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Abstract Changes in land use in the Alo Pohu watershed have concerned the government in preventing the siltation of Limboto Lake, along with floods and slides. On that ground, the present study was conducted to analyze the spatial prediction of land-use changes in the Alo Pohu watershed, Gorontalo Regency, Indonesia, in the 2000-2017 period for the 2030 land use prediction. The method and analysis of spatial data to predict land-use changes involved the Powersim Version 10 and Idrisi apps. Further, the data consisted of two maps, i.e., the Indonesian topographical map and land use map. The Markov chain model applied to predict the land in the site area for the year of 2030 has an excellent suitability/agreement. Based on the validation test with the Kappa Index of Agreement, the value of K-standard gets 0.8 from 0-1 scale. Another validation using Google Earth is also employed, in which it shows an 83% of suitability level. Confirmed by the integration of the dynamic system simulation model, the map of land use resulting from the modeling is therefore scientifically acceptable. The study concluded that land conversion in the Alo Pohu watershed in Gorontalo Province has occurred.

Keywords Alo Pohu Watershed, Cellular Automata, Land Use, Markov Chain, Spatial Prediction

1. Introduction

Land-use changes in the Alo Pohu watershed are a crucial problem for the government to pay close attention to. Such environmental changes will impact environmental aspects, including hydrological function and land degradation [1-3]. Changes in land in this watershed are indicated by changes in vegetation cover for 20 years. The changes also affect the water quality and siltation of Limboto Lake [4,5]. For this reason, predicting the changes in land use is essential to support future land use planning in the Alo Pohu watershed area.

Some studies have been conducted on the land use around the research site. The land use condition in the Limboto watershed serves as an input [6,7]. Also, changes in land use in the Biyonga watershed went through spatial and temporal analysis for the 2000-2020 period. However, their research is only in the current condition and effect of land use and has not considered the changes in future land use in the site area.

Understanding the current and future land use changes is vital for land use planning, especially in the research area [8,9]. One of the techniques to detect and predict the changes in land use is the combination of Cellular Automata and Markov chain [10]. The technique is able to help understand the land-use changes and spatially project the future land use distribution. This study applied the combination of Cellular Automata and Markov chain (MC-CA) to detect changes and simulate future land use conditions.

Drawing upon the above discussion, this research aimed to analyze the changes in land use in the Alo Pohu watershed for the 2000-2017 period. The changes detection and spatial prediction relied on the combination of MC-CA in land use data. The transition probability matrix for each type of land use was generated from the calculation of the Markov chain. Meanwhile, the prediction of land use in 2030 was obtained from Cellular Automata. The simulation output was further compared to the projection from the dynamic system. Such a comparison is intended to comprehend better the changes pattern and result evaluation from the MC-CA simulation.

2. Materials and Methods

2.1. Site

The research area is the Alo Pohu watershed, administratively located in Gorontalo Regency, Gorontalo Province, Indonesia. The watershed has an area of 24,219 Ha at 122° 42' 46”- 122° 54' 33” E and 0° 47' 20.3” - 0° 37' 22.9” N. Administratively, the north part of the site is bordered by Kwandang District, and the east by Limboto Barat District. The west and south parts are bordered by Boliyohuto and Pulubala districts, respectively (Figure 1).

2.2. Geospatial Dataset

The data consisted of two maps, i.e., the Indonesian topographical map and land use map. These data were provided in shapefile (SHP). The 1:50000 scale of the Indonesian topographical map was obtained from the Geospatial Information Agency. Additionally, the land use map of 2000, 2009, and 2017 was from the Forest Area Consolidation Center (Balai Pemantapan Kawasan Hutan - BPKH) for Region XV of Gorontalo. The types of land use in the map comprised forest, dryland farming, shrub, ricefield, and settlement.

2.3. Data Processing

The first stage in data processing was preparing the file used in the application. File preparation started with determining the types of land use, setting the coordinate system, and transforming the format. These stages were carried out using ArcGIS software.

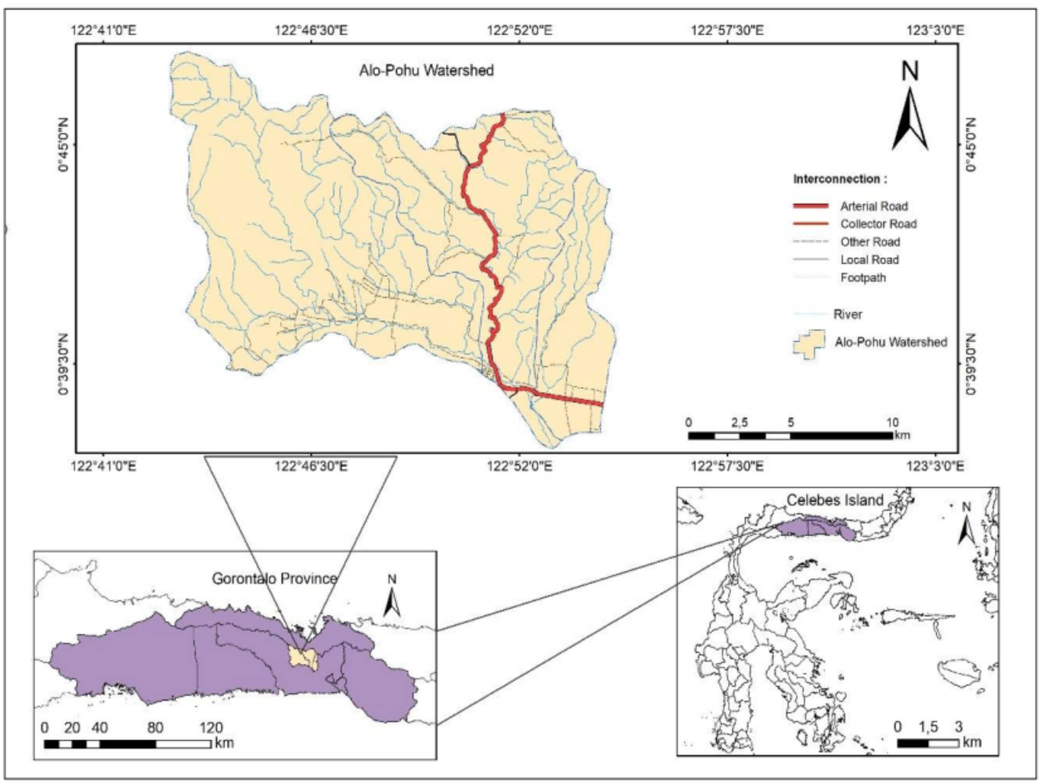


Figure 1. Site map

MC-CA implementation was performed in Idrisi/Terrset software with the Cellular Automata Markov (Markov chain) module. The result of the spatial prediction simulation was integrated with the simulation in the dynamic system to produce data of predicted changes in land use until 2030. The preliminary data from BPKH, i.e., land use in 2000, 2009, and 2017, served as the prediction reference. The prediction result simulated using Powersim 10 combined with the dynamic system was then spatialized employing ArcGIS 10.5 in the form of a map of land use changes prediction in 2030 as the year of projection target.

