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 used Cellular Automata-Markov model to forecast 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 CA- Markov model in Idrisi Selva. Using CA- markov the result revealed that forest cover will decrease to 3019.54ha by 2028. The findings revealed that there is steady increase in the area occupied by sparse forest over time as a result of anthropogenic factors. Based on the key findings of the research, it was concluded using predictive models in forecasting future state of Afaka forest reserve in Kaduna state. Based on the results obtained the following recommendations were put forward to preserve the forest reserve: Geospatial techniques should be employed in monitoring forest resources. CA_Markov models should be used to forecast forest depletion because it adds spatial contiguity. Enforcement of legislation concerning indiscriminate felling of trees.

Keywords: CA- Markov model, Forest depletion, Forest Reserve, Geographic Information System. Markov Chain model, Remote Sensing.

Introduction

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. According to Flazzel and Magrath, 1992, Jones 2000, 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 and Lambin, 2003; Odihi, 2003; Vince and 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. Odihi (2003), the 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.

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 Food and Agriculture Organization 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.

World forests cover 30% of the total land area (FAO, 2005; United Nations Environment Programme, UNEP, 2007). This is approximately 4 billion hectares corresponding to 0.62 hectares per capita; this is unevenly distributed with 62 countries of combined population of approximately 2 billion having less than 0.1 ha per capita (FAO, 2005). By 2005, deforestation rate was about 13 million hectares per year. This includes 6 million of primary/frontier forests (FAO, 2005). Frontier forests are defined as "forests where there are no clearly visible indications of human activity and where ecological processes are not significantly disturbed" (UNEP, 2007). Over the last three decades, almost half of the Earth's original forest cover has been deforested, and only 20% of frontier forests remained by 1997 (Bryant, Daniel & Laura, 1997). Primary forests have no sign of past or present human activities and are considered to be the most biologically diverse ecosystems in the world (Butler, 2005). 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 and Reginster, 2003).

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 had coefficient of Agreement of 0.84; regression had 89.41% and 0.71%.

Akingbogun, Kosoko and Aborisade (2012) studied urban growth effect on the Eleyele Forest reserve in Ibadan, Oyo state, using Remote Sensing (RS) and Geographic Information System (GIS). The results showed that there was a large decrease in forest plantation between 1984 and 2000 from 0.8808 hectares (12.5%) to 0.0094 hectares (0.13%).

However, none of the previous studies made use of CA- Markov model in forecasting Afaka forest depletion. It therefore becomes pertinent for this paper to make use of this predictive model in forecasting Afaka forest depletion. Hence, the aim of this paper is to use CA-Markov model 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 and forecast forest depletion of Afaka forest reserve using CA-markov model.

Description of 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 within Latitudes 10˚33ʹ – 10˚42ʹN of the Equator; Longitudes 7˚13ʹ – 7˚24ʹE of the Greenwich Meridian (Nwadialor, 2001)

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). Kaduna, 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 (Iguisi, 1996). 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 Afaka forest 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 and Adekunle, 2006). Hence, the needs to forecast the future state of this forest reserve using predictive models.

Methodology

The types of data used for this study 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.

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 to the CA- Markov model to forecast for 2028.

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.

Table 1.1 Extent of Forest Cover from 1973-2009.

LAND USE/LAND COVER	1973 AREA (Hectares)	%	1990 AREA (Hectares)	%	2009 AREA (Hectares)	%
Bare Surface	874.23	8.2	982.14	9.2	554.60	5.2
Forest	3724.25	34.9	2858.95	26.8	2988.02	28.0
Water body	851.24	8.0	4724.92	44.3	1622.88	15.2
Farm land	5093.86	47.8	1703.03	16.0	3457.19	32.5
Sparse Forest	119.32	1.1	393.86	3.7	2040.21	19.12
TOTAL	10662.90	100	10662.90	100	10662.90	100

Source: Author's Analysis, 2019

Table 1.1 shows the area covered by land use/land cover for the study area, the forest was established in 1954. However, the first available satellite image available for the study area was captured in 1973.

