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Simulating the Impacts of Climate Change on Water and Crop Productivity in Ogun-Osun River Basin, Nigeria

Defended on 22/09/2020 Before the Following Committee:

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DECLARATION

STUDENT'S DECLARATION

I, Oludare Sunday Durodola, hereby declare that this thesis titled "Simulating the Impacts of Climate Change on Water and Crop Productivity in Ogun-Osun River Basin, Nigeria" is my original work to the best of my knowledge and has not been submitted to the University or any other institute or published earlier for the award of any degree or diploma. I also declare that all the information, materials and results from other works presented in this thesis have been duly cited and recognised as required of academic rules and ethics.

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SUPERVISOR'S DECLARATION

I, Dr Khaldoon A. Mourad, hereby declare that I supervised the preparation of this Master thesis submitted therein in accordance with the guidelines on supervision of Master thesis laid down by the Pan African University Institute of Water and Energy Sciences, Algeria.

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ABSTRACT

African countries such as Nigeria are anticipated to be more susceptible to the impacts of climate change due to the large dependence on rainfed agriculture. Also, there are several uncertainties in the responses of rainfed crop production to climate change. In this regard, the impacts of climate change on crop water requirements (CWR), irrigation water requirements (IWR), yields and crop water productivity (CWP) of rainfed maize and soybeans in Ogun-Osun River Basin, Nigeria were evaluated for the baseline period (1986 – 2015) and future period (2021 – 2099) under RCP 4.5 and RCP 8.5 scenarios. Future climate projections of HadGEM2-ES downscaled by RCA4 were used in simulating future scenarios. The results show that for the baseline period, maize CWR and IWR have a slightly decreasing trend, but soybeans CWR and IWR are increasing significantly. Though, no significant changes in maize yield but the yield trend of soybeans is increasing and CWP is increasing for both crops. For the future period, the CWR is largely dependent on the rainfall pattern. Maize IWR will likely increase significantly up to 140% in some periods while soybeans IWR is projected to continually decline up to 80 % by 2099. Maize yield will likely decline under both scenarios up to 12% while climate change has positive effects on soybeans yield which will increase up to 40% under RCP 8.5. Meanwhile, based on the baseline period, supplemental irrigation shows a promising effect on crop yields and can increase maize and soybeans yields up to about 10% and 35% respectively. Also, in the future scenarios, it can increase crop yields expect in the late century. The results of this study certainly offer useful information on suitable adaption measures which could be implemented by stakeholders and policymakers to counterbalance the negative effects of climate change on crop production in Nigeria.

RÉSUMÉ

Les pays africains comme le Nigéria devraient être plus sensibles aux effets du changement climatique en raison de leur forte dépendance à l'agriculture pluviale. En outre, il existe plusieurs incertitudes dans les réponses de la production des cultures pluviales au changement climatique. À cet égard, les impacts du changement climatique sur les besoins en eau des cultures (CWR), les besoins en eau d'irrigation (IWR), les rendements et la productivité en eau des cultures (CWP) du maïs pluvial et du soja dans le bassin de la rivière Ogun-Osun, au Nigéria ont été évalués pour la période de référence (1986 - 2015) et la période future (2021 - 2099) selon les scénarios RCP 4.5 et RCP 8.5. Les projections climatiques futures de HadGEM2-ES réduites par RCA4 ont été utilisées pour simuler des scénarios futurs. Les résultats montrent que pour la période de référence, les CWR et les IWR du maïs ont une tendance légèrement à la baisse, mais que les CWR et les IWR de soja augmentent considérablement. Cependant, aucun changement significatif dans le rendement du maïs, mais la tendance des rendements du soja est à la hausse et la CWP augmente pour les deux cultures. Pour la période future, le CWR dépend largement de la configuration des précipitations. Les IWR de maïs augmenteront probablement de manière significative jusqu'à 140% à certaines périodes, tandis que les IWR de soja devraient baisser continuellement jusqu'à 80% d'ici 2099. Le rendement du maïs diminuera probablement dans les deux scénarios jusqu'à 12% tandis que le changement climatique a des effets positifs sur les rendements de soja qui augmentera jusqu'à 40% sous RCP 8.5. Pendant ce temps, sur la base de la période de référence, l'irrigation supplémentaire montre un effet prometteur sur les rendements des cultures et peut augmenter les rendements de maïs et de soja jusqu'à environ 10% et 35% respectivement. En outre, dans les scénarios futurs, il peut augmenter les rendements des cultures attendus à la fin du siècle. Les résultats de cette étude offrent certainement des informations utiles sur les mesures d'adaptation appropriées qui pourraient être mises en œuvre par les parties prenantes et les décideurs pour contrebalancer les effets négatifs du changement climatique sur la production agricole au Nigeria.

DEDICATION

This work is dedicated to the Almighty God, the giver of life and wisdom. I also dedicate this work to my parents, Sunday Opoola and Omotayo Olukemi Durodola for their support and encouragements, to my family members, friends and loved one for their support during this programme.

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LIST OF ABBREVIATIONS

CDF	-	Cumulative distribution function
CORDEX	-	Coordinated Regional Downscaling Experiment
CWP	-	Crop water productivity
CWR	-	Crop water requirements
DEM	-	Digital elevation model
FAO	-	Food and Agriculture Organization of the United Nations
GCM	-	Global Climate Model/General Circulation Model
GIS	-	Geographic Information System
IPCC	-	The Intergovernmental Panel on Climate Change
IWR	-	Irrigation water requirements
MAE	-	Mean absolute error
NSE	-	Nash-Sutcliffe Efficiency
PAU	-	Pan African University
PAUWES	-	Pan African University Institute of Water and Energy Sciences
QM	-	Quantile Mapping
RCA4	-	Rossby Centre Regional Climate Model
RCM	-	Regional Climate Model
RCP	-	Representative Concentration Pathway
RMSE	-	Root mean square error
SSA	-	Sub-Saharan Africa
SDGs	-	Sustainable Development Goals
STRM	-	Shuttle Radar Topography Mission
GHGs	-	Greenhouse gases
CO_2	-	Carbon di oxide

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CHAPTER ONE

1. INTRODUCTION

1.1 Background of the study

The Intergovernmental Panel on Climate Change's Fifth Assessment Report (AR5) has warned the entire world more strictly than in previous reports that global climate change is a result of the increase in anthropogenic activities globally (IPCC, 2014). Global temperature is expected to rise and will cause shifts in patterns and quantities of precipitation, which in turn will likely lead to increasing the occurrence of natural disasters such as floods, droughts, heatwaves, and fires (IPCC, 2018; Klutse et al., 2018; Nikulin et al., 2018; Rahman, Haq, & Anjum, 2019). Climate change poses several uncertainties in terms of the natural ecosystem, water resources, agricultural production, energy demand, biodiversity, and forestation, which will critically affect human activities and survival.

It has been predicted that developing countries especially, African countries will be most affected by the impacts of climate change due to the high dependence on natural resources and the high poverty level (Baarsch et al., 2020; Sylla, Nikiema, Gibba, Kebe, & Klutse, 2016). According to Besada & Werner (2015), Africa is anticipated to be more vulnerable to climate change impacts due to the dependence on natural resources; the high level of climate variability; the vast rainfed agriculture; and the low institutional and economic capacity to manage and adapt to climate change.

Currently, Nigeria is experiencing frequent food shortages, hunger and water scarcity due to the rapid population growth, the decline in income, climate change and climate variability (Olomola & Nwafor, 2018; Otekunrin, Otekunrin, Momoh, & Ayinde, 2019). The connection between agriculture and climate change is interwoven. It is predicted that agriculture will be greatly affected by climate change and agriculture will contribute to climate change. According to FAO (2016), a 60% increase above the 2006 global food demand levels is expected in 2050 driven by the rapid population growth, increase in urbanization, as well as income growth. Water withdraws for agriculture amounts to about 70% of all water withdrawals from rivers, lakes, streams and aquifers (FAO, 2017b). However, water resources which are the basis for food production are finite and

currently under serious pressure. Despite this, water resources need to meet up with current and future demands for agricultural use, domestic use and industrial uses.

The main biophysical processes involved in agricultural crop production such as evaporation from soils, transpiration from plants, nutrient cycles and growth of plants are altered by climate change (Rahman et al., 2019). Several studies in Nigeria (Hula & Udoh, 2015; Idowu, Ayoola, Opele, & Ikenweiwe, 2011; Idumah, Mangodo, Ighodaro, & Owombo, 2016; Olayide, Tetteh, & Popoola, 2016) have shown that the increase in temperature, droughts and floods will affect agricultural production. In addition, some crops will likely be affected negatively due to excessive heat as a result of temperature rise which might also cause some crops to need more water than before and affect yields.

Crop Water Requirement (CWR) which is the total amount of water that crops need for growth throughout its lifecycle (Mourad & Berndtsson, 2012) and Irrigation Water Requirement (IWR) which is the amount of water needed to complete rainfall to meet up with CWR (Ewaid, Abed, & Al-Ansari, 2019) are expected to change due to climate change. In addition, there are uncertainties in future crop yield and Crop Water Productivity (CWP). Yield is the harvestable quantity of crops (Raes, Steduto, Hsiao, & Fereres, 2009) and CWP is the ratio of crop yield to the quantity of water consumed by the crop during a growing period (Raes et al., 2009).

Meanwhile, to achieve food security in a changing climate, there must be a corresponding supply of agricultural water essential for food production. Also, water availability from rainfall, surface water and groundwater is a critical factor to consider in assessing the projected impacts of climate change on agriculture and agricultural water management. Therefore, this study seeks to focus on the effects of climate change on water and crop productivity in Nigeria, through the estimation of the changes in water needs due to temperature changes. In addition, this study seeks to simulate the future crop CWR, IWR, yield and CWP under different climate change scenarios.

1.2 Problem statement

Climate change is predicted to affect many aspects of human lives including agricultural production. Agriculture production depends largely on water resources, which are finite and presently under heavy stress. It is predicted that climate change will alter rainfall patterns. Meanwhile, in Nigeria, the majority of farmers depend highly on rainfed agriculture whereas

rainfed agriculture is vulnerable to climate change. It is becoming increasingly difficult to grow crops as climate change impacts on agriculture intensifies. Many studies have been carried out in Nigeria to examine the impacts of climate change on agriculture, but no study has been done on examining the water requirements of crops under a changing climate and using climate change predictions. In addition, changes in CWR and IWR due to the temperature changes caused by climate change is still unknown. These uncertainties pose great challenges to crop productivity, irrigation and water allocation for agriculture.

1.3 Justification of the study

Considering the nexus of water security, food security and climate change, it is necessary to model the impacts of climate change on agricultural production, energy and water resources. Estimating the changes in CWR due to the temperature change is imperative in order to predict the impacts of climate change under different climatic scenarios, which will affect IWR, CWP, crop growth and yields as well as water allocation strategies. In this study, more-water efficient crop production will be proposed which will subsequently improve crop yield and food security. This study will help decision-makers in formulating agricultural and water policies to enhance sustainable allocation plans. Moreover, it aims at reducing water losses and promoting sustainable agriculture practices.

The findings of this research will help in formulating adaptation plans to climate change in terms of food production which will contribute to the realization of the Africa Agenda 2063 of the African Union (AU) and attainment of the United Nation's Sustainable Development Goals (SDGs). The results of this study will contribute to the attainment of SDG 2 (Zero hunger) through increasing crop yields and efficient irrigation, SDG 13 (Climate action) through effective adaptation plans, SDG 1 (No poverty) through increased crop productivity and improved economic standards, and SDG 6 (Water and sanitation) through appropriate allocation of water resources among users.

1.4 Objectives of the study

The main goal of this research is to model the impacts of climate change on water and crop productivity in Ogun-Osun River Basin, Nigeria. The specific objectives are to:

1. Estimate spatio-temporal seasonal CWR, IWR, yield and CWP based on soil, climate and crop data;

2. Estimate the changes in spatio-temporal seasonal CWR, IWR, yield and CWP;
3. Evaluate the effect of supplemental irrigation on yield and CWP based on current climate;
4. Simulate the future spatio-temporal CWR, IWR, yield and CWP under different climate change scenarios;
5. Evaluate the effect of supplemental irrigation on future yield and CWP under different climate change scenarios.

1.5 Research questions

The following are the main research questions:

1. What will be the impacts of climate change on water and crop productivity in Ogun-Osun River Basin, Nigeria?

Specific questions

1. What is the spatio-temporal distribution of seasonal CWR, IWR, yield and CWP within the study area?
2. What are the changes in spatio-temporal seasonal CWR, IWR, yield and CWP;
3. What is the effect of supplemental irrigation on yield and CWP based on current climate;
4. What will be the future spatio-temporal CWR, IWR, yield and CWP under different climate change scenarios;
5. What will be the effect of supplemental irrigation on future yield and CWP?

1.6 Structure of the thesis

The thesis is divided into five chapters as the following:

Chapter One- Introduction: This chapter contains the introduction, background of the study, problem statement, justification of the study, objectives of the study and research questions.

Chapter Two- Literature Review: This chapter has the literature review where studies related to the topic is critically examined for what has been done in this research area and the gaps that this study intends to fill. It explains the strengths as well as the limitations of the models used.

Chapter Three- Methodology: This chapter describes the methods, materials and models that are implored in this study. It explains the reasons for selecting the methods as well as details about models, data preparation, data collection and modelling, and final reporting.

Chapter Four- Results and Discussion: The results of the study are reported and discussed in this chapter. Chapter Five- Conclusion and Recommendations: The conclusions drawn from this study are highlighted and recommendations are given.

CHAPTER TWO

2. LITERATURE REVIEW

In this chapter, existing research works, and studies related to the topic are critically examined for what has been done. The gaps that this study intends to fill are identified. Also, this chapter explains the strengths as well as the limitations of the models used.

2.1 Climate change

Climate change is a serious threat that gains great attention from countries' leaders, policymakers, scientists, engineers, international organizations and civil societies due to the global warming, which will be more harmful in the future. The increased concentration of greenhouse gases (GHGs) in the environment especially carbon di oxide (CO_2) has been described as the main cause of climate change (IPCC, 2018). Although, there are different views and opinions in the scientific community regarding the origin of climate change. However, the effect of climate change is evident as it is causing an increase in temperature, variation in patterns and intensities of precipitation and frequent occurrence of extreme events such as floods and droughts (IPCC, 2018).

If the increase in the concentration of greenhouse gases continues, the average mean temperature of Africa is expected to rise above 2°C in the last two decades of the century. According to an overview of Coordinated Regional Downscaling Experiment (CORDEX) Africa simulations that were done by Nikulin et al. (2018), prominent warming will be experienced in Africa at 1.5°C increase in global warming level and more noticeable hotness will be witnessed in Africa if the rise in global warming level should exceed 2°C. The study shows that there will be higher mean temperatures in hot locations while wet areas will witness fewer wet seasons. Similarly, consecutive dry days will increase in most part of Africa over the Guinea Coast while consecutive wet days will also reduce according to the review of 25 regional climate models over Africa based on the global temperature rise of 1.5°C and 2°C (Klutse et al., 2018).

On the other hand, the mean temperature of West Africa is expected to rise by about 1.5–6.5°C in the future periods under the current trend of increase in the concentration of greenhouse gases based on CORDEX experiments ensemble (Sylla et al., 2016). The predicted changes in temperature, consecutive dry and wet days will have a huge impact on crop production in Nigeria and Africa at large. On a local scale of Nigeria, an increase in temperature of 0.2°C to 0.3°C per

decade has been experienced in Nigeria from 1981-2010 (Enete, 2014). Crop development, water requirements and growth are highly dependent on the number of consecutive dry and wet days. Most agricultural production in Nigeria and Africa are rainfed agriculture which is mainly dependent on rainfall for water availability. Therefore, significant changes in rainfall patterns, the number of consecutive dry and wet days will greatly impact crop production and might lead to food insecurity if proper and urgent actions are not taken. Furthermore, climate change is expected to tremendously affect water availability and energy consumption. It is thus important to examine the impact of climate change on agricultural production due to the fact that impacts of climate change vary across locations and activities.

2.2 Climate and water resources

Climate and water resources are interconnected through several parameters such as precipitation, solar radiation, temperature and evapotranspiration which vary from one location to another. Since climate and water resources are interrelated, it is evident that climate change will affect water resources and vice versa. Meanwhile, Africa's water resources problems are caused by various factors ranging from climate change, diversity of trans-boundary water basins, high spatial and temporal variability of rainfall, depletion of water resources through human activities, inadequate development of available water resources and low financing of required investment in water projects.

However, interest in this study is the factor of climate change. Continental warming and climate change have intensified the changes in weather patterns and water availability (Besada & Werner, 2015). Unfortunately, these trends are more likely to worsen in the future. Furthermore, it has been projected that water cycles, the quantity and quality of both surface water and groundwater as well as rainfall frequencies and intensities will be significantly affected by climate change (Amanambu et al., 2019; FAO, 2017b). An increase in rainfall variability is expected to influence saline intrusion, flooding due to high rainfall intensities and changes in the water retention capacity of soils (Boonwichai, Shrestha, Babel, Weesakul, & Datta, 2018; Valipour, 2015).

The global situation is not entirely different from Nigeria's. Nigeria has been projected to be prone to extreme weather events such as drought and floods. However, Nigeria's case is quite unique. It has been projected that Nigeria will experience combined impacts of climate change in form of increased floods and droughts in various states of the country (Hula & Udoh, 2015; Sylla, et al.,

2016; Thecla, George, & Alice, 2018). According to Sylla, et al. (2016), the rainfall pattern of Nigeria is expected to vary from -30 to 30% under CORDEX experiment if the world continues on the "business as usual" approach to greenhouse gas emissions. As for Nigeria, some parts of the country will experience more drought while other parts will experience floods (Enete, 2014). Rapid population growth is another threat to water availability with a subsequent rapid increase in water demand for domestic use, agricultural use, industrial and energy production despite the fact that water resources are already under climate change threats. Considering the foregoing, it is evident that climate change cannot be isolated from water resources and vice versa which reveals that climate change will definitely affect water resources spatially and temporally. Therefore, this study intends to fill the research gaps and investigate the effects of changes in rainfall patterns, temperature, evapotranspiration, and other water cycle components on crop production in Nigeria.

2.3 Climate change, water security and food security nexus

Food security is the status of ensuring that a population, irrespective of their of socio-economic statuses, have access to enough food required for their well-being and growth (FAO, 2016). On the other hand, water security is the ability of a population to have sustainable access to the quantity of safe water for sustaining lives, good health and the economy as well protecting the environment (UN-Water, 2013). These two definitions embrace the importance of the connection of food security, water security and the environment. Throughout this study, the given definitions of food security and water security will be used.

Climate change, water security and food security are intrinsically linked as shown in Figure 2.1. The link of water-food-energy has been adopted as the best approach towards climate change adaptation. Energy is an essential input in agricultural production especially in irrigation practices, water supply and food processing. Water is also used in generating energy such as hydropower. Also, agricultural production is almost impossible without the input of water.

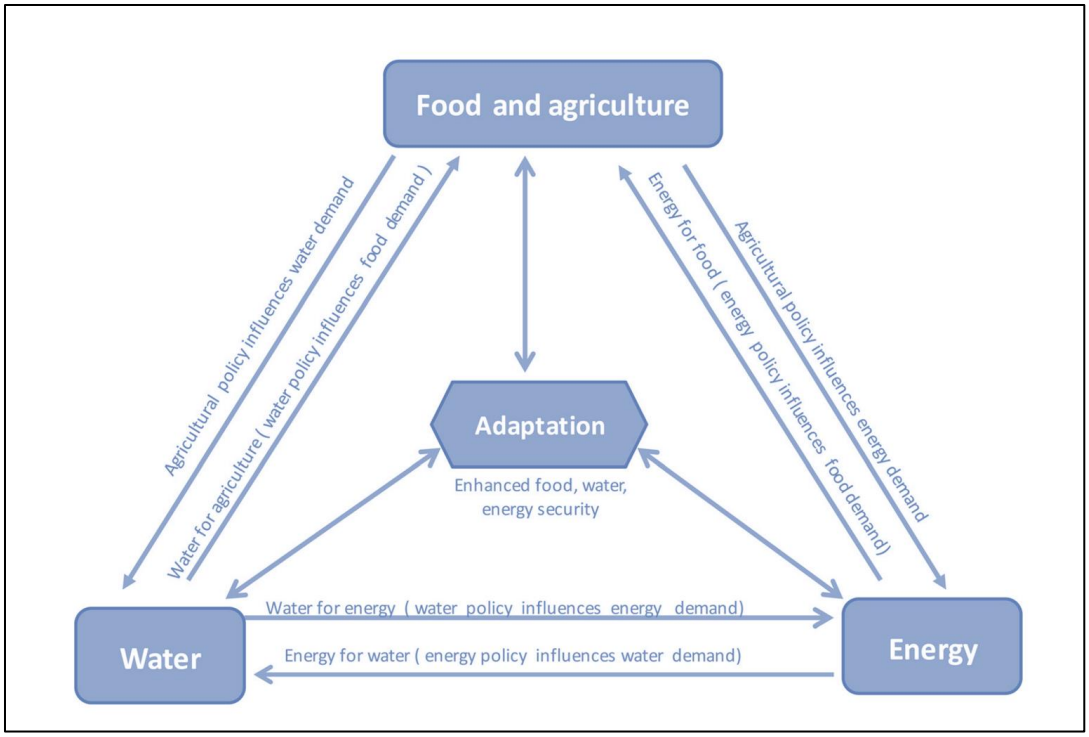

Figure 2.1: The interconnection among water-energy-food and agriculture-climate change

Source: (Rasul & Sharma, 2015)

Agriculture is the main user of water resources globally. It is responsible for about 70% withdrawal of freshwater resources (FAO, 2016). In developing countries like Nigeria, the withdrawal of water for agriculture can rise up to 95% (FAO, 2017b). Promoting sustainable agriculture and improving CWP as well as efficient management of finite water resources are indispensable towards increasing global food production. In Sub-Saharan Africa (SSA), rainfed agriculture is mostly practised covering about 96% of agricultural lands which makes crop production to be majorly dependent on rainfall (Adeboye, Schultz, Adekalu, & Prasad, 2019). Nigerian farmers also depend largely on rainfall for crop production, post-harvest processes, animal husbandry and aquaculture (Adeboye et al., 2019; Partey, Zougmoré, Ouédraogo, & Campbell, 2018).

Climate is a vital factor in crop production and could directly influence crop productivity. Studies have shown that climate change will affect crop productivity differently depending on location, crops and climatic zone. While some crops will benefit, other crops will be affected negatively (Boonwichai et al., 2018). According (FAO, 2017b), some crops will perform optimally with hotter temperatures and lengthier growing periods. However, studies have shown that the negative

effects will exceed the positive effects across different locations (IPCC, 2018). The interaction among water, food and climate change shows that it is important to examine the impacts of climate change on crop productivity. But which crops will perform optimally under various climate change scenarios in Nigeria? Also, with the current growing water demands and the threats of climate change, how will the staple crops behave under a changing climate? What will be the water requirements of crops? In order to provide answers to these questions, it is imperative that more studies need to be done to examine how crops will respond to various locations since the impact of climate change is spatially distributed.

2.4 Agricultural production in Nigeria

Nigeria is a West African country which lies between longitudes 2°49'E–14°37'E and latitudes 4°16'N-13° 52' N with a population of about 196 million as of 2018 estimates, agricultural land of 708,000 km^2 and over 70% of the population engaged in agriculture (World Bank, 2019). Agriculture in Nigeria can be categorized into two main practices namely; crop production and animal farming. Crop production is the cultivation of crops for human consumption and animal feeding while animal farming also known as livestock farming is the rearing of animals for fibre, meats, eggs, milk and other products. Agriculture is the main occupation of Nigerians and widely practised across the country.

The country is divided into seven agro-ecological zones namely; Derived savannah, Humid forest, Mid-altitude, Northern Guinea savannah, Sahel savannah, Southern Guinea savannah and Sudan savannah as shown in Figure 2.2. The zones are characterised with different planting dates of crops and agricultural practices. Rainfall pattern also varies according to these zones. The amount of annual rainfall decreases from the southern part of the country to the northern part of the country. The southern part of the country has the humid forest and derived savannah while the northern part of the country has mid-altitude, Northern Guinea savannah, Sahel savannah, Southern Guinea savannah and Sudan savannah. The case study of this research which is the Ogun-Osun River Basin is located within the derived savannah zone of the country.

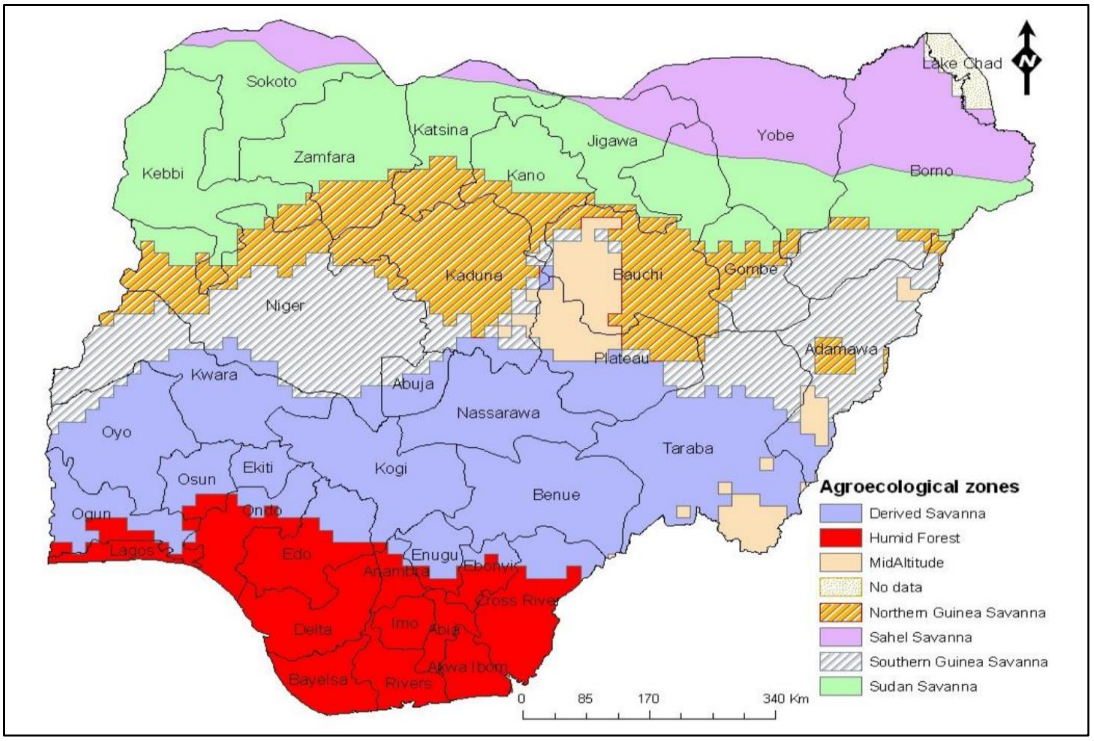

Figure 2.2: Map of Nigeria showing the agro-ecological zones

Source: (Alamu, Amao, Nwokedi, Oke, & Lawa, 2013)

2.4.1 Background of crop production in Nigeria

Crop production in Nigeria is majorly rainfed and the types of crops grown can be categorized into three namely; annual crops, fruit crops and cash crops. The annual crops planted include maize, soybean, yam, cassava, rice, groundnuts, pepper, onion, cowpea, melon, vegetables etc. Fruit crops include mango, cashew, pawpaw, guava and pineapple. While cash crops include cocoa, cotton, oil palm, rubber and coconut. Crop production has increased tremendously in the country over the years as shown in Figure 2.3. Although, the rate of production is still greatly below expectations (Olomola & Nwafor, 2018). Parasitic weed contamination, crop diseases and pests, poor extension services, poor financial support from the government, lack of insurance, inadequate access to seeds and fertilizers, soil infertility, rainfall variability and climate change are some of the limitations in reaching optimum production in the country.

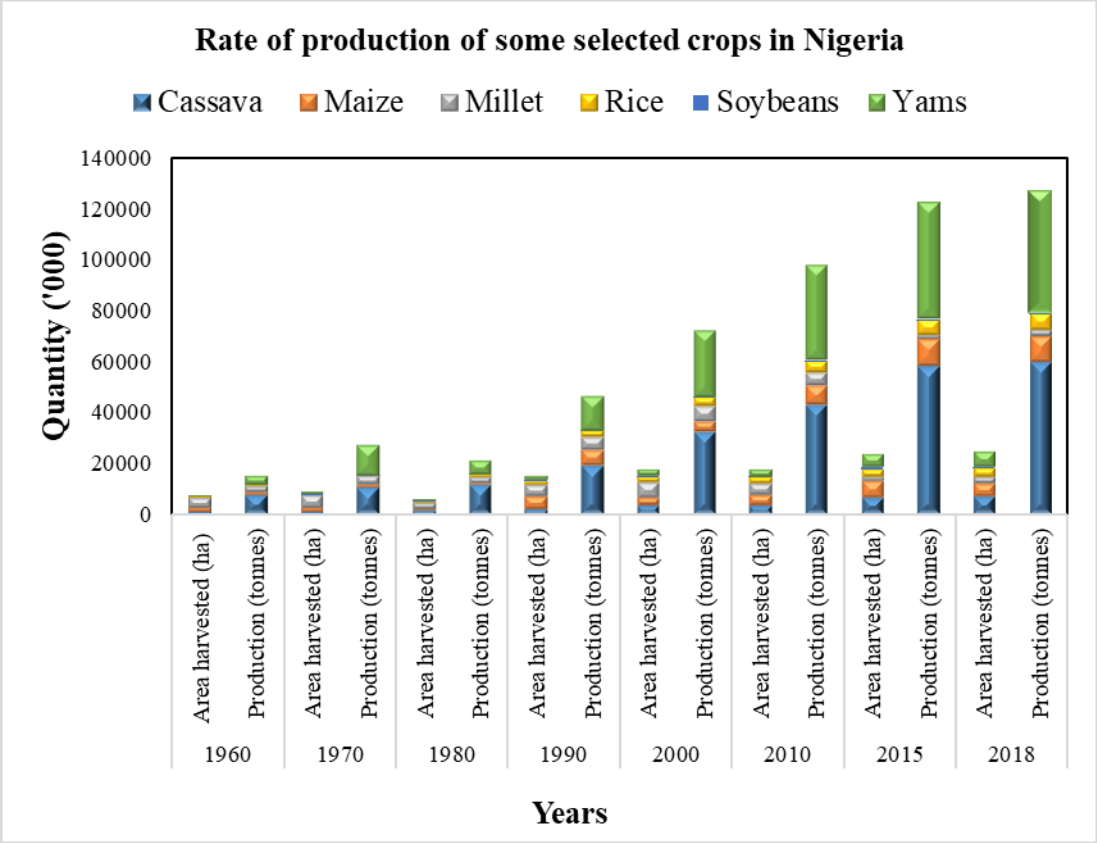

Figure 2.3: Rate of production of some selected crops in Nigeria

Source: Author's compilation using FAOSTAT 2019 Data

2.4.2 Crop production in Nigeria under a changing climate

Climate change will impact crop production in Nigeria in different ways (Olayide et al., 2016; Mereu, Carboni, Gallo, Cervigni, & Spano (2015). While some crops will suffocate under high temperature, some other crops will perform optimally. According to Otitoju & Enete (2016), the principal crops grown in the southwestern Nigeria such as soybean, yam, cocoyam, cassava and maize are sensitive to climate variability and climate change. This further stress the fact that climate change will have impacts on crop production, and it is important to know how crops will be affected. It has been reported that climate-smart agriculture such as irrigation will have a positive impact on agricultural production in Nigeria and has the capacity of improving food security (Olayide et al., 2016).

Meanwhile, in all the reviewed climate change studies on crop production in Nigeria, only few have used crop model to establish the pattern of the crop yield. Many of them were conducted on a national level and nothing much have been done on a basin level. Besides, a biophysical model

and water balance model has not been used to estimate CWR, IWR and CWP. Among those reviewed is the research of Enete (2014) which was a study to examine the impacts of climate change on agriculture in Enugu, Nigeria. The research only examined the impacts of climate change based on a statistical analysis of historical weather data and crop yield without prediction of the future yields on a changing climate. In another study, Idumah, et al., (2016) used econometric tools such as Vector Error Correction (VEC) and Augmented Dickey Fuller (ADF) test to examine the impacts of climate change on food production. The study revealed that crop production in Nigeria is significantly dependent on rainfall variability. Similarly, a study was done in Ile-Ife, Nigeria (Adeboye et al., 2019) that evaluated the performance of AquaCrop in simulating the soil water storage, yield and CWP but did not estimate CWR and IWR. The study did not consider climate change assessments as well.

Evidently, the methods employed in most of those studies are based only on assumptions about the climate in the coming years and have no basis on climate projections. There are uncertainties on how crop will respond to future climate predictions under different climate change scenarios in terms of CWR and IWR, yield and CWP. These uncertainties have not been unravelled by many studies. The impacts of climate change on crop production cannot be totally comprehended without examining the biophysical processes of crops and water requirements of crops for the past and future scenarios. Hence, this study seeks to fill the gap that exists within this research area by examining the effects of climate change on crop production through the study of biophysical processes of crops and climate projections to estimate water requirements of crops in a changing climate.

2.4.3 Maize production in Nigeria and future scenarios

Maize is one of the common annual crops grown in Nigeria. In fact, maize is grown in all parts of the country. Maize is grown in all the seven agro-ecological zones of the country. Maize is also of the staple foods eaten in Nigeria. Apart from that, maize is extensively used as animal feed which is highly nutritious. Therefore, maize is an important crop that needs to be studied from time to time. Maize is a C4 plant. C4 plants are the type of plants that their first products of photosynthesis give a 4-carbon compound i.e. oxaloacetic acid (OAA). Other features of C4 plants are that the optimal temperature required for photosynthesis is high, photorespiration rate is absent, the plants

perform more efficiently when the temperature increases and CO_2 fixation is really faster in C4 plants (Steduto, Hsiao, Fereres, & Raes, 2012).

Many varieties of maize exist in Nigeria. These include WESTERN YELLOW NARZO – 17 NEW (FARZ 7) OLD, 096EP6 NARZO – 18 (FARZ – 23), TZPBSR NARZO – 30 New (FARZ 27) old, TZBSR NARZO 29-New (FARZO – 34) old, TZPBSR-W, TZSR-W-1 NARZO-20, TZESR – 20, EV9043SR, DMR – LSRW, DMR-LSR-Y, TZMSR-W and *Kewesoke* (Iken & Amusa, 2004). However, many challenges such as low yield, pest and diseases problems are associated with these varieties which are making scientists and agronomist embark on hybrid projects which are making tremendous progress.

Furthermore, planting date is another crucial factor in the production of maize. Planting is usually done at the onset of rainfall which varies across the agro-ecological zones of the country. Accurate planting date is highly significant to the amount of yield that will be harvested at the end of the planting season. Earlier planting usually results in low quality yields of grains while late planting also results in a poor quantity of yields. The growing length period of maize in Nigeria and within Ogun-Osun River Basin is approximately 90 – 100 days. Various maize planting dates have been identified according to Olomola & Nwafor (2018), which depends on the agro-ecological zones of the country. The study area falls within the Rain Forest zone which implies that maize planting is usually done from mid-March – mid-April depending on when rain was established in the year.

The maize planting dates are:

1. Rain Forest zone: Mid-March – Late March (4th week),
2. Forest – Savannah transition: Late March (4th week)- 3rd week of April
3. South Guinea Savannah: Late April (4th week) - 3rd week of May
4. Northern Guinea Savannah: Late May – Early June (1st week),
5. Sudan Savannah: Early June (1st -2nd week)

Maize water requirements vary depending on the agro-ecological zones. Generally, maize performs optimally in regions that receive an annual rainfall of 600 – 1000 mm. Maize requires adequate water throughout the growing season to increase yield. Maize is also established to perform better in dry regions under supplemental irrigation. (Liben et al., 2018). Also, maize is known to have the capacity of adapting to any climate which makes it to be widely distributed

across the country. Maize requires a lot of sunshine periods and warmth which makes it to have little sensitivity to photo period (Iken & Amusa, 2004).

On soil requirements, the ideal soil for maize is a deep, medium-textured, well-drained, fertile soil with high water holding capacity and a pH range of 5.5 – 8.0. Generally, the soils within the study area are deep, medium-textured, well-drained, has a pH range of 5.5 – 8.0 but with low to moderate soil fertility. Studies have shown that in order to retain a high level of soil fertility under continuous maize cultivation, no-till and minimum tillage practices are possible methods that can be employed (Iken & Amusa, 2004; Olayide et al., 2016). During land clearing and preparation, in order to maintain the topsoil structure and organic matter, minimum disturbance should be done from farm machinery.

Meanwhile, maize production is majorly done under rainfed agriculture which is causing low yield and little profits for farmers. On the regional and national scales, the rate of production is under optimum and expected values. The problems associated with maize production are similar to other crops within the study area and in Nigeria at large. These problems include insufficient funding for the government, poor post-harvest processing and storage, parasite infections, crop diseases and pests, poor extension services, lack of insurance for farmers, inadequate access to inputs such as seeds, agro-chemicals and fertilizers, soil infertility, rainfall variability, climate variability, uncertainties about the onset of rainfall and planting dates.

Additionally, irregularities in the onset of rainfall, frequencies and intensities are some of the challenges that are ravaging maize production in the country since most of the farmers practice rainfed agriculture. It is becoming extremely difficult to grow maize due to uncertainties in crop yields-climate behaviour. Low yields of maize have huge consequences on food security and income for smallholder farmers in the country and within the study area. Although on a national scale, there are improvements on the rate of production and yield of maize with about 6.5% within the last five years, it is still far below expectations (Olomola & Nwafor, 2018).

Meanwhile, studies have shown that maize is highly sensitive to climate variability and climate change. According to a study done in Iraq which is a dry region, the findings show that maize will require more irrigation water after tomato and wheat among the selected crops that were studied (Ewaid et al., 2019). This implies that water scarcity or irregularities in rainfall patterns which is caused by climate change will have huge impacts on the yield and performance of maize within

that region. However, studies have shown that how maize will perform under climate change predictions depends on the location, global climate model used and CO_2 concentration.

According to (Roudier, Sultan, Quirion, & Berg, 2011), future yields of maize when simulated under increased CO_2 will largely decrease compared with studies that predicted positive impacts. This is basically true for C4 plants such as maize, millet and sorghum. Similarly, this is in accordance with the observations of a similar study in China that used a process-based crop model (AquaCrop) that the yields and water use efficiency of maize increased when simulated under different climate change scenarios (Li, Zhu, Mao, & Adeloye, 2016). However, contrary to these findings is a study in Cameroon by Tingem & Rivington (2009) that also used a process-based crop model (CropSyst) to study the impacts of climate change on maize yield and water need. The results show that there are no or little changes in the simulated yield of maize within the study area based on the global climate models that were used. Hence, there are still uncertainties and unknown details about yield, water requirements and quality of maize grains. Water requirements are expected to increase due to the increase in temperature across all regions, but rainfall is projected to vary across regions and locations. For regions where rainfall is projected to increase, will rainfall compensate for evapotranspiration that is expected to increase as a result of the rise in temperature? In addition, for regions where rainfall is projected to decrease, what will be the response of maize to the shift in rainfall?

On the other hand, the quality of maize grains are likely to reduce due to increased CO_2, the protein content of maize grains will reduce and it will increase the weakness of grains to pests and diseases under this condition (Roudier et al., 2011). According to Corbeels, Berre, Rusinamhodzi, & Lopez-Ridaura (2018), argued that there are variations in the increase in maize yields based on the global climate model that was used. It remains unclear whether it is the global climate model that forces increase in maize yields or rising in atmospheric CO_2 concentration or it depends on the crop model used. Also, it is not clear if it is based on the location as well. Hence, it is imperative to study and have more research on the impacts of increased CO_2 concentration on C4 plants such as maize, millet and sorghum on a regional basis. So, this study seeks to shed more light on these uncertainties through estimation of the impacts of the rise in CO_2 concentration on maize yield, growth, and water requirements in Ogun-Osun River Basin based on different CO_2 concentration levels and climate change predictions for the region.

Globally, in order to combat the threats of climate change, irrespective of the climate projections and results from crop models, farmers and scientists have been motivated to embrace climate-smart agriculture. According to Olayide et al. (2016), climate-smart agricultural practices such as supplemental irrigation on 1% of the current arable land is capable of increasing crop production by 5.99%. This implies that there is an urgent need to further study the responses of maize to a changing climate on a regional scale such as Ogun-Osun River Basin to better understand the dynamics of maize growth based on the climatic and soil conditions of this region.

2.4.4 Soybean production in Nigeria and future scenarios

Soybean is also one of the common staple food grown in Nigeria. Soybean is a profitable crop that is grown in all parts of Nigeria but predominant in the sub-humid and savannah agro-ecological zones (Adeboye et al., 2019). In Africa, Nigeria and South Africa are the two leading countries in the production of soybean responsible for 29% and 40% of total African production respectively (Gbegbelegbe et al., 2019). Soybean is commonly used to produce soybean cake used as animal feeds after cooking oil has been extracted from it. Soybean production is expected to rise due to population growth, an increase in food demand and a shift in food consumption. Currently, there is an increased demand for soybean globally and production is expected to double in 2050 compared to the rate of production in 2010.

Soybean is a C3 plant. C3 plants are the type of plants that their first products of photosynthesis give a 3-carbon compound i.e. phosphoglyceric acid (PGA). Other features of C3 plants are that the optimal temperature required for photosynthesis is really low, photorespiration rate is high, the plants perform more efficiently when the temperature decreases and CO_2 fixation is really low in C3 plants (Steduto et al., 2012).

