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Comparative Analysis of Markov Chain and Cellular Automated Markov Models for Forecasting Forest Depletion in Afaka Forest Reserve, Kaduna State, Nigeria

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Abstract:
The rate of forest depletion in Afaka Forest Reserve is quite alarming; this study aims at a comparative analysis of Markov Chain model and Cellular Automata-Markov model in forecasting forest depletion in Afaka Forest Reserve. LandSat TM of 1990 and NigeriaSat-1 of 2009 were used for the analysis. The datasets were orthorectified, therefore no need for Geometric and Radiometric corrections. However, the datasets were georeferenced. Supervised image classification was used to group the pixels into land use/land cover types. Forecast of forest depletion for 2028 was done using Markov chain model and CA-Markov model in Idrisi Selva. Chi-square was used to test for significant difference between the results of the two predictive models. Forest forecast for 2028 using markov chain model shows that forest will reduce from 3724.25ha in 1973 to 3168.75ha in 2028. Using CA- markov the result revealed that forest cover will decrease to 3019.54ha by 2028. The Chi-Square test reveals a significant difference between the results of the two models.

Keywords: *Forest depletion, Forest Reserve, Remote Sensing. GIS, Markov Chain model, CA- Markov model*

1. Introduction

Nature has endowed man, since ages with many natural resources for the sustenance of his socio-economic needs; but since these needs are ever changing and ever on the increase, these resources are often at the risk of depletion (Nwadialor, 2001). Nwadialor stated that one of the most affected of these resources appear to be “natural forest”, which has been continuously under threats of over-exploitation by man, leading to negative changes in its status and productivity. According to the author, changes occur as human beings attempt to adjust their seemingly endless wants and desires for food, shelter, recreation, infrastructural facilities and so on to the forest resources available to them.

Forest depletion is akin to deforestation which broadly speaking, refers to the gradual or rapid process of temporary or permanent removal of trees, resulting in the partial or complete eradication of tree cover in a locality (Jones, 2000). It can occur due to natural or human factors. In recent times, the rapid rate of deforestation and forest degradation in developing countries has resulted in the annual loss of about 17-20 million hectares of forest (Flazzel & Magrath, 1992). According to the authors, deforestation in simple terms is the gradual reduction of the stocking vegetation cover resulting from human activities.

Human activities are globally recognized as the foremost cause of deforestation, with the agricultural and urban-industrial activity being the most important factors (Geist & Lambin, 2003; Odihi, 2003; Vince & Iovanna, 2006). According to Odihi (2003), poverty and other socio-economic woes which force people in the third world to exploit or pillage forest resources for the purpose of energy and commercial gains are increasingly recognized as important deforestation factors. The author noted that population growth among communities around the forest imposes a lot of pressure on the forest for subsistence farming. Salami and Balogun (2004) noted that the mode of incursion is through agro-forestry.

According to Food and Agriculture Organisation of the United Nations (FAO, 2010) Forest can be defined as land spanning more than 0.5 hectares with trees higher than 5 meters and canopy cover of more than 10 percent or trees able to reach these thresholds *in situ*. However, it does not include land that is predominantly under agricultural or urban land use.

Forestry development began in Nigeria in 1889 with emphasis on forest reservation and regulated timber exploitation (Geometics Nigeria Limited, 1997). Significant portions of the forest reserves in Nigeria that remained relatively undisturbed until the 1980s have been lost in the last two decades. As these natural forest ecosystems disappear, so do many of the animal life, timber pharmaceuticals, fruits and food which they provide (Akpu, Tanko & Yahaya, 2012). In 1980, demand for forest products, especially timber became insatiably high as a result of increasing human population pressure and economic growth. This led to unregulated forest exploitation, thus resulting in degradation of the forest resources in the country (Geomatics Nigeria Limited, 1997). In an attempt to preclude total depletion of the forest resources, the Federal Government of Nigeria has geared effort towards increasing 10 percent (91,000 km^2) of the total land area under forest reserve to 20 percent towards meeting the FAO specification of 25 percent in the future (Ezebilo, 2004). However, the forest reserves are at the risk of depletion due to population pressure and urbanization. For instance, Akingbogun, Kosoko and Aborisade (2012) discovered a large decrease from 12.5% to 0.13% in forest plantation in Eleyele reserve between 1984 and 2000.

