International Journal of Environmental and Ecology Research
www.environmentaljournal.in
Online ISSN: 2664-7117, Print ISSN: 2664-7109
Received: 09-07-2023, Accepted: 24-07-2023, Published: 10-08-2023
Volume 5, Issue 1, 2023, Page No. 12-17

Effects of agro-ecological expansion on carbon stock in south-eastern part of Osun State, Nigeria

Remilekun Eunice Atobatele[1], C O Ikporukpo[2], Olalekan J Taiwo[2], Adekola Oluwaseun Fakunle[3]
[1] Environmental Management Programme, Pan African University, Institute of Life and Earth Sciences, Ibadan, Nigeria
[2] Department of Geography, University of Ibadan, Nigeria
[3] Faculty of Engineering and Sustainable Development, Division of GIScience, University of Gävle, Gävle, Sweden

Abstract
Understanding the inimical impacts of land use/land cover change (LULCC) on forest ecosystems is pivotal to achieve a sustainable environment. Land use/land cover change tremendously influence carbon emissions and storage. Despite the high rate of forest degradation in tropical developing countries little or no study has been conducted on the impacts of land use change on the carbon pools of these land use systems. The magnitude of vegetation biomass and carbon stocks of six (6) land use classes in the southeastern part of Osun State, Nigeria, were quantified in the following carbon pools: trees and roots. The aboveground carbon stocks of the different land use/land cover types decreased in the order: Dense forests (119.37 MgC ha^{-1}) > light forests (90.59 MgC ha^{-1})> Oil Palm Plantations (67.31 MgC ha^{-1}) > Cocoa Plantations (62.58 MgC ha^{-1}) > Cassava farms (15.38 MgC ha^{-1}) > Maize farms (13.14 MgC ha^{-1}). Carbon stocks significantly vary 0.028 across all the considered land use types. Taking dense forest as threshold value, light forest, oil palm plantation, cocoa plantation, cassava farm and maize farm recorded carbon loss of 35.54 Mg C ha^{-1}, 64.29 Mg C ha^{-1}, 70.13 Mg C ha^{-1}, 127.49 Mg C ha^{-1} and 131.19 Mg C ha^{-1} respectively. This result indicated that the conversion of dense forests to agricultural lands have grossly influenced carbon loss as larger amounts of carbon are found in the dense forests.

Keywords: Dense forest, LULC, carbon stocks, inimical impact, plantations, croplands

Introduction

Climate change is a significant environmental issue in the 21st century, with rapid population growth and agricultural production being the primary drivers of land use change. Estimating carbon stock is crucial in mitigating climate change. The conversion of natural ecosystems to agricultural lands alters vegetation carbon biomass and soil carbon stock, leading to declines in carbon sequestration. West-Africa's tropical forests are among the wealthiest carbon ecosystems in the world, with the highest rate of loss. Nigeria, a dominant tropical forest reserve in West Africa, is experiencing large-scale land conversion to different land use types. The rapid increase in human population has led to the growth of urban centers and high demand for natural resources, resulting in the degradation and conversion of natural forest lands into agricultural lands and urban centers.

A 21% increase in agricultural lands between 2010-2050 is predicted, with 13.7% and 4.6% carbon loss in vegetation biomass and soil, respectively. This study assessed the impacts of agricultural land expansion on carbon storage in the South-Eastern part of Osun State, Nigeria. The study quantified the plot level of the above and belowground carbon stock of different land use/land cover types and estimated the variation in carbon storage values of four major arable crop types (cocoa, plantation, cassava, and maize) common in the study area.

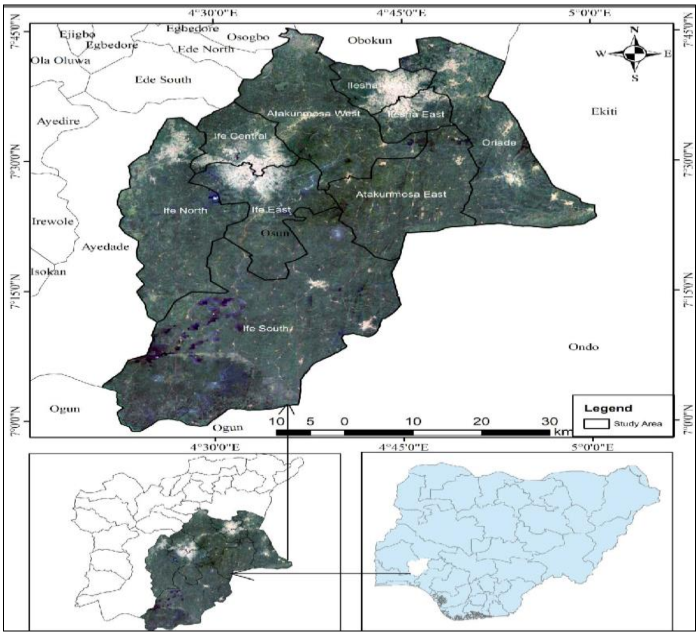

Fig 1: The Study Area

Materials and Methods

Landsat images of the year 2020 with corresponding path 190 and row 055 of the WRS-2 (Worldwide Reference System) was obtained from the United States Geological Survey (USGS) and georecified to Datum WGS84 in UTM zone 31 at 30 meters spatial resolution. False color composite was generated using bands 5,4,3 that conform to

