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Modeling of urban growth in tsunami-prone city using logistic regression: Analysis of Banda Aceh, Indonesia

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A B S T R A C T

The urban development of Banda Aceh, Indonesia was very rapid after the tsunami in 2004, posing critical challenges in planning for its future sustainable development. Scientifically-derived information about its land change patterns and the driving factors of its rapid urbanization might provide vital information. However, the spatio–temporal patterns of its urban land use/cover (LUC) changes have not been examined. Hence, this study aims to: (1) detect and analyze the spatio–temporal changes in the urban LUC of Banda Aceh between 2005 and 2009; and (2) examine the driving factors that influence urban growth. The 2005 and 2009 LUC maps were derived from remote sensing satellite images using a supervised classification method (maximum likelihood). Both LUC maps contained four categories, namely built-up area, vegetation, water body, and wet land. The 2005 LUC map had an overall accuracy of 77.8%, while the 2009 LUC map had 89.4%. The two LUC maps were re-classed into two categories (i.e. built-up area and non built-up area) to facilitate logistic regression analysis. A total of seven variables or potential driving factors of urban growth were identified and examined, including two socio-economic factors (population density and distance to central business district) and five biophysical factors (distances to green open space, historical area, river, highway, and coastal area). The results showed that the LUC of Banda Aceh has changed drastically between 2005 and 2009, particularly its built-up area, which increased by 90.8% (1016.0 ha) at the expense of the other LUC categories. The socio-economic factors showed positive influence to the growth of the city, whereas the biophysical factors showed negative effect, except the distance to coastal areas. The importance of the findings for future landscape and urban planning for Banda Aceh is discussed.

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Introduction

In terms of socio-economic environment, cities change rapidly. Throughout the last decade, many cities in the world have experienced growth, especially in developing countries. This growth is characterized by the transformation of land use/land cover (LUC) to accommodate the increased activity of the city (Yu & Qingyun, 2011). This transformation is caused by an increasing population and economic development (Bounoua et al., 2009).

Banda Aceh, a city affected by the tsunami in 2004, has also experienced growth, both in physical-morphological and economic conditions. Concerning physical-morphological change, the city has undergone a surge in built-up area for residential construction, office buildings, infrastructure, trade, and other urban services, which has increased one-and-a-half times in the past five years. The city has also been expanding economically. One important indicator is the Gross Domestic Product (GDP), which is currently five times greater than in 2000. Similarly, the population has been increasing at an average annual rate of 1.65% since 2009 and is expected to double by 2020. This diverse growth shows that the city of Banda Aceh will continue to grow to accommodate the needs and activities of society.

The tsunami that hit Banda Aceh on December 26, 2004, had a tremendous impact on the city and left badly damaged buildings, infrastructure, and LUC, particularly in the coastal areas. The activities undertaken during the rehabilitation and reconstruction

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period (2005–2008) focused on reconstructing buildings and damaged infrastructure, capacity building and community empowerment, economic activities, and other related social, economic, and cultural agendas. The rehabilitation and reconstruction activities in the regions affected by the tsunami should be a good starting point to structure a sustainable city. These activities optimize the construction of new growth centers that support environmental sustainability, historical preservation, and the mitigation of earthquakes and tsunamis. Urban growth must be controlled so that the city will achieve sustainable development goals.

Sustainable urban growth is a strategic issue in achieving a better quality of life by improving the quality of the urban environment. Through sustainable urban growth, future generations can meet their needs by implementing appropriate urban policies and strategies (Setioko, Pandelaki, & Murtini, 2012). Thus, sustainable development cannot be separated from land use and the potential of existing resources for human development goals and society. As a concept, sustainable development is a response to the challenges that face urban areas, such as globalization, decentralization, and rapid population growth (Rasoolimasnesh, Badarulzaman, Jaafar, 2011).

One way to promote sustainable urban growth is through appropriate policies. To formulate appropriate policies that support urban expansion, we need a growth model that considers the mechanisms of change in LUC (Yu & Qingyun, 2011). Geographic Information Systems (GIS) can facilitate and accelerate the process of urban growth analysis (Musaoglu, Tanik, & Kocabas, 2005). Although urban LUC is a complex system and a challenge for science and practice, GIS-based modeling can measure and visualize the potential trends and spatial patterns of future urban growth (Allen & Lu, 2003). In this research, GIS will show the LUC change in Banda Aceh from 2005 to 2009. This study will also build a model and predict the future potential change patterns in LUC. GIS is also used to assist national and local governments to store and manage large amounts of geographic information (Murayama & Thapa, 2011). Predictions of future urban growth scenarios are made to better understand the dynamics of urban development and to support landscape and urban planning (Hui-Hui, Hui-Ping, & Ying, 2012).

This study (1) detects and analyzes the spatio-temporal changes in the urban LUC of Banda Aceh between 2005 and 2009, (2) examines the driving factors that influence urban growth, and (3) predicts LUC in the year 2029. The year 2029 was chosen because of Banda Aceh's Spatial Plan Regulation 2009–2029. This study contributes to urban development planning for disaster-prone cities by providing information regarding the land changes in Banda Aceh. This information is vital to government officials and urban planners in their planning efforts, particularly in determining the development activities that support sustainable growth for the welfare of the community. Simulations of future urban growth and an associated environmental assessment can help policy makers in evaluating alternative development schemes and can form the basis of policy recommendations for the urban planning of sustainable urban development (Zhang, Ban, Liu, & Hu, 2011).

Materials and methods

Study area

This study focuses on the administrative region of Banda Aceh in the Province of Aceh, which has an area of 61.36 km^2. Geographically, this location is between latitude 05°16′15'–05°36′16″ and longitude 95°16′15″–95°22′35' (Fig. 1). The average altitude of the urban areas is 0.80 m above sea level. The population of Banda Aceh is 255,243 (2012), which is distributed over nine districts and 91 villages. The area is almost uniformly flat.

Banda Aceh, which is the capital of the Aceh Province, has been experiencing rapid infrastructure growth since a tsunami destroyed much of the urban area at the end of 2004. Many landmarks, both old and new buildings, decorate this historical city. The increasing infrastructure growth has not aligned with activities that effectively support the environment. Approximately half of the study area was damaged by the tsunami in 2004. The population just after the tsunami in 2004 was 177,881.

