



## Modeling of Cellular Automata Markov Chain for predicting the carrying capacity of Ambon City

Melianus Salakory<sup>a</sup>, Heinrich Rakuasa<sup>ab</sup>

<sup>a</sup> Education Study Program, Faculty of Teacher Training and Education, Universitas Pattimura, 97233, Indonesia [+62 81342847435]

<sup>b</sup> Department of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, 10430, Indonesia

---

### Article Info:

Received: 02 - 09 - 2021

Accepted: 22 - 04 - 2022

### Keywords:

Ambon city, carrying capacity, cellular automata markov chains, land cover

### Corresponding Author:

Heinrich Rakuasaa  
Department of Geography,  
Faculty of Mathematics and  
Natural Sciences, Universitas  
Indonesia;  
Tel. +6281342847435  
Email:  
heinrich.rakuasa@ui.ac.id

**Abstract.** *Ambon City is a city with the highest economic and population growth in Maluku Province, which makes the land built to have high and rapid growth while the availability of suitable land is relatively fixed. As a result, there will be inconsistencies in the inequality between land needs and available land. This study aims to spatially analyze changes in Ambon City land cover in 2010, 2015, and 2020 to predict Ambon city land cover in 2031 and analyze the carrying capacity of residential land in Ambon City by 2031 using Cellular Automata Markov Chains (CAMC). Based on the prediction of land cover in 2031, residential land has increased to 7 299.17 ha, with the population of Ambon City in 2031, which is predicted to amount to 2 445 961 people. The calculation of the carrying capacity of residential land in 2031 Ambon City gets the result of the value of the settlement land carrying capacity index of 1.87 m<sup>2</sup>/capita, meaning that if  $DDPm > 1$  indicates the carrying capacity of high residential land and is still able to accommodate residents to settle and build houses in the area. This research is an appropriate, preventive, and innovative solution to facilitating the government in spatial planning in Ambon City in the future.*

### How to cite (CSE Style 8<sup>th</sup> Edition):

Salakory M, Rakuasa H. 2019. Modeling of Cellular Automata Markov Chain for predicting the carrying capacity of Ambon City. *JPSL* 12(2): 372-387. <http://dx.doi.org/10.29244/jpsl.12.2.372-387>.

---

## INTRODUCTION

Ambon City is a coastal city located on the island of Ambon bordering Central Maluku Regency. As the capital of Maluku Province, Ambon City is the main destination for population urbanization in Maluku Province (BPS, 2020). The centralization of the population in Ambon City encourages the compaction of the population, which results in the need for residential land/built land continues to increase from year to year. Based on data from the Central Statistics Agency (BPS) of Ambon City in 2020, of the eleven regencies/cities in Maluku Province, Ambon City is the most populous, which is 25.50% of the total 1.74 million residents Maluku Province (BPS, 2020). The increase in population is in line with the increase in human activities in various sectors, especially the social and economic sectors, resulting in the need for land resources also increasing while relatively fixed land availability (He *et al.*, 2018).

This will lead to increased competition in land use so that economic and social needs will always be a priority in land use change, changes in settlement land cover in urban areas that occur will shape the direction of development of residential areas in the future (Pratami *et al.*, 2019). Therefore, the utilization and efficiency of urban land cover should be improved based on rational land cover planning with the aim of sustainable development (Tian *et al.*, 2016) because one of the keys to sustainable development in urban areas is good

planning and spatial planning (Widodo *et al.*, 2015). This condition is a regional problem due to the increasing demands of land needs and land limitations that need to be studied to be able to provide solutions in the arrangement of land use in Ambon City in the future based on ecological aspects (Liu, 2020). In analyzing the carrying capacity of residential land in Ambon City, the amount of settlement land that is suitable for settlement, and the standard area of land needs of each resident (Muta'Ali, 2015). The standard of the area of the population needs per capita according to the Regulation of the Minister of State for Public Housing No.11/PERMEN/2008 concerning (a) Per-Capita Space Needs According to the Regional Zone that in the Downtown Zone The need for space/capita is 16 m<sup>2</sup>/Capita.

Land carrying capacity research uses the Cellular Automata Markov Chain (CAMC) to predict and find a balance between the availability of existing land and built-up areas, so that land carrying capacity can be maintained and sustainable (Fitri *et al.*, 2021). Markov Chains Cellular Automata Modeling is the most reliable modeling and has been widely used by previous researchers to analyze spatial, and temporal changes in land cover and can be used to simulate and predict future land cover (Marko *et al.*, 2016). This modeling is based on the continued increase in population growth that causes the need for land to be higher while the existing land area is fixed (Pratami *et al.*, 2019) and will ultimately reduce environmental carrying capacity (Asfari *et al.*, 2017).

Based on the above problems, this study aims to spatially analyze changes in Ambon city land cover in 2010, 2015, 2020 and predict Ambon city land cover in 2031 and analyze the carrying capacity of residential land in Ambon City in 2031 using CAMC, This modeling is an appropriate, preventive and innovative solution in facilitating the government and stakeholders in handling and managing land wisely so that profitable land use decisions can be taken in the dimension of sustainable land use planning in line with the development of Ambon City in the future.

## METHOD

### Location and Research Time

This study was conducted in Ambon City, Maluku Province, which is geographically located at 3°34'4.80"-3°47'38.4" South Latitude and 128°1'33.6"-128°18'7.20 East Longitude and administratively Ambon City consists of Serimau, Nusaniwe, South Leitimur, Ambon Bay, Ambon Baguala Bay, with an area of Ambon City of 32 573.68 ha (Figure 1).

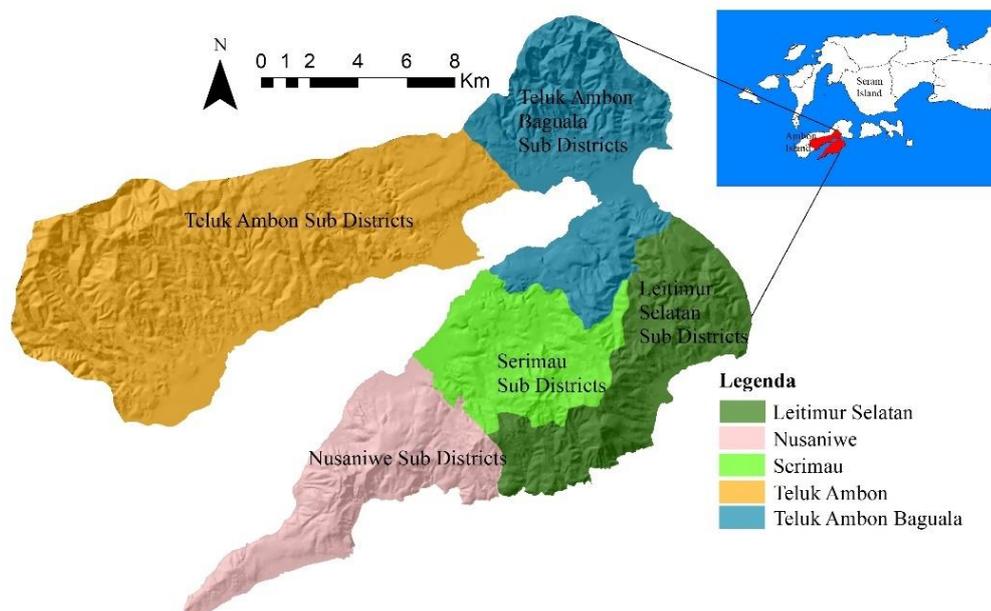


Figure 1 Research location

## Data Collection

To analyze the changes in Ambon City land cover in 2010, 2015, 2020 and predict Ambon city land cover in 2031 and analyze the carrying capacity of residential land in Ambon City in 2031 the data needed in this study includes IKONOS satellite imagery in 2010 and SPOT 6 satellite imagery in 2015 and 2020, administrative map, road network map, river network map, central map of economic activity, altitude data (DEM), slope data (DEM), RTRW map of Ambon City, distance from the beach and population data obtained from relevant agencies. Data collection is carried out through three events, namely literature studies, agency studies, and field surveys.

