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Exploring Locational Criteria to Optimise Biofuel Production Potential in Nigeria

Thesis submitted for the award of Degree of Doctor of Philosophy in Geographical Information Science (GIS)

By

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Sponsored by:

DECLARATION

I Basiru Shehu Gwandu, here by declare that this thesis titled:

Exploring Locational Criteria to Optimise Biofuel Production Potential in Nigeria

was composed by me under the guidance of my supervisors and I declare that it is my own work. Other works were definitely used but appropriately cited or fully acknowledged.

DEDICATION

This work is dedicated to The Almighty God Who spared my life and gave me the ability to conduct this research and also assisted me in making it a success.

Abstract

Energy is one of the important building blocks of any economy and the sustainability of its supply is crucial. Renewable energy sources are being explored with the objective of harnessing their potential to address demand shortages and provide sustainable clean energy. Biofuels, as one of these renewables, continue to expand and their share in global energy consumption continues to increase. Apart from lower net carbon emissions compared to fossil fuels and their role as transitional fuel sources in global shift towards renewable energy, biofuels offer other benefits such as increasing the volume of liquid fuels, improving air quality, expanding trade, import substitution and energy diversification. Therefore, there are strong environmental and economic arguments for the Nigerian Government to embark on deployment of renewable energy, including biofuels. Despite abundant biomass resources, biofuel programmes have not been fully operationalised in the country, partly because biofuels vary in their favourability profiles which depend on local conditions and practices, as well as spatial conflicts between land designed for energy production and other land uses such as agriculture or nature reserves. Consequently, there is a need for robust and detailed approaches to this location-related problem. Although Spatial Multi-criteria Analysis (SMCA) as a support tool has been applied to biofuel production analysis, accounting for multiple stakeholder opinions has been one of the major challenges. In Nigeria, there have been few attempts to apply spatial analysis to locational problems related to biofuel production. In addition, these studies are limited in terms of scope, were based on feedstock other than energy crops, and provided superficial analysis of suitability of the identified sites. The goal of this thesis was to show how to improve the robustness and transparency of spatial analysis in Nigeria through answering some spatial questions about biofuel production, which extends our knowledge of GIS and is relevant to practice. Robustness implies detailed exploration of the required environmental criteria and incorporation of the expert decisions on the criteria preferences. This work transparently demonstrates detailed application of the combined geospatial and multi-criteria methods to make the academic contribution transferable. The technical goal of the work was to conduct spatial optimisation for biofuel production in the country through detailed assessment of environmental criteria, modelling land suitability for cultivating sweet sorghum, sugarcane, cassava, oil palm and jatropha as biofuel crops in Nigeria and modelling optimal sites for biofuel processing and/or blending. This will provide support for spatial decisions regarding establishing biofuel processing plants or expanding the existing ones. Analytical Hierarchy Process (pairwise comparison) was adopted as the multi-criteria analysis method due to its robustness regarding stakeholder inclusion. Weighted overlay was adopted as method of land suitability modelling and supply area modelling was adopted as the method of site optimisation. The analysis showed that northcentral geo-political zone of Nigeria has the largest areas of land that is very suitable for cultivating sugarcane, cassava, oil palm and jatropha, while northeast has the largest areas of land that is very suitable for cultivating sweet sorghum. Based on these, three sizes of service area were considered assuming worst, average and highest crop yields scenarios to optimise processing/blending sites. Existing petroleum depots were considered as the candidate sites. Ilorin petroleum depot was found to be the most optimal location for processing/blending biofuel in Nigeria based on all the crop yields scenarios, within 300 km service area. However, assuming worst case yields scenario within 100 km service area, Maiduguri depot was found to be the best location for sweet sorghum and sugarcane biofuel processing/blending, but Yola depot was suggested as replacement for sugarcane. Ibadan was found to be the best for oil palm and jatropha, but Ikot Abasi depot was suggested as replacement for oil palm. Aba was found to be the best for cassava, but Makurdi was suggested as replacement. This work had demonstrated how robust integration of GIS tools with MCDM techniques could improve the effectiveness of spatial decision-making process regarding positioning biofuel production in developing countries like Nigeria. It is therefore concluded that this work will serve as a point of reference for state-of-the-art application of spatial multi-criteria evaluation analysis, not only for the biofuel industry, but also for other sectors of environmental management such as river basin management, land use or settlement planning. The tendency of a biofuel programme in Nigeria to succeed would greatly be enhanced by adopting sustainability strategies along its value chain through climate smart agriculture, designing and/or adopting a suitable feedstock supply model, effective land use management, realigning policy objectives, enforcing policy directives and balancing between strong and weak sustainability strategies. This will create a conducive environment for stimulating biofuel programme, delivering energy source diversification, economic growth and sustainable development for Nigeria.

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Chapter One – General Background

1 Chapter One – General Background

1.1 Introduction

Energy is one of the crucial building blocks of any economy and the sustainability of its supply is critical. The sustainability of an energy source has been conceptualised as a function of its economic viability, replenishment, environmental friendliness and social acceptability (Abas et al., 2015; Grigoroudis et al., 2019). Since the industrial revolution, humanity's use of energy has relied on fossil fuels and 86% of today's global primary energy comes from fossil fuels (Abas et al., 2015). This reliance on fossil fuels has resulted directly in the climate crisis through unsustainable processes of producing, supplying and utilizing energy. Recent increases in average global temperatures raise concern about future projected warming, which is estimated to range between 2.6˚ – 4.8˚C in the period of 2081 – 2100 relative to 1986 – 2005 global mean surface temperatures (IPCC 2013). Recent IPCC report showed that global surface temperature was higher in 2001 – 2020 decades than that of 1850 – 1900 by 0.95° to 1.20°C (IPCC 2021). The report estimated that the temperature will be higher over 2081 – 2100 by 1.0°C to 1.8°C under very low GHG emissions but will be much higher by 3.3°C to 5.7°C under very high GHG emissions scenario, compared to 1850 – 1900.

Scientists have argued that in order to maintain planetary stability and the safety of humanity, rapid, transformative change towards decarbonisation is necessary (Revill and Harris 2017; Rockström et al., 2017). The target involves pursuing an effort to limit global temperature increase to 1.5˚C above pre-industrial levels. To achieve this, there is a need for detailed accountability by specific sectors and activities, and setting sectoral targets (Nachmany and Mangan 2018). Emissions were suggested to have peaked by 2020 at the latest (Revill and Harris 2017), though it might have long been understood that the peaking time depends on whether negative emissions could be achieved in the long term (van Vuuren and Riahi 2011). There is high confidence that transient climate response to cumulative CO_2 emission (TCRE) remains constant and global CO_2 emissions remain net positive under all illustrative scenarios over 1850 – 2050 time period (IPCC 2021).

The creation of science based targets (SBTs) which guide setting emission targets in line with Paris Agreements might encourage targets implementation though the targets need to be presented in a comparable way to avoid imbalance between time-integrated aggregate SBTs and global allowable emissions (Bjørn et al., 2021).

Historical trends and model-based projections showed that there is no empirical evidence supporting the notion that absolute decoupling from resource use can be attained globally with continued economic growth. Thus, alternative strategies should be explored because, even under optimistic policy plans, absolute decarbonisation is unlikely to be achieved at a rate enough to confine global warming to 1.5°C or 2°C (Hickel and Kallis 2020). Thus, renewable energy sources are being explored with the objective of harnessing their potential to address demand shortages and provide sustainable clean energy while encouraging infrastructure development as stipulated in the Kyoto directive towards global decarbonisation (Mohammed et al., 2013). This is evident in, for example, the national and multi-national climate change commitments called for in the Paris Agreement, such as Nationally Determined Contributions (NDCs).

However, while necessary, this decarbonisation is difficult because energy demand is projected to continue to rise. Further, renewable technologies can be expensive, require wholesale energy system reorganisation, and themselves depend on fossil fuels as, for example, in manufacture of solar panels (Abas et al., 2015).

Biofuels (fuels produced from living materials) have been proposed as a transitionary solution to the dilemma, whereby they permit energy to keep being produced from burning hydrocarbons, but can dramatically reduce CO_2 emission compared to fossil fuels. In this way, biofuels have potential to help achieve some of the Sustainable Development Goals (SDGs). For example, goal seven focusses on ensuring affordable and clean energy through efficient use of energy and investing in clean energy to protect environment. Goal 13 emphasises actions to combat climate change and its impacts by limiting the global mean temperature to 2°C above the pre-industrial levels.

Apart from the potential to reduce net carbon emissions, biofuels offer other benefits such as increasing the supply of liquid fuels, improving air quality, expanding trade through biofuel markets, import substitution and energy diversification (Mandil and Shihab-Eldin 2010). Fossil fuels have been linked to poor air quality and in many countries alternative biofuels synthesised from plant materials have gone some way to improve air quality by deploying fuels that release lower carbon (Yaliwal et al., 2014), while simulteneously meeting increased demand for transport fuels, which is mostly liquid, and meeting climate change targets desired by governments. In-country production of biofuels saves in import revenues, improves balance of trade, diversifies the energy mix and the economy. These benefits of biofuels motivate many national energy systems to adopt different carbon dioxide policies and reduction targets (Vidal-Amaro et al., 2015), planning several forms of renewable energy utilization and energy efficiency measures (MoP 2015). Some target total replacement of the fossil fuels, while others focus on different balances between fossil and renewable energies.

As can be seen in their Nationally Determined Contributions (NDCs) to climate change mitigation, many countries' climate change strategies have some bias towards the energy sector (Nachmany and Mangan 2018), though other sectors such as land use, land use change, forestry and agriculture are also being considered. In this context, biofuels have received much attention, especially for transport fuels. For example, the US Renewable Fuel Standards (RFS), published in 2011, targets production of 36 billion gallons of biofuels by 2022, and there was a report that in 2016 corn ethanol production reached 15 billion gallons (Sharma et al., 2017). The country now targets 15% biofuel blend mandate by 2030 and 30% by 2050 for transportation fuels (Kennedy 2020).

The European Union has set a target of 10% of its transport fuel to be renewable by 2020 (Höhn et al., 2014), and a significant contribution to towards this would come from biomass (Voets et al., 2013). Recent data showed that this target had reached 8.1% in 2018 (EEA 2019). Germany and France have aimed an 80-95% and 60% reduction in Green House Gases

(GHGs) by 2050 and 2040, respectively (Abas et al., 2015). The 2011 white paper set an objective for decarbonising transport fuels in aviation and shipping to reach 40% by 2050. Though advanced biofuels are expected to form the vast majority of the total biofuel volume by 2050 in the EU, it is projected that overall, biofuels will contribute more than 17% of the sustainable alternative fuels by that time (Chiaramonti et al., 2021).

Notwithstanding debates about hidden or unintended impacts of biofuels such as hikes in food prices, food security and land conversion (discussed further below), several countries have recorded significant growth in the industry. Biofuels face challenges such as uncertainties (especially crude oil price uncertainties), political risks and financial challenges. Also, the technological obstacles to commercialising advanced biofuels have proven to be greater than envisioned. However, the biofuel industry continues to expand and its share in the global energy consumption continues to increase. Ethanol has grown into a large global market. Shell reported use of 9.5 billion litres of biofuels in the petrol sold worldwide in 2018 (Shell 2020). Biodiesel is less established though supported by policies and incentives, partly because of the nature of supply that is specific to feedstock that are based on oil crop; yields are very low compared to starch/sugar crops. Some of the determinants of the volume and the direction of the biofuel trade are policies, tariffs, crop yields, feedstock availability and within country biofuel supply and demand (Ebadian et al., 2019).

The current major players in liquid biofuels production and trade are the US, the EU and Brazil. Biofuel production has grown steadily in the US reaching 16.6 billion gallons in 2016 from 14.1 billion gallons in 2012 (EPA 2018). However, the production increase was relatively slow recently likely due to limited sales of E10 (gasoline with 10% ethanol blend). The US biodiesel production also reached a record high of 1.56 billion gallons per annum. According to the US Department of Agriculture (USDA), ethanol fuel production from September 2018 to August 2019 was over 16.929 billion gallons (approximately 64 billion litres). Biodiesel production for the same period was put at more than 1.724 billion gallons (approximately 6.5 billion litres).

Biofuels have continued to increase in production and consumption elsewhere, often at rates faster than the USA. According to the European Environment Agency (EEA), renewable energy is growing as a share of the total amount of energy used by the transport sector. Most of this has been from biofuels that meet sustainability criteria since 2011 when the average share was 4%. Across the 28 member states, the average renewable energy share, relative to overall energy use in transport, grew to 7.4% in 2017 and increased to 8.1% in 2018. Sweden’s and Finland’s share of renewables in transport energy was 32.1% and 18.8%, respectively in 2017 (EEA 2019). In 2018, a target was set that required all EU member states to raise the share of renewable energy in their energy consumption in roads and rail to 14% by 2030. Advanced biofuels and biogas must be at least 1% by 2025 and 3.5% by 2030.

The Government of Brazil authorized the increase in sugarcane-derived ethanol blend from 25 – 27% in March 2015, while the biofuel industry advocated for increase in biodiesel blend from 7 to 10% (Barros 2015). The USDA estimated Brazil’s ethanol and biodiesel production for 2019 at 34.45 and 5.8 billion litres, respectively. This is up 4% and 8% from the 2018 production, respectively (Barros 2019). The operation of biofuel programme in Brazil is based on three main instruments: the annual carbon intensity reduction targets, biofuel certification by efficiency in reducing GHGs emissions and the decarbonisation credits. In China, the government cut incentives for grain-based biofuels, yet different provinces adopt blend mandates ranging from 2.1% to 10%. The focus in China is towards non-grain biofuels such as sweet sorghum and cassava (Anderson-Sprecher and Ji 2015). This global trend shows that biofuel production and use continue to grow despite all the debates. Thus, it is proper to encourage a similar trend in Nigeria as biofuel remains the sustainable and promising option for the country due to biomass potential (Oloruntoba and Adekanye 2019).

1.2 Appraising biofuel debates

1.2.1 Introduction

Although biofuels, as one of the important renewable energy components, have received significant attention and are being promoted especially for transport (heavy duty, aviation and marine), a number of issues associated with its production and use have been highlighted that offer a word of caution against its proliferation. Some of these issues relates to the real contribution of biofuels to GHGs reduction, impacts on food security, biodiversity and conservation, land use change and sustainability. However, a number of interconnected factors determine whether production and use of biofuels will have a positive or negative impact on the environment (Gasparatos et al., 2011), including crop type, geographical settings, and socio-economic and political context.

1.2.2 Greenhouse gas reduction

Biofuels have been proposed as one of the transitional liquid fuels that can contribute to climate change mitigation. Although biofuels' real contribution to climate change mitigation has been argued, biofuels release fewer GHGs in to the atmosphere (Bouet et al., 2010). A Life Cycle Analysis (LCA) of biofuels by the Swiss Federal Institute of Material Science and Technology revealed that 21 out of the 26 biofuels studied reduced net GHGs emissions by more than 30% compared to fossil fuels (Zah et al., 2007). The study considered five main emission components including infrastructure, cultivation, production, transport and operation. Sweet sorghum and sugarcane ethanol were found to have total GHGs emission reductions above 50%, while oil palm was found to be above 30%.

The contribution of biofuels to GHGs emissions reduction is currently not valued economically due to the absence of a specific carbon market through which biofuels' environmental benefits could be recognised and remuneration for this recognition could be formalised (Barros 2019). Formalising this remuneration could allow accelerated carbon mitigation gains since bioenergy is still the largest renewable energy source globally, contributing

9% of the global renewable electricity and 96% of the global renewable heat (WBA 2019).

One of the strategies employed to ameliorate the environmental concerns of fossil fuels and reduce GHGs emission is blending biofuels with petroleum as a transport fuel. Complete replacement of fossil fuels with biofuels may not be feasible in the short-term and may lead to unsustainable land use change in the long-run. Using a blend is advantagious since it negates the challenges of supply and issues of limited storage life while reducing carbon monoxide and particulates. According to the International Energy Agency (IEA 2017), the estimated bioenergy's 20% cumulative carbon savings by 2060 would be difficult to be replaced and thus must be produced and used sustainably.

However, it was argued that there is emerging evidence that using an ethanol and petroleum blend will have some deleterious impacts through an increase in atmospheric ethanol and carcinogenic acetaldehyde in the atmosphere as a result of photolytic oxidation with knock-on increases in ozone and nitrous oxide emissions (Dunmore et al., 2016). These aldehydes affects human health, play important role in photochemical smog formation and formation of tropospheric ozone (Santana et al., 2017). An experiment at the European Commission Joint Research Centre, Italy linked the increase in these compounds to temperature where percentage increase in formaldehyde, acetaldehyde and ethanol was observed to be 0%, 280% and 40%, respectively between 23˚C and – 7˚C (Suarez-Bertoa et al., 2015).

Though the US Environmental Protection Agency's report to Congress in 2011 concluded that use of ethanol increases these compounds in the air (EPA 2011), the National Research Council's review of the report for the Congress concluded that the EPA's draft needed substantial revision (US-NRC 2011). In addition, it was reported that there is a potential source of error in the prediction of the aldehydes due to the high uncertainty in the biogenic emissions that photochemically react to produce the volatile organic compounds (Luecken et al., 2012). Also an analysis of the socioeconomic costs of these compounds in Oslo showed that the costs are expected to be significantly lower than the combined benefits of the reduced emissions of the target compounds such as carbon dioxide and nitrogen dioxide (Sundseth et al., 2015) which were found to have decreased by almost 6% and 30 – 55% respectively, at E85 relative to E10 – E15 (Suarez-Bertoa et al., 2015). The real reduction could have been more apparent if the relative was with 100% fossil fuels. Thus, this shows that though biofuels may not eliminate emissions completely, they can provide significant contributions to reducing it.

An experiment in the US to calculate the potential impacts of sweet sorghum based ethanol production found that a decentralized system (all the processing steps take place on farm except dehydration), resulted in reduced GHGs emissions and use of non-renewable energy by 39% and 27% respectively, as compared to corn (Olukoya et al., 2015). This proportional reduction would be even greater compared with emissions from fossil fuels. Sugarcane ethanol is believed to provide impressive reduction in GHGs emission from transport sector. The introduction of Brazilian ethanol (largely sugarcane based) into automobiles, is believed to have resulted in the reduction of tailpipe GHGs emissions from 50g Km^{-1} in 1980 to 5.8g Km^{-1} in 1995 (Ullah et al., 2015). It was shown that in Nigeria, with a production of 4.64 to 14.53 million tonnes of bioethanol, carbon dioxide savings of 1.87 to 5.89 million tonnes could be realised (Ogundari et al., 2012). Results of an appraisal of a proposed establishment of 10,000 micro scale cassava based biorefineries in the country for cooking fuel showed that the project will, among other benefits, reduce indoor pollution (Ohimain 2012).

Countries seek to provide hedges against the volatile conventional oil prices through exploiting cheaper plant oil and as well cut their GHGs emissions. Oil palm is believed to provide higher potentials to achieving that because oil from other plants are of no quantitative industrial significance and many pre-processing stages are required for extraction and purification of oil before processing into biodiesel (Hayyan et al., 2014a). Aviation biofuels produced by deoxygenation and carbon chain cracking of plant oils are receiving market attention of the aviation industry (Cheng et al., 2014; Shahinuzzaman et al., 2017; Wise et al., 2017). Biojet fuel, which has already been used in some regular flights (Neuling and Kaltschmitt 2018), is said to result in up to 89% reduction in GHGs emission as compared to petroleum fuel, although emissions due to land use change were not included in the analysis (Han et al., 2013). This reduction is said to further be enhanced if the carbon capture and storage is implemented in the conversion process to produce biojet fuel (Wise et al., 2017).

Jatropha oil is said to burn flames that are devoid of smoke (Orwa et al., 2009). A study on Jatropha production systems in Burkina Faso found that all the pathways considered in the research reduced GHGs emission by 68 to 89% and saved energy by 65 to 90% as compared to conventional diesel (Baumert et al., 2018). Jatropha performance as a fuel showed that except for NO_x which increased from 5.58% to 25.97%, all other measured emissions such as PM, CO, HC, and CO_2 decreased by 50 to 72.73%, 50 to 73%, 45 to 67% and 50 to 80%, respectively (Thapa et al., 2018). Akogwu et al., (2018), reported from their analysis that the amount of CO emitted by petroleum diesel was twice the amount emitted by the jatropha biodiesel.

There are indications that policies are being strengthened to increase biofuel consumption and adoption to realise the long-term decarbonisation of heavy transport especially the aviation and marine transport. According to the proposals adopted by the International Civil Aviation Organisation (ICAO), carbon offsetting will be voluntary from 2020 to 2027 and mandatory afterwards. The goal of the offset is to cover an estimated 65% emissions growth above 2020 levels in the voluntary phase and 80% from 2027 to 2035 (Revill and Harris 2017). The authors suggested that access to biofuels should be prioritised for aviation industry ahead of other sectors because it currently has no alternative pathway to reach zero emissions. This priority should also be focused on the marine industry. This is because, it is projected, under business as usual, that the share of the marine sector in the global emissions will double by 2050 from the current estimate of 1.5% of global human-induced emissions (Revill and Harris 2017). For road and rail transport, there is already mass production of electric vehicles and locomotives which, despite challenges, are expected to continue to expand.

1.2.3 Food versus fuel

There are arguments that deployment of crop-based biofuels will lead to hikes in food prices and negetively impact food security. This concern was heightened by the 2008/2009 coincidence of drastic increses in global biofuel production and the hike in a food prices. Yet, subsequent analysis showed that biofuel was only one contributory factor among many including rising energy prices and market speculations (Baffes and Haniotis 2010). The infuence of biofuel on food prices depends on the choice of feedstock and the technology employed. Thus, this issue can best be appraised based on each potential feedstock.

The food versus fuel conflict claimed to be caused by the colossal stress exerted by corn and other bioenergy crops on food markets can be palliated by using sweet sorghum as feedstock (Ahmad Dar et al., 2017). Sweet sorghum is an annual and C_4 (more efficient in photosynthesis) energy plant that can avoid conflict with food growing priority because it does not compete with food and feed unlike grain sorghum that is used as staple (Olugbemi and Ababyomi 2016). Also, sorghum demand for human consumption is dwindling due to availability of other cereals such as rice, and in Nigeria, sweet sorghum has not seen significant commercial utilisation (Nasidi et al., 2010). As such, use of this crop for biofuel will, in any instances. provide income for local communities without compromising food availability.

It may be argued that the syrup from sweet sorghum should be used for sugar production instead of biofuel. Indeed, sugar production could be another sector for sweet sorghum human consumption. However, attempts to develop a sweet sorghum sugar industry have not been successful because of certain limitations that make its sugar more expensive than that of sugarcane (Tew et al., 2008; Sipos et al., 2009; Elbassam 2010). Analysis was conducted for economic trade-offs of using sweet sorghum for ethanol and sugar in northern China (Gnansounou et al., 2005). The results showed that producing ethanol from bagasse (the remaining fibrous matter after syrup is extracted) was more favourable than burning it for power though the relative merit of producing ethanol or sugar from the juice was highly sensitive to sugar price in the country. This means sweet sorghum sugar is only produced at higher sugar prices. Thus, in addition to edible syrup industry, bioethanol could be another great avenue for sweet sorghum market expansion.

One solution to conflict between biofuel and food production is to apply crop rotation techniques. For example, a study in Central America (Cutz et al., 2013) found that with 5% of the croplands in the region, sorghum could supply around 10% of the region's electricity demand and that a sustainable ethanol programme could be maintained during the sugarcane off season period. This has the possibility to expand feedstock supply and increase ethanol production since the crop can be handled by the sugarcane traditional harvesting and processing systems (Kim and Day 2011). Sugarcane is the main crop used for sugar production.

However, it was reported that sugarcane biofuel can be competitive with petroleum at $70 per barrel (Hira 2011). The prices of Brent Crude, OPEC Basket, Bonny Light and West Texas Index (WTI) were $82.39, $80.65, $80.34 and $79.35 per barrel, respectively on the 10th of October 2021, at 7:07 am British Summer Time (OilPrice 2021). While prices for sugar for human consumption is higher than ethanol production from Sugarcane syrup, the huge bagasse from the sugar industry is a good source of raw materials for second generation biofuels. This shows how biofuel production can represent a value-add for existing food crops, without compromising food outputs.

Cassava is increasingly being used in the animal feed and other chemical industries as raw material, serving as one of the major cash crops in Nigeria (FAO and IFAD 2005) thereby providing income to rural farmers. A survey of major cassava producing areas in Nigeria showed that about 50% of the crop produced is sold for cash and about 40% of the produce is consumed as food (Wossen et al., 2017). About one-third of the participants in the survey reported that cassava accounts for 75% of their income. This indicates greater proportion of the crop being used for non-food purposes. Also, there are issues with regards to the use of the crop as a major source of food. These include such limitations as presence of toxic cyanogenic glucosides though it is reduced through processing, low protein content and short postharvest shelf life (Egbe et al., 1995). Cassava has been associated with diabetes mellitus, cancer, iodine deficiency and neurological syndrome though, the association was not established as causal (Oluwole et al., 2007). Thus, cassava should be used more for non-food industrial applications such as biofuel, while healthier staples such as maize should replace food use of the crop.

In similar way to sugarcane, the waste generated from cassava can be used to process biofuels without compromising food production or requiring additional land. In Nigeria, an estimated one billion litres of ethanol could be produced from seven million tonnes of cassava peels (Figure 1.1) generated annually (Anyanwu et al., 2015). This non-food biomass, the amount of which could reach about 14 million tonnes (Lawal 2017), cause serious environmental pollution (Moshi et al., 2015) but can serve as a good source of biofuel raw materials for both 1st and 2nd generation technologies as well as integrated systems (Ozoegwu et al., 2017). Therefore, the crop could be a major source of both food and fuel at the same time.

Figure 1.1: Heap of Cassava Peels Source: Lawal, (2017)

However, this will depend on the economics of collating the biomass to the processing plant and the comparative value of the cassava peels for livestock and fish feeds. Cassava peels are processed into high quality, low cost animal feed (Lawal 2017). It is also believed to possess adequate calories for Tilapia fish though it is considered as low grade livestock feed compared to Maize due to its low protein content and high cyanogenic glucoside (Ubalua and Ezeronye 2008).

Though some 77% of oil palm uses were reported to be for food, the non-food uses continue to expand including the production of oleochemicals (chemicals derived from vegetable oils or animal fats) and biodiesel, both of which increased the demand for the oil and making oil palm overtook soybean as the dominant vegetable oil globally (Lai et al., 2012; Corley and Tinker 2016). While the annual change in food use of oil palm was said to average 7%, the change in industrial use was reported to be expanding at an average rate of about 18% annually since 2000/2001 (Panapanaan et al., 2009). The second largest producer in the world, Malaysia, was estimated to have a 200% demand increase in non-food use of oil palm compared to a projected 50% demand increase for the crop's food use by 2035 (Gan and Li 2014). This shows that the country's industrial need for oil palm at the time will be four times more than food need for the crop. With a blend mandate of 7% (7% biodiesel and 93% petroleum diesel), the country was reported to have consumed 279 million litres in 2016 and a goal was set to scale it up to 15% in 2020 (Wahab 2017). A 10% blend have been fully implemented in 2019 (Yusoff et al., 2020).

Depending on the fossil fuel prices, the food use of palm oil may offer higher prices than biodiesel. However, as with sugarcane and cassava, the non-edible palm oil by-products such as sludge and olein may offer more ethical sources of biodiesel production without compromising food production (Girish 2018). Large palm oil mills produces non edible oils such as Low Grade Crude Palm Oil (LGCPO) and Acidic Crude Palm Oil (ACPO) which are highly acidic but can offer lower biodiesel production costs (Hayyan et al., 2013; Hayyan et al., 2014b). LGCPO is said to be similar to ACPO except that the former is of lower quality due to unflavoured impurities and higher moisture content (Hayyan et al., 2014a). While recent research established that only 10% of the oil palm on-farm biomass is converted to edible oil (Zahan and Kano 2018), it was estimated that as much as 73% olein could be produced from the overall palm oil refining (Herjanto and Widana 2016). Thus, these provide large potential feedstock from non-edible palm oil by-products. Biodiesel mass production from olein is feasible in Nigeria (Ishola et al., 2020).

Though edible varieties may exist in places like Mexico, jatropha is a non-edible crop. Therefore, jatropha does not have direct impact on food security or prices except where crop lands are converted to its cultivation. In a global study of Jatropha projects, 70% of the projects were found to be practicing some form of intercropping, supporting food production rather than conflicting with it (GEXSI 2008). Due to its toxicity, jatropha may not also be in conflict with animal feeds because the by-product of the oil processing, the press cake, is unsuitable for animals but can be used as manure or fuel (CABI 2018).

1.2.4 Land use change and ecosystem services

The work of Searchinger et al., (2008) on indirect land use change emissions estimated that corn ethanol actually increases emissions relative to gasoline due to the carbon released when land is cleared for corn. However, several analyses were published after this work showing results with much lower indirect emissions, suggesting exaggeration in the previous studies because of their reliance on simulation due to the lack of empirical data on biofuel value chain at the time (Hertel and Tyner 2013). Studies from around the world have shown that biofuel crops provide ecosystem services such as fuel and climate regulation, but can compromise other services such as food and freshwater (Gasparatos et al., 2011). The authors accounted for the evidence from diverse academic disciplines and contextualised it on the ecosystem services framework familiarised by the Millennium Ecosystem Assessment. The study provided a critical review of the drivers, impacts and trade-offs of biofuel production and use.

As part of its uses, jatropha has been promoted as suitable for realising some ecological and environmental benefits such as soil carbon sequestration, phytoremediation, reduction of environmental pollutants and soil erosion control as well as other socio-economic benefits such as establishment of jatropha-based companies and employment generation (Pandey et al., 2012). However, it is important to recognise that the ecosystem service benefits (such as carbon sequestration), impacts of biofuels (such as indirect land use change) and the nature of the trade-offs differ according to the crop type, original land use and plantation management practice.

Land conversion issues (both from crop lands and forests) are minimal with respect to jatropha cultivation. In the global study of jatropha projects cited in the previous subsection, only 1.2%, 0.3% and 5% of the areas planted with jatropha were reported to have been crop lands, primary forests and secondary forests respectively, 5 years before the start of the projects (GEXSI 2008). In Ethiopia, jatropha plantations established to rehabilitate degraded forest lands were found to have sequestered 6.94 tonnes of carbon per hectare (Cha^{-1}) considering both above and below ground stocks. While those in live fences were found to have sequestered 178.56 tonnes Cha^{-1} for both above and below ground stocks (Yirdaw et al., 2013).

In Botswana, using a Life Cycle Assessment (LCA) for all activities involved in jatropha cultivation in frost and drought prone areas, it was found that the crop’s emission and absorption are 17 and 21 tonnes of carbon dioxide equivalent per hectare (CO_2eq. ha^{-1}), respectively, presenting a 4 tonnes surplus of absorption over a period of 4 years (Ishimoto et al., 2018). Thus, for rehabilitation of degraded lands, jatropha plantations may turn a source of carbon emission (e.g. deforested land) to a carbon sink. Indeed, adoption of jatropha for biodiesel production may enhance reforestation or afforestation in deforested or desert prone areas and may increase economic growth while supporting environmental regeneration (Faufu et al., 2014). In this regards and based on a pilot project in Mozambique, recommendation was given that development of jatropha plantation should be on grasslands with low biodiversity value and trees (Smit et al., 2018).

Life Cycle Assessment of different jatropha production systems indicated that decentralised production of straight vegetable oil (SVO) using feedstock from hedgerow and intercropping shows less land conversion (Eijck et al., 2013) and seems to be the most promising option (Baumert et al., 2018). In Nigeria, pre-exploited agricultural lands were recommended for feedstock production (Galadima et al., 2011). On a more extreme view, a conclusion was made that the most promising option for jatropha biofuel to sustainably contribute to GHGs reduction is producing feedstock on marginal lands with reduced use of artificial fertilisers and pesticides (Eijck et al., 2010). Sweet sorghum was reviewed to be suitable for environmental phytoremediation (Sathya et al., 2016). The authors reported that a short study indicated that the crop could accumulate heavy metals more than the threshold (100 mg Kg^{-1}) set for hyperaccumulators and that phytoremediation with sorghum can recover soil function. However, factors for successful agriculture should be considered for successful phytoremediation.

The trade-off relationships between biofuel production on one hand and land use change and ecosystem services on the other hand requires appropriate and location specific strategies to protect the social, economic and physical environments from negative consequences. A study on Nigeria's villages found that land use diversity in the rural areas vary across agroecological zones with more diversity in the Guinea Savannah and Humid Forest and comprising of cultivated, unused, forests, floodplains, residential and woodlands (Zhang et al., 2016). The study which was based on the participants' knowledge of their local geography found that unused lands (not under cultivation) in the village areas were most common in the Humid Forest (36.5%) and Guinea Savannah (22.7%) with as little as 0.9% in the Sudan Savannah (Zhang et al., 2016). While the villagers reported 5 years increase in cultivated lands in the Humid Forests and Guinea Savannah, residential areas were reported to have increased at the expense of cultivated lands in the Sudan Savannah.

It is evident from the above that while some degree of land use change is, in most cases, inevitable even without biofuel industry, quantifying biofuel-induced changes may involve significant uncertainties. Researchers continue to update and refine the models for estimating the degree to which the biofuel industry is responsible for land use changes, and reducing these uncertainties and improving these models has been limited (Hertel and Tyner 2013; EPA 2018). The study on the Nigerian village dwellers observed remarkable awareness for provisioning ecosystem services such as crops, biofuel (wood-fuel), wildlife, natural medicine and freshwater, stressing the importance of these services to the rural Nigeria (Zhang et al., 2016). However, villagers' awareness of the regulating and supporting services such as pollination, soil formation, nutrients cycling and regulation of pests and diseases was remarkably low. Studies have shown that the use of perennial feedstock for biofuel can improve soil quality relative to existing conditions and reduce sedimentation and nutrients runoff, while increased use of effective conservation practices can provide protection for pollinator habitat, all of which enhance ecosystem services (EPA 2018).

1.2.5 Biodiversity conservation and environmental protection

Land use trade-offs continue to be a central issue around biofuel development (Acheampong et al., 2017). For example, many countries are simultaneously seeking to increase forest cover on one hand and agricultural productivity on the other (Vongvisouk et al., 2016). This is typical of Nigeria where such programmes as the Great Green Wall (NAGGW 2021) are aimed at combating desertification through afforestation, while other programmes such as the Anchor Borrowers (CBN 2016) were aimed at increasing agricultural productivity.

Tensions between biodiversity conservation and productive outcomes have led to the debate on the concepts of "Land Sharing", which refers to multi-functional landscapes that serve both conservation and agricultural purposes (shared functions on temporal bases), and "Land Sparing", which promotes spatial separation between larger tracts of protected forest or wilderness and more intensive agriculture (Vongvisouk et al., 2016). The debate has eventually led to a widespread acceptance among conservationists that both paradigms have a role to play depending on the context (Mertz and Mertens

2017). Therefore, it may be essential to assess the appropriateness of either land sharing or sparing based on the context or exploring the possibility of concurrent application of both the concepts in the policy formulation and execution. World Wide Fund for Nature (WWF) in collaboration with other organisations developed a methodology for identifying Responsible Cultivation Areas (RCA) which refers to areas and/or models for bioenergy feedstock cultivation with minimal indirect effects (Smit et al., 2018). The area must be used environmentally and socially responsible to cultivate feedstock and the cultivation should not cause unwanted indirect effects.

1.2.6 Multi-dimensional sustainability assessment

Because the viability of biofuel production depends largely on availability of feedstock, its sustainability will hinge on the sustainability of the feedstock production and supply. Sustainability is a function of economic viability, social acceptability, environmental friendliness and technological appropriateness (FAO 2014). Each of these dimensions is complex, nuanced, and there are potential trade-offs in both values and outcomes. As such, it is difficult to ascertain definitively whether or not a particular biofuel crop or plantation is indeed ‘sustainable’. For example, economically, biofuels must be priced below fossil fuels for them to displace fossil fuels via market-based mechanisms. Biofuel production should not induce hikes in food prices for it to be socially acceptable and the energy balance should at least be neutral for it to be environment friendly.

The sustainability challenges of biofuels differ according to crop type. Research efforts are going on around the world for economic, environmental and technological optimisation of ethanol production from sweet sorghum. Sweet sorghum varieties are being bred and selected to achieve human food, animal feed and bioenergy as was reported in Guatemala (Cifuentes et al., 2014). To improve ethanol yield from stalk juice, choosing the right variety and suitable cultivation location is crucial (Nasidi et al., 2013). Intercropping is an agronomic practice believed to have some production benefits. In India, intercropping in sugarcane was found to have reduced weed growth by 60%, provided extra income to farmers and increased the effectiveness of land utilisation (Gujja et al., 2009). Similarly, in Nigeria growth and biomass production of weed were supressed by intercropping sugarcane with soybeans and sesame (Ndarubu et al., 2000).

Though zero tillage was practiced by many cassava farmers in the mid-western Nigeria, conventional ridge tillage farming system was found to have produced 46% higher yields and thus, was recommended (Odjugo 2008; FAO 2013). Research and development especially for yield improvement will help cushion the issues associated with land use change (Agboola and Agboola 2011). It was recommended that vertical integration of cassava ethanol production by on-farm processing is a good strategy that could increase economic viability by significantly reducing the bulk transportation cost of cassava tubers. This will also shield farmers from tubers' market price fluctuations and thus improve their income stability (Ogbonna and Okoli 2013).

Climate change, ecological degradation and ethical issues such as food use are among the heated debates on sustainability of oil palm production, especially for biofuel industry, the global demand for which is increasing (Panapanaan et al., 2009). Many countries were reported to have already been using biodiesel in motor vehicles (Karavina et al., 2011). It is important to optimise oil palm production while minimising the negative impacts on people and the environment for the industry to be sustainable (Rival and Levang 2014). A social and environmental study in Indonesia highlighted periodic water scarcity which severely impacted livelihoods and widen social polarization (Merten et al., 2016). The critical sustainability issues as far as jatropha biofuel production is concerned involve land use change, initial carbon debt, fertilisers and pesticides use, energy use in transportation, energy use at the processing stage, nitrogen emissions and use of by-products (Eijck et al., 2010).

As demonstrated above, if measures could be taken to eliminate or minimise the concerns about biofuel's production and use, they could be an economically viable and environmentally friendly solution to some of the world’s future energy needs. It is observed, in the foregoing biofuel debate appraisal, that blanket association of these issues might not be fair to all forms of biofuels. Some of the biofuels are less associated with of some these issues compared to others. Thus, this might be one of the answers to why biofuel industry continues to grow despite the talk-up issues.

Expanding biofuel production in Nigeria will contribute to the achievement of the SDG 7 (affordable and clean energy) by increasing clean share of the energy mix and SDG 13 (combating climate change and its impacts) by contributing to the reduction in carbon dioxide emissions through clean cooking fuel, implementation of blending policy for transport fuel as well as green electricity. In the context of the need for a global green energy transition, Nigeria must subscribe to this cleaner energy future, especially considering its population size, its current dependence on fossil fuel resources, and thus its contribution to the global carbon emissions.

1.3 Study area

Nigeria is located in West Africa between Latitudes 4˚N and 14˚N and between Longitude 2˚E and 15˚E. The country is bordered by Cameroon and Chad to the east, Benin and Niger Republics to the west, Niger Republic to the north and Atlantic Ocean to the south (figure 1.2).

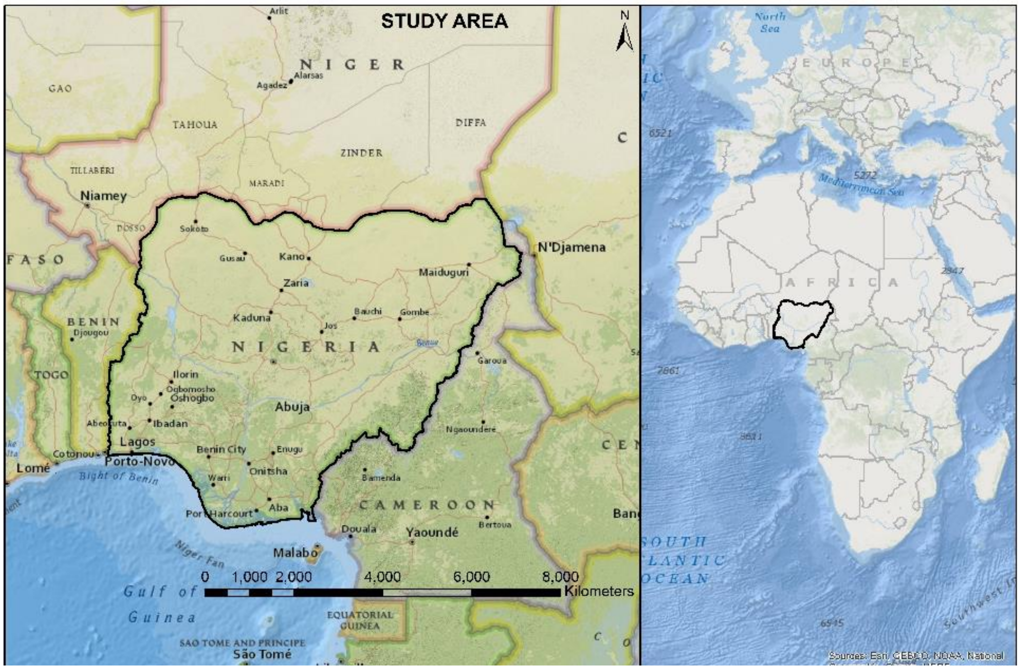


Figure 1.2: Study area

The total surface area of the country is around 92 million hectares. The relief is generally plains throughout the country but broken up by hills and plateaus such as the north central highlands, the western highlands and the eastern highlands. The pricipal rivers in the country are the Niger and the Benue making the major drainage basins of the country together with Chad basin and the Gulf of Guinea basin. Generally, the major soil types consist of loess – most common in the northern region – together with laterite in areas with marked dry season. The forest soils are more common in the south which contains a greater supply of humus from the vegetation. Hydromorphic and organic soils are found along the floodplains and coastal areas commonly underlained by sedementary rocks.

The climate is determined by the major airmasses that prevail in the country throughout the year, namely the Tropical Continental Airmass (the dry Northeast Trade Wind) and the Tropical Maritime Airmass (the moisture laden Southwesterly Airmass). The convergence zone between the two airmasses (the inter-tropical convergence zone, ITCZ) shifts towards Atlantic Ocean making most of the country experience a dry season as the dry wind covers the country. In contrast, the moisture laden airmass covers the whole country as the ITCZ shifts to the north during the rainy season (figure 1.3). The length of the rainy season ranges from about 10 months in the south to about 4 months in the extreme north. Thus, the annual rainfall amount decreases progressively northwards from more than 3000 mm to less than 500 mm per annum. Temperature also varies temporally and spatially. The range between coldest and hottest months can be between 18˚ and more than 42˚C.

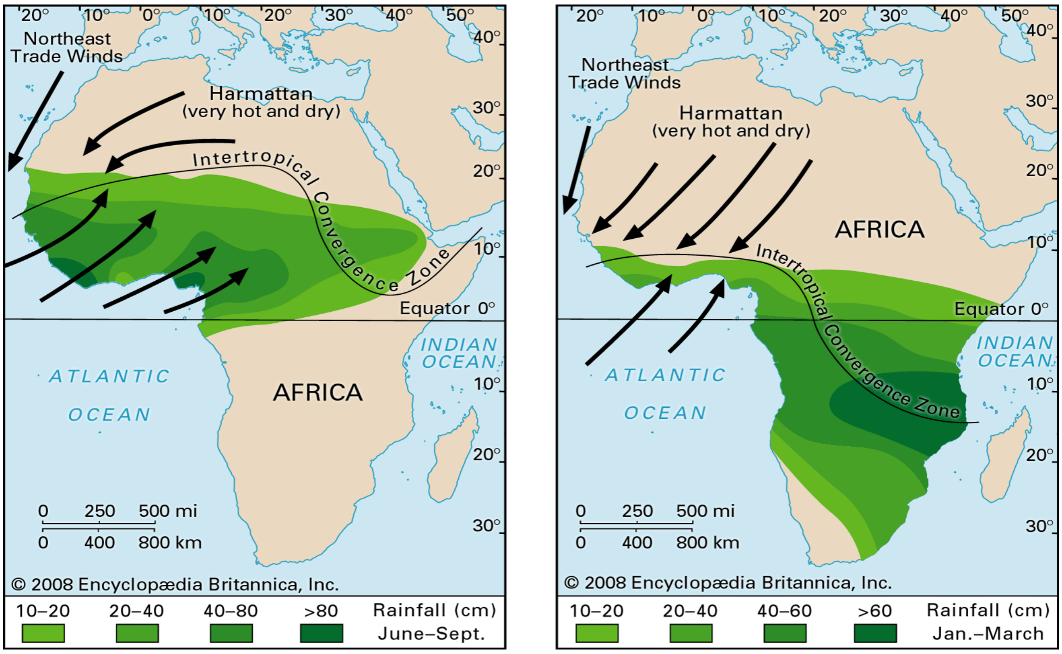


Figure 1.3: Nigeria's Climate seasonality as influenced by two major airmasses

Figure 1.4 shows the distribution of ecological zones or vegetation types (in addition to the location of agricultural research institutions) in the country. It changes from humid forest in the south to quasi-desert sahelian savannah in the northern fringes. This spatial distribution of landscape and habitats might have played the largest role in determining the nature of the farming systems in the country, with tree cropping most common in the south and pastoral agriculture in the north east (figure 1.5). The humid forest zone and southern parts of the derived sannah zone are capable of supporting large plantation crops such as oil palm, cocoa and coffee. The middle belt zones such as the derived savannah and southern guinea savannah are highly favourable zones for tuber crops such cassava, yams, cocoyam and potatoes. Northern guinea savannah and sudan savannah are good for grains such as sorghum, maize, millet and rice. In Nigeria, small-scale farmers have long recognised considerable potential of vegetables as income-generating crops and as dietary supplements. Thus it was reported that the farmers would seldom adopt any intercropping technology that exclude vegetables (Olasantan 1992).

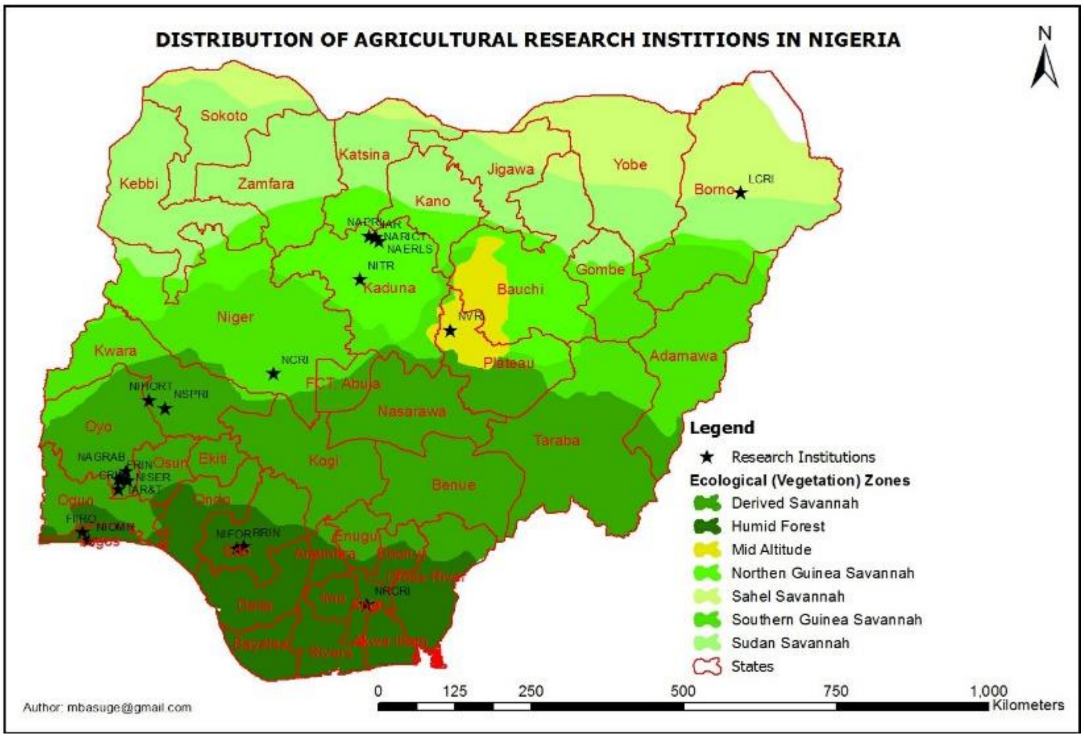


Figure 1.4: Distribution of Ecological Zones in Nigeria

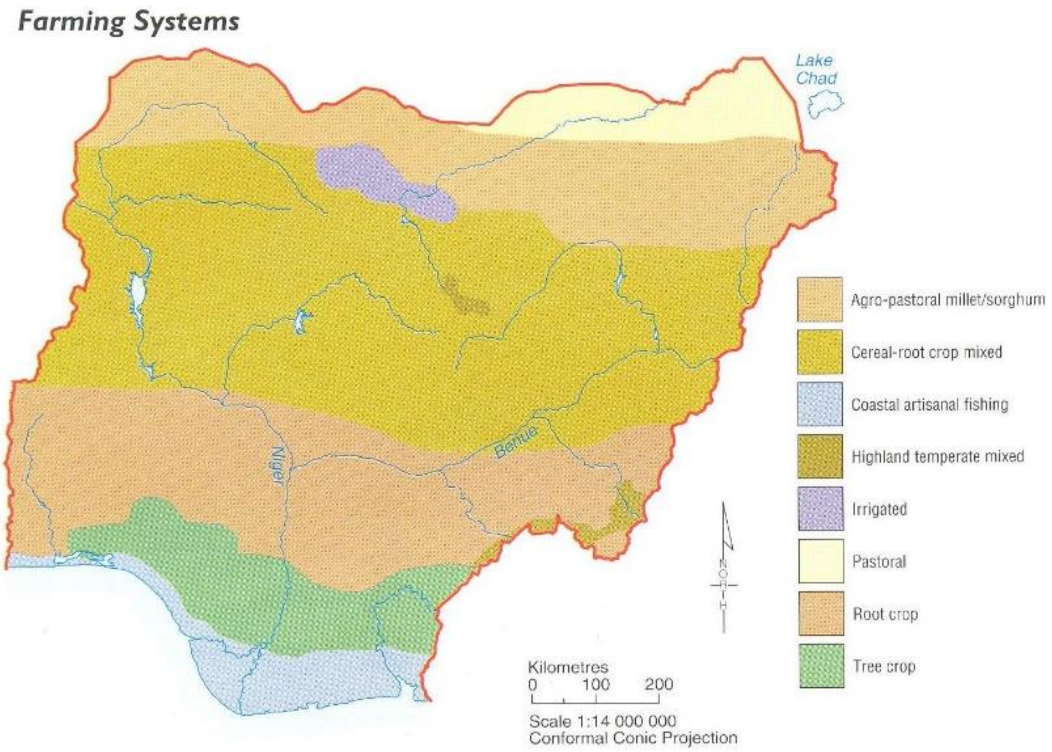


Figure 1.5: Farming Systems in Nigeria Source: (Dada et al., 2008)

In 2021, Nigeria's population is estimated to be 212.64 million (WPR 2021) with an annual growth rate of 3.2% and over 41% under the age of 15 (NBS 2018). This suggests that in a few decades, the country's population will largely be youthful, supporting labour availability, production and consumption of goods and services. On the other hand, it also poses a challenge for unemployment if new job opportunities aren't created for the increasing labour force. Agriculture remains the main bedrock of Nigeria's economy regardless of the oil exports. It employs 36.5% of the entire labour force and contributes 21% of the GDP (FAO 2018c). This shows that the agricultural sector offers significant potential for broadening job opportunities in the country. The sector is very broad consisting food, feeds, fibre, forage and fuel subsectors. Thus, one area for future job creation is developing and expanding the biofuel industry. Globally, the bioenergy supply chain is the second largest renewable energy sector, consisting of 3.2 million jobs in 2018 (WBA 2019) and increasing to 3.58 million jobs in 2019 (WBA 2020).

1.4 Nigeria's carbon emissions

Nigeria has substantial fossil fuel energy resources comprising crude oil, natural gas, tar sands, coal and lignite (Ohimain 2013). Proven stocks comprise of 37.5 billion barrels of crude oil (2.2% of global reserves) and 5.2 trillion m^3 of natural gas (2.7% of global reserves) (BP 2018). Despite this, Nigeria is still unable to meet its energy needs (Osunmuyiwa and Kalfagianni 2017). In 2017, crude oil production increased to 1,988,000 barrels a day with almost all of the daily production exported. Nigeria has limited refining capacity with its 4 refineries processing only 67,000 barrels per day (BP 2018); considerably less than their estimated combined installed capacity of 445,000 barrels per day (PwC 2017). Currently, all the refineries have been closed for total rehabilitation. Therefore, the country still relies on foreign imports for refined products (gasoline, diesel, kerosene and Liquefied Petroleum Gas) to meet domestic energy demand (Ohimain 2012). Though refining activities in Nigeria have dwindled over the decades, oil and gas sector produces substantial emissions throughout its value chain from exploration to end use of the refined products. For example, a Life Cycle

Assessment (LCA) of Self-Generated Electricity (SGE) in Nigeria was conducted. The results showed that based on estimate of diesel electric generators in the country, 389 million Tonnes of CO_2eq. per year is contributed to global emissions, placing the country among the top 20 GHGs emitting countries in the world (Somorin et al., 2017).

Because in-country production of biofuels saves in imports, improves balance of trade and offers an opportunity for diversification, the Nigerian government has developed a focus on biofuels (Anyaoku 2007). Secondly, Nigeria is signatory to the Paris climate agreement that requires countries to commit to cutting down their carbon emissions. Thus, 31 million Tonnes reduction in carbon emissions annually through renewable energy by 2030 has been approved to be part of the Intended Nationally Determined Contribution (INDC) (MoE 2015). Biomass use is part of this renewables deployment to promote efficient use of agricultural residues, municipal waste, animal and human wastes and energy crops as bioenergy sources (MoP 2015). In addition, the biofuel industry can provide jobs for the country’s large and growing youth population. A move towards biofuel expansion would appear to attract public support as well. A public opinion survey about impacts of bioenergy industry in Nigeria showed that 97.3% of the sample expressed optimism for revenue generation to government, investments, job creation, energy access for rural areas and environmental sustainability (Galadima et al., 2011).

Based on the discussed global trend (subsection 1.1) and local commitments, there are strong environmental and economic arguments for the Nigerian Government to embark on deployment of renewable energy, including biofuels. According to Shell (2020), “biofuels and renewables are keynote energies for meeting mobility demands of the 21st century without creating rampant CO_2 emissions”. According to the United Nations, 40 – 60% of the people in Nigeria will live in the cities by 2030 (UN 2021). Therefore, adjusting the energy mix will be crucial to living sustainably and protecting the environment.

In a time of rapid economic & population growth and the need to transform energy systems for a sustainable climate future, difficult decisions must be made related to land use change and financial investment. As such, it is essential that decision-making is grounded in appropriate evidence. Issues that are relevant include how policy decisions are translated into land use change, the reliability and utility of data, and how different social, economic and environmental priorities might be integrated. As such there is need for appropriate and location–specific applied research that can inform appropriate policies, and ensure environmental, economic and social sustainability of various biofuel programmes.

1.5 Defining the Problem

The previous subsection provided some information on Nigeria's energy resources, some partial estimate of the country's GHGs contributions and some strategies the country pursue to make its energy system less dirty. This subsection gives a historical background on how those strategies are being translated into policies and programmes with particular reference to the estimated biofuel demand and production in the country. The Nigerian Government initiated commercial bioethanol production in 1972 (Nasidi et al., 2010). Three decades after, biofuel had hardly expanded largely due to a continuously underperforming agricultural sector because of the government's neglect of the agricultural sector triggered by the oil boom of the 1970s (Michael 2017). However, the focus was renewed in 2005 when the Nigerian National Petroleum Corporation (NNPC) directed its Renewable Energy Division (RED) to pioneer development of the biofuel industry in the country. One of the primary aims was to link the oil and gas sector with agricultural sector through commercial production of biofuels from selected energy crops as blend stock for petroleum fuels (NNPC 2015). This, was envisaged, would contribute to reviving the agricultural sector, create jobs and diversify the economy.

Although some researchers evaluated Nigeria's biofuel programme in 2012, concluded that the progress was "unsatisfactory" (Ishola et al., 2013) and the development process was very slow due to regime change (Ohimain 2013), a huge potential still exists for the industry to be developed (Abila 2010). Biofuel programmes have made significant progress in some countries. For example, despite the inevitable challenges in its biofuel programmes, India attained increase in ethanol production from 1.5b litres (2002) to 2.7b litres (2013) and set a 20% blend mandate by 2017 (Purohit and Dhar 2015), now targeted to be achieved by 2030 (Pavlenko and Searle 2019). Also, some development and adoption of biofuels had progressed since the launch of the Nigeria Biofuel Policy in 2007 (Abila 2012). In April, 2016, the Nigerian National Petroleum Corporation (NNPC) called for strategic investors to fund and operate a variety of projects developed under automotive biofuel industry programme (Okere 2016). As a demonstration, the NNPC showed commitments to start the proposed sugarcane – ethanol project in Agasha-Guma, Benue State (NNPC 2016). The capacity of the project for fuel ethanol is put at 84 million litres per year and consists of a sugarcane feedstock plantation on a 20,000 ha of land (Nnodim 2017).

According to the National Biofuel Policy (2007), it was estimated that the Nigeria's demand for ethanol and biodiesel could be 2 billion and 900 million litres by 2020 respectively, with E10/B20 policies (a blend of 90% petroleum fuel and 10% ethanol / 80% petroleum diesel and 20% biodiesel). According to Agboola et al., (2011), the actual ethanol target was more than 1.27 billion litres of ethanol for blending. Based on Nigeria's daily diesel consumption, blending 20% of biodiesel will require 2.4 million litres daily, aggregating to 876 million litres annually (Agbota 2017). The Department of Petroleum Resources (DPR) reported that the conservative estimated daily consumption of petroleum product is 35, 12 and 8 million litres for PMS (petrol), AGO (diesel) and DPK (kerosene), respectively (DPR 2018). Somorin et al., (2017), concluded that the climate change contribution from self-generated electricity could be reduced in Nigeria by 76% if the fossil diesel is displaced using 100% Jatropha biodiesel provided combined cycle power plants are adopted for embedded power generation. Such a switch in fuel source would substantially increase local demand for biodiesel in the country. The largest Mobile Telecommunication Company in Nigeria – MTN – was reported to have been using 5% of its fuel for generator sets from Jatropha oil (Yammama 2009).

While agriculture is the main employer of the populace, crude oil is the main source of foreign exchange earnings in the country. Thus, commercial expansion of biofuel production is one of the prospective avenues to be exploited and could represent an important sustainable development pathway for the country. Production of biofuels creates opportunities for future development of agricultural sector in Nigeria. Assessment of agricultural residues in the country shows that considering other competing uses, 21.2 million tonnes of field residues are available for bioenergy production (Iye and Bilsborrow 2013). However, commercialisation of cellulosic ethanol was said to be facing technical and economic challenges as seen in the US where the yearly cellulosic ethanol production target could not be achieved, but the target from conventional feedstock (Maize) was achieved (Sharma et al., 2017). Most of the bioenergy industry successes recorded around the world are based on bioenergy crops; Maize (US), Sugarcane (Brazil), Sweet sorghum and Cassava (China), Oil palm (Malaysia) and Jatropha (India).

Energy experts have advised the Nigerian Government to exploit various sources of energy generation to diversify its energy supply base, particularly through increasing renewable sources (Oyedepo 2014). This would contribute to reducing carbon emission and support energy security. These renewable sources include hydro, solar, wind, geothermal and biomass. As a country with vast agricultural land and largely agrarian population, Nigeria has the potential to generate significant amounts of energy (fuel and power) from agricultural crops and their residues. It was estimated that Nigeria's potential for biomass generation could be 49.97 million tonnes of oil equivalent (MTOE) annually and that the feasibility and significance of both bioenergy and solar power are site specific for the country's sustainable development (Giwa et al., 2017).

Sweet sorghum, Sugarcane and Cassava are among the major crops selected for the bioethanol industry in the country (Nasidi et al., 2010). Oil palm (Balogun 2015) and Jatropha (Diop et al., 2013) are among the crops chosen for development of a biodiesel industry. While identification of these crops is crucial for the industry, also crucial is identification of where these crops could most optimally be cultivated. Indeed, a viable, sustainable and ethical biofuel strategy requires explicit consideration of competing spatial priorities such as alternative land uses (e.g food production, infrastructure, biodiversity) and biophysical conditions that underpin crop success (e.g. rainfall, soil, elevation). Effective policies must incorporate this kind of spatial information. The following subsection provides some background on the need for solving this problem in Africa and how spatial analysis is used in solving this locational problem.

1.6 Approaches to spatial decision making

Despite abundant biomass resources, lack of good understanding and application of key biofuel economics concepts is identified as a major barrier to its commercialisation in Africa (Amigun et al., 2006). This problem continues to exist, especially in West Africa, partly because biofuels vary in their favourability profiles which depend on local conditions and practices, as well as the potential conflict between agricultural and energy systems (Araújo et al., 2017). Among the important concepts for understanding and evaluating biofuel systems are the land use efficiency and economics (UNCTD 2008). Feedstock availability, usage and inefficient production strategy constitute the major factors limiting biofuel production (Chiara and Fabrizio 2009). Land use efficiency is said to be the most relevant parameter in the food vs fuel crops discussions (Koppen et al., 2009).

According to the Nigeria Biofuel Policy (2007), one of the responsibilities of the Ministry of Agriculture is to support land acquisition and utilisation strategies by biofuel companies. According to Eboh et al., (2004), only 44% of the cultivable land in Nigeria was said to be under cultivation. However, it could be argued that there are other land uses such as grazing, recreation and reserves. The extent of the arable lands have fluctuated over the decades. According to FAO 2015 estimates, Nigeria's arable lands stands at 34 million ha, 6.5 million ha permanent crops and 30.3 million ha meadows and pasture lands (FAOSTAT 2018). It was estimated that 2% of the arable land will be required to meet biofuel targets stipulated in the biofuel policy (NNPC, 2012). As part of this requirement, 100,000 – 200,000 ha of land will be required to meet demand for biodiesel in the country (Adam 2018).

Major factors for feedstock (raw materials used to process biofuel) adoption include the history of pricing, abundance and available quantity, production pattern and trend, haulage and storage options in the potential processing and production site (Toyin n. d.). A report suggested that feedstock supply comprises 75% of the total biodiesel production cost (Ghazali 2015). The impact of biofuel production and policies on food security, as mentioned in subsection 1.2.3, is shaped by the choice of the preferred feedstock and technology and there is not likely a one-fit-for-all approach but multiple approaches with different crops, production models, fuels and logistics (Das 2017). A study in Nigeria found significant impact of both feedstock yields and cultivation location on biofuel production, plant size and the per unit biofuel production cost (Amigun et al., 2006). While attainment of the highest possible yields is a function of the feedstock variety and ecology, optimal cultivation site is a function of ecology and distance to processing plant. Ecological requirements of the crops are, therefore, crucial considerations for both increasing yields and making informed decisions on cultivation sites.

Assessment of a set of locations for a particular land use is usually complex due to trade-offs among the ecological, economic and socio-political factors which involve conflicting spatial and non-spatial criteria that play varying degrees of importance. This spatial decision-making process is usually approached through a process that combines multiple criteria based on a decision rule that focuses on achieving the central objective which structure the criteria prioritisation. GIS-based multi-criteria decision analysis (GIS-MCDA) is one of the most common and favourable tools used to determine suitable sites for human activities such as housing development or industrial estate (Villacreses et al., 2017; Jelokhani-Niaraki et al., 2018). This model also has shown to be a useful tool for sustainability assessment in project planning (Boggia et al., 2018). Spatial decisions are based on the evaluation of the properties of the multiple geographical entities and relationships that are quantitatively or qualitatively measurable (Drobne and Lisec 2009).

Overlay functions in GIS environment combine multiple criteria that represent the geographical entities that determine a particular spatial goal. Weighted overlay tools support incorporation of criteria weights. Basic GIS-based multi-criteria analysis can use fairly arbitrary criteria weightings that may reflect the views of limited number of people, usually the researchers. However, criteria weightings need to reflect the collective opinions of multiple stakeholders regarding the role of each criterion in achieving the spatial goal. Multi-criteria Decision Making (MCDM) methods complements GIS analysis by providing a systematic way of incorporating criteria weightings from multiple stakeholders. These methods have grown in both number and applications and received great deal of attention from practitioners and researchers (Zyoud and Fuchs-Hanusch 2017). They are generally important methods in management sciences and research operations, and they are more important in spatial analysis because spatial decisions are multi-criteria in nature.

MCDM provides a structure for managing arguments on recognising the factors of a decision problem, ordering the components into a hierarchical construct, discerning the connection among the constituents of the problem and stimulating communication among the participants (Malczewski 2006). The factors which form the decision criteria vary in terms of the influence they exert on the decision. Generating weights for the criteria is an important step in most multi-criteria methods (Behzadian et al., 2010) and several techniques (e.g. TOPSIS, ELECTRE, PROMETHEE) have been developed to handle that. These techniques though fuzzy in their nature, provide realistic estimates and help in capturing the fuzziness in the minds of the people making judgement about the importance of the variables (Suganthi et al., 2015). Though selecting an appropriate multi-criteria analysis method depends heavily on the project or the case study, Analytical Hierarchy Process (AHP) was found to be the best when pre-selected methods were compared against selection criteria, particularly because of its procedure for multi-stakeholder inclusion (Kurka and Blackwood 2013).

AHP is a multi-criteria analyis method developed by Saaty (1980) based on three principles namely; decomposition, comparative judgement and sysnthesis of priorities (Malczewski 1999). Decomposition entails breakingdown of the decision problem into hierarchy. Comparative judgement requires pairwise assessment of the elements within a given level of the hierarchical structure with respect to their parent element in the next-higher level. Synthesis of priorities refers to constructing a global set of priorities for the alternatives. The essence of AHP is to construct a matrix expressing the relative values of a set of attributes (Coyle 2004).

AHP was developed initially to provide a simpler way of handling complex problems and due to its power and simplicity, it has received widespread acceptance and usage (Meng et al., 2011). A review of the state of application of multi-criteria analysis to sustainable hydropower generation over 15 years (2000 – 2015) showed that AHP was mostly the technical feature of the applications (Vassoney et al., 2017). AHP applications increased exponetially during 2005 – 2009 covering such areas as manufacturing, environmental management, agriculture, power/energy, tranportation, construction, health care, education, logistics, e-business, IT, telecommunication, banking/finance, urban management, defence, government, marketing, tourism, mining, archaeology and research (Sipahi and Timor 2010).

Malczewski (2006), conducted a survey of the literature and found over 300 articles published in refreed journals which applied GIS-MCDM approaches from 1990 to 2004. Only about 9.4% (34 publications) applied AHP as the criteria weighting method. Malczewski (2004), also opined that this contributed in shifting GIS from being a mere database for data storage and manipulation to a more complex decision support tool for many applications related to site suitability. Table 1.1 shows some applications of this nature for various disciplines. Of the total 29 publications, 16 indicated how the criteria weighting was done (11 of which were AHP, approximately 38%) though with varying degrees of detail. In two of the publications, sensitivity analysis was used instead of weighting the criteria. Some researchers decided to use mere rating/ranking, while seven of the publications did not show how the relative importance of the criteria was handled. The current trend in spatial multicriteria analysis is to ensure that the assessment of the criteria weights is explicit such that incorporation of the relevant expertise and stakeholders is tranparent and detailed.

Spatial decision making as a support tool has widely been applied to biofuel production analysis and according to De Meyer et al., (2014), it had risen exponentially. Batidzirai et al., (2012), reported that the application varies depending on the feedstock considered. According to De Meyer et al., (2014), the application also depends on the technique employed. While Farahani et al., (2010), suggested that the application varies based on the variables examined. It could also be reasonable to suggest that the applications could depend on the spatial and temporal contexts within which the studies were conducted. Batidzirai et al., (2012) observed that many of the studies in this context are deficient in covering all the basic elements needed in an ideal assessment and that there is an apparent disparity in the level of parametric details and methodological transparency among the studies. In order to help users identify methods or models that meet certain requirements, De Meyer et al., (2014) conducted a review of these methods and classified them into three based on the mathematical optimisation methodology, the decision level and/or decision variables and the objective optimised.

Table 1.2 shows various applications of these methods in the area of spatial decision making related to biofuels. It shows the methodological nature of the application, the techniques used in criteria weighting, the number of criteria considered and what could be deficient in the studies. Of the 10 publications presented in the table, only three were found to explicitly describe how the weights were assigned to the criteria. Most of these studies, thus, focus more on GIS overlay of the criteria maps with limited consideration of the influence of each of the criteria on the decision objective. In fact, in some studies, it is difficult to grasp what the criteria actually are in the biomass assessment. As described by Malczewski (2004), focussing on the power of GIS (in combining maps) can lead to oversimplification of the complexity of the processes involved in land use planning problems, since there is greater emphasis placed on the ‘facts’ (quantitative spatial data) rather than the process of how ‘facts’ are derived or analysed.

It is essential that the weights of each variable are carefully assessed and transparently reported, since this process plays important role in identifying possible disagreements, resolving them and determining the degree of their implications for the final decision (Malczewski 1999). These weights should be interpreted as measures of relative importance rather than measures of absolute importance of each variable. This literature exploration indicates how spatial optimisation continued to be active and relevant in every aspect of environmental analysis through the decades. In the present study, multi-criteria spatial analysis, specifically using AHP, is employed in the context of spatial decision-making for biofuels because of the multiple strength outlined above. Yet this study contributes to this field of research by explicitly attending to the process of determining and applying algorithmic weights to variables, thereby bringing together best-practice GIS methodologies with real-world applicability.

Table 1.1: Examples of GIS-MCDM methods to various application areas

S/N	Application	Methodology	Criteria Weighting Technique	Author(s)
1	Habitat suitability	MCE-GIS	HERO	Store and Kangas (2001)
2	Housing land use suitability	MCDA-GIS	ELECTRE-TRI	Joerin et al., (2001)
3	Siting land fill	MCDA-GIS	AHP	Sumathi et al., (2008)
		GIS-MCDA	AHP	Gorsevski et al., (2012)
4	Site selection for hydropower	MCE-GIS	Rating	Rojanamon et al., (2009)
		MCE-GIS	-	Bódis et al., (2014)
5	Urban infrastructure planning	GIS-MCDM	MCPUIS	Coutinho-Rodrigues et al., (2011)
6	Site selection for wind farm	GIS-SMCA	-	van Haaren and Fthenakis (2011)
		MCE-GIS	-	Satkin et al., (2014)
		GIS-MCDM	-	Al-Yahyai and Charabi (2015)
		PGIS	Ranking	Mekonnen and Gorsevski (2015)
		SDSS	Assumed equal	Kazak et al., (2017)
7	Assessing tidal power potential	MCE-GIS	Assumed equal	Defne et al., (2011)
8	Sites for irrigated agriculture	MCE-GIS	-	Ismail et al., (2012)
9	Site evaluation for solar farm/plant	GIS-MCDM	AHP	Sánchez-Lozano et al., (2013)
		GIS-MCDM	AHP	Uyan (2013)
		GIS-MCDM	-	Sabo et al., (2016)
		MCE-GIS	-	Szabó et al., (2017)

		GIS-MCDM	AHP	Zoghi et al., (2017)
10	Landslide susceptibility mapping	GIS-MCE	AHP	Feizizadeh et al., (2014)
11	Optimising ideal location for *Agave* in the US	GIS-MCE	Sensitivity analysis instead	Lewis et al., (2015)
12	Land suitability for Rubber cultivation	GIS-MCDM	AHP	Bedawi et al., (2017)
13	Land suitability for cultivating arable crops	GIS-Fuzzy set	AHP	Kahsay et al., (2018)
		GIS-MCDA	AHP	Suhairi et al., (2018)
		GIS-MCDM	Analytical Network Process (ANP)	Yohannes and Soromessa (2018)
14	Land suitability for rainfed farming	GIS-MCDM	AHP	Kazemi and Akinci (2018)
15	Land suitability for construction	MCDA-GIS	AHP	Ristić et al., (2018)
16	Assessing flood susceptible areas	GIS-MCDA	Sensitivity analysis instead	Tang et al., (2018)
17	Land suitability for crop rotation	GIS	AHP	Singha et al., (2020)

Table 1.2: Example of biofuel research which applied GIS-MCDM methods and their identified deficiencies

S/N	Application	Methodology	Number of criteria used	Criteria weighting Technique	Author(s)	Remarks
1	Biomass potential for power generation	GIS-DSS	14	-	Voivontas et al., (2001)	A 4-staged analysis that considered certain criteria at each stage. Neither criteria weighting nor sensitivity analysis was explicit in the work.
		GIS-MCE	8	-	Shi et al., (2008)	A 2-stage analysis that estimated biomass using satellite imagery and then optimised sites based on transport cost (distance). Sensitivity analysis would have given an idea on which of the variables played greater role in determining biomass amounts estimates.
			12	-	Voets et al., (2013)	Weighting the criteria for the transport model would have improved it or sensitivity analysis would have shown which of the variables is more important in the model.
		GIS-MCDM	12	F-DEMATEL	Jeong and Ramírez-Gómez (2018)	Detailed description of criteria weighting. Attempt was also made to test the model stability using sensitivity analysis.

2	Assessment of biodiesel impacts on land use change	GIS-MCE	8	-	Yui and Yeh (2013)	What is obvious from this work with respect to what the researchers called weighting is, creating suitability levels within each criterion rather than assigning weights to reflect the importance of each criterion over others.
3	Potential of marginal lands for biofuel production	GIS-MCE	14	-	Boruff et al., (2015)	The approach was additive with criteria being added in stages and neither initial between-criteria weighting was clear nor sensitivity analysis was conducted.
4	Sites allocation for biofuel production.	Regression	12	-	Zhang et al., (2017)	The weighting technique is not clear, if actually was performed.
5	Spatial optimisation of conversion facilities for agricultural residues	GIS-MCDM	8	AHP	Morato et al., (2019)	The weighting process was explicitly explained in detail.
6	Examine available and accessible biomass for biorefinery	GIS-MCE	5 for biomass estimate	-	Zheng and Qiu (2020)	The weighting of the criteria assessing the biomass potential at stage one could not be found.
7	Suitable location for Paulownia cultivation	GIS-MCDM	14	DEA	Abbasi et al., (2020)	Data Enveloping Analysis (DEA) was employed in this work for weighting the criteria.

1.7 Research Gap

In the context of policies supporting the expansion of biofuel production, there is a need for knowledge of where these biofuel crops should be positioned. The typical methodological approach to this kind of spatial analysis is to combine multiple criteria maps through a decision rule. Determining the optimal spatial location of biofuel crops requires information on what environmental conditions are associated with the crop viability and success. In lieu of published literature on the comparative suitability of various crop types under different conditions, it is essential to engage knowledgeable experts to provide this information. This is where most of these analyses are usually deficient as shown in Table 1.2. Thus, spatial analysis requires a collection of literature to identify the environmental criteria that influence crop feasibility combined with more information from stakeholders regarding the importance of each of these criteria in the location decision-making (biofuel crops cultivation sites in the context of this research). Examples of the works that applied spatial multi-criteria analysis on a global scale are identified by Oakleaf et al., (2019). A review of a collection of these kinds of works was conducted in the US (Lewis and Kelly 2014). More specific works of this nature were presented in Table 1.2 with their deficiencies, essentially absence of stakeholder's involvement.

In Nigeria, there has been a small number of attempts to apply standard spatial analysis methods to locational problems related to biofuel production. However, these are limited, for example interms of spatial scope as in Buhari (2014), or based on feedstock other than crops as in Chukwuma et al., (2016). Ayoade (2017), applied spatial analysis to identify suitable locations for rice cultivation in Oyo State of Nigeria. The work was restricted in terms of spatial scope and rice is not one of the identified biofuel crops in Nigeria, even though rice husk is being touted for biodiesel production. More importantly, these existing studies did not include expert participation, relying instead on coarse assumptions. Some studies have attempted to calculate total biomass production potential in the country with little or no spatial consideration, for example Galadima et al., (2011), Ben-Iwo et al., (2016) and Giwa et al., (2017).

These country-wide studies provided limited details with respect to the suitability of the sites identified for biofuel production. For example, the sites suitable for the crops were linked to the ecological zones of the country (Ben-Iwo et al., 2016), which is too generalised to permit real economic and environmental decision-making that requires a finer grain of analysis. For example, an ecological zone identified as ‘best’ for a particular crop will in fact have a variety of soil conditions that may not universally suit its growth. There is a need, therefore, for research that provides greater spatial precision and robustness. Indeed, Dell’Ovo et al., (2018), opined that multi-criteria decision problems are typically ill-structured and thus, tried to improve the transparency and robustness of the process for locating healthcare facilities in Italy.

The researcher, as an MSc student in 2014, conducted spatial analysis to optimise sites for biofuel production in Nigeria considering sweet sorghum, sugarcane and jatropha. The dissertation was published as a book (Shehu 2017) and part of the dissertation was also published as a journal article (Shehu and Williams 2020). However, due to the time and resource constraints, the work was very limited with respect to involvement of stakeholders such as the crop experts, consideration of the required environmental variables such as insolation, as well as detailed consideration of the restrictions such as crop areas. The MSc research was exploratory and identified that there was a key challenge which is being addressed in this thesis, namely, how to conduct a site optimality analysis in a form that is applicable in the real world and engages a range of stakeholders. The first recommendation in the MSc research was that there was need for improvement of both the suitability and optimality models presented in the dissertation. The analysis could be improved in terms of robustness and transparency.

In the present study, therefore, the previous work was extended to demonstrate how the robustness and transparency of applying spatial analysis could be increased and was also extended to include two other biofuel crops – cassava and oil palm – which were not analysed in the MSc work. Robustness, in this respect, is conceptualised as comprising of three aspects. 1) detailed consideration of all the environmental and socio-economic variables, 2) involvement of the feedstock (crops) experts in the spatial analysis and 3) the employment of the standard techniques such as Analytical Hierarchy Process (AHP).

All these three aspects together form the methodological component of the research gap in this work. The gap has four components, namely empirical, spatial, methodological and policy. The empirical component relates to how biofuel crops suitability is related to environmental, social, physical and economic variables. The methodological component relates to how geographical information systems and social-scientific techniques might be integrated to derive this knowledge. In this respect, it is demonstrated in this work how the challenges of developing and applying spatial multicriteria analysis could be fathomed and approached in a structured way. The spatial component relates to where biofuel crops and processing facilities might be located for spatial optimisation. Finally, the policy component relates to what spatial decisions should be made for the future of biofuel production in Nigeria. All the four elements are covered in this thesis.

This research attempts to fill this multi-component gap by providing more robust methodological contribution to spatial analysis for detailed crop-based bioenergy land suitability modelling in Nigeria. The resultant maps from these models are a crucial component of spatial decision-making regarding crop-based bioenergy production. It requires expertise for each of the biofuel crops to be able to judge which of the evaluation criteria have higher preference compared to the others. The subjectivity of this experts' participation is handled by application of AHP.

1.8 Research questions, aim and objectives

This research will focus on GIS and AHP based modelling and estimation of biofuel potential and will address the following questions:

1. What are the ecological requirements for the selected biofuel crops' optimal growth?
2. How do various biofuel crops differ in their potential contribution to biofuel production under a range of environmental conditions?
3. How does combining AHP and GIS-MCDM improve biofuel crops land suitability modelling in Nigeria?
4. Where are the physically available lands for biofuel crops located in the country and how suitable are they for the identified biofuel crops?
5. How much land is physically available for biofuel crops cultivation without conflicting with food crop cultivation and conservation sites?
6. Where should biofuel refineries be optimally sited among the existing petroleum depots in Nigeria based on the suitable areas for biofuel crops?
7. What policy recommendations should be considered to support and enable appropriate biofuel production in Nigeria?

To answer these questions, the following research objectives will be pursued:

i. Produce a synopsis of the identified biofuel crops.
ii. Conduct a requirements analysis to determine the ecological requirements of the identified crops.
iii. Conduct expert group discussion for detailed and standard implementation of Analytical Hierarchy Process (AHP) for criteria weights.
iv. Develop a model for suitable cultivation lands for each of the identified crops using Spatial Multi-Criteria Analysis (SMCA).
v. Map the cultivation lands and their suitability levels for the identified biofuel crops in Nigeria.

vi. Identify and develop a model to eliminate physical constraints to biofuel crops cultivation.
vii. Develop a site optimality model using service area modelling for biofuel processing facilities based on transport cost (distance).
viii. Determine the appropriate scale for the identified sites based on feedstock amount, and determine the most efficient number of biofuel production facilities in Nigeria.
ix. Investigate and discuss the most appropriate technology to be employed in the production system.
x. Investigate and discuss strategies for sustainable biofuel crops cultivation and strategies for sustainable biofuel processing in Nigeria.

The key novelty of the work is thus combining Spatial Multi-Criteria Analysis (SMCA) with Analytical Hierarchy Process (AHP) that involves expert participation to develop a more robust and transparent workflow for modelling optimal sites, the results of which provide a guide for location decisions related to crop-based biofuel production in Nigeria. None of the above research questions were formulated in the previous MSc work. Also, the previous work did not engage with the complexity and challenges of spatial multicriteria analysis as a spatial decision support tool. The current work attempts to demonstrate how these challenges are approached, substantially contributing to knowledge in application of spatial analysis.There were five objectives in the previous work, compared to ten objectives in the current work. Though the first objective in the MSc research was identifying and eliminating constraints, the constraints identified were very limited. For example, agricultural areas were not identified and eliminated and there were only nine reserved areas identified and eliminated. In the current research, comprehensive analysis was conducted to indentify and eliminate agricultral areas and comprehensive data on protected areas was downloaded from the World Database on Protected Areas comprising 988 polygons.

Objective two in the MSc research dealt with mapping suitable areas for cultivating three biofuel crops (sweet sorghum, sugarcane and jatropha). However, 11 environmental criteria were used, unlike 14 criteria in the current work. Also, the rainfall data used for the current work is more comprehensive with 90 sample points than the one used for the MSc work that had 44 sample points. The same weights were applied to all the three crops in the previous MSc work without involvement of the crops experts, unlike in the current work where separate weights were generated for each of the five crops through involvement of the crops experts. The soil data used for the MSc work consists of 28 categories, unlike the more detailed one used for the current work consisting of 51 categories.

Objective three in the previous work dealt with optimal sites for biofuel processing facilities. However, a single scenario was used for both distance and crop yields, unlike in the current work where three scenarios were used for both distance and crop yields parameters to provide a wide range of outputs that can allow for possible application to varied local contexts. Objective four and five in the previous work dealt with brief discussion on strategies for sustainable crop production and biofuel processing. In the current work, lengthy discussion is provided and extends to include such topics as reselient thinking and policy realignment. From the foregoing, it is clear there are some similarity in these objectives, but they have been achieved in the current work in a different and extended way. Table 1.3 maps the relationships between the current research gap, research questions, the objectives as well as the chapter that deals with each of the objectives.

Table 1.3: Thesis structure

S/N	Research Gaps	Research Questions	Objectives	Thesis Chapter(s)
1	An **empirical** component: how is biofuel crop suitability related to environmental, social, physical and economic variables?	1. What are the ecological requirements for the selected biofuel crops' optimal growth? 2. How do various biofuel crops differ in their potential contribution to biofuel production under a range of environmental conditions? 5. How much land is physically available for biofuel crops cultivation without conflicting with food crop cultivation and conservation sites?	i. Produce a synopsis on the identified biofuel crops.	Chapter two
			ii. Conduct a requirements analysis to determine the ecological requirements of the identified crops based on which the criteria will be determined.	Chapter two
			vi. Identify and develop a model to eliminate physical constraints to biofuel crops cultivation.	Chapter five
2	A **methodological** component: how might geographical information systems and social-scientific techniques be integrated for spatial optimisation?	3. How does combining AHP and GIS-MCDM improve biofuel crops land suitability modelling in Nigeria?	iii. Conduct expert group discussion for detailed and standard implementation of Analytical Hierarchy Process (AHP) for criteria weights.	Chapter three
			iv. Develop a model for suitable cultivation lands for each of the identified crops using Spatial Multi-Criteria Analysis (SMCA).	Chapter four
3	A **spatial** component: where might biofuel crops be located as	4. Where are the physically available lands for biofuel crops located in the	v. Map the cultivation lands and their suitability levels for the identified biofuel crops in Nigeria.	Chapter four

	evidence based spatial decision?	country and how suitable are they for the identified biofuel crops? 6. Where should biofuel refinery be optimally sited among the existing petroleum depots in Nigeria based on the suitable areas for biofuel crops?	vii. Develop a site optimality model using service area modelling for biofuel processing faclities' sites based on transport cost (distance).	Chapter six
			viii. Determine the appropriate scale for the identified sites based on feedstock amount and determine most efficient number of biofuel production facilities in Nigeria based on the identified ethanol and biodiesel crops.	Chapter six
4	A **policy** component: what strategic policy recommendations should be adopted for the future of biofuel production in Nigeria?	7. What policy recommendations should be considered to support and enable appropriate biofuel production in Nigeria?	ix. Investigate and discuss the most appropriate technology to be employed in the production system.	Chapter seven
			x. Investigate and discuss strategies for sustainable biofuel crops cultivation and strategies for sustainable biofuel processing in Nigeria.	Chapter seven

1.9 General methodological overview and thesis structure

The sequential analytical structure of this thesis means that results from earlier chapters are regularly used as input for later chapters. As such, no traditional ‘methodology’ chapter is included. Instead, an overview of the methods employed is provided in Figure 1.6. Detailed descriptions of methodological approaches are provided within each subsequent chapter, as they relate to the nature of the analysis contained therein.

In chapter two, the environmental requirements for optimum growth and development of selected biofuel crops are identified via thorough literature review. The optimum values for these requirements are then presented with respect to each of the crops. These environmental requirements (e.g. soil characteristics, climatic parameters) form the criteria for subsequent GIS-based multi-criteria decision making (GIS-MCDM), with the inclusion of each predictor variable into the analysis depending on the relevance of the criterion and the availability of data.

Chapter three focusses on expert consultation regarding the relative importance of each environmental criterion with respect to suitable land for cultivating each crop. Analytical Hierarchy Process (AHP) is used to determine criteria weights which can be used in subsequent spatial analysis.

Chapter four utilises the established criteria weights to provide framework for modelling land suitability which involves developing suitability index levels, creating and executing models, and mapping the suitable areas for each of the five biofuel crops and their suitability levels. To factor in the restricted areas in this suitability analysis, constraints analysis and elimination is dealt with separately in chapter five.

Chapter six then reports on site optimality analysis for biofuel processing plants using Supply Area Modelling (SAM).

Chapter seven includes a general discussion of the analyses and related applications and future direction, while chapter eight present conclusions from the thesis.

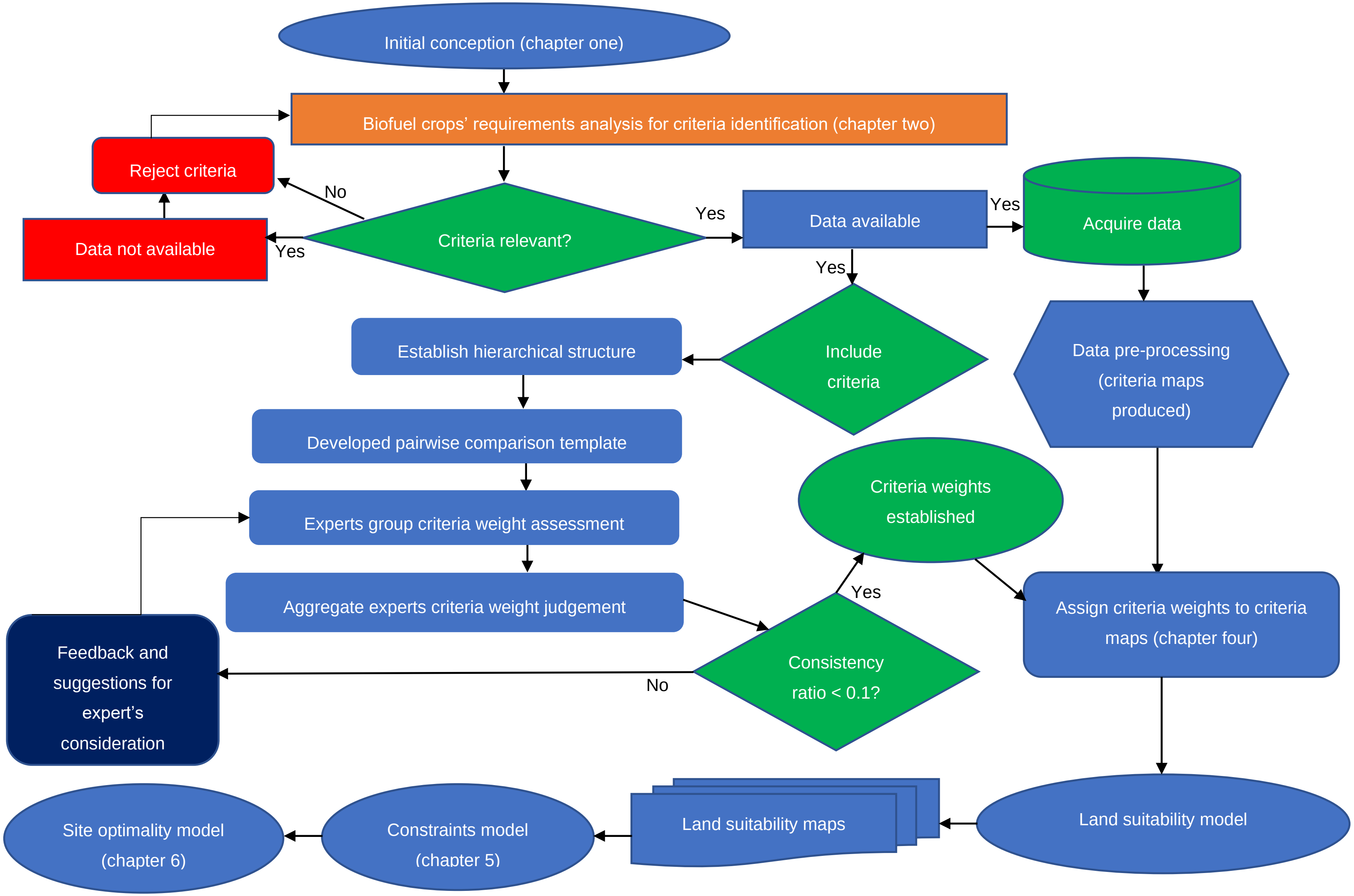


Figure 1.6: Structural flow of the methodology

Chapter Two – Biofuel Crops Requirements Analysis

2 Chapter Two – Biofuel Crops Requirements Analysis

2.1 Introduction

In chapter one, it was mentioned that the feasibility and significance of biofuel is site specific and that sweet sorghum, sugarcane, cassava, jatropha and oil palm have been identified in Nigeria as the focus energy crops for biofuel industry in the country. It was also shown that environmental and socio-economic variables are crucial to both crops' yield improvement and selection of suitable cultivation sites. This chapter provides an overview on the identified biofuel crops as appropriate feedstock for the biofuel industry. Sweet sorghum, sugarcane and cassava are the starch crops for ethanol production, while oil palm and jatropha are the oil crops for biodiesel production. The chapter then presents literature analysis conducted to determine the ecological requirements of these crops as the basis for modelling suitable lands for cultivating the crops. This provides the basis for this work to identify the criteria to be considered in applying the multi-criteria method and identify optimum values for analysing where the biofuel crops could suitably be positioned.

