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Research Paper

Forest cover change in Onigambari reserve, Ibadan, Nigeria: Application of vegetation index and Markov chain techniques

Khadijat Alabi [a], Anthony Tobore [b,*], Ganiyu Oyerinde [c], Bolarinwa Senjobi [b]

[a] Department of Crop Production, College of Agriculture, Kwara State University, P. M. B. 1530, Malete, Ilorin, Kwara State, Nigeria
[b] Department of Soil Science and Land Management, Federal University of Agriculture Abeokuta, P.M.B. 2240, Abeokuta, Ogun State, Nigeria
[c] Department of Soil Science, Faculty of Agriculture, University of Abuja, Nigeria

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ABSTRACT

Forest cover change (FCC) varies globally and is thus considered as one of the drivers of climate change. The present study identified the pattern of the FCC for the years 2010 and 2020 using vegetation index and Markov chain techniques. The Markov chain (MC) was utilized to predict the forest cover map for the year 2030. The vegetation index of Landsat 7 Enhanced thematic mapper plus (ETM+) and Landsat 8 Operational land images (OLI) were employed to assess the forest cover loss for the years 2010 and 2020. The validation result shows that the accuracy of the predicted forest cover map is more than 75 percent (%). The prediction result shows that if the current human activities continue such as deforestation, the forest cover will continue to be endangered and thus leading to a decrease in dense forest, plantation, and sparse vegetation by 20.9%, 16.1%, and 20% respectively. Hence, there is an urgent need to integrate bottom-up and participatory approaches between agriculture activities and forestry for socioeconomic development. This study will ensure sustainable forest management by assisting society, government and stakeholders.

1. Introduction

Forest cover is one of the most important interactions between human and global environmental systems (Bonan, 2008). Tropical forest contributes 5 to 15 percent of anthropogenic carbon emissions to the atmosphere at the global, regional, and local scales (d'Annunzioin et al., 2015). Recent reports indicate that forest cover change (FCC) affects the earth's surface and serves as the second-largest source of atmospheric emission (Achard et al., 2002). In addition, deforestation and degradation processes contribute immensely to forest cover loss (Herold et al., 2011a; UNFCCC, 2014). Nevertheless, ninety percent of FCC in sub-Saharan Africa is altered due to increase in human population, expansion of agricultural activities, and consistent change of land use especially in Nigeria (Oyerinde et al., 2015; FAO, 1999; Ebenezer, 2015).

In Nigeria, forests cover approximately covered 35% of the country's landmass (Nweze, 2002; FAO, 2010). The spectral and time-series data provided by satellite images have opened great opportunities in assessing and monitoring FCC (Hirschmugl et al., 2017). Recently, the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images, together with Landsat 8 Operational Land Images (OLI) are becoming the driving force of mapping and monitoring FCC due to its availability and accessibility (Hansen et al., 2014). Monitoring and choosing a suitable spectral vegetation index can help to understand the dynamics of forest cover (Pereira et al., 1999). For instance, FCC has been widely monitored using vegetation indices at higher accuracy (Zhu and Liu, 2015).

One of the driving mechanisms of modeling FCC is to analyze the past, present, and simulate possible future changes (Wu et al., 2013). However, remote sensing techniques (RST) with Geographic information system (GIS) are recognized as an indispensable tool in storing, displaying, and analyzing the past, present, and possible future changes through various methods such as Cellular automata models (Clarke et al., 1997), Statistical analysis (Ansari, 2016), Markov chain (Wu, 2006), and Artificial neural network (Subedi and Thapa, 2013). Integration of the Cellular automata (CA) and Markov chain (MC) are becoming widely used and acceptable for mapping FCC due to their efficiency and high

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* Corresponding author at: Department of Crop Production, College of Agriculture, Kwara State University, P. M. B. 1530, Malete, Ilorin, Kwara State, Nigeria.

E-mail address: toboreao@funaab.edu.ng (T. Anthony).

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flexibility (Ansari, 2016). Adedeji (2001) implemented the CA-Markov to model changes in forest cover in the Onigambari forest reserve. However, the study was limited in assessing the FCC using a spectral vegetation index. Besides, few studies have been applied to integrate spectral vegetation indices and the Markov chain model in simulating forest cover especially in developing countries such as Nigeria. The approach herein implemented the spectral vegetation indices of Landsat 7 ETM + and Landsat 8 OLI images with an MC model to simulate forest cover in Onigambari forest reserve, Ibadan, Oyo State, Nigeria. Hence, the specific objectives were to (i) assess the forest cover loss for the years 2010 and 2020 using spectral vegetation index (ii) predict the FCC of the study area from the year 2010 to 2030.

2. Description of the study area

The study focused on Onigambari forest reserve, located at Ibadan between Guinea and the derived savanna of Oyo State, Southwest Nigeria. The forest reserve falls between latitude 7°25′ and 7°55′N and longitude 3°53′ and 3°90′ E, zones 31 and covering about 14,506.4 ha (Fig. 1). Out of the existing zones, the forest reserve was made up of Gmelina plantations while the other existing area comprises both Gmelina Arborea and Tectona grandis.

3. Climate

The climate of the study area is well-defined dry and wet seasons (Adebekun, 1978). The rainfall starts from May to July with a short dry spell period in August and relative humidity of about 60 to 80 percent which fluctuates during January and February (Larinde and Olasupo, 2015).

