TELKOMNIKA, Vol.16, No.5, October 2018, pp.2063~2072
ISSN: 1693-6930, accredited First Grade by Kemenristekdikti, Decree No: 21/E/KPT/2018
DOI: 10.12928/TELKOMNIKA.v16i5.9309

Land Use Growth Simulation and Optimization for Achieving a Sustainable Urban Form

Rahmadya Trias Handayanto*[1], Nitin Kumar Tripathi[2], Sohee Minsun Kim[3], Herlawati[4]
[1]Computer Engineering, Universitas Islam 45 Bekasi, Indonesia
[2]Remote Sensing and Geographic Information System, Asian Institute of Technology, Thailand
[3]Urban Environmental Management, Asian Institute of Technology, Thailand
[4]Information System, STMIK Bina Insani, Bekasi, Indonesia
*Corresponding author, e-mail: rahmadya.trias@gmail.com

Abstract

Urban areas have been perceived as the source of environmental problems. To avoid improper land use allocation, negative sprawl effects, and other sources of environmental degradation, city planners need tools for simulating and optimizing their proposed plans. This study proposed a "what-if" analysis model that could help the planners in assessing and simulating their urban plans in Bekasi City, Indonesia. As part of Jakarta Metropolitan Area which exhibited a "post-suburbanization" phenomenon, this city faces many problems because of its high urban growth. Since the urban area has higher land use density than the rural area, especially on built-up class, it needs more consideration when allocating this kind of land use. Because each type of built-up class influences another type, it is difficult to allocate manually. Therefore, this study proposed a land-use optimization application to help planners finding the appropriate land use. This study showed that a model with simulation and optimization can be used to handle urban growth.

***Keywords**: genetic algorithm, particle swarm optimization, bekasi city, urban plan, land-use change*

1. Introduction

Two kinds of modelling, i.e. transformation and allocation, are widely used to simulate the land use [1]. Whereas the transformation models the change of existing land use, the allocation add new parcels to the existing land use; both of these kinds of model are useful for planners to propose the land use plans and avoid the negative effects, e.g. improper land-use location, sprawl-based problem, health and environmental issues, etc. [2]. Most of land-use models use spatial analysis tools of Remote Sensing and Geographic Information System (RSGIS) [3–5]. This RSGIS-based models, which are part of "what-if" analysis model, useful to be implemented in Bekasi City, Indonesia, part of Jakarta Metropolitan Area (JABOTABEK) that exhibits the "post-suburbanization" phenomenon (the edge cities have higher growth and more influent than the central city) [6,7]. RSGIS-based models are useful to ensure the plans meet the Sustainable Development Goals, the concept of development that caters not only present needs but also the future [2,8].

This study focused on creating a simulation and optimization model. Whereas the simulation used Land Use and Land Cover (LULC) change model, the optimization used some models with optimization algorithms. LULC change model predicts the growth based on the driver and showes the change as similar as possible to the real change in the future [9,10]. Planners see the simulation results and sometimes do not satisfied with the result. Therefore, they need another tool to create the optimum land-use composition. Many planners have used land-use zoning to propose the land-use composition, but this method have many drawbacks, i.e. the city become unnatural and difficult to grow because of semi-lattice formation, instead of the tree formation which is more natural [11]. To calculate the relation among land uses, the optimization tools are needed [12-16] because it is difficult to calculate the relation manually. Some evolutionary algorithms are widely used, e.g. Genetic Algorithm (GA) [16–18], Particle Swarm Optimization (PSO) [12,13,19,20], hybrid algorithms [21], etc. Whereas simulation mode usuallyl works on land cover (LC), a class of land that is categorized based on biophysical,

Received March 19, 2018; Revised June 28, 2018; Accepted September 6, 2018

optimization model works on land use (LU), a class of land that is categorized based on the human exploitation of the area [22].

