Land Use Growth Simulation and Optimization in the Urban Area

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Abstract—**Developing countries nowadays have been trying to manage their metropolitan area because of urban growth problem. Improper location, sprawl, environmental degradation, etc. are typical problems appeared in Jakarta Metropolitan Region. Jakarta province exhibits a "post-suburbia" phenomenon which is characterized by a decline of central city population and the growth and the dominance of its vicinity (Bogor, Depok, Tangerang, and Bekasi). Bekasi city, in the Jakarta Metropolitan Region, faces many problems regarding the urban growth. Helping the local city planners by giving a modeling and simulation tool would be beneficial in managing land use. This typical "what-if" analysis model would be able to give the planners the consequences of their plans. However, they need another tool for allocating some land uses through a land use optimization tool. This study showed that modeling, simulation, and optimization can work together to handle the urban growth in an urban area.**

Keywords—jakarta metropolitan region; bekasi city; postsuburbanization; peri-urban; land use allocation; land use optimization

I. INTRODUCTION

Since there is a "post-suburbanization" phenomenon in Jakarta (the central city of Jakarta Metropolitan Region), some interesting characteristics are found, i.e. rapid development and the dominance of its vicinity [1]. The negative effects of the urban growth (improper land use location, sprawl problem, health issues, environmental degradation, etc.) must be handled by the city planners. One of the famous methods is land use/cover (LULC) modeling for simulating the growth through remote sensing and GIS as a tool [2]–[4]. The simulation run for several years ahead with the proposed scenarios to see the best scenario based on sustainable development concept, i.e., "development which caters not only present needs but also for the future" [5], [6].

This "what-if" analysis method, by analyzing the effect of some scenarios, is a useful tool for the planners in land-use management[7].

The "what-if" analysis needs a good understanding of LULC change drivers for simulation. The simulation could figure out the future condition but the local city planners need another tool to achieve a sustainable urban form. To achieve the sustainability, previous studies used optimization tool to allocate LULC [8]–[12]. The evolutionary optimization algorithm such as Genetic Algorithm (GA) [13] and Particle Swarm Optimization (PSO) [14] were used [15]. Most of the previous studies used simulation and optimization separately. Therefore, in the current study the integration of simulation and optimization was proposed for land use in Bekasi city, Indonesia. Previous studies have successfully simulated land cover (LC), a class of land that is categorized based on biophysical, to predict the growth [16], [17]. However, the current study focused on change simulation and optimization of land use (LU), a class of land that is categorized based on the human exploitation of the area.

The current study contained two main parts: land-use change simulation and land-use optimization. Land change model was proposed and used to simulate urban growth after testing and validation. Expected new land-uses in the future (2050) were optimized and discussed.

II. DATA AND METHODOLOGY

A. Dataset

The current study used data from various resources such as Landsat satellite imageries, government data, Google map, Google Street-view, the yellow-pages, and the other data sources (spatial and non-spatial data). Landsat satellite imageries (2000, 2010, and 2015) from United States Geological Survey (USGS) (https://www.usgs.gov/) were used

for land-use change model. The other data were also involved for driving factor maps and the constraints.

Data from satellite were classified using the hardclassification tool (ISOCLAS function) of IDRISI (TerrSeT, v.17). However, IDRISI only classified LC such as agricultural, built-up, vegetation, bare land, and water. Since the current study focused on LU, only urban (built-up area) and non-urban were chosen as LC class. Other vector data were also needed which classified built-up into the more specific LU class, including commercial, educational, industrial, medical, and sport. LU data are provided from previous work which contained vector points of each LU class [11]. The 100 meters radius of buffer was chosen for a particular LU vector when converting a polygon to raster. Such approximation was common in modeling to enable more efficient computation [18]. Spatial analysis module of ArcGIS (ESRI, v.10.1) was used for driver creation and conversion from vector data into raster data.

Fig. 1 shows Bekasi city region as the study area. More than ninety percent of land use is residential class and the remaining are commercial, industrial, educational and other uses [19].
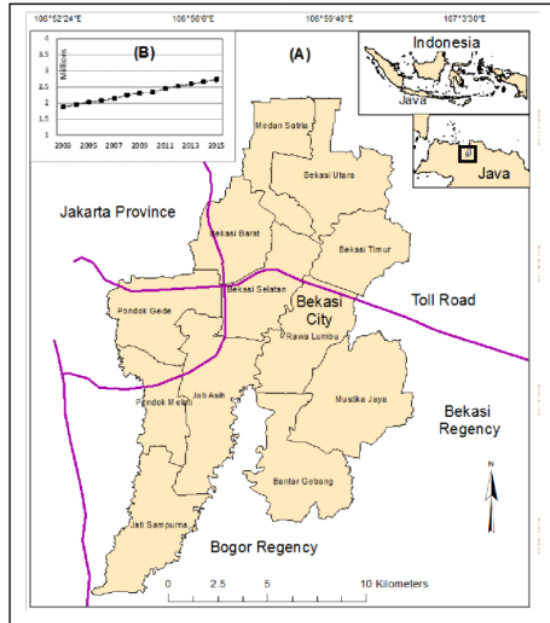

