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Improvement of an Urban Growth Model for Railway-Induced Urban Expansion

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Abstract: Increasing population in urban areas drives urban cover expansion and spatial growth. Developing urban growth models enables better understanding and planning of sustainable urban areas. The SLEUTH model is an urban growth simulation model which uses the concept of cellular automata to predict land cover change using six spatial inputs of historical data (slope, land use, exclusion, urban, transportation, and hill-shade). This study investigates the potential of SLEUTH to capture railway-induced urban growth by testing methods that can consider railways as input to the model, namely (1) combining the exclusion layer with a station map; (2) creating a new input layer representing stations in addition to the default six inputs. Districts in Tsukuba, Japan and Gurugram, India which historically showed evidence of urban growth by railway construction are investigated. Results reveal that both proposed methods can capture railway impact on urban growth, while the former algorithm under the right settings may perform better than the latter at finer resolutions. Coarser resolution representation (300-m grid-spacing) eventually reduces the differences in accuracy among the default SLEUTH model and the proposed algorithms.

Keywords: land use and transport; land cover change; GIS

1. Introduction

Urbanization, which is oftentimes quantified by a population shift from rural to urban areas, is an unavoidable global phenomenon. Meanwhile, an increase in urban population often relates to urban expansion away from the city center (i.e., urban sprawl). A disordered urban sprawl easily modifies surrounding land cover, which could potentially result in ecological degradation, loss of farmland, as well as many other urban issues such as pollution, traffic congestion, residential crowding, local climate change, and others [1–3]. In recent years, drastic urbanization driven by rapid economic growth in developing countries has posed huge challenges. According to the United Nations, 55% of the world's population lived in urban areas in 2018, and the proportion is expected to increase to 68% by 2050, with close to 90% of this increase taking place in Asia and Africa [4]. Countries in which the pace of urbanization is considered to be rapid will face many land-use difficulties to meet the needs of their growing urban populations. To achieve sustainable development, the management of urban growth is necessary. Urban planners and policymakers who are concerned about the long-term condition of the society need to spatially predict land-use changes under various policy scenarios. Furthermore, land-use information is a vital input for various numerical models (e.g., climate and hydrologic models, socio-economic models, food-supply chain). This means that land use is directly or indirectly linked with other crucial factors affecting society such as weather, food supply, and economy. Other studies [5,6] also suggest strong links between urban landscapes and lifestyle of citizens; specifically, health and well-being (e.g., incidents of obesity [5], healthy environment for the

elderly [6]) are largely affected by urban cover changes. Thus, predicting future urban growth patterns is a necessary step for sustainable land-use management.

Computational advancement in recent years has produced many models to aid urban planners in the investigation of land-use dynamics over regions of interest. Cellular automata (CA) modeling is one of the popular spatial modeling approaches which requires spatial information to be discretely represented in grid cells to evaluate changes in spatial states through rules and iterations [7]. With the support of GIS and remote sensing, CA can be applied for capturing complex spatial behavior.

The SLEUTH model [8] is a CA-based urban growth simulation model that predicts future urban growth from historical geospatial datasets [9]. The name SLEUTH is an acronym of six required input layers: slope, land use, exclusion, urban, transportation, and hill-shade [10]. The SLEUTH model requires three phases of implementation (Figure 1) which are data preparation, model calibration, and prediction. In the calibration phase, a calibration procedure needs to be implemented four times to derive five growth coefficients [7,9,10]. In each calibration, values ranging from 1 to 100 are substituted and tested as growth coefficient values. In the final calibration procedure, a final set of values representing each growth coefficient is automatically generated. These values are then used in the prediction phase [10]. The five coefficients control four growth rules that the SLEUTH model follows, namely spontaneous growth, new spreading center, edge growth, and road-influenced growth. The final outputs of the prediction phase are static image files representing urban growth probability and land-use change. A simulation cycle consists of a series of growth cycles that begins in the start year and completes in the stop year [8,10].
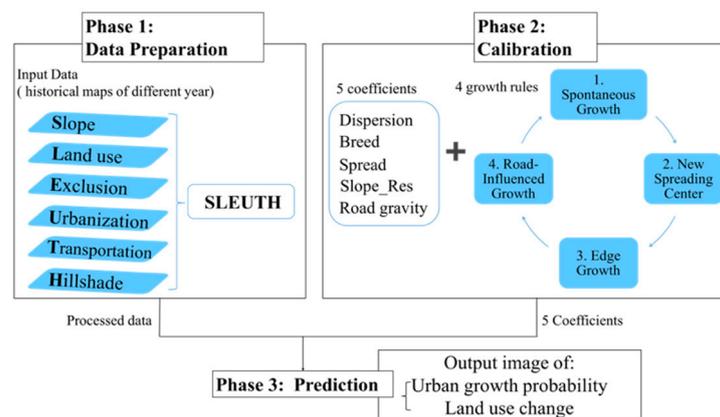

Figure 1. SLEUTH model structure (Source: based on Dietzel and Clarke, 2004 [7]; Clarke and Hoppen, 1997 [8]).

The SLEUTH model has the advantage of simplicity and ease of data preparation as inputs are geospatial images. With this feature, SLEUTH has the potential for use in global scale urban growth studies [11–13]. Meanwhile, the model is coded in the C language and the protocol code could be downloaded for free from the website, which enables users to extend the model flexibly by adding or rewriting code for achieving specific prediction [8,14]. To date, the SLEUTH model has been successfully applied in over 100 cities to simulate future urban growth and land-use change around the world [13–18].

Although the SLEUTH model is one of the few urban growth models which consider transportation effects, the definition of transportation-induced growth in SLEUTH appears to be limited to road-induced growth [9]. Furthermore, the impact of public transport, such as railway transport, in the urban growth model is not reflected. It has been evident that railway operation invites development surrounding railway stations [19,20]. In SLEUTH, this is not yet considered in the transportation layer. Public transportation networks are continually being constructed in developing countries to promote more sustainable urban growth. Thus, it is necessary to investigate the need and possibility to improve SLEUTH in order to capture urban growth surrounding railway stations.