Moreover, the model of land-use changes was displayed in the Causal loop diagram to make it easier into the dynamic system (*FlowRed/Stock Flow*). Causal Loop of Changes in land use of Alo watershed is from 2000 to 2009 and from 2009 to 2017 [8] (Figure 2).

Shown in Figure 3 is the diagram of changes in land use of Alo Pohu watershed in 2000-2009 and 2009-2017.

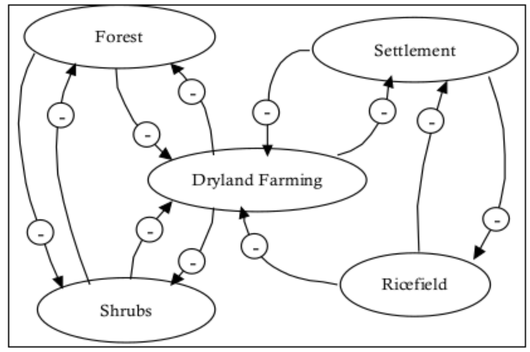


Figure 2. Causal loop of land use from 2000 to 2009 and from 2009 to 2017

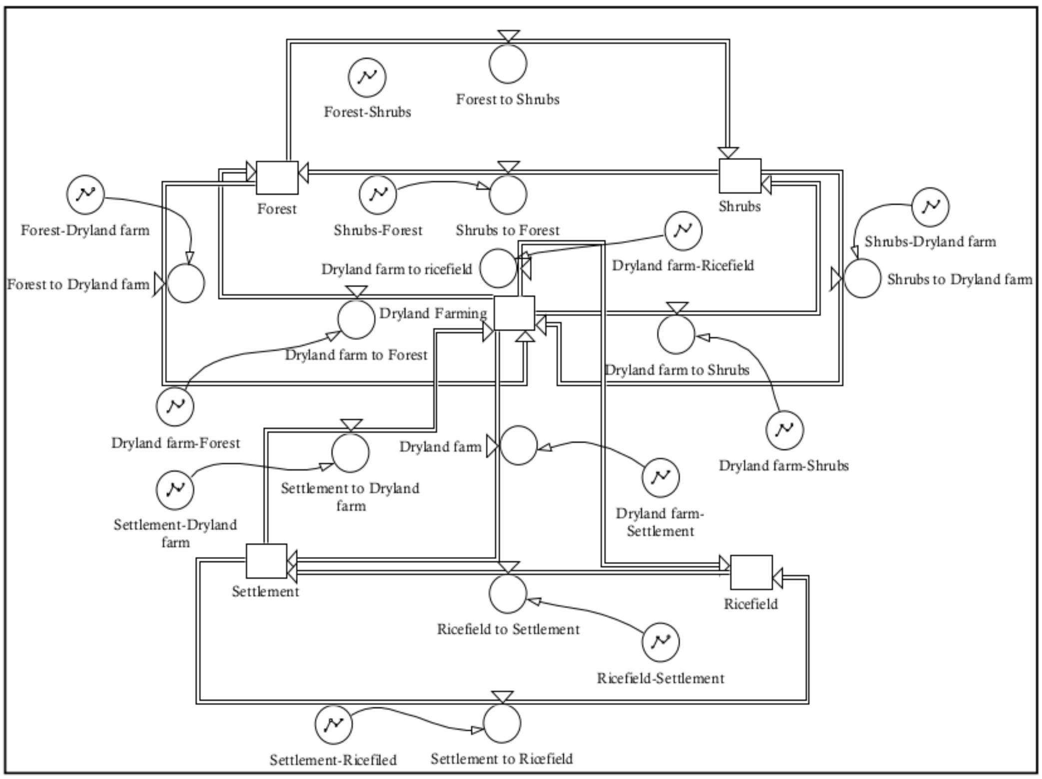


Figure 3. Stock flow diagram of land use changes

2.4. Validation

Validation attempts to determine the suitability of the model compared to actual data. The validation in this study was performed in each developed model. The first one was the dynamic system created on Powersim 10 software by comparing the magnitude of the error and its characteristics by relying on: 1) Absolute Mean Error (AME) is the deviation (difference) between the mean of simulation results towards the actual value; 2) Absolute Variation Error (AVE) is a deviation of simulation variance towards the actual value. The acceptable deviation limit ranges from 1 to 10%. Below is the validation formula of AME and AVE models (1) and (2).

$$AME = [(S_i - A_i)/A_i] \quad (1)$$

Description:

$$S_i = S_i \times N$$

S = simulation value

$$A_i = A_i \times N$$

A = actual value

N = observation time interval

$$AVE = [(S_s - S_a)/S_a] \quad (2)$$

Ss = ((Si – Si) 2 N) = simulation value deviation

Sa = ((Ai – Ai) 2 N) = actual value deviation

On the other hand, the model validation on Idrisi software was done by comparing the land use from simulation in 2017 and the actual land use in the same year. The comparison was based on the automatic validation value applying Idrisi/Terrset in GIS Analysis => Change/Time series => Validate. Manual validation used Microsoft Excel 2010 that was based on the land-use change matrix obtained from the output of ArcGIS Software. The validation test was measured by the Kappa Index of Agreement (Kappa Value) [11], as follows (3).