Fig. 1. Study area: (a). Bekasi city map, and (b) Population

Surveying and other resources such as Google earth, Google Street-view, and other commercial site, e.g. www.streetdirectory.com, were used to capture the LU data and to check the classification accuracy. In addition, a historical imagery module in Google Earth was also used to depict the additional LUs from 2000 to 2010.

B. Methods

Fig. 2 shows the current research framework. It integrated, serially, simulation and optimization. In the first stage, LCM model used two dates of LU, i.e. 2000 and 2010, for predicting LU growth in 2015 after a training process. Predicted LU in 2015 was validated by comparing it with the actual LU in the same year (2015). After validation, LCM model was used to predict LU growth in 2050. The new LUs were allocated through LU optimization with criteria function and constraints.

1) Land Change Modeler (LCM)

Many studies used LCM module of IDRISI to simulate LU growth which based on the LU change drivers [2]–[4], [20]. The current study used drivers similar to the previous study [2] which included biophysical, infrastructure and socioeconomic aspects as the drivers (Table 1). LU images and drivers must be provided in IDRISI format before LU prediction. A GIS tool used for driver creation was the module ArcMAP of ArcGIS (ESRI, v.10.1).
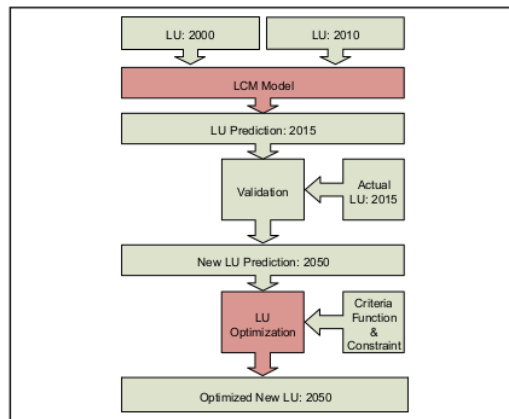

Fig. 2. Research framework

No.	Category	Notation	Driving Factors
	TABLE I.		DRIVING FACTORS AND NOTATIONS
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 center
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

Some pre-processing tasks were employed, i.e. LC classification (ISOCLAS function) and cropping the satellite images according to the study area (WINDOW module of IDRISI). Three main steps for LU change model in IDRISI are: change analysis, transition potentials, and change prediction.

Change analysis need two dates of images which is compatible with each other (extent, projection, and palette). Transition potentials, which depicted the conversion among the five LU classes were generated and trained using multi-layer perceptron neural network (MLPNN) module of IDRISI. The transition potentials that are also called sub-models was for the main component of LCM model. Seven neurons were used in MLPNN with 10000 iterations and other parameters that were set automatically by IDRISI software. MLPNN prediction will be compared with Nonlinear Autoregressive with External Input Neural Receiver Network (NARXNET) in the previous work [11] with the same data. The typical neural network for prediction is shown in Fig 3. Previous data and population as intervention indicator (external input) were used in neural network as an input to predict the future value (output).
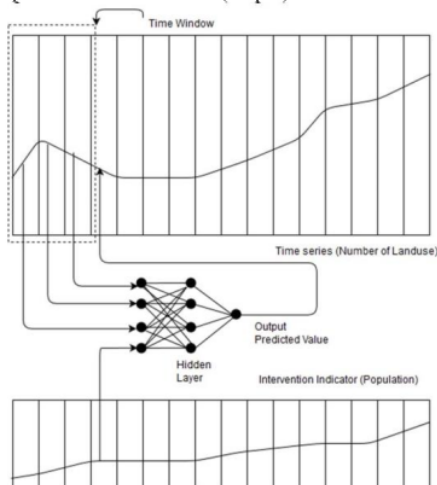

Fig. 3. Neural network prediction scheme

Before LU change simulation in 2050, LCM model must be validated with actual LU in 2015. The area under the curve (AUC) of Receiver Operating Characteristic (ROC) was used for scoring the accuracy of the model. If AUC score is high enough, the LCM model can be used to simulate LU change.

