DOCTOR OF PHILOSOPHY

The development and validation of an integrated framework to predicate the influence of climate change on the efficacy of growing biofuels

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Award date:
2019

Awarding institution:
Coventry University

The development and validation of an integrated framework to predicate the influence of climate change on the efficacy of growing biofuels.

By

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February 2018

A thesis submitted in partial fulfilment of the University's requirements for the Degree of Doctor of Philosophy

Certificate of Ethical Approval

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Project Title:

Effect of future climate change on bioenergy crop yield

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Low Risk

Date of approval:

08 August 2015

Project Reference Number:

P35852

RESEARCH DECLARATION

I declare that this report is entirely my own work and that any use of the work of others has been appropriately acknowledged as in-text citations and compiled in the reference list. I also confirm that the project has been conducted in compliance with the University's research ethics policy.

Signed………………………… Date:

ACKNOWLEDGEMENTS

I am very grateful to my PhD Director of studies, Dr Leslie Duckers and his wife Kim Duckers, for their relentless support throughout my study. They kept cheering me on, as times got harder, always quick to provide insightful feedbacks, which expedited my research. Thank you so much for the support you gave all these years and a family to rely on.

I also appreciate my supervisors; Mrs Wendy Garner, and Dr Matthew Blackett for all the academic support and for believing in my ability to get the job done. Thank you.

Special thanks to the Nigerian Meteorological Agency (NiMet) for providing some climate data for my analysis.

I wish to thank Dr Akenroye for his assistance and my fellow postgraduate colleagues who were my immediate family here at Coventry University. Your support through good and challenging times was invaluable and made my postgraduate experience worthwhile. You are all acknowledged.

Special thanks goes to my friend turned sister Taiwo Sokoya for your sisterly support and making sure that this PhD is a success. Thank you for being selfless and looking out for me. To my beautiful sister Ameze Agenmonmen and family, the Adedayo family and many more, thanks for your love, support, affection and prayers. Further, the encouragement, support and prayers of my family and friends gave me the motivation to complete this PhD.

Finally, to the immortal, invisible, the only wise God who set this path before me and provided me a safe passage to completion, I give you all the glory Lord Jesus.

DEDICATION

To mum and dad of loving memories

Abstract

Climate change is regarded as the greatest threat to the World's ecosystem and hence to the sustainability of human life. Because anthropogenic emissions of greenhouse gasses are held largely responsible for the enhanced greenhouse effect, the international community has committed to reduce emissions, and in particular, to replace fossil fuels with low carbon renewable sources (COP 21 Paris agreement, 2015). Biofuel is a candidate technology, and the concept of growing energy crops represents significant opportunities.

This project aimed to examine the risk that climate change pose to the value of growing energy crops. The concern is that climate change could reduce yield sufficiently for the crop to give less energy than expected, and possibly less energy than was put into growing it, further increasing the carbon footprint. Clearly, this situation is unacceptable. In order to assess the overall energy balance and carbon footprint, farm practices; fertilizer application and tillage management were accounted in the overall life cycle assessment. Thus, this thesis reports the first fully integrated framework for the assessment of the impact of climate change on growing biofuels under various farm management practices.

Climate change impacts on yield varied depending on future GHG scenario pathway and timeline. The LCA results indicate that synthetic fertiliser application contributed the greatest percentage to the total GHG emission, averaging 57.7% of the total GHG emissions, of which 53.4% came from direct and indirect N_2O emissions and 4.3% from CO_2 emissions as a result of urea application. The remaining 42.3% of emissions came from input production (37.8%) and field operation (4.4%). Although increasing fertiliser application contributes to yield increase, the overuse of chemical fertilisers has a greater negative impact on the environment as the results indicate. In particular, the rate of fertiliser application is optimal at 160 kg per

hectare, and generally, this project has determined that yield is more sensitive to fertiliser than to climate change, whilst climate change is the causal driver for the increase in net energy and carbon footprint at most locations.

The integrated framework developed for this project has been validated and tested using maize, but can be applied to other biofuel crops provided that the proposed location has historical weather data, information about soil type and farm management details of the proposed crop type. Given the absolute importance of reducing carbon emissions.

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ACRONYMS AND ABBREVIATIONS

AFOLU	Agriculture, Forestry and Other Land Use
AEZ	Agro-Ecological Zones
AR5	Fifth Assessment Report
ARDL	Autoregressive Distributed Lag
APSIM	Agricultural Production Systems Simulator
ARC	African Rainfall Climatology
$CO(NH_2)_2$	Urea
COP 21	Conference of the Parties-21st conference
CH_4	Methane
CO_2	Carbon dioxide
CO_2-equiv.	Carbon dioxide equivalent
CDD	consecutive Dry Days
CWD	Consecutive Wet Days
CORDEX	Coordinated Regional Downscaling Experiment
CCS	Carbon Capture and Storage
CC	Climate change
CT	Conventional Tillage
CF	Carbon Footprint
CRU	Climatic Research Unit
CSAF	Crop Sustainability Asessment Framework
CERES-EGC	Crop Environment Resource Synthesis - Environnement et Grandes Cultures
CERES-Maize	Crop Environment Resource Synthesis-Maize
CERES-Wheat	Crop Environment Resource Synthesis-Wheat

COP21	21st Conference of the Parties to the United Nations Framework Convention on Climate Change
CMIP5	Fifth Climate Model Intercomparison Project
DAYCENT	Daily Century Model
DSSAT	Decision Support System For Agrotechnology Transfer
DSSAT-CSM	Decision Support System For Agrotechnology Transfer-Crop Simulation Model
DSSAT-Perturb	Decision Support System For Agrotechnology Transfer-Perturb
DNDC	DeNitrification-DeComposition
DSS	Decision Support System
DOE	Design of Experiment
EU	European Union
EF	Emission factor
EFM	Energy-Food Model
EIA	Environmental Impact Assessment
FU	Functional Unit
FAO	Food and Agriculture Organization of the United Nations
GWP	Global Warming Potential
GHG	Greenhouse gas
GCM	Global climate models
GYGA	Global Yield Gap Atlas
GDD	Growing Degree Days
g	gram
ha	Hectare
HCO^{3-}	Bicarbonate
ISO	International Organization for Standardisation

IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IBSNAT	International Benchmark Sites Network for Agrotechnology Transfer
IAMs	Integrated Assessment Models
IITA	International Institute of Tropical Agriculture
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
iLUC	Indirect Land Use Change
IRENA	International Renewable Energy Agency
IEA	International Energy Agency
IPAR	Incident Photosynthetically Active Radiation
LARS-WG	Long Ashton Research Station-Weather Generator
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LCI	Life Cycle Inventory
LAI	Leaf Area Index
kg	kilogram
K_2O	Potassium Oxide
MJ	Megajoule
ME	Marine Eutrophication
MATLAB	Matrix laboratory
NT	No Tillage
N_2O	Nitrous oxide
NH_3	Ammonia
NO_3^-	Nitrate
N	Nitrogen

NE	Net Energy
NH^{4+}	Ammonium
NIMET	Nigerian Meteorological Agency
OECD	Organisation for Economic Co-operation and Development
OH^-	Hydroxyl
P_2O_5	Phosphate
RMSE	Root Mean Square Error
USA	United States of America
UK	United Kingdom
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
USDA	United States Department of Agriculture
UDEL	University of Delaware
RCP	Representative Concentration Pathway
RT	Reduced Tillage
RUE	Radiation Use Efficiency
RCM	Regional Climate Model
RDA	Redundancy Analysis
RWS	Reference Weather Station
SRES	Special Report on Emission Scenarios
SCFs	Seasonal Climate Forecasts
SOC	Soil Organic Carbon
SDG	Sustainable Development Goals
TA	Terrestrial Acidification
WEC	World Energy Council

Chapter 1

1 INTRODUCTION

1.1 Background of study

Climate change has exacerbated the frequency of extreme weather events (Islam et al. 2012, IPCC 2014a, OECD 2015, Lopes and Machado 2018). Research shows that depending on the future path of World emissions, climate change will continue to have an increasingly negative impact on sustainable development (IPCC 2014). This impact will be felt to varying degrees around the World, but will be particularly important to food production and food security, especially evident within the managed ecosystems of food production, which are a pressing concern (OECD 2015, FAO 2016a).

The Intergovernmental Panel for Climate Change's (IPCC 2014) Fifth Assessment Report (AR5) averred that an increase in global greenhouse gas (GHG) emissions, with specific reference to the rapid increase observed between 2000 and 2010, has been largely anthropogenic; borne as a result of increased fossil fuel combustion, land use change (for example development of paddy fields with associated methane emissions), deforestation, agricultural practices (for example application of fertilisers) and cement production (IPCC 2014b, Tian et al. 2015, Houghton and Nassikas 2017). According to the IPCC (2014) report, global GHG emissions recorded between 1970 and 2010 displayed an increase of above 70%, with an annual emission growth rate increase of 1.0 $GtCO_2eq$ (2.2% increase) from 2000 to 2010 compared to 0.04 $GtCO_2eq$ (1.3%) per annum between 1970 to 2000. Global GHG emissions in 2017 was reported to be 40% higher than in 2000 (Olivier and Peters 2018).

Carbon dioxide (CO_2) from fossil fuel combustion and industrial processes is the largest contributing GHG (78%) and accounted for 76% (49 $GtCO_2eq$) of the total anthropogenic GHG emissions in 2010 (IPCC 2014c). In 2017, CO_2 remains the major GHG accounting for 73% of total anthropogenic GHG emissions (Olivier and Peters 2018). The IEA (2011) reported CO_2 emissions increased by 1.4% in 2011, reaching a record 31.6 $GTCO_2$ yr^{-1}. In 2017, energy-related CO_2 emissions reached 32.5 $GTCO_2$, which, according to the IEA (2018) is the highest increase, recorded in history.

Carbon dioxide emissions associated with energy production (predominantly in developed countries) dominate GHG emissions, followed by agricultural GHG emissions estimated at 11% of total global emissions per year (IPCC 2014c, Tubiello et al. 2015). Agricultural emissions are expected to rise the fastest in developing countries driven by expanding economies and total agricultural outputs (Wollenberg et al. 2016, FAO 2016a). An evaluation of global agricultural emissions data averaged over 2000-2010, revealed that 70% of total agricultural emissions from synthetic fertilisers came from developing countries (Tubiello et al. 2013). The FAO (2014) estimated that 13% of agricultural emissions in 2011 was from fertiliser application.

As the impact of climate change varies across regions and continents, there remains a level of uncertainty as to how future climates will respond to ever-increasing GHG emissions. Increase in climate variance have already been observed, and a radical shift outside of the historical bounds of climate variability is projected for tropical regions if nothing is done to curb emissions (Mora et al. 2013, IPCC 2007, 2014d, Harrington et al. 2016). To illustrate this, Mora et al. (2013) developed an index to determine the timing of climate shifts from the range of historical bounds using two model projection pathways (RCP 4.5 and 8.5). According to the Mora index, estimations showed that for near surface air temperature, climate departure - using current projections - will occur by 2047 under RCP 8.5 (Mora et al. 2013). With concerted rapid CO_2 mitigation however, climate departure would later occur by 2069 under RCP 4.5 (Mora et al. 2013). As a result of projections like these, the perceived threats of climate change to global stability continue to be sources of scientific and political concern, which should create a consensus to develop a mitigation strategy, which could prevent further global warming (UNFCCC 2016, IEA and IRENA 2017, Ricke et al. 2017).

Energy is essential for social, economic and environmental developments (Elum et al. 2017). Furthermore, fossil energy is finite and contributes to atmospheric pollution through the release of GHGs, which in turn promotes global warming. Aside from agricultural emissions, the IPCC estimated that in 2010, 14% (37.2 $GTCO_2eq$) of the total CO_2 emissions came from the transport sector and that 27% of the total global energy was used within this period (IPCC 2014c, Dick 2014). Interestingly, global demand for fossil energy is still projected to increase throughout the next century (IPCC 2014).

Earlier mention was made of the fact that developing countries contribute to climate change through agricultural practice however, in an attempt to accelerate economic development these countries are adopting a more carbon intensive mode (Malik et al. 2016). Thus increasing demand for non-renewable fossil fuels despite concerns over climate change, unstable oil prices, depletion of fossil reserves and energy insecurity giving rise to a global discussion on how to offset the deficit (Garba 2014, Dutta et al. 2014). Essentially, this demand could be partially offset by harnessing and developing renewable energy resources, a key route to achieving global temperature stabilisation (Viana and Perez 2013). In support of this, it is important to note that the International Energy Agency (IEA) reported that low-carbon energy technologies such as solar, wind and bioenergy have received much research and policy support in recent years (IEA 2017). This is exemplified by the fact that the work undertaken thus far is gaining momentum as the potential solution for future energy systems (IEA 2017). For example, renewables for the first time accounted for more than half of all new electricity generating capacity installed worldwide in 2015 (IEA 2017).

Bioenergy is a type of renewable energy derived from natural, biological materials (biomass) such as trees, plants, manure and municipal waste (Adams 2011). Using various conversion technologies such as combustion, gasification, or pyrolysis, the biomass is either transformed into biofuel for transportation, bio-heat or bioelectricity (Falano 2012). As a carbon-neutral renewable energy feedstock, if sourced sustainably, biomass is referenced as the fourth largest energy source after non-renewable coal, oil and natural gas (Ladanai and Vinterbäck 2009). Biofuel represents the only renewable energy source that can provide approximately 27% of the world's transport fuels (Souza et al. 2017). Because of this, bioenergy development is important from the perspective of climate change mitigation, energy security and rural economic development strategy (Hsu et al. 2010, Smith et al. 2014, Creutzig et al. 2015, UNFCCC 2016). It also offers the potential for reducing fossil fuel demand. For example, the replacement of conventional transport fossil fuels with biofuels has the capacity to reduce environmental pollution and mitigate CO_2 emissions (Elum et al. 2017).

However, on closer inspection there are sustainability issues that need addressing. For example, Warner et al. (2013) highlights that meeting the demands of approximately 25% of global transportation fuel with the sole use of biofuels by 2050 will require more than double the land used to meet food demands - assuming a 40% increase in food demand per capita. Also, bioenergy deployment can trigger the displacement of people, crops, pastures or forests and the clearing of more pristine land to replace displaced crops therefore causing a run on effect in terms of any environmental impact (Creutzig et al. 2015, Russo et al. 2016). Other concerns include resource competition e.g. water, food price hikes, the loss of biodiversity and increased

GHG emission from intense land use, in addition to human rights abuses, concentration of ownership and potential civil unrest.

Interest in biomass production for biofuels has increased over the last two decades and the focus has shifted towards sustainable feedstock development (Smith 2013, Dutta et al. 2014, Okoro et al. 2018). Biofuel is considered carbon neutral only if the production generates a net reduction in emissions (Creutzig et al. 2015). To determine the sustainability of the product, every aspect of its life cycle has to be considered. Nevertheless, according to Souza et al. (2017), there is growing evidence that bioenergy can be managed and produced sustainably. Souza et al. (2017) and Haus (2018) suggested factors that can significantly reduce GHG emissions from forest biomass production and use to include; adopting approaches such as agro-ecological zoning, best management practices, and the use of eco-hydrology and biodiversity-friendly agricultural management techniques at field, watershed and landscape scales are also suggested.

Fundamentally, there is a global scientific consensus that climate change will have an immense effect on agriculture (Alexander et al. 2018). This is because climate change alters weather conditions, and consequentially crop production becomes influenced by changes in atmospheric CO_2 concentrations, increased temperature and precipitation variability (Long et al. 2015, Atay 2015, Wang, J. et al. 2018). This subsequently has an impact on the timing and length of growing seasons, transpiration rates, water use efficiency, soil carbon and nitrogen biochemical transformations which ultimately results in biomass production disparities (Wang et al. 2014, FAO 2016a, He et al. 2018). The direct biophysical effects of the impact of climate variability on agricultural productivity is significant (Ventrella et al. 2012, Rosenzweig et al. 2014, FAO 2016a). The IPCC Fifth Assessment Report (AR5) on future projections post 2030 suggest that climate change will have an impact on crop yield which will become increasingly negative and severe in all regions (FAO 2016a, Alexander et al. 2018). Thus, assessing the ultimate consequences of these effects will require an integrated assessment approach (Nelson et al. 2014).

In terms of assessment approaches, many studies have documented the GHG mitigation potential of bioenergy systems using life-cycle assessments (Dale et al. 2013). For example, using this method, the total GHG emissions calculated from cassava-based ethanol production was 58.4 gCO_2 MJ^{-1} of the product compared to gasoline (94.0 gCO_2 MJ^{-1}) in Vietnam (Pirelli et al. 2018). The relevance of an LCA is evidenced by the fact that it is the scientific evaluation method of choice used to measure the net environmental burdens associated with producing products such as biofuel (Carus 2017). Haus (2018) utilised a life cycle perspective to analyse climate impact of the production and use of biomass for biofuel.

Crop yield responses to climate change have been and can be analysed using different approaches such as coupling climate to crop models (Wang et al. 2014, He et al. 2018), coupling crop-climate models to economic models (Nelson et al. 2014, Atay 2015, Okoro et al. 2017) and coupling crop-climate to economic and environmental models (Zimmermann et al. 2017). According to Nelson et al. (2014), a major criticism and the implication of a stand-alone crop-climate model assessment is that it may underestimate the capacity to respond to climate impacts. Although Nelson et al. (2014) advocate that the assessment of climate change impacts should include use of integrated assessment models such as climate, crop, and economic models, studies have also featured environmental impact models within the framework (Garba 2014, Nelson et al. 2014, Zimmermann et al. 2017, Arvesen et al. 2018).

Further to an integrated approach to assessment, Zimmermann et al. (2017) quantified climate change impact on crop yield, using an integrated assessment modelling (IAM) framework, coupling three disciplinary models (crop, economic and environmental) by linking model outputs. In support of this, Arvesen et al. (2018) describes the benefits of integrating LCA results in impact assessment modelling as accounting for direct and indirect emissions of technology and scenario alternatives. This is exemplified further in the work undertaken by Garba (2014) who also utilised integrated modelling to study the impact of climate change on GHG emissions of biofuels. However, although the analysis compared GHG emissions from beginning to end, the main weakness of the study was the failure to address why farm level GHG emissions were estimated using generic eco-invent data and synthetic climate change scenarios, instead of more plausible GCM downscaled data. In addition to this, none of the studies reviewed conducted a statistical comparison of the environmental impact against climate change scenarios and varying farm technologies. In contrast, Nelson et al. (2014) statistically quantified the contributions of several sources of variations for each environmental and economic response variable, while Zimmermann et al. (2017) did not attribute the environmental changes to the effect of climate change or any assumptions about crop management during their study. This shows a serious limitation in terms of previous studies.

From the foregoing discussion, there is a knowledge and information gap in terms of integrated assessment analyses that evaluate a holistic combination of factors influencing key environmental impact variables. Understanding environmental impact holistic responses to future climate change and farm management techniques, and the significance of each contributing variable, is key to providing factual and robust support when strategic decision making. With regards to this and due to lack of systematic quantification with the contribution of different factors (e.g. climate change and farm management) to the variability of yield and environmental impact, within the context of assessing climate change and the impact on bioenergy systems; this study will help to address this gap in knowledge. More specifically, this study proposes coupling a regression model with an impact chain, to quantify the effects of climate change and farm management on yield, and environmental variables using a modified integrated impact assessment framework.

1.2 Research Rationale

It is expected that farmers' response to reduced yield due to climate change will be through intensive farming practices, such as increased application of fertilisers, will further increase GHG emissions and the carbon footprint of bioenergy at the cultivation phase (Zimmermann et al. 2017, Maharjan et al. 2018). For biofuel to be certified as ethical, sustainable intensification of the farming process should be adopted to produce higher yields with lower environmental costs (Smith 2013, Smith et al. 2014).

The process of growing feedstock for biofuels contributes to climate change by producing GHGs such as carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) (Hanaki and Portugal-Pereira 2018, Pirelli et al. 2018). In turn, climate change can directly or indirectly influence these GHG emissions from agriculture, thus compounding the sustainability assessment (Ekpenyong and Ogbuagu 2015, Zimmermann et al. 2017). The majority of the life cycle impact assessment on bioenergy crops, assuming current or historical climate timelines, while critical information regarding the dynamic pattern of a life cycle environmental impact response to exogenous factors, such as climate change, is limited. Aside from climate change, other factors such as farm technologies, energy input and transportation can also contribute to agricultural GHG emissions. Therefore, it is imperative to quantify the effects of climate change and farm management practices on future agricultural emissions using an integrated approach.

1.3 Research aim and objectives

The overall aim of the study is to propose an integrated framework for assessing energy crop sustainable production under climate change. By applying an integrated framework, it is possible to extrapolate GHG emissions from farming trends under future climate scenarios and assess any significant contributions to the environmental impacts.

In view of the stated aim, the objectives listed below will be considered in addressing the aim and research questions:

- To generate long-term synthetic time-series from observed climate data and to construct future climate scenarios from an ensemble of Global Climate Models (GCM) downscaled for site-specific crop-climate impact analysis.
- To model and assess the future impact of climate change on maize feedstock yield under varying farm management strategies by considering two RCP scenarios.
- To use LCA to evaluate the environmental impact: GHG emissions, net energy use (including energy use efficiency) and carbon footprint of producing maize feedstock under future climate and farm management scenarios.
- To incorporate a regression model to examine the relationships (correlations) between variables and LCA outputs and identify any significant contribution to yield and environmental impacts.
- To develop an integrated framework consisting of climate-crop models, life cycle assessment (LCA) methods and a regression model coupled with LCA that will holistically assess the sustainability of bioenergy cropping systems. In order to validate the integrated framework, it was applied to the study of maize feedstock.

1.4 Research questions and hypothesis

This study postulates that GHG emission and carbon footprint of bioenergy crop production will increase significantly due to climate change and intensive farm practices for example increased fertiliser application. This study aims to explore the following research questions:

- What is the potential impact of climate change on maize feedstock yield using site-specific downscaled future climate scenarios?
- Under different farm management and climate change scenarios, what are the effects on GHG emission, net energy use and the carbon footprint of maize feedstock?
- What is the correlation between input variables, yield and environmental impact responses; and what factors influence yield and environmental impact the most?

1.5 Research significance and contribution to knowledge

Recent studies to measure maize feedstock sustainable production lack a holistic approach by not assessing changes to environmental responses due to future climate change impacts and farm practices (Oriola and Oyeniyi 2017, Arrieta et al. 2018, Corbeels et al. 2018). Therefore, comprehensive long-term Government policies and farm planning are needed to improve maize feedstock production and management practices under climate change.

The main areas of research in this thesis are:

- A generic integrated framework to assess the sustainability of bio-feedstock production using climate scenarios as indicators of future climate change.
- The integration of a regression model with LCA outputs.

1.6 Thesis Structure

This thesis consists of six chapters.

Chapter 1 presents the research background and the research aims and objectives.

Chapter 2 reviews literature on climate change and adaptations; climate change mitigation, the potential of biofuels, policies for rapid development and the projection of future climate impacts on bioenergy sector. In this chapter, a comprehensive report is presented on climate-crop model uncertainty and applications on a local scale. A life cycle impact assessment of bioenergy feedstock production is also included in the report.

In Chapter 3, the Crop Sustainability Assessment Framework (CSAF), which forms the framework applied in the research, is introduced. The development of the climate-crop model simulation and LCA-linear regression modelling approach are explained in detail in this chapter.

Chapter 4 is divided into two sections and report the results of the climate-crop model simulation and LCA-linear regression modelling data. In the first part of this chapter, downscaled GCM projections for two representative concentration pathways (RCPs 6.0 and 8.5) are evaluated followed by crop yield (kg ha^{-1}) to estimate the impact of farm management scenarios and climate change. In the second section of this chapter, the preliminary analysis of the GHG emission, carbon footprint (CF) and net energy (NE) assessed from LCA is presented, as well as regression modelling results of different factors on the LCA outputs is analysed.

Chapter 5 is used to discuss the results obtained from previous chapter. Here, the results are compared with outputs from similar studies and the implications of the results on future sustainability of bioenergy crop production are evaluated in detail.

Finally, Chapter 6 is used to draw conclusions on the research findings, and hence make recommendations for biofuel strategies and farm management practices and then to suggest directions for future research.

Chapter 2

2 Literature Review

2.1 Introduction

According to IPCC warnings on climate change, issued against the backdrop of global extreme climate events (IPCC 2014b, Lopes and Machado 2018), the level of accumulated heat energy over the Earth's surface plays a key role in observed and unprecedented changes in terms of climate trends. Based on IPCC (2014b) data, global climate temperature is predicted to undergo an increase of up to more than 2°C over pre-industrial levels in the coming decades. As the changes in global warming will not be uniform across regions (IPCC 2014b, 2014d), some continents and regions will experience greater global warming thus becoming more vulnerable to the impacts of climate change than others. With reference to this, the most recent report, known as the Fifth Assessment Report (AR5) by the Intergovernmental Panel on Climate Change (IPCC 2014) gives a robust insight into observed climate variability and change, with representation using climate models and future projections (Van den Hurk et al. 2014, IPCC 2014b). These effects are evidenced by thermal expansion of the Earth's surface waters, melting of glaciers causing rising sea level, flooding, drought, land loss, acidification of water bodies due to CO_2 emissions, saltwater intrusion and the destruction of agricultural lands as a few of the impacting factors (Houghton 2011, Atay 2015, Elum et al. 2017, Lopes and Machado 2018). Because of this, there is increasing concern that climate change poses a threat to global sustainable development.

The agricultural sector is significantly affected by climate change and extreme weather events with the impact varying widely by region (Ventrella et al. 2012, Rosenzweig et al. 2014, Nelson et al. 2014, FAO 2016a). According to Lesk et al. (2016), about one-quarter of climate related damage and crop losses have occurred in developing countries. Further to this, a study by the FAO (2016a) estimated that between 2003 and 2013, about 25% share of the economic impact of climate-related disasters within developing countries were felt in agriculture. As a result, a significant number of studies have documented that the impacts of climate change, especially increasing temperature, have had a largely negative as opposed to positive effect on crops such as wheat, rice and maize amongst others across regions (Ringler et al. 2010, Asseng et al. 2011, Lobell et al. 2011, Rosenzweig et al. 2014, FAO 2016a, Chen et al. 2018). In addition, studies show that climate change could potentially cause a shift in crop suitability to occur, as the climate gets warmer (Rippke et al. 2016). Therefore, urgent adaptive measures such as mixed farming, irrigation to prolong suitability and planting of alternative viable substitutes in many locations are needed in order to mitigate the impact of further climate change on crop productivity.

This review of literature seeks to focus on climate change and its potential impact on agriculture, as well as the assessment of sustainable bioenergy crop production through a life cycle assessment framework. Specifically, a review of historical climate and future climate change projections for Africa and the impact on crop production is presented in sections 2.2 to 2.4. Section 2.5 highlights strategies for climate change mitigation, while sections 2.6 to 2.7 discusses critical issues affecting biofuel sustainability and bio-feedstock availability in Nigeria. Section 2.8 describes the various methods used for assessing climate change impact on crop yield, and the review of an integrated assessment approach. Specific emphasis on life cycle assessment as an important tool is reviewed in sections 2.9 to 2.10. Finally, previous approaches that have attempted to integrate LCA with regression are discussed in section 2.11 and the review outcome and knowledge gaps are summarised in section 2.12.

2.2 Historical impacts of climate change on the sub-Saharan region

Climate change poses the greatest risk to the economies of developing countries that are largely driven by rain-fed agriculture (Atay 2015, FAO 2016a, Magugu 2016, Girvetz et al. 2019). This is particularly important because many studies including the IPCC (2014b) indicate that surface warming in Africa is highly likely to be larger than mean warming globally (Knox et al. 2012, Achike and Onoja 2014). With reference to this, the latest climate projections from the IPCC Fifth Assessment report (AR5) predict a delayed monsoon rain, especially in the western part of the Sahel, with increased adverse warming that will further compound the issue of the global warming impacts within this region of Africa (IPCC 2014d, Sylla et al. 2016). The impact of climate change on such regions as those that are located in as close proximity to the equator will be more significant and could increase in magnitude if no action is taken to reduce global GHG emissions (Singh et al. 2018).

According to Turco et al. (2015) and Welborn (2018) this is particularly so within the Sahel and sub-Saharan African region which have both been identified as hotspots for climate change. These regions have witnessed extreme weather-related incidents, including severe droughts, flooding and rising temperatures which have increased as a result of the direct influence of higher levels of anthropogenic greenhouse gases in the atmosphere, affecting the region's agricultural productivity and raising food security risks (Sheelanere and Kulshreshtha 2013, Dick 2014, IEA 2017, Masipa 2017). Due to the variability in annual monsoon rain, the frequency of extreme precipitation has resulted in increased ocean storminess (severe storm waves), a rise in sea levels and an increase in soil salinity around coastal areas; making farmland in such areas unproductive (Fitzmaurice 2014, Singh et al. 2018).

The uncertainties associated with regional climate change are challenging in terms of the production of reliable scenarios for the adaptive planning of future agricultural production (Sultan et al. 2014). Previous assessment of historical and future climate change over the West Africa region including the Sudanian and Sahelian regions have also shown this (Biasutti 2013, Monerie et al. 2013, Sultan et al. 2013, Alemaw and Simalenga 2015, Sylla et al. 2016, Ekwezuo et al. 2018).

In 2016, Sylla et al. examined both historical temperature and precipitation change over West Africa from 1983 through 2010. This systematic report considered two of three observed datasets, which had the similar grid resolution of 0.5° × 0.5° (University of Delaware (UDEL) and the Climatic Research Unit Anglia (CRU) of the University of East Anglia). The remaining grid resolution for the third dataset, as per the African Rainfall Climatology (ARC), had a resolution of 0.1° × 0.1°. The dataset presented in Figures 2.1 and 2.2 represents these seasonal averages from May to September and shows historical temperature from UDEL and CRU with a clear warming trend within the range of 0.2 °C to more than 0.5 °C per decade; a trend of great significant for countries around the west Sahel and Gulf of Guinea.

Furthermore, similar warming trends have been reported by the IPCC (2014) and are consistent in terms of aligning with observations of 0.5 °C and 0.8 °C for west Africa and the Sahel between 1970 and 2010 (Niang et al. 2014). This shows that overall, temperatures have risen considerably over the last 50 years (Niang et al. 2014); and Girvetz et al. (2019) highlighting the fact that 19 out of the past 20 years have been hotter than any previous year on record in Africa. As a direct result of this, increasing temperatures have resulted in higher rates of evapotranspiration. So, for example, data from 2001 to 2017 shows a consistent increase in evaporative stress in Zambia between the years 2001 to 2017 (Girvetz et al. 2019). Put simply, hotter temperatures are gradually becoming the new normal and there is strong evidence of anthropogenic signals associated with the increase in temperature across the continent (Niang et al. 2014).

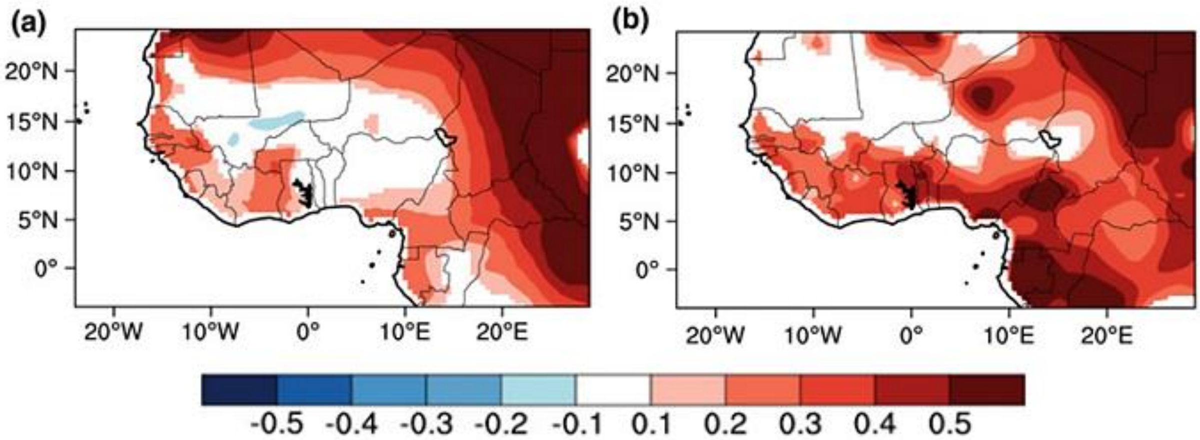

Figure 2.1: Average seasonal temperature trends (May– September) over West Africa climate for the period 1983–2010. Area where the trend is statistically significant at the 90 % level are shaded. (a) UDEL; (b) CRU. (Source: Sylla et al. 2016)

As shown in Figure 2.2, a tendency for increasing precipitation of approximately 0.2–1.0mm/day per decade was observed for countries along the Sahel band, with the exception of the orographic regions and part of the Gulf of Guinea; which displayed negative trends. Nevertheless, the precipitation pattern for all three data sources is similar (UDEL, CRU and ARC), making the positive precipitation signal a robust one (Sylla et al. 2016). The positive trend observed is consistent with other observations of rainfall increase since drought episodes, such as those which occurred during the late 1960s to mid-1980s – a period marked by a steep precipitation decline (Birkel and Mayewski 2015, Niang et al. 2014).

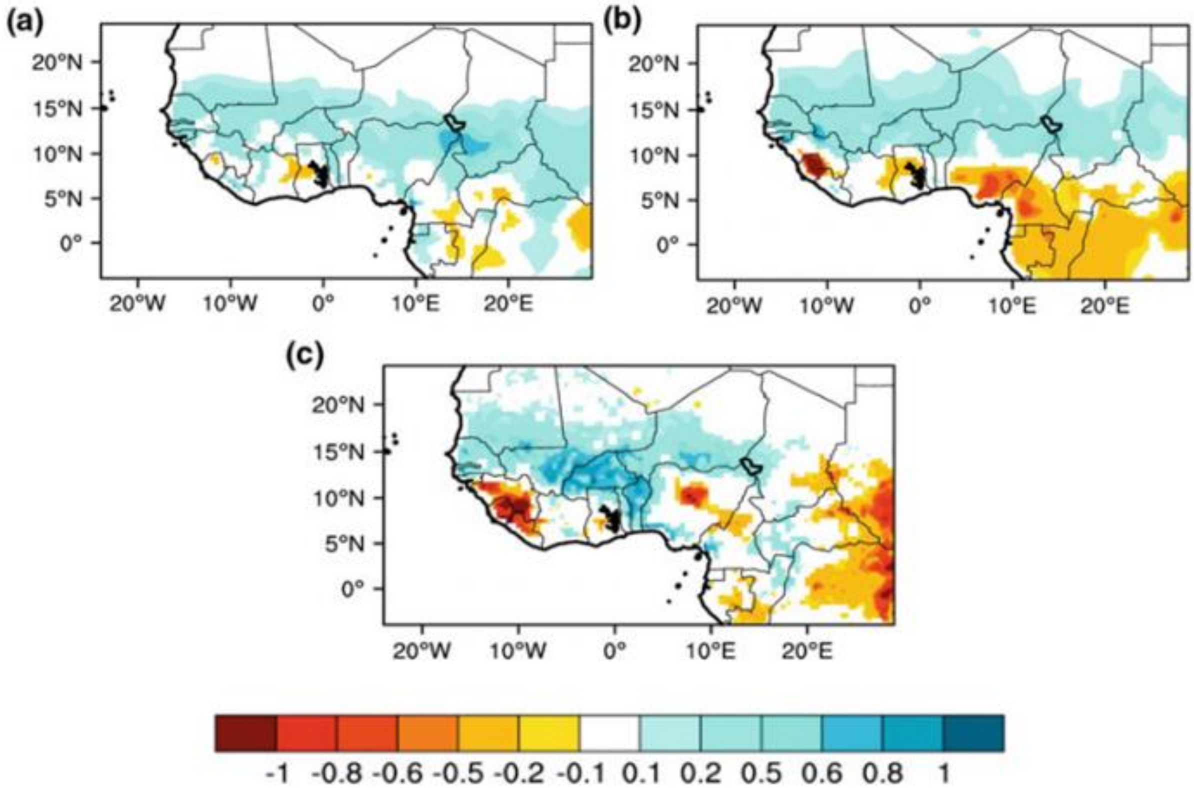

Figure 2.2: Average seasonal precipitation trends (May– September) over West Africa climate for the period 1983–2010. Area where the trend is statistically significant at the 90 % level are shaded. (a) UDEL; (b) CRU (c) ARC. (Source: Sylla et al. 2016)

Although wetter conditions have been reported as a sign that the Sahel region is recovering from its worst ever drought (Druyan 2011), some reports state otherwise. Nicholson et al. (2018) reported on the longest rainfall series (from 1854 to 2014) for thirteen African regions and their analysis revealed that rainfall recovery has been minimal; above the long-term mean from 1968 to 1993. The result also showed an average standardised departure of -0.08 for the years 1993 to 2014 suggesting the region has not fully recovered from the rainfall regime that prevailed during the late 1960s in Sahel prior to its pre-drought conditions.

In 2019, Girvetz et al. published a paper in which they observed that changes in precipitation across Africa vary significantly. They discussed the fact that Zambia and Zimbabwe showed a significant decrease in precipitation, in contrast to an increase in rainfall across South Africa and some parts of East and North Africa. Further to this, Agumagu (2016) observed that the West African Sahel region was characterised by a trend of dryness during the 20th century and then subsequently by multi-decadal dry and wet influences in more recent times. This is exemplified in the work undertaken surrounding this trend as obtained from a synthesis of 100 years of climatology (1910–2009) based on observed climate data from Global Precipitation Climate Centre (GPCC) and Climate Research Unit (CRU) dataset (Agumagu 2016). From the data, a high annual and decadal rainfall variability was observed and Agumagu (2016) noted that the change over the region could be viewed as a characterisation of the weather dynamics of the Sahel region.

Some of the issues preventing a thorough understanding of current climate trends, and as a consequence impede climate change strategic planning include the quality and availability of observed data, the variability in data sources and the imprecise nature of observational records (Niang et al. 2014, Sylla et al. 2016, Agumagu 2016).

2.3 Future climate change projections on the sub-Saharan region

In climate change assessment, scenarios are used to explore alternative futures based on model representation of historical patterns. Climate scenarios can be defined as a plausible representation of future climates constructed from the assumptions of climate system responses to GHG-induced warming (Moss et al. 2010, Kirtman et al. 2013, Snover et al. 2013). Climate scenarios are used to create presumptive emission levels of GHG concentrations and land use change scenarios; which are highly unpredictable largely due to human activity. Climate scenarios can be generated using different methods, such as an analogue or synthetic approach

(McAfee et al. 2017), but using outputs from GCMs make climate impact studies more plausible (Vano et al. 2015).

The IPCC developed a series of climate scenarios known as representative concentration pathways (RCPs), quantified according to changes in radiative forcing over time (van Vuuren et al. 2011). The scenarios are designed to support research on impacts and potential policy responses to climate change. Due to this, they were used for the IPCC Fifth Assessment Report (AR5) and the Fifth Climate Model Intercomparison Project (CMIP5) (Riahi et al. 2011, Taylor et al. 2012). In terms of the process of model specification, radiative forcing measures the imbalance between incoming and outgoing radiation to the atmosphere caused by changes in atmospheric greenhouse gases (Moss et al. 2010, Haus 2018). This means that RCP 2.6 is consistent with the goal of reducing GHG emissions (mitigation scenario) and keeping global warming at less than 2 °C above preindustrial levels (FAO 2016a). In the RCP 2.6 scenario (~490ppm CO_{2eq}), radiative forcing peaks at ~3 W/m^2 and declines thereafter to 2.6 W/m2 by 2100, as GHG emissions are reduced substantially (Wollenberg et al. 2016).

The RCP 4.5 and RCP 6.0 scenarios are two medium stabilisation scenarios with concentration of ~650ppm and ~850ppm CO_2-equivalent respectively. In the RCP 4.5 scenario, radiative forcing stabilises at 4.5 W/m2 shortly after 2100, without overshooting the value. This scenario assumes that climate policies are implemented to attain emission reduction and radiative forcing (Thomson et al. 2011). In the RCP 6.0 scenario, radiative forcing stabilises without an overshoot pathway at 6 W/m2 by 2100 (van Vuuren et al. 2011).

According to Riahi et al. (2011), RCP 8.5 is the mid-21st century scenario, which corresponds to the pathway with the highest GHG emissions. Otherwise known as the 'baseline scenario,' the radiative forcing rises to 8.5 W/m2 by 2100, as GHG emissions continue to increase with no effective mitigation put in place to change current emission trajectory (Li, Y. et al. 2015, Haus 2018). It is projected that this pathway will in the long-term lead to higher energy demand and GHG concentration (a concentration of more than 1,370 ppm CO_{2eq}). Adeniyi (2016) reported that the direction of projected precipitation changes across five regional domains of West Africa under RCP 4.5 (medium) and RCP 8.5 (high) scenarios are almost the same.

The complex interaction between the ocean-atmosphere-sea and ice-land-surface relationships are represented in global climate models (GCMs) and simulated based on a three-dimensional grid over the globe (Lapp et al. 2009). The accuracy with which GCMs reproduce historical climate features and climate changes have increased the confidence of its use to make projections for the future (Taylor et al. 2012). In terms of a study based on this, Ramirez-Villegas et al. (2013) assessed regional differences in seasonal GCM skills. What was noted was that outputs from GCMs cannot be applied directly to impact models at a regional and local scale, due to the coarse resolution and inherent systematic errors (bias), producing inaccurate reproduction of weather statistics including extreme events (Iizumi et al. 2012). Another source of climate impact uncertainty arose from large variations in simulation results amongst multiple GCMs, or the same GCM with different radiative forces (Li and Ye 2011). Thus although climate information from a combination of model ensembles gives a plausible range of eventualities, model selection based on performance is usually constrained due to the large spread of projections from GCMs, and by factors such as the availability of data from models or limited resources for in-depth strategic selection (McSweeney and Jones 2016).

The Coupled Model Inter-comparison Project (CMIP) has, over the years, been the source of key model simulations that have been used in most studies for future climate projections (White et al. 2011, Taylor et al. 2012, Ramirez-Villegas et al. 2013). Its validity is evidenced as the latest release of the CMIP5 (phase 5) GCM model ensemble was adopted for the IPPC Fifth Assessment Report (AR5). Further to this, recent studies have used the Coupled Model Inter-comparison Project Phase 5 (CMIP5) multi-model simulations to determine temperature and precipitation projections over different parts of West and Central Africa (Giannini et al. 2013, Laprise et al. 2013, Roehrig et al. 2013, Biasutti 2013, Mehran et al. 2014, Dike et al. 2015, Adeniyi 2016, Klutse et al. 2018, Diedhiou et al. 2018, Girvetz et al. 2019).

Researchers such as Diedhiou et al. (2018) and Klutse et al. (2018) have examined the effects of changes in regional temperatures and precipitation extremes, based on a 1.5 °C and 2.0 °C global mean temperature change. Diedhiou et al. (2018) confirmed a linear increase of regional temperature with a global mean temperature increase. Diedhiou et al. (2018) also confirmed that larger regional warming is predicted to be highly likely. For example, GCM projections of global warming of 1.5 °C (2.0 °C) induced a regional temperature increase of 1.7 °C (2.3 °C). This is almost consistent with additional regional warming of 0.4 °C and 0.8 °C induced by 2.0 °C global warming as reported by Klutse et al. (2018). In addition, Diedhiou et al. (2018) stated that extreme annual temperature of maximum and minimum daily temperature is projected to increase at higher magnitudes. Similarly, Niang et al. (2014) noted that the expected increase in near surface temperature is projected to rise faster in West Africa: one to two decades earlier than the global average. According to Girvetz et al. (2019), the CMIP5 multi-model simulations based on the RCP 8.5 temperature trajectory for Africa would be 1.7 °C by the 2030s, 2.7 °C by the 2050s and 4.5 °C by the 2080s above pre-industrial levels. Niang et al. (2014) also earlier reported projections of 3 °C and 6°C under RCP 4.5 and RCP 8.5 scenarios for West Africa by the end of the 21st century.

There is a consensus among research undertaken that precipitation change is more difficult to model, compared to temperature change (Giannini et al. 2013, Ramirez-Villegas et al. 2013, Sylla et al. 2016, Girvetz et al. 2019). Klutse et al. (2018) examined the regional risks for West Africa if global warming increases of up to 1.5 °C and 2.0 °C from the RCP 8.5 climate scenario were measured. Compared to a control period between 1971–2000, they evaluated the response of extreme rainfall characteristics such as consecutive dry days (CDD) and consecutive wet days (CWD), to impacts of warming levels and reported an increase in CDD over the Guinea Coast; alongside a decrease in CWD (up to 4 days), at both levels of warming. Klutse et al. (2018) observed that the CDD distribution was similar at 1.5 °C and 2.0 °C global warming levels. Furthermore, Adeniyi (2016) evaluated the performance of an ensemble of 30 CMIP5 models in simulating precipitation from the Sahel to the Guinea coast of West Africa. The result show that the ensemble mean of CMIP5 models best captures the lower percentiles of precipitation distribution; compared to an observed dataset except over the eastern Sahel. This finding was similar to the findings of researchers Mehran et al. (2014).

With reference to the baseline climate (1985–2004), Adeniyi (2016) reported that both RCP 4.5 and 8.5 scenarios projected an increase in precipitation from 2035 to the end of the 21st century. However, the rate of change and intensity increase differed across the region. The only seasonal reduction in precipitation (-2.6 to -17 %) projected from 2035–2065 was in JFM (January, February and March); which according to Adeniyi (2016), would potentially delay the onset of rain and lead to crop failure.

Dike et al. (2015) presented a single GCM projection of future climate changes (2073–2098). The reported temperature change varied from 3 °C to 7 °C (a smaller magnitude for RCP 2.6 and higher warming for RCP 8.5), and a precipitation increase across Africa (with the exception of western Sahel). In addition, the study projected a wetter summer over five cities in Nigeria under the RCP 8.5 scenario. Although Dike et al. (2015) hinted that the HadGEM2-ES model output for precipitation and temperature was close to the CMIP5 multi-model ensemble mean in a comparative study, several factors could still create possible bias in terms of the results. For example, the projection was carried out using a single GCM (HadGEM2-ES) model with very low resolution, hence it was unsuitable for high resolution regional and country specific projections. Furthermore, the performance of the model in reproducing observation data (1901–2002) was evaluated for five cities in Nigeria: Kano, Ilorin, Uyo, Lagos and Owerri. The HadGEM2-ES-model underestimated the annual cycles of mean precipitation for Kano but had similar trends; the correlation coefficient for Ilorin and Lagos were below average (0.46 and 0.44); while the precipitation annual cycles in Owerri and Uyo were well represented by the model. The reanalysis dataset, which the model overestimated, may also have introduced bias (Dike et al. (2015).

Figure 2.3 below depicts the projected changes in total annual precipitation and temperature change for countries in Africa based on an ensemble of CMIP5 models (33 GCM models) guided by the RCP 8.5 scenario for 2050 (Girvetz et al. 2019). The chart shows that annual precipitation is projected to increase mostly across eastern and central Africa, and decrease across parts of southern, western and northern Africa.

Girvetz et al. (2019) acknowledged that GCM outputs resolution are coarse and needs to be bias-corrected by downscaling, hence the projections must be considered with caution.

Similar to the projections presented by Girvetz et al. (2019), Giannini et al. (2013) has also presented multi-model ensembles of CMIP5 projections for Burkina Faso, Niger and Senegal. There are a number of similarities between both studies as all projections point towards the possibility of a wetter trend for the Sahel. This signals the influence of greenhouse gas-induced warming (Giannini et al. 2013).

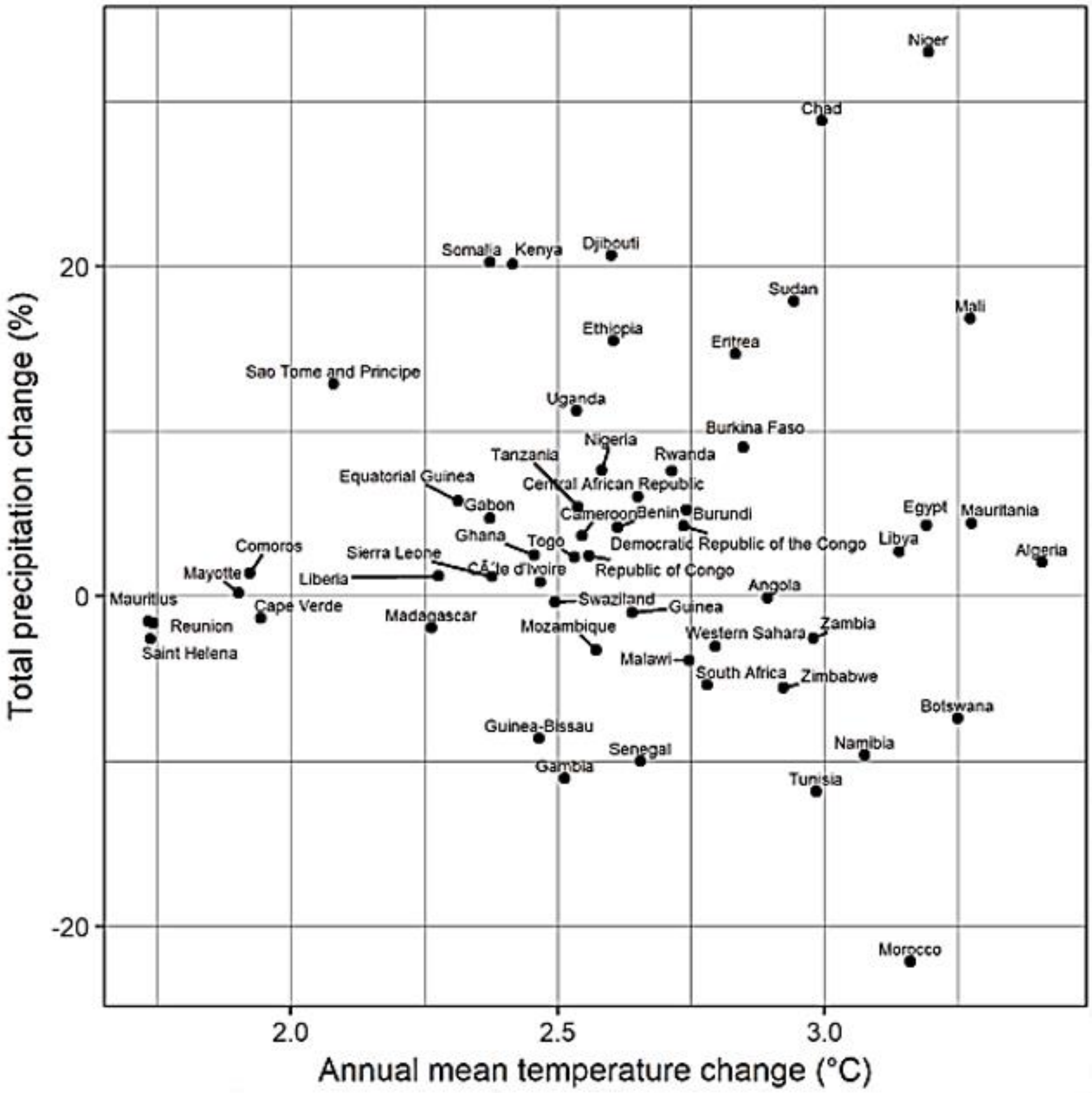

Figure 2.3: Average change in annual total precipitation (%) and mean temperature (°C), by country for the African continent (Source: Girvetz et al. 2019).

Although model agreement for the projections of precipitation varied and model bias still exists, the latest CMIP5 multi-model ensembles and projections confirm the expectations for the rest of the 21st century. All studies above used different climate models of varying resolutions at the regional scale: hence, the robustness of the simulations in terms of model agreements differed. For example, Klutse et al. (2018) reported 80% of model agreement, Diedhiou et al. (2018) observed a large model spread of precipitation and temperature whilst Adeniyi (2016) noted medium to high consensus amongst models. As indicated earlier, the use of single models as used in Dike et al. (2015) could be a source of uncertainty. The work of Klutse et al. (2018), shows it is better to downscale global climate model (GCM) outputs with regional climate models (RCM) in order to enhance the spatial and temporal information required at regional and local-scale level (Laprise et al. 2013). Laprise et al. (2013), Sylla et al. (2016) and Klutse et al. (2018) used downscaled RCMs from the Coordinated Regional Downscaling Experiment (CORDEX) for the West African domain.

2.4 Projected impact of climate change on crop yield

The IPCC fifth assessment report (AR5) estimated that over the last 30 years, global agricultural production has reduced by 1%–5% per decade of total production due to climate change (IPCC 2014b, Ramirez-Villegas and Thornton 2015). To investigate this, Lobell et al. (2011) used historical crop-trial dataset of 20,000 maize trials in Africa to understand climate impacts on yield. As a result, they observed that for every 1°C of warming (above 30°C), maize yield declined by 1%–1.7% under optimal rain-fed and drought conditions. In similar research, Schlenker and Lobell (2010) provided evidence on the relationship between climate variability and crop yield through statistical evaluation of historical crop production and climate data for sub-Saharan Africa. The report highlighted that all models predicted negative impacts of global warming for maize, sorghum, millet, groundnut and cassava. Leng and Huang (2017) however pointed that statistical approaches used in Schlenker and Lobell (2010): that assumed year-to-year distribution of crop is constant over time, could bias the result. By considering crop spatial distribution changes, Leng and Huang (2017) reported that the predicted decline of corn yield under climate change (20%~40%) was 6% to 12% less compared to results assuming a fixed cropping system thus obviating the previous study's limitation. Other studies have noted that the impact of climate variability on crop productivity is significant and the principal source of fluctuations in yield variability (Ventrella et al. 2012, Rosenzweig et al. 2014, FAO 2016a).

Diedhiou et al. (2018) and Klutse et al. (2018) have shown that a global mean temperature change of 1.5 °C and 2 °C could induce more regional warming across Africa, which will have significant long-term negative impact on crop yield. Recent studies based on the updated IPCC Fifth Assessment Report (AR5) have evaluated yield response to climate change, for the near future and towards the end of the century for Africa, guided by RCP scenarios (Knox et al. 2012, Tripathi et al. 2016, Parkes et al. 2018, Girvetz et al. 2019). As explained in Challinor et al. (2014), these studies (AR5) showed a greater risk of yield reductions at moderate warming compared to the Fourth Assessment Report of the IPCC (AR4). The studies evaluated below used different methods, scenarios and crop models to evaluate crop response.

Knox et al. (2012) carried out a meta-analysis of 52 studies that projected climate change impact on staple crops in Africa and Asia at a regional level. Their approach followed a systematic literature review that considered climate change projections up to the 2080s using GCMs. The aggregated dataset was categorised into sub-regional findings, and the mean yield result for West Africa (-12.5%) was close to previous findings. Maize yield change was estimated at -5% across Africa and a general conclusion was that yield productivity decreased with time as the climate signal (changes in the state of the climate system) increases.

The response of maize, millet and sorghum yield to climate change in West Africa is a major area of interest for Parkes et al. (2018). As an investigation, an ensemble of GCMs and RCMs were used that represent a 1.5 °C temperature change above pre-industrial levels, and four crop models to simulate yield under RCP 8.5 scenario. The adaptation measures implemented included using heat stress resistant varieties and rainwater harvesting. Results from the analysis showed that yield response was uncertain under 1.5°C temperature change, and the variation in crop models and farm inputs influenced the results. Further findings revealed that certain projected yields responded to CO_2 fertilisation effect. Parkes et al. (2018) further observed potential increase in yield and yield variability in Côte d'Ivoire and Nigeria, and concluded that rainwater harvesting was less effective as an adaptation method compared to using heat stress resistant varieties. This is because projected higher rainfall in future climates reduces the likelihood of water limiting crop growth. Wang et al. (2018) and Girvetz et al. (2019) suggested the improvement of cultivars such as drought tolerant and heat resistant varieties to mitigate climate change.

Tripathi et al. (2016) assessed the potential impact of climate change on some major crops such as maize, wheat, and rice via literature review, and presented the detailed physiological, biochemical, and phenological effects of climate change on crop growth and development. Similar to previous findings by Schlenker and Lobell (2010), the review concluded that climate change is affecting various aspects of the life cycle of crops and increasing temperature is negating CO_2 fertilisation effects on crop yield such as wheat. Tripathi et al. (2016) further reported that maize crop yields are more impacted compared to wheat and rice. From the foregoing discussion, there is a consensus that changes in temperature and precipitation will have implications for crop yield across Africa. Further research is needed to account for the projected yield reductions amongst studies. According to Dinesh et al. (2015), major crop productivity and climatically suitable areas in Africa are projected to decline by the 2050s under RCP 8.5 projection if no effective mitigation is put in place. For example, as shown in Figure 2.4, areas of suitability for the production of beans and maize could decline by 12%-40% relative to the period 1970-2000. Furthermore, Western Africa could experience a significant reduction (>10%) in suitable land area for crops such as maize, sorghum, banana, finger millet (Figure 2.4). Dinesh et al. (2015) and Challinor et al. (2014) added that adaptation is expected to be helpful in dealing with climate change through exploring autonomous measures such as cultivar substitution and a change in planting dates, to systemic and transformational changes that include climate-smart agriculture.

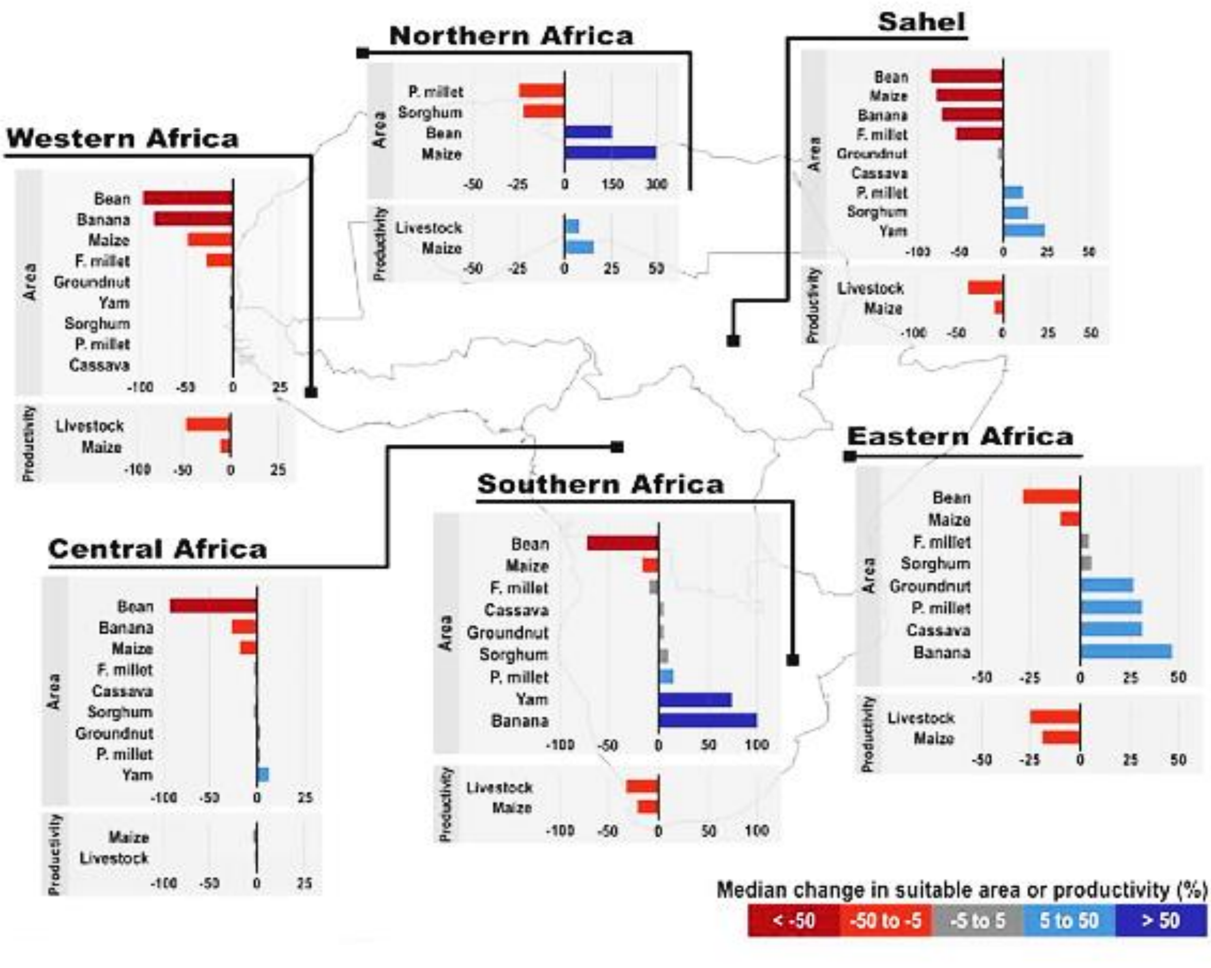

Figure 2.4: Median changes in climatically suitable areas projected for 2050s under the RCP 8.5 scenario, and relative to 1970-2000 historic data (Source: Dinesh et al. 2015).

2.5 Strategies for climate change mitigation

In order to tackle global warming, the United Nations Framework Convention on Climate

Change (UNFCCC) highlights two fundamental response strategies to reduce the impacts of climate change: mitigation and adaptation. The IPCC (2014a) defines mitigation as the process aimed at reducing emissions of GHGs and increasing carbon sequestration opportunities (IPCC 2014a, Locatelli et al. 2015). Adaptation aims to reduce or reverse the adverse effects of climate change; through a range of changes to human actions, or natural systems (IPCC 2014a). Both mitigation and adaptation are complimentary, and equally necessary strategies for managing the risks of climate change (Kongsager 2018). In addition, large-scale deployment of renewable energy, most especially bioenergy can also be viewed as a robust mitigation strategy (Bauer et al. 2018). According to the IPCC, limiting climate change would require a substantial reduction in GHG emissions through reduced energy use, decarbonised energy supply, sustainable technology development and enhanced carbon sinks in land-based sectors. The following sub-sections considers international collaboration and mitigation measures for reducing carbon emissions.

2.5.1 Paris Agreement to keep global warming below 2°C

Through the United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement (COP 21) which came into force on November 2016, the international community agreed to keep the average global temperature rise well below 2°C and pursue efforts to limit this to 1.5°C above pre-industrial levels by the end of this century (UNFCCC 2016, IEA and IRENA 2017). To meet this target, significant GHG emissions abatement continues to be required (Mani et al. 2018). The International Energy Agency (IEA) projects (with a 66% probability) that the share of fossil fuel in primary energy demand would need to halve by 2050 and the deployment of renewable energy technology such as solar, wind and bioenergy for example would require acceleration in order to achieve the “well below 2°C” limit goals (IEA 2017).

The responsibility is now on the 165 Governments that acted as signatories to the Paris 2016 agreement (the Paris Agreement) to review existing national frameworks and enact rules, regulations and policies that will accelerate energy transition and collective reduction strategies of energy related CO_2 emissions by 2.6% per year (IEA and IRENA 2017).

Unlike the Kyoto protocol, that sets binding targets for industrialised countries; under the 2016 Paris agreement, developed and developing countries were to put together nationally appropriate mitigation actions via the Intended Nationally Determined Contributions (INDC). This document was submitted to the UNFCCC and sets out quantitative targets to reduce GHG emissions (Mani et al. 2018, IEA and IRENA 2017, UNFCCC 2016). The reduction of agricultural GHG emission featured in most of the INDCs and some sub-Saharan African countries specifically pledged to promote, low-carbon strategy and adopt climate-smart agriculture (CSA) to reduce GHG emissions (FAO 2016b, UNFCCC 2016, Zheng and Han 2018, Girvetz et al. 2019). In summary, Stirling (2018) gave an overview of the UNFCCC reporting process for national GHG emission reporting of direct nitrous oxide (N_2O) emissions.

The debate about emission mitigation gained prominence with Wollenberg et al. (2016) arguing that it is unclear how much emission mitigation is required and how feasible it is for agriculture to meet the proposed global target of limiting warming by 2°C. To counter this, Wollenberg et al. (2016) proposed a global target emission of 1 $GtCO_2e\ yr^{-1}$ by 2030, to achieve the 2°C warming limit in 2100 under the RCP 2.6 scenario pathway. They noted that the consequences of excluding agricultural emissions from mitigation targets and plans could reduce the feasibility of meeting the 2°C limit and may increase the cost of mitigation in other sectors. Therefore, to meet the 1.5°C or 2°C targets, countries will need to be ambitious in pursuing agricultural emission reductions through technology development and transfer (Richards et al. 2018).

2.5.2 Renewable energy development

Endorsement of the Paris Agreement charts a course for addressing both mitigation of GHG emissions and adaptation to climate change impacts (WEC 2016). It is an important step towards a truly global emission reduction strategy that will stabilise GHG emissions and provide an essential framework for any future international agreement on climate change (Mani et al. 2018). It also has implications for the energy sector, which is the single largest net contributor of GHGs due to the burning of fossil fuels. Hence, the energy sector is at the core of efforts to combat climate change (IEA and IRENA 2017).

Energy plays a central role in the economy because it drives all the other elements of the system: the industrial, agricultural, commercial and government sectors, including private life. It has been estimated that by mid-century, global energy demand could rise by 50% (WEC 2016). Worryingly, developing countries are adopting a more carbon-intensive standard of living increasing the demand for non-renewable fossil fuels (Garba 2014, Dutta et al. 2014). However, this demand could be partially offset by harnessing and developing renewable energy resources. A key route for achieving national binding emission targets would be less dependence on fossil energy and intensification of the production of cleaner forms of low-carbon renewable energy. Many studies have established the climatic and economic benefits of renewable energy technologies in terms of sustainable development (Viana and Perez 2013, IRENA 2016, Souza et al. 2017, Mani et al. 2018). Any increase in the use of energy from renewable sources is an important measure to offset climate change, reduce GHG emissions and promote the security of energy supplies (Pang et al. 2014).

The International Energy Agency (IEA) reported that low-carbon energy technologies such as solar, wind and bioenergy, have received much research and policy support in gaining momentum for future energy systems (IEA 2017). The International Renewable Energy Agency (IRENA) reports that about 90% of the required carbon emission reductions can be achieved by 2050 through accelerated deployment of renewable energy and energy efficiency measures and the remaining reduction obtained by fossil fuel switching and carbon capture and storage (CCS) (IEA and IRENA 2017). Equally, projections from the EIA's International Energy Outlook (2017) shows that renewable energy is expected to increase by 2.8% per year through 2040 as technological improvements and government incentives increase, however, projections still show that global consumption of fossil fuel will remain dominant; leading to higher GHG emissions (EIA 2017, Tabatabaie 2017, Nordin and Sek 2018). To achieve these targets and the Paris agreement goals, renewable energy deployment must be accelerated to limit global temperature rise to 2 °C (Mani et al. 2018).

The World Energy Council (WEC) reported that out of the 18% renewables in the primary energy supply mix, bioenergy makes up around 14%, making it the largest available renewable energy source; additionally, bioenergy contributes 10% of global energy supply (WEC 2016). Bioenergy deployment has been identified in many studies as a potential substitute for fossil fuels; but it is also crucial in achieving ambitious targets to reduce GHG emissions (Creutzig et al. 2015). Bauer et al. (2018) explored sustainability of large-scale deployment of bioenergy for achieving long-run climate goals. The exploratory assessment include eleven integrated assessment models (IAMs) to determine future bioenergy use under harmonised scenarios of future climate policies, availability of bioenergy technologies and limitations on biomass supply. The models indicate that imposing stringent carbon budgets progressively is a major driver of bioenergy use (Bauer et al. 2018). According to WEC (2016), effective policies such as carbon taxes, blending mandates and increased investment in biofuel development are key instruments in transforming economies. For example, Brazil is becoming an oil independent country as a result of increasing its blending of biofuels in the transportation sector.

2.6 Critical issues affecting biofuel sustainability

The demand for biomass energy, especially biofuels on a global scale is growing rapidly. Two factors driving this growth are the anticipation that bioenergy deployment has a key role to play in climate change mitigation, and energy insecurity that stems from the instability in global oil prices and depleting crude oil reserves (Duvenage 2013, Mohammed et al. 2014, Ben-Iwo et al. 2016, Bhutto et al. 2016). Biofuels derived from energy crops, lignocellulosic materials, agricultural waste and industrial waste have been extensively studied and their potential environmental impacts documented (Hsu et al. 2010, Koçar and Civaş 2013, Jeswani et al. 2015, Ohimain 2015, Elum et al. 2017, Dutta et al. 2014). Although the sustainable production of first-generation liquid biofuel from energy crops is a major topical debate (Russo et al. 2016), energy crops continue to be regarded as important resource materials for biofuels (Hammond and Seth 2013, Mohammad et al. 2018).

This is certainly true in the case of Brazil and the United States which are both major producers of sugarcane and corn respectively for bioethanol, and Indonesia which grows palm oil for biodiesel (Enciso et al. 2016, Okoro et al. 2018). This indicates that the potential for agricultural sector to produce energy crops for biofuel in Nigeria is huge, for example out of the 91 million ha of available land area, agriculture covers 71 million ha (FAO 2016c); and validates the many studies that have evaluated this potential (Ben-Iwo et al. 2016, Elum et al. 2017). Biofuel combustion has been taken to be carbon-neutral because the carbon released on combustion had been sequestrated during the growth phase (Cherubini et al. 2011); therefore, its use does not contribute to a build-up of CO_2 in the atmosphere (McKendry 2002, Cannell 2003, Creutzig et al. 2015). However, this assumption is challenged in many studies for disregarding the time lag between CO_2 release, the time it spends in the atmosphere before its uptake by new plants (Cherubini et al. 2011, Haus 2018).

In recent years, there has been an increasing interest in the sustainable production, harvesting and an effective feedstock supply chain to complement and replace fossil fuels. Many researchers have argued that the sustainable sourcing of biomass feedstock and careful management of available resources will provide a clear advantage to biofuel systems over traditional fossil-based fuels and thus can contribute to mitigating climate change through GHG emission savings (Davis et al. 2013, Manning et al. 2015, Carus 2017). For example, Davis et al. (2013) analysed the potential for resource management practices to aid in enhancing GHG mitigation. By reviewing viable traits of different biomass species, Davis et al. (2013) implemented the “management swing potential” which represented management choices tailored to specific energy crops. The resultant GHG mitigation potential from growing *Miscanthus* in the UK, palm oil in Indonesia and corn in the USA, amongst others, proved that resource management was more important compared to crop type in determining environmental impacts. Carus (2017) supports the idea of regional sourcing of bio-based feedstock and suggested that sourcing for alternative biomass feedstock from local agriculture as against importation, could help resolve the issues of transport GHG emissions and reduce the risk of supply failure. However, Carus (2017) agreed that this move could further enhance emissions from land-use change and related emissions.

As more countries in the developing world pursue access to affordable and reliable energy through bioenergy development, the debate centred on bioenergy sustainability is ongoing and controversial; still seeking consensus due to the contrasting expert opinions that have been presented on biofuels sustainability (Bauer et al. 2018). Strong expert views have been expressed stressing that biofuel development competes with food and food resources, and the production does produce negative energy value (Balogun and Salami 2016). For example, Teweldemedhin and Mwewa (2014) reported that biofuel production diverted land and labour meant for food production to the cultivation of *Jathropa* in Zambia. The findings were however based on a survey of 65 contract farmers (out of 8,000 recruited); whom despite owning large hectares of farmland, used approximately 50% for *Jathropa* production.

Kline et al. (2017) suggested that by focusing only on the negative impacts of biofuels, debaters are obscuring the main drivers of local food insecurity, ignoring opportunities for biofuels to contribute to the solution. It was discussed that an understanding the nexus of food security, bioenergy sustainability and resource management could facilitate the goal to end hunger and ensure sustainable energy for all to meet the targets of the 2030 Sustainable Development Goals (SDG) and the United Nations Paris agreement on climate change (Kline et al. 2017).

