ADVANCES IN GEODESY AND GEOINFORMATION
(formerly GEODESY AND CARTOGRAPHY)
Vol. 73, no. 2, article no. e57, 2024

https://doi.org/10.24425/agg.2024.150686

Original paper

Effect of potential Land-Use/Land-Cover (LULC) changes and plant dominance within a tropical rain forest reserve, Southwestern Nigeria

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Received: 2023-10-27 / Accepted: 2024-10-22

Abstract: This study quantified spatial and temporal Land-Use/Land-Cover (LULC) changes within selected six classes of land cover type from 2002 to 2022 in a tropical rainforest reserve, Southwestern Nigeria. It also identified the most dominant plant diversity in the study area. Landsat 7, 8, and 9 imageries of the United States Geological Survey were used to identify and quantify the distribution and extent of selected six classes of land cover type used with the application of Geographical Information Systems and remote sensing techniques. Data on plant dominance were obtained from fieldwork conducted within the study area. The Results revealed that between 2002 and 2022, 15112 pixels in undisturbed forests were converted to disturbed forests, 16902 pixels in disturbed forests changed to built-up, 32233 pixels to built-up, and 60 pixels in disturbed forests were converted to agricultural land. There was a rise in agricultural land (8%) and built-up areas (0.3%) while decreases in forest (disturbed and undisturbed) (5%) and bare land (3%) were observed. Results also indicated there was an increase in water bodies from 2002 to 2014 (0.004%). Health of plant species decreased from the average NDVI (Normalized Difference Vegetation Index) value of 0.60 to 0.51. Results showed that among the plants, *Albizia zygia, Celtis zenkeri*, and *Funtumia elastic* were the dominant. observed rapid conversion of forest to agricultural land and built-up areas was found to be the cause of plant diversity loss in the forest. The Findings from this study have implications for life on land and climate action.

Keywords: GIS, LULC, remote sensing, plant species, forest reserve

1. Introduction

Land is a natural resource that humans have used for survival and a variety of activities (Wang and Azam, 2024). The land sustains billions of people worldwide by offering a variety of means of subsistence. It is the most significant natural resource upon which all socioeconomic activities are based, and it is also dynamic and ever-changing. Due to various socio-economic factors, land that is in flux both spatially and temporally has become a scarce and degraded natural resource (Jones et al., 2017; Wassie, 2020; Wijesinghe and Withanage, 2021). Land-use and land-cover changes have therefore played a significant role in the interaction between humans and their environment (Kayet and Pathak, 2015), and they are now a crucial part of the strategy for managing natural resources and spotting environmental deviations (Kumar and Agrawal, 2019).

Humans have altered more than one-third of the Earth's land surface, and Land-use and land-cover (LULC) changes are a significant factor in global climate change (Winkler et al., 2021; Muche et al., 2023; Afuye et al., 2024). The LULC changes studies' influence on the creation of policies and strategic plans at various levels and scales has been a significant cause for concern. If the global LULC changes are not identified and closely watched, they could have disastrous effects on important ecosystem functions (Abebe et al., 2022). Models for temporal LULC changes, which can be thought of as a conversion or shift from one use to another, are very useful in identifying the causes and patterns of land use land cover changes, which are constantly changing as a result of both human activity and natural conditions (Suzanchia and Kaur, 2011; Amoo et al., 2018; Arfasa et al., 2023). There may also be a change in the types of land use, such as from rangeland to cropland, cropland to urban uses, or cropland to forest (Emili and Greene, 2014).

LULC changes are occurring more quickly than at any time in human history, and plant diversity hotspots have significantly less forest cover (Muche et al., 2023; Dembélé et al., 2024). Numerous factors with taxonomic ramifications, spatial analysis scale, and municipal area growth influence biodiversity and ecosystem services (Ali et al., 2021; Zhu et al., 2023). One of the most severe and frequently irreversible effects of anthropogenic change is plant diversity loss and species extinction. Therefore, plant diversity preservation is essential, and the Convention on Biological Diversity, or CBD, was created as a result of the world's recognition of the importance of plant diversity and its alarming loss (Turnhout and Purvis, 2020; Ekardt et al., 2023). Changes in land use can thwart the natural successional processes that occur in rainforests, causing some pioneer species to be dominant and changing the course of ecosystem development. Dominant plant species may be lost as a result of land clearing for farming or other purposes, which could have a ripple effect on plant communities (Estrada, 2019; Lindenmayer et al., 2023).

