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Modeling Land Use Land Cover Using Cellular Automata - Markov Chain: A Case of Belete Gera Regional Forest Priority Area, South Western Ethiopia

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Abstract: Arrogant practices of land use change including expansion of agricultural land and infrastructural development are resulted to deforestation which goes to climate change. Cellular Automata (CA)-Markov chain combines the advantages of cellular automata and Markov chain analysis to simulate and predict future land use/cover trends depending on the Land Use Land Cover (LULC) changes. Spatial distribution of LULC and area changed were calculated using IDRISI software and GIS technology. Therefore, the forest land cover conversion to other LULC was evaluated to obtain rate of deforestation. Secondly, using transition probability matrices of 1999-2018, CA-Markov chain model was executed to simulate spatial distribution of land use/cover in 2018. Based on the simulated LULC map of 2018 and the actual LULC map of 2018 CA-Markov Model was validated with a kappa index of 1. As a result the kappa index of the validated result was 0.8 means it is accurate for the model. Finally, future land use/cover change of 2018-2037 and 2037-2056 were predicted using CA-Markov Chain Model. Therefore, the results revealed that decreasing of forest land and increasing of agricultural land in the study area are the major results. Specifically forest land was decreased by 52,156.71 hectares from 1980 to 2018, while agricultural land increased by 78,021.35 hectares during 1980-2018. In addition, the rate of deforestation between 1980 and 2018 was 1,372.54 hectares per year. The predicted results of 2037 year would be identified forest cover decreases by 30,204.65 hectares within future 19 years and agricultural land would be increases by 30,693.91 hectares between 2018 and 2037. The result of the study approved concerned bodies those working on the forest protection have to work better on the forest protecting and address a tough land use system.

Keywords: GIS, Remote Sensing, Cellular Automata, Markov Chain, Transition Matrix, Transition Probability Matrix, Transition Suitability Map

1. Introduction

At present time, the most widely used models in land use change monitoring and prediction are analytical equation based models, statistical models, evolutionary models, cellular models, Markov models, hybrid models, expert system models and multi agent models [1]. Land cover change modeling means time interpolation or extrapolation when the modeling exceeds the known period. Cellular automata are discrete models in which the states of the variables, i.e. values associated with grid cell locations, are driven by simple rules dependent on the states of the neighbors of each variable [2]. Cellular Automata (CA) models (deterministic, stochastic or hybrid) have recently garnered tremendous popularity as spatial simulation techniques in a wide range of rural and urban modeling domains and, as such, the vital of research in this direction are rapidly expanding. Over the past few decades, Cellular Automata (CA) models have found application in spatial simulation involving a plethora of themes, including population or land use/ cover dynamics, land use evaluation, urban sprawl and a host of others. Compared to conventional mathematical tools of spatial simulation such as differential equations, partial differential equations and empirical equations, CA models are relatively simple yet produce results that are stunning meaningful and useful to support decision making in a planning context [3]. Operating in synergy with other planning models and such other cutting-edge technologies are GIS and digital image processing. CA can help to portray the dynamics and patterns of growth in a given spatial context.

The behavior of a CA thought of as a Markov process. The Markov process means that future probabilities of an event may be determined from the probabilities of events at the current time [2]. The assumptions of physics in which the probability of a system being a certain state at a certain time can be determined if the earlier time state known [4]. Markov Chain Method works based on developing transition probability matrix of land use change between two different dates derived from observation, which used to provide estimations of the probability that each pixel of certain LULC classes transformed to another class or remain in the same class. Therefore, this model is very good and useful to understand the stochastic nature and the stability of the land use/ cover [5]. The integrated use of CA-Markov Model effectively combines the advantages of the long-term predictions of the Markov model and the ability of the Cellular Automata (CA) model to simulate the spatial variation in a complex system and this mixed model can effectively simulate land cover change [6]. Therefore, this method adopted to obtain accruable and reliable results for Belete Gera Forest Priority Forest Area (BGFPA). In this study, the 2037 and 2056 LULCs were, predicted based on the history of 1999 and 2018 LULCs.

Ethiopia is facing rapid forest cover change and degradation that has been, principally fueled by increase of population. This in turn resulted in extensive forest clearing for agricultural use, resettlements, and exploitation of existing forests for fuel wood, timber and construction materials [7]. Many studies have focused on the LULC dynamics at the rural and urban areas in Ethiopia. While, there are few studies on future LULC prediction in the country especially at the scale of large rural areas such as BGFPA. BGFPA is located in the southwestern Ethiopia it is one of the dominant natural high forests [7]. This study seeks to utilize remotely sensed data and GIS tools to analyze the LULCC in BGFPA, in Ethiopia Country. Detecting changes in the area is, obtained by comparing images between two years. Based on the Markov model, the transfer probability was, established based on the data from 1980 and 1999, and the predicted data of 2018 was, processed using the transfer probability and forest suitability maps in the CA model. After validation, the land use and land cover in 2037 and 2056 were, predicted.

2. Materials and Methods

2.1. Description of the Study Area

Belete Gera forest is one of the regional forest priority areas (RFPA) in the country. The total forest area is about 1,500 square kilometers, an area more than twice as large as Singapore [8]. There are 30 villages and 80 sub-villages in Gera District as well as 14 villages and 46 sub-villages in Shabe Sombo District (Figure 1). The Belete-Gera forest is unique in that it produces wild forest coffee as well as regular garden coffee. In fact, Belete-Gera forest is one of the major candidates for being the ultimate origin of coffee.

2.2. Data Collection and Source

For this study Landsat Thematic Mapper (TM), used for 1980 and 1999 years. Landsat-8 Operational Land Imager (OLI) applied for 2018 years, obtained from USGS Earth Explorer freely, and SRTM elevation data obtained from GLCF (Table 1).

Table 1. *Data collection specification.*

Year	Data Type	Path / Row	Date of acquisition	Resolution	Source
	Satellite Image				
1980	Landsat TM	170 / 055	05/03/1980	60m	USGS earth explorer
1999	Landsat ETM+	170 / 055	08/02/1999	30m	
2018	Landsat OLI	170 / 055	27/01/2018	15m	USGS earth explorer
2018	SRTM	170 / 055	2018	30m	USGS earth explorer

2.3. Methods of Image Classification

After all the pre-processing activities were done one of the important activities of the study is image classification, which is the basis for change detection activity and prediction. As the main objective of the study is Predicting LULC focusing forest cover change in the future land use/cover category were selected based on the purpose of the study. Based on the prior knowledge of the study area and additional information from secondary materials of the area five different types of land uses and land cover classes were identified (Table 2). Landsat 8 image, Landsat 5 TM and Landsat 5 TM images for 2018, 1999 and 1980 were in original 30m resolution applied respectively. Further image analysis processes were carried out using IDRISI selva software. The image was displayed in false color composite using band combination of 3, 2, 1 for Landsat 5 TM and 4, 3, 2 for Landsat 8 (OLI). A maximum Likelihood classification technique was performed using several selected regions for each class.

