The future urban growth under policies and its ecological effect in the Jing-Jin-Ji area, China

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ABSTRACT
Since 2016, the Chinese government has invoked some policies to make Jing-Jin-Ji (JJJ) a new urban agglomeration. However, there has been no research to study the effect of these new policies on future urban growth. This study assessed part of these new policies on JJJ urban growth in 2020–2050 using SLEUTH model. Then the ecological effects of the urban growth are evaluated. Results showed the policies had nearly no obvious impact on the whole JJJ urban growth, but affected sub-regional (Beijing, Tianjin and Hebei, respectively) urban growth. Under ecological protection in future, the value of ecological service in JJJ would increase to a maximum of \(31.7 \times 10^8\) Yuan/km\(^2\) in 2031. The ecological elasticity also increased and the ecological risk was strongly reduced around the present urban area. This ecologically sustainable development is critical to the future urban growth, and should be considered more carefully by urban planners and managers. More policies should be evaluated for JJJ urban growth in future work.

1. Introduction

By 2050, 68% of the world population will live in urban areas, with 255 million of these new urban residents living in China (https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html). With the development of the world’s economy and growth in population, the coverage of urban area is predicted to grow substantially (Miller and Small, 2003). The Government macro-control plays an important role in urban growth. Predicting urbanization under future policies would allow urban planners and managers to better develop urban (Goetz et al., 2011). However, there are still few studies focus on impact of diverse policies on future urban growth. The Jing-Jin-Ji (JJJ) metropolitan region, also known as the Beijing-Tianjin-Hebei region, is the largest urbanized region in Northern China. Since 2016, the Chinese government has implemented several policies to develop the JJJ into a new urban agglomeration, in addition to the Pearl River Delta agglomeration in southeast China and the Yangtze River Delta agglomeration in east China. The new policies include, for example, developing a new city (Xiong-An) to mitigate the growing Beijing population and transportation; building a JJJ regional distribution with the concept “one core, two cities, three axes, four regions, multiple nodes”; developing new railways and motorways. However, there has been no research to assess the impact of the latest policies on JJJ urban growth.

In addition, mostly studies modeled and forecasted future urban growth for studying climate change (Kim et al., 2016; Oo et al., 2019; Yang et al., 2017). However, urban spread and sprawl will bring ecological and environmental problems, e.g. urban heat islands, vegetation degradation, and reduction in biodiversity (Zhan et al., 2017). The ecological effect of the urban spatial-temporal growth is also important for urban plan and urban environment studies (Yang and Lo, 2003). Evaluation of the landscape pattern and ecological effects of urban growth will help to guide urban planning, and to protect and improve the regional ecological environment. Most studies have focused on the historical urban growth’s ecological effect, not the future urban growth (Chen and Zhou, 2018; Zheng et al., 2019; Zhou et al., 2014), which is insufficient for future urban planning.

The SLEUTH (Slope, Land use, Exclusion, Urban growth, Transportation, and Hillshade) model is a cellular automata (CA) model that has become one of the most popular models for urban growth simulation (Chaudhuri and Clarke, 2013). There are some modified versions of SLEUTH model, for example, Guan and Clarke (2010) developed a parallel version of SLEUTH using the parallel Raster Processing Library (pRPL); Liu et al. (2012) utilized ant colony optimization to simplify the
SLEUTH calibration procedures and also introduced sub-regional calibration to replace the entire study area calibration; Clarke (2018) replaced the brute force calibration method with a genetic algorithm (GA), which enhanced the computational speed and yielded the new SLEUTH-GA model. However, SLEUTH-GA is not very consummate and need future improvement. Finally, we selected SLEUTH, which has been widely used in the world, for modelling urban growth.

The aims of this study are: (1) predicting how government macro-control of the JJJ area will affect future urban growth during 2020–2050, by using SLEUTH 3.0 model and including the newest government policies; (2) assessing how the urban growth will impact on the JJJ ecological environment by studying the landscape pattern and ecological effect of future JJJ urban growth.

