

From the testing data shown in figure 3, three values of D_M—0.03/0.04/0.05—were considered to have the largest opportunity to simulate sufficient amount of urban area with fewer clusters. We calibrated the model with the three D_M values (Table 2), and 0.04 was the most suitable value for D_M in our study. Under D_M of 0.04, the maximum value of AFD was 0.783. As discussed in Section 2.5, 0.783 of the maximum value of AFD was appropriate for D_M determination.

Table 2: Coarse calibration performance of the model under different D_M.

D_M	AFD	CFD	Lee-Sallee
0.03	0.002	6.9	0.301
0.04	0.001	5.162	0.351
0.05	0.001	6.283	0.309

3.3 The Socioeconomic Factor

The socioeconomic development indicator (SE) was generated with the following equation (Eq. (8), Section 2.5):

$$SE=8.23\times10^{-7}\times GDP_S+2.74\times10^{-5}\times P_S-0.94 \quad (8)$$

We obtained 30 values of D_M through the method discussed in Section 3.2 for the five different areas (4 cities and the whole region) in the six periods (1989-1999, 1999-2006, 2006-2016, 1989-2006, 1999-2016, and 1989-2016). The relationship between D_M and SE was estimated with regression analysis in SPSS 22.0 (Eq. 9) with a R^2 of 0.981). Therefore, SLEUTH-3r model could predict urban expansion driven by different socioeconomic development conditions by setting the D_M value.

$$D_M=0.083\times SE+0.043\times SE^2-0.011\times SE^3+0.056 \quad (9)$$

3.4 Simulation Accuracy of the Model

The SLEUTH-3r model was calibrated to find a combination of coefficients that best simulated historical urban expansion through the "brute-force" method (Silva and Clarke, 2002). The selection criterion used the minimum absolute value of CFD and AFD of < 0.05. Then the model was initialized in 1989 and ran in predict mode to 2016, with the coefficients derived from calibration. In the prediction mode, we utilized two scenarios, in which one (S_1) came from the suitability map, and the other (S_2) coded water with 100 and other land with 50 as comparison.

To evaluate the simulation accuracy, we calculated the Kappa metric and spatial topology for the predicted maps (Table 3). The Kappa metric (consistency between predicted and real maps) in 2016 under S_1 reached 0.77, while the one under S_2 was 0.56, indicating that S_1 could significantly improve model accuracy. Urban spatial topology can further describe the simulation accuracy (Kantakumar et al., 2016), and was classified based on proportion of built-up area (using 30% and 50% as a boundary) within the neighborhood of 3×3 cells through "block statistics" tool in ArcGIS 10.3. Prediction under S_1 accurately simulated the area of the urban core, 74.82% of the real urban fringe, but 172.86% of the scattered settlement; this indicated that most of the simulation error occurred in scattered settlements. Under S_2, the main error occurred in simulating the urban core (at 78.29%) and urban fringe (at 62.38%). Overall, integrating the effects of multiple drivers into the model can greatly enhance the ability to simulate urban expansion with high spatial heterogeneity.

Table 3: Urban spatial pattern predicted in 2016 under different scenarios.

	Urban area (km^2)	Kappa	Urban topology type		
			Urban core (km^2)	Urban fringe (km^2)	Scatter settlement (km^2)
S_1	1205.81	0.77	1165.67	146.25	349.05
S_2	931.51	0.56	911.66	121.94	212.81
Real	1182.123	—	1164.51	195.48	201.93

4 DISCUSSION

Documentation and source code of the SLEUTH model have been publicly available, thus interested researchers were able to modify and improve it. Several successful efforts reduced computation time and increased model efficiency, including OSM (Charles Dietzel, 2007), pSLEUTH (Guan and Clarke, 2010), SLEUTH-3r (Jantz et al., 2010), and SLEUTH-GA (Shan et al., 2008), among others. These modifications helped to overcome some of the limitations, enhance model applicability, and provide suggestions for more accurate simulation (Chaudhuri and Clarke, 2013). Using the SLEUTH-3r model, we simulated urban expansion in CBYN during 1989-2016. We confronted three main problems. First, the determination methods for D_M were not appropriate for our study as they could not generate sufficient urban growth area. Second, urban growth in China, largely driven by socioeconomic development at macro-scale, could not be effectively expressed in this model. Third, spatial heterogeneity in urban growth, such as city and villages in a large urban agglomeration, was an important source of simulation error that needed to be addressed.

