# Analysis of Urban Space Utilization in Tanjung Bunga Area Case Study : Tanjung Bunga Area, Tanjung Merdeka, Makassar

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#### ABSTRACT -

The concentration of development in urban areas, on the one hand, increases employment in the non-agricultural sector, but also has a negative impact that is less profitable. In the coastal area of Makassar City, housing development, tourism and business, have changed coastal land use rapidly in the last two decades. Uncontrolled land use can threaten coastal areas and change the sustainability of coastal areas. This study discusses the development of predictions of land use change in 2034 using the Celular Automata Markov (CA-Markov) method. The research location of the Tanjung Merdeka coastal area is near the city of Makassar with a research area of 433.14 hectares. The main data sources are downloaded on the Landsat Google Earth satellite imagery map for 2004-2019. By using ArcMap 10.3 and Idris Selva 17.0 the predictive analysis of land change can work well. The results of this study during the period 2004-2019 that land use changed significantly in the Tanjung Bunga area, Tanjung Merdeka Village. Previously built land was only 87.17 Ha (20.13%), which has doubled to 191.26 Ha (44.16%) in 2019. The prediction of land use for 2034 shows that the largest change in constructed land is 262.39 Ha. (60.58%); This means that the increase in built-up land has the largest rate of change compared to other land. The results of the research on vacant land, agriculture, ponds, water bodies and the sea are reduced. To compare the land use between the 2015-2034 RTRW spatial pattern map and the CA-Markov land use prediction map, it was done by comparing the land use of the two.

Keywords- land use, coastal land use, predicted land use 2034, cellular automata Markov.

#### 1. Introduction

Population is used as an indicator of urban growth [1]. The rapid growth of urban areas is indicated by an increase in population. The population concentration of cities in the world is predicted to reach 2.5 million in 2020, nearly 65 percent of which are along the coast (Agenda 21, 1992 referred to in Vallega) [2]. As a case in point, Australia has experienced significant urbanization growth, with more than 86 percent of the population living on the east coast to the south coast, including the cities of Sydney, Brisbane, Melbourne and Perth [3].

In Indonesia, there are 516 mainstay cities with 216 cities of which are waterfront cities that are on the edge of the coast, rivers or lakes [4]. Coastal cities in Indonesia have historically been a starting point for the growth of a city, and have also functioned as a gateway for urban activity, both for economic, social and cultural activities oriented to the sea [5]. Today's coastal areas play an important role in urban development.

The population of South Sulawesi in 2018 reached 8.77 million people. Makassar City is an area that has the largest population in South Sulawesi. The population is 1.5 million people [6]. Of course this is very influential on land in Makassar City.

The very rapid increase in population accompanied by an increase in the capita income

of the community has resulted in an increasing need for land. However, due to limited land supply, land use change occurred. General problems are caused by the growing population, geographical conditions and topography of the region as well as the national and provincial development strategies, so land changes occur rapidly every year, especially in the hinterland and coastal areas of Makassar city. This fact is in line with the idea that land use change dynamics are strongly influenced by driving forces such as population growth, economic growth and also physical factors such as topography, soil type and climate [7].

Changes in land use result in reduced vegetation of plants / plants that function as oxygen producers, absorb carbon dioxide, resulting in an increase in air temperature in cities, this results in climate change. Green open space which is a habitat for animals and plants is decreasing resulting in death animals and plants due to a break in the food chain, this is caused by the development of residential land which is also a business land. The causes of change in use are resource scarcity; changes in market opportunities; outside policy intervention; loss of adaptive capacity and increased vulnerability; changes in social organization in accessing resources and in behavior [8].