Land use/cover mapping and change detection analysis

The data that were used in this research are satellite imaging (Quickbird satellite images) as the primary data and socio-economic information as the secondary data. Quickbird satellite images were obtained from the Regional Planning Board of Banda Aceh. All images were geometrically registered to the Universal Transverse Mercator (UTM46N) coordinate system. The socio-economic data, such as population statistics, were obtained from the Central Bureau of Statistics of Aceh. LUC was interpreted from the satellite images of Quickbird for 2005 and 2009, which have a 0.6 m × 0.6 m resolution with 19,192 × 17,772 pixels. The satellite images have three bands, whereas the socio-economic data, such as population statistics, were used as secondary data. The population data were obtained from the 2009 population based on "Aceh in Figure 2010".

In this study, the land was divided in four categories concerning the urban area of Banda Aceh that were not used for agricultural purposes, namely, the built-up area, vegetation, water body, and wet land. The built-up area includes building structures, such as houses, pavement, bridges, and roads (Estoque and Murayama, 2012a; Karolien, Anton, Maarten, Eria, Paul, 2012). Vegetation includes trees, cropland, and undeveloped land. Water body includes seas and rivers, whereas wet land includes fish ponds and land that is saturated with water. For the logistic regression, both LUC 2005 and LUC 2009 was merged into two categories, namely, the built-up and non-built-up areas (Hu & Lo, 2007; Karolien et al., 2012; Liao & Wei, 2012). The built-up area was not merged. Vegetation and wet land were merged into a non-built-up area. There were "no data" (not defined) regarding the water body persisting in the future.The changing of the land category was conducted by the reclassification tool in ArcGIS® 10.1.

LUC was classified using ArcGIS® 10.1 software. This classification used supervised classification with a maximum likelihood approach. The first step was to create training samples. Training sites for each cover class were delimited through a visual interpretation (Karolien et al., 2012). Approximately 50 samples were derived for each category. There were 200 samples overall for each image (2005 and 2009). The next step was to refine the classifications. In this step, each sample was checked to insure that the land categories were similar to the reference image. A majority filter tool was used in the last step to determine each LUC to find a better LUC.

After forming LUC 2005 and LUC 2009, the next step was accuracy assessment. Accuracy assessment is very important in LUC modeling, and its overall accuracy classification is measured by the correct proportion (Estoque & Murayama, 2012b). To assess the accuracy of LUC 2005 and LUC 2009, the images of 2005 and 2009 were used as references because they were relatively clear and could be used in the assessment process. The assessment was conducted by determining the sample points that were compared with reference images. The stratified random sampling points were determined by the ERRMAT tool in IDRISI® Selva. The overall accuracy value was produced in IDRISI®Selva.

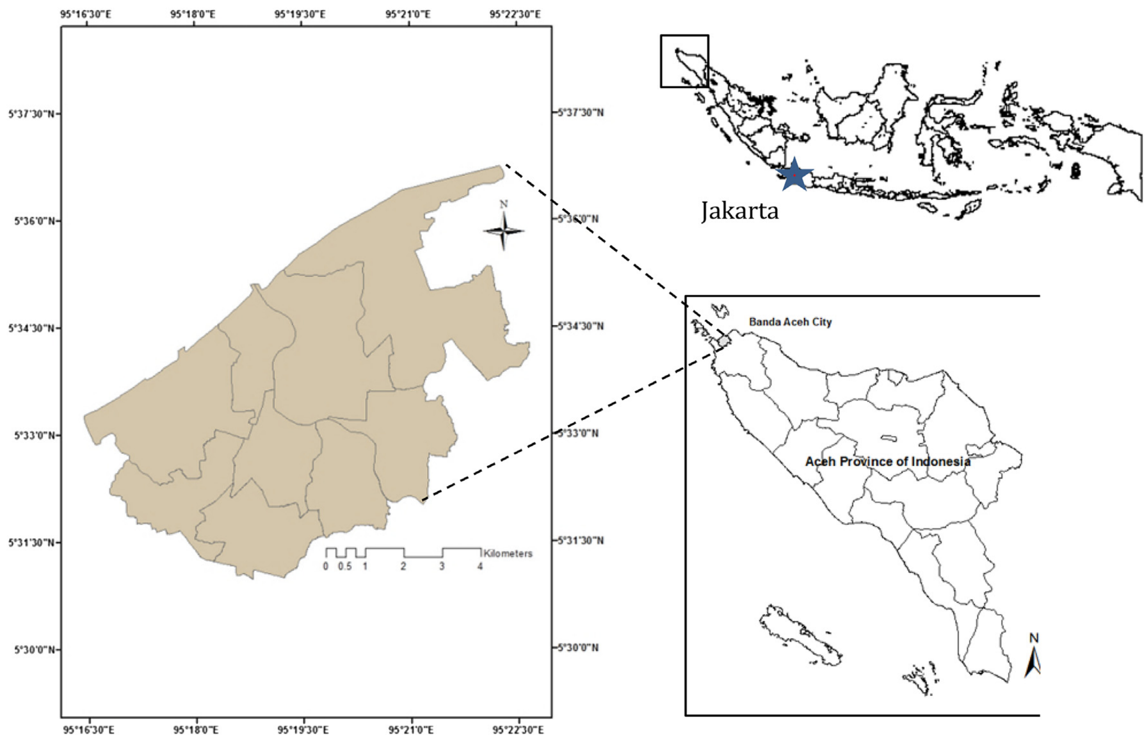


Fig. 1. Study area: Banda Aceh.

Driving factors analysis

Several driving factors have been considered in analyzing urban growth (Zhang, Su, Xiao, Jiang, & Wu, 2013). Some of the determinants that were used in this study are shown in Table 2. The driving factors in this study were divided in two types: density and proximity. The driving factors for urban growth generally consist of socio-economic and biophysical factors (Liao & Wei, 2012; Yu and Qingyun, 2011). The socio-economic factors include population density (POP) and distance to economic activity center (EAC). The biophysical factors comprise the distance to green open space (GOS), distance to historical areas (HIA), distance to road (ROA), distance to river (RIV) and distance to tsunami affected area (TAA). All driving factors in the shape file were analyzed using ArcGIS® 10.1.

POP was analyzed by inputting the amount of people per district and district area (ha) into a shape file. This shape file was changed to raster using Inverse Distance Weighting (IDW) interpolation with a spatial analyst tool. POP is often established as a land use determinant to indicate labor availability, accessibility, or the presence of a local market (Fusilli, Marzialetti, Laneve, & Santili, 2014; Yu and Qingyun, 2011). The distance to EAC is the distance of each pixel, based on an image, to economic activity points that are explained in the spatial regulation of Banda Aceh (Qanun no. 4/2009), as well as the distance to GOS, distance to HIA, and distance to ROA. The construction of a new road link or the enlargement of an existing network influences firm/household location choice, real estate development, land development and building density (Rui & Ban, 2011). Transportation is one of the most important mechanisms behind urban development (Liao & Wei, 2012). In addition, the distance to RIV and the distance to TAA were determined based on observations from satellite images and field study.