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + x_{i+1})}{N^2 - \sum_{i=1}^{r}(x_i + x_{i+1})} \quad (3)$$

Description:

K: Kappa value

x_{ii}: the area of the land number X use type from the simulation result, which corresponds to the area of the land number X use type from the observation result

x_i: the area of the land number X use type from the simulation result

x_{i+1}: the area of the land number X use type from the observation result

N: total area of all types of land use

r: the number of types of land use

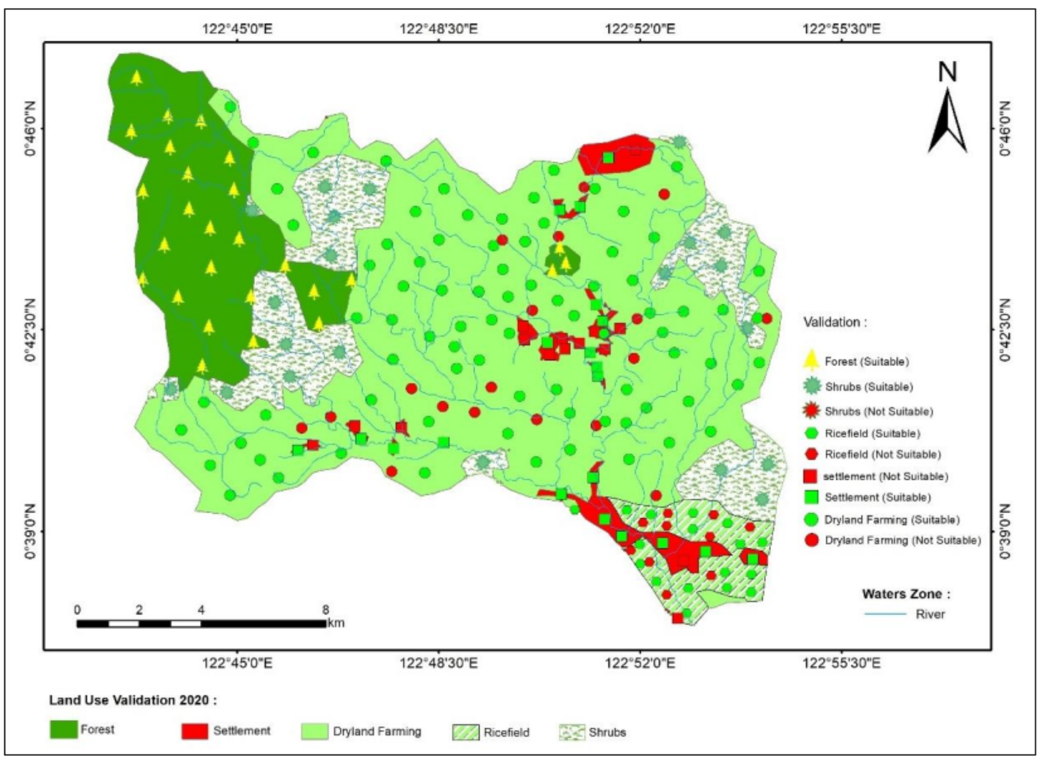


Figure 4. Validation dot of simulation result map of 2020

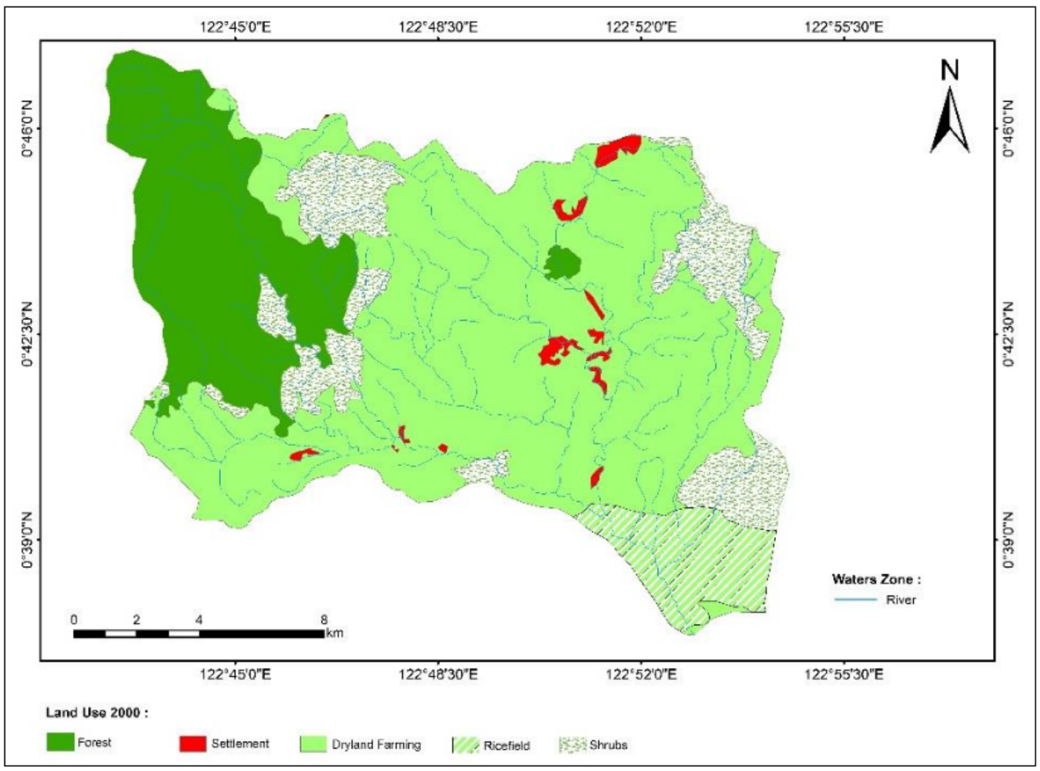
The total validity in Idrisi Selva was employed to calculate the Kappa value. The Kappa value determines whether or not the simulation result is suitable for the area and spatial distribution. Besides, the validation process was also carried out by comparing land use in 2020 from the projection result to the Google Earth image in 2021 to support the developed model accuracy (Figure 4). Once deemed suitable, modeling for land use prediction in 2030 can be executed. The coefficient of Kappa ranges from 0 to 1. The acceptable accuracy of mapping the land classification/cover is 85% or 0.85 [11].