Previous research has proven that the SLEUTH model can reflect different government policies or growth patterns through the exclusion layer [21–25]. However, transit-oriented policy [21] or urban growth surrounding railway stations [25] are manually overlain into an exclusion layer (a geospatial input for SLEUTH), with limited literature discussing the direct integration of public transport (e.g., railway) effects on urban growth prediction into SLEUTH [26]. In this study, we mainly focused on the further improvement of SLEUTH to consider the effect of railway stations on urban growth by evaluating the two following methods:

(1)　Exploring suitable pixel values influencing the probability of urban growth (i.e., Extended SLEUTH);

(2)　Adding a new input layer to represent stations with expected urban growth (i.e., SLEUTsH).

The first method, Extended SLEUTH, follows the method proposed in earlier work [21], where railway-induced urban growth is introduced through modifications in the exclusion layer (a default input of SLEUTH). This method was selected in this study to investigate under which settings in the "exclusion layer" setup will allow, with acceptable accuracy, railway-induced urban growth. Additionally, it is necessary to check the dependency of the settings on location and model resolution. The second proposed method, SLEUTsH, is designed to automatically reproduce railway-induced urban growth by introducing new algorithms in the source code of SLEUTH. The second method has not yet been addressed by previous research; this method hypothetically shows high potential because additional growth rules are directly introduced within the SLEUTH model.

The structure of this manuscript is based on the main objective of introducing railway-induced urban growth into the SLEUTH urban growth component. We begin by testing the model improvements over a railway line northeast of Tokyo, using inputs available only in Japan. Then, we further test the applicability of the improvements over a railway line southwest of Delhi, India, utilizing coarser, globally available inputs. Finally, the dependence of the improvements on resolution, with additional discussion of the urban growth projections of the target areas, is discussed.

2. Materials and Methods

In this section, we discuss the study area, its corresponding model representation, and the proposed model improvements to consider railway-induced urban growth.

2.1. Study Area and Input Data

2.1.1. Tsukuba Express Line

In this study, we selected a domain which historically shows clear evidence of railway-induced urban growth. The Tsukuba Express Line (TX), established in 2005, is a railway line that connects Tokyo and Tsukuba Science City (Ibaraki Province, Japan), a city 50 km northeast of Tokyo. TX was constructed as part of the TX project [27], which involves both TX construction and urban development along the railway line. With the expectation of restructuring Tsukuba City and its surrounding area through new railway construction, the TX project is supported by the municipal government and various housing agencies. One study [28] reveals that there was significant population growth along the TX line after the operation and the number of passengers increased by housing supply stabilized railway management. In this study, we focused on six stations located in the Ibaraki Province (Figure 2).
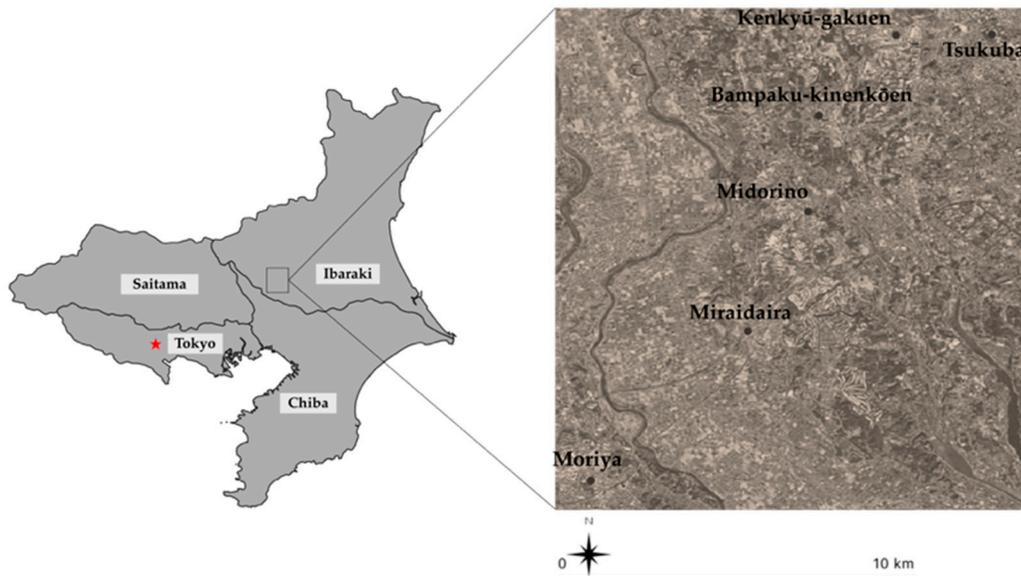
Figure 2. Study area: 6 station areas of Tsukuba Express Line, Length: 13 km, Width: 14 km (Source: Geospatial Information Authority of Japan [29]).

2.1.2. SLEUTH Model Reconstruction of the Tsukuba Express Line

For the original SLEUTH model, six grayscale geospatial data layers (land use, urban, transportation, hill-shade, slope, and exclusion) in GIF format were used as inputs. All inputs were resampled into the same projection, having equal row and column sizes, using QGIS. The naming conventions of the inputs follow the SLEUTH model requirements (Table 1). The land-use layers which indicates historical changes in the land-use type of study area in historical years were downloaded from the National Land Numerical Information Download Service of Japan [30]. Four years were selected for availability, namely 1997, 2006, 2009, 2014. The pixel values of the land-use inputs were reclassified into integer values ranging from 0 to 4 according to the requirements of the SLEUTH model. Each value corresponds to either unclassed, urban, agriculture, forest, and excluded. The land-use data from 2014 were used to measure model accuracy. Reclassification of the raw land cover information was conducted at the data preparation phase, such that farmland was reclassified as agriculture; both forest and grassland were reclassified as forest; barren land was reclassified as unclassed; building area was reclassified as urban area, and river as excluded area. Likewise, urban cover inputs were extracted from the land-use data for each year. Urban layer only shows l urban or non-urban area, where urban pixels and non-urban pixels have values of 1 and 0, respectively. The transportation layer which represents road maps of 1995 and 2011 was downloaded from the Geospatial Information Authority of Japan [29]. The values assigned represent categories of road accessibility levels. A pixel of the transportation layer was assigned an integer value ranging from 0 to 3, where 3 means relatively the highest accessibility. Slope and hill-shade inputs were generated from ALOS World 3D [31]. Hill-shade layer is only included for visualization and the slope layer contains the percent slope in integer values ranging from 0 to 100. Lastly, the exclusion layer represents additional weightings for the possibility of urbanization. A pixel having a value of 100 means urbanization will not happen on that pixel in the future. For example, water bodies are assigned 100, whereas non-water areas are assigned 0 or some other number. The closer a pixel value is to 100, the more restricted is the pixel to urbanize. The historical inputs are shown in Figure 3. The inputs are used to forecast land-use change of the study area from 2010 to 2050.

