Optimizing site-specific variety, sowing density and nitrogen fertilizer recommendations for maize in the Nigerian Savannas using field experiments and modelling

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“Civilization as it is known today could not have evolved, nor can it survive, without an adequate food supply”

(Norman Borlaug, Nobel Lecture – December 11, 1970)

DEDICATION

Dedicated to the two strong women who raised me to be the man I am today. To my mother Hajiya Binta F. Salisu who taught me love, patience and kindness and to my late Aunt Hajiya Hanne Adamu who taught me strength, courage, and sacrifice.

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SUMMARY

Maize (*Zea mays* L.) has over the years become an important crop in the Nigerian Savannas including the semi-arid Sudan Savanna zone where production was initially not feasible. The annual maize output in the country changed from 1.06 million tonnes in 1976 to about 11.6 million tonnes in 2017, but the increase is due to expansion of area and not the much-needed intensification. The average yield per hectare has been below 2 Mg ha^{-1} since the 1970s, although yields >7 Mg ha^{-1} have been reported in research stations and best farmer fields. The reasons for the low per hectare yield have been attributed to the inherently poor soils, frequent droughts, pests & diseases and most importantly to lack of adherence to improved agronomic practices and use of improved inputs like fertilizers and seeds. In recent years, new maize varieties that are tolerant to most of the biotic and abiotic constraints have been developed for the Nigerian Savannas by the International Institute for Tropical Agriculture (IITA) and its partners. Several agronomic technologies have also been developed to increase the productivity of these varieties with a view to increasing maize yields. Dissemination of such varieties and technologies and their subsequent adoption requires setting up expensive and time-consuming multi-locational trials for evaluation. Selection of appropriate varieties across agro-ecologies and adoption of appropriate agronomic practices like optimum sowing density and site-specific fertilizer applications will be the key requirements for increase in production per unit area.

Crop simulation modeling offers an opportunity to explore the potential of new varieties and crop management practices in different environments (soil, climate, management) prior to their release. Since most models have been developed elsewhere in Europe and USA, their use outside their domain of development requires a great deal of data for their calibration and evaluation. In addition, the shortage of technical know-how makes the use of those models more difficult especially by policy makers, farmers, technologists and extension agents.

Overall, this research was conducted to evaluate the ability of a dynamic crop simulation model (DSSAT-CSM-CERES-Maize model) in matching maize varieties to the Sudan and Northern Guinea Savannas of Nigeria. The research also aims to use the model in making agronomic recommendations with respect to optimum sowing densities of the different varieties produced in the Nigerian maize belt. To achieve the set aims and objectives, data sets were collected from

three different sources. Two of the data sets were collected by setting up field experiments while the third was collected from maize breeders in IITA.

The first set of experiments were conducted in the rainy and dry seasons of 2016 in four research stations in the Nigerian Savanna. In the experiments, 26 maize varieties were planted under near-optimal environments (moisture and nutrient non-limiting). Growth, phenology and yield characteristics of each variety were measured with a view to developing “virtual” genotypic characteristics and incorporating it into the model. In addition to crop data, detailed soil data was collected from two profiles pits dug in each location together with daily weather data (minimum and maximum temperatures, daily rainfall and solar radiation). The purpose of these experiments was to calibrate the existing varieties and agro-ecological conditions of our trial sites into the model.

The second sets of experiments were conducted in the rainy seasons of 2016 and 2017 across farmer fields in the Sudan and Northern Guinea Savannas of Nigeria. The experiments consisted of 10 maize varieties (different varieties were used in the two agro-ecologies) planted under three different sowing densities (2.6, 5.3 and 6.6 plants m^{-2}). In each agro-ecology the experiments were conducted in 30 farmer fields in both years, data was collected on the response of the varieties to the elevated sowing densities as well as soil and weather records from each farmer field and trial location. These experiments were conducted to evaluate the response of diverse maize varieties to elevated sowing density and to evaluate the ability of the model to predict the response of increased sowing density.

The third data-set was collected from long-term varietal evaluation experiments conducted by breeders before varietal release. These data-sets were used to demonstrate how available information from breeder trials can be used to develop genotype specific parameters (GSPs) for use in CERES-Maize model.

Using the data from the detailed calibration experiments and the breeder evaluation experiments, two sets of GSPs for 26 current maize varieties produced in the Nigerian maize belts were developed. Comparison of the two different data sources showed that GSPs generated from the detailed experiments were more accurate, but the breeder evaluation experiments could also be used but implied lower accuracy. The sequential approach method used in the genotype calculator (GENCALC) tool for calculating GSPs in the model was also optimized. Additionally, we used the detailed experimental data to evaluate the ability of the model in predicting observed genotype by environmental interaction (GEI). The model accurately predicted the observed GEI and the predicted grain yields were used to rank the stability of the different varieties across different environments. Long-term weather data (1992-2017) from the dry and wet savannas were then used to conduct seasonal analysis. This revealed that, contrary to current recommendations, intermediate maturing varieties which were suggested only for the wet savannas can also be grown in the dry savannas.

Data from the sowing density experiments were used two-fold. First, a detailed analysis of the response of the maize varieties to elevated sowing density was conducted. A heterogenous covariance structure (Eberhart-Russel factor analytic model (FAM)) was used to model the genotype by environment by density (G×E×D) interaction. From this analysis, it was established that higher yields are expected with increasing sowing density only in optimal environments. The results also show that, under optimal environments maize varieties can be sown above 6 plants m^{-2} which is beyond the highest density tested and beyond the current recommendation. Second, the observed grain yields from farmer fields were used to evaluate the already calibrated varieties in the CERES-Maize model. The calibrated and evaluated model was then used to provide sowing density recommendations for the different maize varieties under varying nitrogen fertilizer rates. Detailed bio-physical and economic analyses were conducted using the long-term weather records. The model simulations revealed that, early and extra early maize varieties could be planted under sowing densities of up to 8.8 plants m^{-2} under high Nitrogen (90 kg N ha^{-1}) in the Sudan Savanna providing higher grain yields and money returns per hectare. Sowing density of 6.6 plants m^{-2} and 90 kg N ha^{-1} was shown to produce the highest money returns to family labour. For the late and intermediate varieties in the Northern Guinea Savanna, sowing density of 6.6 plants m^{-2} and N fertilizer application of 120 Kg N ha^{-1} produced the highest grain yields and money returns per unit land. But highest returns to family labour was simulated for sowing density of 5.3 plants m^{-2} and N fertilizer rates of 120 kg N ha^{-1}. These simulated results show that for optimum economic returns, small holder farmers need to increase the planting density of maize in reduced areas of their farms and apply all the N fertilizers they can afford on that area. The remaining area can then be used for legumes and other low input crops.

SAMENVATTING

Maïs (*Zea mays* L.) is in de loop der jaren een belangrijk gewas geworden in de Nigeriaanse savannes, ook in de semi-aride Sudan Savanne-zone waar productie aanvankelijk niet haalbaar was. De jaarlijkse maïsproductie in het land veranderde van 1,06 miljoen ton in 1976 tot ongeveer 11,6 miljoen ton in 2017, maar de toename is te wijten aan uitbreiding van het areaal en niet aan de broodnodige intensivering. De gemiddelde opbrengst per hectare is sinds de jaren zeventig lager dan 2 Mg ha^{-1}, hoewel opbrengsten> 7 Mg ha^{-1} zijn gerapporteerd in onderzoeksstations en op de beste percelen van kleinschalige landbouwbedrijven. De redenen voor de lage opbrengst per hectare zijn toegeschreven aan de inherent slechte bodems, frequente droogtes, plagen en ziekten en vooral aan het niet naleven van verbeterde agronomische praktijken en het niet gebruiken van verbeterde inputs zoals meststoffen en zaden. In de afgelopen jaren zijn door het *International Institute for Tropical Agriculture* (IITA) en zijn partners nieuwe maïsvariëteiten ontwikkeld die de meeste biotische en abiotische beperkingen tolereren. Verschillende landbouwkundige technologieën zijn ook ontwikkeld om de productiviteit van deze rassen te verhogen met het oog op het verhogen van de maïs-opbrengst. Verspreiding van dergelijke rassen en technologieën en de daaropvolgende acceptatie ervan vereist het opzetten van dure en tijdrovende veldproeven op meerdere locaties voor evaluatie van de cultivars. Selectie van geschikte variëteiten in agro-ecologische zones en toepassing van geschikte agronomische praktijken zoals optimale zaaidichtheid en locatie-specifieke bemesting zullen de belangrijkste vereisten zijn voor een toename van de productie per oppervlakte-eenheid.

Gewasmodellering biedt een mogelijkheid om het potentieel van nieuwe rassen en gewasbeheerspraktijken in verschillende omgevingen (bodem, klimaat, beheer) te verkennen voordat ze worden vrijgegeven. Aangezien de meeste simulatiemodellen elders in Europa en de VS zijn ontwikkeld, vereist het gebruik buiten hun ontwikkelingsgebied veel gegevens voor hun kalibratie en validatie. Bovendien maakt het tekort aan technische knowhow het gebruik van die modellen moeilijker, met name gebruik door beleidsmakers, landbouwers, technologen en voorlichters.

Over het algemeen werd dit onderzoek uitgevoerd om het vermogen van een dynamisch gewassimulatiemodel (DSSAT-CSM-CERES-Maize-model) te evalueren in het kiezen van de juiste

maïsvariëteiten voor de Soedan en Noord-Guinea-savannes in Nigeria. Het onderzoek heeft ook tot doel het model te gebruiken om aanbevelingen op te stellen met betrekking tot optimale zaaidichtheden van de verschillende variëteiten die in de Nigeriaanse maïszone worden geproduceerd. Om de gestelde doelen en doelstellingen te bereiken, werden datasets verzameld uit drie verschillende bronnen. Twee van de gegevenssets werden verzameld door veldexperimenten op te zetten, terwijl de derde werd verkregen van maïsveredelaars in IITA.

De eerste set veldproeven werd uitgevoerd in het regenseizoen en in het droge seizoen van 2016 in vier onderzoeksstations in de Nigeriaanse Savanne. In de veldexperimenten werden 26 maïsvariëteiten gezaaid onder bijna optimale omstandigheden (water en nutriënten niet-gelimiteerd). Groei, fenologie en opbrengstkarakteristieken van elke variëteit werden gemeten met het oog op het ontwikkelen van "virtuele" genotypische kenmerken en deze in het model op te nemen. Naast gewasgegevens werden gedetailleerde bodemgegevens verzameld uit twee op elke locatie gegraven profielenkuilen. Ook werden dagelijkse weergegevens (minimum- en maximumtemperatuur, neerslag en zonnestraling) opgemeten. Het doel van deze experimenten was om de bestaande variëteiten en agro-ecologische omstandigheden van onze proeflocaties in het model te kalibreren.

De tweede set veldproeven werd uitgevoerd in de regenseizoenen van 2016 en 2017 op praktijkvelden (velden van boeren) in de Soedan en Noord-Guinea-savannes in Nigeria. De experimenten bestonden uit 10 maïsvariëteiten (verschillende variëteiten werden gebruikt in de twee agro-ecologische zones) geplant onder drie verschillende zaaidichtheden (2.6, 5.3 en 6.6 planten m^{-2}). In elke agro-ecologische zone werden de experimenten uitgevoerd in 30 praktijkvelden in beide jaren, en werden gegevens verzameld over de respons van de rassen op de verhoogde zaaidichtheden. Daarnaast werden ook bodemgegevens van elk praktijkveld en weersgegevens van elke proeflocatie verzameld. Deze experimenten werden uitgevoerd om de respons van verschillende maïsvariëteiten op verhoogde zaaidichtheid te beoordelen, om het model te valideren, en om te evalueren hoe goed het model de respons van verhoogde zaaidichtheid kan voorspellen.

De derde dataset werd verzameld uit lange-termijn rassenproeven die werden uitgevoerd door gewasveredelaars vóór ze de variëteiten introduceerden. Deze datasets werden gebruikt om aan te tonen hoe beschikbare informatie uit rassenproeven kan worden gebruikt om genotype-specifieke parameters (GSP's) te ontwikkelen voor gebruik in het CERES-Maize-model.

Op basis van de gegevens van de gedetailleerde kalibratie-experimenten en de rassenproeven werden twee sets GSP's ontwikkeld voor 26 huidige maïsvariëteiten die in de Nigeriaanse maïszone worden geproduceerd. Vergelijking van de twee verschillende types proeven toonde aan dat GSP's gegenereerd uit de gedetailleerde experimenten nauwkeuriger waren. Maar de rassenproeven konden ook worden gebruikt, maar impliceerden een lagere nauwkeurigheid. De sequentiële benaderingsmethode die werd gebruikt in de genotype calculator (GENCALC) voor het berekenen van GSP's in het model werd ook geoptimaliseerd. Daarnaast hebben we de gedetailleerde experimentele gegevens gebruikt om na te gaan hoe goed het model de interactie tussen genotype en omgeving (*Genotype Environment Interaction*, GEI) kan voorspellen. Het model voorspelde nauwkeurig de waargenomen GEI. De voorspelde graanopbrengsten werden gebruikt om de stabiliteit van de verschillende rassen in verschillende omgevingen te rangschikken. Lange-termijn weergegevens (1992-2017) van de droge en humiede savannes werden vervolgens gebruikt om seizoensanalyses uit te voeren. Hieruit bleek dat, in tegenstelling tot de huidige aanbevelingen, halfvroege variëteiten die alleen voor de humiede savannes werden voorgesteld, ook in de droge savannes kunnen worden gekweekt.

Gegevens van de zaaidichtheidsproeven werden op twee wijzen gebruikt. Eerst werd een gedetailleerde analyse uitgevoerd van de respons van de maïsvariëteiten op verhoogde zaaidichtheid. Een heterogene covariantiestructuur (Eberhart-Russel factor-analytisch model, FAM) werd gebruikt om de genotype × omgeving × dichtheid interactie (G × E × D) te beschrijven. Op basis van deze analyse werd vastgesteld dat hogere opbrengsten alleen worden verwacht bij een toenemende zaaidichtheid in optimale omgevingen. De resultaten laten ook zien dat, onder optimale omgevingen, maïsvariëteiten kunnen worden gezaaid met een dichtheid van meer dan 6 planten per m^2, wat de geteste hoogste dichtheid overschrijdt en de huidige aanbeveling overtreft. Ten tweede werden de waargenomen graanopbrengsten van praktijkvelden gebruikt om de reeds gekalibreerde rassen in het CERES-Maize-model te evalueren. Het gekalibreerd en geëvalueerd model werd vervolgens gebruikt om aanbevelingen voor de zaaidichtheid te geven voor de verschillende maïsvariëteiten onder verschillende stikstofmeststof-dosissen. Gedetailleerde biofysische en economische analyses werden uitgevoerd met behulp van de lange-termijn weersreeksen. De modelsimulaties gaven aan dat vroege en extra-vroege maïsvariëteiten konden worden geplant onder een zaaidichtheid van maximaal 8,8 planten per m^2 onder hoge stikstof-dosissen (90 kg N ha^{-1}) in de Soedan Savanna met hogere graanopbrengsten en financiële opbrengsten per hectare . Een zaaidichtheid van 6,6 planten per m^2 en 90 kg N ha^{-1} bleek het hoogste financiële rendement voor gezinsarbeid te produceren. Voor de late en half-vroege variëteiten in de Noord-Guinea Savanna leverde de zaaidichtheid van 6,6 planten per m^2 en een N bemesting met 120 kg N ha^{-1} de hoogste graanopbrengsten en financiële opbrengsten per landeenheid op. Maar het hoogste rendement op gezinsarbeid werd gesimuleerd voor een zaaidichtheid van 5,3 planten m^2 en een N bemesting van 120 kg N ha^{-1}. Deze gesimuleerde resultaten tonen aan dat kleinschalige boeren voor optimale economische opbrengsten de plantdichtheid van maïs in een deel van hun land moeten verhogen en de N-meststoffen die ze zich kunnen veroorloven op dat gebied concentreren. Het resterende deel van het land kan vervolgens worden gebruikt voor peulvruchten en andere gewassen met een lage input.

ABBREVIATIONS AND SYMBOLS

ADAP – days to anthesis

AgMIP – Agricultural Models Inter-Comparison Project

AICc – Akaike Information Criterion (corrected)

AMMI – Additive Main-effect and Multiplicative Interaction

APSIM – Agricultural Production Systems Simulator

ASV – AMMI stability value

bi – slope of the regression line

BUK – Bayero University Kano

CARBO – daily plant growth

CERES – Crop Estimation through Resource and Environment Synthesis

CPI – Consumer Price Index

CropSyst – Cropping Systems Simulator

CSM – Crop Simulation Model

CWAM – tops weight at maturity

DSSAT – Decision Support System for Agrotechnology Transfer

DTA – days to anthesis

EF – Modelling Efficiency (Nash-Sutcliffe)

EI – Environmental Index

FAM – Factor Analytic Model

FAO – Food and Agriculture Organization

GDD – Growing Degree Days

GEI – Genotype by Environment Interaction

GENCALC - Genotype Coefficient Calculator

GLUE – Generalized Likelihood Uncertainty Estimation

GSP – Genotype Specific Parameter

HWAM – harvest weight at maturity

IAR – Institute for Agricultural Research

ICA – Independent Component Analysis

IFAD – International Fund for Agricultural Development

IITA – International Institute for Tropical Agricultural

k – Light Extinction Coefficient

KADP – Kaduna Agricultural Development Project

KSTRES – potassium stress factor

LAIX – maximum leaf area index

MDAP – days to physiological maturity

MET – Multi-Environmental Trial

MLN – Maize Lethal Necrosis

MSV – Maize Streak Virus

NGS – Northern Guinea Savanna

NSTRES – nitrogen stress factor

OECD – Organization for Economic Co-operation and Development

OPV – Open Pollinated Variety

OSD – Optimum stand density

PAR – Photosynthetically Active Radiation

PD – Prediction Deviation

Pdensity – Plant population effect

PGrate – Potential Growth Rate

PHINT – Phyllochron interval

PRFT – temperature reduction factor

PSO – Particle Swarm Optimization

PSTRES – phosphorus stress factor

QPM – Quality Protein Maize

RCBD – Randomized Complete Block Design

RMSE – Root Mean Square Error

RMSEn – Root Mean Square Error (normalized)

RUE – Radiation Use Efficiency

S^2d – sum of squares for deviation

SA – Simulated Annealing

SAA – Sasakawa Africa Association

SCS – Soil Conservation Service

SD – Standard Deviation

SEM – Standard Error of Means

SLPF – soil fertility coefficient

SS – Sudan Savanna

SSA – Sub-Saharan Africa

SWAFC – soil water stress factor

TAMASA – Taking Maize Agronomy to Scale in Africa

Tbase – base temperature

TDR – Time Domain Reflectometry

Tmax – maximum temperature

Tmin – minimum temperature

Topt – optimum temperature

UCPR – Uniform Covering by Probabilistic Region

UNICEF – United Nations Children's Fund

WAP – Weeks After Planting

WFP – World Food Program

CONTENTS

Table of Contents

LIST OF FIGURES

LIST OF TABLES

1 CHAPTER ONE

INTRODUCTION AND BACKGROUND STATEMENTS

1.1 Need for increased food production – Global, Regional, and National Perspectives

Despite consistent efforts, persistent hunger and malnutrition is still the norm for millions of people all over the world. According to recent estimates by the United Nations Statistics Department (UN, 2018), the number of people who suffer from hunger has been growing over the past three years, returning to levels from almost a decade ago. The same report posits that the absolute number of undernourished people in the world has increased from around 804 million in 2016 to almost 821 million in 2017 (FAO et al., 2018). Reports have also shown that severe food insecurity was higher in 2018 than it was in the period between 2014-2017 in every region except North-America and Europe with notable increase in Africa and Latin America (FAO et al., 2018). This trend sends a clear warning that, if efforts are not enhanced, the Sustainable Development Goal (SDG) target of hunger eradication will not be achieved by 2030.

Sub-Saharan Africa (SSA) continues to be the region at the highest risk of food insecurity because by 2050 its population will have increased 2.5 fold and the demand for food (especially cereals) will be tripled (van Ittersum et al., 2016). The major question asked by researchers and policy makers is whether SSA can meet this tremendous increase in demand for cereals without relying on imports and expansion of production area. Many studies have shown that it is possible to meet projected food demands by reducing yield gaps between actual farm yields and potential yields without expanding production area (Erb et al., 2016; Mueller et al., 2012; Tilman et al., 2011). Closing the yield gaps of most crops in SSA requires adoption of optimal agronomic practices which target optimal water, nutrient and crop management strategies (van Bussel et al., 2015). Unfortunately, most of the food production is still very traditional, with cultivation mostly rainfed and the agriculture landscape dominated by smallholder farmers with very limited adaptation capability (Dennis et al., 2013).

Nigeria, the most populous nation in Africa, is endowed with abundant arable land, suitable climates, and water resources, and has high potentials for increased agricultural growth

(Ahungwa et al., 2014). With all the inherent potentials, attainment of food security in Nigeria remains elusive. This is because the Nigerian agricultural sector is still characterized by small family farms that rely heavily on rain-fed production systems, traditional methods of soil fertility maintenance, and that suffer from lack of access to credits and improved inputs such as fertilizers and seeds (WFP, 2014). According to recent reports "food (crop) production increases have not kept pace with population growth, resulting in rising food imports and declining levels of national food self-sufficiency" (Richard, 2017).

1.2 Maize Production – Regional and National Figures

Maize (*Zea mays* L.) is the most important staple food crop in SSA, it is the crop that is most critical to food security in the region with more than 300 million people in the entire continent depending on it as their main staple food (Badu-Apraku and Fakorede, 2017a). The crop was introduced to SSA just over 500 years ago, but during that period it has become a staple crop with more varieties developed and adopted than even the traditional crops in the area. Currently, maize is produced in about 25 million hectares in SSA, largely on smallholder farms and it accounts for about 20% of the calorie intake of 50% of the population (Badu-Apraku and Fakorede, 2017b). Of the entire 53 countries in SSA, 46 grow maize with only Liberia, Equatorial Guinea, St. Helena, Seychelles, Western Sahara, British Indian Ocean Territories and Mayotte not producing the crop (United Nations, 2019). The crop covers the largest land area in Nigeria (1st in Africa and 7th in the world) followed by Tanzania and South Africa. The highest producers in the region are South Africa (9th in the world but only 1.5% of the total), Nigeria, and Ethiopia (FAO, 2018).

Maize has been considered as the vehicle for the ongoing green-revolution in SSA due to the diversity of food uses as well as its expanding use as a commercial and industrial crop (Badu-Apraku et al., 2012a). In SSA, a considerable proportion of the maize produced is used as human food in various forms. Green maize (a physiologically immature cob) is consumed as a snack after roasting or boiling. The dried kernel is milled and consumed as a starchy base in a wide variety of pastes (tuwo, semovita, ugali), porridges (fate, kunu), gruels, and soups. Dough made from the milled grain can also be cooked or fried in oil. Maize as a food is important due to the nutritive value of the kernels, and research has shown that a large variability exists in the nutritive values of maize in SSA (Ekpa et al., 2019). Maize kernel contains protein between 8–15% (80% in the endosperm, 20% in the germ). Other components of the kernels are fat (or oil), minerals, and vitamins (Nuss and Tanumihardjo, 2010). Industrially, maize is used in making many alcoholic and non-alcoholic beverages. It is also an important component of poultry and other livestock feeds (up to 40–75% of feed rations). Dry milling of maize grain produces corn meal, corn flour, and corn oil. Wet milling produces cornstarch used for food, textile and paper sizing, laundry starch, dextrins, and adhesives such as the gums used for stamps and envelopes. Corn syrup, used frequently as a natural sweetener, is also made from cornstarch (Ranum et al., 2014).

The status of maize in Nigeria has changed from a typical low-value crop produced in the backyard, to a major commercial crop providing food, animal feed, and industrial raw materials (Ammani, 2015). Maize production has significantly increased in Nigeria where it is gradually replacing traditional cereals like sorghum and pearl millet. About 6.5 million hectares (32%) of all arable land in the country was allocated to the crop in 2017, making it the leading country in Africa on the basis of production area (FAO, 2018). The total annual national production of maize has increased from 1.1 million metric tons in 1961, to about 10.4 million metric tons in 2017. The recorded increase in production is attributed to expansion in the cultivated area rather than intensification (FAO, 2018). The area dedicated to maize increased from 1.38 million hectares in 1961 to about 6.5 million hectares in 2017. In the last 15 years, the area increased from 3.2 million hectares in 2001 to 6.7 million hectares in 2015, with slight decreases in 2016 and 2017 (Fig. 1-1). Because of the availability of early and extra early maturing high yielding varieties, maize production is also gradually spreading to more areas of the Northern Guinea and Sudan Savanna Zones of Nigeria and West Africa where it was not traditionally suited (Badu-Apraku et al., 2017). These early and extra early varieties help in covering the hunger gaps that frequently occurs toward the end of the dry season. They are known to escape end of season drought and are also tolerant to intermittent drought that occurs sporadically during the growing season (Badu-Apraku et al., 2011).

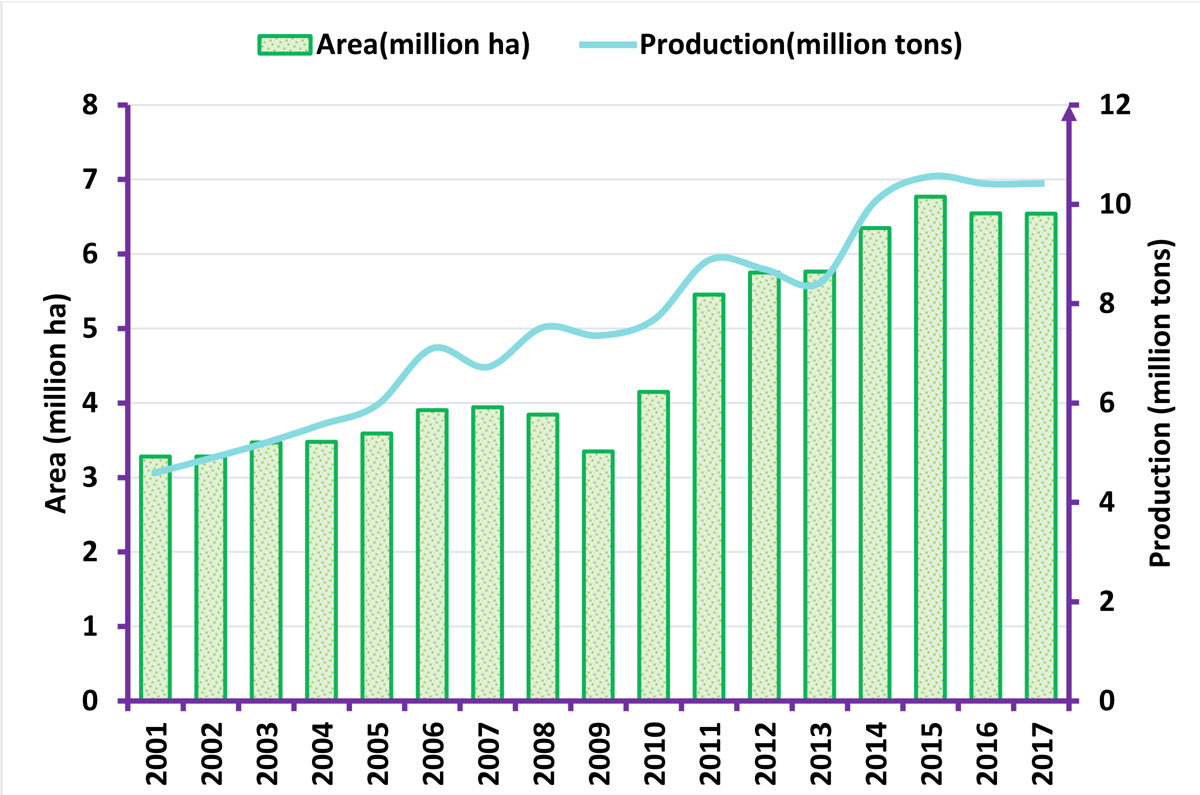


Figure 1-1: Trends in Maize production and allocated area in Nigeria 2001-2017 (Source FAOSTAT,2018)

1.3 Description of Experimental Locations

The vegetation and crop type suited to an area have a direct relationship with the climate of that area. The effect of temperature, rainfall, humidity and sunshine (day length) all have an effect on maize production (Sowunmi and Akintola, 2010). The climatic elements mentioned drives many choices with respect to decision making both in short, medium and long-term planning of agricultural activities including the choice of crop varieties and management practices. The Federal Government of Nigeria (FMARD, 1999) reported that the country has a total landmass of 923,766 km^2. The Nigerian landmass is divided into seven ecological zones among which are the Northern Guinea savanna and Sudan savanna zones. This classification is based on the similarity of climatic elements and the type of vegetation that can be supported (Figure 1-2). The Guinea Savanna (divided into Northern and Southern) is located close to the center of the country. It is the most extensive ecological zone in Nigeria and covers nearly half of the country. The zone is characterized by a unimodal rainfall distribution. Average annual temperature is 27.3^{0}C and average precipitation is 1051.7mm respectively. The Northern Guinea Savanna (NGS) extends from regions in Kwara State in the North-West driving across portions of Sokoto, Kebbi and Zamfara States. The zone covers most of Niger and Kaduna States in the North Central, it also cuts across the southern parts of Kano and Jigawa States moving all the way to the North-Eastern States of Bauchi, Gombe and Borno States. The NGS is typically characterized by few short trees, and short grasses, it happens to be the most luxuriant of the savanna vegetation belts in Nigeria. The zone is also characterized by relatively moderate rainfall and long dry periods (Sowunmi and Akintola, 2010). The NGS is covered by vast swathes of Ferric and Gleyic Luvisols which have well developed structures contributing to high nutrient and water holding capacities. The unique soils of the NGS makes the area to be among the most productive areas for agricultural output in the country (Olaniyan and Ogunkunle, 2007)

The Sudan savanna (SS) zone is dominant in the northwestern part of the country. It stretches from the Sokoto plains in the west, through the northern sections of the central highland. The zone covers almost the entire northern states bordering the Niger Republic and covers over one-quarter of Nigeria's total area. The Sudan Savanna zone is characterized by low average annual rainfall (657.3mm), prolonged dry periods (7-9 months), few trees and short grasses. The zone is the most densely human populated in northern Nigeria and as a result, the vegetation has undergone severe destruction due to intensive cultivation of important economic crops such as cotton, millet, maize and rice. Animal husbandry, especially cattle rearing, is another source of land degradation in the region. The trees of the Sudan savanna include the acacia, the shea butter, baobab and the silk cotton (Sowunmi and Akintola, 2010). In the SS, the major soils are Arenosols with low water and nutrient holding capacities (Olaniyan and Ogunkunle, 2007).

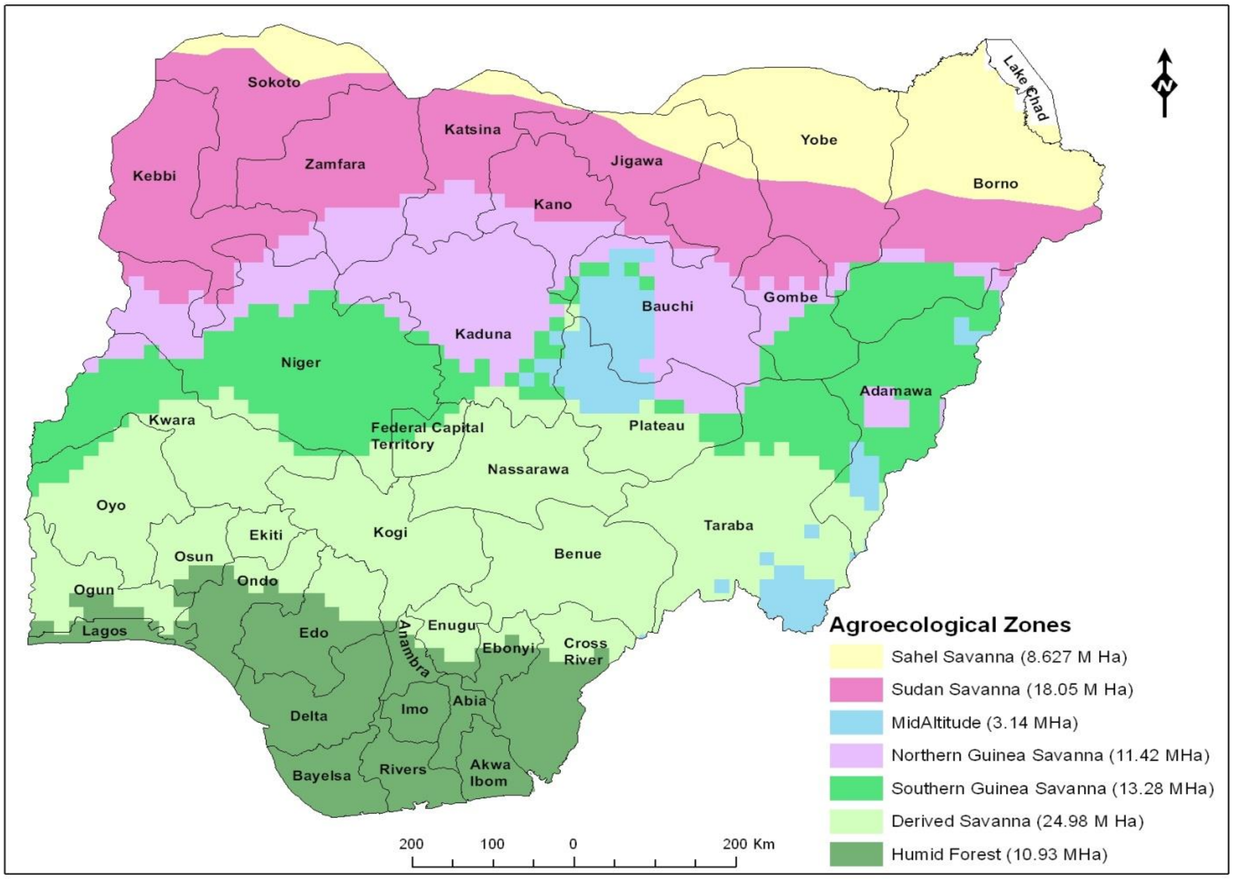


Figure 1-2: Map of Nigeria Showing Agro-climatic zones (Source: International Institute for Tropical Agriculture, IITA)

1.4 Problem Statement and Justification

The constraints to maize production in SSA in general and Nigeria in particular, can be broadly divided into biotic and abiotic constraints. The most common biotic stresses include maize streak virus; weeds (including parasitic weeds such as *Striga* and noxious weeds such as *Imperata cylindrica*); insect pests (stem borers; ear rot organisms and most recently the fall army worm); the gray leaf spot; downy mildew; and the maize lethal necrosis (MLN) (IPBO, 2015). Abiotic constraints are plentiful with respect to maize production in SSA and Nigeria, but the most important are low soil fertility and drought (Bello et al., 2018). The Savanna soils where maize production potential is highest, are low in fertility and have very limited soil organic matter. Most of the stresses often occur together giving rise to severe damages and huge yield and economic losses to the crop. A common example is how the adverse effects of *Striga* infestation is more severe under low nitrogen and drought conditions (Cairns et al., 2013).

Despite the large hectarage allocated to maize in Nigeria, it is still not the largest producer in Africa and is not among the top 10 highest producers in the world (IITA, 2018). For example, South Africa produced 20% of the maize output in Africa in 2018 from 2.6 million hectares, while Nigeria produced 14% of the maize output from 6.5 million hectares (United Nations, 2019). The average yield per hectare in the country is currently 1.8 Mg ha^{-1} although yields of 7.5 – 10 Mg ha^{-1} have been reported in research stations and best farmer fields (NAERLS and FDAE, 2017). This low per hectare yield of maize in Nigeria has been attributed to many reasons which encompass edaphic, climatic, economic, and social factors (Badu-Apraku et al., 2012b). The major factors limiting the yield of maize in Nigeria include the inherently poor soils (Jibrin et al., 2012), frequent droughts and striga infestations (Kamara et al., 2014), and low use of improved inputs such as fertilizers and seeds (Badu-Apraku et al., 2012b). A serious but often overlooked reason is the lack of proper adherence to improved agronomic practices especially with respect to varietal selection, appropriate planting dates and selection of optimum sowing densities (Shaibu et al., 2016).

Wrong selection of varieties is one of the most common yield-limiting practices in the Savannas of Nigeria. Farmers in the dryer areas with shorter rainfall tend to select varieties that mature late, this leads to decrease in yield as a result of end-of-season drought which occurs during the active grain filling stage of the crop. In the wetter areas, farmers also select varieties that mature early, and this means physiological maturity occurs during active rainfall, this always reduces yield as a result of diseases and other factors (Kamara et al., 2009). Research has shown a yield reduction risk from planting early varieties if season length was enough for later maturing varieties (Adnan et al., 2017a). In addition, sowing density is usually non-optimal in the Nigerian maize belts. Optimum stand density (OSD) selection is an important management practice for maize because yield is maximized at an optimum value (Hernández et al., 2014). OSD varies across environments, and there are arguments in the literature suggesting that recently cultivated varieties differ in their OSD even if planted in similar environments (Boomsma et al., 2009). Most farmers do not plant at the recommended density, some plant as low as 2.6 plants m^{-2} which leads to great yield reduction and fiercer weed competition (Kamara et al., 2006). Also, the recommended planting density has been contested because no consideration is made for varietal differences with respect to tolerance to crowding. Most farmers do not consider the soil type, weather conditions, and fertilizer rates when selecting sowing densities. This could be one of the reasons for the very low yields of even cultivars with high yield potentials.

1.5 Research Objectives

The overall concept and objective behind the present research are rooted in optimizing varietal selections specific to locations and variable management conditions in the Savannas of Northern Nigeria. Since such activity requires long-term exhaustive experiments across diverse locations and management conditions, field trials were complemented with the use of dynamic CSM in order to make recommendations across areas where the initial trials were not conducted (Mavromatis et al., 2001). To do this, the model must be calibrated and evaluated using data encompassing crop characteristics (Genotype Specific Parameters – GSPs), soil and weather conditions for the trial locations (Jones et al., 1986). Among all the data required for model calibration, estimation of GSPs is the most difficult aspect because it requires expensive and time-consuming field experiments. When a model is well calibrated, a model evaluation is needed to establish the accuracy of the model by comparing model simulated outputs with observed results from experiments that were not involved in the calibration process. It is expected that the well calibrated and evaluated model can then be used to provide different agronomic recommendations especially when long-term climatic weather is available to show variability and stability of the recommended decisions. To achieve the general objective, four specific research objectives (ROs) were set up as follows:

RO 1. Estimate Genotype Specific Parameters (GSPs) for maize varieties produced in Northern Guinea Savanna (NGS) and Sudan Savanna (SS) of Nigeria. The focus here is to optimize the sequential approach method used in the Genotype Coefficient Calculator (GENCALC) to generate GSPs of maize varieties used in the Nigerian Savannas.

RO 2. Evaluate differences between GSPs generated by using data from field measurements and yield evaluation trials. Here data from field experiments and from long term multilocational breeder evaluation trials are used to develop GSPs of 20 maize varieties using the optimized sequential approach. The accuracy of both GSPs are then compared.

RO 3. Evaluate the effect of varying planting densities of maize across the SS and NGS. Here different maize varieties are planted under varying sowing densities in farmer fields across the maize producing areas of Nigeria and the response to increasing density is evaluated.

RO 4. Conduct scenario analysis (biophysical, and economic) under varying soils, weather, and agronomic conditions in SS and NGS of Nigeria. Here long-term weather records are used to conduct scenario analysis for different management scenarios. First, the response of different maize varieties across different environments of the SS and NGS is conducted to evaluate the stability of each variety to the changing environments. The stability analysis is done using both observed and model simulated grain yields, the ability of CERES-Maize model to capture observed genotype by environment interaction (GEI) is evaluated. Second, different sowing density and Nitrogen (N) fertilizer scenarios are simulated and evaluated with a view to providing location and variety specific sowing density by N fertilizer recommendations.

1.6 Research Hypotheses

1. The sequential approach method, when optimized, can be used to generate accurate GSPs of maize using the GENCALC program of DSSAT.
2. GSPs generated by field trials lead to more accurate calibration of CERES-Maize model than GSPs generated from yield evaluation trials.
3. The planting density adopted for maize in Northern Guinea Savanna and Sudan Savanna of Nigeria is below the optimum
4. The CERES-Maize Model can be used as a tool to aid in identifying GEI and conduct of stability analysis of maize varieties across environments in the maize belts of northern Nigeria
5. The CERES-Maize Model can be used as a tool for optimization of planting density in the NGS and SS of Nigeria.