Constraints were used in LCM to drive the LU growth only for allowable locations. The allowable locations were set to one, whereas the restricted areas (river, road, lake, etc.) were set to zero. The constraints were inserted in "constraints and incentives" module.

The model run to predict the LU growth in 2050 using "change prediction" module in IDRISI. The predicted LUs have to be converted into vector data before optimization that is discussed in the next section.

2) Land Use Optimization

LU optimization also a kind of LU change modeling [21]. Different from transformation method (converting one class to another class), the allocation method was used to allocate expected new LUs (from LCM simulation) through LU optimization [22]. In the allocation problem, the existing LUs were not change and only new LUs are allocated to empty and allowable locations.

Previous works on hybrid multi-criteria evolutionary algorithm (HMCEA) [11] was used to allocate additional LUs 2050. This optimization method combined serially two evolutionary algorithms, i.e. genetic algorithm (GA), particle swarm optimization (PSO), and one local search method, i.e. pattern search. The first stage was PSO which has fast computation characteristic. The PSO parameters in this study, i.e. inertia, c_1, r_1, c_2, and r_2 were set to 2, 0.75, random, 0.25, and random, respectively. The following PSO pseudo-code [23]:

Criteria function $f(x)$, $x = (x_1, ..., x_d)^T$
Setting new locations x_i and velocity v_i of n particles
Find g^* from min $\{f(x_i, ..., f(x_n)\}$ *(at t=0)*
Do while (Reaching the stop condition)
    For loop over all n particles and all d dimensions
        Generate new velocity v_i^{t+1}
        Calculate new locations $x_i^{t+1} = x_i^t + v_i^{t+1}$
        Evaluate objective functions at new locations x_{it+1}
        Find the current best for each particle x_i^*
    End For
    Find the current global best g^* for the next iteration
End
Sending the final Result x_i^* and g^*

Actually, PSO had already given the optimum result [8], [9] but since this study used a lot of constraints (roads, rivers, and other restricted areas), the limit of PSO velocity caused some particles could not overcome the wide constraints. Therefore, a GA was chosen as a second stage because this method could handle the wide constraint problem using its main characteristics: crossover and mutation. In this study, binary GA type was used with single crossover and mutation rate was set to 0.00015. The iteration was used as the stop condition. The following is GA pseudo-code [23]:

Criteria function $f(x)$, $x = (x_1, ..., x_d)^T$
Encode the solutions into bits string as chromosomes Define the fitness scores F (e.g., $F \square f(x)$) for maximization problem)
Setting the initial candidates
Setting the crossover probabilities (p_c) and mutation rate (p_m)
Do while (reaching the stop condition)
    Create new solution by crossover
    Create new solutions by mutation
    Crossover with a crossover probability p_c
    Mutate with mutation probability p_m
    Calculate the fitness values of new solution
    Accept the new solutions if their fitness increase

Select the best individuals for the next generation
End
Converting the results back into real number

The final stage was pattern search method which searched the possibility of more optimum locations around the GA result. In this study, the triangle pattern that checked three location at 250 meters away from every result location was chosen. The second iteration use half of the previous distance (125 m) and continue to the next iteration until reaching the stop condition.

Four criteria, i.e. compactness, compatibility, dependency, and suitability were used as criteria functions. These criteria functions were composed based on two kinds of sustainable urban form: compact city and eco city [24]. The optimization module (HMCEA) was implemented using the Matlab software (Mathworks, v. 2008).

HMCEA was used for maximizing compactness, compatibility, dependency, and suitability of four criteria functions (F_1, F_2, F_3, and F_4) as defined in Equations (1)–(4) [11], [25].

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (1)$$

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (2)$$

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (3)$$

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (4)$$

Variable n represents the number of LUs in the study area, i and j are the current LU and its neighbor respectively. The value of *Compactness*, $\ldots$, $\ldots$, and *Suitability Score* are criteria values based on previous work [11]. Aggregating function method [15] was used to handle multi-criteria problem of maximization.

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (5)$$

$$\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (6)$$

Variable w has to follow the set $w_i \square 0$ which represents the weighting coefficients representing the relative importance of the k criteria functions; F_i is the criteria function of criterion i

from Equations (1) to (4) and H is constraint. In this study, the sustainable-development based constraint was chosen, i.e. inside the study area and outside roads, rivers, lakes, and other restricted areas [26].