On the contrary, some experts, view biofuel development as providing opportunities for rural infrastructural development in ways that may enhance future food security (Omer 2010, Carus 2017, Souza et al. 2017). For example, Mudombi et al. (2018) used a poverty index to determine local multi-dimensional poverty effects of growing biofuels in Malawi, Swaziland and Mozambique. Evaluation of sugarcane production workers when compared to *Jathropa* counterparts using a regression analysis method to estimate poverty effects around biofuel projects, revealed that groups involved in biofuel value chains had lower poverty than the control group. Similarly, Herrmann et al. (2018) used econometrics to assess the implications of expanding biofuel feedstock production on food production. Although food availability for households participating in sugarcane outgrower schemes in Dwangwa, Malawi were not significantly affected and they earned significant higher incomes, the study further revealed that expansion of sugarcane plantations for biofuel and food crop expansion by outgrowers might affect food crop production of other households not involved in the scheme through land competition or labour resources. Furthermore, Herrmann et al. (2018) noted that the scheme provided higher carbon sequestration, but it is a direct driver of land-use change, contributing to ecosystem loss.

Although differences of opinion do exist, there appears to be some agreement from Carus (2017) that local production of bio-based feedstock would be beneficial for the socio-economic development of rural areas. Furthermore, many argue that if bioenergy feedstock is sustainably produced, farmers will in turn, become resilient, and adapt better to climate change (Carus, 2017, Kline et al. 2017). Although there are still concerns over the economic and social viability of biofuels, it remains unclear how sustainable future production will be maintained under climate change. This is because the sustainability of biofuel feedstock sources largely depends on land availability, and despite the huge expanse of available land in Africa, the World Energy Council (WEC 2016) reported that in 2014, the nominal share of biofuel production in Africa was measured at 1% compared to North America (44%), Europe (16.5%) and Asia (10.5%) as shown in Figure 2.5. However, others have highlighted the relevance of biofuel projects that are well into implementation in some developing countries such as Malaysia, Kenya, South Africa, Ghana and Nigeria, using feedstock such as palm oil, sugarcane, sorghum, maize amongst others as for biofuel. Production is ongoing despite the environmental consequences of land use change, impact on ecosystem, biodiversity from high deployment of land-intensive bioenergy feedstock (Creutzig et al. 2015, Okoro et al. 2018).

Table 2.1: Production of liquid biofuels by region (Adapted from the World Energy Council (WEC 2016).

Region	**Percentage**			
	1993	2003	2013	2014
Asia Pacific		3.3%	9.5%	10.5%
Africa				1.0%
Middle East				
Europe & Eurasia	1.1%	11.1%	17.1%	16.5%
South & Central America	71.4%	49.2%	28.5%	28.7%
North America	27.4%	36.4%	44.8%	44.1%

2.7 Biofuel feedstock production in Nigeria

Nigeria is committed to the renewable energy targets set out in the INDC report to reduce climate change (Federal Ministry of Environment 2015). Other motivating factors to promote renewable energy development include the potential of supporting rural development, boosting the agricultural sector and creating huge financial benefits to local farmers, businesses and jobs. Through the national biofuel policy, the government seeks to create an enabling environment for biofuel production investment, utilisation and market orientation (Mohammed et al. 2014, Aliyu et al. 2017). The study by Shaaban and Petinrin (2014), and Aliyu et al. (2015), showed that the renewable energy potential in Nigeria is 1.5 times that of fossil energy, and the available 28.2 million hectares of arable land has the potential to produce up to 0.256 million tons mix of crops per day. The generalisability of much published research on this issue is problematic and (Oyedepo 2014) also notes that renewable development in Nigeria has been sporadic with no consistent national policy in place.

With reference to the debate of sustainable bioenergy development in Nigeria, many studies have reviewed government renewable energy development policy (Ohimain 2013a, 2013b, Shaaban and Petinrin 2014, Aliyu et al. 2017, Elum and Momodu 2017); resource availability (Udoakah and Umoh 2014, Shaaban and Petinrin 2014, Mohammed et al. 2014, Aliyu et al. 2015, Ben-Iwo et al. 2016, Akuru et al. 2017); benefits and cost (Oyedepo 2014, Ohimain 2015, Edomah 2016, Aliyu et al. 2017, Okoro et al. 2018).

More literature has emerged from Edomah (2016) and Elum and Momodu (2017) that highlights the challenges of sustainable bioenergy development in Nigeria; including high investment costs, legal and regulatory barriers. Through the Nigerian Biofuel Policy incentive, bio-refining industries using first generation biomass feedstock are exempt from taxation (Ben-Iwo et al. 2016), however, Edomah (2016) advised on the removal of petrol subsidies to encourage market competition. Furthermore, Akuru et al. (2017) evaluated the availability of biomass resources within the country with respect to its conversion to electricity rather than as a biofuel, while Udoakah and Umoh (2014) suggested that municipal waste in addition to agricultural residue could be a viable alternative to generate electricity and biofuel for automobiles. In addition to this, Oyedepo (2014) is of the opinion that the Nigerian government could consider extending biomass residues into power generation, as the feedstock is widely available and renewable. This review is supported by Mohammed et al. (2014) and Elum et al. (2017), who agree with the idea of substituting agricultural biomass residues as feedstock, because (1) use of biomass residue for energy has little effect on food security (2) modern bioelectric power generation methods using bio-residues are efficient and can minimise energy losses and minimise emissions.

In a follow-up report, Elum et al. (2017) reported on utilising bioenergy to address issues of socioeconomic and environmental concerns in Nigeria. Growing certain energy crops dedicated solely to biofuel production was recommended, as this would create a strong synergy between the energy and agricultural sectors. Amongst the challenges identified to constrain the development of bioenergy in Nigeria, Elum et al. (2017) did not include the impending threat of climate change on the production of energy crops.

Dick (2014) estimated the supply capacity of biofuel feedstock, bioethanol production and the potential and likely impacts of feedstock demand on national energy and food supplies. Findings from the sectoral Energy-Food Model (EFM) suggests that bioethanol from crops will not affect domestic food supply or increase commodity prices due to substantial acreage of fertile lands. Dick (2014) also emphasised that Nigeria has the potential to produce sufficient feedstock to meet domestic bioethanol requirements and an annual production of 5.14 billion litres of ethanol is feasible from all regions.

In addition, Nigeria has an enormous land resource for biofuel feedstock production, and cassava, sugarcane, maize and sorghum are viable energy crops that can be grown on marginal or degraded agricultural land for biofuel (Mohammed et al. 2014, Ben-Iwo et al. 2016). Current investments in sugarcane and cassava feedstock plantations in Nigeria are over $3.86 billion, with up to 10,000 units of mini refineries and 19 ethanol bio-refineries built according to Aliyu et al. (2017). According to Okoro et al. (2018), public support for bioenergy development in Nigeria is still debateable, but there is a consensus that bioenergy as a substitution to fossil-fuel energy could benefit the environment in terms of GHG emission reductions and provide an element of energy security. Balogun and Salami (2016) reviewed responses from local stakeholders on the effects of the development of biofuel production in regions where production has been established in Nigeria. Across all three ecological zones, the perception was that feedstock planting translated to economic gains for rural farmers and improved rural infrastructure. It also showed high employment opportunities as were observed for women and youths. However, the effects on deforestation, water availability on the general environment was significant especially in the North-Western zone of Nigeria. Ohimain (2015) argued that the food versus fuel conflict might not be as severe in other areas of Nigeria since there is no constraint of arable land and most of the first-generation biofuel projects have feedstock plantations.

In addition to resource availability and use as discussed above, other key issues highlighted with regards to biofuel production within the context of sustainability include food versus fuel trade-offs, GHG accounting and land use change (Araújo et al. 2017, Oláh et al. 2017, Okoro 2018). For example, Oláh et al. (2017) examined the link between an increase in food prices and biofuel policies during the period of 2003–2016. The main driver for food price fluctuation was mainly due to the oil price shock, which is similar to findings by De Gorter et al. (2015). In addition to higher oil prices, Araújo et al. (2017) added that biofuel production, weather conditions and investor speculation were factors that stimulated food price fluctuation.

The studies evaluated have considered biofuel sustainability relating to policy, resource availability, use and economic benefits. Though others have argued on the potential impacts on food prices and resource competition, it can however be suggested that, a more holistic approach to the debate should include the environmental impacts of agricultural activities due to the production of biofuel feedstock and the resulting land use change. Aliyu et al. (2017) identified that current biofuel development policy in Nigeria lacks strategies to boost yield of feedstock through improved farm practices. This pre-empted a call for vigorous research in biotechnology and precision agricultural techniques. Scepticism about biofuel sustainability with reference to environmental impacts have equally grown over the years. For example, Achike and Onoja (2014) investigated the increase in agricultural CO_2 emissions in Nigeria. A positive correlation between agricultural land expansion due to policies on bioenergy and increase in fossil fuel demand was then reported. Furthermore, Achike and Onoja (2014) showed the significant increase in agricultural land area under cultivation also confirms FAO's (2011) report that agricultural expansion by foreign investors in Africa due to policies on bioenergy will increase land grab.

Okoro (2018) modelled the environmental and social impacts of cultivating palm oil for bioenergy in Niger Delta region of Nigeria. By using an integrated assessment modelling approach, their study addressed land use change emissions with respect to oil palm cultivation and sustainable development issues. Okoro (2018) reported that climate change impacts on oil palm yield was small and the net impact was positive. Furthermore, the proposed model highlights the effect of bioenergy policies on land use change and reveal that use of emission tax (e.g., carbon tax) is an appropriate instrument in future land–use emission reduction. What is not yet clear is the impact of policies aimed at incentivising landowners to keep land-use areas such as grassland and shrubland due to the challenge of proper measurement of below-ground biomass emissions. This indicates a need for further research.

2.8 Assessing climate change impact of biofuel feedstock production

The impact of climate change on agriculture has been widely studied using different approaches such as field experiments (Chen et al. 2017), artificial climate chamber experiments (Ottman et al. 2012), analysing aggregated data from database and archives of crop yield records (Lobell et al. 2011, Tao et al. 2014, 2015), using statistical approaches. According to Adnan et al.

(2017) and Jiang et al. (2017), field experiments can be expensive, repetitive over long periods to capture seasonal weather variations and may not be representative of site conditions due to spatial heterogeneity. Although computer solutions are not a substitute for field experiments, the use of agricultural and climate models has dominated scientific literature in evaluating the risks of climate change and adaptation assessments (Fealy 2013, Asseng et al. 2015, Zhai et al. 2017, Chen et al. 2018). Over the last decade, there has been an increase in the use of crop-climate models to estimate crop productivity and develop adaptation options, given the growing interest in both the implications of climate change and the uncertainty surrounding future predictions (Challinor et al. 2018).

Crop models are useful tools for assessing the sensitivity of crop growth and yield formation processes to climatic factors. Crop models bring together the best available knowledge on plant physiology, agronomy, soil science and agro-meteorology to predict plant growth under specific environmental conditions (Timsina and Humphreys 2010, White et al. 2011, Asseng et al. 2015). Nevertheless, the strategy has not escaped criticism from researchers and academics. According to Challinor et al. (2013) and Lobell (2013), crop models are simplified representations of reality (therefore will contain inevitable errors) and are therefore tools from which information can be retrieved rather than viewed as such which can compete with reality.

There are various categories in which the application of crop models can be grouped but the main goal of most applications is to predict final yield. In essence, crop models can be applied as strategic, tactical and forecasting management tools (van Keulen 2013, Robert et al. 2016, Han et al. 2017). Under strategic and tactical applications, the models are run prior to planting of a crop to compare alternative crop management scenarios or evaluate various management options with respect to one or more management decisions incorporating historical or generated weather data. Apart from its broad application as an agronomic research tool, areas of specific interest in some cases include the determination of resource use and the environmental impacts of land-use change or associated variables. The most common application of crop models in agricultural production systems however, is to simulate the effects of climate change such as elevated carbon dioxide, changes in temperature and rainfall on crop yield and water use requirements and to identify potential adaptation strategies (Hoogenboom et al. 2012b, Rosenzweig et al. 2014, Challinor et al. 2018).

Most crop models operate at daily time steps which start at planting and end at the prediction of harvest or physiological maturity depending on the crop (White and Hoogenboom 2009). When using crop models to predict crop growth, initial field conditions such as the soil nutrient and water status, the planting date and density are specified. Other crop information such as cultivar characteristics, planting arrangement, irrigation, fertilizer application, tillage events, pest, diseases and other factors may be considered (Hoogenboom et al. 2012b). Most important for modelling crop yield at any particular location is the availability of daily weather data and CO_2 concentration data corresponding with the historic, current or future scenarios of interest (White et al. 2011). It is important to note that crop models are not without limitations. According to Kasampalis et al. (2018), complex models are difficult to use and should be evaluated against the objectives of the study. Availability of sufficient soil profile characteristics, input data quality and extensive growth parameter data for model calibration, have all been identified as input limitations in terms of large area yield projection. Misrepresentation of natural field occurrences within model, model modifications, and over simplification of interactive effects have also been linked to model uncertainty (Palosuo et al. 2011, Lobell 2013).

2.8.1 Types of crop models and model components

Crop models calculate the causal relationships between the various plant functions and the environment, or they apply a statistical approach, using correlative relations between all processes. Crop models can be deterministic in that they make an exact calculation or prediction of the yield or dependent variable; or probabilistic or stochastic, which provide a different output for each calculation along with probabilities (Boote et al. 2013, Lobell 2013, Hoogenboom et al. 2012b, 2015, Islam et al. 2016, Liu et al. 2016).

2.8.1.1 Process-based crop models

Process-based models are computer-based mathematical representations of one or several physiological and physical processes characterising the agroecosystems (Buck-Sorlin 2013).

Process-based models are extensively used in crop-climate modelling studies and have been tested against experimental datasets in different environments (Semenov et al. 2012, Asseng et al. 2015, Reynolds et al. 2018). The models can be data intensive as the processes are defined at a fine scale and calibration can be difficult due to the large number of uncertain parameters (Lobell and Burke 2010, Islam et al. 2016, Jiang et al. 2017). However, process-models are powerful tools designed to assist farmers with crop management decisions, and based on their high geographic resolution and combination of climate and soil data, can facilitate detailed and dynamic weather, soil and farm crop management analysis (van Keulen 2013, Islam et al. 2016, Jones et al. 2017).

The number of process-based models has increased over the last four decades and their applications vary in terms of differences in approaches, parameterisation, assumptions and structures (Challinor et al. 2018). Rosenzweig et al. (2014) grouped seven crop models based on their purpose, structure and processes to determine the source of the variations in model results. The models were categorised into site-based models, which were developed to simulate processes at the field scale (EPIC), agro-ecosystem models which were utilised to simulate carbon and nitrogen dynamics, surface energy balance and soil water balance, and the agro-ecological zone models developed to assess agricultural resources and potential at regional and global scales. The model responses to climate change varied considerably and Rosenzweig et al. (2014) acknowledged that further research is required to ascertain their use for certain assessment studies.

For easy comparison of energy crop models, Jiang et al. (2017) categorised several processed-based models into radiation models, water-controlled crop models and integrated models as shown in Table 2.2. From the 23 energy crop models reviewed, the models grouped into radiation models were concluded to be over simplified as the modelling is based on the radiation use efficiency (RUE) approach. This assumed that radiation use is constant whilst in reality, it varies in range. The typical water-controlled crop models (AquaCrop model) were limited because of a dependence on crop water use and soil water balance in the root zone. Jiang et al. (2017) further argued that in addition to using different sets of parameters to calibrate the model for different crops, under water stress conditions, the water-crop model simulation of biomass yield would not be satisfactory. The integrated models were further categorised into models that utilised biochemical approaches and others that utilised photosynthesis and respiration approaches. The review shows that integrated models were the most versatile, and the models' strengths lies in their individual design structure and principles (Jiang et al. 2017).

Table 2.2: Categories of energy crop models (Source: Jiang et al. 2017)

Categories	Model	Scale	Energy crops covered	Crop model	First reference
Radiation model	EPIC	Field	Switchgrass, Miscanthus	Generic, dynamic	Williams *et al.* (1984)
	ALMANAC	Field	Switchgrass, Miscanthus	Generic, dynamic	Kiniry *et al.* (1992)
	APSIM	Field	Sugarcane	Generic, dynamic	Keating *et al.* (1999)
	ISAM	0.1°, county[1)]	Switchgrass	Crop specific	Jain *et al.* (2010)
	MISCANMOD	Field	Miscanthus	Crop specific	Khanna *et al.* (2008)
	MISCANFOR	Field	Miscanthus	Crop genotype specific	Hastings *et al.* (2009)
	SILVA	Commercial	Eucalyptus camaldulensis	Crop specific	Van den Broek *et al.* (2001)
	DAYCENT	Field, Regional	Miscanthus, Switchgrass	Generic, dynamic	Davis *et al.* (2012)
	APEX	Channel system, watershed	Switchgrass	Generic, dynamic	Gassman *et al.* (2009)
	SWAT	Watershed, ecosystem	Miscanthus	Generic, dynamic	Ng (2010)
Water-controlled crop model	AquaCrop model	Field	Switchgrass, Miscanthus, maize	Generic, dynamic	Ahmadi (2015); Stričević (2015)
Integrated model-photosynthesis and respiration approach	CANEGRO	Field	Sugarcane	Specific, dynamic	Inman-Bamber (1991)
	3PG	Stand level	Hybrid poplar, Willow	Generic growth model	Landsberg and Waring (1997)
	CropSyst	Field	Maize	dynamic	Stöckle *et al.* (2003)
	DSSAT	Field	Maize	Crop specific dynamic	Fosu (2012)
Integrated model-biochemical approach	SECRETS	Stand-ecosystem	Miscanthus, poplar	Generic growth model	Sampson and Ceulemans (2000)
	LPJmL	Ecosystem	Sugarcane	Generic	Bondeau *et al.* (2007)
	Agro-BGC	Ecosystem	Switchgrass	Generic, dynamic	Di Vittorio *et al.* (2010)
	Agro-IBIS	Ecosystem	Sugarcane, Miscanthus	Generic, dynamic	Kucharik (2003)
	WIMOVAC	Field, ecosystem	Switchgrass, Miscanthus	Generic, dynamic	Miguez (2009)
	DNDC	Field	Miscanthus	Generic, dynamic	Li *et al.* (1992)
	DRAINMOD-GRASS	Field, ecosystem	Switchgrass, Miscanthus	Generic, dynamic	Tian *et al.* (2016b)
	AgTEM	Ecosystem	Switchgrass, Miscanthus, Maize	Generic, dynamic	Qin *et al.* (2012)

Process-based models have become more useful with the incorporation of Decision Support Systems (DSSs) which create an interface that integrates climate, crop and economic models to aid risk assessment and economic analysis of management strategies (Palosuo et al. 2011, Mubeen et al. 2016). In order to integrate a process-based model to seasonal climate forecast information, Han et al. (2017) developed a decision support system (DSS) that could effectively translate probabilistic seasonal climate forecasts (SCFs) to crop responses. The Agriculture-

Modelling and Decision Tool (CAMDT) developed links from SCFs to DSSAT-CSM-Rice model and constituted of a user interface where users could create “what-if” scenarios. The tool also possessed a unique feature in which it transforms crop model outputs into economic terms (Han et al. 2017). Model validity of the developed DSS tool was however not presented in the report. One of the most commonly used integrated model is DSSAT (Decision Support System for Agro-technology Transfer) (Jones et al. 2003, Hoogenboom et al. 2015, Dias et al. 2016). DSSAT system is a collection of independent modules for many field crops using a single soil model. This type of Cropping System Model (CSM) is process oriented and predicts daily biomass production and partition to various plant organs that grow in a given period (Liu et al. 2011, Jiang et al. 2017).

In a comparative study of eight widely used process-based crop models, Palosuo et al. (2011) reported that DAISY and DSSAT models performed best in yield estimation compared to observed values while other models underestimated and overestimated crop yield.

The Crop Environment Resource Synthesis group (CERES) are process-based plant growth modules embedded in DSSAT and run on a daily time step driven by daily weather elements (Wang et al. 2011, Ventrella et al. 2012, Msongaleli et al. 2014, Van Wart et al. 2015). The model simulates plant responses to environmental conditions such as soil, weather, water stress and management. To calibrate CERES-maize, site-specific input parameters are required to calculate growth development and partitioning processes from planting to predicted harvest maturity. Like most crop models, plant phonological development in CERES-maize is sensitive to cultivar type, water deficit, temperature, photoperiod and nitrogen stresses, expressed as physiological days per calendar day (PD/day) (Mera et al. 2006).

Li et al. (2015) evaluated the performance of CERES-Maize and CERES-Wheat module of DSSAT-CSM by comparing yield simulation output with long-term experiment data and soil nitrogen data. The simulated grain yields matched the measured values but the model overestimated soil nitrogen, which according to Jones et al. (2012), reflects inadequate model representation of the degraded soil profile. Liu et al. (2017) compared the simulation of a long-term wheat-maize rotation experiment (19 years) using DSSAT model coupled to the CENTURY-based soil C and N module in DSSAT v4.6. DSSAT was found to simulate grain yield with reasonable accuracy (R^2 = 0.72) under no fertiliser treatment in comparison to higher fertiliser rate (R^2 = 0.45). Due to the poor model performance under no fertiliser treatment, both studies noted that DSSAT-CSM model was sensitive to N stress than to real crop growth (Li et al. 2015, Liu et al. 2017). However, DSSAT-CSM model can still indicate the influence of some management practices and used to select optimum N management practices.

2.8.1.2 Statistical crop models

Statistical crop models (also known as empirical models) require the use of historical crop and climate datasets for model calibration (Lobell 2013, Liu et al. 2016, Lobell and Asseng 2017, Tebaldi and Lobell 2018). Most often, statistical models are used to predict values of the dependent variables by generating the prediction equation and are also used to understand the relationships between two or more variables (Ostertagová 2012, Leng and Huang 2017). To date, various methods have been developed but the statistical method is usually preferred to process-based models as the latter requires extensive data input which is sometimes not available, especially in developing countries. However, this method of analysis has a number of limitations thus according to Liu et al. (2016), processes inherent to crop growth are not directly considered in statistical models. That being said however, the indirect effects of climatic variability, are not well captured by process-based models but can be included in statistical models such as those related to pests and diseases. In addition to the above, statistical models provide transparent quantification of uncertainties by using standard statistical techniques such as bootstrap resampling (Lobell 2013, Leng and Huang, 2017).

Some studies have analysed the effect of weather variables such as rainfall (Ifabiyi and Omoyosoye 2011, Adamgbe and Ujoh 2013) and temperature (Peprah 2014), using statistical regression models to investigate the effects of climate change on crop yield and to predict crop response to farm input technologies (Zhai et al. 2017, Sitienei et al. 2017).

Furthermore, Tebaldi and Lobell (2018) modelled the statistical relationship between projected climate scenarios and yields as a linear regression. This method was found to be flexible for estimating crop responses to temperature exposure at critical thresholds during crop growing season, which, according to Tebaldi and Lobell (2018) is a known shortcoming in yield impact models. However, by extrapolating empirical relationships, the model displayed a limitation in accounting for: (1) the effects of transformative adaptation measures and most importantly, (2) the non-linear response of crops to warming above 2–3 °C (Tebaldi and Lobell 2018). As a result, Leng and Huang (2017) state that this method was not always suitable at all locations due to its inability to establish significant relationships in some crop-state combinations.

Semenov et al. (2012) warned that using simple statistical models to construct response functions such as yield to relate risk metrics such as climate could be misleading, as the model may not reflect the complexity of yield response to factors other than climate factors. This highlights the fact that although statistical models can efficiently reproduce historical climate-induced yield variations at regional or farm-scale level (Hawkins et al. 2013), they are not as useful for determining the causes of yield variation (Lobell et al. 2013, Watson et al. 2015). Semenov et al. (2012) further suggest that process-based model provide the possibility to model the complexity of crop responses by including knowledge of crop physiology and responses to environmental factors into process-based models.

In an effort to estimate the relative importance of heat stress, precipitation and technology on yield forecast, Hawkins et al. (2013) fitted a statistical model to historical maize yield and climate. To make the model projection more robust, they included the interaction effects of temperature and precipitation and reported that historically, precipitation variability was the dominant contributor to yield variability nevertheless noting that in recent decades, heat stress variability had become an ever-important factor with precipitation variability. In addition, Hawkins et al. (2013) attempted to reduce climate model bias for future climate projection by calibrating the model using bias correction and change factors. The average number of hot days (above 32 °C) over France was projected to increase further to about 10 to 15 days per summer in the period 2016–2035. Although Semenov et al. (2012) criticised the use of simple empirical relationships between climate and crop yield to infer changes in future yields, Hawkins et al. (2013) fitted the model to encompass nonlinear technology trends and interaction between temperature and precipitation in order to give a more robust maize yield projection.

Statistical models can be subject to the problem of co-linearity between predictor variables. However, according to Lobell (2013), this limitation can be minimised by using large panel time series from multiple locations. In addition, datasets with large correlations among variables should be avoided. With respect to this, most statistical models use aggregate measures of weather such as monthly or growing season averages, however, several sources of error become apparent if important timing of aspects important for crop development and growth transpire as missed (Lobell, 2013). Therefore, a limitation of statistical models is the assumption of stationarity and low signal to noise ratios in yield.

Another assumption in statistical analysis is that data measurement is perfect, even though in reality, errors can exist in yield and weather measurements. As an example, Lobell (2013) estimated the potential bias introduced by measurement error on yield predictions by using statistical crop models. The result suggested large errors with precipitation measurements (up to 30%) significantly biased crop yield output, while the measurement error for temperature was contrastingly small, and therefore yield response changed slightly.

When compared to process-based models, statistical models can test for relatively simple relationships, but can come under the direct influence of climate variability (Tebaldi and Lobell 2018). To evidence this, Roberts et al. (2017) compared climate change predictions of a simple process-based and statistical crop model to actual maize yields. Interestingly, the result show that the statistical model predicted greater impact of climate change on yield compared to the process-based model. A combination of both models gave significantly better results than predictions from either model independently. Roberts et al. (2017) however stressed that because of the simplicity of the models used, a wider set of models should be employed in future using the same framework in order to yield more optimum results (Liu et al. 2016).

2.8.1.3 Crop model uncertainties

Challinor et al. (2013) defined model uncertainty as a lack of predictive precision due to the inherent limitations to predictability. For example, in literature, a lack of predictive skills is associated with errors in model design. Due to this, Corbeels et al. (2018) and Knox et al. (2012) advised that some level of caution was needed when interpreting crop model outputs in any climate impact assessment given the large uncertainties associated with model predictions. The uncertainty in crop model outputs have been analysed and many impact modellers have presented sources of data errors that should be of concern. According to Rotter et al. (2011), Rosenzweig et al. (2013) and Watson et al. (2015), the assessment protocols adopted by many analysts could significantly bias the projected response of crops to climate variability and change. Challinor et al. (2014) who carried out a meta-analysis of more than 1,700 published simulations, to evaluate climate change impacts and the quantitative effectiveness of adaptation using local mean temperature as a metric of change identified that firstly, the differences in experimental design and methods were the main causes of projection differences; and secondly, among other discrepancies in model simulations, they observed a large variation in structural, parameter and bias correction uncertainty in crop and climate models.

He (2008) and Watson et al. (2015) further categorised uncertainties into model parameter uncertainty, model structure uncertainty and scenario uncertainty. Uncertainty in model outputs can be ascribed to a number of factors such as incomplete agronomic management data, crop, soil data and weather data inputs required to run the model. In order to clarify, He (2008) identified weather variability as the dominant uncertainty contributor to model yield and nitrogen leaching outputs. Tao et al. (2018) quantified the contributions from crop model structure, climate projections and crop model parameters to the uncertainty in climate impact assessment. Based on the yield outputs from seven crop models, and eight different downscaled climate projections for the 2050s, Tao et al. (2018) reported that crop model structure contributed the most to the total variance of ensemble output followed by climate projections from GCMs and crop model parameters. In addition to structural differences and weather inputs, Watson et al. (2015) also included input calibration uncertainty in their assessment by comparing a process-based and statistical crop modelling systems. Effort was made to examine interactions between the three sources of uncertainty and how different model types can be influenced by input calibration uncertainty. Watson et al. (2015) pointed out that irrespective of model choice, errors in input data characteristics and climate errors affected model response.

One of the limitations with this explanation is that it does not explain why and to what degree such errors are relevant to each model.

Most impact assessment tended to reduce model uncertainty by employing an ensemble of crop or climate models in simulations (otherwise known as model ensembles). To mention a few, Asseng et al. (2015) evaluated the effects of temperature variability on wheat yield by comparing yield outputs from an ensemble of crop models against field experiments. Tebaldi and Lobell (2018) used an ensemble of climate models to estimate future climate change under the RCP 4.5 and RCP 8.5 scenarios in order to account for model uncertainties. Chen et al. (2018) used an ensemble of GCM datasets to address uncertainties in projected 1.5 and 2.0°C temperature change scenarios. In addition to using a crop model calibrated and validated for the region under study, Chen et al. (2018) used multiple sets of parameters to account for the uncertainties in cultivars and management. Similarly, Leng and Huang (2017) used 97 climate model projections for under four emission scenarios to estimate uncertainty sources in statistical crop models.

The aforementioned studies did address the uncertainties from scenario differences with respect to different initial boundary conditions, however, the uncertainty due to different climate model structure was not accounted for. With the exception of Asseng et al. (2015), uncertainties from crop model type, parameterisation and cultivar type were not addressed. Although using ensembles of multi-models produces robust simulations of crop yield projections and minimises crop model uncertainties, Yin et al. (2017) argued that the detailed response of individual models could be hidden when using the mean or median results of the multi-model ensembles thereby making it difficult to assess the accuracy of each model.

2.9 Integrated Assessment Modelling (IAM) approach for energy crop sustainability

Agricultural response to climate change has been widely represented in many studies using different crop modelling approaches. As earlier reviewed in section 2.6, previous assessment studies coupled climate and crop models to assess how crop yield responded to climate change (Asseng et al. 2015, Liu et al. 2016). However, the consideration of the impact of climate change on crop yield alone is not sufficient to estimate the broader implications of climate change for agricultural, economic and environmental responses. In light of this, more studies are beginning to consider varied integrated assessment approaches for agricultural impact assessment (Purola et al. 2018). To date, various studies incorporated GIS within their farm assessment framework by coupling crop model output into a GIS model to create spatial maps. Rupnik et al. (2018) as an example developed a cloud-based decision support system that can be integrated with existing farm management information systems.

Other studies integrated economic models to climate and crop models (Atay 2015, Okoro et al. 2017) to study the impact of climate change on global crop commodity prices and poverty outcomes (Hertel et al. 2010) in addition to global food systems (Nelson et al. 2014). Islam et al. (2016) used a similar structural framework that integrated climate models to DSSAT crop models combined with the IMPACT global economic model. By including cultivars with drought and heat tolerance traits, they simulated yield response under an extremely dry climate scenario using RCP 8.5. Both exogenous (independent of market effects) and endogenous (dependent on market effects) yields outputs were compared and from the results, drought and heat tolerant crop varieties had the potential to reduce the negative yield impacts due to climate change. In addition, market effects could also dampen the positive impacts as price signals influence incentives to adjust farm management. In order to optimise resource allocation planning in crop models, Vilvert et al. (2018) used the outputs as inputs in bio-economic farm models to estimate production cost and farm income. Further to this, they applied the outputs from crop models in order to simulate supply and market demand to determine prices and trade volumes.

Furthermore, other studies have linked the outputs from climate-crop-economic models to environmental impact models within the IAM framework with the aim of: (1) deriving changes in farm input management, (2) estimating the agricultural GHG emissions to the air, and water (Wolf et al. 2015, Zimmermann et al. 2017, Purola et al. 2018). As evidence of this, Wolf et al. (2015) used combined model analysis to evaluate farming systems. To do so, they integrated four models to estimate future farming systems in Europe considering climate change, price and technology changes. In their approach, yield output from SIMPLACE crop model was linked to (1) a CAPRI model that simulates global product prices (2) a FSSIM model that calculates farm level changes in cropping patterns and net income and (3) yield output which was linked to an INTEGRATOR environmental model to estimate the environmental impacts. Generally, crop yield increases towards 2050 were mainly attributed to higher atmospheric CO_2.

Zimmermann et al. (2017) carried out a sensitivity assessment of climate change impact on different impact variables such as crop yields, land use, production and environmental variables to three crop management adaptations. Similar to Wolf et al. (2015), the crop model was integrated with an economic model (with the exception of a model that calculated farm level changes in cropping patterns and net income) and used an environmental model to evaluate the environmental impacts from nitrogen fertiliser input. The report showed that across Europe, yield sensitivity to sowing dates and crop cultivars was more pronounced under climate change compared to the other variables. Therefore, under the three adaptation measures considered, changes to sowing dates and cultivar improved yield but had less impact on economic and environmental outcomes. Zimmermann et al. (2017) further added that technical progress had more impact on yield compared to climate change, and the reduced sensitivity to management assumptions is indicative that economic and environmental variables were somehow influenced by the physical and economic adjustments along the model chain.

Although van Vuuren and Carter (2014) indicated that very little difference existed between the SRES and the recent RCP scenarios, both Wolf et al. (2015) and Zimmermann et al. (2017) did not compare the SRES scenarios result (published in 2000 by the IPCC) with the current RCP scenarios published by the IPCC (2014). Furthermore, another limitation was that both studies considered fertiliser and manure application as the only changing farm management practice affected by climate change and therefore reported on ammonia (NH_3) and nitrous oxide (N_2O) emission to air and nitrate leaching. Both studies acknowledged the methodological challenges in conducting an integrated assessment especially the iteration of nitrogen use under climate change and maintaining consistent values of nitrogen inputs between models.

Zimmermann et al. (2017) however noted that in addition to model structure and parameter uncertainty, feedbacks between models should be accounted for in subsequent studies. Purola et al. (2018) added that if the expectation of low crop yield potential and farm income could be mitigated under climate change following the adaptation measures such as sowing dates and crop cultivars as suggested in Zimmermann et al. (2017), this may trigger an increase in yield determining inputs such as fertiliser. Purola et al. (2018) therefore suggested that more studies should focus on farm management changes on either land use change or use of agricultural inputs, in including crop yield changes. Based on farm level land use, inputs, production and far income, Purola et al. (2018) estimated changes for future scenarios (2042–2070) using a dynamic economic model (DEMCROP) which also estimates the effects of changed farm management (production, land use and input use) on GHG emissions. However, since the biophysical soil changes, due to climate change were not accounted for in the model, the emission output should be considered as indicative only (Purola et al. 2018).

2.10 Assessing the sustainability of biofuel feedstock production

The cultivation of biomass for biofuel production can bring about the release of atmospheric GHG emissions as well as biodiversity loss, soil degradation and low carbon storage from intensive cropping system. The environmental impact largely depends on the condition of land use change, materials and energy inputs such as fertilisers, pesticides, conventional fuels for transportation and wastes generated. From a life cycle perspective, biofuel production needs to fulfil certain sustainability criterion such as GHG emissions, biodiversity loss, positive energy balance, and impact on food security amongst others before it can be widely adopted (Gasparatos et al. 2013). The development of effective environmental policies and strategies requires the use of techniques to attain the environmental goal of sustainable development and LCA is a recommendable framework for all environmental studies (Bala et al. 2010, Garba 2014, Morero et al. 2015, Lazarevic and Martin 2016). In addition to the array of integrated assessment models employed for the sustainability assessment of bioenergy systems, other environmental assessment tools have been characterised (Finnveden and Moberg 2005, Buytaert et al. 2011, Morero et al. 2015). Buytaert et al. (2011) points out that all environmental tools have their advantages and disadvantages and that the choice of tool depends on the specific objectives of the assessment in addition to which sustainability issues are to be addressed. Morero et al. (2015) found that LCA was a complimentary tool to use in environmental impact assessment (EIA).

Sustainable crop productivity involves a high-yield cropping system that could manage the unprecedented impact of climate, while simultaneously reducing GHG emissions and managing material inputs. The so-called “climate smart agriculture” is an approach that seeks to address these unprecedented challenges. Sustainability assessment has increasingly become associated with the family of impact assessment tools such as LCA, ecological footprint, and strategic environmental impact assessment.

2.10.1 Life Cycle Assessment (LCA)

Life cycle assessment (LCA) is a widely recognised methodology used to analyse the performance of products, processes and services from an environmental perspective (Bacenetti et al. 2014). LCA is conducted in order to supply information for the benefit of policy makers and stakeholders in terms of managing resource use and providing alternative production scenarios that will reduce emissions and environmental impacts throughout the life cycle of products, services and systems (Carus 2017). LCA uses a bottom-up approach often referred to as or ‘cradle to gate’ or ‘cradle to grave’ in attributing impacts that occur in a complex production system to one product (Carus 2017, Arvesen et al. 2018). The general framework for performing LCA follows the ISO 14040/44 guidelines, which involves a phased approach consisting of four interrelated components as shown in Figure 2.5.

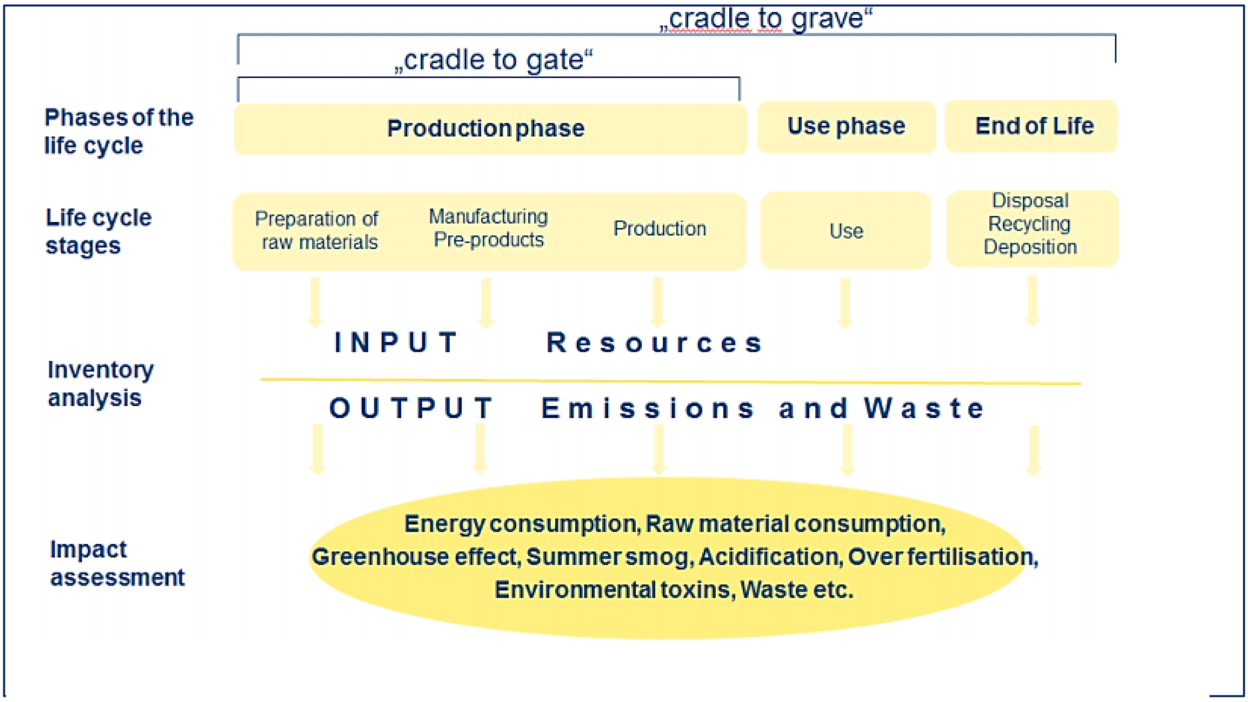

Figure 2.5: Life cycle assessment scheme (Source: Gangaiah et al. 2015)

LCA strives to cover all activities related to production, use and waste of products, including coverage of types of environmental impacts to the ecosystem, resource use and depletion. However, the most important limitation lies in the fact that LCA cannot offer useful information on the absolute magnitude of effects or the timing of effects (Arvesen et al. 2018, Haus, 2018). Although LCA can attribute effects occurring in different stages to a specific product, the system does not take into account social and economic variable and does not capture other types of product consequences such as land use change emissions (Morero et al. 2015). McKone et al. (2011) warned that decision makers should not see LCA as “truth generating machine” but rather LCA can provide valuable insight to decision making as well as providing a basis for adaptive planning.

According to Bala et al. (2010), LCA could be subjective to some degree, following decisions on whether certain stages of a product's life cycle should be included in the life cycle inventory (LCI) or not. This stems from the reality that it is never possible to access fully the required inventory data, thus introducing uncertainty to the LCA results (Bala et al. 2010). A number of studies have noted that data quality, sources of data, system boundary, choice of allocation and emission factors amongst others vary and constitute a major source of uncertainty in many LCA results (Cherubini and Strømman 2011, Brandão et al. 2012, Hanaki and Portugal-Pereira 2018). Kim et al. (2014) observed that fuel input data in LCA studies obtained from external databases such as Ecoinvent, or from literature and by simple estimation varied extensively. Bacenetti et al. (2014) partly estimated farm input data including fuel use from questionnaires, field surveys and from Ecoinvent's own database. This was obtained whilst on-farm emission estimations were carried out using different model estimations. Bacenetti et al. (2014) however noted that because of the significant influence of fertiliser input on different impact categories, it remains imperative to perform the analysis using site-specific models to reduce uncertainty.

Furthermore, geographical boundaries in LCA studies vary and the level of input information could range from state to national averages. In some cases field-level information is used (Kim et al. 2009, Kim et al. 2014). System boundaries set within LCA studies signify which life cycle stages, unit processes, activity type and elementary flows to include or omit from the modelled system and this type of qualitative definition sets the functional unit of the system (Saraiva 2017). System boundary in biofuel LCA can be extended to include the production of biofuel (well-to-tank) or combustion of biofuel in a car (well-to-wheel or cradle-to-grave) (Ndong et al. 2009, Orsi et al. 2016). In addition, some studies have been reported to expand the system boundaries by including the life cycle of co-products, by-products, and residues (Czyrnek-Delêtre et al. 2017). In the biofuel production chain, the first essential step for the whole life cycle assessment is the biomass production phase (cradle-to-gate) which according to Bacenetti et al. (2014), is worth more attention. However, the different use of functional units and lack of standardised sets of criterion does not allow for strict comparison with other LCA studies (Brandão et al. 2012, Bacenetti et al. 2014, Czyrnek-Delêtre et al. 2017).

Many studies have used LCA to report on the sustainability of biofuels, however, the results published for similar products or technology vary and this is largely dependent on different methodological approaches and factors that make each LCA study unique (Cherubini and Strømman 2011, Brandão et al. 2012, Czyrnek-Delêtre et al. 2017). According to Brandão et al. (2012), the increasing use of meta-analysis to synthesise previous LCA results could further strengthen LCA as a decision support tool. Gasparatos et al. (2013) and Brandão et al. (2012), have argued for a consistent conceptual framework that is informed by the needs of the decision-makers and stakeholders to facilitate biofuel policymaking.

Kim et al. (2014) carried out a meta-analysis of twenty-six published LCA studies on energy requirement and GHG emissions of maize production system in the USA. They found large variation in non-renewable energy consumption from cradle-to-farm-gate in the range of 1.44 to 3.50 MJ/kg of maize. The studies with larger energy consumption took into account energy used in farm machinery production, whilst energy associated with maize seed production, and application rates of lime and insecticides increased the overall values. Some studies have estimated that capital goods such as farm machinery required to produce agricultural products can contribute substantially to the non-renewable energy consumption in farm LCA (Frischknecht et al. 2007, Grassini and Cassman 2012, Eickelkamp 2013, Kim et al. 2014).

Kim et al. (2014) further noted that important factors such as crop rotation and tillage practices that could change the dynamics of soil organic carbon (SOC) were not accounted for, as many LCA studies assumed current tillage practices by default. Three studies (out of 26) estimated

GHG emission credits by using the no-tillage practice that increased SOC levels and net soil carbon sequestration. Lu and Liao (2017) estimated that zero-tillage increased SOC sequestration and released less carbon emissions compared to conventional tillage. Zheng and Han (2018) argued that by neglecting changes in soil organic carbon (which represents the net sink fluxes of atmospheric CO_2) in the quantification of GHG footprints estimation, some studies may have biased the footprint results leading to an overestimation or underestimation in many cases.

Bacenetti et al. (2014) evaluated the environmental performance of a single cropping system (involving maize cultivation only) and double cropping system (wheat cultivation followed by maize) to produce biomass for biomethane production using LCA. The field operations encompassed soil tillage, crop growth, harvesting and transport and biomass ensilage and the functional unit (FU) was one normal cubic metre (1 m^3_N) of potential methane. This is in contrast to input-based FU of mass of biomass, per hectare of cultivated land (Moghaddam et al. 2016) or output-based FU based on MJ of energy generated or kilogram of produced fuel used in many LCA studies (Czyrnek-Delêtre et al. 2017). Bacenetti et al. (2014) however explained that the FU adopted was more representative of the final use of the energy crops cultivated compared to the using mass of biomass adopted in many LCA studies. As expected, the double cropping systems produced a greater amount of biomass (silage) for biomethane production but had the worst environmental performance compared to the single cropping system of maize cultivation. Bacenetti et al. (2014) attributed the higher environmental cost to larger quantity of inputs required for the double crop system.

Carbon, energy and GHG emissions are the most prevalent impact categories mentioned in many LCA studies (Cherubini and Strømman 2011, Muench and Guenther 2013, Lazarevic and Martin 2016, Czyrnek-Delêtre et al. 2017). According to Cherubini and Strømman (2011) the scope of many LCA studies on biofuel production have been limited to the assessment of GHG and energy balances primarily because climate change mitigation and reduction of fossil fuel consumption are the main driving factors for biofuel development. GHG accounting has become the focus of many environmental policies and has therefore become popular amongst researchers, industries, authorities and stakeholders (Laurent et al. 2012).

Out of 39 peer-reviewed LCA studies of biofuels sampled by Czyrnek-Delêtre et al. (2017), about 49% reported on GHG emissions and energy use, while 26% reported on other impact categories. In 2007, von Blottnitz and Curran reviewed 47 previous LCA studies that compared bioethanol systems to conventional fuel across North America, Australia, Asia, Africa and Europe. Only seven studies out of the 47 LCA studies evaluated other environmental impact categories aside net energy and GHGs. Lazarevic and Martin (2016) maintained that GHG related emissions and impacts reported in Sweden was by far the most common impact category considered by most biofuel LCA studies.

The overall concern in focusing only on carbon footprint (kg CO_{2eq}) as a metric of climate change impact is the risk of problem shifting, which could increase negative impacts in other categories (Laurent et al. 2012). For example, some LCA studies found that while GHG emissions were reduced in bioenergy systems, other impact categories such as acidification, human toxicity and ecological toxicity where unfavourable (von Blottnitz and Curran 2007, Laurent et al. 2012).

Bessou et al. (2013) used a full-blown attributional LCA to compare first-generation ethanol from sugar beet with gasoline. The estimated result show that sugar beet ethanol had lower impacts than gasoline under the global warming, ozone layer depletion, abiotic depletion and photochemical oxidation impact categories. However, due to losses of reactive nitrogen, the impact for acidification and eutrophication categories was higher when compared to gasoline.

Although generating extensive input data for life cycle inventory has been identified as a limitation to conducting full LCA to provide a comprehensive measure of environmental impact (Laurent et al. 2012), Muench and Guenther (2013), stressed that the insufficient consideration of all impact categories constituted a research gap. A full LCA covers a broad range of impact categories, such as stratospheric ozone depletion, acidification, eutrophication, human toxicity and ecotoxicity, land use, water use and depletion of both renewable and non-renewable resources in addition to global warming potential otherwise known as climate change (Laurent et al. 2012, Simmons et al. 2015).

In addition to tracking of all material flows into the cropping system, the life cycle inventory (LCI) phase of LCA also consisted of detailed estimation of emissions to air, water and land, which could prove to be extremely complex. Field emissions often occur from complex biogeochemical processes that are strongly site-specific and dependent on soil, climatic and management factors (Bessou et al. 2013). Studies have addressed this uncertainty on agricultural field emissions by using diverse methods. For example, GHG emissions can be estimated from field experiments by direct flux measurements (Lebender et al. 2014, Li et al. 2016, Lu and Liao 2017) or by using a controlled experiment facility (Niero et al. 2015). Agro-ecosystem models e.g. APSIM, DNDC, DAYCENT and CERES-EGC models have also been employed to simulate emissions including N emissions to air (as NH_3, N_2 and N_2O) and water (NO_3^-) but with some limitations (Kim et al. 2009, Thorburn et al. 2010, Bessou et al. 2013, Zhang et al. 2015, Mielenz et al. 2016, Deng et al. 2016). Li et al. (2016) compared outputs of APSIM eco-system model with field experiment data in a maize-wheat rotation system. The model captured daily N_2O fluxes under different nitrogen fertiliser treatment very well but underestimated peak N_2O fluxes. Li et al. (2016) further hinted that this was a common issue as other studies have reported similar pattern with other agro-ecosystem models such as DNDC (Zhang et al. 2015) and CERES-EGC (Bessou et al. 2013). According to Li et al. (2016) and Zhang et al. (2015), under different environmental conditions, the number of microbes and their activity during the process of nitrification and denitrification will differ and these dynamics are not well represented within most models. This uncovers the knowledge gap that still exist with regards to the complex interactions between soil moisture, organic matter decomposition and soil nitrogen availability (Li et al. 2016).

Alternatively, in the absence of measured or modelled field emissions, GHG emissions can be estimated by using the default IPCC tier 1 emission factors (EFs) that is based on a simple linear inventory /accounting modelling system (De Klein et al. 2006). Although the estimated EFs is based on a robust methodology (over 900 observation experiments used), in particular, its use for analysis proves problematic. This is because it has been noted that if conditions at the site differ from conditions under which the coefficient was determined, the EF can introduce significant bias into estimated N_2O results (Rochette et al. 2008, Adewale et al. 2018). Therefore, simple models such as the IPCC tier 1 model is more useful only at national scale than at higher resolution scales such as field, farm and territory (Liao et al. 2015, Nitschelm et al. 2018). Another source of uncertainty is connected to the non-representation of the spatial variability of climate and soil on a local and regional level as per (Gabrielle et al. 2006). Bessou et al. (2013) compared modelled field emissions using the dynamic CERES-EGC model with emissions calculated using IPCC tier 1 coefficients. Modelled emissions were within the same order of magnitude as field emissions, however, soil N_2O emissions were slightly underestimated using CERES-EGC model. The overwhelming agreement from most studies on estimating field emission using models is the complexity of model parameterisation using field flux measurement (Uzoma et al. 2015, Wu et al. 2015).

To quantify the carbon footprint in the life cycle of wheat production, Ho (2011) used a spreadsheet that follows the IPCC tier 1 methodology consisting of data and emission factors, to calculate total farm emission on per hectare basis. The calculated direct and indirect N_2O emissions and total GHG emissions were compared to the Agriculture and Agri-food Canada (AAFC) GHG calculator. The total GHG emissions estimated from the spreadsheet (2,963.1 Mg CO_2eq ha^{-1}) was slightly lower to the emissions of the GHG calculator (3,960.2 Mg CO_2eq ha^{-1}). The slight difference was attributed to the lack of data for the manufacture of machinery (e.g. tractors), which was omitted from the spreadsheet. In the same vein, Ali et al. (2017) used similar methodology (IPCC tier 1) to estimate the GHG emissions from wheat production. As demonstrated in Brock et al. (2012), the farm emission inventory can be determined following the IPCC tier method or EFs from field trials.

Zheng and Han (2018) presented a simple generic framework to quantify the GHG footprint of a cropping system. The life cycle assessment framework consists of detailed equations that accounts for all direct and indirect GHG contributors including changes in soil organic carbon which many studies (Grassini and Cassman 2012, Wu et al. 2014, Wang et al. 2015, Ali et al. 2017) often neglect. Wang et al. (2015) analysed the carbon footprint per unit yield of maize in China using LCA by first estimating the total GHG emission per hectare. The results show a strong correlation (r = 0.95) between nitrogen consumption and carbon emissions although the rate of yield increase reduced with increasing nitrogen fertiliser. Wang et al. (2015) projected the carbon footprint (CF) of maize production from 2014–2020 by using the grey system model calibrated with historical carbon emission. The result showed an increasing trend in carbon emission from maize production. This evidence suggest that the emission trend will continue based on current farming practice.

The life cycle inventory (LCI) analysis is followed by a life cycle impact assessment (LCIA) which defines the impact categories and as earlier discussed, different LCA studies cover a broad range of impact categories, with global warming potential (GWP), energy, acidification, eutrophication and land use change, the most commonly assessed in agricultural LCA (Czyrnek-Delêtre et al. 2017). According to Czyrnek-Delêtre et al. (2017), there is no set list of recommended impact categories within the ISO methodology framework but rather, impact categories are chosen in line with the goals and scope of each individual study. In contrast to the above however, Adewale et al (2018) argues that the implementation of a framework on impact categories for biofuels assessment should be supported.

A wide range of models can be used to link the product or process to impact categories. SimaPro (Brock et al. 2012, Onabanjo and Di Lorenzo 2015, Rivera et al. 2017), Gabi (Herrmann and Moltesen 2015, Caldeira-Pires et al. 2018), Biograce excel tool (Czyrnek-Delêtre et al. 2017) amongst others exist and integrated with a number of databases such as Ecoinvent that contains several processes and systems that is customisable. Brock et al. (2012) conducted a "single issue" LCA to determine the GHG emissions (kg CO_{2eq}) associated with the production of a tonne of wheat. The system boundary was limited to pre-farm and on-farm emissions and the impact assessment was conducted using the SimaPro software, which was linked to the Australian LCI database and Ecoinvent database. Brock et al. (2012) termed the assessment as a "single issue" LCA because the impact assessment focus on GHG emissions only. Similar to Simmons et al. (2015) the production and use of fertiliser was the major contributor to GHG emissions from the direct and indirect N_2O emissions. According to Simmons et al. (2015), eutrophication, human toxicity and ecological toxicity impact categories were negatively influenced by inorganic fertiliser input but had a positive impact on land use as yield responded positively. As a result, Simmons et al. (2015) suggested precision fertiliser application and other strategies such as use of nitrification inhibitors and inclusion of N fixing legumes in rotations amongst others to mitigate impacts.

Kim et al. (2009) conducted a life cycle analysis on corn grain and stover production using the DAYCENT model to simulate soil organic carbon and nitrogen dynamics at county level for eight locations. The results showed that corn stover production (consist of the above ground parts of the corn except grain) had a lower impact on fossil energy use, GHG emissions, acidification and eutrophication compared to corn grain production. The sustainability and environmental impact interpretation or evaluation of farm processes is usually quantified in terms of the carbon footprint intensity of the product or process. This is because the carbon footprint is the environmental indicator estimated from the total balance of GHG emissions and sinks from a product or system across its life cycle (Adewale et al. 2018). More recently, Zhang et al. (2018) generated a plot of carbon footprint versus yield to determine the relationship between the two and to distinguish the effects farm management in an intensive maize farming system.

2.11 Quantification of impact assessment using LCA-Regression analysis

To quantify eco-indicators of the biofuel production impact, LCA has been used to first estimate all steps of the farm process life cycle: the agricultural field operations, seeds, fuel, fertilisers, and pesticides production and the associated GHG emissions. However, a major source of uncertainty arises from the fact that very little analysis has been carried out in order to characterise the effects of factors on variations of the LCA environmental responses.

Estimating the significance of each contributing variable is key to providing factual and robust support when decision-making.

Previous studies that have attempted to statistically explain the variations in GHG emissions of biofuels, used harmonised results from previous literature (by constituting a meta-database) that systematically differ in methodological choices, geographical location and different datasets used. Factors found to be influencing such emissions have been explored by Menten et al. (2013) who used a meta-regression analysis (MRA) to quantify and characterise the effects of factors influencing the mean Global Warming impact indicator, expressed in grams of CO_2 equivalent per MJ of biofuel. Through statistical evaluation, Menten et al. (2013) retrieved the main parameters (independent variables) influencing the dependent variable of interest (GHG emissions per MJ of biofuel) from a set of published LCA results. Results show that factors such as geographical location, type of biomass feed, technology type, co-product accounting and LCA methodology (attributional or consequential LCA) all influenced GHG emission results. The limitation of this study resides in the fact that the consideration of second and third generation biofuels greenhouse gas (GHG) emissions only, and energy balance was not included as a dependent variable. Most importantly, weather variability was not identified as a factor that could potentially have had an effect on the variations of GHG emission estimates.

A number of studies have used various approaches such as the meta-analytic procedure called "harmonisation" to estimate the reliability of LCA results with the aim to reduce the variability in calculated outcomes (Heath and Mann 2012, Burkhardt et al. 2012, Heath et al. 2014). Bureau et al. (2010) assessed the main factors responsible for the variability in energy balance of biofuels in many studies. Based on descriptive statistics and variance assessment, Bureau et al. (2010) identified potential sources of variations such as type of feedstock or nitrogen and labour consumption levels assumed in agricultural production. Large differences were observed in the explanatory variables used in many LCA studies and the energy balance of biofuel produced from the same feedstock varied as well. It should be noted however, that meta-analysis could in many ways be limited by the variability of studies selected for the analysis or the lack of study of certain technologies. According to Heath and Mann (2012), meta-analytic harmonisation is not an assessment tool for life cycle GHG emissions and certainly not a predictive tool.

Linear regression methods have been used in several studies as a prediction tool for crop yield forecasting, providing a quantitative estimation of expected future yield using historical statistical information on climate and yield (Mansouri et al. 2015, Sitienei et al. 2017, Najafi et al. 2018). Linear regression has been used to determine the relationships between climate, growing seasons and yield (Najafi et al. 2018) on both global and regional scales. In addition they have also been used to determine effects of technology improvement on future yield change by regressing historical yield trend (Mansouri et al. 2015).

Lehmann (2011) assessed the impact of climate change on wheat yield by applying the simulated climate change data on the developed regression model. Moreover, many researchers have successfully used linear regression models as a simplified tool to predict LCA outcomes based on streamlined LCI datasets (Bala et al. 2010, Padey et al. 2012, Hanes et al. 2013, Duan et al. 2015, Pascual-González et al. 2015). Ekpenyong and Ogbuagu (2015) used the autoregressive distributed lag model (ARDL) method to conclude that climate change impact will negatively affect agricultural productivity in Nigeria in the long-term. Using similar regression analysis, Edoja et al. (2016) found there was no long run relationship between carbon emissions, agricultural productivity and food supply in Nigeria, however it was observed that in the short run, climate variables did have a negative and significant effect. Arrieta et al. (2018) used the multivariate Redundancy Analysis (RDA) approach to determine factors that may have affected yield, GHG and energy efficiencies. Climate was identified as the most important variable compared to crop input variables such as fertilisers, agro-chemicals and fuel (Arrieta et al. 2018).

Although some studies have sought to quantify the effect of factors on global warming impact indicators and yield, an objective of this thesis was to approach this quantification from a different standpoint. This was executed by using multiple regression to estimate the main determinants (or combination of factors) influencing key environmental impact variables including GHG emissions, carbon footprint, net energy and crop yield.

2.12 Summary

A large body of literature exists on the environmental impacts of producing biofuel feedstock however; an integrated assessment of producing biofuel feedstock under climate change in developing countries is limited. So far, existing studies in Nigeria seem to focus on using LCA to quantify the environmental impacts of energy crops such as sorghum and sugarcane (Nasidi et al. 2010, 2013), *Jathropa* (Onabanjo and Di Lorenzo 2015, Somorin et al. 2017) and palm oil (Okoro 2018). Somorin et al. (2017) confirmed that the benefits of developing biofuel in Nigeria depend on plant yield, the system of cultivation and energy efficiency, however, there is less detail regarding environmental responses. Whereas, Ekpenyong and Ogbuagu (2015), Edoja et al. (2016), Zimmermann et al. (2017), Somorin et al. (2017), Jalota et al. (2018), reported on the impact of climate change on issues ranging from food security, agricultural productivity to presenting the environmental burdens from producing energy crops; these studies have not taken into account the changes in environmental impact response as a direct impact of climate change and farm practices.

The economies of developing countries in the sub-Saharan region rely on rain-fed agriculture and particularly vulnerable to climate change. Projections show warming of this region and climate change could reduce crop production and exacerbate environmental impacts. In response to this, previous studies have considered mitigating climate change impacts on crop yield through intense application of agricultural inputs which also has the potential to create a negative environmental impact and may affect long-term biofuel policy. However, there seems to be some ambiguity on the influence of climate change on environmental impact responses in relation to the assessment of the sustainability of energy crop production in developing countries. This calls for further assessment of future adaptation measures for best-scenario options to complement climate change risk assessment. This could offer insights on how policy makers can adapt future cultivation of energy crop like maize towards a more sustainable production, based on a quantitative assessment of potential environmental impacts.

Furthermore, there seems to be a consensus on an integrated LCA methodology as a holistic approach to assessing the environmental impacts of farm management scenarios across varying agro-ecological zones. However, authors who adopted this approach have not considered important factors (e.g. climate change or fertiliser input) influencing key environmental impact responses such as GHG emissions. To address this research gap, the present study proposes a new 'Crop Sustainability Assessment Framework (CSAF) to serve as a guide for researchers and policy makers to adopt a more integrated approach in assessing the sustainability of growing energy crops for biofuels under climate change. The unique integration of regression analysis to the framework is to identify and quantify which factors among (i) climate change

(ii) fertiliser input rate and (iii) changes in tillage method have an impact on variations of the GHG emissions, carbon footprint, net energy and yield estimates. This framework highlights the main determinants of the variability of crop yield and environmental responses of biofuel feedstock production.

The next chapter explains the rationale for the approach used, selected study sites and tools, and further outlines the overall methodology adopted for this research

Chapter 3:

3 Research Methodology

3.1 Introduction

This chapter describes the Crop Sustainability Assessment Framework (CSAF) required to achieve the research aim and objectives stated in chapter one. For this study, the choice of integrated framework largely depended on the objective of study and data availability (Tonnang et al. 2017). As shown in Figure 3.1, the methodology, which develops an integrated life cycle approach; a coupled climate-crop model linked to a life cycle assessment (LCA); and a regression model, aims to illustrate the holistic assessment for production sustainability of maize as an energy crop for bioenergy systems.

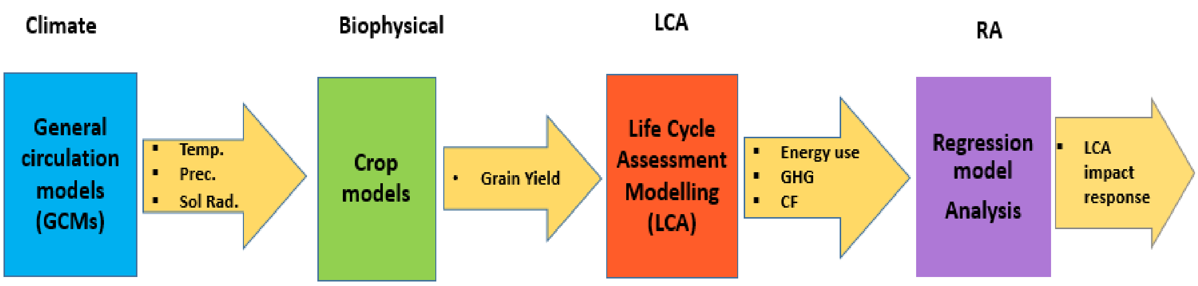

Figure 3.1: A simple outline of the Crop Sustainability Assessment Framework (CSAF) under climate change.

This methodology, which uniquely links the influence of climate change and its consequential environmental impacts on the farming phase correlates yield, embodied energy, GHG emission and carbon footprint, provides a quantitative output for comparison with current baseline impacts. This can be seen as an approach strongly divergent from the research of Dyer et al. (2011) where an environmental impact assessment (EIA) approach was utilised, which is qualitative and does not quantify energy and carbon footprint when determining the sustainability of producing biofuel feedstock crops. Many other researches have also used a stand-alone scenario-led climate change approach (Fealy 2013, Asseng et al. 2015, Zhai et al. 2017, Chen et al. 2018), and it can be noted that some researchers have indeed integrated an environmental LCA into their framework (Garba 2014, Nelson et al. 2014, Zimmermann et al. 2017, Arvesen et al. 2018). To determine the GHG footprint of a crop cultivation system, Zheng and Han (2018) described a simple generic LCA framework that includes quantifying both crop production and total GHG emission.

This study however, differs from previous studies because it incorporates a statistical comparison of the environmental impacts against climate change scenarios and varying farm management practices.

3.2 Integrated modelling framework

The major aim of this study is to develop an integrated framework to assess the impact of climate change and farming strategies on the embodied energy in maize production, taking into account the environmental impacts. In order to meet this objective, a statistical assessment of the correlation between farm net energy demand, GHG emission, carbon footprint (CF), climate change, fertiliser application rate and tillage technology was performed.

The methodological approach taken in this study is a mixed methodology based on the four main components of research: Firstly, in order to construct climate change scenarios, site-specific climate data was obtained, and the time series extended using a weather generator. Climate change scenarios were constructed from downscaled GCM models and the data was coupled with a crop model in order to simulate crop yield under different farm management practices.

Secondly, research was undertaken in order to investigate the combined effects of climate change and farm management strategies on maize grain yield. Maize was selected as the test crop due to availability of substantial historical climate from four sites, representing two agricultural zones in Nigeria.

Thirdly, a lifecycle impact assessment (LCIA) of GHG emissions, net energy and carbon footprints according to the ISO 14044 framework (Haus 2018) were quantified using life cycle inventory data from crop model inputs and outputs as well as data from secondary sources. In addition, energy and materials input per hectare following common farm practice were assumed. Furthermore, the LCA assumed a ‘cradle to gate’ system boundary, encompassing feedstock cultivation only and excluding the transportation of finished product and operation of the bio-refinery and used stages of the fuel.

Fourthly, the output was then analysed using a regression analysis to identify correlations and the significant effects of inputs on said outputs. The resulting data led to conclusions on the sustainability of the system under climate change compared to baseline scenarios. From this, recommendations could be made.

This study contributes to this growing area of research by mainly analysing primary climate data and secondary farm management data from Nigeria. However, the methodology is generic and because of this, can be applied across a variety of crop and geographical contexts. Throughout this work, the focus crop referred to will be Maize. The main reason for choosing Maize (*Zea mays* L.), a C4 plant, as the main plant-based focus of this research is because it is considered to be an optimal first generation biofuel feedstock (Xu et al. 2017). In addition, it is commonly cultivated in Nigeria due to its ability to adapt to different agro-climatic conditions in the country (Oluwaranti and Ajani 2016). The rest of this chapter describes each stage of the methodology in detail and the flowchart that summarises the different studies carried out is presented in Figure 3.2.

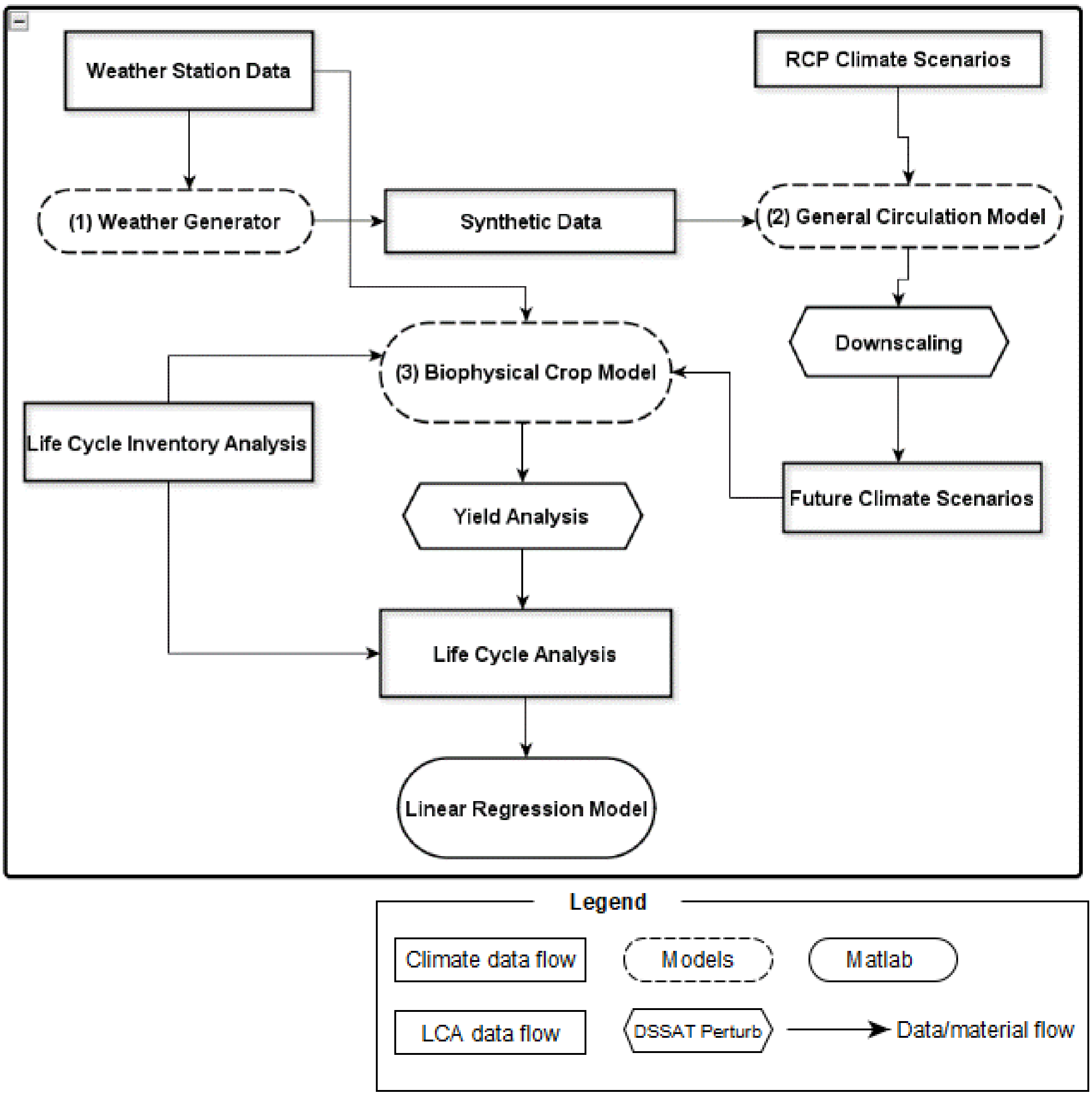

Figure 3.2: Flow diagram showing the core concept of the Crop Sustainability Assessment Framework (CSAF) for climate change impact assessment on bioenergy crop production.

3.3 Site area and climate description

Meteorological data for four sites (Table 3.1) was obtained from the Nigerian Meteorological Agency (NiMet). The locations were of diverse agricultural climates, within the Derived Savannah Agro-ecological zones (AEZs) of Nigeria (Figure 3.3) and were representative of areas where maize crop were typically produced. These representative areas are important to note in particular because Nigeria's latitudinal extent is relatively large and covers virtually all of the climatic belts of West Africa (Odekunle 2006). By way of illustration of Nigeria's latitudinal extent, a closer look at some of the country's varied locations are presented below.

Ilorin is in Kwara State, which is in the Southern Guinea Savannah, and lies within a tropical hinterland (Ifabiyi and Omoyosoye 2011). The average annual temperature ranges between 30°C and 35°C with an average relative humidity of 60%. Annual rainfall ranges from 1,000mm to 1,500mm, with the rain starting around March and ending in October. The dry season lasts from November until early March (Ifabiyi and Omoyosoye 2011). Ibadan lies within the forest grassland boundary of south-western Nigeria and the occurrence of dry (November to February) and wet (March to October) seasons is greatly influenced by its latitudinal location (Ogolo and Adeyemi 2009, Egbinola and Amobichukwu 2013, Eguaroje et al. 2015). Average daily air temperature range between 23.6°C and 33.2°C (Aderemi et al. 2018) and annual rainfall is about 1,205mm with two rainfall peaks in June and September (Egbinola and Amobichukwu 2013).