1.7 Description of trials and data collected for model calibration and on-farm sowing density evaluation

Four different sets of data were used in this research. Two sets of data were collected from detailed experiments that were I conducted as part of my PhD experiments and another two sets were collected from breeder evaluation experiments and from Nitrogen by Variety experiments conducted on station and used for model evaluation.

The first set of experiments (henceforth referred to as on-station experiments) were conducted in the dry (February to May) and rainy (June to October) seasons of 2016. The experiments were on-station trials set up specifically for collecting data to be used for calibrating the 26 maize varieties frequently grown in the Nigerian savannas. They were conducted at the Teaching and Research Farm of the Faculty of Agriculture, Bayero University, Kano (N11.516 E8.516 466m asl), at the Teaching and Research Farm of Audu Bako College of Agriculture Dambatta (N12.333 E8.517 442m asl), at the Irrigation Research Farm of Institute for Agricultural Research (IAR) Samaru, Zaria (N11.187 E7.147 702m asl) and at the Agricultural Research Station of the Kaduna Agricultural Development Project (KADP) in Saminaka, Lere (N10.52 E8.472 786 asl). The experiments were set up as randomized complete block design with the 26 varieties used as treatments and randomized three times. Data from these experiments are used in chapters 3, 4 and 6. More detailed description of the experiments are given in chapter 3.

The second set of experiments (henceforth referred to as on-farm experiments) were conducted in 60 farmer fields across the Sudan (SS) and Northern Guinea Savannas (NGS). These experiments were conducted in the rainy seasons of 2016 and 2017 in three local governments each of the SS and NGS. The experiments consisted of 10 varieties (adapted varieties to each agro-ecology) and three different sowing densities (2.6, 5.3 and 6.6 plants m^{-2}). The farmers selected were of different characteristics according to criteria put in place by the Sasakawa Africa Association (SSA) extension programs. Data from the on-farm experiments are used in chapters 5 and 6 and detailed description is provided in chapter 5.

The third data was collected from breeders at IITA (henceforth referred to as breeder experiments). The data was collected from on-station experiments conducted in seven locations across the SS and NGS for evaluation of varietal performance before they are released. Data from two years (2012 and 2013) were collected and used to calibrate GSPs of the maize varieties and compared with calibration done using data from the on-station experiments. These experiments were conducted by breeders at the IITA following standard breeder evaluation trial protocols and used in experiments presented in chapter 3 where detailed descriptions are also provided.

The fourth data (henceforth referred to as Nitrogen experiments) was collected from a four-year experiment conducted on station in Bayero University Kano during the rainy seasons of 2013 - 2016. The experiments were conducted using 10 maize varieties and four nitrogen rates (0, 60, 90 and 120 kg N ha^{-1}) to measure growth, yield, and nitrogen leaching under different nitrogen applications. The data from the nitrogen experiments were used for evaluating GSP calibrations conducted in chapter 3. Detailed description of the experiments and data sets are presented in chapter 3.

A total of 26 maize varieties were used in our experiments. Detailed descriptions of all the varieties and the chapters they are featured are shown in Table 1-3. Among the varieties, five were early, six were extra-early, six were intermediate and the remaining nine were late. With respect to varietal types, 14 were open pollinated (OPVs), while 12 were hybrids. The varieties used represents majority of the maize varieties that can be found in the seed markets in Nigeria and SSA.

Table 1-1: Overview and characteristics of maize varieties used in the experiments

S/N	Original Name	Common Name	Type	Maturity*	Characteristics	Chapter(s)
1	2011TZEWDTSTRSYN	Early White	OPV¶	Early	Drought/Striga	3 and 5
2	EVDT-W-99STR	SAMMAZ 32	OPV	Early	Drought	3, 4, 5 and 6
3	EVDT-Y-2000-STR	SAMMAZ 34	OPV	Early	Drought/Striga	3 and 5
4	TZEI24 x TZEI25	SAMMAZ 41	Hybrid	Early	Maize Streak Virus	3, 4, 5 and 6
5	TZECOMP3 DT C3	Narzo 22	OPV	Early	Drought/Rust/Blight	3 and 4
6	2013TZEEWPOPDTSTR	E.E White	OPV	Extra Early	Drought/Striga	3
8	2000TZEEWPOPDTSTR	SAMMAZ 54	OPV	Extra Early	Drought/Striga	3 and 5
9	99-TZEE-Y-STR	SAMMAZ 28	OPV	Extra Early	Drought/Striga	3 and 5
10	TZEEI29 x TZEEI21	Ife hybrid 5	Hybrid	Extra Early	Drought	3 and 5
11	TZEE-WPOPSTRC5 x TZEEEI6	Ife hybrid 6	Hybrid	Extra Early	Drought/Striga	3 and 5
12	TZEYPOPDTSTRC4 x TZEEI13	SAMMAZ 42	Hybrid	Extra Early	Drought/Striga	3
13	IWD-C2SYN	SAMMAZ 15	OPV	Intermediate	Drought/Striga	3, 4, 5 and 6
14	M1026-8	SAMMAZ 50	Hybrid	Intermediate	Drought/Striga	3
15	M0926-7	OBA SUPER 11	Hybrid	Intermediate	Drought/Striga	3
16	M1026-10	SC-651	Hybrid	Intermediate	Drought/Striga	3, 4, and 5
17	M1227-12	SC-680	Hybrid	Intermediate	Drought/Striga	3 and 5
18	M1124-31	SC-612	Hybrid	Intermediate	Drought/Striga	3
19	DTSTR-Y SYN2	Sammaz 40	OPV	Late	Striga	3 and 4
20	TZBSR	Narzo21	OPV	Late	MSV/Rust/Blight	3, 4, and 5
21	DTSTR-W SYN 13	SAMMAZ 41	OPV	Late	Striga	3, 4, 5 and 6
22	TZL Composite 4-SR	COMP 4	OPV	Late	Striga	3, 4 and 5
23	TZL COMP1-W	SAMMAZ 11	OPV	Late	Striga	3, 4 and 5
24	PH-6	OBA SUPER 9	Hybrid	Late	QPM#	3, 4, 5 and 6
25	M0926-8	SC-670	Hybrid	Late	Maize Streak Virus	3
26	PVA SYN 13	SAMMAZ 52	OPV	Late	Maize Streak Virus	3

*Extra-Early = 75-85, Early = 90-100, Intermediate = 100-120, Late = above 120. ¶OPV = Open Pollinated Variety, #QPM = Quality Protein Maize.

1.8 Dissertation Outline

This dissertation is written in seven chapters as outlined in Figure 1-2.

The first chapter provides a detailed introduction and evaluates maize production and its underlying problems both in the SSA region at large and Nigeria in particular. The chapter also made a brief introduction to CSMs and how they can be used to aid decision making. Justifications for the studies and research hypothesis are also outlined.

In chapter two detailed descriptions of GSPs, CERES-Maize model and the concept of minimum data sets are provided. Additionally, various methods used in estimating GSPs are discussed.

Chapter three focuses on optimizing methods for generating GSPs using different data sources thus combining research objectives one and two. The data from on-station experiments, the breeder experiments and Nitrogen experiments were used in this chapter.

Chapter four provides detailed outputs on how the calibrated and evaluated CERES-Maize model was used in identifying observed GEI and how long-term weather data were used to conduct stability analysis thereby matching varieties to various environments. This provides answers to some of the requirements of research objective four. For this chapter, data from the on-farm experiments from both SS and NGS were used.

In chapter five the response of different maturing maize varieties to elevated sowing densities across variable environments is evaluated thereby tackling research objective three. In this chapter, the on-farm experiments from the NGS were used.

In chapter six the model was used for optimizing sowing density by N fertilizer applications via scenario analysis. The model outputs were used to provide recommendations of optimum sowing density and N application rates for different varieties across the maize production zones of Northern Nigeria. In this chapter, data from the on-farm sowing density evaluation experiments from both SS and NGS were used

Chapter seven presents conclusions, recommendations and outlook.

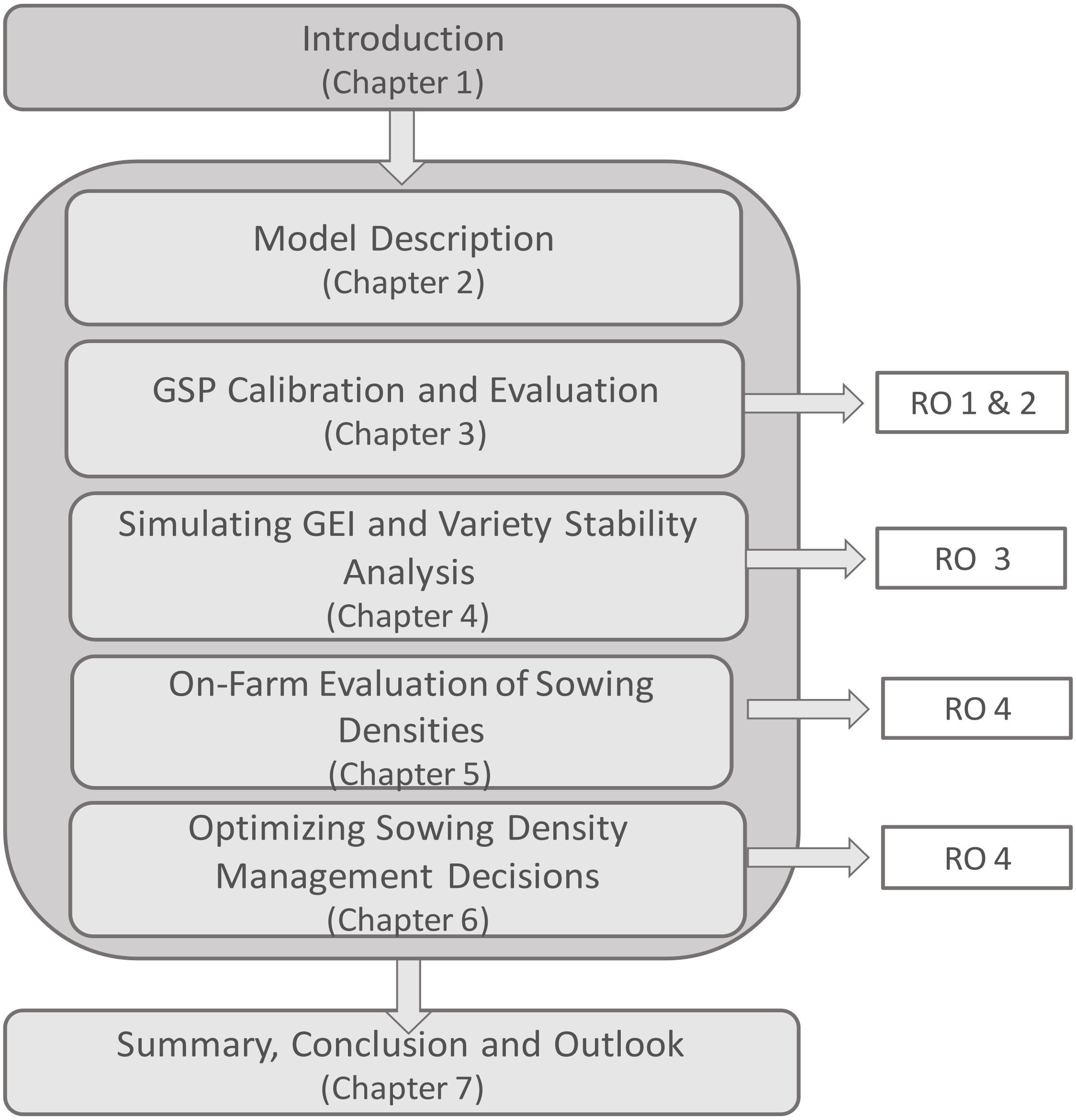


Figure 1-2: Dissertation structure showing research objectives (RO) and corresponding chapters.

2 CHAPTER TWO

CONCEPT OF GENOTYPE SPECIFIC PARAMETERS IN CERES MAIZE MODEL

2.1 Introduction

This chapter introduced crop models and presents a detailed description of the DSSAT-CSM, CERES-Maize model, and the concept of GSPs in the CERES-Maize model. Detailed descriptions of the DSSAT software, and the CERES-Maize model are given followed by a description of the GSP concept and how it is estimated. The different GSPs in CERES-Maize model are also described giving typical ranges of values recorded for the crop. Minimum data sets (MDS) needed for calibrating the CERES-Maize model (including data needed for estimating GSPs) are described in detail. Description of model calibration and evaluation exercises as well as statistics used in evaluating the quality of these exercises are presented.

2.2 Crop Models

It has long been established that in order to overcome the myriads of problems facing agriculture, novel crop management and improvement methods must be developed to increase on farm yields through improved agronomic management decisions. A very important requirement for this is the development of a dependable and reliable quantitative method for predicting the behavior of different crops and varieties in new and changing environments. A new mathematical approach emerged in the 20th century to address this need through development of crop simulation models (CSMs). CSMs are eco-physiological and process-based, incorporating the ability to predict the phenotypic expression of different crops (and varieties) in response to environment and management (Antle et al., 2017). Most of the models use differential equations to represent plant physiology (respiration, photosynthesis, assimilate partitioning, growth and development), chemical (soil chemical transformation and energy flows), physical (diffusion of molecules into cells and tissues) and other processes (Burke and Lobell, 2010). They are also non-linear and complex but still play a critical role in simulating and explaining the behavior of crop-soil-atmosphere system (Román-Paoli et al., 2000).

There are several different crop and soil simulation models available for modelling maize growth and development, such as the Agricultural Production Systems Simulator (APSIM) (Keating et al., 2003), the Cropping Systems Simulator (CropSyst) (Stöckle et al., 2003), the Erosion-Productivity Impact Calculator (EPIC) (Williams, 1995), the World Food Studies Model (WOFOST) (van Diepen et al., 1989), the FAO AquaCrop model (Steduto et al., 2009) and the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2010a). The DSSAT-CSM is a dynamic suite that incorporates different modules for soil, water, crop and management (Jones et al., 2010a).The DSSAT model was selected for this research due to its robustness, applicability and user friendliness and because it contains GSPs that describe how different varieties respond to environments. The DSSAT-CSM has been applied widely all over the world from providing real-time support for crop management (Thorp et al., 2008), to assessing the potential impact of climate change on global food security (Eitzinger et al., 2017). The major reason for selecting the model is that since most of the decisions simulated in our studies will be scaled out, it is best to use a model that can be easily incorporated into GIS and other spatial domains. The DSSAT-CSM was thus the obvious choice as many studies have shown how the model was successfully used for both location-specific and spatial applications (Kadiyala et al., 2015).

2.3 The Decision Support System for Agrotechnology Transfer - Cropping System Model (DSSAT-CSM)

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program that comprises of crop simulation models for over 42 crops as well as tools to facilitate effective use of the models (Hoogenboom et al., 2019). The software contains different tools for managing the crop models which include database management programs for soil, weather, crop management and experimental data. Other utilities and application programs include software for running sensitivity analysis, running evaluations/graphics and calculation of genetic coefficients (Jones et al., 2010b). The DSSAT software and its models have been used for a wide range of applications all over the world. Applications of the software includes on-farm management, precision agriculture, regional assessments of the impact of climate variability and climate change, gene-based modeling and breeding selection, water use, greenhouse gas emissions, and long-term sustainability through the soil organic carbon and nitrogen balances. DSSAT has been in used by more than 14,000 researchers, educators, consultants, extension agents, growers, and policy and decision makers in over 150 countries worldwide (Hoogenboom et al., 2019).

For the crop models in the DSSAT-CSM to run, daily weather data, soil surface and profile information, and detailed management information are provided as inputs. Figure 2-1 presents an illustration of the connection between the primary and secondary modules in DSSAT. The main program controls all the timings for the model, while the Land Unit module is used to control processing and data transfer between all primary modules. Information on crop genotypic characteristics are defined in a crop species file. The DSSAT software usually combines the crop management, soil and weather databases with the specific crop-simulation model and application programs to simulate user specified outputs. The DSSAT-CSM allows for computer integration of soil, crop characteristics, weather and management option and allows the user to create “what-if” scenarios virtually, thereby providing insights and answers into questions that could otherwise be answered only via laborious, costly and time-consuming experimentations.

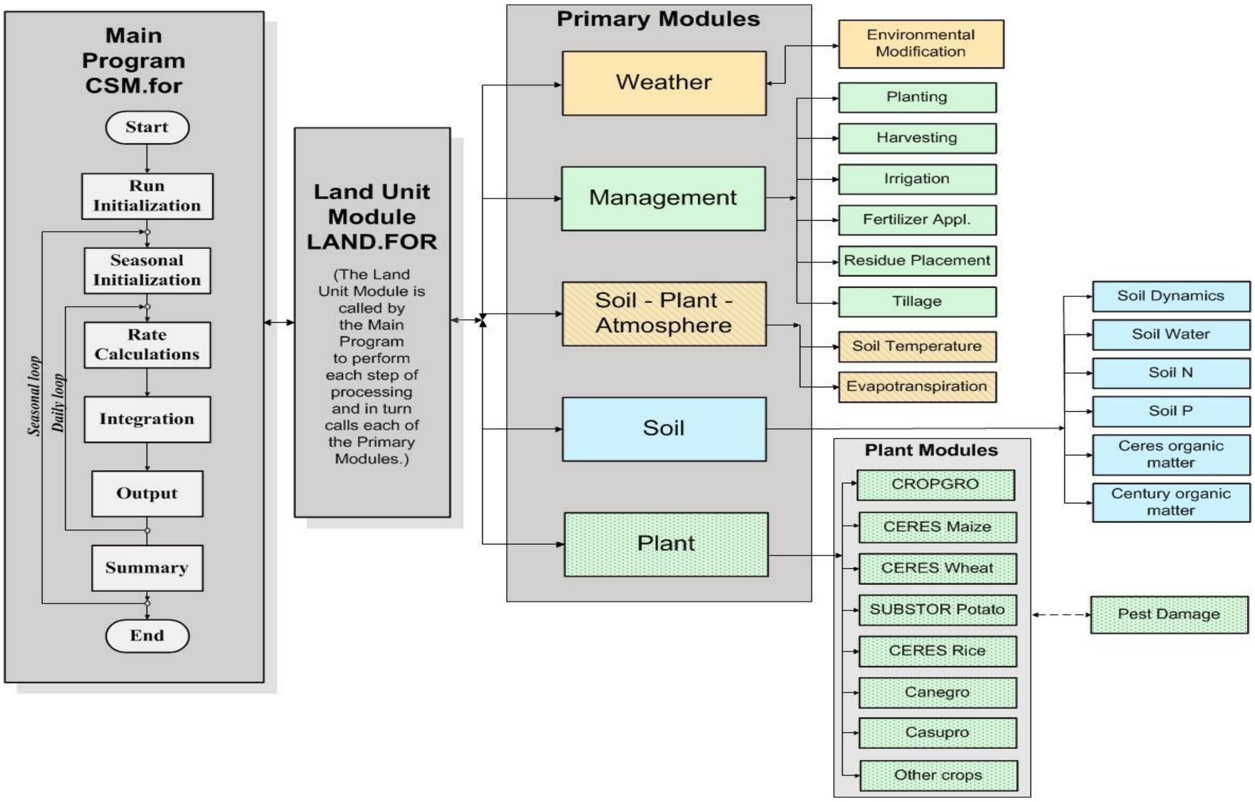


Figure 2-1: Components of the DSSAT-CSM version 4.6 showing data bases, applications, model, and support software

The DSSAT-CSM uses a modular approach where the different modules for crop, soil, and weather are integrated to produce an output following designs and criteria proposed by Acock and Reynolds, (1997). The DSSAT-CSM incorporates 41 crop models as plant modules using a single soil module and a single water module. The design and criteria were proposed in a way that the modules must be like real components or processes that are common to the plant. The modules should also represent separate disciplinary functions and the variables (input and output) should be measurable. The guidelines for operating the modular system in DSSAT were based on the approach of Kraalingen et al., (1995) which was adopted by Kenig et al., (1997). This approach entails that each model should:

- Read its own parameters;
- Initialize its own variables;
- Accept variables passed to it from other modules and the environment;
- Pass variables that are computed within the module;

- Own its set of state variables;
- Compute rates of change for its state variables;
- Integrate its state variables;
- Write its own variables as output; and
- Operate when linked to a dummy test program.

Thus, all data input, initialization of variables, rate calculations, integration calculations and output of data related to a specific function are handled within a single module. Modules can be run as a stand-alone model when linked to a main driver program.

A typical modular structure for running a simple Crop-Soil Water model is given as an example in Figure 2-2. The 'initialization' section is used to input data and initialize variables and is called once per simulation. The 'rate calculation' section computes process rates and rates of change of state variables based on conditions at the end of the previous day of simulation. This routine is called once per time step of simulation. The 'integration' section updates state variables using the rates previously calculated. The 'output' section is called once per day to generate daily output reports. The 'close' section is called once at the end of simulation to close output files and generate summary reports.

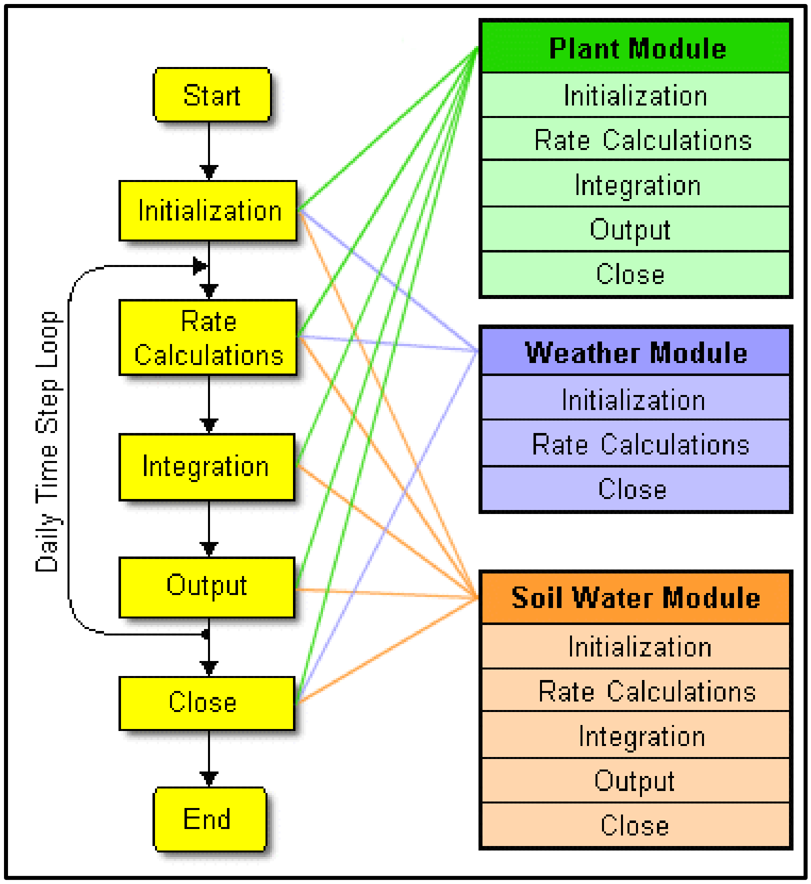


Figure 2-2: Illustration of a modular format used in a simple crop-soil-weather model

2.3.1 The DSSAT soil module

The soil module in DSSAT-CSM incorporates abilities to simulate soil water, inorganic and soil Nitrogen, Phosphorus and Potassium, and soil organic carbon. The module also includes greenhouse gas emission modules (denitrification, N and methane gas emissions), surface organic mulch and flood N dynamics. The soil inorganic N module computes plant nitrate and ammonium uptakes, monitors fertilizer and tillage events, calculates volatilization of ammonium to ammonia gas in the oxidation layer, and hydrolysis of urea to NH_4. It also simulates mineralization and immobilization due to organic matter decomposition, nitrification, denitrification, and movement of nitrate and urea with soil water drainage and flux. The phosphorus and potassium models simulate soil inorganic P balances via transformation of inorganic P pools, addition of P fertilizers, and measuring plant available P. The generic plant P module is currently only linked to the soybean, groundnut, rice and maize models. The DSSAT-

CSM contains two options for soil organic matter accumulation and decomposition, the CENTURY Model (Gijsman et al., 2002), and the Godwin soil organic matter model (Godwin and Singh, 1998). The soil water balance model uses a tipping bucket or cascading approach and requires three critical input; lower limit of soil water holding capacity (LL- permanent wilting point), drained upper limit (DUL – field capacity) and saturated soil water content (SAT) (Ritchie, 1998). All soil data information, profile characteristics and calculations are defined in the Soil Data tool (*SBuild*). *SBuild* allows users to add new soil profiles to the soil database or to edit soil profile information that is already in the system.

2.3.2 The DSSAT weather module

The weather data required to run the DSSAT-CSM includes daily minimum and maximum temperatures, daily values of incoming solar radiation, and daily total rainfall. When available, it is good to include dry and wet bulb temperatures and wind speed, which allow for simulating evapotranspiration with more robust methods. The length of weather records for evaluation must, at minimum, cover the duration of the experiment and preferably should begin a few weeks before planting and continue a few weeks after harvest so that "what-if" type analyses may be performed. The weather data in DSSAT is organized in the *Weatherman* utility software which is used to import and export weather data in DSSAT format, fill missing data, generate stochastic weather data, summarize and visualize weather data. The *Weatherman* utility also contains weather generators that generate daily weather variables for maximum and minimum temperature, solar radiation and precipitation. The generators (WGEN and SIMMETEO) require climate data as input, which must include at least 5 years of daily data.

2.3.3 The minimum data set required to run DSSAT-CSM

The minimum data set (MDS) refers to a minimum set of data required to run the crop models in DSSAT and to evaluate simulations and outputs. To run the DSSAT suite, input data required includes: site weather data for the duration of the growing season, site soil profile and soil surface data, crop management data from the experiments, observed experimental data from the experiments. Detailed general information for each module is listed below:

1. General site information
    - Latitude, longitude and elevation
2. Weather
    - Minimum and maximum temperature
    - Precipitation or rainfall
    - Total solar radiation or sunshine hours
    - Dew-point temperature or relative humidity
    - Average daily wind speed or daily wind run
3. Soil Data Required
    - Latitude, longitude and elevation
    - Soil taxonomy (if available)
    - Soil slope
    - Soil color
    - Stones (%)
    - Soil texture, including % sand, silt, and clay and stones, especially for the surface layers
    - Soil organic carbon
    - Bulk density is desirable
4. Initial Conditions
    - Previous field history
    - Initial soil moisture versus depth
    - Initial nutrients (NO_3^-, NH_4^-, P) by layer
    - Other soil chemical properties as needed for the experimental objectives
    - Surface residues at the start of simulation or at planting
    - Crop type or manure type
    - Total amount as dry weight
    - %N and %C (and %P) contents
    - Incorporation depth and % incorporation
5. Management Data
    - Crop and cultivar name and its characteristics.

- Date of planting
- Plant spacing or density

6. Input information

- Irrigation amount and the timing of the irrigation application
- Fertilizer amount and type, timing of the fertilizer application, placement depth and application method
- Amount of organic manure or residue, composition, time of the application, placement or incorporation depth and method of application
- Amount and type of chemicals applied and for what purposes
- N and P concentrations of grain and other plant components

7. General observations

- Weeds and weed management. It is important to document if the weeds affected the actual outcome of the experiment, such as yield and biomass
- Pests and disease occurrence, including the date of the infection intensity, and actual damage
- Damage due to extreme weather events, such as hail, rainstorms, wind gusts, etc.
- General health of the crop

2.4 CERES Maize Model

The CERES-Maize model (Jones et al., 1986) together with CSM-IXIM (Lizaso et al., 2011) are currently the two maize modules within the DSSAT- CSM suite. CERES-Maize model was selected and used for all the simulations in our studies. The model simulates crop growth, development, and yield of specific maize cultivars based on the effects of weather, soil characteristics and crop management practices. Apart from simulation of crop growth and development, the CERES-Maize model simulates water and nutrient dynamics in the soil and crop, so processes such as leaching, organic matter decomposition, and runoff are also considered. At the core of the CERES-Maize model, components of phenology, growth, soil water, and nitrogen balance enable the model to simulate crop yield, using the soil water and nitrogen dynamics to provide a limitation on yield (Ritchie et al., 1998).

Calibration of the CERES-Maize model involves provision of soil, weather and experimental information of the application sites. It is also critical to provide information on water, nitrogen, tillage and other initial conditions especially if the model is going to be applied under limited water and nutrient conditions. Calibration of crop growth entails first calibrating biomass which is then distributed across the growing periods. The genotype specific parameters (GSPs) which make up the phenology and yield components are also calibrated to match the observed data (Basso et al., 2016).

In the CERES-Maize model, potential growth is driven by photosynthetically active radiation and its interception. Light interception is computed as a function of leaf area index, plant population, and row spacing. The potential growth rate is determined by (2.1).

$$PG_{rate} = \frac{RUE \times PAR}{P_{density}} \left[1 - \exp(k \times LAI)\right] \times CO_2 \tag{2.1}$$

where *PGrate* is potential growth rate of maize biomass per day (g DM plant^{-1} d^{-1}), *PAR* is photosynthetically active radiation (MJ m^{-2} d^{-1}), *Pdensity* is plant population (plant m^{-2}), *k* is the (dimensionless) light extinction coefficient of the canopy, *LAI* is leaf area index, CO_2 is the Carbon dioxide modification factor. *RUE* is radiation use efficiency (g DM MJ^{-1} PAR) and it is defined as an input in the ecotype parameter file. *RUE* varies with temperature, vegetative N concentration, water stress, CO_2 levels and soil fertility.

Daily actual biomass growth rate is a function of the measured *PGrate* and it is constrained by temperatures (too high or too low), soil water deficits, nitrogen, phosphorus and potassium deficiencies, as calculated from (2.2)

$$CARBO = PG_{rate} \times \min(PRFT, SWAFC, NSTRES, PSTRES, KSTRES,) \times Soil_{factor} \tag{2.2}$$

where *CARBO* is daily plant growth (g DM plant^{-1} d^{-1}), *min* is a function that can return the minimum value, *PRFT* is temperature reduction factor, *SWAFC* is soil water stress factor, *NSTRES* is the nitrogen factor, *PSTRES* is the phosphorus factor, *KSTRES* is the potassium factor and *Soilfactor* is the soil fertility factor that accounts for both biotic and abiotic conditions not currently simulated by the model, and it is represented as a soil fertility coefficient (*SLPF*) in the soils file. All the reduction factors are a range of numbers between 0 and 1. Dry matter is usually partitioned to plant components as a function of growth stage. Leaf area is calculated by multiplying the simulated leaf mass with the specific leaf area (SLA).

2.4.1 CERES-Maize Model calibration and initialization

Models have been known to be "representations of reality", meaning that a scientific model always seeks to be representative of empirical objects, phenomena, and physical processes in a logical and objective way. Crop simulation models have been defined as "mathematical equations that represent the reactions that occur within the plant and the interactions between the plant and its environment". These models are highly complex as they seek to represent all components of a system and the interaction between individual components (Jones et al., 2017). When a model is to be used in regions that are different from their domain of development, it is necessary to calibrate the models by inputting parameters that will differentiate crop phenology, soil and weather parameters that differ between the region of development and region of adoption.

In CERES-Maize model, the major calibration activities involve the modification of some model parameters such that data simulated by the model fit the observed data. Model calibrations involves setting up experiments under optimal growing conditions of soil moisture, nutrients, and other biotic/abiotic stresses. Large amount of data is needed for detailed model calibrations, the data needed includes:

(i) Local weather and soil parameters which must be site-specific.
(ii) Management practices
(iii) Initial soil water conditions
(iv) Plant based measurements for estimation of GSPs (phenology, growth and yield: grain yield, yield determining parameters like cob weight and number, weight of reproductive parameters etc).

Our studies with the CERES-Maize model are the types that require elaborate calibrations meaning that data generated from growing maize in field experiments without nutrient and water limitations and without incidence of biotic and abiotic stresses are needed as inputs to generate GSPs. Also, all soil, weather, and management data must be available to provide initial conditions. Other set of data that are not used in the initial calibration process are also needed to evaluate the accuracy of the calibration process. Details of initialization of model runs including initial conditions, soil and species-based coefficients that were calibrated together with the GSPs in our various experiments are given in Table 2-1.

The coefficients RWMX (determines maximum water uptake per unit root length, cm^3 water/cm root) and RLWR (Root length to weight ratio, cm/g) were manually adjusted to capture the drought tolerance characteristics of the varieties that have been reported to be drought tolerant. For all the tolerant varieties, RWMX was set to 0.075 while for the non-tolerant varieties the default values in the specie file (0.03) was used. RLWR was set to 1 for the tolerant varieties and the default value (0.9) was used for the susceptible varieties.

Table 2-1: Description of additional coefficients calibrated and initialization of experiments during calibration of CERES-Maize model.

	Growth, Specie, Ecotype, and Soil coefficients optimized during calibration						
Experiment	Biomass	SLPF*	RUE	KCAN	PRFTC	RGFIL	Chapters
On-Station	Yes	default	Yes	Yes	Yes	Yes	3, 5, 6
Breeder	default	Yes	default	default	default	default	3
On-Farm	Yes	Yes	Yes	Yes	Yes	Yes	5,6
	Model initialization of experimental set up						
Experiment	Water	Nitrogen	Prev. crop	Tillage		Residue	Chapters
				Implement	Depth		
On Station							
BUK- DS[#]	FC[β]	Optimum[φ]	Cowpea	Disk plough	15 cm	Incorporated	3, 5, 6
BUK - RS	FC	Optimum	Maize	Disk plough	15 cm	Incorporated	3, 5, 6
DBT - DS	FC	Optimum	Sorghum	Disk plough	15 cm	Incorporated	3, 5, 6
DBT - RS	FC	Optimum	Maize	Disk plough	15 cm	Incorporated	3, 5, 6
LER - DS	FC	Optimum	Soybean	Disk plough	15 cm	Incorporated	3, 5, 6
LER - RS	FC	Optimum	Maize	Disk plough	15 cm	Incorporated	3, 5, 6
SMR - DS	FC	Optimum	Soybean	Disk plough	15 cm	Incorporated	3, 5, 6
SMR - RS	FC	Optimum	Maize	Disk plough	15 cm	Incorporated	3, 5, 6
Breeder							
Zaria 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Zaria 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Mokwa 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Mokwa 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Bagauda 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Bagauda 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Batsari 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Batsari 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Samaru 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Samaru 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Minjibir 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Minjibir 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Minjibir 2012	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3
Minjibir 2013	Observed	120 kg ha^{-1}	Maize	Disk plough	15 cm	Removed	3

*SLPF = Soil Fertility Factor, RUE = Radiation Use Efficiency Factor, KCAN = Light Extinction Coefficient, PRFTC = Temperature effect on photosynthesis, RGFIL = relative grain fill duration

[#]DS are dry season experiments, and RS are rainy season experiments

[β]FC = initial soil moisture content was set to field capacity

[φ] Nitrogen = Optimum means that N was not simulated, and it was assumed that there was no N-limitation

2.4.2 Genotype Specific Parameters (GSPs)

A genotype by environment interaction (GEI) is the change in relative performance of a character (e.g. yield) of two or more genotypes measured in multiple environments (Yan and Hunt, 2010). This interaction leads to variation in the performance of maize genotypes across different locations (Annicchiarico, 2002). It is usually difficult to distinguish between genotypic and phenotypic variation. Genotypic variation originates from differences in the genome of different varieties while phenotypic variation occurs when individuals are exposed to different environmental parameters. This variation makes recommendation of varieties across environments very difficult, and as a result breeders have to make costly and time consuming evaluation trials across multiple locations before varieties are released (Chapman et al., 2000).

Most crop models integrate genetic inputs, (e.g. the concept of GSPs in all DSSAT models). The presence of GSPs in a crop model provides the potentials for identifying where and when a given combination of alleles confers a positive or negative effect on plant performance (Messina et al., 2011). Many researchers (Chapman et al., 2000; Chapman et al., 2002b; Hammer et al., 2006; Yin et al., 2004) believe that the fastest way of reducing difficulties linked to high GEI is by simulating the yields of crops in large sets of environmental scenarios. Although most of the crop models currently in existence still lack the ability to explain all the complexities associated with variations among genotypes across different environments, they still provide very useful information for understanding mechanisms that determine crop yield in relation to the environment (Boote et al., 2001).

The major physiological processes (photosynthesis, respiration, accumulation and partitioning of assimilates) in the CERES-Maize model are governed by six genetic coefficients (Table 2-1) located in the maize cultivar file (Jones et al., 2010a). The six parameters are user adjustable and they determine growth, phenology, and yield of the cultivars. Growing degree days (GDD) or thermal time, drive the phenological phase of development in the CERES-Maize models. GDD is computed based on the daily maximum and minimum temperature.

$$GDD = \left[\sum_{i=1}^{n}\left(\frac{Tmax_i + Tmin_i}{2}\right) - Tbase\right] \quad (2.3)$$

Where Tmax = maximum temperature, Tmin = minimum temperature, Tbase = base temperature (temperature below which growth is terminated = 10°C in maize). GDD is cumulative and is measured in °C day^{-1}. Constraints are set in order to eliminate growth reduction caused by low or high temperatures. When Tmax or Tmin are below the Tbase, they are set equal to the Tbase, and when Tmax is above the optimum temperature for maize (Topt maize = 30°C), it is set equal to 30°C.

Table 2-2: Description of Maize Genetic Coefficients used in the DSSAT model

Coefficient	Description	Measurement	Range of values
P1 (°C days)	Thermal time from seedling emergence to the end of juvenile phase	Counting of number of days from emergence to tasselling and converting to degree days	130-380
P2 (days)	Delay in development for each hour that day-length is above 12.5 hours	Not measured because day-length does not change in Nigerian Savannas	0-2
P5 (°C days)	Thermal time from silking to time of physiological maturity	Counting of number of days from emergence to physiological maturity and converting to degree days	600-1,100
G2 (#)	Maximum kernel number per plant	Measuring number of kernels per cobs per plant	400-1,100
G3 (mg DM day^{-1})	Kernel growth rate during linear grain filling stage under optimum conditions	10 kernels were excised from the middle part of each ear and dissected into endosperm, embryo and pericarp, weighed separately for each component, and then dried periodically after start of grain filling.	4-11.5
PHINT (°C day tip^{-1})	Thermal time between successive leaf tip appearance	Measuring number of days to successive leaf tip appearance and converting to degree days	30-90

The coefficient P1 is the thermal time from seedling emergence to the end of the juvenile phase, it is the basic vegetative phase before photoperiod sensitivity and it is measured in degree-days, using base temperature of 10^{o}C. P2 is the day-length sensitivity coefficient [the days that development is delayed for each hour increase in photoperiod above the longest photoperiod (12.5h) at which development proceeds at maximum rate]. In the Nigerian Savannas day-length is usually unchanged all year and the varieties used are not sensitive to day-length, the coefficient is therefore not estimated. Together P1 and P2 determine the time taken to flowering.

The coefficient P5 is the grain filling duration (thermal time from silking to the time of physiological maturity) and it determines the length of time in which assimilates will be partitioned to the kernel. For most cultivars, grain filling continues for over 95% of the set grain filling duration. The coefficient PHINT determines the extent of the vegetative stage in the plant. In maize, the vegetative stage is explained by number of collar-leaves (e.g. V2 means vegetative stage 2 and signifies 2 collar leaves). PHINT also signals the end of vegetative and beginning of reproductive stages. G2 is the maximum number of kernels per plant, it determines the sink size and can be estimated by counting the number of kernels per cob (and per plant). G3 is the kernel filling rate under optimum conditions, it is usually measured in mg kernel^{-1} day^{-1}. The coefficients G2 and G3 are very sensitive and they are used to set grain yield for different varieties across environments and seasons. There is a strong linear response of varieties to kernel numbers and kernel growth rate (Boote et al., 2001).

The sequential approach method entails optimizing the different coefficients in stages instead of a blanket approach where all coefficients are optimized and estimated at the same time. The sequential approach used in our experiments starts with first optimization of GSPs that determine phenology in order to generate accurate values of the coefficients P1, P5 and PHINT. When the phenology parameters are accepted, then GSPs that determine yield (G2 and G3) are also estimated.