Additionally, soybean is highly sensitive to changes in climate and soil properties (Dugje et al., 2009). The soil pH requirement of soybean is 4.5 – 8.5 for optimum growth. Furthermore, there are different varieties of soybean in Nigeria. They include TGX 1448-2E which is common in southern and northern Guinea savannahs, TGX 1835-10E and TGX 1485-1D that are common in Guinea savannah. TGX 1448-2E is known to be the best variety because it has medium maturing, high yield, and significant oil content as well as exceptional colour (Dugje et al., 2009). In this study, this variety will be used for simulation because it is mostly planted by the farmers within this study area.

Furthermore, planting date is another crucial factor in the production of soybean. Planting is usually done at the onset of rainfall once rainfall is stabilised. This varies across the agro-ecological zones of the country. Accurate planting date is highly significant to the amount of yield that will be harvested at the end of the planting season. Earlier planting usually results in low-quality yields of grains and permanent wilting of crops might occur if there is a cessation of rain. Also, late planting may expose crops to pest and diseases' attack which may result in a low-quantity of yields. The growing length period of soybean in Nigeria and within Ogun-Osun River Basin ranges from 100 - 120 days.

Various soybeans planting dates have been identified according to (Dugje et al., 2009), which depends on the agro-ecological zones of the country. The study area falls within the Rain Forest zone which implies that soybeans planting is usually done from early June to early July depending on when rain was established in the year.

The soybean planting dates are:

1. Rain forest zone, derived savannah and southern Guinea savannah: early June to mid-June,
2. Northern Guinea savannah: mid-June to early July,
3. Sudan savannah: 1st – 2nd week of July.

Furthermore, the water requirement of soybean varies according to soil type, conservation practices, variety and climate. About 500 – 600 mm of annual rainfall is required for optimum growth and yield of soybean. Soybean is known to perform well under good soil condition most especially on loamy or sandy-loam soils. In a study done in India, the gross water requirements (CWR and IWR) was found to be 637.2 mm when simulated on CROPWAT based on semi-arid climate (Memon & Jamsa, 2018). The limitation of this study is that the soil types and the conservation practices are not explicitly stated. Crop data and climate are part of the crucial factors that affect CWR.

Soybean production is currently facing a lot of problems. These problems include insufficient funding for the government, poor post-harvest processing and storage, parasite infections, crop diseases and pests, poor extension services, lack of insurance for farmers, inadequate access to inputs such as improved seeds, agro-chemicals and fertilizers, soil infertility, rainfall variability, climate variability, uncertainties about the onset of rainfall and planting dates.

In Ogun-Osun River Basin, soybean is predominantly cultivated under rainfed agriculture which means that irregularities in rainfall patterns and rise in temperature can cause water stress for crops and significantly affect yields and water requirements. Soybean has been reported to be highly sensitive to climate change (Gbegbelegbe et al., 2019). Just as other crops, there are a lot of uncertainties on the responses of soybean to rise in temperature, changes in rainfall patterns and an increase in atmospheric CO_2 concentration. However, there are some studies that have been carried out to predict this phenomenon. Significant yield increase is projected in Cameroon when simulated with a process-based crop model (CropSyst) coupled with two global climate models (GCMs) under different climate change scenarios (Tingem & Rivington, 2009). The growing period of soybean is also projected to reduce by two (2) – twenty-three (23) days (Tingem & Rivington, 2009). Similarly, studies have shown that due to carbon fertilization of C3 plants such as soybean, there are tendencies that there will be rapid changes in crop yield especially when soybean yields were simulated on extremely high atmospheric CO_2 concentration (Roudier et al., 2011).

Contrary to the results of these findings is that of Gbegbelegbe et al. (2019), that soybean will experience low yields based on two crop models used which are Decision Support System for Agro-technology Transfer (DSSAT) and Lund–Potsdam–Jena managed Land (LPJmL) models. In addition, soybean yield is predicted to reduce when simulated based on global climate models (Gbegbelegbe et al., 2019).

On global, national and regional scales, farmers and scientists have been encouraged to embrace climate-smart agriculture. In order to combat the threats of climate change, irrespective of the climate projections and results from crop models, it is imperative that conservation practices will go a long way in improving crop productivity. To confirm this is a study done in Ile Ife, Nigeria which falls within the study area. The study shows that water conservation practices such as soil bund and mulch plus soil bund improved soybean yield by 41.7% and 44.3% respectively compared to usual practices (Adeboye, Schultz, Adekalu, & Prasad, 2017). Apart from that, water productivity increased by 14% - 41.8% compared with conventional practises (Adeboye et al., 2017). On-site water conservation practices should be encouraged among farmers in the basin to increase crop yield, water productivity, retain soil fertility, retain soil water and for farmers to

maximise profits (Adeboye et al., 2017). These practices will help farmers to adapt to the threats of climate change coupled with irregularities in rainfall patterns and rise in global temperature.

2.5 Crop modelling and climate change

Crop modelling and crop model applications have gained more interest to examine the impacts of climate change on crop productivity. Due to the threats of climate change on agricultural water use and other demanding uses, simulation models have been found to be significant tools in evaluating the water needs of crops (Adeboye et al., 2019; Basso, Hyndman, Kendall, Grace, & Robertson, 2015; Ding et al., 2017; Li et al., 2016; Roudier et al., 2011; Wang et al., 2018). These models are developed to estimate crop growth, development, yield, water use efficiency, water consumption and irrigation schedules under different climatic conditions, soil types, field management, conservation practices and soil fertility. Outputs from these models can be used to inform farmers, scientists and decision-makers on water allocation, planting dates and field management.

Statistical modelling and process-based crop modelling are the two main methods that can be employed to describe likely agricultural yields as well as crop productivity under different scenarios (Wang et al., 2018). Statistical crop modelling relates crop yields in certain locations to climate parameters that employ statistical functions obtained from observations (Stöckle et al., 2014). Statistical crop models can be used for larger scales (regional and national scales) and longer temporal (20-40 years' studies) and it is also possible for them to be coupled with other hydrologic to estimate both historical and future crop yields and water requirements on different scenarios (Ammar & Davies, 2019). Furthermore, future prices of crops based on simulated crop parameters, climate change scenarios and agronomic conditions can be projected when statistical crop models are coupled with economic models (Roudier et al., 2011). However, despite the good features and capabilities of these models, they are still limited on certain features required for adequately simulating crop growth. The first limitation is that the output from these models depends on the availability of extensive historical data of water variables, climate and crop yields to adequately predict crop yields and water needs. Also, these models cannot effectively capture crop growth yields and water requirements under extensive changes in temperature and increased concentration of atmospheric CO_2 (Basso et al., 2015).

On the other hand, process-based crop modelling describes the biophysical processes of crop growth and development which include nutrients cycles and water cycles. Due to the fact that the

process-based model employs detailed non-linear effects of climate on crop and the inter-seasonal attributes of crops, most recent works in this research area uses process-based models (Adeboye et al., 2019). Process-based crop models overcome the limitations of statistical crop models. These models have been established to give a precise prediction of crop-yield responses to different agronomic conditions, climatic conditions, soil types and conditions as well as field management. (Ammar & Davies, 2019). Examples of these model include EPIC (Erosion Productivity Impact Calculator), APSIM (Agricultural Production Systems Simulator), FAO's AquaCrop (Vanuytrecht et al., 2014), CropSyst (Stöckle, Donatelli, & Nelson, 2003), STICS (Simulator Multidisciplinary for Crop Standard) and WOFOST (World Food Studies). Process-based crop models use deterministic functions and are capable of accurately estimating the effects of climate change including changes in temperature and increasing CO_2 concentration on crop growth, yields and water requirements on different soil conditions and field management (Vote et al., 2015).

However, process-based models do not exist without their own shortcomings. Process-based models are limited in input requirements. Fine-scaled data series which most times are not readily available, difficult to find or to generate are required for an excellent performance of process-based crop models (Basso et al., 2015). In addition, these data series are also difficult to obtain especially in developing countries that have challenges in physical instrumentation, measurements and data capturing for a long period of time. Despite these limitations, process-based crop models have been established to be superior to the statistical crop models for climate change studies (Adeboye et al., 2019; Ammar & Davies, 2019; Umair et al., 2017; Vote et al., 2015).

Crop model applications can also be categorized according to the captured resources used for calculating the rate of biomass production of a crop (Stöckle et al., 2014; Todorovic et al., 2009). The classifications are carbon-driven, radiation-driven, and water-driven (Adeboye et al., 2019). The carbon-driven crop models simulate crop growth and development based on the carbon assimilation by crop leaves and radiations that are intercepted. Examples of the carbon-driven model are WOFOST (World Food Studies) and CROPGRO (CropGrowth). On the other hand, the radiation-driven models are based on using radiation use efficiency that is calculated based on assimilated solar radiation for estimating the production rate of biomass. Examples include CERES (Crop Environment Resources Synthesis), CropSyst and STICS (Simulator Multidisciplinary for Crop Standard). Meanwhile, the water-driven models are based on the estimation of transpiration

obtained from factor known as water productivity for evaluating the rate of biomass production. Examples of water-driven models are CropSyst and AquaCrop. The water-driven models have a lot of advantages over other types of crop models. One of the merits is that these models can be used for extensive spatial and long temporal studies based on the principle that water productivity is normalised for important climatic factors such as the concentration of CO_2 and evaporation (Todorovic et al., 2009). Normalising water productivity for important climatic factors such as evaporation and CO_2 concentration are essential for modelling the impact of climate change on crop growth, development and water requirements.

Nevertheless, it should be noted that there is no single crop model that is most appropriate for all studies, research, and planning as well as policy formulation. The selection of crop model(s) for any study depends largely on the objectives and scope of the study, the discipline and expertise of the researcher, the output of interest, data requirements and availability of input data. Since there is no single crop model that can fit in for all circumstances, it is the responsibility of the modeller to appropriately select a model that will fit into the objectives and scope of the study, data availability, the output of interest and expertise of the modeller.

Based on the foregoing and considering the different merits and demerits of the different categories of crop models available globally; it has been established that process-based crop models are superior to the statistical crop models especially in the assessment of the impact of climate change on crop growth, yields, and water requirements. In addition, based on the second classification of crop models, it has been formulated that models that simulate crop growth based on water-driven are most suitable for climate change studies.

Therefore, considering the objectives and scope of this study, since there is a keen interest on modelling the impact of climate change on crop growth, development and water requirements from the perspective of water engineering and climate change discipline, a process-based crop model that is water-driven which is AquaCrop is selected for this study. AquaCrop was developed by FAO and has been widely used for assessment of climate change impacts on crop growth, development and water requirements.

2.6. AquaCrop

AquaCrop is a crop water productivity and decision-making model that was developed by the Land and Water Division of FAO. One of the outstanding attributes of this model is that it is user-friendly, not complex and requires relatively few parameters for calibration compared to other crop models (Vanuytrecht et al., 2014). The parameters describe the soil, crop and atmosphere interactions that are highly crucial for crop growth.

2.6.1 Description of AquaCrop parameters

AquaCrop requires few input parameters and little calibration irrespective of the study location and time consideration. The input parameters can be categorised into four (4) classes which are climatic data, soil data, crop data and field management.

1. Climatic data

In order to make any simulation in the model daily climatic data are required such as;

a) Daily maximum and minimum air temperature, ^{0}C
b) Evapotranspiration (mm/day)
c) Rainfall (mm/day)
d) Daily wind speed (km/hr)
e) Solar radiation (MJ/m^2/day) and
f) Relative humidity (%)

The most important parameters are maximum and minimum temperature used for calculating growing degree day (GDD) as well as daily rainfall, sunshine hours and evapotranspiration (ET) which are used for measuring the evaporative potential of the atmosphere. Reference evapotranspiration (ET_0) is estimated in AquaCrop from inputted climate data using the Penman-Monteith equation which has been reported as the most effective method of estimating evapotranspiration (Fisher & Pringle III, 2013). The formula is given below in Equation 2.1:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\left(\frac{900}{T_{mean} + 273}\right)U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad \text{Equation 2.1}$$

ET_0 = Daily reference evapotranspiration (mm/day)

Δ = Slope of vapour pressure curve (kPa^0/C)

R_n = Daily net radiation (MJ/m^2)

G = Soil heat flux (MJ/m^2)

γ = Psychometric constant ($kPa^0C.MJ/m^2$)

T_{mean} = Daily air temperature (^0C)

U_2 =Daily wind speed at 2m elevation (m/s)

e_s = Saturation vapour pressure, kPa

e_a = Actual vapour pressure (kPa)

Nevertheless, an ET_0 calculator and CROPWAT developed by FAO can also be used for estimating ET_0.

However, due to the challenges of availability and access to data especially daily climatic data, the model can derive daily climatic data from 10-day or monthly means data using the interpolation procedures (Raes et al., 2009). Although, it is highly recommended to use daily weather data in order to obtain more reliable results during simulations. In addition, the mean annual atmospheric concentration of CO_2 of previous years inputted into the model was retrieved at Mauna Loa Observatory Centre, Hawaii, United States (Raes et al., 2009).

2. Soil data

Soil data are also needed for simulation in the model. Generally, the soil profile has about five (5) distinctive horizon with their own properties. For AquaCrop simulations, the following parameters are needed (FAO, 2017a):

a) Field capacity (Θ_{FC}) (fraction or percentage)
b) Permanent wilting point (Θ_{PWP}) (fraction or percentage)
c) Saturated hydraulic conductivity (K_{sat}) (mm/day)
d) Volumetric saturated water content (Θ_{sat}) (m^3 of water m^{-3} of soil)

In addition, the model gives the user the chance to use some suggestive details given in the model for different textural classes and users can input in-situ parameters. The model can also derive soil properties using pedo-transfer functions (Raes et al., 2009).

3. Crop data

FAO has provided some crop parameters as default values that are not specific for any location but are specific for the crops. This implies that these parameters are conservative parameters and do not usually change based on location, field management practices or time. These values are obtained from experiments of crops grown under favourable and non-stress situations. However, these values can be applied to limiting situations as a result of in-built response algorithms designed for limiting conditions (Vanuytrecht et al., 2014). Nevertheless, the user is expected to provide various specific parameters to improve the output of the model.

Conservative parameters as shown in Table 2.1 are applicable to all locations and time periods of study and require no adjustment at all (Raes et al., 2009). Nevertheless, it is important to calibrate and validate non-conservative parameters shown in Table 2.2 for accurate results because model parameters are location specific and should be adjusted appropriately to fit different climatic and soil conditions, crop varieties, field management as well as water management practices.

4. Field management

In AquaCrop, field management practices are subdivided into two parts which are general and irrigation management. Under general management, the user will need to input the soil fertility level and information on other conservation practises such as mulching, soil cover, and tillage practices. While under irrigation management, the modeller will choose if the crop is rainfed or irrigated. If it is irrigated, the modeller will give details about irrigation dates and depth. The model can also develop irrigation schedules based on some functions in CROPWAT.

Furthermore, AquaCrop projects fluctuations in the amount of water retained in the crop root zone through the estimation of daily water balance that comprises of all water movements both inward and outward movement of water including evapotranspiration, infiltration, runoff, deep percolation, rainfall and irrigation. Also, there are different four factors that are used to estimate the impact of water scarcity on crops. Each factor is a part of the reduction of the total available water (TAW) in the crop root zone. These factors are for harvest index, canopy development, stomatal conductance and canopy senescence. All the factors have their own maximum depletion level and curves.

Table 2.1: AquaCrop conservative crop parameters

Crop development and growth
❖ Minimum and maximum temperatures for growing degree days ❖ Canopy size of the seedling at 90% growth stage ❖ Canopy growth coefficient (CGC) and Canopy decline coefficient (CDC) ❖ Crop determinacy connected or unconnected with flowering; excess of potential fruit (%)
Crop transpiration
❖ Decrease in crop coefficient due to maturity
Biomass production and yield formation
❖ Normalised water productivity WP* for ET_0 and CO_2 ❖ Decline in crop coefficient to show the impacts of the products produced during development of yields on the normalised water productivity ❖ Baseline harvest index (HI_0)
Water stress parameters
❖ Maximum and minimum values of soil-water depletion for canopy development and profile of stress plot ❖ Maximum value of soil-water depletion for stomatal closure and profile of stress plot ❖ Maximum value of soil-water depletion for initial senescence and profile of stress plot ❖ Maximum value of soil-water depletion for absence of fertilization and profile of stress plot ❖ Probable rise in HI value caused by water stress before the stage of flowering ❖ Factor revealing the positive effects of hindered vegetative development during yield development on HI. ❖ Factor revealing the negative effects of stomatal closure during yield development on HI ❖ Upper threshold of the rise in specified HI ❖ Anaerobic point
Temperature stress parameters
❖ Upper and lower values of air temperature lower than the temperature which fertilization begin to decline ❖ Lower values for growing degrees needed for complete development of biomass

Table 2.2: AquaCrop non-conservative crop parameters for calibration and validation

Phenology (Depends on crop variety)
❖ Period to the start of yield development ❖ Time of the flowering stage ❖ Period to begin canopy senescence ❖ Total length of the crop from sowing to maturity or harvesting
Management factors
❖ Plant density (volume per unit area) ❖ Length of sowing to 90% growth ❖ Upper threshold of canopy cover
Soil factors
❖ The maximum rooting depth of crop ❖ Number of days taken to reach maximum rooting depth
Soil and management parameters
❖ Behaviour of crop to soil fertility levels ❖ Topsoil salinity stress

2.6.2 Algorithms of AquaCrop

1. Crop yield

In terms of calculating crop yield, AquaCrop differentiates biomass from harvest index (HI) but uses the multiplication of biomass and harvest index which is different from other crop models as given in Equation 2.2 (FAO, 2017a; Raes et al., 2009).

$$Y = HI \times B \qquad \text{Equation 2.2}$$

Where;

Y = Crop yield (kg/ha or t/ha)

HI = Harvest index (fraction or percent)

B = Biomass (t/ha or kg/m^2)

2. Canopy development

Another algorithm of AquaCrop is that in order to evade the misperception of the impacts of non-useful water consumption by crops, the model separates actual evapotranspiration (ET) into crop transpiration and soil evaporation. In addition, many other models use land area index (LAI) to estimate leaves growth while this model uses green crop cover (CC) (Greaves & Wang, 2016). The initial stage of canopy cover development which is corresponding to the rate of the crop growth is given in Equation 2.3 as reported by (Steduto et al., 2012).

$$CC = CC_0 \times e^{CGC.t} \qquad \text{Equation 2.3}$$

Where;

CC = The percentage of canopy covering the soil at a time "t" (fraction or percent)

CC_0 = Initial CC at time t=0 (fraction or percent)

CGC = Canopy development factor (fraction or percent)

However, the canopy cover development changes for the second stage of crop growth because once canopy growths broader, it covers more surface of the soil, thus photosynthesis and sunshine capture increases as given in Equation 2.4 (Vanuytrecht et al., 2014).

$$CC = CC_x - (CC_x - CC_0) \times e^{-CGC.t} \qquad \text{Equation 2.4}$$

Where;

CC_x = Upper canopy development for ideal environment (fraction or percent)

CC_0 = Initial CC at time t=0 (fraction or percent)

CGC = Canopy development factor (fraction or percent)

3. Water stress factors

The impacts of environmental changes on crop growth and yield are estimated by water stress factor (Ks). Ks varies from one (zero stress) to zero (complete stress). This factor is different from root zone depletion (D_{rel}) which is the fraction of water available for crops compared to the amount of water at field capacity. Dr varies from zero at field capacity (when Ks = 1) and one at permanent wilting point (when Ks = 0). The equation to estimate the water stress factor is given in Equation 2.5 as given by (Raes et al., 2009).

$$0 \le Ks = 1 - \frac{e^{D_{rel} \times f_{shape}} - 1}{e^{f_{shape}} - 1} \le 1 \qquad \text{Equation 2.5}$$

Where:

Ks = Water stress factor (fraction or percent)

D_{rel} = Root zone water depletion (fraction or percent)

f_{shape} = Response of crop to water stress as given in AquaCrop

Furthermore, the water stress coefficient depends on the transpiration rate and subsequently on evapotranspiration. The ET_0 for AquaCrop is 5mm/day thus p is adjusted according to various ET_0 as given in Equation 2.6.

$$0 \leq P_{adj} = P_{given} + f_{adj}\left[0.04 \times \left(5 - ET_0\right)\right] \times \left\lfloor \log_{10}\left(10 - 9 \times P_{given}\right) \leq 1 \right\rfloor \qquad \text{Equation 2.6}$$

Where;

f_{adj} = AquaCrop parameter that is cab be greater than 1 or less than 1.

P_{adj} = Adjusted rainfall (mm)

P_{given} = The inputted rainfall (mm)

4. Crop transpiration

In this model, in order to estimate daily transpiration for non-water stress conditions, the crop coefficient for crop transpiration are employed with CC and ET_0 while the soil coefficient is used with CC and ET_0 in estimating daily soil evaporation as given by (Vanuytrecht et al., 2014) in Equation 2.7.

$$Tr = Ks(Kc_{Tr.x} \times CC^{*})ET_0 \qquad \text{Equation 2.7}$$

Where;

Tr = Crop transpiration (mm/day)

Ks = stress factor (Ks_{sto} or Ks_{aer}) (fraction)

CC* = adjusted green canopy cover (fraction or percent)

$Kc_{Tr.x} \times CC^{*}$ = crop coefficient and

ET_0 = Evaporative potential of the atmosphere (mm/day)

5. Biomass development, water productivity and harvest index

Furthermore, harvest index is one of the conservative parameters that does not require adjustments for simulation. The default value of harvest index can be adjusted to fit into specific location or variety of crop depending on the user of the model. In estimating yield, AquaCrop automatically adjusts HI to respond to temperature changes and water stress conditions which is very crucial for this study. The daily biomass production in the model is calculated as given by (Raes et al., 2009) in Equation 2.8:

$$WP^* = \left[\frac{B}{\sum \left(\frac{Tr}{ET_0} \right)} \right]_{[CO_2]} \qquad \text{Equation 2.8}$$

Where;

B = daily aboveground biomass (t/ha or kg/m^2)

Tr = daily crop transpiration (mm/day)

ET_0 = daily reference evapotranspiration (mm/day)

WP* = water productivity of the crop variety normalised for atmospheric CO_2 concentration levels and evaporation (t/ha or kg/m^3).

6. Soil drainage

Water drainage in soil happens when the soil water content is higher than the field capacity. The quantity of water that moves out of the soil layer at any given time is given in Equation 2.9 as reported by (Raes et al., 2009).

$$\frac{\Delta\theta_i}{\Delta t} = \tau(\theta_{sat} - \theta_{FC}) \frac{e^{\theta_i - \theta_{FC}} - 1}{e^{\theta_{sat} - \theta_{FC}} - 1} \qquad \text{Equation 2.9}$$

Where;

$\frac{\Delta\theta_i}{\Delta t}$ = is the reduction in soil water content within a given time (m^3/m^3/day)

θ_{sat} = Soil water content at saturation (fraction or percent)

θ_{FC} = Field capacity of the soil (fraction or percent)

τ = Drainage factor (dimensionless)

7. Soil evaporation

Soil evaporation occurs in two (2) stages during crop growth which are energy stress stage and the stage when there is a limited upward movement of water from the soil layers to the surface. For the first stage, the equation for estimating soil evaporation is given in Equation 2.10.

$$REW = 1000 \times (\theta_{FC} - \theta_{airdry}) \times Z_{e,surf} \qquad \text{Equation 2.10}$$

Where;

REW: Readily evaporative water at the topsoil (mm)

θ_{FC} = Field capacity of the soil (fraction or percent)

$\theta_{\text{air dry}}$ = Soil water content of the dry soil (fraction or percent)

$Z_{e,\ surf}$ = the thickness of the soil surface (mm)

For the second stage, when REW= 0, the $Z_{e,\ surf}$ changes to $Z_{e,\ top.}$

For a bare soil, the soil evaporation is estimated using Equation 2.11.

$$E = Kr \times E_x = Kr \times Kc_{e,wet} \times ET_0 \qquad \text{Equation 2.11}$$

Where;

$Kc_{e,wet}$ = Evaporation factor for completely wet bare soil (dimensionless)

Kr = Evaporation reduction factor (usually ≤ 1)

In order to compensate for the reduction in hydraulic conductivity when there is reduction soil water, Equation 2.12 is employed in the model.

$$0 \leq Kr = \frac{e^{f_k \times W_{rel}} - 1}{e^{f_k} - 1} \leq 1 \qquad \text{Equation 2.12}$$

Where;

f_k = Reduction factor

W_{rel} = Relative water content of the soil section

8. Atmospheric CO_2 concentration

In AquaCrop, the atmospheric CO_2 concentration is estimated by using Equation 2.13 for the normalisation of water productivity by evapotranspiration (Raes et al., 2009).

$$f_{CO_2} = \frac{\left(C_a / C_{a,0} \right)}{1 + 0.000318 \times \left(C_a - C_{a,0} \right)} \qquad \text{Equation 2.13}$$

Where;

f_{CO_2} = Modification coefficient for CO_2 (dimensionless)

C_a = Atmospheric CO_2 (µL/L)

$C_{a,0}$ = Baseline CO_2 recorded in 2000 at Mauna Loa Observatory Centre, Hawaii which is 369.47 µL/L.

9. Effects of water stress on yield

Water availability plays a vital role on crop yield. However, when there is water stress, crop growth is grossly hindered and could lead to the wilting of crops. The impact of water stress on crop growth as well as the yield depends largely on the period of growth and the extent of water stress. AquaCrop simulates crop yields based on Equations 2.14, 2.15, and 2.16 depending on the stage of crop growth (Raes et al., 2009).

If water stress occurs during reproductive stage;

$$\frac{dHI}{dt} = \left[1 + \frac{\left(1 - Ks_{\exp,i}\right)}{a} \right] \times \left[\frac{dHI}{dt} \right]_0 \qquad \text{Equation 2.14}$$

If water stress deepens that after affect stomata opening;

$$\frac{dHI}{dt} = \sqrt[10]{Ks_{sto}} \left(1 - \frac{1 - Ks_{sto,i}}{b} \right) \left(\frac{dHI}{dt} \right)_0 \qquad \text{Equation 2.15}$$

If water stress intensifies such that pollination is hindered, the effects of water stress on harvest index is:

$$HI_{0,adj} = \left[\sum \left(Ks_{pol} \times a \times F \right) \right] \times HI_0 \leq HI_0 \qquad \text{Equation 2.16}$$

Where;

$\frac{dHI}{dt}$ = Change in harvest index per unit time

$\left[\frac{dHI}{dt}\right]_0$ = Change in harvest index per unit time

$Ks_{\exp,i}$ = Water stress factor during canopy development on the day of recording (dimensionless)

$Ks_{sto,i}$ = Water stress factor during stomatal opening on the day of recording (dimensionless)

Ks_{pol} = Water stress factor during pollination phase (dimensionless)

$HI_{0,adj}$ = Modified HI_0 for decrease in pollination as an effect of water stress (fraction or percent)

HI_0 = baseline harvest index (fraction or percent)

F = Proportion of healthy flower on anthesis during that period (percent or fraction)

a and b = Modifiable crop parameters.

10. Crop water productivity

Crop water productivity is the ratio of crop yield to the quantity of water consumed by the crop during a growing period, Equation 2.17.

$$CWP = \frac{Yield}{Crop\ evapotranspiration\ (ET_C)} \qquad \text{Equation 2.17}$$

CWP = crop water productivity in kg/m^3

Yield in t/ha

ET_c in mm/day, mm/season

In summary, Figure 2.4 depicts and summarises AquaCrop parameters and interactions of soil-plant-environment.

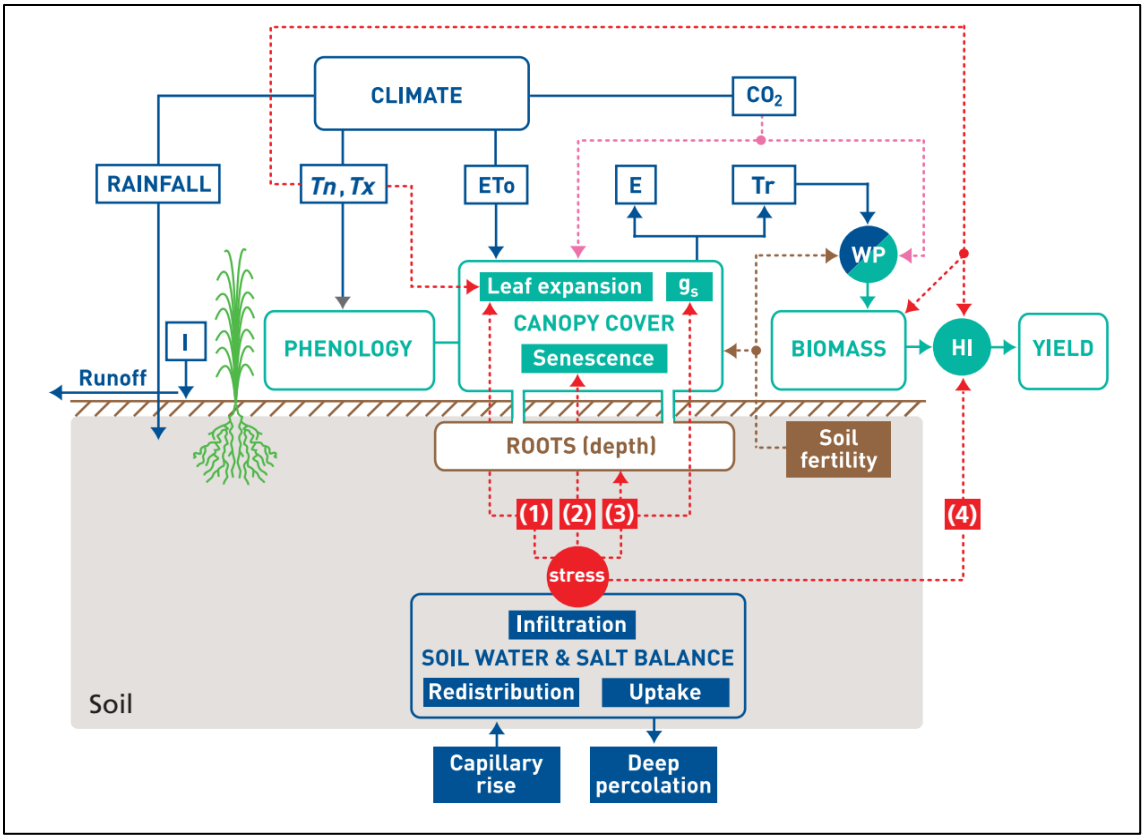

Figure 2.4: Summary of AquaCrop parameters and interactions of soil-plant-environment

Source: (Steduto et al., 2012)

Where:

CO_2 = Concentration of Carbon di oxide; E = Soil evaporation; ET_0 = Reference evapotranspiration; g_s = Stomatal conductance; I = Irrigation; T_r = Crop transpiration; T_n = Minimum air temperature; Tx = Maximum air temperature; WP = Water productivity; HI = Harvest index;

(1), (2), (3) and (4) are functions of water stress reactions to leaf development, senescence, stomatal conductance and harvest index respectively. Continuous lines represent direct connections between parameters and processes while broken lines represent results.

2.6.3 Applications of AquaCrop

AquaCrop has been used extensively in several studies for many crops including maize, sorghum, tomato, potato, rice, soybean, sugar beet, sunflower and wheat. AquaCrop has been evaluated for maize production with excellent performance (Ammar & Davies, 2019; Greaves & Wang, 2016; Li et al., 2016; Raja, et al., 2018; Roudier et al., 2011). It is worthy to note that the model has been

reported to be able to satisfactorily simulate canopy cover, grain yield, biomass development, and water requirements under different sowing dates, climatic and soil conditions, field management practices, as well as the concentration of CO_2 (Li et al., 2016).

Furthermore, AquaCrop has been used in calibration and validation of maize planting dates for grain yield and crop water use under full irrigation schedules and non-water stress simulations that gave excellent results. For instance, grain yield and crop water use of maize were calibrated and validated in India with a high coefficient of efficiency of 0.99 and 0.71 respectively between simulated and experimental observations (Raja et al., 2018). In addition, the model was able to give excellent results for both canopy cover and inter-season biomass development under different planting dates with root square mean error (RSME) of 9.97% and 1.78 t/ha respectively (Raja et al., 2018). This implies that AquaCrop is capable of accurately simulating canopy cover and biomass development for full irrigation treatments and non-water stress situations.

In contrast, AquaCrop has been reported to give fair to unsatisfactory results of maize grain yield, canopy development and biomass development only under extreme water stress situations. For instance, in a study conducted in Italy, AquaCrop and other crop models were used for the simulation of maize grain yield, water requirement, canopy cover and biomass development which shows that AquaCrop performed better under full irrigation treatments and non-water stress situations but gave less satisfactory results under extreme water stress conditions when compared with other crop models (Todorovic et al., 2009). In addition, AquaCrop was also used to simulate the yield, biomass, canopy cover, and crop evapotranspiration of maize in Taiwan under different water regimes (Greaves & Wang, 2016). The results show that AquaCrop performed excellently when simulated under full irrigation and moderate water stress conditions. However, errors of about 9.5 – 22.2 % and 6.0 – 32.2 % were observed for simulations of crop evapotranspiration and water use efficiency under intense water stress situations. This limitation might be not unconnected to the fact that AquaCrop is a water-driven crop model.

AquaCrop has been used in simulating yield, canopy cover, evapotranspiration and water productivity of soybean under rainfed agriculture with different conservation practices such as mulching, bund, tied ridges, tied ridges with bund, and tied ridges with mulch in Ogun-Osun River basin, Nigeria. The results show satisfactory simulated values when compared with observed values (Adeboye et al., 2019). Among all the parameters evaluated, of deep interest is the grain

yield and CWP for this study. The R^2 of the simulated grain yield, evapotranspiration and CWP are 0.99, 0.66 and 0.78 respectively. This implies that AquaCrop is capable of reliably simulating grain yield of soybean within this study area under different climate change scenarios.

2.7 CROPWAT

The Land and Water Division of FAO developed the decision model-CROPWAT in 1992 (Smith, 1992; (Mason, Rufí-Salís, Parada, Gabarrell, & Gruden, 2019). CROPWAT is a computer decision support tool that operates on empirical functions developed based on climate, soil and crop data to estimate CWR and IWR. CWR and IWR are dependent on climate parameters such as rainfall, evaporation, humidity and temperature as well as soil parameters such as soil moisture. The latest version of CROPWAT is 8.0 which can be used to estimate the performance of crops both on rainfed and irrigation practices which are based on a daily soil-water balance. CROPWAT model has been used extensively for simulating CWR and IWR as well as scheduling irrigation with subsequent good performances (Ewaid et al., 2019; Kumari, 2017; Mason et al., 2019; Memon & Jamsa, 2018; Shah, 2018; Vote et al., 2015). The input parameters are the same as for AquaCrop. CROPWAT can also be coupled with CLIMAT 2.0 database files complied by FAO which contains climate data from about 5000 agro-meteorological stations across the globe for simulations. The database contains average monthly climatic data from 1971 - 2000. Furthermore, just like AquaCrop, CROPWAT has some experimental crop and soil data that can be useful when a modeller does not have sufficient data. It is highly recommended that these data should be calibrated and validated with field data obtained from the study area to acquire reliable outputs from the model.

2.7.1 Algorithms of CROPWAT

1. Evapotranspiration and crop yield

According to (Steduto et al., 2012), Equation 2.18 expresses the effects of decrease in evapotranspiration on crop yield. Decrease in evapotranspiration causes decrease in crop yield.

$$\left[1-\frac{Y_a}{Y_{\max}}\right]=K_y\left[1-\frac{ET_a}{ET_{\max}}\right] \qquad \text{Equation 2.18}$$

Where;

$Y_{\max}$ = Maximum crop yield under optimum conditions (kg/ha or t/ha)

Y_a = Actual/obtainable crop yield under limiting conditions (kg/ha or t/ha)

K_y = Water stress factor (fraction)

ET_a = Actual evapotranspiration under limiting conditions (mm)

$ET_{\max}$ = Maximum evapotranspiration under optimum conditions (mm)

Evapotranspiration in CROPWAT is estimated using Penman-Monteith equation given in Equation 2.1.

2. Effective rainfall

In addition, when it rains, not all rainwater is available for crops. Some water losses occur through evapotranspiration, runoff and percolation. The amount of water from rainfall available for crops within the crop root zone after loses is known as effective rainfall. In CROPWAT, the United States Department for Agriculture (USDA) Soil Conservation method is used to estimate the effective rainfall so as to consider water removal through runoff and deep percolation which are components of water balance. The formulas are given in Equations 2.19 and 2.20.

$$P_{eff} = \left[\frac{P_{dec} \times (125 - 0.6 \times P_{dec})}{125} \right] \quad \text{for } P_{eff} \leq 250/3 \text{ mm} \qquad \text{Equation 2.19}$$

$$P_{eff} = \left(\frac{125}{3} \right) + 0.1 \times P_{dec} \text{ for } P_{dec} > 250/3 \text{ mm} \qquad \text{Equation 2.20}$$

Where P_{eff} = Effective rainfall (mm),

P_{dec} = 10-day rainfall (mm)

3. Crop water requirement (CWR)

CWR depends on the properties of crop, stage of growth, climatic factors, soil conditions and field management. CWR is estimated in the model as given in Equation 2.21 (Allen, Pereira, Raes, & Smith, 1998; Ewaid et al., 2019):

$$ET_c = K_c \times ET_0 \qquad \text{Equation 2.21}$$

K_c = Crop coefficient (fraction) which describes the impacts of crop height, crop cover, canopy resistance, and soil evaporation.

ET_c = Crop evapotranspiration (mm/day)

ET_0 = Reference evapotranspiration (mm/day)

K_c is not the same throughout the growing period due to variations in *ET* as a result of different growing stages that characterises crop growth. Crop growing stages are divided into four which are initial, development stage, mid-season and late season (Allen et al., 1998).

4. Irrigation water requirement (IWR)

In CROPWAT, the water balance of the crop root zone is estimated on a daily basis using Equation 2.22.

$$D_{r,i} = D_{r,i} - 1 - (P_i - RO_i) - I_i - CR_i + ET_{c,i} + DP_i \qquad \text{Equation 2.22}$$

Where;

$D_{r,i}$ = Depletion of water at the crop root zone at the end of the day i (mm)

$D_{r,i} - 1$ = The water content available within the crop root zone at the end of the preceding day of the measurement (mm)

P_i = Rainfall on day i (mm)

RO_i = Runoff at the soil surface on day i (mm)

I_i = Depth of net irrigation on day i (mm)

CR_i = Water movement from groundwater table through capillary rise on day i (mm)

$ET_{c,i}$ = Crop evapotranspiration on day i (mm)

DP_i = Water lost from the root zone on day i (mm)

In order to estimate the decadal and seasonal net irrigation water requirements, the difference between crop evapotranspiration (ET_c) and effective rainfall (P_{eff}) is used, Equation 2.23.

$$IWR = ET_c - P_{eff} \qquad \text{Equation 2.23}$$

Where IWR = Net irrigation water requirement (mm/day; mm/stage, mm/season). To calculate the gross irrigation water requirement, the irrigation efficiency must be known.

2.7.2 Applications of CROPWAT

CROPWAT has been used for estimating CWR and IWR for various crops and locations with excellent results. According to Ewaid et al. (2019), CROPWAT model was able to accurately estimate IWR for barley, wheat, tomatoes and white corns in Iraq during various seasons. Similarly, the model was used in India to calculate CWR and IWR for maize, potato, wheat, castor bean, tomatoes and soybean with reliable outputs (Memon & Jamsa, 2018; Shah, 2018).

Irrigation scheduling that enables farmers to plan irrigation period, reduce water stress and improve yields has been done using CROPWAT with satisfactory outputs (Savva & Frenken, 2002). Future climate data from climate models have also be inputted into the model to simulate future CWR and IWR for various crops, soil conditions, field management and climate scenarios with outputs that can be implemented for future planning (De Silva et al., 2007). Likewise, in Bangladesh, the impacts of climate change on rice water requirements considering thirty years climatic data shows that water requirements for rice has decreased drastically and increased in Moulvibazar and Sylhet respectively (Rahman et al., 2019).

However, there are some limitations of CROPWAT that have been identified. First, the model estimate water stress factor K_y through only one empirical method for all crops and varieties which might increase uncertainties in the outputs from the model. In addition, the model is not capable of carrying over soil moisture over many years and has the inability of reflecting changes in soil fertility over a long period of time since the model is designed for separate and single year simulations.

2.8 Climate change models

Climate change models are extremely useful tools for projecting future climate and giving important future climate information. Currently, there are many climate models with distinguished properties, parameters, uncertainties and errors.

2.8.1 Climate change scenarios

Climate change scenarios are aggregate of several climate change indicators that was developed as a comprehensive summary for policymakers and decision-makers. These scenarios describe the future concentration of greenhouses and possible changes in climatic factors. IPCCC currently uses four scenarios known as Representative Concentration Pathway (RCP) which are RCPs 2.6, 4.5, 6.0 and 8.5 to describe the future climate of the globe (Boonwichai et al., 2018). Each scenario describes the projected level of greenhouse gas concentration. RCP 2.6 is the least level of greenhouse gas concentration at 440 ppm CO_2 equivalent by 2100. RCP 4.5 is the second scenario which is more pessimistic as it describes the high concentration level of greenhouse gas at 570 ppm CO_2 equivalent by 2100. RCPs 6.0 and 8.5 are the critical scenarios that describe exceptionally extreme global temperature and high concentration level of greenhouse gas at 730 ppm and 1200 ppm CO_2 equivalent by 2100 respectively.