Enugu has a tropical wet and dry climate, with the rainy season lasting from April to October. The dry season typically occurs from November to March. The average annual precipitation is between 1600-1800 mm with an average temperature of 28°C (Enete 2014). Jos has a wet and dry climate classified as tropical rainy 'Aw' according to the Koppen climate classification

(Eludoyin et al. 2014). The mean annual rainfall is 1,290 mm (1,050–1,403 mm), peaking between July and August. Average temperature is approximately 22°C, but monthly temperatures vary between 19.4°C and 24.5°C. December is usually the coolest month as the area comes under the influence of the cool and dry desiccating north-easterly tropical continental air mass (harmattan). April is the hottest month of the year (Olowolafe 2002, Eludoyin et al. 2014).

Table 3.1: NIMET synoptic weather stations. Fifteen-year average meteorological details of study sites (Source: NIMET 2013, Bala 2016).

Station name	***Latitude (°N)***	***Longitude (°E)***	***Agro-ecological zone***	***Potential Bioenergy Feedstock***	***Total Annual Rainfall (mm)***	***Tmax (°C)***	***Tmin (°C)***	***SRad (MJ/m^2)***
Ibadan	*7°26′ N*	*3°54′ E*	*Derived Savannah*	*Maize*	*1,358*	*32*	*23*	*18*
Jos	*9°52′ N*	*8° 54′ E*	*Derived Savannah/Southern Guinea Savannah*	*Maize/ sorghum*	*1,290*	*28*	*17*	*24*
Enugu	*6°28′ N*	*7° 33′ E*	*Derived Savannah*	*Maize*	*1,924*	*32*	*23*	*19*
Ilorin	*8°29′ N*	*4° 35′ E*	*Derived Savannah/Southern Guinea Savannah*	*Maize/ sorghum*	*1,234*	*32*	*22*	*21*

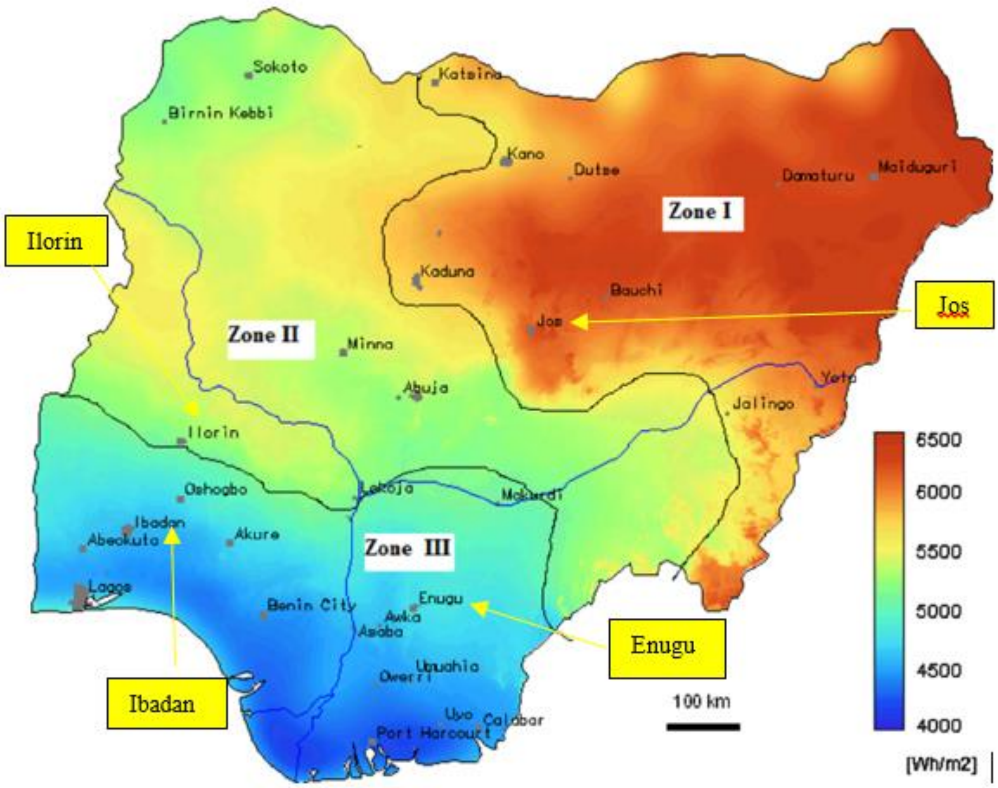

Figure 3.3: Solar insolation in Nigeria showing the location of the selected sites (Source: Ohunakin et al. 2014).

3.4 Data collection

3.4.1 Historical weather data

Historical data; 15 years of daily weather data (1998 to 2012) was obtained from four weather stations managed by the Nigerian Meteorological Agency (NiMet). Weather parameters included maximum and minimum temperature, rainfall and solar radiation. A source of error in terms of the data collection was that almost all of the weather stations had incomplete data for the entire period, missing a significant number of records for rainfall and solar radiation. Due to a lack of station metadata, it was difficult to establish if the value of zero recorded, especially for daily rainfall, represented the absence of rainfall, failure of equipment or lack of recording. Because of this, it was not possible to investigate the significant relationships between metadata and actual rainfall further. The presence of metadata with details of station history documentation could give more insight into the reasons for periods of missing data, such as solar radiation data. Further evaluation of the datasets highlighted the presence of outliers and repetitions.

In order to mitigate incomplete data sets, Rivington et al. (2006) suggests that after vetting the homogeneity of the observed data, blank spaces can be filled by creating a reference series from alternative digital sources of climate data for the same or adjacent weather stations using weather coordinates. By way of illustration, Qian et al. (2011) filled missing data by temporal and spatial interpolation. In order to mitigate missing climate data, a complete set of data from the Global Yield Gap Atlas (GYGA), which consists of propagated data and crude NASA datasets for Nigeria was assessed (Bala 2016). This is because the GYGA website contains generated site-specific data from reference weather stations (RWS). In addition, the site specific-data complements the database with propagated daily weather data or alternative proxy data, such as crude NASA data, which is consequently utilised when no data exists for the site (Grassini et al. 2015, Van Wart et al. 2015). In the same manner, this dataset (GYGA) was used in Bala (2016) to evaluate crop yield in Nigeria.

3.4.2 Generating long-term synthetic climate data

Climate variability is an important factor that affects crop growth and yield, so the limited availability of long-term continuous climate data hampers climate assessments (Antle 2015, Mehan et al. 2017). This meant that in particular, the analysis of climate variability and its impact became problematic because, in order to capture annual fluctuations in weather patterns, long-term daily weather data is required to estimate crop yield and its inter-annual variability

(Mourice et al. 2015). For this, a weather generator is most often used to synthesise long-term climate data. This is important to note because, the synthetisation of long-term climate data can be utilised in particular if available historical data is insufficient or the dataset is incomplete (Mehan et al. 2017). Ultimately, weather generators are not predictive weather tools, but rather employed to generate long-term time series that are, as much as possible, statistically identical to the observed (Chisanga et al. 2017).

The approaches used in this study were selected in order to generate long-term daily climate data for the purpose of evaluating the long-term effects of climate variability on crop yield (Tingem et al. 2008, 2009). The Long Ashton Research Station Weather Generator (LARS-WG v. 4.7) (Semenov and Barrow 2002) was used to produce daily climate reports to supplement the 1998-2012 Nimet data, creating 30 years of climate data for each location. Doing so showed that any desired length of synthetic data could be produced, but that longer time series are more advantageous in terms of estimating statistics more accurately (Qian et al. 2011). However, regardless of the length of the time series, there are limitations. The generated weather data will only reflect the climate of the observed historical data and not the climate that might be observed, e.g. in the next 30 years (Qian et al. 2011).

In generating synthetic weather data, there were three steps involved (Mehan et al. 2017). The first step was to calibrate information as per Lars-WG, using observed daily weather data obtained from the Nigerian Meteorological Agency (NiMet) for the 15-year period (1998-2012). The second step was to use the synthetic weather generated to evaluate the data against observations in order to identify any statistical differences. The final step consisted of the creation of a parameter file (Mehan et al. 2017). With reference to the generation of synthetic weather data, the generator uses the SITE ANALYSIS option to create a parameter file. The parameter file, which contains semi-empirical distributions of length for dry and wet series; wet and dry series for precipitation; minimum and maximum temperature and solar radiation including their correlation and auto-correlation coefficients, ensures that all aspects are calculated separately. Statistics of the observed and generated data are then calculated to include monthly means and standard deviation, daily maxima, daily minima and percentiles of climate variables. To evaluate model performance at a significant level of $p<0.05$, the two-sample Kolmogorov (K-S) tests to check for differences in daily distributions derived from the generated and observed data, a t-test and a F-test were used to compare the monthly means and variances (Semenov and Stratonovitch 2010).

Many studies have evaluated and validated the performance of LARS-WG under diverse climates (Qian et al. 2004, Ventrella et al. 2012, Reddy et al. 2014, Sarkar and Chicholikar 2016, Gitau et al. 2018). To conclude, the justification for the consideration of a weather generator for this study is that it could potentially be applied at a single site to generate synthetic data based on as little as a single year of observed climate data, which proved advantageous (Chisanga et al. 2017).

3.5 Future climate projection – using DSSAT-Perturb software

Future climate scenarios based on two greenhouse gas concentration trajectories (RCP 6.0 and RCP 8.5) were considered for this study (Basso et al. 2016). These two representative concentration pathway (RCP) scenarios were chosen because they represented both moderate and severe paths for future climate change reported in the latest IPCC Fifth Assessment Report (IPCC 2014). Those identified were due to having the highest probability of occurrence given current emissions trends (Cubasch et al. 2013, Magugu 2016, Basso et al. 2016, Magugu et al. 2018). Daily climate change data for the years of analysis (2020, 2050 and 2080) were also derived from an ensemble of 40 GCMs as shown in Appendix A (Table 3.1), using DSSAT-Perturb (version 1.0) downscaling software (Yin et al. 2013). The software was optimal because it follows the IPCC Fifth Assessment Report (AR5) and uses the latest Coupled-Model-Intercomparison-Project phase 5 (CMIP5) datasets with different emission scenarios (Basso et al. 2016, Magugu et al. 2018). The GCM data (obtained from the Earth System Grid (ESG) data portal for CMIP5) within DSSAT-Perturb (version 1.0), was downscaled using a pattern-scaling method (discussed in Chapter 2). The generated climate change factors were used to perturb regional or site-specific historical weather files, using them to explore projected climate change for the specific study areas (Yin et al. 2013, Osborn et al. 2016, Basso et al. 2016).

For this study, the historical climate file presented for perturbation was the synthetic climate data (30 years) generated prior to this step. This does not display the actual time series of 1998 to 2027, rather a statistical representation of the original climate data (1998-2012) simulated by the weather generator (see previous section). Therefore, the synthetic time series over a period of 30 years was perturbed using climate change factors from 40 GCM models (to capture the variability between the GCMs) for three specific scenario timelines (2020, 2050, 2080) and RCP 6.0 and RCP 8.5 GHG concentration pathways. Both climate data hereafter known as the baseline scenario (generated climate data) and future climate scenarios (perturbed climate data) were used for crop simulation.

DSSAT-Perturb software is the preferred downscaling tool developed by CLIMsystems for DSSAT users (http://www.climsystems.com/dssat-perturb/) and provided easy access to create an ensemble of models (Yin et al. 2013, Magugu 2016, Basso et al. 2016). According to IPCC (2014), uncertainties in predictions tend to decrease with the increasing number of model ensembles, which introduces a wider potential range of climate behaviours in the subset. It is, therefore, good practice to include the use of multi-model ensembles in detection and attribution studies (Knutti et al. 2010). Furthermore, the perturbed weather files were compatible with the DSSAT crop model daily weather format discussed in the following section and readily imported directly into the DSSAT crop model. The GCM downscaled weather parameters for each location including minimum and maximum temperature, solar radiation and rainfall values were obtained by utilising site-specific coordinates.

3.6 DSSAT Crop Model Description

Maize (*Zea mays* L.) yield responses to climate change under varying hypothetical farm management strategies were simulated for each site using the DSSAT-CSM crop model. Crop models have long been used to explore crop responses to agronomic and climate changes (Wang et al. 2011, Ahmed et al. 2017). The Crop-Environment-Resource-Synthesis group (CERES) are process-based plant growth modules embedded in the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation models (Jones et al. 2003, Hoogenboom et al. 2012a, 2017). They run on a daily time step, driven by daily weather elements (Wang et al. 2011, Ventrella et al. 2012, Msongaleli et al. 2014, Van Wart et al. 2015). The DSSAT-CSM agronomic cropping system model is a software application program that simulates over 28 crop varieties (Christ 2016) using a combination of crop modules with soil and weather databases and other crop management application programs. The program also includes tools that can facilitate the management of experimental data, soil profile files and weather data files (Jones et al. 2003, White et al. 2011, Hoogenboom et al. 2012b, White et al. 2013).

The model simulates plant responses to environmental conditions such as soil, weather, water stress and management (Ahmed et al. 2017). Site-specific input parameters are required to calibrate the model and calculate growth development and partitioning processes from planting to predicted harvest maturity. Like most crop models, plant phonological development within CERES-maize model (Jones and Kiniry 1986, Tsuji 1998) is sensitive to cultivar type, water deficiency, temperature (growing degree-days: GDD), photoperiod and nitrogen stresses, that are expressed as physiological days per calendar day (PD/day) (Mera et al. 2006). Daily crop growth is calculated by converting intercepted light (Incident Photosynthetically Active Radiation, IPAR, MJ plant^{-1} d^{-1}) into crop dry matter with a crop specific radiation use efficiency (RUE, g MJ^{-1}) parameter (Garba, 2014).

DSSAT-CSM v4.7 software (Hoogenboom et al. 2015) was selected for this study because of its popularity and extensive use in a wide range of settings for studying crop response to climate change (Mourice et al. 2017). DSSAT-CSM has been successfully validated in over 100 different countries worldwide (Jones et al. 2003, Jones et al. 2012, White et al. 2011, Hoogenboom et al. 2012b, White et al. 2013). It has also been validated in recent years using results from long-term field experiments (Musinguzi et al. 2014, Li et al. 2015, Corbeels et al. 2016, Liu et al. 2017), and across different climate and soil conditions and for different varieties of crops, specifically in many sub-Saharan locations (Mourice et al. 2014, 2015, Mtongori et al. 2015, Ahmed et al. 2017, Adnan et al. 2017a, 2017b). The minimum dataset requirement for model operation, as prescribed by the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) (1982-1993), must include a balanced set of information on the site where the model is to be applied. Daily weather during growing cycles, soil characteristics including soil initial conditions at the start of the growing cycle, crop management and cultivar type are also to be included (Hunt and Boote 1998, Mourice et al. 2014, Garba 2014). For this study, three input files – weather, soil and experimental data were created to run the DSSAT model (see Appendix B).

3.6.1 Weather, Soil and Farm Input Data

3.6.1.1 Creating daily weather file

Weather constitutes part of the natural system that is considered a non-controlled input parameter for crop growth and yield estimation. This meant that there was a need for daily weather data to be available beginning from the day of planting, through to harvesting (Dias et al. 2016). In light of this, the 30-year synthetic and perturbed weather files – as discussed earlier - representing baseline and future climate scenarios were incorporated into DSSAT via the Weatherman utility tool. Each of the weather files contained data on daily maximum and minimum temperatures, daily solar radiation and daily rainfall. Weather data files were converted into DSSAT format and exported; ready for use by the CERES-Maize model.

3.6.1.2 Soil data preparation

Soil type at any specific locality can vary, each having a different capacity to support crop growth (Adejuwon 2006). For example, differing soil types such as the Iwo series, Osun series and Apomu series can be found in Ibadan. They are all different in several respects because of having different physical and chemical properties (Adejuwon 2006, Olatunji and Ewetola 2015). As a result, crop yield can vary for each soil type; therefore, it is imperative that the soil data collected represents diverse properties of soil types for each location (Olatunji and Ewetola 2015).

Areas where significant differences have been found according to USDA Taxonomy, include the fact that soils in Ibadan are classed as Alfisols whilst Enugu soil is classed as a coarse textured sandy loam with low organic matter nutrients (Unagwu 2014, Nikejah et al. 2014, Edeh et al. 2015, Ezeaku et al. 2015). Enugu soil belongs to the orders of Ultisols and Vertisols (Edeh et al. 2015). In addition, the soil moisture regime in Jos is ustic and the soil temperature regime is inferred as isohyperthermic (Olowolafe 2002), whilst Ilorin soil is ferruginous tropical (Ifabiyi and Omoyosoye 2011, Daramola et al. 2015). Olaniyan et al. (2018) analysed soil properties (physical and chemical) in Ilorin by classifying the soils according to their respective pedogenic horizon. Overall, the International Institute of Tropical Agriculture (IITA) recommends any well-drained sandy or loamy soil for maize cultivation in Nigeria (Ajeigbe et al. 2010).

CERES-Maize model uses field-specific soil profiles which defines the physical and chemical properties of the soil (Yang 2008). For each location, soil databases were created using the SBuild tool in DSSAT V4.7, which was utilised for crop simulation purposes. The soil module was parameterised with measured experimental data obtained from various literature sources including; soil surface information, soil physical, chemical and morphological properties such as the percentage of nitrogen, the percentage of organic carbon, available phosphate (mg kg^{-1}), exchangeable potassium (cmol kg^{-1}), CEC (cmol kg^{-1}), pH, the percentage of clay, gravel, silt, bulk density and soil water balance, including the saturated upper limit (SAT), lower limit holding capacity (LL) and drained upper limit (DUL) (see Appendix C to F for each location).

3.6.1.3 Crop model calibration using farm input data

Further to this, cultivar estimation is an important step in crop modelling in order to attain accurate predictions and good model-based decisions (He 2008, Christ 2016). Crop models are calibrated by estimating or adjusting various parameters and functions to ensure model predictions are the same, or at the very least, close to field experiment data. To do this involves making initial estimates of the genetic coefficient for a given cultivar and calibrating the model with various crop growth in addition to development and grain formation parameters, such as the silking date, physiological maturity date, number of grains per square meter, leaf area index (LAI) and grain weight (He 2008, Tao et al. 2018).

In terms of this particular study, to establish such coefficients would require conducting field trials which can be both time consuming and expensive (He 2008, Qian et al. 2011, Adnan et al. 2017). This is why, for this study, there were no field-controlled experiments carried out. Hence, the default genetic cultivar coefficients in the CERES-Maize model of DSSAT were adopted without any adjustments, as the objective was to evaluate crop response to climate variability, rather than to predict crop growth. Oba super 2 is a yellow coloured hybrid maize cultivar with a relative maturity of between 90 to 113 days from planting to physiological maturity. The genetic coefficients data of the cultivar pre-existed within the CERES-Maize model and were used due to its popularity and potentials within Nigeria (Iyanda et al. 2014). Further information about this cultivar shows that it belongs to the late/intermediate cultivar varieties developed by the IITA and is known for its high yield, adaptability to the climatic zone and resistance to pests (Undie et al. 2012). Furthermore, Bello et al (2012) have illustrated an advantage of this maize cultivar. A yield evaluation experiment by (Bello et al. 2012) on early and late/intermediate maize varieties reported that most of the late/intermediate maturing varieties like Oba super 2 out-yielded the early maturing varieties analysed. Abayomi et al. (2012) have also evaluated drought tolerance capacity between extra early and early maize genotypes at Ilorin.

CERES-maize model was calibrated with other essential data for crop model operation. This essential data included planting methods, planting dates, plant density, row spacing; and the amount of fertilizer application undertaken was based on common practices and experimental data from previously published literature for the various locations (Lal 1997, Kolawole et al.

2004, Bello et al. 2012, Anjorin 2013, Bello et al. 2014, Iyanda et al. 2014, Amali and Namo 2015, Bala 2016, Imoloame 2017). Planting date information was based on the FAO crop calendar, literature sources and the IITA guidelines for maize cultivation in Nigeria. This is because this approach is representative of common practice. The recommended periods for planting maize in most parts of Nigeria is during the early rainfall season, so approximately March to June depending on the rainfall conditions of the year. As a result of this information, the plantation date of March 5th was set for all sites, regardless of the differential climate scenarios. All plant populations was set at 6.6 plants m^{-2}, with a row spacing set at 75cm and planting depth of 4cm. The initial surface residue from previous harvests (assumed to be maize) remained on the field and was set at 1000 Kg ha^{-1} in X-build. The reason for this amount is that it represented the conservative residue cover typically left during reduced tillage methods to prevent loss of soil fertility (Ozturk et al. 2006). To ensure that the soil contained a sufficient supply of growth nutrients, additional soil nutrient requirement was introduced via inorganic fertiliser application pull down menu.

Other farm management strategies created included four fertiliser application rates and three hypothetical soil tillage operations. Required nutrient sources in the form of nitrogen (N) obtained from urea fertiliser, Potassium (K_2O) from potassium chloride fertiliser and Phosphate (P_2O_5) from Single Super Phosphate fertiliser were selected (Adnan et al. 2017). Fertiliser were applied as per the treatment combinations: 80N+40P+40K; 160N+40P+40K; 200N+40P+40K; 250N+40P+40K, all in Kg ha^{-1}. Amali and Namo (2015) suggested fertiliser application should be attempted at planting and two weeks after planting to influence growth and grain yield. The fertilisers were split applied, with 50% at planting and 50% two weeks after planting. The same level of treatment was applied for all sites and the application method assumed was by broadcast and later incorporated into the soil.

Pesticide spraying is a common practice to control pest, weeds and fungus infestation in farms. DSSAT-CSM has a menu option to include pesticide application as a management strategy, however, one of the main weakness of this approach according to Anderson et al. (2018), is that the model does not predict yield on the basis of pest hazards. Another problem with this approach is that it fails to take into account the fact that pesticide application carries negative environmental impacts. Therefore, the inclusion of this as a rationale is instrumental for this study. Furthermore, according to Kamara et al. (2009), Kamara (2013) and Imoloame (2017), parasitic weed infestation such as Striga has contributed to the decline in maize yield across the sub-Saharan region, potentially causing yield loss from 10% to 100%. In response, the IITA recommendation for best agronomic practice includes judicious use of herbicides for weed management to address these constraints. For this simulation, 2kg ha^{-1} of fungicide and 2kg ha^{-1} Atrazine herbicide (Kamara, 2013, Bello et al. 2014) were included as a management strategy to control any hypothetical pest and weed infestation under climate change (Biber-Freudenberger et al. 2016, Tonnang et al. 2017).

Soil tillage is a primary field operation (Lovarelli et al. 2017) and represented in DSSAT-CSM by tillage date, tillage implement (type) and tillage depth. In 2018, Maharjan et al. reviewed the effects of tillage implements on soil properties using various agro-ecosystem models including DSSAT. For farm-level tillage simulations however, DSSAT-CSM cannot be used to account for field working capacity and energy requirement. Nevertheless, by assuming various tillage type implementations within the crop model, using this method of review can help to achieve the objective of accounting for various farm energy budgets and CO_2 emissions as calculated in section 3.7.

According to Lovarelli et al. (2017), soil variability, implement selection and field shape can significantly contribute to the environmental impact assessment of farm operations. Other models that have the capacity to simulate mechanics of field operations include the 'Farm Fieldwork and Fossil Fuel Energy and Emissions' (F4E2) model (Dyer and Desjardins 2003, 2005), and farm-based web computational tools (Sopegno et al. 2016, Busato et al. 2017). In addition, tillage operations modelling framework (Hameed et al. 2012, Sørensen et al. 2014) can also be applied in order to produce an estimation of various field energy requirements.

For this study, three tillage management strategies were considered:

1. Conventional tillage (CT) employing ploughing with a mouldboard plough at 30cm tillage depth.

2. Reduced tillage (RT) assuming a chisel plough at 30cm tillage depth.

3. No tillage (NT), assuming maize was planted by seed drill without any land preparatory tillage (West and Marland 2002, Soldevilla-Martinez et al. 2013, Ali et al. 2013, Šarauskis et al. 2014, Lu et al. 2018).

Within the XBuild file, 48 treatment levels were created under the seasonal utility mode in DSSAT (see Appendix B). Simulations were performed for each treatment level using baseline climate and six future climate scenarios (RCP 6.0 and RCP 8.5 for the 2020s, 2050s and 2080s). Current CO_2 concentration levels with measurements taken from the Mauna Loa centre in Hawaii (based on the Keeling curve) were used for all scenarios. This study takes the view that not considering the projected CO_2 atmospheric concentration for future scenarios helps to eliminate any fertilisation effect from additional CO_2 emitted during the projected periods.

Simulations were run under nutrient-limiting and water-limiting conditions. Running the simulation under rain-fed conditions was also used to examine the effects of future climate change scenarios on crop yield as both excess and inadequate soil moisture could be detrimental to optimal yield. Also, irrigation application is not a common practice in maize cultivation in some regions of Nigeria (Iyanda et al. 2014, Akinmutimi 2015). This is because, following a study by Folberth et al. (2013) and Iyanda et al. (2014), extended irrigation produced little effect on maize yields for tropical regions in sub-Saharan Africa and some agro-ecological zones in Nigeria.

In addition to the above, the seasonal analysis components in DSSAT were also used to examine year-to-year variation in crop productivity due to changes in weather and the performance of treatment effects on crop yield. The biophysical analysis component was used to determine the maximum and minimum range of yields, and level of variance within yields for each treatment. The model output was further subjected to a means test for significance at p = 0.05 level, and coefficient of variance analysis using the SPSS statistical program. Figure 3.4 illustrates the modelled processes and treatment levels created.

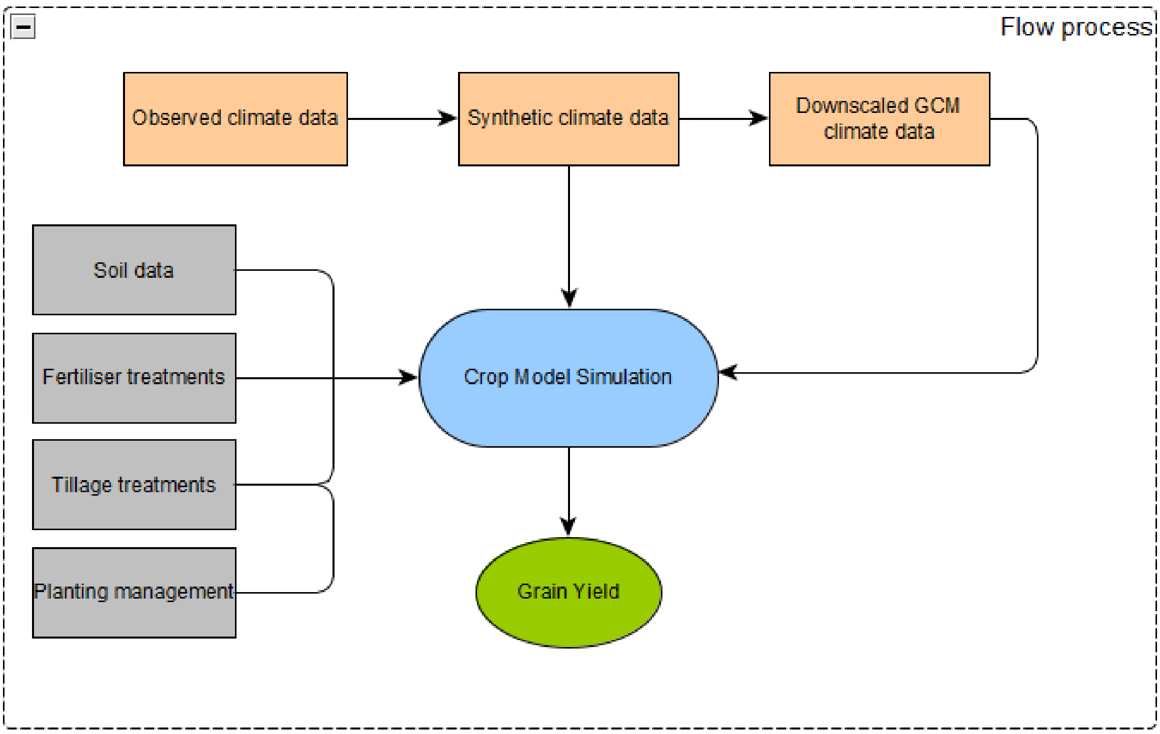

Figure 3.4: Simulation flow process created in CERES-Maize Model in DSSAT-CSM.

3.7 Life Cycle Assessment Modelling

Environmental life cycle assessment (LCA) is the scientific evaluation method used to measure the net environmental burdens associated with producing products such as biofuel (Carus, 2017). ISO 14040-44 provides the general framework and guidelines for conducting a LCA of a material or service using four stages: Goal and Scope, Inventory Analysis, Impact assessment and Interpretation (Russo et al. 2016, Haus 2018). Depending on the boundary definition, LCA assessment may cover all activities from raw material production through to harvesting (cradle-to-gate) or a full cradle-to-grave assessment (this is "up to use of biofuel" phase) (Arunrat et al. 2016, Russo et al. 2016, Czyrnek-Delêtre et al. 2017, Rahman et al. 2019).

In this section, energy consumption and CO_2 emissions for the cultivation of maize energy crop suitable for biofuel feedstock were analysed, keeping in mind that it was in competition with food production. This was followed by an evaluation of the carbon footprint per maize grain yield. Calculations and estimations in this section were carried out by using Microsoft Excel software and SPSS software programs.

3.7.1 Goal and Scope

The main goal of the current study was to determine and evaluate the potential environmental impacts and carbon footprint of the mechanisation of maize production for biofuel by linking the total GHG emissions to grain yield obtained under differing future climate change scenarios. The key question addressed by this was 'Which management option under climate change results has the most reduced energy use, GHG emissions and carbon footprint?'

When quantifying input and output data in the inventory analysis, a functional unit is to be used as a reference (Wang et al. 2015). For this study, a single functional unit of 1kg ha^{-1} of dry matter maize grain produced was selected. Using a cradle-to-gate life cycle approach was chosen in order to set the system boundary around the farming phase and included all direct energy consumption and emissions (fuel for fieldwork), indirect energy inputs and emissions from production and use of materials, direct and indirect N_2O emissions from soil due to N fertiliser application and CO_2 emissions from the hydrolysis of urea fertiliser after application. The system boundary (Figure 3.5) for this study was defined to include production of raw materials and farming inputs such as fertiliser, crop protection products, application and energy use for machinery. Farm equipment production, harvesting, bailing and transportation of product were all outside of the scope of the life cycle inventory (LCI) as the GHG emission is negligible on a per hectare basis.

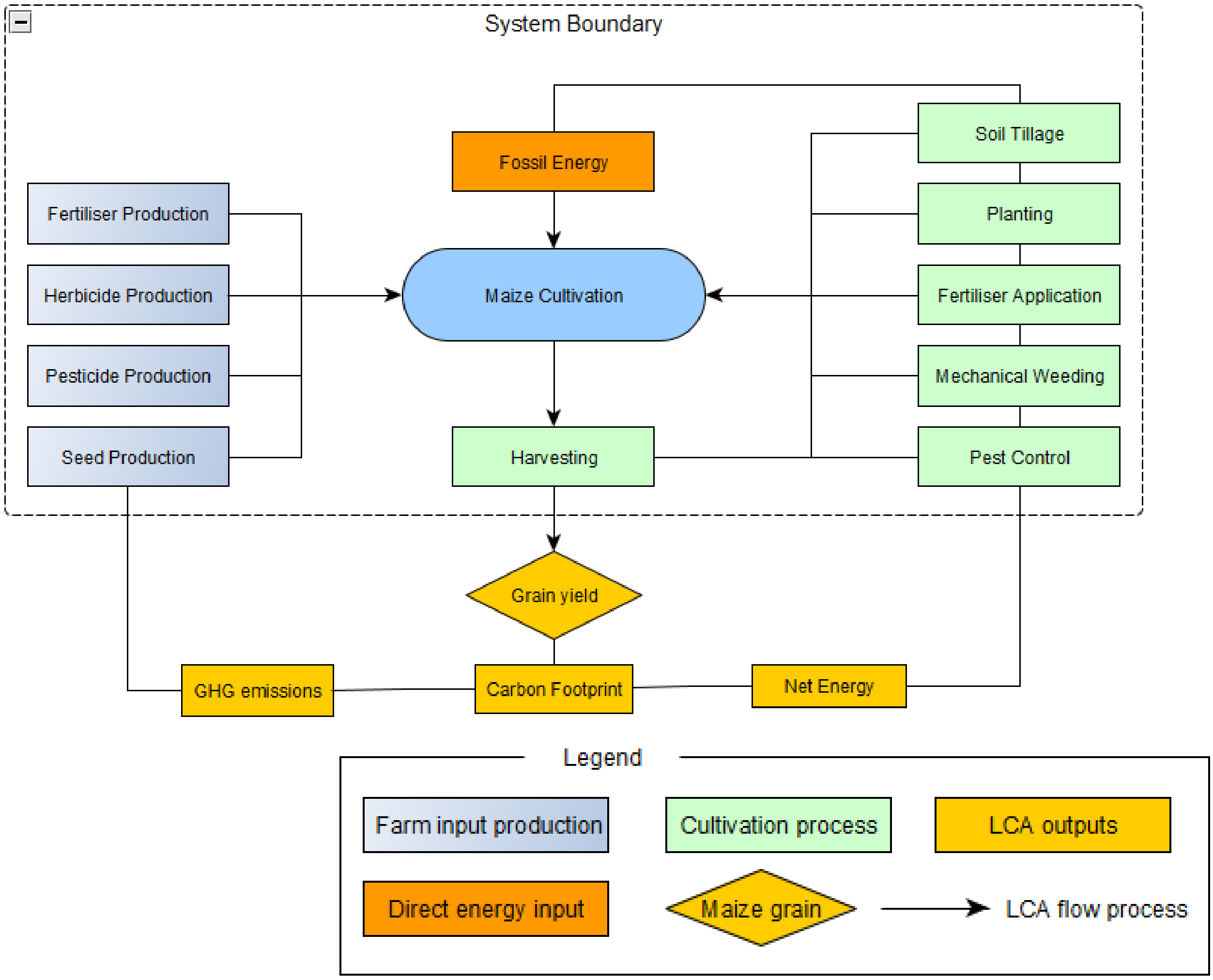

Figure 3.5: Production processes considered within the system boundary of a cradle-to-gate life cycle approach of this study.

3.7.2 Life cycle inventory (LCI)

To estimate net energy use, total GHG emissions and the C footprint, farm inputs, embodied energy of farm inputs, and grain yield data were required. Farm and energy inputs were obtained from literature, and grain yield data from the simulation run in section 3.6. As the three main farm operations for maize production are tillage, planting and harvesting, three tillage management strategies was considered because of their widespread use and advantage in different agro-ecological zones. These were as follows:

1. Conventional tillage (CT) employing ploughing with a mouldboard plough at 30cm tillage depth.

2. Reduced tillage (RT) assuming a chisel plough at 30cm tillage depth.

3. No tillage (NT), assuming maize was planted by seed drill without any land preparatory tillage (West and Marland 2002, Soldevilla-Martinez et al. 2013, Šarauskis et al. 2014, Ali et al. 2013).

Online inventory databases such as Ecoinvent contain generic farm tillage operations, which according to Lovarelli et al. (2017), do not consider actual local conditions (soil texture, field shape ratio and size) and working time. To counter this and because agricultural field production processes are complex, Lovarelli et al. (2017) recommended using primary or secondary process data that represented local conditions for LCA analysis compared to using data from common databases such as Ecoinvent.

In terms of this study, data for the three tillage operations and their energy input was obtained from varying secondary sources with detailed farm machinery operations from field experiments (Adekiya et al. 2009, Yohanna et al. 2014, Igon and Ayotamuno 2016, Zhang, Y. et al. 2018). Energy input data per hectare for different tillage systems, number of hours measured, machinery power and farm size, varied across different pieces of literature depending on the boundary system set (Stubbs 2013, Gemtos et al. 2013).

3.7.2.1 On-farm tillage operations and machines

The extent of agricultural machinery usage and choices is mostly influenced by internal and external factors and characteristics attributed to particular regions (Stubbs 2013). These factors range from land availability to climate, policies and labour cost. For example, Government policies and equipment cost have affected agricultural mechanisation and in particular, tractor use in Nigeria (Takeshima et al. 2015). Therefore, the efficiency and productivity of farm machinery used was outside of the scope of this study but has nevertheless been analysed in many previous research studies (Stubs 2013, Gemtos et al. 2013), where the extent of use was considered. Essentially, most mechanised farming carried out in Nigeria uses conventional tractor-drawn implements for soil preparation, seed planting, fertilising, weed control and harvesting (Yohanna et al. 2014). Although tillage operations are considered to create a reduction in drudgery and labour time, the disadvantage of this approach is the degradation of the soil's physical, chemical and biological qualities over time, making the soil prone to erosion (Lal 1997, Oni 2011).

Manzone and Calvo (2016) described various tillage operations and implement types used in maize cultivation as similar to those reported in Šarauskis et al. (2014). Because of this, the same tillage operations and implement types for maize cultivation were adopted and modified for this study. The management strategies defined by (West and Marland 2002, Ozturk et al. 2006, Lu et al. 2018) include a conventional tillage (CT) that leaves less than 15% residue cover after planting, reduced tillage (RT) and no tillage (NT) methods that leave 15-30% and above 30% residue cover respectively. For the conventional tillage method, ploughing was the primary operation and stubble cultivation, or seedbed preparation was the secondary operation (West and Marland 2002, Košutić et al. 2006). Stubble cultivation is essential for mulch sowing and preparing the ground after ploughing. With reference to optimal cultivation, incorporating straw back into the soil makes this operation generally more useful in regions vulnerable to erosion (Lu et al. 2018). In terms of implement type, Koller (2003) suggests that this operation can be carried out efficiently with a combination of chisels that have forerunning disks and rotary spade harrows. Further to this, Ali et al. (2017) included a sub-soiler in their analysis in combination with a mouldboard plough (as primary tillage) followed by disc harrowing (secondary tillage). Memon et al. (2013) also reported that the sub-soiler consumed the highest fuel (24.14 l/ha) followed by the mouldboard plough (21.25 l/ha) and the disc harrow (7.66 l/ha).

Moitzi et al. (2014) evaluated fuel consumption and working time requirements for CT, RT and NT operations. The results of their study indicated that the number of implements used for each system analysed influenced fuel consumption. In the CT system, the mouldboard plough consumed more fuel in litres per hectare than the power harrow, the seeding machine and the heavy cultivator for stubble field skimming (Moitzi et al. 2014). They further replaced the plough with a heavy cultivator and a seeding machine for stubble field skimming in the RT system. The NT only consisted of a seeding machine, but consumed the least amount of fuel (Moitzi et al. 2014).

Implement types and farm machinery use data of the three soil tillage systems included in DSSAT-CSM simulation were estimated by Ali et al. (2017) and Šarauskis et al. (2014). In this study, for soil preparation, the mouldboard (CT) and chisel (RT) plough system at 30cm tillage depth were used (primary tillage). For mulching and seedbed preparation (secondary tillage), disc harrow was the soil cultivator assumed at 30cm tillage depth, and a planter for secondary tillage. A chisel plough, soil cultivator and a planter were assumed for the reduced conventional tillage system (Lu et al. 2018). In their experiment, Košutić et al. (2006) replaced the mouldboard plough with a chisel plough and multitiller (excluding the disc harrow and without seedbed implementation) and reported an energy saving of 37.5% in comparison to the CT system. Overall, the tillage treatments considered in Olaoye (2002) showed that the highest grain yield was obtained with disc harrowing and no-till treatments.

A tractor (56KW) equipped with a 3-disc furrow 150cm disc plough was assumed to operate the tillage implements for all sites. The performance evaluation of this machinery was reported in Yohanna et al. (2014). Direct energy input from manual labour, embodied energy from manufacture of machinery, indirect energy inputs from lubricants, repair and maintenance, buildings and transport vehicles were difficult to estimate from available resources and were therefore not considered. This difficulty was also acknowledged by Shapouri et al. (2003), Persson et al. (2009), and Gemtos et al. (2013). There is a general consensus that energy from these sources account for only a small proportion of the total indirect energy input. For example, Arrieta et al. (2018) found that the GHG emissions and energy embodied in the manufacture, transport, repair, service and maintenance of farming machinery, was less than 0.5% of the overall results. In addition, embodied energy for the manufacture of the tractor and other machinery in terms of agricultural machinery is a long-term consumable and will pay back over more than one planting season.

3.7.2.2 Net energy analysis procedures

To calculate energy flows during maize production for this particular study, input energy was first specified and then transformed into the appropriate energy term using the equivalent factors for inputs and outputs (Tables 3.2 and 3.3). Energy equivalent coefficients for all farm inputs were taken from available resources to provide an estimate for total energy embodied in farm inputs. Material input for yield simulation included: urea fertiliser (80, 160, 200 and 250 kg N ha^{-1}), Phosphorus (P_2O_5) and Potassium (K_2O) (40 kg ha^{-1} each), plant protection products

(2 kg ha^{-1} pesticide and 2 kg ha^{-1} herbicides) and maize seedling (20 kg ha^{-1}). As earlier indicated, irrigation scheduling was not included in the simulation, hence energy input from irrigation was not considered. Output materials included maize grain only, as the stalk/residue was assumed to be re-invested within the field system. Fertilization application passes (twice), and pesticide application (once) were assumed to be the same for all tillage methods.

For direct energy input, fuel consumption (L h^{-1}) in various field operations for maize production and the working time required to perform the operation were estimated from field measurements published by Ali et al. (2017) and Šarauskis et al. (2014) (Table 3.3). Fuel consumption was then converted to energy by using the energy equivalent of diesel as recommended by previous researchers (Tzilivakis et al. 2005, Mobtaker et al. 2010, Jekayinfa et al. 2012, Rahman and Rahman 2013, Gemtos et al. 2013, Lawal et al. 2014). Indirect energy inputs for farm machinery, fertiliser, protection products, and seeds were also obtained by multiplying the individual input rates by their corresponding energy equivalents (Table 3.2).

Direct and indirect energy input was estimated according to the equation (1):

Energy input = Input quantity x Energy equivalent (Equation 1)

Total energy input and output was calculated per hectare and used to determine four energy indices that were proposed in most research (Tzilivakis et al. 2005, Mobtaker et al. 2010, Jekayinfa et al. 2012, Goglio et al. 2012, Rahman and Rahman 2013, Gemtos et al. 2013, Lawal et al. 2014, Chaudhary et al. 2017, Yadav et al. 2018) based on the equations (2) to (6).

Energy use efficiency = Energy output (MJ ha^{-1}) / Energy input (MJ ha^{-1}) (Equation 2)

Energy productivity = Yield output (kg ha^{-1}) / Energy input (MJ ha^{-1}) (Equation 3)

Specific energy = Energy input (MJ ha^{-1}) / Yield output (MJ kg^{-1}) (Equation 4)

Net energy = Energy output (MJ ha^{-1}) - Energy input (MJ ha^{-1}) (Equation 5)

Energy use efficiency also known as energy efficiency coefficient is calculated as the output-input energy ratio, which gives an indication of how much energy was produced per unit of energy used (Mobtaker et al. 2010, Gemtos et al. 2013). Energy productivity (MJ kg $^{-1}$) gave quantitative information on the maize yield obtained per unit of input energy. Specific energy (energy intensity) is an index which represents energy used to produce one unit of the product (Chaudhary et al. 2017). Net energy was calculated from the difference between the gross energy output produced per hectare and the total energy used in the production measured in MJ ha^{-1}.

Table 3.2: Energy coefficients of inputs and outputs used for maize cultivation.

Energy inputs	Energy equivalent /index (MJ)	Units	Reference
Diesel fuel	35.5	MJ/L	Staffell 2011, Ferreira et al. 2018
Agricultural machinery	69.83	MJ/kg	Mobtaker et al. 2010, Jekayinfa et al. 2012, Lawal et al. 2014
Maize Seed	18.71	MJ/kg	Singh and Mittal 1992, Mobtaker et al. 2010, Rahman and Rahman 2013, Memon et al. 2015
Nitrogen	74	MJ/kg	Singh and Mittal 1992, Jekayinfa et al. 2012, Sadiq and Isah 2015
Phosphorus (P_2O_5)	12.56	MJ/kg	Pellizzi 1992, Pimentel and Pimentel 1996, MBockari-Gevao et al. 2005, Memon et al. 2015
Potassium (K_2O)	6.7	MJ/kg	Pelizzi, 1992, Pimentel and Pimentel 1996, Singh and Mittal, 1992, Memon et al. 2015, Jekayinfa et al. 2012, Lawal et al. 2014, Sadiq and Isah, 2015
Herbicide	254.57	MJ/L	Jekayinfa et al. 2012, Lu et al. 2018
Pesticide	188	MJ/L	Pimentel 1980

Table 3.3: Estimated average working time (hours per hectare) and fuel consumption for various farming operations (Source: Šarauskis et al. 2014)

Mechanical operations	Working time (h/ha)	Fuel consumption (l/ha)
Conventional tillage (CT)		
Stubble cultivation	0.71	10.7
Mouldboard ploughing	1.92	24.5
Pre-sowing cultivation	0.77	4.6
Fertilisation	0.05	0.5
Conventional drilling	0.42	2.3
Spraying (Boom Sprayer)	0.15	0.9
Fertilisation	0.05	0.5
Harvesting	0.8	23.2
Reduced tillage (RT)		
Stubble cultivation	0.71	10.7
Chiselling	1.47	16.5
Pre-sowing cultivation	0.77	4.6
Fertilisation	0.05	0.5
Conventional drilling	0.42	2.3
Spraying (Boom Sprayer)	0.15	0.9
Fertilisation	0.05	0.5
Harvesting	0.8	23.2
No tillage (NT)		
Spraying (Boom Sprayer)	0.15	0.9
Fertilisation	0.05	0.5
Direct drilling	0.45	6.9
Spraying (Boom Sprayer)	0.15	0.9
Fertilisation	0.05	0.5
Harvesting	0.8	23.2

See Šarauskis et al. (2014) for detailed machines technical characteristics

3.7.3 Life Cycle Impact Assessment

3.7.3.1 Estimation of GHG emissions

Synthetic fertiliser contributes directly and indirectly to N_2O emissions and to the overall carbon footprint of maize feedstock production. Because of this, Ma et al. (2012) assessed the sustainability of maize production using various synthetic nitrogen application rates. From their assessment, Ma et al. (2012) reported that increasing N rates affected GHG emissions and the C footprint for all the rotation systems considered. Nitrous oxide (N_2O-N) is a gaseous intermediate in the reaction sequence of denitrification and nitrification of ammonium nitrate as influenced by soil temperature, soil water content, soil compaction, substrate availability and microbial potentials (Bessou et al. 2013). Therefore, the spatial distribution of N_2O in the soil is also influenced by precipitation, evapotranspiration, drainage and slope position (Rochette et al. 2008). This is important because N_2O greenhouse gas is reported to be the third most important and most abundantly emitted ozone-depleting substance and its emissions are also affected by climate change (Kanter et al. 2016).

It is suggested that the future increase in CO_2 concentrations may increase N uptake (due to the CO_2 fertilisation effect) and decrease soil N losses and hence reduce the emission of N_2O (Leakey et al. 2009, Stocker et al. 2013, Myers et al. 2014). As a result, Kanter et al. (2016) tested this hypothesis based on future climate change scenarios. Their findings reported that the CO_2 fertilisation effect does in fact enhance plant N uptake, but their results showed a moderate change in N_2O emissions using future projections (24% to 31% from 42 % to 44%). This shows a significant difference, compared to previously published studies that projected emissions of 38% to 75% (Kanter et al. 2016).

The United Nations Framework Convention on Climate Change (UNFCCC 2016) and the Kyoto Protocol mandated that countries should calculate their GHG emissions and create national inventories of GHG emissions. With links to this, the revised IPCC standard methodology to estimate fertiliser-induced N_2O emissions from agricultural soils includes using the Tier 1 default emission factor (0.01 kg N_2O -N kg $^{-1}$), which according to the IPCC (2006a) is based on more than 900 observations and is therefore robust. It was noted, however, that this emission factor can introduce significant bias into the estimated N_2O results if conditions at the site are different from the conditions under which the coefficients were determined (Rochette et al. 2008). Therefore, as advised by the IPCC, an alternative method should be put in place in order to estimate emissions using country-specific emission factors (EF) where sufficient data is available (IPCC 2006, ADP.org 2010, Lee et al. 2012).

A number of studies have developed country-specific methodologies in order to measure N_2O fluxes and to estimate N_2O emission factors. In addition, country-specific methodologies could also be used in order to measure the fraction of leachable nitrogen. Rochette et al. (2008) developed a Tier II methodology for the inventory of N_2O emissions from agricultural soils in Canada. Li et al. (2016) also used the APSIM model in order to simulate yield and estimate N_2O emissions from soil using factors specific to China.

The main purpose of this section of the study is to address the third objective. This objective aims to estimate GHG emissions and the C footprint associated with maize production as feedstock for biofuel. The conventional IPCC Tier 1 default emission factors was adopted for this assessment due to lack of data on country-specific and site-specific emission factors (Rivera et al. 2017, Arrieta et al. 2018). This is because this approach ensures consistency with previous global and regional estimates and published studies (Tubiello et al. 2013, Wang et al.

2016, Ali et al. 2017). The determination of GHG emissions and the C footprint includes estimating CO_2 equivalent emissions from:

1. Production, storage, transportation and application of N fertilisers

2. Herbicide production and application

3. Seeding production and planting

4. Conventional and no-till operations and harvesting.

Emissions associated with the construction of farm machinery and maintenance were not included as these were taken to be negligible. Total GHG emissions were compiled using estimated GHG values calculated from each agricultural input listed above using (equation 6) as suggested by Wang et al. (2017):

$$\text{Total GHG emissions} = \sum_{i=1}^{n} \mathrm{Al_i} \times \mathrm{EFi} + \mathrm{EN_2 0} \qquad \text{(Equation 6)}$$

To expound; Al_i represents individual inputs such as fertiliser, herbicides, pesticides, diesel fuel and field operations, whilst EF_i is the emission factor used to calculate the specific emission rates for each input (represented by the value n) including production, storage, transportation and application. E_{N2O} is the total N_2O emissions (direct and indirect) from the application of synthetic fertiliser. The functional unit for expressing energy use and GHG emissions was referred to per hectare of maize grain produced. Specific emission values and emission factors for various farm operations and inputs are shown in Table 3.4.

Table 3.4: Estimated emission factors (EF) for various farming inputs and sources

Inputs	Emission item	Emission factor	Reference
Diesel fuel	GHG emissions from production, transportation and combustion	3.22 kg CO_2eq $^{-1}$	Ali et al. 2017
Urea (world average)	GHG emissions from urea production (cradle to gate)	3.97 kg CO_2eq kg^{-1} N	Nasidi et al. (2010)
Direct N_2O emissions from soil	(EF_1) N_2O emissions from N fertilizer application	0.016 kg N_2ON kg^{-1} N input	IPCC 2006, Liska et al. (2009), Wang et al. 2017, Ali et al. 2017
Indirect N_2O emissions from soil	(EF_2) N_2O emission from volatilization	0.01 kg N_2O N / [kg NH_3N + NO_X –N volatilized]	IPCC 2006, Liska et al. (2009), Ma et al. 2017, Ali et al. 2017
	(EF_3) N_2O emission from leaching	0.0075 Kg N_2O N/kg N leaching/runoff	IPCC 2006, Liska et al. (2009), Ma et al. 2017, Ali et al. 2017
Phosphorus (P_2O_5)	CO_2 emission for the production, packaging, storage and transportation of Phosphorus (P_2O_5)	0.73 kg CO_2eq kg^{-1}	Lal (2004)
Potassium (K_2O)	CO_2 emission for the production, packaging, storage and transportation of Potassium (K2O)	0.55 kg CO_2eq kg^{-1}	Lal (2004)
Herbicide	CO_2 emission for the production, packaging, storage and transportation of herbicides	23.1 kg CO_2eq kg^{-1} of a.i. (active ingredient)	Lal (2004)
Pesticide	CO_2 emission for the production, packaging, storage and transportation of Pesticide	25.1 kg CO_2eq kg^{-1}	Liska et al. (2009)
Maize seeds	GHG emission from maize seeds cultivation and transportation to farm gate	4.5 kg CO_2eq kg^{-1}	Wang et al. (2015)
Machinery usage	CO_2 emissions from farm machinery usage differ for each kind of field operation		
	Mouldboard ploughing	55.7 kg CO_2eq ha^{-1}	Lal (2004)
	Chiselling	29.0 kg CO_2eq ha^{-1}	Lal (2004)
	Stubble cultivation (disc harrowing)	21.3 kg CO_2eq ha^{-1}	Lal (2004)
	Pre-sowing cultivation	14.7 kg CO_2eq ha^{-1}	
	Conventional drilling (CT & RT planting method)	11.7 kg CO_2eq ha^{-1}	Lal (2004)
	Direct drilling (NT planting method)	13.7 kg CO_2eq ha^{-1}	Lal (2004)
	Herbicide and fungicide spraying (Boom Sprayer)	5.1 kg CO_2eq ha^{-1}	Lal (2004)
	Fertilisation	3.3 kg CO_2eq ha^{-1}	Lal (2004)
	Harvesting (combine)	36.7 kg CO_2eq ha^{-1}	Lal (2004)

3.7.3.1.1 Estimating CO_2 emissions from fertiliser production

According to many farm tillage studies, intensive mechanised farming causes significant impairment to soil, contributes to soil nutrient loss, hence the increased need to apply more synthetic fertilisers to boost yield. In accordance with this, Wang et al. (2017) calculated GHG emissions from specific fertilisers by dividing their specific emission factor (EF) by the nutrient content. From that, they reported that ammonium hydroxide with EF of 5.23 kg CO_2 eq kg $^{-1}$ had the highest GHG emissions (32.70 kg CO_2 eq kg $^{-1}$) compared to urea with EF of 2.30 kg CO_2 eq kg $^{-1}$ (5.00 kg CO_2 eq kg $^{-1}$). For P and K fertilisers, calcium magnesium phosphate and potassium carbonate produced the highest emission values. From their calculation, it can be seen that varying EF clearly affects the amount of emissions that each fertiliser directly or indirectly produced. Therefore, applying fertilisers with the lowest emission factors will reduce GHG emissions from fertilisers.

According to Maraseni et al. (2010), N, P and K based fertilisers require more energy for their production. The production of urea, phosphorus (P_2O_5) and potassium (K_2O) fertilisers were estimated using the emission factors in Table 3.4. In addition, Liska et al. (2009) used 2.55 kg CO_2eq kg^{-1} N for N, 1.56 kg CO_2eq kg^{-1} and 0.69 kg CO_2eq kg^{-1} for phosphorus and potassium. Values were considered from Lal (2004) for phosphorus (0.73 kg CO_2eq kg^{-1}) and potassium (0.55 kg CO_2eq kg^{-1}) fertiliser and 3.97 kg CO_2eq kg^{-1} N for urea production obtained from Nasidi et al. (2010). Equation (7) was used to estimate CO_2 emissions from fertiliser production.

$$CO_2 eq\ emission\ (kg\ CO_2) = Application\ rate(kg) \times EF(kg\ CO_2 kg^{-1}) \quad \text{(Equation 7)}$$

3.7.3.1.2 Estimating N_2O emissions from N fertiliser application

It has been reported that the amount of synthetic N applied to the soil is correlated with the amount of direct and indirect N_2O emissions (Ma et al. 2012). The total N_2O emissions (E_{N2O}), including direct and indirect N_2O emissions from N application, were estimated using the modified IPCC (2006) Tier 1 methodology (equation 8 - 12) similar to the studies of Ali et al. (2017) and Wang et al. (2016). Emissions of N_2O occur through both a direct pathway from anthropogenic N input and two indirect pathways: (i) from the volatilisation of NH_3 and NOx from soils and fossil fuel combustion; and (ii) from leaching and run-off of N, mainly as NO_3^-. It is important that the modified approach only accounted for emissions of N_2O from synthetic fertiliser application without considering N_2O emissions from crop residue and N-fixing crops. The full description of the generic methodologies for nitrous oxide emissions from managed soils, including indirect emissions, can be seen in the IPCC (2006) guidelines for national GHG inventories.

Total emissions from N fertiliser application were calculated according to the equations below:

$$Total\ E_{N2O}(kg\ CO_2eq\ ha^{-1}) = Direct\ N_2O\ emission\ (kg\ CO_2eq\ ha^{-1}) + Indirect\ N_2O\ emission\ (kg\ CO_2eq\ ha^{-1}) \quad \text{(Equation 8)}$$

The direct and indirect N_2O emissions from N fertiliser application were then calculated:

$$Direct\ N_2O\ emission\ (kg\ CO_2eq\ ha^{-1}) = F_{SN} \times EF_1 \times \frac{44}{28} \times GWP_{N2O} \quad \text{(Equation 9)}$$

$$Indirect\ N_2O\ emission\ (kg\ CO_2eq\ ha^{-1}) = N_2O_{(volatilised)}(kg\ N_2O - Nha^{-1}) + N_2O_{(leached)}(kgN_2O - Nha^{-1}) \times \frac{44}{28} \times GWP_{N2O} \quad \text{(Equation 10)}$$

Where:

1. $N_2O_{(volatilised)}(kg\ N_2O - N\ ha^{-1}) = F_{SN} \times Frac_{GASF} \times EF_2$ (Equation 11)

2. $N_2O_{(leached)}(kg\ N_2O - Nha^{-1}) = F_{SN} \times Frac_{LEACHED} \times EF_3$ (Equation 12)

Direct N_2O emission source is from N fertiliser application; $N_2O_{(volatilised)}$–N is the indirect N_2O emissions from cropping as a result of the atmospheric deposition of volatilised N; and $N_2O_{(leached)}$–N is representative of leaching and run-off. F_{SN} refers to the annual amount of synthetic fertiliser applied. This value is estimated from the total amount of synthetic fertiliser consumed annually. $Frac_{GASF}$ refers to the fraction of synthetic fertiliser N that volatilises as NH_3 and NO_x ($Frac_{GASF}$= 0.1). $Frac_{LEACHED}$ is the fraction of all N added that is lost through leaching and run-off ($Frac_{LEACHED}$= 0.3). Finally, EF_1 is the emission factor of N_2O direct emissions from N fertiliser application.

According to the IPCC (2006), the default for the emission factor (EF_1) is 1 percent of the N applied as fertiliser to soils or released through mineralisation. Therefore, in this case, EF_2 and EF_3 are default emission factors for volatilisation and leaching respectively. The conversion factor that acts to convert N_2 to N_2O is 44/28 and the global warming potential (GWP_{N2O}) conversion parameter of 298 was used to convert N_2O to CO_2eq over 100 years (IPCC 2006). The calculated emissions were then multiplied by these parameters to express the results in CO_2 equivalent. The uncertainties in estimates from direct N_2O emissions relate to the emission factors used, as well as a lack of information on specific on-farm practices (IPCC 2006).

3.7.3.1.3 Estimating CO_2 emissions from urea application

After applying urea fertiliser to the soil, a small amount of CO_2 is released (IPCC 2006, Ma et al. 2017). The amount released is fixed in terms of the industrial production and the occurrence takes place during the process of hydrolysis in the soil when urea ($CO(NH_2)_2$) is converted into ammonium (NH_4^+) hydroxyl ion (OH^-), and bicarbonate (HCO_3^-), due to the presence of water and urease enzymes (IPCC 2006, Ma et al. 2017). The bicarbonate formed evolves into CO_2 and water, according to the following equation (IPCC 2006, Kim et al., 2016).

$$(NH_2)_2CO + 3H_2O \rightarrow 2NH_4^+ + HCO_3^- + OH^-$$

$$H_2CO_3 \leftrightarrow CO_2 + H_2O$$

The method used in estimating CO_2 emissions associated with urea fertiliser use is included in the IPCC (2006) guidelines. Therefore, for this study, CO_2 from urea-based N fertiliser was estimated using the IPCC (2006) Tier 1 method and a default emission factor (0.20) that represents the fraction of C in urea according to equation (13):

$$CO_2 - C\ Emission = M \times EF \times \frac{44}{12} \qquad \text{(Equation 13)}$$

Where:

$CO_2 - C\ Emission$ = annual C emissions from urea application, tonnes C yr^{-1}

M = annual amount of urea fertilisation, tonnes urea yr^{-1}

EF = emission factor, tonne of C (tonne of urea)$^{-1}$

The emission factor of 0.20 (IPCC, 2006) for urea was adopted, which is equivalent to the carbon content of urea on an atomic weight basis (20 percent for $CO(NH_2)_2$). In addition, the conversion factor of 3.667 (44/12) was used to convert C to CO_2eq (IPCC 2006).

3.7.3.1.4 Estimating emissions from production, transportation, storage and transfer of agrochemical inputs

The production of plant protection pesticides such as herbicides, insecticides and fungicides is an energy-intensive process. As a consequence of this, it appears that the estimation of emissions from agrochemical inputs in turn can prove complex (FAO 2015). This is because the energy type and amount used during production varies (FAO 2015). GHG emissions can be estimated either through the energy used in production, packaging, transportation and application or by using the global warming potential of each agrochemical (Maraseni et al. 2010).

Various emission factors have been used to calculate emissions for pesticides based on the amount of active ingredients. For example, Maraseni et al. (2010) used emission factors of 22.8 kg CO_2eq kg^{-1} a.i. (active ingredient) and 24.5 CO_2eq kg^{-1} a.i. respectively for herbicide and pesticide GHG emissions. Liska et al. (2009) used 24.2 kg CO_2eq kg^{-1} a.i. and 25.1 kg CO_2eq kg^{-1} a.i. for herbicide and insecticide respectively. Lal (2004) estimated 14.3 kg CO_2eq kg^{-1} a.i., 18.7 kg CO_2eq kg^{-1} a.i. and 23.1 kg CO_2eq kg^{-1} a.i. for fungicides, insecticides and herbicides respectively, based on the active ingredient. Ali et al. (2017) used 23.1 kg CO_2eq kg^{-1} of a.i. for herbicide adopted from Lal (2004). For this study, average emission factors of 23.1 kg CO_2eq kg^{-1} a.i. for herbicide (Lal 2004) and 25.1 kg CO_2eq kg^{-1} for pesticide (Liska et al., 2009) were used (see Table 3.4). The equation (14) below was used to estimate emissions from herbicide and pesticide:

$$CO_{2eq\ emisson}(kg\ CO_2 ha^{-1}) = EF_{pesticides} \times input\ rate \qquad \text{(Equation 14)}$$

Where $EF_{pesticides}$ is the emission factor for the production of pesticides, kg CO_2eq kg^{-1} a.i. and the input rate is the amount of pesticides, kg a.i. ha^{-1} (a.i. – active ingredient).

3.7.3.1.5 Estimating emissions from production and combustion of diesel fuel

Various studies have estimated GHG conversion coefficients associated with the production, transport and combustion of diesel fuel (per litre). For instance, Beer et al. (2002) reported that 0.45 kg and 2.59 kg of CO_2 is produced for each litre of diesel during production and combustion. AGO (2002) reported 0.46 and 2.69 kg, whilst Nussey (2005) estimated 2.66 kg CO_2 for diesel combustion. In addition, Nasidi et al. (2004) used the IPCC (2006) default values of 0.0741 kg CO_2 MJ^{-1} for the fuel combustion emission factor. Further to this, Maraseni et al. (2010) calculated the average total coefficient combined values from both Beer et al. (2002), AGO (2001) and Nussey (2005). The results obtained from this calculation gave a value of 3.35 kg CO_{2eq} L^{-1}, which was close to that estimated by DEFRA (2010) at 3.18 kg CO_{2eq} L^{-1}, Lal (2004) at 3.48 CO_{2eq} kg^{-1} and at 3.22 kg CO_{2eq} L^{-1} by Ali et al. (2017). However, Maraseni et al. (2010) noted that the GHG emissions from transportation of fuels based on distance from petrol station to the farm was considered negligible and not included in the calculation.

The amount of fuel consumed for each farm process has been estimated in section 3.7.2.2., therefore, to determine the GHG emissions from the production, transport and combustion of diesel fuel (per litre), an emission factor of 3.22 kg CO_{2eq} L^{-1} was adopted (Ali et al. 2017). Thus, the total amount of GHG emissions from fuel use was obtained by multiplying the total amount of fuel consumption for each tillage system by the emission factor as per Table 3.4.

3.7.3.1.6 Estimating emissions from farm machinery

Emissions from farm machinery use during field operations was estimated based on the fraction of time the machine was used, and the average diesel consumption per hectare for each farming activity estimated from Šarauskis et al. (2014). Various farm operation data that represent both direct and indirect emissions arising from fuel use were derived by adopting a modified equation (15) as per Ali et al. (2017).

$$(GHG\ emissions\ kg\ CO_2 ha^{-1}) = EF\ (kg\ CO_2 l^{-1}) \times FC\ (l\ ha^{-1}) \times OTP \times fuel\ production\ ratio \quad \text{(Equation 15)}$$

For clarification purposes, EF refers to the emission factor for the various field operations adopted from Lal (2004) and presented in Table 3.4. *FC* refers to the fuel consumption for each field operation, and *OTP* refers to the number of times a single operation was performed. The *Fuel production ratio* is assumed as 1.24 and is demonstrative of the ratio of the energy content in fuel to the energy used to extract, refine and transport the fuel to the farm (Ali et al. 2017).

3.7.3.2 Estimation of Maize Carbon Footprint

Carbon footprint (CF) expresses the GHG intensity that is produced per unit yield of crop (Ali et al. 2017, Zheng and Han 2018). To determine the CF per kg of maize production, the total GHG emissions obtained are divided by maize yield produced per hectare per year, as shown in equation (16).

$$Carbon\ footprint, (kg\ CO_2eq\ kg^{-1}\ grain\ yield) = \frac{Total\ GHG\ (kg\ CO_2eq\ ha^{-1}}{Yield\ (kg\ ha^{-1})} \quad \text{(Equation 16)}$$

3.8 Regression model

The fifth objective of this study aimed to incorporate a regression model. The objective was put in place to examine the relationships (correlations) between input variables and LCA outputs and identify any significant contribution to yield and environmental impacts.

Essentially regression relies on historical data to apply the model. So, for this analysis, a design of experiment (DOE) based on a full factorial design was used to compute different combinations of the treatment levels (Collins et al. 2014). DOE helps to compute data in the most efficient way and using the DOE procedure helps to ensure the factors are truly independent of one another. It demonstrates how factors affect response and can establish a true cause and effect in order to quantify with clarity how much effect there was. Furthermore, a regression is performed on this data to determine the transfer function.

To initiate this approach, data for maize yield (kg ha^{-1}), GHG emission (kg CO_2 eq ha $^{-1}$), Carbon Footprint (kg CO_2 eq kg $^{-1}$ grain yield) and Net Energy (MJ ha^{-1}) was extracted from the crop model analysis and environmental impact analysis as discussed in previous sections. This data covers all four sites simulated using future climate scenarios and varying farm management technologies.

The following sequential approach was used in this section:

1. Create a full factorial design of experiment in Minitab software.
2. Generate a multiple linear regression model using MATLAB tool, and analyse the effects of independent variables on dependent variables through a regression analysis.
3. Use a simple linear model to determine if a correlation exists between the dominant independent variable and the dependent variable, followed by some significance testing.

3.8.1 Design of experiment

A full-factorial experiment based on 4^1 x 3^1 x 6^1 factor design was created and used to compute data combinations. This meant that there were 3 factors in total (sum of the exponents) and each factor had 4 levels, 3 levels, and 6 levels respectively. Therefore, for each site, a database that consisted of 72 experimental runs was created (4*3*6).

3.8.2 Multi-linear Regression analysis

Using the outcome of each experiment specified in previous sections to create multi-level factorial designs, multiple regression models according to equation (17) was built in Matlab. The reason for building such models was in order to use them for making inferences about the effect and relationship of climate change scenarios, tillage options and fertiliser application (predictor variable) on yield, GHG, CF and Net energy (response variables). This method in particular was selected because it is one that is commonly used when there is more than one independent variable (Sitienei et al. 2017). The regression was carried out using MATLAB statistical software (Version 2018.0.1), with the continuous variables used to denote the coefficients of the regression models. As a result, four multiple linear regression equation with coefficients that best represent the relationship between the variables were generated. The regression model was computed as:

$$Y = \beta_1 \times X_1 + \beta_2 \times X_2 + \beta_3 \times X_3 + \ldots\ldots + \beta_n X_n + K \qquad \text{(Equation 17)}$$

Where;

Y= value of the dependent variable – maize yield, GHG, CF and Net Energy

$\beta_1, \beta_2, \beta_3 \ldots\ldots..\beta_n$ = regression coefficient where each β represents the amount of change in the dependent variable (y) for one unit of change in the corresponding X-value when other X values are held constant.

$X_1\, X_2\, X_3 \ldots\ldots\ldots X_n$ = the independent variables – climate change scenarios, tillage and fertiliser; and K = the error estimate or residuals of the regression and it is a constant.

In addition to the above, the coefficient of multiple determination (R^2) and the RMSE were used to test the viability of the regression fit. The percentage effect of each predictor was determined and the relationship between the response and the predictor with the highest effect was analysed.

A simple linear regression model is similar to a multiple regression model based on the assumptions of error distribution. Because of this, the relationship between the responses (Y) to a predictor with the most significant effect was further developed using a simple linear equation.

Chapter 4

4 Results

4.1 Introduction

This chapter presents the main empirical findings of the research as follows: Firstly, the analysis of temperature and rainfall across four agro-ecological zones in Nigeria and the validation of weather generator synthetic data is presented in section 4.2. This is followed by the presentation of results of downscaled site-specific climate change scenarios in section 4.3. As explained in chapter 3, climate change scenarios was prepared by perturbing generated data using the DSSAT-Perturb software. The 40 GCMs selected contains projections for two climate change pathways: RCP 6.0 and RCP 8.5.

Next, the results of the impact of climate change analysis on yield of maize feedstock for biofuel production are discussed in section 4.4. The analysed result also includes maize yield response to farm management fertiliser application and tillage methods adopted for all of the scenarios and compared to yield output using baseline climate data.

Life cycle assessment (LCA) of the farm phase for biofuel feedstock production is presented is section 4.5 and includes the empirical results obtained for potential GHG emissions, energy use and the carbon footprint calculated per yield.

Lastly, the regression model results on the effect and relationship between factors and responses are presented in section 4.6, based on the factorial design given in chapter 3.

4.2 Analysis of observed and synthetic climate data

4.2.1 Climate data

Figures 4.1 to 4.4 reveal the variability of the average daily historical climate data (1998-2012) of rainfall, minimum and maximum temperature and solar radiation for all four sites. From Figure 4.1, the mean cumulative annual rainfall was 1,207.0mm in Jos (9°52′ N: 8° 54′ E), with the highest value (1,582.7mm) recorded in 2002, and the lowest value (879.5mm) in 2010. Mean minimum temperature (Tmin) ranged between 4.7°C and 16.2°C. The highest Tmin values were between 19.0°C and 22.0°C, and lowest Tmin ranged from 1.0°C to 8.0°C. Mean maximum temperature (Tmax) ranged between 27.5°C and 28.8°C. Extreme Tmax values ranged between 34.0°C and 35.0°C and minimum Tmax values ranged between 19.0°C and 20.0°C. The findings of the current study are consistent with those of Yusuf et al (2017) who similarly, observed mean Tmin value within the range (10.2°C) given above. However, a higher maximum temperature was reported with an average of 36.3°C based on climate data from 2008 to 2011. Mean annual solar radiation values ranged from 15.9 (MJ/m^2/day) to the highest value between 38.2 (MJ/m^2/day) and 41.8 (MJ/m^2/day).