2.4.3 GSP Estimation methods

Several different methods have been used for optimizing parameters for both crop and eco-physiological models. The trial and error is surprisingly one of the most used approaches (Wallach et al., 2001), where model parameter values are tested manually until a match is found between predicted and observed data. The trial and error approach become highly inefficient as the number of model parameters increase. Because of this, numerous off the shelf automated optimization techniques have been used. Some of these includes:

- Simplex Method (Grimm et al., 1993): The downhill simplex method was used to estimate phenological parameters for soybean cultivars. The method minimized the error sum of squares between observed and simulated flowering dates. The authors compared many formulations of the development-rate model. A linear-plateau function for both night length and temperature effects helped in providing best fits and yielded the most consistent results.
- Simulated Annealing (Mavromatis et al., 2002; Thorp et al., 2008): Simulated annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. It is specifically a metaheuristic approach used in approximating global optimizations in a large search space for an optimization problem (Kirkpatrick et al., 1983). To derive GSPs of 10 common soybean cultivars in Georgia and North Carolina, (Mavromatis et al., 2002) used SA in a stepwise procedure and developed GSPs and compare simulated and observed grain yields across farms in Georgia and North Carolina.
- Uniform Covering by Probabilistic Region (UCPR) (Klepper and Hendrix, 1994; Román-Paoli et al., 2000): This method was initially recommended for general use in eco-physiological models by (Klepper and Hendrix, 1994) and later adopted for use in CERES-Maize model by (Román-Paoli et al., 2000). The method has an advantage over other popular methods because in addition to parameters estimates, a joint confidence region is provided for the parameters (Hendrix and Klepper, 2000). The confidence region may have an arbitrary shape; it need not be ellipsoidal, as is common with standard nonlinear regression methods.

- Particle Swarm Optimization (PSO) (Koduru et al., 2007): PSO is a fairly recent biologically inspired optimization method. Population of candidate solutions (particles) are usually maintained in PSO. Exploration of an initial search space is conducted by particles that can move around in the space in a manner like the movement of birds or fishes in swarms. Each particle has its own position (locations within the search space, i.e. candidate solutions) as well as velocity. The trajectory of each particle is guided through iterative velocity updates, by their individual memories (stored previous best positions) as well as by their interaction with other particles. Eventually, the particles converge to suitable optima (Clerc and Kennedy, 2002). To optimize parameter expression in a gene model, (Koduru et al., 2007) compared the PSO and UCPR to find the best prediction of confidence regions.
- Generalized Likelihood Uncertainty Estimation (GLUE) (He et al., 2010): The generalized likelihood uncertainty estimation (GLUE) method is a Bayesian Monte Carlo parameter estimation technique that makes use of a likelihood function to measure the closeness-of-fit of modeled and observed data. It was used by He et al., (2010) to estimate GSPs of maize in Northern Florida.
- Genotype Coefficient Calculator (GENCALC) (Hunt et al., 1993): GENCALC is a software package that facilitates the calculation of GSPs for use in existing crop models. The software uses a gradient search technique (Pabico et al., 1999). It is incorporated in the DSSAT suite and was used in our study. The method of estimation used by GENCALC starts by selecting the initial values (default) for each cultivar coefficient. The difference between the simulated and observed target variables are stored in the model output file. The coefficient is optimized when the algorithm searches the output file and either increases or decreases the value of the coefficient. GENCALC makes the searches based on the order and set-up adopted by the user. When a good fit is found, the software averages the coefficients for all trials included in the optimization set-up and then calculates the root mean square error (RMSE). The RMSE is calculated from model prediction and field observation of the variables listed in the third column of Table 2-1. For every new candidate parameter, the same process is repeated by the user. The error

is reduced in GENCALC via the interactive procedure, where the cultivar coefficient step is changed by the user. At the end of the search, parameters providing the lowest RMSE for a single target trait will be accepted. For multiple target traits, the parameter with the lowest average normalized root means square error (nRMSE) will be accepted.

We selected the GENCALC in our study because it is the most widely used method of GSP parameter estimation and optimization, numerous researches have used it in estimating GSPs for groundnut (Anothai et al., 2008a), soybean (Salmerón et al., 2017), rice (Buddhaboon et al., 2018), wheat (Ibrahim et al., 2016) and maize (du Toit, 2002). Also, the method requires lower amount of computing time and unlike the GLUE method, it is not very complex.

2.4.4 Model Evaluation

A lot of times, even if a model is based on observed data, simulated values could deviate from the observed values and minor adjustments must be made. The deviation of observed values could be due to sampling errors or partial knowledge of the system. It is thus important that the performance of the calibrated model be tested with observed data.

Model evaluation (sometimes erroneously referred to as model validation) is the process of confirming the outputs of a calibrated model to establish how close the predictions are to reality. The model evaluation procedure involves making comparisons between model predicted outputs and real-time observations. Usually when evaluating models, the observed data used for comparisons should not have been used in previous calibration exercises. The procedures and methodologies involved in evaluating crop simulation models are still rudimentary. This is because in the models, many complex hypotheses are tested at the same time. Additionally, because crop models are representing complex biological processes, the complication of some components are not fully understood and therefore not fully explained by the model. Evaluation of crop models is made more difficult because most model parameters are site-specific and need to be very precise. Plant, soil and weather measurements are rarely precise and sometimes measurements may be made from nearby locations not the exact points of simulations. Sampling errors may also add to the errors in observed measurements thereby making the evaluations less accurate.

According to Loague and Green, (1991) “A model is a good representation of reality only if it can be used to predict, within a calibrated and evaluated range, an observable phenomenon with acceptable accuracy and precision”. Model performance is thus compared by adopting a series of statistical evaluators. Statistics used in our experiments are detailed in Box 2.1.

Box 2.1: Model Evaluation Statistics

The following statistics were used for model evaluation in this research:

(i) The root means square index (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n}} \quad (2.4)$$

(ii) The normalized root means square index (nRMSE, %) (Loague and Green, 1991):

$$RMSEn = \frac{RMSE \times 100}{\overline{m}} \quad (2.5)$$

(iii) The index of agreement (d index) (Willmott and Willmott, 1982):

$$d = 1 - \frac{\sum_{i=1}^{n}(m_i - S_i)^2}{\sum_{i=1}^{n}(|S_i| + |m_i|)^2} \quad (2.6)$$

(iv) The modified index of agreement (modified d) (Pereira et al., 2018):

$$d\ mod. = 1 - \frac{\sum_{i=1}^{n}|m_i - S_i|}{\sum_{i=1}^{n}(|S_i| + |m_i|)^2} \quad (2.7)$$

(v) The modelling efficiency (EF) (Loague and Green, 1991)

$$EF = \frac{\sum_{i=1}^{n}(m_i - \overline{m})^2 - \sum_{i=1}^{n}(S_i - \overline{m})^2}{\sum_{i=1}^{n}(m_i - \overline{m})^2} \quad (2.8)$$

Where *n* is the number of observations, S_i is the simulated data, m_i is the measured data, and $\overline{m}$ is the mean of the measured data.

The performance of a model is assumed to be better when d index and modified d index are close to 1, and when nRMSE approach zero. Following Jamieson et al. (1991), model performance can be classified based on nRMSE values as excellent (nRMSE < 10%), good (10% < nRMSE < 20%), fair (20% < nRMSE < 30%) and poor (nRMSE > 30%). EF has no dimension and an EF = 1 corresponds to a perfect match between observed and simulated data. When EF < 0, the simulated values are worse than simply using observed mean.

3 CHAPTER THREE

OPTIONS FOR CALIBRATING CERES MAIZE GSPs UNDER DATA SCARCE ENVIRONMENT

This chapter is based on:

Adnan AA, Diels J, Jibrin JM, Kamara AY, Craufurd P, Shaibu AS, et al. (2019) Options for calibrating CERES-maize genotype specific parameters under data-scarce environments. PLoSONE 14(2): e0200118. https://doi.org/10.1371/journal.pone.0200118

3.1 Introduction

Maize has become an important crop in Nigeria in the past decades due to its importance as food for human consumption; feed for animals and as a source of industrial raw material (Badu-Apraku et al., 2009). Despite its importance, yield of maize has remained quite low in the Savannas mostly due to biotic and abiotic constraints (FAO, 2018). In recent years, new early and extra early maturing maize varieties that are tolerant to most of the biotic and abiotic constraints have been developed for the Nigerian Savannas by the International Institute for Tropical Agriculture (IITA) and its partners. Several agronomic technologies have also been developed to increase the productivity of these varieties with a view to enhancing maize productivity. Before the varieties are released, they are usually grown under multi-locational yield and crop management evaluation trials over several years. Dissemination of such varieties and technologies will require setting up of costly and time-consuming experiments across wide areas. This is needed to adequately evaluate the Genotype × Environment interaction which demonstrates the performance of each variety across diverse environments. Unless this is done, breeders cannot conclusively recommend genotypes for specific environments.

Crop simulation modeling offers an opportunity to explore the potential of new varieties and crop management practices in different environments (soil, climate, management) prior to their release (MacCarthy et al., 2017). Recently, use of crop simulation models, particularly DSSAT, is on the increase in Africa through initiatives such as the Agricultural Models Inter-Comparison Project (AgMIP) (Zinyengere et al., 2015). In West Africa, the CERES-Maize model has been recently used by (MacCarthy et al., 2017) to evaluate climate-sensitive farm management practices in the Northern Regions of Ghana. In Nigeria (Adnan et al., 2017) used the same model to determine the nitrogen fertilization requirements of early maturing maize. CERES-Maize model was also used to identify potential zones for maize production in Nigeria by (Iyanda et al., 2014). One of the major requirements for the use of crop simulations is calibration of Genotype Specific Parameters (GSPs). GSPs are sets of parameters that enable crop models to simulate the performance of diverse genotypes under varying soil, weather and management conditions (IBSNAT, 1994). Like all other parameters in crop simulation models, the GSPs must have a physical or biological meaning (Román-Paoli et al., 2000). Measuring GSPs directly from real systems (farm and field level) is very complex and impractical, and results in highly inaccurate and uncertain values of estimated variables (Jones et al., 1986; Ogoshi et al., 1999). Direct measurement requires setting up of field or growth chamber studies, collection of many samples, and exposure to different photoperiods where necessary. The most common method for deriving GSPs is from field experiments designed specifically for their estimation (du Toit, 2002; Suriharn et al., 2007). This process is quite expensive, time consuming and requires regular sampling of growth, phenology and yield data for each variety following a set of minimum dataset rules (IBSNAT, 1994). Since the movement of models from research and policy to adoption by farmers and extension, the need for rapid estimation of GSPs for newly released varieties has become more urgent (Welch et al., 2002). Several concerns have been raised even in locations where abundant and high-quality data for calibration of GSPs for model uses are available. In a recent publication, Seidel et al. (2018) presented various methods for improving the current methods of calibrating crop models.

Since most models have been developed elsewhere in Europe and USA, their use outside their domain of development requires a great deal of data for their calibration and evaluation. Several approaches for estimating GSPs have been documented. The genetic coefficient calculator (GENCALC) was used by (Anothai et al., 2008a) to determine variety coefficients for new peanut lines in Thailand from standard varietal trials. From their experiments, they were able to successfully calibrate groundnut GSPs using a set of field experiments and yield evaluation experiments using the GENCALC software. GSPs of soybean from crop performance trials were successfully generated in Georgia, USA by (Mavromatis et al., 1998). In Florida, (Bannayan and Hoogenboom, 2009) employed a pattern recognition technique, which is based on similarity measures, to estimate GSPs for maize. In their experiments, pattern recognition was used as an alternative to GENCALC and GLUE in estimation of maize GSPs. GLUE method was used by (He et al., 2010) to successfully estimate maize GSPs in North Carolina. In the soybean belt of the USA, Welch et al. (2002) used data from private-sector variety performance trials to develop soybean GSPs. GSPs of deep water rice were generated using GENCALC and GLUE by (Buddhaboon et al. 2018). Most recently Lamsal et al. (2017) used the independent component analysis (ICA) and separate factor approaches to estimate soybean GSPs from large breeding trial datasets in the USA.

With a growing number of researchers using the DSSAT model in the Savannas of Africa, there is need to evaluate the GSP calibration step as it is the aspect that requires the greatest amount of data and expertise. Calibration of GSPs can also be done using secondary data from breeders who routinely conduct multi-location trials. Such datasets are available in Africa where strong breeding programs are present. Because the conventional method of calibrating GSPs is quite expensive and laborious, there is need to utilize secondary breeder trial data for calibrating maize GSPs and to evaluate the accuracy of this approach by comparing it with calibrations done using detailed calibration experiments. The present research compares data generated from conventional experiments and from breeder evaluation trials. This is done to justify the claim that available data from breeder evaluation experiments can potentially be used for generating maize GSPs when setting up conventional experiments is unfeasible.

The objectives of this research were: i) to determine GSPs of 10 newly released open pollinated (OPV) and hybrid maize varieties for the Nigerian Savannas using data from both field experiments specifically designed for this purpose (on-station experiments) and by using data from breeder varietal evaluation trials (breeder experiments); ii) to compare the accuracy of the GSPs generated using calibration and breeder data; and iii) to evaluate the ability of the GSPs calibrated using the 2 methods to simulate grain yield and tissue/grain nitrogen contents of maize.

3.2 Methodology

3.2.1 Field Experiments

Three sets of data were used in this study: on-station experiments, breeder evaluation experiments and nitrogen experiments.

The first set of data used for the model calibration was collected from experiments conducted during the rainy and dry seasons of 2016 across four locations in northern Nigeria. The experiments were conducted at the Teaching and Research Farm of the Faculty of Agriculture, Bayero University, Kano (N11.516 E8.516 466m asl), at the Teaching and Research Farm of Audu Bako College of Agriculture Dambatta (N12.333 E8.517 442m asl), at the Irrigation Research Farm of Institute for Agricultural Research (IAR) Samaru, Zaria (N11.187 E7.147 702m asl) and at the Agricultural Research Station of the Kaduna Agricultural Development Project (KADP) in Saminaka, Lere (N10.52 E8.472 786 asl). Eight experiments were used for the calibration spanning over four locations, two seasons and eight planting dates (Table 3-1). The calibration experiments were conducted near irrigation facilities to maintain optimum moisture by irrigating when the soil moisture is below field capacity. Moisture conditions were monitored using a Time Domain Reflectometry (TDR) Meter 6050X1 TRASE SYSTEM (Soilmoisture Equipment Corp.). Recommended levels of mineral fertilizers for the region were applied (120N:60P_2O_5:60$K_2$0 kg ha^{-1}). Potassium (K) was applied in form of Muriate of Potash, phosphorus (P) in the form of Single Super Phosphate, and Nitrogen was applied in the form of Urea. While all the P and K fertilizers were applied at sowing; only half of the N fertilizer was applied at the time of sowing and the other half applied 21 days later. In addition, poultry manure (approximately NPK 1.1:0.8:0.5) was added to the fields at the rate of 5 Mg ha^{-1} to maintain optimum nutrient status. The calibration experiments were laid down in a Randomized Complete Block Design (RCBD) with four replications. The gross plot consisted of six ridges, 0.75 m apart and 3 m long (plot area =13.5 m^2). The two innermost ridges were used as the net plot for yield assessment and for sampling purposes. A space of 0.5 m was used between plots and 1m between replications. The experimental fields were cleared, harrowed, ridged and thereafter sprayed with a pre-emergence herbicide, Primextra (Atrazine + Metolachlor) at the rate of 4 liters ha^{-1} before planting. The maize was sown at intra-row spacing of 0.25m at two seeds per hole, and later thinned to one plant giving a population of 53, 333 plants ha^{-1}.

Table 3-1: Description of sites for on-station calibration experiments

Site and Environment	Code	Sowing Date	Ecology*	Dominant Soil Type	Cumulative Rainfall + Irrigation (mm)
Bayero Uni. Farm Dry Season	BUK DS	16-03-2016	SS	Typic Kandiustalf	843
Bayero Uni. Farm Dry Season	BUK RS	25-07-2016	SS	Typic Kandiustalf	705
Dambatta Dry Season	DBT DS	19-03-2016	SS	Typic Kanhaplustalf	976
Dambatta Rainy Season	DBT RS	26-07-2016	SS	Typic Kanhaplustalf	690
Samaru Dry Season	SMR DS	22-03-2016	NGS	Plinthic Haplustult	840
Samaru Rainy Season	SMR RS	29-07-2016	NGS	Plinthic Haplustult	850
Lere Dry Season	LER DS	17-03-2016	NGS	Plinthic Kandihumult	964
Lere Rainy Season	LER RS	31-07-2016	NGS	Plinthic Kandihumult	1054

SS = Sudan Savanna, NGS = Northern Guinea Savanna

For calibration using data from breeder experiments, we collected long-term yield evaluation data from breeders at the International Institute for Tropical Agriculture (IITA), Ibadan. Data for the 10 maize varieties used in this study were selected. The bulk data was subjected to various quality checks. We used data for the 2012 and 2013 seasons from seven locations where weather and soil data were available. Table 3-2 shows the locations and data used in the calibration with breeder experiment. For the breeder experiments, experimental units are one-row plots, each 4 m long with inter-row spacing of 0.75 m and intra-row spacing of 0.40 m. Three seeds were planted and later thinned to two per hill at 2 weeks after emergence to give a final plant population density of about 66,666 plants ha^{-1}. Fertilizer is usually applied at the rate of 60 kg ha^{-1} of NPK 15:15:15 at 2 WAP. An additional 60 kg ha^{-1} N using urea is top dressed at 5 WAP. The trials are kept weed free by applying atrazine (1-chloro-3-ethylamino-5-isopropylamino-2,4,6-triazine) and gramoxone (1,1-dimethyl-4,4-bipyridinium dichloride) as pre- and post-emergence herbicides at 5 L in 220 L of water ha^{-1} and subsequently by hoeing. Grain yield is calculated based on 80% (800 grain kg^{-1} ear weight) shelling percentage and adjusted to 150 g kg^{-1} moisture content.

Table 3-2: Description of sites for breeder experiments

Site and year	Code	Sowing Date	Ecology*	Dominant Soil Type	Rainfall (mm)*
Zaria 2012	ZRA 12	12-06-2012	NGS	Typic Kandiustalf	1123
Zaria 2013	ZRA 13	10-06-2013	NGS	Typic Kandiustalf	1222
Mokwa 2012	MKW 12	08-06-2012	SGS	Oxic Haplustult	1346
Mokwa 2013	MKW 13	28-05-2013	SGS	Oxic Haplustult	1402
Bagauda 2012	BGD 12	13-06-2012	SS	Typic Kandiustalf	882
Bagauda 2013	BGD 13	21-06-2013	SS	Typic Kandiustalf	941
Batsari 2012	BTR 12	22-06-2012	SS	Ustoxic Dystropept	806
Batsari 2013	BTR 13	21-06-2013	SS	Ustoxic Dystropept	854
Samaru 2012	SMR 12	11-06-2012	NGS	Typic Plinthiustalfs	1118
Samaru 2013	SMR 13	14-06-2013	NGS	Typic Plinthiustalfs	1241
Minjibir 2012	MJB 12	21-06-2012	SS	Typic Kandiustalfs	791
Minjibir 2013	MJB 13	18-06-2013	SS	Typic Kandiustalfs	824
Kadawa 2012	KDW 12	23-06-2012	SS	Typic Plinthiustalfs	891
Kadawa 2013	KDW 13	19-06-2013	SS	Typic Plinthiustalfs	913

* Rainfall is total for growing period

For model evaluation, data was collected from field experiments (nitrogen experiments) conducted at the Research Farm (11°59'N, 8°25'E 466m above sea level) of the Faculty of Agriculture, Bayero University, Kano in the rainy seasons between 2013 to 2016 (Table 3-3). The treatments consisted of three rates of nitrogen (0, 60 and 120 kg N ha^{-1}) and ten maize varieties used in the calibration experiments. Treatments were laid out in a split-plot design with three replications. Nitrogen rates were assigned to the main plots while the varieties were assigned to the sub-plot. Although the experiments were conducted in the rainy season, moisture contents were monitored, and supplementary irrigation was provided to ensure no moisture stress. The data collected for model evaluation includes grain yield (Mg ha^{-1}), total grain nitrogen (kg ha^{-1}), total tissue nitrogen (kg ha^{-1}) and nitrogen harvest index (percentage). Total grain and tissue nitrogen were determined using the Micro Kjeldahl method.

Table 3-3: Description of sites for nitrogen experiments

Site and year	Code	Sowing Date	Ecology*	Dominant Soil Type	Rainfall (mm)*
BUK 2013	BUK 13	10-06-2013	SS	Typic Kandiustalfs	892
BUK 2014	BUK 14	21-06-2014	SS	Typic Kandiustalfs	967
BUK 2015	BUK 15	29-05-2015	SS	Typic Kandiustalfs	1021
BUK 2016	BUK 16	09-06-2016	SS	Typic Kandiustalfs	972

* Rainfall is total for growing period

3.2.2 Plant Measurements

Evaluation of crop development was done by observing the phenology of the different maize varieties and recording the length of time (days) it takes to attain each phenological phase. The measurements were then converted to growing degree days (GDD) using a base temperature of 8^{o}C. Ten plants were tagged from the center of each plot in each replication for phenological observations. The end of the juvenile stage (i.e. panicle initiation) was determined through destructive sampling and dissection of three plants, followed by observation of apical meristem to check for floral bud development at 2 d intervals starting from 14d after emergence. The end of juvenile stage was recorded when the male flower primordial were visible in 50% of plants examined. Days to 50% tasseling was recorded when tassels were observed on 50% of the tagged plants. Physiological maturity observations were conducted as follows: kernels were removed from the base, middle and distal end of each sampled ear daily, starting when husks begin to show signs of drying. Days to physiological maturity was recorded when 50% of the kernels in each tagged ear had formed a black layer, indicating physiological maturity.

Plant biomass was taken at four different stages: vegetative, anthesis, grain filling and physiological maturity. Five plants within a one-meter strip in a row were cut at the ground level as suggested by Ogoshi et al. (1999). Leaves were separated from the stem, chopped and dried in the shade for three days. Both stems and leaves were oven dried at 70˚C for 36 - 48 hours until the sample had attained constant weight. Yield and yield component measurements were taken at harvest maturity. Plant height was measured from five randomly tagged plants within the net plot using a standard field meter rule. Other variables measured included: the number of seeds per unit area (seed # m^{-2}), dry seed weight (g m^{-2}), dry cob weight (g m^{-2}), dry husks weight (g m^{-2}), grain yield (kg ha^{-1}) and stover weight at harvest (kg ha^{-1}). Total grain and tissue nitrogen (measured for the evaluation experiments only) were determined using the Micro – Kjeldahl method.

3.2.3 Soil and weather data

Detailed soil studies were conducted for each experimental location before planting. Soil pits were dug in each location, and soil samples were taken from each layer. The collected samples were then analyzed for pH, texture, moisture, bulk density, exchangeable potassium (K), organic matter, phosphorus (P), total nitrogen and CEC. For the detailed calibration and evaluation experiments, daily weather data were collected from weather stations (Watchdog 2000 Series, Spectrum Technologies) adjacent to all experimental sites. All weather stations were less than 5 km away from the experimental sites. Detailed results of soil analysis from each profile is provided in appendix 1.

3.2.4 Initialization of soil and weather parameters

Daily records of minimum and maximum temperature, total solar radiation, and total rainfall are required for the CERES-Maize model weather initialization. The *Weatherman* utility in DSSAT was used to input the weather data to create the weather file used by the CERES- Maize model. The *Weatherman* utility also requires information on name of weather station, latitude, longitude and altitude. Soil data tool (*SBuild*) was used to create the soil database which was used for the general simulation purposes. Name of the country, name of experimental site, site code, site coordinates, soil series and classification were among the data entered in this utility. Initial soil water was set to field capacity for all locations for the calibration experiments, while for the breeder evaluation this condition was not set, leaving the inputted moisture properties of the soils in each location. Measured soil characteristics taken from each profile were used to calculate the soil physical and chemical parameters that are needed to run the model. For calibration experiments, we assumed that N was not limiting while for the breeder evaluation nitrogen was simulated although N stress was not recorded in any of the locations. For the evaluation experiments however, Nitrogen was simulated, and application was done according to treatments. For other simulation options, initial conditions were as reported for each year and location, the Priestly-Taylor/Ritchie method was selected for simulation of evapotranspiration while the Soil Conservation Service (SCS) method was selected for simulation of infiltration. Photosynthesis was simulated using the radiation use efficiency method, while hydrology and soil evaporation were simulated using the Ritchie Water Balance and Suleiman-Ritchie methods respectively. Phosphorus and Potassium were not simulated in all trials and locations.

3.2.5 Estimating genotype specific parameters

The GENCALC program of the DSSAT (Version 4.6) was used to calibrate the GSPs of the maize varieties (See Table 2-1). All the candidate genetic coefficients were selected and calculated using GENCALC except P2 because all the varieties used were day-neutral. Conventionally day-neutral varieties should have constant P2 value, ideally the value should be zero which means that the variety does not generate delays when photoperiods exceed 12.5 hours. In our calibration procedure, a small positive number (0.01) was used as P2 for all varieties so that computer arithmetic problems like division by zero are prevented.

The varieties used in the trials were representative of all the maturity groups, i.e. extra early to late maturity. The default values in DSSAT were therefore used as initial coefficients for the extra-early, early and late maturity classes. Coefficients for each variety are then varied, relative to each simulated and observed measurement. The model algorithm then searches the output file and uses the difference between simulated and observed variables to decide whether to increase or decrease the value of the coefficient that is being estimated. When GENCALC finds a good fit for each observation, it averages the coefficients and calculates the root mean square error (RMSE) (Wallach and Goffinet, 1989). According to each genetic parameter, the process is repeated until the best fit is selected. An interactive procedure is used by GENCALC where the user changes the variety coefficient step to minimize the errors and speed-up the convergence of the algorithm. The search finishes when the user accepts the parameters providing the lowest RMSE for a single target trait.

For calibration of maize genotypes using the data from the on-station experiments, four variables connected to four out of the six coefficients were directly measured (P1, P5, G2 and PHINT), while P2 was not estimated because all the varieties used in the experiments were day-neutral. G3 of the initial genotypes were first selected and later adjusted using a set of truncated rules in the *GENCALC2.rul* file until a good fit is observed. For calibration using data from the breeder experiments, five out of the six coefficients (except P2) were estimated following an optimization procedure (Fig 3-1) similar to that used by Anothai et al. (2008a). This approach has not been reported for maize, especially in Sub-Saharan Africa. At each step of the calibration process in GENCALC, measured number of days from emergence to flowering was compared with days to anthesis (ADAP), measured number of days from emergence to physiological maturity was compared to days to physiological maturity (MDAP), measured grain yield at harvest was compared with harvest weight at maturity (HWAM), measured overall biomass at maturity was compared with tops weight at maturity (CWAM), measured maximum leaf area index was compared with maximum leaf area index (LAIX), while measured harvest index was compared with harvest index at maturity (HIAM). The generated coefficients were then used to run sensitivity analysis, using various iterations (not less than 6000 for each coefficient) to confirm the accuracy of the sequential approach. The adjustment for each target coefficient was done while all other non-target coefficients were kept constant. Despite the sensitivity analysis conducted, there is a possibility that pathologies associated with staged optimizations like GENCALC will occur thereby influencing the goodness of fit (Welch et al., 2001).

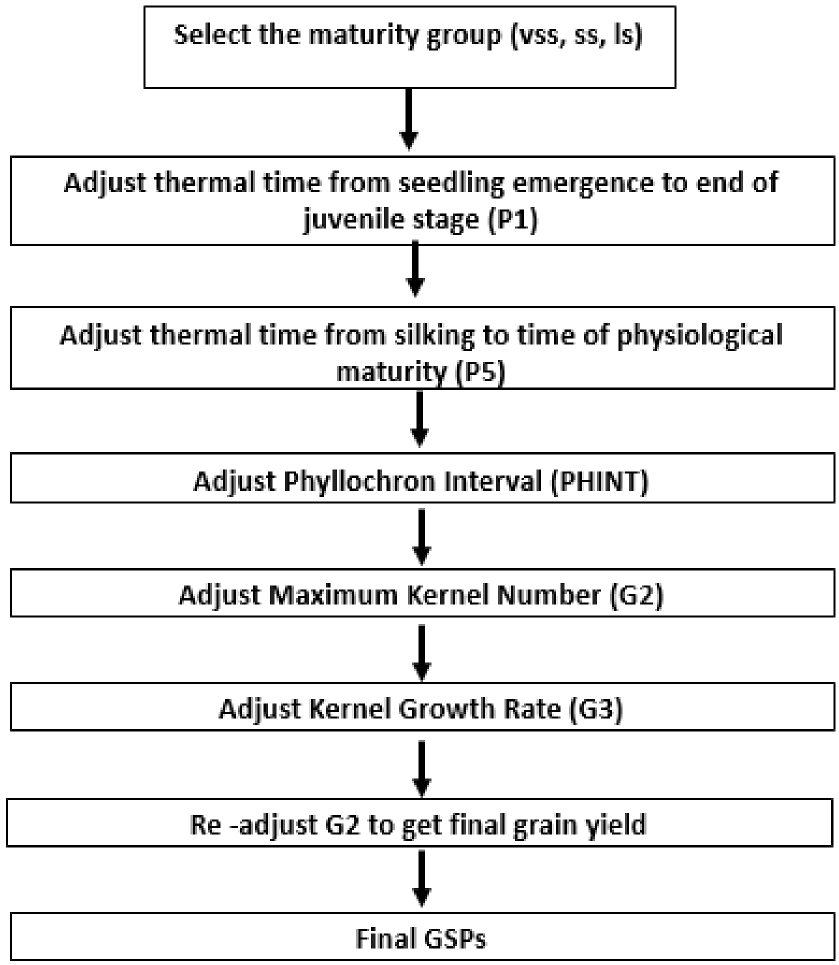


Figure 3-1: Order sequence of optimizations for calibrating the cultivar coefficients using GENCALC

3.2.6 Model Evaluation

Model evaluation was done using data from the nitrogen trials (Table 3-4). The data sets used for model evaluation were of two types; single measured data and time series data. For single measured data, we used d-index and RMSE (Box 2.1, equations 2.4 and 2.5) to evaluate the agreements between simulated and observed values. RMSEn and d-index (Box 2.1, equations 2.6 and 2.7) were used to evaluate the time series data. We used RMSEn for time series data because RMSE varies with growth over time as the magnitude of the growth variables increase. The d-index was used because it gives a single index of model performance, which covers bias and variability; it also indicates 1:1 prediction better than R^2. All model evaluations were done based on the description of the parameters as presented in Box 2.1.

3.3 Results

3.3.1 On-Station and breeder evaluation experiments

Genotype specific parameters

The values of GSPs generated using data from on-station and breeder experiments are shown in Table 3-2. The highest degree days from emergence to end of Juvenile stage (P1) was recorded for OBA 9 using data from both on-station and breeder experiments. For number of days from silking to end of physiological maturity (P5), the highest values were recorded for SC-651 in both the on-station and breeder data. The lowest P1 values were recorded for EE white using both on-station and breeder data. The variety SC-651 produced the largest number of maximum possible kernels (G2) for on station experiment data while OBA S9 had the highest values for breeder data. The value of G3 (kernel filling rate) ranged between 6.55 and 8.42 for the on-station experiment data, and between 6.39 and 8.51 for the breeder data. Phyllochron interval (PHINT) values ranged from 36.9 and 45.5 °C for the on-station experiment data and between 35.7 and 50.2° C for the breeder data. The results show that about half of the GENCALC estimates are near to or beyond two SEMs away from measured values. Majority of these estimates are for the phenology parameters P1, P5 and PHINT.

Table 3-4: Generated genotype specific parameters (GSPs) using on-station (Expt.) and breeder experiments

Variety	P1		P2		P5		G2		G3		PHINT	
	Expt.	Breeder	Expt.	Breeder	Expt.	Breeder	Expt.	Breeder	Expt.	Breeder	Expt.	Breeder
Ife hybrid 6	223.6 (11.16)*	247.4	0.01	0.01	520.7 (6.77)	518.3	706.7 (13.89)	663.7	7.09	6.98	36.90 (0.18)	35.70
Sammaz 41	233.6 (9.77)	263.2	0.01	0.01	550.7 (9.12)	540.4	806.9 (16.33)	782.1	7.76	7.59	37.00 (0.19)	39.66
Ife hybrid 5	213.7 (10.83)	221.6	0.01	0.01	511.6 (6.31)	502.7	518.7 (9.17)	533.7	7.47	6.99	40.00 (0.21)	39.03
Sammaz 42	230.0 (5.75)	244.3	0.01	0.01	683.4 (5.16)	679.2	786.7 (16.44)	806.4	7.59	7.72	45.50 (0.23)	39.98
OBA SUPER 9	293.1 (8.33)	288.6	0.01	0.01	768.1 (7.11)	772.9	828.7 (12.88)	830.7	7.83	7.80	45.00 (0.25)	45.00
SC-651	289.8 (6.98)	284.1	0.01	0.01	781.8 (7.32)	778.8	834.1 (11.13)	829.6	8.42	8.51	41.20 (0.19)	42.90
Sammaz 34	287.0 (8.11)	283.7	0.01	0.01	596.0 (5.12)	589.7	827.0 (9.22)	822.6	6.77	6.39	40.00 (0.21)	40.00
Sammaz 32	282.0 (7.29)	233.9	0.01	0.01	601.0 (4.61)	692.7	822.0 (8.76)	788.1	6.55	6.62	45.04 (0.27)	43.21
IITA E White	270.0 (8.91)	221.6	0.01	0.01	614.3 (5.33)	622.2	713.4 (12.13)	759.7	6.58	7.07	45.00 (0.26)	50.20
IITA EE White	183.6 (9.51)	192.3	0.01	0.01	601.0 (6.19)	627.8	523.3 (10.16)	614.3	6.91	7.32	42.10 (0.21)	44.35

*Numbers in parenthesis are Standard Errors of the means (SEM) for the measured experiment values

Phenology and growth

Evaluation of CERES-Maize for grain yield, number of days to anthesis, number of days to physiological maturity and plant height using both on-station experiments and breeder evaluation are shown in Fig 3-2 for two varieties as an example. Calibration of number of days to anthesis, and plant height, were more accurate when data from on-station experiments were used compared to breeder data for both varieties. Calibration of both variables using on-station data resulted in d-index values in the range of 0.85-0.96 for the trial data. For the breeder data however, d-index values ranged from 0.49 to 0.89. Days to anthesis was calibrated with higher accuracy than plant height for all varieties. Number of leaves per plant and plant height were measured for the on-station experiment data at different time intervals. The simulated values for both plant height and number of leaves were accurate at all sampling periods (Fig 3-3).

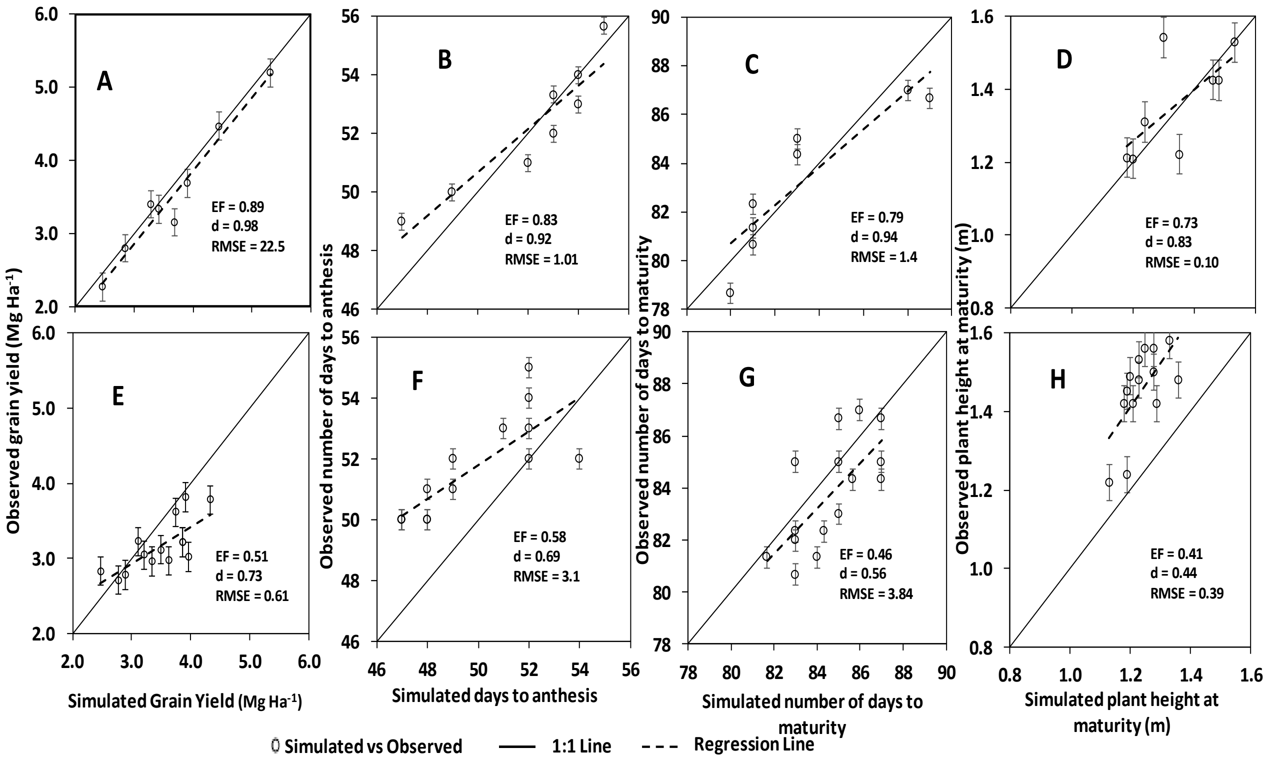


Figure 3-2: Comparisons between simulated and observed grain yield, days to anthesis, days to maturity and plant height at harvest for SAMMAZ 32 using on-station experiment (A, B, C, D) and breeder (E, F, G, H) data. Solid lines = 1:1 line; dashed lines = regression lines.

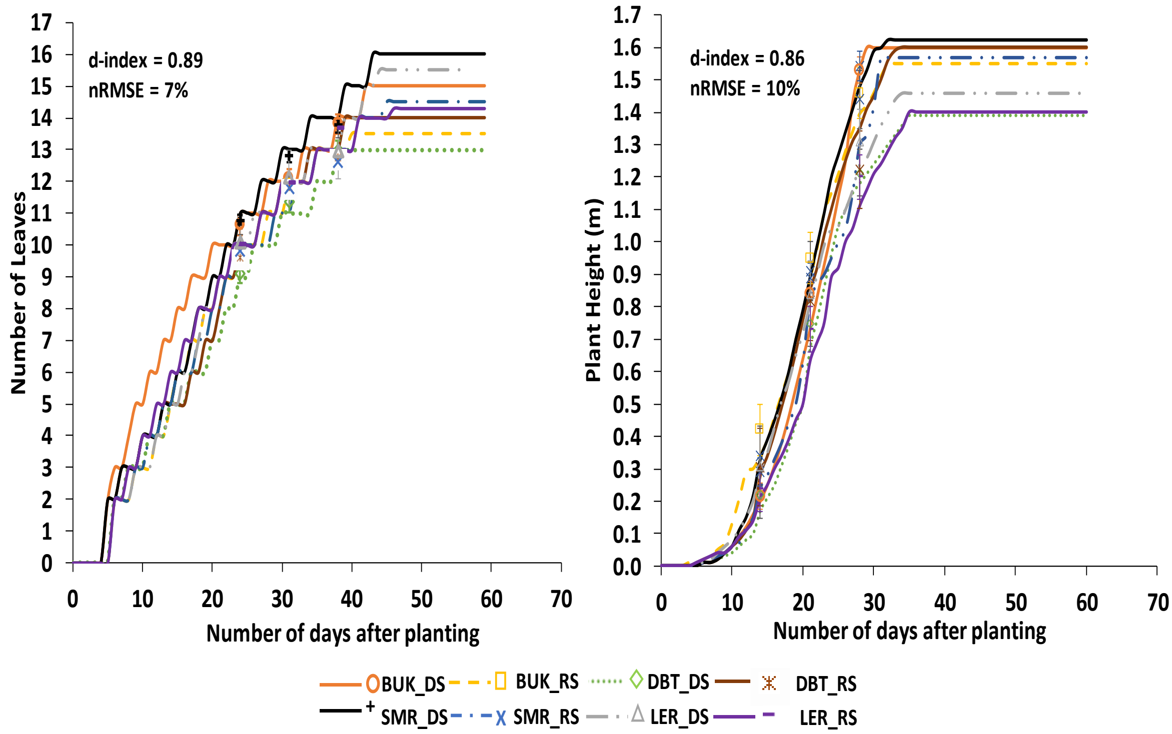


Figure 3-3: Simulated (lines) vs observed (symbols) plant heights and number of leaves of SAMMAZ 32 using experiment data. Error bars denote Standard Error of Mean (SEM)

Biomass and Leaf Area Index

Biomass and LAI were measured at juvenile stage, at anthesis, and at physiological maturity for the calibration data only. Figure 3-4 shows the result of simulation of above-ground biomass and LAI for Sammaz 32 across the trial locations. Good agreements were found between simulated and observed variables for all other varieties. Biomass was simulated with higher accuracy than LAI across all locations. Simulation of both biomass and LAI were most accurate using data from Samaru (d-index = 0.96, RMSE = 547.3 for biomass and d-index 0.92, RMSE 0.022 for LAI). Calibration of both variables had the lowest accuracy at Dambatta. Agreements between observed and simulated LAI were closer for the earliest measurement (juvenile stage), followed by measurement at anthesis, and physiological maturity in all locations except at Samaru where the reverse was observed. For biomass however, measurement at physiological maturity produced the closest agreements between observed and simulated values, while measurement at anthesis produced the lowest agreement between observed and simulated variables.