Table 1. Data conventions of Tsukuba Express Line area.

Format:	Graphic Interchange Format (GIF)
Size, Resolution:	255 × 277, 50-m
Projection:	GCS_Tokyo
Latitude, Longitude:	35.94°–36.09°, 139.99°–140.12°
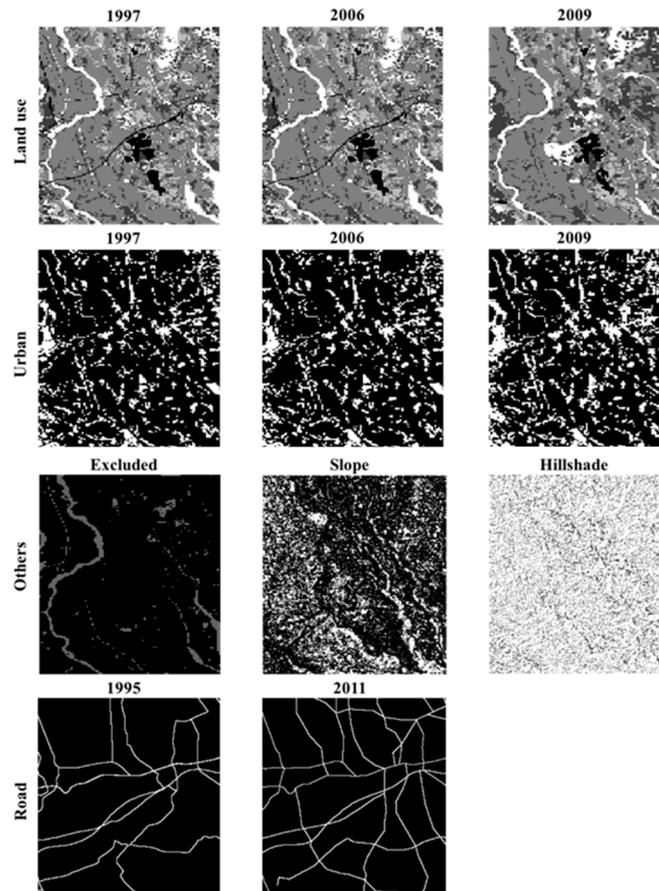
Figure 3. Historical input data of Tsukuba Express Line area.

2.2. Methods to Consider Urban Growth around Station in SLEUTH

2.2.1. Extended SLEUTH

The exclusion layer is a manually configured layer which physically represents how resistant a location is to urbanization (e.g., designated water bodies, national parks, protected areas). Areas where urban sprawl is considered impossible are given a pixel value of 100, meaning that the area represented by the pixel is 100% not allowed to urbanize in the future. The exclusion layer has been proven as an effective tool for exploring urbanization scenarios triggered by government policies by adjusting the pixel values of the layer [22–24]. In this study, we incorporate station information into an exclusion layer and explore various pixel values representing areas surrounding the stations, which can reflect the impact of railways on urban growth.

Geospatial locations of railway stations were acquired and embedded into the exclusion layer. For the Tsukuba Express Line area, vector data of railway stations were downloaded from the National Land Numerical Information Download Service of Japan [30]. Based on the vector data, the station area was buffered with a radius of 300 m from the station node and masked over the existing exclusion

layer using ArcGIS. The pixel values of this new exclusion layer were then adjusted to check the best fit for capturing station impact on urban growth.

To determine the best-fit pixel values, the Extended SLEUTH was run repeatedly while varying uniform pixel values of non-water and non-station areas. The values tested ranged from 0 to 70, with 5 as an interval. Here, pixel values for water bodies and other restricted areas were set to 100, while station pixel values were fixed at 0. Meanwhile, a control case (Original SLEUTH) was set utilizing default settings. A summary is shown in Table 2 of the case setups of Extended SLEUTH. The new exclusion layers of the Extended SLEUTH are mapped in Figure 4.

Table 2. Pixel values of 2 exclusion layers.

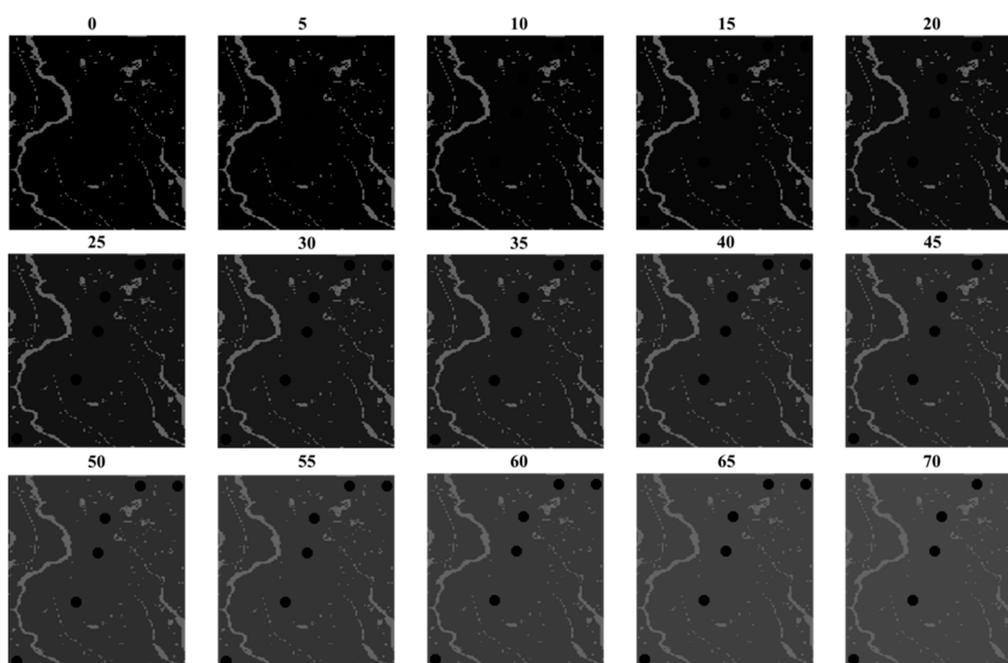|	Class 1: Water Area	Class 2: Non-Water and Non-Station Area	Class 3: Station Area
Original SLEUTH	100	0	-
Extended SLEUTH	100	5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70	0

Figure 4. Exclusion input with different pixel values in class 2 of Extended SLEUTH in Tsukuba Express Line area.

