

Comparing of Land Change Modeler and Geomod Modeling for the Assessment of Deforestation

(Case Study: Forest Area at Poso Regency, Central Sulawesi Province)

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Abstract— *The forest destruction, climate change and global warming can reduce an indirect forest benefit because forest is the largest carbon sink and it plays a very important role in global carbon cycle. To support reducing emissions from deforestation and forest degradation (REDD+) program, there is a need to understand the characteristics of existing Land Use/Cover Change (LUCC) modules. The aims of this study are 1) to calculate the rate of deforestation at Poso Regency; and 2) to compare the performance of LCM and GM for simulating baseline deforestation of multiple transitions based on model structure and predictive accuracy. The data used in this study are : 1) Indonesia topographic map scale 1: 50.000, produced by Geospatial Information Agency (BIG), 2) Landcover maps (1990, 2000, and 2011) which were collected from the Director General of Forestry Planning, Ministry of Environment and Forestry. Meanwhile independent variables (environmental variables) such as : distance from the edge of the forest, the distance from roads, the distance from streams, the distance from settlement, elevation and slope. Landcover changes analysis was assessed by using Idrisi Terrset software and Geomod software. Landcover maps from 1990 and 2000 were used to simulate land-cover of 2011. The resulting maps were compared with an observed land-cover map of 2011. The predictive accuracy of multiple transition modeling was calculated by using Relative Operating Characteristics (ROC). The results show that the deforestation on the period of 1990-2011 reached 19,944 ha (3.55 %) or the rate of deforestation 949 ha year⁻¹. Based on the model structure and predictive accuracy comparisons, the LCM was more suitable than the GM for the assessment of deforestation.*

Keywords— *LULC model, LCM, Geomod, deforestation, REDD.*

I. INTRODUCTION

In 2008, the United Nations launched REDD (United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries) to provide a mechanism to mitigate climate change by sequestering forest carbon. REDD also promotes the secondary ecosystem service benefits associated with this forest conservation, including protection of biodiversity and water quality [1]. Within the climate change mitigation framework, prediction of deforestation is essential for the application of the United Nations Framework Convention on the Climate Change REDD+ Programme, which aims at reducing emissions from deforestation and forest degradation [2].

Reducing carbon emissions from deforestation and forest degradation (REDD) from such large-scale conversions requires reliable estimates of emission levels using business-as-usual (BAU) scenarios against mitigation measures such as forest protection and restoration [3]. An important first step to develop BAU scenarios is application of LUCC models that can project the potential amount of change in forest area through time [4]. Application of remote sensing and geographical information system can be used to estimate land cover changes from multi temporal information [5]. Land-use and land-cover change (LULC) modeling is a partial representation of the real LULC due to a lack of knowledge of coupled human and natural systems. It is a methodology to test our understanding of LULC processes by conducting scientific experiments [6]. LULC modeling is used to simulate trends of business-as-usual deforestation in the future. Spatial models of land cover change require information on the rate of change and where the change will take place. A combination of two models, the Cellular Automata (CA) model and the

Markov model (the CA-Markov model) can simulate the temporal and spatial pattern of LULC change [7].

Spatial models compute and predict deforestation trends by comparing land cover maps at two different dates and generating a transition potential map (per-pixel probabilities of shifting from a forest to a non-forest state or vice versa). In this case, several models that can be used are Clue-S, Dinamica EGO, Geomod and Land Change Modeler [8]. Land Change Modeler (LCM), Cellular Automata (CA), Markov Chain, CA-Markov, Geomod and Stchoice are the commonly used modelling techniques [9].

In this study, we focus on comparing LCM and Geomod. Land Change Modeler (LCM) is an integrated software environment for analyzing and predicting LUCC, and for validating the results. It is embedded in the IDRISI software [9], where only thematic raster images with the same land cover categories listed in the same sequential order can be input for LULCC analysis [10]

LCM evaluates land cover changes between two different times, calculates the changes, and displays the results with various graphs and maps. Then, it predicts future LULC maps on the basis of relative transition potential maps [10] relying upon Multi-Layer Perceptron (MLP) neural networks [11].

Meanwhile, Geomod is a land use change model that simulates the spatial allocation of land transitions from one land use state to another land use state [12]. The model operates in a manner that distinguishes clearly between the quantity of land change versus the spatial allocation of land change [13]. Geomod is used frequently to analyze the effectiveness of conservation projects. Geomod is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backwards in time. [14]

The development of spatial models offers potential benefits in forest conservation to provide a better understanding on how driving factors govern deforestation, to generate future scenarios of deforestation rates, to predict the locations of forest clearing and to support the design of policy responses to deforestation [15].

Indonesia has the highest deforestation rates in the world, exceeding even Brazil while having only a quarter of Brazil's forest area. The average annual deforestation in Indonesia for the period 2000-2012 was 690,796 hectares year⁻¹, accounts for 544,892 ha year⁻¹ of deforestation in mineral land and 145,904 ha year⁻¹ of deforestation in peat land. During this period, 8.68 percent of deforestation occurred in Sulawesi or 60,025 hectares year⁻¹ [16]. Meanwhile, refers to [17] the rate of deforestation in period 2000-2009 for Sulawesi Island was 166,784 ha year⁻¹.

The Central Sulawesi Province has approximately 4.2 million ha of forest, so as to have a strategic role in the

implementation of REDD+. The deforestation occurred in Central Sulawesi Province for 432,111.50 Ha (10.15 %). Poso Regency is one of the regency in Central Sulawesi Province. In the year 2000, it has 556,680 ha of forest [18] while in 2011, the forest only covered 542,790 ha.