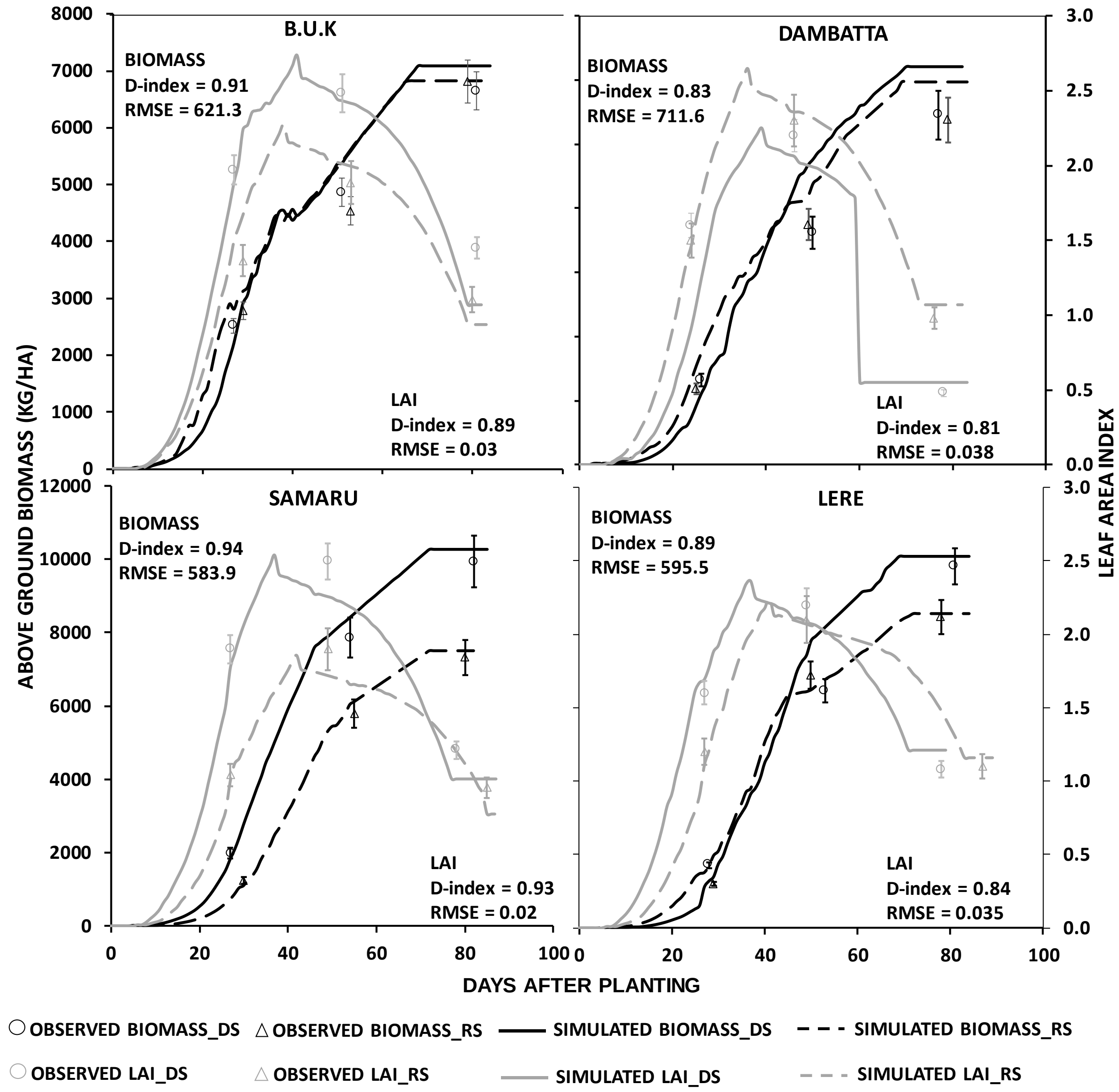


Figure 3-4: Simulated (lines) vs Observed (figures) Biomass and LAI of SAMMAZ 32 using on-station experiment data. Error bars denote Standard Error of the Mean (SEM).

Yield and yield attributes

Yield and yield attributes were well calibrated for all varieties in both on-station and breeder datasets. Table 3-5 shows the result of comparisons between observed and simulated mean grain yields of all varieties across different locations. Calibration of grain yield using on-station experiment data was more accurate, as evidenced by low percentage prediction deviations (3.1 to 12.9). Values for model statistics were also good for the on-station experiment data (RMSE = 264.6 kg ha^{-1}, nRMSE = 11.1%, and d-index = 0.97). For the breeder data however, prediction deviations of up to 24.7% were observed, with higher RMSE (510.1 kg ha^{-1}) and nRMSE (16.1%). Negative prediction deviation which indicate under simulation was only observed in one location (BGD 13) for the breeder evaluation data, while in all instances positive prediction deviations were observed.

Table 3-5: Observed and simulated mean grain yields (kg ha-1) of all varieties across different locations

Data Type	Observed	Simulated	PD%[#]
On-Station Experiment Data			
BUK_DS	3828	4080	6.2
BUK_RS	3209	3489	8.0
DBT_DS	2758	2866	3.8
DBT_RS	2628	2709	3.0
SMR_DS	5030	5259	4.4
SMR_RS	3536	3887	9.0
LERE_DS	4561	4723	3.4
LERE_RS	3452	3896	11.4
RMSE (kg/ha)		264.6	
nRMSE (%)		11.4	
EF		0.91	
d-index		0.97	
Breeder Data			
ZRA 12	2958	3345	5.4
ZRA 13	2969	3625	24.7
MKW 12	3214	3866	15.0
MKW 13	3042	3213	2.5
BGD 12	3812	3913	5.5
BGD 13	2782	2885	3.3
BTR 12	3226	3110	8.9
BTR 13	3112	3487	13.1
SMR 12	3214	3863	18.0
SMR 13	3779	4329	6.3
MJB 12	3612	3746	7.5
MJB 13	2831	2470	5.7
KDW 12	2711	2779	7.5
KDW 13	3017	3956	22.2
RMSE (kg/ha)		510.1	
nRMSE (%)		16.1	
EF		0.52	
d-index		0.78	

PD% = Percentage prediction deviation ((Sim/Obs)/Sim)) *100

3.3.2 Model evaluation experiments

Grain and tissue nitrogen, as well as grain yield, at harvest were simulated using independent datasets from trials conducted at BUK during the rainy seasons between 2013 and 2016.

Simulations were done using GSPs generated from both on-station experiment and breeder data. Table 3-6 shows the comparison between observed and simulated grain yields with accompanying model statistics for the two datasets taking SAMMAZ 32 and EE-White as examples (. Grain yield was well simulated for both varieties using both datasets, although better fits were observed for GSPs from the calibration data. Nonetheless, low values of RMSE (below 2% of mean for experimental and 4.5% for breeder), high values of d index (0.99 for on-station experiment and 0.96 for breeder) and good EF values (slightly less than 1 for both datasets) were observed.

Table 3-6: Simulated vs observed grain yields of Sammaz 32 and EE White in the model evaluation experiments, under different nitrogen levels using GSPs derived from calibration experiment and breeder evaluation experiment

Treatment	Observed	Simulated (GSPs < Calibration on-station experiments)	Simulated (GSPs < Breeder evaluation trials)
		Sammaz 32	
0 kg N	1245	1291	1177
60 kg N	2648	2573	2592
120 kg N	3255	3308	2983
SE±	57.3		
RMSE		36.3	101.1
D-Index		0.99	0.97
EF		0.92	0.91
		EE White	
0 kg N	979	953	1024
60 kg N	2177	2062	2333
120 kg N	3092	3129	3291
SE±	60.6		
RMSE		43.6	90.8
D-Index		0.99	0.98
EF		0.96	0.91

Tables 3-7 and 3-8 show comparisons of simulated grain and stover nitrogen using GSPs generated from on-station and breeder evaluation experiments. Better agreements between observed and simulated grain and stover Nitrogen were observed at high Nitrogen (120 and 60 Kg N) for both on-station and breeder evaluation experiments. At zero nitrogen application however, the agreements between observed and simulated values where low as evidenced by higher RMSE and lower d-index values.

Table 3-7: Comparison of simulated and observed grain nitrogen (kg N ha-1) of SAMMAZ 32 for GSPs generated using calibration experiments and breeder evaluation experiments

	SIM (Calibration Experiments)	SIM (Breeder Evaluation Expts.)	OBS
	120 kg N ha^{-1}		
BUK 13	42.9	44.8	42.1
BUK 14	45.8	46.9	44.3
BUK 15	44.4	45.3	42.2
BUK 16	42.3	45.1	43.3
SE±			0.81
RMSE	1.48	2.59	
d-index	0.67	0.47	
	60 kg N ha^{-1}		
BUK 13	44.0	45.2	43.2
BUK 14	44.9	42.4	43.3
BUK 15	40.6	42.3	41.0
BUK 16	42.7	46.8	43.6
SE±			0.79
RMSE	1.02	2.05	
d-index	0.87	0.59	
	0 kg N ha^{-1}		
BUK 13	12.9	10.7	14.3
BUK 14	20.1	22.3	21.8
BUK 15	21.4	26.8	20.6
BUK 16	7.8	11.6	10.2
SE±			0.94
RMSE	1.68	3.66	
d-index	0.98	0.48	

Table 3-8: Comparison of simulated and observed stover nitrogen (kg N ha-[1]) of SAMMAZ 32 for GSPs generated using data from calibration experiments and breeder evaluation experiments

	SIM (On-Station Experiments)	SIM (Breeder Evaluation Expts.)	OBS
		120 kg N ha^{-1}	
BUK 13	79.6	83.2	78.7
BUK 14	74.7	89.2	76.5
BUK 15	74.6	80.5	72.6
BUK 16	80.4	92.6	76.3
SE±			17.8
RMSE	2.49	11.3	
d-index	0.88	0.31	
		60 kg N ha^{-1}	
BUK 13	64.9	73.8	67.8
BUK 14	81.4	88.5	77.4
BUK 15	86.7	81.3	78.8
BUK 16	70.8	70.0	62.6
SE±			4.6
RMSE	6.2	7.4	
d-index	0.89	0.80	
		0 kg N ha^{-1}	
BUK 13	21.7	27.3	23.2
BUK 14	26.2	32.2	27.4
BUK 15	32.3	40.1	30.6
BUK 16	15.7	16.6	14.3
SE±			2.47
RMSE	1.46	5.8	
d-index	0.97	0.81	

3.4 Discussions

Calibrated GSPs from the on-station experiments and breeder evaluation experiments were similar to GSPs reported for related varieties in West and Southern Africa with respect to yield and yield attributes (Basso et al., 2016). For growth and phenology however, data from our experiments produced better calibration of growth and phenology than earlier reported experiments in the Nigerian Savannas (Jagtap et al., 1999; Jagtap and Jones, 1989). For calibration using both on-station and breeder data, we set the values of P2 to 0.01 to simulate the day-neutral characteristics of all the varieties used. Recent publications by Lamsal et al. (2018 & 2017) highlighted the need to test for possible pathologies while estimating GSPs in crop simulation models. Pathologies like expressivity failure (occur when a model cannot reproduce some observations for any combination of GSP values due to how the models' mathematical structure is set up), equifinality (multiple GSP combinations producing exactly same model predictions), and environmental hypersensitivity (GSP estimates depend on the environments used in generating them) should be checked especially if GSPs generated are to be used for genetic mapping. The presence of equifinality in our results is suggested by the closeness of the predictions generated from the two sets of GSPs even though 50% of the estimates differ by close to two SEMs or more. However, while more detailed testing for this phenomenon might be useful future work, our goal was to assess the degree of alignment between model predictions and observations given different sources of calibration data and this has been shown to be adequate.

A high percentage (75%) of the GENCALC estimates that are near to or beyond two SEMs of the measured values were recorded for coefficients that determine phenology and therefore dependent on accurate measurement of developmental events (in observed days) and subsequent conversion to degree days. This high percentage shows that phenological events like number of days to flowering and number of days to maturity were not accurately measured in the breeder experiments due to small sample sizes and because they are not the traits of interest in the breeding program. This is evidenced for example by the under-simulation of days to flowering by 2.2 days and over simulation of days to maturity by 1.8 days for SAMMAZ 32 shown in Figure 3-2. The implication of poor phenology measurements is seen by a slight over-estimation of yield and yield attributes thereby confirming assertions made by Kumudini et al. (2014) who suggested that accurate prediction of phenology is fundamental to determining crop adaptation and yield potential.

Calibration of the GSPs using the on-station experiment datasets produced better model fits than the breeder evaluation data as expected. The closeness of fit observed for the on-station data could be attributed to better experimental sites (soils with higher fertility and better moisture retention), better crop management (timely weeding, fertilizer application etc.) and higher experimental precision. This is evidenced by the breeder data having higher experimental errors for all measured variables when compared to the evaluation experiments. The evaluation experiments were also done on larger plot sizes and no missing plants were recorded at harvest, while in the breeder data smaller plots were used and there were no considerations for missing plants during yield calculations. In addition, for the experimental datasets more plant-related variables were measured compared to the breeder evaluation experiment data where only grain yield, days to flowering, plant height and days to physiological maturity were measured. For the breeder evaluation experiment, the closeness between observed and simulated plant heights was low. This could be attributed to the fact that most breeder trials are conducted under water limited conditions, thus rainfall variability may affect crop performance and data quality. Although the model can properly simulate water stress, no stress was observed in any of the breeder evaluation sites and years. Grain yield and days to anthesis were simulated more accurately than plant height for the breeder evaluation experiment. This can be attributed to the high number of datasets used (7 locations and 2 seasons). According to Anothai et al. (2008b) more accurate predictions of yield and phenology are observed when data is collected from many locations and seasons. For the on-station experiment, plant height, number of leaves, leaf area index, biomass, number of grains per meter square and grain yields were well calibrated as the differences between observed and simulated values were very minimal.

According to literature (Anothai et al., 2008b; Fensterseifer et al., 2017) when many years and locations are available, GSPs calibrated using breeder evaluation experiments produced very accurate comparisons between observed and simulated growth, yield and phenology of maize. As suggested by Fensterseifer et al. (2017), uncertainties exist in the reliability of model based simulations of growth, yield and phenology when calibrations are done using data from trials conducted under few environmental conditions. Also, other researchers (Ruíz-Nogueira et al., 2001; Xiong et al., 2014) reported that the major factors determining the success of a model calibration process, which determines the applicability of the model on a larger scale is dependent on the wide variability of data used during the calibration process. Thorp et al. (2008), suggested that for accurate calibration of crop models, integration of time variation using different planting dates and seasons, and spatial differences using different locations of datasets should be adopted for calibration of crop models using datasets from yield/breeder evaluation trials. To further verify these claims, we re-ran a couple of contrasting varieties under both on-station experiments and breeder evaluation experiments using different number of trials and data sets. For the on-station experiments, we first reduced the number of experiments by subtracting 2 stations concurrently (i.e. reducing from 8-6, 6-4 and 4-2). With every decrease in number of experiments, a subsequent decrease in model efficiency and increase in prediction error were recorded. The higher the number of trials the better the model fitted the observations, also reducing the number of experiments to 4 led to EF and d-index values below 0.4, while further reduction to 2 reduced the model efficiency to 0.25 and increased the prediction error to 55%. Using 4 experiments and all measured data produced the lowest level of acceptable model statistics (d-index ≥ 0.50, nRMSE ≤ 16% and EF ≥0.4). For the breeder evaluation experiments, every reduction in number of experiments led to a decrease in model efficiency and an increase in prediction error. We also reduced the number of datasets from the evaluation experiments to the same that was used in the breeder evaluation experiments. This resulted in decrease in model efficiency (0.89 to 0.81 for Sammaz 32 and from 0.94 to 0.88 for SC-651). This shows that the number of experimental sites is more important than amount of calibration data if the minimum data sets (MDS) are collected as shown in Table 3-9. This view is supported by Fensterseifer et al. (2017). When many locations and planting dates are available, data from breeder evaluation experiments in the SSA can be used to make good calibration of calibrations with lower RMSE & nRMSE and higher d-index & EF values.

Table 3-9: Model statistics values for reduction in number of experimental sites for both calibration experiments and breeder evaluation experiments

No. Sites	On-Station Experiments	Breeder Experiments
8	EF = 0.93	EF = 0.88
	nRMSE = 6.9%	nRMSE = 8.9%
6 (8-2)	EF = 0.79	EF = 0.67
	nRMSE = 10.4%	nRMSE = 12.6%
4 (6-2)	EF = 0.51	EF = 0.44
	nRMSE = 16.4%	nRMSE = 18.9%
2 (4-2)	EF = 0.44	EF = 0.41

Although the calibration experiments provided more accurate GSPs, they are still very expensive and laborious and thus are nearly impossible to carry out especially in Sub-Saharan Africa where expertise and resources are limiting. Breeder evaluation data could also be used for calibration of GSPs where such data is available. As shown earlier, very accurate GSPs could be generated if large amount of data from many years (also planting dates) and various locations are available. This will go a long way in providing model users with cheap and easy ways of calibrating GSPs of existing and newly released varieties to their locations.

Evaluating the generated GSPs for simulation of grain yield, tissue nitrogen and grain nitrogen using independent datasets resulted in good agreements between observed and simulated values. For grain yield, comparisons of measured and simulated values using both GSPs generated from on-station and breeder data showed very close agreements under medium and high nitrogen applications. For comparisons under nitrogen stressed conditions however, poor agreements existed between observed and simulated grain yields for both GSPs. This is a common occurrence with simulations of grain yield and yield attributes under low nitrogen fertilizer applications. Gungula et al., (2003), reported that the CERES-Maize model poorly predicts performance of maize under low nitrogen conditions in the tropics. The agreements between observed and simulated grain and stover nitrogen for both GSPs under high fertilizer applications is an indication that CERES-model still performs best under high nitrogen applications especially on tropical soils.

The CERES-Maize model has been shown over the years to be an important tool in evaluating crop management (MacCarthy et al., 2017), climate change impacts (Angulo et al., 2013), fertilizer recommendations (Adnan et al., 2017; Gungula et al., 2003) and yield forecasting (Soler et al., 2007). Calibrating the newly released maize varieties currently recommended for the Nigerian maize belts will provide an important input requirement for using crop models to evaluate major production constraints including optimum stand density (OSD), appropriate varietal selection (targeting/stability analysis), choice of major partner crop (in case of mixed cropping) and fertilizer (especially N and P) managements. The availability of accurate GSPs for all major varieties will also increase the applicability of the model on a wider scale and for broader applications.

3.5 Conclusion

Financial as well as time constraints coupled with frequent release of new varieties makes it difficult for model users to conveniently calibrate GSPs of crop models using detailed calibration experiments. Large numbers of evaluation trials are conducted across multiple locations under diverse planting dates by breeders and other growers prior to varietal release. Availability of such datasets, especially from evaluation trials conducted under minimal stress (moisture and nutrient) conditions provides an opportunity for efficient and rapid means of generating GSPs of newly released maize varieties. A systematic approach (as proposed in this study) as well as availability of large datasets from different locations and planting dates provide opportunities for estimation of accurate GSPs. Although it is possible to generate GSPs from breeder evaluation data, care must be taken to collect data from trials conducted under optimal conditions and not too far away from weather stations. Also, breeder data to be used for calibration of crop models must be collected from sites where detailed soil data is available. Additionally, appropriate tests must be conducted to ensure that pathologies such as equifinality, expressivity failures and environmental hypersensitivity are minimized especially when the objective is to generate GSPs for genetic mapping or for application under many environments where the estimation was not conducted. Availability of GSPs of new varieties as soon as they are released will help farmers and growers to make improved site-specific decision support tools (DST). Also, researchers will be provided with new ways to making variety groupings as well as studying complex Genotype, Environment, Management (G×E×M) interactions. Model users should endeavor to join breeding units/teams to ensure collection of robust data needed for model calibrations that are not traditionally collected by breeders.

4 CHAPTER FOUR

CERES-MAIZE MODEL FOR SIMULATING GENOTYPE-BY-ENVIRONMENT INTERACTION OF MAIZE AND ITS STABILITY IN THE DRY AND WET SAVANNAS OF NIGERIA

4.1 Introduction

Over the years, many maize varieties of contrasting characteristics which are adapted to the different regions of Nigeria have been developed by the International Institute of Tropical Agriculture (IITA) and partners (Badu-Apraku et al., 2011). These varieties have high yield potentials and additional characteristics such as tolerance to drought and low nitrogen as well as to biotic stresses including the parasitic weed, *Striga hermonthica* (Ifie et al., 2015). The selection of such varieties by small holder farmers is largely dependent on grain yields because they are always the traits of economic relevance. Grain yield is a quantitative trait and it is usually affected by environment right from development by the breeders, to the stage of evaluation and adoption by the farmers (Bernardo, 2010). Changes in the relative grain yield output and other traits of genotypes in different production environments are usually observed via a phenomenon called genotype by environment interaction (GEI) (Badu-Apraku et al., 2003). The GEI makes it difficult for breeders and growers to select high yielding varieties that are stable across different environments thereby reducing the effectiveness of the selection process (Yan and Hunt, 2010). Furthermore, determining the magnitude of GEI and stability of varieties can be challenging, as such, crop models can be employed to complement this process.

The major goal of plant breeders in any crop improvement program is to maintain high agricultural productivity via the development of varieties with high yield potential. In addition to high yield potential, the newly developed cultivar should have stable performance and be adapted to wide range of environments (Haruna et al., 2017). Significant GEI for quantitative traits like grain yield have severe limiting effects on gains in selecting superior genotypes for improved cultivar development (Kang, 1993). For a variety to be selected and utilized in large group of environments, evaluating stability of performance and range of adaptation has become increasingly important.

Dynamic models that can simulate the response of growth and development of crops to varying abiotic environmental factors such as temperature, solar radiation, and daylength have the potential to explain yield differences due to temporal and spatial variability (Sadras et al., 2003). These models can also be used to explain yield variability for different varieties across varying environments and management conditions thereby quantifying the GEI (Bustos-Korts et al., 2016). The models become more useful when they integrate a plant-soil-weather-management continuum which gives them the potential to provide site and variety specific agronomic recommendations for practices like optimum sowing dates/density and appropriate fertilization requirements (Magaia et al., 2017). Several efforts by researchers to integrate breeding and crop modelling have been well documented (Chapman, 2008; Chapman et al., 2002b). The major objective of linking crop models to breeding programs was primarily to aid in achieving the generation and selection of new gene combinations to create varieties that are superior to the current ones within the target environment (Technow et al., 2015). Crop growth models used in plant breeding are basically centered on explaining resource capture, utilization and allocation among plant organs (Cooper et al., 2009; Hammer et al., 2006). They have also been used to characterize growing environments (Chapman et al., 2000), to predict the influence of trait variation on yield within the context of genotype by environment by management interaction (Löffler et al., 2005), for evaluation of breeding strategies (Chapman et al., 2003) and to assess hybrid performance (Cooper et al., 2014). However, very few studies have reported comparison between simulated and observed values pertaining to GEI and stability analysis.

The CROP-GRO model was used by Salmerón et al. (2017) to simulate GEI of irrigated soybean in the U.S Midwest. Their studies captured GEI when varieties were calibrated by maturity group and via individual varietal calibrations. Data from crop performance studies were used by Mavromatis et al. (2002) to generate soybean genotype specific parameters, they then used the new approach in exploring the ability of the model to reproduce observed GEI. To increase the effectiveness of new phenotyping techniques in plant breeding, van Eeuwijk et al. (2019) combined modelling strategies (APSIM model) and traditional phenotyping to capture GEI in maize. In Australia, Chapman et al. (2002a) used the APSIM model to simulate GEI effects for sorghum in water-limited environments. Findings in most of these researches have shown that models were able to simulate GEI, but all the studies were done in controlled experiments under close supervision of scientists. None of the studies were conducted in farmer fields under partial researcher supervision. Additionally, none of the model-based GEI studies were evaluated using different stability parameters especially for maize. We also could not find any available literature for such model-based studies conducted in Africa.

The CERES-Maize model is a dynamic crop simulation model that estimates maize phenology, dry matter production/partitioning, and yield in daily time steps (Jones et al., 1986). Over the years, use of CERES-maize model in making management decisions has been increasing in Africa. The model has been recently used to evaluate climate-sensitive farm management practices in the Northern Regions of Ghana (MacCarthy et al., 2017) and to identify appropriate sowing dates and nitrogen rates in Zambia (Chisanga et al., 2014). The model also was used to simulate nitrogen and phosphorus uptakes and soil moisture dynamics in West Africa (Amouzou et al., 2018). In Benin Republic, Tovihoudji et al. (2019) recently used the model to support decision making regarding fertilizer micro dosing for maize production. Considering the increased use of the model in Africa, there is need to test the capacity of the model in predicting GEI in field trials and breeders' program. There is also a need to test the stability of the model simulated grain yields of different maize varieties across varying environments.

The objectives of the present research were (i) to evaluate the applicability of the CERES-Maize model in predicting genotype-by-environment interaction and (ii) to compare stability of observed and simulated grain yields of 16 maize varieties across diverse environments.

4.2 Methodology

4.2.1 Experimental Conditions

The on-station experiments for model calibrations described in chapter 3 (section 3.2.1) were used to create eight unique environments (Table 4-1). The detailed description of data collected and methodologies for the experiments are all explained in chapter 3. Data from the experiments and detailed soil and weather characteristics were used to create the unique environments in the CERES-Maize model.

Table 4-1: Description of environments used in the study showing locations, seasons and soil type

Environment	Code	Season	Location	Soil Type
E1	DSBUK	Dry	Bayero University	Typic Kandiustalf
E2	DSDBT	Dry	Dambatta	Typic Kanhaplustalf
E3	DSLERE	Dry	Lere	Plinthic Kandihumult
E4	DSSMR	Dry	Samaru	Plinthic Haplustult
E5	RSBUK	Rainy	Bayero University	Typic Kandiustalf
E6	RSDBT	Rainy	Dambatta	Typic Kanhaplustalf
E7	RSLERE	Rainy	Lere	Plinthic Kandihumult
E8	RSSMR	Rainy	Samaru	Plinthic Haplustult

4.2.2 Initialization of soil and weather parameters

Two soil profile pits were dug in each location before planting, and soil samples were taken from each layer for detailed studies. The samples from each layer were analyzed for pH (in H_20), texture, moisture, bulk density, exchangeable potassium (K), organic matter, available phosphorus (Bray II), total nitrogen and CEC. The soil data tool (*SBuild*) of DSSAT was used to create the soil database which was used for the general simulation purposes. Site information and coordinates, soil series and classification were among the data requirements for the *SBuild* utility. Initial soil water was set to field capacity for all locations for the calibration experiments because sowing was done when the soils were at field capacity to ensure optimum growing condition needed for calibration, while for evaluation and GEI/stability evaluation this condition was not set, leaving the inputted moisture properties of the soils in each location. This was done to ensure that the initial conditions for each season are accurately captured by the model. Measured soil characteristics taken from each profile were used to calculate the soil physical and chemical parameters that are needed to run the model. Tillage was not simulated while residue was set to be removed completely from the field three months after harvest to capture the realities of what is happening in actual farmer fields. Every year, the model simulation start date was set to one week before planting. Sowing was set to start when a total rainfall exceeding 20 mm occurred within the previous three days between June 1 to July 1 in all locations.

Daily weather data was collected from weather stations (Watchdog 2000 Series, Spectrum Technologies) adjacent to all experimental sites. All weather stations were less than 1 km away from the experimental sites. The *Weatherman* utility in DSSAT was used to input the weather data to create the weather file used by the CERES- Maize model. The *Weatherman* utility also requires information on name of weather station, latitude, longitude and altitude. Daily records of minimum and maximum temperature, precipitation, solar radiation and relative humidity were also used as inputs into the *Weatherman* utility.

For other simulation options, initial conditions were as reported for each year and location, the Priestly-Taylor/Ritchie method was selected for simulation of evapotranspiration while the Soil Conservation Service (SCS) method was selected for simulation of infiltration. Photosynthesis was simulated using the radiation use efficiency method, while hydrology and soil evaporation were simulated using the Ritchie Water Balance and Suleiman-Ritchie methods respectively. Phosphorus and Potassium were not simulated, while Nitrogen was added according to experimental conditions.

4.2.3 CERES Maize Model Evaluation

The three locations used for calibration (LER, SMR, and BUK) were deliberately selected because they were optimum sites with minimum nutrient and moisture stresses. The last location (DBT) was not optimal and thereby deliberately selected for model evaluation. For model calibration and evaluation, observed and simulated data for grain yield, number of days to anthesis, and total biomass at harvest were compared. The model calibration inputs include genotype specific parameters (GSPs), weather data (min. and max. temperature, rainfall, solar radiation and relative humidity), initial soil moisture, soil organic carbon, total nitrogen and available phosphorus. Other soil variables include: soil topography, surface information, such as slope, soil color, and crop management details (Jones et al., 1986). Genotype specific parameters (GSPs) for the 16 maize varieties were calibrated and evaluated previously (see chapter 3). Out of the 26 varieties calibrated, 16 were selected and were used for model calibration in this study (Table 4-2). The cultivar coefficients were fixed in the calibration and evaluation exercise, while soil and weather of the different environments were inputted. The records of soil and weather data for individual locations that were already initialized into the *SBuild* and *Weatherman* utilities were used for model simulations. The actual dates of planting, fertilizer application, and harvest were also inputted into the model.

Table 4-2: Calibrated genotype specific parameters of the 16 maize varieties used in the study

Variety	P1*	P2	P5	G2	G3	PHINT
	(°C days)	(°C days)	(° C days)	Kernel plant^{-1}	(mg day^{-1})	(°C day tip^{-1})
Sammaz 54	227.4	0.01	518.3	523.3	6.91	42.10
Sammaz 28	192.3	0.01	527.8	514.3	6.99	36.90
Ife Hybrid 5	213.7	0.01	511.6	518.7	7.09	40.00
Ife Hybrid 6	223.6	0.01	520.7	606.7	7.47	35.70
Early White	270.0	0.01	614.3	713.4	6.58	45.00
Sammaz 32	282.0	0.01	601.0	822.0	6.55	45.04
Sammaz 34	287.0	0.01	596.0	827.0	6.77	40.00
Sammaz 41	233.6	0.01	550.7	806.9	7.76	37.00
M1026-10	288.1	0.01	683.4	819.3	7.80	45.50
M1227-12	288.6	0.01	679.2	816.4	7.72	45.50
IWDC2	290.2	0.01	692.7	829.6	8.51	42.90
M0926-8	289.8	0.01	781.8	834.1	8.42	41.20
Oba Super 9	293.1	0.01	768.1	828.7	7.83	45.00
Sammaz 11	298.6	0.01	772.9	830.7	7.8	45.00
TZL-COMP4	293.7	0.01	769.2	786.7	7.59	39.98
TZBSR	294.1	0.01	789.3	846.9	7.17	45.00

P1, P2, P5, G2, G3 and PHINT are as described in section 2.3 and presented in Table 2-1

Statistics used for model evaluation includes d-index, RMSE, and nRMSE. Detailed description of model statistics is given in Box 2.1

4.2.4 Seasonal Analysis (Model Application)

The seasonal analysis tool of DSSAT 4.7 was used to conduct long term sensitivity analysis of the response of the 16 maize varieties in the wet and dry savannas of northern Nigeria. The seasonal analysis was conducted only for production in the rainy seasons without simulating supplementary irrigation. Long term daily weather data (1992 – 2017) was collected from the Nigerian Meteorological agency (NIMET) for Kano (representing dry savanna) and Zaria (representing wet savanna). Box plots showing the rainfall data are depicted in Figure 4-1. In the seasonal analysis tool, the model was set to plant automatically when moisture is at optimal and set to harvest at full harvest maturity each year. Optimum recommended nitrogen fertilizer rates (120 Kg N ha^{-1}) were applied in two splits, half at planting and the remaining half at 2 weeks after planting (considering moisture availability), both phosphorus and potassium were set at optimum and not simulated.

The weather records confirmed that the dry savannas had a shorter growing season than the wet savannas, with mean rainfall of 825 mm and growing season of 3.5 months. Average rainfall in the wet savannas is 1,125 mm with growing period of 5 months. The rains establish earlier in the wet savannas and end later with better distribution than in the dry savannas where rainfall establishes late and ceases early with more than 50% of the rain received in the months of July and August in most years. Cumulative frequency plots were used to present the results of simulated yields over 26 years.

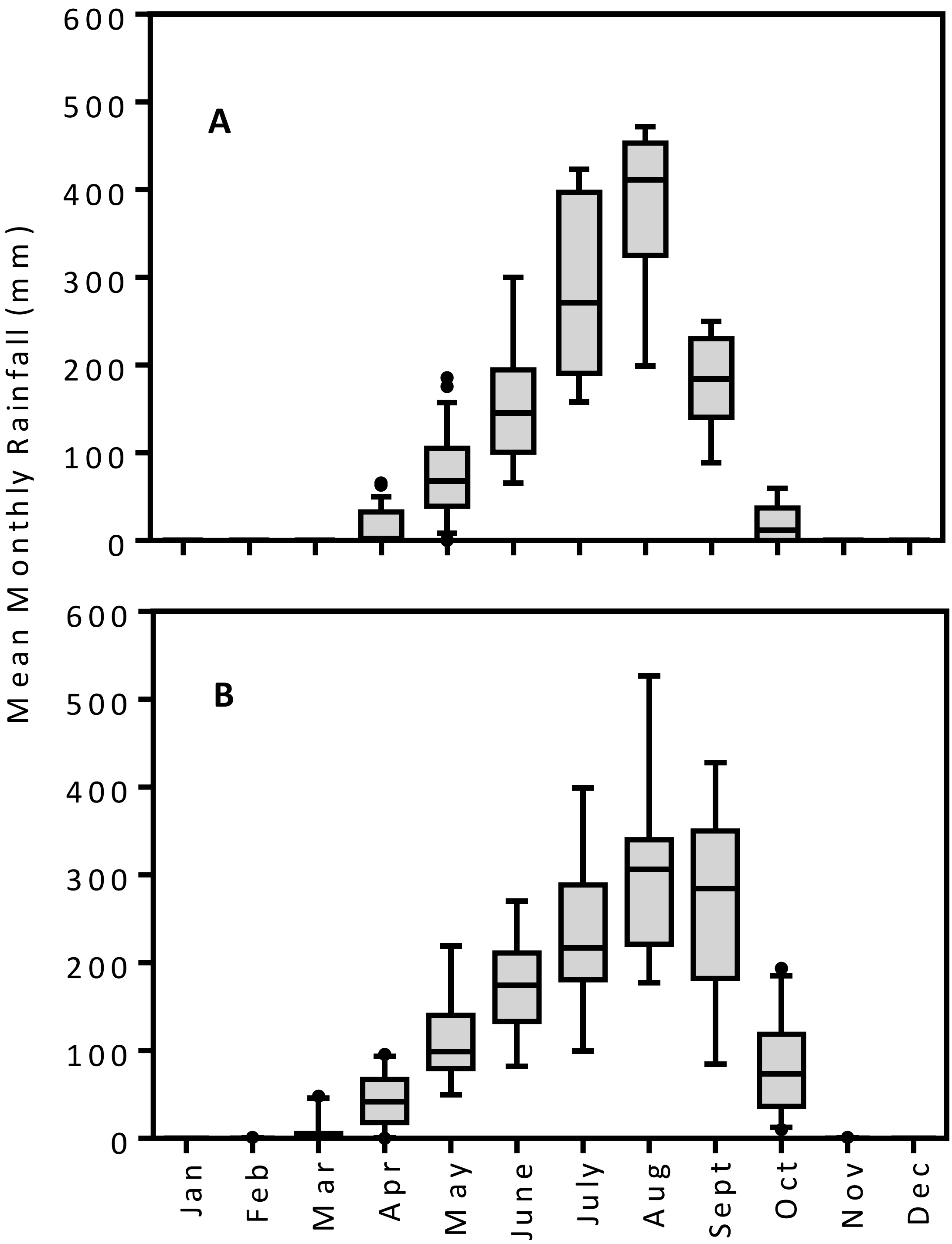


Figure 4-1: Boxplots showing variation of monthly rainfall over 26 years (1992-2017) for dry savannas (Kano, A) and wet savannas (Zaria, B) (Whiskers are 10-90 percentiles)

4.2.5 Estimating GEI and Stability Analysis

To evaluate the potential of using simulated data in determining the magnitude of GEI and stability of maize varieties, data from separate experiments conducted across all four locations and two seasons in 2016 were used. Each location and season combination were considered as a unique environment giving a total of eight environments (Table 4-1). Simulated yields were obtained with cultivar coefficients shown in Table 4-2. Among the 16 maize varieties used in the present study, four varieties were early, four were extra early, four were intermediate and four were late maturing. Simulations were done separately for the two profile pits in each location in order to generate replicated grain yields as required by the analysis. Observed grain yield data from detailed experiments and simulated grain yields from the calibrated model were subjected to analysis of variance using JMP version 14 software (SAS, 2018). After testing for variance homogeneity, a combined analysis of variance was performed to separate the total variation into components due to genotype/variety (G), environment (E) and genotype × environment interaction (GEI) effects.

Because GEI was found to be statistically significant, additional statistics were calculated to determine the stability of each genotype over the eight environments for both observed and simulated data. To adequately evaluate the potential of using simulated data in determining stability, different stability models were used. Univariate stability models based on regression and variance estimates were first considered. According to the regression model, stability is measured based on mean grain yield, slope of the regression line (bi) and sum of squares for deviation from regression (S^2d). High mean of a variety is a precondition of stability according to the slope of regression (bi) method. The slope indicates the response of the variety to an environmental index which is derived from the average grain yield of all genotypes in each environment. A variety with a bi value that is not significantly different from unity indicates that the variety is adapted to all environments. A variety with a bi value greater than unity indicates a higher sensitivity to environmental change meaning the variety has below average stability and is more responsive to higher yielding environments. A variety with bi values less than unity indicates a measure of greater resistance to environmental change, meaning the variety has above average stability and therefore more responsive and adaptable to low yielding environments (Dia et al., 2017). In addition, other stability parameters were calculated including three multivariate parametric and one non-parametric stability measures. The parametric measures include: Wrickes' stability ecovalence (Wricke, 1966), Shuklas' stability variance (Shukla, 1972), and an indices that uses both stability variance and ecovalence (SIGMA) (Kang et al., 1987). The Kang yield stability index (Kang YSi) (Kang, 1993) was the non-parametric index adopted, it considers both mean yield and stability variance. In addition, AMMI stability value (ASV) was calculated following methods described by Purchase et al., (2000). Varieties with the lowest values were considered to be the most stable for comparisons using ecovalence, stability variance, ASV and SIGMA, (Temesgen et al., 2015). For Kang YSi however, only varieties with stability values greater than the mean stability are considered stable, while for *bi* the varieties with values closest to unity were considered most stable. All the stability parameters (except ASV) were estimated using the R-software through an R-language program (RG×E) developed by Dia et al. (2017). The corrected Akaike Information Criterion (AICc) was used to select the best fitting stability model. The smaller the AICc value, the better the model performance, and the varietal ranking of the selected model was given the highest relevance.

4.3 Results

4.3.1 Model calibration and Evaluation

The result of model calibration of grain yield for the 16 maize varieties across three locations and model evaluation in one location are shown in Figure 4-2 and 4-3. For the model calibration, all the varieties had RMSE values that were less than 10% of the mean and d-index values > 0.72 (Fig. 4-2). For model evaluation using a separate environment (Fig. 4-3), there was good agreements between observed and simulated grain yields as shown by high model statistics. All varieties recorded d index values > 0.71 except for Sammaz 54 (d-index = 0.67). For the calibration dataset, the model was less efficient in simulating number of days to anthesis (DTA). One extra early, two early, one intermediate and one late variety, had d-index values below 0.5 (Table 4-3). Generally, there was over-estimation of DTA for all the early varieties, while for extra early and intermediate varieties only one variety each was over estimated. For the model evaluation data set a similar trend was observed, although overall the model calibration and evaluation statistics were all within acceptable ranges for all the varieties.