This study is organized as follows: firstly is Introduction; secondly is Methodology: SLEUTH model and landscape metrics used in the present study; thirdly is Results and Discussion: spatio-temporal variability of JJJ future urban growth and ecological effect of future urban growth; the last part is Summary. The flowchart of this study can be seen in Figure 1.

2. Methodology

2.1. Study area

The JJJ urban agglomeration, with an area of 218,000 km², is located in the northeast of China and belongs to the Bohai Economic Rim. The GDP was equivalent to ca. 10% of China in 2014 (Zhao et al., 2017). In 2016, JJJ had total population of 112 million, similar to that of Mexico (http://data.stats.gov.cn/english/easyquery.htm?cn=E0103). The JJJ includes three provincial-level cities: Beijing (the capital of China), Tianjin (municipality), Shijiazhuang (the provincial capital of Hebei); and ten prefectural-level cities: Baoding, Chengde, Langfang, Cangzhou, Zhangjiakou, Tangshan, Qinhuangdao, Hengshui, Handan, and Xingtai, each incorporating many districts and countries. JJJ is continental monsoon climate, hot and rainy in summer and cold and dry in winter. About 80% of total yearly precipitation appears in summer.

JJJ development will be central to the country’s economic development plan in the next century. The Chinese government is planning the JJJ area as home to 130 million people over the equivalent area of New England, by 2050 (https://www.nbcnews.com). According to the government, the biggest change for JJJ development will be in transportation. The government approved $36 billion to build 700 miles of rail in 2017–2019. Twenty-four intercity railways are planned to be completed by 2050, with eight finished by 2020. According to the government, the goal is a “one-hour commuting circle” across the JJJ region. According to a strategic report, the JJJ megalopolis development is one of the three key infrastructure projects, along with the Yangtze River Delta Economic Region and the “One Belt, One Road” program, aimed at boosting China’s economy over the next 100 years (http://theory.people.com.cn/n1/2017/0703/c412914-29377905.html).

2.2. SLEUTH model

2.2.1. Modeling approach

SLEUTH predicts urban extent based on a summation of four growth types: spontaneous growth, diffusive growth, organic growth, and road-influenced growth (Clarke et al., 1996). The four growth types are controlled by five coefficients: diffusion, breed, spread, slope, and road gravity. The detailed interpretation of four growth types can be seen in Clarke et al. (1996). Each coefficient has an initial range of 0–100, and is narrowed down at each calibration stage by comparing the simulated and historical data (Jantz et al., 2010). Calibration yields a fixed five-coefficient set which is then applied to urban growth prediction. The SLEUTH model can reveal the urban growth characteristics affected by economic, social and political factors in the calibration stage based on the historical data of the JJJ region. The workflow of this study can be seen in Figure 2.

The five input data sets (six if land use is predicted) of this study are listed in Table 1. The present study only simulates urban growth and does not study land use changes, so the land use layer is not included. For optimal calibration of the model, at least four urban time periods must be used, and at least two time periods of road layers. The urban layer was extracted from China land cover/land use products with 1 km spatial resolution (http://www.resdc.cn/data.aspx?DATAID=184). This land use map was derived from Landsat TM/ETM+ and Landsat 8 images in 1995, 2005, 2010 and 2015 using visual interpretation, with overall accuracy of classification of over 90%. The excluded layer included water bodies and 16 national nature reserves. All input layers were unified to 1km spatial resolution and projected to the WGS 84, Zone 50N in the UTM system.