The aims of this study are 1) to calculate the rate of deforestation at Poso Regency; and 2) to compare the performance of LCM and GM for simulating baseline deforestation of multiple transitions based on model structure and predictive accuracy

II. DATA AND METHODS

2.1 Study Area and Data

Poso Regency is one regency that was included in the province of Central Sulawesi. The total area of Poso Regency is 8,712.25 km² or 12.8% of the area of Central Sulawesi Province. Administratively, until the year 2016 is consist 13 districts. Location of Poso town is on the beach overlooking the Gulf of Tomini in one of the arches 'arm' of the island of Sulawesi. This makes the position of Poso Regency to be very strategic in the middle of the island of Sulawesi. Poso regency forest area is 516,636, consisting of protected forest area of 154,906 hectares, production forest area of 228,538 ha (divided into permanent production forest area of 35,928 ha, limited production forest covering 179,761 ha, and production forest that can be converted into non forest area 12,848 ha) and forest reserve area and forest tourism 133,192 ha. Forests are very large with riches in them, with proper management without damaging existing ecosystems is the main economic source [19].

The main data are constituted by three land-cover maps, scale 1 : 250,000; from 1990, 2000 and 2011 with 23 land-cover categories. For simplify of comparison, these categories have been reduced to three categories of primary forest, secondary forest and non forest (Figure 1). Meanwhile independent variables (environmental variable) such as : distance from edge forest, distance from roads, distance from streams, distance from settlement, elevation and slope (Figures 2). The information of environmental variable was extracted from Indonesia Topographic Map, produced by Geospatial Information Agency (BIG).

They all use World Geodetic System (WGS) 84 Universal Transverse Mercator (UTM) Zone 50 South coordinate system and a 30 by 30 m spatial resolution.

2.2 Land Cover Changes Analysis

2.2.1 Land Change Modeler

Analysis land use/ land cover change performed by the method of comparison of land cover map. The determination of land cover area used the spatial analysis which is done by overlaying process of Poso Regency's

landcover map in years 1990, 2000 and 2011. Flowchart

stage research activities are presented figure 3 [20].

