Modeling Environmental and Social Impacts of Bioenergy from Oil Palm Cultivation in Nigerian Niger Delta

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Abstract

Environmental and social sustainability of bioenergy feedstocks especially oil palm is being controversially debated. The commercial cultivation of oil palms and other bioenergy crops have been leading to competition with land and its derivatives causing one of the major challenges confronting many Governments such as Nigeria.

This study shows the policy implications of oil palm as a bioenergy feedstock on social, economic and environmental dynamics of Nigerian Niger Delta and compares it with other feedstocks at the national level. This is achieved by coupling the output of a remote sensing studies (Article I), process-based modeling (Article II) in an integrated assessment method called mathematical inter-temporal partial equilibrium of Forest and Agricultural Sector Optimization Model (NGA-FASOM) (Article III).

The results of the NGA-FASOM simulations reveal that subsidies alone is not sufficient tools to achieve the government objectives defined in the Nigerian bioenergy initiatives; the Renewable Electricity Policy Guidelines (REPG) 2006, the Renewable Electricity Action Programme (REAP) 2006, the Nigerian Biofuel Policy and Incentives 2007 (NBPI) and the National Renewable Energy and Energy Efficiency Policy (NREEEP) 2014. The impact categories consisted of the greenhouse gas (GHG) emissions, direct and indirect land use changes and the aggregated social welfare. The study showed that under the zero emission cost scenarios, with or without bioenergy subsidies about 26 - 68 $MtCo_2e$ will be emitted from the Forest and Agricultural Sector. The study also showed that the share of oil palm area will significantly become higher by 2050 compared with other bioenergy feedstock under the zero emission cost scenarios. The impact of bioenergy policies does not have any significant effect on the total social welfare.

In Nigeria, meeting emission reduction and the accompanying targets entail an implementation of carbon price of $80/ton complimented with initiation of other conservation instruments such as payment for ecosystem services (PES) within the forest and agricultural sectors.

Following the results of this study, it would be ideal for the Government of Nigeria to establish a certification scheme aimed at assuring producer compliance with a set of sustainability criteria within the bioenergy sector.

In addition to the policy relevance, this study provides a detailed history on land use and land cover changes in the Nigerian Niger Delta and also show the impacts of the anticipated climate change on oil palm yields in the Niger Delta, Nigeria. It could serve as a source of information for earth system modelers as well as an information source for regional and global renewable energy modelers etc.

Zusammenfassung

Die Ökologische und soziale Nachhaltigkeit von Bioenergie-Rohstoffen, insbesondere von Ölpalmen, wird kontrovers diskutiert. Die kommerzielle Kultivierung von Ölpalmen und anderen Bioenergie-Pflanzen hat zusammen mit anderen Landnutzungsformen zu einem Wettbewerb um Flächen geführt und ist eine der größten Herausforderungen für viele Regierungen, zu denen auch die Nigerianische zählt.
Die vorliegende Studie zeigt politische Auswirkungen von Ölpalmen als Bioenergie-Rohstoff auf soziale, ökonomische und ökologische Dynamiken im nigerianischen Niger Delta und vergleicht die Auswirkungen mit denen anderer Rohstoffe auf nationaler Maßstabsebene.

Dies wird durch die Kombination von Ergebnissen einer auf Fernerkundungsdaten basierenden Studie (Artikel I) und einer prozessbasierten Modellierung (Artikel II) in einer integrierten Beurteilungsmethode erreicht (Artikel III). Diese Beurteilungsmethode wird "mathematische intertemporale Optimierung des partiellen Gleichgewichts im Agrar- und Forstsektor" (NGA-FASOM) genannt.

Die Ergebnisse der NGA-FASOM-Simulationen zeigen, dass Subventionen alleine keine ausreichenden Manahmen zum Erreichen der Regierungsziele, die in den nigerianischen Bioenergieinitiativen (Renewable Electricity Policy Guidelines (REPG) 2006, Renewable Electricity Action Programme (REAP) 2006, Nigerian Biofuel Policy and Incentives 2007, National Renewable Energy and Energy Efficiency Policy (NREEEP) 2014) definiert wurden, darstellen.

Die Auswirkungen wurden wie folgt kategorisiert: Treibhausgasemissionen, direkte und indirekte Landnutzungsveränderungen und die aggregierte Soziale Wohlfahrt.
Die Studie zeigt, dass beim "Zero-Emission"-Kostenszenario sowohl mit, als auch ohne Bioenergie-Subventionen, circa 26 bis 68MtCo_2e vom forst- und landwirtschaftlichen Sektor emittiert werden. Darber hinaus zeigt die Studie, dass der Anteil der fr den Ölpalmenanbau genutzten Fläche im Vergleich zu anderen Bioenergie-Rohstoffen bis zum Jahr 2050 beim "Zero-Emission"-Kostenszenario signifikant höher werden wird. Die Ergebnisse stellen dar, dass Subventionen keinen substantiellen Effekt auf die aggregierte Soziale Wohlfahrt haben.

Das Erreichen der Emissionsreduzierungsziele und der genannten begleitenden Ziele bedeutet für Nigeria die Implementierung eines Kohlenstoffpreises von 80 US$ pro Tonne sowie die Einführung von anderen Naturschutzmaßnahmen wie zum Beispiel Zahlungen für

Ökosystemdienstleistungen im Forst- und Landwirtschaftssektor.

Aufgrund der Ergebnisse dieser Studie könnte es für die nigerianische Regierung zielführend sein, ein Zertifizierungsschema einzurichten, das die Befolgung der Regeln durch die Produzenten innerhalb des Bioenergiesektors mit einem Satz von Nachhaltigkeitskriterien kontrolliert.

Abgesehen von der politischen Relevanz beinhaltet die Studie detaillierte Informationen zurEntwicklung der Landnutzung und zu Landnutzungsänderungen der Region. Sie zeigt auch den Einfluss des zu erwartenden Klimawandels auf die Erträge der Ölpalmen im nigerianischen Niger Delta.

Die Ergebnisse können unter anderem für zum Beispiel Klimamodelle und Modelle erneuerbarer Energien auf regionaler und globaler Ebene als Informationsquelle dienen.

Acknowledgements

I would first like to thank my advisor, Prof. Dr. Udo Schickhoff. Your guidance, wisdom, perspective, and friendship has made this work possible. I also thank my second advisor, Prof. Dr. Uwe A. Schneider for your guidance and support as I wondered through the world of partial equilibrium modeling in GAMS. For all the hours that you invested. Without them, the black box would have been a black hole. Thank you Prof. Dr. Jürgen Böhner for being the panel chair of my dissertation committee.

I would like to thank Dr. Neil Huth of the Commonwealth Scientific and Industrial Research Organisation(CSIRO) Australia for walking me through the APSIM model.

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My colleagues, Niels, Maria, Birgit, Franzis and Alina I gained a lot through those days of personal and scholarly interactions, thank you guys.

I also would like to thank my uncle Mr. Festus Anunike for the encouragement and support in coming over to Germany.

Most importantly, thanks to my family, my siblings and my mom. Mom, I am forever indebted to you for the unconditional love and support both morally and financially that you have provided over the years towards my education, you are truly an inspiring woman.

In a special way, I would like to thank my wife for her love and understanding all these while.

Above all, I owe it all to Almighty God for granting me the wisdom, health and strength to undertake this research work and enabling me to its completion.

Dedication

This dissertation is dedicated to my late father Humphrey Onyeaghalanwanneya Okoro.

"It always seems impossible until its done."

Nelson Mandela

Declaration on oath

I hereby declare, on oath, that I have written the presented dissertation by my own and have not used other than the acknowledged resources and aids.

Eidesstattliche Versicherung

Hiermit erklre ich an Eides statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Hamburg, 31.01.2018 Stanley Uchenna Okoro

Abbreviations

Co_2 Carbon dioxide

°C Degree Celsius

ABPN Automotive Biomass Programme for Nigeria

API Application Program Interface

APSIM Agricultural Production System sIMulator

ATA Agricultural Transformation Agenda

C Carbon

CDO Climate Data Operator

CPLEX IBM ILOG CPLEX Optimizer's mathematical program

E-10 Mixture of 10% Ethanol and 90% Petrol

ECN Energy Commission of Nigeria

GAMS General Algebraic Modeling System

GCM General Circulation Model

GDP Gross Domestic Product

GHG Greenhouse gas

GIS Geographic Information System

GJ Gigajoules

GNI Gross National Income

ha Hectare

IAM Integrated assessment model

IPCC Intergovernmental Panel on Climate Change

kg Kilogram

km Kilometer

m Meter

MDGs Millennium Development Goals

MJ Megajoules

mm Millimeter

$MtCo_2e$ Metric tonnes of carbon dioxide equivalents

MW Megawatt

N Nitrogen

NBPI Nigerian Biofuel Policy and Incentives

NEEDS National Economic Empowerment and Development Strategy

NGA-FASOM Nigeria Forest and Agricultural Sector Model

NIFOR Nigerian Institute for Oil Palm Research

NNPC Nigerian National Petroleum Corporation

NREEEP National Renewable Energy and Energy Efficiency Policy

P Phosphorus

PES Payment for Ecosystem Services

RCP Representative Concentration Pathway

REAP Renewable Electricity Action Programme

REF Rural Electricity Fund

REMP Renewable Energy Master Plan

REPG Renewable Electricity Policy Guidelines

RETF Renewable Electricity Trust Fund

SAGA System for Automated Geoscientific Analyses

UN United Nations

UNDP United Nations Development Programme

WAM West African Monsoon

yr Year

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Chapter 1

Introduction

The oil palm, Elaeis guineensis Jacq. production is swiftly expanding worldwide, with a planted area expansion of approximately 378% from 1961 to 2012 [20]. Oil palm production had been part of mixed farming activity in West Africa. Currently, oil palm production practice is being expanded to industrial-scale mono-cropping [13], thereby making the local communities vulnerable to environmental and social risks, especially people with limited economic capacities [12]. Oil palm was usually grown in tropical regions mostly for palm oil production, the world's largest yielding and least expensive vegetable oil. The derivatives of palm oil are common ingredients in many packaged and fast foods cosmetic products etc [70]. Due to this multiple use of the product, the demand for oil palm has increased over the last few decades, and it is projected to rise further [13], attracting private and government sectors to invest heavily in the oil palm industry. In recent years, the cultivation of oil palm is generally characterized by large scale monocultures of uniform age structure, low canopy, sparse undergrowth, a low-stability microclimate and intensive use of fertilisers and pesticides [57]. The oil palm tree generates fruits from the third year, with yield per tree increasing gradually until it peaks at approximately 20 years [13, 56]. Oil palm plantations are typically destroyed and replanted at 25 to 30 year intervals. Palm oil production process tends to reduce fresh water and soil quality, and adversely affects local communities which are dependent on ecosystem products and services (such as regulation of the hydrological cycle and soil protection) provided by the forests [22]. Ecologically, oil palm monocultures might form impervious barriers to species migration and result in greater susceptibility to plant diseases. Conversion of natural forests to oil palm plantations has been observed to increase habitat fragmentation and biodiversity loss [70]. According to [12], the global market for palm oil is driving land acquisition in the form of large blocks of land that has frequent link with problems related to tenure systems and land-use rights. Thus, resulting in the exploitation of local communities and frequent abuse of human rights [18]. UN reports have also established that oil palm plantations had caused widespread forest destruction in Indonesia and Malaysia [5] where majority of the worlds plantations are located today. Throughout the life-cycle of oil palm production, environmental impacts are the object of concern. Emissions have to be taken into account from the raw material extraction to the recycling or disposal stages. The environmental impact depends greatly on the land use change conditions, the consumption of conventional fuels, fertilizers, pesticides and wastes generated [70]. Therefore, the concern that palm oil production is largely unsustainable, with issues relating to deforestation, biodiversity, soil degradation, water quantity, local people, land rights and many other matters worth researching. Development of new plantations which has resulted in the conversion of large areas of forests with high conservation value, has threatened the rich biodiversity in these ecosystems. Many of these social, ecological and environmental impacts of oil palm production linked to bioenergy could be associated with land cover and land use change in connection to bioenergy production. Bioenergy-related land use decisions may affect local, regional and global social and environmental systems. Therefore, sustainability is a big challenge to increase development of bioenergy production. To this regards, this thesis investigate the environmental and social impacts of bioenergy production and predict the future impacts of "business as usual" scenario based on current policies for bioenergy deployment in Nigeria and oil palm as a contributing feedstock from the Nigerian Niger Delta.

1.1 Background

Today, climate change is a great challenge for the society. Human influence on the climatic system is evident and predicted with a very high confidence level [38]. This has been linked to energy use thus posing a great challenge to energy security. The worlds energy consumption in 2015 amounted to about 606.65 billion GJ and was made up of about 81% fossil fuels (oil, gas and coal), 10% biomass, 6% nuclear and 2.2 and 0.5% hydropower and other energy respectively [35]. These results to an increase in demand for natural resources. These increase in demand and pressure on natural resources, renewable and non renewable by growing human population calls for efficient use of such resources and ecosystem services if sustainable development and climate change mitigation must be achieved. The search for energy alternatives involving locally available renewable resources has been one of the main concerns of governments, scientists and industries worldwide. Bioenergy is a renewable source of energy from biological materials (biomass) such as trees, plants, manure, municipal waste etc. Using various transformation processes such as combustion, gasification, or pyrolysis, the biomass is either transformed into biofuels, bioheat or bioelectricity. It is a carbon-neutral renewable energy feedstock if the feedstocks are sourced sustainably. Biomass originates from forest, agricultural and waste streams. Forest and wood-based industries produce wood, which is the largest resource of solid biomass. The sector covers a wide range of different biofuels with different characteristics - wood logs, bark, wood chips, sawdust and more recently pellets. Pellets, due to their high energy density and standardised characteristics offer great opportunities for developing the bioenergy market worldwide. Agriculture can provide dedicated energy crops as well as by-products in the form of animal manure and straw. Available land can be used for growing conventional crops such as rapeseed, wheat, maize, oil palm etc. for energy purposes or for cultivating new types of crops such as poplar, willow, miscanthus, jatropha curcas and others. In recent years, many countries around the world have been tapping renewable resources to secure stable sources of energy. This was put to place by high fossil fuel prices, peak oil, rising demand for energy and above all increasing concern about the implications of fossil fuel on the global climate system. Biomass, the fourth largest energy source after non renewable (coal, oil and natural gas), is currently seen as the most important renewable climate friendly energy option [65, 42]. Till date, the availability of this product has been limited or threatening to food security, biodiversity and related problems due to inadequate use of land for its production. The oil palm tree is native to West Africa, where it was traditionally cultivated as a subsistence crop for food, fibre and medicine [37]. In the Niger delta of Nigeria, trees were traditionally inter planted in small-scale agricultural production systems along with other annual and perennial crops (mix-cropping). In Nigeria, Oil palm is one of the most important economic oil crops. As the demand for vegetable oils has risen since the 1970s, the oil palm cultivation has been shifted to large-scale plantations. And such plantations have become one of the fastest-growing mono cropping plantations in the tropics of Africa, as well as in Asia-Pacific, Latin America and the Caribbean. Much of this expansion has occurred in Malaysia and Indonesia but recently becoming the case in Nigeria. By 2016, these two former accounted for just over half of the world's total plantation area (then about 14 million hectares), Nigeria accounted for 3.0 million hectares [21].

Oil palm is among the most productive and profitable of tropical crops for biofuel production. Oil palm products have very high energy content in the form of palm oil which undergoes trans-esterification to become a biodiesel use in transportation. Palm kernel shells are virgin biomass with a high energy content of about 17.58-19.25MJ/kg. High-yielding oil palm varieties developed by breeding programmes can produce approximately over 20 tonnes of fresh fruit bunches/ha/yr under ideal management, which is equivalent to 5 tonnes oil/ha/yr (excluding the palm kernel oil) [56]. The oils form 10% of the total dry biomass produced by the palm, which can be directly processed as first generation biofuel but the 90% left might be a source of fibre and cellulosic material for second-generation biofuel production [54, 65], which is considered as a natural pellet and has high grade solid renewable fuel for burning as received, both in co firing with steam coal or burned at biomass power plants. Production of biodiesel from oil palm is increasing in recent years, particularly in Africa and Latin America [11, 46, 68, 70, 24].

The sustainable use of oil palm as an energy source requires comprehensive management of natural resources such as land and its biodiversity. Unsustainable use of this product prevails in Asia can shift to West Africa (Nigeria), and is capable of eroding its climate-related environmental advantages. Currently, United State of America leads the production of biodiesel with an output of approximately 4983 million litres per annum as of 2016 [53], seconded by Brazil with the production 2804 million litres in 2016 [53]. Studies have shown that African and

Asian countries will grab the highest share of renewable energy market in the coming years [39], thus posing a number of questions on its environmental and social consequences. Hence, high emission burden, food insecurity and great loss of biodiversity that will be emanating from these developing countries with increasing bioenergy production in the near future. These

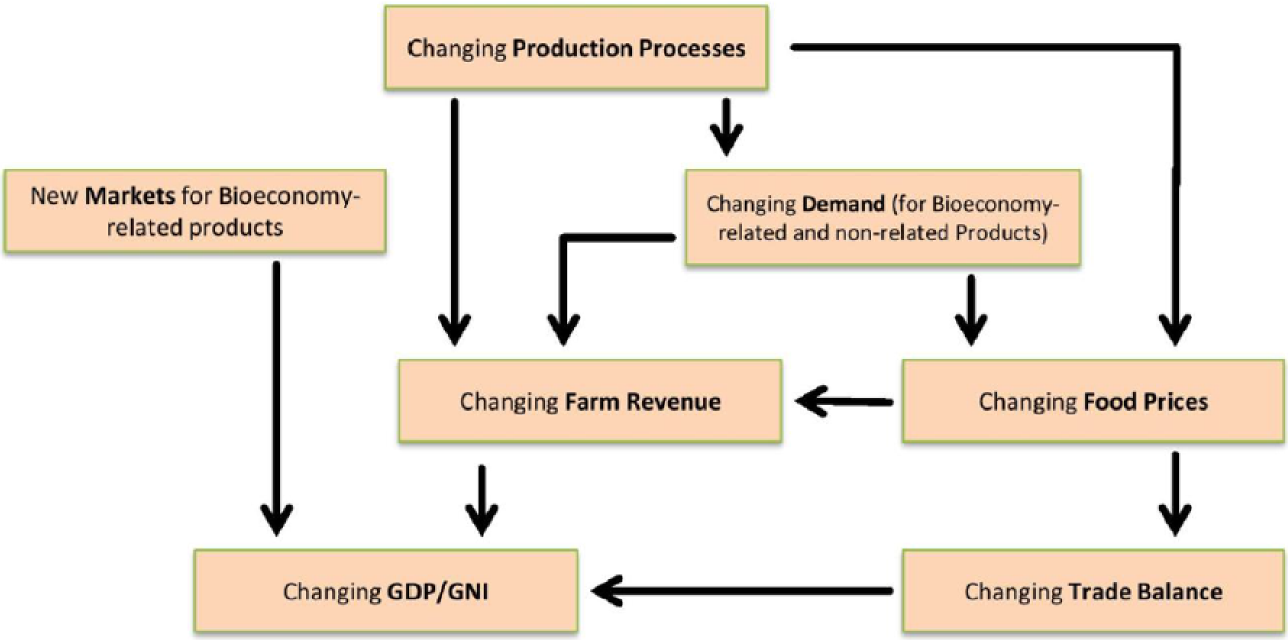

Figure 1.1: Graphical representation of economic impacts of bioenergy deployment (adapted from [27])

pose great challenge for the deployment of bioenergy. See Figures 1.1, 1.2, 1.3 for a general overview of the threefold impacts. Thus a more practical model such as NGA-FASOM [58] was developed to ascertain the state of land use, potential sustainable production capacity as well as scenarios for future trend of the impacts.

1.2 Study Area

1.2.1 Geographic location

The study area, Niger Delta lies in the southern part of Nigeria (figure 1.4), and it is one of the world's largest acute fan-shaped river deltas [43]. The Niger Delta extends over Imo State, Abia State, Bayelsa State, Rivers State, Ondo state, Akwa Ibom state, Edo State, Rivers State

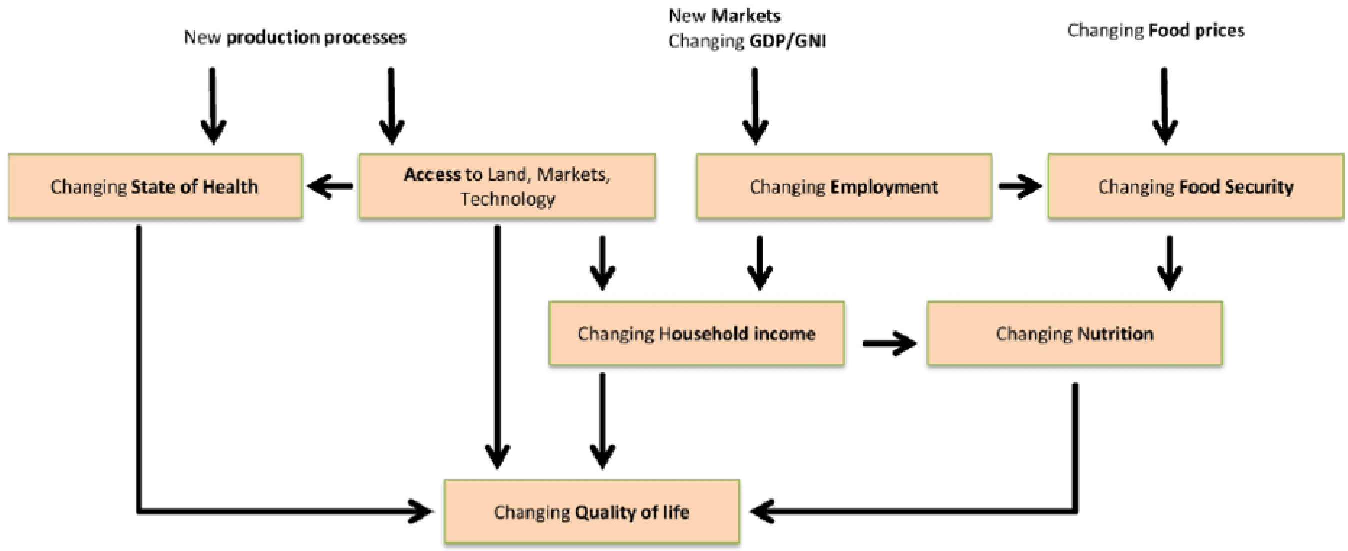

Figure 1.2: Graphical representation of social impacts of bioenergy deployment (adapted from [27])

and Cross Rivers State. It is located between 4.01°and 7.90°North of the equator and between 4.50°and 10.56°East, bordering Cameroun in the South East, the South West Nigeria in the West, Eastern Nigeria in the North East and the Atlantic Ocean in the South. The total land area of the region is estimated at $70,000km^2$ which is 7.5% of the Nigerias total land mass. The extent covered by wetland is about 28.5% of the total area. The Niger Delta has an altitude range of 0-791m see Figure 1.4.

1.2.2 Climate

The Niger Delta region has favorable climate conditions with monthly average rainfall ranging from 200 mm to 400 mm during the rainy season extending April/May to October see figure 1.5. Rainfall in the northern and north- western regions of the Delta may be delayed by as much as four weeks, which results in an extension of dry season to late May, in recent times may be up to four to five months [50]. Rainfall in the Niger Delta has been characterized to exhibit no visible pattern in recent years as fluctuations with no trends has been observed [36]. Temperature in the region is generally high with low variability across seasons. Average monthly temperature ranges from 25°C to 29°C see figure 1.5. In most of the states of the Niger Delta, the warmest months are February, March and early April. There is evidence that

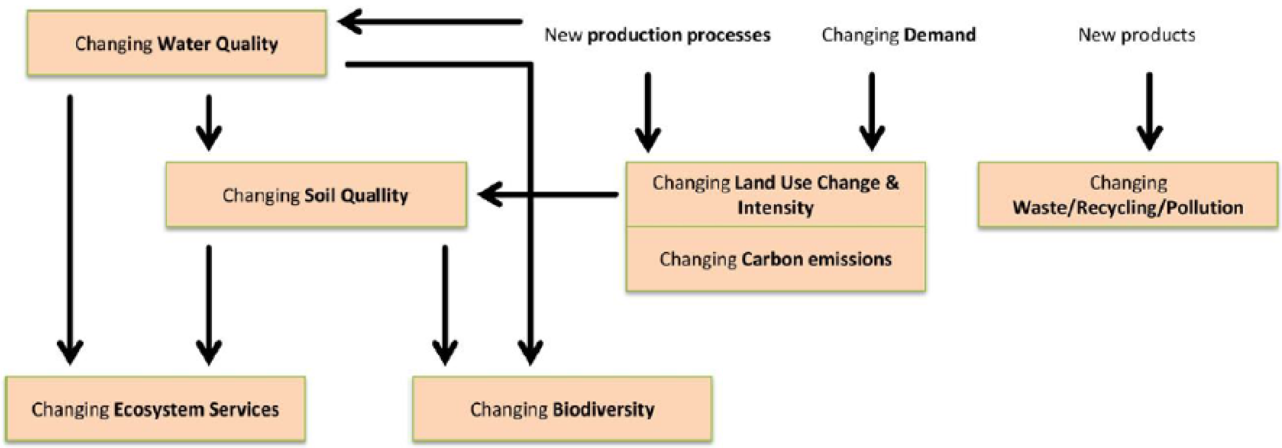

Figure 1.3: Graphical representation of environmental impacts of bioenergy deployment (adapted from [27])

climate change is anticipated to change further the temperature pattern of the region [38]. This potential climate change indicator (Temperature) is plausible and likely to increase further, see [56] with a projected regional increase in temperatures of between 3°C and 8°C by 2100. There are five agro-ecological zones (Rain forest, Savanna, Fresh water swamp, Mangrove, Montane) in Niger Delta region see figure 1.7 with different soil characteristics, altitudes and precipitation regimes. The rain forest is the the largest of the agro-ecological zones and it is characterized by gentle plains with moderately sloping hills, sandy-loam soils [30]. The Mangrove extend between Akwa Ibom state, Delta state and Cross Rivers state. The fresh water swamp lies between Imo and Rivers state through Bayelsa to Ondo and some Savanna cover in Edo and Cross Rivers state. About 40 different tribes have settled in the region including the Bini, Efik, Esan, Ibibio, Igbo, Annang, Yoruba, Oron, Ijaw, Ikwerre, Itsekiri, Isoko, Urhobo, Ukwuani, Kalabari, Okrika and Ogoni etc

1.2.3 Society

The Niger Delta region is experiencing a steady population growth see Table 1.1. The total population of the region amounted to 23% the population of Nigeria, with population density ranking among the highest in the world [50]. About 80% employed persons in the region engaged in the informal sector. The major occupation of the people are agriculture and fishing [59].

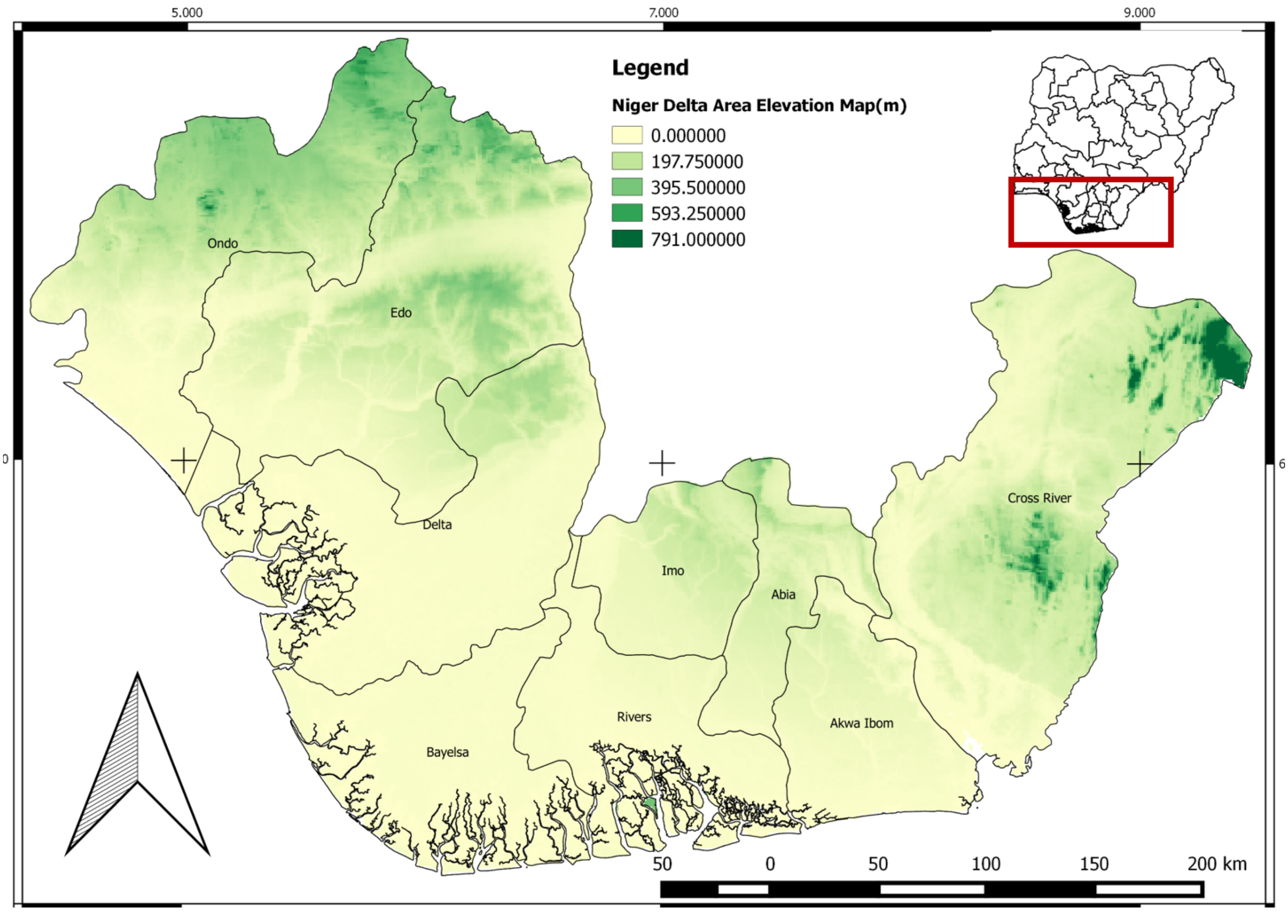

Figure 1.4: Map of Niger Delta Area with elevation

Akwa Ibom state account for the highest number of people engaged in agriculture, seconded by Imo state and Abia state respectively (see Figure 1.6). Medium and large manufacturing plants are only concentrated in Rivers state. The Petroleum industry which is the backbone of the Nigerian economy accounting for about 90% of the country's total foreign exchange revenue is situated in the region.