Afaka forest reserve was established in 1954 as an experimental plantation site to increase the productivity and arrest deterioration and desertification of the semi- arid zone of the Northern Guinea savannah of Nigeria, but human influence has been identified as a critical factor militating against the realization of these noble objectives (Nwadialor, 2001). Due to rapid urban growth coupled with inadequate planning, as well as poor monitoring strategy, this forest reserve is now greatly threatened which could be devastating if no control measure is adopted. The areas under forest cover at the reserve decreased by 48 percent in 1995, which led to opening of forest canopy and exposure of bare forest floor that were subsequently subject to erosion (Fuwape, Akindele & Adekunle, 2006). Akpu, Tanko and Yahaya (2012) in their assessment of the implication of urban growth on vegetation cover in Afaka forest reserve revealed that natural forest/plantation decreased from 20.94% in 1990 to about 11.6% in 2009. The study showed that natural forest/plantation was declining at the rate of 2.23% per year.

A model is a representation of reality used to simulate a process, understand a situation, predict an outcome, or analyse a problem (GIS Glossary, 1996). Detecting past changes and predicting these kinds of changes in the future play a key role in decision making and long-term planning. Predictive models of land use change are important tools for managing ecological issues. Forecast modelling can be used to evaluate land use systems and identify important factors that affect land use decisions (Rounsevell, Annetts, Audsley, Mayr & Reginster, 2003).

Carmel, Kadmon and Nirel (2001) attested that both mechanistic and empirical approaches are widely used in modelling vegetation dynamics. The mechanistic approach assumes that the factors underlying the process are known, and explicit functions are used to connect these independent factors with the modelled variable (Levin, 1997). In empirical models, future changes in vegetation are extrapolations of past changes. In a pure empirical model, no ecological assumptions are built into the modelling processes, which are based on observations only. Transition models (also called Markov models) are the most common empirical models of vegetation dynamics, and are often used to predict expected future vegetation (Callaway & Davis, 1993).

Markov process models are a class of probability used to study the evolution of system overtime. Transition probabilities are used to identify how a system evolves from one-time period to the next. A markov chain is the behaviour of the system overtime, as described by the transition probabilities and the probability of the system in various states (Bhagawat, 2011). Markov chain model analyses two qualitative land cover images from different dates and produces a transition matrix, transition area matrix and a set of conditional probability images. However, Cellular Automata_ Markov is a combined cellular automata/ Markov chain land cover prediction procedure that adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov change analysis (Eastman, 2009).

Previous studies attempted to predict changes using either Markov chain or CA- Markov. For instance, Mubea, Ngigi and Mudia (2010) applied Markov chain analysis in predicting land cover change in Nakuru Municipality, Kenya. The projected land use/land cover for 2015 showed a substantial increase in urban and agricultural land use. Similarly, Islam and Ahmed (2011) predicted land use change in Dhaka city, Bangladesh, using GIS-aided Cellular Automata- Markov, they modelled the land use change based on the past trend (1991-2008) to generate the future land use map of Dhaka city for the year 2020 and 2050. The results showed that the urban built-up areas will increase significantly.

Ongsomwang and Saravisutra (2011) modelled urban growth in Nakhon Ratchasma province of Thailand. They compared results of CA- markov and logistic regression model 2011 using overall accuracy and kappa *hat* coefficient of agreement for urban and built-up areas basis. Results revealed that CA-markov model had overall accuracy of 93.41% and kappa hat coefficient of Agreement of 0.84; while logistic the regression had 89.41% and 0.71%.