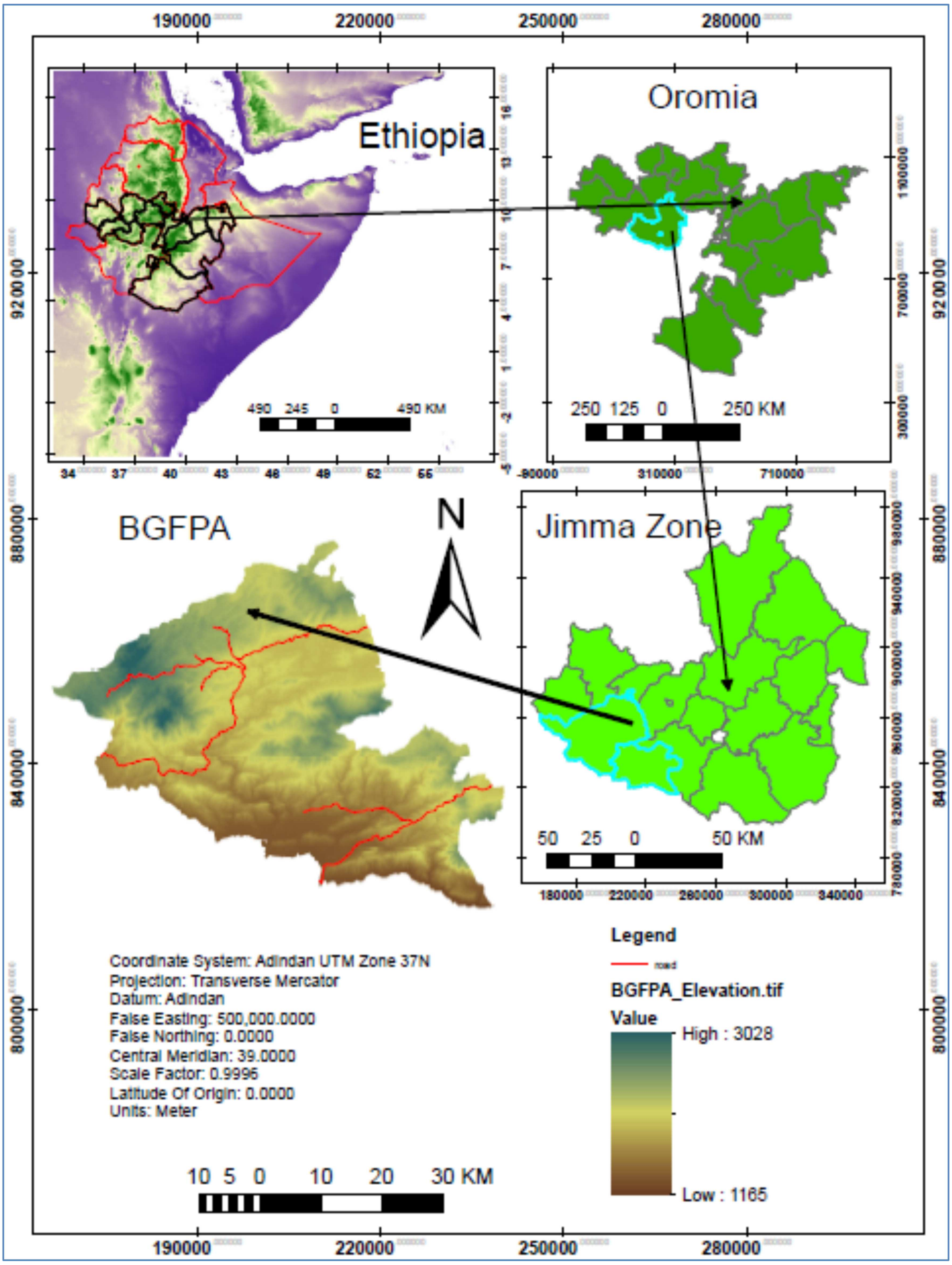

Figure 1. *Locational map of study area.*

Table 2. *Selected LULC classes of the study area and their descriptions.*

No	LULC classes	Description of LULC classes
1	Agricultural Land	The land area that used primarily for production of crop and comprises Agroforestry land (mixture of chat and coffee plantation).
2	Forest Land	It includes all dense natural forest
3	Built-up area	Includes residential areas like town, villages, strip transportation, and commercial areas
4	Grassland	This land cover includes areas of shrubs, short tress, bushes, pasture lands, grazing areas dominantly covered with grasses.
5	Water body	It comprises rivers, streams, and small pounds

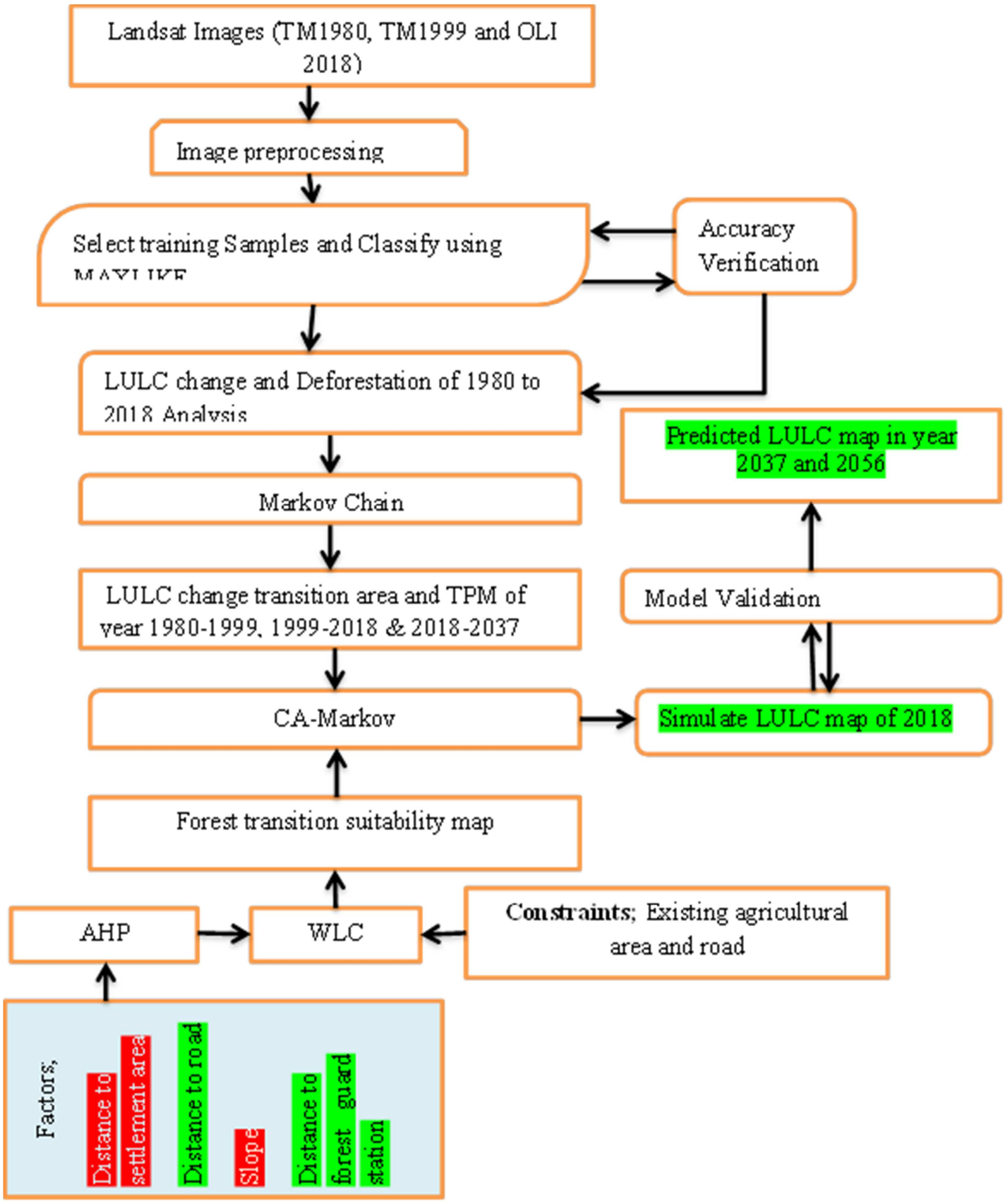

Figure 2. *Workflow chart of Research Methodology.*

2.4. Accuracy Assessment

Accuracy Assessment for the 1980, 1999, and 2018 images were carried out to determine the quality of information provided from the data. For this study Kappa index was used to measure the agreement or accuracy between the information derived from image classification and the reference data collected from field as indicated by the major diagonals and the chance Agreement which was indicated by the row and column totals. The Kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance [9]. The Kappa test is a measure between predefined producer rating and user assigned rating which can be expressed in the formula as:

$$K = \frac{Pa-pe}{1-pe} \tag{1}$$

Where P (a) is the number of time the k raters agree, and P (e) is the number of time the k raters are expected to agree only by chance [10].

