Development of Urban Growth Model for Transit Oriented Development

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According to United Nations, 68% of world population will live in urban area by 2050, with most of the urban population increase in Asian and African countries. There is no doubt that urban population growth will cause the spatial sprawl of urban area where forecasting the future urban using an urban growth simulation model would be helpful for getting a better understanding and providing sustainable urban development plan. SLEUTH model is an urban growth simulation model that uses cellular automata for capturing the pattern of urban growth and land use change from 6 layers of historical data (Slope, Land Use, Exclusion, Urban, Transportation, Hill-shade). Although the transportation layer involved the effect of road network development on urban growth, there is still room for considering public transport in to SLEUTH model. Transit-oriented development (TOD) is a type of urban development strategy that aims to encourage travel mode shift from private vehicles to public transport. TOD is considered as a sustainable urban planning tool and is being applying in many cities in the world. Regarding to the lack of public transportation in SLEUTH and the feature of TOD, the objective of this paper is to introduce public transport into SLEUTH by considering TOD effect on urban growth using two methods: 1) extending the exclusion layer by adding station map; 2) creating a new input layer of station map besides the current 6 inputs. The result shows that both of the two methods successfully captured the urban growth under TOD and the method of extending exclusion layer showed a higher accuracy.

Key Words : *urban growth, transit-oriented development, Cellular Automata, SLEUTH model*

1. INTRODUCTION

Urbanization, which refers to the population shift from rural to urban areas, has been an unstoppable global phenomenon for decades. Meanwhile, an increase of urban population often denotes to an increase in geographic extent of a city. Unfortunately, a disordered urban sprawl is easily correlated with rapid change of land cover which could potentially result to ecological degradation, loss of farm land, as well as many other urban issues such as pollution, traffic congestion, residential crowding, climate change and so on.

In recent years, urbanization along with the rapid economy growth in developing countries such as China, India, Nigeria and so on has become a huge issue. According to the United Nations, 55% of the world's population lives in urban areas in 2018, the proportion is expected to increase to 68% by 2050, with close to 90% of this increase taking place in Asia and Africa[1)]. Countries of low-income and lower-middle-income where the pace of urbanization is considered to be the fastest, will face many challenges on land use planning in meeting the needs of their growing urban populations in the developing of housing, transportation, basic infrastructures. Urban sustainability is becoming an issue to be discussed in 21st century and a sustainable development is highly dependent on the successful management of urban growth. Thus, how to organize the land cover for a sustainable development is becoming a common issue in developing countries, where having a good understanding of future urban growth pattern and future land use tendency is of great importance.

Computational advancement in recent years has generated many models to help urban planners predict and forecast the land use dynamics of future urban. Cellular Automata (CA)[2] modeling is one of the most popular spatial modeling approach which requires the space area be presented as grid of cells that can change their states as the model iterates. This allows the CA model to capture the complex spatial situations and could correspond with Geographic Information System (GIS) very well. To date, the most popular CA model is the SLEUTH model.

The SLEUTH model developed by Dr. Keith C. Clarke in 1997[2], is a CA based urban growth simulation model which assumes that the future urban growth pattern could be captured from historical data. The name SLEUTH is an acronym of 6 required input layers: slope, land use, exclusion, urban, transportation and hillshade. All the 6 input layers are required to be historical grayscale gif images of study area, need to be derived from grids with the same projection and have consistent numbers of rows and columns as well as following same naming conventions. SLEUTH model has a feature of not depending on local specific forces as the inputs are geographical images, which allows it to be generally used in global scale. The model is coded in C language and the protocol code could be downloaded freely from the website. User could extend the model by adding or rewriting code to achieve specific prediction. Currently, it has been applied in over 100 cities to simulate future urban growth and land use change in the world.

SLEUTH model requires 3 phases of implementation (**Fig.1**) which are data preparation, model calibration and prediction. The calibration step needed to be implemented 4 times to derive 5 coefficients.