4. Soil and geology

The parent material of the study area is derived from the basement material with intrusions of quartzite, schist, and gneisses (Jones and Wild, 1975). The soil particle size distribution classification ranged from sandy clay loam to sandy loam with the presence and formation of the argillic horizon and thus classified as Mollic Cambisols and Abruptic Eutric (FAO/IUSS Working Group, 2010).

5. Study methods

5.1. Data description and sources

The fieldwork started with a reconnaissance visit to the study area and was followed by primary data collection. During the survey visit, ground-truthing information was acquired to define the nature of the forest covers with the aid of a GPS (Global positioning system) device. Information such as a base map and reports were acquired through downloading from the USGS (United States Geological Survey) repository website. In this study, Landsat 7 ETM + and 8 OLI satellite data for the years 2010 and 2020 were acquired and used to assess and simulate the FCC. The downloaded satellite images were geo-rectified according to 31-North UTM (Universal Transverse Mercator) coordinate system using path 191 and row 055. Due to the atmospheric error and avoidance of seasonal variation, the Landsat satellite images were downloaded during the dry season and thus ensure the image is free of noise

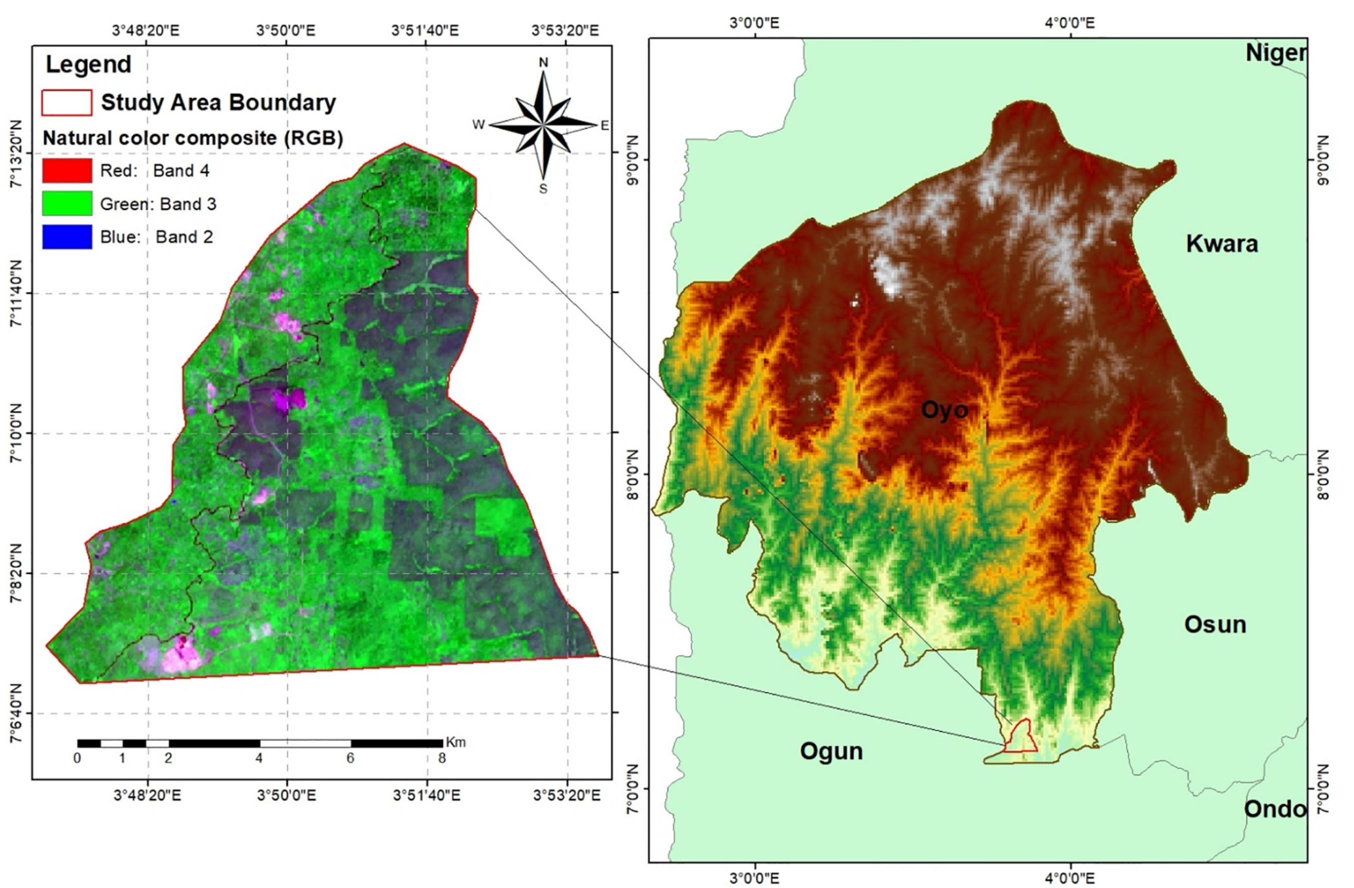

Fig. 1. Study area.

and no further image-to-image registration. Afterward, the image processing and analyses were executed in ENVI 5.1 software. The result of the image processing and analyses was supported with the images downloaded from the Google Earth Pro engine. The essence of supporting Google Earth image is to enable easy identification of AOI (Area of interest) during image processing and analyses.