3. Results and Discussion

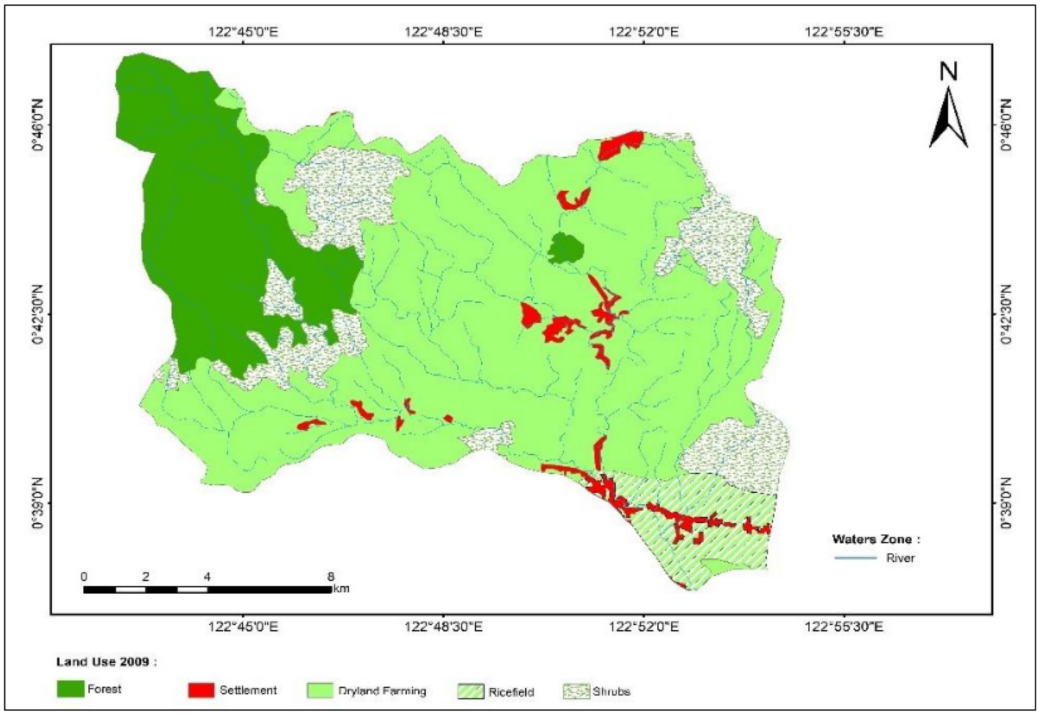
3.1. Land Use

The use of land in 2000 was dominated by dryland farming (59.36%) with 14375.6 Ha, followed by forest (20.57%) with 4981.5 Ha, shrub (12.82%) with 3104.3 Ha, ricefield (6.09%) with 1475.3 Ha, and settlement (1.17%) with 282.5 Ha. Meanwhile, the land use in 2009 was dominated by dryland farming (60.07%) with 14547.35 Ha, forest (18.71%) with 4,530.89 Ha, shrub (13.38%) with 3,239.63 Ha, ricefield (5.34%) with 1,294.37 Ha, and settlement (2.51%) with 607.05 Ha. In 2017, dryland farming (57.94%) still primarily dominated land use with an area of 14032.2 Ha. It was followed by shrub (16.45%) with 3983.70 Ha, forest (15.91%) with 3852 Ha, ricefield (7.04%) with 1706 Ha. Settlement (2.66%) was in the last as the previous periods with an area of 643.20 Ha.

Accordingly, the land use in 2000, 2009, and 2017 was dominated by dryland farming because the local community utilizes the land of Alo Pohu watershed for growing corn and spices. Fertile soil around this watershed influences them to use the land. Such fertility is affected by adequate rainfall [12] (Figure 5).



(A)



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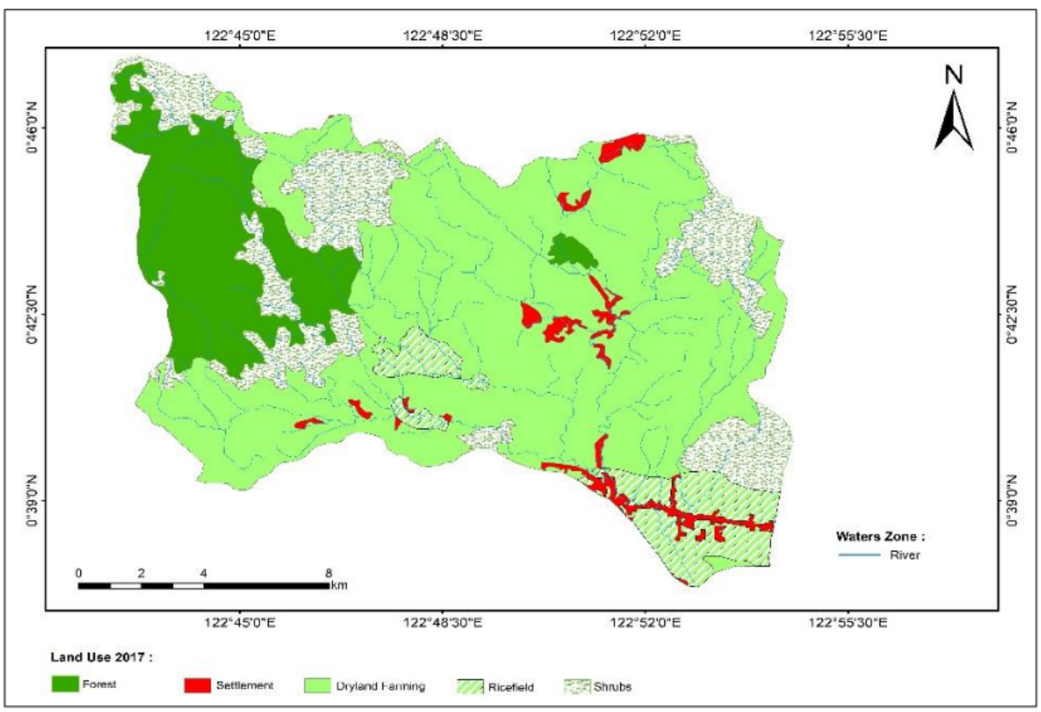

(C)

Figure 5. Map of land use in Alo Pohu Watershed in Gorontalo Province in (A) 2000; (B) 2009; (C) 2017

3.2. Changes in Land Use in 2000-2009

Changes in land use refer to the changing form of land use by the community or other parties. Changes in land use aim to intensify the social and economic values of the land. The analysis result indicates changes in the land use in the Alo Pohu watershed. From 2000 to 2009, the forest turned into dryland farming with an area of 64.9 Ha and into shrub with 386.1 Ha. Further, the settlement area also increased due to the conversion of dryland farming to settlement with an area of 131.3 Ha and ricefield to settlement with 193.3 Ha. The area of dryland farming converted to ricefield was 12.3 Ha. Additionally, shrub also experienced a reduction in area of 250.5 Ha becoming dryland farming. Provided in Table 1 is the matrix of land-use changes from 2000 to 2009.