2.5. Land Use/Cover Change Detection Analysis

In performing LULC change detection the post-classification detection method was applied in the IDRISI Selva environment v.17, which involves two classified images to make a comparison to produce change information on a pixel basis. In other words, the interpretation between two image were provided changes "-from, -to" information. Classified images from two different data sets are compared using cross-tabulation in determining qualitative and quantitative aspects of changes for 1980 to 2018 years. The magnitude of change and percentage of changes are expressed in a simple formula as follows:

K=F-I

$$A = \frac{F-I}{I} * 100 \quad (2)$$

Where (K) is magnitude of changes, (A) is percentage of changes, (F) is first data, and (I), is reference data. Therefore, simulation and prediction of LULC changes for 2018, 2037 and 2056 were employed using IDRISI Selva environment v.17.

2.5.1. Deforestation Analysis

Deforestation map and forest area transition matrix of 1980-1999, 1999-2018, and the overall 1980-2018 were generated. First, the raster images of LULC was converted into feature type and selected the attribute using features names and merged into single features for all class. Then, using intersection tool in Arc GIS environment the data files of 1980 - 1999, 1999 - 2018, and 1980 - 2018 were intersected and area changed added into attribute table which was the attribute of area changed. They are areas which were in one class in the former period but changed to another class in the later period. Finally, the deforestation map and forest area to other LULC change matrix were developed by merging four LULC class matrixes those are agriculture, built-up, grassland and water body. However, amongst the five major classes' forest class change transition matrix was identified as deforestation areas. This kind of change detection method involves where and how much forest cover change has occurred to each land cover. Moreover, three conditions of forest cover change detection characteristics such as, detecting the rate of forest changes, measuring the areal extent of the change, and mapping deforestation pattern of the change are explored. Therefore, forest change detection matrix was produced to quantify the trends and patterns of land use/land cover change in general and forest cover change in particular. For this study, the rate of forest cover change was, also calculated using the formula;

$$r = \frac{a-b}{t} \quad (3)$$

Where, r= Rate of forest cover change in hectare a= recent year forest covers by hectare b= Initial year forest covers by hectare t= is number of years between the two periods.

2.5.2. Markov-Chain Model

The Markov Chain Model is a unique and widely used tool in land use land cover modeling which demonstrates the land use land cover changes as a stochastic process [11]. In the Markovian system, the future state of a land use system is a modeled on the basis of the immediate proceeding state [12]. Markov analysis involves the studying of the present behavior of a system to predict the future behavior of the system. This was introduced by Russian Mathematician, Andrey A Markov. A simple Markov chain is a discrete random process with Markovian property. In general the term Markov chain is used to refer a Markov process that is discrete with finite state space. Usually a Markov chain would be defined for a discrete set of times (discrete Markov chain). Markov process is a stochastic or random process. A stochastic system is said to follow a Markov process if the occurrence of a future state depends on the immediately preceding state only.

Therefore if $t_0 < t_1 < \cdots < t_n$ represents the instants on time scale then the set of random variables $\{X(X_n)\}$ whose state space $S = X_0, X_1, \ldots X_{n-1}, X_n$ is said to follow a Markov process provided it holds the Markovian property:

$$P\{X(X_n) = X_n | X_n(X_{n-1}) = X_{n-1}, \ldots, X(t_0) = X_0\} = P\{X(t_n) = X_n | X(X_{n-1}) = X_{n-1}\}$$

$$for\ all\ X(t_0), X(t_1), \ldots, X(t_n)$$

If the random process at time t_n is in the state, X_n the future state of the random process X_{n+1} at time t_{n+1} depends only on the present state X_n and not on the past states $X_{n-1}, X_{n-2}, \ldots, X_0$.

In a Markov process the possible states i. e, state space that a system under focus could take at any point of time will be clearly defined. As the state changes, it is state randomly it will be difficult to predict the next future state with certainty. In this context the statistical properties of the system for future state will be forecasted. The change of system from one state to other state is called *Transition* and the probability associated with this state transition is termed as Transition probability. The state space and the associated transition probabilities characterize the Markov chain [13].

A stochastic is said to follow a Markov process if the occurrence of a future state depends on the immediately preceding state only. The probability of moving from one land use type to another or remaining in the same land use type during a single period is called *the transition probability*. The initial estimates of p_{ij} can be computed as,

$$p_{ij} = N_{ij}/N_i, (i, j = 1, 2, 3, \ldots, m \quad (4)$$

Where, N_{ij} is the number of units transitioned from the state i to state j, N_i is the number of units in state i.

Therefore the basic hypothesis of Model simulation process mainly produces a land use area transfer matrix and a probability transfer matrix to predict land use change trends [14]. The Markov Chain Model can be described as a set of states. $S = \{S_0, S_1, S_2, \ldots S_n\}$, assuming that the current state is S_t, and then, it changes to state S_j at the next step with a probability denoted by transition probabilities p_{ij}. Thus the state S_{t+1} in the system can be determined by former stage St in the Markov Chain using the following formula [13-15].

$$P_{ij} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}$$

$$(0 \le p_{ij} \le 1\ and\ \sum p_{ij} = 1\ i, j = 1, 2, \ldots, n)$$

$$S_{t+1} = p_{ij} x S_t \quad (5)$$

Where,p_{ij}, is the state transition probability matrix and n is the land represents the number of land use type; S is land use status, t; t+1 is the time point. In this Study, the Markov chain analysis was implemented in three periods; 1980-1999, 1999-2018 and 2018-2037. Thus, the land use area transfer matrix and Transition Probability Matrix for the introduced periods was obtained.

2.5.3. Cellular Automata Model

A CA Model is a dynamic model with local interactions that reflect the evolution of a system, where space and time are considered as discrete units, and space is often represented as a regular lattice of two dimensions. Temporal and spatial complexities of land use land cover systems can be well modeled by properly defining transition rules in CA models. CA simulation provides important information for understanding forest cover theories, such as evolutions of forms and structures [16]. Cellular Automata is a bottom-up dynamic model within a spatio-temporal calculation. It is discrete in space-time and state can carry out complex time-space simulations. The data for every cell in state St+1 are decided by the cell itself and its neighboring cells in state St, meaning that the change in the cell is decided by rules. It is consists mainly of cell, cell space, neighbor, rule and time. The filter of the CA model determines the neighbors [17]. The closer the distance between the nuclear cell and neighbor, the larger the weight factor will be. The weight factor is combined with the probabilities of transition to predict the state of adjacent grid cells, so that land use change is not a completely random decision. In this study, Cellular Automata lattice represented each land use cell, and each lattice have 8 neighboring cells; Cellular state represented land use type of cell; time step is 19 years. Transition rule was used a 3x3 kernel or neighborhood and followed land use transition rules. Land use transition also to be able to follows, Maximum transition probability rule and hysteresis rule; if a cell is allocate with a land use type, the cell will be not changed to other land use types within the simulation period [18, 19].

$$St+1=f\,(St, N) \quad (6)$$

Where, S is the set of states of the finite cells. The t and t+1 are different moments; N is the neighborhood of cells; and f is the transformation rule of local space.