## Data Analysis

### Land Cover

Land cover as a manifestation of the dynamic process of interaction between human activities and land resources, which is spatially distributed from the land surface and identifies land biophysical cover; this includes waters, vacant land, or residential land (Gopalakrishnan *et al.*, 2020). In (SNI 7645:2010), land closure can also mean biophysical cover on the earth's surface that can be observed and is the result of human regulation, activity, and treatment carried out on certain types of land cover to carry out production, alteration, or maintenance activities on the area. Classification of land cover is needed to distinguish the type of land cover that is one with other land cover. The following classification of land cover in accordance with SNI 7645:2010 concerning Classification of Land Cover scale 1:50 000 or 1:25 000 as many as 34 classifications, but in this study the classification was made simply into 5 classifications including agricultural areas, non-agricultural areas, built land/settlements, open land, and waters.

### Driving Factors

Changes in land cover in an area are influenced by several factors, both physical factors, and socio-economic factors. These factors can be used as rules in the analysis of land change predictions (Fitawok *et al.*, 2020). Driving factors are factors given in the modeling process and assumed to be constant (static), used as controllers of the modeling performed (Lisanyoto *et al.*, 2019). The driving factor is very important to project the future development of residential land. Therefore, driving factors are needed to model land cover changes (Irawan *et al.*, 2019). The driving factors used in this study consisted of physical factors, including elevation, the slope of slopes, distance from the coastline, and distance from rivers, while socio-economic factors include distance from the road and distance from the center of economic activity (Table 1 and Figure 2).

All driving factors are then given a weight based on their level of importance (Mansour *et al.*, 2020). The driving factor is basically euclidean distance consisting of a type of interest level, namely cost distance (the farther, the better) and benefit distance (the closer, the better) (Marko *et al.*, 2016). For distance from the river and distance from the coastline use cost distance, while for distance from the road and distance from and distance from the center of economic activity, use benefit distance.

Table 1 Classification of driving factors

No	Parameters	Classification	Weight	Conformity Level
1	Distance from the coastline	0-100 m	1	Not Appropriate
		100-2 000 m	2	Appropriate
		>2 000 m	3	Very Suitable
2	Distance from the road	0-100 m	3	Very Suitable
		100-1 000 m	2	Appropriate
		>1 000 m	1	Not Appropriate
3	Distance from the river	0-100 m	1	Not Appropriate

No	Parameters	Classification	Weight	Conformity Level
4	Distance from the center of economic activity	100-500 m	2	Appropriate
		>500 m	3	Very Suitable
		0-100 m	3	Very Suitable
5	Elevation	100-750 m	2	Appropriate
		>750 m	1	Not Appropriate
		0-7 mdpl	1	Very Suitable
6	Slope	7-25 mdpl	2	Appropriate
		>25 mdpl	3	Not Appropriate
		0-8 %	3	Very Suitable
		8-15%	2	Appropriate
		>15%	1	Not Appropriate

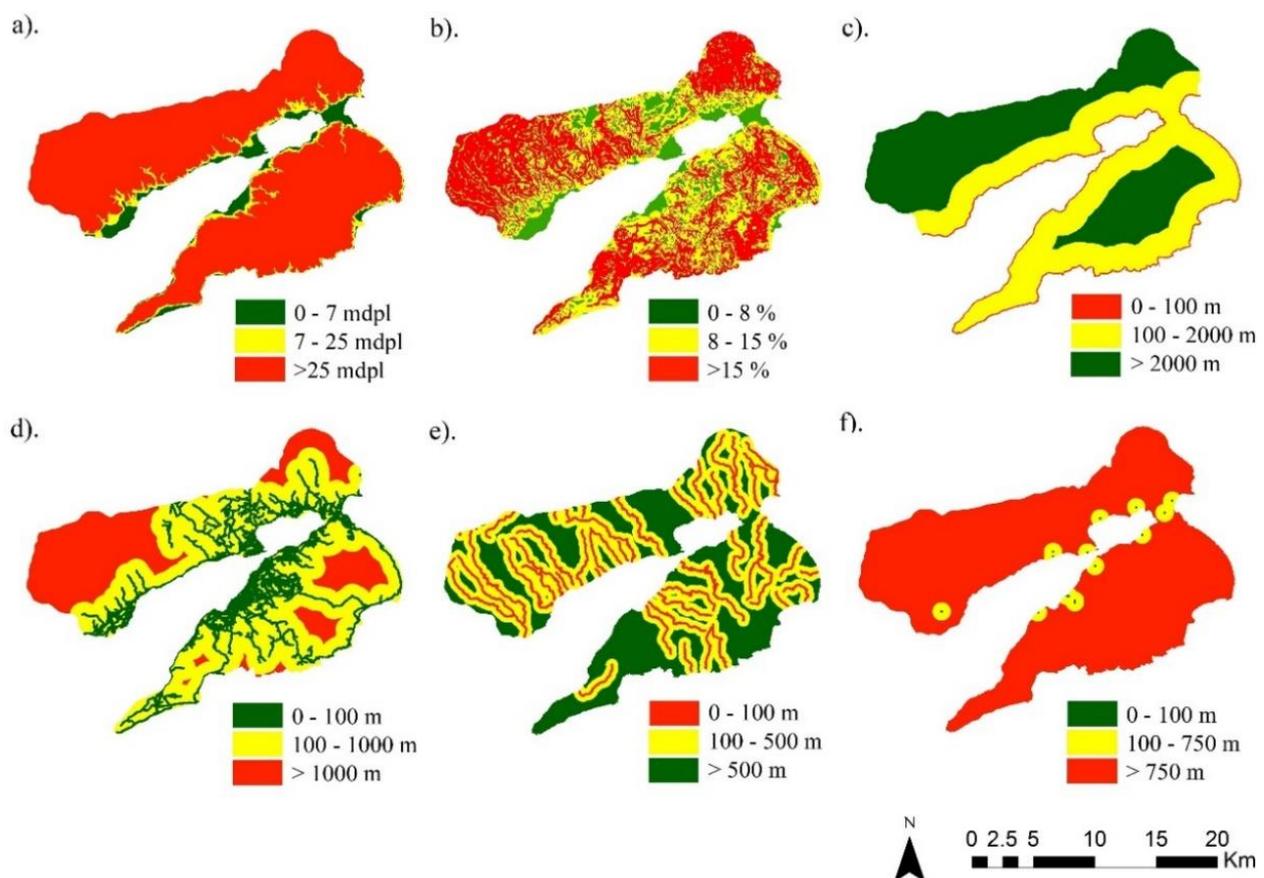


Figure 2 Driving Factor, a) elevation, b) slope, c) distance from the shoreline, d) distance from the road, e) distance from the river, f) distance from the center of economic activity

**Fuzzy Driving Factors**

Fuzzy logic is a branch of artificial intelligence systems (Artificial Intelligence) that emulates the ability of humans to think into the form of algorithms that are then run by machines (Espitia *et al.*, 2021). Fuzzy is a logical system that aims to formalize from estimates to reasoning represented in the form of interest levels that have a range of values 0-1 (Boolean) (Zadeh, 1994). According to Peter *et al.* (2021) logic in fuzzy is a very good thing to interpret data that occurs continuously effectively and efficiently, this is a good way to do cellular automata-based modeling because it uses parallel computing consisting of interconnected cells and has a continuous value, so in this study I processed data driving factors using this fuzzy logic concept (Figure 3).