Figure 1. Location of the Jing-Jin-Ji study area (left) and its land use and land cover in 2015 (right).
2.2.2. Model calibration

Four steps were applied in this study during the calibration progress: coarse, fine 1, fine 2 and final calibration. Each coefficient range was expected to have become narrower at the end of each step. The OSM index (Optimal SLEUTH metric) (Eq. (1)) (Dietzel and Clarke, 2007) was used to derive the best group of five coefficients for prediction; however, there is no uniform standard for determination of the best coefficients (Dietzel and Clarke, 2007; Zhang, 2013). In this study, the top 20 parameter combinations of the OSM metric were used for selecting coefficients. We also tested the top 5 and top 50 selections, but found the top 5 selection missed and limited coefficients variation ranges. The top 20 and top 50 could capture the broad patterns, while the top 50 also capture more detailed variations but increased the number of calibration stages in order to get high OSM values, thereby increasing running time. The top 20 were selected as an intermediate option for SLEUTH model calibration in this study.

\[
OSM = \text{compare} \times \text{pop} \times \text{edges} \times \text{clusters} \times \text{slope} \times X_{\text{mean}} \times Y_{\text{mean}} \times (F - \text{match})
\]  

where \(F\)-match = 1 in this study when land use prediction was not included, and the other seven indices were produced after each calibration step. Compare is the ratio of modeled and actual population for the final year, pop is the least squares regression score of modeled and actual urbanization for the control year, edges is the least squares regression score of modeled and actual urban edge count for the control year, clusters is the least squares regression score of modeled and actual urban clusters for the control year, slope is the least squares regression of average slope of modeled and actual urbanized cells for the control year, \(X_{\text{mean}}\) and \(Y_{\text{mean}}\) are the least squares regressions of average x and y values for modeled and actual urbanized cells for the control year (Nigussie Tewodros and Altunkaynak, 2017).

2.2.3. Model validation

The calibrated model was validated with observed data by comparing modeled and observed urban extent in 2015. The Kappa coefficient and cell-by-cell matching methods were utilized for the validation. The Kappa coefficient defines the agreement between two classifications on ordinal

| Input data       | Data sources                  | Year          | Resolution |
|------------------|-------------------------------|---------------|------------|
| Urban            | Landsat TM/ETM+ and Landsat 8 | 1995, 2005, 2010, 2015 | Raster, 1 km |
| Transportation   | National Geomatics Center of China | 1995, 2015 | vector     |
| Hill-shade       | SRTM DEM                      | 2015          | Raster, 30 m |
| Slope            | SRTM DEM                      | 2015          | Raster, 30 m |
| Excluded         | Landsat TM/ETM+ and Landsat 8 | 2015          | Raster, 1 km |
or nominal scales (Al-shalabi et al., 2013; Fleiss et al., 2004; Watkiss, 2008). The cell-by-cell method involves the spatial matching of pixels and is a good accuracy evaluation technique (Torrens, 2011). The cell-by-cell matching index is defined as the ratio of the number of overlay pixels in both images to the number of pixels in the observed image (Kuhnert et al., 2005).

2.2.4. Scenarios settings for prediction

Four scenarios were established: current trends; managed trends; ecologically sustainable with farmland protection; and ecologically sustainable with farmland, forest and grassland protection (Table 2). This study will evaluate the potential impacts of these new policies on JJJ urban growth. The primary policies are as follows (Figure 3). (1) Construction of railways and motorways in the JJJ area (see Table 2 for detailed information). (2) Synergistic development of Beijing, Tianjin and Hebei province, and developing the Xiong_An new urban area (with an area of 2000 km²) in Hebei province. The goal of this policy is to develop the new JJJ urban agglomeration, and is ranked by the Chinese government as a major event for the next millennium. (3) General urban planning for Beijing during 2016–2035, developing a new super international airport - Beijing Daxing International Airport - with an area of nearly 30 km². (4) Urban planning of the Beijing vice-center, located in the Tongzhou district of Beijing.

From the planning report, the planned railways, motorways, Xiong_An main city (with an area of nearly 100 km²) and the airport (with area of nearly 30 km²) were digitized using ArcGIS 10.3 software, and added to the road layer and urban extent layer for 2015. The planned new Wenyu River wetland park was included in the excluded layer for 2015. The 2015 input layers were used as seed layers for prediction.