Urban growth simulation

Logistic regression analysis was conducted to reveal the relationship between urban growth and the driving factors of socio-economic and biophysical factors (Hui–Hui et al., 2012; Jantz,

Table 1
Variables and their descriptions.

Variable	Nature of variable	Unit	Previous study, e.g.
Dependent variable			
Urban Growth/y	Binary variable, 1 for yes and 0 for no (Dichotomous)	Growth probability (0–1)	Jantz et al., 2003; Vliet et al., 2009; Yu & Qingyun, 2011; Hui–Hui et al., 2012.
Independent Variables			
POP (x_1)	continuous	people/ha	Huang and Cai, 2006; Xiaoqing, Hongshi, Fengming,, Rencang, 2010; Yu & Qingyun, 2011; Omsongwang & Saravisutra, 2011; Hui–Hui et al., 2012
Distance to CBD(x_2)	continuous	km	Xiaoqing et al., 2010; Yu & Qingyun, 2011; Hui–Hui et al., 2012
Distance to GOS (x_3)	continuous	km	Chang, Ryan, Yi-xiang, Dennis, 2006; Uy and Nakagoshi, 2007
Distance to HIA(x4)	continuous	km	Chang et al., 2006; Yue, 2008
Distance to ROA (x5)	continuous	km	Yu and Qingyun; 2011; Hasyim et al., 2011; Hui–Hui et al., 2012; Liao & Wei, 2012.
Distance to RIV (X6)	continuous	km	Luo and Wei, 2009
Distance to TAA (x6)	continuous	km	Chang et al., 2006; Wisyanto, 2009; Murai, 2012; Muck et al., 2012; Luo & Wei, 2009

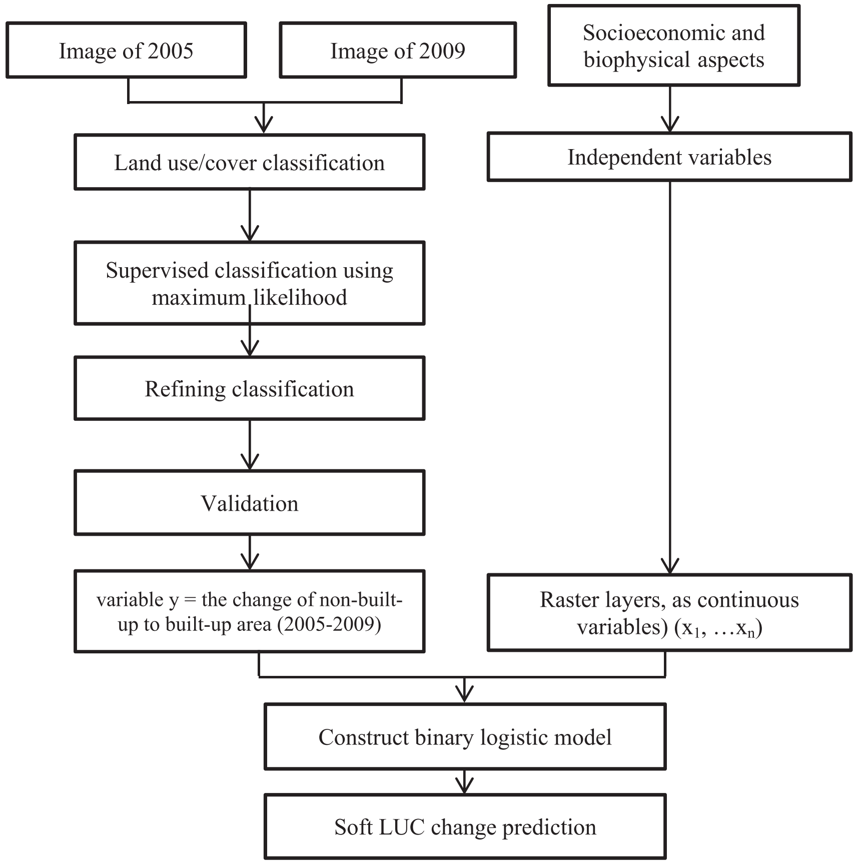


Fig. 2. The flow chart of logistic regression.

Scott, Goetz, Mary, & Shelly, 2003; Lu, Wu, Shen, & Wang, 2013; Yu & Qingyun, 2011; Zheng, Shen, Wang, & Hong, 2015). Urban growth probability (change/y) is the dependent variable, whereas the independent variables (predictors) are the socio-economic and biophysical factors.

The dependent variable was prepared by processing the LUC 2005 and LUC 2009 using the Land Change Modeler (LCM) in IDRISI®Selva. The independent variables were prepared from the shape files of the driving factors. Before this process, however, the accuracy of the LUC maps had to be assessed. A total of 293 truth points were used in the accuracy assessment. A raster layer for population was prepared by using the Kernel Density tool in ArcGIS®10.1. The other variables related to distance. To prepare these variables, we used the Euclidean distance tool in ArcGIS® 10.1. The raster layers for the independent variables were exported to IDRISI®Selva and used with the dependent variable in the logistic regression model that is available in the LCM. The flowchart of the logistic approach is presented in Fig. 2.

The dependent variable in the logistic regression model is a function of the probability that a particular theme will be present in

Table 2
Error matrices of the LUC classifications.

Classified data	Reference data				Total	Error
	Built-up area	Vegetation	Water body	Wet land		
(a) 2005						
Built-up area	46	7	3	1	57	0.1930
Vegetation	11	114	5	3	133	0.1429
Water body	2	11	39	7	59	0.3390
Wet land	3	3	9	29	44	0.3409
Total	62	135	56	40	293	
Error	0.2581	0.1556	0.3036	0.2750		
Overall classification accuracy (%) = 77.82						
(a) 2009						
Built-up area	90	7	0	0	97	0.0722
Vegetation	5	108	0	1	114	0.0526
Water body	1	2	28	1	32	0.1250
Wet land	0	11	3	36	50	0.2800
Total	96	128	31	38	293	
Error	0.0625	0.1563	0.0968	0.0526		
Overall classification accuracy (%) = 89.42						

Table 3
LUC changes 2005–2009.