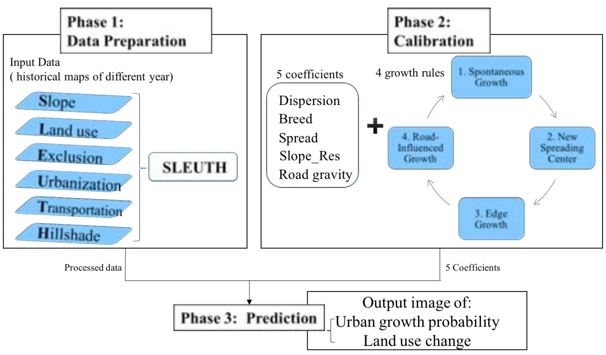

Fig.1 SLEUTH model structure

The initial setting of coefficients are value between 1-100, each time of implementation narrows the values into a smaller range and finally get the best prediction values which is used into prediction step. The 5 coefficients control 4 growth rules that SLEUTH model follows: spontaneous growth, new spreading center, edge growth and road influenced growth. The final outputs from prediction are both spatial images and static files. One simulation cycle consists of a series of growth cycles that begins in the start year and completes in the stop year [3].

One significant urbanization pattern not considered in SLEUTH is transit-oriented development (TOD). TOD, an urban development concept proposed by American urban designer Peter Calthorpe in 1993[4], refers to the high density and mixed use of land that arranges different type of urban functions all around a public transit stop within walking distance, aims to shift the automobile dependency to public transport. TOD has been successfully implemented in many developed countries such as United States as a sustainable urban land use allocation strategy. On the other hand, as many public transportation projects are under construction in developing countries, it is also expected to promote sustainablility for urban growth for those areas.

The SLEUTH model only considered road effect on urban growth which probability due to the main driving force of urban growth in the past decades is private car ownership. However, considering the negative ecological effect of automobile, public transportation system is being encouraged widely in the world especially in developing countries in recent years. Therefore, the impact of public transportation on urban growth could not be overlooked. It is essential to update the SLEUTH model in order to capture a rather sustainable and eco-friendly growth of future urban.

Regarding the variety of public transport, this research only focus on the TOD effect around a railway station.

Previous researches have extended the SLEUTH model to simulate future land use change under government policies including TOD by defining different pixel values to apply different scenarios in the exclusion layer [5) 6) 7)]. However, from the previous work, the impact of TOD on land use change was manually introduced since the relationship between TOD and land use change is still not distinct. In this research, the main effort is to automize the urban growth prediction (2015 to 2050) considering surroundings of a station area. Two methods were tested to achieve this, namely:

1) Extended SLEUTH: exploring suitable pixel value of station area in the exclusion layer which can generate the TOD effect based on previous works;

2) SLEUTsH: adding station map as a new input layer into the model to include TOD impact.

2. METHDOLOGY

(1) Study Area and input data

Tsukuba Express Line (TX) established in 2005, is a railway line that connect Tokyo and Tsukuba Science City (Ibaraki Province, Japan) which is 50km away from Tokyo in 45 mins. The TX project refers to not only the construction of TX but also the urban development of areas along the railway line. It is being supported by municipal government and housing agencies, is a representative of TOD that happens in recent years. 6 stations locate in Ibaraki Province are selected as study area (**Fig.2**).

For the original SLEUTH model, six grayscale data layers in GIF were used as inputs. All the inputs were convert into same projection with same row and column size by ArcGIS and were named by same naming convention as the model required (**Table 1**). The land use layer which indicate the different land use type of study area in historical years were vector data of 4 years (1997, 2006, 2009, 2014), downloaded from National Land Numerical Information download service of Japan[8]. Pixel value of land use input was classified into 0 to 4 according to the scenario file of SLEUTH model which correspond to area of unclassed, urban, agriculture, forest and excluded. According to the original data source and required classification of SLEUTH model, farmland is defined into agriculture, both forest and grassland is defined as forest, barren land is defined as unclassed, building area is defined into urban area and river is excluded area during the data processing. The urban inputs were derived from land use data of the same year. Urban layer only shows the urban or non-urban area by giving urban pixel value as 1 and non-urban pixel value as 0. Transportation inputs which were road map of 1995 and 2011 were downloaded from Geospatial Information Authority of Japan[9] and was classified based on the accessibility. Pixel value of transportation layer was given as 0-3 where 3 means a higher accessibility. Slope and hillshade inputs were generated from ALOS World 3D[10], hillshade layer is only for visualization and slope input indicates percent slope by giving pixel values between 0-100. Lastly, the exclusion layer represents some area which is hard to be urbanized. For example, the water body was valued as 100 and the non-water area was valued as 0 initially in this research means that the water area is 100 percent could not be urbanized and the non-water area has a higher likelihood to be urbanized. The higher the value is, the harder to be urbanized. The historical inputs showing in **Fig.3** is used to forecast land use change of study area from 2015 to 2050.