2.2.2. SLEUTsH

Another approach is to introduce an additional input layer to the SLEUTH model. Here, a station layer is added as a new input in addition to the six default layers. This station layer mainly comprises the buffers introduced in the Extended SLEUTH (Figure 5). Unlike the Extended SLEUTH, where SLEUTH is run multiple times to determine an appropriate exclusion layer, SLEUTsH aims to automatically generate the railway station effect during model execution. In other words, the main difference between this approach and the Extended SLEUTH is that the additional layer is capable of influencing the calibrated growth coefficients. This requires code modifications to consider the station layer and simulate urban growth surrounding railway stations. For further details regarding the SLEUTH source code, readers are advised to refer to the SLEUTH documentation or the code itself. Mainly, the source code of the SLEUTH model was written in the C language. Each urbanization effect is represented by a function or module. For the station layer to be considered in urban growth, modifications of the

following scripts were conducted: *igrid_obj.c*, *scenario_obj.c*, *spread.c*, *utilities.c*, *igrid_obj.h*, *scenario_obj.h*, and *ugm_defines.h*.
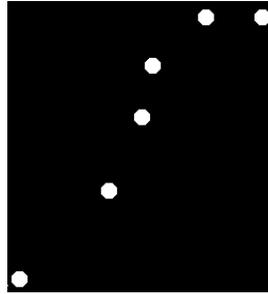

Figure 5. Station input of Tsukuba Express Line area.

The modification could be mainly classified into 3 parts (Figure 6). For the urban growth surrounding the station area (denoted by the buffers in the station layer), we implemented a road-influenced growth rule originally intended for urban growth in the transportation layer, with a few simple modifications. The original growth rule is summarized as follows:

(1) Select a pixel which is newly urbanized by the previous three growth rules as a center;
(2) Search for road pixel within a maximal radius; if a random value is less than the breed coefficient, a temporary urban cell will be created on the road which is nearest to the selected cell and a random walk will be started along the road, with the walking distance determined by the dispersion coefficient;
(3) Consider the final location of the road walk as a spreading center;
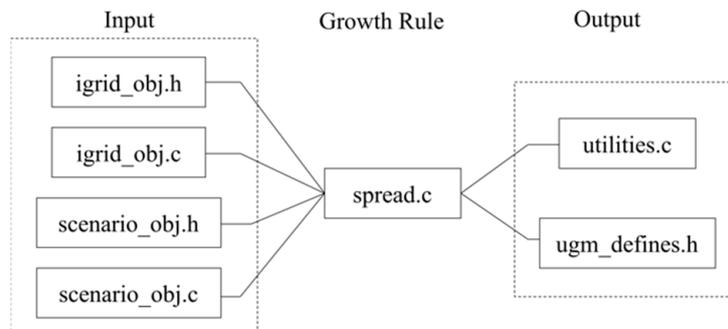(4) Urbanize the neighbor pixels if they are available to be urbanized.

Figure 6. Summary of modifications in source code.

To consider urban growth around the station, the above process was modified (inside the source code of road-influenced growth rule located in *spread.c* file) by adding urban growth priority or weighting around the station rather than along the road. To technically represent this modification, step 2 was changed into the following: search for road pixel with a maximal radius; after the temporary urban cell is created on the road, start the search for nearby station buffer and prioritize this over starting a road walk. This modified SLEUTH is named SLEUTsH because of the introduction of a station layer (represented by "s").

3. Results

3.1. Extended SLEUTH

3.1.1. Urban Growth Probability Output

The urban growth probability output is one of the two image outputs generated from the prediction phase. This output shows the possibility of each pixel to be urbanized in the future. The probability values are represented by colors (Figure 7). The predictions of the Extended SLEUTH for 2050 are shown in Figure 8. In general, when pixel values of class 2 (Table 2; Section 2.2.1) range from 5 to 50, the growth probability along the road is obviously higher than the other areas, indicating that road networks have high influence on the urban sprawl of the target area (darker colors along the road shown in Figure 8). All neighboring areas of road networks have similar urban growth probabilities, suggesting that urban growth will continue to progress over the entire target area. When pixel values of class 2 were set above 50, the urban growth probabilities along roads were reduced, resulting in higher urbanization probability occurring at class 2 locations. With regard to the urban growth surrounding stations, cases where pixel values of class 2 were set to 35, 40, 45, and 50 reveal higher urbanization growth probability in the vicinity of stations (i.e., obvious railway-induced urban growth).

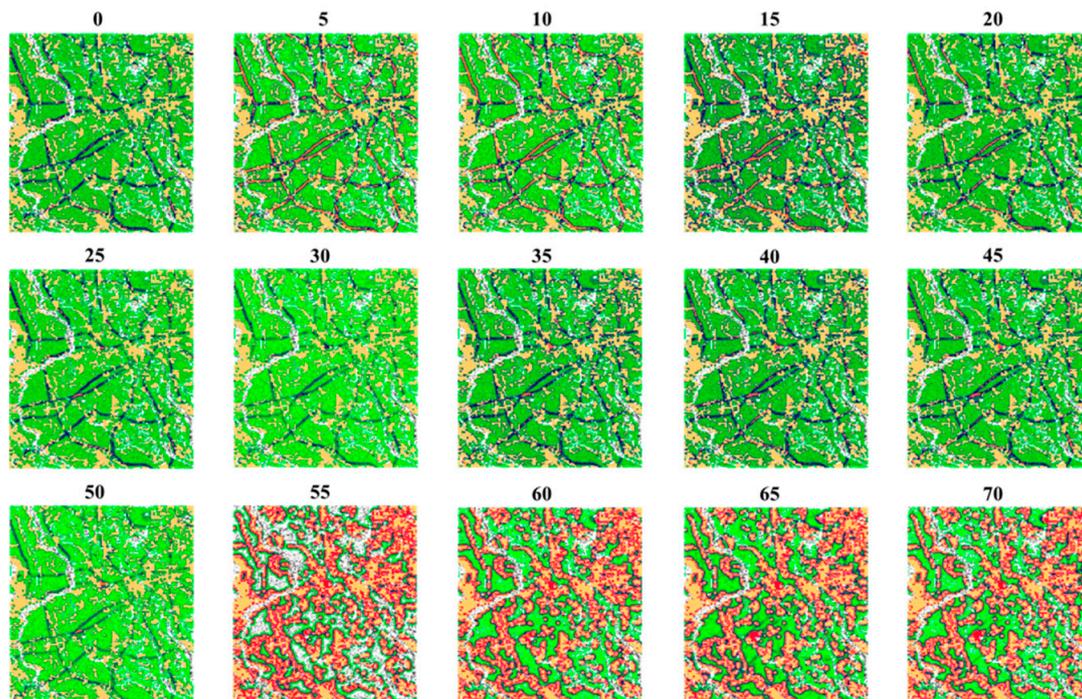| Probability(%)	Color
0~1	Transparent
1~30	
30~60	
60~80	
80~100	