The model was more efficient in estimating biomass at harvest than grain yield for all varieties shown by small RMSEs (0.16 – 0.84), lower average biases (0.17 – 0.61 Mg ha^{-1}) and high d-index (0.41 – 0.85) (Table 4-4).

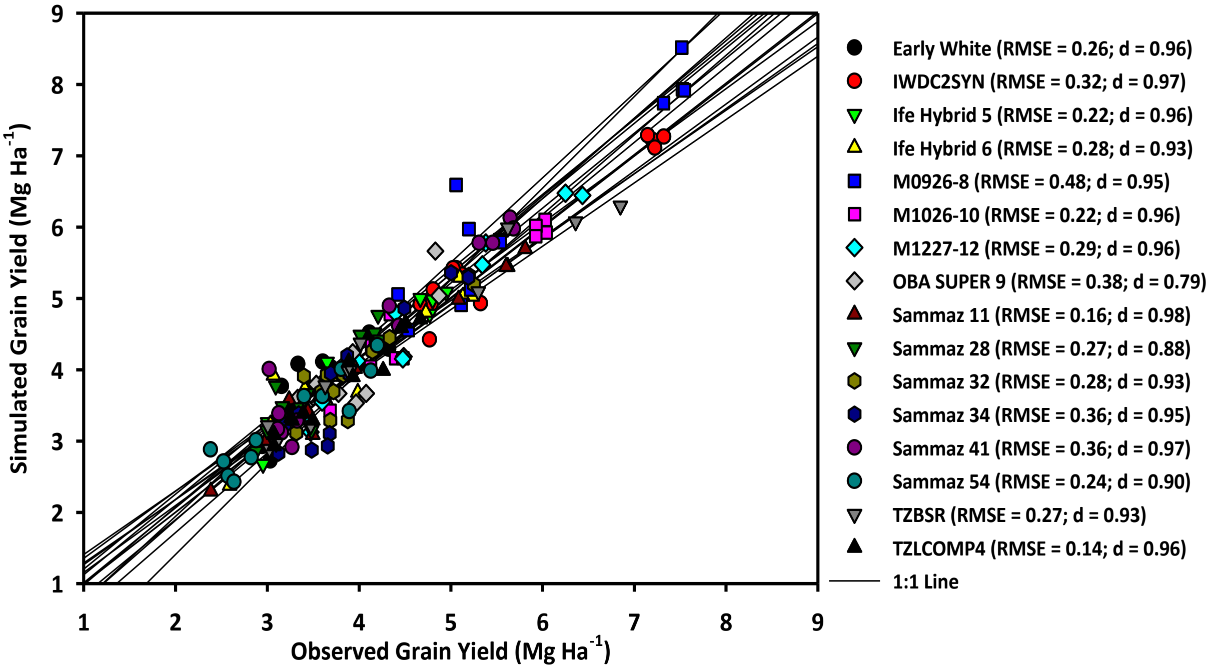


Figure 4-2: Agreements between observed and simulated grain yields of the 16 maize varieties for the model calibration. RMSE = Root Mean Square Error, d = index of agreement

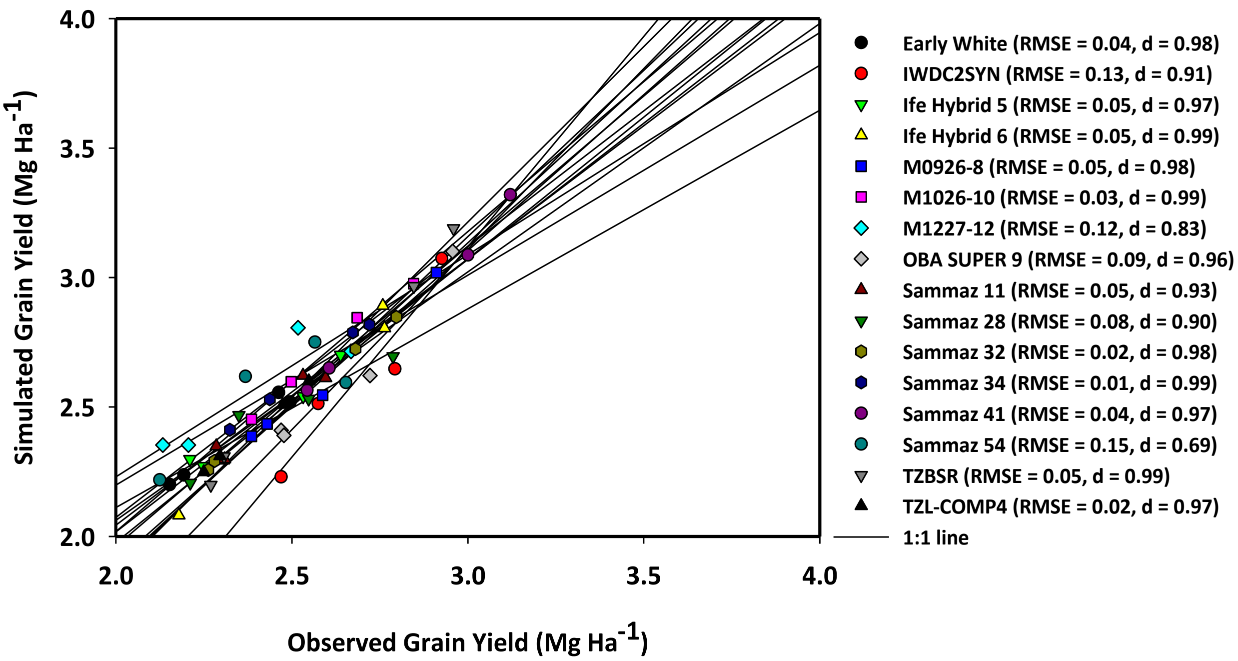


Figure 4-3: Agreements between observed and simulated grain yields of the 16 maize varieties for the model calibration. RMSE = Root Mean Square Error, d = index of agreement.

Table 4-3: Result of calibration and evaluation of number of days to anthesis for 16 maize varieties across multiple locations

Varieties	Calibration dataset				Evaluation dataset			
	Obs	bias	d	RMSE	Obs	bias	d	RMSE
Extra Early								
Sammaz 54	49	-0.2	0.81	0.54	50	0.4	0.56	0.67
Sammaz 28	48	0.3	0.38	0.58	49	0.3	0.42	0.66
Ife Hybrid 5	50	0.4	0.61	0.77	50	0.2	0.34	0.83
Ife Hybrid 6	48	0.2	0.58	1.07	50	-0.3	0.50	1.12
Early Varieties								
Early White	52	-0.8	0.50	1.01	53	0.9	0.49	0.88
Sammaz 32	53	-0.3	0.42	0.88	53	0.2	0.52	0.73
Sammaz 34	52	-0.2	0.77	0.80	53	0.0	0.61	0.76
Sammaz 41	53	-0.4	0.43	0.79	54	0.6	0.41	0.81
Intermediate								
M1026-10	56	0.2	0.79	0.99	57	-0.4	0.62	1.01
M1227-12	55	0.3	0.62	0.52	56	-0.6	0.54	0.69
IWDC2	57	0.2	0.45	0.38	57	-0.3	0.45	1.02
M0926-8	58	-0.4	0.42	0.90	57	-0.5	0.52	0.78
Late								
Oba Super 9	60	0.4	0.90	0.77	60	0.0	0.69	0.84
Sammaz 11	61	0.2	0.53	1.22	60	0.0	0.43	0.98
TZL-COMP4	62	0.0	0.66	0.56	61	0.2	0.49	0.62
TZBSR	61	0.2	0.41	0.73	61	0.0	0.40	1.01

d = index of agreement, RMSE = Root Mean Square Error, bias = Simulated - Obs

Table 4-4: Result of calibration and evaluation of biomass yield at anthesis for 16 maize varieties across multiple locations

Varieties	Calibration dataset				Evaluation dataset			
	Obs	bias	d	RMSE	Obs	bias	d	RMSE
Extra Early								
Sammaz 54	6.55	0.49	0.63	0.28	6.19	0.62	0.61	0.39
Sammaz 28	6.88	0.35	0.77	0.34	6.73	0.47	0.64	0.42
Ife Hybrid 5	7.30	0.44	0.59	0.49	7.41	0.61	0.43	0.52
Ife Hybrid 6	6.92	0.51	0.45	0.29	7.16	0.73	0.50	0.22
Early Varieties								
Early White	6.99	0.37	0.88	0.37	6.59	0.19	0.70	0.41
Sammaz 32	7.62	0.18	0.67	0.45	8.11	0.22	0.61	0.39
Sammaz 34	7.68	0.61	0.82	0.54	8.02	0.37	0.73	0.57
Sammaz 41	8.83	0.44	0.58	0.75	8.93	0.21	0.54	0.67
Intermediate								
M1026-10	8.48	0.38	0.82	0.34	9.03	0.28	0.73	0.28
M1227-12	8.56	0.44	0.62	0.36	8.96	0.37	0.49	0.19
IWDC2	9.13	0.24	0.51	0.37	9.19	0.33	0.44	0.47
M0926-8	11.17	0.43	0.41	0.84	11.31	0.28	0.41	0.92
Late								
Oba Super 9	8.61	0.33	0.39	0.16	8.31	0.41	0.45	0.37
Sammaz 11	9.73	0.17	0.52	0.36	8.97	0.28	0.39	0.49
TZL-COMP4	8.41	0.17	0.55	0.20	8.32	0.32	0.44	0.37
TZBSR	10.08	0.63	0.78	0.36	9.19	0.31	0.58	0.32

d = index of agreement, RMSE = Root Mean Square Error, bias = Simulated - Obs

4.3.2 Observed and simulated grain yield

The effect of varieties and environments as well as the interaction of variety by environment (GEI) were highly significant ($P \leq 0.001$) for both observed and simulated grain yields (Table 4-5). The environmental effect explained 67% of the total variance for the observed grain yield and 64% for simulated grain yield. The main effect of variety explained 19% of the observed variation and 21% of the simulated variation for grain yield. The GEI effect explained 13% and 15% of the observed variation in observed and simulated grain yields, respectively. This result shows that the variance components of observed and simulated yields are very similar and the variance component of GEI is considerable when compared to the variance component of the variety.

The average observed and simulated grain yields of the varieties ranged from 2.36 to 2.51 Mg ha^{-1} in RSDBT and from 5.41 to 5.56 Mg ha^{-1} in DSSMR (Figure 4-3). Among the varieties, M-0926 produced the highest observed and simulated grain yields in all locations except at DSDBT and RSDBT where the highest observed grain yields were recorded for Sammaz 32 and highest simulated grain yield was recorded for OBA Super 9. Sammaz 54 and Early white produced the lowest grain yields in all environments except in DSDBT and RSDBT where the two varieties produced higher yields then M-0926. Yields were higher in the dry season environments than in the rainy season across all locations, while the simulated yields were higher than observed yields in 97% of the data presented. The highest yielding varieties produced consistently highest grain yields across all environments for both observed and simulated grain yields except in the non-optimal environments in Dambatta rainy and dry seasons.

Table 4-5: ANOVA results with variance components for observed (Obs) and Simulated (Sim) grain yields of 16 maize varieties across 8 environments

Source	Sum of Squares		Mean Squares		% Variance estimate	
	Obs	Sim	Obs	Sim	Obs	Sim
Variety	75.41	85.57	5.03***	5.70***	19.2	20.6
Environment	261.73	265.27	37.39***	37.90***	66.7	64.0
Variety*Environment	50.89	63.49	0.48***	0.60***	13.0	15.3
Rep	0.02	0.27	0.02^{ns}	0.27^{ns}	0.0	0.1
Error	4.58	0.08	0.04	0.00	1.2	0.0
Total	392.63	414.68			100	100

*** Significant at the 0.001 probability level, ns = non-significant

4.3.3 Stability Analysis

The best fitting models based on the lowest AICc value for both observed and simulated grain yield (Table 4-6) were the slope of regression (372.7 for observed and 381.6 for simulated) and the ASV model (392.3 for observed and 394.7 for simulated). The parameters of all the stability models are presented in Table 4-7. Based on *bi*, the most stable variety using both observed and simulated grain yield was Sammaz 11 (slope = 1.06 for observed and 0.84 for simulated), while the least stable variety was IWDC2 (slope = 3.51 for observed and 3.45 for simulated). Varietal rankings were different for the multivariate parametric models (ASV, Ecovalence, and SIGMA) when both observed and simulated grain yields were considered. For all the three multivariate parametric models, Ife hybrid 6 (ASV = 0.57 and 0.69; Ecovalence = 687.2 and 932.9, SIGMA = 77.8 and 109.1) was the most stable variety for both observed and simulated grain yields, while the least stable variety was M0926-8. Generally, lower ASV, Ecovalence and SIGMA values were recorded for the simulated grain yields than for the observed grain yields across all the varieties. Ranking of the varieties was different for observed and simulated grain yields according to Shukla. The most stable variety was Sammaz 28 for both observed and simulated yields, while the least stable variety was Sammaz 41 for observed yields and M0926-8 for simulated yields. Varietal stability ranking according to Kang YSi identified nine stable varieties for observed grain yields and eight stable varieties for simulated grain yield. Ife hybrid 6 and Sammaz 32 have the highest stability ranking for observed grain yields according to Kang YSi, while the highest-ranking variety for simulated grain yield was Ife hybrid 6. The lowest ranking variety according to Kang YSi was M0926-8 for observed grain yield, while M1026-10 was the lowest ranking variety for simulated grain yields.

Table 4-6: Corrected Akaike Information Criterion for the parametric stability models

Model	Observed	Simulated
Slope (*bi*)	372.7	381.6
ASV	392.3	394.7
Ecovalence	398.6	404.3
SIGMA	617.2	609.8
Shukla	401.6	411.9

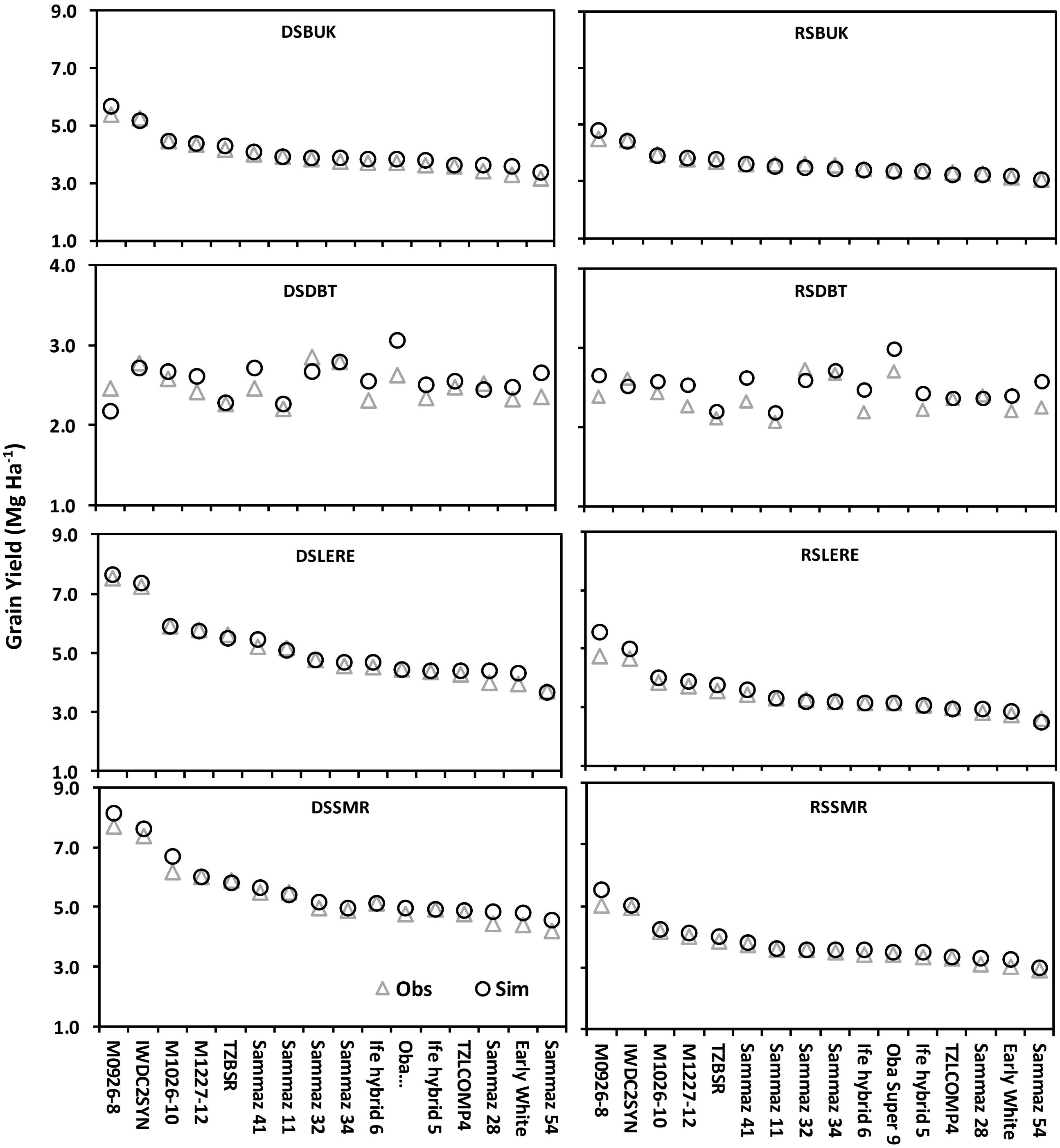


Figure 4-4: Observed and simulated grain yields of different varieties across locations in the rainy and dry seasons of 2016

Table 4-7: Mean grain yield and stability parameters for slope of regression, ASV, Ecovalence, SIGMA, Shukla and Kang YSi for observed and simulated grain yields of 16 maize varieties across the environments

Genotype	GY*		Slope (*bi*)		ASV		Ecovalence		SIGMA		Shukla		Kang YSi	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Sammaz 54	3.0	3.1	0.20	0.27	3.17	2.71	3612.3	6001.5	555.1	936.6	176.1	277.7	-10	-10
Sammaz 28	3.2	3.4	1.62	1.64	2.82	1.04	3034.1	1021.8	460.8	123.6	**70.6**[a]	**54.6**[a]	-8	1
Ife Hybrid 5	3.4	3.6	1.92	0.71	0.98	0.72	839.9	2129.8	102.5	304.5	120.2	362.3	-5	5[+]
Ife Hybrid 6	3.5	3.6	-0.4	1.23	**0.57**[a]	**0.69**[a]	**687.2**[a]	**932.9**[a]	**77.8**[a]	**109.1**[a]	116.7	124.4	**1**[a+]	**4**[a+]
Early White	3.1	3.4	1.2	1.53	2.31	1.15	2496.1	2419.7	372.9	351.9	111.7	173.2	-9	-9
Sammaz 32	3.7	3.7	2.8	2.98	2.23	0.9	1881.0	1156.2	272.5	145.6	110.9	71.7	**1**[a+]	7[+]
Sammaz 34	3.6	3.6	-0.55	-0.54	2.36	1.68	2019.9	2964.9	295.2	440.9	92.7	352.5	-2	-4
Sammaz 41	3.8	4.1	-0.12	-0.63	0.97	0.98	2658.8	3665.1	399.5	555.2	**483.6**[b]	639.2	4[+]	6[+]
M1026-10	4.2	4.2	0.15	0.23	1.96	1.04	1559.7	1699.9	220.2	234.4	150.1	247.1	9[+]	**13**[b+]
M1227-12	4.0	4.1	2.69	2.74	2.01	1.03	2259.1	1706.3	334.2	235.4	156.6	104.8	8[+]	11[+]
IWDC2	4.9	4.9	**3.51**[b]	**3.45**[b]	4.89	3.59	7240.0	9775.2	1147.4	1552.8	168.6	526.9	10[+]	10[+]
M0926-8	5.0	5.4	2.63	3.09	**6.41**[b]	**4.73**[b]	**12593.9**[b]	**17327.9**[b]	**2021.5**[b]	**2785.9**[b]	474.6	**1139.5**[b]	**11**[b+]	11[+]
Oba Super 9	3.5	3.7	1.63	1.71	2.75	1.93	3083.2	5999.5	468.8	936.3	161.5	593.2	-3	1
Sammaz 11	3.6	3.7	**1.06**[a]	**0.94**[a]	0.78	0.79	1405.9	1223.2	194.9	156.5	171.9	187.9	6[+]	5[+]
TZL-COMP4	3.4	3.4	2.04	1.83	1.68	0.71	2349.4	3102.7	348.9	463.4	253.6	367.9	-7	-8
TZBSR	3.9	3.8	0.14	0.23	2.16	1.18	3170.5	2359.8	483.0	342.0	319.1	179.9	6[+]	2

*GY = Grain Yield averaged across environments (Mg ha^{-1}). Boldened entries with parenthesis indicate most stable variety (a) and least stable variety (b) across all environments. Varieties having a cross as superscript are the only stable varieties according to Kang YSi.

4.3.4 Long term varietal simulations

The maximum, minimum and mean simulated grain yields for 26 years in the wet and dry Savannas using seasonal analysis tool of DSSAT version 4.6 are shown in Table 4-8. Varieties IWDC2 and M0926-8 produced maximum yields that are > 5 Mg ha^{-1} in the dry savanna and > 7.5 Mg ha^{-1} in the wet savanna. For the same varieties, minimum yields were below 3 Mg ha^{-1} in the dry savanna and above 4.5 Mg ha^{-1} in the wet savanna. The highest mean grain yield in the dry savanna was simulated for IWDC2, while in the wet savanna the highest yield was recorded for M0926-8. Sammaz 54 recorded the lowest mean grain yield in the dry and wet savannas. All the late maturing varieties (OBA SUPER 9, TZBSR, Sammaz 11, and TZLCOMP4) recorded mean grain yields below 3 Mg ha^{-1} in the dry savannas and above 5.5 Mg ha^{-1} in the wet savannas. A 58% mean yield difference was observed between dry and wet savannas for the variety Sammaz 11, while for Sammaz 54 a mean yield difference of only 8% was observed between the dry and wet savannas. For the highest yielding variety (M0926-8), a yield increase of 39.5% was observed when planting was done in the dry savannas compared to that of the wet season.

Figure 4-4 shows the cumulative distribution function (CDF) plots of 26 years simulated grain yield of the 16 varieties in the dry and wet savannas. In the dry savannas, the highest yielding varieties were IWD C2 and M0926-8. Yields were always below 6 Mg ha^{-1} for all varieties except the two high yielding varieties where yields exceeding 6 Mg ha^{-1} were simulated in 20% of the years. The difference in yield among the varieties in the dry savannas was not very high. Both extra early, early and intermediate maturing varieties produced similar grain yields (largely < 4 Mg ha^{-1}) in about 75% of the years simulated. The late maturing varieties produced lower grain yields than the early varieties in all the simulated years and produced equal or more grain yields than the extra-early varieties in only five of the 25 years simulated in the dry savannas. In the wet Savannas however, nine out of the 16 varieties produced yields > 5 Mg ha^{-1} in 19 out of the 25 years simulated, while yield below 2 Mg ha^{-1} were recorded for only 6 varieties in 2 out of the 25 years simulated. The intermediate and late varieties produced the highest yields in the wet savannas, with all the intermediate varieties producing yields >5 Mg ha^{-1} in all the years and the late varieties producing yields < 4 Mg ha^{-1} in 18 out of the 25 years simulated.

Table 4-8: Maximum, minimum, and mean grain yields (Mg ha^{-1}) for 26-year seasonal analysis of 16 maize varieties using CERES-Maize model

Varieties	Dry Savanna				Wet Savanna			
	Max.	Min.	Mean	SD*	Max.	Min.	Mean	SD
Sammaz 54	3.8	1.4	2.3	0.47	3.6	1.0	2.5	0.69
Sammaz 28	3.6	0.9	2.6	0.66	3.8	1.8	2.6	0.77
Ife Hybrid 5	3.6	1.1	2.4	0.72	3.1	1.4	2.5	0.44
Ife Hybrid 6	4.3	1.3	2.8	0.87	4.4	1.6	2.9	0.62
Early White	4.4	2.0	3.1	0.69	5.2	1.0	3.3	1.05
Sammaz 32	4.8	2.1	3.4	0.78	5.1	2.2	3.6	0.91
Sammaz 34	4.4	2.0	3.3	0.79	4.9	2.7	3.8	0.71
Sammaz 41	4.1	2.0	3.2	0.53	5.7	2.9	4.1	0.76
IWDC2	5.1	2.9	4.0	0.94	7.5	4.8	5.8	0.69
M0926-8	5.4	2.8	4.1	1.02	7.8	4.9	6.2	0.87
M1026-10	4.6	2.4	3.4	2.98	7.7	4.8	6.1	0.76
M1227-12	4.7	2.4	3.5	0.53	6.9	4.4	5.5	0.58
OBA SUPER 9	3.5	1.6	2.7	0.78	7.0	3.5	5.6	0.83
TZBSR	3.5	1.8	2.8	0.78	7.7	4.0	6.1	0.85
Sammaz 11	3.3	1.3	2.3	0.47	6.9	3.4	5.5	0.84
TZLCOMP4	3.7	1.4	2.6	0.73	7.3	3.8	5.6	0.90

Max = maximum value, Min = minimum value, *SD = Standard Deviation

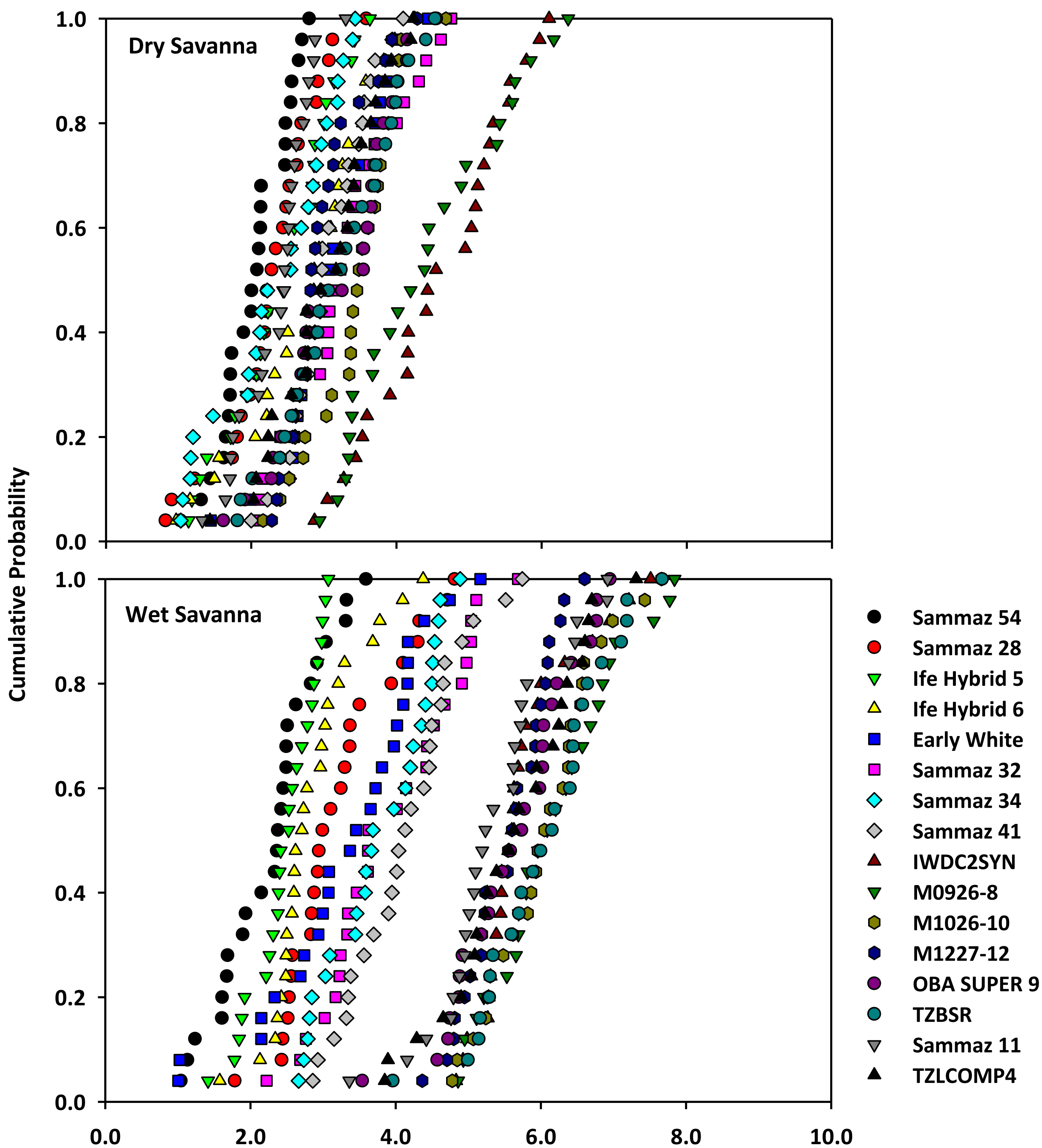


Figure 4-5: Cumulative probability plot for 26 years seasonal analysis of maize grain yield in the dry and wet savannas

4.4 Discussion

Selection of appropriate maize varieties that can withstand both biotic and abiotic site-specific problems is one of the major agronomic decisions that could lead to significant maize yield increases in the Nigerian Savannas. Breeders and agronomists conduct multi-environmental trials (METs) to assess varietal stability and maximum adaptability to target environments before release (Becker and Leon, 1988). When properly calibrated and evaluated, crop models could complement the METs and provide robust data for improved stability analysis and provide insights into existing genotype by environment interactions.

Outcomes of model calibration and evaluation from our research showed very good agreements between observed and simulated grain yield, number of days to anthesis and biomass at harvest as shown by high d-index values (close to 1), low RMSE values (with respect to the mean) and high EF values (close to 1) for all varieties across all the environments. This shows that the efficiency and robustness of the model is quite adequate, and the model can be used to make various predictions in the environments under study. Accurate prediction of phenology (days to anthesis and days to physiological maturity) indicates that the calculated P1 and P5 values for the varieties used in the *genotype file* was close to the actual values for all the varieties, and the calibrated genotype specific parameters were accurate enough. The results of the model evaluation where the trial datasets in both optimal and non-optimal environments were compared is an evidence of the model versatility in reproducing the observed GEI. Accurate prediction of phenology is a major step in the modelling process (Archontoulis et al., 2014), this is because accurate phenology prediction results in proper estimation of all genotypic variations that affect the leaf area development, biomass production, and grain yield (Robertson et al., 2002). Six out of the eight environments used for model evaluation were optimal with respect to both moisture and nutrient conditions. The remaining two environments (DSDBT and RSDBT) were non-optimal environments due to very high temperatures (above 40^{o}C) during the growing period for DSDBT and the evidence of moisture stress for RSDBT. The model was able to reproduce the varietal responses in these environments due to the accuracy of the calibrated GSPs. The early varieties had short vegetative and reproductive stages while the intermediate and late varieties had relatively longer vegetative and reproductive stages. In the optimal environments, the late and intermediate maturing varieties produced higher grain yields because they took longer time to grow and mature and therefore had longer grain-fill durations, and because there were no stresses, they were able to optimally develop. In the stressed environments, the early and extra early varieties produced higher yields because they take shorter time to complete vegetative and reproductive developments and escaped most of the stress periods. The model was able to capture these observed differences through accurate calibration of the parameters P1 and P5 that represents phenological development.

Prediction of grain yields for the calibration and evaluation data-set was highly accurate for 15 out of the 16 varieties, with only one variety (Sammaz 54) having values that are slightly above average. In the CERES-Maize model, grain yield is mostly affected by canopy interception of incident radiation, radiation use efficiency (RUE) and harvest index (Jones et al., 1986). Accurate grain yield prediction in a crop modelling exercise is the most important step needed for improvement of crop management, measuring GEI and varietal stability (Pantazi et al., 2016). The model accurately reproduced these observed yield differences due to accurate calibration of the parameters G2 (representing sink-size) and G3 (representing sink-strength).

Observed and simulated grain yields in each environment were quite variable with two major varieties (M0926-8 and IWDC2) having the highest grain yields in six out of the eight environments. The variation in the environments influenced the final grain yields recorded for all varieties. LER, SMR and BUK locations were consistently good environments during both dry (February to May) and rainy (June to October) seasons whereas DBT location was not appropriate for growing maize during both seasons mostly due to extreme temperatures (39 – 44^{o}C) and very sandy soils with low water holding capacity. Only varieties with tolerance to drought and heat stress were able to produce reasonable yields in the poor environments. The rooting parameters which differentiate cultivars due to their ability to tolerate drought and heat stress were calibrated together with the GSPs. This gave the model the ability to capture well the performance of the drought tolerant varieties in the poor locations in Dambatta. In all environments and for all varietal groups, the hybrid varieties produced the highest grain yields except for IWDC2 which was an open pollinated variety (OPV) producing yields like the highest yielding hybrid. In the poor environments, the highest grain yields were recorded for Oba Super

9 and Sammaz 32 which are both heat and drought tolerant with the former being a hybrid and the latter an OPV. In the high yielding environments, higher grain yields were recorded in the dry season than in the wet season. This is because of the clear skies which leads to high irradiance and subsequently high RUE (Lindquist et al., 2005). Also, during the dry season, temperatures were optimal for photosynthesis and dry matter allocation. Another reason for the high yields is that during the dry season, all the water requirements were met by irrigation with minimal run-off, while in the rainy season the larger amount of rainfall during the months of July and August could facilitate leaching of a lot of the applied fertilizers thereby affecting growth and yield. The model was able to reproduce these observed anomalies because during the GSP calibration steps, other parameters in the ecotype and species files were calibrated together with the reported cultivar coefficients. In the ecotype files, radiation use efficiency (RUE) and canopy light extinction coefficient for daily PAR (KCAN) were adjusted to capture the seasonal variations and effect of supra-optimal temperatures (Lindquist et al., 2005; Zhang et al., 2014). In the species file, coefficients that represent the effect of temperature on photosynthesis (PRFTC) and relative grain fill duration (RGFIL) were already adjusted for the tolerant and susceptible varieties to capture the effects of high temperatures on grain yield.

Very few studies have reported the applicability of crop models in simulating GEI and even fewer have reported using stability analysis techniques in ranking/analysing model simulated grain yields (Chapman et al., 2003, 2002a; Cooper et al., 2014; Hammer et al., 2006; Salmerón et al., 2017). Environments accounted for more than 60% of the variations in observed and simulated grain yields, possibly due to the wide variability in seasonal as well as edaphic factors. Many studies have reported the wide variation of maize producing environments in Nigeria (Badu-Apraku et al., 2015, 2012b; Oyekunle et al., 2017). This is the reason why varietal recommendations must be location specific. The variance explained by the genotype (variety) was larger than that by GEI, indicating the presence of some varieties with consistent performance across environments. This difference among varieties in terms of rank-orders across environments show that selection and recommendation of new varieties would be difficult when GEI is significant (Temesgen et al., 2015). Pham and Kang (1988), reported that GEI confounds yield performances thereby minimizing the utility of genotypes in several environments. Thus, the in-depth study of the yield levels, adaptation patterns and stability of both observed and model simulated yields of maize genotypes in multiple environments becomes imperative. It becomes more important when ranking varieties using simulated grain yields since the models make many assumptions and generalizations.

The results of stability analysis using the slope of regression (*bi*) shows an inconsistent ranking of the varieties with respect to observed and simulated grain yields. All the varieties showed *bi* values that were different from unity signifying that they all had an average response to environments, irrespective of the data type. According to Becker and Leon (1988), varieties with *bi* values close to unity have good response to changing environments, while Eberhart and Russell (1966), found that varieties with high mean grain yields and regression coefficients close to unity (*bi* = 1) are better adapted and more stable across environments. Based on both observed and simulated grain yields, two varieties (Sammaz 11 and Early White) with high mean grain yields and *bi* values close to unity were found to be more stable than all other varieties. Based on the observed grain yield, only Oba Super 9 was stable, while based on simulated grain yield, Ife Hybrid 5, Ife Hybrid 6 and Sammaz 28 were also stable. Varieties M1026-10, Sammaz 54 and TZBSR had *bi* values close to 0 for both observed and simulated yields indicating that they are better adapted to high yielding environments.

For all the three multivariate parametric models, Ife hybrid 6 was the most stable variety based on both observed and simulated grain yields, while the least stable variety was M0926-8. Stability analysis using variance parameter tests did not rank varieties according to high yield unlike the regression-based stability analyses. This variation between the regression-based stability ranking and the multivariate parametric stability ranking is due to the difference in the methodology for ranking the different varieties. While the regression methodology considers high mean as a precondition for the varietal stability, the multivariate parametric methods do not consider means for calculation of stability (Dia et al., 2017). All the stability models used were consistent in their stability rankings for both observed and simulated yield of the varieties except for Kang Ysi. This indicates that the simulated data obtained using CERES-maize model can be used in determining the magnitude of GEI and stability of maize varieties where field data are not available.

In the long-term simulation studies, observed weather data for 26 years were, used meaning that it was possible to do simulations in years with water stress. A high variation in simulated grain yields was observed for the 16 varieties using long term seasonal analysis in the dry and wet savannas. Yields of the early and extra early varieties were not significantly different between the two savannas. This is because they are early maturing and were able to complete grain filling before the early cessation of rains that is prevalent in the dry savannas. All the early and extra early varieties used were drought tolerant and five out of the eight varieties were tolerant to *Striga* infestation. Excessive rains after maize has reached physiological and harvest maturity could lead to significant reduction in harvested grains (Badu-Apraku and Fakorede, 2017b). As this is a common occurrence when early varieties are planted in the wet savannas, lower grain yields were expected from the seasonal analysis, but the model did not simulate low yields for early and extra early varieties in the wet savanna. This is because the model was not able to simulate yield losses due to continuous rainfall after the crop has reached maturity (e.g. factors like lodging and fungal attack on grains). The model simulated high grain yields for the intermediate varieties in both dry and wet savannas, although higher yields were produced in the wet savannas than in the dry savannas. Varieties M0926-8 and IWDC2 produced the highest maximum and mean grain yields in both savannas, while the yield of M1026-10 and M1227-12 were not significantly different between the two zones. IWDC2 and M0926-8 had a yield difference of 45% and 51%, respectively, when simulated yields in the dry and wet savannas were compared. The higher yields recorded by these varieties in the wet savannas could be due to their genotypic make up that allowed them to take full advantage of the extended rainy seasons which are ideal for optimum photosynthetic ability and adequate dry matter accumulation. The model simulated very low yields for all the late maturing varieties in the dry savannas because these varieties take a very long time to reach physiological maturity which results in the period of active grain filling coinciding with the end of the rainy seasons in the dry savanna. Same varieties produced very high grain yields in the wet savannas, indicating that the length of growing season and amount/distribution of rainfall is adequate for proper growth and performance of the late varieties in this zone.

4.5 Conclusion

Crop simulation models are becoming increasingly important tools for explaining the components of GEI that are observed in plant breeding and evaluation trials. Models are used to provide additional environmental indices or 'virtual' entries that could be used in providing robust analysis of varietal performance across multiple observed and simulated environments. This is possible when the calibration and model evaluations are robust enough to capture most of the observed varietal performance across multiple environments. Most of the variations detected in both observed and simulated grain yields in our experiments were attributed to differences in environments that play a key role in determining crop performance. The model accurately captured these variations for most of the varieties due to accurate calibration and evaluation of phenology (P1 and P5) and yield (G2 and G3) parameters in the cultivar file. In addition, calibration of parameters like soil fertility coefficient (SLPF) and root development parameter (RWUEP) captured the soil variations across fields and the ability of some varieties to tolerate drought stress. All the stability models used gave a similar trend for both observed and simulated grain yields and the *bi* model with the lowest AICc value ranked Sammaz 11 as the most stable variety irrespective of data source. The analysis showed the reliability of simulated data generated using CERES-maize model in determining stability of maize varieties. The long-term stability analysis in the dry and wet savannas showed that, long duration varieties produce high yields only in seasons where rainfall distribution is long, the intermediate varieties are good in both long and short seasons, while the early and extra early varieties are more suitable in seasons with short rainfall distribution. Currently, the Intermediate and late varieties are recommended to the wet savannas, while the early and extra early varieties are recommended for the dry savannas. Findings from our experiments have shown that intermediate varieties could also be planted in the dry savannas in seasons where early establishment of rainfall was observed, and when seasonal rainfall advice agencies predict long rainy season with good rainfall distribution.

Results from our experiments have shown that CERES-Maize model correctly predicts the GEI and stability of maize varieties and can hence be used to predict how varieties will behave in locations and seasons where trial data is unavailable.