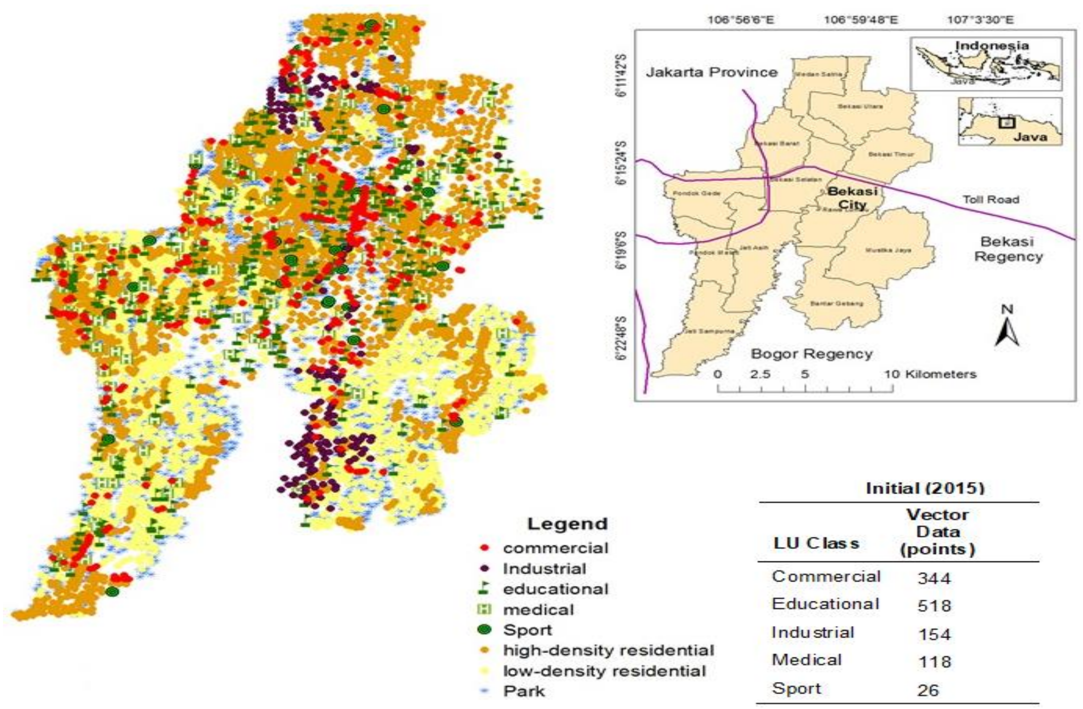
Many studies worked on simulation and optimization separately, but in this study, both simulation and optimization will be integrated in a single framework and prototype following the previous study [18]. There are some issues which are discussed in this study. First, there is a different objective problem between simulation (as similar result as possible with the real condition) and optimization (the optimum or ideal condition) that must be solved before integration. Second, another problem also must be solved related with the compatibility issue between simulation with LULC change (raster data) and LU optimization (vector data). This article contribute to the integration between simulation and optimization in a single framework and prototype.

2. Data and Methodology

2.1. Dataset

Two kinds of data, i.e. raster and vector, were used in this study. Whereas raster data were used for land-use growth simulation, vector data were used for land-use optimization. United States Geological Survey (USGS) site (http://www.usgs.gov) was used to gather the landsat satellite imageries of Bekasi City area in different time frame (2000, 2010, and 2015). Other vector data (streets, rivers, and population) were gathered from Geospatial Bureau Information (BIG) and local government of Bekasi City, which were important as the driver of LULC change in growth simulation.

For land-use optimization, ten land-use classes (commercial, industrial, elementary school, middle school, college and university, sport, medical, park, high density resident, and low density resident) were gathered manually by direct surveying and seeing through Google Earth Pro. Some land-use classes, e.g. schools, hospitals, etc. were based on the local government database (non spatial data) as well as education and health department of Indonesia. For residential area, 100 meters approximation were used for high density (about 150 to 200 buildings) and low density area (about 10 to 150 buildings). Data were based on previous study as shown in Figure 1 [15,23]. Historical imagery module in Google Earth Pro was used to capture the previous data for prediction (2003-2015).



Initial (2015)	
LU Class	Vector Data (points)
Commercial	344
Educational	518
Industrial	154
Medical	118
Sport	26

Figure 1. Study area and Initial Land Use

2.2. Methods
2.2.1. Land Use Growth Simulation

The current study used land-use growth simulation before land-use optimization. The growth was calculated based on previous data through Non-linear Autoregressive Neural Networks with External input (NARXNET). The population was used as external input and number of land-use for each class as time-series data. This study used 9 neuron for hidden layer, and maximum epoch, Mean Absolute Percent Error (MAPE), and learning rate are 1000, 0.1, and 0.001 respectively. NARXNET train several time until reaching the required MAPE number which validated the prediction with the actual data.

As comparison to NARXNET, Land Change Modeler (LCM) module of IDRISI Selva 16 was used to simulate LULC change in the study area Figure 2b. Previous studies classified landsat satellite into some classes before prediction [3–5,24]. Two date of LULC, i.e. 2000 and 2010 were used with driving factors to predict the growth in 2015. Thirteen driving factors were used, i.e. surface elevation, slope, distance to stream/canals/water, housing schemes, roads, city centers, built-up, railways lines, hospitals, schools, waste disposal, land price and population density. After validating the prediction with actual LULC in 2015, LCM would be used to predict the future LULC (2050). The raster data result have to be converted into vector for optimization in this study. Both NARXNET and LCM used Neural Networks for prediction since this method has an ability to handle nonlinear data and machine learning capability as shown in previous works [25–27].