6. Forest cover assessment using spectral vegetation index

In the present study, forest cover loss was assessed using Landsat 7 ETM + and 8 OLI satellite images of the years 2010 and 2020. The satellite images were subjected to image pre-processing in ENVI environments using DOS (dark object subtraction) method. The DOS method was implemented to improve the visual interpretation and better visibility of Landsat images during analyses. The NDVI (Normalized difference vegetation index), and GNDVI (Green normalized difference vegetation index) were used. The vegetation indices were assessed as follows: $NDVI = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED})$, and $GNDVI = (\mathrm{SWIR2} - \mathrm{GREEN})/(\mathrm{SWIR2} + \mathrm{GREEN})$ (Jiang et al., 2006). Thereafter, the vegetation spectral index was assessed and computed in raster math's tool using ArcGIS 10v5 software. The spectral vegetation index was selected based on their sensitivities and higher accuracy to forest cover monitoring (Jiang et al., 2006).

7. Land use and land cover classification processing

The collected Landsat 7 and 8 satellite images were enhanced in ENVI 5.1 Software via (3 by 3) majority filter techniques for better visibility. Natural color composite (NCC) was generated using suitable combinations of bands from the acquired Landsat satellite images (d'Entremont and Thomason, 1987; Good and Giordano, 2019). Considering the "Nigeria Land Classification System" and the goal of this study, Anderson and Hardy's (1976) classification scheme II and reconnaissance survey were utilized to identify the AOI features of the study area. Thereafter, the acquired Landsat images for the years 2010 and 2020 were classified by a supervised classification method in ENVI 5.1 environment. The images obtained from the classified Landsat 7 and 8 were used to identify the forest cover classes based on the Maximum Likelihood Supervised Classification (MLSC) algorithm. The MLSC is applied due to its detail efficiency and easy classification algorithm (Liu, 2005;

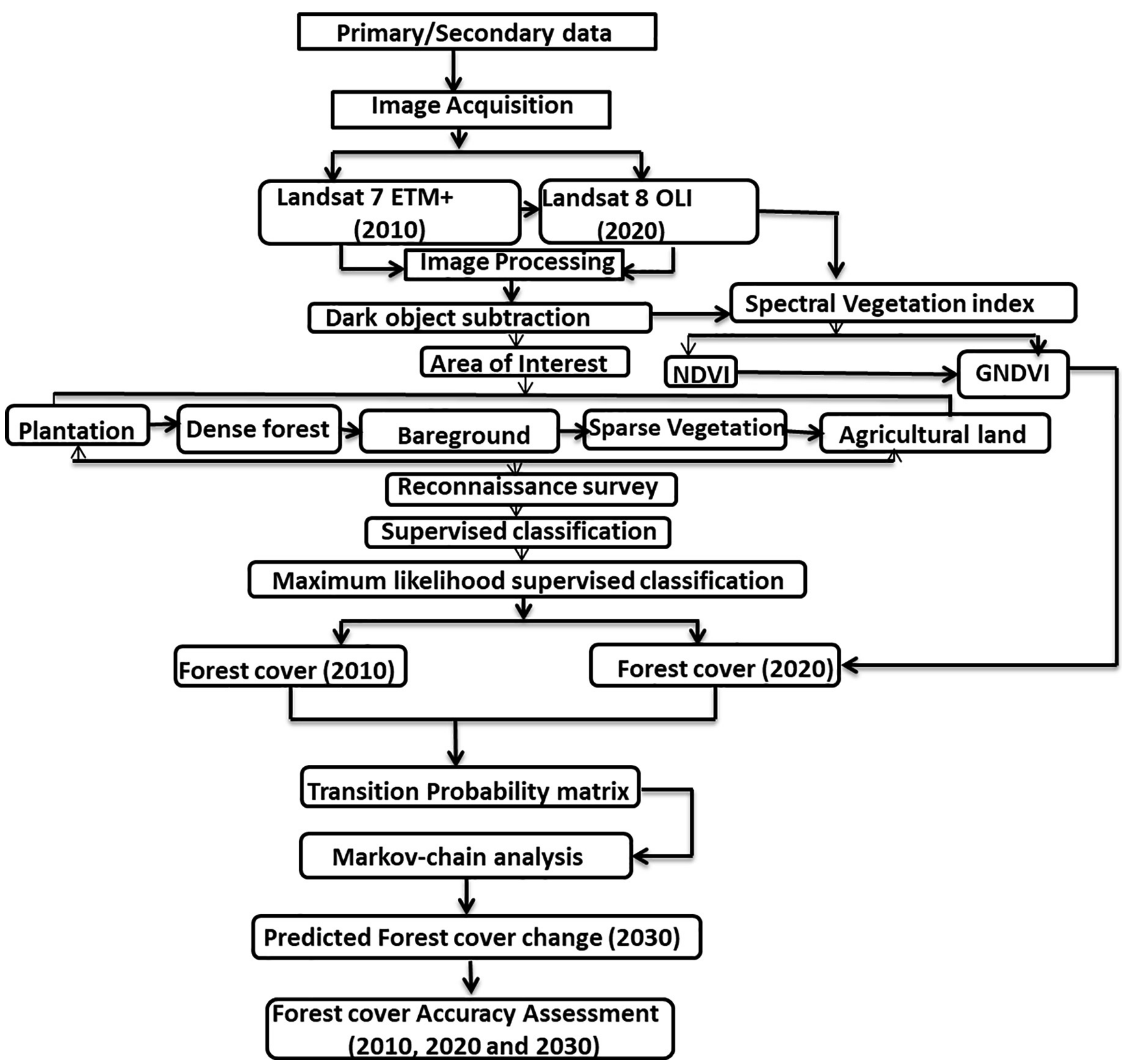

Fig. 2. Workflow of the study area.