5 CHAPTER FIVE

OPTIMUM STAND DENSITY OF TROPICAL MAIZE VARIETIES: AN ON-FARM EVALUATION OF GRAIN YIELD AND YIELD ATTRIBUTES IN THE NIGERIAN SAVANNA

5.1 Introduction

Although maize production has been increasing in Nigeria since the 1960s, this increase is attributed to expansion in production area and not to the much-needed intensification (FAO, 2018). Yield per unit area of maize is quite low in Nigeria, at about 2 Mg per hectare, less than 40% of the yield potential of most cultivars is achieved. The low per hectare yield of maize has been attributed to many factors as highlighted by Adnan et al., (2017b). Research efforts by breeders and agronomists have led to production of many technologies including breeding of high yielding varieties that are tolerant to drought, diseases, low nitrogen, and Striga infestation (B Badu-Apraku et al., 2009; Kamara et al., 2009). Some of these varieties are early or extra early, which led to the expansion of maize into the drier parts of Nigeria where production was originally unfeasible (Badu-Apraku et al., 2011).

An increasing demand for maize in Nigeria for both human and commercial consumption has prompted the need for improved intensification. Furthermore, the rise in population has prevented continuous land expansion, as land is now needed for more non-agricultural activities (Pretty et al., 2011). It has since been agreed that to improve maize intensification, a dynamic change in how maize is produced must be explored. These changes must consider making agronomic recommendations that deviate from the current generalized and blanket advices which do not recognize the wide variations in climatic and edaphic conditions (NAERLS and FDAE, 2017). Firstly, selection of adaptable varieties with traits suitable to the peculiarities of each production zone must be encouraged (Badu-Apraku et al., 2009; Kamara et al., 2009). Secondly, appropriate site-specific fertilizer management that encompasses optimal nutrient-use must be adopted (Bello et al., 2018; Kamara et al., 2014). Thirdly, smart agronomic practices that incorporate appropriate time of sowing and selection of optimal sowing densities must be promoted (Jibrin et al., 2012).

Optimum stand density (OSD) in annual crops is the intermediate seeding density that maximizes yield at harvest (Deng et al., 2012). OSD selection is an agronomic practice that determines the growth and yield of maize, its importance has long been established all over the world (Al-Naggar et al., 2015; Casini, 2012; Duvick et al., 2010; Liu and Tollenaar, 2009). OSD of maize varies across environments and management practices, and several arguments in literature suggest that recent cultivated varieties differ in their OSD even if planted in similar environments (Jia et al., 2018; Li et al., 2015; Mokhtarpour et al., 2011). In optimum environments (neither nutrients nor water limiting), grain yields are maximized under higher OSD due to the following: increase in LAI and net crop assimilation (Echarte et al., 2000; Sangoi et al., 2002), increase in number of cobs per area (Lauer and Rankin, 2004), and the capacity of maize plants to develop new reproductive structures with increase in available resources per plant (Lauer and Rankin, 2004). It is accepted that greater crowding tolerance of newly released maize cultivars allows for using higher stand densities when compared to older ones even under sub-optimal nutrient conditions (Di Matteo et al., 2016).

Currently, sowing densities of up to 8.5 plants m^{-2} are recommended under intensive production in North America (Li et al., 2015). In Nigeria, the recommended sowing density for maize is 5.3 plants m^{-2} irrespective of varietal characteristic, environment or management practice (NAERLS and FDAE, 2017). Under sole cropping, the density is usually achieved by sowing and thinning to 1 plant $hole^{-1}$ at a spacing of 75 cm inter and 25 cm intra row. For mixed cropping, 2 plants are sown $hole^{-1}$ at a spacing of 75cm x 50cm inter and intra row. Most farmers adopt sowing densities below 50% of the recommended rates majorly due to lack of knowledge and fear of yield losses associated with high density sowing under low fertilization and possible intermittent droughts. The low output in smallholder farms in the Nigerian Savannas is partly attributed to adoption of sub-optimal sowing densities (Sani et al., 2008). The absence of a standard OSD for maize varieties in the Nigerian Savannas makes it necessary to undertake research to understand the optimum density of maize in varying environments and management practices. The objective of the present investigation was therefore to evaluate the yield response of different maturity groups of maize to different sowing densities in on-farm conditions of varying management, edaphic and seasonal characteristics.

5.2 Methodology

5.2.1 Experimental sites

On-farm field trials trials were conducted in the rainy seasons of 2016 and 2017 across the Northern Guinea Savanna (NGS) zones of Kano and Kaduna States both located in North-Western Nigeria. One Local Government Area (LGA) was selected in Kano (Doguwa) and two selected in Kaduna (Ikara and Lere). The selection of sites was done purposefully with the intention of covering areas with high maize production potentials and where research for development and extension support activities of the Sasakawa Africa Association (SAA) are active. In each LGA, 10 farmers were selected through stratified random sampling to cover the different groupings of farmers in the SAA extension programs. SAA farmers are grouped into five distinct classes based on how long they have been in the program. Subsequently, two farmers were randomly selected from each group in each LGA to cover all classes; a total of 30 farmers were used for the entire research. The same farmers and fields selected in 2016 were maintained and used in 2017, giving a total of 60 environments (farmer × year combinations). Detailed soil analysis from each farmer field are presented in appendix 2.

5.2.2 Treatments and trial descriptions

Ten maize varieties of varying maturity levels (two early, two intermediate and six late) were used in the experiment (Table 1-3). The varieties were planted under three sowing density levels: the national recommendation (5.33 plants m^{-2}), 50% lower (2.66 plants m^{-2}) and 20% higher (6.66 plants m^{-2}). The density selection was done to capture the reality of sowing densities currently found in farmers' field (2.66 and 5.33 plants m^{-2}) and a slight increase (6.66 plants m^{-2}) over the recommendation. The densities were achieved by maintaining same inter-row spacing (75 cm) and then varying the intra-row spacing. For 2.66 plants m^{-2}, an intra-row spacing of 50 cm was used, for 5.33 plants m^{-2} a spacing of 25 cm was used, and for 6.66 plants m^{-2} a spacing of 20 cm was used. Under all densities, two plants were sown per hole and then thinned to 1 plant per hole at two weeks after sowing. Sowing was carried out in each farmer field as soon as the rains were established. In 2016, sowing was delayed due to late establishment of rains with sowing carried out on 20th June in Doguwa, 21st June in Ikara, and 24th June in Lere. In 2017 however, the fields in Doguwa were sown on 31st May while Ikara and Lere were sown on 2nd and 4th June, respectively. Fertilizer application was done according to the regional recommendation (120N:60P_2O_5:60K_2O kg ha^{-1}); potassium (K) was applied in form of muriate of potash, phosphorus in the form of single super phosphate and nitrogen was applied in the form of urea. While all the P and K fertilizers were applied at sowing; only half of the N fertilizer was applied at the time of sowing (via incorporated band row placement) and the other half applied 21 days later. Each farmer field was planted with 10 plots, ensuring that all 10 varieties are sown together with random combinations of the 3 sowing densities according to the experimental design. The individual plot size was 30 m^2 (8 ridges of 0.75m x 5m length) and the net plot size was 12 m^2 (4m × 4 inner ridges).

5.2.3 Experimental design and data analysis

The on-farm field trials involved a full factorial design of 10 varieties and 3 densities implemented in 30 incomplete blocks. The blocks were the 30 farmers' fields, that each had 10 experimental plots. The treatment combinations were allocated to the blocks using the design of experiment (DOE) platform of JMP version 14 software (SAS, 2018) according to the D-optimality criterion (Atkinson and Donev, 1989) for a model that had variety, experience of farmer, density, density*density, variety*density and variety*density*density as fixed effects and farmer (=block) and farmer nested in locations as random effects.

All measured variables were subjected to analysis of variance. A linear mixed model was adopted, farmer fields nested in both LGAs and years were used as random effects. Main effects of year, sowing density, variety and farmer experience together with their individual second order interactions were all estimated as fixed effects. The result of grain yield, harvest biomass, kernels number per square meter, and 100 kernel weight from the design ANOVA are shown in appendix 3.

For a detailed analysis of grain yield across environments, i.e. the farmers' fields × year combinations, a different approach was adopted. Genotype-environment interactions are best described with multiplicative terms. As the environments are best considered as random, this gives rise to a mixed model with factor-analytic covariance structures (Piepho, 1997). The experimental data were described with the following mixed model:

$$y_{ijk} = (\beta_{1i} + u_{1i}) + (\beta_{2i} + u_{2i})dens + (\beta_{3i} + u_{3i})dens^2 + \varepsilon_k \quad (5.1)$$

where y_{ijk} is the grain yield for variety i sown at a given density in environment j in a field plot k, where the fixed effects parameters β_{1i}, β_{2i}, and β_{3i} describe the (non-linear) response of variety i to sowing density, and d_{1ij}, d_{2ij} and d_{3ij} are random effect parameters that describe the interaction between variety i and environment j in the variety's response to sowing density. A simple multiplicative model for the random effect parameters is given by (Piepho, 1997):

$$d_{1ij} = u_{1i}\ w_j,\ d_{2ij} = u_{2i}\ w_j,\ d_{3ij} = u_{3i}\ w_j \quad (5.2)$$

with u_{1i}, u_{2i} and u_{3i} being the 3 parameters for variety i, and w_j being an underlying (unobserved) environmental factor or index that represents some gradient (e.g., the inherent fertility of a field and/or how well the rainfall was distributed at that location in that year). Eq. 5.2 means that the covariance structure of the random effects corresponds to the Eberhart-Russell stability model (Eberhart and Russell, 1966), a factor analytic model noted as FA(1) in SAS (Piepho, 1999). Such model can be extended to several underlying factors, and one can also add a residual interaction term v_{ij} (Piepho, 1997):

$$d_{1ij} = \sum_{k=1}^{K} u_{1ik}\ w_{jk} + v_{1ij}, \qquad d_{2ij} = \sum_{k=1}^{K} u_{2ik}\ w_{jk} + v_{2ij}, \qquad d_{3ij} = \sum_{k=1}^{K} u_{3ik}\ w_{jk} + v_{3ij} \quad (5.3)$$

which is a factor-analytic model with K underlying factors noted in SAS syntax as FA0(K) if there is no residual interaction term v_{ij}, as FA1(K) when it contains interaction terms v_{ij} that all have the same variance, or as FA(K) when it contains interaction terms v_{ij} that all have different variances (Piepho, 1999).

The data analyzed with the general mixed model given by Eqs. 4.1 and 4.2 with FA(1) covariance structure consisted of grain yields collected from 30 farmer fields in two years with 10 plots in each field, giving a total of 600 plot data. The combination of 30 farmers and 2 years gave rise to 60 environments. The mixed model was fitted to the data using the Mixed procedure in SAS 14.3 (SAS Institute Inc. 2017) using the restricted maximum likelihood (REML) method with variety,

variety×density, and variety×density² as fixed effect, and also as random effects with the field*year environments specified as subject for the random effect (syntax 'random variety variety*dens variety*dens*dens /sub=field*year type=FA0(1)'). This allowed to estimate the 30 fixed effects parameters β_{1i} β_{1i} β_{1i} (10 varieties × 3 parameters: intercept, density and density^2), 60 environmental indices w_j and 30 random effect parameters u_{1i} u_{2i} u_{3i} (10 varieties × 3 parameters). In order to decompose the resulting 30 by 60 matrix ***D*** of random coefficients d_j into a column vector ***U*** of 30 random effect parameters u_{1i} and a row vector ***W'*** of 60 environmental indices w_j (with ***D =U W'*** according to Eq. 5.2) we assumed the variance of the environment indices is equal to one (otherwise the multiplicative model given by Eq. 5.2 is over-parameterized as explained by Piepho (1999)). The model was fitted to the data using SAS following methods described by Raman et al. (2011) and detailed in Littell et al. (2006).

5.2.4 Plant data measurements

Plant measurements were carried out at harvest and post-harvest stages. Plants from the net plot were cut at ground level, ears were removed leaving husks intact on the plant. Ear number was calculated by dividing number of all the ears by the net plot area and expressed as ear number m^{-2}. The weight of all cobs was then taken and recorded. A sub-sample of 10 cobs was sampled following a strategic procedure where all cobs are laid side by side, based on the number of cobs, selections are made at fixed intervals, e.g. cob 5, 10, 15, 20. To measure kernel number per m^{-2} and kernel weight in grams, kernels are removed from the 10 sub sampled cobs before drying, three sets of 100 kernels are counted and weighed, the average weight was then recorded. Cob and kernel subsamples were dried to constant weight at 70^{o}C, after which the seed and cob sub samples were weighed and logged separately. For above ground measurement however, the remaining plant parts (stover without ears) were separated into various components (leaf blade, sheath, husk, and stem including tassel) and weighed separately. The various components are then chopped separately, with each component properly mixed and 500g sub-sample oven dried to constant weight. Measurements of all components followed methods proposed by Ogoshi et al. (1999).

5.2.5 Soil and weather measurements

For soil data measurements, one composite sample was taken from each farmer field from four sampling points collected at 0–20 cm depth using soil augers during establishment before planting and fertilizer application. The V zig-zag random sampling approach was adopted, and the four sampling points were taken from each field. Collected soil samples were thoroughly mixed and passed through a 2 mm sieve. Afterwards, one disturbed composite sample representing each farmer field was taken for laboratory analysis of some major soil characteristics using wet chemistry. Total nitrogen (TN) was determined using the micro-Kjeldahl digestion method (Bremner, 1996). Total soil organic carbon (TC) was measured using a modified Walkley & Black chromic acid wet chemical oxidation and spectrophotometric method (Heanes, 1984). Soil pH in water (S/W ratio of 1:1) was measured using a glass electrode pH meter and the particle size distribution was determined following the hydrometer method (Gee, 2002). Available phosphorus was analyzed based on the Mehlich-3 extraction procedure (Mehlich, 1984) preceding inductively coupled plasma optical emission spectroscopy (ICP-OEC, Optima 800,Winlab 5.5, PerkinElmer Inc., Waltham, MA, USA). One undisturbed core sample was also taken near the four auger points in each field. These undisturbed core samples were used for bulk density (BD) analysis using the thermo-gravimetric core method (Blake and Hartge, 1986); the results were averaged to have one bulk density value per field. Bulk density values ranged between 1.73 and 1.40 g cm^{-3}, with wide variation across farmer fields. The soils are categorized as moderately acidic (5.6 - 6.0) to slightly acidic (6.1 – 6.5). There was a wide variation in the soil organic carbon (TC) contents with all locations in Lere and Ikara having TC contents below 10 $g.kg^{-1}$. Across all locations, total nitrogen (TN) contents were low although moderate variability existed across the different farmer fields. High variability existed in the available phosphorus contents, although all the soils were largely poor in available P. Most of the fields were of sandy clay loam texture, with only a few having sandy loam textures. Detailed soil analysis from individual farmer fields are presented in appendix 2.

5.3 Results

5.3.1 Weather conditions

Figure 5-1 shows the weather conditions of the 3 LGAs in 2016 and 2017. Lere had the highest cumulative rainfall for both years, although the variation between the LGAs was higher in 2016 than in 2017. In 2016, Lere LGA had 78.1 mm more rainfall than Ikara and 148.1 mm more rainfall than Doguwa, while in 2017, the difference was 58.7 and 106.7 mm respectively. Due to early establishment and late cessation of rainfall, the trials were sown earlier and harvested later in 2017 than in 2016 across all 3 LGAs. In 2016, Lere had the least number of rainy days and the highest amount of cumulative rainfall, while Doguwa had the highest number of rainy days and the lowest amount of cumulative rainfall. In 2017 however, Lere had the greatest number of rainy days and the highest amount of cumulative rainfall, while Doguwa had more rainy days but lower cumulative rainfall than Ikara. Overall, 2017 was a better year than 2016 across all 3 LGAs as evidenced by higher cumulative rainfall and a greater number of rainy days.

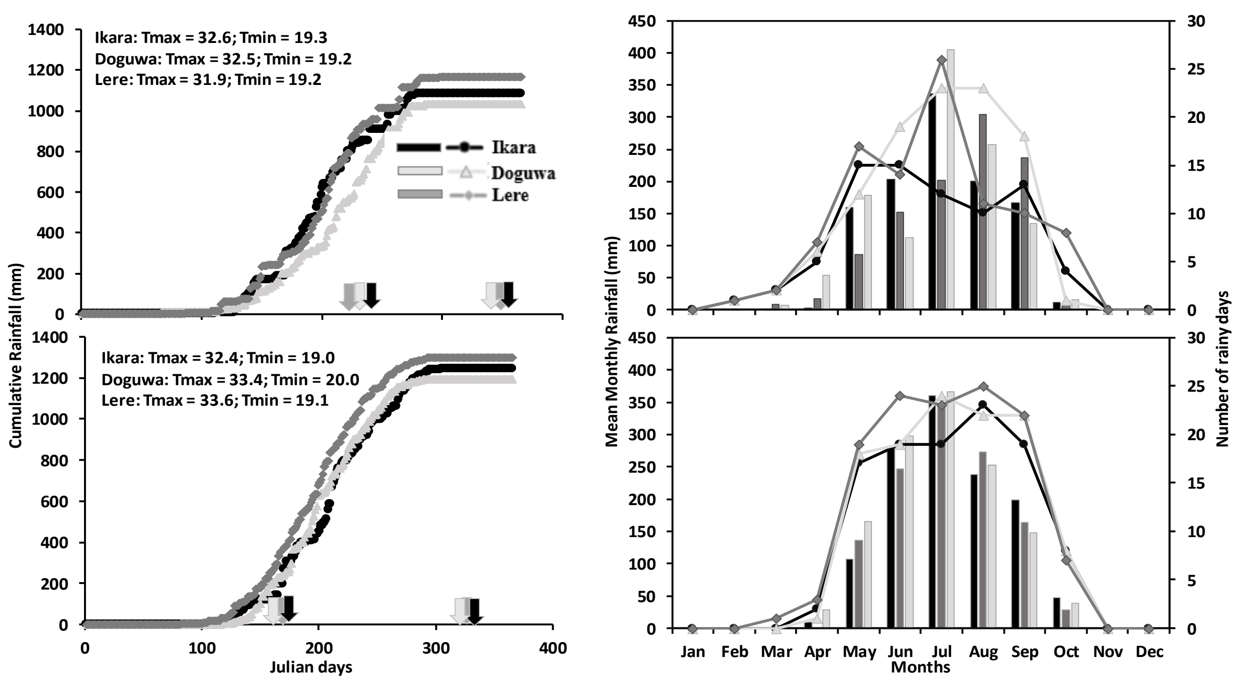


Figure 5-1: Cumulative rainfall (markers), number of rainy days (lines with markers), and monthly rainfall (bars) for the study areas in 2016 and 2017. Arrows indicate sowing and harvest dates for the individual locations in 2016 and 2017.

5.3.2 Environmental indices and FAM parameters

Figure 5-2 shows the results of environmental indices calculated in 2016 and 2017, together with the cumulative probabilities for both years combined. Across both years, the environmental indices ranged between +2.23 to -1.55 (Figure 5-2). Higher value of an environment index indicates optimum conditions for growth and development of maize with respect to soil, management and weather conditions. Out of the 60 environments, 12 environments (20%) had index values between 1.07 to 2.23 and are classified as good environments, 17 environments (28.3%) have indices between 0.006 to 0.89 and are classified as moderate environments, 19 environments (31.7%) have index values less than 0 but greater than -1 and are classified as poor environments, while 12 environments (20%) have index values between -1 to -1.5 and are classified as very poor environments. All 30 environments were classified as very poor or poor in 2016 and shifted to moderate or good in 2017.

Table 5-1 shows the estimated probability values of the fixed effect (intercept, density and density^2) parameter estimates of the ten maize varieties modelled using Eberhart-Russell (FA) model combined across all environments. The intercept was statistically significant for all the varieties except Sammaz 40 and Sammaz 32. The highest estimate for the intercept was observed for Sammaz 15 while the lowest was observed for Sammaz 40. The effect of density was significant only for SC651, Sammaz 11 and OBA98 with Narzo 22 having a P-value slightly higher than 0.05. For the quadratic effect of density however, p-value was significant for SC651, Narzo 22, and OBA98.

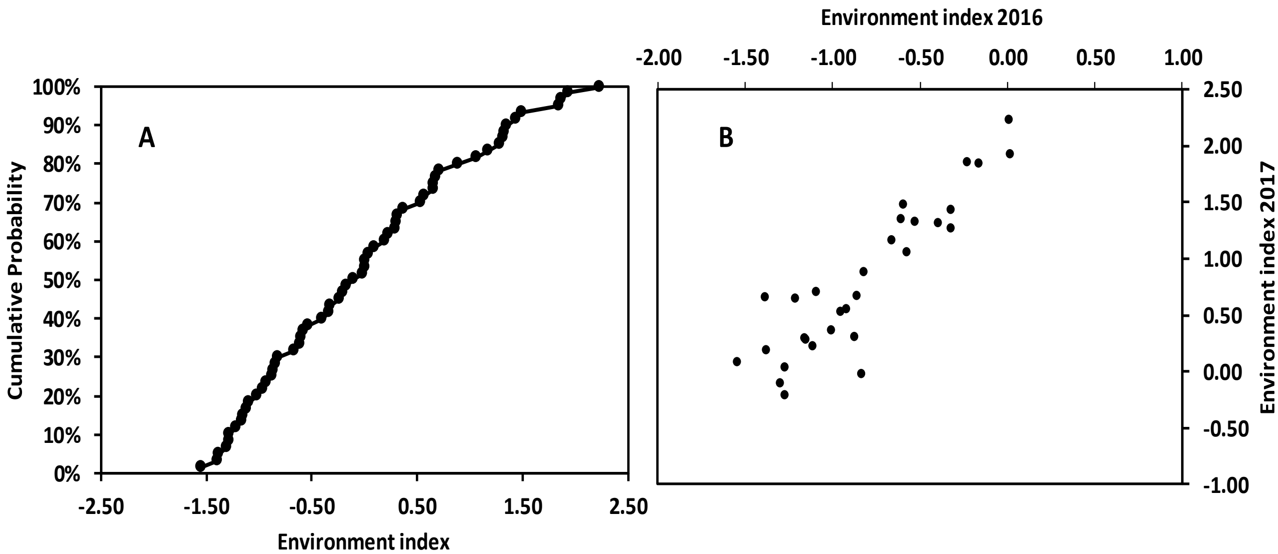


Figure 5-2: Cumulative Probability of environmental indices (A) and actual environmental indices of the 30 farmers' fields in 2016 and 2017.

Table 5-1: Fixed effect parameters probability values averaged across environments for the 10 varieties used in the study (prob value for *Ho*: parameter = 0)

Variety	β_1	β_2	β_3
SC651	<.0001**	<.0001**	<.0001**
Sammaz 15	<.0001**	0.2057	0.127
COMP 4	<.0001**	0.2984	0.478
Narzo 22	0.0001**	0.4252	0.025*
Sammaz 32	0.0566	0.7433	0.145
Narzo 21	<.0001**	0.9599	0.948
Sammaz 11	0.0092**	0.0268*	0.077
Sammaz 41	<.0001**	0.062	0.386
Sammaz 40	0.1056	0.4252	0.545
OBA Super 9	0.0175	0.0079**	0.005**

β_1 = Intercept, β_2 = Density effect, β_3 = Quadratic effect of density
** Significant at 1% level of significance, * Significant at 5% level of significance

5.3.3 Estimated grain yields

Figure 5-3 shows the estimated grain yield of the different maize varieties under varying planting densities. In good environments (Environment index = 1.5) linear increase in grain yield was observed with every increase in planting density for all the varieties except for Sammaz 32, although the magnitude of yield increase was variety specific. In the moderate environment (Environment index = 0.5), a linear increase in grain yield was observed with every increase in planting density up to the highest density tested for Sammaz 15, SC651, OBA98, Narzo 21 and Sammaz 11. For Sammaz 32 and Sammaz 41 however, an increase in planting density from 2.66 to 5.33 plants m^{-2} led to a significant increase in yield, but further increase did not produce any significant yield increase. In poor environments (Environment index = -0.5), a linear increase in grain yield was observed with increase in planting density for Sammaz 32, Sammaz 15, Sammaz 11, Oba 98 and Narzo 21. Sammaz 40 and Narzo 21 did not respond to increasing density while in COMP 4 and SC 651 increasing planting density from 2.66 to 5.33 plants did not lead a significance increase in grain yield but further increase to 6.66 resulted in a significance yield increase. Increasing planting density from 2.66 plants to 5.33 plants per meter square did not have any significant effect on grain yield of all the varieties in very poor environments (Environment index = -1.5).

The response of individual varieties to increased planting density across different environments as estimated by the FAM is shown in Figure 5-4. The highest grain yields were recorded for variety SC 651 irrespective of environment. Grain yields of 9.6, 7.5, 5.4 and 3.4 Mg ha^{-1} were recorded under the highest planting density (6.6 plants m^{-2}) in the good (EI = 1), moderate (EI = 0.5), poor (EI = -0.5) and very poor (-1) environments respectively. When the variety was planted under 5.3 plants m^{-2}, a yield of 6.95, 5.72, 4.48 and 3.25 Mg ha^{-1} was recorded for good, moderate, poor and very poor environments. The variety produced grain yields of 5.12, 4.39, 3.66 and 2.94 Mg ha^{-1} for good, moderate, poor and very poor environments when planted under the lowest sowing density. For the high-density planting, a yield difference of 44.2% was observed between SC 651 and the lowest yielding variety (Sammaz 32) when planted in good environments, while the difference was 86.6 % in the very poor environments. For the medium density planting, a yield difference of 61.7% and 65.5% was observed between the good environments and the poor environments. For the low-density planting however, the difference in yield between SC 651 and Sammaz 32 was 34.4% and 67.8% under the very poor and good environments respectively.

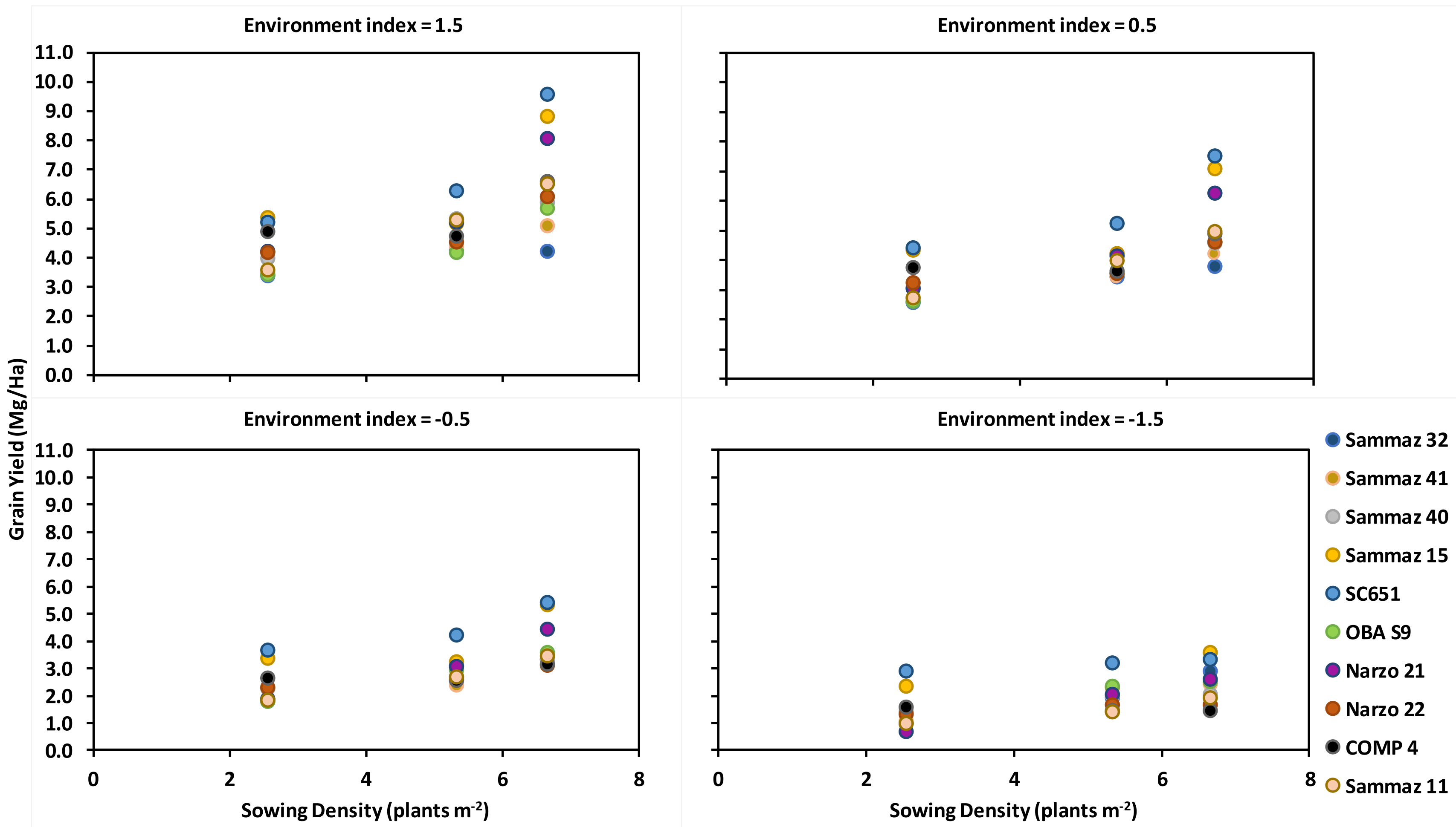


Figure 5-3: Grain yield of ten maize varieties under different environments. Panels represent: very good environments (EI = 1.5), moderate environments (EI = 0.5), poor environments (EI = -0.5) and very poor environments (EI = -1.5)

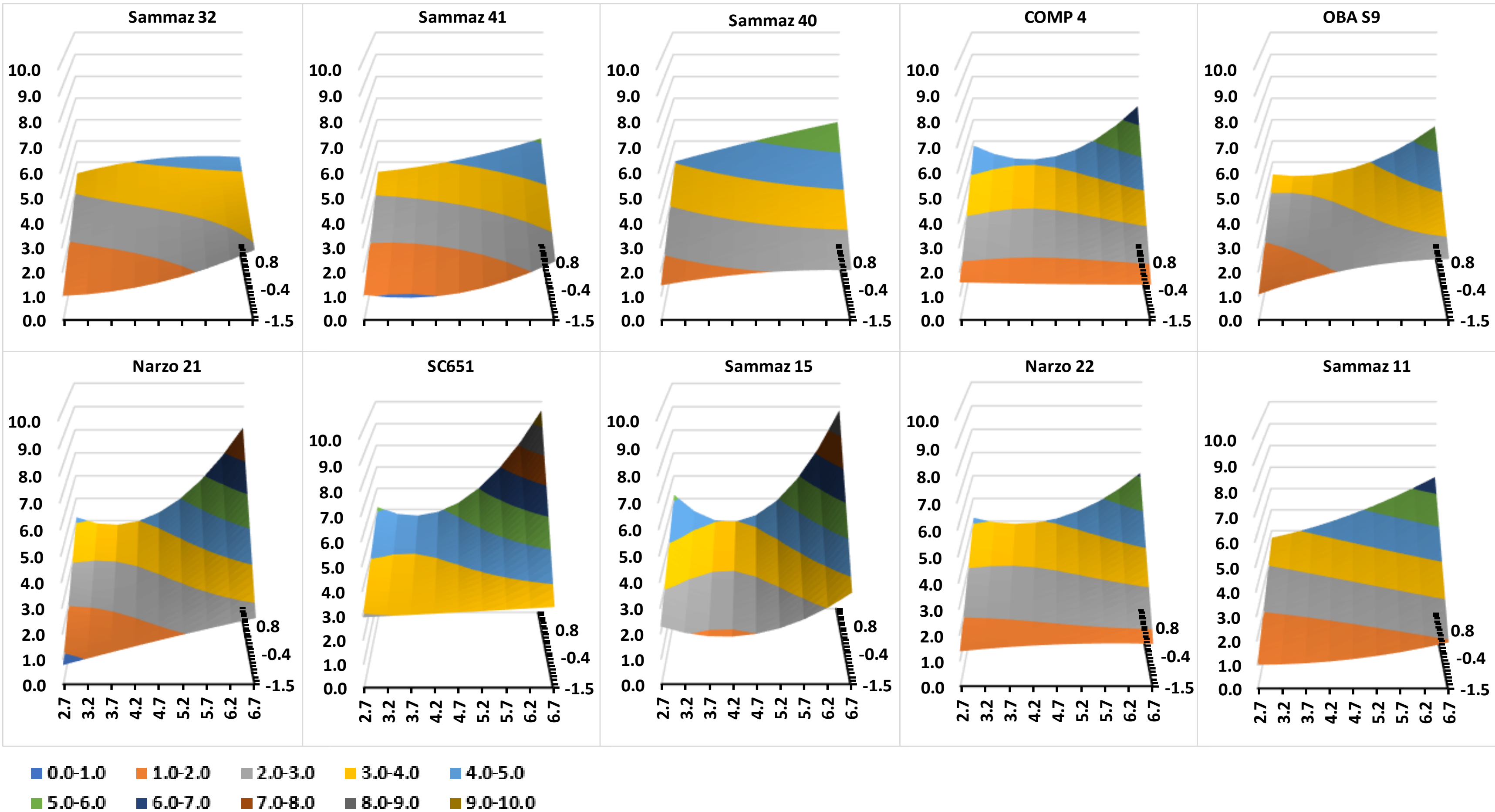


Figure 5-4: Model estimates of mean grain yield of different maize varieties under varying sowing densities across the defined environments. X-axis = sowing density (plants m^{-2}), Y-axis = grain yield (Mg ha^{-1}), Z-axis (vertical) = environmental index (EI) (lower values indicate poor environments)

5.4 Discussions

Several authors reported variation in maize OSDs across diverse environments in the literature (Echarte et al., 2000; Hernández et al., 2014; Sangoi et al., 2002; Tollenaar and Lee, 2002). Yield increases with elevated sowing densities have been reported all over the world. In Egypt for example Al-Naggar et al. (2015) reported yield increase with increasing planting density up to 9.5 plants per meter square under high nitrogen applications. Historical yield gains for maize in the United States have been reportedly attributed to increase in planting density (Tokatlidis and Koutroubas, 2004). Dramatic increases in grain yield due to elevated density have been reported in Brazil, Argentina, Canada and France (Duvick, 2005). In Nigeria, Kamara et al. (2006) and Adeniyan (2014) reported grain yield gains with increase in planting density. Although optimum stand density of maize has been shown to be variety dependent (Sarlangue et al., 2007; Widdicombe and Thelen, 2002), even the best hybrids will produce low yields when agronomic management is not optimum (Boomsma et al., 2009). This is because maize varieties interact with the environment and crop management in producing grain yields (Mastrodomenico et al., 2018). To maximize yield potential of a variety under elevated planting density, therefore, requires adequate understanding of the dynamics between plant genetics and agronomic management (Tollenaar and Lee, 2002).

In our experiments, farmers with varying characteristics were selected such that some groups (A and B) are known to follow all recommended agronomic practices, have good soils due to history of proper residue management and manure application, and have for long belonged to farmer groups where they frequently access extension services. The second group of farmers (C, D and E) are known to follow their own practices which entails non-optimal nutrient management, inadequate weed control, and poor access to extension services. Additionally, the amount and distribution of rainfall in the two years of experimentation were very different thereby leading to variations in the environmental indices observed during analysis. Since the environmental indices were created by combining the farmer characteristics (including soil types), location and year, a tremendous variability among the test environments was observed. About 20% of the environments were found to be very good and are the most optimum for maize production. About 30% of the environments are moderate environments and could be used for maize production but are not optimal. The remaining environments are not appropriate for maize production, basically due to poor soils and improper agronomic management coinciding with low and improperly distributed rainfall. Since agronomic recommendations are blanket in Nigeria, farmers have been consistently told to increase their planting densities especially in sole and strip cropping systems without considering the variation among farmers, soil types and weather conditions (Adeniyan, 2014; Gilbert, 2016; NAERLS and FDAE, 2017). The higher yields recorded in the optimum environments are attributed to better agronomic management, good soils, and higher amount of rainfall. Ruffo et al. (2015) suggested that increased planting density must be synergistic with other optimal management factors including weed control and better soil fertility managements. This was exactly what was observed in Figure 5.3 in our data where the varieties responded to sowing densities increasing in different ways under varying environmental indices. Grain yield responses showed a convex shape in the poor environments where increasing planting density from 2.6 plants to 5.3 plants did not have any effect on grain yield, but further increase to 6.6 plants resulted in yield increases. This response is typical in weed infested maize fields (Page et al., 2012; Tollenaar et al., 1994). Reports have shown that maize suffers competition from early weeds, but the competitive ability is improved by increasing planting density (Tollenaar and Lee, 2002).

Results from the present research showed a clear variation in yield responses due to elevated planting densities across the test varieties. In the optimum environments all the varieties responded to increasing planting density although all the responses were linear with no evidence of attainment of optimum density. Higher grain yields were recorded for the highest planting density for all the varieties in the optimum environments except for Sammaz 32. This is an unexpected result as the variety is early maturing, and previous reports by Edwards et al. (2005) suggested that higher planting densities are expected to be more beneficial for early maturing varieties than full season varieties. This is because early varieties usually have smaller leaves which means more plants are needed per area to reach the same amount of cumulative intercepted radiation (Tollenaar et al., 2006).

The intermediate varieties (SC 651 and Sammaz 15) produced higher yields than the early and late varieties under all tested planting densities and across all environments, although the variation in yield was greater in elevated planting densities. Even though the early varieties mature earlier than the intermediates and share similar morphological characteristics, their lower yields are clearly due to low genetic yield potentials and shorter grain fill durations. Clearly the intermediate varieties had low biomass plasticity and low reproductive partitioning which provided them the ability to respond to increasing population densities due to: (i) reduction of sink limitation which resulted in increased harvest index and (ii) increase in their ability to explore resources and tolerate biotic stresses which leads to higher biomass production (Sarlangue et al., 2007). In addition, all the intermediate varieties were drought and striga tolerant, and because breeding for striga is done under low soil Nitrogen (Ifie et al., 2015), they had the added advantage of utilizing the available Nitrogen even under high density. It is still interesting to note that the early maturing varieties produced grain yields that were statistically similar to the late varieties that have been reported in literature to have relatively higher potential yields. The late maturing varieties produced grain yields that were significantly lower under high density. This could be due to the high shading ability caused by production of vigorous vegetative structures which lowered harvest index. The lower grain yields could also be attributed to the longer time it takes for the late varieties to end juvenility and reach full grain filling (Van Roekel and Coulter, 2011). We concluded that the response of grain yield of maize is dependent on varietal characteristics and environmental conditions in the Nigerian Savannas. Furthermore, under elevated planting densities, varieties with the ability to tolerate the crowding stress and to some extent drought and low nitrogen should be adopted.

5.5 Conclusion

Sowing density recommendations all over Nigeria have been blanket without consideration for varietal characteristic, soil type, climatic conditions, and or management decisions. We conducted experiments in farmer fields with different management skills using maize varieties of different characteristics planted under different stand densities. Yields of tested varieties were different under both low and high stand densities indicating a difference in both potential yield and tolerance to crowding. The intermediate maturing varieties which have both high yield potentials and tolerance to crowding, drought and low nitrogen produced the highest grain yields under all the tested stand densities. The study shows that the planting density of maize can be increased which will lead to corresponding increase in grain yield under suitable environmental condition.

6 CHAPTER SIX

OPTIMIZING SOWING DENSITY-BASED MANAGEMENT DECISIONS IN THE SUDAN AND NORTHERN GUINEA SAVANNAS OF NORTHERN NIGERIA USING DSSAT-CERES-MAIZE MODEL

6.1 Introduction

The major factors limiting the yield of maize in Nigeria include the inherently poor soils (Jibrin et al., 2012), frequent droughts and striga infestations (Kamara et al., 2014), and low use of improved inputs such as fertilizers and seeds (Badu-Apraku et al., 2012b). A serious but often overlooked reason is the lack of proper adherence to improved agronomic practices especially with respect to varietal selection, appropriate planting dates and selection of optimum sowing densities (Shaibu et al., 2016). The dramatic increase in per hectare grain yield of maize world-over in the past 50 years has been attributed to the development of many specialty types of maize all of which are highly responsive to good agronomic practices (Mason and D'croz-Mason, 2002). The agronomic practice with the biggest influence on grain yield of maize over these years has been reported to be increase in sowing density (Hashemi *et al.* 2005; Liu and Tollenaar 2009). Maize varieties currently released in Nigeria are bred and grown in relatively low plant density (5.3 plants per m^{-2}) environments, which is around half of the sowing density adopted in countries with the highest maize grain yields per unit area (NAERLS and FDAE, 2017). Despite the low recommended sowing density of maize in Nigeria, most small-scale farmers plant less than 50% of that recommended density due to lack of access to nitrogen (N) fertilizers (Muoneke et al., 2007). It has been hypothesized that the recommended sowing density could be increased without necessarily applying N fertilizers beyond the current recommendations (Kamara et al., 2006).

