

**APPLICATION AND EVALUATION OF AQUACROP, DSSAT AND SIMPLE  
MODEL IN MODELLING YIELD AND WATER USE OF SELECTED  
UNDERUTILISED CEREAL CROPS**

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## PREFACE


The candidate completed the research in this thesis while based in the Discipline of Crop Science, School of Agricultural, Earth and Environmental Sciences, in the College of Agriculture, Engineering and Science, University of KwaZulu-Natal Pietermaritzburg Campus, South Africa. The research was financially supported by the Water Research Commission (WRC) of South Africa through Project No. K5/2717//4 'Developing a guideline for rainfed production of underutilised indigenous crops and estimating green water use of indigenous crops based on available models within selected bio-climatic regions of South Africa'.

The contents of this work have not been submitted in any form to another university, and, except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

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## **DECLARATION**

I, Thembelihle Nzimande, declare that the research reported in this thesis, except where otherwise indicated, is my original research, and it has not been submitted for any degree or examination at any other university. This thesis does not contain other people's pictures, graphs or other information unless specifically acknowledged as sourced from others. The thesis does not contain other authors' writing unless specifically acknowledged as being sourced from other researchers. This thesis also does not contain text, graphics or tables copied and pasted from the internet unless specifically acknowledged, and the source being detailed in the references section of the thesis.

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Date: 08 June 2021

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## **DEDICATION**

*This thesis is dedicated to my late great grandmother*

## ABSTRACT

The study compared yield, biomass, and water use (WU) for maize, sorghum, and millet simulated using three crop models of varying complexity: AquaCrop, DSSAT and the SIMPLE model. The hypothesis was that there is no significant difference between simple and complex models of estimating yield, biomass and WU. A standard set of crop parameters was used to develop crop files for all three models. Similar soil, climate and management descriptions attained from the Ukulinga Research Farm were used across the models. Six general circulation models (GCMs) were used as climate input data to model past, present, mid-, and late-century climate change impacts on cereal crops. The effect of irrigation (as a management practice) on yield and water use was assessed using the mid-century projections. The performance of the three models was observed to be statistically different. Based on the mean bias error, all models overestimated yield, but the lowest overestimation was with AquaCrop (0.22 t/ha) followed by DSSAT (0.24 t/ha) and the SIMPLE model (0.69 t/ha). Other statistical indicators, viz., RMSE and  $R^2$ , illustrate that the simulation of yield and WP in AquaCrop was more satisfactory than DSSAT and the SIMPLE model. Across all the time scales, it was observed that AquaCrop simulated the highest yield and biomass, and the SIMPLE model simulated the lowest yield across the GCMs, which were inconsistent. Applying a higher amount of irrigation at more frequent intervals resulted in higher yield, biomass and WP. AquaCrop showed the highest simulated mean yield for maize (8.34 t/ha), millet (6.86 t/ha) and sorghum (5.28 t/ha). Highest WP was observed under AquaCrop for maize (21 kg/ha/mm) and millet (15.10 kg/ha/mm), the SIMPLE model for sorghum (13.37 kg/ha/mm). The study confirms that DSSAT requires relatively more input data but does not always perform more satisfactorily. The SIMPLE model requires fewer input requirements than AquaCrop and DSSAT; however, it is less sensitive to management changes. AquaCrop had relatively incomparable results to DSSAT and the SIMPLE model and was observed as the most suitable model for simulating yield, biomass, and WU of the selected cereal NUS under climate change and irrigation management scenarios. Before their application, it is essential to calibrate crop growth parameters for local conditions or use parameters from local field studies when applying complex crop models such as DSSAT specifically for marginal environments, such as South Africa. On the other hand, AquaCrop performed reasonably well with minimal input requirements, confirming its application in data-limited and marginal environments. However, it is recommended that there must be calibration for all the models using inputs specific to locations.

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## **LIST OF ABBREVIATIONS/ACRONYMS**

- APSIM** - Agricultural Production Systems sIMulator
- BEWAP** - BEsproeiingsWATERBestuursprogram
- B** - Biomass
- CERES** - Crop Environment Resource Synthesis
- CO<sub>2</sub>** - Atmospheric CO<sub>2</sub> concentration
- CGMs** – Crop growth models
- CSMs** – Crop simulation models
- DSSAT** – Decision Support System Agrotechnology Transfer
- E** - Soil evaporation
- E/Ex** - Relative soil evaporation (100 E/Ex)
- ET<sub>0</sub>** - Reference evapotranspiration
- FAO** – Food and Agricultural Organisation
- FC** - Field capacity
- GCMs** – General Circulation Models
- GD** - Growing degrees
- HI** - Harvest index
- K<sub>sat</sub>** - Saturated hydraulic conductivity
- MAP** - Mean Annual Precipitation
- MAT** – Mean Annual Temperature
- NUS** – Neglected and underutilized species
- PWP** - Permanent wilting point
- RCMs** - Regional climate models
- SA** - South Africa
- SAPWAT** - South African Program Water
- SPAM** - Soil-plant-atmosphere module
- SH** – Smallholder

**SWB** - Simple Water Balance

**Tr** - Crop transpiration

**Tr/Trx** - Relative total transpiration ( $100 \text{ Tr/Trx}$ )

**UKZN** - University of KwaZulu-Natal

**WGEN** – Weather Generator

**WP** – Water productivity

**WU** – Water use

**WP** – Water productivity

**Y** - Yield

## CHAPTER 1: GENERAL INTRODUCTION AND OVERVIEW

### 1.0 General Introduction and Conceptualisation

South Africa (SA) has a dualistic food system with a polarised food security profile. Population residing in marginal areas are food and nutrition insecure. Agriculture can be the main vehicle that can play a crucial role in alleviating nutritional food insecurity in rural communities (BFAP, 2018). There is a need to increase smallholder farmers' resilience in marginalised communities to enhance food and nutrition security in the region (FAO, 2018a). Regardless of agroecology, maize is the main cropping system for smallholder farmers, providing food, feed, and fodder (AgriSETA, 2018). Over-reliance on a single high calorific food crop has increased vulnerability to climate extremes, exacerbates poor diet diversity and has reduced economic opportunities within the smallholder farmers (Li et al., 2020; Mabhaudhi et al., 2019; Mayes et al., 2012). An increase in crop diversity can improve dietary diversity, resilience to climate change and promote the participation of farmers in wider markets. Neglected and underutilised species (NUS) can improve food and nutrition security and increase resilience in marginal production systems. Therefore, there is a need to promote the production of NUS.