2.3. Landscape metrics

2.3.1. Landscape pattern index

Three commonly used landscape metrics of the Compactness Index (CI), Patch density (PD) and Mean Shape Index (MSI) were selected to analyze landscape pattern of urban growth under the four scenarios (Table 3).

2.3.2. Ecological effects index

The Value of Ecological Service (VES), ECOlogical elasticity (ECO) and Ecological Risk Index (ERI) were selected to analyze ecological ef-

### Table 2. The four scenarios for predictions.

| Scenario | Name                              | Description                                                                                                                                 |
|----------|-----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| Scenario 1 (see 1) | Current trend | This scenario had no additional restrictions and followed the current trend for future urban growth. The excluded layer included all water bodies and 16 national nature reserves with value of 100, which meant that all the water bodies and reserve areas were fully excluded from new urban growth. The road layer also had pixel values of 100. |
| Scenario 2 (see 2) | Managed trend | A policy was included for future urban growth, such as the new roads, new city, and new wetland park. The new railways and motorways included in this study were all projects planned and under construction in JJJ and the Beijing vice-center development (Figure 3). The new roads were the Jing-Xiong railway, Jing-Gang-Tai railway, Jin-Xiong railway, Jing-Kun railway, Shi-Xiong railway, Jing-Xiong motorway, Rong-Wu motorway, Jing-De motorway, and Jin-Shi motorway for the synergistic development of JJJ. In addition, the Jing-Tang railway and Jing-Qin motorway in Beijing vice-center development were added to the road layer. The new urban areas added in the urban extent layer were Xiong_An new city and Beijing Daxing International Airport. The planned Wenyu River wetland park was added to the excluded layer. |
| Scenario 3 (see 3) | Ecologically sustainable I | In addition to the future policy, the farmland was partly protected in this scenario. In this case, urban development was limited and ecological resources were better protected. The farmland pixel values were set at 50, which meant farmland was 50% protected. |
| Scenario 4 (see 4) | Ecologically sustainable II | In addition to policies in Scenario 3, the forest and grassland were also partly protected in this scenario, with values of 80 and 20, respectively. |

Figure 3. (a) The planned railways and motorways and (b) the new city, airport and park in the synergistic development of Jing-Jin-Ji during 2015–2035, according to the online policy report (http://www.gov.cn/).
effects of future urban growth (Table 3). These three indices are all considering all land use types (e.g. urban, farmland, forest, grassland, water, etc.); however, there was only “urban” type and no other land use types in the present study. Therefore, we used ecosystem area change under scenarios to study ecological effect change. For example, $\Delta$VES, $\Delta$ECO and $\Delta$ERI of farmland change between scenario 2 (managed trend) and scenario 3 (farmland protection) were studies here (Eqs. (2), (3) and (4)). The farmland area change between scenario 2 and scenario 3 is equal to the urban area change.

$$\Delta VES = V_{\text{farmland}} \times (S_{\text{urban,sce2}} - S_{\text{urban,sce1}})$$  \hspace{1cm} (2)

where, $V_{\text{farmland}} = 610000$ Yuan/km$^2$, and $S_{\text{urban,sce2}}$ and $S_{\text{urban,sce1}}$ are urban areas in scenario 2 and scenario 3.

$$\Delta ECO = \frac{(S_{\text{urban,sce2}} - S_{\text{urban,sce1}})}{A_{\text{farmland}}}$$  \hspace{1cm} (3)

where, $S_{\text{farmland}} = 0.5$, $A$ is the study area.

$$\Delta ERI = \frac{S_{\text{urban,sce2}} - S_{\text{urban,sce1}}}{A_{0}}$$  \hspace{1cm} (4)

where, $S_{\text{farmland}} = 0.13$, $A_0 = 5 \text{ km} \times 5 \text{ km}$. The study area was divided into 16905 sampling grid units of size $A_0$. $\Delta$ERI was calculated for each sample grid unit, then interpolated by ordinary Kriging and grouped into three grades (low, medium, high) using the Natural Breaks classification method.