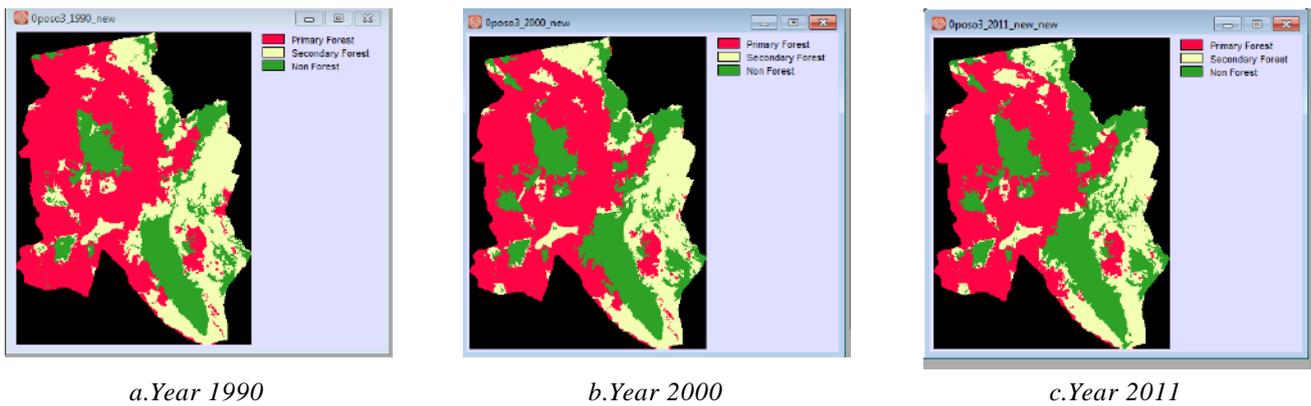


Fig. 1 : Landcover Map of Poso Regency, Central Sulawesi Province

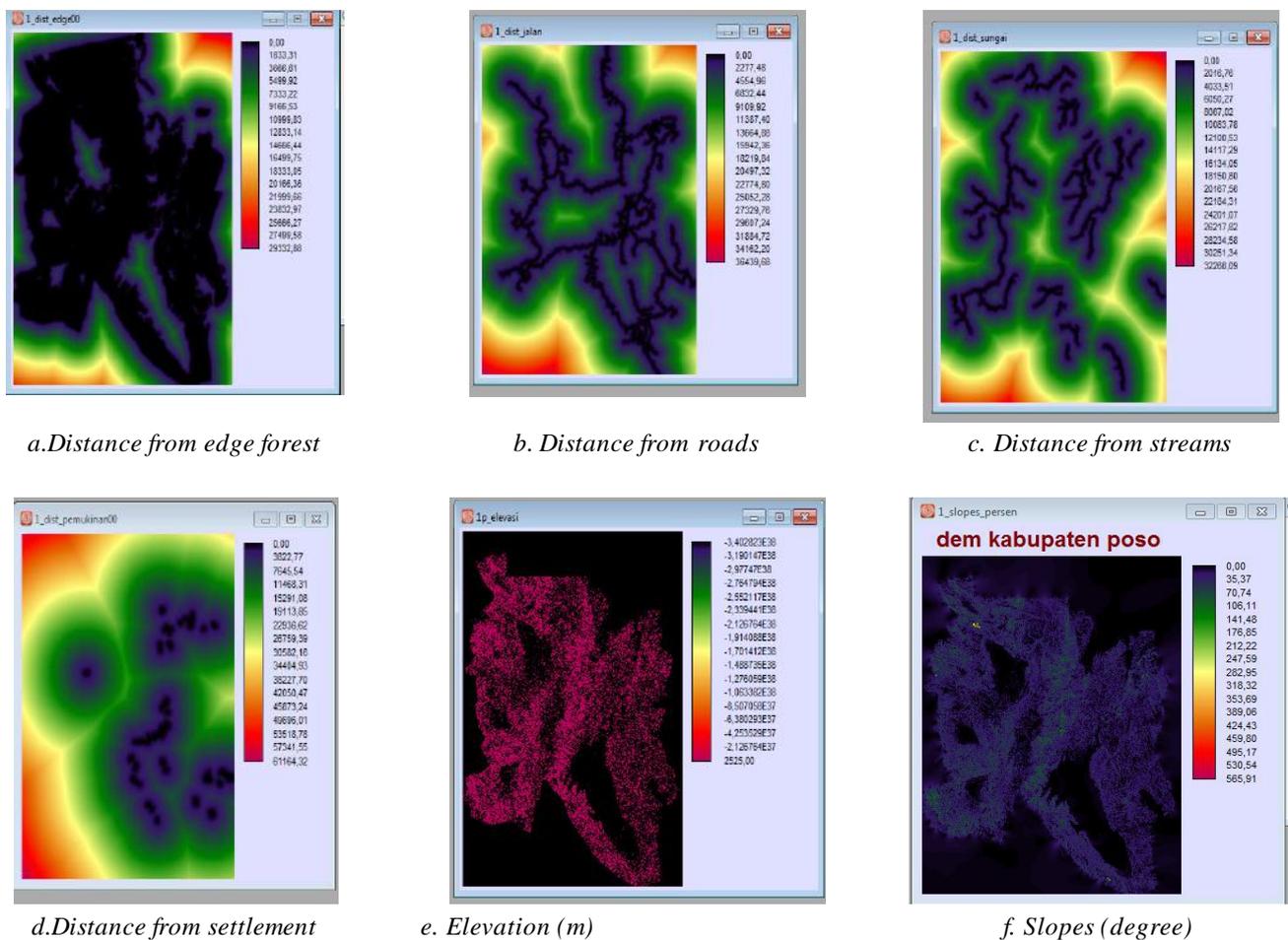


Fig. 2 : Independent Varibael (Enviromental Variabel)

Logistic regression model (LRM) was used to model and analyze the landcover change in IDRISI TerrSet. The objective of the present study was to assess the importance of the explanatory variables on landcover change from 1990 to 2000 and predicting the probability of change by 2011. The binary presence or absence is the dependent variable for the periods 1990–2000. Transition refers to a process in which something go through change from one land-type (e.g. forest) to another (e.g. non forest). The objective of this research in terms of LUCC

modeling is to simulate two transitions, namely “deforestation type 1 (primary forest to non forest) and deforestation type 2 secondary forest to non forest). There is no competition between the two transitions because they begin with different land-cover types.

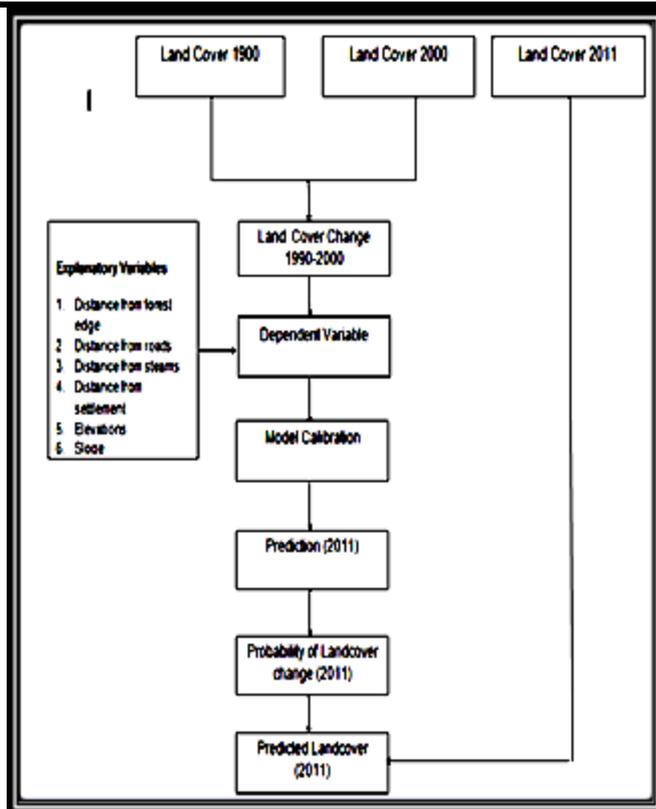


Fig. 3 : Flowchart Stage Research Activities

2.2.2 Geomod Modeling

GM employs Geomod’s pixel allocating process to combine the specified quantity of LUCC with the transition potential maps by EmpFreq. Likewise, LCM employs its own pixel allocating process, to combine the specified quantity of LUCC with the transition potential maps by LogReg and MLP [9].

Geomod simulates the change between exactly two categories, state 1 and state 2. In this case, it could be used to predict areas likely to change from primary forest / secondary forest (state 1) to non-forest (state 2) over a given time interval. The simulation can occur forward in time (future).

Refer [14] The simulation is based on :

- specification of the beginning time (1990), ending time (2000) and time step for the simulation,
- an image showing the allocation of landuse states 1 (primary forest / secondary forest) and states 2 (Non forest) at the beginning time,
- A suitability image to indicate the relative suitability of pixels to transition from land use state 1 to landuse state 2.
- the projected quantity of land use states 1 and 2 at the ending time.