Near-Infrared Red (NIR), Red (R), and Green (G) bands, respectively, because of their usefulness in vegetation and land use monitoring (Lea, 2011 [22]; Lillesand and Kiefer, 2007). Supervised classification was performed utilizing a maximum likelihood algorithm to obtain different land use/cover types in study (Bessah *et al*., 2016) [5]. The coordinates of 138 random Ground Control Points (GCP's) collected during reconnaissance were used in the supervised classification. ENVI 5.3 and ArcGIS 10.4 software were used to identify the various land use and land cover types.

The satellite image was categorized into six (6) classes, which include urban areas, forests, plantations, croplands, rock outcrops, and water bodies. However, only the vegetation classes (Forests, Plantations, and Croplands) were sampled based on the focus of the study. Forests were reclassified into dense and light forests, while two major plantations (oil palm and cocoa) and cropland types (cassava and maize farms) were selected (Table 1).

Table 1: Modified Land Use Classes

Land Use Types	Description
Dense Forest	Evergreen broadleaf forest, deciduous forest, dense forest coverage
Light Forest	Scattered forest, relatively light forest coverage
Oil Palm Plantation	Same species of oil palm trees planted and managed at the same time.
Cocoa Plantation	Same species of cocoa trees planted and managed at the same time.
Maize Farm	Mainly maize fields planted and managed at the same time.
Cassava Farm	Mainly cassava fields planted and managed at the same time.

Following Assefa *et al*., (2013) [4] recommendation, the carbon values in each land use type was determined, using a minimum of six sample plots for each land use type except for cocoa and oil palm plantations, where eight plots were sampled each because of the high cultivation rate as depicted by the area cover (1,586.17sqkm of 3,240sqkm). The random sampling tool (create random points) in ArcGIS 10.4 was used to pre-determine the sampling plots and potential locations in each land use class. Based on accessibility and land use types, 40 points were randomly selected across all the considered land use types in the study area in order to have an even representation. These forty sampling plots were assessed, and the geographical coordinates of plots were generated from KOBO collect application; a free toolkit which helps in collecting and storing primary data using a smartphone. In all the 40-field plots, 12 forests (dense and light forests), 16 plantation sites (cocoa and oil palm plantations), and 12 croplands (cassava and maize farms) were examined based on the methodologies proposed by Hairiah *et al*., (2011) [16]. In order to have an actual representation of the study area, we stratified the large area into smaller segments (Hairiah *et al*., 2011) [16]. Within each quadrant, the above and belowground biomass was derived by using the methodologies recommended by Ponce-Hernandez *et al*. (2004). The measuring tape and haga altimeter were used to measure the height and diameter of the trees at 1.3m height. Each plot has a dimension of 30×30 meters to ensure that the area on the ground corresponds with at least one full 30m spatial resolution of Landsat image. This study used square plots because it captures the heterogeneity of the plants within the plots than circular plots (Assefa *et al*., 2013) [4]. Each square plot (sampling quadrats) with 30×30 meters, 10×10 meters, 3×3 meters, and 1×1- meter dimensions was nested within each other. Trees with or greater than 5cm diameter at breast height (DBH) were measured in the 10×10 meters quadrant. While those with less than 5cm were measured in the 3×3 meters quadrats (Figure 1). The cropland layer (cassava, and maize plants) was collected from the four 1×1-meter quadrats (Figure 1). Freshly weighed immediately after uprooting, oven-dried and then dried-weighed (destructive method). The above-ground and below-ground carbon stocks were estimated according to World Soil Resources Reports, (1999) [38] and United Nations Framework Convention on Climate Change, (2015) [34] recommended methodologies.