Sun et al., 2013; Biro et al., 2013). The identified forest cover classes are Plantation; (timber plantations with Tectona Arborea and Gmelina), Agricultural land; (Arable land, permanent crops, and pastures), Dense forest; (Indigenous species of trees), Sparse vegetation; (secondary forest, Shrubs, and/or herbaceous vegetation), and Bareground; (degraded lands). The classified images were further imported to iDrisi selva using the Envi-iDrisi format tool. Afterward, the classified forest cover map of the study area was subjected to accuracy and validation using the Kappa coefficient through 100 ground truths field data. These 100 ground truth field data were chosen through the random sampling method. However, for the acceptability of the classification accuracy, the classified forest cover classes are over 75% (Pontius and Millones, 2011; Foody, 2002; Story and Congalton, 1986). The Kappa coefficient (K) for the forest cover classification accuracy assessment was shown in Eq. (1):

$$K = \frac{\sum_{i=1}^{r} xii - \sum_{i=1}^{r} (xi \times x + i)}{\mathrm{N}^4 - \sum_{i=1}^{r} (xi = 1 \times x + i)} \tag{1}$$

The K is the kappa coefficient, N is the total number of sites in the matrix, r is the number of rows in the matrix, x_{ii} is the number in rows i and column i.

8. Simulation pattern analysis

To simulate the FCC of the study area, the Markov-chain model was used to determine the FCC for the year 2030. The Cellular automata were used to stimulate the time–space and underlie the dynamics of changes in the study area (Balogun and Ishola, 2017). The Markov chain and cellular automata were supported with the classified forest cover maps of the year 2010 and 2020. Based on the transition probability matrix between the year 2010 and 2020 classified images, the forest cover for the year 2030 was predicted. The CA-Markov model used in this study was described according to Subedi and Thapa (2013) in Eqs. (2) and (3).

$$S_t^{+1} = f(S_t,\ N) \tag{2}$$

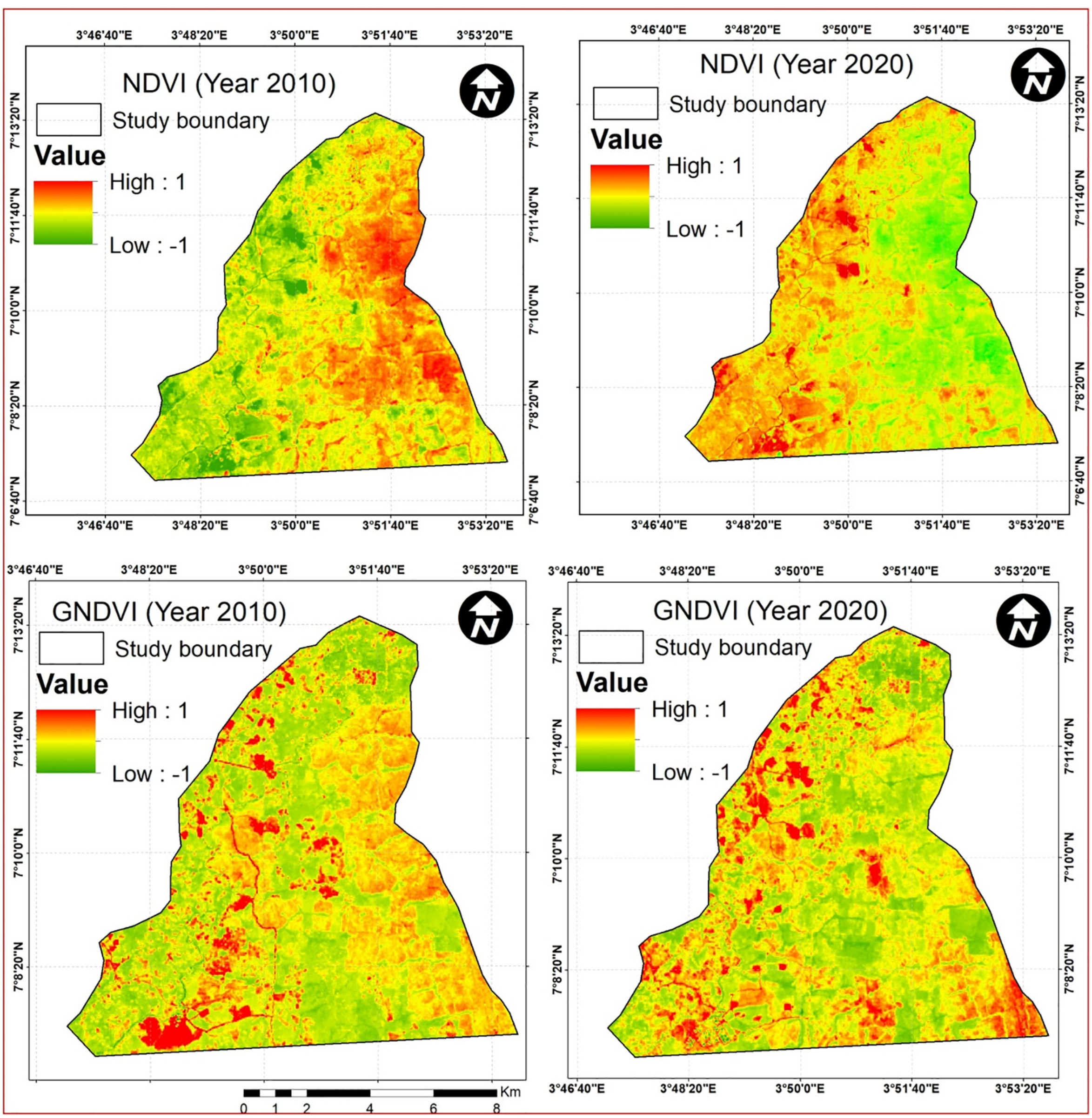

Fig. 3. GNDVI and NDVI of the study area.