Land use change analysis is basically an analysis of the relationship between people and land to answer the questions of why, when, how and where land use change occurs [9]. The purpose of land use change analysis is in the form of: description or explanation, explanation (explanation), prediction, impact assessment (impact study), prescription and evaluation [10]. The conversion of land functions as an act of changing land use that should have been agricultural into non-agricultural is due to the increasing need for land and human wants. Land use is a relationship between human activities in a plot of land [11]. Land use can be grouped into 2 (two) major groups, namely agricultural land use and non-agricultural land use. The increase continues to grow to spur economic growth. [8] stated that there are six factors that trigger land use change. These factors are changes in natural conditions, economic and technological factors, demographic factors, institutional factors. cultural factors and globalization factors. The process of land use change is generally irreversible, meaning when a land has changed its function, it is difficult to change back to its original function whenever it is. Rice fields that are converted into various urban activities are unlikely to be returned to rice fields. Likewise, degraded forests require great efforts to be revegetated [12].

Changes in land use can be triggered by one of the factors that have been mentioned or a combination of several factors which are then interrelated. Building a land use change model is carried out using spatial analysis with the help of remote sensing. [11] states that remote sensing is a science or art to obtain information about objects, areas or symptoms, by analyzing data obtained using tools, without making direct contact with the object, area or symptom to be studied. From the definition that has been described, it can be concluded that remote sensing is the science and art of sensing or analyzing the earth's surface from a distance, where the recording is done in the air or in space using tools (sensors) and vehicles. Remote sensing data can be digital data or numeric data or visual data. Image data is in the form of images that are similar to the original form or at least in the form of planimetric images, while non-image data are generally in the form of lines or graphs [13]. Information-poor systems indicate large entropy conditions that are difficult to manage. The higher the entropy of a system, the more

irregular the system will be because the system becomes more complex, complex, difficult to predict with certainty. The term entropy was first used in information theory proposed in 1948 by Claude Shannon at Bell's laboratory. Then this theory is well clarified in the book Elements of Information Theory by [14]. Information theory uses entropy terminology as a measure of how much information is encoded in data.

Karsidi further argued that the game principle of the Game of Life is a cell-based spatial model where changes depend on the surrounding cell or the closest parcel. A cell or parcel will remain alive if 3 or more of the surrounding cells are living cells. Conversely, the cell will die if 3 or more of the closest cells die. This principle then underlies the principles of the Cellular Automata (CA) model [15].

The CA model is a computational method for predicting changes in dynamic systems that depend on simple rules and develop only according to these rules over time. This method was first introduced by Ulam and von Neumann in 1948 to investigate the behavior of complex systems extensively in biological processes such as multiplying [16].

#### 2. Method of Study

#### A. Area of Study

The location of the research was carried out in Makassar City which is the capital of South Sulawesi Province and is the fourth largest city in Indonesia which has an area of 175.79 km with a line length of 52.8 km which consists of 36.1 km of coastline and island coastlines. islands and gusung along 16.7 km. Makassar City has 14 Districts and consists of 143 villages.



Figure 1. Administrative Map of Makassar City

The location of this research was conducted in the area of Tanjung Bunga, Tanjung

Merdeka, Tamalate Distric, Makassar City. The area is approximately 443 Ha or 3.37Km<sup>2</sup> and consists of 31 RT and 8 RW with a population of 11,414 people consisting of 5,665 men and 5,749 women. Geographical location of Tanjung Merdeka Village 5 ° 11'18.1 "S -119 ° 23'33.6" E, the research was conducted from January to June 2020.



Figure 2. Map of the Research Area

# B. Source of Data

Primary spatial data is in the form of Landsat Earth Images for the City of Makassar for 2004, 2009, 2014 from Google Earth and 2019 Land Use Maps for 2019. Secondary data is population and population data from BPS, geographic data from Bappeda and field surveys. *C. Analysis Tools* 

This study uses a combination of ArcMap10.3 and Idris Selva 17.0 applications as an instrument for analyzing Celular Automata Markov and Global Mapper for map coordinate ratification.

# D. Research Methods

The image map of Makassar City in 2004, 2009, 2014 and 2019 obtained on November 6, 2020 with an eye height of less than 1000 meters is then cut according to the research area. Then the map is completed by placing its graphic coordinates, where the coordinates used are UTM coordinates. Geographical Coordinate, the axes used are longitude (BB and BT) perpendicular to the equator and latitude (LU and LS) parallel to the equator. Geographic coordinate express in degree, minute, and second.