2.5.4. CA and Markov Chain Model

The CA-Markov model is considered a robust approach because of the quantitative estimation and the spatial and temporal dynamic it has for modeling the LULC dynamic [20]. The 1999 LULC image of Belete Gera Forest Priority Area used as the base image while 2018 LULC map as the later image in Markov model to obtain the transition area matrix between 1999 and 2018 years for prediction of LULC in 2037. The image of 2018 used as base image to obtain the transition area matrix between the years 2018 and 2037 for prediction of LULC of the 2056. In addition to validate the model image of 1999 input as base image and the transition area matrix between 1980 and 1999 used as input for simulation of 2018. The real map of 2018 LULC was used as the base map for estimating future LULC scenario of 2037, and the predicted 2037 LULC map was used as a base image for forecasting LULC scenario of 2056. In addition, 1999 LULC map used as base map for simulation of 2018 year. Therefore, a transition area produced by Markov based on one-year increasing steps for projection of future LULC 2037 year the iterations entered was 19 therefore, CA-Markov model was produced the predicted maps based on 1-year increments. While for the second projection 2037 year was set as starting year and transition probability matrix of 2018-2037 periods was used to forecast 2056 year land use land cover change, the number of iterations entered when CA-Markov model was running is not equal to the future prediction date specified in Markov model which was produced transition areas image and transition probability matrix and 2056 prediction map iterations entered was 10 it’s based on two years increments.

2.6. Model Validation

After any model generates it is desirable to validate the accuracy of the prediction. Therefore, model validation is one of the important stages in the prediction regime of land use land cover. The VALIDATE module involves a comparative analysis of the simulated and real maps based on the Kappa Index. However, it is different from traditional Kappa statistics in that it breaks the validation into several components each with special form of Kappa such as K no, K location, K standard, etc. and the associated statistics [21, 22]. The model output was compared to a present or actual land use map. The predicted LULC map of the 2018 LULC was compared with actual LULC map of 2018 based on Kappa Index of Agreement (KIA) approach, which is widely used in validate LULC change predictions [20, 23]. Before CA-Markov model can be applied for estimation of the next 38 years.

3. Results and Discussion

3.1. Land Use Land Cover Change Detection Analysis

Change detection is defined as the temporal effects variation in spectral response involves situations where the spectral characteristics of the vegetation or other cover type in a given location change over time [24]. To address this issue, technology has developed and the possibilities are virtually unlimited in different areas of applications which can be addressed through earth observation satellite data and decisions support tools such as Geographic Information System (GIS) [25].

Table 3. *Total amount of land use/ cover in hectares for each category from 1980-2018.*

LULC type	Study year					
	1980		**1999**		**2018**	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Agriculture	39,180.30	18.24	66,364.09	30.90	117,201.65	54.57
Forest	146,684.23	68.30	139,037.30	64.74	94,527.52	44.01
Built-up Area	0.00	0.00	106.24	0.05	408.16	0.19
Grassland	19,085.37	8.89	4,037.32	1.88	956.30	0.45
Water body	9,828.97	4.58	5,233.90	2.44	1,685.22	0.78
Total	214,778.86	100	214,778.84	100	214,778.84	100

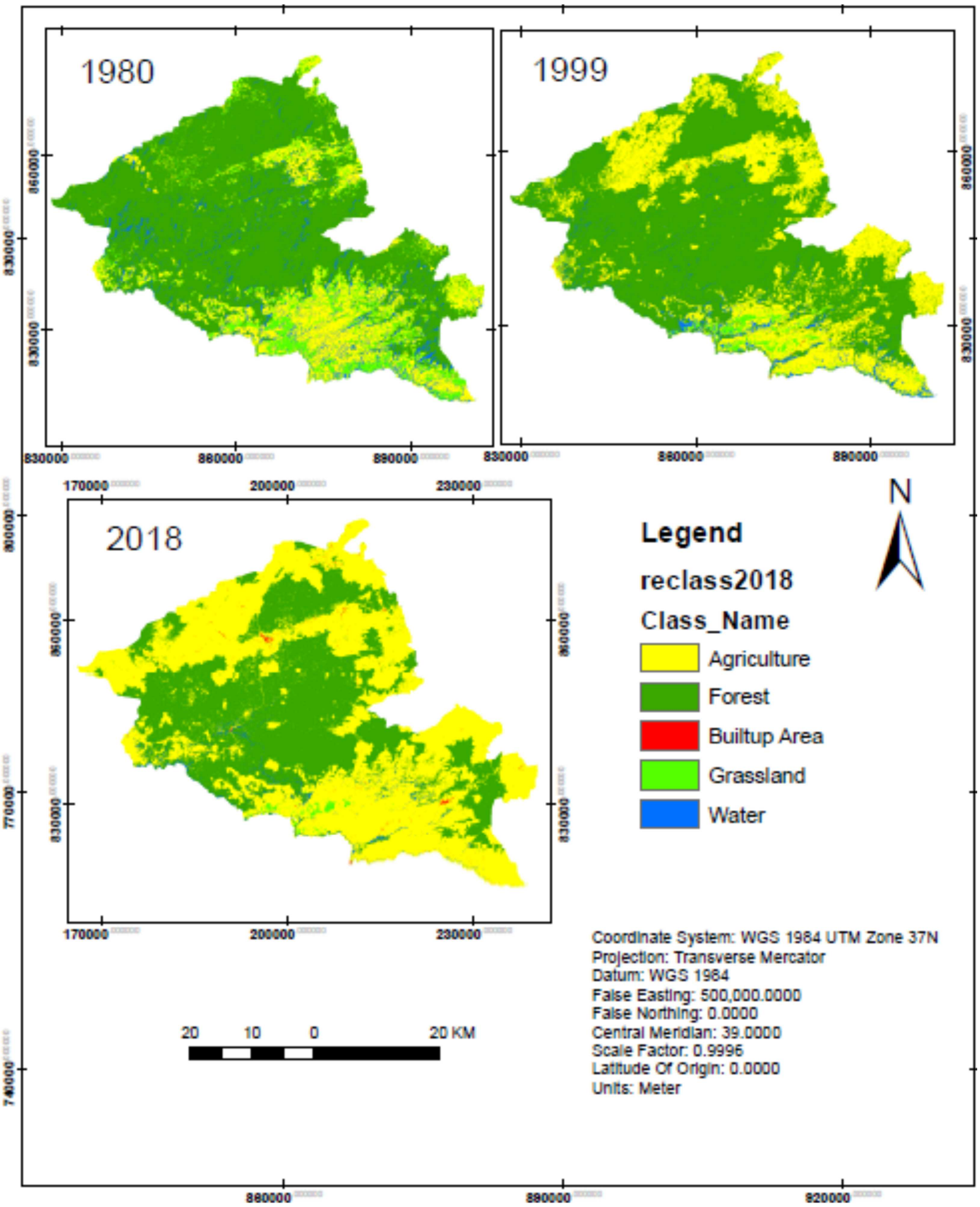

Figure 3. *Land use/ cover maps of Belete Gera Forest priority Area of 1980, 1999 and 2018.*

3.1.1. Area Coverage of the Past 38 Years

The result of LULC change reveals agricultural land increased by 78,021.35 hectares in the four past decades while forest land decreased 52,156.71 hectares. Historically in the study area deforestation was started in 1970s when the Oromo people and Amhara people migrated from central and northern Ethiopia to South western Ethiopia because of drought and political reasons. As well as the coverage of grassland and water bodies declined in the study periods by

18129.07 and 8143.75 hectares respectively. Moreover settlement area was increased by 408.16 hectares there is no urban areas during the initial year of the study year (Figure 3).

3.1.2. Land Use Land Cover Change Matrix

Transition probability matrix (TPM) is from-to information of the land use classes. As a result the first time interval of TPM were calculated for land use/cover maps of 1980 to 1999 years the rows of the table signify the land use status and transferring out situation in the primary period of land use change, while the columns of the table represent the land use status and transferring in situation in the 1999 (Table 4).

