

# CELLULAR AUTOMATA MODELING IN THE BUILT-UP AREAS WITHIN URBAN DEVELOPMENT AT PONTIANAK

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**Abstract:** *This research integrated the GIS-Cellular Automata model with the regression model to predict urban development in Pontianak within the built up area change phenomena approach. The research aimed to understand built-up land use development in Pontianak during 1990-2015 and to predict its regional development in 2033. The employed method were satellite the image interpretation approach, hybrid interpretation, and built up land development prediction using transition rules like driving factors and inhibiting factors of urban development. The driving ones are accessibility related to distances to CBD, to main roads, and to the existing built regional areas while the inhibiting ones are peatland and the protected areas. The result showed that the hybrid interpretation, between visual and digital interpretations from the landsat images, can be used to map the built up lands with 94.8% of sampling point's precision. The non-built up areas in Pontianak during 1990-2015 were 83.52 Ha/year, and the modelling result predicts that non-built regional areas in Pontianak during 2015-2033 will be 80.51 Ha/year heading toward northern and central areas of Pontianak.*

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## 1. INTRODUCTION

The dynamics of land use change always happens in urban and regional planning, so it needs good skills in predicting and making spatial simulations (Wu, 1998). Using GIS technology, cellular automata is one of the best methods available today in performing spatial simulations such as land use (Wu, 1998). CA modeling formulates the urbanization process employing scientific algorithms and raster-based tools that are effective for urban modeling and land use change (Wu, 1998). CA simulation methods are generally applied to assess changes and predict future land use (Aburas et al., 2016; Guan et al., 2011; Wu, 1998). The CA model is appropriate to model the urbanization process underlying the influence of environmental effects (Zhou et al., 2012). CA models are helpful in forming patterns and processes in rules and relationships among spatial elements (Silva et al., 2008). CA models are often used in the study of land use dynamics based on environmental interactions, such as urbanization, residential growth and new housing development (Pan et al., 2010; Fugsang et al., 2013; Guan & Rowe, 2017).

Spatial modeling with CA method aims to examine the relationship between obstacles and existing land conditions, transportation networks and urban growth (He et al., 2006). Moreover, the CA land use transition is used in urban modeling and development within the scope of time, space and particular conditions (Moghadam & Helbich, 2013). CA is a method often integrated in dynamic models because it has a spatial pattern on different temporal and spatial scales (García et al., 2012). Furthermore, CA-based GIS models are widely used to predict land use change and development, using a simple set of transition rules used to control changes in spatial patterns in future planning policy rules (García et al., 2012; González et al., 2015). The CA modeling aims to simulate urban spatial dynamics, urban growth and land use based on parameters related to the consequences of urban spatial change (Aljoufie et al., 2013; Deep, 2014; Guan et al., 2011; Kim et al., 2017; Maria et al., 2014; Votsis, 2017)

The CA-based GIS method is usually employed to present vertical urban growth with a bottom-up approach ( He et al., 2015; Lin et al., 2014). Some of the issues of urban growth cover the issues of urban development and the dynamics of social space (García et al., 2012; Aljoufie et al., 2013). In addition to the bottom-up approach, land use change can be collaborated with a set of driving factors with the integration of bottom-up and top-down approaches, like simulating complex relationships among land use changes, natural factors, and socio-economic factors (Lin et al., 2014; He et al., 2015; Xu et al., 2016). It also simulates land use changes with geophysical factors, socio-economic factors and risk factors as the development driving forces influencing changes in urban land use (Liao et al., 2016).

Changes in spatial and temporal resolutions in land use can be used to map local phenomena such as urban surface dynamics and urban thermal environments that are affected by historical urban growth patterns (Darlington et al., 2017). Hence, the CA model can be used as an urban system such as land use patterns, work sites concentration, population changes, economy, demographics, transportation and the environment (Mitsova et al., 2011). In addition the CA model is also used to test urban theories based on spatial interaction models within urban systems (Mitsova et al., 2011). Over the past 20 years, there are more researches using the CA approach to assess the impact of disaster risks due to urban growth (Hien, 2015; Berberoğlu et al, 2016).

The CA model can present neighboring cell space information, matrix area transition and suitability maps that are used to simulate future land use (Guan et al., 2011). The CA model is implemented to calculate spatial properties since it is closely related to geospatial elements and neighboring cells (Lin et al., 2014; Guan et al., 2011; Rocha & Ferreira, 2016). The modeling is used to understand the diversity of cities in determining development strategies and land-use policies (Wang et al., 2012; Pérez-Molina et al., 2017).