1.2.4 Agriculture

Recently, agriculture is playing a crucial role in the economy of the entire Nigeria. In Niger Delta Nigeria about 80.25% of the land area is dedicated to cropland, 11.28% forest and 5.46% is grassland, see Figure 1.8 [6, 57]. The staple foods in the region are cassava, maize, rice and yam with palm oil and cocoa as cash crops.

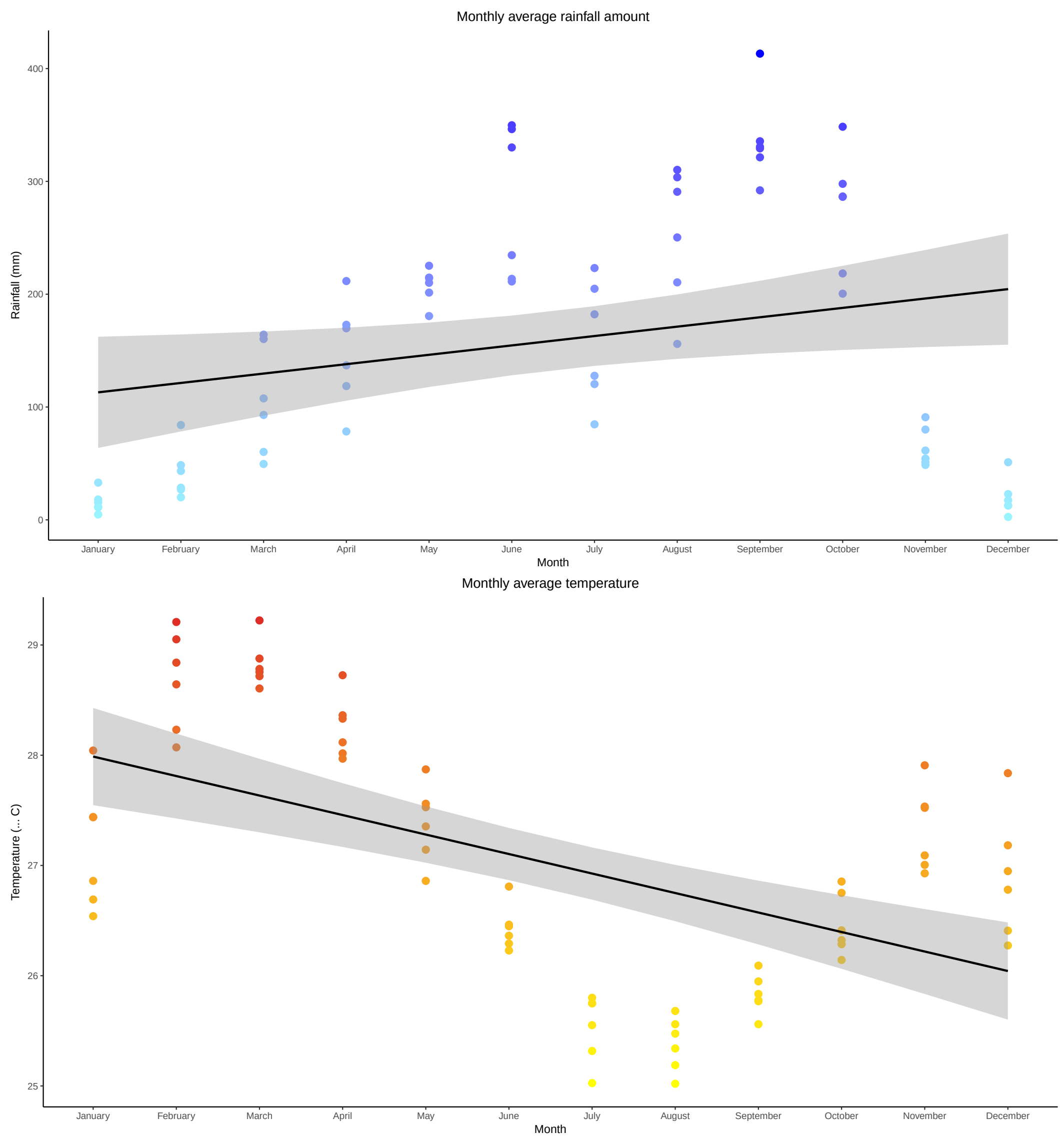

Figure 1.5: Average monthly rainfall amount (mm) and temperature (°C) over Niger Delta Nigeria (source [26])

1.3 Oil palm industry in the Nigerian Niger Delta

Oil palm is indigenous to the people of the Niger Delta region of Nigeria [44], but has now extended to other tropical countries. Oil palm industry in the Niger Delta Nigeria is dated back to pre-colonial era. As at that era Niger Deltans had an established economic system based largely on oil palm [3]. During the colonial era oil palm exploitation was preeminent in the colonial administration motives [31]. Oil palm products is one of the the principal export commodities during the colonial period, palm oil and palm-kernel have the longest histories being some of the earliest commodities exported from the present day Nigeria. Oil

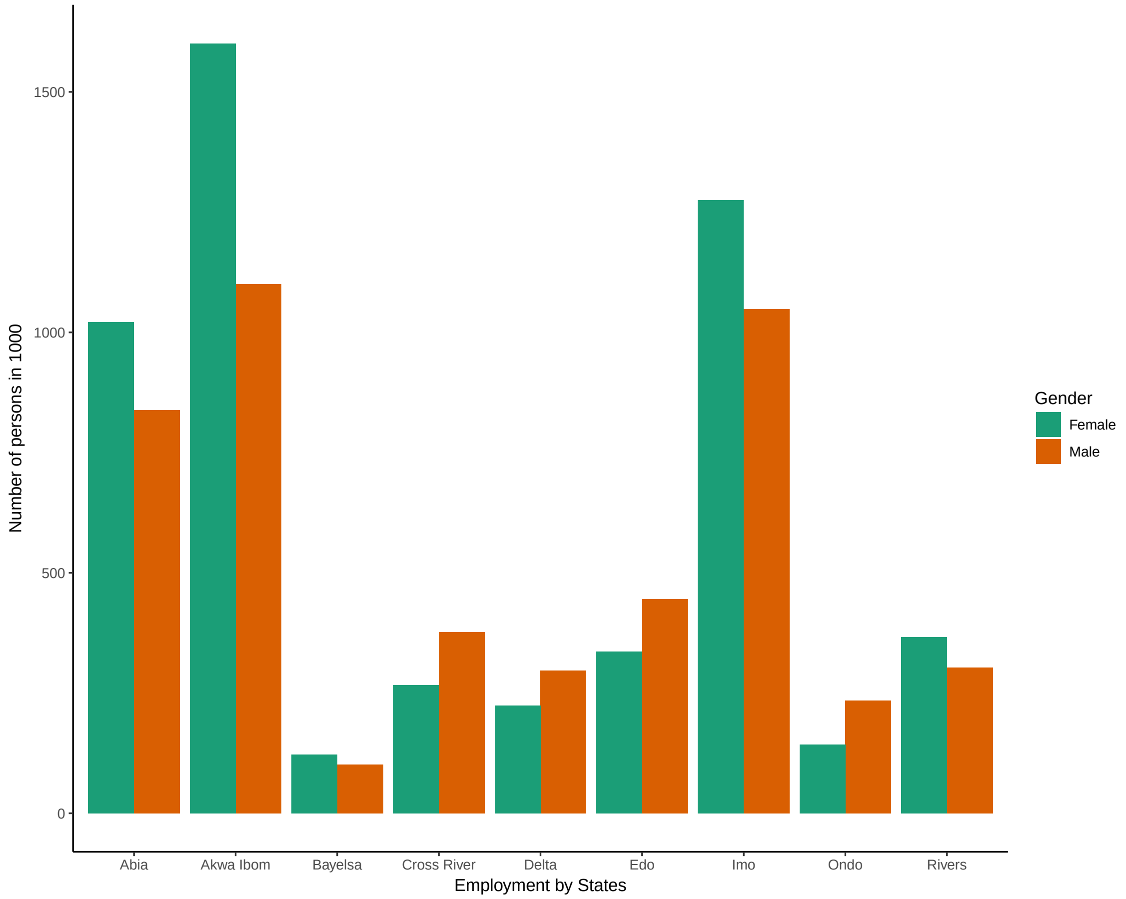

Figure 1.6: Total Employment in Agricultural Sector by states (source [49])

palm products became more important in the late 19th century with the abolition of slave trade, the inauguration of the industrial revolution, and the development of the railway which required palm oil as a lubricant. Nigeria export volume of oil palm products increased with a factor of 2 between 1865 and 1910, she became the lead in West Africa with regards to export volume [66]. Oil palm products export trend in Nigeria later began to decline with the emergence and export of other products such as rubber and cocoa. The lead in the palm produce export trade was further threatened with the growth of plantations in Sumatra, Malaya, and Belgian Congo in the late 1950's [31, 69]. Lately, Since the fall in fossil fuel prices and its volatility rate, issues regarding the adverse effect of fossil fuel usage. Nigerian government has reconsidered to diversify her foreign exchange earning choices. Currently, the central bank of Nigeria has placed a ban on imported crude palm oil [2, 28]. These among other things were in line with the quest for change in energy mix due to climate change. But the actualisation of these multiple objectives required caution as oil palm production activities and its environmental

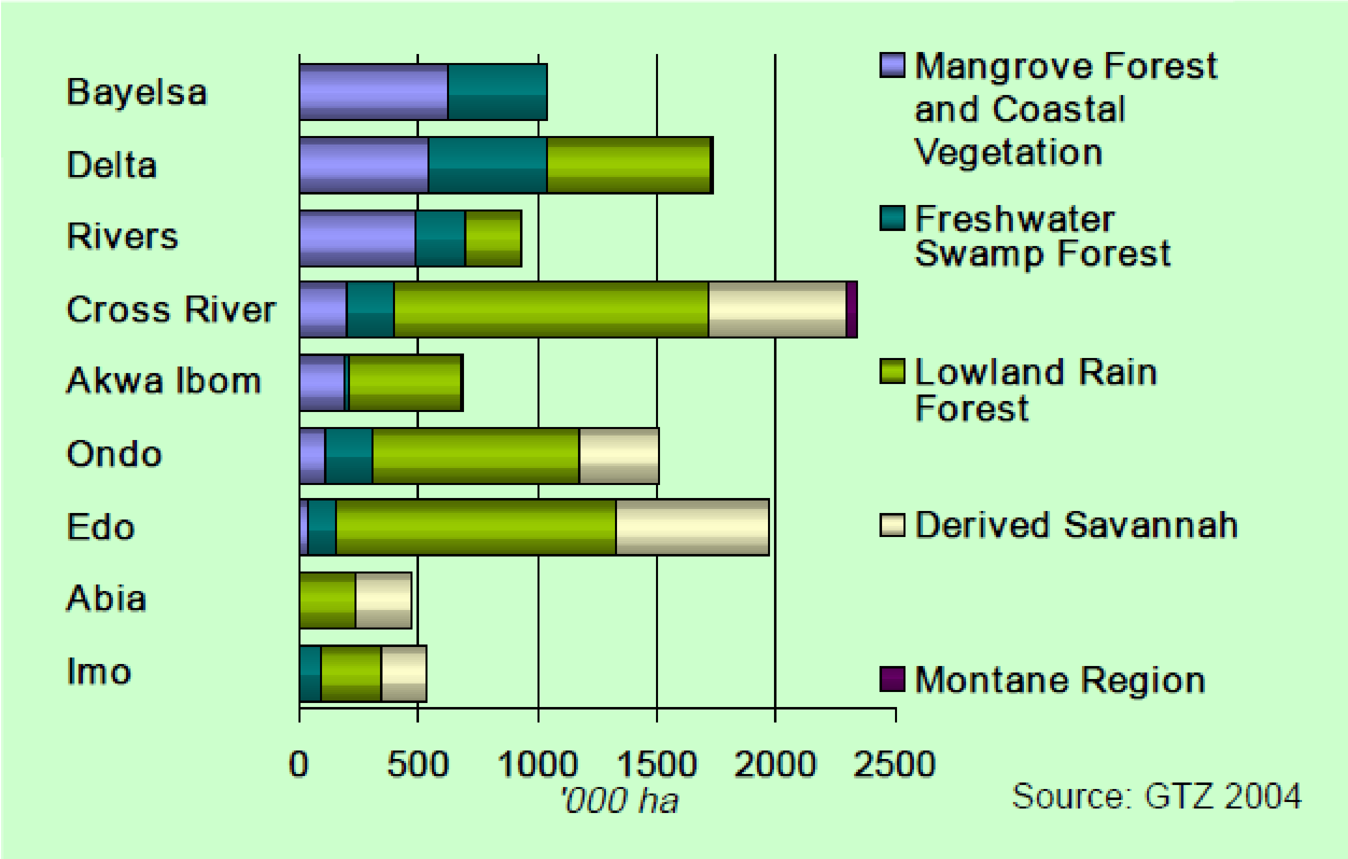

Figure 1.7: Areas of ecological zones by states of the Niger Delta Nigeria

sustainability has been controversially argued [55, 33, 64]. To this regards, a global sustainable palm oil strategy needs to be developed [5].

1.4 Bioenergy policies in Nigeria

The energy supply situation in Nigeria is critical and it is a key constraint for economic development. Approximately 55% of the population has no access to electricity [67]. Traditional biomass (firewood) account for about 70% of the total energy consumption in Nigeria [17]. The exponential increase in demand for energy is attributed to the country's population growth and economic development. Energy consumption is one of the indices used in measuring the development and quality of life of a country, and the necessity of satisfying a forecasted energy demand for a given period is the rationale for energy planning[14]. To this regard, various bioenergy policies have been put in place by the government to enable the contribution of bioenergy to the

Table 1.1: The population of Niger Delta States in 1000 Persons (source [49])

State	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Imo	4609.038	4758.912	4913.66	5073.44	5238.416	5408.756
Bayelsa	1970.487	2028.468	2088.154	2149.597	2212.849	2277.961
Cross River	3344.409	3442.816	3544.12	3648.404	3755.757	3866.269
Akwa Ibom	4625.12	4785.078	4950.568	5121.781	5298.916	5482.177
Delta	4825.999	4982.928	5144.961	5312.262	5485.004	5663.362
Edo	3700.706	3801.987	3906.039	4012.938	4122.764	4235.595
Rivers	6162.063	6375.176	6595.659	56823.767	7059.764	7303.924
Ondo	4020.965	4143.422	4269.608	4399.637	4533.626	4671.695
Abia	3256.642	3345.769	3437.336	3531.408	3628.055	3727.347

country's energy mix. This includes; 1) The Renewable Electricity Policy Guidelines (REPG) 2006. The REPG mandated the Nigerian government to generate a minimum of 5% of the total electricity generation and a minimum of 5TWh from the renewable sector. The REPG has other objectives such as establishment of a stable and long term favorable pricing mechanisms and unhindered access to the grid, guaranteed purchase and transmission of all electricity generated from the renewable sector. Furthermore, the Construction of independent renewable electricity systems in areas not covered by the national grid. The development of innovative, cost-effective and practical measures to accelerate access to electricity services in rural areas through renewable sources. Setting up of a Renewable Electricity Trust Fund (RETF) to be governed by the Rural Electrification Fund (REF). Creation of a multi-stakeholder partnership for the delivery of renewable electricity to meet national development goals. Broadening international cooperation in expanding the role of renewable electricity for meeting national development goals and contributing to global efforts in addressing climate change. 2) The Renewable Electricity Action Programme- REAP (2006) was development for a clear roadmap for the implementation of the REPG. 3) The Nigerian Biofuel Policy and Incentives-NBPI (2007); aimed at developing and promoting domestic bioethanol industry. It was in line with the government's directive on an Automotive Biomass Programme for Nigeria (ABPN) in August 2005 [19]. The Nigerian National Petroleum Corporation (NNPC) was mandated to create an enabling environment for the take-off of the bioethanol industry. Other aims of the policy includes; the reduction on country's dependence on imported gasoline, climate change mitigation and other sustainable

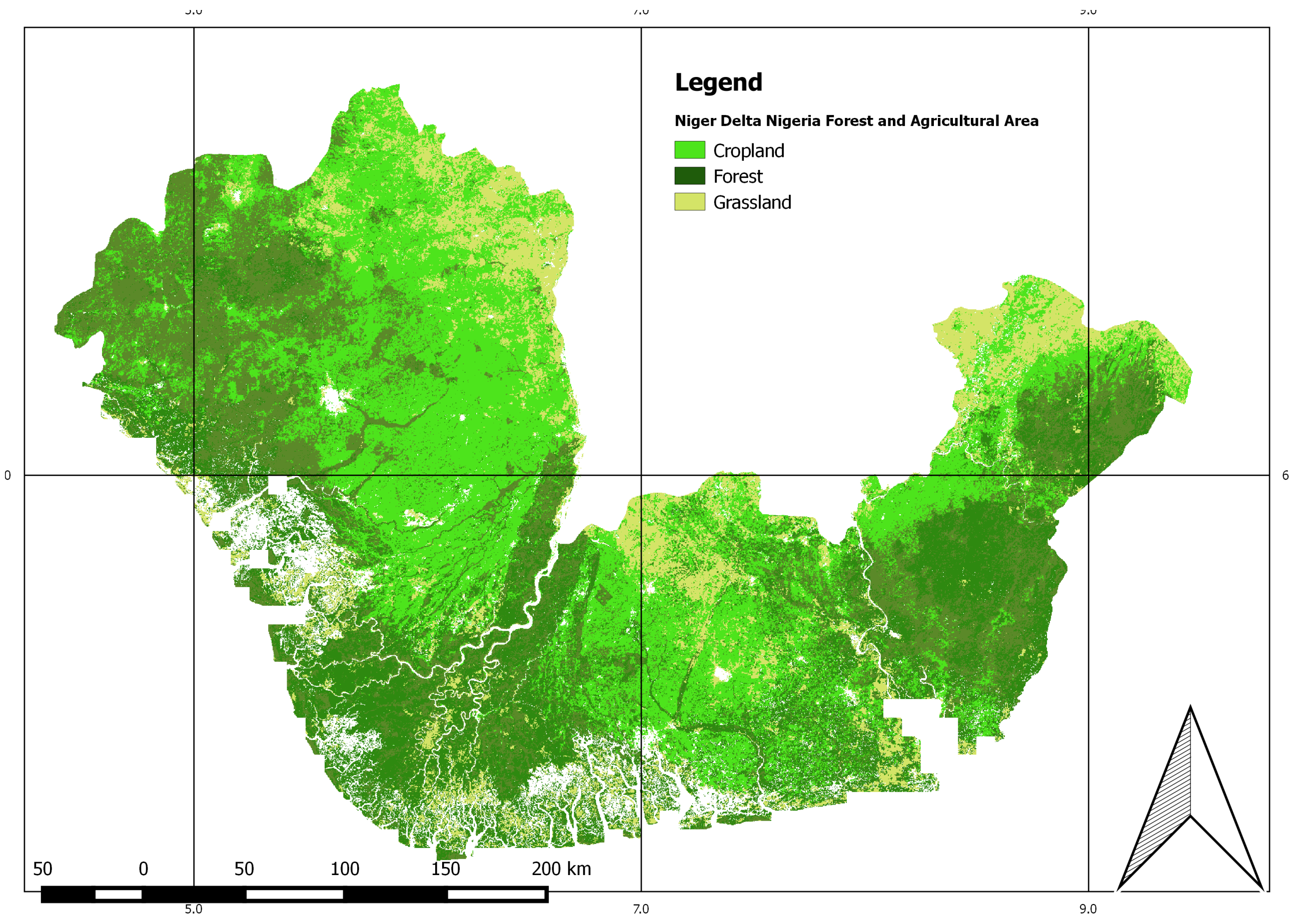

Figure 1.8: Forest and agricultural land use area of the Niger Delta Nigeria(Source [57])

development goals. The NBPI policy targets are to;

- To develop an import duty waiver for biofuels granted for 10 years
- To ensure the contribution of all biofuel companies with 0.25% of their revenue towards funding research into feedstock production, local technology development and improved farming practice
- To launch a special kind of loan for investors in the biofuel industry aided at development of large-scale schemes and large-scale integrated operation including plantation, a plant and within-the-gate collocated power generating plants
- To achieve 100% domestic production of biofuels consumed in the country by 2020
- To ensure an off-take agreement by NNPC for biofuels as buyer of last resort

- To achieve the blending of up to 10% of fuel ethanol with gasoline to achieve a blend to be known as E-10 during the seeding phase of the programme

- An exemption from taxation, withholding tax and capital gains tax imposed in respect of interest on foreign loans, dividends, services rendered from outside Nigeria to biofuel companies by foreigners.

In addition, the stipulated targets are bio-diesel supply at 900 million liters for 2020, 2030, 2040 and 2050. Ethanol demand of 2 billion liters by 2020, 2030, 2040, 2050 for Gasoline 10% ethanol blend ratio (E10) requirement. 4) The Renewable Energy Master Plan (REMP) (2005), (2012); Energy Commission of Nigeria under the Federal Ministry of Science and Technology developed the Renewable Energy Master Plan (REMP), in collaboration with the UNDP in 2005, reviewed in 2012 (REMP 2005, 2012). The REMP shows country's vision and sets out a framework for increasing the role of renewable energy in achieving sustainable development. The REMP revolves around the values, principles and targets as incorporated in the National Economic Empowerment and Development Strategy (NEEDS), National Energy Policy, National Policy on Integrated Rural Development, the Millennium Development Goals (MDGs), and international conventions to reduce poverty and reverse global environmental change (REMP 2012). The REMP has a sub-programme termed the National Biomass Energy Programme with a target of 5MW, 30MW and 100MW of electricity for its short term, medium term and long term targets respectively. The stipulations that by 2025 the 10% nation's electricity consumption should be from a renewable source. 5) The National Renewable Energy and Energy Efficiency Policy (NREEEP) (2014). The Federal Ministry of Science and Technology in 2014 developed the National Renewable Energy and Energy Efficiency Policy [52]. The stipulated objectives with regards to bioenergy include;

- To promote bioenergy production especially in the rural areas.

- To reduce adverse health effect arising from combustion of biomass fuel.

- To focus biomass utilization close to production, for community heating schemes and domestic heating, particularly off the national grid network. With electricity demand target from biomass at 2273.08 GJ, 11560.10 GJ, 16201.61 GJ, 16201.61 GJ by 2020, 2030, 2040 and 2050, respectively.

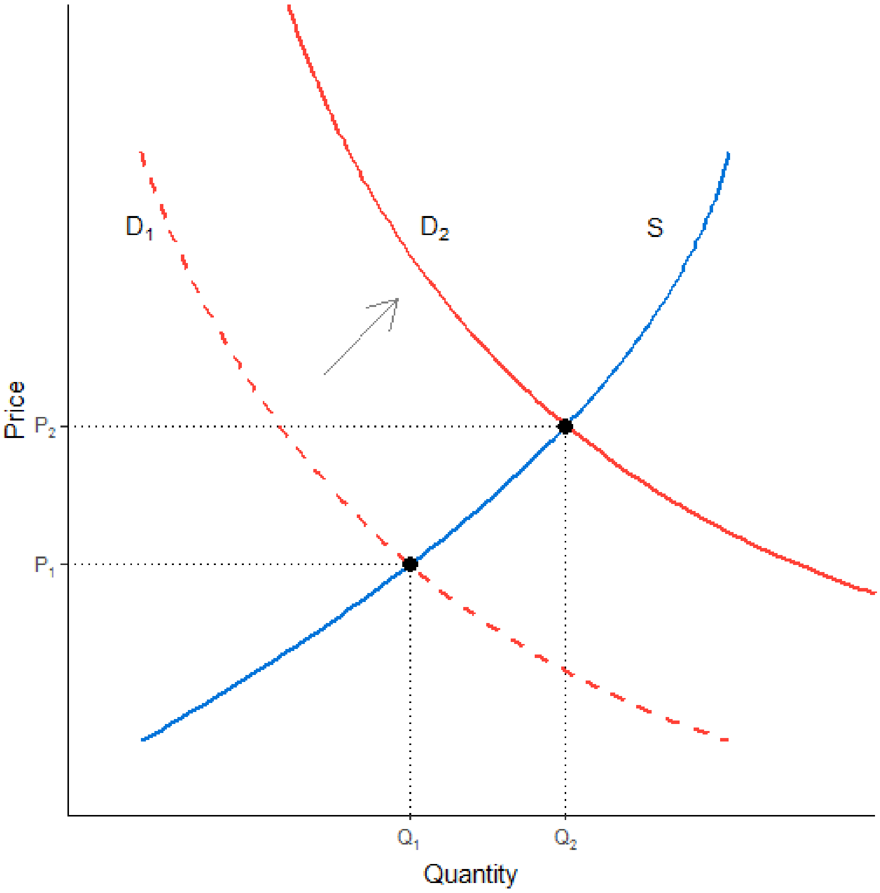

Figure 1.9: Shift in demand equilibrium under subsidy action

1.4.1 Impact of subsidies for bioenergy on agricultural land use change

The ultimate aim of subsidising bioenergy sector is to reduce the use of fossil fuels which has adverse effect on the climate system. Subsidies such as tax credits or exemptions are grants provided by many governments to encourage a particular sector of her economy. It provides a wedge between the price recieved by the producers and price paid by the consumers. Figure 1.9 shows a representation of a the market equilibrium with and without subsidy where subscripts 1 and 2 represents pre & post subsidy respectively for demand and supply curves. Land use change implications of subsidies on bioenergy have caused great concern for both researchers and the policy makers [41]. The amount of available land for agriculture converted to producing energy crops affects the cost of other staple crops that are no longer being produced at the same levels [61]. [41] stated that bioenergy impacts on land use evolves over time. The land use impact of bioenergy depends on policy actions [41], thus necessitates a proper analysis before deployment.

1.4.2 Environmental impacts of agricultural production

Agriculture is key to ensuring food security. The need to provide food for the growing population has led to increase in agricultural activities which in turn puts pressure on the available arable land. As a result a majority of forest is destroyed annually either through burning or logging to create more land for food production, energy crop production as well as the creation of ranches and grazing land for cattle.

Furthermore, agricultural activities have contributed enormously to the depletion of natural ecosystems which threatens biodiversity and ecosystem services that directly contribute to human well-being, such as water purification, air quality regulation and stable climate through carbon storage [15, 48]. In the Niger Delta region, [57] estimated great decrease in forest area due to oil palm cultivation. Land use change and forestry accounted to about 51.06% (253.16MtCo_2e) of the country's total emission in 2014 [20]. Agriculture was responsible for about 13% of this anthropogenic emissions of greenhouse gases in Nigeria (64.24MtCo_2e).