Based on the first satellite image of 1973, farm land has the largest area coverage of 5093.86 hectares, with 47.8%. More of the figures are found in table 1.1. This may not be unconnected with encroachment into the forest reserve by the neighbouring communities whose major occupation was farming. However, forest has the second highest area coverage of 3724.25Ha approximately 34.9% while the least coverage was sparse forest 1.1% by implication tree felling was on the barest minimum.

In 1990, water body had the highest area extent of 4724.92 Ha occupying 44.3%. This was as a result of increase in surface run- off because the soil was exposed through cultivation. There was a reduction in the area covered by forest from 3724.25 to 2858.95 Ha. This explains why there was low infiltration. There was a gradual increase in deforestation reflected through sparse forest. It decreased from 119.32 hectares to 393.86 hectares. In 2009, in response to population growth around the forest, the study area and the need to earn a living, there was more encroachment through farming from 1703.03hectares in 1990 to 3457.19 hectares in 2009. However, forest cover increased from 2858.95 hectares to 2988.02 hectares. This may likely be as a result of natural forest regrowth. It is obvious from the result obtained that deforestation increased, as revealed by the increase in the area covered by sparse forest from 393.86 hectares to 2040.21 hectares.

Result of the Findings

Forecast of Forest Loss Using CA- MARKOV Model

The forecast of Afaka Forest Reserve using CA-Markov is presented in Table 1. It was observed that based on the first satellite imagery available in 1973, the forest cover 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%. Nwadialor (2001) monitored the trend of depletion of natural forest in Afaka forest reserve. The findings revealed that natural forest has decreased from its original status of 95.98% in 1962 to 61.96% in 1994 Flazzal (1992). Tanko (2011) corroborated this in his assessment of the change in vegetation of the same forest reserve using Remote sensing and Geographic Information System stating that the forest plantation decreased from 41.6% in 1973 to about 14.1% in 2009.

Transition Probability Matrix

Markov chain model was used to forecast forest depletion of the study area Markov model is one of the most widely use model for predicting forest depletion as confirmed by literatures. It outputs a transition probability matrix, transition area and condition probability images. Transition area matrix: It gives the probability that a particular land use class will change to every other land uses in the predicted map, while transition area matrix records the total number of pixels that are expected to change to every other one. For the matrix presented below, the rows represented the older land cover and the column represents newer categories. This demonstrates the Transition Probability table below which is derived from Land use/Land cover map of 1990 and 2009.

Table 2.1 Transition Probability derived from Land use/Land cover map of 1990 and 2009

Land use Land Cover	Bare Surface	Forest	Water Body	Farm Land	Sparse Forest
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
Farm land	0.1335	0.5033	0.0531	0.0946	0.2135
Sparse Forest	0.0035	0.3893	0.3023	0.0387	0.2661

Source: Author's Analysis, 2019

The row categories represent land use/ land cover classes in 2009 whilst column categories represent 2028 classes. From the table above, bare surface has a 0.0286 probability of remaining bare surface in 2028 and probability of changing to forest given to be 0.4589. This a desirable change because there is high tendency for bare surface to be transformed into forest which may be through afforestation Forest has a probability of 0.5073 of remaining forest and a probability of changing to sparse forest to 0.2621. This by implication means that the forest land cover will be relatively stable, which may be as a result of legislation against tree felling. Farm land has a probability of remaining forest to be 0.0946 and a probability of being changed to forest to be 0.5033. This is a positive development because there will be more conversion from farm land to forest land cover. Sparse forest has a probability of 0.2661 and a probability of 0.3893 to change to forest ecosystem provided every other factors are held constant in 2028. Based on the transition probability table forest land cover will be the most stable land use category and bare surface least stable.

Table 3.1 Land Use/Land Cover Projection 2028, using CA_Markov

Land use/Land cover Classes		Bare Surface	Forest	Water Body	Farm Land	Sparse Forest
	Area in Hectares (Ha)	442.82	3019.54	1647.32	116.07	2041.18
2028	Area in Percentage (%)	61.1	41.6	22.6	1.6	28.1

Source: Author's Analysis, 2019

The table above reveals that in 2028 forest land cover will occupy 3019.54 hectares representing 41.6% and sparse forest is expected to occupy 28.1%. By implication in 2028, 58.4% of the forest resource will be lost to other land use/land cover.