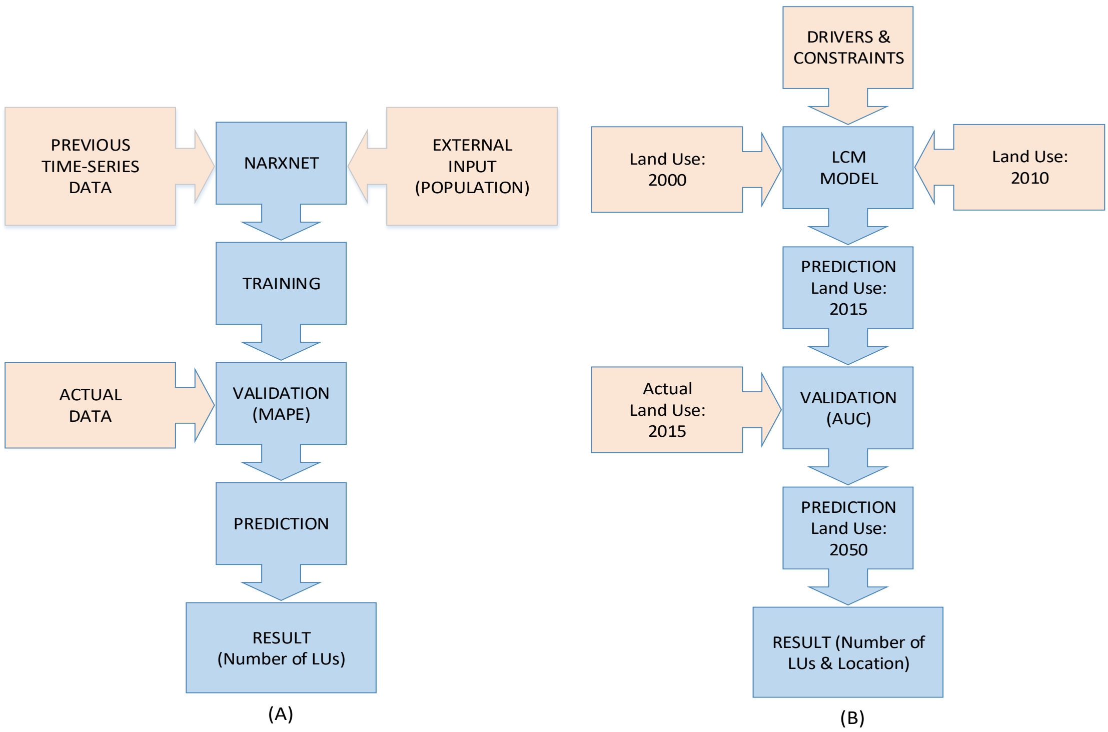


Figure 2. Simulation Framework: (a) NARXNET, and (b) LCM

2.2.2. Land Use Optimization

Land use optimization is different from land-use growth simulation in regard to the goal to be achieved. Whereas the simulation try to depict the condition as similar as possible to the reality, the optimization want to achieve the optimum condition (maximum or minimum). Genetic Algorithm [17], Particle Swarm Optimization [19], and other evoluationary algorithms have been widely used as optimization method. In this study, a combination of genetic algorithm (GA), particle swarm optimization (PSO), and a local search was implemented in an application following the previous study [15]. The objective was to achieve the sustainable urbon form by maximizing compactness (F_1), compatibility (F_2), dependency (F_3), and suitability (F_4) as follows:

$$F_1 : \text{Maximize}\left(\frac{1}{\text{n}}\left(\sum_{\text{i}=1}^{\text{n}} \text{Compactness}\right)\right) \tag{1}$$

$$F_2 : \text{Maximize}\left(\frac{1}{\text{n}}\left(\sum_{\text{i}=1}^{\text{n}} \frac{1}{\text{n}_\text{i}} \sum_{\text{j}=1}^{\text{n}_\text{i}} \left(\text{Comp}_{\text{ij}}\right)\right)\right) \tag{2}$$

$$F_3 : \text{Maximize}\left(\frac{1}{\text{n}}\left(\sum_{\text{i}=1}^{\text{n}} \frac{1}{\text{n}_\text{i}} \sum_{\text{j}=1}^{\text{n}_\text{i}} \left(\text{Dep}_{\text{ij}}\right)\right)\right) \tag{3}$$

$$F_4 : \text{Maximize}\left(\frac{1}{\text{n}}\left(\sum_{\text{i}=1}^{\text{n}} \text{Suitability Score}\right)\right) \tag{4}$$

where n is the number of LUs in the study area, i and j are the current LU and its neighbor respectively. Compactness, Comp_{ij}, Dep_{ij}, and Suitability Score are criteria values based on based on previous work (suitability analysis) [15]. Table 1 shows compatibility and dependency scores which were gathered from survey with VH, H, M, L, and VL represent very high, high, medium, low, and very low, respectively. Aggregating function method [28] was chosen to handle multi-criteria problem (maximization problem):

$$F = \ max \sum_{i=1}^{k} w_i F_i(x) \tag{5}$$

$$H = \ \text{Inside Allowable Location} \tag{6}$$

where wi ≥ 0 are 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 handling based on LU class and scenario. 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.

Table 1. Compatibiliy and Dependency[1] Scores

Class[2]	Com	El Schl	Indust	Mid Schl	Col	Med	Sport	Park	Res_low	Res_High
Commercial	VH(*VH*)	VL (*VL*)	H(*VH*)	L(*VL*)	H(*H*)	L(*VH*)	VH (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
Elementary school		VL (*VL*)	VL(*VL*)	VH(*VH*)	VH (*H*)	VH (*VH*)	VH (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
Industrial			VH(*VH*)	VL(*H*)	H (*VH*)	VH (*VH*)	VH(*M*)	VH(*VH*)	VL(*L*)	VL(*H*)
Middle school				M(*VL*)	VH (*VH*)	VH (*VH*)	VH (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
College					M (*VL*)	VH (*VH*)	VH (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
Medical						VL (*VH*)	VL (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
Sport							VL (*VH*)	VH(*VH*)	VH (*VH*)	VH(*VH*)
Park								VH(*VH*)	VH (*VH*)	VH(*VH*)
resident_low									VH (*VH*)	VH(*VH*)
resident_high										VL(*VH*)

[1]Are showen in bracket; [2]Com, El schl., Indust, Mid schl, Col, Med, Res_low, and Res_high are commercial area, elementary school, industrial, middle school, college, medical, low density residential, and high density residential, respectively.