The primary output of Geomod is a byte binary image that shows the simulated primary forest / secondary forest and non forest at the user-designated ending time.

2.3 Calibration and Validation

In GIS-based LUCC modeling, a simulation can be evaluated by comparing it with its reference map, which is considered as a “true” observation [21]. The common element of these validation processes is separating data for calibration and validation. From this context, the baseline deforestation modeling is calibrated with data from 1990 and 2000, and data from 2011 are used to validate the calibration with three measurements: ROC. A linear extrapolation estimates the quantity of deforestation by interpolating the quantity of forest changes in 1990 and the quantity of forest changes in 2000 using a straight line. Then it is linearly extrapolated to 2011 so that the extended straight line can estimate the quantity of disturbed forest area in that year [14]. This method makes sense when there is only one transition of land-cover change.

Markov Chain determines the amount of using the earlier and later land cover maps along with the ate specified. The procedure determines exactly how much land would be expected to transition from the later date to the predicted date based on a projection of the transition potentials into the future and creates a transition probabilities file. The transition probabilities file is a matrix that records the probability that each land cover category will change to every other category. A Markov Chain is a random process where the following step depends on the current state [22].

This logic produces a transition potential matrix that shows the rates of change for all possible combinations of transitions. The generated transition probability matrix determines the corresponding quantity of LUCC for each transition. Transition potential is defined as “a degree to which locations might potentially change in a future period of time” [23].

In this research, the logic that calculates transition potential in Geomod creates the suitability image by computing for each grid cell a weighted sum of all the reclassified driver images. Hence, the suitability in each cell is calculated according to the following [12]

$$R(i) = \frac{\sum_{a=1}^A W_a P_a(i)}{\sum_{a=1}^A W_a} \tag{1}$$

where

R(i) = suitability is a transition potential value in pixel i,

a = a particular environmental variable,

A = the total number of environmental variables,

W_a = the weight of environmental variable a, and

Pa(i)= the percent of LUCC during the calibration interval in the bin to which pixel i belongs for variable a

Logistic regression (LogReg) detects a statistical relationship in a parametric way between six environmental variables and a binary event such as disturbance versus persistence, where 1 indicates changed and 0 indicates persistence. The basic assumption is that the probability of dependent variable takes the value of 1 (positive response) follows the logistic curve, and its value can be estimated with the following formula:

$$P(y=1|X) = \frac{\exp \sum BX}{1 + \exp \sum BX} \tag{2}$$

where

y = s a binary event,

P = the probability of the dependent variable being 1;

X = the independent variables,

For Geomod validations we also varied the neighborhood constraint, which is based on a nearest neighbor principle, in which an algorithm restricts land change within any one time step to cells that are on the edge of forested and non-forested pixels. This rule simulates the manner in which new deforestation can grow out of previous deforestation [14].

2.4 Relative Operating Characteristic

The predicted landcover of 2011 was validated using ROC / AUC (Relative Operating Characteristic/Area Under Curve) module of IDRISI TerrSet. The ROC module is comparing a suitability image depicting the likelihood of that class occurring (the input image) and a boolean image showing where that class actually exists (the reference image). The ROC curve is the true positive fraction vs false positive fraction and the AUC is a measure of overall performance [20].

ROC requires one or more thresholds, and a threshold refers to the percentage of pixels in the transition potential map to be reclassified as 1 in preparation for comparison with the reference map. For each threshold, one data point (x, y) is generated where x is the percent of false positives, and y is the percent of true positives. These data points are connected to create an ROC curve, and a higher ROC curve implies that its corresponding transition potential map has more agreement with the

reference map than other transition potential maps that have lower ROC curves. The percent of true positives is derived from $A/(A + C)$ while the percent false positives is derived from $B/(B + D)$, where A, B, C, D are pixel counts in Table 5 for each threshold (Pontius and Schneider 2001). Area Under the ROC Curve (AUC), which coarsely summarizes the information of an ROC curve, is calculated according to the following equation [24].

$$AUC = \sum_{i=1}^n (x_{i+1} - x_i) \times \left\{ y_i + \frac{(y_{i+1} - y_i)}{2} \right\} \tag{3}$$

where

x_i = the false positives for the threshold i ,

y_i = the true positives for threshold i , and

$n + 1$ = the number of thresholds.

III. RESULTS AND DISCUSSION

3.1 Land Cover Changes

Landcover change analysis was done for Poso regency data time series comparison data from 1990, 2000 and 2011. Table 1 and Table 2 show the land cover and its changes of Poso regency. The forest cover area in Poso regency in 2011 was 541,866,87 ha or approximately 70,99 % of the total area. It decreased by 7,075,80 ha (1,29 %) compared to 2000 or 19,944.99 ha (3.55 %) compared to 1990. The rate of deforestation 643.25 ha year⁻¹ in period 2000- 2011 or 949.76 ha year⁻¹

The rate of deforestation in this area is lower than deforestation in central sulawesi province. This condition is in accordance with Tumudi's research. Refer [25] Central Sulawesi province has forest area of 4,477,840 ha (year 2000) and 4,360,410 ha (year 2011). The rate of deforestation of Central Sulawesi Province in the period 2000-2011 amounted to 117,430 ha or 10,675 ha year⁻¹. The largest deforestation occurred in the Tojo Una-Una Regency up to 29,170 ha (25.01%) and the second, Morowali with 17,850 ha and Poso 13,890 ha. This condition shows deforestation in Poso district contributes for about 11.83 % of all deforestation in Central Sulawesi Province