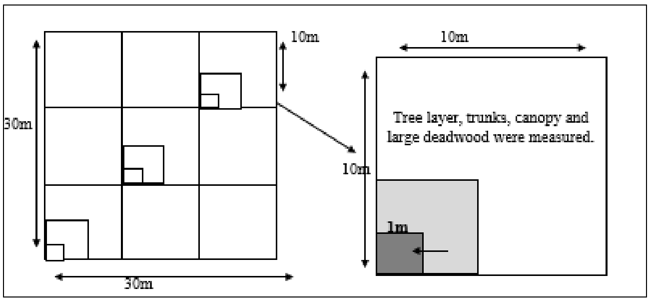

Fig 2: Sampling Quadrat for Biomass Assessment

Sampled points coordinates derived from Kobo collect application, and calculated carbon stocks for each plot were loaded into ArcGIS for spatial analysis. Based on the accuracy level as recommended by Zarco-Perello & Simões, (2017) [40], ordinary kriging method in ArcGIS was used to map the distribution of calculated carbon stocks across the study area.

Vegetation biomass at each sampled plot was quantified under each land use, biomass in trees and roots were calculated. The live aboveground biomass (AGB) in trees and shrubs were summed to determine the Carbon (C) pool. While the root biomass was estimated from the AGB to derive the C pool in belowground biomass (BGB).

Biomass carbon stock was calculated using the following equation (Orians & Millar, 1992 [28]; Walker *et al*., 2018) [36]:

Biomass Carbon Stocks (Mg C ha^{-1}) = Biomass × 0.471

Assumption Carbon stock of biomass (in dry weight) is 0.47.

All plant Carbon pools were depicted in Mg C ha^{-1}.

A total of 320 trees were surveyed across all plots. The trees dendrometry variables were measured and the allometric equation was used to calculate the standing live biomass by aggregating the biomass of each tree (except for oil palm and cocoa). The biomasses of oil palm were quantified, using the equation proposed by World Agroforestry Centre (ICRAF) (Hairiah *et al*., 2011) [16] to convert Height to AGB (Kg). Tree height is used as an independent variable in quantifying the above-ground biomass of oil palm because of its physiological makeup (Yuen *et al*., 2016) [39].

$$AGB\ (Trees\ (Kg)) = 21.297 - 6.953 \times DBH + 0.740 \times DBH^2$$

$$AGB\ (Oil\ palms) = 0.0976 \times H + 0.0706$$

Cocoa Biomass Quantification equation developed by Yuen *et al*., (2016) [39] was applied.

$$AGB\ (Cocoa) = 0.1208 \times DBH^{1.98}$$

Cropland (Cassava and Maize Farms)

$$\frac{\text{Wet Weights}}{\text{Dry Weights}}$$

The non-destructive methods derived from the above-ground biomass (AGB) estimates was used to calculate belowground biomass (BGB) as indicated in the literature.

Therefore, below-ground biomass (BGB) was estimated as a segment of aboveground biomass (AGB) using Mokany *et al*., (2006):

BGB = AGB × 0.235

A total of 320 trees were sampled and measured across the forests (dense and light) and plantations (cocoa and oil palm) land use types. The dense forests are dominated by native deciduous trees with few exotic tree species protected by forest reserve agencies of the state though they experience minimal degradation because of illegal logging and mismanagement for decades. The light forests are dominantly scanty trees consisting of native and exotic trees that have been severely degraded by charcoal merchants, loggers, mining companies, and seldom grazing of animals in dry season. To combat widespread deforestation, the Government planted exotic tree species such as Gmelina Arborea and Tectona grandis for reforestation. These plantations are between the age of 10 to 32 years, and their Diameter Breast Heights ranges from 7 and 49 cm. Some of these two exotic plantations are in their secondary regrowth stage as there was evidence of frequent felling.

Results

Table 2 shows the aboveground live biomass mean calculated from the Diameter at Breast Heights and heights values of the vegetation across the different land uses. The highest biomass values were found in the dense forests, while the least was found in maize farms. Biomass varied significantly across the different land use/cover types considered F (5,3.682), P=0.023). The dense and light forests have the highest AGB values, while oil palm and cassava had the highest values among the plantation and cropland types. Considering the biomass stocks of each land use type, the AGB was 31.17 Mg ha−1 and 21.37 Mg ha−1 more than BGB in the cassava and maize farms, respectively.

The BGB in dense forest (59.56 Mg ha−1) were about 8 and 6 times greater than those of cassava (9.67 Mg ha−1) and maize (6.56 Mg ha−1) farms, respectively. However, there was considerably larger BGB in light forests (45.2 Mg ha−1), oil palm (33.58 Mg ha−1), and cocoa plantations (31.22 Mg ha−1) than in cassava (9.67 Mg ha−1) and maize farms (6.56 Mg ha−1). The total biomass depicts an increasing trend from maize farms to dense forest in ascending order (Figure 3): maize farm (34.46 Mg ha−1) < cassava farm (50.81 Mg ha−1) < cocoa plantation (164.09 Mg ha−1) < oil palm plantation (176.49 Mg ha−1) < light forest (196.86 Mg ha−1) < dense forest (313.01 Mg ha−1). However, it could be seen in Figure 3 that there was an abrupt increase in cassava farms to cocoa plantation (113.28 Mg ha-1) and from light to the dense forest (116.15 Mg ha-1), signifying two rapid biomass increments.