LUC categories	Area (ha)		Change (ha)
	2005	2009	2005–2009
Built-up area	1118.9	2134.9	1016.0
Vegetation	2497.6	2169.7	−327.9
Water body	1446.9	663.2	−783.7
Wet land	934.5	1030.1	95.6
Total	5997.9	5997.9	

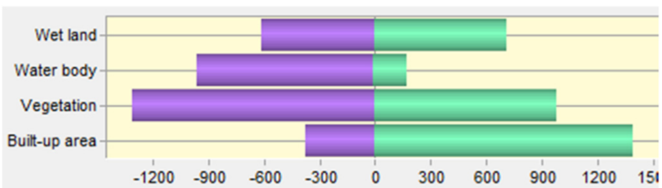


Fig. 3. Gains and losses of the LUC classes (2005–2009).

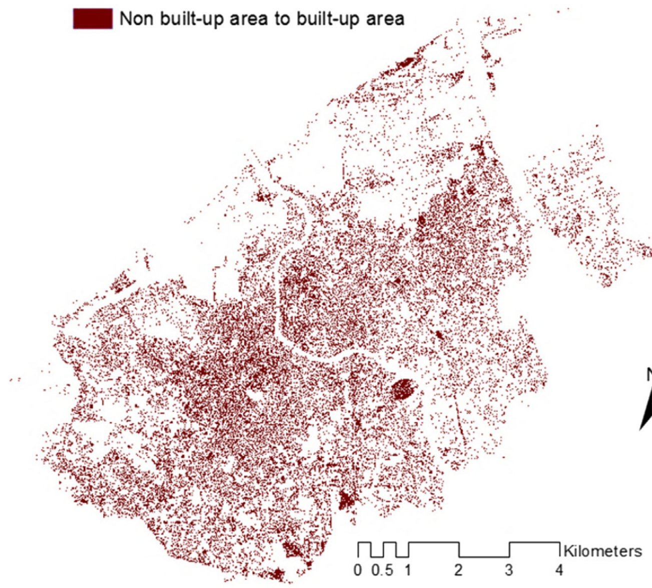


Fig. 5. Dependent variable y; change to built-up area from 2005 to 2009 presented as binary.

one of the categories. For example, the probability of change in a specific land use class is based on a set of scores of the predictor variables, such as proximity to the interchange network (Huang, Zhang, & Wu, 2009). Urban growth as the dependent variable uses a nominal scale (dichotomous). A nominal scale was used to state category, group, or classification constructs that were measured in terms of the variables (Erlina, 2011). The product of the logistic regression model is a probability surface of dependent variable occurrence that indicates urban development (Arsanjani, Helbich, Kainz, & Boloorani, 2013).

If there is growth, the value is 1, and if growth does not occur, the value is 0. The influence of land use is represented by the center of gravity, which is the attraction or repulsion of one land use to another as a function of distance (Vliet, Roger, & Suzana, 2009). This growth factor is determined by distance and kinship (neighborhood) (Hasyim, Hariyanto, Taufik, & Sulistyarso, 2011.

The quantitative relationship among the variables can be expressed as follows:

$$p = \frac{e^z}{1 + e^z} = \frac{1}{1 + e^{-z}} \quad (1)$$

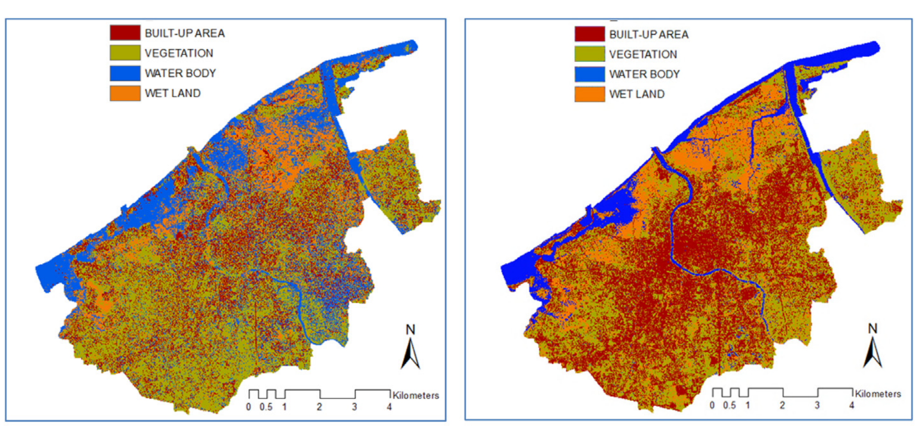
where p is the possibility of the occurrence of an event. In this study, p is the estimated probability of the growth of the city. This probability varies between 0 and 1 on an S-shaped curve. Here, z represents a linear combination. In general, the logistic regression for this study has a model as described below:

$$z = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \ldots + b_nx_n \quad (2)$$

where b_0 is the intercept of the model, $b_i = (i = 0, 1, 2, \ldots, n)$ represents the logistic regression model coefficients, and $x_i = (i = 0, 1, 2, \ldots, n)$ represents the independent variable. By using logistic regression, the logit function can be expressed as

$$\ln\left[\frac{p_i}{(1 - p_i)}\right] = b_0 + \sum_{j=1}^{n} b_jx_j \quad (3)$$

In accordance with the codification of the variables (Table 1), the logistic regression equation is given as follows:



(a) 2005 (b) 2009

Fig. 4. LUC maps of Banda Aceh.