PSO was placed in the first stage in the optimization module because of its fast computation characteristic [29]. The second stage was GA with its robust characteristic. Since the GA need more computation resources (encoding, crossover, mutation, and roullete wheel selection), only the half worst result of PSO were to be optimized, instead of deleting the worst result suggested from previous research [29]. The last stage was local search (using the pattern search method) to refine the result (ensureing the local optimum in every PSO and GA result). The optimization module only optimized the predicted land use (2050) and the existing land uses were fixed but influenced the process of new land-use allocation. The procedure of the optimization module are as follows [15]:

a. Use random initial locations (inside the allowable location) for new predicted land-uses as initial particles of PSO
b. Calculate the global best and local best of each particle (location and velocity)
c. Generate new location and velocity and calculate the fitness score
d. Find the current best of each particle (do until reaching PSO stop condition)
e. Sort the optimum particles and use the half worst as initial individuals in GA stage
f. Calculate the fitness score
g. Encode into binary strings
h. Generate new individual from crossover and mutation
i. Calculate the new fitness score
j. Select new individual based on their probability (roullete wheel method)
k. Decode into real number (do until reaching GA stop condition)
l. Merge with the half best PSO result and use as initial location of Pattern Search Method
m. Find three locations with a distance from each optimum result
n. Chose the best fitness score (do until reaching the stop condition of pattern search)
o. Convert the result into shapefile and latitude and longitude
p. Save the latitude and longitude to MySQL database

In every stage, before using the candidates as the result, the death penalty was implemented to handle the constraints [28]. It returned every candidate outside allowable areas. In this study, the algoritma from Hormann was used [30]. GA (line 5-11) with crossover and mutation characteristics was used to help the candidates handling the wide constraints that difficult with limited velocity in PSO stage (line 1-4). Finally, Local search method (line 12-14) refined the results of PSO and GA The optimization infrastructure of this study is shown in Figure 3 and the softwares used are: Matlab, PHP, MySQL, and ArcGIS.

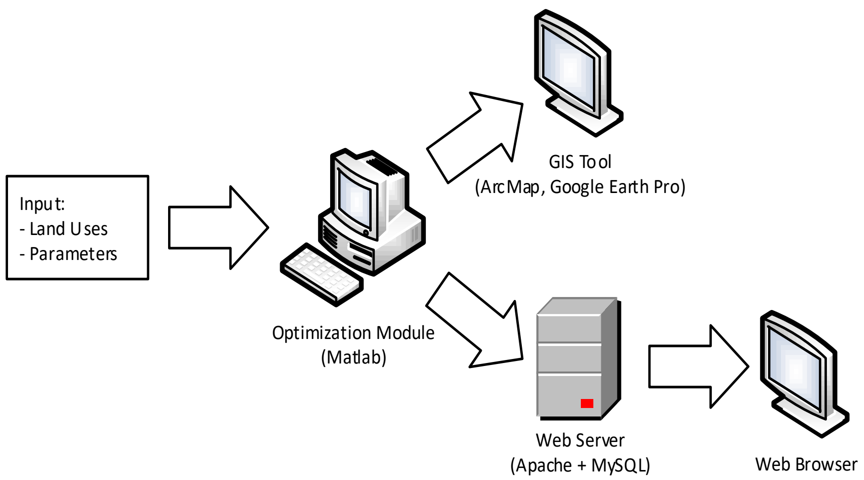


Figure 3. Optimization Infrastructure

Number of land-use class and parameters were used as the input of optimization module. The Matlab-based optimization modul created the results in shapefiles and geographical locations (latitude and longitude). Whereas the shapefiles can be accessed through some GIS tools (e.g., ArcGIS, ArcView, QGIS, Google Earth Pro, etc.), geographical locations can be seen in a Web-GIS (PHP and MySQL).

3. Results and Discussion

3.1. Simulation Result

Simulation module in Matlab was created to predict the land-use growth Figure 4. After several iteration, NARXNET (9 neurons in hidden layer, 1000 max epoch and 0.00000001 Goal) gave the result with MAPE of 0.2% error and LCM (Multilayer Perceptron Neural Network method, gave the AUC value of 71% accuracy as shown in Table 2.