Grid coordinates or UTM (Universal Transverse Mercator), these coordinates represent the position of a point in a measure of the distance of each reference point. The registration is done using the Global Mapper 11 program. Then perform Image Interpretation, digitizing the map with the ArcGis application. The stages in data analysis of land use change in the Celular Automata Markov are as follows:

# Crosstab

To find out whether there has been a change in land use and to find out the location of the change, a crosstab is necessary. In this stage, a spatial analysis of changes in land use for 2004 to 2014 was carried out using cross-classification. Idrisi Selva 17.0 provides a module for this purpose, namely "CrossTab" which is selected in the "GIS Analysis  $\rightarrow$  Change / Time Series  $\rightarrow$  CROSSTAB" menu.

• Markov probability

The probability of land use change can be done with the Markov Chain method. The result of the Markov Chain process is a transition matrix of opportunities for land use change based on observations for a certain time. Markov Chain analyzed two raster data on land use change at different times. Markov Chain can be accessed in Idrisi Selva 17.0 software by selecting the menu "GIS Analysis  $\rightarrow$  Change / Time Series  $\rightarrow$  MARKOV". This research uses raster data of land use change in 2004, 2009. 2014 and 2019, then arranges the Markov module to conduct a probability analysis of land use change transitions for 2009 to 2014. From the 2009 and 2014 data, an estimate of land use change in 2019 is obtained. from the results of the Markov Chain analysis using the Stochastic module. Stochastic analysis can be accessed through "GIS Analysis  $\rightarrow$  Change / Time Series  $\rightarrow$ STCHOICE" using conditional probability raster data from Markov analysis as input.

• Model Validation

In this stage, the model validation is carried out using the kappa model validation method. In the validation stage, what is entered is the raster data for land use change in 2019 from the markov chain process and raster data for land use change in 2019 from the results of digitizing images. The results of the validation procedure are used to see the feasibility of an analysis operation. If the value of the Model Validation result is <70%, a recalibration will be carried out in the process of making map data on land use change in 2004, 2009, 2014 and 2019 from starting geometric corrections, radiometric corrections, area training to multispectral classification. But if the validation result value is sufficient or > 70%the land use change model will be processed to produce land use change in 2034.

• Creating Suitability raster data in the MCE (Multi Criteria Evaluation) Module

In the MCE (Multi Criteria Evaluation) module, a transition suitability image collection is generated by entering the raster data on population and accessibility as driving factors. Push factors are used to adjust the suitability map for any land use change. The first thing that is done in the MCE module is to reclassify all driving factors, where for all criteria the appropriate factors are given a value of 1 while those that are not suitable are given a value of 0. After that, standardize a number of factors. All drivers must be in byte binary format and use the same scale system. All raster data types for each factor that are still in real or interger raster format are converted into byte type raster format by selecting the "Reformat  $\rightarrow$  CONVERT" menu. Next, measure the distance of each factor using the menu "GIS Analysis → Distance Operators  $\rightarrow$  DISTANCE". To create a scale value of 0 255, go to the "Image Processing  $\rightarrow$ Enhancement  $\rightarrow$  STRETCH" menu. After all driving factors have been processed, the next step taken is weighting it to see the relative importance of each factor. Each factor must have a weighted value. This weighting is done in "WEIGHT - AHP weight derivation" by selecting the "Modeling  $\rightarrow$  Model Deployment Tools  $\rightarrow$ Weight" menu. The results of this weighting are used as parameters to determine the factor weight in the MCE module. After all standard raster data factors have been obtained, the MCE module is run by selecting the "Modeling  $\rightarrow$ Model Deployment Tools  $\rightarrow$  MCE" menu by entering a number of driving factors, then taking the factor parameters obtained from the AHP weight derivation. The final result of the MCE module is the transition suitability map used in the Cellular Automata Markov module.

 Model Simulation with CA - Markov Chain Model simulation with Cellular Automata-Markov can be accessed on Idrisi Selva 17.0 on the "GIS Analysis → Change / Time Series → CA-MARKOV" menu. This module is run using raster data of land use change in 2004 and 2019 as a basic drawing of land use., then enter the Markov Transition Area File obtained from the results of the Markov probability transition, then enter the Transition suitability image collection built on the MCE module by entering a number of driving factors determining 10 for the 10 year change and 15 for the 15 year change as the number of CA literacy and selecting the type filter 5 X



5 which is a standard filter in Cellular Automata.

