Characterizing growth types in a metropolitan region as additional factors for simulating a city urbanization

by Rahmadya Handayanto

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***Abstract*— Bekasi city, in the Jakarta Metropolitan Region, is experiencing rapid urban growth and urban sprawl which have negative impacts on the natural resources, economy, public health, and community character. City planners often employ prediction models to forecast the future urban growth for managing policies and practices. This study identified three urban growth types (infilling, outlying, and edge-expansion) through an integrated approach of remote sensing, GIS, and spatial metrics analysis. Characterizing growth types found that infilling and edge-expansion were dominant in Bekasi city. These growth types are feasible for use as driving factors of land change modelling. A multilayer perceptron network was used for modelling urbanization (with and without urban-growth driving factors). It was found that a scenario with urban growth types as driving factors were more accurate than others. Prediction maps for 2030 and 2050 were also produced through this approach with two approaches including conservation and business-as-usual scenarios. Simulation results showed that the conservation scenario could minimize the effects of diminishing vegetation, bare land, and agriculture better than a business-as-usual scenario.**

Keywords*— Driving factors, land use and land cover change, sprawl, neural network, urban growth modelling, spatial metrics

I. Introduction

Developing countries have become the focus of global urbanization since some of the world's largest cities are in these countries [1]. As the capital city of Indonesia, Jakarta is experiencing rapid urban growth. This city is part of the Jakarta Metropolitan Region (JMR), i.e., Tangerang, Bogor, and Bekasi and is experiencing rapid urban growth. Some urban sprawls were created as a result of a "post-suburbia" in Jakarta Province, i.e., a declining population of the former central city and growth of other regions in the vicinity [2]. Cities near the central city became dominant. Post-suburbia create a polycentric structure, a structure with many centres [3]. To control the negative effects of sprawl, city planners have to consider issues not only at a city scale, but also at a metropolitan scale [4] since urban, peri-urban, and rural areas have their own growth characteristics [5], [6].

Previous studies on land use and land cover (LULC) change on different scales in a metropolitan region found that major land transitions varied in the urban and peri-urban zones within a metropolitan region [7], [8]. Another study analysed spatial metrics to understand the urban-growth characteristics in a metropolitan region [9]. These spatial metrics are calculated through remote sensing data to understand the type of growth, e.g., outlying, infilling, and edge-expansion [10]–[14]. In the current study, spatial metrics were proposed as part of the driving factors of LULC change modelling.

There were two parts of the current study. The first goal was to find the best driver compositions and project the LULC in 2030 and 2050. This part analysed the urban growth characteristics in JMR to create additional driving factors for LULC change modelling. In this regard, two models were prepared, i.e., with and without urban-growth driving factors. After the simulation, the results of the simulations were compared and analysed. The second part used the best driving factors found in LULC change prediction for 2030 and 2050 in Bekasi city, Indonesia. Two approaches were used in the simulation of urban growth, conservation and business-as-usual scenarios.

The specific objectives of this study were to (1) quantitatively analyze urban growth characteristics in JMR and the feasibility of using these results as LULC change driving factors, and (2) use the change prediction modelling with different scenarios in the study area in 2030 and 2050.

II. Data and Methodology

A. Study Area

Bekasi City, the study area, is part of the JMR (Fig. 1). It has around 210.49 km2 of area with more than 90% of its land used for residential purposes. The remaining area is for commercial, industrial, education, agricultural, and other uses [15]. Since the prices of housing in Jakarta, the capital city, and Cikarang, the main industrial area are high, many people chose to live in Bekasi. To meet the basic needs of people, many commercial and business locations, especially modern or traditional markets, are spread around the city. Settlements, commercial buildings, and other built-up areas are the main source of LULC conversion in Bekasi city.