Within the framework of geographic concepts, spatial analysis focuses more on investigating patterns and various attributes and regional images, and it uses modeling to improve comprehension and prediction (Rustiadi, 2018). Spatial distribution centers have been discussed more in spatial location theories like Von Thunen's where various centers of activities have different effects on their land use patterns (Rustiadi, 2018). Therefore, location factors such as the distance of economic center, the distance of main roads and the distance of the existing lands potentially influence the development of non-constructed lands to be constructed ones due to the dynamics of the city in fulfilling the supply of urban system including development actors and government policies.

The variables used in this study refer to the spatial and ecological approach (Yunus, 2010). Spatial approaches are related to changes in non-built up and built up land covers over a period of time. On the other hand, the ecological approach is related to changes in protected lands, cultivated lands and peatlands having impacts on the environment particularly in Pontianak that has specific geological conditions (Yunus, 2010).

The Law Number 26/2007 has set up protected areas and cultivated areas that have national strategic values in forest resources utilization. Protected forest area is a forest area that has the main function as a regulator of life support system to regulate water system, prevent flood, control sea water intrusion and maintain soil fertility. Furthermore, the Government Regulation No. 71/2014 on peatland ecosystem protection and management policy stipulates that the water limit is 0.4 meters below the surface of peatlands. Peatlands are very important as water reservoirs throughout the year, and they prevent floods and droughts.

CA modeling uses a mathematical approach in which each cell is given various scores that can change over time according to transition rules (de Almeida & Gleriani, 2005; Fuglsang et al., 2013). These cells may represent several factors existing in urban areas and then model the interactions between these factors (González et al., 2015). The simulation is shown by spaces in the form of grids (rasters) in which the grid attributes calculate attributes of each cell around them (Silva et al., 2008; van Vliet et al., 2009). The cell attributes are basically the part of cell or space elements, limited cell sets, the cell environment, sets of simultaneous rules and time transition. (de Almeida & Gleriani, 2005; van Vliet et al., 2009; Dabbaghian et al., 2010).

From the above explanation, the purpose of this paper is to elaborate the CA transitional rules that were applied to determine the change of non-built land covers into built land used data in 2000-2007 as dependent variables. Meanwhile driving factors in built land change consisting of the distance to the economic centers, the distance to the main road, the distance to the existing built up lands and the peatlands are the independent variables.

## 2. DATA AND METHODS

### 2.1. Research sites

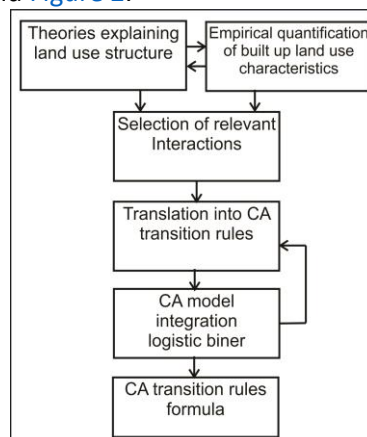
This research took place in Pontianak City. Pontianak city is the capital of West Kalimantan Province located at 002'24 "N - 0001'37" S and 109016'25 "W - 109023'04" W and cleaved by Kapuas river and Landak river. The geological conditions in Pontianak are grouped into the category of peneplant and alluvial sediments that are physically classified as clay type while this kind of land is peat that was mud sediment of Kapuas River.

The peat areas have thickness between 1-6 meters, so it causes decrease of soil bearing capacity when constructing large buildings and agricultural lands. Having these conditions, peat is very unstable and has low bearing capacity. The structure of peat is the layer that was mud sedimentation of Kapuas River. The clay layer can be reached at a depth of 2.4 meters above sea level. Pontianak has tropical climate with the highest temperature between 28-32° C. The data used in this study are:

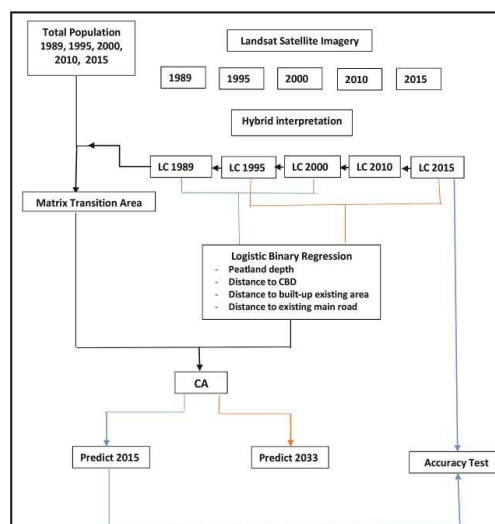
- Landsat 8 OLI Satellite Image in 2015
- Landsat 5 TM Satellite Image in 1995
- Digital Data of Rupa Bumi Indonesia map on the scale of 1: 25.000