Neglected and underutilised crop species are crop species that can reduce food and nutrition insecurity (Chivenge et al., 2015) by improving dietary diversity among rural resource-poor households. These crop species are adapted to various ecological niches and can tolerate both abiotic and biotic stress, mainly heat and water stress (Mabhaudhi, 2012). Numerous representative leafy vegetables, tuber crops, cereal crops, and grain legumes fall under the NUS category (Chivenge et al., 2015). Neglected and underutilized species can be wild or cultivated. Their different statuses are characterized by having different needs such as resources and management practices for their use and development (e.g. Maseko et al., 2015; Modi & Mabhaudhi, 2013; Nyathi et al., 2018). However, information regarding its production, agronomy and eco-physiological responses to perturbation remains limited (Karunaratne et al., 2011). This has resulted in the slow uptake and mainstreaming of NUS in marginal systems. There is a need to accelerate the availability of information. Therefore, there is a need to invest in robust tools to deal with genetic and phenotypic complexity found in NUS.

Crop models are tools used in predicting crop growth, yield and resource use through computers (Sinclair, 1996). Simple crop models are easy to use, apply and understand. Moreover, these crop models often require little input information (Boote et al., 1996). Crop models are identified as complex when they are more difficult to use, apply and understand.

Furthermore, complex models sometimes require more input data (Talbot et al., 2014). Models can assist in making decisions as support tools for predicting yields, planning (Steduto et al., 2009), identifying research gaps and evaluating impacts of climate change on crops. While crop simulation models as decision support tools offer users and policy makers data to manage resources, their uptake and use are low. One major reason for this is that many of them require large data input (e.g. Decision Support System for Agrotechnology Transfer (DSSAT)) and are considered complex models. However, there are simpler models (e.g. SIMPLE and AquaCrop), but the issue with these models is that they are not appropriate because they are not programmed to address a particular phenomenon such as fertilizer management (Boote et al., 1996). However, according to Orrego et al. (2014), a simpler model with less data requirement may be preferred over a data-intensive model.

According to Babel et al. (2019), selecting an appropriate crop model for the intended use depends on several factors, including robustness, accuracy, and input data requirements. The question then becomes, should simple models simulate crop growth and yield or focus still be given to complex models requiring a high level of expertise and data. This is especially important with the current drive for sustainable intensification in the wake of climate change using neglected and underutilised crops. The “one size fits all” approach should not be assumed when promoting any tool to be used for studying NUS. Past experiences of such research have shown low adoption rates of crop models deemed effective and efficient for some crops (Mabhaudhi et al., 2017). Independent studies such as Asseng et al. (2013) and Soltani & Sinclair (2015) are valuable and provide a timely reminder that complexity does not necessarily equate to improved predictive performance. Therefore, comparing different models is needed to decide on the most promising and suitable model for simulating NUS, which is the focus of this study.

### **1.1 Research questions**

- (i) Which model is the best traded for accuracy or performance between AquaCrop, DSSAT, and the SIMPLE model?
- (ii) Which model is best suited for modelling NUS's yield and water use?
- (iii) Which model is best suited for modelling climate change impacting NUS?
- (iv) Which model is best suited for modelling irrigation as a management practice for NUS?

## 1.2 Hypothesis, aim and objectives

It was hypothesised that there is no significant difference between the performance of simple and complex models of estimating yield, biomass and WU. The study aimed to evaluate the performance of the AquaCrop, DSSAT and the SIMPLE model for simulating yield and water use for selected neglected and underutilised cereals. The specific objectives were:

- (i) Assess the performance of three crop simulation models in predicting yield and water use of selected NUS,
- (ii) Assess the performance of three crop simulation models in simulating the impacts of climate change on selected NUS and
- (iii) Assess the effect of irrigation on yield and water use of selected NUS across three crop simulation models

## 1.3 Thesis structure

The thesis has been written in a paper format that consists of interlinked chapters.

**Chapter 1** is the current chapter that seeks to provide the study's background, aims, and objectives. The aim of the study is addressed by accessing the information on the agronomy of maize, millet, and sorghum as NUS and through modelling experiments using AquaCrop, DSSAT and the SIMPLE model conducted for 15 years (2004-2019). Furthermore, the modelling experiments incorporate climate change and irrigation on yield and water use of selected NUS.

**Chapter 2** is a literature review that outlines three simulation models' status in predicting yield and water use of selected NUS. A mixed-method review approach, which incorporated quantitative and qualitative research, was used to compile the review. The database for the review was populated with scientific journal articles, book chapters, technical reports, conference proceedings and other forms of literature. The structure of this review is divided into six sections. Firstly, maize, millet and sorghum production in SA is outlined, followed by the investigation of crop modelling in the second section. In the third section, we review the modelling of maize, millet, and sorghum. In section four, an overview of the AquaCrop, DSSAT and the SIMPLE model was provided. Then, in section five, the calibration of these three models was reviewed. Lastly, the advantages and limitations of AquaCrop, DSSAT and the SIMPLE model are discussed.

The first objective of the thesis is addressed in **Chapter 3**, where yield and water use of selected NUS are quantified through a series of modelling simulations. There is the same input data (crop, soil, and climate) for all three models. No management practices are considered. These inputs were attained from the Ukulinga Research Farm. Maize is used as a base crop since it is a main-stream crop compared with millet and sorghum, identified as NUS.

**Chapter 4** addresses the second objective, whereby six GCMS forced on RCP 8.5 are used as climate input data by the three models in simulating impacts of climate change on selected NUS. These GCMs are divided into projections for the past (1961–1991), present (1995–2025), mid-century (2030–2060) and late-century (2065–2095) periods. Throughout the analysis, the ‘present’ timescale was regarded as the baseline. The description of the crop and soil characteristics is the same for the three models. Management practices are still not incorporated here.

**Chapter 5** addresses objective number three, where the effect of irrigation (as a management practice) on yield and water use of selected NUS across three crop simulation models is compared. The description of the crop and soil characteristics is the same for the three models. The mid-century (2030-2060) projections for the six GCMs are used as climate data.

## **CHAPTER 2: THE USE OF CROP SIMULATION MODELS AS DECISION SUPPORT TOOLS FOR THE PRODUCTION OF MAIZE, MILLET AND SORGHUM**

### **2.0 Introduction**

In the near future, it is anticipated that staple crops will encounter numerous challenges. These challenges arise from inherent water scarcity, which in turn results from the prevalent climate changes. Also, over-reliance on staple crops is another challenge that needs to be investigated further. It is believed that diversification away from the over-reliance on staple crops is a factor that will assist in addressing the goal of achieving sustainable food security production (Mayes et al., 2012). On the other hand, crop species that have been neglected and underutilised are considered to improve food security by reducing the risk of over-reliance on several limited major crops and preserving dietary diversity (Mayes et al., 2012). Furthermore, in general, Neglected and Underutilised Species (NUS) are deemed suitable for marginal agro-ecologies (Mabhaudhi et al., 2019). This is because these crop species are resilient in rainfed cropping systems during global climate change and variability. Moreover, NUS offers ecologically feasible alternatives for improving agricultural production within the marginal areas (Chivenge et al., 2015).