Figure 7. Color legend.

Figure 8. Urban growth output of Extended SLEUTH in 2050.

3.1.2. Land-Use Change Output

The land-use change output forecasts the situation of land cover from 2010 to 2050. Here, the simulation accuracy of the original SLEUTH model was evaluated by using the predicted land use in 2014 compared with actual data in 2014:

$$\text{Accuracy (\%)} = \text{number of match pixels/total number of pixels} \tag{1}$$

The accuracy of original SLEUTH (i.e., pixel value of class 2 = 0) was 84.66% and the accuracy of Extended SLEUTH with different pixel values is summarized in Figure 9. In the case of Extended SLEUTH, the accuracy almost remains around 80% for most cases. However, when the pixel value of class 2 is 50, the model shows the highest accuracy of 86.04%, which is even higher than the original SLEUTH. Recalling the previous discussion, the case in which class 2 was set to 50 shows railway-induced urban growth. Compared to the other cases of different class 2 values (Table 2), this case seems to be at the transition when urban growth along roads is reduced and urban growth farther from the stations is increased.
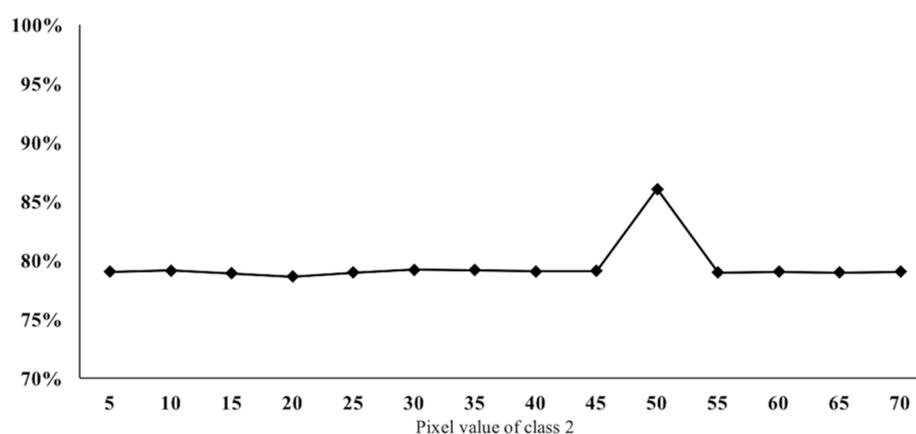

Figure 9. Accuracy (vertical axis) of Extended SLEUTH when changing pixel value of class 2 (non-station and non-water area) from 5 to 70 (horizontal axis). The horizontal axis represents case runs of Extended SLEUTH, where each case represents variations in the representative values of class 2 (e.g., 5 means that an Extended SLEUTH run with all pixels in the exclusion layer representing class 2 were set to 5).

3.2. SLEUTsH

3.2.1. Urban Growth Probability Output

The urban growth probability outputs of 2014 and 2050 of the SLEUTsH model are shown in Figure 10. The region of bright red color in the output of 2014 (Figure 10a) corresponds with a station's immediate surroundings. This suggests that this procedure can capture railway-induced growth automatically. Similar to the results of the Extended SLEUTH (when pixel value = 50), the target area is expected to urbanize along road networks and station surroundings.

3.2.2. Land-Use Change Output

The accuracy of SLEUTsH was also evaluated using the same procedure as in Section 3.1.2. The accuracy of SLEUTsH was 84.92%, which performed better than the original SLEUTH (84.66%) but worse than the case in which class 2 was set to 50 in the Extended SLEUTH (86.04%).
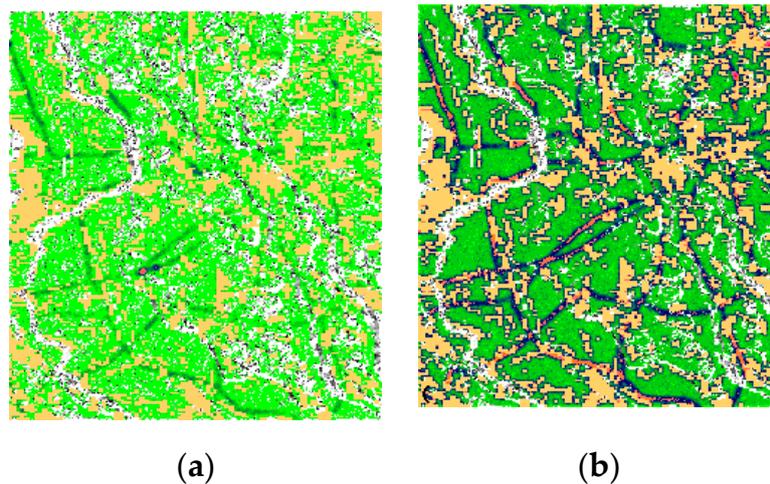
(**a**)　　　　　　　　　　　　　　　　　(**b**)

Figure 10. Urban growth probability output of SLEUTsH: (**a**) 2014; (**b**) 2050.