### 2.2. Research methods

The flow of the research framework started from the theory of land use structures and empirical data of constructed lands. From both concepts and theories were found the relationship of variables with the existing conditions and the concepts of land use. These variables were used as transition rules in the binary logistic model CA assessment. Thus, the output was the equation of the CA transition rules that could be used as a reference for predicting the development of built up lands in certain years. More detail explanation can be seen in [Figure 1](#) and [Figure 2](#).



**Figure 1.** Procedures in defining transition rules (analysis, 2016)



**Figure 2.** The framework of the CA binary logistic binary model (analysis, 2016)

The interpretations of the map image used as a reference map of land developed were pre processing satellite images, hybrid interpretation, and predicted built-up land changes (Danoedoro, 2012). The pre processing satellite images is image conditioning that has provided accurate information both geometrically and radiometrically (Danoedoro, 2012). This process consists of geometry and radiometric correction. Geometry correction was performed by image rectification to the corrected image (Danoedoro, 2012). The process of correction was done by selecting the pair of coordinate points on the images and the corrected images (Danoedoro, 2012). On the other hand, the radiometric correction was conducted by converting the pixel values to the spectral radian values and the reflectant with equation (1) for Landsat 8 (USGS, 2015) and equations (2) and (3) for Landsat 5 (Chander & Markham, 2003).

$$\rho_{\lambda} = \frac{(MpQ_{cal} + Ap)}{\sin(\theta)} \dots\dots\dots(1)$$

In which:

- $\rho_{\lambda}$  = Top-of-Atmosphere Planetary Spectral Reflectance
- $Mp$  = Reflectance multiplicative scaling factor for the band).
- $Ap$  = Reflectance additive scaling factor for the band
- $Q_{cal}$  = The quantized calibrated pixel value in DN
- $\theta$  = Solar Elevation Angle

$$L_{\lambda} = ((LMAX_{\lambda} - LMIN_{\lambda}) / (Q_{cal}MAX - Q_{cal}MIN)) * (Q_{cal} - Q_{cal}MIN) + LMIN_{\lambda} \dots\dots\dots(2)$$

In which:

- $L_{\lambda}$  = Spectral Radiance at the sensor's aperture in watts/(meter squared \* ster \*  $\mu m$ )
- $LMIN_{\lambda}$  = the spectral radiance that is scaled to  $Q_{CAL}MIN$  in watts/(meter squared \* ster \*  $\mu m$ )
- $LMAX_{\lambda}$  = the spectral radiance that is scaled to  $Q_{CAL}MAX$  in watts/(meter squared \* ster \*  $\mu m$ )
- $Q_{CAL}MIN$  = the minimum quantized calibrated pixel value
- $Q_{CAL}MAX$  = the maximum quantized calibrated pixel value
- $Q_{cal}$  = The quantized calibrated pixel value in DN

$$\rho_p = \frac{\pi \cdot L_{\lambda} \cdot d^2}{ESUN_{\lambda} \cdot \cos\theta_s} \dots\dots\dots(3)$$

In which:

- $P_{\lambda}$  = Unitless planetary reflectance
- $L_{\lambda}$  = Spectral radiance at the sensor's aperture
- $d$  = Earth-Sun distance in astronomical units
- $ESUN$  = Mean solar exoatmospheric irradiances
- $\theta$  = Solar zenith angle in degrees

The hybrid interpretation is the extraction of built land information was performed by hybrid interpretation (Danoedoro, 2012). Hybrid interpretation is a combination of visual interpretation and digital interpretation (Danoedoro, 2012). There were several stages performed on the hybrid interpretation process in this study such as visual interpretation to delineate built land areas and digital interpretation

with classification supervised using the maximum likelihood method in the delineated area as the built land area (Danoedoro, 2012).

Next the results of the constructed land interpretation conducted by hybrids were tested for accuracy (Danoedoro, 2012). There were two statistical accuracy test methods, first, relying on the sample data taken as the reference source of the accuracy assessment and second, relying on data sources that were independent and were never used in sampling (Danoedoro, 2012).

The accuracy test in this research was done by referring to second accuracy test technique. The use of independent data was as the reference sources like orthophoto area data of Pontianak City. The test was done on the hybrid interpretation map. This accuracy test method was performed by using points representing each pixel of the hybrid interpretation results, and then they were displayed with the orthophoto data.