#### 3. Result and Discussion

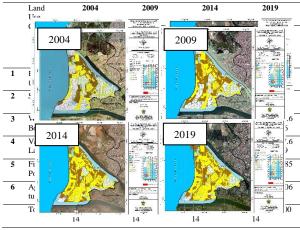
#### A. Land Use Change 2004 to 2019

Before analyzing the dynamics of land use change that occurred in the study area, the researchers first analyzed the Landsat images for 2004, 2009, 2014 and 2019 which were obtained through the streaming process on Google Earth with the help of cache.master and global mapper software. The image is cut according to the research location area and then a visual image interpretation (digitize on screen) is carried out based on the spatial recognition of the object's characteristics in order to homogenize the land use classification data.

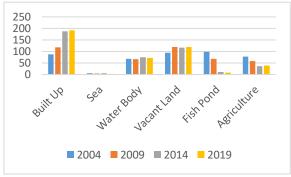
Based on the interpretation of Landsat imagery, it was obtained that the land use classification data in the study area were six classes of land use consisting of built-up areas, empty land, agricultural land, pond land, sea and water bodies with a total area of the research area of 433.14 ha. Land use interpretation and identification from classification can be seen in Figures 4 and 5.

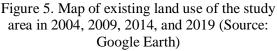


Figure 4. Satellite Image Map of the existing research area in 2004, 2009, 2014, and 2019 (Source: Google Earth)



The following is a map of existing land use :





By using ArcMap 10.3, the interpretation of existing land use data maps for 2004, 2009, 2014 and 2019 can be seen in Figure 5. The classification of land use changes is seen in Table 1.

Table 1. Classification of land use area in 2004-2019 (Source: ArcMap 10.3 analysis) Figure 6. Graph of Land Change from 2004-2019

#### Figure 7.Map of Land Change from 2004-2019 (Source: Google Earth)

Based on the results of the analysis that has been carried out on the map from 2004 to 2019, it can be concluded that changes in land use and its area, where the land class that has the largest increase in area is the built-up land class of 104.09 Ha or 24.03% and is followed by the land class empty with an increase in area of 24.86 ha 5.69%. Whereas the land class that or experienced the largest reduction in area was the pond land class of 91.16 Ha or 21.15%, then the land class that also experienced a decrease in area was the agricultural and marine land classes, respectively 37.94 Ha or 8.74. % and 3.46 Ha or 0.8%. The total area change for all land classes from 2004 to 2019 is 265.56 Ha or 61.37% of the total research area.

From the results of the land use survey from 2004 to 2019, it can be seen that the pond area has experienced a very large decrease due to the reclamation process that occurs from year to year at the research location, which causes the area of empty land to increase. In addition to the increasing area of vacant land, the area of built land has also increased, be it settlements, tall buildings or buildings for commercial functions. This is due to the increasing density of the population in Makassar City, which causes land demand to also increase.

#### B. Validation of the 2018 Land Use Map

Validation process is carried out to test the performance of Markov modeling in GIS software in predicting land use in 2034. Validation is needed to find out how accurate the data predictions made can be. The level of data validity is not less than 80% (Kstandard = 0.80). Data validation was carried out by taking the preceding seven years of time, namely by using land use maps for 2004 and 2011. With the input of land use in 2004 and 2011, prediction of land use was made in the existing year, namely land use in 2011. This aims to obtain a predictive map. which will be used in data validation analysis. A comparison of the existing land use maps in 2004 and 2011 can be seen in Figure 8.And the comparison of the areas is in table 2.