2.8.2 Global climate models (GCMs)

Global climate models are atmospheric ocean-coupled climate models that are based on mathematical functions of the global circulation of the ocean or a global atmosphere (Nematchoua, Orosa, & Reiter, 2019). GCMs are used for analysing the variations in climate, future weather predictions and commonly used in climatic studies. GCMs are usually in high spatial resolutions such as 250 × 250 km or more and high temporal resolutions which are usually too large as input parameters into other models such as hydrological, water balance and crop models for analysis as well as policy planning. In order to obtain finer spatial resolution data that can be inputted into other models for further analysis, a special procedure known as downscaling must be carried out.

2.8.3 Downscaling of climate change data

Downscaling of future climate data can be categorised in two methods which are the statistical downscaling method and dynamical downscaling method which is also known as Regional Climate Models (RCMs). The statistical downscaling method is used for projecting finer-scale data for different variables based on the principle of developing mathematical functions knowns as transfer functions and regression equations from large scale data obtained from GCMs. Another method of statistical downscaling is the use of stochastic weather generators which are commonly used for temporal downscaling of yearly or monthly data into daily data for a specific location (Irwin et al., 2012). Weather generators operate on the basis of adding the differences between

GCM data and observed data to form a regression equation that generates a new dataset that is then run in a weather generator to estimate future daily data for a specific location. Examples are Statistical Down-Scaling Method (SDSM), KnnCAD and Long Ashton Research Station Weather Generator (LARS-WG).

On the other hand, a dynamical downscaling method known as RCMs simulates future climate data using GCMs as boundary conditions to finer scales that are usually within the range of 10 - 50 km resolution. RCMs are capable of depicting the climate change trend within a parent GCM. Even though statistical downscaling is cheap and saves time in computation, one of the demerits is their incapability to estimate weather variables over multiple locations at the same without altering the spatial relationship within the observed data. However, RCMs have been established to reduce the bias embedded in GCM data (Klutse et al., 2018). There are still some questions about the accuracy of RCM data since RCMs simulate the climate change trend, bias and uncertainties embedded in the parent GCM.

2.8.4 Regional climate models (RCMs)

It has been established in several studies that downscaling GCM data with RCM can possibly reduce the uncertainties from coarse spatial resolution in GCMs for localised assessment of climate change (Klutse et al., 2018). Under CORDEX, multiple GCMs have been downscaled using different RCMs to regional levels including Africa. In Africa, the downscaled data from CORDEX have been used extensively with reliable outputs (Akinsanola et al., 2018; Klutse et al., 2018; Mbaye et al., 2016; Nikulin et al., 2018; Sylla et al., 2016). Meanwhile, many RCMs have been used to downscale data from various GCMs under the CORDEX experiment. Under CORDEX experiment, Rossby Centre Regional Climate Model (RCA4) is one of the RCMs downscaled by the Swedish Meteorological and Hydrological Institute (SMHI) under nine GCMs. RCA4 has been used extensively with satisfactory output (Akinsanola et al., 2018; Klutse et al., 2018).

2.8.5 Correction of future climate data

Future climate data are usually characterised with errors known as bias. Biases are methodical errors from climate models as a result of algorithms used in projection and large spatial resolution. In order to correct these anomalies, some correction methods have been established.

1. Change factor method

The change factor method known as delta method is based on the principle of using changes in the mean of simulated historical GCM data and simulated future GCM data which are then applied to observed historical data to obtain corrected future data (Mbaye et al., 2016). The same time period must be calculated which is usually a minimum of 30 years. This method is based on sensitivity analysis and it is one of the earliest methods that has been used to correct future climate data. The limitations include the fact that this method does not capture extreme situations as it considers only mean changes and the same time period must be considered in calculating the changes.

2. Bias correction method (quantile mapping)

In order to overcome the limitations of the change factor method, the bias correction method known as quantile mapping was introduced. It relies on adjusting the cumulative distribution function (CDF) of the simulated historical GCM data based on observed historical data. This method makes the CDF of the simulated historical GCM data and the observed historical data the same thereby correcting the bias in the future GCM data (Heo, Ahn, Shin, Kjeldsen, & Jeong, 2019). Other variations of quantile mapping are quantile delta mapping (QDM) and detrended quantile mapping (DQM). The basic assumption in bias correction is that GCMs will have the same bias in both retrospective and future data. Quantile mapping has been proved to be satisfactory in correcting precipitation data (Boonwichai et al., 2018; Heo et al., 2019). There are various probability distribution models that are used for correcting precipitation data but the commonly used model with satisfactory performance is the Gamma Distribution Model (GAM). Other models are Weibull, exponential (EXP), a mixture of EXP and GAM, kappa (KAP) and Gumbel Distribution Models (GUM).

In this chapter, existing research works, and studies related to the topic are critically examined for what has been done. Also, the gaps that this study intends to fill are highlighted. This chapter explains the trends in the use of climate models as well the inherent limitations of these models.

CHAPTER THREE

3. METHODOLOGY

This chapter describes the methods, materials and models that are implored in this study. It explains the reasons for selecting the methods as well as details about models, data preparation, data collection and modelling.

3.1 Preparation

In order to achieve the goal and the objectives of this study, several methodologies were applied. This involves a critical literature review on the research area and case study, data collection, data preparation and analysis, modelling and the final reporting. Data collection includes fieldwork activities in the collection of spatial, climate and crop data from different sources while data preparation involves processing and organising of data into formats that can be used for further analysis. The modelling stage comprises of model calibration, validation and simulations while the final reporting is the analysis and discussion of the results. The flowchart of the methodology employed in this study is given in Figure 3.1.

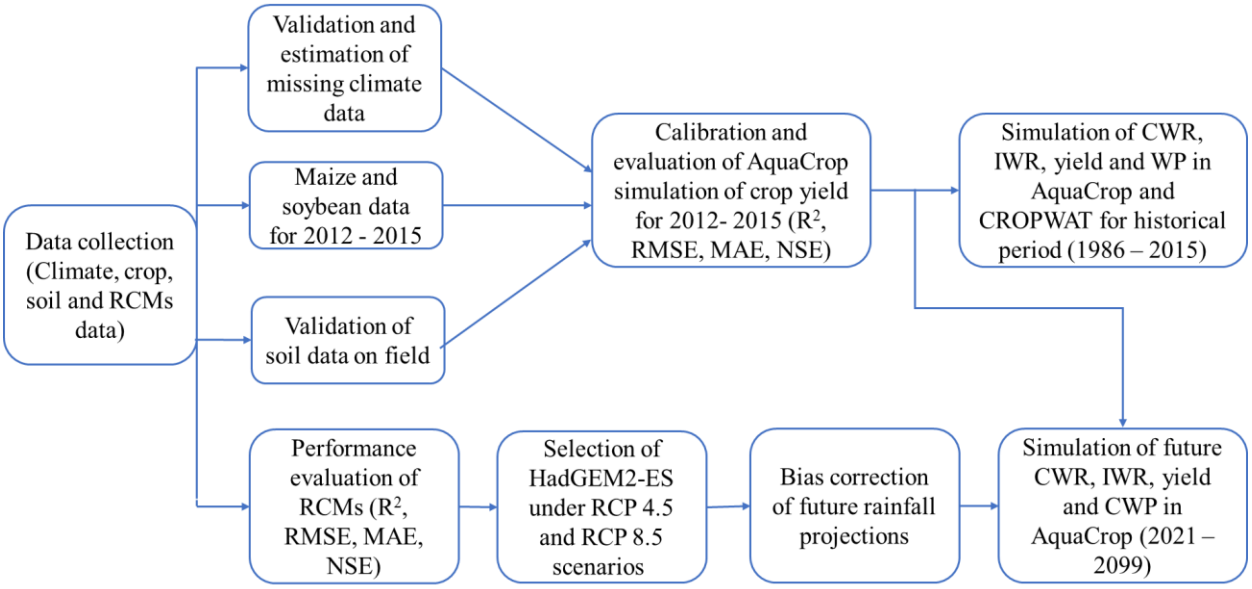

Figure 3.1: Flowchart of the methodology

3.2 Brief description of the study area

The study area of this research is the Ogun-Osun River Basin located in the south-western region of Nigeria. The basin is located between latitude 6° 33’ - 9° 00’ N and longitude 2° 40’ - 5° 05’ E

and covers about 49,580 km^2. Ogun and Osun rivers which the basin derives its name from being the major rivers in the basin. The study area is located in the derived savannah agro-ecological zone of the country which is characterized by tropical climate as well as wet and dry seasons. The temperature of the region ranges from 21°C to 34°C and average rainfall ranges from 1400 and 2700 mm which occurs from March to September (Adeboye et al., 2019). This region is largely agrarian and the population extremely depend on agriculture as the source of income. Several studies have shown that climate change will negatively affect the area which will certainly extend to the agricultural sector. In addition, currently, there are variations in rainfall pattern within the basin which is causing growing concerns for scientists, farmers and policymakers. Also, farmers are worried about their incomes and crop yield since rainfed agriculture is mainly practised.

3.3 Selection of crops and models

In this study, several factors were considered in the choice of crops that were studied as well as the models used.

3.3.1 Choice of crops

Many stable crops are grown in the region to be studied in this area. Crops commonly grown are maize, soybean, cowpea, cassava, yam, plantain, cocoa, okra and vegetables. Due to the scope of this study, only two (2) crops are studied. The crops are maize (*Zea mays*) and soybeans (*Glycine max L.Merr*) which are C4 and C3 plants respectively. The selection of these crops is based on the following:

1. Maize and soybean are among the staple crops grown in the study area.
2. The economy of the region largely depends on these crops. The crops are consumed within the region, processed into several other foods, packaged and about 12,000 tonnes exported annually outside the country (FAO, 2019).
3. It has been predicted that the two crops are largely sensitive to changes in climatic factors and water stress.
4. Nigeria is the second-ranked producer of soybean in Africa and one of the top producers of maize globally.
5. Soybean production is growing rapidly within the study area as farmers are gradually becoming aware of the potential economic and soil fertility benefits.
6. Availability of crop data for the study.

3.3.2 Crop model selection

A notable challenge in selecting a crop model is that there is no single crop model that is most appropriate for all studies, research, and planning as well as policy formulation. The selection of crop model(s) for any study depends largely on the objectives and scope of the study, the discipline and expertise of the researcher, the output of interest as well as the availability of input data requirements. Considering the different merits and demerits of the different categories of crop models available globally as discussed in the literature review, AquaCrop was selected based on the following:

1. Process-based crop models such as AquaCrop are superior to the statistical crop models especially in the assessment of the impact of climate change on crop growth, yields, and water requirements.
2. AquaCrop simulates crop growth based on water-driven which are most suitable for climate change studies.
3. The model fits into the objectives and scope of this study as well as the discipline of the researcher which is water engineering and climate change.
4. AquaCrop has been widely used and validated in various climatic conditions for the assessment of climate change impacts on crop growth, development and water requirements with reliable outputs.
5. It requires relatively few input parameters for reliable outputs compared to other models.
6. The algorithms and equations of the model are well documented as given in chapter two.
7. AquaCrop normalises water productivity for evaporation and CO_2 concentration which makes it suitable for studies from different climatic locations as well as future climate studies.

AquaCrop version 6.1 which is the latest version of the model was used in this study. AquaCrop was used in simulating crop yield and CWP in historical and future simulations as well as IWR and CWR in the future simulations.

3.3.3 Selection of soil-water balance model

CROPWAT that was developed by Food and Agriculture Organisation has been selected based on the following considerations:

1. CROPWAT is a soil-water balance that can accurately simulate daily water balance, estimate reference evapotranspiration as well as the water requirements of crops under different management practices, soil and climatic conditions.
2. The model requires relatively few input parameters for reliable outputs compared to other models.
3. It has been widely used and validated in various soil and climatic conditions for many crops.
4. It can simulate irrigation scheduling useful for farmers, scientists and policymakers.
5. The algorithms and equations of the model are well documented as given in chapter two.

CROPWAT version 8.0 which is the latest version of the model was used in this study. CROPWAT was used in simulating CWR and IWR for the historical simulations.

3.4 Data collection and preparation

The methods of data collection and preparation as well as modelling are discussed in this section.

3.4.1 Geographic map of the study area

The study area was delineated in ArcGIS Desktop 10.6 using the spatial analyst tool and Arc hydro tool in the Arc toolbox. Digital elevation model (DEM) of the Shuttle Radar Topography Mission (STRM) which has a 30 m (1 arc second) resolution was downloaded from United States Geological Survey (https://www.earthexplorer.usgs.gov) (USGS, 2018). The geographical location of the study area is shown in Figure 3.3. Ogun and Osun rivers which the basin derives its name from being the major rivers in the basin. However, there are many other water resources in the basin. The basin covers many cities and towns in the southwest of Nigeria.

3.4.2 Climate data

The climate data from 1976 – 2015 (40 years) of the basin were collected from the Nigerian Meteorological Agency (NIMET). The meteorological stations are located at latitude 3.38 N and longitude 3.90 E and latitude 6.38 N and 3.33 E longitude. The datasets of 1976 – 1985 (10 years) were only daily rainfall, maximum and minimum temperatures used for model evaluation while the datasets of 1986 – 2015 (30 years) were daily rainfall, maximum and minimum temperatures, relative humidity, wind speed and solar radiation used for simulations. The mean monthly values of the climatic parameters from 1986 – 2015 are given in Table 3.1. Figure 3.4 shows the mean monthly temperature and rainfall for the basin which reveals that rainy season starts from April to

July before a short dry period in August known as August break. The peak is around June, July and September with around 200 mm while the lowest rainfall is usually in January and December with less than 10 mm. The mean annual rainfall is 1200 mm while Figure 3.5 shows that there is a slight increase in rainfall according to the trendline. Meanwhile, the annual mean temperature of the basin is 26.7 °C and there is a gradual increase in mean temperature over the period in consideration as shown in Figure 3.6. The months of February and March are usually the hottest periods with a maximum temperature of 34.8 °C and 34.4 °C respectively as shown in Table 3.1 and Figure 3.7. Figure 3.8 shows the monthly variability of the mean relative humidity for the period under study.

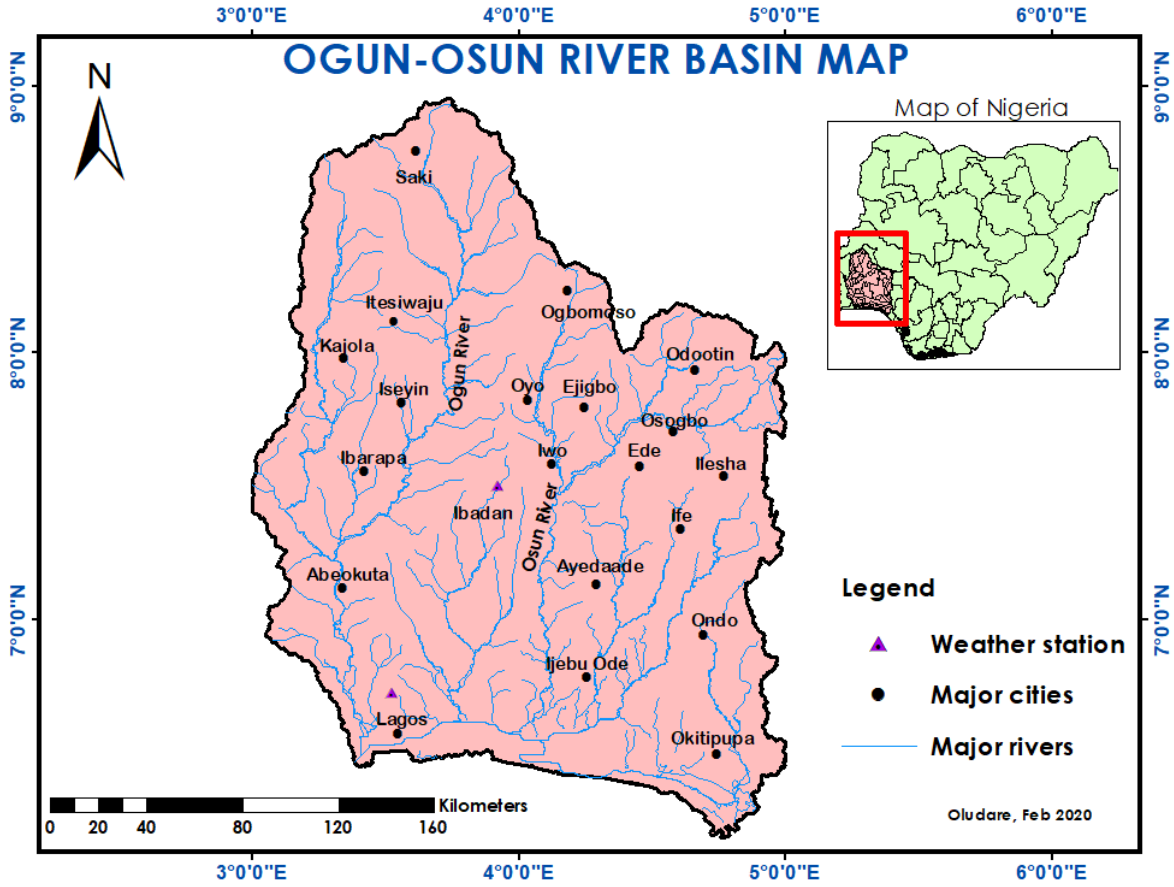

Figure 3.2a: The geographic location of the study area

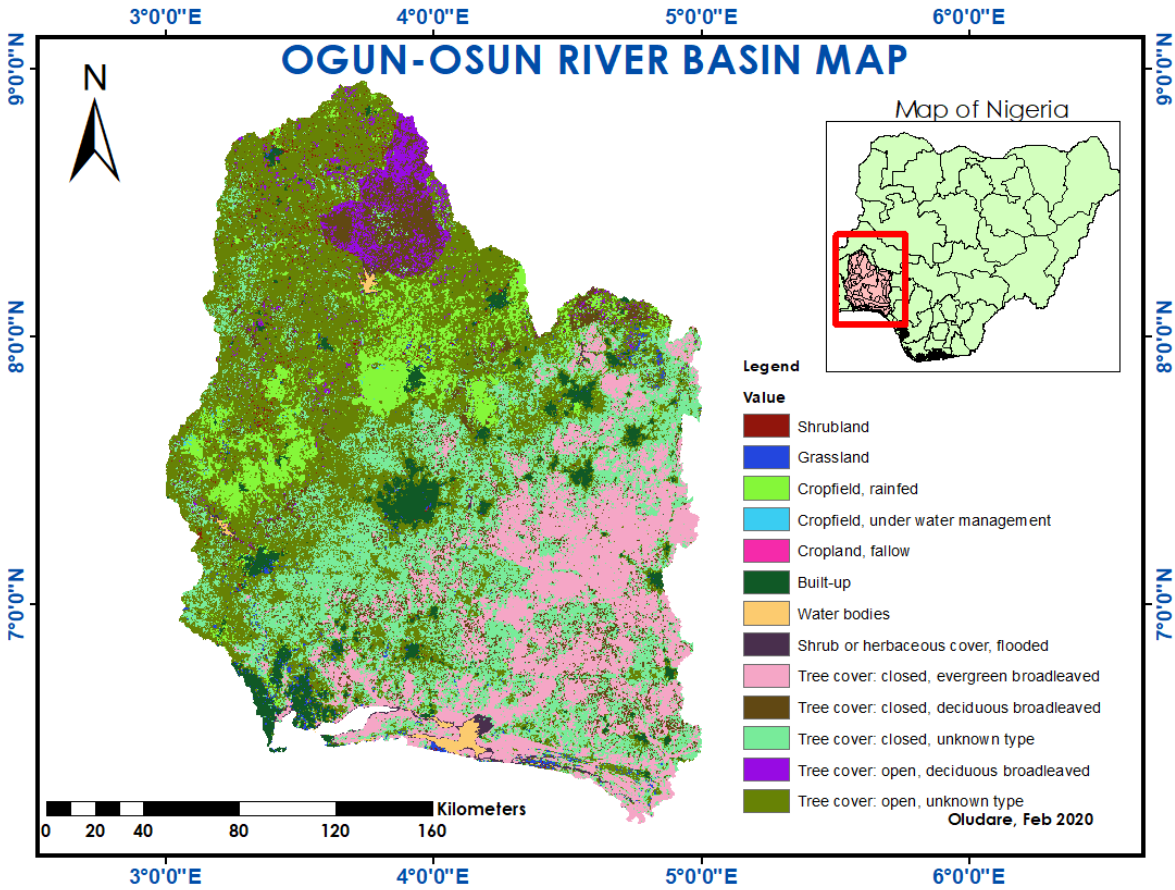

Figure 3.3b: The land use/land cover map of the study area

Table 3.1: Climatic parameters of the basin from 1986 - 2015

Month	Temperature (°C)			Humidity (%)	Wind Speed (km/day)	Solar radiation ($MJ/m^2/day$)	Rainfall (mm/month)
	Ave	Min	Max				
January	27.01	20.99	33.03	61.79	73.86	14.27	5.27
February	28.47	22.14	34.79	61.80	93.85	16.30	31.25
March	28.76	23.17	34.35	68.61	103.97	17.04	73.31
April	27.99	23.08	32.90	75.57	98.31	16.75	127.17
May	27.03	22.51	31.55	78.28	85.06	16.72	148.83
June	26.01	21.97	30.06	80.61	80.27	15.44	201.26
July	25.07	21.83	28.31	83.32	82.03	12.51	195.99
August	24.69	21.63	27.74	84.49	77.62	11.32	121.87
September	25.32	21.61	29.03	82.02	68.77	13.62	232.17
October	26.09	22.01	30.16	80.40	58.94	15.11	178.58
November	27.22	22.40	32.05	72.68	58.88	15.68	23.20
December	26.79	21.07	32.50	66.65	62.71	14.39	6.77

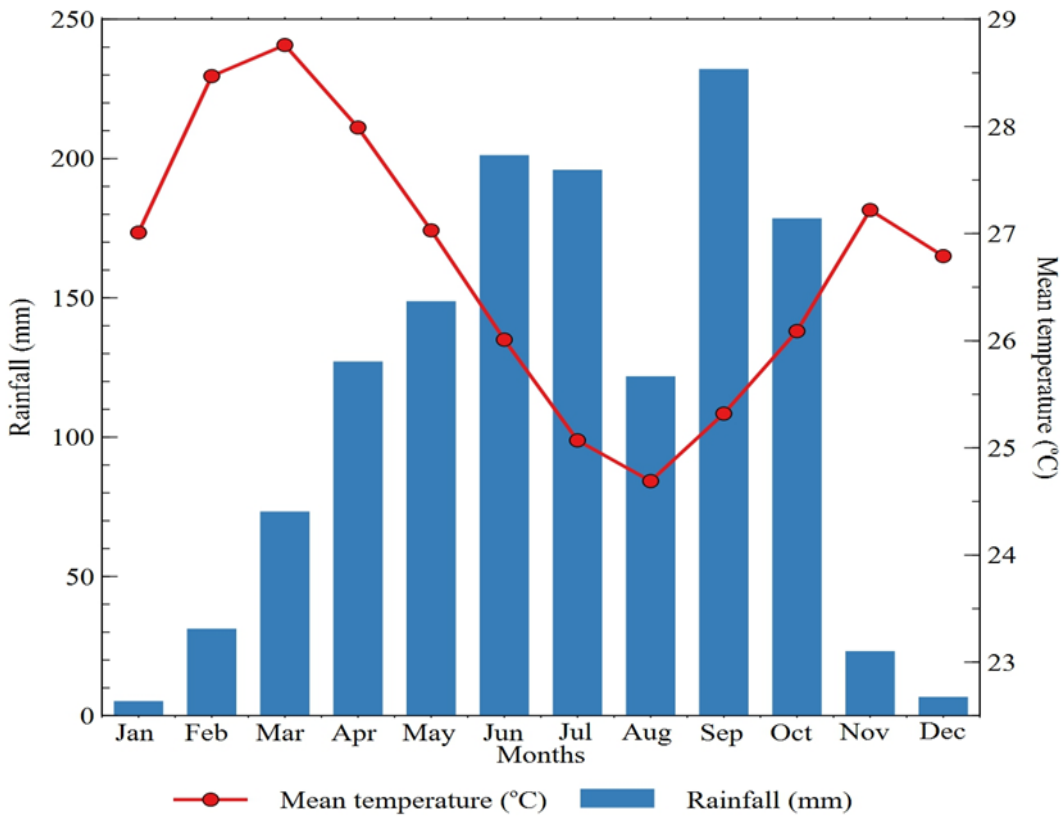

Figure 3.4: Mean monthly temperature and rainfall for the basin from 1986 – 2015

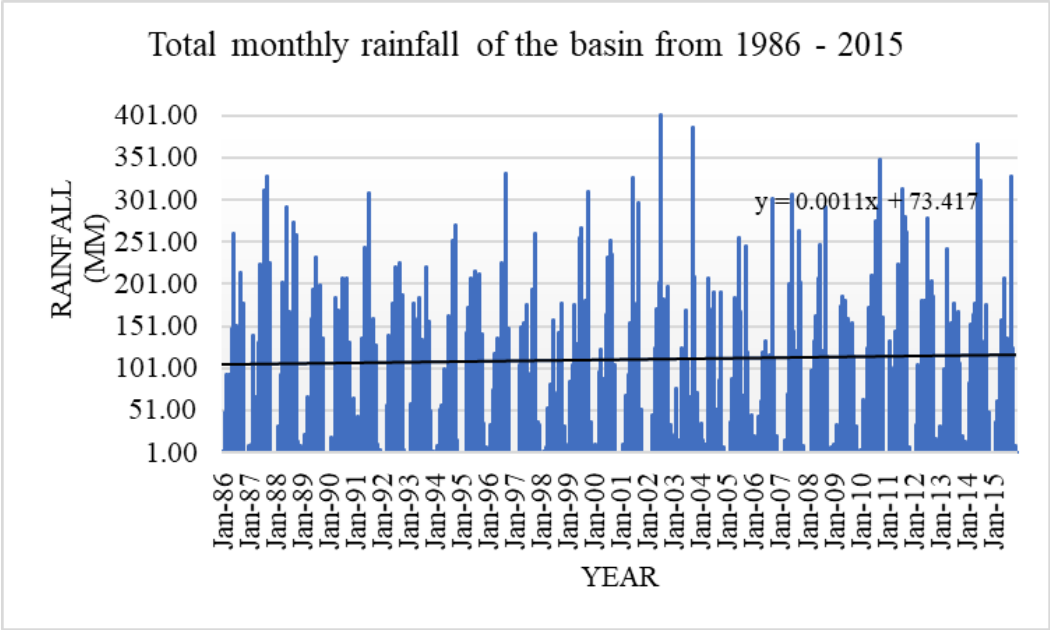

Figure 3.5: Total monthly rainfall from 1986 – 2015

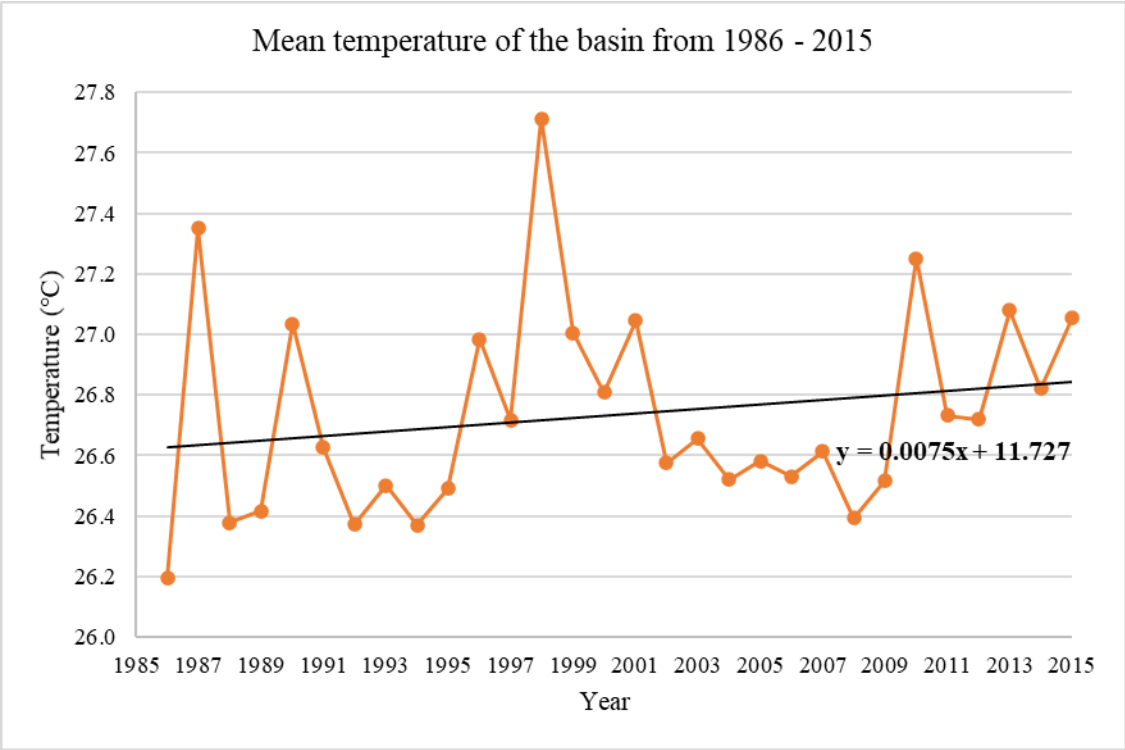

Figure 3.6: Mean annual air temperature of the basin from 1986 – 2015

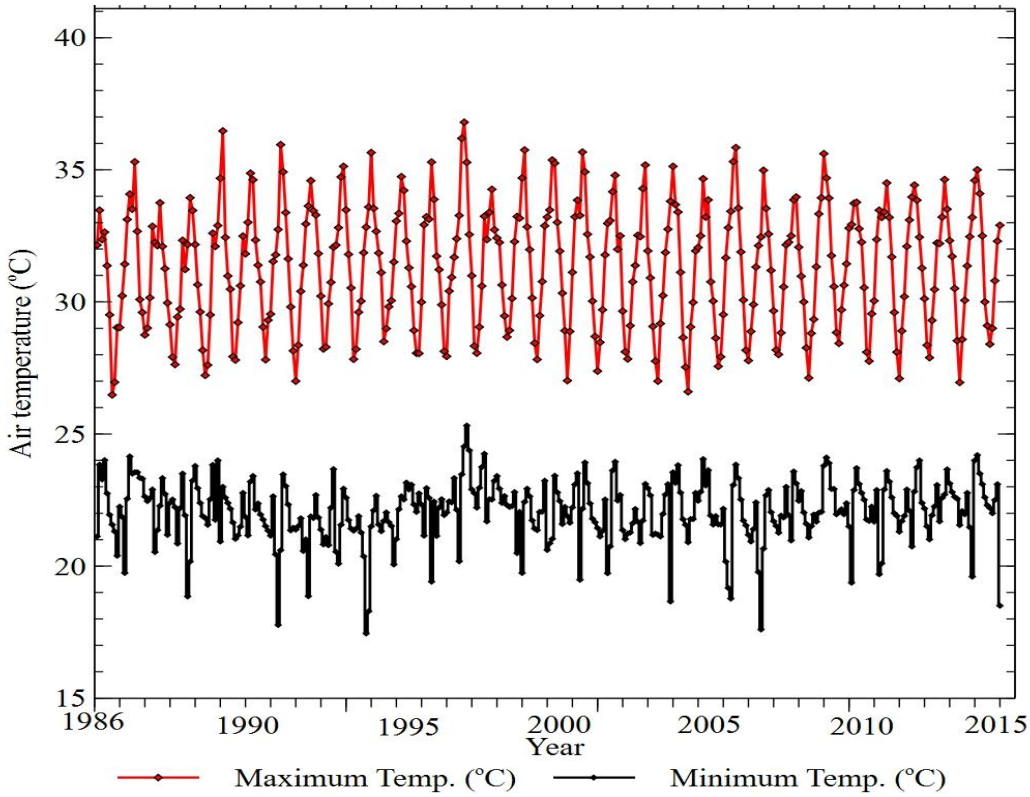

Figure 3.7: Mean monthly maximum and minimum air temperatures from 1986 – 2015

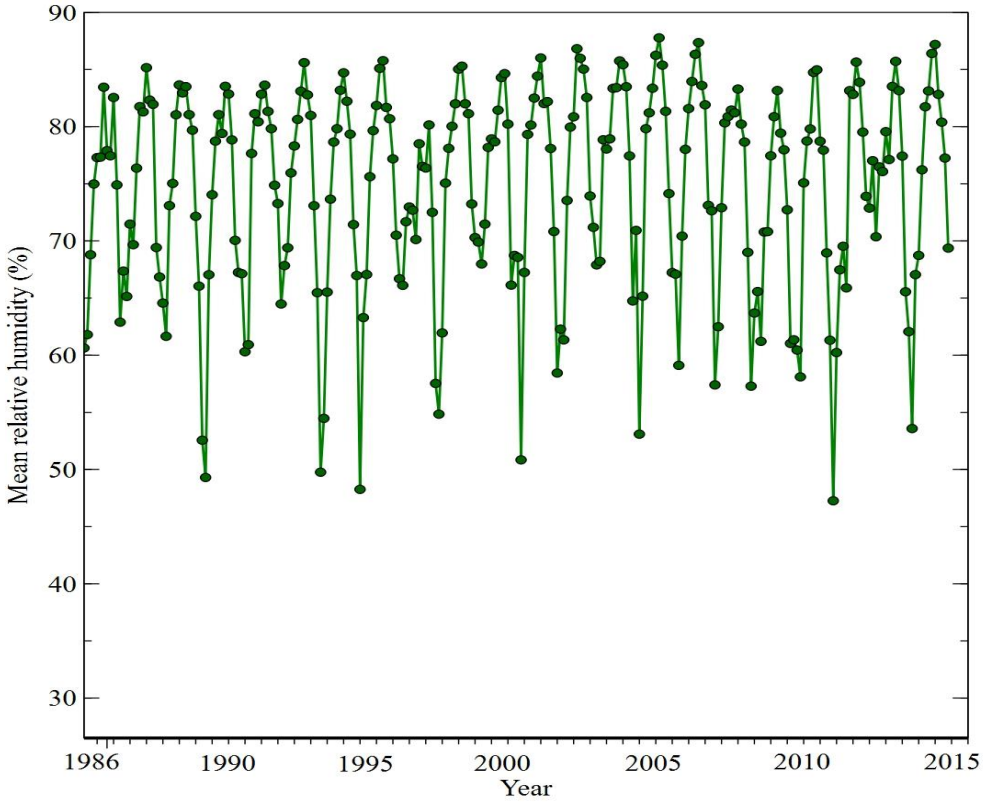

Figure 3.8: Mean monthly relative humidity for 1986 - 2015

3.4.3 Soil data

Soil physical and chemical properties of the basin were obtained from the Harmonised World Soil Database (HWSD) which has a resolution of 1 km (30 arcs second). The data was downloaded from FAO website (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases) (Fischer et al., 2008). The soil in the basin is dominantly Ferric Luvisols and Lithosols (Sotona, Salako, & Adesodun, 2014). There are differences within the soil fertility which mainly depend on fertilisers applied and the conservation practices employed by the farmers. The texture of the topsoil (0-30 cm) is predominantly sandy loam, loamy sand and clay while the texture of the subsoil (30-100 cm) is mainly loamy sand, sandy loam, sandy clay loam as well as clay as shown in Figure 3.9. The pH of the topsoil varies from 5.7 to 7.1 which are optimal for the cultivation of maize and soybean. The map was prepared in ArcGIS Desktop 10.6 using the spatial analyst tool in the Arc toolbox. The soil map was validated with data obtained from the Ogun-Osun River Bain Authority and field experiments.

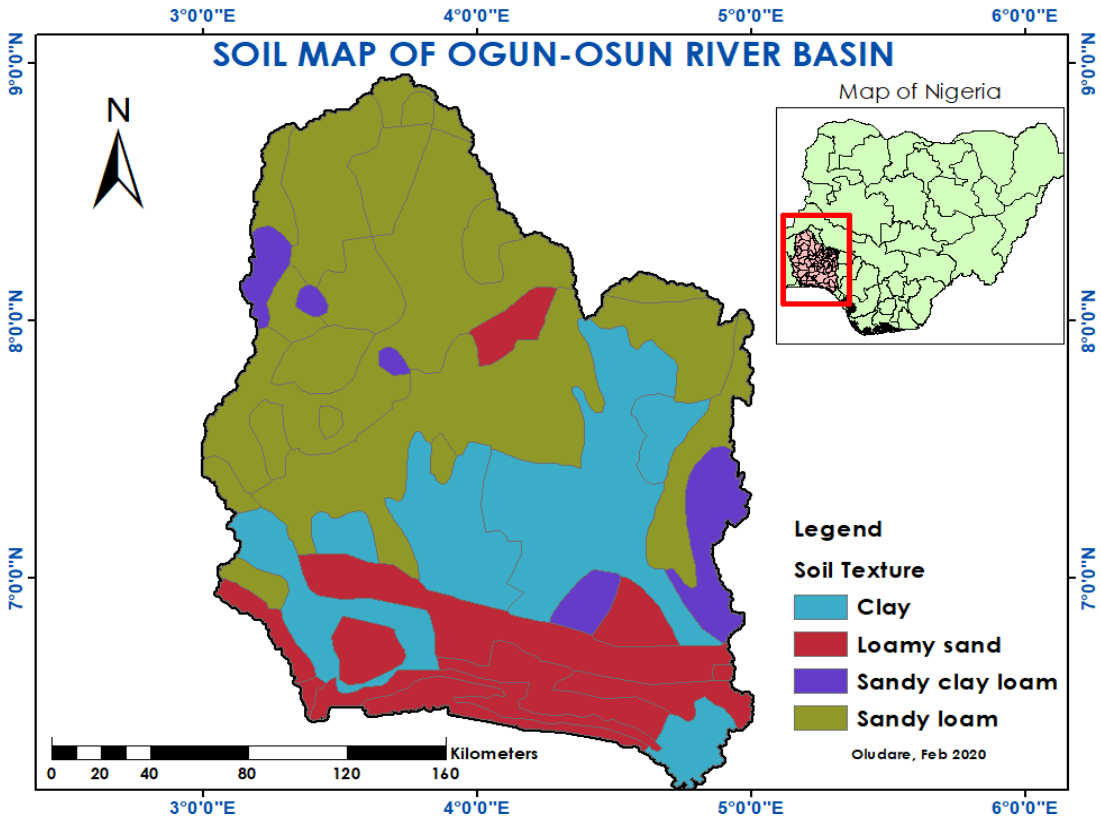

Figure 3.9: The distribution of topsoil textures within the study area

3.4.4 Crop data

Four years of experimental crop data (2012 – 2015) obtained from the Agricultural Development Programme (ADP) were employed in this study. The data which contains crop parameters from different soil types were obtained during experiments that were done within the basin. The information reveals the planting spacing of maize as 30 cm and 60 cm intra and inter-row spacing while soybean spacing was 25 cm and 65 cm intra and inter-row spacing. The varieties of maize and soybean used in experiments were TZPBSR-W and TGX 1448-2E respectively.

3.4.5 Climate projection data

The future climate data employed in this study were obtained from the CORDEX project which was downloaded from the Earth System Grid Federation server (https://esgf-index1.ceda.ac.uk/search/cordex-ceda/). The CORDEX is a project funded to provide assessment of model performance, climate change impact assessments and adaptation researches as well as high-resolution of historical and future climate data on a shared platform which will be easily accessible. In the CORDEX project, multiple GCMs have been downscaled using different RCMs

to regional levels including Africa. Based on extensive literature review, Rossby Centre Regional Climate Model (RCA4) which is one of the RCMs developed by the Swedish Meteorological and Hydrological Institute (SMHI) under nine GCMs in CORDEX- Africa was selected for this study. RCA4 has been assessed with highly satisfactory results in many studies.

The CORDEX – Africa datasets are available in daily, 10-day and monthly periods at a spatial resolution of 0.44° × 0.44° which is approximately 50 km × 50 km for the period of 1951 – 2005 (historical) and 2006 – 2099 (future). However, due to the scope of this study, only one GCM under RCA4 was selected. In order to finally select the GCM, three GCMs which are CCCma-CanESM2, ICHEC-EC-EARTH and MOHC-HadGEM2-ES shown in Table 3.2 were evaluated with a historical dataset. The selection of these three GCMs and RCM is based on the claim that they can effectively capture the future climate of West Africa (Akinsanola et al., 2018).

Historical daily rainfall, minimum and maximum temperatures of the basin simulated by the three RCMs for 1976 – 2005 (30 years) were downloaded for evaluation with the observed data. R-programming studio (version 3.6.2) was utilised to extract the data from NetCDF file format using the coordinates of the weather stations as shown in Annex 1 and Annex 2. The data were prepared and properly arranged in Microsoft Excel 2016.

Table 3.2: Description of the Global Climate Models (GCMs) and Regional Climate Model (RCMs) employed

Model Institute	GCM Name	RCM	RCM Resolution
Canadian Centre of Climate Modelling and Analysis, Canada	CCCma-CanESM2	RCA4	0.44° × 0.44°
Swedish Meteorological and Hydrological Institute, Sweden	ICHEC-EC-EARTH	RCA4	0.44° × 0.44°
Met Office Hadley Centre, UK	MOHC-HadGEM2-ES	RCA4	0.44° × 0.44°

3.4.5.1 Statistical evaluation of climate models

In order to access the performance and ability of the climate models to capture the observed data, four statistical indicators which are coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and Nash-Sutcliffe modelling efficiency (NSE) were employed as given in Equations 3.1, 3.2, 3.3 and 3.4 respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - \overline{O})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2 \sum_{i=1}^{n} (S_i - \overline{S})^2}} \right]^2 \qquad \text{Equation 3.1}$$

$n =$ number of observations

$O_i =$ Observed value

$S_i =$ Simulated value

$\overline{O} =$ Mean of observed values

$\overline{S} =$ Mean of simulated values

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2} \qquad \text{Equation 3.2}$$

Where $RMSE =$ Root mean square error

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |S_i - O_i| \qquad \text{Equation 3.3}$$

$MAE =$ Mean absolute error

$$NSE = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \qquad \text{Equation 3.4}$$

Where $NSE =$ Nash-Sutcliffe modelling efficiency

R^2 is a dimensionless indicator that expresses the fit between observed and simulated values. It ranges from 0 to 1.0 for which a value of 1 shows a perfect fit between the observed and simulated values. RMSE is a measure of the entire and mean deviation between simulated and observed values. It has the unit of the parameter that is being simulated, which implies that the closer the value to zero, the better the performance of the model. MAE gives the mean of the deviation between simulated and observed values and has the unit of the parameter that is being simulated. The closer the value of MAE to zero, the better the performance of the model. NSE is a unitless coefficient that ranges from - ∞ to 1 which measures the general deviation between simulated and observed values. An efficiency of 1.0 reveals a perfect match between simulated and observed values. The closer the efficiency is to 1.0, the better the performance of the model. When NSE is less than zero, it means that the observed mean is a better predictor. Even though there are no

standard intervals that are globally accepted. In this study, the intervals presented by Moriasi et al. (2007) as given in Table 3.3 are adopted.

