UNIVERSITY OF SUSSEX SCHOOL OF GLOBAL STUDIES DEPARTMENT OF GEOGRAPHY

QUANTIFICATION OF REGIONAL CARBON STOCKS IN THE ECOREGIONS OF CROSS RIVER STATE, NIGERIA.

A thesis submitted in partial fulfilment of degree of Doctor of Philosophy.

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ABSTRACTS

Quantification of above-ground biomass over the Cross River State, Nigeria using Sentinel 2 data: *Higher-resolution wall-to-wall carbon monitoring in tropical Africa across a range of woodland types is necessary in reducing uncertainty in the global carbon budget and improving accounting for REDD+. This study uses Sentinel-2 multispectral imagery combined with climatic and edaphic variables to estimate the regional distribution of above-ground biomass (AGB) for the year 2020 over the CRS, a tropical forest region in Nigeria, using the Random Forest (RF) machine learning. Forest Inventory plots were collected over the whole state for training and testing of the RF algorithm, and spread over undisturbed and disturbed tropical forests, and woodlands in croplands and plantations. The maximum plot AGB was estimated to be 588 t/ha with an average of 121.98 t/ha across the entire CRS. The AGB was estimated using Random Forest and yielded an* R^2 *of 0.88, RMSE of 40.9 t/ha, a relRMSE of 30 %, bias of +7.5 t/ha and a total woody AGB of 0.246 Pg for CRS. These results compare favourably to previous tropical AGB products; with total AGB of 0.290, 0.253, 0.330 and 0.124 Pg, relRMSE of 49.69, 57.09, 24.06 56.24 % and -41, -48, -17 t/ha bias over the CRS for the Saatchi, Baccini, Avitabile and ESA CCI maps respectively. These are all compared to the current REDD+ estimate of total AGB over the Cross River State of 0.268 Pg. This study shows that obtaining independent reference plot datasets, from a variety of woodland cover types, can reduce uncertainties in local to regional AGB estimation compared with those products which have limited tropical African and Nigerian woodland reference plots. Though REDD+ biomass in the region is relatively larger than the estimates of this study, REDD+ provided only regional biomass rather than pixel-based biomass and used estimated tree height rather than the actual tree height measurement in the field. These may cast doubt on the accuracy of the estimated biomass by REDD+. These give the biomass map of this current study a comparative advantage over others. The 20 m wall-to-wall biomass map of this study could be used as a baseline for REDD+ Monitoring, Evaluation and Reporting for equitable distribution of payment for carbon protection benefits and its management.*

Digital mapping of soil organic carbon from sentinel-2 data in the tropical ecosystem of Cross River State, southeast-Nigeria: *Digital mapping of Soil organic carbon (SOC) is fundamental in achieving the mandates of the REDD project. As an essential climate variable, SOC is a constituent of the ecological system that supports chemical, biological and physical processes and can be used to infer the quality of the ecosystem. In Nigeria, estimates revealed that 40 percent of greenhouse gas (GHG) emissions comes from the forestry and land use sector. On the strength of this, the quantification of the total SOC stock in CRS Nigeria, will aid in putting in place land use policies that will achieve the twin goal of SOC protection and enhance the living conditions of those whose livelihood is nature dependent. This study used random forest (RF) regression; a machine learning algorithm to identify key predictors of SOC through the integration of field, Sentinel 2A (S2) derived vegetation indices, selected reanalysis climate variables with topography. Three land cover types (LCTs); undisturbed, disturbed and croplands were purposively mapped out, and 72 soil samples collected at soil depth of 20 cm across the study area. 70 % of points data were used to train the RF model while the remaining 30 % was used to validate the predicted SOC model. We estimated 0.147 Pg with mean of 72.94 t/ha of SOC compared to African Soil Information Service (fSIS) 0.124 Pg and Innovative Solution for Digital Agriculture (ISDA) 0.217 Pg of SOC over the area. Model* *analysis indicates that key predictors (topography, rainfall, maximum air temperature, OSAVI, EVI and NDVI) achieved a high prediction accuracy with lower uncertainty unlike the global and continental SOC maps over the study area (R^2 of 0.82, RMSE of 22.54 (t/ha), and uncertainty of 39.4 % compared to AfSIS; RMSE=35.29 t/ha, uncertainty=61.69 % and iSDA; RMSE= 38.58 t/ha, uncertainty=57.21 %). Our results showed lower uncertainty compared to the coarse spatial resolution maps of AfSIS (30 m) and ISDA (250 m). The final model output was used to spatialize the SOC distribution across the CRS subregion using ArcGIS package. The 20 m resolution SOC map of this study could be referenced in the REDD+ Monitoring, Evaluation and Reporting for equitable distribution of payment for carbon protection benefits and its management.*

***Livelihood impacts of forest carbon protection in the context of redd+ in Cross River State, southeast Nigeria**:*

The rate of landcover change linked to deforestation and forest degradation in tropical environments has continued to surge despite series of forest governance policy instruments over the years. These informed the launch of one of the most important international policies called Reducing Emission from Deforestation and Forest Degradation Plus (REDD+) to combat forest destruction. REDD+ assumes that communities will have increased access to natural capital which will enhance their livelihood portfolio and mitigate the effects of climate variability and change across biomes. The aim of this study is to ascertain the livelihoods impacts of forest carbon protection within the context of REDD+ in Cross River State, Nigeria. Six forest communities were chosen across three agroecological zones of the State. Anchored on the Sustainable Livelihood Framework, a set of questionnaires were administered to randomly picked households. The results indicate that more than half of the respondents aligned with financial payment and more natural resources as the perceived benefits of carbon protection. More so, a multinomial logistic regression showed that income was the main factor that influenced respondent's support for forest carbon protection. Analysis of income trends from the 'big seven' non-timber forest resources in the region showed increase in Gnetum africanum, Bushmeat, Irvingia gabonensis, Garcinia kola, while carpolobia spp., Randia and rattan cane revealed declining income since inception of REDD+. The recorded increase in household income was attributed to a ban in logging. It is recommended that the forest communities should be more heavily involved in the subsequent phases of the project implementation to avoid carbon leakages.

Supervisors

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Declaration

I hereby declare that this thesis is my own work, both in concept and execution and besides the normal supervisory and inputs from my external collaborators, I have received no assistant except from what has been acknowledged. I also declare that this thesis has not been and will not be submitted in whole or in part to another university for the award of any other degree. However, chapters two and four of this manuscript have been published in Journal of Remote Sensing and Journal Sustainability respectively. I confirmed that this declaration holds true for the publication too, and the co-authorship; my two supervisors and external collaborators (Francis Ebuta Bisong and Chima Iheaturu) was by way of improving the technical aspects of the paper and advise during the peer-review process.

Brighton, 30th August 2022.

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Ushuki Ayankukwa Amuyou

Dedication

This project is dedicated to all lovers of nature who daily strive to protect mother nature.

LIST OF ACRONYMS

AGB - Aboveground Biomass

ESA CCI+ - European Space Agency Climate Change Initiative

ECC - Essential Climate Variable

CRS- Cross River State

CO2 - Carbon Dioxide

COP2 - Conference of the Parties

DBH - Diameter at Breast Height

DEM - Digital Elevation Model

FRA - Forest Resources Assessment

FCFF - Forest Carbon Partnership Facilities of the World Bank

FAO - Food and Agricultural Organization

DN - Digital Number

ENVI - Environments for Visualizing Images

EVI - Enhance Vegetation Index

GHG - Greenhouse Gas

GOFC GOLD - Global Observation of Forest and Land Cover Dynamics

GSV - Growing Stock Volume

LULCF - Land Use/ Land Cover change and Forestry

GPS - Global Positioning System

IPCC - Intergovernmental Panel on Climate Change

MSAVI - Modified Soil Adjusted Vegetation Index

MRV - Monitoring, Reporting and Verification

MSE - mean Square Error

NFI - National Forest Inventory

NDVI - Normalized Difference Vegetation Index

NGO - Nongovernmental Organization

NIR - Near Infrared

REDD - Reducing Emissions from Deforestation and forest Degradation in Developing Countries

RMSE - Root Mean Square Error

SNAP - Sentinel Application Platform

SOC-Soil Organic Carbon

SOM-Soil Organic Matter

UNFCCC - United Nations Framework Convention on Climate Change

USGS - United State Geological Survey

SLF - Sustainable Livelihood Framework

UTM - Universal Transverse Mercator
VIM - Variable Important Measure
WD - Wood Density

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CHAPTER ONE: INTRODUCTION

1.1 Background

The quantity of carbon dioxide (CO_2) in the atmosphere today of 417.2 part per million (ppm) surpasses pre-industrial levels of 278 ppm (Friedlingstein et al. 2022). Carbon dioxide emission profile further shows that the highest CO_2 emissions was recorded in the last decade as it averaged at 10.9 ± 0.9 petagram per year, with 46 percent of this accumulated in the atmosphere, 23 % taken up by the ocean and 31 % by vegetation of terrestrial ecosystems (Canadell et al. 2021). The elevated atmospheric CO_2 is attributed to fossil fuel combustion and land cover changes sustained by increased peopling of the earth with the attendant economic growth (Jayawardena et al. 2021). From the advent of the industrial era to date, anthropogenic activities have continued to alter the natural dynamics of forests, resulting in much CO_2 entering the atmosphere (Edenhofer et al. 2014; Li et al. 2018; Friedlingstein et al. 2022). Population increase, industrial and energy revolutions, resulted in increased amounts of CO_2 released into the atmosphere. At the turn of the industrial revolution, 277 ppm of CO_2 were concentrated in the atmosphere (Joos and Spahni 2008) and by 2016, the concentration had increased to about 402.8± 0.1 ppm (Dlugokencky and Tans 2018). Human activities associated with the use of energy from fossil fuels and changes in land use are the largest contributors of atmospheric CO_2 (Figure 1), accounting for the mean carbon budget imbalance of 0.6 $PgCyr^{-1}$ between 2007 and 2016 (Le Quere et al. 2018).

The excess CO_2 in the atmosphere warms the biosphere (Friedlinstein et al. 2022). Conversely, it was suggested that an increase in carbon dioxide in the atmosphere increases carbon sequestration potentials of tropical forests (Higgins and Scheiter 2012) and enhances the green status of tropical grasslands and savannas landscapes (Zhu et al. 2016). Similarly, Korch et al. (2021) model analysis forecasted an increase in the capacity of tropical forest to take in more CO_2 and subsequently induced vegetation growth more than vegetal cover loss linked to climate change. However, recent study by Gosling et al. (2022) revealed that carbon dioxide was not a significant contributor to vegetal cover increase rather moisture availability and disturbance regimes were the dominant controlling factors on woody cover increase or decrease in the west African region. Gosling et al result contradicts the outcome of Mndela et al. (2022) meta-data analysis of the effects of atmospheric carbon dioxide on woody cover. Mndela et al. reported that an elevated carbon dioxide increases total biomass within 1 year of exposure however, after prolong exposure (>3 years) biomass significantly decreases. Studies also submitted that though elevated CO_2 leads to forest cover fertilization, nutrient availability constraint of tropical vegetation hampers it growth (Quesada et al. 2012; Walker et al. 2021; Fleischer and Terrer 2022). From the literature, it is evidence that the responses of tropical ecosystems to increase in carbon dioxide remains uncertain, as the scientific community is yet to come to an agreement whether elevated atmospheric carbon dioxide has beneficial effects on tree biomass or not irrespective of the duration of exposure (Fisher et al. 2013; Chris et al. 2013).

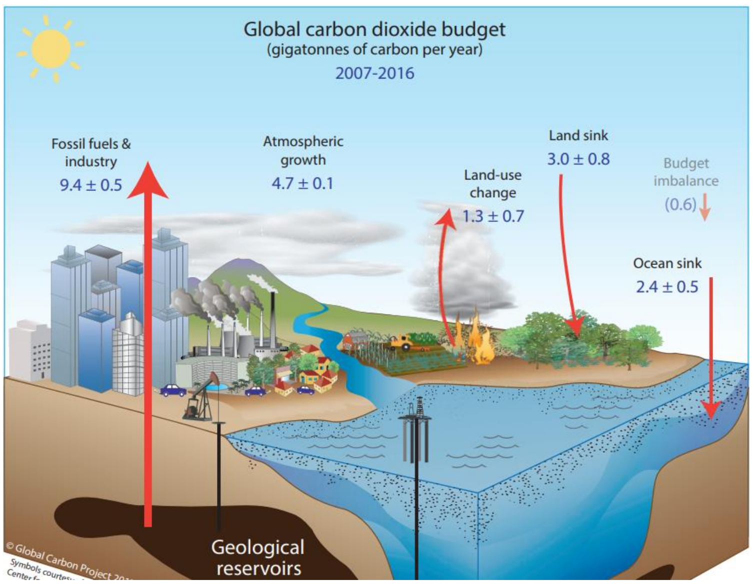


Figure 1: Schematic diagram showing global carbon sources, sinks and fluxes (Le Quere et al. 2018).

However, it is certain that the rate of land cover spoliation largely attributed to increased population, expanding economics, poverty, responses to economic opportunities, government policies among others in the tropics continues to threaten environmental sustainability (Propradit et al. 2015; Guarderas et al. 2022). The removal of forest leads to the emission of carbon into the atmosphere. Houghton (2003) reported that between 1850 and 2000, 156 PgC were released into the atmosphere, with 60 % attributed to land cover changes in the tropics. Land use/cover change is often expressed by the conversion of primary forest to agricultural landscapes, pastures, and civil works; collectively these reduce the carbon sequestration capacity of the land. Don et al. (2011) revealed from a meta-analysis of changes in land use from natural forest to croplands, perennial crops, and grasslands in the tropics leading to 25, 30 and 12 % losses in soil organic carbon (SOC), respectively. The removal of vegetal cover reduces the quantity of leaf fall required for the formation of soil organic matter and subsequently SOC (VeldKamp et al. 2020). Land use change has been central to national and international greenhouse gas monitoring guidelines. Hence, there is a growing need to evaluate carbon and SOC implications of forest management and land-use decisions on carbon stocks status (Puhlick et al. 2017).

However, the terrestrial carbon pool has the potential to absorb 30 % of total atmospheric carbon released from land use changes and fossil fuel combustion (Friedlingstein et al. 2022).The assimilation of atmospheric carbon dioxide (CO_2) during photosynthesis and its subsequent transformation into carbon are processes which can help counteract the amount of CO_2 in the atmosphere (Le Quere et al. 2018), sequestering vast amounts of carbon in global forest biomes ({47.5 to 50 % of forest dry mass is made up of carbon} (Das and Singh 2016). It is estimated that 30 % of the Earth's land area of 149.4 million km^2 is under forest cover (Rodrigues et al. 2017). Forests account for 75 % of global gross primary productivity and store 45 % of terrestrial biomass in different forms (Beer et al. 2010). Carbon is stored in the above-ground biomass, below-ground biomass, litter, dead wood, and soil organic carbon. Despite the many ecological benefits of forest, it remains susceptible to changes mainly in the cover through anthropogenic activities.

In Nigeria, between 2001 and 2017, 171 kha of tree cover disappeared, leading to the release of 3 TgCyr^{-1}, with the highest mean annual value of 11.9 TgC recorded in 2017 (Global Forest Watch 2018). The population of Nigeria was 166.2 million in 2012, increasing to 178.5 million in 2016 (National Bureau of Statistics 2017). The loss of tree cover may be linked to the rise in population fuelling increased demand for land for agriculture and urban expansion, as 80 % of the population are engaged in farming (Abdulahi et al. 2014). In the Cross River State (CRS), a total of 65.2 kha of tree cover was lost between 2001 and 2017, equivalent to an annual loss of 0.6 % (GFW 2018). This led to the release of 6.2 million tons of carbon into the atmosphere (ibid).

Besides the importance of forests in biogeochemical cycles and moderating effects on climate, the forest contains many species of flora and fauna and provide diverse environmental and socioeconomic and cultural services (Food Agricultural Organization 2014). These include purification of water, source of food to over 500 million forest inhabitants, herbs for medicine, energy, shelter, spiritual and cultural values (Bisong et al. 2009; Mfon et al. 2014; FAO 2014). These diverse functions of the forest ecosystem are very important to the livelihoods of many rural populations in Nigeria, especially in CRS, where 50 % of the country's primary forest remains. It is estimated that over 85 % of the rural population of CRS depends on forest products for its livelihood (Bisong et al. 2009). However, the introduction of carbon protection projects in the region is likely to have negative impacts on the livelihoods of the people if such projects are not properly managed (Awoniyi and Amos 2016). Reducing Emissions from Deforestation and Forests Degradation Plus (REDD+) was introduced in the region in 2008 to estimate and protect carbon stocks while maintaining the rural population livelihood portfolios. However, pitfalls have been identified in the implementation of the project in the region. In particular, the rural population is denied access to the resources it has relied on (Ajake and Abua 2009), which arises from the non-inclusion of the people during the design of Readiness Note by the Nigerian government REDD+ team (Adeniran 2018). Denying the people access to a livelihood and leaving them at the mercy of government handouts may lead to carbon leakage, i.e. the relocation of biomass destruction to other locations not covered by the reducing emissions from deforestation and forest degradation project (Agrawal et al. 2011).

In the light of these problems, the accurate quantification of regional forest carbon will reduce uncertainties about the global contributions of land use and land cover change (LULCC) to the carbon cycle (Mitchard et al. 2013). This is especially true in Africa, which is characterized by high level of uncertainties on CO_2 inputs (Ciais et al. 2013). Quantifying and mapping forest carbon under different types of land cover is critical to formulating carbon and climate change policies, tracking, and reporting for the REDD+ project as well as partitioning benefits of carbon sequestration, conservation, and management to the rural populace (Shao and Zhang 2016; Avitabile et al. 2016).

1.2 Justification of the study

Quantification of carbon stocks in terrestrial ecosystems is vital to assessing their productivity, analysing carbon budget trends, determining land cover change effects and their socioeconomic services to humanity (Das and Singh 2016). The burgeoning population is fuelling rapid changes in land cover features in the tropics with attendant impacts on global carbon fluxes. Extant carbon estimation data in the region show conflicting results (Baccini et al. 2008; Saatchi et al. 2011, Avitabile et al. 2016 and ESA CCI 2021), selective estimation of carbon stocks (UN-REDD+ Nigeria 2018), and limited area coverage (Offiong and Iwara 2008; Jimoh et al. 2012; Idiege et al. 2013). For instance, Baccini et al. (2008) estimate of above-ground carbon AGB for the tropics was 457 Pg, Saatchi et al. (2011) 547 Pg and Avitabile et al. (2016) 451 Pg. The disparity and uncertainty in the estimated regional above-ground carbon stocks may be connected to the reliance on look-up tables without many ground plots in all the land cover types in the region as 298, 120 and 75 ground plots were in South America, Asia, and Africa respectively by Saatchi while Baccini established 61, 442 and 942 field plots in Cameroon, Uganda, and the Congo only respectively. In addition, the use of different methods to estimate carbon and the focus on forested landscapes leaving out degraded land cover types, recovered land covers, plantations, mixed forest, and the savannas found in the northern part of the state might have been responsible for the uncertainty on the actual total carbon stocks of the region. The desire for local/regional carbon has also been a focus of the GlobBiomass (ESA 2014) project emphasizing sub-regional carbon estimation using Sentinel-2 data.

UN-REDD+ carried out carbon stock quantification in the CRS in the last two years (UN-REDD+ Nigeria 2018**)**. This effort was limited to AGB and BGB in undisturbed forest while forest parameters like tree height and diameter were estimated by the application of height-diameter equations of Feldpausch (2012), and wood density from Zanne et al. (2009). Furthermore, soil organic carbon was not covered by the Nigeria REDD+ team (UN-REDD+ Nigeria 2018). More so, disturbed landcover and agricultural fields were left out in the biomass estimation. The divergent estimated carbon stocks and neglects of certain forest, and agroecological carbon pools would undermine the integrity of Monitoring, Reporting and Verification (MRV) mechanism of REDD+ in the region.

REDD+ project was designed to measure, protect carbon, and sustain rural livelihoods by encouraging communities to adapt sustainable land use practices **(**UNFCC 2007)**.** This strategy was meant to conserve biodiversity and protect forest carbon under different land cover types by providing incentives to forest dependent communities (Awoniyi and Amos 2016). However, no study has comprehensively examined how the estimation and conservation of forest carbon of REDD+ project will deliver livelihoods benefits to the rural population of Nigeria. These knowledge gaps reinforce the need for a comprehensive quantification of the carbon stocks in the CRS and ascertain the benefits of carbon quantification by REDD+ to rural livelihood of the inhabitants of the region.

1.3 Aim and objectives

The aim of this study is to quantify regional carbon stocks from sentinel-2 data incorporating knowledge on land cover types and assess livelihood benefits of carbon protection goals of REDD+ to forest dependent communities in CRS Nigeria. This was achieved by focusing on the following specific objectives:

1. To estimate regional above ground biomass (AGB) over the CRS region using sentinel-2 data.
2. To map soil organic carbon from sentinel-2 data in the tropical ecosystem of CRS Nigeria.
3. To examine how accurate measuring forest carbon in the context of REDD+ delivers livelihood benefits to forest dependent communities across the CRS.

1.4 Study area

The study was carried out in CRS of Nigeria in west Africa (Figure 2a and 2b). The region is located on latitude $4^{0}\ 34^{I}\ 59.99^{11}$ N and longitude $8^{0}\ 24^{I} 59.99^{11}$ E. It has an area of 20,156 sq. km. It is bounded in the north by Benue State and south by Akwa Ibom State and the Atlantic Ocean while in the east and west, the region shares boundary with the Republic of Cameroon, Ebonyi and Abia States respectively (UN-REDD+ Nigeria 2018**)**. It is situated in the Niger Delta Region (NDR) of Nigeria characterized with diverse geographical features. The regions land cover types are modulated by the interplay of biophysical variables (climate, vegetation, topography, and soils) and subsequent modification by anthropogenic activities (Offiong and Eteng 2014). In terms of land cover regionalization, the influence of Continental Tropical (cT), Maritime Tropical (mT) and the east west equatorial Easterlies delineate the region into three Agroecological zones (Figure 2c); Southern, Central and Northern agroecological zones (Bulktrade 1989).

These broad regions have five different vegetation types: mangrove, swamp, tropical rain forest, montane vegetation, and savanna woodlands (UN-REDD+ Nigeria 2018). The region harbours 50% of tropical forest of Nigeria (Carbon Brief 2020). It is recognized as one of the biological hotspots in the world (USAIDS 2006) and two locations (Oban and Okwongwu) with total land area of 4000 Sq.km are marked out as conservation spots. The Oban Division (OD) covers an area of 2800 Sq.km with 1568 identified plant species while the Okwongwu Division (OkD) has a land area of 800 Sq.km. with 1545 plant species located in the area (Larsen 1997). Analysis of extent of land cover types in the region shows mangrove occupy 480 km^2, swamps 520 km^2, tropical rainforest 729 km^2, plantations 460 km^2, other forest 216 km^2 and other land uses 12,299 km^2 (Fon et al. 2014).

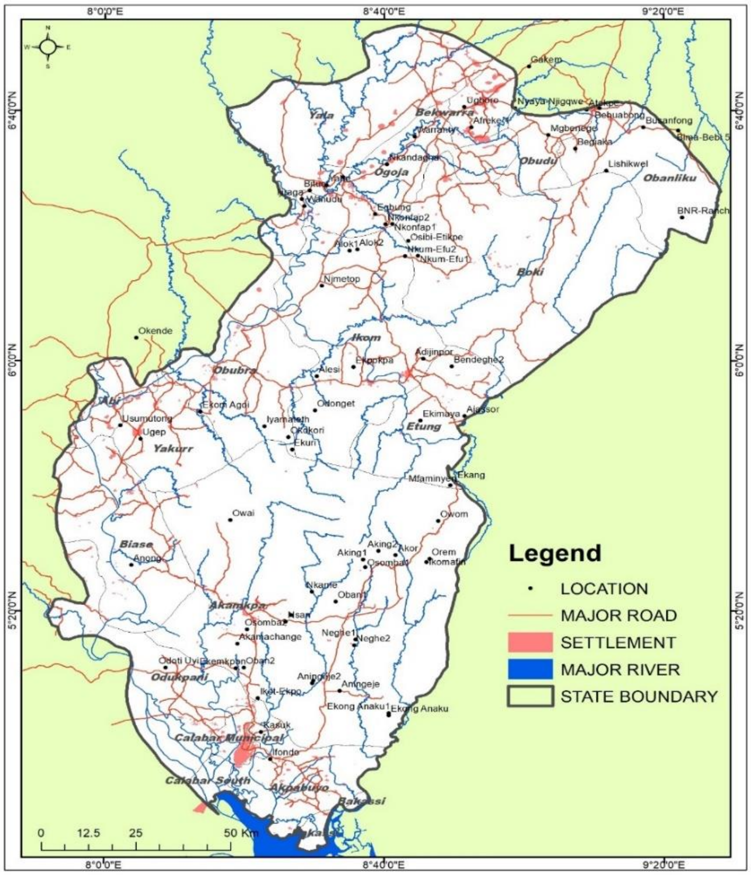


Figure 2a: Map of Cross River State with insert location in West Africa and Nigeria with sample points (black dots) overlaid.

However, these land cover types have at various times been degraded by human activities especially agriculture and urbanization. For instance, historical records indicate that land cover clearing for agricultural purposes especially during the dry seasons (late October to early March) using fire destroyed 47 percent of the land biomass in 2007, about 22 percent in 2009, 10 percent in 2011 and 5 percent in 2012 (FAO 2015). This was a regular feature in the area during the dry season not until global organizations (United Nations, UK Department for International Development, Canadian International Development Agency among others) intensified efforts in protecting the regions forest resources from 2008.

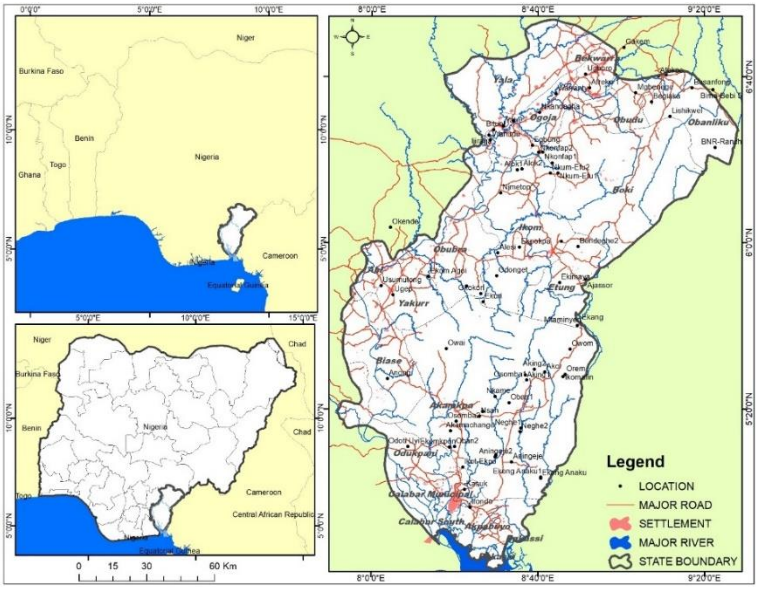


Figure 2b: Map of Cross River State with insert location in West Africa and Nigeria with sample plots overlaid (black dots). Source: Culled from the Cross River State Forestry Commission (2019)

The reduction in forest cover destruction by fire as shown in the statistics of biomass destruction are evidence of these efforts (Fon et al. 2014). In terms of urbanization, recent analysis by Offiong and Eteng (2014) showed that in 2004, total land area developed was 80.965 sq. km., it increased to 111.26 sq. km in 2009 and by 2012, it was 125.25 sq. km. In all of these, tropical forest was most impacted by the rapid rate of urban sprawl as the Great Quo and the Calabar River imposes restriction along the southern and southwest boarder. Other infrastructural development like the proposed 260 km long 'superhigh way' with 70 m wide free forest corridor will bisect parts of the protected tropical forest (Laurence et al. 2017), increasing the vulnerability of the forest to more anthropogenic impacts and subsequently exude carbon into the atmosphere. Another consumer of tropical forest and other natural land cover in the region is oil palm, cocoa, and rubber estates. Analysis of land cover conversion to these estates by Effiong (2011) showed that between 1907 and 2012, about 122,127 ha. of the land was under oil palm, rubber, and cocoa plantations. The rate of conversion of potential carbon sequestration sites to urban centres and agrobusinesses in the region is heightened with burgeoning human agglomeration.

Figure 2c: Agroecological zones of the study area (Bulktrade 1989).

The Tropical Rain Forest (TRF) is characterized by three canopy strata found in the southern agroecological zone (SAEZ) and central agroecological zone (SAEZs), largely in Akamkpa, Biase, and Boki Local Government Areas with an average tree species density of 306 per hectare and richness index of 10.605 (Jimoh et al. 2012). The top canopy layers are characterized by broad leaves with interlocking trees while the second and third tier of the canopy are densely strewn with epiphytes, intertwined with lianas, some exhibiting phototropism. The abundant species identified in the region includes *Funtumia elastica, Uapaca heudelotti, Carapa procera, Pycnathus angolensis, Staudtia stipitata, Sterculia oblonga and Celtis zenkeri* (Aigbe and Omukhua 2014). *Staudtia stipitate* is known to be the most abundant tree type in the region as it recorded an average 22 per hectare. The distribution of tree species by family indicates that *Caesalpinioideae, Mimosoideae* and *meliacea* are most common as each is represented by more species and genera in the TRF (Jimoh et al. 2012).

However, anthropogenic activities particularly logging is pushing species such as *Alstonia boonei, Ceiba pentandra, Detarium macrocarpum, Distemonathus benthianus, Agauria salicifolia, Allanblackia floribunda* etc. to extinction in the area (Jimoh et al. 2012). Analysis of tree species density in the region revealed that the close canopy of the forest limits growth of underwood species. And the lack of viable seeds to replace removed tree species and the microclimate of the forest results in poor species population density (Olajide 2004). Biomass of the region is reduced from land cover destruction by human activities. However, the occurrence of tree species like *Musanga cecropiodes, Aframomum latifolium* and *Thaumatococcus danielli* are signs of forest regeneration after anthropogenic interference in the ecosystem in certain parts of the region (Aigbe and Omukhua 2014). Other land cover types such as mangroves and freshwater swamps (in southern AEZ) is dominated by tree species like *Rhizophora racemose, R. mangle, Avicennia Africana, Chrysobalanus orbicularis* and *Hebiscus tiliaceus* among others (Bulktrade 1989). But within the mangrove's ecosystem, *Nypa frutican* is threatening the original ecosystem as large parts of the coast is now covered by this specie (UN-REDD+ Nigeria 2017).

In the northern agroecological zone (NAEZ), woody savanna is dominant with grassy and herbaceous growth beneath (Afu 2013). Common tree species in the mature forest according to Bulktrade (1989) include *Albizia zygia, Aubrevillea spp., Baillonella taxisperma, Berlinia sp., Irvingia gabuneensis, Lophira alata, Uapaca sp.,* and *Chlorophora excelca*. In the degraded forest, tree species like *Berlina grandiflora, Elaeis guineensis, Phyllanthus discoideus* among others are dominant. Grassy land cover is dominated with species like *Anthropogon sp., Lenchrus prieurii, Penicum sp.,* and *Imperita cylindrical* (Bulktrade 1989). Generally, the land cover types in the region like in other parts of the tropics has some functional relationship with the prevailing geology, soil geomorphology and climate features (Neri et al. 2012).

Geological analysis of the region by Bulktrade (1989) and Ekwueme (2003) shows that the NAEZ is made of Holocene cretaceous and sedimentary sediments continuation of the lower Benue Channel. The sediments are composed largely of sandstones, limestones, marine deposits, and shales. These formations belong to the Eze-Aku shale groups of Precambrian phases (Afu 2013). The crystalline sediments are underlaid by basement complex rocks made up basically of gneisses and schists (Figure 2d**)**. Bulktrade (1989) reports that 75 % of the CRS is underlaid by basement complex formation. Bulk of the basement rocks are in the Oban Massif and Obudu Plateau. The Obudu Plateau which peaked at 1800 square kilometres (km²) above sea level, prolongated from western Cameroon complex basement formation (Ekwueme 2003). The other areas in the NAEZ have gentle to undulating topography (Afu 2013). The crystalline complex rocks in the region are highly weathered from the combine force of intense rainfall and temperature in the area. These formations are reflected in the nature of the soils and subsequent lifeforms of the zone.

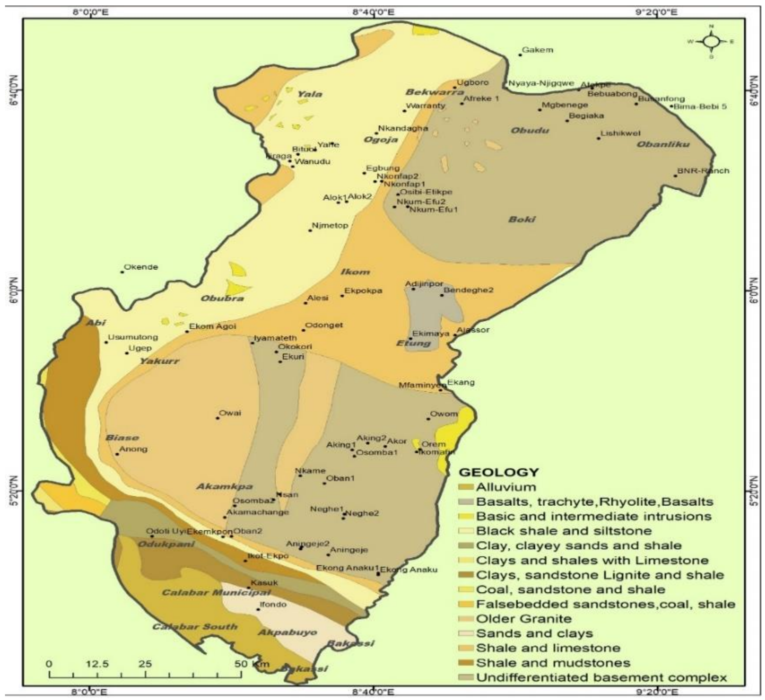


Figure 2d: Geological Map of Cross River State.