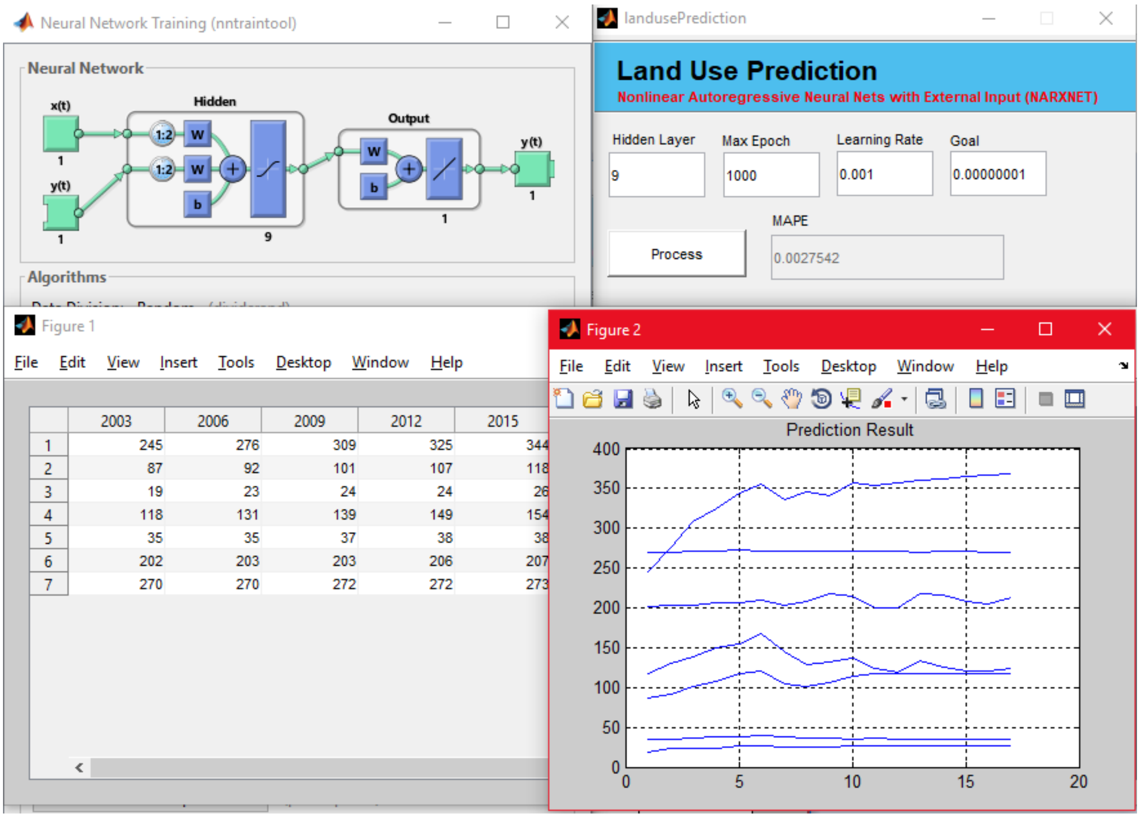


Figure 4. NARXNET Module for LU Growth Prediction

Table 2. Simulation Result

LU Class	Initial (2015) Raster Data (pixels)	Initial (2015) Vector Data (points)	Projection (2050) Raster Data (pixels)	Projection (2050) Vector Data (points) [1] IDRISI	Projection (2050) Vector Data (points) [1] NARXNET[2]
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; [2] From previous study (as comparison) [15]

LCM module in IDRISI Selva Figure 5 showed the LULC change from 2015 to 2050. This method simulated the growth with the prediction of locations, whereas the NARXNET only the number of land-use. However, the simulation from IDRISI based on the driving factors and the constraints and did not show that their locations are optimum Figure 5. This result related to driving factor and markov chain matrix in LCM module in IDRISI Selva. Therefore, further optimization process was needed.

Since the data format of NARXNET (vector) was different from LCM (raster), the conversion was used by comparing raster and vector data in 2015 with their prediction. Table 3 shows the simulation result through NARXNET and LCM not to much different regarding the number of land uses in vector data.

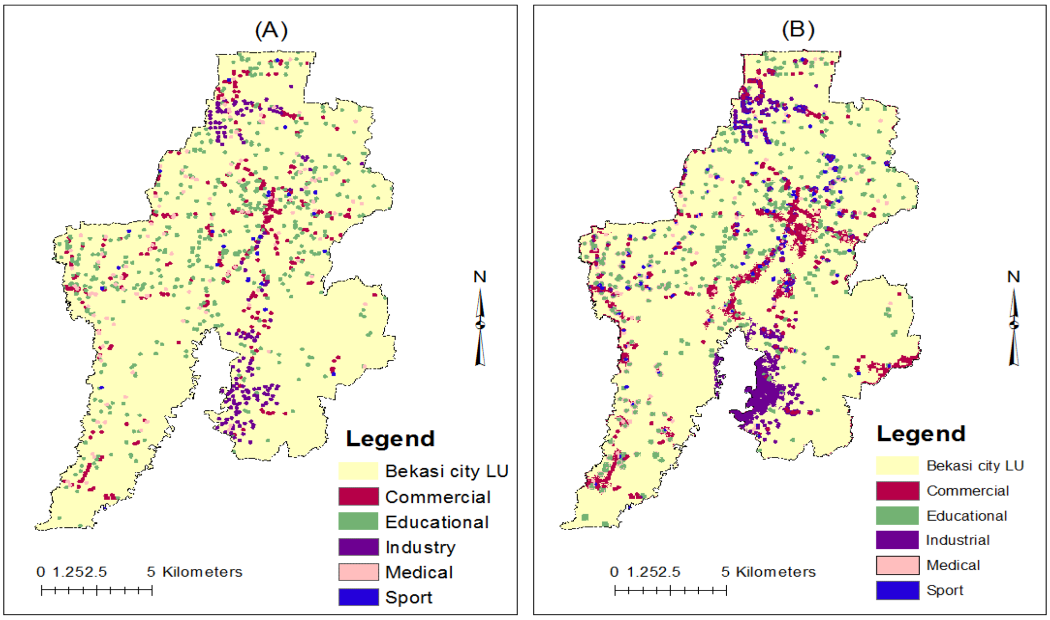


Figure 5. Simulation result: (a) Initial LU (2015), and (b) Predicted LU (2050)

3.2. Optimization Result

To achieve the sustainable urban form, the optimization process based on sustainability criteria (compatibility, dependency, compactness, and suitability) should be done. Figure 6 shows the application for land-use optimization based on the proposed method of this study (intellectual property rights number: EC00201806169).