Table 3.3: Performance rating and classification of NSE

Performance rating	NSE Interval
Very good	$0.75 < NSE \leq 1$
Good	$0.65 < NSE \leq 0.74$
Satisfactory	$0.50 < NSE \leq 0.64$
Unsatisfactory	$NSE < 0.50$

The daily observed and simulated of climatic data for the historical period of 1976 – 2005 were used for the evaluation. The results of the evaluation as given in Table 3.4 reveals that among the three GCMs evaluated, HadGEM2-ES downscaled by RCA4 performed satisfactorily and has the highest NSE value of -0.11, 0.74 and 0.75 in rainfall, minimum and maximum temperatures respectively and was selected for the study. The negative value of NSE for rainfall depicts that the observed mean is the better predictor than the model. In order to correct this and improve the performance of the model, the rainfall dataset for HadGEM2-ES was bias-corrected.

Table 3.4: Statistical evaluation of climate models on historical data (1976 – 2005)

Statistical Parameters	Rainfall				Minimum Temperature			
	R^2	RMSE (mm)	MAE (mm)	NSE	R^2	RMSE (°C)	MAE (°C)	NSE
CanESM2	0.32	3.61	2.60	-0.46	0.82	1.62	1.24	0.30
EC-EARTH	0.44	3.87	2.77	-0.49	0.72	1.74	1.35	0.44
HadGEM2-ES	0.54	3.27	2.25	-0.11	0.84	0.92	0.72	0.74

Statistical Parameters	Maximum Temperature			
	R^2	RMSE (°C)	MAE (°C)	NSE
CanESM2	0.84	1.82	1.43	0.31
EC-EARTH	0.71	1.93	1.62	0.41
HadGEM2-ES	0.85	0.89	0.68	0.75

Thus, future daily rainfall, minimum and maximum temperatures of the basin obtained from HadGEM2-ES (GCM) and RCA4 (RCM) for the period of 2021 – 2099 under RCP 4.5 and RCP 8.5 scenarios under the CORDEX- Africa project was downloaded from the Earth System Grid

Federation server (https://esgf-index1.ceda.ac.uk/search/cordex-ceda/) and used for the study. The dataset was processed in R- Studio and Microsoft Excel 2016.

3.4.5.2 Bias correction of projected rainfall

The bias correction technique applied is Quantile Mapping (QM) with gamma distribution model. The principle of QM technique relies on adjusting the cumulative distribution functions (CDF) of the simulated historical GCM/RCM data based on observed historical data as given in Equation 3.5. This method matches the CDF of the simulated historical GCM data and the observed historical data together thereby correcting the bias (extremes, intensity and frequency) in the future GCM data (Boonwichai et al., 2018). It has been proved that the quality of RCM data and shape of CDF is improved through QM. Daily historical observed and simulated rainfall data from 1976 – 2005 (30 years) were used to bias correct the future simulated data (2021 – 2099). The QM was conducted using MATLAB R2015a (version 8.50).

$$y = F_{\text{obs}}^{-1}\,(F_{RCM}(x)) \qquad \text{Equation 3.5}$$

Where y = bias corrected future rainfall values

F_{obs}^{-1} = inverse of the CDF of the observed values

F_{RCM} = CDF of the historical RCM data

$x =$ RCM values to be corrected

QM technique was able to improve the CDFs of the RCM data as shown in Figures 3. 9 – 3.11. They show that the RCM was overestimating before bias correction. The bias corrected rainfall data were evaluated using R2, RMSE, MAE and NSE as given in Table 3.5. QM was able to increase the R2 and NSE thus reducing the RMSE and MAE compared to Table 3.44.

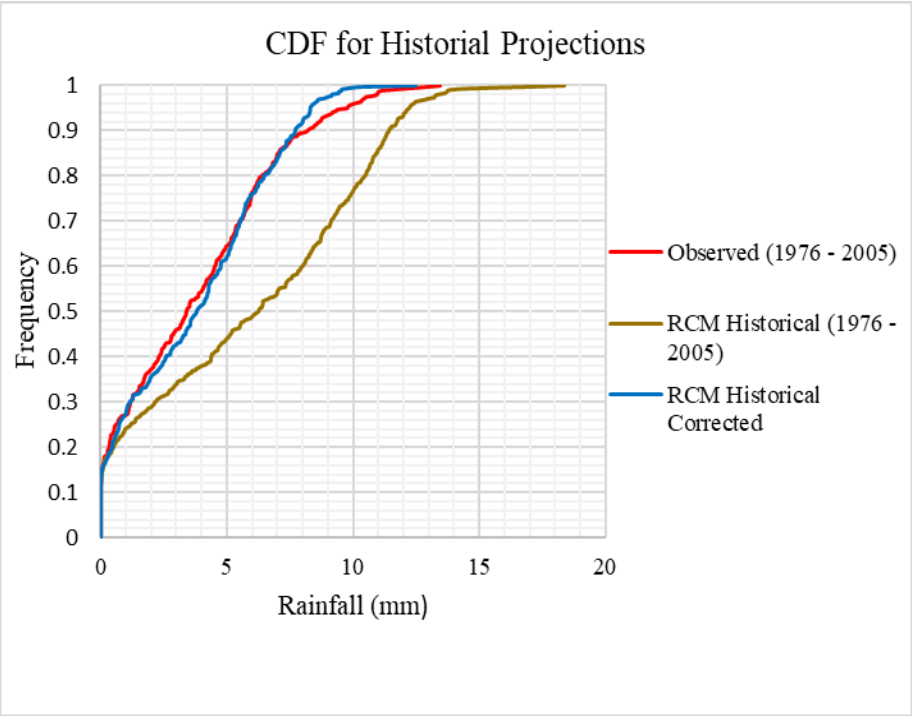

Figure 3.10: The CDFs of projected historical daily rainfall before and after bias correction

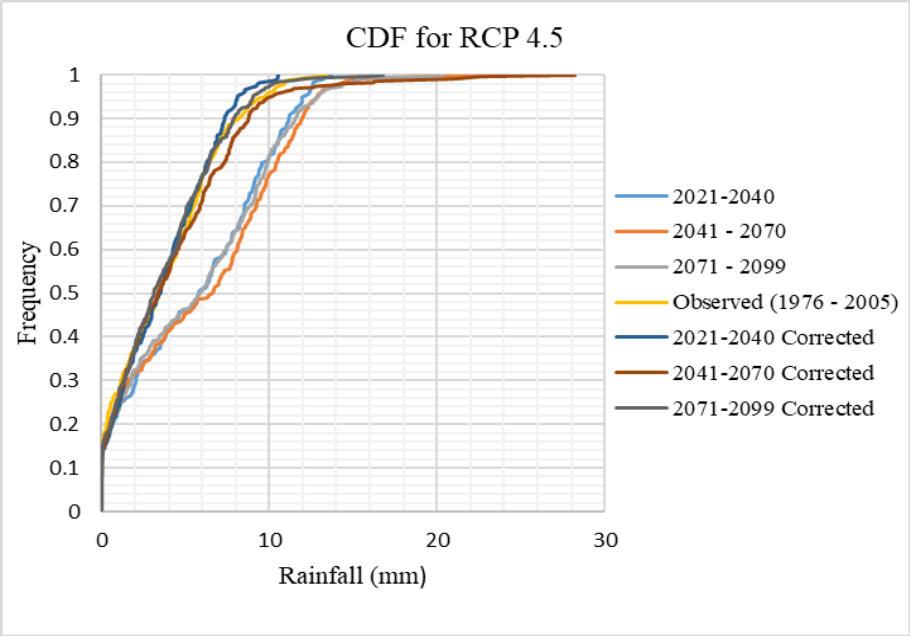

Figure 3.11: The CDFs of projected daily rainfall under RCP 4.5 before and after bias correction

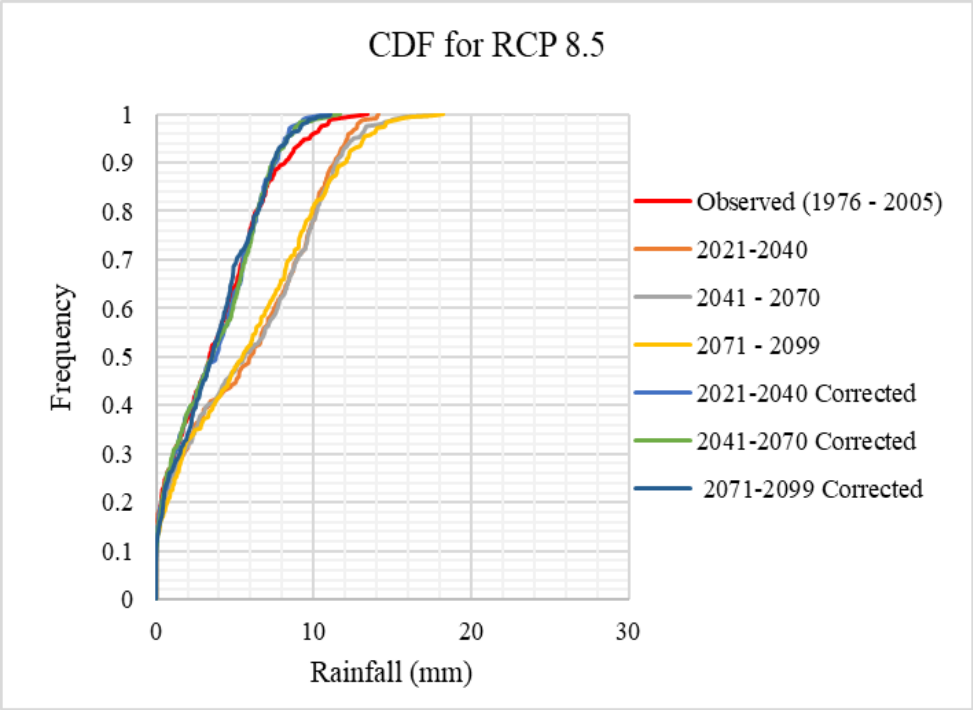

Figure 3.12: The CDFs of projected daily rainfall under RCP 8.5 before and after bias correction

Table 3.5: Statistical evaluation of bias corrected rainfall data

Statistical Parameters	Rainfall			
	R^2	RMSE (mm)	MAE (mm)	NSE
HadGEM2-ES	0.75	0.52	0.43	0.76

3.5 Calibration and validation of data in AquaCrop and CROPWAT

AquaCrop model simulates crop growth, yield and water need based on crop, climate and soil data as well as management practices. Calibration and validation are integral processes in modelling. Calibration is the technique of adjusting the input parameters of a model to appropriately simulate outputs while validation is the process of checking the ability of the model to accurately represent the real world. During validation, the simulated outputs are compared with observed outputs for consistencies. AquaCrop version 6.1 and CROPWAT 8.0 were employed in this study. After the calibration in AquaCrop, the output files of climate, soil, crop and management data were copied to the program files of CROPWAT for the simulations in the model.

In the modelling procedures, the following assumptions were made.

1. The basin belongs to one agro-climatic zone which is derived savannah agro-climatic zone of Nigeria.

2. Farmers practise single cropping throughout the seasons thus, monocropping was selected during simulations.
3. Soil fertility is homogenous across the basin thus, the same soil fertility level was assumed throughout.
4. Each soil type has the same physical and chemical characteristics within the basin.
5. Most farmers practise only rainfed agriculture thus, rainfed management was employed in the historical simulations while irrigation management was only selected for supplemental irrigation simulations.

3.5.1 Climate data

The climate data obtained were prepared in Microsoft Excel 2016, transformed into a text file and then transferred into the data folder of AquaCrop.

3.4.5.1 Historical climate data

For the historical simulations, daily rainfall, maximum and minimum temperatures, relative humidity, wind speed and solar radiation of the basin from 1986 – 2015 (30 years) were inputted into AquaCrop. Since this study is about climate change, the atmospheric concentrations of CO_2 of previous years were taken into keen consideration. CO_2 concentrations already inputted into the model was activated for simulations. CO_2 concentrations of previous years were retrieved at Mauna Loa Observatory Centre, Hawaii, United States

3.4.5.2 Future climate data

Future daily rainfall, minimum and maximum temperatures of the basin obtained from HadGEM2-ES (GCM) and RCA4 (RCM) for the period of 2021 – 2099 under RCP 4.5 and RCP 8.5 scenarios already processed in R-Studio and Microsoft Excel were inputted into AquaCrop. The climate datasets were divided into the near future (2021 – 2040), mid-century (2041 – 2070) and late-century (2071 – 2099). The climate change representative pathways of RCP 4.5 and RCP 8.5 scenarios were selected in AquaCrop to reflect the increase in CO_2 concentration. The CO_2 concentration used was experimented at Mauna Loa Observatory Centre, Hawaii, United States.

3.5.2 Crop

The four years of experimental crop data (2012 – 2015) obtained were employed in the calibration and validation of the model. The data for 2012 and 2013 growing seasons were used for calibration

while validation was done using data for 2014 and 2015 growing seasons. The varieties of maize and soybean used in the calibration of the models are TZPBSR-W and TGX 1448-2E respectively. The information obtained was used in the calibration and validation of the models as required. Some of the non-conservative crop parameters which were not obtainable from government agencies were obtained from the literature (Adeboye et al., 2019; Greaves & Wang, 2016; Iken & Amusa, 2004). Table 3.6 shows the non-conservative crop parameters which were used for calibration of the models.

Table 3.6: Non-conservative crop parameters used for calibration and validation

Parameters	Unit	Maize	Soybean
Plant population	Plants/ha	55, 556	352, 000
Initial canopy cover	% of canopy cover	0.40	0.40
Maximum canopy cover	% of canopy cover	80	90
Days from planting to emergence	GDD (Day)	84 (7)	105 (7)
Days from planting to maximum canopy cover	GDD (Day)	696 (58)	1485 (99)
Days from planting to senescence	GDD (Day)	960 (80)	1725 (115)
Days from planting to maturity	GDD (Day)	1080 (90)	1800 (120)
Days from planting to flowering	GDD (Day)	480 (40)	607 (45)
Days from planting to maximum rooting depth	GDD (Day)	1068 (88)	1635 (109)
Length building up to HI	GDD (Day)	504 (42)	510 (34)
Duration of flowering	GDD (Day)	420 (35)	420 (28)
Maximum effective rooting depth	m	2.00	1.6
Normalized water productivity for climate and CO_2	g/m^2	33.7	15.0
Soil fertility stress	-	moderate	moderate
Sink strength under elevated CO_2	%	50	50
Reference harvest index	%	48	40

3.5.3 Soil

The soil data obtained were validated through filed experiments where the soil types were sampled and tested in a soil science laboratory. Mechanical soil analysis was done using a mechanical shaker to determine the percentages of sand, silt and clay particles. The percentages of sand, silt and clay particles were used to confirm the soil texture on the soil textural triangle. Thereafter, the percentages of sand, silt and clay particles were used to obtain the hydrological properties of the such as permanent wilting point (PWP), field capacity (FC), saturation (SAT), total available water (TAW) and hydraulic conductivity (Ksat) using SPAW model (version 6.02)

(https://hrsl.ba.ars.usda.gov/soilwater/index.htm) which is a soil water properties model previously employed by Ding et al. (2017) and Luhunga (2017). The soil properties used for calibration and modelling are given in Table 3.7.

Table 3.7: Calibrated soil properties and descriptions in models

Soil texture (0-100 cm)	PWP (vol. %)	FC (vol. %)	SAT (vol. %)	TAW (mm/m)	Ksat (mm/day)
Clay	26.2	38.8	47.7	126.0	40.8
Loamy sand	8.0	14.0	46.0	60.0	1560.0
Sandy clay loam	17.7	27.5	43.0	98.0	214.0
Sandy loam	11.5	19.0	43.3	75.0	804.4

3.5.4 Management practices

The calibration of the management practices employed in the models are discussed in the following sections:

a) Planting date: In the AquaCrop model, the planting date window was calibrated between 1 April – 15 April and 1 June – 15 June for planting maize and soybeans respectively. The model was calibrated to automatically select a planting date based on the establishment of rainfall (cumulative rainfall at least 40 mm) within each year according to the inputted rainfall data and starts simulation on that date. This was done to emulate the planting styles of farmers within the study area who plants after the onset of rainfall within those planting periods. The planting dates window was calibrated for both historical and future simulations. The planting dates were recorded and used in CROPWAT.

b) Initial soil conditions: The initial soil conditions were set at field capacity since rainfed agriculture is simulated. Meanwhile, groundwater intrusion has not been established on agricultural fields within the basin, thus, groundwater was not considered similar to Adeboye et al. (2019).

c) Soil fertility and weed management. Soil infertility and weak weed management are common within the study. Hence, the soil fertility and weed management functions were both calibrated as moderate.

d) Irrigation management: When the models were simulated under supplemental irrigation, the allowable root zone depletion was set at 50% of readily available water (RAW).

Then, all the management files were setup as project files. Each field with similar soil type and management practices were grouped into single units to form projects under the historical period (1986 – 2015) and future period (2021 – 2099) for maize and soybeans productions. The simulations in AquaCrop and CROPWAT are shown in Annex 3 and Annex 4 respectively.

3.5.5 Statistical evaluation of AquaCrop performance

In order to assess the performance of AquaCrop, the four years of experimental data obtained were evaluated through R^2, RMSE, MAE and NSE. The results show that the simulated yields match well with the observed yields. The average simulated and average observed maize yields are 2.14 and 2.13 t/ha respectively. While the average simulated and average observed soybeans yields are 2.71 and 2.69 t/ha respectively. The model satisfactorily replicates maize and soybeans yield on different soil types as shown in Table 3.8 and 3.9. It is worthy to note that the NSE for maize and soybeans yields are 0.90 and 0.98 respectively which makes the model reliable and suitable for both historical and future climate conditions of Ogun-Osun River Basin, Nigeria.

Table 3.8: Model evaluation of simulated maize yield in various soil types for four growing seasons.

Year	Soil type	Observation (t/ha)	Simulation (t/ha)	R^2	RMSE (t/ha)	MAE (t/ha)	NSE
2015	Loamy sand	2.08	2.09				
	Sandy clay loam	2.12	2.14	0.99	0.014	0.013	
	Sandy loam	2.09	2.10				
2014	Loamy sand	2.07	2.07				
	Sandy clay loam	2.11	2.12	0.96	0.008	0.007	
	Sandy loam	2.07	2.08				0.90
2013	Loamy sand	2.11	2.13				
	Sandy clay loam	2.21	2.23	0.95	0.016	0.013	
	Sandy loam	2.17	2.17				
2012	Loamy sand	2.13	2.15				
	Sandy clay loam	2.18	2.20	0.95	0.017	0.017	
	Sandy loam	2.15	2.16				

Table 3.9: Model evaluation of simulated soybeans yield in various soil types for four growing seasons.

Year	Soil type	Observation (t/ha)	Simulation (t/ha)	R^2	RMSE (t/ha)	MAE (t/ha)	NSE
2015	Loamy sand	2.79	2.81				
	Sandy clay loam	2.62	2.64	0.99	0.017	0.016	
	Sandy loam	3.06	3.07				
2014	Loamy sand	2.94	2.94				
	Sandy clay loam	2.88	2.92	0.96	0.056	0.003	0.98
	Sandy loam	3.10	3.19				
2013	Loamy sand	2.27	2.31				
	Sandy clay loam	2.06	2.00	0.98	0.043	0.002	
	Sandy loam	2.54	2.56				
2012	Loamy sand	2.57	2.60				
	Sandy clay loam	2.59	2.57	0.99	0.027	0.027	
	Sandy loam	2.86	2.89				

3.6 Assessment of relative changes

The relative changes in CWR, IWR, yield and WP in future periods compared to historical period were evaluated using Equation 3.6 where the baseline is considered as 1986 – 2015. The relative changes in yield and CWP under supplemental irrigation when compared to rainfed were evaluated using Equation 3.7.

$$\text{Relative change (\%)} = \frac{\text{Simulated mean} - \text{Baseline mean}}{\text{Baseline mean}} \times 100\% \qquad \text{Equation 3.6}$$

$$\text{Relative change (\%)} = \frac{\text{Supplemental irrigation mean} - \text{Rainfed mean}}{\text{Rainfed mean}} \times 100\% \qquad \text{Equation 3.7}$$

3.7 Extrapolation of AquaCrop simulations to the basin scale

AquaCrop is a crop model that simulates at farm levels. Simulations were done through loose coupling of AquaCrop and ArcGIS to obtain CWR, IWR, yield and CWP at a basin scale. The spatial variability of soil types, crop type and management practices were formed into units to form projects under historical simulations. Meanwhile, for the future periods, the spatial variability of soil types, crop type, management practices and different climate scenarios were grouped into small units to form projects. The pre-processing and arrangements of input data for each unit and project was done in ArcGIS software through the union function. The input data pre-processed in ArcGIS was transferred to Microsoft Excel for proper arrangement thereafter transferred to AquaCrop. Subsequently, the output files from AquaCrop were transferred to Microsoft Excel then

to ArcGIS through the join function. Therefore, ArcGIS was used for post-processing to display the spatial distribution of CWR, IWR yield and CWP for each project.

CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

In this chapter, the results of the study are reported and discussed. The results of this study are discussed in comparison with the outcomes of similar studies. This chapter concludes with a proposed policy framework that can be implemented in Nigeria.

4.1 Estimation of CWR, IWR, yield and CWP

The seasonal CWR, IWR, yield and CWP of rainfed maize and soybeans within the study area were estimated based on the climate data of 1986 – 2015 and crop data obtained using CROPWAT and AquaCrop.

4.1.1 Seasonal crop water requirements (CWR)

The CWR of maize ranges from 190 to 290 mm depending on the soil types and climate of the growing period as shown in Figure 4.1. The average CWR of maize on the soil types were found to be 229, 233, 246 and 242 mm on clay, loamy sand, sandy clay loam and sandy loam respectively. Huge variability within the years was also observed. It shows that within the study area, the CWR of maize follows this order in decreasing arrangement: sandy clay loam, sandy loam, loamy sand, and clay soils. This confirms that CWR is highly dependent on climate variability, crop and soil types.

Furthermore, the CWR of soybeans were simulated. From Figure 4.2, the average CWR of rainfed soybeans on the soil types were found to be 257, 320, 332 and 341 mm on clay, loamy sand, sandy clay loam and sandy loam respectively. In addition, huge variability within the years was also observed which depicts drought and flooded years. The CWR of soybeans ranges from 110 to 400 mm depending on soil types and climate. As simulated, soybeans require more water for productivity than maize. CWR highly depends on crop, soil and climate of the growing period (Mourad & Berndtsson, 2012; Wang et al., 2018). The amount of CWR can also be attributable to the length of the growing period and the rate of evapotranspiration during the growing period.

4.1.2 Seasonal irrigation water requirements (IWR)

The spatial variability of simulated maize and soybean IWR within the study area are shown in Figures 4.3 and 4.4 respectively. The IWR of maize ranges from 5 to 95 mm depending on the soil type and climate. On the average, the IWR of rainfed maize on the soil types were found to be 39,

14, 23 and 13 mm on clay, loamy sand, sandy clay loam and sandy loam respectively. The IWR of soybeans ranges from 10 to 119 mm. However, the average over the study period was obtained as 41, 31, 36 and 29 mm on clay, loamy sand, sandy clay loam and sandy loam soils respectively.

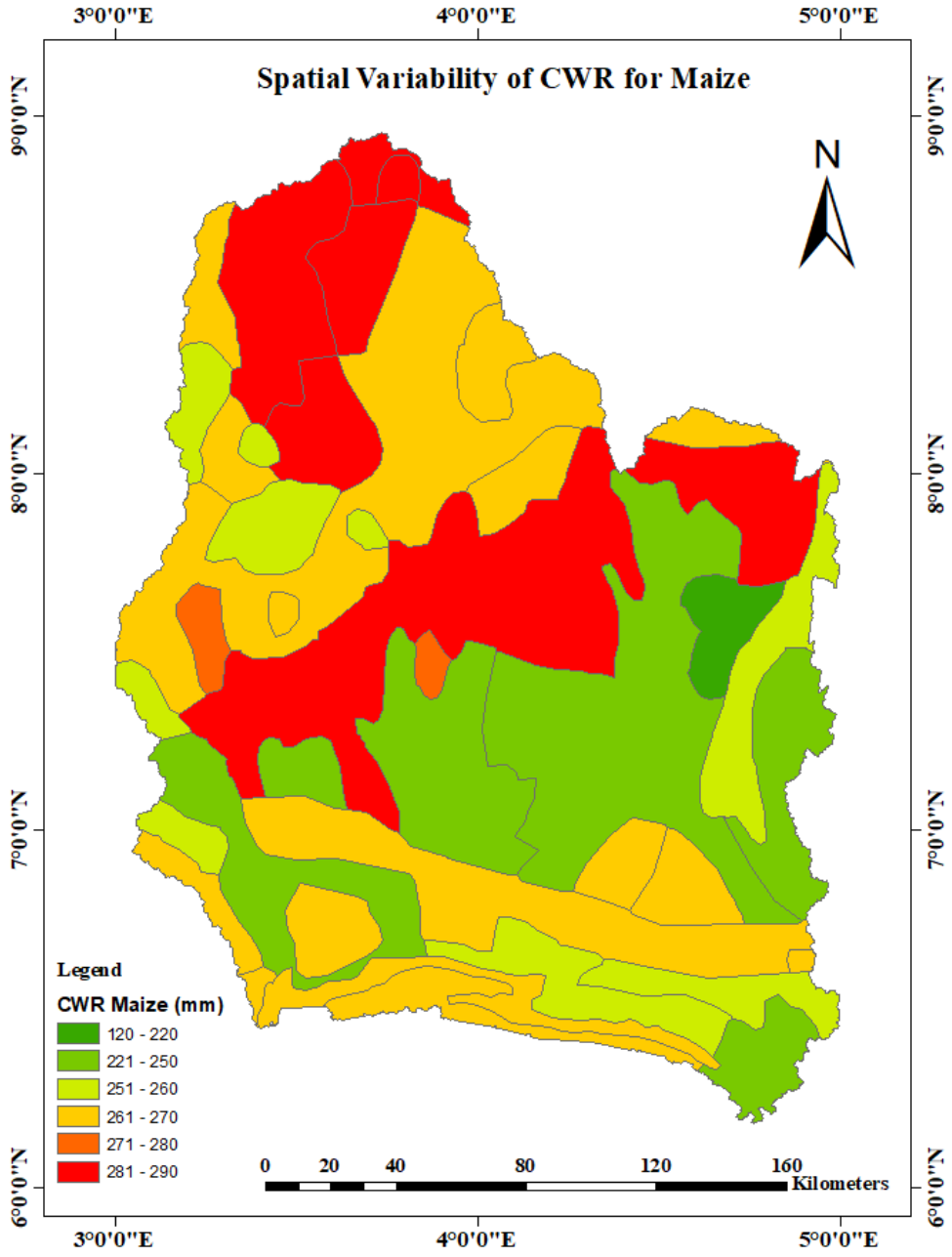

Figure 4.1: Spatial variability of maize CWR

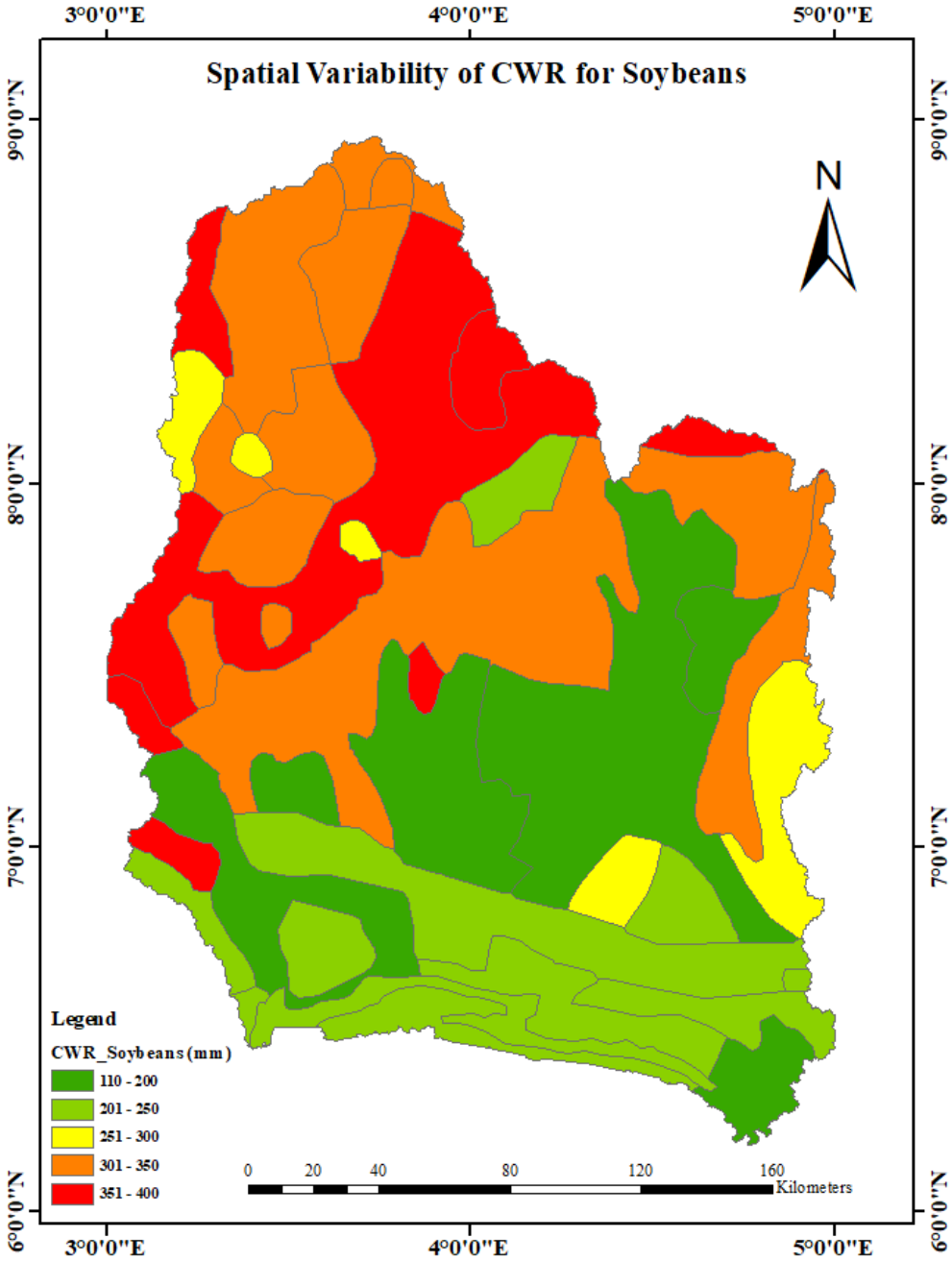

Figure 4. 2: Spatial variability of soybeans CWR

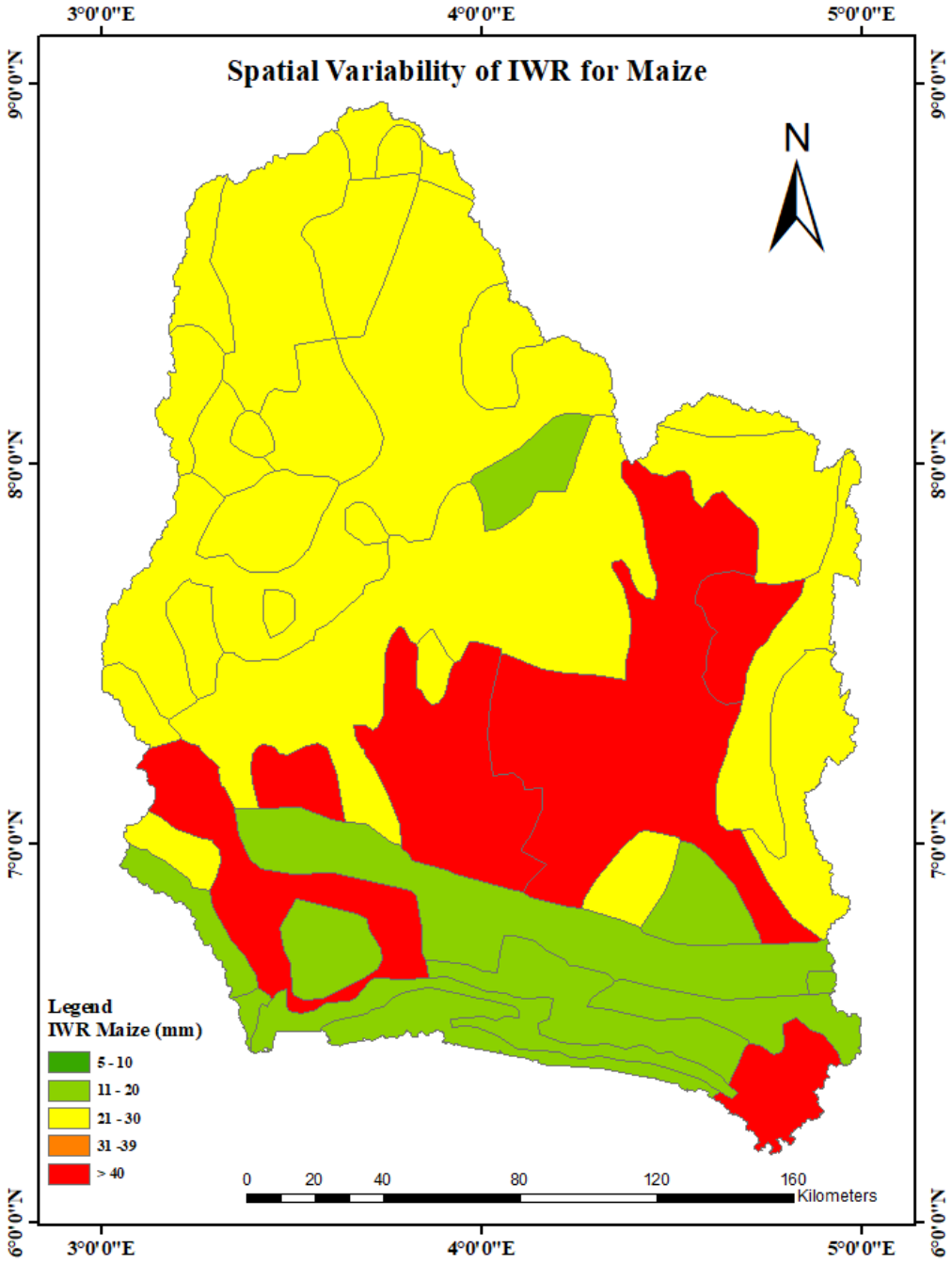

Figure 4.3: Spatial variability of maize IWR

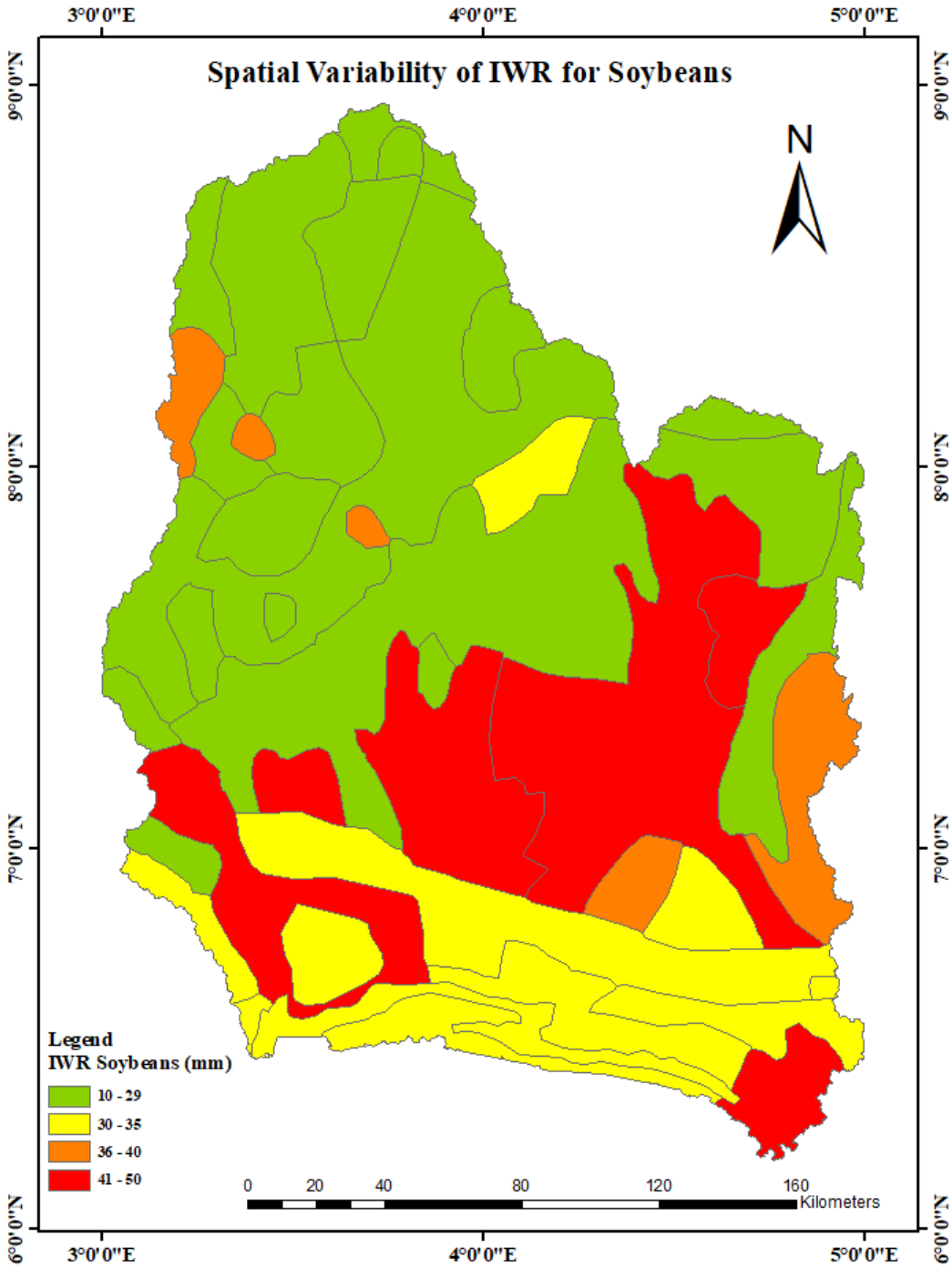

Figure 4.4: Spatial variability of soybeans IWR

The results also show that there will be more dry days within soybeans growing period compared with maize production. The higher IWR of soybeans could also be attributed to the longer length of growing period of soybeans compared to maize. Supplemental irrigation could increase crop

yields in Nigeria (Olayide et al., 2016). But currently, most farmers do not practice supplemental irrigation since it is believed that there is enough rainfall for crop growth. As shown from these results, rainfall variability leads to fluctuations in IWR of crops. The knowledge of IWR of maize and soybeans will provide the basis for policy formulation and implementation with the basin.

4.1.3 Crop yields

Furthermore, the crop yields were also simulated for the period of 1986 – 2015. The results show huge variability in crop yield which is highly dependent on soil fertility and climate. Also, low yields of maize and soybeans which characterises the basin were obtained. Maize yield ranges from 0.61 to 2.26 t/ha as shown in Figure 4.5. In addition, the average yield obtained on clay, loamy sand, sandy clay loam and sandy loam soils were 1.51, 2.11, 2.16 and 2.12 t/ha respectively. Within the period studied, the lowest yield occurred on clay soil with 0.61 t/ha while the highest yield was obtained on sandy clay loam soil with 2.26 t/ha.

However, for soybeans there is a slight increase in crop yield compared to maize. Figure 4.6 shows that the farms within the basin with sandy loams, sandy clay loams and loamy sand soils have much higher soybeans yields than clay soil. Soybeans yield ranges from 0.5 to 3.25 t/ha. In addition, the average yield obtained were 1.52, 2.81, 2.78 and 2.96 t/ha on clay, loamy sand, sandy clay loam and sandy loam soils respectively. Similar to maize yields, lowest yields were only observed on clay soils. The lowest simulated yield within the period under review was 0.5 t/ha on clay soils while 3.25 t/ha yield was the maximum yield which occurred on the remaining soil types.

Poor soil fertility and water limiting conditions are among the major problems of crop production which limits crop yields in Nigeria (Olayide et al., 2016). These problems are not only associated with crop production in Nigeria but with other countries in SSA as well (Besada & Werner, 2015; Luhunga, 2017). Actually, many studies have shown that increasing soil fertility could improve yields (Olayide et al., 2016; Otitoju & Enete, 2016) but many studies have not explored the option of supplemental irrigation to improve crop yields. However, since the use of inorganic fertilizers has been discouraged by scientists, most farmers within this basin do not have access to organic fertilizers. Also, farmers have not been trained on the appropriate use of localised technologies such as mulching and cover cropping to improve crop yields. Hence, in this study, the effect of supplemental irrigation on maize and soybeans yields were examined and discussed in other section of this research.