Over time and space, pressures on natural vegetation are rising. There has been a rise in interest in plant diversity conservation as it is understood that species may have a significant impact on how ecosystems function. Ecologists have participated in studies examining the connection between diversity and ecosystem function over time, and they have come to the conclusion that anthropogenic effects are causing forest structure change and plant diversity loss (Hong et al., 2022; Ali, 2023).

However, the demand for the use of remote sensing data and Geographic Information Systems (GIS) applications for assessing land use and land cover has grown as a result of the need to comprehend how LULC changes affect terrestrial ecosystems Zhao et al., 2024). The effects of landscape changes on natural resources and the environment can be better understood and assessed using these spatial data. Geospatial technologies for managing and monitoring natural resources have made monitoring LULC changes an intriguing area of study (Kayet and Pathak, 2015; Rowland and Ebuka, 2024; Tesfaye et al., 2024). Understanding the dynamics of the landscape is aided by the detection of LULC in any geographic location using multitemporal satellite imagery (Rawat and Kumar, 2015; Selmy et al., 2023; Hussain et al., 2024). GIS and remote sensing are the most crucial methods for detecting LULC changes in both spatial and temporal dimensions (Wijesinghe and Withanage, 2021).

The effectiveness of remote sensing and GIS techniques for tracking vegetation-related indicators has been established over time. The vegetation cover is deciphered and mapped using aerial photos or satellite images in the remote sensing method. Strahler et al. (2006) emphasized that vegetation communities can be evaluated using remote sensing and GIS methods.

Over the years forest reserves were established for the protection and preservation of the plant's species diversity, plant dominance, and limitation of human exploitation on the plant community's structure. However, it has been noted that despite the protective measures put in place by the establishment of forest reserves to protect and preserve plant species diversity and plant dominance, some of the reserve forests are being exploited continuously.

In the same vein, the Ise-Ekiti forest reserve in southwestern, Nigeria has been subjected to various forms of human-induced degradation, including farming, logging, hunting, and illegal marijuana cultivation. According to Greengrass (2006) and Ogunjemite et al. (2011), these activities have significantly impacted the forest in question and its ecological integrity, leading to a decline in biodiversity and overall ecosystem health. The National Drug Law Enforcement Agency of Nigeria (NDLEA) uncovered 2,000 marijuana forms in the Ise-Ekiti forest reserve and the neighbouring town of Ogotun (Linus, 2020). The conservation of this forest in question will not only protect the chimpanzees that it is home but also a variety of other plant species.

Therefore, this study was carried out to assess the impact of potential LULC changes from 2002 to 2022 and identify plant dominance with a view of examining the impacts of human exploitation using the tropical rainforest reserve of Ise-Ekiti, Southwestern, Nigeria as a case study.

2. Methodology

2.1. Description study area

The tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria (5°20.804′E to 5°25.331′E longitude and 7°21.069′N to °25.579′N latitude) is located in the Ise- Ekiti Local Government Area, Ekiti State, Southwestern Nigeria and it covers about 46 km^2. The Forest Reserve is accessible from Ise Ekiti town, which is approximately 6 km^2

to the reserve's northern edge and approximately 9 km^2 to the reserve's southern edge along the Akure-Benin expressway from the Uso community in Ondo State (Olaniyi et al., 2016). The area is primarily rural, with predominant land uses such as settlement, logging, farming, and hunting. Ise-Ekiti Forest Reserve's geographic location falls within the ecosystem of tropical rainforests. The annual temperature ranges between 25^{o}C and 28^{o}C, with a minimum temperature of 19^{o}C and a maximum temperature of 33^{o}C. The annual rainfall is between 1200 mm and 1380 mm (Ikemeh, 2013). Throughout the wet season, rainfall is consistent and evenly distributed (April-October). The Tropical Rain Forest Reserve of Ise-Ekiti is blessed with a diversity of flora species (Greengrass, 2006; Ogunjemite 2011). The description of Tropical Rain Forest Reserve of Ise-Ekiti, Southwestern, Nigeria in Figure 1.