3.3. Generalizability of the Model Improvements—Gurugram Railway

The results so far were conducted for only one railway line (TX). In this section, we investigate the generalizability of the model improvements by evaluating them over another railway line of a different region. Furthermore, we utilized SLEUTH inputs constructed from geospatial datasets that have global coverage. The additional target area, its model representation, and the summary of its accuracy is briefly introduced.

3.3.1. Gurugram City and Its Model Representation

To further evaluate the methods introduced in this study, we selected Gurugram City, India, which has a different socio-cultural background and geology to the Tsukuba Express Line. Historically, the city also shows evidence of railway-induced urban growth similar to that of the Tsukuba Express Line. Gurugram City, which used to be known as Gurgaon, located in Haryana State, India, is one of the major satellite cities in New Delhi [32]. As a result of its close distance to New Delhi, many international companies chose to relocate to Gurugram, providing plenty of job opportunities in the late 1990s. Gurugram was transformed into the financial and industrial center of Haryana State [32,33]. The rapid industrial growth as well as immigration from Delhi due to the affordable housing and close distance to the national capital have caused population explosion and resulted in urban sprawl in Gurugram [32]. The city has an adequate transport system, with the national highway and national railway networks linking Gurugram to cities like Delhi and Mumbai. In order to meet the travel demand between Gurugram and Delhi, the Delhi Metro Yellow Line extended five stations to the center of Gurugram, with an interchange with the Rapid Metro of Gurugram. According to the Department of Town & Country Planning, Government of Haryana [34], there is a plan to further extend the Delhi Metro Yellow Line and Delhi Metro Blue Line to Gurugram City as well as develop new residential areas by 2031.

The inputs of the selected area (Figure 11a) for SLEUTH were processed into consistent projection and size by QGIS. Input of land use, urban, and exclusion layers were derived from the ESA CCI land cover time-series v2.0.7 (1992–2015) [35] dataset. Road network vector data were downloaded from MapCruzin [36]. Hill-shade and slope layers were processed from digital elevation maps of ALOS World 3D [31]. Data on locations of the metro stations of Gurugram were downloaded from HOTOSM [37] in vector format. The input dataset for implementation is shown in Figure 11b. Data convention is summarized in Table 3. Historical data of 1995, 2000, 2005, and 2010 were used for prediction from 2011 to 2050. The Extended SLEUTH (changing pixel value of class 2 locations from 0 to 70), SLEUTsH, and original SLEUTH models were implemented using the same method for the TX domain.

Table 3. Data convention of Gurugram City study area.

Format	Graphic Interchange Format (GIF)
Size, Resolution	95 × 83, 300-m
Projection	WGS 84
Latitude, Longitude	28.31°–28.54°, 76.86°–77.13°
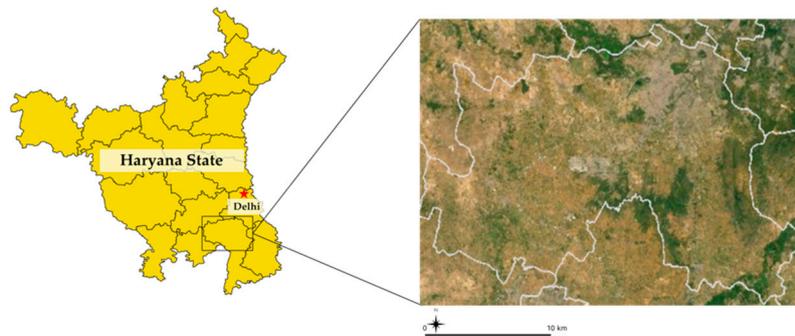
(**a**)
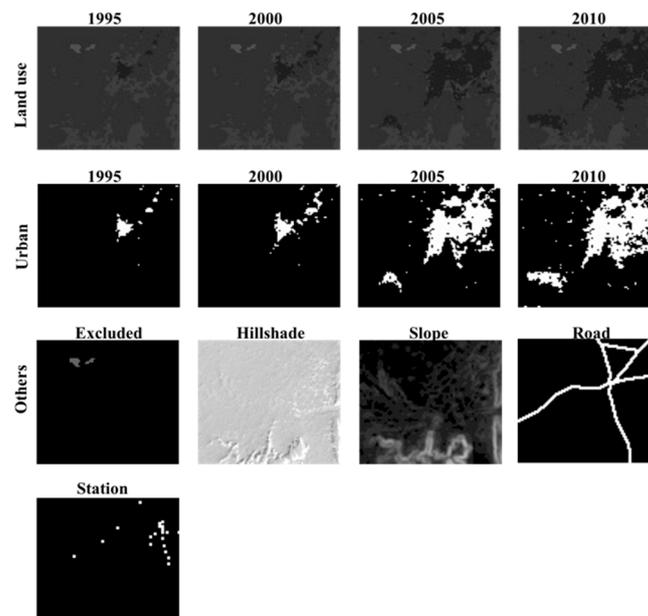
(**b**)

Figure 11. SLEUTH inputs representing Gurugram City. (**a**) Target area (Source: DIVA-GIS [38], Ministry of Electronics & Information Technology, Government of India [39]); (**b**) Input dataset.

3.3.2. Model Accuracy

The land-use change outputs in 2015 of original SLEUTH, Extended SLEUTH, and SLEUTsH were used for accuracy validation by comparing them with actual data using Equation (1). The highest level of accuracy among the three models is 91.88% when the pixel value of class 2 is 5 in Extended SLEUTH. This is followed by SLEUTsH, with an accuracy level of 88.07%. Meanwhile, the original SLEUTH was 87.91% accurate. The results are consistent with the implementation of TX at fine resolution. This suggests the importance of introducing railway-induced urban growth in the SLEUTH model by Extended SLEUTH and SLEUTsH. Furthermore, the globally available inputs enable the global application of the model.

4. Discussion

4.1. Projected Future Urban Growth in Tsukuba and Gurugram

Although the main objective of this study is to evaluate the methods of introducing railway-induced urban growth, it is also informative to discuss the urban cover projections for both the target areas, Tsukuba City and Gurugram City. Land-cover change and urban growth for the Tsukuba Express Line area and Gurugram City from 2010 to 2050 were calculated. For the consistency of both cities, the 300-m resolution models of Tsukuba Express Line were used. For both regions, around 90% of the land cover change in 2050 comes from a shift from agricultural land cover to urban, which may pose challenges to the food supply or hydrology in the future.