In Table 1, the land use from 2000 to 2009 shows the probability of land-use changes in a short period (nine years difference) with approximately 1% to 53.5% of changes. The smallest and largest probability of changes occurs in dryland farming with an area of 170.5 Ha and forest with 451 Ha, respectively.

3.3. Changes in Land Use in 2009-2017

The changes in land use take place in every land use (the area) by the community or other parties to intensify social and economic values of the land. The land use from 2009 to 2017 changed quite significantly, compared to the changes in 2000 to 2009. The data of land-use changes in the Alo Pohu watershed were obtained from the matrix intersection process on ArcGIS 10.5 Software. It provides information on the variation of changes in land use from one type of land use and its changing area.

The use of land in Alo Pohu watershed is classified into five land uses: forest, settlement, dryland farming, ricefield, and shrub. Changes in forest from 2009 to 2017 experienced a reduction in area becoming shrub with an area of 703.1 Ha and increased by 24.3 Ha from dryland farming and 0.7 Ha from shrub. Settlement changed into dryland farming with an area of 3.7 Ha and ricefield with 1.8 Ha. Besides, the area of the settlement also increased by 41.7 Ha from the ricefield area. Dryland farming turned into forest with an area of 24.3 Ha, ricefield with 452.3 Ha, and shrub with 42.2 Ha. Ricefield was converted into a settlement with an area of 41.7 Ha and increased by 452.3 Ha from dryland farming and 1.8 Ha from settlement area. The area of shrub increased by 703.2 Ha from forest area and 42.2 Ha from dryland farming area. The data resulting from the processing of the land-use change matrix are presented in Table 2.

Table 1. Changes in land use in 2000-2009

	Land Use	Land Use in 2009 (Ha)					
		Forest	Settlement	Dryland Farming	Ricefield	Shrub	**Grand Total**
Land Use in 2000 (Ha)	Forest	4530.9		64.9		386.1	**4981.9**
	Settlement		282.5				**282.5**
	Dryland Farming		131.3	14232	12.3	1.3	**14376.9**
	Ricefield		193.3		1282		**1475.3**
	Shrub			250.5		2851.9	**3102.4**
	Grand Total	**4530.9**	**607.1**	**14547.4**	**1294.3**	**3239.3**	**24219**

Source: Analysis result of 2021

Table 2. Changes in land use in 2009-2017

	Land Use	Land Use in 2009 (Ha)					
		Forest	Settlement	Dryland Farming	Ricefield	Shrub	**Grand Total**
Land Use in 2000 (Ha)	Forest	3827,7		24,3		0.7	**3852.7**
	Settlement		601,5		41.7		**643.2**
	Dryland Farming		3,7	14030.9		1,4	14036
	Ricefield		1.8	452.3	1251.8		1705.9
	Shrub	703.2		42.2		3235.8	3981.2
	Grand Total	4530.9	607	14549.7	1293.5	3237.9	24219

Source: Analysis result of 2021

In Table 2, the land use from 2009 to 2017 shows the probability of changes in a short period (eight years difference) with approximately 1% to 61% of changes. The smallest and largest probability occurs in settlement with an area of 36.2 Ha and shrub with 743.3 Ha, respectively.

3.4. Prediction of Land Use Changes in 2000-2030

The prediction result of land use is based on the land use in 2000, 2009, and 2017. The time limit used in the prediction of land use is 30 years. Such a scenario is run without applying time intervals or annual simulation. The scenario, instead, uses a five-year interval to find out the variation of prediction results, making the obtained data more valid and acceptable. Graph and table of the simulation result per year are given in Figure 6 and Table 3.

Table 3. Area of land use changes in 2000-2030

Year	Area (Ha)				
	Forest	Settlement	Dryland Farming	Ricefield	Shrub
2000	4981,90	282,50	14376,90	1475,30	3102,40
2001	4931,79	318,57	14395,84	1455,19	3117,61
2002	4881.57	354.64	14414.78	1435.08	3132.82
2003	4831.57	390.71	14433.72	1414.97	3148.03
2004	4781.46	426.78	14452.66	1394.86	3163.24
2005	4731.35	462.85	14471.60	1374.75	3178.45
2006	4681.24	498.92	14490.54	1354.64	3193.66
2007	4631.13	534.99	14509.48	1334.53	3208.87
2008	4581.02	571.06	14.528.42	1314.42	3224.08
2009	4530.91	607.13	14547.36	1294.31	3239.29
2010	4446.14	611.65	14483.14	1345.87	3332.20
2011	4361.37	616.17	14418.92	1397.43	3425.11
2012	4276.60	620.69	14354.70	1448.99	3518.02
2013	4191.83	625.21	14290.48	1500.55	3610.93
2014	4107.06	629.73	14226.26	1552.11	3703.84
2015	4022.29	634.25	14162.04	1603.67	3796.75
2016	3937.52	638.77	14097.82	1655.23	3889.66
2017	3852.75	643.29	14033.60	1706.79	3982.57
2018	3767.98	647.81	13969.38	1758.35	4075.48
2019	3683.21	652.33	13905.16	1809.91	4168.39
2020	3598.44	656.85	13840.94	1861.47	4261.30
2021	3513.67	661.37	13776.72	1913.03	4354.21
2022	3428.90	665.89	13712.50	1964.59	4447.12
2023	3344.13	670.41	13648.28	2016.15	4540.03
2024	3259.36	674.93	13584.06	2067.71	4632.94
2025	3174.59	679.45	13519.84	2119.27	4725.85
2026	3089.82	683.97	13455.62	2170.83	4818.76
2027	3005.05	688.49	13391.40	2222.39	4911.67
2028	2920.51	693.01	13327.18	2273.95	5004.58
2029	2835.51	697.53	13262.96	2325.51	5097.49
2030	2750.74	702.05	13198.74	2377.07	5190.42