There is an urgent need for a tool or technique that provides easy use with obtaining new data and research findings instantaneously. The aim is to provide the data to various end-users from different sectors to make decisions. Thus, the necessity for using tools, namely cropping simulation models, to project food crop cultivation within different time intervals and scenarios. Essentially, crop models are vital decision-making tools when assessing various climate change and variability factors. Also, the tools are essential for management practices relative to productivity and environmental executions of various cropping methods. This promotes sustainable and improved agriculture practices (Kadiyala et al., 2015; Xiong et al., 2014). Furthermore, crop simulations over different food and agricultural systems imply that inputted data sets will be mandatory to conduct further research. Further research studies would assess the trade-offs and outcomes within alternative farm management procedures, tools, strategies, and different climate conditions. However, such conditions are non-existent in South Africa. Nevertheless, South Africa encounters a shortage of information that narrates the barrier to accurate and efficient crop models. This is due to limited data and sources where input data can be obtained (Kephe et al., 2021).

The Decision Support System for Agrotechnology Transfer (DSSAT) model and various other models have been used in numerous studies conducted in developed countries. However, in South Africa, there have been limitations towards using the DSSAT model because of its difficulty and input requirements (e.g. Chisanga & Phiri, 2017; Corbeels et al., 2016; Jones et al., 2017; Mabhaudhi et al., 2014a). Moreover, results deduced from crop yield estimations show varying substantial accuracy and robustness (Palosuo et al., 2011; Rötter et al., 2012) (Palosuo et al., 2011; Rötter et al., 2012). The variations result from Crop Growth Models (CGMs), which require vast data inputs that obstruct the applicability beyond the research environments. Also, the Food and Agricultural Organisation (FAO) constructed the AquaCrop model (Steduto et al., 2009). Compared with other models such as DSSAT, the model uses lesser parameters and input variables. The simplicity of the AquaCrop model, combined with lesser input conditions relative to other crop models (Vanuytrecht et al., 2014), provides a stimulating mechanism. This is due to its ease of implementation and minimal input requirements as compared with the established models. Accordingly, the modelling space has received a new model called the SIMPLE model. As alluded to in the name, this model is a simple model with minimal data input requirements. Although, South Africa has been utilising the AquaCrop model due to its simplicity.

Since the SIMPLE model has been introduced, evaluating its ease of use for its simplicity attribute and whether the model is a better fit in South Africa as it is believed that it offers lesser complexities. However, one of the challenges that may arise with using crop models would be that users are not familiar with the model's limitations and intended usage. Before using the model, users may not be aware of the models' uncertainty of the results incorporated into the decision-making procedures (Willcock et al., 2016). Therefore, the objectives of this review were to; (i) discuss the production and simulation of maize (*Zea mays*) as a mainstream crop and millet (*Pennisetum glaucum*) and sorghum (*Sorghum bicolor*) as NUS, (ii) evaluate the AquaCrop, DSSAT and the SIMPLE model and (iii) discuss the uncertainties and capabilities of these models.

## **2.1 Materials and methods**

The PRISMA guideline ([www.prisma-statement.org](http://www.prisma-statement.org)) were followed for a structured review. A mixed-method review approach, which incorporated quantitative and qualitative research, was

used to compile the review. The database for this review comprised scientific journal articles, book chapters, technical reports, conference proceedings and other forms of literature. The literature search was conducted using Scopus, Science Direct®, Google™, South African Government Gazettes and FAOSTAT. The main search key terms included “Cereal Production in South Africa”, “Production of Neglected and Underutilized Crops”, “Crop Simulation Modelling”, “Modelling Maize, Sorghum and Millet”, “AquaCrop model”, “DSSAT model”. and “SIMPLE model.” Initially, the literature search was set by limiting results to title, abstract and keywords and a total of papers was 9172. Then there was the screening of literature which then resulted in 104 papers being included in the review. The structure of this review was then divided into six sections. Firstly, maize, millet and sorghum production in SA was outlined, followed by the investigation of crop modelling. Thirdly, there was a review of the modelling of maize, millet, and sorghum. In section four, there was an overview of the AquaCrop, DSSAT and the SIMPLE model. Then, section five showcases how these three models were calibrated in literature. Lastly, the advantages and limitations of AquaCrop, DSSAT and the SIMPLE model were discussed.

## **2.2 Results and discussion**

### **2.2.1 The production of maize, millet, and sorghum in SA**

Maize is a crop that originated in Central America (Hsiao & Fereres, 2012) and has been cultivated in SA for more than 300 years. Within SA, maize is a crop grown in diverse agro-ecological zones and farming systems (AgriSETA, 2018). It is the main staple food crop consumed by people of varying food preferences and socio-economic backgrounds in South Africa (AgriSETA, 2018). Maize seeds are consumed by humans directly or after processing and are often the main component of animal feed. Vegetable oil, sugar syrup, alcohol as biofuel, and feedstock for plastic manufacturing are commonly derived from maize seeds (Hsiao & Fereres, 2012). In 2018 it was estimated that smallholder (SH) farmers produced 594,000 tons of maize on 314 835 ha (1.9 tons/ha), compared with 13,207,000 tons on 2.3 million ha (5.7 tons/ha) in the commercial sector (Beinart & Delius, 2018). Smallholder agriculture, sometimes referred to as subsistence and or small-scale systems, are the predominant form of farm organisation in southern Africa, making up 80% of total farmlands and directly or indirectly employing more than 40% of women in the region (Doss & SOFA Team, 2010). Landholding varies significantly and ranges between 0.5 - 5 ha. Smallholder farmers are often conceptualised as low-input, family-based farming systems characterised by limited resources,

