PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 20 ISSUE 1 (2022), Page 77 – 88

CELLULAR AUTOMATA FOR CIREBON CITY LAND COVER AND DEVELOPMENT PREDICTION

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Abstract

Land changes in urban areas are a common thing. Along with the increase in economic activity, the population also increased and resulted in changes in land use. This results in uncomfortable, unsafe and inefficient urban conditions. This problem can be anticipated by predicting changes in land cover, from the result of prediction of landcover, the direction of urban growth will be known. The purpose of this research is to analyse and modelling land use changes and to predict the urban growth. One methodology for modelling land cover is to use the Cellular Automata model. Using land cover data from Landsat Satellite Imagery in 1999 and 2009, it can predict that land cover in 2019 until 2031, after calculating the validity value using a kappa accuracy test of 0.79. Results of the model are that development of the city of Cirebon leads to the southern part of the District of Harjamukti. It happens because, in the area of Harjamukti District, there is a lot of lands that can convert into developed land.

Keywords: cellular automata, Cirebon, city development, landcover, prediction

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INTRODUCTION

The development of urban areas is a natural thing with many factors influence it which one of the factors driving regional development in developing countries is urbanization. With urbanization, urban areas will increase in number and size which will result in land changes in the area (Mosammam et al., 2017). Land change is the partial conversion of land use by humans, from one land function to another (Schielein et al., 2021). Changes in land use in urban areas that occur will form a pattern and direction of urban development (Samat et al., 2019). These changes can also be seen from the increase in socio-economic activities and the movement of urban population mobility flows which ultimately demand the need for space for settlements, because in an urban environment, residential housing occupies the largest percentage of land use compared to other uses, so that settlements are the main component in the formation of settlements city structure (Xu et al., 2021).

RESEARCH BACKGROUND

Cirebon City is determined as the study location because Cirebon City is an attraction for residents outside Cirebon City to enter Cirebon City, especially after the connection of Cirebon city to the Cikampek - Palimanan (Cipali) Toll Road, economic activity in Cirebon City has increased along with the increase number of visits (Ortega et al., 2021). As a result, the number of residents and population density increases, while the availability of land in urban areas does not experience expansion, which implies that land changes are increasing, especially the addition of built-up land, this makes the city less livable, less safe, inefficient and this has become a classic urban problem everywhere (Cao et al., 2021).

There are many methods that can be used to conduct land change studies, one of which is the Cellular Automata (CA) model. The CA model can describe a complex city situation with a fairly simple rule (Fardani, 2020). Another study uses the Multi Criteria Evaluation (MCE) method, this method makes a transition suitability map with MCE which produces good enough results to predict land cover changes (Pérez-Hoyos et al., 2020). Changes in land cover can be investigated using the Hybrid Urban Expesion model, namely by combining Remote Sensing data and Geographic Information Systems (GIS) which simulate the process of urban change that provides information about environmental influences on future urbanization (Wu et al., 2010).

One of the land cover modeling application is to see urban development which is very important for sustainable urban planning (Bose & Chowdhury, 2020). The factor that influences the pattern of urban development is the urbanization process, using the Geographically Weighted Regression (GWR) technique which has been proven to be effective in showing the relationship between non-stationary spatial data from the influence of urbanization and the condition of urban patterns (Huilei et al., 2017). There are studies that argue that urbanization in poor areas of the country does not lead to urban growth (Koroso et al., 2021). The condition of the area of Cirebon City which is currently developing, becomes very interesting to study whether population development affects the development of the city. Many previous studies have examined urban development using urbanization as a driving factor, but for the existing population density factor compared to the existing residential area (net population density) have not done yet.

Changes in land in the city of Cirebon are always increasing (Nirwansyah & Braun, 2021), then the population factor continues to increase and there are no studies to predict land cover combined with population density factors in the city of Cirebon. The purpose of this research is to analyze and model land change and to see the direction of the development of the city of Cirebon by considering the net population density factor. With this land change study, the local government can anticipate which locations will change drastically and arrange it so that the location does not become slum making this research very useful for the Cirebon City government.

