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Impact of Climate variability on Maize production in the Agroclimates of Cross River State, Nigeria

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Abstract

Climate change is a potent factor in agriculture production, and the sustainability of food security in sub-Saharan Africa (SSA). While many studies have emphasised modelling climate change impacts on crop yield and adaptation strategies on regional scale, there is still limited understanding of smallholder farmers response to climate change and the measures to combat food security in local communities. This thesis explores a mixed methodological approach to understand the impact of climate variability on maize production for the principal maize-producing communities in the rainforest and savannah agroclimatic zones of Cross River State, Nigeria. This was aimed to expand the knowledge of local adaptation to climate change impact on maize crop production. Four research questions were set to guide the study. Observed climate and maize yield data were collected from the Nigerian Meteorological Agency (NIMET) and Cross River Agricultural Development Project (ADP) in the zones from 1990-2016. The DSSAT model was calibrated with existing site-specific soil, weather, and crop data obtained from the field experiments conducted by the CRADP, and the farmers Focus Group Interview (FGI). The measured data on grains yield, days to anthesis, days to physiological maturity, leaf area index, and harvest index data for the growing seasons experiment between 1990 and 2016 were used to validate the model efficacy to simulate these parameters. The results of r-square above 0.6, and the d-index statistics greater than 0.9 for the evaluated parameters in these agroclimatic zones indicates the model ability to simulate the observed and simulated yield adequately. While the Normalized Root Mean Square Error was less than 10% and the agreement index closer to unity also indicates excellent prediction of the model capacity.

The model was applied to test the sensitivity of maize yield response to changes in rainfall using the Environmental Modification Unit (Emu) in DSSAT. This reveals that rainfall has a strong positive correlation with grain yield, and a significant confidence level at (0.05) in the zones. A seasonal analysis for changes in planting date also reveals that the month of April has the highest mean grain yield of 6557kg/ha in the rainforest, while the savannah was 5942kg/ha. Hence, planting Obasuper 2 maize in the month of April was found to be the best time in the year for the zones.

Secondly, the thesis adopted a participatory survey approach to quantify farmers' response to the factors influencing maize yield and adaptation to climate variability in the zone. A five-point Likert scale questionnaire of 35 items was designed, and 68 maize farmers were systematically sampled from communities in each zone. A Varimax orthogonal rotation scheme was adopted and factors loading with Eigenvalues greater than one was extracted for a-Factor solution analysis. Factors scores obtained were run in a multiple regression model. The model results were significant at the 0.05 level with R^2 of 0.73 in the rainforest and R^2 of 0.88 in the savannah. The finding revealed that those crucial factors influencing yield in the zones were climate factor, socioeconomic factor (income), and farm size and fertilizer application

Thirdly, the thesis explores data from eight focus group discussions conducted in the selected communities of the zones to understand farmers’ responses to climate variability and the coping strategies adopted. Their responses were analyzed in NVIVO software. The findings revealed that climate variability was evident with increased levels of rainfall, heatwaves, and widespread insect infestation, which has not been known in the zones. In response to these impacts, farmers change planting dates, adopt an early maturity cultivar, diversify to other crops like cassava and use a native plant called ‘dogoyaro’ to combat insects. Finally, a synthesis of the approaches was employed to explore the nexus between the quantitative modelling and participatory approaches which showed that changes in planting dates to mid-April as noted by the local farmers, also produced a good yield in the model. These approaches provide a holistic understanding and direction for future sustainable interventions of the impacts of climate change on the rainfed maize growers in the agroclimatic zones.

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Chapter 1: Introduction

1.1. Background to the study

Maize (Zea may L.) contributes substantially to food security especially in poor countries (Porter et al., 2015). Maize is an important source of calories in sub-Saharan Africa, grown by 70% of smallholder rainfed farmers for livelihood (Falconnier et al., 2020;Waongo et al., 2014). Since its discovery in Latin America, the crop has spread quickly to SSA due to its adaptability and tolerance to different environments (Kornher, 2018; Otung, 2014). Maize provides more than 500million household nutritional needs in SSA (Olowe et al., 2020; Ruano et al., 2016), where Nigeria only constitutes half of this population in SSA. Maize has been described as the 'queen of cereals' in many regions (Arije et al., 2018; Hinjari et al., 2020; Shrestha et al., 2016). The crop serves extensive purposes for national economic value, and to a greater percentage for smallholders' nutritional requirements (John et al., 2018). Maize is cooked as porridge, roasted, or boiled and eaten with plum. Maize can be converted into flour for 'fufu' or 'pap'. It is brewed into different locally made cheap drinks for family ceremonies. Maize provides an alternative source of carbohydrates, protein, and vitamins (Hinjari et al., 2020; Oliver et al., 2012)). The crop can be sun-dried and sold as a raw material for the formulation of poultry feeds, for infant food, the brewery industries, made as cookies, and ice cream (Sowunmi & Akintola, 2010), and to produce biofuel (Shiferaw et al., 2011). The maize crop is also a potential source of income for smallholder 'farmers (Ammani, 2015).

The domestic consumption rate of maize in Nigeria has risen since 1960 from 914,000 (Thousand tonnes) to 11,800, 000 (Million tonnes), but the production rate has dropped from 50.05% in 1969 to 4.89% in 2020 (Yarnell, 2015; USDA, 2020). Nigeria as the world's 10th largest maize producer and the largest in Africa has faced a declining maize yield rate of about 1.7tha^{-1} compared to the global average threshold of 4.9tha^{-1}, while South Africa produces 4tha^{1} and the USA 10tha^{-1} (Abera et al., 2018; Iyanda et al., 2014). Conversely, maize has contributed about USD25 billion in export, accounting for 90 of the total export for major maize exporting countries like the USA, Brazil, Argentina, and Ukraine (Kornher, 2018; Tigchelaar et al., 2018). Unfortunately, Nigeria's grain yield has remained quite low and highly variable. Nigeria has been importing maize for the last three decades (Daramola et al., 2005). This declining rate in maize yield would trigger a food security problem in Nigeria where its population will be over half a billion by 2100 (Arije et al., 2018; Olowe, 2020). Maize yield is expected to nose-dive under poor crop management practices and poor adaptation measures to climate change (Shikuku et al., 2017: Oloyede et al., 2014). Food demand is estimated to double by 2050, with at least 60% extra food will be required to meet the global population of 9.7 billion (Xu et al., 2016; Zhao et al., 2017).

1.1.2. Climate variability a concern

Climate variability is alluded to influence 30% of maize yield variability in Africa (Gaupp et al., 2020). This has been linked to seasonal and inter-annual climate variability (Ewert et al., 2015; Ray et al., 2014). Climatic anomalies like recurrent drought, ravaging dust storms, high rainfall intensity, floods, and heatwaves have affected negatively crop yields in many regions of the globe (Ekpoh & Nsa, 2011; Gaupp et al., 2020; IPCC et al., 2013). The recent dramatic rise in the frequency and severity of extreme climatic events in regions of SSA (Thornton et al., 2014) and rainfall variability (Sina & T.O, 2007), have a potential impact on crop production (Ndawayo et al., 2017). Climate change would add more strain, resulting in deterioration in food security (Wollenberg et al., 2016), by increasing smallholders farmers vulnerability to climatic shocks (Matthew et al., 2015; Onyeneke et al., 2019; Thornton et al., 2014), and lowering their adaptive capacity to deal with climatic changes, and crop yield in many regions of sub-Sahara Africa (Abdul-Razak & Kruse, 2017; Alcamo et al., 2007; Mabe, 2012). There is evidence that temperature in Nigeria would rise by 1.5°C between 2030 and 2052 under the A2 and B1 scenarios (IPCC, 2018). This rising temperature and rainfall changes might increase insect pests and diseases for maize leading to a decline in yield (Rose et al., 2016).

While many studies to understand the impact of climate variability and change on maize yield have focused more on crop modelling and statistical approaches; such as the use of mechanistic crop models and economic model for maize yield response to climatic change (Araya et al., 2015a; Bassu et al., 2014; Ewert et al., 2015), others have used statistical analysis of growing season precipitation effect on maize yield in eastern USA (Huang et al., 2015), modelling the effect of climate variability on maize yield in the semi-arid and arid region of Kenya (Omoyo et al., 2015a), simulating maize crop growth and yield response to climate variability (Muller et al. 2011), Time series analysis to investigate the impact of climate impact on maize, wheat and rice and soybean yield in china (Tao et al., 2012). Others evaluate the future impact of maize yield by manipulating the weather and CO_2 in the crop model (Hoogenboom et al., 2017). The Decision Support System for Agrotechnology transfer has been used to provide crop management and adaptation decision to climate change (Liu, 2012; Lehmann et al., 2013). Nevertheless, on a larger spatial scale, some studies used outputs from different GCM models to run sensitivity analysis of crop yield response to climate change (Vucetic, 2011), others adopt global climate models (GCMs) , crop simulations models, and statistical downscaling to understand maize yield response to changes in climate (Charles et al., 2017; Kukal & Irmak, 2018; Xu et al., 2016). The GCMs approach is associated with many drawbacks due to model resolution, calibration, and assumptions which creates uncertainty (Hassan et al., 2020). Nevertheless, GCMs simulations are useful in large-scale regional studies where local climate variability and adaptation strategies are not reflected.

A participatory approach emerged as a way of identifying and solving climate-agriculture-related problems. This approach is a medium of engaging local farmers to facilitate appropriate technology transfer, improve agronomic practices, and adapt to climate change (Orabi, 2018; Zakaria et al., 2020). This approach provides an understanding of local farmers' response to crop management practice, and adaptation strategies, which would help in building an evidence-based practice of climate, change adaptation, and mitigation (Few et al., 2007; Beveridge et al., 2018). A participatory approach was adopted in (Ali & Erenstein, 2017a; Ayanlade et al., 2017; Zakaria et al., 2020) where farmers and key stakeholders were involved in identifying problems and proffer solutions participatory. This approach would offer a sustainable and rewarding climate adaptation formulation for future maize production (Ayanlade et al., 2017). The Integration of rural farmers' knowledge of climate variability would promote adaptation and decrease farmers' vulnerability to climate change (Egbe et al., 2014). While a purely process-based modelling approach without a participatory action omits the relevance of the climate change smart approach to improving and implementing adaptation to climate change for local farmers (Shikuku et al. 2017; Guan et al. 2015). This thesis applies a combined approach to assess the impact of climate variability on maize production in the rainforest and savannah agroclimatic zones of Cross River State.

1.2. The research problems

Small holders' farmers are those that cultivate less than 2ha, who rely more on family labour, and have limited capital (Kamara et al., 2019). They characterized more than 80% of the farming population in Nigeria (Cervigni et al., 2013). Smallholders account for about 80% of the food consumed in SSA. There is strong evidence of climate change and variability impact on crop production in SSA (Parry et al., 2004; Nelson et al., 2009.). The smallholders would be at risk of climate variability, leading to their livelihood depletion (Onyeneke et al., 2019; Thornton et al., 2014). The signals of climate variability are visible in the delay and false onset of the growing season and during early cessation before the harvest of crops. Evidence of soil moisture lost due to excessive temperature and soil fertility leached by extreme rainfall is already common. There have been reported cases of anomalous rainfall trends in these agro climate regions which come in different forms, which made make it difficult for most farmers to decipher the actual farming operations. These changes in growing rainfall would influence the planting dates and shift in the harvest season consequently, with an enormous impact on the rainfed maize farming and decline in maize yield. This alarming reduction rate in yield is a potential challenge for future maize demand. The multiplier impacts of climate variability are reflected in the decrease of farmers' incomes, rising hunger, and starvation (Morton, 2007). Yet there are still few studies on the local impact of climate variability on maize yield of smallholders (Odekunle et al. 2007; Omoyo et al. 2015 Morton, 2007).

The knowledge of climate variability would help formulate sustainable strategies to address the adverse impact of climate variability on maize crop production. This knowledge would provide key to building a strong adaptive capacity base which would, in turn, inform sound policy formulation for action at the bottom. Many regions are already grappling with poverty, high population, food insecurity, and drought challenges. Anticipated changes in the climate would further have a significant impact on livelihood. The implications are that farmers would have to develop resilience to cope with any adverse impact of climate change. This study advocates an inclusive approach in understanding the impact of climate variability and adaptations as key to identifying problems and deciding solutions to the challenges of climate variability and change in regions. It is also worthwhile to note that local climate studies knowledge is a basis for understanding and launching specific adaptation measures. This would seemingly bring a closer solution to combat climate change. Climate-induced yield failure should be framed from within the region in line with those peculiar circumstances in context. The non-involvement of local farmers in the framing of adaptation would limit the implementation and increase farmers' vulnerability to climatic extremes. As adaptation is not a one-size fit all approach. It is imperative to apply context-specific and location measures at addressing specific climate societal issues.

The crux of this research is to assess the impact of climate variability on maize yield in the rainforest and savannah agroclimate zones of Cross River State. The study would contribute to the understanding of climate change resilience and adaptation strategies in these agroecological zones. This is to reduce climate change impact and improve maize production in the two biomes of Nigeria. The research uses a three-approach strategy to provide insight into the smallholder farmers' decision-making process in response to climate change. A participatory research approach involving a survey and focus group was adopted in collecting crop management and climate change response strategies data from the local smallholder farmers in the zones. This information generated on crop management/ agronomic parameters during the participatory-based approach should be framed into the modelling section

Decision Support System for Agrotechnology Transfer (DSSAT) crop model work. The understanding from the survey and focus group discussion from the farmers during fieldwork would be used as a potential adaptation strategy in the modelling work for the zones. A pilot survey was carried out with the administration of a few copies of the questionnaires to some farmers for validation. A full questionnaire survey was completed on the farmers in the respecting maize growing communities in the two zones after the focus group discussion. A preliminary modelling exercise was done initially to understand the working of the crop model using some default variables before being calibrated with actual site-specific data in the zones. Figure 1 shows a simple flowchart to demonstrate the approaches used in the thesis to study the impact of climate variability on maize yield concerning some communities in the rainforest and savannah zones of Cross River State.

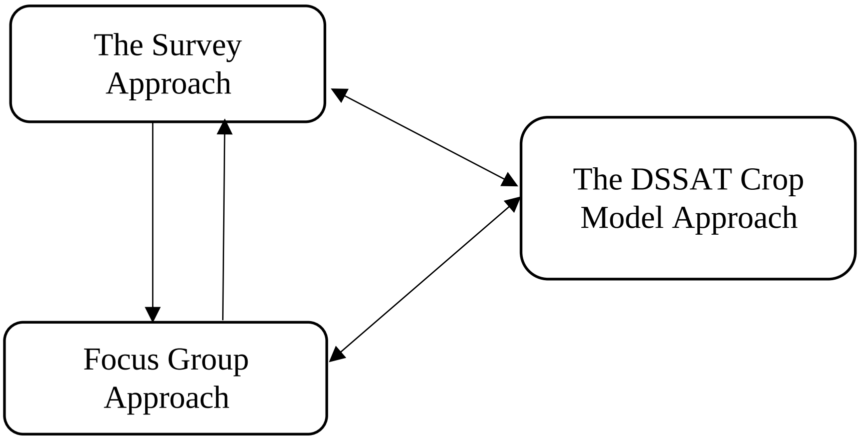


Figure 1. 1: A simple flowchart of the approaches adopted in this thesis to understand the impact of climate variability on maize yield

1.3. Aim and objectives

This research aims to examine the impact of climate variability on maize production (Zea mays L.) in the forest and savannah agro-climate zones of Cross River State, Nigeria. The specific objectives and questions are:

1.3.1. Research objectives

- To assess the relationship between climate variability and maize yield in the rainforest and savannah agro- climate regions**.**
- To use the DSSAT CERES-Maize crop model to simulate maize yield and identify potential adaptation strategies in the region.
- To identify the factors influencing maize yield and adaptation on rain-fed maize production in the zones
- To examine local farmers understanding of climate variability impact on maize crop and the response to adaptation measures in these agro-climate zone**s**

1.3.2. Research questions

- Can the growing season rainfall and temperature mean, be responsible for maize yield changes in these agro-climate zones?
- Can DSSAT CERES-Maize model predict accurate maize yield and identify critical parameters affecting yield in these Agro-climate zones of Cross River State?
- Does management practices or other factors influence maize yield under rainfed in these zones?
- How do local farmers perceive and respond to climate variability and adaptation measures in the zones?

1.4. Organisation of this research

This thesis is organised into eight chapters. Chapter 1 begins with the background of the research and explains the basis for carrying out the study. Chapter 2 dwells on the literature review and conceptual framework upon which the study revolves. It discusses climate variability and trend pattern, crop-climate relationship, the process-based crop model, and participatory farmers' model. Then, it explores the concept of vulnerability to climate change and adaptation strategies, the challenge of farmers' adaptation to climate change. Knitting the chapter with the calibration of the DSSAT crop model and sensitivity analysis methods

Chapter three shows details of the general geography setting of the regions and describes the method of data collection for the calibration of the DSSAT CERES-Maize model using version 4.7 model with site-specific parameters. Chapter 4 presented analysis of climate time series using a simple decomposition method and the results of maize yield response to changes in adaptation strategies adopted in the zone. Chapter 5 addresses the survey of maize farmers' responses to factors influencing maize yield in the rainforest and savannah agroclimatic regions using factor analysis and multiple regression models. While chapter 6 captures the analysis of farmers' adaptation knowledge of the impact of climate variability on maize production in the rainforest and savannah agro-climate zones of Cross River State using Focus Group Discussion (FGDs). Chapter 7 integrates the crop model and participatory results and look at the implications for future climate change on maize production in the rainforest and savannah agroclimate zones. Finally, chapter 8 draws conclusion and make recommendations for policymakers and the farmers in the zones.

Chapter 2: Conceptual Framework and Literature Review

2.1. Introduction

Farmers have become increasingly aware of the changing climate and are adopting different forms of adaptive measures to mitigate the adverse effects of climate change. However, socioeconomic, and cultural variation of farmers from one region to another may impact their response to climate change effort. This research section is dedicated to unravelling this dynamic, through reviewing methods that have been used in understanding how climate influences maize production. In this research, a combined approach (process-based crop model and participatory model) is used as the lynchpin to enrich the current understanding of the impact of climate variability on maize production in the rainforest and savannah zone of Cross River State, Nigeria. Chapter two comprises a review of the literature that provides the basis for this research. There is also a discussion of key conceptual frameworks that underpin this research work. The research theme is centred on assessing the impact of climate variability on maize production in the rainforest and savannah agroclimate zones of Nigeria. It has been reported that the climate is a fundamental element that drives crop production in most regions of sub-Saharan Africa. This section dedicates more time to unravelling this influence with particular interest on maize yield. The section analyses the deep contentions in climate dynamics, and crop management practice within the context of small holders' rain-fed farms in Nigeria.

2.2. The concept of vulnerability and adaptation to climate change

The concept of vulnerability is commonly used in biophysical and socio-economic research. Vulnerability explains the degree to which a system is susceptible to harm due to exposure to perturbation, shock, or stress (Turner et al., 2003; Lokono, 2017). A natural or social system can be damaged by its susceptibility to climate variability or change. The response of a system to changes in climate whether beneficial or harmful effects is a function of its sensitivity (Schneider et al., 2011). The vulnerability of maize farmers to climate variability depends on three key indicators, namely, their exposure, sensitivity, and adaptive capacity (Hassan et al., 2011; Faizi et al., 2017). It is necessary to evaluate farmers' response to adaptation measures to boost their productivity (Ayanlade et al., 2017). However, farmers' ability to implement adaptation strategies differs due to their socio-economic conditions. Identifying farmers' constraints to adopt or vary practice in response to climate change can be helpful to prioritize intervention strategies (Shikuku et al., 2017). Addressing climate variability shocks through sustainable farm management strategies is aimed at improving the traditional old techniques, which tend to compromise the modern food security agenda. The drive is to provide sound decision-making for building adaptation measures for food security (IPCC 2007; Lobell et al., 2011; Wang et al., 2014). This understanding would be relevant at the country level in making decisions, for climate-smart agriculture. The urgent need for a robust assessment mechanism and a realistic adaptation measure to boost maize crop production for the growing population is imperative.

Climate perturbations are external forces that have the potential to impinge on the system. Endogenous forces are the social and ecological factors that can influence the increase of vulnerability (Luer, 2005). Climate variability and change generate such perturbation or shocks that can increase vulnerability. It follows that region with poor technological buffering would have low resilience and high vulnerability to climate variability. Smallholder farmers' capacity to adapt would be constrained, due to low institutional support and technical help, inaccessibility of credit, farm input, and lack of access to climatic forecasting (Serdeczny et al., 2015). Hence, they would be more vulnerable to climate anomalies (Mereu et al., 2015).

Studies have revealed that a poor socioeconomic background and limited knowledge of adaptation 'technology' to cope with climatic variability presents a potential danger for the future food security and sustainable livelihoods in Sub-Saharan countries (Serdeczny et al., 2015; IPCC, 2014; Niang et al., 2014). High climate variability creates more risks in the agriculture sector, especially to smallholders' farmers. These risks are generated from the false onset or early cessation, drought, flood, or other extreme climate events like heat waves. Climate change impacts would be more severe in areas with little or no alternative response options (Jones and Thornton, 2003). Despite, the daunting challenges posed by climate change there is still little understanding or knowledge of climate variability's impact on the livelihood of rain-fed maize farmers in most regions. Hence, formulating adaptation strategies in this sense would be helpful to bridge the knowledge gap of crop response to climate variability. The expectation is that climate-smart response measures that capture agro-climate zone conditions would offer support to smallholder maize farmers who predominantly face more of the brunt from climatic perturbations. A greater percentage of smallholder's farmers in Africa still rely on rain-fed agriculture for their livelihood (Vincent Gitz et al., 2016; Ayanlade et al., 2017). This implies that stresses from climatic shocks are more likely to damage the farmers' capacity to sustain food production (Ama et al.,2013; Ayanlade et al., 2017) due to the seasonal changes in rainfall and temperature (Chabala et al., 2015).

2.3. Climate-crop relationship models

Attempts to assess how climate variability and environmental changes have influenced maize crop production are previously documented (e.g., Lobell et al., 2007; Sultan et al., 2013; Ahmed et al., 2017). Conventional statistical models are used at regional, country, or farm-scale (Parry et al. 2004; Schlenker; Lobell & Thornton, 2003; Liu et al., 2012; Wang 2014), where correlation analysis is often adopted to depict a relationship, or using a regression model to assess the effect of the predictor variables on the response parameter (Zinyingere et al. 2011; Poudel $ Shaw, 2016). A combined simple process-based crop model and statistical model proved very skilful in explaining the impacts of climate change on maize yield (Roberts et al., 2017). The underlying assumption keeps other factors influencing maize production constant, such as soil characteristics, agronomic and crop management practices constant. This approach assumes stationarity of crop-climatic relationships and it is weak in offering a powerful explanation of the climate impacts for adaptive response analysis (Challinor, 2009; Muller et al., 2011; Rosenzweig et al. 2013). Statistical modelling supports an easier understanding of current climate variability interactions with the crop by revealing past or current responses of crop yield to changes in climate variables (Mereu, et al., 2015). Despite this, an appropriate and good combination of statistical models with other techniques like process-based crop modelling would provide impressive and useful results.

2.4. Climate variability and trend pattern

Africa occupies a significant portion of the world’s largest landmasses within the low latitude. The continent is known for its heterogeneity in the landscape in the eastern and western sectors, which may account for the spatial-temporal variations in climate (Balas, 2008). The heterogeneous nature of climate variability in Africa has attracted much research for decades. As more than 80% of agricultural activities and hydro energy production are climates dependent in Africa (Agbossou et al., 2012; Serdeczny et al., 2017). For instance, causes of crop yield failure are widely linked to seasonal rainfall variability- the occurrences of late or onset, dry spell, and multi-annual drought in most parts of West Africa (Bibi et al., 2014). Hence, it is important to understand the cause of the high climate variability of rainfall, and the trend pattern in different regions.

El Nino Southern oscillation called ENSO, has been accepted as an important phenomenon that influences climate variability and trend pattern in part of Africa (Kane, 2000; Lemburg et al., 2019; Nicholson, 2014). El Nino which means ‘The child in Spanish’ develops around

Christmas is known for the birth of Christ. This phenomenon is defined as the warming of the ocean. Besides, extensive landmass, vegetation and, surrounding ocean which also plays a significant role in moderating the regional climate of Africa. Another key driver of the climate is the Inter-tropical Convergence Zone (ITCZ). The variability of rainfall below and above latitude 10^{o}N regions in Africa, denoted as Sahel and Guinea coast has drawn many concerns for investigation following the interdecadal signals of 50% dryness in the 1950 and early 1960 (Nicholson, 2017; Nicholson & Dezfuli, 2013; Norrgård, 2015). A striking spatial scale, and the symmetry coherence of rainfall anomalies have been experienced between the subtropical (Sahel) and equatorial region (Guinea coast). There were years of prevailing dry conditions between the Sahel in the north and Guinea coast in the south, and some wet conditions alternating in a spatially coherent manner. Most conditions were manifesting in annual and decadal scale with the frequent mode of variability expressed in anomalies of similar signs across the continent (Nicholson, 2008; Nicholson, 2014). Rainfall dipole between the Guinea coast and Sahel is consistent with the weakening and contraction of the Tropical Rain belt. This North/South displacement that shows interannual rainfall variability pattern has been referred to in the literature as a dipole (Nicholson, 2008). The results of these shifts bring good rainfall to the Sahel/Guinea region, and this has been revealed in the symmetrical rainfall patterns evident in seasonal, annual, decadal and past rainfall records.

The other key explanation for rainfall variability in West Africa has been attributed to the northward and southward excursion of the Intertropical Convergence Zone (ITCZ) following the seasonal migration of the Sun. The ITD model explains that at the lower troposphere over the tropics, two main air streams exist. There are (a) the moist but rather cool Southerly air with a West-south-westerly component called the Tropical Maritime air masses (mT) and (b) a dry and relatively warm Northerly air with an East-north-easterly component called Tropical continental airmass (cT) (Ayoade, 2004). The obvious result of this interaction is the creation of a pronounced “humidity discontinuity. This tropical rain-bearing belt has been commonly called the ITCZ, with clearly define wind convergence such as the tropical maritime and tropical continent winds (Nicholson, 2008). Rainfall in West Africa is connected to the West Africa Monsoon which is known for the seasonal wind perturbations generated by the thermodynamic contrasts between the ocean and land (Lemburg et al., 2019;Nicholson & Grist, 2001). However, there are also two noticeable circulation features of the tropical atmosphere that governs the variability, propagation and the growth of rainfall over Africa- the Africa Easterly Jet (AEJ and the Tropical Easterly jet (TEJ). The AEJ lies across West Africa, while the TEJ extents much further East of Africa where they play a prominent role in the Asian monsoon rainfall (Nicholson, 2008). And it is adduced that rainfall characteristics is consistent with the strength or weakness of TEJ's over West Africa (Nicholson and Grist, 2001).

In the Sahel region, the position of the AEJ seems to be the most important mechanism that differentiates between a 'wet mode' and 'dry mode'. This dry mode consists of two basic spatial patterns, depending on whether the Guinea Coast Region is anomalously wet or dry (the well-known dipole and no-dipole patterns, respectively. The governing factors that influence rainfall in Western Equatorial Africa (WEA) during April, May, and June seasons have a strong link to changes in local sea surface temperature (SST) and south Atlantic subtropical high. Thus, rainfall variability and local sea surface temperature are related to a remote influence of largescale atmosphere-ocean system forcing (Nicholson & Dezfuli, 2013). This forcing is revealed through variations in the zonal circulation. Recent studies suggest that there has been a significant seasonal increase in temperature in the equatorial and southern regions of Africa since the early 1980s (Suryabhagavan, 2017; IPCC, 2014). This change is expected to result in a shift in rainfall and temperature regimes in many regions (Mereu et al., 2015). The trend may continue, with average temperatures being expected to rise over West Africa between 1.5°C and 4°C by mid-century. A greater increase is likely to be experienced in the Sahel and on the Sahara Desert than the guinea coast (Pokam et al., 2016). In West Africa, there was a remarkable decrease in annual average rainfall northward of the last 40 years, with both delayed onset and early cessation (Traore et al., 2000; Ekpoh & Nsa 2011). While in East Africa, a statistical analysis of 35 years' rainfall data showed strong variability with a tendency towards increased rainfall, but no trend was established (Nouaceur & Mursrescu, 2016).

While the climate of Nigeria is a microcosm of West Africa. Hence, the main mechanisms that govern the spatial-temporal variability of climate in Nigeria are similar except for some small variations in local conditions such as relief, ocean currents, continentality, vegetation, and urban heat effect in the sub-region. Climate variability is reflected in the erratic migration of the inter-tropical Front (ITF) with a slower advancing rate northwards and faster retreat southwards, resulting in abrupt end of rains in the northern parts of the country (Adefolalu, 1989; Olaniran, 1991). There is a warmer hot season from March to May which has hot episodes of heat waves as temperature increases to about an average of 0.4 – 1.5^{0}C with extreme ranges of 2.00 – 3.3^{0}C being observed across the country. It has been noted that in the south more convective activities and cloud formation ushered more precipitation than the north where there is little or no cloud formation which results in lower amount of rainfall (Ayoade, 2004). The main two air masses detect the season of the year, whether dry or wet season. This accounts for the Spatio-temporal distribution of rainfall in Nigeria.

The methods of analysing trend and variability of rainfall and temperature patterns reported in literature are the Mann-Kendall, Sen's slope, coefficient of variability, and linear regression (Mahmood et al., 2019). These tools are vital in hydrology, climatology and agriculture studies for making decision and policy formulation. An analysis of rainfall and temperature variability in Nigeria from 1971-2010 using coefficient of variability, skewness, and Kurtosis revealed that there is an increase in precipitation and air temperature in most of the stations, with an alternating decrease and increase in long times trends in some years (Akinsanola & Ogunjobi, 2014; Obot et al., 2010; Odekunle et al., 2007). The mean annual increase in precipitation and air temperature has relatively upward trend across most stations in Nigeria. However, during the first decade of 1971-1980, air temperature recorded some negative anomaly of -0.2 and 1.6 in some locations (Warri, Kaduna, Bida, and Bauchi). But positive anomalies with normal conditions was notable from 1980-2000. This corroborates with earlier studies that employed statistical and GIS techniques to demonstrate an increasing trend in rainfall in the guineas and forest region of Nigeria (Odekunle et al., 2007). The climate of Nigeria exhibits some form of spatial-temporal variability from individual region analysis. The South-eastern region has a classic characteristic of Savannah and Forest climate which falls within the region of this research. An analysis of rainfall distribution in Enugu, the southeast part of Nigeria agroclimatic zones during the 'little dry season for the month of June, July, August and September from 1990-2005, reveal a downward trend in inter-annual variability of rainfall amount in the month of August for the period of the study (Christian & Izuchukwu, 2009). It was noted that the year 1997 was the wettest, while 1994 was the driest year in the series.

2.5. Climate anomalies and maize yield

Climate plays a key role in rain-fed agriculture activities in sub-Saharan Africa. An anomaly in the climate parameters can impact positively or negatively on crop yield in different regions (Li et al., 2011). Change in precipitation, temperature, and the upsurge in carbon dioxide level has affected cereal production in SSA. Climate variability may well impinge on agriculture at both the pre- and post-planting stage; this presents a daunting challenge for current and future maize crop production (Ali et al., 2017; IPCC, 2014). There is a projected decrease in maize yield from 43% to 24% by the end of 2100 in East Africa (Abera et al., 2018). High interannual variability of growing season rainfall is responsible for about 60 percent of maize variability (Kassie et al., 2015), resulting in US$2billion loss in maize production (Eshetu et al., 2014; Abera et al., 2018). Similarly, variation in regional temperature and economic conditions would exert a substantial impact on maize crop production in sub-Saharan regions (Mereu et al., 2015). Already, a visible decrease of rainfall has been projected in southern Africa, whereas an increase is expected in East Africa (Serdeczny et al., 2015). A better understanding of the local climate trend will provide a better foundation for planning and decision making in different agro-climate zones.

2.6. The participatory farmers (bottom-up approach) model

The Participatory approach builds on the local knowledge base and thus empowers farmers to make decision for future climate (Ross et al., 2015). This concept has link to the Fuzzy Cognitive Mapping (FCM) that originated in 1986 (Kosko, 1986), which aim to elicit knowledge based on key actors' opinions and belief systems. FCM is gaining increasing popularity as a participatory technique for studying climate-society systems. A semi-quantitative derived from graph theory has potency for fostering bottom-up decision making in a complex system. FCM are graphical representations to illustrate relationships between evidence-based indicators in a system with feedback mechanisms (Gray et al., 2015). Its justification is derived from constructivist psychology which has the premise that cognitive maps are external displays of an internal idea, opinion, or beliefs. FCM is used to define positive and negative relationships between variables, placed on a weighted scale between +1 and -1 to show the relationships between components in a system. Variables with a positive sign denote a direct relationship, while variables with a negative sign show that there is an inverse relationship. They can be physical, economic, social, political, or aesthetic entities. Qualitatively assigned scores such as low, medium and, high can be used to show the strength of a relationship. FCM's major strength is in its ability to combine natural and social systems into a model through simple algorithms (Gray et al., 2015). While FCM's weakness is the subjectivity of responses, it still gives a realistic picture of how people perceive and respond to environmental changes.

2.7. Top-down model approaches for crop modelling management decision

A model is simply a powerful tool used to mimic, represent and explain phenomena (natural or man-made). They attempt to demystify natural occurring processes by giving insight into the interaction between morphological, physiological and meteorological parameters (Vučetić, 2011). Models are based on theories of naturally occurring phenomena and future conditions. There are four approaches in modelling the physical processes (climate change) for crop management decision- the process-based model, statistical extrapolation, detail simulation and expert opinion or role-based models (Cuddington et al., 2013). But two distinct approaches are widely considered in evaluating the impact of climate change on agricultural output, the process-based mathematical model of plant growth and seed formation (Jones & Thornton, 2003) and the statistical regression model (Roberts et al., 2017). The statistical model is widely popular in literature (Corbeels et al., 2018) for assessing climate impact on crop production. This method tries to investigate the linear impact of climate change on crop yield. Statistical models predict the impact of climate change using baseline climate and projected GCM climate data to explain crop yield (Zhang et al., 2015). They can also extrapolate impacts to those years where crop yield data are missing thereby fostering the interpretation of the historical impact of climate change (Ayoade, 2008). However, this approach is handicapped in explaining the interactions, and influence of other parameters on yield. Nevertheless, the regression model is still very useful in demonstrating the effect, and contributions of explanatory crop variables on the yield. As crop yield is a function of the interplay of many occurring processes which are intricately connected to a range of agronomic practices, soil properties, and climate regimes.

A process-based crop simulation model is a mechanistic computer-based crop model used to understand the complex interaction between different processes that influence crop production. Process-based modelling was introduced to overcome the limitation of statistical or empirical crop-climate models which only show the linear response of crop yield to climate. It is important to carefully consider which model is best suited in supporting crop management decisions for climate change. Process-based modelling considers the physiological growth and development of a crop as a function of the climate, soil, and crop management parameters (Jones & Thornton, 2003). The process-based crop model parametrizes daily plant processes; it has been used to project future crop yield (Challinor et al., 2014). The key strength of process-based modelling is that it links weather to crop yield outcome, with many of the essential parameters in these models, having been established through laboratory experiments (López-Bernal et al., 2018).