However, none of the previous studies compared markov chain and CA- Markov models in forecasting Afaka forest depletion. It therefore becomes pertinent for this paper to compare these two predictive models in forecasting forest depletion. Hence, the aim of this paper is to compare Markov chain and CA-Markov models for forecasting forest depletion in Afaka forest reserve. The objectives are to; identify and map land use/land cover of Afaka forest reserve, classify the land use/land cover of Afaka forest reserve, forecast forest depletion of Afaka forest reserve using both Markov Chain and CA-markov models and compare the results of the two models.

1.1. Hypothesis

H_o: There is no significant difference between the results of markov model and CA_Markov

2. The Study Area

Afaka forest reserve is situated some thirty (30) kilometres Northwest of Kaduna Township, along Kaduna-Lagos express highway and is about 12,243.760 hectares in areal extent. (Nwadialor, 2001). It is geographically located between Latitudes 10° 33′ N – 10° 42′ N of the equator; Longitudes 7°13′ E – 7° 24′ E of the Greenwich meridian (Nwadialor, 2001) (See figure 1).

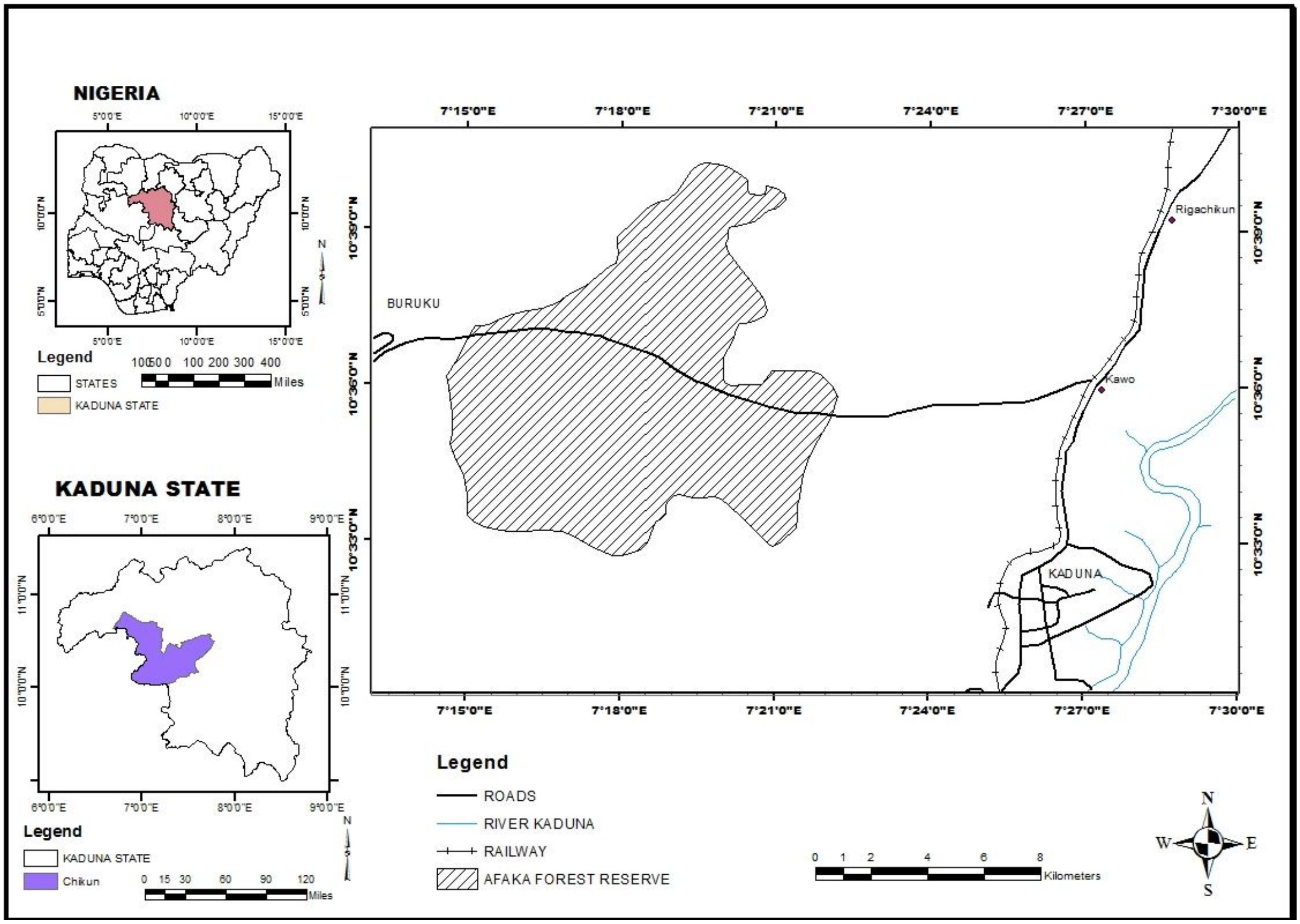

Figure 1: Afaka Forest Reserve and Environs
Source: Modified from Afaka Forest Map (Savannah forestry research, 2013)

The study area has a tropical continental climate (Aw) with distinct wet and dry seasons, reflecting the influence of tropical maritime air mass (mT) and Tropical continental air mass (cT) which alternate over the country. When mT which originates from the Altantic Ocean, prevails over the area, it brings the rainy season while cT originates from the Sahara Desert, it brings in the dry season with cold and dusty air that occasionally limits visibility and reduces solar radiation bringing in harmattan condition in the area (Iguisi, 1996). Northern Nigeria experiences four distinct seasons: dry and cold season which lasts from November to February; dry and hot season, 'March to May,' wet and warm season which lasts from mid-May to early October,' dry and warm season which lasts from Mid-October to mid-November

Afaka forest reserve area are like other parts of northern Guinea Nigeria has mean monthly minimum and maximum temperatures of 15.9°C and 35.35°C respectively with a range of about 19.45°C. The highest temperatures are being recorded in March and April and the lowest in December and January. Average annual rainfall in the area is about 1530mm; ranging from 0.0mm from November to February and 825.0mm in August, which is the wettest month (World 66 Magazine, 2011).