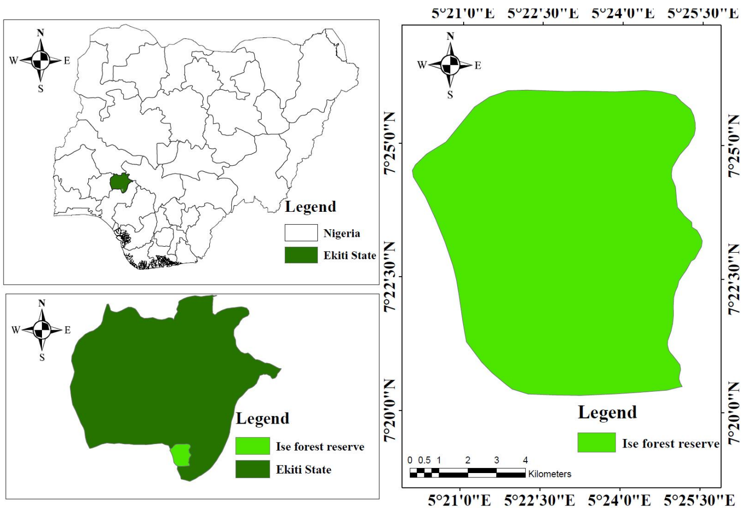

Fig. 1. Description of the tropical rainforest reserve of Ise-Ekiti, Southwestern, Nigeria.
Source (Dada et al., 2024)

2.2. Data collection

Data collected was acquired from ground-based and GIS and remote sensing application which have been proven to be effective over the years for monitoring indicators of vegetation conditions. With the application of GIS and remote sensing, vegetation cover is interpreted from the langsat's images. Landsat imagery (Landsat 7, 8, and 9) covering Ise-Ekiti Forest Reserve (path 190, row 055) was obtained from the USGS (United States Geological Survey) during the dry and rainy seasons (January to December) with less than 10% cloud cover. The satellite images were projected using the Universal Transverse Mercator (UTM) Projection System. Ten plots of land 25 m by 25 m, five in disturbed forest plots, and five in undisturbed forest plots of the study area were mapped out randomly and identification of plant species was done. Changes from 2002 to 2014, 2014 to 2022 and the entire study period (2002–2022) were analyzed.

2.3. Image preprocessing, enhancement, and normalized difference vegetation index

GIS software such as ERDAS Imagine 2015 version, QGIS 3.18.1, and ArcGIS 10.8.2 were used for the analysis and further processing of image classification. Image preprocessing represents a useful calibration procedure as it enables the recorded pixel values to be corrected and establishes a significant relationship between the acquired data and the biophysical phenomena (Coppin et al., 2004). Band 432 combination was used for TM (2002) and ETM+(2014), while band 543 was used for TM OLI (2022) for the enhancement of the images. All the data was projected to a Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 31 North. With the ERDAS imaging 2015 version, the images were layer stacked, and further corrections such as atmospheric correction, geometric corrections, and visual enhancement were made.

Several vegetation indices have been developed to assess forest vegetation, but the Normalized Difference Vegetation Index (NDVI) remains one of the most widely used indexes by researchers to understand and characterize vegetation dynamics (Myeonga et al., 2006). In theory, the NDVI threshold value should be between –1 and +1. The higher the NDVI, the greener the vegetation within a pixel. The red (R) and near-infrared (NIR) bands in Landsat and Sentinel images were used in this study to compute the NDVI for various years using the expression:

$$\mathrm{NDVI} = \mathrm{NIR} - \frac{\mathrm{R}}{\mathrm{NIR}} + \mathrm{R}, \tag{1}$$

where NIR is Near-Infrared, and R means Red Reflectance (Huang et al., 2021).

The algebraic-based image differencing approach was deemed appropriate for detecting vegetation change over time. Standard deviations from a class mean were used to select change threshold values until the resulting image was satisfactory (Chuvieco and Heute, 2009). Values of zero (0) represent no difference between images taken at different times, and the greater the difference, the further the value deviates from zero (>0). A post-classification was performed in ArcGIS-10.8.2 using the combined function to detect and compare changes in land cover classes from 2002 to 2022 while also delineating the spatial pattern of change.

2.4. Image classification

Six different types of land cover, including agricultural land, built-up areas, bare land, forest (disturbed forests, undisturbed forests), and water, were used to categorize the images. The user-defined and made training locations served as illustrations of each type of land cover. Although secondary information like available maps, aerial photos, or the use of software like Google Earth Pro served as guides, the choice used in the creation of training sites is typically based on the analyst or the user. The study used 240 training sites or regions of interest (ROI) (40 per land cover) per map, obtained from Google satellite using a variety of bands. The creation of training sites was done using the polygon tool. The distance between the two newly created training sites was at least 1,000 meters to prevent confusion during training. For the purpose of preventing confusion during the supervised image classification, we created two training sites that were separated by at least 1,000 meters.

The satellite images used in this study were classified into six types of land use and land cover change on Erdas Imagine 2015 version Software using the supervised classification method and maximum likelihood algorithm. The maximum likelihood algorithm is the most accurate classifier and remains one of the most widely used supervised algorithms. Because of the available data and prior knowledge of the study area, supervised classification techniques were chosen to facilitate training. It is also thought to produce very accurate results (Sisodia et al., 2014). Forest (Undisturbed Forest and disturbed forest), agricultural land, water bodies, bare land, and built-up areas are the classes identified and classified. With ArcGIS 10.8.2, the shapefile of the study was created and the area in hectares and percentages of land use land cover change classes were calculated for the years 2002, 2014, and 2022.