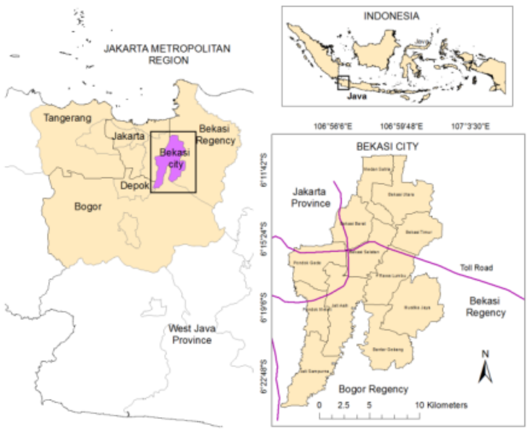

Fig. 1. Jakarta Metropolitan Region and Bekasi City

B. Dataset

For quantifying the different types of urban growth, four cloud-free Landsat TM/ETM+ images of JMR were acquired on July 19, 1988 (TM), July 31, 1998 (TM), August 1, 2010 (TM), and August 31, 2015 (ETM+). These images were rectified to the WGS-84 datum and Universal Transverse Mercator (UTM) Zone 48N coordinate system. Another image acquired on October 8, 2000 (TM) was used for prediction modelling with an image on August 1, 2010 (TM).

Prediction modelling requires other thematic parameters as driving factors including surface elevation, distance to streams/canals/water, housing information that includes roads, city centres, railway lines, hospitals, schools, and waste disposal. Two other socio-economic parameters, land prices and population density, were used as well. Three additional urban-growth based driving factors (infilling, edge-expansion locations, and distance to built-up change during 2010-2015) were created after growth-type analysis. Direct surveying was also conducted since the remote sensing data could not clearly classify particular land use classes that were needed for the LULC change drivers. Five LULC classes were mapped for change prediction. They included agricultural (area used for agricultural activity), bare land (area with no dominant vegetation cover), built-up (residential, commercial, industrial, and transportation), vegetation (trees, shrubs, and grasslands), and water (lakes, streams, canals, and rivers).c

C. Method

Quantifying Different Types of Urban Growth

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$$Patch\ Density\ (PD) = \frac{n_i}{A}(10{,}000).(100) \quad (1)$$

$$Landscape\ Shape\ Index\ (LSI) = \frac{e_i}{\min e_i} \quad (2)$$

$$Euclidean\ Nearest\ Neighbour\ Distance = h_{ij} \quad (3)$$

$$Percentage\ of\ like\ adjacency = \frac{\sum_{i=1}^{m} g_{ii}}{\sum_{i=1}^{m}\sum_{k=1}^{m} g_{ik}} \times 100 \quad (4)$$

where *ni* is number of patches in the landscape of patch type (class) I, A is total landscape area (m2), *ei* is total length of the edge of class I, *min ei* is minimum total length of the edge (or perimeter) of class I, h_{ij} is the distance (m) to a patch of the same type, gii is number of like adjacencies between pixels of patch type, gik is the number of adjacencies between pixels of patch types i and k, and m is the number of pixels in the satellite image.

The PLADJ was also used in the current study because of its intuitiveness and computational simplicity which has led to its common adoption [12]. Fragstats software was used to calculate these four spatial metrics.

Prediction Modelling

The Land Change Modeller (LCM) module in IDRISI Selva software was used for LULC simulation. The LULC maps of 2000 and 2010 were used to prepare the model. Another LULC map (2015) was used for validation. Change prediction was set to years 2030 and 2050. The selection of these years for prediction were based on the fact that the city government authorities have prepared a master city plan for 2030 and the next 20-years (2030 2050). Land transitions were prepared with considerations based on the amount of land area that had changed. These transitions were checked regarding their sensitivity scores through a logistic regression training method. This method calculated a Relative Operating Characteristic (ROC) value for each transition before its use in sub-modelling. Only ROC scores above 0.75 were included in the model. Finally, every sub-model was trained with a Multi-layer Perceptron (MLP) Neural Network before being used for prediction.

Selection of driving factors is a critical aspect in urban growth modelling. Based on previous research, 13 drivers were chosen and analysed before use in prediction [7]. The current study also used three additional drivers from urban-growth type analysis. These 16 drivers were checked using Cramer's V value, defined as:

$$V = \sqrt{\frac{\emptyset^2}{\min(k-1, r-1)}} \quad (5)$$

where Ø is the mean square contingency coefficient, k is the number of columns and r is the number of rows [16]. Table 1 shows driving factors of LULC change modelling used in our study.