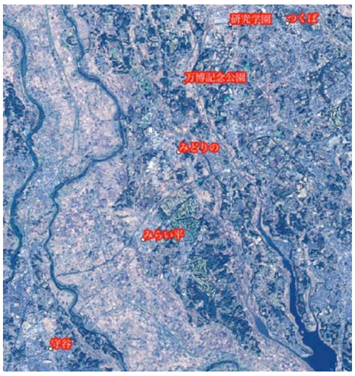

Fig.2 Study area

Table 1 Data Conventions

Format:	Graphic Interchange Format (GIF)
Size, resolution:	250×277, 100 m
Projection:	GCS_Tokyo
Latitude, Longitude:	35.94°~36.09°, 139.99°~140.12°

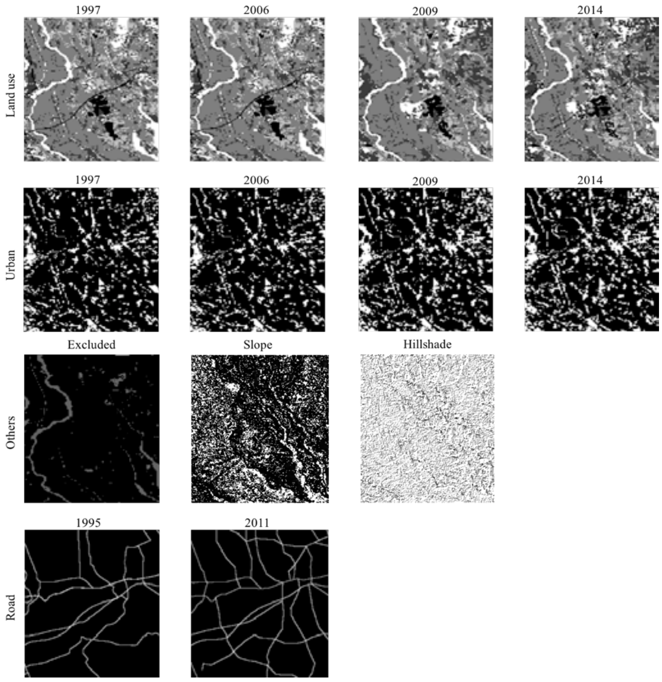

Fig.3 Historical input data

(2) Extended SLEUTH

Exclusion layer defines grid locations resistant to urbanization. Areas such as water body, national park where urban sprawl is considered impossible has been given pixel value of 100, means that this part of area is 100% unable to be urbanized. The exclusion layer has been proven as an effective tool for exploring effect of government policies by creating different scenarios with target region weighted into different pixel values[11]. The following study combines station and excluded map into a new exclusion layer and explore the fit pixel value of station area to reflect TOD.

The vector data of railway station in Japan was downloaded from National Land Numerical Information Download Service of Japan[8] and the six stations in study area were selected. The stations were buffered by radius of 0.3km and the image of station area was processed into same projection and size with the other inputs. The new exclusion layer was generated by merging the original exclusion layer and station area. All the processes above were done using ArcGIS.

Two scenarios were designed for comparison, scenario 1 (S_1) is the original SLEUTH model and scenario 2 (S_2) is the extended SLEUTH model. In order to figure out the best fit pixel value of new exclusion layer, both scenarios were implemented multiple times by defining the pixel in non-water & non-station area into different pixel values of 0 to 70 with every 5 step, the water pixel value and station pixel value remain as 100 and 0 (**Table 2**). The implementation flow is showing in **Fig.4** and the new exclusion layer of 2 scenarios are showing in **Fig.5**.