2.5. Accuracy assessment

Due to the size of the study area, GPS cannot be used to obtain reference data because of limited GPS coverage and signal interference. Using ArcGIS software, 200 randomly generated points were used in the study and used as validation or reference points over a three-year period (2002, 2014, and 2022). For the purpose of creating confusion or error matrices for the generated land cover map from the original satellite images, randomly generated reference points were used as the framework. Manual counting and recording of the correct or incorrectly classified land cover types were done for the confusion matrix. Comprehensive details on the Landsat satellite images that were used for analysis are shown in Table 1.

Table 1. Details of the Landsat satellite images used

Image Acquisition	Spatial Resolution	Path/Row	Sensor
Jan–Dec, 2002	30 m	190/055	Landsat 7 TM
Jan–Dec, 2014	30 m	190/055	Landsat 8 OLI-TIRS
Jan–Dec, 2022	30 m	190/055	Landsat 9 OLI-TIRS

3. Results

3.1. Impact of potential land use land cover changes from 2002 to 2022 in the study area

The comparison map on the impact of potential land use land cover changes in Tropical Rain Forest of Ise-Ekiti Forest Reserve, Southwestern, Nigeria for 2002, 2014, and 2022 was described in Figure 2. It was indicated in Figure 3 that between 2002 and 2022, the same numbers of pixels in Forest (disturbed, undisturbed), built-up, and agricultural land (4040, 2469, 515, and 11020 respectively) were found to be the same. Between 2002 and 2022, 15112 pixels of undisturbed forest and 56 pixels of agricultural land were converted into disturbed forest while 261 pixels of disturbed forest and 92 pixels of agricultural land metamorphized into undisturbed forest (Fig. 3).

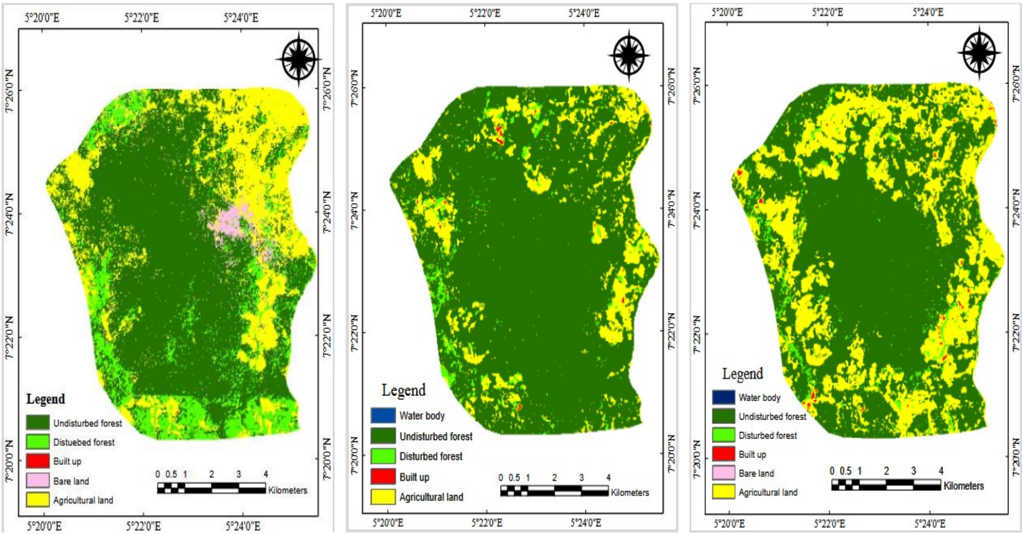

Fig. 2. Comparison of LULC changes of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria in 2002, 2014 and 2022

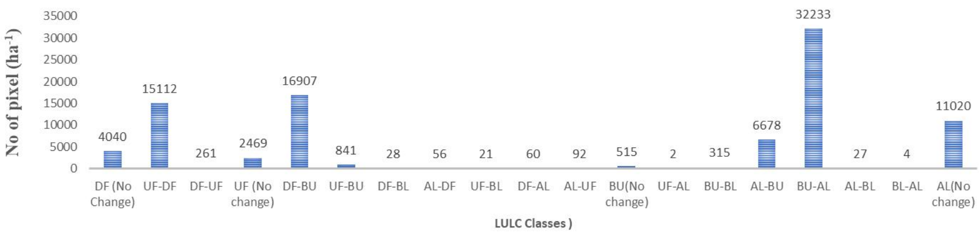

Fig. 3. Detection Analysis of LULC changes classification of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria (2002 -2022). AL, BL, BU, DF, UF mean agricultural land, bare land, built up, disturbed forest, and undisturbed forest, respectively