Source: Culled from Ekwueme (2003)

The NAEZ of CRS, a transition zone between the Guinean savanna ecosystem of northern Nigeria and the Tropical Rainforest of southeast Nigeria is dominated by savanna-like vegetation (Afu 2013). The varied soil types are deep, well drained, and gravelly (Akpan-Idiok and Ofem 2015). They are developed from the dominant parent materials of basement complex, shale stones and acid crystalline rocks. These parent materials in combination with other soil forming factors like climate, vegetation, geology, and topography account for the different soil types in the region. Bulktrade (1989) relied on the

United State Agricultural Development Agency (USDA) and the FAO/UNESCO soil taxonomic scheme to classify the soils as Dystic Nitosol, Dystic Cambisol, Euthric Cambisol, Gleyic Cambisol and Orthic Acrisol. The textural complex of these soils ranged from sandy loam to sandy clay loam at 0-15 cm depth and gravely sandy clay loam, sandy clay to clay at depth of 15-30 cm. The soils hue varied from brown dark brownish to yellowish brown, brownish yellow to yellowish red (Eshett et al. 1990). However, the soils fertility of the region is constantly mined without proper management, hence poor yields of tree and food crops (Okpiliya et al. 2008).

The CAEZ is part of the low lying Ikom-Manfe embayment **(**Figure 2e) sandwich by the Obudu Plateau and the Oban Massif (Obiaku et al. 2017). Dominant parent materials in the region include basalt, basement complex (made up of granite, gneiss, quartzite, and schist), sandstone-shale intercalation and alluvium and the soils derived from these geological materials are predominately sandy loam with hydromorphic soils along the coastal plain (Nsor 2011). Esu (2010) earlier classified the soil types in the area as ultisols, oxisols and inceptisols. These falls within USDA soil taxonomy of Ustic, Udic and Aquic soils with isohydrothermic soil moisture regime. Common tree crops and forest trees in the zone include *Theobroma cacao, Gemilina arborea*, *Oldfiedial africana* and *Khaya sensigalensis, Miliia dederichii, Triplochytor scleroxylon, Nauclea dedirichii*, among others (Nsor 2011). Tropical forest trees in this zone are estimated to reach 36 m height; these classes of trees are mostly found in Boki, Ikom and Biase Local Government Areas while pockets of mangroves and degraded forest cover are in other parts of the zone (Nsor 2011). Most of these land elements exhibit gradual transition from one agroecological zone to the other.

In the southern agroecological zone (SAEZ), different parent materials significantly account for the varying soil types. Land units with coastal plain sands and basement complex rocks have sand texture dominating the textural complex (Afu et al. 2013**)**. In other segments of the zone (Oban Massif syncline) with limestones as prevalent parent material, clay mineral is identified as the dominant soil types. The Oban Massif is a weathered giant spur underlaid by basement complex rocks. It attains a height of 1,125 m above sea level at certain locations, and it is a continuation of western Cameroon Mountains (Ekwueme 2003).

The Oban Massif harbours most of the tropical rainforest in the SAEZ while the Cross River basin described by Murat (1972) as the Calabar Flank has mangroves and swamp forest as dominant land cover types (Effiong 2011). The grouping of the soils of SAEZ by Abua (2012) based on the USDA and UNESCO soil classification schemes described most of Akpabuyo and Bakassi as falling within Ultisols, Drystic Acrisols. Fluvisols and Luvisols groups respectively. The soils are strongly acidic with most of the pedons having Aquic soil moisture regimes. The high fluvial deposit in most part of the ecological zone may not be unconnected to its coastal and high precipitation status (Ekwueme 2003).

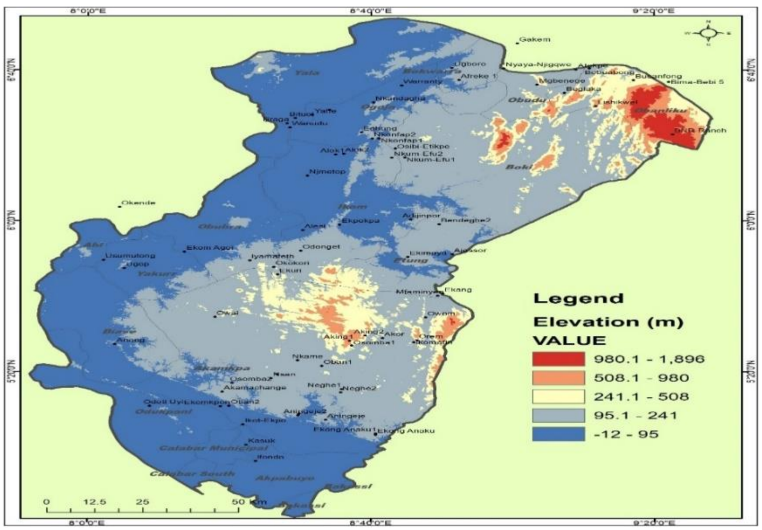


Figure 2e: Relief map of Cross River State.

Source: Culled from Ekwueme (2003)

Rainfall in the study area is bimodal with varying durations of the sessions across the three agroecological zones. The rainfall gradient is largely influence by relief and nearness to coastal environments. The SAEZ has a monsoon tropical climate which is within the tropical monsoon climate '(Am) classification scheme of Koppen. (Ayoade 2004). The climate of the zone is regulated by the southwest monsoon (SWM) and northeast trade winds (NETWs). The SWM is characterized by north bound moist air from the Atlantic Ocean (Nicholson 2013). This air mass signals commencement of the rainy season which last from February or early March to October along the coastal strip of Calabar and only breaks further inland by the Oban Massif where the high relief significantly modulates the climate patterns of adjoining environments (Olaranwaju et al. 2017). The NETW is associated with dry air originating from the norther margin of Sahara landmass. (Nicholson 2013). This air mass introduces the three to four months dry spell in the coastal city of Calabar locally called the harmattan.

An annual mean rainfall of 3500 mm is often recorded in the SAEZ where tropical rainforest and mangroves dominate. Further inland around the Oban Massif and environ, mean annual rainfall ranged from 2500-4000 mm (Jimoh et al. 2012). Analysis of station data covering 1979 to 2009 (Figure 3) showed that Calabar recorded a steady increase in rainfall (Ademola et al. 2015). Similarly, Ekpe et al. (2013) confirmed that 2011 was the wettest year as a mean annual value of 4002.80 mm of rainfall was experienced while the least rainfall of 2328.20 mm was observed in 1983. The mean annual air temperature of the area average around 27^{0} C and is relatively constant throughout the year and within the zone as annual range of monthly mean vary between 3º and 3.5º C. Humidity in the SAEZ fluctuates between 78 % and 91 % (Aigbe and Omokhua 2015).

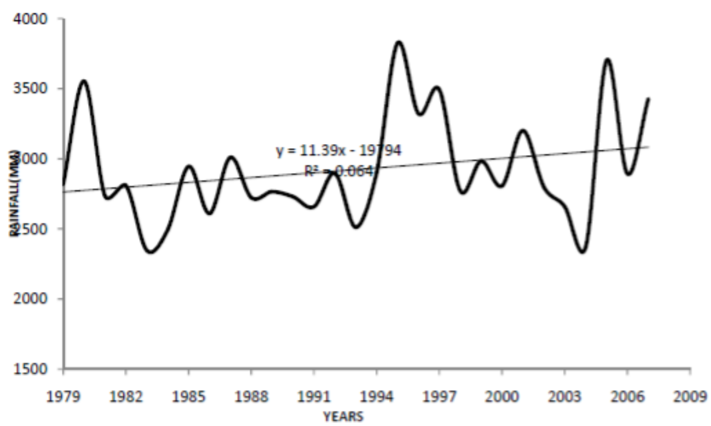


Figure 3: Rainfall trend in Calabar between 1979 and 2009 (Ademola et al. 2015)

In the CAEZ, mean annual rainfall varies from 2332 mm to 3000 mm with short harmattan months. Mean annual air temperature ranged from 26.9 ^{0}C to 30 ^{0}C and humidity of the zone in most parts of the year is about 68 % (Jimoh et al. 2012). The high and prolong durations of rainfall in the zone support the luxuriant vegetation found mostly in Boki, Ikom and Etung Local Government Areas (LGAs).

In the northern parts with savanna ecosystem around the low land area, mean annual rainfall of 123.5 mm is recorded (NIMET 2017). Mean annual air temperature ranged from

15 ^{0}C-30 ^{0}C in most parts of the year. The zone has two climate seasons; rainy season which last for about seven to eight months and the harmattan that last for about four to five months. In the montane ecoregion of Obanliku Mountains (Obudu Cattle Ranch), climatic conditions are markedly different from other parts of the region. Air temperature have mean annual values ranged of 4 ^{o}C to 10 ^{o}C. The terrain is rugged with hilly escarpments, steep valleys and mountains that peaked at about 1800 Sq. km. above sea levels with an elongation into the southwest region of Cameroons (Ekwueme 2003).

Variability of rainfall and air temperature has the potential to modify the rate of organic matter production and decomposition in the tropics. More so, it has been confirmed that increases in air temperature can lead to reduced soil moisture and subsequently emit soil carbon into the atmosphere. While extreme rainfall can lead to the formation of more peatlands and the amount of disposable methane in coastal environments. In addition, the spatial variability of soil types, its fertility status and anthropogenic activities has revealed discernible influence on the vegetation composition and structure (Eni et al. 2015). Specifically, soils fertility is known to regulate tree species height and basal area in tropical environment (Becknell and Power 2014; Rodriques et al. 2018) and the condition of soil-plant community at any point in time and location determine the degree of carbon decay and their subsequent release into the atmosphere (Akpa et al. 2016; Rodriques et al. 2018).

1.5 LITERATURE REVIEW

1.5.1 Introduction

This segment is a critical review of extant literature covering impacts of land cover change on carbon stocks, SOC, methods of biomass estimation and REDD+ project impacts on community's livelihood in tropical countries. This encompassing trajectory is to ensure an in-depth analysis of extant studies on the variables of interest in the tropics with focus on CRS of Nigeria is achieved. The unit ends with a synopsis of gaps in the literature which form the basis of the study.

1.5.2 Impacts of LULCC on carbon stocks in the tropics

Between 1850 and 2015 about 145±16 PgC is believed to have been lost from global land cover change with the highest emission of 102±5.9 PgC recorded for the tropics

(Houghton and Nassikas 2017). Deforestation trajectory in the tropics showed a release of 1.6 ± 1.0 $PgCyr^{-1}$ from tropical deforestation between 1980 and 1996 (IPCC 1996) while Achard et al. (2014) stated that in the 1990s deforestation in the region led to disappearance of 8.0 million $hayr^{-1}$ leading to the loss of 0.887 $PgCyr^{-1}$ while in the 2000s, 7.6 million $hayr^{-1}$ of forest was removed causing the emission of 0.880 $PgCyr^{-1}$ into the atmosphere. Achard et al. further revealed that from 2000 to 2007 a gross release of 0.45-1.7 $PgCyr^{-1}$ was estimated corresponding to 5-19 % of man-made CO_2 emissions recorded in the region. It is estimated that as of 2010, about 228.7 PgC is stored in tropical trees while 1.0 $PgCyr^{-1}$was lost within the said period (Baccini et al. 2017). The total carbon lost from terrestrial ecosystems so far is believed to be about 33 % of the total earth CO_2 exuded into the atmosphere (Le Quere et al. 2018). Left intact, the tropical forest has the potential to sequester about 0.55-1.49 $PgCyr^{-1}$ which is equals to 6-17 % of anthropogenic CO_2 (Van der Werf et al. 2009), as over 50 % of global carbon is in tropical forest even when it constitutes only 15 % of the total land surface (Saatchi et al. 2011).

Before now, it was held that the tropical forest was a major sink of atmospheric CO_2 (Baccini et al. 2008; Saachti et al. 2011). However, with the rate of land cover modifications in the region now, it has become a net emitter of carbon as 0.86 $PgCyr^{-1}$ were lost and 0.4365 $PgCyr^{-1}$ gained between 2003 and 2014 with 59.8, 23.8 and 16.3 % of these losses coming from America, Africa, and Asia respectively (Baccini et al. 2017). This is like Phutchard et al. (2015) earlier assertion that over 60 % of CO_2 absorbed by tropical forest is returned to the atmosphere. The exponential increase in land use/cover change occasioned by deforestation, degradation, and flora species mortality due to climate change were the main reasons adduced for the carbon emissions in tropical region in recent years (Mokri et al. 2018; Curtis et al. 2018). This also reaffirms Food and Agricultural Organization (FAO 2015) concerns that if trends of deforestation in the tropics do not abate, the tropics will lose its unique forest cover by 2035.

Many factors have been adduced for LULCC in the region. For instant, Curtis et al. (2018) identified commercial agriculture, timber logging and wildfires as the predominant factors of deforestation and forest degradation in Asia and Latin America while subsistence agriculture and fuel wood harvesting accounts for deforestation and forest degradation in Africa (Figure 4). Brinck (2017) estimated that over 0.34 $GtCyr^{-1}$ is lost from forest fragmentation in the tropics. This represents 30 % of the total releases from deforestation from the region. Brinck (2017) estimates corroborates Curtis et al. (2018) statistics that slash and burn agriculture and fuel word harvesting along forest corridor in Africa account for over 40 % of forest degradation in the tropics. Fire, according to Valentini et al. (2014) released 1.03 ± 0.22 $PgCyr^{-1}$ into the atmosphere from dry woodland and savannas ecosystems of Africa. And this fragile ecosystem is continually threatened by human activities like logging and firewood extraction (Alexandre et al. 2018). Climate patterns in this ecozone could motivate fire incidences especially in the harmattan months further increasing the rate and quantity of biomass lost and carbon monoxide emissions (Alkama and Cescatti 2016).

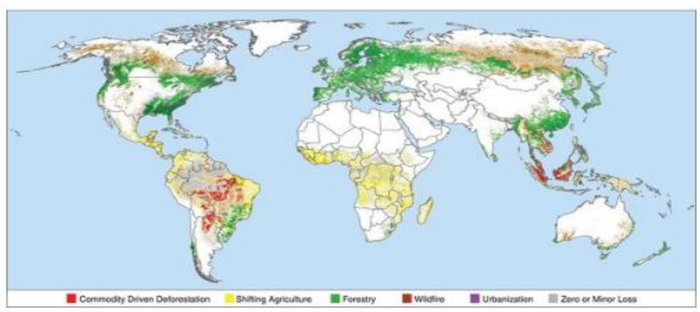


***Figure** 4: Map showing global drivers of deforestation and degradation (Curtis et al. 2018)*

In Nigeria, trends of carbon lost linked to human footprints follow similar trajectory with other tropical countries. For example, Momodu et al. (2011) estimated the total carbon stock in the different forest land cover types of Nigeria for the years 1990 and 1995 and it was revealed that total carbon stock of the country in 1990 was 2.84 TgC and 2.55 TgC in 2000. The difference in the carbon stocks was attributed to urbanization and agricultural expansion. On a regional bases within Nigeria, Abdulahi et al. (2014) estimated the carbon stock of Kpashimi Forest Reserve using field derived allometric equations and satellite images (TM, ETM+ and SPOT) of 1987, 1994, 2001 and 2007. It was reported that 240.2 $TgC/ha^{-1}$was lost between 1987 and 2007 because of forest land conversion. Also, Makinde et al. (2017) estimated the quantity of carbon sequestered in the Oluwo Forest of Nigeria using 760 forest inventory plots. The result showed that about 97.8 TgC was believed to have been sequestered. In CRS, Idiege et al. (2013) used high and medium resolution data supplemented with field inventory to estimate the carbon stock in *Gmelinaaborea* plantation. Olajide (2014) compared the biomass potentials of two plantation trees (*Pirius carribae* and *Nauclea diderrichii)* in southern part of CRS.

Rapid urbanization in the city of Calabar is affecting the vegetation status of the area. In a study by Ewu et al. (2018) in Calabar metropolis, it was observed that between 2002 and 2016, land use gained, sparse vegetation increased while bare land and dense vegetation reduced respectively. The high rate of urban growth and constant loss of bare land points to the fact that, with the continued surge in human numbers, more dense forest will be destroyed to pave way for urban sprawl. This invariably mean the carbon sequestration potentials of the zone will be drastically reduced. This is a common phenomenon in all the development centres in the region (Ewu et al. 2018). The results from these studies showed that biomass carbon stocks in plantations also are decreasing because of fuel wood extraction. Primary forest in the region has continued to be converted or destroyed as urbanization, and other managed landscapes gained in geographical extent across the state.

1.5.3 Impacts of land cover change on Soil Organic Carbon in the tropics

Analysis of global carbon pools shows that soils is a major sink of carbon as globally it holds three times the quantity found in the atmosphere, and four times larger than total living tree biomass stock (Pan et al. 2011). The quantity of terrestrial SOC is on the decline as historical analysis indicates that anthropogenic landscape alteration and prevailing climatic factors like rainfall and temperature are the main drivers in the reduction (Deng et al. 2016). The FAO (2016) reported global loss of 66 billion tonnes of soils of organic carbon from different land cover types since 1860. In Africa, Henry et al. (2009) posited that the total SOC of Africa varied from 133420 to 184116 Tg within soil depths of 0-100cm which is about 68 % of the terrestrial stock of the continent. The highest value of 8.20 Kg m^{-2} was found in DRC with mean values of 3.94 Kg m^{-2} for Nigeria. However, in East Africa, Vagen and Leigh (2013) studied the SOC content of four districts using field and geospatial techniques for data collection and analysis. Vagen and Leigh further reported that the derived model showed a linear relationship exist between SOC and depth as it had an 'R' of 0.90 in all the sampled profile. It is imperative to note that land cover change degrades SOC in the region.

In the eastern part of Africa, Sainepo et al. (2016) investigated land use change effects on SOC and nitrogen in Olesharo catchment of Kenya using 196 composite soil samples and satellite imageries. It was observed that the highest average values of SOC were found in shrublands (22.26 g kg^{-1}). Grass lands and bare lands registered average SOC values of 10.99 g kg^{-1} and 7.56 g kg^{-1} respectively while the least mean values of SOC was in croplands. The change of land cover from forest ecosystem to an agricultural ecosystem accelerates the rate of SOC lost in the region. The rate of conversion of primary forest to agricultural ecosystems in the region is high because of the proportion of the population that practice crop cultivation (Lambi and Geist 2017).

In the western flank of Africa, Adu-Bredu et al. (2010) analysed sampled soils in different land cover types in a district of Ghana and it was shown that higher values of SOC were found in moist ever green natural forest and Teak plantation compared to cultivated fields studied with mean values of 52.02 Mg C/ha^{-1}, 48.82 Mg C/ha^{-1}, and 40. 82 Mg C/ha^{-1} respectively. While Agboadoh, (2011) analysed 78 soil samples collected at depths of 0-15 and 15-30 cm in Bechnem, a forest district of Ghana. It was reported that over 50 % of the total SOC was found in the upper layers of the soils. More so, Bessah et al. (2015) estimated SOC in 34 sampled plots of different land cover types in Kintampo north of Ghana. The result showed that SOC decreased with depth consistently across the study area with mean values ranging from 12 t/ha^{-1} to 33 t/ha^{-1}.

In Nigeria, the diversity in climate, vegetation and land use intensity is also reflected in the quantity of SOC distribution. The northern part of Nigeria characterized with sparse vegetation and scanty rainfall, exposes the soils to the vagaries of climate, hence the low SOC in the region while the southern part rich in tropical, mangrove and montane forest ecosystems is endowed with rich SOC. For instance, Akpa et al. (2016) relied on Legacy soil data to estimate the regional carbon potentials of Nigeria using random forest to derive the mean values. It was observed that average SOC in the country varied from 4.2 to 23.7 g kg-

[1] at 0-30 cm soil depth. It was further reported that the southern region had more CO_2 sequestration potentials than the northern region. On sub-regional basis of SOC estimation in Nigeria, in the south-eastern part, Anikwe et al. (2010) quantified carbon stored in soils under different management regimes using field samples and laboratory analysis. The result indicated that natural forest areas stored about 3.07 % of the total carbon in the area while the least carbon was found in landscapes under intensive cultivation.

Soil organic carbon content varies across land cover types. For instant, in western Nigeria, Makinde et al. (2017) recently used non-destructive and geospatial methods to quantify the total carbon contained in soils of Oluwa forest of western Nigeria and their CO_2 sequestration potentials. It was observed that 46.7 % of total carbon of the forest was contained in artificial forest (*T. grandis*) while the natural forest possessed a paltry 6.7 % carbon of the area. Land cover change alters the chemical composition of the soil, a change from primary to secondary forest reduces the quality of the soils although cover type change is not the only factor as climatic variables of rainfall and temperature can exact or accelerate the rate of soil chemical changes in the tropics. The productivity of the soil is paramount to developing nations whose citizens livelihood is bound to nature. However, measurement of soil parameters and other ecological climate variables in Nigeria rely mostly on traditional methods field inventory.

1.5.4. Methods of forest carbon estimation

In the inventory of tree parameters for carbon estimation, the different methods often used include direct field measurements through allometric equations, remote sensing techniques and modelling (Bhattarai et al. 2012). Direct field estimation of carbon has two genres: destructive and non-destructive inventory method. The destructive technique is an in-situ process involving the destruction of canopy cover and subsequent burning of the biomass and weighing of the carbon residues while the non-destructive method of in-situ measurement relies on allometric models (Rodriques et al. 2017). In the non-destructive method, trees biophysical characteristics like height, diameter at breast height, etc. are measured and used to estimate forest carbon from allometric equations (Chave et al. 2014). However, some of the developed allometric equations are limited to site and species (Navar et al. 2009) but few mixed species allometric models are available (Brown 1997; Chave et al. 2014) and are extensively used to estimate carbon in the tropics. These two approaches are seen to be most reliable, but there are constrained by many limitations such as high cost, time consuming, rigorous, limited in coverage as total census of biomass is probably impossible and above all destroys the ecosystem hence defeating the essence of carbon protection (De Gier 2003). These challenges prompted the use of remote sensing technology for the estimation of forest biomass. Spaceborne remote sensors have either coarse, medium, or high spatial resolutions which provides spatial data required for accurate biomass estimation, mapping, and monitoring (Rodriques et al. 2017).

Optical remote sensors rely on the incident sun rays to measure tree features which are sensitive to the foliage part of trees (Chen et al. 2018). The incident rays not absorbed or scattered by cloud and other atmospheric dynamics is transmitted or reflected by vegetation is captured by the sensor. The chlorophyll in trees foliage causes strong reflection within the visible and infrared segments of the electromagnetic range while it absorbs energy in the red and blue line of the spectrum (Rodriques et al. 2017). The reflected spectral signatures are extracted and transformed into numbers and subsequently correlated with field estimate to predict biomass. The techniques used to extract variables for biomass estimation include vegetation indices, image transformation (e.g. principal component analysis, tasselled cap transform and minimum noise fraction transform), texture measures and spectral mixture analysis (Lu 2006). Optical sensors platforms such as Landsat, SPOT, World View, Quick Bird, MODIS, Sentinel-2 and IKONOS have been extensively used in biomass estimation however, their usage in tropical biomass estimation is challenged majorly by cloud encumbrances and biomass saturation (Hansen and Loveland 2012).

Radar systems such as Terra-SAR, ALO PALSAR, synthetic Aperture Radar (SAR) among others generate land surface data from different frequency bands, polarizations, and imaging geometry (Chen et al. 2018). These earth observation platforms have gained prominence because of their ability to penetrate tree canopy to certain extent, sensitivity to moisture content of vegetation and non-reliance on weather as opposed to optical sensors (Tanase et al. 2014). Radar RS functions within 1mm-1m wavelength of the electromagnetic spectrum and the backscatter signal quality is regulated by the sensor's wavelength (X, C, L and P bands), polarization (vertical transmit-vertical received, horizontal-transmit horizontal received, horizontal transmit vertical received and vertical transmit, horizontal received), incidence angle, land cover and terrain characteristics like roughness and dielectric constant (Lu 2006). However, past studies revealed that longer wavelength L-band and P-band have higher canopy penetration capacity hence provides higher biomass accuracy in complex tree structure against short wavelength C-band and X-bands (e.g., Lu 2006; Antonarakis et al. 2011). The fundamental strengths of SAR sensors are in its wall-to-wall data collection capabilities (Su et al. 2016), although it cannot differentiate vegetation types and can be influence by environmental factors (wind speed, moisture, and temperature) which affects biomass estimation accuracy (Lu et al. 2006). These lapses are reduced when polarization and interferometry (Pol-inSAR) metrics are integrated for biomass estimation (Garistier et al. 2009).

LiDAR is an active remote sensing scheme fitted with laser scanner to collect 3 dimensional features of trees day or night (Chen et al. 2018). The laser sensor mounted on an airborne or spaceborne platform send out signals to the ground where tree canopies, trunks, stems, leaves, branches, and understory vegetation reflects some beams while some beam reaches the ground and return the signal back to the sensor. The 3-dimensional features of the target trees are measured by the returned laser signals, the direction of the beam, and the position and height of the sensor which is observed by the global navigation satellite system (GNSS) and IMU (Garistier et al. 2009). The ability to measure these variables is influenced by the pattern of scanning, the size of the footprint and on whether the laser is fitted with waveform or discrete return signal mechanisms (Lu et al. 2006). It has a high accuracy of estimating vertical tree features, penetrate thick and rugged terrains, provide detailed elevation measurements like ground observations.

However, cost, and logistical challenges limits LiDAR's application in ecological analysis (Gosh and Behera 2018) especially by African scholars (Rodriqus et al. 2017). More so, it has been revealed that LiDAR data underestimate understory tree height in tropical forest (Guo et al. 2014; Chen et al. 2018 and Wilkes et al. 2018). These shortcomings affect the accurate estimation of biomass in tropical countries. Extant studies have shown that the integration of field-based biomass with multi-sensors using either statistical regression models or machine learning algorithms (MLAs) enhances biomass estimation accuracy (e.g., Baccini et al. 2008; Saatchi et al. 2011; McRobert et al. 2013) and the use of this approach to generate spatial explicit estimate carbon stocks has gained popularity (Chen et al. 2018).

However, MLAs are preferred to parametric statistics in estimating forest parameters because forest features are complex and parametric assumptions of normality, linearity, and independence of distribution of sampled population do not apply, hence statistical analysis may not yield persuasive results (Chen et al. 2018). Machine learning algorithms like artificial neural network (ANN), random forest (RF), K-nearest neighbourhood (kNN), Support Vector Machine (SVM) among others are often used to either predict, classify, or extrapolate forest biomass (Baccini et al., 2017; Gautam and Mandal 2017; Chen et al. 2018). ANN and SVM are known to require more processing time, have low capacity to eliminate noise and could overfit sample variables while RF is known to possess the quality of smoothing out noise, block out overfit variables, and has a low correlation among decision trees and it eliminate less important variables during analysis (Karlson et al. 2015).

RF is an ensemble of machine learning techniques used primarily for classification and regression tree (CART) that works by creating variety of decisions trees from training data sets otherwise called bootstrap samples with replacement (Chen et al., 2018). According to Briedman (2001), the thrust of RF is the merging of single trees to create groups of trees, as its accuracy is enhanced when merged. In the RF model, three elements must be parameterized and defined: ntree, which is the number of regression trees developed based on the input from bootstrap sample observation, mtry, the number of predictors tried at each node and node size; minimal size of the terminal nodes of the trees (Briedman 2001). This process in combination with model performance test algorithm will lead to the extraction of variables of importance and perform other functions like graphical representation of output, clustering data with similar features, listing of missing values and scaling of many data plane (Cutler et al. 2007). These qualities accounts for the increased application of RF algorithm with remotely sensed time series data of land cover features as predictors in ecological analysis (Chen et al. 2018).

In this study, spatial background layers of the CRS region from Sentinel-2 and topography from Shuttle Radar Topographic Mission from the USGS Earth Explorer and selected reanalysis climatic variables were integrated into the decision tree of RF as predictor variables for biomass estimation and integrated with reference AGB and SOC from field plots for spatial extrapolation for the entire CRS region. The combination of these data type has been confirmed to boost biomass accuracy in the tropics (Chen et al. 2018).

1.5.5 Impacts of forest carbon storage project (REDD+) on community's livelihood in tropical countries

Forests and its associated resources are part and parcel of the life of over 25 % of world population (FAO 2016). This natural capital forms their principal income sources, food, fodder, building materials, medicine, energy, their way of life, sense of pride and a wide variety of environmental services (Angelsen et al. 2014). Angelsen et al. (2014) surveyed 7973 households in 24 countries of the tropics on the role of environmental services in rural livelihoods and it was reported that 78 % of the sampled households' main income was derived from ecosystem services, such as harvesting of nontimber forest products, fibres, fuel, among others. However, unsustainable land use practices are threatening the health of the terrestrial ecosystems. In CRS, some of these practices includes massive logging, slash and burn agriculture, trans-humane movement, unplan urbanization among others (Mfon et al. 2014).

The need to ensure the design and implementation of any carbon project in forest dependent communities (FDCs) must take cognizance of the intricacies of forest-rural development nexus as a path to successful implementation. Asquith et al. (2002), Smith and Scherr (2006) and Awoniyi and Amos (2016) highlighted these when it was submitted that the success of any forest carbon project hinges on its ability and readiness to incorporate all stakeholders from design to implementation. The institutionalization of land and forest resources use rights, recognizing traditional value systems and compensation packages in the case of loss of rights or any other infringements will enhance sustainable land use practices and forestry with guarantied high returns on investments in terms of carbon sequestration, carbon conservation and carbon substitution visa vice livelihoods protection (Mucahid et al. (2016).

The management of land cover to boost the amount of CO_2 that can be sequestered is vital to meeting the needs of the society. Daniel (2005) noted that carbon sequestration projects often achieve its expected goals of conservation when the livelihoods of the communities are assured and protected. Communities' full participation in carbon projects instil a sense of ownership and this can likely deliver twin benefits; protection of biodiversity and the sustainability of livelihood portfolios of FDCs (Bond et al. 2011). This becomes a win-win situation as anthropogenic contributions to climate change are mitigated and rural development sustained (Agrawal 2009). Dyer and Nijnik (2014) argued that carbon sequestration projects can encourage communities whose livelihood is dependent on nature through agricultural intensification rather than frontal mentality. The intensification of agriculture will mean precision cultivation upon soil quality analysis which can be achieve using indigenous knowledge systems (Amuyou and Kelly 2015). Newbold et al. (2015) gave credence to this assertion when it was averred that a healthy forest visa vice forest carbon delivers both non-forest benefits streams to rural forest dependent communities.

However, Mucahid et al. (2016) observed that three problems common with REDD+ projects implementation are leakage, permanence, and additionality if not properly managed. In leakage, it was noted that the rural poor relocated forest degradation activities to areas not covered by REDD+, this explains why a national REDD+ project is important. In permanence, the protection of forest carbon cannot rule out possible future destruction by natural or anthropogenic events and additionality entails there is a possibility of CO_2 emissions receding without payments. However, experiences in Cross River State shows that the defined land use rights in the readiness mechanism (Readiness Plan Idea Note-RPIN) are not implemented as government halted all forms of forest resources exploitation (Mfon et al. 2014). When forest use and access rights are not implemented, the reverse objective of climate change mitigation becomes the unexpected outcome (Awoniyi and

Amos 2016). Again, worrisome is the concern that it is likely forest dependent communities were not involved in designing RPIN but only during implementation and this is likely to affect the follow up protocol (Mucahid et al. 2016). Mucahid et al. further observed that deforestation and forest degradation especially the later will continue, hence, reducing the forest ability to sequester carbon and on the long run climate change will have its toll on the ecosystem and FDCs. These mediating factors of forest carbon protection and livelihood sustainability need to be fully examined. In view of this the study shall knit together the issues of forest carbon protection and rural livelihood benefits as expected from REDD+ project in rural CRS Nigeria.

1.5.6 Gap in literature

Different carbon maps have been produced for tropical region, which is attributable to the use of different methods, the lack of calibration field plots in most parts of Africa especially in Nigeria, the focus on forested landscapes neglecting regrowth and degraded areas, plantations, savannas, montane forest and missed forest use areas. More so, extant estimates of SOC in the region by Akpa et al. (2016) relied on legacy soil data without field plots on ground to estimate SOC. To the best of our knowledge, no study has integrated extensive field data with high resolution sentinel-2 derived data to quantify regional carbon stocks in the CRS using empirical modelling of RF.

The reviewed literature also revealed that carbon quantification will aid in monitoring and policy formulation on LULCC and climate fluxes, but it ignored the benefits of its estimation to forest dependent communities (FDCs) in CRS. It is on record (Bisong et al. 2009; Mfon et al. 2014; Awoniyi and Amos 2016) that about 85 % of the population of the region depend on land resources for their livelihoods, hence overlooking the effects of carbon projects on these set of people may yield unexpected outcomes. It is therefore pertinent that accurate estimation of carbon stocks be carried out to attract the required value for its protection by FDCs in CRS.