Table 2: Biomass Across the Land Use Types

	Land Use Types: Mean (St. Dev)					
Biomass (Mg ha^{-1})	Dense Forest	Light Forest	Oil Palm Plantation	Cocoa Plantation	Cassava Farm	Maize Farm
Aboveground	253.45 (± 20.25)	192.34 (±30.02)	142.91 (±32.87)	132.87 (±4.9)	41.14 (±5.39)	27.9 (±5.57)
Belowground	59.56 (± 4.76)	45.2 (±7.06)	33.58 (±7.72)	31.22 (±1.15)	9.67 (±1.27)	6.56 (±1.31)
Total	313.01	196.86	176.49	164.09	50.81	34.46

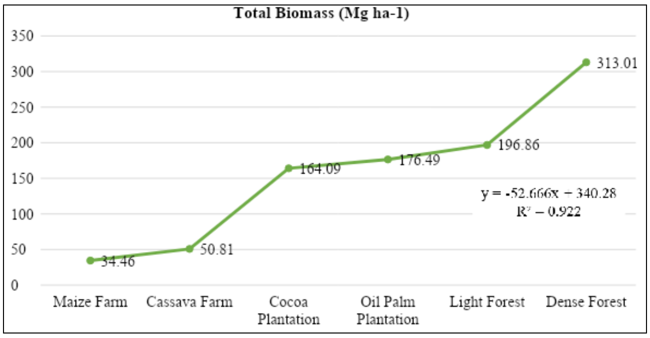

Fig 3: An Increasing Trend of Vegetation Biomass Across the Considered Land Use Types

The biomass carbon stock of various land use classes was estimated in two carbon pools, which are the aboveground (trees and non-trees vegetation) and belowground (roots) parts of the trees and non-trees vegetation. From the estimated carbon stocks, the aboveground carbon pool significantly varies F (5,2.533), P=0.022) across all the investigated land use types, with dense (119.37 Mg C ha-1) and light forests (90.59 Mg C ha-1) having the highest carbon values. While dense and light forests lost carbon to oil palm (64.29 and 28.75 Mg C ha-1), cocoa (70.13 and 34.59 Mg C ha-1), cassava (127.49 and 91.95 Mg C ha-1) and maize (131.19 and 95.65 Mg C ha-1) farms, respectively. Larger carbon loss was recorded in cassava and maize farms as compared to the oil palm and cocoa plantations.

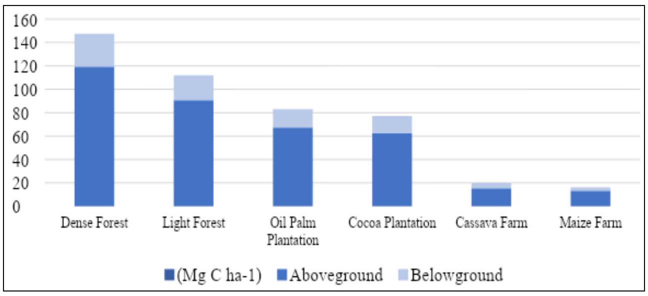

Fig 4: Total Carbon Stock Among the Various Carbon Pool Compartment of Across the Considered Land Use Types

Figure 4 shows that the total carbon stocks (Mg Cha−1) varied across the land uses studied at 95% confidence, the analysis of variance (ANOVA) depicted a significant variation F (5,3.106), P=0.028) across all the sampled land use/cover types but there was no significant variation in carbon stocks within the land use types F (5,6.564), P=1.33). However, the belowground carbon stock contained approximately 19.03% in dense forest, light forest, oil palm plantation, cocoa plantation, and maize farm, while only cassava farm has 22.83%. There were about 7 and 6 times greater belowground carbon values in dense forest (24.7 Mg C ha−1) than in the maize (3.09 Mg C ha−1) and cassava (4.55 Mg C ha-1) farms, respectively.