2.2 Biofuel crops

2.2.1 Ethanol crops

2.2.1.1 Sweet sorghum

Sorghum is the fifth most important cereal crop in the world (Cifuentes et al., 2014). USA, Nigeria and India are the three largest producers of the crop in the world (Elbehri et al., 2013; Mundia et al., 2019). It is one of the oldest cultivated crops in the history and it is believed to originate from Africa (Khawaja et al., 2014). Sorghum exhibits extensive phenotypic diversity, the patterns and the identity of which have been assessed using various taxonomic characteristics (Upadhyaya et al., 2017). They (ibid) analysed the passport and characterization data of 1,206 Nigerian Sorghum Landraces to assess their status and diversity and to identify their geographical and taxonomical gaps. A total of 118 geographical gaps (districts) were identified in Nigeria. Maximum diversity was also observed in the Nigerian collection for both qualitative and quantitative traits. Sorghum is classified as grain, forage or sweet sorghums (Almodares and Hadi 2009). Grain sorghum is usually used as staple food for human consumption, Forage sorghum for animal feeds and Sweet sorghum for edible syrup as well as bioethanol (Cifuentes et al., 2014).

Sweet sorghum is similar to grain sorghum except that it accumulates high fermentable sugars in the thick juicy stalk and can be used for various purposes such as food, fodder, fibre and fuel and due to these, the crop is tagged ‘smart crop’ (Rao et al., 2011; Cifuentes et al., 2014; Khawaja et al., 2014). Sweet sorghum (figure 2.1) has a sugar rich stalk, almost similar to sugarcane, making it a special purpose crop with all its components usable, unlike most of the crops (Reddy et al., 2005; Sarvani 2015). The crop is recently gaining popularity and is being promoted as the major feedstock for commercial bioethanol production (Olugbemi and Ababyomi 2016).

Figure 2.1: Sweet sorghum

Cultivation of the crop was suggested to be encouraged due to the fact that it can be used for the production of food, first and second generation biofuels, as well as fertilizers, although the crop's sustainability was said to be not well envisaged (Koppen et al., 2009). However, the crop's sustainability concern prompted Food and Agriculture Organisation (FAO) to commission an investigation into the environmental impacts of different sweet sorghum production systems. One of the results shows that even if the grains and syrup were used as food, conversion related energy and greenhouse gas expenditure can be compensated by producing second generation bioethanol from bagasse (the remaining fibrous material after extracting the juice), although the balances would be more favourable if electricity is produced from the bagasse. Due to these comparative advantages, sweet sorghum appeals to the biofuel industry and is selected as one of the major agricultural crops for bioethanol production in Nigeria.

2.2.1.2 Sugarcane

Figure 2.2: Industrial Sugarcane Source: Field work

Sugarcane is a strongly growing C_4 crop with wide range of tropical and subtropical climates, soils and cultural adaptability and is cultivated in over 100 countries spread between 37˚N and 31˚S (Meyer et al., 2011). The crop's production cycle lasts for 5 – 6 years with 4 – 5 harvests, although with irrigation and improved varieties the cycle can be extended to over 30 harvests as is the case with some growers in Swaziland (Meyer et al., 2011). For several decades after its establishment, Savannah Sugar Company (now Dangote Sugar Company) at Numan, Adamawa State, Nigeria had grown many Sugarcane varieties in its estate but in 1995, 70% of the cane area was covered by a single variety – B47419 – (Kawuyo and Wada 2004).

Sugarcane breeding and variety improvement are continuous programmes at the National Cereal Research Institute (NCRI), Badeggi which has the mandate for the crop's improvement in Nigeria (Gana 2017). The aim of the breeding programme is to collect and maintain local and exotic sugarcane accessions (unique sets of identifiable sample of seeds representing a cultivar preserved in a storage) in the field Genebanks at Badeggi and Edozhigi. There are 235 germplasm comprised of 188 exotic and 40 local genotypes. The remaining are NCRI releases (NCS 001, NCS 002, NCS 003, NCS 005, NCS 007 and NCS 008). The objective of the varietal improvement is to develop good quality, high yielding, diseases and pest resistant varieties of sugarcane for Nigeria sugar Industry as well as for local chewing cane farmers through hybridization and selection.

Figure 2.3: Chewing Sugarcane

Industrial and soft (chewing) sugarcanes are the two major types of the crop grown in the country (Wayagari et al., 2003). Industrial sugarcane (figure 2.2) has relatively higher brix (total of soluble solids) percentage, less water content, thinner and harder stem and thicker nodes (Ahmed et al., 2014). Chewing sugarcane (figure 2.3) is usually soft with high water and less sucrose content.

Sugarcane ethanol have high production efficiency and relatively lower costs (Zuurbier and Voore 2008) as shown by the Brazilian system where the costs continue to fall over three decades. The breakdown of the sugarcane production costs indicated that though all subsectors contributed to the total reducing costs, the main driving force was the increase in yield (van den Wall Bake et al., 2009). Also, the industrial costs were mainly reduced by the expanding ethanol plants scales. These might suggest the reasons for choosing sugarcane as one of the agricultural crops for ethanol industry in Nigeria (NNPC 2015). However, the major raw material used in Nigeria for sugar production is sugarcane. Also, it is an established fact that the relative higher requirement for water is an economic disadvantage of sugarcane production though this is minimised through efficient irrigation systems.

2.2.1.3 Cassava

Figure 2.4: Cassava farm (Sanyinna) Source: Field work

Cassava (Figure 2.4) is a perennial root crop, mainly propagated through stem cuttings and can be planted and harvested all year round making it more preferable than other seasonal crops (FAO and IFAD 2005; Ohimain 2012). It is one of the earliest domesticated crops (Adeoti 2010) and widely cultivated in the tropics between latitudes 30° north and 30° south over a range of climates, soils and altitudes (Anyanwu et al., 2015). The crop is believed to have originated from the Central Brazilian Cerrado vegetation zone (Hillocks et al., 2002), came to Africa in the 16th century (Ugwu and Nweke 1996; Hillocks et al., 2002; Adeoti 2010; Ikeh et al., 2012) and spread in west Africa in the 20th century (Hillocks et al., 2002). It is said to be more productive within latitudes 15° north and south (DPP 2010) within which the entire Nigeria's territorial borders are located.

By production of more than 59 million tonnes in 2019 (FAOSTAT 2021), cassava is the largest crop in Nigeria by production quantity. It is also the most important food crop by value and significant part of the produce is consumed locally (Asante-Pock 2013), about 90% (Agboola and Agboola 2011). Apart from its ability to support non-stop factory operation as a non-seasonal crop (Ohimain 2012), cassava roots can be stored in the ground for months (FAO and IFAD 2005). The crop is comparatively more resistant to drought, pest and diseases, as well as more tolerant to low soil fertility (FAO and IFAD 2005). These comparative advantages might form some of the reasons why Nigerian Biofuel Project considered cassava as one of the feedstock sources (Adeoti 2010; Agboola and Agboola 2011; Ogundari et al., 2012; Ohimain 2012; Ogbonna and Okoli 2013; Dick 2014; Anyanwu et al., 2015; Ozoegwu et al., 2017).

There were efforts in Nigeria to breed cassava for high yield, pest and diseases resistance, early maturity and good product quality (FAO and IFAD 2005). It was reported that the rate of adoption of improved cassava varieties among farmers is about 60% at country level and the major varietal traits preferred by about 70% of the farmers were high quality *garri* (a form of coarse grain flour), high root yield, big root size, high market demand and early maturity (Wossen et al., 2017).

In Africa, many cassava varieties exist but the crop is generally classified into Bitter and Sweet cassava (DPP 2010; Wangpor et al., 2017). The hydrocyanic content which determines the bitterness is not stable; it may depend on the environmental conditions because a sweet variety from certain zone may become Bitter variety in another (CIAT 1984). Generally, cultivars with <100 mg Kg^{-1} of fresh weight are classified as 'sweet', while those with 100 – 500 mg Kg^{-1} are classified as 'bitter' (Hillocks et al., 2002). Through research, many cassava varieties were developed and are available for cultivation in Nigeria (Anyanwu et al., 2015). The number of Nigerian cassava accessions (collated cultivars) held by the Centro Internacional de Agricultura Tropica (CIAT, Colombia), National Root Crops Research Institute (NRCRI, Nigeria) and the International Institute of Tropical Agriculture (IITA, Nigeria) were put at 19, 435 and 2861, respectively (Hillocks et al., 2002). With the latest update in July, 2021, data view on the Genesys of the IITA website, showed that there are almost 4,000 accessions of cassava (*Manihot Esculenta*) in Nigeria (IITA 2021).

2.2.2 Biodiesel crops

2.2.2.1 Oil palm

Though there are divergent views as to where oil palm originated, a majority of opinions support the claim that it originated from West Africa, specifically from Nigeria (Panapanaan et al., 2009; Elbassam 2010; Lai et al., 2012; Corley and Tinker 2016). One of the evidences to this view was the presence of fossil pollen similar or identical to that of African Oil palm (*E. guineensis*) in Miocene strata dating back to 15 million years BP (Before Present: 1950 when the calibration curve was established for radiocarbon dating). Though the main concentrated zone lies between 3˚N and 7˚S, the distribution of African Oil palm occurs within the African continent from 16˚N in Senegal to 15˚S in Congo to as far south as 21˚S on the west coast of Madagascar (Lai et al., 2012; Corley and Tinker 2016).

Oil palm (figure 2.5) is generally classified in to three – *Dura, Tenera and Pisifera* (Lai et al., 2012). *Dura* has thin mesocarp, thick endocarp (shell) and generally large kernels. *Tenera* has thick mesocarp, thin endocarp and reasonably sized kernels. While *Pisifera* is shell-less (does not have endocarp) but has thick mesocarp with very little oil content and small kernels. Due to their more flavour characteristics and better fluid properties, *Dura* types have consumers' preference over *Tenera* and thus are favoured in palm groves (Lai et al., 2012).

Figure 2.5: Oil palm nurseries (NIFOR, Benin) Source: Field work

Palm groves have long played significant role in the economy of the West Africa region, initially for domestic market, then export with European merchants from the 16th century and by 19th century, the trade substituted the slave trade (Lai et al., 2012). Some of the initial uses include the use of palm oil for cooking, tapping palm for palm wine, medicinal purposes, the use of fronds for thatching and fencing and harvesting edible palm hearts. The exported oil was also initially used in industrial manufacture of such goods as soap and candles as well as antioxidants. It was estimated that 80%, 19% and 1% are the global use of palm oil for food, oleochemicals and biofuels, respectively though it seemed to be attractive option for meeting global biodiesel demand, the influence of which is believed will contribute to doubling the oil palm production by 2030 (Bicalho et al., 2016). The crop is used as a source of feedstock for biodiesel production, not only for agricultural machinery but for road transportation.

Oil palm is said to be the crop with highest potential for biodiesel production globally (Castiblanco et al., 2013). The crop is said to give 3 to 8 more oil ha^{-1} than the traditional oil crops such as groundnut and soybeans, and although its commercial yields are said to decrease after 30 years of age, the crop can live up to 200 years (Verheye 2010; Wahid et al., 2015). It supplies 20% of the world's vegetable oils (Tao et al., 2018). Oil palm is believed to provide higher potentials for providing hedges against the volatile conventional oil prices (Hayyan et al., 2014a) and considered to be highly efficient in terms of oil production and energy balance because the fruit yields range from 10 to 30 tonnes ha^{-1} depending on location and agricultural practices (NaanDanJain 2013). Thus, biodiesel is believed to have the potential to become the largest component of growth in vegetable oils as seen in 2004 when the EU became second largest importer of palm oil, almost exclusively due its use as fuel, though largely for electricity generation (Panapanaan et al., 2009). For these and other reasons it is likely that the crop is attractive and appropriate for biodiesel production in Nigeria.

2.2.2.2 Jatropha

Jatropha (figure 2.6) is a drought resistant perennial (2 to 3 years gestation period) crop that can be grown on lands with limited water supply and has a productive life of 40 to 50 years (Elbehri et al., 2013; Laviola et al., 2017). The crop is said to start bearing fruit within 9 months and reach commercial productivity within 3 years (Islam et al., 2011). While some scholars believe that the crop originate from South/central America (Orwa et al., 2009; Achten et al., 2014), others opined that it could have its provenance in Gondwanaland, but most of them held that the crop was spread by the Portuguese Seafarers to Africa and Asia (ETB 2007; Grass 2009; Jimu et al., 2009). The distribution of the crop is said to be highly successful in the tropics, it is adapted to arid and semi-arid areas as well as seasonally dry areas such as grassland-savannah, thorn forest scrub and it is very tolerant and thrives under wide range of climatic and edaphic conditions (Orwa et al., 2009).

Figure 2.6: Jatropha Plantation (IAR, Zaria) Source: Field Work

That jatropha will not produce good yields in poor soils is a fact that cannot be denied (JA 2009) but the crop can help improve soil condition and the yields can increase after few years of establishment. Due to its inherent toxicity for many species, jatropha may have little issues with pests and diseases (FF 2006), but when cultivated in higher densities the situation changes, though the diseases and pests are less detrimental and are of low economic importance (JA 2009).

With a comparatively short gestation period and with a 42% potential oil, the crop forms a good source for biodiesel (Deeb n. d.) though, some scholars claim that it could best be used profitably for indigenous production of cosmetics, particularly soap (Warra 2012). Pure plant oils (PPOs) can also be used in agriculture to power irrigation pumps and generators (Achten et al., 2007). This makes this segment of energy use to be carbon neutral because any emissions from plant oil is from biogenic, unlike from fossils which are considered to be anthropogenic (Somorin and Kolios 2017).

These comparative advantages make jatropha attractive to be identified as appropriate crop for biodiesel in the world. Jatropha found in Nigeria are of the wild species (Yammama 2009), but compared to other woody species, the crop is said to be suitable for quick and efficient domestication (Achten et al., 2014). The crop is recommended as a good feedstock for biodiesel production in Nigeria (Aransiola et al., 2012a), tropical and subtropical developing countries (Thapa et al., 2018) and in the southern Italian region of Calabria (De Rossi et al., 2016). However, the positive characteristics that lead to promotion of the crop may not necessarily be attributable to all the accessions (Jongschaap et al., 2007).

Jatropha is said to be cross-pollinated and has significant genetic variability in many characters (Pandey et al., 2012) though, low level of variation was observed in landraces from several African countries and elsewhere in the world (Achten et al., 2014; Ribeiro et al., 2017). Thus, selecting genotypes with wider environmental adaptation may be more promising (Montes and Melchinger 2016) because estimated oil content were found to be dependent on phenotypic variation and site of the candidate trees (Achten et al., 2014) as well as several other important traits (Laviola et al., 2017).

Land requirement, whether for food-based or biofuel-based crop production, needs optimisation to maximize productivity and minimize negative impacts. Crucial consideration would, therefore, be ecological requirement of the crop and appropriately improved varieties. While this section had touched on the varietal diversities of the crops, the following section explored the ecological requirements of the crops.

2.3 Ecological requirements

2.3.1 Introduction

After examining the biofuel crops in the previous section, this section explores the literature to collate information regarding the crops' ecological requirements. Ecology in this context refers to climatic elements (rainfall, relative humidity, insolation, temperature and length of daylight), edaphic factors (soil and soil pH) and geomorphological variables (elevation, slope and aspect). Every crop has its ecological requirements for optimum growth and development. In other words, environmental characteristics play varying degree of roles at different phases of plants' growth from germination to maturity (gestations) and these vary from crop to crop. Though some of the biofuel crops may have certain degrees of adaptability to varied ecology, their productivity could be maximised by optimising the environmental parameters that are ideal for the crops. Losses could also be minimised in similar ways. Optimising the criteria entails maximising benefits or minimising losses for a specific land use (Beek and KJ 1978).

The following subsections present biofuel crops' requirements for these ecological parameters. In addition, the extent to which freight transport plays great role in determining the cost and the CO_2 savings of biofuel suggests that land transport modes (rail and road) be factored in this spatial optimisation. Presence and sufficiency of transport system are important factors to be considered (FAO 2007). Settlements also offer such services as labour supply, indicating the need for their proximity to feedstock production sites. Some crops at certain locations may require irrigation. Thus, the proximity of the cultivation sites to surface water bodies would be crucial in this case.

2.3.2 Aspect

Aspect (orientation of the slope) plays important role in microclimate of a site. Thus, its effect is indirect and may not always differ on its influence from crop to crop. However, crops with higher solar radiation favourability may prefer slope orientations that do receive higher insolation. In the northern hemisphere, south facing slopes may receive six times more solar radiation than north facing slopes (Auslander et al., 2003). Nigeria lies in the northern hemisphere (4°N to 14°N), south facing slopes might generally be expected to receive higher insolation than north facing slopes though, some exceptions may occur due to local microhabitat or local deviations from general landscape pattern.

2.3.3 Elevation

Incident sunlight increases with altitude, thus for many hours of the day at high altitudes, solar radiation may be well above saturation level for photosynthesis of C_3 plants but providing greater photosynthetic opportunities for C_4 plants like sweet sorghum (Gale 2004). However, in most cases temperature decreases with altitude in the troposphere and when there is less than the average lapse rate of the ambient temperature, there could be a potential transpiration increase. Sorghum can be found at elevations ranging from mean sea level to 1,500 m, though cold tolerant varieties are grown at elevations between 1,600 and 2,500 m in Mexico (Srinivasa Rao et al., 2013). The altitude for growing sugarcane ranges from sea level to 1,000 m (Ridge 2013) or a little above 1000 m (Duong 2007).

Though highest cassava production is expected at tropical lowlands, below 150 m asl, varieties exist that can grow at altitudes above 1,500 m asl (DPP 2010; USDA n. d.), especially near the equator where it can be found at about 2000 m asl (CIAT 2011). But the crop grows better below 1,500 m (Kouakou et al., 2016). The altitude for the crop range from sea level to 2,300 m asl (Hillocks et al., 2002). However, the field should not be in low-lying and flood-prone areas (DPP 2010). A research in Nigeria and Tanzania – the largest cassava producers in Africa – linked altitude with cyanogenic compound in the crop (Oluwole et al., 2007). The mean levels were found to be 162 mg HCN (hydrogen cyanide) $eqKg^{-1}$ for cassava planted on areas <100 m above sea level as compared to 70 mg HCN $eqKg^{-1}$ for those on areas >100 m above sea level. In Nigeria, a research found that only 2% of the sampled cassava fields lie 800 m asl and above, notwithstanding the sampling bias towards cassava producing areas (Ugwu and Nweke 1996).

Oil palms are found to be surviving at altitudes as high as 1,700 m asl though, the densest, semi-natural populations are generally confined at or below 500 m asl (Elbassam 2010; Lai et al., 2012) and thrive best between 300 and 400 m asl (Verheye 2010; Corley and Tinker 2016). While the West African Oil palm belt was observed to be within 400 m asl, the drier East and Southeast Africa have occurrence of the crop only within 1,000 m asl near lakes or water courses with reasonable rainfall, but observed at 1,300 m asl on Mount Cameroon (Verheye 2010). Though Jatropha can be grown at any altitude (Laviola et al., 2017), the mainly recommended altitude is in the range of 0 to 500 m asl (Orwa et al., 2009; FAO 2010; Islam et al., 2011; Pandey et al., 2012; Vera Castillo et al., 2014) up to 1,200 m (Deeb n. d.) and 1,800 m (Achten et al., 2008; Martin and Gunter 2013) in some areas.

2.3.4 Insolation

Solar radiation is one of the crucial climate elements that influence plants growth and development (Campillo et al., 2012). The radiation intercepted by the plants brings the light energy for photosynthetic processes together with water and carbon dioxide. Radiation Use Efficiency (RUE) of sweet sorghum is high at about 1.3 to 1.7 g MJ^{-1} (Srinivasa Rao et al., 2013) and can remain fairly constant throughout the growing season (Ceotto et al., 2013). High light intensity promotes tillering in sugarcane and growth increases with insolation intensity of 18 to 36 MJm^{-2} (Duong 2007). Reduction of 78% insolation was found to significantly reduce tuber and leaf growth in younger cassava plants by 86% and 47%, respectively (Fukai et al., 1984). The researchers also found that 32% insolation reduction decreased crop growth rate by half of the control regardless of the crop growth stage.

For oil palm, the ideal solar radiation requirements is put at 15 MJm^{-2} per day (Stenek and Connell 2011; Corley and Tinker 2016). In Malaysia, a theoretical model was used to deduced that a radiation change from 6.23 to 5.69 $GJm^{-2}year^{-1}$ led to oil palm yields loss of 2.6 tonnes of Fresh Fruit Bunch (FFB) $ha^{-1}year^{-1}$ (Corley and Tinker 2016). Adult Jatropha leaves are said to adapt to high radiation intensities (Jongschaap et al., 2007) and are unsuited to growing under shade (FAO 2010).

2.3.5 Photoperiodism

The amounts of daylight and darkness in 24 hours daily cycle is called photoperiod and this influences plants growth and development depending on the plant type, time of the year and the location (Jackson 2009). Sweet sorghum is a short-day plant with 10 to 11 hours optimum photoperiod during flower initiation and a range of 10 to 14 hours (Turhollow et al., 2010; Srinivasa Rao et al., 2013). The number of days from sowing to panicle initiation (vegetative phase) in sorghum is affected by photoperiod and temperature (Ellis et al., 1997). Short days and cloudy days adversely affect sugarcane while high light intensity and longer days promote tillering. Growth increases with 10 to 14 daylight hours (Duong 2007).

Cassava roots development may not be limited by photoperiodism in the tropics as the day length in the region are very small, ranging from 10 to 12 hours. But experiments where day lengths were artificially adjusted shows that 12 hours may be optimal for the crop though, with probable varietal differences (Hillocks et al., 2002). Generally, shorter days promote storage roots development, while longer days promote growth of shoots and decrease storage roots development (Hillocks et al., 2002). Thus, more than 12 hours day light can cause low roots yield, while flowering is enhanced by short day periods (DPP 2010). Cassava needs large amounts of Sunshine with an optimum of 5 to 6 hours per day (Elbassam 2010; Corley and Tinker 2016).

Though oil palm is a typical of rainforest, it rarely regenerate under dense forest due to lack of sunshine (Verheye 2010). The crop is called light-loving crop with an ideal sunshine duration of at least 5 hour per day in all months and 7 hours per day in some months (Kee 1972; Verheye 2010; Stenek and Connell 2011; Corley and Tinker 2016). Yields are directly related to sunshine as 1,000 and 2,250 hrs per annum could give potential yields of 17.6 and 30 tonnes per year, respectively (Verheye 2010). Jatropha is reported to be not sensitive to day length (Orwa et al., 2009; FAO 2010).

2.3.6 Rainfall/water

Sweet sorghum can tolerate the two extremes of water stress – dry spells and water logging (Ahmad Dar et al., 2017). Under the former, it can resume growth at the receipt of water. And it can grow under flood conditions unlike maize that can die immediately. Unless the soil can hold much water, rainfall of 500 to 600 mm is best for sweet sorghum if ideally distributed across the growing season (Reddy et al., 2012). Though the crop can survive supply of less than 300 mm up to 100 days, it grows well in areas receiving rainfall of more than 700 mm and typically it needs between 500 and 1,000 mm to achieve good yields while optimum rainfall amounts range from 550 to 800 mm (Rao et al., 2009; Srinivasa Rao et al., 2013).

In the case of sugarcane fields, water requirements refers to the total amounts needed to successfully cultivate the crop and is usually met through rainfall, irrigation and groundwater where it is within the reach of the roots (Shrivastava et al., 2011). Where irrigation is not practiced (completely rain-fed), it requires a minimum of 1,500 mm (Verheye n. d.) or even 2,000 mm per year (NETAFIM 2014). Other different ranges were also found to span between 1,250 and 2,500 (Chandrasekaran et al., 2010) or 1,500 and 2,500 mm (Oleivera and Ramos 2015). Depending on climate condition and the crop's gestation period, sugarcane's seasonal water requirement ranges from 1,100 to 1,500 mm (Duong 2007) with daily evapotranspiration rate of 4 to 7 mm (NaanDanJain 2013). The crop requires a minimum of 600mm (ETB 2007).

Most sugarcane cropping systems in Sub-Saharan African countries rely on irrigation. In Nigeria, abrupt cessation of rainfall during the growing season hinders increased sugarcane production and thus necessitates irrigation (Ishaq and Olaoye 2009). In addition, efficient supply of water to the field is crucial to saving production costs. For sugarcane farm, bulk water supply usually costs 19% and 4% for total capital and operating expenditures, respectively (NETAFIM 2014). However, these vary depending on the distance of the water source from the field, type of the source (surface or underground) and the nature of the topography between the field and the source.

Cassava is a valuable crop in areas with rainfall uncertainties (availability and distribution) and can be grown in areas with as low rainfall as 500 mm and as high as 5,000 mm (DPP 2010; USDA n. d.). Though the crop is found in areas with rainfall amounts between <600 and >1,500 mm, adequate is considered to be between 1,000 and 2,000 mm per year (Hillocks et al., 2002). It grows better in regions with rainfall between 1,000 and 1,500 mm per year (Kouakou et al., 2016). Though the crop is drought tolerant with a two to three months dormancy period, it produces higher yields if it is regularly watered and the soil is not left completely dried (DPP 2010). An experiment in Nigeria shows that with 730 mm effective rainfall, rain-fed plots produced less than 5 tonnes ha^{-1}. While plots supplemented with 100% rainfall drip irrigation produced 28.1 tonnes ha^{-1} of roots yields (FAO 2013).

In another experiment, total water use of 1,491.57 and 1,701.13 mm were recorded for 100% available water cassava drip irrigation in the 2006/07 and 2007/08 cropping season, respectively. While 729.00 and 651.13 mm were recorded for 0% irrigation in the same seasons, respectively. The total dry matter obtained in the two seasons, respectively, were 49.12 and 37.62 tonnes ha^{-1} for 100% irrigation and 7.12 and 5.92 tonnes ha^{-1} for the 0% irrigation (Odubanjo et al., 2011). Available soil moisture, which is in most cases associated with precipitation, is said to influence the crop yields more than any other single factor (Aiyelari et al., 2002). Drier areas with 400 mm of rainfall were also reported to support cassava growth, but in Thailand, maximum roots yields were correlated with 1,700 mm during 4^{th} to 11^{th} months after planting (FAO 2013).

Rainfall or water availability seems to be the major climatic factor affecting the distribution of oil palm (Kee 1972; Lai et al., 2012; Corley and Tinker 2016). It was observed that the West African Oil palm belt is limited to 1,200 mm of rainfall per annum and an area around Accra, Ghana was also observed to have absence of oil palm estates due to what was described as low rainfall of 650 mm per annum (Verheye 2010). In addition, the crop cannot tolerate droughts longer than 3 months and the annual rainfall should be in the range of 1,500 to 3,000 mm per annum (Elbassam 2010).

Over 4,500 mm per annum was observed to support production on Mount Cameroon where the rains concentrate in the afternoon heavy downpours with enough sunlight hours in between (Verheye 2010). In areas of summer rainfall and winter drought where the crop is adapted, drought should not be more than 3 months (Verheye 2010) though this may not markedly reduce the crop's health but bunch production is reduced (Kee 1972). Rainfall regime is believed to influence mill activity where it can support continuous operation in areas without deficit, while in areas of irregular rainfall pattern, the mills are forced to slow down production in some parts of the year (Verheye 2010).

Together with soil, rainfall amounts and distribution are the major ecological factors limiting jatropha yields (Concenco et al., 2014). Optimum annual rainfall ranges from 1,000 to 1,500 mm (Jongschaap et al., 2007; Elbehri et al., 2013) though in some areas lower optimum amounts of 600 mm was given (Deeb n. d.). Though the crop is said to survive with annual rainfall of 400 mm, for production purposes it requires 900 to 1,200 mm (Maes et al., 2009; FAO 2010) evenly distributed within the year, otherwise irrigation would be needed (Grass 2009). Mean annual rainfall is in the range of 300 to 1,000 mm or more (Orwa et al., 2009) and the upper limit can reach up to 2,000 mm (CABI 2018) though it was found to occur naturally in areas with up to 3,121 mm (Achten et al., 2014) and above 4,000 mm (Jongschaap et al., 2007).

Jatropha can be found in areas with as low rainfall as 250 mm (Pandey et al., 2012) and can withstand up to two years of drought after which it grow again with rain, while 1,500 mm was reported under irrigation especially in the first year for proper establishment of the plant (Deeb n. d.). Its water consumption rate is put at 6 litres per week throughout the growing season (Giwa et al., 2018). This irrigation amounts was also reported in India to be the optimum and that under rainfall, oil content is better in the range of 600 to 1,300 mm (Kumar et al., 2011). However, irrigation is reported to be less meaningful both socially and financially after first 3 months and that the crop can survive 200 mm and grows well with 600 mm annual rainfall (JA 2009). But the plant is said to produce better annual seed yields with irrigation than without irrigation (Phiwngam et al., 2016).

2.3.7 Relative humidity

Relative humidity (RH) affects many physiological and morphological processes displayed by plants (Rodrigues et al., 2016) and this can be directly or indirectly. It reduces plant productivity when it is too much high (air is saturated) by reducing transpiration activities which aid translocation of nutrients in the plants. High humidity of >90% together with temperature range of 25 to 35˚C are favourable for infections and mold development (Reddy et al., 2012). When RH is too low, plants close stomatal openings to reduce water loss which results in less photosynthetic activity and thus, slowed growth. On the other hand, high humidity together with high temperature increases rate of organic matter decomposition (Peer 2010) which increases humus content and thus fertility of the soil. Rate of photosynthesis is accelerated by RH range of 75% – 85% though, this depends on the environmental changes (Rodrigues et al., 2016). On a trade-off note, high humidity is associated with unfavourable fungi development (Peer 2010; Rathore et al., 2015).

Relative humidity for Sweet sorghum ranges from 15% to 50% (Rao et al., 2009; Srinivasa Rao et al., 2013). Sugarcane is one of the C_4 crops that thrives in high humidity areas (Chandrasekaran et al., 2010). The most conducive relative humidity for grand growth range from 80 to 85% though, during ripening phase 45 to 65% is favourable together with limited water supply (Duong 2007). For proper growth, cassava requires a fair degree of relative humidity as it absorbs moisture from the unsaturated air layer like many other plants. According to Cock et al. (1985), leaf photosynthesis and air humidity were positively and significantly related though both misted and unmisted experimental fields were irrigated. The highest photosynthetic rate, which resulted in higher root yields, were observed when relative humidity was between 70% and 80% (El-Sharkawy 2007).

In a field experiment to examine the relationship between the increase in the height of cassava growth rates and agro-climatic parameters in Ilorin, Nigeria, the highest rate of increases in cassava plant growth was recorded in June when the relative humidity was 85% though, cassava flowering occurs at the beginning of dry season when the relative humidity falls below 70% (Yahaya et al., 2016). Field trials in Indonesia showed that relative humidity is partly positively associated with oil palm yields (Tao et al., 2017). Throughout the year, relative humidity should be above 75% (Verheye 2010). Preferably, It should be greater than 80% and 3 consecutive months of less than 50% may not be suitable for the crop due to stomatal opening restriction which highly reduce CO_2 intake (Stenek and Connell 2011).

Jatropha is said to be able to survive almost entirely with air humidity; without rainfall (ETB 2007). Its seeds germination may take less than 10 days if the RH is right and temperature is greater than 25˚C (Öhman 2011) and the higher the humidity, the faster the rooting (Peer 2010). High humidity created the special condition in Cape Verde which support growth of the crop in areas with only 250 mm rainfall (DB n. d.). Jatropha was planted in areas with an average daily RH ranging from 20% to 48% (Niu et al., 2012) and 30% to 80% (Sapeta et al., 2013). The crop growth was found to be higher under high RH (80%) condition compared to low RH (40%) condition irrespective of different treatments of sodium and potassium ions (Rodrigues et al., 2016). In a 12 weeks experiment on sowed jatropha seedlings during rainy season in Kano, Nigeria, the lowest RH recorded was about 45% and the highest was about 75% both of which were recorded in the shade experiment though, seedlings nurtured in the sun showed faster growth than those in the shade (Adamu et al., 2017).

2.3.8 Slope

Interacting processes across a typical soil catena influence plant growth and development at specific landscape positions and thus, the spatial and temporal variations of these processes need to be understood to optimise crop placements at the fields scale (Thelemann et al., 2010). Soil loss increases with slope gradient up to 40% at which point it decreases with slope gradient up to 50% (Kapolka and Dollhopf 2010). In Indonesia, slope that are <8% are suitable for sweet sorghum (Nurjaya et al., 2013). Gentle to moderate slopes are suitable for sugarcane cultivation though, smaller plantations may occupy marginal slopes depending on rainfall/water availability (James 2004). However, sheet and gully erosions are frequent in areas of torrential rainfall especially with steeper slopes.

Sugarcane is usually cultivated in rows, the typical gradient of which is rarely steeper than 2.0 to 2.5%, except on very short rows (James 2004). Furrow irrigation system is said to be suitable for land surfaces with less than 3% slopes (Qureshi et al., 2001). Difficulty might be experienced on slopes greater than 12.0% with higher soil erosion potential (Ridge 2013). Cassava was reported to have been cultivated on slopes as high as 35% and 85% at some extreme in Southern Mindanao, Philippines. However, massive soil losses are associated with slope cultivation such that 1%, 5% and 15% slopes are said to cause soil loss to the tune of 3, 87 and 221 tonnes ha^{-1} per year, respectively (Proud and Viloria 2004). The recommendation was, therefore, that cassava cultivation should only be supported on flat fields and valley bottoms or where terraces ranging from 0% to 3% have been formed (Proud and Viloria 2004). Cassava field was also recommended not to have slopes higher than 8% and it was recommended to make the field across the slope or slightly inclined to the contours in order to minimize soil erosion (DPP 2010).

Oil palm fields should be flat (Stenek and Connell 2011) where possible or undulating because steep slopes increase soil erosion and costs of production (Verheye 2010). Paramanthan (2000) classified slopes into five categories based on its limiting effects on oil palm cultivation. These are non-limiting (0 to 4%), minor limitation (4 to 12%), moderate limitation (12 to 23%), serious limitation (23 to 38%) and very severe limitation (>38%). The best slopes for the crop are those less than 23% (Corley and Tinker 2016). It was also reported that the crop can be grown on slopes with 38% inclination, but extensive areas should not have slopes greater than 29% to avoid excessive management costs, harvesting problems and extensive erosion (Kee 1972).

Slope is one of the physical factors affecting the adoption of jatropha in Nigeria (Mas'ud 2016). Though the crop can grow on sloping lands (Deeb n. d.), intercropping with crops that help soil conservation was recommended on sloping fields to further reduce rate of erosion (Phiwngam et al., 2016) and/or the rows should be along the contours to minimize erosion (Peer 2010). On the other hand, where the soil is heavy, sloping field is desired to increase drainage (Peer 2010). But it is recommended that slope should not exceed

30% (Borman 2011). An analysis in China classified slopes for jatropha into 3 – less than or equal to 15˚ (26.8%) as suitable, 15˚ to 25˚ as moderate and above 25˚ (55.55%) as unsuitable (Wu et al., 2009), above which was excluded in another research in the same country (Zhuang et al., 2011). Optimal slope is given as 3˚ (7%) to 10˚ (22%) (Borman 2011).

2.3.9 Soil

Soil is the medium for plant root development, nutrients and moisture supply and as the support for the stem/stalk erection. Soils vary spatially (vertically and horizontally) and the effects of these variation on different land uses are well appreciated (Olaniyan and Ogunkunle 2007). In 1991, Nigeria's Federal Department of Agricultural Land Resources (FDALR) identified five orders of the USDA's soil taxonomy from the country's soil system (Essoka and Essoka 2014). These are Alfisols, Inceptisols, Vertisols, Ultisols and Entisols. Among these, the best soils for sorghum are said to be Alfisols (red) or Vertisols (black clay loamy) with 6.5 to 7.5 pH, organic matter >0.6%, depth >80 cm, bulk density <1.4 gcc (gram per cubic centimetre) and water holding capacity >50% field capacity (Rao et al., 2009).

Sugarcane can successfully be grown on diverse soils (Elbehri et al., 2013; Ridge 2013), ranging from sandy to clay-loams and heavy clays (Duong 2007) and therefore, does not require any specific soil types. However, the crop grows well on good soils with relatively less management requirements but not on poor soils where higher conservation and management practices are necessary (Meyer et al., 2011). This is because sugarcane is a heavy nutrients consumer (NaanDanJain 2013), thus soil replenishment may be needed to maintain sugarcane productivity. In Nigeria, sugarcane varieties cultivated on vertisols comparatively presented higher yields than those cultivated on alluvial soils (Kawuyo and Wada 2004).

Though cassava does not have much requirements for soil, its yields depend to some extent on soil condition (FAO 2013). The crop gives good yields on loamy soils with medium soil fertility and good drainage, but grows poorly on waterlogged, clayey and stony soils which should be avoided (Abass et al., 2014; Kouakou et al., 2016; Adekunle et al., n. d.). On heavy soils, cassava can be killed by one day waterlogging (CIAT 2011). It is frequently cultivated on leached oxisols, ultisols and alfisols as well as some patches of inceptisols and entisols (CIAT 2011). Well drained, deep, loamy soils were recommended for cassava in Nigeria though, if loamy is not available, sandy and clayey soil must be appropriately managed (ICS-Nigeria and IITA n. d.). On very rich soils, cassava may produce leaves and stems at the expense of tubers (DPP 2010).

Oil palm requires deep soils and especially at juvenile stage. The crop cannot withstand permanent flooding but can thrive well in areas of fluctuating water table and lateral flow and these areas are found to be amongst high yielding (Elbassam 2010; Verheye 2010; Lai et al., 2012; Corley and Tinker 2016). For best planting, soil is described to be flat, deep, uncompacted alluvial clay with high and balanced nutrient elements (Stenek and Connell 2011). Though Olivin (1986) gave five grading levels for soils suitable for oil palm cultivation, he generally described its good soil as having little gravel, reasonable drainage with enough exchangeable cations and good level of organic matter (Corley and Tinker 2016). Some of the soil types reported to be unfit for oil palm are saline, poorly drained, acid sulphate, leached, deep sandy, volcanic ash, lateritic and highly sloppy or hilly soils (Kee 1972; Corley and Tinker 2016). Physical soil properties such as depth, texture and structure largely determine the suitability of soil for oil palm production (Kee 1972) with structure and soil moisture said to be more important than nutrients as far as the crop is concerned (Verheye 2010).

Jatropha is reported to tolerate free or impeded drainage, alkaline or neutral reactions, light or medium texture and possess some special tolerances for infertile, saline, shallow and sodic soils (CABI 2018). Though jatropha has less rigid requirements for soil, seed yields of 2 to 5 tonnes ha^{-1} per year were believed to be attained on fertile soils and high inputs as compared to 1 to 2.5 tonnes ha^{-1} per year on degraded lands and low inputs amounts (Elbehri et al., 2013). Thus the plant can only provide commercially viable yields if sufficient amounts of nutrients are available (Wahl et al., 2012). Soil of the optimum areas should be free-draining sands and loams with no risk of waterlogging (Orwa et al., 2009; FAO 2010; Elbehri et al., 2013; Deeb n. d.). Because sandy soils are usually poor in nutrients, sandy clay loams was given as the best soil texture for jatropha (Rashad 2013). In India, jatropha withstand very poor soils and saline conditions and its highest oil contents were found to be obtained in sandy, well drained soils (Kumar et al., 2011). Heavy soils restrict roots development (Orwa et al., 2009).

2.3.10 Soil pH

Soil pH influences solubility of many nutrients where acidic increases solubility while basic increases insolubility (Peer 2010). This, therefore, affects the availability of nutrients to plants and the rate at which the plants take up the nutrients. Hayward and Berstein (1958), reported that sweet sorghum can tolerate pH levels of 5.5 to 8.5 (Elbassam 2010). Suitable soil pH for sugarcane ranges from 5.0 to 8.5, though the optimum hovers around 6.5 (NaanDanJain 2013). It was reported that there are varieties that can tolerate pH levels as low as 4.2 and as high as 8.6 (James 2004). Cassava yields are usually not affected by low soil pH until it reaches below 4.2 (FAO 2013) and can tolerate wide range of 4 to 8 pH (USDA n. d.). However, Islam (1979), reported that cassava had optimum growth at pH 5.5 to 7.0 but top growth declined markedly above 7.5 to 8.0 (CIAT 2011). If provided with correct fertilizers, oil palm can thrive at soil pH 4, but the optimum range between 5.5 to 7 (Elbassam 2010) or 5.6 to 6.0 (Stenek and Connell 2011). The maximum soil fertility for jatropha is said to be at pH range of 6.0 to 7.0 (Peer 2010). Wider ranges were given as 5.5 to 8.0 (Rashad 2013) and 6.0 to 8.0/8.5 (FAO 2010), not exceeding 9 and the crop might require addition of Calcium and Magnesium fertilizations on very acidic soils (Achten et al., 2008; Pandey et al., 2012).

2.3.11 Temperature

Temperature plays important role in plant growth and development. Plants differ in their cardinal, optimum, lethal minimum, lethal maximum as well as failure point temperatures (Luo 2011). Plants' resuscitation is possible within cardinal but not at lethal temperatures. Temperature is also shown to have promote or discourage pests and pathogen attacks on plants (Jiang et al., 2017). Sweet sorghum can tolerate temperature range of between 12˚ and 37˚C and with an optimum of 32˚ to 34˚C for growth and photosynthesis (Srinivasa Rao et al., 2013; Khawaja et al., 2014). The minimum ranges from 7˚ to 10˚C for germination and 15˚C for growth (El Bassam, 2010). However, planting should occur when the temperature reaches 18˚C at 5.1 to 10.2 cm depth (Turhollow et al., 2010).

The optimum temperature for sugarcane range from 26˚C to 32˚C (Chandrasekaran et al., 2010). Germination requires a base temperature of 12˚C (Duong 2007), it slows down below 18˚C and fails at temperatures below 11˚C though, varieties differ in their temperature sensitivities (Ridge 2013). The optimum for sprouting ranges from 28˚C to 30˚C and for tillering and grand growth, it hovers around 30˚C (Duong 2007). But germination of stem cuttings requires a range of 32˚C to 38˚C, while temperature above 38˚C reduces photosynthetic activity, increase transpiration and the spread of red not disease is higher. Bull (2000), reported that pathogens are more likely to cause the death of setts (cane cuttings) at temperatures below 18˚C. If the mean daily temperature falls below 24˚C, stalk elongation during grand growth phase could be affected but elongation rates increases as it climbs above (Ridge 2013).

Temperature is important to cassava such that all growth stops at 10˚C and requires warm humid climates where temperature averages between 25˚C and 29˚C (DPP 2010; Yahaya et al., 2016; USDA n. d.) or between 23˚C and 25˚C (Kouakou et al., 2016). Though it can tolerate 16˚C to 39˚C and photosynthesis reaches its maximum at 30°C to 40˚C, the crop’s behaviour indicates that its growth is favourable under mean annual temperatures ranging from 25˚C to 29˚C (Hillocks et al., 2002).

Oil palm yields are low in cool conditions and requires mean temperatures between 24˚C and 28˚C though, palms grown at high elevations or beyond latitudes 15˚ North and South may be growing with mean temperatures of less than 20˚C (Elbassam 2010; Corley and Tinker 2016). Growth of seedlings was found to be best at 25˚C in a controlled experiment and only 43% and 14% growth was recorded at 20˚C and 17.5˚C, respectively while at 15˚C growth is halted (Kee 1972; Verheye 2010; Stenek and Connell 2011; Corley and Tinker 2016). The ideal maximum temperature should rage between 29˚C and 33˚C, while the ideal minimum should be between 21˚C and 24˚C and the site should be devoid of extreme temperatures and wind (Kee 1972; Verheye 2010; Corley and Tinker 2016; Kamil and Omar 2016). Though it was reported that stomata begins to close at 32˚C, a couple of researches have shown that the optimum rate of photosynthesis occurs at 33˚C and can remain constant up to 38˚C provided stomatal closure did not occur due to difference in the leaf and air temperatures (Corley and Tinker 2016).

Optimum temperature for jatropha ranges from 20˚C to 28˚C (Orwa et al., 2009; FAO 2010; Elbehri et al., 2013). In an attempt to define jatropha climate in its area of natural occurrence as compared to that of its plantations sampled world-wide, 95% of the specimens were found to grew in areas with average minimum temperature of the coldest month above 10.5˚C and the mean annual temperature range was 19.3˚C to 27.2˚C though, 11% of the plantations were found in areas with minimum temperatures below 7˚C (Maes et al., 2009). It was also reported that mean annual temperature ranges between 11˚C and 28˚C (CABI 2018) or 25˚C to 35˚C (Thapa et al., 2018). A wider range of 15˚C to 40˚C was also reported and that the crop is altered more by lower temperatures than by altitude or length of daylight (Pandey et al., 2012).

2.3.12 Nearness to railways

The cost of feedstock haulage is said to be higher than the cost of transporting the products (Searcy et al., 2007). Thus, in-bound movement of feedstock to the processing refinery is a crucial consideration in biofuel production. As a variable in this context, nearness here refers to the closeness of the feedstock production sites to the railway lines. Railways are said to be capable of boosting both market potential and utilisation of biomass because it offers less energy use and less cost per tonne moved as compared to roads (Bonilla and Whittaker 2009). Depending on the nature of the research, spatial analysis for biofuel supply chain mostly assumes feedstock source or biorefinery to be within the shortest possible distance of railway lines (Ng et al., 2018) because it is budget friendly for long distances and moving bulk amounts (Aboytes-Ojeda et al., 2019).

Transportation by railways is suitable for haulage of large feedstock quantities in areas with railway networks (WBA 2018). However, for short distances, biomass transportation by rail is not cost effective due to its relative high fixed costs (Lin et al., 2016). The impact of the high fixed cost diminishes with distance, making this mode of transport ideal for long hauls (Searcy et al., 2007). Though the nearness between the transport network (rail and road) and the farm is based on Euclidean distance, the freight movement is assumed to be along the actual network. This improves the GIS modelling of the reality in planning feedstock movement from the farms to the processing plants (Mohd Idris et al., 2018).

2.3.13 Nearness to roads

As seen in the previous subsection, it is more cost effective to move feedstock or products on roads than railways within relatively shorter distances because of its high variable cost. Road transport is said to be the most important freight mode because it can provide within farm connectivity (in large farms), provides greater accessibility to farms and in most cases where railways are used, feedstock collated in farms must be brought by roads to the nearest railway station (Zandi Atashbar et al., 2018). Apart from distance, other items believed to influence freight movement are biomass moisture content, dry matter loss, bulk density, delivered energy content, drying rate, storage location and period, payload constraints, yields of the land, vehicle size and warehousing and spatial distribution of the biorefinery (Bonilla and Whittaker 2009).

In general, where pre-treatment technologies does not exist or are inefficient and the spatial distribution of the feedstock is dispersed, the local transport costs tend to be higher (Bravo et al., 2012). Thus, for individual processing facility, there is need for location-specific analysis through application of geospatial tools and transport road infrastructure (Golecha and Gan 2016). The network pattern may affect transport tortuosity factor which is the ratio of the actual Manhattan distance to the Euclidean distance (Voets et al., 2013). Local conditions of the road infrastructure may also influence emission due to freight. In Finland, a study that evaluated, among other things, the effect of road network condition on GHGs emissions of supplying biomass to Rovaniemi and Mikkeli found that the emissions were 31% larger in Rovaniemi supply chain than Mikkeli even though the transport distances were 22% larger. The researchers opined that this disproportionate emission was due to the quality and density of the road network which is poorer in Rovaniemi than in the Mikkeli region (Jäppinen et al., 2011). Therefore, optimising logistics over roads network plays significant role in biofuel production and making the business more efficient and profitable (Alam et al., 2012)

2.3.14 Nearness to settlements

Because the processing facilities would need to be sited as much near to the settlements as possible, the feedstock cultivation site would need to be as much close to the settlements as possible to minimise haulage costs and carbon footprints as seen in the two previous subsections. Human settlements are said to only be rationally planned if done within the framework of good understanding of the potentialities of the surrounding region, not only for managing population flow, but also designing its economic role, particularly siting industries and residential areas which not only satisfy economic requirements but also minimise environmental disruption (Ramachandran 1980). In fact, it is said that settlements' sustainability has economic dimension which if failed, social, historical and environmental dimensions would need governance arrangements to lead to revitalisation and continued use (Minnery 2012). Developed countries like UK have long realised the benefits of boosting growth through nurturing clusters and connectivity across cities and their vicinities to make them capable of developing and attracting successful businesses (BEIS 2017).

It is believed that as a general guideline, processing facilities placed in remote areas would have 10% higher operating costs than those sited near populated areas due to such reasons as accessibility, labour and need for higher salaries to attract workers to remote areas (Searcy et al., 2007). The same could also be said for the farms that produce the feedstock for the processing facilities. Farms are characterised with economic activities and thus requires labour supply and other services. According to King (2020 ed.), the benefits of placing economic activities within and around cities are highlighted under capitalism and even in countries where this system of economy is denounced, cities remained the leading hubs for economic activities. Economists refers to this as agglomeration economics, comprising such benefits as being close to suppliers or markets, mutual relations with other industries, easier access to such services as banking, insurance, utilities and enjoying access to labour, market and other amenities (King 2020).

2.3.15 Nearness to surface water

Water is not usually available at the sites where and the time when it is most needed (Winter et al., 1998). Surface water bodies are highly significant in crop cultivation especially for the crops that require irrigation such as sugarcane for improved productivity (Sultana and Kumar 2012). Section 2.3.6 had discussed extensively the water requirements of the biofuel crops. Realisation of this importance led to the suggestion in the UK that in places without surface water bodies, systems should be installed to harvest and store the increased winter rainfall to balance farms summer supply and demand (Benn 2008). This could be applied to Nigeria where the heavy downpours during the peak of the rainy season could be captured to balance dry season shortages. Where surface water exists, such as rivers and lakes, they provide important source of water for human life and industrial purpose (Jiang et al., 2020). Apart from irrigation, which is one of the main human uses, surface water could provide a means of freight movement and power generation (Munagala 2017). Though there may be possibility of drawing water from underground, only proximity to surface water bodies is factored in this work due to complexity that may ensue if underground water is considered considering the spatial scope of the study area (Morato et al., 2019).

2.3.16 Summary

This chapter covered two important topics; overview on the selected crops in Nigeria showing some of their advantages over others as biofuel crops and some detailed information on the requirements of the crops showing how important these requirements may be for their growth and development as well as some reference to the ideal values for these requirements. Table 2.1 shows some of the optimal values for the crops. This list of 14 requirements for siting a feedstock cultivating farm though not exhaustive, provides strong basis for almost all the spatial variables that need to be considered for this purpose.

Looking at what the literature suggests as the optimum requirement (considered in this work as most suitable), it is obvious the crops differ in terms of favourability for these environmental variables. While some favour higher values of the data range, others favour lower values. For example, while sweet sorghum is favoured best by rainfall of 500 to 1000 mm per annum, oil palm is favoured best by a range of 1800 to 2500 mm. Some crops have narrower range of optimal requirement than others. For example, while sugarcane requires an optimal soil pH of 6.5, what is optimal soil pH for jatropha range from 6.0 to 8.0. Sweet sorghum has the narrowest range of optimal temperature, while jatropha has the widest range. Cassava has the narrowest range of optimal elevation, while sweet sorghum has the widest.

This variability in environmental requirements confirm the statement in section 1.6 that biofuels (which are crop – based in this research context), vary in their favourability profiles and these fine details need to be captured in order to provide meaningful analysis that can serve as a useful support for spatial decisions. It is not obvious from the literature cited in this chapter for the proximity variables (nearness to water, settlements, roads and rails) whether they are more important for some crops than others. This suggests the need for incorporating expert knowledge to determine this. Except for surface water, under which sugarcane was mentioned due to its often requirement for irrigation, these geographical entities (proximity variables) are generally important for all the crops. Next chapter deals with creating the criteria maps and analysing the criteria weights, generating information regarding the importance of each criterion for a crop relative to other criteria. A discussion about comparing the crops in terms of these variables is added in subsection 3.4.5 based on the expert judgement.

One very important aspect not considered in this list is the energy supply. Powering on-farm operations such as irrigation, planting, harvesting or ploughing usually uses liquid fuels most of which come from fossil fuels in Nigeria (Mkpadi 1987). This would offset some emission savings that could be realised from deploying biofuels. Potential energy alternative sources for rural agriculture were identified in the country as biomass, wind, solar, and small hydropower (Onyema 2010). Other operations such as on-farm storage may be powered with electricity from the grid which might be generated from hydro or natural gas sources. However, with gross inadequacy of electricity supply in Nigeria (Ezennaya et al., 2014), and to ensure at least emission neutrality of biofuels, powering feedstock production would be more appropriate if it is based on decentralised, renewable-source-based energy system which was shown to offer considerable advantages over the conventional grid system in terms of such benefits as protecting the environment, cleaner economy, energy efficiency, security and reliability (Oyedepo et al., 2018). Thus, the assumption here is that powering farm operations would be from off-grid, renewable-source-based system such as biomass or solar panels. Also, because the existing NNPC petroleum depots are considered to be the potential biofuel processing sites, the depots are assumed to have an existing power connection.

Table 2.1: Summary of criteria and parameter values for the biofuel crops

Criteria	**Sweet sorghum**	**Sugarcane**	**Cassava**	**Oil palm**	**Jatropha**
Water/Rainfall (mm)	500 – 1,000 (Rao et al., 2009; Reddy et al., 2012; Srinivasa Rao et al., 2013)	1,500 (Chandrasekaran et al., 2010; Oleivera and Ramos 2015)	1,000 – 2,000 (Hillocks et al., 2002; Odubanjo et al., 2011; Kouakou et al., 2016)	1,800 – 2,500 (Kee 1972; Verheye 2010; Stenek and Connell 2011; Corley and Tinker 2016; Kamil and Omar 2016)	600 – 1,500 (Jongschaap et al., 2007; JA 2009; Elbehri et al., 2013; Deeb n. d.)
Soil (Type)	Vertisols, Alfisols (Rao et al., 2009)	Vertisols (Kawuyo and Wada 2004; Ridge 2013)	Loamy Soils (Abass et al., 2014; Kouakou et al., 2016; Adekunle et al., n. d.)	Deep, Alluvial Clays (Elbassam 2010; Verheye 2010; Stenek and Connell 2011; Lai et al., 2012; Corley and Tinker 2016)	Free drained sandy clay loams (Orwa et al., 2009; FAO 2010; Elbehri et al., 2013; Deeb n. d.)
Soil pH	6.5 – 7.5 (Rao et al., 2009)	6.5 (NaanDanJain 2013)	5.5 – 7.0 (CIAT 2011)	5.6 – 6.0 (Stenek and Connell 2011)	6.0 – 8.0 (Achten et al., 2008; FAO 2010; Peer 2010; Pandey et al., 2012)
Temperature (˚C)	32 – 34 (Srinivasa Rao et al., 2013; Khawaja et al., 2014)	26 – 32 (Duong 2007; Chandrasekaran et al., 2010)	23 – 29 (DPP 2010; Yahaya et al., 2016; USDA n. d.) (Hillocks et al., 2002;	25 – 32 (Kee 1972; Verheye 2010; Stenek and Connell 2011; Corley and Tinker 2016; Kamil and Omar 2016)	20 – 28 (Orwa et al., 2009; FAO 2010; Elbehri et al., 2013)

			Kouakou et al., 2016)		
Relative Humidity (%)	50 (Rao et al., 2009; Srinivasa Rao et al., 2013)	65 – 80 (Duong 2007)	70 – 85 (El-Sharkawy 2007)	75 – 85 (Stenek and Connell 2011; Tao et al., 2017)	75 – 85 (Rodrigues et al., 2016)
Elevation (m asl)	0 – 1500 (Srinivasa Rao et al., 2013)	< 1000 (Ridge 2013)	150 (DPP 2010; USDA n. d.)	300 – 500 (Elbassam 2010; Verheye 2010; Lai et al., 2012; Corley and Tinker 2016)	0 – 500 (Orwa et al., 2009; FAO 2010; Islam et al., 2011; Pandey et al., 2012; Vera Castillo et al., 2014)
Slope (%)	< 8 (Nurjaya et al., 2013)	< 2.5 (James 2004)	8 (DPP 2010)	0 – 4 (Corley and Tinker 2016)	7 – 22 (Borman 2011)
Aspect (Bearing)	$140^{\circ} – 230^{\circ}$	$140^{\circ} – 230^{\circ}$	$140^{\circ} – 230^{\circ}$	$140^{\circ} – 230^{\circ}$	$140^{\circ} – 230^{\circ}$
Surface water proximity (km) (Sultana and Kumar 2012)	0 – 5	0 – 5	0 – 5	0 – 5	0 – 5
Road proximity (km) (Zandi Atashbar et al., 2018)	0 – 5	0 – 5	0 – 5	0 – 5	0 – 5
Settlement proximity (km) (King 2020)	0 – 15	0 – 15	0 – 15	0 – 15	0 – 15

Chapter Three – Criteria Maps and Weights

3 Chapter Three – Criteria Maps and Weights

3.1 Introduction

An overview of the methodology was presented in section 1.9. The current chapter is dedicated to production of maps for the criteria identified in the previous chapter. These criteria maps will serve as the inputs for the models that follows in the subsequent chapter. This chapter also presents the details regarding implementation of the AHP that was briefly discussed in section 1.9.

3.2 Data identification and acquisition

3.2.1 Data identification

The local geography and infrastructure (roads, power, water) availability are crucial in determining biorefinery location together with other important factors such as labour and tax incentives (Efroymson et al., 2016; Sharma et al., 2017). Land available and suitable for this purpose is determined by ecological factors such as climate, topography, soil and water, and socio-economic factors such as labour, legal reserves, markets, investment and policies (Zhang et al., 2017). Relevant ecological requirements of biofuel crops were identified via literature investigation, as presented in the previous chapter. These requirements formed the criteria for the land suitability modelling. Once key criteria were identified, data on their distribution throughout Nigeria were gathered from different sources as described in the following subsections.

3.2.2 Data acquisition

Table 3.1 summarises the identified datasets to be used at this stage and the sources. 20 years of meteorological data (1993-2012) was procured in 2014 from Nigerian Meteorological Agency (NiMet) for the purpose of the MSc research project mentioned in section 1.7. The data includes rainfall, temperature and relative humidity. An attempt was made to update the data with an additional 4 years of data (2013-2016) from the NiMet. However, this was not possible due to prohibitive cost. Further, the dataset contained substantial errors as the weather stations are not spatially randomly distributed and there was insufficient number of samples (only 44 points for the whole Nigeria which is more than 900,000 km^2). This error is more apparent in the rainfall data. It was deemed necessary to explore other sources. This is because it is a common knowledge that rainfall and soil factors are the major ecological variables for plants growth and development, and this was proven as shown by the weights generated (table 3.4) in section 3.4.5. Also, there is wide spatial variation for annual rainfall in Nigeria with less than 500 mm in the north and around 3000 mm in the south, suggesting the need for using dataset that has lower levels of errors. Thus, *Gaisma* (Latvian word which means light used as the website name) data for rainfall, insolation and length of daylight were extracted. It is a global meteorological data sourced from the NASA Langley Research Centre (Atmospheric Science Data Centre - https://asdc.larc.nasa.gov/) and a published high resolution dataset of the surface climate over global land areas (New et al., 2002). The *Gaisma* data is scaled down to a number of spatially randomly distributed towns for each country (https://www.gaisma.com/en/dir/ng-country.html) and is obtained as point dataset (90 points for Nigeria). Temperature and Relative Humidity were sourced from the Nigerian Meteorological Agency (NiMet) as points dataset obtained from 44 meteorological stations spread across Nigeria.

Table 3.1: Data Description and Sources

S/N	Data	Description/Attribute	Source
1	Agro-meteorology1	Rainfall, Insolation and Sunshine Duration	Gaisma
2	Agro-meteorology2	Temperature Maximum and Relative Humidity	NiMet
3	DEM	Elevation, Slope and Aspect	USGS (SRTM)
4	Soil pH	Point Data	NPFS
5	Soil	Soil Map (categorical)	OSGoF
6	Water Bodies	Areas and lines	Open Street Map
7	Road Network	lines	Open Street Map
8	Rail Lines	lines	Open Street Map
9	National, States and LGAs Boundaries	Polygons	Open Street Map
10	Settlements	Points	Open Street Map

Shuttle Radar Topography Mission (SRTM) was downloaded from the US Geological Survey website (EarthExplorer) for elevation, slope and aspect datasets. It is the global elevation data freely available with relatively high spatial resolution (30m) and covering the whole Nigeria. SRTM is the most widespread used source of digital elevation models (DEMs) in geosciences (Chen et al., 2020). This wide spread acceptance of the data might be due to the mission's success in achieving its goal of an absolute vertical accuracy within 16 metres (with 90% confidence) based on ground validation through various studies using global positioning system (Mukul et al., 2015). There was a study that reported even much greater absolute vertical accuracy of 6.87 metres for the 30 metres SRTM elevation data (Elkhrachy 2018). In Lagos, Nigeria, the SRTM's absolute vertical accuracy was also found to be much higher than the reported SRTM specification (Olusina and Okolie 2018).

Soil map was obtained from the Office of the Surveyor General of the Federation (OSGoF). It was converted to raster on a 30 m spatial resolution. This was the same source from which the soil data obtained for the MSc work in 2014 was obtained. When compared, it seemed the current data is more detailed in terms of describing the soil categories. The soil data was obtained as shapefile with long categorical class description but did not come with any accompanying document. However, an online search revealed that the origin of the soil map was field survey by the Soil Survey Division of the Federal Department of Agricultural Land Resources (FDALR) based on which the map was produced at a scale of 1:1,000,000 (https://esdac.jrc.ec.europa.eu/ESDB_Archive/EuDASM/Africa/lists/y5_cng.htm) and published in 1990. Other alternative soil data sources sought were the FAO Harmonised World Soil Database (https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/) and the ISRIC World Soil Information (https://www.isric.org/explore/soilgrids).

While the former is based on 30 arc second raster, the later is based on 250 metres grid cells. The class description for both of these two dataset was considered more generic and would make it difficult to match with the description of favoured soils mined for each of the crops from the literature compared to the data used in the study. For example, a category description ‘deep, poorly drained soils; sandy clay loam to sandy clay subsoil’ is more detailed description than the term ‘acrisols’ and would be easier to be matched with the mined literature that sugest a favoured soil for a crop should be deep, free drained and loamy sand. Data on soil pH was obtained from the Office for the National Programme on Food Security (NPFS).

Other datsets were extracted from the OpenStreetMap (OSM) for surface water bodies, roads, railway lines, settlements and boundaries for local government areas (LGAs), states and national territories. As at the time of this work, there was no other source for these particular datasets available for use in this work than OSM. OSM emphasises local knowledge and the contributors use aerial imagery, GPS and low-technology field maps to verify that the product is accurate and up to date. Because of the frequency of the product update, it was made sure that the latest version of the product was downloaded as at the time of data preprocessing (November, 2019). Though it is a product of Volunteered Geographic Information (VGI), OSM was described as one of the most successful VGI-based mapping projects (Yuan et al., 2018). The quality of the product is continousely being improved since inception. OSM have been reported to have compared favourably with other sources of spatial data in terms of quality (Mooney and Minghini 2017). Also, the spatial resolution based on which the current analysis was conducted is 30 metres. Thus, the OSM data would be expected to be correct within this resolution. After six years of its launch starting in London, information from OSM was reported to be fairly accurate within about six metres of the position recorded by the UK’s Ordnance Survey Map (Haklay 2010). Though this may not be the same for Nigeria, we believe OSM would be useful for this work within 30 metres accuracy.

3.3 Data pre-processing

When combining maps of various spatial resolutions, the most coarse resolution must be adopted (Malczewski 1999). This is because resampling from fine resolution to coarse resolution is expected to be less in introducing errors than resampling from coarse to fine resolution. In this work, the satellite imagery acquired with coarser spatial resolution are SRTM, from which elevation, slope and aspect criteria were derived, and Landsat 8 (OLI), one of the two datasets with which land cover mapping was performed. Both were acquired with 30 metre spatial resolution. Though climate and soil data would be coarser than 30 metre spatial resolution from their origin, the two were obtained as points and categorical datasets, respectively. Both were rasterised to 30 metres spatial resolution, using the elevation dataset as the snap raster to match both datasets to the satellite imagery as described in Burrough and McDonnell (1998). Thus, the common spatial resolution adopted in this analysis is 30 metres. This implies that each of the map pixels represent an area of 900 square metres. This is about one-tenth of a hectare. On average, Nigeria's small family farmers own a half of a hectare of land (FAO 2018c). Thus, it is believed that the adopted spatial resolution is appropriate for this analysis since one of the fundamental objectives of the analysis is to identify lands suitable for cultivating the biofuel crops. This adopted spatial resolution would allow for within-farm area descrimination even within small holder farms.

Though it is generally understood that no data is perfect, the problem of spatial data quality is more pronounced in areas with relatively sparse spatial data. Because the study area (Nigeria) is one of the data-sparse areas of the world, balancing between data availability and quality is one of the challenges of conducting spatial analysis that aim to produce meaningful outputs. As presented in the following subsections, attempt was made to ensure each data is as much complete, accurate and precise as possible. Where available, selection was made of the data source that is believed to provide relatively closer representation of the real world (relatively better accuracy). For example, rainfall data was sourced from a global database because it provides higher amounts of sample points (90 random locations) and thus might have less accuracy problem by providing better representation of rainfall distribution for the study area than the NiMet data that is based on 44 sample locations. As mentioned in the previous paragraph, 30 metre spatial resolution was adopted for the analysis and this would allow for relatively higher precision in the datasets. For example, fine spatial resolution is expected to provide more precise spatial variation especially for variables with narrow data range such as soil pH. It is however noted here that based on the adopted spatial resolution, the research is being presented at a spatial precision higher than the spatial accuracy of some underlying spatial data such as the several climate and soil layers. This was due to the problem of trade-off between data availability and quality as mentioned earlier.

3.3.1 Pre-processing meteorological data

The data sample points from *Gaisma* were tested for spatial randomness (figure 3.1) and then interpolated to create raster dataset covering the whole country. Interpolation is the process for predicting the value of attributes at unsampled sites from measurements made at point locations within the same area or region (Burrough and McDonnell 1998). One of the situations in which interpolation is necessary is where the data measurements do not cover the entire domain of interest. It is thus applied to create a surface that covers the domain.

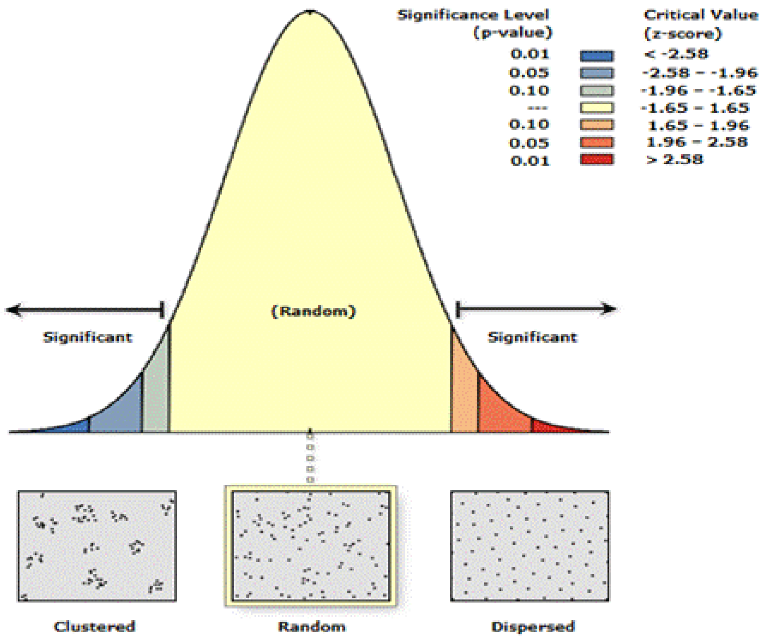


Figure 3.1: Assessing the Randomness of the GAISMA Data Points

The interpolation algorithm applied in this work was the IDW of the Geostatistical Analyst toolbox of the ArcMap. IDW is Inverse Distance Weighted tool that use certain number of sample points' values (known) to predict other (unknown) values based on the distances of the sampled points to the predicted point. The tool parameters used here were standard search neighbourhood, 3 minimum points, 5 maximum points and 4 sectors for ellipse shifting. Default was used for the other parameters such as power (2), major and minor semiaxis, angle (0) and weight (blank; computed from a function of distance between the selected neighbouring samples to the point being predicted).

The choice of low number of 3 to 5 values of known points and the default power of 2 is to make sure the interpolated values are more localised (closer to reality) and that the interpolated values are not excessively smoothed out. This created a continuous surface that looks smoothed (figure 3.5). However, the trend of the surface shows similar pattern to what was shown in figure 1.3 where study area was described. Rainfall in Nigeria progressively decreases from south to north. The surface was manually classified into 5 classes to improve visual understanding of the spatial distribution. It is obvious from figure 3.5 that the amounts of annual rainfall decrease progressively northwards. Though IDW always produces smoother surfaces than the underline reality, it seemed to produce the most natural looking surfaces but would require to be checked using a separate, independently sourced data set (Burrough and McDonnell 1998).

IDW method combines the idea of proximity and gradual change of the trend surface assuming that some unknown attribute value at a point is a distance weighted average of the values within a neighbourhood of the point. The problem of this method is lack of an in-built means of assessing the quality of the prediction which can only be done by taking extra samples (Burrough and McDonnell 1998). The method also restricts the prediction to the range of values of the sample points; if the sample do not capture the extreme highs and lows, those extreme values are smoothed. To assess the performance of the IDW tool and the data accuracy, a different set of rainfall data sample was obtained from International Water Management Institute (IWMI) and the two sample points datasets (figure 3.2) were correlated. The correlation showed almost perfect direct relationship (figure 3.3) though correlation is limited in the sense that it does not reflect the unit of measurement and is not useful where the relationship is non-linear. The same process was applied to Insolation (figure 3.5) and Length of Daylight (figure 3.5) datasets.

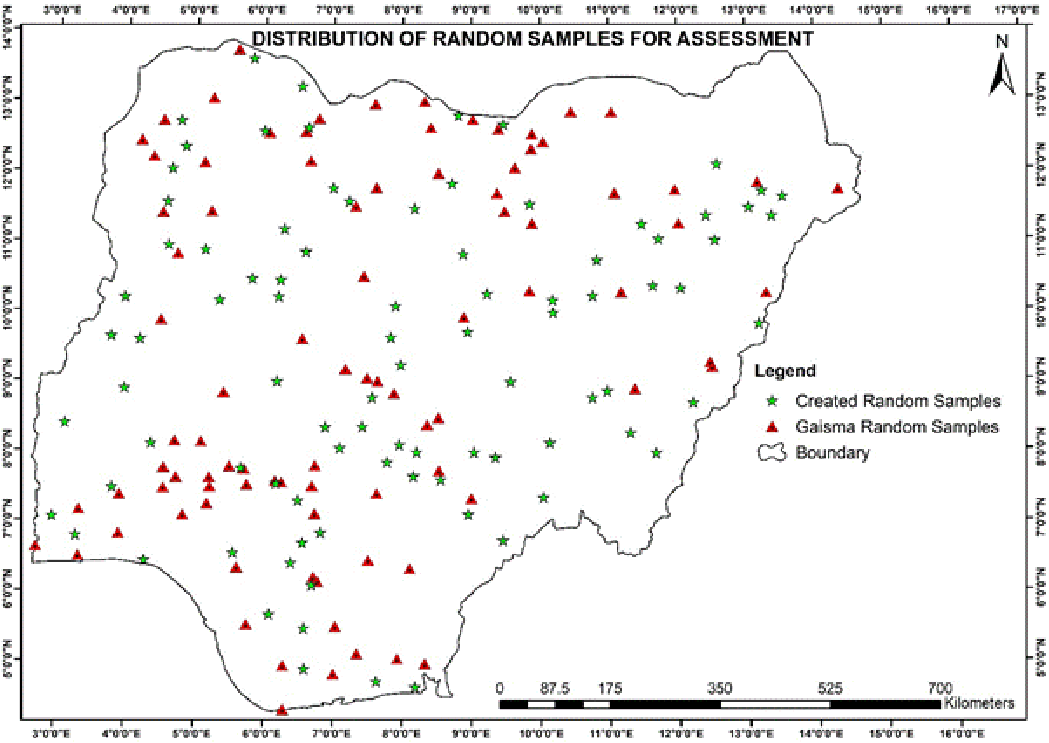


Figure 3.2: *Gaisma* random sample and the IWMI random sample for assessment of the IDW performance

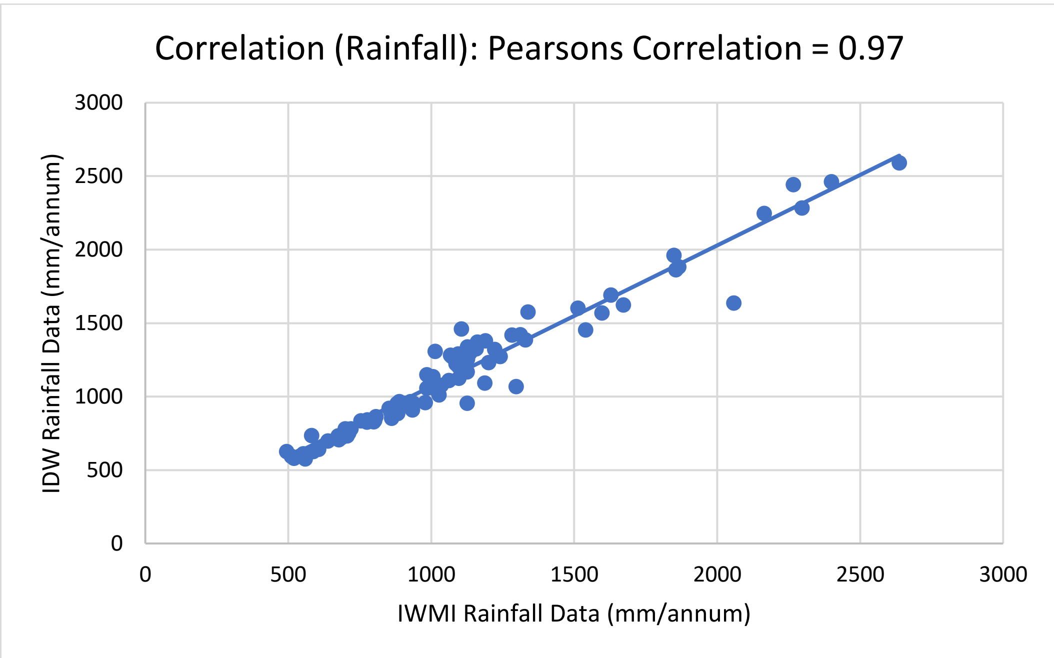


Figure 3.3: Correlation Between *Gaisma* and IWMI Datasets to Assess Performance of the IDW Tool

Insolation decreases progressively southwards. The actual sunshine hours are highly varied spatially and temporally though with small range (about 11.5 – about 12.5 hours). For the scope of this work that considered the whole country as study area, variations of minutes may be negligible and using a single date data may consist higher fallacy than using annual average. Thus, average daylight hours was used and it is about 12 hours throughout the country. It may be argued here that this criterion may not be needed to be included because there is no spatial variation as would be used in the model. However, as shown in subsection 3.4.5 (table 3.4), the weight of influence of this criterion is high compared to several other criteria for all the biofuel crops. This criterion weighed the third highest for sweet sorghum, the fourth highest for oil palm and the fifth highest for sugarcane, cassava and jatropha among the 14 criteria. Due to rank reversal problem (Malczewski 1999), all options must be considered because the preferred alternative may change with introduction of new predictor(s). In other words, because alternatives are directly or indirectly related to the decision criteria, inclusion or exclusion of a decision criteria would affect choice of the model for the best alternative. Since the whole country is assigned the same value for sunshine duration, the whole country therefore would be assigned the same suitability class for this particular predictor.

The data from NiMet was used to create rasters for Relative Humidity (figure 3.5) and Temperature Maximum (figure 3.5) using the same procedure as for the *Gaisma* data. However, the tool parameters used here are standard search neighbourhood, 2 minimum points, 3 maximum points and 4 sectors for ellipse shifting. Fewer search points were used for the NiMet samples because there were fewer sample points than in *Gaisma* data. Default was used for the other parameters. Relative humidity data from IWMI was correlated with the raster created from NiMet data also to check for accuracy and IDW performance. The correlation showed near perfect direct relation (figure 3.4).

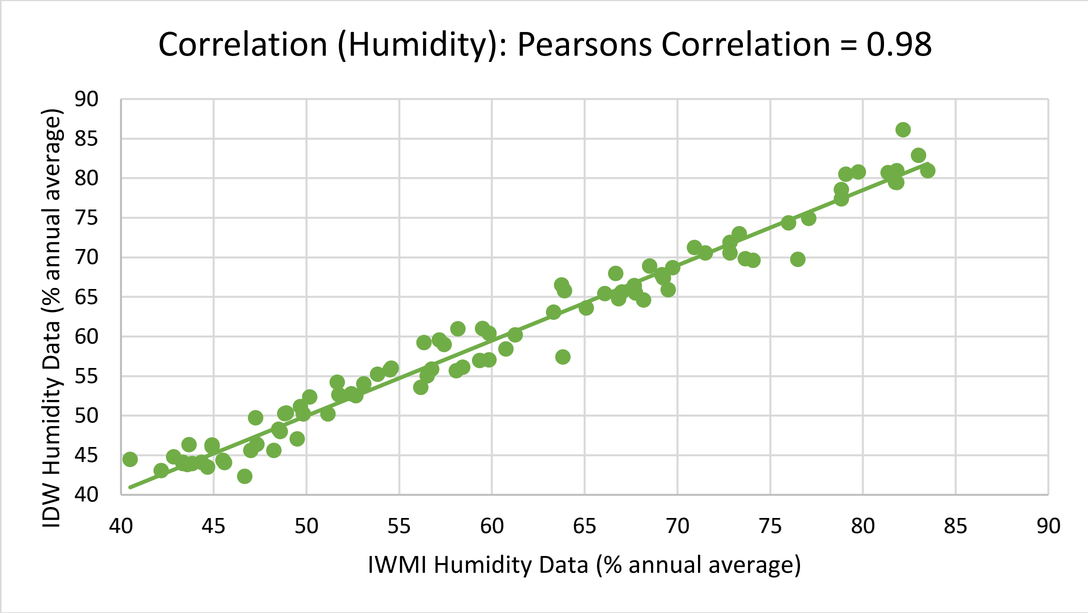


Figure 3.4: Correlation between NiMet and IWMI Datasets as a form of Accuracy Assessment

Though there was a record low temperature of 0°C on the northern hilltops, the average monthly temperature of the coldest month at the coldest location in Nigeria does not fall below 10°C. Thus, the prevailing minimum temperature in Nigeria does not extend to failure limit for all the biofuel crops considered in this work. In the doldrum, maximum temperature may exert more influence than minimum temperature, though at some high-altitude areas, the weather may prevail temperate characteristics. This is why only maximum temperature was used instead of both the maximum and minimum or the average of both. The same interpolation process was applied as above.

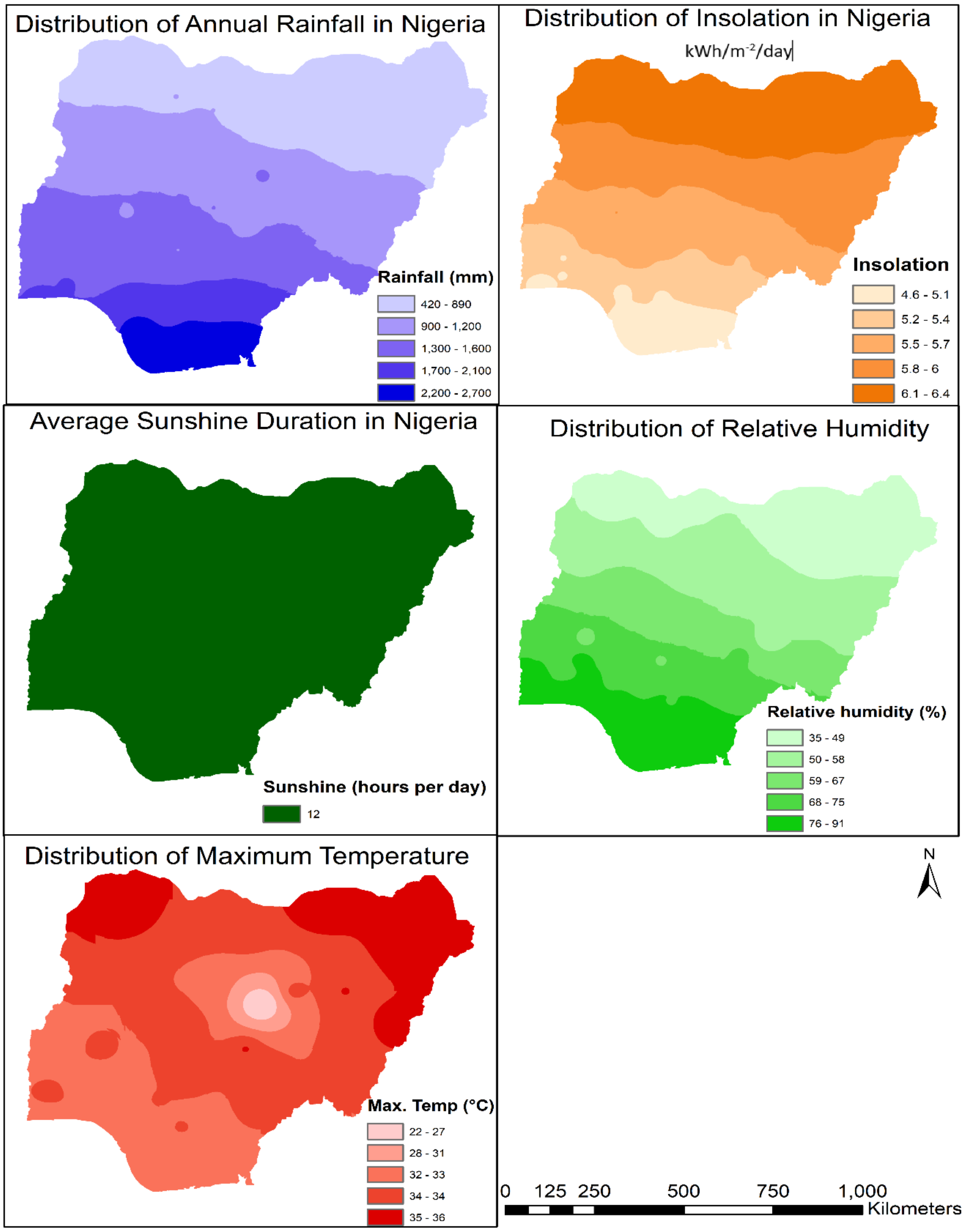


Figure 3.5: Pre-processed meteorological data

3.3.2 Pre-processing geomorphological data

Geomorphological data here refers to soil, soil pH, elevation, slope and aspect. Soil pH data was obtained as a point data in Excel format. It was thus tested for spatial randomness (figure 3.6) and then IDW algorithm was used to create raster covering the whole country (figure 3.7). There was not much pre-processing for the soil data (figure 3.7). The detail descriptions of the soil types are presented in appendix I.

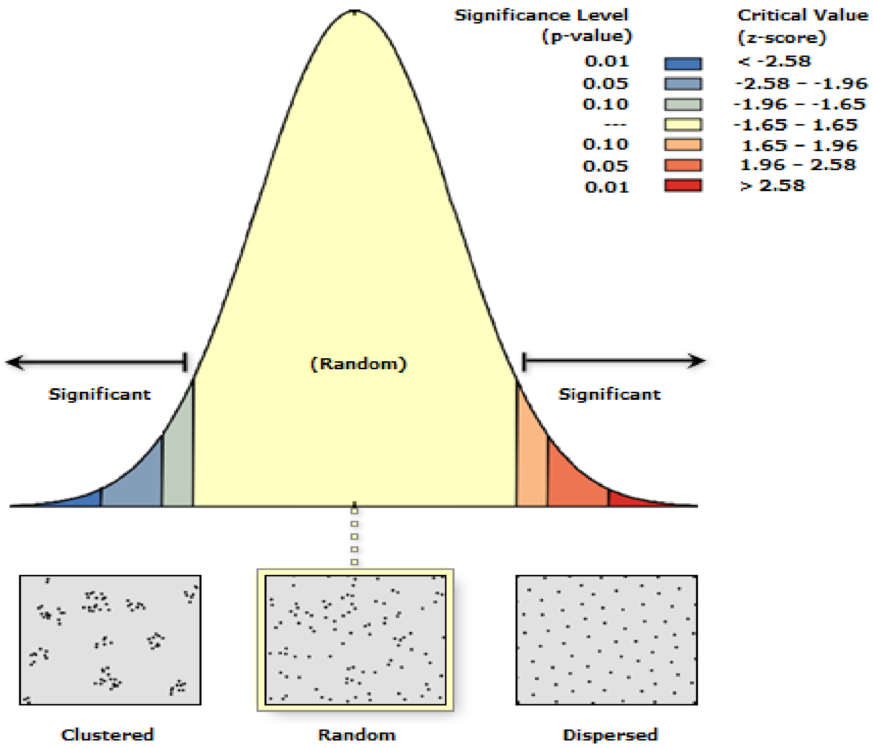


Figure 3.6: Assessment of Randomness for the Soil pH Data Points

The preliminary Shuttle Radar Topography Mission (SRTM) products consist of voids due to the impacts of the sensing device properties and the interactions with the surface features. Although the providers used interpolation algorithms and multi-source data fusion to fill these voids, this data cleaning process introduces new errors into the data (Zhang et al., 2016). 101 SRTM tiles covering Nigeria were mosaicked in Erdas-Imagine. Digital Elevation Model (DEM) was thus prepared for the whole Country (figure 3.7). By inspection, the minimum value was found to be 1 metre, thus, it was believed there were no extreme low values that would need to be masked.