In the same vein, the results indicated that 62 pixels in forest (60 pixels in disturbed and 2 pixels in undisturbed), 32233 pixels in built-up, and 4 pixels in bare land were converted to agricultural land. 17748 pixels in forest (16907 pixels in disturbed and 841 pixels in undisturbed), and 6678 pixels in agricultural land changed to built-up, while 49 pixels (21 pixels in undisturbed and 28 pixels in disturbed), and 27 pixels in agricultural land metamorphosed to bare land between 2002 and 2022 (Fig. 3). The details of a pattern in LULC changes classes (in percentage) between the years 2002, 2014, and 2022 are shown in Figure 4.

The pattern of changes (in hectares and percentage) between the years 2002, 2014, and 2022 also indicated that the water body experienced an increase from 0.000 to 0.140 ha

Fig. 4. Pattern in LULC change classes (in percentage) of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria in 2002, 2014, and 2022

(0.004%) between 2002 and 2014 and dropped from 0.140 to 0.000 (0.004%) between 2014 and 2022 (Table 2). Between 2014 and 2022, disturbed forest declined from 101.610 to 93.220 ha, with a change of 0.25% and undisturbed forest dropped from 2623.600 to 2057.270 ha with a change of 17.53% (Table 2). Agricultural land increased from 443.640 to 1000.490 ha, bare land increased from 0.000 to 0.120 ha and built-up area increased from 5.730 to 8.450 ha with 17.69%, 0.004%, and 0.09% increase respectively. The sudden increase in agricultural land, built-up, and bare land caused a decrease in disturbed and undisturbed forests. Between 2002 and 2014, undisturbed forest and built-up increased drastically whilst disturbed forest, agricultural land, and bare land decreased (Table 2). The overall accuracy for the map was 81%, 92%, and 98%, and overall kappa statistics of 0.73%, 0.83%, and 0.87% for the years 2002, 2014, and 2022 (Table 3).

Table 2. Total areas covered, area change, and % cover of classes of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria in 2002, 2014, and 2022 in Hectare

Classes	Δ 2002–2014 (ha)	Area 2002 (ha)	% (ha)	Area 2014 (ha)	% (ha)	Area 2022 (ha)	% (ha)	Δ 2014–2022 (ha)
Waterbody	0.000	0.000	0.000	0.140	0.004	0.000	0.000	0.140
Disturbed forest	318.99	420.600	13.250	101.610	3.201	93.220	2.937	8.39
Undisturbed Forest	–738.87	1884.730	59.372	2623.600	82.640	2057.270	64.815	566.33
Built-up	–5.31	0.420	0.013	5.730	0.180	8.450	0.266	–2.72
Bare land	94.700	94.700	2.983	0.000	0.000	0.120	0.004	–120
Agricultural land	330.36	774.000	24.382	443.640	13.974	1015.490	31.993	–571.85
Ground total	–330.49	3174.450	100.000	3174.720	100.000	3174.06	100.000	–104.71

Table 3. Accuracy assessment of land use land cover changes classification of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria in 2002, 2014 and 2022

Satellite image	Accuracy assessment (%)	Kappa statistic (%)
Landsat 7	81	0.73
Landsat 8	92	0.83
Landsat 9	98	0.87

3.2. Health vegetation of forest reserve and NDVI values of the study area

The results of the NDVI of The Tropical Rain Forest Reserve of Ise-Ekiti showed the variation in plant diversity structure. The vegetation vigour increased from an average NDVI value of 0.42 to 0.60 between 2002 and 2014 and the health of the plant species community decreased from an average NDVI value of 0.60 to 0.51 between 2014 and 2022 (Fig. 5). This indicated that a reduction in plant biodiversity community in some parts of the study areas occurred. This may be due to increased demand for trees and increasing pressure of human activities on the plant biodiversity community.