TABLE I. DRIVING FACTORS AND NOTATIONS

No.	Category	Notation	Driving Factors
1	Biophysical	Elev	Surface Elevation
2		Slope	Surface Slope
3		DStr	Distance to stream/canals/waters
4	Infrastructure	DHsc	Distance to housing schemes
5		DRd	Distance to roads
6		DCc	Distance to city centre
7		DBu	Distance to built-up
8		DR	Distance to railways lines
9		DH	Distance to hospitals
10		DS	Distance to schools
11		DWd	Distance to waste disposal
12	Socioeconomic	LPr	Land price
13		Pop	Population density
14	Urban Growth	Dedge	Distance to edge-expansion type
15		Dinfil	Distance to infilling type
16		DBuc	Distance to built-up change from 2010 to 2015

Scenarios

In the current study, the scenario was used for comparing many factors in the simulation. The initial part employed two scenarios regarding urban-growth based drivers. The first scenario only used three biophysical-type, eight infrastructure-type, and two socioeconomic-type driving factors. The second scenario added three urban-growth type driving factors for land change modelling. The best scenario was chosen for prediction, based on the area under the ROC curve (AUC) [17].

In the second part of this study, LULC change predictions were made for 2030 and 2050 with two approaches, business-as-usual (BAU) and environmental conservation (CON) scenarios. Whereas there are no constraints in BAU (except the river within the study area), the CON scenario used constraints based on environmental issues, i.e., vegetation, parks, water, open spaces, and risk areas, among others. These constraints were used to handle the negative effects of land use, e.g., environmental degradation and climate change. [18].

III. RESULT AND DISCUSSION

A. Types of Urban Growth

Three types of urban growth (outlying, infilling, and edge expansion) were assessed by measuring urban changes during three-periods, 1988-1998, 1998-2010, and 2010-2015 (Fig. 2), and by analyzing spatial metrics (Fig. 3).

Fig. 3a shows the changes of Patch Density (PD). This spatial metric increased exponentially, reaching its peak in 1998. Euclidean Nearest-Neighbour Distance (ENN) reached its highest value in 1988. After some urban centres appeared, the urban patches fused and the boundaries of these urban areas dissolved. The ENN value decreased to its lowest value in 2010 (Fig. 3b). The Landscape Shape Index (LSI) increased steadily in the early stages of urbanization and decreased during the period of 2010-2015 (Fig. 3c). The Percentage of Like Adjacency (PLADJ) metric reached its highest value in 1989, then decreased steadily and reached its lowest value in 2010 before starting to increase in 2015 (Fig. 3d).

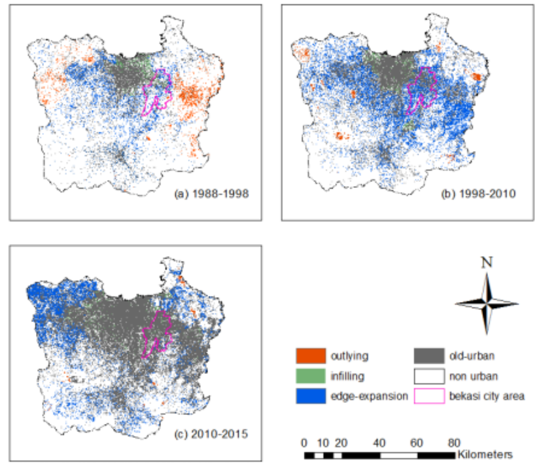

Fig. 2. Spatial distribution of three types of urban growth within JMR during three periods: (a) 1988-1998, (b) 1998 2010, and (c) 2010-2015

The spatial metrics result showed that PD and LSI scores were related to outlying (Hoffhine et al., 2003; Mcgarigal et al., 2015; Pham & Yamaguchi, 2011; Sun et al., 2013; Yue et al., 2013). When the PD and LSI decreased, outlying also decreased while infilling and edge-expansion increased. On the contrary, lower ENN scores and PLADJ metrics resulted in higher numbers of outlying regions. When they started to increase in 2010, the types of growth were predominantly infilling and edge-expansion.

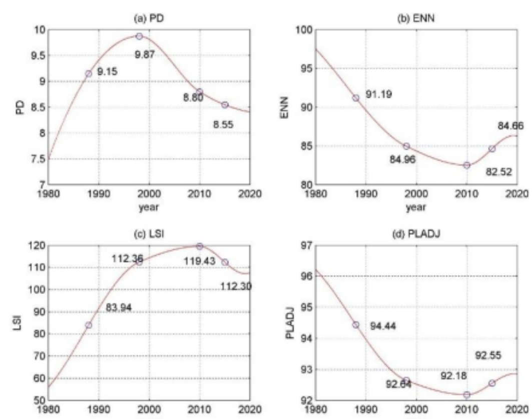

Fig. 3. Spatial metrics of JMR growth during the period 1988-2015: (a) PD, (b) ENN, (c) LSI, and (d) PLADJ. The lines shows curve-fitting of the four spatial-metric points

Based on the characteristics of growth in 2015, only two urban-growth types were significant, infilling and edge-expansion. Therefore, the distances to the infilling and edge expansion were also used as additional driving factors. They were categorized as urban growth with other factors, i.e., the distance to built-up change (2010 2015).