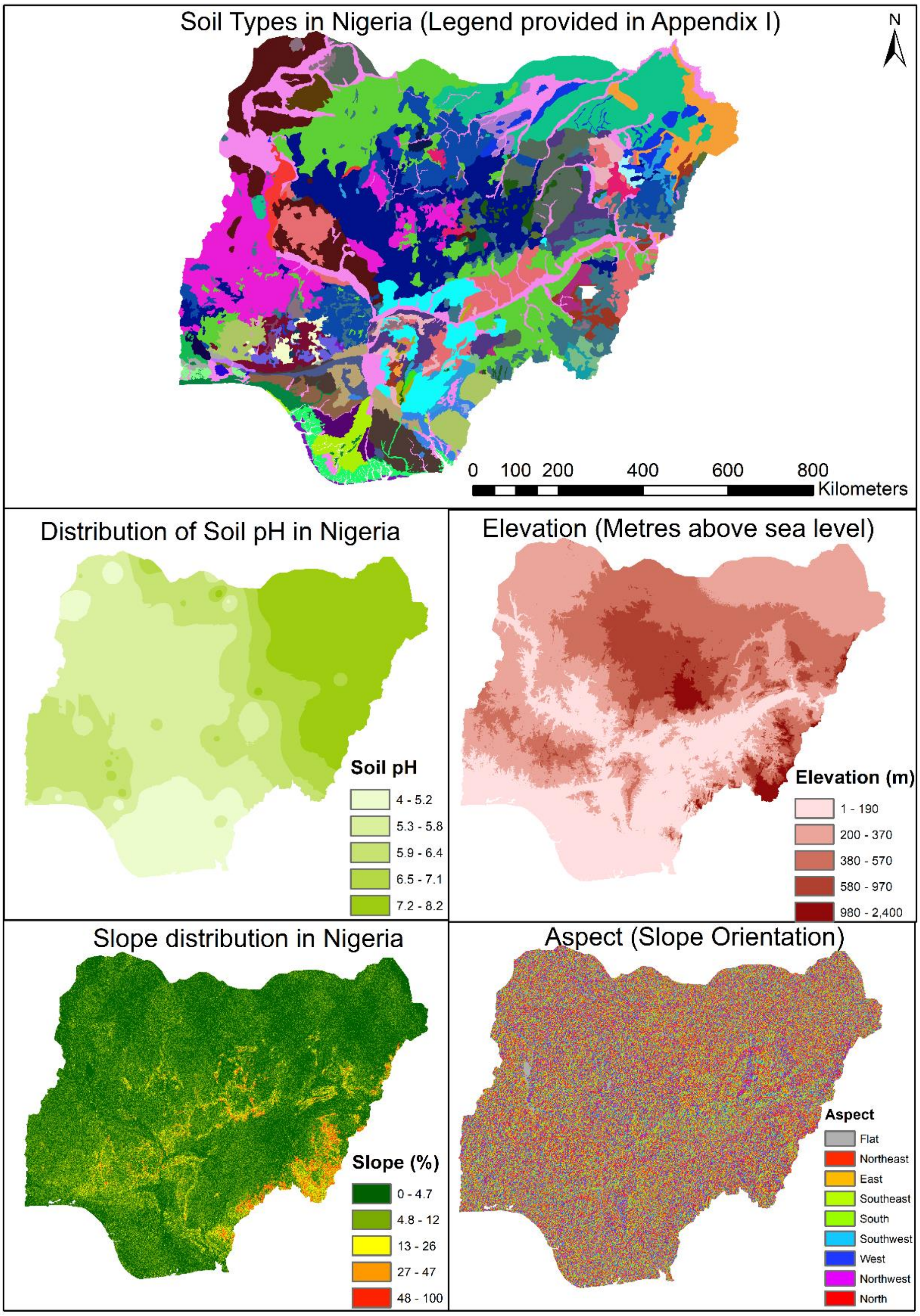


Figure 3.7: Pre-processed geomorphological datasets

On the other hand, because the highest altitude in Nigeria is 2,419 metres above sea level, any values above this figure was filtered using ArcMap filtering syntax. To further ensure any value in the DEM is 2,419 or below, raster calculator was used with a conditional statement to mask other values to NoData. Some published works are available that tested the accuracy of SRTM DEM using field experiments, for example Zhang et al., (2016). Slope (figure 3.7) and aspect (figure 3.7) were derived from the DEM using the default ArcMap tools.

3.3.3 Pre-processing other data (creating distances)

Distance of an infrastructure or certain services play some important roles in determining where a biofuel crop cultivation could be sited. Settlements could provide labour; surface water may serve as a source of irrigation; and closeness to roads and rail networks may provide some transport cost savings. This has been discussed in detail in chapter two. Euclidean distances were thus created from 564 cities and towns, important surface water bodies, roads and rail lines (figure 3.8).

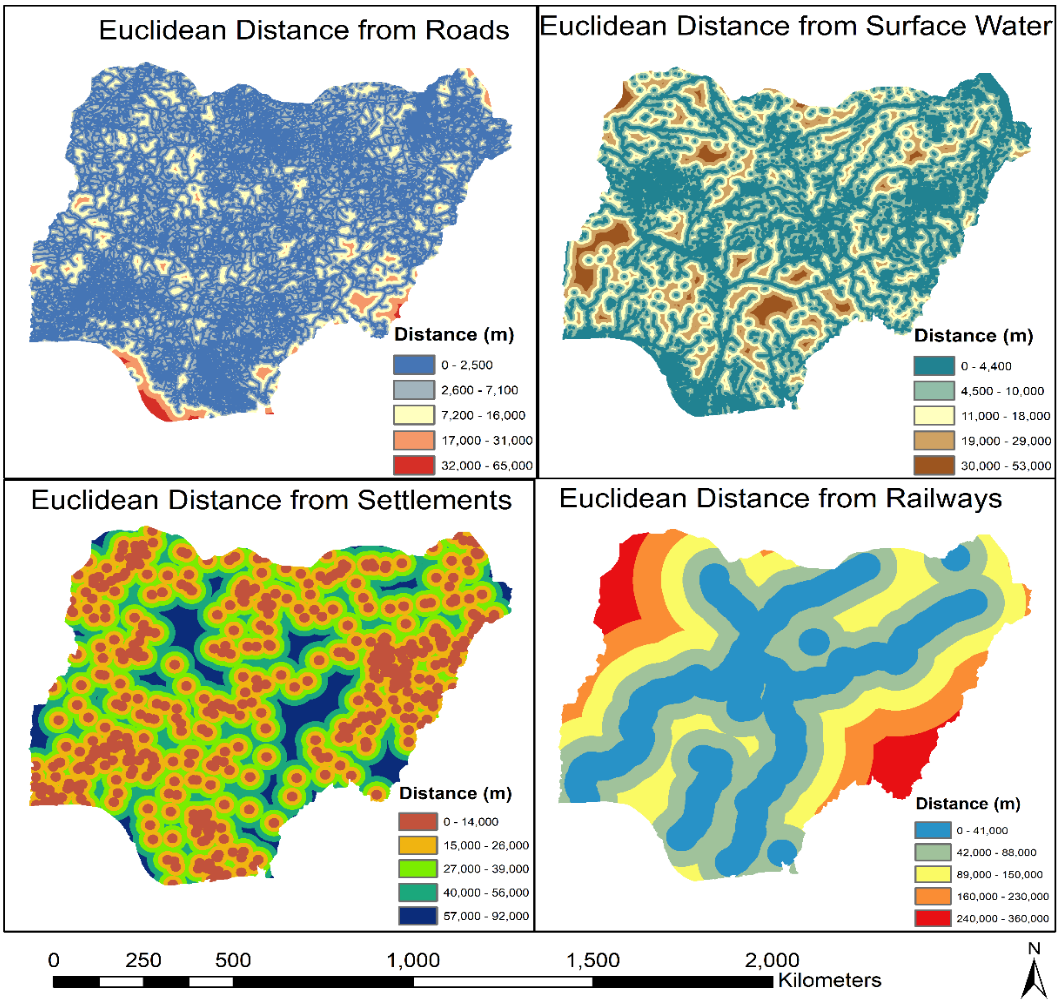


Figure 3.8: Other datasets (Euclidean distances)

Though there was no means of confirming the percentage coverage, efforts were exerted to ensure that the 564 settlement points cover all the cities, towns and main villages. Thus, populated areas are assumed to have been largely captured. As mentioned in section 3.2.2, the data was obtained from OpenStreetMap and each record is classified based on the size (population). In other words, there is a field that described each record as either city, town or village.

3.4 Criteria weighting

3.4.1 Introduction

The factors involved in land acquisition especially for industrial-scale use are complex in nature. The factors are usually large in number, multi-faceted and may do trade-off depending on the intended use. They involve socio-economic, techno-scientific, socio-poiltical and environmental considerations. While some factors trade for others for example low fertility soil trading for best rainfall amounts, some are not substitutable for example a game reserve. Some are unpredictable and thus cannot be modelled notwithstanding the details considered, for example environmental shocks.

Apart from the amounts of details needed to be considered in the analysis, the spatial scope of the area being analysed could also increase this complexity (Aly et al., 2017). Therefore, site selection represent a strategic decision (Sharma et al., 2017) because success or otherwise of an industry depends on its location to a greater extent (Gurder and Yilmaz 2012; Sharma et al., 2015). But how to select sites for biofuel facilities is still crucial decision in order to provide balance for bioenergy crops cultivation, biofuel processing, energy consumption and environmental conservation (Zhang et al., 2017). This dimensionality can be approached using Geographical Information System (GIS) and Remote Rensing (RS) technologies that are effective decision support tools and often applied in conjunction with other mathematical techniques such as Analytical Hierarchy Process (AHP) for Multi-Criteria Decision Making (MCDM) (Sharma et al., 2017).

Most researchers who used these techniques in the past applied geospatial modelling to determine suitable locations for bioenergy facilities, while others use integrated techniques where mathematical modelling and geospatial techniques were combined (Sharma et al., 2017). Several of these works have been cited in section 1.6 and it was shown that AHP scored the best when three MCDA methods were assessed based on 23 criteria of selecting methods (Kurka and Blackwood 2013). AHP scored high in its ability to deal with uncertainty, its multi-stackholder inclusion and its tranparency and communication. It, however, scored medium in user friendliness and flexibility.

3.4.2 Analytical Hierarchy Process (AHP)

As discussed in the last paragraph of section 1.6 (chapter one), the power of GIS in combining maps oversimplifies the complexity of the processes involved in land use plannning problems. This is a GIS limitation in the sense that it leads users to focussing on individual facts rather than the right combination of facts and value judgements. This limitation is overcomed by intergrating it with MCDM (Malczewski 2004). Among the most widely applied MCDM techniques are AHP and Technique for Ordered Preference by Similarity to Ideal Solution (TOPSIS). A bibliographic analysis of data harvested from Scopus Database showed that GIS is one of the major areas that dominate AHP application and will continnue to be active (Zyoud and Fuchs-Hanusch 2017).

AHP method had been applied in two distinctive ways in the GIS industry. Generating criteria weights, ranking the attribute maps and assigning weights to the attribute maps before combining the maps to determine best alternative (Malczewski 2004). Or aggregating the priorities for all levels of the hierarchy structure including the level representing the alternatives and then order the alternatives to determine the highest ranked alternative (Jankowski and Richard 1994). When it is possible to apply pairwise comparison of alternatives, the former is particularly important in solving problems involving large number of alternatives (Malczewski 2006) and this was adopted in this work. AHP provides some level of objective mathematics to deal with inevitable subjectivity and personal preferences of individual or group making the decision (Saaty and Vargas 2012). This subjectivity is usually high and associated with directly eliciting criteria weights (Zyoud and Fuchs-Hanusch 2017).

AHP’s advantage of reducing complex decisions to Pairwise Comparison could be exploited to reduce this subjectivity. It is a robust way that transform criteria preference judgements from qualitative scale to a quantitative scale (Afolayan et al., 2020). It has a system of checking the consistency of the decision thereby detecting inconsistent judgements and reducing bias in the decision analysis (Coyle 2004; Alami Merrouni et al., 2018). This consistency verification is one of the great strengths of AHP and acts as feedback for decision makers to review and evaluate their judgements (Zyoud and Fuchs-Hanusch 2017). A drawback with this technique is its estimate of the reciprocals of the importance preference between criteria which some scholars consider to be reasonable, while others are not happy with it (Coyle 2004). The question is whether the reciprocals actually represent the actual inverse relationship. Another issue is that the end values of the comparison change if the scale change, but that does not matter since the value simply says that something is better than the other in meeting some objective (Coyle 2004). The initial comparison matrix is genetrated through individual or group expert judgement on the criteria preferences (Drobne and Lisec 2009).

As discussed extensively in section 1.7, the need for the knowledge of where to position biofuel feedstock could not be overemphasised in the context of biofuel expansion. Spatial multi-criteria positioning process has been helpful in this context and applied in various contexts. With regards to Nigeria, the few published research found to have been conducted in Nigeria lack explicit application of AHP with its requirements for expert participation in spatial decision making that concerns criteria value judgements. The attempts were either deficient in terms of scope, relevance to biofuel expansion or more importantly, lack explicit participation of experts in criteria preference judgement. As discussed in section 1.7 also, the researcher made similar attempt during an MSc programme. However, the work could only be considered as a pilot attemt due to time constraints and resources. The work though published as a book and a journal article could not involve experts for the criteria judgement which is necessary for effective application of AHP. While the MSc work showed the possibility of conducting spatial analysis for crop-based biofuel context at a country level despite the challenges such as data availability for the study area, the current PhD work demonstrates how the identified challenges of conducting spatial analysis could be approached through a more robust procedure.

In the current work, an attempt was made to increase the robustness of the process in the context of Nigeria. This robustness refers to detailed consideration of all the relevant parameters, explicit participation of the feedstock experts and transparent application of the AHP. Also, a recent publication shows the necessisity of incorporating a feedback mechanism to ensure that the expert judgement conforms with the standard consistency (Afolayan et al., 2020). In this research, Stakeholders' (a group of experts engaged by the researchers) judgement and the feedback mechanism were adopted. Because this level of analysis is based on agricultural crops, the experts on these crops would be more appropriate to make the judgements. Agricultural research institutions in Nigeria that have the research mandate on the five identified biofuel crops were selected for visitation to explore the experts judgements.

3.4.3 The AHP hierarchical structure

One of the advantages of AHP over the other MCDM techniques is its ability to decompose multi-criteria problem into its essential components, facilitating rational comparison among the design alternatives underpinned by the conflicting criteria (Nesticò and Somma 2019). The overall goal in this work is to find optimal sites for processing biofuel based on agricultural crops. This is decomposed into hierarchical order with objectives, subobjectives and alternatives. The goal stand at the height of the hierarchy (figure 3.9). Objectives followed such that very suitable areas are identified for cultivating the crops, crop yields are determined based on literature and adopted, distance threshold are defined and the feedstock amounts are aggregated.

Subobjectives represent the level at which meteorological, geomorphological and distance criteria (C_1, C_2, C_3, C_4, …, C_{14}) were aggregated to assess land suitability for the crop cultivation. Suitability here is a function of suitable rainfall for the crops, suitable soil, temperature as well as the rest of the predicting variables.

Getting most out of each of these forms a part objective that contribute to achieving the main objective of identifying suitable lands and determining how suitable it is. The alternatives (A_1, A_2, A_3, A_4, …, A_{23}) represent the NNPC petroleum depots spread across Nigeria and adopted in this research as the potential candidate sites for processing biofuel and blending with petroleum fuels in the country (section 6.2).

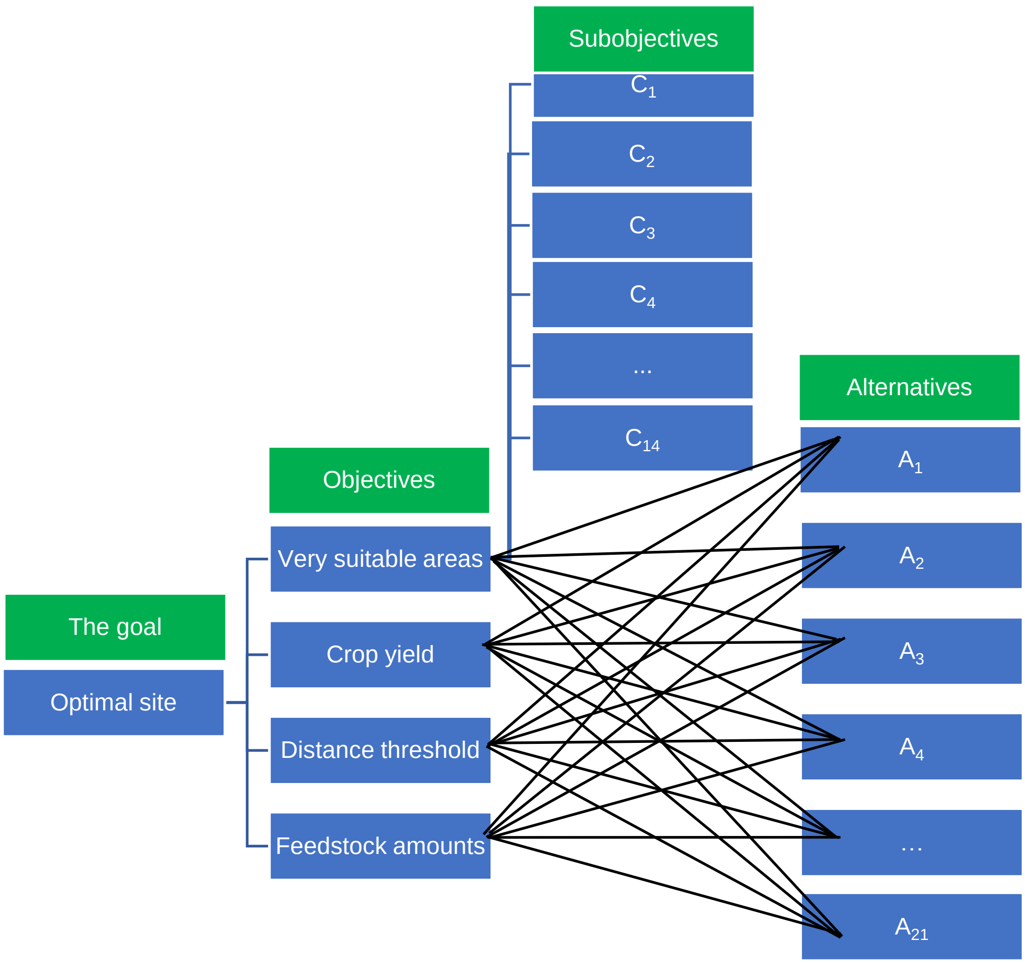


Figure 3.9: GIS-MCDM hierarchical structure

3.4.4 Experts group discussion

According to Zhang et al., (2015), the AHP's dependence on subjective assignment of relative importance between criteria could be handled through a procedure comprising four ways. 1) Utilising objective and scientific data to derive the pairwise comparison matrix where data is available. 2) Involve scientists and related persons (the authors might mean other relevant stakeholders) in estimating the relative importance of the criteria. 3) Pay particular attention to the consistency ratio. 4) Conduct validation tests in future studies to confirm the results.

In this work, organisations with expertise on crop performance in Nigeria were selected for these consultations. These were 1) Institute for Agricultural Research (IAR) located in Zaria, Kaduna State. It has national research mandate on several crops including sorghum and jatropha. 2) National Cereal Research Institute (NCRI) located in Badeggi, Niger State. It has the national research mandate on cereal crops and Sugarcane. 3) National Root Crops Research Institute (NRCRI) located in Umudike, Abia State. It has the national research mandate on root crops including cassava. 4) Nigerian Institute for Oil palm Research (NIFOR) located in Benin City, Edo State. It has national research mandate on Oil palm and other palm trees. These institutions are most appropriate to be selected for consultations with respect to expertise and experiences related to research on these crops.

Though spatial decision-making problems usually involve several interest groups and/or decision-makers, it is obvious that the nature of this work assumes homogeneity within the group to some extent such that there are more convergent judgements than there are divergent. This does not entail absolute homogeneity; the experts would be expected to differ in their area of specialisation, their experience and perspective. It has been observed that individuals who collaborate on a project and agree on pairwise comparison matrix of criteria usually hold different perspectives on the system (Ivanco et al., 2017). These disparities are believed to have effect on the resultant criteria weights. It was observed that though AHP has been thoroughly researched and applied, it still shows some limitations with regards to user profile disparities (Ivanco et al., 2017).

However, AHP applied in a group mode is said to provide for a much more informed opinion by allowing a structured debate focused on specific and relevant points (Malczewski 1999). At each of the institutions, a group was formed constituting of experts on crop production, agronomy, soil science, plant pathology and agricultural economics. There was a minimum of five participants for each of the crops. In addition to these, for jatropha there was a PhD candidate who was working on agronomic improvement of jatropha for biodiesel production at the institute and the jatropha plantation manager of the institute who participated in the discussion. With regards to time spent at each sitting, this was not recorded. Consequently, an estimated range is provided. The shortest time was approximately two hours for sweet sorghum and the longest was about four hours for cassava. However, the researcher spent whole day at each of the institutions because the field work involved visiting a farm at each of the institutions and gathering some secondary materials like publications of the institutions.

The participants discussed and deliberated, during the sitting, on each pair of the criteria until a consensus was reached on the value to be assigned for the relative importance of one criterion over the other based on the scale developed by Saaty (1980) as shown in table 3.2. The relative importance here refers to preference of the crop for the variable with regards to its growth and development which is the main determinant of the crop's productivity (yields) as discussed in subsection 2.3.1. In other words, which among a pair of criteria variables plays greater role in supporting the crop to achieve higher yields.

Table 3.2: Saaty's (1980) Preference Scale

Intensity of Importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very strong to extreme importance
9	Extreme importance

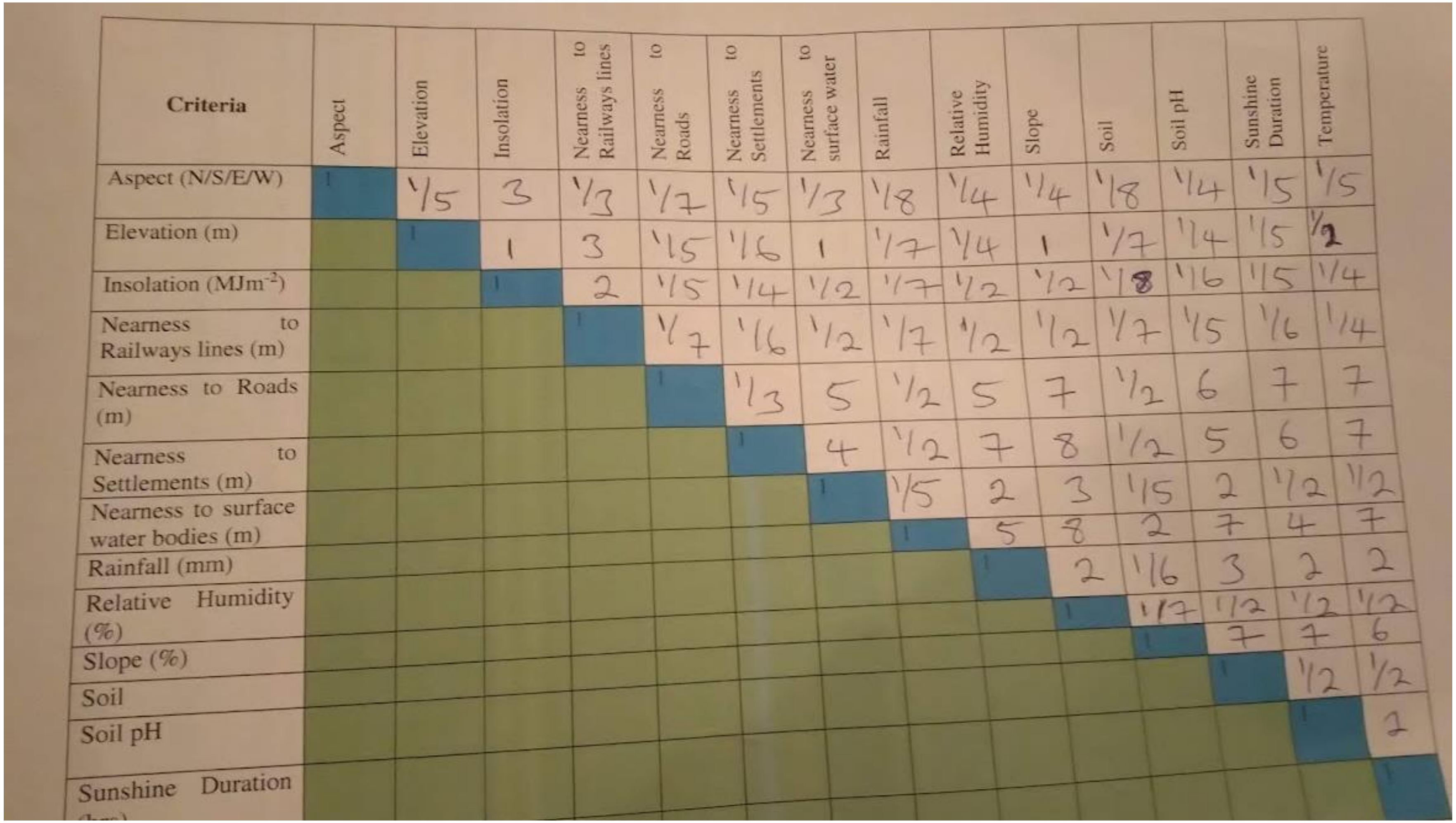
In the case of this work, the group members making the judgement discuss, deliberate and then agree on the values to be assigned which represent the group preferences with respect to the criteria as described in Malczewski (1999). This is based on the principle of Pairwise Comparison technique of the AHP which is an effective way of generating meaningful judgement figures where empirical observation is either not available or impossible. Ranking, rating, pairwise comparison and trade-off analysis are the four AHP techniques of assessing criteria weights. It is suggested that if accuracy and theoretical foundation are the main determinant of choosing a technique, pairwise comparison and trade-off analysis are more appropriate (Malczewski 1999). Pairwise Comparison is more trustworthy, easier to be used and be understood and can be applied to variables that are based on ratio response scale.

A template was produced and presented to the experts. The template comprised of a table (table 3.3) used as the pairwise comparison matrix table and a question is posed as, for example, how does aspect compare to elevation in terms of importance for sugarcane. In other words, which of the variables plays greater role in supporting sugarcane achieve higher yields? Using the above scale of 1 – 9, the experts compared the intensity of importance of each criterion in the **row** over the other criterion in the **column**. Thus, the upper right diagonal halve of the matrix table is filled (Malczewski 1999). The researcher sat together with the experts, set the question and listened to the experts deliberate. The researcher could not recall having difficulty in getting the expert to understand what the matrix is doing; all of them seemed to have at least some idea about the technique.

The advantages of the criterion are compared to that of the other as regards the cultivation of the considered crop. For example, while discussing the importance of the settlements it was observed that they provide sources for domestic market, labour supply, security and social amenities. Relative humidity regulates excessive evaporation. The importance of each criterion over each of the remaining criteria is judged and the value of the intensity is inserted by the researcher in the unshaded-empty boxes along the row.

Table 3.3: Pairwise Comparison Matrix Table

Criteria	Aspect	Elevation	Insolation	Nearness to Railways	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1													
Elevation (m)		1												
Insolation (MJm^{-2})			1											
Nearness to Railways (m)				1										
Nearness to Roads (m)					1									
Nearness to Settlements (m)						1								
Nearness to surface water bodies (m)							1							
Rainfall (mm)								1						
Relative Humidity (%)									1					
Slope (%)										1				
Soil											1			
Soil pH												1		
Sunshine Duration (hrs)													1	
Temperature (^0C)														1



Criteria	Aspect	Elevation	Insolation	Nearness to Railways lines	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1	1/5	3	1/3	1/7	1/5	1/3	1/8	1/4	1/4	1/8	1/4	1/5	1/5
Elevation (m)		1	1	3	1/5	1/6	1	1/7	1/4	1	1/7	1/4	1/5	1/2
Insolation (MJm^{-2})			1	2	1/5	1/4	1/2	1/7	1/2	1/2	1/8	1/6	1/5	1/4
Nearness to Railways lines (m)				1	1/7	1/6	1/2	1/7	1/2	1/2	1/7	1/5	1/6	1/4
Nearness to Roads (m)					1	1/3	5	1/2	5	7	1/2	6	7	7
Nearness to Settlements (m)						1	4	1/2	7	8	1/2	5	6	7
Nearness to surface water bodies (m)							1	1/5	2	3	1/5	2	1/2	1/2
Rainfall (mm)								1	5	8	2	7	4	7
Relative Humidity (%)									1	2	1/6	3	2	2
Slope (%)										1	1/7	1/2	1/2	1/2
Soil											1	7	7	6
Soil pH												1	1/2	1/2
Sunshine Duration (hrs)													1	2
														1

Figure 3.10: Pairwise Comparison Matrix (Cassava)

The diagonal boxes represent the comparison of each criterion to itself, therefore, these boxes are filled with values representing equal importance. Where the criterion in the **row** is agreed to be less important than the criterion in the **column**, an inverse value of the intensity of importance is inserted in the box (e.g 1/3 is the inverse of 3). That means the degree of the ‘less importance’ has to be based on the same Saaty’s scale. Is it moderate less importance, strong less importance, very strong less importance, extreme less importance or any of the intermediate levels? All the shaded boxes are filled with the reciprocal values.

3.4.5 Pairwise Comparison Matrix analysis

Five Matrix tables were filled, one each for the five biofuel crops, at the expert group meeting during the visits. As an example, figure 3.10 shows the matrix table for cassava. Other tables are presented as appendix II. Microsoft Excel was used to calculate through the steps involved in generating the weights and calculating the consistency ratio (CR) as described in (Malczewski 1999). These steps include filling the lower part of the matrix to complete the table, normalising the matrix and calculating the weight for each of the criteria. Checking for the consistency involves calculating the weight sum vector. Then consistency vector, the sum of which gives lambda that is divided by the number of the criteria to get Consistency Index (CI).

CI is divided by Random Index (RI) to determine the Consistency Ratio. RI is given in a table developed by Saaty (1980) and adapted by (Malczewski 1999). Its value depends on the number of the criteria. It is 1.57 in this case as there are 14 criteria in the analysis. The standard is that CR must be less than 0.1 for the matrix to produce acceptable criteria weights. Thus, the matrix tables were adjusted, in consultation with the experts, depending on the distance of the ratio from the set limit. Both the initial ratios (***CR**) and the ratios obtained after the adjustments (**≈CR**) were given in table 3.4.

Table 3.4: Criteria Weights for the Biofuel Crops

S/N	Criteria	Sweet sorghum	Sugarcane	Cassava	Oil Palm	Jatropha
1	Aspect	1	1	1	1	1
2	Elevation	1	2	2	5	1
3	Insolation	2	13	2	3	15
4	Nearness to Railways	4	1	2	1	5
5	Nearness to Roads	6	5	16	4	5
6	Nearness to Settlements	7	5	16	3	5
7	Nearness to Surface Water	5	14	4	6	5
8	Rainfall	20	14	19	23	17
9	Relative humidity	4	6	5	3	17
10	Slope	2	5	2	9	1
11	Soil	19	14	18	13	3
12	Soil pH	8	6	4	12	1
13	Sunshine Duration	11	7	5	11	8
14	Temperature	10	7	4	6	16
	Total	**100**	**100**	**100**	**100**	**100**
	***CR (initial)**	**0.141133**	**0.15**	**0.108958**	**0.165592**	**0.2864994**
	≈CR (adjusted)	**0.0734**	**0.0598**	**0.0713**	**0.0733**	**0.0529**

It was agreed during the expert group meeting with the experts that these adjustments would be inevitable to achieve the required consistency and thus the adjustments would be sent to them as a feedback mechanism and for their perusal. Copies of the excel spread sheet used in calculating the weights and the consistency ratios were sent to the experts with the recommended adjustment such that they can see the consistencies changing in real time as they adjust the matrix table. This guided them in ensuring that the adjustment is within the required consistency if they feel the need to further readjust the matrix. Each excel document for each of the crops was sent to the head of each team who also serves as the crop production expert in the institute. The person then consulted with the other expert that were involved in the initial group discussion. The experts perused the recommended adjustments that are within the required consistency ratio and they did not object the adjustments.

These criteria weights that were based on the adjusted matrix were then confirmed as the established criteria weights to be assigned to the criteria maps as an important aspect of the land suitability analysis for each of the biofuel crops. It is obvious from the table that jatropha has clearly distinct pattern of criteria weights especially looking at soil, relative humidity and temperature for which the crop has very much higher weights than other crops. This might be connected to the fact that jatropha can live entirely on relative humidity without rainfall as reported in subsection 2.3.7. The same pattern could be seen in insolation except that sugarcane also compare closely to jatropha in this criteria variable. Insolation and temperature seemed to influence jatropha more than any of the other crops and this is in line with what was reported from the literature (subsections 2.3.4 and 2.3.11) that jatropha is affected by low temperatures and is not suited for growing under shade.

Oil palm shares the same characteristic of love for insolation and it is relatively being influenced by elevation higher than the other crops. Proximity to roads and settlements received more than twice weights for cassava than the weights received by these criteria variables for the other crops. Cassava is a bulky crop, therefore, cultivating it close to roads and settlements will save costs and energy in conveying the produce as discussed in subsections 2.3.13-14. Not unexpectedly, proximity to surface water received more than double weights for sugarcane than for the other crops because sugarcane most often require irrigation to produce better yields. Sweet sorghum and oil palm seemed to be influenced more by soil and rainfall, respectively than any of the other crops. These comparison shows in some way how the biofuel crops vary in their favourability profiles. Chapter four deals with modelling and estimating suitable lands for the crop’s cultivation.

3.5 Discussion

The results presented in table 3.4 shows how the criteria importance compares for each of the crops in modelling cultivation sites. Looking at all the crops together, not unexpectedly, rainfall turned out to be the most important criteria for each of the crops though with varied weights. Aspect seemed to be the least important criteria in all the crops and showing similar weights for all the crops. Looking at each of the crops, the result suggests that most of the criteria show weight similarity with at least one other criteria, with greater similarity in sugarcane and greater weights variability in sweet sorghum.

It is worthy of note here that the actual weights values were in fractions with many decimal places. These decimal numbers would not be accepted by the GIS environment and thus, were approximated to the nearest whole numbers. The approximation was monitored closely to ensure it did not change the ranking of the weights, assuming the alternative choice is sensitive to the ranking of the criteria weights. Though the goal of sensitivity analysis is to show how changes in the criteria weights lead to changes in the alternatives, sensitivity analysis is said to be not enough to base conclusions about the reliability of the multi-criteria decision methods. It is necessary to check the consistency of the result based on the measurement units of the criteria and the formulation of the criteria (Pamucar et al., 2017). Availability of this mechanism for consistency check is one of the strengths that AHP has, as discussed at several points earlier.

Although a review of the MCDM tools observed that all of the methods tend to favour the same alternatives (Huang et al., 2011), for decades, AHP tends to enjoy more confidence of researchers because it is the most used MCDM methods (Aly et al., 2017). AHP possess a crucial advantage over other techniques such as TOPSIS and ELECTRE because, due to its hierarchical structure, it allows complex problems to be broken and be dissected with greater detail at each level. AHP is thus more effective where criteria and sub-criteria exist in a multi-criteria analysis (Nesticò and Somma 2019). AHP offers a mechanism whereby subjective elicitation of criteria preferences by individual or group of experts can be captured and processed in such a way to permit their integration with other quantitative spatial datasets, allowing for more robust spatial decision-making (Saaty and Vargas 2012). This subjectivity of criteria weights elicitation is usually high, especially where the elicitation is direct (Zyoud and Fuchs-Hanusch 2017).

As mentioned in subsection 3.4.2, checking the consistency of the pairwise comparison is one of the great strenghts of the AHP. Where the consistency ratio is above the threshold, the initial pairwise comparison matrix assessed by the experts must be revisited. However, to keep the iteration of this revisit to single round or utmost twice, a recommendation could be given to the experts with regards to the adjustment of the matrix values within which the required consistency ratio could be achieved. The experts would assess the recommendations and adjust their initial judgement to a new set of comparison of criteria importance. These would then be aggregated again. Then the criteria weights are established.

In addition to AHP's subjective assignment of relative importance between two criteria, it was said that it ignores the criteria interdependence (Li et al., 2012). An improved version of AHP called Analytical Network Process (ANP) was developed to handle AHP's deficiency in handling the criteria interdependency and was expected to gain popularity afterwards. The ANP modification is said to allow representation of the identified relationships between intangible assets and the strategic goal (Akpoti et al., 2019). However, ANP was concluded to be less preferred due to its deficiencies regarding its complexities, user friendliness, transparency and, more importantly, multi-stakeholders involvement (Kurka and Blackwood 2013). Though some scholars recommended use of Principal Component Analysis (PCA) to identify criteria that are highly correlated and reduce criteria redundancy, Zhang et al., (2015) applied this on climate and soil criteria but found it not helpful, probably because PCA requires existence of strong correlation. In the context the current work, the correlation could be negligible.

AHP was also criticised of showing rank reversal when exact replica or a copy of an alternative was introduced (Belton and Gear 1983). However, the same effect was said to have been found in other decision making approaches such as TOPSIS, Simple Additive Weighting (SAW) and Borda-Kendal and might be normal phenomenon (Wang and Luo 2009). When compared with DELTA and PROMETHEE, AHP scored best based on 23 criteria for selecting MCDM methods (Kurka and Blackwood 2013). AHP is said to be an effective and superior method for criteria weighting in a systematic and logical way (Zhang et al., 2015).

The application of the AHP in this work was done as much transparent and detailed as possible unlike in many applications where the details are very low and more opaque than transparent. Huang et al., (2011), assessed more than 300 published articles and reported that though they did not classify the articles based on quality and sophistication of the analysis, some articles were obviously very superficial, while others were deep and detailed. Figure 3.12 shows visually how the criteria compare between the crops. Obviously, rainfall and soil take larger share of the weights in all the crops except jatropha for which rainfall compare closely to relative humidity than any other criteria. Apart from aspect, elevation seems to play lowest role except for oil palm, for which elevation has higher weight than six other criteria. Nearness to railways also has low weights probably not only because there are few railway lines in Nigeria, but also because use of the existing railways as means of transportation is still very low in Nigeria.

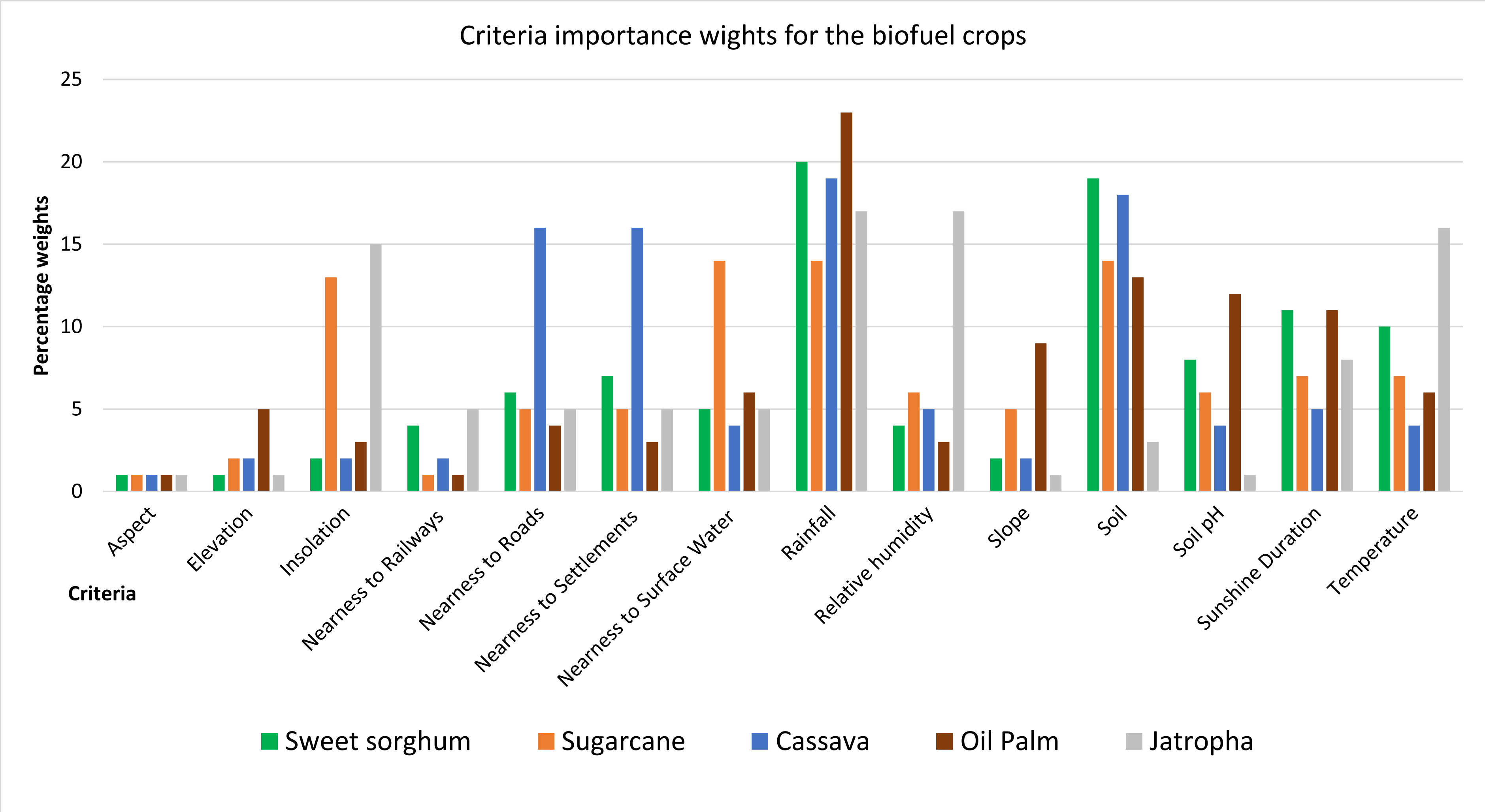


Figure 3.11: Comparing criteria weights among the biofuel crops

Chapter Four – Land suitability Models

4 Chapter Four – Land suitability Models

4.1 Introduction

As discussed in chapter one, the overall technical goal of this research work is to optimise locations for processing biofuels in Nigeria through robust application of multi-criteria evaluation. Representing the decision problem about the suitable location of biofuel crops requires consideration of a large number of criteria, as alluded in subsection 3.5. However, conversely, restricting the model to a small number of criteria may lead to oversimplification of the decision problem. Thus, a balance must be struck between these two tendencies to ensure the criteria selection is underpinned by a reasonable mechanism (Malczewski 1999).

It should be noted here that two forms of evaluation criteria are usually used in spatial decision making (Abudeif et al., 2015). Factors (suitability criteria) directly support selection of the land for the intended purpose or indirectly contribute to the achievement of the objective. Constraints (restricting criteria) prohibits the selection of the particular land for the intended purpose or indirectly restrict attainment of the objective. It was suggested that if factors do trade-off (as does the suitability criteria in this context) and do not trade-off (as the constraints do not in this context), they should be considered separately in two stages analysis (Drobne and Lisec 2009). The factors should first be aggregated using multi-criteria techniques, then the result should be used as a new factor to analyse the constraints. This chapter deals with the former, while chapter 5 deals with the later.

Discussion was given in length in chapter two about the criteria required to be considered for identifying suitable lands for cultivating the biofuel crops in Nigeria. In chapter three, datasets determined and acquired based on these criteria were presented and pre-processed. The AHP application was also presented in chapter three showing the procedures followed to determine the weight of influence for each of the evaluation criteria. As a requirement for multi-criteria analysis, the values contained in each criterion indicator must be transferable to a common unit because the scales on which the criteria are measured vary (Malczewski 1999). This chapter deals with implementation of the land suitability model, defined in the previous chapters, and shows how the criteria values and the maps were standardised to a common scale as prerequisite for the execution of the model for each of the five biofuel crops. The modelling here involves combining all the 14 criteria maps, each assigned its criteria weight generated in the previous chapter. A model was developed for each of the five biofuel crops. The results of the models were also presented.

4.2 Suitability class levels (standardising criteria scores)

As seen in chapter three, the fundmental objective to achieving the goal of positioning biofuel processing is identifying areas that are ‘very suitable’ for cultivating the biofuel crops that serves as the feedstock. These levels of suitability are determined by combining expert assessments of the importance of environmental determinants for crop growth. To achieve this, quantitative scales of assessment are needed to quantify the contribution of different environmental variables and indicate suitability (Malczewski 1999). According to Voogd (1982), enough quantitative information should be available for formulating an indicator where direct quantitative determination approach is followed. Also, the author suggests that where it is possible that different result (e.g. crop suitability) may be obtained from using different choices of variables for the same indicator (e.g environmental variable), an ordinal interpretation of the result should be adopted. In other words, the quantitative values are aggregated into a ranked indicator values that are further analysed. This is called direct qualitative determination. This concept is based on fuzzy set theory which can facilitate standardising criteria for use in multi-criteria analysis (Malczewski 1999).

The traditional (crisp) sets allow only binary membership functions; all the members match the class attribute and the boundaries are sharp (Burrough and McDonnell 1998). For example, these sets only allow that there is rainfall at a given location or there is not (i.e true or false, conventionally called boolean operation). However, fuzzy sets allow for possibility of partial membership. For example, it allows for all possible conditions from total absence of rainfall to availability of extremely heavy rainfall. To define what is, or what is not moderate rainfall requires not strict allocation to an exactly defined class; a qualitative judgement that by implication allows for partial membership suffice (Burrough and McDonnell 1998). A fuzzy set, defined on the domain of real numbers called fuzzy numbers, can be manipulated in the same manner as can be done on crisp numbers. These standard fuzzy numbers, also called standard membership functions provide basis for defining linguistic variables. In other words, a linguistic variable takes fuzzy variable as its values (Zadeh 1975). This is based on the extension principle which is a principle that makes it possible to extend functions from subsets into subsets and/or extend functions from sets into real numbers (Gerla and Scarpati 1998).

Linguistic variables, in this context, are usually defined by relative terms such as best, better, very good, good, and so on. Assignment of these linguitistic terms is done in terms of a base value which is defined by real numbers within a specific range, for example as in high rainfall, moderate elevation or low distance (Malczewski 1999). Aly et al., (2017), used a scale of four classes described by four linguistic terms as ‘most suitable’, ‘suitable’, ‘moderately suitable’ and ‘least suitable’. It could be argued that the second class ‘suitable’ is not appropriately described in the study; a question may be asked how different it is from the first or the third class interms of suitability. Similarly, Ayoade (2017), used four classes defined by the terms ‘very suitable’, ‘suitable’, ‘moderate’ and ‘fairly moderate’.

The use of the determiners (most, less and least) or the adverbs (very and moderately) to qualify the adjective ‘suitable’ for each of the classes in descending order of suitability is considered best to ensure absence of ambiguity between the terms describing the classes. El Baroudy (2016), used four land quality classes – ‘high quality’, ‘moderate quality’, ‘low quality’ and ‘very low quality’. Ayehu and Atnafu (2015), also used four suitability class levels with such linguistic terms as ‘highly suitable’, ‘moderately suitable’, ‘marginally suitable’ and ‘not suitable’ though there was no explanation as to how and why these classes were adopted. Attempt was made in this work to use unambigous linguistic terms for the class categories and detailed explanation was given on how the classes were created.

Several numerical approximation systems were proposed for systematically converting linguistic terms to their corresponding fuzzy numbers and it was recommended that a minimum of two linguistic terms is required for this purpose, though it can be extended to a larger odd number and can also be with intermediate even numbers (Malczewski 1999). Five linguistic terms were adopted in this work to form five classes. Five classes might provide better quantitative differences between classes, avoiding the limitation of generalisation in case of few classes, and the limitation of stretching data ranges as in the case of higher number of classes.

Although this reclassification creates in a new constructed scale called “subjective scale” because it is usually based on personal judgement (Malczewski 1999), the optimal criteria values in the current study were determined from published field experiments. The references were presented in section 2.3 in detail with all the citations for each of the biofuel crops. These optimal values were considered the best alternative and thus were classified as the most suitable. Also, when converting the linguistic terms used in these empirical studies, the terms “best”, “optimal”, “most appropriate” or “most favourable” ranges were interpreted as the ‘most suitable’ for a particular crop.

The other descending classes were extracted by grouping similar observations based on the assumption that a shift from the optimal values implies decreasing suitability of the criteria values for cultivating each of the biofuel crops. A number of methods are used in this kind of data manipulation including natural breaks, quantile and equal intervals. Equal intervals may provide a better index differential between classes. It can show relative differentials in data value (Malczewski 1999) and tends to provide best display (Milic et al., 2019). It is best applied on data ranges that are not skewed but spread across the breath of the data range and does not have large outliers. As presented in the previous chapter, the data pre-processing involved checking for and filtering outliers where they were found. Thus, the prepared data would be appropriate for the use of equal interval. Also, as mentioned in the next section, all the datasets are continuous in reality. Thus, using a continuous measurement such as interval scale could be best because observations can be placed at any position along the data range. Equal interval may work best to group observations of similar numerical values unlike quantile method that may separate location of similar values. Equal interval would also work better where a set of datasets are compared by providing the same classification scheme across all the datasets unlike natural breaks that creates unique scheme for each dataset, making comparison impossible. Equal interval may also work better than standard deviation due to the need for handling the opposing direction of the data ranges.

Attempts were made to use equal intervals to form other classes in descending order (even though the real numbers defining the classes may either be decreasing or increasing) based on the data ranges. This transformation implies linear progression with regards to the relationship between the means objectives (for example favourable rainfall or soil pH) and the alternatives (different potential land areas). This linearity assumption suggests that desirability or otherwise of an additional unit of a variable is constant within the range of the variable (Malczewski 1999). For example, the assumption means that the effect of adding (or subtracting) 100 mm of rainfall is the same regardless of whether the addition (or subtraction) is to (or from) 500 or 1000 mm. Also, since the entities, the attributes of which the datasets represent, are all continuous in the real world, an interval scale of measurement would be more appropriate. Because it is a continuous measurement, equal interval can measure differences between different levels of an attribute though not in absolute terms (Malczewski 1999). Since the measure is relative not absolute, the linearity relationship with the outcome would also be expected to be relative rather than absolute. However, it provides possibility for ordering attributes into classes that would predict an ordered group of alternatives.

The exceptions to use of equal interval were where it is impossible (for example in the case of soil types). These exceptions are actually few. The principle aims to provide an appropriate representation of the meaning of the linguistic terms. Therefore, ‘Most suitable’ was coded as 1, denoting the most optimal value within the variable range as suggested by the literature. ‘Very suitable’ was coded as 2, repesenting the closest range to the most suitable, ‘moderately suitable’ was coded as 3, ‘less suitable’ as 4, and ‘least suitable’ as 5. These are presented in table 4.1 (sweet sorghum). Other tables are presented in appendix III for sugarcane, cassava, oil palm and jatropha.

Each of the 14 criteria presented in chapter three, with the data ranges as mentioned above, was transformed into the 5 classes for all the biofuel crops. Due to the length of the descriptions in the soil data attribute table, a number code (1 - 56) was used to identify and ease handling of the soil categories. The soil categories do not represent rankings; rather, they state the soil properties, the importance of which depends on the crop type. For each of the crops, literature was the basis for identifying major soil suitability characteristics which were then compared with the soil properties descriptions to assign suitability class to each of the categories.

For example, literature suggests that sweet sorghum is best produced on loam or sandy silt loam and that deep soils are preferred with moderate drainage. Sweet sorghum will produce low yields with poor quality on clay-like or shallow soils. It is thus identified that ‘most suitable’ soil for sweet sorghum should be 1) deep, 2) have moderate drainage, 3) be loam, sandy or silt loam and 4) must not be clay or shallow. Any soil that met all these four characteristics was assigned ‘most suitable’ soil for sweet sorghum. The categories that met three of the characteristics, were assigned ‘very suitable’. Those that met two of the characteristics, were assigned ‘moderately suitable’ and those that met only one were assigned ‘less suitable’. Those that did not meet any of the characteristics, were assigned the ‘least suitable’ because literature suggests that the crop can survive on poor soil.

Table 4.1: Suitability class levels for sweet sorghum based on the criteria indicators

S/N	Criteria (Suitable)	Most (1)	Very (2)	Moderately (3)	Less (4)	Least
1	Soil	6, 8, 11-13, 17, 23, 27, 36, 41-43, 45-49, 51-53 & 55.	9, 10, 15-16, 18-20, 22, 24-26, 29, 37-38, 40, 44 & 50.	3, 5, 14, 21, 28, 30, 32-35 & 54.	4, 7, 31 & 39.	1, 2 & 56.
2	Soil pH	6.5 – 7.5	6.0 – 6.5 7.5-8	5.5 – 6.0 8.0-8.5	5.0 – 5.5	Others
3	Rainfall/Water (mm)	700-1000	600-700 1000-1500	500-600 1500-2000	400-500 2000-2500	Others
4	Temperature (˚C) -Maximum	30 – 33	33-35 28-30	35-36 26-28	36-37 24-26	Others
5	Relative Humidity (%)	45 – 55	35-45 55-65	25-35 65-75	15-25 75-85	Others
6	Elevation (m asl)	0 – 1000	1000 – 1300	1300 – 1600	1600 – 1900	Others
7	Slope (%)	<3%	3 – 5%	5 – 8%	8 – 35%	Others
8	Aspect in direction (Bearing in degrees)	S, SSE & SSW (157.5 – 205.5) & Flat (-1)	SE & ESE (112.5 – 157.5) SW & WSW (202.5 – 247.5)	E & ENE (67.5 – 112.5) W & WNW (247.5 – 292.5)	NE & NNE (22.5 – 67.5) NW, NNW (292.5 – 337.5)	N (0 – 22.5 & 337.5 – 360)
9	Insolation	6.0 – 6.4	5.7 – 6.0	5.3 – 5.7	4.9 – 5.3	4.5 – 4.9
10	Sunshine ($hday^{-1}$)	All	-	-	-	-
11	Nearness to water (Km)	0 – 5	5 – 10	10 – 20	20 – 40	Others
12	Nearness to roads (Km)	0 – 5	5 – 10	10 – 20	20 – 40	Others
13	Nearness to settlements (Km)	0 – 15	15 – 30	30 – 45	45 – 60	Others
14	Nearness to railways (Km)	0 – 50	50 – 100	100 – 150	150 – 200	Others

Equal intervals were used for assigning the descending linguistic values in the case of the other criteria variables. However, the last class (least suitable), may be narrower or wider than the rest of the suitability classes depending on the size of the values remaining for the class. The remaining variable values are assigned to the 'least suitable' class after all the four classes. As mentioned in chapter three, average sunshine duration was used throughout the country and as the literature reported this value as highly favourable for all the biofuel crops, the entire study area was classified as 'most suitable'. Even though this means sunshine duration will not present spatial variation, not including it will lead to inflating the criteria weights of the other variables especially for crops that highly require sunshine for their growth such as oil palm. Also, including the criteria in the analysis ensures this methodology is transferable to other study areas where there is considerable spatial variation in sunshine.

4.3 Standardising criteria maps

After going through the process of identifying, securing and refining the data for the criteria and generating the criteria weights, it was necessary to standardise all the datasets that represent the criteria to a scale that allow all the criteria to be analysed simulteneously in the GIS environment. While the degree to which an alternative meets certain criterion in a multi-criteria evaluation depends on the scores of the criterion, these criteria values are usually mutually incomparable because they are recorded in different units (Voogd 1982).

Rainfall is measured in millimetres, soil is categorical, temperature is in degree Celsius, relative humidity and slope are measured in percentages, elevation and distances are measured in metres, soil pH is a measure of relative acidity or alkalinity on a scale of 0 to 14, bearing is the unit for aspect ranging from 0° to 360° and the length of daylight is measured in hours. While insolation is measured in kilowatt-hour per metre square per day, the radiation use of plants is measured in megajoule per metre square.

According to the data acquired and processed, soil pH in Nigeria ranges from 4.0 to 8.2. Altitude range from sea level to 2,419 metres. Slope ranges from 0% to 100%, while relative humidity ranges from 35% to 91% according to the acquired and processed datasets. The data also shows a mean annual maximum temperature range of 22 to 37° Celsius and annual rainfall range of 419 to 2,730 millimetres. The length of daylight ranges from 11.5 to 12.5 hours, while insolation ranges from 4.2 to 6.4 kilowatt-hour per square metre per day.

Looking at these varied scales, it is obvious that only soil is qualitative and nominal in nature. The rest are quantitative in nature, but some are measured on interval scale such as aspect, soil pH and temperature (degree Celsius), while others are measured on ratio scale such as elevation, insolation, length of daylight, rainfall, relative humidity, slope (percentage) and the distances. Further, the direction of the criterion values differs between variables. Some higher scores may imply best case for the objective, while in some, it is the low values that favours best alternative.

For example, the higher the insolation of a given area, the more suitable it is for cultivating the crops, at least considering the data range for Nigeria. On the other hand, the lower the distance value to surface water, the more suitable the land is for crop cultivation especially for crops that require irrigation such as sugarcane. In this work, these opposing directions do not apply to some of the criteria. Neither the highest value nor the lowest value indicates the best alternative for rainfall criteria. The rainfall criterion is a vector, and the best case is indicated by a particular range above the lowest and below the highest values. Soil is nominal and the relative importance of a category over the other depend on the crop in question. The purpose of pointing these out is to show the need for all these criteria to be transformed into a common scale to make it possible to combine all the data for the suitability classes at the same time. All standardised scores should have the same direction (Voogd 1982). This standardisation allows for a dimensionless score to be assigned to different measurement units for aggregation and comparison (Dell'Ovo et al., 2018).

Fuzzy logic can be used to represent indeterminate boundaries and, as in the case of this study, to handle uncertainty of hard class membership. As seen in section 4.2, direct qualitative determination is based on fuzzy sets which, in the context of GIS databases, can be used to represent geographical entities with imprecisely defined boundaries as fuzzy objects or regions. One interpretation of the fuzzy region is given as the concentration of some attributes associated with an entity at a particular point (Malczewski 1999). It could also be interpreted as the degree to which that point is inside or part of an entity. This provides important utility for spatial decision analysis and other GIS-based operations.

An organised GIS system usually consists of a set of datasets or thematic maps (known as map layers) describing a single characteristic of each point or location within an area. Representation of the real world in a GIS system can be done through either cell-based (raster) or object-based (vector) model. Raster models are structured as an array or grid cells, often referred to as pixels. These models are able to represent a large range of computable spatial objects (Worboys 1995). A single cell may represent a point, a sequence of neighbouring cells may represent an arc and a collection of continuous cells may represent a connected area. Vector models are entities represented by strings of coordinates; a point is one coordinate, a number of connected coordinates along an arc represent a line, while a chain of connected coordinates linking back to starting point or a set of coordinates at a polygon’s corners represent an area (Malczewski 1999).

Practically, a pragmatic decision on choosing the data model to be adopted should be based on the aim of the user of the database (Burrough and McDonnell 1998). Though it is computationally inefficient, an important advantage of raster models is that they make it possible to represent continuously varying data. On the other hand, though vector models are efficient computationally, their major disadvantage is that they are unsuitable for continuous surfaces (Malczewski 1999). Therefore, where map layers describe continuous (field) geographical entities, a raster-based data model may be more appropriate. This was adopted in this work because all the 14 criteria entities are continuous in space including the soil dataset that comes as categorical. They do not have crisp boundaries in the real world. The implementation of the reclassified attribute values as in table 4.1 to reclassify map layers was based on the comparisons operation (equal to, greater than, less than, …) which can be combined to perform ranged classification (Malczewski 1999).

Criteria maps were created displaying spatial distribution of suitability levels of each of the criteria for each of the biofuel crops. Each of these criteria maps was presented and discussed in chapter three (section 3.3). In this section, reclassification tool of the ArcMap was used for the transformation to classes of suitability. It is worth noting here that the reclassification was based on the thematic attributes of the data layers though the distances might be seen as being reclassified based on the connectivity/proximity operation (nearness or proximity of a location to the entities). This means, a cell value indicates its suitability for a crop with respect to a theme at its location in a thematic map. While the cell value indicates its proximity to a location with respect to an entity at that location on a proximity map.

The reclassified maps show the suitability index as in figure 4.1 for sweet sorghum. Other reclassified maps were presented in appendix IV for sugarcane, cassava, oil palm and jatropha, respectively. Except for sugarcane and jatropha that show some similarity in pattern in terms of elevation favourability, all the crops seemed to show great disparity for this criterion. Aspect was standardised in similar way for all the crops because the slope orientation influences all the crops in similar way as seen in chapter two. The same also applies to the spatial distances with slight difference for sweet sorghum in terms of surface water and proximity to roads due to its comparatively less requirement for water and the extent to which it is widely being cultivated in the country.

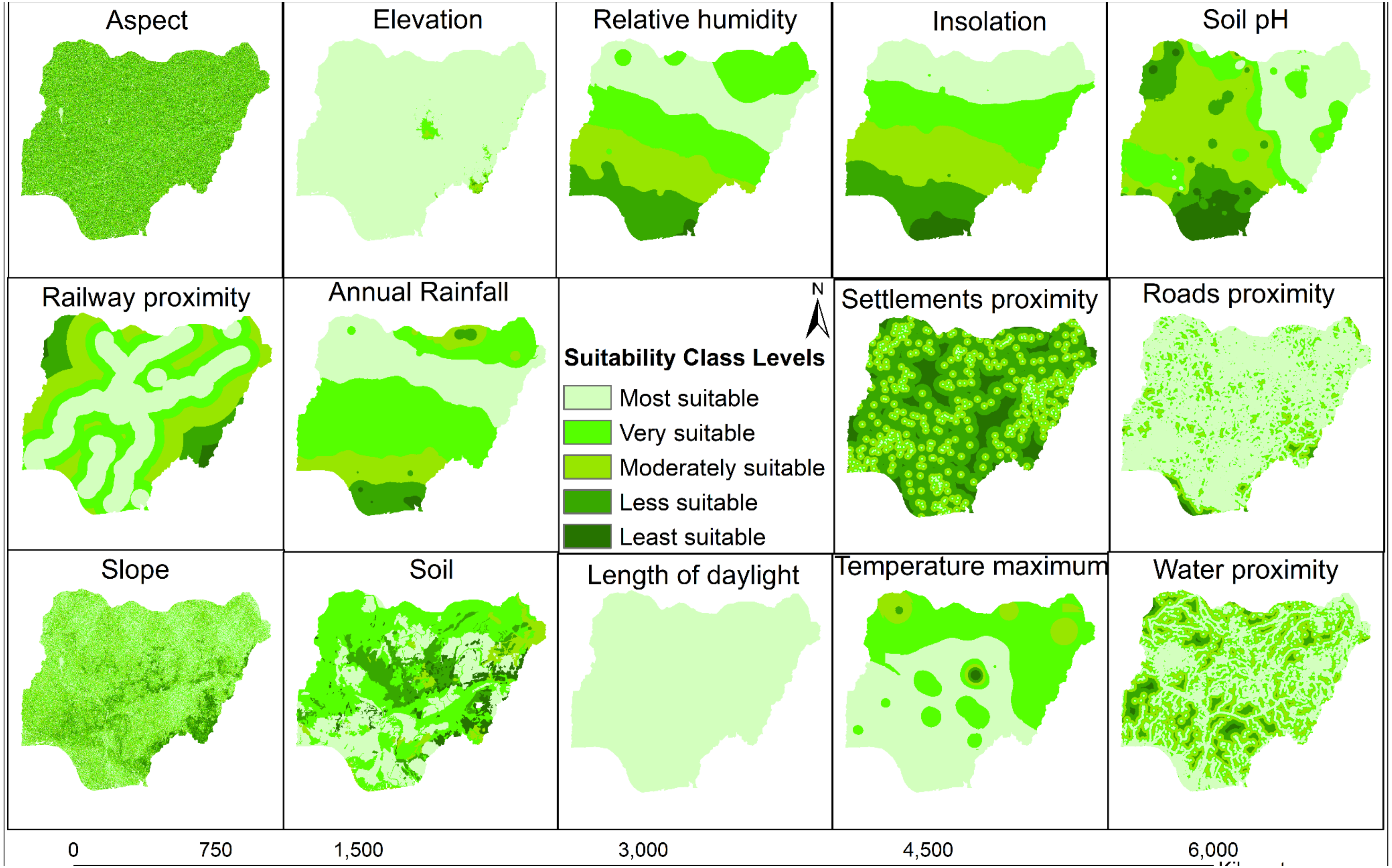


Figure 4.1: Reclassified criteria suitability maps for sweet sorghum

Except for oil palm, relative humidity seems to favour more than half of the country for all the crops, with large area classed as either most suitable or very suitable. A similar result was found for rainfall, insolation and temperature for all crops. A similar pattern could also be seen with regards to soil pH, though, some deviations are obvious on cassava and jatropha maps. Large parts of the soil categories seem to favour all the crops as either most or very suitable except for oil palm for which most of the soil categories are either moderate or less suitable. Some similarity in favourability is also obvious for slope distribution though it shows more influence on oil palm than sugarcane. As mentioned in the previous subsection, the average sunshine duration of about 12 hours in Nigeria favours all the biofuel crops except jatropha which was reported in chapter two as being not sensitive to sunshine duration (section 2.3.5).

4.4 Biofuel crops land suitability models and results

One of the FAO's fundamental principles for land evaluation is that land suitability should be assessed and classified based on the specified kind of uses because different uses have different requirements (FAO 2007). For example, in this work, the specific land use target is cultivating the identified biofuel crops on one hand, and ensuring the restricted areas are avoided on the other hand. As seen in the previous subsections, all the criteria map layers were standardised to the adopted suitability scale of five levels described by the five linguistic terms (most suitable, very suitable, moderately suitable, less suitable and least suitable).

The next process involves combining all the criteria maps through an overlay operation. The outputs of the previous processing (map layers) would be the inputs to the overlay operation. This overlay procedure requires that all the map layers are on a common grid reference. These maps can only overlay if georeferenced to a common coordinate system. In this analysis, UTM (WGS 1984) was used as the common coordinate system. Though the UTM zones divide Nigeria in to three (zone 31N, 32N and 33N), zone 32N was adopted being the central zone since all the three cannot be used at the same time and the whole country is covered by this analysis. Zone 31N or 33N would be more appropriate if the analysis is restricted to western or eastern part of the country, respectively.

The overlay procedure generates an output layer as a function of more than one input layers. As seen earlier, the input layers were derived from the identified criteria. The term criterion is a generating term that connotes both attributes (which are properties of geographical entities or phenomena for example ‘favourable rainfall’) and objectives (which indicates the direction of improvement of one or more attributes for example ‘high crop yield’). Attributes form the means available to decision makers for formulating and achieving their objectives based on the fact that there is one-to-one relationship between an objective and its underlined attributes (Malczewski 1999). Thus, the alternatives are defined explicitly in Multi-attribute Decision Making (MADM) and implicitly in Multi-objective Decision Making (MODM).

This is a crucial distinction in Multi-criteria Decision Making (MCDM) implemented in a GIS environment. It is usually impossible to implement MODM in a GIS environment. This is because GIS have a very limited capability for comparing alternatives and producing desired output where alternatives are defined implicitly by a causal relationship rather than explicitly by the attributes. Standard GIS systems are sufficient for most MADM decision rules such that the decision variables can be assigned to the spatial entities modelled in a GIS database. Because the analysis in this section is raster based, each pixel is an alternative and the attributes (decision variables) are assigned to each of the rasters.

Addditive decision rules are the best and most widely applied methods of MADM (Malczewski 1999). Analytical Hierarchy Process (AHP) is one of the three methods of the additive decision rule. AHP has been discussed and presented in chapter three where the criteria weights were generated. These weights are called decision alternative scores and serves as ratings of the effectiveness of each alternative in achieving the objective. They indicate the importance of each factor as compared to all other factors and they control how these factors compensate for each other (Drobne and Lisec 2009).

These weights are assigned to the map layers (each pixel receive a weighting) in the GIS operation called weighted overlay (WO).

WO Function is a GIS tool developed based on the concept of Weighted Linear Combination (WLC) and was extended to Ordered Weighted Average (OWA). The function was extended to handle the limitation of the WLC with regards to the absence of real threshold that could allow definitive allocation of areas (Drobne and Lisec 2009). OWA was suggested as the solution based on set theory and application of fuzzy measures. Due to the degree by which weights are evenly distributed across all positions in OWA operations, trade-offs between conflicting criteria are allowed and implies global evaluation of alternative decisions that takes a middle position between the worst and the best ratings. It averages the pessimistic and optimistic decisions by providing intermediate solutions that for example allows a poor performance of an alternative with regards to a criterion to be compensated by a higher performance in another criterion though there is a continuous control over the degree of the compensation. It is weighted sum with ordered evaluation criteria that allow for direct control over the levels of trade-offs among the criteria (Malczewski 1999). This means compensation among criteria is only allowed according to the order; one criterion at a particular level of the order cannot compensate for other criteria at a different level of the order.

It was shown in section 4.3 how the concept of fuzzy sets was used to reclassify and order the values of each of the map layers in descending order of suitability classes. WO provides fewer risks in suitability analysis as compared to Boolean Operation (BO) which eliminates any candidate that did not score highly in any of the decision criteria (Abudeif et al., 2015), as alluded in section 4.2. WO function in the GIS environment can only accept weights but cannot generate them, making the role of AHP crucial. The overlay function multiplies the weights by the standardised attribute scores (map layers) and the products are added to obtain the overall score for each of the alternative. In other words, the suitability index maps were combined with the weights generated in the previous chapter to model and assess land suitability for sweet sorghum (figure 4.2).

For each of the criteria maps, first order (denoted as ‘1’) represents the first and most preferred alternative class. The second order (denoted as ‘2’) represents the second alternative class. The third, fourth and fifth orders (denoted as ‘3’, ‘4’ and ‘5’) represent the third, fourth and fifth alternative classes, respectively. These 14 reclassified raster datasets were imported into the overlay tool and each was given its percentage influence as in table 3.4 summing up to 100%. The evaluation scale chosen was ‘1 to 5 by 1’. Because the raster datasets were already classified with field values 1 to 5, the scale values were assigned such that they correspond to the field values. Similar models were also developed for all the four other crops (appendix V). The land suitability index for each of the crops were presented in maps as shown in figure 4.3. According to Beek and KJ (1978), the suitability class expresses the degree of a given type of land for a specific use that the best results are the ones that are in agreement with the criteria for optimal use.

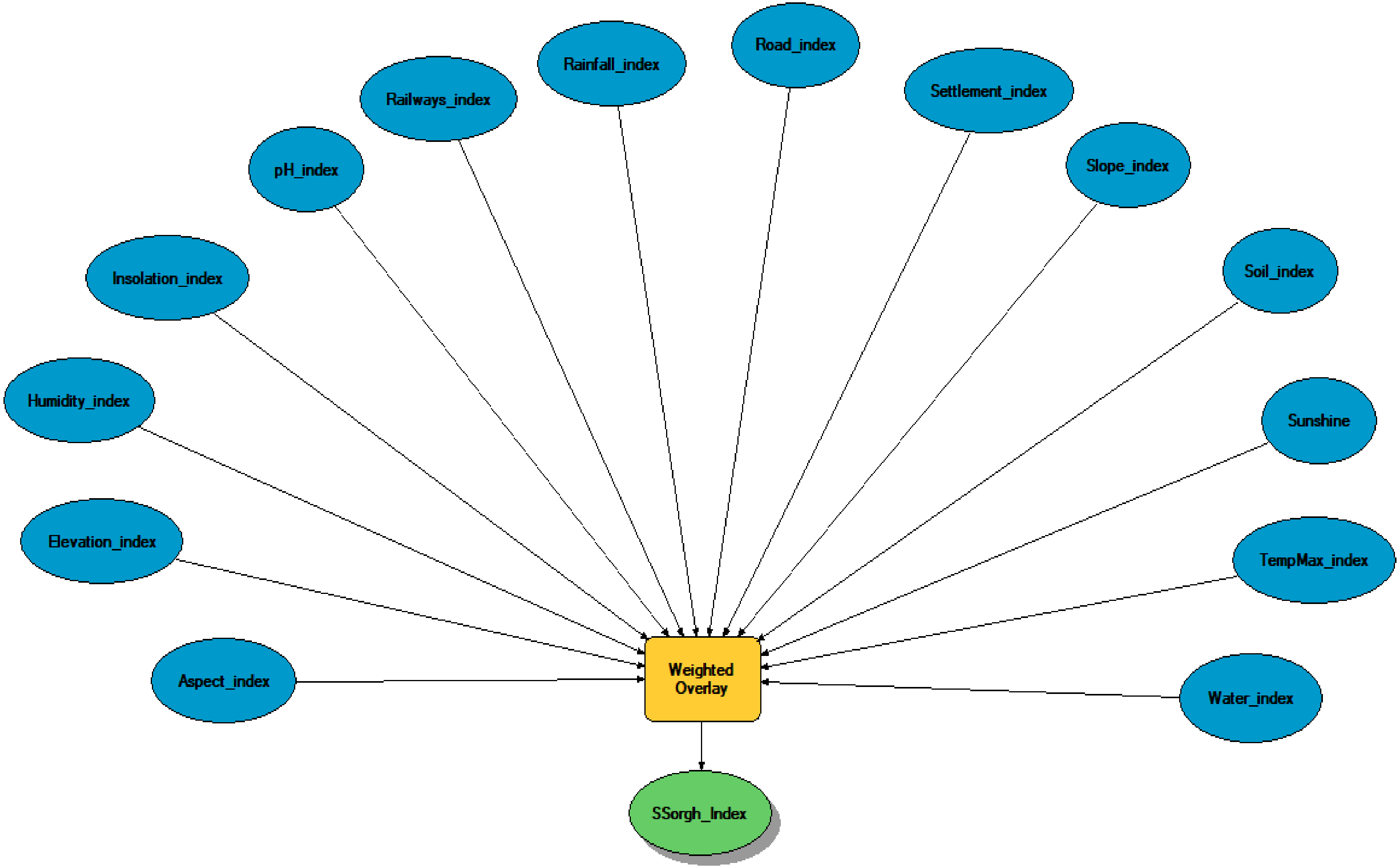


Figure 4.2: Land suitability model for cultivating Sweet sorghum in Nigeria

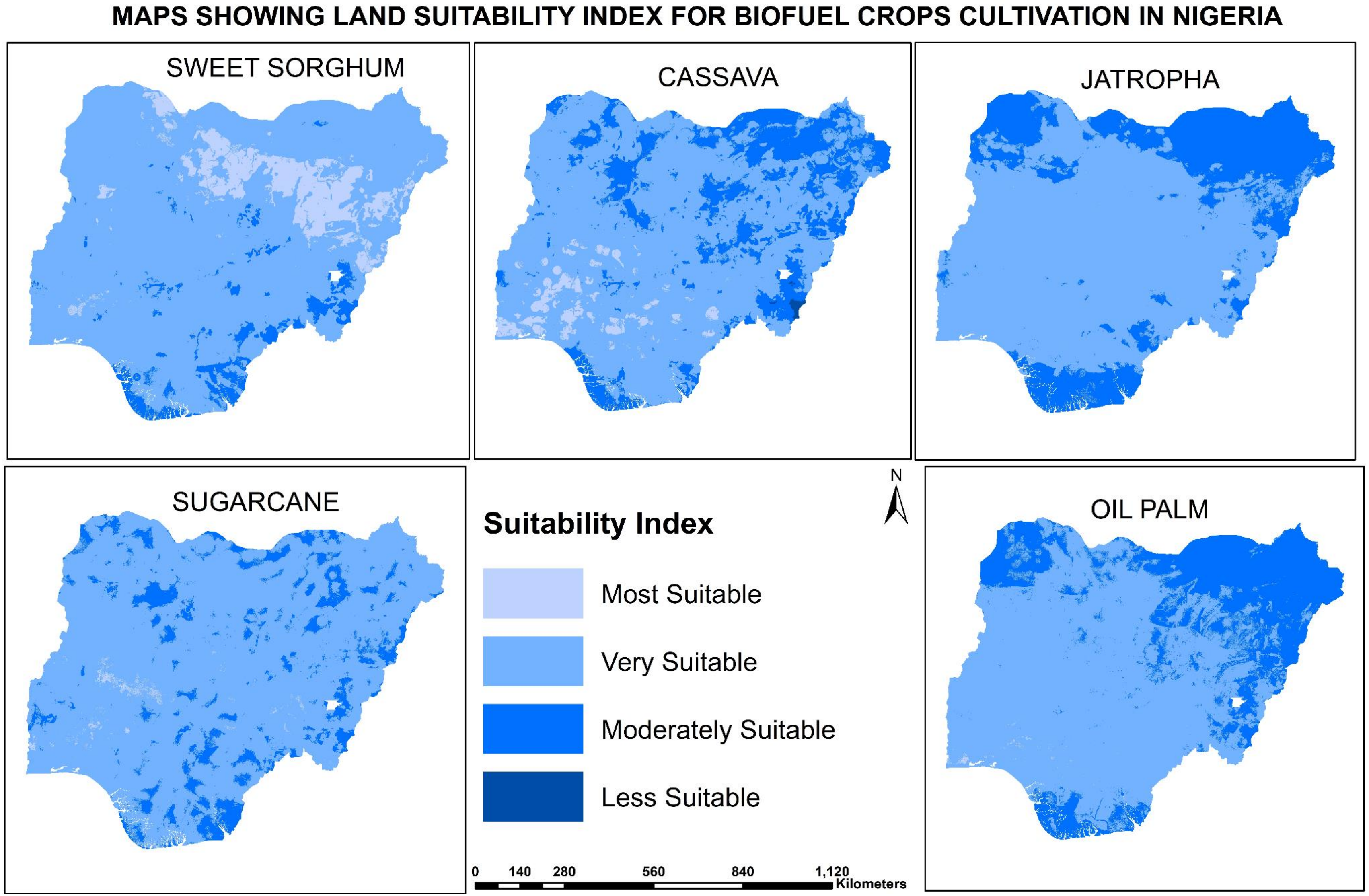


Figure 4.3: Land suitability maps for cultivating biofuel crops in Nigeria

4.5 Results and discussions

The generation of land suitability maps (figure 4.3) represents objective five of this thesis. Land suitability classification is defined as “an appraisal and grouping, or the process of appraisal and grouping of specific type of land in terms of their absolute or relative suitability for a specific kind of use” (FAO 1976). Though efforts were exerted in getting enough quantitative information for the adopted qualitative scale, it should be stressed at this level of the analysis that the suitability classes are rather relative; are not absolute (clear-cut) and are only valid for the study area and based on the available data. Looking at the maps in figure 4.3, it is obvious that the models classified large parts of the country as ‘very suitable’ for cultivating all the crops. While very little areas were found to be ‘most suitable’ for some crops, no part of the country was identified as ‘least suitable’ for any of the crops. Thus, it could be inferred that large part of Nigeria is ‘very suitable’ for the cultivation of all the five biofuel crops. This conclusion would provide an important basis for the optimisation analysis that comes in chapter six.

The maps show that the model recognised sweet sorghum with the largest extent of areas identified as ‘most suitable’ in the country. It could be inferred that there is convergence of favourable variables for the crop in those areas. Some few areas identified as ‘most suitable’ are also apparent on cassava, sugarcane and oil palm maps. Lots of areas were identified as ‘moderately suitable’ especially for oil palm and Jatropha both of which show some similar spatial pattern. Except perhaps for cassava, areas identified as ‘less suitable’ are not easily obvious from the maps. At this point, objective six have been achieved and table 4.2 shows the land proportions of the suitability classes for each of the crops. Comparing figure 4.3 to figure 4.4, it is obvious that this work provided greater details regarding potential areas for cultivating biofuel crops in Nigeria than what is available in the public domain.

Table 4.2: Percentage Nigeria lands suitability for biofuel crops cultivation

Class	Linguistic Term	Sweet sorghum	Sugarcane	Cassava	Oil palm	Jatropha
1	Most suitable	10.36	0.69	3.77	0.14	0
2	Very suitable	84.18	87.49	74.40	70.56	71.60
3	Moderately suitable	5.47	11.82	21.60	29.31	28.40
4	Less suitable	0	0.000064	0.23	0.00029	0
5	Least suitable	0	0	0	0	0

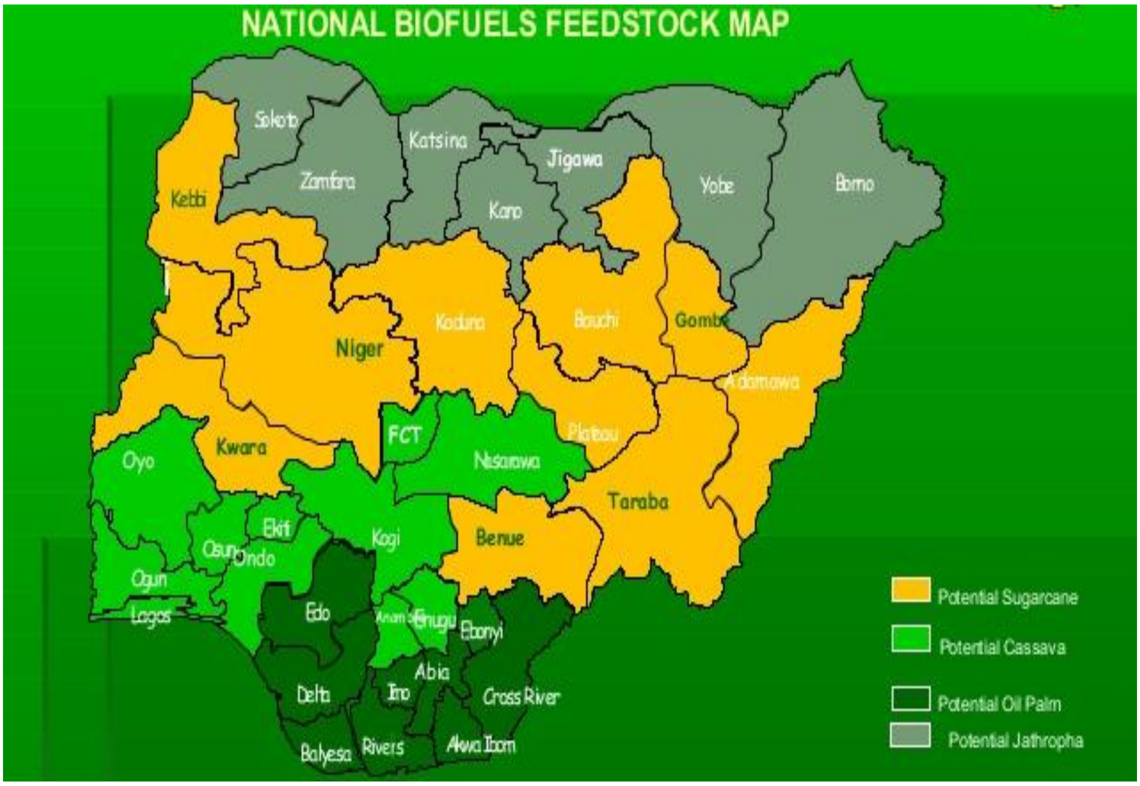


Figure 4.4: Very low detail map of biofuel feedstock in Nigeria Source: (NNPC 2012)

Though the researcher could not obtain detail information about how figure 4.4 was produced and on what basis, it obvious that the map follows the vegetation zones of the country rather than the actual individual crop's ecological favourability. Oil palm is assigned to the mangrove and freshwater swamp forest zones, cassava to the tropical rainforest, sugarcane to the derived and guinea savannah and jatropha to the sudano-sahelian savannah. Some explanations could be decerned from the information the map is communicating. For example, because oil palm require high amounts of rainfall, it is expected to do well in the Niger Delta where highest amount of rainfall is received in the country. Also, because jatropha has high tolerance to drought, it may perform well in tolerating the sudano-sahelian harsh environment. However, the map lack information with regards to suitability of the other biofuel crops in the respective assigned zones. For example, it may implicitly communicate the wrong information that jatropha may not do well in the Niger Delta or that cassava may not do well in the sudano-sahelian vegetation.

While figure 4.4 grouped states, following ecological pattern of the country, to show potential areas for the crops, this research provided more details by analysing the suitability levels of the areas. Further detail would be provided on this in chapter five after the restricted areas are identified and eliminated. Before eliminating restricted areas, it could be seen in table 4.2 that more than 84% and 87% of Nigeria's land is classified as 'very suitable' for cultivation of sweet sorghum and sugarcane, respectively. Also, for cassava, oil palm and jatropha, more than 70% of the study area is classified as 'very suitable' for each of the crops. Less than 0.25% is classified as 'Less suitable' for any of the crops. It was alluded in section 3.5 that sensitivity analysis may not be an absolute basis for drawing conclusions about reliability of multi-criteria decision methods and that in the case of applying pairwise comparison technique, what is necessary is ensuring the results are based on a consistent comparison. However, sensitivity analysis may provide some insights into how sensitive the results might be to the changes in the criteria weights. Some of the approaches to sensitivity analysis include assigning equal weights to all the criteria, setting one or more criteria weights to zero or altering the criteria weights using a defined interval, one at a time (Höfer et al., 2016). In this work, equal weights were used to conduct the sensitivity analysis. Figure 4.5 (full extent) and 4.6 (zoomed in) show the comparison between the results for each of the crops.

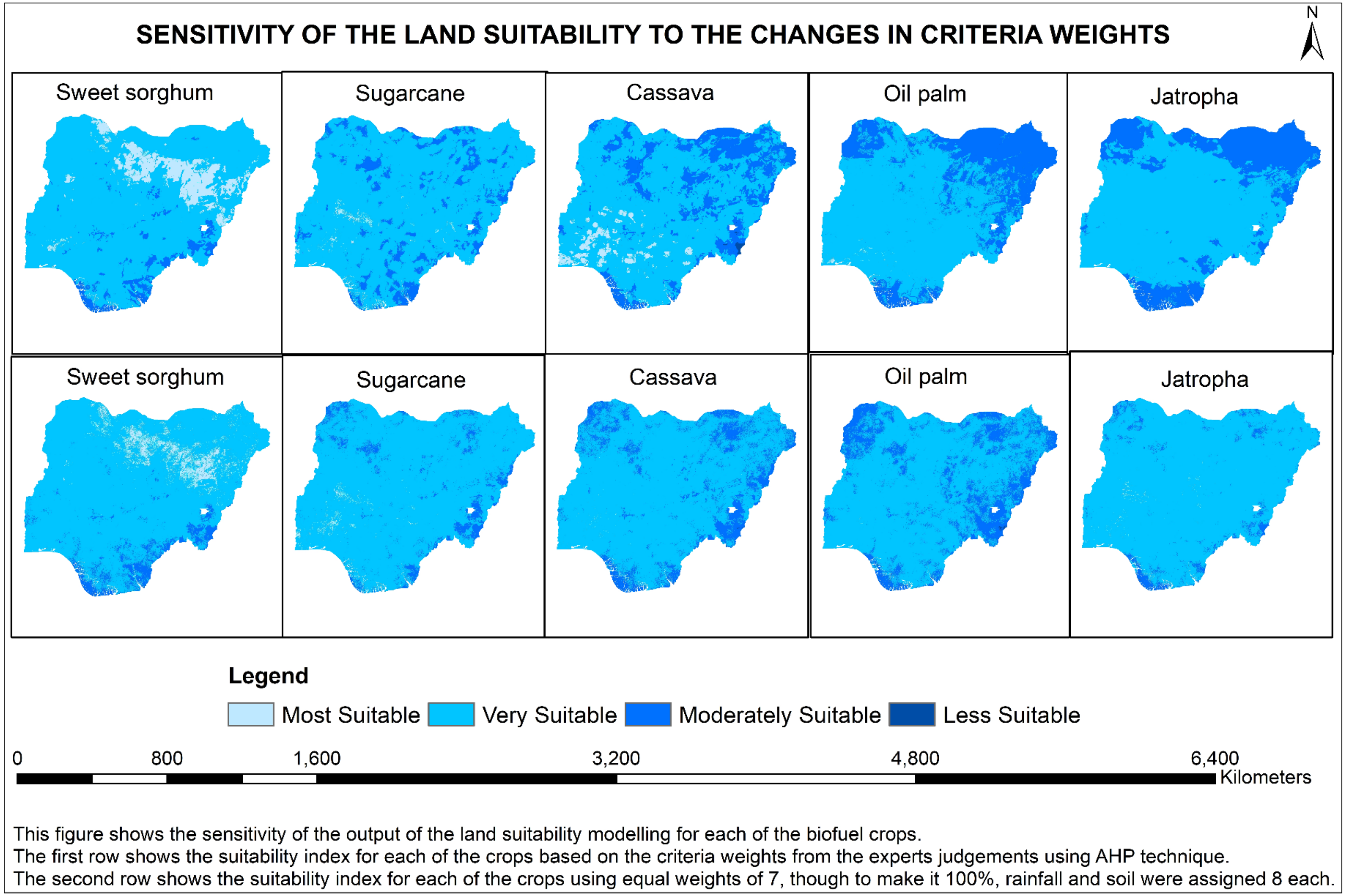


Figure 4.5: Maps showing sensitivity of the land suitability index to changes in criteria weights

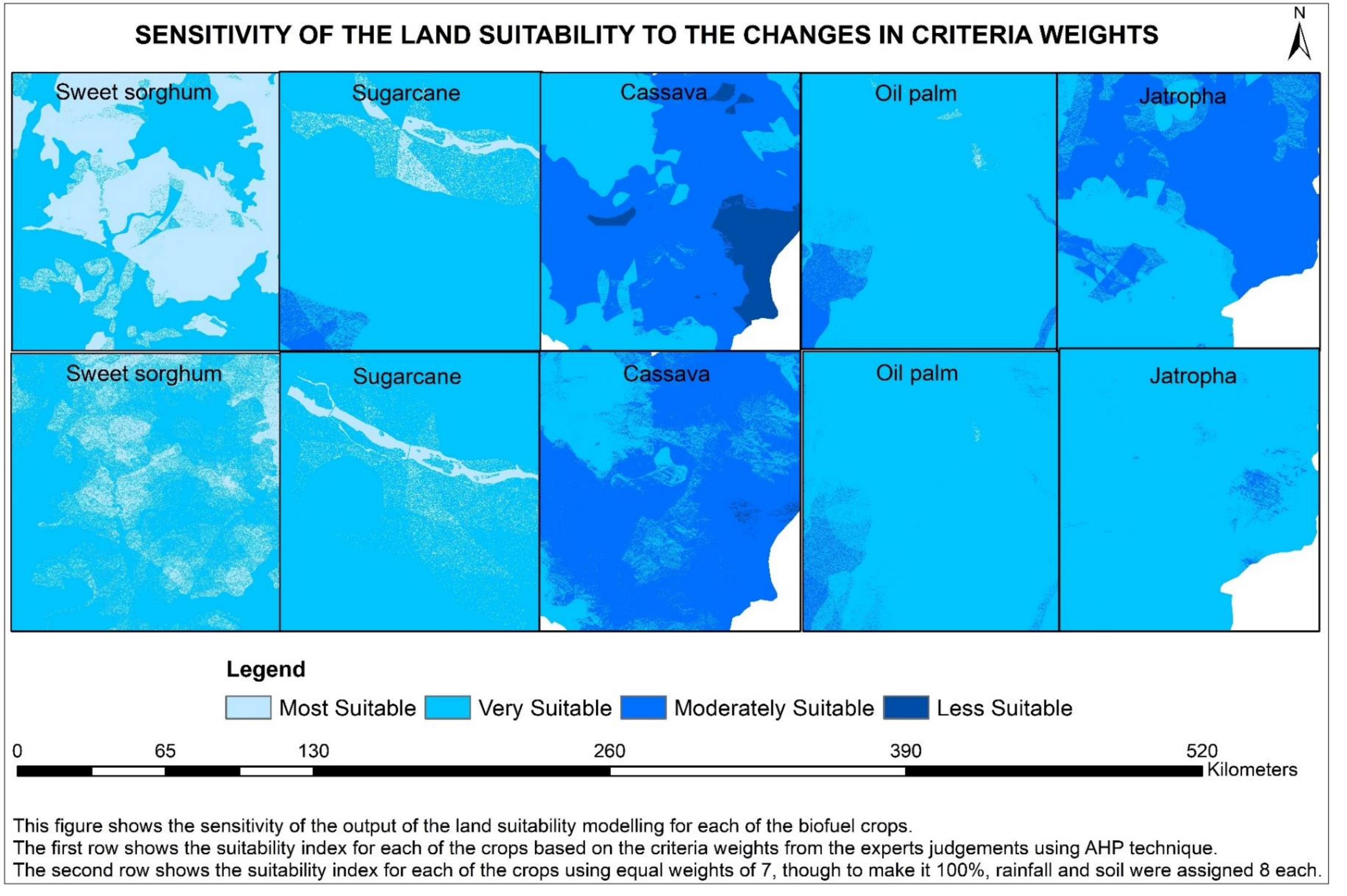


Figure 4.6: Sensitivity shown in some zoomed part of the country

It is obvious from figure 4.5 that even though both the two results show similar patterns, there are significant differences between the two. Taking each pair of the maps for each of the biofuel crops, it is easily decernible that the results are sensitive to changes in the criteria weights. As explained by the text on the figure, equal weights of 7 were assigned to each of the 14 criteria. This sums up to 98. The GIS tool for this operation requires that the total weights add up to 100. Thus, because rainfall and soil are the major factors for plants' growth and development, the two were assigned a weight of 8 each. Similar to the AHP generated weights, the model output from these equal weights did not classify any part of the country as least suitable for cultivating any of the five biofuel crops. However, for jatropha, some small parts of the country were classified as Most suitable using these equal weights, unlike the AHP weighted model which did not identified any part of the country as most suitable for the crop. Also, areas identified as most suitable for cassava, almost disappeared in the sensitivity analysis results (table 4.3).