RESEARCH METHOD

Satellite Image Data

In the study using image data for 1999 (Landsat TM 5), 2009 (Landsat TM 5) and 2019 (Landsat 8) which is shown in Figure 1. This satellite image data will later be used to create a land cover map in Cirebon City.

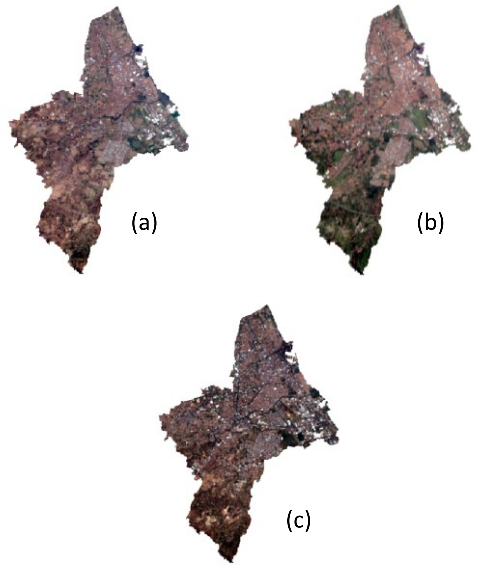

Figure 1: Landsat Satellite Image Data (a) 1999 (b) 2009 (c) 2019

Demographic Data

One of the factors that drive the change of a region is the population factor, especially in the case of land conversion (Zainudin et al., 2021). With the increase in population, the need for land will increase, which causes changes in the function of a land. The data used in this study is population density data as can be seen in Table 1.

Table 1: Cirebon City Population Density in 2018

No.	District	Population	Area (Ha)		Density (Person/Ha)	
			Total	**Built-up**	**Bruto**	**Netto**
1	Harjamukti	109.005	1773.83	306.60	61	356
2	Lemahwungkuk	56.353	637.58	206.16	88	273
3	Pekalipan	30.880	158.68	95.00	195	325
4	Kesambi	74.894	851.79	276.52	88	271
5	Kejaksan	45.145	424.03	140.12	106	322
Total		**316.277**	**3845.91**	1024.40	364	1254

Seen in Table 1, the highest net density is in Harjamukti District with a population density of 356 people/ha, while the lowest net population density is in Kesambi District, which is 271 people/ha.

Cellular Automata

The concept of Cellular Automata (CA) was first developed by Johann Louis Von Neuman in the late 1940s and early 1950s. The idea was the development of information from stem cells to other cells in a cellular automaton, which was thought to be able to explain the structure of space-time. and the limitations of the speed of light (Beuchat & Haenni, 2000). CA is a form of model that is very dynamic and combines the dimensions of space and time (Cavalcante et al., 2021). In this model, space is the land cover of an urban area, then time is in the form of time series data from the land cover of an urban area. In the CA concept, predictions for the future of data from a cell depend on the surrounding cells or what is known as Cell Neighborhood. Neighborhood Cells are used in modeling "Von Neumann Neighborhoods", i.e. a cell has 4 cells that are directly neighbors, namely to the north (N) of the cell, to the east (E) of the cell, to the south (S) of the cell and to the west. (W) the cell. An example of a Von Neumann neighboring cell can be seen in Figure 2 below. The surrounding cells, which will affect changes in the cells in the middle (C).

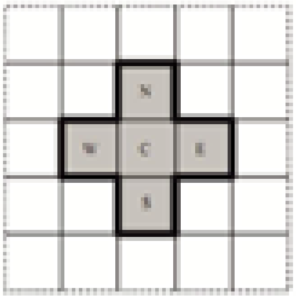

Figure 2. Illustration of the definition of neighboring CA on the Bon Neumann concept.

RESULT AND DISCUSSION

Land Cover

From the existing Landsat satellite imagery data, land cover classification was carried out using the Supervised classification method. Supervised Classification is a method for classifying satellite images with the help of samples from the Digital Number (DN) for each land cover class. Supervised classification is very easy to use and produces reliable classification results. The results of land cover classification can be converted into different land cover areas each year as can be seen in Table 2.