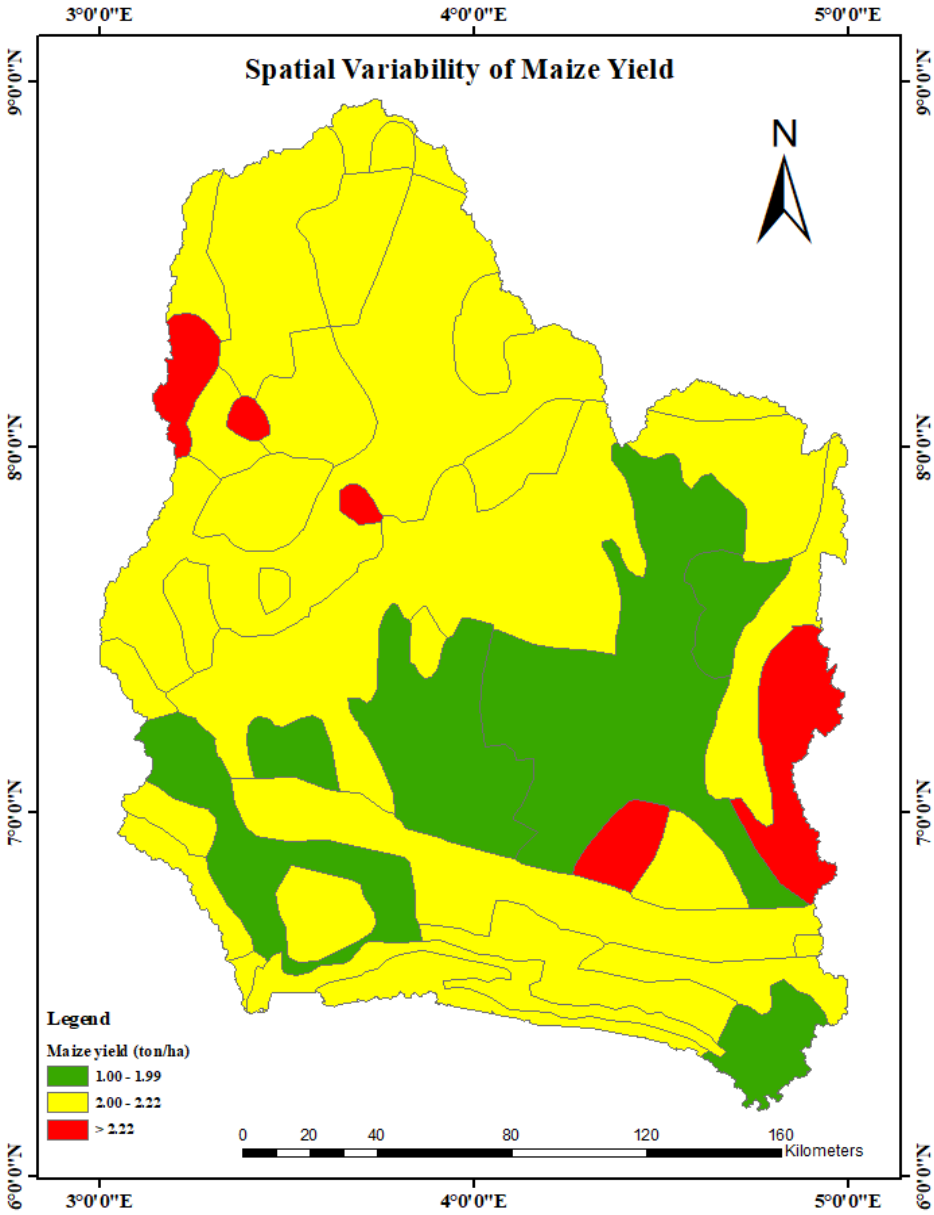

Figure 4.5: Spatial variability of maize yield

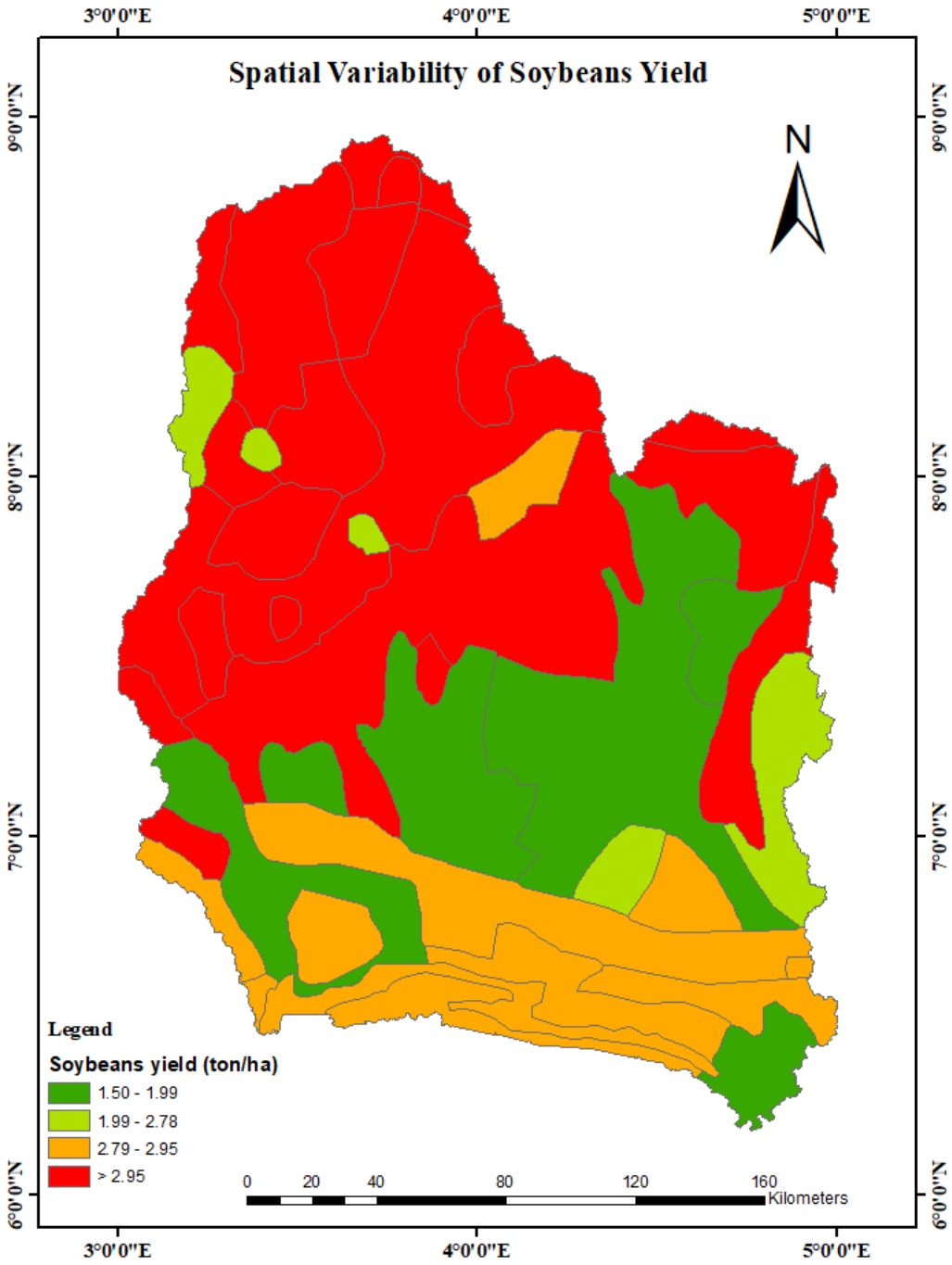

Figure 4. 6: Spatial variability of soybeans yield

4.1.4 Crop water productivity (CWP)

The CWP of maize and soybeans were also simulated for the period of 1986 – 2015 on the soil types within the basin. Figure 4.7: Spatial variability of maize CWP shows the spatial variability of average maize CWP within the basin. The results show that maize CWP ranges from 0.40 to 1.13 kg/m^3 which shows the huge variability of yields within the period under review. Simulated average maize CWP on clay, loamy sand, sandy clay loam and sandy loam soils were 0.75, 0.96, 0.95 and 0.93 kg/m^3 respectively. In addition, the results show that maize CWP within the basin is almost the same for loamy sand, sandy clay loam and sandy loam soils which are the agricultural lands for maize production within the basin.

Furthermore, the CWP of soybeans simulated ranges from 0.30 to 1.13 kg/m^3 on all the soil types. Figure 4.8 shows the spatial variability of soybeans CWP within the study area. It shows that soybeans CWP is almost the same for the fertile soils for soybeans production which are loamy sand, sandy clay loam and sandy loam soils. Based on the simulations, the average soybeans CWP observed were 0.52, 0.89, 0.86, and 0.90 kg/m^3 clay, loamy sand, sandy clay loam and sandy loam soils respectively. Actually, the simulated low CWP shows that the crops are not effectively converting consumptive crop water to quantifiable crop yields. When compared with other studies done in China, United States of America and Germany, maize CWP ranges from as 1.91 to 2.21 kg/m^3 (Li et al., 2016; Steduto et al., 2012). This is not unconnected with higher yields obtainable in these countries which is quite different from SSA situation.

It is noteworthy that CWP is recently gaining attention from engineers, scientists, policymakers and farmers. With the emerging threats of climate change to water resources and increasing water prices in some regions of the world, it is not wise enough to encourage supplemental irrigation without any evident benefits. Even within regions where there is no significant increase in water prices, the benefits in terms of increased crop yields need to be considered. Therefore, increasing research on CWP will be helpful in increasing agricultural productivity. It will also be helpful in appropriate water allocation where necessary.

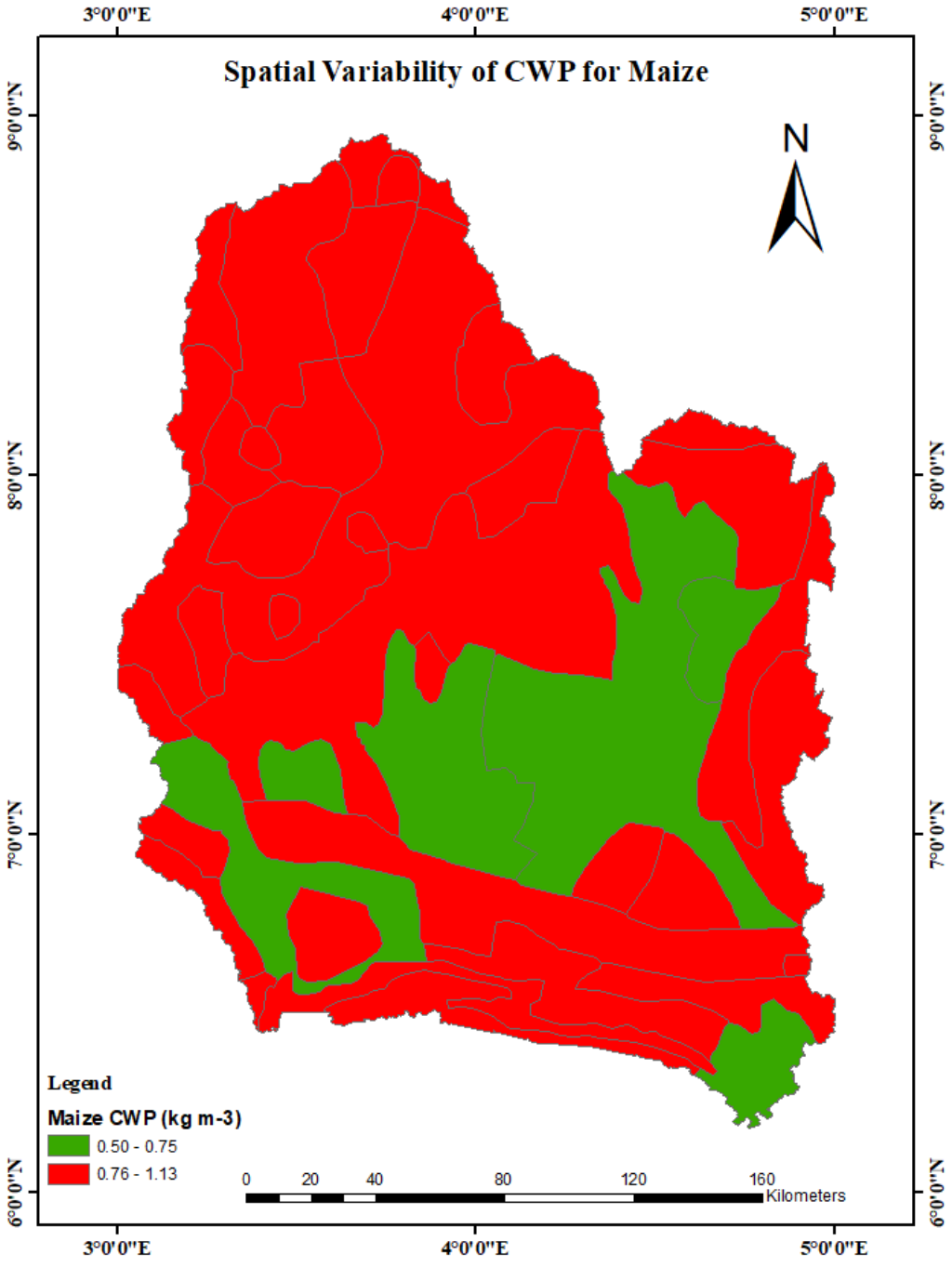

Figure 4.7: Spatial variability of maize CWP

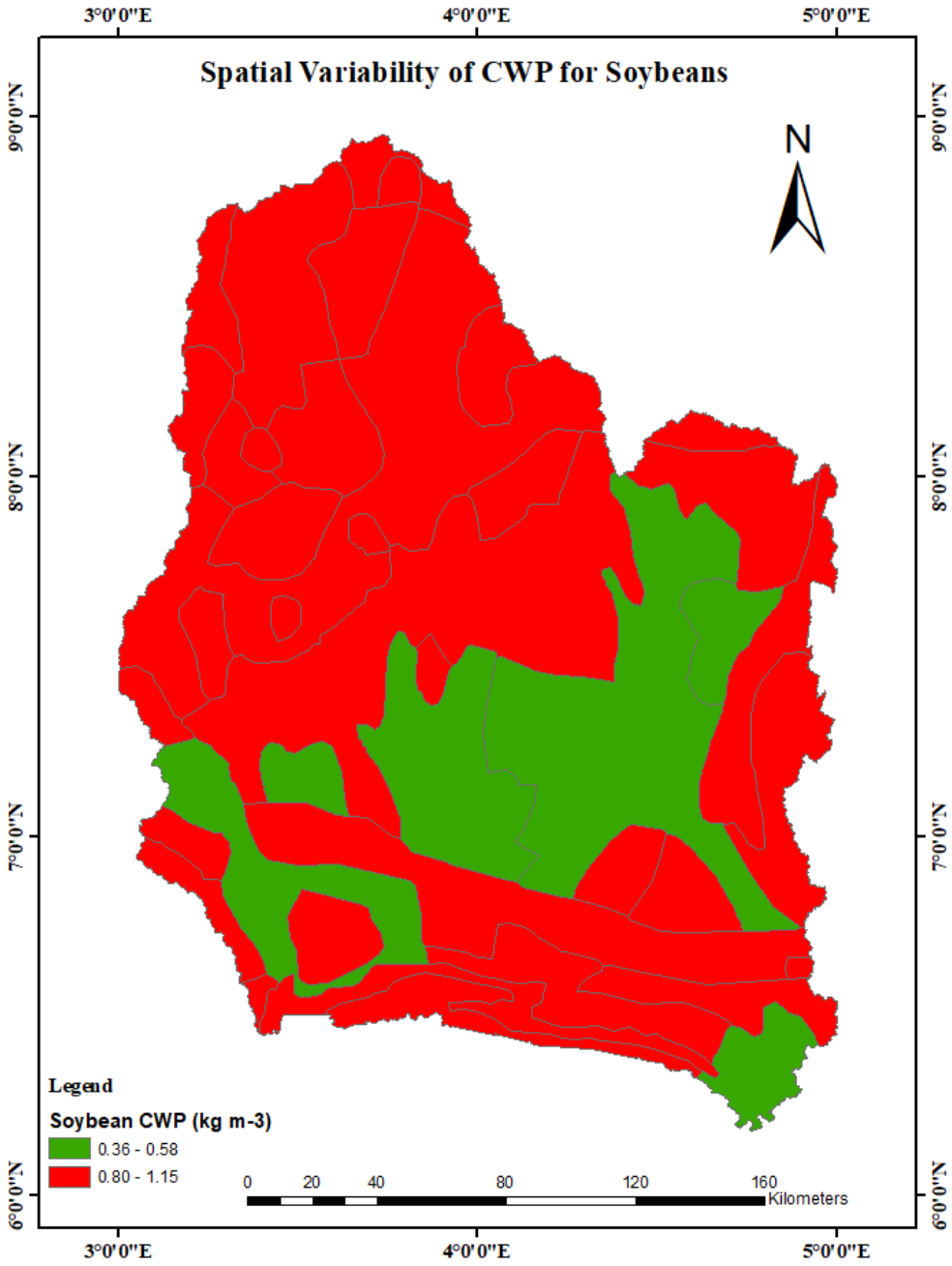

Figure 4.8: Spatial variability of soybeans CWP

4.2 Changes in CWR, IWR, yield and CWP in the past decades

The CWR, IWR, yield and CWP of maize and soybeans were simulated from 1986 – 2015 (30 years) on the soil types within the study area to estimate the changes in the trend of production and examine temporal variability of these parameters.

4.2.1 Changes in seasonal CWR

The simulated maize CWR on the soil types for the years under review is given in Figure 4.9. The results show that there is a slight decreasing trend of maize CWR within the study area. Maize CWR were found to be decreasing with the slope values of -0.42, -0.07, -0.15 and -0.12 mm/year on clay, loamy sand, sandy clay loam and sandy loam soils respectively. Although, it is worthy to note that the results show a clear decreasing trend from 1986 to 2006 before a rise occurred in 2007 up till 2013 before rising. Similarly, Ding et al. (2017) projected a decreasing trend and observed slope values of about 0.9 – 1.5 mm/year in rice CWR between 1960 – 2010 in China.

The decreasing trend of CWR could be attributed to the shortened growing period caused by increased temperature as suggested by (Boonwichai et al., 2018; Wang et al., 2018). From the results, it can be argued that climate change is affecting maize CWR within the basin. The decreasing trend of maize CWR can cause lower maize yield since the crop would not have enough consumptive crop water for a good yield. It shows that there is an urgent need to counterbalance the effects of climate change on this crop within the basin.

Interestingly, the case is different for soybeans compared to maize. According to Figure 4.10, there is a significant increase in soybeans CWR within the basin. Soybeans CWR on all the soil types shows an upward surge. The trendlines show a slightly increasing trend with the slope values of 0.24, 0.11, 0.18, and 1.01 mm/year on clay, loamy sand, sandy clay loam and sandy loam soils respectively. Although, CWR was decreasing from 1986 to 2006 but later increased in 2007 up till 2015. From this study, climate change is causing a decreasing trend in maize CWR but an increasing trend in soybean CWR in the basin.

CWR can be affected majorly by rainfall variability, change in temperature and CO_2 concentration (Wang et al., 2018). The analyses show that climate change through increased temperature and huge variability of rainfall within the basin is causing an increase in the CWR of soybeans. It shows that soybeans CWR is mostly affected by rainfall variability than all other factors. Furthermore, it shows that even though the temperature is increasing, and the growing period is

reducing, still soybeans CWR is increasing. It could be argued that the dry days within the growing period of soybeans is actually more than maize CWR.

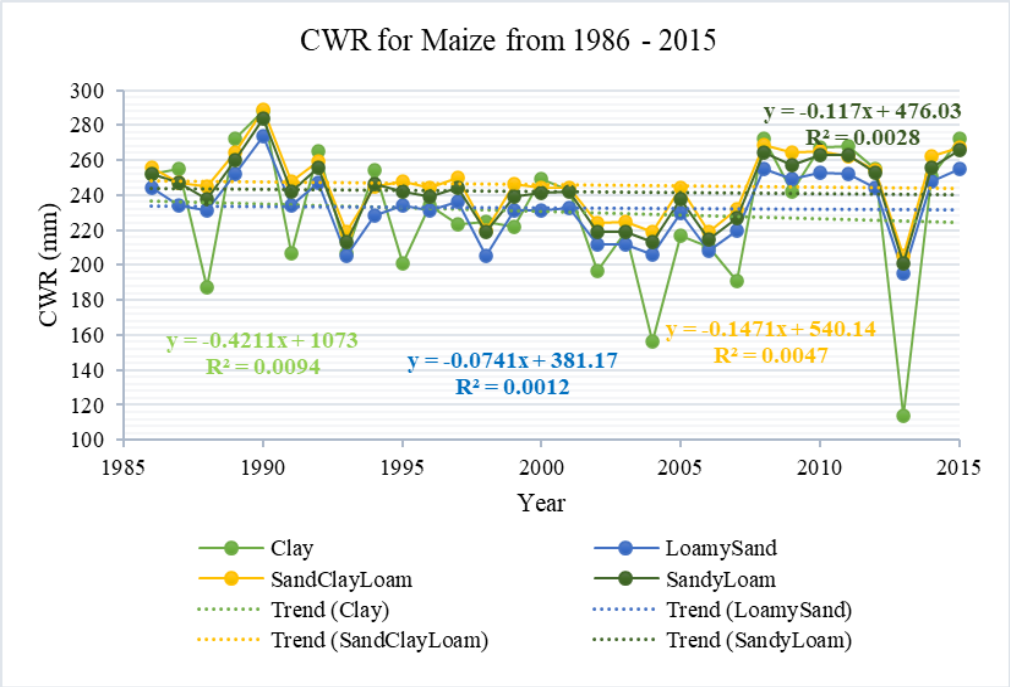

Figure 4.9: Temporal variability of maize CWR

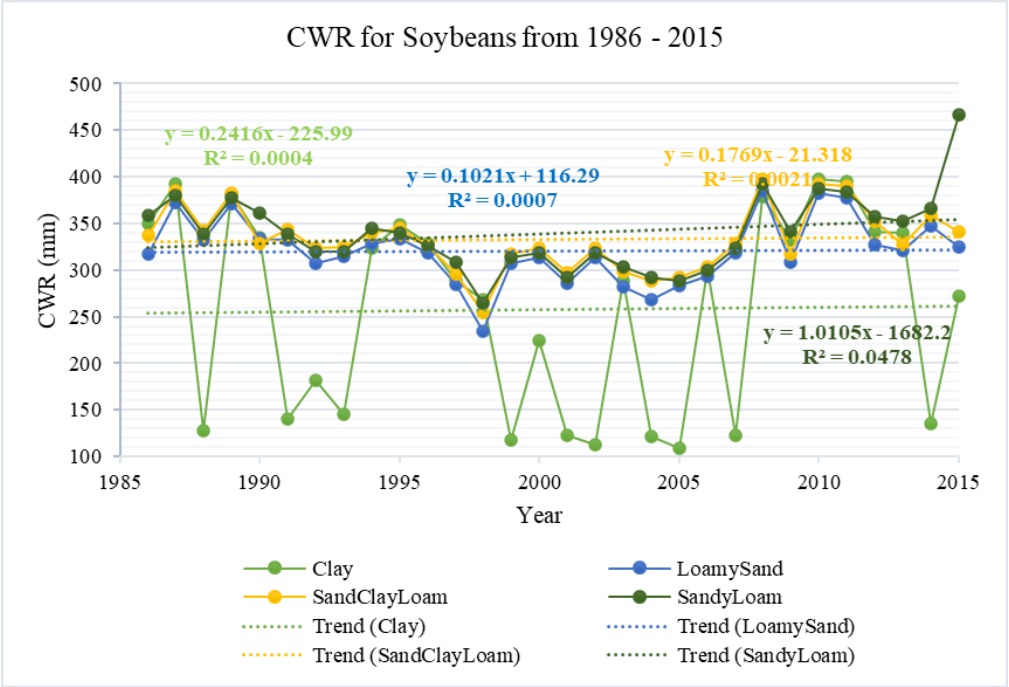

Figure 4.10: Temporal variability of soybeans CWR

4.2.2 Changes in seasonal IWR

According to Figure 4.11, the IWR for maize from 1986 – 2015 has a decreasing trend all across the soil types within the basin. The figure also shows that irrigation was not required for optimum growth during some growing periods which had sufficient rainfall while high irrigation water was required during the drought years. Based on the trendlines, significant decrease slopes of -0.42, -0.39, -0.38 and -0.36 mm/year were found out on clay, loamy sand, sandy clay loam and sandy loam soils respectively. The decreasing trend of maize IWR can also be attributed to a reduction in the growing period (Boonwichai et al., 2018). Similarly, there is a decreasing trend of about 0.27 – 2.00 mm/year in rice IWR between 1960 – 2010 in China depending on each region (Ding et al., 2017).

Contrary to the findings on maize IWR, the IWR of soybeans has an increasing trend within the study area. Figure 4.12 shows that from the analyses there is an increase in soybeans IWR. The figure shows that there are significant increase slopes of 0.74, 0.59, 0.61 and 0.55 mm/year on clay, loamy sand, sandy clay loam and sandy loam soils respectively. The results also depict the variability in rainfall patterns of the basin characterised by years of drought and years of abundant rains. In addition, the figure shows that within the period under review, there are alternate dry and wet periods within the growing seasons in the study area. At least after two years, there is usually a sharp increase in soybeans IWR from 1986 to around 2011 when there were consistent dry growing periods that needs more irrigation water for optimum growth.

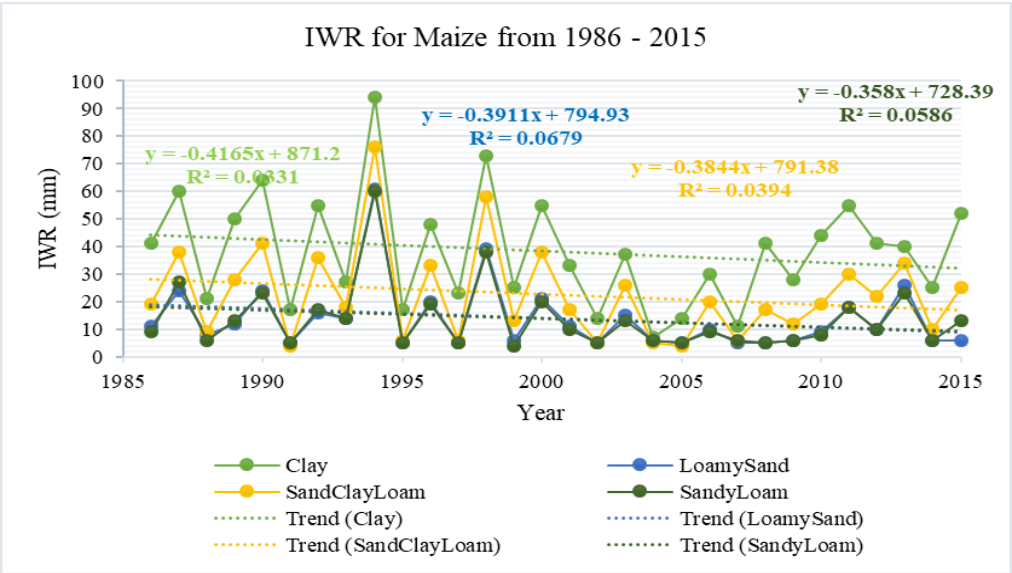

Figure 4.11: Temporal variability of maize IWR

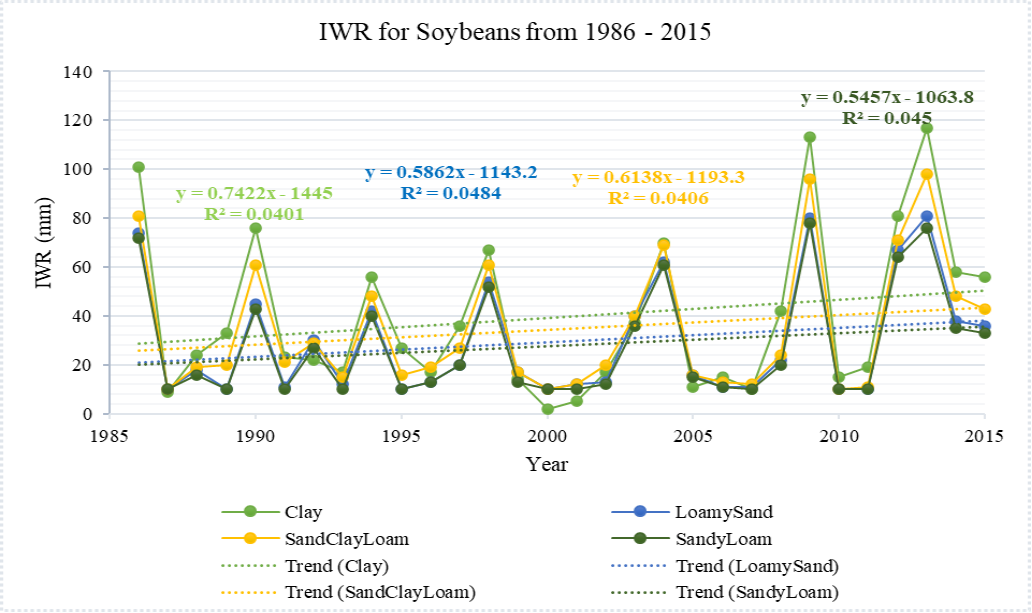

Figure 4.12: Temporal variability of soybeans IWR

4.2.3 Changes in crop yield

The yield of maize and soybeans for the period under review were also simulated to examine the impacts of climate change on them. According to Figure 4.13, clay soils usually produce low yields when compared with loamy sand, sand clay loam and sandy loam soils which produce higher yields. In terms of the effects of climate change on maize yields, the trendlines show an insignificant increase of slope values of 0.0016, 0.0017 and 0.0017 t/ha/year on loamy sand, sand clay loam and sandy loam soils as well as insignificant decrease of slope values of 0.0033 t/ha/year on clay soils.

Generally in SSA, maize yield is expected to decline under climate change (Luhunga, 2017; Tingem & Rivington, 2009). However, from this study and based on the current climate, there seem to be no significant changes in maize yield within the historical period reviewed. Nevertheless, a decline in maize yields is anticipated in most parts of SSA under elevated temperature and CO_2 concentration. Therefore, the responses of maize yield to climate change in the future period are analysed in other sections of this research.

Meanwhile, for soybeans yields, according to Figure 4.14, the trendlines show that there is a significant increase in yield across the basin. The results show significant increase slopes of 0.007, 0.006, 0.002 and 0.006 t/ha/year on clay, loamy sand, sandy clay loam and sandy loam soils

respectively. Clay soils show a trend of low yields for all the years under review while higher yields were simulated on other soils.

It is interesting to see that the trend in maize and soybeans yield are contradictory within the basin for the historical period. While maize yield has no significant changes, soybeans yield is significantly increasing. The increasing trend in soybeans yield is attributable to CO_2 fertilisation (Liben et al., 2018) which has more influence than rainfall variability and increasing temperature. The contradictory results show that while some crops are negatively affected, some crops are benefitting from climate change. Thus, within the basin, climate change has not had any significant changes in maize yields while climate change has a positive impact on soybeans yields.

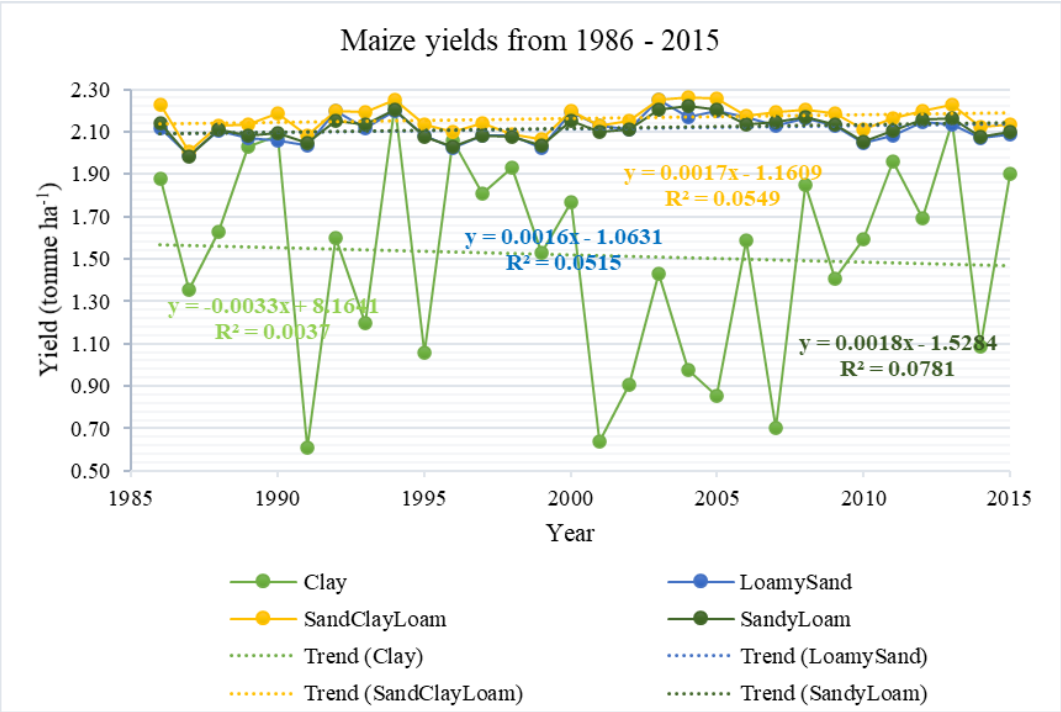

Figure 4.13: Temporal variability of maize yields

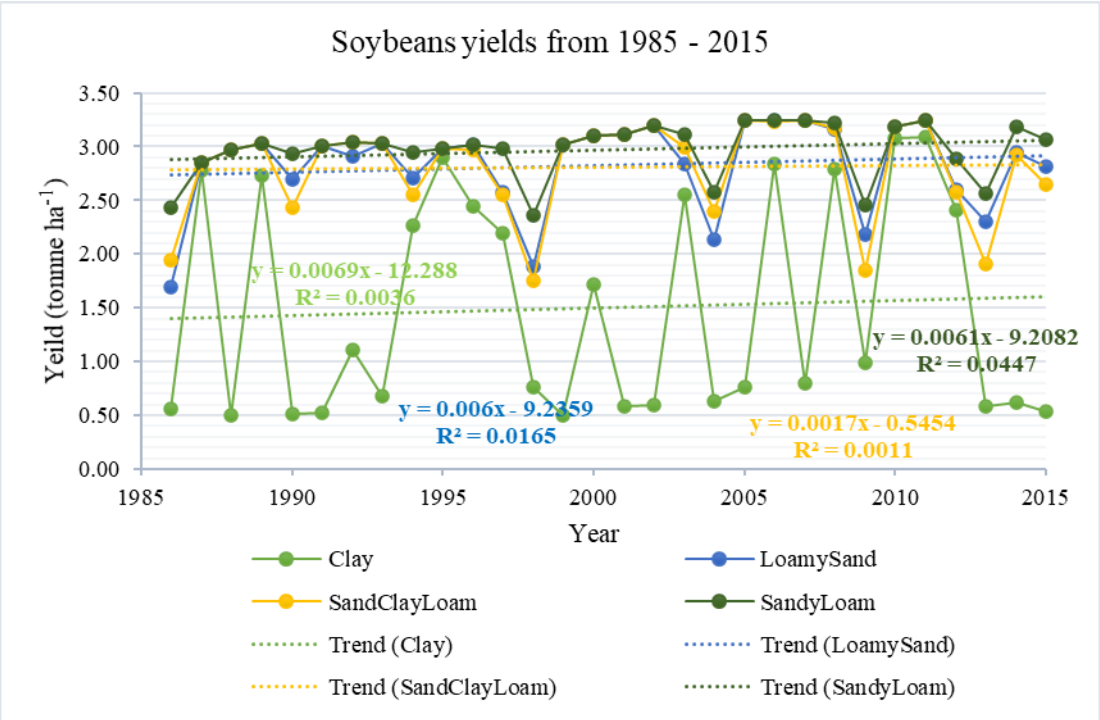

Figure 4.14: Temporal variability of soybeans yields

4.2.4 Changes in CWP

The impact of climate change on CWP of soybeans and maize was evaluated through the temporal variability of maize and soybeans within thirty years. According to Figure 4.15, the trendlines show that there is a slight increase in CWP of maize on loamy sand, sand clay loam and sandy loam soils with slope values of 0.0013, 0.0006 and 0.0015 kg/m^3/year respectively while no changes were found on clay soils. It is worthy to note that there was a clear upward movement of maize CWP on all the soil types except clay from 1986 till it peaked in 2007 before declining from 2008 till 2015. This follows the same trend of maize yields since CWP is the ratio of crop yields to the amount of water consumed by the crop.

Similarly, according to Figure 4.16, a clear upward movement of soybeans CWP was observed on all the soil types except clay from 1986 till it peaked in 2007 before declining from 2008 till 2015. In addition, the trendlines show that there is a slight increase in CWP of soybeans on loamy sand, sand clay loam and sandy loam soils with slope values of 0.0014, 0.0004 and 0.001 kg/m^3/year respectively while a decrease slope value of -0.0032 kg/m^3/year was found out on clay soils. Apart from that, sporadic values of CWP for soybeans were also simulated on clay soil.

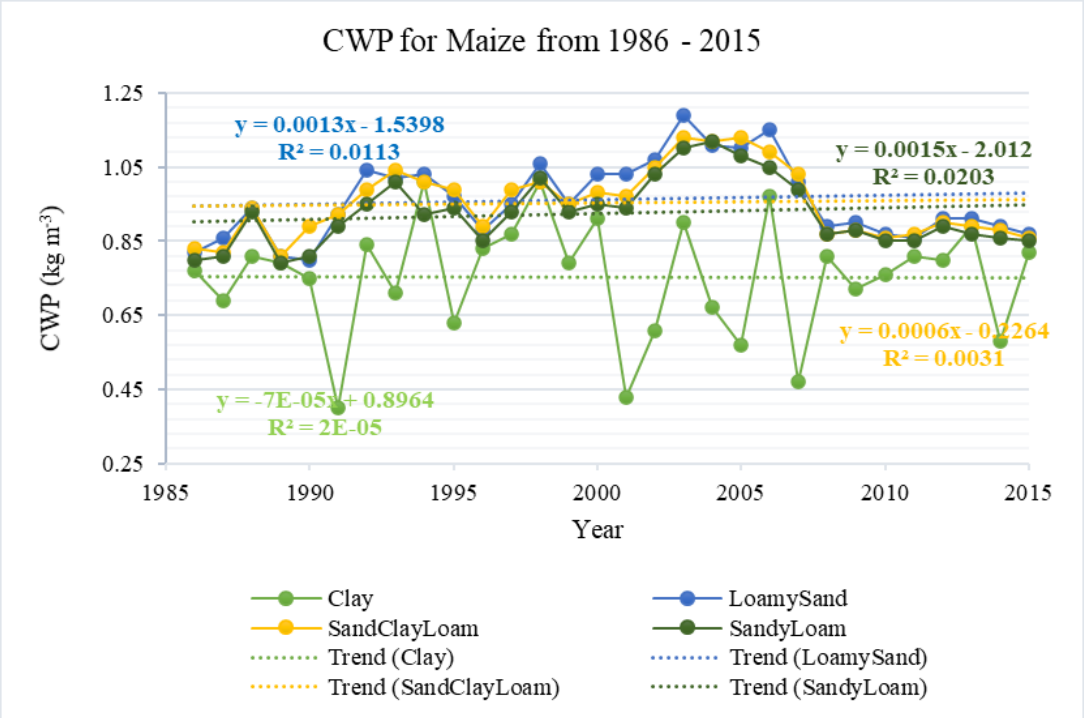

Figure 4.15: Temporal variability of CWP for maize

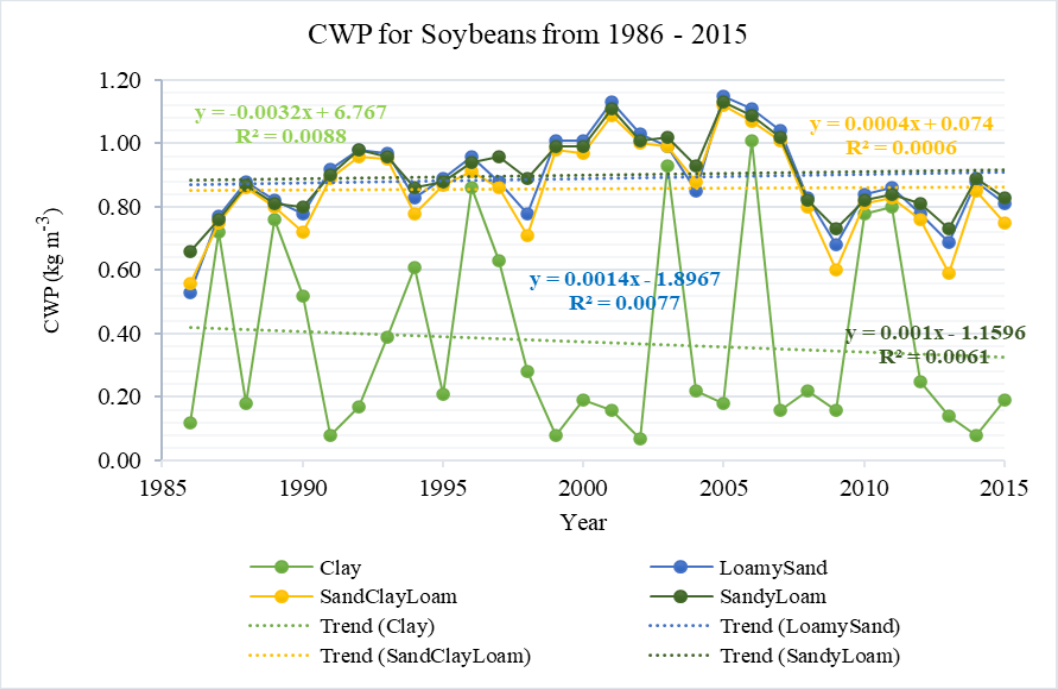

Figure 4.16: Temporal variability of CWP for soybeans

4.3 Planting dates and growing days

One of the most important factors that affect agricultural production both positively and negatively is planting date. During the simulations, the planting date window was calibrated between 1 April – 15 April and 1 June – 15 June for planting maize and soybeans respectively. The results in Table 4.1 show that the planting of maize was done within 1 – 5 April except for a few years when planting took place on 15 April. Likewise, based on the simulations, the planting dates simulated for soybeans were within 1 – 4 June except for years when rainfall delayed and occurred on 15 June. In addition, from the simulations, maize growing period ranges from 72 – 80 days while the mean growing day simulated was 76 days. The growing days were largely dependent on the climate and did not vary spatially. Meanwhile, the growing period of soybeans ranges from 108 – 116 days while the mean was 112 days.