Table 2 Pixel values of 2 exclusion layers

	Class 1: Water area	Class 2: Non-water & Non-station area	Class 3: Station area
S_1	100	0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50,55, 60, 65, 70	—
S_2	100	0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50,55, 60, 65, 70	0

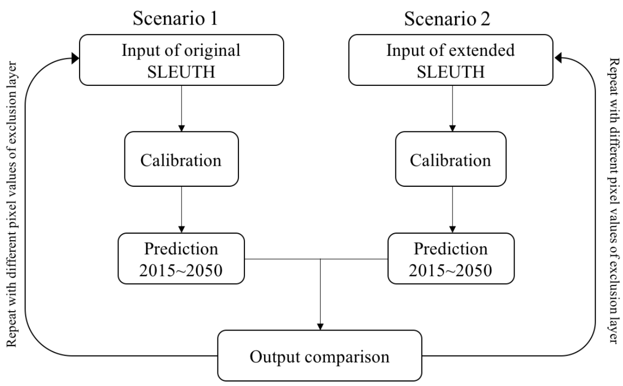

Fig.4 Flow chart of implementation SLEUTH with 2 scenarios

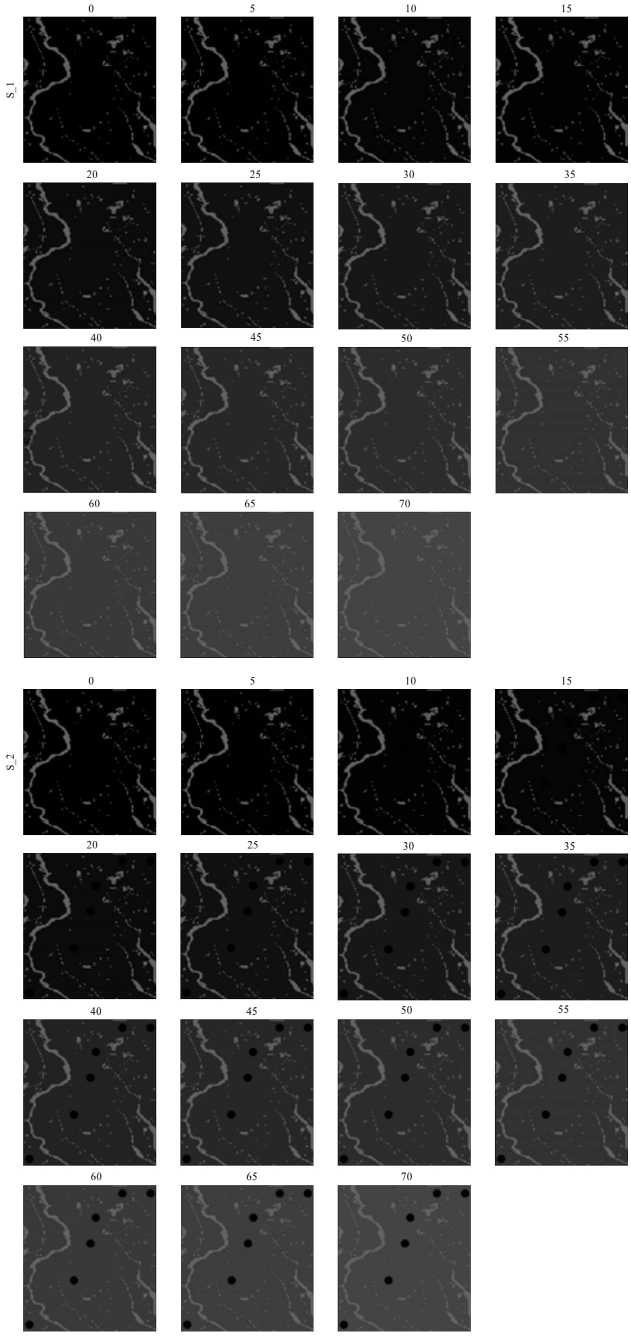

Fig.5 Exclusion input with different class 2 pixel values of S_1, S_2

(3)SLEUTsH

In this part of research, a station input was added as new layer besides the six initial layers. This approach aims to obtain the TOD effect automatically through modifying the code to make urban growth concentrate in station area. The input data of station layer is the same image as previous method (**Fig.6**). SLEUTH model consists of many files, all coded in c language which have different functions and could link with each other when implementation. After understanding the protocol code, several changes have been made on following files: *igrid_obj.c*, *scenario_obj.c*, *spread.c*, *utilities.c*, *igrid_obj.h*, *scenario_obj.h*, and *ugm_defines.h*. The modification could be mainly classified into 3 parts (**Fig.7**).

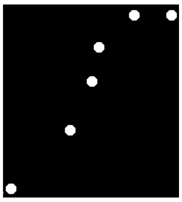

Fig.6 Station input

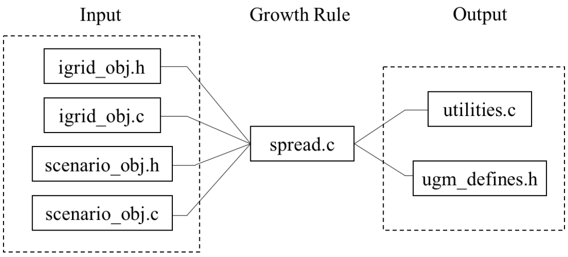

Fig.7 Connections between changed files

For the input and output part, codes of importing station layer and exporting station layer information are added by imitating codes of the other layers. For the urban growth in station area, we assumed that urban growth in station area could be affect by road-influenced growth rule which is designed to simulate the urban growth of transportation layer. The growth rule could be summarized as:

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