Table.1a. Poso Regency Land cover from 1990 to 2011

No	Landcover type	Year 1990		Year 2000		Year 2011	
		Ha	Percent	Ha	Percent	Ha	Percent
1	Primary dryland forest (PDF)	376,645.23	49.34	361,262.25	47.33	360,161.19	47.18
2	Secondary dryland forest (SDF)	183,972.69	24.1	186,486.48	24.43	180,511.74	23.65
	Dryland Forest (DF)	560,617.92	73.44	547,748.73	71.76	540,672.93	70.83
3	Primary mangrove forest(PMF)	219.15	0.03	-	-	-	-
4	Secondary mangrove forest.SMF)	974.79	0.13	1,193.94	0.16	1,193.94	0.16
	Mangrove forest (MF)	1,193.94	0.16	1,193.94	0.16	1,193.94	0.16
	Forest (F)	561,811.86	73.60	548,942.67	71.92	541,866.87	70.99
5	Non Forest (NF)	201,521.25	26.4	214,390.44	28.09	221,466.24	29.01
	Total	763,333.11	100.00	763,333.11	100.01	763,333.11	100.00

Dryland forest conditions in Poso regency in 1990 covered 560,617 ha and reduced into 540,672 ha in 2011. The reduction of 19,944 ha or approximately 3.55 % over the 21 years. The average deforestation of dryland forest occurred in Poso was 0.17 % per year or about 949 ha year⁻¹. This reduction was caused by deforestation which has changed dryland forest into a non forest.

Meanwhile in 1990 until 2011, mangrove forest area in Poso regency was 1,193 ha. The condition of mangrove forests is relatively fixed for twenty-one years. But there is a change of primary mangrove forest into secondary mangrove forest. This reduction of mangrove forest was caused by the deforestation, which has changed mangrove forest converted into ponds.

Table.1b: Poso Rgency Land cover from 1990 to 2011

No	Landcover type	Year 1990		Year 2000		Year 2011	
		Ha	Percent	Ha	Percent	Ha	Percent
1	Primary forest (PF)	376,864.38	49.37	361,262.25	47.33	360,161.19	47.18
2	Secondary forest (SF)	184,947.48	24.23	187,680.42	24.59	181,705.68	23.80
	Forest (F)	561,811.86	73.60	548,942.67	71.91	541,866.87	70.99
5	Non Forest (NF)	201,521.25	26.40	214,390.44	28.09	221,466.24	29.01
	Total	763,333.11	100.00	763,333.11	100.00	763,333.11	100.00

Primary forest conditions in Poso regency in 1990 covered 376,864 ha and reduced into 360,161 ha in 2011. The reduction of 16,703 ha or approximately 4.43 % over the 21 years. The average deforestation of primary forest occurred in Poso was 0.21 % per year or about 79.39 ha per year. This reduction was caused by deforestation which has changed primary forest into

secondary forest and non forest. Meanwhile in 1990, secondary forest area in Poso regency was 184,947 ha and decreased to 181,705 ha in 2011.

The average deforestation of secondary forest occurred in Poso was 0.08 % per year or about 154.37 ha per year. This reduction was caused by deforestation which has changed secondary forest into non forest.

Table.2: Poso Regency Recapitulation of land cover change from 1990 to 2011

No	Land Cover Type	1990 – 2000		2000 – 2011		1990 – 2011	
		Hectare	Percent	Hectare	Percent	Hectare	Percent
1	Forest (F)	-12,869.19	-2.29	-7,075.80	-1.29	-19,944.99	-3.55
2	Non Forest (NF)	12,869.19	6.39	7,075.80	3.30	19,944.99	9.90

Source : Result of Analysis of Landcover Map from 1990 to 2011

Over 19,944 ha were lost between 1990 and 2011 inside the study area (12,869 h betwen 1990-2000) and (7,075 ha between 2000-2011). This roughly corresponds to 3.55 % of the forest area that existed in the year 1990 (561,811ha). Between 1990 and 2000 the deforestation gross rate was 2.29 %, whereas between 2000-2011 reaching 1.29 %.

The average annual deforestation in Poso Regency for the period 1990- 2000was 1,287 ha year⁻¹, decreased to 643 ha year⁻¹ in period 2000-2011. Over all, in period 1990-2011 annual deforestation up to 949 ha year⁻¹.

Over the 21 years (1990-2011) the increase of non-forest area was 19,994 ha or 9,909 %. The cause of deforestation is plantation activity. The increase of non-forest areas was caused by the activity of forest area conversion into non-forest areas (other uses).

Meanwhile, there were no change on the water bodies. The water bodies category recorded neither increase nor decrease. Refer [26] conveys that no changes in the body of water in certain period of time indicate that the changes

of land cover are mostly oriented on agriculture and new settlements.

3. Comparing of Land Change Modeler and Geomod Modeling

The transition potential maps for primary forest to non-forest generated by EmpFreq, LogReg and MLP are presented in figure 4, while those for secondary forest are presented in figure 7. In figure 4 and 7, a higher degree (or a lighter pixel) shows that the corresponding location has more potential to be transformed into a different land-use and land-cover category in the future than a lower degree (or a darker pixel). Land-cover map of 1990 and 2000 were used to simulate land-cover in 2011, as presented in figure 5 (for primary forest) and figure 8 (for secondary forest). The ROC curves of the transition of primary forest to non-forest are presented in figure 6 while those of secondary forest are in figure 9. The corresponding AUC statistics is presented in Table 3.