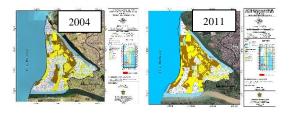


Figure 8. Comparison of existing land uses 2004-2011 (ArcMap 2020)

No	Land Use Class	Area (Ha)		
		2004	2011	
	Built Up	87,17	126,10	
;	Sea	6,02	4,27	
;	Water Body	68,11	65,89	
	Vacant Land	95,07	115,90	
	Fish Pond	99,17	62,61	
	Agriculture	77,17	58,37	
	Total	433,14	433,14	

Table 2. Comparison of existing land uses 2004-

#### (Source: ArcMap 2020 analysis)

The process of validating land use is carried out by overlaying the existing 2019 land use map with the 2019 land use map predicted by the Markov modeling. The overlay results processed in GIS software show an accuracy value of 0.8000. This accuracy value shows that the land use in 2018 prediction results of the Markov modeling with the existing 2011 land use corresponds to 80.00 both interms of area and spatial distribution. This shows that the results of the data validation of the Markov prediction have a balanced kappa accuracy value, so it can be concluded that the prediction results of land use in 2034 can be said to be very good and acceptable.

Table 3. Comparison of existing land use areas in	
2019 and prediction results	

No Land		Are	a (Ha)	Percentage (%)			
	Use Class	Existing	Prediction	Existing	Prediction		
1	Built Up	191,26	224,66	44,16	51,87		
2	Sea	2,56	9,73	0,59	2,25		
3	Water Body	72,16	64,19	16,66	14,82		
4	Vacant Land	119,93	94,11	27,69	21,73		
5	Fish Pond	8,01	4,93	1,85	1,14		
6	Agriculture	39,23	35,52	9,06	8,20		
	Total	433,14	433,14	100	100		

C. Prediction of Land Use 2034

Prediction of land use change in 2034 is carried out using Markov modeling in GIS software. The prediction results are obtained by multiplying the Markov transition matrix for the period 2004-2019 with the vector (one column matrix) the chance of changes in each land use class in 2019. The Markov transition matrix is obtained from the calculation of the land use change matrix using the Markov equation (Table). The markov transition matrix for 2004-2019 and the probability vector for changes in each land use class in 2019 can be seen in table 4.

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Figure 9. Map Accuracy Value for 2019 Prediction Results. Kappa = 0.80

Table 4. Markov Transition Matrix for 2004-2019

	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5	Cl.6	Total	
Class 1	<mark>64,79</mark>	1,32	0	0	0	3,01	69,14	
Class 2	0,53	<mark>47,53</mark>	2.04	0,81	0	28,27	79,18	

Class 3	0	1,97	<mark>0,09</mark>	0	0	0	2,06
Class 4	1,90	24,44	0	34,94	0	15,93	77,20
Class 5	4,94	38,72	3,61	2,71	<mark>8,01</mark>	41,29	99,29
Class 6	0	5,31	0	0,77	0	100,2	106,28
Total	72,17	119,29	5,74	39,23	8,01	188,7	433,14

Ket:

- Class 1 = Water Body
- Class 2 = Vacant Land
- Class 3 = Sea
- Class 4 = Agriculture
- Class 5 = Fish Pond
- Class 6 = Built Up

# Figure 10. Markov Probability Transition Matrix (Source: Analysis Results, 2020)

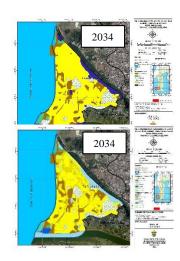


Figure 11. Comparison of predictive maps of land
use in 2034 and land use change in 2034 (Source:
2020 analysis results)

Table 5.	Comparison	of land	use in	2004,	2019
	an	d 2034			

No	Land Use Class	Area (Ha)						
		2004	2019	2034				
1	Built Up	87,17	191,26	262,39				
2	Sea	6,02	2,56	9,31				
3	Water Body	68,11	72,16	55,64				
4	Vacant Land	95,07	119,93	64,69				
5	Fish Pond	99,17	8,01	4,92				

6	Agriculture	77,17	39,23	36,19
	Total	433,14	433,14	433,14

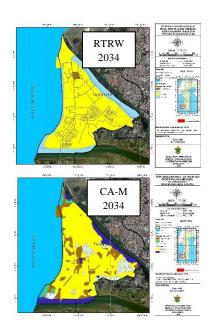
# (Source: Analysis Results, 2020)