1.5.7: Contribution of this study to knowledge

Extant local and regional studies on above-ground biomass estimation over Nigeria did not use local forest inventory plots in model calibration while studies that used local points data were restricted to forest lands only (Baccini et al. 2008; Saatchi et al. 2011; Djomo et al. 2016; Avitabile et al. 2016). Specifically, regional studies over Nigeria relied on reference points from the Republic of Congo, Uganda, Ghana, Cameroon etc. in model calibration and the results were extrapolated to Nigeria despite the differences in vegetation disturbance history, plant functional types, soils, and climate which affect biomass density (Djomo et al. 2016). This approach falls short of the IPCC biomass estimation guide (IPCC 2007b) where its encouraged Tier three level (which is country or subnational) biomass estimation. However, in this study, local reference plots were used in model calibration and validation and subsequently produce sub-regional AGB map with better accuracy unlike other regional studies without or inadequate reference points established in the Cross River State.

More so, the relationship between SOC and sentinel-2 derived vegetation indices and selected soil forming factors based on random forest regression model within the framework of REDD+ has not been carried out in the CRS of Nigeria. Available SOC literature over the study area either relied on legacy data, use inadequate point data, established biased field sample locations, used course spatial resolution imageries, relied only on conventional survey methods, or presented fragmented soil information (Akpah et al. 2016; Hengl et al. 2017; 2021). In fact, the UNREDD+ Nigeria project (2018) did not present any information on SOC because of the lack of data and cost involved in collecting such data (see Page 11 in FREL report). To effectively account and manage SOC of the study area, we used a robust models like random forest regression in estimating and presenting spatially explicit and continuous map of the total soil organic carbon of the state at 20 m resolution. A finer resolution SOC map than the existing maps over the CRS.

The study also analysed extent of forest dependent communities' participation in REDD+ implementation and the benefits of forest carbon protection. The results indicate that FDC engagement was low, but forest protection increased the income status of the people. Despite the improvement in family income from forest related resources, the study encouraged putting FDCs in the drivers' seat in subsequent carbon projects in the area. The holistic participation of the people will create sense of ownership and serves as motivation for programme sustainability. Overall, the AGB and SOC maps of this study will aid in the monitoring, verification and reporting of biomass stocks status in the study area, and the FDCs will take full advantages of the ensuing benefits.

1.5.8 Overview and structure of the thesis

The thesis is subdivided into five chapters. Chapter one focused on the introduction and literature review. This chapter provides a detail background information about what the research is about, presenting existing views on the topic under investigation from other areas and outlining the focus of the study. Chapter two and three are the natural science sections. They cover aboveground carbon quantification and soil organic carbon in ecological zones of CRS Nigeria. Here, each chapter starts with an abstract, followed by introduction interwoven with theoretical background, methods unique to each chapter, results, and discussion. Chapter four is the social science chapter that captures the livelihood benefits of carbon measurements with focus on REDD+ project. Chapter five of the thesis provides the conclusion of study. Here the key findings of the research are presented in a concise way. And the chapter ends with suggestion of themes that need further research and recommendations.

CHAPTER TWO

QUANTIFICATION OF ABOVE-GROUND BIOMASS OVER THE CROSS-RIVER STATE, NIGERIA USING SENTINEL 2 DATA.

This chapter is based on:

Amuyou, U.A.; Wang, Y.; Ebuta, B.F.; Iheaturu, C.J.; Antonarakis, A.S. Quantification of Above-Ground Biomass over the Cross-River State, Nigeria, Using Sentinel-2 Data. Remote Sens. 2022, 14, 5741. https://doi.org/10.3390/ rs14225741

Abstract: *Higher-resolution wall-to-wall carbon monitoring in tropical Africa across a range of woodland types is necessary in reducing uncertainty in the global carbon budget and improving accounting for REDD+. This study uses Sentinel-2 multispectral imagery combined with climatic and edaphic variables to estimate the regional distribution of above-ground biomass (AGB) for the year 2020 over the CRS, a tropical forest region in Nigeria, using the Random Forest (RF) machine learning. Forest Inventory plots were collected over the whole state for training and testing of the RF algorithm, and spread over undisturbed and disturbed tropical forests, and woodlands in croplands and plantations. The maximum plot AGB was estimated to be 588 t/ha with an average of 121.98 t/ha across the entire CRS. The AGB was estimated using Random Forest and yielded an* R^2 *of 0.88, RMSE of 40.9 t/ha, a relRMSE of 30 %, bias of +7.5 t/ha and a total woody AGB of 0.246 Pg for CRS. These results compare favourably to previous tropical AGB products; with total AGB of 0.290, 0.253, 0.330 and 0.124 Pg, relRMSE of 49.69, 57.09, 24.06 56.24 % and -41, -48, -17 t/ha bias over the CRS for the Saatchi, Baccini, Avitabile and ESA CCI maps respectively. These are all compared to the current REDD+ estimate of total AGB over the Cross River State of 0.268 Pg. This study shows that obtaining independent reference plot datasets, from a variety of woodland cover types, can reduce uncertainties in local to regional AGB estimation compared with those products which have limited tropical African and Nigerian woodland reference plots. Though REDD+ biomass in the region is relatively larger than the estimates of this study, REDD+ provided only regional biomass rather than pixel-based biomass and used estimated tree height rather than the actual tree height measurement in the field. These may cast doubt on the accuracy of the estimated biomass by REDD+. These give the biomass map of this current study a comparative advantage over others. The 20 m wall-to-wall biomass map of this study could be used as a baseline for REDD+ Monitoring, Evaluation and Reporting for equitable distribution of payment for carbon protection benefits and its management.*

1.1 Introduction

Tropical forests encompassing less than a fifth of the Earth's terrestrial area (Dinestern et al. 2017) are one of the most important components of global terrestrial ecosystems, accounting for around 55 % of total above-ground biomass (Baccini et al. 2017; Lin et al. 2018; Philipson et al. 2020), holds two-thirds of global biodiversity (Moon et al. 2018; Sullivan et al. 2020), sustain the economy of millions of rural populations and contribute to climate regulation (Markey et al. 2021). However, a recent analysis revealed that the tropics are now a net carbon source rather than a carbon sink, attributed mainly to anthropogenic land cover changes (Siyum et al. 2000; Le Quere et al. 2018; Friedlingstein et al. 2020). In addition, changes in climate patterns and variability will also begin to have a serious impact on tropical forested landscapes of Africa (Lewis et al. 2009).

African land cover encompasses diverse types of woody and forested landscapes as well as a patchwork of undisturbed and disturbed forests, and wood species present within heterogeneous farmed lands (Burges et al. 2004). These diverse land cover types have varied aboveground biomass (AGB) density even within a landcover type (Bouvita et al. 2018). For instance, Saugier et al. (2001), Keelling et al. (2007), IPCC (2007a), Gibbs et al. (2007), estimated mean AGB of 390 Mg/ha, 190 Mg/ha, 400 Mg/ha and 198 Mg/ha respectively in African intact forests. Bouveta et al. (2018) summed the varied estimates of AGB in Africa and concluded that the regions savanna and woodlands contained 52 % of the total AGB while intact forests contained 48 % of AGB. One of the reasons for this variation is that tropical forests do not have a universally agreed definition, and in Africa, there are a variety of tropical landscapes from wooded savannas, to humid tropical, to closed tropical and dry tropical forests (Chave et al. 2019). In effect, nearly 75 % of Africa's forests are considered woodland savannas and dryland forests (Brandt et al. 2018), with carbon storage in African tropical forests only accounting for around 48 % of the total (Ter Steege et al. 2015). Another reason is the paucity of forest inventory plots available in Africa to estimate AGB and calibrate/validate remote sensing derived biomass products (Solomon et al. 2017), compared to other tropical regions.

Different tropical-wide AGB maps have been produced in the last decade using a combination of satellite data and ground-based plots. Saatchi et al. (Saatchi et al. 2011) first produced a biomass map using satellite LiDAR and MODIS data and a machine learning spatial extrapolation method at a fine resolution of 1 km. They used 75 calibration forest inventory plots over Africa, producing a total AGB estimate of 124 Pg with an uncertainty of ±32 %. Baccini et al. (2008), also used satellite LiDAR and MODIS data within the RF framework to predict AGB over the tropics at a 500 m resolution. They calibrated their product using 283 plots throughout the tropics, producing a total Africa AGB estimate of 129 Pg and an average RMSE of 38 t/ha. In a more recent study, Avitabile et al. (2016), fused the Saatchi and Baccini products at 1 km, producing AGB over Africa of 96 Pg with an RMSE of 83.7 t/ha (a reported improvement of around RMSE 20-30 t/ha compared to the Saatchi and Baccini products). Furthermore, they used 953 reference points over Africa out of over 14000 in the tropics. Therefore, Saatchi et al. (2011), Baccini et al. (2008) and Avitabile et al. (2016) studies produced their products with limited calibration and validation plots in Africa. Similarly, Santoro and Cartus (2021) henceforth referred to as European Space Agency Climate Change Initiative (ESA CCI) Biomass project estimated total tropical AGB to be 331.3 Pg and Africa having AGB stocks of 84.4 Pg. These varied estimates over the same region from different authors derived from various remote sensing instruments and protocols with little variation in the years of biomass estimation contributes to the high AGB uncertainty and lack of effective carbon stock tracking and management.

Article 2.1 of the Kyoto Protocol highlighted the need for individual countries to reduce GHGs to 'a level that would prevent dangerous anthropogenic interference with the climate system' (UNFCCC 1998; FAO 2015). The articulation of the Kyoto protocol was the seed that led to the formation of REDD (Agrawal et al. 2011). REDD, created by the UNFCCC Conference of Parties, encourages countries to contribute to climate change mitigation through reducing emissions from deforestation and forest degradation, and increasing the removal of greenhouse gases ({GHGs} through sustainable management of forests and the conservation and enhancement of forest carbon stocks. To attain this goal, developed countries were encouraged to focus on fossil fuel related emissions while tropical developing economies were commissioned to concentrate on LULCCs linked emissions especially from the forestry sector (Borrili et al. 2013; Bojinski et al. 2014). More so, tropical country AGB quantification supports the monitoring of biodiversity status (Nuru et al. 2018), protects carbon pools (Adam et al. 2010), and increases social and environmental ecosystem services to forest communities who largely depend on natural resources for daily subsistence (Larson 2011).

In addition, studies determining above-ground biomass density in Nigeria, and specifically tropical Nigeria, have not used local forest inventory plots to calibrate biomass estimation (Baccini et al. 2008; Saatchi et al. 2011; Djomo et al. 2016; Avitabile et al. 2016). In these studies, reference points from the Republic of Congo, Uganda, Ghana, Cameroon etc. were used for model calibration and results were extrapolated to Nigeria without any point dataset collected from there despite the differences in vegetation disturbance history, plant functional types, soils, and climate which affect biomass density (Djomo et al. 2016). In addition, the IPCC biomass estimation guide (IPCC 2007b) advised that for better biomass estimation accuracy, Tier three level (which is country or subnational) estimation of biomass should be encouraged. These sub country regional biomass estimation can then be agglomerated to get national biomass density and spatial variations for effective verification, reporting, monitoring, (MRV) and subsequent payments of subventions under the REDD+ initiative.

CRS has more than 50 % of Nigeria's remaining tropical intact forest and is one of the 25 biodiversity hotspots of the world (Carbon Brief 2020). However, the ecological integrity of the region is under threat from anthropogenic destruction (Enough and Bisong 2015). In 2020, GFW (2020), revealed the state lost 12.7 Kha of its tree cover. The rate of land cover change (at 3.7 %) in Nigeria per year remains among the highest in the world (Carbon Brief 2020). The destruction of tracks of forest cover leads to biomass loss, but REDD+ in 2018 (UN-REDD+ Nigeria 2018) estimated 0.267 Pg of above ground biomass in the state. The REDD+ project in CRS did not carry out wall-to-wall AGB estimation and the field campaign was restricted to tropical forested zones. Other land cover types like disturbed forests, mixed agroforest areas and savanna landscapes were left out of the UN-REDD+

Nigeria study (UNREDD-Nigeria 2018). Tree heights were not measured in the field but were derived using the Feldspausch et al. (2011) height-diameter tropical forest allometry.

In these contexts, the aim of the study is to derive high spatial resolution (20 m) above-ground biomass for the whole of the CRS, Nigeria using Sentinel-2 data, climatic and edaphic variables, and with local reference forest inventory plots taken from undisturbed, disturbed, and cropland areas. We use Sentinel-2 data and forest inventory plots collected concurrently in 2020 to produce a regional AGB map. Specifically, the study planned to 1) Establish a network of forest inventory plots in a variety of forest and woodland landscapes for AGB estimation and 2) use Sentinel-2, climate, and soil variables to predict and spatially extrapolate AGB to the CRS using RF machine learning, and 3) Compare the AGB map of this study with well-known products from Baccini, Saatchi, Avitabile, and ESA CCI as well as comparing to the REDD+ AGB estimates published over the CRS.

2. Materials and Methods

2.1. Study Area

The study area is the CRS in southeast Nigeria, with an area of 20,156 km^2 (Figure 5). The area covers an elevation range from 1800 m (5, 936 ft) in the extreme north to 103 m above sea level in the southern part of the State (UN-REDD+ Nigeria 2018). It shares boundaries with Benue State in the north, Akwa Ibom, Ebonyi and Abia States in the west and the Atlantic Ocean in the south. CRS has five different vegetation types; mangrove, swamp, and tropical rain forest which dominates the southern and central parts of the region, montane vegetation and savanna woodlands are dominant in the northern portion of the study area (Enoug and Bisong 2015). It is recognized as one of the biological hotspots in the world (USAIDs 2006) and two locations - Oban and Okwangwo - are marked out as conservation spots. The Oban Division (OD) covers an area of 2800 km^2 with 1568 identified plant species while the Okwangwo Division (OkD) has a land area of 800 km^2 with 1545 plant species located in the area (Larson 1997). Analysis of the extent of land cover types in the region show mangroves occupy 480 km^2, swamps 520 km^2, tropical rainforest 7,290 km^2, plantations 460 km^2, other forests 216 km^2 and other land uses 12,300 km^2 (Fon et al. 2014).

Rainfall in the CRS is bimodal with varying durations of sessions across the three agroecological zones (AEZs). The rainfall gradient is largely influenced by relief and nearness to the coastal environment. The southern AEZ has a monsoon tropical climate with an annual mean rainfall of 3500 mm which sometimes peaked at 4000 mm around the Oban Massif (Jimoh et al. 2012). The climate of the region is within the Tropical Monsoon (Am) classification scheme of Koppen (Ayoade 2004). The mean annual air temperature of the zone averages around 27 ^{0}C with little variation throughout the year, and with humidity between 78 % and 91 % (Aigbe and Omokhua 2015). In the central AEZ, the mean annual rainfall varies from 2300 mm to 3000 mm. The zone records mean annual air temperature ranging from 26.9 ^{0}C to 30 ^{0}C and the humidity of the zone in most parts of the year is about 68 % (Jimoh et al. 2012). In the northern AEZ, the savanna ecosystem is common with a mean annual rainfall of 1120 mm and air temperature ranging from 15 to 30 ^{0}C (NIMET 2017). The zone has two climate seasons; rainy season which lasts for about eight months and the harmattan which lasts for about four months. In the montane ecoregion of Obanliku Mountains within the northern AEZ, climatic conditions are markedly different from other parts of the region. Air temperature have a mean annual range of 4 ^{o}C to 10 ^{o}C. The terrain is rugged with hilly escarpments, steep valleys and mountains that peaked at about 1800 km^2 above sea levels with an elongation into the southwest region of Cameroons (Jimoh et al. 2012).

2.2. Forest Inventory Survey

A land cover map (Figure 5) developed by the Cross River State Forestry Commission (CRSFC 2019) was used in establishing the plots for tree parameters inventory. The study area was classified into; Undisturbed Forest (UF), Disturbed Forest (DF) and croplands based on the Cross River State Forestry Commission staff guide and with modification of Gautam and Mandal (2016) delineation. The undisturbed land cover considered in this study were unbroken stretches of land covered with diverse tree species with little or no human interference in the ecological structure while those with evidence of anthropogenic activities like tree stumps and patches of logging, roads, pronounced footpaths, banana and cocoa farmland patches, farm hots, and any gap in the forest land were attributed to human activities (UN-REDD+ Nigeria 2015). It is pertinent to note that the disturbed and undisturbed forests are either under the management regime of the Cross River National Park, State Government Reserves or Community Forest (Enoug and Bisong 2015). On the other hand, croplands or agroforestry areas are woodlands with different species of crops cultivated in them at the same time.

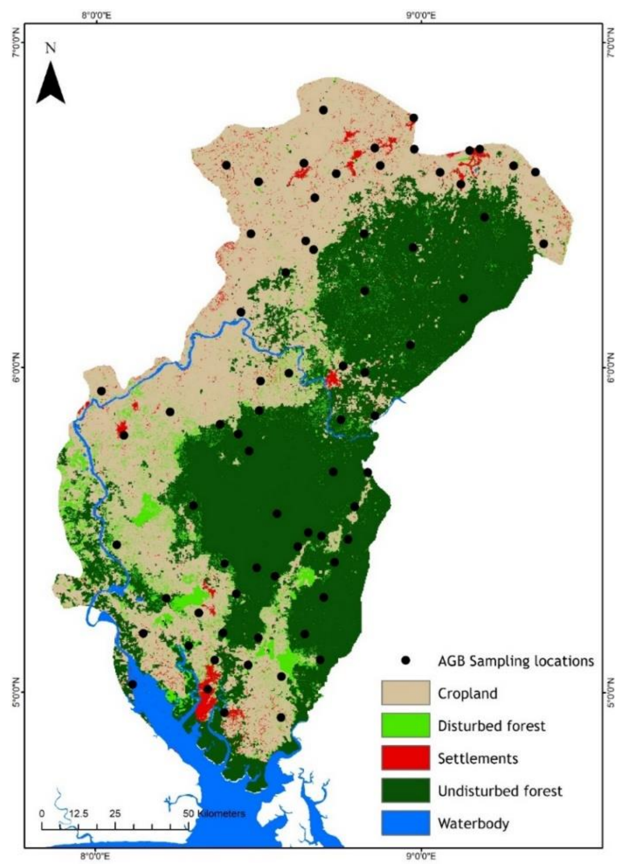


Figure 5. Forest inventory plots throughout the Cross River State were established with Forestry Commission guidance following their land cover classification (Cross River State Forestry Commission Forestry Manual 2019).

The GPS points of purposively chosen locations were overlaid on a map of the CRS across the landcover types identified for this study. Thereafter, GPS coordinates of each chosen sample point were inserted into the GPS Garmin eTrex model (with accuracy of 3 meters), and on the ground, the Goto function was used to locate the plot for the inventory.

In all sample locations, entry point was through a known community (UN-REDD+ Nigeria 2018). Accordingly, 29 plots were established in undisturbed landcover, 18 in disturbed land cover and 25 were established in croplands. It should be noted that chosen plots that were difficult to assess on account of geomorphic features like river, flooded streams, steep slopes, or security challenges like intercommunity or interstate clashes, resulted in other alternative locations being chosen.

The field campaign commenced in March 2020 and ended in November of the same year. In this study, 72 nested square plots of 20 m X 20 m were established. Trees of sizes >50 cm, 20 cm-50 cm and <20 cm diameter at breast height (1.3 m) were inventoried in the 20 m X 20 m plots and subplots of 15 m X 15 m and 7 m X 7 m respectively (UN-REDD+ Nigeria 2015). In each of the 72 plots, all tree species were identified, numbered and DBH measured using a measuring tape and the total height was taken with Trupulse Criterion RD 1000. Given that the wood density of tropical trees species is erratic (Wieman and William 2013), the study extracted wood density of each tree species identified from the African Wood density Database provided by the World Agro-forestry Centre (Carson et al. 2012; Chave et al. 2014) and the African Wood Density of the Food and Agricultural Organization (FAO 1997). However, where the tree species wood density was not found in either of these databases, the mean wood density of the plot was used as the wood density of the tree species (UN-REDD+ Nigeria 2015).

The allometric equation of Chave et al. (2014) was used to estimate the AGB of each tree in each forest inventory plots. Chave's allometric equation requires total height *H* (m), species wood density ρ (g/cm^{-3}) and diameter at breast height *DBH* (cm) to estimate tree-level AGB. Chave et al. AGB estimation equation is given as:

$$AGB_{est.}\,(kg) = 0.0673*(\varrho*DBH^2*H)^{0.976} \qquad (1)$$

The biomass of each tree within a plot was summed up to get the total biomass per 400 m^2 plot ($Plot_{AGB}$) in Kilogram (kg/m^2) (UN-REDD+ Nigeria 2016). This is converted to tons per hectare. Figure 8 provides a synopsis of the dataset sources, analytical procedures and final AGB product of the study.

2.3. Regional Above-Ground Biomass Estimation

This segment presents the relevant spatial variables used in predicting regional aboveground biomass in the CRS Nigeria, from the different sources and techniques used in the acquisition of Sentinel 2 vegetation indices, mean air temperature and the mean rainfall data over the study area.

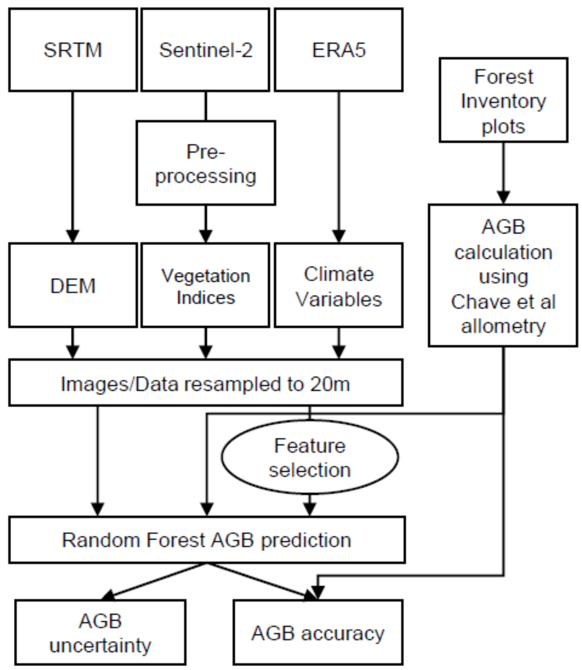


Figure 6: Methodological workflow showing data sources, analytical procedures, final output, and accuracy assessment. Climate variables used were air temperature, precipitation, relative humidity, and soil moisture. Vegetation Indices are given in Table 1.

2.3.1. Satellite, Climatic and Topographic variables

In this study, we utilized a total of eight Sentinel 2A multispectral images (hereafter called S2) alongside climatic and topographic variables. The S2 data were downloaded from the United States Geological Survey (USGS) Earth Explorer site at: https://earthexplorer.usgs.gov/. The downloaded S2 level-1C (LIC) images were then transformed from radiance to surface reflectance aided by the Dark Object Subtraction (DOS) method based on the semi-automated classification plugin in QGIS version 2.14 software (Roteta et al. 2019). With this process, all the darkest pixels caused by atmospheric scattering that may reduce the image quality are reduced (Saugier et al. 2001). The S2 images were atmospherically modified, orthorectified and spatialized on the global reference system UTM/WGS 84, 32N Minna datum on the SEN2COR tools of SNAP (Sentinel Application Platform) toolbox of the European Space Agency. Top-of-atmosphere (TOA) reflectance was converted to top-of-canopy (TOC) reflectance (Permantier et al. 2007; Sun et al. 2014). Sub-setting and mosaicking were carried out to produce a single image for the study area (Criesmeire et al. 2021). The S2 MSI (10 m) images were resampled to 20 m resolution to match the plot size (20 m) and this was done using the nearest neighboured resampling technique in ArcMap (Criesmeire et al. 2021). This interpolation method was used because its processes are faster, the algorithm has less rigorous implementation procedures and it is suitable for discrete data such as AGB (Drusch et al. 2012; Louis et al. 2016; Castillo et al. 2017; Chen et al. 2018). The benchmarked image was then subjected to a geometric pre-processing protocol. All the images were downloaded from the last month (November 2020) of the field data campaign. The weather conditions in the region from November to March are often less cloudy, hence all the data were obtained on dates of less cloud cover.

Various signal bands and vegetation indices were considered in this study and are shown in Table 1. The vegetation indices include the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index 2 (EVI 2), Optimized Soil Adjusted Vegetation Index (OSAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Atmospherically Resistant Vegetation Index (ARVI), Inverted Red-Edge Chlorophyll Index (IRECI), Modified Red-Edge Normalized Difference Vegetation Index (MRENDVI), Modified Red-Edge Simple Ratio (MRESR), and Red-Edge Normalized Difference Vegetation Index (RENDVI). In each of the delineated plots, the spectral reflectance values at the centre point of the plot were extracted using the 'Extract Values to Points' Spatial Analytical tool in ArcGIS. This tool extracts the cell values of the raster dataset based on the plots (point features taken at the centre of the plot). The equations used to calculate the above vegetation indices and their references are shown in Table 1. These vegetation indices were used because previous studies (Saatchi et al. 2011; Djomo et al. 2016; Avitabile et al. 2016; Santoro and Cartus 2021), established that these VIs are sensitive to phenological dynamics in vegetation, hence can be used as proxies of forest biomass. More so, 30 m elevation data from the Shuttle Radar Topography Mission (SRTM) was downloaded from the United State Geological Survey services Earth Explorer (https://earthexplorer.usgs.gov/.) and subsequently resampled to 20 m spatial resolution using the nearest neighbourhood method of ArcMap (Sun et al. 2014).

Thirty-five years (1985-2020) mean annual air temperature, precipitation, relative humidity and soil moisture data over the CRS, Nigeria were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset, downloaded from the Copernicus Climate Change Service (S3C) Climate Data Store (https://cds.climate.copernicus.eu/) (C3S 2019). The ERA5 are 5th generation elite model-based data produced on ECMWF Integrated Forecasting System (IFS). The ERA5 merged model-derived data with historical in-situ and space-borne observational data under a robust quality control protocol. The ERA5 data is presented with a resolution of around 30 km. Subsequently, these climate parameters were upscaled to 20 m spatial resolution using the nearest input grid points as provided by Digital Earth Africa User Guide https://docs.digitalearthafrica.org/en/latest).

Table 1. Vegetation indices calculated from Sentinel-2 used in the study. Blue, Red, RE1, RE2, and NIR correspond the Sentinel-2 bands 2,4,5,6, and 8.

Vegetation Indices	Equations	References
NDVI	*(NIR-Red)/(NIR+Red)*	(Rouse et al. 1973)
EVI	*2.5*((NIR-Red)/(1+NIR+6Red-7.5Blue)*	(Heute et al. 2002)
OSAVI	*(NIR-Red)/(NIR+Red+0.16)*	(Baret et al. 1992; Rondeaux et al. 1996)
MSAVI	$(2*NIR+1-sqrt[(2*NIR+1)^2-8*(NIR-Red)])/2$	(Qi et al. 1994)
ARVI	*(NIR-(2Red-Blue))/ (NIR+(2Red-Blue))*	(Kaufman and Tanre 1992)
IRECI	*(NIR − R)/(RE1/RE2)*	(Frampton et al. 2013)
MRENDVI	*(RE2-RE1)/(RE2+RE1-2*Blue)*	(Qi et al. 2000)

RENDVI	*(RE2-RE1)/(RE2+RE1)*	(Gitelson et al. 1994; Karlson et al. 2015)
MRESR	*(RE2-Blue)/(RE1-Blue)*	(Sims and Gamon 2002)

2.3.2. Regional AGB estimation using Random Forest

Estimation of AGB across the CRS was based on Breiman's (2001) RF model. The RF is an ensemble decision tree algorithm used in both classification and regression analysis (Mathias and Rosie 2020). In regression analysis, the algorithm builds a series of decision trees on bootstrap samples and then takes the average of the output of each tree. The averaging reduces the variance of the model and improves its prediction accuracy. The accuracy of the prediction increases with an increasing number of trees (Biau 2012; Wu et al. 2016; Hovera et al. 2018). The inherent ease of manipulation, the capacity to be executed with small sample sizes (Qi et al. 2012; Luan get al. 2020) and most importantly overcoming overfitting and collinearity of variables challenges associated with complex data domains (Briedman 2001; Matsuki and Kuperman 2016; Li et al. 2019) make this method very appropriate in determining above-ground-biomass (Prasad et al. 2006; Cutler et al. 2007; Baccini et al. 2008). In this study, RF has two important features: Ntree and Mtry. Ntree is the number of decision trees formed based on the bootstrap samples of the observation which by default is 500, while Mtry is the number of variables used as potential candidates at each split (Matsukim and Kuperman 2016). Furthermore, to optimize model performance, given the field samples and input layers, Ntree and Mtry were tested in the range of 250 and 1000 and 1 to 16 respectively. The optimal combination of Ntree and Mtry for AGB prediction was 400 and 3 respectively. The Ntree and Mtry used were enough to stabilize the error as too many Ntry may over correlate the ensemble and subsequently lead over overfitting (Wu et al. 2016).

Concerning training and testing, 70 % of the data (in bag sample) were used to train the model while the remaining 30 % of the data (out-of-bag sample-OOB) were used for the internal cross-validation procedure for estimating the OOB error (Prasad et al. 2006; Biau

2012). The R^2, RMSE and Relative RMSE (relRMSE) of the model were used to interpret the relationship between the field obtained AGB and predicted AGB (Mitchard et al. 2014; Pandit et al. 2020). The relRMSE is defined in this study as the RMSE divided by mean of the observed values. In addition, the selection of important features becomes crucial because of the interconnectedness and high dimensional properties of biophysical parameters (Pandit et al. 2020; Junior et al. 2020). Feature selection in random forest can be conducted using the filter, wrap or embedded method (Guyon and Elisseff 2003; Hengl et al. 2017). Filter feature selection technique is a pre-processing step that is based on an assessment of the statistical scores of correlations between the data subsets and the outcome variable independent of the machine algorithm. One limitation of the filter method of feature selection is that it does not resolve the problem of data multicollinearity (Khan et al. 2020). On the other hand, the wrap method relies on the machine searching for the best subset of variables through backward, forward, or recursive techniques. These techniques work by adding (forward selection), eliminating (backward selection) or searching for the optimal subsets of variables (recursive selection) and ordering them based on their performance.

In this study, the recursive feature selection wrap method was used (Freeman et al. 2015). This aided us in the reduction of the computational time, improvement in model performance with the right subset combinations, reducing overfitting, and increasing the ease of data interpretation among others (Pandit et al. 2018). The RF algorithm has an inbuilt capacity to calculate the contribution of each of the explanatory variables to the model. The increased percentage in mean square error (% inMSE), computed as the prediction error of each tree on the out-of-bag samples as the data are randomly shuffled (Briedman 2001), is one measure that revealed the contribution of a variable to the model. Variables with higher values are indicative of their robustness in the model (Yu et al. 2019). Node impurities tell us how well the variables split. It expresses the total decrease in impurities as the variables are divided during permutation and averaged over all the trees. In other words, it is the residual sum of squares as the features are divided (Briedman 2001). MSE and node purities in random forest algorithms are the most widely used variable scores of importance in ecological studies (Rouse et al. 1973; Rondeaux et al. 1996). The model parameter optimization process of RF model is provided in the supplementary material.

2.3.3. Model evaluation and Uncertainty mapping:

To evaluate the effectiveness of the random forest model, the coefficient of determination (R^2), root mean square error (RMSE), and the percentage mean square error (i.e., relRMSE) were used to determine the general error of the AGB estimation Generally, a high R^2, with low RMSE and relRMSE is an indication of a good predictive model (Kaufman and Tanre 1992).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{n}} \tag{2}$$

$$relRMSE\% = 100 \, . \left(\frac{RMSE}{\hat{Y}}\right) \tag{3}$$

where y_i is the predicted value series, $\hat{y_i}$ is the observed value series, n is the sample size, and $\bar{Y}$ is the average value of the observed series. In addition, the field plot data were compared with the extracted AGB values from Saatchi, Baccini, Avitabile and ESA CCI AGB maps using the Willmott's agreement index, as shown in equations 4.

$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad , \quad 0 \le d \le 1 \tag{4}$$

where 0_i is the AGB from field plots, $\bar{O}$ is the observed mean AGB, and P_i is the AGB values from each of the maps used in this study (Willmott et al. 2012). An index of 1 implies a perfect agreement between a pair of datasets. The Willmott Index (d) is a standardized statistical technique used to establish the extent of prediction error which varies between 0 and 1 (Willmott et al. 2012). Willmott et al. (2012) reported that the Index of similarity is not sensitive to errors concentrated around outliers. In addition, it is simple to implement and dimensionless hence, the unit of data collection does not count. The Willmott Index was used to support traditional model evaluation measures of R^2, RMSE and bias (Willmott et al. 1985; Asker et al. 2018).

Errors in the AGB estimation could filter in at any stage of the research process; plot design, data collection, model formulation and parameterization or analysis (Chave et al. 2019). To create the AGB uncertainty we assumed that the identified error sources are independent and random, and we propagated these errors to the pixel level using the formula (Baccini et al. 2008):

$$\varepsilon_{AGB} = \left(\varepsilon_{measurement}^2 + \varepsilon_{allometry}^2 + \varepsilon_{sampling}^2 + \varepsilon_{prediction}^2\right)^{1/2} \quad (5)$$

This study uses Chave's et al. (2014) pan tropical allometric equation in estimating the AGB and is associated with an error margin of 5 %. The measurement errors of wood density, tree height and diameter at breast height in the region are estimated to be 10, 2.5 and 4.47 % respectively (Saatchi et al. 2011). Similarly, the sampling error was taken from Saatchi (2011) to be 22.8 % for the tropics. The prediction error is calculated based on the uncertainty in the Random Forest AGB predictions using the testing field plots. Spatial prediction uncertainty was determined for biomass ranges dividing the RMSEs with the observed mean AGB in each biomass range, and then attributing to each pixel.