here, S represents the set of states of the finite cells; t and t + 1 are the early years and the later year; N is the neighborhood of cells, and f is the conversion rule of local space.

$$\begin{bmatrix} P_{11}P_{12} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1}P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{3}$$

where P stands for the probability matrix in the Markov model, and P_{ij} is the probability of converting from current state i to state j in the next period. S is the land use status, and t; t + 1 is the time point and this was described according to Subedi and Thapa (2013) using Equation (4). The workflow of the present study was shown in Fig. 2.

$$0 < Pij < 1and\sum\nolimits_{j=j}^{n} Pij = 1, i, j = 1, 2, 3 \cdots n. \tag{4}$$

9. Results and discussion

9.1. The sensitivity of spectral indices to forest cover

The present study utilized the Landsat 7 ETM + and 8 OLI spectral vegetation index of the year 2010 and 2020 to assess the rate of forest cover loss. The NDVI and GNDVI of the study area were classified as (−1) low and (1) high. The result of the NDVI and GNDVI reveals that the study area demonstrates low forest cover densities in the year 2020 than in the year 2010 (Fig. 3). However, it was also observed during the reconnaissance survey that the forest cover of the present study had experienced consistent changes such as an expansion of agricultural practices, and degradation of the study area. Besides, the sensitivity of the spectral vegetation index used in this study has also provided evidence and easy assessment of the past and present forest cover of the present study. According

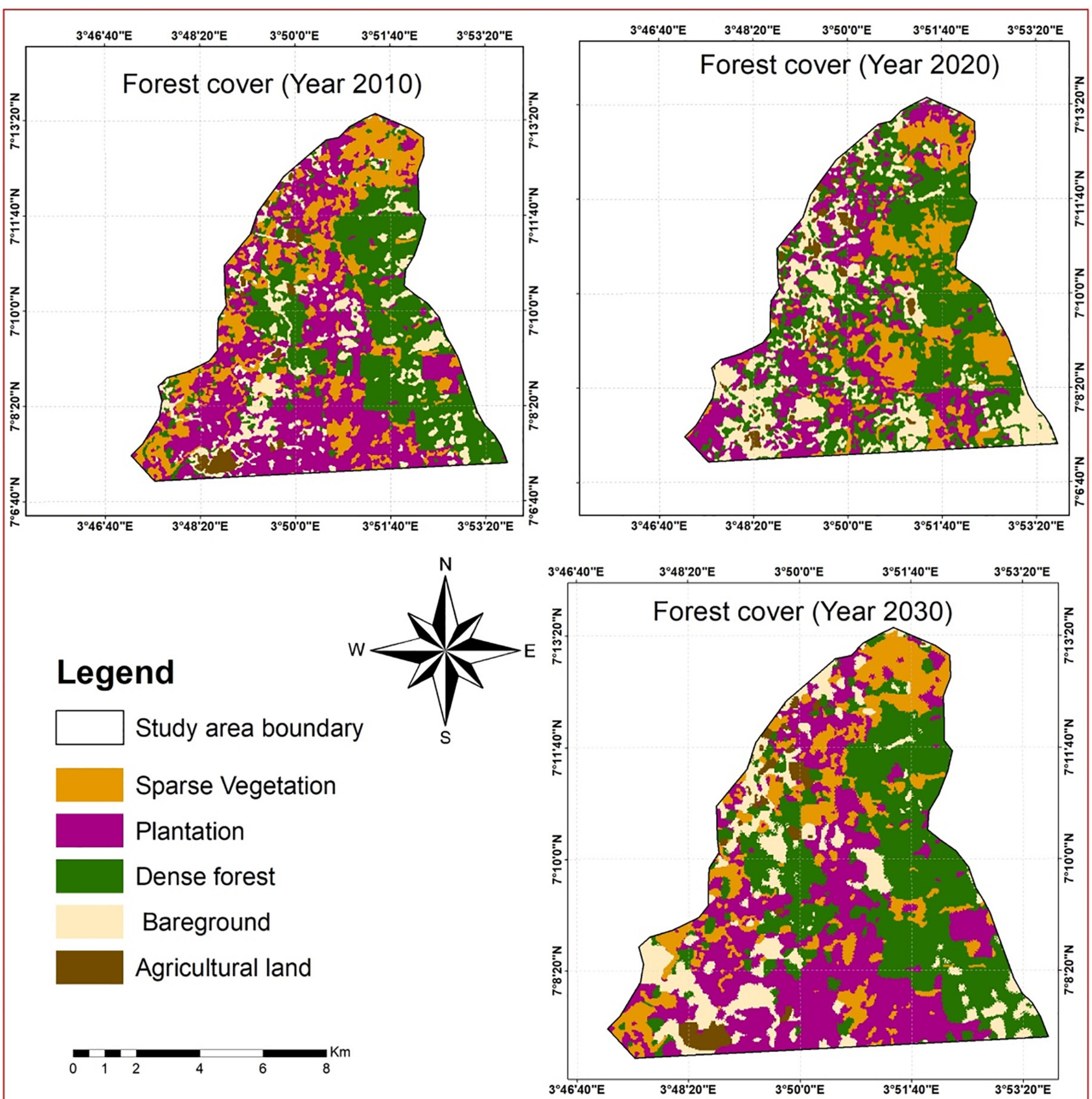

Fig. 4. The forest cover change.

to Aman et al. (1992), the abrupt or gradual change of the past, present and possible future changes of forest cover are better assessed using spectral vegetation index and this is similar to the present result obtained. Warner et al. (2016) also highlighted that mapping and monitoring forest cover changes using NDVI and GNDVI are regarded as one of the most correlated spectral vegetation indices with higher validation accuracy. Also, the present study correlates with the study conducted by Oyerinde et al. (2015) that Nigeria's forest cover is faced with sudden and gradual deforestation.