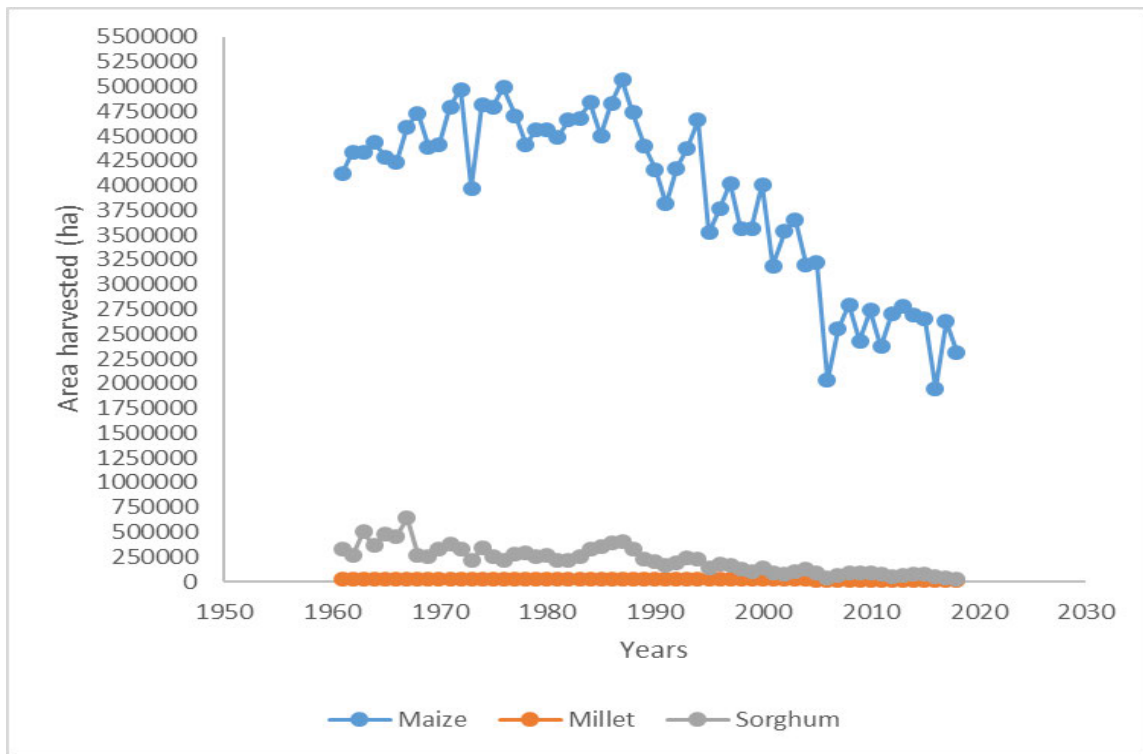
technology, capital, and information, and their subsistence nature rather than producing surplus for the market (Netting, 1993). They operate in fragile environments where their integrated activities are strongly constrained by socioeconomic, biophysical, and institutional constraints (Cervantes-Godoy & OECD, 2015; Cousins, 2010; Netting, 1993).

Current trends show that over the last 20 years, there has been a decrease in the area under maize production (Figure 2.1) but an increase in yield (Figure 2.2). The resultant increase in productivity has been attributed to improved agronomy and resource use efficiency. However, due to the increased demand for fuel and feed crops and the increased incidence of severe climate events such as the 2015/16 El Niño induced drought, maize and other cereal grains across several sectors exceed supply (Muza, 2017; SAGIS, 2019). To meet the growing demand for maize, the South African government has had to import the deficit. In addition, and guided by the National Development Plan, SA has embarked on several initiatives to boost smallholder farmer productivity (National Planning Commission, 2012). This move is also meant to address poverty, food and nutrition insecurity, and youth unemployment within marginalised communities where SH farming is often practised.

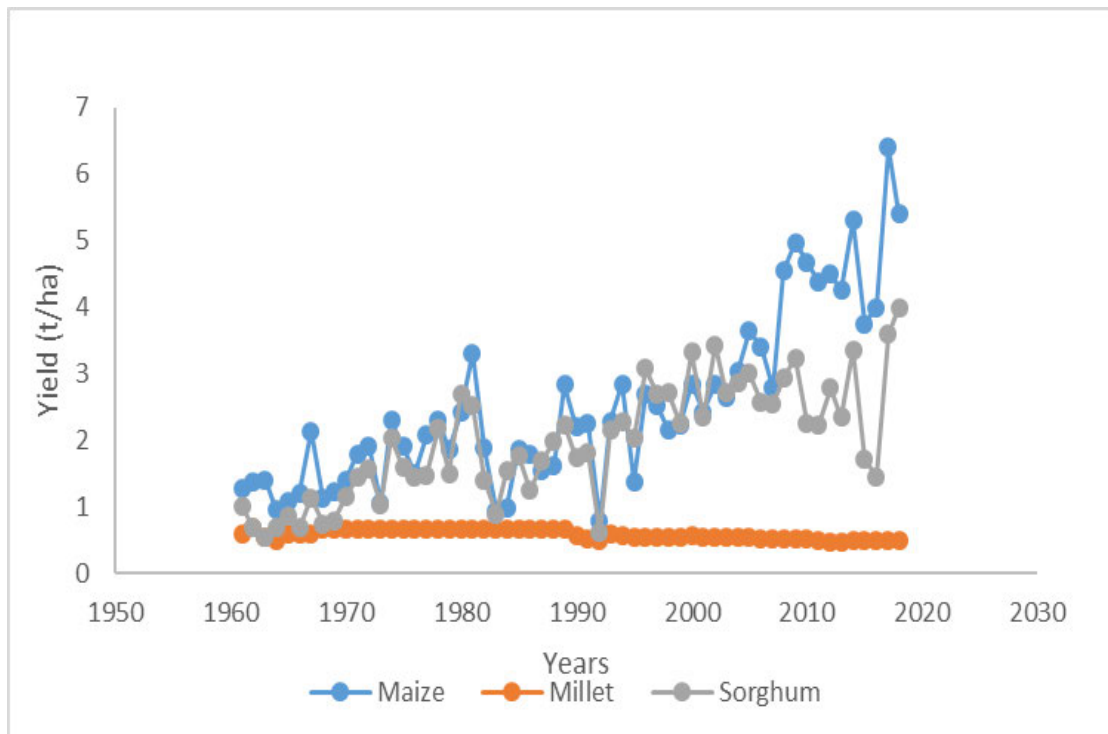
Sorghum, also known as Mabele thoro (Bapedi), Amazimba (Xhosa), and Amabele (Ndebele), is the second most important cereal in SA. Sorghum is well adapted to tropical climates with several traits, making it a drought-tolerant crop that survives under adverse climatic conditions and is often relegated to poor soils and low-input management. In South Africa, sorghum is produced in the drier regions of Limpopo, KwaZulu-Natal, Free State, North West, Northern Cape, Eastern Cape, and Gauteng provinces. It is extensively grown under rain-fed conditions for grain and forage production. High production may be achieved when sufficient water and nutrients are applied, especially at critical crop growth stages (Wani et al., 2012). Sorghum meal is mainly used to make porridge, unleavened bread, cookies, cakes, couscous, and malted beverages. Parched seeds are used as a coffee substitute. Also, sorghum is regarded as an important animal feed (DAFF, 2010). Although sorghum grain is not usually fed to livestock, sorghum stover is used for fodder and fuel and material for building and roofing houses (Orr et al., 2016). In the last 20 years, the area under sorghum production varied from 50 000 ha to 150 000 ha per annum (Figure 2.1). Sorghum production in SA has decreased dramatically over the past decade as producers preferred to plant more profitable crops like maize and oilseeds. In this regard, sorghum has become underutilised as its production and use is on the decline.

Millet is an important crop in the semi-arid tropics of Asia and Africa and is favoured due to its productivity and short growing season under dry, high-temperature conditions. Specifically, pearl millets are produced in the Limpopo, KwaZulu-Natal, and the Free State provinces. Millet is used mainly as a whole, cracked or ground flour, dough, or grain-like rice. These are made into fermented bread, foods and thick porridges, steam-cooked dishes, non-alcoholic beverages, and snacks. Millet is also grown for silage and hay production. Crop residue and green plants provide building materials for fencing, thatching, and making basketry (DAFF, 2014). According to Knoema (2019), millet production of 5 160 tonnes was attained in SA in 2019. “Since millets can be kept for up to 10 years without significant storage losses, farmers may not plant millets every year but only in the years following a poor maize harvest when all their millet has been consumed, and they need to replenish their stores” (Orr et al. 2016, p. 34). Under good conditions, pearl millet hybrids can yield 3-4 tons/ha compared to 300 to 800 kg/ha when moisture and soil fertility become limiting factors. The uses of millet are numerous; however, its production and use are very low.