Figure 4.2 presents weather trend for Ibadan (7°26′ N: 3°54′ E). Mean Tmax was recorded as 31°C. The highest recorded Tmax ranged from 37.0°C to 40.0°C, whilst the lowest Tmax values ranged from 24°C to 25°C. Some missing data in the year 2000 reduced the mean daily Tmax values between the 32nd and 60th days of the year, causing a slight dip on the graph. Mean Tmin value was recorded as 23.0°C, and the highest values were recorded as 26.0°C to 27.0°C. The lowest values ranged between 17.5°C and 20.0°C. Cumulative mean rainfall was measured as 1,392.2mm. The highest recorded value was 1,745.8mm, recorded in 2008, and the lowest value was 920.6mm, recorded in 1998. A limitation of this study was that the range of solar radiation was varied and inconsistent due to a lack of consistent data measurements. Nevertheless, mean solar radiation was valued at 14.0 ($MJ/m^2/day$) whist maximum values based on the data presented ranged from 34.2 to 40.7 ($MJ/m^2/day$).

In Enugu (6°28′ N: 7° 33′ E), the highest and lowest Tmax values ranged from 37.0°C to 39.0°C, and 24.0°C to 26.0°C respectively (Figure 4.3). Mean Tmin value was measured as approximately 21.0°C. The highest and lowest Tmin values ranged from 26.0°C to 28.0°C and 15.0°C to 17.0°C respectively. It should be noted however, that a significant amount of data (2002 – 2008) was missing which limits results. Nevertheless, the rainfall cumulative daily mean was measured at 1,709.4mm. The highest amount of rainfall was recorded in 2006 measuring 2,084.3mm, with the lowest recorded in 2012, measuring 1,049.6mm. Solar radiation maximum values ranged between 37.4 and 46.1 ($MJ/m^2/day$) and the mean range values ranged from 18.4 to 20.0 ($MJ/m^2/day$).

Figure 4.4 shows the climate trend of Ilorin (8°29′ N: 4° 35′ E). The mean Tmax recorded for this site was 30.9°C. The lowest Tmax values were within the range of 19.0°C to 26.0°C, while the highest Tmax values ranged between 36.0°C and 40.0°C. The observed climate data also shows the mean Tmin was recorded as 21.0°C at this site. The highest recorded Tmin temperatures were within the range of 26.0°C and 27.0°C, while the lowest Tmin values ranged from 12.0°C to 15.0°C. The highest rainfall was recorded in 2008 as 1,574.1mm, whilst 2001 had the lowest recorded rainfall 697.7mm. The mean was calculated to be 1,152.5mm. The findings of the current study are consistent with those of Ifabiyi and Omoyosoye (2011) who estimated similar rainfall statistics for Ilorin. Limitations were attributed to the fact that there was no observed data recorded in 2012 for rainfall and the solar radiation dataset for this site was very sparse. The mean daily solar radiation was recorded as 11.3 ($MJ/m^2/day$), and the highest range of solar radiation values ranged between 32.8 and 43.2 ($MJ/m^2/day$).

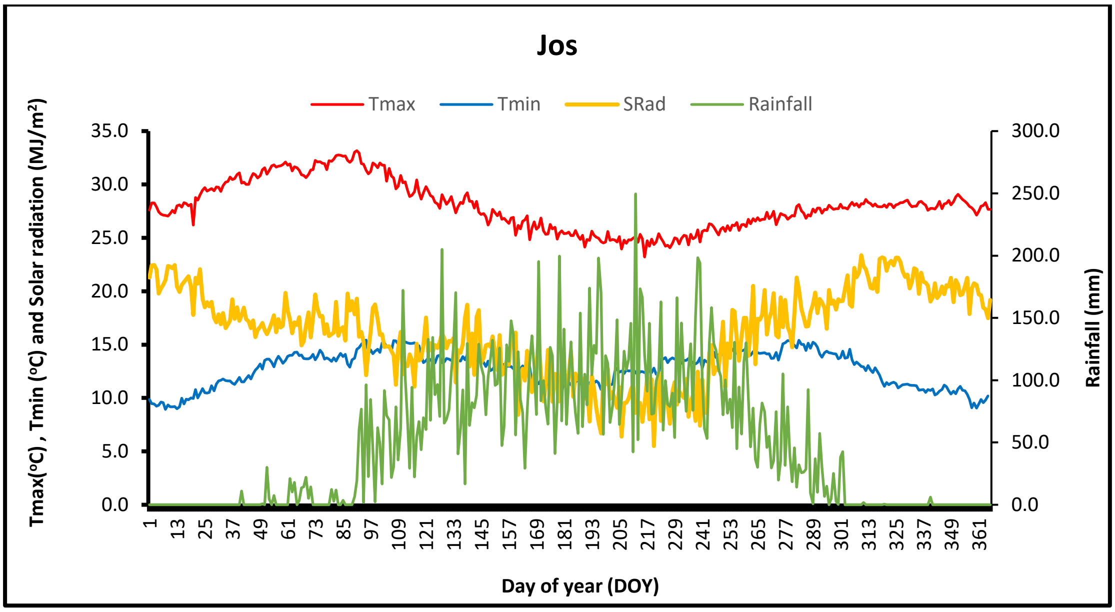

Figure 4.1: Average values of climatic variables computed from the 15-year observation data obtained for Jos location.

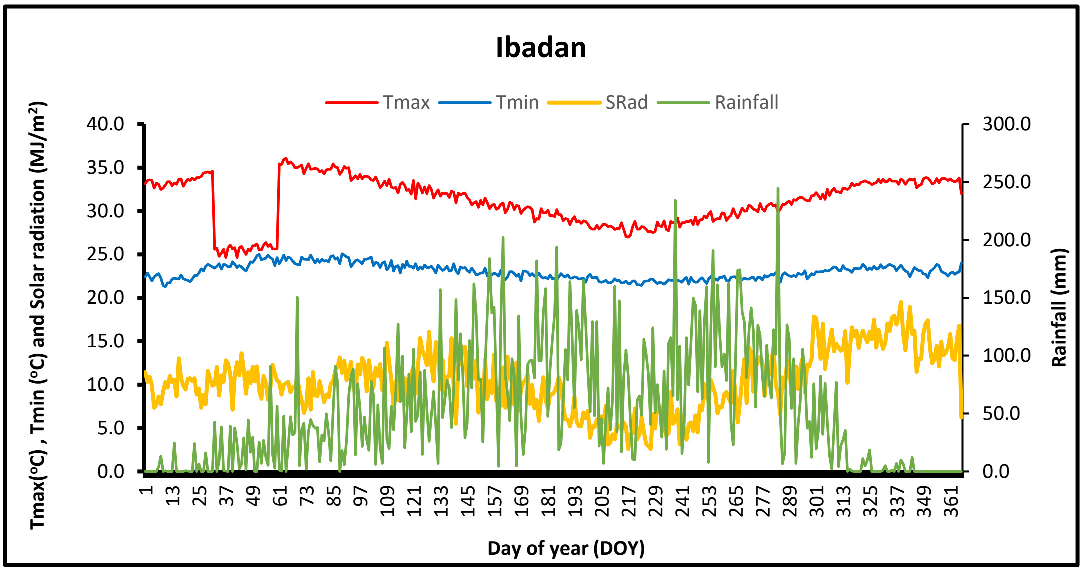

Figure 4.2: Average values of climatic variables computed from the 15-year observation data obtained for Ibadan location.

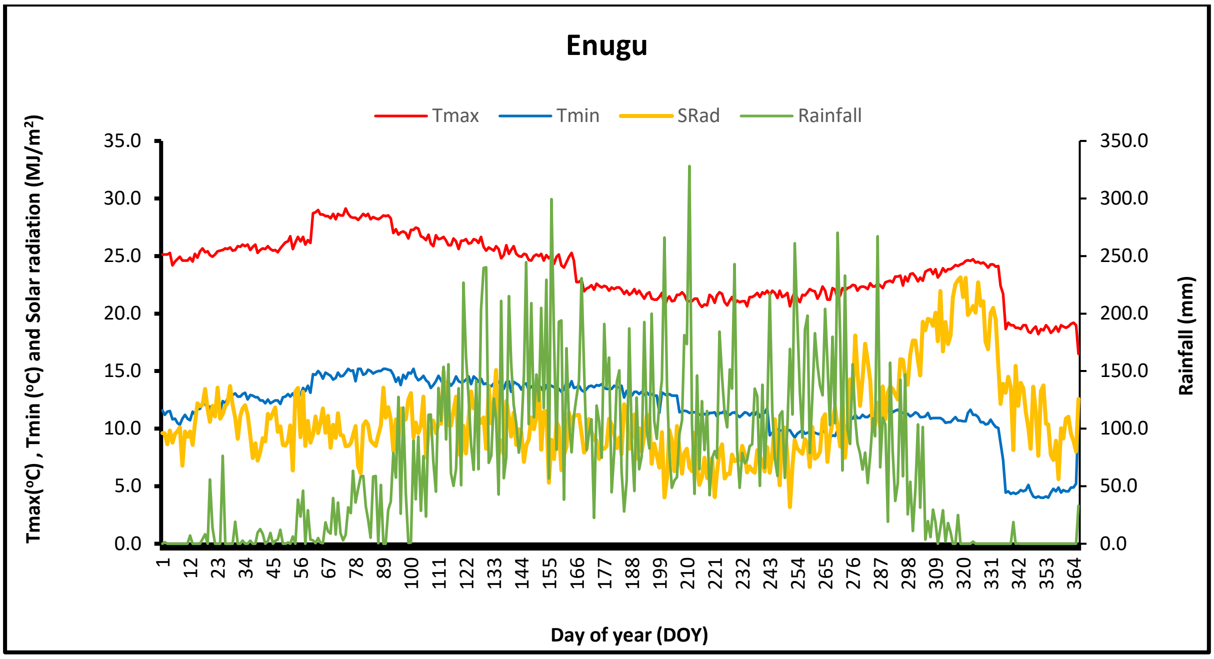

Figure 4.3: Average values of climatic variables computed from the 15-year observation data obtained for Enugu location.

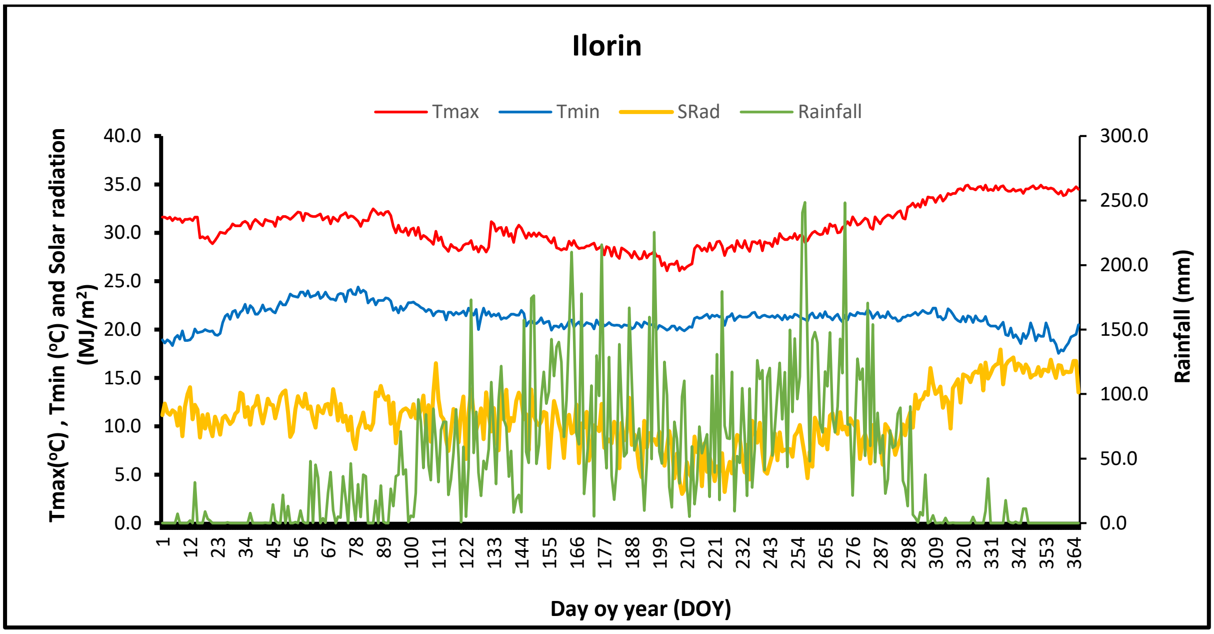

Figure 4.4: Average values of climatic variables computed from the 15-year observation data obtained for Ilorin location.

4.2.2 Validation of LARS-WG results

Figures 4.5 to 4.8 show the calculated monthly means of minimum and maximum temperature, total rainfall and solar radiation data for each location. Each chart shows a combination of weather variables and compares monthly mean observed data for a 15-year period (1998 to 2012), with 30-year generated synthetic data using the weather generator (LARS-WG). The rainfall season starts as early as March for all sites, except in Jos, where it begins in April. Maximum temperatures occur during March-August. The temperature during planting seasons range between 32°C and 28°C for Jos; 35°C and 32°C for Ibadan; 35°C and 32°C for Enugu; and 36°C and 32°C for Ilorin.

The effectiveness of Lars-WG in reproducing essential characteristics of the observed data at the four weather stations was analysed. As shown in Figures 4.5 to 4.8, generated monthly means for minimum and maximum temperature as well as solar radiation align closely with the mean observations for each location and imply similar climatological characteristics. In contrast, the monthly rainfall generated shows the most repeated discrepancy. According to Figures 4.5 to 4.8, rainfall was sometimes either overestimated or underestimated. Nevertheless, this result was consistent with findings in Gitau et al. (2018) and Mehan et al. (2017) from which the WG exhibited similar tendencies.

As highlighted in the previous section, the quality of observed rainfall data was characterised by missing data over a long period. This limitation may have created a monthly misfit of the generated data observed for the sites.

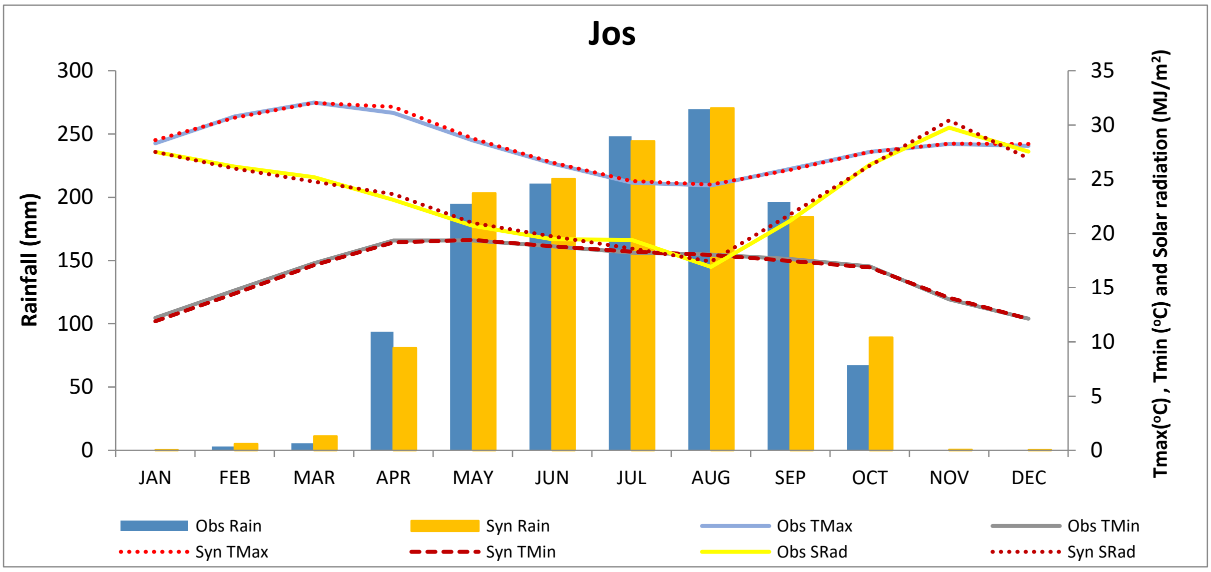

Figure 4.5: Comparison of the mean monthly rainfall, minimum and maximum temperature and solar radiation of observed 15-year climate data and Lars-WG generated 30-year climate data in Jos station.

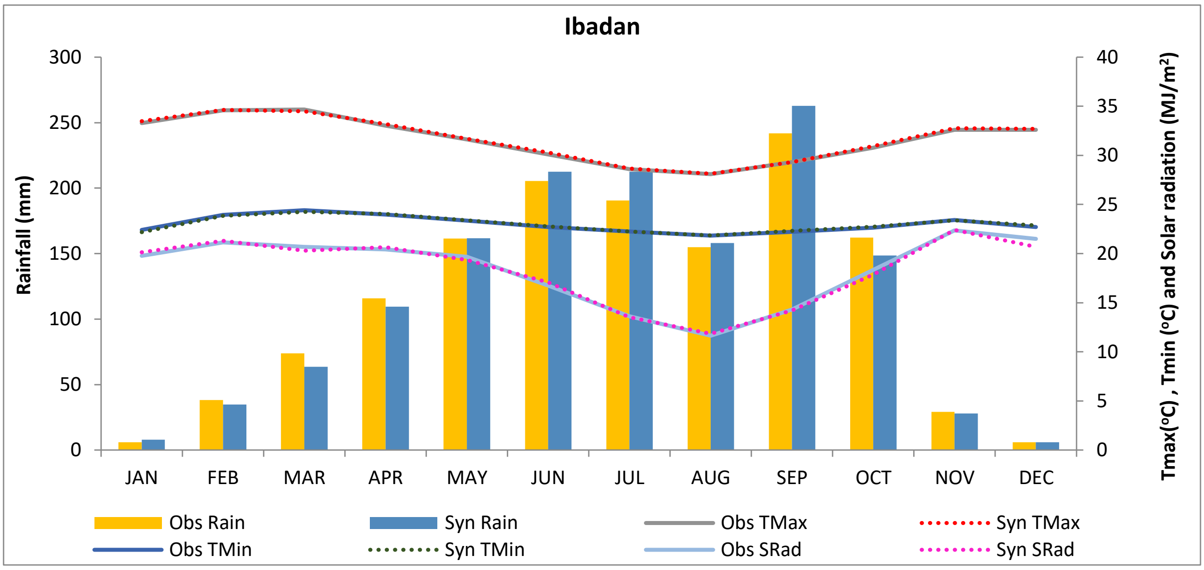

Figure 4.6: Comparison of the mean monthly rainfall, minimum and maximum temperature and solar radiation of observed 15-year climate data and Lars-WG generated 30-year climate data in Ibadan station.

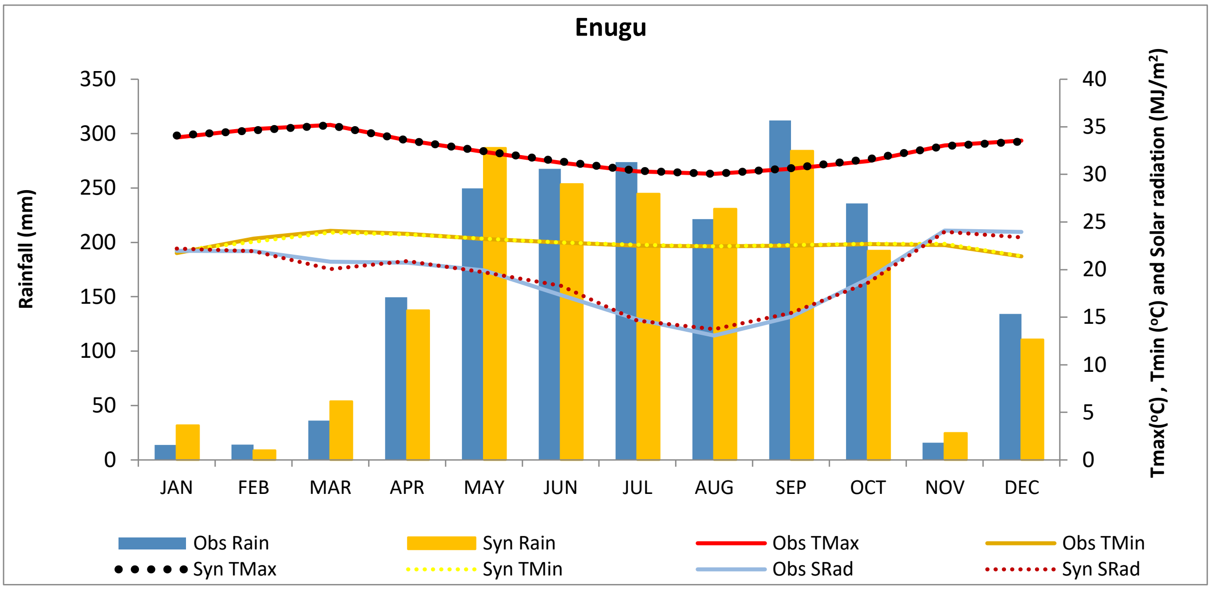

Figure 4.7: Comparison of the mean monthly rainfall, minimum and maximum temperature and solar radiation of observed 15-year climate data and Lars-WG generated 30-year climate data in Enugu station.

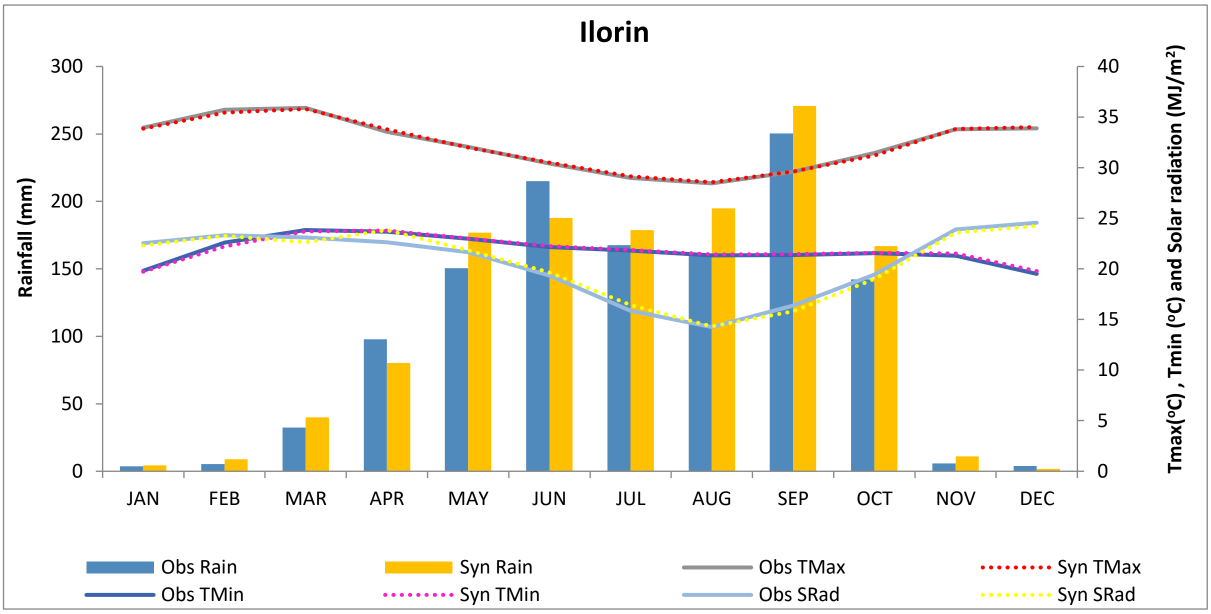

Figure 4.8: Comparison of the mean monthly rainfall, minimum and maximum temperature and solar radiation of observed 15-year climate data and Lars-WG generated 30-year climate data in Ilorin station.

In addition to graphical presentation, statistical significance testing was also used to compare synthetic and observed data (Gitau et al. 2017, Chisanga et al. 2017). Gitau et al. (2018)

explained that the choice of statistical characteristics used to evaluate model effectiveness should be based on the intended requirement of the simulated data. Hence, for crop-climate impact assessment, the generated data should accurately represent the mean of the observed as well as extreme properties of temperature (frost and heat spells) and precipitation (length wet/dry spell). Model performance was evaluated at a significant level of $p<0.05$, using the two-sample Kolmogorov (K-S) tests, a t-test and F-test to compare the monthly means and variances.

From the goodness of fit test (K-S test), results presented in Appendix G show that the two samples come from the same distribution, as each monthly p-value was higher than the acceptable level of significance (<0.05). LARS-WG performance in simulating daily rainfall distributions was faultless for all sites except for during November in Jos and December in Enugu. Rainfall data at the observed stations was sparse and therefore may have affected the distribution series in the weather generator (Chisanga et al. 2017). For all four sites, daily distributions of both minimum temperature, maximum temperature and solar radiation matched accurately, with the exception of February and August in Jos; February and May in Ilorin for solar radiation. Similarly, the model performed well in terms of fitting the length of wet and dry spells for December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON) for all four locations with the exception of Ilorin where the model performed poorly in fitting the DJF (wet) season as shown in Tables 4.1 to 4.4. These results show that Lars-WG has the ability to reproduce the seasonal and daily rainfall distributions quite well. Therefore, the null hypothesis that the two samples (observed and generated data) have the same probability distribution using the two-sample Kolmogorov-Smirnov test was not rejected at the 0.05 significance level for the extreme climate indices compared.

Extremely hot temperatures known as heat spells were defined as periods where maximum daily temperature reached 30°C or above. Extremely cold temperatures known as frost spells were defined as periods where minimum daily temperature fell below 0°C. The seasonal distribution of wet and dry spells and the length of occurrences of extremely hot or cold temperatures were often similar between observed and generated data. These are important climate indices for extreme temperature events when studying climate impact studies on crop yield. As shown in Tables 4.1 to 4.4, the performance of Lars-WG in simulating correctly the observed heat spells varied for each location. For example, the model failed to predict heat spells around "JJA" for Jos; as well as "DJF" for Ilorin and Enugu. This could be due to a number of reasons, such as errors in the observed data, random monthly variations in observed data and climate anomalies. A re-run to minimise errors as suggested in the manual was done and the model re-evaluated for each station (Semenov and Barrow 2002, Ababaei et al. 2010). Other than the prediction of heat spells, it should be noted that there was no p-value measurement for frost spells as none were likely to occur at the study sites.

More results on model performance for daily distributions, a *t*-test for means and *f*-test for variances are also presented for all the sites in Appendix H. The results show no significant difference (at $p = 0.05$ significance level) in terms of the monthly means of minimum and maximum temperature, solar radiation and total rainfall compared with observed values.

Table 4.1: K-S test: The quarterly probability distributions for the length of wet and dry series and length of frost spells (minimum temperature < 0°C) and heat spells (maximum temperature >30°C)

Jos			Seasonal wet/dry SERIES distributions					Seasonal frost/heat SPELLS distributions	
			K-S statistic	p-value				K-S statistic	p-value
DJF	wet	12	0.131	0.982	DJF	No frost spells			
DJF	dry	12	0.261	0.359	DJF	heat	12	0.255	0.388
MAM	wet	12	0.03	1.000	MAM	No frost spells			
MAM	dry	12	0.073	1.000	MAM	heat	12	0.076	1.000
JJA	wet	12	0.088	1.000	JJA	frost	12	1.000	0.000
JJA	dry	12	0.13	0.984	JJA	heat	12	0.478	0.006
SON	wet	12	0.144	0.957	SON	No frost spells			
SON	dry	12	0.291	0.238	SON	heat	12	0.044	1.000

Table 4.2: K-S test: The quarterly probability distributions for the length of wet and dry series and length of frost spells (minimum temperature < 0°C) and heat spells (maximum temperature >30°C)

Ilorin			Seasonal wet/dry SERIES distributions					Seasonal frost/heat SPELLS distributions	
			K-S statistic	p-value				K-S statistic	p-value
DJF	wet	12	0.913	0.000	DJF	No frost spells			
DJF	dry	12	0.165	0.884	DJF	heat	12	0.436	0.017
MAM	wet	12	0.091	1.000	MAM	No frost spells			
MAM	dry	12	0.038	1.000	MAM	heat	12	0.136	0.974
JJA	wet	12	0.212	0.625	JJA	No frost spells			
JJA	dry	12	0.272	0.311	JJA	heat	12	0.108	0.999
SON	wet	12	0.205	0.667	SON	No frost spells			
SON	dry	12	0.05	1.000	SON	heat	12	0.061	1.000

Table 4.3: K-S test: The quarterly probability distributions for the length of wet and dry series and length of frost spells (minimum temperature < 0°C) and heat spells (maximum temperature >30°C)

Ibadan			Seasonal wet/dry SERIES distributions					Seasonal frost/heat SPELLS distributions	
			K-S statistic	p-value				K-S statistic	p-value
DJF	wet	12	0.089	1.000	DJF	No frost spells			
DJF	dry	12	0.094	1.000	DJF	heat	12	0.382	0.0512
MAM	wet	12	0.106	0.999	MAM	No frost spells			
MAM	dry	12	0.080	1.000	MAM	heat	12	0.139	0.9685
JJA	wet	12	0.096	1.000	JJA	No frost spells			
JJA	dry	12	0.104	0.999	JJA	heat	12	0.216	0.6013
SON	wet	12	0.030	1.000	SON	No frost spells			
SON	dry	12	0.188	0.767	SON	heat	12	0.166	0.8795

Table 4.4: K-S test: The quarterly probability distributions for the length of wet and dry series and length of frost spells (minimum temperature < 0°C) and heat spells (maximum temperature >30°C)

Enugu			Seasonal wet/dry SERIES distributions					Seasonal frost/heat SPELLS distributions	
			K-S statistic	p-value				K-S statistic	p-value
DJF	wet	12	0.014	1.000	DJF	No frost spells			
DJF	dry	12	0.086	1.000	DJF	heat	12	0.609	0.0002
MAM	wet	12	0.057	1.000	MAM	No frost spells			
MAM	dry	12	0.079	1.000	MAM	heat	12	0.154	0.9271
JJA	wet	12	0.082	1.000	JJA	No frost spells			
JJA	dry	12	0.080	1.000	JJA	heat	12	0.22	0.5777
SON	wet	12	0.289	0.245	SON	No frost spells			
SON	dry	12	0.100	1.000	SON	heat	12	0.2	0.6967

Overall, LARS-WG performed well in terms of the monthly means of each variable. These findings are supported by the fact that there are similarities between the consistency of these simulation results and those of Gitau et al. (2018), Mehan et al. (2017), and (Chisanga et al. 2017). In addition, the variance value, which measures inter-annual variability in monthly means, is an important parameter in agricultural application. According to Qian et al. (2011), crop responses to climate are non-linear, therefore inter-seasonal and inter-annual variability of weather sequences should be incorporated for climate change impact assessment. Based on the performance of the weather generator in simulating the statistical characteristics of the observed, the utilisation of synthetic data proved suitable as a baseline for climate-crop impact analysis. Taking everything into account, the null hypothesis that the means from two samples (observed and generated data) are equal was not rejected at the 0.05 significance level in t-test for all comparisons.

4.3 Analysis of projected climate change

Results reported in this section are in regard to the climate change scenario data obtained from an ensemble of 40 GCMs (see list in Appendix A) and downscaled with DSSAT-perturb tool. The variables perturbed for each local site are rainfall, minimum and maximum radiation and solar radiation. Based on the site-specific scatter plot presented in Figure 4.9 and 4.10, predicted rainfall changes increased under RCP 8.5 compared to RCP 6.0 and tended to be more variable across all sites. Jos had the smallest increase of rainfall; by 0.2% to 0.7% under RCP 6.0, and 0.3% to 1.1% under RCP 8.5. Across both scenarios, the relative increase in rainfall on average was 0.5% and 0.6% for 2020, 2050 and 2080. Similarly, Ibadan showed an increase in rainfall (1.4% to 4.6% RCP 6.0; 1.6% to 6.8% for RCP 8.5) and the projected average from 2020 to 2080 was set at 3% and 3.7% for RCP 6.0 and 8.5 respectively.

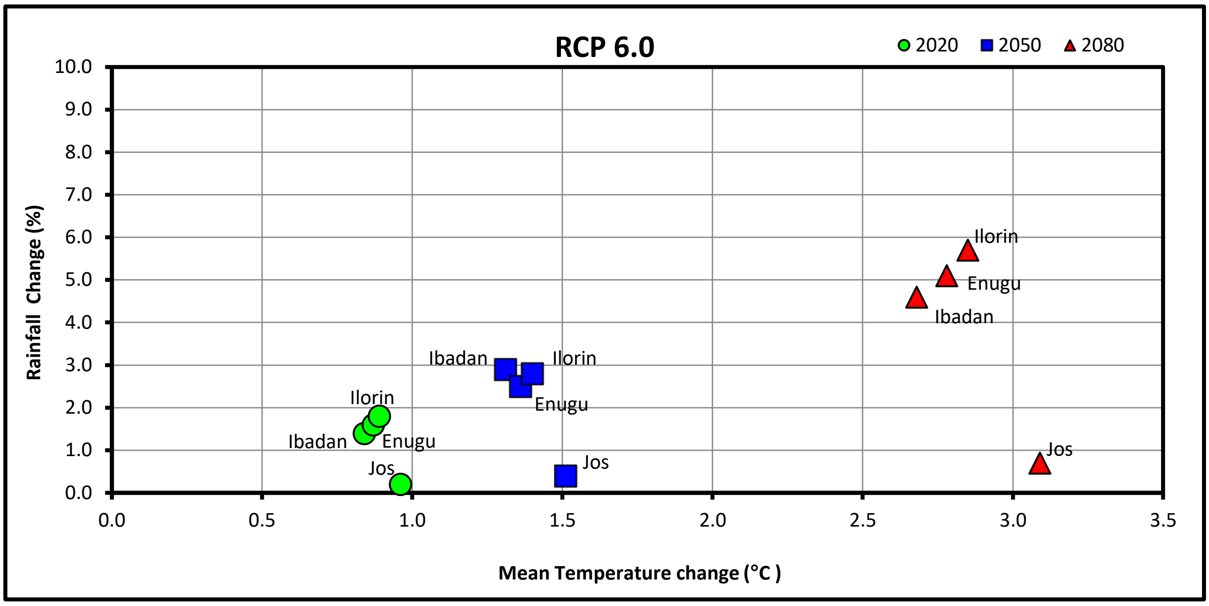

Figure 4.10: Scatter plot used to visualise the spread of future changes in rainfall (%) and mean temperature (°C) change with respect to baseline under RCP6.0 scenario pathway. Each scenario year is colour coded (green – 2020; blue – 2050; red – 2080).

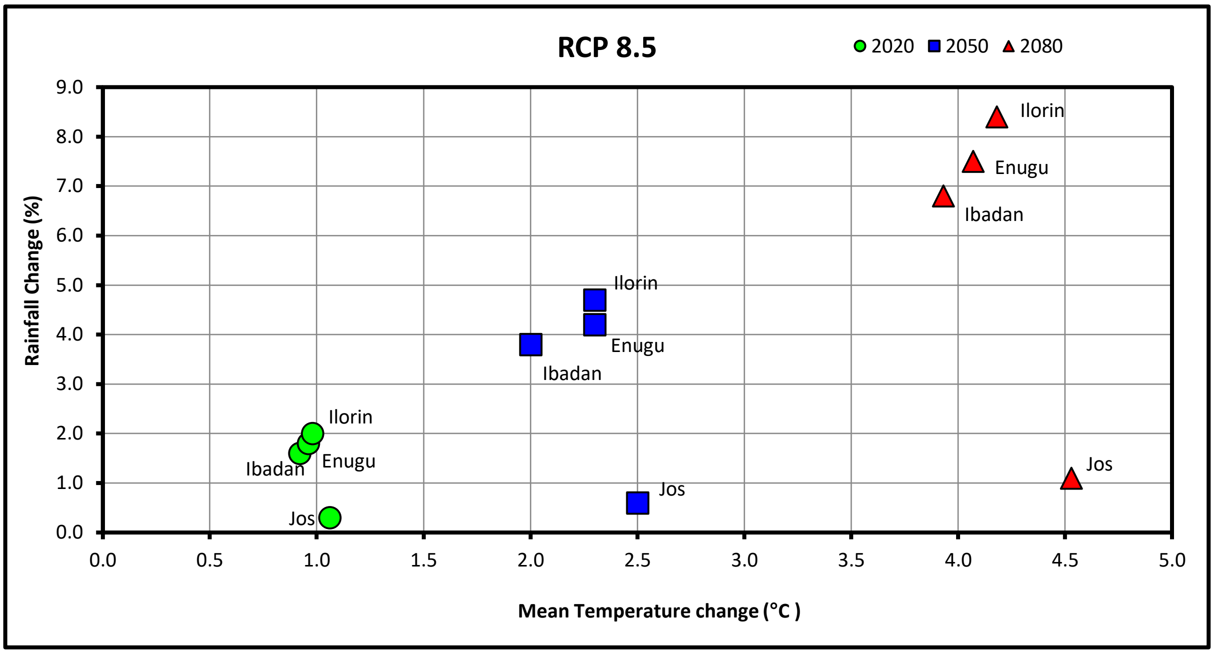

Figure 4.9: Scatter plot used to visualise the spread of future changes in rainfall (%) and mean temperature (°C) change with respect to baseline under RCP 8.5 scenario pathway. Each scenario year is colour coded (green – 2020; blue – 2050; red – 2080).

However, the data showed that Ibadan will experience about 7% more rain by 2080. Ilorin and Enugu showed similar characteristics in terms of rainfall change values. For both sites, rainfall is predicted to increase on average by approximately 3.5% in 2050 under RCP 6.0, and by approximately 5% in 2080 compared to baseline climate. For an RCP 8.5 scenario, the projected average rainfall increase by 2080 is projected as approximately 8%.

Predicted changes in temperature present as warmer under RCP 8.5 compared to RCP 6.0 from 2020 to 2050 and 2080. In addition to this, temperature change projected for Jos is shown as in contrast to the very low rainfall increase earlier presented. Minimum and maximum temperature increase is the highest for the Jos site as compared to the other three sites. Mean temperature increase is projected from 0.9°C to 3.1°C for RCP 6.0, and 1.1°C to 4.5°C under RCP 8.5 for 2020, 2050 and 2080 respectively. Projected data shows that under the RCP 8.5 scenario, Jos will experience an increase in mean temperature with a change of 2.7°C compared to 1.9°C under an RCP 6.0 scenario between 2020 and 2080. Furthermore, the mean temperature change in 2080 will increase by between 3.0°C and 5.0°C on average under RCP 6.0 and 8.5 projections. Mean temperature change at Ibadan will increase by 0.8°C, 1.3°C and 2.7°C for RCP 6.0, and 0.9°C, 1.7°C and 3.6°C under the RCP 8.5 scenario pathway by 2020, 2050 and 2080 respectively. The minimum and maximum temperature values prove to be similar for each scenario pathway, giving average values of 1.9°C (RCP 6.0) and 2.2°C (RCP 8.5). The expected temperature rise is highest by 2080, showing between a 3.0°C and 4.0 °C increase on average.

Projected changes for Ilorin and Enugu are similar for each site but differ significantly between scenarios for 2080. For example, the result shows a 2.8°C mean temperature change for RCP 6.0 for both sites in 2080, compared to a 4.1°C projection for the RCP 8.5 scenario. These findings are supported by the fact that a similar range of projections in average change in precipitation and temperature for 2050 was reported by Girvetz et al. (2019) for various different countries in Africa including Nigeria (see Figure 2.1 in Chapter 2). Furthermore, Figure 4.11 shows the average minimum and maximum temperature change values and percent change in rainfall relative to baseline climate.

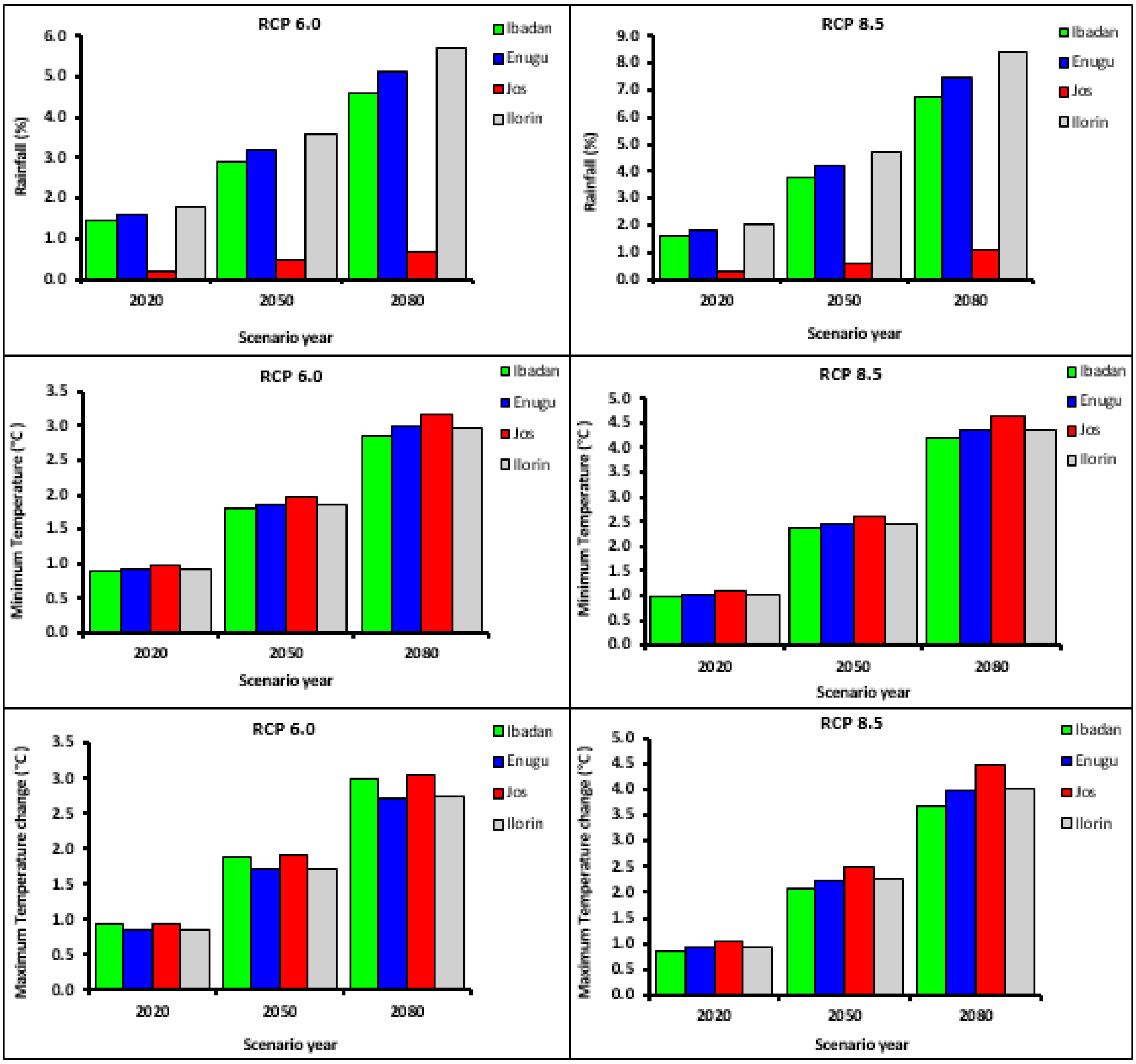

Figure 4.11: Representative climate change scenarios showing relative change in rainfall and absolute changes in average minimum and maximum temperature for RCP 6.0 and RCP 8.5 scenarios. Values are relative to baseline climate data.

4.4 Climate change impact on maize grain yield

Results presented in this section outline the following three topics: 1. Baseline yield results. 2. Simulation results on the impact of climate change scenarios on yield compared to baseline. 3. Effect of nitrogen treatment on yield.

4.4.1 Baseline yield results

Maize yield was simulated using 30-years of climate data synthesised from observed weather station data (1998 – 2012). Figure 4.12 presents the results of the annual variability of baseline yield, stabilised using a 5-year moving average. The unexplained variations in yields between the years could be attributed to varying physiochemical characteristics of the soil, texture type and soil water–storage capacity, which are different for each site. This should be noted in addition to crop response to climatic variability since the planting date (15th March), and other farm management parameters which were fixed, and therefore the same for each location. From all of the sites, Ibadan produced the highest yield (3,971 kg ha^{-1}), followed by Ilorin (2,147 kg ha^{-1}) and Jos (1,960 kg ha^{-1}). The least yield was obtained for Enugu (1,691 kg ha^{-1}). Evaluation of the planting season climate (March-April-May) shows that Jos had highest rainfall of 1,304mm and solar radiation (24 MJ/m^2/day) but the lowest maximum and minimum temperatures (28°C and 16°C).

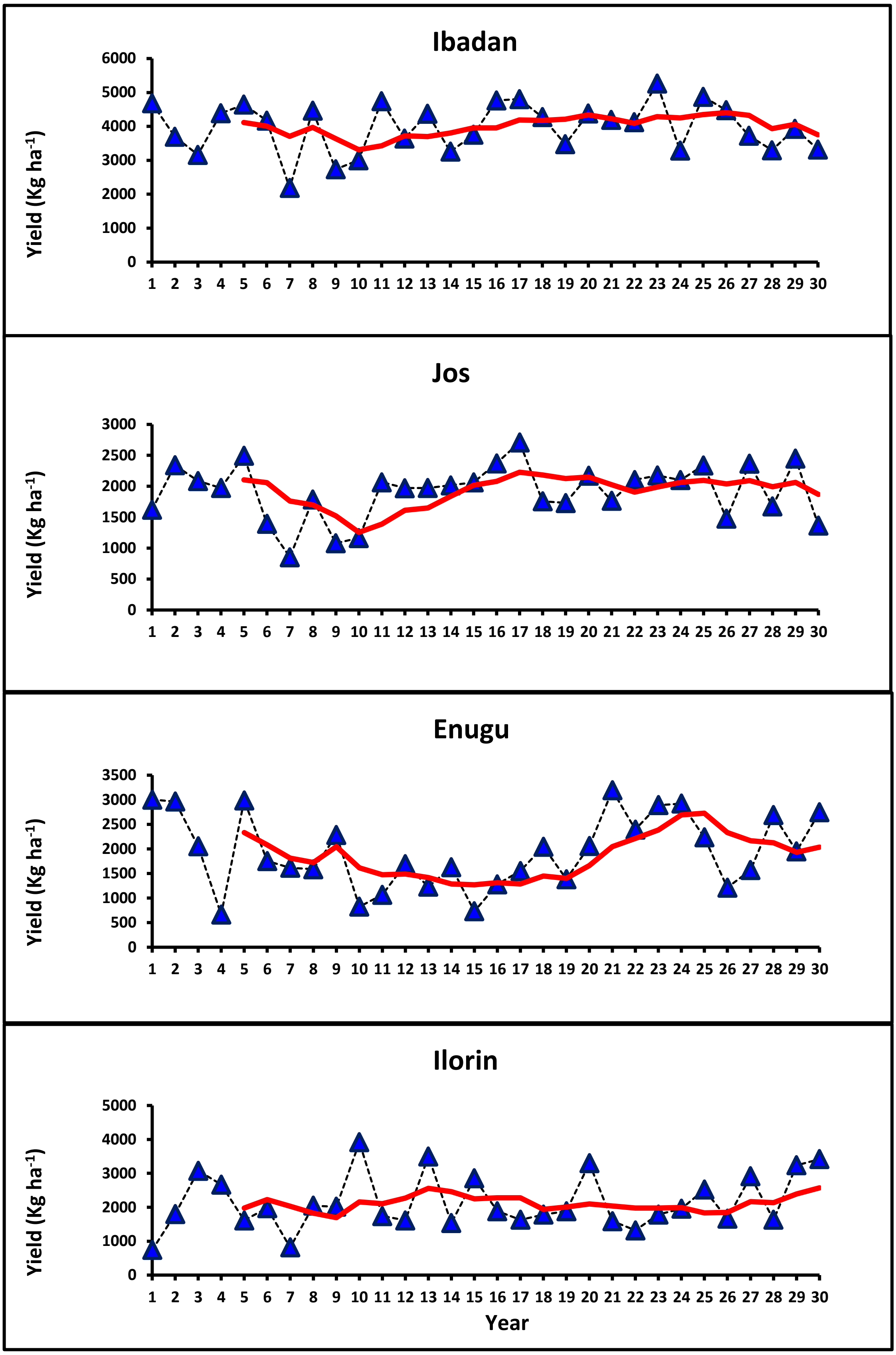

Figure 4.12: Simulated yield trends for 30 years baseline climate data. Annual (triangles) and 5-year moving average (red line) yields.

An evaluation of the observed climate data used for baseline simulation shows high variability in temperature, and lower average temperature values in Jos when compared to Ibadan. Thus, variability in weather temperature may have contributed to low yield at Jos site, despite the increase in rainfall. Further data showed that Enugu also had high total rainfall (504mm) which varied during the growing season compared to Ibadan (364mm), and Ilorin (319mm). Temperatures and solar radiation were at similar levels at all sites except Ilorin, which had slightly higher solar radiation (22 $MJ/m^2/day$). Therefore, in addition to the effect of observed climatic variation, soil type and soil water capacity could be a modifying factor, as other factors are constant during simulation.

Inter-annual variability of yield is an important parameter compared to the mean when simulating crop yield (Qian et al. 2011). Using single-factor ANOVA, the statistical description of baseline yield data including mean, standard deviation and coefficient of variation are listed in Table 4.5. From this, it can be see that the variability in annual yield was smaller for Ibadan compared to other sites, and the highest variability occurred in Jos yield. This implies that the simulated yield data was more homogeneous at Ibadan as compared to Jos. The difference in mean yields is statistically different for Ibadan and Enugu but not significant at $p < 0.05$ for Jos and Ilorin when compared to published national average of about 2,000 kg ha^{-1} (Shehu et al. 2018) .

Table 4.5: Descriptive statistics of maize yield (kg ha-1) simulated under baseline climate (estimate of 30-year data)

Study location	Mean (kg ha^{-1})	Std. Dev	Min	Max	CV (%)
Ibadan	3,971**	726.18	2,185	5,262	18.3
Jos	1,960	3,072.96	1,124	7,296	156.8
Enugu	1,691**	976.07	666	3,192	34.4
Ilorin	2,147	803.03	740	3,918	37.4

Mean values (**statistically significant p ≤ 0.05 confidence level) are based on an average of the 30 years simulated for baseline. (Min and Max – minimum and maximum values; St.Dev – standard deviation; CV-Coefficient of variation)

4.4.2 Impact of climate change scenarios on yield

Average Maize yields varied for each site, reflecting differences in their response to climate change. From Figures 4.13 and 4.14, yield generally declined from year 2020 to 2080. On closer inspection, it was noted that the decline was larger in 2080 under the high emission scenario RCP 8.5 except for in Enugu where yield improved slightly under this scenario. Although the highest rainfall was projected to increase under RCP 8.5 scenario, mean yield decreased largely under this scenario between 2050 and 2080. This suggests a greater negative influence due to warmer climate. This result is consistent with the projections of Corbeels et al. (2018) who found average maize yield would significantly decline in Southern Africa under the RCP 8.5 scenario.

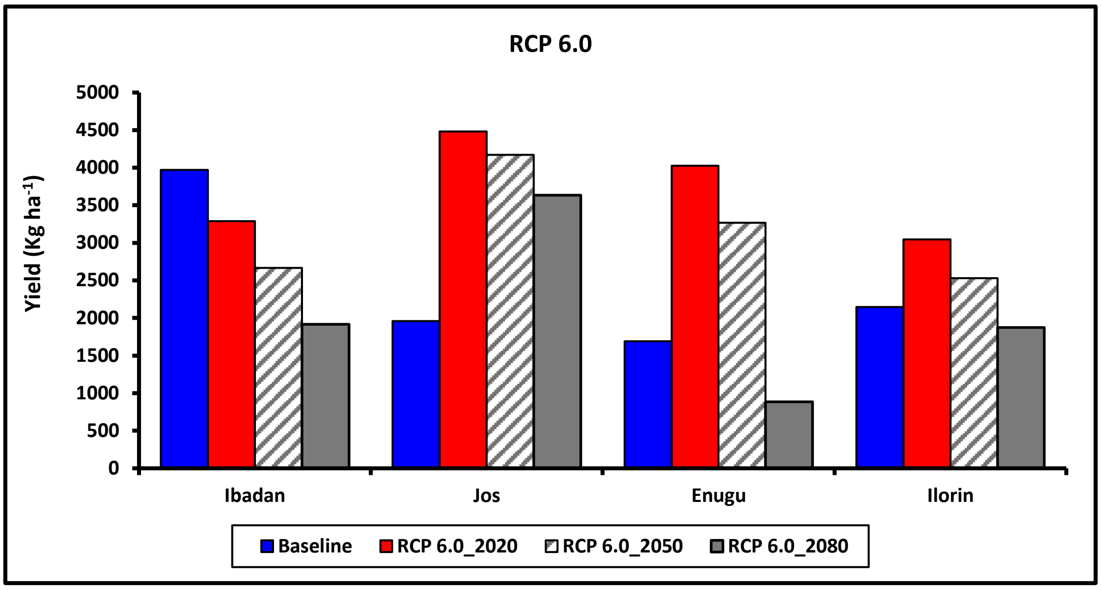

Figure 4.13: Chart of simulated maize yield output for baseline and RCP 6.0 scenarios for the period 2020–2080 at four study sites.

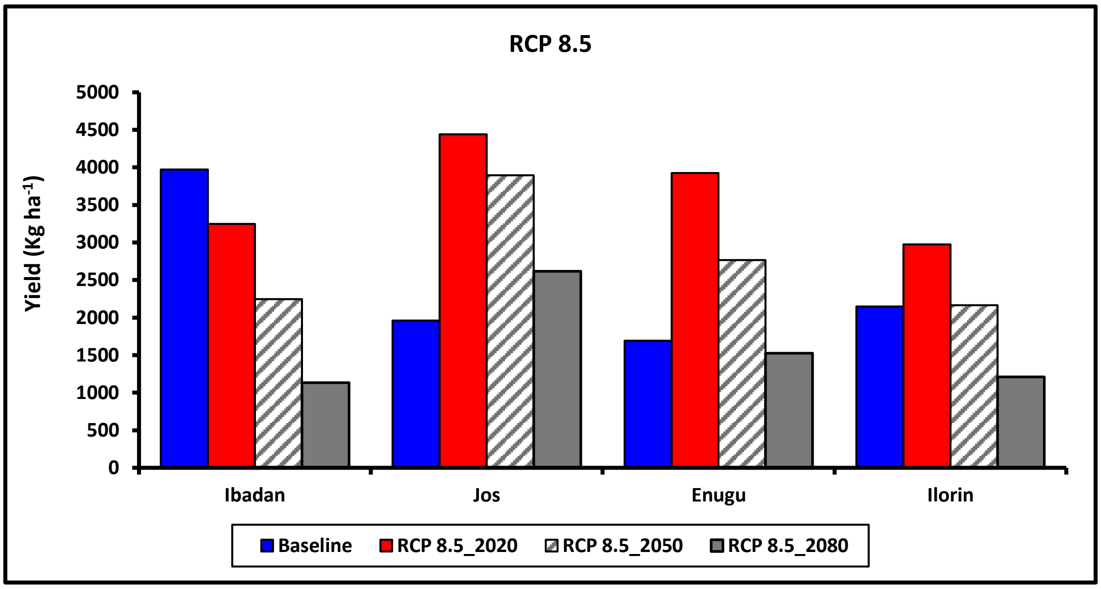

Figure 4.14: Chart of simulated maize yield output for baseline and RCP 8.5 scenarios for the period 2020–2080 at four study sites

Table 4.6: Coefficient of variation (CV %) of simulated maize grain yield under two scenarios RCP 6.0 and RCP 8.5.

Study location	RCP 6.0_2020	RCP 6.0_2050	RCP 6.0_2080	RCP 8.5_2020	RCP 8.5_2050	RCP 8.5_2080
Jos	71.1	70.1	74.0	71.2	72.7	84.6
Ibadan	18.9	21.1	23.2	18.9	24.9	25.6
Enugu	39.4	41.0	54.8	39.7	42.3	53.0
Ilorin	44.5	45.4	52.1	43.7	49.2	57.1

Similar to changes obtained for mean yields, future projections show an increase of the year-to-year variability of maize yields for each site as shown by the coefficient of variation estimated in Table 4.6. Data suggests that the magnitude of change in yield variation will be positive for all sites over time, under two climate scenarios and illustrated by predictions dated from 2020 to 2080. Between the years 2020 and 2080 (under RCP 6.0), variation in yield at Enugu will increase by 15% compared to a 13% increase under RCP 8.5 within the same timeline. For Jos, climate change under RCP 8.5 will increase yield variation by 13% compared to 3% increase under RCP 6.0. Similarly, yield variation will increase by 13% in Ilorin under RCP 8.5 compared to 7% under RCP 6.0 (changes from 2020 to 2080). It should be noted that the CV at Ibadan was small compared to the other sites, reflecting a slight rise (4.3% and 6.7%) for RCP 6.0 and RCP 8.5 respectively. However, this result is consistent with the results obtained by Parkes et al. (2018) for northern and southern Nigeria. In further support of the findings of this study, Parkes et al. (2018) also reported an increase in maize yield variability in response to future climate change using crop-climate model simulations. This variability represents the risk of crop failure and loss in some locations.

Yield deviation from the baseline for Ibadan, shows a more pronounced reduction in maize yield with an average difference in the mean of between -1,348 Kg ha^{-1} and -1,763 Kg ha^{-1} across all three time-periods under RCP 6.0 and 8.5 scenarios according to Figure 4.15. This represents yield loss of -34% and -44% on average for both scenario paths. The most affected scenario years with yield loss above -30% was 2050 (-33%) and 2080 (-52%) under RCP 6.0, while for RCP 8.5, yield declined by -43% and -71% for 2050 and 2080 respectively. By contrast, maize yield increased above baseline values at Jos for 2020, 2050 and 2080 by an average of 2,136 Kg ha^{-1} (109%) and 1,690 Kg ha^{-1} (86%) under RCP 6.0 and 8.5 scenarios respectively. However, as shown in Figure 4.16, yield gained will further reduce from 2020 to 2050, with a significant decrease obtained in 2080.

The average maize yield in Enugu also increased by 2,005 Kg ha^{-1} (115%) and 1,704 Kg ha^{-1} (98%) in year 2020 and 2050 but decreased by an average of 506 Kg ha^{-1} (-29%) in year 2080 under both scenarios as shown in Figure 4.17. Interestingly, a similar trend to Enugu was obtained for Ilorin however; the difference in the means compared to baseline was not statistically significant for 2050 and 2080 in RCP 6.0 and 2050 in RCP 8.5. The negative deviation from the baseline only occurred in 2080 by -13% and -44% under both scenarios as shown in Figure 4.18. The significance of the difference in average yield for each climate scenario compared to baseline yield was determined using standard Student's *t*-test (see result in Appendix I). The projected changes in maize yield for Ibadan and Enugu (with exception of RCP 8.5 2080 for Enugu and Jos) were statistically significant for all climate change scenarios at 0.05 significance level, therefore the null hypothesis of no difference in the mean yield was rejected as there was a difference. At Jos, there was significant difference between the baseline yield and RCP 6.0 in 2080, RCP 8.5 in 2050 and 2080 respectively. The difference in yield under RCP 6.0 (2050 and 2080), and RCP 8.5 (2050) for Ilorin was not significant compared to the baseline, therefore the null hypothesis of no difference was not rejected in that case.

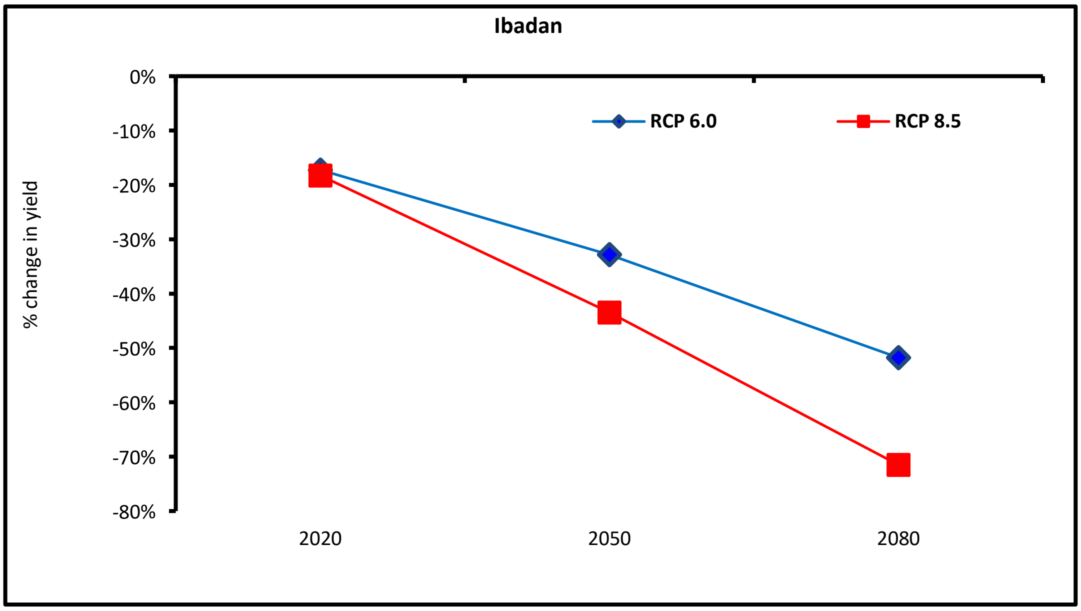

Figure 4.15: Effect of climate change on relative changes (%) in mean crop yield for Ibadan.

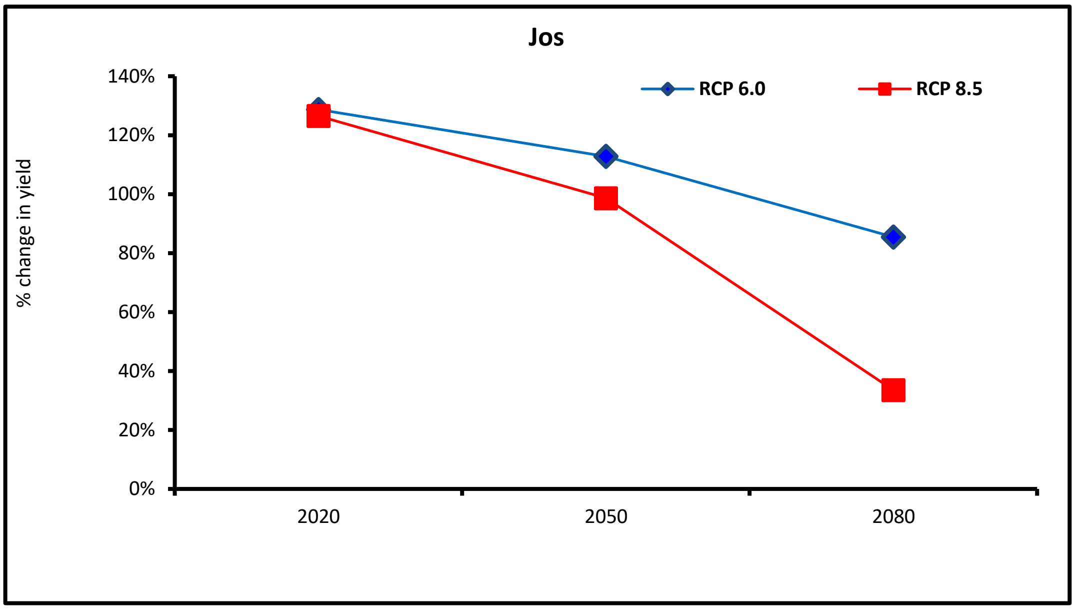

Figure 4.16: Effect of climate change on relative changes (%) in mean crop yield for Jos.

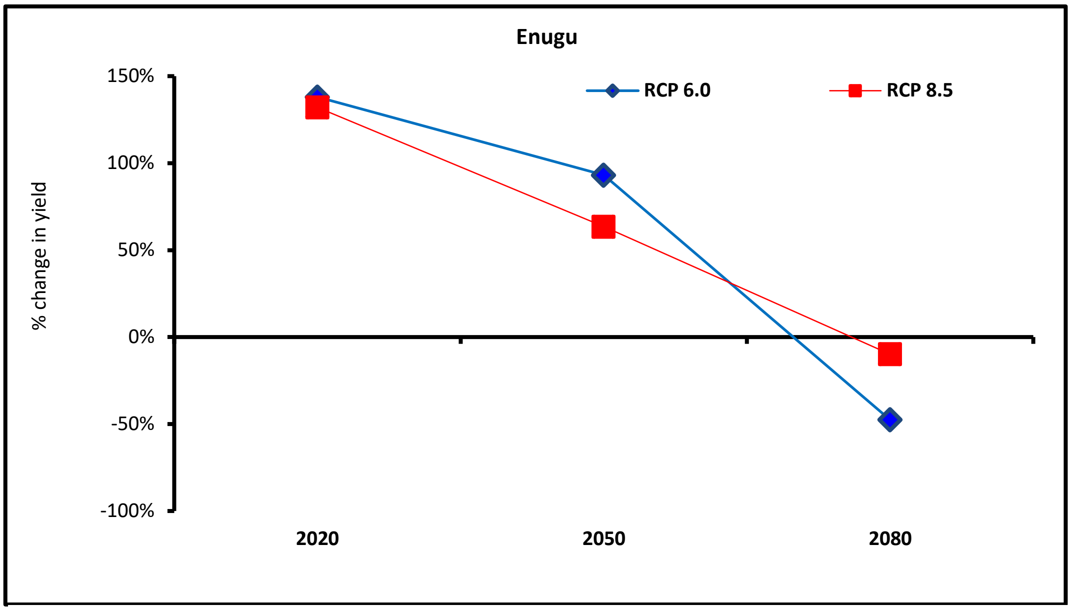

Figure 4.18: Effect of climate change on relative changes (%) in mean crop yield for Enugu.

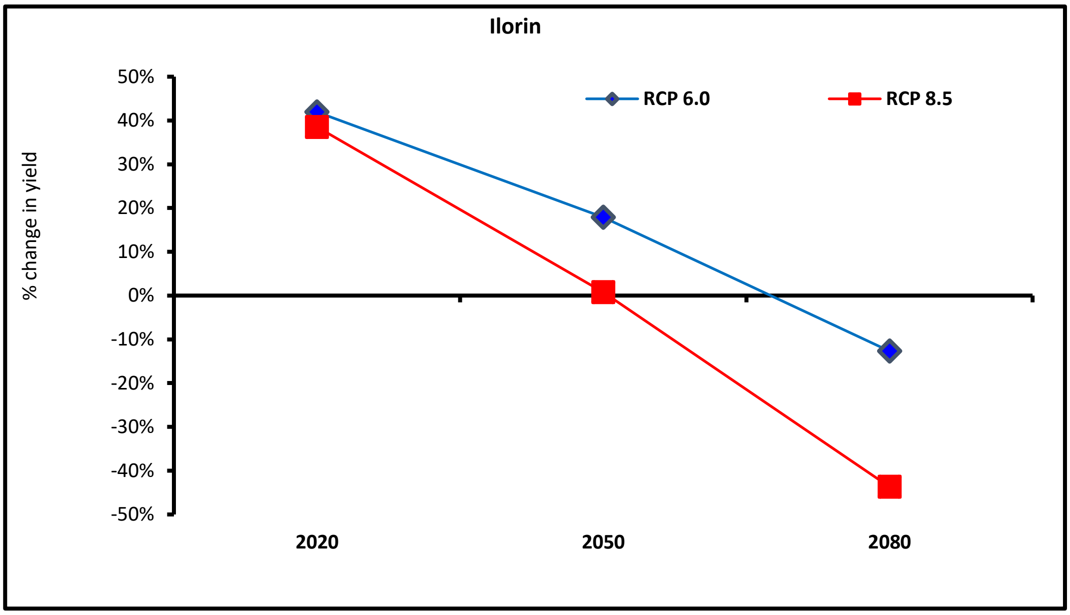

Figure 4.17: Effect of climate change on relative changes (%) in mean crop yield for Ilorin.

4.4.3 Effect of fertiliser treatment on yield

Figures 4.19 to 4.22 show that the relationship between fertiliser rates (kg N ha^{-1}) and yield (kg ha^{-1}) was linear, and that yield increased significantly at 160 kg N ha^{-1} application rate. The trend line plot for Jos in Figures 4.19, shows that on average, 80 kg N ha^{-1} fertiliser rate increased yield by 14% and 13% under RCP 6.0 and RCP 8.5 scenarios between 2020 and 2080. Similar to the baseline, yield improved significantly as the fertiliser application rate increased to 160 kg N ha^{-1} from 80kg N ha^{-1} for both RCP scenarios but, the difference on average compared to the baseline was marginal in terms of increase or decrease (from +1% to -6%). At 200 kg N ha^{-1}, yield difference from 160 kg N ha^{-1} was not statistically significant at $p < 0.05$ level under RCP 8.5 (2080). Similarly, yield declined by -9% and -17% under maximum rate of 250 kg N ha^{-1} for both RCP scenarios by 2080 but the difference in means is not significant and therefore the null hypothesis is not rejected as there is no difference between the means of the group. Fertiliser increase at Jos did not give significant increase in yield compared to baseline and overall yield slightly dipped for both scenarios towards 2080 despite increasing fertiliser rate to 250 kg N ha^{-1}.

Raising the fertiliser rate from 80 kg N ha^{-1} to 160 kg N ha^{-1} increased maize yield by 45% under the baseline scenario at Ibadan. The yield difference is significant for 80 kg N ha^{-1} to 160 kg N ha^{-1}. Higher application rates (200 kg N ha^{-1} and 250 kg N ha^{-1}) only improved yield by +4% and +1% respectively. As shown in Figure 4.20, yield declined significantly from the baseline despite fertiliser increase. For instance, during 2050 and 2080, yield declined by -12% and -26% at 80 kg N ha^{-1}, for both scenarios. Despite increasing the rate from 160 kg N ha^{-1} to 250 kg N ha^{-1}, further decline in yield was observed ranging from -37%, -39% and -40% in 2080 under RCP 8.5. The difference in yield between 160 kg N ha^{-1}, 200 kg N ha^{-1} and 250 kg N ha^{-1} was not significant for all scenarios including the baseline.

Figure 4.21 shows the yield response per hectare with respect to applied N fertiliser rate for the Enugu site. In contrast to other locations, the highest increase was obtained at this location under all climate scenarios (except RCP 6.0 in 2080). Yield increased with increase in N rates, and showed significant yield increase at rates from 80 kg N ha^{-1} to 250 kg N ha^{-1}, compared to baseline. At 80 kg N ha^{-1}, yield difference from baseline was 192% and 140% for RCP 6.0 and 8.5 scenarios on average and statistically significant. Yield gap further increased significantly at 160 kg N ha^{-1} from the baseline but, the difference at 200 kg N ha^{-1} and 250 kg N ha^{-1} was not significantly different when compared to 160 kg N ha^{-1}. Yield difference from all application rates were not statistically significant for RCP 8.5 in 2080.

Figure 4.22 shows results for Ilorin, with an increase in maize yield under all scenarios and years compared to baseline. Difference in yield obtained between 80 kg N ha^{-1} and 160 kg N ha^{-1} application rate was in the range of 18% to 40% for all scenarios including baseline. The difference in yield was statistically significant for the above-mentioned rates and scenarios except under RCP 8.5 in 2080, where the yield output for all treatment combinations was not significant. The difference at 200 kg N ha^{-1} and 250 kg N ha^{-1} was not significantly different when compared to 160 kg N ha^{-1}.