The predicted model of built up land changes is the built land prediction model in this study calculated both driving factors and inhibiting factors of the development of built up lands. Driving factors were the distance to the activity centers, accessibility, and distance to existing built up lands while the inhibiting factor was the peat depth. The parameters were analyzed using a binary logistic regression model that would produce probability values related to changes of non-built up lands to the built-up lands.

The integration of the CA-binary logistic regression model predicted the number of built up lands in 2033 using built land maps from hybrid interpretation results in 2015 and in 1995. In this study, the prediction results of land expansion results were limited based on the need for built up lands. Built up lands were classified into the population number in the area of study and the non-built up land covers except rivers and protected areas like urban forests, municipal parks, and protected areas in peatlands.

### **3. RESULTS AND DISCUSSION**

#### **3.1. Development of Built Land at Pontianak City in 1990-2015**

The results showed that hybrid interpretation between visual interpretation and digital interpretation of Landsat satellite images can be used for built up land mapping with accuracy of 94.8%. The built up lands at Pontianak City in 2015 were 4,250.36 Ha in width while the built up lands in 1990 were 2,162.35 in width. Within 25 years, the built up lands in Pontianak will have doubled. The development of built up lands in Pontianak from 1990-2015 was 83.52 Ha / year. More details can be seen in [Figure 3](#).

Based on the analysis using spatial interpolation polynomial order 3 to the location of built land expansion 1990-2015 at Pontianak City showed the development center of built up lands was in the middle and the south of the city, precisely in Pontianak Kota and Pontianak Selatan subdistricts. Based on the data and field observation, these areas before were forests and mixed plantations before converted into built up lands.

The northern parts of Pontianak Selatan and Pontianak Kota subdistricts are strategic areas for economic sectors. These areas cover the trade area on Tanjung Pura and Jalan Gajah Mada road. In addition, there is also Port Seng Hie, a strategic area for distribution of goods, services and for people movement through the cross-city/district river transportation. On the other hand, in the middle part between the two districts are offices and government areas. Pontianak Selatan is located around Ahmad Yani and Sutoyo street while in Kota Pontianak Subdistrict on Jalan Rahadi Usman, Jalan Alianyang and Jalan Sutan Syahrir.