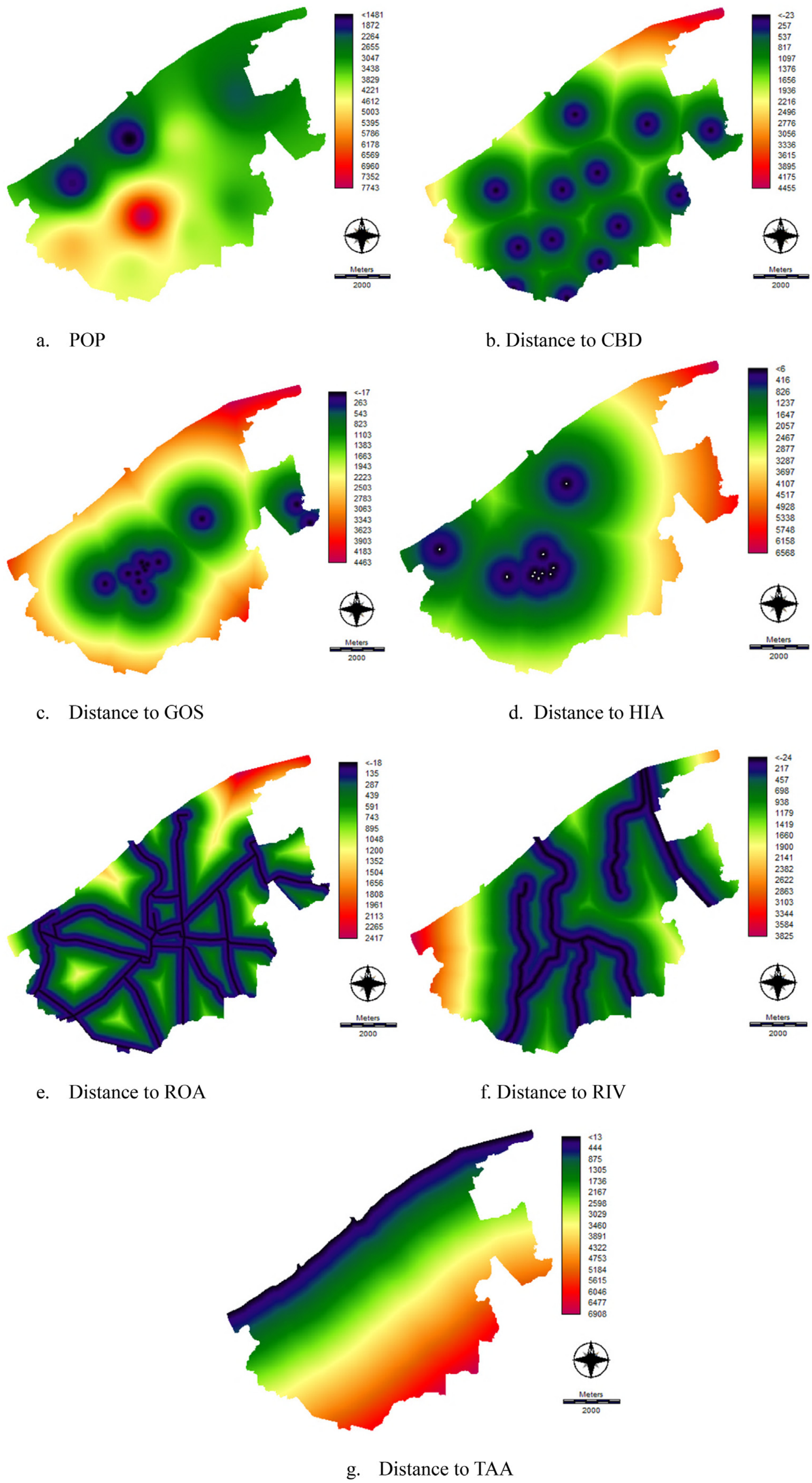


Fig. 6. Raster layers of the independent variables for the optimum model that are represented as continuous variables.

$$\ln\left[\frac{p_i}{(1-p_i)}\right] = b_0 + b_1POP + b_2CBD + b_3GOS + b_4HIA + b_5ROA + b_6RIV + b_7TAA + \varepsilon \quad (4)$$

The independent variables are presented in Table 1.

ROC assessment

The next step is to validate the logistic regression model. This validation test uses ROC to measure the relationship between the changes that result from the simulation and the actual changes (Pontius, 2000; Schneider & Pontius, 2001). ROC is an indicator of goodness of fit, and it measures the area beneath the curve that relates the true positive proportion and the false positive proportion for a range of cut-off values in classifying probability (Verburg, Ritsema van Eck, de Nijs, Dijst, & Schot, 2004). The area under the ROC curve is particularly important for evaluating how good the decision making is at discriminating between stable compared with unstable areas. An ideal model would have an area of 1.000 (Yu & Qingyun, 2011).

Results

Accuracy of the LUC maps

The accuracy assessment was aided by IDRISI® Selva. A total of 293 reference points for both LUC maps (2005–2009) were generated by using stratified random sampling. The overall classification accuracy is measured in terms of the proportion of correctly classified reference points (Estoque & Murayama, 2012b), which was 77.82% for the 2005 LUC map and 89.42% for the 2009 LUC map, with a Kappa (K) coefficient of 0.68 and 0.84, respectively (Table 2); K coefficient between 0.6 and 0.8 represents high agreement and K coefficient above 0.8 represents strong agreement (Landis & Koch, 1977; Zheng et al., 2015).

The accuracy result of the 2009 LUC map is much better than the accuracy of the 2005 LUC map. Several pixels were misclassified in the 2005 LUC map, which resulted in many errors, especially among water body, vegetation and wet land. The shadows and dark areas in some parts of the image contributed to the errors in classification.

Land use/cover changes

The identification of land use classes was conducted by using a supervised classification approach that is available in ArcGIS® 10.1. Land use is divided in built-up area, vegetation, water body, and wet land. The built-up area includes concrete structures, such as buildings, pavement, houses, roads, bridges, etc. Vegetation consists of trees, crop land, and other undeveloped land. Water body consists of rivers and seas. Finally, wet land includes ponds and other land that is saturated by water. The LUC changes from 2005 to 2009 are presented in Table 3.

Based on Table 3, the built-up area has doubled in four years (2005–2009). This rapid growth was the result of an urgent need for housing and communities. In addition, the population has increased because Banda Aceh is a city dominated by trade and services and is also a leader in the field of education. The city is characterized by a rapid increase in the population in the past four years, with a growth rate of 4% per year. The gains and losses of the LUC classes are presented in Fig. 3, and LUC map 2005 and LUC map 2009 are presented in Fig. 4.

Driving factors of urban growth

The LUC maps of 2005 and 2009 contain four classes that were simplified into two classes, namely, built-up and non-built-up areas (Fig. 4). The non-built-up area is the combination of vegetation and wet land. The water body is masked out. This simplification is performed because logistic regression works only with binary data (dichotomous) for the dependent variable. The dependent variable in this study includes sections that grew from non-built-up areas to built-up areas (Arsanjani et al., 2013; Liao & Wei, 2012; Park, Jeon, & Choi, 2012). A value of 1 indicates a change in the pixel in question, and a value of 0 indicates no change in the studied time period, i.e., 2005–2009 (Fig. 5).