The theoretical understanding of key ecological processes that are embedded in a process-based model tend to provide us with a useful framework in which to add specific responses to changing environmental conditions (Cuddington et al., 2013). Processed-based modelling provides notable advantages in predicting the effect of climate change on crop yield when compared to using purely statistical models. A process-based model helps unpack this complex interaction. The application of process-based modelling has increasingly become common. For example, the application of climate models coupled with process-based crop models (Wallach et al., 2016) has been applied to understand how crop yield responds to changes in the natural system. Hence, the process-based approach has gained more usage in climate-crop yield understanding than any model (Lobell et al. 2013; Sultan et al. 2013; Ahmed et al 2015). It has been argued that an integrated approach is more efficient in evaluating the impact of climate change on crop yield (Cuddington et al., 2013; Monier et al., 2018; van Loon et al., 2019), as shown in Figure 2.1.

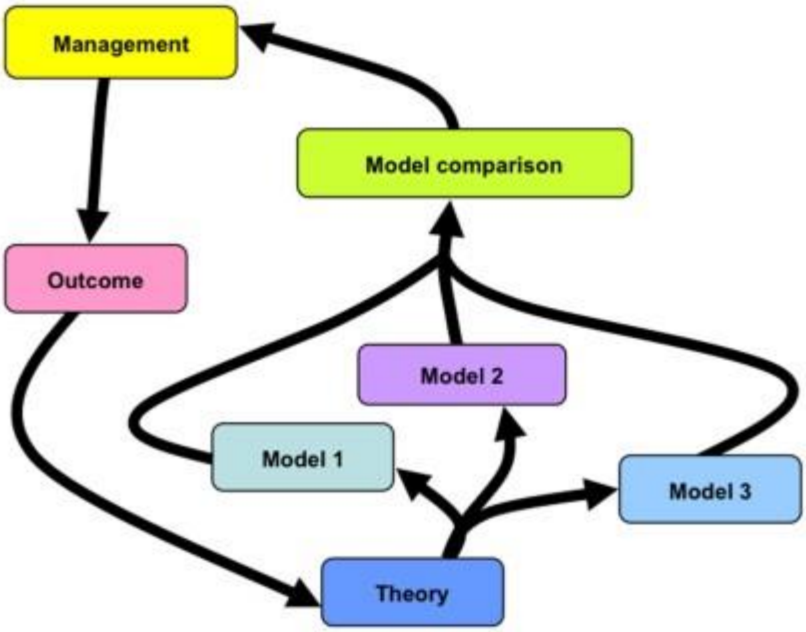


Figure 2.1: Schematic depiction of the relationship between theory, model and management (Cuddington et al., 2013)

The application of multimodal ensembles has gained popularity in the assessment of the impact of global climate change on agricultural productivity, but there are a few drawbacks with this robust methodology for local climate analysis. There are problem of scale, irregularities or variations in regional climate, and differences in model efficiency or powers to reproduce the climate (Christian et al., 2020; Wallach et al., 2018). Modellers have argued that if one or more models used have large variability and biases in prediction, the reliability of the mean predictive quality becomes questioned (Wallach et al., 2018). They thought that such ensemble predictors may compromise crop management decision-making. However, no model appears to answer all questions and no model is a best fit for all conditions. Even a very simple model can be powerful in assessing crop management decisions for climate variability/change (Wallach et al., 2018).

2.7.1. History of process-based Agricultural system

Process-based Agricultural system models have a rich history following the quest to overcome food shortage amidst population growth. Crop modelling has become an even more important tool in addressing crop management decisions in this era where the world is grappling with climate change. The history of model development in agriculture is characterised by several key events, drawing in scientists from different disciplines. One of the earliest modelling efforts was carried out by Earl Heady and his students. He tried to optimize decisions at a farm scale and assess the effects of policies on the economic benefits of rural development (Jones et al., 2016).

This milestone opened further opportunities for different disciplines to venture into agricultural modelling. The creation of the International Biological Program (IBP) during the late 1960s and early 1970s led to the development of many ecological models (Jones et al., 2016) for studying grazing by livestock and looking at the complex behaviour of the ecosystem as affected by different environmental drivers (Worthington, 1975; Van Dyne & Anway, 1976). The footprint of IBP opened doors for the application of mathematical system modelling in understanding the complex interaction of the natural system in a comprehensible manner. The pioneering work of physicist C. T. de Wit of Wageningen University in the 1960s led to more insight in agricultural system modelling as he combined physical and biological principles (de Wit, 1958). The work of engineer C.W. Duncan whose paper on modelling canopy photosynthesis made way for the initiation of regional research in the USA at the end of the 1960s by crop modelling scientists.

In the early 1970s, a major boost was recorded in crop modelling when the USA witnessed a high volume of wheat purchases by the Soviet Union. The development led to increased funding of research in crop modelling and remote sensing for the prediction of major crops in the world. This resulted in the emergence of CERES- Wheat and CERES-Maize models by Ritchie and his teammate in Texas, USA (Ritchie, 1995; Ritchie & Otter, 1985). These models are contained in the DSSAT modules suit and have been widely applied in climate change impact studies (Gijsman et al., 2002; Jones et al., 2016). The application of the concept of integrated pest management in the plantation region of Malaysia drove mathematical modelling of pest and disease management during the second half of the 20th century (Conway, 1987).

The International Benchmark Sites Network for Agrotechnology Transfer Project (IBNAT) led to the development of full crop system models. The most widely versatile mechanistic model, the Decision Support System for Agrotechnology Transfer (DSSAT), which assesses the impact of climate change on crop yields was developed between 1983 and 1993. This was funded by United States International Development (USAID).

The last two decades have witnessed tremendous advances in crop modelling, such as representing the land in regional and global climate models for modelling agricultural systems (Jones et al., 2016 Osborne et al., 2009). Some modelling group also represent CO_2, water, and greenhouse gas (GHG) fluxes in models. The creation of the Agricultural Modelling Intercomparison Project (AgMIP) in 2010 ushered in a common forum of global community of modellers to share knowledge and engage in improving model development for informing policy formulation and management decision-making. The different scales of agricultural model usage, and policy application are encapsulated in Figure 2.2

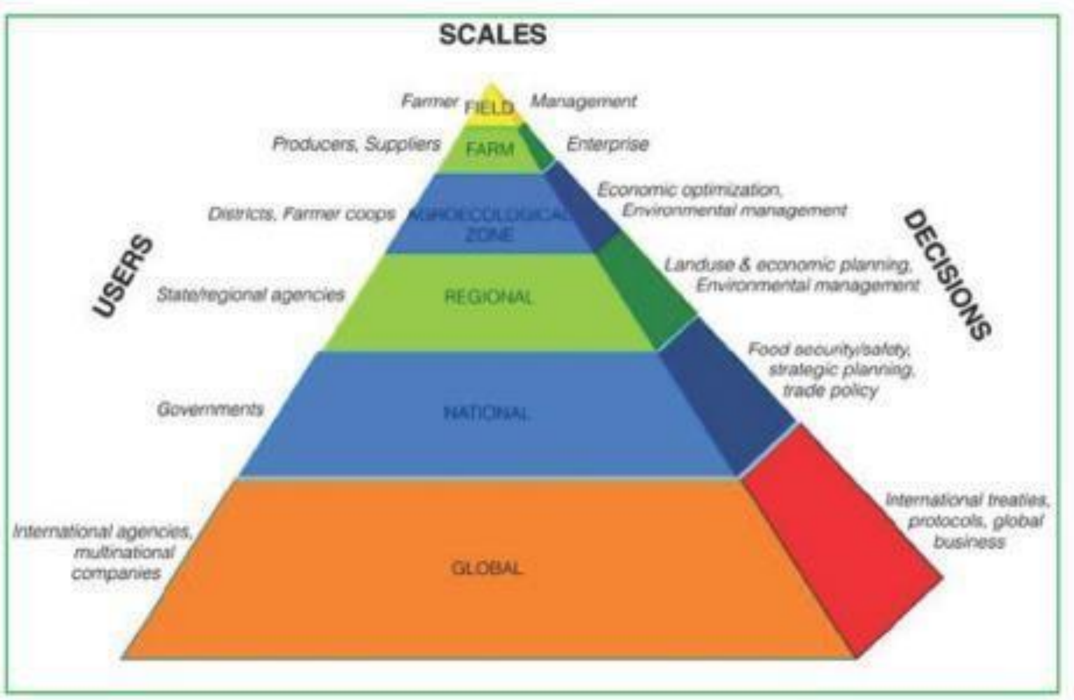


Figure 2. 2: Different scale level of agricultural system models, users, and policy interest (Jones et al., 2016)

2.8. Sensitivity analysis of model parameters (meaning)

Sensitivity analysis (SA) is the connection between input and output variables in a computational model (King & Perera, 2013). It is used to examine how variations in an input variable of a model can be linked to changes in its output factor under given assumptions. SA investigates how changes in output variables can cause variations in different input variables $x_1, x_2 \ldots x_n$. The concept of SA is often applied in climate and atmospheric studies to evaluate 'what if' analysis where input variables in a simulation procedure are varied one at a time to verify the consistency of the model behaviour, or to check the robustness of the simulation outcomes to model assumptions (Pianosi et al., 2016b). SA is a common practice in climate and environmental science, used to evaluate the efficacy of a model to respond to changes in environmental conditions. SA can be used to verify or validate a model, identify critical control points or for selecting data collection for research (Frey & Patil, 2002). SA is also used for making valid management or adaptation decisions for future climate change. Some classic questions SA addresses are succinctly captured in Pianosi et al. (2016). 'What input variable would cause changes in the output'? Is there any factor that when varied may cause a negligible effect on the output? Can variability in an individual factor intensify or reduce interactions? As part of the objectives of this study, sensitivity analysis of the DSSAT model was carried out to identify the critical climate variables that would influence maize yield.

2.8.1. Types of sensitivity analysis

There are broadly two main types of sensitivity analysis application: local and global sensitivity analysis (Cariboni et al., 2007; Pianosi et al., 2016b). Some scholars classified them into qualitative and quantitative sensitivity analysis. There is 'no one size fit all' approach to adopt in sensitivity analysis methods, since the adoption of its application rests on the purpose or aim it is intended to achieve. The use of sensitivity analysis whether type or method is based on any of these four criteria: the purpose of the study, the ease and clarity of the sensitivity analysis, computational intensiveness and the applicability of the method for different types of model (Frey & Patil, 2002). Hence, the framing of research question can affect what type and method of sensitivity analysis is to be adopted.

Local sensitivity analysis (LSA) is applied to explore the variability in output factor against the changes in input factors around a specific value $\bar{x}$. LSA is performed around a point of reference in a model input space (Borgonovo & Plischke, 2016). It requires nominal values $\bar{x}$ to be specified. This kind of sensitivity is evaluated by keeping other input factors constant when studying the influence of one factor on the output (Cariboni et al., 2007). The method considers how model performance would vary when moving away from a particular reference parameter. In contrast, global sensitivity analysis (GSA) looks at model parameters along with other input factors of the simulation procedure such as the model forcing data or its resolution concurrently (Pianosi et al., 2016a). Although GSA method does not have the likely limitation of specifying a nominal value x̄, it still must state the input variability space when the nominal value. But in LSA this is poorly known. However, conclusions from GSA must be considered with great care due to the tendency of making spurious conclusions (Pianosi et al., 2016b).

The quantitative sensitivity analysis is designed to give insight about the amount of variance explained by each factor (Cariboni et al., 2007). It is a method where each input variable is connected to a quantitative and reproducible evaluation of its close influence say a set of sensitivity indices. The contrasting qualitative sensitivity analysis is aimed at picking (Screening) the few active factors in a system amongst the many non-influential factors (Cariboni et al., 2007). It deals with visual inspection of model predictions like using a "tornado plot" (Borgonovo & Plischke, 2016).Visualization of predictions is usually complemented quantitatively to give relative difference of importance of factors to aid interpretations (Pianosi et al., 2016b).

2.8.2. Methods of Sensitivity analysis

There are several methods of SA in the literature: the OAT (One-At-a-Time) and the AAT (All-At-a-Time) method. Some scholars like Frey and Patil (2002) reviewed ten and categorised them into mathematical, statistical and graphical methods of sensitivity analysis. Any of these ten techniques can be adopted in local or global sensitivity analysis depending on the aim of the analysis. Making a choice of selecting these methods is ultimately guided by the purpose or goal of the analysis and driven by the computational cost (Cariboni et al., 2007). It is not within the goal of this research to review all the methods of sensitivity analysis, but it is worth mentioning these approaches. The OAT method is used to estimate variation in output induced by changing the input factors one at a time while holding other factors constant. In contrast, for AAT, variations in the output are induced by varying all the input factors at once. Local sensitivity analysis employs mostly the OAT method. But Global sensitivity analysis can be used for either OAT or AAT technique in modelling. For instance, Corbeels et al. (2016) adopted global sensitivity analysis in DSSAT to assess maize yield response to different parameters under conservation agriculture in Zambia.

The mathematical methods are used for the assessment of model output to a range of variation of an input factor. A few values of the input are used in calculating output from a range of an input variable (Frey & Patil, 2002). The approach does not address variance in the output due to variation in the input factor, but they can assess the impact of a range of variation in the input values on the output. There are different mathematical methods such as break-even analysis, nominal range sensitivity analysis, and automatic differentiation analysis. These methods can be used for screening important input variables, for verification and validation, and data acquisition (Cariboni et al., 2007; Saltelli et al., 2008).

Statistical methods for sensitivity analysis assigned probability distributions to input factors when running a simulation, and it assesses the effect of variance in the inputs on the output distribution (Frey & Patil, 2002). One or more Input variables can be varied one at a time in this approach which allow researchers to identify the effect of interactions among multiple inputs. The sensitivity of model output to individual input or group of input are evaluated with techniques like regression analysis, analysis, analysis of variance, response surface method, Fourier amplitude sensitivity test and mutual information test.

Graphical methods of sensitivity analysis are represented in the form of graphs and charts which gives a visual understanding of the inputs and output relationship. It visually shows how output is affected by variation in the input factors (Pianosi et al., 2016b). Scatter plot is a good example of graphical method where visual assessment of the influence of individual inputs on the output factor is clearly established. It is applied often as a first step before regression analysis. This approach allows for the identification of potentially complex dependencies.

2.8.3. Importance of sensitivity analysis

- Sensitivity analyses provide a basis for identification and planning of key adaptation strategies to reduce the risk of climate change on crop production (Jones, 2000).
- Sensitivity analysis is important for identifying critical input variable for calibration of a model (Frey & Patil, 2002). SA helps to identify critical regions in inputs space.
- It is used for the exploration of how model output is linked to different sources of variation in input factors (Confalonieri et al., 2010).
- Sensitivity analysis helps in assessing the riskiness of a strategy (Jones, 2000).
- SA indicates the sensitivity of simulation uncertainty in the input values of the model. It is an important tool in explaining uncertainties (Frey & Patil, 2002).
- Sensitivity analysis is useful for screening important input factors (Saltelli et al., 2008).
- SA helps in predicting the outcome of a decision if a situation turns out to be different compare to the key prediction.
- It is used to prioritize data collection needs and to detect interactions between factors to rank important area of research (Frey & Patil, 2002).

- SA is a useful tool for model building in any field or setting which uses model (Bert et al., 2007)

2.9. Application of local sensitivity analysis in DSSAT Process-based crop model

Sensitivity analysis is a veritable tool for evaluating the response of model output to variations in input variables. The local and global sensitivity analysis approaches are the most adopted to evaluate crop model response to changes in management practice, crop yield, and climate condition (Bert et al., 2007; Borgonovo & Plischke, 2016; Freduah et al., 2019). In doing this sort of analysis, different environmental, crop or climate models have been employed and tested to ascertain model response to changes in input parameter.

Local sensitivity-the OAT method involves changing one parameter by ±α at a time while other inputs variables are held constant or kept at default values (Zhoa et al., 2014). The local sensitivity approach would be adopted for its suit the purpose of this study. Besides, the local sensitivity analysis is computational less expensive and easy to implement (Frey & Patil, 2002). This approach uses the nominal range of input variable (mean values). Bert et al., (2007) described the nominal range method as an intermediate between local and global sensitivity analysis. LSA method helps to reduce simulation runs and detect relationship between output and input parameters (Saltelli et al., 2008). However, it has the drawback of not able to compare interaction across parameters and not stable for nonlinear application (Saltelli et al., 2010).

DSSAT process-based model is widely used for conducting sensitivity analysis in many regions. For example, sensitivity analysis of DSSAT was carried out for spring wheat and maize under humid conditions in Saskatchewan and Wood lee, Ontario Canada using the local sensitivity approach (He et al., 2016). In this study, nominal, regression and graphical sensitivity analysis methods for crop yields, soil inorganic N, biomass, management practices and precipitation adopted, revealed that maize yield was highly sensitive to precipitation, fertilizer nitrogen rate and soil water hydraulic in the two locations (He et al., 2016). A similar approach of graphical and mathematical method of sensitivity analysis of DSSAT CERES-maize model response to input and output variable evaluated in the pergamino region of Argentine Pampas, showed higher sensitivity to changes in radiation with normalised sensitivity range of 0.69 for rainfed cultivation and for irrigation condition a range of 0.45 respectively (Bert et al., 2007).

The local sensitivity analysis approach would be applied to analyse the DSSAT CERES-Maize model response to changes in temperature and rainfall under similar management conditions in the agro climate zones of Cross River State. The regression and graphical technique would be adopted. Regression methods help to quantify the relationship between the output and input parameter, while the graphical (scatterplot) fit response curve for each input variable and provide preliminary qualitative description of non-linearity in the model response (Bert et al., 2007; He et al., 2016). The output parameter would be simulated maize yield (kg) of dry kernel Y. while, the inputs variables are vector x_1, x_2, x_3 in this case, daily rainfall (mm), daily maximum temperature $^{(o}$C) and minimum temperature $^{(o}$C and solar radiation (MJm^{-2}d)

2.10. Conclusion

The chapter discusses key concepts and explores a gamut of literatures on different themes that underpin this research. The top-down and bottom-up model approaches appears to be the two critical ways in understanding the impact of climate variability on maize production. The chapter provided an insight into the trend pattern of climate variability in sub-Saharan Africa. The major attribution of climate variability was link to the northward and southward excursion of the Intertropical Convergence Zone (ITZC). The concept of vulnerability and adaptation to climate change was explored with particular focus on the smallholders' farmers in sub-Saharan countries of Africa. Smallholders' farmers were identified as the key actors in the food production chain for the million's populations in SSA, and they are the most exposed to the impact of high climate variability due to their poor socio-economic background and limited knowledge of climate change.

Chapter 3: Geographic setting and Method

3.1. Introduction

This chapter describes the characteristics of the geography of the Cross River State rainforest and savannah agroclimate zones. It explains the climate, hydrology, geology and soil, vegetation, the people, and their economy activities which gives a vivid background of the region. The section also highlights the processes of data collection, the statistical techniques for data analysis for maize yield simulation and the sensitivity analysis to changes in climate parameters in chapter four.

3.2. Description of the geographic setting

3.2.1. Location

The Cross River State rainforest and savannah zones are the epicentres of crop production in Nigeria. These zones lie approximately around latitude $4^{0}30^{'}$ N and $6^{0}55^{'}$ N of the equator, between $8^{0}00^{'}$E and $9^{0}15^{'}$ E of the Greenwich meridian. They are bounded by the Republic of Cameroun in the East, Abia and Ebonyi State in the West, Benue State in the North and the Atlantic Ocean in the South (Figure 3.1). The political region is made of 18 local council areas and three senatorial districts which forms the political hub in the south, central, and northern part of the State. Its geographical extend and configuration, gives the State four major distinct agroecological zones namely: mangrove swamp forest, rainforest, and savannah and montane. Agro business is the major occupation in the rainforest and savannah zones of the State. Maize production predominantly thrives in these agro-climate zones.

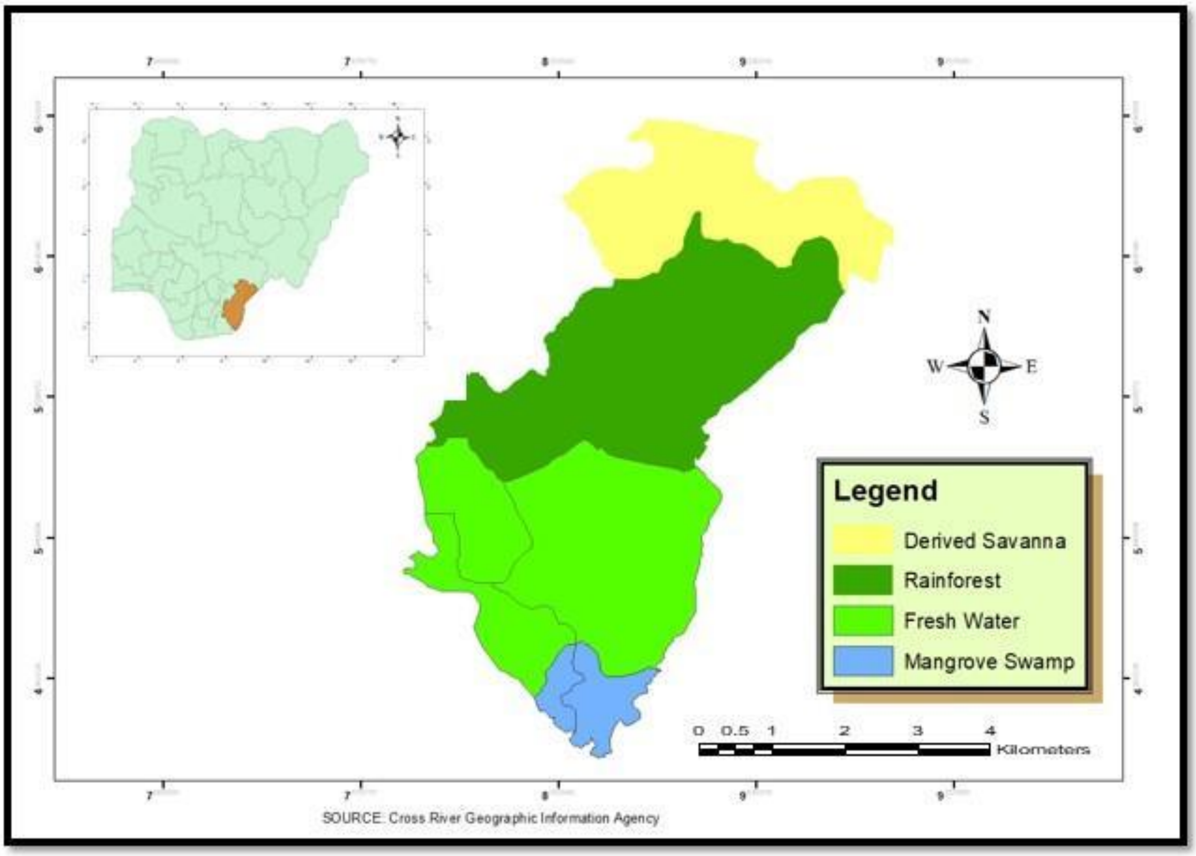


Figure 3. 1: Map of Cross River State Agroclimate zones Source: Author's work.

3.2.2. Climate

The region is characterised by the tropical humid climate of AF and Aw type based on the Koppen's classification scheme (Ayoade, 2004). There is a marked dry and wet season which are influenced by two air masses: the tropical continental air mass (cT) and the tropical maritime air mass (mT) respectively. The tropical continental air mass is also known as the north east trade wind. This is the dusty, dry and cool harmattan wind from the Saharan desert ((Sharon E. Nicholson, 2017). While the other airmass, is the rain bearing, moisture laden tropical maritime air mass (mT) which blows from the Atlantic Ocean and brings rainfall to the region. The length of the rainy season decreases northward which depends on the location of the pressure front called the intertropical convergence zone (ITCZ). The ITCZ is also called the climate equator because it lies near the geographic equator and divides the general global circulation patterns into two 'mirror' images north and south of the equator. The rainfall characteristics in tropical Africa are influenced by the movement of tropical moist oceanic air from the Atlantic and Indian oceans toward an equatorial low-pressure zone (Nicholson, 2017). The rainy season in these regions usually begins between March and April and ends in November. The rainfall reveals a bimodal type where long rainfall starts from March to July with a break in August and short rainfall in September and October. Table 3.1 shows the average monthly climate parameters in the rainforest and savannah.

Table 3. 1: Average monthly climate parameters in the Agroclimate zone

Zones	Rainforest Zone				Savannah Zone			
Month	Tmin	Tmax	Rainfall	RH	Tmin	Tmax	Rainfall	RH
Jan	20.5	33.2	9.6	72.1	22.2	35.0	13.3	49
Feb	22.5	35.0	24.6	71.5	23.6	36.5	10.7	53
Mar	23.7	34.6	79.6	74.5	23.4	36.7	43.0	63
April	23.3	33.3	176.7	77.1	22.9	34.7	152.7	70
May	22.9	32.4	252.9	80.1	22.7	33.0	279.8	76
June	22.7	30.9	335.5	82.5	22.5	31.8	305.8	77
July	22.6	29.6	311.4	84.5	22.4	30.6	291.3	79
Aug	22.6	29.1	344.3	85.5	22.4	30.1	297.4	82
Sept	22.5	30.3	322.3	83.9	22.6	31.0	362.3	80
Oct	22.6	31.5	338.6	81.4	22.4	31.9	306.7	77
Nov	22.4	32.3	58.1	78.7	19.7	33.5	39.3	70
Dec	20.8	32.6	9.9	76.4	22.3	34.5	9.3	56

Source: NIMET Ikom and Ogoja

However, the rainy season might sometime extend to December in the rainforest area of Ikom, Biase, Akamkpa and Calabar. While the dry season occurs from November to March generally, it could start earlier in late October or prolong further to early April in the savannah zones. In the rainforest, annual record of rainfall is above 1500mm, but in some years it can be as high as 2500mm-3000mm. In the savannah zone annual average rainfall in some years usually exceeds 1300mm.The effective growing season is around seven months except where cultivation extends along riverbanks or in irrigated areas. Maximum temperature ranges from 29°C-36°C, and minimum temperature is between 19.5°C-25°C. Relative humidity is between 60-92% throughout the year, but with above 70% in the rainforest region (Ayoade, 2003). The regional climate is also influenced by local relief, vegetation, and in the south by ocean currents. There is high variability in rainfall and temperature within the region. This accounts for spatial temporal variability in crop production. Farmers take advantage of planting during the growing season when the first and second rainfall events occur in early April. Sometimes, this is not the case in the Rainforest zone of the State. Rainfall comes quite early in February or March and this do trigger the farmers to swing immediately into serious cultivation of their crops.

3.2.3. Hydrology

The rainforest and savannah agro-climate zones are marked with important rivers and their tributaries. These rivers play a substantial role in shaping the agro-economy of Cross River State. The Aya River system flows from the Eastern flank of River Suwo in Kwande Council area of Benue State, through the savannah region and is approximately 1364.5km in length (Utang, 2009). The River is oriented towards Southwest and Northeast, with key tributaries like the Asham and Be, Echin Debekim and Moniaya covering the West and Southern borders. Other important rivers like the Ochu, Atai and Uyie flow from the Eastern highlands of Obanliku to join the Aya River system. The lowland flood plains of River Ochu, Atai, Abeb, Moniaya and Aya in the savannah part of Cross River State form a significant portion of the agricultural activities along the floodplain of Aya. It is important to note that the Aya River Basin is a division of the geo-morphological and political region of Cross River Basin which has been used for different agricultural programs fashioned toward food security and improve livelihood of the people.

The Aya and Afi systems join the main Cross River in the North, while Qua Iboe, Calabar and Akpayefe are the main tributaries that drain into the estuary in the southern region. The Cross River flows a long way, almost across half of the State, being approximately 304miles in length, from the boundary with the Cameroun highland. The estuary in the south, with a mix of fresh, brackish and marine ecology provides a favourable environment for many aquatic and terrestrial organisms. This region hosts more than 80% of the fishing communities in the State. Thus, the estuary can be described as the Cross River fish hub. There are wetlands across the forest and savannah regions which serves as ecological sponges and recharge the groundwater reservoir during dry spell (Ashua, 2015).

3.2.4. Geology and Soil

The region is underlain by Benin Formation of sedimentary origin, and Basement Complex Formation of igneous origin as shown in Figure 3.2 (Edet 2004). There is a massive presence of igneous rocks around Obudu plateau (Sankwala Mountain) in Obanliku in the savannah region, and the Oban Massif in the rainforest zone.

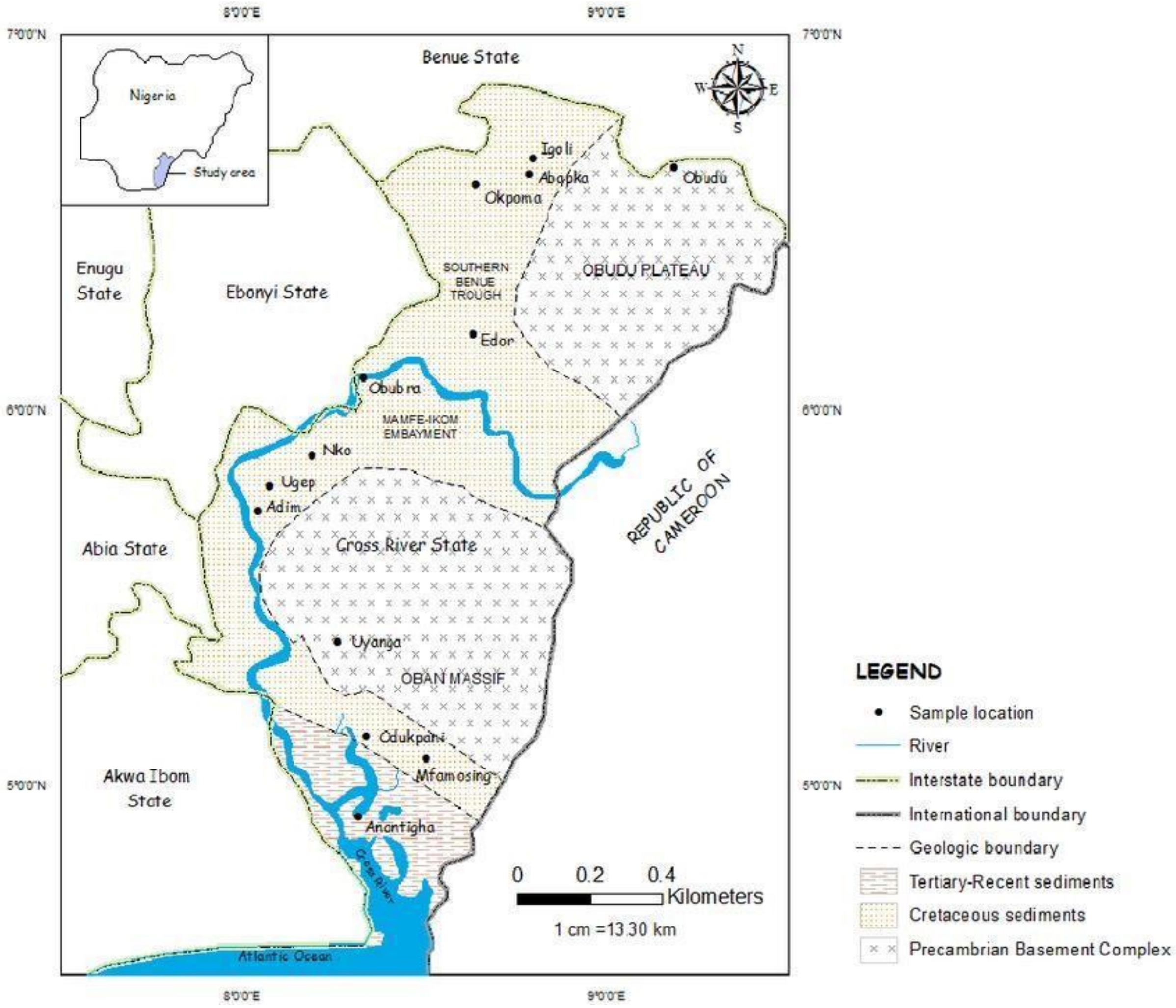


Figure 3. 2: Geology map of Cross River State (Culled from Edet, 2004)

The zones are composed of Precambrian igneous and cretaceous sediments deposit which formed the principal parent materials in the soils. There are, however, some heterogeneity in the soil types across the agro-climate zones. The coastal sandy soils of the Eze-Oku group are predominant in the mangrove forest in southern Cross River. Those that originate from basement rock are basaltic soils which are found in the central to the northern part of the rainforest and savannah zones of the State. There is a conspicuous presence of vertisol soils in most parts of the rainforest. The soil's physical and chemical properties are reflected in the parent materials from which they are derived, and there is considerable differentiation in structure, texture, and colour. These soils are rich in natural fertility and respond positively to good management. Hence, they are excellent for agricultural practices. Continuous cropping is encouraged as the soil temperature regime appears favourable in the rainforest zone (Abam & Orji, 2019). The major cereal crops are maize, rice, and sorghum. Other principal crops cultivated include cassava, yam, cocoyam, potatoes pineapple, plantain and banana. There are also tree crops like cocoa, orange and cashew. But a few are now attracted to large scale farming with modern equipment owing to government policies to boost food production through a World Bank soft loan.