Furthermore, the belowground carbon stock significantly varies across all the land use types ($p < 0.036$). The total carbon stock (aboveground and belowground) under the various land use types decreased in the following order: dense forest > light forest > oil palm plantation > cocoa plantation > cassava farm > maize farm with values 147.42 Mg C ha−1 > 111.88 Mg C ha−1 > 83.13 Mg C ha−1 > 77.29 Mg C ha−1 >19.93 Mg C ha−1> 16.23 Mg C ha−1 (Figure 5 and Table 3). The total carbon ranges between 16.23 Mg C ha−1 and 147.42 Mg C ha−1 and differed significantly among the six (6) land use/cover types. Dense forests had a total carbon stock twice and thrice greater than cassava and maize farms, respectively (Figure 4). The total carbon stock of dense forest was significantly higher than that of cassava and maize farms, moderately higher than oil palm and cocoa plantations, and slightly higher than the light forest. Taking dense forest as the threshold value (147.42 Mg C ha−1), dense forests was 35.54 Mg C ha−1 lesser than light forests and 64.29 Mg C ha−1 and 70.13 Mg C ha−1 lesser than oil palm and cocoa plantations, while it was 6 and 10 times greater than cassava and maize farms (19.93 Mg C ha−1 and 16.23 Mg C ha−1) respectively, reflecting an increase in carbon loss as agricultural practices have been broadly accepted in the study area.

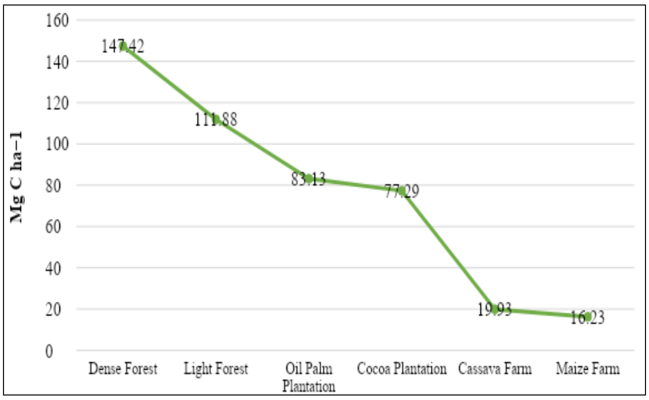

Fig 5: A Decreasing Trend of Total Carbon Stock Across the Considered Land Use Types

The spatial distribution of carbon stock using the ordinary kriging is contained in Figure 6. The carbon stocks range from 15 Mg C ha^{-1} to about 150 Mg C ha^{-1}. The least estimation was observed in the northern part of the study area. This can be attributed to the predominance of farm plantations which store less carbon than forests (Ane *et al.*, 2020) [2]. On average, the study area stores about 80 Mg C ha^{-1}. There is a high probability that the study area will continually witness carbon loss with the current agricultural expansion, especially with the exponential rate of plantation cultivation. However, the least values were found in the urban area followed by the northern part, where the dominant land use type are urban land use, cropland, and plantation.