From the results of the classification of satellite images, there are 5 land covers, namely: Mangrove Forest, Built Land, Vacant Land, Waters and Mixed Gardens. In 1999 it was seen that the dominant land cover was Mixed Gardens, while in 2009 and 2019, the dominant land cover was Built-up Land. This data shows that there is a rapid development in the city of Cirebon which is marked by an increase in the percentage of its land cover almost reaching 30% in the period 1999 to 2009.

Table 2: Land Cover Area in 1999 and 2009

No	Land Cover Types	Area		Percentage	
		1999	**2009**	**1999**	**2009**
1	Mangrove Forest	34.92	9.32	0.89	0.24
2	Built-up Area	1163.63	1994.63	29.63	50.78
3	Empty Land	397.95	388.83	10.13	9.90
4	Water	99.54	247.49	2.53	6.30
5	Field	2231.71	1287.49	56.82	32.78
	Total	3927.76	3927.76	100.00	100.00

Land Cover Prediction Results (2019)

The first step in doing CA modeling is to make a land cover model whose condition is known by using 2 datasets of land cover data in the previous period. In this model, 1999 and 2009 land cover are used to predict 2019 land cover. The results of the 2019 land cover prediction will be compared with the existing 2019 land cover. The map in Figure 6 is a comparison between the 2019 (existing) land cover map and the 2019 land cover prediction map, it can be seen that the land cover classes are not much different when viewed for the distribution in the city of Cirebon, meanwhile for the difference in area between land cover the existing 2019 land cover with the predicted 2019 land cover can be seen in Table 3.

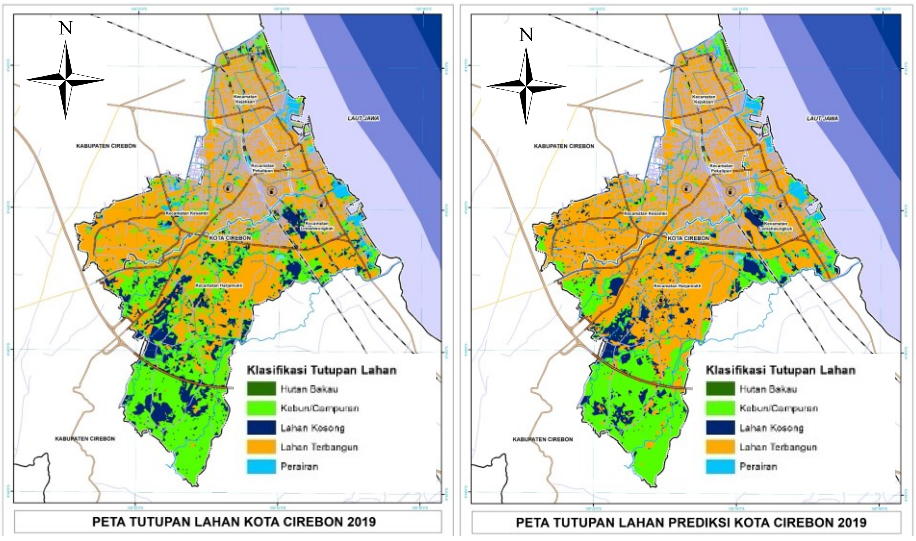

Figure 3: Land Cover Map 2019 and Predicted Land Cover Map

Table 3: Comparison of Existing Land Cover Area and Prediction Results for 2019

No	Land Cover Type	Land Cover Area 2019 (Ha)		Land Cover Perc. 2019 (%)	
		Existing	Prediction	Existing	Prediction
1	Mangrove Forest	11.26	9.22	0.29	0.23
2	Built-up Area	2224.37	2564.17	56.63	65.28
3	Empty Land	443.43	296.44	11.29	7.55
4	Water	131.01	232.33	3.34	5.91
5	Field	1117.69	825.61	28.46	21.02
Total		**3927.76**	**3927.76**	**100.00**	**100.00**

Accuracy Test
In a modeling, accuracy test is mandatory. The accuracy test shows the difference between the actual condition and the expected condition (the result of the model). In this model, an accuracy test using the Kappa method is applied.