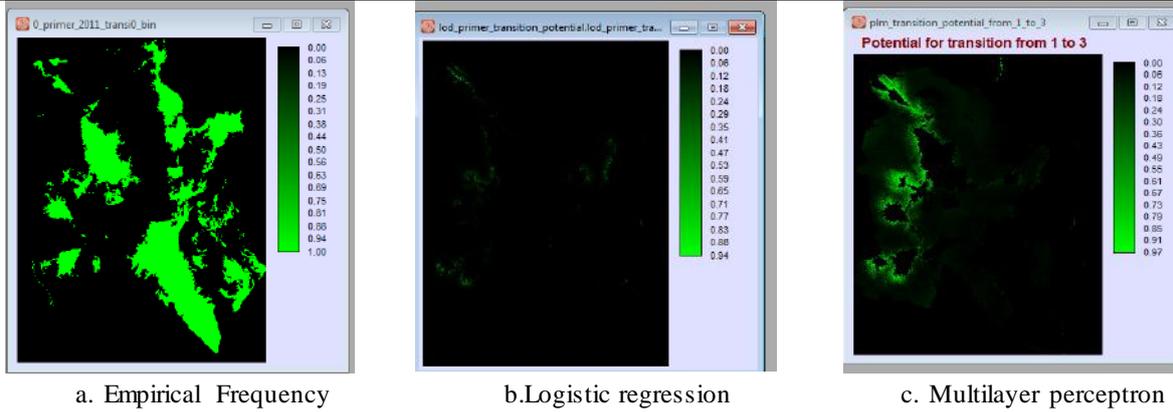


Fig. 4 : Transition Potential Map for Primary Forest to Non Forest

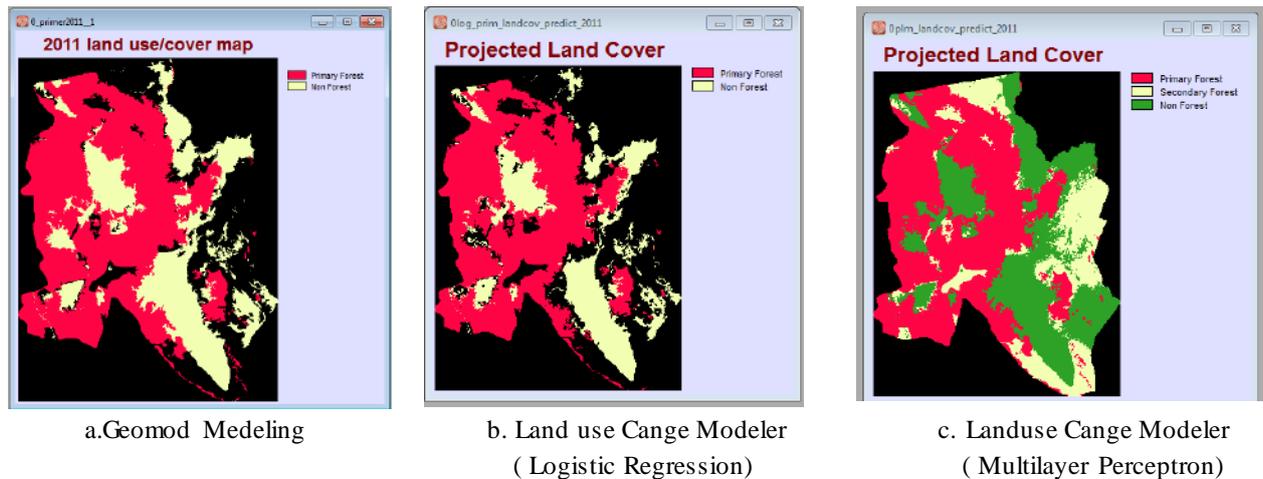


Fig. 5 : Projected Land cover Map (Primary Forest) generated by Geomod and Land Changes Modeler

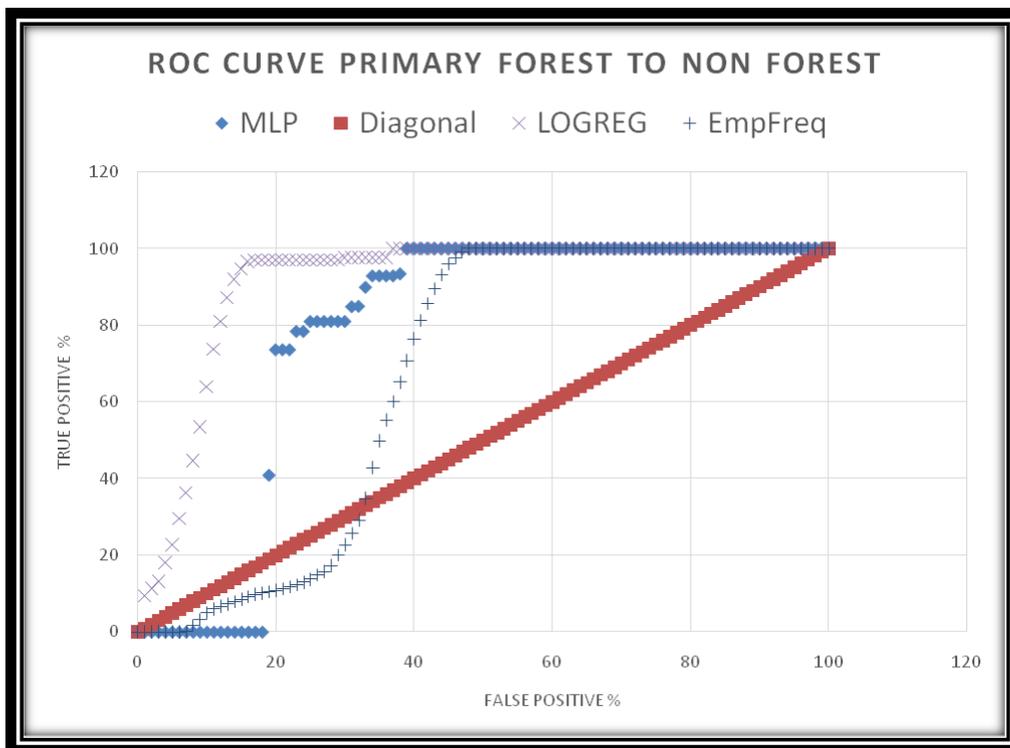


Fig. 6 : ROC Curves (Transition of Primary Forest to Non Forest)