Table 4. *Transition probability matrix between 1980-1999 land use/cover changes.*

LULC type		Land class 1999					
		Agriculture	**Forest**	**Built-up**	**Grassland**	**Water body**	**Total**
Land class 1980	Agriculture	26,223.58	8,430.68	75.34	2,372.50	2,078.20	39,180.30
	Forest	27,301.16	118,678.10	10.90	33.17	660.90	146,684.23
	Built-up	0.00	0.00	0.00	0.00	0.00	0.00
	Grassland	10,835.22	5,964.09	18.34	1,430.69	837.03	19,085.37
	Water body	2,004.13	5,964.44	1.67	200.96	1,657.78	9,828.97
	Total	66,364.09	139,037.30	106.24	4,037.32	5,233.90	

Transition probability matrix of 1980 and 1999 periods reveals the highest proportion of net increase in area is agricultural land the net increase areas of agricultural land is 27,183.79 hectares. The main factor for the increasing of the agricultural land was the conversion of land from forest and grassland. The amounts of their transferred areas were 27,301.16 and 10,835.22 hectares respectively. The other highest proportion of net increase of the area is built-up which accounts for 106.24 hectares the net increase area of built-up was mainly from agricultural land transfer-in and grassland transfer-in, and their transfer-in areas are 75.34 and 18.34 hectares respectively. In contrast forest, grass- land and water body areas were decreased as such the forest area decreased 7,646.93 hectares mainly transferred into agricultural land whose changed-out areas were 27,301.16 hectares. In addition, grassland transferred-out 15,048.05 hectares more areas were transferred into agricultural land and forest land whose areas were 10,835.22 and 5,964.09 hectares respectively. Water bodies reduced 4,595.07 hectares transferred into forest and agricultural land the changed areas were 5,964.44 and 2,004.13 hectares respectively (Table 4).

Transition probability matrix of the second time interval developed from land-use maps of 1999 and 2018. The rows of the table represent the land use status and transferring out situation in the 1999 period of land use change, while the columns of the table represent the land use status and transferring in situation in the 2018 (Table 5).

Table 5. *Transition probability of area and matrix calculated using land-use maps of 1999-2018.*

LULC Type		Land Class 2018					
		Agriculture	**Forest**	**Built-up**	**Grassland**	**Water body**	**Total**
Land Class 1999	Agriculture	65,455.26	244.47	258.20	376.48	29.69	66,364.09
	Forest	44,482.54	93,143.90	98.40	26.09	1,286.37	139,037.30
	Built-up	77.90	0.06	27.90	0.20	0.18	106.24
	Grassland	3,629.02	10.32	7.54	383.11	7.32	4,037.32
	Water body	3,556.93	1,128.77	16.11	170.42	361.67	5,233.90
	Total	117,201.65	94,527.52	408.16	956.30	1,685.22	159,371.85

According to the results of 1999 to 2018 agricultural land added time to time when forest land was decreased in greater amount. The result shows the major economic activities of the communities are crop production. Agricultural land gained from forest land, grassland and water bodies the amount of the transferred areas were 44,482.54, 3,629.02 and 3,556.93 hectares respectively.

3.2. Deforestation Analysis

3.2.1. Forest Cover Change of the Past 38 Years

Deforestation map of 1980 to 2018 was presented in the (Figure 4). The result indicated there are high deforestation rate accounted in the study periods. Forest change map of 1980-2018 generated from change map of 1980 and 2018. The change map shows northern, southern, north western and eastern part of the forest were changed to other land classes (Figure 4). In this case the forest cover change was due to expansion of agricultural land area which was related to resettlements and population growth.

Deforestation is increased in the area after millennium as a result of the migration of people in to areas that resulted to expansion of agricultural land and used forest for their usual income. The rate of forest cover change from year 1980 to 1999 is 402.5 hectares per year. From 1999 to 2018 years the rate of deforestation was 2342.62 hectares per year. The annual rate of forest cover change between 1980 and 2018 was 1372.54 hectares per year (Table 6). The result checked as deforestation was high in the area from 1980s up to now.

Table 6. *Trends of forest change between study periods and Rates of Forest cover change hectares per year.*

Forest cover in hectares for three years			Rate of change					
			1980-1999		1999-2018		1980-2018	
1980	1999	2018	Change (ha)	(ha/year)	Change (ha)	(ha/year)	Change (ha)	(ha/year)
146684.23	139,037.30	94,527.52	-7646.93	-402.5	-44509.78	-2342.62	-52156.71	-1372.54

Table 7. *Change Detected from Forest Land to other Land use/cover.*

Forest cover change	B/N 1980 & 1999		B/N 1999 &2018		B/N 1980 & 2018	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest to Agriculture	2,7301.16	97.48	44,482.54	96.93	58,841.77	98.27
Forest to Built-up	10.9	0.04	98.40	0.21	166.91	0.28
Forest to Grassland	33.17	0.12	26.09	0.06	0.57	0.00
Forest to Water Body	660.9	2.36	1,286.37	2.80	871.39	1.46
Total change	28,006.13	100	45,893.40	100	59,880.64	100