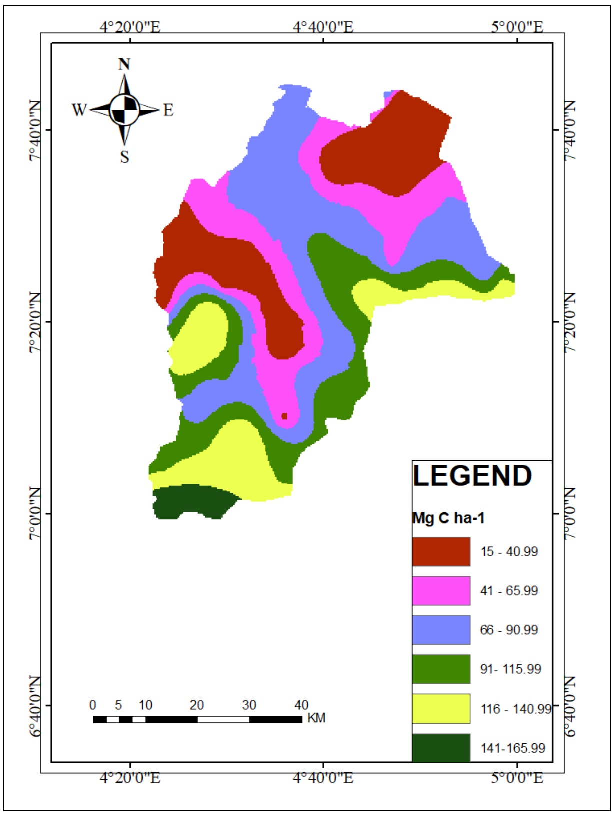

Fig 6: Spatial Distribution of Carbon Stock

Discussion

Dense forests have a higher carbon stock (147.42 Mg C ha−1) compared to other land use/ cover types, while croplands comprising of cassava (19.93 Mg C ha−1) and maize farms (16.23 Mg C ha−1) had the lowest carbon stocks, because of the presence of abundant trees (Gebrewahid & Meressa, 2020) [14]. The results obtained is in consonance with earlier study by Martin & Thomas, (2011) [23], Pragasan & Karthick, (2013) [31] and Pragasan, (2016) [30] which attributed the large carbon biomass stocks between 73.7-255 Mg C ha−1 to tropical rainforests in African. This study found that loss of carbon storage was caused by the conversion of forests to agricultural land (Gebrewahid *et al.*, 2018 [13]; Olorunfemi *et al.*, 2020 [27]; Vicharnakorn *et al.*, 2014) [35]. Approximately 45% of the total vegetation carbon stocks was found in the dense forests which has the least coverage. Hence, further decrease in dense forest areas because of agricultural land use expansion will lead to additional carbon loss. Rodríguez-Veiga *et al.*, (2017) [32] noted that forests store > 45% of terrestrial carbon stocks and hence, they are referred to as the highest yielding terrestrial ecosystems. Land use/land cover change (LULCC) modification appeared to be the causative factor of carbon loss as more carbon are contained in the dense forest (undisturbed and natural ecosystem). Similarly, IPCC, (2014) asserted that the second anthropogenic source of carbon emissions is land use change (LUC). Overall, dense forests depicted the highest carbon storage potential among all the considered land use types, while the least was found in maize farms. This is because of the large amount of organic concentration and vast litter layers which range from understory to dead roots. The influences of land use/land cover change on carbon storage and emissions accounts for about 15% in Sub-

Saharan Africa (SSA) compared with other regions across the globe (Houghton & Hackler, 2006) [17]. Since the industrial revolution, carbon emissions caused by human activities are approximately 33% because of LULCC (Houghton and Hackler, 1999). Similarly, from 2000 to 2009, land use changes emitted about 12.5% carbon into the atmosphere (Guo *et al*., 2019) [15].

LULCC significantly influences carbon storage and emissions, hence disrupting the global carbon cycle balance (Houghton & Hackler, 2006) [17]. The incessant increase in the carbon concentrations resulting from LULCC constitutes about one-third of the total forces exacerbating global warming and climate change (IPCC, 2014). Therefore, mitigation measures (such as improving the conservation of carbon-enriched land use such as forests) that stores more carbon should be considered while developing strategies that could enhance carbon balance (Thomas & Martin, 2012 [33]; Zomer *et al*., 2017 [41]). Additionally, land parcels should be considerably used in a way that carbon emissions can be reduced. Also, managerial failures in the forest resources conservation, and illegal logging should be addressed. Therefore, information about carbon emissions and storage should be adequately provided to broaden knowledge and define their spatial variability over time (Amara *et al*., 2020) [1]. Finally, institutional policies that will abate deforestation and increase afforestation and carbon sequestration should be implemented adequately.

Conclusion

The study attributed an apparent loss in the study area's carbon storage to the agricultural land expansion. Although dense forest is having the least area coverage (592.61 sq km of 3,240 sq km) among the various land use types considered (light forest, oil palm plantation, cocoa plantation, cassava farms, and maize farms), the most significant biomass and total carbon stocks are found in this natural ecosystem. While lower carbon storage values were present in the agricultural land use types. Though the cropland and plantation lands possess low carbon stocks, their values varied across the crop types. More carbon values were discovered in the plantation, with oil palm possessing more carbon stock than cocoa plantation, and cassava farm had more carbon stocks than maize farm in the cropland. The conversion of dense forests to agricultural lands led to a loss in carbon stock as the total vegetation carbon stocks reduced by 81.5% (maize farm), 61% (cassava farm), 56.5% (cocoa plantations) and 30% (oil palm plantations) in the ecosystem. AGB stored a more significant proportion of biomass carbon than other compartments. Above and belowground carbon pools are essential components in the evaluation of carbon stocks in agricultural lands. Agricultural land expansion seems to be the primary driver of carbon loss, judging from the reduction in carbon values of maize farms, cassava farms, cocoa plantations, and oil palm plantations. However, a continuous expansion of agricultural land will cause significant carbon loss. Hence, the land use types with high carbon values (forest) should be protected from further encroachment by agricultural land. Furthermore, carbon loss caused by agricultural land expansion should be given serious attention when designing carbon sequestration policies.

Acknowledgements

This work is supported by the Pan African University Student Research grant funded by the African Union.