The projected urban area of the Tsukuba Express Line in 2020 is double that of 2010. On the other hand, the projected urban area of Gurugram City triples under the same time period. The main reason for the lower rate of urbanization of Tsukuba Express Line to that of Gurugram City is related to the urban cover percentage (Equation (2)) in the final year.

$$\text{Urban cover percentage (\%) = number of urban pixels/total number of pixels} \tag{2}$$

The urban cover percentage in 2050 of the Tsukuba Express Line for original SLEUTH, Extended SLEUTH (when the pixel value of class 2 = 45), and SLEUTsH is projected to be 85.22%, 84.41%, and 89.61%, respectively. Meanwhile, for Gurugram City, its urban cover percentage for original SLEUTH, Extended SLEUTH, and SLEUTsH is 65.69%, 53.76%, and 77.12%, respectively. This means that Gurugram City has more room for urban expansion than the Tsukuba Express Line. Moreover, the initial year when the railway system started operation was later for Gurugram City than the Tsukuba Express Line.

4.2. Resolution Dependence

An additional set-up for TX was also constructed using the same input data sources as in the Gurugram City case. The aim of this was to confirm the dependence of the aforementioned results on spatial resolution and to strengthen the applicability of globally available geospatial datasets as inputs for SLEUTH.

The target area was expanded from six stations of TX to 12 stations (Figure 12a), with 97 rows and 101 columns. The total dimension is 27 km and 28 km along its length and width, respectively. The 300-m resolution land use layer, urban layer, and excluded layer were processed from ESA CCI land cover time-series v2.0.7 (1992–2015) [35], while the transportation layer, slope layer, hill-shade layer, and station layer were resampled to 300-m resolution from the previous dataset. Historical data of 1997, 2006, and 2009 were used for prediction from 2010 to 2050 (Figure 12b).

Accuracy validation for a 300-m Tsukuba Express Line area in 2014, a 300-m Gurugram city in 2015, and a 50-m Tsukuba Express Line area in 2014 is summarized in Figure 13. For the 300-m Tsukuba Express Line case, the Extended SLEUTH was still able to achieve the highest performance, with accuracy of 91.22% (when the pixel value of class 2 = 45); this was followed by the original SLEUTH with 90.96% and 86.51% for SLEUTsH. The lack of improvement in the performance of SLEUTsH model in the 300-m resolution cases could possibly be influenced by the 300-m buffer radius assigned for stations. Fixing this parameter leads to a significant difference in the number of pixels that are within the buffer radius between the 300-m case and 50-m resolution. In comparison with different resolutions, the 300-m resolution cases are constantly higher than the 50-m case. Future studies could consider testing the SLEUTsH's sensitivity to the buffer radius. Overall, the results suggest the suitability of global land cover dataset as inputs. In addition, the current findings also highlight the challenges of SLEUTH or CA algorithms when applied at finer resolutions.
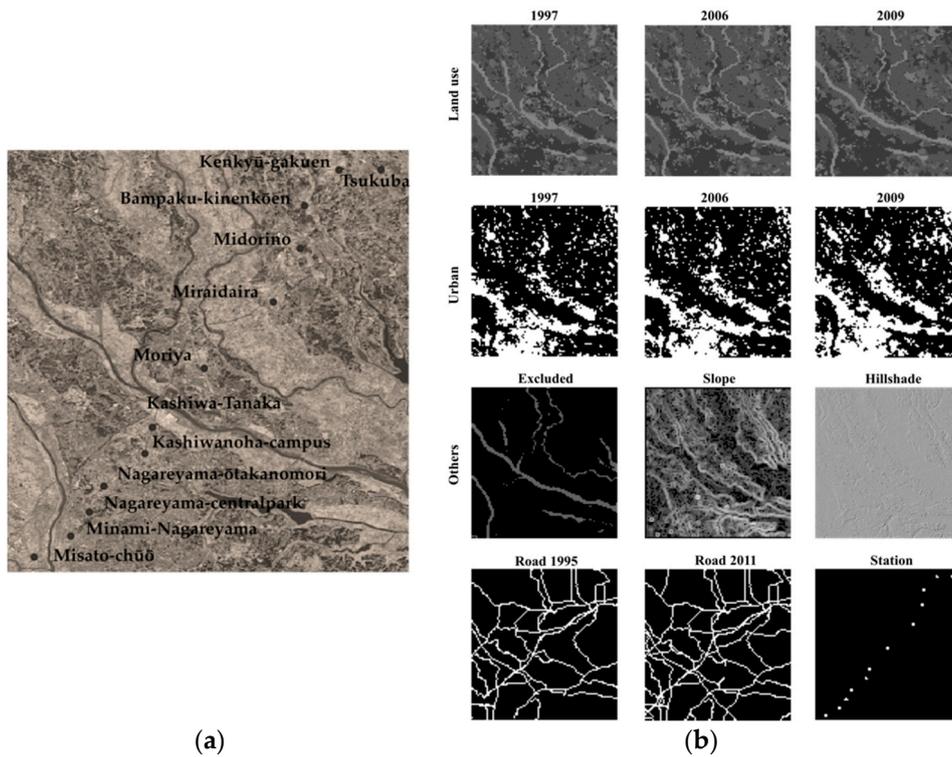
Figure 12. SLEUTH inputs representing rescaled Tsukuba Express Line area. (**a**) Latitude: 35.82°–36.09°, Longitude: 139.99°–140.12° (Source: Geospatial Information Authority of Japan [29]); (**b**) Input dataset.
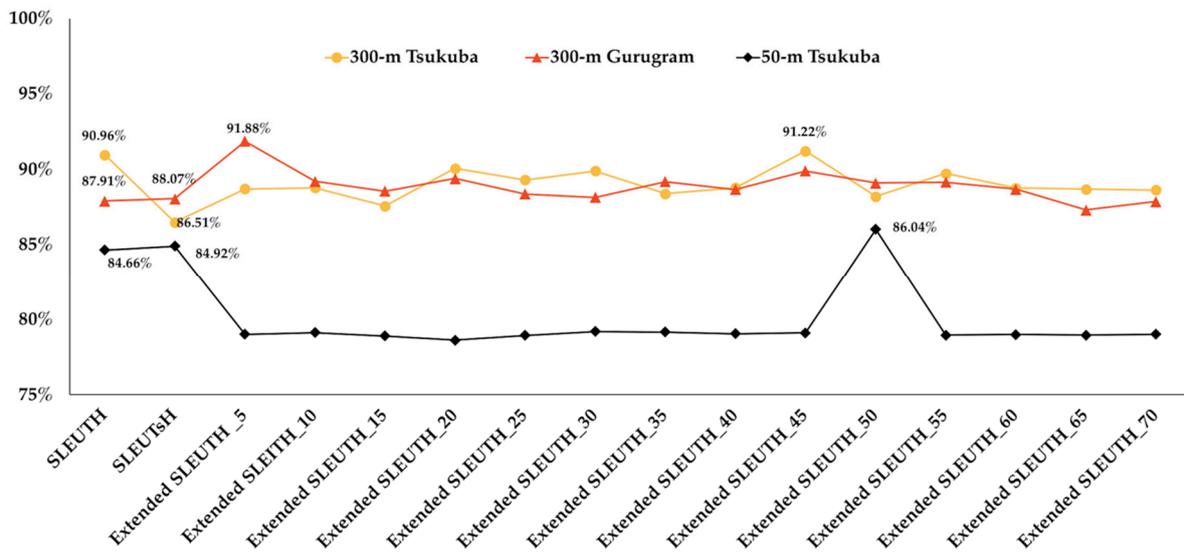