Maize grain yields decrease with increasing sowing density beyond the optimum, but modern maize varieties have been known to tolerate high densities even under low nitrogen fertilization (O'Neill et al., 2004). Finding the best interactive function of adequate sowing density and nitrogen fertilizer application has been the focus of much research (Al-Naggar et al., 2015; Bhatt, 2012; Qian et al., 2016). Stresses caused by low N application frequently occur under high sowing density conditions (Bänziger and Lafitte, 1997). Because most small-holder farms in the maize belts of Nigeria have low inherent soil N contents and N fertilizers are expensive, it is important to provide sowing density management decisions for the low input and sub-optimal management conditions that are specific to fields and regional scales. Most studies on elevating maize sowing density in Nigeria are reported from on-station experiments under optimal management (Abubakar and Manga, 2017; Kamara et al., 2006; Muoneke et al., 2007; Sani et al., 2008). There is a need to conduct researches in farmers' fields and if possible, incorporate the result of actual experiments to crop simulation models in order to have more spatial coverage and make better variety and location- specific recommendations for maize sowing density and nitrogen fertilizer recommendations.

Combining results from short-term experiments with robust, well calibrated and evaluated dynamic crop simulation models has been a common strategy for studying the effect of long term climatic and edaphic variabilities while avoiding costly and time-consuming experiments (Holzworth et al., 2014; Rezzoug et al., 2008). The two most widely used models in Sub-Saharan Africa (SSA) are APSIM (Keating et al., 2003) and DSSAT (Jones et al., 2003).

CERES-Maize is one of the maize models in the DSSAT suite. The potentials and limitations of the CERES-Maize model particularly with respect to sowing density effects in Nigeria has been documented by an initial study conducted by Jagtap et al., (1998) in South-West Nigeria 21 years ago. In their experiments, they studied the response of maize to different row arrangements/densities and tested the ability of the model to simulate the development, growth and yield of maize over a range of planting densities. They concluded that the variety used in the study did not respond to planting density beyond 6.9 plants m^{-2} and nitrogen fertilizer application beyond 75-100 kg ha^{-1} because of the genetic makeup of the variety. They also posited that the use of CERES-Maize model may be limited due to inaccessibility of soil and weather data, but most importantly due to lack of detailed crop data for calibrating the genotype specific parameters (GSPs) of different varieties. The study claimed that upon the development of high yielding varieties with upright leaf orientation and greater response to applied nitrogen, response to higher densities should be expected in the region. Having initially calibrated GSPs of 26 modern maize varieties hypothesized to be tolerant to high sowing density (Table 3-2), the current research was conducted with the following objectives: (i) calibrate CERES maize model using data collected from researcher managed experiments conducted in farmers' fields of varying management conditions in two contrasting environments; (ii) evaluate the ability of the model to simulate the effect of elevated sowing density on different maize varieties used in Nigeria and sub Saharan Africa; (iii) use the calibrated and evaluated model in making recommendations for optimum sowing density and N fertilizer application of maize in two contrasting environments and (iv) Determine the economic profitability of different management scenario of maize in the SS and NGS.

6.2 Methodology

6.2.1 Experimental locations, design, and statistical analysis

On-farm field trials were set-up in three Local Governments Areas (LGAs) each of the Sudan (SS) and Northern Guinea (NGS) Savannas of the Nigerian Maize Belt during the rainy seasons of 2016 and 2017. Detailed descriptions of the experiments, the design and data collected are presented in chapter 5 (section 5.2.1).

6.2.2 Model calibration and evaluation

Data on grain yield, biomass at harvest, number of days to maturity and harvest index from the best farmer fields under the recommended sowing density (5.3 plants m^{-2}) in 2016 and 2017 experiments in the 3 LGAs for each agroecology (2 farmers' fields, 2 varieties, 2 years and 3 LGAs) were used for model calibrations. Separate calibrations were done for the SS and NGS agroecological zones. The DSSAT model inputs include cultivar coefficients, weather records (min. and max. temperature, rainfall, and relative humidity), initial soil moisture, soil organic C, N and soil inorganic N and P, soil topography/surface information, such as slope, soil color, and crop management details (Jones et al., 2010a). The target of the calibration process was to minimize RMSE and RMSEn (Box 2.1, eqns. 2.5 and 2.6).

The calibrated model was evaluated using data from all the tested sowing densities in the remaining farmers' fields (four farmers out of six) in 2016 and 2017. Like the calibration exercise, the evaluation was done separately for SS and NGS. Data for grain yield, biomass and number of days to maturity were used for the model evaluation. In addition to RMSE and RMSEn, modified d index and EF (Box 2.1, eqns. 2.7 and 2.8) were calculated.

6.2.3 Model application: Long-term seasonal analysis

The calibrated and evaluated CERES-Maize model was then used to assess the response of maize varieties to different sowing density-based management decisions in the maize belts of Northern Nigeria. Planting density, varietal selection and N fertilization were simulated. The following set-up was used in the seasonal analysis tool for the long-term simulations:

Climate and soil data inputs

Long term weather data (1992 – 2017) were collected from the Nigerian Meteorological agency (NIMET) for Bunkure (representing Sudan savanna) and Zaria (representing wet savanna). The data used was rainfall, maximum and minimum temperature, and solar radiation. The data for the selected location and periods were used because they represent the wide extremes of conditions where maize is grown in Nigeria. The long-term simulations were done on a Typic Kanhaplustalf from Bunkure representing the SS and a Typic Kandiustalf from Samaru to represent the NGS. Nitrogen (mineral and organic), soil water content, and organic matter content were allowed to be carried over between seasons, thereby not necessitating the need for re-initialization. Following typical farmers' traditions in the study area, all residues were removed on 1st of April.

Crop management inputs

For each simulation year, sowing was set to start when a total rainfall exceeding 20 mm occurred within the previous three days between June 1 to July 1 in the NGS and between June 10 to July 10 in the SS. The selected periods capture the normal sowing windows for maize in the study area (Kamara et al., 2009). Four maize varieties, SAMMAZ 41, SAMMAZ 32, SAMMAZ 15 and Oba Super 9, were used which represents the extra-early, early, intermediate and late maturity groups respectively. The model was set to harvest when the crop reached harvest maturity every year.

Simulation scenarios

Table 6-1 shows the different scenarios adopted for the long-term simulations. Twelve standard scenarios were created by combining four sowing densities (2.6, 5.3, 6.6, and 8.8 plants m^{-2}) and three N fertilizer rates (30, 90 and 90 (120 in NGS) kg N ha^{-1}). In each agroecology, the 12 scenarios were simulated using the two varieties adapted to that agroecology. For all simulated scenarios, the model was set up to apply N fertilizers in two equal splits, half at planting and the other half at three weeks after sowing (conditions were set to postpone the second dose until the moisture conditions are sufficient in the rainfed scenarios). Phosphorus and potassium were assumed to be non-limiting, so P and K sub-models were switched off. The planting densities were done by setting a constant inter row spacing of 0.75 m and changing the intra-row spacing to meet the different density scenarios. Intra row spacings of 0.15, 0.20, 0.25, and 0.50 m were adopted to provide the selected sowing densities of 8.8, 6.6, 5.3, and 2.6 plants m^{-2} respectively. Among the selected densities, 2.6 plants m^{-2} is used commonly by farmers especially under low fertilization, while 5.3 plants m^{-2} is the national recommendation. Findings by (Kamara et al. (2006) indicate that modern maize cultivars could be planted under higher densities in the Nigerian savannas as long as adequate nitrogen fertilizer management is adopted.

Table 6-1: Long-term scenario analyses conducted using calibrated and evaluated model

Scenario	Label*	Sowing density	N Fertilizer
		(plants m^{-2})	(Kg ha^{-1})
1.	LDLN	2.6	30
2.	LDMN	2.6	60
3.	LDHN	2.6	90 (120 in NGS)
4.	MDLN	5.3	30
5.	MDMN	5.3	60
6.	MDHN	5.3	90 (120 in NGS)
7.	HDLN	6.6	30
8.	HDMN	6.6	60
9.	HDHN	6.6	90 (120 in NGS)
10.	VHDLN	8.8	30
11.	VHDMN	8.8	60
12.	VHDHN	8.8	90 120 in NGS)

* LD, MD, HD, and VHD are low, medium, high and very high density; LN, MN, and HN are low, medium and high N fertilizer

Economic analysis inputs

Because income is more important to farmers than yield, an economic profitability analysis was performed using the economic and risk analysis tool of DSSAT. To set-up the economic analysis requirements, historic market price data (2004-2017) of maize was collected for the SS and NGS from the Famine Early Warning Systems Network (FEWSNET) data repository (USAID, 2019). Input price data including labour and base production costs were collected from 3 years (2015 – 2017) survey data (unpublished, Centre for Dryland Agriculture, BUK) conducted in the study areas. All the nominal price data were adjusted for inflation to come up with real price data by dividing the nominal price of an item (input or output variable) by the consumer price index (CPI). The historical data was then appreciated to current prices in order to have a single price of both inputs and outputs across years of simulations in the analysis. Simulated net revenue per unit of land (money ha^{-1}) and family labour (not including hired labour) were calculated for each scenario. The labour cost per hectare for each household was converted to adult equivalence scale using the modified OECD scale (Litchfield, 1999).

6.3 Results

6.3.1 Climatic conditions across locations during experimental years

The total monthly rainfall and mean monthly minimum and maximum temperature for the three LGAs in NGS and SS are shown in Figure 6-1. The amount and distribution of rainfall during the experimental periods were different between the two seasons and the agro-ecologies. Higher rainfall was recorded in 2017 (1140 mm in NGS and 821 mm in SS) than in 2016 (1079 mm in NGS and 712 mm in SS). In 2016, an average of 93 and 68 rainy days were recorded in the 3 locations across the NGS and SS. In 2017 however, 115 and 82 rainy days were recorded in the NGS and SS respectively. Maximum average daily temperatures of 32.5°C and 33.9 °C were recorded in the NGS and SS in 2016. While in 2017, the maximum temperatures were 33.9 and 34.1°C in the NGS and SS. In the NGS, the average minimum daily temperatures were 19.3 °C in 2016 and 19.4 °C in 2017. In the SS, average minimum daily temperatures of 19.7 and 20.2°C were recorded in 2016 and 2017.

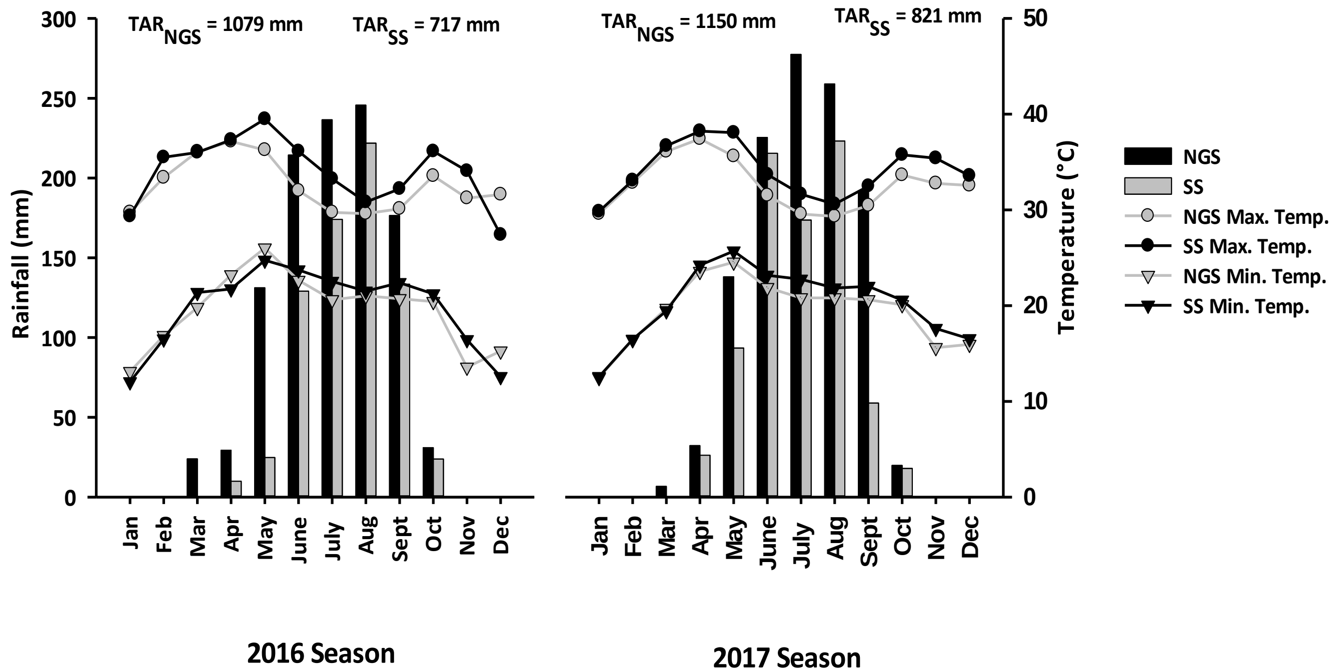


Figure 6-1: Records of monthly rainfall (bars) and minimum and maximum temperatures (lines and markers) for the NGS and SS in 2016 and 2017. TAR = Total Annual Rainfall

6.3.2 Model calibration and evaluation

Observed and simulated grain yields, biomass at harvest, number of days to physiological maturity, and harvest index were compared for the different varieties across locations in 2016 and 2017 (Table 6-2). In the Sudan savanna, the model predicted grain yield and number of days to maturity of both varieties very accurately with prediction deviations (PD) below 9% and RMSEn below 7%. For harvest biomass and harvest index, the model predictions were good for both varieties with prediction deviations (PDs) below 15% and RMSEn <12% for biomass and <10% for harvest index. In the NGS however, all measured parameters were also predicted very accurately for both varieties as evidenced by PDs ≤ 5% and RMSEn < 8%. In both environments and for all varieties, the model predicted phenology (no of days to physiological maturity) more accurately than grain yield, biomass and harvest index although prediction of harvest index had the lowest accuracy.

Table 6-2: Comparisons of observed and simulated grain yield, number of days to maturity, harvest biomass and harvest index for model calibrations in the SS and NGS

	Sudan Savanna						**Northern Guinea Savanna**				
	Grain Yield (Mg ha^{-1})						*Grain Yield (Mg ha^{-1})*				
	Obs	Sim	PD (%)	RMSE	RMSEn (%)		Obs	Sim	PD (%)	RMSE	RMSEn (%)
V1	3.7	4.0	8.1	0.22	5.9	V3	5.4	5.6	3.7	0.28	5.2
V2	3.2	3.4	6.3	0.22	6.8	V4	5.3	5.5	3.8	0.24	4.6
	Number of days to maturity						*Number of days to maturity*				
	Obs	Sim	PD	RMSE	RMSEn (%)		Obs	Sim	PD (%)	RMSE	RMSEn (%)
V1	87	88	1.1	1.08	5.8	V3	96	98	2.1	1.12	6.2
V2	76	78	2.6	2.01	7.3	V4	118	121	2.5	1.19	7.2
	Harvest Biomass (Mg ha^{-1})						*Harvest Biomass (Mg ha^{-1})*				
	Obs	Sim	PD (%)	RMSE	RMSEn (%)		Obs	Sim	PD (%)	RMSE	RMSEn (%)
V1	7.27	8.39	15.4	0.71	10.4	V3	9.0	9.3	3.3	0.49	5.4
V2	5.82	5.18	-10.9	0.57	11.3	V4	8.3	8.2	-1.2	0.57	5.2
	Harvest index (%)						*Harvest index (%)*				
	Obs	Sim	PD (%)	RMSE	RMSEn (%)		Obs	Sim	PD (%)	RMSE	RMSEn (%)
V1	33.7	32.2	-4.3	0.015	5.5	V3	37.5	37.6	0.2	0.017	3.9
V2	35.5	39.6	11.7	0.016	9.1	V4	39.0	40.1	3.2	0.018	4.7

V1 = Sammaz 32, V2 = Sammaz 41, V3 = Sammaz 15, V4 = Oba Super 9
PD = Prediction Deviations (negative values indicate under-simulation)

Following accurate calibration, the performance of the model was evaluated using data from the remaining farmer fields and sowing densities not used in the calibration exercise. The model evaluation was done separately for the two agro-ecologies with SAMMAZ 41 and SAMMAZ 32 used in the SS and SAMMAZ 15 and OBA Super 9 in the NGS. Comparisons between measured and simulated grain yield, biomass at harvest and number of days to physiological maturity are shown in Figure 6-2 (A-F) for the SS and Figure 6-3 (A-F) for the NGS. The model predicted grain yields well for all the varieties in both agro-ecologies with RMSE values ranging between 0.21 to 0.34 Mg ha^{-1}, modified d index values ranging between 0.88 - 0.96, model efficiency values ranging between 0.39 – 0.84 and nRMSE values below 10% in all measurement. Evaluation of above ground biomass at harvest was not as accurate as that of grain yield especially for the two varieties in the SS. For the variety SAMMAZ 32 (Figure 6-2B), model evaluation statistics were lowest (RMSE =1.1 Mg ha^{-1}, RMSEn = 15%, EF = 0.61 and, mod. d = 0.89) among all the evaluations. The variety Oba Super 9 had the best model evaluation statistics for biomass yield with RMSE value of 0.48 Mg ha^{-1}, EF of 0.81, modified d index value of 0.87 and RMSEn of 5.4%.

Evaluation of number of days to maturity was highly accurate for the two varieties in the NGS and for one variety (SAMMAZ 15) in the SS. For the other variety (SAMMAZ 41) in the SS, the model was just accurate with RMSE values of 2.2 days, EF of 0.53, and RMSEn of 11.1%. Overall, the model evaluation statistics were within acceptable ranges for all varieties across the two agro-ecologies. The model simulations showed no nitrogen stress for both years across all treatments. Dry spells were experienced around 38 – 42 and 66 - 73 days after sowing (DAS) in all three locations of the SS in 2016. The model accurately simulated the observed moisture stress in two of the three locations (data not shown).

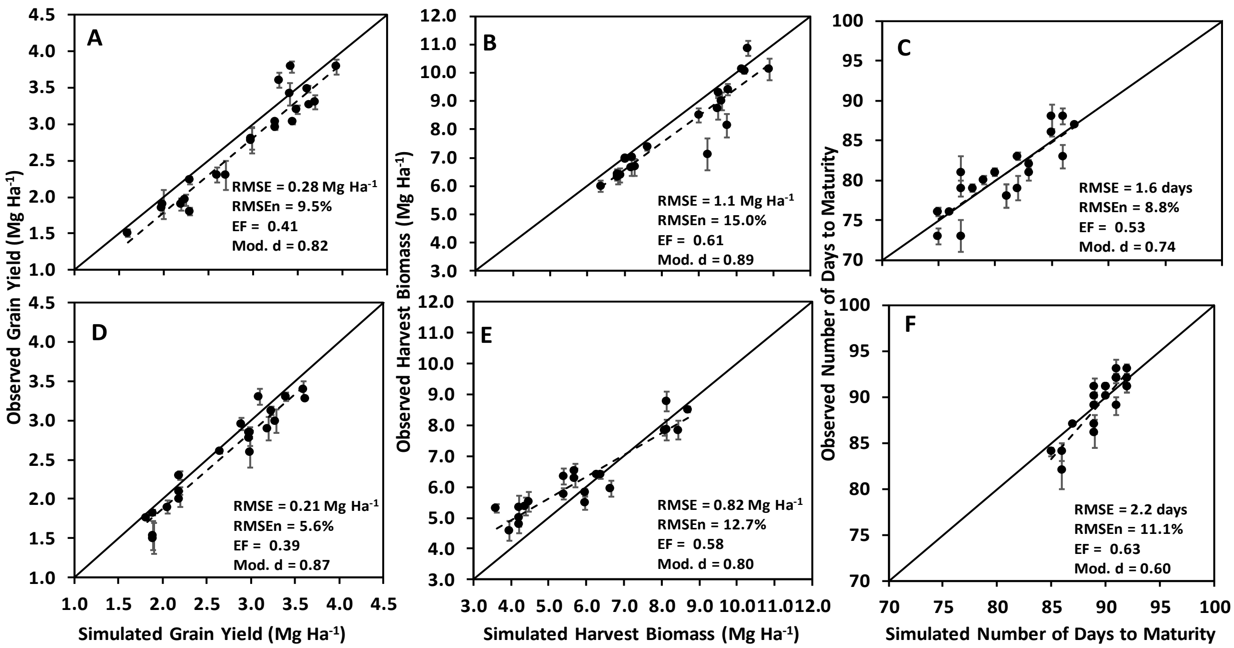


Figure 6-2: Observed vs Simulated grain yields, harvest biomass, and number of days to physiological maturity of Sammaz 41 (A, B, and C) and Sammaz 32 (D, E and F) for model evaluation data in the SS

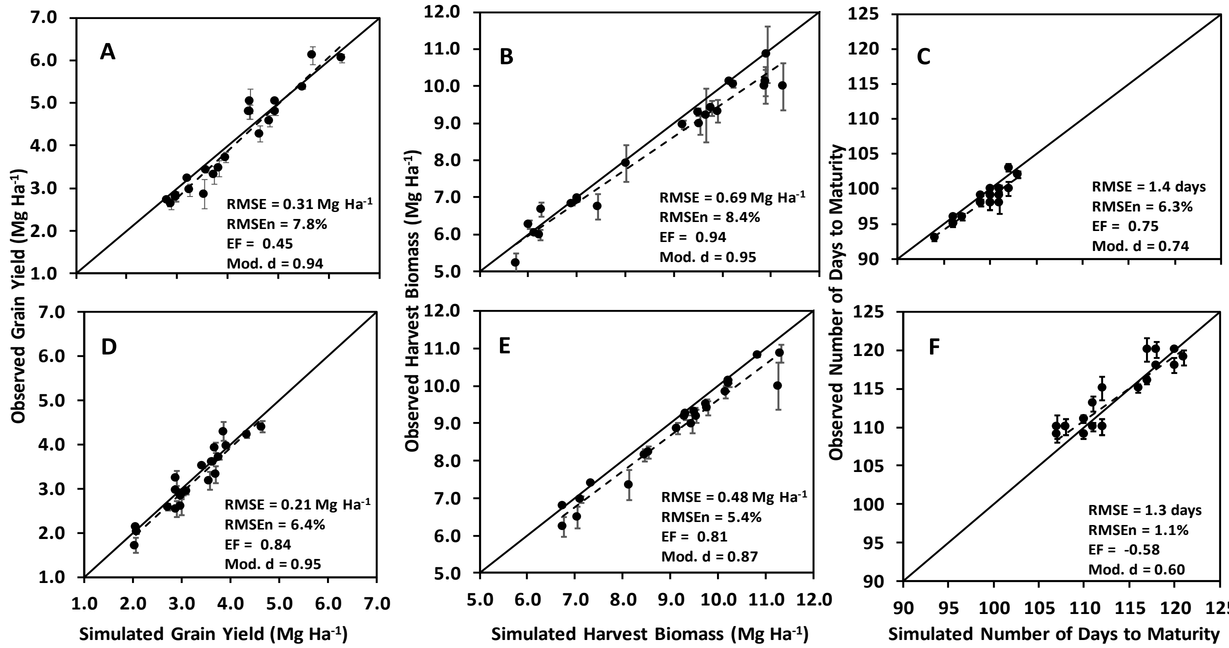


Figure 6-3: Observed vs Simulate grain yields, harvest biomass, and number of days to physiological maturity of Sammaz 15 (A, B and C) and Oba Super 9 (D, E and F) for model evaluation data in the NGS

6.3.3 Simulated sowing density studies

A sensitivity analysis to test for the effect of elevated density was conducted after calibrating and evaluating the model. The analysis was done using soils from the best farmer fields in SS and NGS and using observed weather records for the year 2017. Recommended nitrogen fertilizers for early/extra early maize (90 kg N ha^{-1}) and intermediate/late (120 kg N ha^{-1}) maturing maize were adopted. The purpose of the sensitivity analysis was to confirm the model calibration and evaluation and check if the model can simulate conditions which were not used in the calibration and evaluation exercise. The early and extra early varieties were tested in the SS while the intermediate and late varieties were tested in the NGS. Planting density was increased by 2 plants m^{-2} starting from 4 plants m^{-2} to 14 plants m^{-2}. Grain yields were simulated for each variety under the different planting densities.

The result of the sensitivity analysis for the four varieties is shown in Figure 6-4. For SAMMAZ 41, grain yield was very sensitive to increase in number of plants per meter square. Linear increase in grain yields was recorded with increasing sowing density up to 12 plants m^{-2} with further increase to 14 plants m^{-2} resulting in yield decline. The yield differences between 8, 10, and 12 plants m^{-2} was negligible. For SAMMAZ 32 however, highest grain yields were simulated for 8 plants m^{-2} with high planting densities (10 and 12 plants m^{-2}) producing grain yields similar to the lowest planting density. The intermediate and late varieties produced higher grain yields under lower planting densities, for both varieties the highest grain yields were simulated for sowing density of 6 plants m^{-2}, although for OBA Super 9, the yield variations between sowing of 4, 6 and 8 plants m^{-2} was not very high.

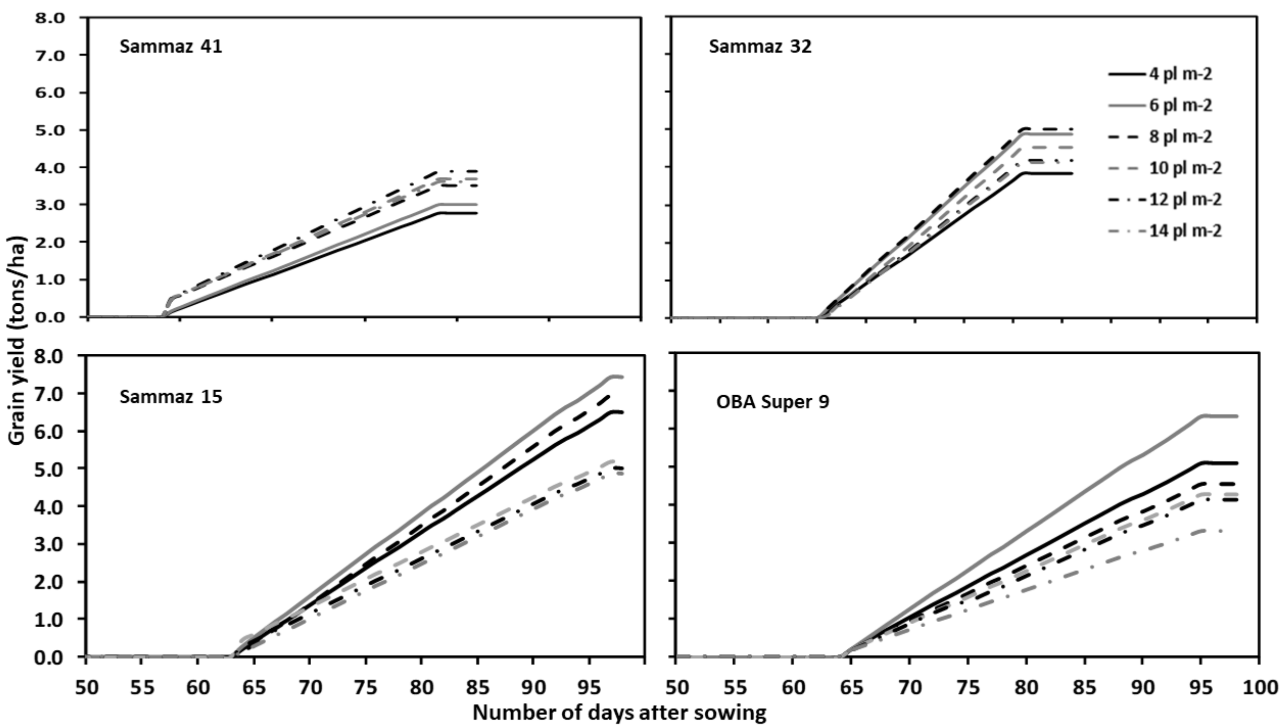


Figure 6-4: Sensitivity Analysis of calibrated and evaluated model for Sammaz 41 and Sammaz 32 (SS) and Sammaz 15 and Oba Super 9 (NGS)

6.3.4 Model application

The result of simulation of the 12 scenarios is shown in Figure 6-5. In the SS, consistent yield increases were observed with increasing planting density up to 8.8 and 6.6 plants m^{-2} for SAMMAZ 32. The yield increase existed only when the increase in density is followed by subsequent increase in N fertilizer application. The magnitude of yield increase with addition of N fertilizers is also density dependent. For instance, looking at SAMMAZ 41, average grain yield increased by 53.4% when N fertilizers were increased from 30 to 60 kg N ha^{-1} and only to 63.3% when further increased to 90 kg N ha^{-1} under the lowest sowing density (2.6 plants m^{-2}) scenarios. Under medium (6.6 plants m^{-2}) and high (8.8 plants m^{-2}) sowing density scenario however, yield increase of 87% and 140% were observed when nitrogen fertilizers were increased from 30 to 60 and 60 to 90 kg N ha^{-1} respectively. For the varieties in the NGS, consistent yield reductions were observed when sowing density was increased under low (30 kg N ha^{-1}) and medium (60 kg N ha^{-1}) N fertilizer applications for both varieties. When 120 kg N was applied however, an increase in grain yield was observed up to 6.6 plants ha^{-1}, further increase in sowing density to 8.8 plants ha^{-1} resulted in significant yield decline for both varieties.

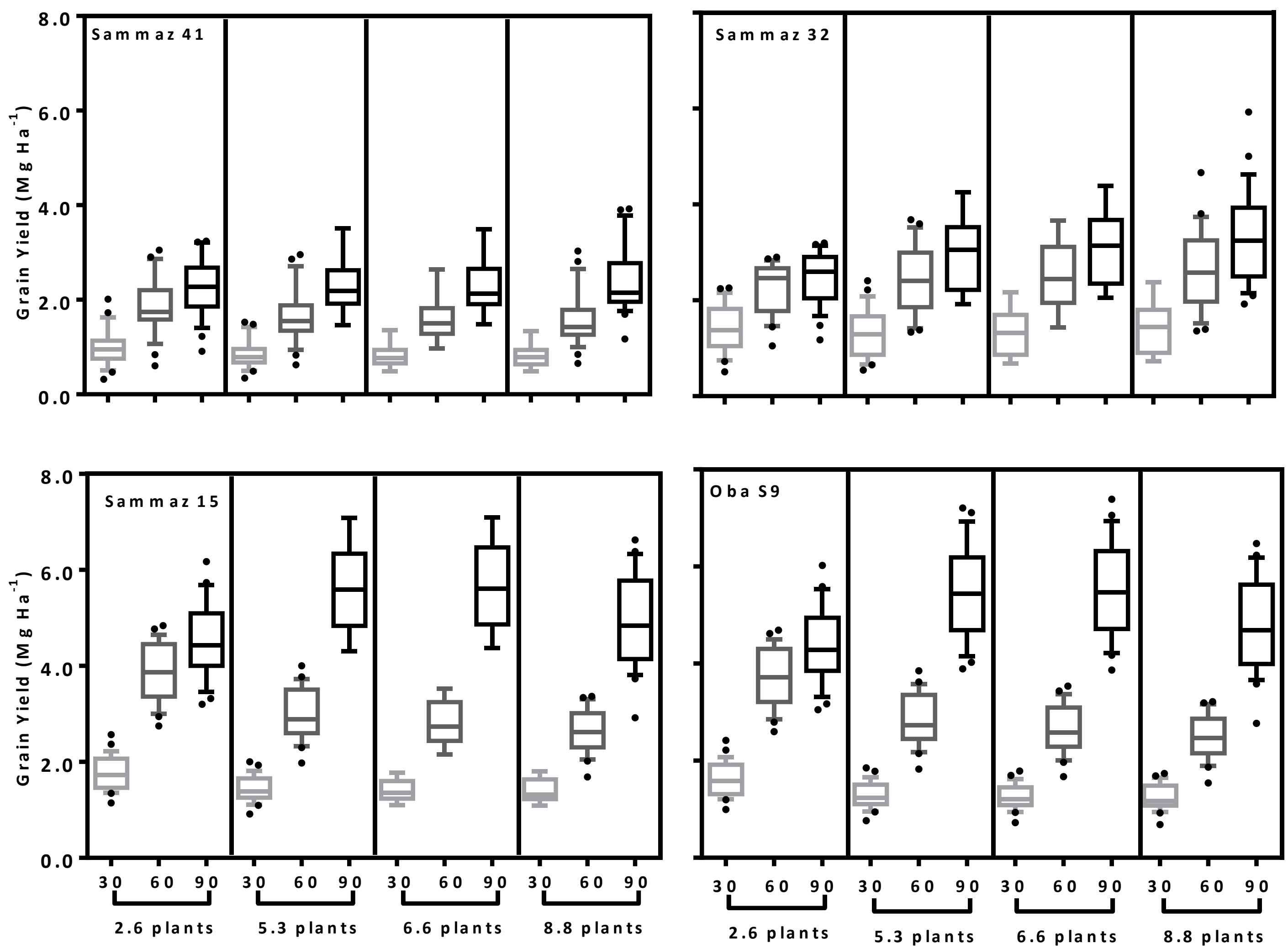


Figure 6-5: Box plots showing 26 years of simulated grain yields (Mg ha^{-1}) of different maize varieties in the SS (Sammaz 41 and 32) and NGS (Sammaz 15 and Oba Super 9) under different sowing density and nitrogen scenarios

6.3.5 Economic analysis

The returns to land and labour measured in monetary (dollar) returns per unit area and monetary returns per unit of family labour are presented in Figure 6-6 for SAMMAZ 41 (A and B) in the SS and SAMMAZ 15 (C and D) in the NGS. The cumulative distribution function (CDF) plot for SAMMAZ 41 shows that at 50% probability of non-exceedance, all the low-density (LD) scenarios will return less than \$500 per hectare, except for scenario 1 (low-density and low N, LDLN) where a return of \$600 ha^{-1} is possible. For the same low intensity scenarios, the chances of getting a return to land above \$1,000 ha^{-1} is only possible at 10% probability (i.e. only in 2.6 out of the 26 years simulated). Increasing sowing density from 2.6 to 5.3 plants m^{-2} (MD) has a 75% chance of producing ≥40% increase in monetary return to land for all N applications. For the low and medium N application scenarios, an increased return of 44 and 46% was recorded, while an increase of just 47% was recorded for the high N scenario. For the high (6.6 plants m^{-2}, HD) and very high (8.8 plants m^{-2}) scenarios however, a 75% possibility of exceeding a return of over \$ 1,000 per hectare was possible when the recommended N fertilizers were applied. The lowest monetary returns to land were recorded when the very high-density (VHD) scenarios were planted under low nitrogen fertilization.

For monetary return to labour however, all the low-density (LD) scenarios had only a 25% probability of returning ≤\$500/person/season and none of the low-density scenarios returned up to \$1,000 per person/season. The high-density + high-N (HDHN) scenario has the highest probability of producing more monetary returns to labour (\$500 - \$700 at 75% probability, above \$ 1,000 at 50% probability, and up to \$2,000 but with only a 5% probability). Negative returns to family labour were reported for 4 out of the 26 years for the very high density + low N (VHDLN) scenarios and two years for the high-density + low N (LDHN) scenarios. The possibility of negative returns to land was simulated in 3 years for the very-high density + high N (VHDHN) applications scenario and only one year for the HDHN application scenario. For SAMMAZ 41 in the SS, mean monetary return per unit area increased with increasing sowing density for all the low N application scenarios up to the highest sowing density tested. The lowest mean return to land was recorded for scenario 1 (2.6 plants m^{-2} + 30 kg N ha^{-1}) while the highest was recorded for scenario 10 (8.8 plants m^{-2} + 30 kg N ha) indicating that elevating sowing density could increase income even under low N application rates. The highest mean return to land ($1336.1) was recorded for scenario 9 (8.8 plants m^{-2} + 90 kg N ha^{-1}). For mean return to labour however, the lowest amount ($150.6) was recorded for scenario 10 (8.8 plants m^{-2} + 90 kg N ha^{-1}). The highest mean return to labour ($957.7) was also recorded for scenario 9.

More monetary returns to both land and labour were recorded in the NGS than in the SS. The mean money returns to land were higher under high N applications for the low, medium and high sowing densities. Under the VHD scenario however, monetary returns per hectare were low even when the highest level of N were applied. All the low sowing density scenarios (scenarios 1, 4, 7 and 10) had only 25% chance of returning ≥ $500 per hectare, although its only in 1 of the 26 years simulated (3.8% chance) that a low sowing density could return up to $1,000 ha^{-1}. All the LD scenarios have less than 50% chance of producing above $500 per hectare and person/season. The scenario with the highest mean monetary return per unit land was scenario 9 (HDHN) although the difference with scenario 6 (medium density + high N) was just about 3.3%. Scenario 6 recorded the highest returns to labour followed by scenario 9. Mean negative returns were recorded for scenarios 10 (8.8 plants m^{-2} + 30 kg N ha^{-1}) and 7 (6.6 plants m^{-2} + 30 kg N ha^{-1}).

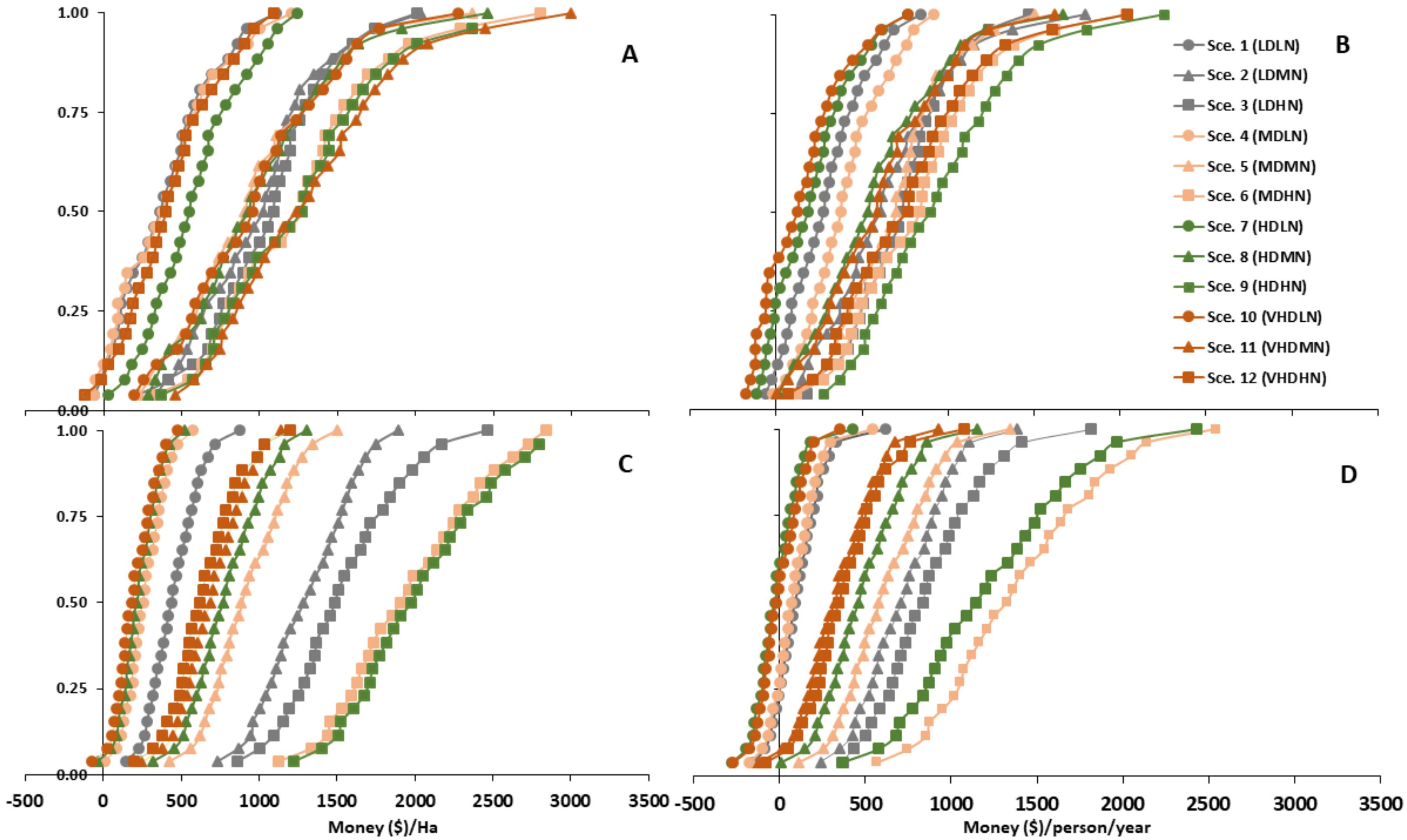


Figure 6-6: CDF plot for money return per hectare and per unit of family labour (A and B = for Sammaz 41) and (C and D = Sammaz 15) under different sowing density and N fertilizer scenarios

6.4 Discussion

6.4.1 Model calibration and evaluation

The model calibrations resulted in accurate predictions of field measured phenology and yield parameters with high degree of confidence as indicated by the model statistics. This close agreement between predicted and observed yield and phenology variables for both calibration and evaluation experiments is an indication that the model can be used to predict performance of the maize genotypes across different locations and variable management conditions in the Nigerian Savannas. Phenology (flowering and maturity) is controlled by the coefficients P1 and P5 in CERES-Maize model, the present calibration showed accurate prediction of phenology which is the most important step in the model calibration exercise (Archontoulis et al., 2014). According to Robertson et al., (2002), accurate calibration of phenology makes models able to capture all genotypic variations that affect the leaf area development, biomass production, and grain yield. Very good agreements were observed between observed and simulated grain yields in both calibration and evaluation experiments. This can be attributed to accurate measurement of the coefficients G2 (sink size) and G3 (sink strength). The accurate capture of seasonal and locational variations is as a result of adjustments made to the coefficients RUE and SLPF. The closeness of fit between observed and predicted parameters in the calibration and evaluation steps is an indication that the model is robust and accurate enough to make wider applications across the environments under study. The results are also within the range of previous findings from the same agro-ecologies (Gungula et al., 2003; Jagtap et al., 1998; Jibrin et al., 2012; S.S. et al., 1999).