Table.3 :: Area Below the ROC Curve (AUC) statistics

No	Model type	Primary Forest to Non Forest			Secondary Forest to Non Forest		
		Ordinary AUC	Predicted AUC _p	The true AUC _t	Ordinary AUC	Predicted AUC _p	The true AUC _t
1	EmpFreq	0.665482	0.000325	0.000504	0.625846	0.002115	0.018873
2	LogReg	0.962557	0.000356	0.000538	0.912744	0.002127	0.020653
3	MLP	0.778188	0.000350	0.000541	0.772005	0.001735	0.015732

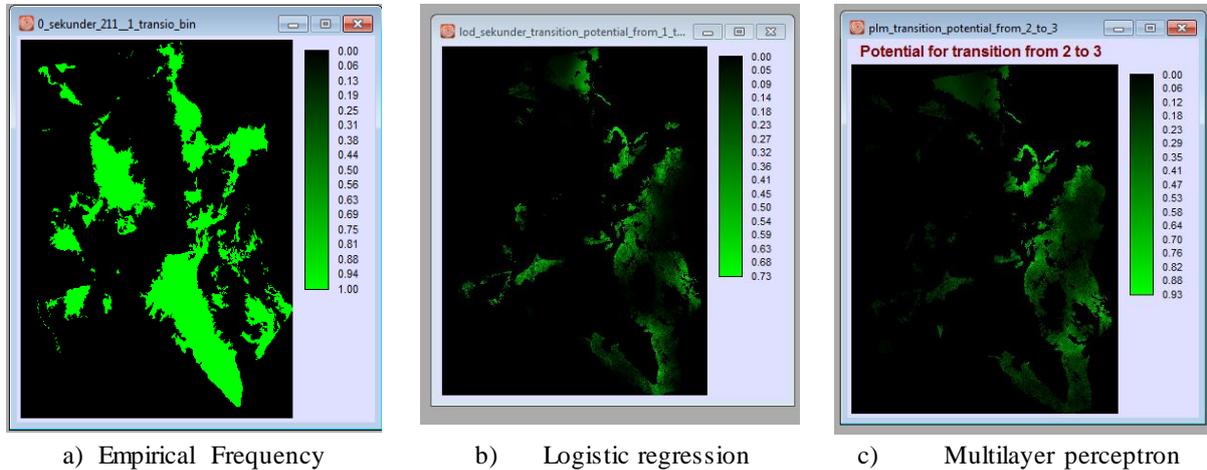


Fig. 7: Transition Potential Map for Secondary Forest to Non Forest

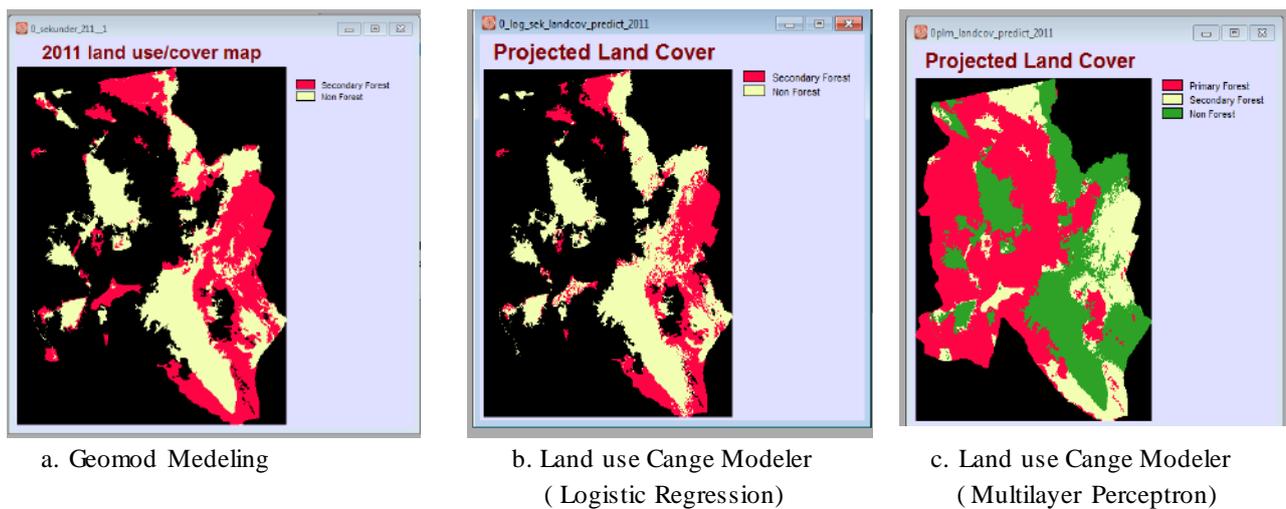


Fig. 8 : Projected Landcover Map (Secondary Forest) produced by Geomod and Land Changes Modeler

The diagonal line was derived from an input image in which the locations of the image values were assigned at random (AUC=0.50). Comparing ROC Curves, three lines were derived from different models. The model produced by EmpFreq (AUC = 0.63) is shown to be performing more poorly than model produced by MLP (AUC = 0.77) and LogReg (AUC = 0.91).