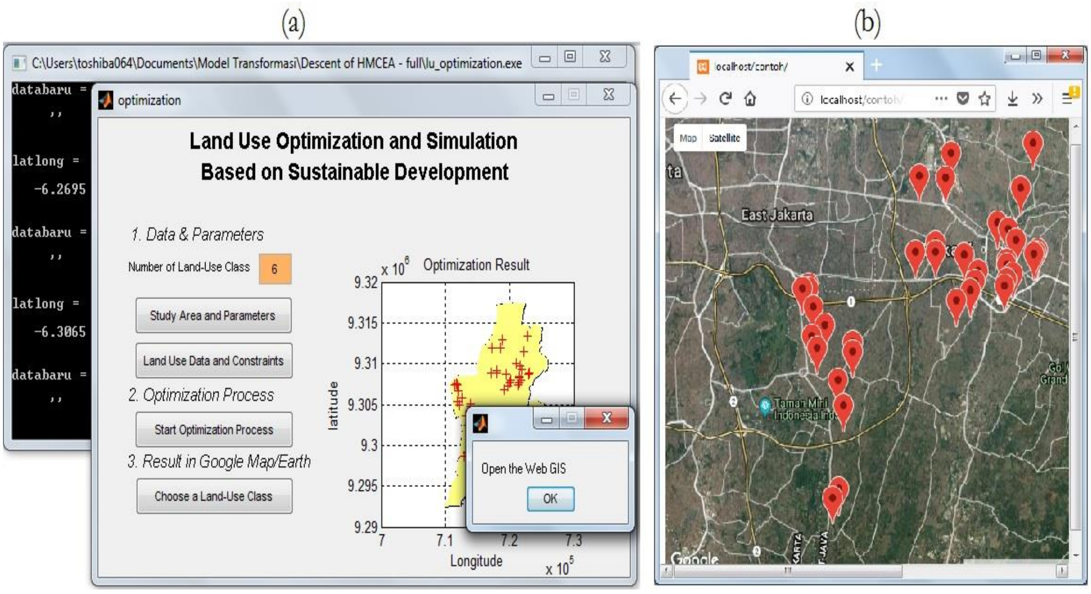


Figure 6. Optimization module application: (a) Desktop Optimization Module in Matlab, and (b) Web-GIS (PHP & MySQL) for showing a particular land-use class

LU optimization run several times to achieve a sustainable urban form following criteria functions and the constraints with the data were from land-use growth prediction in simulation (NARXNET and LCM). The fitness score increased until it reached saturation at about 30 optimization run Figure 7. The optimization module also converted the results into shapefile maps for depicting the result through GIS tools with better visibility (ArcView, ArcGIS, QGIS, Google Earth Pro, etc.). Figure 8 shows optimization result using ArcGIS software; LUs were allocated optimally without violating any constraints. It shows the new land use allocation that spreaded around the study area instead of allocated near the previous locations Figure 5b.