1.5 Motivation and Objectives

The global demand for modern bioenergy, and especially liquid biofuels, is rapidly growing.This is driven mainly by climate change mitigation policies and increasing oil prices. This creates both opportunities and risks for developing countries such as Nigeria [8]. Bioenergy potentially offers developing countries many advantages such as enhanced energy security, reduces dependency on fossil fuels and also can provide social economic welfares. Increase in energy security can in turn have positive effect on food security, create markets as well as employment opportunities and also contribute potentially to greenhouse gas reduction. Nevertheless, recently bioenergy developments have also become a cause for deep concern. In many cases increased bioenergy production had serious social, economic, and environmental implications due to the potential negative impacts on food security and on the environment caused by food production and natural resource competition [7, 45, 23]. Palm products are increasingly marketed for the fast growing domestic and international markets and compliance with policy restrictions from users is only grudgingly followed. For palm biofuels, the focus has mostly narrowed to only specific regional Southeast Asian subsidies for blending. To satisfy the exponentially increasing global demand for palm products, unlike traditional smaller plantations of thousands of hectares, plantations are now scaling vast monocultures of tens of thousands of hectares by clear-cutting swaths of tropical rainforest now becoming the case for African countries e.g. Nigeria [71]. One of the missions of the Nigerian Institute for Oil Palm Research (NIFOR) is to enable the nation attaining self sufficiency in palm oil production and regain the leading position in international oil palm production and trade in the commodity [51]. Since the end of Nigerias military rule in 1999, the government has been actively pursuing the commercialization of the agricultural economy through market-led reforms, as has been formally articulated in the 2003 National Economic Empowerment and Development Strategy (NEEDS) and the 2012 Agricultural Transformation Agenda (ATA) [1]. This has involved among other things the privatization of the states agricultural assets and the promotion of private-sector investment in priority value chains [1]. According to [4], energy markets are a significant driver in the overall trend of large scale land acquisition. A clear link can be established between the EU bioenergy policy and the strong interest of European companies to acquire agricultural land in developing countries, especially in Africa [16]. This also entails that the development of conventional biofuel production has an impact on access to natural resources, such as land and water and often leads to an increase in land concentration to the detriment of small holder farming practices. [16] proposed that the Bioenergy impact analysis should be on regional basis rather than on a global scale. Scientists who try to analyse the issues regarding oil palm plantation in the Nigeria's Niger Delta mostly emphasise on growth perspectives [60, 37], only [63] shed little light from the conservation point of view and focused on a particular state in this region.Therefore, there is a knowledge gap on an integrated assessment analysis of oil palm as bioenergy feedstock. Hence this dissertation project sheds light on the aforementioned issue by using an integrated approach to address land use with respect to oil palm cultivation and sustainable development issues. More specifically, the study aims at analysing effects of oil palm bioenergy development on climate and environment, investigating how impacts of oil palm cultivation on food security can be reduced, how Nigeria bioenergy policies could affect the environment of the Niger Delta in Nigeria, revealing and elucidating the respective feedbacks.

1.5.1 Research Questions

- What could be the impact of Nigerian bioenergy policies with regard to energy crops cultivation (e.g.oil palm) on land use change and social welfare of the Niger Deltan Nigeria?
- How can land use with respect to energy crops cultivation (e. g. oil palm) be adapted to climate change, be sustainable and at the same time allow for climate and environmental protection?
- What are the main ways in which potential adverse impacts of bioenergy development on land use change could be reduced?

1.6 Research Approaches

1.6.1 Spatial analysis (GIS analysis)

The spatial analysis address the issues regarding land use and land cover changes by employing remote sensing techniques to identify the current land use situation. This is done to generate the land use and land cover change data. The approach used also estimate the spatial distribution of existing oil palm plantation and it's trajectories thereby generating secondary data that will be applied to the Nigerian Forest and Agricultural Sector Optimization Model (NGA-FASOM).

Remote sensing is defined as the science of deriving information about the earth's surface (land and water areas) from images acquired at a distance [10]. It relies upon measurement of electromagnetic energy reflected or emitted from the features of interest. This approach was used to map the extent and distribution of oil palm plantation derived from land cover maps of Niger Delta in Nigeria [57] with spatial resolution of 30 meters. These land cover maps are based on Landsat mission of Landsat 5 7 and 8 images acquired from the Landsat's Earth Observing System Data set. The multi-temporal Landsat data was accessed from Google Earth Engine [25].

1.6.2 Process-based modeling analysis

Process-based models are mathematical (and mostly computer-based) representation of one or several processes characterizing the functioning of well-delimited biological systems of fundamental or economical interest [9]. APSIM2015.06.22 next generation is process-based model built on a dynamic daily time-step that combines biophysical and management modules within a central engine to simulate crop or cropping systems. APSIM is a modeling framework with the ability to integrate models derived in fragmented research efforts (www.apsim.info). This facilitates research from one discipline or domain to be linked to the benefit of some other discipline or domain. It also enables comparison of models or sub-models on a common platform [40, 32, 34]. This functionality uses a plug-in-pull-out approach to APSIM design. The user can configure a model by choosing a set of sub-models from a suite of crop, soil, and utility modules. Any logical combination of modules can be simply specified by the user “plugging in” required modules and “pulling out” any modules no longer required. It's crop simulation models share the same modules for the simulation of the soil, water, and nitrogen balances. APSIM can simulate more than 20 crops and forests (e.g.,oil palm alfalfa, eucalyptus, cowpea, pigeonpea, peanuts, cotton, lupin, maize, wheat, barley, sunflower, sugarcane, chickpea, and tomato). APSIM is capable of simulating soil water, C, N, and P dynamics and their interaction within crop and management system, based on daily solar radiation, maximum and minimum temperature, and rainfall data [40, 32, 34, 56].

1.6.3 Integrated assessment modeling analysis

Integrated assessment models (IAM's) are models that represents a broader set of information than is normally derived from a standard research activity. Integrated assessments bring together and summarize information from diverse fields of study, they are often used as tools to help decision makers understand very complex environmental problems. IAM's are mostly mathematical computer models based on explicit assumptions about how the modeled system behaves. IAM's are also seen as methodologies that can be used for gaining insight over arrays of environmental problems spanning wide variety of spatial and temporal scales. They have the ability to calculate the consequences of different assumptions and to interrelate may factors simultaneously, but IAM's are constrained by the quality and character of the assumptions and data that underlie the model. Within this project the Nigerian Forest and Agricultural Model (NGA-FASOM) is developed [58]. NGA-FASOM include the analysis of cost-supply, environmental or ecological impacts, thereby serving as an integrated assessment model that will generally optimize the aforementioned research questions by making use of constraint optimization tool. The model is used to compute the competitive economic potential of oil palm plantation for bioenergy production. NGA-FASOM is an inter-temporal partial equilibrium model of the Nigerian Agricultural and Forestry Sectors, that is adapted to analyze economic and environmental impacts of changing policies, technologies, resources, and markets. NGA-FASOM is a model with the possibility to track net GHG emissions from all type of land uses and productions/consumptions related to the products (integrated life cycle assessment). It is a regional, multi-periodic model depicting land resource transfers between and within agricultural and forest sectors. Land is transferred between sectors/type of land-use according to its marginal profitability in all alternative forest and agricultural uses included in the model, over the time horizon of the model. The model integrates observed land qualities and technologies with environmental impacts and regional market feedbacks e.g. the Nigeria market for bioenergy. The approach enabled the quantification of economic potentials, environmental impacts mitigation and, also leakage effects. This was achieved by setting up scenarios, e.g. bioenergy policies as stipulated in [52] targets. The model estimates proportion of palm plantation required to generate an approximate percentage of the current total electricity consumption in each region. This modeling approach has successfully been used to analyze the interdependencies between food and biofuel production [62, 47, 29].

1.6.4 Structure of the PhD thesis

The thesis is divided into three chapters. The first chapter presents the scientific background and the overall research objectives of the dissertation project. Chapter two is the research results written in form of journal articles representing the originality of the work with the respective statement of contributions. While in chapter three the overall conclusions, future work prospects and tools used within the project are presented.

Chapter 2

Statement of Originality

2.1 Statement of Originality

The objective of this dissertation project is to assessment the Environmental and Social Impacts of Bioenergy from Oil Palm Cultivation in Nigerian Niger Delta. In this chapter, the different original publications in the framework of the cumulative dissertation and the extent of my contributions are presented. All papers were published in international journals, all under a lead authorship [57, 56, 58]. Every publication underwent a peer review process to ensure a high scientific standard.

2.2 Publications and Statement of contributions

List of Publications

Article I

A novel approach in monitoring land-cover change in the tropics: oil palm cultivation in the Niger Delta, Nigeria

Status: published in DIE ERDE Journal of the Geographical Society of Berlin Vol. 147, No. 1 22 March 2016

Stanley U. Okoro designed the overall study, wrote the scripts, run the analysis, analysed the results and wrote the manuscript. All authors discussed and commented on the manuscript.

Okoro, S. U., Schickhoff, U., Bhner, J. and Schneider, U. A., 2016. 'A novel approach in monitoring land-cover change in the tropics: oil palm cultivation in the niger delta nigeria', DIE ERDE Journal of the Geographical Society of Berlin 147(1).

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Journal of the
Geographical Society
of Berlin

A novel approach in monitoring land-cover change in the tropics: oil palm cultivation in the Niger Delta, Nigeria

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Abstract

The increasing demand for palm oil and bioenergy has promoted the expansion of tropical farmland covered with oil palms (Elaeis guineensis), resulting in increased competition with food production as well as environmental degradation. Moreover, oil palm cultivation may have increased greenhouse gas (GHG) emissions through deforestation. The overall impact estimation of oil palm related land-use change requires spatiotemporal land-use maps. So far, the Roundtable on Sustainable Palm Oil (RSPO) has not established guidelines on how to measure and evaluate oil palm related land-cover change. While remote sensing methods are suitable in general, the use of Landsat images in the tropics for the monitoring and modeling of land-cover changes has been restricted due to the influence of cloud cover. This study presents a novel approach for mapping tropical land-cover change using the Google Earth Engine (GEE) cloud-based platform and the System for Automated Geoscientific Analysis (SAGA) GIS. Spatiotemporal land-use and land-cover changes in relation to oil palm cultivation are assessed using a median pixel composite mosaic of Landsat 5, 7 and 8 image scenes for the time periods 1999-2005 and 2009-2015. The proposed approach yields an overall accuracy and kappa coefficient of 70.33 % and 0.62 for the first image composite period, and 84.5 % and 0.80 for the second image composite period respectively.

Zusammenfassung

Die steigende Nachfrage nach Palmöl und Bioenergie fördert die Ausweitung von mit Ölpalmen (*Elaeis guineensis*) bestandenen tropischen Nutzflächen und intensiviert zugleich Nutzungskonflikte mit der Nahrungsmittelproduktion sowie Umweltdegradation. Des Weiteren erhöht die Abholzung von Regenwald zur Errichtung von Ölpalmenplantagen in der Regel den Ausstoß von Treibhausgasen. Umfassende Wirkungsanalysen zur Ausbreitung von Ölpalmenplantagen benötigen Zeitreihen von Landnutzungskarten. Der Runde Tisch für nachhaltiges Palmöl (RSPO) hat bisher keine Leitlinien für die Evaluierung von Landnutzungsänderungen erstellt. Obwohl Fernerkundungsmethoden für die Beobachtung und Modellierung von Landnutzungsänderungen allgemein gut geeignet sind, wird die Nutzung von Landsat-Aufnahmen aus tropischen Regionen durch Bewölkung beeinträchtigt. Diese Studie präsentiert einen neuen Ansatz, welcher die Google Earth Engine (GEE) und das „System for Automated Geoscientific Analysis" (SAGA) GIS nutzt. Zeitlich und räumlich aufgelöste Landnutzungs- und Landbedeckungsänderungen durch den Anbau von Ölpalmen werden mit einem „*median pixel composite mosaic*" von Landsat-5-, 7- und 8-Szenen für die Zeiträume 1999-2005 und 2009-2015 erfasst. Für die erste Periode erreicht das Verfahren eine Gesamtgenauigkeit von 70,33 % und einen Kappa-Koeffizienten von 0,62. In der zweiten Periode steigen diese Werte auf 84,5 % und 0,80.

Okoro, Stanley U., Udo Schickhoff, Jürgen Böhner and *Uwe A. Schneider* 2016: A novel approach in monitoring land-cover change in the tropics: oil palm cultivation in the Niger Delta, Nigeria. – DIE ERDE **147** (1): 40-52

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Keywords Oil palm mapping, Google Earth Engine, SAGA GIS, Landsat image, land use/land cover

1. Introduction

Traditionally, oil palm production has been a part of mixed farming activities in West Africa. However, in the current practice, most production has expanded as an industrial-scale mono-crop (*Corley* and *Tinker* 2016). This imposes greater environmental risk on local societies, particularly on those with limited economic capacities (*Colchester* 2011). Currently, oil palm cultivation is characterized by large monocultures of uniform age structure, low canopy, sparse undergrowth, a low stability microclimate and intensive use of fertilizers and pesticides. Land-cover patterns reflect the underlying natural and social processes which, thus, helps to provide essential information for modeling and understanding many phenomena on Earth (*Liang* 2008). Furthermore, understanding the complex interaction between human activities and global change requires the analysis of land cover data (*Gong* et al. 2013). The conversion of natural forest to agricultural uses such as oil palm etc., has been reflected in regional land-use maps in most of the tropical regions. This conversion can result in a series of negative impacts (*Carlson* et al. 2012), e.g., forest estate loss, social cost (private cost plus externalities as a result of forest to oil palm estate conversion), loss of biodiversity and ecosystem services, alternative revenue loss and greenhouse gas emissions etc. (*Sayer* et al. 2012; *Sheil* et al. 2009). To date, comprehensive regional land-use maps of the Nigerian Niger Delta which incorporate oil palm cultivation have not been produced. The lack of detailed land-use maps may be due to the limited availability of cloud-free satellite images and the unattractiveness of such studies for most private actors and non-governmental sectors. Consequently, scientists have not been able to carry out such research, possibly a result of the cost of acquiring high-resolution satellite images like IKONOS etc. in the region.

Satellite remote sensing technology provides promising approaches for monitoring land-cover change. In many studies in southeastern Asia, continuous observations of the land surface have been used to map oil palm cultivation (*Kamaruzaman* and *Setiawan* 2003; *Santoso* et al. 2011; *Tan* et al. 2012). The classifications of satellite imagery for land-cover mapping, however, often require extensive skills of an experienced environmental analyst (*Aitkenhead* and *Aalders* 2011). If such skills have not been available, land cover classification maps have been developed from ground surveys and base maps such as digital topographic maps. In addition, land-use maps and soil suitability agricultural maps (although not available for public use in the study area) have increased the accuracy of land-cover classification maps (*Razali* et al. 2014; *Reichenbach* and *Geng* 2003). Replacing or updating these maps with a large amount of remotely sensed data remains a very challenging task in land-use and land-cover mapping (*Franklin* and *Wulder* 2002). Different methods have been implemented; these can be divided into two categories: phenology and image-based approaches. The latter make use of spectral signatures to delineate different types of land cover, e.g. oil palm trees (e.g. *Shafri* et al. 2011; *Thenkabail* et al. 2004). The former relies on the temporal signal of optical sensors to identify various land covers using coarse resolution data from the Moderate-resolution Imaging Spectroradiometer (MODIS), e.g. *Gutierrez-Velez* et al. 2011. This is not ideal for monitoring oil palm distribution because the saturation of optimal images due to canopy closure causes a reduction in the possibility of detecting structural features (*Shafri* et al. 2011). Cloud cover issues are most common in tropical regions and have been a great challenge in land-cover monitoring. Due to the reduced monitoring options of cloudy images, Synthetic Aperture Radar (SAR) data were frequently used as a major alternative in tropical studies (*Koo* et al. 2012; *Li* et al. 2015, *Morel* et al. 2011). The reason for this has been attributed to SAR's all-weather and all-time capability. On the other hand, due to their coarse resolution of 50 m, SAR data are difficult to be used in a detailed monitoring of tropical land cover.

The GEE, which is an online environmental geoprocessing platform that incorporates data from the National Aeronautics and Space Administration (NASA) and the Landsat Program, has created an avenue which allows users to assess records of Landsat imagery and process them over its online platform. This process reduces users' computational processing times when analysing Landsat imagery, making global- and regional-scale Landsat projects achievable (e.g., *Hansen* et al. 2013).

The objective of this study is to provide a novel approach in monitoring and analyzing oil palm related land-cover issues in the tropics using Landsat data with a resolution of 30 m via GEE and SAGA GIS (*Conrad* et al. 2015). We implement the Voting Support Vector Machine (SVM) classifier in GEE to map oil palm plantation in the Nigerian Niger Delta. To investigate the biases of our classifier, the analysis of its error matrix which includes overall accuracy, user accuracy and producer accuracy and the computation of its kappa coefficient were performed.

2. Study area

The study area covers the southern part of Nigeria where the oil palm production is concentrated (see *Fig. 1*). Currently called the Niger Delta region, it is one of the world's largest acute fan-shaped river deltas. The settlements that are covered in this study include: Imo State, Abia State, Bayelsa State, Rivers State, Ondo state, Akwa Ibom state, Edo State and Cross River State. The Niger Delta is defined officially by the Nigerian government to extend over about 70,000 km^2 which is 7.5 % of Nigeria's total land mass. The region lies between 4.01°N and 7.90°N and between 4.50°E and 10.56°E in the West African section of the tropical rainforest belt and has a humid tropical climate. The area homes the country's wetlands which is also one the largest wetland in the world with a very high biodiversity rate. The riverine area of the Niger Delta is a coastal belt of swamps bordering the Atlantic Ocean. The swamps are vegetated tidal flats formed by a reticulate pattern of interconnected meandering creeks and tributaries of the River Niger. The Niger Delta has one of the highest population densities in the world with approximately 265 inhabitants per square kilometer. The population in the delta produces crops that are in high demand in the world market, such as palm oil and cocoa.

3. Materials and methods

3.1 Satellite data

Landsat 5, 7 and 8 orthorectified and coregistered scenes were used in this study, capturing identical

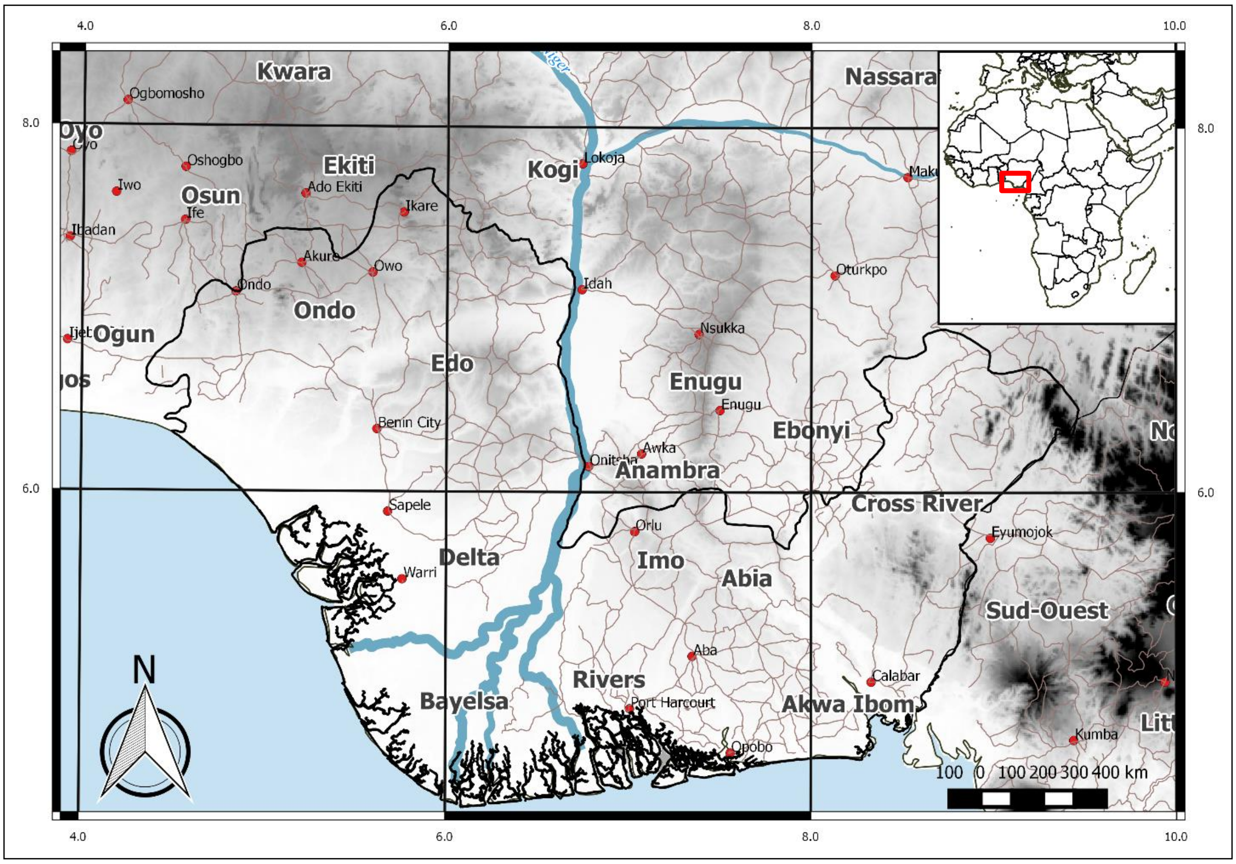

Fig. 1 Map of the study area

periods of calendar days (270-365) for 1999 through 2005 and 2009 through 2015. We did not consider using surface reflectance data following *Song* et al. (2001), who stated that an atmospheric correction was unnecessary for a change detection based on a classification of multitemporal composites in which multiple dates of remotely sensed images are rectified and placed in single dataset as long as the training dataset is derived from the image being classified.

We decided to work with the images of calendar days 270-365 in each year in order to avoid seasonality issues of oil palm reflectance values that may arise from seasonal variation of chlorophyll concentration, foliar pigments and other reflectance properties. We consider the image collection composite range used in this study as ideal for oil palm mapping studies. We worked with Landsat mosaic images only because they are consistent with a resolution of 30 m and the combination of different Landsat sensors has only minor effects on the output of the images. Landsat has a high degree of similarities among its different sensors (*Li* et al. 2014), a notable advantage compared to working with the fusion of Landsat and MODIS images with a coarser resolution of 50 m as in *Bisquert* et al. (2015).

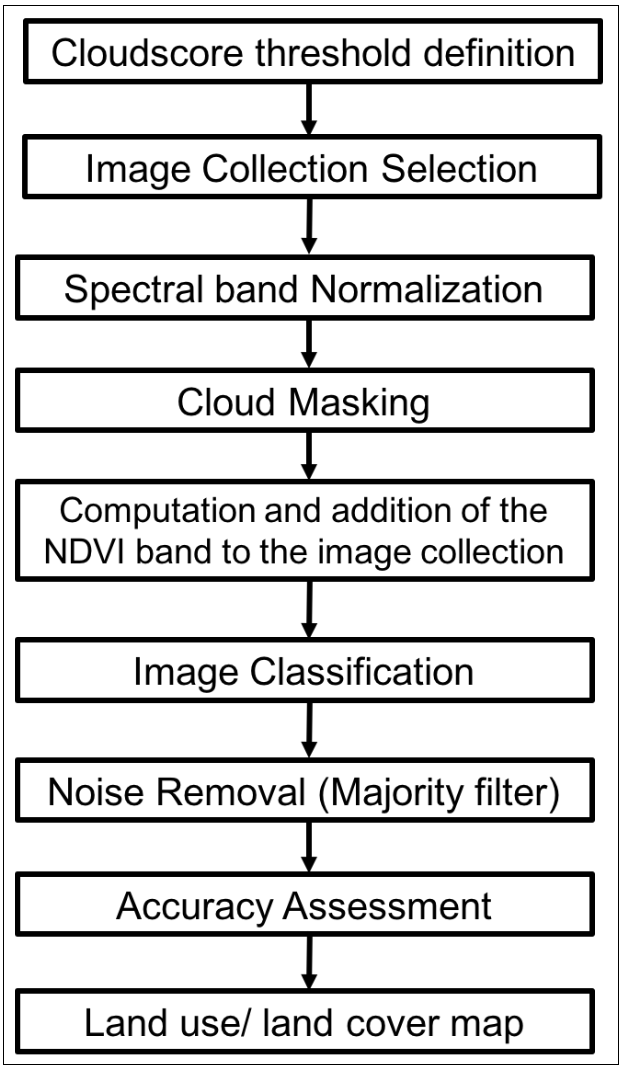

Fig. 2 Graphical representation of the processing approach

3.2 Data pre-processing

Landsat 5, 7 and 8 data of the time periods from 1999 to 2005 and from 2009 to 2015 were combined in one mosaic by taking the median pixel from the entire Landsat image collection. The overall procedure is graphically represented in *Fig. 2* and involves nine steps. The first six steps were done in GEE and the remaining three in SAGA GIS.

Spectral band normalization: Due to differences in the spectral band numbering system among the different Landsat missions – Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager & Thermal Infrared Sensor (TIRS) (*Li* et al. 2014) – a normalization process is required. Therefore, we carried out a normalization to make the images from the different sensors suitable for combination by matching the bands from the different Landsat sensors (e.g. red band from Landsat 5 to Landsat 7 red band).

Cloud score analysis: Cloud cover problems were tackled by using the simple cloud score algorithm implemented in the GEE. This algorithm computes a simple cloud likelihood score threshold that ranges from 0 to 100, making use of brightness, temperature and Normalized Difference Snow Index (NDSI). The algorithm is mainly intended to compare multiple looks at the same point for relative cloud likelihood. For this study, a cloud score threshold of 20 was used. The threshold is subjective; the choice, however, was based the visual interpretation of the Landsat images.

Training data: While focusing on oil palm plantation mapping, other land-cover types considered in this study include water (rivers, lakes, swamps), built-up areas (including bare lands), cropland (croplands that are not covered by oil palm trees) and forest. We incorporated the ground truth data, Google Earth data and Landsat image data in our training sample. The ground truth data were collected during a field work between November and December 2014.

Reference data: Due to the costs of acquiring reference data for using our sampling approach at a regional scale, we collected our reference data by combining Landsat image and Google Earth imagery. In a similar case, *Pulighe* et al. (2015) assess the horizontal accuracy of Google Earth images and conclude that they have an overall positional accuracy close to 1 m. This suggests that this is sufficient for deriving a reference data set for land-cover mapping. The sampling method used is the stratified random sampling method (*Husch* et al. 2003). The points were stratified according to the distribution of land-use/cover classes, in order to lessen the possibility of biases from misclassification. The choice of this sampling method was based on the recommendations of *Olofsson* et al. (2014) regarding good practices for estimating area and assessing accuracy of land cover and land use maps.

Signature analyses of reflectance values of land cover types: To determine and understand the spectral separability of the Landsat reflectance bands of the various land-cover types, to enable the choice and order of spectral bands to be used, the Landsat image reflectance at known land-cover types against the bands were plotted. Furthermore, the reflectance values against the different wavelengths at various land-cover types were also plotted.

Image classification: The approach is based on the supervised classification of multispectral, multisensor data, using the Landsat image collection of Landsat 5, 7 and 8 combined in one mosaic. Supervised classification is a method often used for the quantitative analysis of remote sensing images. It aims at grouping the spectral domain into regions that can be associated with ground cover classes of interest for a particular application (*Richards* 2013). The Landsat image bands were chosen and their arrangements were Near Infrared (NIR), Shortwave Infrared 1 (SWIR1), Red, Green and the computed Normalized Difference Vegetation Index (NDVI) band. The NDVI is an index of plant greenness, which is also an indicator of density of plants. It is calculated using the formula in *Equation 1*.

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (Eq.\ 1)$$

Fig. 3 Screen shot of a Google Earth image showing the various land-cover classes analyzed in this study

The classification scheme employed to create a land-cover/land-use map was a modification of *Omodanisi* (2013) to incorporate oil palm and cropland and to combine high forest and light forest in a single land-cover type (*Fig. 3*), thus differentiating between i) water bodies, ii) a built-up areas class which also includes bare ground, roads and building facilities, iii) cropland which includes all agricultural land that does not have oil palms planted as mixed crop, iv) forests, including primary and secondary forests, v) oil palms.

Classifiers voting support vector machine (SVM): The concept of SVM is based on decision plains that define decision boundaries. The classifier takes inputs from training data and makes predictions based on given inputs. The classes input is formed by relating the training data set to each pixel in an image (*Kavzoglu* and *Colkesen* 2009). The algorithm was first introduced as a machine learning method by *Cortes* and *Vapnik* (1995) based on a non-probability binary function because it predicts for each of a series of given inputs the possible input that the input belongs to. Originally, the approach was designed to solve binary problems. In remote sensing applications, however, the problem often involves multiclass/non-binary problems. Various approaches have been proposed to address multiclass problems (m-class), e.g. *Schölkopf* and *Smola* (2002), where the problem is usually split into a set of binary classifiers before combining them. The one-against-all classification strategy splits the problem into multiple binary sub-problems. The one-versus-one classification strategy creates *Equation 2* binary sub-problems and later combines the following adopting a majority voting scheme. The approach has shown to be more suitable for large problems like ours (cf. *Hsu* and *Lin* 2002). Its operation is carried out in feature space, where classes are separated by a boundary that is as wide as possible. Our choice of choosing this algorithm as classifier algorithm was based on the finding that it performs well in mapping oil palm plantation (*Li* et al. 2015; *Nooni* et al. 2014).

$$\frac{M(m-1)}{2} \qquad (Eq.\ 2)$$

3.3 Post-processing

Noise filtering (majority filter): In order to reduce noise in the classification result, we applied a majority filter algorithm as implemented in SAGA GIS in the post-processing, which removes isolated cells. The majority filter considered a search radius of 3 x 3 cells to improve the homogeneity of the classified raster.