The prediction results of land use in 2034 show that each class has the opportunity to experience an increase and decrease in area. In general, the prediction results of the land use of the Tanjung Merdeka Research Area, which is located on the coast of Makassar City in 2034, shows that land use classes that are natural in nature have decreased significantly, this is inversely proportional to land use classes that are influenced by human activity which has increased. wide such as built up land and empty land. The built-up land class is increasing due to the settlement development

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Class	3	:	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000		
Class	4	5	0.0300	0.3325	0.0000	0.3464	0.0000	0.2911		
Class	5	1	0.0482	0.3211	0.0722	0.0241	0.0421	0.4923		
Class	6	1	0.0000	0.1552	0.0000	0.0305	0.0000	0.8144		
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process that has and will always occur in the research area, the built-up land replaces the function of empty land, ponds, water bodies and the sea.

D. Comparison of the 2034 RTRW Spatial Pattern Map with the CA-Markov 2034 Prediction Map



# Figure 12. Comparison of the 2034 RTRW map with the CA-Markov 2034 prediction (Source: 2020 analysis results)

The results of the comparison between the 2015-2034 RTRW spatial pattern map for Makassar City and the results of the CA-Markov analysis can be seen in Table 4.27. The results show the difference in land use area between the RTRW Map and the Map Results of the CA-Markov analysis. The largest area difference occurred in the built-up land class, namely 76.59 hectares or 17.68% of the total area of the study area with the area in the RTRW space pattern greater than the area of the CA-Markov analysis, for sea class the difference in area was 8.13. Ha or 1.88% of the total area of the study area, where the area of the RTRW spatial pattern is greater than the area of the CA-Markov results. For agricultural land, the difference is 36.19 Ha or 8.36% with the resulting area of the RTRW spatial pattern smaller than the CA-Markov result. Meanwhile, the difference in area in the fish pond land class is 4.92 Ha or 1.14%, with the resulting area of the RTRW space pattern being smaller than the CA-Markov result. The wide difference occurs in the vacant land class, which is 58.66 Ha or 13.54%, with the resulting area of the RTRW space pattern smaller than the area of the CA-Markov result, while the area difference occurs in the water body land class, which is 15.05 Ha or 3.47% of the total area of the study area, where the area of the spatial pattern of the RTRW is greater than the area of the CA-Markov result. So the total area difference between the results of the spatial pattern of the RTRW and the results of the CA-Markov analysis is 199.54 Ha, while the total percentage difference in area is

46.07% so that the corresponding area is 233.6 Ha or 53.93%. So it can be concluded that there is a significant difference between the 2015-2034 RTRW spatial pattern map of Makassar City and the predictive map of the CA-Markov analysis results.

#### E. Conclusion

The research area which is located on the coast of Makassar City, namely the Tanjung Merdeka Coast, in the period 2004-2019 experienced changes in land use. Changes in land use from 2004 to 2019 which experienced

an increase in which the land class that had the largest increase in area was the built-up land class of 104.09 Ha or 24.03% and followed by the vacant land class with an increase in area of 24.86 Ha or 5, 69%. Whereas the land class that experienced the largest reduction in area was the Fish pond land class of 91.16 Ha or 21.15%, then the land class that also experienced a decrease in area was the agricultural and sea classes, respectively 37.94 Ha or 8.74. % and 3.46 Ha or 0.8%. The total area change for all land classes from 2004 to 2019 is 265.56 Ha or 61.37% of the total research area.

Cellular Automata-Markov modeling can be used for the research area under study by the author, this is indicated by the accuracy value obtained based on the validation process which shows an accuracy value of 0.8000 or 80%. This shows that the results of the data validation of the Markov prediction have a balanced kappa accuracy value, so it can be concluded that the prediction results of land use in 2034 can be said to be very good and acceptable.

Based on the analysis using the CA-M modeling from 2004 to 2019, it produces predictions for the year 2034 with the extent of land use change. The area of land use that has increased is built land and sea with an area of 262.39 Ha and 9.31 Ha, respectively. Meanwhile, the area of land use change that has decreased is vacant land, fish pond land, agriculture and water bodies, namely 64.69 Ha, 4.92 Ha, 36.19 Ha and 55.64 Ha, respectively.