A set of predictors (independent variables) was chosen based on preliminary research (e.g., Allen & Lu, 2003; Arsanjani et al., 2013; Hu & Lo, 2007; Liao & Wei, 2012; Yu & Qingyun, 2011), which have been selected based on the specific conditions of Banda Aceh, such as the tsunami-affected (coastal) area. These predictors are shown in Table 1. There were seven independent variables, and they are presented in Fig. 6. The socio-economic variables were POP and distance to CBD, whereas the biophysical variables were the distance ROA, distance to GOS, distance to HIA, distance to RIV, and distance to TAA.

Future LUC changes

Fig. 6 presents the urban growth probability in every section of Banda Aceh from 2009 based on LUC 2005 and LUC 2009. The simulation for the future was conducted by combining LR with the Markov probability matrix. This simulation was performed with the LCM tool in IDRISI®Selva. The probability matrixes for 2029 are shown in Table 5. By using the probability values between 2005 and 2009, the LUC can be observed in Fig. 7.

Discussion

An LUC map is an important component in urban growth modeling. The maps are a fundamental prerequisite for modeling future growth (Moghadam & Heilbich, 2013). LUC was identified by using RS and GIS as a modern geospatial technique, which may be helpful in explaining spatial analysis (Estoque & Murayama, 2013). In this study, LUC derived from spatial analysis explains land use

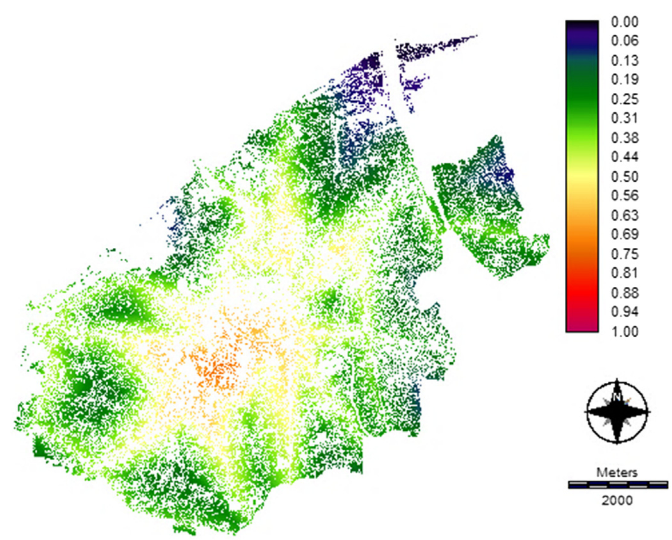


Fig. 7. Soft LUC change prediction (2009–2029).

changes between the two images, the gains and losses, and future urban growth probability. The proximity and density of the independent variables could also be identified with RS and GIS and quantitatively used for the simulation of urban growth modeling.

In a city that has been affected by a major disaster, the urgent need for physical and social development cannot be avoided in the development of the housing and human settlement sector, infrastructure, and other areas. In addition to the provision of houses for tsunami-affected communities, the development of settlements increased with the rapid population growth in Banda Aceh from 2005 to 2009 that reached an average growth rate of 4.8% per year, which is higher than the Indonesian national average (1.49% per year). As the center of trade, services, government, education, and tourism, Banda Aceh is an interesting place to visit.

The growth of the built-up area was a redevelopment of land that was affected by the tsunami, particularly parts of the city that are adjacent to the beach. New settlements are not as dense as previous settlements. The population in coastal areas, excluding restricted areas, also decreased (Fig. 5). Settlement construction was directed to areas that were far from the coast; therefore, the eastern and southern parts of the city became new growth points. Fig. 7 shows that the growth opportunities in the east and south are approximately 0.4–0.5, respectively.

Vegetation in this study includes not only trees but also vacant land that has not been used, whereas water body includes seas and rivers. The analysis shows that water body had a very sharp decline, which reaches half. There were errors in water body identification in the 2005 image because the dark sections and sea conditions that recently experienced a tsunami caused confusion in identification; therefore, some wet land and vegetation were misclassified as a water body (Table 3).

The identification of water body was better in 2009. Water body is a type of land use that will be retained. There is no development on a water body, except city infrastructure such as bridges and ports. In the logistic regression analysis, water body was masked out so that its existence is not disturbed by the development that will occur.

The results of the logistic regression (Table 4) showed that socio-economic factors and distance to the coastal areas had a positive influence. The socio-economic factors, namely, population density and distance to CBD, have a positive influence (Arsanjani et al., 2013; Hu and Lo, 2007; Liao & Wei, 2012). Other factors, such as the distance to green open space, distance to historical area, distance to river, and distance to road had a negative effect. Urban growth tends to occur in parts of the city that have a higher population density. The probability of growth of the city will be even greater in the proximity of CBD. This result is possible because Banda Aceh is not a large city based on its size and population; therefore, it is easy to access each area. Previous studies have been conducted on large cities (e.g., Allen & Lu, 2003; Arsanjani et al., 2013; Hu & Lo, 2007; Liao & Wei, 2012; Yu & Qingyun, 2011).

Table 4
Results of logistic regression analysis.

	Variable	Coefficient
Urban growth between 2005 and 2009	Intercept	0.07430000
	POP	0.00010620
	Distance to CBD	0.00004218
	Distance to GOS	−0.00024860
	Distance to HIA	−0.00022950
	Distance to RIV	−0.00006493
	Distance to ROA	−0.00130000
	Distance to TAA	0.00003565
Number of total observations		90,904,710
−2log likelihood		10,355,539.1696
Relative operating characteristic (ROC) value		0.6833

Table 5
Markov transition probabilities matrix of 2029.

Transition matrix	Land category	Built-up area	Non-built-up area
Probability value of 2029 based on transition matrix from 2005 to 2009	Built-up area	0.5761	0.4239
	Non-built-up area	0.5761	0.4239

The distance to TAA had a positive effect; the further the city is from the coast, the city had greater chances for growth. This result is caused by the establishment of the region as an area with a low density and the restrictions on development there. Only special buildings are permitted, such as the escape building, office, shops, and the settlements of previous residents who still inhabit this region, especially because of job location, for example, in the case of fishermen.

Additionally, the distances to green open space, historical areas, rivers, and roads were negative. The further the sections of the city are from these locations, urban growth is less likely. Development tends to occur in green open spaces, historical areas, roads, and rivers. Green open space is needed in the current urban environment and provides oxygen (O_2), recreation, and beauty. Urban growth will increase near historical areas and green infrastructure. The historical areas are important because Banda Aceh has been established by the Indonesian government as a heritage city.