### 3. Results

#### 3.1. Calibration and validation of the SLEUTH model

(1) Calibration

Calibration was carried out under phases termed coarse, fine 1, fine 2, and final. After each calibration phase, the OSM index was calculated based on Eq. (1) and the top 20 highest OSM values were used to narrow down the coefficient ranges. The ranges of the five coefficients after each calibration phases are listed in Table 4. The highest OSM index value after the final calibration was 0.7, which is higher than that achieved in other studies, e.g. 0.5 (Nigussie Tewodros and Altunkaynak, 2017; Zhang, 2013), 0.49 (Sakieh et al., 2015b), 0.44 (Sakieh et al., 2015a). A higher OSM indicates that the urban extent was simulated more accurately when compared with the historical urban extent data. The best-fit coefficients after final calibration were (1, 1, 1, 99, 48); these values were used for prediction. The slope and road coefficients had large values, which showed slope and road extent had the greatest impacts on urban growth between 1995 and 2015.

(2) Validation

The simulated urban growth in 2015 using the best-fit coefficients of (1, 1, 1, 99, 48), with 2010 as a seed year, was compared with the observed urban extent in 2015 (Figure 4); this showed strong similarity between modeled and observed extent, with only a few pixels being over-

### Table 3. Description of landscape pattern metrics and ecological effect metrics used in this study.

| Landscape pattern metrics | Equation | Ecological significance |
|---------------------------|----------|------------------------|
| Compactness index (CI)    | $CI = \frac{\sum_{i=1}^{n} S_i / \sum_{i=1}^{n} P_i}{A}$ | The larger the CI value, the more compact the land space pattern. |
| Patch density (PD)        | $PD = n/A$ | PD is the opposite of CI. |
| Mean shape index (MSI)    | $MSI = \frac{\sum_{i=1}^{n} P_i}{n \sum_{i=1}^{n} S_i}$ | A larger MSI value indicates the space form is less coherent and the land space pattern is more dispersed. |

| Ecological effect metrics | Equation | Ecological significance |
|--------------------------|----------|------------------------|
| Value of Ecological Service (VES) | $VES = \sum_{j=1}^{m} \frac{V_j S_j}{10000} \text{Yuan/km}^2$ | The ability of the ecosystem to return to its original state after disturbance. A higher ECO value indicates the ecosystem is more stable. |
| Ecological elasticity (ECO) | $ECO = \sum_{j=1}^{m} \frac{r_j e_j}{100} \text{Yuan/km}^2$ | ECO ranges from 0 to 1. |
| Ecological risk index (ERI) | $ERI = \sum_{j=1}^{m} \left( \frac{S_j}{A_0} \right)$ | The lower ERI value, the better for ecosystem. ERI value ranges from 0 to 1. |

### Table 4. Selected top 20 of each coefficient for the next calibration stage, corresponding to the top 20 highest OSM values.