6.4.2 Sensitivity and scenario analyses

The result of the sensitivity analysis follows expected trends of published data on sowing density with the extra-early and early varieties showing greater response to sowing density increases than the late and intermediate varieties (Edwards et al., 2005; Sangoi et al., 2002; Tollenaar and Lee, 2002). The extra early variety produced highest grain yields under sowing density of 10 plants m^{-2}, the early varieties at 8 plants m^{-2}, while the late and intermediate varieties producing the highest grain yields at 6 plants m^{-2}. Previous reports by Edwards et al. (2005) suggested that higher planting densities are recommended for early maturing varieties than full season varieties. This is because early varieties usually have smaller leaves which means more plants are needed per area to reach the same amount of cumulative intercepted radiation (Tollenaar et al., 2006). The particularly low simulated yield for the late maturing varieties under sowing densities beyond 6 plants m^{-2} could be due to the shading ability and the longer grain filling duration of such varieties (Van Roekel and Coulter, 2011). The fact that the model was able to capture these expected variations is a pointer to the robustness of the calibration and evaluation steps.

It is important to identify the best combination of agronomic practices that will optimize yield observed by maize growers. Owing to the time and cost-consuming nature of large field trials, crop models can be used to simulate such practices if properly calibrated and evaluated. Here, we used the CERES-maize model to create two different scenarios with various combinations of sowing density and N rates. Result of the scenario analysis shows that under low N fertilization (30 kg N ha^{-1}), increasing planting density did not increase grain yields. For the extra-early and late varieties, yields stagnated when planting densities were increased under low N applications, while for intermediate and late varieties a linear decline in yield was observed with every increase in planting density under low N application. Similar trends were observed with application of 60 kg N ha^{-1} for the late and intermediate varieties, but slight gains in yield were observed for the early varieties where increasing density from 2.6 to 5.3 and 6.6 plants m^{-2} produced yield increases of 8.8 and 12.3% respectively. This indicates that for early varieties, higher densities could lead to increased grain yields even when non-optimal N fertilizers are applied.

Under high nitrogen applications (90 in SS and 120 in NGS), yield gains were observed for every successive increase in planting density up to 8.8 plants m^{-2} for extra early and early varieties and 6.6 for intermediate and late varieties. This finding confirms previous claims by Jagtap et al., (1999) who posited that increased responses to sowing density elevations are possible for small, compact varieties with erect leaves in Nigeria. Interestingly, the findings also show that there is a possibility for yield increase when maize is planted above the recommended sowing densities without increasing the recommended fertilizer rates. In fact, for the early varieties, the simulations show that high grain yields are possible with increasing densities even if N applications were 30 kg lower than the current recommendations.

6.4.3 Economic Analysis

For smallholder subsistence farmers, the economic risk associated with the adoption of a new technology is more important than yield variability. Clearly, any new technology that could increase income per unit of land and labour is a welcome development to those farmers. The results of economic analysis using our simulated yields and historical input and output prices shows that increasing sowing density leads to economic gains in both agro-ecologies if the sowing-density increases are done together with increasing N application rates. Traditionally, farmers in the study location choose both sowing densities and N fertilizer rates below the recommendation believing that additional number of plants per area will mean additional nitrogen fertilizers that they can ill afford. Our findings confirm that sowing density of maize can be increased while maintaining the current N fertilizer recommendations.

The dramatic increase in monetary return per hectare is because of the extra yield from the highest planting density even under low N application. This finding is a clear indication that even under low N application in smallholder farms, sowing density of the extra early and early varieties could be increased to produce higher yields and more income per unit area. Mean returns to land and family labour decreased continuously when sowing density was increased in the low N scenarios for SAMMAZ 15 in the NGS. Applying 30 kg N ha^{-1} and planting 2.6 plants m^{-2} produced a mean return of \$457.6 ha^{-1}, but when sowing density was increased to 5.3, 6.6 and 8.8 plants m^{-2}, a decline in income of 40.9, 50.1, and 55.9% were recorded respectively. This means that increasing sowing density under low N leads to huge reduction of economic returns per unit area. Highest returns to land were recorded for the high density + high nitrogen (6.6 plants m^{-2} + 120 kg N) scenarios, while highest returns to labour was recorded for the medium density + high nitrogen (5.3 plants m^{-2} + 120 kg N ha^{-1}) scenarios. This result indicates that for the intermediate varieties, very high densities (above 6.6 plants m^{-2}) will lead to reduced income, besides these, very high densities become even more un-economical under high N application because the yield increase is negligible and does not cover the additional expense of fertilizers and the labour requirements.

6.5 Conclusions

In the current study, we examined the ability of the CERES-Maize model to accurately predict the response of different maturity maize to increased sowing density across two contrasting environments in the maize belts of Northern Nigeria. Using weather records from 26 years for both SS and NGS agro-ecologies, the model produced long term simulations for grain yield and money returns per unit area and per unit labour applied. Combining high sowing densities and application of recommended N fertilizer increased grain yield up to a sowing density of 8.8 plants m^{-2} for the extra-early and early varieties in the SS. In the NGS where intermediate and late varieties are usually planted, yield responses to additional sowing density are positive up to 6.6 plants m^{-2} above which the yield will decline even when N fertilizers are not limiting. Findings from the simulation studies indicate that contrary to most assertions, the sowing density of all the current varietal groups of maize in Nigeria and sub Saharan Africa in general could be increased without applying N fertilizers above the recommended rates in the Sudan and Northern Guinea Savannas. For the early and extra early varieties, the highest grain yields were simulated for sowing density of 8.8 plants m^{-2} and N rate of 90 Kg N ha^{-2}, while for the intermediate and late varieties the highest grain yields were simulated for sowing density of 6.6 plants m^{-2} and N rate of 120 Kg N ha^{-2}. In SS, the extra-early and early varieties could provide more money per unit area under the intensive systems (8.8 plants m^{-2} and 90 kg N ha^{-1}), but the highest amount of money return to labour can be achieved under the semi intensive agronomic practice (6.6 plants m^{-2} and 90 kg N ha^{-1}). In NGS, return to land is maximized under semi intensive agronomic practices (6.6 plants m^{-2} and 120 kg N ha^{-1}) and return to labour is maximized when the recommended sowing density of 5.3 plants m^{-2} is combined with high N (120 kg ha^{-1}) applications.

7 CHAPTER SEVEN

GENERAL CONCLUSIONS AND RECOMMENDATIONS

7.1 General conclusions

The importance of maize in Nigeria cannot be over emphasized. It is the crop with the highest yield potential in both the semi-arid and sub-humid areas and it is an indispensable choice for the campaign to end hunger and malnutrition in Nigeria and Sub-Saharan Africa in general. The current yields of the crop are very low and although outputs have increased in the country, average yields per hectare have stagnated since the 1970s at rates lower than 40% of the potential of most varieties.

The practice of blanket recommendations for varieties, planting densities, sowing dates, and fertilizer application rates play a significant role in low per hectare yields in Nigeria and sub-Saharan Africa. Varieties are usually bred for specific zones and contain genetic characteristics that are peculiar to those regions. Despite efforts by breeders and agronomists, varietal selections are made without considering the specific characteristics that makes them more appropriate to specific production zones. Many varieties have been developed recently by the IITA and its partners, these varieties have unique characteristics and are tailor-made for specific production zones. Early and extra-early varieties have been developed for the dryer zones in the Sahel and Sudan-Savanna. They are early maturing (70-80 days) making them able to escape the late season drought prevalent in those areas due to early cessation of rains. Some of them have combined abilities to tolerate drought and heat stress, and very few have the additional ability of tolerating low soil nitrogen and the devastating effects of parasitic weed *Striga hermonthica*. The early and extra-early varieties have relatively lower grain and stover yield potentials. Intermediate and late maturing varieties have been bred for the wetter areas in the Northern and Southern Guinea Savannas, and the Forest zones. These varieties mature later (100-120 days) and can utilize the longer rainfall duration in the wet zones. They have high grain and stover yield potentials and some have the added abilities to tolerate diseases like maize streak virus (MSV) and resist root and stem lodging. Some of them are genetically fortified with pro-vitamin A and protein giving them a unique advantage in improving nutrition requirements.

The overall aim of this research as stated in Chapter 1 was to evaluate the ability of the DSSAT-CERES-Maize model in matching maize varieties to specific production zones in the Sudan and Northern Guinea Savannas of Northern Nigeria. In addition, the model was used to make agronomic recommendations with respect to optimum sowing densities of the different varieties produced in the Nigerian maize belt. The findings from this research are synthesized and final recommendations are given based on the four main chapters (chapters 3, 4, 5 and 6). The chapters were developed following the four research objectives as follows:

RO 1. Estimate Genotype Specific Parameters (GSPs) for maize varieties produced in Northern Guinea Savanna (NGS) and Sudan Savanna (SS) of Nigeria.

RO 2. Evaluate differences between GSPs generated by using data from field measurements and yield evaluation trials.

RO 3. Evaluate the effect of varying planting densities of maize across the SS and NGS.

RO 4. Conduct scenario analysis (biophysical, and economic) under varying soils, weather, and agronomic conditions in SS and NGS of Nigeria.

From the research objectives, five hypotheses were formulated and discussed hereafter.

7.1.1 Research Hypothesis 1: The sequential approach method, when optimized, can be used to generate accurate GSPs of maize using the GENCALC program of DSSAT

The sequential approach method used for calibrating GSPs in the GENCALC software of DSSAT has been developed and optimized for crops like soybean and groundnut but not for maize. In our research, we developed a detailed sequential approach for calibrating maize GSPs using GENCALC. We used data from detailed experiments conducted specifically for generating the GSPs and collected data from multi- year/multi-locational varietal evaluation trials conducted by breeders. Our findings proved that indeed, when the sequential approach is optimized more accurate GSPs are generated. Our approach entails that to get accurate GSPs the sequence of optimizations to follow are as follows: first select the maturity group to which the variety belongs, then adjust the coefficient that measures thermal time from seedling emergence to end of juvenile stage (P1), then adjust thermal time from silking to time of physiological maturity (P5) coefficient, then the coefficient for Phyllochron interval (PHINT) is adjusted, the coefficient maximum kernel number (G2) is then adjusted followed by an adjustment of kernel growth rate (G3) coefficient. Finally, G2 is re-adjusted to get final grain yield. This sequential approach is only applicable to tropical maize varieties that do not respond to day-length. This is because the coefficient that measures delay in development for each hour that day-length is above 12.5 hours (P2) was not adjusted.

7.1.2 Research Hypothesis 2: GSPs generated by field trials lead to more accurate calibration of the CERES-Maize model than GSPs generated from variety evaluation trials

Generating GSPs of maize varieties is the most difficult requirement for calibrating the CERES-Maize model. The process requires a lot of data from detailed, expensive and extensive experiments in order to generate coefficients that accurately characterize the genetic components of each variety. To reduce the difficulty of this approach, many researchers have used readily available data to generate GSPs for many crops (including maize) all over the world. The most common approach is to use data from varietal evaluation experiments by maize breeders. Despite the availability of such data set, no attempt was made to generate maize GSPs from breeder evaluation trial data in Africa.

From our research, it became apparent that GSPs generated from detailed experiments were more accurate than those generated from the breeder variety evaluation trials as expected. A very important finding was that the GSPs generated from the breeder evaluation experiments were within range of acceptable accuracies and can therefore be used when data from detailed experiments is unavailable.

7.1.3 Research Hypothesis 3: The planting density recommended for maize in Northern Guinea Savanna and Sudan Savanna of Nigeria is below the optimum

Optimum sowing density management decisions are very important requirements to increase maize grain yield per unit area. The monumental increase in grain yield all over the world has been attributed largely to increase of planting density. Studies have shown that sowing density is variety and environment specific, and varieties have been shown to respond differently to increased sowing density in similar environments.

In Nigeria and sub-Saharan Africa at large, maize has been consistently planted under sub-optimal densities. In some countries in SSA, recommendations for maize sowing densities do not even exist. In Nigeria, the recommended sowing density of maize is currently 5.3 plants m^{-2} (53,333 plants ha^{-1}). Most of the farmers do not plant up to 50% of the recommendation. These recommendations are made irrespective of varietal types and locational characteristics. Evidences have shown that modern varieties can tolerate sowing density increases without providing extremely high fertilizer inputs. From both field trials and model simulations, we found that the current recommended sowing density for maize is below the optimum. In the field trials, most varieties responded to sowing densities above 6.6 plants m^{-2}. In the simulation studies, an optimum density of 8.8 plants m^{-2} was simulated for the early and extra-early varieties. For the intermediate and late varieties, an optimum sowing density of 6.6 plants m^{-2} was simulated.

7.1.4 Research Hypothesis 4: The CERES-Maize Model can be used as a tool to aid in identifying GEI and to conduct a stability analysis of maize varieties across environments in the maize belts of northern Nigeria

Genotype by environment interaction (GEI) is a phenomenon that inhibits efficient selection of high yielding varieties that are stable across different environments by breeders and growers. Furthermore, determining the magnitude of GEI and stability of varieties can be challenging, as such crop models can be employed to complement this process. Several studies have shown that dynamic models that can simulate the response of growth and development of crops to varying abiotic environmental factors such as temperature, solar radiation, and daylength have the potential to explain yield differences due to temporal and spatial variability. The ability of the CERES-Maize model to predict observed GEI was evaluated. Stability analysis of the predicted grain yields of different maize varieties were also conducted. The model was able to adequately capture observed GEI and the stability analysis of the predicted grain yields matched exactly with that of the observed grain yields. Results from our experiments have shown that the CERES-Maize model correctly predicts the GEI and stability of maize varieties and can hence be used to predict how varieties will behave in locations and seasons where trial data is unavailable.

7.1.5 Research Hypothesis 5: The CERES-Maize Model can be used as a tool for optimization of planting density in the NGS and SS of Nigeria

When properly calibrated and evaluated, the CERES-Maize model should be able to serve as a tool for making many agronomic management decisions. A long-term seasonal analysis was conducted using 26- year weather data with a view to making sowing-density based management recommendations for maize varieties in the maize belts of northern Nigeria. The model was used to provide recommendations for sowing density by nitrogen fertilization applications. Biophysical (grain yield) and economic (money returns per unit land and per family labour) were conducted. The model outputs show that for early and extra early varieties planted in the Sudan savannah, highest grain yields and money returns ha^{-1} could be realized by planting maize at a sowing density of 8.8 plants m^{-2} and applying the recommended N fertilizer rate of 90 kg ha^{-1}. The highest money returns to family labour in the same agro-ecology was simulated for sowing density of 6.6 plants m^{-2} and 90 kg N ha^{-1}.

7.2 Recommendations

Based on the field and simulation studies conducted in this research, the following recommendations are given to farmers, researchers and policy makers:

1. A systematic approach (as proposed in this study) as well as availability of large datasets from different locations and planting dates provide opportunities for estimation of accurate GSPs using data from both detailed experiments as well as from breeder varietal evaluation experiments. Breeder data to be used for calibration of crop models must be collected from sites where detailed soil and climate data are available. The data must also be from trials without moisture and nutrient stresses, and not be under any diseases.
2. Model users should endeavor to join breeding units/teams to ensure collection of robust data needed for model calibrations that are not traditionally collected by breeders.
3. Recommendation of varieties must be made according to agro-ecologies in exclusively rain-fed systems. Currently, the government extension agencies recommend intermediate and late varieties to the wet savannas, while the early and extra early varieties are recommended for the dry savannas. Findings from our experiments have

shown that intermediate varieties could also be planted in the dry savannas in seasons when early establishment of the rains was observed, and when seasonal rainfall advice agencies predict a long rainy season with good rainfall distribution.

4. The CERES-Maize model correctly predicts the GEI and stability of maize varieties and can hence be used to predict how varieties will behave in locations and seasons where trial data is unavailable. The model can complement the breeder evaluation experiments and aid selection of varieties that are specific to certain locations.
5. Intermediate and late varieties are recommended for the wet savannas (Northern and Southern Guinea), while the early and extra early varieties are recommended for the dry savannas (Sudan and Sahel). Findings from our experiments have shown that intermediate varieties could also be planted in the Sudan savanna in seasons where early rainfall establishment of rainfall was observed, and when seasonal rainfall advice agencies (e.g. FEWSNET/NiMET in Nigeria) predict long rainy season with good rainfall distribution.
6. The sowing density of all the current varietal groups of maize in Nigeria could be increased without applying N fertilizers above the recommended rate in both Sudan and Northern Guinea Savannas. For the early and extra early varieties planted in the dry Savannas, sowing density of 8.8 plants m^{-2} and N rate of 90 Kg N ha^{-2} is recommended for higher grain yields and more money return to land. For intermediate and late varieties planted in the wet savannas, sowing density of 6.6 plants m^{-2} and N rate of 120 Kg N ha^{-2} is recommended for higher grain yields and more money return to land.
7. It is recommended that small holder farmers need to increase the planting density of maize in reduced areas of their farms and apply the N fertilizers available, the remaining areas can then be used for legumes and other low input crops. The current practice of widening the spaces between stands in order to optimize fertilizers applications is not profitable.

7.3 General outlook and future research focus

General outputs from this research includes development of GSPs of 26 most produced maize varieties in the Nigerian Savannas and development of optimum sowing density of maize in the locations under study. These outputs could play a major role in future research where other maize-based management decisions could be exploited by the model. Some of the ongoing activities linked to this research as well as plans for research are given in the subsequent sub-sections.

7.3.1 Development of maize variety selector (MVS) for Nigeria

Growing varieties of any crop species that are well adapted to a location is very important for productivity. In the rainfed environments in which maize is predominantly grown in SSA, adaptation is largely determined by the timing of sowing, flowering and maturity in relation to rainfall and available soil moisture. Following various consultations with stakeholders in the maize belt of Nigeria through activities of the Taking Maize Agronomy to Scale project, it was clear that farmers and extension agents need information about maize varieties, their suitability to regions, and the additional characteristics they may possess. Farmers and extension agents need to know that in rain-fed systems maize varieties will perform best in optimum environments. For every environment, there is a variety that is suitable. Figure 7-1 adapted from (https://tamasa.cimmyt.org) and developed from data collected in this research shows how varieties behave in a typical rainfed production systems that are prevalent in the Nigerian maize belts.

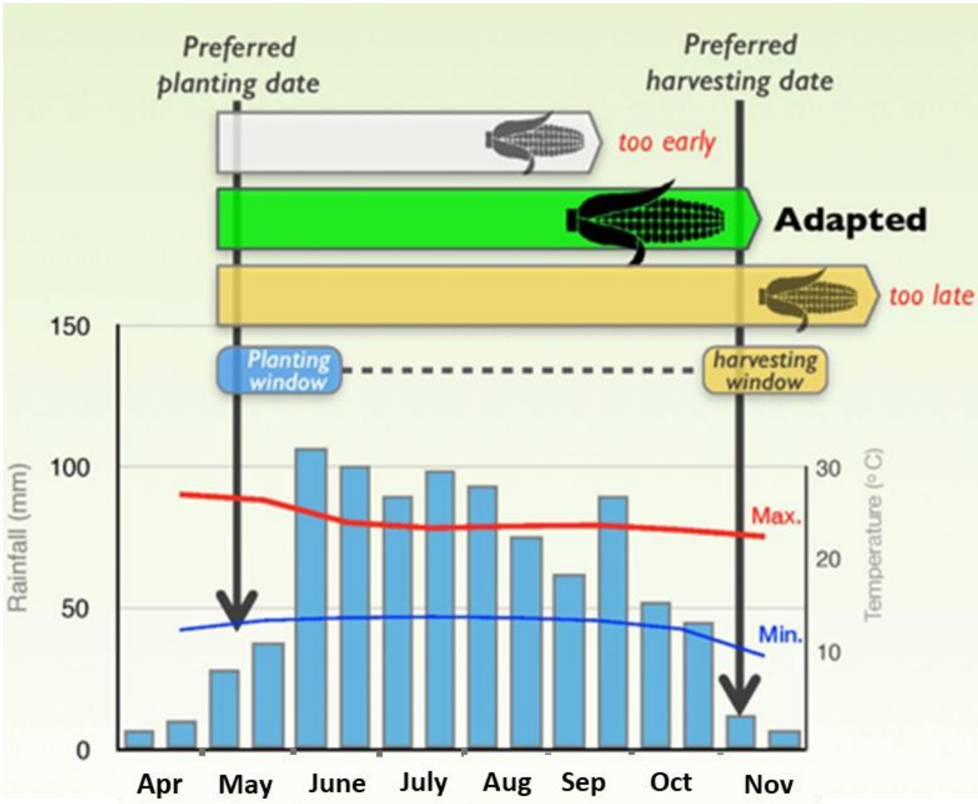


Figure 7-1: Typical growing season (Zaria in Nigeria) showing the rainfall pattern, preferred planting and harvesting dates, and the duration of three hypothetical varieties. (Taken from https://tamasa.cimmyt.org)

At the early stage of the TAMASA project, it was agreed that a simple and user-friendly tool must be developed to aid spatial recommendations of maize varieties in Nigeria. An alpha version of the maize variety selector (MVS) was developed by the project with the data from the varietal calibration experiments presented in this research. The first version of MVS was an Android application based on spatial simulations at 1 km using WorldClim monthly gridded weather data.

A second version was developed with additional data from the observed sowing density experiments and from simulations made by the calibrated model. The beta version predicts phenological development of maize varieties and provides spatial recommendations of varieties based on locations and sowing windows. The tool was limited in that it does not provide detailed information on potential yields of recommended varieties. This version also incorporates information on agro-dealers that sell the different recommended varieties. Figure 7-2 shows an outline of the user interphase and output of the beta version of MVS.

The user version of the MVS is currently under production and it incorporates all the observed and simulated data generated from this research in addition to more data generated from other experiments. The released version of the tool will provide users with location specific variety recommendation based on selected sowing windows. The tool will also provide recommended sowing density that is specific to the varieties. Additionally, some economic analysis will be provided by the tool. TAMASA intends to provide extension workers with tools that provide not just varietal advice but also advice on nutrient applications (Maize Nutrient Expert).

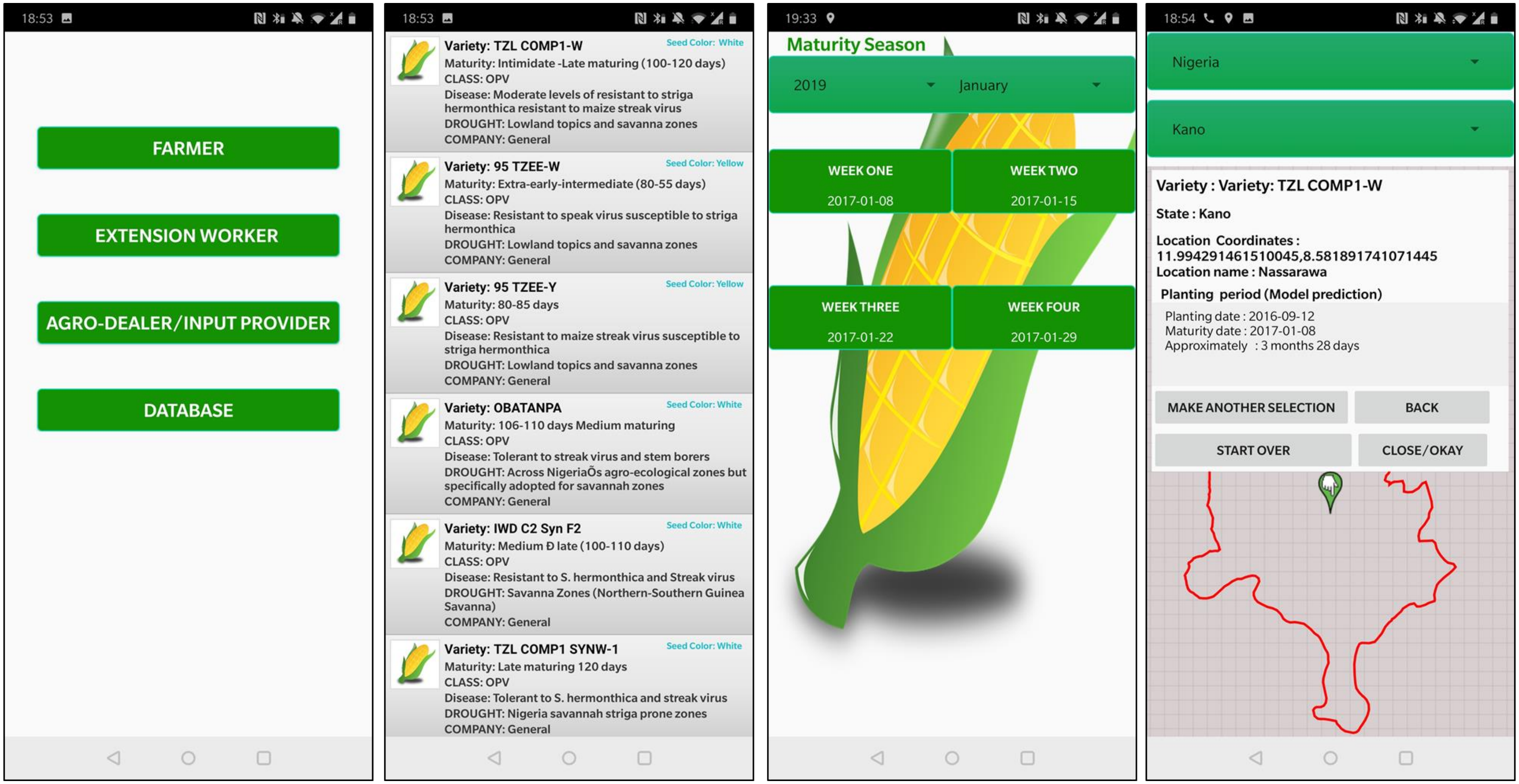


Figure 7-2: Outlook and overview of the beta version of the Maize Variety Selector

7.3.2 Field evaluation of simulated returns to elevated density in typical farmer fields

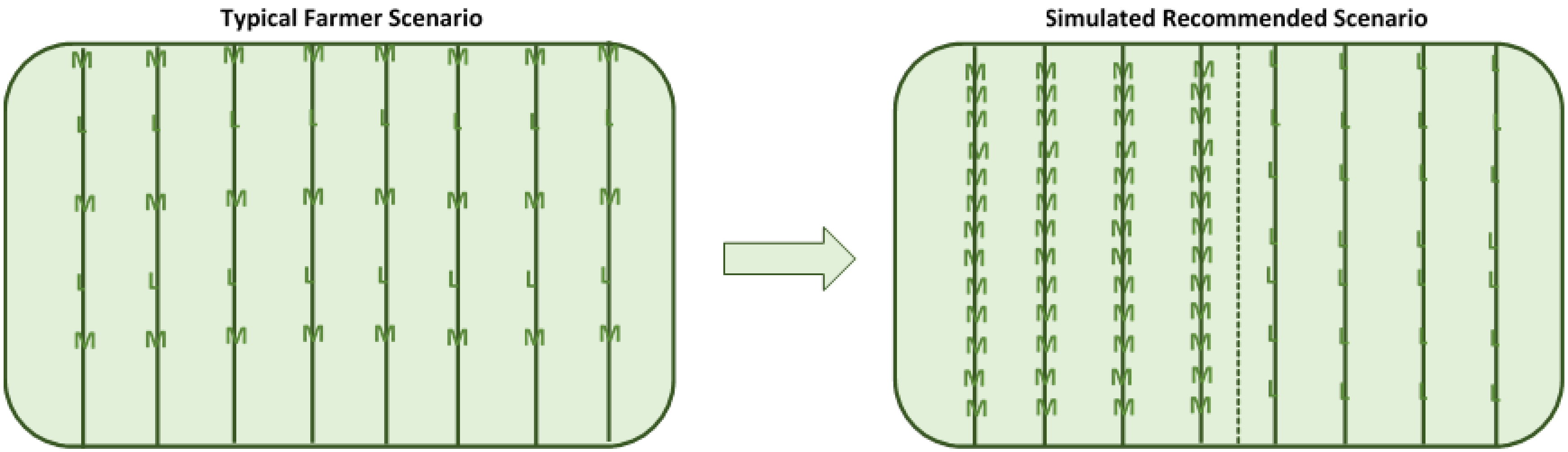
In the Nigerian Savannas, most of the farmers majorly plant maize as an intercrop. The maize is usually planted in the same rows with a partner legume (cowpea, groundnut or soybean), and in some cases with a partner cereal. This approach ensures that the farmers get some output in the event of the failure of one crop, and from both crops they get enough stover to feed their animals. Many researches have shown that this approach is not efficient, but rather recommended strip cropping where 2 or more crops can be planted on the same field (farm) but not on the same row.

From this research we recommended that farmers should increase planting density in reduced areas of their farms and concentrate the N fertilizers they can afford on that part of the field. The remaining areas can then be used for the legumes and other low input partner crops. Across farmer fields, maize is planted under sub-optimal densities (lower than 2.6 plants m^{-2}), while the partner legumes are planted under densities slightly above 4.0 plants m^{-2}. Most farmers can only afford fertilizer amount that is typically less than 30% of the recommendation (usually below 30 kg ha^{-1}). This amount is used on all the farm because most of the farmers broadcast the fertilizers thereby fertilizing the whole farm instead of the crops. Maize yields in this typical scenario (as shown by survey data) were averaged at 1.8 Mg ha^{-1} and a subsequent income of about \$457 ha^{-1}. This result is similar to outputs from the low-density low-nitrogen scenarios in our simulations (chapter 6, Figures 6-5 and 6-6) although we did not simulate an intercrop. From the results of our simulations, increasing the density and maintaining the same amount of N fertilizers will not increase the yield significantly for all the varieties.

A new scenario analysis was considered based on the recommendations from this research where instead of using all the 30 kg N ha^{-1} on an entire 1 hectare of land, we divided the farm into two and increased the sowing density of maize from 2.6 to 6.6 plants m^{-2} and then applied the fertilizer to only the maize. In this scenario we assumed that maize was in strips (i.e. intercropping not done on the same row) and planted the legumes to the rest of the land in higher density. Figure 7-3 shows the result of the comparison between the typical farmer field and our recommendation. Our recommended practice presented a yield of increase 89% (from

1.8 Mg ha^{-1} to 3.4 Mg ha^{-1}) and a corresponding increase in money return ha^{-1} of 86% (from $457 to $850). The income from the farmer scenario is including the sales of the partner legume, while from our recommendations we calculated income only from the maize.

There is need to conduct research in farmer fields to test the recommendations made from this research as it has a potential of almost doubling yield outputs and incomes of farmers and lifting them out of hunger and poverty.



Typical Farmer Scenario

M = Maize, L = Legume
Area: 1 hectare(same row intercrop)
Density: Maize = 26,666 plants/ha
Legume = 40,000 plants/ha
N-Fertilizer:30 KgN (appliedto all field)
Yield: Maize = 1.8Mg ha^{-1}
Legume = 0.5Mg ha^{-1}
Income: $ 457 dollars(including that from legume)

Simulated Recommended Scenario

M = Maize, L = Legume
Area: 1 hectare(strip cropping)
Density: Maize = 66,666 plants/ha
Legume = 60,000 plants/ha
N-Fertilizer:30 KgN (applied to maize)
Yield: Maize = 3.4Mg ha^{-1}
Legume = 0.85 Mg ha^{-1}
Income: $ 850 dollars(income from maize only)

Figure 7-3: Comparisons between typical farmer practices and simulated scenario from recommendations made by this research

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9 APPENDIX

Appendix 1: Profile characteristics of soils used in detailed calibration experiments

Site	L (cm)	LL (cm^3/cm^3)	DUL (cm^3/cm^3)	SAT (cm^3/cm^3)	BD g/cm^3	OC %	TN %	pH
SMR1	12	0.092	0.239	0.391	1.35	0.56	0.14	6
	44	0.155	0.285	0.429	1.38	0.2	0.11	5.8
	85	0.234	0.353	0.372	1.59	0.12	0.07	5.8
	142	0.265	0.381	0.393	1.54	0.1	0.01	5.8
	182	0.275	0.395	0.408	1.55	0.08	0.01	6.1
SMR2	23	0.092	0.239	0.391	1.54	0.62	0.17	5.3
	47	0.155	0.285	0.429	1.25	0.56	0.07	5.4
	75	0.234	0.353	0.372	1.56	0.38	0.04	5.9
	119	0.265	0.381	0.393	1.58	0.24	0.04	6.2
	170	0.275	0.395	0.408	1.61	0.22	0.04	6.3
LER1	7	0.085	0.235	0.496	1.26	0.48	0.14	5.5
	36	0.106	0.279	0.521	1.19	0.18	0.04	5.6
	63	0.149	0.299	0.463	1.35	0.12	0.07	5.8
	106	0.07	0.196	0.47	1.33	0.1	0.07	5.9
	154	0.083	0.248	0.517	1.2	0.06	0.14	5.9
LER2	19	0.109	0.239	0.391	1.36	0.34	0.18	5.8
	43	0.155	0.285	0.429	1.56	0.26	0.14	5.5
	128	0.237	0.353	0.372	1.68	0.2	0.21	5.7
DBT1	26	0.082	0.206	0.379	1.36	0.25	0.07	6.1
	63	0.155	0.259	0.429	1.63	0.21	0.04	5.9
	142	0.234	0.282	0.372	1.63	0.11	0.04	6.1
	220	0.265	0.308	0.271	1.9	0.08	0.03	6.1
DBT2	10	0.072	0.139	0.361	1.36	0.25	0.08	5.8
	35	0.085	0.185	0.389	1.63	0.12	0.05	5.9
	60	0.134	0.235	0.389	1.63	0.1	0.021	6.4
	114	0.154	0.297	0.389	1.9	0.07	0.018	6.3
BUK1	12	0.075	0.178	0.48	1.28	0.69	0.11	6.8
	40	0.058	0.125	0.394	1.55	0.33	0.09	6.3
	94	0.122	0.224	0.415	1.48	-99	0.06	6.2
	165	0.114	0.219	0.413	1.49	-99	0.04	6.2
BUK 2	11	0.074	0.122	0.388	1.56	0.43	0.08	6
	15	0.055	0.12	0.402	1.52	0.2	0.07	5.5
	31	0.094	0.187	0.406	1.51	0.1	0.06	5.7
	65	0.073	0.135	0.385	1.57	0.07	0.06	6
	113	0.148	0.208	0.367	1.62	0.06	0.02	5.9

LL, Lower limit; DUL, drained upper limit; SAT, Saturated water content; BD, Bulk density; OC, Organic carbon; L is layer depth

Appendix 2: Soil properties of farmer fields used in sowing density experiments (Chapters 5 and 6)

	Doguwa					Lere					Ikara				
	BD	pH_{H2O}	TC	TN	Avl. P	BD	pH_{H2O}	TC	TN	Avl. P	BD	pH_{H2O}	TC	TN	Avail. P
Farmer	$g.cm^{-3}$		$g.kg^{-1}$	$g.kg^{-1}$	$mg.kg^{-1}$	$g.cm^{-3}$		$g.kg^{-1}$	$g.kg^{-1}$	$mg.kg^{-1}$	$g.cm^{-3}$		$g.kg^{-1}$	$g.kg^{-1}$	$mg.kg^{-1}$
A	1.58	6.2	10.8	0.48	3.67	1.62	5.8	8.6	0.59	6.97	1.62	6.0	7.9	0.58	4.11
B	1.51	6.3	10.9	0.52	3.88	1.64	5.5	8.3	0.28	5.26	1.74	5.7	5.6	0.36	8.61
C	1.56	5.6	10.3	0.46	4.93	1.62	5.6	7.6	0.37	6.77	1.73	5.5	6.9	0.44	5.54
D	1.50	5.5	10.7	0.48	3.65	1.75	5.4	5.6	0.31	3.90	1.65	6.3	9.7	0.39	2.67
E	1.48	6.5	13.2	0.67	5.33	1.65	5.8	4.5	0.32	3.29	1.67	5.4	6.1	0.37	7.62
F	1.40	6.3	14.3	0.80	3.26	1.57	5.6	4.6	0.25	2.67	1.63	5.5	10.2	0.32	3.90
G	1.62	5.9	12.0	0.63	4.11	1.75	6.4	6.1	0.54	1.85	1.50	5.6	6.6	0.54	10.66
H	1.63	5.8	15.5	0.87	3.67	1.62	6.1	5.2	0.37	3.90	1.58	6.1	7.0	0.54	4.72
I	1.49	5.8	9.6	0.37	4.06	1.65	5.8	4.0	0.39	4.04	1.64	6.1	9.9	0.37	4.11
J	1.69	6.2	9.4	0.72	3.90	1.70	5.9	8.4	0.29	2.26	1.73	5.9	11.2	0.39	5.95

Appendix 3: Mean values of 100 kernel weight, kernels number, cob yield and tops weight of maize as affected by year, variety, stand density, farmer and farmer experience for main

Factor	100 Kernel Weight	Kernels number	Grain Yield	Biomass
	grams	# '000 sq. meter^{-1}	Mg ha^{-1}	Mg ha^{-1}
Year (Y)				
2017	24.56	2.35	4.51	9.26
2016	21.76	1.84	2.73	5.13
SED±	0.183	0.054	0.122	0.237
Variety (V)				
SC651	23.84	2.44	5.18	7.03
Sammaz 41	21.42	1.39	3.48	4.75
Narzo 21	21.36	1.41	3.86	4.81
COMP 4	21.52	1.47	3.48	4.66
Sammaz 15	23.18	2.42	4.61	6.55
Narzo 22	21.74	1.48	3.26	4.92
Sammaz 32	19.71	1.46	2.95	4.40
Sammaz 40	20.79	1.28	3.00	5.10
Sammaz 11	21.06	1.36	3.26	5.63
Oba Super 9	21.26	1.95	3.21	4.89
SED±	0.393	0.119	0.212	0.668
Stand Density (SD)				
6.66 plants m^{-2}	26.07	3.25	4.48	7.06
5.33 plants m^{-2}	22.96	2.45	3.52	5.94
2.66 plants m^{-2}	21.76	1.84	2.79	5.13
SED±	0.184	0.055	0.105	0.238
Experience (E)				
Class A	22.91	1.98	3.49	6.88
Class B	21.78	1.94	3.09	5.95
Class C	21.58	1.70	2.66	4.85
Class D	21.14	1.79	2.30	4.14
Class E	21.35	1.80	2.40	3.83
SED±	0.347	0.103	0.203	0.545
Interactions				
YxV	***	ns	***	ns
YxSD	***	ns	***	**
YxE	***	ns	***	***
VxSD	***	***	***	*
VxE	ns	ns	ns	ns
SDxE	ns	ns	ns	ns

* = Significant at 1%, ** = Significant at 5%, ns = not significant at 1 and 5% levels of significance

10 CURRICULUM VITAE

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List of Publications

Articles published in international, peer-reviewed academic journals

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