The soils are Ferric Luvisol0 (FAO, 1974) and are derived from Precambrian Basement Complex formations. The surface horizons are greyish brown, sandy loam or loamy sandy with a moderate medium sub angular, blocky structure. The underlying horizons are light yellowish-brown or yellowish-white with few faint or distinct mottles, sandy clay loam to clay loam and strong medium sub angular, blocky structure (Jaiyeoba, 1998).

The Afaka Forest Reserve is drained by two of the tributaries of Kaduna River and its vegetation is diverse because it is a combination of plantation and natural forests. In this area, the main indigenous forest species are *Pakia biglobolsa* (Dorawa*), Ceiba petandra* (Silk Cotton), and *Andasonia digitata* (Kuka) while the exotic forest species include *Azadiracta indica* (Neem), Tectona *grandis* (Teak), Eucalyptus spp., Gmelina spp., and Pinus caribea (pine) (Adewuyi & Olofin, 2014).

3. Materials and Methods

The types of data used for this research were satellite imageries obtained from National Centre for Remote Sensing, Jos and via satellite protocol and downloading links of earth explorer, since Afaka forest reserve lies on Row 189 Path 53 on World Referencing System. LandSat (MSS) acquired in 1973, Land Sat (TM) of 29th September 1990 and Nigeria sat – 1 of 26th December, 2009 with spatial resolutions of 79m, 30m and 32m respectively were used to forecast forest depletion in 2028. Ground Control Points (GCPs) were obtained using Global Positioning System (GPS) to validate the coordinates of the classified imageries.

A subset covering Afaka forest reserve was extracted from the full scene of the satellite imageries using ERDAS IMAGINE 9.2 software. The image bands were layer stacked to produce a colour composite. Since the datasets were orthorectified, there was no need for Geometric correction and radiometric rectification. Nigeria Sat- 1 with spatial resolution of 32m and LandSat MSS with spatial resolution of 79m were resampled to 30m. This was done to bring all the satellite imageries to a common spatial resolution of 30m. The satellite imageries were projected to Universal Transverse Mercator (UTM) zone 32. Georeferencing was done to bring all the satellite images to the same coordinate referencing system to allow overlay analysis to be carried out.