RF is a non-parametric ensemble technique which does not require direct quantification of prediction error like the traditional regression approaches (Coulston et al. 2016), we therefore, rely on the Monte Carlo model in quantifying the prediction uncertainty. The underlying principle of the Monte Carlo model is the repeated simulation of the occurrence of a random event and the subsequent estimation of its probability features based on the frequency of the said random event (Xiang et al. 2021). The repeated simulation of the Monte Carlo samples (in our case, 500 iterations), the probability distribution of biomass estimates, and errors are obtained from the series of iterations which resulted in a stable and reliable quantification of biomass and the error map (Tang et al. 2020). These diverse error sources are propagated during the geospatial modelling process assuming all errors were independent and random; hence it is imperative to know their size and the pattern of distribution in accordance with IPCC and Carbon Fund Methodological Framework (UN-REDD+ Nigeria 2018).

2.4. Comparisons to other regional to global AGB products

A few tropical and global remote sensing based AGB maps have been produced in the past decade. In this study we will compare our AGB product over the CRS with that of Saatchi et al. (2011), Baccini et al. 2008), Avitabile et al. (2016), and the ESA CCI (2021). These studies are summarized thus:

Saatchi: Saatchi integrated plot based AGB and GLAS (Geosciences Laser Altimeter System) LiDAR heights derived AGB with MODIS (NDVI and Leaf area index), QSCAT (NDVI and LAI), and SRTM (topography) to extrapolate AGB over the tropics at 1 km spatial resolution using the Maxent machine learning tool. Saatchi used 75 plots of 0.1 ha in size (493 in all tropics) scattered across tropical African forests, wood savanna and dry forests of Cameroon, Uganda, Libera, and Gabon and inventoried trees with DBH of 10 cm and above. Saatchi used an allometric equation that included tree DBH and wood density in estimating plot AGB. The model predicted the total AGB for Africa to be 62 Pg. In addition, 40 % of the point dataset were reserved for model testing while field plot datasets were bootstrapped and used with GLAS LiDAR to account for pixel per pixel error through the Maxent model. Saatchi examined the model performance based on two parameters: the segment of predicted area and extrinsic omission rate at a selected threshold and the area under the receiver curve (AUC). The Maxent model revealed that the AUC ranged between 0.86 and 0.98, indicating that the prediction did not happen by chance. The overall uncertainty averaged over all continents was also reported to be ±30 % and ±32 % over Africa.

Baccini: Baccini determined a pan-tropical map using similar methods to Saatchi, but with the use of RF. Baccini measured all trees with DBH of 5 cm and above and produced the AGB map at 500 m spatial resolution. The AGB over the study area was predicted and mapped using a random forest learning algorithm. Baccini used an allometric equation that includes tree DBH, height and wood density in estimating plot level AGB and 10 % of the data were used to test the RF model. Additional spatial layers used as input data included surface temperature from MODIS bands, EVI2, NDVI2 and all land bands. Baccini produced a total AGB of tropical Africa at 64.5 Pg. Validation using their testing dataset resulted in an RMSE of around 50 t/ha for all tropical regions, with 38 t/ha for tropical Africa.

Avitabile: The AGB products of Saatchi and Baccini were combined into a pan tropical AGB map at 1 km resolution, using an independent reference dataset of field observations and locally calibrated high-resolution biomass maps. The data fusion approach used bias removal and weighted linear averaging incorporating the biomass patterns indicated by the reference data. Avitabile screened and selected 14,477-point data across the tropics and 953 were taken from Africa (DRC, Tanzania, Ghana, Ethiopia, Sierra Leone). Trees with a DBH range of 5-10 cm were used in model calibration and subsequently estimated 84 Pg as the total carbon stocks over Africa. The plots and GLAS LiDAR derived AGB were spatialized using a random forest model. This fused product compared to the Saatchi and Baccini product, using its own validation dataset, reported RMSEs of 89, 104, and 112 t/ha and bias of 5, 21, and 28 t/ha respectively.

ESA CCI: Here, the authors estimated growing stock volume (GSV) obtained from mainly from radar data with a spatial resolution of 1km. The GSV was converted to AGB using wood density and stem-to-total biomass expansion factor. A total of 110, 897 plots scattered across the globe were used in model validation. ESA CCI derived AGB was integrated with CCI Land Cover datasets and using the Forest Resources Assessment (FRA) ecological zones of 2010. The ESA CCI estimated total AGB of 84.8 Pg for Africa against FRA estimates of 95.5 Pg with a mean AGB of 108 t/ha and 142 t/ha respectively. The large variance between the two studies was attributed to the use of more forest area in the ESA CCI studies compared to FRA. AGB was predicted with a standard deviation around 50% for tropical forests and tropical mountain forests. RMSEs were provided with a range of AGB values, giving RMSEs of 30-50 t/ha for AGB>100 t/ha and 50-100 t/ha for AGB < 100 t/ha.

UN-REDD+ Nigeria project: Nigeria secured approval for the REDD+ project in implementation in 2010 with Cross River State as a demonstration model. Cross River State holds 50 % of the remaining 9.6 million hectares of Nigeria's forest area but is under threat of deforestation (UN-REDD+ Nigeria 2018). In addition, the region was selected for the first REDD+ implementation in the country based on the streams of forest governance structures, and its carbon sequestration potentials (Agrawal et al. 2011). The project established 77 nested plots of 35 m X 35 m across 13 land cover types for tree parameters inventory. Tree

DBH was measured in the field while height and wood density were derived from the equations of Feldpausch et al. (2011) and Zanne et al. (2009). The Chave et al. (2014) allometric equation was used to estimate tree AGB. Tree AGB was summed to get plot based AGB. Using a biomass conversion factor of 0.47, the estimated AGB of the region was given as 2544 t/ha.

Extracting AGB from the regional products: The four AGB products of Saatchi, Baccini, Avitabile and the ESA CCI were evaluated against the 22 testing forest inventory plots collected as part of this study. The Saatchi, Baccini, Avitabile and ESA CCI products were downloaded, the study area cropped, and projection parameters selected to conform with the coordinate system of the study area (UTM/WGS 84, 32N Minna datum) on the SEN2COR tools of SNAP (Sentinel Application Platform) toolbox of the European Space Agency. To ensure effective comparison, each of the products native resolution was used (Santoro and Cartus 2021). The inventory plots of this study were then overlaid independently on the subset AGB maps of Saatchi, Baccini, Avitabile, and ESA CCI. The extracted AGB values were then evaluated (described in 2.3.3) and the results were compared to the AGB product determined from this study.

3. Results

3.1. Summary Analysis of Plots AGB

Descriptive characteristics of forests stand features are presented in Table 2. Overall, there were 29 plots collected in undisturbed forests (Figure 5), 18 plots collected in the disturbed forests, and 25 plots collected in crop field plots (henceforth UF, DF and CF). The mean DBH of trees in the UF, DF, and CF plots were 38.8, 4.02, and 25.2 cm respectively, while the mean height of trees in these three land cover types was 23.6, 22.0, and 8.2 m respectively. Basal areas on average were 35.5, 28.8, and 15.9 m^2/ha and average AGB was 222.5, 106.5, and 24.4 t/ha in the UF, DF, and CF plots respectively. Specific wood density (g/cm^3) ranged from 0.20 to 0.93 across all sites, with average wood densities of 0.71, 0.55, 0.50 g/cm^3 in UF, DF, and CF plots respectively.

Table 2. Descriptive statistics of forest inventory plots.

Landcover type	Undisturbed forest (n= 29)			Disturbed forest (n= 18)			Crop fields (n=25)		
Parameters	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean
DBH (cm)	164.4	5.1	38.8	164	5.1	40.2	82.6	5.1	25.2
Tree height (cm)	67.0	2.8	23.6	45	4.1	22.0	30.0	1.5	8.2
BA (m^2/ha)	77.4	6.3	35.5	105.4	5.9	28.8	43.6	2.7	15.9
WD(g/cm^3)	0.51	0.23	0.71	0.93	0.20	0.55	0.87	0.23	0.50
AGB (t/ha)	588.3	11.5	222.5	203.3	14.4	106.5	107.3	3.0	24.4

3.2. Predicting AGB using Random Forest Algorithm:

The result of the random forest training performance using all the explanatory variables (n=16) gives a coefficient of determination of 0.85, a RMSE of 28.71 t/ha, and MAE of 30.02 t/ha. As stated in the methodology, performing feature elimination is an important step in reducing the effects of multicollinearity and overfitting. The RF algorithm has an inbuilt capacity to calculate the contribution of each of the explanatory variable to the entire model through the variable important measures (VIMs). This is achieved using the IncMSE and IncNodePurity (Figure 7)**.** The MSE and Node Purity are filters used to rank and removed irrelevant variables from the model. The higher the increase percent MSE and increase node purity values the better (Biau 2012).

As shown in Figure 7, top parameters that made significant contributions to predicting AGB includes topography, rainfall, NDVI, RENDVI, minimum yearly air temperature and OSAVI. For instance, the elimination of topography and RENDVI as a predictive variable reduces the model performance to 55 % against 85 % when all the explanatory variables are included in the model. Conversely, variables like minimum relative humidity, ARVI, MSAVI, EVI, maximum relative humidity, MRESR, soil moisture and maximum yearly air temperature may not have large effects on the model performance as shown in Figure 7. However, as revealed in Figures 7 considering both the %IncMSE and Node purity, the important parameters exhibit instability in ranking. This could be due to parameter variations and permutations influenced by forest covariates known to be characterized by high-order and nonlinear interactions and or attributed to the small sample size used in this study (Willmott 1985).

In view of this, the top six parameters of the %incMSE were used to spatialize the AGB of the study area. From the literature, studies established that mean annual minimum air temperatures, rainfall and topography are important predictors of AGB in the tropics (see Poorter et al.2015; Poorter et al. 20117; Balima et al. 2021) while Sentinel 2 VIs of OSAVI, NDVI, RENDVI have equally been established to be good predictors of AGB due to their red edge content (see Dube and Mutanga 2016; Antonelli et al. 2018; Yu et al. 2019). The application of these top six variables in AGB prediction saw a change in the model training accuracy to an R^2 of 0.78, an RMSE of 54.7 t/ha and an MAE of 34.89 t/ha compared to the training accuracy of the full predictors yielding an R^2 of 0.85 and an RMSE of 28.7 t/ha.

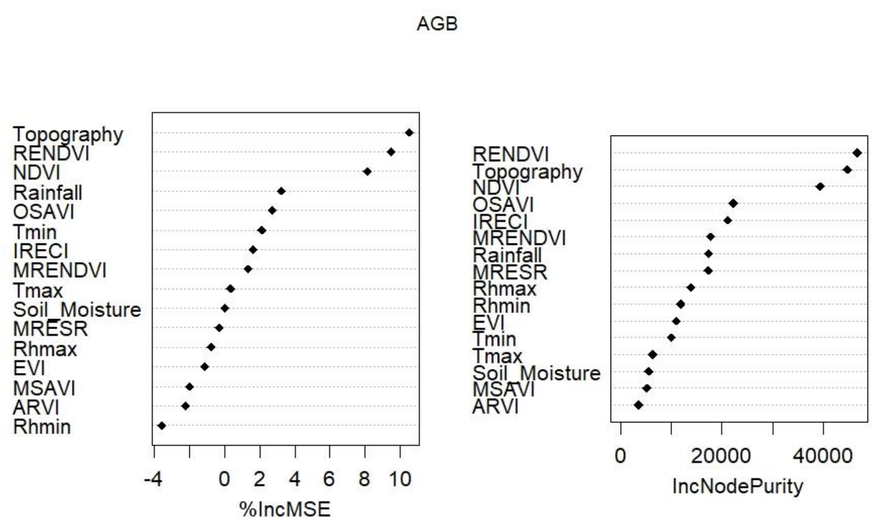


Figure 7. Variable importance plots for random forest regression model. Variable importance plots showing the relative importance of each variable as a predictor of aboveground biomass in the Cross River State, Nigeria. %IncMSE; Increasing percentage mean square error. InNodePuirty; Increasing Node Purity.

AGB from the testing forest inventory plots were used to determine the predictive accuracy of the final constrained RF model (Figure 8). The scatter plot of observed forest inventory AGB versus predicted RF AGB shows the observed AGB aligned with predicted AGB to an R^2 of 0.88, a RMSE of 40.9 t/ha and a relRMSE of 29.96 %. Separating this into 100 t/ha bins, AGB <100 t/ha is predicted with an RMSE of 21.7 t/ha (66.5 % relRMSE / 10.1 t/ha bias), AGB between 100-200 t/ha is predicted with an RMSE of 47.5 t/ha (29.3 % relRMSE /

22.8 t/ha bias), and AGB >300 t/ha is predicted with an RMSE of 57.25 t/ha (18.5 % relRMSE / -19.3 t/ha bias).

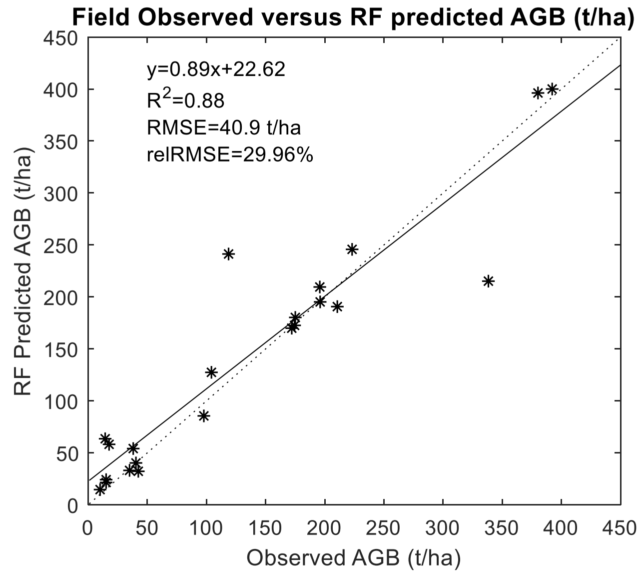


Figure 8. Evaluation of the Random Forest predicted AGB over the 22 testing forest inventory plots using the six most important predictor variables of %incMSE shown in Figure 2.

The spatial distribution of predicted AGB values and associated uncertainty over the CRS are presented in Figure 9. Over the CRS, high AGB is concentrated in two pockets: the southern eastern areas of the state (Oban area) and the north-eastern areas (Okwango area) coinciding with much of the CRS National Park. This area sees AGB above 200 t/ha and up to 500 t/ha. Areas around the Cross River to the south of the state, and scattered areas to the west of the state see AGB values of 150-350 t/ha. Areas to the far south, far west and north of the state have the lowest AGB below 100 t/ha. Average uncertainty over the CRS is estimated to be 34.6 %, with lower percent uncertainty (0-50 %) in higher biomass areas.

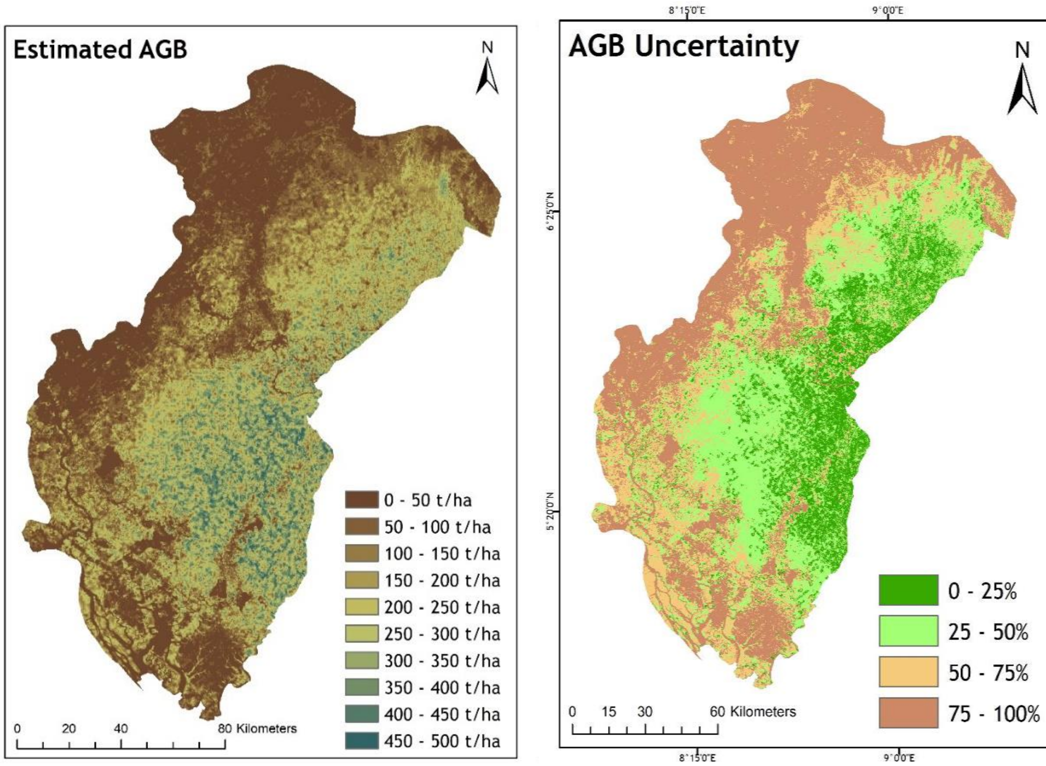


Figure 9. Estimated 20 m resolution map of Above-Ground Biomass for the Cross River State (left-panel), with the resulting uncertainty in AGB incorporating prediction, measurement, and allometry errors (right-panel).

3.3. Comparison with other Above-Ground Biomass products.

The CRS AGB product developed in this study is compared to the products from Saatchi, Baccini, Avitabile, and ESA CCI+. We also included the REDD+ estimate of total AGB over the whole of CRS. Here, we compare distribution patterns, model performances of the four products as well as the mean, maximum, and total AGB estimated over the CRS (Table 3). The average and total woody plot AGB estimated for the region in the current study is 121.98 t/ha and 0.25 Pg. REDD+s product is the closest to these results, with mean and total biomass at 132.9 t/ha and 0.27 Pg respectively. Saatchi's product has mean and total biomass values of 143 t/ha and 0.29 Pg respectively, and Baccini product has estimated mean and total AGB of 148and 0.30 Pg. Similarly, the Avitabile's product has mean and total biomass values of 155.8t/ha and 0.31 Pg respectively. The ESA CCI+ product is the most different with mean and total biomass of 61.5 and 0.12 Pg respectively. The distribution patterns of the regional estimates of AGB between the four products and the current study are given in Figure 10.

Table 3: mean, maximum, and total AGB by products and study over Cross River State-Nigeria.

Product/Study	Mean AGB t/ha	Maximum	Total AGB (Pg)
Saatchi et al. 2011	143	365.9	0.28
Baccini et al. 2012	148	244	0.30
Avitabile et al. 2016	155.8	443.1	0.31
UN-Nigeria REDD+ 2018	132.9	-	0.27
ESA CCI+ 2021	61.5	205	0.12
Current Study	121.9	588	0.25

All the regional Above-Ground Biomass products over the CRS considered in this study are presented in Figure 10. Saatchi map aligned in most regions of the AGB map of this study. The Saatchi product has similar magnitude AGB in the central and north-eastern highland areas, with high AGB values reaching 350-500 t/ha in these areas for both products. In addition, the Saatchi product contained low AGB along the western, southern, and north-western areas of the CRS with many of the predicted AGB values < 50 t/ha. The Baccini product has more consistent AGB to the current study in the western, southern, and north-western edge, but has lower AGB in the central and north-eastern highland areas with AGB values from 250-350 t/ha.

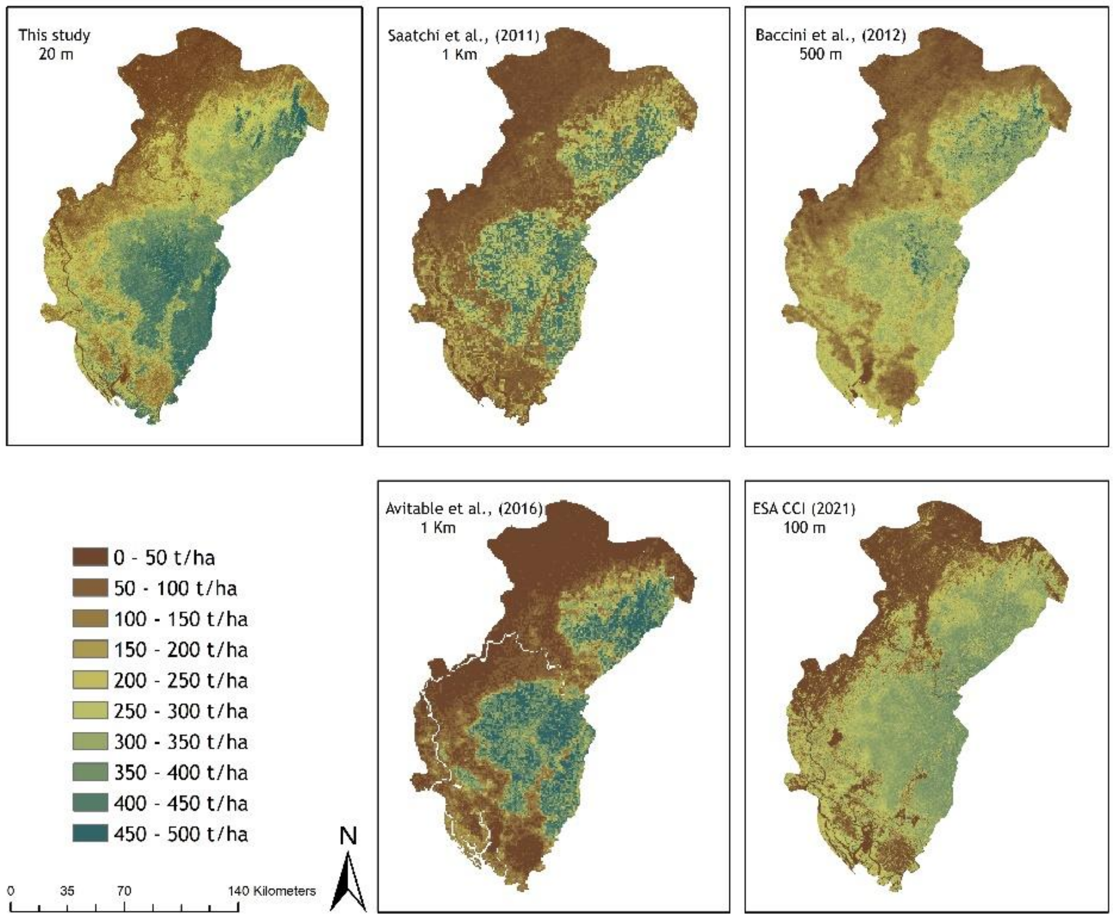


Figure 10. AGB products over the Cross River State of this current study and the Saatchi, Baccini, ESA CCI+ and Avitabile at their respective resolutions.

The Avitabile product qualitatively compares most favorably to the AGB map of this current study in the central and northeastern highlands with AGB values >350 t/ha. Yet, as with Saatchi, southern, western, and northwestern areas contained lower biomass values regularly below 50 t/ha. The current AGB map of the CRS by ESA CCI is more homogenized AGB across much of the CRS. For instance, in the central and north-eastern parts of the study area, the ESA CCI product shows biomass only up to 350 t/ha with a gradual drop in AGB in the southern, western, and north-western regions. Note that the dates of each product are 10 years apart (2011-2021) and so biomass may be affected by anthropogenic and climate disturbances as well as natural ecological growth and mortality processes.

The performance of the four regional biomass maps is assessed against the 22 testing forest inventory plots with resulting metrics given in Table 4. The product that is closest to the observed forest inventory plots is the Avitabile product resulting in a RMSE of 32.89 t/ha and a relRMSE of 24.06 %. The Saatchi AGB product contains errors of RMSE 67.62 t/ha with a relRMSE of 49.69 %. The Baccini and ESA CCI products performed worse compared to others as they recorded a RMSE of 78.03 t/ha and a relRMSE of 57.09 % and 78.87 and 56.24 respectively. These results are also confirmed using the similarity agreement index of Willmott, with the Saatchi and Baccini products yielded indices of 0.89 and 0.85, while the Avitabile and ESA CCI products yielding indices of 0.98 and 0.85 compared to the 0.97 obtained for this study. Concerning the bias and MAE, all products performed worse than the current study, with the Avitabile product being the closest (bias of -17.3 t/ha compared to +7.5 for the current study).

Table 4. Predictive mean errors of the AGB products of the Saatchi, Baccini, Avitabile and ESA CCI products over the Cross River State, Nigeria.

AGB product	RMSE (t/ha)	MAE	Bias (t/ha)	RelRMSE%	Willmott index
Saatchi	67.93	41.35	-40.9	49.69	0.89
Baccini	78.03	48.41	-48.4	57.09	0.85
Avitabile	32.89	23.57	-17.3	24.06	0.98
ESA CCI	78.87	59.52	-49.9	56.24	0.85
This study	40.95	23.14	+7.5	29.95	0.97

4. Discussions

Nigeria with over 200 million people and a land area of 923, 768 km^2, has the highest rate of deforestation in Africa (Enough and Bisong 2015). According to Global Forest Watch (2020), in the last 20 years Nigeria has lost 11,415 km^2 of tree cover equivalent to 587 Mt of carbon dioxide emissions and 1,530 km^2 of humid primary forest. To halt this trend, Nigeria keyed into REDD+ in 2008 and formally received approval to kick start the project in the Cross River State in 2009. The decision to start with CRS was informed by the fact that 50 % of the nation's remaining track of forest is found in the region, a valuable part of the Guinean forest biodiversity global hotspot (Gantum and Mandal 2016). The Paris agreement recognized forest protection as part of the strategy to counteract global carbon dioxide emissions, hence the need to quantify and track changes in biomass in forest and woodlands (IPCC 2006a). To achieve this, the IPCC (2007b) places emphasis on tier 3 level carbon accounting: reliance on local reference plots, tracking changes in activity data and institutionalization of Monitoring, Reporting and Verification (MRV). However, existing efforts by the CRS REDD+ and other regional products fall shorts of internationally recognized standards due to a lack of local reference biomass data in both space and time in the region and across Africa, and a lack in consistency in data collection for monitoring and reporting on carbon dynamics at regional scales within the framework of REDD+ (Dube and Mutanga 2016). Subsequently, global, and regional attempts at carbon accounting (Baccini et al. 2008; Saatchi et al. 2011; Avitbaile et al. 2016) are characterised by large uncertainties attributed to this lack of or inadequate reference plots in the region. Coupled with the need for better forest inventory reference data, new higher resolution remote sensing techniques such as Sentinel-2 and non-parametric machine learning methods can aid in reducing uncertainties in the prediction of tropical forest biomass pertinent to national carbon accounting, sustainable forest management, strategic policy making and REDD+ payment.

In view of these, the study aimed at deriving a high spatial resolution (20 m) above-ground biomass map for the year 2020 for the whole of the CRS, Nigeria using Sentinel-2 data, climatic and edaphic variables, and local reference forest inventory plots taken from undisturbed, disturbed, and cropland areas. In addition, the constraining of predictor features in Random Forest model helped in improving biomass prediction over the CRS while reducing predictor feature multicollinearity (Guyon and Elisseff 2003). This study predicted spatially resolved AGB over the CRS of 0.246 Pg (average of 121.98 t/ha) with an RMSE of 40.9 t/ha, a bias of 7.5 t/ha, a relRMSE of 30 %, and an overall uncertainty of 34.6 %. REDD+ produced a single AGB estimate over the CRS of 0.268 Pg. The AGB prediction of this study is better compared to the regional products of Saatchi, Baccini, and ESA CCI which yielded a relRMSE of 49.69 %, 57.09 % and 56.24 % respectively (bias of -41, -48, -50 t/ha), and like the Avitabile product (relRMSE of 24% and bias of -17 t/ha).

4.1. Above-Ground Biomass estimation over the Cross River State

Using all 16 predictor features including Sentinel-2 derived indices, climate variables and edaphic conditions resulted in a predicted AGB with a training RMSE of 28.7 t/ha and an R^2 of 0.85. Subsequently, the feature selection process was down to six features resulting in final training accuracy with a RMSE of 54.7 t/ha and an R^2 of 0.78. Of the 16 features two climatic features were the most important; mean annual rainfall and minimum yearly air temperature and three Sentinel-2 derived indices were selected; NDVI, RENDVI, and OSAVI and topography.

Topography exerted a very high influence on the distribution of AGB in the CRS (Figure 7), with higher AGB coinciding with areas of the CRS with higher topography. A principal reason for this is anthropogenic drivers of land cover change at lower elevations globally, but also around the CRS (UN-REDD+ Nigeria 2018; Bouvita et al. 2018). Deforestation and a history of agricultural use results in a loss of above ground biomass from agroforestry areas to larger-scale commercial cropland with limited tree cover. Most croplands identified by the CRS Forestry Commission are in the lower elevation areas of the state (Figure 5). Second, much of the upland areas of the CRS are occupied by the forest reserves such as the Cross River National Park separated into the Okwango (northeast) and Oban (southeast) sections consisting primarily of high biomass moist tropical forest. Third, topography itself can be a driver of higher biomass and biodiversity. Topography can shape climate regimes and influence diversification (Antonelli et al. 2018) as well as being linked to a range of abiotic conditions such as soil water and nutrient availability, soil texture, exposure, and flood regimes (Markey et al. 2021).

Rainfall and minimum yearly air temperature also exerted a strong influence on the distribution of AGB over the CRS. Climate heterogeneity is among the leading drivers of forest structure, biodiversity, and aboveground biomass of tropical forest ecosystems (Poorter et al. 2015; Poorter et al. 2017). Precipitation has a positive correlation with AGB (Malhi et al. 2004; Slik 2012) and over Africa has been estimated to be more important than other tropical continents due to lower average rainfall and larger water limitation over Africa (Slik 2012). Temperature has been shown to be negatively correlated to tropical forest AGB (Malhi et al. 2004; Slik 2012) with the temperature of the coldest month also negatively correlate with AGB (Slik 2012). Studies in Western Africa, including Balima et al. (2021), Maukonen and Heiskanen (2005) have also shown that within the west African region, mean annual rainfall from 800-1200 mm has a positive correlation with AGB and negatively correlated with mean air temperature from 27-29 ^{o}C. Similarly, Poorter et al. (2017) study revealed that lower air temperature support soil fertility increase, and subsequently plant growth. Conversely, higher air temperature may reduce rate of biomass growth. The Cross River State Agroecological Zones are characterised by varying climatic conditions (UN-REDD+ -Nigeria 2015). The density of AGB across the three ecological zones (North, South and Central) possibly reflects the gradients of air temperature and precipitation conditions of the area. In the northeast and southeast flanks where rainfall often exceeds 2500 mm in most parts of the year, AGB is observed to reached 200 t/ha, whereas in northwest and southwest areas with less precipitation, AGB is generally below 150 t/ha (Figure 9 -left panel).

Sentinel-2 derived NDVI, RENDVI and OSAVI were important predictors identified in this analysis to predict regional AGB over the study area (Figure 7). Specifically, the use of the red edge in the RENDVI has recently been shown to be effective in predicting forest AGB relaying issues with saturation at high biomass values and reducing uncertainties in complex and dense tropical forest (Slik 2004; Zhang et al. 2016; Asker et al. 2018). Adan (2017), for instance, compared the strength of red-edge and broad band-based VIs derived from Sentinel-2 in predicting total AGB in the tropical forest of Malaysia, concluding that the red-edge VIs like REDNVI, performed better than the non-red-edge VIs in predicting AGB. OSAVI was also used in this study to predict AGB. OSAVA is a known VI that enhances the contrast between soil and vegetation but aid in reducing the brightness effects of the soil (Muukkonen and Heiskanon 2005).

4.2. Comparison to other Regional AGB products

As with this study, prior pan-tropical and global above-ground biomass products shown in Figure 6 have used a combination of satellite data and machine learning methods calibrated and validated using available forest inventory reference data. The total AGB predicted in this study over the CRS is closest to the Saatchi and UN REDD+ estimates, and furthest away from the ESA CCI product (Table 4). Concerning the accuracy assessment

(Table 4), this study performed better than the Saatchi, Baccini, and ESA CCI products with around a 20-27 % reduction in relRMSE and around a 27-38 t/ha reduction in RMSE. The Avitabile product has a similar but lower relRMSE (~6 % better) but larger bias compared to our study (Table 4).

The Baccini (2008), Saatchi (2011), and Avitabile (2016) products used the GLAS satellite sampling LiDAR (i.e. not wall-to-wall), calibrated using reference plots over the tropics to predict AGB, and then used MODIS multispectral data and satellite topography data to spatially extrapolate to the tropics using machine learning algorithm. Avitabile is an improved product fusing Saatchi and Baccini using over 14000 reference datasets (953 in Africa) to create a nearly unbiased product with a published mean bias of +5 t/ha and <+10 t/ha bias over Africa. The Avitabile product achieved prediction of higher AGBs in dense tropical forests >400 t/ha in Africa, around 100 t/ha more than the Baccini and Saatchi products (2011). Yet, Avitabile over the CRS still has an overall negative bias of -17 t/ha compared to our study with a +7.5 t/ha bias. The method developed here over the Cross River State has used localized forest inventory reference data collected explicitly for this purpose using the REDD+ Nigeria field team and spatially extrapolated using higher resolution multispectral Sentinel-2 data at 20 m as well as topography and climate data. Recent studies have begun to use Sentinel-2 to produce AGB maps for forests in Nepal (Pandit et al. 2018), Indonesia (Dube et al. 2018), Senegal (Soto-Navarro et al. 2019) amongst others. The ability in these Sentinel-2 studies, and the current study over the CRS, to predict AGB using various VIs outweighs the use of similar spatial resolution Landsat (Banskota et al. 2014). The ESA CCI+ biomass product has included over 110,000 forest inventory reference plots from various global ecosystems and has largely used C and L-band radar data to determine global biomass (Santoro and Cartus 2021). Given the use of radar, the ESA CCI product begins to saturate at AGB values >200 t/ha with a bias at 300 t/ha greater than -50 t/ha (Santoro and Cartus 2021). This study over the CRS predicts large AGB values (regionally > 400 t/ha) with a bias from 200-400 t/ha at -19 t/ha and a relRMSE of 18.5 %.