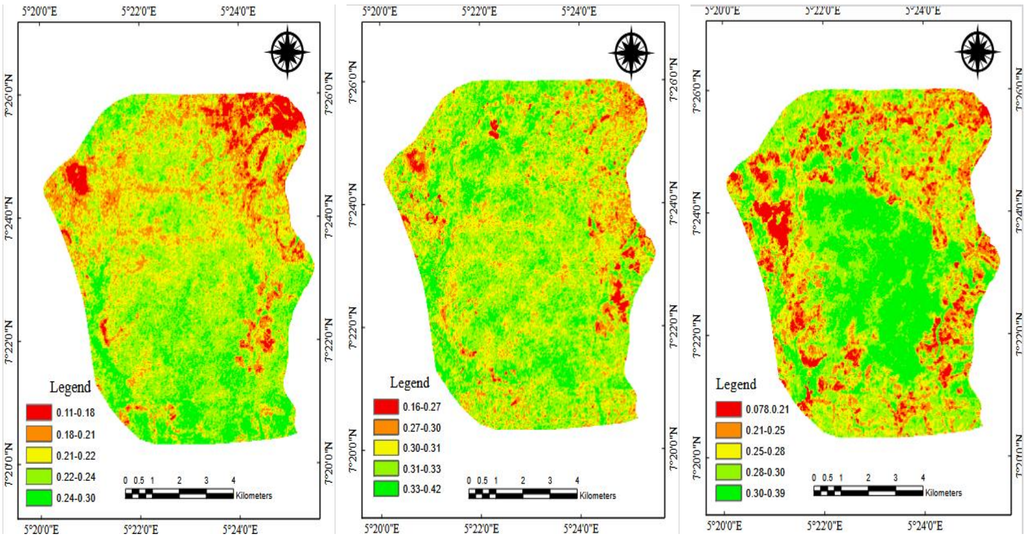

Fig. 5. Aggregate NDVI of tropical rain forest reserve of Ise-Ekiti, Southwestern, Nigeria in 2002, 2014 and 2022

3.3. Status of plant species in the area

The dominant plant species identified from the ground-based study in the Tropical Rain Forest Reserve of Ise-Ekiti, Southwestern, Nigeria were *Funtumia elastica, Mansonia altissima, Sterculia rhinopetala, Albizia zygia*, and *Celtis zenkeri* while the least dominant plant species were *Albizia ferruginea, Alchornea cordifolia, Bombax buonopozense*, *Carpolobia lutea*, and *Chrysophyllum alnifolium*. The dominant plant species identified belong to the following family: Apocynaceae *(Funtumia elastica)*, Sterculiaceae *(Mansonia altissima)*, Sterculiaceae *(Sterculia rhinopetala)*, Leguminosae (*Albizia zygia) and* Ulmaceae *(Celtis zenkeri)* while the least dominant identified belong to the following family Leguminosae *(Albizia ferruginea)*, Euphorbiaceae *(Alchornea cordifolia)*, Bombacacea *(Bombax buonopozense)*, Polygalaceae *(Carpolobia lutea)* and Sapotaceae *(Chrysophyllum alnifolium).*

4. Discussion

LULC change is a significant aspect of environmental studies, especially concerning the dynamics of agricultural land, built-up areas, bare land, and forest cover (Chisanga et al., 2024; Terfassa et al., 2024). Changes in land use and land cover can impact agricultural land by converting it to built-up areas for urban development (Rahman et al., 2023). Conversely, deforestation for agricultural expansion reduces forest cover, affecting biodiversity and ecosystem services (Shiferaw et al., 2023). Urbanization leads to the conversion of agricultural land and forests into built-up areas, impacting biodiversity, water resources, and climate regulation (Ancha et al., 2021; de Barros Ruas et al., 2022). Bare land refers to areas with no dominant vegetation cover. It may change due to human activities like infrastructure development or natural processes such as erosion (Rowland and Ebuka, 2024). Deforestation can contribute to the creation of bare land. Land use change often involves deforestation for agriculture or urbanization, leading to the loss of forest cover. Reforestation efforts aim to restore forested areas, mitigating the impacts of land use change on ecosystems and climate regulation (Mishra and Agarwal, 2024).

Complex interactions between land use changes and water quality parameters can result in minimal observable changes in water bodies (Dibal and Yarima, 2020; Ayeni, 2024). Changes in land use and land cover may lead to alterations in infiltration rates, affecting water movement and potentially masking changes in water bodies (Sugianto et al., 2022; Besha et al., 2024). The decrease in water bodies between the years 2014 and 2022 could be due to an intense disturbance of natural resources by both human and natural activities (irrigation, dam building, soil erosion, and climate change). European Environmental Agency (2018) reported that there was evidence of climate change causing the reduction of water bodies on the earth's surface, particularly in Europe where oceans, seas, rivers, and lakes are being impacted. This finding is consistent with current observations of water body reduction in the tropical rainforest reserve of ise-Ekiti, southwestern, Nigeria. It is important to note that the effects of climate change are not limited to land, but also extend to aquatic environments (Ghosh et al., 2020; Weiskopf et al., 2020). The findings from this study are also consistent with Kanianska (2016) who stated that the increasing agricultural intensity generates pressure not only on land resources but also across the whole environment.