However, the urban growth could follow the development along road while in the TOD case, urban growth is designed to mainly happen around a station. Considering the difference, we modified the source code of road-influenced growth rule which is located in *spread.c* file by making the growth happen priory around a station instead of along road, which also corresponds the goal of achieving sustainable development for future urban. In the new road-influenced growth rule, step 2) is changed into: search for road pixel with a maximal radius, after the temporary urban cell is created on the road, start to search for station area instead of start road walk. The flow chart of modified road-influenced growth is showing in **Fig.8**. The modified SLEUTH is named as SLEUTsH.

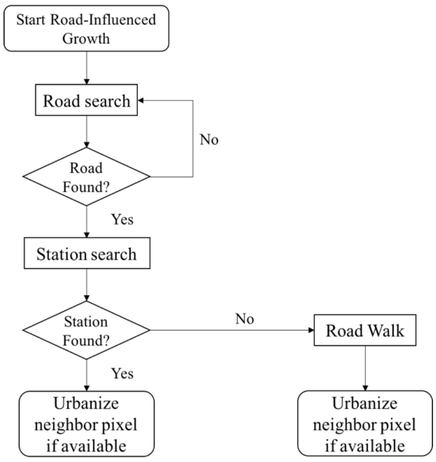

Fig.8 Flow chart of modified road-influenced growth

3. RESULTS

(1) Extended SLEUTH

a) Urban Growth Probability Output

The urban growth probability output is one of the 2 image outputs generated from the prediction phase. This output shows the possibility of each pixel being urbanized in future year by different color. As **Table 3** showing, different color represents different probability of urban growth and the darker color indicates higher probability. The final prediction year 2050 is selected for comparison. The outputs for scenario 1 and scenario 2 is showing in **Fig.9** and **Fig.10**.

From the two sets of figures, we could tell that the result are more or less similar to each other in the two scenarios. For both cases, when pixel value of class 2 ranges from 0 to 50, the growth probability along road is obviously higher than the other area. This indicates that road network highly affect urban sprawl. In the meantime, all the areas besides pixels nearby road network has the similar probability to become urban in the future, represents that the urban growth will spread to the entire area instead of only focus on road network area. However, when pixel value is higher than 50, the growth probability along road somehow disappeared and the pixels nearby the original urban pixels are highly probable to be urbanized in the future, means that in these cases, future urban growth will grow base on the existing urban areas.