References

1. Amara E, Adhikari H, Heiskanen J, Siljande M. Aboveground Biomass Distribution in a Multi-Use Savannah Landscape in Southeastern Kenya: Impact of Land Use and Fences. *Land*,2020:9(381):1–24.
2. Ane E, Id D, Martins F, Id P, Lima LB, Costa H. *Carbon stocks and dynamics of different land uses on the Cerrado agricultural frontier*. *C*, 2020, 1–22. https://doi.org/10.1371/journal.pone.0241637
3. Arowolo AO, Deng X. Land use/land cover change and statistical modelling of cultivated land change drivers in Nigeria. *Regional Environmental Change*,2018:18(1):247–259. https://doi.org/10.1007/s10113-017-1186-5
4. Assefa G, Mengistu T, Getu Z, Zewdie S. *Training Manual on: Forest Carbon Pools and Carbon Stock Assessment in the Context of SFM AND REDD*, 2013.
5. Bessah E, Bala A, Agodzo SK, Okhimamhe AA, Krakauer N. Dynamics of soil organic carbon stocks in the Guinea savanna and transition agro-ecology under different land-use systems in Ghana. *Cogent Geoscience*,2016:*2*(1):1140319. https://doi.org/10.1080/23312041.2016.1140319
6. Bufebo B, Elias E. Land Use/Land Cover Change and Its Driving Forces in Shenkolla Watershed, South Central Ethiopia. *Scientific World Journal*, *2021*. https://doi.org/10.1155/2021/9470918
7. Chaplin-kramer R, Sharp RP, Mandle L, Sim S, Johnson J, Butnar I. Spatial patterns of agricultural expansion determine impacts on biodiversity and carbon storage, 2015, 112(24). https://doi.org/10.1073/pnas.1406485112
8. Climate Change Synthesis Report IPCC. 2014. Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. *Ipcc*, 2014, 31.
9. Ekoungoulou R, Liu X, Loumeto JJ, Ifo SA. Tree Above-And Below-Ground Biomass Allometries for Carbon Stocks Estimation in Secondary Forest of Congo. IOSR Journal of Environmental Science, Toxicology and Food Technology,2014:*8*(4):09–20. https://doi.org/10.9790/2402-08420920
10. Ekoungoulou R, Niu S, Joël Loumeto J, Averti Ifo S, Enock Bocko Y, Mikieleko F, Eusebe DM, *et al*. Evaluating the Carbon Stock in Above-and Below-Ground Biomass in a Moist Central African Forest " Evaluating the Carbon Stock in Above-and Below-Ground Biomass in a Moist Central African. Applied Ecology and Environmental Sciences,2015:3(2):51–59. https://doi.org/10.12691/aees-3-2-4
11. Elmhagen B, Destouni G, Angerbjörn A, Borgström S, Boyd E, Cousins SAO, *et al*. Interacting effects of change in climate, human population, and land use. *Ecology and Society*, 2015, *20*(1).
12. Food and Agriculture Organization of the United Nations. *Rome, 2020*. 61.
13. Gebrewahid Y, Gebre-Egziabhier TB, Teka K, Birhane E. Carbon stock potential of scattered trees on farmland along an altitudinal gradient in Tigray, Northern Ethiopia. *Ecological Processes*, 2018, *7*(1). https://doi.org/10.1186/s13717-018-0152-6