3.2.5. Vegetation

There are four vegetation types in the State: rainforest, savannah, montane and mangrove forest. However, the dominant vegetation covers in the zone are rainforest and savannah. These vegetation types are differentiated along the path of the climatic regime. The Northern fringe contains more savannah vegetation and experiences a much lower rainfall regime than the Southern part, with its higher mean annual rainfall. However, the mountain regions, reveal a distinctive abundant vegetation on the rain shadow side, and sparse growth on the leeward side due to orographic uplift and a rainfall shadow. The savannah vegetation is typical in Bekwarra, Yala, Obanliku, Obudu and Ogoja which are characterised by the mixture of tall grasses and trees. The grasses consist mainly of *Imperica Cylindrical,* the *andropogons* and the *Pennisetum spp*. while, the mangrove forest in the oceanic zone consists of rich flora and fauna species. One of the formers is *nypa fruticans* which provides a buffer to the ecological problem in the region. Other mangrove plants are the *Avecinia Spp* (white Mangrove), *Rhizophora spp* (Red Mangrove), *Bambusa Vulgaris, Raphia vinifera, cocus nucifera* and the *Lagunculeria racemosa*. Nevertheless, the rainforest houses a very abundant number of plants and animals' species and is the home of approximately 75% of endangered animals' species found south of the Gulf of Guinea, which is one of the richest biodiversity hotspots in Africa (Fon et al., 2014). Some of the tree and shrubs species composition in the rainforest and savannah regions are: *Khaya spp* (Mahogany*), Milicia excels (*Irok*o) Musanga cecropiodes,* and *Uapaca guineensis.*

3.2.6. Population and economy activities

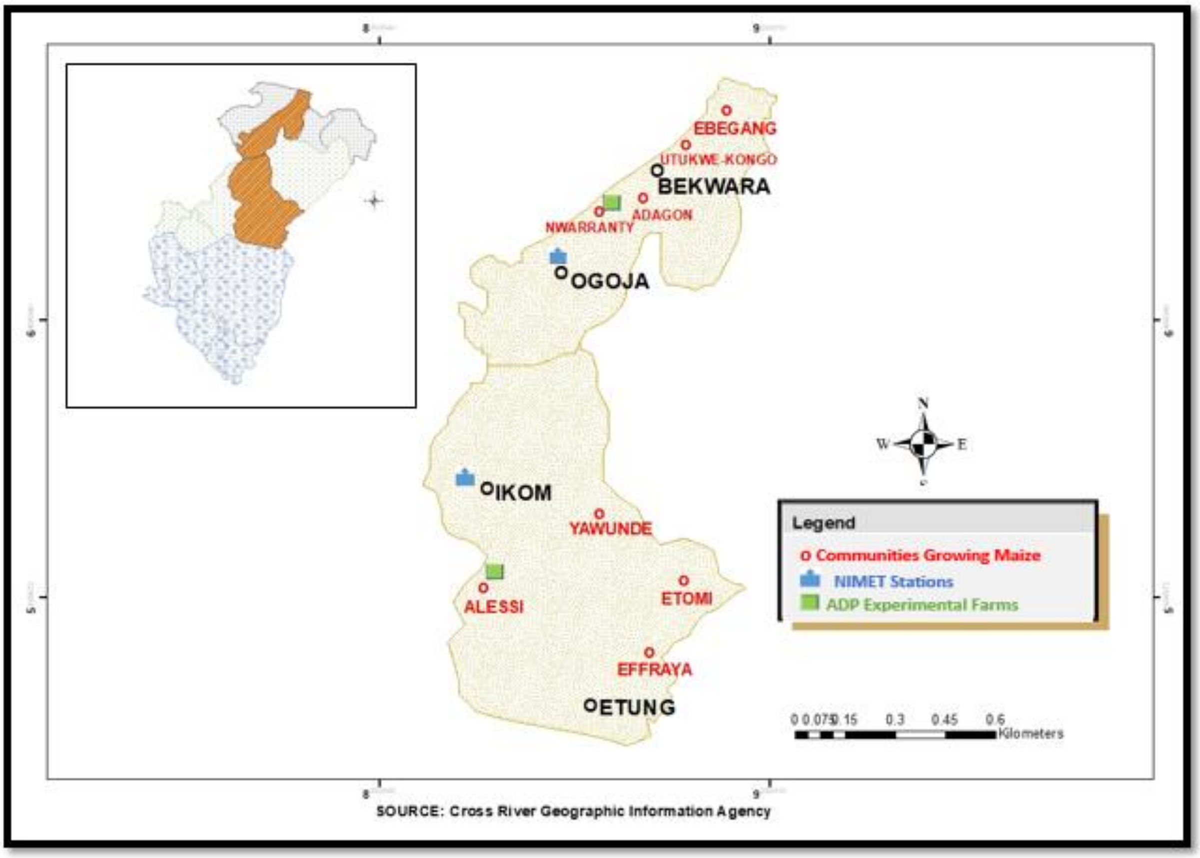
Cross River State population consists chiefly of the Efik, Ekoi, and Bette and Bekwara ethnic group. They are primarily agrarians, with only a fraction of the population in secondary and tertiary occupations. The population survey of 2016 puts the State's population at 3.866 million, and a population density of 191.8km^2, with an annual population growth rate of 2.94% across the 18 Local Government Areas (Census, 2016). The population of the local area councils in the rainforest was 1,360, 325 million and those area in the savannah was 1,015, 300 million. These figures revealed a higher average population in the Forest zone than the Savannah. There are apparently more geopolitical divisions in the rainforest. However, the rich rainforest environment and presence of fertile soils such as those around Ikom and Etung, has propelled rural migration from other parts of the State to reside in the zone. Calabar is the State headquarter of Cross River State with dense population due to the presence of social amenities, employment, and education. The rural farming population in the rainforest is amazingly dense especially around the maize and cocoa belt areas of Ikom, Etung and Boki.

Nevertheless, the rainforest and savannah zones are the key regions for economic activities in Cross River State. One important economic activity that has helped to improve the livelihood of the people is farming. A classic example is the cultivation of rice and maize around the Aya basin, and the annual maize farming in Ikom, Etung and Obudra Akamkpa and Odukpani region. While perennial crops like cocoa, banana, citrus and cola have made substantial contribution as revenue spinning point for the rural economy. Fishing activities around the maritime and freshwater environment, and some private fishpond in the zone have increased the protein and income needs of most households.

These zones have served as the hub for high agricultural productivity for cash crops such as tree, tuber and cereal crops even before the crude oil boom of the 1970s. Common crops like oil Palm (*Elaeis guineensis*), cocoa (*Theobroma cacao*), banana (*Musa acuminate*), plantain (*Musa paradisiaca)*, yam (*Dioscorea spp.*), cassava (*Manihot esculenta)*, maize (*Zea mays L.*), rice (*Oryza Sativa*) and groundnut (*Arachis hypogaea*), are cultivated on different scales in the forest agro-climate zone. The most typical crops in the savannah are groundnut, rice, maize, cassava, potatoes and yam. However, small scale producers form the bulk of the economy. There are also artisan activities of various kinds undertaken by majority of smallholders. A pocket of animal farming is carried out in the zones, such as those in the Cattle Ranch Resort in Obanliku local Government. A few industrial activities are going on in the zones like the Unicem cement plant in Mfamosing, the garment factory in Calabar, Cocoa processing plant in Ikom and the rice mill factory in Ogoja and the gigantic poultry industry in Calabar. The establishment of poultry industry will require more feeds. The Government of Cross River State industrialization drive on agriculture is expected to create a major industrial growth. In the zones.

3.2.7. Experimental Field sites and crop data for this research

Field data for crop modelling were collected from the Cross River Agricultural Development Projects office (CRADP). The experiment were ran by CRADP at their farm fields in two locations: one in Ikom within the rainforest zone and the other in Ogoja, within the savannah zone during the growing season. These experiments were run in different growing seasons to evaluate the response of this maize crop variety for early maize production from 1990. The land preparation in the two sites were carried out by manual clearing, and tillage was also carried out by local staff. Planting was done in late March and early April in the rainforest and mid-April for the savannah. The row spacing was between 75cm and 25cm with three seeds sowed and later thinned to two seeds per stand after 14days of sowing. The plant density was between 4.4m^2 and 6.6m^2. Fertilizers application was done in two doses: a week after planting and 6 weeks after days of sowing at 80kg/ha and 120kg/ha respectively. Weeding of the farms were carried out using human labour. Data on grain yield, physiological maturity, days to anthesis, leaf area index, and harvest index that were measured during the periods were collected and calibrated in the model. These experiments were performed without irrigation. The maize residues were incorporated into the soil after harvest at the sites. Unfortunately, there is paucity of data with most local government agency in the global south. Adequate record keeping is also a grave challenge in most government managed parastatals in Cross River State. Only the available and accessible information were obtained from the CRADP office during a visit to the Calabar headquarters in 2018. This is a key limitation in this research work. The location of these experimental farms is within a few kilometres from the weather stations and the surrounding maize growing communities (Figure 3.3). The Field survey was carried out for the smallholders' maize farmers in the communities of the agroclimate zones in Cross River State. Two communities were chosen in each of the rainforest agroclimate zones (FACZ) and savannah agro-climate zone (SACZ) respectively. Ikom and Etung Local Government Areas were chosen as the main maize production zone to represent the rain forest, and Ogoja and Bekwara Local Government Areas for the savannah zone. The choice of these locations is informed by their long practice of maize (*Zea mays L.*) cultivation under a rainfed system, and the distinctive agro-climatic differentiation. Maize is considered in this study due to its economic importance as a cereal crop and being the top source of calories, fat and protein for household nutrition in sub-Sahara Africa (Lobell et al., 2011). Maize has been grown for many decades as a grain and food crop. It is a major stable food in every household in Nigeria. Maize is consumed in different forms – as cooked, roasted, pap, fufu and sometime brewed as wine. Maize provides sustenance for many households, and it is an important raw material for industry and livestock production. The crop contributes immensely to the economy of households in Cross River State and Nigeria at large.



SOURCE: Cross River Geographic Information Agency

Figure 3.3: Locations of Experimental Farm, Mets Stations and maize Communities

3.3. Description of DSSAT (CERES-Maize) model (Flowchart) of model

The DSSAT model is a process-based crop model which has been of increasing importance for many decades following the adverse impact of climate change on crop production (Zhang et al., 2015). Many researchers have used this DSSAT model approach (Alexandrov & Hoogenboom, 2000; Araya et al., 2015c; Jones & Thornton, 2003; Lobell et al., 2011; Thorp et al., 2008; Yakoub et al., 2017) to understand crop yield response to climate variability and change. For example, DDSAT was used to quantify the impact of variation in climate change on maize yield under current agricultural practices in Senegal and Ghana (Freduah et al., 2019). DSSAT has also been used to analyse future climate change for the mid-century under different representative concentration pathways respectively (Freduah et al., 2019), DSSAT has been applied for crop management application ((Adnan et al., 2017; Soler et al., 2007a). For fertilizer micro dosing management ((Tovihoudji et al., 2019), for crop variety evaluation (Bhusal et al., 2009), assessing different planting dates and moisture regime (Soler et al., 2007b) and for identifying potential zones for maize production (Iyanda, et al., 2014). it is widely used in most regions of the world to simulate maize yield, growth and development, including soil water, nitrogen, and carbon and management practices (Tovihoudji et al., 2019). The model has been applied to assess the potential impact of climate variability on maize production in Nigeria (Ahmed et al., 2017; Iyanda et al., 2014). DSSATCSM is used to solve practical farm, field and complex higher level agronomic problems (Jones et al., 2003).

DSSAT process-based model predict outcomes slightly better than statistical model, but more analytical and vivid results when also combined with statistical models to predict maize yield over a considerable area of a farmer's fields (Roberts et al., 2017). Hence using the DSSAT crop model and statistical model approach offers impressive results (Roberts et al., 2017). These approaches can be tailored to examine crop yield response to climate change. The DSSAT process-based modelling considers the processes of crop growth and development, simulating the intra-seasonal crop cycle (Roudier et al., 2011). Thus, the nonlinear effect of climate on crop development is adequately captured using process-based modelling approach. DSSAT crop model is able to simulate historic spatial yield variability over time and estimate maize yield response to environmental impact of nitrogen, plant population, cultivar and irrigation (Chisanga et al., 2014; Eitzinger et al., 2017; Thorp et al., 2008). A comparison of The Agricultural Production Systems Simulator (APSIM-maize) and DSSAT CERES-maize model in Ethiopia (Araya et al., 2015b; Charles et al., 2017) showed that both models can reproduce observed crop yield efficiently, with good index of agreement of 0.86, 0.80 and 0.70 for DSSAT and 0.50, 0.60 and 0.89 for APSIM. A study of APSIM and DSSAT in predicting wheat and Maize in arid area of Pakistan indicated APSIM predicted wheat yield efficiently than DSSAT, but DSSAT predicted yield in maize more accurately than APSIM (M. Ahmed & Fayyaz-Ul-Hassana, 2011). The overall goodness-of-fit indicates that DSSAT was useful in predicting maize yield in the region.

A wide variety of maize crop models have been applied in Intercomparison studies (Bassu et al., 2014; Ewert et al., 2015; Rosenzweig et al., 2013; Seidel et al., 2018; Wallach et al., 2018). The results from these papers indicates that there is extensive variability between crop models, and even among model predictions (Confalonieri et al., 2016). Each model has their own strength and weaknesses as the choice of selecting any relied on the application, minimum data requirement and largely depend on the subjectivity of the modelling community or modeller (Wallach et al., 2016). DSSAT-CERES-maize model ranked among the highest typically adopted maize crop model in predicting maize grain yield and biomass (Falconnier, Corbeels et al., 2020). DSSAT-CERES-maize model is chosen over other crop models for its wider applications in maize simulations. The model is well developed, calibrated, and validated for maize simulation in many regions of Africa, and in Nigeria (Adnan et al., 2020; Araya et al., 2015; Arije et al., 2018) (Toure et al., 2018). The model is cost effective and requires minimum data set for model operation (Jones et al., 2003). It is easily access and used in research for decision-making (Soltani & Hoogenboom, 2007).

The Decision Support System for Agro-technology Transfer (DSSAT) Cropping System Model was employed in this work to run a sensitivity analysis of maize yield to changes in rainfall and temperature for the two agroclimates, rainforest and savannah zones in Cross River State respectively. The DSSAT-CSM is a versatile model that consist of an ensemble of sub plant modules like the Crop-Environment-Resource-Synthesis)—Maize module within the DSSAT model (CERES maize), CERES wheat, CERES Rice and Potatoes. It was crafted by an international network of scientists, involving the international Benchmark Sites for Agrotechnology Transfer Project (IBSNAT PROJECT) (Ahmed et al., 2017). The model has been validated under different scenarios of planting dates, fertilizer application and climate regimes (Iyanda, et al., 2014). The current version of DSSAT (4.7) is made up of separate models, combined to simulate the growth, development and yield of cereals, legumes, root crops, oil crops, fibre, forages, and fruits (Figure 3.3). There are over 42 crop simulation submodules to guide effective application in the new software application version (Nouri et al., 2017; Zhang et al., 2015).

3.4. Data requirement for model set up

3.4.1. Weather data

Weather information is a basic data requirement, and it is a component in the primary modules for simulation runs. The weather module reads daily weather data inputted in the weather file weatherman utilities. The minimum weather data required are daily maximum air temperature (Tmax), minimum air temperature (Tmin), solar radiation (SRAD) and rainfall (R) (. Jones et al., 2003). The weather data for this experiment were obtained from two Nigerian meteorological stations in the rainforest and savannah agroclimate zones respectively: Ikom station (Lat (5.96°N; 8.72°E; 117m asl) and Ogoja station (6.65°N; 8.79°E; 57m asl). Complete data for the simulations were available from the year 1990-2016. The challenge was mostly associated with having complete solar radiation data. But there were complete and available datasets for rainfall, maximum and minimum temperature from 1982-2016. This informed the decision to adopt years with available data and reduce missing values and errors. The weatherman software in DSSAT model assists greatly in detecting errors and missing values, hence enhancing the quality of simulation results.

3.4.2. Soil characteristics data

The site-specific soil data for the simulation runs were collected from the CRADP office located in the rainforest and savannah agroclimate zone for the experiment. The soil data comprises of different soil parameters, silt clay and sand, lower drained limit, upper drained limit, bulk density, pH, organic Carbon, Total Nitrogen and Saturated water contents for each site displayed in Table 3.2 and Table 3.3. The textural characteristics of these soils are generally loamy sandy in nature for the two sites.

Table 3.2: Soil properties at the calibrated site in Ikom Rainforest zone

Soil Depth cm	**Sand %**	**Silt %**	**Clay %**	**Drained Lower Limit**	**Drained Upper Limit**	**SSAT**	**Bulk Density g/cm^3**	**T N %**	**O.C. %**	**pH**
0-20	73	11	8	0.052	0.176	0.359	1.61	0.05	0.72	5.5
20-50	63	11	8	0.052	0.176	0.359	1.61	0.05	0.72	5.5
50-90	66	11	8	0.073	0.232	0.361	1.61	0.05	0.43	5.5
90-150	68	11	8	0.143	0.243	0.361	1.62	0.05	0.12	5.5

Source: (CRADP, 2018) and (Abam & Orji, 2019)

Table 3.3: Soil properties at the calibrated site in Ogoja Savannah zone

Soil Depth cm	**Sand %**	**Silt %**	**Clay %**	**Drained Lower Limit**	**Drained Upper Limit**	**SSAT**	**Bulk Density g/cm^3**	**T N %**	**O.C. %**	**pH**
0-20	14	23	22	0.03	0.11	0.47	1.5	0.11	1.98	5.7
20-50	17	19	36	0.06	0.16	0.42	1.5	0.08	1	5.3
50-90	30	33	36	0.12	0.19	0.38	1.5	0.07	0.79	5.1
90-150	10	29	36	0.21	0.31	0.35	1.5	0.06	0.53	4.4

Source: (CRADP,2018) and (Afu, 2013)

3.4.3 . Crop variety and management data

During a reconnaissance survey conducted in 2018 with key informants; Agricultural development project officers and the communities' agricultural extension workers in the main maize growing areas in the rainforest and Savanah agroclimate zones of the State, some basic crop data were collected. The management data used in DSSAT 4.7 for this experiment was the improved maize crop cultivar OBA SUPER 2. This crop cultivar has been calibrated in Nigeria (Adnan et al., 2019). The cultivar specific parameters of Obasuper 2 in DSSAT 4.7

adjusted and used to calibrate the model (Adnan et al., 2019). Other management information such as the planting date, row spacing, plant spacing, and fertilizer-Nitrogen, level, and tillage were obtained from CRADP and during interviews with the maize farmer. The Information on crop management, crop variety were obtained from Cross River State Agriculture Development Project (CRADP), and for weather, from the Nigerian Meteorological stations near the site. These data were used for the calibration of the model for the Ikom and Ogoja locations within the rainforest and savannah zones. Maize crop OBA SUPER 2 was adopted. This improved drought resistant and intermediate maturity variety is popular and has an extensive acceptability (Iyanda et al., 2014; Ahmed et al., 2017). It has been used in different locations in Nigeria for the calibration of DSSAT model with the most common crop cultivar coefficients, which were built in the new version of the software; Adnan et al., 2019).

The planting date for the rainforest and savannah was 7th and15th April respectively, however the planting window is from 1st April to 30th for both the Ikom and Ogoja zones. The sowing in the model was carried out after satisfactorily onset of precipitation for the growing season. The recommended rate of fertilizer for agroclimate zones was applied. The amount of fertilizer was 100 kg/ha urea before planting, 80kg/ha after 4weeks of planting. The total application of fertilizer was 180kg/ha for the zones with the fertilizer placed approximately 1-2cm below the soil surface. Row spacing was 75 cm and planting density between 4.4 and 6.6 plants/m^2 for the Ikom and Ogoja site respectively. This maize variety selected for the experiment is accepted and widely acknowledged for high yielding potential and its nutritional values in the zones.

3.5. DSSAT CSM crop simulation

The figure 3.4 show the processes in simulating maize yield in DSSAT 4.7 CERES-Maize model. The DSSAT-CSM consist of the main program, the land unit modules and primary component modules linked the land unit of the cropping system. The primary modules house the weather, soils, plant, soil-plant interface, and management component of the system (Jones et al., 2003). The main driver program reads information from the standard files for a particular experiment and sets a few variables in controlling a simulation run. A model runs a time loop which starts as the cropping season begins. The land unit is called by the main driver program to process the primary modules by initialization of the variables on a daily time loop. The land unit module is called three times in sequence, computes rate and integrate them and finally reports daily output at the end of the cropping season. Outputs at the end of the runs or cropping season are produced in the summary output files (Jones et al., 2003).

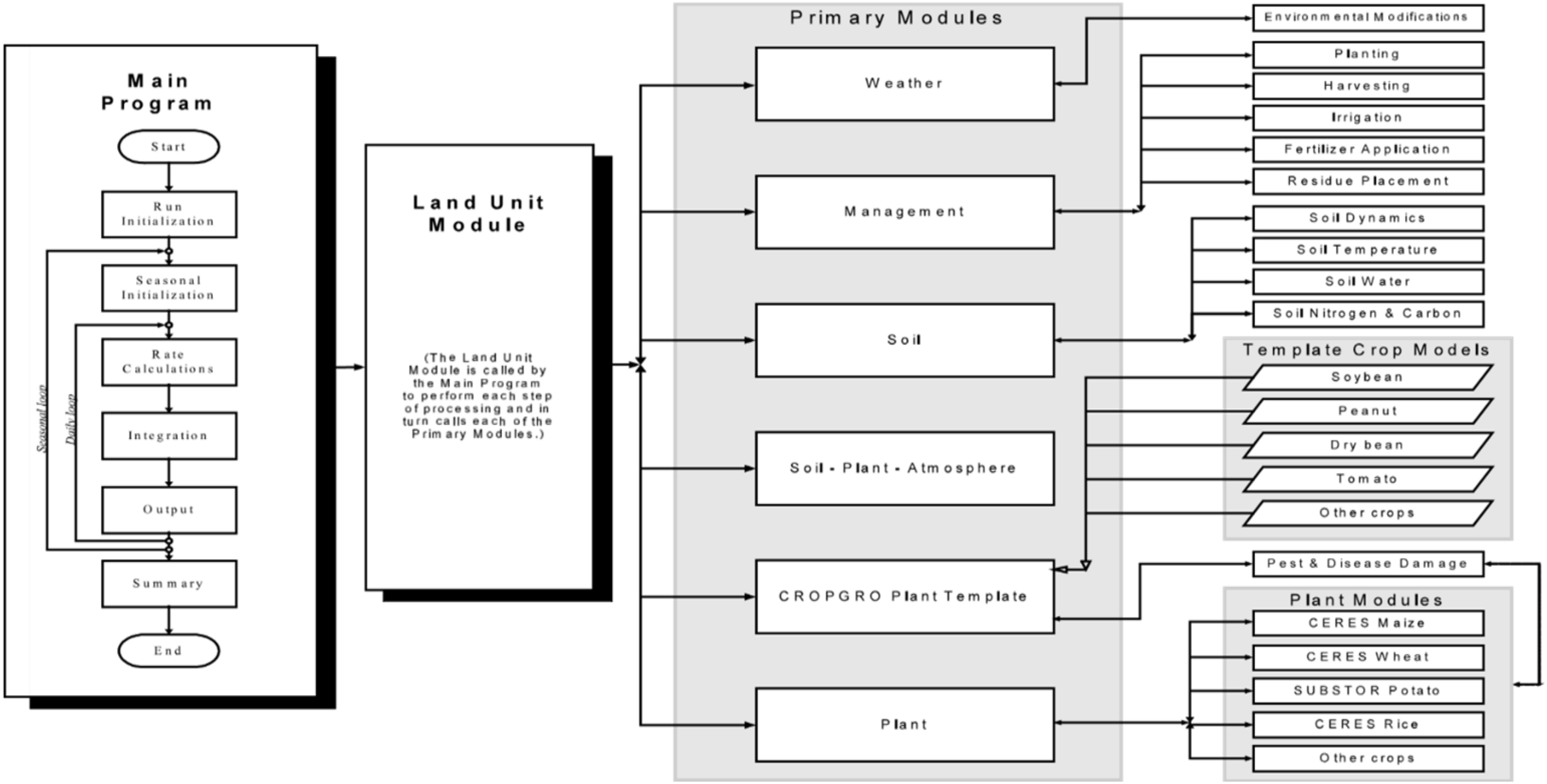


Figure 3.4 : DSSAT Crop model Flowchart (J. W. Jones et al., 2003)

3.6. Model evaluation of crop data parameters

3.6.1. Model evaluation

The model was evaluated using the data of observed anthesis, physiological maturity Leaf area index, harvest index and grain yield which were compared with the simulated results for the rainforest and savannah agroclimate zones. The relevant evaluation statistics which include root mean square error (RMSE), index of agreement statistics (d-statistics) and the normalised root mean square error NRMSE) were applied.

$$\mathrm{RMSE} = \left[\sum_{i=1}^{n} \frac{(S_i - O_i)^2}{n} \right]^{1/2} \qquad (3.1)$$

$$\mathrm{NRMSE} = \left[\sum_{i=1}^{n} \frac{(S_i - O_i)^2}{n} \right]^{1/2} / \mathrm{Oi\ mean} \qquad (3.2)$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1} (|S_i| + |o_i|)} {}_{2} \right] \qquad (3.3)$$

Where:

RMSE = Root mean square error

NRMSE = Normalised root mean square error

D = index of agreement

Si = simulated values of variables in the rainforest and savannah agroclimate zones

Oi = Observed values of the variables in the rainforest and savannah agroclimate zones

N = number of observations in the rainforest and savannah agroclimate zones

3.6.2. Sensitivity analysis.

A local sensitivity analysis was carried out to evaluate the impact of changes of rainfall and temperature on maize yield in DSSAT 4.7 CERES-maize model. Using the environmental modifications application in DSSAT 4.7, changes in climate parameter were applied one at a time (OAT). The information for management variable were obtained from the maize farmers and the Agricultural Development Project office of the communities in the zones. Site specific soil data were used for both rainforest and savannah agro-climate zones. Management information from the farmers were used in running the seasonal analysis to evaluate how changes in climate parameters impact on maize yield in the regions. Planting was set at 7th and 15th April for the early maize planting season; plant population of 440000 to 660000 plants per hectare, with row spacing between 75cm and 25cm, and plant depth of 5cm. The chosen maize crop cultivar was the OBA SUPER 2. Two doses of urea fertilizer application were applied: one before planting and the second four weeks of planting. The cultivar's specific parameter of OBA SUPER 2 in DSSAT 4.7 were used to calibrate and modelled maize yield from the crop genetic information provided in DSSAT species file adjusted (Hoogenboom et al. 2017) Table 3.4. There was no irrigation application during the experimental season. Cultivation was mainly under rain-fed conditions.

Table 3.4: Maize (Obasuper 2) genotype specific parameter coefficient in DSSAT

CULTIVAR OBA SUPER	**DESCRIPTION**	**VALUES**
P1 (C day)	Thermal time from seedling emergence to the end of juvenile phase	270
P2 (C day)	Delay in development for each hour that day-length is above 12.5 hours	0.01
P5 (°C day)	Thermal time from silking to time of physiological maturity	780
G2 (#)	Maximum kernel number per plant	840
G3 (mg day^{-1}):	Kernel growth rate during linear grain filling stage under optimum conditions	7.8
PHINT (°C day tip^{-1})	Thermal time between successive leaf tip appearance	45.00

Source : (Adnan et al 2019 : Hoogenboom et al., 2017*)*

The study adopted incremental climate scenarios approach as adopted (Adejuwon, 2006; Corbeels et al., 2016) and the IPCC 1.5°c (Adejuwon, 2006; Hoegh-Guldberg et al., 2018). The experiment was carried out using an arbitrary increment of ±1.5°c for Tmax and Tmin. Also, ±10%, ±20%, ±30% ±40% and ±50% changes in rainfall from the baseline period of 1990-1996 and 2010-2016 were analysed in the Environmental Modification Unit of DSSAT crop model to evaluate to maize yield response to changes in climate parameter. The experiment was run for all the parameters at once for the period. A separate experiment was run one at a time for individual change in a climate parameter while others were held constant. This was repeated for all the scenarios created for the rainforest and savannah agroclimate zones to evaluate how maize yield would response given a ±1.5^{o} change in maximum temperature, minimum temperature and given a ±10%, ±20%, ±30% ±40% and ±50% in rainfall (Table 3.5).

Table 3.5: Summary of selected inputs variables for the local sensitivity analysis in DSSAT crop model for the rainforest and savannah agroclimate zones.

Category	**Variables**	**Unit**	**Scenarios**	**Acronym**
Crop growth and development	Harvest Grain yield	Kg ha^{-1}	-	Yield
Climate parameter	Maximum temperature	^{0}C	±1.5^{0}C	Tmax
Climate parameter	Minimum Temperature	^{0}C	±1.5^{0}C	Tmin
Climate parameter	Rainfall	mm	±10%, ±20%, ±30% ±40% and ±50%	Rains

Source: Adejuwon, 2006

3.6.3. Statistical analysis of climate trend and sensitivity analysis results.

A simple seasonal decomposition of times series and coefficient of variability (CV) tools were employed to analysis the trend and variability in rainfall amount, Tmax and Tmin from 1982-2016 in the rainforest and Savannah. The results are represented in chapter four. The analysis of the model output of maize yield response to changes in rainfall and temperature for the different scenarios were analysed using scatter plot and regression technique as reported by (Pianosi et al., 2016b). The observed maize yields were compared with simulated maize with different statistical tools such as normalized root mean square error (RMSE) and d-statistics according to (Loague & Green, 1991).

3.7. Conclusion

This section of the thesis provides a general view of the geographic setting of the rainforest and savannah agroclimate zones. It explains the climate, geology, vegetation, hydrology, the people and economy activities of the zones. Part of this chapter describes the trend analysis of rainfall and temperature, and the sensitivity analysis method used in DSSAT for maize yield response to critical climate parameters (Tmax, Tmin and rainfall). The next chapter 4 presents analysis of the climate variability time series trend. Including model evaluation statistics of crop parameters of the modelled and observed yield and the sensitivity results for maize yield response to changes in the climate parameter for the zones.

Chapter 4: A Sensitivity analysis of maize yield response to climate variability in Rainforest and Savannah Agro-Climate Zones

4.1. Introduction

This chapter begins with the analysis of the climate variability trend for the rainforest and savannah from 1982-2016) growing season. It presents a simple time series decomposition of monthly rainfall amount and Temperature (minimum and maximum) using the seasonal and Trend decomposition (STL) Loess method (Cleveland et al 1990) with a view to understanding the climate trend in the region. A seasonal analysis of maize yield response to changes in planting dates due to changes climate was carried out using the DSSAT crop model for the growing seasons of 1990-2016 periods. The model was applied to evaluate yield changes during the early maize growing season from February to April following the understanding of a shift in growing season climate pattern in the rainforest and savannah agroclimate zones of Cross River. The response of the model to these key parameters was done by varying the values of input variables one at a time, and holding others fixed (Corbeels et al., 2016). Maize (Zea mays L.) was used for this experiment due to its diverse economic applications in Nigeria, and Cross River State. A seasonal sensitivity experiment in DSSAT model was conducted for the early maize growing season for February, March, and April from 1990-2016 to determine the impact of a shift in the planting date due to climate change. The month of April was commonly adopted as planting date in the rainforest and Savannah in consideration that the rains have fully begun for planting of maize crop. The data were analysed with mean, root mean square Error (RMSE), d-index statistics, and regression analysis. Results were graphically represented in bar graphs and scatter plots for simulated and observed maize yield in the rainforest and savannah zones of Cross River State.

4.2. Climate variability trend in the rainforest and savannah Agroclimate.

4.2.1. Rainfall trend pattern in the rainforest and savannah agroclimate zones of Cross River State (1982-2016)

The monthly growing season time series of rainfall was decomposed using a simple decomposition procedure based on Loess method in R package for the rainforest and savannah agroclimate zones are shown in Figure 4.1. A significant upward trend in rainfall was established in the savannah zone ($P < 0.001$), while in the rainforest monthly annual rainfall fluctuated during the era with no significant trend. There were however fluctuations in rainfall during the periods for both agroclimate. But there were discernible dips in 1990 and 2009, while 2009 to 2014 reveals a rise in the rainforest. This time series revealed that 2013 coincided as a year with the highest amount of rainfall in both regions. There were a mark slow seasonal changes in monthly rainfall over time in rainforest and savannah (Figure 4.1). A stable and steady increase in trend was noted in rainfall from 2005 to 2014 in rainforest but in the savannah, a rising trend was recorded from 1982 to 1990 with a dip, and a ten year of continuous rise in monthly rainfall regime from 2010 to 2016 in the zone. Contrarily to the rainforest with observed rising and falling trend from 1992 to 1997 and 2009 to 2013 respectively. There were consecutive five years steady increase between 1990 and 1997, and between 2010 and 2013 in the rainforest

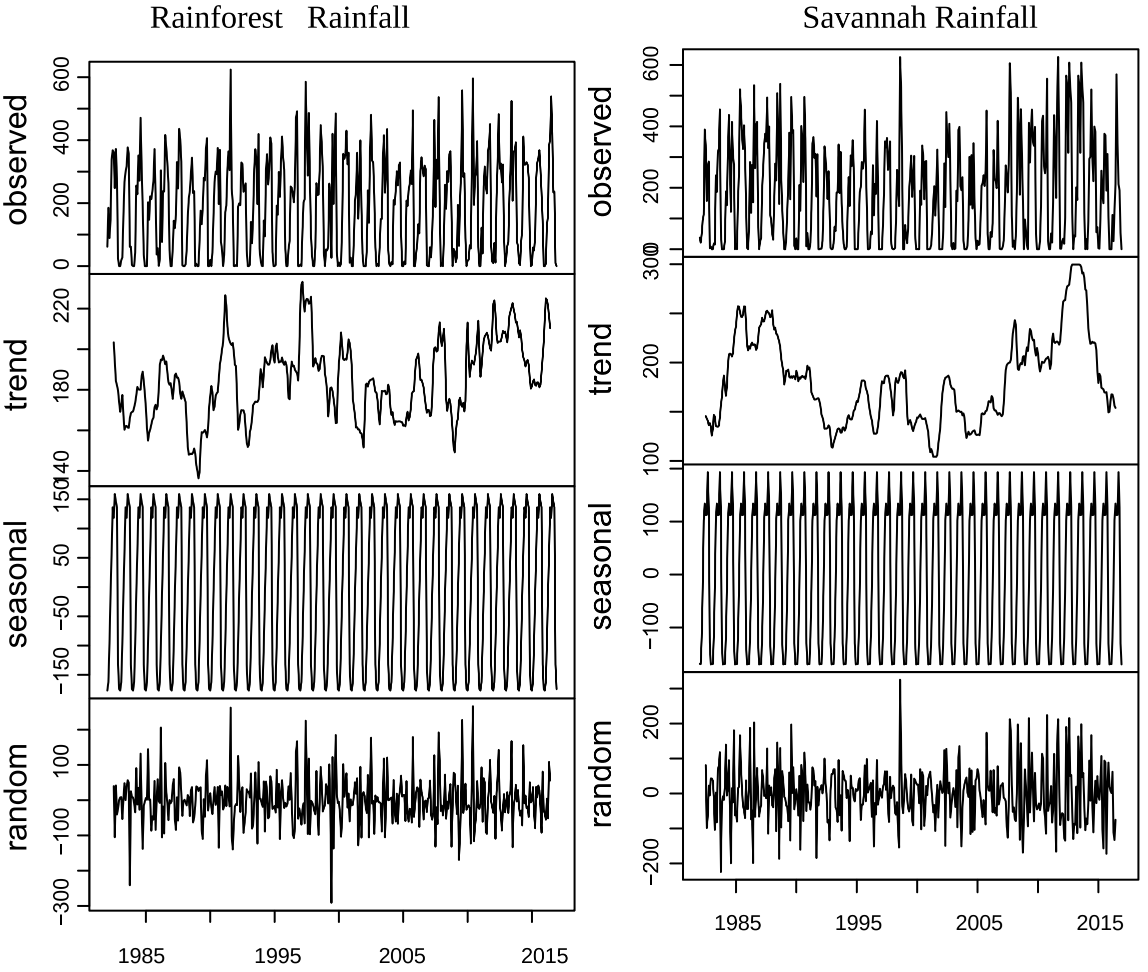


Figure 4. 1: Simple decomposition of monthly Growing Season Rainfall (mm) in rainforest and savannah

4.2.2. Maximum temperature trend pattern in the rainforest and savannah agroclimate zones of Cross River State (1982 -2016)

The trend pattern of maximum temperature for the rainforest and savannah is shown in Figure 4.2. Maximum temperature in the rainforest revealed a steady fluctuation from 1982 -2016 with no statically significant upward trend ($P < 0.001$). While in the savannah a significant upward trend was established in the same period, which is consistent with the finding of an increase in temperature over most regions in Nigeria (Haider, 2019). The lowest values of 31.6°**C** and highest values of 33°**C** monthly maximum temperature was noted in 1994 and 2016 respectively in the rainforest zone**.** While the savannah had 32, 4°C and 34.2°C as the lowest and highest values in 1992 and 2010. Both the rainforest and savannah indicate a significant increase in minimum temperature ($P < 0.001$) Figure 4.3. The year with the monthly lowest minimum temperature was 1997 and the highest monthly minimum temperature in 2007 in rainforest. For the savannah, 1997 was the lowest and 2004 the highest minimum temperature. A marked increase in minimum temperature was observed from 2000 to 2002 in the rainforest and 2000 to 2015 in the savannah agroclimate zone respectively.