Accuracy assessment: Many factors affect the accuracy of an image classification, this includes preprocessing of remote sensing data, precision and resolution of remote sensing data and training sample selection. Accuracy assessment allows the analyst to compare certain pixel values in a raster layer to the reference pixels for which the class is known (*Mani Murali* et al. 2006), in order to establish the error margin of the classified image. This requires a simple cross-tabulation of the class labels allocated by a classification of the remotely sensed data against the reference data. The error matrix aids in quantifying image classification accuracy and its area estimation.

The accuracy assessment computation we carried out includes:

– **Confusion matrix**: The confusion matrix is calculated by comparing the location and class of each reference pixel with the corresponding location and class in the classification image.

– **Producer accuracy**: This is the measure that indicates the probability that the classifier has labeled an image pixel into class A given that the reference class is A.

– **User accuracy**: This measures the probability that a pixel is class A given that the classifier has labeled the pixel into class A.

– **Overall accuracy**: This is calculated by summing the number of pixels classified correctly, divided by the total number of pixels in that land-cover class.

– **Kappa coefficient**: The kappa coefficient (k) measures the agreement between the classification result with that of the reference pixels. Perfectly agreed means that the kappa coefficient tends to 1 or is very close to 1. It is calculated using the formula

$$k = \frac{\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i\ C_i)}{N^2 - \sum_{i=1}^{n}(G_i\ C_i)} \qquad (Eq.\ 3)$$

where i is the class number, N is the total number of classified pixels that are compared to reference data, $m_{i,i}$ is the number of pixels belonging to the reference class i, which have been classified with a class i, C_i is the total number of classified pixels belonging to class i, G_i is the number of reference pixels belonging to class i.

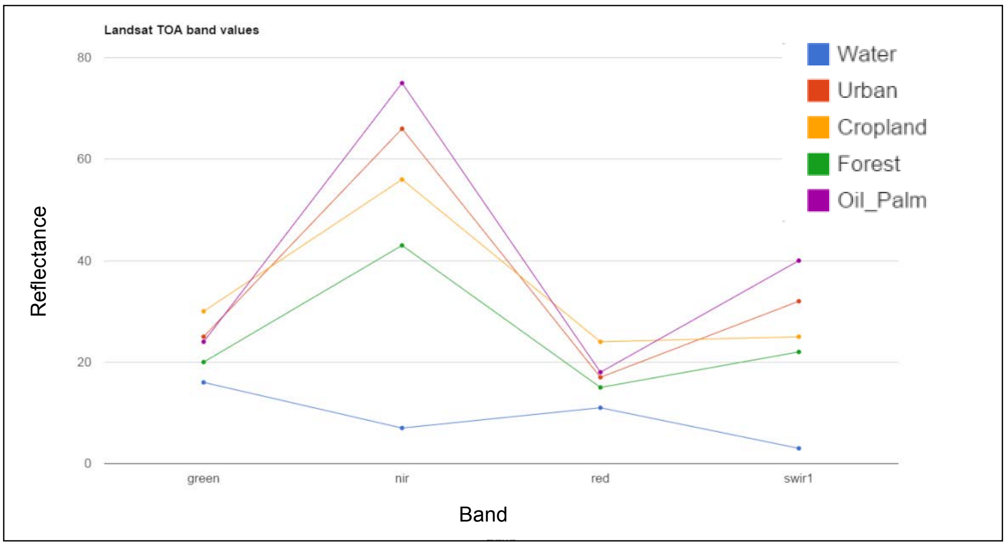

Fig. 4 *Landsat reflectance data for the various land-cover types*

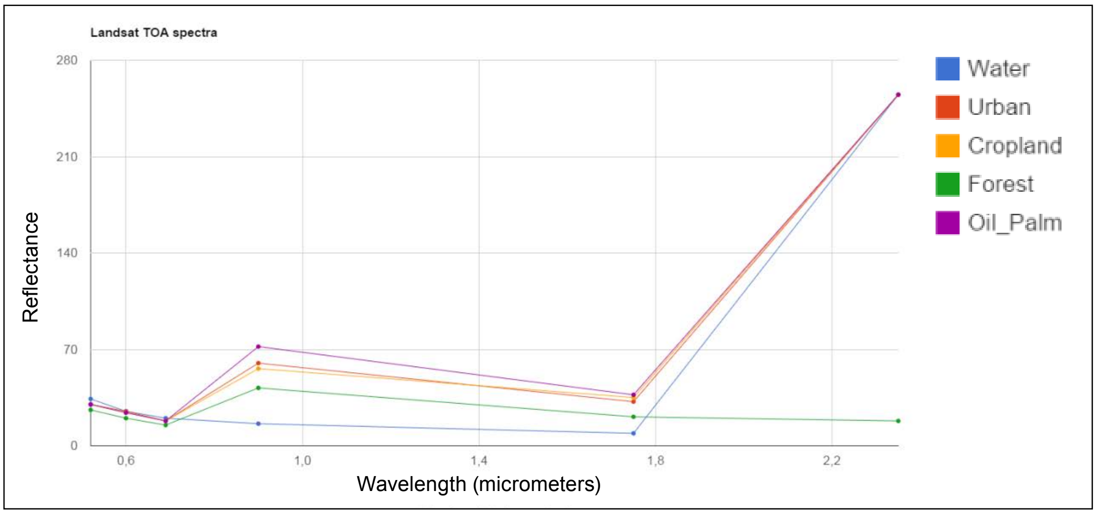

Fig. 5 *Landsat reflectance data for the various land-cover types plotted against wavelength*

Change detection: Change detection is a process of identifying differences in the state of an object or phenomenon by observing it at different times (*Jensen* 1996). Change detection analyses can be deducted in many ways. In land-use/land-cover change analyses, three categories are mostly used: i) algebra-based approach image differencing, image regression, image rationing, vegetation index differencing and change vector analysis (*Singh* 1989); ii) transformation principal component analysis, tassled cap, Gramm-Schmidt and Chi.square test (*Nielsen* and *Canty* 2008); iii) classification-based spectral-temporal combined analysis, post-classification comparison, unsupervised change detection, hybrid change detection, artificial neutral networks and electromagnetic transformation (*İlsever* and *Ünsalan* 2012). We decided to work with post-classification comparison because this technique makes use of thematic maps (classified images) as input and does image differencing on a pixel-wise basis. The main advantage of post-classification comparison is that it avoids problems encountered at the image original pixel level, for example shadows and reflections (*Jensen* 1996).

4. Results and discussion

A total of five land-cover types were identified and classified in this study. These were water, built-up

Table 1 Land-cover/land-use change in the Nigerian Niger Delta

Land-cover class	1999-2005		2009-2015		Change	
	Area (ha)	%	Area (ha)	%	ha	%
Water	384918.52	3.59	415545.38	3.87	30626.86	7.95
Built-up area	468342.99	4.36	313990.09	2.92	-154352.90	-32.95
Cropland	4037477.94	37.66	4318065.23	40.28	280587.29	6.94
Forest	2917374.90	27.21	2824880.57	26.35	-92494.33	-3.17
Oil palm	2910695.95	27.15	2846329.03	26.55	-64366.92	-2.21

areas, cropland, forest and oil palm as shown in *Figure 4*. Following our approach, we were able to get little or no cloud cover in our image composite.

The plot of the reflectance values against the chosen Landsat image bands and reflectance values against wavelengths of the land-cover types at known points in our study area (*Figs. 4* and *5*) show a very clear spectral separability of the land-cover types within our chosen image bands. The near-infrared band has the highest spectral separability to distinguish among the different land-cover types. Thus, the band arrangement of the classification follows the order of its separability among the land-cover types.

In the 2005 land-cover map, cropland, oil palm, forest, built-up and water body occupy 37.66 %, 27.15 %, 27.21 %, 4.36 % and 3.59 % respectively (cf. *Table 1*).

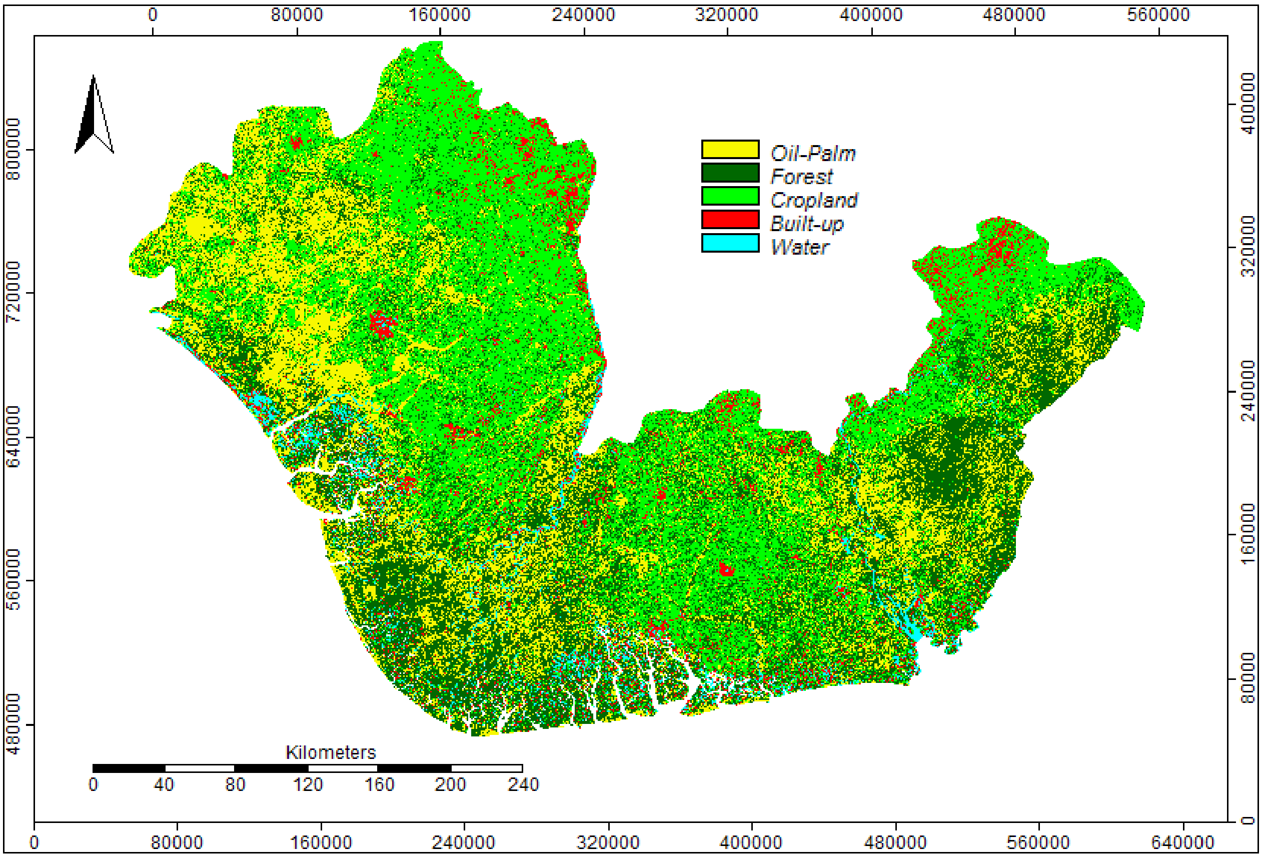

Fig. 6 Land-use/land-cover map based on the 1999-2005 median composite

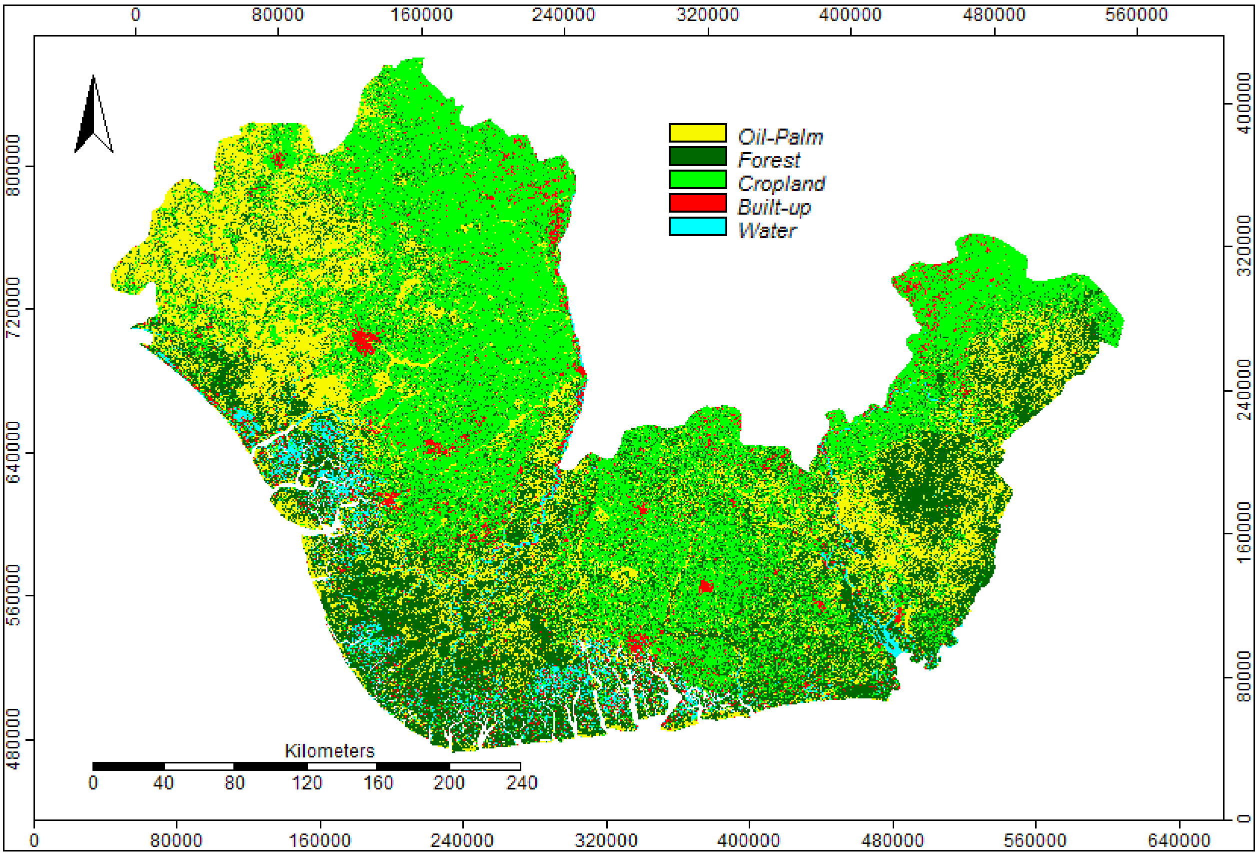

Fig. 7 Land-use/land-cover map based on the 2009-2015 median composite

According to the results obtained for the 2015 land-cover map, cropland occupies 40.28 %, oil palm 26.55 %, forest 26.35 %, built up area 2.92 %, and waterbodies 3.87 % of the study area (cf. *Table 1*). It could be observed from our maps for both years that the oil palm plantation operations are mostly concentrated at the western and eastern parts of our study area (*Fig. 6* and *Fig. 7*). The larger forest extent was observed in the eastern part, where the altitude is slightly higher.

The result of the post-classification comparison approach employed for the detection of land-cover changes is shown in *Table 1* and *Fig. 8*. It is clearly observed that forest had a decrease of 3.17 % from 2005 to 2015, which is very significant compared to the time interval. Field observations and research findings reveal that the high rate of change observed in the forest area has to be attributed to the conversion to cropland and to oil palm cultivation. Our findings are in line with those of *Abbas* (2012) in his study of a smaller area within our study area. Cropland experienced an increase, which has to be largely attributed to forest area decrease, reflecting, according to the locals, the governmental policies on agriculture (see also *Orimoogunje* et al. 2013). The decrease in built-up area resulted from the conversion of bare lands into mostly agricultural land. According to our analysis the land-cover type that was most heavily converted to oil palm cultivation and cropland was forested areas (cf. *Fig. 8*). Other land-cover changes encountered include: from cropland to forest, built-up areas to cropland (which is basically the cropland areas that were initially cleared for cultivation during the first image acquisition period), cropland to built-up areas which is due to the increase in urbanization. Our study also reveals an increase in water body area.

The accuracy of the classification results for land-cover maps for 2005 and 2015 is reported in *Tables 2* and *3* respectively. The producer accuracy for all the land-cover types for the 2015 land-cover map ranges from 74.69 % to 90.00 % and the user accuracy from 72.72 % to 97.82 %. Our approach was able to produce an overall accuracy of 84.51 % with a Kappa coefficient of 0.80.

Global change and energy transition have triggered a lot of land-use/land-cover changes. The RSPO has not yet come up with a standard to map and monitor oil palm plantations. There is a serious concern that palm

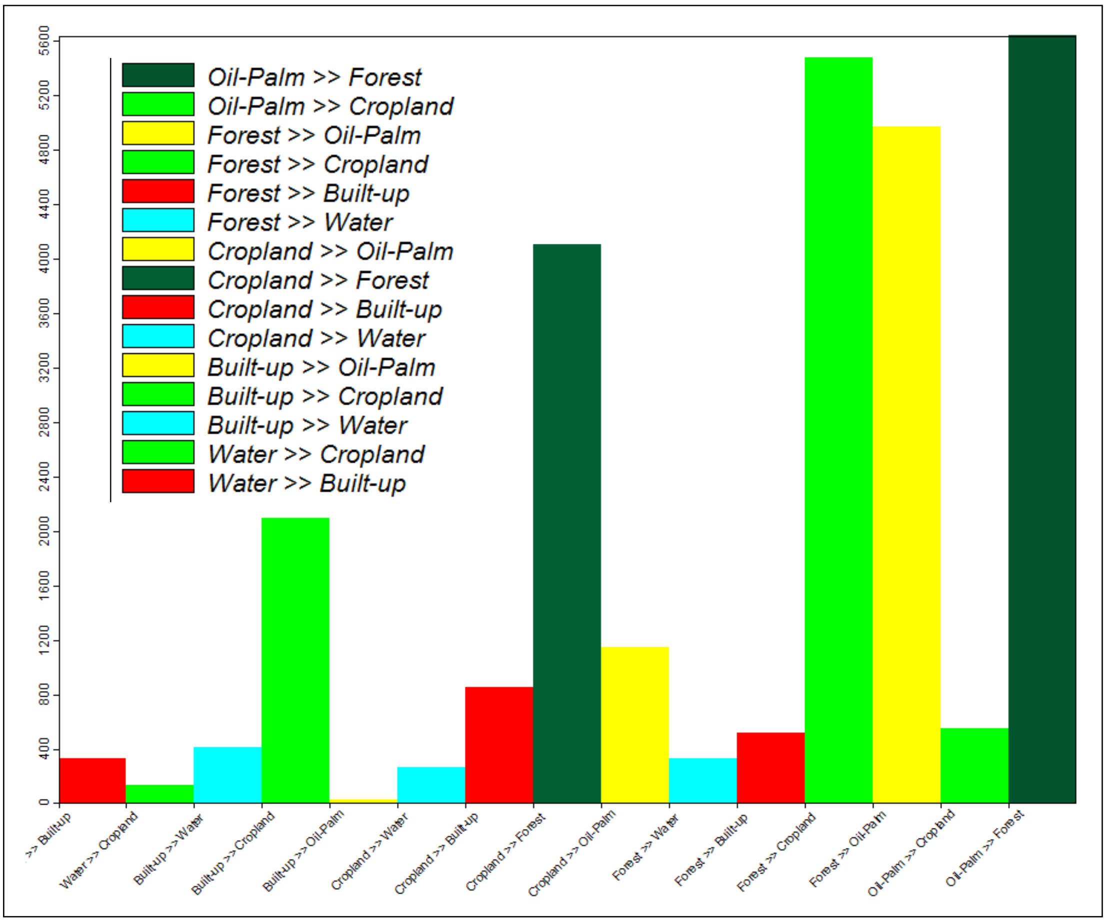

Fig. 8 *Land-use/land-cover change 2005-2015*

oil production is largely unsustainable, with issues relating to deforestation, biodiversity, soil degradation, water quantity, local people, land rights and many other aspects. The development of new plantations has resulted in the conversion of large areas of forests with a high conservation value and threatens the rich biodiversity in these ecosystems. Many of these social, ecological and environmental impacts of oil palm production can be associated with land-cover and land-use change in connection with bioenergy production (*Elbehri* et al. 2013). Bioenergy-related land-use decisions may affect local, regional and global social, ecological and environmental systems. Therefore, sustainability is a big challenge with regard to the increased development of bioenergy production. It is important to develop a standard approach that aids in the determination of the main resource availability (land).

To investigate the environmental and social impacts of unsustainable oil palm cultivation for bioenergy production, the land-use/land-cover maps of oil palm production are among the data basically needed. To this end, our study has come up with an approach to get rid of cloudiness challenges in mapping oil palm trees in the tropical region at a regional scale using Landsat images. This tool is useful when the land cover is very heterogeneous, and thus requires a medium- to fine-image resolution. Therefore, our approach could serve as a baseline for policy makers, land managers in the tropical region to map and monitor land-use/land-cover change on a local to regional scale.

5. Conclusions

Oil palm related land use/land cover change can be monitored in the tropics at a regional scale by using a median composite image, combining Landsat 5, 7 and 8 data in a single mosaic via GEE and SAGA GIS. The approach assists in getting rid of cloud problems in tropical regions, which also helps in understanding the nature of change in the use of land

Table 2 Confusion matrix for land-use/land-cover map 1999-2005 composite

	Water	Built-up	Cropland	Forest	Oil palm	Classification overall	Producer accuracy (%)
Water	61	1	0	37	1	100	61.00
Built-up	4	61	13	3	2	83	73.49
Cropland	0	8	78	10	8	104	75.00
Forest	2	1	3	66	21	93	70.96
Oil palm	0	0	12	17	73	102	71.56
Truth overall	67	71	106	133	105	483	
User accuracy (%)	91.04	85.91	73.58	49.62	69.52		

Table 3 Confusion matrix for land-use/land-cover map 2009-2015 composite

	Water	Built-up	Cropland	Forest	Oil palm	Classification overall	Producer accuracy (%)
Water	90	2	0	8	0	100	90.00
Built-up	1	62	17	3	0	83	74.69
Cropland	0	0	89	8	7	104	85.57
Forest	1	0	0	80	8	89	89.88
Oil palm	0	0	8	11	83	102	81.37
Truth overall	92	64	144	110	98	478	
User accuracy (%)	97.82	96.87	78.07	72.72	84.69		

resources. This approach can also facilitate proper planning, management and regulations of the use of land resources now that there is a quest for energy transition due to climate change. The change detection analysis shows that there is a decrease in the forested area in the study area, with a much greater forest area that changes to oil palm than other land-cover types. The overall classification accuracy is sufficient in order to establish management strategies based on the map results.

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Article II

Climate impacts on palm oil yields in the Nigerian Niger Delta

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Stanley U. Okoro designed the overall study and prepared the input data. Okoro and Huth did the model calibration.

Okoro run the analysis, analysed the results and wrote the manuscript. All authors discussed and commented on the manuscript.

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Climate impacts on palm oil yields in the Nigerian Niger Delta

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ABSTRACT

Palm oil production has increased in recent decades and is estimated to increase further globally. The optimal role of palm oil production, however, is controversial because of conflicts with other important land uses and ecosystem services. Local conditions and climate change affect resource competition and the desirability of palm oil production in the Niger Delta, Nigeria.

The objectives of this study are to (1) establish a better understanding of the existing yield potentials of oil palm areas that could be used for integrated assessment models, (2) quantify for the first time uncertainties in yield potentials arising from the use of climate output data from different Global Circulation Models (GCM's) with varied West African Monsoon (WAM) system representations forced to the same Regional Climate Models (RCM's). We use the biophysical simulation model APSIM (Agricultural Production Systems Simulator) to simulate spatially variable impacts of climate change on oil palm yield over the Nigerian Niger Delta. Our results show that the impact of climate change on oil palm yield is considerable across our study region. The yield differences between the IPCC RCPs were small. The net impact of climate change on oil palm is positive and is dynamically inconsistent. There is no significant change in the simulated yield arising from the differences in the forcing's data. We found the most effective strategy for oil palm yield optimization under climate change to be shifting of sowing dates and introduction of irrigation.

1. Introduction

Earth's ecosystems have been changing due to the emission of anthropogenic greenhouse gases (GHG's) which has resulted in an increase of global mean temperature, a change in precipitation regimes and an increasing frequency of extreme weather events (IPCC, 2015; Padgham, 2009). The oil palm belt of the Niger Delta, Nigeria, has been an area prone to climate change. Temporal air temperature trend has remained on the increase for the past 105 years (since 1901); temperatures have increased by 1.2 °C in the coastal cities of the Niger Delta during this period (Odjugo, 2010).

Climate change is predicted to have a great impact on agriculture and thus on global food security in the coming decades (FAO, 2016). The impact of climate change on the main crops in West Africa are controversial (Mereu et al., 2015), and the region had been identified to be a hotspot of climate change (IPCC, 2015). Estimates include both positive or negative impacts depending on the employed GCM, the climate scenario, and the chosen crop model (Mereu et al., 2015; Roudier et al., 2011). Previous studies to understand crop yield potentials under climate change regime in the Niger Delta region have focused on statistical approaches and were mostly based on single climate scenarios, not considering differences in GCM's forcing data and rarely considering the range of various IPCC (Intergovernmental Panel on Climate Change) Representative Concentration Pathways (RCPs).

While there is general agreement among GCM's about regional temperature changes, large uncertainties remain regarding the projections of the monsoon system which triggers precipitation in the region (Niang et al., 2014). Many of the studied crops were found to be more sensitive to water limitation than to temperature change. So far, analyses of climate change impacts at regional level in the Niger Delta have been done using statistical models (Idumah et al., 2016), which are not able to capture the entire sub-seasonal weather variability and are limited in their ability to project changes into the future. Such statistical models often assume stationarity of the relation between crop and weather and are not applicable outside the range of the historical weather conditions within which they were developed (Challinor et al., 2009). Furthermore, statistical models have limited explanatory power, and are not applicable to the development of climate

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change adaptation measures (Challinor et al., 2009; Müller et al., 2011; Rosenzweig et al., 2013). Improved understanding of climate change impacts can, however, be derived from outputs of biophysical modelling approaches (Araya et al., 2015). These biophysical modelling approaches can facilitate the development of potential adaptation and mitigation options that will benefit agriculture and enhance energy production when energy crops are grown for bioenergy (Holzworth et al., 2014). Biophysical modelling at various scales (e.g. Challinor et al., 2009; Holzworth et al., 2014; Hoogenboom et al., 2004) have been deployed on various occasions to assess the impacts of climate change on crop production and/or to develop agro-management strategies for adaptation to future climate change events (e.g., Challinor, 2009; Holzworth et al., 2014; Kim et al., 2013; Lehmann et al., 2013; Masutomi et al., 2009). Biophysical models have been widely used to evaluate climate change impacts on crop production globally, but rarely applied to the oil palm belt of the Niger Delta region. In response to this research need, this study employs the biophysical simulation model APSIM (Agricultural Production Systems Simulator) to (1) investigate and present a better understanding of the regional variability of yield potentials of oil palm under different climate change scenarios across the Nigerian Niger Delta based on existing oil palm areas (Okoro et al., 2016) that could be used for integrated assessment models, and (2) to examine the effect of output of different GCM forcing data with varied West African Monsoon (WAM) representations in regional impact models (e.g. APSIM). APSIM had been widely used in farming systems which includes agroforestry to simulate yield, crop/tree growth and development based on environmental variables (e.g. Amarasingha et al., 2015; Anwar et al., 2015; Bayala, 2016; Holzworth et al., 2014; Huth et al., 2002; Lv et al., 2015; Matere et al., 2015). Finally, several adaptation strategies (e.g., full irrigation, adjustment of planting date, planting depth and density, fertilization) are evaluated with the aim to reduce the negative impact of climate change on palm oil production.

2. Study area

2.1. Description of study area

The Niger Delta region is located in the southern part of Nigeria. The broader Niger Delta region consists of nine states (Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo and Rivers) and 185 local government areas (Fig. 1). It covers an area of about 70,000 km^2, i.e., about 7.5% of Nigeria's total area. Ondo state has the highest average altitude (183 m). The Niger Delta region's climate is characterised by two distinct hygric seasons: the rainy season (April to mid-October) and dry season (mid-October to end of March), whilst seasonal temperature variations are low. The region has a tropical savanna climate at higher elevations and rainforest climate at middle and lower elevations. Daily average temperature within the region is mostly above 18 °C and monthly temperatures show a low range throughout the year. The annual rainfall is in the range of 1500–3000 mm.

Oil palm grows well within the temperature range of this region and requires about 120–150 mm of water per month to meet its water needs. The planting of oil palm in this region mostly commences around late March till June, and could as well be grown during the summer period with sufficient irrigation. Harvesting takes place throughout the year with an interval of 11–14 days.

3. Data and methods

We used the APSIM model, which requires daily weather data, and detailed soil and management information. Both the model and data sources are described below.