Supervised classification was used to classify the images into land use/land cover classes because of its high accuracy in mapping of classes; however, it depends heavily on the cognition and skills of the image specialist (Short, 2013). Training samples were identified and delineated on the digital image of 1973, 1990 and 2009. The objective was to identify set of pixels that accurately represents spectral variation present within each information region. The datasets were classified into the following classes: Agriculture, Built-up land, Natural forest/Plantation, Water body and bare surfaces using maximum likelihood algorithm. Ground truthing was used to verify the accuracy of the image classification.

The classified imageries of 1990 and 2009 were supplied as input for the Markov chain model, with the year interval of nineteen (19) years. The forecast for the next nineteen (19) years (2028) was done by markov chain model. The classified imageries of 1990 and 2009 were equally supplied to the CA- Markov model to forecast for 2028. Chi- square statistical test was used to test for significant difference in the results of the two models.

4. Results and Discussion

The results are presented in Table 1, 2 and 3. Other results are presented in maps form, Figure 1, 2, 3 and 4

LAND USE/LAND COVER 2009	Bare Surface	Forest	Water Body	Farm land	Grassland
Bare Surface	**0.0286**	0.4589	0.2398	0.0041	0.2686
Forest	0.0521	**0.5073**	0.1645	0.0141	0.2621
Water body	0.0451	0.3679	**0.2335**	0.0088	0.3446
Farmland	0.1355	0.5033	0.0531	**0.0946**	0.2135
Grassland	0.0035	0.3893	0.302S3	0.0387	**0.2661**

Table 1: Transition Probability derived from Land use/Land cover map of 2028
Source: Authors' Analysis, 2015

The row categories represent land use/ land cover classes in 2009 whilst column categories represent 2028 classes. From table 1, bare surface has a 0.0286 probability of remaining bare surface in 2028 and probability of changing to forest given to be 0.4589.

Forest has 0.5073 probability of remaining forest and 0.2621 probability of changing to grassland. This means that the forest land cover will be relatively stable.

Probability of grassland surviving is 0.2661 and probability of being converted to forest is 0.3893, provided every other factor is held constant in 2028. Based on the transition probability table forest will be the most stable land cover category and bare surface least stable.

4.1. Projected Land Use/Land Cover

Table 2 shows land use/land cover projection for 2028. Markov model is one of the most widely used models in monitoring vegetation dynamics. The result revealed that 12558.85 of the forest may be converted to bare surface, if nothing is done to salvage the forest reserve.

Land use/land cover Classes	2028	
	Areas in hectares (ha)	Areas in Percentage (%)
Bare surface	12558.85	64.4
Forest	3168.75	16.3
Water body	1618.98	8.3
Farmland	139.14	0.7
Grassland	2016.33	10.3
Total	19502.05	100

Table 2: Projected land use/Land cover for 2028, Using Markov Model
Source: Authors' Analysis, 2015

The results suggest that tree felling will have a great impact on the future of the forest. The area covered by forest will reduce to 3168.75ha from 3724.25ha in 1973. By implication 555.5ha of the forest will be lost to other land use/land cover in 2028. Figure 2 reveals that bare surface will increase more than any other land use/ cover class. This is similar to the findings of Akingbogun *et al.,* (2012) which reveals that communities around Eleyele forest reserve imposes a lot of pressure on the forest plantation, if the it persists in a matter of time the whole reserve would have been converted to bare ground. There is a decline in the area covered by forest and an increase in the area covered by other land use/cover, this is similar to the findings of Rimal (2011) that a growth in urban land use might threaten the areas that are currently reserved for forest reserve and agricultural purposes in 1976 urban land cover in Birantnagar Sub Metropolitan city of Nepal was 4.8% but increased to 38% in 2009. Figure 2 shows the spatial distribution of land use/ cover change in Afaka forest reserve for 2028.