The dead penalty was chosen for constraint handling in this study. This method forces the violated candidates back to their original locations. The in-polygon function in Matlab was employed in the optimization module [27], [28]. In the current study scenario which adopted sustainable development concept was chosen since it had better performance [11]. Weighted ratio from survey data with ratios for compatibility, dependency, compactness, and suitability were 0.402, 0.237, 0.115, and 0.247 respectively, following the previous work [11] since this ratio has been checked using pareto-front optimal set. The paretofront optimal set are widely used to ensure there are no dominant criteria in multi-criteria problem.

III. RESULT AND DISCUSSION

A. Simulation Result

Fig. 4 shows training and testing of LCM model. Model was trained based on LU in 2000 (Fig. 4a) and 2010 (Fig. 4b). It included drivers and the constraints. The model was tested by predicting the LU in 2015 (Fig. 4c). Before used for predicting, the model must be validated.

Validation result is shown in fig. 4d which is based on the hard-prediction. Green areas show the area that the model predicted change and it changed. But, red areas (Misses) show the area that the model predicted persistence but it changed. The third areas, False alarm (the yellow areas), show the area that model predicted change, but it persisted. It is difficult for the model to locate exactly the new land use. However, another method, Area under the Curve (AUC) calculation, was used in this study. This method uses soft-prediction instead of hardprediction for counting the accuracy by comparing the softprediction (contained the probability of prediction) with the current LU (2015). ROC module of IDRISI was used to calculate AUC value and gave the result of 0.71. Therefore, the model was confident enough to predict LU in 2050.
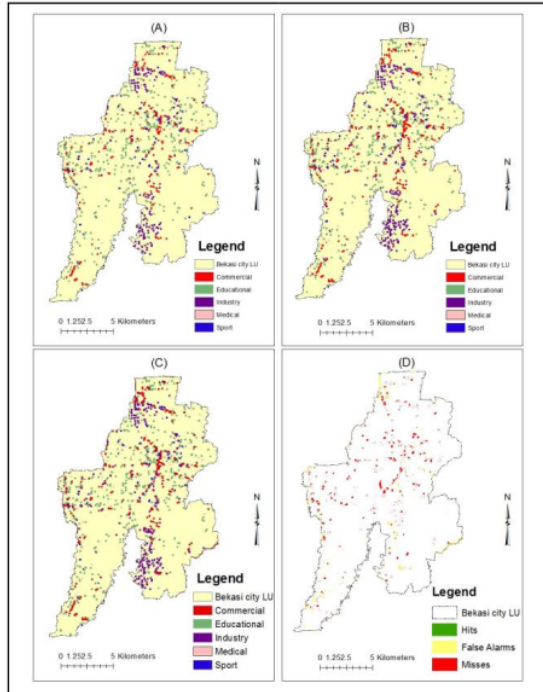
Fig. 4. Training and testing result: (a) LU in 2000, (b) LU in 2010, (c) Predicted LU in 2015, and (d) Validation with actual LU in 2015

TABLE II.   SIMULATION RESULT

LU Class	Initial (2015)		Projection (2050)		
	Raster Data (pixels)	Vector Data (points)	Raster Data (pixels)	Vector Data [1] (points)	
				IDRISI	NARXNET[1]
Commercial	8806	344	14656	573(229)	601(257)
Educational	14177	518	15896	581(63)	581(63)
Industrial	6299	154	9801	240(86)	198(44)
Medical	2868	118	4491	185(67)	277(159)
Sport	2140	26	3120	38(12)	43(17)

[1] Number in bracket shows additional data

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[1] From previous study (as comparison) [11]

Vector points in 2050 were calculated based on percentage of additional pixels from 2015 to 2050 and vector points in 2015 for each LU class. For example, percentage of additional pixels for commercial class from 2015 to 2050 is (14656-8806) divided by 8806 which is equal to 0.664. Since the vector data in 2015 for commercial class was 344, the additional vector data in 2050 is proportional with additional pixels, approximately, by multiplying 0.664 with 344 which is equal to 229 (shown in bracket in Table 2).