However, in case of scenario 2, the urban growth probability around station area was able to be captured.

Table 3 Color Legend

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

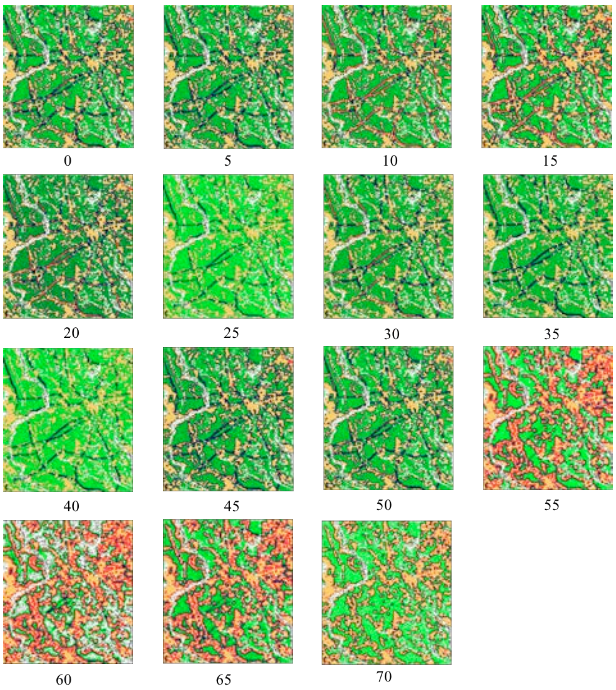

Fig.9 Urban growth probability in 2050 with pixel value of class 2 from 0 to 70 in scenario 1

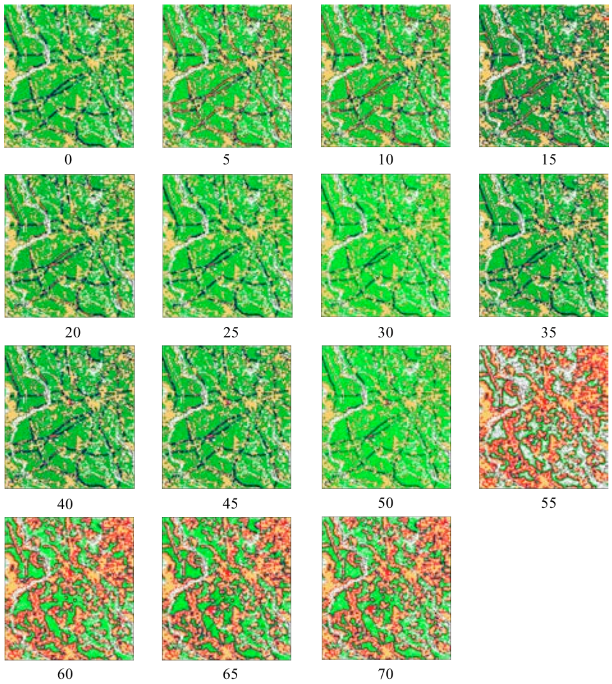

Fig.10 Urban growth probability in 2050 with pixel value of class 2 from 0 to 70 in scenario 2

b) Land Use Change Output

This output forecasts the future situation of land cover following the same classification of land use input. The urban pixel number and natural resources pixel number of 2050 is counted due to the previous classification and the urban rate of station area (number of station area urban pixel / total urban pixel) as well as rate of natural resources (total number of natural pixel / total pixel number) are compared between two scenarios. The total pixel of station area is 1111 and the entire pixel number is 69250.

Trend line generated from two scenarios (**Fig.11**) showed that the station area urban rate of scenario 2 increased with pixel value of class 2 increase, while in scenario 1, station area urban pixel rate decreased as pixel value increase. The gap between scenario 1 and scenario 2 is most obvious when pixel value of class 2 is 50.