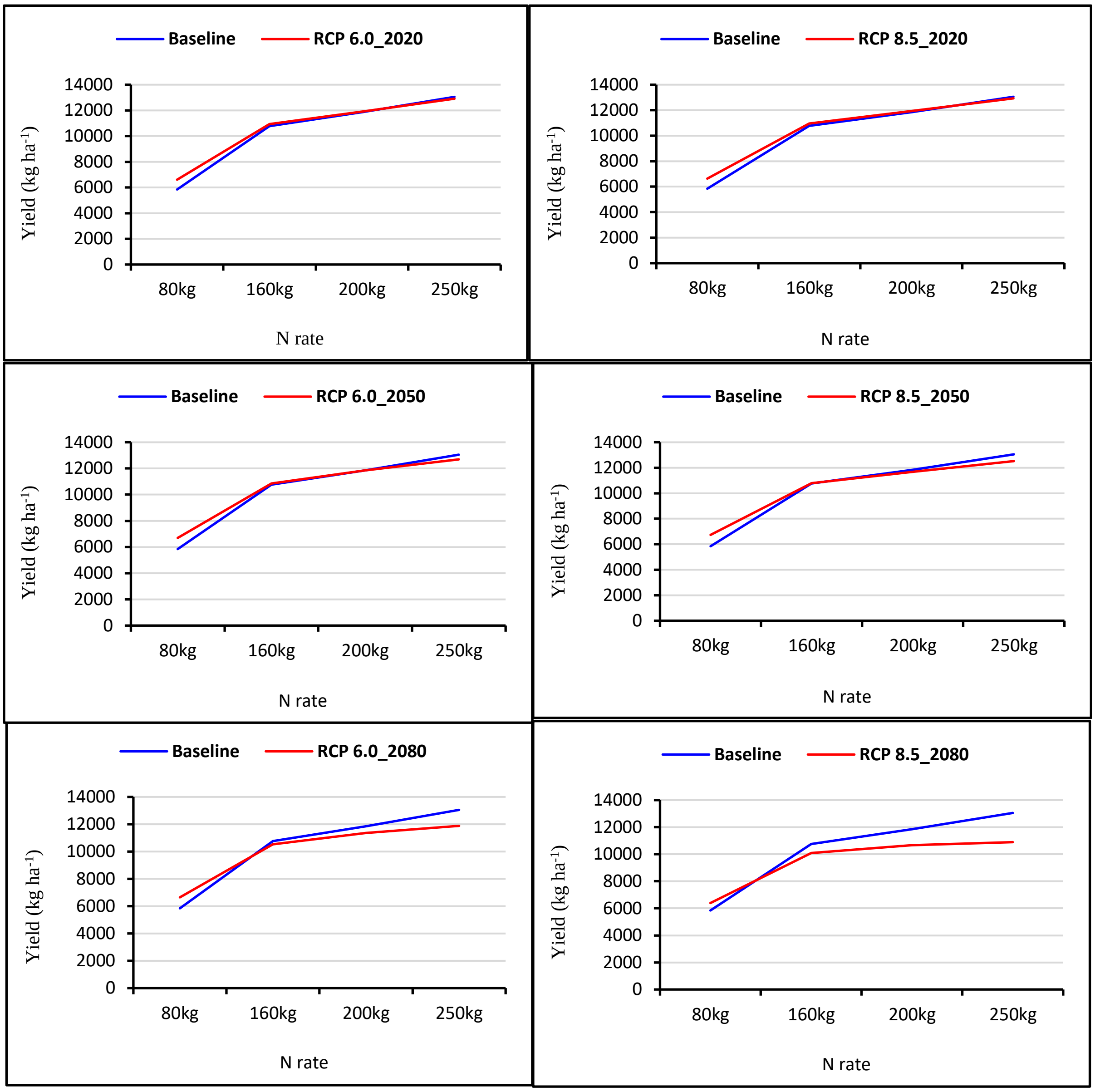

Figure 4.19: Results of average maize yield for baseline and six climate scenarios under varying N applications at Jos.

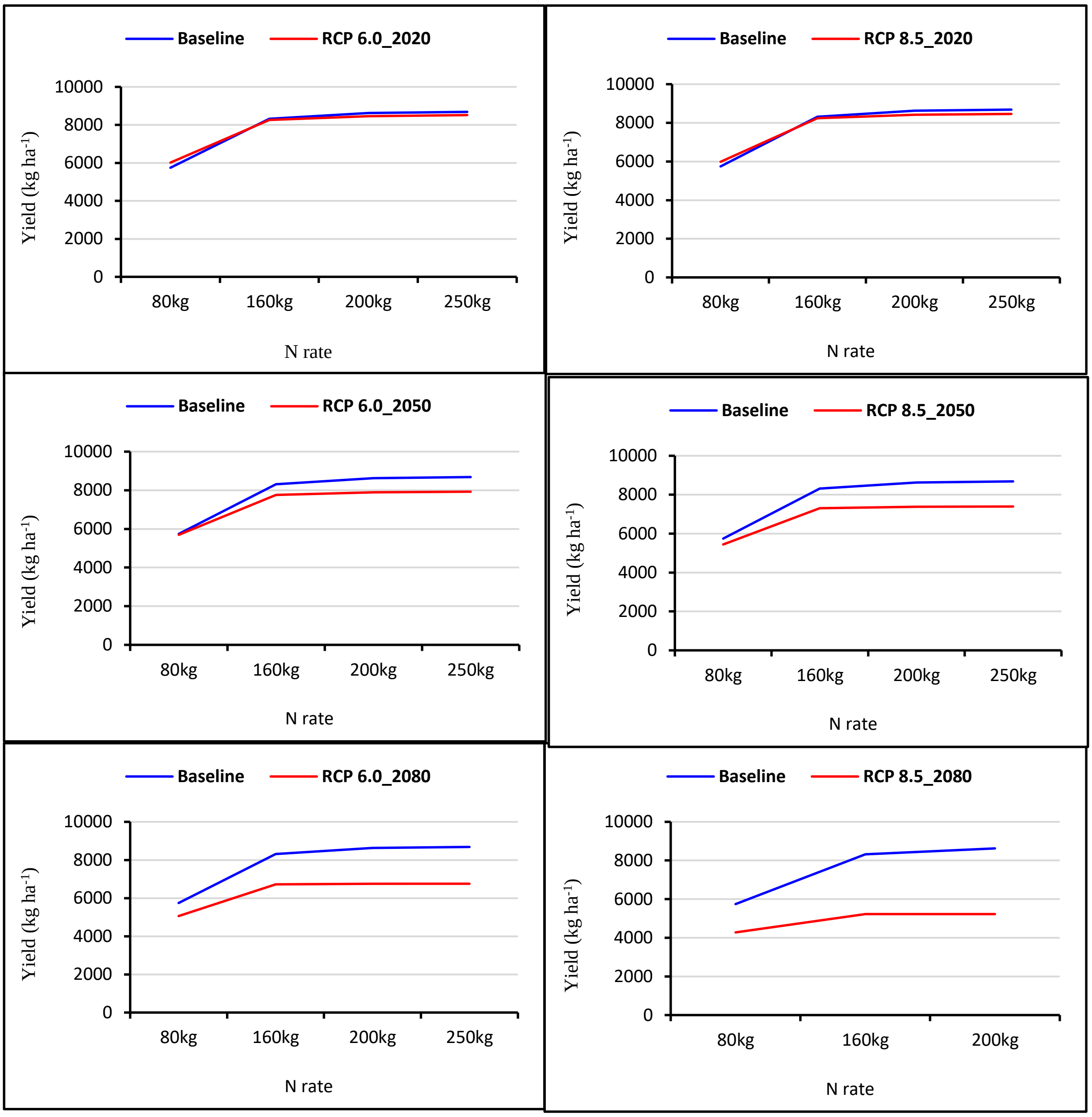

Figure 4.20: Results of average maize yield for baseline and six climate scenarios under varying N applications at Ibadan.

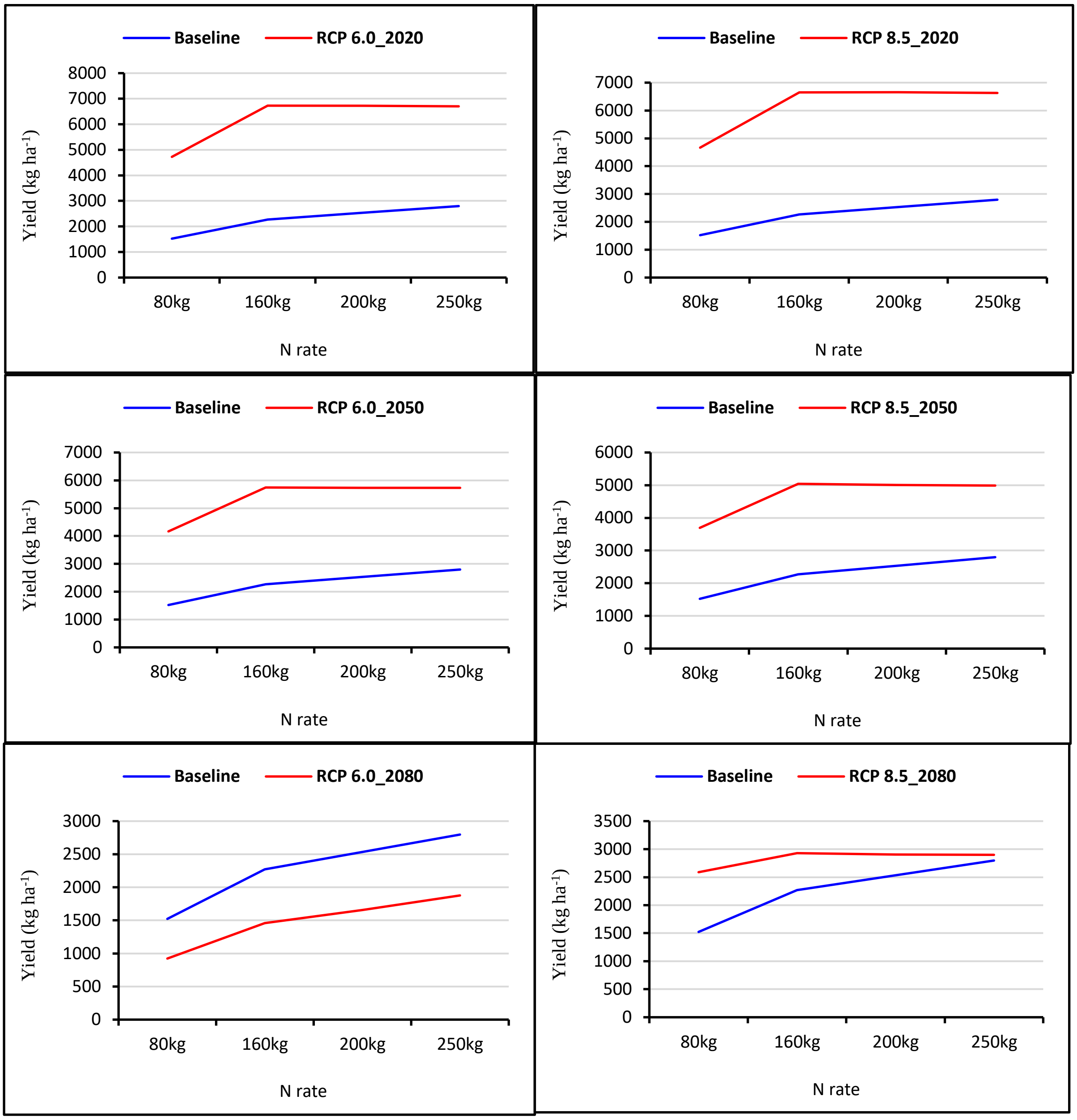

Figure 4.21: Results of average maize yield for baseline and six climate scenarios under varying N applications at Enugu.

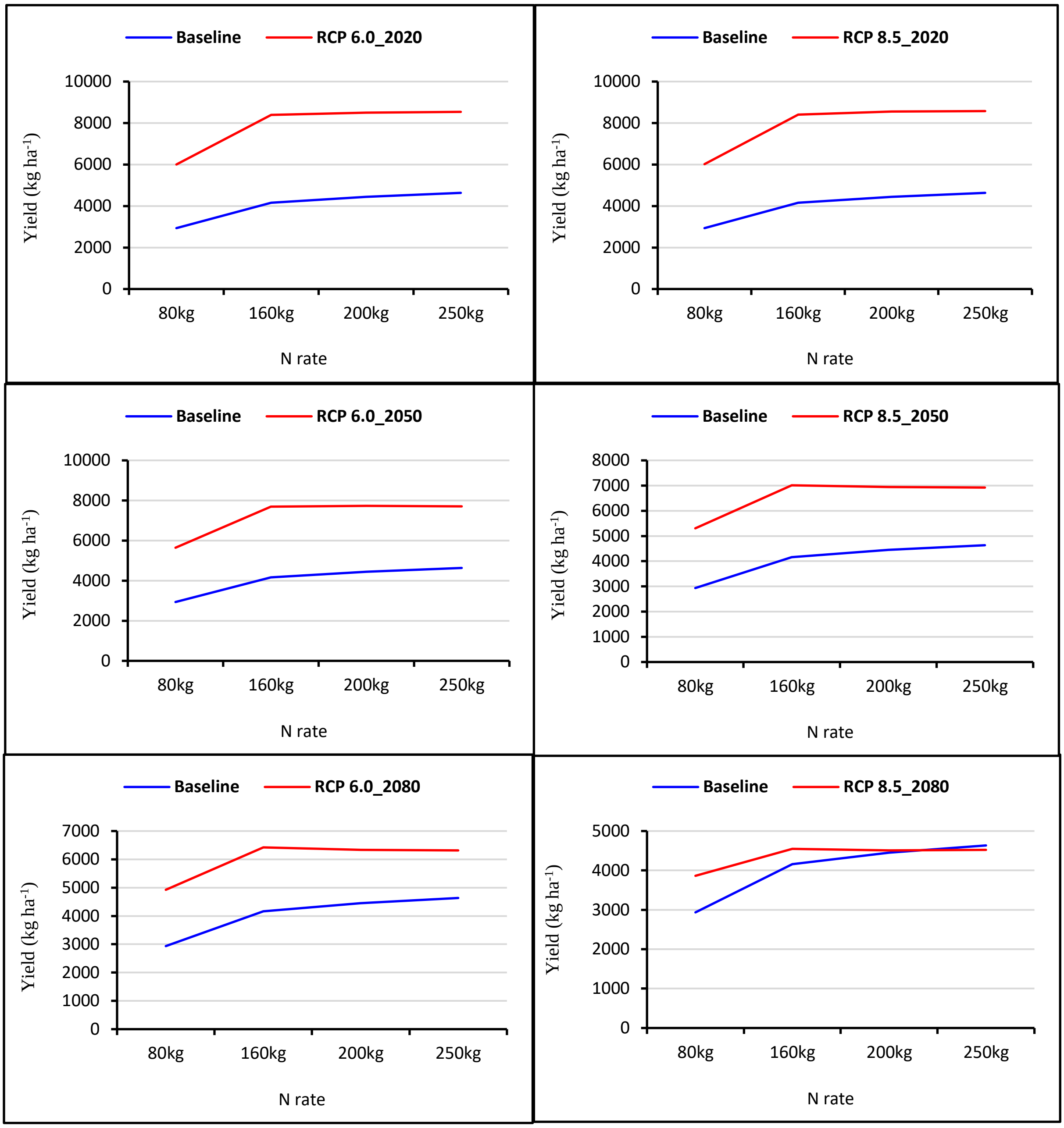

Figure 4.22: Results of average maize yield for baseline and six climate scenarios under varying N applications at Ilorin.

4.5 Farm energy use, GHG emissions, Carbon footprint

Total energy inputs and the resultant energy outputs based on maize yield, are presented in this section. The energy equivalents and results of energy indices (energy use efficiency, energy productivity, specific energy and net energy) used to establish system efficiency are described in this section. The farm phase life cycle assessment results of GHG emissions and the carbon footprint per maize grain are also presented in this section.

4.5.1 Energy input results and analysis

Material inputs and the related energy budgets estimated for maize production per hectare are presented in Tables 4.7 and 4.8. Average fuel consumption across all scenarios was 53.1 L ha^{-1}. The estimated working time and energy coefficients presented in Chapter 3 (see section 3.7.2.2; Table 3.2 and 3.3) was used to determine the amount of diesel required for the three type of tillage method, and Figure 4.23 shows the aggregated fuel values for each field operation per hectare. Fuel consumption varied according to intensity of mechanisation for the three type of tillage systems.

As examples, conventional tillage (CT) and reduced tillage (RT) were responsible for 42% and 37% of all fuel consumed in order to carry out farming operations, whilst the no tillage method (NT) consumed only 21% of the total fuel. For soil preparation (primary tillage), use of a mouldboard plough in CT and chisel plough in RT at 30cm tillage depth, consumed 24.5 L ha^{-1}, and 16.5 L ha^{-1} respectively or 36% and 28% of the total diesel used. In both CT and RT, stubble cultivation (secondary tillage) consumed 10.7 L ha^{-1} and was responsible for 16% and 18% of the total diesel fuel used in both systems respectively. Direct seed drilling operation in NT system consumed 21% diesel, which remains less compared to the amount of diesel used for primary and secondary tillage operations as well as pre-sowing cultivation in CT, and RT combined. However, harvesting operation was responsible for the biggest contribution of 71% under the NT system, compared to 35% and 39% for CT and RT systems respectively.

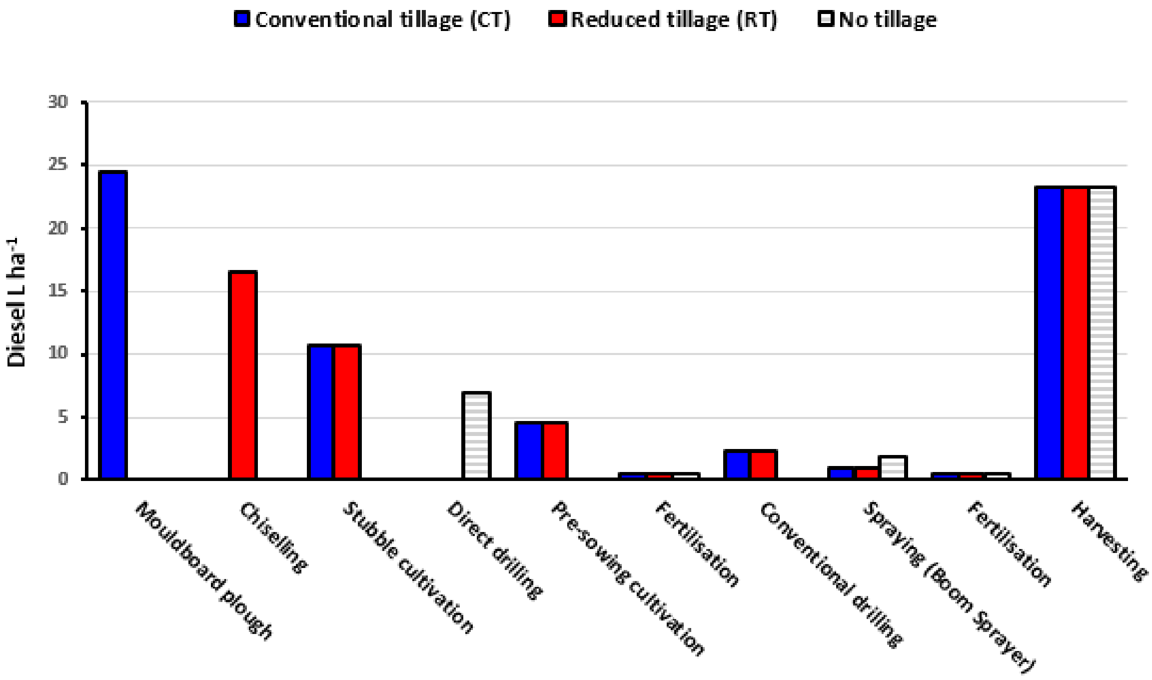

Figure 4.23: Different field operations and aggregated diesel fuel used on a per hectare basis of maize production.

The total input energy (MJ ha^{-1}) for each farm implement (CT, RT and NT) and other material inputs for maize cultivation based on four N fertiliser rates are shown in Table 4.8. The amount of energy consumed in descending order was nitrogen > diesel > phosphorus (P_2O_5) > insecticide > machinery > maize seed > potassium (K_2O) > herbicide. The average total energy input of 14,096 MJ ha^{-1} was obtained in a range between a minimum of 7,648 MJ ha^{-1} to a maximum of 19,370 MJ ha^{-1} (Table 4.8). CT had the highest total energy input of 14,673 MJ ha^{-1} followed by RT with 14,361 MJ ha^{-1} and NT had the lowest energy input of 13, 254 MJ ha^{-1}. Figure 4.24 shows the relative energy contribution of each input materials to the total energy input. It shows a higher proportion of input energy was attributed to nitrogen fertiliser and diesel fuel in all 12 management scenarios, with averages of 71% and 14% respectively. At relatively low levels, average energy inputs of machinery were 1.7%; maize seed 2.3%, phosphorus 4%, potassium 2.1%, herbicide 7.4% and insecticide 2.9%. Table 4.8 shows that a linear relation exists between nitrogen rate and total energy input. Energy input for each tillage systems increased considerably due to the intensity of each tillage operation system. Average percentage of tillage varied and measured at 18%, 16% and 10% in CT, RT and NT respectively. Overall, adoption of NT saved 1,419 MJ ha^{-1} energy (~ 10%) over that used under CT and 1,107 MJ ha^{-1} energy (~8%) over RT method.

Table 4.7: Amount of different inputs for maize production under different farm management scenarios

Parameters	Unit	Conventional tillage				Reduced tillage				No tillage			
		80 kg	160kg	200kg	250kg	80 kg	160kg	200kg	250kg	80 kg	160kg	200kg	250kg
Diesel fuel	L ha^{-1}	67.2	67.2	67.2	67.2	59.2	59.2	59.2	59.2	32.9	32.9	32.9	32.9
Machinery	h ha^{-1}	4.87	4.87	4.87	4.87	4.42	4.42	4.42	4.42	1.65	1.65	1.65	1.65
Maize Seed	Kg ha^{-1}	20	20	20	20	20	20	20	20	20	20	20	20
Nitrogen	Kg ha^{-1}	80	160	200	250	80	160	200	250	80	160	200	250
Phosphorus (P_2O_5)	Kg ha^{-1}	40	40	40	40	40	40	40	40	40	40	40	40
Potassium (K_2O)	Kg ha^{-1}	40	40	40	40	40	40	40	40	40	40	40	40
Herbicide	Kg ha^{-1}	2	2	2	2	2	2	2	2	2	2	2	2
Insecticide	Kg ha^{-1}	2	2	2	2	2	2	2	2	2	2	2	2

Table 4.8: Total input energy equivalent (MJ ha-1) under different farm management scenarios

Parameters	Unit	Conventional tillage				Reduced tillage				No tillage			
		80 kg	160kg	200kg	250kg	80 kg	160kg	200kg	250kg	80 kg	160kg	200kg	250kg
Diesel fuel	L ha^{-1}	2,385.6	2,385.6	2,385.6	2,385.6	2,101.6	2,101.6	2,101.6	2,101.6	1,168.0	1,168.0	1,168.0	1,168.0
Machinery	h ha^{-1}	305.3	305.3	305.3	305.3	277.1	277.1	277.1	277.1	103.5	103.5	103.5	103.5
Maize Seed	Kg ha^{-1}	294	294	294	294	294	294	294	294	294	294	294	294
Nitrogen	Kg ha^{-1}	4,848.0	9,009.6	12,120.0	15,150.0	4,848.0	9,696.0	12,120.0	15,150.0	4,848.0	9,696.0	12,120.0	15,150.0
Phosphorus (P_2O_5)	Kg ha^{-1}	502.4	502.4	502.4	502.4	502.4	502.4	502.4	502.4	502.4	502.4	502.4	502.4
Potassium (K_2O)	Kg ha^{-1}	268	268	268	268	268	268	268	268	268	268	268	268
Herbicide	Kg ha^{-1}	95.2	95.2	95.2	95.2	95.2	95.2	95.2	95.2	95.2	95.2	95.2	95.2
Insecticide	Kg ha^{-1}	369.4	369.4	369.4	369.4	369.4	369.4	369.4	369.4	369.4	369.4	369.4	369.4
Total input energy	MJ ha^{-1}	9,068	13,230	16,340	19,370	8,756	13,604	16,028	19,058	7,648	12,496	14,920	17,950

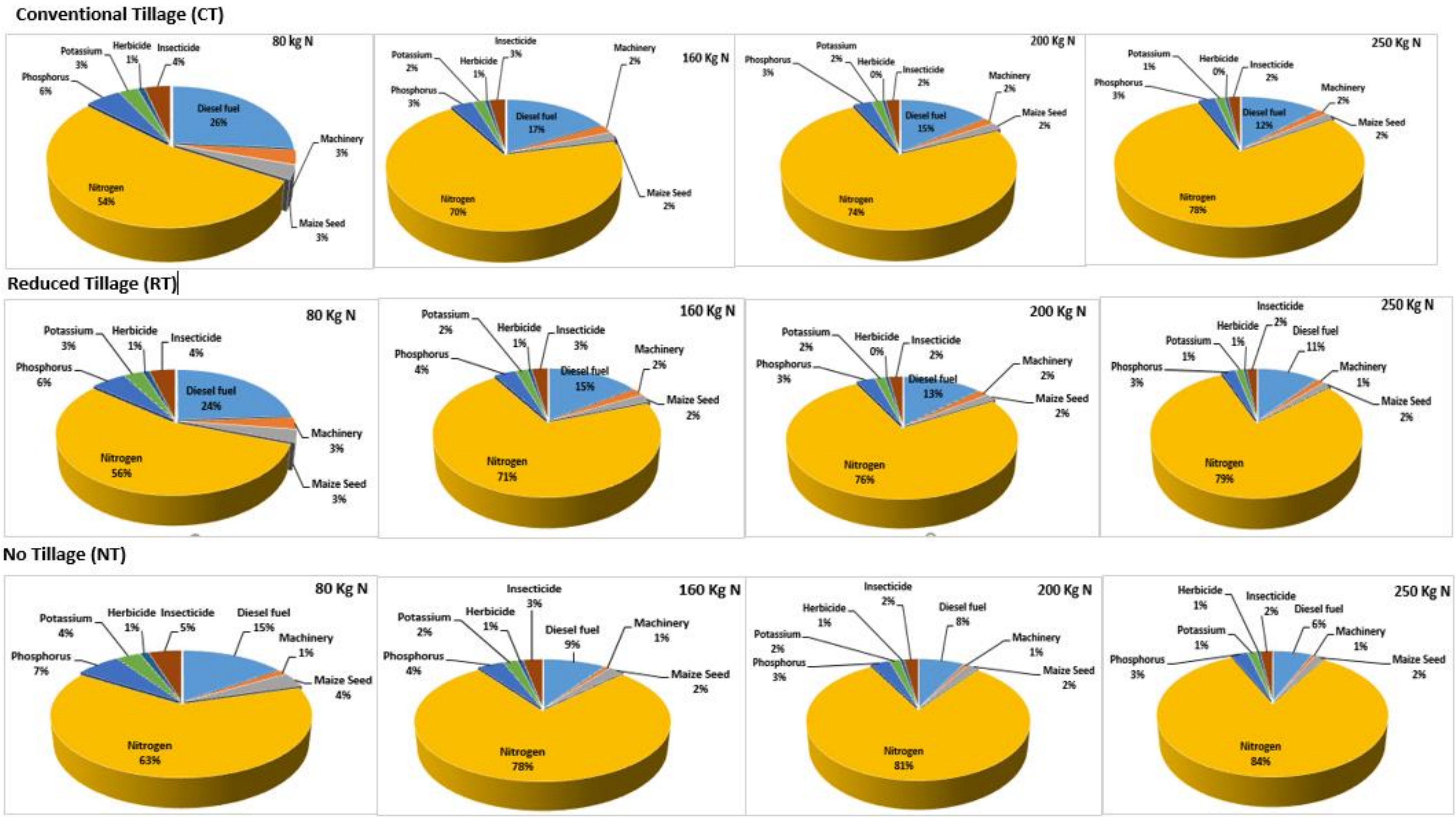

Figure 4.24: % contribution of different parameters to the total input energy under three different farm tillage and fertiliser management scenarios. Conventional tillage (CT); Reduced tillage (RT); No-tillage (NT). Nitrogen fertiliser rates are – 80 kg N, 160 kg N, 200 kg N and 250 kg N

4.5.2 Total energy output under climate change and farm management scenarios

The energy equivalent of maize grain produced was calculated for both baseline and projected maize yield outputs, multiplied by the grain energy index of 14.7 MJ kg^{-1}. As shown in Table 4.9, energy output was positive for each scenario which indicates energy gain overall. When compared to the baseline climate, energy gain (MJ ha^{-1}) will reduce for maize produced under RCP 6.0 and 8.5 scenarios from 2020, 2050 to 2080. Figure 4.25 represents significant deviations from the baseline for the maximum fertiliser rate of 250 kg N ha^{-1}. The highest decline in energy output (-26,241 MJ ha^{-1} and -45,767 MJ ha^{-1}) was at Ibadan for 2080 under RCP 6.0 and 8.5 scenarios. The lowest was Ilorin (-11,685 MJ ha^{-1} and -22,577 MJ ha^{-1}).

As shown in Table 4.9, energy output trend under three tillage systems varied for each location. CT method produced the highest energy output compared to RT and NT at Ibadan. However, the NT method gave the highest energy output in Jos and Ilorin, whilst the highest output in Enugu was under the RT method. According to the deviation chart presented in Figure 4.25, the effect of tillage practices under possible climate scenarios will reduce maize energy output from 2020 to 2080 for both RCPs. However, the mean difference is not statistically significant at $p < 0.05$.

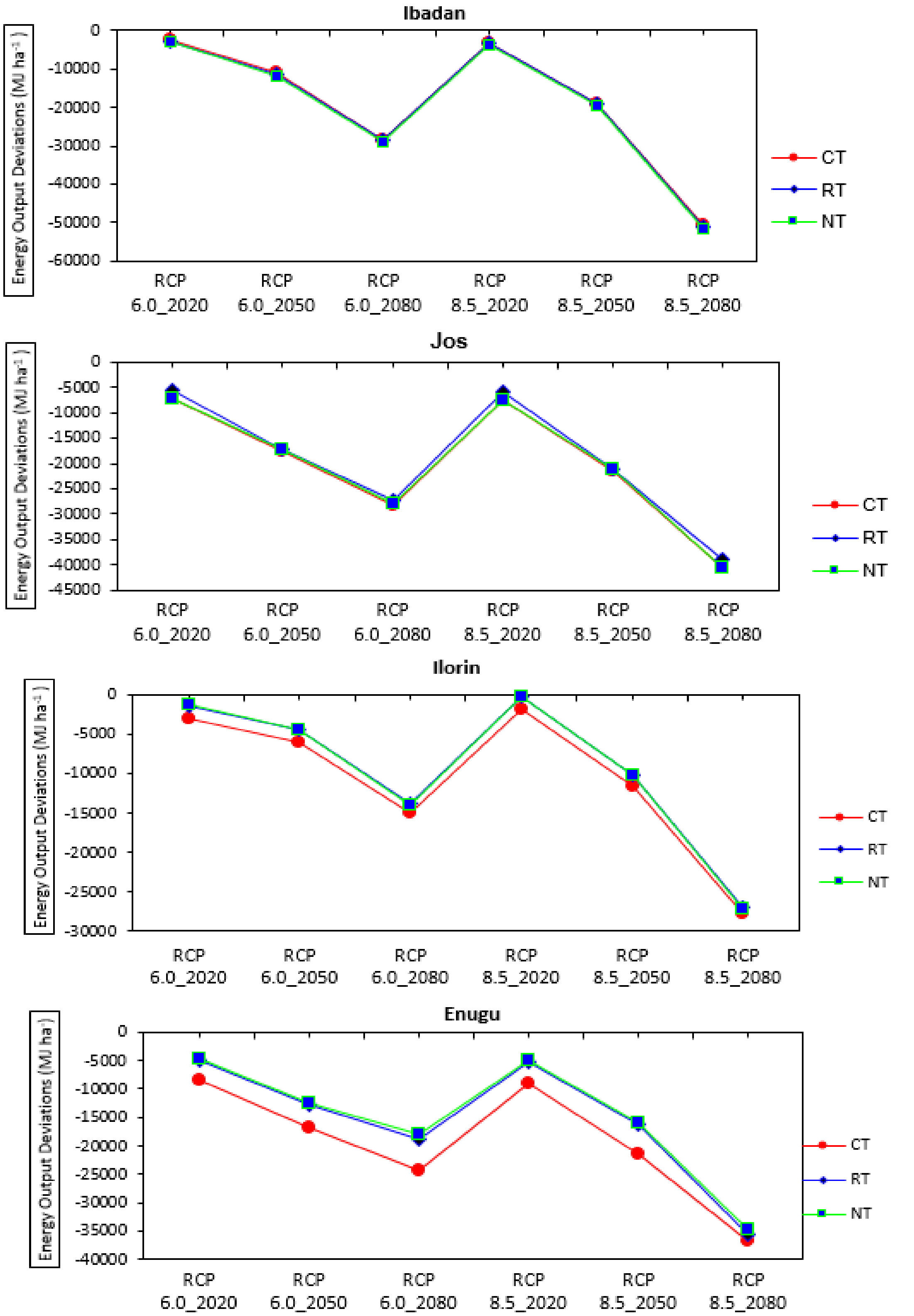

Figure 4.25: Energy output (MJ ha^{-1}) deviations of RCP 6.0 and 8.5 scenarios from baseline at Ibadan, Jos, Ilorin and Enugu sites. Results are based on 250 kg N ha^{-1} rate. CT- (Conventional tillage); RT – (Reduced tillage); NT – (No tillage).

Table 4.9: Total energy output (MJ ha^{-1}) for each site for baseline, climate change scenarios and twelve farm management scenarios. CT – (Conventional tillage); RT – (Reduced tillage; NT – (No tillage)

	CT				RT				NT			
	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg
Ibadan												
Baseline	84,437	122,251	126,787	127,659	81,216	121,018	126,127	127,123	80,885	120,516	125,713	126,816
RCP 6.0_2020	88,411	121,338	124,366	125,177	84,794	120,087	123,468	124,419	84,481	119,526	122,897	123,811
RCP 6.0_2050	83,716	113,964	116,013	116,536	80,540	112,882	115,098	115,617	80,150	112,307	114,444	115,131
RCP 6.0_2080	74,386	98,925	99,229	99,310	71,418	97,955	98,370	98,451	70,890	97,350	97,723	97,889
RCP 8.5_2020	87,953	121,028	123,795	124,383	84,362	119,698	122,749	123,615	84,078	119,171	122,186	122,935
RCP 8.5_2050	80,003	107,466	108,433	108,690	76,807	106,256	107,525	107,880	76,432	105,584	106,832	107,302
RCP 8.5_2080	62,896	76,840	76,748	76,844	60,728	75,793	75,722	75,885	60,448	75,222	75,139	75,313
Jos												
Baseline	88,914	160,072	175,740	192,761	86,516	155,362	170,357	186,786	89,742	160,627	176,038	193,032
RCP 6.0_2020	87,457	156,568	170,955	185,426	86,123	152,605	166,609	181,101	88,384	157,000	171,431	185,769
RCP 6.0_2050	85,345	150,299	162,866	175,217	82,194	145,107	157,309	169,398	86,401	150,669	163,216	175,811
RCP 6.0_2080	83,299	144,372	155,352	164,467	80,590	139,668	150,434	159,553	84,568	144,732	155,975	164,980
RCP 8.5_2020	87,851	156,640	171,087	185,185	86,465	152,755	166,895	180,846	88,845	157,136	171,657	185,500
RCP 8.5_2050	84,774	147,733	159,764	171,382	81,840	142,976	154,388	165,648	85,833	148,217	160,208	171,789
RCP 8.5_2080	77,827	138,527	147,528	152,235	76,191	135,333	144,207	148,002	79,750	139,192	148,154	152,566
Enugu												
Baseline	37,870	57,860	63,045	67,002	38,330	58,362	63,584	67,702	37,939	57,719	62,937	66,716
RCP 6.0_2020	30,320	50,388	55,023	58,564	36,123	55,702	59,559	62,751	35,821	55,225	59,036	62,104
RCP 6.0_2050	25,672	42,562	46,919	50,227	30,739	47,832	51,883	54,941	30,496	47,322	51,386	54,356
RCP 6.0_2080	22,834	37,366	40,594	42,654	28,195	43,812	46,710	49,027	27,910	43,465	46,388	48,706
RCP 8.5_2020	30,121	50,113	54,612	58,064	35,842	55,508	59,296	62,582	35,529	54,898	58,760	61,894
RCP 8.5_2050	23,815	39,341	43,006	45,483	29,007	45,644	48,875	51,345	28,740	45,181	48,435	50,845
RCP 8.5_2080	17,142	26,307	27,864	30,246	20,914	29,740	31,107	32,286	20,661	29,532	30,977	32,065
Ilorin												
Baseline	43,144	61,185	65,387	68,133	42,734	60,942	65,157	68,052	43,846	61,677	65,599	68,287
RCP 6.0_2020	36,374	57,404	61,941	65,076	42,188	60,420	64,164	66,697	43,476	61,168	64,587	67,022
RCP 6.0_2050	35,151	55,139	59,473	62,063	40,898	58,314	61,526	63,625	42,090	58,954	61,876	63,824
RCP 6.0_2080	30,818	48,359	51,306	53,139	36,108	50,906	52,915	54,327	37,169	51,348	53,178	54,355
RCP 8.5_2020	36,983	58,681	62,925	66,202	42,971	61,752	65,360	67,795	44,315	62,342	65,731	68,049
RCP 8.5_2050	32,725	51,463	54,669	56,583	38,157	53,961	56,229	57,821	39,344	54,372	56,445	58,001
RCP 8.5_2080	25,037	37,752	39,296	40,462	28,737	39,350	40,542	41,153	29,529	39,533	40,650	41,176

4.5.3 Energy indices in maize production assessment

Energy indices such as energy use efficiency (EUE), energy productivity (EP), specific energy (SE) and net energy (NE) were calculated for baseline climate, climate change and farm management scenarios, shown in the appendices (Appendix J).

The EUE illustrated in Table 4.10 outlines only high EUE values obtained for varying fertiliser rate (marked with an asterisk) and tillage scenarios. For each location, there is a declining trend in efficiency as the climate scenario changed from 2020 to 2080, with the RCP 8.5 scenario pathway recording the lowest EUE values. In addition, the highest efficiency values were obtained in Jos. This was followed by Ibadan, with the lowest value obtained in Enugu. This indicates that maize farming could be more sustainable in the aforementioned locations in the future. The average efficiency ratios for both RCP 6.0 and RCP 8.5 scenarios were calculated as 8.1 for Ibadan, 10.4 for Jos, 4.0 for Ilorin and 3.2 for Enugu. At Ibadan, the combination of 80kg N fertiliser and NT method was more efficient under future climate scenarios. Data showed 160kg N and NT for Jos, in addition to 80kg N and NT for Ilorin and Enugu respectively was more efficient. Although, across the scenarios, better efficiency was obtained for CT and RT methods combined with 160kg N. The best combination, showing the effective use of inputs was NT combined with 80 kg N, although this treatment combination did not boost maize yield under future climate scenarios. To support this, it should be noted that Sarauskis et al. (2014) reported energy ratios for maize cultivation that ranged on average from 5.4 to 19.7 using a range of tillage methods.

Energy productivity (EP) shows similar trends to EUE in terms of efficient tillage methods (NT) and fertiliser rate (80 and 160 kg N) that produce the highest EP. The average EP of maize was 0.6 kg MJ^{-1} (Jos), 0.5 kg MJ^{-1} (Ibadan) and 0.2 kg MJ^{-1} (Ilorin and Enugu) respectively. The lower index implies that lower units of yield outputs was obtained for Enugu and Ilorin when compared to Ibadan and Jos.

The specific energy (SE) which represents energy input (MJ ha^{-1}) per maize grain output (kg ha^{-1}), registered increasing trend under the worst climate scenarios as grain yield reduced in 2080 for both RCPs. For all locations, with the exception of Jos, high fertiliser input of 250 kg N increased SE irrespective of the tillage method. Enugu had the highest SE (9.2 to 10.1 MJ kg^{-1}) followed by Ilorin (6.7 to 7.1 MJ kg^{-1}) under RCP 8.5 scenario in 2080 as shown in Table 4.10. These high values indicate poor energy output per kg of maize produced. Jos however, had the lowest SE overall, but under certain scenarios, a combination of 80 kg N and tillage gave higher SE values. The net energy (NE) calculated was positive which represents energy gain for all sites across the scenarios (see Table 4.11). When compared to baseline, a high NE gain was obtained by adopting the NT method for all climate scenarios. This occurred with the exception of Ibadan, where using CT method with 160 kg N gave a higher NE in 2080 (RCP 6.0 and 8.5). Jos and Enugu had similar trends and high NE for NT (250 kg N).

Table 4.10: Calculated energy indices for each site under baseline, climate change scenarios and twelve farm management scenarios. CT – (Conventional tillage); RT – (Reduced tillage; NT – (No tillage)

		Energy use efficiency (EUE)			**Energy productivity (EP)**			**Specific energy (SE)**		
Location	**Scenario**	**CT**	**RT**	**NT**	**CT**	**RT**	**NT**	**CT**	**RT**	**NT**
Ibadan	Baseline	8.4**	8.2**	9.7**	0.6**	0.6**	0.7**	2.4****	2.3****	2.2****
	RCP 6.0_2020	8.4*	8.5*	10.1*	0.6*	0.6*	0.7*	2.4****	2.4****	2.2****
	RCP 6.0_2050	8.0*	8.1*	9.6*	0.5*	0.5*	0.7*	2.6****	2.6****	2.2****
	RCP 6.0_2080	7.1*	7.2*	8.5*	0.5*	0.5*	0.6*	3.1****	3.0****	2.8****
	RCP 8.5_2020	8.4*	8.4*	10.1*	0.6*	0.6*	0.7*	2.5****	2.4****	2.2****
	RCP 8.5_2050	7.6*	7.7*	9.2*	0.5*	0.5*	0.6*	2.8****	2.8****	2.6****
	RCP 8.5_2080	6.0*	6.1*	7.3*	0.5*	0.4*	0.5*	4.0****	3.9****	3.6****
Jos	Baseline	10.9**	10.5**	12.2**	0.7**	0.7**	0.8**	1.7*	1.7*	1.4*
	RCP 6.0_2020	10.7**	10.3**	11.9**	0.7**	0.7**	0.8**	1.8*	1.7*	1.5****
	RCP 6.0_2050	10.3**	9.8**	11.4**	0.7**	0.7**	0.8**	1.7****	1.8*	1.6****
	RCP 6.0_2080	9.9**	9.4**	11.0**	0.7**	0.6**	0.7**	1.9****	1.9****	1.7****
	RCP 8.5_2020	10.7**	10.3**	11.9**	0.7**	0.7**	0.8**	1.8*	1.7*	1.5****
	RCP 8.5_2050	10.1**	9.6**	11.2**	0.7**	0.7**	0.8**	1.8*	1.8*	1.6****
	RCP 8.5_2080	9.5**	9.1**	10.6**	0.6**	0.6**	0.7**	2.0*	2.0****	1.8****
Ilorin	Baseline	4.2*	4.3*	5.3*	0.3*	0.3*	0.4*	4.5****	4.4****	4.0****
	RCP 6.0_2020	3.9*	4.2*	5.2*	0.3*	0.3*	0.4*	4.7****	4.5****	4.1****
	RCP 6.0_2050	3.8*	4.1*	5.1*	0.3*	0.3*	0.3*	4.9****	4.7****	4.3****
	RCP 6.0_2080	3.3*	3.6*	4.5*	0.2*	0.2*	0.3*	5.7****	5.5****	5.0****
	RCP 8.5_2020	4.0*	4.3*	5.3*	0.3*	0.3*	0.4*	4.6****	4.4****	4.0****
	RCP 8.5_2050	3.5*	3.8*	4.7*	0.2*	0.3*	0.3*	5.4****	5.2****	4.7****
	RCP 8.5_2080	2.6*	2.9*	3.5*	0.2*	0.2*	0.2*	7.5****	7.2****	6.7****
Enugu	Baseline	4.0*	3.9*	4.6**	0.3**	0.3**	0.3**	4.6****	4.4****	4.1****
	RCP 6.0_2020	3.4*	3.8*	4.3**	0.2**	0.3**	0.3**	5.2****	4.8****	4.4****
	RCP 6.0_2050	2.9*	3.2*	3.7**	0.2**	0.2**	0.3**	6.1****	5.4****	5.0****
	RCP 6.0_2080	2.6*	3.0*	3.3**	0.2**	0.2**	0.2**	7.2****	6.1****	5.6****
	RCP 8.5_2020	3.4*	3.7*	4.3**	0.2**	0.3**	0.3**	5.3****	4.8****	4.4****
	RCP 8.5_2050	2.7*	3.1*	3.4**	0.2**	0.2**	0.3**	6.7****	5.8****	5.4****
	RCP 8.5_2080	1.8*	2.1**	2.5**	0.1**	0.1**	0.2**	10.1****	9.2****	8.5****

Values with (*), (**), (***) and (****) represents efficiency at 80 kg N, 160 kg N, 200 kg N, and 250 kg N per hectare.

Table 4.11: High net energy values calculated for each site under baseline, climate change scenarios and twelve farm management scenarios. CT – (Conventional tillage); RT – (Reduced tillage; NT – (No tillage)

		Net energy (NE)		
Location	**Scenario**	**CT**	**RT**	**NT**
Ibadan	Baseline	109,048.8***	108,867.3***	110,108.3***
	RCP 6.0_2020	106,709.8**	106,208.1***	107,291.8***
	RCP 6.0_2050	99,335.7**	98,046.0**	99,125.9**
	RCP 6.0_2080	84,296.7**	83,119.7**	84,169.2**
	RCP 8.5_2020	106,400.0**	105,489.3****	106,580.9****
	RCP 8.5_2050	92,837.8**	91,420.8****	92,402.7****
	RCP 8.5_2080	62,212.3**	60,957.1****	62,041.3****
Jos	Baseline	171,992.8****	166,495.9****	174,393.5****
	RCP 6.0_2020	164,657.5****	160,810.9****	167,131.2****
	RCP 6.0_2050	154,448.4****	149,108.2****	157,172.9****
	RCP 6.0_2080	143,698.7****	139,263.1****	146,341.9****
	RCP 8.5_2020	164,416.4****	160,556.0****	166,862.2****
	RCP 8.5_2050	150,614.1****	145,358.7****	153,151.0****
	RCP 8.5_2080	131,466.8****	127,711.8****	133,928.3****
Ilorin	Baseline	47,648.3***	47,897.6***	49,993.7***
	RCP 6.0_2020	44,307.6****	46,903.9***	48,981.8***
	RCP 6.0_2050	41,734.5***	44,266.7***	46,271.2***
	RCP 6.0_2080	33,730.6**	36,070.4**	38,166.4**
	RCP 8.5_2020	45,433.6****	48,099.9***	50,125.5***
	RCP 8.5_2050	36,930.6***	39,125.1**	41,191.3**
	RCP 8.5_2080	23,124.1**	24,514.7**	26,352.1**
Enugu	Baseline	46,233.3****	47,412.6****	48,077.4****
	RCP 6.0_2020	37,796.1****	42,461.2****	43,466.0****
	RCP 6.0_2050	29,458.2****	34,651.6****	35,781.2***
	RCP 6.0_2080	22,856.2***	29,450.6***	30,782.7***
	RCP 8.5_2020	37,295.2****	42,292.2****	43,255.8****
	RCP 8.5_2050	25,268.02***	31,615.3***	32,829.5***
	RCP 8.5_2080	11,678.7**	14,904.3**	16,350.8**

Values with (*), (**), (***) and (****) represents efficiency at 80 kg N, 160 kg N, 200 kg N, and 250 kg N per hectare

4.5.4 GHG emissions from fertiliser production and application

Fertilisers are required to increase soil nutrients, and to improve crop growth and yield. During the process of fertiliser production and application, emission of greenhouse gases such as CO_2, N_2O and CH_4 occur in the atmosphere and groundwater, causing varying degrees of environmental problems and inducing climate change. In this section, emissions of CO_2 and N_2O from fertiliser production and application were calculated. According to the IPCC Tier 1 guidelines, direct and indirect emissions of N_2O from agricultural soils was first estimated, followed by the emission of CO_2 from urea hydrolysis in the soil.

4.5.4.1 CO_2 emissions from fertiliser production

Calculated CO_2eq ha^{-1} emissions from fertiliser production (urea, phosphorus and potassium) varied as the application rate per hectare increased as shown in Figure. 4.26. Within the pre-farming category (production of input materials), urea production was the most CO_2-intense process, followed by diesel production and maize seed production. Estimated emissions from urea production were 318 kg CO_2eq ha^{-1}, 635 kg CO_2eq ha^{-1}, 794 kg CO_2eq ha^{-1} and 993 kg CO_2eq ha^{-1} in relation to fertiliser application rates of 80 kg N ha^{-1}, 160 kg N ha^{-1}, 200 kg N ha^{-1} and 250 kg N ha^{-1} respectively. Emissions from phosphorus (P_2O_5) and potassium (K_2O) production were 22.9 kg CO_2eq ha^{-1} and 22 kg CO_2eq ha^{-1} based on the application rates of 40 kg ha^{-1} (Figure. 4.26). The average emission value of 684.8 kg CO2eq ha^{-1} contributed to the total GHG emissions by 23.4% for urea, and 1.0 % and 0.8 % for phosphorus (P_2O_5) and potassium oxide (K_2O) respectively. Therefore, CO_2 emissions from fertiliser production was calculated at 25.2% of the total GHG emissions (kg CO_2eq ha^{-1}).

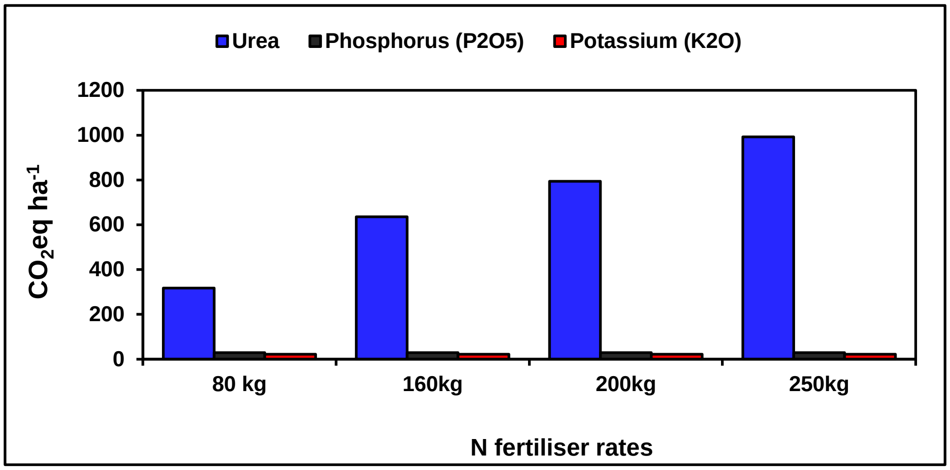

Figure 4.26: Estimated emissions of CO_2 from production of urea, phosphorus and potassium per hectare.

4.5.4.2 N_2O emissions from fertiliser application (direct and indirect emissions)

Figure 4.27 shows a linear increase of the direct and indirect N_2O soil emissions with increasing fertiliser rate. Direct N_2O_{direct} (kg N_2O–N ha $^{-1}$) emissions results were equivalent to 599.4 kg CO_2eq ha^{-1}, 1,198.8 kg CO_2eq ha^{-1}, 1,498.5 kg CO_2eq ha^{-1} and 1,873.1 kg CO_2eq ha^{-1} GHG emissions from fertiliser rates at 80 kg N ha^{-1}, 160 kg N ha^{-1}, 200 kg N ha^{-1} and 250 kg N ha^{-1} respectively (Figure 4.28). The average contribution of direct N_2O emission to the total N_2O emission was 83% (1,292.5 kg CO_2eq ha^{-1}). Indirect soil N_2O emissions from leaching and volatilisation from fertiliser application were found to be relatively small (average of 0.4 kg N_2O–N ha $^{-1}$ and 0.2 kg N_2O–N ha $^{-1}$). Leaching was the dominant source of indirect emissions with an average CO_2 equivalents of 181.8 kg CO_2eq ha^{-1} (12%) compared to 80.8 kg CO_2eq ha^{-1} (5%) for volatilisation. The total indirect N_2O emissions (leaching + volatilisation) represented on average, 262.5 kg CO_{2eq} ha $^{-1}$ and the average contribution of indirect N_2O emission to the total N_2O emission was 17%. The contribution of direct and indirect N_2O emissions to the GHG emissions was

44.1% and 9.3% respectively, therefore bringing the total N_2O emissions from fertiliser application to 53.4% of the total GHG emissions from maize production per hectare.

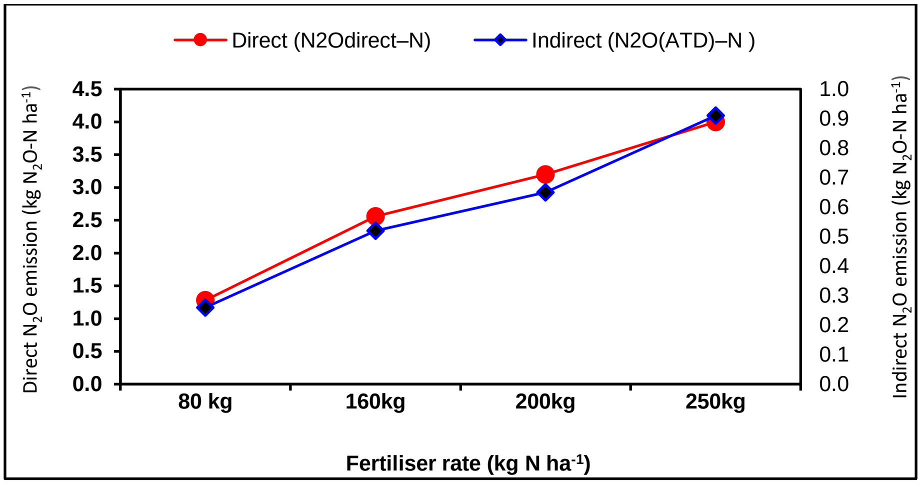

Figure 4.27: Direct and indirect N2O emissions (kg N2O–N ha -1)

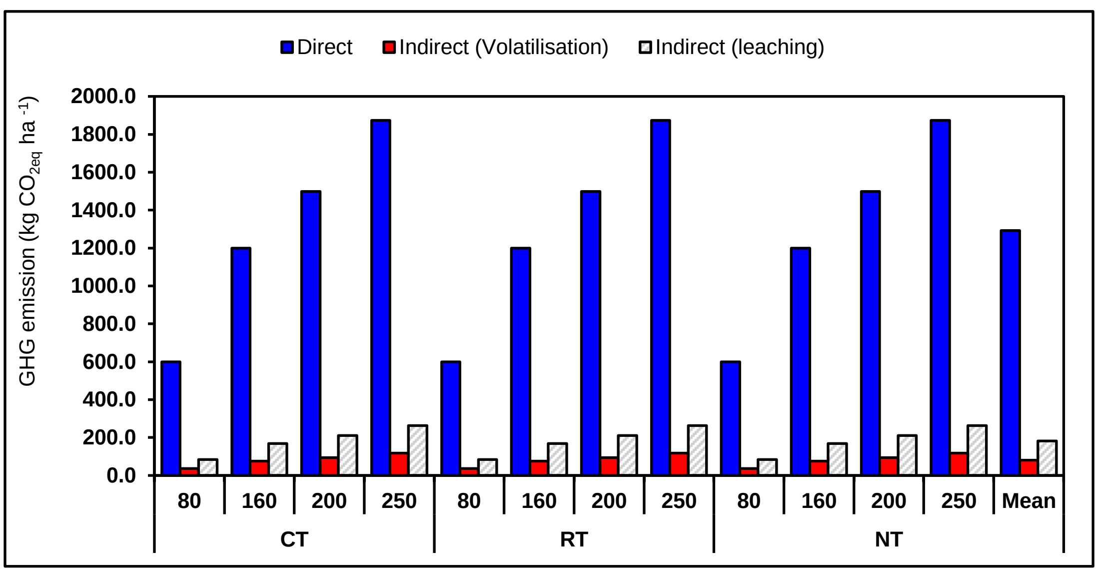

Figure 4.28: Direct and indirect GHG emissions (kg CO_2eq ha^{-1}) from soil for three fertiliser application rates (80, 160, 200, 250 kg N ha^{-1}) for three tillage systems (Conventional tillage – CT; Reduced tillage – RT; No tillage – NT).

4.5.4.3 CO_2 emissions from urea application

The amount of CO_2 emissions from urea application was estimated at 58.7 kg CO_{2eq} ha $^{-1}$, 117.3 kg CO_{2eq} ha $^{-1}$, 146.7 kg CO_{2eq} ha $^{-1}$, and 183.4 kg CO_{2eq} ha $^{-1}$ as shown in Table 4.12 for the four fertiliser application rates and three tillage methods. This represents the amount of CO_2 released during soil hydrolysis. The contribution of CO_2 emissions from urea application was 4.3% to the total GHG emissions.

4.5.4.4 CO_2 emissions from diesel fuel production and combustion

CO_2 emissions resulting from diesel production, transport and combustion per litre of diesel fuel were estimated using the relevant emission factor. As shown in Table 4.13, total diesel consumption of 67.2 l ha^{-1}, 59.2 l ha^{-1} and 32.9 l ha^{-1} for each tillage process produced CO_2 emissions of 216.4 kg CO2eq ha^{-1}, 190.6 kg CO_2eq ha^{-1} and 105.9 kg CO2eq ha^{-1} respectively. The result indicates that NT emitted 110.5 kg and 84.7 kg less CO_2 emissions per hectare from diesel than those emitted under CT and RT and the differential was due to the difference in the quantity of diesel consumed. The highest emitter of CO_2 emission under the CT method was the mouldboard ploughing process (78.9 kg CO_2eq ha^{-1}). Particularly, harvesting operations required a higher volume of diesel that significantly affected CO_2 emissions regardless of the tillage method. For instance, at the rate of 23.2 l ha^{-1} of diesel fuel, the equivalent CO_2 emission during harvesting was 35%, 39% and 71% for CT RT and NT respectively. Chisel ploughing in RT consumed less diesel fuel (16.5 l ha^{-1}) compared to mouldboard ploughing (24.5 l ha^{-1}), thereby contributing about 28% to GHG emissions from diesel fuel according to Table 4.13.

Across all tillage systems, the average GHG emissions from diesel fuel production, transport and combustion were 171.0 kg CO2eq ha^{-1}, which shows the second most emission-intense process under input production (5.8%) after urea according to Table 4.14 (input production). The NT system produced less GHG emissions because of saving fuel by avoiding any form of soil disturbance. The direct drilling method under the NT system consumed more fuel and emitted more GHG (21%) compared to the conventional drilling method used in CT and RT (3-4 %). In addition, for NT, more herbicides were required (two spray passes), thereby using more fuel and contributing more (5 %) to the GHG emissions compared to the other two systems.

Table 4.12: N_2O and CO_2 emissions from fertiliser application (direct and indirect emissions)

	Conventional tillage				Reduced tillage				No tillage			
	80 kg N ha^{-1}	160kg N ha^{-1}	200kg N ha^{-1}	250kg N ha^{-1}	80 kg N ha^{-1}	160kg N ha^{-1}	200kg N ha^{-1}	250kg N ha^{-1}	80 kg N ha^{-1}	160kg N ha^{-1}	200kg N ha^{-1}	250kg N ha^{-1}
$N_2O_{(direct)}(kgN_2O - Nha^{-1})$	1.3	2.6	3.2	4.0	1.3	2.6	3.2	4.0	1.3	2.6	3.2	4.0
$N_2O_{(volatilised)}(kg\ N_2O - Nha^{-1})$	0.1	0.2	0.2	0.3	0.1	0.2	0.2	0.3	0.1	0.2	0.2	0.3
$N_2O_{(leached)}(kgN_2O - Nha^{-1})$	0.2	0.4	0.5	0.6	0.2	0.4	0.5	0.6	0.2	0.4	0.5	0.6
Direct N_2O emission $(kg\ CO_2eq\ ha^{-1})$	599.4	1,198.8	1,498.5	1,873.1	599.4	1,198.8	1,498.5	1,873.1	599.4	1,198.8	1,498.5	1,873.1
Indirect N_2O emission $(kg\ CO_2eq\ ha^{-1})$	121.8	243.5	304.4	380.5	121.8	243.5	304.4	380.5	121.8	243.5	304.4	380.5
Total $E_{N2O}(kg\ CO_2eq\ ha^{-1})$	721.2	1,442.3	1,802.9	2,299.3	721.2	1,442.3	1,802.9	2,299.3	721.2	1,442.3	1,802.9	2,299.3
CO_2 emission (kg $CO_{2\ eq}$ ha^{-1})	58.7	117.3	146.7	183.4	58.7	117.3	146.7	183.4	58.7	117.3	146.7	183.4

Table 4.13: GHG emissions from diesel fuel production and combustion used for various field operations and tillage systems for maize production.

Mechanical operations	*Duration*	***Conventional tillage (CT)***			***Reduced tillage (RT)***			***No Tillage (NT)***		
	Operation time [a] hour ha^{-1}	Diesel [b] l ha^{-1}	GHG kg CO_{2eq} ha^{-1}	%	Diesel l ha^{-1}	GHG kg CO_{2eq} ha^{-1}	%	Diesel l ha^{-1}	GHG kg CO_{2eq} ha^{-1}	%
Stubble cultivation	0.7	10.7	34.5	16%	10.7	34.5	18%	na	na	na
Mouldboard ploughing	1.9	24.5	78.9	36%	na	na	na	na	na	na
Chiselling	1.5	na	Na	na	16.5	53.1	28%	na	na	na
Pre-sowing cultivation	0.8	4.6	14.8	7%	4.6	14.8	8%	na	na	na
Fertilisation **	0.2	1.0	3.2	1%	1.0	3.2	2%	1.0	3.2	3%
Conventional drilling	0.4	2.3	7.4	3%	2.3	7.4	4%	na	na	na
Direct drilling	0.5	na	Na	na	na	na	na	6.9	22.2	21%
Spraying (Boom Sprayer) ***	0.2/0.4	0.9	2.9	1%	0.9	2.9	2%	1.8	5.8	5%
Harvesting	0.8	23.2	74.7	35%	23.2	74.7	39%	23.2	74.7	71%
Total		**67.2**	**216.4**	**100%**	**59.2**	**190.6**	**100%**	**32.9**	**105.9**	**100%**

[a, b] – *Average operation time and diesel consumption for various cultivation operations obtained from Šarauskis et al. (2014).*

*Fertilisation ** - operation was carried out twice; Spraying (Boom Sprayer) *** - spraying was done twice for NT system only.*

na = not applicable

4.5.4.5 CO_2 emissions from Machinery usage

Table 4.14 shows the estimated average GHG emissions from farm machinery use (field operation), based on emission factors for various farm operations, data for working time (h ha^{-1}) and fuel consumed for each operation. Across all treatments, GHG emissions associated with field operations in maize cultivation accounted for 4.4% of the total emissions (129.6 kg CO_2eq ha^{-1}). Regardless of the fertiliser application rate, it was clear that soil tillage activity (CT and RT) influenced emissions the most. For all field operations, the total emissions of 209.7 kg CO_2eq ha^{-1}, 131.0 kg CO_2eq ha^{-1}, and 48.2 kg CO_2eq ha^{-1} were credited to CT, RT and NT. Maraseni et al. (2010) calculated total GHG emissions of CO_2e (kg ha^{-1}) from use of machinery in maize cropping per annum as 46.72 kg CO_2eq ha^{-1}, but their result included weight of machine and fraction of lifespan not considered in this study.

Figure 4.29 shows the percent contribution of each field operation to the total GHG emissions. On average, carbon emissions for mouldboard ploughing were 132.6 kg CO_2eq ha^{-1}, having the highest average share of 1.5% for field operations. Chiselling emissions were 53.9 kg CO_2eq ha^{-1}, contributing less (0.6%) compared to harvesting, which emitted an average of 36.4 kg CO_2eq ha^{-1} and contributed 1.2%. Stubble cultivation was 18.8 kg CO_2eq ha^{-1} (0.4%) and the lowest carbon-intensive processes were fertilisation and chemical spraying, with both contributing average GHG emissions of 0.1%. Between the three tillage systems, the differences in emissions were mainly due to the number of field operations carried out. CT and RT had seven field operations undertaken hence higher emission values compared to NT, which had only four operations. The exclusion of tillage and soil cultivation operations in the NT system reduced emissions from field operations by a higher percentage (77% and 63% in CT and RT, respectively) and reduced total emissions by 6%.

Fertiliser application was split applied within the farm management option in DSSAT-CSM, with 50% during planting and 50% two weeks after planting. Therefore, fertilisation calculation was based on two passes hence, the amount of GHG emissions calculated from fertilisation doubled to 0.8 kg CO_2eq ha^{-1} on average for all tillage methods. Herbicides were assumed to be sprayed once for CT and RT and twice for NT, which increased CO_2 emissions to 2.5 kg CO_2eq ha^{-1} for NT, compared to 0.9 kg CO_2eq ha^{-1} for CT and RT. The conventional drilling method used in the CT and RT systems emitted less (6.1 kg CO_2eq ha^{-1}) compared to the direct drilling (8.5 kg CO_2eq ha^{-1}) used in the NT system.

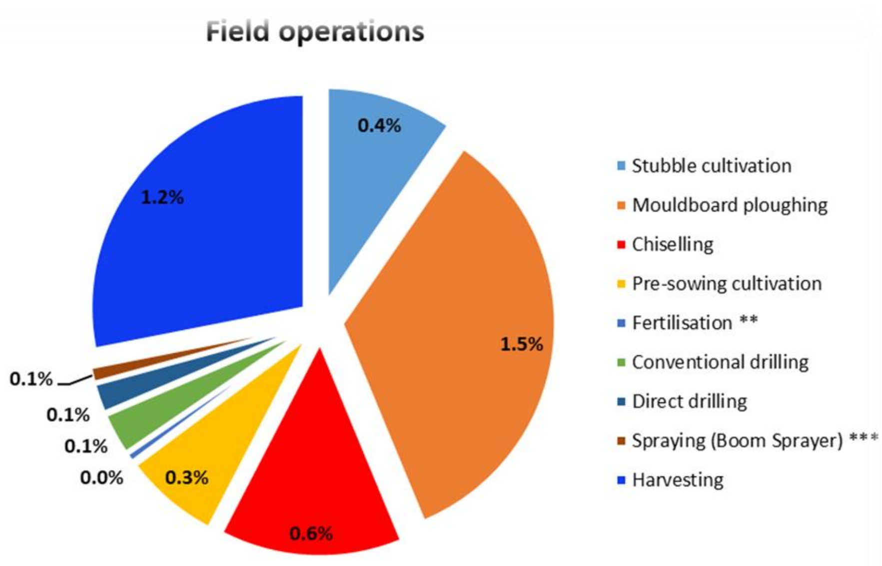

*Figure 4.29: Pie chart displaying percentage contribution of various field operations to the total GHG emissions. Fertilisation** - two passes; Spraying (Boom sprayer) *** - herbicide spraying was done twice for NT system.*

Table 4.14: Calculated GHG emissions from the production of farm inputs and emissions from various field tillage operations. Table includes the percentage contribution to the total GHG emissions for different management systems.

Emission source	Conventional tillage				Reduced tillage				No tillage					
	80 kg N	160kg N	200kg N	250kg N	80 kg	160kg	200kg	250kg	80 kg	160kg	200kg	250kg	Average	% of total GHG emissions
Input production														
Maize Seeds	90	90	90	90	90	90	90	90	90	90	90	90	90	3.1%
Diesel fuel	216.4	216.4	216.4	216.4	190.6	190.6	190.6	190.6	105.9	105.9	105.9	105.9	171.0	5.8%
Urea	318	635	794	993	318	635	794	993	318	635	794	993	684.8	23.4%
Phosphorus (P2O5)	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	29.2	1.0%
Potassium (K2O)	22	22	22	22	22	22	22	22	22	22	22	22	22.0	0.8%
Herbicide	46.2	46.2	46.2	46.2	46.2	46.2	46.2	46.2	92.4	92.4	92.4	92.4	61.6	2.1%
Pesticide	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	50.2	1.7%
Sub total	771.58	1,089.18	1,247.98	1,446.48	745.80	1,063.40	1,222.20	1,420.70	707.34	1,024.94	1,183.74	1,382.24	1,108.80	0.38
80 kg, 160 kg, 200 kg, 250 kg are the fertiliser application rate (kg N ha^{-1})														
Field operation														
Stubble cultivation	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8	0.0	0.0	0.0	0.0	12.5	0.4%
Mouldboard ploughing	132.6	132.6	132.6	132.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	44.2	1.5%
Chiselling	0.0	0.0	0.0	0.0	53.9	53.9	53.9	53.9	0.0	0.0	0.0	0.0	18.0	0.6%
Pre-sowing cultivation	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0	0.0	0.0	0.0	0.0	9.4	0.3%
Fertilisation **	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.0%
Conventional drilling	6.1	6.1	6.1	6.1	6.1	6.1	6.1	6.1	0.00	0.00	0.00	0.00	4.1	0.1%
Direct drilling	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.5	8.5	8.5	8.5	2.8	0.1%
Spraying (Boom Sprayer) ***	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	2.5	2.5	2.5	2.5	1.5	0.1%
Harvesting	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	36.4	1.2%
Sub total	209.7	209.7	209.7	209.7	131.0	131.0	131.0	131.0	48.2	48.2	48.2	48.2	129.6	4.4%

*Fertilisation ** - operation was carried out twice; Spraying (Boom sprayer) ***- spraying was done twice for NT system only.*

4.5.4.6 *CO_2 emissions from Herbicides, Pesticides and Maize seeds*

Emissions of CO_2 from herbicides (2kg ha^{-1}), pesticides (2kg ha^{-1}) and maize seed production (20kg ha^{-1}) were 61.6 kg CO_2eq ha^{-1}, 50.2 kg CO_2eq ha^{-1} and 90 kg CO_2eq ha^{-1} respectively. As shown in Figure 4.30, these inputs contributed on average small emission amounts (2.1%, 1.7% and 3.1%) to the total GHG emissions, compared to other parameters such as diesel and urea. The average amount of CO_2 emissions for maize seed production reported by Wang et al. (2015) was 111.8 kg CO_2eq ha^{-1} from 25 kg, which makes a 0.5% contribution. When the CO_2 emissions were compared for the three crop management practices, a higher emission value of 92.4 kg CO_2eq ha^{-1} for herbicide production was estimated in the NT treatment system. This was due to applying double the amount of herbicide (4 kg ha^{-1}) for weed control, as the NT system required less mechanical agitation of the soil compared to the CT and RT systems (2kg ha^{-1}). Therefore, CO_2 emissions from herbicides, pesticides and maize seed production was 6.9% of the total GHG emissions (kg CO_2eq ha^{-1}).

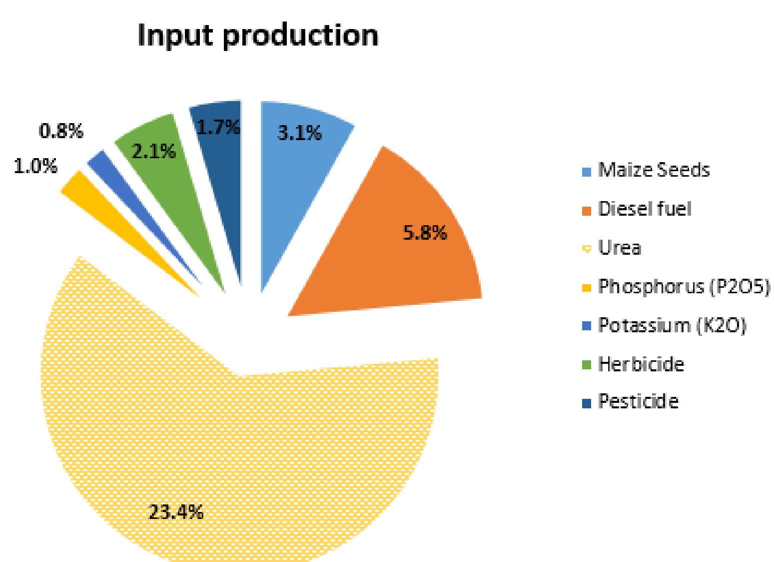

Figure 4.30: Percentage contribution of various inputs to the total GHG emissions.