Classification agreement/disagreement
According to ability to specify accurately quantity and allocation

	Information of Quantity		
Information of Allocation	No[n]	Medium[m]	Perfect[p]
Perfect[P(x)]	P(n) = 0.5183	P(m) = 0.9500	P(p) = 1.0000
PerfectStratum[K(x)]	K(n) = 0.5183	K(m) = 0.9500	K(p) = 1.0000
MediumGrid[M(x)]	M(n) = 0.4420	M(m) = 0.8747	M(p) = 0.8714
MediumStratum[H(x)]	H(n) = 0.1667	H(m) = 0.4146	H(p) = 0.4109
No[N(x)]	N(n) = 0.1667	N(m) = 0.4146	N(p) = 0.4109

```
  AgreementChance = 0.1667
AgreementQuantity = 0.2480
  AgreementStrata = 0.0000
AgreementGridcell = 0.4601
 DisagreeGridcell = 0.0753
   DisagreeStrata = 0.0000
 DisagreeQuantity = 0.0500

              Kno = 0.8497
        Klocation = 0.8593
  KlocationStrata = 0.8593
        Kstandard = 0.7860
//Ending of run:              1
```

Figure 4: Kappa Test Results Classification of Land Cover Prediction 2019

The accuracy test results show an accuracy value of 0.7860 which is shown in Figure 4. The accuracy value shows that the 2019 land cover predicted using the CA model with the existing 2019 land cover corresponds in terms of area and spatial distribution. This shows that the validation of the CA prediction data according to the kappa index has a kappa accuracy value included in the good category so it can be concluded that the 2031 land cover prediction results can be said to be good and acceptable.

Land Cover and City Development Prediction Result
In this model, land cover predictions are carried out until 2031. Based on the model results, it can be seen that in each class there is an increasing and decreasing trend in area which can be seen in Figure 8. For vacant land there is an upward trend in 2009-2019 but between 2019 and 2031 there is a downward trend in area, this can be seen in the land cover map that in 2009 to 2019 there has been a conversion from garden/mixture to vacant land resulting in an increase

in land area. empty, while in 2019 to 2031 there was a fairly large conversion from empty land to build up land.