4.4 Effects of supplemental irrigation on yields and CWP

Rainfed maize and soybeans were simulated under supplemental irrigation within the basin based on the climate data of 1986 – 2015. The results as shown in Table 4.2 reveals that on the average, supplemental irrigation alone can raise rainfed maize yield by 93.3, 35.1, 31.3 and 32.3% on clay, loamy sand, sandy clay loam and sandy loam soils respectively. On rainfed soybeans, supplemental irrigation alone can raise yield by 30.4, 9.3, 10.5, 12.0% when simulated on clay, loamy sand, sandy clay loam and sandy loam soils respectively within the basin as shown in Table 4.3. Some studies (Basso et al., 2015; Liben et al., 2018; Olayide et al., 2016) similarly show that supplemental irrigation could increase maize yield if properly adopted by farmers.

Similarly, the CWP of maize and soybeans increased when simulated on supplemental irrigation. As shown Table 4.4, based on historical climate data and crop data, supplemental irrigation alone is capable of increasing CWP of maize by 13.9, 9.2, 6.0, and 5.9% on clay, loamy sand, sandy clay loam and sandy loam soils respectively. The CWP of soybeans can be raised through supplemental irrigation by 70.4, 10.1, 12.0 and 6.5% on clay, loamy sand, sandy clay loam and sandy loam soils respectively within the basin as shown in Table 4.5. Based on the results of this study, it shows that if supplemental irrigation could be adopted by farmers within this region, it will likely boost their productivities and improve the food security of the region and the country at large.

Table 4.1: Simulated planting dates of maize and soybeans

S/N	Year	Maize (Day in April)	Soybeans (Day in June)
1	1986	5	3
2	1987	15	3
3	1988	3	3
4	1989	15	3
5	1990	3	5
6	1991	5	3
7	1992	4	3
8	1993	15	3
9	1994	15	15
10	1995	3	4
11	1996	4	5
12	1997	4	3
13	1998	15	3
14	1999	3	3
15	2000	4	4
16	2001	5	2
17	2002	4	3
18	2003	4	3
19	2004	3	3
20	2005	3	3
21	2006	15	4
22	2007	15	2
23	2008	4	3
24	2009	4	3
25	2010	4	3
26	2011	5	3
27	2012	13	3
28	2013	3	4
29	2014	3	2
30	2015	5	3

Table 4.2: Effects of supplemental irrigation on maize yields

Soil type	Rainfed yield (t/ha)	Supplemental irrigation yield (t/ha)	Change (%)
Clay	1.62	2.11	30.4
Loamy sand	2.11	2.31	9.3
Sandy clay loam	2.16	2.39	10.5
Sandy loam	2.12	2.37	12.0

Table 4.3: Effects of supplemental irrigation on soybeans yields

Soil type	Rainfed yield (t/ha)	Supplemental irrigation yield (t/ha)	Change (%)
Clay	1.50	2.90	93.3
Loamy sand	2.83	3.82	35.1
Sandy clay loam	2.80	3.68	31.3
Sandy loam	2.97	3.93	32.3

Table 4.4: Effects of supplemental irrigation on CWP for maize

Soil type	Rainfed CWP (kg/m^3)	Supplemental irrigation CWP (kg/m^3)	Change (%)
Clay	0.75	0.86	13.9
Loamy sand	0.96	1.05	9.2
Sandy clay loam	0.95	1.01	6.0
Sandy loam	0.93	0.98	5.9

Table 4.5: Effects of supplemental irrigation on CWP for soybeans

Soil type	Rainfed CWP (kg/m^3)	Supplemental irrigation CWP (kg/m^3)	Change (%)
Clay	0.52	0.89	70.4
Loamy sand	0.89	0.98	10.1
Sandy clay loam	0.86	0.96	12.0
Sandy loam	0.90	0.96	6.5

4.5 Future changes in climatic parameters under different climate change scenarios

The future changes in rainfall, minimum and maximum temperatures for future periods of near future (2021 – 2040), mid-century (2041 – 2070) and late-century (2071 – 2099) relative to mean of 1986 – 2015 under RCP 4.5 and RCP 8.5 scenarios were estimated based on the projections of HadGEM2-ES model. The analysis shows that the basin will experience a reduction in annual rainfall across all scenarios and future periods except in the period of 2041 – 2070 when there is likely going be a 3.33% increase. From Table 4.6, under the RCP 4.5 scenario, rainfall will decrease by 10.0% in the near future, increase by 3.3% in mid-century and decrease by 9.17% in the late century. While under RCP 8.5, rainfall will decrease by 10.0, 9.17 and 10.0% in the near future, mid-century and the late century respectively.

In addition, both minimum and maximum temperatures will increase gradually from 2021 up till 2099 under both RCP 4.5 and RCP 8.5 scenarios. RCP 8.5 is expected to be generally hotter than RCP 4.5 since RCP 8.5 is referred to as the worst-case scenario of elevated CO_2 concentrations and temperature. The maximum temperature is projected to increase up to 33.8 ℃ and 35.8 ℃ by the late century under RCP 4.5 and RCP 8.5 scenarios respectively as shown in Table 4.6. Similarly, minimum temperature projected to increase up to 24.5 ℃ and 26.3 ℃ by the late century under RCP 4.5 and RCP 8.5 scenarios respectively.

Table 4.6: Changes in rainfall, minimum and maximum temeperatures for future periods relative to mean of 1986 – 2015 under RCP 4.5 and RCP 8.5 scenarios

Climatic parameters	Baseline (1986-2015)	Relative changes					
		RCP 4. 5 (570 ppm CO_2)			RCP 8. 5 (1200 ppm CO_2)		
		2021 - 2040	2041 - 2070	2071 - 2099	2020 - 2040	2041 - 2070	2071 - 2099
Rainfall (mm)	1200	-120 (-10.0%)	40 (3.33%)	-110 (-9.17%)	-120 (-10.0%)	-110 (-9.17%)	-120 (-10.0%)
Minimum temperature (℃)	22.1	0.9 (4.07%)	1.5 (6.79%)	2.4 (10.86%)	1.3 (5.88%)	2.4 (10.86%)	4.2 (19.00%)
Maximum temperature (℃)	31.4	1.2 (3.82%)	1.9 (6.05%)	2.6 (8.28%)	1.5 (4.78%)	2.7 (8.60%)	4.4 (14.01%)

4.6 Future seasonal CWR, IWR, yield and CWP under different climate change scenarios

Climate change is capable of significantly affecting agricultural production globally which is expected to be temporally and spatially distributed. The future CWR, IWR, yield and CWP of maize and soybeans were simulated for future periods of near future (2021 – 2040), mid-century (2041 – 2070) and late-century (2071 – 2099) under RCP 4.5 and RCP 8.5 scenarios based on the projections of HadGEM2-ES model.

4.6.1 Future seasonal crop water requirements (CWR)

The simulations show that climate change (change in rainfall and temperature) will significantly affect both maize and soybeans CWR. The CWR of maize under RCP 4.5 and RCP 8.5 scenarios are projected to decrease gradually from 2021 – 2099 depending on soil types. Under RCP 4.5, the average CWR of maize on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 209, 219, 231 and 227 mm in the near future; 215, 214, 225 and 222 mm in the mid-century and 205, 213, 224 and 221 mm in the late century respectively as shown in Figure 4.17. Under RCP 8.5, CWR of maize will reduce significantly when compared with the results under RCP 4.5 in all future periods. Under RCP 8.5, the average CWR of maize on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 213, 223, 236 and 231 mm in the near future; 198, 213, 226 and 221 mm in the mid-century and 178, 195, 206 and 202 mm in the late century respectively as shown in Figure 4.18.

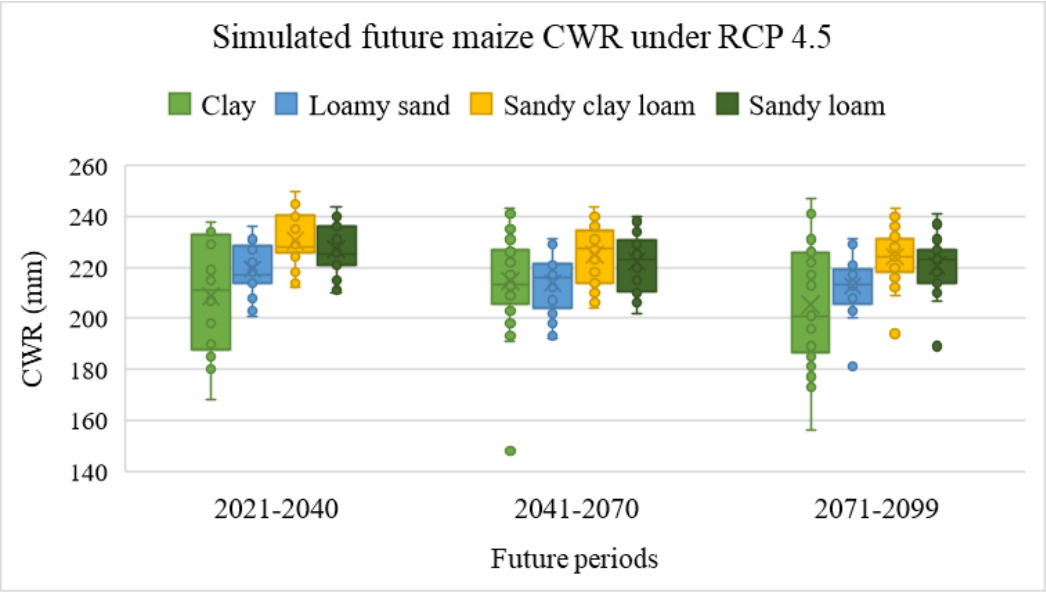

Figure 4.17: Simulated future maize CWR under RCP 4.5

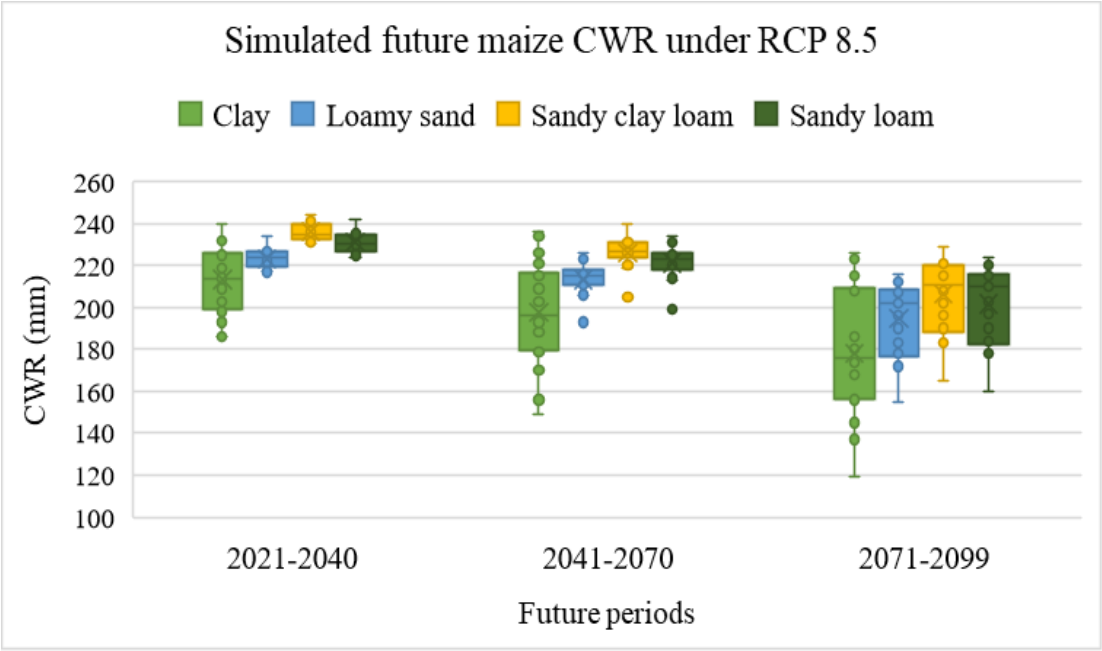

Figure 4.18: Simulated future maize CWR under RCP 8.5

Similar to the CWR of maize, the CWR of soybeans is also projected to decrease gradually from 2021 – 2099. According to Figure 4.19, under RCP 4.5, the average CWR of soybeans on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 280, 340, 347 and 351 mm in the near future; 302, 321, 332 and 330 mm in the mid-century and 290, 329, 334 and 337 mm in the late century respectively. Meanwhile, under RCP 8.5, CWR of soybeans will reduce largely when compared with the results under RCP 4.5 in all future periods. Under RCP 8.5, the average CWR of soybeans on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 276, 328, 337 and 341 mm in the near future; 294, 320, 330 and 332 mm in the mid-century as well as 226, 293, 301 and 303 mm in the late century respectively as shown in Figure 4.20.

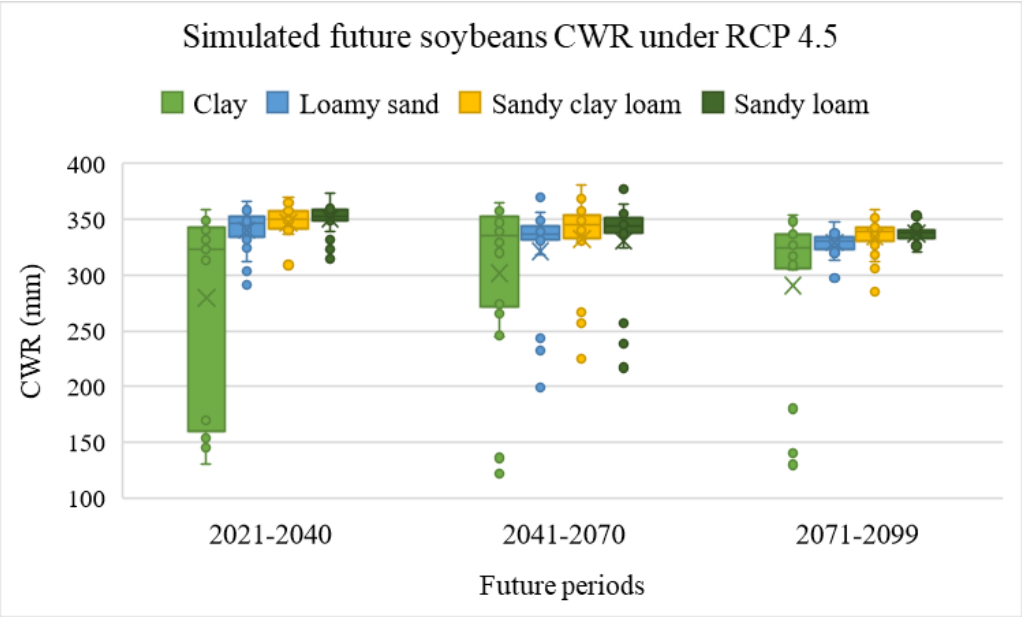

Figure 4.19: Simulated future soybeans CWR under RCP 4.5

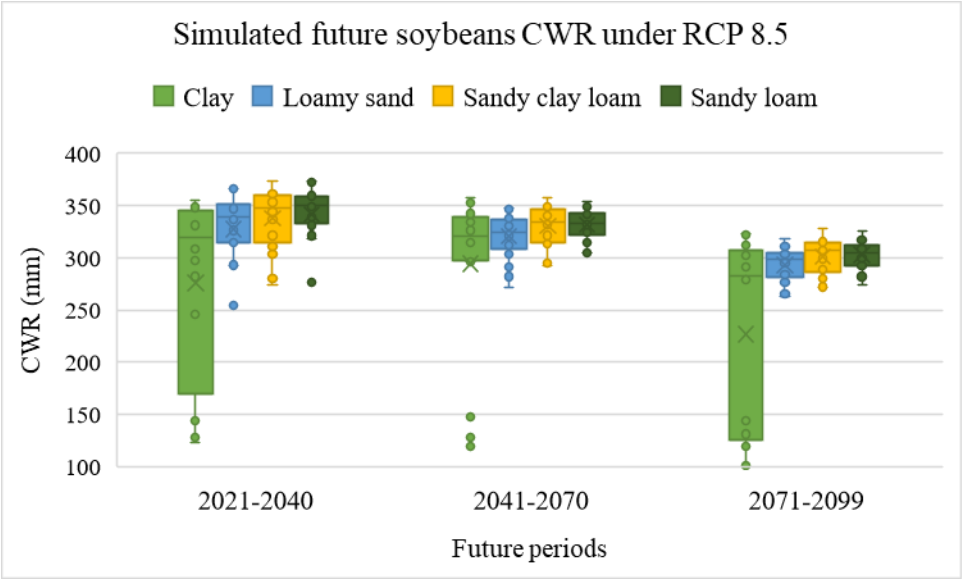

Figure 4.20: Simulated future soybeans CWR under RCP 8.5

4.6.2 Future seasonal irrigation water requirements (IWR)

The future IWR was simulated for maize and soybeans within the basin. The simulations show that climate change (change in rainfall and temperature) will significantly affect both maize and soybeans IWR. The IWR of maize under RCP 4.5 scenario is projected to be high in the period 2021 – 2040, then decrease in the period of 2041 – 2070 and eventually rise in the period of 2071 – 2099. In contrast, under RCP 8.5, IWR of maize is projected to have insignificant differences

across all the future periods. Under RCP 4.5, the average IWR of maize on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 67, 36, 49 and 36 mm in the near future; 45, 16, 28 and 15 mm in the mid-century and 65, 34, 47 and 34 mm in the late century respectively as shown in Figure 4.21. Under RCP 8.5, the average IWR of maize on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 41, 13, 24 and 12mm in the near future; 45, 16, 28 and 15 mm in the mid-century and 36, 15, 25 and 13 mm in the late century respectively as shown in Figure 4.22.

In addition, according to Figure 4.23 and Figure 4.24, the IWR of soybeans under RCP 4.5 and RCP 8.5 scenarios are projected to be high in the period 2021 – 2040, then decrease in the period of 2041 – 2070 and then no significant differences in the period of 2071 – 2099. Meanwhile, under RCP 4.5, the average IWR of soybeans on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 44, 13, 22 and 13 mm in the near future; 33, 12, 13, and 11 mm in the mid-century and 35, 13, 19 and 13 mm in the late century respectively. Under RCP 8.5, the average IWR of soybeans on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 50, 22, 27 and 22 mm in the near future; 36, 18, 21 and 18 mm in the mid-century and 33, 16, 20 and 13 mm in the late century respectively. IWR of maize is projected to range from 5 to 130 mm and 5 to 112 mm in the future periods under RCP 4.5 and RCP 8.5 respectively. Similarly, IWR of soybeans is projected to range from 6 to 98 mm and 6 – 117 mm under RCP 4.5 and RCP 8.5 respectively.

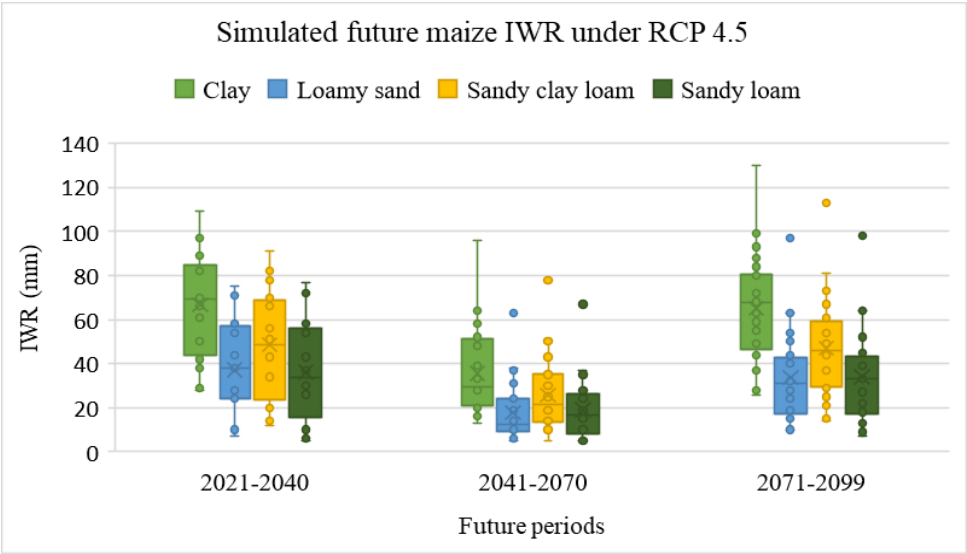

Figure 4.21: Simulated future maize IWR under RCP 4.5

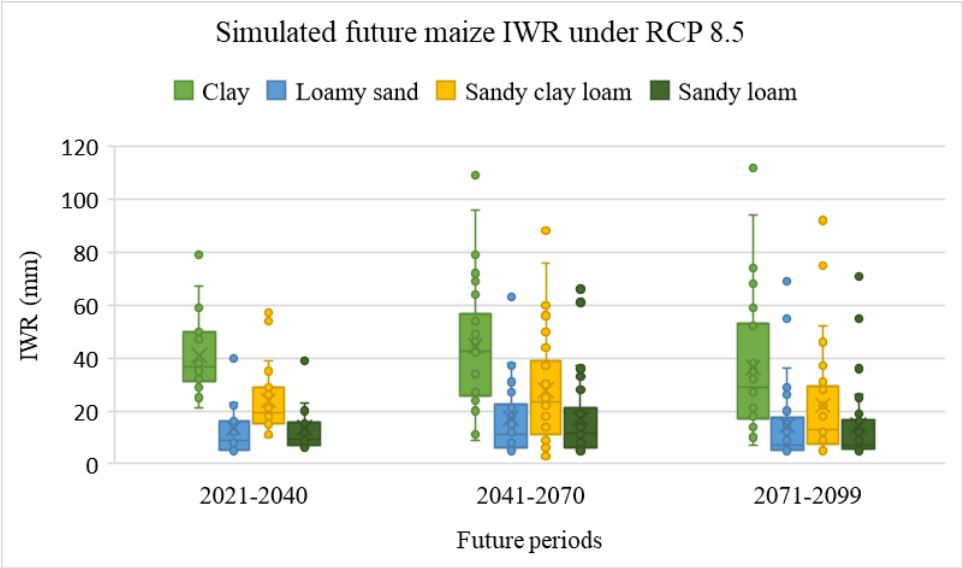

Figure 4.22: Simulated future maize IWR under RCP 8.5

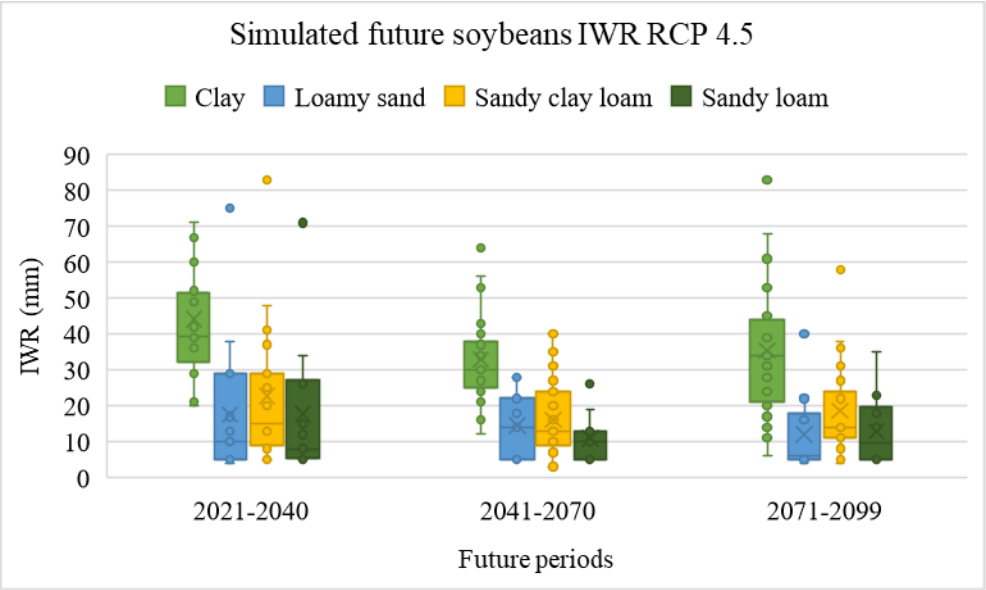

Figure 4.23: Simulated future soybeans IWR under RCP 4.5

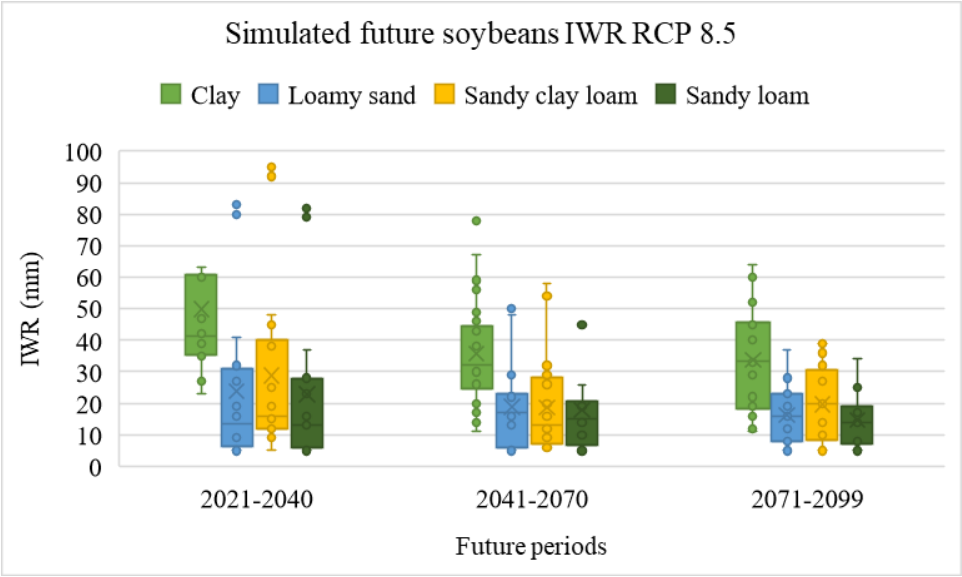

Figure 4.24: Simulated future soybeans IWR under RCP 8.5

4.6.3 Future crop yields

The future maize and soybeans yield were simulated for future periods of near future (2021 – 2040), mid-century (2041 – 2070) and late-century (2071 – 2099) under RCP 4.5 and RCP 8.5 scenarios. The results show contradictory projections of maize and soybeans yields. According to Figure 4.25 and Figure 4.26, maize yield is projected to decline from 2021 – 2099 under both RCP 4.5 and RCP 8.5 scenarios within the basin. The results show that maize cultivated on clay soils will have high yield variability while yields are almost similar on loamy sand, sandy clay loam and sandy loam soils which are the agricultural lands within the basin.

Under RCP 4.5, the average maize yield on clay, loamy sand, sand clay loam and sandy loam soils are projected to be 1.79, 2.08, 2.09 and 2.07 t/ha in the near future; 1.93, 2.00, 2.01 and 1.99 t/ha in the mid-century and 1.71, 1.94, 1.97 and 1.96 t/ha in the late century respectively. Similarly, under RCP 8.5, the average maize yield on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 1.76, 1.99, 2.00 and 1.99 t/ha in the near future; 1.58, 1.95, 1.96 and 1.95 t/ha in the mid-century and 1.42, 1.90, 1.91 and 1.90 t/ha in the late century respectively. The decline in maize yield under climate change in the future periods is similar to the results of future maize yields in Tanzania as well (Luhunga, 2017).

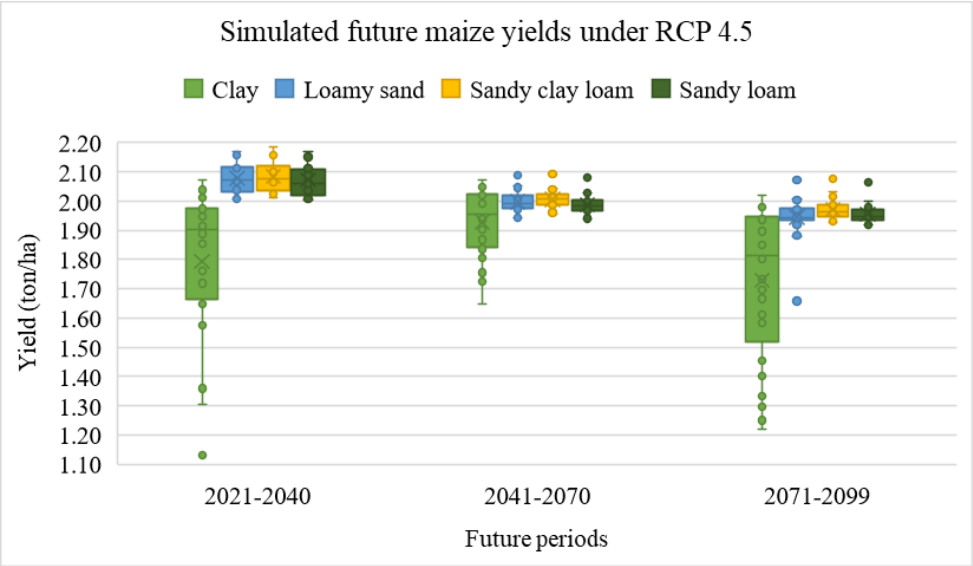

Figure 4.25: Simulated future maize yields under RCP 4.5

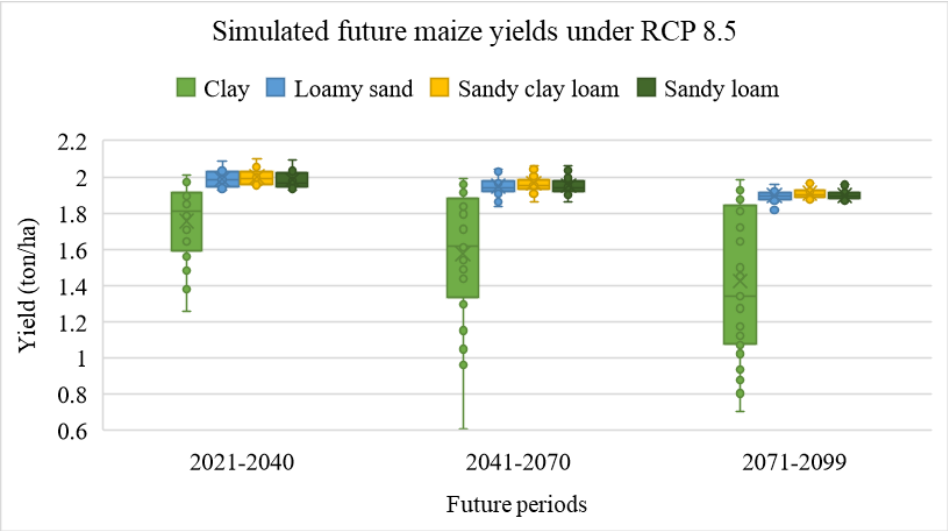

Figure 4.26: Simulated future maize yields under RCP 8.5

According to Figure 4.27 and Figure 4.28, soybeans yield is projected to increase from 2021 – 2099 under both RCP 4.5 and RCP 8.5 scenarios within the basin. Also, the results show that soybeans cultivated on clay soils will have high yield variability while yields are almost similar on loamy sand, sand clay loam and sandy loam soils which are the agricultural lands within the basin. Under RCP 4.5, the average soybeans yield on clay, loamy sand, sand clay loam and sandy loam soils are projected to be 2.00, 3.33, 3.26 and 3.41 t/ha in the near future; 2.75, 3.58, 3.5 and 3.55 t/ha in the mid-century and 2.52, 3.55, 3.29 and 3.60 t/ha in the late century respectively. Similarly, under RCP 8.5, the average soybeans yield on clay, loamy sand, sandy clay loam and

sandy loam soils are projected to be 2.60, 3.22, 3.19 and 3.26 t/ha in the near future; 2.88, 3.60, 3.57 and 3.70 t/ha in the mid-century and 2.75, 3.92, 3.83 and 4.01 t/ha in the late century respectively.

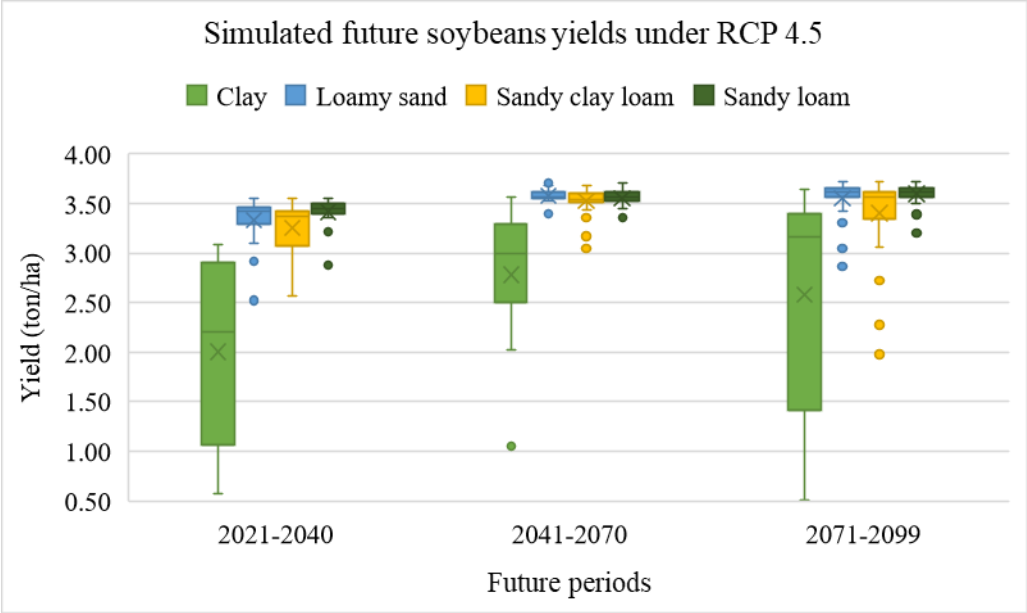

Figure 4.27: Simulated future soybeans yields under RCP 4.5

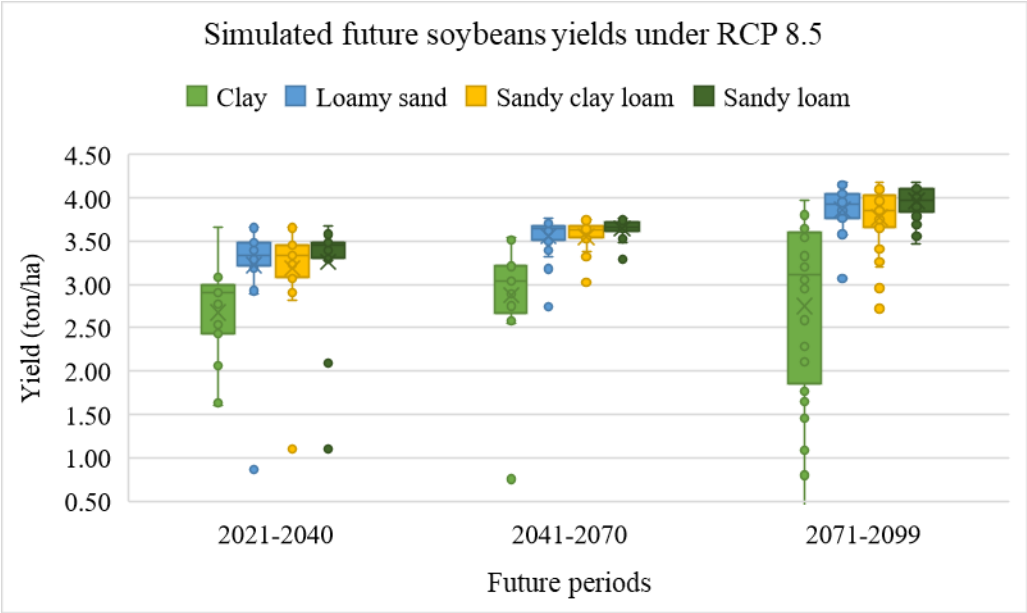

Figure 4.28: Simulated future soybeans yields under RCP 8.5

4.6.4 Future crop water productivity (CWP)

The simulated future CWP of maize and soybeans within the basin show different variations for the future periods as well as under different climate change scenarios. According to the simulations, there will be huge variability within the soil types and the growing seasons. The results also show that some years will have high CWP up to 1.08 kg/m^3 while some will have low CWP up to 0.66 kg/m^3. The results show that under RCP 4.5, CWP on all the soil types will likely decrease gradually from 2021 – 2099 except clay soils that will have fluctuations within the future periods. Under RCP 4.5, the average CWP of maize on clay, loamy sand, sand clay loam and sandy loam soils are projected to be 0.87, 0.96, 0.92 and 0.92 kg/m^3 in the near future; 0.90, 0.95, 0.92 and 0.91 kg/m^3 in the mid-century and 0.84, 0.93, 0.89 and 0.90 kg/m^3 in the late century respectively as shown in Figure 4.29.

However, contrary to the declining trend of maize CWP under RCP 4.5, maize CWP under RCP 8.5 is projected to rise steadily. It is worthy to note that the CWP of maize for under RCP 4.5 is higher than under RCP 8.5 in the near future (2021 – 2040) and mid-century (2041 – 2070) except in the late century (2071 – 2099). Moreover, under RCP 8.5, the average CWP of maize on clay, loamy sand, sand clay loam and sandy loam soils are projected to be 0.83, 0.90, 0.85 and 0.87 kg/m^3 in the near future; 0.80, 0.92, 0.88 and 0.89 kg/m^3 in the mid-century and 0.80, 0.99, 0.94 and 0.96 kg/m^3 in the late century respectively as shown in Figure 4.30.

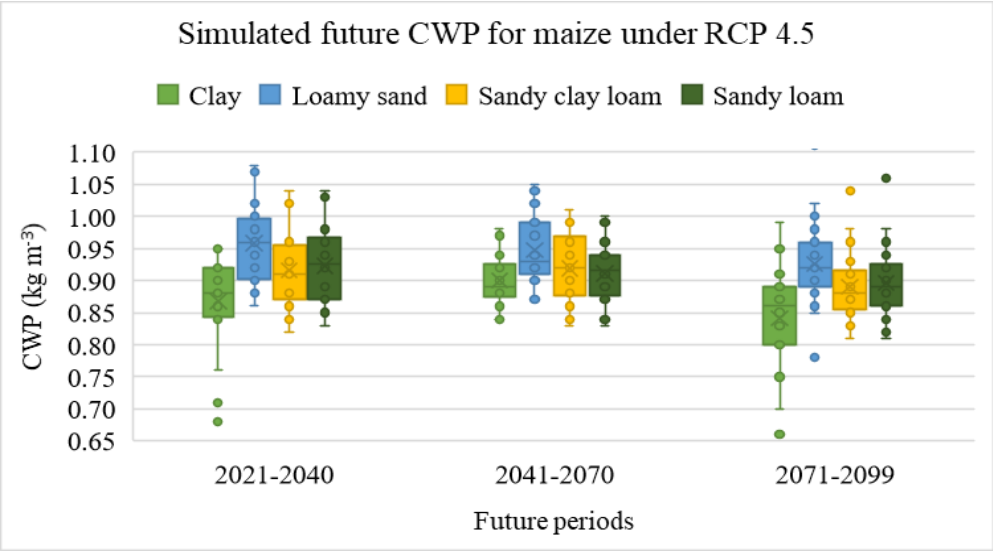

Figure 4.29: Simulated future maize CWP under RCP 4.5

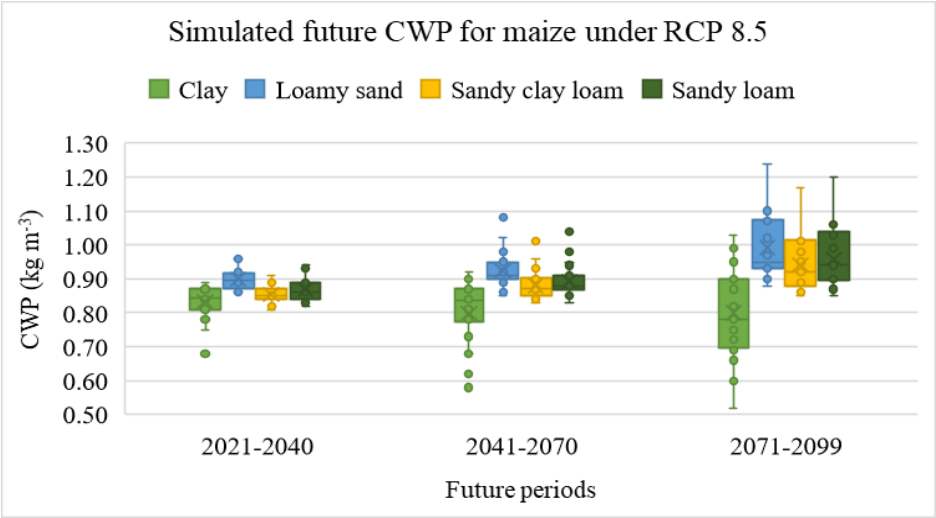

Figure 4.30: Simulated future maize CWP under RCP 8.5

Moreover, the simulations of soybeans CWP under both RCP 4.5 and RCP 8 scenarios show an increasing trend in the future years. Under RCP 4.5, the average CWP of soybeans on clay, loamy sand, sand clay loam and sandy loam soils are projected to be 0.73, 0.99, 0.94 and 0.98 kg/m^3 in the near future; 0.86, 1.06, 1.02 and 1.05 kg/m^3 in the mid-century and 0.81, 1.09, 0.99 and 1.08 kg/m^3 in the late century respectively as shown in Figure 4.31. Meanwhile, under RCP 8.5, the average CWP of soybeans on clay, loamy sand, sandy clay loam and sandy loam soils are projected to be 0.75, 0.94, 0.90 and 0.96 kg/m^3 in the near future; 0.88, 1.13, 1.12 and 1.13 kg/m^3 in the mid-century and 0.89, 1.35, 1.28 and 1.34 kg/m^3 in the late century respectively as shown in Figure 4.32.