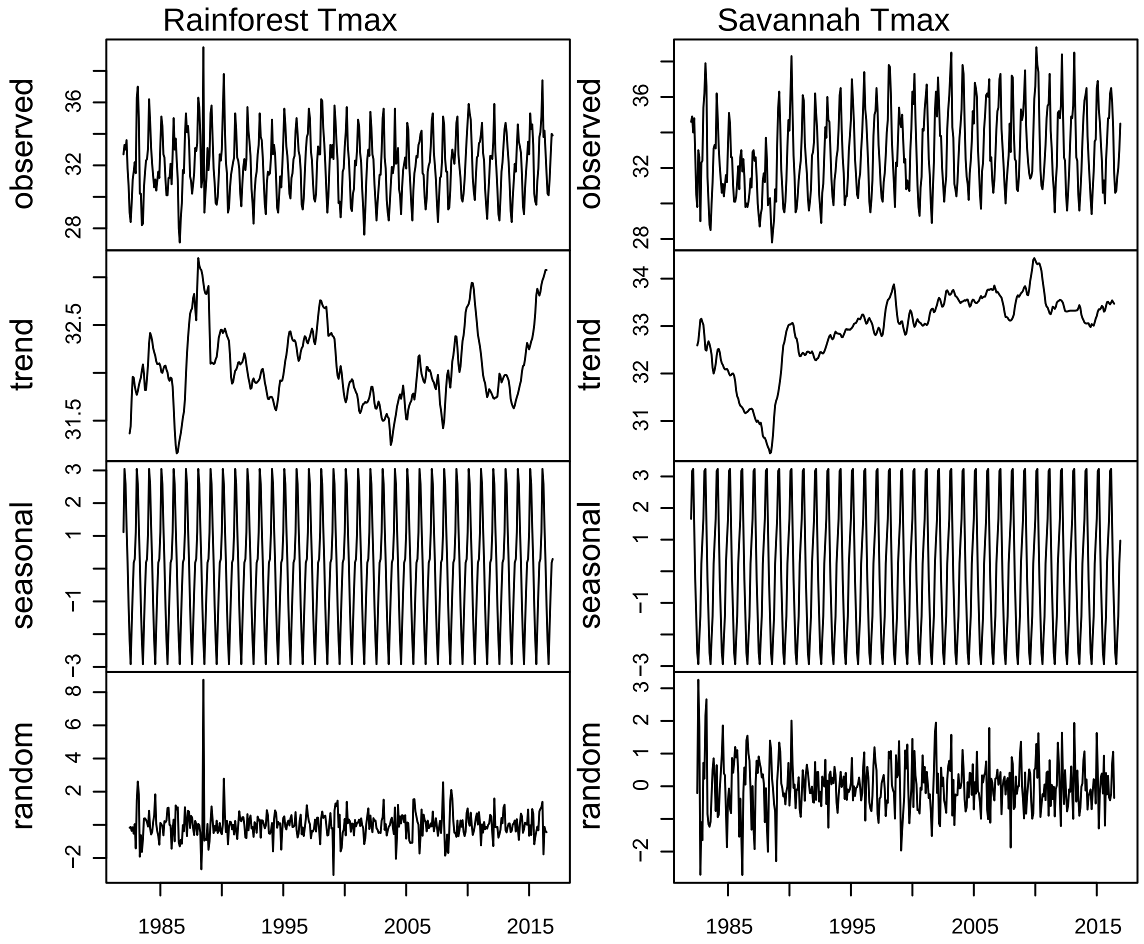


Figure 4.2: Time series of Growing Season Maximum Temperature (^{0}C) Rainforest and savannah

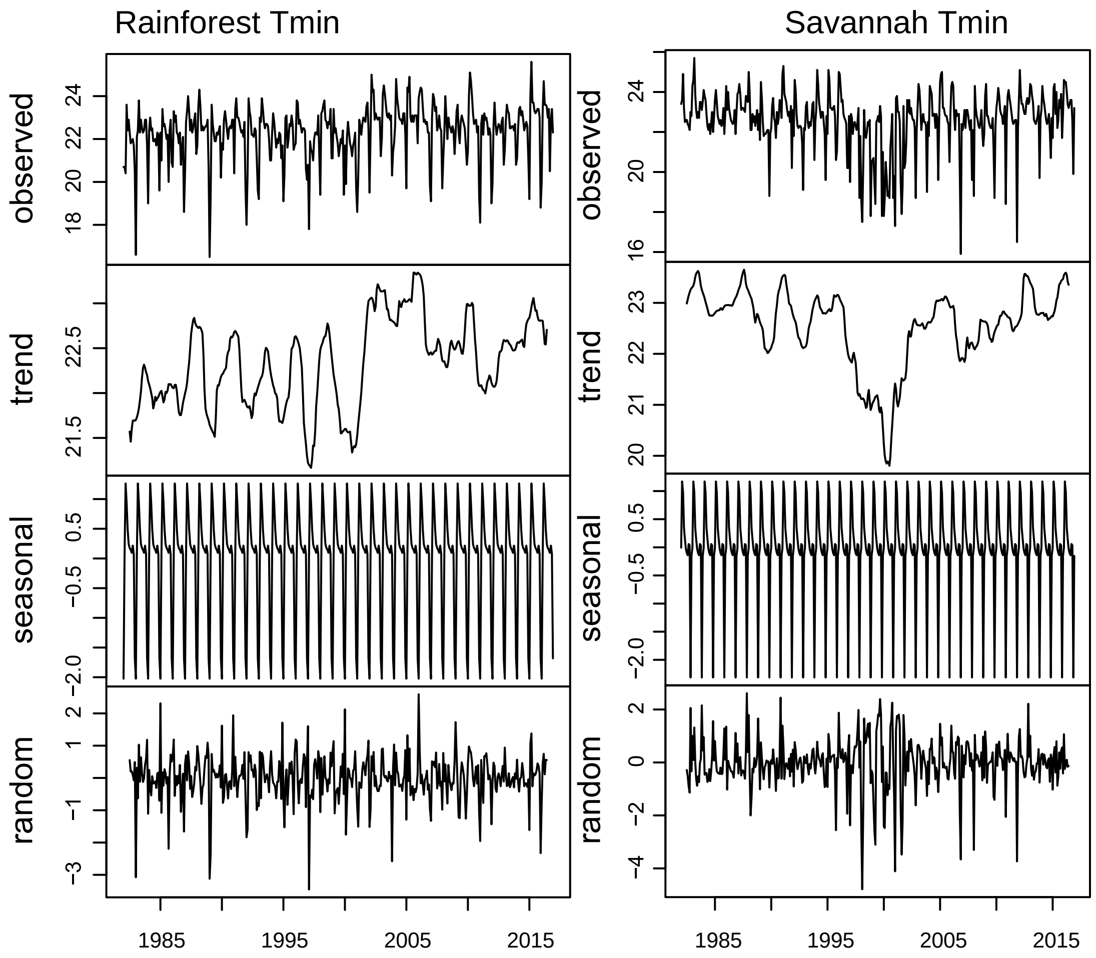
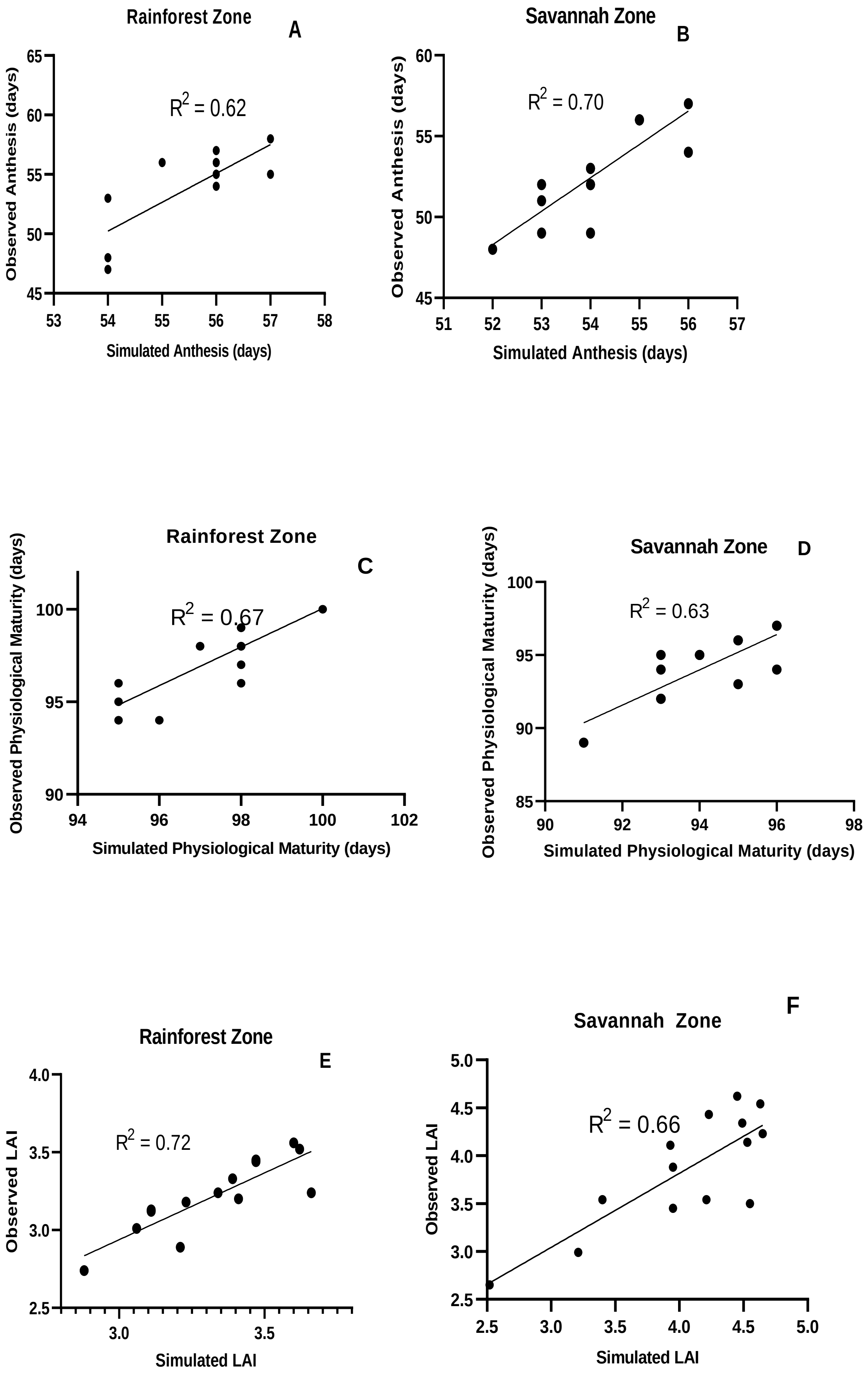


Figure 4.3: Time series of Growing Season Minimum Temperature (^{0}C) Rainforest and Savanna

4.3. Model Evaluation results of crop parameters in the rainforest and savannah

The model was calibrated with site-specific soil, crop data and weather data using the growing season experiment of 19990-2016 from the Cross River Agricultural Development Project. The evaluation was carried out for days to anthesis, days to physiological maturity, leaf area index, harvest index, and grain yield by comparing the simulated parameters with the observed parameters. The results are shown in Table 4.1 and Table 4.2. While the scatter plots are displayed in Figure 4.4. A higher r-square and d-index statistics were obtained for the modelled and observed parameters, with a lower RMSE for both the rainforest and savannah.


Rainforest Zone
A
Observed Anthesis (days)
65
60
55
50
45
R2 = 0.62
53
54
55
56
57
58
Simulated Anthesis (days)
Savannah Zone
B
Observed Anthesis (days)
60
55
50
45
R2 = 0.70
51
52
53
54
55
56
57
Simulated Anthesis (days)
Rainforest Zone
C
Observed Physiological Maturity (days)
100
95
90
R2 = 0.67
94
96
98
100
102
Simulated Physiological Maturity (days)
Savannah Zone
D
Observed Physiological Maturity (days)
100
95
90
85
R2 = 0.63
90
92
94
96
98
Simulated Physiological Maturity (days)
Rainforest Zone
E
Observed LAI
4.0
3.5
3.0
2.5
R2 = 0.72
3.0
3.5
Simulated LAI
F
Savannah Zone
Observed LAI
5.0
4.5
4.0
3.5
3.0
2.5
R2 = 0.66
2.5
3.0
3.5
4.0
4.5
5.0
Simulated LAI

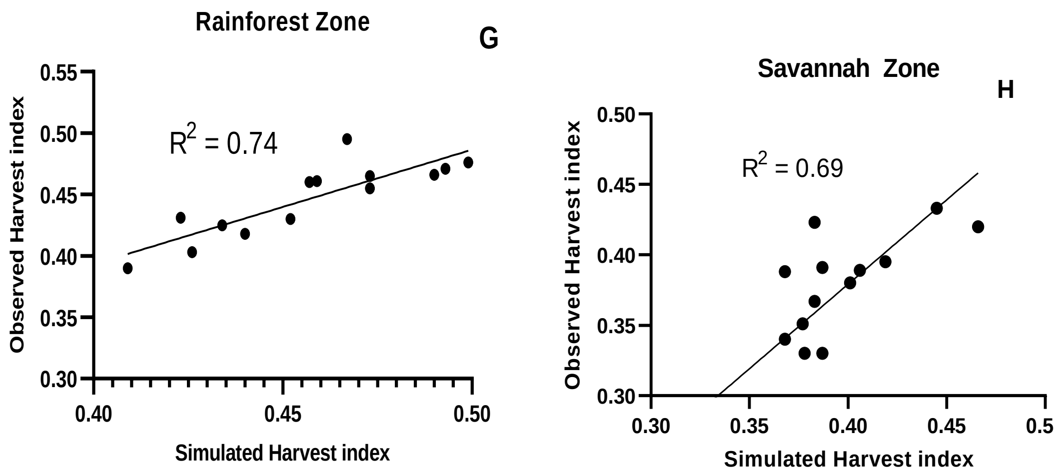


Figure 4.4: Comparison of observed and simulated parameters of days to anthesis, AB, Physiological maturity CD, Leaf area index EF and harvest index GH in rainforest and savannah zone.

Table 4.1: Model evaluation statistics during the early maize season period in Rainforest zone

Parameters	Sim Mean	Obs Mean	R-square	d-stat	RMSE	NRMSE (%)
Anthesis (days)	55	54	0.61	0.98	2.72	5.02
Physiological Maturity (days)	97	97	0.68	0.99	0.88	0.91
Leaf Area index	3.3	3.1	0.71	0.90	0.04	1.41
Harvest index	0.46	0.45	0.73	0.98	0.025	0.020

Source: Author's analysis

Table 4.2: Model evaluation statistics during the early maize season period in Savannah zone

Parameters	Sim Mean	Obs Mean	R-square	d-stat	RMSE	NRMSE (%)
Anthesis (days)	54	53	0.70	0.96	2.39	4.56
Physiological Maturity (days)	94	94	0.69	0.98	1.28	1.36
Leaf Area index	4.21	3.54	0.66	0.87	0.10	2.84
Harvest index	0.39	0.36	0.69	0.82	0.010	2.78

Source: Author's analysis

4.4. Comparison of simulated and observed maize parameters in the rainforest and savannah

The seasonal analysis of simulated and observed maize yield for the rainforest and savannah in DSSAT crop model during the growing season of 1990-2016 are shown in Table 4.1. The simulated mean maize yield for the rainforest was 6557kg/ha and the observed mean yield was 6238kg/ha for 1990-1996 and 2010-2016, with a root mean square error values of 160kg/ha, normalised RMSE in percentage of 3.01%, R square 0.67 and agreement-index statistic of 0.96. While for the savannah region, the simulated mean yield was 5942kg/ha and observed yield of 5826kg/ha, with RMSE of 175kg/ha, RMSE in percent 2.57%, R square 0.63, and the agreement index-statistic 0.95. The root mean square (RMSEn) values less than 10% indicates the excellent prediction of the model in the rainforest and savannah. The agreement index (D-statistics) and R square been e closer to unity reveal a good fit of the model to predict maize yield properly. The scatter plots between simulated and observed maize yield for 1990-2016 in the rainforest and savannah are presented in Figure 4.5. The scatter plots revealed good agreement between the simulated and observed maize yield. The regression R square of 0.67 and 0.63 shows a good fit of the model prediction capacity for maize grain yield in both agroclimate zones. The model slightly over estimated maize grain yield over the observed maize yield in the rainforest than in the savannah zone. Figure 4.6 and Figure 4.7 indicates slightly higher modelled grain yield in the rainforest with fluctuations in yield for both regions. Maize yield decline in the savannah than the rainforest from 1990 as shown in time series comparison of the modelled and observed grain yield. This could be attributed to the differences in the climate and planting time.

Table 4.3: summary statistics of simulated and observed yield in rainforest and savannah

Parameters	Rainforest zone	Savannah zone
Mean observed yield	6238 (kg/ha)	5826 (kg/ha)
Mean simulated yield	6557(kg/ha)	5942 (kg/ha)
RMSE	160.8 (kg/ha)	175.9 (kg/ha)
RMSEn%	3.01 %	2.57 %
D-statistic	0.96	0.95
R square (R^2)	0.67	0.63

*The simulation is excellent with RMSEn% <10%, Good if 10-20%, fair if 20-30% (*OM, et al., 2016*)*

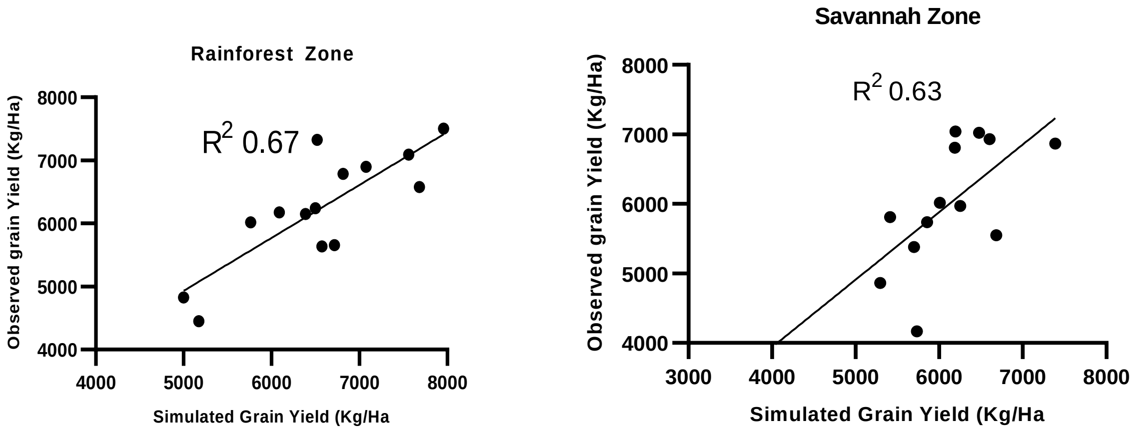


Figure 4.5: Scatter plot of Observed and simulated grain yield in rainforest and savannah

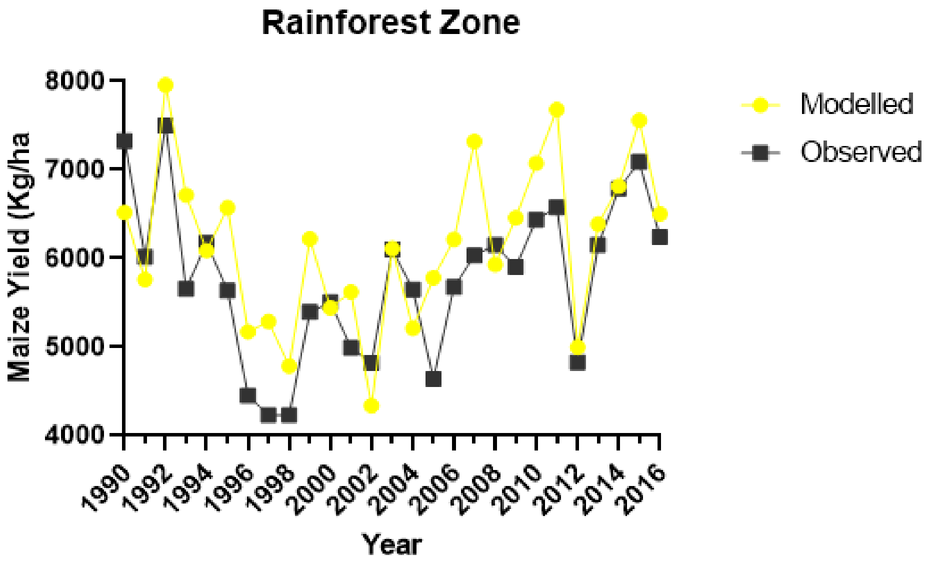


Figure 4.6: Time series comparison of modelled and observed yield in the rainforest

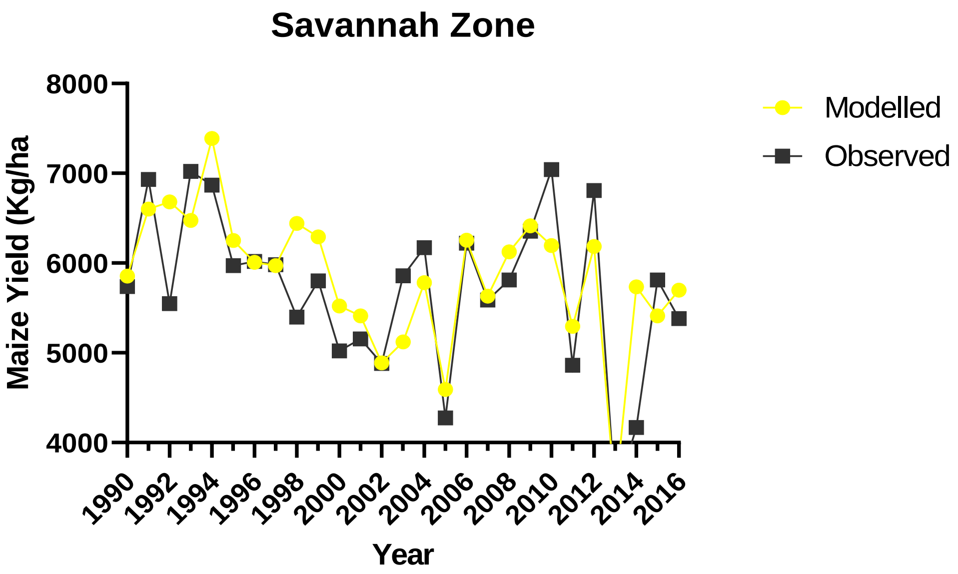


Figure 4.7: Time series comparison of modelled and observed yield in the rainforest and savannah

A multiple regression analysis results for simulated maize grain yield and climate parameters in the rainforest and the savannah agroclimate zones are presented Table 4.4 and Table 4.5. The dependent variable was maize yield, and the three independent variables were minimum temperature (°C), maximum temperature (°C) and rainfall (mm). The data were run in SPSS version 26. The multiple regression model for the rainforest and savannah revealed R^2 of 0.69 and 0.86 respectively. The R^2 of 0.69 in the rainforest means 69% of the explanatory variables accounted for the influence on the dependent variable (maize yield). While R square of 0.86 for the savannah means that 86% of the predictors' variables explained the effect of changes in the responding variable (maize yield). In other words, the remaining 16% refers to the unaccounted effect in the model. These unaccounted parameters in the model, that can be pest and diseases, harvest losses, soil factors, income, management techniques, cultivar selection, fertilizer management, and land which the model did not represent in the rainforest and savannah. The multiple regression model results in the rainforest and savannah were significant at ($P < 0.05$). Considering each predictor variable, it was observed that the relationship between rainfall and maize yield was statistically significant in the rainforest and savannah with ($P < 0.05$), but temperature (minimum and maximum) was not significant in both agroclimate zones. There is a positive relationship between growing season rainfall and maize yield as revealed in figure 4.8. The scatter plots demonstrated a perfect positive influence of growing season rainfall on maize yield in the regions. The year-to-year variability of maize yield consequent upon climate variability was shown in the model. The implication is that growing season rainfall plays significant impact on maize crop production in both regions. Tingem, Rivington & Colls, (2008) have also shown that yield variability is occasioned by the interactions of precipitation and temperature effect in southern Cameron ecological zone. They noticed a less than 12% variance in mean maize yield across six selection locations in Cameroun. Though this study did not take into consideration agroclimate differences in the selection of the six locations. Climate variations certainly accounts for yield variability in the different agroclimate zones. It is necessary to carefully consider the choice of management practices and adaptation technology to inform decisions. The overall results of the statistical analysis of climate parameters showed the great potential of DSSAT model to stimulate the effect of changes in climate parameters on maize yield in the rainforest and savannah agroclimate zones. The study established a good correlation of maize yield with growing season rainfall.

Table 4.4: Multiple Regression analysis of climate parameters and maize yield in rainforest and savannah

Source	ANOVA SS	DF	Standard Error Estimate	Mean square	R Square	F Value	P Value
Rainforest	11534083.2	3	722.09	3844694.4	0.69	7.37	0.000
Savannah	15035092.1	3	488.76	5011697.3	0.86	20.97	0.007

Dependent variable: Maize yield, predictor (constant) Tmin, Tmax and rainfall P < 0.05

Table 4.5: Regression coefficient of climate parameters in the rainforest and savannah

	Rainforest zone				Savannah zone			
Predictors	Unstandardized Coefficient B	Std Error	T value	P value	Unstandardized Coefficient B	Std Error	T value	P value
Rainfall	3.76	0.96	3.89	0.003	4.51	0.61	7.39	0.000
Tmax	769.42	570.75	1.348	0.207	-10.96	208.62	-.053	0.959
Tmin	112.884	473.32	0.238	0.816	69.53	237.07	0.293	0.775

Rainfall significant at P < 0.05, Tmax and Tmin not significant at P < 0.05

4.5. Sensitivity analysis of maize yield response to changes in climate parameter in the Rainforest and savannah agroclimate zone

The results of the key climate variable rainfall in the sensitivity analysis conducted for the regions are shown in Figure 4.8. The simulated mean maize grain yield for the historical year 1990-1996 and 2010-2016 was 6557kg/ha in the rainforest and 5942kh/ha in the savannah. The change in rainfall indicates that maize yield positively to the increase or decrease in the growing seasonal rainfall. For instance, for ±20% change in rainfall, maize yield was higher and in rainforest than in the savannah. A strong positive correlation between the changes in rainfall and maize yield in the rainforest and savannah zones was found as displayed in Figure 4.8 with r-square of 0.65 in the rainforest and 0.56 in the savannah. This corroborates with studies that a projected decrease in rainfall of 20-50% h in most regions of Africa would impact yield negatively (Kima et al., 2015) and that maize yield in West Africa will be affected due to climate change (Freduah et al., 2019).

From the analysis, a 50% decrease in rainfall was most prominent to cause yield reduction than 10% or 20% changes. Studies in Africa have revealed that crop yield would probably decrease by 15% and 40% due to climate change (Toure et al., 2018). Rainfall is an important element in rainfed cultivation in West Africa. Climate variability can affect maize yield positively or negatively. But the negative impact is more devastating than the positive as seen in this analysis. The reduction in grain yield for a decrease in rainfall for both zones revealed that climate change can impact negatively on crop yield. Following the scientific report of yield decline due to climate change, the intergovernmental panel on climate change stressed that farmers would need to build resilient and adaptive capacity to reduce vulnerability (Denton et al., 2014; Buyana et al., 2020).

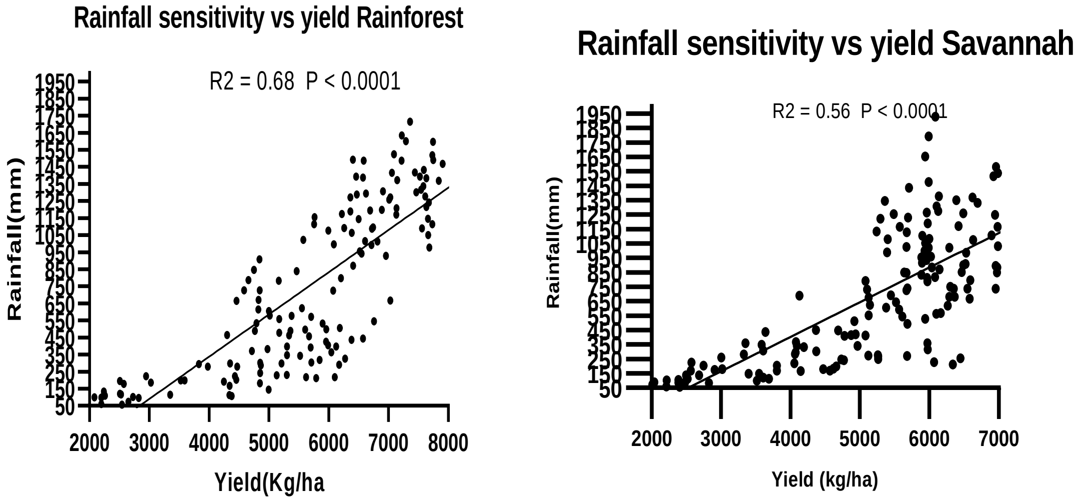


Figure 4.8: Sensitivity analysis of maize yield response to changes in rainfall in rainforest and savannah

4.6. Conclusion

This chapter analyses the monthly climatic trend from 1982-2016. The results reveal a significant upward trend in minimum temperature for both the rainforest and savannah region. While there was a statistically significant upward trend in the time series of maximum temperature linear for the savannah region. An increasing monthly trend in growing season rainfall amount was also established in the savannah zone. Though rainfall increase was known in the rainforest, there was no established upward trend during this period. The statistical multiple regression results indicate that growing season rainfall amount was positively significant with maize yield in the rainforest and savannah. While temperature (Maximum and minimum) was not of any significant effect on maize yield in the model for both zones.

Chapter 5: A survey of factors influencing maize yield and adaptation to climate variability in the rainforest and savannah agro-climate zones

5.1. Introduction

This section employs a survey approach to analyse the critical parameters influencing maize yield and adaptation to climate variability within the rainforest and savannah agroclimate zones of Cross River State. Thirty-five questions were designed for the maize growers to be able to draw inferences and explore factors influencing maize yield in the rainforest and savannah agroclimate zones of Cross River State. The survey approach allows the inclusion of the local farmers' knowledge in diagnosing problems affecting maize production and the barriers to the adaptation of new practices (Orabi, 2018; Shikuku et al., 2017). It helps farmers to highlight the key factors impacting maize yield and the best possible options for resolving yield problems in the zone. Local farmers have a diversity of understanding of the interplay of factors in crop yield productivity (Zakaria et al., 2020; Ayanlade et al., 2017). Since the 1970s and 1980s, farmers' inclusion in research has taken a centre stage in most parts of Africa (Orabi, 2018). This inclusive approach puts the farmers at the fulcrum of active participation at farm level, where their views are considered important and can be shared (Orabi, 2018; Mutami, 2015). Local farmers are not ignorant of their environment and the impact of climate on crop production (Egbe et al., 2014).

In other words, it is important to mention that the local farmers are stakeholders in the research process (Egbe et al., 2014. Their views about what influences maize yield and adaptation to climate variability are necessary for the formulation of key policies. Hence, the inclusion of a survey methodology is expected to provide further insight into key limiting factors influencing maize yield and adaptation to climate variability in the rainforest and savannah agroclimate zones of Cross River State. While Process modelling approach has become highly important in understanding the response of crop yield to changes in climate (Ewert et al., 2015), it is mostly a top-down approach and not inclusive of local understanding of the smallholder farming population (McDonald et al., 2019). This chapter endeavours to fill this gap in knowledge, and to help build sounds scientific understanding of the constraints to maize productivity in the zones. This would improve adaptation and resilience for the farmers against the threat of climate change and variability of maize yield (Egbe et al., 2014) vis-a-vis Cross River State. Thus, a cross-sectional survey design suggested in (Levin, 2006) was used. This was carried out at one time over a season to elicit responses of outcome factors influencing maize yield in the agroclimates zones.

5.2.1. A reconnaissance survey of maize growing communities in rainforest and savannah

A reconnaissance survey was first carried out to establish the main maize growing communities in the rainforest and savannah agroclimate zones of Cross River State before the actual task of administering questionnaires. A letter of introduction was presented during this visit to the state agriculture development project office and to the local area agriculture officers of the respective agricultural development zones (Appendix 5). The State is delineated into three geopolitical senatorial zones, the North, the Central, and the South. The northern zone is mostly a savannah area, the central and the southern are rainforest and mangrove swamp. There are 18 local area councils in the State: seven in the south, six in the centre, and five in the north. The Agricultural development project managers and communities' agents in the zone assisted in identifying and mapping the maize growing areas during this survey. It was also easier to exclude farmers of other crops and to identify and mobilise maize growing farmers in the communities with this preliminary plan. The survey was implemented during the early maize growing season in May of 2018. This plan was assisted by the State agricultural project coordinators, the agriculture extension officers in the two zones who also help in explaining difficult concepts to the farmers during administration. They provided information on key informants in the maize growing communities who helped in the mobilization process. The youth leaders and extension agents played a major role in the administration and collection of the questionnaires in the respective farming communities of the rainforest and savannah agroclimate zones. The essence of the survey was aimed at eliciting responses from the maize farmers on their perceived knowledge of factors influencing maize yield, crop management techniques, and adaptation response strategies to climate variability. The questionnaire survey approach was adopted to elicit responses from maize growers using structured questionnaires designed using a five-point Likert-scale: (Osborne et al., 2011; Allahyari et al., 2016) strongly adopted (5) Always adopted (4) undecided (3) rarely adopted (2), not adopted (1), and the strongly agreed (5), agreed (4), Undecided (3), disagreed (2), strongly disagreed (1). The questions were split into socioeconomic factors, crop management practices, and climate change factors.

5.2.2 Population, sampling procedure and sample size

The potential sample population consists of the entire group of maize growing farmers in the rainforest and savannah zones. A multistage sampling technique was utilised in because of the setting of the region of study. Cross River State is delineated into different geopolitical units, and agroclimate zones. The multistage technique involves two or more stages in sample selection in other to make primary data collection easier and manageable. The rainforest and Savannah agroclimate zones were selected as they are the epicentres of local maize cultivation zones, with distinctive climate regimes. There are two geopolitical districts in the zones: the central senatorial district with six Local Government Areas, namely, Ikom, Etung, Boki, Obubra, Ugep and Abi, and the northern senatorial district consisting of the five Local Government Councils of Obudu, Bekwarra, Ogoja, Yala, and Obanliku. Two major maize growing Local Government Councils from each agroclimate zones, and two communities from each council, were chosen randomly. For the rainforest, Ikom and Etung local government areas were selected. For the savannah, Ogoja and Bekwarra local government areas were picked. The four communities randomly selected for questionnaire administration in the rainforest were Alesi, Yawunde, Etomi and Effraya (Figure 5.1). In Savannah, the four communities randomly selected were Nwarranty, Ebegang, Adagom and Utukwe-kongo (Figure 5.2). The sample only involved those maize growers with more than three years of experience in farming. A systematic sampling technique was used to pick the number of samples from each community cooperative group of maize farmers. This was intended to provide even coverage of the population within the sampling frame (Nicolas & Gill, 2003). The selection of sample size was initiated with the application of this simple equation $K = N/n$ (Nicolas & Gill, 2003; Ayanlade et al., 2017), where K stands for maize growers drawn from the register, N the total number of maize growers in the cooperative group register, and n is the desired sample size from using the equation $n = N/2$. This was implemented by drawing the first farmer randomly and subsequently, every second farmer on the register was selected from the total population in each community list. Table 5.1 shows the sample sizes for each community in both the rainforest and savannah zones.