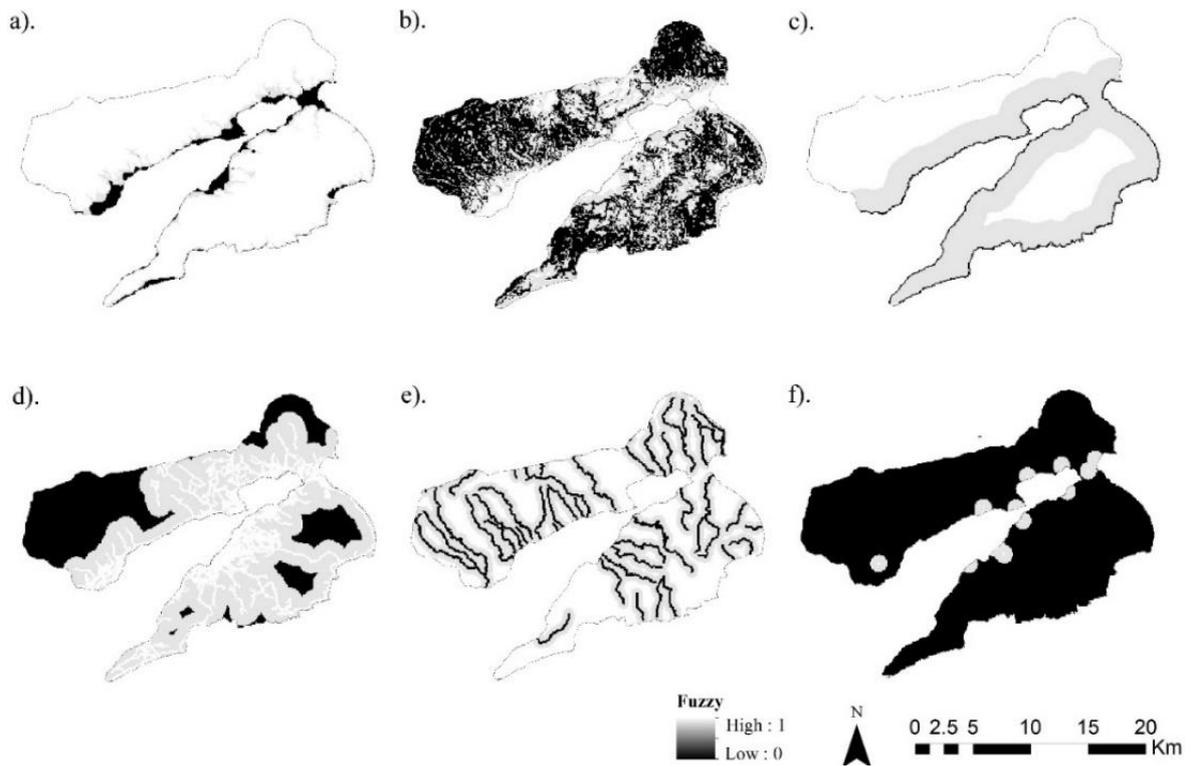


Figure 3 Fuzzy Driving Factors, a) elevation, b) slope, c) distance from the shoreline, d) distance from the road, e) distance from the river, f) distance from the center of economic activity

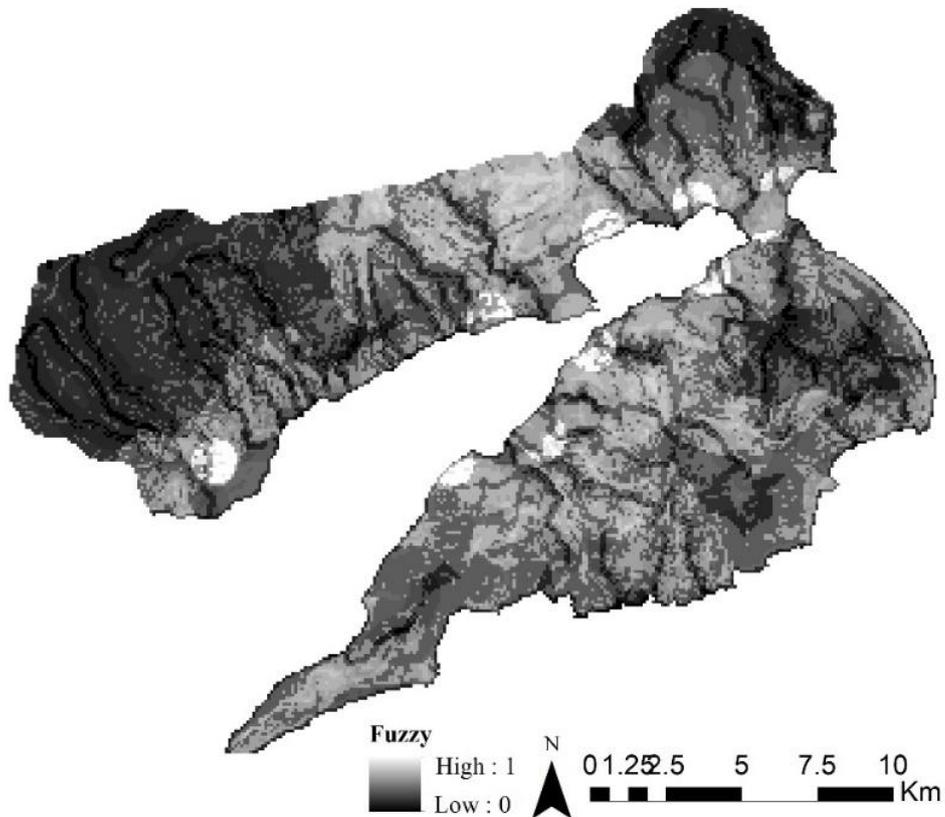


Figure 4 Driving fuzzy factor overlay

Ambon City driving factor consists of six parameters (Figure 3 and Figure 4) after classification and weighting must be converted to fuzzy values (value range 0-1) to facilitate the next analysis process for CA MC modeling in Idrisi Selva software (Wang *et al.*, 2022; Mwabumba *et al.*, 2022). Fuzzy analysis in this study was used to standardize the driving factors that have been combined and provide the previous weighting. This fuzzy logic describes if the value is getting closer to 1, then the value has a high level of importance and vice versa. According to Akbar and Supriatna, (2019) fuzzy logic is also used to create probability values to become residential land by using real-binary format so that it can be processed in Idrisi Selva software. Akbar and Supriatna, (2019) explained that in processing land cover predictions in the future, the driving factor used must be continuously formatted (Binary 0-1) to be processed in Selva Idrisi. The results of this processing will output containing all the combined driving factors that can be seen in Figure 4.

Fuzzy logic values are displayed with black-and-white gradations, where the whiter the color gradations produced, the higher the value, meaning that the higher the development of airfields or settlements in the area. The six variables that have been done fuzzy membership are then over-covered with fuzzy gamma logic in the Arc Map 10.8 application which can then be generated as a combination of the suitability of all variables, as shown in Figure 4. The result can be known that areas that are close to rivers and coastlines have a lower value while areas that are close to the road network and economic activity centers have a higher value. So the potential for the development of settlements in Ambon City is close to the road network and the center of economic activity.

### ***Cellular Automata Markov Chains***

Spatial modeling is needed to be able to perform land use change modeling analysis by combining GIS analysis with dynamic system analysis (Pravitasari *et al.*, 2020). Modeling with a dynamic system approach has dynamic properties in time, so it can predict the conditions of the future time. Modeling with a geographical information systems (GIS) approach, based on spatial data, so that it can analyze and present data spatially. Spatial-based and dynamic modeling can be done with the Markov chain-cellular automata approach (Marko *et al.*, 2016).

Markov chain First introduced by a Russian mathematician named Andrei A. Markov in 1970, this study shows that there is a dependency between the results of future predictions and the historical data used (Al-Shaar *et al.*, 2021). But in land use modeling, it was first used by Burnham (1973) entitled Markov Intertemporal Land Use Simulation Model. The markov chain model uses a stochastic process to illustrate the possibility that one condition, i.e., a particular class of land cover, will switch to another condition over a certain period (Parsa *et al.*, 2016). The main advantage of this markov chain is that the algorithm is simple so that it is easy to apply (Susilo, 2011).