Source: Analysis result of 2021

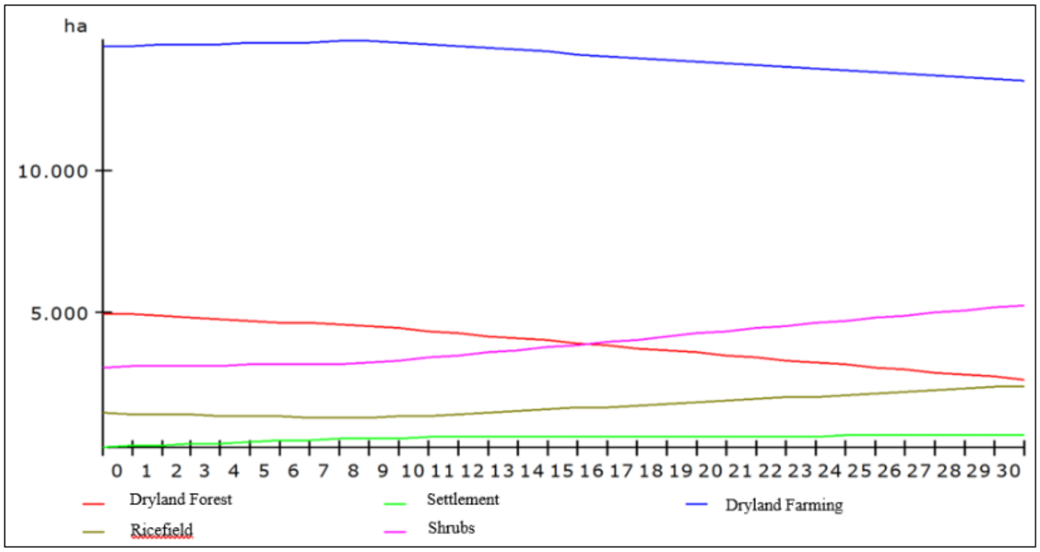

Figure 6. Graph of land use changes in 2000-2030

According to Table 3, it is predicted that the land use until 2030 shows various changes based on the types of land use. The changes in dryland forest in the graph are decreased from year to year which had previously risen and been stable from 2000 to 2010. The decrease or reduction of forest area is started in 2011 until 2030, becoming dryland farming and shrub types of land. However, the settlement area has continued to increase from 2000 to 2030 on account of the high demand for land for the residents. The land used for dryland farming is predicted to get low from 2018 to 2030. In the simulation result, the area of ricefield experiences an increase starting in 2010, and until 2030, the area changes by 50% from the base year of 2000. Shrub that was initially stable from 2000 to 2009 continues to increase in 2010 until 2030 (Figure 6).

Ricefield and dryland farming undergo small changes; on the other hand, settlement, dryland forest, and shrub have changed quite a lot.

3.5. Validation of Land Use Prediction Result

The validity test shows the deviation of the simulation result compared to the actual data. In terms of the area of land use in 2009 (in Absolute Mean Error or AME), the deviation from the actual data reaches an average of 0.00812%. In Absolute Variation Error (AVE), the deviation arrives at an average of 0.8%. Further, in 2017, the deviation from the actual data gets an average of 0.026% (AME) and 3.48% (AVE). The deviation limit based on this testing result is <10%. All in all, the validity test signifies that the developed model is able to simulate the changes in land use that take place.

3.6. Prediction of Land Use in 2030

Before predicting the land use in 2030, an analysis of land use prediction in 2000 and 2009 was carried out to predict the land use in 2017. The projection intends to map the 2017 prediction to be validated with the actual land use map in 2017 that had been created. The validation was executed manually in the Kappa Coefficient method and automatically in the Validate tool. The validation result will produce the Kappa Value obtained from Validate tool on Idrisi selva.

The stage of classification accuracy test was conducted by the accuracy-test method employing the Kappa coefficient method. Kappa coefficient ranges from 0 to 1. In mapping the land classification/cover, the acceptable accuracy value is 85% or 0.85 [11]. Kappa coefficient is based on the assessment consistency by taking into account all aspects, i.e., (producer's accuracy/omission error) and (user's accuracy/commission error) acquired from the error matrix or comparison matrix in Table 4.

The manual calculation method of the Kappa coefficient produces 90% of Kappa accuracy (coefficient of 0.90). Such a percentage proves that the map of land cover resulting from the projection is valid. The validation value depicted in the Kappa value has a maximum level of correspondence between the number of rows and columns of 1.00. The Kappa value of >0.75 indicates an excellent agreement/suitability, the value of = 0.04–0.75 signifies a good agreement/suitability, and the value of <0.40 makes a poor agreement/suitability [11].

The validation results between the 2017 prediction and the 2017 actual data show a Kappa value (K-standard) of 0.9, implying that the scenario result and actual land cover have great suitability in terms of area and spatial distribution of up to 90%. The land use in 2000 and 2019 can be used to project the land use in 2030 with the Markov chain of the 2017 projection. The projection from 2000 to 2030 is based on the land cover/use in 2000, 2009, and 2017 in transition probabilities generated from the Markov process between 2000 and 2009. Map of the 2030 land use of the prediction result is displayed in Figure 7.