This biases and uncertainty within biomass products, emphasized the necessity for spatial extrapolation using field plots and remote sensing (Mitchard et al. 2013), and the uncertainties when comparing between products is likely responsible for the reluctance of the IPCC to recommend Baccini et al. (2008), Saatchi et al. (2011), and Avitabile et al. (2016) biomass maps, hence its reliance on national forest inventories for subregional and regional biomass spatialization (Chave et al. 2019). However, all the regional products and our AGB map clearly identified similar areas – north-eastern and south-eastern flanks of the Cross River State - as areas with high biomass density. The differences observed in other locations of the study area and in the magnitude of the high AGB areas supports the need for better localized reference data (Chave et al. 2019) with higher resolution spatial imagery.

4.3. REDD+ Implications and Future Work

The leading mandates of REDD+ are to facilitate robust forest carbon quantification at different jurisdictional levels and maintain and improve on carbon status for carbon emissions reduction (Agrawal et al. 2011). Because of this, nations are granted financial benefits based on their performances; judged on demonstrable evidence at slowing, halting, or reversing forest cover destruction and carbon loss (Agrawal et al. 2011; Shoko and Mutanga 2017). Therefore, the accurate estimation of aboveground biomass and mapping is pertinent, and this will reduce uncertainty in carbon stocks and cycle models especially in this part of the world where airborne LiDAR and field data remain a challenge (Duncanson et al. 2019). The integration of AGB derived from satellite remote sensing and field measurements in our study increases confidence in our aboveground biomass estimation unlike the UN-Nigeria REDD+ team, Saatchi, Baccini, and ESA CCI products that either estimated AGB from field measurements alone or estimated AGB regionally with limited forest inventory plots over Nigeria. The method presented in this current study also does not rely on the improvement or fusing of prior products as with the Avitabile product. The disparity in the estimated AGB from these products has been linked to the different empirical modelling tools, calibration datasets and extrapolation techniques (Mitchard et al. 2014; Duncanson et al. 2019; Santoro and Cartus 2021). IPCC Tier 3 Good Practice Guidebook emphasized accurate AGB reference data as vital in sustainable forest management and climate mitigation (IPCC 2007a). In addition, the accurate quantification of AGB is a requisite for meeting the four pillars of REDD+; National REDD+ strategy, national forest monitoring system and system of tracking REDD+ impacts on safeguards (UNFCCC 2011). The Cancun Agreement outlined the social and environmental safeguards in Appendix 1 that implementing partners need to uphold (ibid). Factual AGB estimation and monitoring of carbon stocks is one fundamental pathway to achieving this. In addition, with accurate AGB quantification in the region, land use policies will be put in place towards meeting land degradation neutrality target 15:3:1 of UNEP/CBD/SBSTTA (FAO 2017) and better the livelihood of forest dependent communities.

Future work may improve the AGB prediction of the CRS. First, the Global Ecosystem Dynamics Investigation (GEDI) satellite LiDAR has recently been attached to the International Space Station providing samples of forest structure globally. These LiDAR samples, coupled with on-the-ground biomass validation, could provide updated AGB maps with spatial extrapolation like Baccini and Saatchi. Furthermore, a new 1km AGB product will soon be released by GEDI, which may provide improved estimates (Duncanson et al. 2019). Second, Sentinel-1 radar could also be used to estimate biomass in isolation or using a fusion approach with Sentinel-2 (Forkour et al. 2020). Third, a better disaggregation of forest and land cover types over the region could have improved this work. These could include undisturbed tropical rainforests vs dryer tropical forest and sparse forests, various managed plantation forests, mangroves, forest disturbance history, and trees in non-forest environments such as urban, agroforestry, pastures, etc.

This study faced challenges of adequate forest inventory plots. The cost of gathering data on trees limited the numbers of plots in this study to 72 despite the size of the study area. We recognize that a higher sample size may have improved the accuracy of the AGB estimates. In addition, management of forest communities' expectations was tricky; to achieve results, we remained upright with all community opinion leaders as previously similar exercises exaggerated the benefits of forest protection through promised of handouts from government. Whereas in our study, we emphasized more on the environmental benefits of forest carbon protect.

5. Conclusion

Reduced uncertainty high-resolution carbon monitoring in tropical Africa across a range of woodland types is crucial to REDD+ improving carbon accounting, facilitating robust quantification at all jurisdictional scales, and understanding areas of high biomass and biodiversity importance. The lack of reliable tree structure parameters for wall-to-wall aboveground biomass estimation and validation in CRS, Nigeria as in other parts of the tropics, remain an immediate factor of high AGB uncertainty. In view of this, the study integrated in situ forest inventory plots collected over the whole state, selected reanalysis environmental data with Sentinel-2 derived vegetation indices to estimate regional aboveground carbon using RF at 20 m resolution. The result revealed that Sentinel-2, climate variables, and local forest inventories effectively predicted AGB over the whole of the CRS, Nigeria with an RMSE of 40.9 t/ha, R^2 of 0.88, relRMSE of 30 %, and bias of +7.5 t/ha.

More so, the uncertainty and bias values obtained here unlike the relatively high uncertainty of the Saatchi, Baccini, and ESA CCI AGB products reinforces Chave's et al. (2019) call for the establishment of sampling plots across the tropics to improve biomass estimations. REDD+ in Nigeria provided only regional biomass rather than pixel-based spatially resolved biomass and used estimated tree height rather than the actual tree height measurement in the field. The AGB product derived from this study can served as a baseline for REDD+ implementation, boost confidence in investment in tree carbon stocks, increase the conservation value of natural resources, reduce climate change impacts, and enhance the living standards of forest buffer communities.

Authors' contributions: Amuyou Ushuki A. with doctoral supervision from Alexander Antonarakis and Yi Wang, conceptualized the study, led the field work team, analysed the data, and wrote the paper. Technical inputs were offered from Bisong Francis Ebuta and Chima Jude Iheaturu.

CHAPTER THREE

DIGITAL MAPPING OF SOIL ORGANIC CARBON FROM SENTINEL-2 DATA IN THE TROPICAL ECOSYSTEM OF CROSS RIVER STATE, SOUTHEAST-NIGERIA.

ABSTRACT

Digital mapping of Soil organic carbon (SOC) is fundamental in achieving the mandates of the REDD project. As an essential climate variable, SOC is a constituent of the ecological system that supports chemical, biological and physical processes and can be used to infer the quality of the ecosystem. In Nigeria, estimates revealed that 40 percent of greenhouse gas (GHG) emissions comes from the forestry and land use sector. On the strength of this, the quantification of the total SOC stock in CRS Nigeria, will aid in putting in place land use policies that will achieve the twin goal of SOC protection and enhance the living conditions of those whose livelihood is nature dependent. This study used random forest (RF) regression; a machine learning algorithm to identify key predictors of SOC through the integration of field, Sentinel 2A (S2) derived vegetation indices, selected reanalysis climate variables with topography. Three land cover types (LCTs); undisturbed, disturbed and croplands were purposively mapped out, and 72 soil samples collected at soil depth of 20 cm across the study area. 70 % of points data were used to train the RF model while the remaining 30 % was used to validate the predicted SOC model. We estimated 0.147 Pg with mean of 72.94 t/ha of SOC compared to African Soil Information Service (fSIS) 0.124 Pg and Innovative Solution for Digital Agriculture (ISDA) 0.217 Pg of SOC over the area. Model analysis indicates that key predictors (topography, rainfall, maximum air temperature, OSAVI, EVI and NDVI) achieved a high prediction accuracy with lower uncertainty unlike the global and continental SOC maps over the study area (R^2 of 0.82, RMSE of 22.54 (t/ha), and uncertainty of 39.4 % compared to AfSIS; RMSE=35.29 t/ha, uncertainty=61.69 % and iSDA; RMSE= 38.58 t/ha, uncertainty=57.21 %). Our results showed lower uncertainty compared to the coarse spatial resolution maps of AfSIS (30 m) and ISDA (250 m). The final model output was used to spatialize the SOC distribution across the CRS subregion using ArcGIS package. The 20 m resolution SOC map of this study could be referenced in the REDD+ Monitoring, Evaluation and Reporting for equitable distribution of payment for carbon protection benefits and its management.

1.1 **INTRODUTION**

Soil organic carbon (SOC) is a fundamental constituent of the ecological system formed from animals and plants materials and microbial biomass that are at different phases of decomposition (Lal 2018). As a constituent of soil organic matter (Lal 2004; Lal et al. 2018; FAO 2020b), its amount in an ecological system defines the soil quality hence, the destruction of soil organic matter affects SOC and other physicochemical properties of the soil (Deng et al. 2010, Onti and Schulete 2012; Zhang et al. 2015). The destruction of SOM and ultimately SOC leads to the release of carbon dioxide into the atmosphere (McBratney et al. 2014; Zhange et al. 2015; Beveye et al. 2020). It follows that the alteration of natural landscapes by anthropogenic related activities leads to SOM withering which subsequently fastens the rate of soil organic carbon depletion in soil (Lal 2018; IPCC 2000). This accelerated SOM degradation supports the oxidation of carbon dioxide into the atmosphere and changes global carbon cycle and the climate (Pan et al. 2011). The increased quantity of carbon dioxide released into the atmosphere and its impacts have become a subject of concern to stakeholders across the globe (Lal et al. 2015; Termeer et al. 2017; Li et al.2018; Chen et al. 2019; FAO 2019; Wiesmeer et al. 2020). Soil carbon-climate change nexus partly accounts for the increased traction in the call for the quantification of the pattern of SOC concentration under different land cover types (Lal et al. 2015; Poulton et al. 2018; Harvey 2020; Wang et al. 2021). In addition, the Food and Agricultural Organization (2017) Intergovernmental Technical Panel on Soils acknowledged that the loss of SOC is a form of land degradation with cascading and diverse environmental implications.

More so, it is estimated that generally the total organic carbon stocks in soils are 3.3 times of total carbon pool of the atmosphere and 4.5 times the total amount held in floral biomass (Lal 204; Johnson et al. 2014). Sanderman et al. (2017) decomposed the distribution on regional basis by reporting that 30 percent (155 gigatons) of tropical forest carbon is stored in soils. These large quantity of SOC in the terrestrial environment propelled the need to understudy the factors affecting its distribution and management. In addition, the identified roles of soil carbon pool in climate change mitigation, and associated benefits led to the launched of different projects (O'neill et al. 2014). Some of such projects include REDD+, the '4 per 1000' initiative in 2015 under the Lima-Paris Action Plan (LPAP) of the United Nations, the Soils and SOC for climate change mitigation in 2018, and the RECSOIL focused on the recarbonation of soils by the United Nation Framework Convention on Climate Change (FAO 2019; 4/1000 Initiative undated; Rumpel et al. 2018; Amelong et al. 2020). The main goal of these projects is the protection and increase the soil carbon stocks through natural strategies as pathway to climate change mitigation; it is expected that this will maintain the global temperature in line with the Paris Agreement and the enhancement of the living conditions of those who rely largely on natural resources for sustenance (FAO 2020) However, soil carbon sustenance in soils is modulated by complex interwoven environmental covariates (Lal 2018).

The quantity of SOC within any ecological system is influenced by natural and anthropogenic activities (Sokol et al. 2019; Zhang et al. 2020). Environmental variables such as soil type, depth, elevation, slope position, vegetation lifeforms, climates, parent materials and time are fundamental in SOC distribution (McBratney et al. 2003; Huang et al. 2018; Fahimeh et al. 2020). Besides natural factors and processes, management approaches also influence the spatial and temporal distribution patterns of SOC especially in the tropics where the soil is believed to store about 30-60 % of the total carbon (Don et al. 2011; Leib et al 2016). Researchers have established the effects of vegetation (Bhuniah et al. 2017), topographic elements (Tsui et al. 2013), Soil types (Wang et al. 2003), soil properties (Were et al. 2015), climate variables (Luo et al. 2017), land use types (Stumpf et al. 2018) among others on SOC variability and concentrations across varying biomes. In the tropics, it is estimated that land cover conversion account for over 70 % SOC destruction in the region (Lal et al. 2004; Villarino et al. 2019). Similarly, Paustian et al. (2016) analysis shows that within two to eight years of forest cover conversion to farmlands in the tropics, over 40 % of the SOC within such an area is lost. Navarret et al. (2016) reported that 20 years after conversion from forests to pasture, SOC decreased by 20 % while under intense grazing while areas under low grazing regime showed marginal increase in SOC. The sustained and massive deforestation in the tropic's accounts for the yearly release of 0.2 gigaton of carbon into the atmosphere (Mitchell and Maxwell 2010; Beveye et al. 2020). This quantity of carbon emission represents 30 % of global carbon emissions linked to land use/cover change (Beveye et al. 2020). This confirmed the assertion that the quality and quantity of the turn-over rate (that is carbon recycling rate) impacts on volume of carbon emission. It suffices that the balance between the inputs of plant debris or re-carbonization, decomposition and human activities largely determines its status in space and time (Jobbay and Jackson 2000; FAO 2015).

However, tracking SOC status and trends in a spatiotemporal plane in Africa remains a challenge as most parts of the region are still enmeshed in traditional soil survey techniques (McBratney et al. 2003). The traditional technique of land resources mapping is slow, labor intensive, costly, sometimes poor in exactness of soil information, dominantly qualitative and lacks the capacity of continuous spatiotemporal display of soil information (Crowther et al. 2016). These challenges are resolved with digital mapping of soil information aided by traditional soil forming factors and auxiliary environmental data as exemplified in series of African Soil Information Service {(AfSIS) projects (O'Neill 2014; Hengl et al. 2017; Hengl et al. 2021). Digital mapping of soil information in Africa is scant and where available are in course spatial resolutions, limited in sampling density, lacks in cognizance of the variability of environmental covariates or used unreliable legacy soil data for model calibration and validation among others (Sanchez et al. 2009; Hengl et al. 2015; von Fromm et al. 2020). These gaps do not permit optimized SOC management with regards to precision agriculture, balanced ecological interface, and implementation of climate change mitigation policies envisioned by the REDD+ and other clean development mechanisms that enthrone climate change mitigation and foster sustainable livelihoods. Specifically, the recognition of SOC status as an indicator of land quality in Sustainable Development Goals (SDGs) 15.3.1 (UN 2015) makes its quantification with certainty inevitable. More so, the FAO Global Soil Organic Carbon Map (GCSOCMap) strongly advocates for digital mapping of national SOC (Wang et al. 2021), which is within the Monitoring, Reporting and Verification (MRV) framework of the Reducing Emission from Deforestation and forest Degradation (REDD) project (USAID and FCMCs undated).

The complex, diverse processes and spatial variability of ecological variables linked to SOC makes the applications of linear model in their prediction inappropriate as such models may be low in robustness with regards to SOC prediction (Hengl et al. 2015). Digital soil organic carbon prediction with machine learning algorithms is reputed in improving model performance irrespective of the data size and complexity as no assumptions in its distribution is required (Wadoux 2020). For instance, studies of Grimme et al. (2008), Guo et al. (2015), Hengl et al. (2015), Atah et al. (2016), Leib et al. (2016), and Wadoux et al. (2020)

confirmed that random forest in combination with the right predictors can yield a robust model of SOC in areas characterized by complex environmental covariates. More so, the RF regression built digital soil mapping is an apt approach in the regionalization of soil information using scant field samples (Leib et al. 2016). However, the relationship between SOC and sentinel-2 derived vegetation indices and selected soil forming factors based on random forest regression within the framework of REDD+ is rarely reported in the CRS of Nigeria. Extant studies over the area either relied largely on legacy data, use inadequate point data, established bias field sample locations, used course spatial resolution imageries, relied only on conventional survey methods, and or presented fragmented soil information (Akpah et al. 2016; Hengl et al. 2017; 2021). The UNR-EDD+ Nigeria project (2018) did not present any information on SOC because of the lack of data and cost involved in collecting such data (see Page 11 in FREL report). To effectively account and manage SOC of the study area, it is imperative that robust models like random forest regression be used to estimate and present spatially explicit and continuous map of the total soil organic carbon of the state at 20 m resolution. The relevance of this lies on the fact 50 % of rainforest of Nigeria is found in the state (Adeniyi et al. 2016; Carbon Brief 2020). And these tracks of forests are constantly threatened by anthropogenic expansion as trend analysis revealed that in 2005, deforestation rate of Nigeria was 12.5 %, and in CRS it was 5 % between 2010 and 2015 (FAO 2016). Based on these, Nigeria was ranked 17th in global carbon dioxide emission index in 2016 (Carbon Brief 2020). The Federal Government of Nigeria promised to reduce greenhouse gas emissions (GHE) by 20 % in 2030 can partly be achieved through optimized SOC mapping and management by capturing the full variability of soil organic carbon information and its predictive environmental covariates. In view of these, we attempt to provide consistent, spatially explicit, continuous, and reliable soil organic carbon information across the varied agroecological units of CRS, Nigeria taking advantage of the random forest regression based digital mapping suits. The study is focused on (1) Prediction of relevant environmental covariates of soil organic carbon distribution in the CRS (2) validate the soil organic carbon maps of African soil information service of 2017, and 2021 over the CRS (3) To present a digital soil organic carbon map of CRS, Nigeria at 20 m resolution.

2 Materials and methods

2.1 Study area

The study was carried out in CRS of southeast Nigeria. It has a total land size of 20,156 km^2. And is made of varying terrain characteristics with mountains ranges peaking at 1800 m (5, 936 ft.) in the extreme north and 103 m above sea level in the southern part of the State (UN-REDD Nigeria 2018). It is bounded in the north by Benue State, west and the Atlantic Ocean by Akwa Ibom, Ebonyi and Abia states. The CRS contains various land cover types including mangroves, swamps, tropical rainforests which is common in the southern and central parts of the region, montane vegetation and savanna woodlands which are prevalent in the northern portion of the study area (UN-REDD Nigeria 2018). The United State Agency for International Development (USAID) in 2006 accorded two biological hotspots over the Cross River State (USAIDs 2006); the Oban Conservation Park with 1568 identified plant species and the Okwongwu Park with 1545 named plant species (Larsen 1997). Land use and land cover identified in Fon et al. 2014 include mangroves occupying 480 km^2, swamps 520 km^2, tropical rainforest 729 km^2, plantations 460 km^2, other forest 216 km^2 and other land uses 12,300 km^2 (Fon et al. 2014). The CRSFC (2019) has sought to identify undisturbed forests from disturbed forests and cropland, and these are shown in Figure 10.

Rainfall in the Cross River State has two seasons with varying durations in the three agroecological zones: the northern (NAZ), southern (SAZ), and central agroecological zones (CAZ). In the SAZ, the monsoon tropical climate is common, with a mean rainfall of 3500 mm which sometimes reaches 4000 mm around the Oban Massif (Ayoade 2004). The climate features of this area match the Tropical Monsoon (Am) classification scheme of Koppen (Aigbe and Omokhua 2015). The average yearly air temperature of the zone is 27 ^{0}C with little fluctuations throughout the year, and humidity is between 78 % and 91 % (NIMET 2017). Mean annual rainfall in the CAZ vary between 2300 mm to 3000 mm, with mean annual air temperature ranges from 26.9 ^{0}C to 30 ^{0}C and humidity in most parts of the year is about 68 % (Ayoade 2004). In the NAZ, savanna ecosystem is prevalent with a mean annual rainfall of 1120 mm and air temperature range of 15 to 30 ^{0}C (Fon et al. 2014). Two climate seasons is observed in the NAZ; rainy season last for about eight months and the harmattan last for about four months, though these varies yearly. In the montane ecoregion of Obanliku Mountains within the NAZ, climatic conditions are markedly different from other parts of the region. Air temperature have mean annual ranged of 4 ^{o}C to 10 ^{o}C. The terrain is rugged with hilly escarpments, steep valleys and mountains that peaked at about 1800 sq. km. above sea levels with an elongation into the southwest region of Cameroons (Ekwueme 2003).

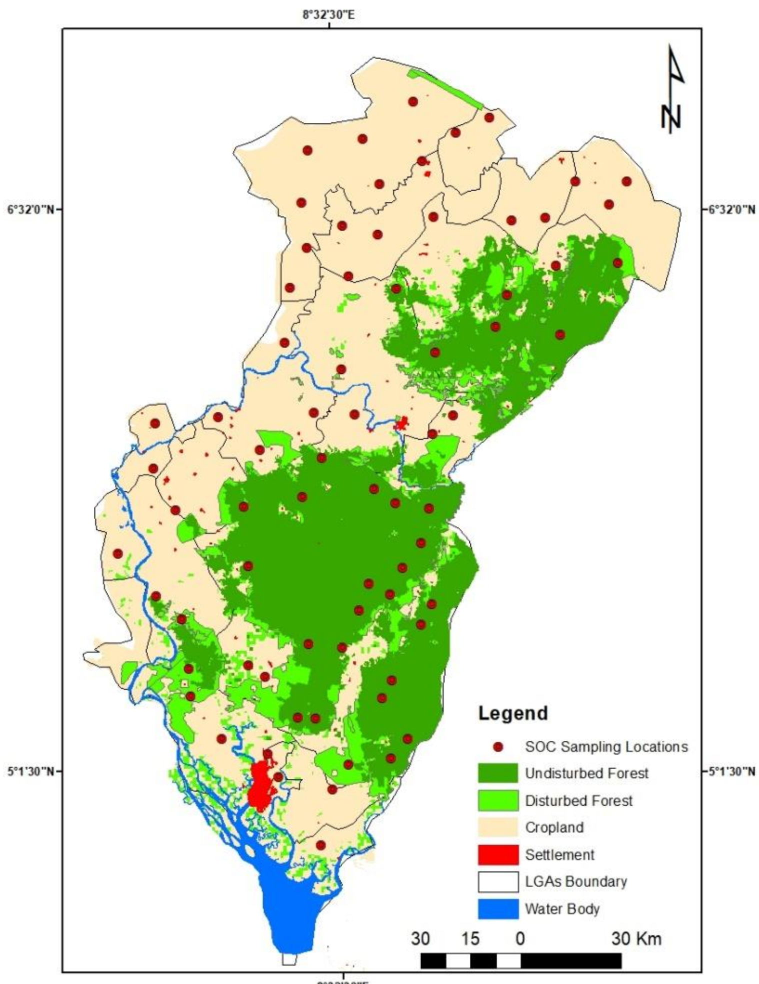


Figure 10: Sample plot locations of soil samples across the CRS.

Source: Cross River State Forestry Commission Forestry Manual (2019).

2.2. Field and laboratory procedures

A land cover map (Figure 10) developed by the Cross River State Forestry Commission (CFSFC 2019) was used in establishing the plots for soil samples collection. Based on the CRSFC map, the study area was classified into; Undisturbed Forest (UF), Disturbed Forest (DF) and croplands and following Gautam and Mandal (2016) delineation. The Undisturbed Forests considered in this study were unbroken stretches of land covered with diverse tree species with little or no human interference in the ecological structure while those with evidence of anthropogenic activities like tree stumps and patches of logging, roads, pronounced footpaths, banana and cocoa farmland patches, farm hots, and any gap in the forest land were considered Disturbed Forests (UNR-EDD Nigeria 2015). It is pertinent to note that the disturbed and undisturbed forest areas considered in this study for measurement are either under the management regime of the Cross River National Park, State Government Reserves or Community Forest (Enuoh and Bisong 2015; Enuogh and Ogogo 2018). On the other hand, the crop fields or agroforestry areas are woodlands with different species of crops cultivated in them at the same time.

Overall, 29, 18 and 25 samples were purposively distributed across the CRS in undisturbed, disturbed and cropland areas respectively. The locations of each plot in the field were determined using the Garmin etrex GPS (Genova and Barton 2004). Access into each of the plot was made possible through park rangers or local community (UN-REDD-Nigeria 2015). Alternative plots were laid when it became impossible to access the predetermined plot, a similar in practice by REDD+ (UN-REDD Nigeria 2017). The field study commenced in the month of March and ended in November 2020.

Soil samples were collected within each 20 m plot. A soil screw auger of 30 cm long and 3.5 cm in diameter was used to collect composite soil samples along the diagonal of each 20 m X 20 m plot for the first 20 cm of depth of the mineral soil layer. The spacing of soil samples was 6.7, 6.7 and 6.6 meters along the diagonal of each plot with a total of 3 soil samples collected within each plot. Each sample was then labelled, parcelled, and transported safely to the laboratory for analysis for organic carbon using the modified

Walkley and Black wet oxidation method (Walkley and Black 1934), where organic carbon (OC) was calculated as:

$$OC(\%) = \frac{0.003\text{g}\ x\ \text{N}\ x\ 10\text{mL}\ x\left(1-\frac{T}{S}\right)\ x\ 100}{ODW}$$

(6)

Where N is the normality of the potassium dichromate ($K_2Cr_2O_7$) solution, T is the volume of iron sulphate ($FeSO_4$) used in the sample titration (in mL), S is the volume of iron sulphate used in the blank titration (in mL), and ODW is the Oven dry sample weight in grams. One sample at the center of each 20 m plot was collected with a cylindrical core to determine the bulk density (BD) calculated as:

$$BD(g/cm^3) = Oven\ dry\ weight\ of\ mineral\ soil/volume\ of\ mineral\ soil$$

(7)

Soil organic carbon (SOC) in t/ha^{-1} at plot location x, is then calculated as:

$$SOC_x = OC_x * BD_x * Depth_x * 100$$

(8)

Where *Depth* is the depth to which samples were collected in sample plot, and the 100 multiplier is the conversion from gC cm^{-2} to t/ha^{-1}.

2.3 Regional predictor layers

Several variables are first extracted to use as predictor variables in spatially extrapolating soil organic carbon to the full CRS. Sentinel 2 (S2) is a wide-swath, high resolution, multispectral imager made up of Sentinel-2A and Sentinel-2B. Sentinel-2A was launched in June 2015 and Sentinel-2B = was launched in 2017. Sentinel-2 is made up of 13 spectral bands located from the visible to the shortwave infrared with spatial resolutions of 10 m (red, green, blue, NIR), 20 m (red edge and short-wave infrared bands) and 60 m (atmospheric bands). In this study all bands except the 60 m atmospheric bands were included in the analysis. Relevant digital pre-processing techniques like atmospheric modification, orthorectification and spatialization on the global reference system UTM/WGS 84 datum on the SEN2COR tools of SNAP (Sentinel Application Platform) toolbox was carried out (Roteta E, Bastarrika 2019). Top-of-atmosphere (TOA) reflectance was converted to top-of-canopy (TOC) reflectance (Drusch et al. 2012). The images were sub-set and mosaicked to produce a single image for the study area (Castillo et al. 2017). The images used in the study were downloaded on the last month (November 2019) of field collection, limited the influence of cloud cover.

Vegetation indices, with influences of soil as well as vegetation reflectance, were extracted from Sentinel-2 as predictor variables extrapolating soil organic carbon across the CRS. These included the Optimized Soil Adjusted Vegetation Index (OSAVI) from Baret et al. (1993), the Modified Soil Adjusted Vegetation Index (MSAVI) from Qi et al. (1994), the Atmospherically Resistance Vegetation Index (ARVI) (Kaufman and Tanre 1992), the Modified Red Edge Normalized Difference Vegetation Index (MRENDVI) based (Datt 1999), the Red Edge Normalized Difference Vegetation Index (RENDVI) from Giytelson and Merzhynak (1992), modified red edge simple ratio (Gara et al.; Kross et al. 2015; Sharma et al. 2015), as well as the Normalized Difference Vegetation Index (NDVI) and Enhance Vegetation Index (EVI2). In addition, topography also has an important influence in soil organic carbon (von Fromm et al. 2021), hence the 30 m Digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) was used in the study (Castillo et al. 2017).

The ERA5 and CHIRPS gridded rainfall and air temperature time-series data for the last 35 years per pixel were used to assess climate variability over the study area. All images used in this study were resampled to 20 m resolution using the nearest neighbourhood method. This resampling method was used because it is known to be computationally efficient and often maintain the image pixel values (Roy et al. 2016). The resampling was required to ensure plot size matches with pixel size at point of SOC extraction.

2.4 Deriving Regional Soil Organic Carbon

RF is used in this study to spatially extrapolate the plot-level estimates of soil organic carbon to the whole of the CRS. RF is a supervised machine learning algorithm that uses several decision trees on subsets of predictor datasets (R Development Core Team 2016). It is characterized by a tree-like sequence of decisions nodes, that splits into different branches continuously until it reaches the tree leaf. At this point, the algorithm has reached the prediction of a decision (Briedman 2001). Some of the advantages of RF over traditional statistical models include its ability to handle many explanatory variables at a time, it can manipulate very complex interwoven sets of variables, it is not affected by highly covariate variables, hence do not require data transformation, and most importantly reduces overfitting with the right number of subset data (Pandaran et al. 2020). The optimal features for a robust model can be reached through the process of feature selection. Random Forest has in-built mechanism that checks for important variables to the model (Botchkarey 2018; Franky 2020). Feature selection provides an opportunity for the less relevant features to be removed, thereby enhancing the model performance and generalization of the result (Fox et al. 2020).

In this study, the recursive feature selection method was used (Venter et al. 2021) in selecting the relevant environmental variables in soil organic carbon prediction. This aided the analysis in reduction of the computational time, improvement in model performance with the right subset combinations, reduces overfitting, increases the ease of data interpretation among others (Khaledian and Miller 2020). The random forest was operationalized by the optimization of the number of trees (Ntree). The RF has a default value of 500, while the number of variables to use at each split (Mtry; p/3) is determined by dividing, the number observation to select at each iteration, and the total of number of experiments to carry out at each terminal node (Cawley and Talbot 2010). These variables can be manipulated until high model accuracy is reached (Venter et al. 2021). The important features were displayed as increasing node purity. This is calculated as the variance in mean square error (MSE) before and after variable split that is, it depicts the variance of the estimator (Briedman 2001; Francky 2020). Of the 72 sample plots determining SOC, 70 % were used in training the data (in-bag samples), and 30 % of the data (out-of-bag sample-OOB) were used to test the resulting Random Forest models. The number of trees was set to 400 and in each iteration, the number of variables used at each node (mtry) was set to the square root of the numbers of covariates (Segal 2004).

Four sets of experiments were conducted to evaluate the best environmental covariates in predicting SOC using RF. The first RF model (Model 1) predicts SOC with climate and topography predictor variables only, i.e. mean annual maximum and minimum temperature, rainfall, and topography. The second model (Model 2) used vegetation indices derived from Sentinel-2A in predicting SOC including NDVI, EVI, OSAVI, ARVI, MSAVI, IRECI, MRESR, RENDVI, and MRENDVI. And the third model (Model 3) integrated Model 1 (climate and topography covariates) and Model 2 (spectral indices covariate) in predicting SOC (Hengl et al. 2021). Model 4 reduces all input variables from Model 3 to only important variables.

2.5. Model evaluation and Uncertainty analysis

The prediction accuracy of the RF model was assessed using testing and training field plots. The performance of the four RF models described above are assessed using the 50 training forest inventory plots evaluating the coefficient of determination (R^2) and root mean square error (RMSE) of each model. The best model with the lowest RMSE is then chosen to create regional soil organic carbon over the whole CRS. This best model is then evaluated using the 22 testing plots.

The digital mapping of SOC requires the use of different data types and processes such as point data, empirical prediction models, and a set of environmental layers (Uusitalo et al. 2015). These processes are often associated with uncertainties which are present in the independent model residuals and because these uncertainties may be large and varied, their estimation is as important in the landscape management decision process as the predicted SOC themselves. The empirical prediction model used in this study (i.e. the RF) is a machine learning algorithm which does not need direct estimation of the prediction error unlike the traditional regression models (Coulston et al. 2016). Based on this, we use the decision support function in R package to run the Monte Carlo simulation in estimating the uncertainties in model outputs of soil organic carbon prediction. The principle of the Monte Carlo model is the repeated simulation of the occurrence of a random event and the subsequent estimation of its probability features based on the frequency of the said random event (Xiang et al. 2021). The repeated simulation of the Monte Carlo samples (in our case, 600 iterations), the probability distribution of soil organic carbon estimates, and errors are obtained from the series of iterations which resulted in a stable and reliable quantification of SOC and the error map (Tang et al. 2020).

2.6. Assessment of available regional SOC products

Two existing SOC products available over the CRS were assessed using the SOC derived from the sample plots collected in this study. The data sources are the iSDA-innovative Solutions for Decision Agriculture (Hengl et al. 2021) and the African Soil Information Service (AfSIS) (Hengl et al. 2017). The iSDA project was launched in 2008 with the goal of providing digital tools to support African Soil Information System (AfSIS). The project aimed to support the agricultural development, environmental, nutritional, and investment agendas of the continent. To achieve the aims of these thematic sectors, iSDA used the services of experts to gather primary soil parameters of the continent and deliver the products in digital formats to stakeholders (Hengl et al. 2021). Because of these, 150,000 geo-referenced soil metadata scattered over the continent in combination with earth observation data were used in predicting relevant soil parameters. In Nigeria, a total 1251 profiles were georeferenced and added to the iSDA soil database. Soil parameters were predicted at 0, 20 and 50 cm of depth. The method involved the use of 2-scale 3D ensemble machine learning workflow implemented in Machine Learning in R package. The layers used as covariates were 250m resolutions MODIS EVI and land surface temperature, Sentinel-2 SWIR and Landsat NIR, and 30m resolution DEM from SRTM. A fundamental concern over the integrity of the SOC data used by iSDA is the lack of uniformity in field and laboratory protocol of 150,000 data point used.