The distance to road is important in developing a region because of accessibility concerns. The distance to road has a negative influence on urban growth. Areas that are closer to roads have a higher likelihood of urban growth. The distance to river has the same effect as the distance to road, which means that there is less chance of urban growth the greater the distance to a river.

Urban growth must be controlled to achieve a sustainable city. This model should be used by the government when making decisions concerning urban development. Urbanization is influenced by the spatial expansion of built-up areas, technological developments, and demographic pressures (Estoque & Murayama, 2013) and will continue to occur in Banda Aceh. Growth should be balanced with economic development, social well-being, and environmental protection and conservation (Estoque & Murayama, 2013). In Banda Aceh, a sustainable city also includes mitigation for earthquakes and tsunamis because tsunamis are a significant risk for residents and can cause substantial damage in the coastal areas (Jelinek et al., 2012). Furthermore, earthquakes and tsunamis can reoccur at any time (Burbidge et al., 2008).

Conclusion

In this study, a logistic regression is used for urban growth modeling in a tsunami-prone city. A logistic regression is useful to quantitatively explain the relationship between urban growth and its driving factors (Arsanjani et al., 2013; Park, et al., 2012). Remote sensing and GIS have an important role in achieving success in a logistic regression, especially in mapping the transformation of land use classes from time series satellite images and identifying the driving factor data for modeling.

Banda Aceh is an important city in the province of Aceh. Its position as a center of trade, services, tourism, culture, and education cause the city to continue to expand – both in terms of built environment and population growth. This development has occurred through reconstruction efforts because of the tsunami. This study analyzes and explains the changes in urban land use from 2005 to 2009 and provides predictions so that governments and developers can better plan according to local conditions to achieve sustainable development. The influence of the factors driving the growth of the city is important in drafting regulations that involve spatial planning of areas for future development.

Based on the LUC changes between 2005 and 2009, the growth of built-up areas, on average, reached 19.85% per year. This result is because of the many disaster-affected communities that required housing and infrastructure facilities and the number of migrants to Banda Aceh. The probability of growth of the built-up areas becomes increasingly smaller and tends to be steady. This result can be observed in Table 5. The non-built-up areas are also increasingly diminishing because sections are being used for built-up areas and green infrastructure. Water body has not changed because it is not categorized as a built-up area or a non-built-up area.

The probability of urban growth in general is less in the coastal areas located in the western part of the city. Future growth is likely to occur in the central, eastern, and southern parts of the city. The determination of the beach area as an area with a low density was sufficiently effective to encourage urban growth away from the coast from 2005 to 2009. Fig. 6 also shows that high growth has a low probability of occurring in the areas adjacent to the beach.

Logistic regression explains the extent of the driving factors that affect the growth of the city. The socio-economic factors, namely, population density and the distance to CBD, have a positive influence, whereas the biophysical factors, except the distance to coastal areas, have a negative influence. The growth tends to occur near the green open spaces, historical areas, roads, rivers, and city locations with a high population density. The growth of the city tends to avoid the beach and economic centers of the city.

An urban growth model that also considers disaster mitigation is a fundamental instrument to make public policies for future urban development to achieve a sustainable city. The regulation of land use in the areas adjacent to the coast in the western part of the city should be important in policy making for Banda Aceh urban development. Overall, urban development should be balanced between economic development and environmental protection and conservation. The improvement of a city following a tsunami can be a good beginning for sustainable city planning, which optimizes the built-up area of the new growth centers that support environmental sustainability and historical preservation.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2015.05.001

References

Allen, J., & Lu, K. (2003). Modeling and prediction of future urban growth in the Charleston region of south carolina: a GIS-based integrated approach, copyright © 2003 by the author(s). published here under license by the resilience alliance. *Conservation Ecology, 8*(2), 2 ([online] URL).

Arsanjani, J. A., Helbich, M., Kainz, W., & Boloorani, A. D. (2013). Integration of logistic regression, markov chain, and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation, 21*(2013), 265–275.

Bounoua, L., et al. (2009). Impact of urban growth on surface climate: a case study in oran, algeria. *Journal of Applied Meteorology and Climatology, 48*(2), 217–231.

Burbidge, D., Cummins, P. R., Mlecko, R., & Thio, H. K. (2008). A probabilistic tsunami Hazard assessment for western Australia. *Pure and Applied Geophysics, 165*(2008), 2059–2088.

Chang, H. J., Ryan, H., Yi-xiang, L., & Dennis, J. O. (2006). 2006. Reconstruction after the tsunami: ecological and cultural considerations from case studies. *Landscape and Ecological Engineering, 2*, 41–51. http://dx.doi.org/10.1007/s11355-006-0035-3.

Erlina. (2011). *Metodologi penelitian*. Medan: USU Press.

Estoque, R. C., & Murayama, Y. (2012). Examining the potential impact of land use/cover changes on the ecosystem services of baguio city, the philippines: a scenario-based analysis. *Applied Geography, 35*, 316–326.

Estoque, R. C., & Murayama, Y. (2012). Introducing new measures of accuracy for land-use/cover change modeling. *Tsukuba Geoenvironmental Sciences, 8*, 3–7. Dec. 28, 2012.

Estoque, R. C., & Murayama, Y. (2013). Landscape pattern and ecosystem service value changes: implications for environmental sustainability planning for rapidly urbanizing summer capital of the philipines. *Landscape and Urban Planning, 116*(2013), 60–72.

Fusilli, L., Marzialetti, P., Laneve, G., & Santili, G. (2014). Urban growth assessment around winam gulf of Kenya based on satellite imagery. *Acta Astronautica, 93*(2014), 279–290.

Hasyim, A. W., Hariyanto, T., Taufik, M., & Sulistyarso, H. (2011). Urban land use change analysis using temporal multispectral. *International Journal of Academic research*. ISSN: 2075-4124, *3*.

Huang, Q.-hao, & Cai, Y.-long (2006). Simulation of land use change using GIS-based stochastic model: the case study of shiqian county, southwestern china. *Stochastic Environmental Research and Risk Assessment, 2007*(21), 419–426.

Huang, B., Zhang, L., & Wu, B. (2009). Spatiotemporal analysis of rural-urban land conversion. *International Journal of Geographical Information Science, 23*(3), 379–398.

Hui-Hui, F., Hui-Ping, L., & Ying, L. (2012). Scenario prediction and analysis of urban growth using SLEUTH model. *Pedosphere, 22*(2), 206–216.

Hu, Z., & Lo, C. P. (2007). Modeling urban growth in atlanta using logistic regression. *Computers, Environment and Urban Systems, 31*, 667–688.