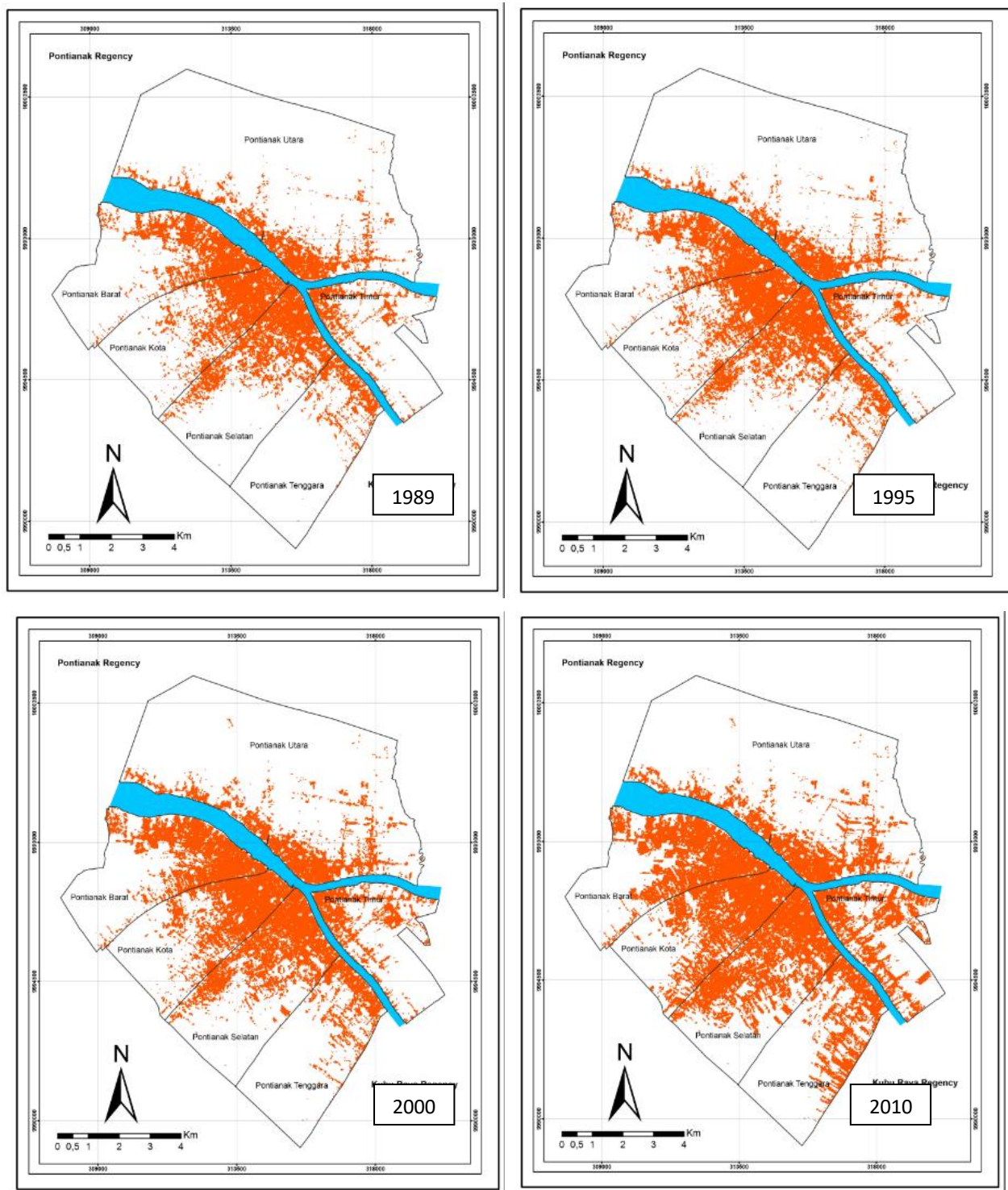


Figure 3. The Map of Land Use Development in Pontianak (analysis, 2016)

### 3.2. The Prediction of Land Use Development at Pontianak

Before performing the process of automaton in the prediction of built up land at Pontianak city, binary logistic regression analysis was firstly conducted to know the driving factors of built up lands development in Pontianak. Analyzes on equations (4) and (5) were performed to predict the width of built up areas based on the population growth. More details can be seen in Table 1.

**Table 1.** The Population growth and built up land development in Pontianak (analysis, 2016)

No.	Year	Population	Built up lands (Ha)
1.	1990	396,658	2,162.35
2.	1995	447,632	2,267.36
3.	2000	464,532	2,593.31
4.	2010	554,764	3,536.33
5.	2015	590,606	4,250.36

Binary logistic regression analysis was used to find out the changes from non-built up land covers to built up lands in 2000-2007 as dependent variable while the driving factors of the change of built up lands consisted of the distance to the economic centers, the distance to the main roads, the distance of existing built up lands and the depth of the peatland as an independent variables. The binary logistic regression analysis equation is described by equation (4) below.

$$Y = 0.1443 - (0.000637 * X1) - (0.000652 * X2) - (0.067940 * X3) - (0.120945 * X4) \dots\dots\dots(4)$$

- Y: Logit changes from non-built up lands to built up lands
- X1: The distance to the main roads
- X2: The distance to the economic centers
- X3: The distance to existing built up lands
- X4: The depth of the peatland

Equation (4) showed that the biggest regression coefficient was found in the peatland variable (-0.12). It indicated that the peatland depth variables had the most significant effect on the conversion of non-built up lands into built up lands in 1990-2015. The aforementioned equation has a negative coefficient value. It means that the peatland has a low depth. On the other hand, the non peatland is likely to change from non-built up lands to built up lands.

Some driving factors of built up lands will change over time. The number of main roads in 2007 was different from the number of main roads in 2015, because in 2015 there was an addition and construction. Binary logistic regression analysis aims to predict the built up lands in 2033. Variables used are still the same as the ones used before, and the difference is only at the current time 2015.