For the AfSIS product, 59,000 georeferenced soil point data covering Sub Saharan Africa was gathered between 2008 and 2016. 18000 soil samples were obtained from 60 sites at 10 by 10 km at depth of 0-30 cm. Other samples were collected from various governments, institutions, NGOs, and published sources (Hengl et al. 2017: 79). 40 % of the data used in this study were collected between 1980 and 2008 while the other 60 percent were obtained between 2008 and 2016. The samples were examined for 15 soil nutrients including organic carbon and total nitrogen which were analysed using wet chemistry: Mehlick-3 and thermal oxidation. Point datasets of SOC data were integrated with spatial covariates including DEM at 250 m resolution, MODIS EVI at 250 m, land surface temperature at 1 km resolution, monthly precipitation from CHELSA at 1km resolution, global cloud dynamics layers at 1 km resolution, global land cover map at 300 m resolution among others (see Hengl et al. 2017:81-83) to produce spatial distribution of the various soil nutrients using two ensemble methods: random forest and Gradient Boosting algorithms. In addition, multivariate and clustering statistical model was used to established cross correlation and groupings in the values. The model was able to explain 66 % of the variation in the distribution of SOC in the region.

The iSDA and AfSIS Soil Grid maps were downloaded, the study area cropped, and projection parameters selected to aligned with the coordinate system of the study area (UTM/WGS 84, 32N Minna datum) on the SEN2COR tools of SNAP (Sentinel Application Platform) toolbox. To ensure effective comparison of the different products with our 20 m resolution SOC map, each of the products' native resolution was maintained (Santoro and Cartus 2021). The sampling locations of this study were then overlaid independently on the subset SOC maps of the two products under review, and spatial analysis tools manipulated to extract values to point.

3 Results and analysis

3.1 Field Measured Soil Organic Carbon

Soil Organic Carbon estimated within 20 cm of depth at the 72 field plots throughout the CRS (Table 5) ranged from 0.08 to 230 t/ha with a mean SOC across all sites of 72.94 t/ha. Furthermore, in the 29 undisturbed forest plots the average SOC was 112.12 t/ha, in the 18 disturbed forest plots the average SOC was 94.97 t/ha, and in the mixed woodland and cropland plots the average SOC was 15.49 t/ha. This means that the undisturbed forests contained around 14 % more SOC than the disturbed forests, and around 6.7 times more SOC than the cropland sites.

Table 5: Descriptive statistics of SOC (t/ha) collected over the Cross River State, Nigeria.

Landcover	N0 Plots	Minimum	Maximum	Mean	St. Dev	CV (%)
Undisturbed	29	10.0	230	112.12	53.26	47.5
Disturbed	18	10.0	187.0	94.97	58.08	61.15
Crop field	25	0.08	56.0	15.49	13.63	87.9
All plots	72	0.08	230	57.218	62.36	108.9

3.2. Soil Organic Carbon prediction from environmental covariates

The resulting training accuracy of the four Random Forest models with different predictor variables is shown in Table 6. The RF configurations with climate/topography predictors or spectral indices (Model 1 and 2 respectively) perform at a similar level with training accuracies of R^2 of 0.70, 0.67, and RMSEs of 34.01, 36.9 and 36.9 t/ha respectively. Including all the 13 variables improves the accuracy of the RF prediction for Model 3 to an R^2 of 0.70 and RMSE of 42.22 t/ha. Model 4 seeks to reduce unimportant variables to improve the robustness of the model and reduce multicollinearity, it is imperative that outliers and redundant variables be removed (Kumar et al. 2016). Figure 11 shows the ranking of important features in the prediction of soil organic carbon in the CRS of Nigeria considering topography, climate, and vegetation indices. Using the mean increasing node purity, Figure 11 indicates that OSAVI was the most important variable in predicting SOC with the highest node purity. The other five variables used in Model 4 to predict SOC are taken to be mean annual maximum air temperature, rainfall, topography, enhance vegetation index, and normalized difference vegetation index. The use of these variables only in predicting SOC improved the model accuracy to an R^2 of 0.73 and RMSE of 34.31 t/ha (Table 6).

Table 6: SOC training accuracy prediction using Random Forest predicted using four models.

Model	R2	RMSE (t/ha)	MAE
Model 1 (climate/topography)	0.70	34.01	28.41
Model 2 (spectral indices)	0.67	36.9	31.63
Model 3 (model 1 + model 2)	0.70	42.22	36.34
Model 4 (important features)	0.73	34.31	27.23

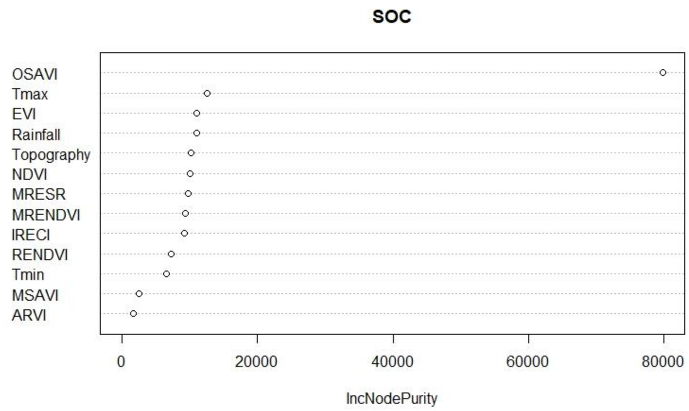


Figure 11: All environmental covariates (topography, climate, and vegetation index variables) used to predict SOC using Random Forest, ranked from highest to lowest node purity. Model 3 configuration uses all these 13 covariates in predicting SOC, while Model 4 chooses the first five most important covariates.

Model 4 (Table 6) was chosen as the model to predict regional SOC over the CRS due to its higher coefficient of determination, lower MAE and lower RMSE. This model was also chosen as the feature selection methods can reduce overfitting and multicollinearity in predicting SOC. This model is then used to test the accuracy of the prediction using the 22 independent testing forest inventory plots. The resulting testing accuracy is given in Figure 12 as a scatterplot of observed vs predicted SOC values. This SOC prediction has an RMSE of 22.5 t/ha, a bias of +3.7 t/ha, and an uncertainty of 39.4 %. This shows a small overestimation of RF predicted SOC values. Separating this into 50 t/ha bins, SOC <50 t/ha is predicted with an RMSE of 10.9 t/ha (62.2 % relRMSE / -0.3 t/ha bias), SOC between 50-100 t/ha is predicted with an RMSE of 24 t/ha (39.1 % relRMSE / +7.7 t/ha bias), and SOC > 100 t/ha is predicted with an RMSE of 34.5 t/ha (26.4 % relRMSE / +6.2 t/ha bias).

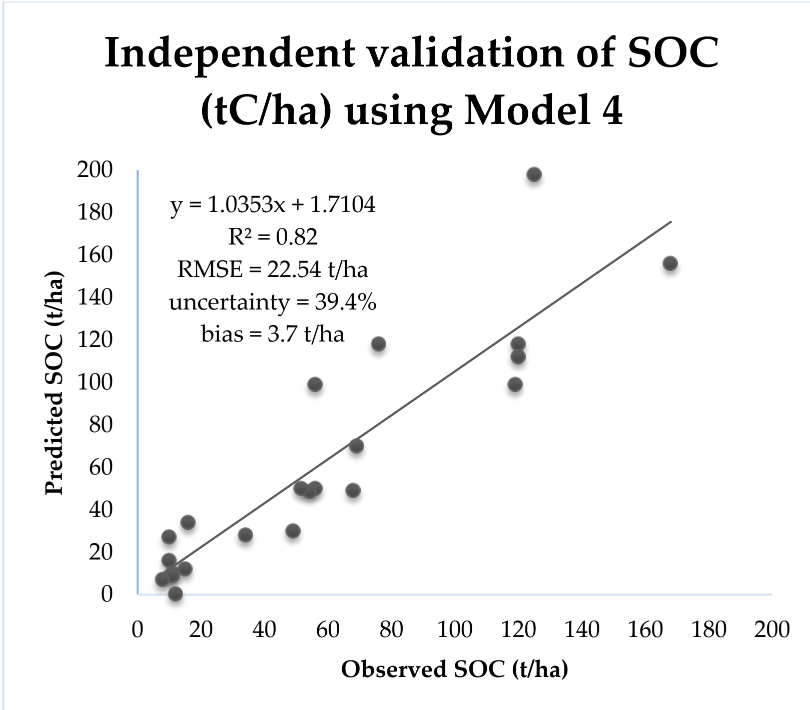


Figure 12: Evaluation of the Random Forest predicted SOC over the 22 testing forest inventory plots using Model 4.

The spatial distribution of predicted SOC with associated uncertainty over the CRS are presented in Figure 13. Over the CRS, high SOC > 100 t/ha is concentrated in three areas which are largely protected forest areas: the northeast of the CRS, in and around the Okwango and Afi Forest of the CRS national park, the central areas around the Oban Hills also a division of the CRS national park, and the coastal areas south of Calabar. Low SOC < 50 t/ha is predicted in the northwest extreme of the state occupied by dryer savannas. From the SOC distribution in Figure 13, high SOC correspond with forested areas and conversely, areas with low SOC concentration aligns with areas with sparely distributed forest.

3.3 Comparison of SOC prediction of this study with AfSIS and iSDA SOC maps

The SOC maps of AfSIS and iSDA (Figure 14) showed significant spatial variations between them and when compared to the SOC map of this study. Overall, the iSDA map overestimated SOC while AfSIS map underestimated the SOC of the study area when compared with the estimates of this study. Spatially, the patterns of large SOC in central and northeastern areas are consistent in all three maps, with values reaching 120-150 t/ha.

In fact, many of these areas with high SOC also are mountainous regions including the Oban hills in the center and the Sankwala Mountain range (Okwango Division of the CRS and Afi Forest) in the Northeast. The iSDA spatial patterns are closer to this study than the AfSIS in that there are low SOC regions < 50 t/ha in the northwest, high SOC regions in the central and northeast as well as high SOC on the central eastern areas around the Cameroon boarder and in the far south of the state. The AfSIS map does not represent the lower SOC areas in the northwest, and the SOC is more heterogeneous than the other two maps.

To evaluate the level of accuracy of the two SOC products, we compared the AfSIS and iSDA products against the 22 testing forest inventory plots with results given in Table 7. From table 7, the total SOC values of the AfSIS and iSDA maps are 0.217 Pg and 0.124 Pg unlike our study where the total and mean SOC recorded for the study is 0.147 Pg and 72.94 respectively. The AfSIS and iSDA products performed worse in estimating SOC over the CRS with RMSEs of 35.29 t/ha and 38.58 t/ha t/a, RelMSE of 61.69 % and 67.34 %, and bias of 8.73 t/ha and 10.14 t/ha respectively.

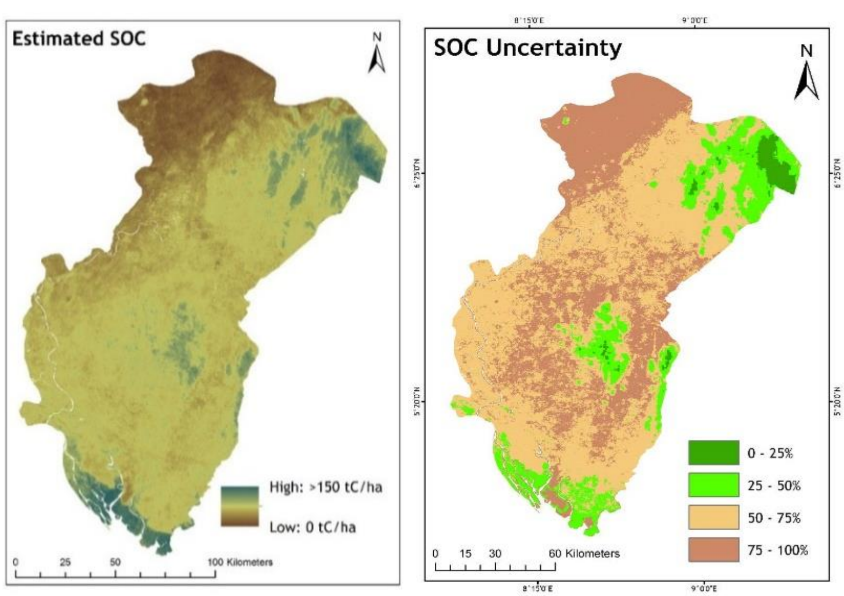


Figure 13: Estimated 20 m resolution map of Soil Organic Carbon for the Cross River State (left-panel), with the resulting uncertainty in SOC incorporating prediction, measurement, and allometry errors (right-panel).

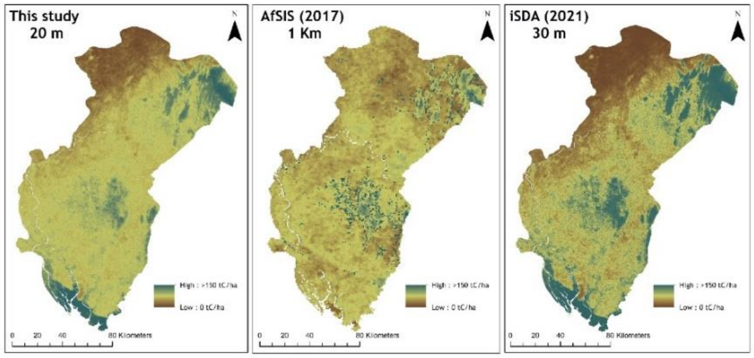


Figure 14: Soil Organic Carbon products over the Cross River State of this current study (left panel) and the AfSIS (middle panel), and iSDA (right panel) at their respective resolutions.

Table 7: SOC predicted over the Cross River State using the current study and the AfSIS and iSDA products, with accuracy metrics

Parameters	This study	AfSIS	iSDA
Absolute mean	72.94	61.8	108
RMSE (t/ha)	22.5	35.29	38.58
MAE (t/ha)	14.45	24.55	31.32
RelMSE (%)	39.40	61.69	67.34
Bias (t/ha)	+3.73	8.73	10.14
Total SOC stocks Peta-gram (Pg).	0.147	0.124	0.217

4.1 **Discussion**

Spatially referenced soils information of African ecological zones is required to understand land-atmosphere interface and feedbacks and plan for the effective implementation of the REDD+ project. The extensive utilization of refined optical sensors in soil resources assessment and planning in European countries is a trajectory that has not been fully adopted in Africa. The density of soil maps in European countries outstrips those of Africa despite the prevalence of weathered and poor nutrient soils in the later (FAO 2019). The high human population and the prevalence of unsustainable land use practices and other multiple stressors further compounds African vulnerability to climate change and other natural extremes (United Nations undated). In this study, different parameters combinations derived from sentinel-2 MSI, and gridded climate and topographic data were simulated to test their capability in estimating soil organic carbon with random forest regression algorithm and the results were compared to the FAO and AfSIS SOC maps over the CRS, Nigeria.

Soils vary. This study used the SCORPAN model of McBratney et al. (2003) derived from modified Jenney's (1994) famous factors of soil formation in predicting and accounting for SOC variability in the Cross River State, Nigeria. Using selected factors of soil formation as predictors, the random forest regression model yielded a relatively high model accuracy with a coefficient of determination of 0.70 (with a RMSE of 34.01 t/ha). This implies that 70 % of the variation in soil organic carbon in the region was accounted for by the selected soil forming factors. Further analysis of the predictive factors revealed that rainfall, mean annual minimum air temperature, vegetation, and topography (Figure 11) were the major factors of soil organic carbon prediction in the region. This corroborate earlier studies where it was reported that SOC stocks variability in tropical and subtropical regions correspond with vegetation patterns (Lal et al. 2015; Kumar et al. 2016). These authors further argued that wet areas on a broad scale often have more SOC stocks than arid or semiarid areas. More so, Kpade (2018) also carried out a similar study in the west African nation of Burkina Faso and the result indicated elevation, temperature, and precipitation were the leading predictors of SOC in the study area.

Similarly, Ramifehiarivo et al. (2016) hyperspectral estimation of SOC tropical forest of Madagascar identified mean annual rainfall, elevation and NDVI as main variables of its prediction. Recent study by Hengl et al. (2021) also reported that SOC distribution in Africa is sensitive to vegetation, land cover types and climate conditions. The identification of climatic, and vegetation parameters as important features in SOC prediction in Cross River (Figure 11) supports an earlier assertion of Vagen and Winowieki (2013) who submitted that lower air temperature, elevation, and relatively high rainfall helps in SOM accumulation and decomposition in the tropics. The presence of dense vegetation helps in soil nutrient accretion and protection. This confirms that the concentration and variability of SOC in Cross River State like other parts of the tropics is attributed to a web of interrelated environmental covariates and the dominant anthropogenic elements. More so, elsewhere within the tropics, it was revealed that topography is the leading variable of SOC prediction

(Grimme et al. 2008). This also agrees with the findings of Were et al. (2015) who listed satellite bands, silt content and elevation as prominent features of SOC prediction in the tropics. Despite the seeming disparity in the main features of SOC prediction in the tropics, the generality of the different parameters identified in this study and those of previous analysis is informative as stakeholders can optimized in the management of these features to enhance carbon sequestration potentials of the region.

The fine spatial and spectral resolutions of S2 couple with its red edge portion unlike other optical sensors is known to optimally map large areas in real time with improve accuracy (Cho et al. 2012). In this study, selected vegetation indices were used to predict the spatial distributions of soil organic carbon as defined by the phenotypic characteristics of the soil (Zhang et al. 2019). The analysis of the empirical relationships between SOC and remotely sensed reflectance data derived from S2 revealed that the model was able to account for 67 % (Table 7) of the variation in SOC in the study area. This result further confirmed that S2 derived vegetation indices can be used as proxies of environmental variables in SOC prediction (Kumar et al. 2016). The results also support the assertion that chlorophyl content of terrestrial surfaces will respond to the same environmental signatures as SOC (Nocita et al. 2013). This research finding is in line with earlier studies (see Kumar et al. 2016; Zhang et al. 2019; Hengl et al. 2021) where it was established that S2 has the potential of accurate estimation of soil organic carbon in tropical climates.

Similarly, studies on the potential of S2 sensors in predicting SOC in other parts of the world show commendable results. For instance, Gholizade et al. (2018) examined the possibility of using S2 sensor in predicting selected soil parameter in the Czech Republic. The result revealed that S2 bands B4, B5, B11, and 12 showed a strong correlation with SOC. More so, In Heihe River Basin of northwestern China, Zhou et al. (2020) also confirmed that S2 derived covariates in combination with rainfall, air temperature and topographic elements explained 75 % of the variation of SOC in the region. The affinity of SOC to this VIs may be attributed to the hue of the soil and the absorptive nature of the incident surfaces around VIs and SWIR spectral regions (Viscarra Rossel et al. 2018). These studies corroborate the fact that the 20 m resolution soil organic carbon map and the low prediction uncertainty reported in our study is of fine scale that provide detailed distribution of SOC in the region. This result is better than extant maps over the region (Figure 14) where largescale SOC maps assume homogeneity in landscape features in neglects of the influence of on-site environmental factors that are heterogenous even at farm-scale (Willaart et al. 2016).

However, when all the variables where ordered based on their relevance in predicting SOC in the region (Figure 11), OSAVI, mean annual air temperature, rainfall, topography, and NDVI were the topmost important environmental covariates with model accuracy of 73 % and RMSE of 34.31 t/ha. This also confirms the results of a recent study in Africa by Hengl et al. (2021) where S2 sensor derived vegetation indices combined with parent materials, landform parameters and climatic variables predicted selected soil properties with SOC prediction resulting in goodness of fit in the model. More so, elsewhere in the tropics, it was advised that because of the potential intrusion of photosynthetic and non-photosynthetic vegetation cover, difference in soil moisture or surface roughness in signal quality when estimating soil organic carbon, there is need to integrate spectral-based signatures with the soil forming factors in model training (Hengl et al. 2017). Similarly, the model recorded improvement when only top five relevant predictive parameters were used. In brevity, vegetation, and climatic elements exact moderating role on the variability of SOC in the study area.

4.2 **Conclusion**

The study has established that vegetation, climatic parameters, and topography have significant control on the variability and concentration of soil organic carbon in the CRS, Nigeria. Specifically, it was observed that forested landscape contained more SOC than disturbed forest and disturbed forest has more SOC than cultivated fields. The result of the research is in concordance with extant studies on environmental predictors of SOC in tropical African countries with similar ecological settings. More so, the lower prediction uncertainty recorded in our study unlike the results of the AfSIS and iSDA maps over the region further reinforces the need for the establishment of more reference data for model calibration and validation in regional studies of this type. In addition, the transformation of cultivated fields from carbon source to carbon sink while maintaining the status of intact forest will aid boosting the concentration of SOC in the area.

However, if the heightened extractive activities in the protected areas continuous at the current rate, then the level of decomposition will exceed carbon inputs to the soil, and this will not benefit humanity especially in this part of the world where vulnerability levels remain frightening. The highlight of this study is the need for the optimal management of the identified important features of SOC prediction as packaged in the 20m SOC map of the area to meet carbon stocks additionality precepts of REDD+ and subsequently take full advantages of the carbon offset opportunities. However, more study is required to track and understand land use/cover change effects on the distribution of SOC in CRS, Nigeria.

Authors' contributions: Amuyou Ushuki A. with doctoral supervision from Alexander Antonarakis and Yi Wang, conceptualized the study, led the field work team, analysed the data, and wrote the paper. Technical inputs were offered from Bisong Francis Ebuta and Chima Jude Iheaturu.

CHAPTER FOUR

LIVELIHOOD IMPACTS OF FOREST CARBON PROTECTION IN THE CONTEXT OF REDD+ IN CROSS RIVER STATE, SOUTHEAST NIGERIA. *

***This chapter is based on:**

Amuyou, U.A.; Wang, Y.; Ebuta, B.F. & Antonarakis, A.S. Livelihood impacts of forest carbon protection in the context of redd+ in Cross River State, southeast Nigeria. *Sustainability* **2021**, *13*(9), 5081; **https://doi.org/10.3390/su13095081**

ABSTRACT

The rate of landcover change linked to deforestation and forest degradation in tropical environments has continued to surge despite series of forest governance policy instruments over the years. These informed the launch of one of the most important international policies called Reducing Emission from Deforestation and Forest Degradation Plus (REDD+) to combat forest destruction. REDD+ assumes that communities will have increased access to natural capital which will enhance their livelihood portfolio and mitigate the effects of climate variability and change across biomes. The aim of this study is to ascertain the livelihoods impacts of forest carbon protection within the context of REDD+ in Cross River State, Nigeria. Six forest communities were chosen across three agroecological zones of the State. Anchored on the Sustainable Livelihood Framework, a set of questionnaires were administered to randomly picked households. The results indicate that more than half of the respondents aligned with financial payment and more natural resources as the perceived benefits of carbon protection. More so, a multinomial logistic regression showed that income was the main factor that influenced respondent's support for forest carbon protection. Analysis of income trends from the 'big seven' non-timber forest resources in the region showed increase in Gnetum africanum, Bushmeat, Irvingia gabonensis, Garcinia kola, while carpolobia spp., Randia and rattan cane revealed declining income since inception of REDD+. The recorded increase in household income was attributed to a ban in logging. It is recommended that the forest communities should be more heavily involved in the subsequent phases of the project implementation to avoid carbon leakages.

Keywords: *Cross River; forest carbon; livelihood; REDD+; southeast Nigeria*

1.1 **Introduction**

The Food and Agricultural Organization of the United Nation (FAO 2020) assessment report showed that 30 % of world land is covered with forest while tropical and subtropical zones have 42 % of their land under open and closed forest. In Africa, dry forest occupies 42 % of its forested area, moist forest 33 % and rainforest across 25 % of the land (Bodart et al. 2013; Enuoh and Bisong 2015). Over the years, anthropogenic activities have and continue to attenuate African forest extent. The FAO (2020) submitted that 3.9 million hectares of African forest was destroyed between 2010 and 2020 (compared to 3.4 million hectares between 2000 and 2010). It is also on record that between 1990 and 2015, African forest cover reduced by 3.5% (FA0 2015). In 2014, it was estimated that about 3148 flora species of Africa were at the verge of extinction (UNEP-WCMC 2016). Forest Resources Assessment report (FAO 2020) indicated that Africa lost 3.3 million ha and 3.4 million ha of her forest cover from 1990 to 2000 and 2000 to 2010, respectively. Most of these forest cover destructions are taking place in west Africa where it is estimated that 90 % of the regions natural forest has been cleared (Enuoh and Bisong 20015; Steve 2019; Krause et al. 2019). Deforestation in Nigeria has remained steadfast compared to other west African countries. The FAO (2015) indicates that tree cover of the country in 1990, 2000, 2005 and 2010 was estimated to cover 17,234, 13,137, 11,089, and 9041 ha, respectively. In 2005, the Nigerian rate of deforestation of 12.5 % was the highest in the world (FAO 2010). Nigeria is among the leading emitters of carbon dioxide in the world, ranked 17th in global greenhouse emission profile (Carbon Brief 2020). It is believed 87 % of CO_2 emissions in Nigeria comes from deforestation (Odjogo 2010; Inyang and Esohe 2014). About 50 % of Nigeria's remaining rainforest is in the CRS. However, deforestation accounted for 5% of forest loss in the State between 2010 and 2015 (FAO 2016), which was significantly ahead of the annual rate of forest cover loss of 1.32 % for the region between 1991 and 2001 (Bisong 2007). The increasing trend in the rate of forest loss in the region is spurred by population growth, agricultural expansion, rapid urbanization and most recently by foreign direct investment economies (Enuoh and Bisong 2015; Moon et al. 2018; Alister 2018).

Drastic decreases in global as well as African tropical forest and their effects on carbon emissions resulted in the forest governance scheme called Reducing Emission from Deforestation and Forest Degradation (REDD) in 2007 (Agrawal et al. 2011). REDD, as conceived by the Coalition of Rainforest Nations, led then by Papua New Guinea at the 11th Conferences of Parties (COP11) of the United Nations Framework Convention on Climate Change (UNFCCC) was created to reduce GHG emissions from forest cover loss. However, at the COP13 meeting held in Bali, Indonesia, the forest governance program was renamed REDD+. REDD+ is a unique conservation instrument that is meant to mitigate global climate change and enhance the living standards of forest-dwelling communities (Irawan et al. 2013). REDD+ was projected to reduce global greenhouse gases from land cover related anthropogenic activities in 2030 by 17 and 25 % (IPCC 2007; Stern 2007). However, the mode of its implementation will determine the outcomes particularly in Nigeria where there are multifaceted and intertwined competing realities; poverty, a surging population, weak institutions, corruption, widespread legacies of natural resource cursed nations (Amuyou et al. 2016).

CRS is a pilot state for the implementation of the UNREDD+ project in Nigeria due to its sizeable tropical forest cover. Nigeria began the process of securing approval for the implementation of REDD+ project in 2008. The paperwork with the UNREDD+ was concluded in 2010 (Krause et al. 2019). It should be noted that the CRS before the advent of UN-REDD+ was deeply involved in conservation projects and policies. The presence of many local and international consortiums of biodiversity conservation like CIDA, ODA, United Purpose, WWF, NGOOCE among others is a testament to the value attached to protecting the environment of the region. In addition to securing the remaining tropical forest in Nigeria, Adeniyi et al. (2017) believed the dwindling revenue base of the CRS was another motivation that propelled the need to key into REDD+. As a sign of its readiness, the government under Senator Liyel Imoke declared a halt on wood harvesting especially by multinational companies operating in the State (e.g., WEMCO) in 2008 (Enuoh and Bisong 2015). The suspension of logging of any form particularly as a source of revenue to the government and the public has remained effective to this day. In addition to the highlighted factors, the government of the Federal Republic of Nigeria (FRN), was motivated to kick-start REDD+ in CRS on the understanding that the structures on ground, lessons learnt from government and non-government agencies in the State (CRS), will be useful in the subsequent implementations of REDD+ in other regions of the country (UNDP 2017). To understand how REDD+ has fared in Cross River State, it is imperative that its impacts on the poor be explained. Sustainable Livelihood Framework provides a yardstick for assessing the effects of REDD+ on the poor.

1.2 The Sustainable Livelihood Framework (SLF)

Sustainable Livelihood Framework (SLF) according to United Nation Development Programme (Chambers and Conway 1992) involves all the skills, resources and practices used by individuals or a community to earn a living at any time. A key tenet of sustainable rural development is the need for development interventions to create an enabling environment that will embolden the capacity of intended local beneficiaries to always sustained project outcomes (Chambers and Conway 1992). Chambers and Conway (1992) further opined that the SLF is used to sustain livelihoods under varying scenarios; periods of stability, stress and shock and maintaining its natural potentials. In the last four decades, the precepts of SLF have been applied in analyzing the livelihood impacts of forest governance interventions in the tropics (Mucahid and Lawal 2016). The framework identifies five types of livelihood capital; physical, social, financial, human, and natural, needed to better the wellbeing of mankind (Chambers and Conway 1992; Agrawal et al. 2014). However, Odero (2006) had argued for the inclusion of 'information' among the assets. These livelihood assets are influenced by transformative dynamics expressed in the laws, policies, cultures, and institutional processes used to manage them (Scoones 1998; Agrawal et al. 2014; Barnes 2017). How these instruments are used to manage a project determines it outcomes. Scoones (1998, p. **3**) rightly pointed out that 'of particular interest in this framework are the institutional processes (embedded in a matrix of formal and informal institutions and organizations) which mediate the ability to carry out such strategies and achieve (or not) such outcomes. Lawson (2011) opined that the process should be 'inclusive and non-threatening' to the livelihood of the people. Lawson (2011) also submitted that the usual top-down approach that undermined the intended beneficiaries will spur livelihood sustainability challenges. These challenges may threaten project outcomes as contemplated by the framework. The SLF template of expected project outcomes includes more income, improved wellbeing, reduced vulnerability, improved food security, inclusive participation in forest governance and more sustainable use of natural resources (Lawlor et al. 2013; Barnes and Laerhoven 2015). These go to attest that forest governance interventions are meant to put strategies in place that will lead to increased access to livelihood sources (Barnes and Laehoven 2015; DFID 2000).

Putting the SLF within REDD+ context, the authors hinge the analysis on how institutional processes, in terms of forest communities' awareness and participation in REDD+ project, influence their access to forest resources and income flow patterns with the inception of REDD+ in the sampled forest communities. Mucahid et al. (2013) buttressed the link between forest governance processes and livelihood outcomes when they argued that institutional processes have significant impacts on livelihood developments patterns with Free, Prior, and Informed Consent (FPIC) providing the gateway of interpreting the nature of the interface and the resultant outcomes. The aim of FPIC is to ensure that the local communities have control over how REDD+ is implemented especially when it comes to benefit sharing. For instance, Stern (2007) had argued that REDD can not only achieve emission reduction but encourage socioeconomic development if wholesome participation of the local communities is consummated. The participation of forest-dependent communities (FDC) in REDD+ activities is one of the many ways of creating social safeguards. These safeguards are codified within the United Nations Declarations on the Rights of Indigenous People (Mucahid et al. 2013).

In brevity, FPIC in the lens of the SLF is a right-based (substantive or procedural rights) approach that boosts social and environmental benefits ensuing from the proper implementation of REDD+ activities. The SLF was used to understand how the implementation of REDD+ so far involved the forest-dependent communities and the impacts on selected sustainable livelihood outcomes. In view of these, the aim of this study is to determine the livelihood impacts of REDD+ projects on forest-dependent communities of CRS, Nigeria. To achieve this, this study was guided by the following objectives: (1) To examine the influence of forest-dependent communities' (FDCs) socioeconomic variables on awareness and participation in REDD+ processes. (2) To assess the impacts of REDD+ intervention on FDCs livelihood portfolio. (3) To investigate the effects of FDCs socioeconomic status on the choice of perceived carbon stocks measurements benefits.

2. Materials and Methods

2.1. Study Area

The study area is the CRS in southeast Nigeria, with an area of 20,156 km^2 (Figure 15) with three agroecological zones (AEZ). The area covers an elevational range from 1800 m (5936 ft.) in the extreme north to 103 m above sea level in the southern part of the State (UN-REDD+ Nigeria 2018). It shares boundaries with Benue State in the north, Akwa Ibom, Ebonyi and Abia states in the west and the Atlantic Ocean in the south. CRS has five different vegetation types; mangrove, swamp, tropical rainforest which dominate the southern and central parts of the region, montane vegetation and savanna woodlands are dominant in the northern portion of the study area (UN-REDD+ Nigeria 2018). It is recognized as one of the biological hotspots in the world (USAIDS 2006) and two locations—Oban and Okwongwu—are marked out as conservation spots. The Oban Division (OD) covers an area of 2800 km^2 with 1568 identified plant species while the Okwongwu Division (OkD) has a land area of 800 km^2 with 1545 plant species located in the area (Larsen 1997). Analysis of extent of land cover types in the region shows mangrove occupy 480 km^2, swamps 520 km^2, tropical rainforest 729 km^2, plantations 460 km^2, other forest 216 km^2 and other land uses 12,300 km^2 (Fon et al. 2014).

Rainfall in the CRS is bimodal with varying durations of sessions across the three agroecological zones. The rainfall gradient is largely influenced by relief and nearness to coastal environment. The southern agroecological zone (SAZ) has a monsoon tropical climate with an annual mean rainfall of 3500 mm which sometimes peaked at 4000 mm around the Oban Massif (Jimoh et al. 2012). The climate of the region is within the Tropical Monsoon (Am) classification scheme of Koppen (Ayoade 2004). The mean annual air temperature of the zone averages around 27 °C with little variation throughout the year, and with humidity between 78 % and 91 % (Aigbe and Omokhua 2015). In the central agroecological zone (CAZ), mean annual rainfall varies from 2300 to 3000 mm. The zone records mean annual air temperature ranges from 26.9 to 30 °C and humidity of the zone in most parts of the year is about 68 % (Jimoh et al. 2012). In the northern agroecological zone (NAZ), savanna ecosystems are common with mean annual rainfall of 1120 mm and temperature ranges from 15 to 30 °C (NIMET 2017).