Table 4. Comparison matrix

		Land Use in 2017 (Actual)					
		Dryland Forest	Settlement	Dryland Farming	Ricefield	Shrub	**Grand Total**
Land Use in 2017 (Projection)	Dryland Forest	3654.3		9.4		681.9	**4345.6**
	Settlement		566.6	86.4	75.9		**728.9**
	Dryland Farming	32.5	27.4	13840.6	67.7	219	**14187.2**
	Ricefield		49.6	63.8	1563.2	3	**1679.6**
	Shrub	165.2		31.7	1.1	3080.6	**3278.6**
	Grand Total	**3852**	**643.6**	**14031.9**	**1707.9**	**3984.5**	**24219.9**

Source: Analysis result of 2021

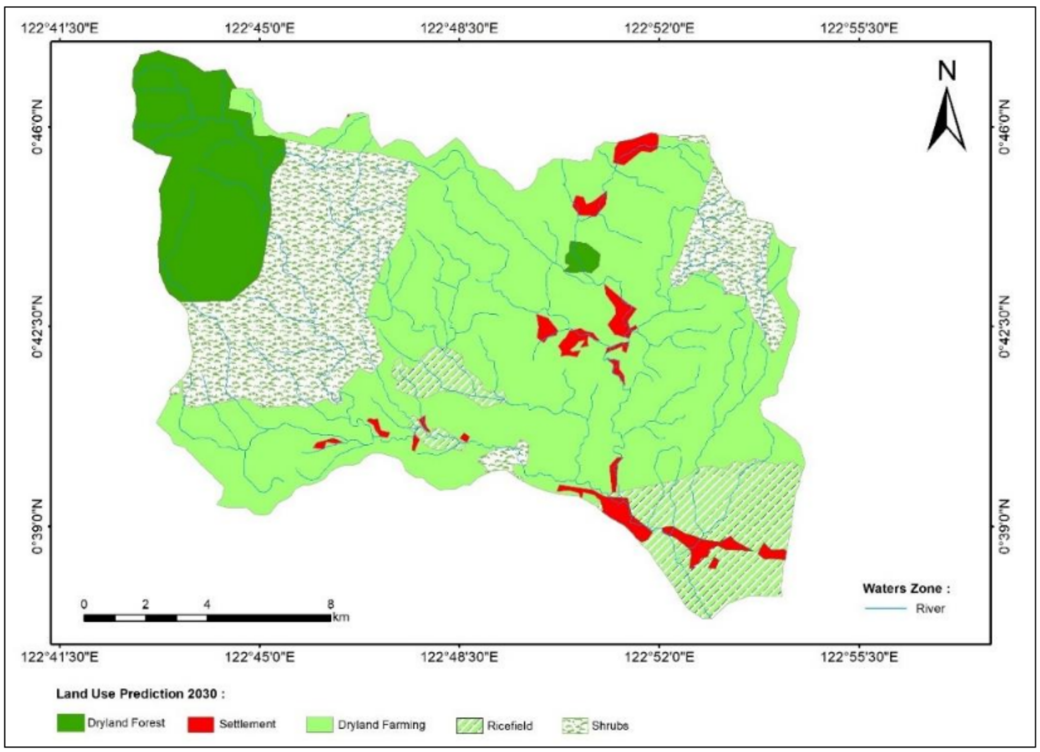

Figure 7. Map of the 2030 prediction land use

Table 5. Changes in land use in 2000-2030

The 2030 Projection	Land Use in 2000 (Ha)						
		Dryland Forest	Settlement	Dryland Farming	Ricefield	Shrub	**Grand Total**
	Dryland Forest	2746		6			**2752**
	Settlement		262	203.5	249		**714.5**
	Dryland Farming	59.3	20	12828.5	0.9	510.5	**13419.2**
	Ricefield		0.2	631.3	1225	437	**2293.5**
	Shrub	2174.3		708.5		2157	**5039.8**
	Grand Total	**4979.6**	**282.2**	**14377.8**	**1474.9**	**3104.5**	**24219**

Source: Analysis result of 2021

After the validation, the first stage is producing the projection of the 2017 land use by simulating the changes in land use in 2000 and 2009 for model accuracy validation. Next, the second stage generates the 2020 land use to be validated with Google Earth image, comparing the changes in land use of the 2020 projection result and the image of the 2020 interpretation result. This is done to confirm data validity used in the land use projection in 2030.

The accuracy test of land use/land cover classification relied on 200 test dots by randomly distributing the dots (Figure 4). Drawing upon the error visual analysis in the present work, the accuracy value measures 83%. The validation result of the Google Earth image also shows that the simulation result is categorized excellent so that it can further analyze land use.

The land use prediction in 2030 is then overlaid with land use in 2000 to see how significant the changes are. Changes in land use in 2000-2030 are presented in Table 5.

Table 5 shows that the 2030 land use prediction has quite rapid changes compared to the 2020 land use. The forest area is the one that experienced a significant decrease. Meanwhile, the land use of settlements and shrub has significantly increased. This indicates that there will be less forest land converted into agricultural/plantation land from the projection. Land management should be well implemented to manage certain land-use types to suppress the decline in land quality.

The concept that underlies the model preparation changes in land use is influenced by land conversion due to land demand. A relatively fixed land availability may lead to land competition in its utilization, consequencing quick land-use changes. Humans have changed land for several types of use, including ricefield converted into built-up land or non-vegetated land. As part of human life in meeting their needs, economic and social factors are the most dominant factors for changing land use. Also, the increase in farmers' incomes is among the determinant factors for land conversion.

The dynamic analysis of change in land use through the simulations model is crucial for predicting land demand and making future land use planning more reasonable [13]. Each model has its advantages and disadvantages. The study's limitation is due to the lack of factors exploration to promote land use change. Based on literature searches for land use change, there are three dominant aspects: physical, social, and economic. The physical variable which can be the driving factors includes road distance, proximity to settlements [14], soil fertility [10], slope, and elevation [15]. Other aspects that also contribute are social and economic. One of the social variables often discussed in many studies related to the effect of land use change is the total population. The rise in the use of settlement area as indicated in the study is undoubtedly connected to meeting human needs. Research by [16] also shows the involvement of population density variables in the spatial dynamics of land use change. According to [17], economic variables such as land prices and wages are the positive driving factor in land use change.

Additionally, these three factors contribute the various intensities of land use transformation. According to the study [8], social and economic factors have a significant influence on the dynamics of land usage. On the other hand, [18] show that physical factors dominate the land use dynamics of change in the watershed environment.

Therefore, land resource management, especially in the Alo Pohu watershed, requires a comprehensive understanding of these driving factors. The model simulations that integrate the driving factors may provide better information about the area's characteristics [19]. In further research, it is necessary to involve some or all of the variables from the aforementioned aspects in the model simulation. The involvement of these variables in the simulation of land use change is likely to produce outputs that can record real problems in the Alo Pohu watershed.