| Coefficient | Coarse calibration | Fine1 calibration | Fine2 calibration | Final calibration | Best-fit | 100 MC average | Highest OSM |
|-------------|--------------------|------------------|------------------|------------------|----------|----------------|-------------|
| Diffusion   | 0 25 100           | 0 15 75          | 0 5 30           | 0 3 30           | 27 1     | 0.7            |            |
| Breed       | 0 25 100           | 0 20 100         | 0 12 60          | 0 10 50          | 40 1     |                |            |
| Spread      | 0 25 100           | 0 1 25           | 0 1 5            | 0 1 5            | 2 1      |                |            |
| Slope       | 0 25 100           | 0 20 100         | 0 10 100         | 10 10 90         | 90 99    |                |            |
| Road        | 0 25 100           | 0 20 100         | 0 12 60          | 0 10 50          | 50 48    |                |            |
The CI increased annually from 2020 to 2050 under the four scenarios, while the PD decreased (Figures 7a, 7b), showing that the future JJJ urban growth was characterized by compact development meeting the current planning strategy for intensive urban development. However, the government policies had no obvious effect on CI or PD. The MSI decreased during 2020–2050, showing the spatial pattern of urban growth was becoming increasingly regular and compact (Figure 7c). Nonetheless, the MSUs under scenarios 1 and 2 before 2027 were evidently different. Between 2020-2025, the spatial pattern of urban areas in JJJ under scenario 2 was more regular than that in scenario 1; however, the distribution was irregular and dispersed, with a larger MSI, than that in scenario 1 during 2026–2027 (Figure 7c).

The value of ecological service would be increased during 2020–2050 under scenario 3 with farmland protection when compared to scenario 2 without environmental protection, to a maximum value of 31.7×10^6 Yuan/km^2 in 2031 (Figure 8a). The ecological elasticity was also increased under scenario 3 when compared to scenario 2 (Figure 8b). The proportion of land with a high reduction of ecological risk increased from 2020 to 2050, while the area with a low reduction decreased and the area with moderate reduction showed no obvious change (Figure 8c). The region of high reduction of ecological risk was distributed in farmland surrounding urban areas, showing that farmland around cities was more exposed to ecological risk than farmland far away from cities.

### 4. Conclusions

In order to develop JJJ area as a new urban agglomeration, the Chinese government has implemented some policies since 2016. Some of these policies are clear (for example, a new city, wetland boundary, motorway route, etc.), but some are undefined (for example, the nine wedge-shaped green corridors have no explicit boundary at present). This study assimilated the explicit city planning policies based on the JJJ synergy development report and Beijing general plan report.
Figure 5. Urban area growth in different regions under four scenarios during 2020–2050 (a. JJJ, b. Beijing, c. Tianjin, d. Hebei) and the difference in urban area between different scenarios (e. between sce1 and sce2, f. between sce2 and sce4). The ratios in (e) and (f) are the contributions to changes in urban area from each-subregion.
(2016–2035), including railways, motorways, Xiong An new city, a new airport, wetland park, and Beijing vice-center. We investigated the impact of these policies on JJJ future urban growth and resulting ecological effects. The temporal and spatial patterns of JJJ future urban growth during 2020–2050 were simulated by the SLEUTH model under four different scenarios. The urban area in JJJ increased annually during 2020–2050 under all four scenarios, but the urban areas in scenarios 3 and 4 (with ecological protection) were much smaller than those under current (scenario 1) and managed policies (scenario 2). The new policies had a negligible effect on the JJJ urban growth, with very similar urban areas under scenario 2 and scenario 1. However, sub-regional urban growth showed some small differences: the urban areas in Beijing and Tianjin decreased, while that in Hebei increased, under the new policies. With ecological protection, urban area reduced in the order Tianjin > Beijing > Hebei > JJJ, which showed that Tianjin would undergo the greatest conversion of natural surfaces to urban areas if there was no environmental protection.

The landscape pattern and ecological effects of future urban growth under the four scenarios were also analyzed. This study utilized the compactness index (CI), patch density (PD) and mean shape index (MSI) to characterize variations in the landscape patterns, and value of ecological service (VES), ecological elasticity (ECO) and ecological risk index (ERI) to assess ecological effects. Results showed that future urban growth in JJJ was characterized by compact development, with increased CI and decreased PD and MSI. However, the government policies showed no obvious impact on changes in landscape patterns, with very similar CI, PD and MSI values under scenarios 1 and 2. With farmland protection, VES in the JJJ region was increased during 2020–2050, reaching a maximum value of $31.7 \times 10^6$ Yuan/km$^2$ in 2031; the ecological risk was obviously reduced around urban areas and the ecological elasticity was also improved. Therefore, the urban planners and managers should consider not only the economic benefits of urban growth, but also the ecological effect. The ecological environment is very important for human health and comfort.