Table 4.3: Land suitability proportion using equal criteria weights

Class	Linguistic Term	Sweet sorghum	Sugarcane	Cassava	Oil palm	Jatropha
1	Most suitable	5.60	0.60	0.04	0.0065	0.19
2	Very suitable	88.30	93.05	84.98	78.47	95.50
3	Moderately suitable	6.04	6.89	14.96	21.47	4.31
4	Less suitable	0	0.000033	0.009329	0.054644	0
5	Least suitable	0	0	0	0	0

Comparing table 4.2 with table 4.3, it could be concluded that the application of AHP had improved the land suitability modelling because the results are sensitive to changes in the criteria weights. Table 4.4 shows the proportional change in land suitability for each class, based on each of the biofuel crops. 'Very suitable' class increased for all the crops. While 'Most suitable' class decreased for all the crops except jatropha, ‘Moderately suitable’ class decreased for all the crops except sweet sorghum. ‘Less suitable’ class decreased for both sugarcane and cassava, unlike sweet sorghum for which it had increased.

Table 4.4: Percentage change (sensitivity) in land suitability proportions

Class	Linguistic Term	Sweet sorghum	Sugarcane	Cassava	Oil palm	Jatropha
1	Most suitable	-4.76	-0.09	-3.73	-0.1335	+0.19
2	Very suitable	+4.12	+5.56	+10.58	+7.91	+23.90
3	Moderately suitable	+0.57	-4.93	-6.64	-7.84	-24.09
4	Less suitable	0	-0.000031	-0.220671	+0.054354	0
5	Least suitable	0	0	0	0	0

The use of MCDM approach had been shown to be very useful in increasing the effectiveness of GIS as a tool that assists in supporting spatial decision making. Huang et al., (2011), noted that the differences in the choice of MCDA approaches may be based more on familiarity and available opportunity than on their comparable merits. While the isssue of familiarity could be takled through extended literature exploration on the methods, the issue of available opportunity may be difficult to be addresed. Lengthy discussion was given in chapter three on the reasons for choosing AHP as the method for criteria weighting in this work. It was mentioned there that AHP is a superior method of criteria weighting in a systematic and logical way.

In this chapter, only the favourability factors were considered in determining the suitability of the land for the biofuel crops cultivation in Nigeria. The intended land use may have some strong spatial implications that may lead to various adverse effects on the landscape such as pollution (air, water and noise), land degradation and biodiversity disturbance. These effects caused by sub-optimal siting of some land uses were said to have induced an increasing gap against the social acceptance of these land uses on both local and global scales (Höfer et al., 2016). The following chapter is dedicated to identifying and eliminating restricted areas to determine areas that could potentially be used for biofuel crops cultivation in the country.

Chapter Five – Constraints Modelling

5 Chapter Five – Constraints Modelling

5.1 Introduction

In the previous chapter, analysis was presented that combined all the factors that support cultivation of crops for biofuel feedstock in Nigeria. As discussed in section 4.5, these factors form one category of the evaluation considerations for spatial analysis. The other category of considerations forms the evaluation constraints such as agricultural and protected areas. As indicated in section 4.1, factors that do allow for compromise should be aggregated first before analysing factors that do not. In other words, factors that can compromise between one another should be analysed together before factoring in the factors that cannot allow for trade-off. This provides an overview of the overall land potential suitability before incorporating restricting factors. Also, the restrictions may change, for example, due to change in regulations, or what is considered restriction may change in itself. Therefore, it is more useful to start with all the possible land areas and then eliminate the restricted areas.

This chapter is dedicated to analysing these constraints and the process of their elimination. In other words, these areas that are restricted or that may not be used for biofuel crop cultivation would be identified and a model would be developed for their elimination. The result would be combined with the result of the land suitability model to provide more detailed discussion on the potential areas that may be available for cultivating biofuel crops in Nigeria. In chapter two (section 2.2), an overview was provided of the crops deemed appropriate for biofuel production in Nigeria. In chapter seven, discussions will be provided on strategies to make biofuel production in the country feasible and sustainable.

5.2 Identifying restricted areas

The basis for identifying the constraints were the principles put forward as a standard by Roundtable on Sustainable Biomaterials (RSB) as contained in their published document (RSB guide to the RSB standard). RSB is a global, multi-stakeholder independent organisation that drives the development of a new world bio-economy through sustainability solutions, certification, innovation, and collaborative partnerships (RSB 2017). Because it was not possible to obtain all the data needed to incorporate all the 12 RSB principles, only those for which data is available were considered in the elimination modelling.

Table 5.1 shows the RSB principles indicating for which data was available. It might be observed that most of the principles are non-spatial; they are not directly related to locating the land in and of itself but related to management strategies or compliance with regulatory guidelines. Principle 6 (local food security) requires that human rights to adequate food and improved food security are ensured. One of the basic means of ensuring these is making sure that the existing food crop areas are not converted to feedstock production because this will have direct impact on the supply and indirect effect on the price of food stuff. Thus, compliance with principle 6 is represented in this work as avoiding currently cultivated agricultural areas. Section 5.3 deals with identifying existing agricultural areas in Nigeria.

Table 5.1: Roundtable on Sustainable Biomaterials (RSB) principles

S/N	Principle	Data
1	Legality	Non spatial
2	Planning, Monitoring and Continuous Improvement	Non spatial
3	Greenhouse Gas Emission	Not available
4	Human and Labour Rights	Non spatial
5	Rural and Social Development	Non spatial
6	Local Food Security	Available
7	Conservation	Available
8	Soil (maintenance and reversing degradation)	Available
9	Water (right)	Available
10	Air (quality)	Not available
11	Use of Technology, Inputs and Management of Waste	Non spatial
12	Land rights	Non spatial

The World Database on Protected Areas was explored as the source for data to identify other protected areas including reserves and conservation areas. This covers RSB principle 7 which requires avoidance of negative impacts on biodiversity, ecosystem and conservation values. Since the 2010 COP10 in

Aichi, Japan, parties established national targets to contribute to the achievement of the targets set at the conference. The Aichi target 17 (https://www.cbd.int/sp/targets/) required that by 2015 each party has developed, adopted as a policy instrument and has commenced implementing an effective, participatory and updated national biodiversity strategy and action plan. Target 5 required that the rate of loss of all natural habitats, including forests, is at least halved by 2020 and where feasible brought to zero, and degradation and fragmentation is significantly reduced. However, in a press release, the United Nations showed that despite encouraging progress in several areas, the natural world is suffering badly and getting worse (UN 2020).

There is likelihood that these global targets will be renegotiated at COP15 in October, 2021, with some suggestions that parties increase the coverage of their protected areas to 30%. However, this will have profound consequences for land use. Schleicher et al., (2019), analysed the ambitious proposal of protecting half the earth and found that at least one billion people live in the areas that would be protected if this proposal is implemented within all ecoregions. Implementing this will cause huge human displacement and thus, the authors recommended that the framework should apply more holistic and interdisciplinary approaches that take into account social and economic implications across all scales. This will also greatly affect land availability for biofuel crops cultivation.

The Nigeria's revised National Policy on the Environment (FME 2016) reported that an estimated 0.4% and 8.5% of the plant species (more than 5000 recorded) are threatened and endangered, respectively. Similarly, 0.14% and 0.22% of the animals and insect species (22,090) are threatened and endangered, respectively. This clearly shows that there are more endangered than threatened species of both plants and animals. Thus, the focus of the Nigeria's national policy on the environment, among other strategies, was on encouraging sustainable use of farmlands, forests and wetlands outside protected areas (5.7% of the landmass) while promoting in-situ (within protected areas) and ex-situ biodiversity conservation. It is, therefore, necessary to identify these protected areas as much as possible to make sure they are avoided. With only 5.7% of Nigeria's landmass protected, the country is far below the global target though there could be lots of unused areas that could be added to the protected area system without hampering existing land uses.

RSB Principle 8 requires maintenance of soil health and/or practices to reverse soil degradation. Though this could be approached through farming practices, in this work, severe erosion sites were avoided as part of spatial compliance to this principle. The Nigeria's national environment policy reported that in the south-eastern states of the country, gullies and areas exposed to erosion increased from about 1.33% (1,021 km^2) in 1976 to about 3.7% (2,820 km^2) in 2006. The policy indicated that particular attention would be given to erosion-prone areas in formulation and enforcement of regulation for soil and water conservation.

Major surface water bodies were also identified, and this covers principle 9 of the RSB. Aichi target 11 requires that by 2020 17% terrestrial and inland water and 10% of coastal and marine areas are conserved through connected systems of protected areas and other effective area-based conservation measures. The Nigeria's environment policy focus, among other things, on promoting sustainable use of freshwater, wetland (estimated to cover about 13 million hectares) and groundwater (the annual recharge of which is estimated at about 9.5 trillion litres) resources and conservation of vulnerable river and lake ecosystems in particular and biodiversity in general.

Section 5.4 of this chapter deals with combining all these identified constraints in a model to eliminate them, making sure these areas were not identified as potential for biofuel feedstock cultivation. The last chapter of the thesis will provide recommendations that will cover considerations for the other principles which could not be included in the elimination modelling due to the nature of the principle or data unavailability as mentioned earlier.

5.3 Land cover mapping

5.3.1 Background

As mentioned in the previous section, part of the compliance with RSB principle 6 is ensuring that the existing food crop areas are not converted to biofuel feedstock production. The spatial analysis must, therefore, aim to avoid identifying existing agricultural areas as suitable for biofuel crops cultivation. Identifying these lands is very crucial in this regard and could be achieved through exploring land cover maps of the study area. At the initial stage of this research, the most recent land cover map covering Nigeria that was available to the researcher was the one developed by CILSS and published in 2016 as a series of three maps showing land changes from 1975 to 2000 and to 2013. The map was produced at regional scale (for the whole West Africa) and the most recent of the maps was based on 2013 datasets. In addition, the spatial resolution of the map is 500 metres which could be regarded as too coarse to provide useful details of several land covers such as water bodies and the many agricultural land parcels, the identification of which forms a crucial aspect of this research.

At a later stage of the work, the attention of the researcher was drawn to the recent global land cover produced by the European Space Agency (ESA) based on Sentinel data products and published in October, 2017. The map was produced using a 12 months (December, 2015 to December, 2016) Sentinel 2A imagery at a fine spatial resolution of 20 m (ESA 2017). However, country specific assessment of the map showed that it has very low overall accuracy in many countries especially in West Africa where the 47% accuracy in Ivory Coast was attributed to fragmented land cover which makes it a difficult country to map with remote sensing (Lesiv et al., 2019). Most West African countries including Nigeria share similar pattern of land cover system. Though Sentinel 2 data shows great potential for land management applications, it faces challenges such as mismatch with Landsat 8 OLI, differences in spatial resolution and lack of thermal bands (Phiri et al., 2020).

Especially of particular interest to this work, assessment of the ESA Africa land cover map shows that there is massive overestimation of croplands which were mapped with low user's and producer's accuracies and the highest confusion is between croplands and grasslands (Lesiv et al., 2017). Using this map in this work would mean eliminating massively overestimated agricultural area. Also, the map has a continental scale (Africa) and thus might not be ideal to depict regional environment and its heterogeneity (Schulz et al., 2021). Dozens of global and continental land cover maps have been produced but their use is limited, partly, due to their being produced independently and for specific point in time, lacking coherency and continuity (Costa et al., 2018). Nabil et al., (2020) examined most recent and available cropland maps for Africa to assess factors impacting the spatial discrepancies of remote sensing-based cropland products. They reported that all the maps have accuracies below 65% and they identified land cover richness as the main contributor to these spatial disagreements over Africa, among other factors such as high frequency of cloud cover, fragmented field sizes and elevation complexities. They, therefore, encouraged use of multi-classification approach and incorporation of multi sensor to improve cropland mapping processes.

Therefore, it was thought that it would be better to explore the possibility of producing a land cover map focussing on agricultural areas, using recent datasets and at a fine spatial resolution. This might be the best option despite the challenges of satellite imagery classification, especially considering the spatial variability in Nigeria's ecology as discussed in section 1.3. Attempt was made to combine both optical and radar imagery. Though traditional imagery classifiers were adopted in order to keep the process simple and faster, a new procedure was developed for combining different classification outputs to improve classification accuracy.

5.3.2 Methodology

Over the decades, many satellite imagery classification methods have been developed as well as several classifiers. Classifiers are set of software algorithms or packages used in discriminating spectral patterns within an image to enable grouping of image segments with similar patterns into classes. In a particular classification method, a combination of classifiers may be used to achieve a particular purpose (Lillesand et al., 2008). Classification is the procedure that generally involves acquiring the satellite imagery, pre-processing, classification and accuracy assessment. Accuracy of the maps is the most important aspect of the process but is affected by all the other aspects. Combining different remotely sensed data in mapping land cover was shown to increase classification accuracy (Chen et al., 2017; Sekertekin et al., 2017). Specifically, combining optical with radar data was shown to have made it possible to map land covers in areas that present many challenges due to structural complexities (Ianninia et al., 2013; Haas and Ban 2017; Baumann et al., 2018; Whyte et al., 2018; Yang et al., 2018).

Because there is no single ‘right’ manner in which to approach image classification, choice of approach depends upon the nature of the data, the software available and the intended application (Lillesand et al., 2008). It is an unrealisable dream for the remote sensing experts to attain totally automatic image classification in land cover mapping (Sun et al., 2016) and the major issue is said to be classifier selection (Heydari and Mountrakis 2018). Many factors such as spatial resolution of the imagery, the source of the imagery, the classification system and software availability are some of the necessary considerations when selecting a classifier (Lu and Weng 2007). Despite a large number of publications on methods and classifiers, classification still remains a challenging task in remote sensing (Shivakumar and Rajashekararadhya 2018). However, to improve accuracy, some researchers applied a combination of classifiers and/or a combination of methods (Petropoulos et al., 2010; Petropoulos et al., 2013).

Some of the most widely used classifiers in satellite imagery classification and which were reported to have produced outputs with impressive accuracies are Random Forest (RF) and Support Vector Machine (SVM) though, in land cover classification, RF compared better than SVM in terms of the required user-defined parameters and ease of defining the parameters (Pal 2005). RF has been a popular classifier in remote sensing community due its classification accuracy and has been used in many different applications based on different imagery sources (Belgiu and Drăguţ 2016). An improved version of the RF was developed and reported to have shown an increased accuracy of about 6% over standard RF (Izquierdo-Verdiguier and Zurita-Milla 2020). SVMs were reported to be appealing to the remote sensing community due to their ability to perform well with limited number of training samples (a common remote sensing challenge) though, they suffer from the issue of parameter assignment that can significantly affect the results (Mountrakis et al., 2011). Deep Learning Techniques were integrated with SVM to improve its performance on classifying hyperspectral imagery (Okwuashi and Ndehedehe 2020).

Initially, the intention was to adopt RF classifier in this segment of the research work. However, both RF and SVMs were shown to have suffer from correlation bias though this can be corrected using related methods for group selection based on feature clustering (Toloşi and Lengauer 2011). To improve both the stability and accuracy of these modern methods, several bootstrap subsets of the training sample are selected and aggregated as stable solution in a procedure called ‘ensemble feature selection’ (Gregorutti et al., 2017). SVM was reported to be highly time consuming in training the classifier, difficult to understand, highly depends on user-defined parameters and difficult in determining the optimal parameters (Muthu and Ranjani 2020). Therefore, it is obvious that though these classifiers are powerful, using them would require much more time than could be apportioned for this segment of the research. The software available for the researcher at the time of this analysis was Erdas-Imagine. None of these classifiers is available in this software. Using RF would require learning some coding software such as R and SVM would require use of ENVI.

There was not enough time to learn and use these powerful software packages. The main aim of this land cover mapping is to identify agricultural areas which is only one of several constraint areas that need to be identified and eliminated though surface water and settlements would also be extracted from the mapping output. In addition, traditional classifiers, which are available in Erdas-Imagine, are still being used for satellite imagery classification. In an assessment of four traditional classifiers such as Maximum Likelihood Classifier (MLC), Minimum Distance Classifier (MDC), Spectral Angle Mapper (SAM) and Spectral Correlation Mapper (SCM), Sharma et al., (2018) found that MLC and SAM performed better than others, in terms of accuracy, when applied to Landsat datasets. A recent article showed, in a particular application, that SAM and MLC could even perform better than SVM, with SAM yielding 92% overall accuracy in an independent field verification (Mafanya et al., 2022). The two algorithms were used to investigate land use change in the Middle East and North African region (Riad et al., 2020). SAM was used to identify individual trees in the Matang Mangrove Forest Reserve of Malaysia (Zulfa et al., 2021). MLC was reported to have performed better than Artificial Neural Network (ANN) in labelling rock units (Shebl and Csámer 2021) and the algorithm was used to investigate land use/land cover change in Sierra Leon, located in West Africa (Tarawally et al., 2019).

As discussed in the next subsection, optical and radar data were combined to perform this analysis due to the structural nature of the study area. However, it was observed that there are certain issues that limits wider use of this kind of data combination (Schulte to Bühne and Pettorelli 2018). These include lack of contextual understanding of the need for the combination or lack of reporting the reasons for the data selection, lack of capacity in terms of hardware and skills and data accessibility. In the current research, though there was a limit to which software the researcher could use in the analysis, both optical and radar datasets were accessible for the study area. The researcher gained some understanding of both the optical and radar data from previous courses on advanced image processing. Due to seasonal variability in Nigeria, especially in the southern part of the country, cloud cover makes sole use of optical data for land cover mapping extremely difficult. Therefore, combining the optical data with the radar data could result in better land cover mapping of the area with relatively higher accuracy than using optical data alone, though with careful temporal consideration. August

SAR data was found to have increased per-pixel classification accuracy by 5% (Ban 2003).

The method and the classifier used may affect achievement of higher classification accuracy through data combination. For arid and semi-arid areas, it was shown that Random Forest performed better (85%) with pixel-based analysis of fused data than SVM (81.46%), while the RF performed worst with object-based analysis (70.2%) (Wang et al., 2016). Fused optical and radar data was also shown to have significantly improved classification accuracy (84.9%) compared to optical (75.5%) or radar (64.2%) data alone, and multiple files composite (75.5%) as well (Hong et al., 2014). However, maintaining spectral fidelity is a challenge in using fused multi-source imagery for land cover classification which underscores the importance of carefully selecting appropriate fusion method for a particular application (Lu et al., 2011). Furthermore, it was suggested that the best strategy would be to fuse more useful extractions of both optical and radar data for the particular application rather than absolute best extractions (Lisini et al., 2011). For topographical mapping applications, VIR and SAR combinations are used (Pohl and Van Genderen 1998).

Due to their complexity, open-ended difficulties and their consequences on their outputs, simple image fusion techniques are recommended not to be used for real world applications (Kaur et al., 2021). For example, though Principal Component Analysis have good spatial advantage, it degrades image spectral integrity. It is their major drawback that they cause spectral distortions (Thomas et al., 2008). In this respect, band stacking may perform better to preserve spectral integrity of the imagery. Band stacking was found to have produced higher classification accuracies than PCA band fusions when SVM and MLC were applied on multiple band combinations at seven different spatial resolutions (Luo et al., 2016). In the current analysis, band stacking was adopted as presented in subsection 5.3.4.3.

Two supervised traditional classifiers were chosen to be used in the current analysis. These are Maximum Likelihood Classifier (MLC) and Spectral Angle

Mapper (SAM). SAM is based on the estimation of the spectral similarity in the feature space. The signatures of the endmember (known or reference pixel) and image (unknown pixel) is described by a vector, starting at the coordinate system's origin, while the length of the vector indicates reflection intensity (figure 5.1). Thus, the difference between spectra is described by the angle; it is the angle that is assessed not the length of the vector. The *n*-dimensionality equals the number of bands (Hasan et al., 2016). Apart from being easy and fast approach, SAM has relative robustness against illumination differences and offers possibility for comparison between image and lab spectra. However, some physiological changes may not be detected due to insensitivity to illumination. Some attempts were made to improve the performance of the basic SAM classifier (Luc Bertels et al., 2005; Zhang and Li 2014).

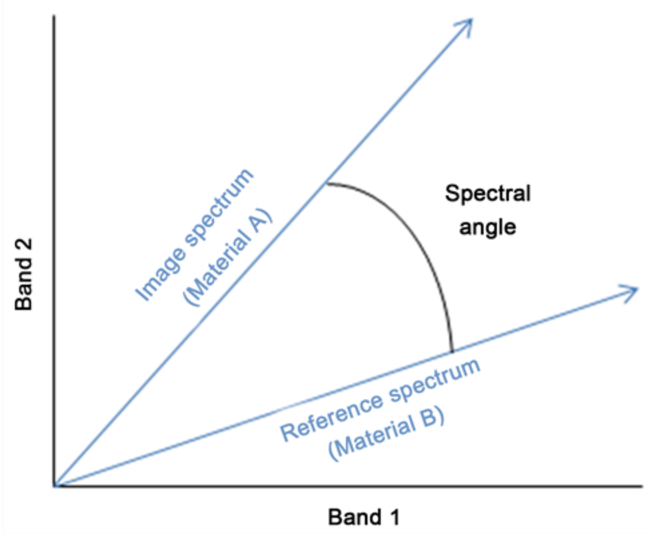


Figure 5.1: Depiction of Spectral Angle Mapper (Hamza et al., 2016)

MLC is based on K-dimensional normal distribution and the class membership is based on the highest probability density. The discriminator is the isolines with equal probability density between the respective classes. The probability density function is calculated on the basis of mean vector and covariance matrix. As a parametric method, MLC is relatively simple to apply. Using a small set of statistical parameters, parametric methods prove to be advantageous for classification with simple formulation and fast computational ability and are even more useful when probability distributions are valid, though its assumption of normal distribution is a drawback (Chakraborty et al., 2017). These two algorithms were implemented on several band combinations and assessed for the final classification. Figure 5.2 depicts the classification process.

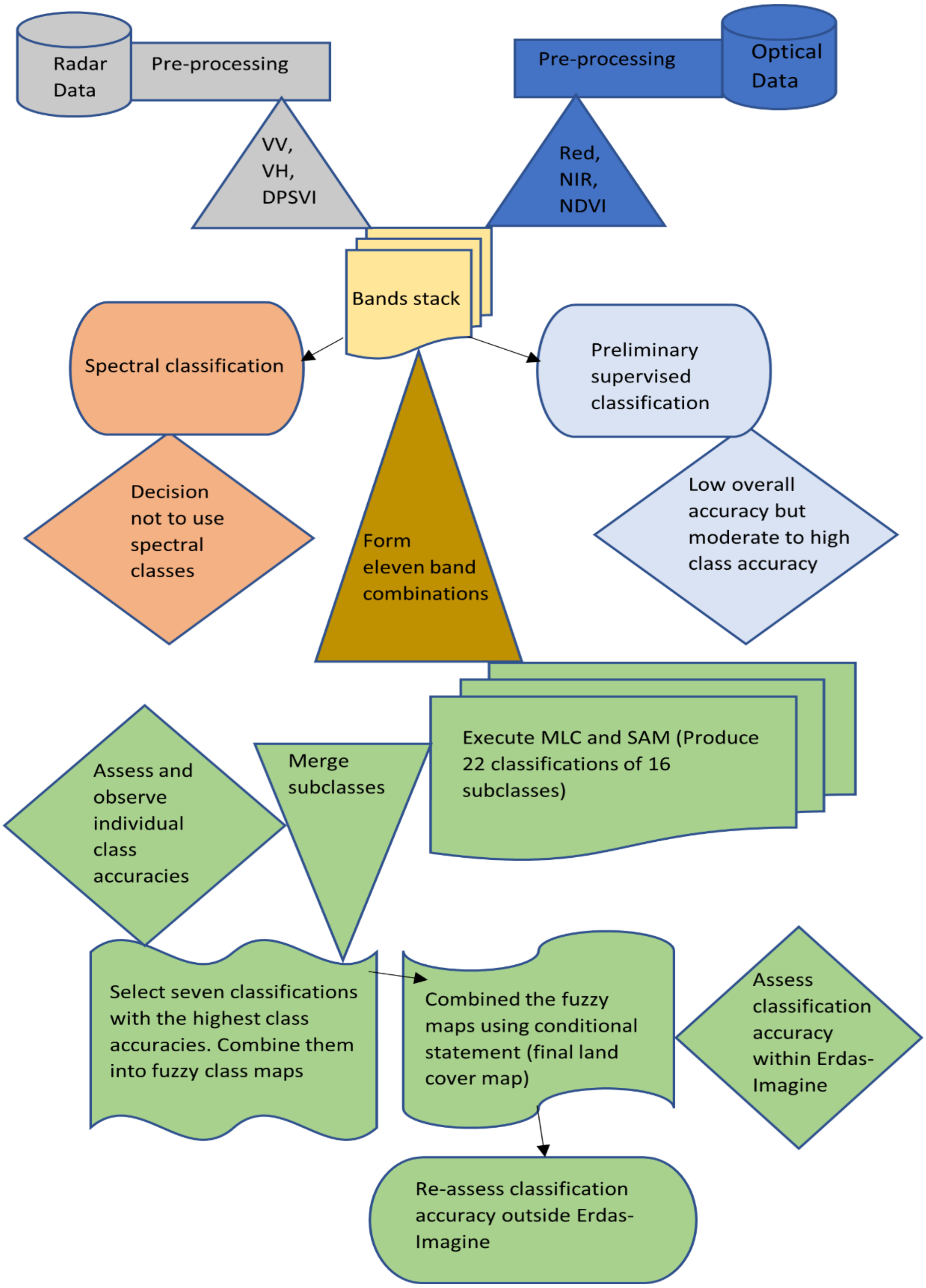


Figure 5.2: Land cover mapping procedure. Touches or arrow indicate progression

In summary, the classification schema consists of acquiring the datasets, pre-processing, extraction of VV and VH radar bands, extraction of Red and NIR of the optical bands, driving the optical and radar vegetation indices, stacking the bands, spectral classification, initial supervised classification (8 classes), accuracy assessment, eleven band combinations, 16 sub-classes, 22 classification outputs, selection of seven classification outputs with the highest class accuracies, combining the seven outputs for each of the classes, recoding the fuzzy outputs into binary maps using a threshold, combining the binary maps using a conditional statement, correction for obvious errors, accuracy assessment within the Erdas-Imagine and accuracy assessment using excel spreadsheet, final land cover map.

5.3.3 Data and pre-processing

Acquiring the data was a challenging task due to the spatial extent and ecological complexity of the country. While the seasons are clearly defined (dry and wet) in the northern two-third of the country with seasonal length ranging from four to eight months, the dry season in the coastal areas is more or less two months. Thus, obtaining usable optical satellite imagery covering the country was tedious due to cloud cover. Most of the tiles, especially for the southern region, have unacceptable level of cloud cover. Thus, radar data was combined with optical data for the mapping analysis. The European Space Agency’s (ESA) radar product (sentinel 1) was used. Attempt was made to use the ESA’s optical product (Sentinel 2) but that was not possible. At the time of obtaining the imagery, the available scenes at the ESA science data website were not found to cover Nigeria for the period of August 2018 and the available ones contain unacceptable amounts of cloud cover. Also, though the Sentinel-2 Global Mosaic service of the Copernicus Global Land Service provides surface reflectance products, the algorithms used to produce these products were said to have relied upon Sentinel-2 L2A data which is prone to such errors as confusion between clouds and high reflectance built-up areas (Corbane et al., 2020). Thus, Landsat 8 OLI was used instead of Sentinel 2. Forty-nine Landsat 8 tiles were obtained as surface reflectance imagery.

It is possible at any part of the rainy and most part of the dry seasons that the farmlands can be identified through photo interpretation techniques such as shape of the field, tone, texture, pattern and association. Thus, avoiding cloud cover was the most important criteria for choosing which Landsat scene to be used. Thus, not all the 2018 scenes were found to be usable (table 5.2). However, an attempt was made to ensure that almost all the scenes coincided with the same period of the year (November). Although rainfall stops in many parts of the north in November, the main harvesting time for rainy season crops is between October and January. Thus, many crops are expected to be in the field in November. Because radar is not affected by cloud cover, imagery sensed during the peak of the rainy season (August) were acquired. Thirty-eight Sentinel-1 tiles were downloaded from the ESA Science data website (table 5.3). These were calibrated, speckle filtered (Lee Filter), geometrically corrected (ellipsoid – Range Doppler) using the Sentinel Toolbox – the SNAP (Filipponi 2019). Each of the imagery was then exported to Erdas Imagine.

Table 5.2: Optical (Landsat 8 OLI) Data

Sensing date	2018	33 scenes
	2017	7 scenes
	2016	4 scenes
	2015	5 scenes
Sensor	Landsat 8 OLI	
Orbit mode	Descending (Day time)	
Processing level	At surface reflectance	
Bands	VIS - NIR	
Cloud cover	0%	17 scenes
	< 10%	27 scenes
	< 20%	5 scenes
Spatial Resolution	30 metres	

Table 5.3: Radar (Sentinel-1) Data

Sensing date	August, 2018
Orbit mode	Ascending
Satellite	S1A
Product type	Ground Range Detected (GRD)
Polarization	VV+VH
Sensor mode	Interferometry Wide (IW)
Spatial Resolution	20 X 5 metres (10 metres)

Both the radar and the optical datasets were mosaicked and a subset of each was clipped using Nigeria’s international boundary (figures 5.3). It is obvious from tables 5.2 and 5.3 that the two datasets have different spatial resolutions. Landsat 8 is 30 metres, while Sentinel 1 is 10 metres. This analysis was conducted using 30 metres spatial resolutions. Sentinel 1 was captured as 20 by 5 metres pixels but supplied as 10 metres. This is understandable because two pixels of 20 by 5 metres equal 20 by 10 metres (which could be resampled into two pixels of 10 by 10 metres). Therefore, the Sentinel 1 data was resampled from 10 metres to 30 metres as part of the pre-processing in the Sentinel toolbox. As mentioned in the previous subsection, combining both radar and optical data is believed to improve land cover mapping accuracy (Steinhausen et al., 2018; Whyte et al., 2018). Two bands were extracted from each of the optical and radar datasets. Red and Near Infrared (NIR) bands from the optical data and VV and VH polarizations from the radar data.

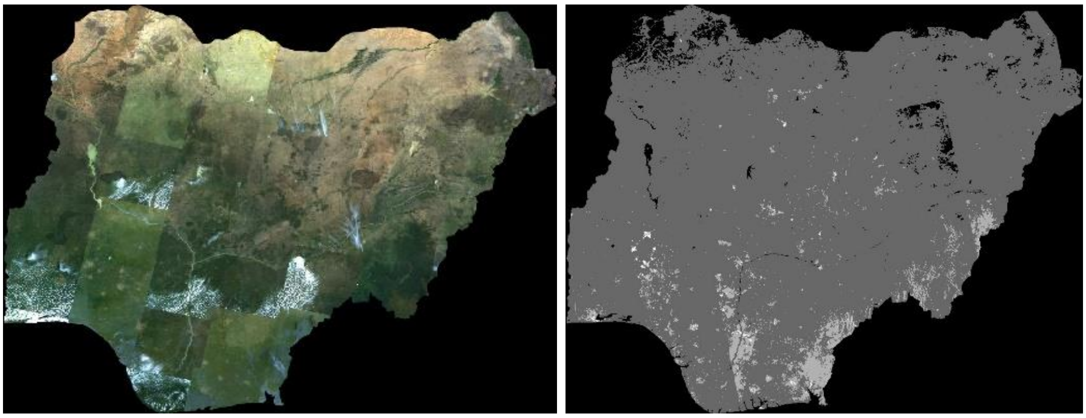


Figure 5.3: Subset of the mosaicked Landsat 8 tiles (left) and Sentinel-1 imagery (right)

Then, Normalised Difference Vegetation index (NDVI) which is derived from the Red and NIR bands of the optical data was derived (figure 5.4). NDVI has widely been applied in studies of terrestrial vegetation. A model called 'Dual Polarization SAR Vegetation Index (DPSVI)' was published in 2018 and was developed for extracting vegetation index based on the system and target parameters of the Synthetic Aperture Radar (SAR) system (Periasamy 2018). DPSVI was also derived (figure 5.4). Scatter plot (figure 5.5) and correlation coefficient of ≈ 0.43 showed substantial positive correlation between the NDVI and the DPSVI.

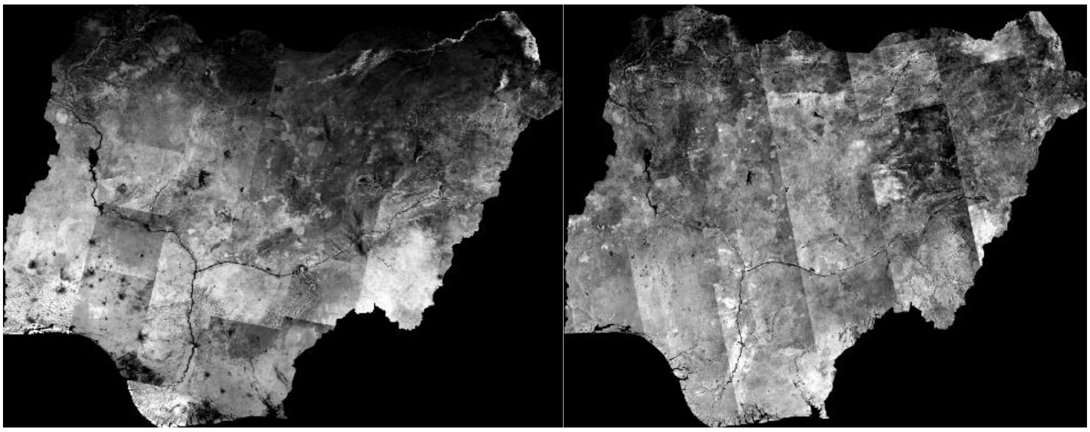


Figure 5.4: NDVI from the optical bands (left) and DPSVI from the VV and VH radar bands (right)

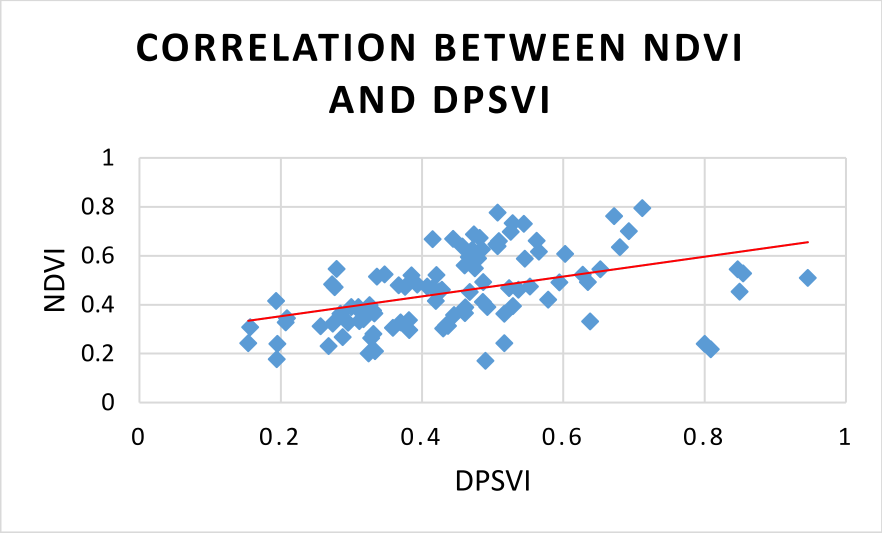


Figure 5.5: Correlation between NDVI and DPSVI

Presenting this NDVI-DPSVI correlation serve as a validation of the DPSVI model as used by the developer of the model (Periasamy 2018), assuming NDVI does well in areas with less cloud problem. The reason for using both the optical and radar vegetation index in the mapping analysis is the expectation that the radar vegetation index may work better in the southern region of the country where the rainy season is temporally very wide; up to 10 months as mentioned earlier.

It is obvious from the scatter plot that DPSVI showed some very high values of more than 0.9 where NDVI showed less than 0.6 and this is expected to be in areas with very high vegetation cover which is more common in the southern part of the country. For example, in the sample points used for the scatter plot, a point with FID 30, located in the southern part of the country showed approximately 0.85 for DPSVI and 0.54 for NDVI. A look at Google Earth showed that this point is located in the Cross River National Park, an evergreen area in the Cross River State of the southern region. This suggests that DPSVI is more accurate for this point.

The scatter plot, also, showed that there are more high values in the DPSVI with corresponding low values in the NDVI than vice versa. However, with clear sky in most part of the year in the northern part of the country, NDVI may perform better than DPSVI. For example, a point with FID 46, located in

Kaduna State in the north, showed a value of approximately 0.28 for DPSVI and 0.55 for NDVI. A look at this location on the Google Earth showed that it is an area of short tree cover with some scattered tall trees. Therefore, NDVI values could be closer to reality than DPSVI for this point. Therefore, both the NDVI and the DPSVI would be useful in the mapping analysis. All the 3 optical bands and the 3 radar bands were stacked into a single image, respectively (figures 5.6).

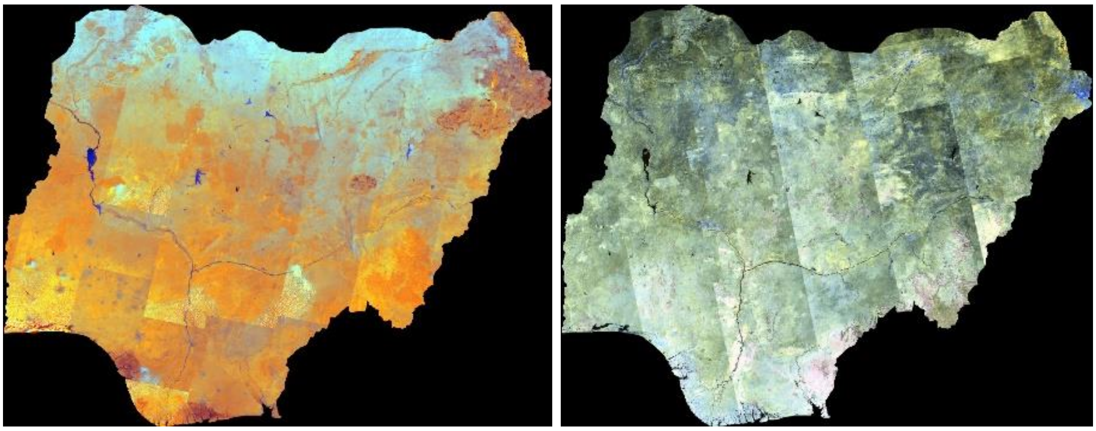


Figure 5.6: The 3 optical (left) and 3 radar (right) bands

5.3.4 Classification

5.3.4.1 Spectral classes

After stacking the radar bands, the optical bands and the combined bands, unsupervised classifications were executed on each of the stack to observe the spectral distribution and exploit the possibility of extracting usable spectra for the target information classes. Both ISODATA and K-Means algorithms within Erdas Imagine were used. A closer look at the map produced using both the radar and optical bands (VV, VH, Red, NIR, NDVI and DPSVI) (figure 5.6) showed that though some features such as water bodies (class 2), settlements (class 5) and some forest reserves (class 7) could be identified even at the full extent of the study area, these spectral classes may not successfully be used for information classification due to high misclassification. Bare grounds were merged into the same class with water bodies, settlements merged with agriculture and more importantly for this research, agriculture was merged into the same class with uncultivated areas such as grasslands and sparse woodlands.

Because the mapping analysis would be using limited number of land cover classes, eight classes were applied for the combined radar and optical data as shown in figure 5.6. Few classes for automated clustering of the pixels may limit the ability of the algorithm to adequately provide meaningful groupings of the pixels. Thus, the misclassification may be due to limited number of the classes rather than the spectral pattern within the data. The output showed that without training the classification algorithm, the algorithm may not successfully separate many of the clearly different land covers. It also shows that there is need for systematic handling of the classifier training to achieve usable supervised classification.

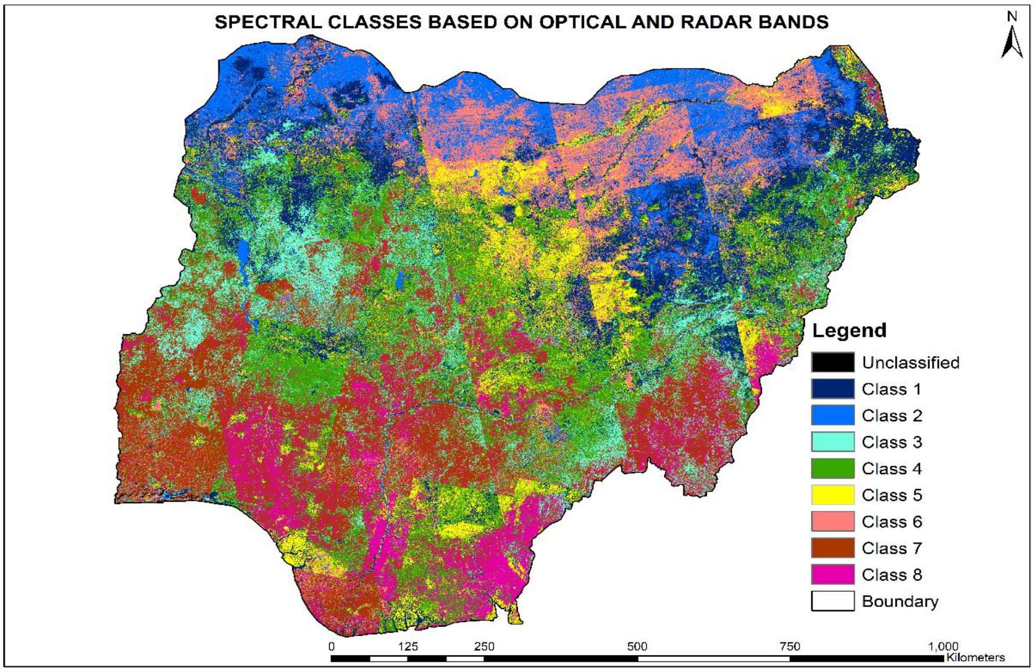


Figure 5.7: Unsupervised Classification produced from both the radar and optical data using ISODATA in the Erdas-Imagine Software

5.3.4.2 Training Sample

At the initial stage of this research work, a plan was made to create random points, conduct a field visit to those random points and collect feature information that would be used for training the classifiers and also for accuracy assessment. Points were iteratively generated in ArcMap, making sure that they are randomly distributed. Random in this context refers to the spatial distribution of the sample points. Though complete randomization entails locating each point individually (which might be tedious) and may lead to bias among the classes (Burrough and McDonnell 1998), random pattern suggests absence of interaction between the points, providing equal chance for each location to be selected as part of the sample points. A stratified sampling is used to reduce the bias in allocating the points among the classes. Several trials failed to produce random points until when a minimum distance limit of 15 km was used. Therefore, 400 points were generated using a convex hull of the map of Nigeria as the extent limit and the points were clipped for the target states to remove the points that fall outside the map of Nigeria and, as well, those that fall into the states not selected.

The output dataset produced 351 points and the pattern analysis showed that the points does not appear to be significantly different than random. These 351 points were supposed to comprise the training points and the accuracy assessment points. Each of the points needs to be classified as either training point or accuracy assessment point right at the data collection stage for easy identification during the analysis. The points were divided into two; 176 points for analysis (training) and the pattern analysis showed that they were still random. However, the remaining points were not found to be random. Thus, 200 new random points were created and the same procedure was followed. The result produced 173 random points. The two datasets were displayed in ArcMap to visually check if there is any overlap of points (figure 5.8). Near analysis was also executed to spatially confirm there is no training point that overlaps with any accuracy assessment point. The report showed that the two closest points are approximately 3,424 meters apart. If the closest distance is more than 3 km, it shows that even with a spatial resolution and/or accuracy of 1 km there is no overlap of any pair of points between the two datasets.

As part of the field work discussed in section 3.4.4, a plan was made to collect feature information about these points in Nigeria. The sample collection was planned to be caried out by hired surveyors from the 1st of July to 11th of August, 2018, but due to logistics hurdles, the work extended to September. Appendix VII presents the budget submitted to the funding body for the field work. An attempt was made to visit all of these points. However, some of these points could not be accessed mostly due to physical challenges. A typical example was a point in Sokoto State (northwest) which could not be reached due to a bridge broken by flood water. There were other challenges such as security. It was agreed that for any point that could not be reached, the closest reachable location to that point should be observed and its feature information be captured instead. This was possible because there is a minimum 15 km distance between any two points within each of the datasets and there is more than 3 km distance between any point in the training points and any point in the accuracy assessment points, as seen above. Within a maximum of 3 km of any of the points, it is expected that a substitute location could be obtained.

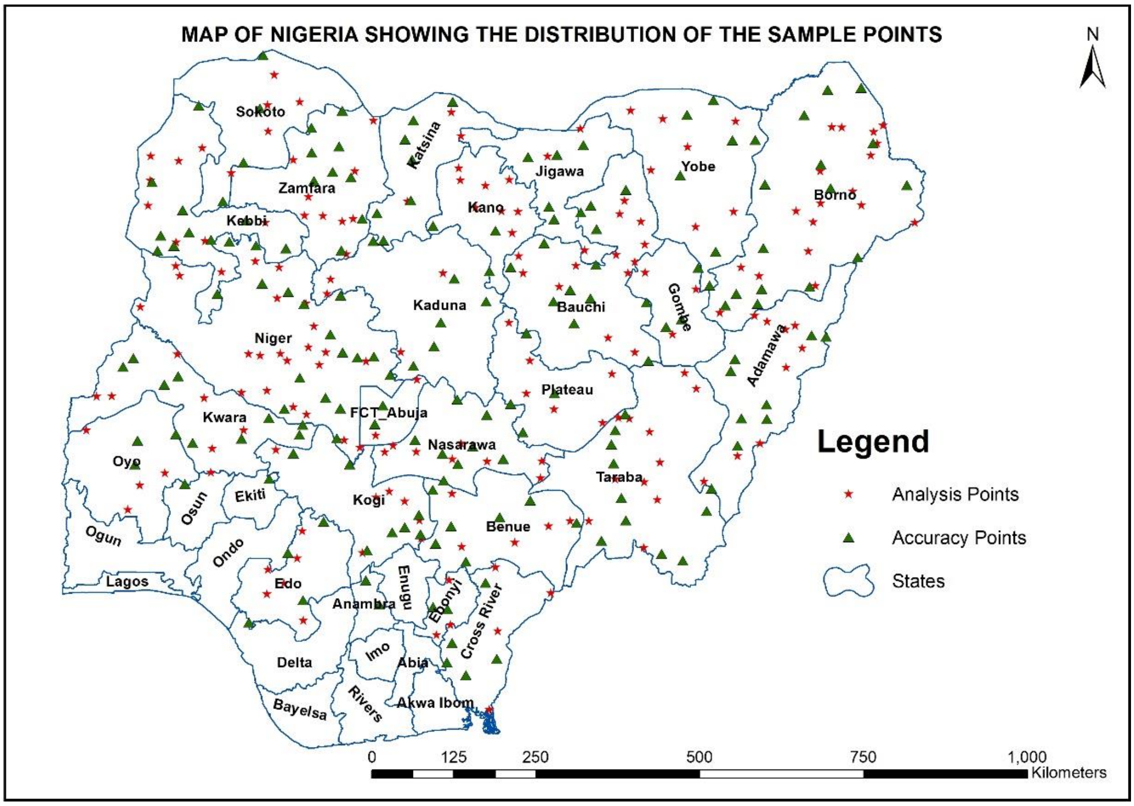


Figure 5.8: Random analysis (training) and accuracy assessment points

Out of the 176 training sample points planned to be visited, 92 were visited by the two sets of surveyors, both using Garmin GPS (GPSMAP 78sc) with ±3 metres horizontal and vertical accuracies. Another 33 were captured by the researcher during the field work discussed in subsection 3.3.4 and used an android app (Simple GPS) which averages 12 satellites with ±16 metres accuracy. It is obvious the 125-points information collected out of the 176 planned to be visited (51 could not be visited due to logistics and security issues) would be too small sample size for the study area. Appendix VIII provides the longitudes, latitudes and feature information of the sample points. At least for the purpose of this analysis in which the focus is on identifying cultivated areas, it is possible these limited field sample could be complemented using other acceptable sources of spatial information that can be used to train and validate classifiers such as Open Street Map (Schultz et al., 2017) and Google Earth (Olofsson et al., 2013; Chen et al., 2017; Ali et al., 2018; Steinhausen et al., 2018).

Open Street Map (OSM) data (figure 5.9) was explored in order to improve the quality of the sample points with other locations not visited. It was ensured that the sample information from OSM, as merged with the field information, was random. Also, because the focus of this analysis is to identify land areas under cultivation, a limited number of classes was used with more emphasis on cultivated and uncultivated lands. Though there is a focus on a particular category of land cover, using conventional supervised classification techniques require that the classifier is trained for all the identifiable classes that occur in the study to avoid commissioning other classes into the classes of interest (Foody et al., 2006).

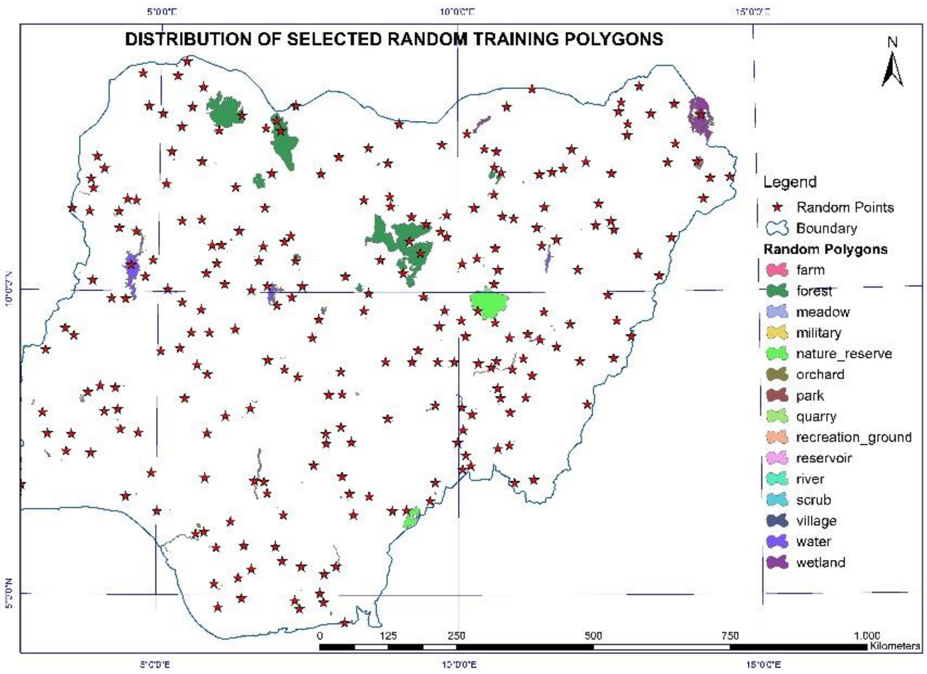


Figure 5.9: Spatial distribution of the training samples

Attaining all these – covering the study area as much as possible, making the sample as representative as possible and making the sample spatially random – proved challenging due to the nature and extent of the study area which spans more than 923,000 square kilometres. Thus, the high-resolution Google Earth Image was incorporated in addition to the limited field data and the OSM data to train the classifiers and conduct the accuracy assessment. Because Google Earth is mostly based on optical satellite imagery, its interpretation was based on photo interpretation techniques, such as association, size and shape, as mentioned in subsection 5.3.3. This improves the understanding of whether a field is cultivated or uncultivated. Shape may not do well in areas where farms have been abandoned for long period due to security challenges or other reasons. Table 5.4 shows the class distribution of the training sample data. It is important to make it clear here that the subclasses were developed later after the initial classifications showed low accuracies, as explained in the next subsection.

Table 5.4: Class distribution of the training sample

S/N	Subclass	Field data (Points)	OSM (Polygons)	Google Earth Polygons (Areas of Interest)	Subclass total	Total training data
1	Intensive agriculture	10	14	7	31	Agriculture **124**
2	Irrigation agriculture	Nil	6	4	10	
3	Seasonal agriculture	31	14	13	58	
4	Wetland agriculture	9	15	1	25	
5	Bare ground	4	2	5	11	Bare ground **11**
6	Dense forest	4	19	9	32	Forest **70**
7	Sparse forest	16	9	10	35	
8	Mangrove forest	Nil	Nil	3	3	
9	Settlement	4	5	8	17	Settlement **17**
10	Dense shrub	16	Nil	13	29	Shrub **49**
11	Sparse shrub	14	Nil	6	20	
12	Deep water	Nil	4	5	9	Water **40**
13	Seasonal water	2	8	4	14	
14	Turbid water	Nil	10	7	17	
15	Dense woodland	8	Nil	16	24	Woodland **42**
16	Sparse woodland	7	Nil	11	18	
	Total	**125**	**106**	**122**	**353**	**353**

OSM data description helps in identifying the type of the land cover existing in the selected sample location without physical visit to the locations. For example, the term ‘farm’, ‘orchard’ or ‘plantation’ indicates that the area is cultivated, while the term ‘forest’ or ‘scrub’ indicates uncultivated areas. Forest may be protected or unprotected, thus, the other dataset from World database on Protected Areas would help in identifying protected forest areas later in the modelling analysis that eliminates restricted areas. Figure 5.10

shows the spatial and class distribution of the field and OSM derived samples. Areas of Interest from Google Earth were used directly in Erdas-Imagine. Because it is possible to show historical images in the Google Earth and there is a slider for viewing the historical images, the 2018 imagery were used in the extraction of the sample data from the software except where a location could not be found in 2018 image, 2017 or 2019 was used if available for the location of interest. Otherwise, other locations were explored for which an image is found in one of these three years. The time scale of these sources is assumed not to render the data unusable for the analysis.

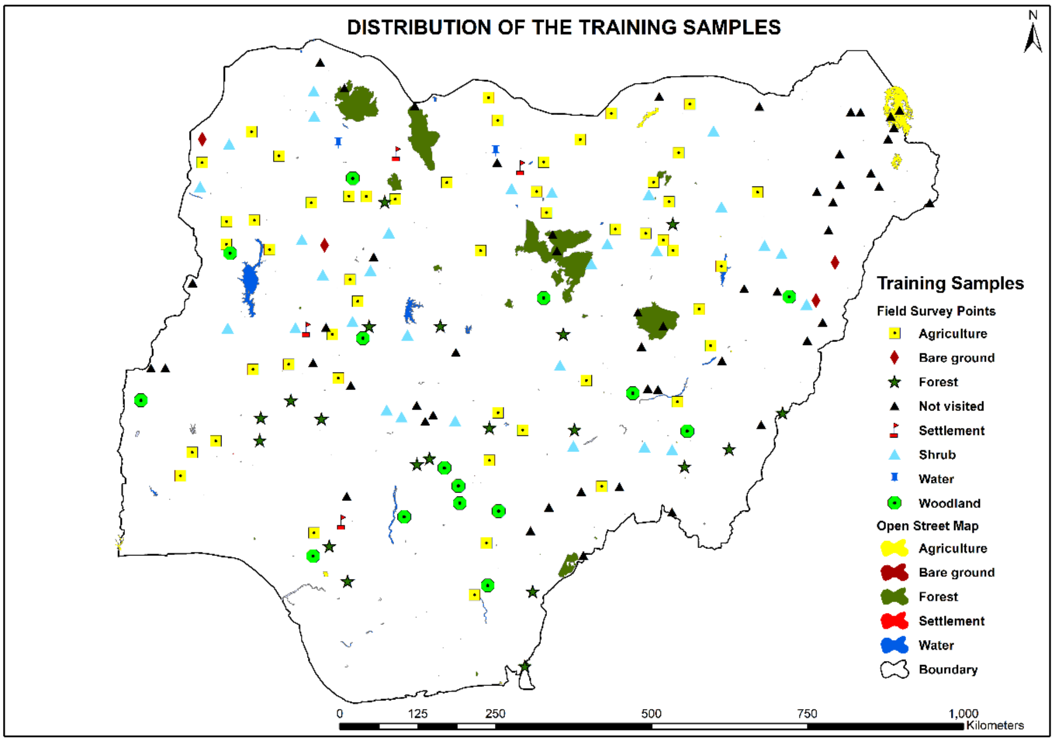


Figure 5.10: Spatial and class distribution of the training samples

It could be seen from table 5.4 that 353 samples were used in training the classification algorithms. More than 35% of the samples were from field surveys, while approximately 30% and 35% were extracted from the OSM and Google Earth, respectively. The last column in the table shows the distribution of the samples among the main classes. The class distribution is stratified with agriculture class (cultivated area) taking more than 35% of the sample. Shrub and woodland (uncultivated areas expected to be potential for biofuel crops) were allocated approximately 26% of the samples. Areas of interest (AoIs) were created from OSM polygons, directly by linking and synchronising view between Erdas-Imagine and Google Earth and around the field collected sample points. Though the researcher could not remember to record the number of pixels per AoI, efforts were put to ensure that the AoIs consists of pure pixels and that boundaries with other land cover categories were avoided even for the OSM polygons because a polygon may be impure in terms of the reference classification (Olofsson et al., 2014). Google Earth was helpful as a control in ensuring pure pixels were extracted as the AoIs.

Though there is no generally agreed required minimum number of training sample that is sufficient for training satellite imagery classifiers, studies show that overall accuracy increases with increasing sample sizes (Huang et al., 2002). However, a downward trend is possible at certain maximum size of the sample size, as shown in a pixel-based, high spatial resolution image classification (Doma et al., 2015). Though there have been suggestions that the minimum number of sample per category should be 50 to 100, determination of sample sizes has primarily relied on expert knowledge and conditional assumptions (Ren et al., 2019). The central problem is that different allocation of the sample favour different objectives such as whether the main aim is to raise user's accuracy, overall accuracy or area estimation (Stehman 2012). The necessary trade-off to obtaining large sample sizes is affordability which is usually prohibitive (Olofsson et al., 2014). Increasing sample size and periodicity raises costs to unaffordable level (Costa et al., 2018), but tailoring focus on a class of interest may drastically reduce requirement for large sample size (Foody et al., 2006). The field work in this research has been constrained by logistics, time and security situation in some locations in Nigeria, leading to small sample size for training classifiers and accuracy assessment. However, cultivated (Agriculture) and expected usable uncultivated (woodland and shrub) areas were allocated more than 60% of the training sample.

5.3.4.3 Information classification

The bands were stacked in the order shown in table 5.5. Traditional classifiers – Maximum likelihood classifier (MLC) and Spectral Angle Mapper (SAM) – were employed. Based on the available training data, with a focus on cultivated and uncultivated lands as well as the assistance of Google Earth, a system of eight classes was developed iteratively. These include the seven classes in table 5.6 and 'Mangrove Forest' which was later merged with other forest subclasses. An initial information classification was executed, and all were assessed to have very low classification accuracies. Unfortunately, all of those initial classification outputs were discarded except two maps presented in figure 5.11.

Table 5.5: Stacked six bands

Band	1	2	3	4	5	6
Number in the stack	Red	VV	VH	DPSVI	NDVI	NIR

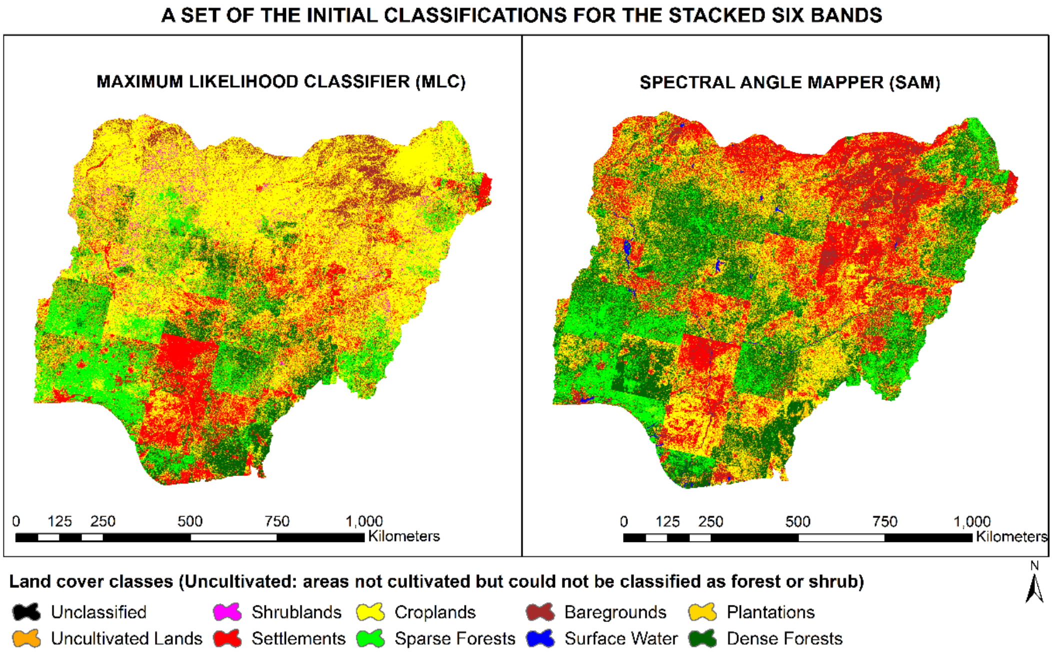


Figure 5.11: Initial classifications

The initial classifications as shown in figure 5.11 showed very low clasification accuracies such that the outputs could not be used as inputs for any further spatial analysis and thus, the researcher discarded all of the outputs and could not keep the detail records of these output. Though some classes such as croplands, forest, water and settlements were classified correctly in few locations, these classes were highly misclassified with other classes (figure 5.11). For example, large extent of uncultivated areas, including forests and shrubs were classified as settlements on both the classification outputs. Almost all the surface water bodies on the MLC output were classified as settlements. Large vegetated area was classified as bare ground.

These misclassifications could be attributed to the issues discussed in subsection 5.3.2 regarding the nature of the datasets, the choice of the classifier and the manner in which the classification was executed. As discussed in subsection 5.3.2, traditional classifiers such as MLC and SAM usually produce low classification accuracy, thus, more advanced classifiers such as deep learning algorithms would have produced better outputs. However, there was not software and enough time to learn and apply those advanced algorithms as at the time of the analysis. Also, these advanced algoritms have their own issues too as discussed in subsection 5.3.2. In addition, as discussed earllier, the complex ecological nature of the study area would have played significant role in confusing the classifiers. Though all the optical scenes were ensured to be of the same period of the year (November), it is obvious from the initial classifications that there are artefacts resulting from those scenes outside 2018 as presented in table 5.2.

Further, the surface behaviour with electromagnetic spectrum differs depending on the nature of the surface for example the population of the plant, its height, type of the underlying soil and several other factors. Surfaces also behave differently with backscatter in the case of the radar data depending on the roughness or smoothness of the surface. Therefore, the same type of plant cover may show different spectral signature at different locations or times of the year, though it is possible that in some areas mean spectral separability remain the same with wider spatial scope (Verhulp and Van Niekerk 2016). A decision was made to explore a means of raising the accuracy of the maps by painstakingly executing the classifiers and combining the maps through employing a fuzzy concept. The initial classifications were discarded. It was thus agreed that different band combinations be made and to observe their performances with the classifiers.

Finally, 16 classes were created with four classes representing agriculture, three for water bodies, two each for forests, woodlands and shrubs. One class each for mangrove, bare ground and settlements (table 5.6). The rationale for creating subclasses for most of the classes was to account for within-class differences. For example, wetland agriculture may not have exact spectral signature with seasonal agriculture. Reflectance from turbid water will not be exactly the same as the one from clean water. If this is captured in training the classifier, misclassification will greatly be reduced. Thus, Google Earth was linked and synchronised to Erdas-Imagine in the process of creating the subclasses.

Table 5.6: The information classes

S/N	Initial subclasses	Final class groupings
1	Intensive agriculture	Agriculture
2	Irrigation agriculture	
3	Seasonal agriculture	
4	Wetland agriculture	
5	Bare ground	Bare ground
6	Dense forest	Forest
7	Sparse forest	
8	Mangrove forest	
9	Settlement	Settlement
10	Dense shrub	Shrub
11	Sparse shrub	
12	Deep water	Water
13	Seasonal water	
14	Turbid water	
15	Dense woodland	Woodland
16	Sparse woodland	

As mentioned in section 5.2, agriculture in this analysis refers to currently cultivated land areas without differentiating between food crops and cash crops. Intensive agriculture refers to areas of dense farmlands where the underlying soil is highly exploited with more than one crop cycle as a result of relatively longer rainy season unlike seasonal agriculture which support only one crop cycle and would have dryer underlying soil and less green cover due to less dense farm population. Wetland agriculture may be cultivated throughout the year and have highest moisture-laden underlying soils. It doesn’t usually have organised pattern of farm arrangement but have association with large surface water bodies unlike irrigation agriculture which usually have organised farm structure with visible irrigation infrastructure and less moist soil due to controlled water management. All these variations will affect the nature of spectral reflectance such that areas with higher soil moisture will absorb more radiation in some regions of the spectrum than areas with less soil moisture. Other factors such as plant height and canopy or irrigation will affect the reflected albedo.

It is perhaps necessary to differentiate between woodland and forests. While forests represent large areas of closed canopy, including the evergreen and short period deciduous tree vegetations, woodland areas are open, drier and often dispersed tree populations characterised with varying degrees of grass growth (MacGregor 1937). The reflection of the electromagnetic spectrum (EMS) and the backscatter will depend on interference due to tree denseness or sparseness, the height and canopy of the trees and interference of the open spaces where there are grass growth or open ground. Bare ground may have the highest reflectance or longest range of backscatter compared to the surrounding areas depending on the nature of surface (colour, roughness). Similarly, the backscatter from short, woody plants in shrub areas differ from tall woodland areas and the interference of the open soil on the reflectance would be higher in sparsely populated shrub areas than densely populated shrub areas.

Deep water in the context of this analysis refers to very large surface water expected to be less disturbed and thus clean. Due to the nature of their reflectance, these have been used for dark object subtraction in surface reflectance correction of optical satellite imagery. Turbid water bodies are disturbed, usually thicker due to dirt and reflect higher albedo in some regions of EMS than deep water. Seasonal water may be clean or dirty depending on location and associated features, only that there is high interference of surface soil or nearby plant cover in their reflectance due to narrowness of their channels or surface. Backscatter from wide surface water would differ from narrow surface water especially in areas with undulating topography.

Eleven different band combinations were produced (table 5.7) and both the MLC and SAM algorithms were executed producing 22 different land cover classifications. However, two of the outputs were discarded and their detail record was not kept. Band combination number seven as in table 5.7 was the one that was lost as indicated in the table. Band combination may improve classification accuracy such that some combinations could produce maps with higher accuracy than others. The classes were recorded such that all the 4 agriculture classes were merged into one. The same was applied to the water, forest, woodland and shrub classes and the total number of the classes became 8 – agriculture, bare ground, forest, mangrove, settlement, shrub, water and woodland. Mangrove was later merged with forest and thus, the accuracy assessment data was adjusted to reflect seven classes.

Table 5.7: Different band combinations for classification. *denotes the band combination that was lost.

S/N	Band combinations	S/N	Band combinations
1	NDVI, DPSVI	7	VV, DPSVI, NIR*
2	NDVI, DPSVI, NIR	8	VV, VH
3	NDVI, DPSVI, VV	9	VV, VH, DPSVI
4	Red, NIR, NDVI	10	All the 6 bands
5	Red, NIR, NDVI, DPSVI	11	All the 6 bands except VH.
6	VV, VH, DPSVI, NDVI		

Accuracy assessment was conducted on 20 of the classifications. The same method, as was described for the training sample in the previous subsection, was employed to select a random accuracy assessment sample. However, a stratified sampling was further used to increase the number of samples for some classes deemed to have less representation. 372 locations consisting of field data, OSM polygons and Google Earth AoIs were generated in total and their spatial distribution is shown in figure 5.12. Pure pixels at or near the centroids of the polygons and AoIs were extracted from the OSM and Google Earth as points representing the polygons. This sample size is small for the study area, but the researcher could not go beyond this size due to logistics and time constraints, as discussed in the previous subsection. However, when it is possible that the analysis can focus on a certain class or few classes, the allocation could be stratified with a bias towards the focused classes (Olofsson et al., 2014) and this will reduce size required of the sample for the assessment (Foody et al., 2006).

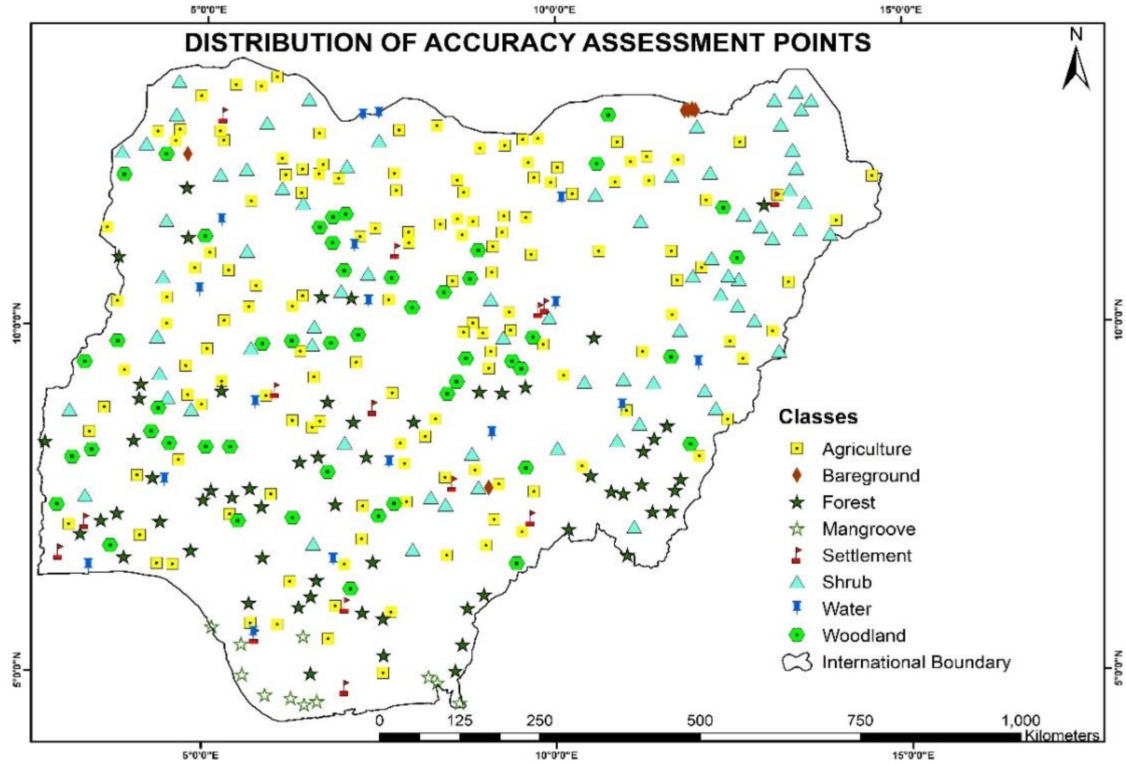


Figure 5.12: Spatial distribution of the accuracy assessment points

The distribution of the sample among the classes was based on the relative importance of the classes. Agriculture, shrubs, forests and woodlands were allocated 137, 75, 57 and 53, respectively. Location information for the accuracy assessment points is presented in appendix IX. Identifying cultivated areas (Agriculture) and potentially usable uncultivated areas (shrub and woodland) forms the main focus of the analysis. Approximately, cultivated and uncultivated area classes were allocated 37% and 34% of the sample, respectively. It was recommended that the number of samples for each category might be adjusted based on the relative importance of that category for a particular application (Lillesand et al., 2008) and this may be based on ‘Neyman Optimal Allocation’ (Stehman 2012). This also reduces the requirement for large sample, as discussed in the previous subsection. Moreover, it was shown that increase in training/testing data does not necessarily increase classification accuracy (Gopal et al., 1999). The stratified accuracy assessment points were assessed for spatial randomness.

The overall accuracies for the 20 classifications range from approximately 28% to approximately 50% before correcting for obvious errors as determined within the processing software. However, the individual class accuracies range from approximately 0% to 100% as shown in appendix X. Thus, the user’s and producer’s accuracies were observed for each class in each of the 20 classifications. For each class, seven classifications with the highest accuracies (four user’s and three producer’s) were chosen and combined. User’s accuracy is more important in this context because the aim is to correctly identify cultivated areas. The combination was achieved using binary and overlay operations. Each of the seven selected output maps were converted into binary map with 1 representing the class and 0 representing other classes. For each class, these seven binary maps were combined using overlay operations, producing a single map for each class with pixel values ranging from 0 to 7. An example is depicted in figure 5.13.

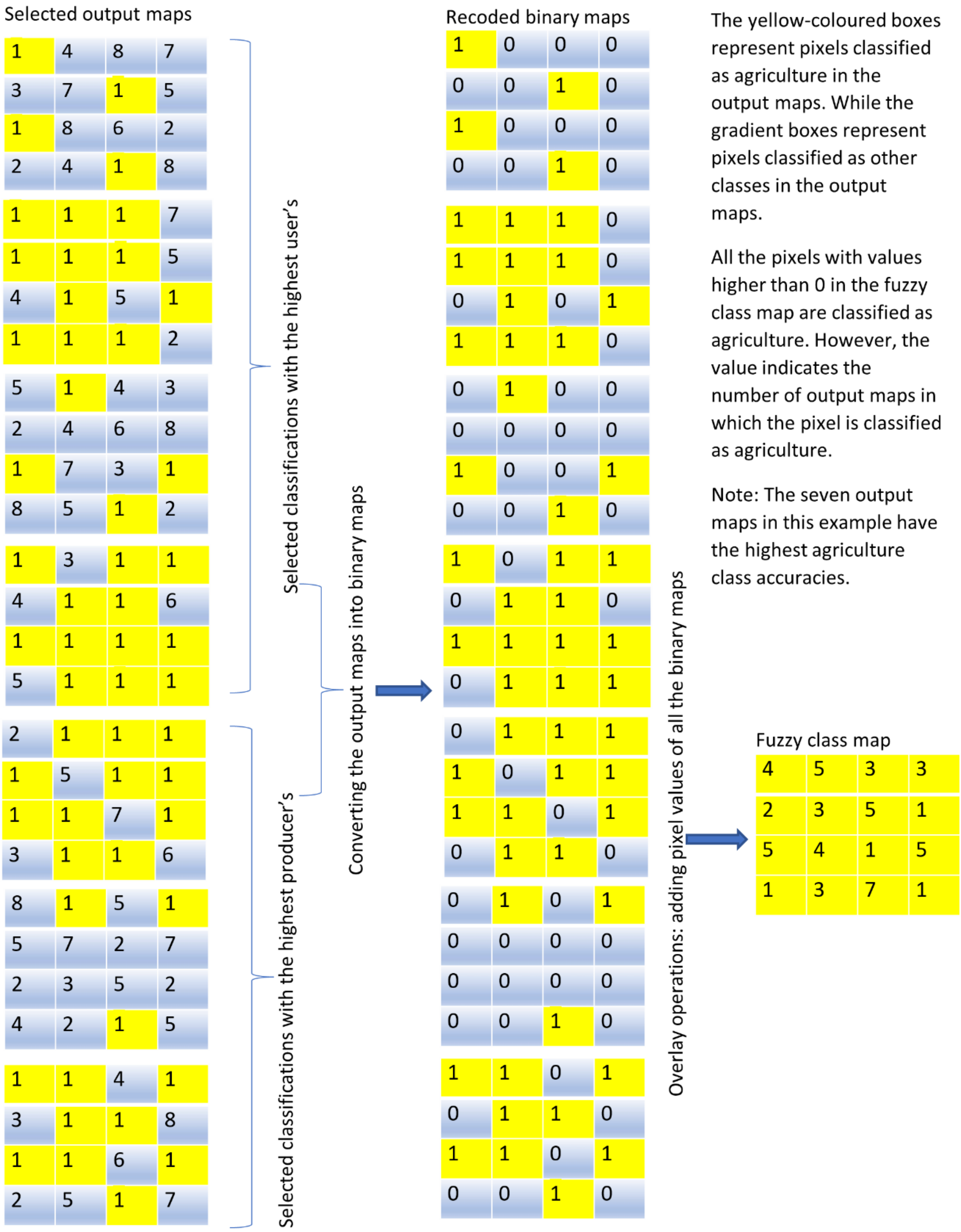


Figure 5.13: Example of combination procedure for each class map

The output maps in figure 5.13 represent the various classifications with very low accuracy. Based on the fuzzy membership concept, the pixel values in each of the combined output for each class represent class membership of each pixel for that class (figure 5.14). The larger the value of a pixel, the larger the number of the selected output maps in which the pixel is classified as that class, the higher the probability that the pixel belongs to that land cover class. Though most methods, such as fuzzy k-means, use a range 0 to 1 to assign grades of membership (Burrough and McDonnell 1998), in this work the membership grades are functions of the number of the selected output maps in which the pixel is classified as that class. Thus, a grading of 0 to 7 was used.

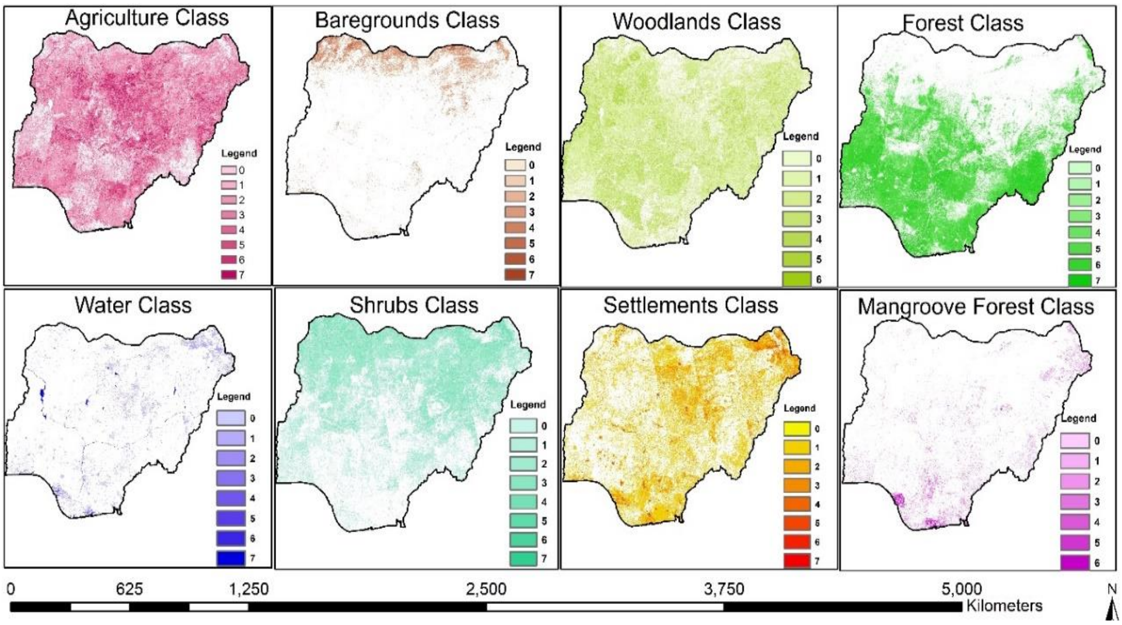


Figure 5.14: Combined seven classifications for each class

The fuzzy set theory was originally developed by Zadeh (1965) who defined fuzzy set as a class of objects with a continuum of grades of membership. One of the advantages of fuzzy membership is that it allows for the use of natural language (for example, ‘near’) to describe uncertainty (Huisman and de By 2009). Among the earliest reasons for adopting fuzzy concept in satellite imagery classification was the issue of mixed pixels during the 1980s and 1990s when the methods were almost entirely per-pixel based (Li et al., 2014). Fuzzy clustering is one of the most widely used application of fuzzy concept in remote sensing and is said to be the approach that retains more information from the original image than the hard clustering methods such as K-Means and ISODATA (Zhong et al., 2014).

The fuzzy maps were recoded into binary again and combined using conditional statement (figure 15). With the aid of Google Earth image and other secondary information such FAO statistics, a threshold was set for each class map and all were converted into binary maps (0s and 1s) where 1 represent pixels for the class and 0 represent pixels not for the class (table 5.8). For example, values from 3 to 7 were recorded into 1 and 0 to 2 were recoded into 0 for the agriculture class map. Values 6 to 7 were recoded into 1 and 0 to 5 into 0 for the settlement class map. This threshold was pragmatically set based on the assumed coverage of the classes in the country. For Woodland and Mangrove, there is no pixel that is classified as such in all the seven selected output maps. The highest value for a pixel in these two classes is six.

Table 5.8: Thresholds used in converting fuzzy class maps into binary maps. *Fuzzy class maps with 6 as the highest value.

Class	Number code	Class values coded to 1	Class values coded to 0	Colour code
Agriculture	1	3 to 7	0 to 2	
Shrub	2	4 to 7	0 to 3	
Woodland	3	4 to 6*	0 to 3	
Water	4	3 to 7	0 to 2	
Bare ground	5	4 to 7	0 to 3	
Forest	6	3 to 7	0 to 2	
Settlement	7	6 to 7	0 to 5	
Mangrove	8	5 to 6*	0 to 4	

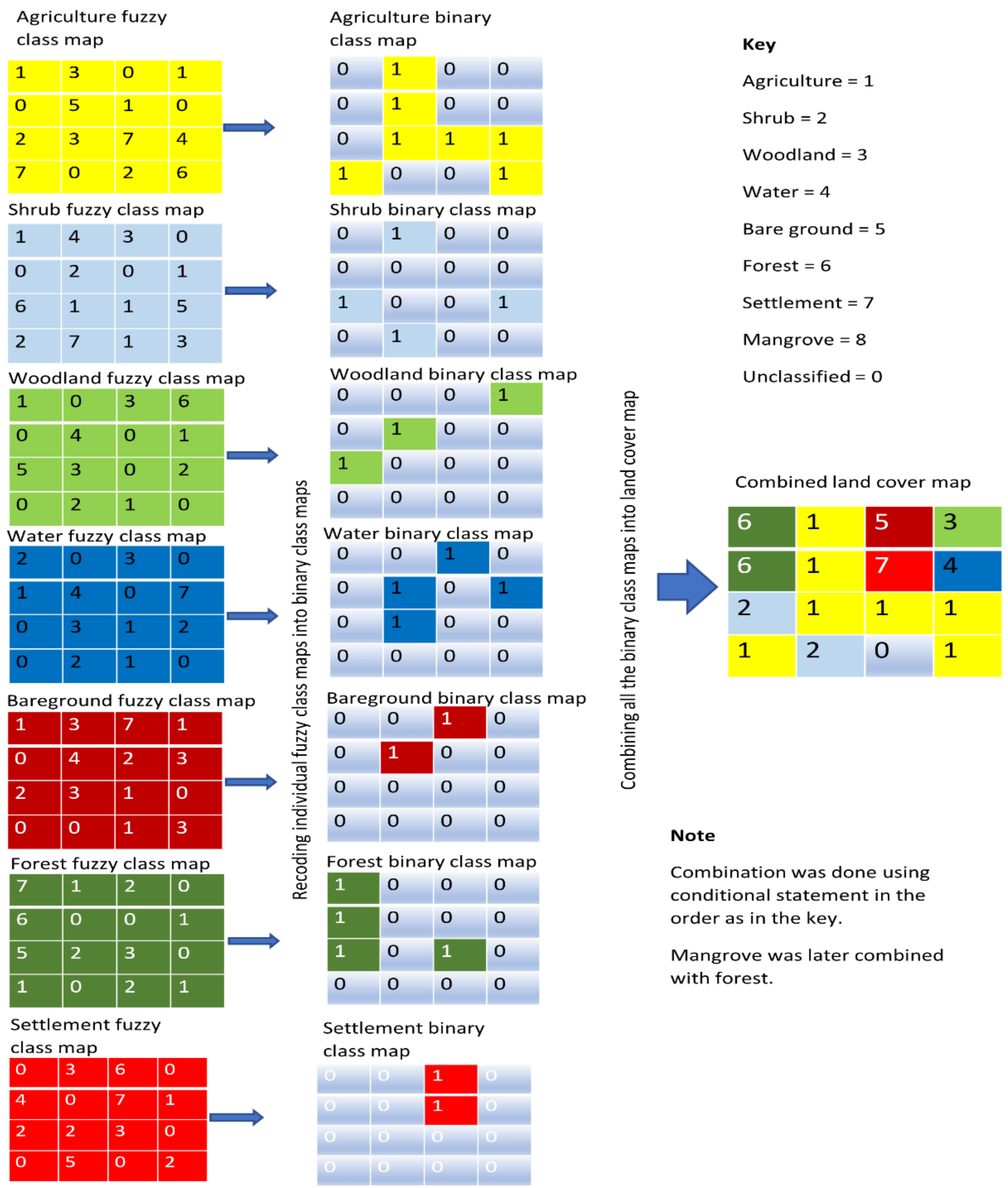


Figure 5.15: Procedure for combining the fuzzy class maps into land cover map

The conditional statement is given below as coded in the Erdas-Imagine raster calculator.

Con[(agriculture==1)1, (shrub==1)2, (woodland==1)3, (water==1)4, (bareground==1)5, (forest==1)6, (settlement==1)7, (mangrove==1)8, 0]

The statement looks at agriculture class first, then shrub and in that order. Where agriculture is 1, it is assigned 1, else if shrub is 1, it is assigned 2, else if woodland is 1, it is assigned 3 and so forth. This was to ensure conflict between classes for any pixel is removed. The limitation of this is that some classes are given priority over others. For example, for any pixel to be assigned ‘woodland’, agriculture and shrub must hold 0 for that pixel. Pixels which did not fulfil any of the combining conditions hold 0 as the value instead of any of the values for the classes. The proportion of pixels not classified is approximately 33% based on pixel counts and this might be due to the pragmatic threshold used in converting the fuzzy class maps to binary class maps. With the aid of the Google Earth image, areas with large extent of pixels having 0 were filled using the ‘fill’ tool in Erdas (figure 5.16). Since it is possible to link and synchronize views between Erdas-Imagine and Google Earth, it was possible to see those areas with large extent of 0-value pixels and pure among these pixels were filled with the relevant class value.