According to FAO (2018b), millet and sorghum production is lower than maize production in South Africa. In Figure 2.1, it is depicted that maize cultivated crop compared to sorghum, followed by millet which has less cropland area in 1961-2018. Figure 2.2 shows that maize produces more yield when compared with sorghum and millet in SA, even though a more significant production of maize is seen starting from 2010.



**Figure 2.1:** Area harvested for maize, millet, and sorghum in 1961-2018 (FAO, 2018b)



**Figure 2.2:** Yield produced for maize, millet, and sorghum in 1961-2018 (FAO, 2018b)

### 2.2.2 Crop simulation modelling of growth (yield and biomass)

It is important to note that crop models are beneficial in integrating knowledge and data across disciplines (Singels et al., 2010), as the focus has been given to promoting multidisciplinary research as the future of research. The relationship between crop yield and resources (such as CO<sub>2</sub>, plant nutrients, solar radiation, and water supply) traditionally has been based on empirical production functions (Doorenbos & Kassam, 1979), which cannot be extrapolated reliably beyond the location for which they were developed. Calibrated crop simulation models, therefore, increasingly are being used as alternative means for rapid assessment of water-limited crop yield over a wide range of environmental and management conditions (Foster et al., 2014; García-Vila & Fereres, 2012; Grassini et al., 2011; van Ittersum et al., 2013). Crop models as support tools in decision making are categorised into three classes of support. These are strategic (land-use, changes in climate, sustainability) and tactical (fertilisation, cultivar selection, plant populations etc.) classes of support proposed by Steduto et al. (2009). A third class called operational support (irrigation scheduling, weeding etc.) was added by Singels et al. (2010). Modelling is done on a day-by-day basis at an individual plant level. Therefore, data requirements are rigorous and include detailed and sophisticated measurements of environmental conditions (soil, site, climate and management) to which the plant is exposed (France & Thornly, 1984). This then means that crop models can be differentiated and categorised.

Over the last five decades, research teams have produced hundreds of crop models differentiated by the crops covered, the targeted regions, the temporal and spatial scales, the approach (statistical or process-based), the input data required and the output variables (FAO, 2017b). Various statistical, mechanistic, deterministic, stochastic, dynamic, and static models assess and predict crop growth and yield (Rauff & Bello, 2015). According to FAO (2017), the classification of models may rely on the purpose for which the models were developed. There are three criteria against which crop models may be differentiated.

The first criterion may be the scientific understanding of crop growth (mechanistic or functional/empirical models) or supporting decision-making processes (predictive or descriptive models responding to external drivers). For example, models like AquaCrop, DSSAT and SIMPLE are categorised as mechanistic models. Empirical models are defined as direct descriptions of observed data and are generally expressed as regression equations and estimate the final yield. This approach primarily examines the data, deciding on an equation or

set of equations and fitting them to data. These models give no information on the mechanisms that give rise to the response (Oteng-darko et al., 2013). A mechanistic model describes the behaviour of the system in terms of lower-level attributes. Hence, there is some mechanism, understanding or explanation at the lower levels (e.g. cell division). These models can mimic relevant physical, chemical or biological processes and describe how and why a particular response occurs. The modeller usually starts with some empiricism, and as knowledge is gained, additional parameters and variables are introduced to explain crop yield. The system is therefore broken down into components and assigned processes (Oteng-darko et al., 2013). The descriptive model defines the behaviour of a system in a simple manner reflecting little or none of the mechanisms that are the causes of phenomena. It consists of one or more mathematical equations (Rauff & Bello, 2015).

Secondly, the modelling approaches separate statistical models from dynamic simulation models. Dynamic simulation models form a group of models that are designed to imitate the behaviour of a system. Since they are designed to mimic the system at short time intervals (daily time-step), variability related to the daily change in weather and soil conditions is integrated. The short simulation time-step demands that a large amount of input data (climate, soil, and crop parameters) be available for the model to run. These models usually offer the possibility of specifying management options, and they can be used to investigate a wide range of management strategies at low costs (Oteng-darko et al., 2013). A statistical model combines inferences based on collected data and population understanding to predict information in an idealized form (Allison & Goldstein, 2014).

The spatial and temporal scales are the third criterion against which to differentiate models. In terms of space, the scale may range from field-scale (point models with homogeneous conditions within the field) to regional scale; as for time, the scale ranges from hourly steps (for pest management processes) to ten-daily steps (for delivering seasonal yield predictions) (FAO, 2017).

Process-based crop simulation models (CSMs) are dynamic computational tools that simulate environmental conditions and management practices (Muller & Martre, 2019). CSMs differ according to their choice of relationships and hypotheses regarding process functioning and feedback loops, and their combinations of mechanical components (e.g., photosynthesis, soil water transport) and functional components (also termed phenomenological, e.g., radiation use efficiency, stomatal conductance) (Parent & Tardieu, 2014; van Ittersum et al., 2013). While

early models focused on canopy architecture, light interception, and carbon assimilation, subsequent efforts have considered a wider breadth of processes over the crop life cycle with a focus on development and growth dynamics, carbon partitioning, and water/nitrogen balances in the crop and soil (Boote et al., 2013).

Plant models have been developed with an explicit description of 3-dimensional (3D) morphology and form of plants, known as functional–structural plant models (FSPMs; Prusinkiewicz & Runions, 2012; Vos et al., 2010). In contrast with CSMs, which generally model processes at the canopy level, FSPMs consider processes at the level of individual plants and organs, from which complex properties at the plant community level emerge. Different FSPMs have a focus either on the above- or below-ground parts of the plant. Most of them do not consider the whole plant life cycle and instead only consider a limited number of processes, depending on the research questions being addressed. However, the breadth of processes considered in FSPMs has greatly increased in recent years, allowing them to address questions related to the interactions of crops with the environment and management that could previously only be addressed by CSMs (Evers et al., 2018). CSMs and FSPMs are complementary and can inform each other on processes acting at different scales.

The crop growth models can predict crop performance in regions where the crop has not been grown before or not grown under optimal conditions. Such applications are valuable for regional development and agricultural planning in developing countries (Kiniry et al., 1998). It can be developed at various levels of complexity. The level of complexity required depends on the objective of the modelling exercise (Rauff & Bello, 2015). Studies done by Yin & Struik (2010) have shown that combining physiological modelling and genetic mapping (molecular genetics) into a quantitative trait loci (gene)-based modelling could be powerful to resolve complex environment-dependent traits on a genetic basis. Uses of physiological understanding and mathematical tools can overcome the apparent empiricism of many current crop models. There are opportunities to develop a ‘crop systems biology’ model given the rich history in biochemistry and the advent of the ‘-omics’ (Yin & Struik, 2010).