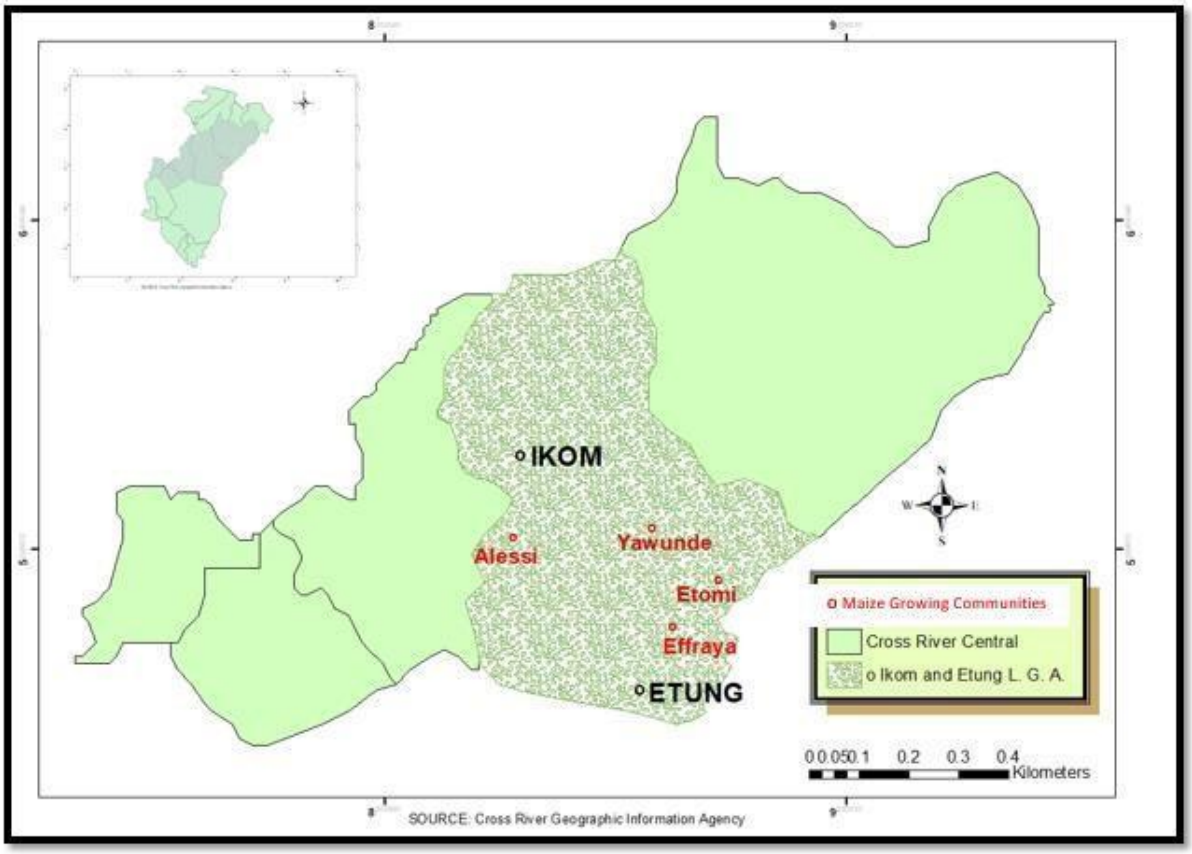


Figure 5. 1: Location of four maize growing communities in the rainforest agroclimate zone

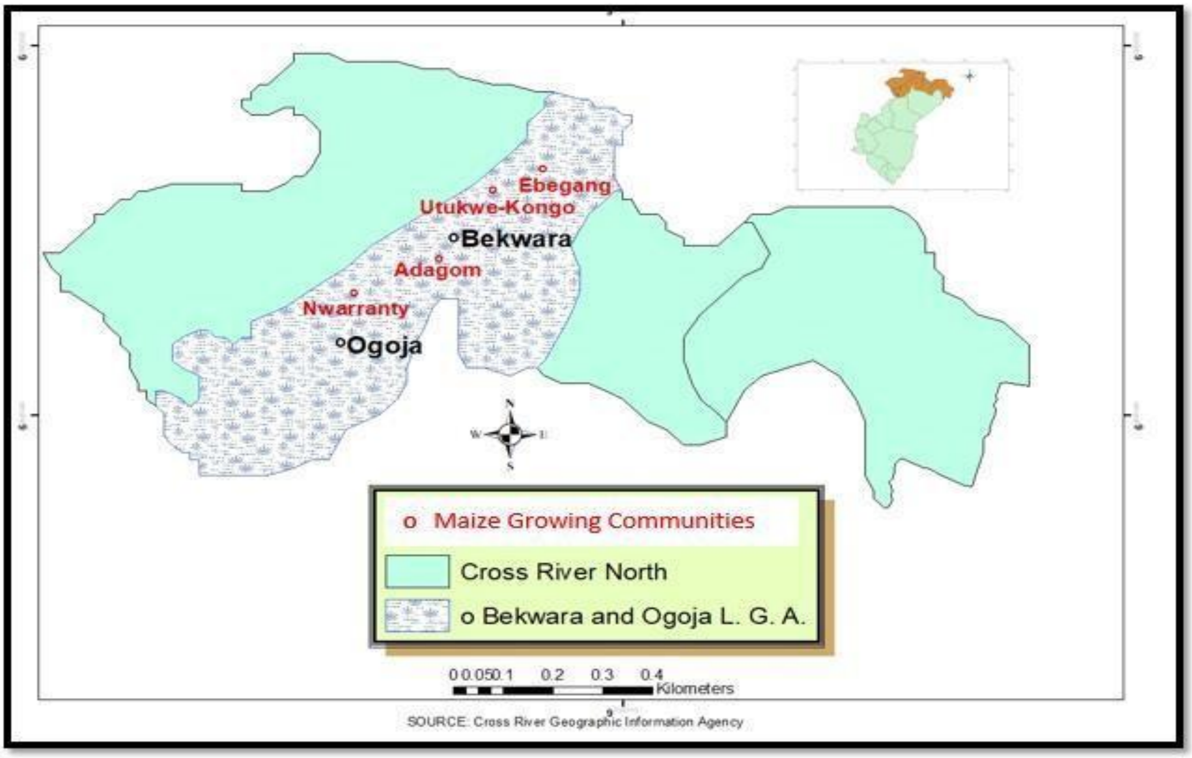


Figure 5. 2: Location of four maize growing communities in savannah agroclimate zones

Table 5. 1: Population and sample size of maize growers in selected communities in rainforest and savannah agroclimate zones

Rainforest Communities	Population (N)	Sample size (n)	Savannah communities	Population	Sample size
Alesi	32	16	Adagom	36	18
Yawunde	30	15	Nwarranty	28	14
Etomi	40	20	Ebegang	32	16
Effraya	34	17	Ntukwe-kongo	40	20
Total	136	68		136	68

Source: Author's fieldwork

5.2.3. Questionnaire validation, administration, and reliability test.

The questionnaires addressed specific key objectives of the research questions. It focuses on the socio-economic characteristics of the farmers, the crop management practices adopted such as fertilizer application, planting, time, crop varieties and the plant density. And the climate change adaptation factors that impact on maize yield in the rainforest and savannah agroclimate zones. A copy of the questionnaire is found in Appendix 3. The questionnaire was structured in a closed-ended, and a few open-ended questions which were re-coded. The questionnaire was face-validated by my supervisor, and by two agronomy experts before been administered to the respondents in the field. A pilot study was conducted in different areas for the purpose of authenticating the questions and avoiding errors of inconsistency. The use of community extension agents and cooperative leaders to administer the questionnaires was most effective as all the questionnaires were filled and returned. The questionnaires were subjected to a Cronbach alpha reliability test according to Cortina (1993), and the selection was based on variables with high Cronbach alpha (Luu et al., 2019), which was analysed in SPSS version 26. A Cronbach alpha of 0.82 was obtained in the rainforest and 0.79 in the savannah for all the items respectively, implying that the items have very high internal consistency.

Table 5. 2: Reliability test rainforest and savannah agroclimate zones

Agroclimate Zone	**Cronbach's Alpha**	**N of items in Likert scale**	**N of respondents**
Rainforest	0.82	35	68
Savannah	0.79	35	68

Source: Author's field work

5.3. Technique of data analysis

5.3.1. Descriptive analysis, factor analysis and multiple regression model

The socioeconomic characteristics of the maize farmers were descriptively analysed using percentages as presented in Table 5.3. Factor analysis was employed as a variable reduction method, to explore the key underlying variables that influence maize production and adaptation to climate variability in the rainforest and savannah agroclimate zones. Factor analysis has been employed by different researchers for different purposes. For instance, a four-factor analytical technique and multiple regression model was applied to investigate the relationship between daily milk yield and 10 udder traits in goats (Keskin et al., 2007). They concluded that a relationship existed between milk yield and some udder traits. Factor analysis was utilised to investigate climate change adaptation barriers to tomato yield in the Offonso district of Ghana (Godaar et al., 2018). A 7-factor solution was adopted to unpack the critical factors that hinder tomato farmers from adapting quickly to climate change in order to improve tomato productivity. Factor analysis is a potent tool for exploring and reducing a large set of measured variables for further analysis (Raven, 1994; Ifeanyi-Obi et al., 2014). The essence of applying factor analysis in this research is to simplify the data and reduce the number of variables to a suitable dimension for a regression model (Ifeanyi-Obi et al., 2014). Factor analysis seeks to identify those essential unobservable (latent) variables which are reflected in the observed variables (Ford et al, 1986; Raven, 1994). A common factor analysis extraction method – the maximum livelihood extraction - was used to extract factors and the orthogonal rotation scheme varimax (variable maximization) was adopted. This is a common rotation scheme which tries to redistribute each factor loading such that a variable measures each factor accurately (Osborne et al., 2011). The Kaiser criterion of selecting a factor proposes that a meaningful factor should be greater than one (Osborne et al., 2011; Raven, 1994). Thus, eigenvalues with factors greater than one were selected. The Barlett's Test of Sphericity and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy were used as a benchmark for the selection of underlying factors and proceeding with factor analysis. It measures the strength of the relationship among the variables. The values of Kaiser-Meyer-Olkin are between 0 and 1. Any value toward 1 is good and acceptable (Osborne et al., 2011). The scree plot is commonly used to select the factors by looking at the point where the curve breaks below the elbow. A scree plot shows a graphical representation of the eigenvalues plotted against the factors. The graph slopes from the left to the right and tails off toward infinity showing that each successive factor is accounting for a smaller portion of total variance.

The curve becomes flattened on the horizontal axis. Those factors above the elbow of the curve with eigenvalues greater than one are retained (Osborne et al., 2011). A seven-factor solution was adopted (high loading factor) using the varimax rotation orthogonal rotation scheme to ascertain which factor is meaningful. The observed data were transformed into a factor score by a regression estimation method and used to run a multiple regression model.

5. 4. Results and discussions

5.4.1. The Socioeconomic characteristics of maize farmers in the rainforest and savannah agroclimate zones

Table 5.3 showed the socioeconomic characteristics of maize farmers in the rainforest and savannah agroclimate zones. The results indicate small household size constitute only 10.3% and large household size 86.8% in the rainforest, while in the savannah, small house size was just 4.4% and large household was 83.8% respectively. Majority of rural farming population in Nigeria are characterised by larger household sizes like many parts of West African. This result is consistent with the findings of (ifeayi-Obi et al., 2014) which indicates that many household sizes in rural farming areas are larger and more than 6 people per household. The high sizes of household could serve as good source of labour force. Farmers conceived the notion that having large households would boost productivity of maize and reduce the cost of paying for labour. The finding showed that 72.1% male, and 27.9% female cultivate maize in the rainforest and 66.2 % male, and 33.8% female in the savannah agroclimate zones. This is common practice in most regions in Nigeria and West Africa where married women are dependent on their husbands for agricultural activities and so this distribution is not surprising (Theriault et al., 2017; (Olakojo, 2017). In some areas, annual crops like okra, maize, cucumber, pumpkin, beans, and groundnut are exclusively cultivated by females. There is a cultural difference in most parts of West Africa where males dominate the cultivation of certain crops (Theriault et al., 2017). This is also reflected in who is deemed head of the household, as 95.2% were males in the rainforest and 80.9% in the savannah zone. The disproportionality in male number in cultivating crops is mostly linked to masculinity and cultural understanding in Nigeria (Olakojo, 2017).

Furthermore, Table 5.3 shows that farmers who had no education background were just 1.5% in the rainforest and 0% in the savannah, while those who attended primary education level were 11.8% in the rainforest, and 30.9% in the savannah. For the rainforest, junior secondary education level was 7.4% and 17.6% for savannah. Farmers with senior education level were 38.2% in the rainforest and 32.4% in the savannah. The number of maize farmers with tertiary education in the rainforest were 41.2%, and 16.2% in the savannah zone. This revealed that a significant percentage of the maize growing population in the rainforest zone attended higher education than those in the savannah zone. The statistics showed that more maize growers attended primary and secondary education in the savannah than the rainforest. Education is key for the understanding of new technology and adaptation measures to improve maize cultivation in Nigeria. Poor education of farmers has been a limiting factor to the acceptance of improved crop management techniques and crop productivity in Nigeria (Infeayi-Obi et al., 2014; Ogunniyi et al., 2021). The rejection of new hybrid crop varieties in the local areas of West Africa is common for some superstitious reasons, like respect for ancestral belief that hybrids come with disease infestation, and that local varieties have a better taste (FGD, 2018). This is really a barrier to the acceptance of high yielding varieties of maize in most regions of Nigeria. The acquisition of education is key to improving farming in West Africa, (Infeayi-Obi et al., 2014). Farmers need a basic level of education to enhance their understanding of modern farming techniques.

The years of experience in maize crop production in the agroclimate zones was analysed. It was observed that 64.7% of maize farmers in the rainforest and 51.5% in savannah have more than ten years of experience in farming maize. Many farmers have been in the farming business for several decades. Those with less than five years' experience in maize cultivation represented only 16.2% and 10.3% in the rainforest and savannah respectively.

Large farm sizes of more than five hectares were represented by 33.8% in the rainforest and 25% in the savannah. There were thus larger maize farm sizes in the rainforest than the savannah agroclimate zones. However, in terms of crop yield, most farmers recorded smaller yields in both agroclimate zones, 73.5% and 69.1% respectively. Notably, only a smaller proportion of 25.6% and 2.5% recorded yield above 5 000kg^{-1} in the rainforest and savannah respectively. Yield levels also reflect relative income: just 14.7% and 5.9% earn above N500, 000 (£1000) annually from maize in the rainforest and savannah respectively. A greater percentage of farmers fall within small income earners from maize sale of 73.5% in the rainforest and 69.1% in the savannah.

Table 5. 3: Descriptive statistics of the socioeconomic factors of sampled maize farmers in rainforest and savannah agroclimate zones

Variables	Rainforest Frequency.	Percentage (%)	Savannah Frequency	Percentage (%)
Small household size (< 3 occupants)	7	10.3	3	4.4
Medium HHS (3-5 occupants)	2	2.9	9	13.2
Large HHS (> 5 occupants)	59	86.8	57	83.8
Gender (male)	49	72.1	45	66.2
Gender (female)	19	27.9	23	33.8
Head of Household (Male)	65	95.6	55	80.9
HHS (Female)	3	4.4	13	19.1
No education	1	1.5	0	0.0
Primary School Education	8	11.8	21	30.9
Junior secondary Education	5	7.4	12	17.6
Senior Secondary Education	26	38.2	22	32.4
Tertiary Education	28	41.2	11	16.2
High experience (>10yrs)	44	64.7	35	51.5
Medium experience (5-10yrs)	13	19.1	26	38.2
Low experience (< 5yrs)	11	16.2	7	10.3
Small farm size (< 1 hectare)	30	44.1	50	73.5
Medium farm size (1-5hectares)	15	22.1	11	16.2
Large farm size (> 5 hectares)	23	33.8	17	25.0
Small yield (< 1000kg/ha)	50	73.5	47	69.1
medium yield (1000kg 5000kgha/ha)	4	5.9	9	13.2
Large yield (>5 000kg/ha)	14	20.6	2	2.9
Small income (< N50,000 pa)	50	73.5	47	69.1
Medium income (N50,000-500,000 pa)	8	11.8	7	10.3
Large income (>N500,000 pa)	10	14.7	4	5.9

Source: Author's field work

5.5. Factor analytical model to examine factors influencing maize production and adaptation to climate variability in the agroclimate zones

5.5.1. Factor analytical and regression model of factors influencing maize yield and adaptation to climate variability in the rainforest zone

A factor analysis of 35 items was carried out and a 7-factor solution was adopted to determine the minimum factors influencing maize yield in the rainforest zone. Factorability of the items were done using established criterion. A Cronbach alpha of 0.82 was obtained for all the items which implies that they have high internal consistency and reliability. The Kaiser-Meyer- Olkin measure of sampling adequacy was 0.60, and the Bartlett's test of sphericity was significant ($\square^2$ (703) = 1400.28, $P < 0.05$) in Table 5.4. The eigenvalues for the 7 factors extracted in Table 5.5 were above 1, and only the factors in the scree plot (Figure 5.3) above the second elbow were taken. The analysis revealed the following eigenvalues of 7.73, 3.47. 2.69, 2.45, 1.95, 1.85 and 1.65 for factors 1-7. While the total percentage variance for the 7 factors were 20.35%, 9.13%, 7.10%, 6.46%, 5.13%, 4.87% and 4.43% respectively. A cumulative percentage variance of 57.49% for all the respective factors was obtained. Those items which had a loading below 0.03 were not considered significant to be included in the factor naming, hence they were subsequently eliminated. Items that loaded high under each factor were used in naming the factors.

Factor 1 was named the fertilizer application factor because its principal loadings were fertilized after planting (0.78), quantity of 200kg NPK per/ha (0.759), quantity of 100kg urea per/ha (0.62), row spacing (0.76), no fertilizer before planting (0.55). Factor 2 was named the plant density factor as it loaded high for improved variety (0.53), plant density or population (0.71), level of education (0.58). Factor 3 is socioeconomic as it loaded high for farm size (0.77) and low-income level (0.63). Factor 4 is a climate change factor as its high loadings were the shift in growing season rainfall (0.89), and land tenancy (0.76). Factor 5 was labelled extension agent influence as it loaded high for farming experience/low-income level (0.49), extension agent problem (0.61), and farming experience (0.53), and level of education (0.48), while factor 6 was named the planting date factor as it loaded high for planting date (0.41), row spacing 0(.48) and negative correlation for gender (-0.41). Finally, factor 7 was labelled soil conservation as loaded high for rainfall changes (0.59), soil conservation (0.45) and land tenancy (0.37).

The factor scores generated in Table 5.5 for factors 1-7 (independent variables) were used with the maize yield values (outcome variables) from the respondents to produce a multiple linear regression model. The results of the model showed good fit, with R^2 =0.733 in Table 5.6. The

R^2 means that all the explanatory variables explained 0.73 of the maize yield changes in the rainforest. The analysis of variance of the model F (7, 60) = 23, $P < 0.05$) was significant, and this revealed the model predicted the maize yield well in Table 5.7. When maize yield was predicted in Table 5.8, it was found that the socio-economic factor was statistically significant ($P < 0.05$), while crop fertilizer application and extension agent (factor 1, and 5) were almost significant, at 10%.

Table 5. 4: Rainforest Zone KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.604
Bartlett's Test of Sphericity	Approx. Chi-Square	1450.289
	Df	0.703
	Sig.	0.000

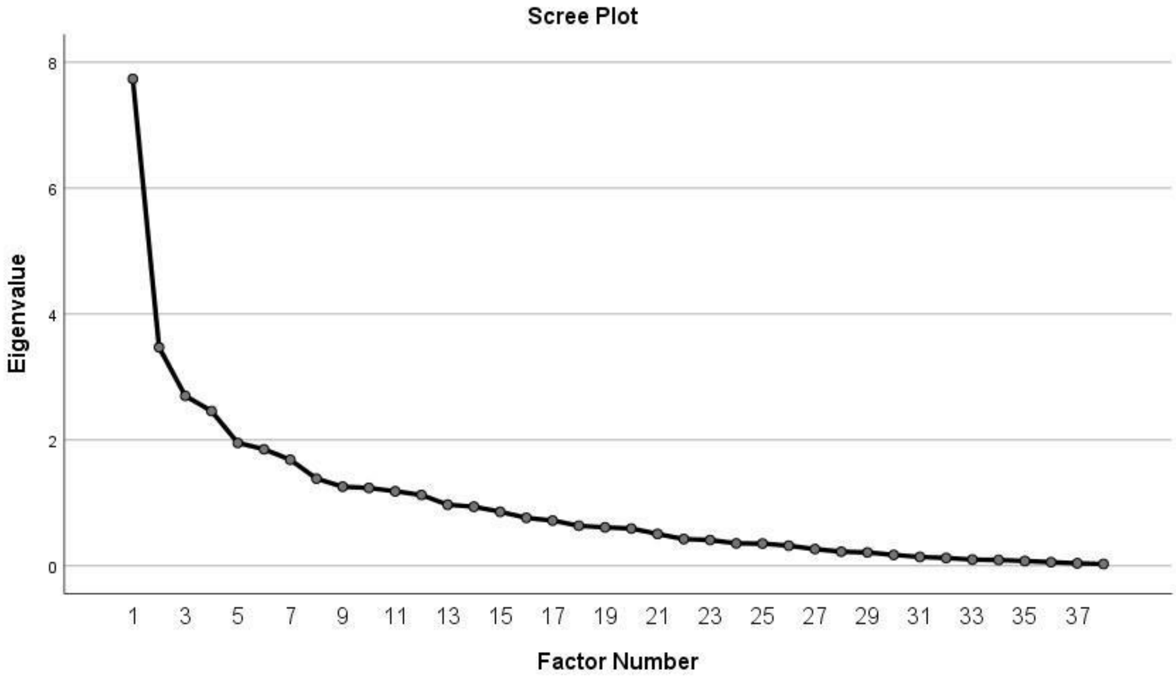


Figure 5. 3: Scree plot of factors in the rainforest agroclimate zone

Table 5. 5: Factor analysis loading for factors influencing maize yield and adaptation to climate variability in the rainforest zone

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Fertilize after planting	0.780						0.345
Apply 200NPK per hectare	0.759						
Apply 100kg urea per hectare	0.623						
Soil fertility	0.667						
No access before planting	0.549						
Disease Resistant V	0.459						
Improved variety		0.538					
Planting date		0.613				0.541	
Soil conservation							0.456
Standard Plant density		0.713					
Row spacing	0.765		.			0.481	
Gender						-0.418	
Level of Education		0.587			0.486		
Farming Experience					0.537	.	
Farm size			0.779				
Shift in growing season (CC)				0.890			
Rainfall changes							0.559
Irrigation in spell		0.439					
Low-income level			0.638		0.493		
Extension agents					0.618		
Land tenancy				0.766			0.376
Political factor			0.352				
Eigenvalues	7.73	3.47	2.69	2.45	1.95	1.85	1.68
Total % Variance	20.35	9.13	7.10	6.46	5.13	4.87	4.43
Cumulative %	20.35	29.48	36.58	43.05	48.18	53.06	57.49

Extraction Method: Maximum Livelihood, Rotation method: Varimax with Kaiser Normalization

Table 5. 6: Model summary of factors in rainforest

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.856^a	.733	.702	587.552

Table 5.7: ANOVA of Factors in the Rainforest

Model	**Sum of Squares**	**DF**	**Mean Square**	**F**	**Sig**
Regression	56878311.652	7	8125473.093	23.537	0.000^b
Residual	20713018.865	60	345216.981		
Total	775911330.51	67			

a. Dependent Variable: maize yield

b. Predictors: (Constant).

Table 5. 8: Multiple regression of factors in rainforest

Model summary		Unstandardized Coefficients		Standardized Coefficient	t	Sig.
		B	Std Error	Beta		
1	(Constant)	939.191	71.251		13.181	0.00
	Fertilizer Application.	106.653	76.639	0.093	1.392	0.109
	Plant density	25.891	77.412	0.022	0.334	0.739
	Socio-economic factor	973.574	78.189	0.832	12.452	0.000
	Climate change factor	98.975	76.645	0.086	1.291	0.002
	Farming experience	124.193	78.742	0.105	1.577	0.120
	Planting time factor	-46.063	80.381	-0.038	-0.573	0.569
	Soil conservation	-33.372	82.747	-0.027	-0.403	0.688

Source: Author's analysis, 2020.

5.5.2. Factor analytical and regression model of factors influencing maize yield and adaptation to climate variability in the savannah zone

Items selected were put to a reliability test for internal validity and consistency before factorability (Osborne et al., 2011; Neill, 2008). A Cronbach's Alpha of 0.79 was achieved. This value shows that the items were internally valid and consistent for factor analysis. The Kaiser-Meyer- Olkin measure of sampling adequacy was 0.62, and the Bartlett's test of sphericity was significant at ($\square^2$ (666) = 1337.979, $P < 0.05$) in Table 5.9 which also met the criteria for a factor analysis to be carried out. A 7-factor solution was initiated as recommended by most researchers (Guodaar et al, 2018) using varimax rotation scheme. The results are shown for factors 1-7 in Table 5.10 and the eigenvalues chosen through the scree plot in Figure 5. 4 are 7.93, 3.47, 3.07, 2.29, 2.07, 1.97, and 1.68. The eigenvalues greater than 1 were retained which satisfied the robustness of the factor analysis model.

The factor scores for high loading items in Table 5.10 were merged and renamed to give a unique name for the underlying construct of factors influencing yield in the zone. Factor 1 was re-named the fertilizer factor due to the high loading for fertilizer after planting (0.81), quantity 200NPK per/ha (0.75), quantity 100 urea per/ha (0.74), Soil fertility (-0.66), and improved variety (0.52). Factor 2 was named the farm size/income factor due to loadings of farm size (0.88), income level (0.83), and political factor (0.61). Factor 3 was renamed the climate change factor as it loaded high for changes in rainfall (0.619), row spacing (0.61), and planting date (0.54), extension agent (0.66). Factor 4 is a socioeconomic factor as it loaded negatively high for Gender (-0.801), Household head (-0.803), and low income (0.93). Factor 5 was named the management practice factor due to high loadings for row spacing (0.59), irrigation (0.59) and Plant density (0.34). Factor 6 was classified as the poor farm credit and education factor as it loaded for farm credit and input (0.55), farm experience (0.41), Plant density or population (0.93), and level of education (0.36), while Factor 7 is the soil problem factor as it loaded high only for soil conservation problem (0.66), and land tenancy (0.38).

The factor scores (independents variables) were used to run a multiple linear regression model with maize yield (dependent variables). The results of this analysis are presented in Tables 5.11, 5.12 and 5.13. The R^2 obtained was 0.88 which shows the percentage of variance accounted for by the explanatory variables in the model. The model showed the best predictor of the outcome variables, significant at F (7, 60) = 62.59, $P < 0.000$), see Table 5.12. The individual predictor variable was significant with fertilizer application factor ($b_1 = 272$, $P = 0.000$), farm size ($b_2 = .177$, $P < 0.000$) climate change factor ($B_3 = .847$, $P < 0.000$), socioeconomic factor ($B_4 = .132$, $P < 0.003$), and m ($b_5 = .137$, $P < 0.005$), were significant predictors of maize yield in the savannah agroclimate zones ($P < 0.05$) (Table 5.13). However, years of experience ($b_6 = -.050$, $P > 0.274$), and soil conservation factor ($b_7 = -.034$, $P > 0.460$), were not significant in explaining the variation in maize yield.

Table 5. 9: Savannah zone KMO and Bartlett's test of variables

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.621
Bartlett's Test of Sphericity	Approx. Chi-Square	1337.979
	Df	666
	Sig.	0.000

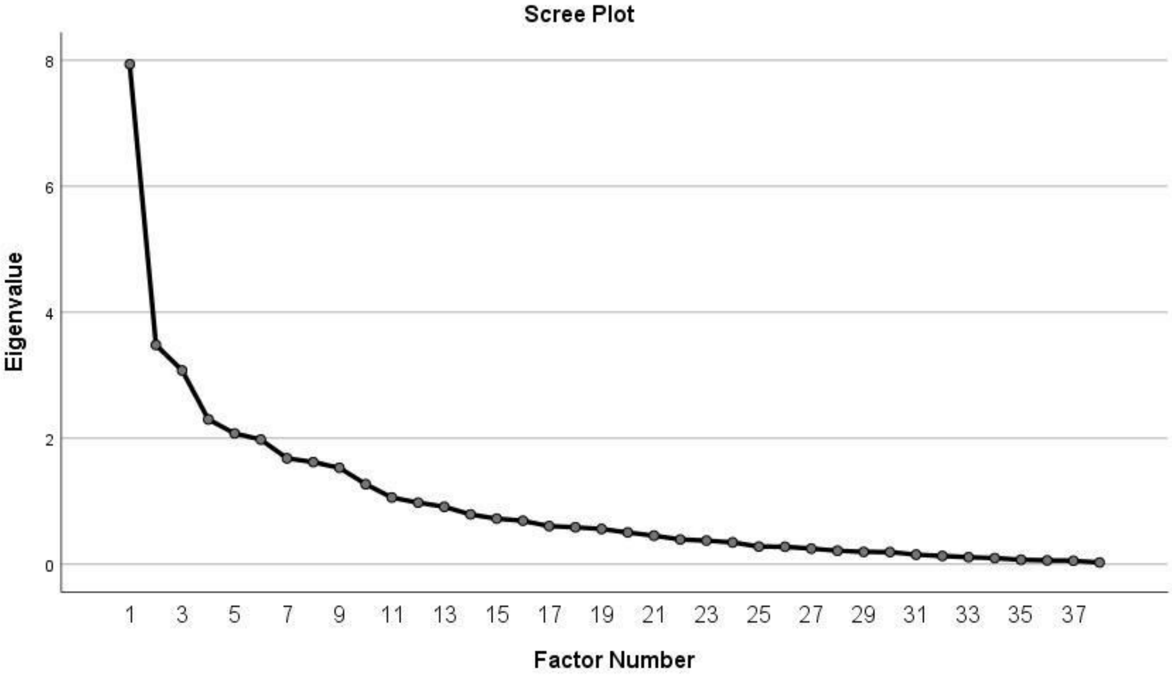


Figure 5. 4: Scree plot of factors in the savannah agroclimate

Table 5. 10: Factor analysis loading for factors influencing maize yield and adaptation to climate variability in Savannah Zone

Variables	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 7**
Apply Fertilizer after planting	0.811				.		
Quantity 200NPK per hectare	0.759						
Quantity 100kg urea per hectare	0.745						
Soil fertility	-0.667						
Disease Resistant V	0.459						
Improved variety	0.523						
Planting time Change			0.547				
Soil conservation							0.661
Standard Plant density					0.339	0.939	
Row spacing			0.612		0.590		
Household size							
Gender				-0.801			
Household head				-0.803			
Level of Education						0.360	
Farming Experience					0.361	0.405	
Farm size		0.889					
Changes in rainfall CC			0.619				
Shift in growing season (CC)			0.449				
Irrigation					0.595		
Farm credit & input						0.550	
Low income	0.323	0.833		0.931			
Extension agents			0.660				
Land tenancy	.302					.	0.385
Political factor		0.610	0.618				
Eigenvalues	7.93	3.47	3.07	2.29	2.07	1.97	1.65
Total % Variance	20.88	9.15	8.09	6.04	5.46	5.20	4.42
Cumulative %	20.88	30.04	38.13	44.18	49.64	54.84	59.26

Extraction Method: Maximum Livelihood, Rotation method: Varimax with Kaiser Normalization

Table 5. 11: Multiple linear regression of factors in savannah

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig
1	.938[a]	.879	.865	155.827	62.59	0.000

Table 5. 12: ANOVA[a] of factors in the savannah zone

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	10591906.882	7	1513129.555	62.591	.000
	Residual	1450483.398	60	24174.723		
	Total	12042390.279	67			

a. Predictors: (Constant)

b.

Table 5. 13 : Savannah zone coefficients of multiples régressions variables

Model		Unstandardized Coefficients	Std Error	Standardized Coefficient	t	Sig.
		B		Beta		
1	(Constant)	421.397	18.897		22.300	0.000
	Fertilizer application	120.622	19.953	0.272	6.045	0.000
	Farm size	80.246	20.378	0.177	3.938	0.000
	Climate change factor	368.681	19.560	0.847	18.849	0.000
	Socioeconomic factor	61.185	20.855	0.132	2.934	0.005
	Irrigation	58.773	19.235	0.137	3.056	0.003
	Years of experience	-22.629	20.515	-0.050	-1.103	0.274
	Soil conservation	-15.992	21.501	-0.034	-0.744	0.460

Source: Author's analysis, 2020

5.6. Discussions

This section discusses maize farmers' perception of the factors influencing maize yield under the following: crop management practices, climate change, and the socioeconomic factors in the rainforest and savannah zones. It looks at how farmers in the zones have responded to the challenges of climate variability impact on maize yield.

5.6.1. Crop management practices.

Fertilizer application loaded high in the factor score model in Table 5.5 and Table 5. 10. This factor was statistically significant ($P < 0.05$) in the rainforest and savannah zones as shown in Table 5.8 and Table 5.13. Most smallholders' maize farmers practice single fertilizer application to boost the soil fertility and improve yield due to the impact of climate variability. This result is consistent with the findings of MacCarthy et al., (2018) who stated that improved usage of fertilizer has the potential to boost maize yield and increase food security. Many farmers apply a limited amount of fertilizer and few doses per hectare of land. This agrees with the findings that there is low adoption of standard dosage per hectare, and poor access to the fertilizer during the growing season (Otitoju & Ochimana, 2016). Good maize yield has been linked to proper dosage and timing of fertilizer application during the growing season (Arije et al., 2018). The use of fertilizer for maize production is estimated on high demand among smallholders' farmers in Nigeria contrary to the low use of fertilizer in some regions in SSA (Liverpool-Tasie et al., 2017). However, the accessibility of smallholder farmers to fertilizer during the growing season appears more cumbersome than adopting a recommended dosage and the methods (Liverpool-Tasie et al., 2017). Several factors have been alluded to the poor accessibility of fertilizer to farmers in Nigeria, such as the socioeconomic status, high transportation cost, politicians and middlemen activities (Liverpool-Tasie et al., 2017). This problem leads to artificial scarcity and inflation of the product price (Liverpool-Tasie et al., 2017). Thought the Government provides fertilizers to the local poor farmers as incentives to enhance their crop yield, it was observed that the products hardly reach the smallholder farmers during planting season due to the diversionary antics by politicians and the middle distributors (FGD, 2018). These farmers have poor income capacity to buy from the market which leaves them frustrated. Unfortunately, access to fertilizer products is made difficult as most farmers must travel far to the town or cities for the product. Also, most of the politicians who promised farmers fertilizer do not keep their promises as they reside in the cities, and care less about the challenges of the rural farming population (FGD, 2018).