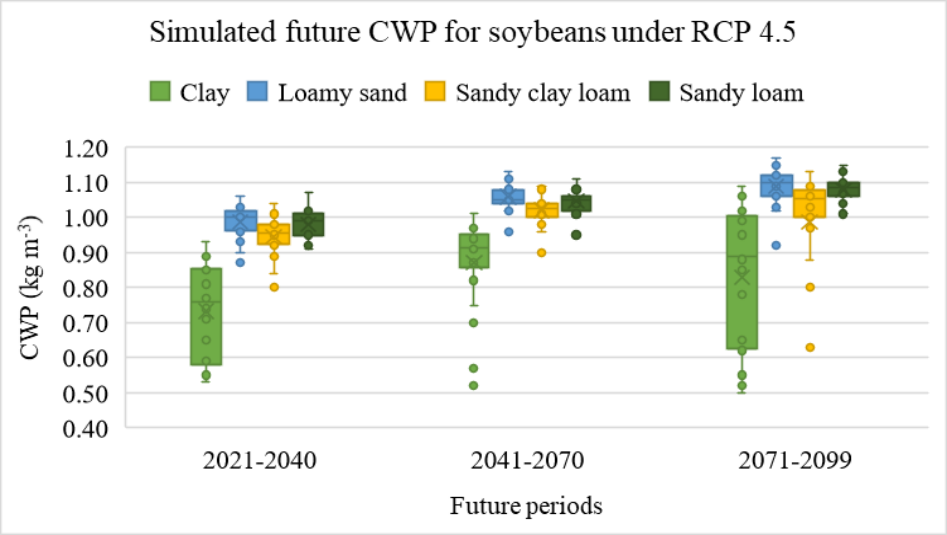

Figure 4.31: Simulated future soybeans CWP under RCP 4.5

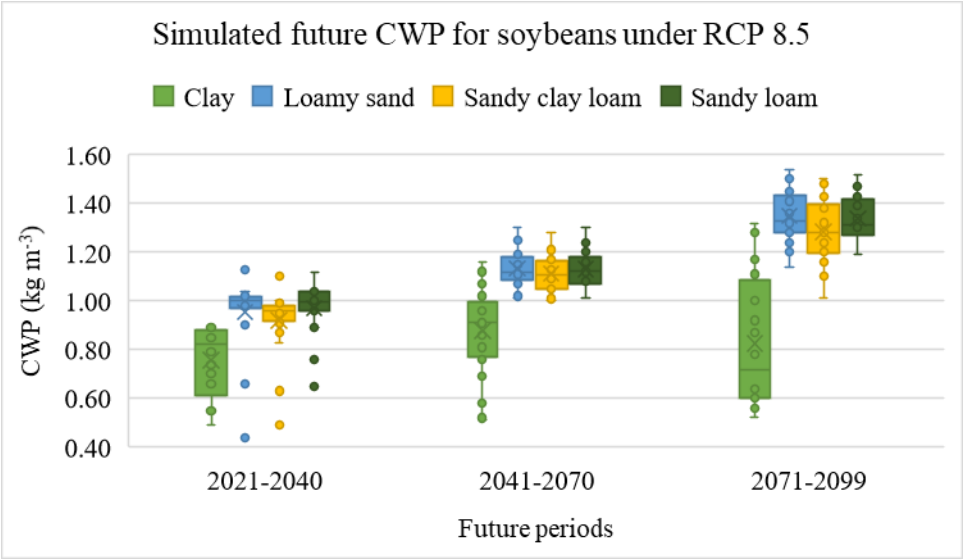

Figure 4.32: Simulated future soybeans CWP under RCP 8.5

4.7 Spatial and temporal changes in future seasonal CWR, IWR, yield and CWP under different climate change scenarios

The period of 1986 – 2015 was used as baseline period to estimate the spatial and temporal changes in CWR, IWR, yield and CWP of maize and soybeans across the basin in three future periods of near future (2021 – 2040), mid-century (2041 – 2070) and late-century (2071 – 2099) under RCP 4.5 and RCP 8.5 scenarios.

4.7.1 Changes in future seasonal CWR

The changes in future CWR of maize in the future periods and under RCP 4.5 and RCP 8.5 scenarios relative to the baseline were estimated. The analyses as shown in Figure 4.33 depict that relative to the baseline period, there will be a range of 4.5 to 22.0% decrease in maize CWR in the future periods for all soil types under both RCP 4.5 and RCP 8.5 scenarios while the highest decline is expected in the late-century under RCP 8.5. According to Wang et al. (2018), CWR could likely decrease due to a reduction in the growing period caused by an increase in temperature. This study shows that the effects of increased temperature are more evident on maize CWR.

However, the future changes in soybeans CWR are projected to fluctuate when compared with the average of the baseline. According to Figure 4.34, under RCP 4.5, small positive changes ranging from 3.0 to 8.73% are projected in the near future, while in the mid and late centuries, only a change of 10% is projected on clay soils and no changes on other types of soil. In addition, under

RCP 8.5, positive changes ranging from 1.0 to 7.73% are projected in the near future, while in the mid-centuries, the change range from -3 to 8% depending on the soil types. However, under RCP 8.5 in the late-century, the worst changes which range from -11.25 to -8.37% are projected.

Meanwhile, the increase in soybeans CWR is not unconnected to the combined effects of CO_2 fertilisation and elevated temperature. It is arguable that for soybeans, CO_2 fertilisation has the tendency of suppressing the negative effects of increased temperature. Compared with wheat's response to climate change in China, it is evident that wheat also has the tendency of suppressing the negative effects of increased temperature through CO_2 fertilisation and could increase CWR 3.1 – 15.8% (Wang et al., 2018). However, the results of this study show that under RCP 8.5 in the late century, soybeans CWR will decrease. This could be attributed to the fact that under this scenario and year period, the negative effects of elevated temperature will likely suppress the positive effects of CO_2 fertilisation.

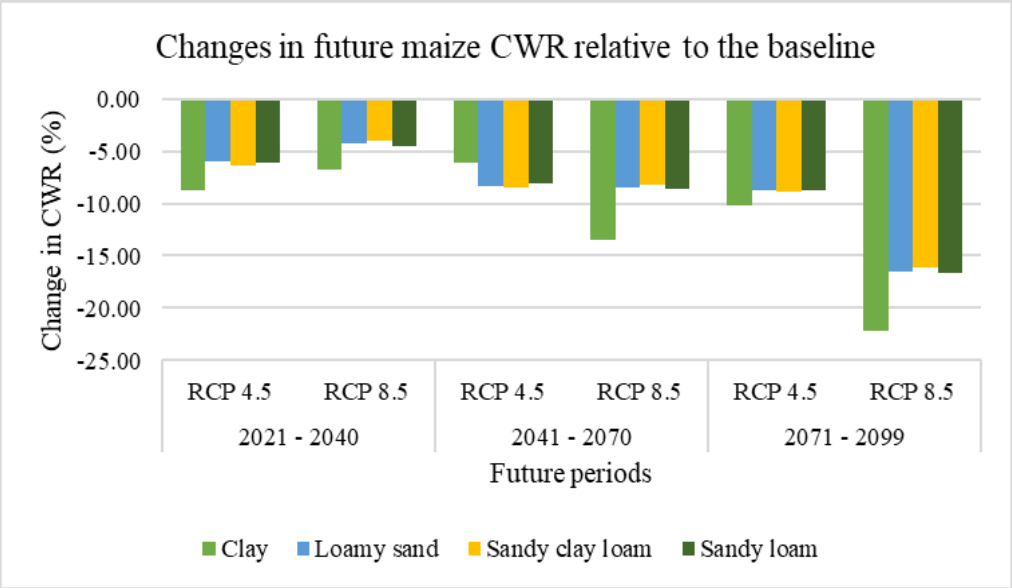

Figure 4.33: Spatial and temporal changes in future maize CWR under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

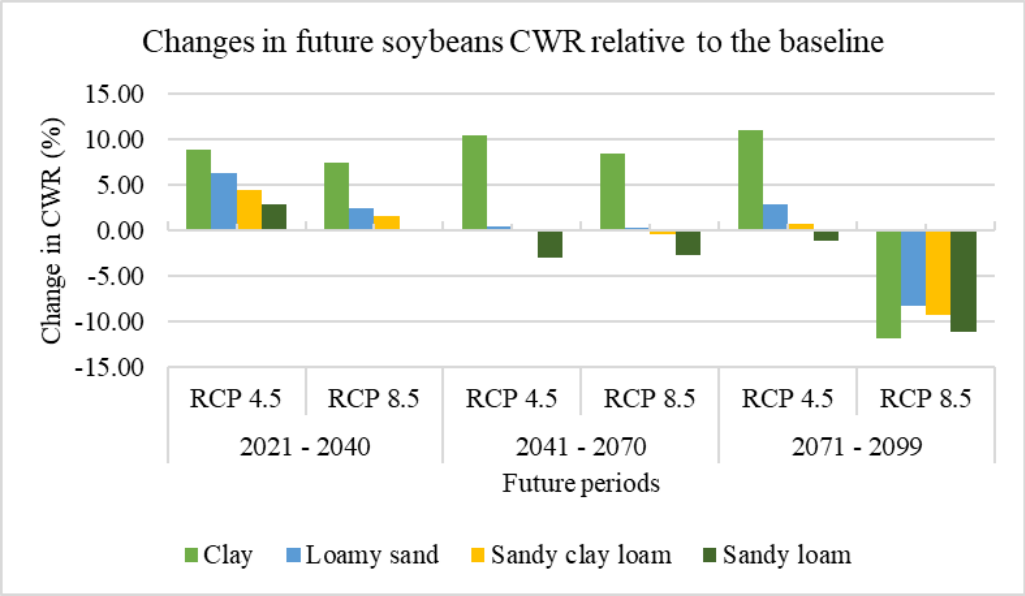

Figure 4.34: Spatial and temporal changes in future soybeans CWR under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

4.7.2 Changes in future seasonal IWR

Meanwhile, for the future IWR, there are huge variations within the future periods, soil types, crops as well as the climate change scenarios. Figure 4.35 shows that under RCP 4.5, the change ranges from 71.58 to 168.5 %, 9.96 to 40.48 % and 67.25 to 152.6 % in 2021 – 2040, 2041 – 2070 and 2071 – 2099 respectively. Under RCP 8.5, there likely going be no or little change in maize IWR compared to RCP 4.5. It is projected that under RCP 8.5, the change ranges from -10.49 to 5.29%, 12.39 to 18.39 % and -6.79 to -4.81% in 2021 – 2040, 2041 – 2070 and 2071 – 2099 respectively.

On the other hand, a decreasing trend in future soybeans IWR when compared with the baseline is projected. Figure 4.36 shows that under RCP 4.5, the changes range from -60.56 to 7.81%, -82.46 to -17.57% and -79.49 to -13.65% in near future, mid-century and late century respectively. Additionally, under RCP 8.5, the change ranges from -41.19 to 21.86%, -71.29 to -12.81% and -67.55 to -20.65% in near future, mid-century and late century respectively.

The maize IWR under RCP 4.5 clearly follows the pattern of rainfall projections for the future periods. However, under RCP 8.5, the effect of reduction in the growing period (Luhunga, 2017) is more evident, thus reducing maize IWR. Meanwhile for soybeans, there is a likelihood of a decline in IWR throughout all future periods and under both scenarios due to reduction in the

growing period as well (Wang et al., 2018). The increase in rainfall within the growing period of soybeans could also be responsible for a decline in IWR as predicted by the RCM. Clearly, rainfall patterns and an increase in temperature are the main factors that are likely to affect IWR (Boonwichai et al., 2018).

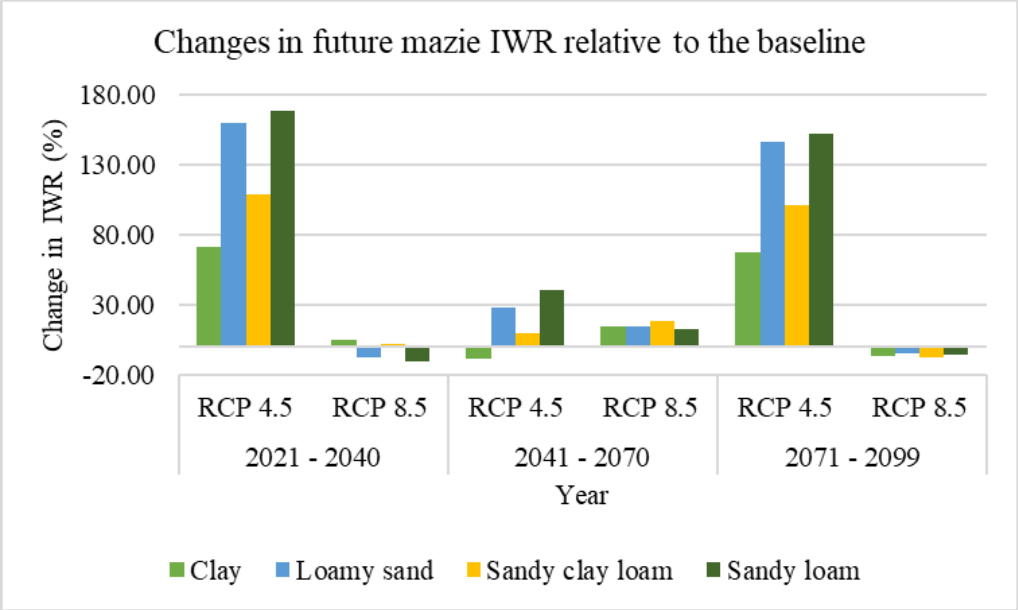

Figure 4.35: Spatial and temporal changes in future maize IWR under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

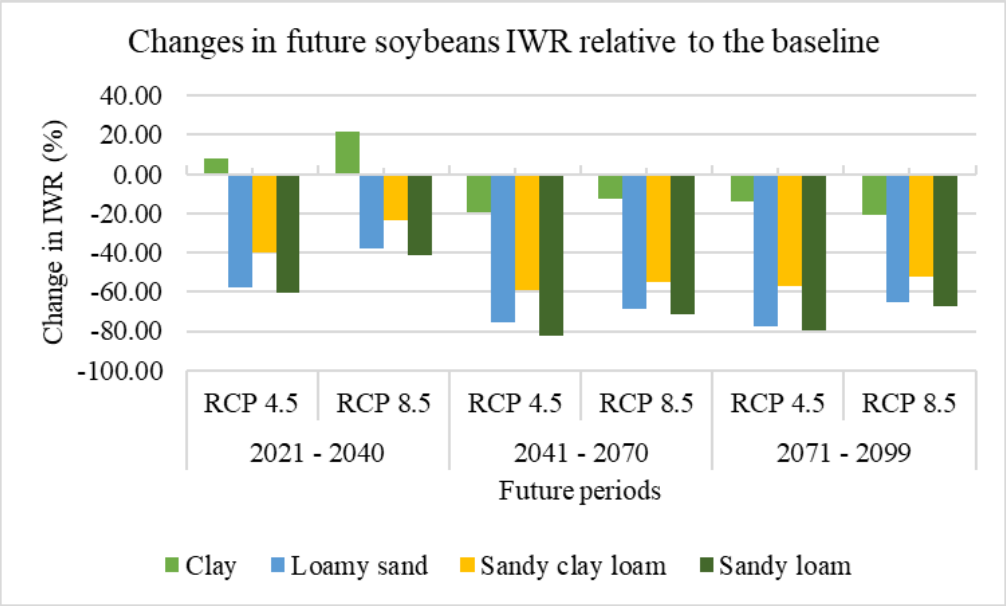

Figure 4.36: Spatial and temporal changes in future soybeans IWR under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

4.7.3 Changes in future crop yields

According to Figure 4.37, maize yields will generally decrease gradually until the late-century under both RCP 4.5 and RCP 8.5 scenarios. The results show that under RCP 4.5, the change range from -4.0 to 11.00%, -7.16 to -8.00%, and -9.0 to 6.0% in the near future, mid-century and late century respectively. Also, under RCP 8.5, there is likelihood that maize yield will decline throughout. The decline will likely range from 7.0 to 8.00%, 9.0 to 3.00%, and 12.0 to 10.0% in the near future, mid-century and late century respectively. Among the soil types, an increase is only projected on clay soils. On all the agricultural lands (loamy and sandy soils), there will be a decrease compared with the baseline.

Meanwhile, according to Figure 4.38, positive changes are projected for soybeans yields in future periods in all scenarios. The results show that under RCP 4.5, the change ranges from 15.19 to 23.70%, 21.04 to 53.83%, and 18.23 to 39.36% in the near future, mid-century and late century respectively. While under RCP 8.5, the change ranges from 10.06 to 36.87 %, 24.94 to 61.40 %, and 18.09 to 39.70 % in the near future, mid-century and late-century respectively.

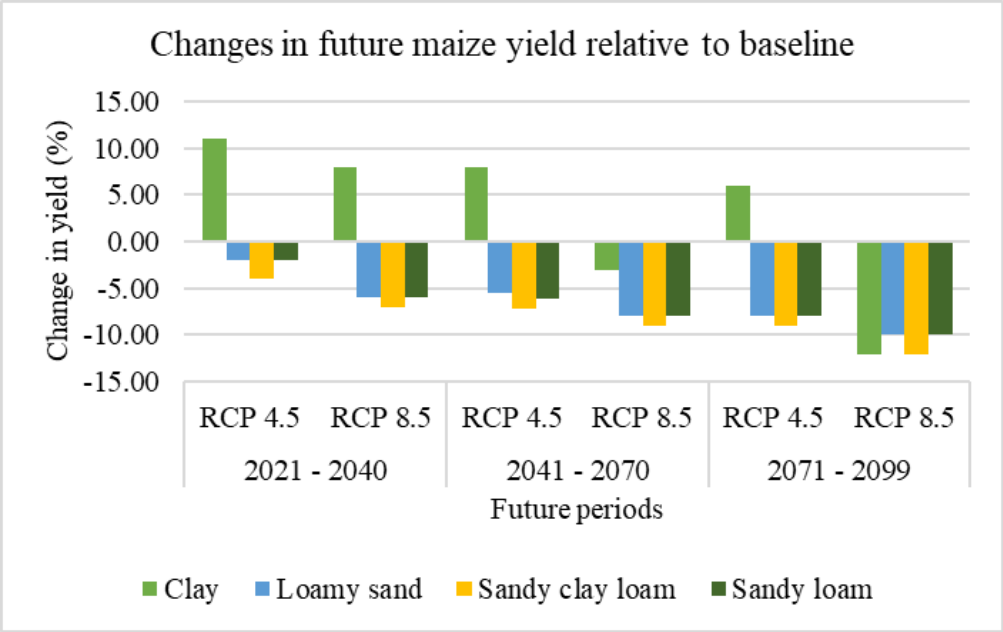

Figure 4.37: Spatial and temporal changes in future maize yields under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

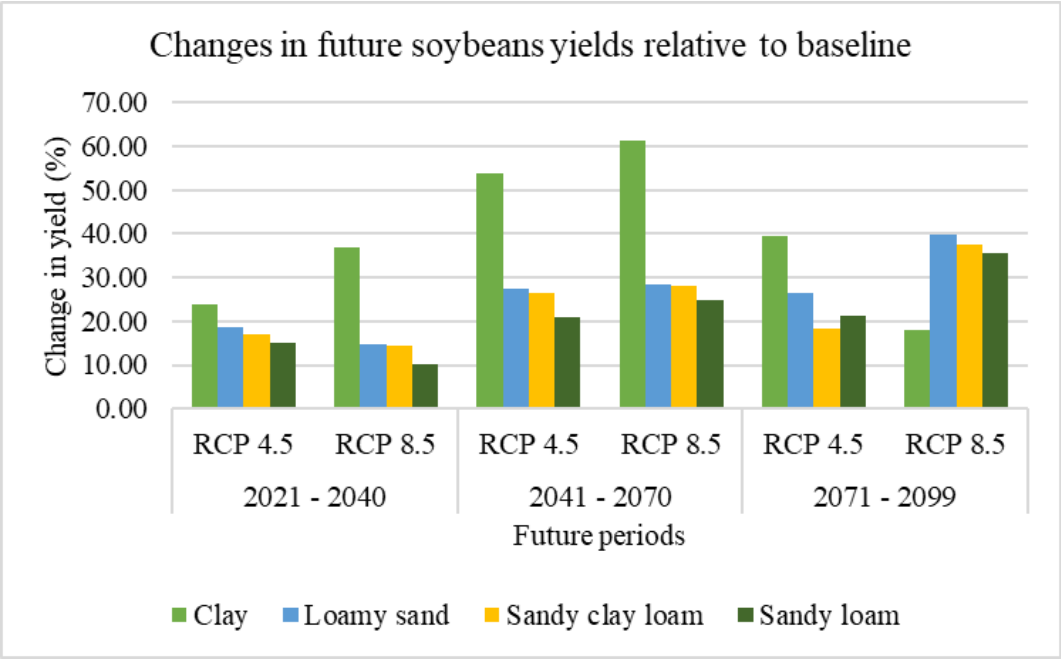

Figure 4.38: Spatial and temporal changes in future soybeans yields under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

The decline in rainfall within the growing period and increase in temperature are the major factors likely responsible for the decline pattern of maize yields in the future periods. Most similar studies in SSA have also projected a decline in maize yields (Luhunga, 2017; Tingem & Rivington, 2009). In contrast, soybeans yields will likely be benefitted by CO_2 fertilization which will have more influence than other factors such as an increase in temperature and rainfall pattern. The rate of changes will depend on the concentration levels of CO_2.

4.7.4 Changes in future CWP

According to Figure 4.39, the results show fluctuating changes in future CWP for maize. The results show that generally, maize CWP will decrease compared to the baseline except in the late century under RCP 8.5 when a small increase is expected. Most of the projected rise in maize CWP are expected on clay soils which are generally not agricultural land within the basin. The results show that under RCP 4.5, the changes in future maize CWP range from -4.04 to 15.52%, -3.71 to 14.94%, and -6.64 to 12.09% in the near future, mid-century and late century respectively. Besides, under RCP 8.5, the changes in future maize CWP are projected to range from -10.44 to 10.93%, -7.76 to 6.36%, and -1.26 to 6.58% in the near future, mid-century and late-century respectively.

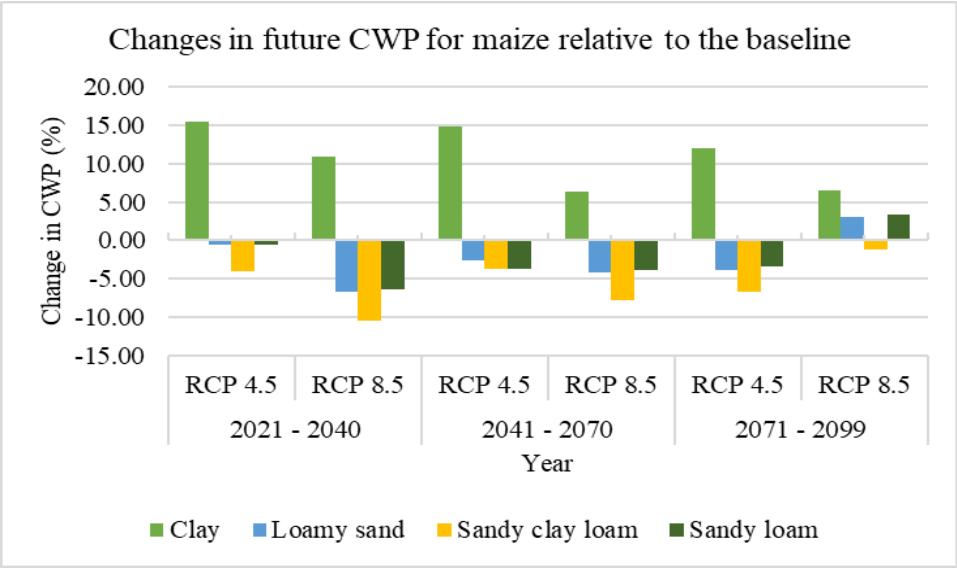

Figure 4.39: Spatial and temporal changes in future maize CWP under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

In contrast to maize, changes in future soybeans CWP will increase gradually across all future years under RCP 4.5 and RCP 8.5. According to Figure 4.40, the results show that under RCP 4.5, the changes in future soybeans CWP range from 8.89 to 22.50%, 11.35 to 17.36%, and 12.79 to 24.23% in the near future, mid-century and late century respectively. Under RCP 8.5, the changes in future soybeans CWP are projected to range from 4.94 to 19.71%, 21.22 to 52.02%, and 41.86 to 45.79% in the near future, mid-century and late century respectively.

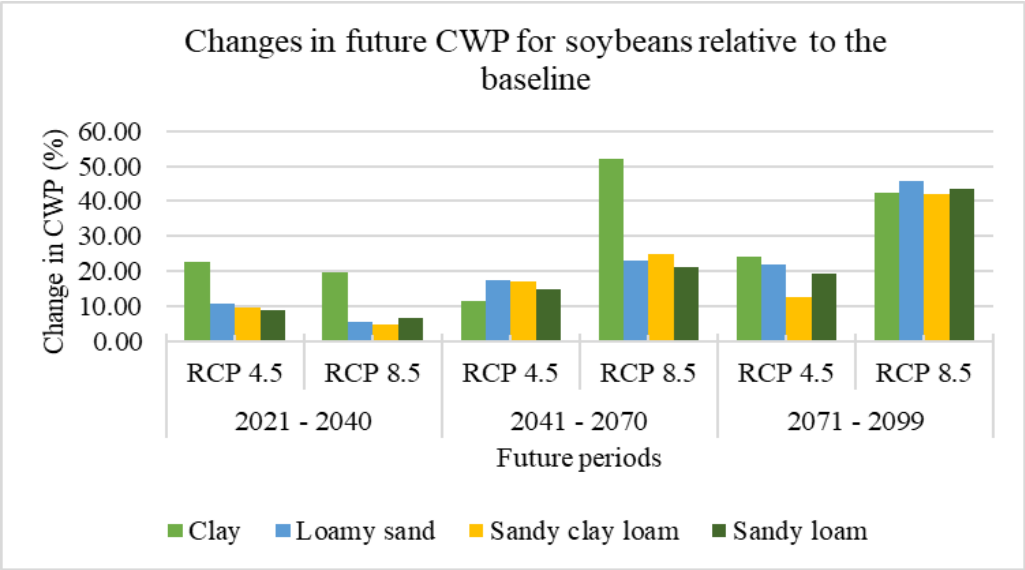

Figure 4.40: Projected temporal changes in future soybeans CWP under RCP 4.5 and RCP 8.5 (2021 – 2099) relative to the baseline (1986 – 2015)

Similarly, Wang et al. (2018) argued that in some crops such as wheat, increased temperature will negate the positive effects of CO_2 fertilisation thus decreasing CWP. This claim is similar to the case of maize in this report where CWP will likely decrease as a result of increased temperature and insignificant positive effects of CO_2 fertilisation. The likely increase in soybeans CWP is not unconnected to that the fact that CO_2 fertilisation has more influence than other factors on soybeans CWP. Due to the increase in CO_2 concentration which triggers early fertilization of soybeans, soybeans yield will likely increase thus increasing CWP (Steduto et al., 2012).

4.8 Future changes in planting dates and growing days

Optimum planting dates contribute immensely to crop yield and productivity. This study shows that climate change will significantly affect the planting dates of maize under RCP 4.5 while no significant changes are expected under RCP 8.5 as shown in Table 4.7. Meanwhile for soybeans, under both scenarios, no substantial changes in planting dates are projected as shown in Table 4.8. Moreover, climate change will significantly reduce the growing period of maize and soybeans. From the simulations, the range of the growing period of maize is projected to be 64 to 70 days while that of soybeans range from 96 to 112 days. When compared with the baseline, the reduction in maize growing period will vary from 8 to 10 days while for soybeans, it will vary from 4 to 12 days.

4.9 Effects of supplemental irrigation on yields and CWP under different climate scenarios

The effects of supplemental irrigation on crop yields and CWP under different climate change scenarios were studied rainfed agriculture for the future periods. The results of the study depict that supplemental irrigation will go a long way in adapting to climate change as well as improving crop yields and CWP within the basin. Based on Table 4.9, on an average, under RCP 4.5, supplemental irrigation is projected to increase rainfed maize yield by 4.06 – 9.33%, 2.07 – 6.15%, and 4.59 – 11.11% in the near future, mid-century and late century respectively. Under RCP 8.5, the average yield of maize can be increased by 5.03 to 12.70% and 3.59 to 17.35% in the near future and mid-century respectively but supplemental irrigation alone will not improve maize yield under RCP 8.5 in the late century within the basin. In addition, according to Table 4.10, on an average, supplemental irrigation is projected to increase rainfed soybeans yield by 3.11 to 50.0%

and 3.43 to 27.64% under RCP 4.5 and RCP 8.5 respectively depending on the soil type and future period.

Table 4.7: Simulated future planting dates for maize

Maize Planting dates (Day in April)								
Year	RCP 4.5	RCP 8.5	Year	RCP 4.5	RCP 8.5	Year	RCP 4.5	RCP 8.5
2021	3	5	2041	15	4	2071	15	5
2022	4	3	2042	15	4	2072	15	4
2023	4	4	2043	15	3	2073	15	5
2024	4	3	2044	4	3	2074	15	15
2025	4	3	2045	15	4	2075	15	5
2026	15	5	2046	4	15	2076	15	4
2027	4	3	2047	15	15	2077	15	3
2028	15	4	2048	15	12	2078	5	5
2029	15	3	2049	15	5	2079	15	4
2030	15	3	2050	15	15	2080	13	4
2031	15	3	2051	2	3	2081	15	4
2032	15	4	2052	15	4	2082	13	15
2033	5	3	2053	15	3	2083	15	14
2034	15	4	2054	15	14	2084	15	5
2035	15	4	2055	15	4	2085	15	4
2036	15	5	2056	15	4	2086	15	4
2037	15	4	2057	15	3	2087	15	5
2038	15	4	2058	15	4	2088	15	4
2039	15	4	2059	15	3	2089	15	4
2040	15	5	2060	5	3	2090	15	3
			2061	15	5	2091	5	4
			2062	15	15	2092	4	5
			2063	15	3	2093	5	5
			2064	15	5	2094	5	15
			2065	15	4	2095	3	3
			2066	15	5	2096	15	3
			2067	15	14	2097	15	4
			2068	15	4	2098	15	5
			2069	15	4	2099	15	4
			2070	15	4			

Table 4.8: Simulated future planting dates for soybeans

Soybeans Planting dates (Day in June)								
Year	RCP 4.5	RCP 8.5	Year	RCP 4.5	RCP 8.5	Year	RCP 4.5	RCP 8.5
2021	3	3	2041	3	4	2071	3	3
2022	3	3	2042	3	3	2072	3	4
2023	3	3	2043	4	3	2073	3	3
2024	4	3	2044	3	3	2074	3	4
2025	3	3	2045	3	4	2075	4	4
2026	3	3	2046	3	4	2076	3	3
2027	3	3	2047	3	3	2077	3	3
2028	3	3	2048	4	3	2078	4	3
2029	3	3	2049	3	4	2079	3	3
2030	3	3	2050	4	3	2080	4	3
2031	3	3	2051	4	2	2081	3	3
2032	4	3	2052	4	3	2082	4	3
2033	3	3	2053	3	3	2083	3	3
2034	3	4	2054	4	3	2084	4	4
2035	3	3	2055	4	4	2085	4	3
2036	3	3	2056	3	3	2086	3	3
2037	3	3	2057	3	3	2087	4	3
2038	3	3	2058	3	3	2088	3	3
2039	3	3	2059	3	3	2089	3	4
2040	3	3	2060	5	3	2090	3	4
			2061	3	3	2091	3	4
			2062	3	3	2092	3	4
			2063	3	3	2093	4	3
			2064	3	3	2094	3	3
			2065	3	3	2095	3	4
			2066	3	4	2096	3	3
			2067	3	3	2097	3	3
			2068	4	3	2098	3	3
			2069	3	3	2099	3	4
			2070	3	3			

Table 4.9: Effects of supplemental irrigation on maize yields under RCP 4.5 and RCP 8.5

Climate change scenario	Future periods	Soil type	Rainfed yield (t/ha)	Supplemental irrigation yield (t/ha)	Change (%)
RCP 4.5	2021 - 2040	Clay	1.79	1.96	9.33
		Loamy sand	2.08	2.17	4.46
		Sandy clay loam	2.09	2.17	4.06
		Sandy loam	2.07	2.17	4.76
	2041 - 2070	Clay	1.93	1.95	2.07
		Loamy sand	2.00	2.11	5.64
		Sandy clay loam	2.01	2.11	5.16
		Sandy loam	1.99	2.11	6.15
	2071 - 2099	Clay	1.71	1.90	11.11
		Loamy sand	1.94	2.05	5.67
		Sandy clay loam	1.97	2.07	5.08
		Sandy loam	1.96	2.05	4.59
RCP 8.5	2021 - 2040	Clay	1.76	1.98	12.70
		Loamy sand	1.99	2.10	5.60
		Sandy clay loam	2.00	2.10	5.03
		Sandy loam	1.99	2.10	5.79
	2041 - 2070	Clay	1.58	1.85	17.35
		Loamy sand	1.95	2.02	3.59
		Sandy clay loam	1.96	2.04	4.08
		Sandy loam	1.95	2.03	4.10
	2071 - 2099	Clay	1.42	1.55	8.85
		Loamy sand	1.90	1.89	-0.26
		Sandy clay loam	1.91	1.89	-0.91
		Sandy loam	1.90	1.89	-0.38

Table 4.10: Effects of supplemental irrigation on soybeans yields under RCP 4.5 and RCP 8.5

Climate change scenario	Future periods	Soil type	Rainfed yield (t/ha)	Supplemental irrigation yield (t/ha)	Change (%)
RCP 4.5	2021 - 2040	Clay	2.00	3.00	50.00
		Loamy sand	3.33	3.47	4.07
		Sandy clay loam	3.26	3.47	6.55
		Sandy loam	3.41	3.55	4.02
	2041 - 2070	Clay	2.75	3.20	16.36
		Loamy sand	3.58	3.69	3.11
		Sandy clay loam	3.52	3.70	5.02
		Sandy loam	3.55	3.68	3.54
	2071 - 2099	Clay	2.52	2.90	15.08
		Loamy sand	3.55	3.55	0.00
		Sandy clay loam	3.29	3.33	1.22
		Sandy loam	3.60	3.62	0.55
RCP 8.5	2021 - 2040	Clay	2.60	3.03	16.54
		Loamy sand	3.22	3.48	8.00
		Sandy clay loam	3.19	3.48	9.20
		Sandy loam	3.26	3.51	7.65
	2041 - 2070	Clay	2.88	3.63	26.04
		Loamy sand	3.60	3.75	4.14
		Sandy clay loam	3.57	3.75	5.12
		Sandy loam	3.70	3.89	5.09
	2071 - 2099	Clay	2.75	3.40	23.64
		Loamy sand	3.92	4.02	2.54
		Sandy clay loam	3.83	3.92	2.35
		Sandy loam	4.01	4.00	0.25

Similarly, the effect of supplemental irrigation was simulated on CWP of soybeans and maize. Table 4.11 shows that supplemental irrigation will improve maize CWP under both scenarios in all future periods except during the late century when CWP will decrease. Supplemental irrigation is projected to improve maize CWP by 3.26 to 8.77% and 6.43 to 10.12% under RCP 4.5 and RCP 8.5 respectively depending on the soil type and future period. However, in the late century, supplemental irrigation will cause a decline in CWP that is expected to range from 0.73 to 3.99%. For soybeans, supplemental irrigation is projected to improve CWP by 1.02 to 29.79% and 0.44 to 28.27% under RCP 4.5 and RCP 8.5 respectively depending on the soil type and future period as shown in Table 4.12.

Table 4.11: Effects of supplemental irrigation on maize CWP under RCP 4.5 and RCP 8.5

Climate change scenario	Future periods	Soil type	Rainfed CWP (kg/m^3)	Supplemental irrigation CWP (kg/m^3)	Change (%)
RCP 4.5	2021 - 2040	Clay	0.87	0.90	3.75
		Loamy sand	0.96	1.01	5.37
		Sandy clay loam	0.92	0.99	8.14
		Sandy loam	0.92	0.99	7.32
	2041 - 2070	Clay	0.90	0.93	3.26
		Loamy sand	0.95	1.01	6.62
		Sandy clay loam	0.92	1.00	8.77
		Sandy loam	0.91	0.99	8.63
	2071 - 2099	Clay	0.84	0.82	-3.15
		Loamy sand	0.93	0.91	-1.97
		Sandy clay loam	0.89	0.86	-3.99
		Sandy loam	0.90	0.88	-2.15
RCP 8.5	2021 - 2040	Clay	0.83	0.89	6.84
		Loamy sand	0.90	0.99	10.12
		Sandy clay loam	0.85	0.92	7.67
		Sandy loam	0.87	0.95	9.51
	2041 - 2070	Clay	0.80	0.85	6.43
		Loamy sand	0.92	0.99	7.18
		Sandy clay loam	0.88	0.95	7.95
		Sandy loam	0.89	0.96	7.62
	2071 - 2099	Clay	0.80	0.88	10.04
		Loamy sand	0.99	0.99	-0.73
		Sandy clay loam	0.94	0.92	-1.83
		Sandy loam	0.96	0.95	-0.83

Table 4.12: Effects of supplemental irrigation on soybeans CWP under RCP 4.5 and RCP 8.5

Climate change scenario	Future periods	Soil type	Rainfed CWP (kg/m^3)	Supplemental irrigation CWP (kg/m^3)	Change (%)
RCP 4.5	2021 - 2040	Clay	0.73	0.95	29.79
		Loamy sand	0.99	1.03	4.41
		Sandy clay loam	0.94	1.02	7.99
		Sandy loam	0.98	1.02	4.08
	2041 - 2070	Clay	0.86	0.99	15.12
		Loamy sand	1.06	1.11	4.93
		Sandy clay loam	1.02	1.09	7.03
		Sandy loam	1.05	1.09	4.28
	2071 - 2099	Clay	0.81	1.03	27.73
		Loamy sand	1.09	1.10	1.02
		Sandy clay loam	0.99	1.06	7.82
		Sandy loam	1.08	1.10	1.85
RCP 8.5	2021 - 2040	Clay	0.75	0.96	28.27
		Loamy sand	0.94	1.02	8.36
		Sandy clay loam	0.90	0.99	9.42
		Sandy loam	0.96	1.00	4.26
	2041 - 2070	Clay	0.88	1.08	23.18
		Loamy sand	1.13	1.19	4.99
		Sandy clay loam	1.12	1.18	5.83
		Sandy loam	1.13	1.19	5.16
	2071 - 2099	Clay	0.89	1.28	43.55
		Loamy sand	1.35	1.37	1.48
		Sandy clay loam	1.28	1.33	3.28
		Sandy loam	1.34	1.35	0.44

4.10 Discussions

The range of maize CWR simulated within this basin located in a humid area is smaller when compared with the CWR of rainfed maize in India, a semi-arid area, which ranges from 265 to 465 mm (Shah, 2018). Also, the results are in conformity with the assertion that even for the same crop, CWR is usually smaller in humid areas compared to arid and semi-arid areas (Mourad & Berndtsson, 2012). Additionally, the CWR of soybean is different from maize's and also dependent on soil types. The CWR of soybeans follows this order in decreasing arrangement: sandy loam, sandy clay loam, loamy sand and clay soils which is different from the maize arrangement where loamy sand soils require highest water. Also, the results ascertain that soybeans require more water than maize (Memon & Jamsa, 2018; Tingem & Rivington, 2009).

Based on the simulated maize IWR, in some years little supplemental irrigation was required, while many other growing periods were highly different. This means that during drought years, the crop required more water despite being rainfed. The results show that for rainfed agriculture, the irrigation requirements vary and heavily dependent on rainfall amounts (Ewaid et al., 2019). Meanwhile, the IWR of soybeans is higher than that of maize within the study area. This is could be attributed to the short dry period called "August break" when there is a decline in rainfall which usually fall within the growing cycle of soybeans (Adeboye et al., 2019). The results show that the longer the August break, the higher the IWR for soybeans. It confirms that unlike maize production, supplemental irrigation need is higher for soybeans productions irrespective of the soil types (Gbegbelegbe et al., 2019; Memon & Jamsa, 2018).