Fig. 5b shows the simulation result. Compared with the initial LU in 2015 (Fig 5a), the new LUs were located near the initial LUs. The new commercial areas were concentrated in the middle and industrial areas similar with the initial in 2015. Although LU change prediction using LCM model might be accurate (with 0.71 AUC value), the predicted LU locations must be analyzed whether they are optimum or not. Therefore, the additional new LUs must be optimized and allocated to the proper locations.
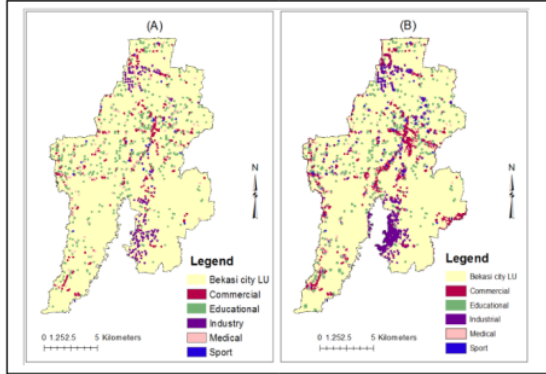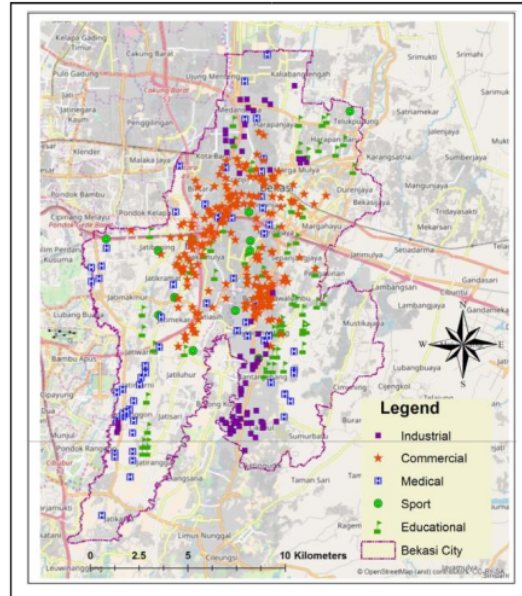
LUs in 2050 were accurately located inside Bekasi city and

Fig. 5.   Simulation result: (a) Initial LU (2015), and (b) Predicted LU (2050)

allocated optimally without violating the constraints.

B. Optimization Result

Optimization module used additional vector data in 2050 from the simulation (Table 2). Whereas the initial vector data in 2015 were used as initial locations, the additional land uses in 2050 (showed in brackets in Table 2) were randomly located. LU optimization run several times to achieve sustainable-urbanform objective based on criteria function and the constraints. The fitness score increased until it reached saturation at about 30 optimization run (Fig. 6).
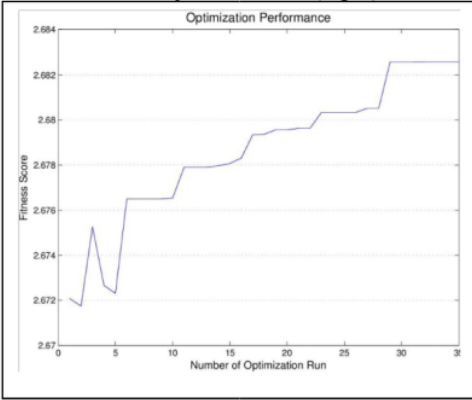

Fig. 6. LU optimization performance

The optimization module also converted the Matlab result into shapefile to depict the result through GIS tools. Fig. 7 shows optimization result using ArcGIS software. Some expected new

Fig. 7. Optimization result (expected new LU allocation in 2050) in ArcGIS

C. Discussion

Simulation result shows LU growth in Bekasi city, Indonesia, in 2050. Usually LCM model is used to predict LC, but in the current study LCM model was successfully used for LU as well.

Previous study used a non-linear autoregressive neural network with external input (NARXNET) with population growth as external input [11]. However, in the current study LCM model used MLPNN to create Markov chain matrix for change prediction. This model not only predicted numbers of LU change but also their locations. However, LCM model only predicted LU locations as similar as possible with actual growth based on its drivers but not for the optimal locations. Therefore, the other module, i.e. LU optimization, was needed to optimize the location for new LUs. The optimization result showed the increasing of overall fitness score and presented the result in a GIS tool.

The current study has some limitations. Firstly, there was a different data format between simulation and optimization. However, raster data from simulation has been successfully converted into vector for optimization. Secondly, there were only five LU classes in the current study. Specific LU classes might also be implemented such as a specific building, e.g. gas stations [12], offices, important building, etc.

IV. CONCLUSION

The current study showed the possibility to integrate simulation and optimization of LU growth. LCM model in IDRISI was used to simulate LU growth. The simulation result showed some additional LUs for every class. Additional LUs from LCM model were allocated through LU optimization to achieve sustainable urban form. The new allocation showed fitness score improvement. The new allocation result might be useful for local city planners as additional information for preparing the next Bekasi city's-LU plan (2030-2050).

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