In practice, the markov chain is usually represented as a matrix that presents the probability of transition between all classes of land cover in the study area based on two consecutive land use/cover maps (Andaryani *et al.*, 2021). The disadvantage of the Markov chain is that it only calculates the probability of changes occurring but cannot explain spatial changes that occur explicitly (Moghadam and Helbich, 2013). Noszczyk (2019) argues that the markov chain process assumes that future circumstances can be emulated based on previous circumstances. This is confirmed by Rahnama (2021), who stated that the markov chain model could describe land use changes from one period to another and use it to predict future changes.

Cellular Automata was first introduced by John Von Neumann and Stanislaw Ulam between 1940 and the early 1950s (Al-Shaar *et al.*, 2021). According to Mohamed and Worku (2020) Cellular Automata (CA) is a discrete dynamic system in which the condition of each cell at the time of  $t + 1$  is governed by the situation of its neighboring cells at a time based on a predetermined transition procedure. Munthali *et al.* (2020) explain that the CA Model is a discrete model with a spatially expanded dynamic system based on defined transition rules that link the new state to the previous state of the existing land use type. In addition, CA-based models have the ability to represent non-linear and complex processes that are distributed spatially so as to provide an

idea of the patterns of land use change that occur (Liping *et al.*, 2018). Gomes *et al.* (2019) Added that CA is one application in modeling excellent spatial dynamics and is often used in simulating land use changes.

Akbar and Supriatna (2019) revealed that Cellular automata are a modeling method that can be used as a tool in supporting land use planning and spatial and temporal policy analysis by analyzing the complexity of urban growth that produces simulations, predictions, and planning. According to Nahib *et al.* (2015) Cellular Automata consist of several components, namely cell (pixel), state, environment (neighborhood) and transition ruler/transition function.

### **Carrying Capacity of Residential Land**

Land carrying capacity is a scientific concept for measuring the relationship between economic, social, and environmental and is one of the basic assessments of sustainable development (Ma, 2017). The carrying capacity of residential land is simply defined as the relationship between land resources and their maximum population capacity (Yang *et al.*, 2019). Land carrying capacity for settlements is the ability of an area to have the availability of suitable residential land as a place to live. The population is the first indicator used to determine the area of land for the carrying capacity of residential land (Fitri *et al.*, 2021). Determination of the method of calculating the projection of the number of residents in 2031 can be done by the geometric method.

The formula for preparing the carrying capacity of residential land requires the amount of land area that is feasible for settlement and the standard area of land needs of each resident (Muta'Ali, 2015). Standard of the area of the population needs per capita according to the Regulation of the Minister of State for Public Housing Number 11/PERMEN/M/2008 regarding the Guidelines for the Compatibility of Housing and Settlement Areas, (a) the need for space per capita according to the regional zone that in the downtown zone the need for space /capita is 16 m<sup>2</sup>/Capita, the level of space needs per capita

The carrying capacity of residential land is useful as a measure or tool for development planning and provides an overview of land cover, relations between residents, and the environment. Therefore there are at least two main variables that must be known with certainty to analyze carrying capacity, namely the potential of available land including land area and population (Soerjani *et al.*, 1987). The carrying capacity of settlements can be calculated using the settlement land carrying capacity formula (Hasmita *et al.*, 2020). It can be seen as follows:

$$DDPm = \frac{\left(\frac{LPM}{JP}\right)}{\alpha}$$

Information:

DDPm : Carrying capacity of settlement land

LPM : Settlement land area

JP : Population

$\alpha$  : Coefficient of area of space needs

1. If  $DDPm > 1$  m<sup>2</sup>/capita, it means that the carrying capacity of the settlement is high, it is still able to accommodate residents to settle (build houses) within the area.
2. If  $DDPm = 1$  m<sup>2</sup>/capita, it means that the carrying capacity of the settlement is optimal, there is a balance between the population who live (build houses) with the area of the existing area.
3. If  $DDPm < 1$  m<sup>2</sup>/capita, it means that the carrying capacity of the settlement is low, it is not able to accommodate the population to settle in the area.

In this study, the carrying capacity of residential land in Ambon City was calculated using the results of modeling Cellular Automata – Markov Chain settlement land area in 2031, standard area of space needs, and projected population in 2031. Detailed processing stages in the study can be seen in Figure 5.

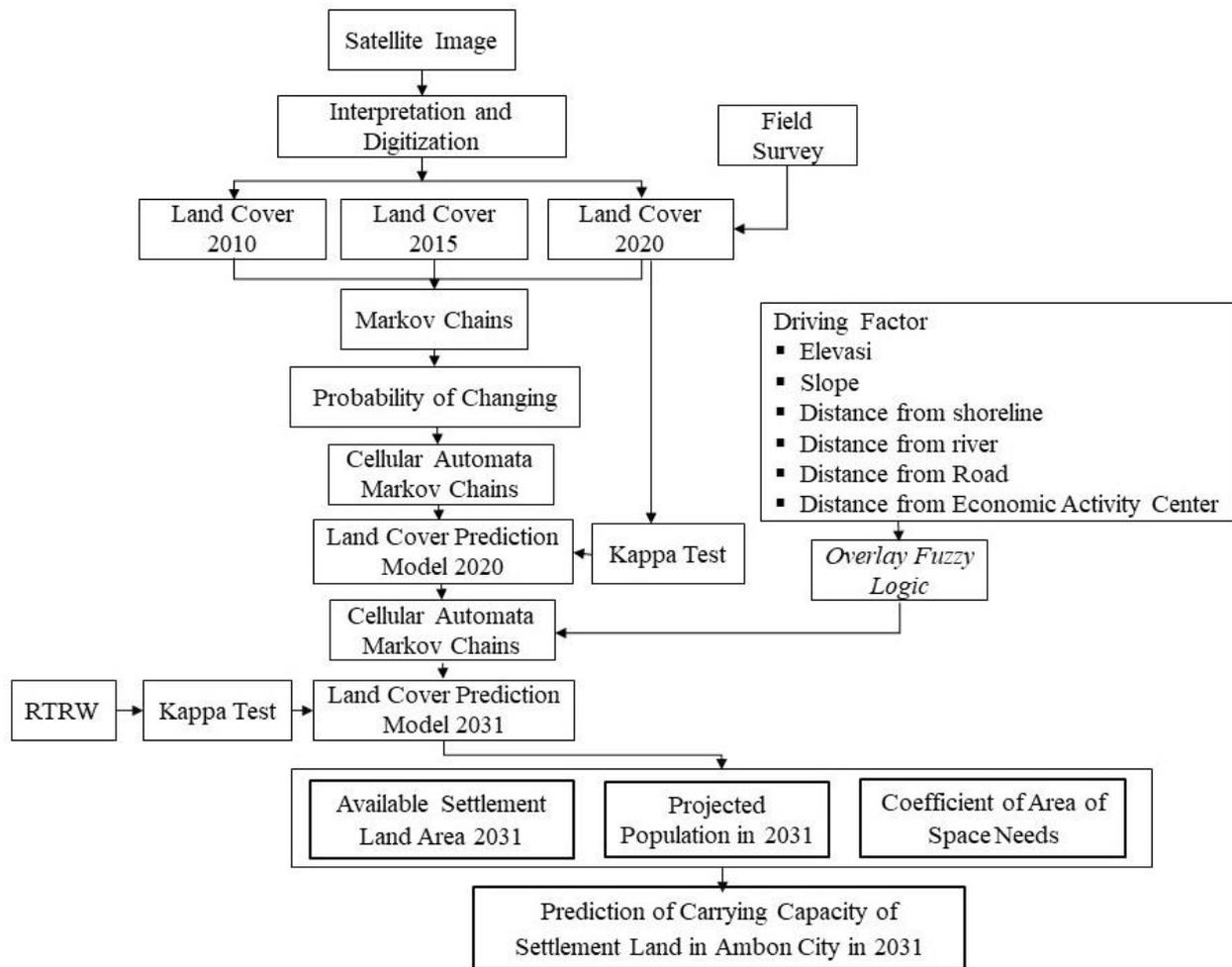


Figure 5 Research workflow

**RESULTS AND DISCUSSIONS**

**Ambon City Land Cover in 2010, 2015 and 2020**

The results of the analysis showed that the cover in Ambon City in 2010, 2015, and 2020 continued to change. The types of land cover that continue to increase in the area are the type of cover of residential land and open land, while agricultural land and non-agricultural land continue to experience a decrease in area. This is due to the increased needs of the people in Ambon City for land to be built more and more from year to year. For this type of land cover, water bodies do not experience an increase or decrease in area. Spatially, the cover of the land cover area of Ambon City can be seen in Table 2 and Figure 6.