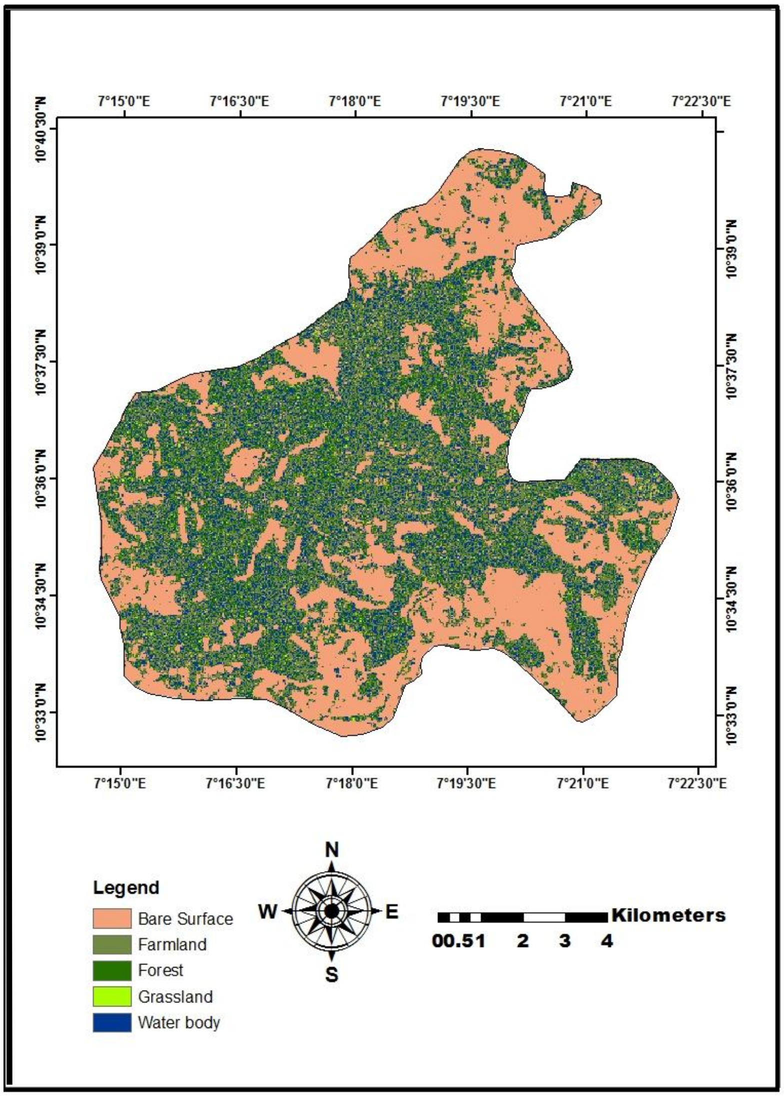

Figure 2: Forecast of Afaka for 2028, using Markov Chain
Source: Authors' Analysis, 2015

4.2. Forecast of Forest Loss using CA- MARKOV model

The forecast of Afaka Forest reserve using CA-Markov is presented in Table 3 and Figure 3. It was observed that based on the first satellite imagery available in 1973 forest will decrease from 3724.25ha in 1973 to 3019.54ha in 2028. This signifies that 18.9% of the forest area will be lost to other land use/land cover in 2028, while grassland will increase from119.32ha in 1973 to 2041.18ha in 2028, gaining about 1610.7%. This is in conformity with the forest loss predicted by Kushwaha, *et al.,* (undated) when they assessed forest ecosystem dynamics in parts of north- east India. The authors predicted that by 2028 forest area of 4,563.34km^2 will be lost.