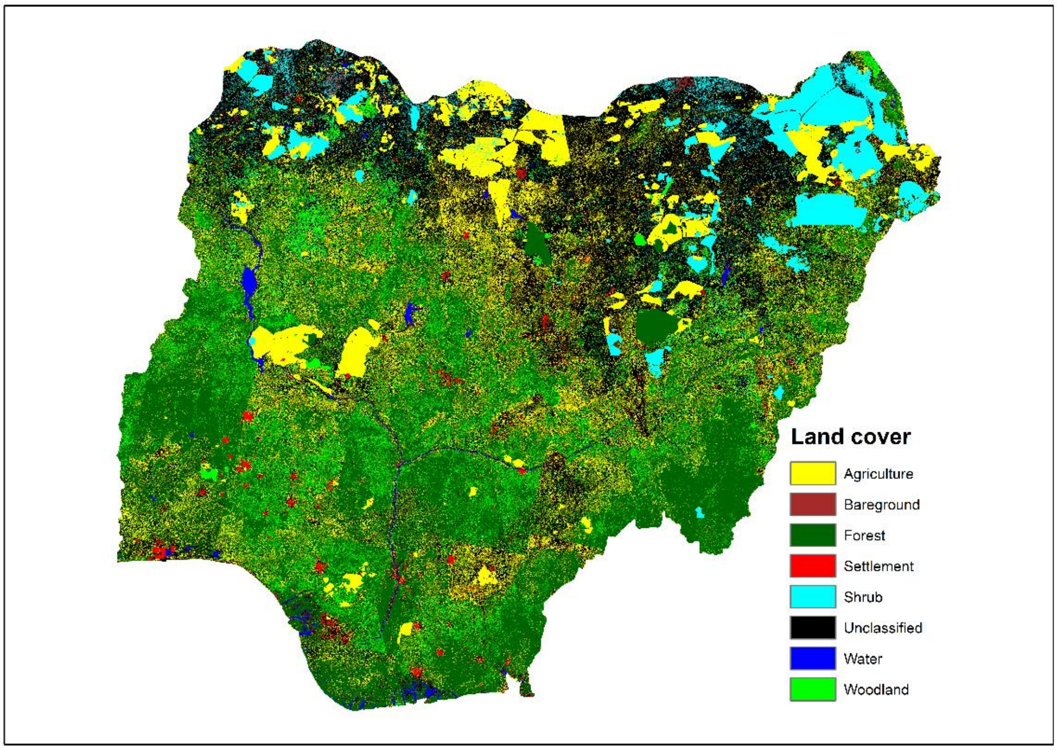


Figure 5.16: Filled Output Map. The filling process was repeated several times. The image was saved after the first few filling operations.

These unclassified pixels are obvious on figure 5.16 (dark areas). There are scattered classified pixels within the dark areas but are not obvious from figure 5.16 due to the zooming extent of the map. Thus, filtering could be ideal and was employed to filter the unclassified pixels where they are not many or are not connected extensively. The filter size used was 7x7 to allow for some obtainable pixel values in the moving filtering window at any instance. Where large cluster of pixels exist such that the filter holds 0-value pixels in all its squares, fill tool was necessary and was used to correct this. With photo interpretation techniques, Google Earth helped in identifying the land cover in those 0-value (dark) areas since it is possible to link views between Erdas and Google Earth. Thus, the remaining pixels were filtered using the Thematic Neighbourhood tool (7x7 majority filter) producing the final land cover map for Nigeria (figure 5.17). During this filtering process, where obvious errors were discovered, they were corrected to the appropriate classes. Correction for obvious errors is inevitable in satellite imagery classification.

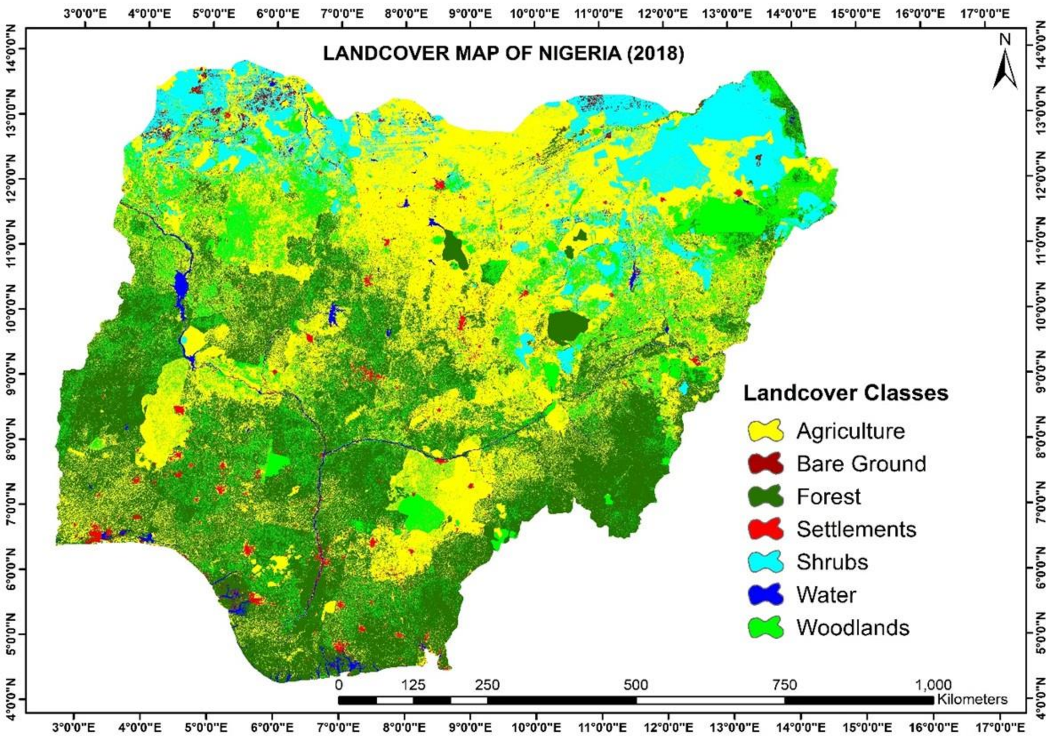


Figure 5.17: The final land cover map

This combination procedure applied to satellite imagery classification is novel. It was not found in any other work, but solely conceptualised and developed in this work. The idea, in summary, was to produce multiple band combinations, apply multiple classifiers on each combination, select a number of outputs with highest class accuracies for each class, combine the outputs into one map for each class, convert the combined class map to binary and then combine all the binary class maps into a single map consisting of all the classes.

5.4 Results

5.4.1 Accuracy assessment

The filling and the neighbourhood tools were iteratively applied and the accuracy is assessed at each round. This was continued until some reasonable accuracies were attained for each class considering both the producers and users' accuracies. For the Agriculture class, the producer's accuracy reached 85.92%, while the users accuracy reached 96.83% and the Kappa coefficient reached 0.9487. Users' accuracies are more important as the figures are measures of error of commission that indicate the probability that a pixel classified into a class actually represents that category on the ground (Lillesand et al., 2008). The producer's accuracies indicate how well the training set pixels of a class were classified. The overall accuracy reached 88.2%, while the overall Kappa coefficient reached 0.8466 (table 5.8). Kappa indicates the extent to which percentage correct values of the error matrix is due to true agreement as compared to chance agreement between the reference (observed) data and the classified data.

Table 5.9: Results of the accuracy assessment for the final map

S/N	Class	Producers Accuracies	Users Accuracies	Kappa
1	Agriculture	85.92%	96.83%	0.9487
2	Bare grounds	100.00%	100.00%	1
3	Forests	86.11%	78.48%	0.7333
4	Settlements	92.86%	92.86%	0.9258
5	Shrubs	89.04%	98.48%	0.9812
6	Water	70.59%	100.00%	1
7	Woodlands	100.00%	69.57%	0.6507
	Overall	**88.2%**		**0.8466**

Table 5.8 shows the accuracy values as they were obtained from the processing software. Though accuracy assessment is the most common means of assessing classification performance (Lu and Weng 2007), it is

critical that the approaches for the accuracy assessment are robust and transparent to ensure the integrity of the classification result (Olofsson et al., 2014). The robustness and transparency suggest implementation of the recommended good practice in the accuracy assessment.

The good practice ensures that the sampling design achieves the priority objectives of the accuracy, the respond design (the design for assessing the output of the analysis) is based on the reference data and that the analysis is consistent with sampling design and respond design protocol. It was shown in subsection 5.3.4.3 that stratified random sampling design was used in developing the accuracy assessment sample. Based on the error matrix generated in the processing software and the reference data, the accuracy was reassessed outside the processing software using Microsoft Excel and the overall accuracy dropped to approximately 82% (table 5.9). The accuracy dropped by about 6%, bringing it below the widely used target of 85% which may often be unfair, commonly being rather harsh and misleading (Foody 2008). On the other hand, this decreased accuracy values led to reduced tendency of committing error for cultivated land by about 5% (compare users' accuracy for Agriculture in tables 5.8 and 5.9).

Table 5.10: Classification accuracies as calculated in Excel

S/N	**Class**	**Producers acc.**	**Users acc.**	**Com. error**	**Omission error**
1	Agriculture	0.8686	0.9154	0.0846	0.1314
2	Bare ground	0.8333	1	0	0.1667
3	Forest	0.8382	0.76	0.24	0.1618
4	Shrubs	0.6933	0.9123	0.0877	0.3067
5	Settlement	0.9286	0.9286	0.0714	0.0714
6	Water	0.6316	1	0	0.3684
7	Woodland	0.8868	0.5949	0.4050	0.1132
	~Overall	**0.82**			

5.4.2 Methodological insights

This mapping workflow provided a new way of combining multiple satellite imagery classification outputs for improving the classification accuracy. The new workflow is flexible in such a way that it can be applied to any combination of the imagery classifiers and can be applied for both small and large geographic scales. Though the complexity may be higher where complex classifying algorithms are used, the workflow in itself is not complex. However, on large scale analysis, the workflow may be labour intensive as it requires that classes are treated individually at the first step towards combining different classifications. Also, the workflow is information dependent in a way that there may be unclassified pixels at the end that would need to be filled though, this is normal for imagery classification because it always requires correction for obvious errors.

Notwithstanding the caveats, it could be concluded that this new way of combining different satellite imagery classifications can improve classification accuracy especially if synthesis of optical and radar data and different band combinations are explored. This workflow could further be enhanced by applying Principal Component Analysis (PCA) which aggregates most important information in the spectral bands thereby reducing data redundancy. This may provide a basis for conducting a weighted classification using the derived components. However, use of PCAs requires caution because they cause spectral distortions (Thomas et al., 2008). Also, spectral separability could be employed to examine the ability of spectral bands in detecting and discriminating land cover types (Huang et al., 2016). This is applied to parametric classifiers such as Maximum Likelihood Classifier and can improve the performance of imagery classifier. Jefferies Matusita was combined with Spectral Angle Mapper to develop a new algorithm for spectral matching which was found to have produced higher classification accuracies than the separate algorithms (Padma and Sanjeevi 2014). Employing this could improve the performance of the new workflow.

An assessment could be executed on the classification outputs to determine which of the band combinations produced best overall results. In this work, the focus was on the individual classes in selecting the best results. As presented in appendix X, the band combination that produced highest overall accuracy (approximately 50% before correcting for obvious errors) is the optical bands + radar vegetation index (Red, NIR, NDVI and DPSVI) classified using maximum likelihood. It has the highest user accuracy (56%) for agriculture. The combined two radar bands (VV and VH) classified using spectral angle mapper has the second highest overall accuracy (approximately 39%) but has the highest producer accuracy for agriculture class (68%). These show that though there is no clear pattern as regards the performance of the band combinations with the classifiers from the output maps, MLC performed better than SAM mostly in combinations which have more optical bands than radar band. SAM performed better mostly in combinations where there are more radar data than optical bands.

Despite low accuracies in all the classification outputs, it could be noticed in appendix X that of the 20 outputs maps, seven in which there is combination of the optical and radar bands have higher accuracies than all the four combinations in which only optical or radar bands were combined. It has been found that adding SAR bands to optical bands increases classification accuracies (Whyte et al., 2018) due to the complementarity of the two types of remote sensing data (Joshi et al., 2016) and the results seen in this thesis support this. For example, while optical data is limited in identifying scattered woody vegetation, radar sensor have great capabilities in responding to scattered woody plants (Baumann et al., 2018).

It could also be useful to determine how much conflicts were there between classes at the stage of combining the individual classes into single map. Although the estimated distribution pattern of the classes in the real world was the basis for assigning the threshold with which the fuzzy classes were converted into binary classes, it would be more reasonable to use the class proportions as determined by the reference sample (accuracy assessment sample) to apply the threshold. These could not be implemented due to impacts of the pandemic and because this mapping analysis is only a small part of the whole research work.

5.4.3 Cultivated area estimate

The areas were calculated for each class (table 5.10) based on the initial results of the accuracy assessment (table 5.8). Nigeria's total surface area is put at 92,376,800 hectares (CILSS 2016). Comparing this with the total in table 5.10 showed that there is a difference of 1,547,699 hectares missing from the analysis. This may be due to some unclassified pixels. In other words, the filtering process could not capture some pixels perhaps due to the absence of classified pixels in their reference filtering window. As mentioned in subsection 5.3.4.3, the filter used in the filtering process is the majority filter with 7X7 squares. Thus, in calculating the value of a pixel, if all the squares in the filter holds 0, then that pixel will still be assigned 0. This means that though filtering process was executed, there is possibility that unclassified pixels exist in the land cover map. However, the result showed that about 34.6 million hectares were cultivated in Nigeria during the 2018 rainy season.

Table 5.11: Calculated areas for each class

S/N	Class	Area (Hectares)
1	Agriculture	34,584,731
2	Bare grounds	682,070
3	Forests	33,061,378
4	Settlements	1,386,721
5	Shrubs	9,361,478
6	Water	772,992
7	Woodlands	10,979,731
	Total	**90, 829,101**

It was reported that of the Nigeria's total surface area, 82 million hectares is arable (assumed in this work to mean cultivable) out of which about 32-34 million is cultivated (Akomo 2018). Another 2016 report by Pricewatercoopers cited an article that put the estimate of the cultivated land area at 34 million hectares (PwC 2017). Based on table 5.8, Agriculture omission and commission errors are approximately 14% and 3%, respectively. This means, though about 14% of the cultivated areas could not be identified by the analysis, about 3% of the pixels classified as agriculture might actually not be agriculture on the ground. In other words, about 1.1 million hectares might not be agriculture in reality, though were classified as such. The confusion matrix suggests that some of these pixels misclassified as agriculture are actually shrubs (6%), woodlands (38%) and forest (56%). This means about 66,000, 418,000, and 616,000 hectares classified as agriculture might actually be shrub, woodland and forest, respectively. Thus, these wild vegetations appear to the software as cultivated areas.

On the other hand, according to the accuracies as calculated in Excel (table 5.10), producer's and user's accuracies for agriculture are approximately 87% and 92%, respectively. In other words, though about 13% of the cultivated areas could not be identified, about 8% of the classified pixels for agriculture may not be cultivated land on the ground. Thus, the commission error (8%) suggests that about 2.8 million hectares of the identified agriculture is probably not agriculture.

Considering the proportion of the cultivated lands that could not be identified by the analysis, it could be concluded that there is an estimated 41 million hectares of land cultivated in Nigeria during the 2018 rainy season. Of this, about 35 million was identified by the analysis. The analysis has produced some results that could be considered as close to reality, at least for the agricultural land parcels, the identification of which is the focus of the analysis. Overall, this may be considered to have shown that huge areas of unutilised arable land exist in Nigeria considering that there are more than 9 million hectares of shrub lands and about 11 million hectares of woodlands in the country (table 5.10). It is assumed that if not all, large part of the shrub and woodland would be potential for agriculture considering that more than 80 million hectares of Nigeria's land is said to be arable.

According to the CILSS published map of 2016 produced with 2013 datasets, rainfed agriculture accounted for 38 million hectares, covering over 40% of the country's territorial area (CILSS 2016). This compared less with the 41 million hectares estimated by the current mapping analysis to have been cultivated in the 2018 rainy season. The current 2018 map suggested there are estimated 3 million more cultivated areas than estimated by the CILSS 2013 map. As explained in subsection 5.3.1, due to its coarse spatial resolution, regional scope and relatively older datasets, the current map might provide more useful details with regards to identifying cultivated areas due to its finer spatial resolution, more recent dataset and relatively smaller spatial scope. The researcher could not find country specific assessment of the ESA 2016 global land cover map for Nigeria. However, as mentioned in subsection 5.3.1, the accuracy of the map for some West African countries, as assessed by Lesiv et al., (2019), compared less with the current 2018 map as produced from the current work. Thus, it is believed that the mapping analysis conducted in this work provided more useful detail for identifying cultivated areas in Nigeria that would need to be eliminated.

5.5 Constraints masking

Agricultural areas, surface water bodies and major settlements were extracted from the land cover map produced in the previous section. As discussed in section 5.2. Datasets for the other constraints were obtained from secondary sources. All the constraints datasets were merged together into a single map. Figure 5.18 shows the spatial distribution of the constraint areas, while figure 5.19 shows a comparative area coverage of each constraint as well as the amounts of areas potentially physically available for biofuel crops cultivation in the country. It also showed that there is more than 40 million hectares of land that could potentially be used for biofuel crops cultivation in Nigeria (coloured green).

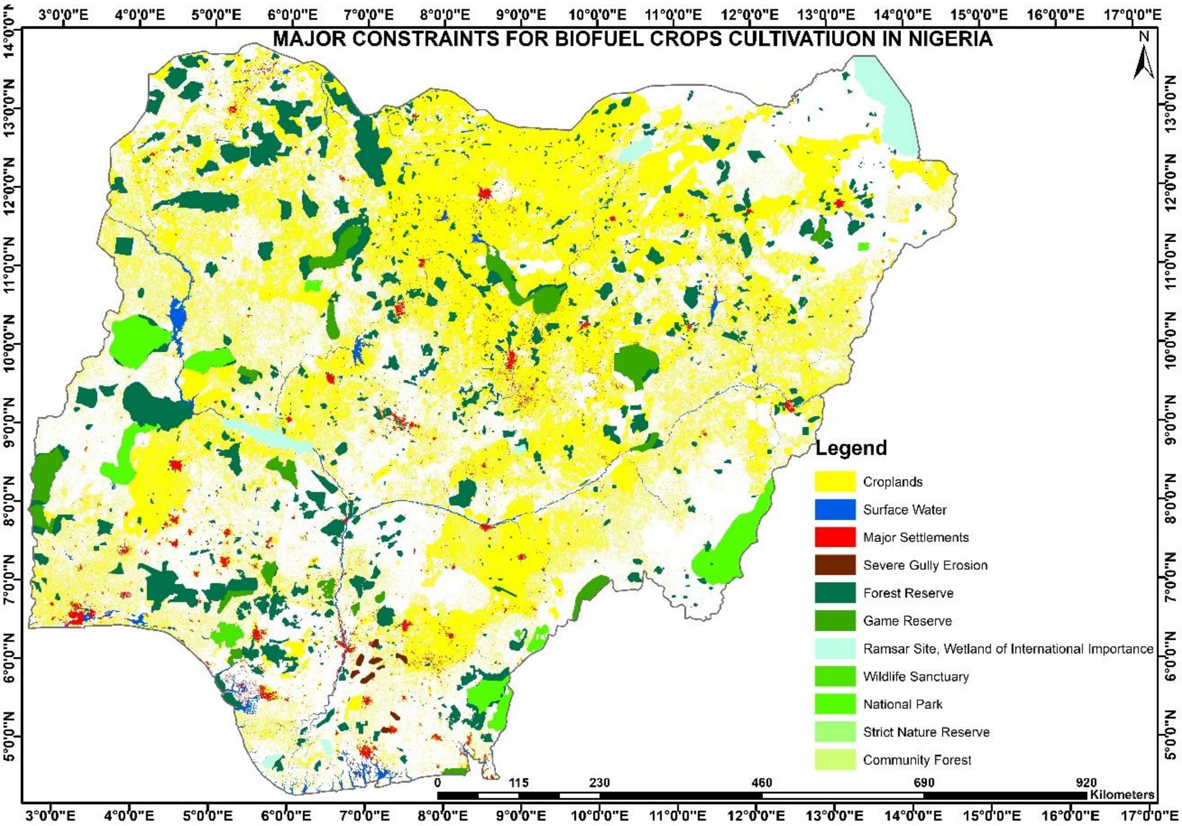


Figure 5.18: Map of the restricted areas in Nigeria that cannot be used for biofuel crops cultivation

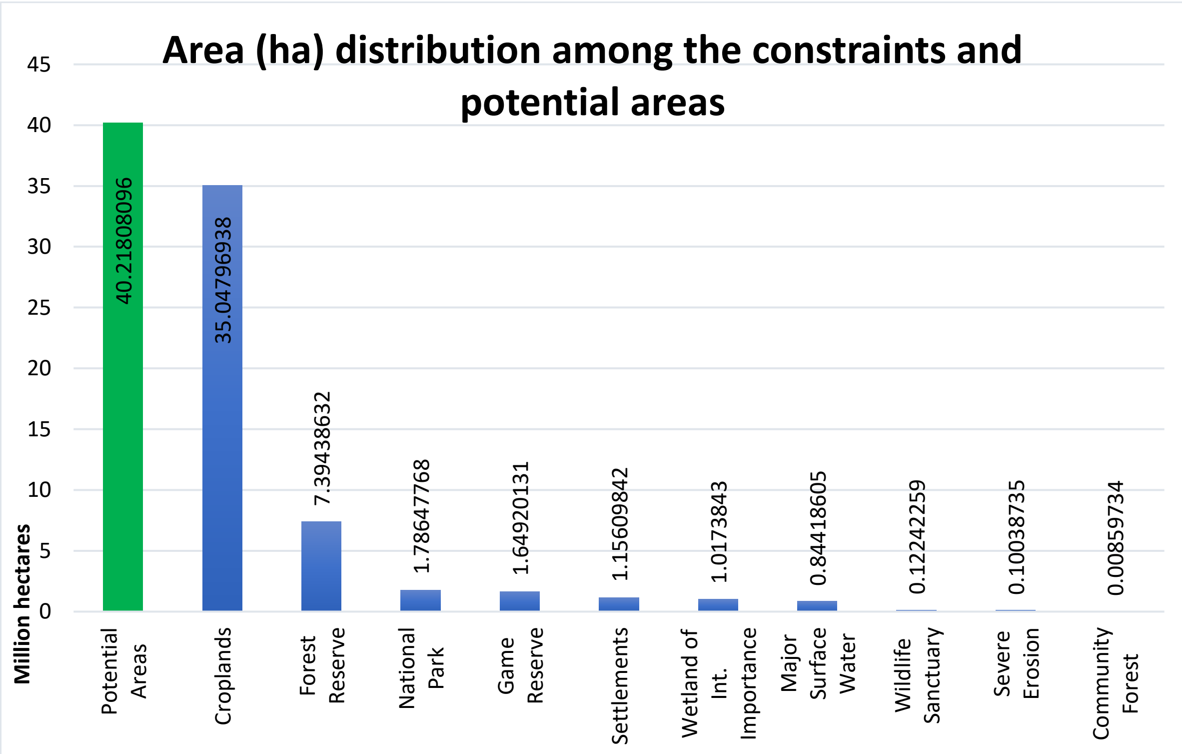
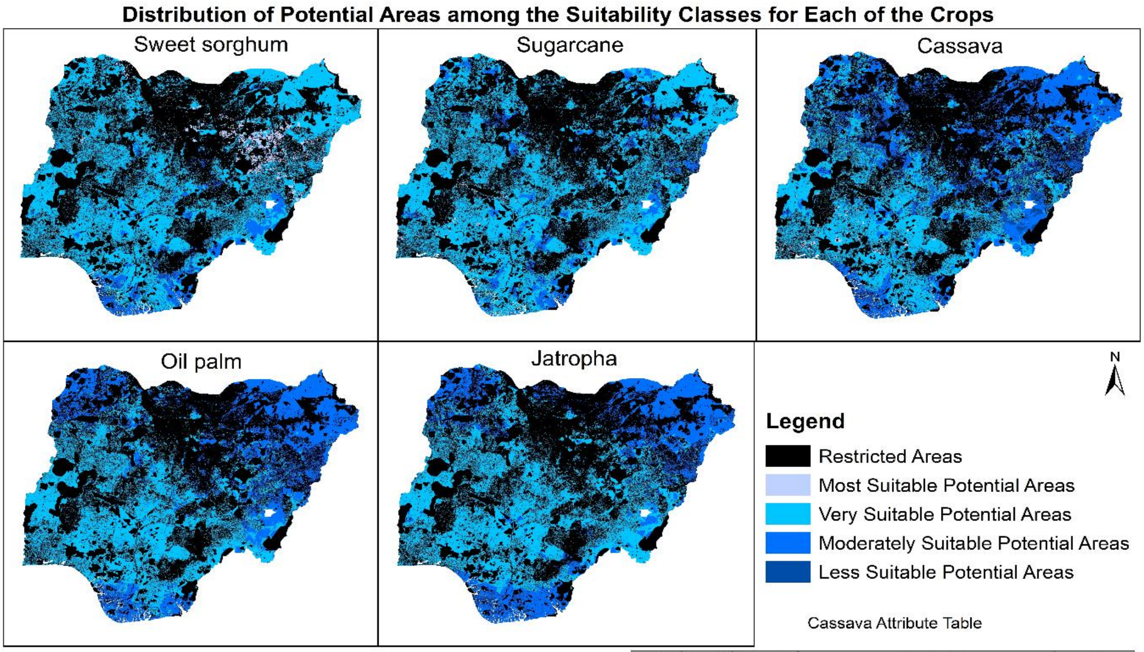


Figure 5.19: Amounts of the potential areas in comparison with individual constraint areas

Figure 5.20 shows the result of overlaying the suitable land for each crop on the potentially available lands. Potentially available here means not part of the restricted areas. Thus, the potential areas are assigned suitability classes based on the land suitability modelling conducted in chapter four. The table on the figure is the result for cassava showing areas that are most, very, moderate or less suitable for cassava cultivation in Nigeria. Figure 5.21 shows the areas in hectares for all the crops considering the whole country. Considering the proportions of Nigeria's land areas identified as suitable for cultivating each of the crops, table 5.12 shows the proportions of land areas that are potentially available for cultivating the crops after masking the restricted areas.



Rowid	VALUE	COUNT	DESCRIPTION	AREA
0	0	509792014	Restricted Areas	45881281.26
1	1	4300596	Most Suitable Potential Areas	387053.64
2	2	271740705	Very Suitable Potential Areas	24456663.45
3	3	209042521	Moderately Suitable Potential Areas	18813826.89
4	4	8418953	Less Suitable Potential Areas	757705.77

Figure 5.20: Maps showing varied suitability of the potential areas for each of the crops

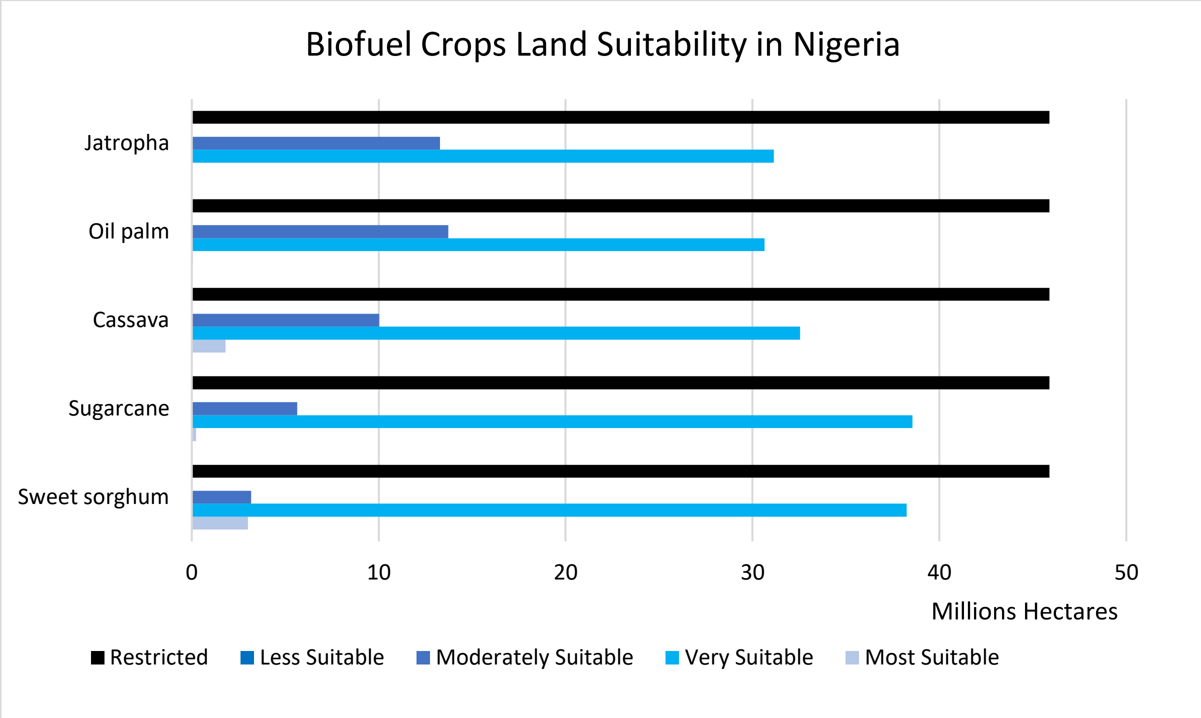


Figure 5.21: Amounts of land areas suitable for cultivating each of the crops in Nigeria

Table 5.12: Approximate proportions of Nigeria's land area potentially suitable and available for cultivating biofuel crops

Suitability	Sweet sorghum	Sugarcane	Cassava	Oil palm	Jatropha
Most suitable	3.32	0.25	2.00	0.06	0
Very Suitable	42.35	42.69	36.04	33.93	34.50
Moderately suitable	3.51	6.25	11.10	15.20	14.70
Less suitable	0	0	0.04	0.0003	0

Comparing the above table with table 4.2 in chapter four, it could be seen that huge amounts of land areas have been masked as restricted, denoting that those masked areas would not be available for biofuel crops cultivation in Nigeria. For example, while table 4.2 shows 10.36% of Nigeria's land areas could be most suitable for cultivating sweet sorghum in the country, table 5.12 shows that only about 3.32% could be available. In other words, 7.04% of Nigeria’s land areas that would have been most suitable for cultivating sweet sorghum is restricted and would not be available for this purpose. Also, of the 87.49% (table 4.2) of Nigeria’s land areas that is very suitable for cultivating sugarcane, only about 42.69 would potentially be available; 44.8% is restricted. Only 11.10% is potentially available for cultivating cassava out of the 21.60% that is moderately suitable; 10.5% is restricted. All the land areas identified as less suitable for cultivating sugarcane are not available. While approximately all areas identified as less suitable for cultivating oil palm are available. Less than half the land areas (71.6% as in table 4.2) identified as very suitable for cultivating jatropha could be available; 37.1% is restricted (table 5.13). As could be understood from table 5.13, for each of the crops, about half of the land areas classified as very suitable for cultivation is restricted. However, this suitability class has the largest area potentially available for cultivating each of the crops as shown in table 5.12.

Table 5.13: Approximate proportions of Nigeria's land areas masked by the constraints per crop suitability class

Suitability	Sweet sorghum	Sugarcane	Cassava	Oil palm	Jatropha
Most suitable	7.04	0.44	1.77	0.08	0
Very Suitable	41.83	44.80	38.36	36.63	37.10
Moderately suitable	1.96	5.57	10.50	14.11	13.70
Less suitable	0	0.000064	0.19	0	0

The availability of the potential areas was further analysed scaling down to the country's six geopolitical zones. Figures 5.22 and 5.23 showed the spatial distribution and area distribution by zone, respectively.

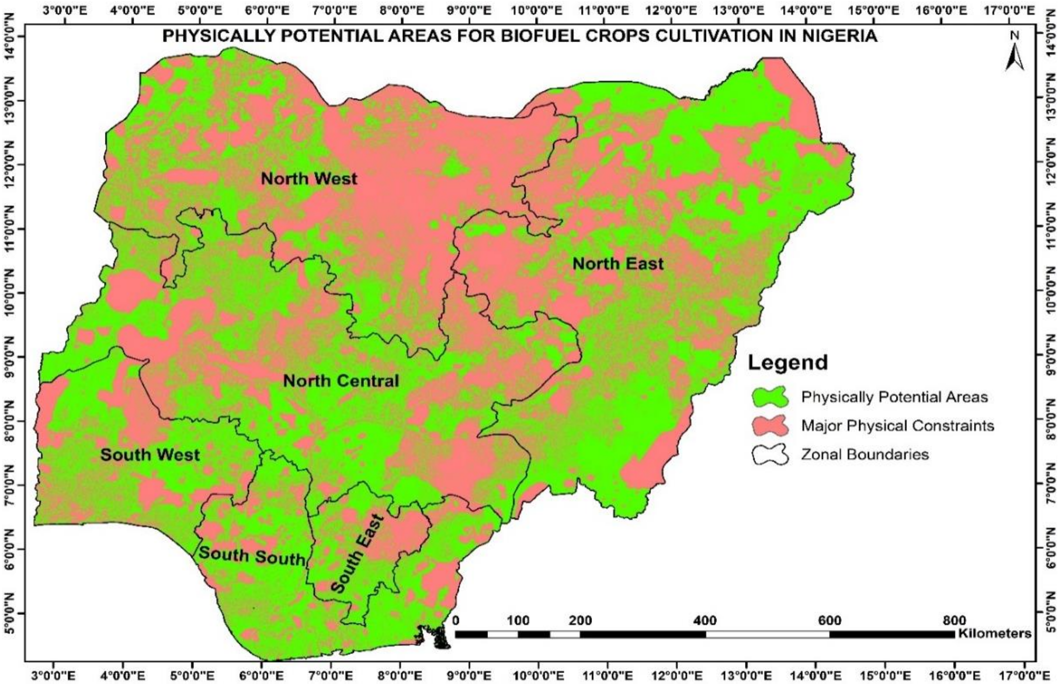


Figure 5.22: Zonal Distribution of Potential Areas by geo-political zone in Nigeria

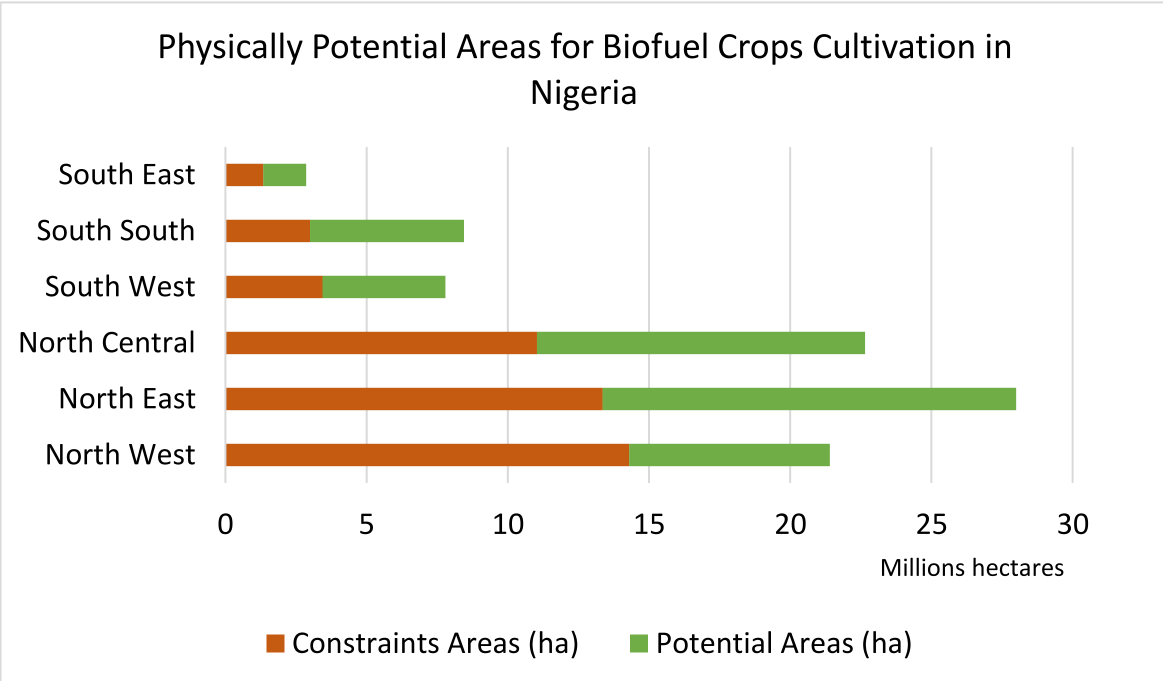


Figure 5.23: Amounts of Potential Areas in Each Geo-political Zone

As discussed in section 5.2, not all data was available to identify and eliminate all the restricted areas. An attempt was made to obtain data on grazing areas, cultural sites and other major commercial land uses but this was not achieved. Thus, not all of the 40 million hectares identified as physically potential for biofuel crop cultivation would realistically be available. However, it is obvious from figure 5.23 that some amount of land is physically available for biofuel crops cultivation in each of the six geo-political zones of Nigeria and these amounts could be in millions of hectares considering the country. This physical availability was further analysed to determine within zone distribution. Figure 5.24 shows spatial distribution of the suitability classes for each crop within each geo-political zone.

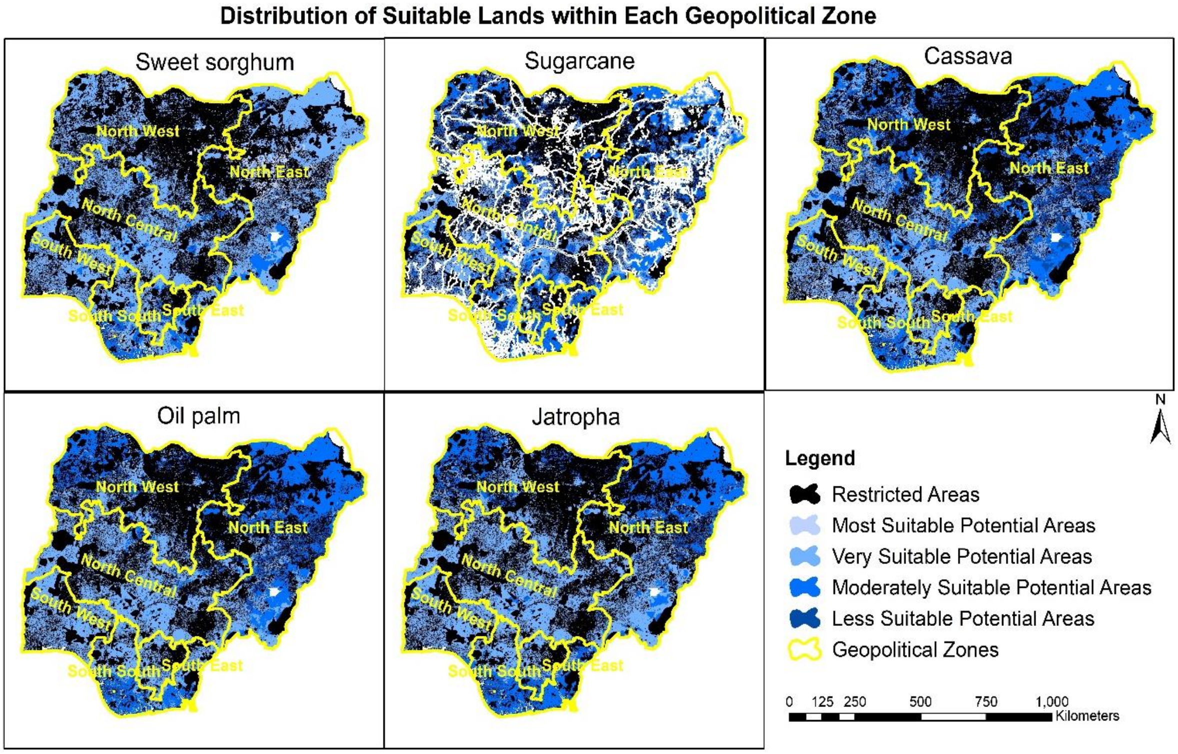


Figure 5.24: Maps showing land suitability for each of the crops within each zone

Figures 5.25 to 29 show these distributions by area vis a vis the restricted areas. As mentioned earlier, 'Very Suitable' seemed to have larger coverage though there are variations from crop to crop and from zone to zone. Ideally this variation should consider state level rather than zonal level because land governance is vested on the state governors and the rules may differ based on states. However, because there are 37 of these smaller regions, the work will be lengthy if each state is analysed.

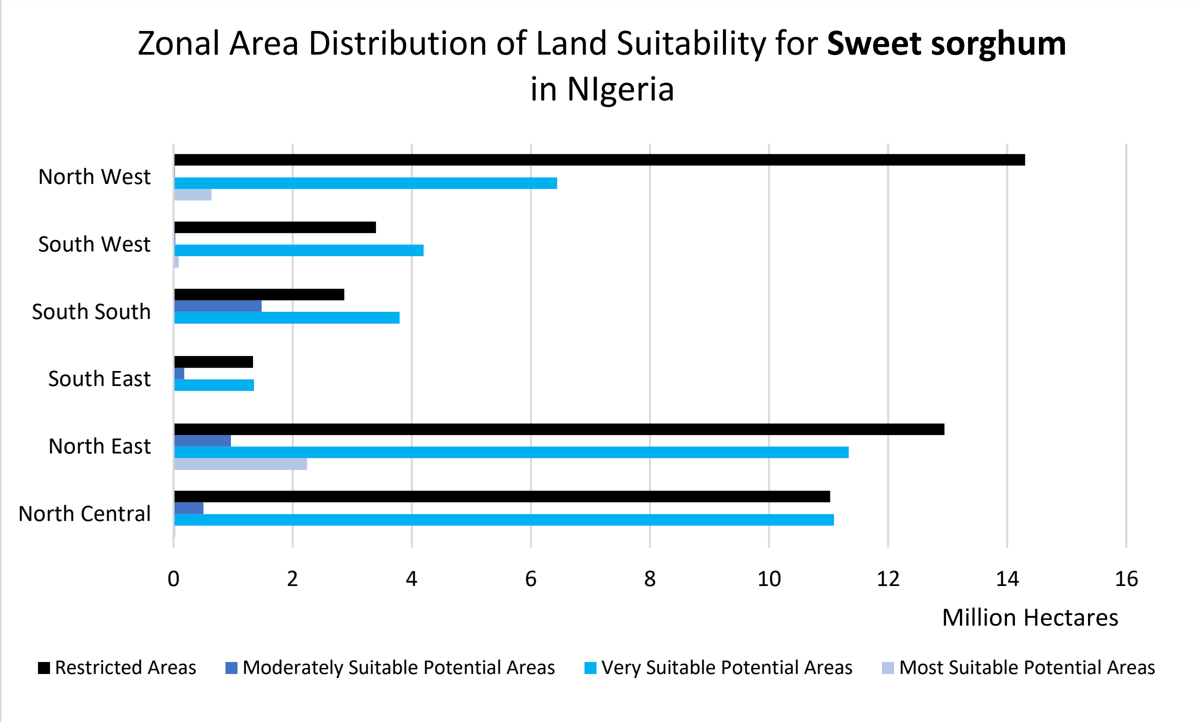


Figure 5.25: Comparison of land suitability between the zones for Sweet sorghum cultivation

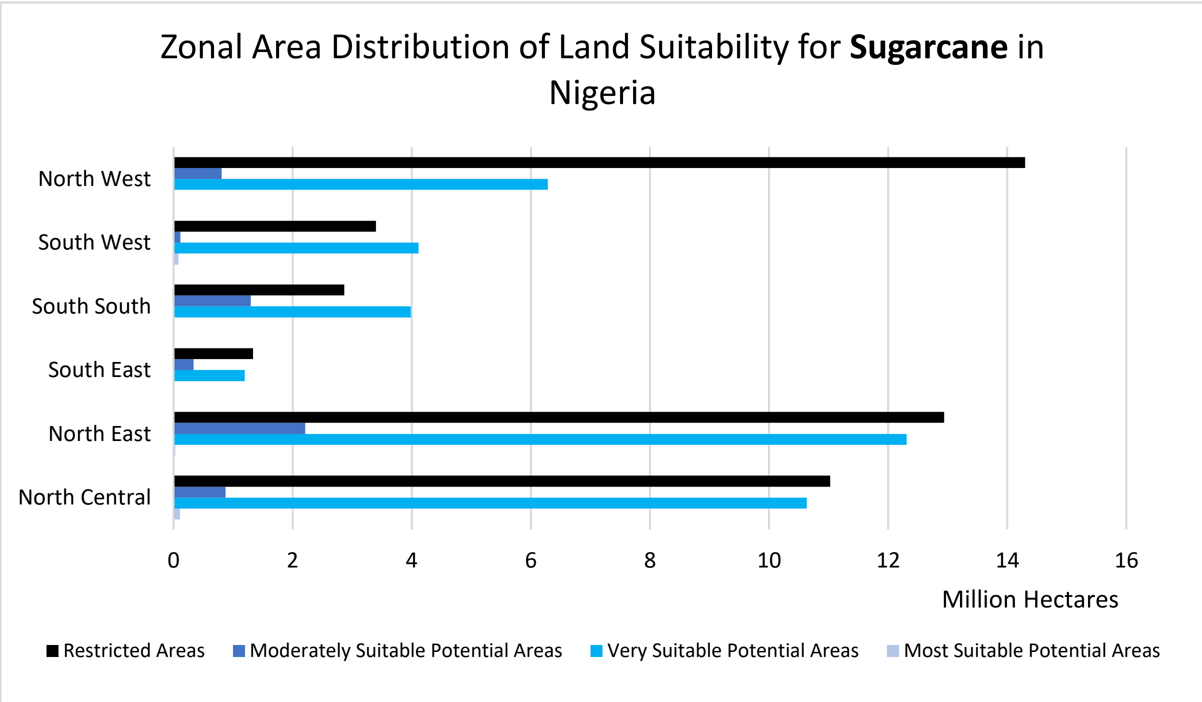


Figure 5.26: Comparison of land suitability between the zone for Sugarcane cultivation

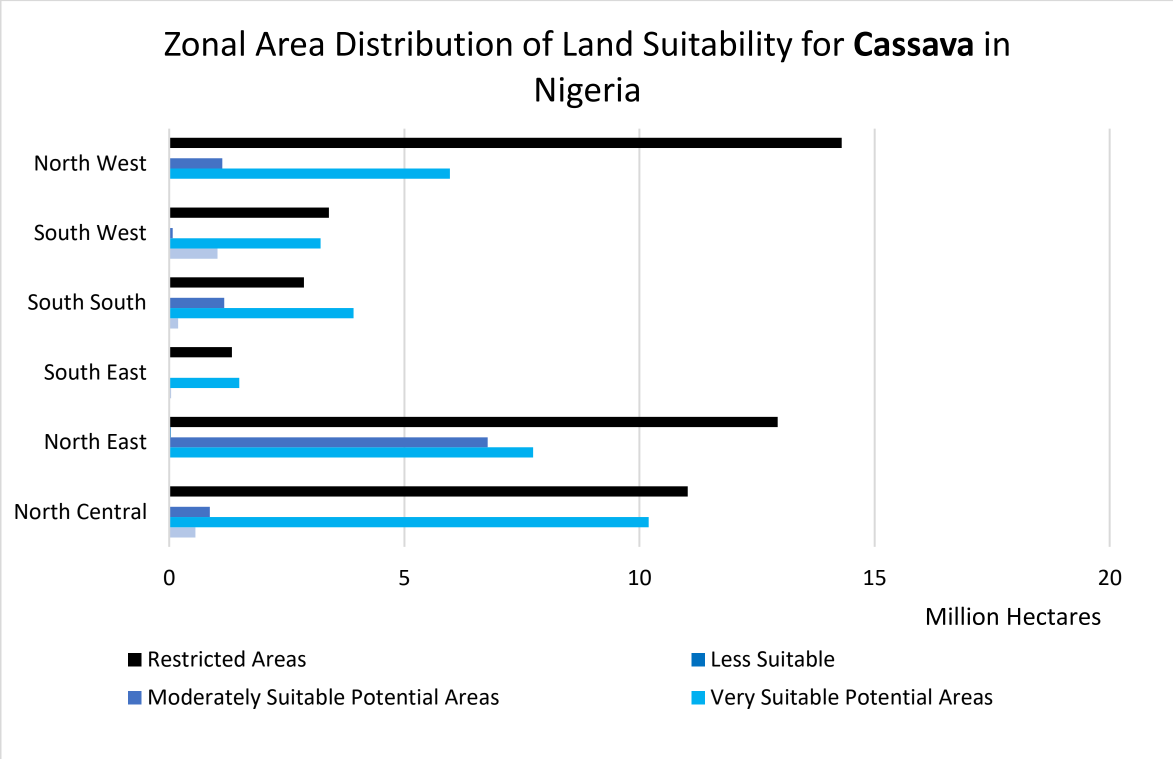


Figure 5.27: Comparison of land suitability between the zone for Cassava cultivation

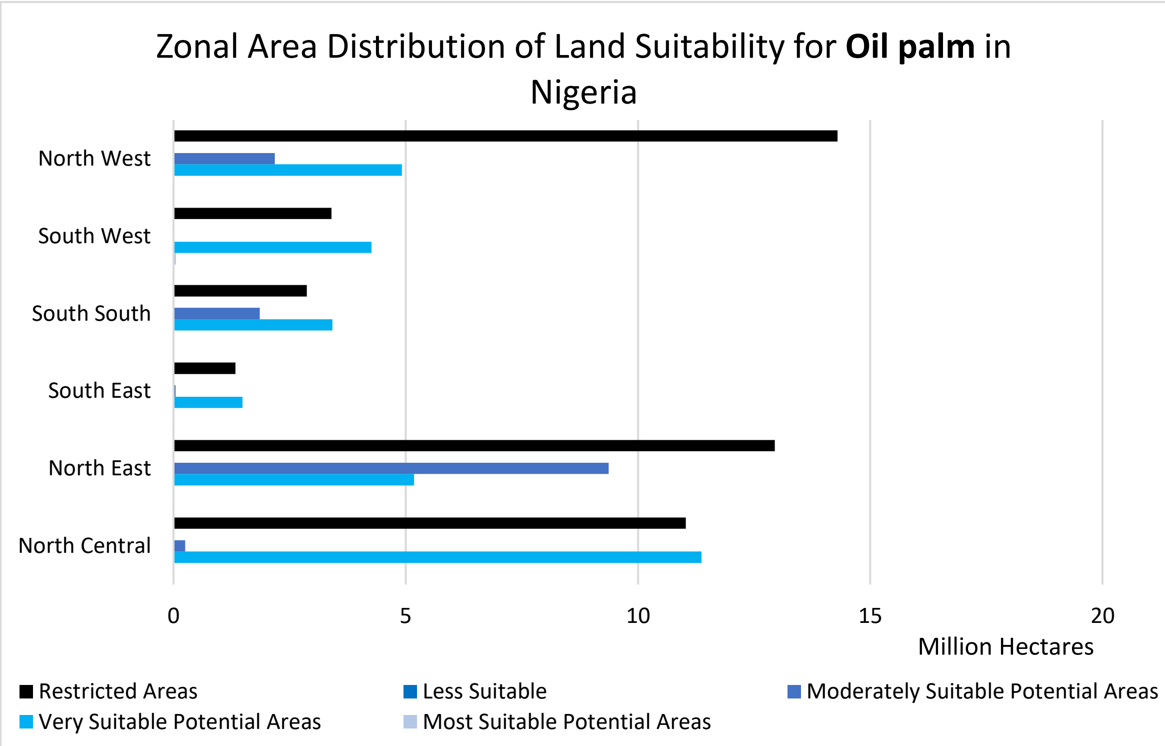


Figure 5.28: Comparison of land suitability between the zone for Oil palm cultivation

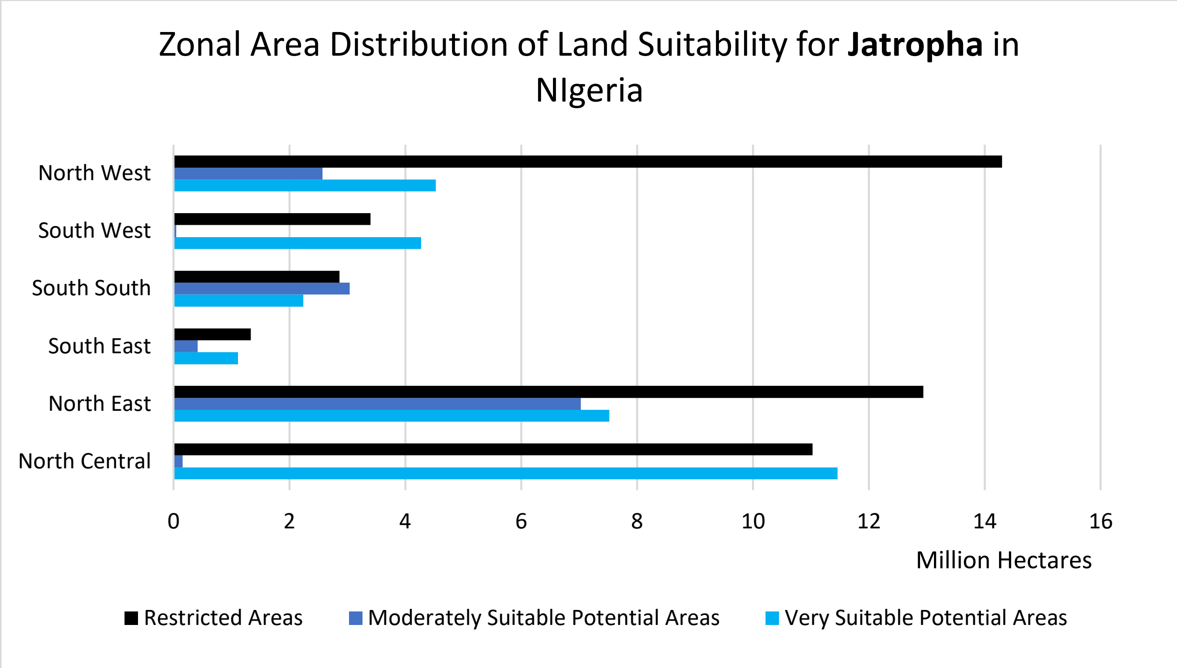


Figure 5.29: Comparison of land suitability between the zone for Jatropha cultivation

5.6 Discussion and conclusions

In this chapter, research questions 4 and 5 have been addressed, namely;

- How much land is physically available in Nigeria for biofuel crops cultivation without conflict with food crops cultivation?
- Where are these physically available lands located in the Country and how suitable are they for the identified biofuel crops cultivation?

The analysis showed that there are approximately 41 million hectares that potentially could be explored for biofuel crops cultivation. Of this, table 5.14 shows how much area could be available for this purpose in each of the country's geo-political zones. Presently, most of these areas are covered by shrubs (more than 9 million hectares) and woodland (more 10 million hectares). Though there are caveats as mentioned earlier, based on these results, it is safe to believe a few millions of hectares of lands could actually be realistically available for biofuel feedstock cultivation without conflict with food crops cultivation. According to the National Biofuel Policy, 2% of the arable land will be required for the biofuel project (NNPC, 2012). As mentioned in subsection 5.3.6, about 82 million hectare of Nigeria's landmass is arable (Akomo 2018). This means about 1,640,000 ha of arable land would be required for the project. Thus, there could be more than enough available land to support this project.

Table 5.14: Estimates of the potential areas by geo-political zone in sq.km

Zone	**Total Area (sq.km)**	**Restricted Areas (sq.km)**	**Potential Areas (sq.km)**	**Proportion of the Potential Areas**
Northwest	214045.67	143023.67	70992.83	33%
Northeast	280106.79	133593.85	146423.01	52%
Northcentral	226504.48	110281.58	116203.68	51%
Southwest	77866.21	34425.54	43428.33	55%
South-south	84551.01	29990.46	54519.78	64%
Southeast	28658.79	13358.87	15299.93	53%
Total (Nigeria)	**911732.96**	**464673.97**	**446867.57**	**49%**

It could be argued that this zonal distribution follows the sizes of the zones such that the zone with the largest area extent (Northeast) has the largest share and the zone with the smallest area extent (Southeast) has the smallest share. Looking at figure 5.23, it could be seen that though northeast is the largest in size, there are more restricted areas in the northwest than any other zone. This is also true comparing south-south and southwest. Deeper look at crop suitability reveals more variability. Figure 5.21 of course showed that for all the crops, largest area was identified as ‘very suitable’ compared to the other suitability classes. However, looking at the zones, there are more very suitable areas for sweet sorghum in the northeast than any other zone (figure 5.25).

For all the other crops, there are more very suitable areas in the North central than any other zone (figures 5.26 to 5.29). Also, this zone has less restricted areas compared to northwest and northeast looking at all the crops. Though Southwest is only second to the smallest in terms of area, the areas classified as ‘very suitable’ for cassava in the zone is almost the same as in the Northeast zone which is the largest zone in terms of area (figure 5.27). The same could be said considering jatropha, comparing Northwest and Southwest (figure 5.29) though Northwest is the 3rd in terms of size. Very suitable area for oil palm is even larger in the Southwest than in the

Northeast (figure 5.28). There is also more ‘very suitable’ area for sugarcane in the Southwest than in the Northwest (figure 5.26). Therefore, this suitability distribution is not entirely dependent on the sizes of the zones. This suitability distribution provides guidance with regard to spatial decision for establishing biofuel feedstock production sites in the country.

In this chapter, research questions 4 and 5 were addressed and objective 6, which deals with mapping crop lands was achieved. It could be concluded at this stage that Northcentral zone of Nigeria presents largest land areas that are ‘very suitable’ for the cultivation of all the five biofuel crops except sweet sorghum for which Northeast present largest area that is ‘very suitable’ for its cultivation. In general, it could be concluded from this analysis that there could be more than required hectares of land in Nigeria that could realistically be put to biofuel crops cultivation without conflict with food crops cultivation. The following chapter will focus on optimising sites for locating biofuel processing plants based on the suitable areas identified. Because for all the crops, the suitability category identified with the largest coverage is ‘very suitable’, this class will be used. However, it may be reasonable to include ‘most suitable’ areas for the crops that have some areas identified in that category.

Chapter Six – Site Optimality Modelling

6 Chapter Six – Site Optimality Modelling

6.1 Introduction

This chapter focuses on optimising sites for biofuel processing and/or blending in Nigeria, using the locations of the existing petroleum depots as the basis for the analysis. As discussed in section 1.6, feedstock availability constitutes the major factor limiting biofuel production because it takes about three quarters of the production costs and thus, forms the major consideration in deciding a processing location. Because agricultural crops are considered in this work as the feedstock, areas that are 'very suitable' for cultivating each of the biofuel crops, as determined in the previous chapter, were considered as the potential sources of feedstock. Areas identified as 'most suitable' were also considered.

As discussed in section 3.4.3, the major considerations for optimality modelling are the suitable lands, the crop yields, a distance threshold and the potential amounts of the feedstock, in relation to each of the processing plants. The suitable lands were determined through land suitability modelling in chapter four. Areas that are not only unsuitable but also restricted or considered restricted were then removed as outlined in chapter five. However, this was limited to those restricted areas for which data was available. Crop yields were determined from the literature and three yields scenarios were adopted. Due to transport costs, the distance that can be covered to supply feedstock to the processing site depends on the production scale of the plant. Thus, a three-distance threshold was adopted because at the time of this work, there is no information regarding the scale of operation of the processing plants. Therefore, the work focused more on assessing the potentiality of the proposed processing sites and then determined their potential capacities.

6.2 Optimal sites modelling

6.2.1 Methodology

The two major approaches to applying mathematical models in solving spatial problems are optimisation, the output of which is broadly a prescription of strategy, and simulation which is broadly descriptive. As a normative approach, optimisation seeks to find the best (maximum or minimum) solution to a well-defined management problem (Malczewski 1999). In the context of biofuel production, optimality analysis looks at the relationships between feedstock and processing plant and aims to find an optimal location to minimise costs (Shi et al., 2008). Though experts in spatial analysis classify spatial operations into attribute, distance/location and topological operations (Burrough and McDonnell 1998), usually a particular spatial analysis would involve all the three. For example, while ‘feedstock’ is a qualitative attribute that described the entity being considered, the location of the farm on which the feedstock was cultivated defines whether the feedstock is within or beyond the viable supply distance from the potential processing location.

The farms might be connected to potential processing location by a topological network such as roads or other lines of communications or the two might be direct neighbours (contiguous). One of the most widely applied spatial decision models is network optimisation which consists of nodes (points of supply, demand and transhipment for resources) and arcs (the flow paths for the resources). It optimises a function of the flow of resources between nodes with the objective of determining the best allocation of resources among the nodes, subject to resource availability and flow restriction along the arcs. While converting some linear programming problems to network flow problems might not be feasible or might be too abstract, network flow models improve solution times over standard linear programming models and make problems more intuitive to users of the models through graphical representation of the network (Malczewski 1999).

Location-allocation and Supply Area Modelling (SAM) are usually the two broad techniques used in optimising locations for biomass processing plants. Transportation of feedstock is usually in two stages – from the production location to an aggregation point and from the aggregation point to the processing plant (Dharmadhikari and Farahmand 2019). In the context of Origin-Destination (OD) analysis, location-allocation has its origin at the feedstock producing locations. It identifies the closest collation point feedstock producers take their produce to without distance limit. The destination is the collection point (this may be the collation point or the processing plant itself). Thus location-allocation is applied where the objective is to aggregate all the usable biomass in a given area to a processing plant without transportation limit. This has been applied in various studies with different contexts around the world, for example Sultana and Kumar (2012), Buzai (2013), Voets et al., (2013), Sahoo et al., (2016), Aremu and Vijay (2016) Kim et al., (2018), Sahoo et al., (2018), Dharmadhikari and Farahmand (2019), Chukwuma (2019), Abdelkarim (2019), and Rahman et al., (2021).

SAM puts a threshold beyond which biomass cannot viably be transported to the processing plant due to transport costs, making it more practical, in this context, compared to location-allocation, because transport costs account for a large part of the overall biofuel costs as discussed in subsections 2.3.12 to 13. Supply Area Modelling was adopted in this work. The origin is the processing plant in this context, while the destination is the feedstock production points. An area is created around a candidate site based on the distance threshold.

SAM has also been applied in various context around the world for example O'Neill (1995), Horner and Murray (2004), Swapan et al., (2006), Murad (2007), Shi et al., (2008), Rentizelas et al., (2009), Ocalir et al., (2010), Zhang et al., (2011), Hashemi Beni et al., (2012), Doi et al., (2013), Höhn et al., (2014), Higgs et al., (2015), Brahma et al., (2016), Gonzales and Searcy (2017), Sánchez-García et al., (2017), Calovi and Seghieri (2018), Laasasenaho et al., (2019) and Nguyen et al., (2020). The assumption in this research is that feedstock transportation is along the road network of the country. Though there is apparent commitment on the part of the government for railway revival and expansion, the road network is far more extensive and provides wider reach to most part of the country. Roads are thus adopted as the connecting path between the feedstock cultivating farms and the potential processing locations.

6.2.2 Supply Area Models

Five models were developed and executed to determine locations that are optimal for processing and/or blending biofuel, one model each for a crop. Figure 6.1 shows the model for sweet sorghum. The remaining four models can be found in appendix VI. As alluded to in section 3.4.3, there are four important components based on which the model was executed, as explained in the introduction (section 6.1). The feedstock cultivation areas, the crop yields, the distance threshold and the estimated feedstock amounts.

The system of biomass assessment depends on the type of feedstock considered in the analysis. For example, using municipal waste, Laasasenaho et al., (2019) obtained secondary data from the municipal authority responsible for waste collection. Sánchez-García et al., (2017), estimated wood fuel from the crown and barks of Eucalyptus, Gonzales and Searcy (2017), estimated herbaceous biomass yield from the US National Land Cover Data (NLCD), Brahma et al., (2016), estimated domestic waste (food and animal droppings) using household level survey and Shi et al., (2008) estimated usable biomass using the land use data produced from 1998 Landsat TM. Where agricultural crops are considered as the feedstock, crop yields are used as the basis for biomass estimation (Nurjaya et al., 2013; Enciso et al., 2015; Lewis et al., 2015). Thus, literature was explored to extract information regarding field observed yield estimates for each of the crops considered in the work. Table 6.1 shows the crop yields that were found reported in the literature.

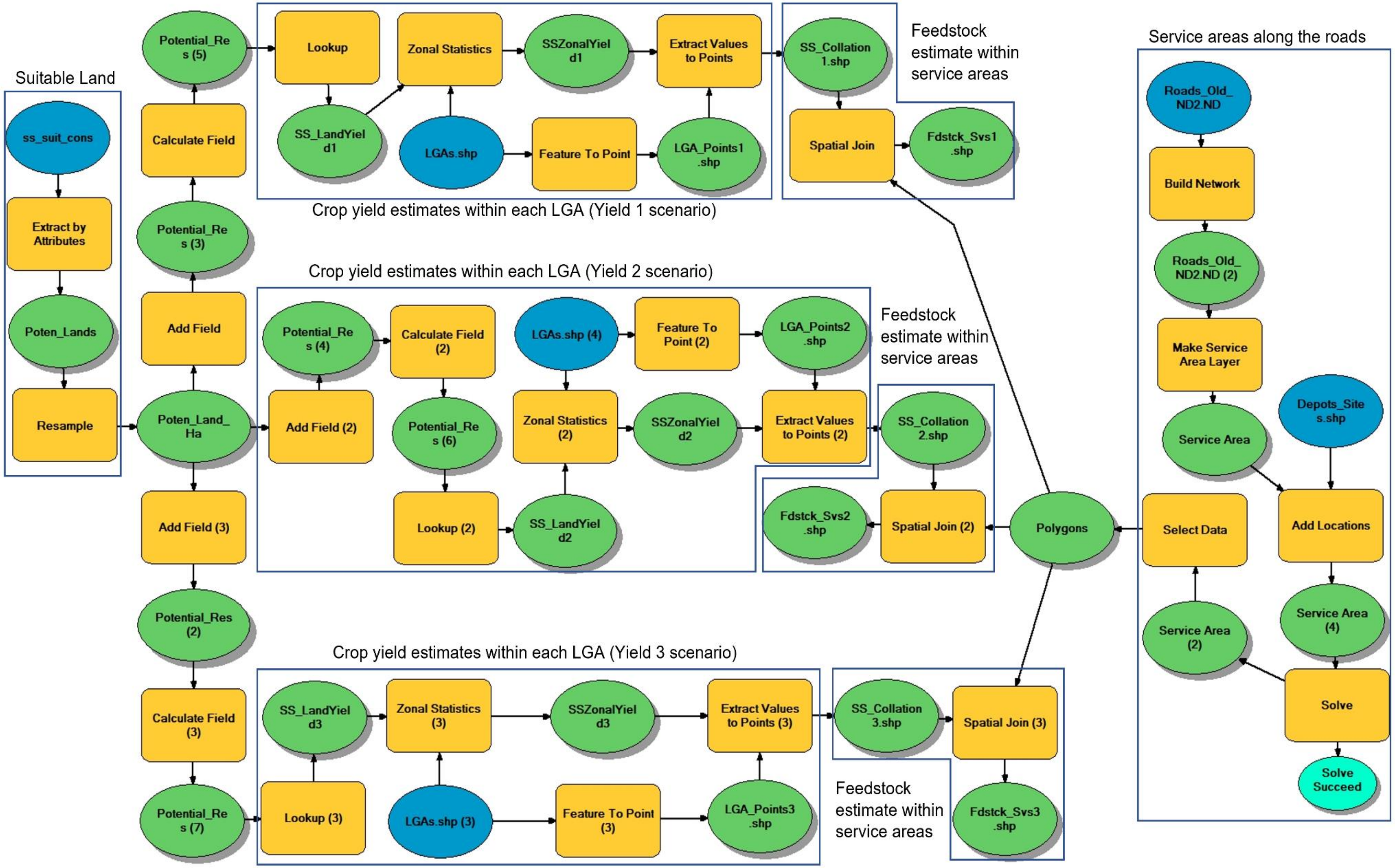


Figure 6.1: Supply Area Model (SAM) in ArcMap modeller

Table 6.1: Crop yields as mined from the literature

Crop	Yields (Tonnes ha^{-1})	Reference
Sweet sorghum	8.6	Tang et al., (2018b)
	27	
	37	Nasidi et al., (2015)
	42.15	Cifuentes et al., (2014)
	46 and 92	Nasidi et al., (2010)
Sugarcane	15.4	Knoema (2018)
	21.6 (FAO average 1997-2016)	FAOSTAT (2021)
	60	Gana (2017)
	70	Nasidi et al., (2010)
Cassava	11	Abdoulaye et al., (2014)
	15	Agboola and Agboola (2011)
	30 (average of locally improved varieties)	Adekunle et al., (n. d.)
Oil palm	2.6 (average 1997-2016)	FAOSTAT (2021)
	20	NIFOR (2018)
	30	Verheye (2010)
Jatropha	2 (Minimum recommended)	Somorin and Kolios (2017)
	6	Wahl et al., (2012)
	12.5	Hagman and Nerentorp (2011); Vera Castillo et al., (2014)

Based on these yields, three-yield scenarios were adopted to compare worst-case, average case and best-case scenarios. The worst case represents attainable yields under minimum required ecological conditions and agronomic practices. The average case is assumed to be attainable under good ecological conditions and agronomic practices. The best-case scenario is only attainable under the most favourable ecological conditions and best agronomic practices. The values used in this work were 27, 37 and 42 tonnes ha^{-1} (sweet sorghum), 15.4, 21.6 and 60 tonnes ha^{-1} (sugarcane), 11, 15, and 30 tonnes ha^{-1} (cassava), 2.6, 20 and 30 tonnes ha^{-1} (oil palm) and 2, 6 and 12.5 tonnes ha^{-1} (jatropha). The 'most suitable' and 'very suitable' classes were extracted from the suitability map. This was resampled from its original 30 metre to a resolution of 100 metre. By resampling the raster to 100 metres, each pixel represents a hectare of land. A field was added to calculate the crop yields for each of the three scenarios. The yields are measures of weights of fresh stalks (sweet sorghum and sugarcane), fresh tubers (cassava), Fresh Fruit Bunches (oil palm, except for FAO average which is based on Oil Palm Fruit) and seed yields (jatropha).

The feedstock is aggregated first at the farm level before being transported to a storage site or collection centre. Where the scope allows, this can be captured in the optimisation model as could be found in Voets et al., (2013) who used farm parcels' centroids as the aggregation centres. However, where the scope is larger, different methods are used in these kinds of analysis for identifying or designating a collection centre within a defined geographic area. Centroids of a collection of villages (Brahma et al., 2016) or centroids of counties (Gonzales and Searcy 2017) were used for this purpose. Shi et al., (2008), used intersections of two or more road lines as the aggregation points. In the context of the current work which considers the whole country as the study area, using road junctions may not be suitable for all locations in the country. It was deemed better to leave this open for localised assessment after a processing plant site is decided. Therefore, Local Government Areas (LGAs) administrative boundaries were used as the feedstock mapping unit and their centroids were assumed to be the initial feedstock collation centres.

There are 774 LGAs in Nigeria. Thus, all the potential feedstock within an LGA were aggregated to the centroid (figure 6.2). Though in reality feedstock collation may cross borders, this work assumed that all the feedstock within each LGA is collated to the centroid of the LGA. Depending on the nature of the supply chain and the feedstock type, these could serve as storage centres and some initial feedstock processing may occur before being transported to the processing plant. Because biofuel feedstocks are usually distributed at very wide extent of areas needing for collation and storage facilities, existence of logistics facilities is very crucial in deciding where to site a processing plant. The consideration is whether it is more practical to process the biofuel near the raw materials and transport the product to the demand or process near the demand while transporting the raw materials (Höhn et al., 2014). Establishing new processing sites entails land use change that may lead to unwanted environmental consequences. It also requires huge capital investments, depending on the scale.

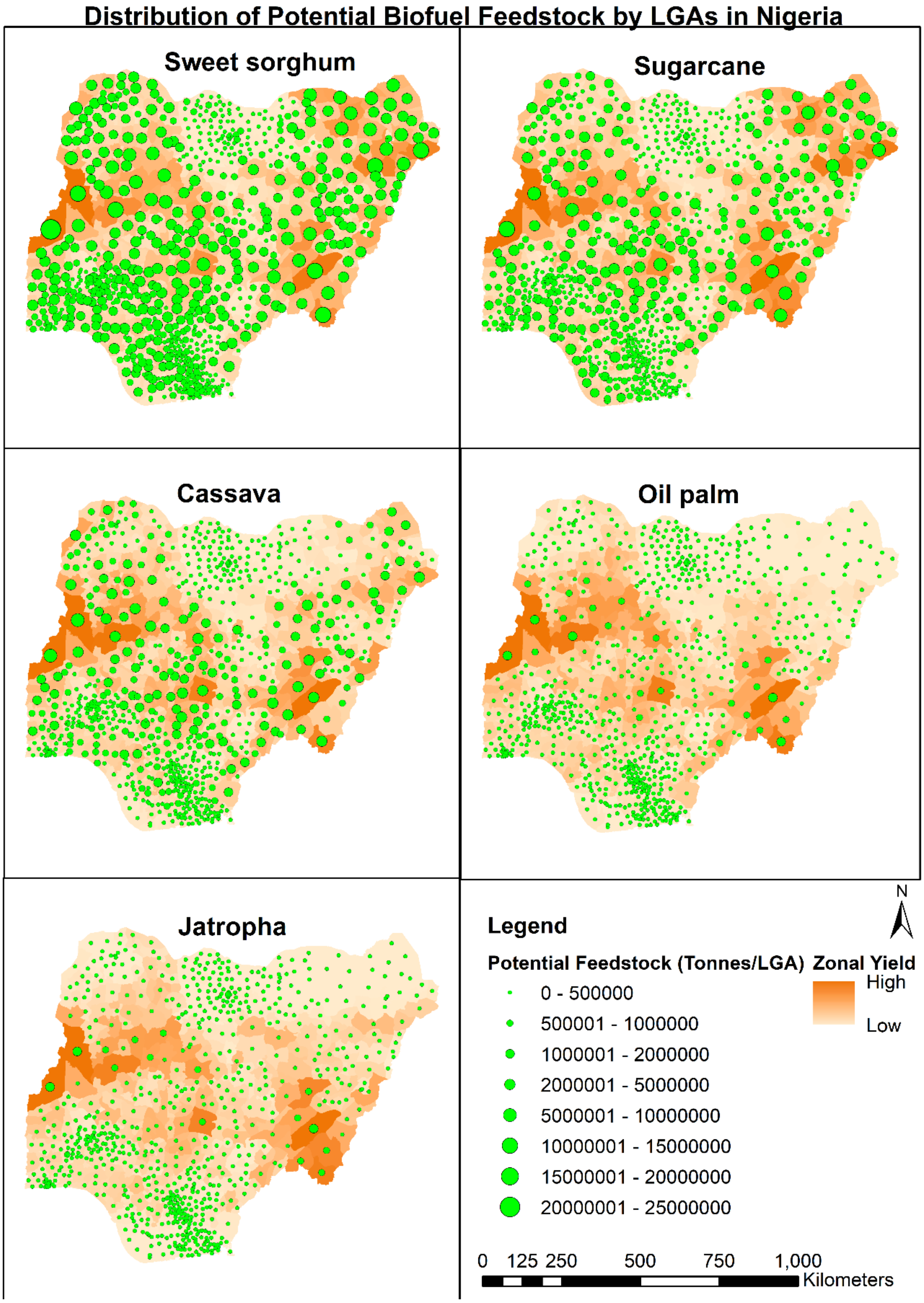


Figure 6.2: Potential Feedstock aggregated to centroids of LGAs

In Nigeria, using the existing petroleum refineries for processing and blending biofuel will incur huge transport costs for conveying the feedstock because, except for one located in Kaduna state in the north, all the refineries are located in the Niger Delta, while the biofuel feedstock could be sourced from around the country, as clearly shown on figure 6.2, though with some areas having more potentials than others. Also, these refineries will require upgrade to make them capable of handling biofuel processing and storage.

On the other hand, petroleum depots are relatively more dispersed around the country, making them more appropriate for optimising transport costs. The depots will require upgrading to handle biofuel processing, storage and blending, but would be expected to require much less capital for the upgrade compared to the refineries. It was reported that biofuel handling facilities were installed at two of these depots (Ohimain 2013). The depots are also located near cities and major towns, thus having good access to settlements services. Though the depots may require area expansion, they are sites already dedicated to oil and gas services. Thus, they may have less impact regarding land use change compared to opening a new site. The existence of the petroleum pipelines connecting all the depots and the petroleum refineries makes them appropriate for processing biofuel and blending with the refined petrol that can be pumped from the refineries. Refined petroleum is usually pumped to the depots through the pipelines for distribution. This positioned them as good sites for blending with biofuel before loading on trucks for retail distribution.

In this work, existing petroleum depots were considered to be the candidate sites for processing and blending biofuel. According to the Department of Petroleum Resources (DPR), there are 124 petroleum depots in Nigeria (DPR 2021) and are all clustered in 24 locations around the country. Independent marketers and major marketers owned 79 and 23 of the depots, respectively. The Nigerian National Petroleum Corporation (NNPC) owned 22 of the depots. Because all the depots are located in 24 locations, these locations were used in this work to represent all the depots. One of the locations (Abuja) was left out because of its position as the capital of the country and there is another depot (Suleja) nearby. Thus, a network dataset was created from the road dataset and service areas were created around the depots using three distance thresholds of 100, 200 and 300 km (Figure 6.3).

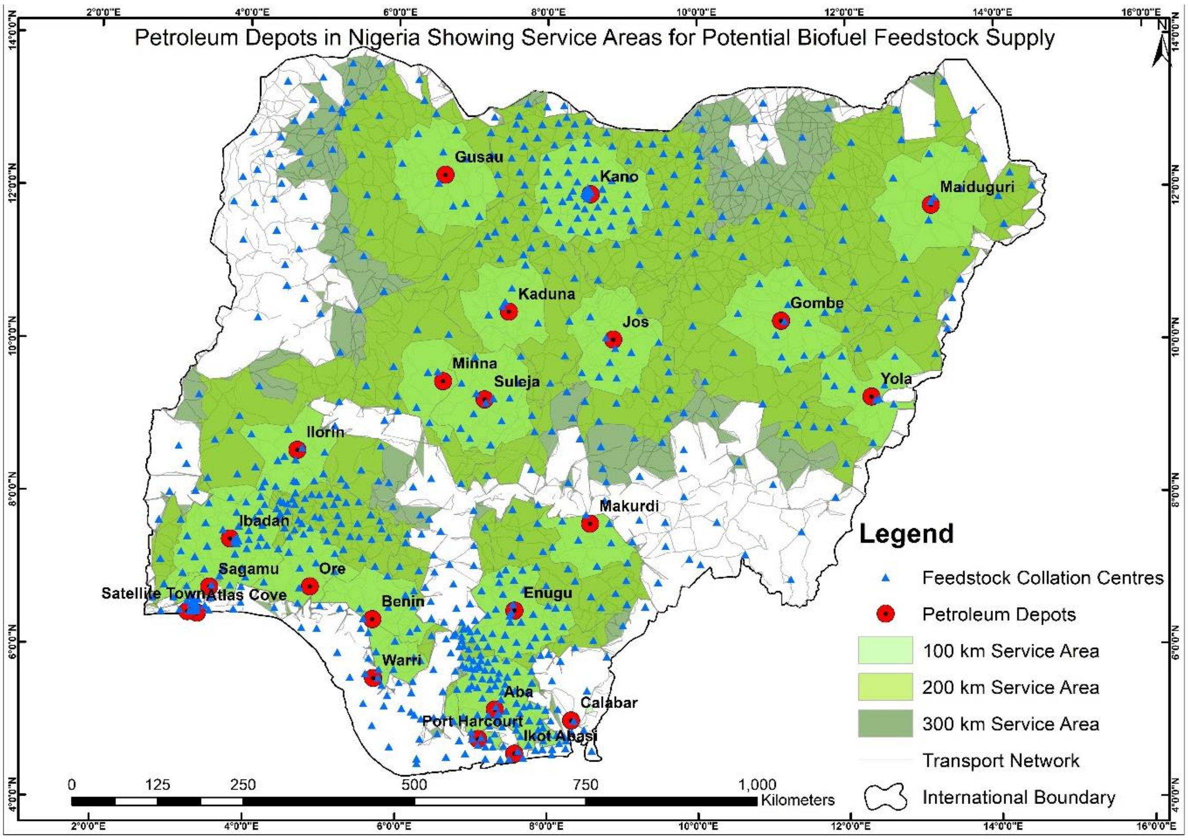


Figure 6.3: Locations of petroleum depots in Nigeria

As mentioned in the previous paragraph, because there was no information regarding the scale of operation for the proposed processing site, it may not be possible to know the exact distances required to be covered in supplying enough feedstock to the proposed processing sites. A previous work of the same nature could not be found for the study area to be used as a reference. However, the unit cost of biofuel processing decreases with increasing plant size, unlike fossil fuels processing plants (Wright and Brown 2007). Considering the size of the study area, the extent of the roads network, the distribution of the potential feedstock and potential processing sites, it is possible that some feedstock could be supplied within 1 km and from 1000 km of the processing sites. Limiting the supply area would exclude many potential locations, supply limited amounts of feedstock and thus support small scale of operation for the processing plant. On the other hand, extending the supply area to a very large distance entails very high cost of transporting the feedstock because of the variable nature of the road transport.

The three distance scenarios considered in this work would not be very narrow to be too exclusive of many areas and would be wide enough not to limit the scale of operation of the proposed processing plants. Because the relative efficiency of bioconversion depends on the chemistry of the feedstock (Iye and Bilsborrow 2013), it may not be appropriate to assume a uniform minimum scale of operation for the proposed processing facilities. With these varied distance scenarios, a number of varied scales are expected to be identified for each of the proposed facility sites, providing wider range of options for decision making that may be more practical within the contexts of the local realities of the proposed sites, serving as a back-room assessment of the result of the analysis.
The three distance thresholds will provide insight into how much potentiality each of the candidate site could have within the threshold and whether optimality of these locations could change with different sizes of service areas. All the potential feedstock within each of the service areas were aggregated to the depots (the candidate sites) for each of the crops. The software was instructed not to overlap the service areas to make sure each of the feedstock collation centres supplies only one depot. However, the implication of using this road dataset is that areas where there is no road connectivity due to absence of road or areas where the dataset did not cover or places where bridges are not captured in the data would be excluded in the analysis. This will limit the extent of the service area zones as could be seen in some places like Makurdi where the northern side is completely omitted for the Makurdi depot (Figure 6.3). Some of the collation centres that fall in the 300 km service area of Jos depot would have made it to 100 km service area of Makurdi depot. This could be assessed for more localised

decision as to which processing site a collation centre in this area could best service.

6.3 Biofuels estimate and Optimal Biofuel Processing Sites (results)

As explained in the previous subsection, the assessment of the potential biofuel feedstock within a service area of a potential biofuel processing location was based on the potential land availability for cultivating the biofuel crops within the service area and the crop yields information mined from the literature. Therefore, the figures for the potential feedstock amounts are highly exaggerated because, practically, not all of these lands will be available for biofuel crop cultivation in particular, or agriculture in general. In other words, the model assumes all the land that is physically available is put to the biofuel crop cultivation. Also, the following results emphasize the worst-case scenario for each of the crops with different service areas because the final result for site optimisation will be the same for all the yields scenarios but will differ with different service areas.

Though the varied yield values provide more information about biofuel potential for each of the candidate processing sites, of more concern for this work is that the values provide a basis for comparing the locations in order to determine which have higher potential for hosting a biofuel processing and/or blending service. This has been discussed for each crop in the following subsections. More focus was given to 100 km service areas because choosing an optimised site with less transport distance may be best for both costs saving and reducing emissions due to transport.

6.3.1 Sweet sorghum

It is obvious from figure 6.2 that there is high potential for sweet sorghum production all over Nigeria. Almost every LGA shows higher amounts of potential sweet sorghum feedstock than for any other crop considered in this work. This is not unexpected because, as mentioned in subsection 2.2.1.1, Nigeria is the second largest producer of sorghum in the world. In section 4.5, it was shown that 10.36% and 84.18% of the land that may be physically available in Nigeria is most suitable and very suitable for cultivating sweet sorghum, respectively. It may be good to have an idea on the land estimate that is potentially available for cultivating sweet sorghum within each supply area. Looking at figure 6.4, there may be about 1.5 million hectares of land within 100 km of Maiduguri depot that may be used for cultivating sweet sorghum. More than 1 million hectares may be available within 100 km of Ibadan and Gombe depots and about 1 million hectares may be available within 100 km of Suleja and Aba depots. There is more than 100% increase in potential land availability within 200 km of these 5 depots except Aba. While Ilorin is only the 12th in terms of potential land availability within 100 km, it is the 1st with more than 6 million hectares within 300 km service area.

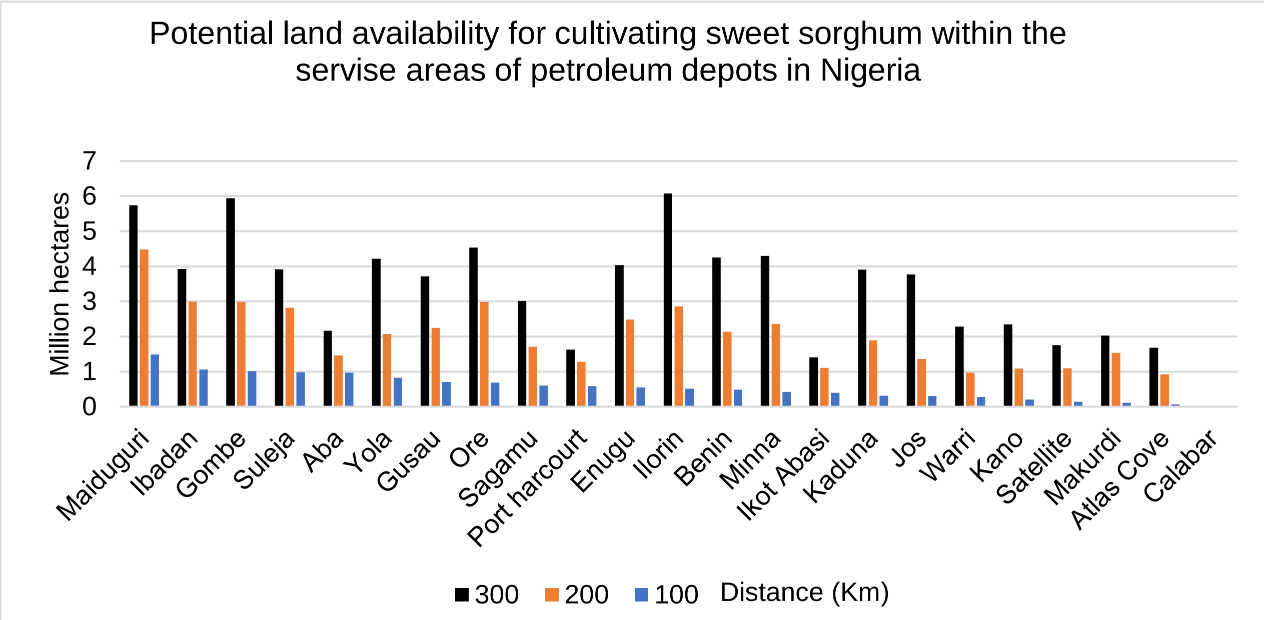


Figure 6.4: Potential land availability for cultivating sweet sorghum

The data show that there could be more sweet sorghum feedstock supplies within 100 km of Maiduguri depot than any other depot. This is followed by Ibadan, Gombe, Suleja and Aba (figure 6.5). While the figure shows that Maiduguri depot could be supplied with more than 40 million tonnes of feedstock within 100 km service area, it shows that the other 4 depots could be supplied with more than 25 million tonnes within 100 km service area. Within 200 km service area, Maiduguri could still have the highest feedstock supplies with more than 121 million tonnes, followed by Ibadan and Gombe depots both with more than 80 Million tonnes of potential feedstock supplies.

However, Maiduguri became third after Ilorin and Gombe when 300 km service area was applied.

Ethanol (biofuel) estimation was based on the potential feedstock supplies within the service areas. Several empirical studies have reported ethanol yield estimates for sweet sorghum feedstock around the world. These reports show that ethanol yields from sweet sorghum feedstock can range from 1,000 to about 15,000 litres ha^{-1} (table 6.2) depending on the location and of course the processing technology.