Table 2 Composition of Ambon City land cover

Types of Land Cover	Area (ha)		
	2010	2015	2020
Settlements	3 730.29	4 173.84	4 433.36
Open land	338.97	627.36	837.94
Agricultural area	16 828.76	16 309.66	15 853.49
Non-Agricultural area	11 499.12	11 286.29	11 272.36
Water bodies	176.53	176.53	176.53
Total		32 573.68	

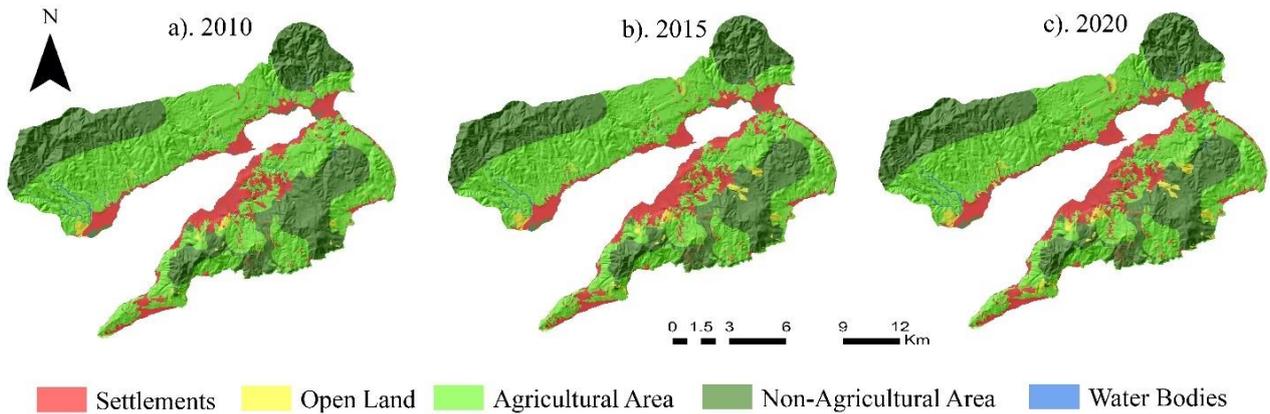


Figure 6 Ambon City land cover in a) 2010, b) 2015 and c) 2020

**2020 Actual and Simulated Land Cover**

Ambon City land cover modeling in 2020 was carried out using CAMC, and driving factors data that had been prepared. The magnitude of the possibility of land cover changes is called the Transition Probability Matrix (TPM), while the Figures contained in the TPM table indicate the possibility of land cover that has changed to other land covers. Table 3 is a TPM in 2010-2020 where the Roman numeral I is a settlement, roman numeral II is open land, roman numeral III is an agricultural area, Roman numeral IV is a non-agricultural area and roman numeral V is waters. A value of 0 in the (TPM) indicates that there is no change in land cover from one area to another. While the value of 1 indicates that the land cover will remain and not change to another land cover (Table 3). Based on Table 3, it is known that open land cover has a higher probability of changing to residential land with a TPM value of 0.1870, and water bodies have a value of TPM 0, indicating no change in land cover in one area to other land cover.

Table 3 Transition Probability Matrix (TPM) from 2010-2020

	I	II	III	IV	V
I	0.8457	0	0.0812	0.0731	0
II	0.1870	0.7875	0.0255	0	0
III	0.1222	0.0549	0.8199	0.0030	0
IV	0.0157	0.0972	0.0543	0.8327	0
V	0	0	0	0	1

Information: I. Settlements; II. Open land; III. Agricultural Area; IV. Non-Agricultural Areas; V. Water Bodies

Table 4 Comparison of actual land cover area and simulation in 2020

Types of Land Cover	Area (ha)	
	2020 Actual	2020 Simulation
Settlements	4 433.36	5 720.54
Open Land	837.94	990.17
Agricultural Area	15 853.49	14 585.78
Non-Agricultural Area	11 272.36	11 100.67
Water Bodies	176.53	176.53
<b>Total</b>	<b>32 573.68</b>	

The results of the comparison of actual land cover and simulations in 2020 in Figure 7 and Table 4 show that the results of the 2020 land cover simulation are different from the actual land cover results of Ambon City in 2020. The simulation results on each type of land cover have a wider area compared to the results of land cover digitization in 2020.