The accuracy of the present results may be increased when more policies are included, e.g. green corridors, parks around Beijing’s 5th and 6th roads, permanent farmland, etc. However, these boundaries are not clear at present and it is unable to include that in the present study. As more policies are established, we will continue to study the urban growth and ecological effects of these additional policies, so that we can provide more comprehensive guidance for urban planners and managers.
climate effect of the future JJJ urban growth under government policies should also to be studied in next step.

Declarations

Author contribution statement

Nana Li: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Shiguang Miao: Performed the experiments.
Yaoting Wang: Analyzed and interpreted the data.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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References

Al-shalabi, M., Billa, L., Pradhan, B., Mansor, S., Al-Sharif, A.A.A., 2013. Modelling urban growth evolution and land-use changes using GIS based cellular automata and SLEUTH models: the case of Sana’a metropolitan city, Yemen. Environ. Earth Sci. 70, 425–437.
Chaudhuri, G., Clarke, K., 2013. The SLEUTH land use change model: a review. Environ. Resour. Res. 1, 88–105.
Chen, L., Fu, B., 1996. Analysis of impact of human activity on landscape structure in Yellow River Delta-A case study of Dongying region. Acta Ecol. Sin. 16 (4), 337–344.
Chen, X., Zhou, H., 2018. Research hotspots and prospects of urbanization and ecological environment relationship based on visual knowledge mapping. Prog. Geogr. 37 (9), 1171–1185.

Clarke, K., Hoppen, S., Leonard, J.G., 1996. Methods and Techniques for Rigorous Calibration of a Cellular Automaton Model of Urban Growth. Private. http://www.ncgia.ucsb.edu/projects/gpp/Pub/SLEUTHPapers_Nov24/Clarke_Hoppen_Gaydos1996.pdf. (Accessed 15 July 2015).

Clarke, K.C., 2018. Land use change modeling with SLEUTH: improving calibration with a genetic algorithm. In: Camacho Olmedo, M.T., Paegelow, M., Mas, J.-F., Escobar, F. (Eds.), Geomatic Approaches for Modeling Land Change Scenarios. Springer International Publishing, Cham, pp. 139–161.

Dietzel, C., Clarke, K.C., 2007. Toward optimal calibration of the SLEUTH land use change model. Trans. GIS 11, 29–45.

Fleiss, J.L., Levin, B., Paik, M.C., 2004. The Analysis of Data from Matched Samples, Statistical Methods for Rates and Proportions. Wiley, Hoboken, NJ, pp. 373–476.

Goetz, S.J., Jantz, C.A., Sun, M., 2011. Forecasting Future Land Use and its Hydrologic Implications: A Case Study of the Upper Delaware River Watershed. http://whrc.org/wp-content/uploads/2015/09/GoetzetalWatershedSci.11.pdf.

Guan, Q., Clarke, K.C., 2010. A general-purpose parallel raster processing programming library test application using a geographic cellular automata model. Int. J. Geogr. Inf. Sci. 24, 695–722.

Hou, L., Qiao, B., 2012. Study on urban expansion and its ecological effect in Beijing city. Res. Soil Water Conserv. 19 (6), 193–196.

Jantz, C.A., Goetz, S.J., Donato, D., Claggett, P., 2010. Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. Comput. Environ. Urban Syst. 34, 1–16.

Kim, H., Kim, Y.K., Song, S.K., Lee, H.W., 2016. Impact of Future Urban Growth on Regional Climate Changes in the Seoul Metropolitan Area, Korea.

Kuhnert, M., Voinov, A., Seppelt, R., 2005. Comparing raster map Comparison algorithms for spatial modeling and analysis. Photogramm. Eng. Rem. Sens. 71, 975–984.