In this study, disturbed forests keep reducing and this could be as a result of their conversion to built-up and agricultural land. The undisturbed forests which are defined as any areas covered with evergreen or deciduous canopy-like trees and undergrowth plants which remain untapped for many years experienced a pattern of increment between 2002 and 2014 and a decrease between the years 2014 and 2022. All these could be as results of measures put in place by the community and state government to conserve the plant diversity in the reserved forest and the intense agricultural activities, built-up, and several conversion processes that eventually resulted in deforestation of the forested areas thereby leading to the reduction in tree cover and vegetation community. This fluctuation pattern is consistent with the findings of Mlotha (2018), who reported that between the first periods of land use land cover change analysis, there was an increment in the coverage of forest while between the second and third periods, there was a decrease in forest cover. Results indicated that the vegetation community had reduced over the twenty years and this could be attributed to more built-up, more agricultural activities, and other conversions (Zaitunah and Sahara, 2021; Habib-ur-Rahman et al., 2022).

There has been an increase in the presence of built-up and agricultural land devoted to the controlled use of other forms of life from 2014 to 2022, leading to a reduction in forest cover and this is consistent with the findings of Charlotte Remteng et al. (2015), Milkessa et al. (2020) who indicated that increment in agricultural land, grassland, and built-up led to the declining trend of dense and open forest cover. The decline in undisturbed forest areas is likely to have negative impacts on the environment and human well-being, according to the Food and Agricultural Organization (FAO, 2010). The conversion of forest to agricultural land could be driven by a reliance on agriculture as a primary source of livelihood (Declee et al., 2014). Human activities such as illegal logging and the clearing of forest land for farming might have also contributed to this decline (Boakye et al., 2008; FAO, 2010).

Furthermore, the reduction in agricultural activities, bare land, and disturbed forests between 2002 and 2014 led to the expansion of undisturbed forests between 2002 and 2014. The increase in built-up areas over the 20 years could be a result of continuous agricultural activities going on in Ise-Ekiti Forest Reserve which has a telling effect on the vegetation community. An increase in buildings without reforestation results in the destruction of vegetated areas. This result agrees with the findings of McKinney (2002) who established that built-up tends to result in low plant diversity because of the overwhelming negative impact on native species and topsoil.

In the same vein, the change detection analysis that occurred between 2002 and 2022 revealed different degrees of conversions as regards the pixels in the imagery among the six classes of Land Use and Land Cover Changes Forest (Disturbed and Undisturbed), Water body, Agricultural land, Built-up, and Bare land) occurred from one particular period to another. This result is consistent with the findings of Keerthirathne et al. (2019), who stated that land use changes constantly due to both natural conditions and human activities as a result of conversion or shift from one use type to another. FAO (2016) has also pointed out that land use types may change, for example, from cropland to urban uses, or cropland to the forest. This also aligns with the findings of Odiwe et al. (2012), who reported that the conversion of forest land into tree crop plantations plays a significant role in the loss of biodiversity. Therefore, it is essential to understand the impacts of land use and land cover changes on plant biodiversity for the proper functioning and stability of ecosystems.

Accuracy in LULC change analysis is crucial for understanding the dynamics of landscapes and making informed decisions regarding land management, conservation efforts, and policy interventions (Bojer et al., 2023; Aziz et al., 2024). Accuracy refers to the degree of correspondence between the classification of land cover or land use derived from remote sensing data and ground truth information (Comber and Tsutsumida, 2023). Ensuring accuracy in LULC change analysis requires careful consideration of classification methods, data quality, validation techniques, and contextual factors. By addressing these factors, researchers and land managers can generate reliable LULC change information to support effective land use planning, conservation strategies, and sustainable development initiatives (Krishnan et al., 2024). In this study, the overall accuracy of the integration of visual interpretation with classified images and field survey data was found to be 81%, 92%, and 98% for the years 2002, 2014, and 2022 respectively. These results fall within the commonly accepted threshold of 85% accuracy and the range of 80% to 90% accuracy as reported by Janssen and Vanderwel (1994).