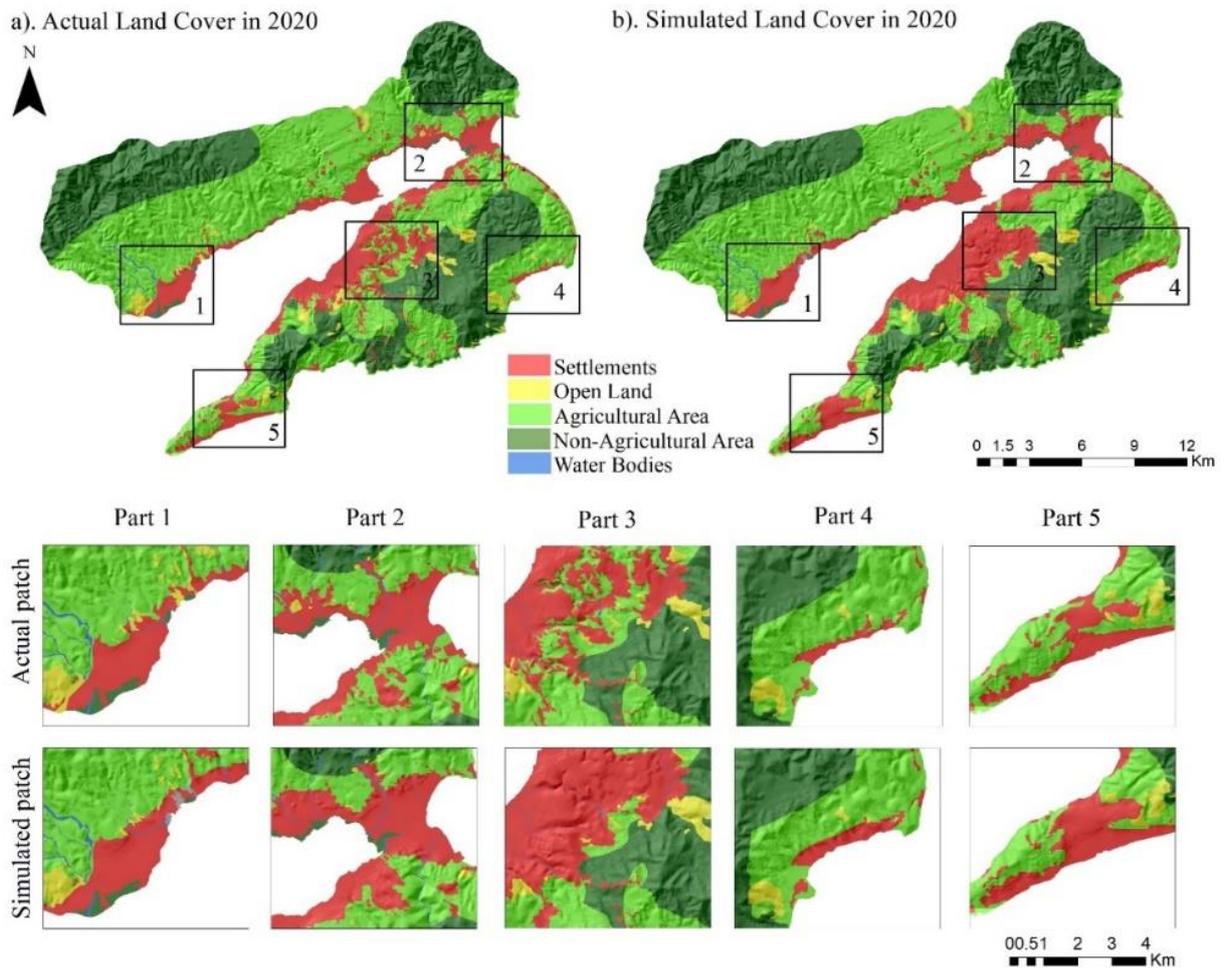


Figure 7 Actual land cover of Ambon City 2020 and simulation results in 2020

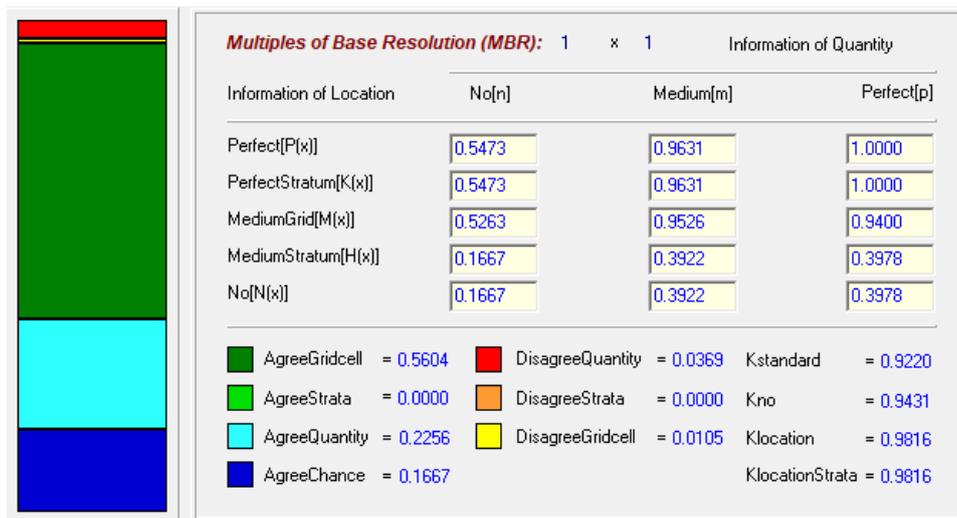


Figure 8 Kappa Model 2020 value accuracy test validation results

After 2020 land cover modeling, an accuracy test needs to be done to find out if the first resulting model can be used to create a second prediction model. The accuracy test was conducted with actual 2020 land cover data as primary data (reference image) and 2020 land cover simulation data as a comparison image. The accuracy test results can be seen in Figure 8 showed that the kappa (K standard) value is 0.9220 or 92.20%, which shows that this accuracy value is said to be very good and can be continued to model Ambon city land cover in 2031.

**Predicted land cover in 2031**

Ambon City land cover prediction model in 2031 is the second modeling that uses the same driving factor as in the previous modeling, but the TPM value is different from the first modeling. Based on Table 3, it is known that open land cover has a higher probability of changing to residential land with a TPM value of 0.4449, and the body of water has a value of TPM 0, indicating no change in land cover in one area to another land cover. For more details, it can be seen in Table 5, while spatially, it can be seen in figure 9.

Table 5 Transition Probability Matrix (TPM) from 2020 – 2031

	I	II	III	IV	V
I	0.8224	0	0.0281	0.1495	0
II	0.4449	0.5551	0	0	0
III	0.1851	0.1040	0.7105	0.0004	0
IV	0	0.1956	0.0884	0.7160	0
V	0	0	0	0	1

Information: I. Settlements; II. Open Land; III. Agricultural Area; IV. Non-Agricultural Areas; V. Water Bodies

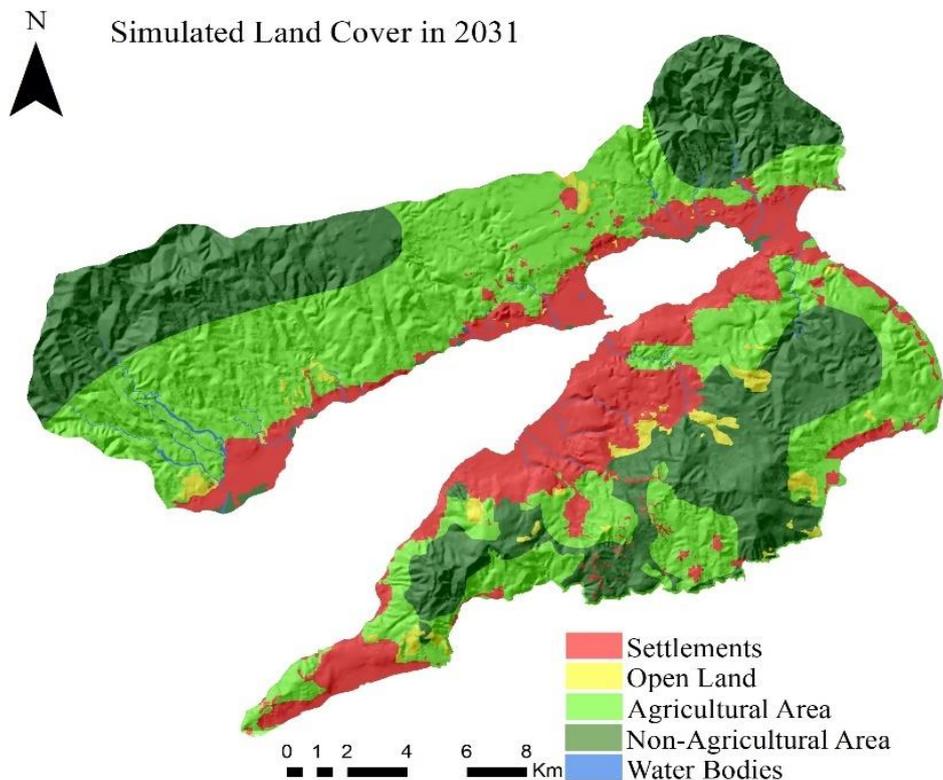


Figure 9 Ambon City land cover simulation in 2031

The results of the predicted land cover in 2031 in Figure 9 show that the type of residential land cover and open land continues to increase in area. This is inversely proportional to the type of agricultural land cover and non-agricultural land that continues to decrease in area. Figure 9 shows the prediction of the 2031 land cover model of Ambon City. This 2031 land cover modeling is used as a reference in determining the area of residential land to be included in the calculation of the carrying capacity of Ambon city settlement land (Figure 9).