4. Conclusions

This study has found that land conversion in the Alo Pohu watershed in Gorontalo Province has occurred. A significant decrease in area is experienced by forest by 2,226.8 Ha (9.3%) and dryland farming by 956.8 Ha (4%).

In contrast, shrub, ricefield, and settlement significantly increase by 1933.2 Ha (8%), 819.4 Ha (3.4%), and 431 Ha (1.8%), respectively. The Markov chain model applied to predict the land in the site area for the year of 2030 has an excellent suitability/agreement. Based on the validation test with the Kappa Index of Agreement, the value of K-standard gets 0.8 from 0-1 scale. Another validation using Google Earth is also employed, in which it shows an 83% of suitability level. Confirmed by the integration of the dynamic system simulation model, the map of land use resulting from the modeling is therefore scientifically acceptable.

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REFERENCES

[1] Engida TG, Nigussie TA, Aneseyee AB, Barnabas J. Land use/land cover change impact on hydrological process in the upper baro basin, Appl Environ Soil Sci, Vol.2021, No.1-15. https://doi.org/10.1155/2021/6617541

[2] Tisnasuci, Sukmono A, Hadi F. Analisis pengaruh perubahan tutupan lahan daerah aliran sungai Bodri terhadap debit puncak menggunakan metode soil conservation services (SCS) [Analysis of the effect of changes in land cover of Bodri watershed on peak discharge using soil conservation services (SCS) Method], J Geodesi UNDIP, Vo.10(1), No.105-114.

[3] Negese A. Impacts of land use and land cover change on soil erosion and hydrological responses in Ethiopia, Appl Environ Soil Sci, Vol.2021, No.1-10. https://doi.org/10.1155/2021/6669438

[4] Lihawa F, Mahmud M. Evaluasi karakteristik kualitas air danau Limboto [Evaluation of Limboto lake water quality characteristics], J Nat Resour Environ Manag, Vol.7(3), No.260–266. https://doi.org/10.29244/jpsl.7.3.260-266

[5] Lahay RJ, Koem S. Ekstraksi perubahan tutupan vegetasi di kabupaten gorontalo menggunakan Google Earth Engine [Extraction of changes in vegetation cover in Gorontalo regency using Google Earth Engine], Jambura Geosci Rev, Vol.4(1), No.11–21. https://doi.org/10.34312/jgeosrev.v4i1.12086

[6] Umar HR. Model terpadu pengelolaan daerah aliran sungai (DAS) Limboto [Integrated model of Limboto watershed management], J Green Growth Manaj Lingkung, Vol.1(1), No.11–26. https://doi.org/10.21009/jgg.011.02

[7] Ayuba SR, Nursaputra M, Manyoe IN. Simulasi arahan penggunaan lahan di DAS Limboto dalam rangka pengendalian kekeringan [Simulation of land use instruction in Limboto watershed for drought control], Maj Geografi Indonesia Vol.33(2), No.87-94. https://doi.org/10.22146/mgi.37460

[8] Widiawaty M, Ismail A, Dede M, Nurhanifah N. Modeling land use and land cover dynamic using geographic information system and Markov-CA, Geosfera Indonesia, Vol.5(2), No.210-225. https://doi.org/10.19184/geosi.v5i2.17596

[9] Ghalehteimouri KJ, Shamsoddini A, Mousavi MN, Binti-Che-Ros F, Khedmatzadeh A. Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environment Chall, Vol.6, No.1-19. https://doi.org/10.1016/j.envc.2021.100399

[10] Gharaibeh A, Shaamala A, Obeidat R, Al-Kofahi S. Improving land-use change modeling by integrating ANN with cellular Automata-Markov chain model, Heliyon, Vol.6(9), No.1-18. https://doi.org/10.1016/j.heliyon.2020.e05092

[11] Anderson JR, Hardy EE, Roach JT, Witmer RE. A land use and land cover classification system for use with remote sensor data. USGS, Vol.964, No.1-34. https://doi.org/10.3133/pp964

[12] Nurdin. Penggunaan lahan kering di DAS Limboto Provinsi Gorontalo untuk pertanian berkelanjutan [Dryland use in Limboto watershed of Gorontalo Province for sustainable farming], Jurnal Penelitian dan Pengembangan Pertanian, Vol.30(3), 98-107. http://dx.doi.org/10.21082/jp3.v30n3.2011.p98-107

[13] Jafarpour Ghalehteimouri, K., Shamsoddini, A., Mousavi, M. N., Binti Che Ros, F., & Khedmatzadeh, A. Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges, 6(July 2021), 100399. https://doi.org/10.1016/j.envc.2021.100399

[14] Kamwi, J. M., Cho, M. A., Kaetsch, C., Manda, S. O., Graz, F. P., & Chirwa, P. W. Assessing the spatial drivers of land use and land cover change in the protected and communal areas of the Zambezi Region, Namibia. Land, Vol.7(4), No.1-13. https://doi.org/10.3390/land7040131

[15] Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data: A Case Study of Linyi, China. Land, Vol.11(3), No.1-24. https://doi.org/10.3390/land11030419

[16] Dede, M., Asdak, C., & Setiawan, I. Spatial dynamics model of land use and land cover changes : A comparison of CA, ANN, and ANN-CA. Jurnal Ilmiah Teknologi Sistem Informasi, Vol.8(1), No.38–49. https://doi.org/10.26594/register.v8i1.2339

[17] Jiang, L., & Zhang, Y. Modeling urban expansion and agricultural land conversion in Henan province, China: An integration of land use and socioeconomic data. Sustainability (Switzerland), Vol.8(9). No.1–12. https://doi.org/10.3390/su8090920

[18] Dibaba, W. T., Demissie, T. A., & Miegel, K. Drivers and implications of land use/land cover dynamics in Finchaa Catchment, Northwestern Ethiopia. Land,Vol.9(4), No.1–

22. https://doi.org/10.3390/land9040113

[19] Jafarpour Ghalehteimouri, K., Shamsoddini, A., Mousavi, M. N., Binti Che Ros, F., & Khedmatzadeh, A. Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges, 6(July 2021), 100399. https://doi.org/10.1016/j.envc.2021.100399

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