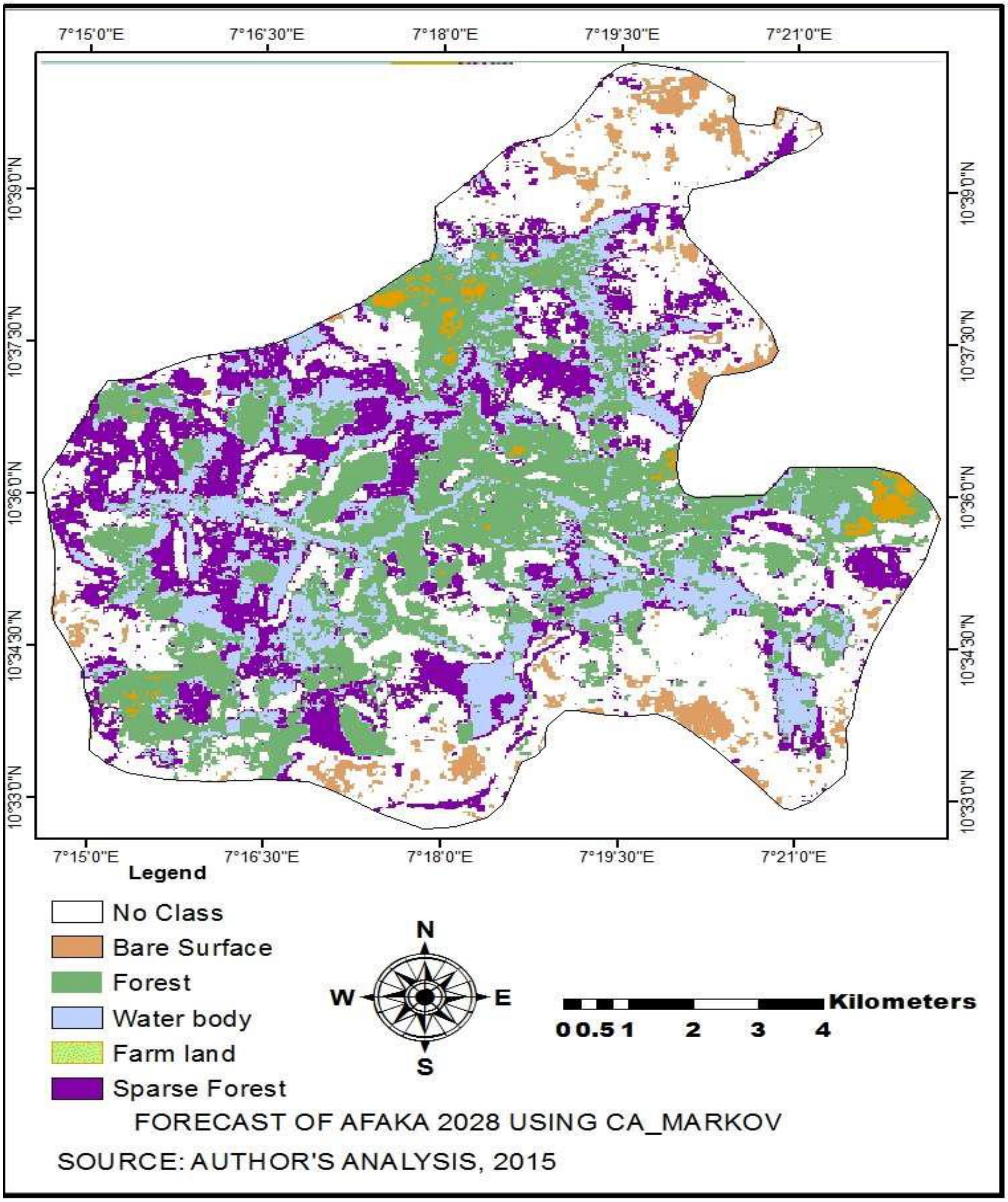

Fig 1.1 The map indicated that sparse forest is more prominent in the western part of Afaka. This may be as a result of intrusion from neighboring communities. More bare surfaces tend to be in the Northern part of the study area. It is also observed that other land use/land cover classes aside the once mentioned are likely to emerge.