3.1. Crop model

APSIM is a modelling framework that allows individual process-based models to be combined into a farming system simulation. The structure of APSIM includes biophysical modules, management modules, data input and output modules (Keating et al., 2003), and it is possible to add and remove modules based on the user's interest (Kirschbaum et al., 2001). Component-based design in APSIM enables models to interact via a communication protocol (Moore et al., 2007). APSIM has models for over thirty crop, pasture and tree species as well as for the main soil processes affecting agricultural systems. One of the main advantages of APSIM is its ability to integrate models derived in fragmented research efforts.

3.2. APSIM Oil Palm

APSIM Oil Palm (Huth et al., 2014) has been developed to simulate the growth of fronds, stem, roots and bunches of oil palm in response to inputs of daily weather, soil and management practices. The climate data requirements include daily minimum and maximum temperature, rainfall and solar radiation (Kirschbaum et al., 2001). The Oil Palm model calculates the growth, development, resource use and organic matter flows for the plant and communicates this information to the soil and management models within the simulation.

The existing parameterization of the APSIM Oil Palm model was based upon data from Papua New Guinea. This model parameterization was adapted to Nigerian planting material using data from the literature and local plantations. The potential frond appearance rate and maximum bunch size were adapted using yield and bunch size information for planting material used within the study region. All other palm parameters were taken from Huth et al. (2014).

Further details on the individual modules within APSIM Oil Palm are provided by Huth et al. (2014). Further information on APSIM and the community development framework can be found at www.apsim.info.

3.3. Model setup

We calculated daily weather data of rainfall, maximum temperature (Tmax) and minimum temperature (Tmin) from 1997 to 2014 from monthly averages obtained from Okomu Oil Palm Plc (5.07N–5.25N and 6.16E–6.23E). The scaling disaggregation method was employed using daily rainfall, Tmax, Tmin estimates from National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resource-POWER (Stackhouse et al., 2014) while conserving the monthly totals. The daily solar radiation data from 1997 to 2004 was obtained from NASA POWER and used uncorrected.

3.4. Soil data and soil properties

Soil textural data were obtained from the ISRIC—World Soil Information/AfSIS project (Hengl et al., 2015). The soil volumetric water content at −33 kPa and −1500 kPa as required by APSIM were calculated from these data following Minasny and Hartemink (2011) (see Table 1).

3.5. Crop data and management

Crop management data used for APSIM calibration were obtained from Okomu Oil Palm Plc (See Table 2). APSIM validation was undertaken using also data from the Okomu Oil Palm Plc for the period 2003–2013. Data included fresh fruit bunch yield (FFB, t/ha), mean bunch size (kg) and mean bunch number (/palm). Plantation records were used to derive representative data for crop

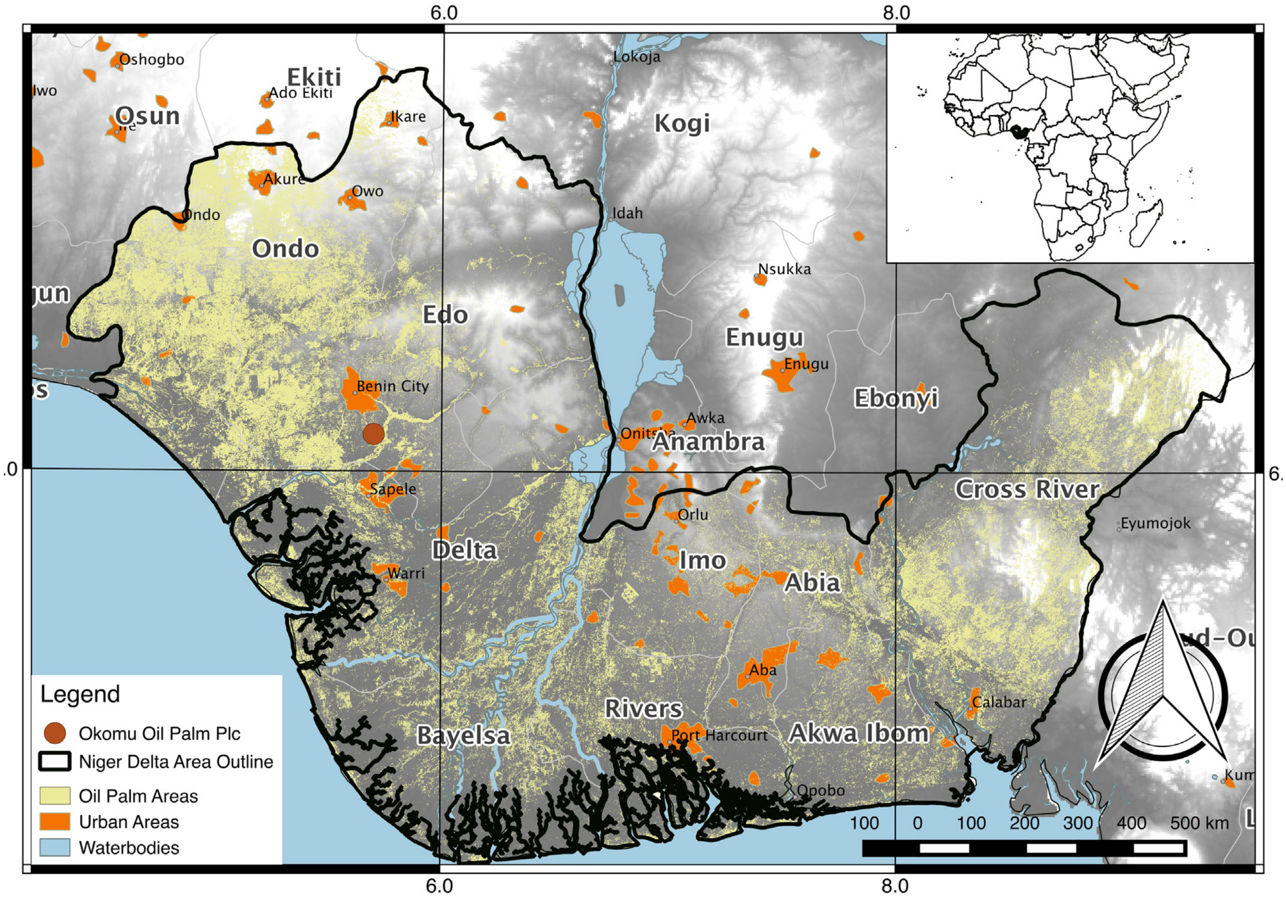

Fig. 1. Map of the study area.

Table 1
Soil parameters used in APSIM for calibration.

Layer depth (cm)	AirDry (mm/mm)	LL15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	Bulk density (g/cc)	OC (%)	FBiom (0–1)	Finert (0–1)
0–5	0.07	0.22	0.31	0.48	1.30	3.20	0.040	0.200
5–15	0.08	0.23	0.31	0.48	1.32	2.20	0.030	0.500
15–30	0.08	0.24	0.31	0.46	1.35	1.70	0.015	0.750
30–60	0.08	0.24	0.31	0.44	1.40	1.10	0.010	0.950
60–100	0.08	0.24	0.31	0.42	1.46	0.60	0.010	0.950
100–200	0.08	0.23	0.30	0.40	1.51	0.40	0.010	0.950
200–300	0.08	0.23	0.30	0.40	1.51	0.40	0.010	0.990

Table 2
Crop parameters used in APSIM for Current Tech simulation.

Description	Value
Sowing date	01.05.Year
Plant population (plants/ha)	135
Cultivar	Nigeria_IRHO
Sowing depth (mm)	200
N applied in year 1 (kg/palm)	0.14
N applied in year 2 (kg/palm)	0.25
N applied in year 3 (kg/palm)	0.5
N applied in year 4 (kg/palm)	0.5
N applied to mature palms (kg/palm)	0.5
Water source	rainfed
Weekly water requirement young palms (mm)	20
Weekly water requirement mature palms (mm)	40

management, such as planting dates, plant populations and fertilizer rates. Yield data were aggregated for plantation blocks per year of planting to provide mean yields for palms of similar ages. Simulations were developed for each year of planting from 2000 to 2008 assuming a similar soil type of clay loam soil across the estate.

3.6. Climate scenarios and climate impact modelling

Climate impact was assessed using regional climate model (RCM) simulations of the RCP 4.5 & RCP 8.5 scenarios, performed with the regional climate model SMHI-RCA4 of the Swedish Meteorological and Hydrological Institute, Rossby Centre. Model simulations for the period 1951–2100 were conducted in the framework of the Coordinated Regional Downscaling Experiment (CORDEX, cf. Jones et al., 2011) available for Africa at a horizontal resolution of 0.44° (lat/long). The RCP's selection was based on authors choice. To enable an evaluation of uncertainties that could arise due to different GCM forcings, we considered two alternative SMHI-RCA4 realizations, forced with 1) the MPI-ESM-LR coupled model of the Max Planck Institute (MPI) for Meteorology Hamburg and 2) the CanESM2 model of the Canadian Centre for Climate Modelling and Analysis (CCCMA), thereafter referred to as MPI and CCCMA respectively. Our choice of these forcings is based on the model ability to simulate the WAM system. Both GCMs differ in their representation of seasonal cycle of the WAM system simulation (Niang et al., 2014; Roehrig et al., 2013; see also Figs. 3 and 4).

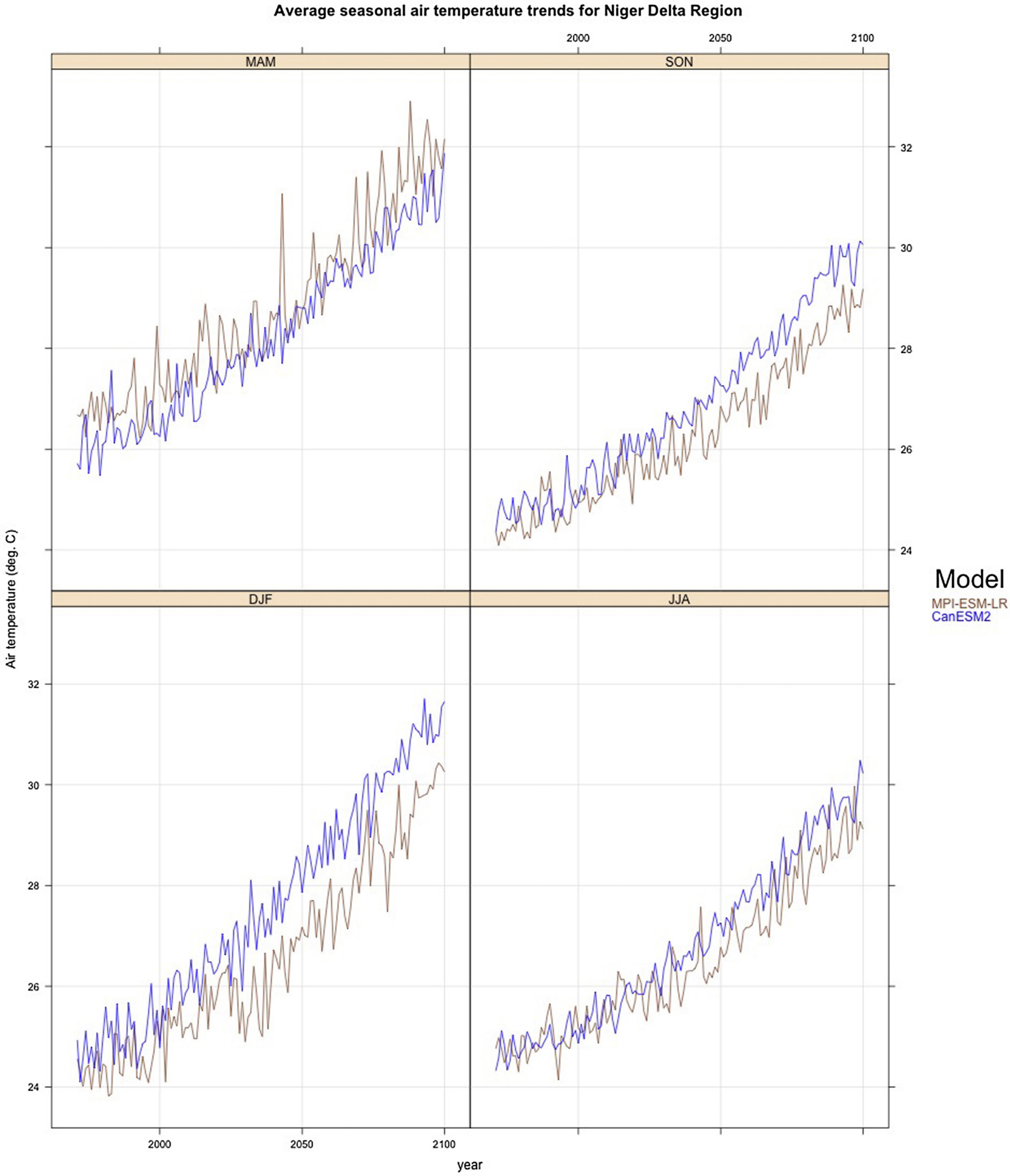

Fig. 2. Time-series of the two GCMs for seasonal air temperature in the Niger Delta region.

As input climate data are the key drivers for crop yield simulation, the climate data were quality controlled and bias corrected using the WATCH Forcing Data methodology applied to ERA-Interim reanalysis-WFDEI data (Weedon et al., 2014). For the temperature and solar radiation data, we used the linear scaling approach to do the bias correction following Hashino et al. (2006) using Climate Data Operator (CDO) software of the Max Planck Institute for Meteorology, Hamburg. The precipitation data were bias corrected using quantile mapping approach following Gudmundsson et al. (2012) as implemented in the R package qmap version 1.0–3. Assuming a linear temperature evolution over 130 years from 1971 to 2100 the average yearly temperature increase from the two GCM's for

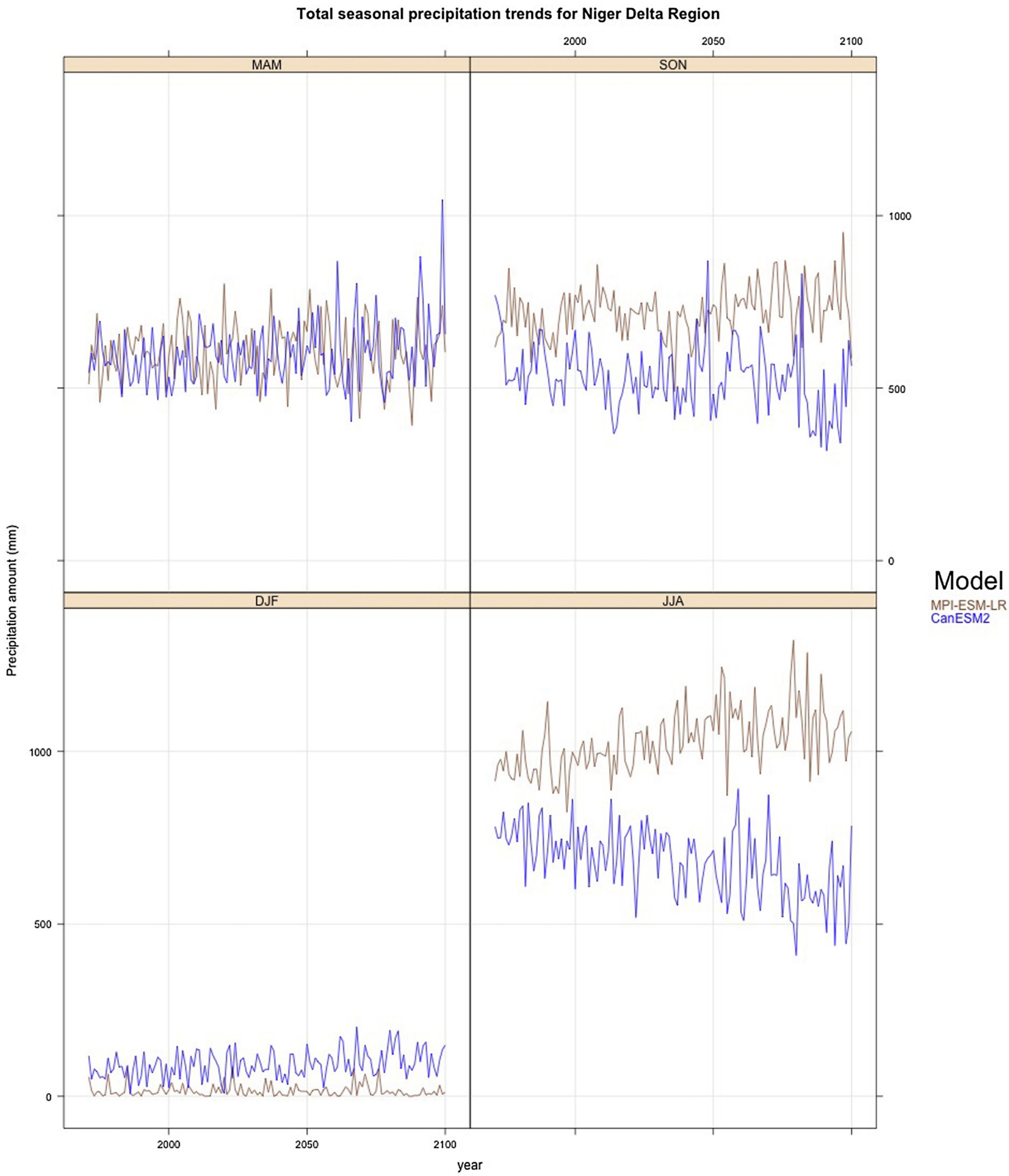

Fig. 3. Time-series of the two GCMs for seasonal precipitation amount in the Niger Delta region.

RCP8.5 is estimated to be 0.04 °C/year and the average year to year natural variability is 0.97 °C (see Fig. 2). The total seasonal precipitation trend for the two GCM's and its model to model variability are reported in Fig. 3. The total precipitation pattern showed a shift towards early rain in the region.

3.7. Analysis

We used the crop yield data obtained from Okomu Oil Palm Plc (2000–2014) for validation of APSIM Oil Palm.

The goodness of fit of simulated- observed data was assessed using the coefficient of determination for linear regression (R^2) and four other statistical measures in order to properly evaluate the model performance. The four statistical measures include:

(i) Index of agreement (I) (Willmott, 1981)

$$I = 1 - \frac{\Sigma_{i=1}^{n}(P_i - O_i)^2}{\Sigma_{i=1}^{n}(|P_i - P_m| + |O_i - O_m|)^2}$$

(ii) Percentage of bias (PBias)

$$PBias = 100\frac{\Sigma_{i=1}^{n}(P_i - O_i)}{\Sigma_{i=1}^{n} O_i}$$

(iii) Mean Absolute Error (MAE)

$$MAE = \frac{i}{n}\Sigma_{i=1}^{n}|(P_i - O_i)|$$

(iv) Root Mean Square Error (RMSE) which is the overall relative error and can be calculated as:

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(P_i - O_i)^2}{n}}$$

where O_m and P_m are the means of observed and predicted yields, and O_i and P_i are the corresponding observed and predicted yields for year i.

We explore the impact of climate change on palm oil production in the different spatial zones delineated for our study according to Homogenous response units (HRU) of Skalský et al. (2008). The impact of climate change on oil palm production in the different spatial zones was determined by simulating future climate scenarios using two climate output based on one RCM but with two different GCM forcings. We ran two simulations for each of the RCP's: 1) Current Tech (current management practices); and 2) High Tech (adapted management practices) (see Tables 2 and 3, respectively). The Current Tech simulation uses all management parameters as reported from Okomu Oil Palm Plc. The High Tech simulation uses a planting date of 01.04.year instead of 01.05.year, introduction of irrigation and an increment in fertilizer use a nd every other parameter remain the same like in the case of Current Tech.

Table 3
Crop parameters used in APSIM for High Tech simulation.

Description	Value
Sowing date	01.04.Year
Plant population (plants/ha)	135
Cultivar	Nigeria_IRHO
Sowing depth (mm)	200
N applied in year 1 (kg/palm)	0.14
N applied in year 2 (kg/palm)	0.25
N applied in year 3 (kg/palm)	0.5
N applied in year 4 (kg/palm)	0.5
N applied to mature palms (kg/palm)	1.0
Water source	irrigated
Weekly water requirement young palms (mm)	20
Weekly water requirement mature palms (mm)	40

4. Results

4.1. Model performance

The model performance was evaluated by comparing the simulated data with the observed data obtained from Okomu Oil Palm Plc for FFB and bunch sizes for the period of 2003–2014 (Fig. 4).

For the annual FFB and annual bunch size our model was able to replicate the trend with an R^2 of 0.66 and 0.95 respectively (Fig. 4). The value of RMSE for FFB and bunch sizes are 3.99 t/ha and 1.20 kg respectively implying that for both FFB and bunch size the model performances are acceptable. The model efficiency is also sufficient for bunch size, but is obviously less satisfactory for FFB. The MAE for FFB is 3.83 t/ha and bunch size is 0.97 kg. The model index of agreement with the observed yield is 0.85 t/ha and 0.97 kg for FFB

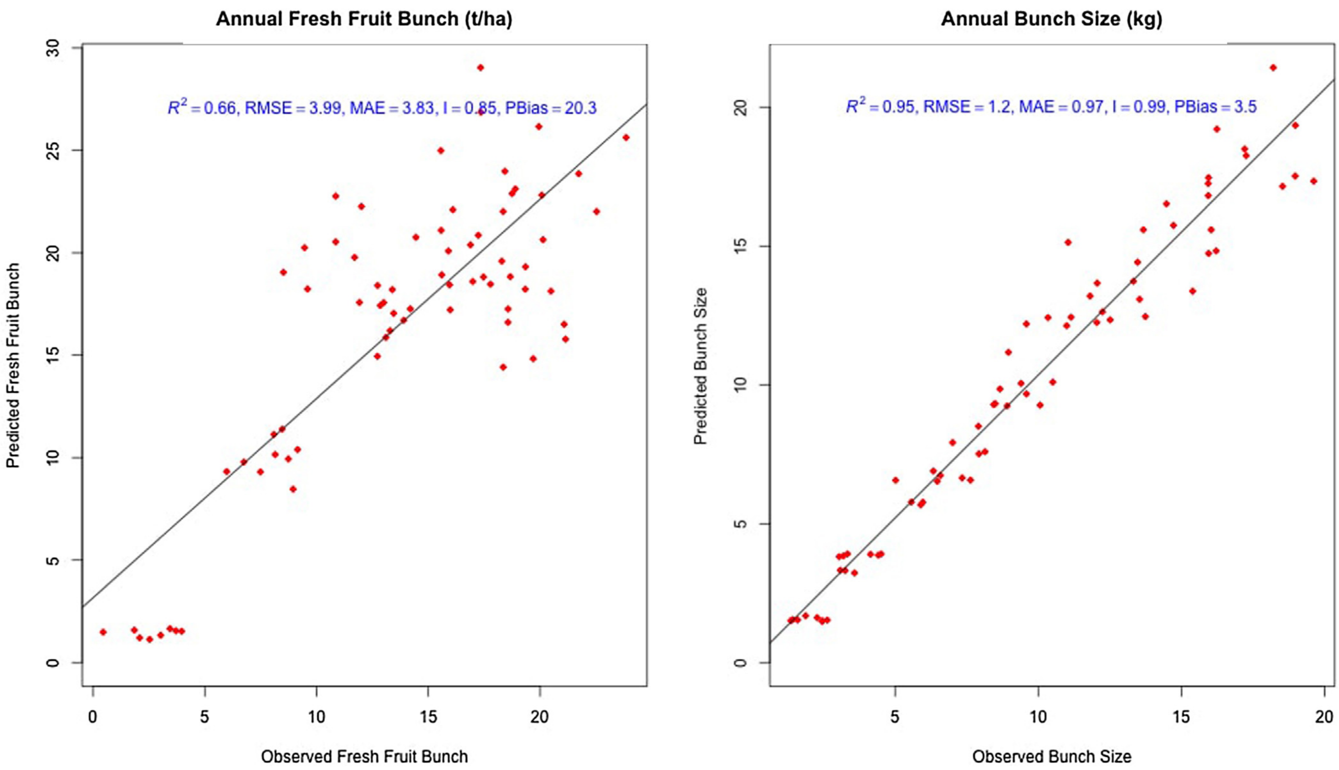

Fig. 4. Scatter plot of simulated versus observed yields from Okomu Oil Palm Plc.

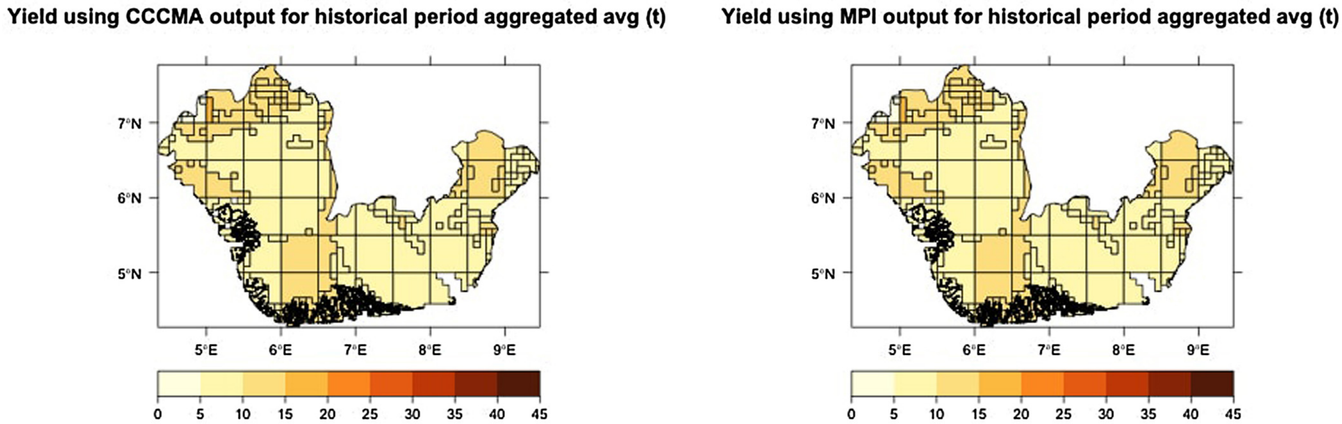

Fig. 5. Simulated yearly aggregated average oil palm yield for 1980–2004.

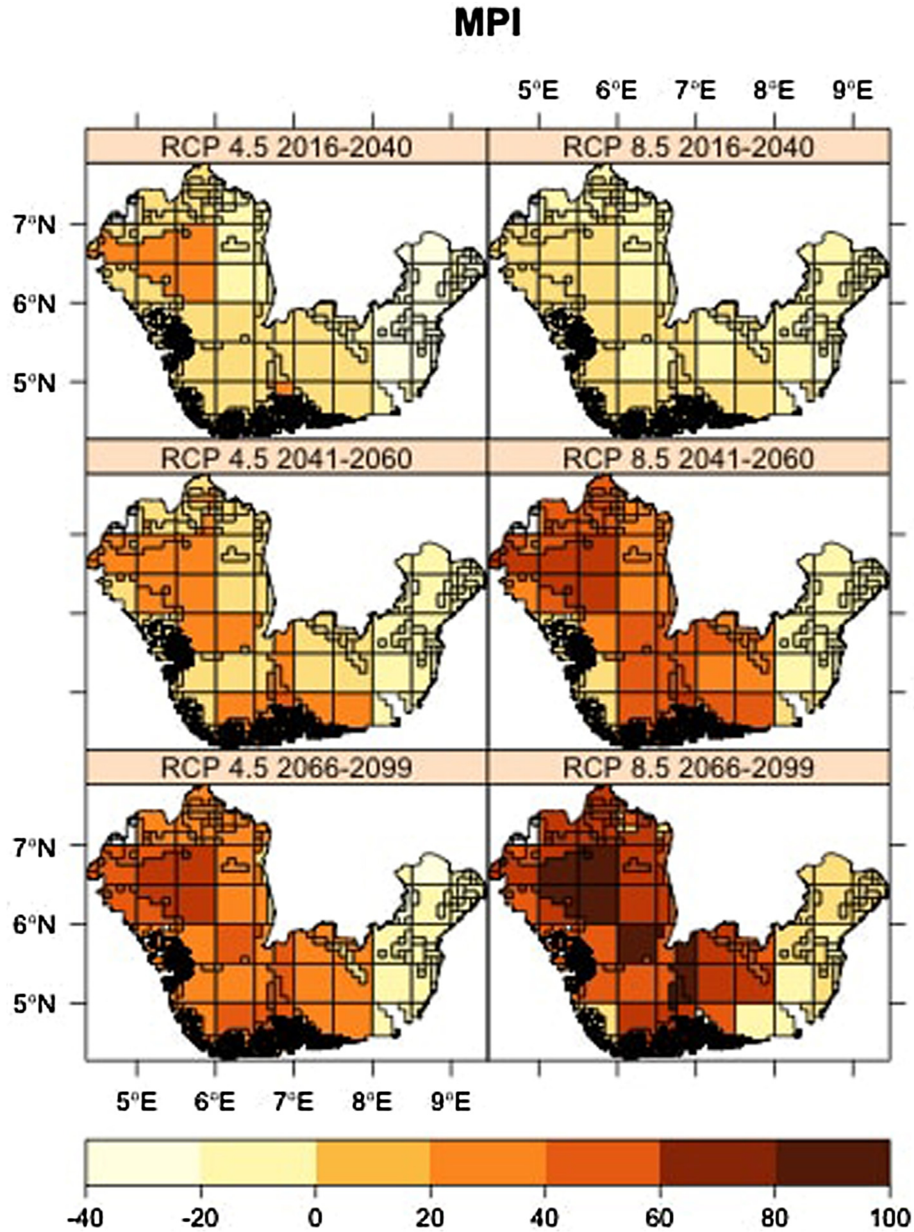

Fig. 6. Simulated change in yield (%) compared to 1980–2004 for MPI forcing under RCP4.5 and RCP8.5 emission scenarios.