Crop simulation models are used to predict how climate changes, cultivar selection, management options, soil type, and weather might affect future agriculture and studies to be chosen for adaptation by policymakers and local stakeholders. It was reported by Azam-Ali et al. (1994) that at the core of any crop model, there are equations formulated to forecast the production rate of biomass from resources such as carbon dioxide, solar radiation, and water.

Modelling biomass production was classified into three approaches: carbon-driven, radiation-driven, and water-driven models (Steduto, 2003). In a carbon-driven growth engine, growth is based on the carbon assimilation by the photosynthetic process, e.g. WOFOST (van Diepen et al., 1989). The crop model derives the biomass directly from the intercepted solar radiation through a coefficient called radiation use efficiency (RUE) in solar energy-driven growth-engine, e.g. DSSAT-CERES-Maize (Jones et al., 2003) and the SIMPLE model (Zhao et al., 2019). For a water-driven growth engine, biomass is calculated through transpiration and normalized water productivity (WP\*), e.g. AquaCrop (Steduto et al., 2009). Usually, the simulation of responses to carbon dioxide includes adjusting daily radiation use efficiency and transpiration. This is done to prevent considering the effects of carbon dioxide, canopy temperature and stomatal conductance.

“The mechanics of simulating crop responses to specific changes in temperature, CO<sub>2</sub> or other abiotic factors may appear straightforward: one provides the model with initial field conditions, crop information and the daily weather and CO<sub>2</sub> data corresponding to the historical, current or future scenarios of interest. The simulation is then run, and the outputs are compared to those of other simulations where different initial conditions, management practices, or weather and CO<sub>2</sub> scenarios were used” (White et al., 2011). There are methodological matters of interest when studying the impacts of changes in climate on agroecosystems. These matters include the initial evaluation and selection of crop models, sampling of geographic regions, down-scaling of outputs of general circulation models (GCMs) or regional climate models (RCMs) to locations or sub-regions and consideration of adaptation strategies, in an example, changes in cultivars or planting dates (White et al., 2011).

Future climate change scenarios are usually generated using GCMs (Asseng et al., 2015). Climate change impact studies have shown that GCM outputs have the most influence on output results (Bavani & Morid, 2006; Minville et al., 2008; Prudhomme & Davies, 2005). Climate change scenarios produced by GCMs have large uncertainties arising from three sources: the modelled processes within the GCMs; initial conditions; and future greenhouse gas emissions (IPCC, 2013). Downscaling GCM scenarios to local scales for use in crop simulation modelling adds another dimension of uncertainty (Wilby et al., 2004). However, the reliability of such downscaling can be critical for the outcomes in terms of crop impact (Asseng et al., 2015). The uncertainties and limits in downscaling need to be considered when studying the impact of climate change. One way of dealing with these uncertainties is to use a range of

possible future climate change scenarios to assess climate change impact, i.e. using ensemble climate projections (Tao & Zhang, 2012, 2013) rather than a single projection.

### 2.2.3 Modelling of maize, millet, and sorghum

Modelling has evolved over the last 100 years as a means of describing and interpreting complex and variable performance and increasingly as a means of predicting likely performance in prescribed circumstances for better decision making (Keating & Thorburn, 2018). Scopus was used as a search engine for literature on models that have been used for simulating maize, millet, and sorghum over the past 15 years. This literature was identified by limiting Scopus results to title, abstract and keywords (crop model\* and maize/sorghum/millet). In Table 2.1, it is depicted that there has been little attention given to publishing papers on simulating millet and sorghum from 2005-2020. There is 514, 61 and 26 published papers on simulating maize, sorghum, and millet, respectively (Table 2.1). This information further concludes that more attention has been given to staple crops than NUS over the past 15 years.

**Table 2.1:** Published information on modelling maize, sorghum, and millet from 2005-2020

<b>Crops</b>	<b>Models used</b>	<b>Number of published papers</b>
Maize	ACRU, BEWAB, SARRAH, CANE-GRO, CERES, PUTU, SAPWAT, SWB CropSyst, APSIM, CERES, CROPSYST, COUP, DAISY, EPIC, FASSET, HERMES, WOFOST MONICA, STICS, SIMPLE, AquaCrop, DSSAT	1250
Sorghum	APSIM, DSSAT, Samara, PILOTE-N, CERES, STICS, FAO-AEZ, AquaCrop, SARRA-H, EPIC	96
Millet	DSSAT, Système d'Analyse Régionale des Risques Agronomiques, SARRAH, CYGMA, CERES, STICS, AquaCrop, EPIC	56

A variety of crop simulation models have been used to simulate maize, millet, and sorghum results. In Table 2.1, it is presented that there has been the use of crop models like AquaCrop,

DSSAT, STICS, SARRA-H, Simple water balance (SWB), Agricultural Production Systems sIMulator (APSIM), ACRU, BEsproeiingsWaterBestuursprogram (BEWAB), CANE-GRO, Crop Environment Resource Synthesis (CERES), PUTU, South African Program Water (SAPWAT) and CropSyst to model maize, millet and sorghum. Additionally, it is evident that the SIMPLE model is included in the list; however, it has only been used to simulate output for maize and not sorghum and millet. For some published literature, the names of crop models were not stated.

Crop models have been successfully used to provide simulations of the growth, development and yield of crops. Modelling has been applied to a wide range of NUS (e.g., (Chimonyo et al., 2016; Mabhaudhi et al., 2018; Ullah et al., 2019). Crop models are widely implemented in simulation frameworks such as DSSAT (Jones et al., 2003) and AquaCrop (Steduto et al., 2009). The SIMPLE (Zhao et al., 2019) model is a tool that has been recently introduced into the scene of crop modelling but does not have a body of studies published on simulating NUS. These models differ in their degree of complexity and/or simplicity. Comparing different modelling approaches can help reveal the uncertainties relating to crop growth and yield predictions (Palosuo et al., 2011), including model structure, the most difficult source of uncertainty to quantify (Chatfield, 1995). Model comparison will also help identify those parts of the model that produce systematic errors and require improvements (Adam et al., 2012). The body of studies comparing models for simulating NUS increases (Asseng et al., 2013; Salo et al., 2016). However, there has not been a comparison of AquaCrop, DSSAT and the SIMPLE model in simulating NUS based on the models' complexity and/or simplicity level.