Other crop management practices that influence maize yield and adoption to cope with climate variability perceived by the farmers in the zones are planting date, improve cultivar, row spacing and plant density. These components identified loaded high as important practices that can affect yield changes. The result revealed that adopting crop management practice was statistically significant in both agroclimate zones ($P < 0.05$) in Table 5.13. The improved varieties are the early maturing, diseased-resistant and the drought-resistant cultivars tolerant to adverse climate conditions. It is important to involve the farmers in the introduction of new maize varieties as they may oppose the new and stick to their old and low productive variety (Joshi & Witcombe, 1998; Liverpool-Tasie et al., 2017). The findings revealed that plant density can reduce yield to a greater extent when farmers sow too many seeds in a hole or very few seeds. In the event of many seeds sprouting, thinning is expected to be done (Mourice et al., 2014). Also, when the seeds do not sprout, supply is expected to be carried out. Plant density was not a significant predictor variable in the zone as most farmers do not have enough seeds and lack the improved variety of maize. The government extension workers have a key role to play in mobilizing, and sensitizing farmers through different media which can be in a form of non-formal or formal education to enhance modern farm innovations and technologies adoptions (Shiferaw et al., 2011; Fadina & Barjolle, 2018).

5.6.2. Climate change factor

These include the changes in growing season rainfall; the onset and early cessation rainfall can also influence crop management practices. The results in Tables 5.8 and 5.13 revealed that changes in the growing season rainfall were statistically significant. The change in climate factor influences other crop management practices like the planting time, plant density, fertilizer application and generally the crop management practices adopted. The irrigation option during dry spells is crucial to boosting local productivity (Utang and Ekpoh, 2011). Rainfall comes too early during the growing season and ceases when most needed. Agricultural activities in these zones are rain-fed and 98% of crop cultivation follows the annual or seasonal rhymes of the rainfall (Ekpoh & Nsa, 2011). The challenge of climate change and variability is noted through the shifts in onset and cessation of rainfall during the growing season (Ekpoh & Nsa, 2011; Sowunmi & Akintola, 2010). The most daunting problem faced by farmers is the uncertainty surrounding the arrival of rainfall, and often the rainfall intensity of onset rainfall. Maize seeds become rotten in the soil or dry up quickly. It has been highlighted in (Utang & Ekpoh, 2011) that the most common characteristic of the local farmers in these zones is adapting to flood recession agriculture. The farmers often wait for rainfall to commence before venturing into any form of farming operations. This is a common adaptation measure along the Aya River in the Savannah zone.

5.6.3. The socio-economic factor

The socioeconomic factor was a significant predictor of maize yield changes in the multiple linear regression model ($P < 0.05$) in Table 5.8, Table 5.13. The income of the smallholder is low (Survey 2018), and this posed a big challenge for them to adopt practices to improve maize yield. The high loading of low income of farmer’s household size, and farm size play a key role in maize productivity. The farmer level of income determines how they can adopt improved strategies like improved cultivars, fertilizers, herbicides, and pesticides to control weeds, pests and diseases (Ogunniy et al., 2021). Incomes affect the expansion of the farm and hiring of labours where the household labour is inadequate (FGD, 2018). However, the household sizes of farmers in the region fall in the category of a large household (Survey, 2018). This is particularly consistent with the idea of reducing labour cost in the farm as the family labour is cheap and the best labour alternative in the smallholder setting (Ifeanyi-Obi et al., 2014; Ogunniyi et al., 2021). Low per capita income and standard of living has impeded sustainable farming development (Shiferaw et al., 2011; Ifeanyi-Obi et al., 2014). This is worsened with low food productivity and climate change ravaging Nigeria and other parts of Africa (Oyeneka et al., 2019). Farmers are constrained in managing and expanding crop productivity due to their low capacity to purchase inputs and adapt to climate variability. Farm credit has been low and unavailable to farmers in the zone. The multiple regression model in Table 5.17 predicts farm credit influence on maize yield is significant in the zone. The access to loans, grants, and subsidies for maize expansion is low and when there is government support, the powerful and influential personalities block access and take the place of those who most needed this form of support (FGD, 2018). There are several World Bank-assisted projects ongoing through the central bank of Nigeria in the zones. These programs are targeted on smallholder farmers, with the goal, to enhance agricultural productivity and livelihood through the cooperative groups. It has been noted that World Bank grants would leverage the impact of climate change on the poor and increase sustainable development (Ogunniyi et al., 2021).

5.7. Conclusion

This chapter analysis the response of maize farmers to the impact of crop management practices, climate variability, and the socioeconomic factors on maize yield in the rainforest and savannah using a survey approach. The factor analytical and multiple linear regression model was adopted in looking at the crucial parameters impacting on maize yield and adaptation to climate variability. A 7-factor solution structure was modelled. The model was very significant in predicting the impact of maize yield in the zones. In the rainforest, the model predicts 73.3%, savannah 88%. The next chapter would be considering options of adaptation mechanisms in respond to the impact of climate variability on maize production.

Chapter 6: Response of maize farmers to the impact of climate variability on maize production: adaptations and crop management strategies.

6.1. Introduction

The objective of this chapter is to explore the maize farmers' perspectives on the adoption of adaptation and crop management strategies as a response to the impact of climate variability in the agroclimate zones. The study maintains that local participation in understanding climate adaptation measures is key for the formulation and implementation of meaningful and sustainable agricultural decisions to increase food security in the zones. This is affirmed in Few et al., (2007) that the inclusion of the participatory approach is a vital normative goal to respond to the changes in climate. However, there are very limited works that addressed local participation and action to climate variability in the zone. Using the lenses of a focus group discussion (FGDs), the study examines farmers perceived response strategies to the impact of climate on maize yield. Data were collected from maize growing farmers and analysed in NVIVO software. The responses were done by thematic analysis, generated from the leading questions.The findings and discussions in the chapter are categorised into four sections; farmers' perception of climate variability and impacts on maize yield, adaptations and crop management strategies adopted, and the factors limiting choices of the adoption of adaptation strategies in the communities of these agroclimate zones.

Studies have shown that climate change would alter environmental conditions for the growth of crops in sub-Saharan Africa (SSA), (Akumaga et al., 2018; Lehmann et al., 2013). Thereby increasing the negative impacts on cereal crops like maize, rice, wheat, soya bean and sorghum in SSA (Lobell & Field, 2007; Sultan & Gaetani, 2016; Van Ittersum et al., 2016). Adjustments of adaptation and crop management practices are important for climate-resilient strategies of the high population of vulnerable farmers in sub-Saharan Africa regions (Akumaga et al., 2018). Research revealed that a vast percentage of this population in SSA are Nigerians, with over 260million people (Ayanlade et al., 2017). The concern that food shortage would increase due to climate change is already projected in Africa (Rurinda et al., 2015). More than approximately 90% of the domestic economy in SSA relies on rainfed agriculture. These will have a devastating impact on crop productivity under high climate variability and affect food security, income level, poverty and disease (Pathway, 2020; Thornton et al., 2014).

While most studies have attempted to examine the impact of climate change and variability on maize yield using different approaches (Bassu et al., 2014; Ewert, et al., 2015; Kassie et al., 2015; Mandryk et al., 2017). These studies employed modelling approaches to assess impact and advise on adaptation response strategies to climate change on yield. But there are very limited studies of local participation in response to climate variability and change and the climate-smart coping strategies adopted (Abraham et al., 2020). There are non-existent studies of local participation in climate change adaptation response in the savannah and rainforest zone of Cross River State using a focus group approach. Suwanmontri et al., (2018) stated succinctly that understanding climate resilient and adaptation measures for future climate problems in SSA would enhance sustainable agricultural practices against future climate change on crop yield. This research derived it motivation from the participatory model concept which its major tenets emphasised sharing knowledge, identifying challenges in a system, and finding ways of solving problems participatory (Chanie, 2015; Gray et al., 2015; Orabi, 2018).

Smallholders' farmers' inclusion in local climate remains crucial to the adoption of climate change adaptation measures. There is the need for a deliberate collaboration in the inclusion of local knowledge of the changes in the climate, and how the farmers are responding to changes. Vermeulen et al., (2012) emphasised that the link of local and global knowledge of climate change would enhance practices, technologies for adaptation and mitigation on climate change. Local knowledge of adaptation strategies is crucial to complement the stakeholder's intervention measures that can confront the negative impacts of climate variability. This is an emerging trend of indigenizing participation in the understanding of climate change for intervention (Ross et al., 2015). The incorporation of rural people knowledge in climate research has been acknowledged as a sustainable means of generating new knowledge to enhance effective climate-agriculture policies and practices (Nkomwa et al., 2014; Ayanlade et al., 2017).

6.2. Study Area and Methods

The study was conducted in maize growing rural communities of the Cross River State rainforest and savannah agroclimate zones. These communities are Alesi and Makono in Ikom, Effraya and Etomi communities in Etung. These communities are found in the rainforest agricultural development project area. In the savannah zone areas are Unwarranty and Adagon communities in Ogoja, and Utukwe and Abegang in Bekwarra Local Government Area. These are communities in Ogoja Agricultural development project area. The Focus group discussion was adopted to answer the research question. This method allows participants to respond to problems that concern them, and for which they have good understanding.

6.2.1. Focus group methodology

Since the 1980s, focus group methodology has added new insight to the study of people perceptions and public policy formulation (Denzin & Lincoln, 2005). It is a popular methodology, and an increasingly useful tool in qualitative inquiry (Cloke et al., 2004). FGDs provide quicker results and generate more complete information faster at a low cost. It is an important participatory research methodology, which provides a friendly, level play environment and opportunity for respondents to air their views on issues affecting them in a language in which they can communicate better (Denzin & Lincoln, 2005. This methodology has expanded usage. For example, Mwaijande et al., (2009) employed focus group discussion to understand the barriers to agriculture tourism in developing regions. They gathered information using focus groups to help stakeholders identify and characterise barriers to developing a link between agriculture and the hospitality industry. FGD was used in the assessment of maize growth and yield in south-western Ethiopia (Araya et al., 2015b), and for assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan (Ali & Erenstein, 2017b). These are some of the studies which showed that a focus group is an important tool for gathering information to identify policies options for climate change adaptation and mitigation measures at the local scale.

Focus group discussions revolve around a specific topic under the moderation of a trained person or expert (Kitzinger 2005; Liamputtong, 2015). It brings participants of similar social and cultural experiences such as ethnicity, age, language, educational and religion background together. Focus groups deal with a range of answers that provide a better understanding of participants' perceptions or opinions on issues (Hennink 2007). Their attitude, reactions, or behaviour can be analysed. This approach allows better participation and engagements with the farmers, as that helps them to communicate in their own environment and dialect. Focus groups support a search for opinions held by the farmers about a problem and the reasons for holding such an opinion about that issue. It is a key tool in the participatory approach as it provides insight into differences and similarities of views around a topic (Steward, 2018). This method helps the researcher to explore the gap between what people say and what they do (Liamputtong, 2015).

In addition, FGD puts control of interactions in the hands of the participants. The participants are drawn primarily from those with an understanding of the topic. The FGD discussions normally takes place in a comfortable and enjoyable setting free of intimidation (Jowett & O'Toole 2006). FGD is good for respondents who fear one-on-one interview. However, this methodology is not suitable for discussions that relate to respondent's personal information or health challenges (Liamputtong, 2015). The view is that the respondents would not be ready to disclose personal details in the public domain. Nevertheless, it is common to see some respondents more active than others when a question is asked. It is recommended that a focus group discussion should be between 6- 10 persons (Liamputtong, 2015; Milligan, 2016). It must not be a large group so that rooms exist for others to speak. The moderator can be the researcher or someone else trained in the community for this purpose

6.2.2. Organisation and analysis of Focus Group Discussions (FGD)

Ethical consideration for the research was completed prior to the planning for fieldwork. As a key requirement of the University, a project must abide by the University Research Ethics Policies. An ethics application was directed to the department of Geography University of Sheffield Ethics Committee in early 2018 for ethical approval. The committee granted full approval with optional amendments and advised that the fieldwork can proceed. A copy of the ethics approval letter is found in Appendix 4. The essence of this application was to clarify any ethical issues in the research to avoid conflict of interest and compromises in the data collection process.

6.2.3. Positionality statement of the researcher

It is a common practice in qualitative studies for a researcher to state positionality in terms of their views of the research task, their reflection as an insider, or outsider or both insider-outsider. The positionality defines the angle the researcher is coming from, the choice of the research design adopted which may influence how the research is carried out and its outcome (Darwin & Holmes, 2020). The debate on positionality in relation to insider-outsider and reflexive approach attempts to give an insight into the researcher's world view of the study with the intention to minimise and eliminate bias (Rowe, 2014). The researcher can draw from different assumptions such as ontological beliefs (social reality), epistemological assumptions (nature of knowledge), or his interaction with the environment (Darwin Holmes, 2020; Marsh et al., 2018). Positionality locates three key areas of the research process, the subject of research, the participants, and the research context (Savin-Baden & Major (2013). Positionality guides the researcher to consider how they navigate around the beliefs, values, religion, sexuality, geographical location, gender, faith and ethnicity and race which may shape his research process (Marsh et al., 2018). I have my childhood life, education, training, and work taken in these zones. I spent more than three decades as a student, teacher and farmer in the zones. The choice of this research context was motivated by accumulated experiences gained from undertaking several field studies during my undergraduate and postgraduate training in the zones. I identified rainfed crop cultivation as the major occupation of the people of Cross River State. The farmers speak different dialects but have one common language called Pidgin

English which they used for everyday communication in the marketplace, churches, and ceremonies to non-dialect speakers. This experience was helpful to navigate and overcome the religion, culture, language, ethnicity, and political barriers. Since I understood the sociocultural characteristics and the environmental terrain of the people, it was easier for me to access the key informants and contact authorities concerned in the zones. My reconnaissance survey of the zones was useful in linking key informants to connect to the maize farmers and arrange dates with the target participants for the FGDs. The focus group discussion was undertaken during the period when the farmers were available. I assumed the position of an outsider during the discussion. But had an opportunity as an insider with the insight into the location of interest and the key informants to contact. My understanding of the area was an advantage to know the best time of the season to engage farmers for better result. This is consistent with similar a researcher's experience of the insider-outsider, in-between position reported in (Milligan, 2016).

The exercise was designed for the early growing season of May 2018 with maize farmers as the main respondents. Eight Focus group discussions took place in the respondents' community town hall. Four FGDs were in the rainforest communities' zone, and four in the savannah communities. The process of organising the focus group meeting was simple and included the help of agriculture extension agents and the youth leaders in the various communities. Participants for the focus group were about 6-10 in number, with all being above the age of 18years, with more years, with most having many years of experience in farming maize in the region. The Purpose of the FGD was explained to the participants in simple language using the participant information sheet in Appendix 2. On some occasions, local dialects were used to convey the meaning of technical terms. It was generally accepted that the purpose of the research was understood, and they were prepared to participate. They had the consent forms signed or thumb printed after reading the contents Appendix 1. For those who were not literate, the moderator read and explained the contents of the form to them. Their acceptance to participate was very important and no one was coerced in any way to participate. The farmers willingly offered to share their views about the subject. The services of a trained agriculture extension agent working in the community were used to moderate the leading questions for the discussions.

6.2.4. Key questions for the Focus Group Discussion (FGD) and Rules of Engagement

The key questions used in all the FGDs in the rainforest and savannah communities are given below.

1. What is your perceived experience of climate variability and change in the community?
2. How do you notice there is a change in the climate?
3. How is climate variability and change affecting maize yield?
4. In your local practice, how have you coped with changes in the climate over time?
5. What kind of intervention strategies do you adopt to tackle the impacts of climate variability or climate in your area?
6. What are the coping strategies you have adopted in farming maize as you face this changing climate?
7. What factors affect your choice of adaptation measure to the impacts of climate on maize yield?

Rules of engagements were initiated. As a practice in Nigeria, before the most meeting commences, prayers must be ushered to God. The moderator asks for a volunteer or appoints a willing participant to say the prayers. Other participants responded Amen at the end of each round of a prayer. There was an introduction for each participant. One of the participants called himself
"I am a small-scale farmer", while another could be heard loudly "I am a maize farmer". You could hear the chant of these slogans: "great farmers, great nation". Everybody responded with a resounding echo, "no farmers, and no food". In each meeting before commencement, ground rules of engagement were set by the participants to avoid distraction during discussion. Such rules were that all phones must be on silent, there should be no picking up of calls in the hall, no loitering around, indicate with a raised hand before speaking, no interference when another is talking. The participants fully cooperated and obeyed the ground rules. It appears they were already familiar with these routine norms and exercises in meetings.

The voices of respondents were tape-recorded, with everyone's permission in each of the sessions of the focus groups for all the communities in the agroclimate zones. The voices were transcribed into English because most of the communications were carried out in 'pidgin'. Responses were transcribed into themes using the leading questions. The focus group discussions were analysed in NVIVO software specially designed for all forms of qualitative research analysis. The research used anonymised names of respondents in the discussions

6.3. Results and discussions

The results and discussions would be carried out in four themes derived from the leading questions in the FGD; perceived knowledge of climate variability, the impacts on maize yield, adaptation and crop management strategies adopted in the zones. Figure 6.1 and Figure 6.2

summarises the keywords that were most used in the focus group meeting during discussions on the impact of climate variability on maize yield

Figure 6. 1: A word cloud of the elements of discussion on the impact of climate variability on maize yield

Figure 6. 2: A word cloud of the elements of discussion on adaptation to the impact of climate variability on maize yield

6.3.1. Maize Farmers Perceived knowledge of climate variability in the agroclimate zone community

Question 1 and 2 (see the previous section) which address this theme. Key responses from the farmers are displayed in the excerpts. Farmers said they experienced unusual patterns in the rainfall in the zones. One farmer noted that they expected rainfall in March and not February in the rainforest. However, in 2017 there was more rainfall in February and less in May. For instance, in Etomi community of the rainforest zone, during the focus group discussion, the farmers understand climate variability as:

. "The changes in rainfall, wind, and sunshine in the area. In the past rainfall used to fall from April continuously to show the beginning of the rainy season, which gives farmers hope to start full planting".

"There was higher rainfall in late April, May and a peak in June before. But heavy rainfall came in March and then stopped. It has been inconsistent. Due to the cutting down of trees, the land has been exposed to desert-like conditions".

"The real peak of the rainfall in my region is around July and August. Too much rainfall in these months cut maize growing time…In the past we experienced night-time rainfall in October, but this has changed, we now see rainfall extending to December elongating the rainy season"

The patterns of rainfall in the zones have changed from what the farmers have known. There inter-annual and seasonal variability been observed in the zones.

.."In the past five years compared to this year, rainfall has a drastically changed pattern. This is to say that the previous years' experience reveals rainfall was evenly distributed and the intensity was fair, but now this has changed."

…" uncertainty in rainfall, which characterised early-onset and disappearance during planting season. We depend on the rain-fed system of farming only. I do experience one small rainfall in February and a big rain in March, then sudden seizure. One cannot comprehend when actual planting should commence now because of this uncertainty".

While in the savannah communities, climate variability and change were aptly described by some farmers in different ways.

"… Ten years ago, rainfall starts early, break-in August…. But this day's heat is high, rainfall is highly variable. We suddenly have rainfall in March, and then between March and June, the crops do not have enough rainfall to do well".

."I experienced first rainfall in January about 3-4years, but little rainfall in March. Comparing the rainfall pattern three years ago for Jan-May is better than this year 2018 Jan- May. There was a break in rainfall for two weeks during the planting season.

…" I used to experience my first rainfall in January. But in 2017 it started in February and ended on October 23rd" … I experience excessive heat now … I observed that the climate has changed because of this heat".

“2018 appears to be favourable because the rainfall does not have too much of a gap, just a week or days before starting again. Many crops did very well in April and May. From May to October is our full rainy season or normal season of rainfall”.

” I have experienced a change in the weather, as heat has increase more than expected, compared to other years and places"

“From February and March, the rainfall is not constant. It is usually from April to June that you are sure of the rainfall. Even the wind pattern has changed too”.

The respondents’ viewed clearly that they were experiencing climate variability and its grip in their communities. This was evidenced in the delayed onset of rainfall manifested in the rainforest in some years and the early cessation in other years. The savannah region was characterised by an unpredictable rainfall regime during the planting season with early cessation in October. A sudden break during the growing seasons for both the rainforest and savannah agroclimate zones was common. Ayoade, (2004) confirmed that rainfall variability is an important feature of the climate pattern in Africa. Climate change alters this pattern and affects the predictability of growing season rainfall as seen in many SSA countries (Nkomwa et al., 2014). The rainfall timing was observed to be inconsistent with what was needed for cultivation. This depicts the erratic nature of the rainfall in recent years. As noted in their studies Egbe et al., (2014) showed that 71.7% of the people in some communities of rainforest zone are aware of climate variability. This revealed that rural farmers are aware of delayed onset and early cessation being different from what was observed in the past. They also understand the trajectory of rainfall patterns. Local understanding of climate variability and change is important for a climate change intervention. Ama, et al., (2013) posited that maize farmers may have little understanding of the climate, nevertheless, undermining their knowledge pool of the climate can be a setback for achieving progress in the implementation of coping strategies. Rural farmers are much closer to their immediate environment (Egbe et al., 2014). This means they observe the everyday changes in the climate and have an in-depth understanding of the possible measures for responding to climate anomalies. Based on their repository knowledge of their environment, they tend to know what the past climate was, and what the current climate is.

The Increased temperature was implicit in the region FGDs, as more excessive heatwave was observed which indicates that maximum temperature was rising in the zones. This agrees with studies in Nigeria that maximum temperature was increasing (Ndawayo *et al.*, 2017). The farmers’ perceptions are confirmed by many scientific studies that report an upward trend in temperature and heatwave in Africa (Suryabhagavan, 2017), which is also evident in the meteorological data analysis of temperature in chapter 4. Increased frequency of prolonged dry spells in some years, and unfavourable rainfall occurrence would lead to a detrimental impact on maize yield in the agroclimate zones. It was also noted that the rainforest now had extended rainfall regime to December, unlike in the savannah where rainfall stops abruptly in October (FGD, 2018). These findings corroborate with the study of (Akinsanola & Ogunjobi, 2014) that there were more wet years than dry years over the rainforest zone. While the studies of (Nkomwa et al., 2014) also showed that unpredictable rainfall and increases in dry spells were common in Africa. The results further agree with many studies that predicted temperature increases, has been experienced widely over Nigeria (Adakayi, 2012; Akinsanola & Ogunjobi, 2014; Diallo et al., 2012).The inclusionary approach of understanding local people's views of the climate is a logical step to build and improve scientific understanding and addressing climate risk at local scale (Few et al., 2007; Nkomwa et al., 2014; Ross et al., 2015).

6.3.2. The farmers' opinion of the impacts of climate variability on maize yield

This section explains the farmers' discussions on the impact of climate variability on maize yield which focus on the planting time, seed density, insect infestation and weeds growth as addressed in question number 3. Farmers revealed how the changes in the rainfall have affected their farming practices and maize yield production. The farmers in both rainforest and savannah zones clearly stated that false onset and abrupt cessation of rainfall is detrimental to crop germination and its production (FGD, 2018). Arrival of early rainfall in February and March do prompt farmers in the Rainforest to start sowing maize. This contrasts with the case in the savannah, where rainfall arrives much later in April. The maize farmers in the rainforest tend to have early cultivation of maize during the growing season but the changes in the pattern of rainfall have altered their planting time. This has shifted to April planting as succinctly observed by the farmers in the communities. Rainfall is a key factor that affect maize production significantly (Adejuwon, 2006).

"*…I planted maize four times in March this year because of failure of the rain after onset…" "February and March are not the actual planting time, but March and April. The rainfall is not consistent with our old calendar knowledge". Abrupt cessation in rainfall during the planting season post a challenge to our crop"*

"Planting season has changed; we wait for the rainfall to reach the soil properly before planting maize. The weather is highly variable. Now we plant in April and May…."

Climate variability affects negatively on the availability of maize seed for the next farming season. Temperature increases, and poor rainfall during the growing season causes about

~10.7% decline in yield Poor (Ndawayo et al., 2017). High rainfall destroys sown seeds and their availability for next season cultivation. Their plant density is also affected as some farmers sow more seeds if some seed fail to sprout. A maize farmer in the savannah agroclimate zone lamented over his inability to cultivate maize in the previous year because of excessive heat, with lack of rainfall during planting season. In addition, excessive rainfall without enough sunshine can inhibit the germination of maize seeds and cause more havoc to smallholder farmers. Climate variability would render farmers unable to procure seeds for planting due to rot, wilting, and so further increase the farming cost. It is common practice for local farmers in Nigeria to safe seeds for the coming growing season. Nevertheless, when there is excessive rainfall or heat, this results in a poor harvest and prevents smallholder farmers from being able to keep more seeds for the coming year. This contrast with cassava (*Manihot spp*), which tends to cope with such conditions (Jones, 2018).

"1 experience severe heat. I lost many of my crop seeds. Excessive rainfall without sunshine caused poor yield"

"Maize is not as tolerant as cassava crop. When rainfall was more constant or normally distributed, planting maize would not be seriously affected".

Rainfall variability was associated with an increase in insect infestation in the zones. This was revealed as a strange experience by farmers in the savannah and rainforest zone of Cross River State. *"When there is no rainfall more insects attack due to climate variability".* A voice from another farmer added that.

"*Insect infestation is high now than before due to climate change…. While the high sun scorched the crops, too much rainfall at a time destroys the seeds even before germination. High temperature squeezes the leaves and folds them".*

They contended that insects ravaging maize have doubled compared to previous years. This proliferation of new insects was linked to the changes in climate, which provided a favourable condition for their growth. These insects eat the maize cobs, stems and leaves, and render the crop unproductive. Examples of the insects are armyworm, stem borers, white ants and young caterpillar (FGD, 2018).

Weed infestation in the zones was rampant. The farmers noted that weed infestation was most common in their farm in recent years than before ["*Weeds are more prevalent than before*" …. *late planting may cause poor harvest"]*. They observed that rainfall favours these weed growth because of the timing of the rainfall. Late planting of maize in June during the early growing season rainfall encourages weed growth and high competition for soil nutrients. Weed flourished faster in the early part of the reproductive growth of maize in late May and June planting, and there tends to overshadow maize growth. Ahmed and Fayyaz-Ul-Hassana, (2011) confirmed that weed management and sowing time under changing climate are important parameters to be modelled for improved crop productivity in a rainfed agriculture (Ahmed & Fayyaz-UlHassana, 2011). The need to be an increase in understanding of the processes in modelling impact of crop management on maize production under climate change. In line with the opinions of most participants, rainfall patterns, and timing of sowing maize were connected to weed infestation (FGD 2018).

6.3.3. Maize farmers' adaptation and crop management strategies

The section analysis farmers' response strategies to climate variability on the following: fertilizer application, soil conservation and insect pests control techniques, flood recession and irrigation practice, Variety adoption, changing planting time and crop diversification. The local maize farmers understand that the climate has changed and is changing. The FGDs showed that different approaches of adaptation and crop management techniques were adopted as measures to cope with climatic perturbations.

The application of fertiliser was the most common strategy adopted, as discussed during the focus group meeting. It was revealed that Fertilizer application using the ring method was an efficient way of combating the impact of climate variability. The downward movement of soil nutrients below the root zone during leaching enhanced by torrential rainfall, has impacts on the maize to obtain nutrients from the soil for high productivity. Since maize plant have shallow root system, they are affected by the leaching (Ogbazghi., 2019). The practices of inorganic and organic use of fertilizer are adopted in many regions of Nigeria to enrich the poor soil as an aid maize production. Arije et al., (2018) observed that maize yield has declined and that organic fertilizer application using cow dung and poultry droplets are now a trend adopted in local agronomic practices in Nigeria to boost maize yield. In general, in SSA, smallholders' maize farmers' adoption of inorganic fertilizer is low in SSA (Liverpool-Tasie et al., 2017). The reasons advanced for the low adoption of inorganic fertilizer are inadequate and untimely availability of the input, low agronomic knowledge, and poor credit (Liverpool-Tasie et al., 2017). However, in most parts of southern Nigeria, inorganic fertilizer application is conceived as destructive, and inherently poisonous to those living organisms. A smallholder farmer in the rainforest who was so conscious of the danger of inorganic fertilizer maintained.

"Initially we plant without fertilizer and have good yield, my worries about the destructive effort of fertilizer are that any time you stop, the soil becomes poor... This fertilizer also destroys snails and micro-organisms in the soil".

Nevertheless, other discussants think differently as a farmer voice in Effraya of the rainforest reiterated clearly that

"*I adopt a ring method in fertilizer application so that rainfall will not wash away the chemical. I try to assess the size of the land before planting to help me manage my resources; I do fertilizer application more now than before"* while a male farmer in Nwarranty community of the savannah zone says

"*I consider the weather before applying my fertilizer" and I apply fertilizer around the maize crop"*

The adoption of the ring method of fertilizer application is a good management technique for the smallholder to meet their basic fertilizer needs on the farm. While the broadcasting method of the fertilizer application requires more fertilizer in a plot of a farm than the ring method. It was observed that local Farmers dig a little ring of a centimetre deep around the maize stand and apply fertilizer in such a manner that there is no contact with the tender crop. This approach was consistent with (Adiaha & Agba, 2016) who stated that the ring method of fertilizer application was more appropriate for maize production at 1m distance from the planting. The disparity in practice of fertilizer application between the two agroclimate zones was found in the season of planting. There was the demand for high fertilizer application in the savannah zone during the early growing season, while in the rainforest zone communities, the late maize farming got more fertilizer concern. Late maize cultivation was higher in the rainforest due to the elongation of the growing season rainfall. They are conscious that heavy rainfall and wind can affect fertilizer application. Farmers do not apply fertilizer during heavy rainfall and or dry spells as a practice that agrees with studies that the efficiency of soil fertilizer management practices may be affected by high variability and uncertainty associated with seasonal rainfall in Africa (Worou et al., 2019).

Conservation techniques such as crop rotation, planting legumes, and mulching were was the common strategies adopted for improving soil fertility and controlling pests and diseases in the zone. Insect infestation and the growth of weeds were associated with the change in climate ["*Insect's infestation is high now than before due to climate change"]*. The local farmers' have designed a coping technique to fight the threat of insects by using agroecosystem analysis where the farmers visit the farm very early to ascertain the health of their maize crop. This assessment is made by looking at the insect and disease load. The indigenous knowledge of adaptation to control insects revealed that they spray maize leaves with dogoyaro (*Azadirachta* *indica*) paste soaked in water. This approach has effectively reduced more than 50% of the damage caused by insects in the zones.

[*"The use of 'dogoyaro' leaves can prevent insects from destroying crops. Pluck the leave and pound in a mortar to a pastry then soak in water and filter" …also run agroecosystem analysis in the farm early in the morning to ascertain whether the crop is infested by disease or not"*].

In addition, agroecosystem analysis of the farm during critical stages of growth, (tassling, silking and cob formation) is routinely carried out to check the health of the crop. Agroecosystem analysis of crop helps early prevention of disease outbreak, and prompt immediate action of pest control. It is argued that this method requires the understanding of the ecosystem (abiotic and biotic environment. Local farmers are in constant harmony with their immediate surroundings, and this makes them acquainted with crop changes, and what may be responsible for such changes. The farmers have the understanding that Azadirachta indica contains a chemical substance that controls pests.

The deleterious effect of heavy rainfall was prevented through simple mulching and terracing management techniques. Maize farmers in the rainforest avoid use of the slash and burn system and those in the savannah do mulching to conserve moisture, reduce transpiration, and prevent a heavy rainfall from damaging the topsoil and crops. Conservation measures such as making big mounds and mulching were evident. The farmers in the savannah agroclimate zone asserted:

"I apply mulching and make proper drainage by making a bigger soil heap" Those of us that farm close to the riverside, adopt irrigation methods", another said, "I adopt irrigation for my maize crop by using simple way of irrigation using watering can".

"Most often, I do mulch ("wear the mount with cap") to reduce transpiration".

Irrigation was not a common practice in the zones. However, the application of irrigation was adapted during critical climate dry spells condition in the savannah zone. Growing maize along a river plain was an effective alternative, if local geography allowed. The flood recession approach of agricultural practice in Aya river basins was used as an adaptive coping mechanism in the savannah. This is the cultivation of maize along the flood plain of Aya in the savannah zone. This approach enables the farmers to farm maize after the recession of flood which is common after the rainfall season. The flood plain communities along Aya River in the savannah zone have adopted a sustainable agriculture approach of recession flood farming.as an intervention strategy (Utang & Ekpoh, 2011).

Another adaptation measure is the planting of early and drought-resistant varieties in response to climate variability. Early growing white (Ikom White) and yellow (OBASUPER) maize varieties were adopted in both the rainforest and savannah zones coping strategies [...*Early maturing maize variety is another option I do in my farm” … “Scarcity of improved variety is a big limitation”*].

The old variety takes a longer time to mature and was susceptible to insect infestation. The new varieties grow faster and matures quicker. They were seen to be resistant to water stress in the soil and diseases. [*“I look for an improved variety that can withstand stress, and grow faster”]*

The Ikom white variety (Ikanabang) early growing season maturity cultivar was widely planted in the zones. Nevertheless, the local variety of maize has not been completely replaced amongst smallholders’ farmers due to inaccessibility and the cost of acquiring the new improved variety. However, some famers still believe that the local variety is sweeter than the new variety, even though the improved variety is rich in vitamin.

The farmers acknowledged that considering the prevailing wind direction when planting helps to minimise later damage to the maize crop when the stem is upright [“*…” I take into consideration the wind direction to avoid damage when the maize stem is upright.*]. They also consider the planting density as a factor that affect yield. While some observed that planting more seeds would develop into small cob, others think it saves to do thinning by planting more seeds due to climate variability.

“I do not plant many seeds because it will develop small cob”. My plant density is between 3-4 seeds per hole. Our variety is called Ikom white since is it eaten by many. Though yellow maize is good for vitamin A, and for fowl feeds.]

The adjustment of planting time and crop diversification was practiced as coping strategies. There is a shift in the paradigm of planting time from February/ March to April and May for the growing maize season. The month of April favours early growing season maize cultivation. It was hypothesised that the amount of moisture supplied by rainfall during this month can sustain the growth of maize [“I *adjust the time of planting due to changes in climate. I used to plant in February/March but now in April and May. … I choose to follow the season by changing the timing of planting. I alter my planting date in order not to be vulnerable. I now wait until rainfall start in April before I sow”*]

Crop diversification is a strategy to improve climate resilient. It is the practice of moving to the cultivation of other crops not previously grown [*I diversify to another crop like cassava and melon is my option" another farmer said"*]. Many farmers have opted to switch to cocoa and palm production, melon, rice in the rainforest, while, groundnut, rice, cassava, citrus and some cocoa cultivations have been adopted in the savannah zone. Studies have confirmed that crop diversity is related to climate-sensitivity, and that it was an effective measure to buffer households (Fadina & Barjolle, 2018; Santpoort, 2020; Ziervogel & Calder, 2003). Rainfall is a key component leading to crop diversification in these zones. A survey of 160 farmers in Niger affirmed that rainfall variability was the most important risk which causes crop yield changes and diversification (Ado et al., 2020). However, a study in Bangladesh concluded that the effects of rainfall scenarios on crop diversity are much lower compared to the effects of temperature. In their findings, a 1.1°C rise in temperature by 2030 and 2.4°C by 2100 would lead to 26% and 150% rise in crop diversity compared to the 2010 baseline year of the study (Shailk, 2019).