Figure 13. Accuracy (vertical axis) of 300-m resolution Tsukuba Express Line area (yellow line), 300-m Gurugram City (red line), and 50-m Tsukuba Express Line area (black line) under various cases (horizontal axis). The cases are the original SLEUTH, the SLEUTsH, and variations of Extended SLEUTH (when changing pixel value of class 2 (non-station and non-water area) from 5 to 70; see Figure 9 caption).

4.3. Extended SLEUTH vs. SLEUTsH: Advantages, Disadvantages, and Limitations

Based on the previous section, it can be said that both model improvements are able to perform better than the original SLEUTH, which underestimates urban growth because of the lack of consideration of railway representation. The performance of both improvements is also dependent on

the resolution of the inputs where, at coarser resolutions, both methods can be chosen flexibly to reflect railway-induced urban growth. Based on the current findings, the advantages and disadvantages of their implementation are summarized.

The Extended SLEUTH, which can be incorporated into the exclusion layer (default SLEUTH input), was capable of predicting with higher accuracy than the original SLEUTH and SLEUTsH. Its simplicity enables urban planners to directly implement government policies by setting appropriate pixel values of specific areas. The Extended SLEUTH has already been introduced in an earlier work by Yin et al. [21]. They introduced various scenarios by adjusting the exclusion layer input to model urban growth in Jinan City, China, using SLEUTH. One scenario showcased railway-induced urban growth in Jinan. To achieve this, multiple values were introduced in the non-station and non-water area of the exclusion layer. In their work, the appropriate values were mainly assumed as a means to introduce policy effects and no accuracy testing was done. In the current study, we wanted to test further the method initiated by Yin et al. [21] by measuring the sensitivity of the accuracy to the values set in the exclusion layer. Our results show that the setting of pixel values in the exclusion layer is arbitrary and its effects on the accuracy would vary depending on the target area. To overcome this weakness, users who plan to implement the Extended SLEUTH have to measure accuracy under various pixel values in the exclusion layer.

The SLEUTsH model could automatically incorporate railway-induced urban growth in the calibration of growth rules in SLEUTH. Its accuracy (Figure 13) also appears to have closer ranges compared to the original SLEUTH and Extended SLEUTH. The main attracting feature of the SLEUTsH compared with the Extended SLEUTH is that it reduces the uncertainty of regional dependence and may be useful when predicting urban growth simultaneously for multiple regions (e.g., GUGPS [13]). The impacts of the additional rules set in SLEUTsH (Section 2.2.2) need further investigation in the future in order to consistently provide better accuracy than the original SLEUTH and the Extended SLEUTH.

Based on the current findings and scope, the limitations are discussed. In this work, we investigated the railway-induced urban growth of two cities. More cities of investigation are needed in order to further strengthen the comparison results among methods and determine appropriate settings for each model improvement. There also remains uncertainty regarding the buffer size (Section 2.2) used to represent the railway stations. The dependence of the results on the buffer size needs to be further evaluated in the future. In this work, all historical inputs (e.g., land cover, transportation network) used in SLEUTH are assumed to be of sufficiently good quality. The accuracy of the inputs affects the accuracy of the predictions. Finally, the disadvantages of both proposed model improvements indicate the limitations of use of each model improvement.

5. Conclusions

Predicting future urban growth patterns is a necessary step for sustainable land-use management. In this study, railway-induced urban growth was considered in an urban growth model (SLEUTH) using two methods: 1) Extended SLEUTH, exploring suitable pixel value of station area in the exclusion layer; 2) SLEUTsH, adding station as a new input layer.

Through the implementation in the Tsukuba Express Line area and Gurugram City, both Extended SLEUTH and SLEUTsH are applicable in areas where railway transport is prevalent. For the first method, the Extended SLEUTH was able to perform best among the three models after manually selecting suitable pixel values in the exclusion layer. However, the Extended SLEUTH appears to be sensitive to different combinations of pixel values representing the station area and non-station area in the exclusion layer under varying locations and resolution. The second method, the SLEUTsH model, automatically captured urban growth concentrations surrounding stations. This method performs better or on par with the original SLEUTH. The SLEUTsH model has the main advantage of automatically considering railway-induced urban growth from the calibration phase and thus offers wider applicability.

This study also further confirmed the dependence of SLEUTH on resolution. The current result, where the accuracy of the 300-m resolution appears generally higher than the 50-m resolution, hints at the difficulty of SLEUTH to capture land cover changes at finer scales. Future steps in the work are underway to address the current limitations of the study (Section 4.3) and to advance the investigation of railway-induced urban growth across multiple cities. It is recommended to conduct further comparisons of the model improvements in more cities, test model sensitivity to the quality of inputs and treatment of railway stations (i.e., buffer size), and incorporate other validation metrics. Finally, since the geospatial inputs needed to run SLEUTH have global coverage, it is our final goal to predict future railway-induced urban growth across all cities worldwide.

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