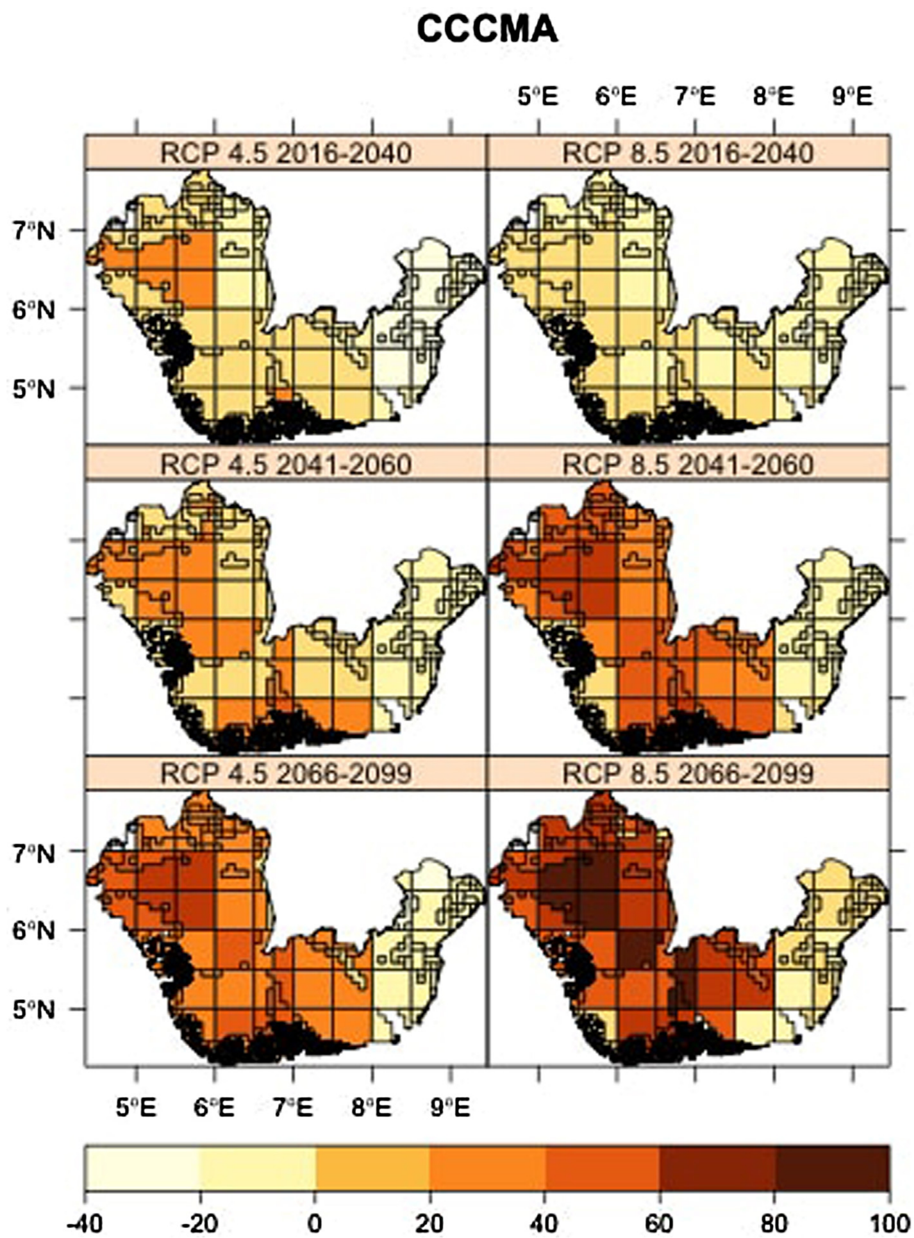

Fig. 7. Simulated change in yield (%) compared to 1980–2004 for CCCMA forcing under RCP4.5 and RCP8.5 emission scenarios.

and bunch size respectively. The bias was higher for FFB (20.3%) than for bunch size (3.5%).

4.2. Oil palm yield response to climate change

We examined the oil palm yield response to principal meteorological variables which include: solar radiation, minimum and maximum daily temperature and precipitation. For the historical period, the two simulations run using the two climate model outputs showed the same trend in FFB yield (Fig. 5). The outputs for the periods of 2016–2040, 2041–2065 and 2066–2099 of the RCP scenarios from both climate model setups followed essentially the same patterns, with RCP 8.5 having slightly higher impact on yields compared to RCP 4.5 (Figs. 6 and 7). The change in yield is expressed in% of the aggregated average yield obtained compared to base historical period (1980–2004 aggregated average).

The impact for this period is positive. In all cases, our High Tech simulation followed the same pattern, after optimization of some farming practices with slight difference noticed at the 2066–2099 simulation time interval. The change in yield is expressed

in% of the aggregated average yield obtained due to adaptive measure (High Tech) compared to current Tech (2016–2099 aggregated average). RCP8.5 showed lower yield difference in comparison with RCP4.5 for this same time interval (2066–2099). The percentage change in yield under the two climate outputs and its respective RCP's falls within the range of −40% to +100% for the entire time interval (Figs. 8 and 9).

There is an increase in yield in the western part of the study area. The highest yield decrease occurs in 2016–2040 for both RCP's, with RCP8.5 taking the lead. The difference between our High Tech simulation and business as usual (Current Tech) showed in all time intervals positive changes in yield across our study region (Fig. 8 and 9), for both climate output simulations. Weighted average yields within our study area (Fig. 10) showed varying effects across the different time intervals. The time interval of 2016–2040 showed a slightly negative to moderately positive climate change

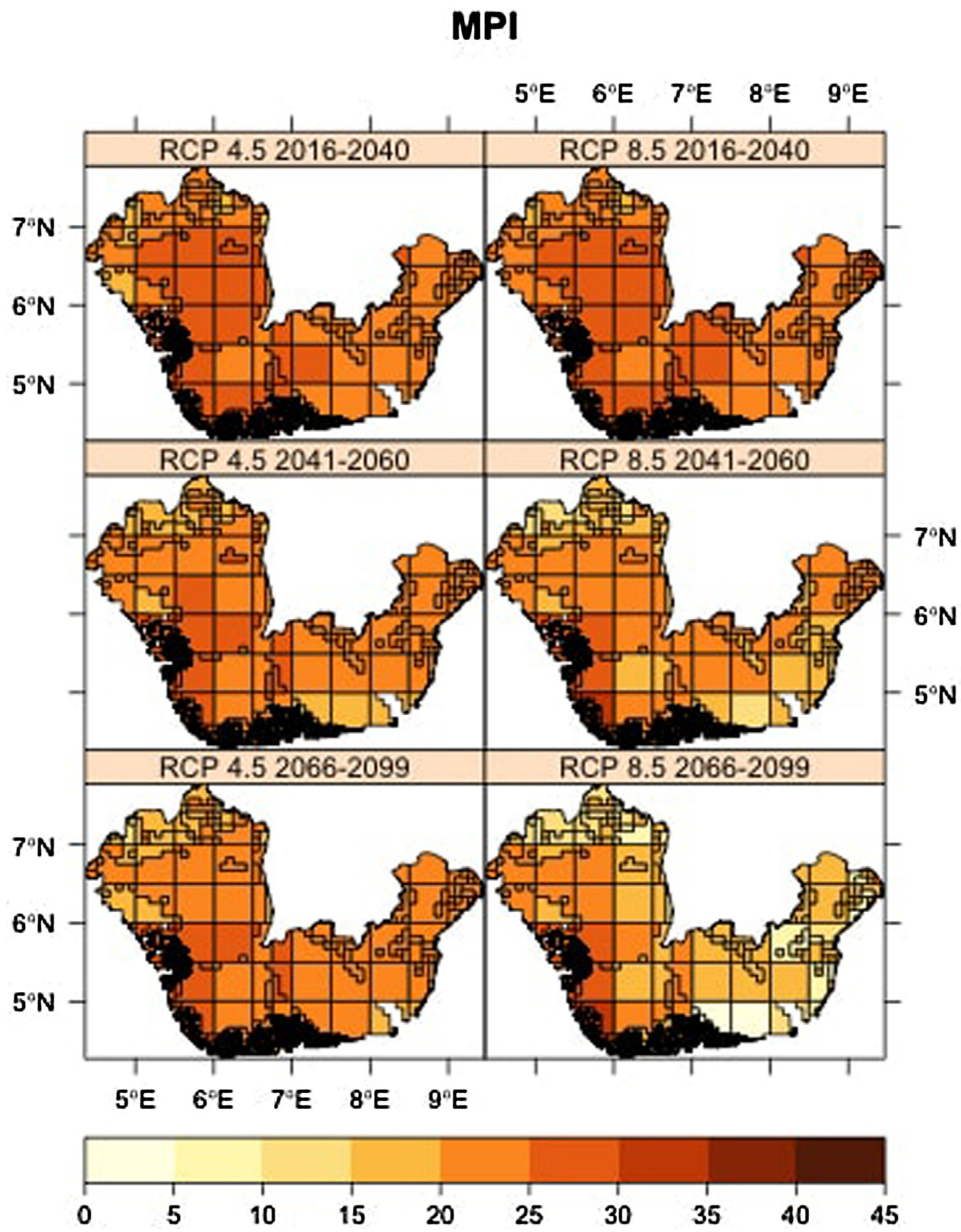

Fig. 8. Simulated change in yield (t) due to Tech for MPI forcing under RCP4.5 and RCP8.5 emission scenarios.

effect on the simulated yield. RCP4.5 showed a positive moderately spread range effect for time intervals 2041–2065 and 2066–2090. Whereas, RCP8.5 showed a positive slightly spread range effect for time interval 2041–2065 and positive moderately spread range effect for 2066–2090. The net impact of climate change on oil palm yield is positive.

5. Discussion

There are several possible reasons for the differences among the FFB and the Bunch size in our model performance results. First, bunch sizes reported in the observation data were consistent across plantation blocks with similar ages. As a result, predictions were able to closely follow the observations. However, observed yields varied widely for both similarly aged blocks within the estate and between years for any given block. This suggests large variations in annual numbers of bunches produced, possibly due to large spatial variability across the estate, localized impacts on palms during the time period, or errors in attribution of fruit yield to blocks at the mill. The model is only compared against average yields in each year for blocks of a certain age because soil and management data were not available at this finer scale. Among all the most likely error in our case is attributed to the scale issue.

The argument behind the use of multiple models in climate change research is to cover different sources of uncertainties (Deser et al., 2012; Hawkins and Sutton, 2012), given that different models or model setups differ in terms of projected climate change signals. Even though it is advisable to consider all climate model data in impact analysis (Knutti et al., 2010), this is not feasible in most cases. Our results show that the projected impact differs spatially within our study area and this is in line with results of Idumah et al. (2016), thus making discussion on its projected impact slightly controversial (i.e. it could be positive or negative). The net impact of climate change had been projected to be negative for cereal crops in our study region according to previous studies (Abiodun et al., 2011). In contrast, we found that the net impact

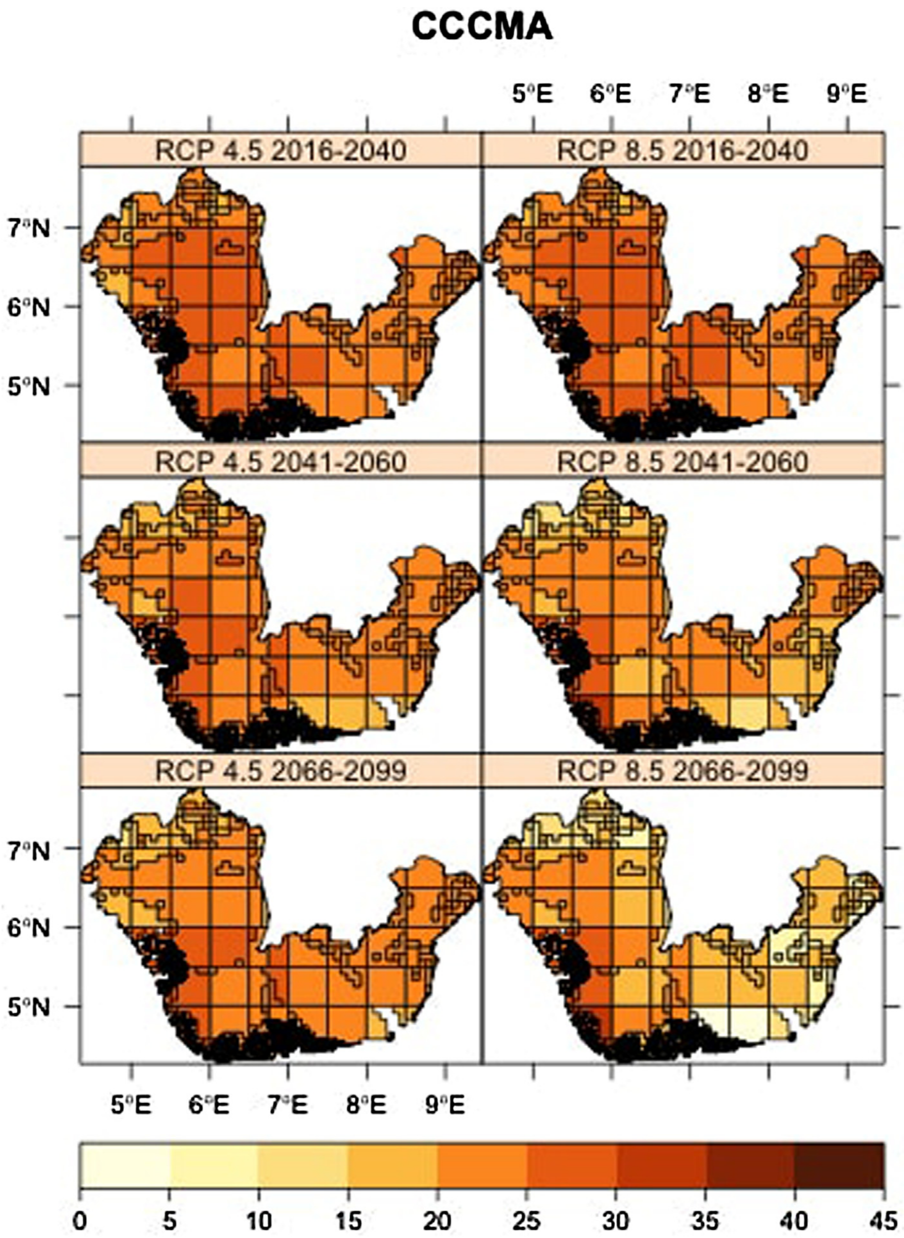

Fig. 9. Simulated change in yield due to Tech for CCCMA forcing under RCP4.5 and RCP8.5 emission scenarios.

of climate change on oil palm is positive. However, understanding adaptation measures and reducing uncertainties associated with different crop yield projections within the agricultural context requires detailed crop by crop analysis. Moreover, based on our results, one may argue that uncertainties associated with crop yield simulations do not rely on different GCM forcing (only), even if the GCM's have differences in their representation of the seasonal cycle of the WAM system. Because, after the calibration of the model across our study region using two different GCMs as forcings for the same regional climate model, the differences in predicted yields among different climate output for specific year intervals and spatial points were not significant. We can further argue that differences in yield simulation under different GCM forcing could be obtained based on the extent of climate change signal differences of the GCM's. Slight differences in climate variables insignificantly influence the expected yield. Climate model ensembles with participating models having higher range could potentially produce high uncertainties. Therefore, care should be taken in choosing participating model in climate model ensemble projects.

However, based on the results of this study, we can support the findings of Waongo et al. (2014) that one of the most effective adaptation measures in the West African region during this climate change reign is planting date optimization together with other management strategies like application of irrigation in order to obtain a maximized yield.

We further emphasize the importance of accuracy in the reference observation dataset used in bias correction of the climate model output, since this could be the way the climate signal might be altered (see also Macadam et al., 2016; Ruiz-Ramos et al., 2016). Therefore, climate impact studies should verify the accuracy of reference observation data used for bias correction, as this may help capture the climate signal more correctly. This could help in the correction of similarity in the yield simulations across GCMs and RCPs in such studies by better reference observation data.

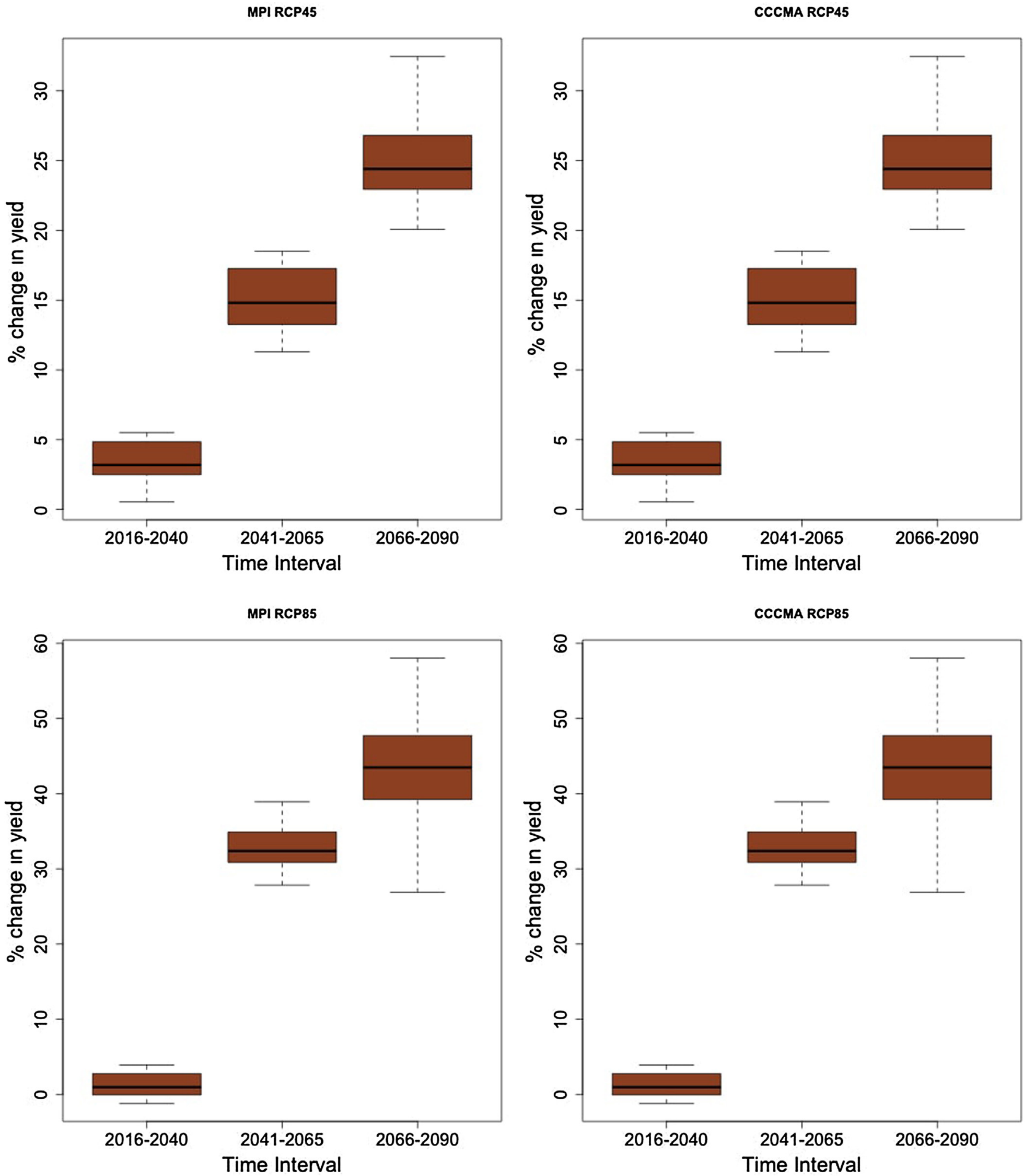

Fig. 10. Oil palm grown area-weighted average yield (t) change in the Nigerian Niger Delta compared to 1980–2004.

The limitations of this study include non-incorporation of the effects of CO_2 fertilization in APSIM simulation. For further studies, we recommend the investigation of the effect of CO_2 fertilization on oil palm yield in the Niger Delta. Furthermore, another limitation of this study is that APSIM validation was done by simulating a block and comparing it to the average of all the blocks obtained from Okomu farm Plc. We also recommend efforts that foster validation data improvement and availability at finer scales. Notwithstanding these uncertainties, the model provided realistic estimates of production for the location.

Based on this, it is clear that the Nigerian palm oil industry has the potential to reduce poverty and provide economic growth for African nations as exemplified by improved livelihood conditions of smallholder farmers having adopted oil palm production.

We therefore strongly recommend that the government provides enabling environment for the implementation and monitoring of sustainable practices like those stipulated by the Round Table on Sustainable Palm Oil (RSPO) in oil palm production. Current land use systems which expose the country to the risk of land grabbing, loss of other (food) crop lands, deforestation etc. might jeopardize the positive climate change impacts on palm oil yields.

6. Conclusions

Climate change impacts on crop yields are projected to be considerably different across the Niger Delta region. Our results showed that the net impact of climate change on oil palm is positive and is dynamically inconsistent across the interval of our simulations. In addition, we showed that oil palm yields are more robust to an increase in precipitation compared to an increase in temperature. Slight differences in GCM's ability of capturing the WAM system do not necessarily lead to differences in yield. Climate impact studies with climate model ensembles output and the participating models having higher range could potentially produce new sets of uncertainties.

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Article III

Impacts of Bioenergy Policies on Land-Use Change in Nigeria

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Stanley U. Okoro designed the overall study and prepared the input data. Stanley U. Okoro and Schneider developed the model coding and calibration. Stanley U. Okoro run the analysis, analyzed the results and wrote the manuscript. All authors read, discussed and approved the manuscript.

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Article

Impacts of Bioenergy Policies on Land-Use Change in Nigeria

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Abstract: In recent years, bioenergy policies have increased the competition for land as well as the risk of adverse environmental impacts resulting from deforestation and greenhouse gas emissions (GHGs). Primary land-use objectives confronting society today include meeting the growing demand for agricultural products, especially energy crops, preserving essential ecosystem services for human well-being and long-run agrarian production, and contributing to the climate policy target. Here, future agricultural, societal and environmental consequences of bioenergy policies under different global climate and societal development scenarios were assessed using a novel Forest and Agricultural Sector Optimization Model for Nigeria (NGA–FASOM). The results reveal that, in Nigeria, meeting emission reduction requires an implementation of a minimum carbon price of $80/ton within the forest and agricultural sectors. A carbon price alone is not sufficient to preserve the remaining forests and pasture land in Nigeria when bioenergy is subsidized. Furthermore, the result shows that subsidy on bioenergy does not have any significant effect on the total social welfare. The findings in this study provide a guide for policymakers in designing appropriate policies addressing bioenergy industry issues in Nigeria.

Keywords: bioenergy mandates; bioenergy subsidies; carbon pricing; climate target

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1. Introduction

One of the most significant challenges for sustainable development today is how to manage limited land resources to achieve an optimal balance between market commodities production, especially food production, and provision of non-market services. To meet the growing demand for agricultural products while preserving essential ecosystem services on which human well-being depends, various government policy actions are implemented. Many countries, including Nigeria, initiated different bioenergy policies with the underlying aim of decarbonizing their economy [1–5]. Current bioenergy policies in Nigeria include the Renewable Electricity Policy Guidelines (REPG, 2006), the Renewable Electricity Action Program (REAP, 2006), the Nigerian Biofuel Policy and Incentives (2007), and others. These Nigerian bioenergy policies are in line with the United Nations Framework Convention on Climate Change entitled National Adaptation Strategy and Plan of Action on Climate Change for Nigeria (NASPA–CCN) as part of its commitment to the Global Climate Action Plan [6]. There is agreement that the mitigation efforts and investments over the next two to three decades will have a substantial impact on opportunities to achieve lower stabilization levels of greenhouse gas emissions (GHGs) [7]. Controversial opinions exist, however, about the feasibility of a decarbonized economy with current policies. Many studies have debated the expected results of different bioenergy mandates, which include its risks as related to indirect land-use impact concerning GHGs, food security, land grabbing, etc. [7–12].

In scenario assessments with high demand for crop-based bioenergy, food production is often achieved by a substantial expansion of cropland area [13]. The projected global demand for transportation fuel in 2050 requires about twice the land used to meet food demand under the presumed 70% increase in per capita food demand [14]. Thus, in developing bioenergy policies, the inclusion of land-use change (LUC) impacts is necessary [15].

Many developed countries and emerging economies have implemented biofuel development initiatives; for instance, the European Union, United States of America, Brazil, etc. The adoption of similar actions in Africa requires a proper assessment of the complex and heterogeneous interactions between land use, society and environment. Currently, bioenergy policy impact assessments in Africa involve only low-resolution studies or studies with limited scope. In Nigeria, however, significant emphasis is placed on researching bioenergy potential. Integrated assessment review studies have drawn their policy recommendations from reviews on modeling studies done in other countries. These assessments have been made neglecting the uncertainties from the economic perspective of bioenergy policies and only taking into consideration spatial and technological assessment methods, with little impact scope [16].

Few studies shed light on LUC implications for Nigeria with a broader scope and higher-resolution modeling framework [17]. Existing model-based studies on various energy demand and supply pathways for Nigeria are limited by a low range and a coarse resolution [18]. While trade had internalized agricultural products and welfare distribution, environmental impacts are not internalized. Appropriate policies should be drawn from detailed scientific-modeling studies because their effects can be heterogeneous.

To study bioenergy policies in Nigeria in a more comprehensive way, we develop here a novel Forest and Agricultural Sector Optimization Model for Nigeria (NGA–FASOM). It is a partial equilibrium model that combines complex natural conditions for agricultural and forest production and aggregate commodity-market demand functions. It integrates engineering, geographical and economical methods in addressing policy recommendations regarding bioenergy deployment. One of the novelties of this modeling work is that it is among the few models of its kind that adequately capture the biophysical aspect of oil palm as a bioenergy feedstock/crop by incorporating the model output of [19]. The objectives of this study are to show trajectories of the future agricultural, societal, and environmental outcomes of various bioenergy policies in Nigeria under different global climate and societal development scenarios.

2. Methodology and Data

2.1. Description of Forest and Agricultural Sector Optimization Model for Nigeria (NGA–FASOM)

The Nigeria Forest and Agricultural Sector Model (NGA–FASOM) is a bottom-up approach economic model which implies that supply is formed from the bottom (land cover, land use and management systems) to the top (markets/trade/demand) (see Figure 1). NGA–FASOM is a recursive dynamic partial equilibrium model which integrates bioenergy production processes, crop products as well as livestock and forestry products. All land-cover types are explicitly represented in the model across each time horizon. The optimal decision in time-step t depends on decisions that the agents have taken in time-step $t - 1$. When each new time-step starts, the conditions for land use are updated using the solutions of the simulations from the previous time-step. NGA–FASOM is brought up to date for each time step using exogenous drivers such as population and bioenergy policies. Bioenergy conversion processes in the model are also well represented according to the conversion processes, technological cost, conversion efficiencies and their corresponding co-product.

The model design concept and structure is similar to the US Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model [20], and its derivative the Global Biomass Optimization Model (GLOBIOM) [8]. Market equilibrium is computed by choosing land use, processing, and trade activities which maximize the sum of the producer and consumer surpluses as stated in the objective function

(W) subject to resource, technological and policy constraints (see Appendix A for model equations) [21]. In NGA–FASOM, agricultural production faces a downward-sloped commodity-demand function (see also Appendix A). Land-use equations are part of the block equations of NGA–FASOM. To restrict extreme specialization in the model, we implemented the so-called crop mix equation which makes the share of each crop mimic and stay within observed bounds. NGA–FASOM is based on the decision and rational theory [22], consumer economics and law of demand [23], resource economics and law of supply [21,22], as well as market equilibrium with trade [23–26]. Market prices and resource values are endogenous outputs of the model. The model comprises 36 states of Nigeria plus the federal capital territory. Trade with other countries is kept exogenous. Here, a spatial equilibrium approach following [20] is used. Therefore, trade and demand adjustments occurred at the 37 economic units of the model according to marginal production prices and transportation cost assuming homogeneous goods across states. We represented the following bioenergy conversion processes in the model: combined heat and power production, heat, fermentation of ethanol, power and gas production, and gasification for methanol and heat production. NGA–FASOM is solved for 5 decadal time steps (2011–2050). For more details about the model structure and philosophy see [8,20,21,27,28].