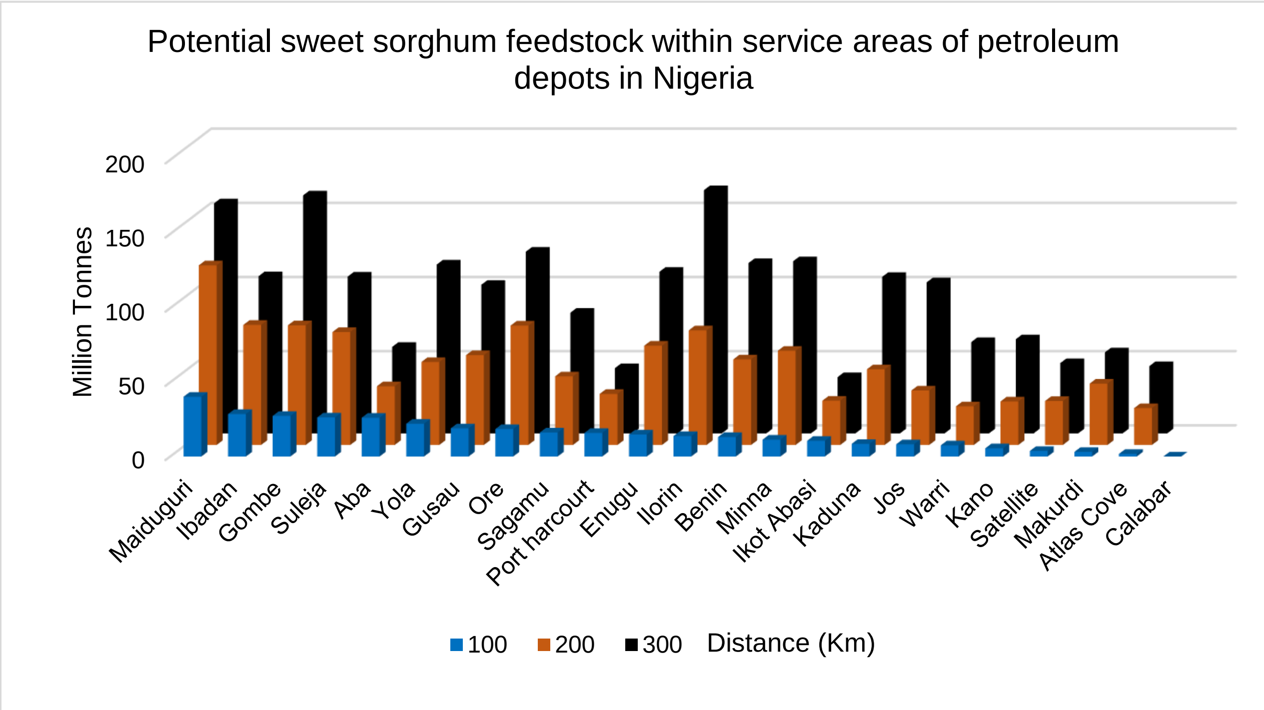


Figure 6.5: Potential sweet sorghum feedstock supply

Table 6.2: Ethanol yields from sweet sorghum feedstock as reported in the literature

S/N	Ethanol yield (litres per hectare per crop cycle)	Reference
1	1,000 (Mexico)	Packer and Rooney (2014)
2	2,465 (Guatemala)	Cifuentes et al., (2014)
3	2,062 (Kano, Nigeria) and 2,595 (Kaduna, Nigeria)	Nasidi et al., (2013)
4	3000 (Iran)	Almodares and Hadi (2009)
5	13,600 (Brazil)	Barcelos et al., (2016)
6	10,000 (may be possible)	Elbassam (2010)
7	14, 913 (China)	Tang et al., (2018b)

An empirical research shows that 31.29 litres of ethanol per tonne could be extracted from sweet sorghum feedstock in Nigeria (Nasidi et al., 2010). This was adopted as the basis for estimating biofuel potential within service areas of the petroleum depots in Nigeria. Maiduguri showed highest potential within 100 km with more than 1.2 billion litres of potential biofuel (figure 6.6). This was followed by Ibadan, Gombe, Suleja and Aba each with more than 800 million litres of potential biofuel. Similarly, within 200 km service area, Maiduguri shows highest potential with more than 3.7 billion litres of potential biofuel, followed by Ibadan, Gombe, Ore, Ilorin, Suleja and Enugu, all with more 2 billion litres of potential biofuels. However, with 300 km service area, the depot with the highest potential is Ilorin followed by Gombe, both with more than 5 billion litres of potential biofuel. Maiduguri became third with more than 4.8 billion. It seemed Maiduguri depot is the most optimal location for processing and blending sweet sorghum biofuel based on this analysis.

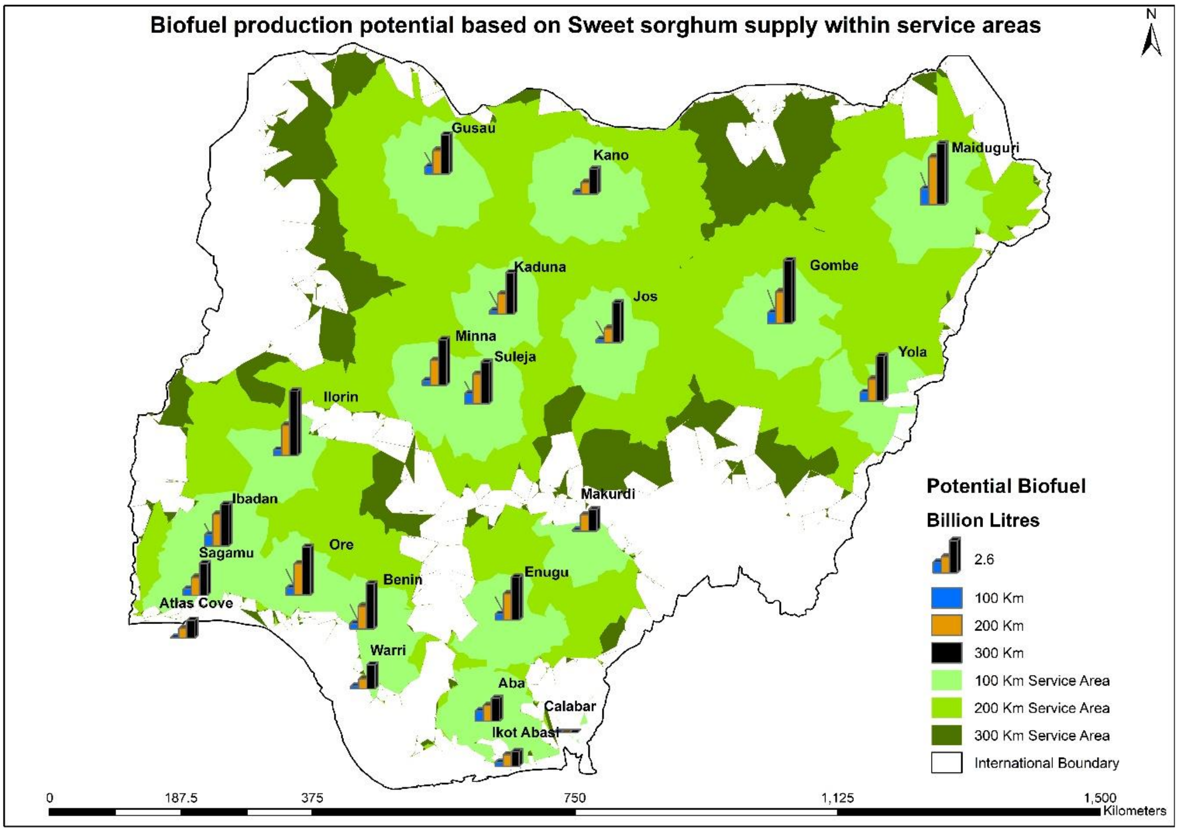


Figure 6.6: Potential sweet sorghum biofuel amounts for each of the petroleum depots

From this analysis, Maiduguri petroleum depot seems to be the best location for processing and blending biofuels from ethanol crops. Generally, this is not surprising because Maiduguri is in the north where the savannah vegetation and wider climate seasonality support arable crops such as sweet sorghum and sugarcane. Maiduguri is the capital of Borno State which is one the major sorghum producing states in Nigeria and where 55% of the farmers are said to be growing sorghum (Ajeigbe et al., 2020).

Sorghum is said to be grown mostly in Borno, Adamawa and Yobe States and Nigeria would have been the largest sorghum producer in the world if not for the crisis in the northeast where these states are located (Izuaka 2021). Therefore, the authorities would need to work more on the security of the region to explore this huge potential for sorghum production in general and sweet sorghum, in particular. As shown earlier in this subsection, there could be more than 1.5 million hectares of land within 100 km of Maiduguri petroleum depot that potentially can support processing of more than 1.2 billion litres of biofuel from sweet sorghum feedstock at the depot. In 2018, 20% of the total sorghum produced was bought by industries in Nigeria (Akinyoade et al., 2020).

6.3.2 Sugarcane

Though less when compared to sweet sorghum, figure 6.2 shows widespread sugarcane production potential all over Nigeria. This might indicate that although Nigeria is not one of the major sugarcane producers in the world, most parts of the country ecologically support the cultivation of the crop. As shown in subsection 4.5 about 0.69% and 87.49% of the potentially available land areas in Nigeria are most suitable and very suitable for cultivating sugarcane, respectively. Figure 6.7 shows that more than 1.3 million hectares of land could be available for cultivating sugarcane within 100 km service area of Maiduguri depot. Followed by Ibadan depot with more than 1 million hectares within 100 km service area. Gombe and Suleja could have almost 0.9 million hectares, while Aba and Ore could have more than 0.7 million hectares. Similarly, Maiduguri and Ibadan may have the largest land areas for cultivating sugarcane within 200 km service area with more than 4 and 3 million hectares, respectively. These are followed by Ore, Ilorin and Gombe with more than 2.9, 2.8 and 2.7 million hectares, respectively. However, with 300 km service area, Maiduguri became third with more than 5.09 million hectares after Ilorin with more than 6 million and Gombe with more than 5.33 million hectares.

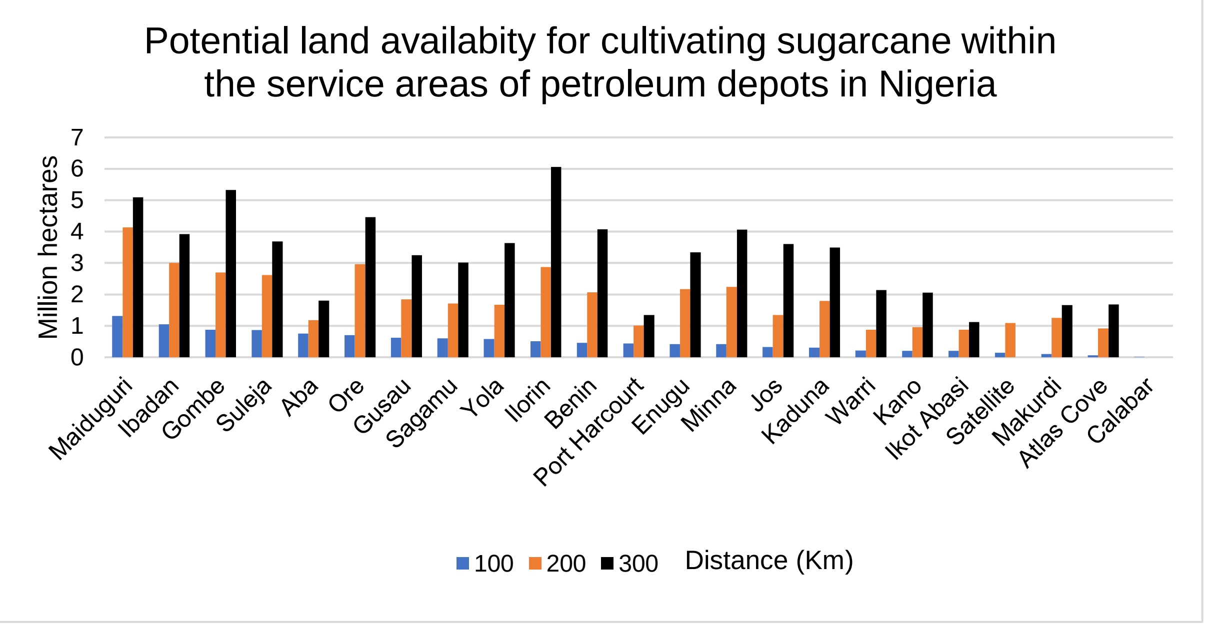


Figure 6.7: Potential land availability for cultivating sugarcane

Maiduguri, as expected, shows more sugarcane feedstock potential both within 100 and 200 km supply area with more than 20 and 63 million tonnes, respectively (figure 6.8). Ibadan depot followed in both the cases with more than 16 and 46 million tonnes, respectively. Gombe, Suleja and Aba followed with more than 13.5, 13.4 and 11.6 million tonnes, respectively within 100 km service area. Within 200 km service area, Ore, Ilorin and Gombe followed with more 45.7, 44.2 and 41.5 million tonnes of sugarcane feedstock, respectively. Within 300 km service area, Ilorin showed highest feedstock potential with more than 93 million tonnes, followed by Gombe and Maiduguri with more than 82 and 78 million tonnes, respectively.

Ethanol (biofuel) yields from sugarcane feedstock have been reported based on empirical studies or estimates (table 6.3). The lowest ethanol yield reported based on feedstock weight in Nigeria was adopted as the basis for the sugarcane biofuel estimate. As shown in the table, Nasidi et al., (2010), reported that sugarcane in Nigeria yielded 8.25 litres of ethanol per tonne of feedstock. This was calculated for each of the petroleum depots in the country.

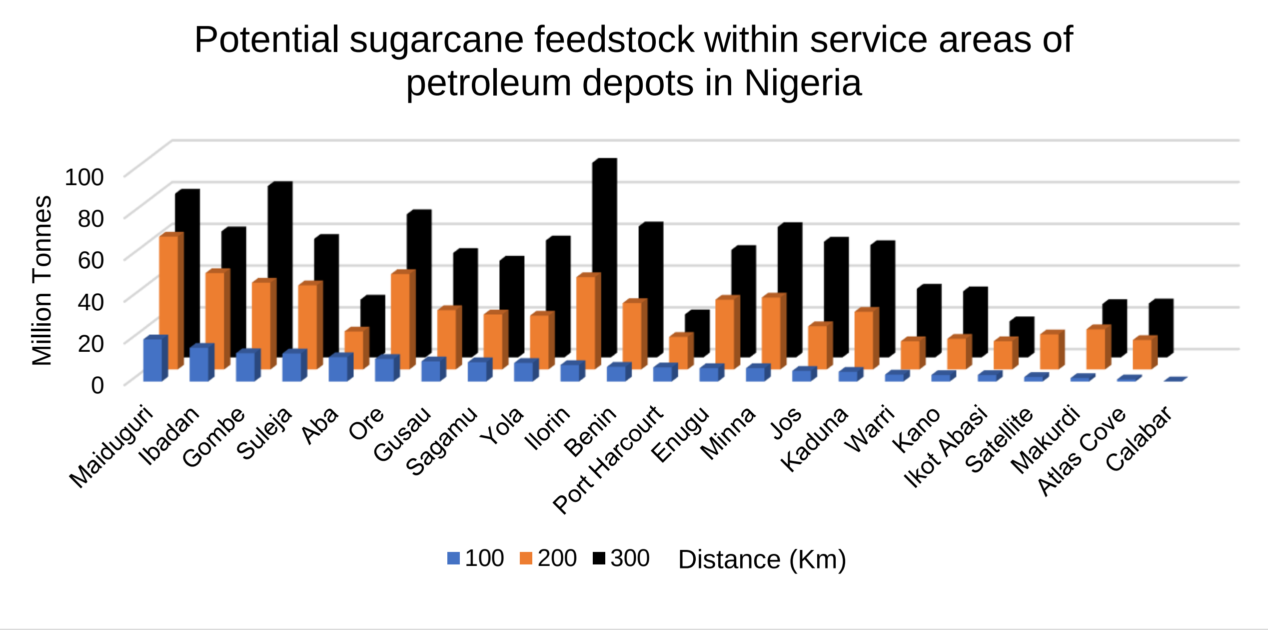


Figure 6.8: Potential sugarcane feedstock supply

Table 6.3: Ethanol yields from sugarcane feedstock as reported in the literature

S/N	Ethanol yield (litres per Tonne)	Ethanol yield (litres ha^{-1})	Reference
1	70 (Europe)	4550	Rajagopal et al., (2007)
2		7000 (Brazil)	Zuurbier and Voore (2008)
3	8.25 (Nigeria)		Nasidi et al., (2010)
4	79.59 (Brazil)		Escaramboni et al., (2018)

Maiduguri and Ibadan showed highest biofuel potential with more than 166 and 133 million litres, respectively within 100 km service area (figure 6.9). The value 0.38 on the legend indicates the volume of biofuel represented by the tallest bar in the legend. This value is in billions as indicated in the legend and its length and that of the other yellow and blue bars indicates the potential volume of biofuel for each of the sites. Gombe and Suleja followed, both with more than 11 million litres. Similarly, within 200 km service area, Maiduguri depot possess highest potential with more than 525 million litres. It is followed by Ibadan, Ore, Ilorin, Gombe and Suleja with more than 381, 377, 364, 343 and 332 million litres of potential biofuel, respectively. However, with extended service area of 300 km, Ilorin shows highest biofuel production potential with more than 769 million litres. It is followed by Gombe and Maiduguri with 677 and 647 million litres, respectively. Ore, Benin and Minna showed more than 566, 518 and 515 million litres, respectively. Based on this analysis, Maiduguri depot could also be the most optimal site for processing and blending sugarcane biofuels in Nigeria.

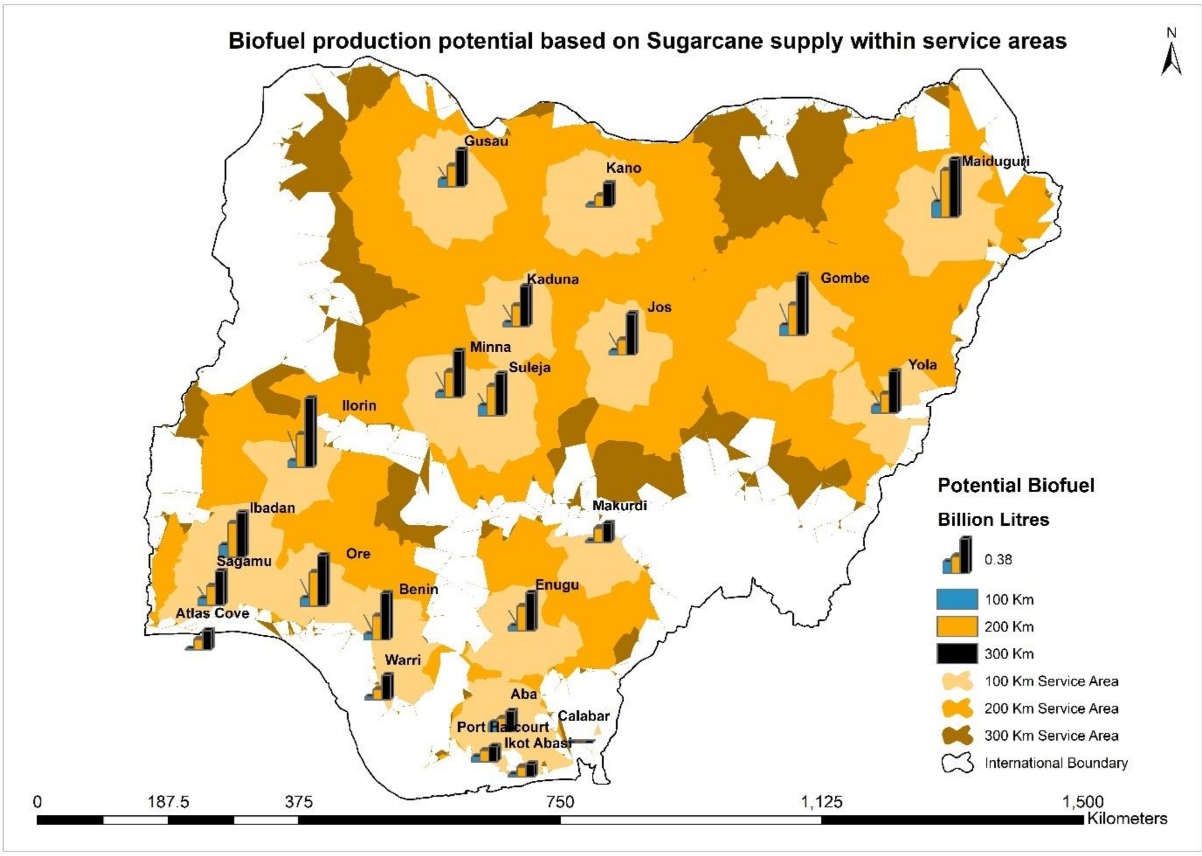


Figure 6.9: Potential sugarcane biofuel amounts for each of the petroleum depots

Northeast is also a region with high sugarcane potential. Large scale cultivation of the crop is said to be feasible in most of the northern states in areas where there is enough water for irrigation (Sulaiman et al., 2015). Though Borno State is not among the largest producers of the crop, the neighbouring Adamawa State is among the major producing states (Boluwade 2021) and houses the largest sugar mill in the country (Gourichon 2013). The sugar company is located around 300 km from Maiduguri by road. The company lies less than 100 km from Yola petroleum depot. Yola depots ranked only the 9th in terms of biofuel potentiality within 100 and 300 km service area from this analysis and ranked number 13th within 200 km service area. This points to the availability of more potential land areas around Maiduguri depot than Yola depot. The presence of this sugar company in this area may support the view from this work that the area has great potential for sugarcane-based biofuel production. Perhaps, edge effects might have contributed to downscaling the potentiality of Yola depot in the analysis. However, this analysis is restricted to Nigeria and cannot cross over to the neighbouring Cameroon though it is possible, in reality, that feedstock could be sourced from across the international boundary.

According to the National Sugar Development Council, sugar production was estimated at 38,597, consumption at 1,401,891 and importation at 1,363,294 tonnes in 2019 (NSDC 2021). The importation cost was estimated to be more than 382 million US dollars during the year. This shows huge room for local expansion of sugar production providing large markets for sugarcane producers. It was mentioned in subsections 1.2.3 and 2.2.1.2 that industrial production of sugarcane in Nigeria is mainly for sugar production and these annual sugar statistics show that there is still a need for large sugarcane production to supply the sugar industry in the country. The National Sugar Master Plan mandates all the sugar millers to implement backward integration by including sugarcane cultivation in their supply chain and, as a policy, must source at least 40% of their total cane demand from out-growers' farms around their estates.

Though this analysis identified Maiduguri as the best location for sugarcane-based biofuel production and blending, sweet sorghum might be more appropriate for the location. Thus, it is suggested that Yola or Ilorin be considered for sugarcane. Because of its closeness to Maiduguri (the location optimised by the model for sugarcane) and because of the existence of the sugar milling company within its 100 km, Yola might be an alternative. This analysis estimated that there could be more than 576,000 hectares of land within 100 km of Yola petroleum depot that could potentially be use for sugarcane expansion. Also, Yola is the capital of Adamawa State which neighbours Taraba State that is among the top five sugarcane producing states (Igwenagu 2020). Ilorin, the capital of Kwara State, showed highest potential for biofuel production based on all the five crops within 300 km. Also, there are existing sugar companies in Bacita (Kwara State) and Sunti (Niger State) the location of both of which is nearer to Ilorin than Minna (capital of Niger State). There could also be more than 511,000 hectares of land potentially available for sugarcane expansion within 100 km of the Ilorin petroleum depot.

6.3.3 Cassava

Figure 6.2 shows widespread cassava production potential in Nigeria though relatively less than sweet sorghum and sugarcane. As mentioned in section 2.2.1.3, the crop is the largest in the country by production quantity. The 2019 global production data shows that Nigeria is the largest producer of the crop in the world (https://www.tridge.com/intelligences/mandioca/production). As shown in subsection 4.5, 3.77% and 74.4% of the lands potentially available in Nigeria are most suitable and very suitable, respectively, for cultivating cassava.

Figure 6.10 shows that there could be more than 1.1 million hectares of lands for cultivating cassava within 100 km service area of Aba depot, followed by Ibadan with more than 1 million hectares, potentially available for cultivating cassava. Also, within 100 km of Suleja and Gombe depots, there could be about 0.9 million hectares. With 200 km service areas, Ibadan and Ore could have the largest amount of land with more than 3 million hectares potentially available for cultivating cassava. Followed by Ilorin, Enugu, Suleja, Gombe, Benin, and Minna with more than 2.88, 2.80, 2.61, 2.27, 2.21 and 2.14 hectares, respectively. Ilorin shows largest amounts of potential land availability for cultivating cassava within 300 km service area with more than

6 million hectares. This is followed by Ore, Enugu, Benin, and Gombe with more than 4.62, 4.49, 4.49, and 4.09, million hectares respectively.

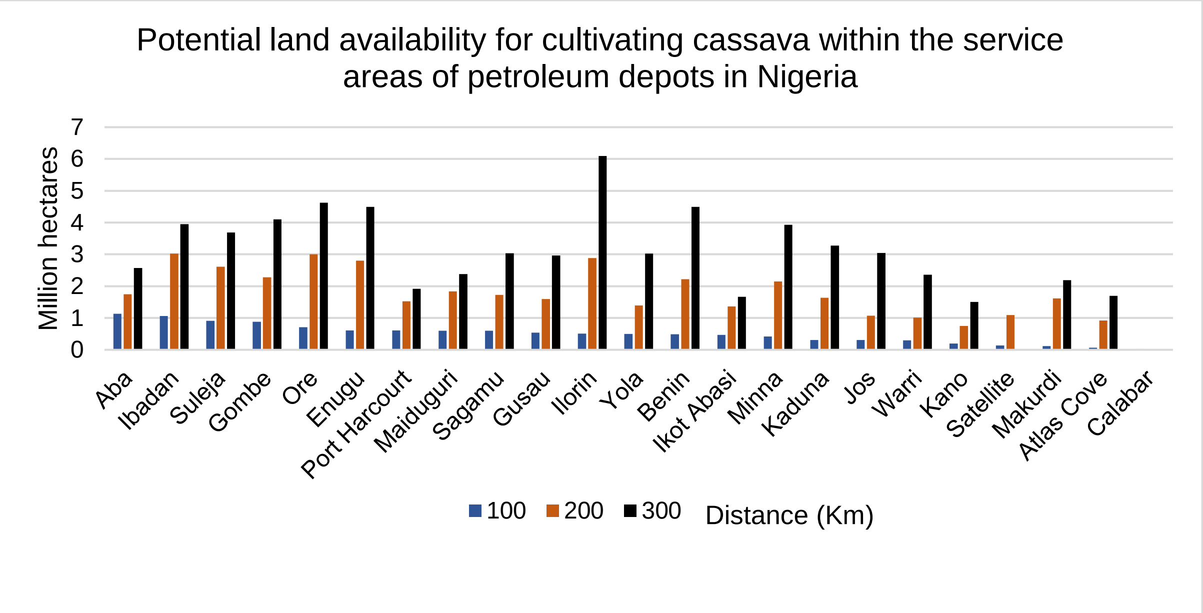


Figure 6.10: Potential land availability for cultivating cassava

As expected, Aba petroleum depot showed the highest potential for cassava feedstock supply within 100 km supply area with about 12.5 million tonnes, followed by Ibadan with more than 11.6 million tonnes of potential cassava feedstock. Suleja and Gombe could also be supplied with about 10 million tonnes of cassava feedstock (figure 6.11). Within 200 km service area, Ibadan could have the largest cassava feedstock supplies with more than 33 million tonnes of potential cassava feedstock, followed by Ore, also with about 33 million tonnes. Ilorin and Enugu followed with 31 and 30 million tonnes of potential cassava feedstock, respectively. Extending the service area to 300 km showed that Ilorin could have the largest cassava feedstock supplies with more than 66.99 million tonnes of potential cassava feedstock supplies. Ore, Enugu and Benin followed with about 5 million tonnes.

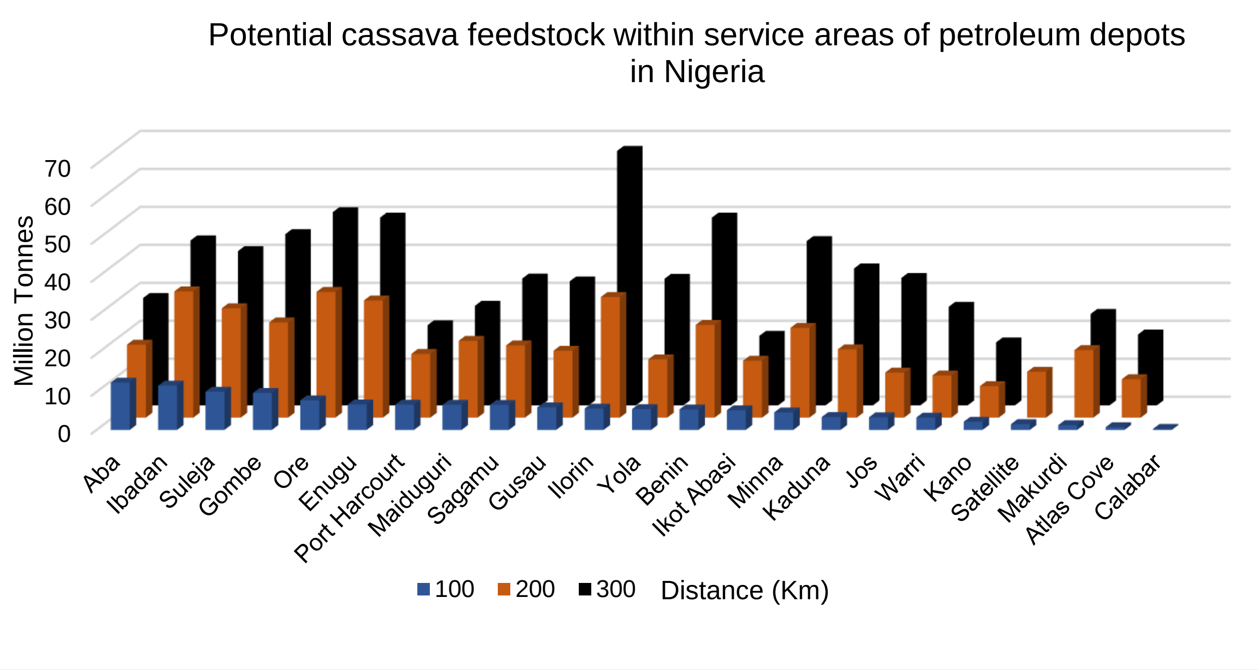


Figure 6.11: Potential cassava feedstock supply

Elbehri et al., (2013), reported that literature shows that ethanol (biofuel) yields from cassava feedstocks can range from 3,705 to 6,313 litres ha^{-1}. A lower yield of 2,400 litres ha^{-1} was also reported by Marx and Y. (2013). Different values were also reported based on feedstock weight instead of hectarage (table 6.4). The yield value of 137 litres per tonne (based on feedstock weight) looks similar to 2,400 litres ha^{-1} (based on land yields) and agrees more with the reported average cassava feedstock yield in Nigeria (15 tonnes ha^{-1}) as reported by Agboola and Agboola (2011). Thus, 137 litres per tonne was adopted as the basis for estimating ethanol potential from cassava feedstock.

Table 6.4: Ethanol yields from cassava feedstock as reported in the literature

S/N	Yield (litres per tonnes)	References
1	93.57 – 263.94 (cassava bagasse)	Escaramboni et al., (2018)
2	150 (fresh roots)	Kuiper et al., (2007)
3	333 (cassava chips)	Kuiper et al., (2007)
4	530 (unpeeled roots)	Marx and Y. (2013)
5	100 (Nigeria)	Agboola et al., (2011)
6	137 (Nigeria)	Naylor et al., (2007)

Aba petroleum depot shows highest potential for cassava biofuel within 100 km service area with more than 1.7 billion litres (figure 6.12). This is followed by Ibadan, Suleja, Gombe and Ore with more than 1.59, 1.37, 1.33 and 1.06 billion litres of potential biofuel within 100 km service area. Within 200 km service area, Ibadan depot shows highest biofuel potential with more than 4.55 billion litres, followed by Ore, Ilorin and Enugu with 4.53, 4.34 and 4.22 billion litres of potential biofuel. Extending the service area to 300 km revealed that Ilorin has the highest potential for cassava biofuel with more than 9 billion litres. Ore, Enugu, Benin and Gombe followed with 6.966, 6.774, 6.770 and 6.174 billion litres of potential cassava biofuel. Ibadan depot, which has the second highest potential within 100 km and highest within 200 km service areas, seemed to be the most optimised site for processing and blending cassava biofuel in Nigeria.

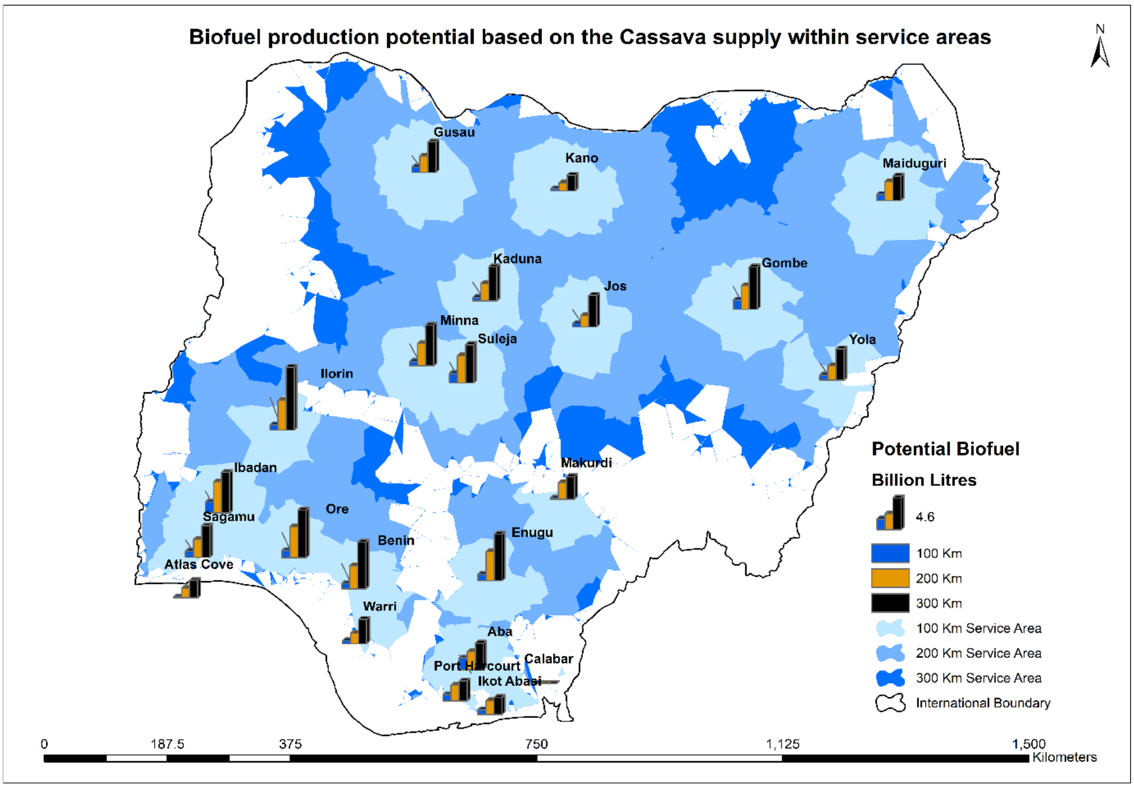


Figure 6.12: Potential cassava biofuel amounts for each of the petroleum depots

This work identified Aba (Abia State) as the optimised location for cassava-based biofuel production in Nigeria within 100 km service area. Within 200 and 300 km service areas, Ibadan (Oyo State) and Ilorin (Kwara State) represent optimal site for this, respectively. None of these states is listed among the top cassava producing states in the country. In 2020, Benue, Kogi, Ondo, Imo and Rivers States were the five largest producing states (NAERLS 2020). Makurdi which is the capital of Benue State, ranked 21^{st} out of the 23 petroleum depots for cassava-based biofuel potentiality within 100 km service area though the state is the largest cassava producer in the country. It ranked 13^{th} and 17^{th} within 200 and 300 km service areas, respectively. The main explanation for this is that existing farmlands were eliminated in the constraints modelling in the previous chapter. This means that all the cassava production from the farms accurately captured as constraints cannot factor in the potentiality estimate. The estimate was based on potentially non-cultivated and available lands. This was necessary due to food-vs-fuel debate under which biofuel programmes are being accused of converting food crop land to biofuel crops cultivation. The constraints elimination model did not differentiate between food and cash crop lands but considered all the cultivated areas as constraints.

In subsection 1.2.3, where food-vs-fuel debate was appraised, it was mentioned that a survey in the cassava producing areas of Nigeria showed that about 50% of the cassava is sold for cash and about 40% is consumed (Wossen et al., 2017). The health issues of consuming cassava were also discussed in that subsection. The advantage of expanding crop production in areas where the crop is already established is that there may not be change in the livelihood of the locals. This may also ease engagement of the feedstock suppliers because of their experience and familiarity with the crop.

Thus, while this analysis suggests Aba, Ibadan or Ilorin as the optimal sites for cassava-based biofuel production and blending due to the availability of uncultivated land, the existing cassava production data suggests that Makurdi could be a good consideration too. This analysis showed that Makurdi petroleum depot could be supplied with enough feedstock to process 200 million litres, 2.4 billion litres and 3.3 billion litres of cassava-based biofuel within 100, 200 and 300 km service areas, respectively. This showed that there is enough potential to process and blend cassava-based biofuel at Makurdi depot even within 100 km service area. Figure 6.10 showed that there could be more than 138,000 hectares of lands potentially available for cultivating cassava within 100 km of the Makurdi depot, indicating room for expansion in addition to the current cassava production in the state.

6.3.4 Oil palm

Figure 6.2 indicates the possibility of cultivating oil palm in many parts of Nigeria with higher potentiality along the central longitudinal stretch of the country. As discussed in subsection 2.2.2.1, oil palm is believed to have highest potential for biodiesel and has high oil production and energy balance potential. It was mentioned in subsection 1.2.3 that the non-food uses of oil palm continue to expand, with Malaysia as an example of a country targeting a 200% increase in its non-food use of the crop by 2035.

As shown in subsection 4.5, 0.14% and 70.56% of the potential available land in Nigeria is most suitable and very suitable for cultivating oil palm in Nigeria, respectively. Figure 6.13 shows that within 100 km of Ibadan service area there could be more than 1 million hectares of land that could be used for cultivating oil palm. This is followed by Suleja, Aba and Ore with more than 0.9, 0.8 and 0.7 million hectares. Within 200 km service area, Ibadan still showed highest potential land availability with more than 3 million hectares, followed by Ore, Ilorin and Suleja, all with almost 3 million hectares. Within 300 km service area, Ilorin showed highest potential for land availability with more than 6 million hectares, followed by Ore, Benin and Minna, all with more than 4 million hectares.

Ibadan petroleum depots shows highest feedstock supply potential within 100 km with more than 2.7 million tonnes, followed by Suleja and Aba with more than 2.5 and 2.3 million tonnes, respectively (figure 6.14). The highest potential feedstock supply within 200 km is also around Ibadan depot with more than 7.8 million tonnes, followed by Ore, Ilorin, Suleja and Enugu with 7.7, 7.5, 7.2 and 7.1 million tonnes. Ilorin showed about 16 million tonnes potential for oil palm feedstock within 300 km service area, followed by Ore, Benin and Minna, all with more than 11 million tonnes.

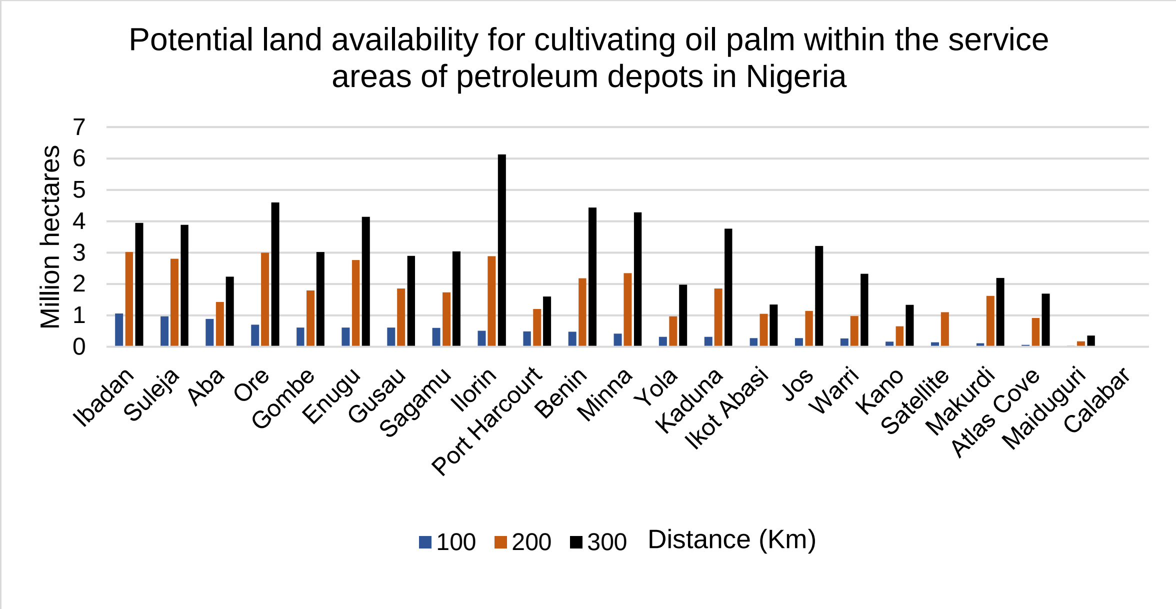


Figure 6.13: Potential land availability for cultivating oil palm

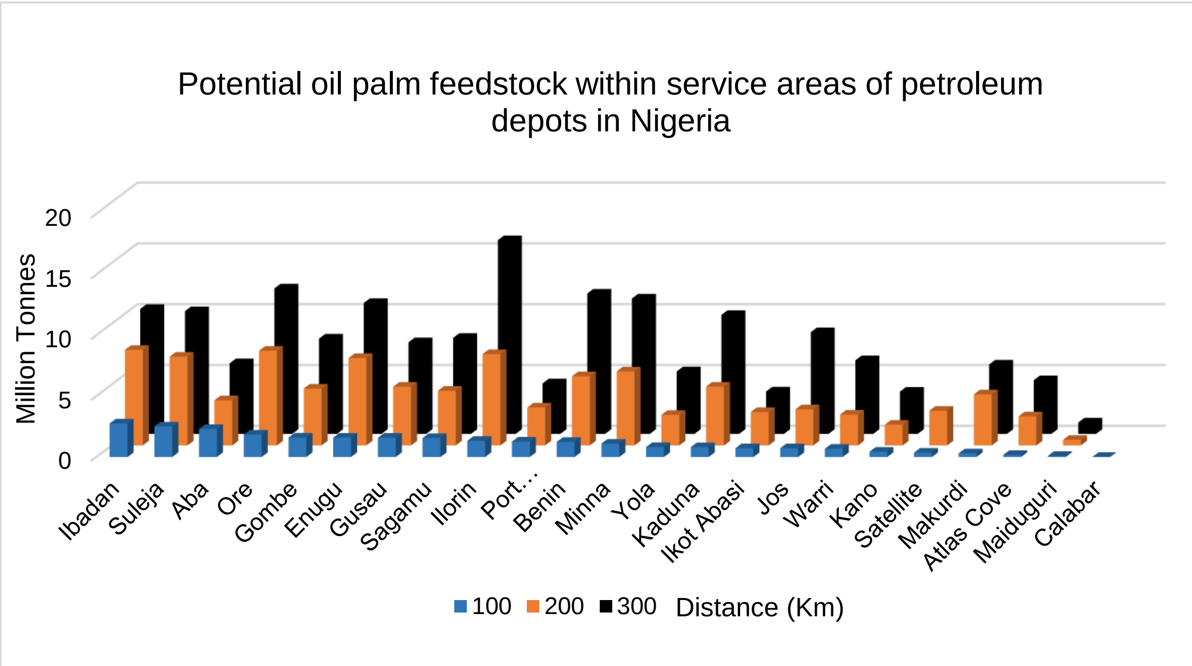


Figure 6.14: Potential oil palm feedstock supply

Biodiesel is extracted from various oil palm products such as Crude Palm Oil (CPO), Refined Palm Oil (RPO), Sludge Palm Oil (SPO) and palm olein. Various proportions of oil were reported to have been extracted from oil palm feedstock (fresh fruit bunches) including 96% (Hayyan et al., 2014b) and 81 to 95.3% (Kareem et al., 2017). Zahan and Kano (2018) reported 5 tonnes of oil ha^{-1}, while Ohimain and Izah (2014) reported a range of 63.4 to 77.1 litres of CPO per tonne of FFB, both in Nigeria. Various biodiesel output proportions were reported depending on the oil palm resource and processing technology used (table 6.5).

Table 6.5: Proportion of biodiesel derived from oil palm products

S/N	Biodiesel (%)	Resource used	Reference
1	62.5	Palm olein	Ishola et al., (2020)
2	82.8	Crude palm oil	Kansedo et al., (2009)
3	88.15	Crude palm oil	Endut et al., (2017)
4	88.67	Low grade crude palm oil	Hayyan et al., (2014a)
5	92.7	Refined palm oil	Chen et al., (2014)
6	93±2.2	Refined palm oil	Suryaputra et al., (2013)
7	95.3	Crude palm oil	Kareem et al., (2017)
8	95.61	Crude palm oil	Margaretha et al., (2012)
9	98.8	Palm olein	Boey et al., (2009)

Though edible oils may offer higher biodiesel yields, food security issues may offset this advantage, but the non-edible palm oil by-products such as sludge and olein may offer more ethical sources of biodiesel production (Girish 2018). According to Zahan and Kano (2018), research established that only 10% of the oil palm on-farm biomass is converted to edible oil. Herjanto and Widana (2016), estimated that as much as 73% olein could be produced from the overall palm oil refining. Palm olein is said to be in abundance in Nigeria and could be a sustainable bioresource for mass production of biodiesel in the country (Ishola et al., 2020).

It is assumed in this work that biodiesel production from oil palm in Nigeria is based on palm olein. Thus, 63.4 litres of CPO per tonne of FFB (Ohimain and Izah 2014) is adopted as oil yield, 73% (Herjanto and Widana 2016) is adopted as the proportion of olein production from CPO and 62.5% (Ishola et al., 2020) is adopted as the proportion of biodiesel production from olein. Based on these, table 6.6 shows the estimates of olein supply potential within service areas of the petroleum depots. The table shows that Ibadan, Suleja and Aba depots could have more than 127, 116 and 106 million litres of olein within 100 km service area. Ibadan could also have the highest supply of olein within 200 km service area with more than 363 million litres but followed by Ore and Ilorin with more than 360 and 347 million litres of olein, respectively. With 300 km service area, Ilorin shows highest olein supply potential with 737 million litres, followed by Ore and Benin with more than 553 and 534 million litres of potential olein supply.

Table 6.6: Potential olein production from oil palm feedstock suppliable within service areas of petroleum depots

S/N	Petroleum depots	100 Km service area (Million litres)	200 Km service area (Million litres)	300 Km service area (Million litres)
1	Ibadan	127.57	363.71	475.39
2	Suleja	116.08	337.79	467.03
3	Aba	106.52	171.70	268.79
4	Ore	85.13	360.47	553.46
5	Gombe	73.94	216.36	362.70
6	Enugu	73.63	332.48	498.50
7	Gusau	73.35	223.52	348.67
8	Sagamu	72.16	208.02	365.43
9	Ilorin	61.61	347.67	737.27
10	Port Harcourt	58.64	144.46	192.19
11	Benin	57.37	263.09	534.07
12	Minna	50.66	281.70	515.35
13	Yola	37.81	116.12	237.83
14	Kaduna	37.56	223.76	452.85
15	Ikot Abasi	33.42	126.87	161.64
16	Jos	33.21	137.47	386.98
17	Warri	31.34	117.41	280.23
18	Kano	19.98	78.75	160.67
19	Satellite	16.68	132.04	
20	Makurdi	13.84	194.49	264.06
21	Atlas Cove	7.78	110.68	204.14
22	Maiduguri	4.01	21.14	43.29
23	Calabar	0.38	0	0

Biodiesel production potential follows this distribution with Ibadan showing the highest biodiesel potential of almost 80 million litres within 100 km service area (figure 6.15). Suleja and Aba followed with more than 72 and 66 million litres of potential biodiesel production. Within 200 km service area, Ibadan, Ore and Ilorin may have feedstock supply amounts to support processing of more than 227, 225 and 217 million litres of biodiesel. Ilorin depot shows 460 million litres of potential biodiesel within 300 km service area, followed by Ore and Benin with more than 345 and 333 million litres of potential biodiesel. Ibadan petroleum depot seemed to be the optimal site for processing and blending oil palm biodiesel in Nigeria.

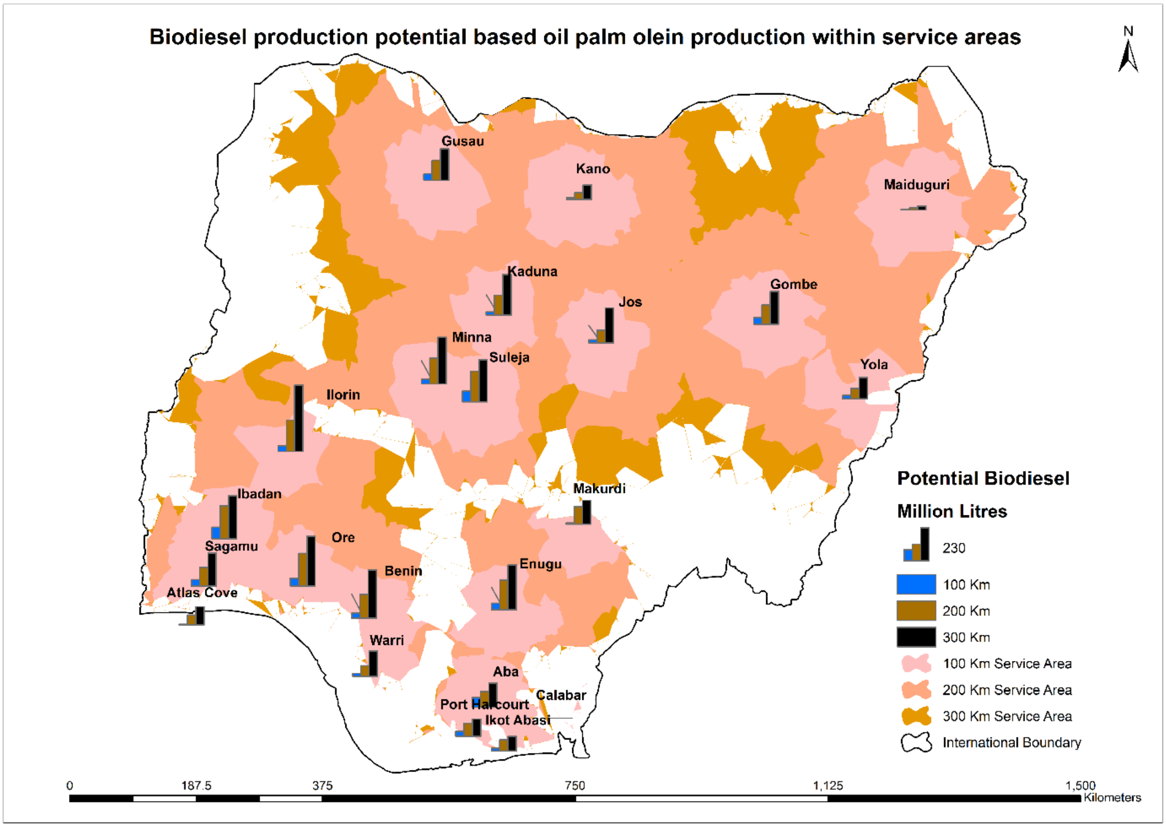


Figure 6.15: Potential olein biodiesel amounts for each of the petroleum depots

This work identified Ibadan petroleum depot as the optimal location for oil palm-based biofuel processing and blending, within 100 and 200 km service areas. This is not surprising because Ibadan (capital of Oyo State) is in the south where forest vegetation and longer rainy season support tree crops such as oil palm. However, Oyo State is not among the usually listed oil palm producing states in Nigeria. Niger Delta states are the major oil palm producing states which are said to account for 57% (about 1.5 to 1.8 million hectares in 2008) of the oil palm area in Nigeria (PIND 2011). This may be connected to the high amounts of annual rainfall in the area as presented in section 3.3 because rainfall/water is the major factor that determines oil palm distribution as discussed in subsection 2.3.6.

Cross River and Akwa Ibom States are the largest oil palm producing states with an estimated more than 295,000 and 280,000 hectares of combined estate plantations, wild groves and small and medium holders. Because the analysis avoided existing farmlands as constraints however, the oil palm production in the states was not captured in the potential estimate. Therefore, Calabar (the capital of Cross River State) and Ikot Abasi (a town in Akwa Ibom State) petroleum depots ranked the 15th and the 23rd, respectively, in terms of their potential for processing oil palm-based biofuel within 100 km service area despite being the largest oil palm producers.

While Ibadan presented the highest potential for oil palm-based biofuel processing due to the potential availability of uncultivated land for cultivating oil palm, the analysis showed that these two largest oil palm producing states could have more than 227,000 (Ikot Abasi) and 3,000 (Calabar) hectares of uncultivated lands within 100 km service area for expanding oil palm cultivation leading to the potential of processing more than 20 and 0.2 million litres of biofuel, respectively. As discussed in subsection 6.3.4, this work assumed production of oil palm-based biofuel from the olein rather than the edible oil. Thus, availability of large quantities of olein is expected in areas of large oil palm production and processing.

In Cross River, Creel Oil is a processing centre reported to be operating on 240 tonnes per day capacity (NAERLS 2020). Because they are neighbours, the two largest oil palm producing states may combine to present greater potential for processing and blending olein-based biodiesel in Nigeria. Ikot Abasi, Port Harcourt and Aba petroleum depots are located within 100 km of each other and Calabar is located within 150 km of Aba and Ikot Abasi petroleum depots. Therefore, with these depots located in the region and the potential availability of olein in this region, this region presents greatest potential for processing and blending olein-based biodiesel in Nigeria. However, Ibadan may be best option when large expanse of land is need for expanding oil palm production in the country.

6.3.5 Jatropha

It could be understood from figure 6.2 that it is possible to cultivate jatropha in many parts of Nigeria with some locations showing higher potentiality than others. As discussed in subsection 2.2.2.2, jatropha in Nigeria is wild species, but it is more suitable for quick and efficient domestication compared to other woody species. As discussed in subsection 1.2, jatropha is a promising crop for emission reduction and carbon sequestration. It was shown in subsection 4.5 that 71.6% of the land that may physically be available in Nigeria is very suitable for cultivating jatropha. Figure 6.16 shows that there could be more than 1 million hectares of land that could be used for cultivating jatropha within 100 km of Ibadan service area. This is followed by Suleja and Gombe with more than 0.97 and 0.82 million hectares, respectively. Within 200 km service area, Ibadan still shows highest potential land availability with more than 3 million hectares, followed by Ore, Ilorin and Suleja with more than 2.97, 2.88 and 2.86 million hectares, respectively. Ilorin petroleum depot showed highest availability of potential land within 300 km service area with more than 6 million hectares. Ore, Minna, Gombe and Benin followed with more than 4.5, 4.3, 4.2 and 4.1 million hectares of potential land, respectively.

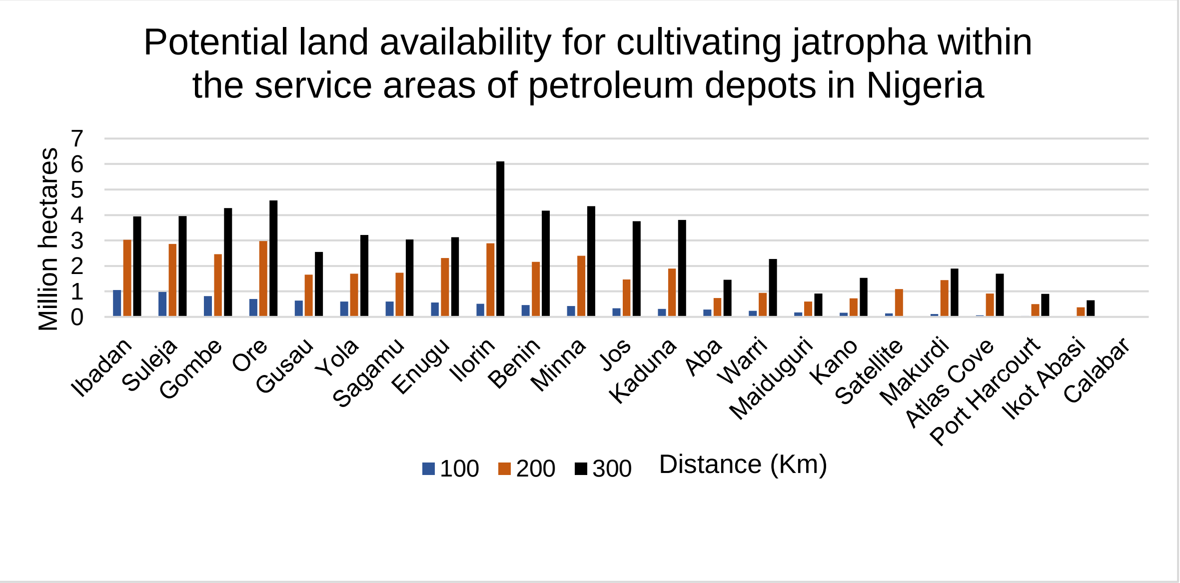


Figure 6.16: Potential land availability for cultivating jatropha

As expected, Ibadan shows highest jatropha feedstock supply potential within 100 km service area with more than 2 million tonnes (figure 6.17). It is followed by Suleja, Gombe and Ore with more than 1.9, 1.6 and 1.4 million tonnes, respectively. Ibadan also has the highest potentials for feedstock supply within 200 km service area with more than 6 million tonnes of jatropha feedstock, followed by Ore, Ilorin and Suleja with more than 5.95, 5.77 and 5.72 million tonnes, respectively. Within 300 km service area, Ilorin could be supplied with more than 12 million tonnes of jatropha feedstock, followed by Ore, Minna, Gombe and Benin with more than 9.1, 8.6, 8.5 and 8.3 million tonnes, respectively.

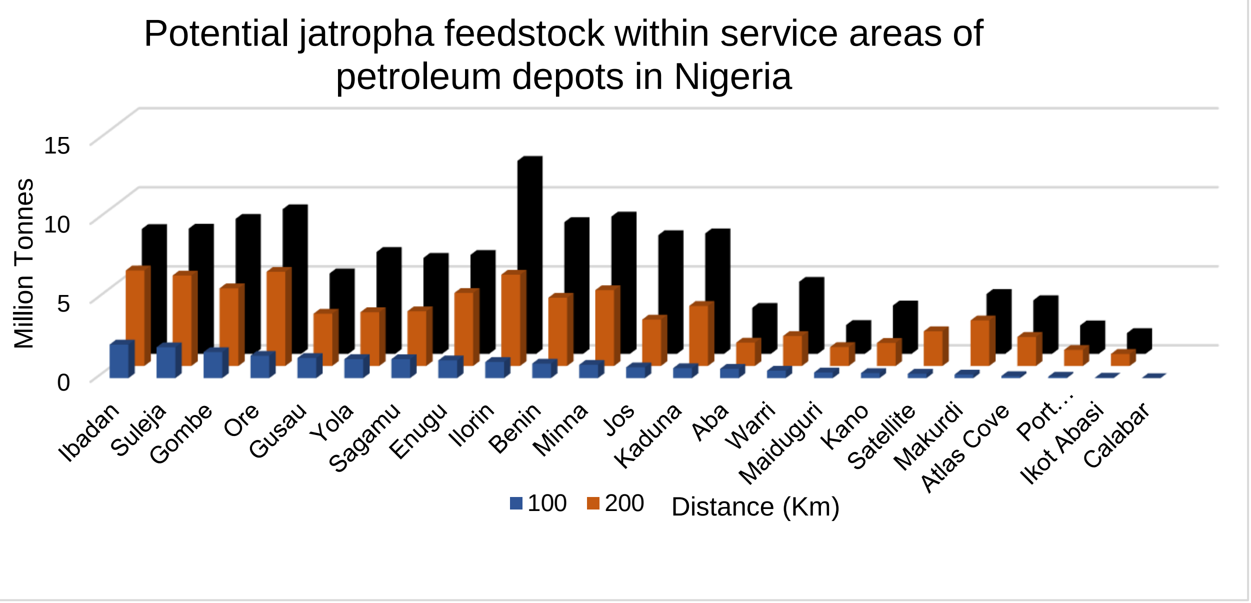


Figure 6.17: Potential jatropha feedstock supply

According to FAO (2010), 4 to 5.5 kg of jatropha seeds can produce one litre of oil. Several proportions of oil extracted from jatropha seeds were reported in the literature (table 6.7). Ibrahim and Bugaje (2018), concluded from their analysis that it is too expensive to use jatropha biodiesel in Nigeria because of seeds costs and low yields. They extracted 2.33 litres of oil from 21.3 kg of 3 years old seeds, 8.6 litres from 66.67 kg of dried seeds (age unknown) and 5.7 litres from 30 kg of fresh seeds. However, as could be seen in table 6.7, Akogwu et al., (2018), extracted 1 litre of oil from 3 kg of Nigerian jatropha seeds. This could be translated to 333 litres of oil per tonne. It is clear from table 6.7 that higher oil proportions were extracted from Nigerian jatropha seeds, showing more viability than suggested by Ibrahim and Bugaje (2018).

Table 6.7: Jatropha oil yields as reported in the literature

S/N	Oil yields	Country	Reference
1	2,200 litres ha^{-1}	Sub-Saharan Africa	ETB (2007)
2	40% (seeds weight)	Nigeria	Warra et al., (2012)
3	1 litre $3kg^{-1}$ of seeds	Nigeria	Akogwu et al., (2018)
4	1 litre $5kg^{-1}$, $8kg^{-1}$ and $9kg^{-1}$ of seeds	Nigeria	Ibrahim and Bugaje (2018)
5	52.2% (seeds weight)	Nigeria	Aransiola et al., (2012a)
6	47.25% (seeds weight)	Nigeria	Akintayo (2004)
7	49.1% (seeds weight)	Cuba	Martín Medina et al., (2010)
8	63.16% (seeds weight)	Malaysia	Akbar et al., (2009)
9	61% and 80% (seeds weight)	Nigeria	Belewu et al., (2010)

Oil extraction from jatropha seeds is said to depend on the extraction method applied. Warra (2012), reported that 60 to 65% of oil can be extracted using manual press, and 75 to 80% oil can be extracted using a mechanical press. Belewu et al., (2010), reported 61% oil extraction using mechanical methods and 80% oil using chemical methods. Sambo and Salihi (2008), mentioned that it is possible to achieve 3000 litres of oil ha^{-1} from jatropha seeds. To estimate potential oil within service areas, this work assumed extraction of 1 litre of oil per 5kg (200 litres per tonne) of jatropha seeds and 2,200 litres per hectare. This was calculated for each of the petroleum depots based on each of the service areas (table 6.8). Similarly, several biodiesel yields were reported to have been obtained from jatropha oil (table 6.9). A low biodiesel yield or proportion (87%) reported for Nigerian seeds was adopted for estimating biodiesel potential within service areas of the petroleum depots (figure 6.18).

Table 6.8: Potential oil from jatropha feedstock suppliable within service areas of petroleum depots

S/N	Petroleum depots	100 Km service area (Million litres)	200 Km service area (Million litres)	300 Km service area (million litres)
1	Ibadan	424.1848	1208.46	1578.7192
2	Suleja	390.0788	1144.596	1584.1512
3	Gombe	329.1836	982.5536	1707.7124
4	Ore	282.3912	1191.572	1830.2944
5	Gusau	255.1888	661.7316	1017.9152
6	Yola	240.8236	680.8156	1288.576
7	Sagamu	239.8528	691.6536	1214.5328
8	Enugu	224.3816	924.2268	1251.1848
9	Ilorin	204.7268	1155.1888	2441.674
10	Benin	183.676	863.2008	1666.9076
11	Minna	168.7676	958.7968	1736.5524
12	Jos	136.648	586.8912	1502.3896
13	Kaduna	126.1108	759.4416	1524.5656
14	Aba	117.6548	295.708	581.8888
15	Warri	93.9668	378.8596	911.4576
16	Maiduguri	71.3668	239.1564	364.976
17	Kano	63.7908	292.0892	612.5248
18	Satellite	55.4308	438.9368	0
19	Makurdi	45.5068	576.1344	757.3812
20	Atlas Cove	25.8652	367.9112	678.77
21	Port Harcourt	17.1156	203.1848	359.964
22	Ikot Abasi	5.8916	151.8104	262.19
23	Calabar	0	0	0

Table 6.9: Biodiesel yields from jatropha oil as reported in the literature

S/N	Biodiesel yields (% of oil)	Country	References
1	93.03	Nigeria	(Betiku et al., 2014)
2	94 and 96	Egypt	(Kamel et al., 2018)
3	87	Nigeria	(Aransiola et al., 2012a)
4	86.6	Nigeria	(Aransiola et al., 2012b)
5	90.8	Mexico	(Torres-Rodríguez et al., 2016)
6	93	India	(Choudhury and Srivastava 2014)
7	90	Nigeria	(Folaranmi 2012)
8	100	Nigeria	(Akogwu et al., 2018)

Similar to oil yields, Ibadan and Suleja showed the highest potential biodiesel production by the petroleum depots within 100 km service area with more than 369 and 339 million litres, respectively. Gombe, Ore, Gusau, Yola and Sagamu followed with more than 286, 245, 222, 209 and 208 million litres, respectively. Ibadan still shows the highest biodiesel potential within 200 km service area with more than 1.051 billion litres but was followed by Ore and Ilorin with more than 1.036 and 1.005 billion litres, respectively. Extending the service areas to 300 km showed that Ilorin has highest biodiesel potential with more than 2.124 billion litres, followed by Ore and Minna with more than 1.59 and 1.51 billion litres, respectively.

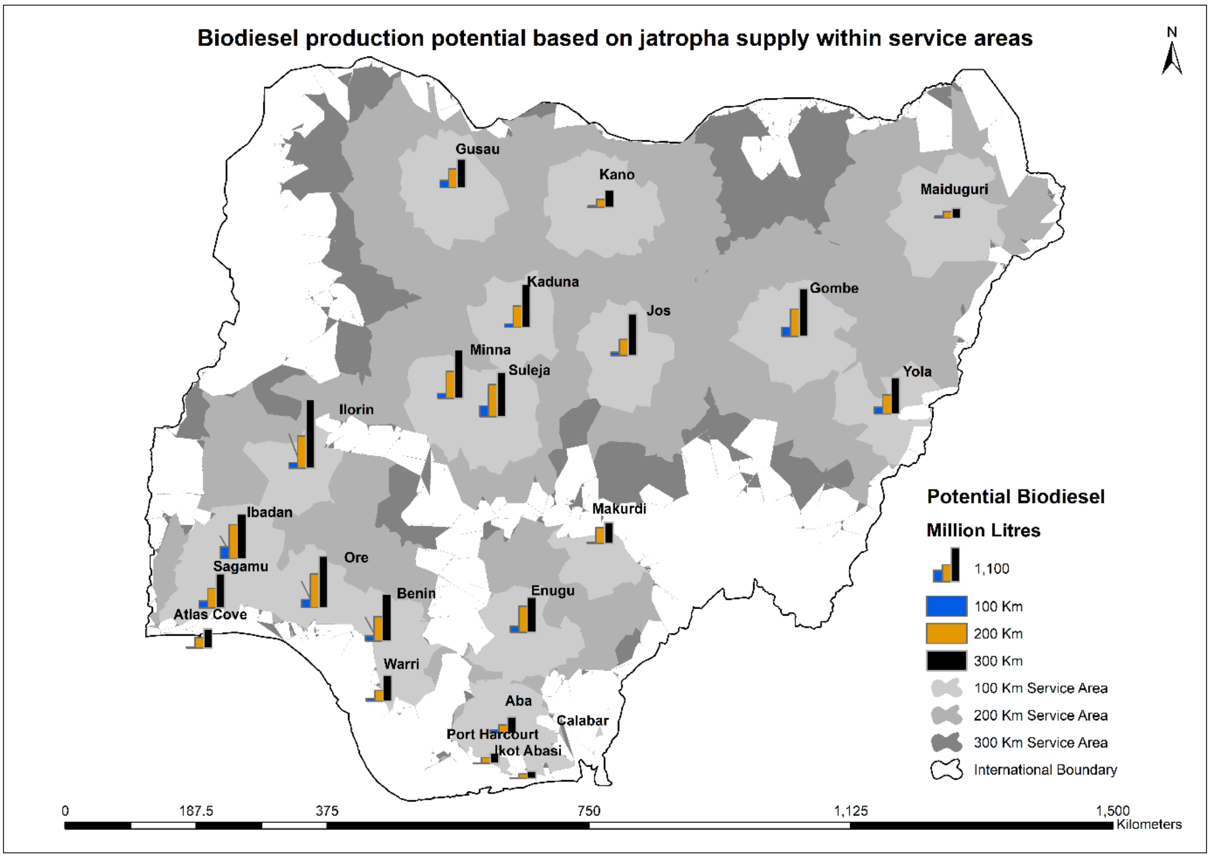


Figure 6.18: Potential jatropha biodiesel for each of the petroleum depots

This work identified Ibadan petroleum depot as the optimised location for jatropha-based biofuel processing and blending in Nigeria. Jatropha is also a woody perennial crop, making forest climes favourable for the crop. Ibadan is in the southwest of Nigeria where Adepoju and Oloyede (2018), found that jatropha has a competitive advantage though incentive policies need to be enhanced to make the cultivation profitable. Because it is relatively a new crop, only getting much attention in the last two to three decades, production information on jatropha is scarce in Nigeria. A few published works, however, reported jatropha cultivation activities in such areas as Kano State (Yahuza et al., 2020) and Benue State (J.A.C et al., 2016). Some jatropha plantations were visited as part of the field work in Zaria (Kaduna State) and Ilorin (Kwara State).

Activities for promoting jatropha in Nigeria are said to date back to 1998 (Yammama 2009). By 2011, about 7,500 hectares of land was covered with the crop in the country (Wahl et al., 2012) and later in the decade the jatropha growers association reported planting about 100,000 hectares (Adam 2018). It was not possible to obtain any documented information regarding distribution of jatropha production volumes in Nigeria. Therefore, since Ibadan petroleum depot showed the highest potential for jatropha-based biofuel production within both 100 and 200 km service areas, this location seemed to be the best for this purpose. The analysis showed that there could be more than 1 and 3 million hectares of land for cultivating jatropha within 100 and 200 km service areas of the Ibadan petroleum depot, respectively, for farmers to expand their production. The jatropha farmers association in Ibadan (Oyo State) is one of the foremost jatropha-based farmers association in Nigeria with 106 members (Olowoake et al., 2018). The farmers group, assuming they are experienced in jatropha cultivation, increases the potentiality of Ibadan for Jatropha-based biofuel processing and blending.

6.4 Summary

This chapter discussed biofuel potentials based on feedstock supply potentials within service areas threshold of 100, 200 and 300 km around the petroleum depot locations in Nigeria. The petroleum depots that showed the highest potential for processing and blending biofuels based on sweet sorghum, sugarcane, cassava, oil palm and jatropha within 100 km service area are Maiduguri, Maiduguri, Aba, Ibadan and Ibadan, respectively. Within 200 km service areas, Maiduguri, Maiduguri, Ibadan, Ibadan and Ibadan showed highest biofuel potential for sweet sorghum, sugarcane, cassava, oil palm and jatropha, respectively. Extending the service areas to 300 km, Ilorin showed highest potential for biofuel processing and blending based on all the five crops. This showed that depending on the scale of operation, the optimal site for processing biofuel base on agricultural crops may change. For example, according to these results, while it may be best to site cassava-based biofuel processing plant in Aba if the feedstock can only be supplied within 100 km, Ibadan may be the best if the supply can extent to 200 km. However, Ilorin may be the best if the supply can extend to 300 km. When considering sweet sorghum, sugarcane, cassava, oil palm and jatropha in conjunction with their production data, results show that Maiduguri (Borno State), Yola (Adamawa), Makurdi (Benue State), Ikot Abasi (Akwa Ibom State) and Ibadan (Oyo State) petroleum depots are the optimal sites for processing and blending these biofuels, respectively (figure 6.19).

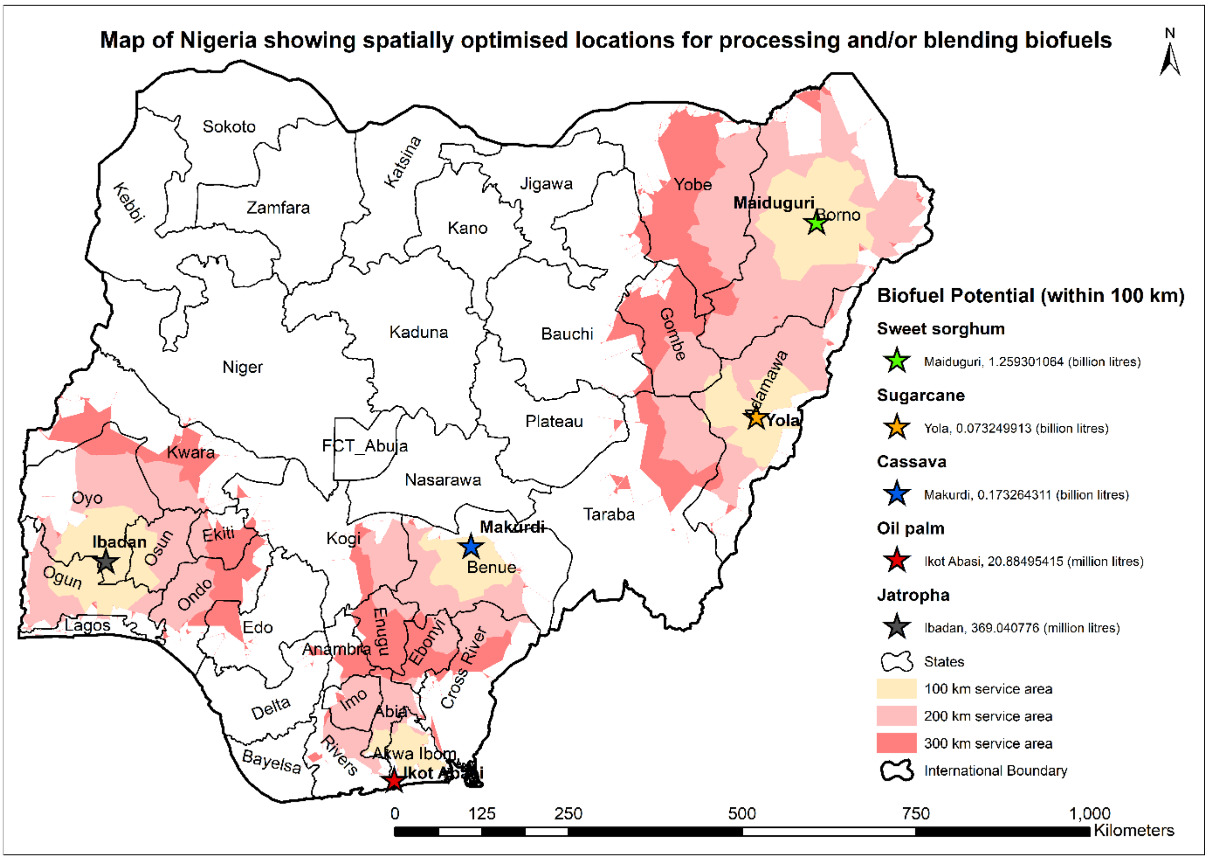


Figure 6.19: Optimised locations for processing and blending biofuels in Nigeria

It is obvious from figure 6.19 that there is emphasis on the crop production data with some deviation from the result of the analysis in making conclusion about the optimal sites for processing biofuel based on each of the crops. The main reason for this is the understanding that the land cover mapping conducted in chapter five to identify and eliminate agricultural areas did not differentiate between food crops and other non-food crops. All cultivated areas were considered in the elimination process and this would include existing land areas dedicated to biofuel crops cultivation such as sweet sorghum and jatropha. Therefore, since assessment of the land potential was based on land availability for cultivating the crop, areas with larger potential areas would show greater potentiality than areas with smaller potential areas even if the particular crop is being cultivated in the area. As would be discussed in the next chapter (subsection 7.2.1), these are some of the local factors that may play important role in making decision regarding choice of the site for processing biofuel from among the optimised sites. This is because the results from this analysis are not perfect as discussed in subsection 7.2.2.

6.5 Conclusion

Based on feedstock supply potentiality, it could be concluded that within 100 km service areas, Maiduguri depot is the optimal location for processing sweet sorghum and sugarcane-based biofuel. While Aba is the optimal location for cassava, Ibadan is the optimal location for both oil palm and jatropha. Alternative locations could also be considered depending on local conditions, the scale of operation and other important consideration such as the need for the petroleum depots to be upgraded for handling biofuels. These results provided an informed guidance for making spatial decision regarding crop-based biofuel processing and blending sites in Nigeria. Some discussion is provided in chapter seven about the implication of this analysis.

Chapter Seven – Discussions

7 Chapter Seven – Discussion

7.1 Summary of key findings

In this research, an attempt was made to explore locational criteria in order to conduct spatial optimisation for biofuel production in Nigeria considering five agricultural crops as biofuel feedstock. Chapter one covered an overview of the need for biofuels as part of the transitional energy sources, the debates about biofuel as well as its global production trends. An overview was also given in the chapter on Nigeria's energy sector and emissions to contextualise the research gaps, questions and objectives which were handled in the subsequent chapters. There were 10 research objectives mapped onto seven research questions that were derived from four research gaps related to four themes – empirical, methodological, spatial and policy. Though these components are actually interwoven, the following subsections give an overview of the contribution of the thesis to these four areas.

7.1.1 Empirical contribution.

There were three research questions in this component from which the research objectives were derived. The first research question was: "what are the ecological requirements for the selected biofuel crops' optimal growth?" The objective was to conduct a requirements analysis to determine the ecological requirements of the identified crops from which the land suitability criteria were derived. This is related to research question two namely "how do various biofuel crops differ in their potential contribution to biofuel production under a range of environmental conditions?" The objective here was to write a synopsis on the identified biofuel crops.

Chapter two attempted to achieve these two objectives and answer the two research questions. An overview was given on each of the five crops to show how each differ in terms of production, other uses than biofuel and some advantages each may have for use as biofuel feedstock. In section 1.2, the discussion on biofuel debates had also touched on these differences between the identified crops with regards to their use as biofuel crops. Extensive literature analysis was presented in chapter two regarding ecological requirements of the identified biofuel crops. In total, 14 criteria were identified including those related to distance such as roads. Optimal values required by each of the crops were mined from the literature and served as the basis for analysing how these crops differ with respect to land suitability for cultivation.

It was found empirically that the crops differ regarding how much contribution each can hypothetically provide in terms of land, given the suitability criteria. There are more than 38.5, 38.2, 32.5, 31.1 and 30.6 million hectares of land that is very suitable for sugarcane, sweet sorghum, cassava, jatropha and oil palm, respectively. While there was no area identified as less suitable for sweet sorghum, sugarcane and jatropha, it was only for jatropha that no area was identified as most suitable. Oil palm has the highest amount of land identified as moderately suitable with more than 13.7 million hectares. For jatropha, cassava, sugarcane and sweet sorghum, 13.2, 10.0, 5.6 and 3.1 million hectares of land were identified as moderately suitable, respectively. While this level of detail is not obtainable in other studies, it may not be surprising that the values for sugarcane and sweet sorghum are close considering the observable similarity of the optimum criteria values between the two crops, as well as their physiological similarities. Though cassava is also an ethanol crop, it differed from the other ethanol crops by showing about 6 million hectares less land areas that are very suitable for cultivating the crop, reflecting its difference in physiology and thus its requirements for the environmental variables. This, therefore, suggests the importance of being careful and systematic about establishing appropriate criteria given the sensitivity the results showed to changes in criteria weights.

The fifth question also falls under the empirical component and reads; “how much land is physically available for biofuel crops cultivation without conflict with food crops cultivation and conservation sites?” The objective was to identify and develop a model to eliminate physical constraints to biofuel crops cultivation. This objective was achieved in chapter five. It was found empirically that an estimated 41 million hectares of land was cultivated during the 2018 rainy season. This was identified as a constraint to land availability for cultivating biofuel crops based on the assumption that existing food production would be conserved and existing protected areas would be avoided. However, the analysis looked at all the cultivated areas without discrimination between food crops and cash crops. The implication of this is that the areas currently under biofuel crop cultivation were recognised by the analysis as constraints, therefore weighing down the potential of the areas for biofuel production. About 82 million hectares of Nigeria's land is said to be arable and according to the country's biofuel policy only 2% percent of the arable land is required for the programme. Therefore, this analysis showed that there is much more than needed land for the programme without conflict with food production.

This work provided data that can be explored to further determine how much of the land is available within each state or even local government area for the programme. These identified areas could further be explored to conduct empirical research to determine their productivity for each of the crops under various agronomic practices. It is empirically found that more than 40 million hectares of land could be explored in Nigeria to cultivate feedstock crops for biofuel production in the country. These areas comprised of more than 10 million hectares of woodland and more than nine million hectares of shrub land. Others might be unprotected forest areas. However, this finding could suggest that the demand for land from the biofuel programme could be attained without touching open forest areas and would not compromise ambitions to expand protected areas in the future. In fact, these identified potentially available areas could be explored to determine their appropriateness for expanding protected areas in Nigeria.

7.1.2 Methodological contribution

There was one research question under this component: "how does combining AHP and GIS-MCDM improve biofuel crop land suitability modelling in Nigeria?" There were two objectives, to conduct expert group discussion for detailed and standard implementation of AHP for generating criteria weights and to develop a model for suitable cultivation lands for each of the identified crops using multi-criteria analysis. The former was handled in chapter three, while the later was handled in chapter four. Chapter three provided detailed participatory criteria preference assessment, which is usually absent or often implicit in most spatial multi-criteria analysis.

Experts on each of the crops were consulted through group discussion for the purpose of assigning the criteria weights. Their judgements were assessed for consistency compliance which necessitated consulting them for the second time to reassess their judgement. Final weights were generated and the required consistency ratio was achieved for each of the crops. In chapter four, a model was developed for each of the five crops to assess land suitability for cultivation. Sensitivity analysis showed that the results were very sensitive to changes in criteria weights, emphasising the importance of developing a careful and systematic approach to establishing the weights which was provided by AHP in support of spatial multi-criteria analysis and as a support for spatial decision-making process.

In the context of the complexity of environmental assessments due to the conflicting or compromising nature of the parameters needed to be considered (section 1.6), it was found that GIS-based multi-criteria analysis (GIS-MCA) also known as Spatial Multi-criteria Analysis (SMCA) provides a useful pivot to approach this as a multi-criteria spatial decision support system (MC-SDSS). Notwithstanding the caveats, the land suitability analysis in chapter four, constraints analysis in chapter five and the optimisation modelling in chapter six, combined, showed how GIS-MCA methods serve as useful support for the spatial decision-making process. Though the application in this work relates to the biofuel industry, it was shown in section 1.6 that the method has been applied to many contexts such as housing or habitat suitability planning, urban infrastructure planning, hazards mapping, agriculture planning or monitoring and other renewable energy sectors such as hydro-power or solar energy planning. The diversity of these applications is said to drive continued expansion of these applications into foreseeable future, enabled by progress in geospatial technology and data availability (Malczewski and Jankowski 2020).

From a methodological perspective, it was found that application of Analytical Hierarchy Process (AHP), as a technique for sourcing knowledge of experts, improves the results of land suitability modelling as compared to techniques that does not incorporate this knowledge. This is shown in chapter four by the sensitivity analysis. Equal weights assigned to the environmental criteria produced results that deviated substantially from the results obtained using the experts' judgements. In other words, without the experts' opinions regarding criteria weights, the result might contain high inaccuracies, or at least not based on the available knowledge. The experts with their various specialisations could make better judgement through consensus.

As an example, in this work the experts that participated in the focus group discussion for cassava include the director of cassava research in the Institute, the plant pathologist, the soil scientist and the institute's business development manager. They discussed and sometimes delibrated over the appropriate judgement at any instance of comparing a pair of criteria. These structured debates allowed focus on specific points and the consensus represent the group preferences, providing better way of generating meaningful judgement compared to an arbitrary judgement from a single expert or by the analyst who does not have the required expertise for making the judgement. As done in this work, bringing the experts to a single sitting provides the best way of handling the fuzziness of human decision making as their different judgements are synthesised instantly in a systematic fashion. This eliminates the subjectivity that may arise when the analyst tries to reconcile different judgements obtained from different experts at different instances. Other environmental management scenarios such urban infrastructure planning could also benefit from this structured way of involving stakeholders for effective decision-making.

Another methodological contribution of this work is the novel map output combination procedure conceptualised and demonstrated in chapter five. It involves producing multiple band combinations by integrating optical and radar data bands, executing multiple classifiers, extracting classifications outputs with higher class accuracies and combining the outputs with the aim of improving satellite imagery classification accuracy. What makes this procedure novel is the manner in which the outputs were combined. It involves mainly two stages. The outputs are converted into binary and then fuzzy class maps in stage one. Then the fuzzy class maps are converted into binary and then combined into a single land cover map in stage two. This particular procedure has never been found to have been conceived or implemented in any previous work.

7.1.3 Spatial contribution

There were two research questions under this component. The first question reads; “where are the physically available land areas for biofuel crops located in the country and how suitable are they for the identified biofuel crops?” The objective deals with mapping the land areas and their suitability levels for the identified biofuel crops in Nigeria. Land suitability levels were determined in chapter four and the potential availability was determined in chapter five. Based on geopolitical zones of the country, about 64%, 55%, 53%, 52%, 51% and 33% of the south-south, southwest, southeast, northeast, northcentral and northwest are potentially available for biofuel crops cultivation, respectively. These zones are groups of neighbouring states that do not have constitutional backing or formal administrative structure but are usually used for regional analysis.

The results also showed that more than 10 million hectares could be very suitable for all the five considered biofuel crops in the northcentral zone. While more than seven million hectares are very suitable for cassava and jatropha in the northeast, more than 11 million and more than 12 million hectares are very suitable for sweet sorghum and sugarcane, respectively. Also, more than five million hectares are very suitable for oil palm in the zone. While about six million hectares were found to be very suitable for sweet sorghum, sugarcane and cassava in the northwest, less than five million hectares were found to be very suitable for oil palm and jatropha in the zone. It was found that more than four million hectares could be very suitable for all the crops in the southwest except cassava for which less than four million hectares were found to be very suitable. Less than four million hectares were found to be very suitable for all the crops in the south-south except jatropha for which a little more than two million hectares were found to be very suitable. In the southeast, more than one million hectares could be very suitable for cultivating all the five crops.

In summary, the northcentral geopolitical zone of Nigeria may have the largest amount of land that is ‘very suitable’ for cultivating sugarcane, cassava, oil palm and jatropha. While the northeast may have the largest amounts of land that is ‘very suitable’ for cultivating sweet sorghum. This work provided more details regarding land suitability for cultivating selected crops as feedstock for a biofuel programme in Nigeria. It has gone beyond attributing land suitability for a biofuel crop to vegetation zones, as done in some previous studies (section 1.7) but estimated how much of the land is most suitable, very suitable and moderately suitable and where these varying land suitability levels could be obtained.

The second research question under this component reads: where should biofuel refineries be optimally sited among the existing petroleum depots in Nigeria based on the suitable areas for biofuel crops? The first objective deals with site optimality modelling for biofuel processing facilities based on transport cost (distance along road network). This was conducted in chapter six. The results showed that Maiduguri petroleum depot might be the most optimal site for processing and blending biofuel based on sweet sorghum and sugarcane. However, either Yola or Ilorin petroleum depot was suggested as the best possible alternative for sugarcane-based biofuel processing and blending. Both the two alternative depots have more than 500,000 hectares of land potentially available for sugarcane expansion and there is presence of sugar milling companies within 100 km of their locations. The results also showed Ibadan petroleum depot as the most optimal for biofuel processing and blending based on cassava, oil palm and jatropha. However, Makurdi and Ikot Abasi petroleum depots were suggested for cassava and oil palm, respectively. Makurdi is the capital of the largest cassava producing state in Nigeria, while Ikot Abasi depot is located approximately at the centre of the largest oil palm producing states in the country.

The second objective was to determine potential operation scales for the identified processing sites and determine the most efficient number of biofuel production facilities in Nigeria based on the identified biofuel crops. In most processes of establishing new processing companies or expanding existing ones the scale of operation is predetermined. Thus, the question is which site would have the capacity to support the predetermined operational scale. On the other hand, a site might already be identified and thus the question would be what operation capacity the site potentially allows for optimal operation. The current study provided a range of options.

Based on potential feedstock availability within certain supply area thresholds, potential operation scales were determined for each of the sites. This was part of the results in chapter six. For sweet sorghum, the scale ranges from 0.77 million litres at Calabar depot (within 100 km service area) to 5.13 billion litres at Ilorin depot (within 300 km service area). For sugarcane, the scale ranges from 0.21 million litres at Calabar depot (within 100 km service area) to 0.77 billion litres at Ilorin (within 300 km service area). For cassava, the scale ranges from 36 million litres at Calabar depot (within 100 km service area) to 9.17 billion litres at Ilorin (within 300 km service area). For oil palm, the scale ranges from 236 thousand litres at Calabar depot (within 100 km service area) to 460 million litres at Ilorin depot (within 300 km service area). For jatropha, the scale ranges from 5.12 million litres at Ikot Abasi depot (within 100 km service area) to 2.124 billion litres at Ilorin depot (within 300 km service area).

The efficient number of processing facilities for the country would depend on the amount of biofuel required to meet the demand for the blending policy. In section 1.5, it was mentioned that Nigeria's daily consumption of petrol (PMS) and diesel (AGO) culminates into annual demand for over 1.27 billion litres of ethanol and over 876 million litres of biodiesel to implement the blending policy. From this analysis, it is clear that several of the petroleum depots showed potentiality to process these amounts of biofuel to meet the policy targets.

Considering sweet sorghum only (assuming sugarcane is only used for sugar production, while ethanol from cassava is used for other industrial applications), a combination of Maiduguri and Gombe showed a potential capacity of more than 2 billion litres of ethanol within 100 km supply area for blending with petrol. Maiduguri alone, showed potential capacity of about 3.8 and 4.8 billion litres of ethanol if the feedstock could be supplied within 200 and 300 km, respectively. Therefore, Maiduguri alone can potentially supply all the needed ethanol for blending, but would require support from Gombe depot if feedstock supply is restricted to 100 km.