## 2.2.4 Overview of the AquaCrop, DSSAT and the SIMPLE model

### 2.2.4.1 AquaCrop Model

AquaCrop is defined as an engineering type, a canopy-level model that (Raes et al., 2009; Steduto et al., 2009) simulates crop yield as a function of water consumption under conditions of being rainfed and irrigated (Mabhaudhi et al., 2014b). Also, the model is an adopted framework of Doorenbos & Kassam's (1979) initiative, which was published in the FAO's Irrigation and Drainage Paper No.33. Crops grow in a soil-crop-atmosphere environment, usually described by the relatively trivial input data (Greaves & Wang, 2016). The AquaCrop model requires 29 input parameters. Similarly to other models, the AquaCrop's model component structure consists of a plantation, atmosphere, and soil (soil water balance) (Steduto et al., 2009). Furthermore, the similarity of the AquaCrop model is most prevalent in the

constituents of the atmosphere and soil. Thus, the difference of the AquaCrop model, compared to other cereal crop development models, exists based on soil and plant components (Mabhaudhi et al., 2014a). Essentially, when the AquaCrop executes the simulation functionality, four files are used. These files are namely soil, crop, climate and management file. According to Farahani et al. (2009) and Geerts et al. (2009), it is recommended that the AquaCrop retains an accepted and consistent equilibrium between its accuracy and robustness.

#### 2.2.4.2 DSSAT model

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program of crop simulation models for over 42 crops as of Version 4.7. DSSAT is a cropping system simulation model that has been continuously improved over the years (Corbeels et al., 2016). The DSSAT is a crop model that helps decision-makers by reducing the time and human resources required for analysing complex alternative decisions (Tsuji et al., 1998). DSSAT model simulates crop yield under different management strategies, optimizing resource use, yield trend simulation under different soil and climate scenarios, and crop risk analysis (Jeffrey et al., 2010; Jones et al., 2003; Sarkar, 2009). Thus, DSSAT is said to be useful for estimating short-, medium- and long-term impacts of specific land management practices on crop yield, soil water storage, nitrate-N leaching losses, etc. (Boote et al., 2010). The DSSAT primary modules include weather, soil, plant (cultivar/genotype coefficients), soil-plant-atmosphere interface, and management components. DSSAT was first released (v2.1) in 1989 and has been utilised by more than 16,500 researchers, educators, consultants, extension agents, growers, and policy and decision-makers in over 174 countries all over the globe (DSSAT, 2021).

#### 2.2.4.3 SIMPLE model

The SIMPLE model can be defined as simulating crop growth, development, and yield utilising a daily time step, with equations that consider the impact of daily temperature, heat stress, rainfall, and atmospheric CO<sub>2</sub> concentration. The SIMPLE model incorporates nine species parameters for the specification of crop types and four cultivar parameters characterizing cultivar differences (Zhao et al., 2019). In order to run the SIMPLE model, input variables required include weather, atmospheric CO<sub>2</sub> concentration, sowing/harvesting date, irrigation, initial variables (biomass/cumulative temperature/fraction of solar radiation interception if different from zero), and four variables characterizing the soil, including fraction of plant-available water-holding capacity, runoff curve number, deep drainage coefficient, and root zone depth (Zhao et al., 2019).

## 2.2.5 Input requirements for AquaCrop, DSSAT and the SIMPLE model

### 2.2.5.1 Soil

The soil file forms part of the input requirements for AquaCrop, DSSAT and the SIMPLE models. Generic parameters of the soil for all these three models include soil profile, soil chemical properties, soil texture, field capacity, saturation point, permanent wilting point and total available water. Additionally, there is bulk density, hydraulic conductivity, and run-off coefficient (Table 2.2). The soil file of the AquaCrop model considers the possibility of occurrences of water, soil fertility, and soil salinity stresses. The application of irrigating the soil is another available section in the AquaCrop, DSSAT and the SIMPLE model. The soil profile is characterized by its soil textural class. The water balance simulation uses a simple water budget routine to determine drought stress without detailed soil profile water holding characteristics. Unlike AquaCrop and DSSAT, the SIMPLE model does not divide  $ET_0$  into soil evaporation and crop transpiration (Zhao et al., 2019). The DSSAT soil module calculates potential ET using two current options, the default Priestley & Taylor (1972) method and the Penman-FAO method. Meanwhile, AquaCrop uses only the Penman-FAO method, and SIMPLE uses the Priestley & Taylor (1972) method to calculate  $ET_0$ . Due to enough severity of the drought stress, the radiation interception of the SIMPLE model is affected, similar to the AquaCrop model (Steduto et al., 2009).

Unlike in AquaCrop and the SIMPLE model, the soil module in DSSAT consists of several vertical soil layers. The soil module information from four sub-modules (soil water, soil temperature, soil carbon and nitrogen, and soil dynamics) is integrated. The soil dynamics module is designed to read in soil parameters for the land unit and modify them based on tillage, long-term changes in soil carbon, or other field operations (Jones et al., 2003). This one-dimensional model computes the daily changes in soil water content by soil layer due to infiltration of rainfall and irrigation, vertical drainage, unsaturated flow, soil evaporation, and root water uptake processes. In the new DSSAT-CSM, soil evaporation, plant transpiration, and root water uptake processes were divided into a soil-plant-atmosphere module (SPAM) to create more flexibility for expanding and maintaining the model (Dias et al., 2016).

The soil has parameters that define its surface conditions and layer-by-layer soil water holding and conductivity characteristics (Jones et al., 2003). The DSSAT model has two options to simulate the soil organic matter and nitrogen balance. Soil temperature is computed from air temperature and a deep soil temperature boundary condition calculated from the average annual

air temperature and the amplitude of monthly mean temperatures. It also incorporates a simple approach to calculate the effect of solar radiation and albedo on the soil surface temperature. However, differences in soil wetness or surface conditions are not considered. The soil-plant-atmosphere module combines soil, plant, and atmosphere input and computes light interception by the canopy, potential evapotranspiration (ET), as well as actual soil evaporation and plant transpiration (Jones et al., 2003).

#### 2.2.5.2 Climate

This file consists of three sub-files: rainfall, minimum and maximum air temperature, and evapotranspiration ( $ET_o$ ), and values collected daily. FAO's  $ET_o$  CALCULATOR is a useful utility for estimating  $ET_o$ . The climatic data required to run AquaCrop includes humidity, wind speed, sunshine, and solar radiation. The SIMPLE model consists of daily maximum/minimum temperature, rainfall, and solar radiation (Zhao et al., 2019). DSSAT contains a module called "Weather", which generates daily weather data. This module reads daily weather values (maximum and minimum air temperatures, solar radiation, and precipitation, relative humidity, and wind speed when available); this module generates daily weather data using the Weather Generator (WGEN) (Richardson, 1981, 1985) or SIMMETEO (Geng et al., 1986, 1988) weather generators. Based on the inputs provided from the management file, the Weather module knows whether to just read in daily values or generate or modify them (using the Environmental Modification sub module).