The zone has two climate seasons; the rainy season which lasts for about eight months and the harmattan that lasts for about four months. In the montane ecoregion of Obanliku Mountains within the NAZ, climatic conditions are markedly different from other parts of the region. Air temperature has a mean annual range of 4 to 10 °C.

2.2 Data Collection

The data for the study were gathered between March and September 2019 using structured interviews and in-depth content analysis. Before the administration of the questionnaire, one community liaison was picked from each of the sampled communities and trained on the process of data collection in the field. The questionnaire was personally administered to forest-dependent communities in CRS using a multistage sampling frame (Olanrewaju et al. 2017). The sampling plan involved the stratification of the study area into the three agroecological zones (Bulktrade and Investment 1998), SAZ, CAZ, and NAZ. The second stage was the purposive selection of two forest-dependent communities per agroecological zone. The communities were selected either because there are REDD+ communities or they share boundary with REDD+ communities. Finally, random selections of household for the administration of the instruments of data collection was carried out (Olanrewaju et al. 2017; Atele et al. 2018).

The total households per sampled community was generated with the help of the community liaisons and 10 % of the total household was randomly picked for the administration of the questionnaire (UN-REDD+ Nigeria 2013) as shown in Table 8. To obtain questionnaire responses on the day, the researchers waited in the village while it was being filled without interference. Respondents were informed that they were free to withdraw their consent to be interviewed at any period of the interview in line with the research ethics of the University of Sussex, United Kingdom. Respondents were informed that any information provided is confidential, with no information disclosed leading to the identification of any individual either by the researcher or by any other party.

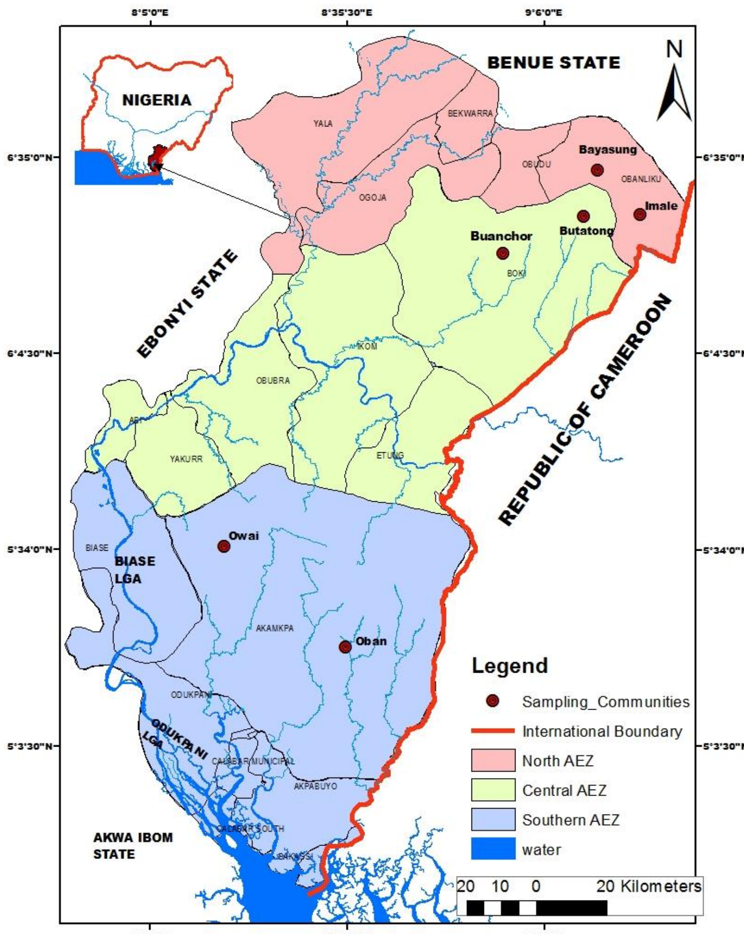


Figure 15. Location of sampled communities in Cross River State, Nigeria. Culled from the Cross River State Forestry Commission (2019).

Table 8. Sample size at 10 % of the total households.

Community	Agroecological Zone	Total Households	10 %
Beyasung	NAZ	480	48
Imale	NAZ	210	21
Butatong	CAZ	690	69
Buachor	CAZ	510	51
Uwai	SAZ	340	34
Oban	SAZ	660	66
Total		2890	289

2.3. Analysis of Interview Data

The data collected from the administered questionnaire were coded and entered in SPSS (Statistical Package for Social Sciences) Version 22.0. Thereafter, the data were cleaned, and the variables named and categorized for analysis. Both descriptive and inferential statistical tools were used to analyze the data. The descriptive tools used included tables and percentages, while the inferential techniques employed were stepwise multiple regression and logistic regression. Multiple regression analysis was used to understand the influence of household income, education, household size and gender on the awareness of REDD+. The test was used to identify the main factor(s) that contribute to the respondents' awareness of REDD+ as well as show the extent of explanation accounted by the identified predictor.

In addition, logistic regression analysis was used in the study to predict the influence of a set of predictors on a single criterion variable. Specifically, it was employed to examine the influence of education, income, household size and gender on carbon measurement benefits. The logistic model output via the *Odd Ratio* enabled us to identify the main socioeconomic variables that contributed most to carbon measurement benefits.

3. Results

3.1. Socioeconomic Profile of Respondents

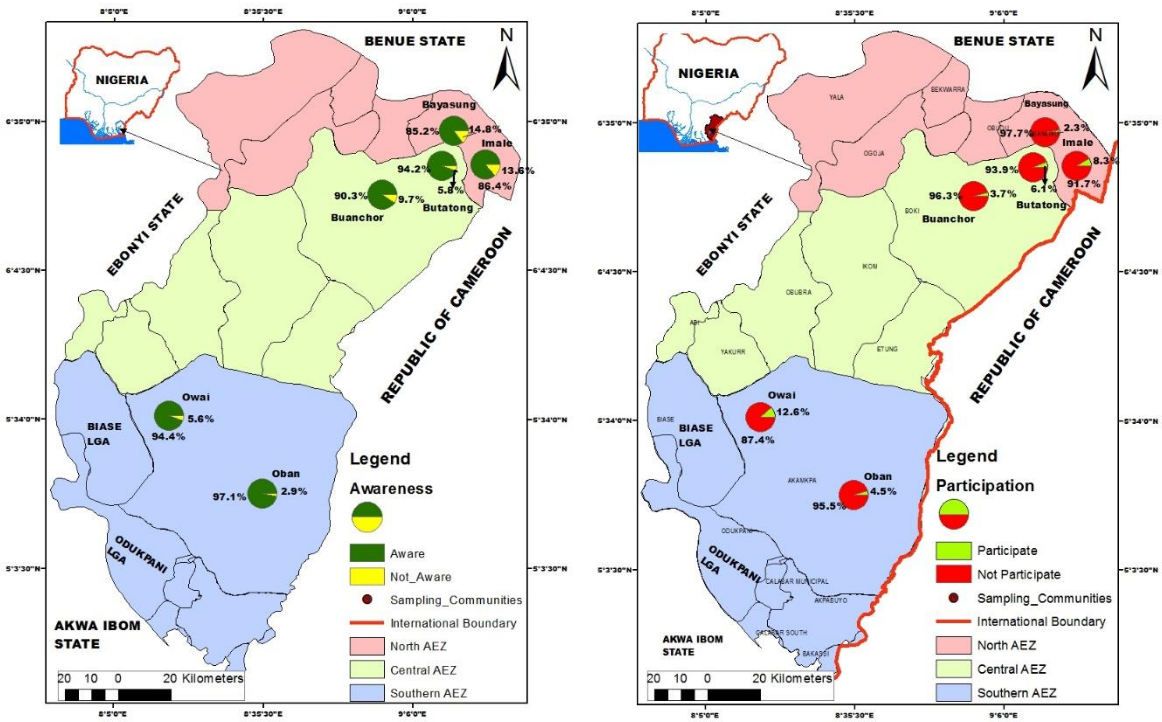
Disaggregating the sampled respondents by sex showed that 48.1 % were male while 51.9 % were female across the three zones. More so, 19.7 % of the respondents claimed to have First School Leaving Certificate while 41.2 %, 34.3 % and 4.8 % of the sampled population said the highest level of education they have is Senior School Certificate (SSC), National Diploma or its equivalent (ND or NCE), and First Degrees and above, respectively. In terms of household size, 17.3 % of the sampled households have a household size of between 1 and 3, while 46.4 % have a household size of about 4–6 people and 36.3 % have a household size of 7 and above. Analysis of the responses further revealed that 5 (1.7 %) claimed to have an estimated monthly income of GBP 25. More so, 13.1 % of the sampled population claimed to have mean monthly income of GBP 56 while 54 and 31.1 % of the interviewed households said their monthly income ranges from GBP 81 to 92. On the main income source, 4.2 % of the respondents said the earnings were from salary. In addition, 9 % of those interviewed got their income from salary and sales of farm produce while 67.5 % said farm produce is their main source of income. Analysis of the data further indicates that 18.3 % of the respondents said farm produce sales and petty businesses constitutes their income sources and 1.0 % claimed salary, farm produce and petty trading forms their major source of monthly revenue. On main source of household energy, many of the respondents rely on fuelwood as energy source (248 or 85.8 %) while only 1.4 % of those interviewed said gas is their main source of household energy.

3.2. REDD+ Project Design and Community Participation

Community awareness and participation of REDD+ processes are shown in Figure 16 a,b. It revealed that most of the sampled population in Beyasung, Imale, Buanchor, Butatong, Uwai and Oban (85.2 %, 86.4 %, 90.3 %, 94.2 %, 94.4 % and 97.1 %, respectively) claimed to be aware of REDD+ in their community. The figure also showed that only 14.8 %, 13.6 %, 9.7 %, 5.8 %, 5.6 % and 2.9 % of respondents in the respective sampled communities said they were not aware of the project. It is imperative to note that the high level of awareness arises by the restriction imposed on the community with regards to harvesting from the forest. However, the awareness level did correlate with the extent of participation in the decision and implementation process of REDD+ in the community. For instance, Figure 16b indicates that 97.7 %, 91.7 %, 93.9 %, 96.3 %, 87.4 % and 95.5 %, respectively, in Beyasung, Imale, Butatong, Buachor, Uwai and Oban of the respondents did not participate in any kind of REDD+ activity in the communities.

Although Nigeria UNREDD+ readily recognized the need for holistic consultation and participation of forest-dependent communities in her Readiness Preparation Proposal (R-PP) document (UN-REDD Nigeria 2013), realities on the ground are not congruent with the preparatory document. In the R-PP, it was expressly stated that 'attention will be given to all …especially women, youths, children, and people with disabilities' (UN-REDD+ Nigeria 2013, p. 9). This level of community involvement as seen here is within the tokenistic consultation frame of Armstein (1969) cited in Lawlor et al. (2013). Here, government officials invited few chiefs and passed on the directives from His Excellency the Governor on what REDD+ project intends to do in the community. The participants thereafter were asked to sign papers as indication of attendance and transportation subsidies released to them. That was the end of it, as every other thing about REDD+ according to the key informant interview was heard from the media or family members.

To enhance our understanding of the rationale behind the low-level of participation of community members on REDD+ activities, the socioeconomic variables and level of awareness were subjected to inferential analysis. Results obtained (Table 9) show that household income, education, household size and gender were significant ($F = 10.135$, $p < 0.05$), and responsible for 12.5 % of the variation in awareness of REDD+. The result further showed that household income, education, household size and gender had positive regression coefficients indicating increase in REDD+ awareness correlates with the increase in household income, education, household size and gender.



(**a**) (**b**)

Figure 16. (**a**,**b**) Distribution of community awareness and participation in REDD+ activities obtained through questionnaire administration across the agroecological zones of Cross River State Nigeria.

Table 9: Summary of multiple regression of the influence of household income, education, household size and gender on REDD+ awareness.

Independent Variables	**Coefficients**		
	B	**B**	***t*-value**
Education	0.246	0.274	4.859 *
Household income	0.196	0.155	2.767 *
Gender	0.081	0.088	1.572
Household size	0.089	0.075	1.342
F-value	10.135 *		
R	0.353		
R^2	0.125		
Constant	0.899		10.195 *

* Significant at 0.05 significance level; probability value = 0.000.

The results in Table 9 also showed that among the independent variables, household income ($t = 2.767$, $p < 0.05$) and education ($t = 4.859$, $p < 0.05$) exerted significant influence on REDD+ awareness, while household size and gender did not. The unstandardized regression coefficient also showed that education and household income had higher weights (0.246 and 0.196, respectively). It therefore means that education followed by household income are principal factors that influence REDD+ awareness.

3.3. Impacts of REDD Intervention on Forest Communities' Livelihoods

The implementation of UN-REDD+ project is believed to have varying effects on the livelihood of tropical forest communities. The respondents' general views on the areas of REDD+ intervention in the sampled communities is presented in Table 10. From the table, it can be observed that 93.4 % of the sampled population said REDD+ did not provide any infrastructure while 5.2 % and 1.4 % of the respondents said REDD+ project trained them on domestication of non-timber forest products (NTFPs) and supported small and medium scale (SMS) business ventures, respectively. None of the sampled households were trained on forest governance or carbon accounting methods.

Table 10. Community perceived area of REDD+ intervention.

Areas of Intervention	Frequency	Percentage
NTFP domestication training	15	5.2
Finance to SMS	4	1.4
Forest governance/carbon	0	0
No infrastructure interventions	270	93.4
Total	289	100

More so, Figure 17 shows the perception of the respondents on the effects of REDD+ intervention on income stream from non-timber forest products once community forest protection has begun. Respondents were asked if their income flow associated with the 'Big Seven' NTFPs (*Gnetum africanum*, *Carpolobia*, *Irvingia gabunensis*, Bush meat, *Rattan, Randia* and *Garciana kola*) changed after the advent of REDD+ projection on the bases of increase or decrease in income status. These NTFPs are the most economically valued in the Cross River State (Adiniyi et al. 2017). Out of 289 respondents sampled across the six communities, 71.3 % said their income from *Gnetum africanum* (Afang) remained high even after REDD+

started while 28.7 % said low income from the sales of the NTFPs became common. However, with the introduction of REDD+, 75.8 % of the respondents said income from the sales of *Carpolobia* sp. (cattle stick) dropped while only 24.2 % of those sampled agreed that money from *Carpolobia* has increased.

On the trend of income from the sales of *Irvengia gabunensis* (Bush mango), 77.2 % of the sampled population agreed that there has been an increase in income from these valued NTFPs while 22.8 % said otherwise. The figure also indicates that income from bushmeat after REDD+ was higher compared to when REDD+ was not introduced in the community as revealed by 85.1 % of the respondents. On income from *Rattan cane* (Cane robe), 24.2 % of the sampled population believed they experienced increase in income after REDD+ while most of the respondents said they have recorded less income since the inception of REDD+ project in their community. In addition, 84.4 % accepted to have also gained less income from *Randia* (chewing stick) while about 15 % claimed increased in income recorded. On the respondent's perception on income trends from the sales of *Garciana* kola, it was observed that 75.1 % of those sampled said it increased compared to 24.9 % who submitted on the contrary.

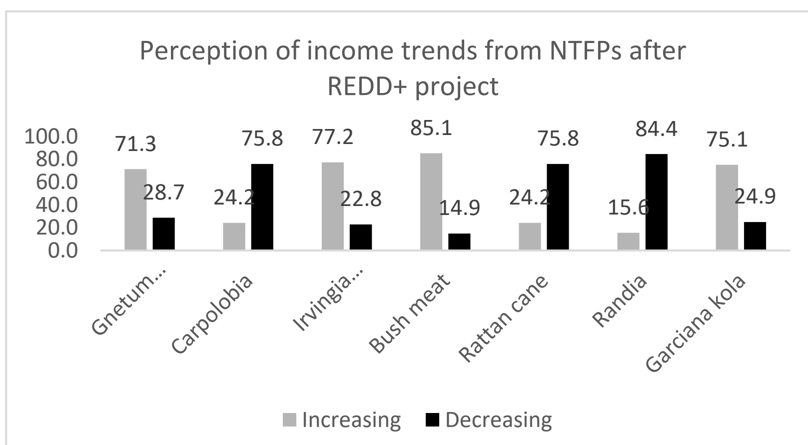


Figure 17. Perception of income trends NTFPs after REDD+ project.

With the advent of REDD+ project in study area, farmers' access to forest land for farming of staple food and cash crops showed a decreasing trend. Analysis of Figure 18 revealed that most of the sampled head of household claimed they had reduced access to forest land for agriculture unlike when REDD+ project has not been introduced in the community. It also showed that 44 (15.2 %) of those sampled said they experienced no change while 66 (22.8 %) of the sampled population support the fact that access to forest land has since increased with the launch of REDD+ project in the community.

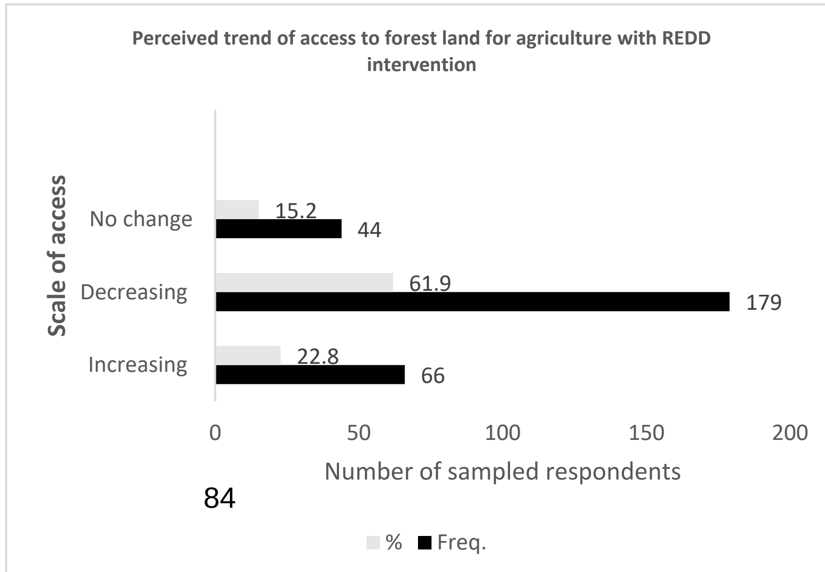


Figure 18. Perceived trend of access to forest land for agriculture with REDD+ intervention.

The distribution of the perceived benefits of carbon measurements and protection in the context of REDD+ is presented in Table 12. The table shows that 34.9 % of the sampled population said the protection of forest carbon will lead to payments for environmental services in the community. This was followed by the belief that REDD+ will lead to more natural resources for community members (34.3 %). Table 11 also revealed that 20.4 % of the respondents expect increases in community employment with the efficient implementation of REDD+ while 10.4 % expect multiple economic returns from forest carbon protection in the community.

Table 11. Perceived carbon protection benefits.

Carbon Measurement Benefits	Frequency	Percentage
Monetary payment	101	34.9
More natural resources	99	34.3
Employment	59	20.4
Multiplier economic effects	30	10.4
Total	289	100.0

To understand how carbon benefits were influenced by the respondent's socioeconomic variables, multinomial logistic regressions were used with results shown in Table 12. The result showed significance using a multivariate logistic regression ($X^2 = 15.365$, $p < 0.05$) when using socioeconomic information on education, income, household size and gender. Yet only two of the four variables contained significant coefficients; education ($X^2 = 6.438$, $p < 0.05$) and income ($X^2 = 4.946$, $p < 0.05$), while gender and household size did not contribute significantly to the prediction of carbon measurement benefits ($p > 0.05$). To recognize variables that contribute considerably to the prediction of carbon measurement benefits, the odds ratio (OR) was used. The result in Table 12 indicates that income had an odds ratio greater than 1 implying that it is more probable to predict carbon measurement benefits.

4. Discussions

This paper investigates how forest carbon measurement and protection for REDD+ have influenced livelihood systems of forest-dependent communities in Nigeria. The discussion is based on the study objectives; community awareness and participation in REDD+, livelihood impacts of REDD+ and respondents' socioeconomic variables in relation to their perception of carbon measurement benefits. The discussion is further guided by the sustainable livelihood outcomes.

Table 12. Summary of logistic regression result showing influence of education, gender, household size, and income on carbon measurement benefits.

Variables		**Coefficient(b)**	**S.E.**	**Wald**	**Df**	**Sig.**	**Exp(E) Odds Ratio**
Sex		0.182	0.245	0.550	1	0.458	0.834
Education		0.632	0.249	6.438 *	1	0.011	0.532
Household size		0.392	0.332	1.393	1	0.238	0.676
Income		0.828	0.372	4.946 *	1	0.026	1.437
Constant		1.596	0.471	11.476	1	0.001	4.933
Overall model estimation							
		Chi-square		Df		Sig.	
	Step	15.365 *		4		0.004	
	Block	15.365 *		4		0.004	
	Model	15.365 *		4		0.004	

Nagelkerke R square = 0.069; * Significant at 5% confidence level.

4.1. Local Community Awareness and Participation in REDD+ Activities

It is imperative to note that effective participation of community members in natural resources governance processes, either directly or by dependable representation, brings about shared benefits. More so, participation of local communities in forest carbon projects diminishes likely opposition to the project and will most probably enhance the success chances (Chhatre et al. 2012; Bisong and Larwanou 2019). In addition, the holistic involvement of forest-dependent communities in forest carbon activities may likely lead to enhancements in livelihood portfolios, sustain biodiversity and mitigate the effects of climate change (Tien et al. 2017). However, this study indicates that many of the sampled respondents were aware of REDD+ programs in their community but only a handful of the sampled population agreed to have participated in any form of REDD+ activities in the community. This contradicts a similar study carried out by Appiah et al. (2016) in Ghana where 99 % of the sampled respondents (155 respondents) claimed not to be aware of REDD+ project implementation in their community. However, the non-involvement of the locals in REDD projects in tropical Africa is corroborated in earlier studies by Agrawal et al. (2014), Lawlor et al. (2013), and Awono et al. (2014). These authors stated that forest governance instruments implemented by outsiders continue to neglect local communities in conservation policy designs and implementations.

Awono et al. (2014, p. 77) specifically concluded that 'local communities are often marginalized in policy making processes, lacking official recognition of property rights to land'. The lack of inclusion of most of the locals in REDD+ project life cycle is a total deviation from the standards as recommended by Ostrom et al. (2010), United Nations and World Bank (Mucahid and Lawal 2016). This negates the Sustainable Development Framework where participation in decisions and involvement in natural resources governance is emphasized as the foundation for better livelihood outcomes.

The non-participation of forest communities in REDD+ activities lead to many challenges. Some of which included denying forest communities' access to forest resources, destabilization of cultural institutions, centralization of forest governance, distortions of forest tenure systems, among others (Phelps et al. 2010; Hayes 2010; Larson 2011; Mucahid et al. 2013). These intended and unintended distortions were aimed at maintaining land sparing regimes (Paul and Knoke 2015). These styles of forest governance led to reduced income among forest-dependent communities (Barnes and Laehoven 2015) and exacerbated poor land use practices with attendant consequences of more carbon emissions (Lawlor et al. 2013).

Content analysis of CRS REDD+ documents showed that the processes of the project design fall short of the protocols of Voluntary Carbon Standards (VCS) and Climate Community and Biodiversity (CCB) Standards (Wildlife Works 2011). There was no evidence to show that the project was certified by either VCS or CCB. This further confirms that the locals may have been neglected at the designing stages of the project (Sunderlin et al. 2014). The lack of FDCs participation in REDD+ project lifecycle and loose FPIC by UN-Nigeria REDD+ in the CRS region may threaten the livelihood of FDCs. The low participation of the locals in the implementation of REDD+ project in CRS has several implications; prominent among all is the negation of the people's livelihood portfolios. This is contrary to the letter and spirit of Article 12.2 of the Kyoto Protocol which expressly advised carbon protection project technical teams to ensure the sustainable development of communities that may likely be impacted by its policies (UNFCC 1997; Smith and Scherr 2003).

The non-involvement or low engagement of forest-dependent communities in forest carbon governance in tropical countries of the world has been linked to some socioeconomic variables like income status, educational qualifications, gender, among others Apipoonyanon et al. (2020), Atele et al. (2017). The results in this study revealed that awareness and participation in REDD+ project activities are influenced by respondent's household income, education, household size, and gender ($F = 10.135$ $p < 0.05$). The result further showed that household income and education had significant positive regression coefficients indicating that increase in REDD+ awareness and participation correlates with the increase in household income and education. Although, the brunt of poverty-environment trap is felt by farmers who may not have formal education, they are often neglected when it comes to decisions that directly affect them (Lawlor et al. 2013). In addition, farmers or households with high income are often involved in community decisions (Mucahid et al. 2013) and hence their awareness of REDD+ programmes. The implication of this is that a unit increase in the income status by way of payment for environmental services of the residents may likely stimulate their interest and participation in forest carbon protection activities. This is in line with an earlier study by Tien et al. (2017) where it was stated that payment for environmental services can on average help local people increase their household income as well as get their attention on forest governance programs.

4.2. Livelihood Impacts of REDD+

The aim of REDD+ is to ensure forest carbon protection and enhance social safeguards (Mucahid et al. 2013). These are some of REDD+'s pathways to carbon emissions reduction (Odero 2006; Agrawal et al. 2014). The non-carbon (social safeguards) aspects of REDD+ are meant to cushion any negative outcomes that may arise from the protection of forest carbon. Despite the interest of REDD+ on social safeguard outcomes, the implementation of REDD+ in CRS was observed to negate some principles common with non-carbon components of the project. The sampled population opined that no community member was trained on forest governance/carbon accounting. Extant studies (Bisong 2001; Agrawal et al. 2014; Atele el al. 2018) showed that participatory forest governance is a conservation paradigm that has boosted forest biodiversity and forest carbon in tropical regions. Training of FDCs on forest governance thematic areas like participatory forest carbon assessment, participatory monitoring, reporting and verification (MRV), among others, has been identified elsewhere as veritable strategies that aided in compensated reduction (Sunderlin and Sills 2013). This is apt in CRS where three tiers of forest management regimes abound: national parks, forest reserves and community forests (USAIDS 2006). The failure to train the FDCs in MRV (a vital step to receiving carbon credit) simply implies that government will be the sole appropriator of the carbon credits. This could possibly reinforce and sustain governance issues (Igiebor 2019) that have bedeviled the nation for too long.

In CRS like other parts of sub-Saharan Africa, non-timber forest products (NTFPs) hold high economic value to the rural population especially from *Gnetume africanum*, Bushmeat, *Irvingia gabonensis*, Rattan cane (*Laccosperma* and *Eremospatha* spp.), *Garcinia kola*, Randia and *Carpolobia* spp. These 'big seven' NTFPs constitute the economic buffers as they make up 60 % of households' income especially among the most vulnerable groups (women and children) (Bisong and Ajake 2001) and the poorest households in the study area (Sunderlin and Sills 2013; Olanrewaju et al. 2017). Estimated annual income derived from the sales of Afang, rattan cane, carpolobia, garciana, randia and irvengia gabunensis in CRS is put conservatively at GBP 104,512, GBP 29,579.00, GBP 23,663.190, GBP 177,473.93, and GBP 244,528.625, respectively, while bush meat is believed to generate GBP 808,660.865 per year in the region (Sunderland 2001). However, these figures are simple estimates as there is no possible way of tracking all the harvested and sold NTFPs in the region (Enuoh and Bisong 2015).

From the study, income status of the respondents after the advent of REDD+ projects showed increases except incomes from *Carpolobia* spp., *Randia* and Rattan cane which showed decreases in income trends. The overall increase in income from NTFPs in the study area (for four out of seven NTFPs) could be attributed to the moratorium on logging put in place in the early stage of REDD+ by the state government since 2008 (UN-REDD+ Nigeria 2015). This according to Langat et al. (2016) can be attributed to the fact that the elites in the forest-dependent communities extract capital intensive forest products like logging of trees, establish large scale cocoa, banana, plantain farms, among others, and have access to markets. Income from these sources is used to support the regular income stream (emoluments from salaries). Lower-income members of the community do not have capital intensive and large-scale agricultural enterprises neither do they have a steady source of income outside the natural capital. Additionally, most importantly they do not also have access to capital intensive markets as they are content with subsistence-related livelihoods (Sunderland 2001).

Therefore, REDD+ initiatives to ban logging has resulted in four out of seven NTFPs becoming more valuable for the communities within the Cross River State. Extant studies confirmed that forest cover removal correlates with reduction in NTFPs availability and consequently in income (Menton 2003; Gillet et al. 2016). Ngansop et al. (2019) also observed that the destruction of NTFP habitat by capital driven logging or commercial farming in southeast Cameroon was a major cause of income reduction of forest communities over the years. Conversely, when the habitat is good for non-timber forest products like *Gnetum africanum* which according to Ali et al. (2011) is 'a shade-loving climbing gymnosperm liana' it grows into abundance within a short period of time. This partly explains the increased income experienced by farmers in the study communities from sales of *Gnetum africanum*. However, the decline in income from *Carpolobia* spp., Rattan cane and *Randia* after REDD+ project initiation may not be unconnected to the preferred harvesting method. *Carpolobia* spp. is often harvested at the tender age denying them opportunity to be sustained through re-shooting or seedling (Sunderland 2001; Nwidu et al. 2015). This approach leads to massive destruction of its ecology and importantly too, it is largely sought for by non-indigenes (Hausa and Fulani's) in collusion with the locals. The control of the influx of these categories of buyers into the forest communities by Green Police (Forest Guard) in the region may also account for the fall in income from *carpolobia* spp. More so, the reduction in income from *Rattan cane* (*Laccosperma robustum* and *L. secundiflorum* and *Eremospatha macrocarpa*) may be linked to the control of the influx of buyers and its low economic rating by households in the study area. It is estimated that rattan cane makes up 0.8 % of family income in Cross River State (Sunderland 2001; Zeh et al. 2019). The low rating of rattan cane was confirmed during focus group discussions with selected NTFPs collectors. Most of those in the discussion session said choices of what NTFPs to harvest and sell is often determined by its economic value. Recently, most of the harvested rattan cane is for domestic usage. It is imperative to note that NTFPs with high economic value in the study area is highly favored by most of the households. For instance, *Irvingia gabonensis* is one of those NTFPs with high economic rating hence it constitutes about 50 % of households' yearly income in the study area and the adjoining Cameroon border communities (Sunderland 2001; Sunderland et al. 2008).

More so, one major livelihood sector that is negatively affected by REDD+ project implementation in the study area is access to forest lands for food and cash crops cultivation. More than half of the sampled population claimed that their farm sizes have reduced because government officials banned the opening of the forest for agricultural activities. Most often, where the local communities succeed in establishing farmlands deep in the forest, they are later destroyed by government officials upon discovery. The respondents complained about the effects of government restrictions and other hampering activities on food security and their overall wellbeing. The repercussion of restricted access to farmland may deepen the worsening poverty situation as over 65 % of the people of the study area rely on farming and forest related resources for subsistence (Sunderland 2001). Considering that part of the outlined objectives of the forest carbon protection scheme is to strengthen the forest community rights of access and sustainable utilization of natural capital (IPCC 2007) as climate change mitigative measures, it is therefore imperative that Nigeria-REDD+ should incorporate social safeguards while implementing its components in the region.

4.3. Influence of Forest-Dependent Communities' Socioeconomic Status on Perceived Carbon Measurement Benefits

Analysis of the socioeconomic variables that determine the choice of carbon protection benefits showed that education, income, household size, and gender can predict carbon measurement (as the logistic regression was significant; $X^2 = 15.365$, $p < 0.05$) but only education and income were the statistically significant predictors of the motivation for forest biomass protection in the study area. Subjecting the results to further statistical analysis revealed that only income had odds ratio of one (1), implying the expected income from non-timber harvesting and sales is a factor that encourages community members' participation and are willing to support REDD+ in the State. This is expected as household income is one of the attractions for forest-dependent communities to adopt REDD+ programs which in the long-run help to increase household sources of income. This result and assertion lend support to the study of Druckman and Jackson (Drunkard and Jackson 2016) where they saw income as one of the key drivers of carbon emissions and rebound effect—which is a way of reducing carbon footprints. In another study, Liu, Zhang, and Liu (2020) found changes in household income associated with income inequality to significantly impact on household carbon emissions. The logistic regression result therefore identifies household income as a principal factor that influences carbon protection benefits.

More so, results from the expected benefits of carbon measurements and protection revealed that the majority of those interviewed have the expectation of receiving payments for carbon protection as well as more natural resources within their reach. This was followed by employment and multiplier economic benefits. It is imperative to note that FDCs expectations are within the mandate of REDD+ which, among others, includes cash payment for carbon protection in biomass, equitable benefits sharing, enhancement of livelihood of local and indigenous communities and importantly carbon ownership (Mucahid et al. 2014). Nigeria has expressed her commitment to these precepts in the Readiness Plan Idea Note (R-PIN) submitted to the Forest Carbon Partnership Facility in 2013 (UN-REDD+ Nigeria 2013). However, the loose interface of UN-Nigeria REDD+ team with a select opinion leader (Chiefs) of FDCs, ban of NTFPs collection, restriction of access to forest land for food and cash crops farming and the presence of Green Police without concrete supports or alternative means of livelihoods to the people, negates the spirit and letter of the R-PIN. These are disturbing facts especially in Nigeria like most African governments where a history of financial dishonesty in investment portfolio that will benefit the poor has remained fertile. The negation of FDCs in the design and implementation of REDD+ processes will not permit the people to own and benefit from the proceeds of forest carbon payments. Page and Okeke (Page et al. 2019) detailed how billions of Naira meant for small and medium scale schemes for the poor in Nigeria were stolen by government officials between 2014 and 2018. Such financial malfeasance is likely to be sustained if FDCs are not carried along in all the steps of REDD+ processes.