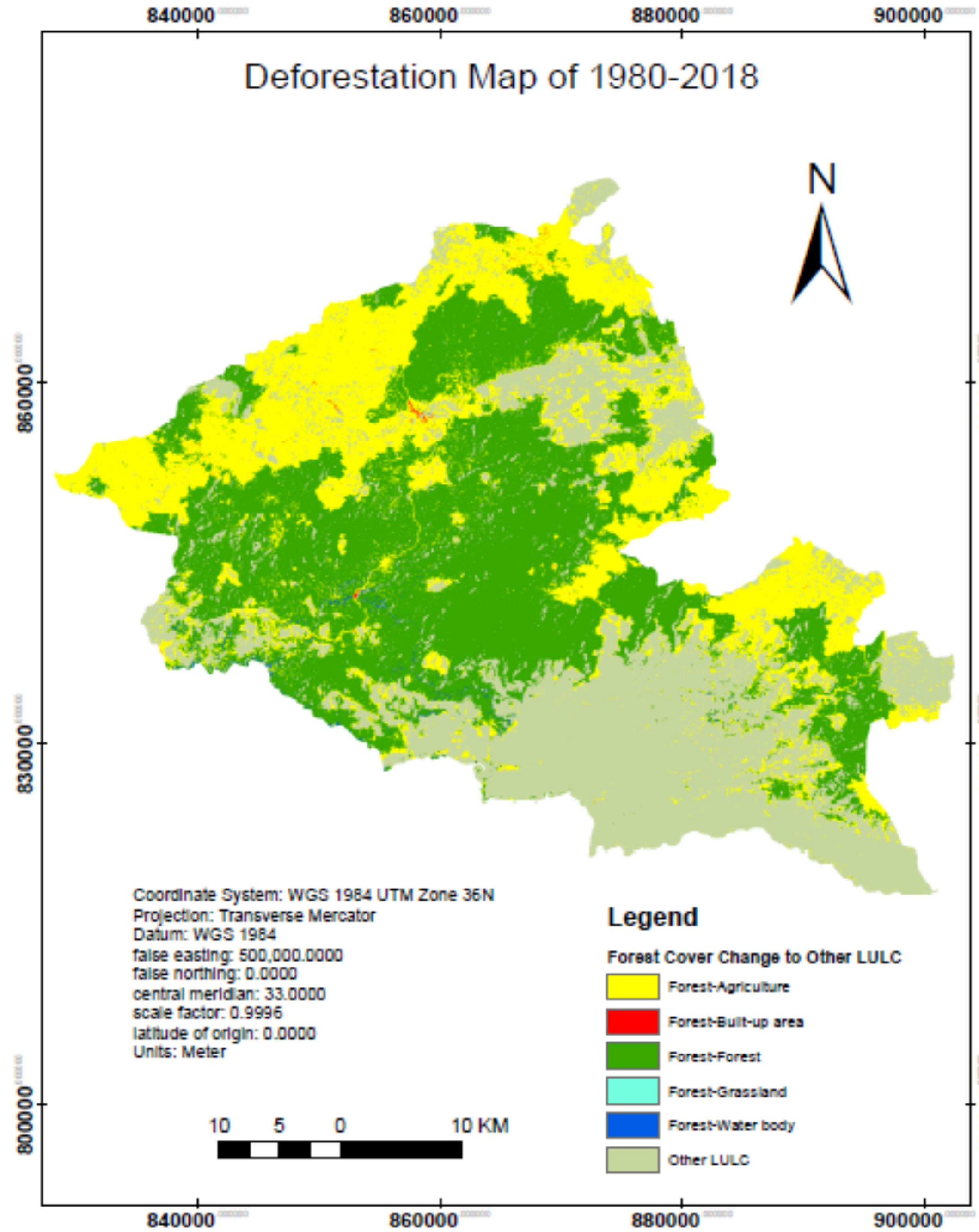

Figure 4. *Deforestation map of 1980 to 2018 years.*

The pattern of forest cover change into other land use/ land cover units between 1980 and 1999, 1999 and 2018 and 1980 and 2018 periods were presented in Table 7. Therefore, 28,006.13 hectares of forest cover land were changed into other land cover and land use units between 1980 and 1999. Specifically, 97.48% of the forest land was changed into agricultural land followed by forest cover transformed in to water bodies was 2.36%. The remaining 0.04% and 0.12% of the forest cover land were converted into built-up and grassland respectively. From the 1999 and 2018, 45893.40 hectares of forest cover land were changed in to other land cover units. The conversion of forest land to agricultural land was the lion share accounted about 96.93%. The remaining 2.8%, 0.21% and 0.06% of the forest were transformed into other land use/cover classes like water body, built-up land and grassland respectively.

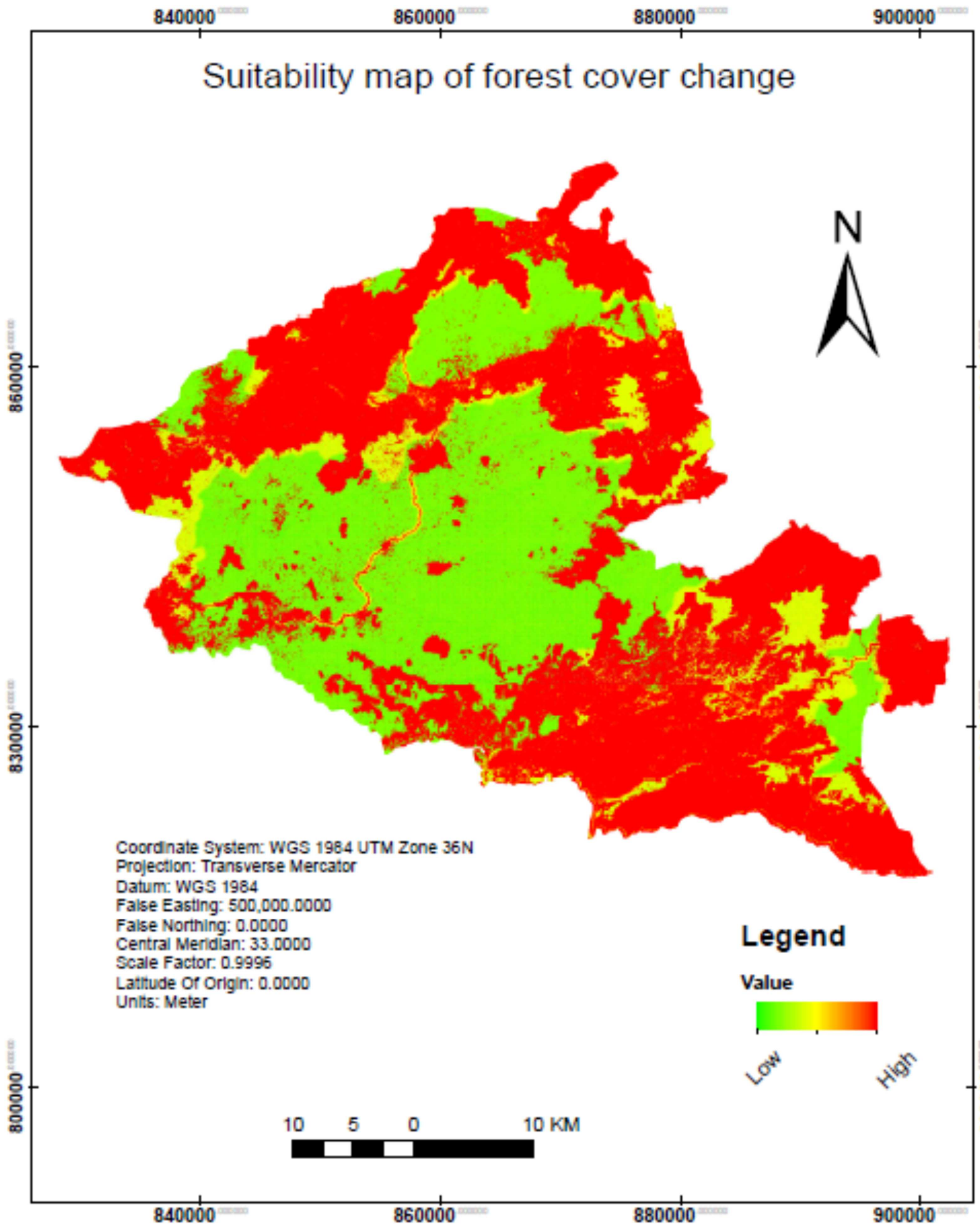

Figure 5. *Suitability map of forest cover change.*

3.2.2. Transition Probability of Forest Cover Change

In order to produce deforestation suitability map the researcher attributed four different factors of driving forces or decision variables for forest cover change. These factors served as criteria that defined some degree of suitability for an activity under consideration and accordingly individual factor scores were assigned. Individual factor scores either enhanced or weakened the overall suitability of an alternative depending on the relative importance factor [26]. Therefore, forest suitability map was prepared by assigning weights for the selected factors like; distance from road, slope, distance from settlement area and distance from forest guard station their weights were 0.3888, 0.2793, 0.1745 and 0.1574, respectively, with consistency ratio of 0.02.

Deforestation is a complex ecological and socio-economic process caused by a number of human and natural factors [27]. Distance to the edge of the village or distance to the boundary of village acts as proximate cause for deforestation. This indicated that deforestation was heaviest around the boundary of the local village and roads. The changes of forest due to resettlements following road network is very high. The forest area within the slope less than 65 degree mostly converted in to agricultural land. Generally the forest suitability map was used for simulation and prediction of land use land cover as input in the model. The transition suitability map of forest was presented in the figure 5.

3.3. Markov Chain Model

Markov chain model was generating transition probability matrix of land use classes from one period to another periods depending on discrete random process with Markovian property. Transition probability matrix of land use/cover conversion for each class took place between 1999 and 2018 years. In order to predict the land use/cover of 2037 and 2056 years Markov chain output of the time periods between 1999-2018 and 2018-2037 were used to calculate the transition probability matrix. For 2018 simulation 1999 and 2018 of land use/cover maps were used to developing the transition probability matrix and transition area matrix (Table 8). Concerning the prediction of 2037 the land use/cover map of 1999 and 2018 were used. The result shows 67.07% of forest would be persist and 31.94% of forest area would be changed to agriculture, with 0.0038% back to forest, while, the probability of agricultural land persist would be 98.57%, in 2037.

Table 8. *Transition probability matrix derived from the LULC maps of BGFPA during 1999- 2018.*

Changing from 1999	Probability of changing by 2018 to;					Subtotals	
	Agriculture	Forest	Built-up	Grassland	Water body	Total	Loss
Agriculture	0.9857	0.0038	0.0040	0.0061	0.0004	1.00	0.0143
Forest	0.3194	0.6707	0.0007	0.0002	0.0090	1.00	0.3293
Built-up	0.7443	0.0007	0.2520	0.0022	0.0007	1.00	0.748
Grassland	0.9017	0.0027	0.0018	0.0922	0.0016	1.00	0.9078
Water body	0.6578	0.2312	0.0032	0.0326	0.0753	1.00	0.9247
Total	3.6089	0.9091	0.4897	0.1333	0.087	5.00	
Gain	2.6232	0.2384	0.2377	0.0411	0.0117		

On the other hand, the transition probability matrix and transition area matrix of the second time interval were developed for year 2037 using images of 2018 land use/cover map to predict 2037 land use/cover map. For prediction of 2056 land use/cover map the 2018 images and predicted land use/cover map for 2037 were used (Table 9). According to the transition probability of 2018 and 2037 the expected self-replacement probability for forest would be 67.71%, while the self-replacement of agricultural land would be 99.65%. The transition probability of forest to agricultural land will be 31.81% as well as 0.08% and 0.37% to built-up and water body respectively. In this transition periods the probability of forest to grassland is 0.03 percent it would be the lowest one.