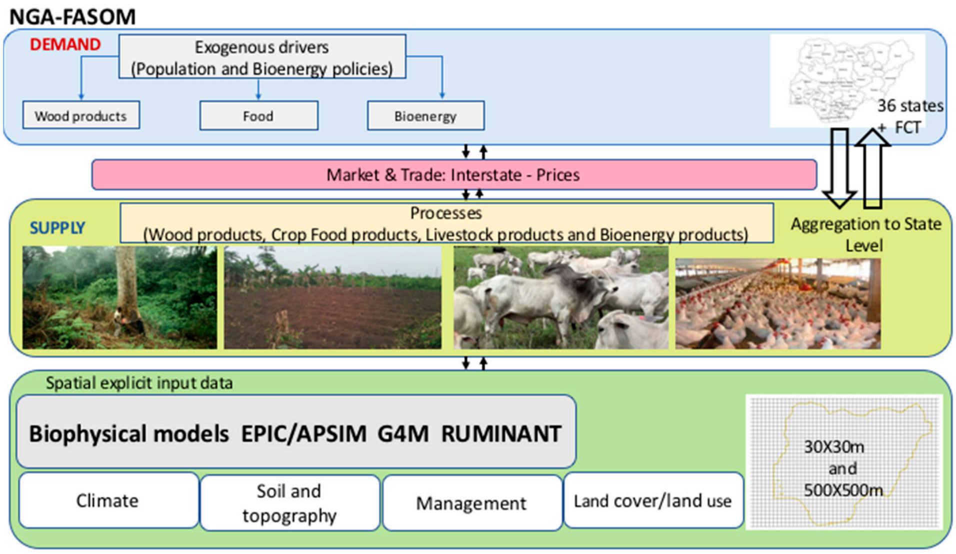

Figure 1. Structure of the Nigeria Forest and Agricultural Sector Model (NGA–FASOM).

2.2. NGA–FASOM Baseline

The NGA–FASOM baseline model is calibrated to reference data through a physical gap parameter and a linear activity cost adjustment. The gap parameter corrects data deficiencies and implicitly depicts all model-exogenous activities. For example, NGA–FASOM depicts eight important agricultural crops. Resources used by other crops are exogenous to the model and are assigned to the gap parameter. The linear cost adjustment is performed such that at baseline activity levels, marginal cost equals marginal revenue according to microeconomic theory. The model assumes a \$200/ha and \$500/ha cost for crop management change (CMC) and LUC respectively [29]. Furthermore, we assume constant cost functions throughout the entire model horizon. The LUC impacts of the Nigeria REPG (2006), REAP (2006), and the Nigerian Biofuel Policy and Incentives (2007) are assessed in comparison to a policy baseline with and without emission tax. The baseline represents the way Nigeria develops between 2011 (the model base year) and 2050 with our modeled bioenergy policy mix and no tax on GHG emissions. We chose 2011 as the baseline because the National Bureau of Statistics of Nigeria provides state-level data for this year on crop areas and crop yields, commodity-market indicators, population, consumption patterns and exchange rates. Population is assumed to increase continuously until 2050 with a growth rate equal to the averaged growth rate for the past 10 years in each state.

The assumption and calculation result is in line with the projected population of Nigeria according to [30]. Food commodity-demand functions are shifted in proportion to population growth. Other factors that influence demand for land-based products, e.g., Gross Domestic Product (GDP) and dietary patterns, are not explicitly modeled in this study because of insufficient data availability.

2.3. NGA-FASOM Scenarios

The main driving forces for the scenarios are the bioenergy mandates as stipulated in the Nigeria REPG (2006), REAP (2006), the Nigerian Biofuel Policy and Incentives (2007), and the National Renewable Energy and Energy Efficiency Policy (NREEEP, 2015). Tax abatement is modeled as a subsidy which implies a reduction in the producer's price of bioenergy products. Electricity demand from biomass is 2273.08 GJ, 11,560.10 GJ, 16,201.61 GJ, 16,201.61 GJ by 2020, 2030, 2040 and 2050, respectively [31]. Bio-diesel demand is planned at 900 million liters for 2020, 2030 and 2040 [32]. Ethanol demand is 2 billion liters by 2020, 2030, 2040, 2050 for the gasoline 10% ethanol blend ratio (E10) requirement [32]. The assessed bioenergy support instruments include: (a) a 50% subsidy at the price of $0.044097/GJ for electricity; and (b) a 50% subsidy for biodiesel and ethanol at the price of $0.88/L. As an incentive to reduce GHG emissions from deforestation, we implemented and compared three carbon tax levels of $40, $80 and $120 per ton of carbon. The combination of carbon tax and bioenergy subsidies resulted in eight scenarios, which were simulated and compared to the baseline of the bioenergy mandate. This analysis does not intend to evaluate the feasibility of Nigerian government policies on the bioenergy target incorporated in the study. Instead, the scenarios aim to assess the impacts of different policy actions on the LUC, GHG emission and agricultural welfare, with future welfare being discounted at 5% following [33,34], and including the implications for Nigeria under constrained technology. Our approach is in line with the findings of the Intergovernmental Panel on Climate change (IPCC) [34], that the mitigation response of implementing carbon pricing is consistent across models and studies. The opportunity costs of carbon sequestration (break-even carbon price) for most countries in Africa is still unknown. In this study, the base year was calibrated using the above carbon prices to help give more insight into the implications of the different carbon prices for the case of Nigeria.

2.4. Data

Land resources are the only resources explicitly incorporated in the current version of the model; this is crucial to this modeling. To enable regional biophysical process characterization modeling of agricultural and forest production, a detailed land delineation was used [29]. The land-cover/land-use data of the forest and agricultural area of Nigeria used is a combination of [30] and [31]. Three different land-cover types were represented; forest land, grassland and cropland. The crop species disaggregation was done using the crop-area statistical estimates from the National Bureau of Statistics of Nigeria at the state level. The study chose to use remotely sensed data and survey statistics as a scaling factor in disaggregation since political and economic pressure, combined with inconsistencies in reporting, often results in over/underestimates of the quantity of agricultural land. Government statistics underestimate agrarian area as well as the rate at which it is converted to non-agricultural use (see also [32]). The biophysical model outputs used include those of the Environmental Policy Integrated Climate Model (EPIC) [33] and the Agricultural Production Systems Simulator oil palm (APSIM) [19,34]. To explore different biophysical model output scenarios with the IPCC Representative Concentration Pathway 4.5 (RCP4.5) scenario, three productivity pathways are considered which include subsistence agriculture, low input, and high input (see Table 1 and [19] for a detailed description of the input assumptions). In total, 8 crops were represented in the model; cassava, corn, cotton, dry beans, millet, oil palm, rice, and sugarcane. The IPCC tier 3 digestion and metabolism model for ruminants (RUMINANT) model output was used for livestock production representation in the model [35]. In the current version of NGA–FASOM, we incorporated the updated International Livestock Research Institute/Food and Agriculture Organization (FAO) production systems classification. Twelve livestock production systems from this nomenclature were represented: livestock-only systems, arid and semi-arid (LGA); livestock-only systems, humid and sub-humid (LGH); livestock-only systems, hyper-arid (LGHYP); livestock-only systems, highland/temperate (LGT); irrigated mixed crop/livestock systems, arid and semi-arid (MIA); irrigated mixed crop/livestock systems, humid and sub-humid (MIH); irrigated mixed crop/livestock systems, hyper-arid (MIHYP); rain-fed mixed crop/livestock systems, arid and semi-arid (MRA); rain-fed mixed crop/livestock systems, humid and sub-humid (MRH); rain-fed mixed crop/livestock systems, hyper-arid (MRHYP); rain-fed mixed crop/livestock systems, highland/temperate (MRT); built-up areas (URBAN); and, root-crop based and root-based mixed systems (Others) [36,37]. Seven livestock products are present in the model; cow meat, cow milk, pig meat, poultry meat, poultry eggs and sheep and goat meat. We also used the output of the Global Forest Model (G4M) model for that of the forestry sector [38]. The forest products considered consist of saw logs, pulp logs, other industrial logs, traditional fuelwood, and biomass for energy. Biomass, pulp logs and saw logs further undergo processing for their respective bioenergy products. The processing cost and conversion coefficients for both forest and crop biomass, and crop to ethanol and/or methanol are sourced from [39–41] and Brunus Enterprises Nigeria Ltd. To enable quantitative comparison, all energy products were converted to gigajoules. LUC and livestock CO_2-equivalent emissions are derived from [8]. Market data are sourced from the National Bureau of Statistics of Nigeria, FAO and from literature. Where market data is available at the national level, disaggregation using state population was done. For more details on each of the input data, see appropriate citations above.

Table 1. Input assumption for the different productivity pathways. Adapted from [42].

Productivity Input Pathways	Crop Management	
	Fertilizer Adjustment	Other Input Adjustment
High	Yes	Yes
Low	No	Yes
Subsistence	No	No

2.5. Model Uncertainties

The study model, NGA–FASOM is robust to input data; therefore, our analysis relies on the available data which are plausible but might be a potential source of uncertainty. Future climate and socioeconomic development pathways could be another source of uncertainty in the model.

3. Results and Discussion

3.1. Land-Use Change Implications of Bioenergy Policy in Nigeria

The relative area for bioenergy feedstocks becomes evenly distributed when the carbon tax is implemented (Figures 2 and 3). The oil palm area is slightly larger with a low and high tax scenario when there is subsidy action (Figures 2 and 3). The percentage change in land-use area by 2050 compared to the base year of our model run shows that all the grassland area will be converted to cropland across all model scenarios after the first model horizon. In all the scenarios, the land-use change trajectory goes from cropland and grassland to forest within the first two decades and afterwards entirely from forest and grassland to cropland by 2050. The introduction of carbon tax shrinks the total area of oil palm (Figures 2 and 3). About 4.94% of the forest area will remain forest under zero carbon taxation and carbon price of $40/ton. When carbon tax above $40/ton is implemented, however, all the area will be converted to cropland. Interestingly, the study found that carbon tax alone even with a relatively high conversion cost ($500/ha) of forest to another land-use type is not sufficient to retain the existing forest area in Nigeria. A sensitivity analysis revealed that Nigerian policymakers should place a much higher conversion cost for converting forest to other land-use types in order not to allow the conversion of the remaining forest area to cropland due to bioenergy policy action. This result suggests that farmers are rational decision makers. However, several caveats are worth commenting. For instance, land-use change restriction strategies, e.g., carbon pricing (market-based instrument) are not appropriate for ecosystem conservation in Nigeria. Our result is in agreement with that of [43], that market-based instruments can be controversial and may not signify the setting as a priority of nature conservation. We further argue that multiple policy actions should be put in place to enable the realization of the multiple objectives. If nature conservation takes precedence for policymakers, facilitation of effort to map protected areas should follow alongside the bioenergy mandates. Conservation instruments such as payment schemes and tradable land-use permits need to be implemented. The study result also demonstrates that policymakers will be required to make trade-offs between bioenergy production and nature conservation as the cost of carbon alone cannot offset the profitability of subsidized bioenergy. High-incentive payments like payment for ecosystem services (PES) and reduced transaction costs can improve the outcomes of forest conservation [44].

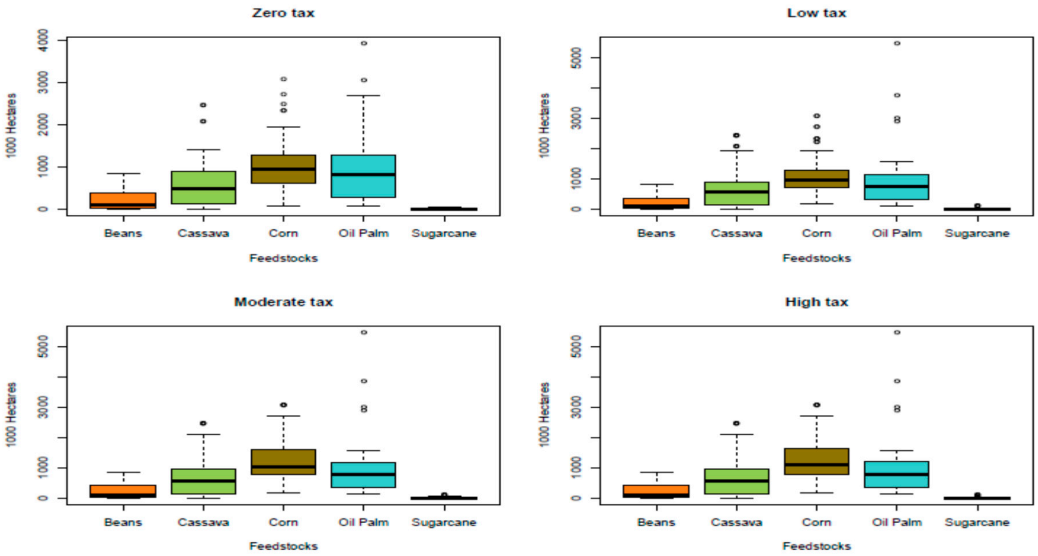

Figure 2. Bioenergy feedstock area by 2050 under subsidy action.

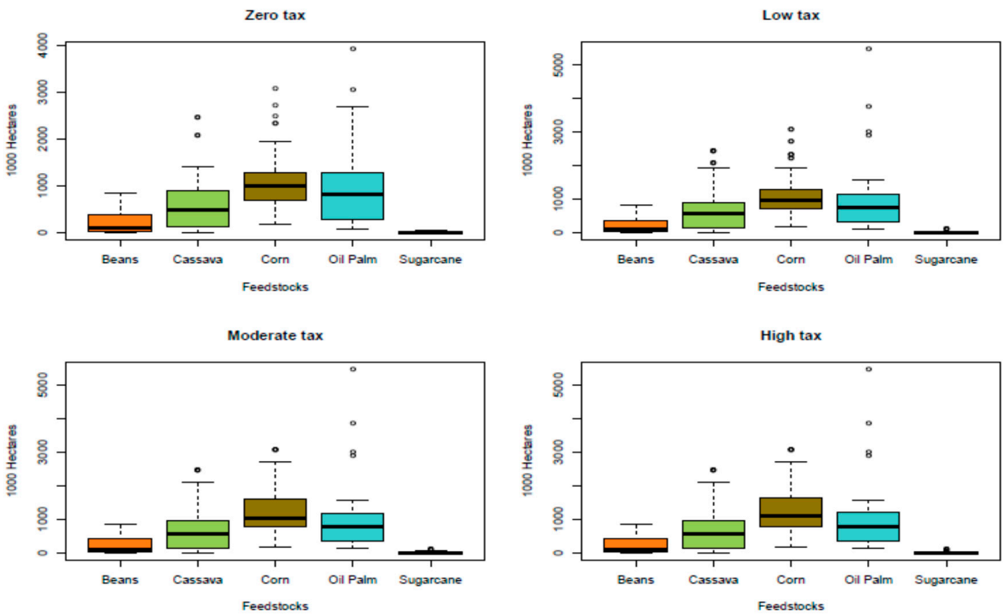

Figure 3. Bioenergy feedstock area by 2050 under no subsidy action.

The argument behind this is that the physical process of sequestering carbon can take several years; the cost of carbon sequestration cannot be estimated without making assumptions (implicitly or explicitly) about its fate over time [45]. This creates a massive vacuum for uncertainty although we assume that the price of carbon remains constant in real time. The opportunity cost of converting land from its current use to one with higher carbon sequestration may not be profitable when comparing the rate of sequestration in the agricultural area that has been converted.

The study also finds that subsidy for the bioenergy industry in Nigeria does not mean that some feedstock will have comparative advantages over others. The share of the total area for oil palm in the baseline scenario will substantially become higher by 2050 compared with other feedstocks. But when the carbon tax is implemented the other feedstocks will come into play in the bioenergy feedstock mix as shown in Figures 2 and 3. This is also replicated in the total agricultural crop area (see Figures 4 and 5).

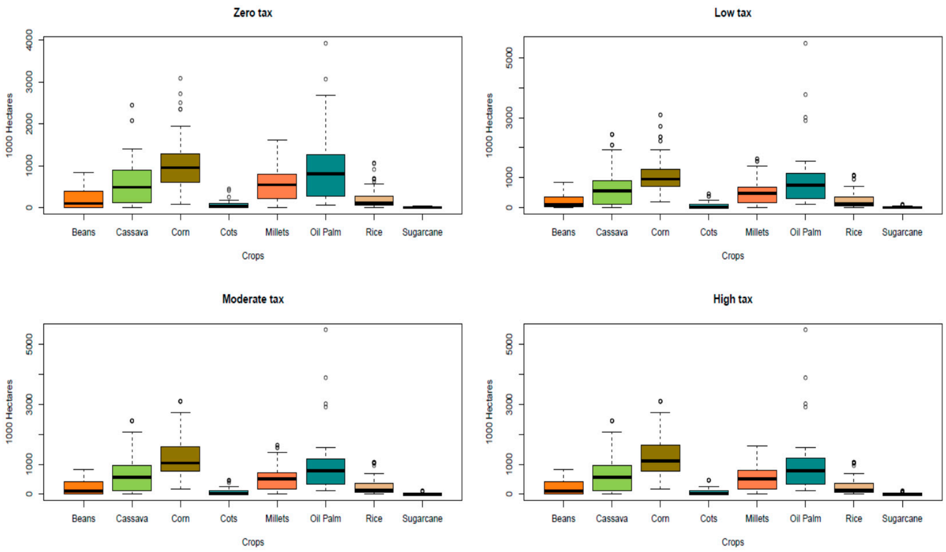

Figure 4. Agricultural crop area by 2050 under subsidy action.

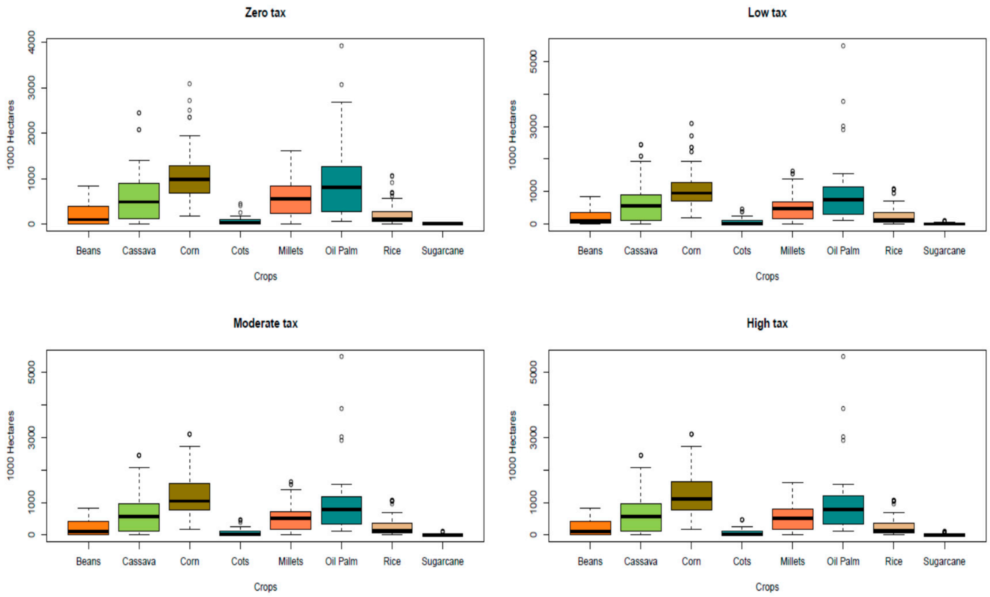

Figure 5. Agricultural crop area by 2050 under no subsidy action.

3.2. The Effect of Direct and Indirect Land-Use Change Greenhouse Gas Emissions (GHGs) as a Consequence of Bioenergy Policy Mix

Total potential GHG emissions of the bioenergy scenarios (no carbon tax, low carbon tax, moderate carbon tax, and high carbon tax) for both subsidy and no subsidy action (Figures 6 and 7) indicate that the use of emission tax is an appropriate instrument for Nigeria if emission reduction is to be achieved when compared to the baseline scenario of zero-emission cost. Therefore, implementation of a carbon tax is essential for the slope of the land-use change emission supply function. Nevertheless, policies that could allow a win–win situation are needed. We further argue that policies should aim at subsidizing landowners for their below- and above-ground biomass because vegetation carbon transpiring in the first two-time horizons of our result is very likely. This might happen because there are no incentives to keep land-use areas such as grassland and shrubland. However, challenges such as the proper measurement of below-ground biomass are an open research area for scientists. The result of this study concurs with the consensus that carbon pricing will be a useful strategy for meeting the Paris Agreement [46].

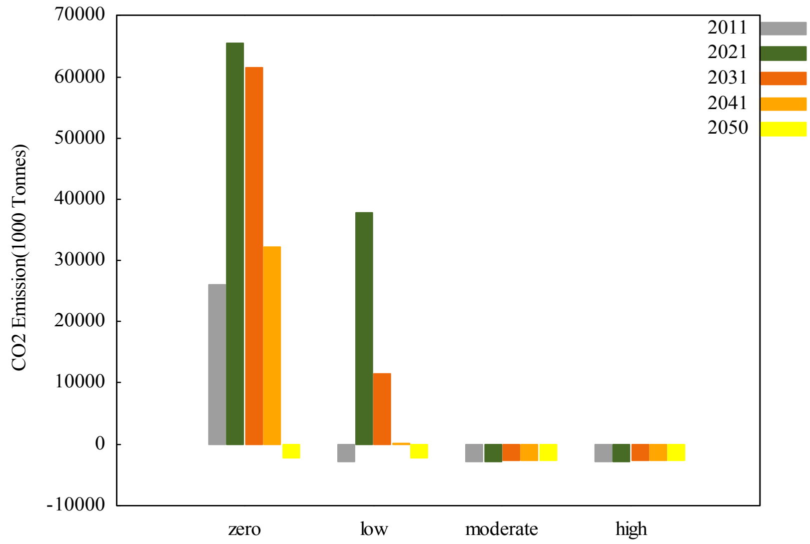

Figure 6. Total greenhouse gas (GHG) emission under subsidy action.

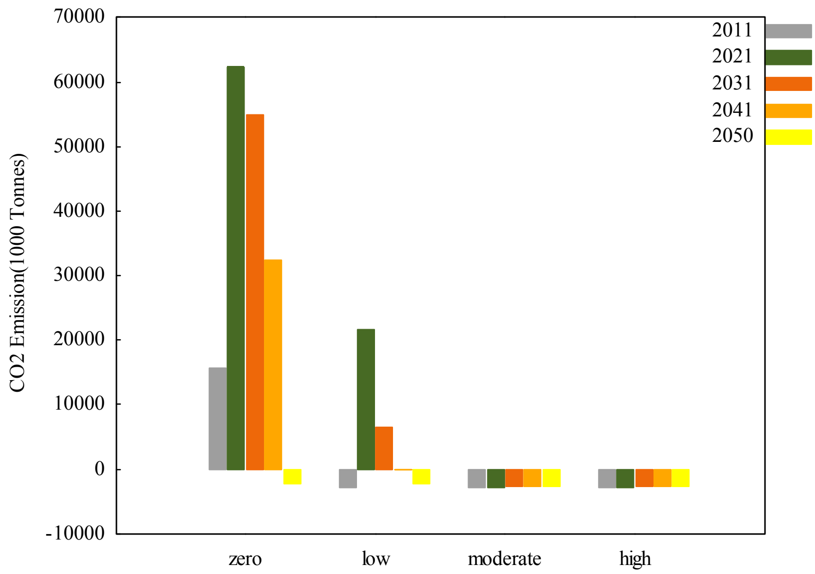

Figure 7. Total GHG emissions under no subsidy action.

As shown in Figures 8 and 9, the indirect land-use change emissions reduction will only be feasible if a carbon price of a minimum of $80/ton is implemented. The calculation of LUC emissions is based on the assumptions from [8], that agricultural practices do not have an impact on soil carbon emissions, and deforestation is defined as the expansion of cropland into the forest, so the total carbon contained in above- and below-ground biomass is emitted. The study result shows that a substantial amount of emission could be saved by implementation of a carbon tax whether there is a subsidy on bioenergy production or not. However, another interesting point from this result is the break-even carbon price of $80/ton. The result shows that support for the bioenergy industry does not have any substantial effect on LUC emissions. NGA–FASOM is subject to limitation based on data availability.

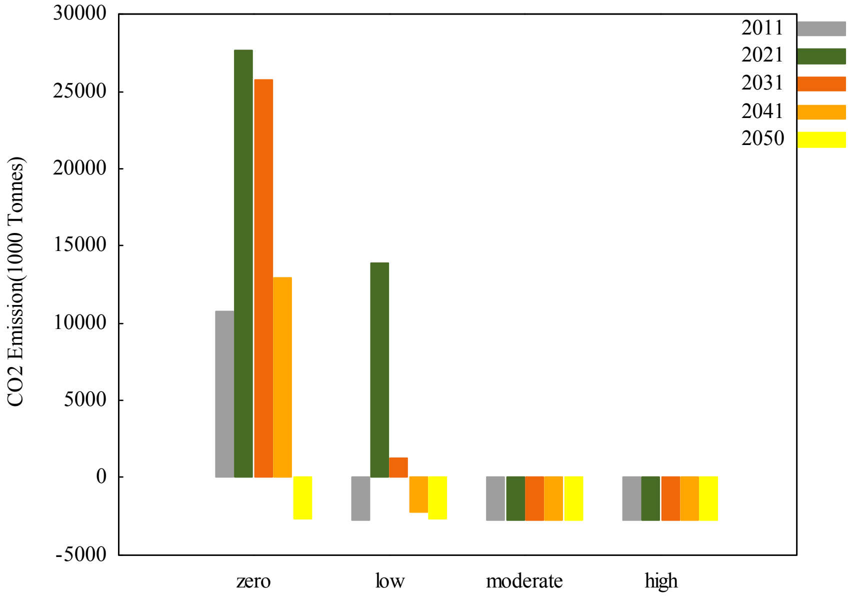

Figure 8. GHG emissions due to land-use change (LUC) under subsidy action.

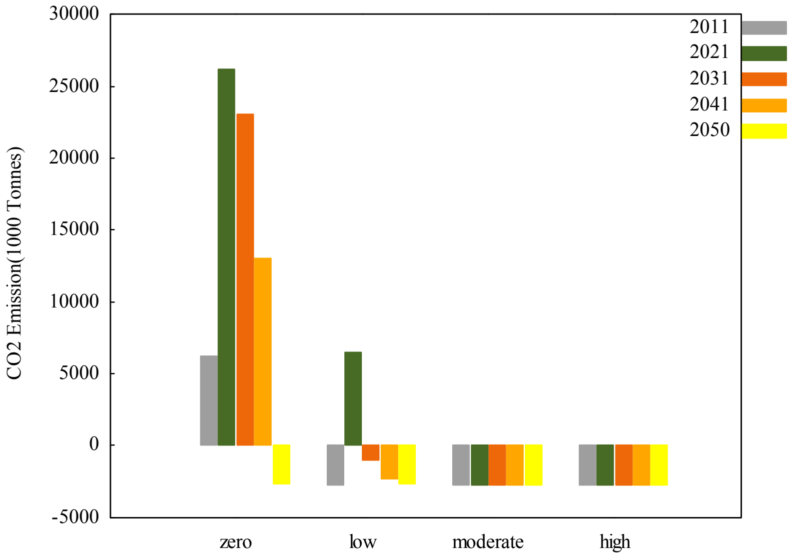

Figure 9. GHG emissions due to LUC under no subsidy action.

One of these limitations includes the limited data on crop-management system areas in Nigeria. This deficiency leads to an improper representation of the crop-management system within the crop-mix equation where we restricted the crop area to mimic the crop area share of the observation.

On a sensitivity analysis, we find that a negative indirect land-use change GHG emission is achievable with the implementation of a carbon tax of \$40/ton if, and only if, the Nigerian government places a land-use conversion cost of \$10,000/ha with or without subsidy on the bioenergy industry.

3.3. Implications of Bioenergy Subsidies on Food Prices, Total Welfare and Bioenergy Consumption Pattern

The results reveal that combining a volume mandate with a carbon price policy does not provide any substantial change in bioenergy consumption due to the energy products' elasticity (see Figures 10–13). Instead, at optimal control, a carbon tax tends to favor the disposable income with regards to bioenergy at the expense of other competing agricultural products. Our results reveal that by 2050 the biofuel and bioelectricity consumption trend by states showed very little difference across the three tax scenarios with or without a subsidy on bioenergy (see Figures 10–13). Kogi state showed the highest consumption share when a carbon price is implemented in scenarios for both biofuel and bioelectricity by 2050. Bayelsa state consumes the highest bioenergy when there is no carbon tax, and decreases its consumption share by almost a factor of 5 with the introduction of a carbon tax. Putting this into perspective, one could translate this into changes in land use, principally those associated with deforestation of the mangrove forest, land-use change emissions cost and the trade cost with other states due to proximity challenges. The result also replicates the same issue as with Bayelsa state in the case of Akwa Ibom state with a factor of 4 when a carbon tax is implemented.