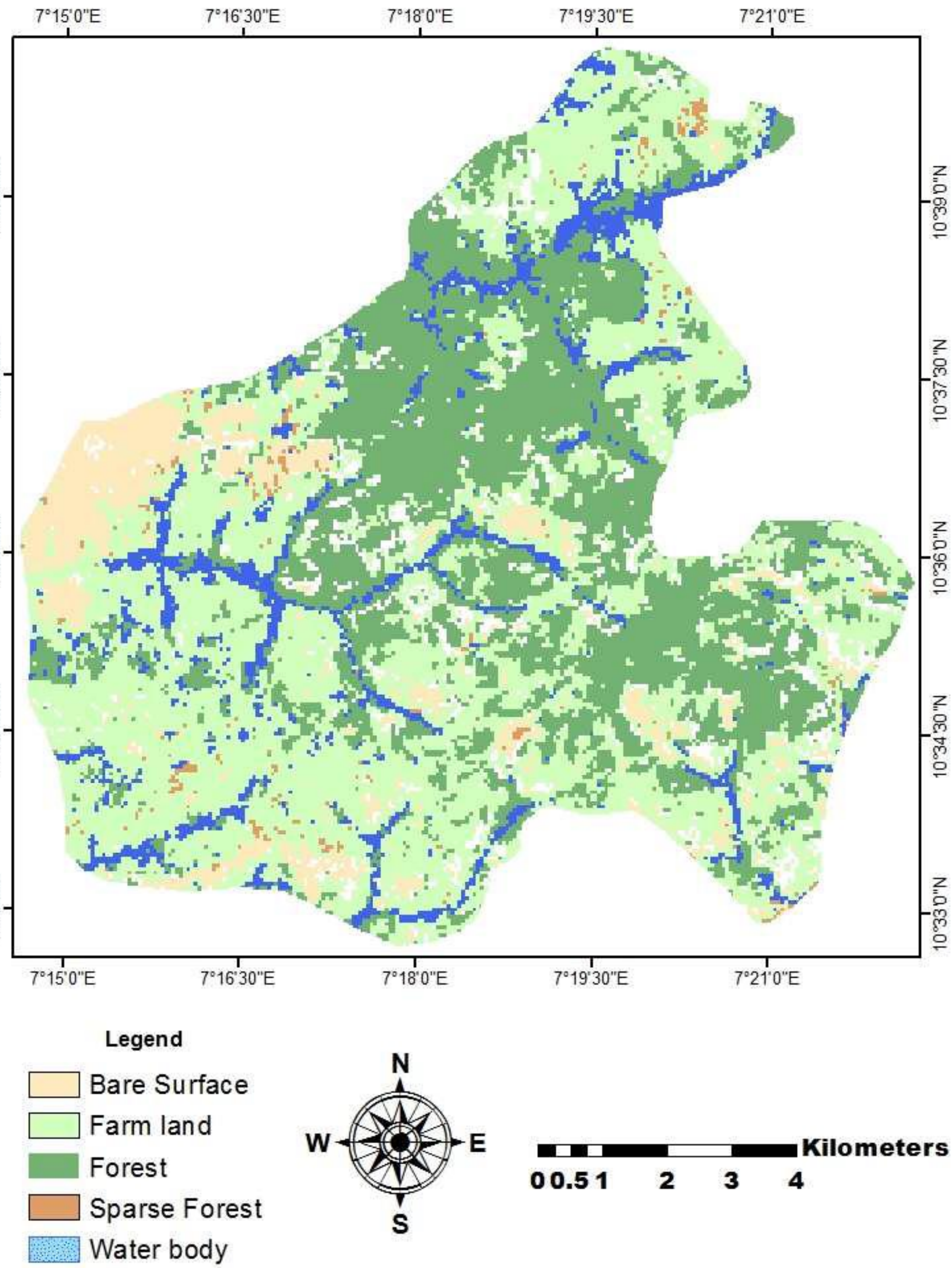

FIGURE 4.1: SUPERVISED CLASSIFICATION OF AFAKA 1973

SOURCE: AUTHOR'S ANALYSIS, 2015

Table 4.1 Land use/land cover Distribution of Afaka Forest Reserve (1973, 1990 and 2009)

LAND USE/LAND COVER	1973 AREA (Hectares)	%	1990 AREA (Hectares)	%	2009 AREA (Hectares)	%
Bare Surface	874.23	8.2	982.14	9.2	554.60	5.2
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Sparse Forest	119.32	1.1	393.86	3.7	2040.21	19.12
TOTAL	10662.90	100	10662.90	100	10662.90	100

Source: Authors' Analysis, 2019

Classification of result for 1973, 1990 and 2009

Table 4.1 shows the area covered by land use/land cover for the study area, the forest was established in 1954. However, the first available satellite image available for the study area was captured in 1973. Based on the first satellite image of 1973, farm land has the largest area coverage of 5093.86 hectares, with 47.8%. This may not be unconnected with encroachment into the forest reserve by the neighbouring communities whose major occupation was farming. However, forest has the second highest area coverage of 3724.25Ha approximately 34.9% while the least coverage was sparse forest 1.1% by implication tree felling was on the barest minimum.