Table 9. *Transition probability matrix derived from the LULC maps of BGFPA during 2018-2037.*

Changing from 2018	Probability of changing by 2037 to;					Sub-total	
	Agriculture	Forest	Built-up	Grassland	Water body	Total	Loss
Agriculture	0.9965	0.0013	0.0017	0.0005	0.0000	1	0.0035
Forest	0.3181	0.6771	0.0008	0.0003	0.0037	1	0.3229
Built-up	0.1055	0.0000	0.8945	0.0000	0.0000	1	0.1055
Grassland	0.2388	0.0002	0.0004	0.7605	0.0001	1	0.2395
Water body	0.5341	0.0495	0.0029	0.0157	0.3978	1	0.6022
Total	2.193	0.7281	0.9003	0.777	0.4016	5	
Gain	1.1965	0.051	0.0058	0.0165	0.0038		

3.4. Validation

The simulation of land use/cover change map of the 2018 year was based on change in factor's impact with time and trend of forest cover change from 1980 to 1999. In order to validate the land use/cover simulation generated using the CA-Markov model, the simulated land use of 2018 year were relate with the actual land use. Comparison of simulated and actual map for the year 2018 can be shown in (Figure 6). Visual analysis shows that simulated land use/cover map and actual map have close resemblances but not exactly matched especially for Grass- land and water body classes. Hence, the detailed statistical analysis based on the Kappa coefficient is used to measure the overall agreement of matrix, the ratio diagonal values summation versus total number of pixel counts within matrix, and the non-diagonal elements will be the best approach to consider the model accuracy [28]. A kappa value of 0 illustrates the agreement between actual and reference map (equals chance agreement), the upper and lower limit of kappa is +1.00 (it is occur when there is total agreement) and -1.00 (it is happen when agreement is less chance). Accordingly if the results are greater than 0.8 for each kappa index agreement the K statistics are considered accurate [25]. The accuracy assessment of the study was done using VALIDATE module in IDRISI Selva environment v.17. The results reveals that K values (K standard = 0.8370; K no = 0.8780; K location = 0.9033; K location Strata = 0.9033) above 0.8 showing satisfactory level of accuracy. Therefore, CA-Markov Model is suitable to accurately predict the future land use/cover of the study area. Moreover, this study was useful for natural resource management as well as decision making and planning which involved on protecting Belete Gera Forest Priority Area in particular and Ethiopia forest in general.

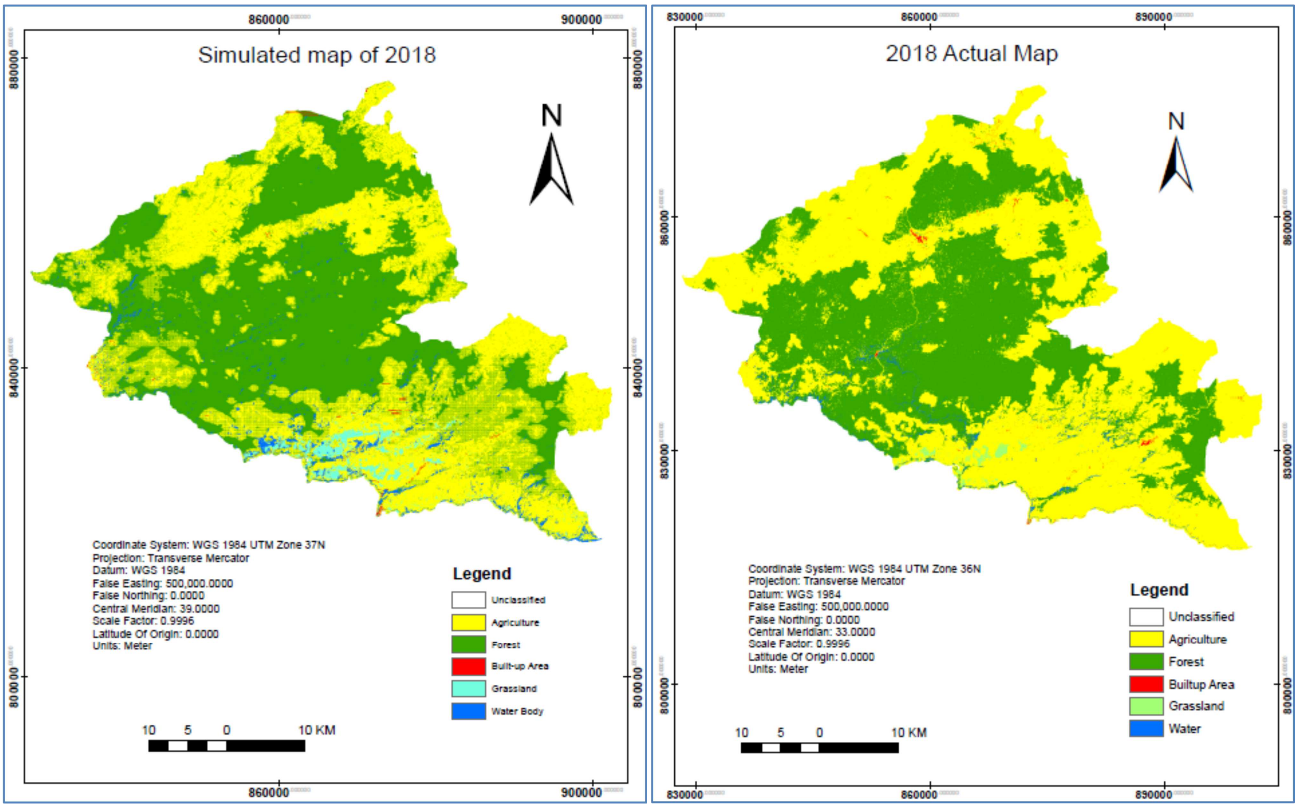

Figure 6. *Actual map and simulated map of 2018.*

3.5. Land Use Land Cover Change Prediction

In the prediction of future land use/cover change scenarios, land use change maps were produced for 2037 and 2056 years. It followed n-step Markov chain transition probability and Von Neumann's self-Reproducing Cellular Automata 3x3 kernels that have 8 neighboring pixels processed in IDRISI Selva using spatial modeling tools.

As mentioned in the methodology the Markov model followed n-step transition probability matrix. Therefore, in this study the researcher used the transition probability matrix of the 1980-1999, 1999-2018 and 2018-2037 to forecasting land use/cover change of 2018, 2037 and 2056 years respectively. For 2037 year prediction 2018 land use/cover map was set as starting year and transition probability matrix of 1999-2018 periods were employed. In this projection the number of iterations specified was equal to the future prediction date time when Markov was running to produce transition areas image and transition probability matrix. The expected area to change in transition area matrix was observed to be forest, water body and grassland (Table 10). It was observed that agricultural land expansion is the main driving force for change especially in forest, water body and grassland. Conversion to settlement area, and agricultural land was due to rapidly increasing village population in Belete Gera Forest Priority Area. The predicted maps shows forest land area was reduced in dramatic manner, while agricultural land area increased speedily. In some manner grassland area and water body were reduced as it was visible in the predicted maps of the future 2037 and 2056 years (figure 7).