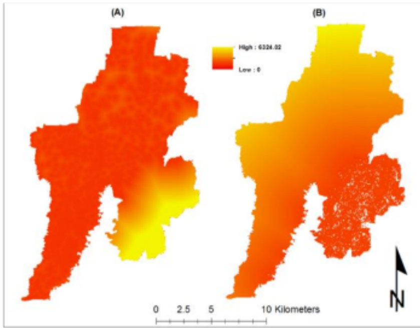

Fig. 4. Driver maps for the Land Change Modeller based on urban growth: (a) Distance from infilling growth LUs, and (b) from edge-expansion growth LUs

B. *Land use Growth Modelling*

Fig. 5 shows LULC change from 2000 to 2010. The agriculture and bare land classes decreased by 2% and 15% respectively. The vegetation class sharply decreased by 40%, the built-up class increased greatly from 24% to 81%. The water class, which was dominated by the rivers, was stable at 2%.

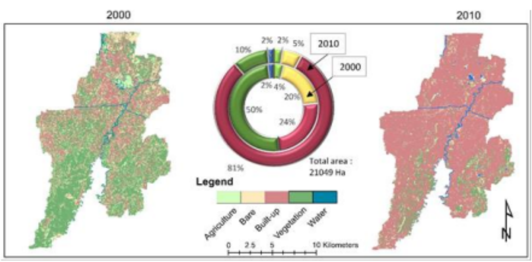

Fig. 5. LULC maps and area graph of 2000 and 2010

Table 2 shows the cross tabulation results. It depicts the conversion from one class to the other classes. There were nine significant conversions: agriculture to bare land, agriculture to built-up, agriculture to vegetation, bare land to agriculture, bare land to built-up, vegetation to agriculture, vegetation to bare land, vegetation to built-up, and water to built-up.

TABLE II. CROSS TABULATION OF LULC CHANGES BETWEEN 2000 AND 2015 (IN HECTARES)

To (2010)	From (2000)					
	Agri	Bare land	Built-up	Vege-tation	Water	Total
Agri	32.41	259.53	7.88	212.93	2.45	515.20
Bare land	126.13	212.58	83.12	656.92	41.60	1120.35
Built-up	408.60	3683.04	5034.98	7764.61	111.33	17002.55
Vege-tation	158.1	0.79	1.66	1874.85	20.15	2055.54
Water	44.85	0.88	0.44	40.12	269.07	355.35
Total	770.08	4156.81	5128.09	10549.42	444.60	21049

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TABLE III. CRAMER'S V COEFFICIENTS SHOWING THE QUANTIFIED ASSOCIATION BETWEEN SELECTED LULC CLASSES AND THE DRIVING FACTORS

Driving Factors	Overall	Agri-culture	Bare land	Built-up	Vege-tation
Biophysical					
Elev	0.0134	0.0024	0.0061	0.0239	0.0071
Slope	0.0520	0.0212	0.0119	0.0978	0.0715
DStr	**0.4252**	0.0840	**0.2116**	**0.7929**	**0.2571**
Infrastructure					
DHsc	**0.4437**	0.0840	**0.2101**	**0.7845**	**0.2398**
DRd	**0.4434**	0.0754	**0.2032**	**0.7826**	**0.2633**
DCc	**0.4605**	0.0985	**0.2152**	**0.7941**	**0.3466**
DBu	**0.4437**	0.0840	**0.2101**	**0.7845**	**0.2398**
DR	**0.4626**	0.1059	**0.2136**	**0.7933**	**0.3639**
DH	**0.4566**	0.0798	**0.2036**	**0.7896**	**0.3520**
DS	**0.4507**	0.0791	**0.2044**	**0.7866**	**0.3152**
DWd	**0.4638**	0.1005	**0.2186**	**0.7941**	**0.3658**
Socioeconomic					
LPr	**0.4633**	0.1023	**0.2221**	**0.7963**	**0.3549**
Pop	**0.4637**	0.1009	**0.2133**	**0.7969**	**0.3620**
Urban Growth					
DBUC	**0.3871**	0.1271	**0.2768**	**0.5264**	**0.3493**
Dinfill	**0.4684**	0.1071	**0.2188**	**0.8063**	**0.3672**
Dedge	**0.4612**	0.0984	**0.2118**	**0.7970**	**0.3460**