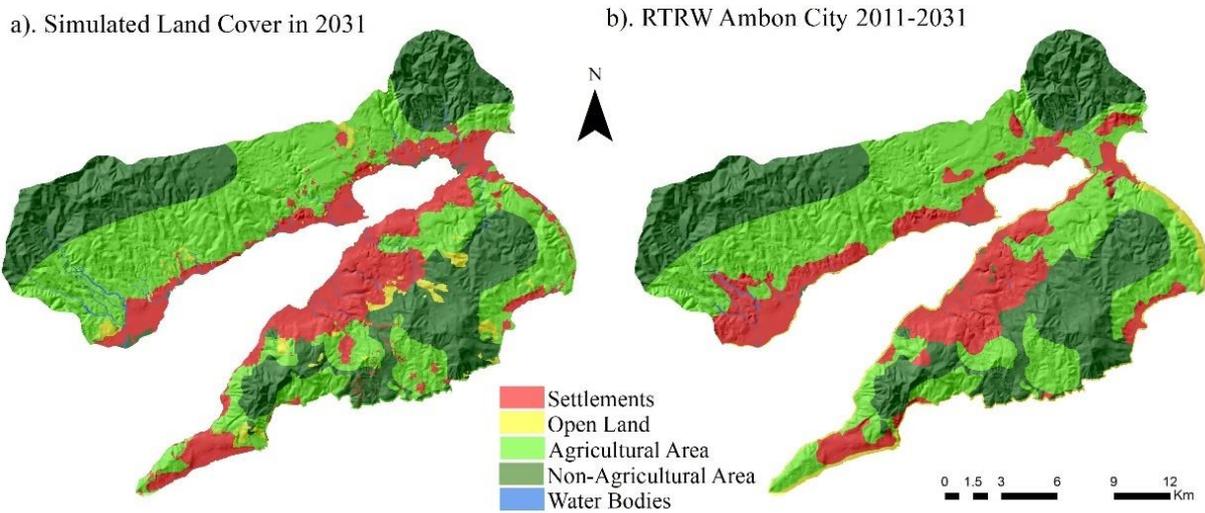


Figure 10 Comparison of simulation of land 2031 and RTRW of Ambon City.

The results of the prediction of Ambon City land cover in 2031 were then compared with the Spatial Plan (RTRW) of Ambon City (Figure 10). In the PERDA RTRW Ambon City, the government focuses Ambon City more on the development, one of which is realizing Ambon City as a waterfront city so that the direction of development of residential areas is more centered in the coastal areas of Ambon Bay. A comparison of the area of land cover resulting from the simulation in 2031 and the simplified RTRW land cover from the polar map of the Ambon City RTRW money 2011-2031 can be seen in Table 6.

Table 6 Comparison of land cover area simulated 2031 and RTRW Ambon City 2011-2031

Types of Land Cover	Area (ha)	
	2031 Simulation	RTRW
Settlements	7.299.17	6.590.35
Open Land	894.32	1.012.55
Agricultural Area	14 101.00	13 289.86
Non-Agricultural Area	10 102.67	11 504.01
Water Bodies	176.53	176.92
<b>Total</b>	<b>32 573.68</b>	

Just like the land cover model in 2020, the prediction model for land cover changes in 2031 is also conducted an accuracy test (Figure 11). Unlike the accuracy-test in the 2020 model, the 2031 prediction model was conducted an accuracy test using the 2011-2031 Ambon City RTRW space pattern map, which has been generalized into a land cover map. The results of the accuracy-test showed that the 2031 model year had an accuracy value of 0.8386 or 83.86%. This means that the 2031 land cover prediction model is said to be very good to be used to calculate the land carrying capacity of Ambon City in 2031.

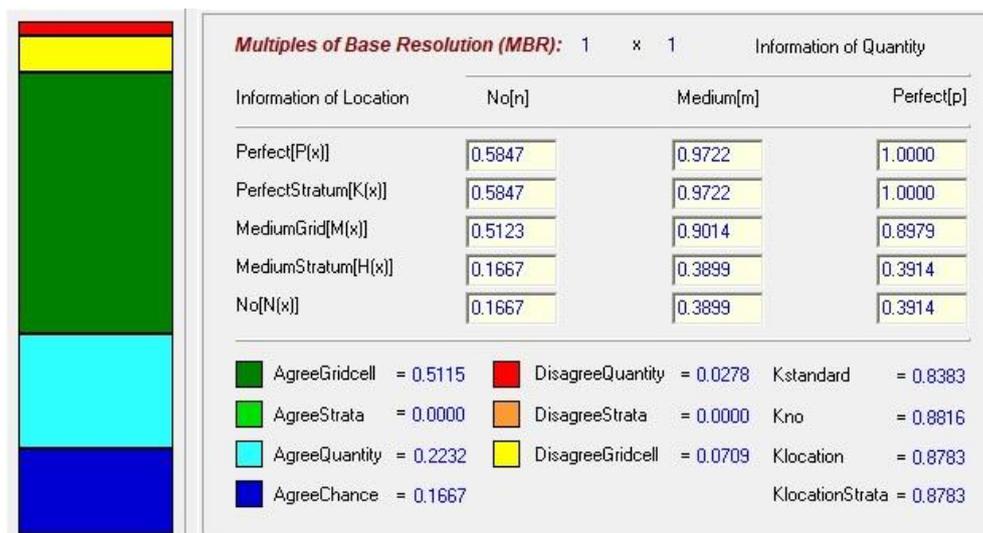


Figure 11 Kappa Model 2031 value accuracy test validation results

### Ambon City Land Carrying Capacity in 2031

Cellular Automata Markov Chain modeling results show the area of land for settlements in 2031 is 7 299.17 or 72 991 652 m<sup>2</sup> while the coefficient of area of space needs refers to the Regulation of the Minister of State for Public Housing No.1/PERMEN/2008 concerning (a) According to the Regional Zone, the need for space/capita is 16 m<sup>2</sup>/capita and the population of Ambon City in 2031 is obtained from the calculation of population projections using geometric methods, namely 2 445 961 people. Based on the results of the calculation of DDPm 2031 obtained, the results of the settlement land carrying capacity index of 1.87 m<sup>2</sup>/capita, meaning that if DDPm >1 indicates the carrying capacity of high residential land and still able to accommodate residents to live and build houses in the region. In other words, Ambon City can still accommodate an increase in settlements of 1.87 m<sup>2</sup>/capita.

### CONCLUSION

During the last 15 years, from 2010, 2015, and 2020, land cover in Ambon City has continued to change in an area, the type of land cover that has increased in the area, namely land cover of residential land and open land, while the land cover of non-agricultural areas and agricultural areas has decreased and for water bodies has not increased or decreased. The development of residential land cover leads to the east and south at most.

Based on the results of the prediction of land cover in 2031 using CAMC, obtained the area of residential land cover is 7 299.17 ha, and based on the calculation of the projected number of residents of Ambon City in 2031 using geometric methods, namely 2 445 961 people and refers to the Regulation of the Minister of State for Public Housing No.11/PERMEN/2008 concerning (a) Per Capita Space Needs According to the Regional Zone that in the Downtown Zone The need for space/capita is 16 m<sup>2</sup>/Capita. So the results of calculating the carrying capacity of residential areas in 2031 in Ambon City resulted in an index value of 1.87 m<sup>2</sup>/capita or DDPm >1 m<sup>2</sup>/capita, which signifies the carrying capacity of high residential land and still able to accommodate residents to settle and build houses in Ambon City.

### ACKNOWLEDGEMENTS

The author would like to thank the Department of Geography, Faculty of Mathematics and Natural Sciences, Indonesia University, who have always helped the author in this research.