The simulation accuracy of original SLEUTH model is verified by using the historical data of 1997, 2006, 2009 and 2014 to predict the situation of 2014 and compared with actual data since the latest source data is of 2014. The accuracy of normal SLEUTH(original SLEUTH with pixel value of class 2 =0) is 84.67% and the accuracy of Extended SLEUTH is shown in **Fig.12**. In case of Extended SLEUTH, the accuracy almost remain around 80% for most of the cases, however when pixel value of class 2 is 50, the model shows the highest accuracy of 86.04% which is even higher than the original SLEUTH.

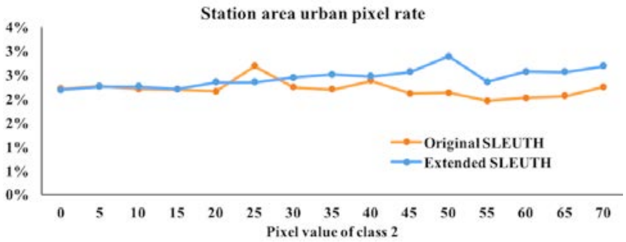

Fig.11 Station area urban pixel rate of scenario 1 and scenario 2 in 2050

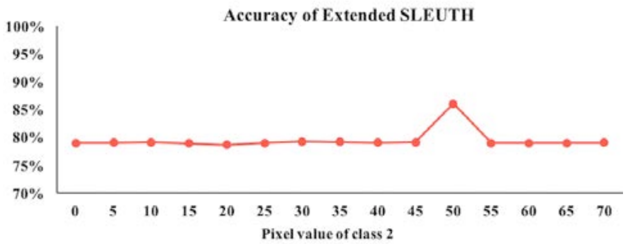

Fig.12 Accuracy verification of Extended SLEUTH with different pixel values of class 2

(2) SLEUTsH

a) Urban Growth Probability Output

The urban growth probability output in 2050 of SLEUTsH model is showing in **Fig.13**. Similar to the Extended SLEUTH (when pixel value =50), the growth probability along road network is still higher than the other areas. Green is also the dominant color of the area but color in SLEUTsH is darker means that urban pixels will spread to the entire study area under higher growth probability.

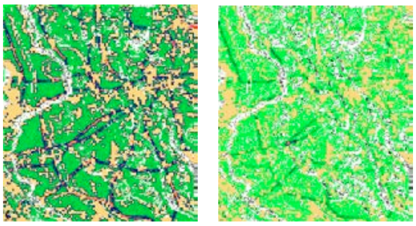

Fig.13 Urban growth probability in 2050 (left) and 2014 (right) of SLEUTsH (refer to Table 3 for color legend)

b) Land Use Change Output

The station area urban rate of SLEUTH is calculated as 2.26%. The accuracy of SLEUTsH is 84.92%, which performs in the middle of original SLEUTH and Extended SLEUTH.

4. DISCUSSION

By implementing the SLEUTH model in this research, it is considered that the outputs of SLEUTH model are highly dependent on input images from the aspect of output quality and accuracy. From **Fig.14**, number of water pixel has slightly changed although the water area should be 100% resistant to be urbanized, this probably due to the latest exclusion layer used for prediction is 2009 and the classification from original land use data source could be different between different data year. In the meantime, some road pixels are defined into urban area in some historical input years while in the other year the classification became another class. The unclear classification of land use source data could affect the quality and accuracy of outputs.

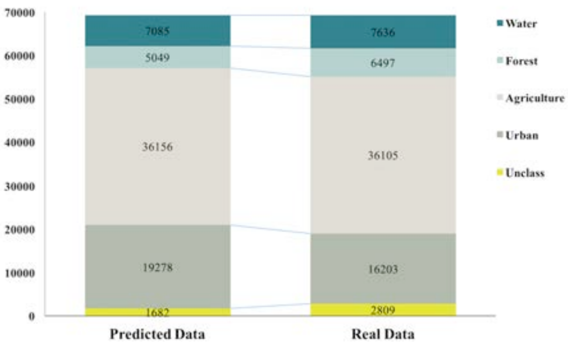

Fig.14 Land use class evaluation

The performance of 3 models are double checked by using the calibration method of Optimal SLEUTH Metric proposed by Charles Dietzel and Dr. Keith C. Clarke in 2007[12], and the results are showing in **Fig.15**. The accuracy of Extended SLEUTH was improved to 87.76%, however the performance of original SLEUTH and SLEUTsH have no significant differences. This some suggests that SLEUTH model is very sensitive to the exclusion layer.