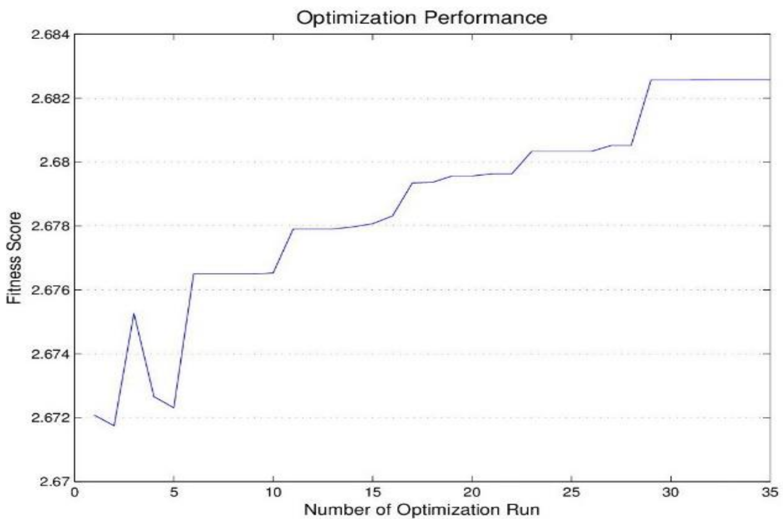


Figure 7. LU optimization performance

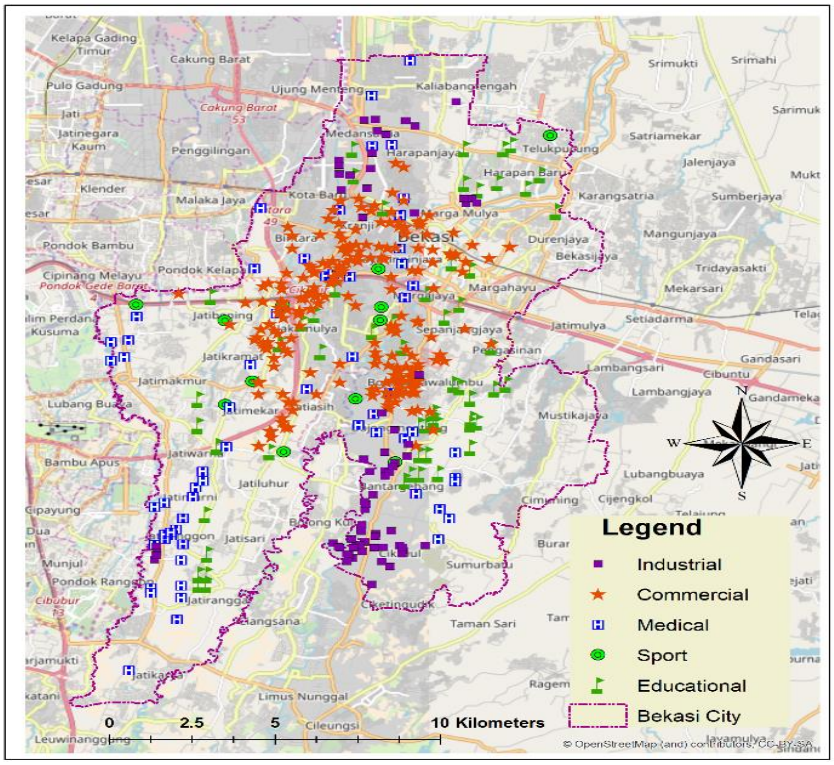


Figure 8. Optimization result (expected new LU allocation in 2050) in ArcGIS

3.3. Discussion

NARXNET and LCM showed the ability to predict land-use growth within the study area. LCM which uses driving factors and constraint showed the new land-use locations, but these locations need further analysis regarding the optimization to achieve the sustainable development condition. With the four criteria functions based on sustainable development concept, optimization module allocated new land-use location in 2050 and showed better fitness score than before.

Some limitations have to be addressed in simulation, i.e. the growth in Bekasi City that is affected by its vicinity [3], and the different data format between LCM simulation (raster data in pixels) and optimization (vector data). Integration with another method should be checked for better accuracy, such as Support Vector Regression (SVR), Support Vector Machine (SVM), with the optimization method to improve performance [31-33]. However, the integration between simulation and optimization can be used by the planners to see the feasibility of their plans and achieving the sustainable development goals [34].

4. Conclusion

In managing land use, planners need spatial and temporal analysis. LULC Change module in LCM and NARXNET prediction could simulate the change in the future through temporal anlaysis. Not only simulating the future condition, but planners also need a tool to achieve the desired condition through land-use optimization. Since a lot of constraints and criteria involved, the optimization process needed constraint and multicriteria handlings. The death penalty constraint handling and aggregation function for multiconstraint handling have successfully implemented to optimize land use based on sustainable development criteria (compatibility, dependency, compactness and suitability) in this study. The proposed framework (simulation and optimization) in desktop and web-GIS application can be used by local city planners to propose the new city plans.

Acknowledgment

The authors thank to Research, Technology and Higher Education Department (RISTEK-DIKTI) of Indonesia, local government of Bekasi City during, Higher Education in Informatics and Computer (APTIKOM), Asian Institute of Technology (AIT) Thailand, and Universitas Islam 45 Bekasi. Also for the reviewers for the comments and valuable suggestions.This research is funded by RISTEK-DIKTI as Nasional Strategic Research Grant No. SP DIPA-042.06.1.401516/2018 entitled “Optimalisasi dan Simulasi Penataan Ruang Kota Bekasi Menggunakan Algoritma Genetika untuk Mendukung Pembangunan Berkelanjutan: Kajian terhadap Perencanaan Kota Bekasi (2010-2030)”.

References

[1] Loonen W, Heuberger P, Kuijpers LM. Modelling Land-Use Change: Progress and Applications. In: Koomen E, Stillwell J, Bakema A, et al. (eds). Dordrecht: *Springer Netherlands*. 147-165.
[2] Steiner F. The living landscape-An Ecological Approach to Landscape Planning-Second Edition. Washington DC: ISLAND PRESS. 2008.
[3] Bhatti SS, Tripathi NK, Nitivattananon V, et al. A multi-scale modeling approach for simulating urbanization in a metropolitan region. *Habitat Int*. 2015; 50: 354-365.
[4] Pham HM, Yamaguchi Y. Urban growth and change analysis using remote sensing and spatial metrics from 1975 to 2003 for Hanoi, Vietnam. *Int J Remote Sens*. 2011; 32: 37-41.
[5] Sun C, Wu Z, Lv Z, et al. Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *Int J Appl Earth Obs Geoinf*. 2013; 21: 409-417.
[6] Firman T, Fahmi FZ. The Privatization of Metropolitan Jakarta’s (Jabodetabek) Urban Fringes: The Early Stages of “Post-Suburbanization” in Indonesia. *J Am Plan Assoc*. 2017; 83: 68–79.
[7] Fragkias M, Seto KC. Urban Land-Use Change, Models, Uncertainty, and Policymaking in Rapidly Growing Developing World Cities: Evidence from China. In: Aspinall RJ, Hill (eds) Land Use Change: Science, Policy, and Management. United States of America. 2008: 139–160.
[8] UN. Sustainable Development Goals. https://sustainabledevelopment.un.org/topics (2015, accessed 25 November 2015).