The level of responses of smallholder farmers to climate variability adaptation strategies in the zones are shown in Figure 6.3. The figure reveals Etomi community in the rainforest zone responded 22% and Abegang community in the savannah zone 21%. The least responses were 8% in Adagon and Nwarranty both in the savannah zone. The level of responses to adaptation strategies differs within the communities in the zones. This might be linked to differences in socioeconomic conditions and the perception held about climate change.

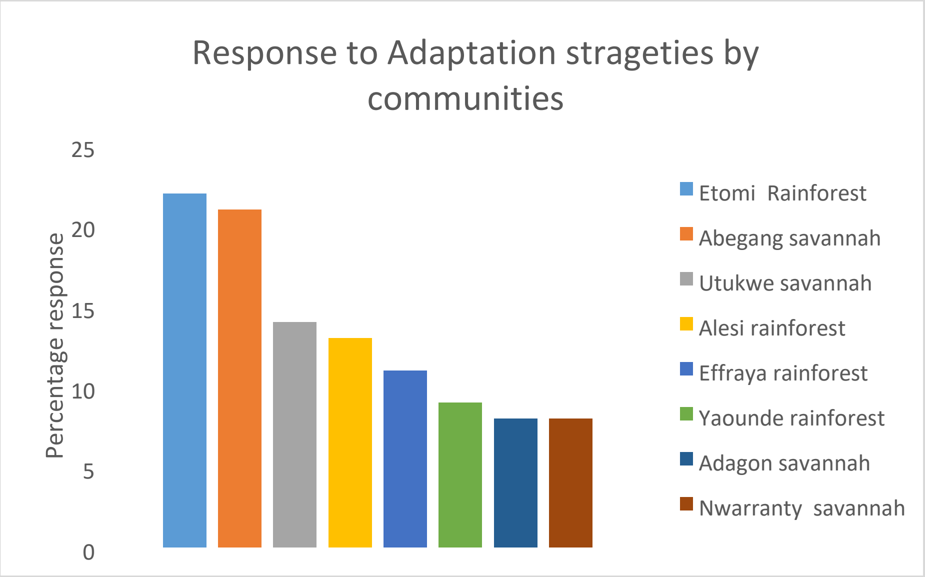


Figure 6. 3: Percentage Coverage of Community response to adaptation strategies in the agroclimate zones

6.3.4. Factors limiting the choice of adaptation and crop management strategies

Despite, the understanding by smallholders' farmers that adapting to climate variability is important, there are a range of factors limiting adoption of adaptation in the discussion groups. They revealed that factors limiting their actual choice of whether a strategy is possible include; finance and hoarding of fertilizer, ignorance and poor knowledge and inadequate extension services. The farmers in the zones observed that

"...financial difficulty is a major limiting factor that decreases adoption of adaptation strategies. Fertilizers are hoarded by politician for their own selfish interest and sometime diverted for sale to other regions where they are not allocated thereby increasing their own allocation of fertilizer".

"Limited availability of facilities to use in the farm like fertilizers, farm machinery and, politician's diversion of farm inputs to relatives". Poor accessibility to farm inputs limit expansion"

Finance is the engine that drives response to, and the acquisition of new technology. Poor finance hinders the adoption of improved farming methods and their expansion. This is consistent with (Guodaar, et al., 2018) who found that finance is the fulcrum that propels the farming business. Despite that finance affects the ways in which poor farmers cope with climate change, the diversion of farm inputs to unknown locations for business by politicians is also widespread. Some politicians and take credit facilities meant for farmers for themselves by creating false cooperative groups. This makes it difficult to access farm inputs in the regions. Famers are compelled to travel several kilometres to access fertilizer and credit facilities. Procuring herbicide and insecticides also appears as a challenging factor for the small-scale farmers. Farmer's ignorance and poor knowledge of new farm technology have been exploited by fraudsters who exposed them to out-of-date chemicals, which caused havoc to their crops.

"...to get herbicide and insecticide is a challenge. Sometimes they are exposed to bad chemicals or expired products which end up causing more harm than good in the farm. Ignorance or poor knowledge prevent one from adapting...."

"Lack of improved variety... and the market for this improved variety after harvest is poor. And there is a lack of extension services". Poor attitude of farmers to agriculture, due to government policy in the past to agriculture discouraged us. Lack of credit facilities to farmers"

Farmer's ignorance and poor knowledge of information of new technology has been identified as crucial to adapting to climate perturbations. The State Government has shown deep interest in improving food production in recent times through new partnerships with the World Bank and the central Bank of Nigeria. Different agro value chain programmes for small-scale agriculture productivity have been promoted. This recent initiative has increase participation in food production. But there is poor inclusion of local farmers in climate change adaptation discussion at stakeholder meetings in the zones (FGD, 2018). And the limited access to weather information and farm assets, which has the potency to cripple development and widen the knowledge gap of the farmers. This non-involvement would hinder response to the use of improved crop variety, fertilizer application, and other agricultural technologies. The inclusiveness of smallholders would provide insight to climate variability and enhance the implementation of improved adaptation strategies (Wood et al., 2014). Farmers' sensitization and mobilization is crucial to improving crop productivity. This is where the role of extension services must come in. The lack of extension workers in the dissemination of climate agricultural information is detrimental to limiting climate impact on food security (Guodaar et al., 2018). Extension services must consider farmers experience, as well socio-economic and environmental conditions in spreading climate-resilient strategies to increase adaptive capacity to climate change (Wood et al., 2014). The agricultural extension workers are trained to serve as a link between farmers and scientists in providing up-to-date knowledge of farming practices and innovation. This can reduce ignorance of the local farmers to new knowledge (Enete et al., 2011).

6.4. Conclusion

In this part of the study farmers' response to the impact of climate variability on maize yield in the rainforest and savannah was studied using the approach of focus group discussions. Data were analysed in the NVIVO software. Maize farmers revealed that climate variability was evident in the agroclimate zones occasioned by inconsistent rainfall patterns, delayed onset and early cessation, heatwave prevalence, and insect infestation of the maize crop. The poor yield was fundamentally linked to rainfall and financial poverty which hinders the acquisition of new technologies for farming maize. However, maize farmers have different local ways of confronting the problem of climate variability. These include adjusting planting time from February and March to April and May. Other approaches included planting an early maturity maize variety, the use of dogoyaro a native plant to kill insects, the examination of prevailing wind direction in deciding planting, in terms of its the space and density, carryout agroecosystem analysis of their farm to prevent pests and disease outbreak and crop diversification. The study concludes that the local inclusion of adaptation views on climate variability would promote climate-resilient strategies and food security. This leads to the chapter of bringing together information from the modelling and qualitative approaches.

Chapter 7: Maize modelling and the participatory approach nexus: implications of future Climate change for maize production in the rainforest and savannah agroclimate

“A Single Methodology Cannot Be the Only Hammer to Nail All the Solutions.” *By ULF Erikson 2016 (*https://reqtest.com/author/ulf/)

7.1. Introduction

Chapter 7 explores the nexus between the participatory (Focus group and survey) and the modelling approach. What are the implications for effective adaptation to climate change for the local farmers? The chapter pulls together outcomes from the focus group and survey conducted in the rainforest and savannah zones for the maize growing farmers. The key crop management decision by the smallholders was used to determine some crop model parameters that guide modelling work. Scholars have noted that using a predictive and interactive approach would foster smallholders to cope and adapt to climate change like the “seeds for need” approach (Fadda et al., 2020). The seeds for need approach emphasized a participatory crop improvement strategy for smallholder farmers to include the local adaptability, cultural, historic, religious values, and the traditional farming system to enhance adoption of new maize varieties (FAO,2019). This chapter employs both the DSSAT model sensitivity analysis and the farmers’ perceived knowledge results to provide better understanding of maize yield response to climate variability. The modelling approach is predictive while the latter is interactive. The chapter discusses farmers’ perceived responses to adaptation to climate variability to guide policymakers for intervention. The chapters hypothesised that adaptation strategies need to be locally appropriate and climate-informed to be sustainable (Beveridge et al., 2018). Using this combined approach helps in demystifying complex and multifaceted processes (Fetters et al., 2013; Noyes et al., 2019) which enhances knowledge generation with greater clarity in problem-solving (McCrudden & McTigue, 2019). Process-based crop modelling and Participatory or interactive place-based approaches are useful tools for identifying potential areas of sustainable adaptation for future climate variability in local communities (Beveridge et al., 2018). This mixed approach captures the complexities of assessing the “status” of a crop better than any model (Liu & Basso, 2020; Begueriá & Maneta, 2020). A simple flowchart of this synthesis is shown in figure 7.1. The understanding derived from combining these two approaches would expand knowledge and bridge the pedagogical gap in understanding the impact of climate variability on crop production in the zone. The chapter concludes with an examination of evidence-based intervention measures for rain-fed smallholder farmers against future climate change impact with respect to maize crop yield in the Cross River Agroclimate zone .

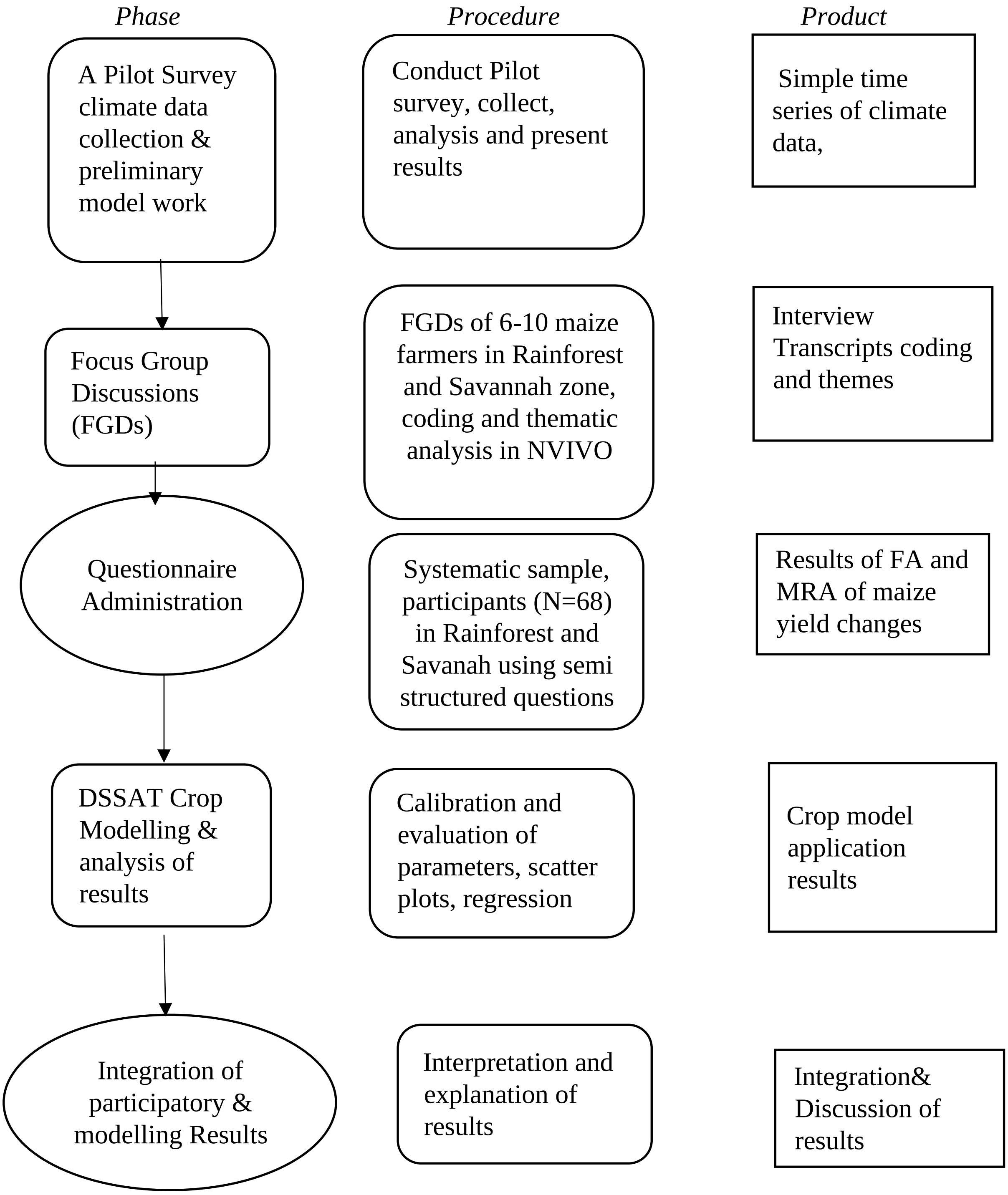


*Figure 7. 1: A simple flow chart of the combined approach Source: Adapted from (*McCrudden & McTigue, 2019*)*

7.2. The crop modelling and the participatory approach nexus

The DSSAT CERES- maize crop model is a computerized assisted process for mimicking the impact of climate change on maize production (Jones & Thornton, 2003). This has been described as a top-down approach (Beveridge et al., 2018; Mimura et al., 2015). For instance, DSSAT crop models have been used to mimic a real-world situation of maize growth and yield under changing climate (Jones & Thornton, 2003). Crop models are used in supporting decision and policy making on agricultural adaptation for future climate change (Beveridge et al., 2018; Liu & Basso, 2020; McCauley, 2020), for developing new crop varieties to curb the challenge of the climate emergency (Godfray et al., 2010; Ripple et al., 2020). Crop modelling can direct future research and crop breeding (Dodds et al., 2019). They also provide insight into complex processes and are useful to support discussion in participatory research to solve agro-ecology resource management problems (Fadda et al., 2020). Crop models are a useful tool to guide farmers to change management practices for improving crop productivity (Soltani & Hoogenboom, 2007)). For crop models to be more relevant, they would need to be validated and fitted for the environment of the application (Gunarathna et al., 2019). In the words of Dodds et al. (2019) crop simulation provides quicker decision alternatives, and it is the best way to examine the interaction between climate variability, management decisions, and crop yields in comparison to traditional research experimental farms. Crop simulations run experiments quicker and more cost-effectively and generate useful information for recipients (farmers) to improve their crop productivity (Dodds et al., 2019).

The participatory approach is referred to as people-centred and a place-based method. It is primarily a context-specific and area-specific approach where farmers share, identify, and proffer solutions to perceived problems within their locality (Krueger & Casey, 2015; Liamputtong, 2015). The approach is used to transmit information on crop improvement for smallholders to cope with climate change such as providing advice on the choice of planting dates, cultivar choice, and a fertilizer management and sowing density (Fadda et al., 2020). It connects the local farmers and scientists in understanding climate change adaptation decisions (Beveridge et al., 2018; Mimura et al., 2015; Ross et al., 2015). This method opens an opportunity for farmers to discuss a wide range of issues in climate adaptation and farming practices affecting crop productivity which is akin to the bottom-up concept of the IPCC (Mimura et al., 2015). The Participatory techniques connect the farmers towards adopting new technologies for sustainable farming practice. Such technologies for pest control, weed control, and fertilization application at the farm level are better adopted by engaging farmers (OECD, 2001). The inclusion of farmers in the driving of technology adoption creates a greater sense of recognition in the agri-food chain. The modelling community can also learn from farmers about the outcome of the implementation of new technologies in the agro-food chain (OECD, 2001). And this would give local farmers the opportunity to improve upon the farm management practices and build their confidence in the global sustainable agenda to curb with the challenges of climate change on food security.

7.3. An integrated analysis of impacts on maize production in the rainforest and savannah zones of Cross River State:

This section evaluates maize yield response to climate variability in the rainforest and savannah using crop management information from participatory approach results which were framed into the crop model to understand the potential adaptation strategies of climate change impact on maize yield in the rainforest and savannah zone. These areas are the epicentre of agricultural activities in Cross River State. Maize is widely cultivated in the early growing season rainfall. Recent extreme environmental events in these zones such as dry spells, high temperatures, rainfall changes, heatwaves, weed spread, and insect infestation leading to crop yield decline have been consistent with similar reports across SSA (Folberth et al., 2014; Omoyo et al., 2015; Leng & Huang, 2017; Obara, 2019). As the population increases, cereal demand is projected to double in the coming century in SSA (Ben-Ari & Makowski, 2014). Food security is likely to be poorer with climate variability, combined with the impacts of the covid-19 outbreak (Ayanlade & Radeny, 2020). Climate variability impact ~ 60% of global crop yield variability (Kukal & Irmak, 2018; Ray et al., 2015), and ~78% variability was observed on maize crop (Ray et al., 2015).

This study analysis the robustness of these findings in Cross River State rainforest and savannah zones by carrying out a sensitivity model analysis of maize yield response to shift changes in planting dates following the results drawn from the focus group and survey. The cultivation of maize was noted to be carried out under rain-fed conditions. In the study, a range of rainfall and temperature scenarios were considered for the zones as reported (Adejuwon, 2006; Salami, 2010). It was found that a 50% decrease in rainfall leads to a decline in maize yield of 61.9% in the rainforest, and 70.1% in the savannah zone. These findings are consistent with (Abam et al., 2018) projection of 24% and 43% decrease in maize yield in two areas of Ethiopia occasioned by rainfall variability. This finding is consistent to studies in the savannah part of Gboko which revealed rainfall having a strong positive correlation of 0.74 and 0.59 with maize yield (Adamgbe & Ujoh, 2013). Experts have revealed that rainfall is the main driver of interannual variability of crop yield in Africa (Lobell & Field, 2007; Omoyo et al., 2015b), Positive rainfall has been associated with a favourable maize yield than negative rainfall events in Mbeya region of Kenya (Batho et al., 2019) and in inter-annual rainfall variability has been confirmed to affect maize yield in SSA (Mereu et al., 2015; Odekunle et al., 2007). Crop yield is more sensitive to changes in precipitation (Kang et al., 2009)

Furthermore, there were positive correlations between rainfall changes at (±) 10%, 20%, 30%, 40%, and 50% with the simulated maize yield in the sensitivity analysis. The simple regression results revealed $R^2 = 0.68$ in the rainforest and $R^2 = 0.56$ in the savannah (Figure 4.8). The scatter plot further confirmed this relationship.

During participatory focus group discussion, maize farmers emphasised the importance of rainfall in the planting season, supporting the modelling results. They confirmed that the farmers' perceived rainfall as a major factor that affects maize yield in both zones *{"Rainfall influences the growth of maize. Excessive rainfall without sunshine would cause poor yield. Planting season has changed; we wait for the rainfall to reach the soil properly before planting maize"*}. It was discussed that rainfall and sunshine are important factors that determines high maize yield {*Good rainfall and sunlight promote good maize yield*}. Farmers also observed that a persistent rainfall during the harvest months can affect maize yield significantly {..." *The time of harvesting can affect the yield. Especially when rainfall persist during harvest season"}.* An analysis of maize farmers' opinions in a survey of key factors influencing maize production indicates that the climate change factor was statistically significant ($P < 0.05$) in the zone (Table 5.13). In the participatory discussion, Farmers in the rainforest perceived an increasing trend in rainfall in some periods of the growing season and a decreasing trend in some other seasons {*I experienced more rainfall in February every day, then less rainfall in May*}. Farmers also observed a change in the patterns of rainfall from what they have known {"*in the past five years compared to this year, rainfall has a drastically changed patterns. Rainfall regime is unpredictable now than before. The big rain usually comes after February in the past"}.* Similarly, in the savannah zone, rainfall was perceived to be better 10-15 years ago {" *I noticed increased rainfall ten and fifteen years ago…comparing the rainfall pattern three years ago for Jan-May is better than this year 2018 Jan- May. There was a break in rainfall for two weeks during the planting season and that impacted the maize growth. About ten years ago, rainfall starts early and breaks in August and begins again in November. But in these days heat is high, rainfall is highly variable. We suddenly have rainfall in March, and* *then between March and June, the crops do not have enough rainfall to do well"*}. The rainfall time series analysis from 1990-2016 in the rainforest shows that the upward trend in rainfall was not statistically significant ($P < 0.05$), however there were years of a constant increasing trend. For instance, there were observed increase for the periods 1992-1997 and 2010-2013 (Figure 4.1) in the rainforest. While an upward trend was noticeable from 2004-2013 in the savannah (Figure 4.2). For the savannah zone, an upward trend was significant in rainfall. The last ten years revealed increase trend and fluctuations in rainfall patterns across the agroclimate zones. These results are similar to studies that revealed changes in the trend and pattern of rainfall in Enugu, south east Nigeria (E. Christian & Izuchukwu, 2009; Mercy, 2015).

The sensitivity analysis results for a projected 1.5^{o}C increase in temperature from the base year revealed yield decrease for Tmax and Tmin in the rainforest and savannah zone. The multiple regression model results revealed no significant relationship of maize yield with temperature increase in the zone as shown in Table 4.5. An increasing trend in temperature and reduction in rainfall amount can be detrimental to crop yield as reported in the northern savannah and Sahel agroecological zone of Nigeria that maize yield would decline more rapidly with a decrease in rainfall (Mereu et al., 2015; Ndawayo, et al., 2017).

7.4. Local farmers' adaptation and management strategies in the rainforest and savannah zones of Cross River State

Adaptation is an eclectic word with different applications and meanings. This study limits the discussion of climate adaptation strategies to smallholder's farmers. Climate adaptation strategies are well-planned actions made to ecological or human systems, tailored to respond to perceived climate change by reducing vulnerability to the impacts of climate change (IPCC et al., 2013; Mimura et al., 2015). Adaptation involves articulating policies and planned actions targeted at addressing anticipated and potential climate change problems. These are the measures, or the actions farmers adopt in adjusting to adverse climate conditions which may counteract the impacts of climate variability on their livelihood (Haider, 2019; Mimura et al., 2015; Ola, 2018). However, adaptation response strategies can be hindered by poor adaptive capacity such as income, low technology, poor information, socio-economic and socio-cultural conditions (Haider, 2019; Mimura et al., 2015; Ola, 2018).

Maize farmers have established that climate variability does occur, and there were different adaptation and crop management techniques adopted in the zones. They had confirmed incidents of rainfall variability, dry spells, heatwaves, and insect infestation. The local adaptation measures adopted in the zones change in planting time, use of a high yielding and early maturity variety, crop diversification, and fertilizer application is consistent with practices in most zones in SSA (Fadina & Barjolle, 2018). The application of adaptation strategies was based on their local understanding of climate variability. This approach agrees with a study that adaptation strategies need to be locally appropriate and climate-informed (Beveridge et al., 2018).

7.4.1. Change planting date and sowing density coping strategies.

The planting time and planting density were observed as crucial measures to reduce the adverse impact of rainfall change, late-onset, and early cessation of rainfall in the zones. Farmers in the rainforest stated that they have altered their planting time from February and March to April *{"I plant maize two times, early and late maize, for early maize planting is in March... now plant my maize in April due to the change of climate"}*. Others in the savannah plant in

April and the early part of May {." *We shift planting of maize to April and May"},* been consistent with farmers response to adaptive capacity in other parts of Nigeria that 88.4% changed planting date, 85.4% harvesting date, and 56.8% adopt multiple cropping (Farauta et al., 2013). Findings from the FGDs approach suggests that alteration of planting date helps them cope with climate variability {I *alter my planting date in order not to be vulnerable*}. The model application for different planting dates in the zones was carried out following farmers' perception of a shift in the weather pattern. The mean simulation runs from February, March and April in the seasonal analysis in Figure 7.1 reveals different grain yields when Obasuper 2 was planted. The highest mean grain yield of 6557kg/ha was obtained in the rainforest and 5941kg/ha in the savannah during April planting. In March planting, 6400kg/ha mean grain yield was recorded in the rainforest and 4855kg in the savannah zone. While the February planting produced the lowest mean grain yield of 4920kg/ha in the rainforest and 1706kg/ha in the savannah. The month of February has the highest percentage difference of 65.3% in the mean yield during this month planting in the zone, while a 9.4% difference in mean yield was obtained in April. A shift in planting from February to April was more favourable in the rainforest and savannah. However, mean grain yields were higher in the rainforest than in the savannah during the period. In Nigeria, local knowledge is key in determining planting window of maize crop. Farmers rely on the understanding of climate and weather patterns to choose their planting dates. Early planting during the onset of rainfall in February or March by farmers is risky. This can lead to maize yield reduction following the sudden cessation of onset rainfall. The application of crop models to evaluate change in planting dates is a veritable tool in advancing adaptation strategies to climate change crops (Adnan et al., 2017). The change in crop management revealed that farmers sowed from late March to April in the rainforest and the mid-April and early May in Savannah. Planting windows have changed due to variability in the pattern of growing season rainfall which is consistent with (Bilirwa, 1992; Olaniyan & Lucas, 2004). The sowing rate per hole differs between the cultivar adopted in the zones. More seeds of 3-5 per hole for the old variety, and 2-3 seeds for the improved variety. They observed that excess rainfall can cause seeds to rot in the soil before germination which might influence yield of maize (Bhusal et al., 2009; Ruffo et al., 2015) Hence, the ultimate target of adaptation response on climate change is to reduce vulnerability (Mimura et al., 2015).

Table 7.1: Model application of maize yield response to changes in planting dates 1990-2016

Planting Window	Rainforest Mean yield (kg/ha)	Savannah Mean yield (kg/ha)	Percentage Difference (%)
April	6557	5941	9.4
March	6400	4855	24.1
February	4920	1706	65.3

Source: Author’s analysis.

7.4.2. Adopting improved high yield variety

Local farmers were aware and adopted the application of improved maize variety in the zones. The study observed that smallholder maize farmers have a preference for using a particular maize variety but that seeds were not easily accessible to them. It was confirmed during discussions that improved varieties have high yielding potentials compared to the local maize variety {“we *use improved maize variety seeds because it increases yield”}.* However, some farmers contended that the market for this variety was still low in the zone. Nevertheless, they grow the local variety primarily for their family consumption, and the local market to improve their livelihood. It was noted that the local maize variety was highly susceptible to diseases and climatic stress compared to the improved hybrid. The farmers observed that the use of an improved maize variety is an effective measure to offset the dangerous impact of climate change and variability (*{I look for improved variety that can withstand stress and grow faster}* another farmer said *{"I adopt the improve variety because it has high demand"}).* A simple seed test was performed before sowing to ascertain the quality of the seeds. Bad seeds were said to float in water while the healthy seeds remain underneath {*I do a seed test as a very important test before planting*}. On the adoption of the improved variety, studies have argued that a decentralised participatory approach enhances the use of the high-tech cultivar (Fadda et al., 2020). Adopting new crop varieties requires a carefully planned implementation strategy with involvement of all the stakeholders (government, farmers and non-governmental organisation) from the local, state and national level (Mimura et al., 2015). Local farmers would resist and or respond slowly to new varieties when their cultural and socioeconomic conditions are undermined (Wood et al., 2014). It is important to engage in a participatory approach to encourage cultivar adoption while you consider both the environmental friendliness and cultural acceptability of the varieties (Elum et al., 2017). This helps with mobilizing local communities for the transfer of relevant farming technology for climate change adaptation adoption aimed at reducing climate shocks and vulnerability (Elum et al., 2017; Yohe et al., 2006)

7.4.3. Diversification of crop production

Crop diversification is a means of creating many opportunities for survival and livelihood through a multiple cropping initiative. The apparent decline in maize yield occasioned by recent climate events has caused most maize farmers to diversify to other crops. Some farmers in the rainforest maintained that they have moved to cocoa and palm oil production {"*I diversified to cassava and other crops when there is a failure…I also complement with Planting of cocoa and palm tree"}.* This finding is in line with a study conducted in three provinces of South Africa where over 49% of farmers perceived crop diversification and relocated to be important compared to single crop dependence (Elum et al., 2017). Diversification is primarily a vulnerability reduction strategy by farmers with a high exposure rate to crop failure during the growing season (Gezie & Tejada Moral, 2019) (Luu et al., 2019). Many farmers in the savannah zone of the State have also diversified to other crops like rice, groundnut, and yam cultivation. A few of them have also adopted tree crop cultivation e.g., cocoa.

7.4.4. Local insects' control and fertilizer application

Farmers have perceived increasing insect attacks such as stem borers on maize plants in the rainforest. As measures to control insect pests, they emphasised an agroecosystem analysis on the farm early in the morning. This is what a farmer said {*Insect infestations are high now than* *before due to climate change. While the high sun scorched the crops, too much rainfall at a time destroys the seeds even before germination. High temperature squishes the leave and fold them. Do agro-ecosystem analysis to confirm whether the crop is diseased or not}. This must be done very early in the morning"}.*The observed increased in temperature and pests is consistent with farmers' perception. They have adopted a local plant called "dogoyaro" (scientific: *Azadirachta Indica*") for controlling the new insects invading their crops. This is an environmentally friendly sustainable and less costly approach. The plant leaves are plucked and pounded into paste, soak in water and sprinkled on the maize plant during the early growth season *{we use to dogoyaro leaves to prevent insects from destroying crops. We pluck the leave and pound in a mortar to a pastry then soak in water, filter and apply on the plant}.* This method has been effective and cheaper than buying agro-chemicals. This indigenous approach can be further investigated and expanded through scientific research to test the robustness of this plant's efficacy in controlling pests and insects.

Fertilizer application was a common measure to improve maize crop productivity due to climate change {*we apply fertilizer after three weeks of growth. after this period, if you apply fertilizer, the maize will not perform well"} and {*"*those that apply fertilizer in their maize farm had better yield than those who did not"}.* Fertilization of the crop is important to improve the soil fertility due to leaching by rainfall. Nevertheless, some farmers argued that the inorganic fertilizer destroys their snails and some micro-organisms living in the soil {"*fertilizers also destroy snails and micro-organism in the soil"}*

7.4.5 Soil conservation practices

Different approaches were employed by the farmers for soil conservation. Crop rotation and mixed cropping were commonly adopted to improve soil fertility and control pests on the farm {we *adopt leguminous crops or mixed cropping to improve soil fertility like planting groundnut, beans and melon. I practiced crop rotation system to control disease and improve the soil fertility}.* The slash and burn system of farming was avoided as this exposes the soil to erosion and depletes essential soil nutrients. In most communities of the savannah, mulching has been implemented to control heat and erosion. The mulch material also adds nutrients to the soil when it has decomposed {"Most *often, I 'wear the mount with cap' mulch to reduce transpiration"}*

7.5. Implications for future climate change on maize production in the zones

Maize is a major staple cereal food crop consumed in Nigeria and is an important crop for domestic and industrial purposes. The reported decline in maize yield has been a concern for future maize need and food security (Arije et al., 2018; Olowe, 2020). All the efforts by the government to support local maize production have not yielded better results, even the ban on maize importation by the Federal Government of Nigeria to improve local production has not cause any change. Rather, with the exponential increase in population and climate change factor in SSA, food security is likely to be compromised (Olowe, 2020; Onyeneke et al., 2019; Tilman et al., 2011). The situation would be particularly bad for Nigeria, as its population is predicted to reach more than half a billion by 2100 (Worldometers, 2021; Haider et al., 2019). A quarter of the population currently depends on rain-fed agriculture for their livelihoods and more than 50% of the population lives in rural areas (Olowe, 2020).

A more realistic approach to evaluate maize yield decline to boost future domestic and industrial production is important. Such evaluations have been done on different spatial and temporal scales with crop modelling and statistical approaches (Liu & Basso, 2020; Lobell & Field, 2007; Obara, 2019), field survey with crop modelling (Liu & Basso, 2020), and a participatory decentralised method to support crop yield improvement (Fadda et al., 2020). This thesis, however, argues that combining a crop-model and participatory approach would provide a better local understanding of the impact of climate variability on maize yield, and drive the adoption of improved management practices to boost maize productivity. Local maize farmers' involvement in identifying problems and solutions is fundamental to increasing resilience and reducing vulnerability to future climate change (Abdul-Razak & Kruse, 2017; Onyeneke et al., 2019). This study advocates the need to carry out a climate change impact adaptation assessment in local communities using a strengths, weaknesses, opportunities and threat (SWOT) indicator-based framework (Abdul-Razak & Kruse, 2017; Mumo et al., 2018; Olowe, 2020). This analysis would strengthen understanding and consolidate assessment of local farmers' capacity to adapt to climate variability and change. This thesis recognises the need of the combined approach to evaluate this impact.

7.6. Conclusion

The chapter synthesises results from the crop modelling and the participatory approaches to assess the impact of climate variability on maize yield in the rainforest and savannah agroclimate zones of Cross River State. Farmers' perception of high climate variability agreed with many scientific reports in sub-Saharan regions of Africa and other areas outside Africa.

Farmers perceived that years with good rainfall favours maize yield. The farmers changed their planting date as a measure to avert climate the impact of climate change. The inclusion of this changes in planting dates in the crop model shows that April planting window yielded better results in both zones. But in the rainforest more yields were obtained than the savannah. The study reveals that local farmers use their knowledge of adaptation strategies to curb the adverse climate situation by using local resources to combat insect pests. They also adopt a range of adaptation practices, such as choosing different planting dates, and the ring method of fertilizer application. Local resources can be harnessed to improved resilience to climate change in Africa (Buyana et al., 2020). The ring method is most economical and effective in reducing weeds. Other measures like crop diversification and soil conservation measures were practiced. However, low income and farmers' poverty were the major constraints for the adoption of improved management techniques.

Chapter 8: Conclusions, recommendation and further work

8.1. Conclusion

The rainforest and savannah region are the epicentre of maize production in Cross River State, Nigeria. Maize is an important staple crop for domestic and industrial purposes and provides a livelihood to many smallholder farmers and their families in the zones. Unfortunately, maize yield has dropped in the last few decades while the demand for maize is rising. There are worries about the future food security with climate change. To compound these problems, Nigeria population has been projected to hit more than half a billion by 2100 (Olowe, 2020).

This would increase local farmers' vulnerability to climate variability and hunger in the zones. With most of the population depending on rain-fed farming for survival, climate variability would expose the poor farmers to more climatic shocks and reduce their capacity to produce more maize (Vincent Gitz *et al.*, 2016; Ayanlade, Radeny and Morton, 2017). This thesis addressed the following research questions linked to this problem:

1. Can the growing season mean rainfall and temperature (minimum and maximum) be responsible for maize yield decline in the rainforest and savannah zone?
2. Can the DSSAT CERES model predict accurate maize yield, and identify critical parameters affecting yield in the agroclimate zones?
3. Do crop management practices, or other factors, determine maize production in these agroclimate zones?
4. How do local maize farmers perceive and respond to climate variability and adaptation strategies in the zones?