4.1 Parameters Driving Urban Growth

Similar to most studies that analysed urban expansion, the factor system we built in this study was incomplete, due to lack of data and the presence of unknown urban-growth driving factors (Hietel et al., 2007). For example, urban planning has been shown to greatly affect urban expansion (Long et al., 2012), however, it has not been included in this study due to lack of data. The incomplete picture of the factors driving urbanization was one source of simulation error.

In 1989-2016, physical factors impacted urban expansion more than socioeconomic conditions did at spatial scale. Elevation and morphology exhibited significantly negative effects on urban expansion in CBYN, while low elevation and flat areas were more suitable for urban growth. Previous studies suggested that the effects of elevation on urban expansion depended on the topography (Li et al., 2013). Positive effects of elevation on urban expansion have been shown in Lagos and Nigeria, where low elevation areas necessitated drainage, possibly increasing the cost of building construction (Dewan and Yamaguchi, 2009). In CBYN, areas of high elevation were more likely to be situated in the mountains, where costs of development were higher than at low elevations.

The significant relationships between urban expansion and social factors of proximity to urban centers (negatively correlated), and growth rate of GDP and population (positively correlated) were consistent with previous findings (Luo and Wei, 2009, Poelmans and Rompacy, 2009). Moreover, the effects of proximity exceeded those of economic development and population growth. This was mainly due to the coarser resolution of census data compared with other factors. The spatial heterogeneity of urban and suburban areas could not be expressed by GDP or population data, indicating that data at finer-scales were needed.

Previous studies on megacities in China and USA have shown that positive relationships existed between socioeconomic development and urban expansion, especially in developing countries (Kuang et al., 2014), and that the socioeconomic factors would play an increasingly important role in urbanization. For example, studies in Beijing (Liu et al., 2014) suggested that the importance of urbanization drivers varied over time, and the effects of physical and neighborhood factors decreased with increasing socioeconomic factors. Compared with Beijing, CBYN developed at a slower pace in the past thirty years, as indicated by urban population rate of 67.56% in CBYN in 2015, and 86% in Beijing in 2010 (Liu et al., 2014). As a result, the impacts of socioeconomic development were less important than those of geophysical conditions, but would increase in the future.

4.2 Implications of Model Simulation

Chinese megacities are in a stage of development at which population growth, economic development, and policy significantly influence urban expansion patterns and rates. This is unlike megacities in developed countries where population and economic conditions are not important forces of urban growth (Kuang et al., 2014). The effects of socioeconomic development on urban expansion were classified in this study into two categories: spatial heterogeneity and temporal dynamics; the former was expressed in the excluded layer from the suitability map, and the latter was reflected in the changing value of D_M.

Spatial differences in physical conditions, cultural background, socioeconomic development, and human preferences were responsible for the high heterogeneity in urban distribution and expansion (Lin et al., 2014); this was also reflected in D_M with value ranging from 0.008 to 0.38 among different cities. This heterogeneity improved the difficulty in precise urban simulation, and can be an important source of simulation error. Linear or logistic regression-based models cannot calculate heterogeneous urban expansion due to their dependability on weights (Hu and Lo, 2007). Artificial neural network models also have limited capacity for accurate modeling of spatial heterogeneity (Almeida et al., 2008).

The SLEUTH model can simulate urban growth at coarse resolution well, and has been successfully applied to cities all over the world (Akın et al., 2014, Al-shalabi et al., 2012, Bihamta et al., 2014). However, the SLEUTH model is still inadequate for simulating urban growth with high heterogeneity, or at high resolution at large-scales (Jat et al., 2017). In our study, integrating various spatial factors into the model greatly enhanced the simulation accuracy in an urban agglomeration. The influence of socioeconomic growth on urban expansion, and the fundamental function of D_M in controlling the magnitude of urbanization (suggested by Eq. (9)), allowed D_M to exert temporal influence in the model. The high correlation between D_M and SE further supports this conclusion. Future research needs to focus on predicting urban expansion under different socioeconomic growth scenarios, and on comparing the effects of government policies on urbanization.

5 CONCLUSIONS

Urban expansion is unavoidable and has significant impacts on ecosystem services and functions. The successful application of the SLEUTH-3r model in the City Belt along the Yellow River in Ningxia at a resolution of 30 m has shown its utility in simulating urban expansion in a large area with high precision.

In the past 27 years, the effects of elevation and geomorphology on urban expansion exceeded those of socioeconomic development. We quantitatively integrated these factors into the model to simulate urban expansion with high heterogeneity across a large area with high accuracy.

The influence of socioeconomic development was introduced into model with D_M, which can be set interactively. Both of these actions improve model accuracy in simulating urban expansion in urban agglomerations. However, the excessive amounts of scatter settlements in the simulation indicated the need for further research.

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