Li, G., Du, P., Wang, X., Yuan, L., 2009. Consistency evaluation and integration results from multi-source remotely sensed images. Geogr. Geo-Inf. Sci. 25, 68–71.

Liu, X., Sun, R., Yang, Q., Su, G., Qi, W., 2012. Simulating urban expansion using an improved SLEUTH model. J. Appl. Remote Sens. 6, 1–20, 20.

Miller, R.B., Small, C., 2003. Cities from space: potential applications of remote sensing in urban environmental research and policy. Environ. Sci. Pol. 6, 129–137.

Nigusie Tewodros, A., Attunkaynak, A., 2017. Modeling urbanization of istanbul under different scenarios using SLEUTH urban growth model. J. Urban Plann. Dev. 143, 04016037.

Oo, H.T., Zin, W.W., Kyi, C.C.T., 2019. Assessment of future climate change projections using multiple global climate models. Civ. Eng. J. 5, 2152–2166.

Sakieh, Y., Amiri, B.J., Danekar, A., Feghhi, J., Dezhkam, S., 2015a. Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of Karaj City, Iran. J. Hous. Built Environ. 30, 591–611.

Sakieh, Y., Salamannahiny, A., Jafarnezhad, J., Mehri, A., Kamyab, H., Galdavi, S., 2015b. Evaluating the strategy of decentralized urban land-use planning in a developing region. Land Use Pol. 48, 534–551.

Tian, G., Zhang, Z., Zhou, Q., Zhao, X., Wang, C., Liu, B., Tan, W., 2003. Research on dynamic land-use pattern of Beijing by remote sensing and GIS. Remote Sens. Inf. 1, 1–10.

Torrens, P.M., 2011. Calibrating and validating cellular automata models of urbanization, urban remote sensing. In: Yang, X. (Ed.), Urban Remote Sensing.

Watkins, M., 2008. The SLEUTH Urban Growth Model as a Decision Making and Forecasting Tool. Ph.D. thesis. Stellenbosch Univ., South Africa.

Xu, M., Li, J., Peng, J., Niu, J., Cao, L., 2010. Ecosystem health assessment based on RS and GIS. Ecol. Environ. Sci. 19 (8), 1809–1814.

Yang, X., Lo, C.F., 2003. Modelling urban growth and landscape changes in the Atlanta metropolitan area. Int. J. Geogr. Inf. Sci. 17, 463–488.

Yang, X., Ruby Leung, L., Zhao, N., Cian, Q., Hu, K., Liu, X., Chen, B., 2017. Contribution of urbanization to the increase of extreme heat events in an urban agglomeration in east China. Geophys. Res. Lett. 44, 6940–6950.

Ye, Y., Zhang, H., Liu, K., Su, Y., 2012. Spatial analysis of construction land expansion in the Pearl River Delta during 1988-2006. Trop. Geogr. 32 (5), 493–500.

Zhan, Y.J., Zhu, Jieyuan, Yan, Yan, 2017. Dynamic simulation of urban space based on the cellular automata model. Acta Ecol. Sin. 37, 4864–4872.

Zhang, C.M., 2013. Research on Urban Expansion Analysis and Scenario Simulation of Yinchuan Plain. Master thesis. Lanzhou University.

Zhao, D., Tang, Y., Liu, J., Tillesen, M.R., 2017. Water footprint of Jing-Jin-Ji urban agglomeration in China. J. Clean. Prod. 167, 919–928.

Zheng, J., Wang, Y., Tian, Y., He, S., Wang, J., 2019. Study on ecological environment effects of urban spatial expansion: taking Inner Mongolia Hohhot City as an example. Geogr. Res. 38 (5), 1080–1091.

Zhou, D., Shi, P., Wu, X., Ma, J., Yu, J., 2014. Effects of urbanization expansion on landscape pattern and region ecological risk in Chinese coastal city: a case study of Yantai city. Sci. World J. 9, 2014.