In response to research question one and two, data for the growing season mean rainfall, solar and temperature (maximum and minimum) were collected from the Nigerian Meteorological Agency (NIMET). The observed maize yield, days to anthesis, days to physiological maturity, leaf area index, and harvest index were obtained from the Agriculture Development Project (ADP) located in the rainforest and savannah zones of the region. Chapter four analyses the time series of mean growing rainfall and temperature (maximum and minimum) from 1982-2016 to establish any trends. The chapter performs a local sensitivity analysis in DSSAT model to assess the response of maize yield to changes in planting dates and critical climate parameters in the rainforest and savannah. Results revealed an increasing trend in rainfall in the rainforest and savannah, with a significant trend in the savannah ($P < 0.05$). The last decades indicates an upward trend in growing season rainfall in the savannah. Also, the regression analysis between maize yield and the growing season climate parameters were performed. The growing season rainfall was found to have a strong positive relationship with maize yield ($P < 0.05$) in the regions. The local sensitivity analysis results indicate that a projected decrease (negative) in growing season rainfall of 50% from the baseline would affect maize yield significantly in the future. In contrast, positive temperature change does not have a significant impact on maize yield. The RMSE and agreement statistics revealed an excellent fit between the observed and simulated yield in both regions.

In answering the third research question, a survey approach was employed in chapter 5 where a set of structured questions were designed on a five-point Likert scale to elicit responses from the local farmers covering socioeconomic characteristics, management practices, and climate change factors. Eight major maize growing communities were chosen for this survey, with four communities in each agroclimate zone. Contacting the farmers was made easier by liaising with the agricultural officers and extension agents in the communities of the zones. The factor analysis model and multiple regression employed revealed a significant prediction of R^2 of 0.73 and an R^2 of 0.87 in the rainforest and savannah agroclimate zones respectively. Management practices, fertilizer application, farm size and climate change factor, income as well as gender, loaded high in the factor analysis. The multiple regression model showed a significant relationship at ($P < 0.05$) between the maize yield and the explanatory variables. The chapter demonstrated that farm size was a major challenge, besides rainfall in the rainforest. Lands are converted for cocoa production and other developments, reducing arable land for maize production. However, in the savannah, management practices, climate change (rainfall) and farm size and gender were very important factors.

Research question four was addressed in chapter 6 using farmers' participatory model approach where the local maize farmers were engaged in a series of focus group discussions in their own community environment on their perceived understanding of climate variability and the adaptation strategies that needed to be adopted. It was revealed that high climate variability was evident in the zones as observed by the farmers, and that the incidence of heatwaves, late onset and early cessation of rainfall, as well as short dry spells occurred on their farms. They indicated that in the past 10 years they had experienced high rainfall in both regions. However, there was a higher trend of rainfall in the savannah. Farmers reported that the incidence of insect pest attack on the maize crop was very high and has triggered the decrease in yield. They feel that climate change was the main cause of these insect infestations. In response to the changing climate, different adaptation measures were adopted such as changing planting dates, diversifying to other crops, local soil conservation measures, and use of insect pest control using local plants in the savannah zone, and adopting improved maize varieties. However, farmers were constrained by the poor accessibility to new technology, finance, and politician influence.

Finally, the thesis synthesises the results of the crop model and the participatory approach in chapter 7 where the nexus of the approaches sheds holistic understanding of the impacts of climate variability on maize yield in the agroclimate zones. The thesis hypothesis that rainfall variability was a key constraint in deciding when to plant maize and what management and adaptation measures to adopt. Famers shift to April planting in the rainforest, and to early May planting in the savannah was evident. The adjustment in planting date was found to be consistent with many studies (Adejuwon, 2006; Barimah, 2014; Haider, 2019).

The thesis hypotheses that an inclusive approach to the conventional crop modelling and statistical methodology is critical to understand maize yield decline. It further establishes that local farmers understanding of climate impact assessment is key for diagnosing and supporting sustainable solutions for the improvement of crop yield and adaptation strategies to climate change. Most previous work has focused on modelling the impact of climate change on maize yield over a global or regional domain using either a process-based or statistical modelling approach. Little attention has been given to local understanding of adaptation to climate variability and change, and its impact on crop yield in most regions of SSA, and particularly in Cross River State region of Nigeria. This study fills this gap by expanding on the methodological approach, hence the adoption of a crop modelling and participatory approach to aid the understanding of the impact of climate variability on maize yield in the rainforest and savannah agroclimate zones.

8.2. Recommendations

1. The research identified rainfall as key to maize yield in the rainforest and savannah agroclimate zones and this determines the planting date for the farmers. It is important to note that planting time can adversely impact maize yield when the optimum planting season or window for the crop is exceeded. Hence, the thesis recommends that weather forecasts in the region be readily available to the farmers through various agents using the community agriculture extension workers, community leaders, the churches, cooperative association etc. This would complement local weather understanding and provide farmers with relevant information to prepare for the planting season. Unfortunately, climate information and forecasting are not easily accessed by the local farmers.

2. Crop management was highlighted as crucial in maize yield production. The local farmers depend on their old variety of maize called Ikom white (Ikanabang), while very few have access to the new maize varieties that have high yielding potential and are resistant to drought stress, insect pests and diseases. Government and Non-Governmental Organisations, and development partners in agriculture and food security should support the local farmers with improved seeds at reduced cost. Fertilizer should be available to the local maize farmers at a subsidized rate. The diversion of farm inputs by politicians should be checked as this has left farmers more vulnerable to climate variability and change. The application of an integrated approach is an effective tool to advance sustainable adaptation measures by farmers to climate change.

3. Agricultural extension workers should be trained and equipped on a regular basis to aid them mobilize communities to hold training workshops, as well as organise participatory discussions on new improve crop management techniques and technologies.

4. The Government should encourage local communities' participation in climate change and adaptation strategies. Local farmers' knowledge of the climate adaptation strategies should not be ignored. A joint SWOT analysis on climate change impact on crop yield should be carried out in the agroclimate communities on a regular interval of 5 years. This would help with the quick identification of local potential for change and improvement, as well as to inform sustainable policies and decision for adaptation using the bottom-top approach.

8.3. Limitations and assumptions

The dearth of solar radiation data and agronomic information constrained the extent of the crop modelling work. There were only two Nigerian Meteorological Stations in the rainforest and savannah zones, which were run by only a few staff taking between 12 hour and 24-hour shifts. A good number of years had no solar radiation data due to instrumentation problems or other reasons. In carrying out this thesis some assumptions were considered as important in analysing climate variability impact on maize yield:

1. Only the available site-specific soil parameters and crop management data were used for model calibration for the rainforest and savanna zones. The crop model however works with the minimum parameters inputted into the model for both zones.
2. The assumptions that projected changes in the critical climate parameters for Nigeria would be the same for the rainforest and savannah agroclimate zones of Cross River State. The thesis considered percentages in rainfall from (±) 10% 20%, 30%, 40% and 50% for the

local sensitivity analysis and a mean projection of 1.5°C (±) increase in the values of maximum and minimum temperature.

3. The same structured survey questions on socio-economic characteristics, crop management and climate factor were used to interview farmers for both regions.

8.4. Further work

The thesis emphasised a participatory approach in understanding local farmers' response to climate variability and adaptation measure as key to expanding the body of knowledge on local climate studies. Using the DSSAT crop modelling and participatory approach, the thesis identifies that rainfall was a critical factor for maize. However, a more robust application of a multi model crop comparison approach would be worth exploring to investigate maize yield response to different climate, soils, and management parameters in the rainforest and savannah zones. However, this kind of study is challenging due to the dearth of data and resources in developing countries, especially in rural climate impact studies. This work was limited to maize yield in the rainforest and savannah agroclimate zones using a combined methodology. A similar study can be extended to include other crops and other agroclimate zones of Nigeria.

8.5. References

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Appendix

Appendix 1: CONSENT FORM

Title of research project: Impacts of climate variability on maize production in agro-climate zones of Cross River State, Nigeria.

SUNDAY WAYAS ASHUA
FT PhD Student

Department of Geography

The University of Sheffield, UK

Email:swashua1@sheffield.ac.uk

		Tick the boxes
1	I confirm that I understand the importance of the interview as explain to me.	
2	I also know that my participation is voluntary, and I am free to withdraw at any stage of the interview	
3	I understand that my responses will be treated strictly confidential. I give my consent to the research team to publish my responses in anonymity.	
4	I am also made to know that I cannot withdraw my responses after the data have been analysed.	
5	I agree that the interview can be audio recorded	
6	I therefore, consent to participate willingly in the above study	

Sign/Thumbprint: ………………………. Date: ….…………………….

Interviewee/Respondent

Appendix 2: PARTICIPANT INFORMATION SHEET

Research title: Impact of climate variability on maize production in Agro-climate zones of Cross River State, Nigeria

Invitation to take part in this study:

You are cordially requested to take part in this research project. Before you decide to participate, it is important for you to know why the research is being carried out and the involvement. Please listen carefully to the following information and ask question where necessary.

Purpose of the study:

The purpose is to assess the impact of climate variability on maize production in the forest and savannah agro-climate zone with a view to develop a sustainable crop management and adaptation strategies to caution the impact of climate change on maize production in Cross River State.

Aim of the Project
The aim of this project is to assess the impact of climate variability on maize production in the agro-climate zones of Cross using process-based modelling and participatory focus group framework

Why have you been invited to participate?

You are invited as maize farmers to provide information of your perception of climate variability/change, crop management practices and adaptation strategies has influenced maize yield in your area. In this light I would like to interview you (maize famers) as stakeholders **Do I have to take part?**

This exercise is voluntary. Hence, you are free to join or withdraw from it at will. If you choose to participate, you will be given a copy of this information sheet to keep and be asked to sign a consent form.

What will happen to me if I take part?

You will be involved in a focus group interview where you will meet other participants. The interview will be conducted in a group in your town hall or any suitable civic centre within the community. There is no right or wrong answer to the questions, and you will speak by indicating with a lift of hand. There should be no interruption during the interview which should last approximately 90 minutes. The questions are set of open-ended use to elicit key evident opinions on adoption of crop management practices and adaptation measures to climate variability/change. The interview will be audio-recorded.

What are the possible disadvantages and risks of taking part?

There is no form of psychological, emotional or physical risk in this interview. The research will not create any form of distress or shock to you.

What are the possible benefits of taking part?

Whilst the benefits are not immediate, the products of the research would advised farmers on sustainable climate smart responses to be adopted on crop management to improve maize production, and this would informed government policy to help farmers curtail the negative consequences of climate change on maize production.

What do I do if I have any issues of complaints?

If you have any complaints about this research or researchers, please contact: Professor Grant R. Bigg, Department of Geography, The University of Sheffield, Western Bank, Sheffield S10

2TN, UK. Tel: +44 114 222 7905. Email: Grant.Bigg@Sheffield.ac.uk **Will my taking part in this project be kept confidential?**

Your opinions will be kept strictly confidential. Your name will not be mentioned in any reports or publications.

What type of information will be sought from me and why is the collection of this information relevant?

The information is geared towards the achievement of the research project's objectives. You will be asked some interview questions, these questions border around your knowledge of climate variability/change in your area, crop management practices and adaptation measures adopted

What will happen to the results of the research study?

It will be used for publication in learned journals, research seminars and in academic conferences. The data from this research may be useful to other researchers **Who is organising and funding the research?**

This research is organised by Sunday Wayas Ashua and funded partly by Tertiary Education Trust Fund of Nigeria (TETFUND)

Who has ethically reviewed the project?

This research has been ethically approved via the Department of Geography Ethics review committee. The University's Research Ethics Committee monitors the ethics application.

Contact for Further Information
If you have questions about this study and the interview, please contact Sunday Ashua, The Department of Geography, The University of Sheffield, Western Bank. Sheffield S10 2TN, UK Email: swashua1@sheffield.ac.uk Thank you.

Yours faithfully

Sunday Ashua

Appendix 3: FARMERS RESPONSE TO CLIMATE VARIABILITTY (FRECV) IN RAINFOREST AND SAVANNAH ZONES OF CRS QUESTIONNAIRE

This survey is designed to elicit responses on the impact of climate variability on maize production in the rainforest and savannah agro-climate zones of Cross River State. The survey will examine farmer's response to impact of climate variability on maize in respect to crop management practices and adaptation measures. Hence, your candid answers to this survey will be useful to develop viable climate smart agriculture policies to boost food security in the State. Do feel free to complete the questions as stated below. All responses will be treated anonymously and confidentially

SECTION A: DEMOGRAPHIC/SOCIO-ECONOMIC CHARACTERISTICS

1. What is your household size (number)……………………?

2. What is your gender A Male ( ) B. Female ( )?

3. Your household head is A. Male ( ) B. Female ( )?

4. What is your highest level of education A.? None ( ) B. Primary ( ) C. Junior Secondary ( ) D. Senior Secondary ( ) E. Tertiary ( )
5. How long have you been farming maize (years of experience) …………………...?

6. What is your farm size (m^2) …………………………?

7. What is your average annual farm yield (kg)………………………?

8. What is your average annual income from this farm (#) ……………..?

CROP MANAGEMENT PRACTICES IMPACTS ON YIELD IN THIS AGRO-CLIMATE ZONE

No	Items	Strongly adopted	Always adopted	undecided	Rarely adopted	Not adopted
9	I adopt standard plant density of 2-3 seeds per hole					
10	I Plant distance 75cm to 25cm for seed per hole					
11	I adopt 1st dose of fertilizer application 9-10days after planting and 2nd dose 4-5weeks					
12	Apply only 100kg NPK per hectare					
12	Adopt random row spacing during planting					
13	I do soil conservation measure (no till and bush burning) during farming seasons					
14	Adopt early planting date					
15	I adopt the Ikom or Obubra white					

No	Items	Strong Agreed	Agreed	Undecided	Disagreed	Strongly Disagreed
17	Depend on soil fertility					
18	High plant density of 3-4 seeds per hole reduces yield					

19	fertilizer application adds to yield					
20	Close row spacing is the cause of poor yield					
21	chemical application controls weed and grain quality					
22						
23	Delay in planting date during the growing season reduce grain yield					
24	Use of improve varieties increase yield					
25	wrong fertilizers or pesticide caused wilting and low yield					

OTHER FACTORS INFLUENCING MAIZE YIELD AND ADAPTATION STRATEGIES TO CLIMATE VARIABILITY

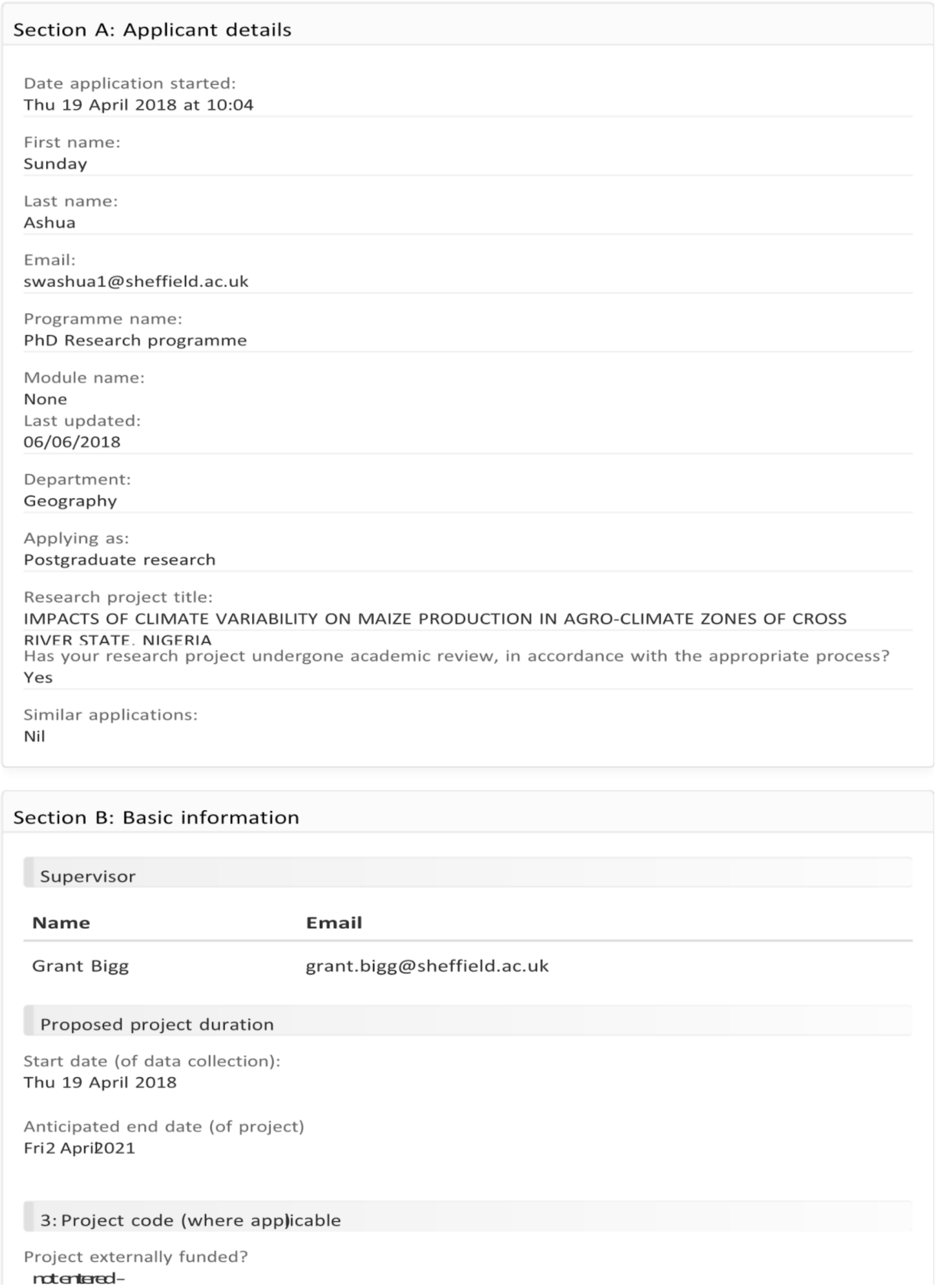
No	Items	Strong Agreed	Agreed	undecided	Disagreed	Strongly Disagreed
26	Years of experience as a farmer is the basis for your yield change/ adoption of strategies					
27	Level of education affects adoption of improve yield adaptation strategies					
28	Household size increases the chances of adoption of improved measures and yield					
29	Access to farm credit enhances yield and acceptance to vary strategies to climate change					
30	Low-income limit yield and your acceptance of new technologies to farming					
31	Awareness by extension workers promotes yield and your acceptance of adaptation strategies					
32	Land tenancy influences yield and your chances of change in farming techniques from perceive climate change.					
33	changes in rainfall influences yield and adoptions of strategies					

34	Political factor influences yield and the adoption of adaptation measures					
35	Size of land area own by farmers determines change in yield					

Appendix 4: Ethic approval letter

The
University
Of
Sheffield.

Application 018982



Section A: Applicant details

Date application started:
Thu 19 April 2018 at 10:04

First name:
Sunday

Last name:
Ashua

Email:
swashua1@sheffield.ac.uk

Programme name:
PhD Research programme

Module name:
None
Last updated:
06/06/2018

Department:
Geography

Applying as:
Postgraduate research

Research project title:
IMPACTS OF CLIMATE VARIABILITY ON MAIZE PRODUCTION IN AGRO-CLIMATE ZONES OF CROSS RIVER STATE, NIGERIA

Has your research project undergone academic review, in accordance with the appropriate process?
Yes

Similar applications:
Nil

Section B: Basic information

Supervisor

Name	Email
Grant Bigg	grant.bigg@sheffield.ac.uk

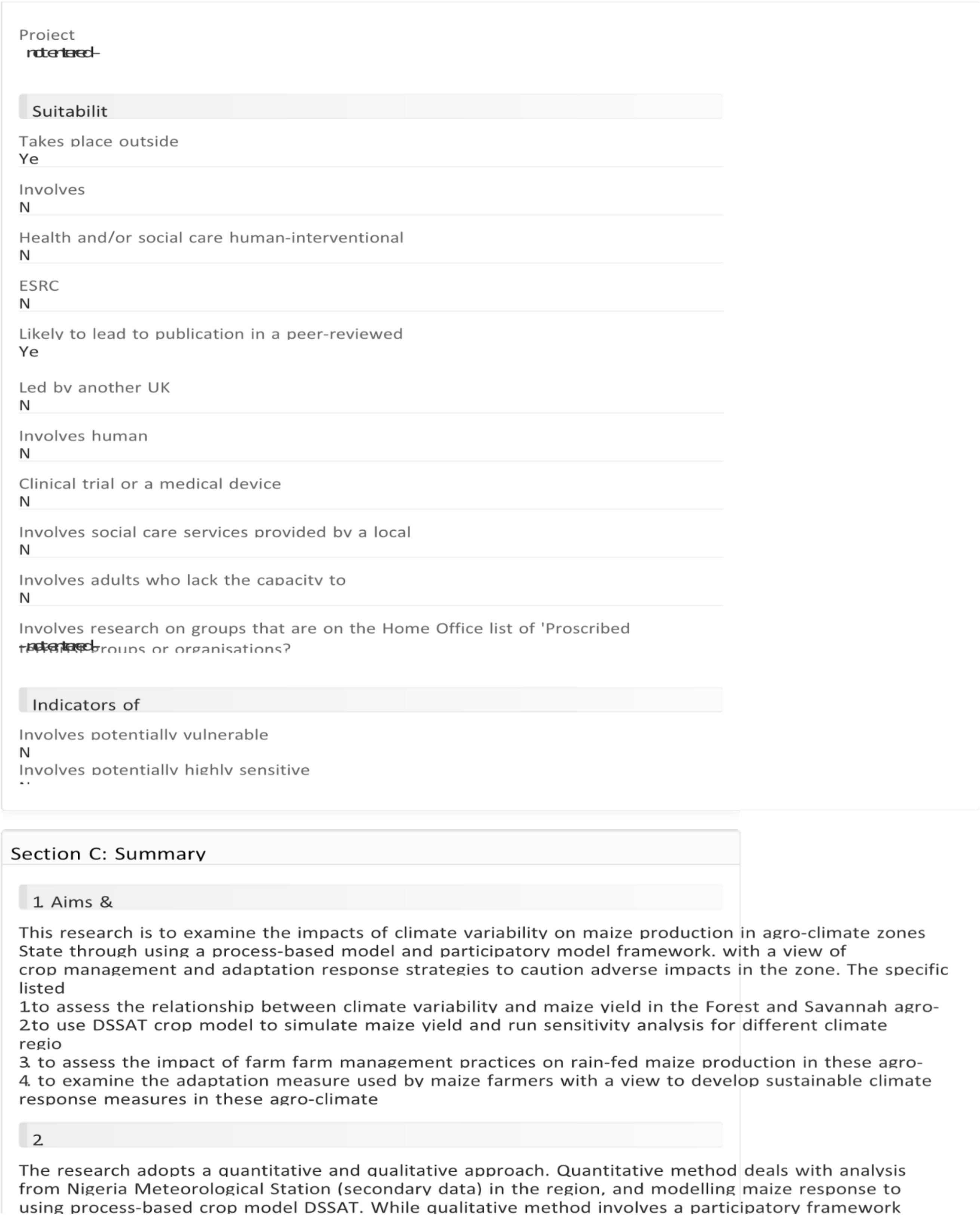
Proposed project duration

Start date (of data collection):
Thu 19 April 2018

Anticipated end date (of project)
Fri 2 April 2021

3: Project code (where applicable

Project externally funded?
not entered -



Project
- not entered -

Suitabilit

Takes place outside
Ye

Involves
N

Health and/or social care human-interventional
N

ESRC
N

Likely to lead to publication in a peer-reviewed
Ye

Led by another UK
N

Involves human
N

Clinical trial or a medical device
N

Involves social care services provided by a local
N

Involves adults who lack the capacity to
N

Involves research on groups that are on the Home Office list of 'Proscribed terrorist groups or organisations?
- not entered -

Indicators of

Involves potentially vulnerable
N

Involves potentially highly sensitive

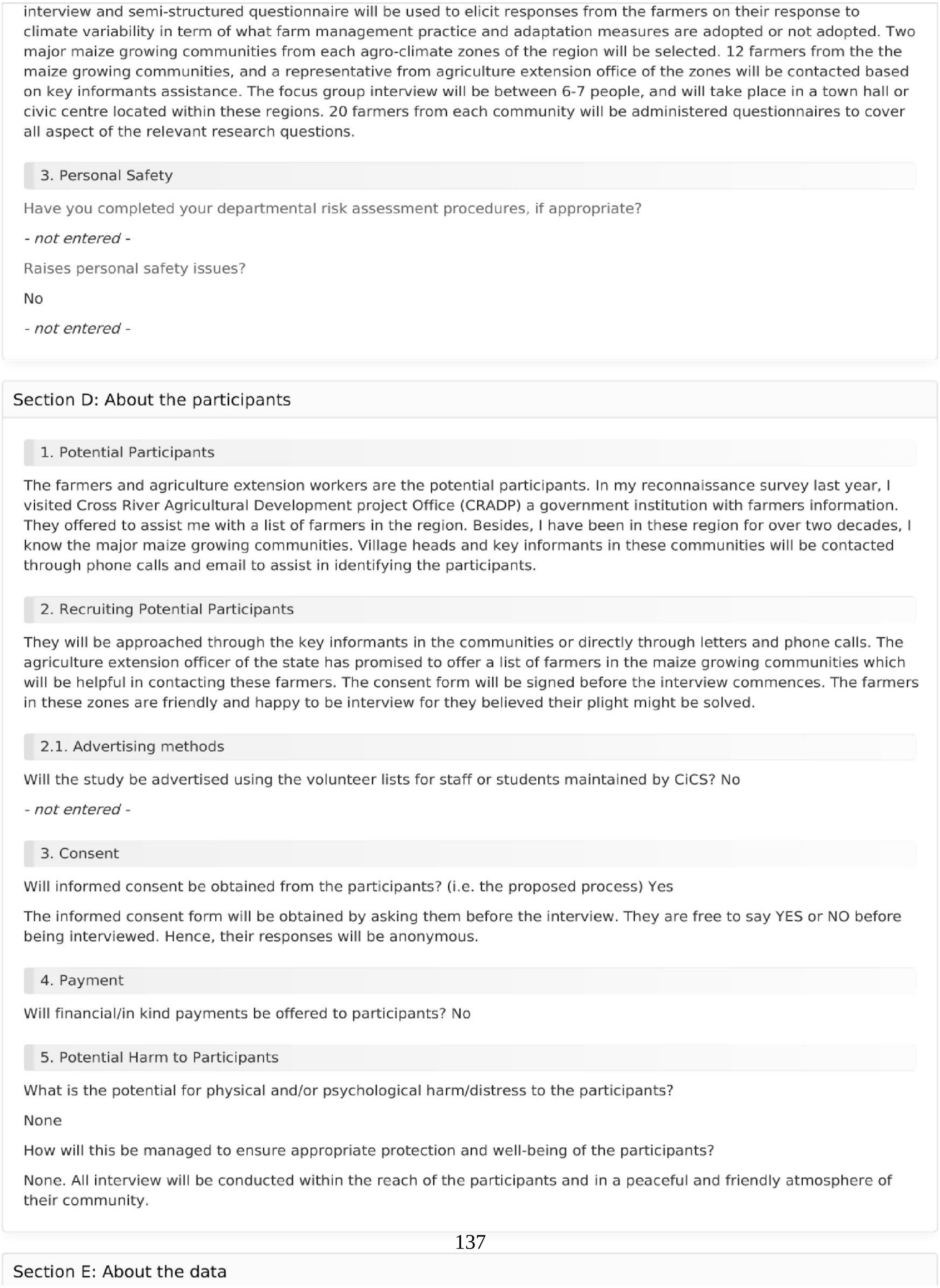
Section C: Summary

1. Aims &

This research is to examine the impacts of climate variability on maize production in agro-climate zones
State through using a process-based model and participatory model framework. with a view of
crop management and adaptation response strategies to caution adverse impacts in the zone. The specific
listed
1.to assess the relationship between climate variability and maize yield in the Forest and Savannah agro-
2.to use DSSAT crop model to simulate maize yield and run sensitivity analysis for different climate
regio
3. to assess the impact of farm farm management practices on rain-fed maize production in these agro-
4. to examine the adaptation measure used by maize farmers with a view to develop sustainable climate
response measures in these agro-climate

2

The research adopts a quantitative and qualitative approach. Quantitative method deals with analysis
from Nigeria Meteorological Station (secondary data) in the region, and modelling maize response to
using process-based crop model DSSAT. While qualitative method involves a participatory framework



interview and semi-structured questionnaire will be used to elicit responses from the farmers on their response to climate variability in term of what farm management practice and adaptation measures are adopted or not adopted. Two major maize growing communities from each agro-climate zones of the region will be selected. 12 farmers from the the maize growing communities, and a representative from agriculture extension office of the zones will be contacted based on key informants assistance. The focus group interview will be between 6-7 people, and will take place in a town hall or civic centre located within these regions. 20 farmers from each community will be administered questionnaires to cover all aspect of the relevant research questions.

3. Personal Safety

Have you completed your departmental risk assessment procedures, if appropriate?

- not entered -

Raises personal safety issues?

No

- not entered -

Section D: About the participants

1. Potential Participants

The farmers and agriculture extension workers are the potential participants. In my reconnaissance survey last year, I visited Cross River Agricultural Development project Office (CRADP) a government institution with farmers information. They offered to assist me with a list of farmers in the region. Besides, I have been in these region for over two decades, I know the major maize growing communities. Village heads and key informants in these communities will be contacted through phone calls and email to assist in identifying the participants.

2. Recruiting Potential Participants

They will be approached through the key informants in the communities or directly through letters and phone calls. The agriculture extension officer of the state has promised to offer a list of farmers in the maize growing communities which will be helpful in contacting these farmers. The consent form will be signed before the interview commences. The farmers in these zones are friendly and happy to be interview for they believed their plight might be solved.

2.1. Advertising methods

Will the study be advertised using the volunteer lists for staff or students maintained by CiCS? No

- not entered -

3. Consent

Will informed consent be obtained from the participants? (i.e. the proposed process) Yes

The informed consent form will be obtained by asking them before the interview. They are free to say YES or NO before being interviewed. Hence, their responses will be anonymous.

4. Payment

Will financial/in kind payments be offered to participants? No

5. Potential Harm to Participants

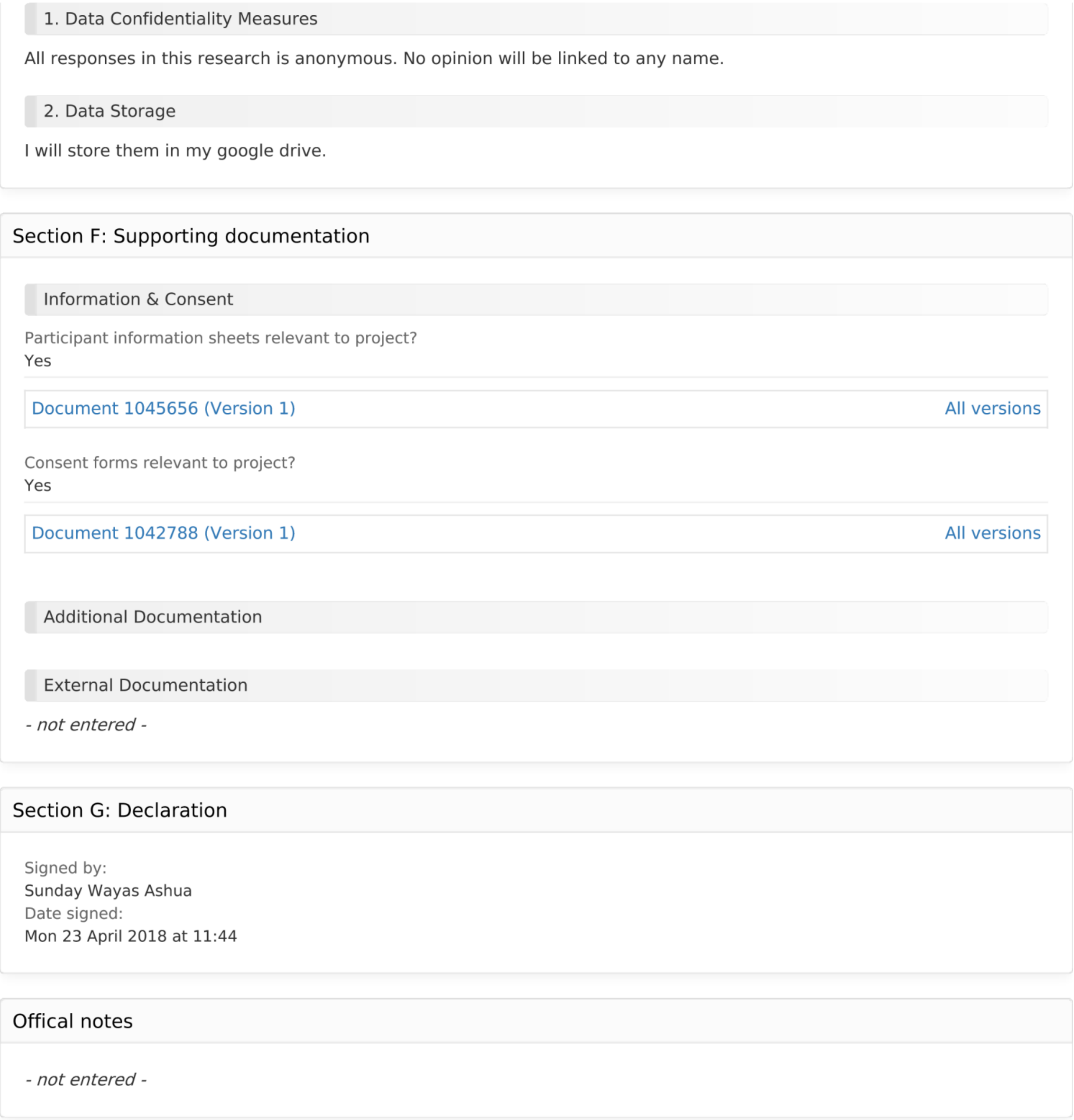
What is the potential for physical and/or psychological harm/distress to the participants?

None

How will this be managed to ensure appropriate protection and well-being of the participants?

None. All interview will be conducted within the reach of the participants and in a peaceful and friendly atmosphere of their community.

Section E: About the data



1. Data Confidentiality Measures

All responses in this research is anonymous. No opinion will be linked to any name.

2. Data Storage

I will store them in my google drive.

Section F: Supporting documentation

Information & Consent

Participant information sheets relevant to project?
Yes

Consent forms relevant to project?
Yes

Additional Documentation

External Documentation

- not entered -

Section G: Declaration

Signed by:
Sunday Wayas Ashua
Date signed:
Mon 23 April 2018 at 11:44

Offical notes

- not entered -

Appendix 5: Letter of introduction

The University Of Sheffield.

Department Of Geography.

Department of Geography
University of Sheffield
Winter Street
SHEFFIELD
S10 2TN

8 May 2018

Telephone: 0114 222 7905

Secretary: 0114 222 3601
Fax: 0114 279 7907
Email:
grant.bigg@sheffield.ac.uk

To whom it may concern

This letter is to confirm that Sunday Wayas Ashua is a PhD student in the Department of Geography of the University of Sheffield under my supervision. An important part of his research work on the effect of climate variability on maize production in Cross River State, Nigeria, is the collection of information from local authorities and farmers about their experience with respect to maize production. I therefore ask you to help Mr. Ashua with his research by providing information in either questionnaire or interview form as requested.

If you have any questions about Mr. Ashua's work, please feel free to contact me at the above address or email.

Yours sincerely,

Prof. Grant R. Bigg

Professor of Earth System Science