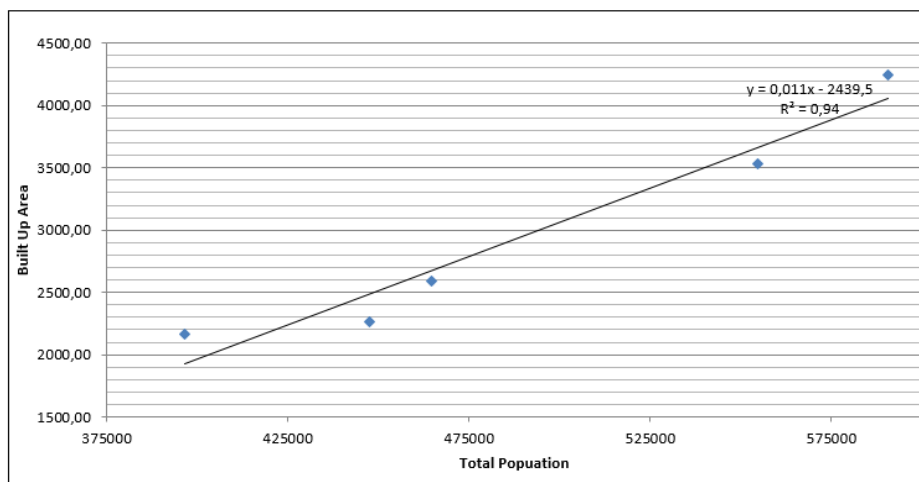
Binary logistic regression analysis between the changes of non-built up land cover to built-up lands in 1995-2015 was used as the dependent variable. The driving factors of the land conversion included the distance to the economic centers, the distance to the main roads, the distance to existing built up lands and the depth of the peatland as independent variables. The binary logistic regression analysis equation is described by the following equation (5).

$$Y = 1.0233 - (0.000121 * X1) - (0.000060 * X2) + (0.029974 * X3) - (0.068942 * X4) \dots\dots\dots(5)$$

- Y: Logit changes from non-built up lands to built up lands
- X1: The distance to the activity centers
- X2: The distance to the main roads
- X3: The depth of the peatland
- X4: The distance to existing built up lands

Equation (5) showed that the biggest regression coefficient was in the distance of existing built up land variable (-0.000060). This indicated that the smaller the distance variables (the closer a site to the existing built up lands), the bigger the possibility of non-built up land covers to be built up lands. This research used CA Markov method to predict built up lands width in 2033. To limit the number of pixels that changed during the automaton process, a transition area matrix was made. The transition area matrix was based on a simple equation between the population increase and the expansion of built up lands. Changes in the size of built up lands were obtained from the process of hybrid interpretation while the population numbers

were obtained from the Central Bureau of Statistics in Pontianak (Table 1). More details can be seen in Figure 4.



**Figure 4.** The linear graph of land use development and the population numbers in Pontianak (analysis, 2016)

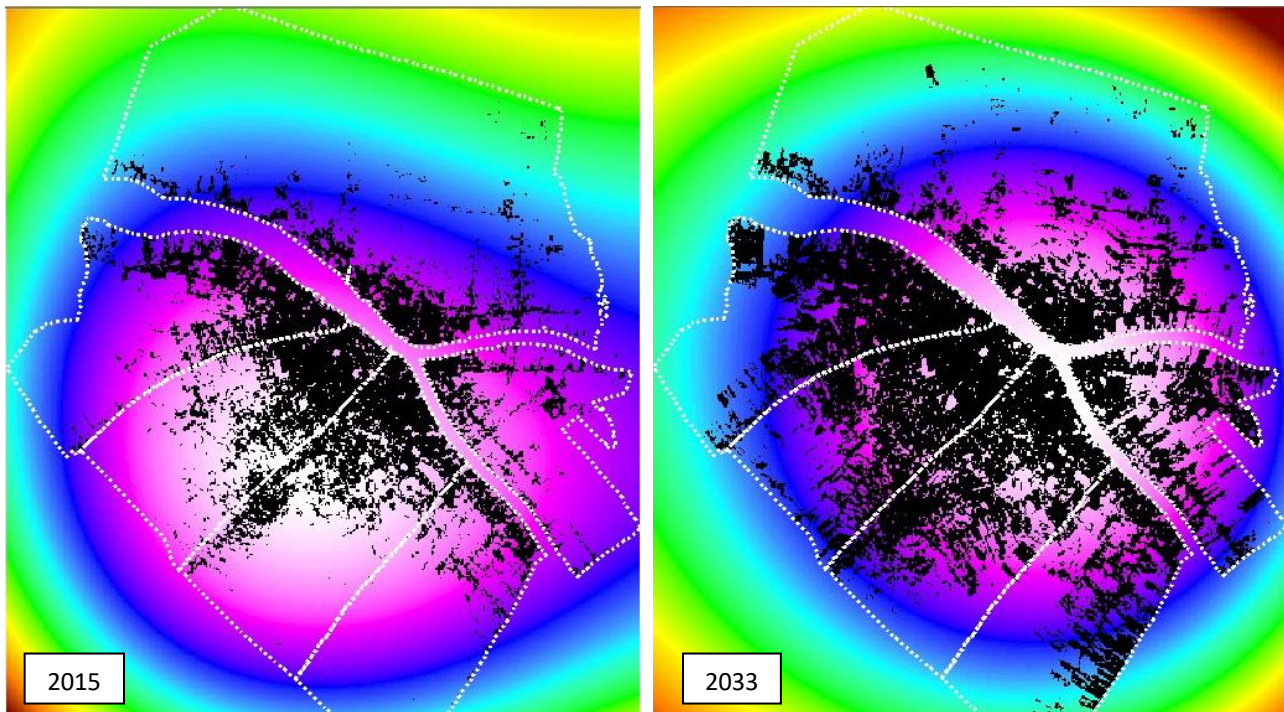
The population of Pontianak City in 2033 was predicted as much as 739.913 inhabitants. Figure 4 shows that the equation  $y = 0.011x - 2,439.5$ . The prediction of the size of built up lands in 2033 is 5,699.54 Ha. Therefore, it can be seen that the development of built up lands in Pontianak 2015-2033 slightly declined from the previous period of 80.51 Ha / year.