With regard to biodiesel, combination of a number of depots would be required to supply enough amounts for blending with petroleum diesel. Assuming biodiesel is produced only from olein (the oil palm by-product), this analysis showed that restricting feedstock supply to 100 km would not allow for enough biodiesel processing to meet the blending target even if all the depots (considered) are used to their full potentials. Their total potential is about 745.4 million litres of biodiesel. However, if the feedstock supply area is extended to 200 km, combination of Ibadan, Ore, Ilorin, Suleja and Enugu would potentially process more than 1 billion litres of biodiesel for blending with petroleum diesel. Ilorin, Ore and Benin also showed the potential to process more than 1 billion litres of biodiesel if the feedstock supply area could extend to 300 km. Therefore, while three or five depots may potentially process enough biodiesel for blending with 300 km or 200 km feedstock supply distance, respectively, all the depots may not potentially process enough within only 100 km. With jatropha as the feedstock, the feedstock potentials within 100 km service area showed that Ibadan, Suleja and Gombe could process enough biodiesel for the country’s demand. With 200 km service area, Ibadan alone showed the potential to process all the needed biodiesel to meet the demand.

This work has provided estimates for scale of operation for each of the candidate processing sites, suggested options for a combination of sites to meet the demand for biofuel blending policy and this illustrates how the approach adopted allowed a better granularity and more detail of spatial analysis than is typically done. Most studies would stop at analysing land capability for feedstock cultivation as could be found in Boruff et al., (2015) and Zhang et al., (2017). The estimates from the current study provide the Nigerian government, the state governments and the private investors with data that could be used as an input in formulating policies and executing practical business solutions related to biofuel. Therefore, it could not be emphasised enough that the analysis from which the data and the recommendations are derived is underpinned by a detailed, transparent and systematic set of workflows.

7.1.4 Policy contribution

There was one research question under this component. It reads; “what policy recommendations should be considered to support and enable appropriate biofuel production in Nigeria?” Two objectives were derived from this. The first deals with investigating literature to discuss the most appropriate technologies for biofuel production systems – feedstock cultivation and biofuel processing. The second objective deals with investigating literature and other secondary sources to discuss strategies for a sustainable biofuel industry in Nigeria – optimal decisions and resilient thinking. This covers sustainable feedstock cultivation and sustainable biofuel processing. Discussion around these aspects is the main focus of this chapter and is discussed in section 7.2 as the policy recommendations from this work.

7.2 General discussion

To support spatial decisions that have policy implications, it is really important to develop detailed, systematic and transparent workflows. In the following subsections, broader discussions are provided as reflections on the work done in this research and other related themes. Though there may be overlap, these themes relate to the different components of the contributions as discussed in the previous section. Feedstock supply chain design (subsection 7.2.1) relates to some aspect of the empirical contribution. The land availability for feedstock cultivation and the nature of the feedstock would have great influence on the design of the feedstock supply chain.

Discussion around strength and challenges of spatial decision-making and the role of people (subsections 7.2.2 and 7.2.3) relates to the methodological contribution. Complexity in biofuel production and sustainability of biofuel industry (subsections 7.2.4 and 7.2.5) relate to the spatial contribution. The relationships between the location and a particular biofuel feedstock are crucial in adopting strategies for the sustainability of the industry. Resilient thinking in biofuel production (subsection 7.2.6) relates to the policy contribution. Strategies that make the biofuel industry resilient would ensure not only its success but also its long-term sustainability.

7.2.1 Strength and Challenges for spatial decision-making

Progress in geospatial technologies and data availability enabled continued expansion of the application of spatial multi-criterial analysis (SMCA) in many environmental analyses. The exponential expansion of these applications might indicate that these applications are useful though, as cited in subsection 1.6, some studies lack the required details regarding criteria preferences and/or managing uncertainties. According to Malczewski and Jankowski (2020), a majority of these applications are said to be implicit, meaning that the methods are premised on the implicit assumption that the model parameters and the result of the GIS-MCA do not vary as a function of geographical space. Thus, the growing awareness of this deficiency partly led to a paradigm shift in GIS-MCA to improve the implicit practices that were prevalent. Though the whole process is highly iterative to allow for learning to take place and improve the model, building an SMCA system was divided into five steps through which eight key challenges in designing SMCAs were identified (Ferretti and Montibeller 2016). The steps include designing, structuring standardisation function, partial performance and analysis of results and recommendations.

Ferretti and Montibeller (2016) identified key challenges in designing and applying GIS-MCA methods and suggested meta (most effective technique available) choices. The key challenges are associated with the meta-choices confronting developers and users of the SMCAs (Ferretti and Montibeller 2016). The authors suggested that there is a need for increased awareness regarding available choices in designing and implementing these SMCAs; better understanding of the alternatives for each of these choices based on recent development in the literature; and clearer appraisal about the inherent trade-offs between advantages and disadvantages of each alternative. The challenges include participation (e.g. who and how to participate), designing objectives (e.g. how the objectives are defined), spatial standardisation (e.g. who provide and the information how for spatial standardisation), partial performance (e.g. how to deal with sustainability concerns and how to elicit criteria weights) and analysis of results and recommendations (e.g. how to efficiently perform spatial sensitivity analysis). Thus, there is a push towards spatially explicit spatial multi-criteria analysis through developing new approaches for structuring spatial problems, combining spatial and preference information, estimating model parameters, defining context and scales, handling uncertainties, supporting decision making and visualisation of problems and solutions (Malczewski and Jankowski 2020).

Addressing these challenges in developing an SMCA support system may explain how implicit or explicit the system would be. This work addressed these challenges to make the analysis as explicit as possible. The cutting edge trend or emerging paradigm has been spatially explicit conceptualisation of the multi-criteria problem with a focus towards analysis with geographically varying outcomes and local multi-criteria analysis (Malczewski and Jankowski 2020).

This work applied cutting edge best practice science to provide spatial optimisation for biofuel production in Nigeria based on agricultural crops. It considered the details needed, especially regarding land suitability for the agricultural crops, to conduct a meta-analysis as a support for spatial decision-making regarding biofuel production in Nigeria. These details could not be found in publicly available literature being explicitly implemented in the context of Nigeria and there was little found elsewhere as seen in the previous paragraphs. These meta-analyses could be explored for application to other non-biofuel spatial contexts in Nigeria and elsewhere. They may provide strong support for agricultural land planning, river basin management, grazing route planning, transport planning, pipelines projects, urban and rural planning, housing development as well as business planning. SMCA is powerful in the sense that it measures not only the geographical entities that forms the criteria to be considered, but also measures the relationships between the entities, as discussed in subsection 1.6 and 3.5. The following paragraphs discuss how these challenges of developing SMCAs were addressed in the current work.

The first challenge deals with who should participate and how. As discussed in section 3.4.4, because this analysis considered agricultural crops as the biofuel feedstock, experts on these crops, working in the research institutions with national research mandate on these crops were selected for gathering experts' opinions regarding criteria priorities for each of the crops. The experts participated through a focus group discussion for each of the crops at each of the institutions where the group sat at the same time interacted and agreed on priority judgement. The scope and resources available for this work would not allow for involvement of other important stakeholders such as farmers, biofuel processors, local authority and non-governmental organisations. Nevertheless, the work offers a good example of how stakeholders can be factored into projects like this.

The second challenge deals with the appropriate method. As discussed in subsection 3.4.2, pairwise comparison technique of the Analytical Hierarchy Process (AHP) was adopted as the best method considering its advantages (subsection 3.4.4) and the limited time and resources available for this work. The third challenge deals with sources of defining criteria objectives and ensuring only the fundamental objectives are included. The meta-choice adopted was expert-based sources (literature) which has the possibility of taking into account the most well-documented and up-to-date scientific evidence and has opportunity to provide objectives which reflect best available knowledge. Chapter two was dedicated towards this and detailed discussion was provided on how each of the means objectives (e.g., best soil, optimal rainfall or minimal distance from surface water) relate to the fundamental objective (suitable land for cultivating a crop).

The fourth challenge relates to the availability of spatial data. For the compromising criteria (rainfall, soil, distance to roads), the sources and pre-processing of the datasets were provided in chapter three. Chapter five was dedicated to identifying, obtaining data for and removing non-compromising criteria (e.g., cultivated areas, protected areas). The fifth challenge deals with the spatial standardisation function. In section 4.2, a lengthy discussion was provided on how the criteria scores were standardised and that the basis for this standardisation was published empirical experiments which might be more reliable than expert interviews. It was suggested that scientific evidence should be given priority over expert opinions which should only be sought for where there is insufficient empirical evidence (Herman and Raybould 2014). The suitability classes that resulted from the criteria standardisation in this work were therefore based on scientific evidence which provided practical standards especially where there were multiple empirical results showing similar values or range of values.

The sixth challenge covers handling sustainability concerns; whether the criteria should be assessed using weak or strong sustainability approaches. A weak sustainability approach allows substitutability between man-made capital and natural capital, while strong does not allow such substitutability. In this work, factors that allow for compromise such as rainfall, and soil were treated separately (chapter four) from those that do not allow for compromise such as protected forests (chapter five). Eliminating non-compromising criteria from the analysis may reflect a strong sustainability perspective.

The seventh challenge pertains to how to elicit criteria weights from experts/public. It was mentioned that AHP was adopted as the method and an expert/focus group workshop was used as the means for assessing criteria weights. The weights were based on experts' opinion not the pragmatic judgement of the analyst. Some reflection on AHP were provided in subsection 7.1.2 and a lengthy discussion could be found in section 3.5. The eighth challenge have to do with how to efficiently perform sensitivity analysis. In section 4.5, a sensitivity analysis was conducted showing considerable change in land suitability as a response to change in criteria weights. Maps were presented to visualise the sensitivities due the criteria weights change as recommended in Feick and Hall (2004). In modelling site optimality (chapter six), three distance scenarios were applied to serve as a back-room analysis showing how optimality changes with changing supply area distance giving wider room for comparing alternative solutions.

Despite considering the required details for SMCA especially in land suitability analysis, this work has not provided a perfect solution to this spatial problem. The attempt made here was to strike a balance between the best use of computer optimisation and the reality of its application. The analysis tried to avoid providing an unworkable precision. For example, in the supply area modelling, centroids of the LGAs were used as the proposed feedstock collation (or storage) centres rather than giving a precise location due to the reality that local decision-making structures would be expected to differ locally and capturing this diversity may not be possible in this work considering its spatial scope. The complexity of this degree of precision is often missing in SMCAs. Therefore, it is suggested here that matching scientific evidence with the reality of decision context is an important area that should be expanded as part of the changing paradigm towards explicit spatial multi-criteria analysis.

From the foregoing, it is obvious that best practice science was applied within the limited resources and time to conduct this research. This could be one of the strengths of this work in the context of Nigeria’s biofuel analysis and may be replicated in other land use planning contexts in Nigeria. This could be explored for use in spatial decision-making processes related to other spatial problems such as flooding (e.g. planning channel diversion or identifying suitable rainwater harvesting sites). Thus, this work could serve as a reference for state-of-the-art application GIS-MCA in the Nigerian context and other parts of the world where application of these methods is still at rudimentary stage.

7.2.2 Feedstock supply chain design.

As discussed in subsection 6.2.2, one of the major assumptions in this work was that processing and blending of biofuel with petroleum fuel is sited at the existing petroleum depots rather than identifying new sites. Thus, the assessment looked at feedstock supply potential within certain distances of the depots. This is similar to Voets et al., (2013), in the sense that there were predetermined sites to be optimised. As discussed in the previous chapter, this approach is suitable in the context of this analysis because of the spatial distribution of the depots and wide extent of the areas that could be used for feedstock cultivation. However, depending on the nature of the supply chain design, there may be need for storage sites to serve as collation centres for feedstock.

Though it was assumed that these storage centres are sited at local government area (LGA) level, prescribing a precise location was avoided considering that local governing structures may differ among the LGAs in Nigeria. Land governance is statutorily vested on the state governors who are assisted in this regard by the chairpersons of the local councils. Therefore, the decision on a precise collation site should be made in collaboration with state government, assisted or represented by the local authority. The best this analysis could suggest was the feedstock potential by LGAs to shape focus on where to source feedstock from for biofuel processing. This was the rationale behind arbitrarily using LGA centroids as the collation centres in the supply area modelling.

As discussed earlier, the major challenge of using petroleum depots for processing and blending biofuels could be the need for capital investment to upgrade the depots for biofuel services. Additionally, the petroleum facilities have aged, with some of it existing for more than four decades. However, this may not pose an insurmountable challenge because, as reported in section 6.2.2, two of the depots have been upgraded with facilities to handle biofuels. In 2020, the Nigerian National Petroleum Corporation (NNPC), invited interested companies to bid for its contracts to be awarded for rehabilitation and/or construction of pipelines and upgrade of the depots described to have aged over the years, giving rise to frequent failures, consequential operational downtimes, high maintenance costs and revenue losses. It was reported that 70% of the pipelines linking the depots have exceeded their life span (Okafor 2017). Though it was not clear in the contract advert document whether the rehabilitation considered installation of biofuel handling facilities, 12 of the petroleum depots were identified for rehabilitation. It was reported that the project had moved one step where 96 companies indicated interest to participate in the build, operate and transfer (BOT) financing model (Adaramola 2021). This indicates the corporation's commitment to investing in its infrastructure and may be a pointer that upgrading the depots with biofuel facilities may not be an insoluble challenge.

Due to the limitations discussed above and in the previous subsection, the results of this work would require further refinement for practical application as support for spatial decision-making regarding placing biofuel processing plants in Nigeria. For example, upon deciding to fucus on Maiduguri depot or Ibadan depot for processing sweet sorghum biofuel or jatropha biofuel, respectively, a more localised assessment of the supply area would need to be conducted to identify most optimal locations for placing the feedstock collation centres as could be allowed by the socio-economic and political structures of the localities. This may involve conducting a panoramic study of the focused local area, selecting potential sites and assessing the sites through field surveys.

7.2.3 The role of people in spatial decision-making

As discussed in section 1.7, because multi-criteria analysis involves criteria prioritisation, stakeholders' participation is crucial. This is because criteria prioritisation depends on the objective which differs among stakeholders. Prioritisation may also depend on the geographical or conceptual context of the analysis. To translate the dimensionality of the decision-making into a practical procedure, Renn et al., (1993) grouped stakeholders into three categories based on the knowledge they represent: those that represent common sense and personal experience; those that represent technical expertise; and those that represent social interest and advocacy.

Stakeholder participation is cost- and time-intensive and can sometime lead to stalling decision process (Ferretti and Montibeller 2016). Therefore, the best practice is to identify who and how can participate given the context, time and resources for an analysis. By the nature of this work which sought to assess biofuel production potential based on agricultural crops in Nigeria, stakeholders' involvement was restricted to only the category that represented technical expertise for two reasons. First, there was no time and resources to cover all the stakeholders such as farmers, biofuel processors, crop trade dealers, community leaders and environmental regulators. Secondly, this study focused on developing a model rather than implementing solutions and thus, the results and the recommendations have the overall caveat that they were not based on the ideal situation but were based on simulation that the data and the methods could allow.

Because this study covered the whole country, only stakeholders of focused localities should then be involved in further localised evaluations of identified potential processing sites. In subsection 3.4.4, details were presented of how the experts were determined and involved in assessing the criteria priorities. This further makes this work stand out as similar details of this nature could not be found in public domain with regards to crop-based biofuel analysis in Nigeria. In fact, there was relatively little or implicit mention of this stakeholders' participation in many similar projects in other countries as cited in section 1.6.

According to Gregory and Wellman (2001), it is wiser to incorporate stakeholder values, good science and economic valuation directly into the design of project or programme alternatives in order to increase its probability of receiving broad-based approval and success in achieving its set goals. However, because stakeholders' involvement is costly, time consuming as mentioned in the previous paragraph, it is necessary to identify the relevant stakeholders through stakeholder analysis. It is neither everyone who has an interest in acting nor whoever should act is necessarily a stakeholder (Dente 2014). Thus, stakeholder analysis might help in identifying and selecting relevant stakeholders necessarily needed to be involved.

The identified stakeholders could be involved through online or physical interactions. Online methods may provide wider and asynchronous involvement of both experts and general public, but it limits interaction between the participants and the analyst and advantage of face-to-face group decision-making (Ferretti and Montibeller 2016). Physical interaction may enable facilitated modelling and promote interaction among participants, but it may limit the number of people that may be involved and may be costly and time consuming. In this work, the identified stakeholders were met physically through group discussion. The experience of factoring in stakeholders and use of AHP technique to handle their views in a systematic way suggests that this should be an important element of such decision-making framework not just for biofuels in Nigeria but in other contexts elsewhere.

7.2.4 Complexity in biofuel production

Though this work considered only agricultural crops as the feedstock source for biofuel in Nigeria, it is obvious from the analysis that biofuels are complex and therefore spatial decisions regarding them would be influenced by this complexity. Lengthy discussion was provided in section 1.2 showing how the debate about biofuels takes different patterns depending on what is considered as feedstock. In the subsequent chapters, it was shown how different crop requirements and characteristics lead to varying priority judgements by the experts resulting in varying spatial outcomes. Cultivating, collecting, packaging and transporting feedstock is complex. Thus, designing a supply chain for biofuel would vary with the varying feedstock. While some of these crops can be used for food, feed and fuel such as sweet sorghum, some are neither edible nor useable for animal feeds such as jatropha. While the same raw material from some crops used for biofuel is used for other important uses such as sugar from sugarcane syrup, which may indicate an important opportunity cost and may cause ethical concerns, other crops provide more ethical raw material and may have lower opportunity cost. For example, while edible oil from oil palm can solely be used for human consumption, abundant olein would be available for biofuel from the same oil palm.

Many technologies for fermentation, gasification, etc. have been developed for processing different feedstocks. These complexities would understandably affect how spatial decisions would be made. The decision should attempt balance among economic, environmental and social goals of a biofuel programme. This also indicates how important it would be to manage details in conducting spatial multi-criteria analysis for biofuels. As discussed in section 1.7, this work attempted to improve the robustness of spatial analysis in the context of Nigeria. Thus, the research considered in great detail, all the environmental and socio-economic variables needed to be considered in modelling site suitability for cultivating the crops. The research involved people with expertise on these crops and executed best practice AHP application to determine the weights of the variables, albeit with scope to further expand the range of stakeholders. In section 4.5, it was shown that this work presented maps with greater detail regarding suitable areas for cultivating biofuel crops in Nigeria. Therefore, regardless of the scope, greater detail in spatial analysis allows generation of knowledge that should better support spatial decision making.

Though the details considered in this work does not necessarily mean the resultant maps are perfect, the work demonstrated that it is important to take such care at each stage. For example, the crop land mapping in chapter five was handled in detail even though the data might not be perfect. However, at least, some robust analysis was offered and transparency was embraced throughout all the stages of the whole work which is crucial when handling detailed data because the results would suggest very local implication. This work, therefore, highlighted how spatial analysis for crop-based biofuel production could be improved in Nigeria. It showed the necessity of considering all relevant variables in spatial analysis for not only biofuel but also other land use planning processes such as urban, rural or industrial sites planning, water resources management, transport infrastructure planning and other social amenities planning (education, health, sport, tourism). For example, establishing a new school would need to consider the demographics, land availability/transferability, budget size, security, proximity, existing schools, staff availability and the intended structure of the new school. Greater detail consideration of these criteria would lead to better understanding of the context and more informed spatial decisions.

7.2.5 Sustainability of the biofuel industry

Both feedstock production and biofuel processing would require spatial strategies that ensures both success and sustainability of the industry. While the desire for energy sustainability is one of the major drivers of biofuel adoption (Acheampong et al., 2017), the sustainability of biofuel production itself has been questioned (Maconachie 2019). Land access, land use change, food prices and real reduction in emissions are some of the issues centred around biofuel sustainability controversy. Some discussion about sustainability of the biofuel industry was presented in subsection 1.2.6 as part of appraising the debate about biofuels. It was shown that sustainability comprises of four components – economic viability, social acceptability, environment friendliness and technological appropriateness.

There is growing recognition of the significance of charting new ways of striking the balance between maximising economic benefit and minimising environmental footprints (Jia et al., 2017). Through coordination by the United Nations, 193 countries created 17 sustainable development goals (SDGs) with implementation timeframe of 15 years (2016-2030). Acheampong et al., (2017), in their assessment of the potential of biofuels for contributing to achievement of SDG goal 7 (affordable and clean energy) opined that biofuels possess immense potential and their constant improvement increases the possibility of foreseeable carbon neutral energy future. However, there is a need for careful management of traditional biofuels and steady development of advanced biofuels for this to be realised. Also, despite information regarding favourable environmental conditions, there is a need to consider the sustainability credentials of the biofuel crops, though this is a decision process beyond the scope of this study.

A multi-stakeholder group of industries, NGOs, CSOs and governments developed a standard which is widely recognised as the most trusted and credible approach for growing a truly sustainable transition to a net zero carbon economy (RSB 2017). As discussed in section 5.2, the standard consists of 12 principles that contribute to not only food security, rural development and restoration of ecosystems, but also provide tools and solutions that mitigate business risks and contribute to achievement of the UN SDGs. The standard has four major components – legal, social, environmental and management. The legal component ensures legal compliance of biofuel projects including land and water rights. The social component ensures the sanctity of human and labour rights, local food security and rural and social development.

The environmental component ensures the preservation of conservation values, soil health, water availability and quality, air pollution control and mitigation of climate change. The management component ensures reduction of risks and continuous improvement through effective management approaches. This standard was the basis for identifying factors that may not compromise, specifically, for biofuel feedstock production (section 5.2). Eliminating these constraints was considered crucial for biofuel sustainability. Because of their complexity as seen in the previous subsection, the measures necessary for sustainability of biofuels would be highly dependent on the adopted feedstock. Sustainable feedstock production and appropriate processing technology are fundamental to sustainable biofuel industry.

Sweet sorghum has been a target biofuel crop (Cifuentes et al., 2014) because of its multiple use (food, feed, fibre and fuel) and is said to be useful in resolving food versus fuel conflict (Ahmad Dar et al., 2017). The strategies for cultivating the crop are said to depend on the objective (grain, biomass or both), the site conditions (moisture, temperature, soil), the available variety and the requirements of the preceding crop (Turhollow et al., 2010). Some sweet sorghum varieties that could be use in Nigeria include SWSV 2006-3, SPV 422, SSV2 and SW Dansadau 2007. Integrating sweet sorghum with sugarcane could also be a sustainable strategy (Kim and Day 2011; Cutz et al., 2013; Cutz and Santana 2014).

A decentralised sweet sorghum biofuel production system where all processing take place at the farm except dehydration is said to reduce emission and use of non-renewable energy by 39% and 27%, respectively, as compared to corn (Olukoya et al., 2015). Sweet sorghum was also reported to be useful for phytoremediation (Sathya et al., 2016). SWOT analysis was conducted on sweet sorghum (Rutz and Janssen 2012). The analysis showed that the crop has more strengths (26) than weaknesses (24) and more opportunities (24) than threats (19) if considered for biofuel production. This work has shown that with sweet sorghum alone, enough ethanol could be processed to meet the demand for blending with petrol. Though the results showed that the crop could suitably be cultivated in many parts of the country, selecting most appropriate variety may be necessary.

Breeding and variety improvement of sugarcane is a continuous programme in Nigeria (Gana 2017). Intercropping could be one of the sustainability strategies for sugarcane production. Though sugarcane growth may also be supressed before intercrops such as benniseed, guinea corn, soybean and ground nut are harvested, this agronomic practice in Nigeria is said to greatly supress weed growth (Ndarubu et al., 2000). Similar effect was reported in India (Gujja et al., 2009) and Australia (Park et al., 2010). Because of the sugarcane demand for refine sugar in Nigeria, use of bagasse may be more sustainable than the sugarcane syrup. A research on the Nigerian sugarcane bagasse showed non-catalytic pyrolysis may produce higher biofuel yields than catalytic pyrolysis (Rabiu et al., 2017).

Because cassava is said to have high seasonal independence (Ohimain 2012) and the volume of its production in Nigeria (the country is the largest producer in the world), the sustainability of using the crop for biofuel may be strong. Nigerian varieties such as 30572 and 4(2)1425 are said to give yields higher than 25 tonnes ha^{-1} (Adekunle et al., n. d.). The amount of cassava peel generated in the country could be used to process more than 1 billion litres of biofuel (Anyanwu et al., 2015). Running hydrolysis of cassava starch and cassava cellulose simultaneously and fermenting the sugars released from both the sugars and cellulose (Co-SSF) was recommended as the most cost effective technology for commercial scale cassava biofuel processing (Zhang et al., 2013). Other sustainability strategies include intercropping with such crops as maize and cowpea (Njoku et al., 2010; ICS-Nigeria and IITA n. d.), conventional ridge tillage (Odjugo 2008; FAO 2013), on-farm ethanol production (Ogbonna and Okoli 2013) and integrating microalgal cultures to deal with cassava processing wastewaters (de Carvalho et al., 2018).

Selective breeding, improved cultivation practices and exploitation of optimum environment had all contributed to the progressive increase in oil palm (Lai et al., 2012). Therefore, though very suitable areas for cultivating the crop were mapped in this work, yields are believed to double with improved management, pest and disease control, improved harvesting methods, reduced losses from spoilage during transportation and storage and improved processing technologies (Verheye 2010). Rival and Levang (2014), suggested that some of the sustainability strategies for oil palm plantation development include agroforestry, patchwork development and ecological planning.

Among the policy focus and strategies of the Nigeria’s revised National Policy on the Environment, was on encouraging sustainable use of farmlands, forests and wetlands outside protected areas (FME 2016). Following the guidelines set by the Roundtable on Sustainable Palm Oil (RSPO), a system of planning is implemented to prevent certain areas from being converted to plantations (Shehu and Clarke 2020). According to WWF et al., (2012) these include areas regarded as of High Conservation Value (HCV) or High Carbon Stocks (HCS). RSPO is a multi-stakeholder initiative launched in 2004 with about 10 members and was said to have reached 1500 members consisting of growers, processors, traders, manufacturers, banks, investors, retailers, government organisations, nature conservation NGOs and developmental (social) NGOs (WWF et al., 2012; Rival and Levang 2014).

In Nigeria, through research conducted over many decades, NIFOR had demonstrated suitable intercropping systems which allows simultaneous cultivation of oil palm and food crops in the early years of the palm establishment and with no adverse effects. Some of the crops used were Soybeans, Cassava, Maize and Pineapple and this provides space for food production on palm lands, providing some offsets of the initial investment in oil palm which has long gestation period (Verheye 2010). It was reported that a World Bank project failed in several parts of the oil palm producing areas of Nigeria due to the Bank's insistence on sole crop which the small holder farmers refused to adopt. The Bank thus allowed for the palm/arable crops intercropping as a sound system for both economic and agronomic benefits (NIFOR 2018). Tao et al., (2017) opined that with increasing demand for oil palm and changing climate, optimising ecology and agricultural practices become highly essential to maintaining sustainable intensification of the crop's production.

Jatropha found in Nigeria is of the wild species (Yammama 2009), but the crop is said to be suitable for efficient domestication (Achten et al., 2014). The crop was used in Cape Verde for erosion control (Orwa et al., 2009). San Diego start-up (SGB) was able to domesticate Jatropha using molecular genetics and DNA sequencing and has been growing hybrid strains of the plant called Jatropha 2.0 from which biofuel quantities competitive with petroleum at $99 a barrel can be produced (Woody 2013). Genomic wide selection supported with recurrent selection was recommended as an appropriate strategy for Jatropha breeding (Laviola et al., 2017).

Jatropha yield is said to be directly related to plant spacing (Yammama 2009), genetics, ecological conditions, plant age, management, propagation method, pruning, fertilisation and irrigation (Wahl et al., 2012). Jatropha had long been found to be suitable for intercropping especially at the early stage of growth before it start bearing fruits (Elbehri et al., 2013). Shade loving herbal plants such as tomatoes, chilly, onions, pepper and other medicinal/perfume plants were suggested as appropriate intercrops (Deeb n. d.). Jatropha plants propagated generatively (through seeds) were believed to be suitable for erosion control and mitigation (Achten et al., 2007). Jatropha cake calcinated or activated with potassium hydroxide is said to be useful as catalyst for processing biodiesel from jatropha oil (Kamel et al., 2018).

The central point of focus around whether sustainability measures are strong or weak is the substitutability between the economy and the environment or between natural capital and manufactured capital (Ayres et al., 1998). Strong sustainability perspectives hold that certain human actions entails irreversible consequences, while weak sustainability suggests technological innovations and monetary compensation for environmental degradation (Pelenc et al., 2015). Therefore, strong sustainability encourages conservation of the irreplaceable stocks of natural capital for the sake of future generations, while weak sustainability suggests that the total value of the aggregate stock of capital should be at least maintained or ideally increased for future generation.

The conflict between these two interpretations are said to be more evident in the context of centralised than decentralised systems of decision-making (Ayres et al., 2001). These interpretation could relate to the concept of resilience in the sense that strong sustainability may denotes better resilience than weak sustainability though, it was opined that weak sustainability is an illegitimate interpretation because it leads to contradiction with acknowledged assumption that the current state is unsustainable (Biely et al., 2018). However, if applied to biofuel context, these debates and interpretations could expand thinking and widen understanding of the complexity of decisions needed to achieve resilient biofuel programme.

A review and analysis of the latest available evidence was conducted to provide greater clarity and understanding of the environmental impacts of different liquid biofuels (Jeswani et al., 2020). Their review showed that the LCA studies are highly situational and dependent on many factors such as type of feedstock, production route, data variations and methodological choices. This means that resilience of biofuel programme would highly depend on the context (conceptual and spatial), choices or decisions made and the implementation strategies adopted. In other words, though the results from this work suggested that it is possible to adopt strong sustainability measures for biofuel programme in Nigeria, local contexts would greatly determine the validity of that suggestion. A review article has been published in the Journal of Renewable and Sustainable Energy Reviews discussing biodiesel production in Nigeria (Shehu and Clarke 2020). Due to the maximum words count limit for the thesis, the abstract of the article is attached in appendix XI because the whole article could not have space to be accommodated. Link to the article is also provided in the appendix.

7.2.6 Resilience thinking in biofuel business

How to approach the complexity and dynamism of the world systems is one of the cardinal questions related to resilience. It was already shown in the previous subsections how biofuel as a system is complex and how its sustainability differs with respect to this complexity. The complexity widens considering that biofuel itself, as a system, is a part of a bigger energy system, which is also a part of larger societal system. Changes at either lower or higher-level system affects other lower or larger systems and the degree may depend on the strength of the connection between the systems and subsystems. In section 3.7.1, an attempt was made to identify and model predictable factors that may allow for compromise and those that may not with respect to optimising biofuel production in Nigeria. Some factors are unpredictable such as shocks related to social, economic or environmental dynamisms. Resilience thinking is crucial to prepare a system to absorb these shocks. These relate to the concept of sustainability touched upon in the previous subsection which aims to strike a balance between efficiency in production based on the prevailing conditions and anticipating future trends. These could be optimisms such as new sustainable management approaches or challenges such as avoiding unwanted impact on food production.

On the other hand, resilience thinking is a way of thinking about change with respect to resources. It ensures that the inevitability of change (both slow and drastic) is recognised and that ignoring or resisting this dynamism increases the vulnerability of the system, restricts opportunities and reduces the availability of options in the event of shocks (Walker 2006). Models designed for optimum efficiency may not actually promote resilience, and thus would require strategies that ensure their results are applied painstakingly. Though not as an absolute solution, in the following subheadings, strategies are suggested that may support a resilient biofuel programme in Nigeria, informed by the experiences of the current research and a synthesis of current literature and media reports. Because biofuel crops would differ with regards to these aspects, the discussions would be tailored towards one crop or the other. This ensures that the suggestions are in line with transparency in supporting spatial decisions related to biofuel development in Nigeria.

7.2.6.1 Climate smart agriculture

It was mentioned in section 1.5 that most of the successful and voluminous biofuel production around the world are based on agricultural crops. Crops were also adopted in Nigeria as part of the feedstock sources. Resilient production of these crops is therefore fundamental to the resilience of the biofuel industry. Suggestions were provided in chapter five of the areas that may be very suitable for cultivating each of the five biofuel crops considered in this work. Cultivation of these crops in these very suitable areas would only be sustainable and resilient if climate smart agriculture is adopted. Climate Smart Agriculture (CSA) is an innovative agricultural approach aimed at achieving increased agricultural productivity and income, enhancing adaptation and building resilience of people and agriculture systems to climate change, and reducing or avoiding GHG emissions (FAO 2021). Some of the aspects of CSA include management of land and crops to balance crop production and livelihood needs with priorities for adaptation and mitigation, conserving ecosystem services and providing services to farmers and land managers that enable them to manage risks and impacts of climate change.

Some CSA practices reported in the south-western Nigeria include planting cover crops, minimum tillage practice, soil amendments, conversion of waste to compost, agro-forestry, resource conservation and use of other agro-weather related initiatives (Olorunfemi et al., 2020). It was reported that ActionAid was supporting programmes in Nigeria that aim to enhance climate resilient sustainable agriculture (OSSAP-SDGs 2017). A study in south-eastern Nigeria showed that some constraints the farmers face in coping with climate change could be grouped into cultural impediments, weak knowledge/information, ineffective agricultural extension services and weak policy and institution (Chukwuone and Amaechina 2021). Liverpool-Tasie et al., (2020), examined climate change perceptions among economic agents along the maize-poultry value chain in Nigeria. They found that economic actors along the value chain (not only the farmers) perceive those climate events that have direct effects on their activities. However, very few of the actors believe that their economic activities have negative effects on the environment and contribute to climate change. This suggests the need for enhanced awareness among economic agents about the effects of their agriculture related activities to encourage adoption of climate smart practices. Adopting CSA in biofuel crops production will ensure resilience in feedstock supply.

7.2.6.2 Feedstock supply model

Generally, there are five feedstock supply models – pure plantation, pure out-growers, pure farmer owned, combined plantation and out-growers and farmer participation. The choice of the best model or combination of models depends on the costs and risks involved. The best balance was suggested to be combination of plantation and out-growers which is more common than the other models (Hagman and Nerentorp 2011). Though the out-grower scheme is also associated with logistics costs, initial capital investment in plantation will be much higher. Also, smallholder systems do not cause many land issues as land transfer is usually not involved, unlike in plantation systems where incidental land rights problems arise, in some cases, even where formal legal procedures seemed to have been followed in the acquisition process (Eijck et al., 2013).

However, it was recommended to investigate impact of land pressure on vulnerable groups to ensure their access to land is not tampered with due to Jatropha development (Eijck et al., 2010) because Jatropha promotion may increase land value which may increase pressure on land due to increased demand (Salfrais 2010). Farmer centred models reach more people and have less negative impact on biodiversity than plantation models (Eijck et al., 2010). On the other hand, pure out-growers entails less control on the feedstock supply and with sparsely distributed out-growers, feedstock collation increases production costs. And functional policy machineries must be put in place to protect out-growers from the impacts of lack of commitment to contract agreement on the part of firms and ensure market for farmers' produce (Kunda-Wamuwi et al., 2017).

Large plantations in one place increases the risks of crop failures, but the very much discussed invasiveness potential of biofuel plants was investigated in Burkina Faso and the results of the experiments failed to provide convincing evidence on the invasiveness of Jatropha or any significant negative impacts on the surrounding environment (Negussie et al., 2014). Comparatively, out-grower schemes provide more part time seasonal jobs and income, while plantations create more permanent full time jobs (Eijck et al., 2013). Which supply model to adopt depends on the local context, the existing policies and the priorities of the investors.

7.2.6.3 Carbon sequestration as part of land use management

Plants use carbon dioxide in the photosynthetic process. Jatropha plantations are said to possess all the requirements for carbon credit but may create a negative baseline if natural forests are cleared to pave way for the plantations (Hagman and Nerentorp 2011). Therefore, the 'carbon debt' due to clearing forests needs to be paid off first before any earnings can be accounted for. A carbon debt of 34.7 tonnes C ha^{-1} was reported as a result of converting fallow land to Jatropha plantation in Mali though, converting cropland did not show significant carbon loss (Degerickx et al., 2016). However, where food crops are replaced by Jatropha, food security may negatively be impacted especially where market for the Jatropha seeds is not present (Eijck et al., 2010).

Sequestration rate of 2.3 tonnes C ha^{-1} was reported after the 4^{th} growing year (Degerickx et al., 2016) which the authors attributed to adverse growing conditions and poor local management and considered as very low rate compared to other regions. Some 32 month old jatropha plants were found to have sequestered 13.0 tonnes C ha^{-1} in Malaysia (Firdaus et al., 2010). In Senegal, a model revealed that jatropha plantations may be valuable carbon sinks with a storage capacity of 5.7 kg $tree^{-1}$ (Diédhiou et al., 2017). Jatropha carbon sequestration rate was said to be higher than that of the waste lands vegetation (Achten et al., 2007) and that emission was found to be decreased where biofuel crops are cultivated on degraded lands or former farmlands (Wahl et al., 2012).

Differences in the original land use and probably plantation management practices might determine whether carbon sequestration will be positive or negative. In Ethiopia, plantations established to rehabilitate degraded forest lands were found to have sequestered 6.94 tonnes C ha^{-1} considering both above and below ground stocks. While those in live fences were found to have sequestered 178.56 tonnes C ha^{-1} for both above and below ground stocks (Yirdaw et al., 2013). In Botswana, using an LCA for all activities involved in jatropha cultivation in frost and drought prone areas, it was found that the crop's emission and absorption are 17 and 21 tonnes of CO_2eq. ha^{-1}, respectively, presenting a 4 tonnes surplus of absorption over a period of 4 years (Ishimoto et al., 2018). Thus, for rehabilitation of degraded lands, jatropha plantations may not present issues of carbon debt for land use change. Rather, it will turn a source of carbon emission (deforested land) to a carbon sink (Jatropha Plantation). In other words, adoption of Jatropha for biodiesel production will assist in decreasing deforestation and increasing economic growth (Faufu et al., 2014). In this regards and based on a pilot project in Mozambique, recommendation was given that development of jatropha plantation should be on grasslands with low biodiversity value and trees (Smit et al., 2018).

LCA of different jatropha production systems indicated that decentralised production of straight vegetable oil (SVO) using feedstock from hedgerow and intercropping seems to be the most promising option (Baumert et al., 2018) showing less land conversions (Eijck et al., 2013). In Nigeria, pre-exploited agricultural lands were recommended to be given emphasis for feedstock production (Galadima et al., 2011). On a more extreme view, a conclusion was made that the most promising option for Jatropha biofuel to sustainably contribute to GHGs reduction is producing feedstock on marginal lands with reduced use of artificial fertilisers and pesticides (Eijck et al., 2010). In general, integrating carbon sequestration in planning biofuel programme would be a significant strategic thinking towards making the programme resilient. As mentioned earlier, the models developed in this work may assist in implementing an efficient biofuel system but not necessarily a resilient one. Therefore, policies should be formulated such that strategies like carbon sequestration are embedded and enforced to ensure resilience of the system.

7.2.6.4 Policy objectives and institutional realignment

Policy is identified as one of the major non technological barriers to successful and sustainable commercialisation of biofuels in Africa in general (Sekoai and Yoro 2016) and Nigeria in particular (Ohimain 2013; Balogun 2015). This is a fundamental problem that differentiates the developed from developing countries in terms of harnessing this important source of energy (Amigun et al., 2006). The scope of this research work is limited such that detail review of all the biofuel-related policies in Nigeria may not be possible. However, the objectives of biofuel development and adoption were broadly classified into ecological, economic and social (Abila 2012). Reviews were conducted on the main Nigeria biofuel policy (Anyaoku 2007) and many gaps were identified and recommendations were presented (Abila 2012; Ohimain 2013).

Ecological policy objectives of biofuel adoption in Nigeria constitute rehabilitation of the environment in the southern parts of the country through phytoremediation, fight against desert encroachment in the norther fringes through reforestation/afforestation, as well as other ecological benefits that can be derived from ecologically planned biofuel crops plantations such as biodiversity conservation, drought control and carbon sequestration. Social policy objectives constitute job creation, rural development through diversified rural livelihoods and infrastructure, increasing rural access to electricity, ensuring the sustainability of fuel supply as well as improving health quality. Economic policy objectives include provision of employment, diversifying energy sources, return on investment, infrastructure development, economic growth and inter sectoral integration.

A biofuel programme implementation strategy is hereby recommended for Nigeria. Adopting the timeframe of the SDGs, a 15-year implementation period, 3 stage approach is hereby recommended. The purpose of this recommendation is to demonstrate how policy objectives and implementing institutions could be realigned to support a successful and resilient biofuel programme. The stages should be categorised into initial stage, take-off stage and consolidation. The 3 broad policy objectives should be given priority based on the stage of implementation, assuming 5 years is enough for reviewing achievements recorded at each stage.

The initial stage should give priority to ecological objectives. Capturing environmental benefits was recommended as a practical step to develop Nigeria’s biofuel potential (Akande 2009). At this stage, biofuel crops should be developed as a means of environmental rehabilitation rather than a for-profit business. Jatropha can serve this purpose as it can be cultivated in both northern and southern Nigeria. At this stage also the blend mandate must be very low due to expected low feedstock supply. The Take-off stage should then focus on economic objectives especially return on investments. It is expected that after 5 years of taking good care of the plantations, reasonable levels of yields could be achieved (Wahl et al., 2012; Deeb n. d.) and reasonable amounts of feedstock could be generated which might be enough to seed the market and the blend mandate could be increased. Within these 2 stages it is expected that enough experience is accumulated and the farming techniques could be replicated paving the way for the third stage. At the consolidation stage, all the three broad objectives could be given certain consideration though the market forces may play greater role, supported and controlled by policy reviews. Both land suitability and site optimality models would be needed at all the stages because it is expected that both feedstock cultivation and biofuel processing would continue to expand through the stages. Recommendations on resilient biofuel industry would also be useful in implementing this strategy.

Bottlenecks are typically found in developing countries when it comes to policy implementation especially where the policy has high sectoral dimensionality. Based on the recommendations in the previous paragraph, the Federal Ministry of Environment (FME) should spearhead the implementation of the first stage. As part of its revised policy on the environment, the Ministry is set to establish 1500 km by 15 km of 'green wall' in the frontline states to halt the advance of the Sahara desert (FME 2016). This can be implemented using biodiesel crops. The Federal Ministry of Agriculture and Rural Development (FMA&RD) should play the role of providing high yielding seed varieties, technical support in such areas as agronomic practices and farming systems.

Funding could be explored with a bias towards local sources such as use of the Ecological Fund, Central Bank of Nigeria (CBN) intervention fund, Federal and States Governments appropriations and the private investors that have long term investment portfolios. International sources such as International Development Partners (IDPs), green bonds and other lending mechanisms could also be explored. Oil and gas industry players, both public and private could participate at this stage as long-term investors or provide funding as part of their corporate social responsibility (CSR) service. The policy could also mandate the oil and gas players to commit certain percentage of their CSR to establishing plantations in their host communities.

Stage 2 may be more appropriate for private sector participation and NNPC should spearhead the implementation of this stage in two ways. The plantations developed from the first stage could be transferred to investors through business agreements. On the other hand, the ownership of the plantations could be retained as it is from the first stage, but a feedstock supply business agreement entered into between the plantation owners and the biodiesel processors. As discussed in section 7.3.6.2, the feedstock production and supply model to be adopted may depend on what is considered as most efficient and sustainable between the farmers and the processors. The consolidation stage may be characterised with expansion of plantations, widening the processing scales and reviewing up the blend mandate. This may not seem to be simple but with careful policy synthesis involving all the stakeholders, backed up with required commitment, the biofuel programme is bound to be successful and sustainable (Patrick et al., 2013).

7.3 Areas for further research

From the foregoing discussions, there may be need for further research into how effectively scientific evidence from SMCAs could be matched with the reality of their implementation context. This should form part of the paradigm shift towards explicit SMCAs. For example, a focus on the solutions from SMCAs should not concentrate on only how the results of the analysis vary geographically but should also provide enough alternatives to allow for varied implementation contexts. In other words, while the explicit paradigm suggests that the results of SMCAs present how the results could differ from one geographical area to another within the study area, the SMCAs should also be explicit about the realities of implementing the decision recommendations. These realities may be multi-dimensional such that there may be administrative bottlenecks, cultural hinderances, social reluctances or political summersaults. Therefore, SMCAs results, especially for localised spatial scopes, should be explicit about these realities. Further research is thus needed on how this can best be approached. For example, how political summersaults militate against designing and implementing SMCAs and what could be the possible solutions.

Because there were no data for such other restricted areas as grazing reserves and areas reserved for cultural values, further research is needed within the identified potentially available areas to ascertain their true availability. These areas such as shrub, woodland or degraded unprotected forests could be explored for cultivating biofuel crops, but there may be a need to conduct empirical research to determine the carbon debt that will accumulate from using any of those types of available land areas. Exploring shrub land areas may be expected to have less carbon debt than woodland and exploring woodland may be expected to have less carbon debt than forest areas. The identified unprotected forest areas could further be investigated to determine their potential for being used in extending protected areas. This is especially so in the south where forest vegetation is more extensive. There may be degraded unprotected forests that may be available for biofuel crops within the identified available land areas. Furthermore, these results opened areas for further empirical research to determine the productivity of these identified land areas for each of the crops under different agronomic practices. There are other biofuel crops not considered in this work. However, this work provides the basis for conducting similar assessment of the other biofuel crops such as switchgrass and sugar beet.

As discussed in subsection 7.2.3, because not all stakeholders were involved in this work, a further localised assessment of stakeholders would be needed after a location of focus is identified. For example, the relevant actors should be determined and their interests or power must be assessed in relation to the project to determined their degree of relevance and basis for their participation. Because it is expected that the spatial scope would be narrowed at this stage, the challenges for involving all the necessary stakeholders might be surmountable. Though optimising efficiency might oppose resilience measures, an assessment could be carried out to chart best ways to incorporate resilience in implementing the optimised solutions.

Chapter Eight – Conclusion

8 Chapter Eight – Conclusion

This work highlighted how to improve the application of spatial multi-criteria analysis as a support for location-related decisions in Nigeria, particularly in the context of biofuel development. This was demonstrated through best practice application of science to simulate optimal biofuel processing sites. It is therefore concluded that this work will serve as a point of reference for the state-of-the-art application of spatial multi-criteria evaluation analysis, not only for the biofuel industry, but also for other sectors of environmental management such as river basin management, grazing route planning or settlement planning. One of the most important aspects of the state-of-the-art application is the involvement of key stakeholders. Without the input of experts in the study area, the resulting spatial analyses may contain high degrees of inaccuracy and suggested solutions may not be practically implementable. It is, therefore, concluded that there is great value to effectively factoring stakeholder perspectives into spatial decision-making of this kind and scale and that AHP showed great promise as a technique for systematic handling of these inputs.

It is concluded from this work that biofuel crop cultivation in Nigeria could conveniently be expanded in to the more than 19 million hectares of either shrub or woodland without compromising food production or encroaching into protected areas. Furthermore, with less than two million hectares of land demand for biofuel programme in the country, there is sufficient unused land to meet this demand, but also to allow for additional expansion for more than two decades, assuming small annual land demand increase for the programme. This will not conflict with ambitions to expand protected areas, which could be tailored towards unprotected forest areas in the country. The criteria assessment followed a strong sustainability approach by ensuring all non-compromising variables for which datasets were available were treated as non-substitutable.

It is concluded from this work that spatial decision-making can be enhanced by including more detailed criteria in SMCA, which would reflect a better understanding of the application context. In the case of establishing biofuel crops or expanding existing biofuel production in Nigeria, time and energy would be saved by focussing on areas of higher suitability for a given crop. The specificity of the conditions in Nigeria meant that determining crop suitability in this setting required development of new models based on context-specific information, rather than extrapolating from studies in other settings.

Emissions due to transporting feedstock can undermine the carbon emission reductions from biofuel. Therefore, minimising feedstock transport distance and blending at the processing site (that is eliminating transportation of the processed biofuels) are crucial to its carbon savings. Based on feedstock potential within 100 km, Maiduguri and Gombe petroleum depots were found to have potential to process enough biofuel to meet the bioethanol demand for implementation of the Nigeria's blending policy. Within the same feedstock supply distance, Ibadan, Suleja and Gombe may be needed to process enough biodiesel for the blending policy. However, because three different yields scenarios and three distance scenarios were adopted, there is wider room for comparing optimal solutions to accommodate different local contexts and implementation situations. These options could also provide some pivots for adjustments that may be needed to accommodate greater range of stakeholders or handling changes in criteria weights.

The sustainability of feedstock production, though dependent on the type of feedstock adopted, could be enhanced through compliance with sustainability guidelines developed by such organisations as RSB and RSPO. This must be combined with improved varietal selection, optimum environment, improved cultivation practices and striking a balance between the quest for increased agricultural productivity and environmental conservation, integrating principles of both land sharing and land sparing. The sustainability of biofuel processing would also depend on the feedstock adopted but would generally be enhanced through selection of environmentally and economically appropriate processing technologies that would allow for balance between economic returns and environmental conservation.

Overall, the long-term success of a biofuel programme in Nigeria would be greatly enhanced by adopting resilience thinking, exemplified by an emphasis on adaptability, diversity and sustainability rather than prioritising maximum yields and one-dimensional optimisation of biofuel production. This will require embracing climate smart agriculture, designing and/or adopting a suitable feedstock supply model, effectively managing diverse land uses and realigning policy objectives to work with existing environmental, social and economic capabilities. This will create a conducive environment for stimulating an effective and environmentally responsible biofuel programme, delivering energy source diversification, economic growth and sustainable development for Nigeria.

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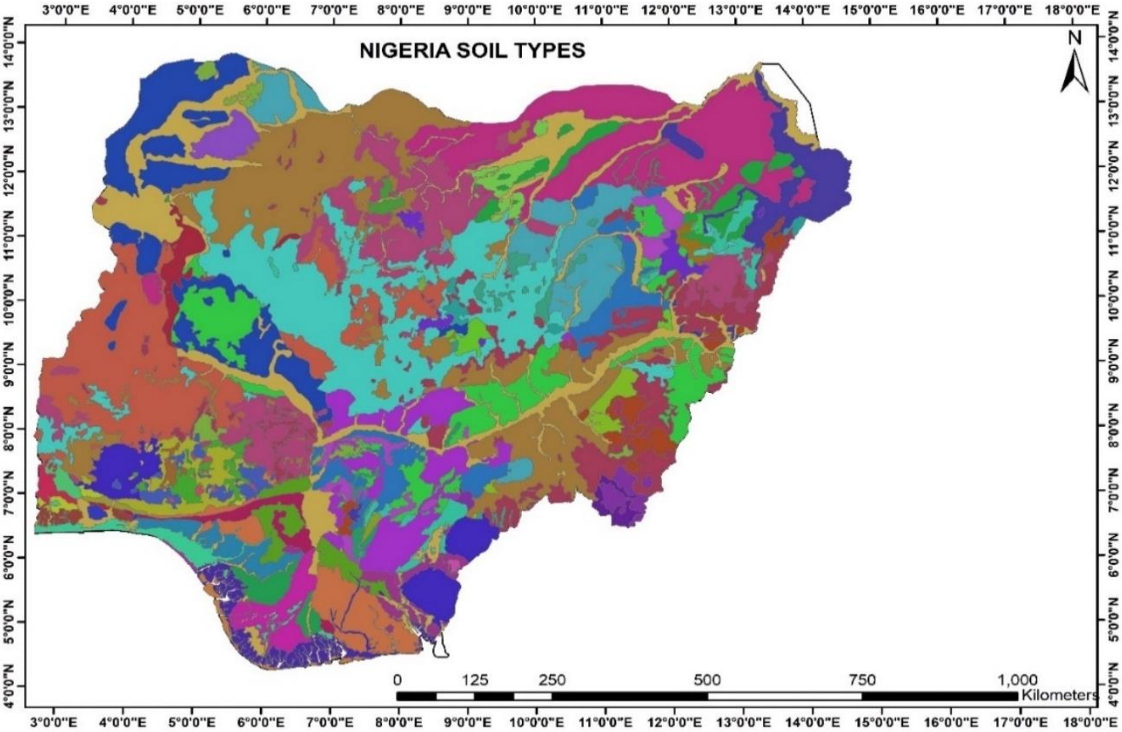
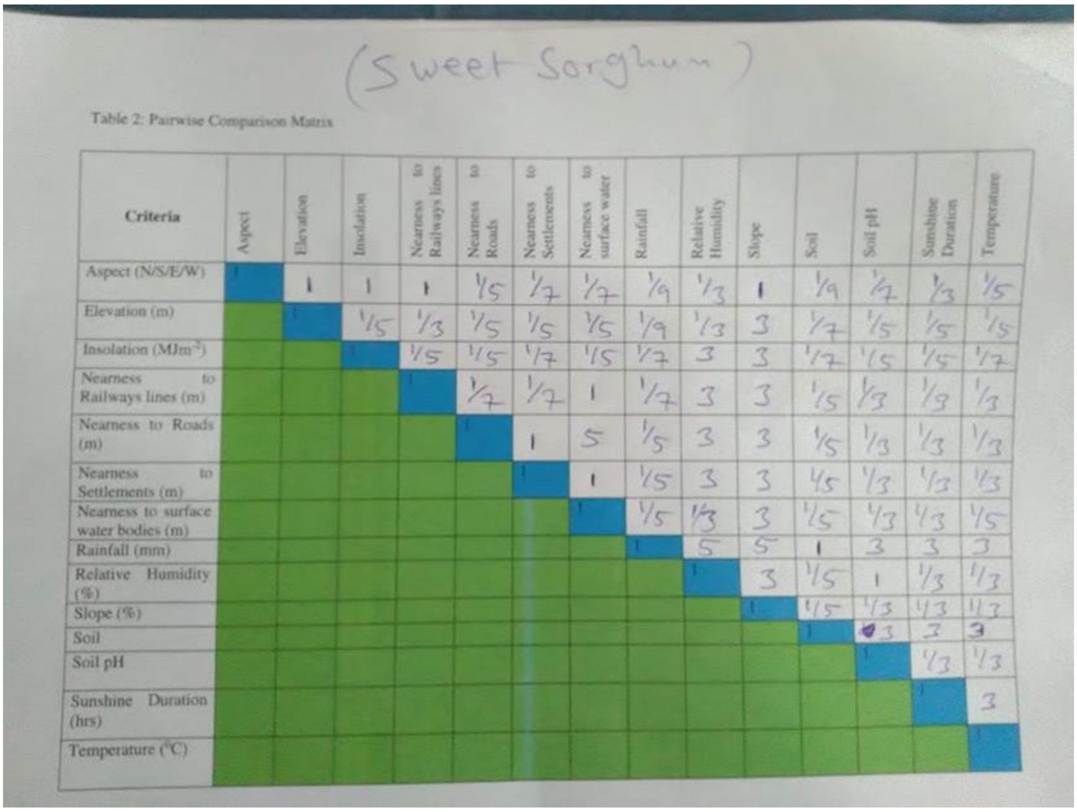
Appendix I: Soil dataset description



Appendix II: Pairwise comparison matrix tables



(Sweet Sorghum)

Table 2: Pairwise Comparison Matrix

Criteria	Aspect	Elevation	Insolation	Nearness to Railways lines	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1	1	1	1	1/5	1/7	1/7	1/9	1/3	1	1/9	1/7	1/3	1/5
Elevation (m)		1	1/5	1/3	1/5	1/5	1/5	1/9	1/3	3	1/7	1/5	1/5	1/5
Insolation (MJm⁻²)			1	1/5	1/5	1/7	1/5	1/7	3	3	1/7	1/5	1/5	1/7
Nearness to Railways lines (m)				1	1/7	1/7	1	1/7	3	3	1/5	1/3	1/3	1/3
Nearness to Roads (m)					1	1	5	1/5	3	3	1/5	1/3	1/3	1/3
Nearness to Settlements (m)						1	1	1/5	3	3	1/5	1/3	1/3	1/3
Nearness to surface water bodies (m)							1	1/5	1/3	3	1/5	1/3	1/3	1/5
Rainfall (mm)								1	5	5	1	3	3	3
Relative Humidity (%)									1	3	1/5	1	1/3	1/3
Slope (%)										1	1/5	1/3	1/3	1/3
Soil											1	3	3	3
Soil pH												1	1/3	1/3
Sunshine Duration (hrs)													1	3
Temperature (°C)														1

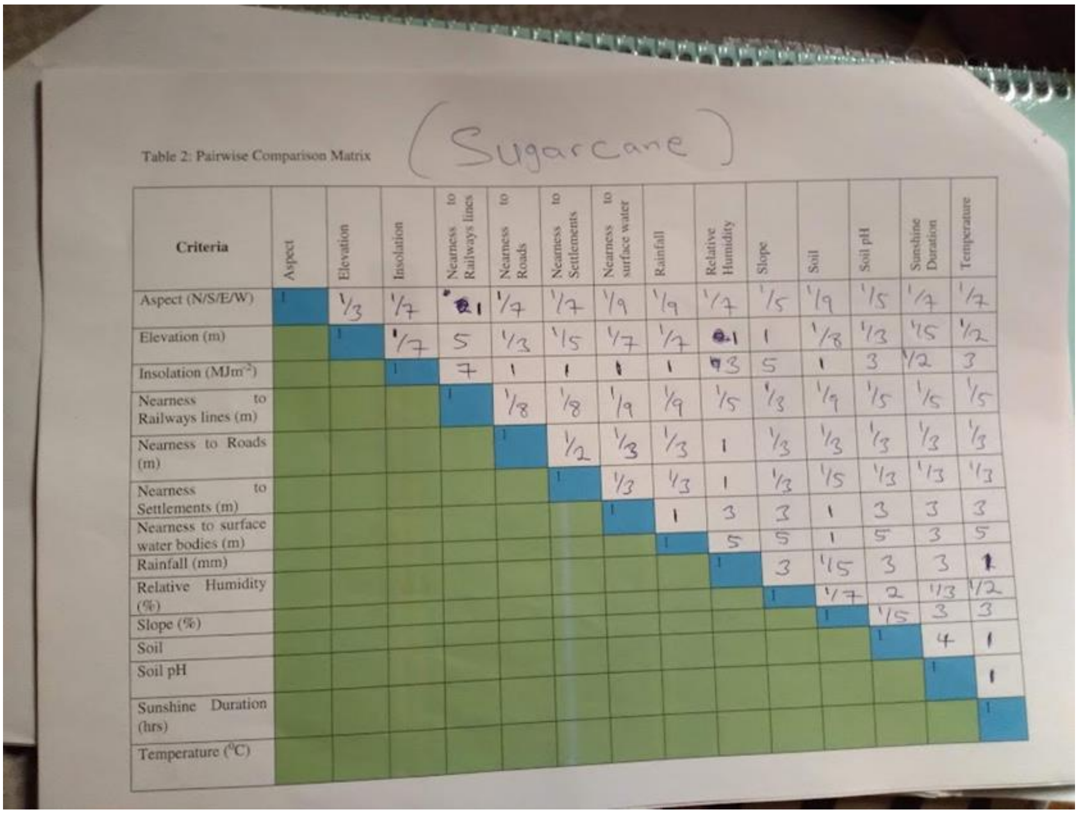


Table 2: Pairwise Comparison Matrix

(Sugarcane)

Criteria	Aspect	Elevation	Insolation	Nearness to Railways lines	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1	1/3	1/7	1	1/7	1/7	1/9	1/9	1/7	1/5	1/9	1/5	1/7	1/7
Elevation (m)		1	1/7	5	1/3	1/5	1/7	1/7	1	1	1/8	1/3	1/5	1/2
Insolation (MJm⁻²)			1	7	1	1	1	1	3	5	1	3	1/2	3
Nearness to Railways lines (m)				1	1/8	1/8	1/9	1/9	1/5	1/3	1/9	1/5	1/5	1/5
Nearness to Roads (m)					1	1/2	1/3	1/3	1	1/3	1/3	1/3	1/3	1/3
Nearness to Settlements (m)						1	1/3	1/3	1	1/3	1/5	1/3	1/3	1/3
Nearness to surface water bodies (m)							1	1	3	3	1	3	3	3
Rainfall (mm)								1	5	5	1	5	3	5
Relative Humidity (%)									1	3	1/5	3	3	1
Slope (%)										1	1/7	2	1/3	1/2
Soil											1	1/5	3	3
Soil pH												1	4	1
Sunshine Duration (hrs)													1	1
Temperature (°C)														1

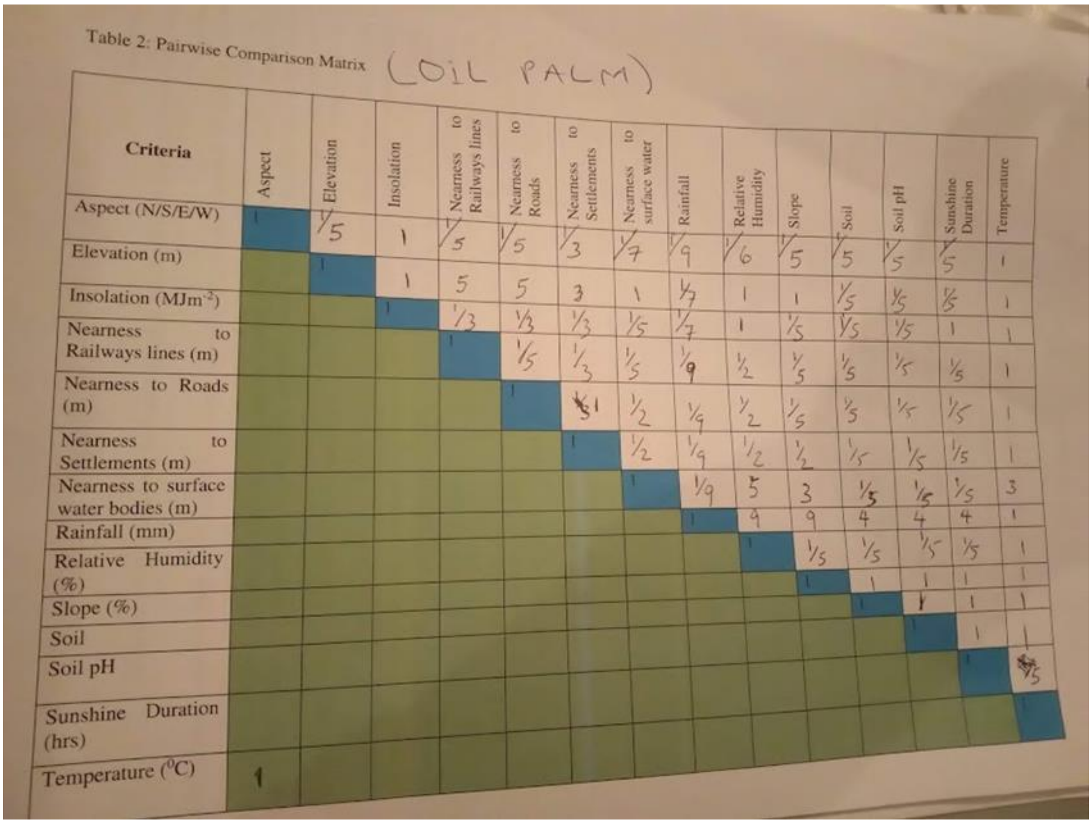
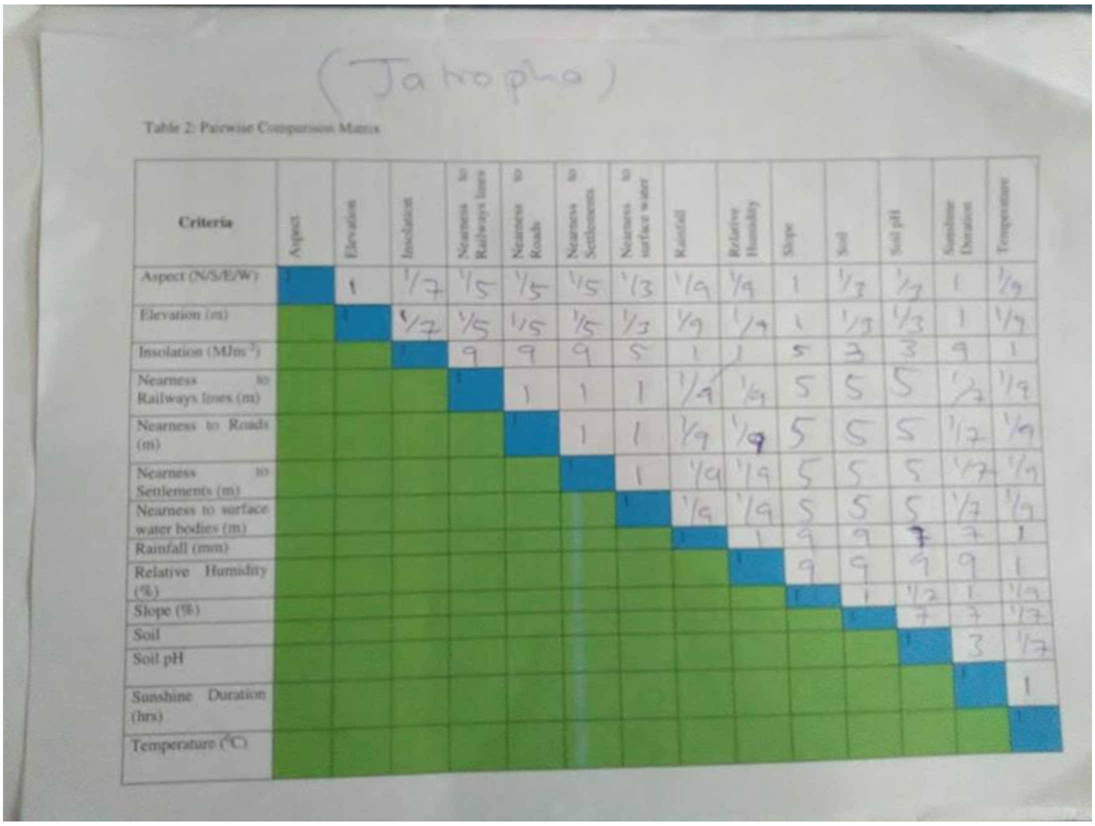


Table 2: Pairwise Comparison Matrix (OIL PALM)

Criteria	Aspect	Elevation	Insolation	Nearness to Railways lines	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1	1/5	1	1/5	1/5	1/3	1/7	1/9	1/6	1/5	1/5	1/5	1/5	1
Elevation (m)		1	1	5	5	3	1	1/7	1	1	1/5	1/5	1/5	1
Insolation (MJm^{-2})			1	1/3	1/3	1/3	1/5	1/7	1	1/5	1/5	1/5	1	1
Nearness to Railways lines (m)				1	1/5	1/3	1/5	1/9	1/2	1/5	1/5	1/5	1/5	1
Nearness to Roads (m)					1	~~1/3~~ 1	1/2	1/9	1/2	1/5	1/5	1/5	1/5	1
Nearness to Settlements (m)						1	1/2	1/9	1/2	1/2	1/5	1/5	1/5	1
Nearness to surface water bodies (m)							1	1/9	5	3	1/5	1/5	1/5	3
Rainfall (mm)								1	9	9	4	4	4	1
Relative Humidity (%)									1	1/5	1/5	1/5	1/5	1
Slope (%)										1	1	1	1	1
Soil											1	1	1	1
Soil pH												1	1	1
Sunshine Duration (hrs)													1	1/5
Temperature (^{0}C)	1													1



(Jatropha)

Table 2: Pairwise Comparison Matrix

Criteria	Aspect	Elevation	Insolation	Nearness to Railways lines	Nearness to Roads	Nearness to Settlements	Nearness to surface water	Rainfall	Relative Humidity	Slope	Soil	Soil pH	Sunshine Duration	Temperature
Aspect (N/S/E/W)	1	1	1/7	1/5	1/5	1/5	1/3	1/9	1/9	1	1/3	1/3	1	1/9
Elevation (m)		1	1/7	1/5	1/5	1/5	1/3	1/9	1/9	1	1/3	1/3	1	1/9
Insolation (MJm^{-2})			1	9	9	9	5	1	1	5	3	3	9	1
Nearness to Railways lines (m)				1	1	1	1	1/9	1/9	5	5	5	1/7	1/9
Nearness to Roads (m)					1	1	1	1/9	1/9	5	5	5	1/7	1/9
Nearness to Settlements (m)						1	1	1/9	1/9	5	5	5	1/7	1/9
Nearness to surface water bodies (m)							1	1/9	1/9	5	5	5	1/7	1/9
Rainfall (mm)								1	1	9	9	7	7	1
Relative Humidity (%)									1	9	9	9	9	1
Slope (%)										1	1	1/2	1	1/9
Soil											1	7	7	1/7
Soil pH												1	3	1/7
Sunshine Duration (hrs)													1	1
Temperature (^{0}C)														1

Appendix III: Classified criteria values for suitability classes

Suitability class levels for Sugarcane based on the criteria indicators

S/N	Criteria (Suitable)	Most (1)	Very (2)	Moderately (3)	Less (4)	Least (5)
1	Soil	5-7, 10, 44-46 & 55.	2-4, 8-9, 12, 15-20, 23, 25-27, 37, 41-43, 47-48 & 50-53.	1, 11, 13-14, 22, 24, 28-30, 32-35, 38 & 49.	21, 31, 36, 40 & 54.	39 & 56.
2	Soil pH	6.0 – 7.0	5.5 – 6.0 7.0 – 7.5	5.0 – 5.5 7.5 – 8.0	4.5 – 5.0 8.0 – 8.5	Others
3	Rainfall/Water (mm)	1100 – 1500	900 – 1100 1500 – 1800	700 – 900 1800 – 2100	600 – 700 2100 – 2400	Others
4	Temperature (˚C) -Maximum	29 – 31	27 – 29 31 – 33	25 – 27 33 – 35	23 – 25 35 – 36	Others
5	Relative Humidity (%)	65 – 85	55 – 65	45 – 55	35 – 45	Others
6	Elevation (m asl)	0 – 500	500 – 1000	1000 – 1500	1500 – 2000	Others
7	Slope (%)	≤ 2.5	2.5 – 5.5	5.5 – 8.5	8.5 – 12	Others
8	Aspect in direction (Bearing in degrees)	S, SSE & SSW (157.5 – 205.5) & Flat (-1)	SE & ESE (112.5 – 157.5) SW & WSW (202.5 – 247.5)	E & ENE (67.5 – 112.5) W & WNW (247.5 – 292.5)	NE & NNE (22.5 – 67.5) NW, NNW (292.5 – 337.5)	N (0 – 22.5 & 337.5 – 360)
9	Insolation	6.0 – 6.4	5.5 – 6.0	5.0 – 5.5	4.5 – 5.0	Others
10	Sunshine ($hday^{-1}$)	All	-	-	-	-
11	Nearness to water (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
12	Nearness to roads (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
13	Nearness to settlements (Km)	0 – 15	15 – 30	30 – 45	45 – 60	Others
14	Nearness to railways (Km)	0 – 50	50 – 100	100 – 150	150 – 200	Others

Suitability class levels for Cassava based on the criteria indicators

S/N	Criteria (Suitable)	Most (1)	Very (2)	Moderately (3)	Less (4)	Least (5)
1	Soil	8-9, 12, 17, 19-21, 23-24, 27, 31, 36-37, 40-42, 47-48 & 51-52.	7, 11, 13, 18, 29, 35, 43-46, 49-50 & 53.	3-4, 6, 10, 14-16, 22, 26, 28, 30, 34, 38-39 & 54-55.	1-2, 5, 25, & 32-33.	56.
2	Soil pH	5.5 – 7.0	5.0 – 5.5 7.0 – 7.5	4.5 – 5.0 7.5 – 8.0	4.2 – 4.5 8.0 – 8.2	Others
3	Rainfall/Water (mm)	1500 – 1700	1200 – 1500 1700 – 2000	900 – 1200 2000 – 2300	600 – 900 2300 – 2600	Others
4	Temperature (˚C) -Maximum	27 – 30	25 – 27 30 – 32	23 – 25 32 – 34	21 – 23 34 – 36	Others
5	Relative Humidity (%)	70 – 80	60 – 70 80 – 85	50 – 60	40 – 50	Others
6	Elevation (m asl)	200 – 700	100 – 200 700 – 1200	0 – 100 1200 – 1700	1700 – 2200	Others
7	Slope (%)	0 – 1	1 – 3	3 – 5	5 – 8	Others
8	Aspect in direction (Bearing in degrees)	S, SSE & SSW (157.5 – 205.5) & Flat (-1)	SE & ESE (112.5 – 157.5) SW & WSW (202.5 – 247.5)	E & ENE (67.5 – 112.5) W & WNW (247.5 – 292.5)	NE & NNE (22.5 – 67.5) NW, NNW (292.5 – 337.5)	N (0 – 22.5 & 337.5 – 360)
9	Insolation	6.0 – 6.4	5.5 – 6.0	5.0 – 5.5	4.5 – 5.0	Others
10	Sunshine ($hday^{-1}$)	All	-	-	-	-
11	Nearness to water (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
12	Nearness to roads (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
13	Nearness to settlements (Km)	0 – 15	15 – 30	30 – 45	45 – 60	Others
14	Nearness to railways (Km)	0 – 50	50 – 100	100 – 150	150 – 200	Others

Suitability class levels for Oil palm based on the criteria indicators

S/N	Criteria (Suitable)	Most (1)	Very (2)	Moderately (3)	Less (4)	Least (5)
1	Soil	1, 8 & 27.	9, 12-13, 22-26, 30, 38, 41, 47-49 & 51-52.	2, 7, 11, 14, 17-21, 29, 31, 34-37 & 42-46.	3-5, 15-16, 32, 39-40, 50, 53-54 & 56.	6, 10, 28, 33 & 55.
2	Soil pH	5.5 – 6.0	5.2 – 5.5 6.0 – 7.0	4.9 – 5.2 7.0 – 7.5	4.5 – 4.9 7.5 – 8.0	Others
3	Rainfall/Water (mm)	1500 - 2000	1200 – 1500 2000 – 2300	900 – 1200 2300 – 2600	600 – 900 2600 – 2900	Others
4	Temperature (˚C) -Maximum	29 – 32	27 – 29 32 – 34	25 – 27 34 – 36	23 – 25 36 – 38	Others
5	Relative Humidity (%)	80 – 85	75 – 80	70 – 75	65 – 70	Others
6	Elevation (m asl)	300 – 500	200 – 300 500 – 800	100 – 200 800 – 1100	0 – 100 1100 – 1400	Others
7	Slope (%)	0 – 4	4 – 12	12 – 23	23 – 38	Others
8	Aspect in direction (Bearing in degrees)	S, SSE & SSW (157.5 – 205.5) & Flat (-1)	SE & ESE (112.5 – 157.5) SW & WSW (202.5 – 247.5)	E & ENE (67.5 – 112.5) W & WNW (247.5 – 292.5)	NE & NNE (22.5 – 67.5) NW, NNW (292.5 – 337.5)	N (0 – 22.5 & 337.5 – 360)
9	Insolation	6.0 – 6.4	5.5 – 6.0	5.0 – 5.5	4.5 – 5.0	Others
10	Sunshine ($hday^{-1}$)	All	-	-	-	-
11	Nearness to water (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
12	Nearness to roads (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
13	Nearness to settlements (Km)	0 – 15	15 – 30	30 – 45	45 – 60	Others
14	Nearness to railways (Km)	0 – 50	50 – 100	100 – 150	150 – 200	Others

Suitability class levels for Oil palm based on the criteria indicators

S/N	Criteria (Suitable)	Most (1)	Very (2)	Moderately (3)	Less (4)	Least (5)
1	Soil	8-9, 12-13, 20-24, 26-30, 35-38, 41-42 & 47-53.	7, 17-19, 25, 31, 34, 40, 43-46, 54 & 56.	1-4, 6, 11, 15-16, 32, 39 & 55.	5, 10 & 14.	33
2	Soil pH	6.0 – 8.0	5.5 – 6.0 8.0 – 8.5	5.0 – 5.5	4.5 – 5.0	Others
3	Rainfall/Water (mm)	900 – 1300	700 – 900 1300 – 1600	500 – 700 1600 – 1900	300 – 500 1900 – 2200	Others
4	Temperature (˚C) -Maximum	25 – 28	28 – 31 23 – 25	31 – 33 21 – 23	34 – 35	Others
5	Relative Humidity (%)	75 – 85	65 – 75 85 – 95	55 – 65	45 – 55	Others
6	Elevation (m asl)	0 – 500	500 – 900	900 – 1400	1400 – 1800	Others
7	Slope (%)	7 – 22	0 – 7	22 – 27	27 – 40	40 – 55
8	Aspect in direction (Bearing in degrees)	S, SSE & SSW (157.5 – 205.5) & Flat (-1)	SE & ESE (112.5 – 157.5) SW & WSW (202.5 – 247.5)	E & ENE (67.5 – 112.5) W & WNW (247.5 – 292.5)	NE & NNE (22.5 – 67.5) NW, NNW (292.5 – 337.5)	N (0 – 22.5 & 337.5 – 360)
9	Insolation	6.0 – 6.4	5.5 – 6.0	5.0 – 5.5	4.5 – 5.0	Others
10	Sunshine ($hday^{-1}$)	All	-	-	-	-
11	Nearness to water (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
12	Nearness to roads (Km)	0 – 5	5 – 10	10 – 15	15 – 20	Others
13	Nearness to settlements (Km)	0 – 15	15 – 30	30 – 45	45 – 60	Others
14	Nearness to railways (Km)	0 – 50	50 – 100	100 – 150	150 – 200	Others

Appendix IV: Reclassified criteria maps

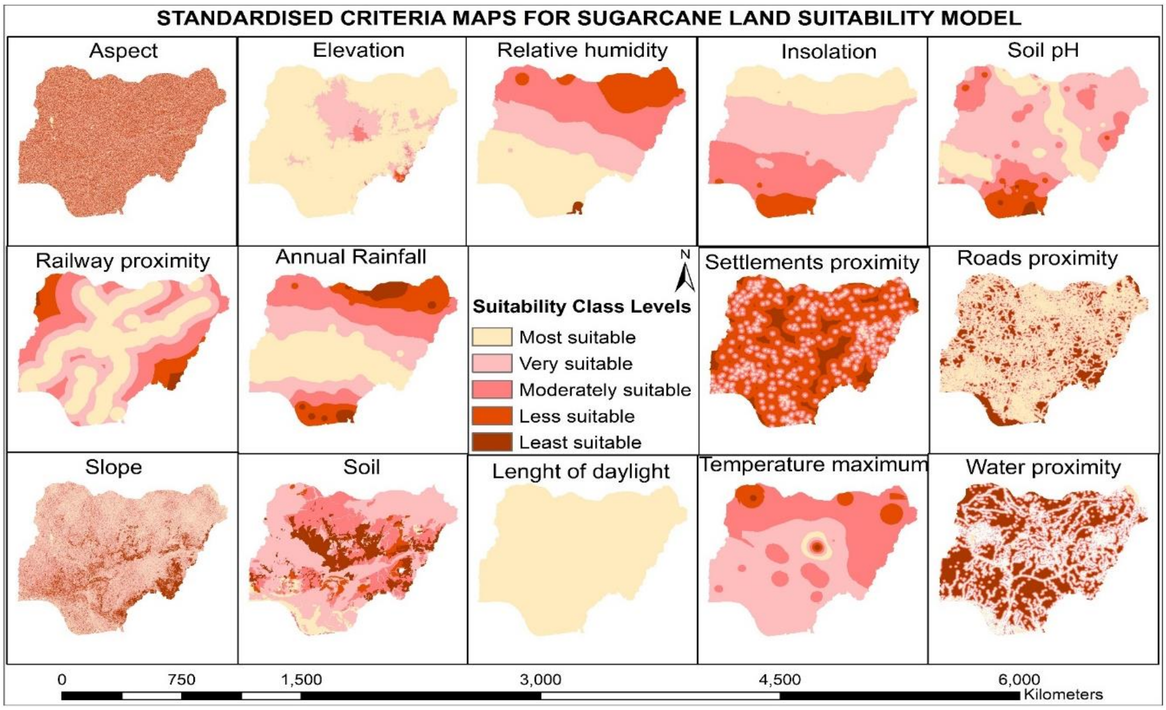


Figure 0.1: Reclassified criteria suitability maps for Sugarcane

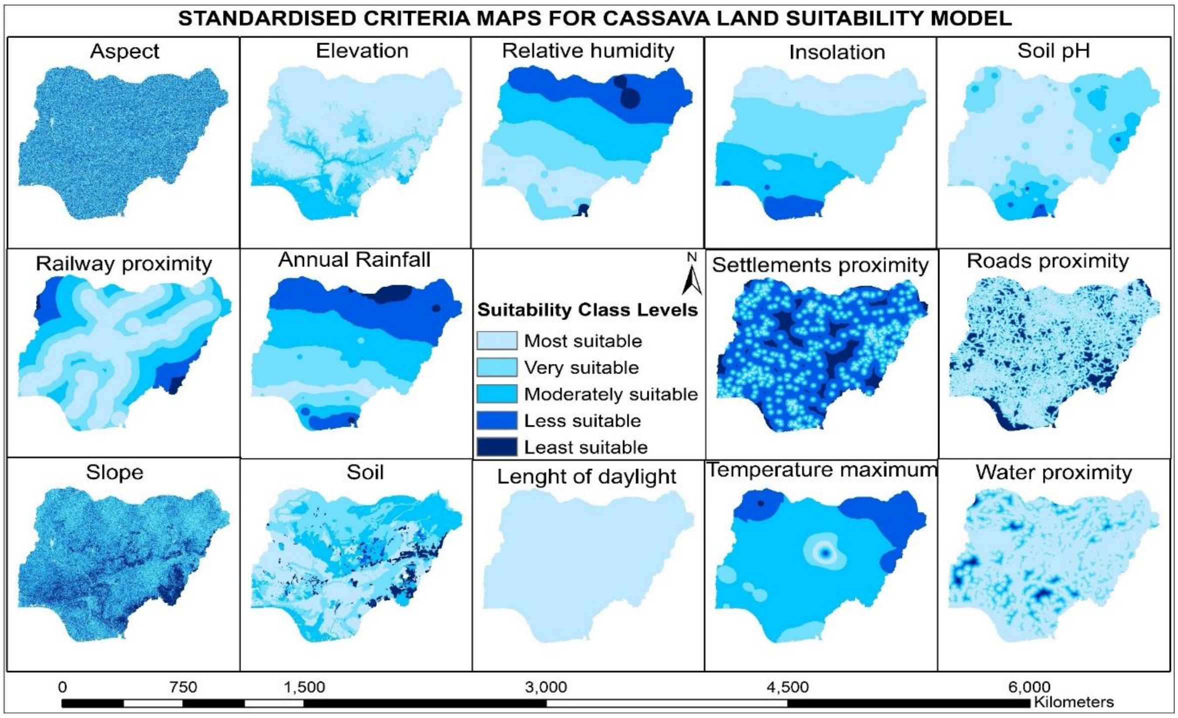


Figure 0.2: Reclassified criteria suitability maps for Cassava

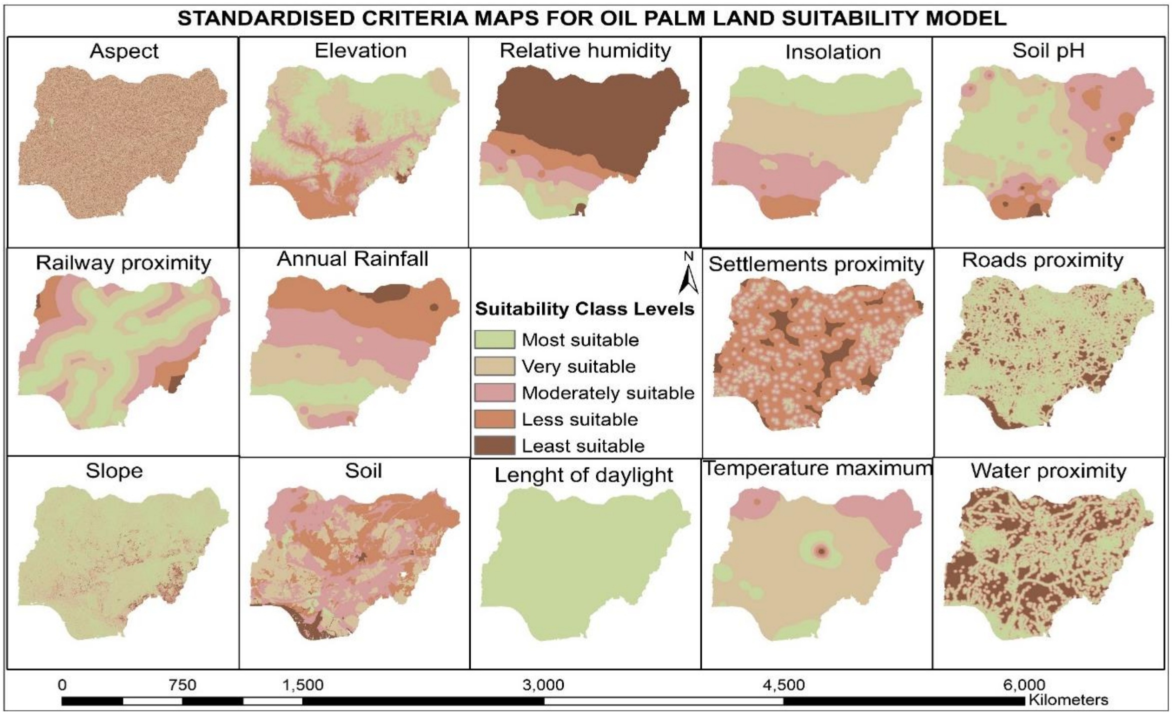


Figure 0.3: Reclassified criteria suitability maps for Oil palm

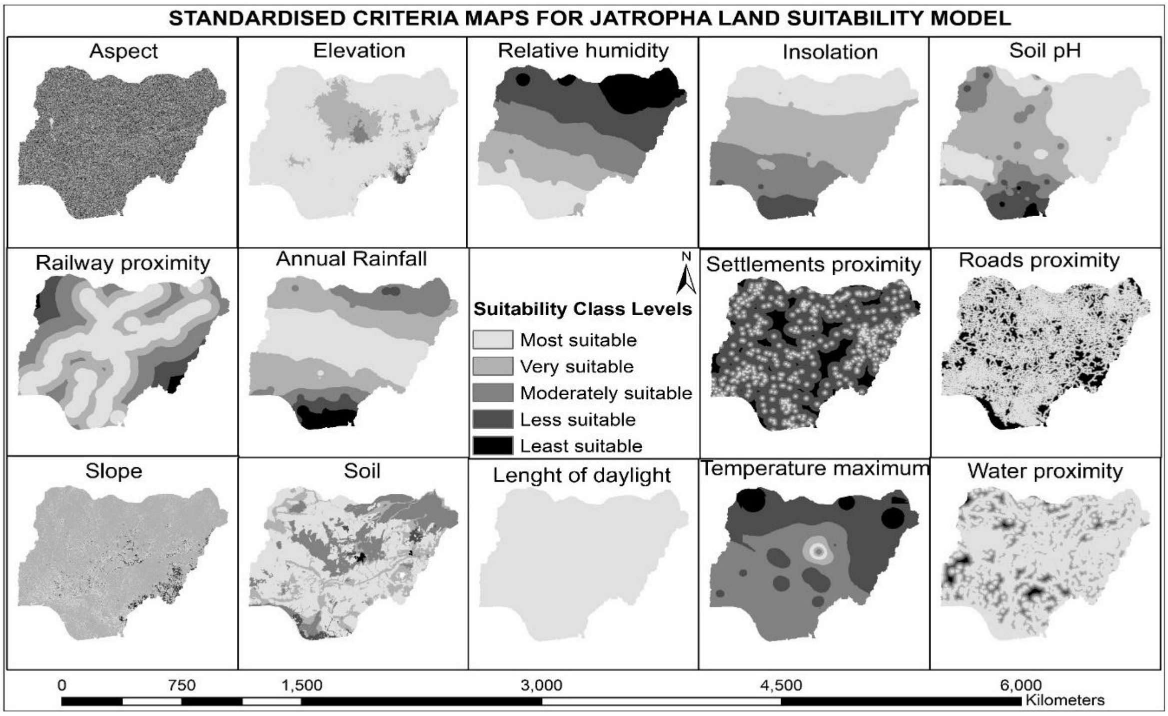
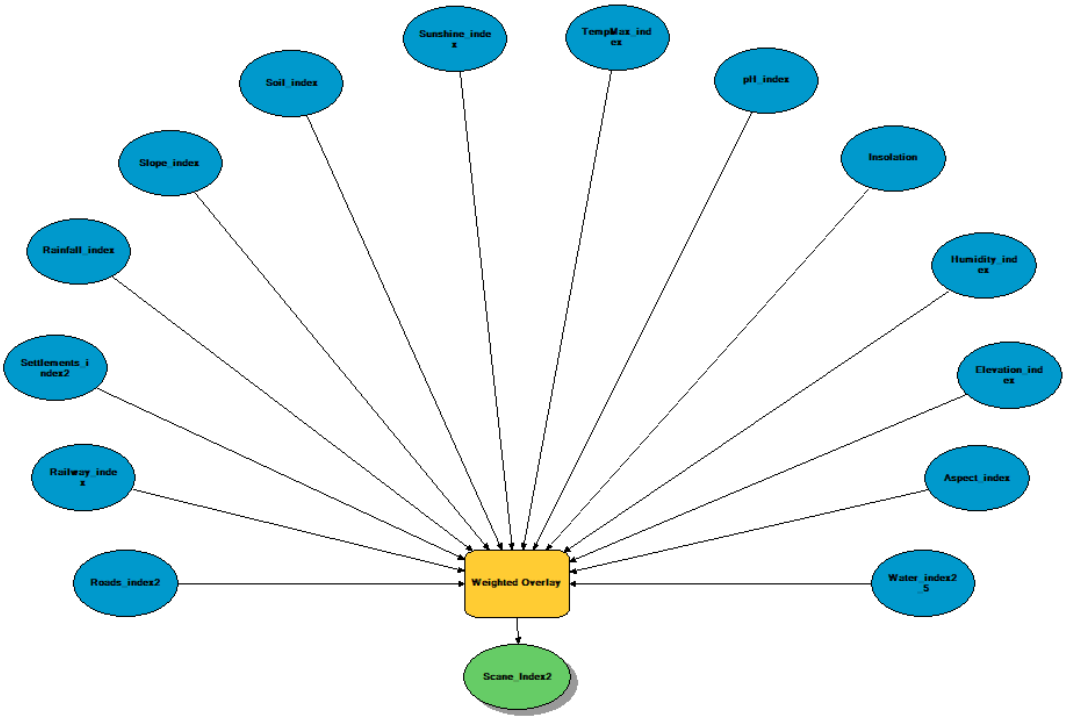