10. Forest cover mapping from the year 2010 to 2030

The periodical assessment characteristics and the analyzed Natural color composite (NCC) were used to specifically classify the FCC. The MLSC algorithm was applied to the Landsat 7 ETM+ and 8 OLI satellite images for the years 2010 and 2020 focusing on the plantation, agricultural land, dense forest, sparse vegetation, and bareground using the Envi 5.1 software. The CA-Markov model was implemented and subjected to visual image interpretation, cognition of patterns, and colors which shows great efficiency in simulating the year 2030 forest cover of the study area (Fig. 4). Bakx et al. (2019) and Bank (1991) posit that one of the easy and accurate ways of extracting information from remotely sensed data is by cognition of patterns and colors. The overall classification accuracy for the years 2010, 2020, and 2030 of the forest cover map was 80.00%, 81.47%, and 89.77%. After the prediction, it was found out that the Cohen kappa statistics were greater than 0.75 and thus show substantial classification agreement with the present study (Tables 1–3). According to Li, (2005) kappa statistics remains one of the standard procedures of validating the accuracy of classified Landsat images at different levels. The statistical analysis of the multi-temporal forest cover revealed that significant changes have taken place in the study area (Table 4). From the statistical change analysis, it was observed that the AOI features in the year 2010 are in the following order: 34.6% (plantation), 27.4% (sparse vegetation), 24.6% (dense forest), 11.4% (bareground), and 2.0% (agricultural land). However, the significant changes observed from the year 2020 forest cover classification map revealed that plantation, sparse vegetation, and dense forest decreased from 34.6% to 25.9%, 27.4% to 21.0%, and 24.6% to 22.5% while agricultural land and bareground increased from 291.7 Ha (Hectares) to 1000.0 Ha and 1654.1 Ha to 3453.3 Ha. Moreover, the increase observed in the agricultural land and bareground translated to the reduction or decrease in the dense forest, plantation, and sparse vegetation in the year 2030. Furthermore, the decrease observed in the forest cover features (such as a dense forest) in the year 2030 can be attributed to the persistent increase in human activities in the study area. Garg et al. (2006) and Adepoju et al. (2006) noted that a substantial increase in human activities such as deforestation and expansion of agricultural practices are known to be one of the major factors contributing to the sudden or gradual

Table 1
Error Matrix of the study area for the year 2010.

Forest cover	SV	PL	DF	BG	AL	Total	Producer Accuracy (%)	User Accuracy (%)
SV	41	4	0	1	5	51	74.60	80.40
PL	0	54	8	3	0	65	87.10	83.10
DF	4	0	54	0	6	64	65.10	84.40
BG	0	4	3	84	0	91	90.30	92.30
AL	10	0	18	5	43	76	79.60	56.60
Total	55	62	83	93	54	347		
Overall accuracy = 80.00% Kappa coefficient = 75.00%								

SV: Sparse vegetation; PL: Plantation; DF: Dense forest; BG: Bareground; AL: Agricultural.

Table 2
Error Matrix of the study area for the year 2020.

Forest cover	SV	PL	DF	BG	AL	Total	Producer Accuracy (%)	User Accuracy (%)
SV	51	4	2	1	0	58	78.50	87.93
PL	2	41	4	0	3	50	54.70	82.00
DF	2	10	67	2	0	81	87.01	82.71
BG	10	0	0	80	4	94	85	85.10
AL	0	20	4	0	60	84	71.42	71.4
Total	65	75	77	83	67	367		
Overall accuracy = 81.47% Kappa coefficient = 76.25%.								

SV: Sparse vegetation; PL: Plantation; DF: Dense forest; BG: Bareground; AL: Agricultural.

Table 3
Error Matrix of the study area for the year 2030.

Forest cover	SV	PL	DF	BG	AL	Total	Producer Accuracy (%)	User Accuracy (%)
SV	30	1	2	1	1	35	69.76	85.71
PL	2	51	0	0	0	53	79.68	96.22
DF	1	0	70	2	0	73	92.10	95.89
BG	5	2	4	76	0	87	96.20	87.35
AL	5	10	0	0	89	104	98.88	85.57
Total	43	64	76	79	90	352		
Overall accuracy = 89.77% Kappa coefficient = 85.89%								

SV: Sparse vegetation; PL: Plantation; DF: Dense forest; BG: Bareground; AL: Agricultural.

Table 4
Forest cover classification of the study area.