4.5.4.7 Total GHG Emissions per hectare of maize production

This section presents the estimated total GHG emissions for each proposed farm management scenario. Overall average GHG emissions were 2,931.4 kg CO_2eq ha^{-1} which varied across all twelve management scenarios, within the range of 1,535.4 kg CO_2eq ha^{-1} to 4138.8 kg CO_2eq ha^{-1}. Each tillage system produced an average of 3,041.4 kg CO_2eq ha^{-1}, 2,937.0 kg CO_2eq ha^{-1}, and 2,815.7 kg CO_2eq ha^{-1} respectively for CT, RT and NT tillage scenarios. As shown in Figure 4.31, CT produced the highest net emissions under the high fertiliser input system, while the lowest emissions came from the NT under the low fertiliser input system. From Figure 4.32, results show that soil emissions (NO_2 and CO_2) represent the largest proportion of emissions (57.8%) based on the fertiliser input rate. This is followed by farm input production (37.8%). Under this category, urea production was responsible for 684.8 kg CO_2eq ha^{-1} (23.4%), followed by diesel production (5.8%). For on-farm soil emission, direct N_2O emission was responsible for the highest contribution to the total GHG emission (44.1%), while indirect N_2O emissions produced through leaching and volatilisation contributed only 9.3%. In addition to this, CO_2 emission from urea application contributed 4.3%. During field operations, the effect of tillage type on total GHG emission varied. The CT scenario produced an average of 209.7 kg CO_2eq ha^{-1} followed by RT with 131.0 kg CO_2eq ha^{-1} and NT producing GHG emission savings of 48.2 kg CO_2eq ha^{-1}. Although the calculated emissions from diesel production accounted for 5.8% under the input production category, its use in farm machinery accounted for 4.4% thereby producing a net contribution of 10.2% towards the total GHG emissions.

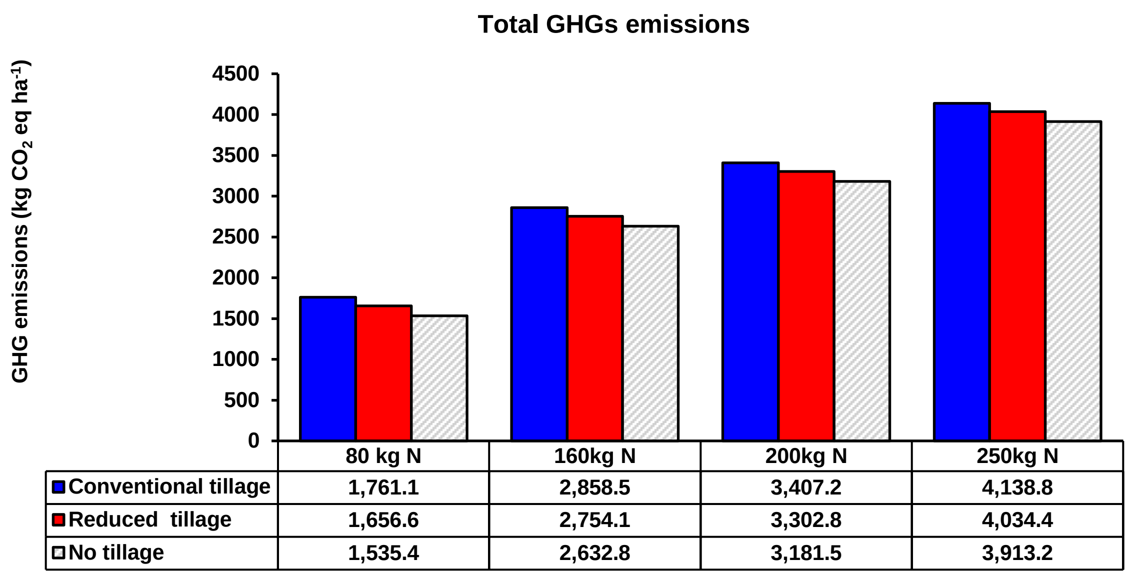

Figure 4.31: Total GHGs emission summary for the twelve farm management scenarios.

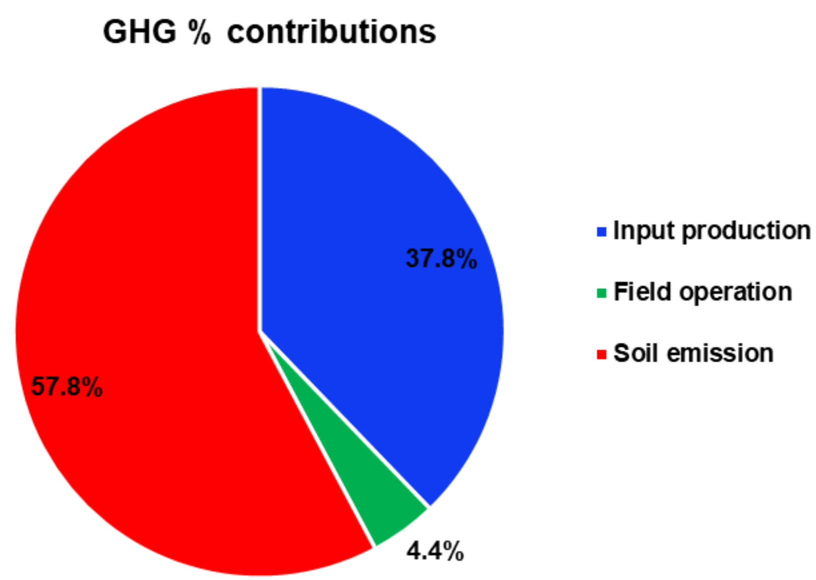

Figure 4.32: Proportions of different inputs to the total GHG emissions.

4.5.4.8 *Carbon footprint per yield of maize production*

Maize grain yield (kg ha^{-1}) is the functional unit used to express carbon footprint (CF). The results varied considerably among sites and climate scenarios due to yield value, input quantities, farm management options, and associated GHG emissions per unit area. The range of CF recorded was 0.271 kg CO_{2eq} kg^{-1} to 0.344 kg CO_{2eq} kg^{-1} for Jos, 0.357 kg CO_{2eq} kg^{-1} to 0.601 kg CO_{2eq} kg^{-1} for Ibadan; 0.672 kg CO_{2eq} kg^{-1} to 1.231 kg CO_{2eq} kg^{-1} for Ilorin and Enugu had the highest range values between 0.718 kg CO_{2eq} kg^{-1} to 1.729 kg CO_{2eq} kg^{-1}.

For all study sites, with the exception of Ibadan, the lowest carbon footprint was obtained using 80 kg N ha^{-1} fertiliser for all climate scenarios including baseline as shown in Figures 4.33 to 4.34. For Ibadan, the fertiliser rate with the lowest CF was 160 kg N ha^{-1}. With regards to tillage, the lowest emission intensity was found using the NT method, with an average carbon intensity of 0.287 kg CO_{2eq} kg^{-1} for Jos, 0.923 kg CO_{2eq} kg^{-1} for Enugu and 1.073 kg CO_{2eq} kg^{-1} for Ilorin.

The high CF obtained in Enugu and Ilorin under CT and RT systems, are a testament to the projected decline in future yield under the two studied RCP climate scenarios. Higher N fertiliser rate for example 250 kg N ha^{-1} caused higher GHG emissions and therefore, a higher impact per kg of maize grain was observed for all sites. Further examples show that for instance, at 250 kg N ha^{-1} rate, a high CF of 1.426 kg CO_{2eq} kg^{-1} and 2.012 kg CO_{2eq} kg^{-1} was recorded at Enugu under RCP 6.0 and 8.5 for the 2080 scenario year compared to baseline CF of 0.908 kg CO_{2eq} kg^{-1}.

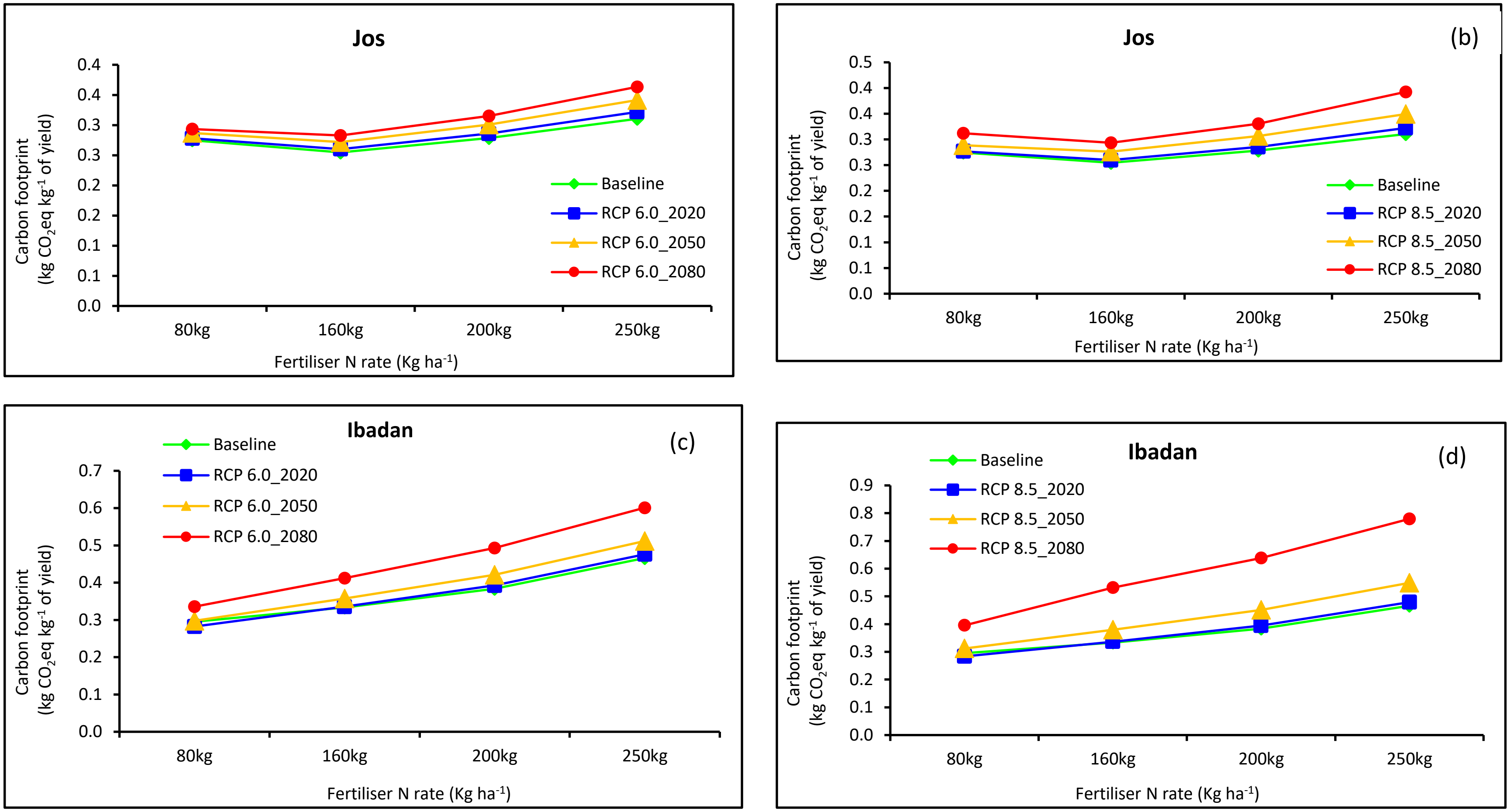

Figure 4.33 Carbon footprint (kg CO2eq kg-1 yield) of maize grain production under baseline and two RCP climate scenarios: Jos (a) RCP 6.0 and (b) RCP 8.5; Ibadan (c) RCP 6.0 and (d) RCP 8.5.

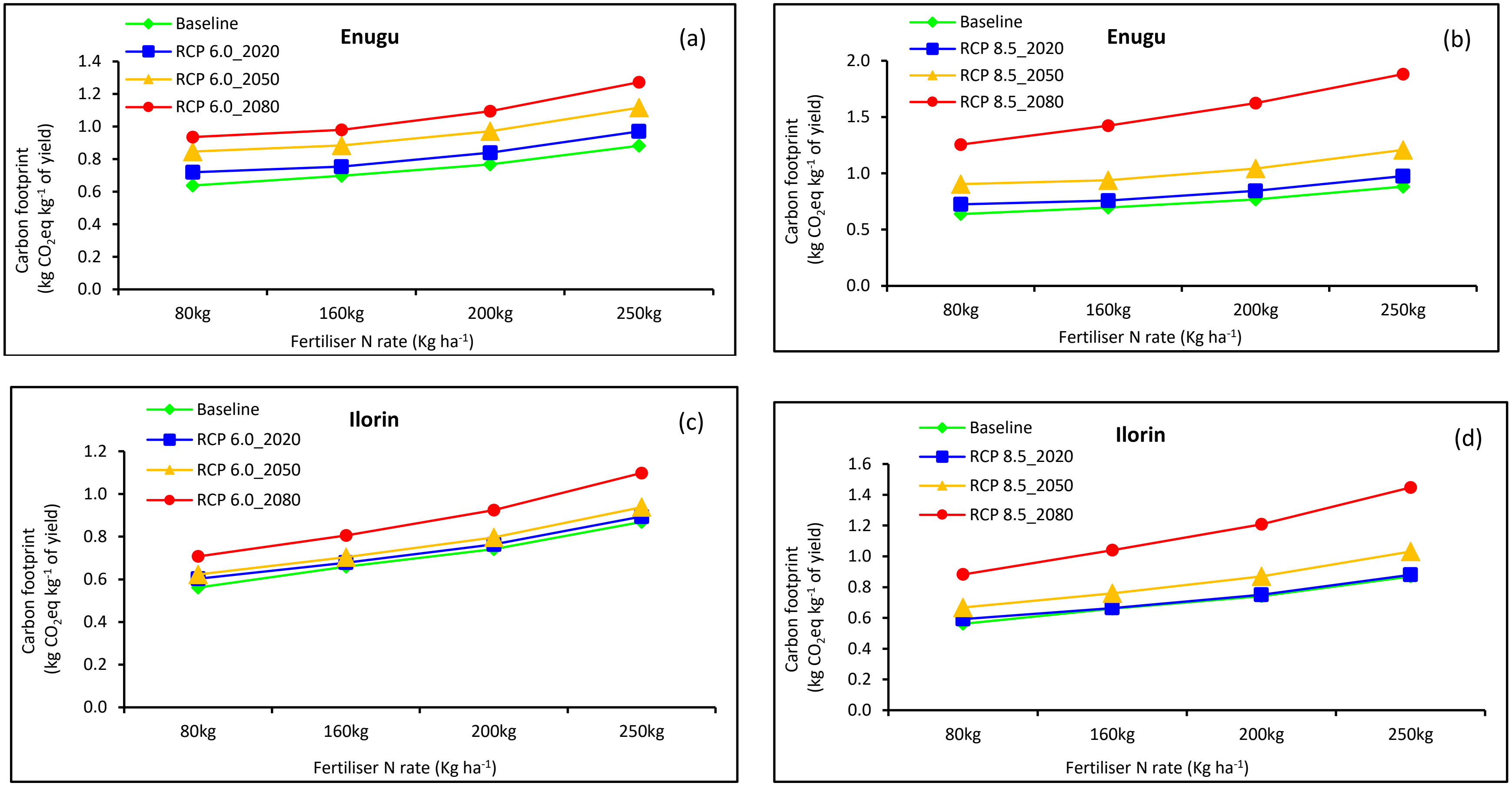

Figure 4.34; Carbon footprint (kg CO2eq kg-1 yield) of maize grain production under baseline and two RCP climate scenarios: Enugu (a) RCP 6.0 and (b) RCP 8.5; Ilorin (c) RCP 6.0 and (d) RCP 8.5.

4.6 Regression model analysis

This section describes multiple and simple linear regression models developed using results obtained in previous sections for grain yield, net energy, GHG and carbon footprint. The models tested the effects of multiple variables on yield and LCA responses as well as the interrelationships between the variables. For each location, the regression models were developed using three predictor variables: climate change, tillage and fertiliser. The dataset used to 'train' the models for all response variables was yield data (from climate-crop model simulation experiment), estimated net energy data, and life cycle impact assessment data (for GHG and CF).

4.6.1 Design of experiment

Table 4.15 and 4.16 shows the coded format created for the factorial combination between factors and responses. Table 4.17 gives an overview of 72 possible data combination generated for each site and imported to MATLAB.

Table 4.15: Generated codes used to create the experiment design.

Factors and Levels	**Code**
Climate	Ai
RCP 6.0_2020	1
RCP 6.0_2050	2
RCP 6.0_2080	3
RCP 8.5_2020	4
RCP 8.5_2050	5
RCP 8.5_2080	6
Tillage	Bi
CT	1
RT	2
NT	3
Fertiliser (kg ha^{-1})	Ci
80	1
160	2
200	3
250	4

Table 4.16: Database created in Minitab showing design matrix for the statistical analysis.

		Factors			Response			
	Experiment no	Climate (i1)	Tillage (i2)	Fertilizer (i3)	Yield (kg ha^{-1})	NE (MJ ha^{-1})	GHG (kg CO_{2eq} kg^{-1})	CF (kg CO_{2eq} ha^{-1})
Level	1	Ai(1)	x	x	5,949	164,657.5	1,761	0.296
	2	Ai(2)	x	x	5,806	154,448.4	1,761	0.303
	3	Ai(3)	x	x	5,667	143,698.7	1,761	0.311
	4	Ai(4)	x	x	5,976	164,416.4	1,761	0.295
	5	Ai(5)	x	x	5,767	150,614.1	1,761	0.305
	6	Ai(6)	x	x	5,294	131,466.8	1,761	0.333
Level	7	x	Bi(2)	x	5,949	164,657.5	1,761	0.296
	8	x	Bi(2)	x	5,859	160,810.9	1,657	0.283
	9	x	Bi(2)	x	6,013	167,131.2	1,535	0.255
Level	10	x	x	Ci(3)	5,949	76,990.91	1,761	0.296
	11	x	x	Ci(3)	10,651	141,940.23	2,859	0.268
	12	x	x	Ci(3)	11,630	153,216.38	3,407	0.293
	13	x	x	Ci(3)	12,614	164,657.50	4,139	0.328

Table 4.17: An extract of the experimental design exported to MATLAB software for training the models.

Regression Analysis data

Climate	Tillage	Fertiliser	VarName4	VarName5	VarName6	VarName7	VarName8	Code	VarName10	Var...	Var...	Experime...	A	B	C	Yieldkgha1	GHGkgCO...	CFkgCO2e...	NetEnerg...
Text	Categorical	Categorical	Categorical	Categorical	Number	Number	Number	Text	Number	T...	T...	Number	Number	Number	Number	Number	Number	Number	Number
Example 1													Factors			Response			
Climate	Tillage	Fertiliser						Code				Experiment ...	A	B	C	Yield (kg ha-...	GHG (kg CO...	CF (kg CO2e...	Net Energy (...
RCP 6.0_2020	CT	80kg		Climate (A)	Tillage (B)	Fertilizer (C)		Climate	A			1	1	1	1	5.9495e+03	1.7611e+03	0.2960	7.6991e+04
	RT	160kg		1	1	1		RCP 6.0_2020	1			2	1	1	2	1.0651e+04	2.8585e+03	0.2684	1.4194e+05
	NT	200kg			2	2		RCP 6.0_2050	2			3	1	1	3	1.1630e+04	3.4072e+03	0.2930	1.5322e+05
		250kg			3	3		RCP 6.0_2080	3			4	1	1	4	12614	4.1388e+03	0.3281	1.6466e+05
RCP 6.0_2050	CT	80kg				4		RCP 8.5_2020	4			5	1	2	1	5.8587e+03	1.6566e+03	0.2828	7.6135e+04
	RT	160kg		2	1	1		RCP 8.5_2050	5			6	1	2	2	1.0381e+04	2.7541e+03	0.2653	1.3777e+05
	NT	200kg			2	2		RCP 8.5_2080	6			7	1	2	3	1.1334e+04	3.3028e+03	0.2914	1.4935e+05
		250kg			3	3						8	1	2	4	1.2320e+04	4.0344e+03	0.3275	1.6081e+05
RCP 6.0_2080	CT	80kg				4			Code			9	1	3	1	6.0125e+03	1.5354e+03	0.2554	8.0051e+04
	RT	160kg		3	1	1		Tillage	B			10	1	3	2	1.0680e+04	2.6328e+03	0.2465	1.4382e+05
	NT	200kg			2	2		CT	1			11	1	3	3	1.1662e+04	3.1815e+03	0.2728	1.5583e+05
		250kg			3	3		RT	2			12	1	3	4	1.2637e+04	3.9132e+03	0.3096	1.6713e+05
RCP 8.5_2020	CT	80kg				4		NT	3			13	2	1	1	5.8058e+03	1.7611e+03	0.3033	7.4879e+04
	RT	160kg		4	1	1						14	2	1	2	1.0224e+04	2.8585e+03	0.2796	1.3567e+05
	NT	200kg			2	2			Code			15	2	1	3	1.1079e+04	3.4072e+03	0.3075	1.4513e+05
		250kg			3	3		Fertiliser	C			16	2	1	4	1.1920e+04	4.1388e+03	0.3472	1.5445e+05
RCP 8.5_2050	CT	80kg				4		80kg	1			17	2	2	1	5.5914e+03	1.6566e+03	0.2963	7.2206e+04
	RT	160kg		5	1	1		160kg	2			18	2	2	2	9.8712e+03	2.7541e+03	0.2790	1.3027e+05
	NT	200kg			2	2		200kg	3			19	2	2	3	1.0701e+04	3.3028e+03	0.3086	1.4005e+05
		250kg			3	3		250kg	4			20	2	2	4	1.1524e+04	4.0344e+03	0.3501	1.4911e+05
RCP 8.5_2080	CT	80kg				4						21	2	3	1	5.8776e+03	1.5354e+03	0.2612	7.8068e+04
	RT	160kg		6	1	1						22	2	3	2	1.0250e+04	2.6328e+03	0.2569	1.3749e+05
	NT	200kg			2	2						23	2	3	3	1.1103e+04	3.1815e+03	0.2865	1.4761e+05
		250kg			3	3						24	2	3	4	1.1960e+04	3.9132e+03	0.3272	1.5717e+05
						4						25	3	1	1	5.6666e+03	1.7611e+03	0.3108	7.2832e+04
												26	3	1	2	9.8212e+03	2.8585e+03	0.2911	1.2974e+05
												27	3	1	3	1.0568e+04	3.4072e+03	0.3224	1.3761e+05
		Factors			Resonse							28	3	1	4	1.1188e+04	4.1388e+03	0.3699	1.4370e+05
	Experiment ...	Climate (i1)	Tillage (i2)	Fertilizer (i3)	Yield	Net Energy	GHG	CF				29	3	2	1	5.4823e+03	1.6566e+03	0.3022	7.0603e+04
Level	1	Ai(1)	x	x	5.9495e+03	1.6466e+05	1.7611e+03	0.2960				30	3	2	2	9.5012e+03	2.7541e+03	0.2899	1.2483e+05
	2	Ai(2)	x	x	5.8058e+03	1.5445e+05	1.7611e+03	0.3033				31	3	2	3	1.0234e+04	3.3028e+03	0.3227	1.3317e+05
	3	Ai(3)	x	x	5.6666e+03	1.4370e+05	1.7611e+03	0.3108				32	3	2	4	1.0854e+04	4.0344e+03	0.3717	1.3926e+05
	4	Ai(4)	x	x	5.9763e+03	1.6442e+05	1.7611e+03	0.2947				33	3	3	1	5.7529e+03	1.5354e+03	0.2669	7.6235e+04
	5	Ai(5)	x	x	5.7670e+03	1.5061e+05	1.7611e+03	0.3054				34	3	3	2	9.8457e+03	2.6328e+03	0.2674	1.3155e+05
	6	Ai(6)	x	x	5.2943e+03	1.3147e+05	1.7611e+03	0.3326				35	3	3	3	1.0611e+04	3.1815e+03	0.2998	1.4037e+05
												36	3	3	4	1.1223e+04	3.9132e+03	0.3487	1.4634e+05
Level	7	x	Bi(2)	x	5.9495e+03	1.6466e+05	1.7611e+03	0.2960				37	4	1	1	5.9763e+03	1.7611e+03	0.2947	7.7385e+04
	8	x	Bi(2)	x	5.8587e+03	1.6081e+05	1.6566e+03	0.2828				38	4	1	2	1.0656e+04	2.8585e+03	0.2683	1.4201e+05
	9	x	Bi(2)	x	6.0125e+03	1.6713e+05	1.5354e+03	0.2554				39	4	1	3	1.1639e+04	3.4072e+03	0.2928	1.5335e+05
												40	4	1	4	1.2598e+04	4.1388e+03	0.3285	1.6442e+05

4.7 Jos location

4.7.1 Multiple regression analysis

Table 4.18: Estimated coefficients of the multiple regression for Jos.

Responses	Climate Change	Tillage	Fertiliser	Intercept	RMSE	R^2
Yield	-420.4**	17.541	2138.8**	5726.6**	1105.30	0.7939
GHG	1.37×10^{-13}	-112.85**	768.2**	1236.6**	125.79	0.9795
CF	0.0064**	-0.0133**	0.0197**	0.2521**	125.79	0.6307
Net Energy	-3071.5**	1294.4	24597.2**	75466.3**	15862	0.7597

**Significant at 5% level

Table 4.18 shows the estimated coefficients of the multiple regression model describing the magnitude of the effect each factor has on model responses. This is important because positive or negative coefficients determine direction of the effect. A positive coefficient implies an increase in the dependent variable based on a per unit increase of the independent variable, while a negative coefficient implies a decrease in the dependent variable per unit increase of the independent variable. As shown from the results, all of the derived coefficients are statistically significant at 5% confidence level except the coefficient of climate change for GHG and coefficient of tillage for NE.

The intercept represents the predicted response value a dependent can have when all the independent variables are equal to zero. The RMSE is an absolute measure of fit and estimates the standard deviation of the random component of the data (smaller RMSE means better model performance). R^2 is the coefficient of determination and represents how much variance of the data the model explains (relative measure of fit). If the value is close to 1, this shows a close correlation between the modelling and the data.

The next section presents the constant terms of the independent variables expressed as equations to predict the effect on each model response (equations 1 to 4).

$$Yield = -420.4 \times X_1 + 17.541 \times X_2 + 2138.8 \times X_3 + 5726.6 \qquad (Equation\ 1)$$

RMSE		1.11×10^3
R^2		0.7939
Effects (%)		
Climate Change	X_1	16.3%
Tillage	X_2	0.7%
Fertiliser	X_3	83%

The model coefficient for fertiliser (X_3) is positive and predicts that maize grain yield will increase by 2,138.8 kg ha^{-1} following a unit increase of fertiliser (equation 1). The coefficient for climate change is negative(X_1), depicting a negative effect on yield.

The model predicts that fertiliser had more effect (83%) on yield, followed by climate change scenarios (16.3%) with tillage only having an effect of 0.7% which is essentially statistically insignificant (p value > 0.05). The amount of variance (R^2) explained by the model is 0.7939 which means that all three independent variables explained 79% of the variations in yield. This suggests that other factors not considered could account for the remaining 21% of the variation in yield.

$$GHG = 1.37 \times 10^{-13} \times X_1 + (-112.85) \times X_2 + 768.2 \times X_3 + 1236.6 \quad (Equation\ 2)$$

RMSE		125.79
R^2		0.9795
Effects (%)		
Climate Change	X_1	0%
Tillage	X_2	9.7%
Fertiliser	X_3	90.3%

Equation 2 shows that the fertiliser effect was positive and will increase GHG for the linear terms. In addition, the estimated negative coefficients for tillage (X_2) will decrease GHG emissions by 112.85 kg CO_2eq ha^{-1}. The climate change impact coefficient (X_1) is also positive but not statistically significant at $p<0.05$ level. Fertiliser mostly affected GHG emissions as deduced from the model (90.3%), and climate change had no statistically significant effect on GHG. The coefficient determination (R^2) of 0.9795 shows that the independent variables collectively explain the variation in GHG of more than 97%.

$$CF = 0.0064 \times X_1 + (-0.0133) \times X_2 + 0.0197 \times X_3 + 0.2521 \qquad (Equation\ 3)$$

RMSE		125.79
R^2		0.6307
Effects (%)		
Climate Change	X_1	28.2%
Tillage	X_2	23.8%
Fertiliser	X_3	48%

According to the linear terms expressed in equation 3, tillage has a negative coefficient and therefore CF will decrease by 0.0133 kg CO_{2eq} kg^{-1} grain per unit of tillage increase. The positive coefficients for fertiliser (X_3) and climate change (X_1) indicate CF will increase by 0.0197 and 0.0064 kg CO_{2eq} kg^{-1} grain (relative to the range of the response variables), for every unit increase of model predictors. The model predicts that fertiliser has the highest effect (48%) on CF followed by climate change and tillage as per equation 3. The R^2 of 0.6307 and a large RMSE value of 125.79 suggest a relationship between the dependent and independent variables but the linear model explained only 63% of the variance in CF. The remaining 36.9% of the variations in CF can be attributed to other unexplained factors not included in the analysis. Further data collection would be required to establish exactly what those determiners could be.

$$Net\ Energy = -3071.5 \times X_1 + 1294 \times X_2 + 24597.2 \times X_3 + 75466.3 \quad (Equation\ 4)$$

RMSE		1.59×10^4
R^2		0.7597
Effects (%)		
Climate Change	X_1	17.7%
Tillage	X_2	3.1%
Fertiliser	X_3	79.2%

Equation 4 shows the estimated model coefficient for fertiliser (X_3) and tillage (X_2) were positive. Per unit increase of fertiliser, NE will increase by 24,597 MJ ha^{-1} and 1,294 MJ ha^{-1} respectively. This model also predicts a decrease in NE by 3,071.5 MJ ha^{-1} following a unit increase of climate change. Fertiliser had the most effect on NE (79.2%) Fertiliser and tillage have a modest effect of 31.5% and 17.2% respectively according to equation 4. Using the R^2 of 0.7597, the model explains about 76% of the variance in NE.

4.7.2 Simple linear regression analysis

The previous section has shown the predicted effect of factors on model responses using multiple linear regression. In order to assess the linearity of the relationship between the dominant predictor and model responses, a simple linear regression analysis was subsequently conducted. Table 4.19 outlines the coefficients obtained for the simple linear regression, and the main effects are positive and statistically significant. The model results indicate that fertiliser accounts for high variation in yield, GHG, CF and NE. Equation 5 to equation 8 outline the linear models, whilst a scatter plot shows the regression line of the linear model (shown in Figure 4.35). A straight positive regression line shows that a positive relationship exists and a falling regression line denotes a negative relationship.

Table 4.19: Estimated coefficients of the simple linear regression for Jos

Responses	Fertiliser	Intercept	RMSE	R^2
Yield	1901.59**	4933.5**	1170.96	0.7687
GHG	768.2**	1010.9**	155.35	0.9687
CF	0.0197**	0.2513**	0.0269	0.3977
NE	24597.19**	65768.96**	168889.9	0.7276
		**Significant at 5% level		

$$Yield = 1901.6 \times X_3 + 4.933 \times 10^3 \qquad (Equation\ 5)$$

$$GHG = 768.20 \times X_3 + 1.01 \times 10^3 \qquad (Equation\ 6)$$

$$CF = 0.0197 \times X_3 + 0.2513 \qquad (Equation\ 7)$$

$$Net\ Energy = 2.459 \times 10^4 \times X_3 + 6.577 \times 10^4 \qquad (Equation\ 8)$$

From equation 5, the model reveals that a linear relationship exists between fertiliser and yield. Therefore, for every unit increase of fertiliser input, yield increases by 1,901.59 kg ha^{-1} and based on the R^2 value (0.7687), fertiliser explains 77% of the variance in yield. GHG also responds positively to fertiliser, increasing by 768.2 kg CO_2eq ha^{-1} per unit increase of fertiliser (equation 6). A high R^2 (0.9687) indicate fertiliser explains the variation in GHG by more than 97%. CF and NE will also increase by their positive terms per unit of fertiliser increase (equation 7 and 8). For NE, the coefficient of determination ($R^2 = 0.7276$) shows that fertiliser explains approximately 73% of the variation but only about 40% of the variance in CF could be explained from fertiliser input in this study.

According to the regression trend line in Figure 4.35, all model responses show a positive response to fertiliser input which confirms linearity of the regression model.

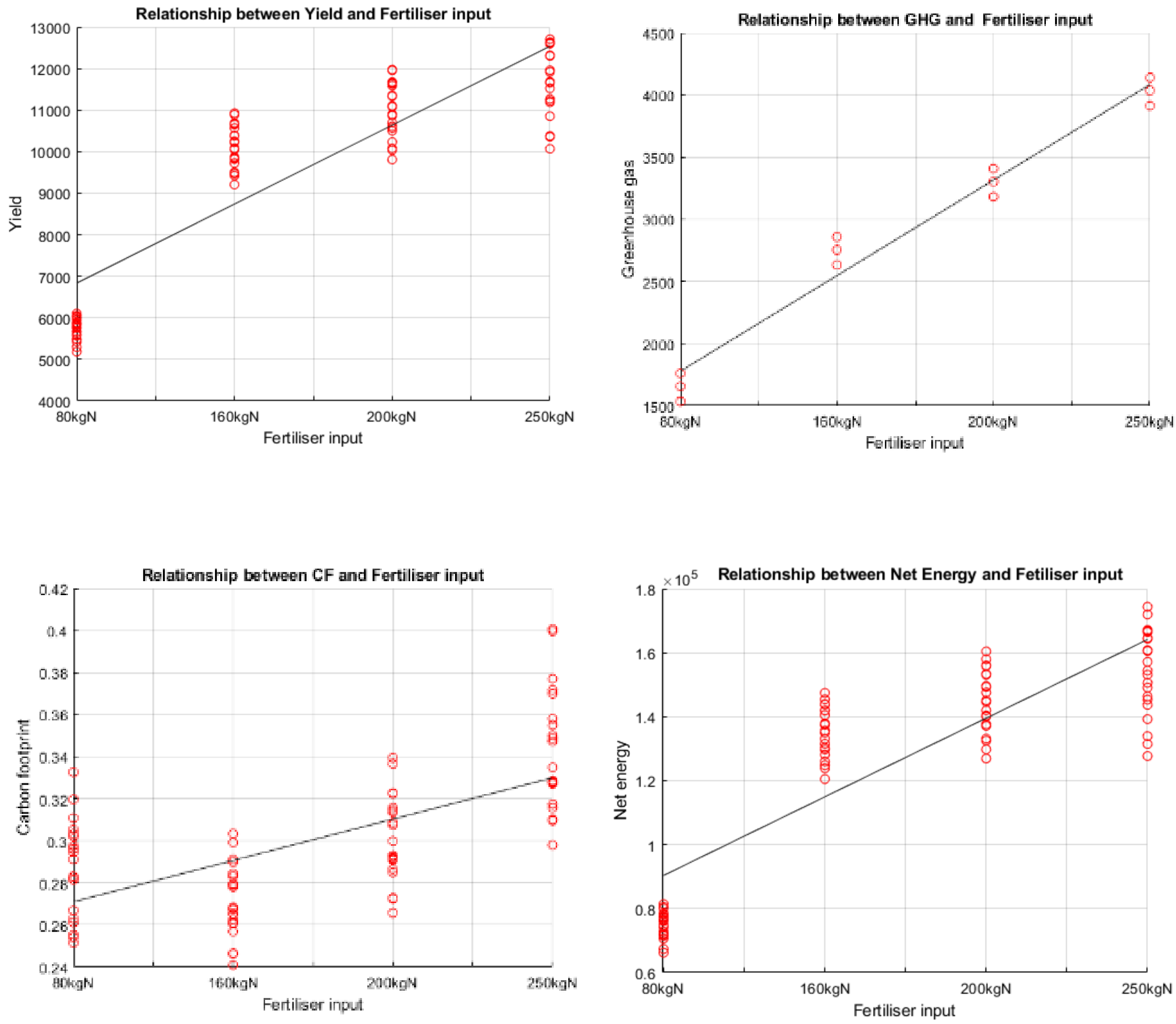

Figure 4.35: Relationship evaluation between input (fertiliser rate) and response variables (yield GHG emissions, carbon footprint and Net energy).

4.8 Ibadan location

4.8.1 Multiple linear regression analysis

Table 4.20: Estimated coefficients of the Regression Analysis for Ibadan

Responses	Climate Change	Tillage	Fertiliser	Intercept	RMSE	R^2
Yield	-715.52 **	-56.29	761.29**	6778.9**	905.54	0.565
GHG	1.81×10^{-13}	-112.85**	768.2**	1236.6**	125.79	0.9795
CF	0.0260**	-0.0127	0.0780**	0.1521**	125.79	0.7569
Net Energy	-5528.1**	-627.82	6112.8**	94942.0**	12949.0	0.4963

**Significant at 5% level

Table 4.20 shows the estimated coefficients for Ibadan. Fertiliser coefficients are positive and statistically significant ($p<0.05$). The climate change coefficient is negative for GHG and the coefficient is not significant. The derived coefficients for tillage are negative and not significant for yield, CF and NE, but significant for GHG. Equations 9 to 12 show the multiple linear model based on three independent predictors.

$$Yield = -715.52 \times X_1 + -56.29 \times X_2 + 761.29 \times X_3 + 6778.9 \qquad (Equation\ 9)$$

RMSE		905.54
R^2		0.565
<u>Effects (%)</u>		
Climate Change	X_1	46.7%
Tillage	X_2	3.7%
Fertiliser	X_3	49.7%

Based on the negative coefficient value generated by the model (equation 9), climate change scenarios (X_1) and tillage (X_2) negatively affected yield with the exception of fertiliser (X_3). The variable that has more effect on yield is fertiliser (49.7%) but nevertheless, climate change has a considerable share of effect (46.7%) as compared to fertiliser. From the model coefficient, yield will increase by 761.29 kg ha^{-1} per unit increase of fertiliser input; furthermore, yield will decrease by 715.52 kg ha^{-1} per unit change in climate change. The effect of tillage is not statistically significant as it remained at the 0.05 significant level. The model explains approximately 56% of the variation in yield; therefore, approximately 44% of yield variance is unexplained.

$$GHG = 1.81 \times 10^{-13} \times X_1 + (-112.85) \times X_2 + 768.2 \times X_3 + 1236.6 \quad (Equation\ 10)$$

RMSE		125.79
R^2		0.9795
Effects (%)		
Climate Change	X_1	0%
Tillage	X_2	9.7%
Fertiliser	X_3	90.3%

The coefficient value obtained for climate change (X_1) is very low and not statistically significant (equation 10). The fertiliser effect (X_3) is positive indicating an increase in GHG emission per unit increase of fertiliser. On the contrary, the tillage coefficient value (X_2) is negative and statistically significant. This is because GHG emissions will decrease based on an increase in tillage. It is possible to interpret the model results to mean that by reducing soil tillage intensity, GHG emissions will reduce. To exemplify, GHG emissions are mostly affected by fertiliser input (90.3%) and climate change has no effect as earlier stated. The model explains approximately 98% of the variation in GHG.

$$CF = 0.0260 \times X_1 + (-0.0127) \times X_2 + 0.0780 \times X_3 + 0.1521 \qquad (Equation\ 11)$$

RMSE		125.79
R^2		0.7569
Effects (%)		
Climate Change	X_1	34.8%
Tillage	X_2	7%
Fertiliser	X_3	58.3%

From equation 11, climate change (X_1) and fertiliser (X_3) both have positive coefficients and the values are statistically significant. Results indicate an increase in CF by 0.0780 kg CO_{2eq} kg^{-1} grain for an increase in fertiliser unit and 0.0260 Kg CO_{2eq} kg^{-1} grain for a unit change in climate scenarios. The tillage coefficient (X_2) is negative, indicating that a decrease in tillage intensity will decrease CF, and this effect is not statistically significant as shown in Table 4.6. The fertiliser effect on CF is dominant (58.3%) when compared with climate change having a moderate effect (34.8%). The model explains 75% of the variation in CF, therefore 25% variation can be attributed to other factors not considered in this analysis.

$$Net\ Energy = -5528.1 \times X_1 + -627.8 \times X_2 + 6112.8 \times X_3 + 94942 \quad (Equation\ 12)$$

RMSE	1.29 x 10^4
R^2	0.4963
Effects (%)	
Climate Change X_1	60.1%
Tillage X_2	2.8%
Fertiliser X_3	37.1%

Equation 12 is the regression model for NE, and the climate change coefficient (X_1) is large compared with the other two independent variables. Due to this, the effect on NE is negative. This means that climate change variability will negatively affect NE by 5528.1 MJ ha^{-1} per unit change. Fertiliser coefficient (X_3) is positive, increasing NE by 6112.8 761.29 kg ha^{-1} per unit increase in fertiliser. Tillage has a negative coefficient value that is not statistically significant. Climate change has a 60% effect on NE compared with fertiliser effect of 37%. The model was able to explain only 49% of the variation in NE. This means that other factors could account for 51% of NE variance.

4.8.2 Simple linear regression analysis

Table 4.21 shows the coefficients derived for each dominant variable predicted from the multiple linear regression analysis. Fertiliser was the dominant predictor in the yield, GHG and CF models, while climate change was the dominant predictor in the NE model.

A scatter plot in Figure 4.36 visually represents the linearity of the models expressed in equations 13 to 17 below.

Table 4.21: Estimated coefficients of the simple linear regression for Ibadan

Responses		**Climate Change**	**Fertiliser**	**Intercept**	**RMSE**	**R^2**
Yield			679.85**	5219.4**	1149.53	0.299
GHG			768.2**	1010.9**	155.35	0.9687
CF			0.0781**	0.2307**	0.0785	0.5532
NE	(RCP 6.0)	-5325.11		107821.8**	12936.0	0.081
	(RCP 8.5)	4054.6		66167.6**	13578.0	0.0315
				**Significant at 5% level		

$$Yield = 676.9 \times X_3 + 5.22 \times 10^3 \qquad (Equation\ 13)$$

$$GHG = 768.2 \times X_3 + 1.01 \times 10^3 \qquad (Equation\ 14)$$

$$CF = 0.0780 \times X_3 + 0.2307 \qquad (Equation\ 15)$$

$$Net\ Energy = -5325.1 \times X_1 + 1.0782 \times 10^5 \text{ (RCP 6.0 scenario)} \qquad (Equation\ 16)$$

$$Net\ Energy = 4054.6 \times X_1 + 6.6168 \times 10^4 \text{ (RCP 8.5 scenario)} \qquad (Equation\ 17)$$

Positive coefficient values were obtained for fertiliser in the regressed models for yield, GHG and CF (equation 13 to 15). According to model coefficients, yield increases by 676.9 kg ha^{-1}, GHG increases by 768.2 kg CO_2eq ha^{-1} and CF increase by 0.0780 kg CO_{2eq} kg^{-1} grain respectively per unit increase of fertiliser. The model R^2 value for yield was 0.299, which suggest that fertiliser only accounts for about 30% of variation in yield. Therefore, 70% of the disparity or changes observed were due to other factors. The model for GHG shows that 97% of the variation was due to fertiliser and fertiliser explains 55% variation in CF.

From equations 16 and 17, it can be interpreted that climate change scenarios have opposite relationship with NE. For example, the coefficient for RCP 6.0 climate scenario denotes a negative relationship moving from the years 2020 to 2080 whilst RCP 8.5 scenario has a positive coefficient. This implies that NE will decrease by 5325.1 MJ ha^{-1} per change in a climate scenario timeline (under RCP 6.0). It also implies that NE will increase by 4054.6 MJ ha^{-1} per change in a RCP 8.5 climate scenario timeline. From Table 4.21, the coefficient of determination of $R^2 = 0.081$ for RCP 6.0 and $R^2 = 0.0315$ for RCP 8.5 means that approximately 92% and 97% of the variance cannot be explained by the model. This type of result could indicate a limitation in that other important variables influencing the results are missing from the model.

Figure 4.36 is a graphical representation of the linear model showing how yield, GHG and CF vary with different fertiliser input rates. This further confirms that a linear relationship exists between fertiliser and the variables. The linear slopes for NE show a negative correlation between climate change timelines (2020, 2050 and 2080) under RCP 6.0 and a positive correlation between the timeline for RCP 8.5 scenarios.

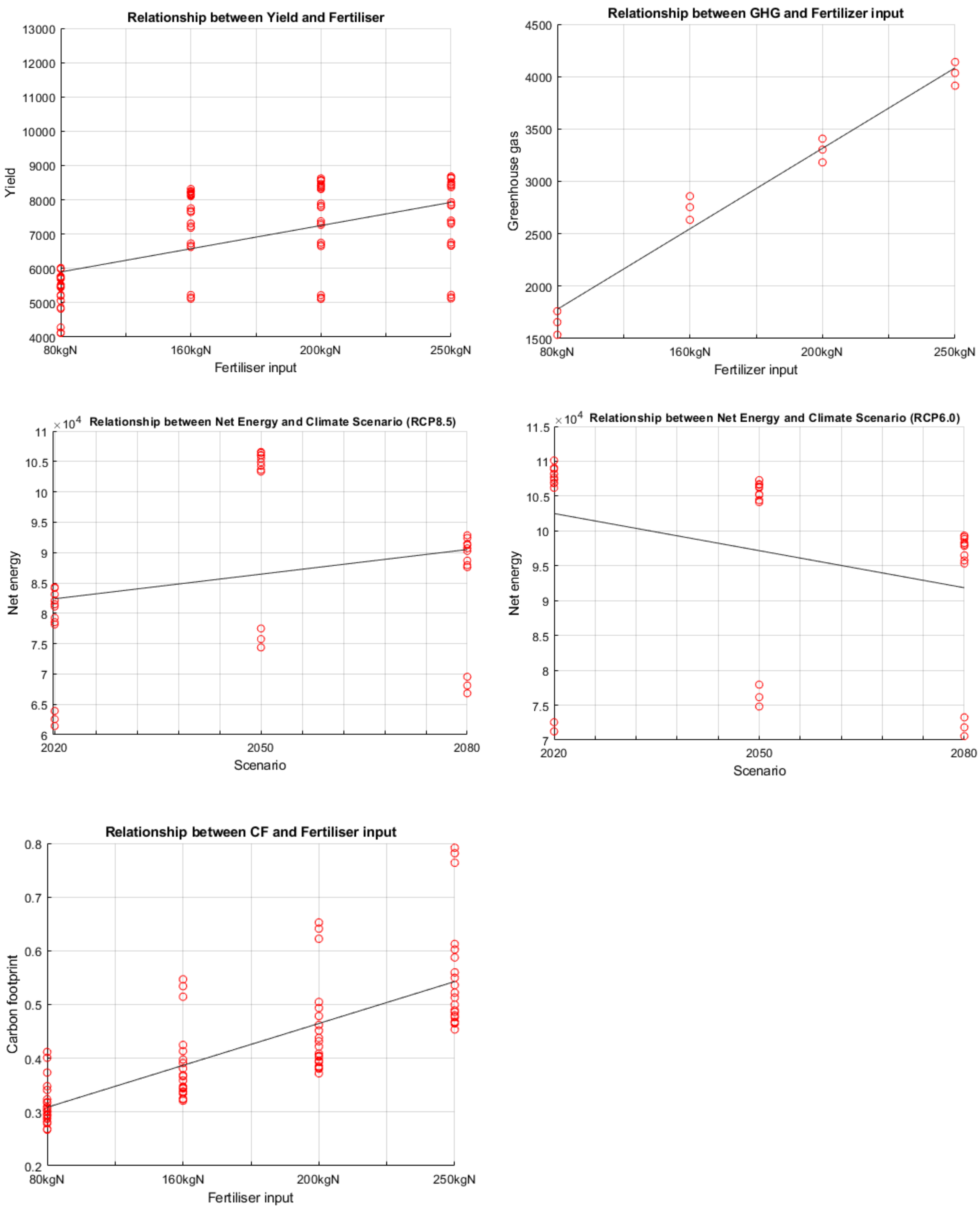

Figure 4.36: Relationship evaluation between input (fertiliser rate, climate change scenarios) and response variables (yield GHG emissions, carbon footprint and Net energy) for Ibadan.

4.9 Enugu location

4.9.1 Multiple linear regression analysis

Table 4.22: Estimated coefficients of the multiple linear regression for Enugu

Responses	Climate Change	Tillage	Fertiliser	Intercept	RMSE	R^2
Yield	-492.73**	109.79**	558.45**	2513.9**	490.53	0.6987
GHG	1.81×10^{-13}	-112.85**	768.2**	1236.6**	125.79	0.9795
CF	0.0955**	-0.0952**	0.1084**	0.5354**	125.79	0.6389
Net Energy	-3600.0**	2945.2**	3942.5**	28240**	6924.3	0.6139

**Significant at 5% level

Table 4.22 shows the estimated coefficients of the multiple regression model describing the magnitude of the effect each factor has on model responses. Positive or negative coefficients determine direction of the effect. A positive coefficient implies an increase in the dependent variable based on a per unit increase of the independent variable, whilst a negative coefficient implies a decrease in the dependent variable per unit increase of the independent variable. As shown from the results, all the derived coefficients are statistically significant at 5% confidence levels except climate change. The intercept represents the predicted response value a dependent can have when all the independent variables are equal to zero. The RMSE estimates the standard deviation of the random component of the data and R^2 is the coefficient of determination and represents how much variance of the data the model explains. Using the constant terms of the independent variables shown in Table 4.22, equations 18 to 21 express the multiple linear regression to predict the effects of each independent variable on the model response.

$$Yield = -492.73 \times X_1 + 109.79 \times X_2 + 558.45 \times X_3 + 2513.9 \quad (Equation\ 18)$$

RMSE		490.53
R^2		0.6987
Effects (%)		
Climate Change	X_1	42.4%
Tillage	X_2	9.5%
Fertiliser	X_3	48.1%

Equation 18 predicts that an increase in fertiliser and tillage will result in an increase in maize grain yield. Note that the coefficient associated with the climate change is negative. This reflects that a change in future climate scenario will decrease the value of maize yield by 492.73 kg ha^{-1}. Per unit increase of fertiliser and a change in tillage system, will increase yield by 558.45 and 109.79 kg ha^{-1} respectively. The model predicts that fertiliser had more effect (48.1%) on yield followed by climate change scenarios (42.4%) with a modest effect of 9.5% from tillage.

The results gave a coefficient of multiple determination (R^2) of 0.6987, computed to be 69.9%. This means that the three independent variables can jointly explain 69.9% of the variations in maize yield. The remaining 30.1% of the variations in the yield can be attributed to other unexplained factors not accounted for in the analysis.

$$GHG = 1.81 \times 10^{-13} \times X_1 + (-112.85) \times X_2 + 768.2 \times X_3 + 1236.6 \quad (Equation\ 19)$$

RMSE		125.79
R^2		0.9795
Effects (%)		
Climate Change	X_1	0%
Tillage	X_2	9.7%
Fertiliser	X_3	90.3%

Equation 19 shows that an increase in fertiliser will increase GHG emissions by 768.2 kg CO_2eq ha^{-1}, whereas a unit change in tillage system will decrease GHG emissions by 112.85 kg CO_2eq ha^{-1}. Although the coefficients associated with climate change scenarios are positive, the changes are not statistically significant at $p<0.05$ level. From model prediction, fertiliser have the highest effect on GHG emissions (90.3%), followed by tillage methods (9.7%), while climate change scenarios have no effect on GHG emissions. The R^2 of 0.9795 shows that the independent variables collectively explain the variation in GHG by more than 97%.

$$CF = 0.0955 \times X_1 + (-0.0952) \times X_2 + 0.1084 \times X_3 + 0.5354 \quad (Equation\ 20)$$

RMSE		125.79
R^2		0.6389
Effects (%)		
Climate Change	X_1	49%
Tillage	X_2	20%
Fertiliser	X_3	31%

Similarly, equation 20 shows that an increase in fertiliser and climate change scenario will increase the carbon footprint of maize by 0.1084 kg CO_{2eq} kg^{-1} grain, whilst a change in tillage system will decrease CF by 0.0952 kg CO_{2eq} kg^{-1} grain. In contrast to prior model predictions, climate change scenarios affected CF the most (49%) followed by fertiliser input (31%) and tillage (20%). The R^2 value of 0.6389 means that 63.9% of the variance in CF was due to the combined impact of climate change, tillage and fertiliser input.

$$Net\ Energy = -3600.0 \times X_1 + 2945.2 \times X_2 + 3942.5 \times X_3 + 28240 \quad (Equation\ 21)$$

RMSE		6.924×10^3
R^2		0.6139
Effects (%)		
Climate Change	X_1	51.4%
Tillage	X_2	17.2%
Fertiliser	X_3	31.5%

Equation 21 shows the estimated model coefficient for fertiliser and tillage were positive but climate change had a negative coefficient. This means that a unit increase in climate change will decrease NE by 3,600MJ. Similar to CF, the model predicts that climate change scenarios had the most effect on NE (51.4%). Fertiliser and tillage have a modest effect of 31.5% and 17.2% respectively according to equation 21. Using the R^2 of 0.7549, the model explains about 75.5% of the variance in NE.

4.9.2 Simple linear regression analysis

Table 4.23 displays the coefficients of each dominant predictor variable in the model. Significant coefficients are marked with signs explained at the bottom of the table. Using coefficients values from results in Table 4.23, a simple linear equation model based on one dominant predictor variable is used to test if a relationship exists between the dominant predictor and independent variable as shown in equations 22 to 27. A visual assessment of the regression line using a scatter plot graph further confirms the linearity of the regression model (see Figure 4.37).

Table 4.23: Estimated coefficients of the simple linear regression for Enugu

Responses		**Climate Change**	**Fertiliser**	**Intercept**	**RMSE**	**R^2**
Yield			496.51**	1801.7**	701.92	0.3831
GHG			768.2**	1010.9**	155.35	0.9687
CF	(RCP 6.0)	0.1043**		0.6318**	0.1205	0.3267
	(RCP 8.5)	-0.0239		1.0920**	0.1890	0.0111
NE	(RCP 6.0)	-6060.4**		47861.4**	7472.6	0.2948
	(RCP 8.5)	919.0		24554.9**	8460.1	0.0083
				**Significant at 5% level		

$$Yield = 496.5 \times X_3 + 1.801 \times 10^3 \qquad (Equation\ 22)$$

$$GHG = 768.2 \times X_3 + 1.01 \times 10^3 \qquad (Equation\ 23)$$

$$CF = 0.1043 \times X_1 + 0.6318 \quad \text{(RCP 6.0 scenario)} \qquad (Equation\ 24)$$

$$CF = -0.0239 \times X_1 + 1.092 \quad \text{(RCP 8.5 scenario)} \qquad (Equation\ 25)$$

$$Net\ Energy = -6030.4 \times X_1 + 4.7861 \times 10^4 \quad \text{(RCP 6.0 scenario)} \qquad (Equation\ 26)$$

$$Net\ Energy = 919.02 \times X_1 + 2.4554 \times 10^4 \quad \text{(RCP 8.5 scenario)} \qquad (Equation\ 27)$$

Equation 22 and 23 both have positive coefficient values that are statistically significant at 0.05% confidence level. Results indicate that a unit increase in fertiliser will increase maize yield by 496.5 kg ha^{-1} and GHG emissions will increase by 768.2 kg CO_2eq ha^{-1}. From the R^2 values (Table 4.23), the model only explained 38% of the variance in yield. This means that 62% of the variance is controlled by factors other than fertiliser. The model explains 97% of the variance in GHG emissions.

Climate change scenarios affected CF and NE, and the linear model show the impact is both positive and negative depending on the climate scenario pathway (equations 24 to 27). Interestingly, CF will increase under the RCP 6.0 scenario and decrease under the RCP 8.5 scenario, but the negative impact is not statistically significant. NE response to the RCP 8.5 climate scenario is not statistically significant but results indicate that NE will increase by 919.02 MJ ha^{-1} for every unit of increase in that scenario category. On the contrary, for every unit increase under RCP 6.0 category, there is a statistically significant decrease in NE by 6,030.4 MJ ha^{-1}.

Figure 4.37 shows the regression line that represents the linear relationship between the independent and dependent variables. A straight positive regression line shows a positive relationship exists. It is clear from the data that fertiliser input has a direct positive correlation with maize yield and GHG emissions according to the linear slopes obtained in Figure 4.37. A falling regression line denotes a negative relationship, therefore it is evident that the correlation between CF and climate change scenario RCP 8.5 is negative. Similarly, NE and climate change scenario RCP 6.0 also have a negative relationship.

How well the linear model explains the response variable variation is further evaluated using the R^2 values in Table 4.23. For GHG response model, fertiliser input explains 97% of the variation ($R^2 = 0.9687$) indicating a good fit, while only 38% of the variation in yield response can be explained by fertiliser ($R^2 = 0.3831$). Very low R^2 values obtained for climate change RCP 8.5 for both CF and NE indicate a weakened relationship between the model and response variables. Predictions from the multiple linear regression implied climate change mostly affect CF and NE (equations 24 and 27). However, the simple linear model could not explain the variances in the response variables, indicative that other factors other than climate scenarios (RCP 8.5) which could be responsible.

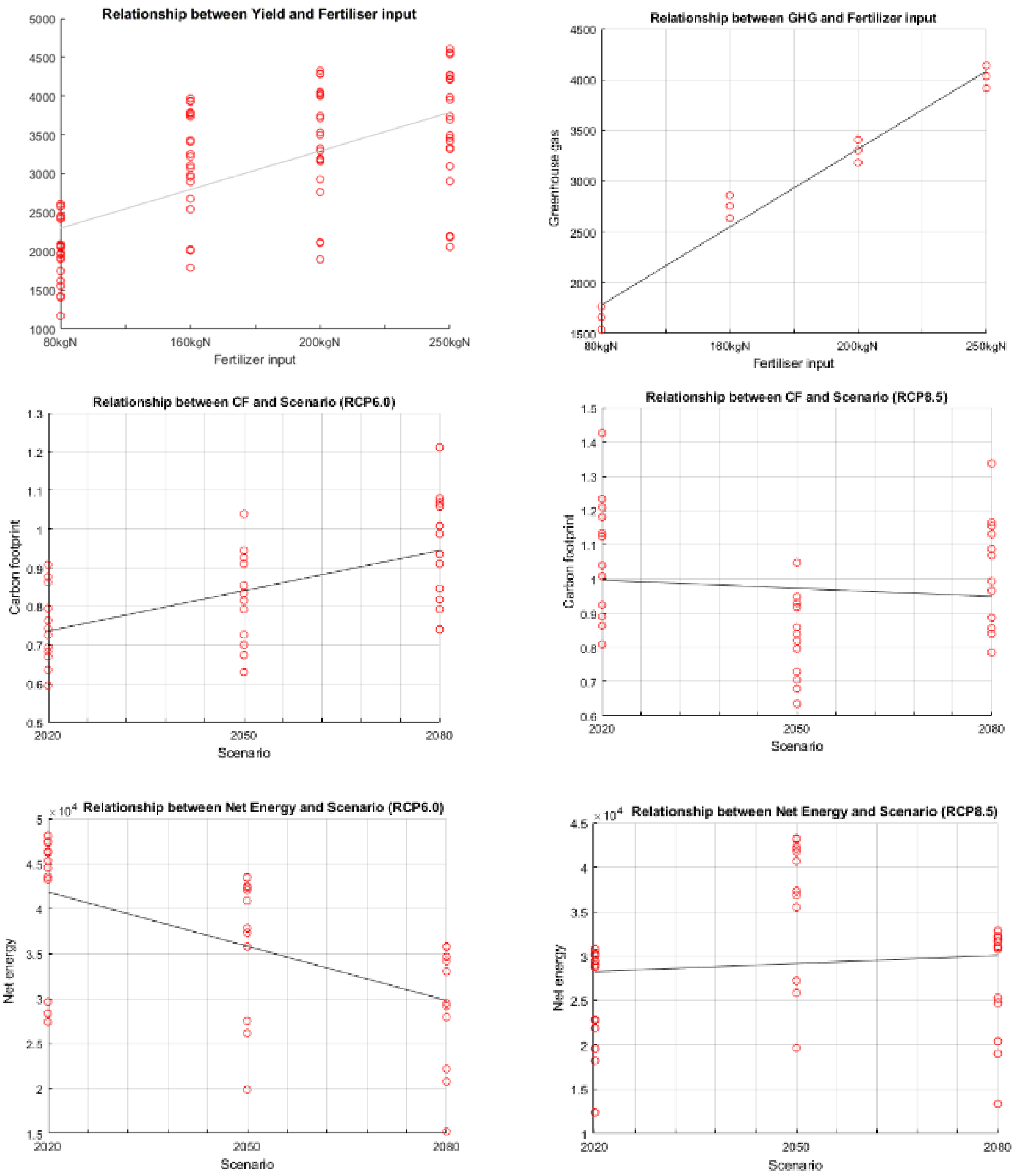

Figure 4.37: Relationship evaluation between input (fertiliser rate, climate change scenarios) and response variables (yield GHG emissions, carbon footprint and Net energy) for Enugu.

4.10 Ilorin location

4.10.1 Multiple linear regression analysis

Table 4.24 outlines the estimated coefficients of the multiple regression model for Ilorin. With the exception of tillage and climate change coefficient values estimated for yield and GHG response variables, the derived coefficients are statistically significant at a 0.05% confidence level.

Table 4.24: Estimated coefficients of the multiple linear regression for Ilorin

Responses	Climate Change	Tillage	Fertiliser	Intercept	RMSE	R^2
Yield	-380.51**	80.897	526.15**	2951.4**	460.57	0.6647
GHG	1.81×10^{-13}	-112.85**	768.2**	1236.6**	125.79	0.9795
CF	0.0522**	-0.0585**	0.1186**	0.4388**	125.79	0.7192
Net Energy	-2780.1**	2428.2**	3520.3**	34671**	6485.3	0.5402

**Significant at 5% level

Equations 28 to 31 expresses the multiple linear regression to predict the effect of each independent variable.

$$Yield = -380.51 \times X_1 + 80.897 \times X_2 + 526.15 \times X_3 + 2951.4 \quad (Equation\ 28)$$

RMSE	460.57
R^2	0.6647
<u>Effects (%)</u>	
Climate Change X_1	38.5%
Tillage X_2	8.2%
Fertiliser X_3	53.3%

According to equation 28, positive coefficients obtained for fertiliser and tillage suggest maize yield will increase by 526.15 kg ha^{-1} and 80.9 kg ha^{-1} per unit of increased independent variable. The coefficient determined for tillage is however not statistically significant. As shown in equation 28, a unit change in future climate scenarios will decrease yield by 380.51 kg ha^{-1} because of the negative coefficient value estimated. Model predictions on the effect of independent variables on yield show that fertiliser influenced yield the most (53.3%) compared to climate change scenarios (38.5%) and tillage (8.2%). The coefficient of determination (R^2) is 0.6647. This means that the three independent variables that collectively explain 66% of the variance in yield. Further data collection would be required to ascertain the other factors not considered in this particular study to explain the remaining 34%.

$$GHG = 1.81 \times 10^{-13} \times X_1 + (-112.85) \times X_2 + 768.2 \times X_3 + 1236.6 \quad (Equation\ 29)$$

RMSE	125.79
R^2	0.9795
Effects (%)	
Climate Change X_1	0%
Tillage X_2	9.7%
Fertiliser X_3	90.3%

From equation 29, the coefficient value for climate change (X_1) is small and not significant. Fertiliser has a much larger coefficient that is significant and as a result, GHG emissions will increase by 768.2 kg CO_2eq ha^{-1} per unit increase of fertiliser. Due to the negative coefficient obtained for tillage, GHG emissions will decrease by 112.85 kg CO_2eq ha^{-1} per unit change in tillage system. Fertiliser had the highest effect on GHG emissions (90.3%), followed by tillage methods (9.7%), while climate change scenarios had no effect on GHG. The R^2 of 0.9795 shows that the independent variables collectively explain the variation in GHG of more than 97%.

$$CF = 0.0522 \times X_1 + (-0.0585) \times X_2 + 0.1186 \times X_3 + 0.4388 \qquad (Equation\ 30)$$

RMSE	125.79
R^2	0.7192
Effects (%)	
Climate Change X_1	36.6%
Tillage X_2	16.8%
Fertiliser X_3	46.6%

From equation 30, a positive coefficient was obtained for fertiliser and climate change. For example, based on fertiliser increase, CF will also increase by 0.1186 kg CO_{2eq} kg^{-1} grain. Tillage has a negative coefficient therefore CF will decrease by 0.0585 kg CO_{2eq} kg^{-1} grain per unit change in tillage system. Fertiliser input affected CF the most (46.6%) followed by climate change scenarios (36.6%) while tillage has a modest effect of 20% on CF. The coefficient of determination (R^2 = 0.7192) indicate that 71.9% of the variance in CF is due to the combined impact of climate change, tillage and fertiliser input.

$$Net\ Energy = -2780.1 \times X_1 + 2428.2 \times X_2 + 3520.3 \times X_3 + 34671 \quad (Equation\ 31)$$

RMSE		6.485×10^3
R^2		0.5402
Effects (%)		
Climate Change	X_1	48.4%
Tillage	X_2	17.3%
Fertiliser	X_3	34.3%

Equation 31 shows that the estimated model coefficient for fertiliser and tillage was positive but climate change has a negative coefficient. This means that a unit increase in climate change will decrease NE by 2,780.1MJ. The model predicts that climate change scenarios had the most effect on NE (48.4%). Fertiliser and tillage had a modest effect of 34.3% and 17.3% respectively according to equation 31. The R^2 of 0.5402 means that the model explains approximately 54% of the variance in NE.

4.10.2 Simple linear regression analysis

For the simple linear regression, Table 4.25 displays the coefficients of each dominant predictor variable (fertiliser and climate change). Significant coefficients are marked with signs explained at the bottom of the table. Equation 32 to equation 36 outlines the linear models, whilst a scatter plot graph depicting the linearity of the regression model was assessed (Figure 4.38).

Table 4.25: Estimated coefficients of the simple linear regression for Ilorin

Responses		Climate Change	Fertiliser	Intercept	RMSE	R^2
Yield			467.79**	2391.9**	600.11	0.4307
GHG			768.2**	1010.9**	155.35	0.9687
CF			0.1186**	0.5305**	0.1587	0.4101
NE	(RCP 6.0)	-2133.69		46556.3**	6801.72	0.038
	(RCP 8.5)	1493.4		29800.1**	7602.3	0.0265

**Significant at 5% level

$$Yield = 467.79 \times X_3 + 2.392 \times 10^3 \qquad (Equation\ 32)$$

$$GHG = 768.20 \times X_3 + 1.01 \times 10^3 \qquad (Equation\ 33)$$

$$CF = 0.1186 \times X_3 + 0.5305 \qquad (Equation\ 34)$$

$$Net\ Energy = -2133.7\ \times\ X_1\ \ + 4.6556 \times\ 10^4 \text{ (RCP 6.0 scenario)} \quad (Equation\ 35)$$

$$Net\ Energy = 1493.4\ \times\ X_1\ \ + 2.9800 \times\ 10^4 \text{ (RCP 8.5 scenario)} \quad (Equation\ 36)$$

For simple linear models for yield, GHG and CF (equation 32 to 34), fertiliser is the only predictor variable regressed. Based on the data, the coefficient of fertiliser was 467.79, 768.20 and 0.1186 for yield, GHG and CF response models respectively, with a constant term of 2.392 x 10^3, 1.01 x 10^3 and 0.5305. This means that the dependent variables will increase by the coefficients values per unit increase of the independent variables. Equation 35 and 36 shows the relationship model between NE and climate change. The coefficient is both positive and negative for RCP 6.0 and RCP 8.5 climate scenarios, and not statistically significant. Results indicate that NE will decrease by 2133.7 MJ ha^{-1} for every increase in RCP 6.0 scenario category whilst units under RCP 8.5 scenarios will increase NE by 1493.4 MJ ha^{-1}.

Figure 4.38 depict scatter plots for the linear regression models described above. As observed, the independent variables show a linear relationship with all response variables for example, yield, GHG and CF were positively correlated with fertiliser. The negative trend for NE implies a decline as the climate change timeline under RCP 6.0 changes. NE and climate change scenario RCP 8.5 however shows a positive relationship.

In addition, based on the coefficient of determination obtained, the linear regression equation for GHG provided a model that accounted for 97% of the variability in the estimation of GHG response (R^2 = 0.9687). The model explains on average 42% of the data variation in yield and CF (R^2 = 0.4307 and 0.4101). Whilst in terms of the limitations of the study, the model was unable to explain the variability in NE (R^2 = 0.038 and 0.027).

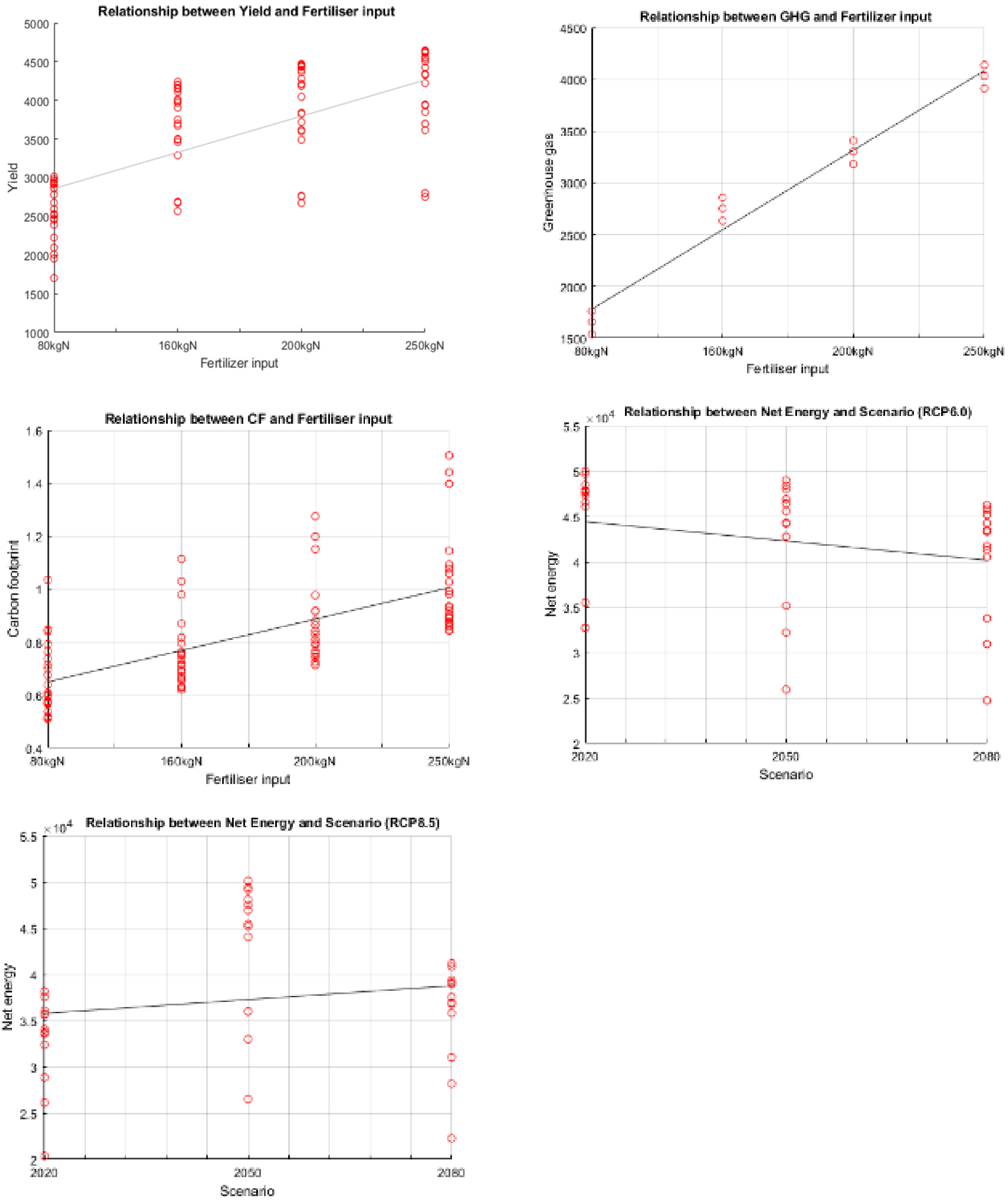

Figure 4.38: Relationship evaluation between input (fertiliser rate, climate change scenarios) and response variables (yield GHG emissions, carbon footprint and Net energy).