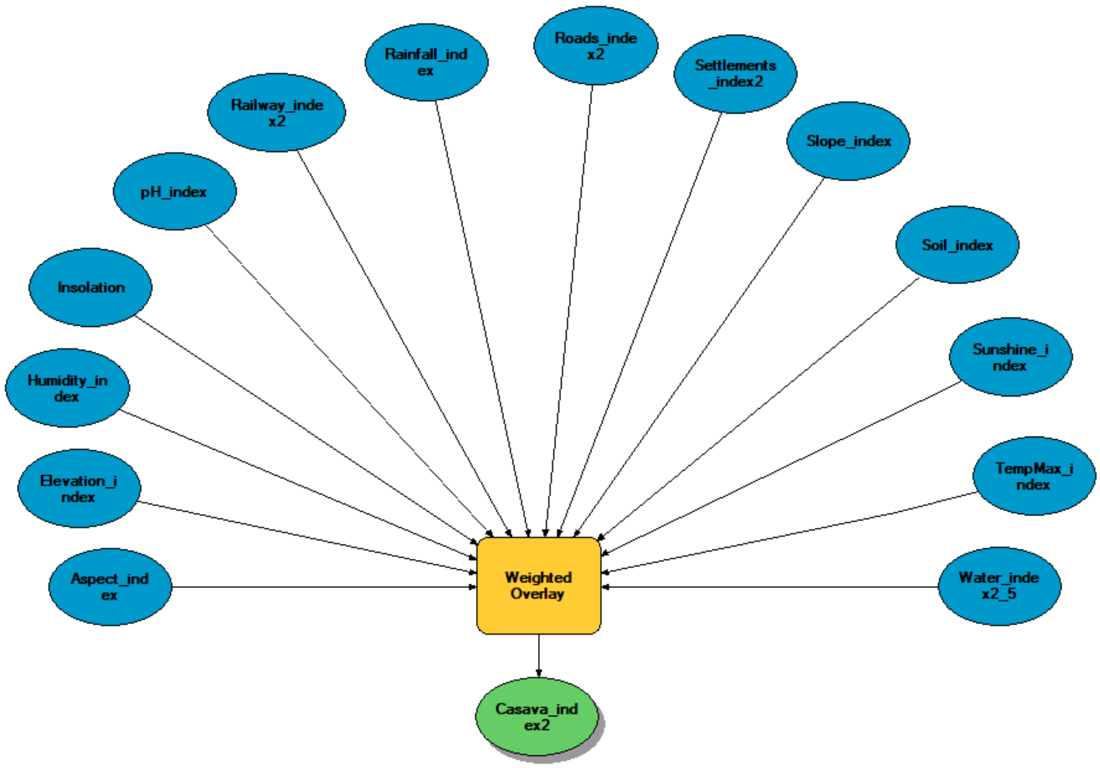
Figure 0.4: Reclassified criteria suitability maps for Jatropha

Appendix V: Land suitability models

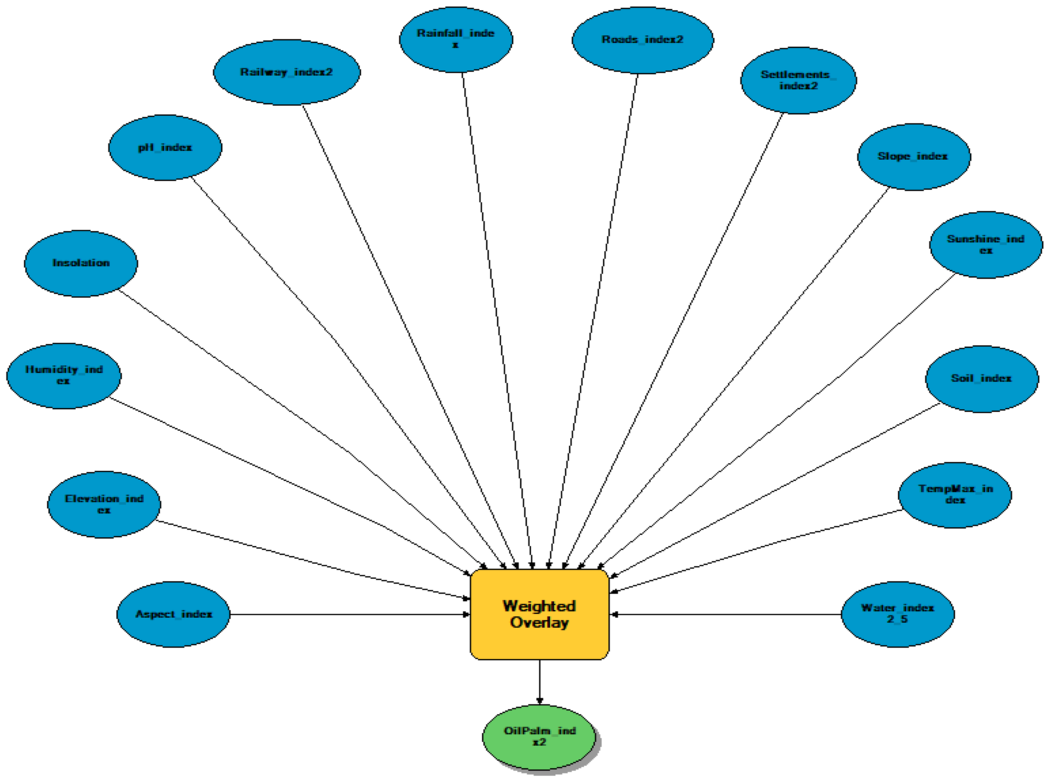
Sugarcane



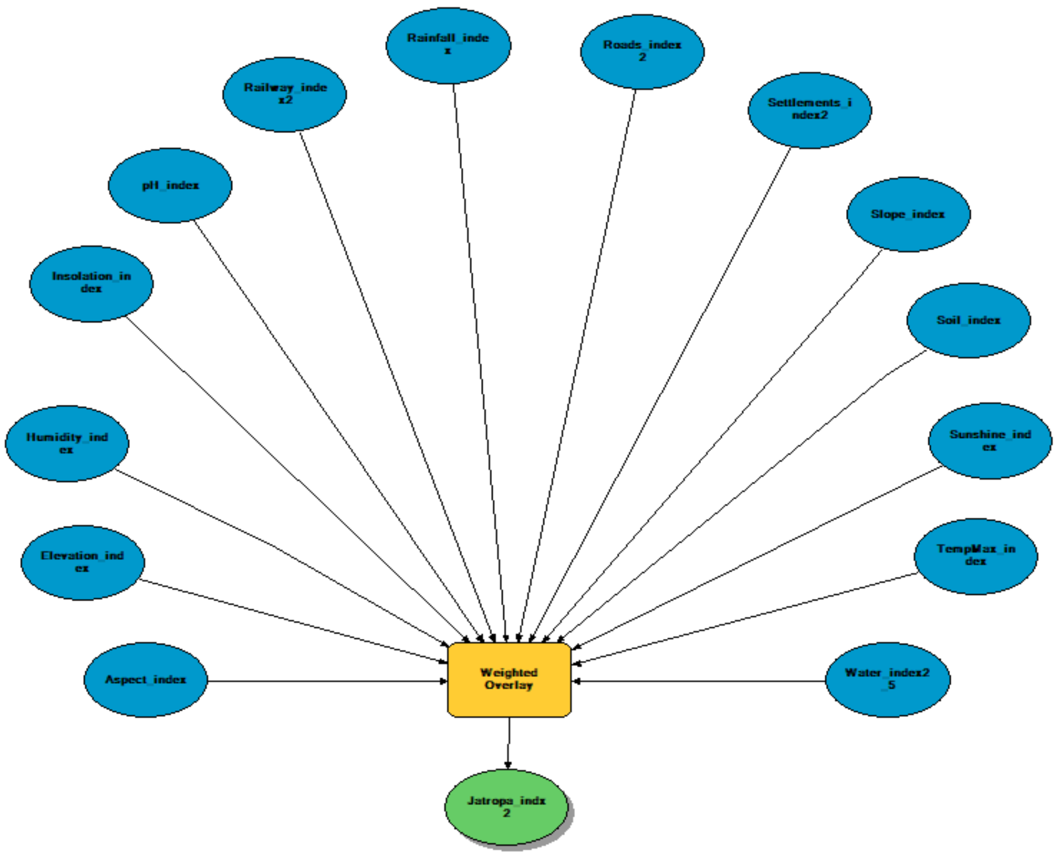
Cassava



Oil palm

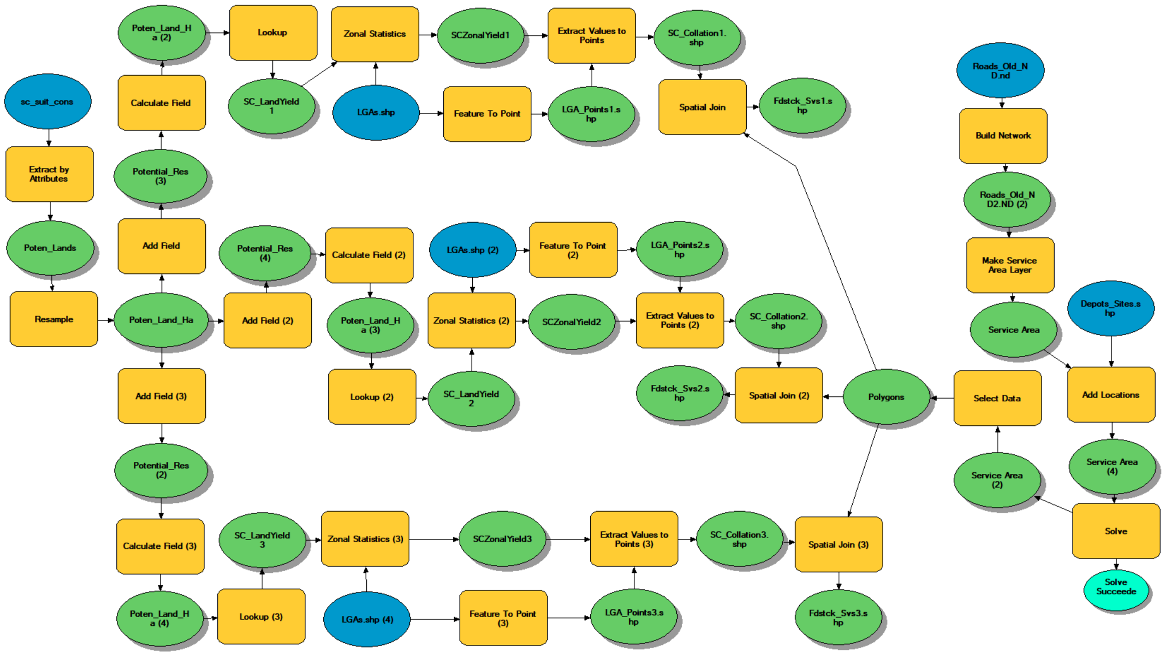


Jatropha

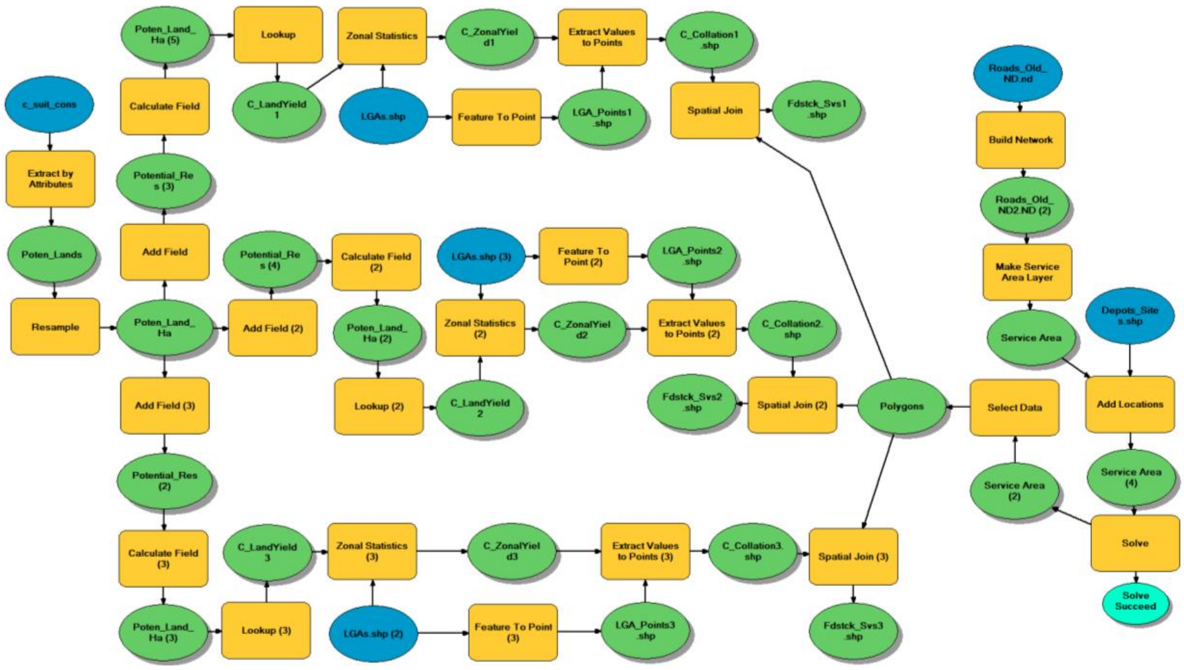


Appendix VI: Site optimality models

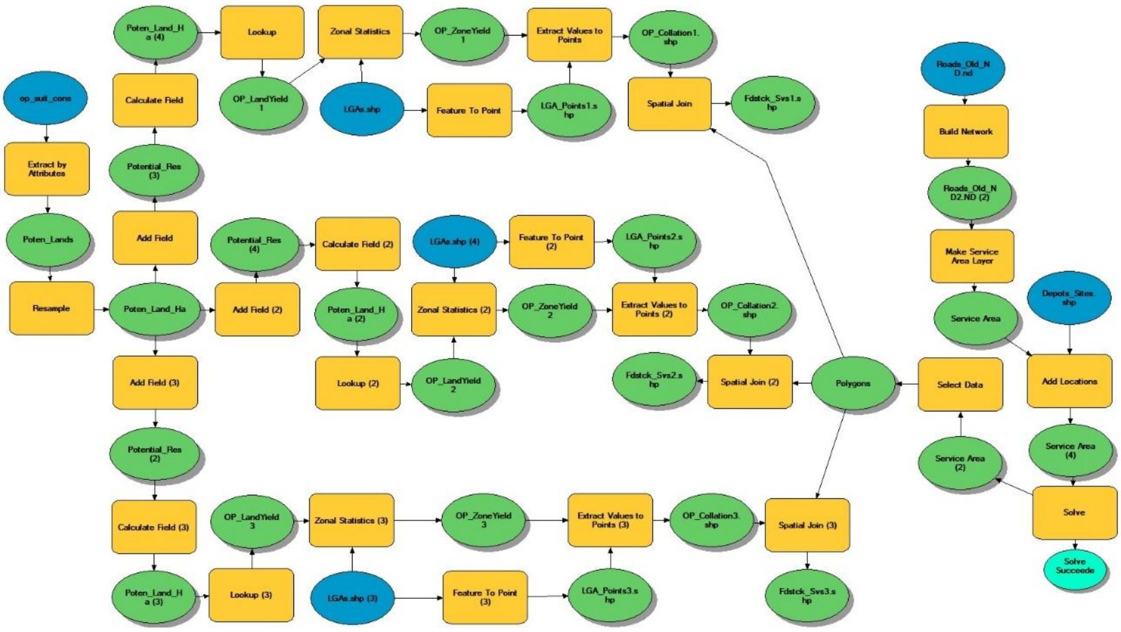
Sugarcane



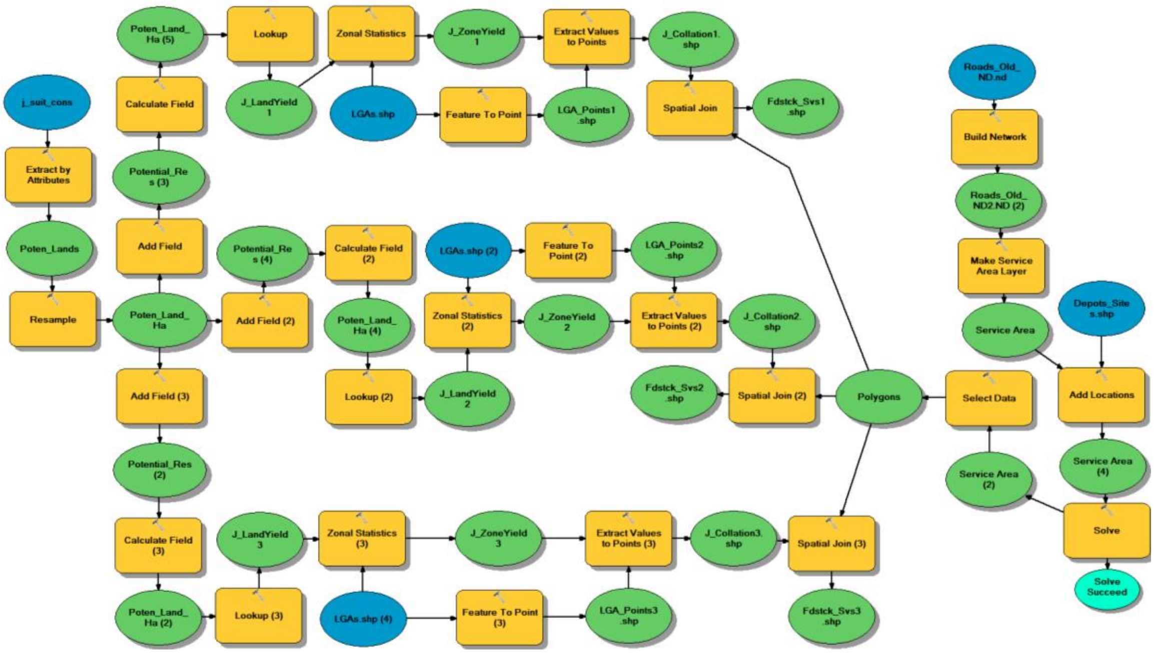
Cassava



Oil palm



Jatropha



Appendix VII: Expenditure for collecting information for training and accuracy assessment point

BREAKDOWN OF THE FIELD WORK EXPENDITURE (ATTACHMENT 2)						
DAYS	**STATE**	**TEAM MEMBERS**	**TRANS (NGN)**	**ACCOMODATION (NGN)**	**FEEDING (NGN)**	**ALLOWANCE**
DAY 1 SUNDAY 1ST-07-2018	NIGER	**Basiru Shehu Gwandu** **Suleiman Abdulkadir** **Abdullahi Hamza A.** **Chukwuemeka Ofili T.**	**5,000**	**10000**	**6000**	**10000**
DAY 2 MONDAY 2ND-07-2018	NIGER		**5000**	**10000**	**6000**	**10000**
DAY 3 TUESDAY 3RD-07-2018	KEBBI		**5000**	**10000**	**6000**	**10000**
DAY 4 WEDNESDAY 4TH-07-2018	KEBBI		**5000**	**10000**	**6000**	**10000**
DAY 5 THURSDAY 5TH-07-2018	SOKOTO		**5000**	**10000**	**6000**	**10000**

DAY 6 FRIDAY 6TH-07-2018	SOKOTO		**5000**	**10000**	**6000**	**10000**
DAY 7 SATURDAY 7TH-07-2018	KATSINA		**5000**	**10000**	**6000**	**10000**
DAY 8 SUNDAY 8TH-07-2018	KATSINA		**5000**	**10000**	**6000**	**10000**
DAY 9 MONDAY 9TH-07-2018	KADUNA		**5000**	**10000**	**6000**	**10000**
DAY 10 TUESDAY 10TH-07-2018	KADUNA		**5000**	**10000**	**6000**	**10000**
DAY 11 WEDNESDAY 11TH-07-2018	PLATEAU		**5000**	**10000**	**6000**	**10000**
DAY 12 THURSDAY 12TH-07-2018	PLATEAU		**5000**	**10000**	**6000**	**10000**

DAY 13 FRIDAY 13TH-07-2018	BAUCHI		**5000**	**10000**	**6000**	**10000**
DAY 14 SATURDAY 14TH-07-2018	BAUCHI		**5000**	**10000**	**6000**	**10000**
DAY 15 SUNDAY 15TH-07-2018	KANO		**5000**	**10000**	**6000**	**10000**
DAY 16 MONDAY 16TH-07-2018	KANO		**5000**	**10000**	**6000**	**10000**
DAY 17 TUESDAY 17ST-07-2018	JIGAWA		**5000**	**10000**	**6000**	**10000**
DAY 18 WEDNESDAY 18TH-07-2018	JIGAWA		**5000**	**10000**	**6000**	**10000**
DAY 19 THURSDAY 19TH-07-2018	GOMBE		**5000**	**10000**	**6000**	**10000**

DAY 20 FRIDAY 20TH-07-2018	GOMBE		**5000**	**10000**	**6000**	**10000**
DAY 21 SATURDAY 21ST-07-2018	ADAMAWA		**5000**	**10000**	**6000**	**10000**
DAY 22 SUNDAY 22ND-07-2018	ADAMAWA		**5000**	**10000**	**6000**	**10000**
DAY 23 MONDAY 23RD-07-2018	TARABA		**5000**	**10000**	**6000**	**10000**
DAY 24 TUESDAY 24TH-07-2018	TARABA		**5000**	**10000**	**6000**	**10000**
DAY 25 WEDNESDAY 25TH-07-2018	NASARAW A		**5000**	**10000**	**6000**	**10000**
DAY 26 THURSDAY 26TH-07-2018	NASARAW A		**5000**	**10000**	**6000**	**10000**

DAY 27 FRIDAY 27TH-07-2018	BENUE		**5000**	**10000**	**6000**	**10000**
DAY 28 SATURDAY 28TH-07-2018	BENUE		**5000**	**10000**	**6000**	**10000**
DAY 29 SUNDAY 29TH-07-2018	CROSS RIVER		**5000**	**10000**	**6000**	**10000**
DAY 30 MONDAY 30TH-07-2018	CROSS RIVER		**5000**	**10000**	**6000**	**10000**
DAY 31 TUESDAY 31ST-07-2018	EBONYI		**5000**	**10000**	**6000**	**10000**
DAY 32 WEDNESDAY 1ST-08-2018	EBONYI		**5000**	**10000**	**6000**	**10000**
DAY 33 THURSDAY 2ND-08-2018	KOGI		**5000**	**10000**	**6000**	**10000**
DAY 34	KOGI		**5000**	**10000**	**6000**	**10000**

FRIDAY 3RD-08-2018						
DAY 35 SATURDAY 4TH-08-2018	EDO		**5000**	**10000**	**6000**	**10000**
DAY 36 SUNDAY 5TH-08-2018	EDO		**5000**	**10000**	**6000**	**10000**
DAY 37 MONDAY 6TH-08-2018	OYO		**5000**	**10000**	**6000**	**10000**
DAY 38 TUESDAY 7TH-08-2018	OYO		**5000**	**10000**	**6000**	**10000**
DAY 39 WEDNESDAY 8TH-08-2018	KWARA		**5000**	**10000**	**6000**	**10000**
DAY 40 THURSDAY 9TH-08-2018	KWARA		**5000**	**10000**	**6000**	**10000**
DAY 41 FRIDAY	FCT		**5000**	**10000**	**6000**	**10000**

10TH-08-2018						
DAY 42 SATURDAY 11TH-08-2018	FCT		**5000**	**10000**	**6000**	**10000**
		Subtotals	**5000 X 42 = 210,000**	**10000 X 42 = 420,000**	**6000 X 42 = 252,000**	**10000 X 42 = 420,000**
		Total	**210,000 + 420,000 + 252,000 + 420,000 = 1,302,000**			
		Pound Equivalent (27/04/2018)	**CBN Rate**		**Parallel Market Rate**	
			1,302,000 / 427 = £3,049		**1,302,000 / 500 = £2,604**	
		Return Flight Ticket (London – Abuja using Lufthansa)	**£756**		**£756**	
		Grand Total	**£3,805**		**£3,360**	

Appendix VIII: Location information of the training sample

The field information was collected during the months of July and August, 2018. For the information extracted from OSM data and Google Earth images, it was ensured that the period is 2018 or 2019 and that months are neither later than November nor earlier than July. Rainy season crops are still available on farms in most parts of Nigeria between July and November.

As discussed in subsection 5.3.4.2, the following table consists of the 125-points information collected from the field and the 51 points that could not be visited, making a total of 176 points. Of the 125 points visited, 92 were visited by two sets of surveyors and 33 were visited by the researcher. To argument this limited number of sample points for training the classifiers, as detailed in table 5.4, 106 polygons were extracted from OpenStreetMap and converted to Areas of Interests in Erdas-Imagine. Additional 122 Areas of Interest were added directly in Erdas-Imagine using linked and synchronized view with Google Earth.

FID	POINT_X	POINT_Y	Landcover	Description
0	44912.58118	1200956.459	Agriculture	Intensive agric
1	454127.7565	532439.413	Forest	Dense forest
2	627072.5222	970451.1213	Woodland	Dense woodland
3	18416.12038	1008420.941	Agriculture	Seasonal agric
4	-161409.4894	958961.3882	Woodland	Sparse woodland
5	958778.5885	1354598.723	Not visited	Not visited
6	484126.5976	1123325.509	Woodland	Sparse woodland
7	599242.6313	1233819.376	Agriculture	Seasonal agric
8	877977.3548	1125082.544	Woodland	Sparse woodland
9	410925.8677	939171.3679	Agriculture	Intensive agric
10	111810.2797	1275888.922	Agriculture	Wetland agric
11	484416.6357	1341450.276	Agriculture	Seasonal agric

12	-24772.59784	1209446.286	Agriculture	Seasonal agric
13	769285.2183	1174384.166	Agriculture	Seasonal agric
14	951591.5798	1179899.488	Bare ground	Open soil surface
15	394284.5263	661780.4786	Woodland	Sparse woodland
16	710199.4546	853064.101	Forest	Dense forest
17	769104.5185	1269703.998	Shrub	Sparse shrub
18	751933.5349	1046696.635	Agriculture	Wetland agric
19	1054723.144	1424621.238	Not visited	Not visited
20	941035.6071	1232170.855	Not visited	Not visited
21	-18635.92298	1195107.666	Woodland	Sparse woodland
22	432831.5257	1299044.1	Shrub	Sparse shrub
23	172022.2098	1286710.348	Agriculture	Seasonal agric
24	343341.919	1036207.149	Not visited	Not visited
25	-63082.11471	1377884.178	Bare ground	Open soil surface
26	178026.6191	1315412.32	Woodland	Sparse woodland
27	905884.6098	1113114.907	Shrub	Sparse shrub
28	246109.8313	1281827.029	Agriculture	Seasonal agric
29	533790.8718	911952.0151	Forest	Sparse forest
30	497475.2773	1292730.772	Shrub	Dense shrub
31	641003.9019	1045192.745	Not visited	Not visited
32	318789.3985	1078583.989	Forest	Sparse forest
33	211724.915	1189350.399	Not visited	Not visited
34	301121.1834	865915.2689	Forest	Sparse forest
35	560594.0737	1178300.447	Shrub	Sparse shrub
36	-41575.22484	893660.2358	Agriculture	Seasonal agric
37	409664.7135	1340784.389	Not visited	Not visited
38	829888.5232	1430727.499	Not visited	Not visited
39	145382.2874	1064984.239	Agriculture	Intensive agric

40	373348.2757	646658.1282	Agriculture	Seasonal agric
41	79008.43379	959121.9827	Forest	Sparse forest
42	229494.7451	1277889.782	Forest	Sparse forest
43	392405.9395	730239.2751	Agriculture	Seasonal agric
44	781556.3014	881058.629	Forest	Sparse forest
45	922209.1457	1293937.22	Not visited	Not visited
46	28980.68227	894899.077	Forest	Sparse forest
47	492591.2447	787528.0503	Not visited	Not visited
48	125899.4788	1501662.878	Not visited	Not visited
49	204462.4576	1077960.096	Forest	Sparse forest
50	838235.3012	1207794.437	Shrub	Sparse shrub
51	959526.1613	1305506.941	Not visited	Not visited
52	407205.4201	1359273.585	Water	Seasonal water
53	718714.3095	1434284.719	Agriculture	Seasonal agric
54	232514.5756	943708.9242	Shrub	Sparse shrub
55	1040586.396	1414738.071	Not visited	Not visited
56	-63395.1971	1340401.473	Agriculture	Seasonal agric
57	552586.4568	990979.5276	Agriculture	Intensive agric
58	698601.3562	956514.2335	Agriculture	Seasonal agric
59	248382.3136	1354809.032	Settlement	Village
60	992121.8424	1421392.146	Not visited	Not visited
61	86251.65489	1075637.31	Shrub	Dense shrub
62	577430.8403	820711.745	Agriculture	Intensive agric
63	466724.0283	652324.3719	Forest	Sparse forest
64	665684.1468	1198968.911	Shrub	Dense shrub
65	30808.96682	931059.7915	Forest	Sparse forest
66	463131.1798	749766.5351	Not visited	Not visited
67	173945.4332	1152653.309	Agriculture	Seasonal agric
68	667448.7194	976656.7	Not visited	Not visited
69	498558.3482	1225151.933	Not visited	Not visited
70	690184.4578	879834.2124	Shrub	Dense shrub
71	114353.4448	1019410.068	Not visited	Not visited

72	510334.7004	1015318.385	Shrub	Sparse shrub
73	1022006.495	1302539.162	Not visited	Not visited
74	691660.121	1199683.506	Agriculture	Seasonal agric
75	104082.4211	1072958.065	Settlement	Town
76	505522.2599	1198937.178	Not visited	Not visited
77	488966.3693	1260378.803	Agriculture	Seasonal agric
78	140688.3269	725251.6612	Forest	Sparse forest
79	160454.1487	763454.9143	Settlement	Town
80	116043.9065	746214.4359	Agriculture	Seasonal agric
81	-145504.4733	1010808.209	Not visited	Not visited
82	281091.4987	856568.555	Forest	Dense forest
83	920869.6806	1119018.404	Bare ground	Bare hill side
84	660149.0221	1309257.752	Agriculture	Intensive agric
85	256209.341	932593.0834	Shrub	Sparse shrub
86	948065.4498	1277144.916	Not visited	Not visited
87	329104.6037	1308251.744	Agriculture	Seasonal agric
88	647578.3715	1226717.524	Agriculture	Seasonal agric
89	669576.2541	1446811.95	Not visited	Not visited
90	199882.4734	1286293.167	Agriculture	Seasonal agric
91	154847.5679	994397.8918	Agriculture	Wetland agric
92	756633.0376	1391588.607	Shrub	Sparse shrub
93	342277.0688	926224.7462	Shrub	Dense shrub
94	586235.7524	1210081.888	Shrub	Sparse shrub
95	397434.8397	915000.9488	Forest	Sparse forest
96	127967.3132	929275.0243	Forest	Sparse forest
97	931561.1775	1084191.452	Not visited	Not visited
98	114512.2713	709095.0588	Woodland	Dense woodland
99	805641.1259	1138531.076	Not visited	Not visited
100	652763.276	1289483.989	Shrub	Sparse shrub
101	547779.9838	710346.7049	Not visited	Not visited

102	450604.655	911302.2923	Agriculture	Seasonal agric
103	-24356.57902	1245878.616	Agriculture	Wetland agric
104	235976.0841	1227945.352	Shrub	Dense shrub
105	96500.16709	1217066.264	Shrub	Dense shrub
106	395847.7121	1444727.729	Agriculture	Seasonal agric
107	832793.7405	919854.1832	Not visited	Not visited
108	1008813.074	1323689.542	Not visited	Not visited
109	75674.62454	1016528.462	Agriculture	Wetland agric
110	472792.5503	1293933.281	Agriculture	Seasonal agric
111	130094.4075	1160748.837	Shrub	Dense shrub
112	-98020.24045	837948.7484	Agriculture	Seasonal agric
113	515892.9321	1065411.302	Forest	Sparse forest
114	645838.6284	884175.5027	Shrub	Dense shrub
115	60044.22016	1351451.84	Agriculture	Wetland agric
116	651167.7154	978138.5851	Not visited	Not visited
117	277288.8324	1431883.537	Not visited	Not visited
118	116303.4651	1415419.229	Shrub	Dense shrub
119	15832.12206	1389837.957	Agriculture	Wetland agric
120	544372.7847	812663.4715	Not visited	Not visited
121	605677.7361	820445.2729	Not visited	Not visited
122	265817.6037	1064006.495	Shrub	Dense shrub
123	186039.9694	1117871.985	Agriculture	Intensive agric
124	174924.7528	983151.7671	Not visited	Not visited
125	1036379.973	1378729.112	Not visited	Not visited
126	-79471.7369	875190.56	Agriculture	Seasonal agric
127	733549.1418	1105275.729	Agriculture	Intensive agric
128	280531.341	951147.5879	Not visited	Not visited
129	906764.3511	1055014.955	Not visited	Not visited
130	865649.467	1194684.922	Shrub	Sparse shrub
131	691386.9241	1242680.753	Forest	Dense forest
132	827090.788	1292928.165	Agriculture	Seasonal agric

133	-20096.52867	1370501.507	Shrub	Dense shrub
134	447961.2203	1332398.02	Settlement	Kano City
135	20230.91415	1247852.43	Agriculture	Seasonal agric
136	700726.0572	1356180.005	Agriculture	Seasonal agric
137	867341.8207	938903.1586	Forest	Sparse forest
138	689917.5198	779945.0271	Not visited	Not visited
139	-78725.04651	1147436.781	Not visited	Not visited
140	1045842.215	1396841.046	Not visited	Not visited
141	347273.2365	821618.7902	Woodland	Dense woodland
142	154929.5414	1371749.194	Water	Seasonal water
143	206462.2625	1167643.973	Shrub	Sparse shrub
144	-66719.90548	1302064.679	Shrub	Dense shrub
145	976712.0584	1422070.283	Not visited	Not visited
146	592774.1933	1419514.818	Agriculture	Seasonal agric
147	-22363.52339	1075154.013	Shrub	Dense shrub
148	411815.9252	781103.4548	Woodland	Dense woodland
149	135072.2983	1076276.674	Not visited	Not visited
150	115575.9721	1455264.584	Shrub	Dense shrub
151	349720.2231	794086.1695	Woodland	Dense woodland
152	306915.1541	935524.4995	Not visited	Not visited
153	676007.9562	1215998.227	Agriculture	Seasonal agric
154	714379.9067	909815.7839	Woodland	Dense woodland
155	1103360.174	1276163.097	Not visited	Not visited
156	397113.7356	862449.0957	Agriculture	Intensive agric
157	635197.9332	1100264.293	Not visited	Not visited
158	-122476.4842	1011079.222	Not visited	Not visited

159	132959.7723	1207799.911	Bare ground	Bare hill surface
160	770075.1394	1022611.686	Not visited	Not visited
161	542844.5392	1377428.168	Agriculture	Wetland agric
162	260582.6414	772099.1604	Woodland	Dense woodland
163	177776.5719	1085694.429	Shrub	Sparse shrub
164	194356.8604	1058789.943	Woodland	Sparse woodland
165	168332.414	805256.7167	Not visited	Not visited
166	685181.2138	1277609.733	Agriculture	Seasonal agric
167	531857.6619	885910.1442	Shrub	Dense shrub
168	324940.294	850493.2873	Woodland	Dense woodland
169	858741.4014	1133781.191	Not visited	Not visited
170	294166.1859	925470.5175	Not visited	Not visited
171	675829.954	1078207.927	Not visited	Not visited
172	169892.0199	668798.0965	Forest	Sparse forest
173	164693.6171	1460350.052	Not visited	Not visited
174	383000.1023	1199069.924	Agriculture	Intensive agric
175	410630.7065	1408196.032	Agriculture	Wetland agric

Appendix IX: Location information for Accuracy Assessment Sample

The accuracy assessment sample consists of field points, points extracted from Open Street Map polygons and points extracted from Google Earth. The field information was collected during the months of July and August, 2018. For the information extracted from OSM data and Google Earth images, it was ensured that the period is 2018 or 2019 and that months are neither later than November nor earlier than July. Rainy season crops are still available on farms in most parts of Nigeria between July and November.

FID	Class	POINT_X (Longitudes)	POINT_Y (Latitudes)
0	Agriculture	99543.81124	1197883.809
1	Agriculture	528689.5395	1284363.122
2	Agriculture	754706.608	1341521.07
3	Agriculture	429458.3597	1271152.006
4	Agriculture	513490.2794	797497.6469
5	Agriculture	-73934.80562	1148779.64
6	Agriculture	-117870.0979	939131.644
7	Agriculture	-13052.53883	727551.0746
8	Agriculture	896499.9307	1403776.993
9	Agriculture	456485.0148	1279888.249
10	Agriculture	130990.8237	1138875.272
11	Agriculture	56830.6772	982170.9552
12	Agriculture	1102769.483	1349521.305
13	Agriculture	789867.4106	1228388.336
14	Agriculture	157594.7102	996458.5875
15	Agriculture	328125.4917	1264930.786
16	Agriculture	526152.8602	1258499.604
17	Agriculture	463745.5635	1253903.233
18	Agriculture	308483.8093	818994.1547
19	Agriculture	601303.6408	1338477.756
20	Agriculture	833366.494	899349.2241
21	Agriculture	536926.3281	1129857.9
22	Agriculture	-63227.29244	1037771.292
23	Agriculture	194769.4949	697880.0419
24	Agriculture	745318.6289	1067059.558
25	Agriculture	354718.1756	1000327.446
26	Agriculture	557122.6262	777633.1539
27	Agriculture	135061.0775	1309079.249
28	Agriculture	566098.5009	1370381.697

29	Agriculture	480190.5476	1275639.76
30	Agriculture	484051.3323	876869.4694
31	Agriculture	373394.1662	887072.5318
32	Agriculture	265681.3613	658593.7273
33	Agriculture	17014.57062	1405708.575
34	Agriculture	635398.9118	1320249.481
35	Agriculture	571265.7623	1222726.854
36	Agriculture	358366.0456	1353018.893
37	Agriculture	183321.8387	1377541.936
38	Agriculture	901651.6878	1056147.134
39	Agriculture	46513.33713	1201456.524
40	Agriculture	437134.9	865000.1529
41	Agriculture	360780.0515	1325616.023
42	Agriculture	379997.2657	1258693.303
43	Agriculture	365259.2719	1422499.753
44	Agriculture	151051.5977	1493222.532
45	Agriculture	214596.2284	1359898.013
46	Agriculture	65696.34851	1071617.476
47	Agriculture	380512.4376	1241522.296
48	Agriculture	298443.8227	1049789.605
49	Agriculture	495999.934	1096919.794
50	Agriculture	726497.3821	1372048.933
51	Agriculture	799774.5758	1375060.673
52	Agriculture	271002.134	1345000.162
53	Agriculture	240500.6107	1352055.742
54	Agriculture	539107.6318	1101142.292
55	Agriculture	701823.0677	1339627.272
56	Agriculture	2801.422083	1154537.042
57	Agriculture	563008.1878	1282049.278
58	Agriculture	405948.9329	930595.2066
59	Agriculture	480430.773	1112716.938
60	Agriculture	-43448.49259	868999.9977
61	Agriculture	133034.4084	631285.4921
62	Agriculture	466405.1015	1322506.101
63	Agriculture	581913.6243	1408737.465
64	Agriculture	11486.99615	725928.585
65	Agriculture	100940.04	806288.3094
66	Agriculture	214984.9101	1156719.335
67	Agriculture	229894.4319	945300.3776
68	Agriculture	844486.7903	1310577.299
69	Agriculture	719763.2872	972551.1003
70	Agriculture	376721.4426	825932.9328
71	Agriculture	650762.6104	883083.6934
72	Agriculture	529958.02	1397719.506

73	Agriculture	421700.1665	958803.8673
74	Agriculture	57676.05692	1477676.333
75	Agriculture	306843.688	766075.7808
76	Agriculture	456240.0585	1342594.271
77	Agriculture	241452.6782	1417514.12
78	Agriculture	508245.1043	1066943.972
79	Agriculture	111499.0408	1495765.046
80	Agriculture	611998.7529	1362631.247
81	Agriculture	246590.1293	1367555.238
82	Agriculture	70024.05392	1226191.362
83	Agriculture	705368.5744	1403564.622
84	Agriculture	509875.8956	1194251.431
85	Agriculture	877546.3011	958601.8487
86	Agriculture	279878.5461	725379.9133
87	Agriculture	2505.023891	1112272.714
88	Agriculture	232667.1099	1026301.278
89	Agriculture	575665.3111	842341.7003
90	Agriculture	590019.7064	1078499.785
91	Agriculture	575463.3792	1346122.084
92	Agriculture	955341.5601	1318779.929
93	Agriculture	676740.3065	1228527.564
94	Agriculture	188752.8459	1350717.225
95	Agriculture	199223.1014	1139872.632
96	Agriculture	92312.90246	1116876.913
97	Agriculture	91976.92772	1406335.133
98	Agriculture	-94846.40341	978453.9168
99	Agriculture	621651.7792	1028860.282
100	Agriculture	520932.4674	853992.3035
101	Agriculture	254567.2362	605722.1445
102	Agriculture	948165.5566	1100385.112
103	Agriculture	142393.8739	1173101.835
104	Agriculture	424260.7597	1429584.553
105	Agriculture	304622.4791	1251603.396
106	Agriculture	558356.2896	1407448.657
107	Agriculture	21151.56945	893801.0456
108	Agriculture	505152.4093	1040074.115
109	Agriculture	751323.6489	1380152.627
110	Agriculture	-39177.55994	772601.4013
111	Agriculture	175409.5121	1508199.965
112	Agriculture	349629.5833	1150106.353
113	Agriculture	-89731.49047	1267001.641
114	Agriculture	465579.8487	1097851.326
115	Agriculture	448600.5412	1180157.235
116	Agriculture	790981.2612	1126468.125

117	Agriculture	491410.1611	1393702.888
118	Agriculture	972694.9387	1179068.189
119	Agriculture	-10717.20698	1420538.862
120	Agriculture	198745.8117	956445.4999
121	Agriculture	88585.83492	1019527.115
122	Agriculture	241839.8631	955258.2252
123	Agriculture	86900.46014	1421457.409
124	Agriculture	32556.8624	1044452.117
125	Agriculture	35602.47146	997821.8829
126	Agriculture	511610.8034	1235589.891
127	Agriculture	23873.50218	1423796.399
128	Agriculture	213487.9597	1321915.487
129	Agriculture	500730.3467	755878.0828
130	Agriculture	837277.8472	1202062.835
131	Agriculture	439423.1564	739919.0572
132	Agriculture	174934.0918	628906.7324
133	Agriculture	367293.305	919564.1759
134	Agriculture	-149806.3561	790581.9322
135	Agriculture	798979.762	1181702.115
136	Agriculture	352835.2919	648937.0128
137	Bare ground	35969.59311	1384538.372
138	Bare ground	505323.7849	848593.3588
139	Bare ground	827403.1588	1455071.574
140	Bare ground	822482.2832	1456386.931
141	Bare ground	816296.5369	1454368.003
142	Bare ground	810522.4928	1454329.731
143	Forest	696309.134	842498.2293
144	Forest	-132079.7172	775388.3453
145	Forest	526144.0145	1001152.796
146	Forest	464347.9825	596625.312
147	Forest	715365.9667	839177.5759
148	Forest	104873.1469	833631.9041
149	Forest	40135.70202	748025.7805
150	Forest	804589.7446	862202.5596
151	Forest	210159.6643	890031.3339
152	Forest	-48760.4297	925199.6144
153	Forest	236258.6453	699699.3945
154	Forest	71965.47471	844264.1077
155	Forest	340092.9751	638301.3211
156	Forest	226973.3952	550290.5084
157	Forest	-37333.00842	1015264.932
158	Forest	-64257.18553	737970.8994
159	Forest	-71537.71264	1220523.079
160	Forest	152119.4912	736665.7684

161	Forest	669517.9916	1089543.026
162	Forest	453295.3631	554494.579
163	Forest	36640.65813	1250488.185
164	Forest	59517.19901	829362.0448
165	Forest	294176.7645	954127.0071
166	Forest	208408.3157	657131.9883
167	Forest	562650.439	1010241.706
168	Forest	314352.3124	898038.9723
169	Forest	-74952.93858	808340.1697
170	Forest	783342.7079	947972.9958
171	Forest	150829.5246	818197.4749
172	Forest	265948.776	821846.3186
173	Forest	-7621.330533	794697.1794
174	Forest	746300.4432	907109.8049
175	Forest	721491.7003	740462.1805
176	Forest	291031.7587	1153318.251
177	Forest	244506.3572	1155613.177
178	Forest	-186831.3773	923769.4631
179	Forest	-99968.99309	796808.2201
180	Forest	308045.2025	648039.2107
181	Forest	760871.123	809780.7431
182	Forest	795710.5723	844363.7021
183	Forest	490563.0836	1002392.699
184	Forest	630086.8117	782126.2459
185	Forest	253680.0451	986466.895
186	Forest	388143.8476	954635.0068
187	Forest	132460.9528	847366.6277
188	Forest	934649.3994	1302829.997
189	Forest	-19272.10115	865094.8194
190	Forest	763401.969	927139.8234
191	Forest	472216.2721	654943.9553
192	Forest	130803.9348	663544.0217
193	Forest	341338.9077	579536.5688
194	Forest	744002.9515	853901.1582
195	Forest	498133.426	676722.7332
196	Forest	227527.2691	673948.8447
197	Forest	324340.1329	729241.016
198	Forest	34674.10719	1330622.005
199	Forest	88455.5633	1004228.248
200	Mangrove	196072.0187	510971.5718
201	Mangrove	215660.7616	610138.5508
202	Mangrove	217257.3816	500380.2452
203	Mangrove	155875.7648	516009.1998
204	Mangrove	237100.5487	505553.8406

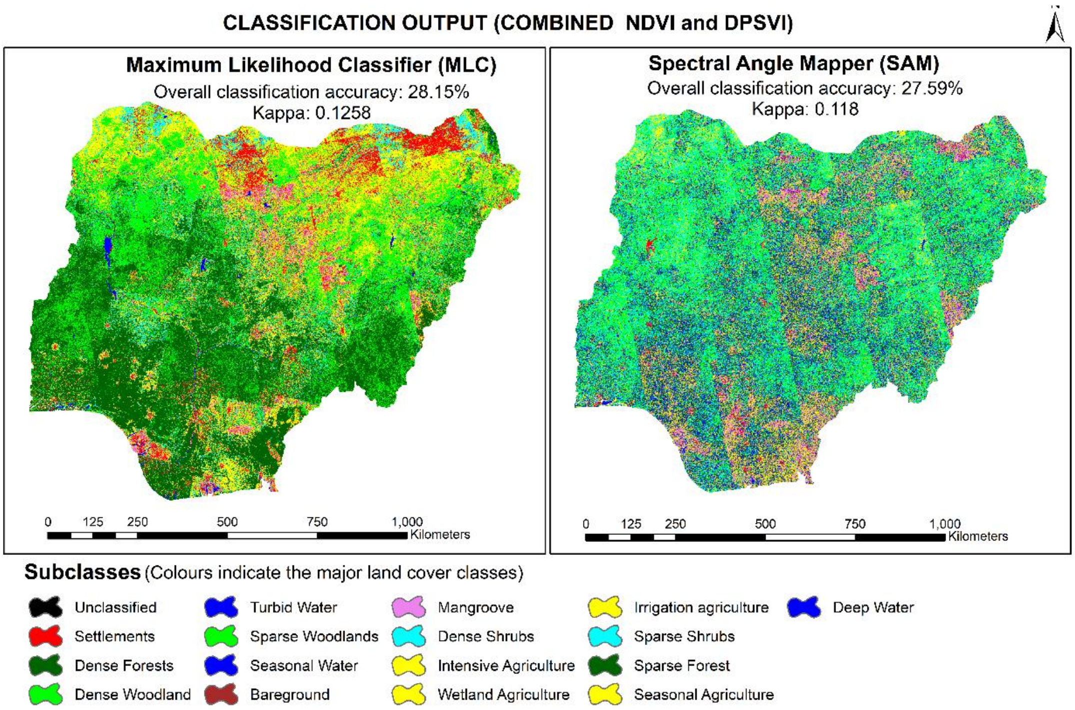
205	Mangrove	459879.1701	503212.2152
206	Mangrove	118921.4565	598012.7793
207	Mangrove	120205.4827	549137.7459
208	Mangrove	72777.63585	625732.563
209	Mangrove	411358.3725	544841.0961
210	Mangrove	424888.2569	535333.3941
211	Settlement	570600.9447	799797.7995
212	Settlement	-165874.0308	745984.7276
213	Settlement	281259.5765	659843.9838
214	Settlement	583372.4002	1133728.742
215	Settlement	324656.0807	976962.1908
216	Settlement	139829.5697	610796.0351
217	Settlement	280262.1291	527297.4615
218	Settlement	-125042.358	795399.42
219	Settlement	952790.9008	1312181.835
220	Settlement	449101.5227	854616.376
221	Settlement	91804.4938	1446920.217
222	Settlement	592569.2171	1140336.291
223	Settlement	360084.6415	1228829.868
224	Settlement	172023.5737	1005414.187
225	Shrub	859513.649	976184.1835
226	Shrub	803581.1129	1101019.971
227	Shrub	233182.7085	1107146.176
228	Shrub	974589.9254	1326970.605
229	Shrub	134484.6811	1072843.528
230	Shrub	231387.7659	758169.9933
231	Shrub	489350.543	849200.5989
232	Shrub	128502.7326	1228468.885
233	Shrub	-148844.3939	974322.7106
234	Shrub	895205.9362	1183506.034
235	Shrub	216262.2431	1305158.532
236	Shrub	386604.0004	749246.0831
237	Shrub	508356.6597	1150669.348
238	Shrub	842206.4818	1004753.027
239	Shrub	992621.0649	1456060.277
240	Shrub	527875.7394	1089626.373
241	Shrub	437893.4309	821270.2505
242	Shrub	893624.4867	1140437.27
243	Shrub	-11862.75349	1091462.55
244	Shrub	879090.7885	1189165.648
245	Shrub	334187.9609	1405600.6
246	Shrub	317011.5012	1191839.682
247	Shrub	654600.9576	1018202.646
248	Shrub	-28494.0513	1401232.45

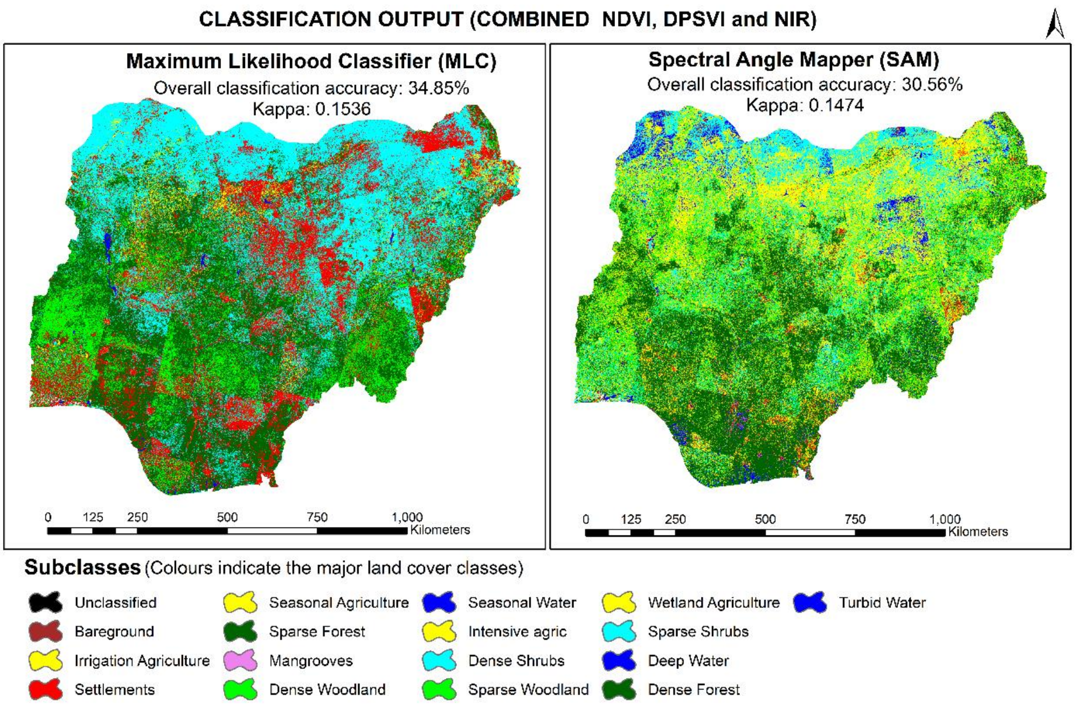
249	Shrub	1007976.73	1470846.571
250	Shrub	479160.0047	903201.4443
251	Shrub	790727.7603	1349379.803
252	Shrub	823869.1189	1188377.636
253	Shrub	165163.0755	838111.5296
254	Shrub	415094.1876	832654.8094
255	Shrub	4556.196036	993848.4844
256	Shrub	740641.3461	951165.6249
257	Shrub	928971.0364	1267459.581
258	Shrub	866993.0439	1158887.952
259	Shrub	984219.8962	1484088.642
260	Shrub	762236.9835	1017189.038
261	Shrub	950752.5247	1471181.464
262	Shrub	239062.8321	898219.743
263	Shrub	23027.38671	1501309.112
264	Shrub	881386.3056	1083791.215
265	Shrub	998085.9354	1306598.142
266	Shrub	852857.7547	1217117.998
267	Shrub	919563.3617	1117115.824
268	Shrub	-8259.43386	1031894.092
269	Shrub	159856.3176	1433822.112
270	Shrub	978828.421	1391049.527
271	Shrub	1038047.854	1256414.219
272	Shrub	829937.3545	1428600.338
273	Shrub	902967.8552	1286858.105
274	Shrub	850749.2393	1354224.498
275	Shrub	715269.2781	1022631.539
276	Shrub	612455.1095	912003.2635
277	Shrub	280577.7616	920897.2981
278	Shrub	742218.7481	1276241.535
279	Shrub	-66420.89422	1388458.898
280	Shrub	229839.7751	1078369.884
281	Shrub	599400.6844	1121354.206
282	Shrub	732229.1565	785399.6929
283	Shrub	947645.3583	1248848.251
284	Shrub	2693.579003	1277623.906
285	Shrub	984869.8223	1361543.43
286	Shrub	183580.4505	1329162.048
287	Shrub	-39988.84144	992234.1636
288	Shrub	211052.8508	1067546.393
289	Shrub	958257.2043	1068165.154
290	Shrub	41203.31504	974361.9777
291	Shrub	-124642.1451	836447.3104
292	Shrub	340186.5303	551043.8743

293	Shrub	705510.3305	924003.1796
294	Shrub	87286.7342	1351338.701
295	Shrub	284183.2089	1364612.138
296	Shrub	275087.0397	1163998.975
297	Shrub	18728.36037	1447887.951
298	Shrub	990965.6225	1262841.785
299	Shrub	-2747.841351	1186641.412
300	Water	89124.8041	1277918.952
301	Water	510039.2604	935569.5674
302	Water	-119332.0146	723779.2591
303	Water	140769.3253	985232.1057
304	Water	832579.0445	1049081.655
305	Water	137973.6532	614904.6194
306	Water	349953.2291	888413.6215
307	Water	309316.6173	1445548.222
308	Water	334020.915	1448311.759
309	Water	618972.3922	1312315.388
310	Water	1046719.226	1277959.508
311	Water	960711.4506	1431384.89
312	Water	609745.17	1144004.949
313	Water	54509.78037	1166689.472
314	Water	-931.78995	860872.7184
315	Water	295787.1874	1236418.131
316	Water	713268.429	980216.9009
317	Water	262749.5354	732229.6163
318	Water	317830.6613	1146776.004
319	Woodland	488765.4563	1229503.499
320	Woodland	541582.0373	1051693.088
321	Woodland	63100.17132	1252390.442
322	Woodland	-10255.60033	976484.0587
323	Woodland	253941.1409	873717.2689
324	Woodland	6816.770166	919978.6927
325	Woodland	-63014.63642	1351698.189
326	Woodland	289654.2829	685735.6354
327	Woodland	261656.4049	1241593.419
328	Woodland	2848.283778	1384532.505
329	Woodland	357724.1453	822729.0228
330	Woodland	353732.1359	1185373.277
331	Woodland	152231.6199	1079525.316
332	Woodland	385750.7742	1137524.384
333	Woodland	870934.0471	1297942.697
334	Woodland	548812.1536	726874.4428
335	Woodland	-168611.9762	822387.3645
336	Woodland	563151.1341	880118.6886

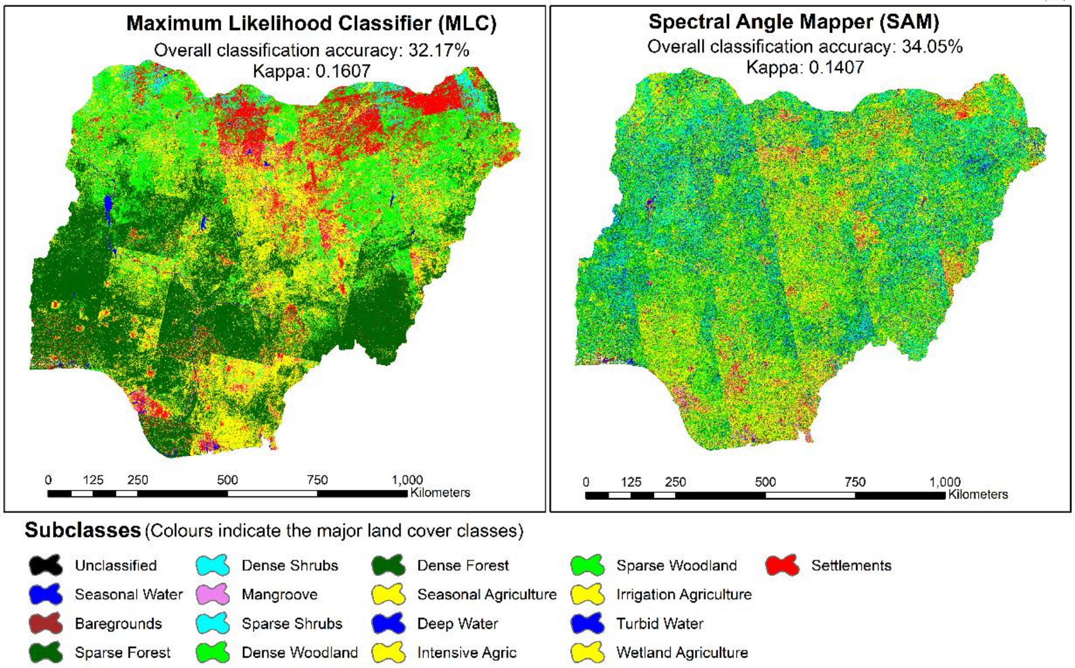
337	Woodland	-144640.3351	898642.892
338	Woodland	101751.2717	914195.7799
339	Woodland	476116.7304	1183938.636
340	Woodland	469613.0899	1055663.537
341	Woodland	225500.4135	1472006.745
342	Woodland	573982.8938	1089858.078
343	Woodland	113874.1614	795399
344	Woodland	673608.0724	1368525.491
345	Woodland	282116.2959	1287455.694
346	Woodland	555633.2183	1039304.775
347	Woodland	435336.6311	1161961.153
348	Woodland	258981.8347	1080711.028
349	Woodland	691602.4286	1446625.988
350	Woodland	279572.2437	1196927.598
351	Woodland	301444.5946	1093631.76
352	Woodland	455407.6931	1018499.109
353	Woodland	-73552.70168	1084451.492
354	Woodland	333425.6892	802802.4099
355	Woodland	199096.635	800443.7732
356	Woodland	-113991.869	910299.3954
357	Woodland	198306.4687	1084094.148
358	Woodland	63856.88175	914417.8044
359	Woodland	789203.8764	810737.7117
360	Woodland	789577.9996	1058236.432
361	Woodland	671663.1867	1319033.882
362	Woodland	262280.9123	1282476.816
363	Woodland	-85336.92213	756297.5055
364	Woodland	-124843.0473	1051519.196
365	Woodland	892484.5175	1217386.768
366	Woodland	819989.8289	918394.8101
367	Woodland	241598.5027	1266308.989
368	Woodland	128028.2338	1359717.154
369	Woodland	440694.162	999052.2235
370	Woodland	-21364.88799	939306.7844
371	Woodland	664107.302	867858.8667

Appendix X: The Classification Outputs

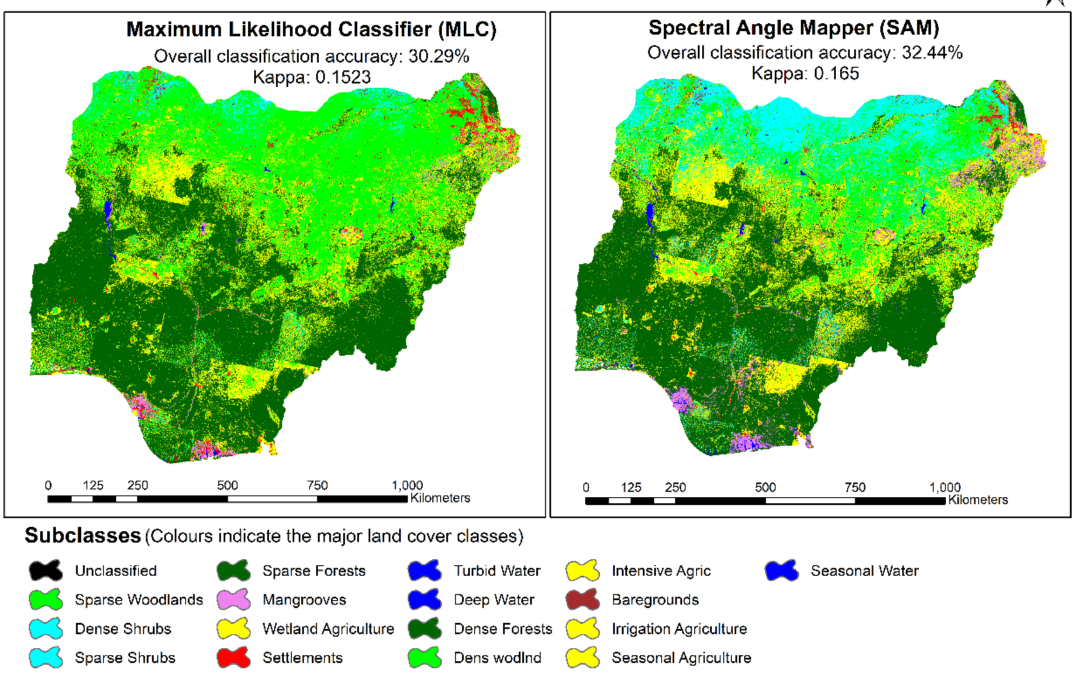


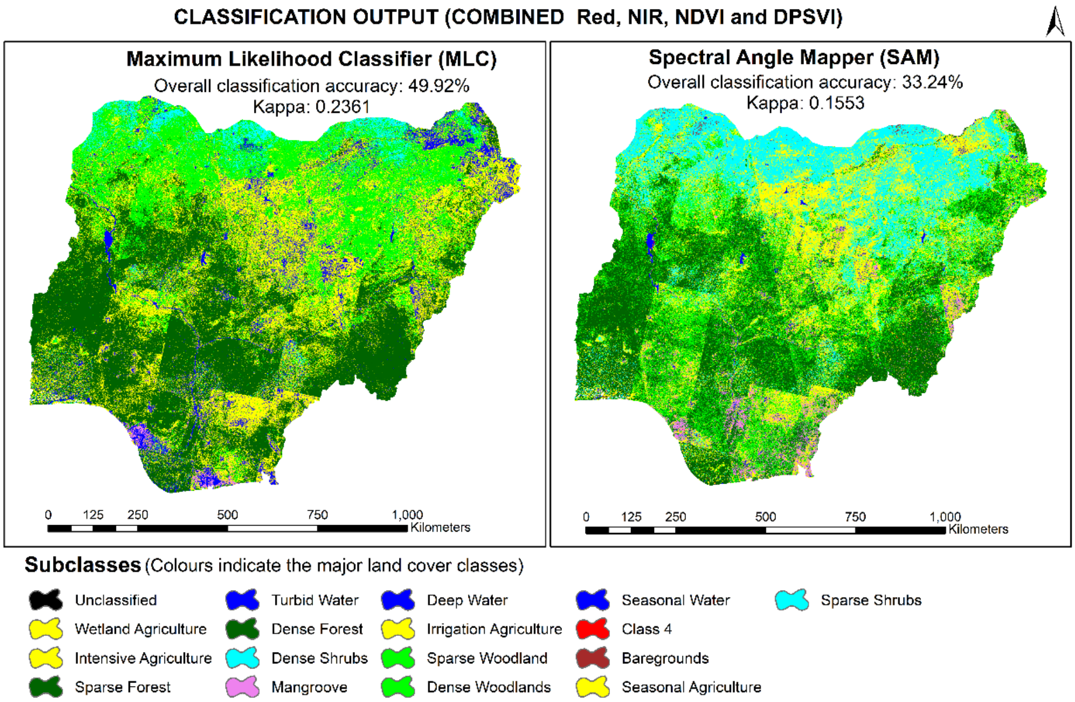


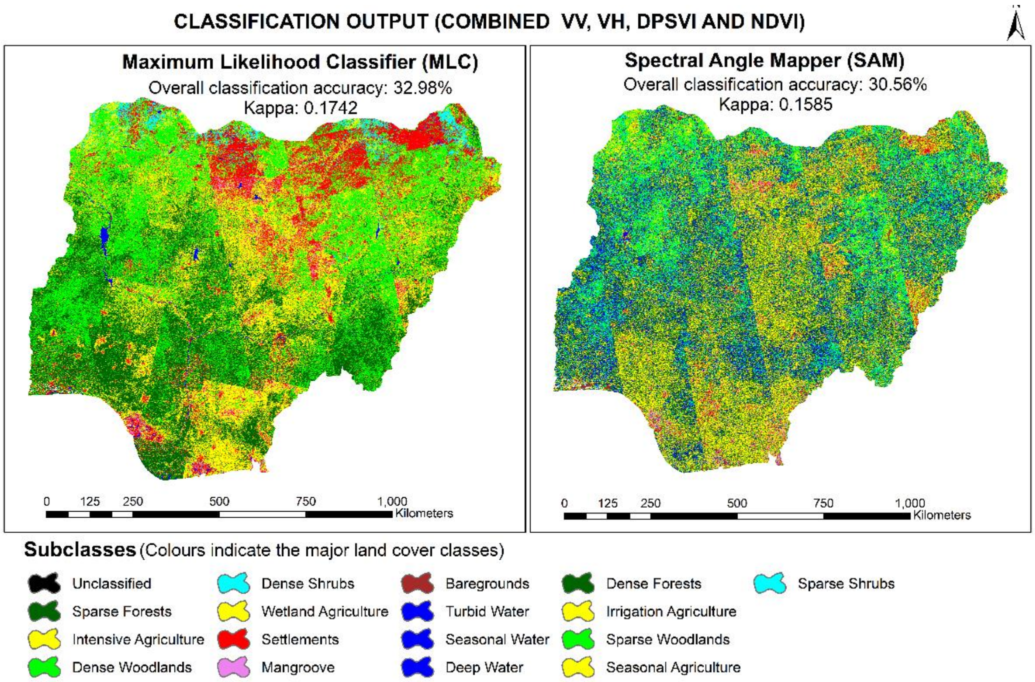
CLASSIFICATION OUTPUT (COMBINED NDVI, DPSVI and VV)

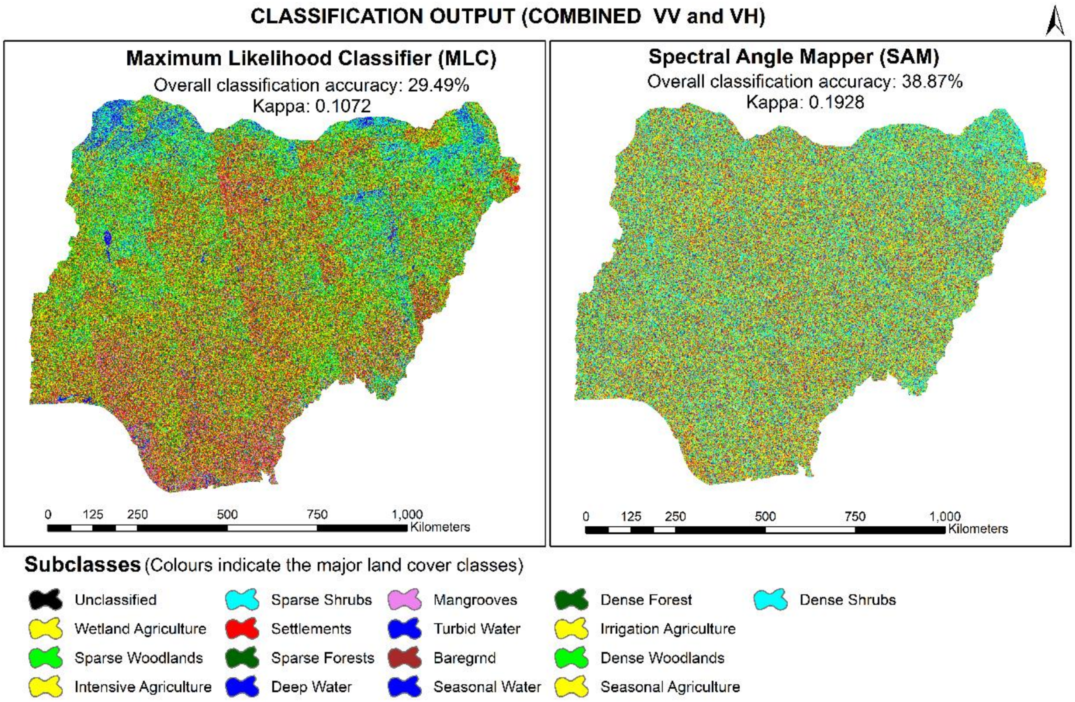


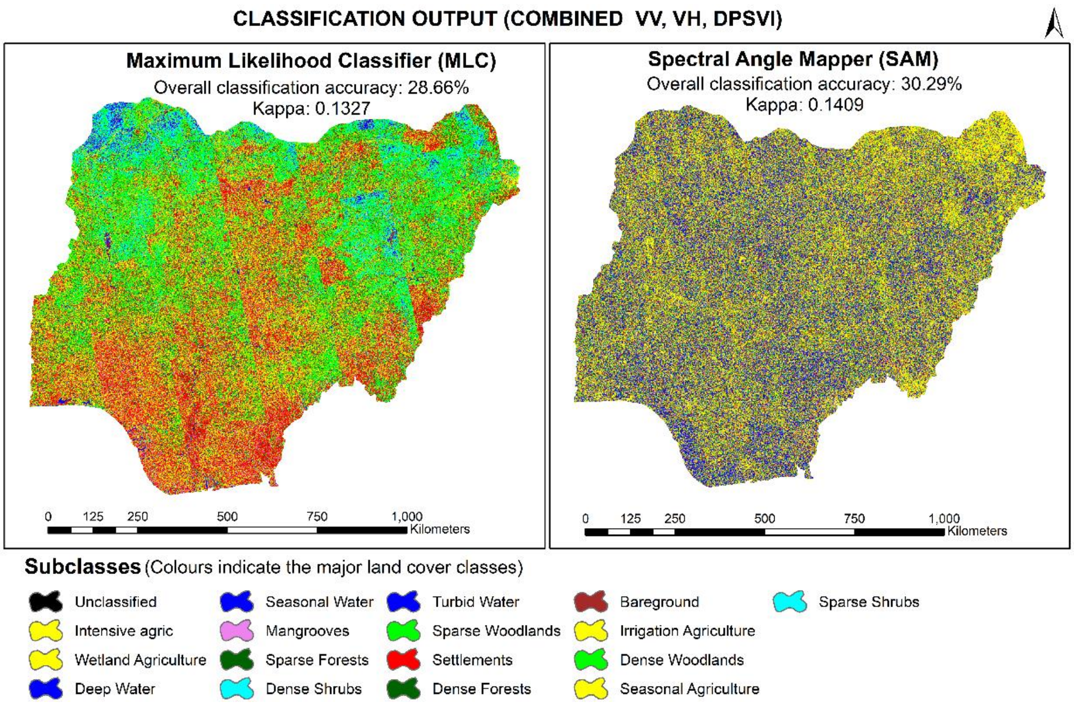
CLASSIFICATION OUTPUT (COMBINED Red, NIR and NDVI)

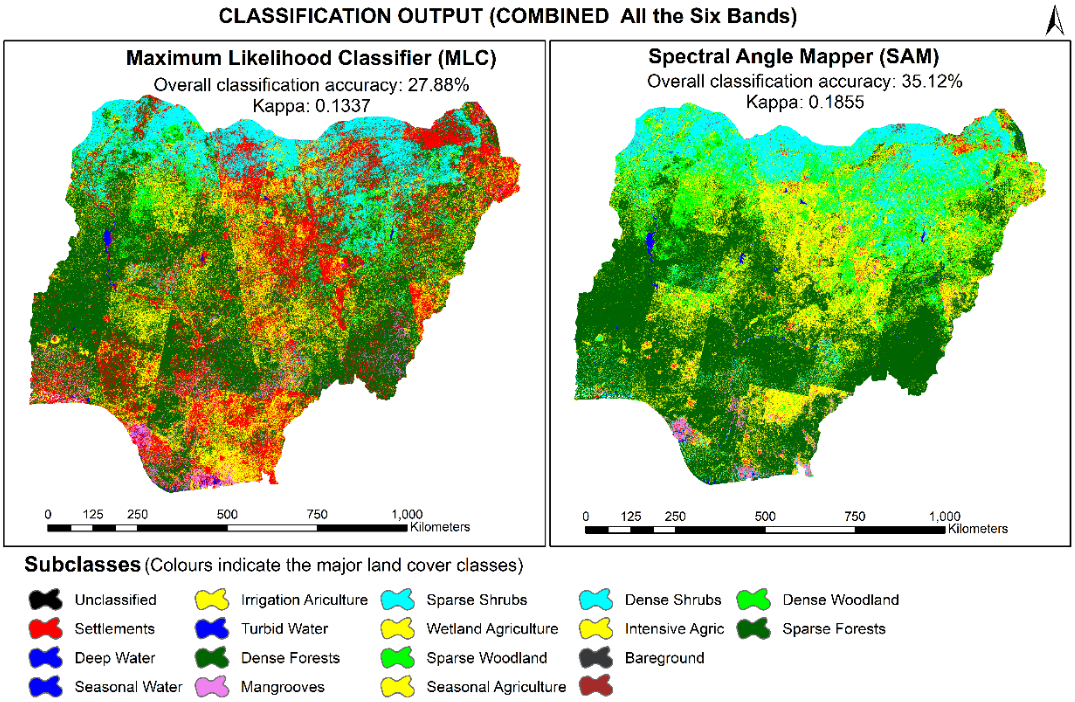


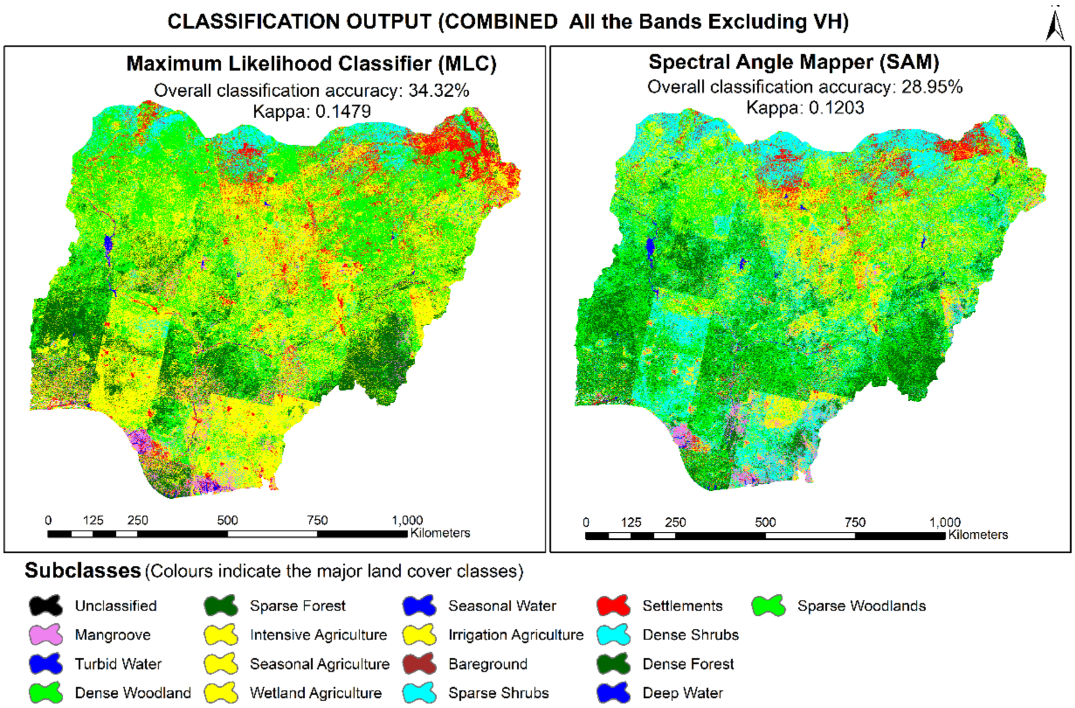

CLASSIFICATION OUTPUT (COMBINED Red, NIR, NDVI and DPSVI)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 49.92%
Kappa: 0.2361
Spectral Angle Mapper (SAM)
Overall classification accuracy: 33.24%
Kappa: 0.1553
0 125 250 500 750 1,000
Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Turbid Water
Deep Water
Seasonal Water
Sparse Shrubs
Wetland Agriculture
Dense Forest
Irrigation Agriculture
Class 4
Intensive Agriculture
Dense Shrubs
Sparse Woodland
Baregrounds
Sparse Forest
Mangroove
Dense Woodlands
Seasonal Agriculture


CLASSIFICATION OUTPUT (COMBINED VV, VH, DPSVI AND NDVI)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 32.98%
Kappa: 0.1742
Spectral Angle Mapper (SAM)
Overall classification accuracy: 30.56%
Kappa: 0.1585
0 125 250 500 750 1,000
Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Dense Shrubs
Baregrounds
Dense Forests
Sparse Shrubs
Sparse Forests
Wetland Agriculture
Turbid Water
Irrigation Agriculture
Intensive Agriculture
Settlements
Seasonal Water
Sparse Woodlands
Dense Woodlands
Mangroove
Deep Water
Seasonal Agriculture


CLASSIFICATION OUTPUT (COMBINED VV and VH)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 29.49%
Kappa: 0.1072
0 125 250 500 750 1,000
Kilometers
Spectral Angle Mapper (SAM)
Overall classification accuracy: 38.87%
Kappa: 0.1928
0 125 250 500 750 1,000
Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Wetland Agriculture
Sparse Woodlands
Intensive Agriculture
Sparse Shrubs
Settlements
Sparse Forests
Deep Water
Mangrooves
Turbid Water
Baregrnd
Seasonal Water
Dense Forest
Irrigation Agriculture
Dense Woodlands
Seasonal Agriculture
Dense Shrubs


CLASSIFICATION OUTPUT (COMBINED VV, VH, DPSVI)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 28.66%
Kappa: 0.1327
0 125 250 500 750 1,000
Kilometers
Spectral Angle Mapper (SAM)
Overall classification accuracy: 30.29%
Kappa: 0.1409
0 125 250 500 750 1,000
Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Intensive agric
Wetland Agriculture
Deep Water
Seasonal Water
Mangrooves
Sparse Forests
Dense Shrubs
Turbid Water
Sparse Woodlands
Settlements
Dense Forests
Bareground
Irrigation Agriculture
Dense Woodlands
Seasonal Agriculture
Sparse Shrubs


CLASSIFICATION OUTPUT (COMBINED All the Six Bands)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 27.88%
Kappa: 0.1337
0 125 250 500 750 1,000 Kilometers
Spectral Angle Mapper (SAM)
Overall classification accuracy: 35.12%
Kappa: 0.1855
0 125 250 500 750 1,000 Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Irrigation Ariculture
Sparse Shrubs
Dense Shrubs
Dense Woodland
Settlements
Turbid Water
Wetland Agriculture
Intensive Agric
Sparse Forests
Deep Water
Dense Forests
Sparse Woodland
Bareground
Seasonal Water
Mangrooves
Seasonal Agriculture


CLASSIFICATION OUTPUT (COMBINED All the Bands Excluding VH)
Maximum Likelihood Classifier (MLC)
Overall classification accuracy: 34.32%
Kappa: 0.1479
0 125 250 500 750 1,000 Kilometers
Spectral Angle Mapper (SAM)
Overall classification accuracy: 28.95%
Kappa: 0.1203
0 125 250 500 750 1,000 Kilometers
Subclasses (Colours indicate the major land cover classes)
Unclassified
Sparse Forest
Seasonal Water
Settlements
Sparse Woodlands
Mangroove
Intensive Agriculture
Irrigation Agriculture
Dense Shrubs
Turbid Water
Seasonal Agriculture
Bareground
Dense Forest
Dense Woodland
Wetland Agriculture
Sparse Shrubs
Deep Water

Class accuracies for the classifications of the 20 different bands combinations as discussed in subsection 5.3.4.3. The seven classification outputs selected for combination due to relatively higher accuracies are highlighted in colours. Note; Mangrove was later combined with forest.

Classification	Accuracies	Agriculture	Bareground	Forest	Mangrove	Settlement	Shrub	Water	Woodland	Overall	Kappa
	Producers	52.55%	_	33.33%	27.27%	42.86%	5.33%	31.58%	32.08%		
Max_All_Bands_Ex_VH	Users	45.00%	_	37.25%	33.33%	20.69%	30.77%	100.00%	16.50%	34.32%	0.1479
	Producers	29.93%	_	61.40%	18.18%	57.14%	9.33%	26.32%	9.43%		
Max_All_Bands	Users	55.41%	_	23.03%	22.22%	9.41%	22.58%	100.00%	33.33%	27.88%	0.1337
	Producers	21.17%	_	78.95%	0.00%	28.57%	8.00%	36.84%	24.53%		
Max_NDVI_DPSVI	Users	42.03%	_	30.41%	0.00%	12.50%	24.00%	100.00%	15.85%	28.15%	0.1258
	Producers	53.28%	33.33%	1.75%	0.00%	64.29%	45.33%	42.11%	3.77%		
Max_NDVI_DPSVI_NIR	Users	45.91%	40.00%	33.33%	0.00%	12.33%	30.91%	80.00%	18.18%	34.85%	0.1536
	Producers	32.12%	_	77.19%	0.00%	50.00%	6.67%	42.11%	20.75%		
Max_NDVI_DPSVI_VV	Users	44.44%	_	33.59%	0.00%	16.28%	50.00%	100.00%	14.10%	32.17%	0.1607
	Producers	21.90%	16.67%	92.98%	18.18%	42.86%	2.67%	10.53%	30.19%		
Max_Red_NIR_NDVI	Users	50.00%	100.00%	31.93%	40.00%	50.00%	28.57%	100.00%	13.56%	30.29%	0.1523
	Producers	47.96%	_	77.19%	18.18%	_	22.67%	57.89%	42.64%		
Max_Red_NIR_NDVI_DPSVI	Users	56.43%	_	50.99%	100.00%	_	42.22%	44.00%	34.81%	49.92%	0.2361
	Producers	35.04%	_	64.91%	0.00%	64.29%	5.33%	42.11%	30.19%		
Max_VV_VH_DPSVI_NDVI	Users	50.00%	_	33.94%	0.00%	19.57%	44.44%	100.00%	15.84%	32.98%	0.1742
	Producers	48.69%	0.00%	24.04%	0.00%	74.29%	19.33%	21.05%	28.87%		
Max_VV_VH_DPSVI	Users	49.85%	0.00%	32.22%	0.00%	22.00%	43.33%	44.44%	20.53%	28.66%	0.1327
	Producers	51.09%	_	24.56%	9.09%	35.71%	14.67%	26.32%	5.66%		
Max_VV_VH	Users	46.05%	_	23.73%	6.67%	7.25%	35.48%	21.74%	13.64%	29.49%	0.1072

SAM_All_Bands_Ex_VH	Producers	29.93%	0.00%	31.58%	27.27%	14.29%	18.67%	36.84%	41.51%	28.95%	0.1203
	Users	53.95%	0.00%	29.51%	37.50%	12.50%	17.50%	100.00%	18.18%		
SAM_All_Bands	Producers	35.77%	0.00%	89.47%	9.09%	28.57%	12.00%	36.84%	16.98%	35.12%	0.1855
	Users	52.69%	0.00%	30.36%	100.00%	44.44%	23.68%	100.00%	16.98%		
SAM_NDVI_DPSVI	Producers	24.09%	0.00%	29.30%	19.09%	24.29%	43.33%	25.79%	26.98%	27.59%	0.118
	Users	42.86%	0.00%	33.40%	15.88%	43.33%	33.58%	16.67%	26.98%		
SAM_Red_NIR_NDVI	Producers	24.09%	50.00%	91.23%	18.18%	21.43%	10.67%	36.84%	22.64%	32.44%	0.165
	Users	45.83%	100.00%	31.52%	25.00%	60.00%	16.00%	100.00%	19.67%		
SAM_Red_NIR_NDVI_DPSVI	Producers	37.96%	_	64.91%	9.09%	0.00%	17.33%	21.05%	30.19%	33.24%	0.1553
	Users	52.00%	_	30.33%	16.67%	0.00%	22.81%	40.00%	21.33%		
SAM_VV_VH_DPSVI	Producers	35.04%	16.67%	17.54%	0.00%	28.57%	29.33%	42.11%	35.85%	30.29%	0.1409
	Users	52.17%	25.00%	37.04%	0.00%	23.53%	28.57%	13.11%	20.65%		
SAM_VV_VH_DPSVI_NDVI	Producers	34.31%	_	80.70%	_	64.29%	17.11%	15.79%	0.00%	31.90%	0.1585
	Users	50.00%	_	35.94%	_	12.33%	20.97%	100.00%	0.00%		
SAM_NDVI_DPSVI_NIR	Producers	18.25%	50.00%	89.47%	_	28.57%	30.67%	36.84%	_	30.56%	0.1474
	Users	43.10%	21.43%	33.77%	_	16.00%	19.83%	100.00%	_		
SAM_VV_VH	Producers	67.88%	50.00%	47.27%	_	50.00%	2.67%	31.58%	11.32%	38.87%	0.1928
	Users	49.21%	16.67%	30.59%	_	30.43%	18.18%	100.00%	18.18%		
SAM_NDVI_DPSVI_VV	Producers	30.66%	50.00%	64.91%	_	28.57%	25.33%	36.84%	26.42%	34.05%	0.1407
	Users	55.26%	12.00%	33.33%	_	23.53%	24.36%	100.00%	24.56%		

Appendix XI: Abstract of the review article published from this work

Biofuel programmes are characterised with failures especially in Africa, including Nigeria. One of the major factors causing these failures is embarking on programmes that are not based on profound knowledge of the feedstock ecology. In Nigeria, biofuel feedstock land suitability maps that exist provided very low details regarding the suitability of the lands. Broadly, this research seeks to provide more robust workflow for producing biofuel crops land suitability maps with higher details. Thus, this review aims to collate information necessary for this robust spatial analysis. The article examines the production trends for oil palm and Jatropha as identified biodiesel crops in Nigeria. It then assesses the local demand for and processing of biodiesel and explored the ecological requirements of the crops. It also investigated the sustainability issues, identified some policy gaps and proffered a policy realignment strategy to ensure successful and sustainable biodiesel industry in the country. The review showed that though not without criticisms, the choice of oil palm and Jatropha for biodiesel production in Nigeria is appropriate. However, the potentials of these crops have not duly been exploited and Jatropha might have an edge due to the ecological advantages it presents. It is concluded here that the pathways to successful and sustainable biodiesel programme in Nigeria must give due consideration to cultivation sites optimisation based on the crops ecological requirements and the crops yields improvement. These must be supported by appropriate agronomic practices and processing technologies, informed business planning and policy realignment and effective policy enforcement.

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