LULC	2010		2020		2030	
	Ha	%	Ha	%	Ha	%
Sparse vegetation	3972.2	27.4	3042.8	21	2901.6	20
Plantation	5026.2	34.6	3752.6	25.9	2338.3	16.1
Dense forest	3562.2	24.6	3257.7	22.5	3034.9	20.9
Bareground	1654.1	11.4	3453.3	23.8	4914.3	33.9
Agricultural Land	291.7	2	1000	6.9	1317.3	9.1
Total	14506.4	100	14506.4	100	14506.4	100

loss of forest cover. Moreover, the rate of deforestation and the substantial loss of forest cover in the study area could also support the gradual or sudden increase of climate change. Abubakar et al. (2014); and Lepers et al. (2005) stated that deforestation is one of the main driving forces predicted to forest cover change in developing countries such as Nigeria. The present study also interdem the view of Akinsoji (2013) that tropical forests are faced with persistent encroachment of human activities such as deforestation and expansion of agricultural activities.

11. Conclusion

This study intended to evaluate the significance of FCC in Onigambari forest reserve Ibadan, Nigeria using CA-Markov and vegetation index. Prediction of FCC shows that such kind of prediction can help to manage the gradual or sudden change of forest cover caused by human activities such as deforestation and expansion of agricultural practices. The use of spectral vegetation index reveals that NDVI and GNDVI serve as indispensable techniques used in assessing and monitoring forest cover loss with higher accuracy and less time. Based on the forest cover analysis, it was discovered that the forest cover pattern varied significantly from the year 2010 to 2030. The findings of the FCC reveals that the dense forest, plantation, and sparse vegetation will decrease by 20.9%, 16.1%, and 20%, while bareground and agricultural land will increase by 33.9%, and 9.1% respectively. This indicates that the Onigambari forest reserve experienced deforestation and expansion of agricultural activities thereby contributing to climate change. Hence, there is an urgent need to integrate bottom-up and participatory approaches between agriculture activities and forestry for socioeconomic development. The present study demonstrated the efficiency of GIS and RST in the study of FCC using the vegetation index and Markov chain model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abubakar, A., Abdulkadir, A., Jibrin, A., Abubakar, R.B., 2014. An Appraisal of Forest Degradation and Carbon Sequestration of Effan Forest Reserve in Kwara State. Glob. J. Scie. Front. Res.: Environ. Earth Sci. 14 (3), 57–65.
Achard, F., Eva, H.D., Stibig, H.J., Mayaux, P., Gallego, J., Richards, T., Malingreau, J.P., 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583), 999–1002.
Aman, A., Randriamanantena, H.P., Podaire, A., Frouin, R., 1992. Upscale Integration of Normalized Difference Vegetation Index: The Problem of Spatial Heterogeneity. IEEE Trans. Geosci. Remote Sens. 30, 326–337.
d'Annunzioin, R., Sandker, M., Finegold, Y., Min, Z., 2015. Projecting global forest area towards 2030. For. Ecol Manage 352 (7), 124–213.
Adebekun, O., 1978. Atlas of the Federal Republic of Nigeria. 1st Edn., Under the Chairmanship of the National Atlas Committee, p. 136.
Adedeji, O.H., 2001. Tropical Forest Dereservation and Degradation: Challenges to Stabilizing Soil Resources and Sustainable Development in Nigeria. Knowledge Review. Multidiscip. J. Nat. Assoc. Adv. Knowl. 4, 114–126.
Anderson, J.R., Hardy, E.E., 1976. A land use and land cover classification system for use with remote sensor data: U.S. Geological Survey Professional paper 964.
Adepoju, M.O., Millington, A.C., Tansey, K.T., 2006. Land Use/Land Cover Change Detection in Metropolitan Lagos (Nigeria):1984–2002, American Society for Photogrammetry and Remote Sensing, Annual Conference, Reno, Nevada, May 1–5.
Akinsoji, A., 2013. Vegetation Analysis of NgelNyaki Forest Reserve, Mambilla Plateau Nigeria. J. Nat. Sci. Res. 3 (12), 121–125.
Ansari, A., 2016. The final report of the research project "Identification of harvesting centres' and effective factors of dust storms in Mighan Desert Wetland" Arak University.
Bank, 1991. Forest Sector Policy Paper.The World Bank. Washington. DC.
Bakx, T.R.M., Koma, Z., Seijmonsbergen, A.C., Kissling, W.D., 2019. Use and categorization of LiDAR vegetation metrics in avian diversity and species distribution research. Dryad Digital Repository. https://doi.org/10.5061/dryad.tm28hb6.
Balogun, I., Ishola, K., 2017. Projection of future changes in landuse/landcover using cellular automata/markov model over Akure city, Nigeria. J. Remote Sens. Technol. 5 (1), 22–31.
Biro, K., Pradhan, B., Buchroithner, M., Makeschin, F., 2013. Land use/Land cover change analysis and its impact on soil properties in the northern part of Gadarifregion, Sudan. Land Degrad. Dev. 24 (1), 90–102. https://doi.org/10.1002/ldr.v24.110.1002/ldr.1116.
Bonan, G., 2008. Forest and climate change: forcing, feedbacks and the climate benefits of forests. Science 320 (5882), 1444–1449.
Clarke, K.C., Hoppen, S., Gaydos, L., 1997. A self-modelling cellular automata model of historical urbanization in the San Francisco bay area. Environ. Plan 24, 247–261.
d'Entremont, R.P., Thomason, L.W., 1987. Interpreting meteorological satellite images using a color-composite technique. Bull. Am. Meteorol. Soc. 68 (7), 762–768.
Ebenezer, T., 2015. Drought, Desertification and The Nigerian Environment : A Review 7, 196–209. Https://Doi.Org/10.5897/JENE2015.
FAO, 2010. Global Forest Resources Assessment 2010 – Main report. FAO Forestry Paper No. 163, Rome. Online available at: www.fao.org/docrep/013/i1757e/i1757e00.htm.
FAO/IUSS Working Group, 2010. A framework for land evaluation. Rome: Soils Bulletin 31, FAO, pp 25–42.
FAO, 3rd Edition., 1999. State of the World's Forests. Food and Agriculture Organization of the United Nations, Rome. http://www.fao.org/forestry/FO/SOFO/SOFO99/sofo99-e.stm or http://www.fao.org/forestry/en/.
Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80 (1), 185–201.
Garg, S.K., Garg, R., Garg, R., 2006. Environmental Science and Ecological Studies. Khanna Publishers, New Delhi, India.
Good, T., Giordano, P.A., 2019. Methods for Constructing a Color Composite Image: Google Patents.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, O.L., Townshend, J.R.G., 2014. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science, 850–853.
Herold, M., Hirata, Y., Van Laake, P., Asner, G., Heymell, V., Román-cuesta, R.M., 2011a.A review of methods to measure and monitor historical forest degradation. Victoria, 62, pp. 1–31.
Hirschmugl, M., Gallaun, H., Dees, M., Datta, P., Deutscher, J., Koutsias, N., Schardt, M., 2017. Methods for Mapping Forest Disturbance and Degradation from Optical Earth Observation Data: a Review. Curr. For. Rep. 3, 32–45.
Jones, M.J., Wild, A., 1975. Soils of the West African Savanna, the Maintenance and Improvement of Their Fertility. Commonwealth. Agricultural Bureau, p. 246.