Prior to the modeling of built up lands in Pontianak in 2033, the model of built up land conditions in Pontianak in 2015 was firstly made referring to the pattern of built up land use development in 2000 and 2007. The results then could be used to test the accuracy. In predicting process of built lands at Pontianak in 2015, the number of pixels were limited based on the equation  $y = 0.011x - 2,439.5$  which was 45,089 pixels or 4,058 Ha. The results of the accuracy test showed that cellular automata integration and binary logistic regression in the prediction of land change in Pontianak produced overall accuracy as much as 79.70%, and the highest kappa index was 0.65.

The prediction result showed that the built up land in Pontianak in 2033 was 5,699.54 Ha. The result of spatial interpolation of polynomial order 3 to the location of land up expansion was built in 2015-2033 in Pontianak City indicates that the center of built up land development will be in Pontianak Selatan and Pontianak City in the north; since these area are strategic economic center areas, such as the trade area on Jalan Tanjung Pura road, Jalan Gajah Mada and Port Seng Hie.

Pontianak Timur and the southern of Pontianak Utara are the center of the built up land use development because Pontianak Timur develops as the economic zone, the service area and the tourist destination (Keraton Kadariah and Jami Mousque). On the other hand, Pontianak Utara with its inter cities/regencies roads develops as the economic zone, the industrial area (factories), the tourist destination (The Equator Monument and Batu Layang Cemetery), and regencies.





**Figure 5.** Land use development trend map at Pontianak (analysis, 2016)

Land use development trend at Pontianak can be described into two periods in 1995-2015 and 2015-2033. The trend of the development in 1995-2015 was toward the Pontianak Kota and Pontianak Subdistricts. Both areas are the government and trade centers, and there are also public facilities such as hospitals, schools, campuses, trade and service areas and offices. Since the built up land was already densely populated, the trend of the built up land development center in 1995-2015 was in white color gradations to brown color. Where white is the center of the development. That the development centers from 1989 to 2015 were in Pontianak Kota and Pontianak Selatan subdistricts was because these areas were the government and trade centers, the government center is at Jalan Sultan Abdurahman (the new city area), and the economic center is at Jalan Tanjungpura and Jalan Gajah Mada. More details can be seen in [Figure 5](#).

The trend of development in 2015-2033 was towards Pontianak Selatan, some part of Pontianak Kota, Pontianak Timur and Pontianak Utara. Both regions develop in economic, trading, industrial and service sectors. In Pontianak Timur 2 markets were built including Pasar Belimbing and Pasar Anggrek while in Pontianak Utara Subdistrict; there is an agribusiness terminal (Budi Utomo road). There is a plan to develop new formal market in this area like the one in Pontianak Timur Subdistrict facilitated by the municipality because of the density of street vendors and unorganized activities in this area. In addition, that there is a traffic growth towards Tayan (Trans Kalimantan) dividing the Kapuas River will eventually cause the development trend to head toward Pontianak Timur area. More details can be seen in [Figure 5](#).

Some CA modeling studies aim to simulate urban growth in the Changjiang Delta region based on scenarios to quantify city growth predictions ([Guan & Rowe, 2016](#)). CA modeling is used to prove the hypothesis that the CA-Markov model can serve as an alternative tool for regional assessment and simulation of land use management ([Zhou et al., 2012](#)). CA modeling is used to develop an integrated planning strategy in the metropolitan areas through application of SLEUTH and CVCA ([Silva et al., 2008](#)). CA modeling of SLEUTH and CVCA methods aims to derive values and compare the resulting of urban growth ([Silva et al., 2008](#)). CA modeling is used to simulate land-use change, urban growth patterns and future policy development ([Aburas et al., 2016](#)).