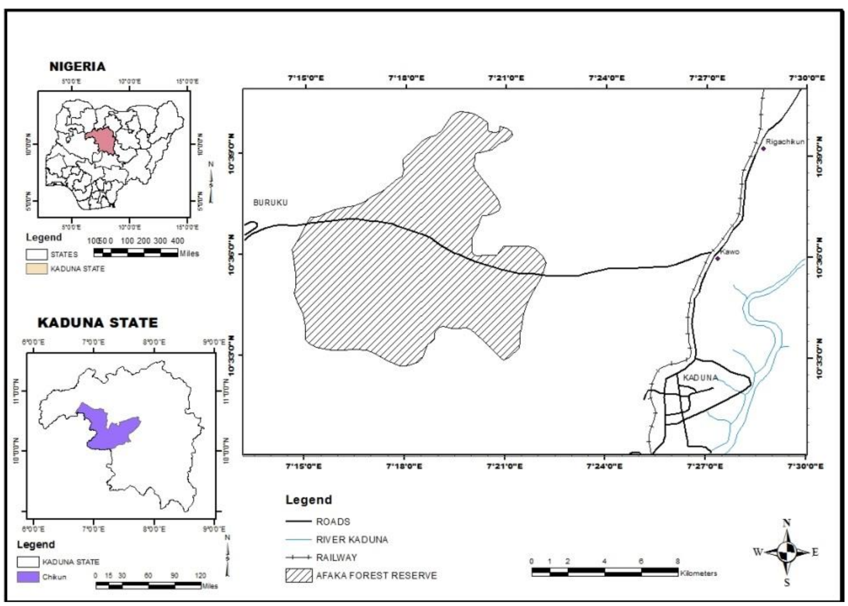

Figure 3.1: Afaka Forest Reserve and Environs

Source: Modified from Afaka Forest Map (Savannah Forestry Research, 2019)

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.

Conclusion

Based on the predictive models in forecasting future state of Afaka forest reserve, the study revealed a decrease in forest land cover. This is majorly due to anthropogenic factors.

Based on the results obtained CA_Markov gives a better result in forecasting because spatial dimension of the changes was considered. 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. 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.Based on the key finding of the research,it was concluded using predictive model in forcasting future state of afaka forest reserves

Recommendations

Therefore the following recommendations were made.

1. Legislation to protect forest reserves.
2. Proper monitoring using space technology
3. Geospatial techniques should be employed in monitoring forest resources.

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