Based on Table 3, LogReg has the highest predictive accuracy in most cases as measured by regular AUC. In the conversion of primary forest to non-forest (AUC value = 0.96) and in the case where secondary forest became non-forest (AUC value = 0.91), the two values were the highest compared to the AUC values in other

models. This finding was in accordance with the research of [27] for transition potential map for forest to anthropogenic in the territory of Santa Cruz, Bolivia. But the opposite happened for transition potential map from Savana to anthropogenic.

MLP models had the second highest predictive accuracy (when measured by AUC) for transition of both primary and secondary forest to non-forest, but MLP models contained weakness, that was stochastic elements. Multilayer perceptron (MLP) is a type of artificial neural network that mathematically mimics how a human brain perceives a particular pattern from complex data (Kim 2005). By nature, MLP is a distribution-free, non-linear

and black box-like estimator. MLP is often referred to as

a black box [23]

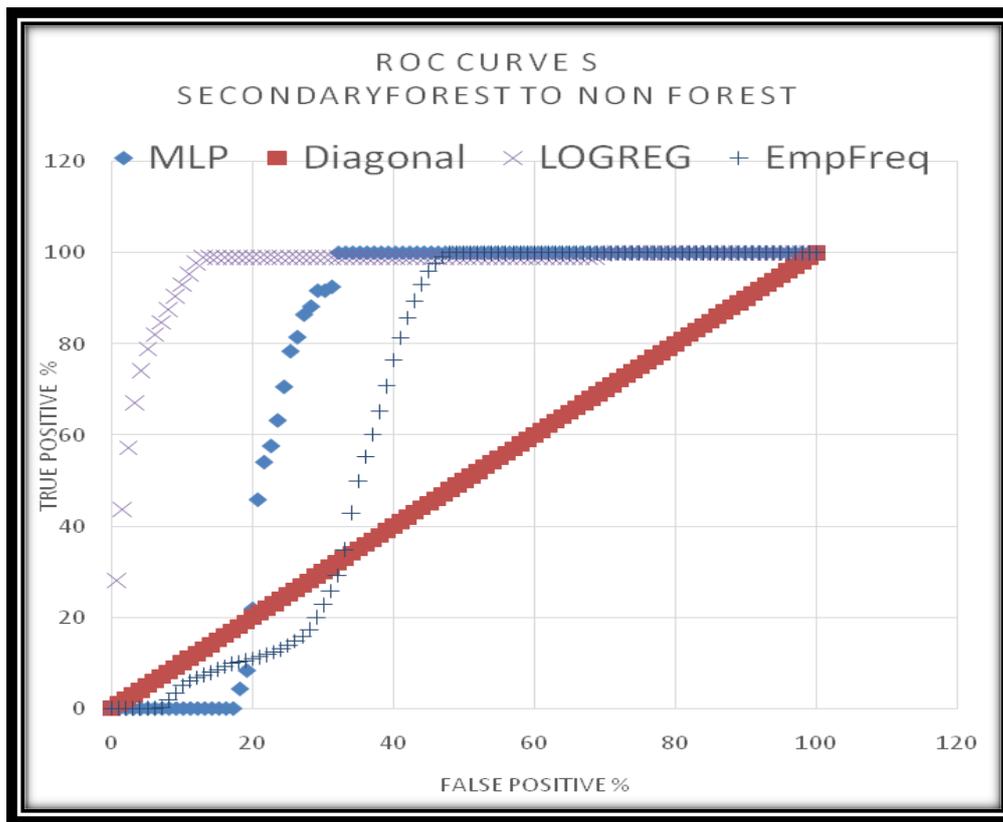


Fig. 9 : ROC Curves (Transition of Secondary Forest to Non Forest)

Based on the model structure and comparison of predictive accuracy, LCM (LogReg) seemed to be better than Geomod model for predicting forest change to non-forest (deforestation) when considering multiple transitions. This result was in line with the research conducted by Kim (2010) on the territory of Santa Cruz, Bolivia that the LCM seemed to be more suitable than the Geomod model for setting an REDD baseline in this particular case study.

The making of a relatively long time-varying model, between the Geomod model and the LCM, makes it possible to refine the initial model. Geomod model was published earlier than LMC model, therefore by studying the limitations of the former models, then these weaknesses could be improved in newer models. This is the case with both models.

Another research on the deforestation of peat swamp forest in Central Kalimantan was done by [28]. The research suggested that the most appropriate model to simulate quantity of change was linear extrapolation; whereas the various LCM configurations might be most appropriate to project the allocation of change. However, any given model might produce different outputs due to variations of the input parameters.

Thus, the differences between the models should not be interpreted as a function of the models themselves, but how they were parameterized for these simulations. In the

case where the primary interest was to explore change quantity, the Geomod simulations may be more appropriate. However, as more spatial information became available on landscape-level carbon content, accurate simulation of allocation might become a higher priority and therefore LCM simulations might provide more meaningful output. Meanwhile, according to [29] who had reviewed the approaches and software used for modelling land use and land cover changes, the LCM developed by IDRISI for analyzing land cover changes for ecological sustainability, was the most widely used spatial model for prediction.

IV. CONCLUSION

The results show that the deforestation on the period 1990-2011 reached 19,944 ha (3.55 %) or the rate of deforestation 949 ha year⁻¹. A deficiency GM cannot guess some transitions, GM is only able to make one potential transition. GM does not have the potential to model multiple transitions, and while the benefits of an LCM multilayer perceptron can produce different results for each simulation because of its stochastic elements. Based on model structure and comparison of predictive accuracy, LCM is more suitable than GM to establish deforestation

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