14. Gebrewahid Y, Meressa E. Tree species diversity and its relationship with carbon stock in the parkland agroforestry of Tree species diversity and its relationship with carbon stock in the parkland agroforestry of Northern Ethiopia. *Cogent Biology*, *2025*. https://doi.org/10.1080/23312025.2020.1728945
15. Guo X, Chuai X, Huang X. A land use/land cover based green development study for different functional regions in the Jiangsu Province, China. International Journal of Environmental Research and Public Health, 2019, 16(7). https://doi.org/10.3390/ijerph16071277
16. Hairiah K, Dewi S, Agus F, Velarde S, Ekadinata A, Rahayu S, Van Noordwijk M. Measuring carbon stocks: across land use systems: a manual, 2011.
17. Houghton RA, Hackler JL. Emissions of carbon from land use change in sub-Saharan Africa. Journal of Geophysical Research, 2006, 11. https://doi.org/10.1029/2005JG000076
18. Johnson AJ, Runge FC, Senauer B, Foley J, Polasky S. Global agriculture and carbon trade-offs. Proceedings of the National Academy of Sciences of the United States of America, 2014, 12342–12347. https://doi.org/10.1073/pnas.1412835111
19. Judex M, Menz G. Modelling of land-use changes in a West African catchment. *ISPR Archives*,2006:36(7):18.
20. Karel Mokany, Raison JR, Prokushkin Anatoly. *Critical analysis of root: shoot ratios in terrestrial biomes*, 2006, 84–96. https://doi.org/10.1111/j.1365-2486.2005.001043.x
21. Koko AF, Yue W, Abubakar GA, Hamed R, Alabi AAN. Monitoring and predicting spatio-temporal land use/land cover changes in Zaria City, Nigeria, through an integrated cellular automaton and markov chain model (CA-Markov). *Sustainability (Switzerland)*,2020:12(24):1–21. https://doi.org/10.3390/su122410452
22. Lea C. Vegetation Classification Guidelines. Natural Resource Report, 2011, 2.0.
23. Martin AR, Thomas SC. A Reassessment of Carbon Content in Tropical Trees. PLoS ONE,2011:6(8):*6*(8). https://doi.org/10.1371/journal.pone.0023533
24. Mathewos M. Reported driving factors of land-use/cover changes and its mounting consequences in Ethiopia: A Review. African Journal of Environmental Science and Technology,2019:13(7):273–280. https://doi.org/10.5897/ajest2019.2680
25. Mogollón JM, Beusen AHW, van Grinsven HJM, Westhoek H, Bouwman AF. Future agricultural phosphorus demand according to the shared socioeconomic pathways. Global Environmental Change,2018:50:149–163. https://doi.org/10.1016/j.gloenvcha.2018.03.007
26. Molotoks A, Stehfest E, Doelman J, Albanito F, Fitton N, Dawson TP, Smith P. Global projections of future cropland expansion to 2050 and direct impacts on biodiversity and carbon storage. *Global Change Biology*,2018:*24*(12):5895–5908. https://doi.org/10.1111/gcb.14459
27. Olorunfemi IE, Fasinmirin JT, Olufayo AA, Komolafe AA. Total carbon and nitrogen stocks under different land use/land cover types in the Southwestern region of Nigeria. *Geoderma Regional*, 2020, *22*. https://doi.org/10.1016/j.geodrs.2020.e00320
28. Orians GH, Millar CI. Forest lands. Agriculture, Ecosystems and Environment,1992:42(1–2):125–140. https://doi.org/10.1016/0167-8809(92)90023-5
29. Owar Othow O, Legesse Gebre S, Obsi Gemeda D. Analyzing the Rate of Land Use and Land Cover Change and Determining the Causes of Forest Cover Change in Gog District, Gambella Regional State, Ethiopia. *Journal of Remote Sensing & GIS*, 2017, *06*(04). https://doi.org/10.4172/2469-4134.1000219
30. Pragasan A. Assessment of Carbon Stock of Tree Vegetation in the Kolli Hill Forest Located in India,2016:14(2):169–183.
31. Pragasan A, Karthick A. Carbon Stock Sequestered by tree plantations in university campus at. International Journal of Environmental Sciences,2013:3(5):1700–1710. https://doi.org/10.6088/ijes.2013030500038
32. Rodríguez-Veiga P, Wheeler J, Louis V, Tansey K, Balzter H. Quantifying Forest Biomass Carbon Stocks from Space. In Current Forestry Reports, 2017, 3(1). Springer International Publishing. https://doi.org/10.1007/s40725-017-0052-5
33. Thomas SC, Martin AR. Carbon content of tree tissues: A synthesis. In Forests,2012:3(2):332–352. https://doi.org/10.3390/f3020332
34. United Nations Framework Convention on Climate Change, 2015. Measurements for Estimation of Carbon Stocks in Afforestation and Reforestation Project Activities under the Clean Development Mechanism A Field Manual. http://www.unfccc.int
35. Vicharnakorn P, Shrestha RP, Nagai M, Salam AP, Kiratiprayoon S. Carbon stock assessment using remote sensing and forest inventory data in Savannakhet, Lao PDR. Remote Sensing,2014:6(6):5452–5479. https://doi.org/10.3390/rs6065452
36. Walker SM, Pearson TRH, Casarim FM, Harris N, Petrova S, Grais AM, *et al*. Standard Operating Procedures for Terrestrial Carbon Measurement. Winrock International, February, 2018, 42.
37. West Paul C, Gibbs HK, Monfreda C, Wagner J, Barford CC, Carpenter SR, *et al*. Trading carbon for food: Global comparison of carbon stocks vs. crop yields on agricultural land. Proceedings of the National Academy of Sciences of the United States of America,2010:107(46):19645–19648. https://doi.org/10.1073/pnas.1011078107
38. World Soil Resources Reports. 1999. Prevention of Land Degradation, Enhancement of Carbon Sequestration and Conservation of Biodiversity through Land Use Change and Sustainable Land Management with a Focus on Latin America and the Caribbean.
39. Yuen JQ, Fung T, Ziegler AD. Review of allometric equations for major land covers in SE Asia: Uncertainty and implications for above- and below-ground carbon estimates. Forest Ecology and Management,2016:360:323–340. https://doi.org/10.1016/j.foreco.2015.09.016
40. Zarco-Perello S, Simões N. Ordinary kriging vs inverse distance weighting: Spatial interpolation of the sessile community of Madagascar reef, Gulf of Mexico. Peer Reviewed Journal, 2017, (11). https://doi.org/10.7717/peerj.4078
41. Zomer RJ, Bossio DA, Sommer R, Verchot LV. Global Sequestration Potential of Increased Organic Carbon in Cropland Soils. Scientific Reports, 2017, 7(1). https://doi.org/10.1038/s41598-017-15794-8