Jantz, C. A., Scott, J. G., & Mary, K. S. (2003). Using SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in baltimore-Washington metropolitan area. *Environmental and Planning B: Planning and Design, 30, 251–271.*

Jelinek, R., Krausmann, E., Gonzales, M., Alvares-Gomez, J. A. A., Birkman, J., & Welle, T. (2012). Approaches for tsunami risk assessment and application to the city of Cadiz, Spain. *Natural Hazards, 60*, 273–293. http://dx.doi.org/10.1007/s11069-011-0009-0.

Karolien, V., Anton, V. R., Maarten, L., Eria, S., & Paul, M. (2012). urban growth of Kampala, Uganda: pattern analysis and scenario development. *Landscape and Urban Planning, 106*, 199–206.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159–174.

Liao, F. H. F., & Wei, Y. H. D. (2012). Modelling determinants of urban growth in dongguan, china: a spatial logistic approach. *Stochastic Environmental Research and Risk Assessment*. http://dx.doi.org/10.1007/s00477-012-0620y.

Luo, J., & Wei, Y. (2009). Modeling spatial variations of urban growth patterns in Chinese cities: the case of Nanjing. *Landscape and Urban Planning, 91*(2), 51–64.

Lu, C., Wu, Y., Shen, Q., & Wang, H. (2013). Driving force of urban growth and regional planning: a case study of china's Guangdong province. *Habitat International, 40*(2013), 35–44.

Moghadam, H. S., & Heilbich, M. (2013). Spatiotemporal urbanization processes in the megacity of mumbai India: a markov chains-cellular automata urban growth model. *Applied Geography, 40*, 140–149.

Muck, M., Taubenbock, H., Post, J., Wegscheider, S., Strunz, G., Sumaryono, S., et al. (2012). Assessing building vulnerability to earthquake and tsunami Hazard using remotely sensed data. *Natural Hazards Springer Science+Buisiness Media Dordrecht*. http://dx.doi.org/10.1007/s11069-012-0481-1.

Murai, S. (2012). *Lessons from east Japan earthquake and tsunami, knowing to manage the territory, protect the environment, evaluate the cultural heritage* (pp. 6–10). Rome: Italy.

Murayama, Y., & Thapa, R. B. (2011). Spatial analysis and modeling in geographical transformation process, the geojournal library 100. *Science + Business Media B.V.* http://dx.doi.org/10.1007/978.94-007-0671-2. _1@Springer.

Musaoglu, N., Tanik, A., & Kocabas, V. (2005). Identification of lan-cover changes through image. processing and associated impacts on water reservoir conditions. *Environmental Management, 35*(2), 220–230.

Omsongwang, S., & Saravisutra, A. (2011). Optimum predictive model for urban growth prediction. *Suranaree Journal.of Science.and Technology, 18*(2), 141–152.

Park, S., Jeon, S., & Choi, C. (2012). Mapping urban growth probability in South Korea: comparison of frequency ratio, analytic hierarchy process, and logistic regression models and use of the environmental conservation value assessment. *Landscape and Ecological Engineering, 8*, 17–31.

Pontius, R. G. (2000). Quantification error versus location error in the comparison of categorical maps. *Photogrammetric Engineering and Remote Sensing, 66*(8), 1011–1016.

Rasoolimasnesh, S. M., Badarulzaman, N., & Jaafar, M. (2011). Achievement to sustainable urban development using city development strategies: a comparison between cities alliance and the world bank definitions. *Journal of Sustainable Development, 4*(5).

Rui, Y. and Ban, Y.., (2011). Urban growth modeling with road network expansion and land use development, A. Ruas (ed.), Advances in cartography and GIScience. Volume 2: Selection from icc 2011, Paris, Lecture Notes in Geoinformation and Cartography 6, DOI 10.1007/978-3-642-19214-2_27, © Springer-Verlag Berlin Heidelberg.

Schneider, L., & Pontius, R. G. (2001). Modeling land use change in the ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems and Environment, 85*, 83–94.

Setioko, B., Pandelaki, E. E., & Murtini, T. W. (2012). Towards sustainable urban growth: the unaffected fisherman settlement setting (with case study Semarang coastal area), the 3rd International Conference on Sustainable Future for human Security SUSTAIN 2012. *Procedia Environmental Sciences, 17*, 401–407.

Uy, P. D., & Nakagoshi, N. (2007). Analyzing urban green space pattern and econetwork. *Landscape and Ecological Engineering, 3*, 143–157. http://dx.doi.org/10.1007/s11355-007-0030-3.

Verburg, P. H., Ritsema van Eck, J. R., de Nijs, T. C. M., Dijst, M. J., & Schot, P. (2004). Determinants of land-use change patterns in the Netherlands. *Environmental and Planning B: Planning and Design, 31*, 125–150.

Vliet, J. V., Roger, W., & Suzana, D. (2009). Modelling urban growth using a variabel grid cellular automaton. *Computers, Environment and Urban Systems, 33*, 35–43.

Wisyanto. (2009). Perencanaan Tata Ruang Pesisir Kota Agung Berbasis Analisis Resiko Bencana tsunami. *Jurnal Sains dan Teknologi Indonesia, 11*(1), 18–24. April 2009, Hal.

Xiaoqing, W., Hongshi, H., Fengming, X., & Rencang, B. (2010). Study of forecast scenarios for simulation of future urban growth in shenyang city based on SLEUTH model. *Geospatial Information Science, 13*(1), 32–39.

Yu, N., & Qingyun, D. (2011). Urban growth pattern modelling using logistic regression. *Geo-spatial Information Science, 14*(1), 62–67. http://dx.doi.org/10.1007/s11806-011-0427-x.

Yue, Z. (2008). Steering towards growth: symbolic urban preservation in Beijing, 1990–2005. *Town Planning Review, 79*(2–3).

Zhang, Q., Ban, Y., Liu, J., & Hu, Y. (2011). Simulation and analysis of urban growth scenarios for the greater shanghai area, China. *Computers Environment and Urban Systems, 35*, 126–139.

Zhang, Z., Su, S., Xiao, R., Jiang, D., & Wu, J. (2013). Identifying determinants of urban growth from a multi-scale perspective: a case study of the urban agglomeration around hangzhou bay, China. *Applied Geography, 45*, 193–202.

Zheng, H. W., Shen, G. Q., Wang, H., & Hong, J. (2015). Simulating land use change in urban renewal areas: a case study in Hong Kong. *Habitat International, 46*, 23–34.