In addition, simulations show that the farms within the basin with sandy loams, sandy clay loams and loamy sand soils have much higher maize yields than clay soil. This is in accordance with the assertion that maize performs best on loamy and sandy soils (Greaves & Wang, 2016; Iken & Amusa, 2004; Olomola & Nwafor, 2018). The low yield of maize is one of the major setbacks of maize production in Africa (Adeboye et al., 2019; Dugje et al., 2009) when compared with other countries such as China, France and the United States of America where an average yield of 10 to 11 t/ha is usually obtained (Li et al., 2016; Steduto et al., 2012). Similarly, such low maize yields of about 2 t/ha obtained in this research is common in other African countries such as Tanzania, Cameroon, Guinea and Ivory Coast (Luhunga, 2017; Roudier et al., 2011; Tingem & Rivington, 2009) which shows that Africa needs to improve maize production and management to achieve higher yields. Similar to maize yields, simulated soybeans yields are also far lower than the achievable yield. The soybeans yield obtained in the basin is far lower compared with the average yields in Italy and the United States which could go up to 3.5 and 5.0 t/ha respectively (Liben et al., 2018; Steduto et al., 2012). Although, the soybeans yield obtained within the basin is still better than China and India with average yields of 1.6 and 1.0 to/ha respectively (Steduto et al., 2012).

Meanwhile, the low CWP observed is not unconnected with the low yields observed. Also, the simulated CWP is extremely low in comparison with maize CWP in China where CWP is usually above 2.0 kg/m^3 (Li et al., 2016). The simulated low CWP depicts that the crop is failing to maximise the water supplied and not converting it to enough crop yields. In addition, it shows that there is a need to encourage climate-smart practices that will help to improve CWP (Adeboye et

al., 2019). Similar to simulated maize CWP, the soybeans CWP are also very much lower than the achievable CWP which could range from 1.2 to 1.6 kg/m^3 in countries with higher soybeans yields such as the United States and Canada (Steduto et al., 2012). However, lower CWP of about 0.30 to 0.50 kg/m^3 is common on rice farms (Boonwichai et al., 2018). This further depicts that rice is a crop with higher CWR but lower yields in terms of quantity thus cannot be compared with soybeans and maize. The main goal of crop productions is to maximise CWP which is to produce large crop yield at minimum crop water. Thus, the results show that it is important to consider the impacts of climate change on CWP and estimate the likely changes in future CWP in order to recommend climate smart practices that will improve the yield and maximise CWP.

Meanwhile, the decreasing trend in maize CWR is attributable to climate change as a result of increased temperature which subsequently reduces growing days similar to simulated rice in Bangladesh and China (Ding et al., 2017; Rahman et al., 2019). The fact that the decreasing trend occurred all over the basin, that is, across all soil types shows that increase in temperature and variability in rainfall is causing a decreasing trend in maize CWR. The increase in soybean CWR could be attributed to the increase in dry days with the "August break" of the basin which falls within the growing cycle of soybeans. The variability in dry days and wet days even during rainy season within the basin is one of the uncertainties that need to be investigated further. The differences in the temporal trends of soybeans CWR and maize CWR further consolidates the fact that climate change impact is both temporal and spatial as well as dependent on crops in terms of food security (Boonwichai et al., 2018; FAO, 2017b). Consequently, these uncertainties need to be unravelled as this will go a long way in provoking breeding of climate-resilient varieties, sustainable policy formulation and implementations.

Furthermore, the decreasing trend in maize IWR could be attributed to declining in growing days of maize as well as an increase in rainfall frequencies and intensities within the growing period (Ewaid et al., 2019). This highlights the fact that rainfall variability and patterns have huge impacts on maize growth and productivity. The fluctuations in IWR of maize and soybeans follow the same pattern as the variability of rainfall in the future periods as projected by the RCM. According to the projections of RCM, there is a likelihood of rainfall shortage within the basin in the near period and then an increase in the mid-century and finally a shortage in the late century when compared to the baseline. The results show that there is likelihood of delay in the onset of rainfall compared

to the baseline coupled with higher transpiration and this means that maize production will require more irrigation water compared to the baseline for optimum production.

For RCP 8.5, the little or no changes can be attributed to early stomatal closure as a result of the high concentration of CO_2 and elevated temperature. The results of this study show that maize IWR will likely depend on rainfall and temperature projections while higher concentration CO_2 will shorten growing periods and indirectly influence maize IWR within the basin. Similar increases in IWR has been simulated for rice (Ding et al., 2017) and will range from 65 to 176% while the peak will be in the late century under RCP 8.5 (Boonwichai et al., 2018). This reflects that crop IWR is largely dependent on climate projections thus, sustainable planning and implementation are required to achieve food security.

Meanwhile, this research reveals that soybeans IWR is increasing and it shows that there have been more dry days during the growing periods. Considering the temporal variability of soybeans IWR, there are significant changes that are gradually being experienced due to climate change. Therefore, there is a likelihood that more uncertainties exist in the future periods. However, the future scenarios show that generally, soybeans IWR will decrease compared to the baseline. This phenomenon could be attributed to two factors. First, there is a probability of higher rainfall frequency and intensity in the basin within the growing period (June – September) portraying that rainfall will compensate for the effects of the increase in temperature. Second, the higher CO_2 concentration will trigger carbon fertilization and eventually shorten the growing period (Gbegbelegbe et al., 2019).

In terms of crop yields, the results further consolidate that loamy and sandy soils are the best soils for optimum maize and soybeans yields (Dugje et al., 2009; Iken & Amusa, 2004) and they are the main agricultural areas where crops are cultivated within the basin. Within the baseline period, climate change did not have any significant impact on maize yields in the basin. Meanwhile, a 60% increase above the 2006 global food demand levels is expected in 2050 (FAO, 2016) which shows that there is an urgent need to improve maize yields to reach optimum yields in order to satisfy the current and future food demand within the basin. In contrast, the increasing trend in soybeans yield confirms that soybeans (C3 crop) have the tendency of producing higher yields when subjected to increased temperature (Roudier et al., 2011; Steduto et al., 2012). The

significant increase trend can, however, be attributed to elevated temperature and the slight increase in CO_2 concentration.

For CWP, the results stress the fact that maize and soybeans cultivated on sandy and loamy soils are more productive and have higher water productivities (Steduto et al., 2012) than those cultivated on clay soils which does not follow any particular pattern. Moreover, despite the increasing trend of soybeans yields on clay, the CWP is decreasing. This shows the urgent need to improve crop yields and at the same time improve CWP for optimum growth and production (Adeboye et al., 2017). Therefore, the impact of climate change on CWP of both crops within the basin is significant based on the baseline period.

In terms of planting dates, the simulated planting dates are similar to the usual planting dates of the crops within the basin (Dugje et al., 2009; Iken & Amusa, 2004). This further consolidates the fact that planting date is a huge factor that contributes to crop productivity. Delay in the onset of rainfall could be challenging for farmers, thus delay or early planting dates could lead to low yields and productivity. Climate change has been projected to alter growing periods (Ding et al., 2017) which will likely give rise to quicker maturity of crops and could lead to bad quality of crops. It is worthy to note that the simulations show a gradual reduction in growing days occasioned by increased temperature and huge variability in growing days as a result of climate variability.

For the future periods, it also worthy to note that under both climate change scenarios, huge variability in CWR is projected to occur in the period of 2071 – 2099. This means that elevated temperature and increased CO_2 concentration will affect CWR significantly and will result in a decrease in maize CWR. There is a likelihood of huge spatial variability of maize CWR within the basin. Sandy clay loams will require more water than any other soil type within the basin. Similarly, reduction in maize CWR under elevated temperature and increased CO_2 concentration, when simulated with AquaCrop model, will likely occur in China (Li et al., 2016). Even though the increase in temperature is expected to increase evapotranspiration (Boonwichai et al., 2018), but due to the reduction in the growing period, the seasonal maize CWR will likely decrease compared to the baseline. The shortened growing period is occasioned by early stomatal closure as a result of triggered fertilization through high CO_2 concentration and elevated temperature (Luhunga, 2017), In the late century under the combined effects of highest CO_2 concentration and highest temperature (RCP 8.5), the reduction in maize CWR is projected to be the extreme.

Similarly, there are several uncertainties in the responses of other crops to climate change. According to Chattaraj et al. (2014), reduction in CWR of wheat will likely occur in the future period and this could be attributed to the shortened growing period as well. Comparing with rice, an increase in CWR is expected in the future years and will range from 16 to 20 % while the peak will be in the late century under RCP 8.5 (Boonwichai et al., 2018). In contrast, the CWR of rice has been predicted to increase (Ding et al., 2017). These contradictions further stress the fact that the effects of climate change will be spatially and temporally distributed as well as crop dependent. Either the effect of climate change is positive or not, late century under RCP 8.5 is projected to have an extreme impact.

Furthermore, results of this study show that the CWR of soybeans on clay soils will likely vary spatially under elevated temperature especially when compared with other soil types. In addition, sandy clay loam soils are projected to have the highest CWR while soybeans planted on clay soils will have the lowest CWR in all the future periods under both climate change scenarios. According to Gbegbelegbe et al. (2019), soybeans are highly sensitive to climatic changes and the results of this study also suggest that. It is evident that the future changes in CWR will largely depend on the crop and the projected climate.

It is important to note that this study shows that the changes in future CWR under RCP 8.5 are somewhat different from the changes under RCP 4.5 due to increased CO_2 concentration under RCP 8.5 compared with RCP 4.5. Even though CO_2 fertilization which triggers early stomatal closure is more significant for soybeans (C3 crop) than maize and millet (C4 crops) (Roudier et al., 2011; Steduto et al., 2012), it will not really affect soybean CWR within the basin except in the late century under RCP 8.5. In addition, the results of this study prove that the late century (2071 – 2099) under RCP 8.5 will be the worst-case scenario of climate change as it will greatly affect CWR for maize and soybeans.

The results of future scenarios show that the IWR of maize under RCP 4.5 will follow the same trend of rainfall within the basin. However, under RCP 8.5, due to elevated temperature, shortage of rainfall will not cause an increase in maize IWR due to early maturity occasioned by a reduction in the growing period. While maize might require little irrigation water in the mid and late centuries, the quality of maize grains are likely to reduce because with increased CO_2, the protein content of maize grains will reduce and it will increase the weakness of grains to pests and diseases

under this condition (Roudier et al., 2011). However, it is worthy to note that the simulations show that there will be many growing periods that will require supplemental irrigation for optimum production especially, when compared with the baseline. This study further shows that future IWR will vary temporally and spatially.

In terms of future yield, several studies have shown that maize yield is highly sensitive to climate change and will be spatially and temporally distributed. In this study, a gradual decline in maize yield is projected. Similarly, most studies conducted in SSA have shown that there is a likelihood that maize yield will decline in the future periods under climate change. However, the range of changes depends on the location and methods employed. In Tanzania, a decline in maize yield will range from 3.1 to 5.3 % under RCP 4.5 and RCP 8.5 while the peak decline will likely be up to 9.6 % in the late century under RCP 8.5 (Luhunga, 2017). The gap identified in that study which this study filled is that, even though an ensemble of climate models was used, increased CO_2 concentration was not considered.

Likewise, a declining trend in future maize yield is likely expected in southern Africa as projected by a process based model (ASPIM) coupled with 17 GCMs (Corbeels et al., 2018). In addition, Corbeels et al. (2018) argued that there are variations in maize yields based on the global climate model that was used despite a general decline trend. Maize yields will likely decline gradually until the late century in the United States of America, as projected by SALUS (System Approach to Land Use Sustainability), a process-based crop model coupled with an ensemble of GCMs (Basso et al., 2015). The different rate of decline can be attributed to climate projections and different assumptions employed in those studies.

Similarly, maize yield could decline up to 10% by 2050 without any adaptation measure in the derived savannah region of Nigeria (Mereu et al., 2015). Also, in Cameroon, reduction up to 14.6% in maize yield is expected in the future periods without any adaption measures as simulated under GCMs based on some global climate models (Tingem & Rivington, 2009). According to Roudier et al. (2011), future yields of maize in West Africa region will decline up to 5% based on simulations under climate change projections that considered CO_2 induced increase. This further confirms that maize yields in SSA will decline under increased CO_2 concentration and elevated temperature under both RCP 4.5 and RCP 8.5 scenarios across all future periods.

However, some studies have reported an increase in maize yields under elevated temperature and increased CO_2 concentration. Maize yield will likely increase up to 5.77% in China as simulated under different climate change scenarios and increased CO_2 concentration without using any GCM (Li et al., 2016). The contradictions in the findings of Li et al. (2016) and this study could be attributed to the influence of GCM projections employed in this study just as suggested by Corbeels et al. (2018) that GCM projections are highly influential on the effects of climate change on maize yields. Hence, from the foregoing, there is evidence that GCMs projections will largely influence the projections of maize yield while higher CO_2 concentration has slight effects. In addition, it is obvious that a decline in maize yields is likely expected in Ogun-Osun River Basin as well as in SSA at large. Currently, African countries are suffering from low maize yields and lower yields in the future are likely to be tantamount to food insecurity. Consequently, to limit the decline in maize yields, sustainable adaptation measures will be inevitable.

The projected increase in soybeans yields is attributed to carbon fertilization of C3 plants such as soybean, which reveals that there will be a rapid increase in crop yield especially when soybean yields were simulated on extremely high atmospheric CO_2 concentration (Roudier et al., 2011). Soybeans are highly sensitive to changes in climate and soil properties (Dugje et al., 2009) and have been reported to be highly sensitive to climate change (Gbegbelegbe et al., 2019). Similarly, increase in soybeans yields will likely range from 5.5 to 162% and 5 to 18% in Cameroon and West Africa respectively (Roudier et al., 2011; Tingem & Rivington, 2009). In contrast, soybeans yield will likely decline in SSA (Gbegbelegbe et al., 2019). Moreover, the decline could be attributed to the GCM and crop models employed.

The contradictory results in projected soybeans yields further stress the fact that climate change impacts on soybeans yields are temporal and spatially distributed as well as crop and GCM dependent. Therefore, from this study, it shows that climate change will significantly affect soybeans yields which will likely be positive impacts within the basin. It confirms that while some crops will benefit from climate change, other crops will be affected negatively (Boonwichai et al., 2018). It is worthy to note that the increase in soybeans yields is linearly proportional to the increase in CO_2 concentration. The results also show that fluctuations in rainfall and elevated temperature will likely have a slight influence on future soybeans yields within the basin. However, it is still unclear if all C3 crops will be positively affected by climate change especially

CO_2 fertilization and if the effects will be location specific or not. Furthermore, the quality of soybeans has not to be evaluated under elevated temperatures and increased CO_2 concentration. Even though there is a likelihood of an increase in soybeans yields, it is important to research on the quality of soybeans under these conditions. Achieving food security is not just about increased yields but improving the quality of yields as well.

Considering CWP, the low maize CWP under RCP 4.5 shows that higher crop consumptive water use will not certainly lead to higher maize yield. The results depict that under RCP 8.5, as the temperature increases in the future years, maize has the tendency of converting lesser crop consumptive water use into higher yields which are contrary to the results of RCP 4.5 scenario. Similarly, maize CWP is projected to increase from 1.44 to 6.25% as a result of the increase in yields in the future years due to increased temperature of 2.8°C (Li et al., 2016). In addition, the results show that the effect of elevated CO_2 concentration is not significant on maize yield and CWP. This is attributable to the claim that CO_2 fertilisation effects on triggering photosynthesis in C4 crops such as maize are mild (Corbeels et al., 2018) when compared to C3 crops such as soybeans.

It is worthy to note that for each future period, soybeans CWP under RCP 8.5 is projected to be higher than that of RCP 4.5 which is attributable to CO_2 fertilization. This trend is the same as the future yields of soybeans. Among all the soil types within the basin, clay soils have the least CWP compared to others. In addition, the results show that as the temperature increases in the future years, soybeans has the tendency of converting lesser crop consumptive water use into higher yields despite reduced growing periods under both scenarios. This phenomenon can be attributed to the claim that C3 crops such as soybeans are projected to have higher CWP under higher CO_2 concentration due to positive effect of carbon fertilisation (Roudier et al., 2011; Steduto et al., 2012; Tingem & Rivington, 2009).

Moreover, evidence from this research shows that under RCP 4.5, the optimum planting dates for maize within the region based on the RCM projection will be around mid to late April while under RCP 8.5, the planting can be still done in early April. Besides, since RCP 4.5 has been described as the most realistic scenario at least up to 2050, therefore, within this region, a shift in planting date of maize from early April to mid/late April will be inevitable for optimum production. Likewise, shifting planting dates of maize is an adaptation measure for climate change effects on

maize production in other countries such as Cameroon and United States of America (Basso et al., 2015; Tingem & Rivington, 2009).

On the other hand, evidence from this study shows that climate change will likely affect the growing periods of crops. Simulations show a reduction in the growing period of the two crops. It is worthy to note that the highest decline in growing period for both crops is projected in the late century (2071 – 2099) under the worst-case scenario of climate change, that is, RCP 8.5. This is a result of higher temperature and CO_2 fertilisation will trigger early stomatal closure. However, there are still uncertainties about the effects of triggered fertilisation and early stomatal closure on the nutritional composition of crops.

In addition, supplemental irrigation shows a promising effect on improving crop yields and water productivity. The results obtained are in accordance with Olayide et al. (2016) that climate-smart agricultural practices such as supplemental irrigation on 1% of the current arable land is capable of increasing crop production by 5.99%. Maize is also established to perform better under supplemental irrigation (Basso et al., 2015; Liben et al., 2018). Although according to Gbegbelegbe et al. (2019), supplemental irrigation is used in soybeans production in some part of SSA, it is not being used presently within the study area. Therefore, supplemental irrigation will help to cushion the impacts of elevated temperature within the basin in order to meet with up with the demand. Thus, this study has revealed that if farmers could employ supplemental irrigation, it will improve crop yields and CWP.

Globally, there is increasing food demand thus, if supplemental irrigation is employed, there will be adequate food production even sufficient for more export and will increase farmers' profits. Furthermore, some farmers intend to practice irrigated agriculture during dry seasons thus they will benefit from the facilities of supplemental irrigation both under rainfed and irrigated productions. Also, most farmers practice multi-cropping so they will likely benefit from increased yields on crops planted at the same time. Some other climate smart agricultural practices such as soil conservation practices will also help in improving yields and CWP (Adeboye et al., 2017).

Similarly, for future periods, supplemental irrigation is capable of improving crop yield and water productivity except in the late century under both RCP 4.5 and RCP 8.5 due to elevated temperature and CO_2 concentration. Likewise, supplemental irrigation can improve rainfed maize yields but it will have no or little effect in the late century (Basso et al., 2015). The results of the

study show that supplemental irrigation will be a worthwhile adaption measure to the effects of climate change within this basin. It is important to note that the least improvements in CWP are observed in the late century similar to crop yield. The lower and decline in CWP under supplemental irrigation shows that under elevated temperature and CO_2 concentration (late century), higher water consumptive use will not certainly result in higher yields. Thus, a combination of climate-smart agriculture practices such as soil and water conservation practices (Adeboye et al., 2017; Partey et al., 2018), use of organic fertilizers and cultivation of climate resilient varieties will be helpful in improving CWP under supplemental irrigation.

4.11 Adaptation measures and policy framework

In order to counterbalance the negative effects of climate change, certain adaptation measures need to be employed. Based on this study, there is a tendency that shift in planting dates of maize will result in higher yields than the current planting dates. Therefore, a shift in planting dates of maize will likely go a long way in reducing the negative effects of climate change on maize production within the basin. Additionally, supplemental irrigation is capable of improving crop yields and productivities within the basin. Rainwater harvesting is a common water storage system within the basin that can be adapted for agricultural production. It will also be beneficial for farmers that cultivate crops during dry seasons (Durodola et al., 2020).

In addition, soil and water conservation practices such as mulching, soil bunds and tied ridges, which are climate smart agricultural practices, combined with supplemental irrigation can improve crop yields and water productivity, thus it should be encouraged by the stakeholders. New crop varieties that are resilient to higher temperature are also crucial to sustainable production. Figure 4.41 shows the policy framework which summarises the adaptation measures that can be adopted and implemented to achieve sustainable agriculture in Nigeria.

Meanwhile, the roles of each stakeholder identified in the policy framework cannot be overemphasised. All hands must be on desk to counterbalance the effect of climate change on crop production as well as to realise SDGs 2, 1, 13 and 6 in Nigeria. As shown in the framework, the government as the major stakeholder has a lot of roles to play in achieving these goals. First of all, government across all levels needs to show the “political will” and recognise climate change as an urgent issue that needs to be address. The government needs to know that this is not “business as usual” thus, needs to formulate and adopt appropriate policies and frameworks. Increasing

budgetary allocation to agricultural and climate research, providing organic fertilizers at affordable prices for farmers as well as enhancing climate early warning systems should be the priorities of government actions. Investments in irrigation (micro and macro) schemes and infrastructures by government need to be implemented. These schemes and infrastructures can be coordinated by the existing River Basin Development Authorities in Nigeria (Olayide et al., 2016).

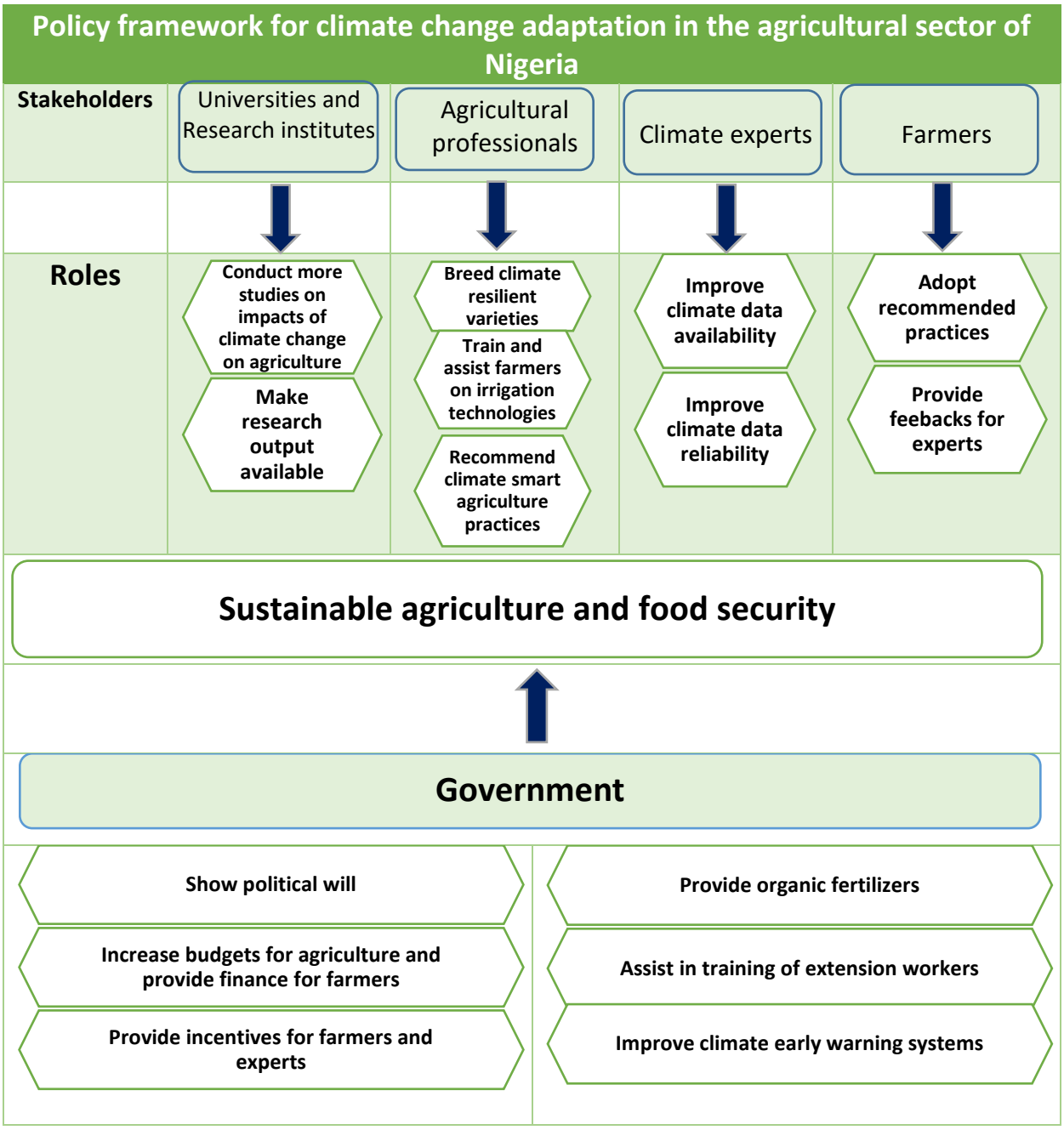

Figure 4.41: Proposed policy framework for sustainable agriculture

The universities and research institutes in Nigeria are already saddled with the responsibility of conducting timely research on climate smart agriculture. However, limited funding and resources are major constraints to this responsibility. Hence, there is an urgent need for funding from both the public and the private sectors to catalyse research on adaption measures of climate change in the agricultural sector. Investments in research from both public and private sectors will drastically improve farmers' access to modern water and soil management technologies (Partey et al., 2018). It is also expected that research outputs from the universities and research institutes will be readily available for other stakeholders especially in open access format to transform the outputs into actions. Most times, there is usually a wide gap between research output and its implementation on the ground. This gap needs to be filled up through intensive extension services to promote sustainable agriculture.

Many studies (Boonwichai et al., 2018; Luhunga, 2017; Partey et al., 2018; Tingem & Rivington, 2009) have recommended breeding of new crop varieties that are resistant to high temperature. It is therefore necessary for agricultural professionals and crop scientists to take up this responsibility and come up with new crop varieties that will adapt to climate change. Additionally, farmers need to be adequately trained in the emerging soil and water management practices. In this case, the provision of incentives such as free fertilizers, seedlings and consultation services will go a long way in encouraging farmers to adopt new technologies.

Most African countries including Nigeria have fewer meteorological stations compared to their land mass. Although, recently a lot of improvements have been done especially in providing automated weather stations (AWS) but there are still a lot of gaps. Therefore, there is a need for more funding and monitoring of meteorological stations in Nigeria. This will drastically improve climate data availability and reliability. Also, there should be training and retraining of climate experts on the use of automated weather stations.

However, what will happen if all these recommended actions are taken without farmers' adoption? Farmers play critical roles in achieving sustainable agriculture in Nigeria. Framers usually find it difficult to adopt new practices. Hence, farmers need to be encouraged by all other actors to embrace recommended and modern practices. It is also expected that farmers will provide timely feedback to other stakeholders for necessary actions. For instance, based on the results of this study, a shift in panting date of maize could help minimize the negative impacts of climate change.

In addition, this study shows that supplemental irrigation will likely help to increase crop yields and CWP. So, it is expected that farmers will adopt these changes to boost their production and the economy of the region.

The importance of synergy among these stakeholders cannot be overemphasised. From the proposed policy framework, it shows that all the stakeholders need to be connected and work together to achieve sustainable agriculture within the country. The actions of each stakeholder need to be connected to make a joint progressive effort. In addition, this study shows that supplemental irrigation offers a great approach in enhancing sustainable agriculture and all-year-round crop production to meet up with the ever-increasing food demand in the country. Thus, appropriate policies to support and encourage it will trigger an increase in arable land under irrigation and would increase productivity in Nigeria.

4.12 Limitations of the study

Some limitations are identified in this study. First, only one variety per crop, due to insufficient data availability, was simulated in this study which could not possibly alter the results. As suggested by the literature, it is assumed that climate change will have almost the same effects on all the current crop varieties. That is the main reason for breeding new cultivars that will adapt to climate change. Second, only one RCM was used in the study. The GCMs have different climate projections and this could possibly influence the results of any study. In order to minimise the biases, the RCM data were bias corrected and evaluated. The evaluations show highly satisfactory results which depict that the RCM sufficiently captures the climate of the region thus, it is highly reliable. So, the results of this study provide a solid basis and useful information for further studies in the basin as well as the research area. Hence, the use of an ensemble of RCMs or GCMs will enhance the information on the effects of climate change on crop production within the basin.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

The conclusions drawn from this study are highlighted and recommendations are given in this chapter.

5.1 Conclusions

The seasonal crop water requirements (CWR), irrigation water requirements (IWR), crop yield and crop water productivity (CWP) of rainfed maize and soybeans in Ogun-Osun River Basin in Nigeria based on the climate data of 1986 – 2015 (30 years) were simulated. The regional average of CWR, IWR, yield and CWP of rainfed maize were found to be 237 mm, 25 mm, 1.98 t/ha and 0.90 kg/m^3 respectively while that of rainfed soybeans were found to be 311 mm, 34 mm, 2.25 t/ha and 0.79 kg/m^3 respectively. Trendline analyses show a slight decreasing trend for maize CWR and IWR while soybeans CWR and IWR are increasing. Furthermore, there are no significant changes in maize yields, but significant increasing trend was estimated for soybeans yields. CWP trendlines for the two crops show an increasing trend as well.

In addition, HadGEM2-ES downscaled by RCA4 is capable of simulating the future climate of the region satisfactorily while quantile mapping bias correction method performed satisfactorily in removing the biases in the projected rainfall thus making it a reliable bias correction method. Just as the global temperature is expected to continually rise, the climate projections of the region also show that minimum and maximum temperatures will continually increase up to 4.4°C by 2099 under RCP 8.5 while rainfall will likely reduce by 10% within the basin in the future periods.

The future scenarios show that maize CWR will continually decline up to 20%, while that of soybeans will range from 10 to -10 % in the future periods under RCP 4.5 and RCP 8.5. Maize IWR will increase significantly up to 140% in the near future and late century under RCP 4.5 while increasing rainfall within the growing period of soybeans will cause its IWR to likely decline continually up to 80% by 2099. CWR and IWR were found to be largely influenced by changes in rainfall than temperature rise and increased CO_2 concentration. The days of growing period of both crops will be shortened due to early stomatal closure caused by temperature rise. Moreover, maize yield is projected to continually decline under both scenarios up to 12%, compared to soybeans yield which is projected to have positive effects of climate change, hence increasing up to about

40% under RCP 4.5 and RCP 8.5. CWP of maize will likely have more negative effects while soybeans CWP will largely increase up to 40% when compared with the baseline period. The study shows that crop yield of maize (C4 crop) is significantly influenced by changes in rainfall and temperature rise contrary to soybeans (C3 crop) yield that is significantly influenced by increasing CO_2 concentration than other changes in climate parameters. However, there are still uncertainties and research gaps on the response of other C3 crops to increased CO_2 concentration thus, it is still unclear if the positive effects of climate change will be the same globally.

Meanwhile, supplemental irrigation shows a promising effect on crop yields based on the current trend of climate as it can increase maize and soybeans yields up to about 10% and 35% respectively. Also, in the future, it can increase crop yields expect in the late century under RCP 4.5 and RCP 8.5 when supplemental irrigation will not improve crop yields and CWP. Thus, a combination of climate smart agricultural practices will better improve crop yields and CWP. The outcome of this study and the proposed policy framework certainly offer useful information which could be implemented by stakeholders and policymakers to adopt suitable adaption measures to counterbalance the negative effects of climate change on crop production in Nigeria.

5.2 Recommendations

This research has shown that supplemental irrigation can improve crop yields, hence it is recommended for implementation within the basin. Rainwater harvesting commonly used for household activities is recommended as a suitable strategy for irrigation management due to its many benefits. In addition, a shift in planting date of maize is suggested for optimal production due to delay in the onset of rainfall. Appropriate and suitable weed and pest management should be encouraged, and organic fertilizers should be available as the difference between average yields and maximum obtainable yields are huge. Breeding of new crop varieties that can withstand elevated temperature and still produce good and nutritional values is recommended. The combination of soil and water conservation practices with supplemental irrigation would be helpful in improving yield and water productivity, hence they should be encouraged.

Further research on the impacts of climate change on other crops within the region and the country at large is strongly suggested as this will assist in formulating appropriate policies. Studies on irrigation scheduling are also recommended as this will be helpful for farmers to know when to apply their irrigation water. Furthermore, more studies on bias correction methods of climate

projections obtainable from GCMs and RCMs are recommended in order to improve the reliability of climate projections. Hence, for further studies, the use of more than one GCM or RCM is recommended.

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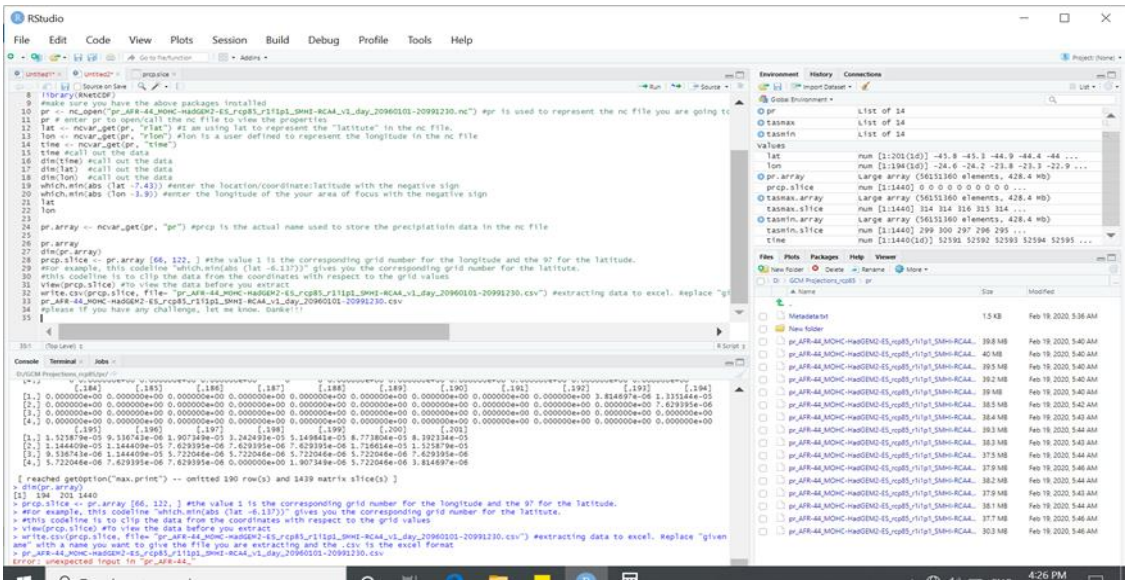
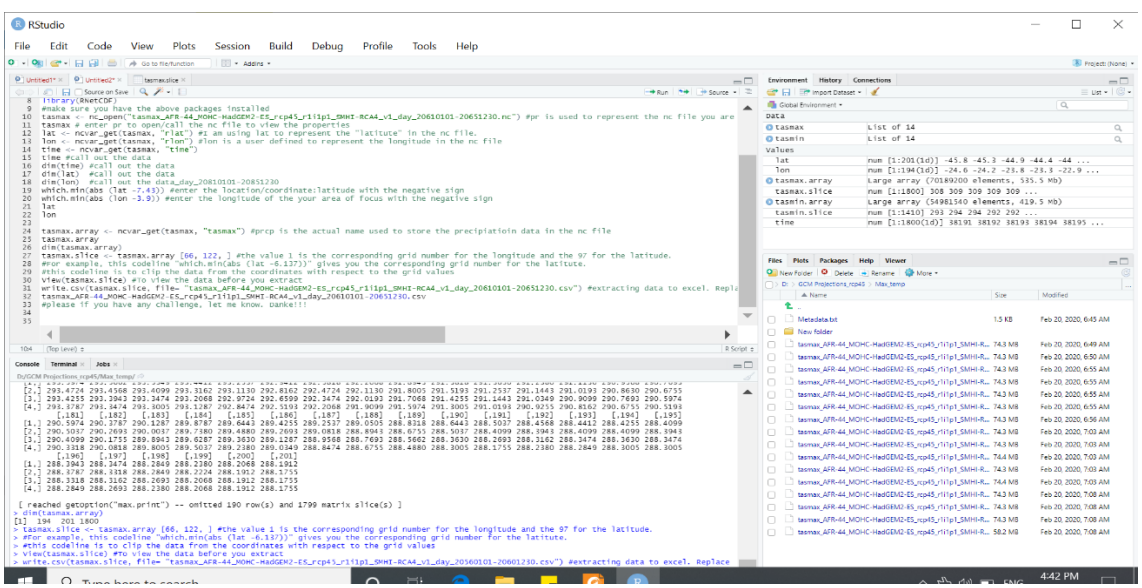
ANNEXES

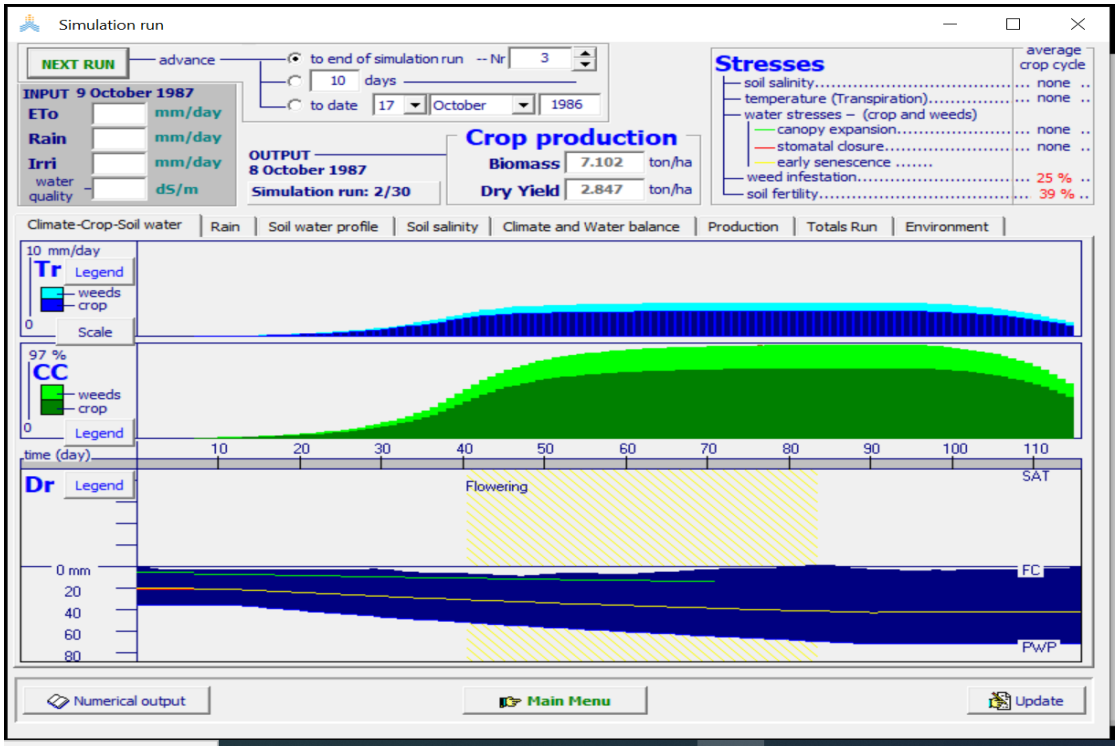
Annex 1: Extraction of air temperature from NetCDF file in R-Studio.



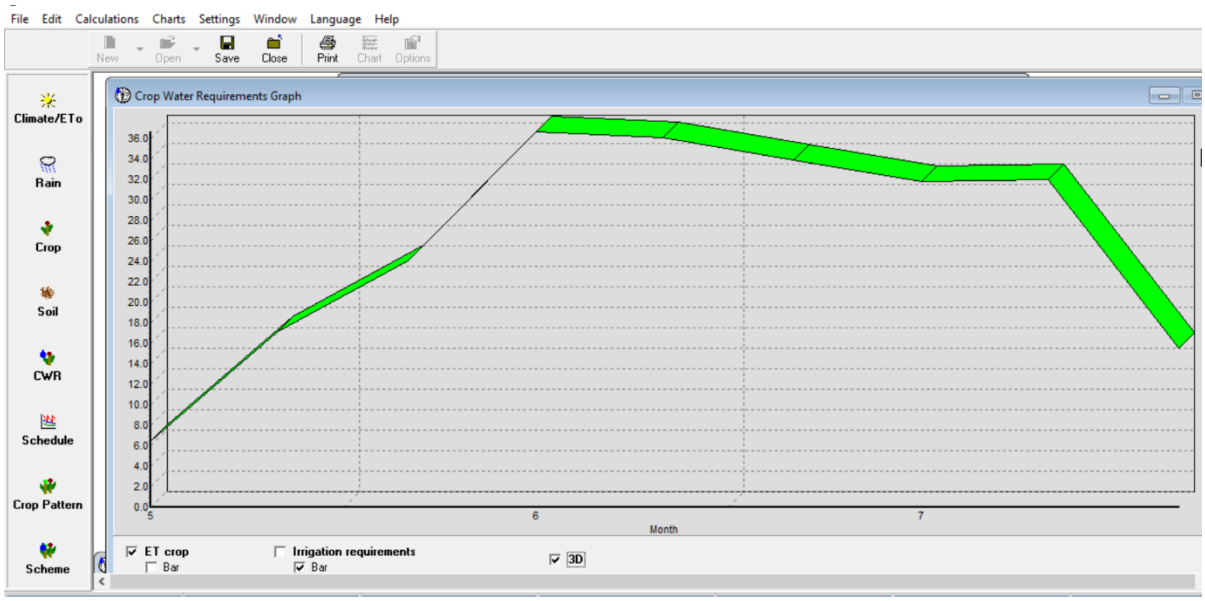
Annex 2: Extraction of rainfall from NetCDF file in R-Studio.



Annex 3: Interface of AquaCrop during simulations



Annex 4: Interface of CROPWAT during simulations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