Table 4 shows that some sub-models had the same targeted LULC transition, i.e. 'to built-up', 'to bare land, 'to agriculture', and 'to vegetation'. Sub-models having the same targeted LULC transition were grouped into one new sub-models to speed up the training process. The multi-layer perceptron (MLP) neural network method was chosen as a training method since the other methods (logistic regression and SIMWEIGHT) cannot be used to train the grouped sub-models. Automatic training and dynamic learning rates were used with parameters of the start learning rate, end learning rate, momentum factor, sigmoid constant, the number of layers at one node were 0.01, 0.001, 0.5, 1.0, and 7, respectively. The training process was run until achieving the stop condition. The stop conditions parameters, i.e., the Root Mean Square (RMS), number of iteration, and accuracy rate were set to 0.01, 10000, and 100 percent respectively. The logistic regression method, however, was still used to determine the Receiver Operating Characteristic (ROC) of every transition potential (Table 4). Since the ROC score of vegetation-to-agriculture was low (below 0.75), this LULC transition was dropped from the model.

TABLE IV. ROC VALUES SHOWING THE LEVEL OF ASSOCIATION BETWEEN SELECTED LAND TRANSITIONS AND THE DRIVING FACTORS FACTORS

Sub-Model	LULC Transition	ROC
1	Agriculture to Bare land	0.8023
2	Agriculture to Built-up	0.9178
3	Agriculture to Vegetation	0.7801
4	Bare land to Agriculture	0.8414
5	Bare land to Built-up	0.9856
6	Vegetation to Agriculture	**0.7189**
7	Vegetation to Bare land	0.8130
8	Vegetation to Built-up	0.9701
9	Water to Built-up	0.9686

A MLP Neural Network was used to train the model. The MLP Neural Network parameters, the start learning rate, end learning rate, momentum factor, sigmoid constant, and the number of layer 1 nodes were set to 0.01, 0.001, 0.5, 1.0, and 6, respectively. Additionally, the automatic training and dynamic learning rate were chosen with a stopping criterion that included the RMS, number of iterations, and accuracy rate equal to 0.01, 10000, and 100% respectively. Four sub-models (to built-up, to bare land, to vegetation, and to agriculture) were trained through the MLP Neural Network before change-prediction simulation.

To analyze the effects of urban-growth driving factor (distance to infilling, edge expansion, and built-up change), the Land Change Modeller with two scenarios was trained through a MLP Neural Network method. Fig. 7 shows the predictions of LULC in 2015 for both scenarios. The AUC score of the model with urban-growth factors was slightly higher than the model without these factors. Therefore, the model with urban-growth factors was chosen as a model for predicting the LULC change in 2030 and 2050.

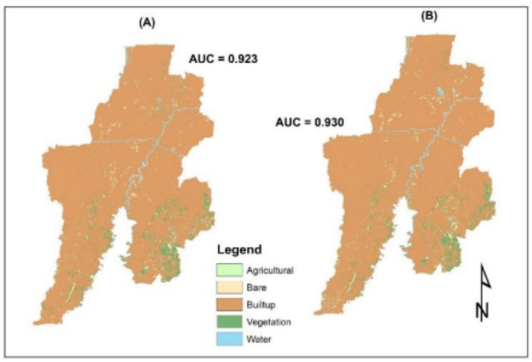

Fig. 6. Prediction results of LULC in 2015: (a) without urban-growth-drivers (AUC = 0.92), and (b) with urban-growth drivers (AUC = 0.930)

C. Land use Growth Projections (2030 and 2050)

The Land Change Modeller with urban-growth driving factors, which had a better AUC score, was chosen for land-use growth projection in 2030 and 2050. Sixteen driving factors and two scenarios (BAU and CON) were used. The scenarios differed in regard to constraints use. Whereas the CON scenario used many constraints and incentives for change prediction (Fig. 7), the BAU scenario only used water conservation (the river in Bekasi city) as a constraint.