Land use/land cover Classes	2028	
	Areas in hectares (ha)	Areas in Percentage (%)
Bare surface	442.82	6.1
Forest	3019.54	41.6
Water body	1647.32	22.6
Farm land	116.07	1.6
Grassland	2041.18	28.1
Total	7266.93	100

Table 3: Land use/land cover Projection 2028, using CA_Markov
Source: Authors' Analysis, 2015

The projected map indicates that grassland will be more prominent in the western part of Afaka. This may be as a result of intrusion from neighbouring communities. More bare surfaces tend to be in the northern part of the study area. It is also observed that other land use/land cover classes aside the ones mentioned are likely to emerge. These new classes are represented by as 'others' in figure 3

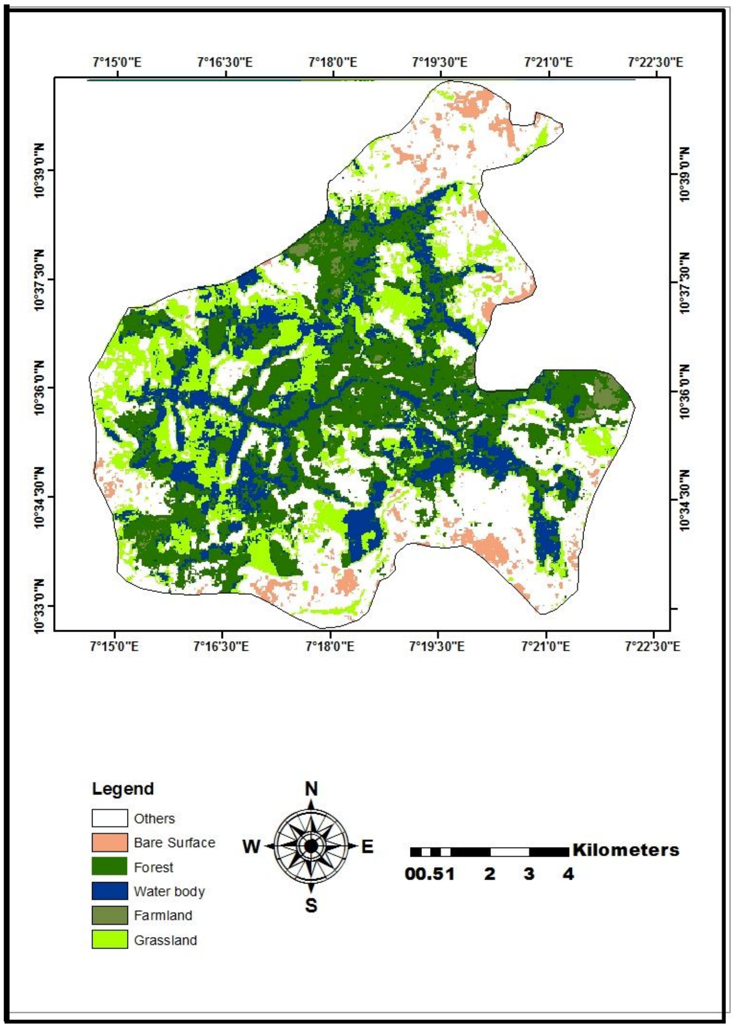

Figure 3: Forecast using CA_Markov model
Source: Authors' Analysis, 2015

4.3. Differences between Markov Chain and Cellular Automata Markov Chain Model

From figure 4 the total area that will be covered by bare surface using markov model is 12558.35ha. This is in sharp contrast with that of CA_ Markov that has 442.82 ha. This is because in markov chain model new land use/ land cover classes that emerged were grouped under bare surface. The area covered by forest using Markov is 3168.75 ha while that of CA_ Markov is 3019.54 ha. There exists a difference of 149.21 ha. Water body also has a difference of 28.34 ha. Farmland results revealed a difference of 23.07 ha. Grassland results differ by 24.85 ha (see figure 4).