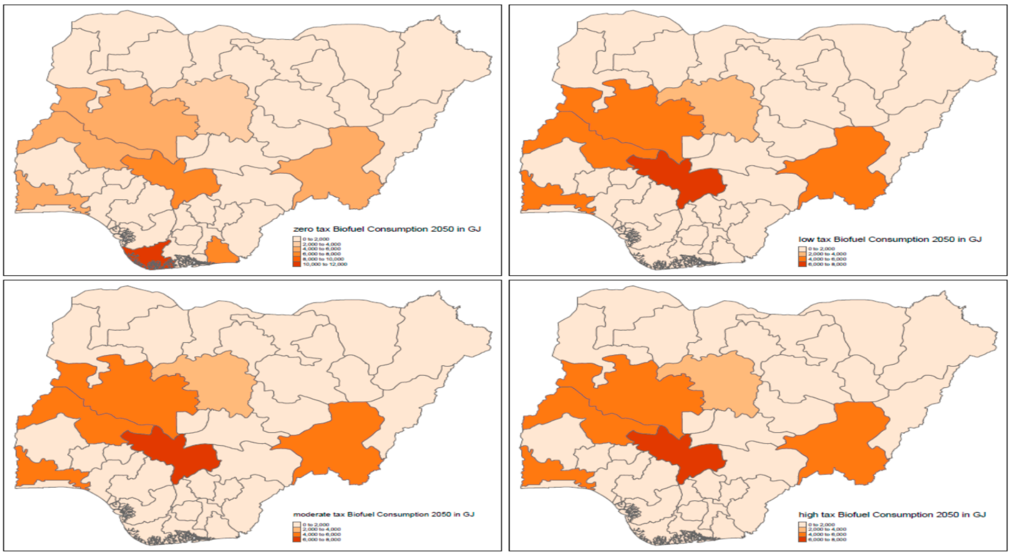

Figure 10. Biofuel consumption by 2050 under subsidy action.

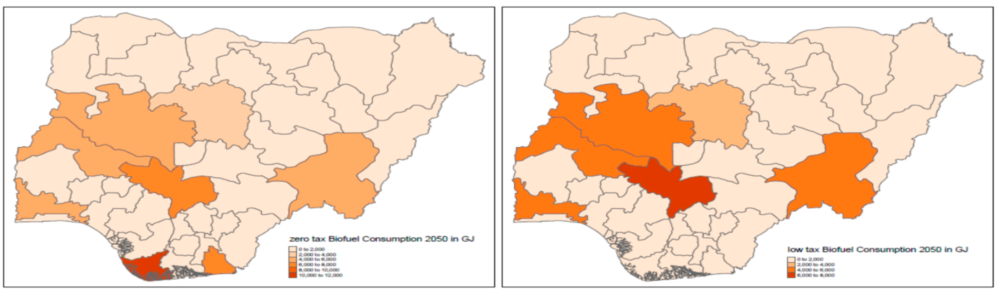

Figure 11. *Cont.*

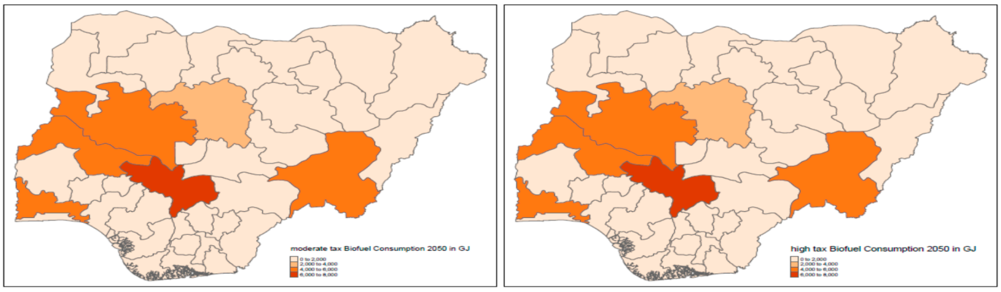

Figure 11. Biofuel consumption by 2050 under no subsidy action.

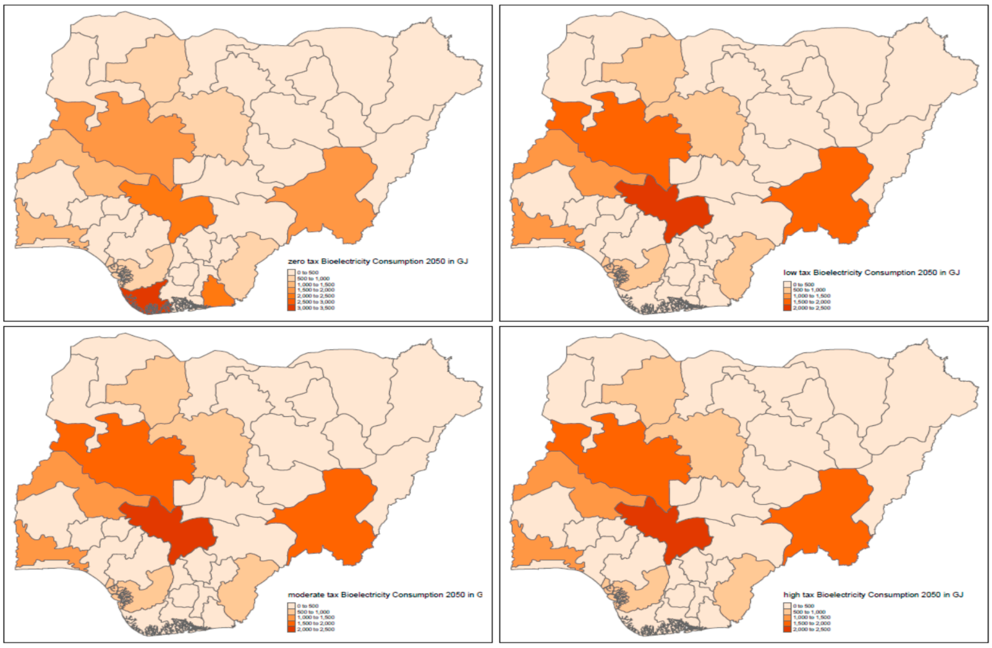

Figure 12. Bioelectricity consumption by 2050 under subsidy action.

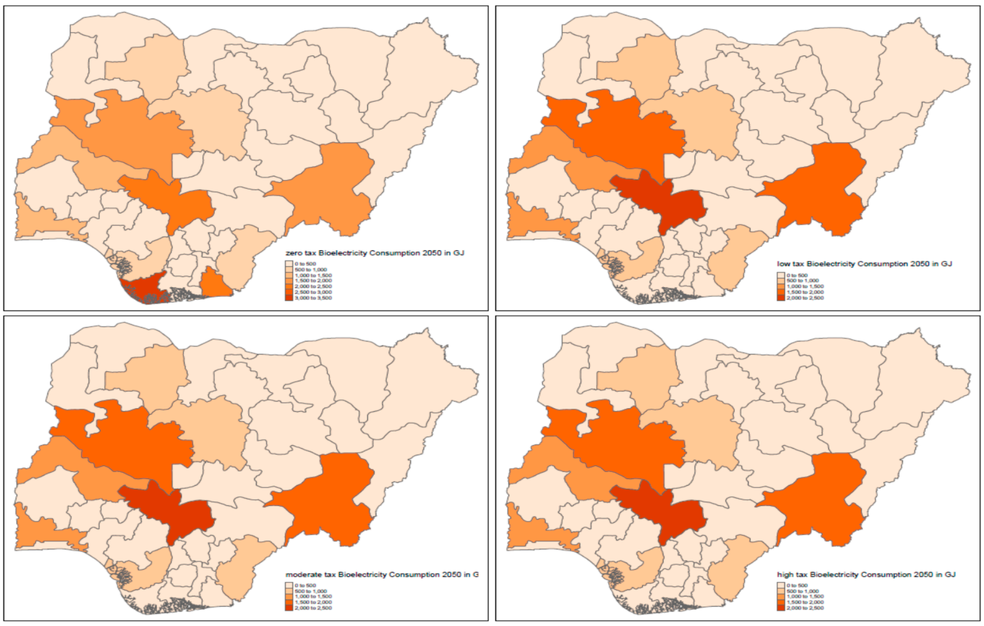

Figure 13. Bioelectricity consumption by 2050 under no subsidy action.

The study result also shows that a subsidy does not have any significant effect on the total welfare due to deadweight loss (Figures 14 and 15). The economic inefficiency caused by the grant is because of the cost of enacting the government support, which is more than the marginal benefit of the subsidy to the producers and consumers.

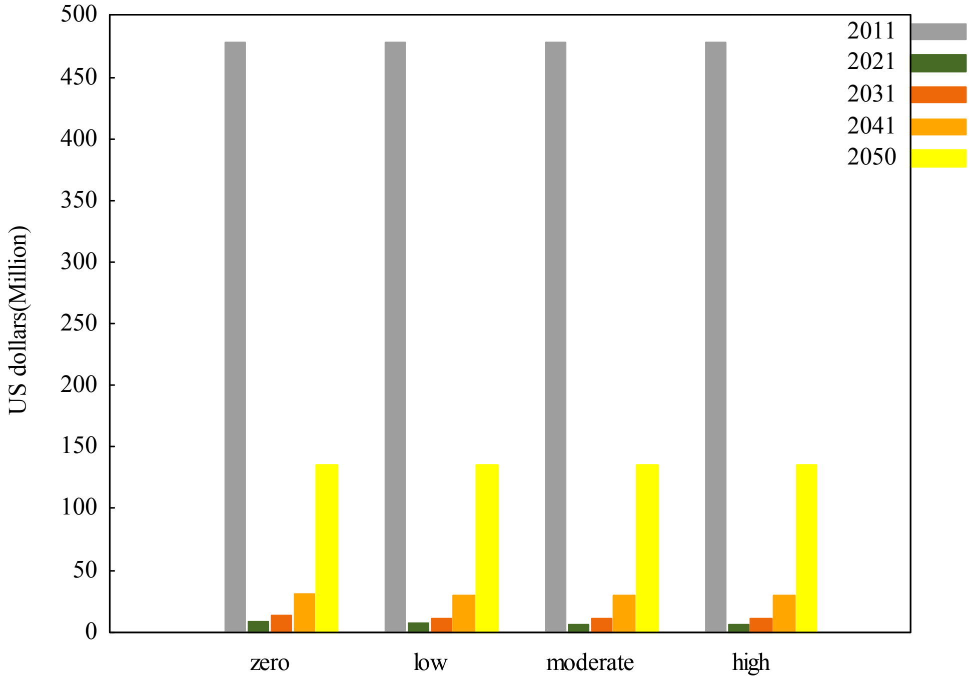

Figure 14. Total social welfare under subsidy action.

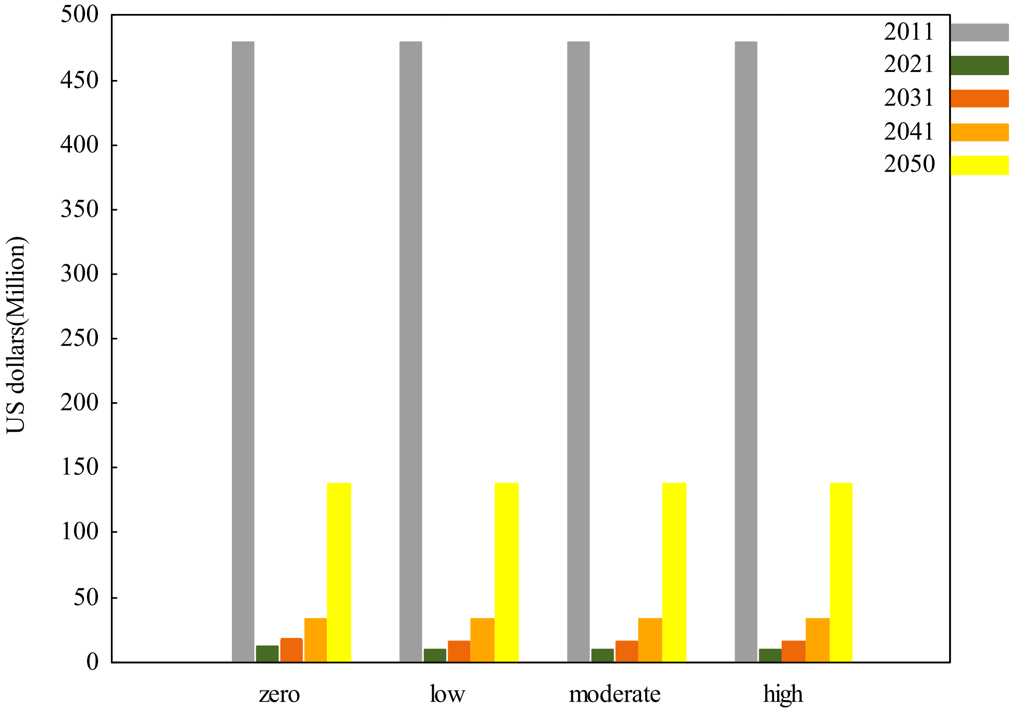

Figure 15. Total social welfare under no subsidy action.

Our result shows that the bioenergy policy target in Nigeria will translate to very high food prices by 2050 under all the scenarios with or without a carbon tax (see Figures 16 and 17). This result is in accord with that of [47]. The food-price dynamics across the model horizon as seen in without subsidy scenarios (Figure 17) are caused by the land-use change trajectories.

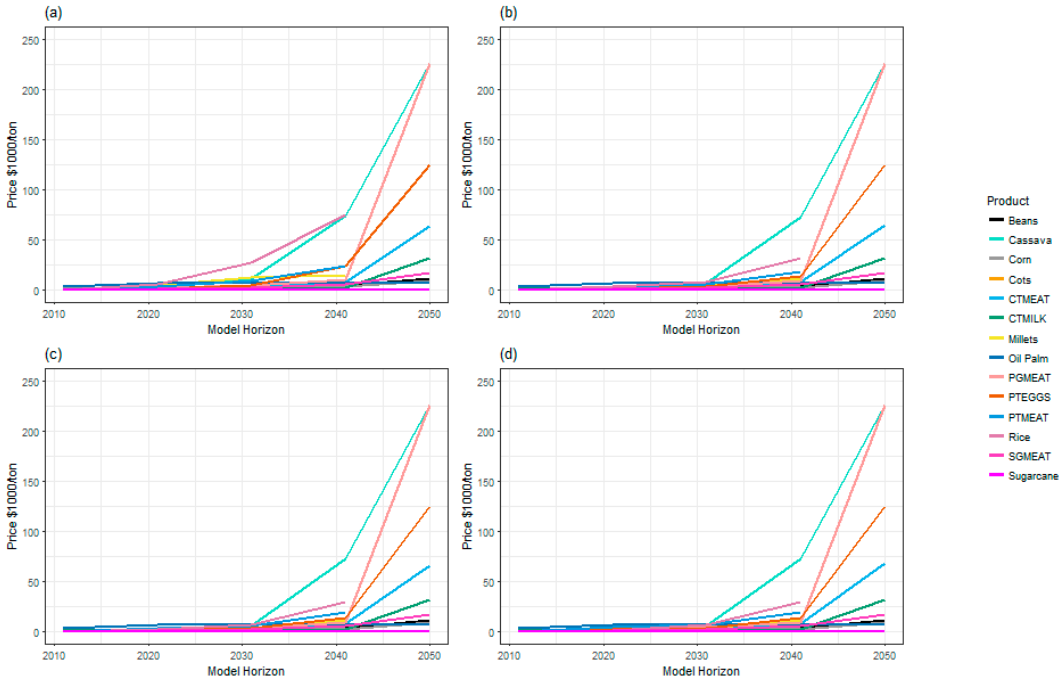

Figure 16. Agricultural product prices: (**a**) Baseline; (**b**) $40 carbon tax; (**c**) $80 carbon tax; (**d**) $120 carbon tax, under subsidy action.

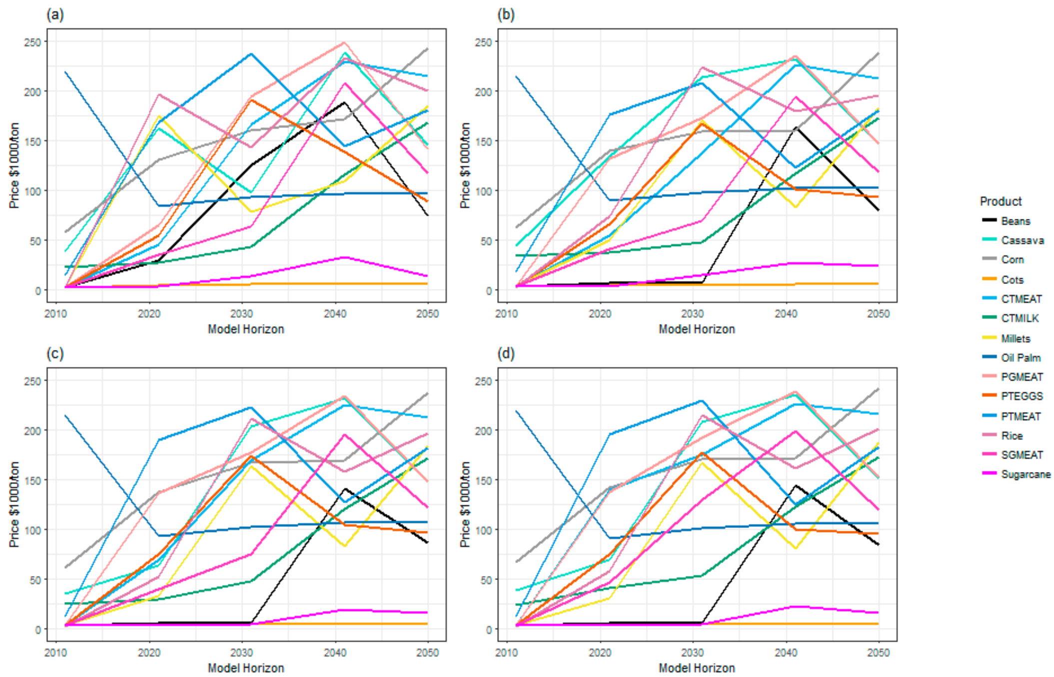

Figure 17. Agricultural product prices: (**a**) Baseline; (**b**) $40 carbon tax; (**c**) $80 carbon tax; (**d**) $120 carbon tax, under no subsidy action.

4. Conclusions and Policy Implications

Public support for bioenergy deployment is widely debated, and it is agreed that the substitution of traditional fossil-fuel energy sources by bioenergy can provide benefits for energy security and potential for GHG mitigation. However, the rapid expansion of biofuels production from some feedstocks (e.g., oil palm) has raised concerns regarding land use and the implications of cropland expansion for net GHG emissions. Thus, the focus for future bioenergy use has shifted toward second-generation feedstocks that may alleviate these issues of converting forest land to cropland. However, there are some technological and logistical hurdles to overcome before second-generation feedstocks can be used to generate large quantities of bioenergy at competitive costs [48]. Conclusions from this study are that market-based instruments such as a carbon tax alone are not sufficient for preserving the remaining forest area in Nigeria. Therefore, political willingness to support an infant industry such as the bioenergy industry have to couple a carbon tax with conservation instruments such as Payment for Ecosystem Services (PES). NGA–FASOM showed that, to achieve a negative GHG reduction in the forest and agricultural sector in Nigeria, a carbon tax above $80/ton is required. In Nigeria, a subsidy on bioenergy products does not have any significant effect on total social welfare. Another general conclusion that emerges from this study is that a subsidy on the bioenergy industry in Nigeria does not translate into any substantial comparative advantage on bioenergy feedstocks. Furthermore, bioenergy consumption will not be significantly affected by a subsidy. In addition, we conclude that following the stipulated bioenergy mandates will cause a substantial hike in food prices in Nigeria. We recommend further studies to look at the potential and realization of the bioenergy targets as stipulated above using second-generation feedstocks and placing a physical restriction on land-use change.

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Author Contributions: Stanley U. Okoro designed the overall study and prepared the input data. Stanley U. Okoro and Schneider developed the model coding and calibration. Stanley U. Okoro run the analysis, analyzed the results and wrote the manuscript. All authors read, discussed and approved the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Model Equations

$$W = \sum_t \left\{ \delta_t \cdot \left[\begin{pmatrix} +\sum\limits_{r,y} \left(\int \phi_{t,r,y} (D_{t,r,y}) dD_{t,r,y} \right) \\ +\sum\limits_{r,e} \left(\int v_{t,r,e} (E_{t,r,e}) dE_{t,r,e} \right) \end{pmatrix} - \begin{pmatrix} +\sum\limits_{r,s,m} (c_{t,r,s,m} \cdot A_{t,r,s,m}) \\ +\sum\limits_{r,a,m} (c_{t,r,a,m} \cdot L_{t,r,a,m}) \\ +\sum\limits_{r,\tilde{r},y} \left(c_{t,r,\tilde{r},y} \cdot T_{t,r,\tilde{r},y} \right) \\ +\sum\limits_{r,m} (c_{t,r,\_,m} \cdot P_{t,r,m}) \end{pmatrix} - \begin{pmatrix} +\sum\limits_{r,i} \left(\int \phi_{t,r,i} (S_{t,r,i}) dS_{t,r,i} \right) \\ +\sum\limits_{r,u,\tilde{u}} \left(\int \chi_{t,r,u,\tilde{u}} (U_{t,r,u,\tilde{u}}) dU_{t,r,u,\tilde{u}} \right) \end{pmatrix} \right] \right\}$$

$$s.t. \qquad D_{t,r,y} + \begin{pmatrix} -\sum\limits_{\tilde{r}} T_{t,\tilde{r},r,y} \\ +\sum\limits_{\tilde{r}} T_{t,r,\tilde{r},y} \end{pmatrix} - \begin{pmatrix} +\sum\limits_{s,m} (a_{t,r,s,m,y} \cdot A_{t,r,s,m}) \\ +\sum\limits_{a,m} (a_{t,r,a,m,y} \cdot L_{t,r,a,m}) \\ +\sum\limits_{m} (a_{t,r,\_,m,y} \cdot P_{t,r,m}) \end{pmatrix} \leq 0 \qquad \forall t,r,y \qquad \text{Commodity Supply Demand Balance Equations}$$

$$\begin{pmatrix} +\sum\limits_{s,m} (a_{t,r,s,m,i} \cdot A_{t,r,s,m}) \\ +\sum\limits_{a,m} (a_{t,r,a,m,i} \cdot A_{t,r,a,m}) \\ +\sum\limits_{m} (a_{t,r,\_,m,i} \cdot P_{t,r,m}) \end{pmatrix} - S_{t,r,i} \leq 0 \qquad \forall t,r,i \qquad \text{Resource Accounting Equations}$$

$$\begin{pmatrix} +\sum\limits_{s,m} (a_{t,r,s,m,e} \cdot A_{t,r,s,m}) \\ +\sum\limits_{a,m} (a_{t,r,a,m,e} \cdot L_{t,r,a,m}) \\ +\sum\limits_{m} (a_{t,r,\_,m,e} \cdot P_{t,r,m}) \\ -\sum\limits_{\tilde{r},y} \left(k_{t,r,\tilde{r},y,e} \cdot T_{t,r,\tilde{r},y} \right) \end{pmatrix} - E_{t,r,e} \leq 0 \qquad \forall t,r,e \qquad \text{Environmental Impact Accounting Equations}$$

$$\sum_{s \in u} A_{t,r,s,m} + \begin{pmatrix} +\sum\limits_{\tilde{u}} U_{t,r,u,\tilde{u}} \\ -\sum\limits_{\tilde{u}} U_{t,r,\tilde{u},u} \end{pmatrix} - \left(\sum_{s \in u} A_{t-1,r,s,m} \right)_{t>1} = b_{t_0,r,u,\_}|_{t=1} \qquad \forall t,r,u \qquad \text{Land Use Change Accounting Equations}$$

$$S_{t,r,i} \leq b_{t,r,i,\_} \qquad \forall t,r,i \qquad \text{Physical Resource Restrictions}$$

$$U_{t,r,u,\tilde{u}} \leq b_{t,r,u,\tilde{u}} \qquad \forall t,r,u,\tilde{u} \qquad \text{Land Use Change Restrictions}$$

$$\sum_{y} \left(k_{t,r,\_,y,z} \cdot D_{t,r,y} \right) \leq = \geq b_{t,r,z,\_} \qquad \forall t,r,z \qquad \text{Commodity Restrictions}$$

Linearization Equations

Table A1. Description of Variables, Parameters, Functions and Indices.

Variable	Description	Unit
W	Welfare	million USD
D	Domestic demand quantity	1000 tons
S	Domestic supply quantity	1000 units
T	Trade quantity	1000 tons
A	Land-use activity	1000 ha
L	Livestock production activity	1000 units
P	Processing activity (also used to depict product substitutions)	1000 units
E	Environmental impacts	1000 units
U	Land-use change	1000 ha
Parameter	**Description**	**Unit**
a	Technical coefficient containing productivities, input coefficients, per-unit cost, environmental impact coefficients	product or resource unit/activity unit
b	Endowments	1000 units
c	Objective function coefficients	USD/activity unit
k	Commodity coefficients	attribute unit/product unit
δ	discount factor	unit less
ε	elasticity	unit less
Function	**Description**	
ϕ	inverse demand/supply function	
χ	marginal cost function	
ν	marginal value function	
Index	**Description**	**Elements**
t	time	decades
r	region	36 States + FCT
y	commodity	food commodities, forest products, and bioenergy
i	input (resource)	land and energy (implicitly represented)
e	environmental impact	GHG emissions (CO_2eqv.)
s	species	~8 Crops, ~1 forest type
a	animal	~6 animal types
m	management	land, livestock production, and processing alternatives
u	land-use type	cropland, forest land, and grassland
z	commodity attribute	food commodities, animal feedstuffs, and bioenergy products

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Chapter 3

Conclusion

3.1 Overall conclusions

This thesis investigates the environmental and social impact of oil palm cultivation as a bioenergy feedstock using an integrated assessment method. It concludes that from the oil palm related land use/land cover change monitoring on a spatiotemporal scales, the proposed approach from the study in Article I could render a reliable outcome with an overall accurancy of about 85%. The result of the study also show that the Niger Delta, Nigeria had experienced a decrement in its forest reserve. The approach can enhance the facilitation of a proper planning, management and regulations of the use of land resources especially during this time of energy mix change due to climate change.

The conclusions from the study in Article II suggest that climate change which triggers the bioenergy deployment will have impacts on crop yields and are projected to be considerably different across the Niger Delta. Another conclusion from the study is that the net impact of climate change on oil palm as bioenergy crop is positive and is dynamically inconsistent across the interval of the study simulation. The study also showed that oil palm yields are more robust to an increase in precipitation compared to an increase intemperature. Also, slight differences in GCM's ability of capturing the WAM system do not lead to variations in yield. The study further suggests that climate model ensembles output and the participating models having higher range could potentially produce new sets of uncertainties in the projected yields.

Furthermore, the conclusions from the third study in Article III, which is the integrated assessment modeling, coupling the outputs from Article I & II and putting the overall research questions into perspectives. First, the impact of Nigerian bioenergy policies with regards to energy crops cultivation (e.g.oil palm) on land use change and social welfare of the Niger Deltan Nigeria based on the current Nigerian land use act of 1990 would be that, Nigerian Niger Delta forest and Pasture land stand chance of being converted to cropland by 2050 according to the findings of this study. The result showed that policy-induced comparative advantage among the bioenergy feedstock is not substantially feasible with regards to the total area of the feedstocks. Bioenergy consumption pattern in the Niger Delta will remain unchanged with or without policy action. Following the stipulated bioenergy mandates will cause a hike in food prices in the Niger Delta. Subsidy on bioenergy does not have any significant effect on the aggregated social welfare.

In addition, the concepts of land use with respect to energy crops cultivation (e. g. oil palm) can be adapted to climate change, be sustainable and at the same time allow protecting climate and environment, as well as potential adverse impacts of biofuel development on land use change could be reduced, if the political willingness to support nascent industries such as bioenergy industry couple carbon tax with conservation instruments for instance Payment for Ecosystem Services (PES).

The study also suggest that, potential adverse impacts of biofuel development on land use change could be reduced and /or avoided, when a minimum carbon tax of $80/ton is implemented. Another conclusion from the study is that market-based instruments such as carbon tax alone are not sufficient in preserving the remaining forest area in Nigeria.

3.2 Future Work

Using NGA-FASOM to calculate the marginal abatement cost of agricultural management change for CO_2 emission reduction for Nigeria

Tools and Resources

The results of this thesis rely on model-based computer analysis. A number of tools and resources were used for preparing input data, source code management, running the model simulations, and analysing and visualizing the results. Below is a lists these tools and resources.

Remote Sensing

The remote sensing analysis and GIS work was done using the SAGA GIS and the Google earth engine API.

Modeling

The process based modeing was done using the APSIM2015.06.22 next generation. NGA-FASOM is a mathematically programming model that is written in GAMS and uses the CPLEX solver.

Data processing

The statistical programming software R was used for the preprocessing of input data (aggregation and transformation etc.), Climate Data Operators (CDO) was used for part of the climate data processing and the postprocessing of some output data (graphs, validation).

Source code management

The source code of the NGA-FASOM model and the data processing scripts were managed using the Subversion version control system.

Typesetting

This document was prepared with Microsoft Word 2011 and Latex

Literature management

Zotero was used for literature management and generating the bibliography of the entire dissertation project.

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