Chapter 5

5 Discussion

5.1 Introduction

With widespread recognition of the grave importance and irreversible impact of climate change (COP21), there has been several aspects, which have rightly received attention. One of those aspects is energy - largely because of the preeminence of fossil fuels from the industrial revolution to date. Replacing fossil fuels has been significantly challenging for technical, social, political and economic reasons, nevertheless, the pressure to find alternative energy sources has slowly led to the greater use of renewables. As a result of this, the advantages of limitless supply and low carbon emissions are now broadly accepted, however, there remains an argument for examining and/or developing renewable technical solutions which are sustainable in a social, political and economic sense.

This study was designed to support the examination of the feasibility of utilising biofuel. In doing so, this study has addressed the impact of a changing climate, induced by global warming on the production and efficacy of maize as a biofuel feedstock. Under the present conditions maize could, on average, yield 2,442 kg ha^{-1} and then be employed as a biofuel with a net energy contribution of 94,014.1 MJ ha^{-1} whilst emitting the equivalent of 2,931 kg $CO_2eq\ ha^{-1}$. Whilst a number of studies have estimated variations to farm yield when future climates are changed in terms of temperature, rainfall and CO_2 levels etc., these studies have only considered the LCA of the production system for current climates. This study however, not only models future climates for the target regions, but also considers other factors which might have a significant influence on crop yield, GHG, CF, net energy yield, and hence the environmental gearing of adopting renewable solutions such as biofuels. The integrated framework (CSAF) developed for this study is therefore its unique key strength. Furthermore, the framework is detailed and thus can be applied to specific areas, rather than to a broad geographical area. This is notable because broader application is the case for most similar modeling framework, which in turn leads to a more generalised outcome. This study target areas are all in Nigeria, but specifically represents four different agro-ecological zones. For each zone, a substantial body of historical climatic records was available.

5.2 Climate data

Climate data analysis shows how the climate varied for each location. For example, the highest maximum temperature in Jos was approximately 5 °C lower, compared to Ibadan, Enugu and Ilorin. A minimum temperature as low as 1 °C was recorded at Jos, and attributed to the high altitude of the location (Adejuwon 2006, Ezeaku et al. 2014, Yusuf et al. 2017). The observed mean daily temperature ranged from 25 °C and 37 °C across all sites.

The seasons were distinctly rainy from March to October and followed a reverse of this from November to February due to the tropical nature of the climate in Nigeria (Ezeaku et al. 2014). Ayinde et al. (2011) also reported large inter-annual variation for rainfall and temperature across the country and recently observed changes showing evidence of climate change (Danladi et al. 2017). The Nigerian Meteorological Agency in 2012 reported severe temporal and spatial shifts in weather variability and change (NIMET 2013). The range of mean values for maximum and minimum temperature for each location was similar to values reported by Amadi et al. (2014), Ezeaku et al. (2014) and Yusuf et al. (2017) for Ibadan, Jos, Enugu and Ilorin.

5.3 Validation of LARS-WG results

In order to model future climates, arbitrary incremental scenarios can either be used to predict change i.e. temperature +2.5 °C, rainfall -20% (Garba 2014) or a weather generator can be calibrated using historical data for the chosen site and then used to generate long synthetic weather scenarios for further downscaling of GCM outputs. The use of weather generators in simulating climate data is becoming popular and LARS-WG is one of the most commonly used weather generators because it is open, free and validated for many sites globally (Mehan et al. 2017, Gitau et al. 2017, Chisanga et al. 2017). LARS-WG performed fairly well for this study, in representing the statistical characteristics of the site-specific observed daily rainfall, minimum and maximum daily air temperatures and solar radiation values. The number of tests with p-value of less than 0.05 (significant result at the 95% confidence level) was small and the differences in variances were not statistically significant. The only shortcoming found with using LARS-WG was an over-estimation and under-estimation of the monthly mean rainfall compared to the observed data (Chisanga et al. 2017).

Underestimation of inter-annual variability is a common issue with most weather generators according to Qian et al. (2011) and Smith et al. (2013). Therefore, further evaluation is required concerning the inter-annual variability assessment, as the accuracy of the generated data is an important factor for climate impact assessment. The trend line graphs in section 4.2.2 of observed versus simulated data in this study produced a good match overall, with the exception for rainfall. Fundamentally, this study supports the findings of other scientific conclusions in that weather generators can reproduce statistical representations of site-specific observed climate data, and reliable synthetic data applied in crop modelling experiments in the absence of long-term observed data.

5.4 Analysis of projected climate change

An ensemble of 40 GCMs were used to project climate change for the years 2020, 2050 and 2080. Average projected temperature change was +2.4 and +3.3°C under RCP 6.0 and RCP 8.5 scenarios - similar to typical rates of warming projected by Mereu et al. (2018) for Nigeria. The IPCC AR5 report (2014) on annual temperature change indicated that the West African region is getting warmer, although the degree of predicted warming was quite variable. The projections from this study are also consistent with findings from Hartley et al. (2015) who reported mean annual temperature increases of between 2.5 and 5.5°C as well as a change in precipitation of between -60% and +50% in West African countries by the end of the century relative to a 1971-2000 baseline. Chen et al. (2018) used global warming scenarios of 1.5°C and 2.0°C to estimate impacts of climate change on major crop productivity including maize in China. Their findings are based on data projected from four GCMs, and the temperature changes of +1.5°C and +2.0°C used in their analysis were weighted between RCP 2.6 and RCP 4.5 scenarios, compared to the projected output based on the RCP 6.0 and RCP 8.5 scenarios in this study.

According to Magugu (2016), local physiographic and atmospheric effects makes future rainfall projections less certain compared with temperature projections. Ekwezuo et al. (2018) examined the possible effects of increasing greenhouse forcing on seasonal-mean precipitation over West Africa using the Norwegian Earth system (NorESM1-M) model. Although Ekwezuo et al. (2018) used a single GCM model in their projections, the pattern of projected RCP scenario changes in seasonal-mean precipitation over West Africa varied, and they observed that there is little sensitivity of West African precipitation to GHG forcing. This is illustrated by the fact that in the mid-twenty first century, intensified GHG forcing seems to have very little effect on seasonal precipitation especially if prevailing conditions based on RCP 8.5 were realised.

Furthermore, climate projections for the maize growing regions of sub-Saharan Africa suggest increased temperatures, evapotranspiration, lower soil moisture levels and frequency of droughts, will adversely impact the sustainable production of maize and other cereals (IPCC 2007, Cairns et al. 2013). Lobell et al. (2011) reported that maize yield would decline by 65% in Africa following every 1°C warming increase under non-drought conditions.

For this study, projected changes in annual rainfall for each location generally followed an increasing trend however, the change values were negligible increases. The results were in alignment with Ekwezuo et al. (2017) and Klutse et al. (2018) who projected a similar future rainfall pattern over West Africa. In addition, they reported that projected changes in mean rainfall would increase over the Guinea coast and decrease inland. Projected increase in rainfall amount and variability for the locations, though in smaller amounts could compound the problem of significant yield loss, erosion and plant nutrient loss due to leaching (Gbangou et al. 2018). Magugu (2016) also obtained a negligible rise in precipitation from GCM projections under climate change scenarios in Arkansas.

Based on evidence from the latest IPCC Report (AR5), global warming in Africa is likely to become larger than global annual average warming (Niang et al. 2014, Hartley et al. 2015). The impact of climate change on yields of major cereal crops in sub-Saharan Africa will be negative overall, with strong regional variation in terms of the degree of reduction (Niang et al. 2014, Ezeaku et al. 2014, Parkes et al. 2018). Although different GCMs tend not to agree with predictions of the average amount of rainfall for the region, there is a consensus that the inter-annual variability of the amount of rainfall will increase (Traore 2014).

Many studies have examined the degree of correlation between seasonal weather variability and maize yield anomalies using archival data (Adamgbe and Ujoh 2013). Traore (2014) analysed historical long-term trends in climate variability and its effect on yield, using data from archives and the coefficient of variation used to describe the relationships. Both Adamgbe and Ujoh (2013) and Traore (2014) reported a positive correlation between rainfall and maize yield but, Magugu (2016) observed that temperature based indicators were more strongly correlated to crop yields than precipitation indicators. Based on the projected GCM results, which are indicative of gradual site-specific warming, it is highly likely that climate change will have profound effect on maize crop productivity in the agro-ecological zones studied. Hartley et al. (2015) advised that robust resilience should be put into place based on the uncertainty of future projections, especially due to precipitation variability.

5.5 Analysis of climate change impact on maize yield

The impact of climate change on yield was evaluated (using the CERES-maize crop model) by comparing yields simulated using historical climate data and future climate predictions under six farm management scenarios, (including a no treatment scenario) for all four locations. Without considering any farm adaptation strategy, results show yield increase for some locations as well as decline in yield depending on the GHG scenario pathway and timeline. To be clear, the baseline climate of all four sites is different, spatially variable and inconsistent therefore, climate-induced impact on yield is consequently spatially dependent as well.

In Ibadan, climate change reduced yield under all scenarios. In contrast, yield increased in Jos, Enugu and Ilorin for both projected scenarios (RCP 6.0 and 8.5) and declined as the timeline shifted from 2020 to 2050, further declining below baseline levels by 2080. Although this trend is consistent with the projections made by Adejuwon (2006) for similar AEZs; both Mereu et al. (2015) and Mereu et al. (2018) reported a decline in yield for all locations within the derived savanna AEZ (Ilorin, Ibadan and Enugu) using the same CERES-maize crop model. When compared to the results of this study, the difference in GCM model projections are clearly responsible for the different projections obtained for similar AEZs. For instance, Mereu et al. (2018) used GCM models based on A1B SRES GHG emission scenarios, developed in 2000 by the IPCC. When compared to the RCP scenarios, SRES scenarios represent possible futures from a socio-economic perspective. This is in direct contrast to the former, which calculates basic climatic outcomes based on specific radiative forcing projections developed in 2014, thus superseding the SRES (see Chapter 2).

Similarly, Ezeaku et al. (2014) used SRES scenarios and reported a decline in yield within the derived savanna AEZ of Nigeria. This occurred as a result of using GCM change values arbitrarily. As already mentioned however, the pattern of maize response reported in Adejuwon (2006) was similar to this studies' results for Jos and Ilorin despite using different IPCC scenarios. For example, the lowest yield for Jos was recorded during the baseline climate, whilst yield increased continually until the end of the century. Interestingly, Adejuwon (2006) however, attributed this increase in part to a CO_2 fertiliser effect (assumed 1% increase in atmospheric CO_2 per annum) in addition to the decline in water and temperature stress compared to that of the baseline at Jos.

According to Mereu et al. (2015), higher maize yield reduction in the Southern Guinea savanna of Nigeria (Ilorin) was due to a projected temperature increase of above 2°C, projected under the A1B emission scenario. This is consistent with the declining yield outcome obtained in this study for 2080 (under RCP 6.0 and 8.5 scenarios), also with projected temperature increase above 2°C (2.8°C and 4.1°C). In contrast, climate change did not present as a limiting factor but rather produced positive yield results at Ilorin and Enugu under projected temperatures of below 2°C during 2020 and 2050 under RCP 6.0 and 8.5 scenarios. Bassu et al. (2014) reported a 10% decline in yield under 2°C increase in temperature and 20% reduction in precipitation in Tanzania. In addition, Msowoya et al. (2016) projected maize yield decline in Malawi by 13% and 33% by mid and end of the century respectively.

The effect of climate change is positive in Ilorin and Enugu (except in the 2080s) despite low maize yield recorded under baseline climates. This suggests the positive effect of warmer temperature, which can influence maize phenology (flowering and grain-filling period). In contrast however, several studies have identified temperature increase and heat stress accumulation as a threat for maize crop production (Boote et al. 2005, Hatfield et al. 2011, Oluwaranti and Ajani 2016, Lizaso et al. 2018). This is because as temperature rises above optimum levels, yield first reduces by a shortening of seed-filling phase along with lesser assimilation. As the temperature increases further, pollination and fertility increasingly fail and seed growth rate reduces to the point where grain yield, harvest index, and seed number becomes zero (Oluwaranti and Ajani 2016). Therefore, identifying temperature thresholds for maize crop and quantifying the probability of exceeding temperature thresholds is important to crop system modelling and the use of risk assessment with regards to climate change (Oluwaranti et al. 2015, Luo 2011).

As an example of the above discussed, Hatfield et al. (2011) estimated the optimum temperature range for maximum (grain) maize yield as 18°C to 25°C. The failure point temperature remained at 35°C (ceiling temperature at which grain yield falls to zero yield). Interestingly, this correlation relates to other studies which have also found that temperatures of above 35°C become lethal to maize pollen viability (Luo 2011, Sánchez et al. 2014, Lizaso et al. 2018). In addition to this, changes in maximum and minimum temperatures projected for the study sites ranged between 0.9°C and 4.0°C. Assuming the temperature accumulation in terms of degree-day upper bound temperature for maize is 34°C, it would follow that maximum air temperatures would increase for Jos (32°C), Enugu (36°C) and Ilorin (36°C) using upper levels of the projection.

Maize is a C_4 plant and research has shown that exposure to higher temperatures at current CO_2 levels will reduce yield (Garba 2014). However, it should be noted that maize does have lower sensitivity to high levels of CO_2 concentration compared to C_3 crops (Meza and Silva 2009) . According to the results of experiments in which the concentration of CO_2 was doubled, a combination of higher CO_2 and a mean temperature increase of above 2°C will progressively reduce yield (Hatfield et al. 2011, Ko et al. 2012, Ezeaku et al. 2014, Mereu et al. 2015, Parkes et al. 2018). However, in contrast to the aforementioned authors, the evidence presented by He et al. (2018) reports no notable impact on maize yields under increased CO_2.

Unlike previous research that analysed the effect of CO_2 fertilisation on future maize yield (Garba 2014, Chen et al. 2018, He et al. 2018), this study assessed the impact of projected changes in temperature and precipitation and did not consider scenarios for CO_2 change effect. This is because Chen et al. (2018) found that the results between simulated maize yields with CO_2 fertilisation were quite similar to those without CO_2 fertilisation effects. They also reported that maize yield declined by around 10% to 15% under 1.5°C and 2.0°C warming without considering CO_2 fertilisation effects. They explained that the parts of China that experienced yield increase (due to fertilization effects of elevated atmospheric CO_2 concentration) would have up to 10% decrease in the future, when the global temperature rises above 2.0°C.

5.6 Effect of N fertiliser treatment on yield

There is ample evidence that as climate change affects agricultural systems, farmers will adopt different management practices such as increasing synthetic fertiliser to boost yield (Meza and Silva 2009, Mahama and Maharjan 2017). For example, a field survey from Ghana reveals that 93.9% of farmers respond to climate change by arbitrarily increasing fertiliser input (Mahama and Maharjan 2017). To support this statement, Kikoyo and Nobert (2016) also reported on adaptation to climate change through optimal fertiliser application. Nasim et al. (2016) however stressed that in addition to inorganic fertiliser use, adding mulching and surface water management would be more beneficial in the event of climate change.

The role of fertiliser in maintaining soil fertility and hence increasing` crop yields is undisputed; however, excessive fertiliser use increases nitrous oxide emissions to the air as well as nitrate leaching which correlates with excessive rainfall (or irrigation) and run-off (He 2008). According to Aina (2011) and Abayomi et al. (2012), climate change and the demand for high agricultural output is responsible for a decline in soil fertility and can further damage the ecosystem causing major economic and ecological constraints. Liverpool-Tasie et al. (2017) suggested that with management choosing to increase fertiliser use in maize production, there should be an awareness around other factors for consideration such as cost and the environmental effect of fertiliser use. Suggestions made by Blessing et al. (2017) to adopt effective techniques such as micro-dosing of inorganic fertiliser can improve nutrient use efficiency by crops, benefit farmers economically and contribute to sustainable agricultural development, especially when integrated with organic amendments.

For this study, intensification of nitrogen fertiliser use (from 80 kg N ha^{-1} to 250 kg N ha^{-1}) to determine yield responses under climate change scenarios was simulated. In Jos, yield increased by almost 100% using the highest fertiliser rate of 250 kg N ha^{-1} (compared to 80 kg N ha^{-1}) under RCP 6.0 and 8.5 scenarios, for the years 2020 and 2050. By 2080 however, the most significant yield output was produced as a result of applying 200 kg N ha^{-1} fertiliser. For the other sites, the effect of increasing N rates above 160 kg N ha^{-1} on maize yield was not significant for all climate scenarios, except for Enugu where yield improved by 83% using 250 kg N ha^{-1} under RCP 6.0 in 2080.

Overall, this study is the first to present a projected optimum fertiliser treatment combination under climate change as 160 kg N ha^{-1} + 40 kg P ha^{-1} + 40 kg K ha^{-1} except for in the Jos location which required higher levels of fertiliser. Field studies by Onasanya et al. (2009) and Anjorin (2013) for similar locations confirmed optimal application rates of between 100 kg N ha^{-1} and 120 kg N ha^{-1} + 40 kg P ha^{-1} as the best combination to significantly enhance grain yield. Both studies reported that maize varieties responded differently to inorganic nitrogen fertilisation and as a further example, hybrid maize cultivars required high fertiliser rates for optimum yield. This is evidenced via the work of Takim et al. (2017) who used 80 kg N ha^{-1} + 60 kg P ha^{-1} + 60 kg K ha^{-1} application rate to analyse the best producing maize cultivar under drought conditions in Nigeria.

One of the limitations with the abovementioned studies is that they only considered local current climate conditions. Therefore, further evaluation of cultivar responses to the rates applied in this study under future climate conditions give a much better indication of optimum fertiliser rate for sustainable maize yield increase under climate change. For example, further evaluation of the recommended maize genotypes reported in Takim et al. (2017) and Anjorin (2013) is required to determine yield response to optimal fertiliser rates as suggested in this study under climate change.

Crop models such as CERES-Maize model, designed to evaluate crop-climate environments are useful management tools for not only simulating yield and nitrate movement through soil profiles, but also yield response to future weather changes. When incorporated into a decision support system (e.g. DSSAT-CSM), crop models can evaluate the best management strategy in which fertiliser application can be undertaken under site-specific weather conditions to maintain balanced soil nutrients and avoid excessive leaching of nitrates. Basso et al. (2016) reviewed studies that have validated crop models, such as CERES-maize and CERES-wheat models, on soil nitrogen content and nitrate leaching predictions. Tetteh and Nurudeen (2015) in addition to Gungula et al. (2003) evaluated the CERES-maize model for its response to fertiliser treatments. They reported that the model was sensitive to low fertiliser treatments, adding that the model underestimated yields at a low nitrogen level. Therefore, nitrogen stress factors should be incorporated into CERES-maize model, to use the model in low-nitrogen tropical soils (Tetteh and Nurudeen 2015). The model can however, be reliably used for predicting maize phenology under non-limiting nitrogen conditions. To evidence this, it should be highlighted that Adnan et al. (2017) used the CERES-Maize model to determine the fertiliser requirement of maize in Nigeria.

5.7 LCA analysis of energy use, GHG and Carbon footprint

The environmental impact assessment of a farming system using the LCA framework is very common. This is because its holistic approach makes it possible to identify hot spots for environmental pollution, but also to avoid pollution trade-offs across the life-cycle stages (Bessou et al. 2013). Many studies have used averages of regional/country management data as input data for the life-cycle inventory instead of generated site-specific data, which can lead to different results consequently, affecting the reliability of the LCA study (Notarnicola et al.

2017, Corrado et al. 2018). Due to the variation in specific characteristics in many LCA studies, such as differences in cropping system used, production region, feedstock type, energy sources and crop yields, comparison of LCA results is very uncertain (Ndong et al. 2009). Since this study focused specifically on a maize feedstock production system within the biofuel production network, a streamlined method accounted for the effects of local factors including climatic factors within the farm-to-gate system boundary. The results discussed below therefore represent LCA outputs based on the functional unit of 1 kg ha^{-1} maize grain using site-specific input data simulated by a process-based model and other inventory sources to reduce much of the uncertainty associated with emissions from agricultural fields.

5.7.1 Energy use assessment

Energy parameters are important for comparing the environmental effects of agricultural practices (Lu et al. 2018). Energy efficiency in maize production was estimated by varying both farm management and equipment use energy input. Results show that climate change affected all energy indicators used to assess the efficiency of maize production but at varying degrees for each location studied, and dependent on the tillage method and fertiliser application rate adopted. In all farm management scenarios, the highest energy consumption corresponded with the application of fertilisers and diesel fuel consumption during land cultivation similar to the findings in Lu et al. (2018).

The farm tillage method that registered the highest amount of diesel use was the conventional tillage method (CT). This was as a result of increased working time and fuel use per hectare. Estimated input energy from fuel was within a similar range to the energy required per hectare (2,168 MJ ha^{-1} – 2,732 MJ ha^{-1}) in order to cultivate maize in Zambia (Stubbs 2013). However, when compared to soybean cultivation, Stubbs (2013) reported that maize cultivation required less input energy. According to Grassini and Cassman (2012) and Bilalis et al. (2013), generally energy inputs tend to vary with different farm management practices.

In a similar fashion to higher fuel consumption through mouldboard ploughing under the CT system, harvest operation was the second most fuel intensive process irrespective of the tillage method. Memon et al. (2013) in addition to Manzone and Calvo (2016) both reported a higher value for ploughing followed by harvesting operations in their studies. The no-tillage system (NT) decreased energy input by 51% based on the results of this study, which can be attributed to the elimination of soil tillage practices. In support of this, Grassini and Cassman (2012) also reported that conservative tillage practices and efficient production of agricultural inputs have contributed to the rising maize grain yield in the US Corn Belt area, without increasing fertiliser and irrigation input.

The estimated result also shows that increasing fertiliser rates increased total energy input with a consequent reduction in energy use efficiency. Bilalis et al. (2013) similarly reported that fertiliser consumed the bulk energy input in conventional maize production under Mediterranean conditions, while Rathke and Diepenbrock (2006) reported between 20% and 51% in fertiliser contributions to the total energy in winter oilseed cropping systems. According to Sadiq and Isah (2015), 85.2% of input energy was contributed by agrochemical input for maize production in Niger state, Nigeria. Ibrahim et al. (2014) found that the average value for fertiliser use was a huge range of between 3.093 kg N ha^{-1} to 743.93 kg N ha^{-1} from a survey of three agro-ecological zones in Nigeria.

Increasing non-renewable fossil fuel energy input in agricultural production is a direct response to increased cropping intensity that requires more fertiliser and crop protection products in modern farming (Pimentel 2009, Kazemi et al. 2018). Crop yield produced per hectare has been increasing and thus, energy output per unit area and per unit of input have also increased

(Tzilivakis et al. 2005). The direct environmental effects as a result of the release of CO_2 and other GHG emissions, as well as the excessive use of natural resources are global concerns that must be addressed through efficient use of material inputs. The NT technology system and a low fertiliser input of 80 kg N ha^{-1} (160 kg N ha^{-1} for maximum yield output) show a potential to reduce total energy input by a significant amount and could translate to reduced operational costs for farmers. These combinations should seriously be considered for future maize cultivation systems.

Energy assessment of future maize production under climate change was determined using energy indicators such as energy use efficiency (EUE), energy productivity (EP), specific energy (SE) and net energy (NE) values (see Appendix J). Energy assessment is particularly crucial because empirical studies that measure the effect of future climate change variation on the efficiency of maize production in Nigeria are almost non-existent. For instance, the only study found to have addressed the effect of climate variation on the technical efficiency of maize production in Nigeria was based on historical climate and farm level data obtained from maize farmers cross different agro-ecological zones (Ibrahim et al. 2014).

For each future climate scenario considered in this study, EUE declined towards 2080 from the baseline. This suggests that climate change has an effect on the EUE. However, each location responded differently to the combination of climate and farm management strategies, so for example, the highest EUE obtained in Jos was an average of 10.4, which proved high compared to other sites, which were typically lower under future scenarios (ratios of 3.2 to 8.1). This result was due to the combination of using the NT method and 160 kg N ha^{-1} to boost maximum yield. These results were nevertheless, consistent with the findings of other researchers. As an example, the EUE values for NT were similar to estimates made by (Sørensen et al. 2014).

Sarauskis et al. (2014) also reported a higher EUE within the range of 10.4 to 18.6 for maize production under the NT tillage system compared to other conventional tillage methods. As per both reports, a higher EUE was attributed to favourable weather conditions during the studied years and good maize yield. However, contrast must be noted. More recently, Lu et al. (2018) attributed EUE observed under the NT system mainly to low energy input. In support, Kazemi et al. (2018) also suggested that unsuitable climate and infertile soils affected energy use efficiency in cotton production systems. Interestingly, this trend was also observed for this study. This is because as climate change got worse (increasing mean temperature) towards the end of the century (year 2080 under both RCP 6.0 and 8.5 scenarios), the EUE declined. This denoted that lower values of EUE indicated inefficiency in energy use.

Lawal et al. (2014) calculated lower EUE (3.5) compared to the average of 8.1 calculated for the Ibadan baseline in this study. Their study revealed that maize farmers were inefficient in the use of all energy inputs, especially chemical fertilisers, diesel and labour, contributing more to the total energy input. For example, farmers on average applied up to 200 kg N ha^{-1} of nitrogen fertiliser (Lawal et al. 2014), compared to the baseline rate of 160 kg N ha^{-1} application rate for this study. This was in addition 80 kg N ha^{-1} application rate for future projections which produced better EUE for Ibadan. As shown in Table 4.9, energy efficiency significantly reduced in locations such as Ilorin and Enugu, which may indicate a higher energy footprint in terms of the production system (Khan et al. 2009). The results on EUE therefore align with many studies that reported an increase in EUE when soil tillage practices are reduced.

5.7.2 GHG emission evaluation

The findings of this farm LCA is that emissions from soil due to fertiliser application adversely influenced the total GHG emissions, and carbon footprint increased per kg of maize produced. The impact of N fertiliser is therefore significant and underlines the importance of efficient N management.

On average, total GHG emissions under farm management scenarios (fertiliser rate x tillage methods) was 2,931.4 kg CO_2eq ha^{-1}. These findings align with those of Ma et al. (2012) who reported a similar GHG emission range from a maize farm experiment based on three rotation systems. Direct and indirect soil N_2O emissions associated with the application of urea fertiliser were the main emitters (53.4%) followed by GHG emissions from the production of farm input materials (37.8%). Within this category, CO_2 emissions from fertiliser production was the highest. CO_2 emissions from field machinery operation and from urea application (emission due to soil hydrolysis) contributed small shares to the total GHG emission (4.4% and 4.3%).

According to Silalertruksa and Kawasaki (2015), differences in the production of bioenergy crops, management technologies and assumptions made during calculation, will vary GHG emission results. Energy and GHG emission coefficients used are major factors causing variability in many published results (Camargo et al. 2013). Similar to other research, this study modified the IPCC (2006) Tier 1 methodology, excluding emissions from carbon stock changes caused by land-use, and land clearance before cultivation. In addition, GHG emissions caused by transportation of raw materials and harvested products, as well as energy used in the drying of grain were not calculated.

5.7.2.1 CO_2 emissions from fertiliser production

Some studies were explicit in their report that pre-farm emissions from the production of farming inputs, dominated total GHG emissions (Brock et al. 2012). As evidence of this, Lu and Liao (2017) reported an average contribution of 60% to total C emissions from farm inputs for the four tillage systems analysed. This study shows that the production of farm input was the second most dominant contributor (37.8%) to total GHG emissions. Within the pre-farm category, urea production produced the highest CO_2 emissions (23%), followed by diesel production and maize seed production. This is consistent with emissions from a 19-year maize experiment reported by Ma et al. (2012), in which the average contribution was 25%. Ali et al. (2017) and Brock et al. (2012) reported an average of 15.2 % and 16% of CO_2 emission contribution from urea production. In these studies, the embodied emissions (cradle to gate) associated with fertiliser production were not only affected by the quantity applied, but also the emission factor used for estimation. Further to this, Nasidi et al. (2010) used an emission factor of 3.97 kg CO_{2eq} kg^{-1} N based on average GHG emissions from urea production for Nigeria. Ali et al. (2017) adopted an average value of 5 kg CO_{2eq} kg^{-1} N based on World average; Ma et al. (2012) used 4.8 kg CO_{2eq} kg^{-1} N adapted from Lal (2004) for Canada. Lu and Liao (2017) adopted 3.1 kg CO_{2eq} kg^{-1} N from a study carried out by West and Marland (2002) for the US; and finally, Jayasundara et al. (2014) used 2.8 kg CO_{2eq} kg^{-1} N for Canada.

Selecting fertilisers with the lowest GHG emission coefficients can significantly reduce CO_2 emissions from mineral fertilisers. Wang et al. (2017) analysed GHG emissions from different inorganic fertilisers based on their respective emission factors. Nitrogen fertilisers with the lowest emission factor such as ammonium bicarbonate (EF 0.65) had the lowest carbon emissions compared to urea (EF 2.30) and ammonium hydroxide (EF 5.23). Using fertilisers with the lowest EFs such as ammonium bicarbonate, calcium superphosphate and potassium chloride, reduced GHG emissions by 88.34 %, 94.25 % and 93.92 % respectively when compared with NPK fertilisers with higher EF values (Wang et al. 2017).

Based on the results, and in line with common views, CO_2 emissions from fertiliser production is significant and increases linearly with fertiliser application rates. Hence, fertiliser input and EFs of mineral N fertiliser are key factors to consider in GHG emission savings from the pre-farm input category in maize cultivation.

5.7.2.2 N_2O emissions from fertiliser application

The application of mineral nitrogen (N) fertilisers to agricultural soils contributes significantly to global GHG emissions (Gao et al. 2011, Uzoma et al. 2015, Li et al. 2016, Parihar et al. 2018). Particularly, the emission of anthropogenic nitrous oxide (N_2O), a gas with a large global warming potential (GWP) of 298 (Del Grosso et al. 2009, Bessou et al. 2013).

Results from this study showed that N_2O emissions increased linearly with fertiliser application rate, an assumption based on the global 1% default emission factor (EF) suggested in the Intergovernmental Panel on Climate Change Tier methodologies (Stirling 2018). Previous studies support the assumption of a linear relationship between N application rates and N_2O emissions (Lebender et al. 2014, Hinton et al. 2015, Li et al. 2016, Ma et al. 2016, Ali et al. 2017). However, there are publications that have established that a non-linear relation unlike the IPCC tier 1 model is common at different scales (Van Groenigen et al. 2010, Vyn et al. 2016, Wang et al. 2018). For example, Shcherbak et al. (2014) found that from a meta-analysis, nonlinear responses in global N_2O emissions were possible as a result of adding N fertiliser to an already excessively fertilised system (exceeding crop N demand). In addition, several authors maintained that in addition to N uptake, crop type, N fertiliser type, soil organic carbon, soil temperature and soil pH are factors that contribute to the non-linearity observed (Shcherbak et al. 2014, Regaert et al. 2015). Shcherbak et al. (2014) further suggested that the global 1% default emission factor was too conservative for high N-input rates. However, Stirling (2018) recently cautioned that comparing the IPCC 1% EF with EFs at scales less than the global mean is not appropriate. Some studies have experimentally linked the non-linearity to surplus N not taken up by the crop (Bouwman et al. 2002, Grant et al. 2006, Van Groenigen et al. 2010), while Freibauer (2003) measured a much smaller correlation of 0.4%. Therefore, to minimise N_2O emissions per crop yield, efficient application of fertiliser such as using the split application method to match crop demand and the use of enhanced efficiency fertilisers (EEFs) to improve the N-use efficiency of crops would be a straightforward option (Uchida and Rein 2018, Van Groenigen et al. 2010, Regaert et al. 2015, Chen et al. 2018, Rein and Uchida 2018). For this study, a split application approach in fertiliser application was used (Chapter 3); however, Uchida and Rein (2018) as well as Chen et al. (2018) suggest the use of EEFs, which prove more promising in maximising N-use efficiency and the reduction of N_2O emissions.

In this study, denitrification of the N fertiliser applied was responsible for direct N_2O emissions contributing a large portion (83%) of the total N_2O emissions. This occured in the absence of crop residue, which also contributes directly and indirectly to N_2O emissions (Ma et al. 2012). As previously mentioned, the equation (see section 3.7.3.1.2) used to calculate direct N_2O emissions from fertiliser application was modified to exclude N_2O emissions from crop residue and N-fixing crops. Brock et al. (2012) reported that N_2O emissions from crop residue contributed about 9% to the total C footprint; in support, Ma et al. (2012) also noted that crop residue represented only a small portion of total GHG emissions for maize cultivation. Both Ali et al. (2017) and Ma et al. (2012) however reported different values for direct N_2O emissions compared to the results of this study because emissions from the decomposition of crop residues were included in their respective studies. Ali et al. (2017) reported N fertiliser application affected direct field emissions by 62.5%, while plant residue decomposition contributed 37.5% of direct emissions to total N_2O emissions. Similarly, Ma et al. (2012) found that higher N fertiliser rates influenced emissions from crop residue, which in turn, also affected the total N content in crop residue.

The relationship between farm management systems and N_2O emissions is more than just a consideration of N fertiliser input only (Van Groenigen et al. 2010, Li et al. 2016). A more robust approach, such as the adoption of tier 2 and tier 3 methodologies for estimating EFs (Adewale et al. 2018), is required in order to estimate further factors controlling N_2O emissions such as climate, soil type, soil water content, soil temperature, soil pH and type of mineral fertiliser (Gao et al. 2011). Several studies have reported that fertilisers such as anhydrous ammonia (NH_3), urea [$CO(NH_2)_2$; 46 % N] or ammonium nitrate (CAN: NH_4NO_3; 27% N) can potentially enable nitrification and denitrification to occur in the soil (Brentrup et al. 2000, Smith et al. 2012, Hinton et al. 2015). For example, from a field experiment on wheat, Lebender et al. (2014) reported that different forms of mineral fertiliser induced N_2O emissions at different rates. Further to this, when compared to ammonium nitrate, urea fertiliser produced higher N_2O emissions (Lebender et al. 2014). Similarly, Tierling and Kuhlmann (2018) reported higher cumulative N_2O emission rates from urea compared to ammonium sulphate.

Indirect emissions resulting from leaching and volatilisation (using only N fertiliser rates), were found to contribute 17% to total N_2O emissions, increasing average CO_2 emissions by 426.1 kg CO_{2eq} ha $^{-1}$. This evidences the fact that several factors such as N rates, tillage, crop category and climatic conditions affect emissions from leaching and volatilisation (Ali et al., 2017). Nitrate leaching is strongly affected by soil texture and is significant in areas of high rainfall

(Del Grosso et al. 2009). According to Brock et al. (2012), limitations come from the fact that many studies do not account for indirect N_2O emissions from leaching and run-off, especially for dryland cropping regions such as Australia where the ratio of evapotranspiration to rainfall is between 0.8 and 1.0. The fraction of N lost by leaching and run-off, currently estimated at 0.3% by the IPCC (2006) as a default value could be as low as 0.05% for regions where rainfall is much lower than potential evapotranspiration (Rochette et al. 2008). In response, Brock et al. (2012) found that by adopting EF of 0.45% from field research increased soil emission by about 7% compared to using the default value. For this study, the default IPPC EF of 0.3% was used, however, it is recognised that this may lead to a considerable under or over estimation of soil N_2O.

According to Parihar et al. (2018), apart from soil attributes, tillage practices affect several soil variables, thus contributing to N_2O emissions. This statement comes as many researchers claim that some studies maintain that ploughing in conventional tillage affects N_2O emissions compared to no tillage practices. For example, He et al. (2018) found that conventional tillage methods used in maize cultivation increased N_2O emissions by 10.7% and 9.5% under the RCP 4.5 and RCP 8.5 respectively. Janzen et al. (2006) and Rochette et al. (2008) however reported that the effect of tillage on N_2O emissions was not consistent, arguing that emission varied for different experiments and was sensitive to the local environment; mainly the type of soil. Further to this, Uzoma et al. (2015) also found that the magnitude of N_2O emissions was similar between both intensive and minimum tillage methods. Thus the contribution of tillage to N_2O emissions will require the measurement of N_2O fluxes based on initial soil physical and chemical properties using a coefficient or ratio factor (He et al. 2018). In the absence of measured field data, this study did not consider the effect of soil tillage on N_2O emissions.

Many studies have revealed that climate change will have significant effects on soil N_2O emissions from maize production, based on model predictions (Smith et al. 2013, He et al. 2018). As a result, climate change effect on soil N_2O emissions could be estimated using agro-climatic models. This however, would involve the complexity of model parameterisation using field flux measurement (Wu et al. 2015, Uzoma et al. 2015). Due to the lack of available soil emission fluxes to calibrate a model, this study estimated soil N_2O emissions using the IPCC tier 1 coefficients and fertiliser application rates.

Bessou et al. (2013) obtained field N_2O fluxes using the modified agro-ecosystem model CERES-EGC and compared the emission data with observed data and outputs from calculated IPCC tier 1 coefficients. Firstly, they reported that simulated soil N_2O emissions were underestimated; and secondly, they found that modelled emissions were within the same order of magnitude as the calculated emissions using IPCC tier 1 coefficients, albeit, slightly lower. As a result of their findings, Bessou et al. (2013) also emphasised the sensitivity of impact categories to climatic conditions. For example, simulated drier years resulted in lower direct and indirect N_2O emissions, leading to reduced eutrophication and acidification impacts, however, this reduced both biomass and ethanol yields.

Notwithstanding resource availability, future evaluation should seek to apply processed based models such as DNDC or DAYCENT calibrated for each study location to explore the impacts of climate change and management strategies on soil N_2O emissions. By doing so future researchers could compare the results based on IPCC tier 1 methodology used in this study. Uzoma et al. (2015) and Del Grosso et al. (2009) explained the difficulties, advantages and disadvantages of model use in soil N_2O emission analysis. For this study, total N_2O emission from fertiliser application was greatly influenced by direct soil N_2O emission from fertiliser application, contributing significantly to the overall GHG emissions (44.1%). This was compared to indirect N_2O emissions from leaching and volatilisation (9.3%). Consequently making the application of fertiliser the most emission-intense process contributing to production in maize cultivation.

5.7.2.3 Emissions from machinery use and diesel input

In addition to emissions from fertiliser production and application, emissions from machinery used for cultivating the land and diesel input also contributed to the total GHG emissions. Results showed that field operations contributed a small percent to the total GHG emissions from maize production. In addition, frequent machinery used with intense farming under the CT method resulted in more diesel use and hence increased GHG emissions. Therefore, a no-tillage practice can significantly reduce GHG emissions, since it uses less fuel than both conventional and reduced tillage methods.

The estimated values closely agree with most reports on machinery use, tillage intensities, fuel use and the associated GHG emissions (West and Marland, 2002, Maraseni et al. 2010, Jayasundara et al. 2014, Ali et al. 2017, Lu and Liao 2017). Furthermore, Rivera et al. (2017) reported that harrowing and ploughing contributed generally (33 % and 24 % respectively) to the field operation stage, which affected all diesel-related environmental impacts, with fertilising and harvesting contributing less (15% and 17 %). West and Marland (2002) previously reported higher CO_2 emission for CT, primarily due to fuel use in mouldboard plough operations. In addition, average net C flux from three cropping systems (corn, soybean, and wheat) were reduced in no-tillage system (-200 kg C ha^{-1} per year) compared to conventional tillage (+168 kg C ha^{-1} per year) per year (West and Marland 2002).

This analysis suggests that a change from the CT system that uses mouldboard ploughing to a RT or NT system could result in CO_2 emission savings of approximately 25.8 kg CO_2eq ha^{-1} and 110.4 kg CO_2eq ha^{-1} for each system. Across all treatments, GHG emissions associated with field operations in maize cultivation accounted for 9.2% of the total emissions (129.6 kg CO_2eq ha^{-1}). In support of these findings, Jayasundara et al. (2014) reported that fieldwork at county-level contributed a similar value of 9% to total GHG emission from corn production in Ontario, Canada. In addition, Ali et al. (2017) reported an 11.4 % contribution from field operations.

Regardless of the fertiliser application rate, it was clear that soil tillage activity influenced GHG emissions the most. Therefore, reducing tillage activity by changing implements and adopting a NT conservative method had the potential to contribute to GHG emission savings for maize production. An example of this is evidenced by Lu and Liao (2017) who achieved 12.3% C emission reduction using either rotary tillage (RT) or chisel plough tillage (STS) instead of mouldboard ploughing for conventional (CT) tillage. Ali et al. (2017) also found that by moving from CT to NT systems, they achieved an average reduction in GHG emissions of 43%. Similarly, Sørensen et al. (2014) evaluated the influence of tillage methods on the total emission of GHG from four different crop productions. They reported a larger reduction in GHG emission per kg of product by adopting the RT method and that the NT method did not reduce GHG emission further. On the contrary, West and Marland (2002) did not observe a significant difference in CO_2 emissions from agricultural inputs and machinery combined in CT and NT for corn production (228 and 225 kg C ha^{-1} yr^{-1} respectively).

5.7.2.4 Analysis of CO_2 emissions from Herbicides, Pesticides and Maize seeds

Results show that maize seeds for sowing accounted for 6.3% of the total GHG emissions. Other farm consumables such as pesticides and herbicides contributed approximately 4.3% and 3.5% respectively to the total GHG emissions. Similar to other farm inputs as discussed, this study used emission factors weighted by the proportion of each product applied, to calculate the relative CO_2 emission contributions to the total GHG emission. This is similar to the calculation process used by both Ali et al. (2017) and Wang et al. (2015).

Using similar emission factors but different application rates, Ali et al. (2017) and Wang et al. (2015) reported a similar share of 2.6% and 3% contribution from spraying herbicides. In addition to this, Godard et al. (2012) used the dynamic model Pest-LCI to estimate the fate of pesticides and their emissions from soils and crop leaves. They reported that emissions from pesticides dominated (67%) in the ecotoxicity impact category compared to climate change (global warming category) and that this emission was mainly as a result of pesticide production and in-field emissions after application (Godard et al. 2012). The flexibility of this approach began with the possibility to couple the Pest-LCI model with a crop simulation model, parameterised with site-specific farm management data. Parajuli et al. (2017) also evaluated the risks of pesticides leaching to freshwater ecosystems as well as emission distributions of the active ingredients to air. They opined that the characterisation factors of pesticide types and application rate affected the emissions on the freshwater ecotoxicity impact category.

The GHG emissions contribution as per Jayasundara et al. (2014), from combined agronomic inputs in maize production was 4%. Further to this, Gan et al. (2011) reported an average of 36.3 kg CO_2eq ha^{-1} from pesticides in the production of durum wheat. They maintained that because the carbon footprint from pesticides used in agriculture is small, the relative values of the carbon footprint for the various cropping systems analysed would be reasonable. It is important to note however, that under the NT tillage system, more herbicide was used (for two spray passes) therefore a higher emission value of 92.4 kg CO_2eq ha^{-1} for herbicide production was estimated compared to 46.2 kg CO_2eq ha^{-1} estimated for CT and RT systems (one spray pass each). Nevertheless, all the agronomic inputs (maize seed, pesticide and herbicides) together represented only a small proportion (6.9%) of the total GHG emission overall. Therefore, it can be established that any modification of these agronomic inputs have no appreciable influence in reducing/improving the total GHG emission from maize production.

5.7.2.5 Total GHG Emissions from maize production systems

Total GHG emissions varied under each farm management scenario (fertiliser rates + tillage method) and thus, the average total GHG emissions per hectare ranged from 1,535.4 kg CO_2eq ha^{-1} to 4,138.8 kg CO_2eq ha^{-1}. The total GHG emissions estimated for maize production are consistent with emissions from other resources. For example, Zhang et al. (2018) and Qi et al. (2018) reported average GHG emission of 3,820 kg CO_2eq ha^{-1} and 3,798.8 kg CO_2eq ha^{-1} for rain-fed maize production in China. Camargo et al. (2013) reported net GHG emission of 3,283 kg CO_{2eq} ha^{-1} per year for corn silage production using an energy analysis tool. Similarly, in Iran, Mohammadi et al. (2014) estimated GHG emissions of corn silage at 2,288 kg CO_{2eq} ha^{-1} attributing the main source of CO_2 emission to electricity (for irrigation) and diesel fuel.

In terms of this study, the estimates were generally lower than the emission value (7,910 kg CO_2eq ha^{-1}) presented by Felten et al. (2013) for maize produced in Western Germany over 16 years. This may be because their system boundary accounted for methane emissions as well as emissions from transport, engine oils and lubricants for machinery not accounted for in this study. Manzone and Calvo (2016) in Italy also reported a much higher emission rate in maize production (26,370 kg CO_2eq ha^{-1}). They determined that mineral fertilisation (31.1%), top dressing (31.2%) and biomass harvesting and transport (31.2%) contributing the most whilst lower values were obtained for planting/seeding operations (0.4%), ploughing and harrowing was 1.2% and 0.5% respectively. It should be noted that their system boundary however, included irrigation in addition to higher amount of herbicides and fertiliser usage (500 kg ha^{-1} of NPK and 87 kg ha^{-1} of Urea).

As already mentioned, the life cycle analysis carried out excluded emissions induced by land use change (LUC), transportation of harvested grain and emissions accompanying grain storage. According to Tubiello et al. (2015) in addition to Castanheira and Freire (2013), land use change is one of the major contributors to climate change. Because of this, tillage methods greatly affect soil organic carbon dynamics. Kim et al (2009) further explains that variables such as sustainable cropping management practices i.e. no-tillage and no-tillage plus cover crops are key factors in estimating GHG emissions associated with LUC. A bioenergy evaluation in Nigeria suggests that intensive land use and the transformation of forest and grassland areas to cropland for biofuel feedstock production will increase by 2050 (Okoro et al. 2018). Similarly, Hartley et al. (2015) reported that increased human LUC could have large negative impact on the projected increase of carbon stored in the tropical parts of West Africa under the effects of climate change. For example, from their projections, land use scenarios in Southern Nigeria will increase, hence the importance of protecting existing stands of tropical forest in the area. Therefore, a life cycle GHG balance of energy crop production such as maize should include an awareness of carbon emissions from direct LUC.

Castanheira and Freire (2013) highlight the criticality of alternative LUC scenarios, farm management practices and transportation systems in terms of GHG emission evaluation and results. Qin et al. (2018) applied the concept of land management change (LMC) into the LCA framework instead of the conventional LUC, as the former accounted for emissions from corn stover removal, organic matter additions and tillage methods. They explained that land management practices incorporating cover crop planting or manure application under a no-tillage system could mitigate GHG emissions from residue removal; such as corn stover, from the farm. This practice system reduced GHG emissions from corn stover ethanol by 26% and 98% under RT and NT systems respectively compared with CT. Soil organic carbon loss also reduced significantly (Qin et al. 2018).

Ma et al. (2012) reported that higher N rates in the soil influenced crop residue contribution to GHG emissions. However, the environmental impacts resulting from complete removal of annual crop residue are concerning. This is specifically because in addition to maintaining the level of soil nitrogen required for crop uptake and improving soil organic carbon (SOC), crop residue can potentially reduce off-site environmental impacts such as leaching (Adler et al. 2015, Yadav et al. 2018).

For this study, it was estimated that synthetic fertiliser application contributed the greatest percentage to the total GHG emission, averaging 57.7%of the total GHG emissions, of which 53.4% came from direct and indirect N_2O emissions and 4.3% from CO_2 emissions as a result of urea application. The remaining 42.3% of emissions came from input production (37.8%) and field operation (4.4%). Similar to these results, Sørensen et al. (2014) also reported that CO_2 and N_2O from soil emissions contributed the most (50-60%) followed by emissions from fertiliser production (28-33%). In addition, Godard et al. (2012) found that nitrogen fertilisation in potato production affected not only the climate change (CC) impact category, but also terrestrial acidification (TA) and marine eutrophication (ME) impact categories.

Overall, maize production highlights better environmental results through improvements in fertiliser input efficiency. On average, GHG emission savings of 2377.8 kg CO_2 eq ha^{-1} and

1,280.3 kg CO_2 eq ha^{-1} could be achieved if 80 kg N ha^{-1} and 160 kg N ha^{-1} were used compared to 250 kg N ha^{-1}. This is because the emissions associated with applying 250 kg N ha^{-1} were 2.4 times the emissions of applying 80 kg N ha^{-1} and 1.5 times more than applying 160 kg N ha^{-1}. Although increasing fertiliser application contributes to yield increase, the overuse of chemical fertilisers has a greater negative impact on the environment as the results indicate. Worryingly though, previous studies revealed that farmers' perception typically resides with applying more fertiliser to increase yield (Wang et al. 2015). It is important to note, as shown in this study, that excess nitrogen fertiliser application does not always translate to significant yield increase, especially at higher yield levels. Therefore, in addition to crop-specific recommended application rates, educating farmers and stakeholders of the need to determine soil nutrient status first, before any application takes place is paramount. This is because it could prevent over fertilisation, which further results in yield decrease once crop N intake limits reach their optimum level.

Total GHG emissions across the tillage system decreased from CT to NT suggesting the potential to reduce emissions overall by adopting the NT method. Lu and Liao (2017) estimated that different tillage practices affected net C flux in a winter wheat-summer maize rotation system. They noted that C sequestration was highest in the NT system compared to the CT system; hence, the net C flux for the CT system was positive and negative for NT. Similarly, Kim et al. (2009) quantified the effects of CT compared to NT on the environmental performance of corn grain and the corn stover system in the Corn Belt region of the US. Using a simulation model (DAYCENT), higher reduction in diesel fuel (12% to 44%) and reduced GHG emissions (53% and 45%) due to increased soil organic carbon and less N_2O emissions was achievable by using the NT method. This concept is supported by the findings for this study as the CT system gave the highest emission rate compared to both RT and NT methods.

Goglio et al. (2018) compared measured emissions from a specific location to GHG emission calculated based on the IPCC tier I methodology and other commonly used methods. All five methods gave varying output for cereals and the report highlighted the issue of misrepresentation of local conditions as a result of using default global emission factors. According to Goglio et al. (2018), use of a simple model in combination with IPCC tier II or use of DNDC agroecosystem model gave similar results to observed emissions. However, in reality, the difficulty and technicality of model parameterisation and availability of data to calibrate the models, still makes the simple IPCC tier I method a more attractive option albeit with some uncertainty in the results.

5.7.2.6 Carbon footprint of maize production

According to Grassini and Cassman (2012), LCA assessment of maize production that is weighted on GHG emissions in relation to grain yield level, rather than emissions on a per hectare basis shows more relevancy and helps to relate global warming potential to crop yield. For this study, carbon footprint (CF) was estimated based on the total GHG emissions from input production, field operation, soil emission, and the localised climate change impact on yield under farm management scenarios. Positive values of emissions expressed as CO_2 equivalents per kg of maize grain produced, indicate a net source of GHGs to the atmosphere. Negative values indicate net sinks of GHG to the soil (Ma et al. 2013). The CF indicator estimates the amount of CO_2 emissions directly produced per kilogram of maize grain and to date, very few LCA studies have made a distinction between the contribution of yield changes due to future climate change, N rate and tillage method when calculating the CF of maize.

Ma et al. (2012), Yang et al. (2014) and Qi et al (2018) for example, quantified the correlation of CF and grain yield for various rotation systems and farming patterns based on experiments that estimated annual GHG emission fluxes. Their research assessed the effects of rotation systems, N inputs on the annual CF of maize per kg of grain yield, while this study has gone one-step further in terms of correlating the effect of future climate change on CF of maize grain production. Li et al. (2016) also produced a limited study; only considering the influence of historical climate variations and management practices on aggregated GHG emissions and CF on a wheat-maize rotation system. Moreover, Jebari et al. (2018) only simulated soil carbon response to climate change and farm management scenarios, whilst Zhang et al. (2013) did not include soil emissions within their CF evaluation citing strong fluctuations in N_2O emissions. As previously discussed, emissions due to land-use change were not included in the footprint of this study as is consistent with some methodologies such as the PAS-2050 methodology (British Standards Institute 2011). The main focus of this study centres on emissions per kg of maize grain produced (farm to gate LCA) and therefore, the CF of transportation of produce was not accounted for.

Across all locations, CF increased from 2020 to 2080 under both RCP 6.0 and 8.5 climate scenarios. The highest CF was associated climatically with the highest temperature increase scenario (RCP 8.5) in 2080, irrespective of the fertiliser rate or tillage system. This reflects the impact of harsher climate change on crop productivity compared to baseline. It indicates that generally, as grain yield declines under climate change, CF per kg of maize grain increases as expected, although with some exceptions. As an example, when considering CF response to fertiliser rates, results show that irrespective of the climate scenario, CF as well as yield increased as the amount of fertiliser increased. This was due to the higher GHG emissions (soil emissions) from higher fertiliser rate. Therefore, it did not matter if yield increased at any location, essentially, higher fertiliser rates affected CF (Qi et al 2018).

However, the generalisation/generalisability of these results are subject to certain limitations. For instance, this trend was not consistent at the Enugu site where CF under 160 kg N ha^{-1} decreased compared to 80 kg N ha^{-1}. In addition, despite increased yield observed under higher N rates, CF were higher. The highest CF obtained under the RCP 8.5 scenario during 2080 timeline were 0.400, 0.792, 2.012 and 1.504 kg CO_{2eq} kg^{-1} of grain for Jos, Ibadan, Enugu and Ilorin respectively. Fertiliser rate above 160 kg N ha^{-1} led to no beneficial effect on maize yields but contributed significantly to increased carbon footprints. Wang et al. (2016) estimated that 180 kg N ha^{-1} was the best application rate to achieve a low carbon footprint for the winter wheat system.

In general, CF under NT decreased with either increasing or decreasing yield for all scenarios. The findings of the current study are consistent with those of Jebari et al. (2018) who states that under NT soil management, the rate of soil carbon sequestration quadrupled under a high temperature scenario. These results certainly confirm that NT will be beneficial in reducing CF under climate change. Of interest was the observation at Ilorin, which displayed yield increase as well as CF decrease under NT technology.

Zhang et al. (2013) reported no significant difference between CT and NT, but, NT still produced the lowest carbon productivity. On account of this, they arrived at a similar conclusion on the adoption of NT technology to reduce GHG emissions in China. These results are consistent with those of other studies and suggest that NT enhances soil organic carbon (SOC) sequestration, which had a strong effect on CF. For example, CF changed to a negative value under NT when SOC was included (Sainju et al. 2014, Zhang et al. 2016). Elsewhere, contrasting results showing CT system improved yield and reduced CF compared to NT system have been reported (Wang et al. 2016). This result was limited as it essentially considered one single management practice at a time, not considering the effects of any interaction between management systems.

Overall, the estimated CF values were similar to published values except that of Ilorin and Enugu which were on the high end of the estimated CF emission range especially under RCP 8.5 climate scenarios in 2080. To further illustrate, Kim et al. (2009) estimated CF of 0.25-0.82 kg CO_{2eq} kg $^{-1}$ corn produced in the United States. In China, Liu et al. (2015), Cheng et al. (2015) and Yan et al. (2015) reported the average CF of maize as 0.230 kg CO_{2eq} kg^{-1}, 0.44 kg CO_{2eq} kg^{-1}, and 0.33 kg CO_{2eq} kg^{-1} respectively. Xue et al. (2018) maintained that by excluding soil organic carbon storage, CF ranged from 0.44 kg CO_{2eq} kg^{-1}, to 0.59 kg CO_{2eq} kg^{-1}, but when soil organic carbon (SOC) was considered, CF decreased within range of 0.27 kg CO_{2eq} kg^{-1}, to 0.36 kg CO_{2eq} kg^{-1}. This result is similar to 0.48 to 0.64 kg CO_{2eq} kg^{-1} estimated in Qi et al. (2018). Xue et al. (2018) attributed the varying CF results to differences in the calculation method, regional scale, and emission factors considered. They explained that the extent of inventory data collected for the LCA assessment and emission factor could result in larger GHG emissions. A significant factor influencing CF estimation is the difference in maize yield gap at varying locations due to climate variability and farm management practices.

This is the first study to contribute to the understanding of the carbon and energy footprint of maize production in several agronomic zones in Nigeria. Increasing the awareness of climate change impact has spurred the current investigation to include assessment of the combined effect of various farm management scenarios on CF at yield scale. The results give a clear indication that in order to maintain or reduce the C footprint of maize under climate change, efficient N application and tillage method are key factors to consider (Grassini and Cassman 2012). Chen et al. (2014) suggest that reduction in GHG emission per unit yield production is achievable by utilising an integrated soil–crop management system. Although Chen et al. (2014) obtained higher yields, and GHG emissions reduced substantially under the integrated management system from historical field experiments, their analysis did not consider future climate variability due to climate change. Therefore, the GHG emission intensity per grain yield would need to be determined for future production systems using the integrated soil–crop system management suggested by Chen et al. (2014) under projected climate change scenarios. It is clear however, that the significant differences found in the productive efficiencies question the environmental viability of expanding the agricultural frontier to less suitable locations for maize crop production under climate change.

5.8 Regression analysis

As was mentioned in previous sections, the impacts of climate change and farm management scenarios on maize yield and life cycle analysis (LCA) were evaluated in order to determine the environmental impact, particularly in relation to Greenhouse Gas emissions (GHG), energy use and carbon footprint. In addition to gaining knowledge of the level of impacts associated with producing maize as biofuel feedstock, it is imperative to know whether the likelihood of increasing the environmental impacts is influenced by factors such as fertiliser, climate change or tillage systems. Hence, the objective of this section was to estimate the variation and response of yield and LCA outputs to each input variable using multiple regression analysis.

Regression analysis is an important tool in environmental impact assessment and climate impact analysis. As a result of its advantageousness, various studies have used regression analysis to predict yield, LCA outcomes, and to determine the combined effect of climate change and farm management on yield (Lobell and Burke 2010, Pascual-González et al. 2015, Duan et al. 2015, Mansouri et al. 2015, Sitienei et al. 2017, Najafi et al. 2018). However, the generalisability of much published research on this issue is problematic. This is because none of these studies have taken into account the combined effects of wide-ranging predictor variables on the response of LCA outcomes hence, this study aims to close the knowledge gap in this area.

Other studies have considered the relationship between LCA and regression thus for example, DeVierno et al. (2012) adopted this concept to modify significant design characteristics in order to reduce product environmental impacts. Padey et al. (2012) also developed a regression using LCA results to quantify the GHG performance of a wind turbine system. The present study adopted a similar strategy albeit in a different context by combining life cycle assessment (LCA) and regression modelling in order to determine the significant effects of predictors such as climate change, fertiliser use and tillage on GHG, CF, NE and yield responses. This study is possibly the first to combine both methods to evaluate the effect of climate change scenarios and input factors on LCA outcomes. By including the analysis of maize yield, based on climate change projections, and the environmental impact assessment outputs (e.g. GHG, net energy and carbon footprint), this study extends existing knowledge on the sustainability of energy crop production.

The multiple regression model predicted the effects of each factor on model responses and results show that some predictor variables had more influence on the response variables than others. In Nigeria, Oriola and Oyeniyi (2017) used similar regression analysis to determine the contribution of climatic elements on yield. They calculated that 87% of the variation in maize yield could be due to other factors outside of climatic elements. From this study, the results, by implication, show that fertiliser rate has a positive and significant effect on yield, GHG emissions and CF at all sites with the exception for the CF response at Enugu. Similarly, fertiliser had the highest effect on NE at Jos and Enugu only, while climate change affected

NE response at Ibadan and Ilorin. This means that climate change scenarios, not fertiliser or tillage, mostly influenced CF at Enugu, NE at Ibadan and Ilorin locations. A positive coefficient obtained for fertiliser for all models indicate that an increase in fertiliser would cause an increase in all response variables. It is important to note that in Ibadan and Enugu, fertiliser and climate change had almost equal effects on yield, and climate change would have the potential to put yield at risk due to the negative coefficient obtained.

In order to design well-targeted adaptation measures to mitigate climate change impact on energy crop production including maize, it is important to identify the causal drivers of the increase in net energy and carbon footprint. Net energy (MJ ha^{-1}) is an important energy footprint indicator in LCA, and a high NE reflects greater energy-input use efficiencies (Grassini and Cassman 2012). According to the FAO (2016), energy demand in crop production has a direct link to climate change and farm management practices such as soil tillage technologies and fertiliser application rates; therefore, the need to understand the relationship between NE and climate change and further promote climate-smart agricultural activities through informed policies is even greater.

Previous research to validate these findings for location-specific CF and NE response to climate change scenarios is almost non-existent. While many studies across Nigeria have used statistical approaches to link the effect of climate change on yield variation, the effect on other response variables such as CF and NE have rarely been addressed. Eregha et al. (2014), Ekpenyong and Ogbuagu (2015), and Edoja et al. (2016) developed frameworks by building regression models that accounted for the effect of historical climate variability and CO_2 emissions on yield. For example, Eregha et al. (2014) estimated that as temperature and CO_2 emissions increased, maize yield would decrease. The inclusion of future climate scenarios in this study, accounted for future changes in CO_2 concentration based on the RCP 6.0 and RCP

8.5 scenario pathways. Estimating accurately the relationship between GHG, CF and NE of energy crops and climate change is an important step in determining the environmental shifts to climate change response.

There are similarities between the approaches described in this study and those utilised by Arrieta et al. (2018). In the case of Arrieta et al. (2018), multivariate redundancy analysis statistics were used to determine the effect of climate and no-tillage technology on maize and soybeans yield, GHG and energy intensities for 18 agronomic regions in Argentina. Bioclimatic variables from historical archive were also used while this study utilised climate change scenarios, and farm input variables varied including fertiliser input, diesel, and pesticides. They reported that climate, particularly mean annual precipitation, explained the variation in yield, GHG and energy efficiencies.

Similarly, by using a factorial decomposition procedure to determine the effects of climate emission scenarios (RCP 2.6 and 8.5), cropping year and fertiliser management on maize yields, Corbeels et al. (2018) reported that the variation in yields was mostly due to climate change variability and not fertiliser for all sites except one. Their study did not consider the environmental life cycle assessment from the production system; however, they attributed their findings to large uncertainties in terms of different GCM outputs and limited capability of crop models in simulating nutrient-limited yield (Corbeels et al. 2018). Likewise, Najafi et al. (2018) built a regression model to predict the effect of climate systems and technology improvement on crop yields in 160 countries. The study however, did not account for future climatic changes, but nevertheless, the model captures past impacts of climate predictors that explained more than 70% of the residual variance for crops. Although extensive research has been carried out on regression, none of the three recent studies discussed accounted for the combined effect of the factors identified in this study, especially with regards to the effect on NE and CF.

Concerning the relationship between fertiliser use and the response variables, coefficients from the simple linear regression have shown that positive relationships exist between fertiliser increase and increase in yield, GHG emissions, CF and NE. For locations where climate change had a greater effect on CF and NE, depending on the climate scenario pathway, the relationship was either negative or positive. Specifically, the correlation between NE and climate change RCP 8.5 scenario (Ibadan), NE and climate change RCP 6.0 scenario (Ilorin), CF and climate change RCP 8.5 scenario (Enugu) was negative. This implies that climate change has a negative effect on NE and CF.

A previous study undertaken by Zhai et al. (2017) used the ARDL regression model (autoregressive distributed lag) to test short and long-term relationships between historical wheat yield, climate change and farm technology. Their results demonstrated that climate change had a weak effect on yield but fertiliser and farm machinery use also jointly affected yield in the long-term. Zhai et al. (2017) acknowledged the difficulty in separating one factor's influence on yield from other factors influence. In terms of this study, what is evident is the possibility of determining the variation in yield, GHG emissions, carbon footprint and net energy by predicting the effect of climate change scenarios, tillage and fertiliser use for maize production and evaluating the linearity that could exist between variables. Further research is required to assess the relative importance of each predictor and compare each contribution made. Further to this, metrics other than coefficients could be used to interpret model results (Nimon and Oswald 2013). This could help identify inter-correlations or co-linearity between predictors and determine the relative importance of the predictors within the model (Lobell and Burke 2010, Nimon and Oswald 2013).

More research is required to determine if the results obtained are a characteristic of this study, the locations or if they can be reproduced within and across varied and wide-ranging contexts.

It would be beneficial to establish a validation system (or measure model performance) to test robustness of the LCA-regression system and whether, based on the validity of the results, the model could be used as a reference for making decisions and also as comparison within specific climate change assessments. If more prognoses such as the ones obtained from this study become available to environmental professionals and bioenergy policy makers, then extended information on changes within the environmental impacts and yield of future maize production would be available for appropriate/adequate mitigation and adaptive planning. This would consequently reduce environmental impacts due to climate change. Nonetheless, in future modelling, the model performance could be enhanced by considering a wider range of environmental data and LCA impact categories other than GHG and CF over a broader range of locations.

Estimating model validity and usefulness could be done through comparison with literature surveys (Padey et al. 2012). However, this strategy may not be explicit in terms of result interpretation because many studies have used methods based on different objectives and scopes thus resulting in different outputs. In comparison to some study examples mentioned above, this study focused attention on the effect of predictors on variations in CF and NE. It is also important to note the possibility that the conclusions drawn from this study would vary when locations are changed. Najafi et al. (2018) and Dimobe et al. (2018) used the split sampling technique to validate a Bayesian model and RF regression model respectively but this process in itself has limitations. According to Oredein et al. (2011), data splitting could be inconsistently done, resulting in different validated results and the technique requires a significantly larger sample otherwise the results are likely to vary. The LCA-regression method is adaptable to other regions and crops. Therefore, similar model development is feasible for other biofuel energy crops in different agro-ecological zones.

In summary, the present study, developed to exploit weather prediction techniques together with an LCA-regression method, has the potential for wide application in the biomass arena. It has been applied to maize growth in four agro-ecological zones in Nigeria, where different conditions obtained, but where a sufficiently long weather record existed in order to permit the calibration of the weather model. The outcome of the study of these four sites clearly points to future climate as a major influence, but there still remains an emphasis on the fact that maize yield, net energy and carbon footprint are extremely sensitive to the application of fertilizer. Indeed, beyond a modest application rate, it can be argued categorically that increased fertilizer use progressively reduces NE and increases CF.

These results are similar to those of Khoshnevisan et al. (2013), but inconsistent with previous studies exemplified by Arrieta et al. (2018) and Corbeels et al. (2018) who suggested that climate change mostly explained the variation of maize yield as compared to fertiliser. Although tillage was not the dominant factor in GHG and CF responses, tillage coefficient values were negative and statistically significant suggesting that an application of no-tillage method could diminish some of the impacts from diesel use. Findings from analysis also suggests that climate change scenarios was the critical factor in explaining the variation in NE and CF responses at some sites (Ibadan, Enugu and Ilorin) and that the relationship is linear with both positive and negative impacts. Further research however, is necessary to support this conclusion. Overall, the model presented in this thesis can be used to assess future agricultural/bio-energy strategies and guide towards lowering the current and future CF and NE of maize in keeping with the objectives of IPCC to reduce GHG emissions from agricultural practices.

Chapter 6

6 Conclusion and recommendations

6.1 Conclusion

There are indications that demand for energy crops will continue to rise with the increase in biofuel consumption (Beckman and Nigatu 2017). This is partly due to the enactment of policies put in place in order to curb the use of fossil fuels, thus mitigating climate change and energy insecurity; which stems from the instability in global oil prices and depleting crude oil reserves (Liu et al. 2017). Presently, many emerging economies including Nigeria, are beginning to invest in biofuel production. These investments, which take place alongside those of large biofuel economies (such as the US, Brazil and China), possess the underlying aim of decarbonising the economy, a trend that currently adds to the demand in biofuel feedstock cultivation at a significant level (Aliyu et al. 2017). Thus, in 2016, bioethanol production in the USA, using domestic grown maize as primary feedstock, was estimated at 57.7 billion litres (Jones et al. 2017, Beckman and Nigatu 2017). This was followed closely by Brazil, with an estimated production of 30.4 billion litres of bioethanol from sugarcane in 2016 (USDA 2016).

Further to the above, crop yield and cropping area (production per hectare) are two major factors that impact on biofuel feedstock supply. Therefore, meeting the increasing demand for biofuel feedstock requires an increase in either one or both of these factors. In Nigeria for example, maize (*Zea mays*) has been identified, as a viable feedstock for bioethanol production because of its high sugar content, high productivity per unit of land, and high yield output. In addition, this energy crop type has the capacity to grow on both marginal and degraded agricultural land (Ben-Iwo et al. 2016).

In addition to the increasing demand for biofuel feedstock comes increasing concern with regards to competition with food production. Several studies suggest that maize grown specifically for biofuel has the potential to increase land grabbing, possibly resulting in direct or indirect land use change (Okoro et al. 2018). Maize is grown in temperate climates and regions with high amounts of annual precipitation. However, in recent times, new varieties of maize with shorter growing periods (early and extra early maturing) and varieties that can adapt to low precipitation and high temperatures have been developed, thereby improving yields and expanding the potential cropping area for maize cultivation. A clear benefit of this move towards more adaptable maize varieties according to Ben-Iwo et al. (2016), is that bioethanol from maize has the potential to reduce GHG emissions by 40%.

In common with many crops, climate change can significantly exacerbate the risk of crop failure in the future; based on projected temperature increases and erratic rainfall patterns. Therefore, sustainable management of maize production is important, in order to mitigate significant impacts on biofuel feedstock supply. In light of the challenges of climate change impact on yield productivity, it is also imperative to consider the impact of climate change on the potential environmental response of producing maize. Consequently, many studies have taken the direct and indirect contributors to GHG emissions from maize production systems in to account (e.g. He et al. 2018, Corbeels et al. 2018, Anderson et al. 2018, Jebari et al. 2018, Garba 2014 and Zhang et al. 2018). But even amongst these, few studies such as Ma et al. (2012), Jayasundara et al. (2014), Cheroennet and Suwanmanee (2017), and Nitschelm et al. (2018) have addressed the local effect of climate change on the carbon footprint of maize feedstock produced for biofuel.

Clearly, it is imperative that the impact of climate change on maize production is incorporated into its cultivation; consequently, this study set out to holistically determine the impact of climate change and farm technology on yield, and to evaluate the environmental response based on a life cycle assessment (LCA).

For the purposes of achieving the aforementioned aim, a generic framework (CSAF) was developed that integrated climate change projections and cropping system modelling coupled to life cycle assessment and linear regression analysis. The rationale for doing so was to improve the evaluation process, by considering the individual effects of climatic and agronomic factors on the environmental footprint of maize feedstock. This study has applied a linear regression to assess the relative influence of predictors on LCA outputs such as GHG emissions, net energy and carbon footprint linked to climate change.

To answer the first research question, site-specific downscaled climate scenarios were used to project future maize yield change. Based on climate projections under the representative concentration pathways (RCP) 6.0 and 8.5 future scenarios, the results show that average projected temperature will increase by 2.4 °C and 3.3 °C towards the year 2080 relative to a 2010 climate baseline. Likewise, rainfall will increase slightly (±0.3 to ±8 %) across the locations studied: Ibadan, Jos, Enugu and Ilorin. Hence, adequate adaptation measures will be required to overcome the effects of these climatic changes on crop yield.

Climate change will significantly affect yield by 2080, when compared to the results obtained for 2020 and 2050 under both RCP climate scenarios. The research found that yield response varied across locations and that Jos was the location that produced the highest yield under climate change. In contrast, yield declined significantly in Ibadan when compared to baseline yield. By estimating the impact of climate change using a crop model, the results gave an insight into yield response under fertiliser and tillage treatment combinations. Equally, the crop model made it possible to consider local factors in the life cycle inventory stage.