The results of the comparison between the 2015-2034 RTRW spatial pattern map of Makassar City and the results of the CA-Markov analysis show the difference in land use area between the RTRW Map and the Map of the CA-Markov analysis results. The largest area difference occurred in the built-up land class, namely 76.59 Ha, with an area in the spatial pattern of the RTRW larger than the area of the CA-Markov analysis and the smallest area difference in fish pond land with a difference of 4.92 Ha. So the total area difference between the results of the spatial pattern of the RTRW and the results of the CA-Markov analysis is 199.54 Ha, while the total percentage difference in area is 46.07% so that the corresponding area is 233.6 Ha or 53.93%. So it can be concluded that there is a significant difference between the 2015-2034 RTRW spatial pattern map of Makassar City and the predictive map of the CA-Markov analysis results.

The results of this research in the future need to control the development of the coastal city of Makassar, in order to protect coastal resources. In addition, the government also needs to emphasize not to change physically, to maintain coastal and river boundaries and to maintain natural resource conservation.

## F. References

- [1] Cheng, J and Masser, I., 2003. Urban growth pattern modeling: a case study of Wuhan city, PR China," Landscape and urban planning, vol. 62 (4); 199-217
- [2] Vallega, A. 2005. From Rio to Johannesburg: The role of coastal GIS," Ocean & Coastal Management, vol. 48 (7-8); 588-618.
- [3] Norman B., 2011. From Integrated Coastal Management (ICM) to Sustainable Coastal Planning, Spatial Planning Bulletin 4:19, 2
- [4] Suprijanto. 2007. Specific characteristics, problems & potentials for the development of coastal cities in Indonesia, "Proceedings of a Study on Reciprocal Impacts between Urban Development & Housing in Indonesia and the Global Environment. Center for Research and Development of Settlements
- [5] Laras, B. K., Nurjaya, I .W and Budiharsono, S. 2011. Dimensions of Sustainable Management of a Coastal City (Semarang City Case Study)
- [6] BPS . 2019. Makassar City in Numbers.
- [7] Skole D and Tucker C. 1993. Tropical deforestation and habitat fragmentation in the Amazon: satellite data from 1978 to 1988," Science, vol. 260, (5116) ; 1905-1910
- [8] Lambin E. F, Geist, H. J and Lepers E, 2003. Dynamics of land-use and land-cover change in tropical regions," Annual review of environment and resources, 28 (1); 205-241,
- [9] Sukamto, S and Buchori, I. 2018. Projection Model of Land Use Change in Main Road Corridor Area Based on Cellular Automata and GIS, "Journal of Regional and City Development," vol. 14, no. 4, pp. 307-322, 2018.
- [10] Briassoulis, H. 2000. Analysis of land use change: theoretical and modeling approaches, the web book of regional Science, Regional research institute, West Virginia University, USA.
- [11] Lillesand, T., Kiefer, R. W. and Chipman, J. 1979. Remote sensing and image interpretation. John Wiley & Sons. New York.

- Paharuddin, 2012. Geospatial Simulation Based on Cellular Automata Changes in Land Use for Sedimentation Prediction, "p. Makassar. Hasanuddin University Postgraduate Program
- [13] Sutanto, P. 1986. Remote sensing, Volume I," pp. Faculty of Geography, Gadjah Mada University Press.
- [14] Cover T.M and Thomas J.A. 1991. The Gaussian Channel," Elements of Information Theory, pp. 261-299,
- [15] Karsidi, A. 2004. "Analysis of Changes in Dynamic Land Use with Geographic Information Systems Based on Markov Cellular Automata, "No. In Book: Arranging Integrated Marine Spaces, First Printing, Pradnya Paramita, p. Jakarta.
- [16] Von Neumann and Burks, A.W, 1966. Theory of self-reproducing automata, IEEE Transactions on Neural Networks, vol. 5, no. 1, pp. 3-14, 1966.