5. Conclusion and Policy Recommendations

The researchers investigated the governance dynamics of REDD+ project in relation to the livelihood benefits of carbon measurements and protection in six purposively sampled forest-dependent communities in CRS, southeast Nigeria. The results from the study indicated that most of the sampled respondents were aware of REDD+ project. However, they were not involved in the design and implementation processes. The study further observed that only the community chiefs were invited to REDD+ meetings. However, their participation in the meeting was restricted to listening to the planned activities of government with regards to REDD+ project. In addition, the study used the logit regression model to establish the socioeconomic variables that determined sampled households’ awareness and participation in REDD+ activities. The result showed that income, education, household size and gender had significant influence on the level of awareness and participation in the REDD+ project in the study area.

More so, assessment of the livelihood impacts of carbon protection indicated that income status of the respondents increased after the REDD+ project commenced. This was noted in the income flow from *Gnetume africanum*, Bushmeat, *Irvingia gabonensis* and *Garcinia* sp. while Rattan cane (*Laccosperma* and *Eremospatha* spp.), Carpolobia spp. and Randia indicated a decline in income. The decline of income from *Carpolobia* spp. Rattan cane and

Randia is most likely attributed to the harvesting system, which involves large scale destruction of the stems and the increased surveillance of forest in the region. The results of logit regression analysis of the socioeconomic determinants of forest carbon measurements and protection benefits revealed that income, household size, and gender of the sampled population were able to predict forest carbon measurement benefits. Specifically, education and income were significant predictors of carbon measurement and protection benefits in the study area.

Another fundamental sector that is negatively impacted by the implementation of REDD+ in the area is access to farmlands for food and cash crops cultivation. Almost every respondent complained about the reduction in access to land for farming. The government in recognition of the effects of deforestation and forest degradation and in keeping with requirements to secure funding from international donor agencies set up a security outfit (Green Sheriff) to guard the forest. The enforcement of forest protection is reducing the rate at which closed forest is opened for farming. However, those who succeed in cultivating in the forest may not harvest the crops as they are likely to be destroyed by the forest guards. This has affected the food and cash crops turnover rate in the study area since the inception of REDD+.

In view of the results, it is recommended that subsequent activities of REDD+ in the study area should be conducted in ways that meet international best practices as outlined by the sponsoring agencies. This will mean the holistic involvement of the population that may be directly or indirectly impacted by REDD+ project activities. The activities of REDD project should be seen to be creating opportunities that will enhance the standard of living of the people rather than accentuating poverty. REDD+ handlers should create avenues that increase the population access to food security, increase income from farm and off farm activities and at the same time protect the environment. In addition, such programs should promote good health of the people, as well as guarantee the sustainability of all the social safeguards.

It is imperative to note that forest carbon protection is one major strategy to reverse the strong hold of socioeconomic exclusion associated with poverty-environment trap in

Nigeria and other tropical economics. With the increased access to livelihood assets, the living standard of the people could be enhanced. However, for such programs to achieve social inclusion, all stakeholders should be carried along from project design through implementation to evaluation. It is therefore apposite to counsel that achieving emission reduction is strongly correlated with community's participation, provision of adequate safeguards and sustainability of the project. As this study rightly pointed out, tokenistic models have failed in the protection of forest lands in the region, therefore, the locals need to be in the driver's seat. This way the people will own the processes and ensure its success. This approach, as has been established elsewhere, will ensure biodiversity stability, forest carbon increase and most importantly guarantee sustainable utilization of forest resources for livelihoods. In addition, forest-dependent communities should be trained on forest carbon estimation and periodic evaluation. This way, the people can determine biomass trends and take the full advantage of the benefits of REDD+. After the training, the Cross River State Forestry Commission may henceforth conduct participatory forest carbon measurement, reporting and validation (MRV).

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CHAPTER FIVE

CONCLUSION AND FUTURE WORKS

5.1 Overview

The emergence of the REDD+ project at the Conference of Parties (COP 15) in 2009 reinvigorated global community interest in tropical forest dynamics. With a land area of 18 million km^2 (FAO 2011), tropical forest land is projected to store about 271±16 Pg. (Ciais et al. 2014). However, unsustainable land use practices account for the yearly loss of 2.01±1.1 Pg C in the region (Ciais et al. 2014), leading to global climate flux (Le Quere et al. 2018). It is confirmed that the sustainable management of tropical terrestrial carbons pools is one of the cost-effective strategies in curbing regional carbon dioxide emissions and climate change (IPCC 2014). It is a scientific fact that trees capture carbon from the atmosphere and store it as biomass in trees, hence tree biomass is made up of 45 to 50 % carbon (Chan 1982). Invariably, the destruction of these trees will lead to the release of carbon into the atmosphere (Pan et al. 2011). It is therefore not surprising that the proportion of carbon emitted from land cover change is among the leading sources of greenhouse gases in the world today (Le Quere et al. 2018). However, it is postulated that sustainable management of tropical land cover has the potential to sequester 1.85±0.09 Pg every year (Pan et al. 2011, Avitabile et al. 2016). This is apt given that the region is projected to contain over 500 Mg/ ha^{-1} of biomass (Mitchard 2018). In view of these, tracking and management of regional carbon requires accurate estimation of the carbon pools in the region given it huge carbon sequestration potential (Mitchard et al. 2013).

In Africa, accurate estimates of terrestrial carbon pools fall shorts of expectations (Chave et al. 2019). The subsisting estimates are either characterized by high uncertainties, not spatially explicit and continuous hence not replicable, or limited in scale (Baccini et al. 2008; Saatchi et al. 2011; UN-REDD+ Nigeria 2013; Mitchard et al. 2013; Avitabile et al. 2016). This study made bold efforts in filling these gaps. The project provides insight into the total quantity of aboveground biomass and soil organic carbon, their spatial variability, and the relevant environmental covariates derived from sentinel -2 imagery and reanalysis datasets. The robust and high confident model of random forest regression, a machine learning algorithm was used to understand the strength of auxiliary environmental datasets in predicting AGB and SOC in the ecological zones of CRS, Nigeria. The application of fine spatial resolution sentinel 2 imagery in data acquisition and analysis provides confident and reliable estimates of biomass that meets the IPCC 2006 Tier 3 biomass estimation good practice guidelines (Kumah et al. 2016). Using sampled respondents, the study also examined the perceived direct and indirect benefits of biomass accounting to forest dependent communities of CRS within the REDD+ framework. This was anchored on the sustainable livelihood postulations of IFAD (2009). Overall, reliable carbon pool estimate is pertinent in carbon credit mechanism as espoused by REDD+ Monitoring Reporting Verification (Agrawal et al. 2011).

5.2 Quantification of above-ground biomass over the Cross River State, Nigeria using sentinel 2 data.

The estimation of above ground biomass in tropical Africa is required to constrain the uncertainty in regional carbon budget and meet climate change mitigation strategies of the REDD+ project. The quantification of carbon stocks, its monitoring, verification, and reporting (MVR) framework is recognized as one of the cost-effective natural means of maintaining the global carbon dioxide threshold below two degrees centigrade (2 ^{0}C). Tree biomass can basically be estimated either through the direct method or indirect method. The direct method of tree biomass estimation involves the cutting down of trees, burning and then weighing the burnt residues (Chave et al. 2014). This process gives accurate carbon content of the tree (Chave et al. 2014). However, the direct method of carbon estimation is expensive, time consuming and most importantly very destructive hence its applicability is limited (Dube et al. 2018). The indirect method on the hand involves the use of mathematical models in its estimation. This is has become the most widely used technique of tree biomass estimation. The advent of sophisticated technological wares has made the use of allometry equations in tree biomass estimation a proficient means to determine the total biomass in trees (Chave et al. 2019).

The use of modern technologies like remote sensing and Geographic Information System (GIS) in the collection of spatially explicit and continuous AGB data and its subsequent calibration and validation with sufficient point data with robust model like random forest regression as done here reduces the high uncertainty often linked to tropical carbon estimation (Baccini et al. 2008; Saatchi et al. 2011; Mitchard et al. 2013; Avitabile et al. 2016). On this premise, the study established a network of field plots in a variety of forest and woodland landscapes for AGB estimation. Sentinel-2, selected climate, and soil variables were used to predict and spatially extrapolate AGB over the study area at 20 meters resolution. And the AGB map of this study was compared with the Baccini, Saatchi, Avitabile, ESA AGB maps and REDD+ AGB estimates. These efforts will aid in the effective monitoring of changes in forest biomass in the region, creating an opportunity for the initiation and implementation of sustainable natural resources management policies.

Using vegetation density and level of human interference (presence or absence of tree stumps, footpaths, farmlands) as criteria, the total land area of the region was delineated into three; undisturbed, disturbed and crop fields land cover types following the Cross River State Forest Commission (2019). In each of the mapped-out land cover types, 20 meters by 20 meters plot were measured out in 72 sample points purposively. The attributes of each tree (height and diameter at breast height) in all the demarcated plots with DBH of 5 cm and above were measured using TruePulse and measuring tape while the wood density of the tree species was obtained from the African wood density database of agroforestry and Food and Agricultural Organization (FAO 1997). However, where any of the tree species is not captured in these databases, the mean wood specific gravity (WSG) value of the plot was used as the WSG of the tree. The measured values were substituted in the Chave's et al. (2014) pantropical allometry for AGB estimation. The per tree AGB were summed up to get the total AGB per plot across the land cover types.

5.3 Digital mapping of soil organic carbon from sentinel-2 data in the tropical ecosystem of Cross River State, southeast Nigeria.

Land degradation in Africa remains a topical subject in the region. The multiplier effects of an upsurge in anthropogenic pressures on land resources and its attendant climate change connection makes meeting livelihood goals in the region daunting. This is assuming a crisis dimension as over 80 % of the population in the region rely on rainfed agriculture as the main source of livelihoods (FAO 2009). More so, the immense role of SOC in the global carbon budget is attracting interest on how it is managed especially in tropical regions. To tackle these challenges, soil organic carbon spatial information is required for sustainable land use decisions to be made. Padarian et al. (2020) lucidly captured the essence of digital soil mapping when they averred that spatial variability in soil properties can only be full captured when every component of the pixel covering an area is integrated into the general model. More so, it is imperative to note that because of the need to account for every subtle variability in soil quality, finer scale maps are therefore inevitable (McBratney et al. 2003). This is the most probable course of action towards sustainable land use planning in the region because the existing products on SOC over the region either in coarse scale or are products obtained from traditional soil surveys (Hengl et al. 2015, 2017, 2021).

The advent of modern technique of soil information acquisition known as digital soil mapping anchors on the technological information revolution relies on correlated variables in predicting soils using limited point data (Kumar et al. 2016). The integration of legacy data with spatially obtained variables within advanced statistical algorithms like random forest regression reduces common noises associated with complex interwoven environmental variables (Atah et al. 2016, Venter et al. 2021). This is very pertinent as redundant covariates are removed thereby improving model accuracy (Venter et al. 2021).

With the land use map of the Cross the River State Forestry Commission (2019) as a baseline, three land lover types were delineated based on the degree of foliage density, presence of stumps, extent of farmlands among others. In each land cover type, 20 meters by 20 meters plot was delineated and within each of the plot, composite soil samples were collected diagonally at 20 cm depth using a soil auger. The samples were then parcelled, labelled, and taken to the laboratory for soil organic carbon analysis using the Walkley Black wet oxidation method (Walkley and Black 1934). Besides this, another sample was taken from each of the plot but from undisturbed point using 1.4cm rim soil sampler for bulk density analysis in the laboratory.

SOC was predicted from environmental covariates including relative humidity, mean annual rainfall, mean annual air temperature, aboveground biomass as proxy of vegetation, topography derived from digital elevation model. Other auxiliary datasets derived from sentinel 2 and incorporated into the random forest model included, optimized soil vegetation index (OSAVI), normalized vegetation index (NDVI), modified red edge simple ratio (MRESR), atmospherically resistant vegetation index, modified red edge normalized vegetation index, invented red edge chlorophyl index (IRCEI), enhanced vegetation index (EVI), modified soil adjusted vegetation index (MSAVI), and red edge normalized difference vegetation index. The study has demonstrated that random forest regression can predict soil organic carbon accurately despite the limited numbers of field sample points.

The result of the study shows that 59.7 % of the total SOC (3139.6 t/ha) sampled in the study area were in intact forest and 32.6 % representing 1709.6 (t/ha) were estimated in disturbed land cover. In crop fields, a total of 402.74 (t/ha) was estimated in the area. The estimated soil organic carbon in this study was 0.147 Pg. with mean of 72.94 (t/ha) of SOC compared to AfSIS 0.124 Pg with mean of 61.8 (t/ha) and iSDA 0.217 Pg of SOC with absolute mean values of 108 (t/ha) over the area respectively. The analysis indicates that the key covariates achieved a high prediction accuracy with lower uncertainty unlike the global and continental SOC maps over the study area. Our results showed lower uncertainty compared to the coarse spatial resolution maps of AfSIS (30 m) and ISDA (250 m). The final model output was used to spatialize the SOC distribution over the Cross River subregion using ArcGIS package. The result of this study is a confirmation that there is an empirical relationship between soil organic carbon and terrain features. These variables can therefore be adjusted to obtained other leading outcome variables.

The density of soil organic carbon in undisturbed land cover types in this study revealed that the improvement in soil organic matter of cultivated fields will invariably enhance the carbon sequestration potential of such agricultural lands (IPCC 2007), restore soil productivity for enhance food production as reports indicates that poor soil fertility is a major constraint to food security in west Africa (UNEP 2002). More so, the restoration of SOM in such lands will protects the soil against soil degradation and helped in regulating global climate (IPCC 2011). The high carbon emissions and its climate implications from agricultural lands was part of the reasons the European Commission MRV policy document on REDD+ emphasized the used of hyperspectral techniques in the quantification of SOC in African, Caribbean, and Pacific countries (de Brogniez et al. 2011).

However, in Nigeria like other tropical African countries, the challenges faced in protecting forested areas including but not limited to ineffective and poor implementations of protected area laws as such has become 'paper Parks' or 'paper Reserves' at best (Carey et al. 2000), upsurge in economic hardship, couple with increasing population, tribal conflicts with attendant environmental refugees (Serdencny et al. 2017; Solomon et al. 2018) and declining soil fertility which motivates farmers to open up the forest for farming (World Bank 2013), among others questions the readiness of political leaders to follow through with recent clean development initiative encompassing REDD+. However, it is our aspirations that the result of this study will reawaken the political class interest to invest in forest carbon protection which is generously accepted as a cost-effective strategy to climate change mitigation in the tropics.

5.4 livelihood impacts of forest carbon protection in the context of REDD+ in Cross River State, southeast Nigeria.

Forest degradation and deforestation in tropical and subtropical regions remain the main source of greenhouse gases. Because of this, it estimated that land cover change/conversion accounts for 15-20 % of carbon dioxide emissions into the biosphere (IPCC 2007; van der Werf et al. 2009; IPCC 2014) with tropical countries identified as major source and sink of carbon dioxide (Pan et al. 2011; Hubau et al. 2020). These huge emissions from the land use and forestry sector led to the need to harness resources for forest protection and sustainable land use practices as the cheapest means of reducing the quantity of carbon dioxide in the environment. This presented the theoretical background for United Nation Framework Convention on Climate Change (UNFCCC 2010) to midwife the Reducing Emissions from Deforestation and Forest Degradation in Developing countries Plus (REDD+) project. It is recognized as a cheap and effective strategy in protecting tropical forest, sustaining the livelihoods of those whose daily living is dependent on natural capital and importantly, bringing down air temperature to pre-industrial levels (Angelsen 2009; Adeniyi 2016). The aim of the project (REDD+) is to provide tropical developing countries financial incentives to manage and protect the natural capital within their domain (Awono et al. 2014). It is a market-based framework that aimed at providing financial incentives to tropical developing countries to stop or reduce forest cover destruction. However, many have argued that the implementation of the project may be counter-productive; poverty levels may spike leading to a plethora of socio-cultural conflicts especially in Africa where poverty remains acute and endemic (Hilson and Hirons 2011). It is in recognition of this, that this study was undertaken to understand how locking carbon in forest will enhance the livelihoods of forest dependent communities in CRS, Nigeria.

To ascertain the impacts of REDD+ on the livelihood portfolios of forest dependent communities, six forest communities were chosen across three agroecological zones of the State. Based on the Sustainable Livelihood Framework (SLF), a structured set of questionnaires were administered to randomly picked households. Descriptive and inferential statistics were used to analyse the collected data. The results revealed that more than half of the respondents agreed that financial payment and more natural resources are the perceived benefits of carbon protection. In addition, the data were subjected to multinomial logistic regression analysis and the result indicates that income was the main factor that influenced respondent's support for forest carbon protection. Analysis of income trends from the 'big seven' nontimber forest resources in the region showed increase in *Gnetum africanum*, Bushmeat, *Irvingia gabonensis*, *Garcinia kola*, while *carpolobia spp.*, Randia and rattan cane revealed declining income since inception of REDD+. The recorded increase in household income was attributed to a ban in logging. The highlight of the study is the confirmation that carbon protection enhances the peoples' livelihoods and helps in slowing down climate fluxes.

However, it was observed that implementations of the policy thrust of REDD+ was not holistic as prior and informed consent was either not secured or carried out haphazardly. This is against the spirit and letter of the UN guidelines on REDD+ design and implementation (Adeniyi et al. 2017). The non-involvement or haphazard engagement of the natives on REDD+ design and implementation may hamper the high positive social and livelihood expectations on the project (Karsenty 2011). According to Awono et a. (2014), forest dependent communities excluded in the entire stages of REDD+ implementation is a precursor to denying them carbon benefits. State actors in forest and its resources management often do not recognize the right of indigenous people to land. This marginalization is partly responsible for the consistent carbon leakage in most tropical African countries despite series of laws that locked in carbon.

5.5 Recommendations

- ✓ The subsequent monitoring, reporting and verification of soil organic carbon of Cross River State should incorporate geospatially reference framework as the SOC profile in the database of the region are purely point data. This SOC map of this study can be included as reference data to compare and validate the existing maps over the area. The biomass maps of this study can be used as reference in subsequent studies of the biomass in the region.
- ✓ The conflicting AGB and SOC stocks predicted over the Cross River State calls for the establishment of a repository of standard methods of data collection, analysis and presentation from point data collection stage, laboratory analysis, hyperspectral data collection to medium of presentation. This will allow for effective MRV and full utilization of the advantages of carbon credits within the framework of REDD+. In addition, a local soil spectral library (SSL) needs to be established for spatiotemporal analysis and tracking of changes in SOC. The available maps SOC (Akpa et al. 2016, Hengl et al. 2017; 2021) are quite limited in applications due to the unreliability of the soil legacy data used for model training, and validation. In addition, the IPCC Best Practice Handbook (IPCC 2006) identified five cardinal criteria required in REDD+ data collection to include a) temporal consistency of measurements. b) transparency of the estimates. c) comparability of the methods. d) completeness of the pools. e) Accurate documentation.
- ✓ The land cover map of the Cross River State should be updated to reflect the current land cover types. Nigeria like most African, Caribbean, and Pacific countries lack the

capacity of data collection and management; hence it will be a plus to the REDD+ team if the locals are supported to delineate and map the land cover types of the state.

- ✓ The government and non-governmental organizations in Cross River State should carry out massive afforestation and reforestation programs to increase the carbon stocks. This is pertinent as the European Commission MRV document clearly instructed that without carbon additionality no country should be paid monitory incentives.
- ✓ The subsequent implementations of REDD+ program should be fully participatory; all stake holders including women, youths, and men in every REDD+ community should be carried along. Allowing elite capture of the process at the data collection stage as reported by most residents in the sampled communities clearly indicates that the monitory payments will not benefit everyone.
- ✓ Based on the findings of this study, it is imperative that farmers are encouraged to engage in farming activities that increases the soil organic matter status. This will not only boost the soil health and productivity but increase the quantity of carbon the soil sequesters. Improving the ecosystem carrying capacity will surely benefit man and nature. Fallows periods should be increased to allow for the full recuperation of the destroyed ecosystems.
- ✓ In addition, farmers should be supported to establish alternative means of livelihood outside farming, like petty trading and youths train on any craft of their interest. This will help in reducing their reliance on forest-based resources. In fact, most of the nontimber forest products harvested from the forest should be domesticated to reduce reliance on forest resources.

5.6 Future works

Based on the result of this study, the relatively high AGB and SOC estimation uncertainty (30 % and 39 % respectively) affects the accurate understanding of land surface-atmosphere interface in relation to carbon budget (Kumar et al. 2016). Because of this, it is germane that further study be carried out in the region to decompose the effects of scale and environmental controls on land cover biomass (McBratney et al. 2003). More so, extant studies have established the range of saturation experienced with increasing biomass in tropical environments common with optical remote sensors (Baccini et al. 2008; Saatchi et al. 2011; Mitchard et al. 2014, Avitabile et al. 2016). On this note, it is apposite for improve biomass accuracy to be achieved. To attain this goal, it may be necessary to use sensors that are known to penetrate and maintain its sensitivity to high, complex missed tree species structures. Such enhance capacity will also boost model accuracy and give the actual stocks of carbon in the region, hence true carbon credit payment to the government of Nigeria. The Light Detection and Ranging (LiDAR) sensor is one of the reputed remote sensing sensors with such technological capability (Chavi et al. 2019). Therefore, researchers should be motivated through sponsorship to carried out such a large-scale study to determine the actual biomass stocks across the pools in the Cross River State.

In this study, the spatial distribution of SOC was estimated. However, SOC variability is known to vary horizontally and vertically (Hengl et al. 2021). Whereas this study focused on a single soil depth (20 cm), it is imperative that subsequent studies investigate the influence of soil depths on SOC stocks in the Cross River State. The high rate of rainfall in the southern and central ecological zones of the region may promote SOC movement beneath the earth surface (Offiong and Iwara 2008). In addition, the rugged topography in certain parts of the study area possibly influence the infiltration rates, hence lateral and vertical movements of soil materials.

Tropical forest of Africa which is only 7 % of the total land area sustains 60 % of the known species in the zone (Dirzo and Raven 2003). However, conspicuous evidence abounds at subregional levels that support the claim that this unique ecosystem is under threat of annihilation by anthropogenic factors (Siyum 2009, Avitabile et al. 2016). The continued expansion of cultivated fields into forest lands across African protected areas is responsible for the loss of SOM and accelerated carbon emission into the atmosphere (Tranquilli et al. 2014). It is estimated that about 70 % of deforestation in Africa is caused by farming activities (FAO 2014). This is worrisome given the fact that SOC in cultivated fields is known to be very volatile, hence requires practices that ensures fast restoration of destroyed SOC and the sustenance of the available stocks. However, this is often not the case with reduction in fallow periods, subsistence of slash and burn practices couple with the insatiable drive to open new or recuperating land facets among others exuberate over benign land utilization practices (Soh et al. 2019). The difficulty in secondary forest attaining successional climax in Africa and the low SOC associated with cultivated fields reinforces the need for better land management practices. Most African farmlands now lacks the capacity to restore SOC as the subsisting fallow periods of less than 15 years do not support adequate litter fall for reasonable restoration (Harvey et al. 2017). Importantly, forest dependent communities should be train on and involve in participatory MRV. This is one sure means of ensuring effective realization of the benefits of forest carbon storage in the region.

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Appendix one

Parameter optimization process of RF model

```
#installation of packages
library(randomForest)
library(caret)
library(party)
library(Boruta)
library(readr)
library (rasterVis)
#Reading the data
AGB_sent <- read_csv("PhD_work/AGB_sent.csv")
View(AGB_sent)
set.seed(666)
library(readr)
#picking out important variables
boruta<-Boruta(AGB~., data = AGB_sent, doTrace=2, maxRuns=400)
plot(boruta, las=2)
#seting up the RF regression model
ind<- sort(sample(x=c(2: nrow(AGB_sent)), round(0.7*nrow(AGB_sent)), replace = TRUE))
train<-AGB_sent[ind,]
test<-AGB_sent [-ind,]
#train data experiment
RF<-randomForest(AGB~.,data =train)
fit<-cforest(AGB~.,data = train,controls = cforest_unbiased(ntree=400,mtry=3))
fit
cforestStats(fit)
RF
#test data experiment
ind<- sort(sample(x=c(2: nrow(AGB_sent)), round(0.7*nrow(AGB_sent)), replace = TRUE))
train<-AGB_sent[ind,]
test<-AGB_sent [-ind,]
RF<-randomForest(AGB~.,data =test)
```

```
fit<-cforest(AGB~.,data = test,controls = cforest_unbiased(ntree=400,mtry=3))
fit
cforestStats(fit)
RF
#Predicting the AGB for test and train data
test_data=cbind(test$AGB, rf)
colnames(test_data)=c("observed","predicted")
#train
train_data=cbind(train$AGB, p1)
colnames(train_data)=c("observed","predicted")
        write.table(train_data, "C:/Users/amuyou/Documents/PhD_work/train_data.csv", sep =",", dec = ".",
         row.names = F)
write.table(test_data, "C:/Users/amuyou/Documents/PhD_work/test_data.csv", sep =",", dec = ".",
         row.names = F)
#Integrating important variables in the RF model to estimating AGB
NDVI_OSAVI_EVI_RENDVI=stack("C:/Users/amuyou/Documents/Raw_sentinel_products/sent19.tif")
NDVI_OSAVI_EVI_RENDVI=as.data.frame(NDVI_OSAVI_EVI, xy=T)
Rainfall=stack("C:/Users/amuyou/Documents/Raw_sentinel_products/Rainfall.tif")
Rainfall=as.data.frame(Rainfall, xy=T)
Tempmin=stack("C:/Users/amuyou/Documents/Raw_sentinel_products/Tmin.tif")
Tempmin=as.data.frame(Tempmin, xy=T)
Topo=stack("C:/Users/amuyou/Documents/Raw_sentinel_products/Topo.tif")
Topo=as.data.frame(Topo, xy=T).
```

Appendix two

Approved questionnaire by the Ethical Review Committee

HEAD OF HOUSEHOLD QUESTIONNAIRE FOR PhD RESEARCH PROJECT TITLED

Livelihood benefits of carbon protection by REDD+ in rural Nigeria.

Department of Geography, University of Sussex- Falmer Village, East Sussex-United Kingdom.

Dear sir/Madam,

My name is Amuyou Ushuki Ayankukwa. I am a doctoral researcher in the University of Sussex, United Kingdom conducting research on 'Livelihood benefits of carbon (biomass) protection by REDD+ project'. This community is one of the sampled communities for this research. It was chosen because it has large track of forest land and i have decided to choose you to participate in this research because you live here.

This research is for academic purposes only, it has nothing to do with government or taxes. There is no place in this questionnaire that requires your name or any of your personal details. The report from this study will be published in a journal and it will be in the University of Sussex repository for reference purposes. You will not be given any financial benefits, but it is my hope that the results will inform policies development that may have positive impacts on you and members of your households. You are very free to stop answering the questions at any point in time. If at the end of this exercise, there is need to get clarification about the research, feel free to contact me through the community youth leader. Are you ready to fill the questionnaire?

Section A: DEMOGRAPHIC PROFILE OF HOUSEHOLD

(1) Gender of respondent (a) Female {} (b) Male {}

(2) How long have you lived in this community? (a) less than 30 years {} (b) 31-45 years {} (c) 46-60 {} (d) 61 and above {}

(3) Are you the head of the household? (a) Yes {} (b) No {}

(4) What is your highest educational level? (a) First school leaving certificate {} (b) Senior secondary school certificate {} (c) Diploma, NCE {} (d) First degree and above {}

(5) What is your age cohort? (group) (a) 25-30 years {} (b) 31-45 years {} (c)46-60 years {} (d) 60 years and above {}.

(6) How many people in your house cook and eat from the same pot? (a) less than 3 {} (b) 3-4 {} (c) 5-6 {} (d) 7 and above {}

(7) What is your monthly income range? (a) less than N18,000.00 {} (b) N19000 to N35,000.00 {} (c) N36,000.00 to N45,000.00 {} (d) N46,000.00 & above {}

(8) What is the relative importance of these income sources?

I. Crop cultivation (a) very poor {} (b) least {} (c) medium {} (d) High {}

II. Livestock rearing (a) very poor {} (b) least {} (c) medium {} (d) High {}

III. Forest products (a) very poor {} (b) least {} (c) medium {} (d) High {}

IV. Petty trading (a) very poor {} (b) least {} (c) medium {} (d) High {}

V. Remittances (a) very poor {} (b) least {} (c) medium {} (d) High {}

(9) What has been the flow trend of these income sources (a) high {} (b) moderate {} (c) low {} (d) I have no idea {}.

(10) What is the major source of energy for cooking in your household?

(a) Kerosene {} (b) Electricity {} (c) Fuel wood {} (d) others (Specify)---------

SECTION B: FOREST RESOURCE USE AND RIGHTS OF ACCESS

(1) How will you rank your household reliance on the forest for the following?

I. Food stuff(a) very poor {} (b) least {} (c) medium {} (d) High {}

II. Fuel wood (a) very poor {} (b) least {} (c) medium {} (d) High {}

III. Medicine (a) very poor {} (b) least {} (c) medium {} (d) High {}

IV. Building materials (a) very poor {} (b) least {} (c) medium {} (d) High {}

V. Bush meat (a) very poor {} (b) least {} (c) medium {} (d) High {}

(2) Has the trend of household reliance of these forest resources changed in the last ten years?

(a) Yes {} (b) NO

(3) What is the direction of the change in:

VI. Food stuff? (a)Very small {} (b) small {} (c) medium {} (d) High {}

VII. Fuel wood?(a)Very small {} (b) small {} (c) medium {} (d) High {}

VIII. Medicine?(a)Very small {} (b) small {} (c) medium {} (d) High {}

IX. Building materials?(a)Very small {} (b) small {} (c) medium {} (d) High {}

X. Bush meat?(a)Very small {} (b) small {} (c) medium {} (d) High {}

(4) Tick all the forest products that your household harvest from the forest

(a) Firewood {} (b) Barks of tree {} (c) charcoal {} (d) poles {} (e) Timber {} (f) fodder {} (g) snails {} (h) Bush mango {} (i) Chewing stick {}

Use high or low to rank these items in order of economic value to your household

Fire wood	Bark of trees	Charcoal	Poles	Timber	Fodder	Snails	Afang	Chewing stick

SECTION C: AWARENES & LEVEL OF PARTICIPATION IN REDD+ PROJECT

(1). Have you heard of REDD+ project and its activities? (a) Yes {} (b) No {}

(2). If yes, how did you hear about REDD+ project? (a) Friends {} (b) Radio, Television, Newspaper {} (c) Community leaders/town crier {} (d) I cannot remember how I heard about REDD+ {}

(3). Have you or any member of your household been invited to a meeting where REDD+ was discussed? (a) Yes {} (b) No {}.

(4). If yes, at what time were you or member of your household invited (a) After we were asked not to harvest from the forest again {} (b) Before we were informed not to harvest from the forest again {} (c) When REDD+ came to tell us what they will do for the community {} (d) I can't remember the specific period {}.

(5). What do you think REDD+ has done in your community in the last five years? (a) Built school/health center (b) Train community on various skills (c) Support us to start small businesses (d) Others (specify)---.

(6) What livelihood activities have REDD+ train your community members on? (a) How to domestic some NTFP {} (b) Rearing of live stocks {} (c) we were given improved crop species {} (d) Others (Specify)---

(7) How has your experience in the following areas been with the introduction of REDD+ project in your community.

I. Climate change awareness (a) More now {} (b) Less {} (c) Same {} (d) Have no idea {}
II. NTPFs quantity (a) increase {} (b) Less {} (c) Same {} (d) Have no idea {}
III. Fertile land (a) more {} (b) Less {} (c) Same {} (d) Have no idea {}
IV. Destruction of buildings by windstorms a) More now {} (b) Less {} (c) Same {} (d) Have no idea {}
V. Availability of clean drinking water a) More now {} (b) Less {} (c) Same {} (d) Have no idea {}

SECTION D: IMPACTS OF REDD+ PROJECT COMMUNITY LIVELIHOOD SYSTEMS

1) How has REDD+ programme affected your income status (a) It has increased {} (b) It has reduced {} (c) It has not change {} (d) I don't know {}.
2) How will you rank the impacts of REDD+ programme in your community in the following areas?

I. Impacts on traditional knowledge systems. (a) least {} (b) medium {} (c) High {} (d) Very poor{}

II. Impacts on religious practices connected to the forest. (a) least {} (b) medium {} (c) High {} (d) Very poor{}

III. Have forest tenures/rights to forest (a) least {} (b) medium {} (c) High {} (d) Very poor{}

IV. Impacts on food security status of my household (a) least {} (b) medium {} (c) High {} (d) Very poor {}

V. Income streams of my household (a) increased {} (b) same {} (c) moderate increase {} (d) decrease {}

VI. Size of farm land (a) increase {} (b) same {} (c) moderate increase {} (d) decrease {}

VII. Impacts on crop yields (a) low {} (b) moderate {} (c) High {} (d) Very high {}

3) On a general note, how will you rate your livelihood conditions before REDD+ was introduced? (a) very good {} (b) just good {} (c) worst {} (d) same {}

Thank you.

Amuyou, Ushuki Ayankukwa
(Researcher)

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