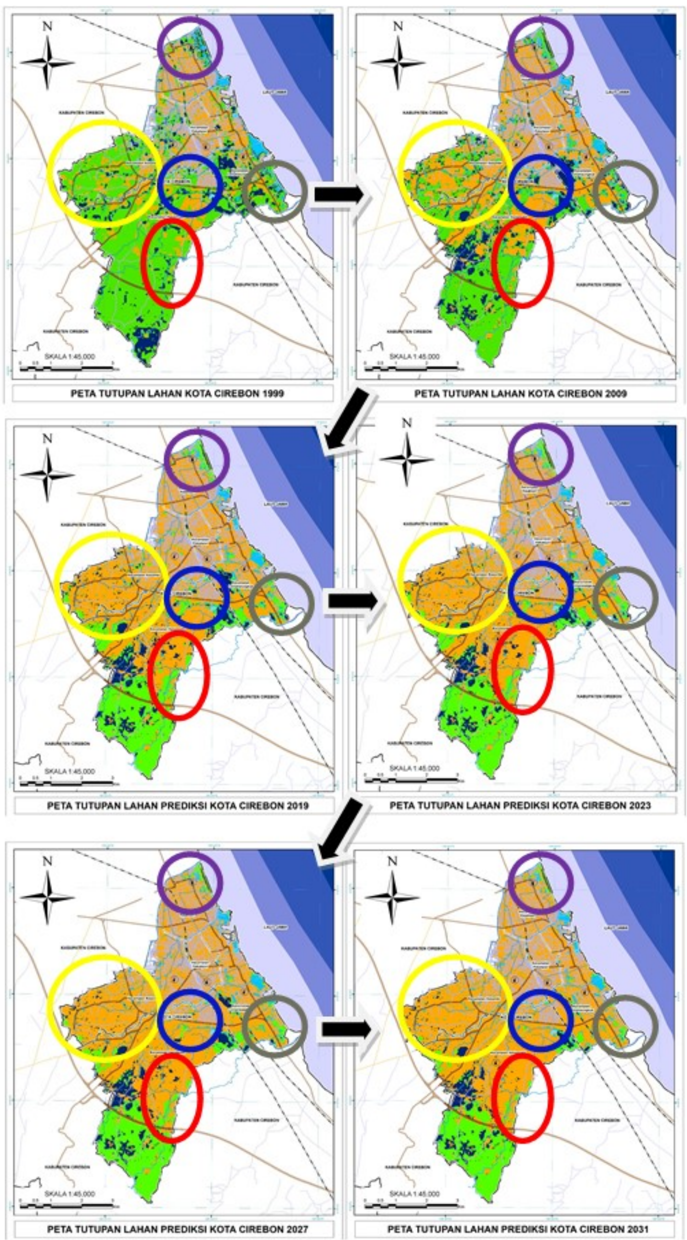

Figure 5. Locations of Land Cover Changes in Cirebon City

Figure 5 shows the development of the existing land cover of Cirebon City from 1999 to 2009 and the prediction of land cover from 2019 to 2031. Seen in the purple circle, namely in the northern area of Cirebon City, namely the District Attorney's Office, the mangrove forest land cover appears to decrease from 1999 to 2031. For the western part, namely Kesambi District, which is indicated by a yellow circle, there is a conversion from mixed plantation land to residential land cover classes, this is possible seen from the driving factor, namely the number of road networks in the area and the slope factor which is quite gentle which allows mixed gardens. converted into built-up land. For the southern area, namely Harjamukti District, which is indicated by the red circle, there was a fairly massive land cover change from mixed garden land cover to built-up land, but the spread to the south stopped in 2023, because the area further south than Harjamukti District has a height and the slope is quite high, which causes the built-up land to not continue to expand to the south. For the eastern area, namely Lemahwungkuk District, the expansion of built-up land is not too much, because the land in the sub-district is already the majority of built-up land. Just like the area east of the city of Cirebon, the area in the middle of Cirebon is not much converted, there are only a few mixed gardens that are converted into residential land. For the northern region, there is not much land conversion, but there is one important thing to note, that it is indicated that there will be conversion of mangrove forests into built-up land.

From the model results, it is shown that the development of Cirebon City leads to two parts, namely the western and southern parts. If it is associated with population density, the southern area of Cirebon city, namely Harjamukti District, has the highest net population density and has the largest area in the city of Cirebon, this means it is very suitable for the direction of urban development in the future and in line with Previous research has shown that population has a close relationship with urban development (Elsawahli et al., 2016). When viewed from the side of the topography and slope, which is one of the factors controlling urban development, the southern region is limited because it has a fairly high slope and steep topography, making it unsuitable to be developed for residential areas. In the western area, which can be an alternative for urban development, this is considering that the area is close to toll access which will facilitate settlements or industries in and out of the city of Cirebon.

CONCLUSION

From the results of the study, it can be seen that the CA model can describe the prediction of the development of the city of Cirebon in the future. By adding the net population density factor, a better model is produced, which can be seen from the fairly high kappa accuracy test value. The development of the area that Cirebon City will mostly lead to the south is the Harjamukti sub-district. The driving factors of this model are elevation, slope, distance from the road, distance from urban areas and population density.

From the model results, it can be seen that the built-up land class has a positive trend, namely its area increases every year, while the mixed garden class has a negative trend, which is it decreases every year. This can be used as input for the Cirebon City government to oversee the development of Cirebon City. The Cirebon City Government can anticipate the development of the city to the south and west, namely by optimal settlement planning and supporting facilities in the two areas.

By doing land cover modeling, it will be easier to do spatial planning. Spatial planning in regional planning is generally carried out by considering physical, economic, social and cultural analysis. With the results of land cover predictions, and knowing the direction of urban development, it can be used by planners as an additional analytical tool for regional planning. With this, spatial planners will be able to better have a basis in determining the direction of inner urban development, namely in determining spatial patterns and spatial structures

ACKNOWLEDGEMENT

We would like to thank the Indonesian Ministry of Education, Culture, Research and Technology, the National Unity and Political Agency of West Java Province, the UNISBA Research and Community Service Institute for the cooperation and research funding for the Matching fund program wave VIII in 2021.

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Received: 3rd January 2022. Accepted: 12th April 2022