To answer the second and third research question, a quantitative farm life cycle assessment of maize production was conducted. The LCA and crop model outputs were regressed to estimate the effects of input factors and the correlation between input variables.

The evaluation of maize yield response to each input variable, using a linear regression approach provided much-needed evidence as to the factors that significantly affected yield response. Using the same approach on LCA outputs, this study contributes to creating an understanding of carbon footprint and net energy responses to predictors such as climate change scenarios, fertiliser and tillage methods.

The three contributing factors affecting the observed variation in yield, GHG, CF and NE are climate change, fertiliser and tillage method. These independent variables were statistically evaluated for significant effects and the regression model confirms the following:

1. Fertiliser had a dominant effect on all response variables at Jos, while climate change had a dominant effect on NE at Ibadan, Enugu and Ilorin; the effect of tillage was not significant on yield and NE at Jos, Ibadan and Ilorin and negatively correlated with GHG and CF across all sites. The statistical model did not show any interaction effect of tillage systems and climate change on yield. For example, tillage use in controlling weeds, incorporating residues into the soil, aerating the soil and further aiding crop growth, can influence soil temperature, moisture and length of growing season in response to climate change, which in turn, could lead to decline in yield.

2. From the linear regression model, it can be deduced that there are some effects of climate change on yield, but at slightly lower levels as compared to fertiliser. For

example, the combined effect of climate change scenarios (RCP 6.0 and 8.5) on yield at Ibadan, Enugu and Ilorin were 47%, 42% and 39% compared to 50%, 48% and 53% for fertiliser respectively. This shows that although fertiliser rate had more effect on yield, climate change is also responsible for a significant level of variance observed in yield.

3. The carbon footprint of maize production had a positive relationship with fertiliser, which infers that as fertiliser rate increases, the CF of maize will also increase. In addition, no relationship existed between GHG and climate change scenarios however; the effect of climate change on agricultural GHG emissions cannot be underestimated. This was discussed in depth in Chapter 5. For example, studies based on model predictions have shown that climate change is one of the factors controlling soil N_2O emissions, which is the dominant GHG from this study (Smith et al. 2013, Bessou et al. 2013, Uzoma et al. 2015, He et al. 2018). The direct impact of climate change on soil N_2O emissions was outside the scope of this study and therefore not considered. As a result, the linear model did not establish if a relationship between climate change and GHG emissions existed.

A major finding of this study is the confirmation that across the agro-ecological zones studied in Nigeria, fertiliser application rate is a more important factor than climate change as was observed by previous studies. Furthermore, this is the first known study to report other impact categories such as net energy and carbon footprint that also responded to climate change at these locations. This indicated that climate change and not tillage or fertiliser application is the causal driver for the increase in net energy and carbon footprint. In addition, it was observed from the regression analysis that fertiliser rate, and not climate change had more effect on maize yield, contrary to conclusions drawn from previous studies that name climate change as having an adverse effect on yield (Islam et al. 2012, Mereu et al. 2015, Ndawayo et al. 2017). These findings are presented with the exception of Enugu, where both fertiliser application and climate change impacted equally on yield

Overall, the findings of this study point to a possible risk in that future climate change will make maize less valuable as a potential biofuel feedstock in net energy terms and GHG emission terms across the agro-ecological zones in Nigeria. As a result, the carbon footprint of maize will increase, as more energy and fertiliser inputs are required to mitigate the impact of future climate change, and improve optimal yield response. However, the literature review found that policy makers tend not to consider the environmental impact of biofuel feedstock production; caused by climate change, when designing policies to promote large-scale farm production at local or regional level (Bessou et al. 2011, Duvenage 2013).

According to the FAO (2016), energy use efficiency, climate change and agriculture are intricately linked. Net energy is an important energy footprint indicator that relates the reliance of crop production to energy use; the intense usage of farm machinery for soil tillage and fertiliser application increases the use of energy. This further leads to increasing GHG emissions, which in turn, increases the carbon footprint per kg of crop produced under climate change. It is possible to improve yield and reduce C footprint of maize production through appropriate N application and efficient tillage operation; irrespective of the future climate scenario.

This study shows that moderate fertilisation application rate of 160 kg N ha^{-1} produced the most significant yield increase and a relatively lower GHG emissions and lower C footprint compared to higher fertiliser rates of 200 kg N ha^{-1} and 250 kg N ha^{-1}. Overall, total GHG emissions of maize production were highly correlated with the amount of N fertiliser; while the carbon footprint was more correlated with climate change and tillage system.

The application of a conservative no-tillage method (NT) has the potential to reduce GHG emission by 51% compared to the conventional method (CT). The best combination, which represents the effective use of farm resources was NT combined with 80 kg N ha^{-1}, although this treatment combination did not boost maize yield under future climate scenarios. As expected, NT technology and lower fertiliser rate of 80kg N ha^{-1} had the highest NE, the lowest emission intensity per kg of yield under both RCP 6.0 and RCP 8.5 climate scenarios. Locations with low yield produced a higher carbon footprint, however, boosting yield under climate change by increasing fertiliser input increased GHG emissions and further increased carbon the footprint of maize per kg of yield.

Although climate change impact can be mitigated through careful selection of farm management techniques, this study suggests that maize may not be a sustainable biofuel feedstock of choice for all locations studied, with the exception of Jos. Despite the huge potential for maize cultivation for biofuels, this may not be viable environmentally when climate change is factored in. Nonetheless, in order to ensure a successful strategic move towards a low carbon future, and sustainable implementation of biofuel policies, this study provides valuable information for the Nigerian government and policy makers on potential AEZs to cultivate maize under climate change. Further research on the carbon footprint of alternative feedstocks to assess their environmental carbon footprint and net energy is strongly suggested.

This study has presented evidence on the impact of climate change and farm technology on maize yield, and the environmental response of the farming system under climate change. Such detailed insight is required in order to promote climate-smart agricultural practices in Nigeria. Alternatively, based on the findings of this study, well-targeted adaptation measures to mitigate climate change impact on maize production and reduce the carbon footprint of maize, should be sought.

The integrated modelling framework adopted for this study is a structured procedure, incorporating multiple field-specific analytical methods and models, for specific applications and decision-making in a broad context. In terms of this study, however, it provides an improved approach for understanding the environmental response of energy crop to climate change.

6.2 Research limitations

Although the methodological approach and tools used were carefully considered, further reflection shows aspects of the study's limitations.

The geographical scope of the agricultural and LCA study was limited to specific agro-ecological zones in Nigeria and, therefore, representative of future sensitivity of the carbon footprint of maize production to local climate change projections and management scenarios; which in itself limits the application of the results to other regions. On the other hand, the integrated framework can be widely applied subject to availability of historical weather data, soil data and other farm management data.

The sustainability assessment of biofuel feedstock cultivation was assumed on existing cropland, hence, changes in emission intensity due to direct land transformation such as conversion of grasslands and tropical forest for energy crop production, under similar climate scenarios, was not included in this study. This is because, as suggested in many studies, land-use impact assessment has proven difficult to quantify and emission results tend to vary greatly

(Czyrnek-Delêtre et al. 2016). Hence, the environmental impacts and carbon intensity result can only be interpreted for arable land scenarios and are not representative of emissions from direct LUC in the maize GHG balance.

Furthermore, the Life Cycle Impact Assessment (LCIA) specifically focused on the global warming impact category, relating farm energy use and GHG emission intensity, in response to climate change agricultural management practices. However, agricultural activities are responsible for impacts on biodiversity, ecotoxicity, acidification and eutrophication of water bodies not categorised in this study. Therefore, including other non-GHG and energy related environmental impact factors such as acidification, eutrophication, human health, and toxicity, will present a complete picture of biofuel sustainability within a full-blown attributional LCA.

Finally, a general limitation of the LCA methodology is that it does not quantify other social sustainability concerns related to biofuel feedstock production. Nevertheless, a general consensus is emerging as the environmental and social sustainability of biofuels production are key factors for the development of biofuel support policies and, as such, it would be a valuable research topic to integrate within a LCA framework.

6.3 Recommendation for future research

The crop sustainability assessment framework (CSAF) is adaptable to other regions and can also be applied to other types of biofuel feedstock. What is now needed are similar studies that could be carried out to further support the conclusion drawn from this study; as well as other statistical methods such as the split sampling technique, in order to validate the regression model. The main advantage of the multi-model approach, using multiple linear regression, is that the main effect of each predictor on LCA responses can be specified. Further expansion of the regression model is encouraged to include evaluation of the interactive effect of multiple factors, to give a robust variable response.

Due to the intense farm management practice adopted, increasing fertiliser rates theoretically had varying effects on N_2O and CO_2 emissions and these were considered as the main contributing GHGs to global warming impact categories. According to Besson et al. (2013), LCA results are widely sensitive to changes in fertiliser inputs; specifically affecting impact categories such as acidification and eutrophication. Further research is needed to determine the impacts of local climatic changes and farm management strategies on the aforementioned impact categories. In addition, if resources are available (e.g. field flux measurement), future evaluation should seek to apply processed based models such as DNDC or DAYCENT (Smith et al. 2013, He et al. 2018); calibrated for each study location, to explore the impacts of climate change, and compared to the IPCC tier 1 methodology used in this study.

In order to extend this study, obtaining more information on long-term station-observed climate data and the downscaling of regional climate models (RCMs) that have been bias-corrected, instead of GCMs, would help to establish a greater degree of accuracy. The application of other emission pathways and different climate sensitivities, to cover a wide range of future possibilities; consideration of renewable energy use in the production of agrochemical to reduce CO_2 emissions, and use of biodiesel in farm machinery also to reduce CO_2 should also be considered.

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Appendices

Appendix A

Table A-1: Ensemble of CMIP5 GCMs available in DSSAT-Perturb tool for downscaling site-specific future climate projections as discussed in Chapter 3 (Source: Yin et al. 2013).

	Model	Country	Spatial resolution for atmospheric variable (longitude*latitude)	Spatial resolution for ocean variable (longitude*latitude)
1	ACCESS1.3	Australia	192*145	360*300
2	ACCESS1.0	Australia	192*145	360*300
3	BCC-CSM1-1	China	128*64	360*232
4	BCC-CSM1-1-m	China	320*160	360*232
5	BNU-ESM	China	128*64	
6	CanESM2	Canada	128*64	256*192
7	CCSM4	USA	288*192	320*384
8	CESM1-BGC	USA	288*192	320*384
9	CESM1-CAM5	USA	288*192	320*384
10	CMCC-CM	Italy	480*240	182*149
11	CMCC-CMS	Italy	192*96	182*149
12	CNRM-CM5	France	256*128	362*292
13	CSIRO-Mk3-6-0	Australia	192*96	192*189
14	EC-EARTH	Netherlands	320*160	362*292
15	FGOALS-g2	China	128*60	360*196
16	FGOALS-s2	China	128*108	360*196
17	GFDL-CM3	USA	144*90	360*200
18	GFDL-ESM2G	USA	144*90	360*210
19	GFDL-ESM2M	USA	144*90	360*200
20	GISS-E2-H	USA	144*90	144*90
21	GISS-E2-H-CC	USA	144*90	144*90
22	GISS-E2-R	USA	144*90	288*180

23	GISS-E2-R-CC	USA	144*90	288*180
24	HADCM3	UK	96*73	96*73
25	HadGEM2-AO	UK	192*145	360*216
26	HadGEM2-CC	UK	192*145	360*216
27	HadGEM2-ES	UK	192*145	360*216
28	INMCM4	Russia	180*120	360*340
29	IPSL-CM5A-LR	France	96*96	182*149
30	IPSL-CM5A-MR	France	144*142	182*149
31	IPSL-CM5B-LR	France	96*96	182*149
32	MIROC4H	Japan	640*320	1280*912
33	MIROC5	Japan	256*128	256*224
34	MIROC-ESM	Japan	128*64	256*192
35	MIROC-ESM-CHEM	Japan	128*64	256*192
36	MPI-ESM-LR	Germany	192*96	256*220
37	MPI-ESM-MR	Norway	192*96	802*404
38	MRI-CGCM3	Japan	320*160	360*368
39	NorESM1-M	Norway	144*96	320*384
40	NorESM1-ME	Norway	144*96	320*384

Appendix B.

Figure B-1: Screen shot of experiments created within the DSSAT v4.5 Cropping System Model (CSM) interface.

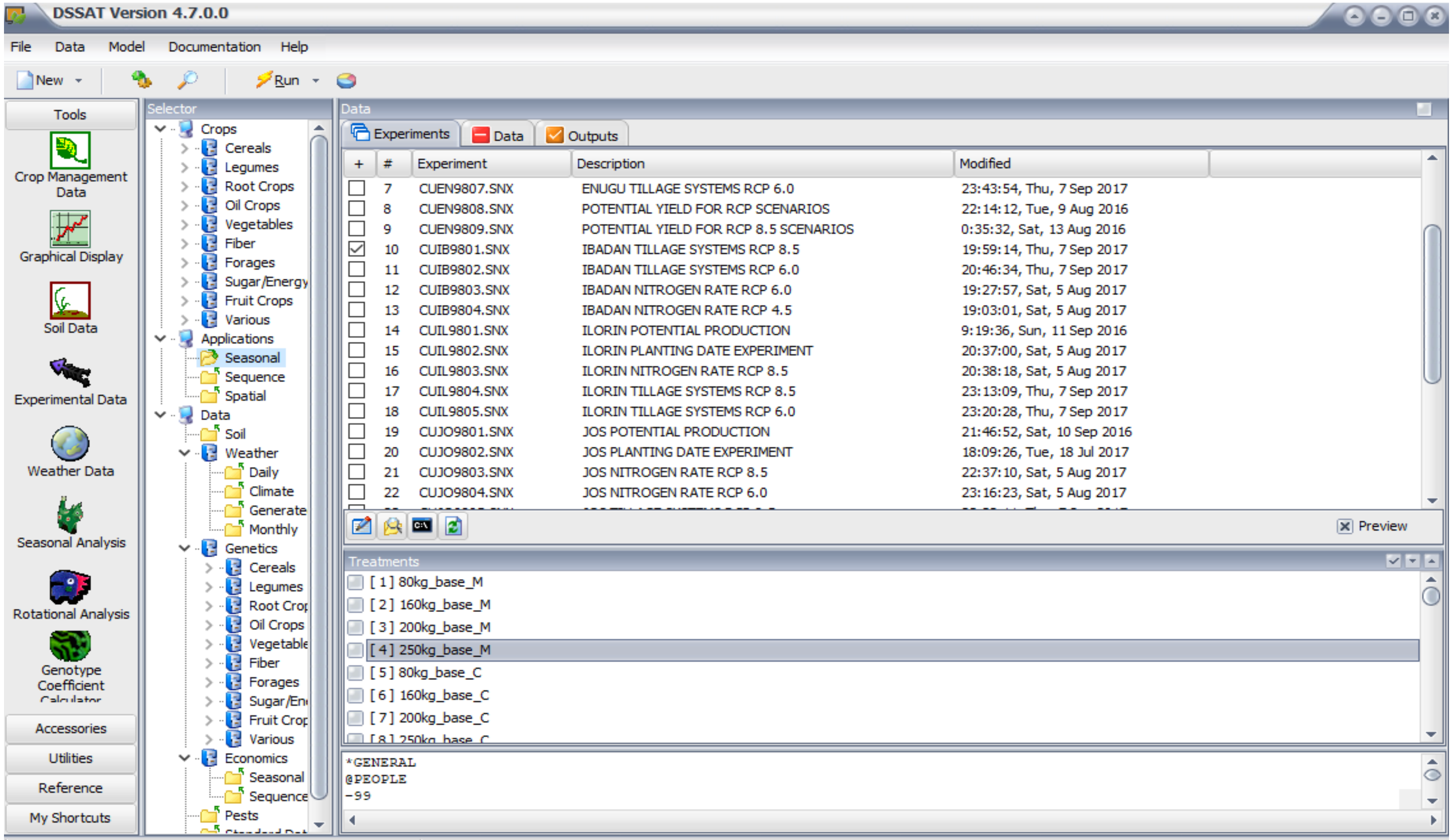
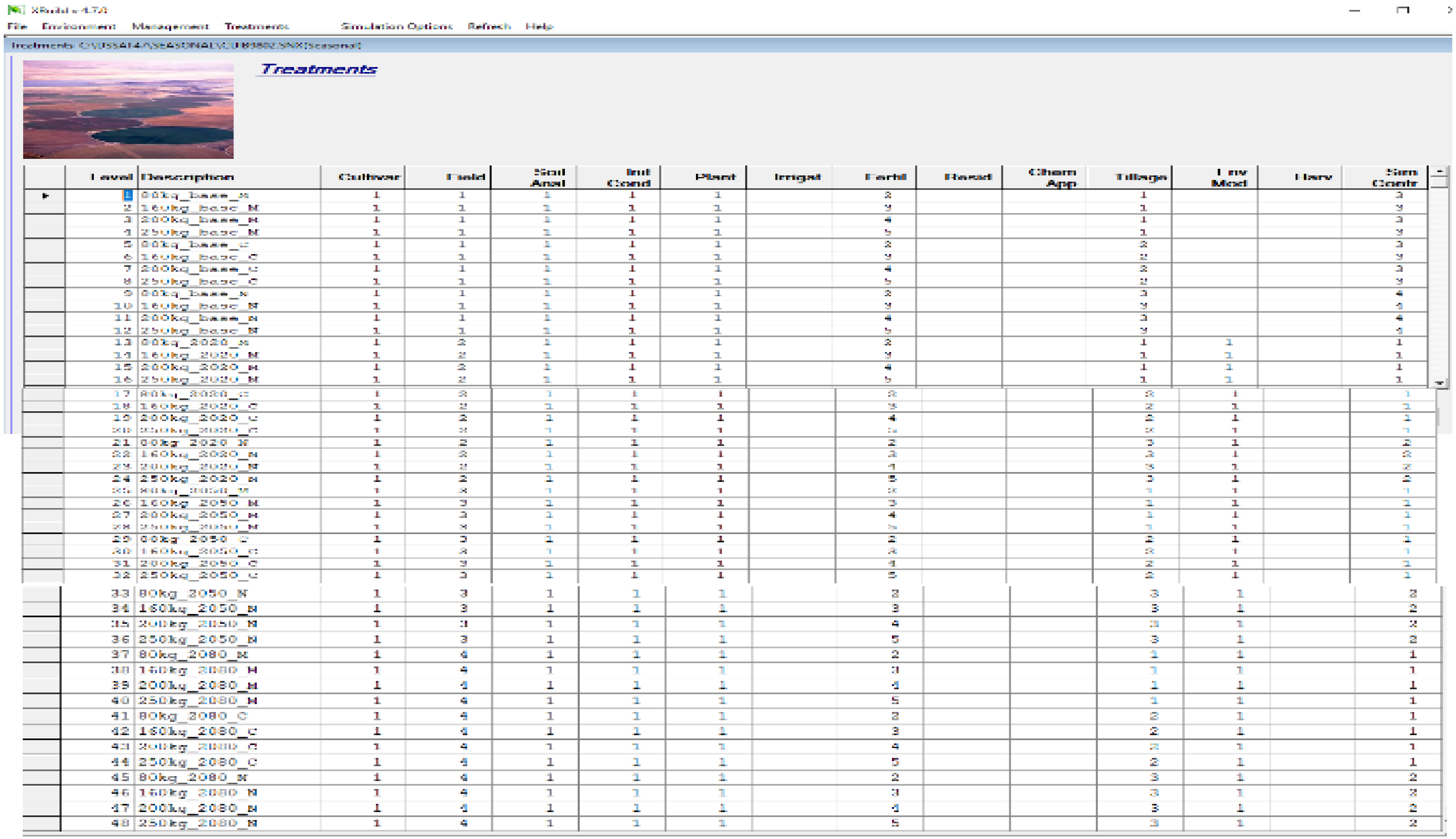


Figure B-2: Example of experimental treatments created within the DSSAT v4.5 X-build interface.



Level	Description	Cultivar	Field	Soil Anal	Init Cond	Plant	Irrigat	Fertil	Resid	Chem App	Tillage	Env Mod	Harv	Sim Contr
1	80kg_base_N	1	1	1	1	1		2			1			3
2	160kg_base_N	1	1	1	1	1		3			1			3
3	200kg_base_N	1	1	1	1	1		4			1			3
4	250kg_base_N	1	1	1	1	1		5			1			3
5	80kg_base_C	1	1	1	1	1		2			2			3
6	160kg_base_C	1	1	1	1	1		3			2			3
7	200kg_base_C	1	1	1	1	1		4			2			3
8	250kg_base_C	1	1	1	1	1		5			2			3
9	80kg_base_N	1	1	1	1	1		2			3			4
10	160kg_base_N	1	1	1	1	1		3			3			4
11	200kg_base_N	1	1	1	1	1		4			3			4
12	250kg_base_N	1	1	1	1	1		5			3			4
13	80kg_2020_N	1	2	1	1	1		2			1	1		1
14	160kg_2020_N	1	2	1	1	1		3			1	1		1
15	200kg_2020_N	1	2	1	1	1		4			1	1		1
16	250kg_2020_N	1	2	1	1	1		5			1	1		1
17	80kg_2020_C	1	2	1	1	1		2			2	1		1
18	160kg_2020_C	1	2	1	1	1		3			2	1		1
19	200kg_2020_C	1	2	1	1	1		4			2	1		1
20	250kg_2020_C	1	2	1	1	1		5			2	1		1
21	80kg_2020_N	1	2	1	1	1		2			3	1		2
22	160kg_2020_N	1	2	1	1	1		3			3	1		2
23	200kg_2020_N	1	2	1	1	1		4			3	1		2
24	250kg_2020_N	1	2	1	1	1		5			3	1		2
25	80kg_2050_N	1	3	1	1	1		2			1	1		1
26	160kg_2050_N	1	3	1	1	1		3			1	1		1
27	200kg_2050_N	1	3	1	1	1		4			1	1		1
28	250kg_2050_N	1	3	1	1	1		5			1	1		1
29	80kg_2050_C	1	3	1	1	1		2			2	1		1
30	160kg_2050_C	1	3	1	1	1		3			2	1		1
31	200kg_2050_C	1	3	1	1	1		4			2	1		1
32	250kg_2050_C	1	3	1	1	1		5			2	1		1
33	80kg_2050_N	1	3	1	1	1		2			3	1		2
34	160kg_2050_N	1	3	1	1	1		3			3	1		2
35	200kg_2050_N	1	3	1	1	1		4			3	1		2
36	250kg_2050_N	1	3	1	1	1		5			3	1		2
37	80kg_2080_N	1	4	1	1	1		2			1	1		1
38	160kg_2080_N	1	4	1	1	1		3			1	1		1
39	200kg_2080_N	1	4	1	1	1		4			1	1		1
40	250kg_2080_N	1	4	1	1	1		5			1	1		1
41	80kg_2080_C	1	4	1	1	1		2			2	1		1
42	160kg_2080_C	1	4	1	1	1		3			2	1		1
43	200kg_2080_C	1	4	1	1	1		4			2	1		1
44	250kg_2080_C	1	4	1	1	1		5			2	1		1
45	80kg_2080_N	1	4	1	1	1		2			3	1		2
46	160kg_2080_N	1	4	1	1	1		3			3	1		2
47	200kg_2080_N	1	4	1	1	1		4			3	1		2
48	250kg_2080_N	1	4	1	1	1		5			3	1		2

Appendix C

Figure C-1: Soil profiles created in DSSAT for Ibadan

... Editing soil profile : IBCU950001 ...

General Information

Country	Nigeria	Soil Data Source	IITA
Site Name	Ibadan	Soil Series Name	NG 18 - Egbeda
Institute Code	IB	Soil Classification	Udic Kanhaplustalf
Latitude	-99		
Longitude	-99		

Surface Information

Color	Red	% Slope	3
Drainage	Well	Runoff Potential	Moderately High
		Fertility Factor (0 to 1)	1

... Editing soil profile : IBCU950001 ...

Input Table

Depth (bottom), cm	Master horizon	Clay, %	Silt, %	Stones, %	Organic carbon, %	pH in water	Cation exchange capacity, cmol/kg	Total nitrogen, %
15	-99	19	12	-99	1.42	6.4	-99	0.16
40	-99	26	11	-99	0.35	6.4	-99	0.05
70	-99	47	12	-99	0.27	6.5	-99	0.04
100	-99	52	18	-99	0.16	6.1	-99	0.02
130	-99	50	20	-99	0.12	6	-99	0.02
155	-99	52	22	-99	0.14	6.1	-99	0.02
180	-99	44	21	-99	0.15	6.1	-99	0.02
280	-99	36	22	-99	0.17	6	-99	0.03
400	-99	29	25	-99	0.09	5.2	-99	0.01

... Editing soil profile : IBCU950001 ...

Calculate/Edit Soil Parameters

Surface Parameters

Runoff Curve Number	Albedo	Drainage Rate
84	0.14	0.6

Depth (bottom), cm	Clay, %	Silt, %	Stones, %	Lower limit	Drained Upper limit	Saturated Water Content	Bulk density, g/cm3	Sat. hydraulic conduct, cm/h	Root growth factor, 0.0 to 1.0
15	19	12	-99	0.16	0.261	0.433	1.41	2.59	1
40	26	11	-99	0.166	0.243	0.384	1.57	0.43	0.577
70	47	12	-99	0.268	0.359	0.41	1.5	0.06	0.333
100	52	18	-99	0.29	0.393	0.443	1.41	0.06	0.183
130	50	20	-99	0.275	0.384	0.44	1.42	0.06	0.1
155	52	22	-99	0.25	0.4	0.447	1.4	0.06	0.058
180	44	21	-99	0.25	0.354	0.425	1.46	0.06	0.035
280	36	22	-99	0.211	0.312	0.407	1.51	0.23	0.01
400	29	25	-99	0.173	0.275	0.401	1.53	0.43	0.001

Appendix D

Figure D-1: Soil profile for Jos

... Editing a soil profile : JOCU950001 ...

General Information

Country	Nigeria	Soil Data Source	-99
Site Name	JOS	Soil Series Name	JOS basaltic sandy clay loam
Institute Code	JO	Soil Classification	Inceptic Haplustalfs
Latitude	-99		
Longitude	-99		

Surface Information

Color	Brown	% Slope	1
Drainage	Well	Runoff Potential	Moderately Low

... Editing a soil profile : JOCU950001 ...

Input Table

Depth (bottom), cm	Master horizon	Clay, %	Silt, %	Stones, %	Organic carbon, %	pH in water	Cation exchange capacity, cmol/kg	Total nitrogen, %
20	-99	32	20	-99	3.07	5.6	22.1	0.13
42	-99	36	20	-99	2.19	5.4	20	0.08
69	-99	36	22	-99	0.44	5.4	8.9	0.05
82	-99	44	22	-99	0.3	5	9.2	0.03
107	-99	48	26	-99	0.14	5.1	12.3	0.03

... Editing a soil profile : JOCU950001 ...

Calculate/Edit Soil Parameters

Surface Parameters

Runoff Curve Number	73	Albedo	0.13	Drainage Rate	0.6

Depth (bottom), cm	Clay, %	Silt, %	Stones, %	Lower limit	Drained Upper limit	Saturated Water Content	Bulk density, g/cm3	Sat. hydraulic conduct, cm/h	Root growth factor, 0.0 to 1.0
20	32	20	-99	0.27	0.435	0.556	1.05	0.43	1
42	36	20	-99	0.266	0.412	0.602	0.94	0.23	0.538
69	36	22	-99	0.218	0.326	0.6	0.97	0.23	0.33
82	44	22	-99	0.254	0.363	0.604	0.96	0.06	0.221
107	48	26	-99	0.27	0.386	0.605	0.96	0.06	0.151

Appendix E

Figure E-1: Soil profile for Enugu

... Editing a soil profile : ENCU950001 ...

General Information

Country	Nigeria	Soil Data Source	-99
Site Name	Enugu	Soil Series Name	Enugu soil
Institute Code	EN	Soil Classification	Typic Paleustult
Latitude	-99		
Longitude	-99		

Surface Information

Color	Brown	% Slope	1
Drainage	Well	Runoff Potential	Lowest
		Fertility Factor (0 to 1)	1

... Editing soil profile : EBPI080100 ...

Input Table

Depth (bottom), cm	Master horizon	Clay, %	Silt, %	Stones, %	Organic carbon, %	pH in water	Cation exchange capacity, cmol/kg	Total nitrogen, %
15	-99	20.9	17	0	0.65	4.9	6.4	0.05
30	-99	26.2	22	0	0.54	5.1	3.7	0.1
55	-99	32.7	22	0	1.1	5	3.7	0.04
90	-99	34.8	20	0	0.3	5.8	2.3	0.11
115	-99	39.4	22	0	0.7	5.4	2.7	0.06
140	-99	43.5	20	0	0.4	5.5	2.8	0.12
180	-99	48.9	20	0	0.4	4.6	2.8	0.01

... Editing soil profile : EBPI080100 ...

Calculate/Edit Soil Parameters

Surface Parameters

Runoff Curve Number: 70 Albedo: 0.14 Drainage Rate: 0.2

Depth (bottom), cm	Clay, %	Silt, %	Stones, %	Lower limit	Drained Upper limit	Saturated Water Content	Bulk density, g/cm3	Sat. hydraulic conduct, cm/h	Root growth factor, 0.0 to 1.0
15	20.9	17	0	0.242	0.366	0.48	1.37	0.38	1
30	26.2	22	0	0.242	0.366	0.48	1.37	0.38	1
55	32.7	22	0	0.242	0.366	0.48	1.37	0.38	0.87
90	34.8	20	0	0.24	0.34	0.49	1.13	0.4	0.55
115	39.4	22	0	0.242	0.366	0.48	1.35	0.4	0.79
140	43.5	20	0	0.24	0.34	0.48	1.15	0.4	0.7
180	48.9	20	0	0.24	0.34	0.49	1.15	0.4	0.62

Appendix F

Figure F-1: Soil profile for Ilorin

... Editing a soil profile : ILCU950001 ...

General Information

Country	Nigeria	Soil Data Source	-99
Site Name	Ilorin	Soil Series Name	Feralsols and Hydromorphic soils
Institute Code	IL	Soil Classification	OXISOLS
Latitude	-99		
Longitude	99		

Surface Information

Color	Brown	% Slope	12
Drainage	Well	Runoff Potential	Moderately Low
		Fertility Factor (0 to 1)	1

... Editing soil profile : ILCU950001 ...

Input Table

Depth (bottom), cm	Master horizon	Clay, %	Silt, %	Stones, %	Organic carbon, %	pH in water	Cation exchange capacity, cmol/kg	Total nitrogen, %
5	-99	6	6	2.1	0.2	6.8	1.6	1.7
10	-99	7.8	8	3.2	0.27	6.8	7	1.9
15	-99	7.5	4	1	0.14	6.8	1.6	0.21
20	-99	7.5	7.4	6.5	0.24	6	1.4	2.2
25	-99	9.8	8	13.7	0.1	6.4	1.8	1.2
30	-99	11.8	8	17.2	0.34	6.6	1.5	1.9
35	-99	13.9	6	10.3	1.07	7.1	2.1	2.2

... Editing soil profile : ILCU950001 ...

Calculate/Edit Soil Parameters

Surface Parameters

Runoff Curve Number	81	Albedo	0.13	Drainage Rate	0.6

Depth (bottom), cm	Clay, %	Silt, %	Stones, %	Lower limit	Drained Upper limit	Saturated Water Content	Bulk density, g/cm3	Sat. hydraulic conduct, cm/h	Root growth factor, 0.0 to 1.0
5	6	6	2.1	0.078	0.161	0.391	1.55	6.11	1
10	7.8	8	3.2	0.075	0.155	0.387	1.56	6.11	1
15	7.5	4	1	0.074	0.157	0.395	1.54	6.11	1
20	7.5	7.4	6.5	0.073	0.153	0.387	1.56	6.11	1
25	9.8	8	13.7	-99	-99	-99	-99	-99	-99
30	11.8	8	17.2	-99	-99	-99	-99	-99	-99
35	13.9	6	10.3	-99	-99	-99	-99	-99	-99

Appendix G

Jos

Table G-1: The probability distributions of daily precipitation, maximum and minimum temperature and radiation for each month are compared using K-S test

		daily **RAIN** distributions			daily **MIN** distributions			daily **MAX** distributions			daily **RAD** distributions	
	Effective N	K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value
J		No precipitation			0.106	0.999		0.138	0.971		0.087	1.000
F	12	0.218	0.590		0.158	0.913		0.21	0.637		0.392	0.042
M	12	0.224	0.554		0.106	0.999		0.211	0.631		0.087	1.000
A	12	0.064	1.000		0.316	0.163		0.106	0.999		0.044	1.000
M	12	0.054	1.000		0.106	0.999		0.105	0.999		0.261	0.359
J	12	0.03	1.000		0.105	0.999		0.106	0.999		0.218	0.590
J	12	0.074	1.000		0.106	0.999		0.106	0.999		0.261	0.359
A	12	0.054	1.000		0.053	1.000		0.158	0.913		0.392	0.042
S	12	0.062	1.000		0.106	0.999		0.158	0.913		0.087	1.000
O	12	0.06	1.000		0.106	0.999		0.106	0.999		0.174	0.842
N	12	0.565	0.001		0.105	0.999		0.158	0.913		0.174	0.842
D	12	0	1.000		0.158	0.913		0.105	0.999		0.218	0.590

Ilorin

Table G-2: The probability distributions of daily precipitation, maximum and minimum temperature and radiation for each month are compared using K-S test.

		daily **RAIN** distributions			daily **MIN** distributions			daily **MAX** distributions			daily **RAD** distributions	
	Effective N	K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value
J	12	0.174	0.842		0.105	0.999		0.105	0.999		0.087	1.000
F	12	0.131	0.982		0.210	0.637		0.263	0.350		0.392	0.042
M	12	0.120	0.994		0.211	0.631		0.158	0.913		0.348	0.096
A	12	0.061	1.000		0.106	0.999		0.158	0.913		0.044	1.000
M	12	0.045	1.000		0.106	0.999		0.158	0.913		0.392	0.042
J	12	0.057	1.000		0.106	0.999		0.210	0.637		0.261	0.359
J	12	0.009	1.000		0.210	0.637		0.106	0.999		0.174	0.842
A	12	0.065	1.000		0.158	0.913		0.106	0.999		0.305	0.193
S	12	0.056	1.000		0.316	0.163		0.158	0.913		0.218	0.590
O	12	0.063	1.000		0.211	0.631		0.158	0.913		0.087	1.000
N	12	0.174	0.842		0.263	0.350		0.369	0.066		0.087	1.000
D	12	0.174	0.842		0.158	0.913		0.106	0.999		0.087	1.000

Ibadan

Table G-3: The probability distributions of daily precipitation, maximum and minimum temperature and radiation for each month are compared using K-S test.

		daily **RAIN** distributions		daily **MIN** distributions		daily **MAX** distributions		daily **RAD** distributions	
	Effective N	K-S statistic	p-value	K-S statistic	p-value	K-S statistic	p-value	K-S statistic	p-value
J	12	0.305	0.193	0.158	0.913	0.106	0.999	0.087	1.000
F	12	0.139	0.969	0.316	0.163	0.106	0.999	0.044	1.000
M	12	0.119	0.994	0.158	0.913	0.263	0.350	0.131	0.982
A	12	0.064	1.000	0.105	0.999	0.158	0.913	0.044	1.000
M	12	0.062	1.000	0.106	0.999	0.158	0.913	0.044	1.000
J	12	0.061	1.000	0.106	0.999	0.158	0.913	0.044	1.000
J	12	0.090	1.000	0.158	0.913	0.158	0.913	0.044	1.000
A	12	0.112	0.998	0.106	0.999	0.106	0.999	0.044	1.000
S	12	0.058	1.000	0.211	0.631	0.210	0.637	0.087	1.000
O	12	0.078	1.000	0.158	0.913	0.106	0.999	0.087	1.000
N	12	0.063	1.000	0.158	0.913	0.158	0.913	0.044	1.000
D	12	0.217	0.595	0.106	0.999	0.105	0.999	0.131	0.982

Enugu

Table G-4: The probability distributions of daily precipitation, maximum and minimum temperature and radiation for each month are compared using K-S test.

		daily **RAIN** distributions			daily **MIN** distributions			daily **MAX** distributions			daily **RAD** distributions	
	Effective N	K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value		K-S statistic	p-value
J	12	0.131	0.982		0.158	0.913		0.158	0.913		0.087	1.000
F	12	0.143	0.960		0.211	0.631		0.211	0.631		0.087	1.000
M	12	0.132	0.981		0.105	0.999		0.210	0.637		0.044	1.000
A	12	0.053	1.000		0.105	0.999		0.158	0.913		0.044	1.000
M	12	0.058	1.000		0.158	0.913		0.210	0.637		0.087	1.000
J	12	0.103	0.999		0.158	0.913		0.158	0.913		0.087	1.000
J	12	0.054	1.000		0.158	0.913		0.106	0.999		0.087	1.000
A	12	0.059	1.000		0.158	0.913		0.158	0.913		0.044	1.000
S	12	0.043	1.000		0.158	0.913		0.106	0.999		0.087	1.000
O	12	0.067	1.000		0.315	0.165		0.263	0.350		0.131	0.982
N	12	0.219	0.584		0.210	0.637		0.158	0.913		0.131	0.982
D	12	0.435	0.017		0.211	0.631		0.106	0.999		0.174	0.842

Appendix H

Table H-1: Results of the statistical test (at $p = 0.05$) showing the comparison of observed and simulated monthly means and variances for rainfall (mm), minimum and maximum temperature (°C) and solar radiation (MJ/m^2). Obs, Observed; Gen, Generated.

Jos	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rain - Monthly Mean												
Obs mean	0.00	3.6	10.61	114.84	199.11	202.22	229.43	224.63	163.75	58.23	0.17	0.52
Obs variance	0.000	9.426	23.902	77.364	68.055	72.979	106.062	92.729	83.663	57.942	0.502	1.819
Gen mean	0.00	7.25	13.49	99.47	214.66	188.16	201.74	245.59	189.49	58.32	0.32	1.05
Gen Variance	0.000	12.349	21.617	84.607	71.794	58.674	60.675	70.784	35.065	44.99	0.717	2.388
t-test	0.000	-1.006	-0.406	0.59	-0.696	0.698	1.117	-0.843	-1.46	-0.006	-0.688	-0.684
p-value	1.000	0.32	0.686	0.558	0.49	0.489	0.27	0.404	0.152	0.995	0.496	0.498
f-test	1.000	1.716	1.223	1.196	1.113	1.547	3.056	1.716	5.693	1.659	2.04	1.723
p-value	1.000	0.287	0.624	0.744	0.862	0.312	0.011	0.214	0.000	0.243	0.192	0.342
Tmin - Monthly Mean												
Obs mean	11.46	14.35	16.46	18.61	18.4	17.36	15.62	15.59	16.47	15.65	13.07	11.33
Obs variance	1.562	1.816	1.105	0.529	0.452	0.442	4.935	4.688	1.178	1.753	1.005	0.69
Gen mean	11.5	14.12	16.62	18.42	18.5	17.34	16.02	16.9	16.79	15.69	12.93	11.64
Gen Variance	0.517	0.318	0.417	0.243	0.208	0.379	0.7	0.204	0.2	0.392	0.318	0.322
t-test	-0.117	0.671	-0.66	1.675	-0.956	0.179	-0.44	-1.552	-1.476	-0.105	0.677	-1.926
p-value	0.907	0.506	0.513	0.102	0.345	0.859	0.662	0.128	0.148	0.917	0.502	0.061
Tmax - Monthly Mean												
Obs mean	28.32	30.84	31.92	30.76	28.13	26.25	24.95	24.88	26.34	27.6	28.13	28.09
Obs variance	1.088	1.415	0.724	1.634	1.161	0.647	1.227	1.663	0.942	0.855	0.568	0.55
Gen mean	28.35	30.61	31.85	31.06	28.24	26.32	25	24.7	26.09	27.58	28.17	28.32
Gen Variance	0.499	0.353	0.307	0.701	0.429	0.464	0.429	0.431	0.377	0.234	0.217	0.314
t-test	-0.119	0.84	0.464	-0.86	-0.455	-0.429	-0.182	0.553	1.259	0.115	-0.345	-1.675
p-value	0.906	0.405	0.645	0.395	0.651	0.67	0.857	0.583	0.215	0.909	0.731	0.102
SRAD - Monthly Mean												
Obs mean	20.41	17.1	17.21	14.83	15.13	12.62	10.45	9.67	15.95	17.6	21.73	19.99
Obs variance	16.181	16.621	14.672	12.689	11.18	10.894	9.339	8.914	11.04	14.238	17.824	17.662
Gen mean	21.05	18.13	16.7	16.49	15.5	12.72	9.65	9.83	14.61	19.59	20.87	19.84
Gen Variance	3.448	3.647	2.275	2.461	2.513	2.644	2.365	2.171	2.955	3.522	3.131	3.17
t-test	-0.211	-0.327	0.189	-0.698	-0.173	-0.048	0.448	-0.096	0.625	-0.729	0.258	0.045
p-value	0.834	0.745	0.851	0.489	0.864	0.962	0.657	0.924	0.535	0.47	0.798	0.964

Table H-2: Results of the statistical test (at $p = 0.05$) showing the comparison of observed and simulated monthly means and variances for rainfall (mm), minimum and maximum temperature (°C) and solar radiation (MJ/m^2). Obs, Observed; Gen, Generated

Ilorin	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rain - Monthly Mean												
Obs mean	3.72	4.75	32.95	95.76	148.13	217.09	167.91	160.86	253.89	136.72	6.99	3.29
Obs variance	9.193	7.479	20.668	46.973	77.413	85.348	83.638	80.292	67.754	85.225	12.329	7.021
Gen mean	2.78	6.27	38.04	74.83	148.58	225.63	199.53	195.62	249.93	170.92	9.26	3.14
Gen Variance	7.985	10.884	23.449	49.745	80.185	80.890	106.734	83.966	84.131	97.270	18.178	6.538
t-test	0.353	-0.483	-0.713	1.322	-0.017	-0.320	-0.975	-1.296	0.154	-1.128	-0.424	0.068
p-value	0.726	0.631	0.480	0.193	0.986	0.750	0.335	0.202	0.878	0.266	0.674	0.946
f-test	1.325	2.118	1.287	1.122	1.073	1.113	1.629	1.094	1.542	1.303	2.174	1.153
p-value	0.504	0.140	0.632	0.859	0.931	0.775	0.355	0.900	0.413	0.629	0.140	0.719
Tmin - Monthly Mean												
Obs mean	19.81	22.59	23.83	23.79	23.07	22.12	21.86	21.33	21.31	21.48	21.19	19.27
Obs variance	1.527	1.421	0.62	0.56	0.384	0.467	0.254	0.949	1.072	0.677	1.161	1.522
Gen mean	20.01	22.24	23.58	23.84	23.12	22.26	21.9	21.39	21.4	21.53	21.1	19.25
Gen Variance	0.699	0.517	0.391	0.169	0.284	0.204	0.182	0.25	0.258	0.395	0.443	0.64
t-test	-0.609	1.22	1.688	-0.459	-0.457	-1.371	-0.454	-0.365	-0.458	-0.315	0.399	0.064
p-value	0.546	0.229	0.099	0.649	0.65	0.178	0.652	0.717	0.649	0.754	0.692	0.949
Tmax - Monthly Mean												
Obs mean	34.06	36.16	36.51	34.56	32.73	30.88	29.37	28.63	29.81	31.71	34.19	34.46
Obs variance	0.781	0.695	0.756	0.843	0.893	0.569	0.44	0.506	0.36	1.21	0.693	0.471
Gen mean	34.15	35.87	36.29	34.57	32.62	30.92	29.45	28.81	29.67	31.52	34.03	34.52
Gen Variance	0.316	0.314	0.317	0.365	0.363	0.292	0.28	0.304	0.251	0.331	0.242	0.267
t-test	-0.554	1.92	1.326	-0.06	0.538	-0.298	-0.773	-1.503	1.41	0.82	1.116	-0.514
p-value	0.583	0.062	0.192	0.953	0.594	0.767	0.444	0.14	0.166	0.417	0.271	0.610
SRAD - Monthly Mean												
Obs mean	11.00	11.98	11.27	11.10	11.07	9.65	7.47	6.77	8.62	9.59	14.47	15.96
Obs variance	12.716	13.407	12.645	13.336	13.275	11.585	9.012	7.564	9.02	11.612	15.045	15.438
Gen mean	10.02	11.53	11.2	11.43	11.11	9.33	8.18	6.58	8.62	8.65	13.75	16.04
Gen Variance	2.923	2.871	2.136	2.537	1.726	3.047	2.306	1.733	2.037	2.54	2.65	2.891
t-test	0.402	0.174	0.031	-0.133	-0.018	0.141	-0.409	0.137	-0.002	0.43	0.255	-0.026
p-value	0.69	0.863	0.975	0.895	0.986	0.888	0.685	0.892	0.999	0.669	0.8	0.979

Table H-3: Results of the statistical test (at $p = 0.05$) showing the comparison of observed and simulated monthly means and variances for rainfall (mm), minimum and maximum temperature (°C) and solar radiation (MJ/m^2). Obs, Observed; Gen, Generated

Ibadan	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rain - Monthly Mean												
Obs mean	6.41	36.12	76.51	110.50	164.28	201.87	195.31	165.91	242.69	162.05	27.90	3.38
Obs variance	10.767	41.237	37.255	46.121	40.980	89.704	88.402	96.735	74.640	78.637	40.344	6.332
Gen mean	12.43	33.33	61.71	108.82	177.54	180.02	195.69	168.31	267.10	155.78	35.10	4.01
Gen Variance	13.096	39.500	49.031	53.290	67.466	62.875	87.216	81.682	114.150	87.354	36.719	7.275
t-test	-1.498	0.215	1.001	0.102	-0.677	0.934	-0.013	-0.086	-0.728	0.228	-0.588	-0.253
p-value	0.142	0.831	0.323	0.920	0.502	0.356	0.989	0.932	0.470	0.820	0.560	0.802
f-test	1.479	1.090	1.732	1.335	2.710	2.035	1.027	1.403	2.339	1.234	1.207	1.320
p-value	0.461	0.809	0.296	0.594	0.061	0.109	0.907	0.434	0.108	0.709	0.646	0.667
Tmin - Monthly Mean												
Obs mean	22.48	23.98	24.41	23.95	23.31	22.65	22.22	21.85	22.17	22.59	23.4	23.11
Obs variance	1.005	0.915	0.57	0.667	0.354	0.399	0.373	0.316	0.29	0.361	0.566	0.844
Gen mean	22.19	23.87	24.31	24.18	23.42	22.72	22.25	21.87	22.21	22.57	23.35	23.25
Gen Variance	0.451	0.388	0.239	0.276	0.248	0.232	0.166	0.132	0.147	0.239	0.229	0.433
t-test	1.322	0.579	0.809	-1.629	-1.181	-0.715	-0.31	-0.239	-0.687	0.263	0.437	-0.66
p-value	0.193	0.565	0.423	0.111	0.244	0.479	0.758	0.813	0.496	0.794	0.665	0.513
Tmax - Monthly Mean												
Obs mean	33.51	35.21	35.04	33.37	31.91	30.28	28.7	28.14	29.46	30.99	32.9	33.45
Obs variance	0.395	0.686	1.014	0.919	0.709	0.69	0.34	0.625	0.509	0.65	0.43	0.429
Gen mean	33.46	35.22	34.77	33.55	31.98	30.4	28.73	28.1	29.42	31.11	32.83	33.43
Gen Variance	0.245	0.258	0.299	0.33	0.303	0.331	0.353	0.331	0.29	0.201	0.19	0.184
t-test	0.495	-0.021	1.338	-0.937	-0.462	-0.798	-0.266	0.314	0.349	-0.993	0.744	0.2
p-value	0.623	0.983	0.188	0.354	0.646	0.429	0.792	0.755	0.729	0.326	0.461	0.842
SRAD - Monthly Mean												
Obs mean	19.59	21.53	19.64	21.67	20.81	16.55	11.25	8	13.28	18.63	26.25	23.83
Obs variance	2.291	2.848	4.53	2.996	2.839	4.22	2.17	2.094	2.505	3.114	2.368	2.126
Gen mean	21.11	22.54	18.85	22.42	20.47	17.15	10.88	8.64	12.91	17.15	26.27	22.92
Gen Variance	1.218	1.61	1.49	1.718	1.447	1.671	1.183	1.086	1.624	1.981	0.983	1.601
t-test	-2.474	-1.286	0.815	-0.9	0.476	-0.637	0.663	-1.233	0.519	1.708	-0.022	1.273
p-value	0.018	0.207	0.42	0.374	0.637	0.528	0.512	0.226	0.607	0.096	0.983	0.211

Table H-4: Results of the statistical test (at $p = 0.05$) showing the comparison of observed and simulated monthly means and variances for rainfall (mm), minimum and maximum temperature (°C) and solar radiation (MJ/m^2). Obs, Observed; Gen, Generated

Enugu	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rain - Monthly Mean												
Obs mean	12.37	14.05	46.97	147.71	279.00	262.09	246.61	234.78	306.12	193.44	12.58	4.74
Obs variance	18.996	16.481	46.645	61.213	92.918	61.090	100.609	99.260	68.904	105.047	18.682	11.012
Gen mean	12.16	15.86	39.31	132.20	300.51	242.71	269.89	234.90	307.74	230.66	16.91	8.49
Gen Variance	15.885	22.962	38.170	95.554	102.190	84.463	88.897	78.877	93.641	87.984	25.589	10.761
t-test	0.040	-0.273	0.589	0.571	-0.685	0.790	-0.793	-0.004	-0.058	-1.228	-0.565	-0.981
p-value	0.969	0.787	0.559	0.571	0.497	0.434	0.432	0.997	0.954	0.226	0.575	0.333
f-test	1.430	1.941	1.493	2.437	1.210	1.912	1.281	1.584	1.847	1.425	1.876	1.047
p-value	0.403	0.191	0.351	0.081	0.727	0.201	0.554	0.295	0.243	0.414	0.231	0.863
Tmin - Monthly Mean												
Obs mean	21.83	23.94	24.71	23.86	23.16	22.67	22.66	22.61	22.51	22.42	21.58	19.68
Obs variance	2.03	1.709	0.718	1.069	0.947	0.651	0.65	0.57	0.547	1.104	1.717	2.226
Gen mean	21.41	23.35	24.65	24.07	23.12	22.72	22.82	22.6	22.5	22.53	21.75	19.83
Gen Variance	0.658	0.595	0.365	0.343	0.365	0.225	0.166	0.176	0.253	0.29	0.608	0.78
t-test	0.989	1.619	0.306	-0.971	0.173	-0.378	-1.237	0.042	0.057	-0.483	-0.434	-0.274
p-value	0.329	0.114	0.761	0.338	0.863	0.708	0.224	0.967	0.955	0.632	0.667	0.786
Tmax - Monthly Mean												
Obs mean	34.29	35.33	35.63	33.46	31.95	30.73	30.05	29.79	30.36	31.76	33.73	34.00
Obs variance	0.74	0.982	0.675	0.83	1.009	0.721	0.331	0.553	0.439	1.266	0.494	0.644
Gen mean	34.2	35.1	35.6	33.73	31.83	30.85	30.09	29.81	30.39	31.54	33.86	33.73
Gen Variance	0.241	0.326	0.27	0.281	0.388	0.284	0.302	0.249	0.312	0.377	0.209	0.264
t-test	0.576	1.172	0.222	-1.58	0.582	-0.828	-0.33	-0.15	-0.269	0.866	-1.216	1.819
p-value	0.568	0.248	0.825	0.122	0.564	0.412	0.743	0.881	0.789	0.392	0.232	0.078
SRAD - Monthly Mean												
Obs mean	24.25	21.53	20.73	22.78	20.08	17.49	14.42	11.01	15.38	22.64	28.96	29.07
Obs variance	2.557	3.273	2.93	2.839	3.577	3.526	1.943	2.011	1.93	4.402	2.927	4.328
Gen mean	23.83	21.67	20.73	23.02	20.28	17.16	14.41	11.22	14.76	21.6	28.85	26.76
Gen Variance	1.715	1.853	1.841	1.834	1.678	1.539	1.465	1.634	1.64	1.414	1.436	1.299
t-test	0.528	-0.159	0	-0.279	-0.236	0.399	0.008	-0.324	0.922	1.134	0.159	2.468
p-value	0.601	0.875	1	0.782	0.815	0.692	0.993	0.748	0.363	0.264	0.875	0.019

Appendix I

Table I-1: Student's *t*-test significance result of the mean yield, comparing baseline and climate scenarios for Ibadan and Enugu.

Ibadan

	RCP6.0_2020	RCP6.0_2050	RCP6.0_2080	RCP8.5_2020	RCP8.5_2050	RCP8.5_2080
Mean Difference	684.3	1303.133	2055.9	725.1	1724.867	2838.733
Std. Error Difference	174.442	167.825	155.399	173.462	167.397	142.725
p-value	0.000	0.000	0.000	0.000	0.000	0.000
t-test interpretation	**S**	**S**	**S**	**S**	**S**	**S**
F	2.087	3.712	9.086	2.485	3.306	24.732
t	3.923	7.765	13.23	4.18	10.304	19.89
p-value	0.154	0.059	0.004	0.12	0.74	0.000
variance test interpretation	**NS**	**NS**	**S**	**NS**	**NS**	**S**

S* Significant NS* Not significant

Enugu

	RCP6.0_2020	RCP6.0_2050	RCP6.0_2080	RCP8.5_2020	RCP8.5_2050	RCP8.5_2080
Mean Difference	-2823.333	-1998.967	658.033	-2711.767	-1452.267	-109.167
Std. Error Difference	181.184	172.668	126.459	181.958	165.534	157.706
p-value	0.000	0.000	0.000	0.000	0.000	0.000
t-test interpretation	**S**	**S**	**S**	**S**	**S**	**S**
F	1.163	0.68	2.247	1.402	0.836	0.663
t	-15.583	-11.577	5.204	-14.903	-8.773	-0.692
p-value	0.285	0.413	0.139	0.241	0.364	0.419
variance test interpretation	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**

Table I-2: Student's *t*-test significance result of the mean yield, comparing baseline and climate scenarios for Ilorin and Jos.

Ilorin

	RCP6.0_2020	RCP6.0_2050	RCP6.0_2080	RCP8.5_2020	RCP8.5_2050	RCP8.5_2080
Mean Difference	-900.067	-383.667	272.567	-826.5	-16.767	937.967
Std. Error Difference	287.64	255.785	230.841	278.786	243.515	193.426
p-value	0.003	0.139	0.243	0.004	0.945	0.000
t-test interpretation	**S**	**NS**	**NS**	**S**	**NS**	**S**
F	4.646	1.011	0.286	3.399	0.361	0.648
t	-3.129	-1.5	1.181	-2.965	-0.069	4.849
p-value	0.035	0.319	0.595	0.070	0.550	0.424
Variance test interpretation	S	NS	NS	NS	NS	NS

S* Significant **NS* Not significant**

Jos

	RCP6.0_2020	RCP6.0_2050	RCP6.0_2080	RCP8.5_2020	RCP8.5_2050	RCP8.5_2080
Mean Difference	54	571.967	1192.3	254.067	904.367	2344.2
Std. Error Difference	386.108	361.284	378.8	389.82	376.365	416.856
p-value	0.889	0.119	0.003	0.517	0.019	0.000
t-test interpretation	**NS**	**NS**	**S**	**NS**	**S**	**S**
F	1.163	0.182	0.932	1.637	0.911	3.54
t	0.14	1.583	3.148	0.652	2.403	5.624
p-value	0.285	0.671	0.338	0.206	0.344	0.065
variance test interpretation	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**

Appendix J

Table J-1: Energy indices calculated for Ibadan.

		80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg
Baseline	EUE	8.1	8.4	7.1	6.1	8.1	8.2	7.3	6.3	9.7	9.1	8.1	6.8
	EP	0.5	0.6	0.5	0.4	0.6	0.6	0.5	0.4	0.7	0.6	0.5	0.5
	SE	1.8	1.8	2.1	2.4	1.8	1.8	2.0	2.3	1.5	1.6	1.8	2.2
	NE	107,622.6	107,622.6	109,048.8	106,890.5	71,227.9	106,182.1	108,867.3	106,833.0	72,552.2	107,335.4	110,108.3	108,177.8
RCP 6.0_2020	EUE	8.4	8.3	7.0	6.0	8.5	8.1	7.2	6.1	10.1	9.1	7.9	6.6
	EP	0.6	0.6	0.5	0.4	0.6	0.6	0.5	0.4	0.7	0.6	0.5	0.5
	SE	1.7	1.8	2.1	2.4	1.7	1.8	2.1	2.4	1.4	1.6	1.9	2.2
	NE	77,944.4	106,709.8	106,627.7	104,408.5	74,806.8	105,251.5	106,208.1	104,129.6	76,147.8	106,345.0	107,291.8	105,172.7
RCP 6.0_2050	EUE	8.0	7.8	6.5	5.6	8.1	7.6	6.7	5.7	9.6	8.5	7.3	6.2
	EP	0.5	0.5	0.4	0.4	0.5	0.5	0.5	0.4	0.7	0.6	0.5	0.4
	SE	1.8	1.9	2.2	2.6	1.8	1.9	2.2	2.6	1.4	1.6	1.9	2.2
	NE	73,249.8	99,335.7	98,275.1	95,767.4	70,552.1	98,046.0	97,837.9	95,326.8	71,816.7	99,125.9	98,838.8	96,493.3
RCP 6.0_2080	EUE	7.1	6.8	5.6	4.8	7.2	6.6	5.7	4.9	8.5	7.4	6.3	5.3
	EP	0.5	0.5	0.4	0.3	0.5	0.4	0.4	0.3	0.6	0.5	0.4	0.4
	SE	2.1	2.2	2.6	3.1	2.1	2.2	2.6	3.0	1.7	2.0	2.3	2.8
	NE	63,920.1	84,296.7	81,490.7	78,542.0	61,430.3	83,119.7	81,110.8	78,161.6	62,557.2	84,169.2	82,117.6	79,251.1
RCP 8.5_2020	EUE	8.4	8.3	7.0	6.0	8.4	8.1	7.1	6.1	10.1	9.0	7.8	6.6
	EP	0.6	0.6	0.5	0.4	0.6	0.5	0.5	0.4	0.7	0.6	0.5	0.4
	SE	1.7	1.8	2.1	2.5	1.7	1.8	2.1	2.4	1.5	1.6	1.9	2.2
	NE	77,486.3	106,400.0	106,056.3	103,614.7	74,374.6	104,862.4	105,489.3	103,325.5	75,744.6	105,989.9	106,580.9	104,296.5
RCP 8.5_2050	EUE	7.6	7.3	6.1	5.2	7.7	7.2	6.2	5.3	9.2	8.0	6.8	5.8
	EP	0.5	0.5	0.4	0.4	0.5	0.5	0.4	0.4	0.6	0.5	0.5	0.4
	SE	1.9	2.0	2.4	2.8	1.9	2.1	2.4	2.8	1.6	1.8	2.1	2.6
	NE	69,536.5	92,837.8	90,694.3	87,922.0	66,819.4	91,420.8	90,264.9	87,590.2	68,098.5	92,402.7	91,227.2	88,663.5
RCP 8.5_2080	EUE	6.0	5.3	4.3	3.7	6.1	5.1	4.4	3.7	7.3	5.7	4.8	4.0
	EP	0.4	0.4	0.3	0.3	0.4	0.3	0.3	0.3	0.5	0.4	0.3	0.3
	SE	2.4	2.8	3.4	4.0	2.4	2.9	3.4	3.9	2.0	2.6	3.1	3.6
	NE	52,429.6	62,212.3	59,009.4	56,075.5	50,740.5	60,957.1	58,461.9	55,595.1	52,114.8	62,041.3	59,534.4	56,674.4

Energy use efficiency (EUE); Energy Productivity (EP); Specific Energy (SE); Net Energy (NE)

Table J-2: Energy indices calculated for Jos.

		CT				RT				NT			
		80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg
Baseline	EUE	8.5	10.9	9.9	9.3	8.7	10.5	9.9	9.2	10.8	12.2	11.3	10.4
	EP	0.6	0.7	0.7	0.6	0.6	0.7	0.7	0.6	0.7	0.8	0.8	0.7
	SE	1.7	1.3	1.5	1.6	1.7	1.4	1.5	1.6	1.4	1.2	1.3	1.4
	NE	78,448.1	145,443.7	158,001.7	171,992.8	76,528.7	140,526.7	153,097.6	166,495.9	81,408.9	147,446.2	160,432.8	174,393.5
RCP 6.0_2020	EUE	8.4	10.7	9.6	8.9	8.6	10.3	9.7	8.9	10.6	11.9	11.0	10.0
	EP	0.6	0.7	0.7	0.6	0.6	0.7	0.7	0.6	0.7	0.8	0.7	0.7
	SE	1.8	1.4	1.5	1.6	1.7	1.4	1.5	1.6	1.4	1.2	1.3	1.5
	NE	76,990.9	141,940.2	153,216.4	164,657.5	76,135.2	137,769.0	149,349.7	160,810.9	80,050.7	143,819.3	155,825.9	167,131.2
RCP 6.0_2050	EUE	8.2	10.3	9.2	8.4	8.2	9.8	9.1	8.3	10.4	11.4	10.5	9.4
	EP	0.6	0.7	0.6	0.6	0.6	0.7	0.6	0.6	0.7	0.8	0.7	0.6
	SE	1.8	1.4	1.6	1.7	1.8	1.5	1.6	1.8	1.4	1.3	1.4	1.6
	NE	74,878.5	135,671.1	145,127.4	154,448.4	72,206.3	130,270.9	140,049.0	149,108.2	78,068.1	137,487.6	147,610.5	157,172.9
RCP 6.0_2080	EUE	8.0	9.9	8.8	7.9	8.1	9.4	8.7	7.9	10.1	11.0	10.0	8.9
	EP	0.5	0.7	0.6	0.5	0.5	0.6	0.6	0.5	0.7	0.7	0.7	0.6
	SE	1.8	1.5	1.7	1.9	1.8	1.6	1.7	1.9	1.4	1.3	1.5	1.7
	NE	72,832.3	129,744.1	137,613.8	143,698.7	70,602.6	124,831.9	133,174.2	139,263.1	76,235.0	131,550.7	140,369.7	146,341.9
RCP 8.5_2020	EUE	8.4	10.7	9.6	8.9	8.7	10.3	9.7	8.9	10.7	11.9	11.0	10.0
	EP	0.6	0.7	0.7	0.6	0.6	0.7	0.7	0.6	0.7	0.8	0.7	0.7
	SE	1.8	1.4	1.5	1.6	1.7	1.4	1.5	1.6	1.4	1.2	1.3	1.5
	NE	77,384.9	142,011.8	153,348.7	164,416.4	76,477.7	137,918.9	149,634.8	160,556.0	80,511.8	143,955.0	156,052.2	166,862.2
RCP 8.5_2050	EUE	8.1	10.1	9.0	8.3	8.2	9.6	8.9	8.2	10.3	11.2	10.3	9.2
	EP	0.6	0.7	0.6	0.6	0.6	0.7	0.6	0.6	0.7	0.8	0.7	0.6
	SE	1.8	1.5	1.6	1.8	1.8	1.5	1.6	1.8	1.4	1.3	1.4	1.6
	NE	74,308.2	133,105.1	142,025.7	150,614.1	71,852.1	128,140.5	137,128.1	145,358.7	77,499.8	135,035.6	144,603.3	153,151.0
RCP 8.5_2080	EUE	7.4	9.5	8.3	7.3	7.6	9.1	8.4	7.3	9.6	10.6	9.5	8.2
	EP	0.5	0.6	0.6	0.5	0.5	0.6	0.6	0.5	0.7	0.7	0.6	0.6
	SE	2.0	1.6	1.8	2.0	1.9	1.6	1.8	2.0	1.5	1.4	1.5	1.8
	NE	67,360.4	123,899.4	129,789.4	131,466.8	66,203.4	120,496.9	126,947.3	127,711.8	71,417.3	126,010.7	132,548.4	133,928.3

Energy use efficiency (EUE); Energy Productivity (EP); Specific Energy (SE); Net Energy (NE)

Table J-3: Energy indices calculated for Ilorin.

		CT				RT				NT			
		80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg
Baseline	EUE	4.1	4.2	3.7	3.3	4.3	4.1	3.8	3.4	5.3	4.7	4.2	3.7
	EP	0.3	0.3	0.3	0.2	0.3	0.3	0.3	0.2	0.4	0.3	0.3	0.2
	SE	3.6	3.5	4.0	4.5	3.4	3.6	3.9	4.4	2.8	3.1	3.5	4.0
	NE	32,677.8	46,557.4	47,648.3	47,364.3	32,746.2	46,106.1	47,897.6	47,762.0	35,513.0	48,496.1	49,993.7	49,648.8
RCP 6.0_2020	EUE	3.5	3.9	3.5	3.1	4.2	4.1	3.7	3.3	5.2	4.6	4.1	3.6
	EP	0.2	0.3	0.2	0.2	0.3	0.3	0.3	0.2	0.4	0.3	0.3	0.2
	SE	4.2	3.7	4.2	4.7	3.5	3.6	4.0	4.5	2.8	3.2	3.6	4.1
	NE	25,907.8	42,775.5	44,203.1	44,307.6	32,200.3	45,584.2	46,903.9	46,407.6	35,143.2	47,987.1	48,981.8	48,383.6
RCP 6.0_2050	EUE	3.4	3.8	3.4	3.0	4.1	3.9	3.6	3.1	5.1	4.5	4.0	3.4
	EP	0.2	0.3	0.2	0.2	0.3	0.3	0.2	0.2	0.3	0.3	0.3	0.2
	SE	4.4	3.9	4.4	4.9	3.6	3.7	4.1	4.7	2.9	3.3	3.7	4.3
	NE	24,684.8	40,510.7	41,734.5	41,294.7	30,910.6	43,478.8	44,266.7	43,335.3	33,757.0	45,772.8	46,271.2	45,185.9
RCP 6.0_2080	EUE	2.9	3.3	2.9	2.6	3.6	3.4	3.1	2.7	4.5	3.9	3.4	2.9
	EP	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.2	0.2
	SE	5.0	4.4	5.1	5.7	4.1	4.3	4.8	5.5	3.3	3.8	4.3	5.0
	NE	20,351.8	33,730.6	33,568.1	32,370.7	26,119.9	36,070.4	35,654.9	34,037.1	28,836.3	38,166.4	37,573.2	35,717.1
RCP 8.5_2020	EUE	3.5	4.0	3.5	3.2	4.3	4.2	3.8	3.3	5.3	4.7	4.2	3.7
	EP	0.2	0.3	0.2	0.2	0.3	0.3	0.3	0.2	0.4	0.3	0.3	0.2
	SE	4.2	3.7	4.1	4.6	3.4	3.5	3.9	4.4	2.8	3.1	3.5	4.0
	NE	26,517.0	44,053.4	45,187.0	45,433.6	32,983.3	46,916.5	48,099.9	47,505.2	35,981.5	49,161.2	50,125.5	49,411.1
RCP 8.5_2050	EUE	3.1	3.5	3.1	2.7	3.8	3.6	3.3	2.8	4.7	4.1	3.6	3.1
	EP	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.3	0.3	0.2	0.2
	SE	4.7	4.2	4.8	5.4	3.8	4.0	4.5	5.2	3.1	3.6	4.1	4.7
	NE	22,258.4	36,835.2	36,930.6	35,814.5	28,169.5	39,125.1	38,968.8	37,530.8	31,010.4	41,191.3	40,840.0	39,362.7
RCP 8.5_2080	EUE	2.4	2.6	2.2	1.9	2.9	2.7	2.3	2.0	3.5	3.0	2.6	2.2
	EP	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2
	SE	6.1	5.7	6.6	7.5	5.1	5.5	6.3	7.2	4.1	4.9	5.6	6.7
	NE	14,571.2	23,124.1	21,557.7	19,693.5	18,748.9	24,514.7	23,282.5	20,863.0	21,195.8	26,352.1	25,045.3	22,538.1

Energy use efficiency (EUE); Energy Productivity (EP); Specific Energy (SE); Net Energy (NE)

Table J-4: Energy indices calculated for Enugu.

		CT				**RT**				**NT**			
		80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg	80kg	160kg	200kg	250kg
Baseline	EUE	3.6	4.0	3.6	3.2	3.8	3.9	3.7	3.3	4.6	4.4	4.0	3.6
	EP	0.2	0.3	0.2	0.2	0.3	0.3	0.3	0.2	0.3	0.3	0.3	0.2
	SE	4.1	3.7	4.1	4.6	3.8	3.7	4.0	4.4	3.2	3.4	3.6	4.1
	NE	27,403.8	43,232.2	45,306.6	46,233.3	28,342.6	43,526.2	46,324.1	47,412.6	29,606.1	44,538.0	47,331.5	48,077.4
RCP 6.0_2020	EUE	2.9	3.4	3.1	2.8	3.6	3.8	3.5	3.1	4.3	4.2	3.8	3.3
	EP	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.3	0.3	0.3	0.2
	SE	5.1	4.3	4.7	5.2	4.1	3.9	4.3	4.8	3.4	3.5	3.9	4.4
	NE	19,853.5	35,759.6	37,284.2	37,796.1	26,135.1	40,866.0	42,298.8	42,461.2	27,487.4	42,043.4	43,430.5	43,466.0
RCP 6.0_2050	EUE	2.5	2.9	2.6	2.4	3.1	3.2	3.0	2.7	3.7	3.6	3.3	2.9
	EP	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	SE	6.0	5.1	5.6	6.1	4.8	4.6	4.9	5.4	4.0	4.1	4.5	5.0
	NE	15,205.3	27,934.4	29,180.7	29,458.2	20,751.5	32,996.6	34,623.5	34,651.6	22,162.5	34,141.1	35,781.2	35,717.6
RCP 6.0_2080	EUE	2.2	2.6	2.3	2.1	2.8	3.0	2.7	2.4	3.3	3.3	3.0	2.6
	EP	0.1	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	SE	6.7	5.8	6.4	7.2	5.2	5.0	5.4	6.1	4.4	4.5	4.9	5.6
	NE	12,367.7	22,737.9	22,856.2	21,885.7	18,207.3	28,976.2	29,450.6	28,737.3	19,576.8	30,283.4	30,782.7	30,067.9
RCP 8.5_2020	EUE	2.9	3.4	3.1	2.8	3.6	3.7	3.4	3.1	4.3	4.2	3.8	3.3
	EP	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.3	0.3	0.3	0.2
	SE	5.1	4.3	4.8	5.3	4.1	3.9	4.3	4.8	3.4	3.5	3.9	4.4
	NE	19,654.4	35,485.3	36,873.7	37,295.2	25,854.3	40,671.9	42,036.1	42,292.2	27,196.4	41,716.5	43,155.2	43,255.8
RCP 8.5_2050	EUE	2.3	2.7	2.4	2.2	2.9	3.1	2.8	2.5	3.4	3.4	3.1	2.7
	EP	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	SE	6.5	5.5	6.1	6.7	5.1	4.8	5.2	5.8	4.3	4.3	4.7	5.4
	NE	13,349.2	24,712.6	25,268.0	24,714.5	19,019.4	30,808.2	31,615.3	31,054.9	20,407.3	31,999.8	32,829.5	32,207.3
RCP 8.5_2080	EUE	1.6	1.8	1.6	1.5	2.1	2.0	1.8	1.6	2.5	2.2	2.0	1.7
	EP	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1
	SE	9.0	8.2	9.4	10.1	7.0	7.3	8.2	9.2	5.9	6.6	7.4	8.5
	NE	6,675.4	11,678.7	10,126.0	9,477.4	10,926.4	14,904.3	13,847.4	11,996.4	12,328.2	16,350.8	15,371.8	13,426.6

Energy use efficiency (EUE); Energy Productivity (EP); Specific Energy (SE); Net Energy (NE)