The constraints were created through merging of some restrictions, i.e., vegetation, park, lake, water, open spaces, and disaster risk areas (flood and polluted areas). Some incentive locations were also included, e.g., bare lands and other non-productive lands for new built-up locations. Fig. 8 shows the projection result in 2030 and 2050 for both scenarios after the simulation process under CON and BAU scenarios.

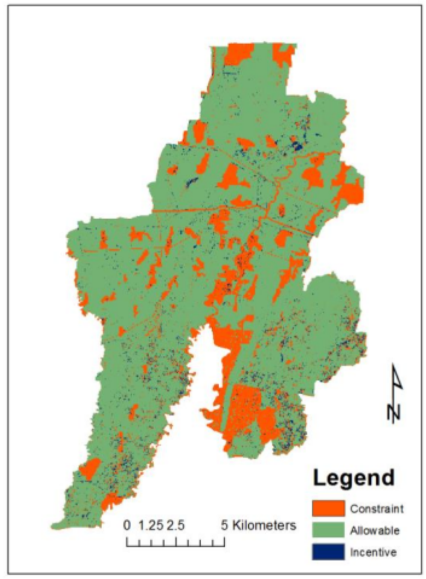

Fig. 7. Constraint for CON scenario

Both scenarios showed decreasing agriculture, bare land, and vegetation areas and increasing built-up areas. However, the CON scenario could keep the vegetation to more than 2 percent compared to BAU in which predicts almost 0% vegetation will remain, and that is a very dangerous situation (see Table 5 for the exact areas in hectares). The agriculture class was predicted to have almost disappeared in 2030 and 2050 under both scenarios within the study area. This is usual in a city region. The CON constraint saved parks, vegetation, risk areas, and open spaces from changing into the other classes (usually into the built-up class). The city, which primarily consists of built-up areas, needs land-use optimization and management based on more specific land uses, e.g., settlements, schools, commercial areas, and industrial zones, among others.

TABLE V. LULC PROJECTION FOR BAU AND CON SCENARIOS IN 2030 AND 2050 (IN HECTARES)

Scenario		BAU		CON	
Year	**2015**	**2030**	**2050**	**2030**	**2050**
Agri-culture	453.62	36.79	13.051	82.77	85.40
Bare land	568.89	131.73	71.823	306.82	274.94
Built-up	19075.88	20397.86	20588.631	19741.12	19794.63
Vege-tation	668.22	127.27	20.146	566.35	544.28
Water	282.39	355.35	355.349	351.93	349.74

It is recommended for the planners to use urban growth as a factor to manage their city land uses. The future generation should be considered when managing the current land use following the sustainable development concept as well as controlling the population growth.

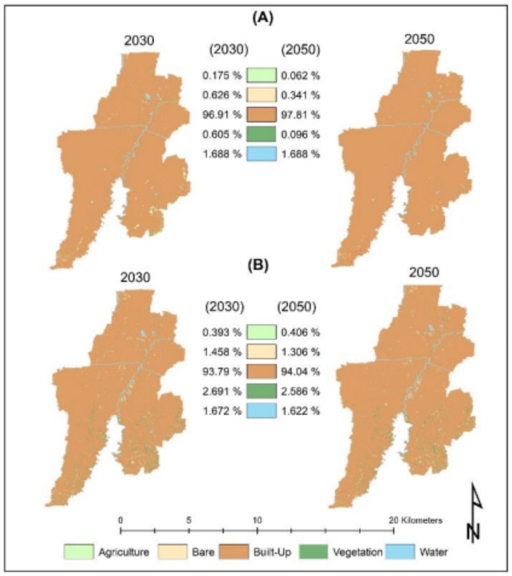

Fig. 8. Prediction result of LULC in 2030 and 2050: (a) Prediction result in 2030 and 2050 for the BAU scenario, and (b) Prediction result in 2030 and 2050 for the CON scenario

IV. Conclusion

The current study shows the feasibility of urban growth analysis used as LULC driving factors. It applied spatial metrics at the scale of a metropolitan region to increase the model accuracy. This study concluded that urban growth factors (infilling, edge-expansion, and built-up change) can be successfully used as driving factors for higher accuracy.

The projection of LULC in 2030 and 2050 predicted that the CON scenario could better manage LULC in 2030 and 2050 than the BAU scenario. The current study can be used as additional information for the local city planners to prepare their next city plan (2030-2050).

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