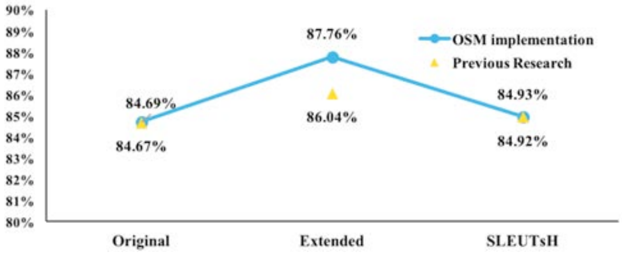

Fig.15 Accuracy checked by Optimal SLEUTH Metric

Meanwhile, it is unexpected that there is big difference in output of urban growth probability between pixel value over 50 and below 50 in both of the two scenarios since the weight of class 2 compare to station area should be weakened when pixel value increases. From the change of 5 coefficient values with different pixel value (**Fig.16**), we could tell that the SLEUTH model has a pretty high sensitivity, the sudden decrease of diffusion and breed coefficient and the increase of spread coefficient might be the reason of visually different growth probability outputs. The growth probability of road pixels decreased significantly compare to pixel value lower than 50 although the road gravity coefficient did not have big change. This might due to pixel value of class 2 which represents the disability to be urbanized increased so the entire growth possibility decreased. In the cases of scenario 2 with pixel value 55 and scenario 1 with pixel value 60, the output image are somehow visually similar. After comparing the coefficient values of these two cases, it was found that the diffusion coefficient of two cases decreased. This could be the reason of this situation since the diffusion coefficient controls the spontaneous growth, which will affect the number of pixels to be selected as a newly urbanized pixel. Another thing noticeable is that spread coefficient kept to a low value while in the cases of pixel value over 50, it increased rapidly. These differences indicate that exclusion layer might not be the only dominating reason controls future urban growth since the SLEUTH model includes a complex simulation system. However, the reason of growth type change after pixel value over 50 still needs further investigation.

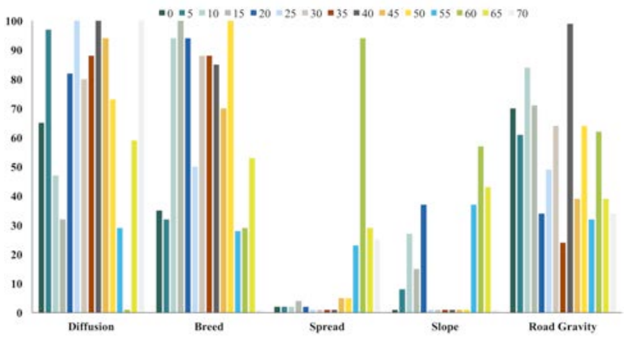

Fig.16 Prediction coefficients

5. CONCLUSION

In this research, the TOD effect around station area was successfully considered into SLEUTH by 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.

For the first method, when considering TOD effect on urban growth, the most suitable pixel values of this study area for Extended SLEUTH are 100 of water area, 0 of station area and 50 of the other area, since in this case the urban growth could more focus on station area. The Extended SLEUTH shows better performance than original and SLEUTsH. However, as the exclusion layer is used in calibration phase for deriving coefficients from historical inputs for study area, it has limitation of the result might be only suitable for this specific area.

The SLEUTsH model successfully make the urban growth concentrate more on station area which corresponded with TOD strategy. The SLEUTsH model has advantage of automatic considering TOD, thus it has pontential to be generally applied in global scale. However, the pixel value and radius of station area of station input still need to be discussed when processing the station input.

Future research could focus the questions unsolved: 1) reason of Extended SLEUTH pixel value of class 2 equals to 50 shows the best performanece; 2) no specific growth rule for how TOD impact on urban growth; 3) reason of Optimal SLEUTH Metric only improved the accuracy of Extended SLEUTH.

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