In the other studies, CA modeling was used to determine the impact of variations in the scale of land use change, so that small cell and environmental-size combinations can resulted in improper land use transitions ([Pan et al., 2010](#)). CA modeling is used to explore the impact of coastal flood risk management strategies on urbanization parameters and property prices, zoning planning and adaptation strategies ([Votsis, 2017](#)) CA modeling is used to measure the urban growth through analysis of land use change and to predict the sustainable urban scenarios ([Deep, 2014](#)). CA modeling is used to identify and to evaluate the

drivers and inhibiting factors of land-use change that are integrated with economic, political, environmental, biophysical, institutional and cultural factors (Basse et al., 2014).

In relation to environmental ecosystems, CA modeling research is used to predict LUCC and ecosystem changes using SWAT methods that aim to support South Korea's water catchment laws (Kim et al., 2017) and to project city growth through prediction changes in land use and green areas, thus its contributing to the city green infrastructure planning (Mitsova et al., 2011). Whereas in relation to building structures, CA modeling is used to visualize the application of strategies and to visualize the building structures using the LUCIA model, thus indicating that the suitability between homogeneous building structures with the speed of work and energy (Fuglsang et al., 2013).

In relation to the urban development approach, CA modeling was used to track the past developments and to predict the future expansion plans, the results show a new urban expansion scenario model in a bottom-up and top-down approaches based on CA modeling (He et al., 2006). CA modeling is used to develop GIS-CA models in exploring vertical growth in urban areas, the results show the compact development trends in high-rise buildings, phase transitions from mono centers to bi-centers, building growth balance of low, medium and high (Lin et al., 2014). In relation to climate change, CA modeling is used to determine the impact of urban growth on microclimate, to predict land use distribution and to analyze soil surface temperatures, so that the thermal temperature and comfort temperature can be used as the influence factors in urban growth (Darlington et al., 2017).

The authors found a weakness in obtaining the data used in this study. In predicting the development of built up land in Pontianak, the weakness is the limited map image data used in CA modeling. However, these weaknesses are corrected through steps in the accuracy process such as interpretation of landsat image maps (Danoedoro, 2012) and comparison of population growth. The result of accuracy in predicting the land use development in this research is 94.8%. This results have good accuracy to prove that the method used in this study is feasible to predict the development of built up land. Particularly the parameter of peatland depth can be used as an alternative in inhibiting factor of urban growth and urban development.

#### 4. CONCLUSION

GIS-CA modeling research with binary logistic regression algorithm approach has novelty in preparing predictions of urban development emphasizing built up land use aspects. This CA modeling is able to give contribution in determining the direction of urban planning and development policies. There are driving factors and inhibiting factors as parameters used as transitional rules such as the land use map, the distance to economic centers, the distance to main roads, the existing built up lands and the peat depth.

Variables like transportation network, land conditions, and existing built up lands have proven able to influence the development of land use in Pontianak. These variables can be used as a reference in planning the direction of urban development and growth in Pontianak. Variables like peat depth and the distance to existing built up lands have greater influence than variables like the distance to economic centers and the distance to main road toward the change and development of land use in Pontianak.

The result of this research is the hybrid interpretation in mapping of built up land use that has accuracy 94.8%. The built up land areas at Pontianak City in 2015 was 4,250.36 Ha while in 1990, it was 2,162.35 Ha. Within 25 years, the area of built up land in Pontianak has doubled while the development of built up lands in Pontianak in 1990-2015 was 83.52 Ha / year.

The prediction result of binary logistic CA model showed that built up land expansion in 2015 - 2033 was took place in the central area of built up land development, such as in Pontianak Selatan, Pontianak Kota, Pontianak Timur and Pontianak Utara. The trend of built up land use development in 1995-2015 headed toward Pontianak Kota and Pontianak Selatan. Meanwhile the development trend of built up land use in 2015-2033 headed toward the areas of Pontianak Selatan, part of Pontianak Kota, Pontianak Timur and Pontianak Utara.

Both periods of the development trends in built up land use above indicate that these developments took place in centers of activities that have been very surfeited and crowded, and such condition is due to the development of urban centers from various sectors especially the built up lands for housing construction, economic centers, trade and service centers, and education centers. The prediction of built up land use development will take place in the suburbs of city/subdistrict close to the Trans Kalimantan

roads, and it will bring a positive impact on the urban development in the province of West Kalimantan generally.

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