Jiang, Z., Huete, A.R., Chen, J., Chen, Y., Li, J., Yan, G., Zhang, X., 2006. Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote Sens. Environ. 101, 366–378.
Larinde, S.L., Olasupo, O.O., 2011. Socio-Economic Importance of Fuelwood Production in Gambari Forest Reserve Area, Oyo State, Nigeria. J. Agric. Soc. Res. (JASR), 11.
Lepers, E., Lambin, E.F., Janetos, A.C., DeFries, R., Achard, F., Ramankutty, N., Scholes, R.J., 2005. A synthesis of information on rapid land-cover change for the period 1981–2000. Bioscience 55, 115–124. https://doi.org/10.1641/0006-3568(2005)055[0115:ASOIOR]2.0.CO;2.
Liu, H., Zhou, Q., 2005. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. Int. J. Remote Sens. 25 (5), 1037–1050. https://doi.org/10.1080/0143116031000150004.
Nweze, N.J., 2002. Implementing Effective Local Management of Forest Resources in Poor Forest Community of Nigeria. In: Onokala, P.C., Phil-Eze, P.O., Madu, I.A. (Eds.), Environment and Poverty in Nigeria. Enugu Jamoe Pub..
Oyerinde, G.T., Hountondji, F.C.C., Wisser, D., Diekkruger, B., Lawin, A.E., Odofin, A.J., Afounda, A., 2015. Hydro-climatic changes in the Niger basin and consistency of local perceptions. Reg. Environ. Change. 15 (8), 1627–1637. https://doi.org/10.1007/s10113-014-0716-7.
Pereira, J.M.C., Pereira, B.S., Barbosa, P., Stroppiana, D., Vasconcelos, M.J.P., Grégoire, J.-M., 1999. Satellite monitoring of fire in the EXPRESSO study area during the dry season experiment: Active fires, burnt area, and atmospheric emissions. J. Geophys. Res. [Atmos.] 104, 30701–30712.
Pontius Jr., R.G., Millones, M., 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int. J. Remote Sens. 32 (15), 4407–4429.
Story, M., Congalton, R.G., 1986. Accuracy assessment: a user's perspective. Photogramm. Eng. Rem. Sens. 52 (3), 397–399.
Subedi, P., Thapa, B., 2013. Application of a Hybrid Cellular Automaton–Markov (CA-Markov) Model in land use change prediction: A case study of SadleCrek Drainage Basin, Florida. Appl. Ecol. Environ. Sci. 1 (6), 126–132.
Sun, Y., Zhou, Q., Xie, X., Liu, R., 2013. Spatial, sources and risk assessment of heavy metal contamination of urban soils in typical regions of Shenyang, China. J. Hazard. Mater. 174 (1–3), 455–462. https://doi.org/10.1016/j.jhazmat.2009.09.074.
UNFCCC, 2014. Key Decisions Relevant for Reducing Emissions From Deforestation and Forest Degradation in Developing Countries (REDD+). Framew. Conv. Clim. Chang. p. 44.
Wu, C.D., Cheng, C.C., Lo, H.C., Chen, Y.K., 2013. Application of SEBAL and Markov Models for Future Stream Flow Simulation Through Remote Sensing. Water Resour. Manage. 24 (14), 3773–3797. https://doi.org/10.1007/s11269-010-9633-9.
Wu, F., 2006. Simland: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. Int. J. Geogr. Inf. Sci. 12, 63–82.
Warner, T.A., Skowronski, N.S., Gallagher, M.R., 2016. High spatial resolution burn severity mapping of the New Jersey Pine Barrens with WorldView-3near-infrared and shortwave infrared imagery. Int. J. Remote Sens. 38 (2), 598–616. https://doi.org/10.1080/01431161.2016.1268739.
Zhu, X., Liu, D., 2015. Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS J. Photogramm. Remote Sens. 102, 222–231.