NDVI is a widely used metric in remote sensing to assess and monitor vegetation health and dynamics over time. It's calculated from satellite imagery and provides valuable insights into land use and land cover changes (Hussain et al., 2024. NDVI plays a crucial role in monitoring and understanding land use and land cover changes by providing quantitative and spatially explicit information on vegetation dynamics, health, and distribution over time. Its integration with other data sources enhances our ability to manage and sustainably utilize natural resources while mitigating the impacts of human activities on the environment (Huang et al., 2021). The NDVI is a widely used index in the analysis of vegetation using satellite imagery (Bakr et al., 2009). The NDVI is often used to detect changes in vegetation and non-vegetation (Huang et al., 2021). The NDVI scale is -1 to 1, with 0 representing non-vegetated land and values greater than 0 representing vegetated land (Bakr et al., 2009).

The NDVI results in the Tropical Rain Forest Reserve of Ise-Ekiti, Southwestern, Nigeria revealed variations in plant biodiversity structure and community. The vegetation vigour increased from the average NDVI value of 0.42 to 0.60 between 2002 and 2014 and the health of the plant biodiversity community decreased from the average NDVI value of 0.60 to 0.51 between 2014 and 2022. This indicated a decrease in the plant biodiversity community in some study areas and this could be due to increased demand for trees and increased human pressure on the plant biodiversity community. This result aligns with the results of Peña-Arancibia et al. (2019), who posited that forests have a positive effect on soil infiltration capacity and wetness, leading to a higher water table and increased dry season spring flow in forested catchments. On the other hand, deforestation has a negative impact on water recharge and dry season discharge through its effects on overland flow and infiltration in previously forested areas.

Plant dominance within a tropical rainforest is a key aspect of its ecological structure and function, and changes in land use and land cover can have profound impacts on this dominance pattern (Velastegui-Montoya et al., 2022). Plant dominance within tropical rainforests is intricately linked to land use and land cover change, with human activities often disrupting natural patterns and processes (Lewis et al., 2015). Results showed that Funtumia *elastica, Mansonia altissima, Sterculia rhinopetala, Albizia zygia*, and *Celtis zenkeri were* the dominant plant species identified during the ground-based study while *Tabernaemontana pachysiphon, Alstonia boonei, Cola millenii, Ficus exasperate* and *Glyphaea brevis* were the least dominant plant species. This diversity of plant species, which is necessary for human survival, economic well-being, and forest ecosystem stability, is also a sign of how well-preserved forest ecosystems are found in Ise-Ekiti Forest Reserved suggested the forest-rich in plant biodiversity. Greengrass (2006) and Ogunjemite (2011) have earlier stated that Ise-Ekiti Forest Reserve is blessed with a diversity of species such as *Gmelina arborea, Mansonia altissima, Tectona grandis, Alstonia boonei, Ceiba pentandra, Entandrophragma cylindricum, and Milicia excelsa*. Study also indicated that Ise-Ekiti Forest Reserve serves as a hotspot of plant biodiversity as some common trees in Nigerian forests such as Iroko (*Melicia excelsa*), Obeche (*Triplochiton scleroxylon*), Mansonia (*Mansonia altissima*), Omo (Cordia millenii), Aye (*Sterculia rhinopetalia*), Afara (*Terminalia superba*) and Ayinre (*Albizia*) reported present in Tropical Rain Forest Reserve of Ise-Ekiti, Southwestern, Nigeria.

5. Conclusion

The research examined and provided information on the spatial and temporal alterations in LULC within six chosen land cover categories between 2002 and 2022 within the Tropical Rain Forest Reserve of Ise-Ekiti, Southwestern, Nigeria. The study also showed the plant species that were most dominant and less dominant within the forest area. The aim was to offer insights into the impacts of potential changes in land use on both plant diversity and Tropical Rain Forest Reserves over a twenty-year timeframe. This study has examined that a sudden increase in agricultural land, built-up, and bare land between 2014 and 2022 caused a decrease in Forested areas (disturbed and undisturbed) and reduction in the water bodies within the Forest Reserve. It also revealed that plant structure was majorly converted to agricultural land and built-up areas, and different degrees of conversion among the land cover types occurred from one particular year to another. The result of this study has implications for sustainable development goals (SDG) 15 (Life on Land) and SDG 13 (Climate Action). It can be recommended that the information from this study might be very crucial to effective land management, conservation efforts, and sustainable practices.

Author contributions

Conceptualization: D.A., A.O., O.M.; methodology: D.A.; data analysis: D.A.; formal analysis and investigation: D.A.,; writing – original draft preparation: D.A.; writing – review and editing: D.A., A.O., O.M..; supervision: A.O., O.M.

Data availability statement

The data used or analyzed in this study will be available from the corresponding author upon request.

Acknowledgements

The authors thank Ekiti State Government and SW/Niger Delta Forest Project director for permitting authors to make use of the Ise-Ekiti Forest Reserve for the work.

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