Antonio, C. A. states that migratory agriculture account for 70 percent of deforestation in Africa [28]. According to [29] Africa accounts -0.18% of forest loss per annum while in Latin America the rate of deforestation is -0.23% per year and in the World the rate of deforestation accounts -0.07% per year. According to transition probability matrix of 2018 and 2037 (Table 9) forest cover would be loss 32.29% within 19 years out of this 31.81% of forest area conversion is expected to agricultural land. This would be identifies more area of forest cover would be converted to agriculture and the rest 0.08%, 0.03% and 0.37% would be expected to change built-up, grassland and water body classes respectively. Depending on this transition probability matrix forest would be gain 5.1% from other land use land cover it means the rate of deforestation would be occurred within the future 19 years in BGFPA is 27.19%. Concerning this result the rate of deforestation in BGFPA is 1.43% annually which should be the highest annual rate of deforestation. Therefore, the rate of deforestation expected in the study area is high due to increasing of agricultural land expansion would drastically changing and harms natural forests of the area. If this action would be continued in BGFPA the forest area is cleared within next seven decades.

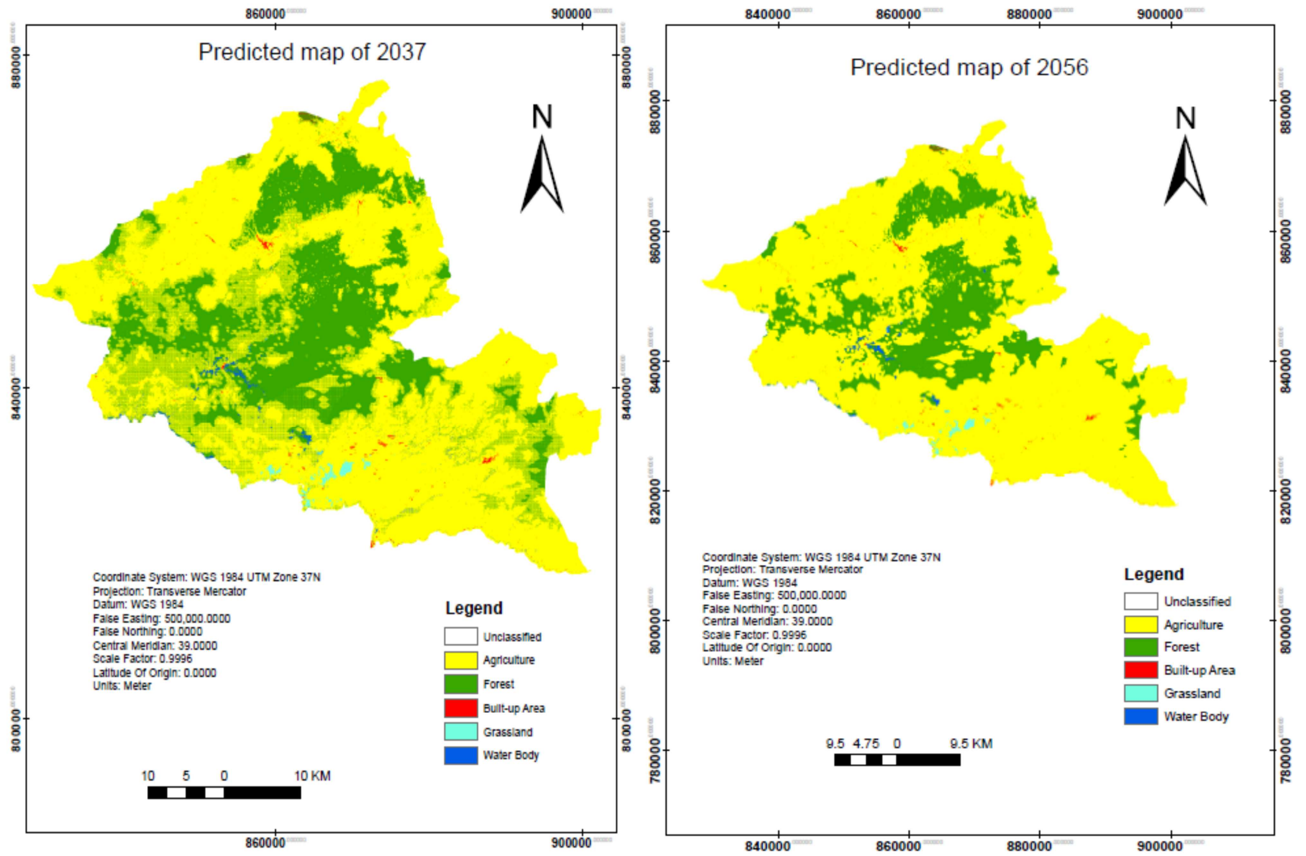

Figure 7. *Land use/cover change prediction map of 2037 and 2056.*

In addition, the predicted land use/cover change area of future 2056 year is exhibited in the (Table 9) it represents forest land would be cover 20.44% out of the total land area covered in the study area. Forest land cover comprised 44.01% in 2018 year out of total land area in the study area as such it would be decreased to 20.44% in the future 2056 year. In other way agricultural land area shares 54.57% out of total land area of the Belete Gera Forest in 2018 and would increase to 78.59% in the future 2056 year out of the total land area of the study area. The other land use/cover grassland and water body would be decreased from 0.45% and 0.78% in 2018 to 0.41%, 0.86% respectively in 2056 year out of total land coverage of the study area, on the other hand built-up area should be increased by 0.30% in 2056 year than that it shared 0.19% in 2018 year out of total land of the area.

Table 10. *Expected land use/cover change predicted area in (hectare) and Percent for 2037 and 2056 years.*

LULC type	Year							
	2037		2056		2018-2037		2037-2056	
	Area (ha)	%	Area (ha)	%	changed (ha)	%	changed (ha)	%
Agriculture	147895.56	68.86	168791.90	78.59	30693.91	14.29	20896.34	9.73
Forest	64322.87	29.95	43906.50	20.44	30204.65	14.06	20416.37	9.51
Built-up Area	647.19	0.30	663.30	0.31	239.03	0.11	16.11	0.01
Grassland	882.27	0.41	763.65	0.36	74.03	0.03	118.62	0.06
Water Body	1030.95	0.48	653.49	0.30	654.27	0.30	377.46	0.18
Total	214778.84	100	214778.84	100				

Moreover, the rate changes of predicted forest land, grassland, and water body were higher in the both prediction periods. Whereas, the change rate of agricultural land was negative. Deforestation would be occurred as a result of conversion of the forest land cover into agriculture and settlement area. Therefore, decreasing the areal of forestland formation leads to increasing deforestation and drought, which interns to climate change and disturbs ecosystems.

As a result, model suggests that forestland should reduce more around gentle slope and horizontal surface which was proper for wild animals and the prediction of decreasing of forest land may be due to population growth and expansion of agricultural land area. Contemporary agricultural land increasing would be improved the amount of crop production in the BGFPA in the next 38 years. In this study, geophysical and distance based factors were considered to generate transition suitability map of forest. However, presence of these factors may reduce differences in simulation results of land use structure. In general, prediction are intended to provide environmental management decision makers for protecting, controlling and monitoring the potential forest cover occasions and challenges future circumstances.

4. Conclusion

Land use land cover changes of the study area from 1980-2018 were mainly related to the influence of human activities. The forest land and grassland changed areas were large, and their changes were due to expansion of agricultural land areas, and water areas were reduced following the reduction of forest cover which was mandatory for protecting water quantity and quality. In other way agricultural land and built-up areas were drastically increased from the initial to the end as a result of forest land, grassland and water body areas converted to others. BGFPA has experienced deforestation due to the increasing of population and expansion of agricultural land area. It could be resulted to uncontrolled and un- manageable of land use development. Therefore, improper continuous development of land use has led to increasing forest destruction and ecosystem degradation in the study area. Hence, future land use/cover change maps can be used as a premature warning system for proper land use development to control undisturbed area of natural resources and ecosystem from human activities. Likewise, a future prediction of land use land cover change maps were help for planning and management of natural resources.

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