[9] Kolb M, Mas J, Galicia L. Evaluating drivers of land-use change and transition potential models in a complex landscape in Southern Mexico. *Int J Geogr*. 2013: 37-41.
[10] Thapa RB, Murayama Y. Scenario based urban growth allocation in Kathmandu Valley, Nepal. *Landsc Urban Plan*. 2012; 105: 140-148.
[11] Alexander C. A city is not a tree. In: LeGates RT, Stout F (eds) The City Reader. Great Britain: Routledge. 1996: 118-131.
[12] Ma S, He J, Liu F, et al. Land-use spatial optimization based on PSO algorithm. *Geo-Spatial Inf Sci*. 2011; 14: 54–61.
[13] Masoomi Z, Mesgari MS, Hamrah M. Allocation of urban land uses by Multi-Objective Particle Swarm Optimization algorithm. *Int J Geogr Inf Sci*. 2013; 27: 542-566.
[14] Loonen W, Heuberger P, Kuijpers-Linde M. Spatial Optimisation In Land-Use Allocation Problems. In: E Koomen, J Stillwell, A Bakema, H Scholten. (ed) Modelling Land-use Change. Springer-Verlag. 2007.
[15] Handayanto RT, Tripathi NK, Kim SM, et al. Achieving a Sustainable Urban Form through Land Use Optimisation : Insights from Bekasi City's Land Use Plan (2010-2030). *Sustainability.* 2017; 9.
[16] Handayanto RT, Srie Gunarti AS, Samsiana S, et al. A Web-GIS based integrated optimum location assessment tool for gas station using genetic algorithms. *ARPN J Eng Appl Sci*. 2015; 10: 1383-1388.
[17] Holland JH. Genetic Algorithms. Scientific American. 1992: 66-72.
[18] Handayanto RT, Kim SM, Tripathi NK, et al. *Land use growth simulation and optimization in the urban area*. Proceedings of the 2nd International Conference on Informatics and Computing, ICIC 2017. 2018.
[19] Kennedy J, Eberhart R. *Particle swarm optimization*. IEEE Int Conf Neural Networks 1995; 4: 1942-1948.
[20] Ab Ghani MR, Hussein ST, Jano Z, et al. Particle Swarm Optimization Performance: Comparison of Dynamic Economic Dispatch with Dantzig-Wolfe Decomposition. *TELKOMNIKA (Telecommunication Comput Electron Control)*. 2016; 14: 1042.
[21] Handayanto RT, Tripathi NK, Kim SM, et al. Achieving a sustainable urban form through land use optimisation: Insights from Bekasi City's land-use plan (2010-2030). *Sustain*. 2017.
[22] Baja S. Perencanaan Tata Guna Lahan dalam Pengembangan Wilayah-Pendekatan Spasial & Aplikasinya. Yogyakarta. Andi Offset. 2012.
[23] BAPPEDA. Rencana Tata Ruang Kota Bekasi. 2013.
[24] Thapa RB, Murayama Y. Drivers of urban growth in the Kathmandu valley, Nepal: Examining the efficacy of the analytic hierarchy process. *Appl Geogr*. 2010; 30: 70-83.
[25] Wang H, Ma R. Design of Neural Networks for Intrusion Detection. *TELKOMNIKA (Telecommunication Comput Electron Control)*. 2016; 14: 321.
[26] Rahmani B, Aprilianto H. Early Model of Student's Graduation Prediction Based on Neural Network. *TELKOMNIKA (Telecommunication Comput Electron Control)*. 2014; 12: 465.
[27] Handayanto RT, Haryono, Prianggono J. *Real-time neural network-based network analyzer for hotspot area*. ICACSIS 2011-2011 International Conference on Advanced Computer Science and Information Systems, Proceedings. 2011.
[28] Coello CAC. Evolutionary Multiobjective Optimization: Theoretical Advances and Applications. In: Abraham A, Jain L, Goldberg R (eds). London. Springer London. 7-32.
[29] Eberhart RC, Shi Y. *Comparison between Genetic Algorithms and Particle Swarm Optimization*. Proceedings of the 7th International Conference on Evolutionary Programming VII. London, UK, UK: Springer-Verlag. 611-616.
[30] Hormann K, Agathos A. The point in polygon problem for arbitrary polygons. *Comput Geom Theory Appl*. 2001; 20: 131-144.
[31] Soebroto AA, Cholissodin I, Frestantiya MT, et al. Integration Method of Local-global SVR and Parallel Time Variant PSO in Water Level Forecasting for Flood Early Warning System. 16. Epub ahead of print 2018. DOI: 10.12928/TELKOMNIKA.v16i3.6722.
[32] Novitasari D, Cholissodin I, Mahmudy WF. Hybridizing PSO With SA for Optimizing SVR Applied to Software Effort Estimation. *TELKOMNIKA (Telecommunication Comput Electron Control).* 2016; 14: 245.
[33] Syarif I, Prugel-Bennett A, Wills G. SVM Parameter Optimization using Grid Search and Genetic Algorithm to Improve Classification Performance. *TELKOMNIKA (Telecommunication Comput Electron Control).* 2016; 14: 1502.
[34] UN. Habitat III Issue Papers-Public Space. United Nation Conference on Housing and Sustainable Urban Development. New York. United Nation. 2015.