## REFERENCES

- [BPS] Badan Pusat Statistik. 2020. *Kota Ambon Dalam Angka 2020*. Ambon (ID): BPS Kota Ambon.
- [Permen] Peraturan Menteri. 2008. Peraturan Menteri Negara Perumahan Rakyat Nomor:11/PERMEN/M/2008 Tentang Pedoman Keserasian Kawasan Perumahan dan Pemukiman. Jakarta (ID): Kementerian Negara Perumahan Rakyat.
- [SNI] Standar Nasional Indonesia. 2010. *Klasifikasi Penutup Lahan. SNI 7645:2010*. Jakarta (ID): Badan Standarisasi Nasional.
- Akbar F, Supriatna. 2019. Land cover modelling of Pelabuhanratu City in 2032 using cellular automata-markov chain method. *IOP Conference Series: Earth and Environmental Science*. 311(1): 1-8.
- Al-Shaar W, Gérard JA, Nehme N, Lakiss H, Barakat LB. 2021. Application of modified cellular automata Markov chain model: Forecasting land use pattern in Lebanon. *Modeling Earth Systems and Environment*. 7(2): 1321-1335.
- Andaryani S, Sloan S, Nourani V, Keshtkar H. 2021. The utility of a hybrid GEOMOD-Markov Chain model of land-use change in the context of highly water-demanding agriculture in a semi-arid region. *Ecological Informatics*. 64: 1-12.
- Asfari A, Supriatna NR. (2017). Spatial Dynamics Model of Population Growth Relationship with Land Availability in Northern Cianjur Regency, West Java Province. *Prosiding Industrial Research Workshop and National Seminar*. vol(no): 254-260.
- Burnham BO. 1973. Markov intertemporal land use simulation model. *Journal of Agricultural and Applied Economics*. 5(1): 253-258.
- Espitia H, Soriano J, Machón I, López H. 2021. Compact fuzzy systems based on boolean relations. *Applied Sciences*. 11(4): 1-23.
- Fitawok MB, Derudder B, Minale AS, Passel SV, Adgo E, Nyssen J. 2020. Modeling the impact of urbanization on land-use change in Bahir Dar City, Ethiopia: An integrated cellular automata-markov chain approach. *Land*. 9(4): 1-17.
- Fitri NI, Damayanti A, Indra TLL, Dimiyati M. 2021. Cellular automata and markov chain spatial modeling for residential area carrying capacity in Samarinda City, East Kalimantan Province. *IOP Conference Series: Earth and Environmental Science*. 673(1): 1-12.
- Gomes E, Abrantes P, Banos A, Rocha J. 2019. Modelling future land use scenarios based on farmers' intentions and a cellular automata approach. *Land Use Policy*. 85: 142-154.
- Gopalakrishnan R, Seppänen A, Kukkonen M, Packalen P. 2020. Utility of image point cloud data towards generating enhanced multitemporal multisensor land cover maps. *International Journal of Applied Earth Observation and Geoinformation*. 86: 1-11.
- Hasmita L, Sekarrini CE, Septiana KN. 2020. Study of environmental carrying capacity for settlement development in Ranah Batahan District, Pasaman Barat Regency. *IOP Conference Series: Earth and Environmental Science*. 412: 1-8.
- He Q, He W, Song Y, Wu J, Yin C, Mou Y. 2018. The impact of urban growth patterns on urban vitality in newly built-up areas based on an association rules analysis using geographical big data. *Land Use Policy*. 78: 726-738.
- Irawan IA, Supriatna S, Manessa MDM, Ristya Y. 2019. Prediction model of land cover changes using the cellular automata – markov chain affected by the BOCIMI toll road in Sukabumi Regency. *KnE Engineering*. 4(3): 247-256.
- Liping C, Yujun S, Saeed S. 2018. Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLOS ONE*. 13(7): 1-23.
- Lisanyoto L, Supriatna, Sumadio W. 2019. Spatial model of settlement expansion and its suitability to the landscapes in Singkawang City, West Kalimantan Province. *IOP Conference Series: Earth and Environmental Science*. 338: 1-10.

- Liu Y. 2020. Sustainable development in urban areas: Contributions from generalized trade. *Sustainable Cities and Society*. 61: 1-7.
- Ma B. 2017. Literature review on land carrying capacity of the coordinated development of population, resources, environment and economy. *AIP Conference Proceedings*. 1890(1): 1-6.
- Mansour S, Al-Belushi M, Al-Awadhi T. 2020. Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *Land Use Policy*. 91: 1-15.
- Marko K, Zulkarnain F, Kusratmoko E. 2016. Coupling of Markov Chains and cellular automata spatial models to predict land cover changes (case study: upper Ci Leungsi catchment area). *IOP Conference Series: Earth and Environmental Science*. 47: 1-10.
- Moghadam HS, Helbich M. 2013. Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model. *Applied Geography*. 40: 140-149.
- Mohamed A, Worku H. 2020. Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *Urban Climate*. 31: 1-17.
- Munthali MG, Mustak S, Adeola A, Botai J, Singh SK, Davis N. 2020. Modelling land use and land cover dynamics of Dedza District of Malawi using hybrid Cellular Automata and Markov model. *Remote Sensing Applications: Society and Environment*. 17(100276).
- Muta'Ali L. 2015. *Regional Analysis Techniques for Regional Planning, Spatial Planning and the Environment* Jogjakarta Board of Publishers. Yogyakarta (ID): Faculty of Geography Universitas Gadjah Mada..
- Mwabumba M, Yadav BK, Rwiza MJ, Larbi I, Twisa S. 2022. Analysis of land use and land-cover pattern to monitor dynamics of Ngorongoro world heritage site (Tanzania) using hybrid cellular automata-Markov model. *Current Research in Environmental Sustainability*. 4: 1-11.
- Nahib I, Turmudi T, Suwarno Y. 2015. Spatial modeling of deforestation in Tasikmalaya District, West Java Province. *Globe Scientific Magazine*. 17(2): 155-164.
- Noszczyk T. 2019. A review of approaches to land use changes modeling. *Human and Ecological Risk Assessment: An International Journal*. 25(6): 1377-1405.
- Parsa VA, Yavari A, Nejadi A. 2016. Spatio-temporal analysis of land use/land cover pattern changes in Arasbaran Biosphere Reserve: Iran. *Modeling Earth Systems and Environment*. 2(4): 1-13.
- Peter A, Zachariah B, Damuut LP, Abdulkadir S. 2021. *Efficient Traffic Control System Using Fuzzy Logic with Priority*. In: Misra S, Muhammad-Bello B, editors. *Third International Conference Information and Communication Technology and Applications*, 2020 Nov 24-27. Minna, Nigeria. Minna (NG): Springer. p 660-674.
- Pratami M, Susiloningtyas D, Supriatna. 2019. Modelling cellular automata for the development of settlement area Bengkulu City. *IOP Conference Series: Earth and Environmental Science*. 311(012073): 1-8.
- Pravitasari AE, Rustiadi E, Adiwibowo S, Wardani IK, Kurniawan I, Murtadho A. 2020. Dynamics and projections of land cover changes and spatial inconsistencies in the Kendeng Mountains Region. *Journal of Regional and Rural Development Planning*. 4(2): 99-112.
- Rahnama MR. 2021. Forecasting land-use changes in mashhad metropolitan area using cellular automata and Markov chain model for 2016-2030. *Sustainable Cities and Society*. 64(102548).
- Soerjani M, Ahmad R, Munir R. 1987. *Environment: Natural Resources and Population in Development*. Jakarta (ID): University of Indonesia.
- Susilo B. 2011. Modeling spatial integration probabilistic markov chain and cellular automata for the study of land use changes regional scale in DIY Yogyakarta. *Jurnal Gografi GEA*. 11(2): 163-178.
- Tian G, Ma B, Xu X, Liu X, Xu L, Liu X, Xiao L, Kong L. 2016. Simulation of urban expansion and encroachment using cellular automata and multi-agent system model—A case study of Tianjin metropolitan region, China. *Ecological Indicators*. 70: 439-450.

- Wang Q, Wang H, Chang R, Zeng H, Bai X. 2022. Dynamic simulation patterns and spatiotemporal analysis of land-use/land-cover changes in the Wuhan metropolitan area, China. *Ecological Modelling*. 464(109850).
- Widodo B, Lupyanto R, Sulistiono B, Harjito DA, Hamidin J, Hapsari E, Yasin M, Ellinda C. 2015. Analysis of environmental carrying capacity for the development of sustainable settlement in Yogyakarta urban area. *Procedia Environmental Sciences*. 28: 519-527.
- Yang N, Li J, Lu B, Luo M, Li L. 2019. Exploring the spatial pattern and influencing factors of land carrying capacity in Wuhan. *Sustainability*. 11(10): 2786.
- Zadeh LA. 1994. Fuzzy logic, neural networks, and soft computing. *Communications of the ACM*. 37(3): 77-84.