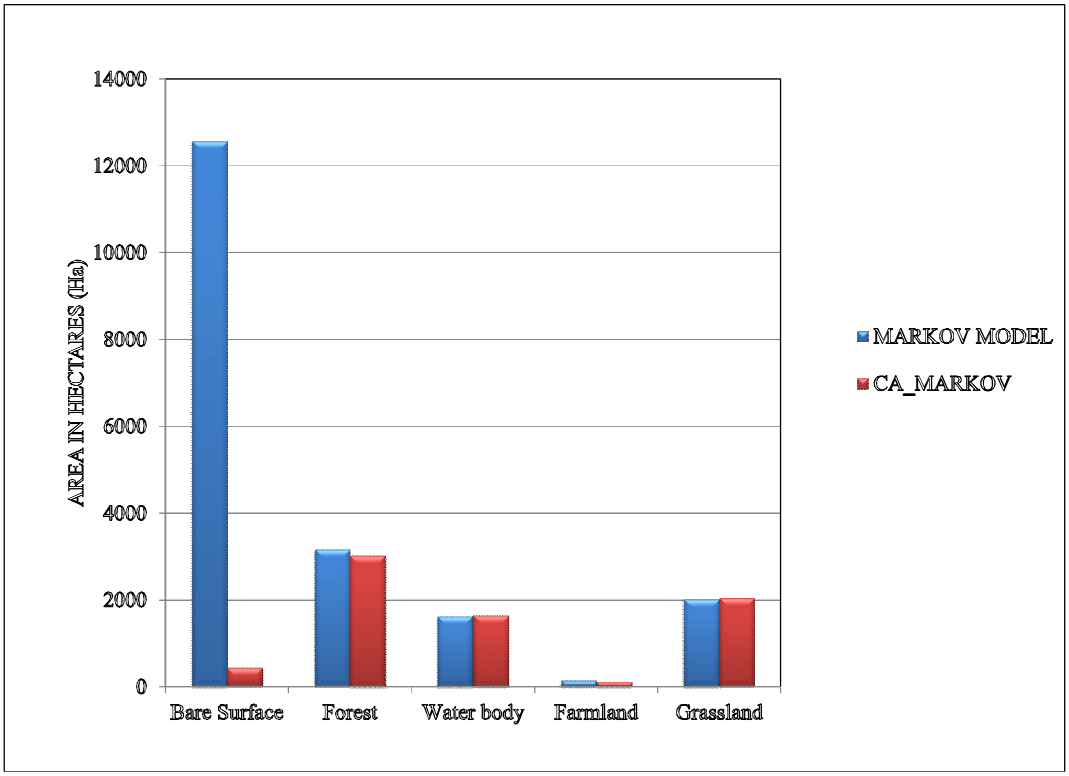

Figure 4: Land use/Land cover Forecast, 2028
Source: Authors' Analysis, 2015

The rates of change from 1973 - 2009 was observed to be -45.77 ha per annum (-1.28%). By implication 45.77 ha of the forest cover is lost annually. There was a sharp contrast in the results of the two models under consideration.

The calculated value (233373.52) is greater than the critical value (9.591) at α = 0.05, the null hypothesis. The chi square result established that there is significant difference between the results of Markov Model and CA_Markov model. However, CA-markov model is a better model because it shows the spatial distribution of the land use/ cover and new land use/cover that are likely to emerge in future.

5. Conclusion and Recommendations

Both markov chain and CA-markov can be used to forecast forest depletion. Both models reveal that forest in essence will decrease by 2028, while land cover like bare surface will increase significantly. The study shows that there is significant difference between the results of the two models.

Markov model did not consider the spatial distributions of the changes; the locations of these changes were not indicated. For instance, areas of dense forest cover cannot easily be identified, but this was considered in CA_Markov model. The differences between the two models in forecasting forest depletion are quite significant with an indication that other Land use/land cover classes are likely to emerge in future.

CA_Markov gives a better result because it gives the spatial distribution of these changes, where it is more concentrated and where the changes are sparse. The new classes that emerged are grouped into a 'new class' and it is labelled 'others' for easy identification but Markov grouped these new classes under bare surface making it difficult for users to identify new classes that are likely to emerge. Therefore, CA- Markov is a better model for forecasting forest depletion. Based on the findings, following recommendations are put forward

- ✓ CA_Markov models should be used to forecast forest depletion because it indicates the spatial distribution of the forest change as well as new classes.
- ✓ Legislation to protect forest reserve.
- ✓ Proper monitoring using space technology

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