The AquaCrop, DSSAT and SIMPLE model utilises default atmospheric  $CO_2$  from 1902 to 2099; this was measured at Mauna Loa Observatory in Hawaii. The annual  $CO_2$  concentration data from Mauna Loa Observatory is inbuilt into the AquaCrop and DSSAT model but manually recorded in the SIMPLE model input file for simulation. AquaCrop uses the day-to-day minimum and maximum air temperature to calculate growing degree days (GDD). The users are provided with two simulation modes [thermal time (GDD) and calendar time] by the model (Mabhaudhi et al., 2014b). Hsiao et al. (2009) stated that the climate file is user-specific and comprises three sub-files: rainfall, minimum and maximum air temperature, and  $ET_o$  (Table 2.2), collected values daily.

#### 2.2.5.3 Crop

AquaCrop is a model that is most common and can be used for various herbaceous crops. These crops are oil, fruit, grain, vegetable, root, forage, and tuber crops (Hsiao et al., 2009). Moreover,

the simulation of crop growth and yield are affected by environments that experience high degrees of soil moisture. These environments have been a catalyst towards the success of crop growth, such as sunflowers (Todorovic et al., 2009), groundnuts (Karunaratne et al., 2011), and winter wheat (Rezaverdinejad et al., 2014). In AquaCrop, the crop file consists of user-specific and conservative parameters (some of which are cultivar-specific). DSSAT has a plant module designed to link modules that describe growth, development and yield for individual crops (Jones et al., 2003). In DSSAT, crop parameters are separated into three subsets: species, ecotype, and cultivar-specific (or genetic coefficients) parameters (Corbeels et al., 2016).

The AquaCrop model simulates the crop based on its five key constructs and their associated responses to water stress. Raes et al. (2009) mentioned that these components consist of canopy cover, biomass production, rooting depth, phenology, and yield, which can be harvested. Canopy expansion is simulated in terms of proportional green canopy cover as opposed to leaf area index. This approach has the advantage of simulated model outputs related directly to easily accessible data from visual field observations and remote sensing. For instance, there is a strong correlation between vegetation indices attained from earth observation satellites and fractional green canopy cover (Calera et al., 2001; Carlson & Ripley, 1997; Jiang et al., 2006; Johnson & Trout, 2012; Kim & Kaluarachchi, 2015), enabling the use of such indices (e.g. NDVI) to calibrate and validate AquaCrop simulation outputs quickly over huge regional domains (Kim & Kaluarachchi, 2015).

Ran et al. (2020) reported that DSSAT derives the biomass directly from the intercepted solar radiation through a radiation use efficiency coefficient and simulates the grain yield through the grain numbers and the filling rate per kernel. AquaCrop estimates biomass production directly from actual crop transpiration through a water productivity parameter and calculates the crop yield as the proportion of biomass that goes into the harvestable parts (Ran et al., 2020). In the SIMPLE model, photosynthesis is based on the concept of radiation-use efficiency (Monteith, 1965), by which a fraction of daily photosynthetically active radiation is intercepted by the plant canopy and translated into crop biomass. The calculation for the final yield is the product of biomass and harvest index (HI) (Amir & Sinclair, 1991). The concept of HI used here is the same as the one used in the AquaCrop (Steduto et al., 2009) model; however, it is utilised as a constant without considering other environmental factors (Table 2.2). In the SIMPLE model, the cumulative temperature is utilised to determine phenological development. A cumulative temperature requirement from sowing to maturity is used to reach physiological maturity in the model. The model does not consider any other growth stages (Zhao et al., 2019).

**Table 2.2:** A comparison of the AquaCrop, DSSAT and the SIMPLE model

	AquaCrop	SIMPLE	DSSAT
Approach	Mechanistic	Mechanistic	Mechanistic
Growth stages considered	Sowing to senescence	Sowing to maturity	Sowing to senescence
Biomass partition	Species dependent	Species dependent	Species dependent
Stress factors affecting canopy growth	Water	Heat stress, rainfall, and atmospheric CO <sub>2</sub> concentration	Heat stress, rainfall, and atmospheric CO <sub>2</sub> concentration
Parameters required	29	23	56
Harvest Index (HI) concept	Functional relationship with the environment	Used as a constant without considering other environmental factors	Functional relationship with the environment
Segregate (ET) into (E) and (Tr)	√		√
Impacts of diseases, pest and frost not considered	√	√	
Root growth	Canopy size influences root growth		
Soil generic parameters	Soil profile, soil chemical properties, soil texture, field capacity, saturation point, permanent wilting point, total available water		
Bulk density	√	√	√
Hydraulic conductivity (Ksat)	√	√	√
Run-off coefficient	√	√	√
Climatic generic parameters	Tmax, Tmin, daily rainfall, daily radiation		
Wind speed	√	√	√
Humidity	√	√	√

#### 2.2.5.4 Management

The AquaCrop management file considers ‘rainfed cropping’ as a default mode, irrigation, field surfaces practices, soil fertility, mulches and weed management. The required field parameters vary with the type of management (FAO, 2017a). DSSAT management module determines when field operations are performed by calling sub-modules. Currently, these operations are planting, harvesting, applying inorganic fertilizer, irrigating, and applying crop residue and organic material. Users specify whether any operations are automatic or fixed based on input dates or days from planting. The management file also provides scope to define multiple crops and management strategies for crop rotations and sequencing (Jones et al., 2003). In the SIMPLE model, crop management variables needed to run the model are sowing, harvest, and irrigation (Zhao et al., 2019).

de Wit et al. (1985), Hanks (1983) and Tanner & Sinclair (1983) stated that the water productivity (WP) parameter seems to be constant across diverse climatic conditions and soils. In turn, this is considered as one of the basics for AquaCrop’s second equation. Furthermore, standardising WP for various climatic conditions creates a conservative parameter (Steduto et al., 2007). This is an indication that the AquaCorp model is primarily robust, universal, and flexible. In addition, a vital improvement from the first equation to the second equation is that the second equation can function daily. Thus, proceeding towards the time scale of plant reactions to water stresses (Acevedo et al., 1971). Whereas the first equation functioned on a seasonal time scale (Mabhaudhi, 2012).

At the core of FAO’s Irrigation and Drainage Paper No.33, the following equation was evident:

$$\left(\frac{Y_x - Y_a}{Y_x}\right) = Ky \left(\frac{ET_x - ET_a}{ET_x}\right) \dots \quad (1)$$

where  $Y_x$  = maximum yield,

$Y_a$  = actual yield,

$ET_x$  = maximum evapotranspiration,

$ET_a$  = actual evapotranspiration, and

$Ky$  = proportionality factor between relative yield loss and reduction in evapotranspiration.

It is believed that understanding the progress of plant water relationships would influence the need for enhanced water productivity due to increasing water scarcity. Therefore, the FAO had to upgrade Eq. 1 (Mabhaudhi, 2012). After that, a decision was taken to formulate a new crop model, evolving from Doorenbos & Kassam (1979). The newly designed model has the objective of improving yet still maintaining the components of robustness and simplicity of the model. FAO has developed the AquaCrop model (Raes et al., 2009; Steduto et al., 2012; Steduto et al., 2009).

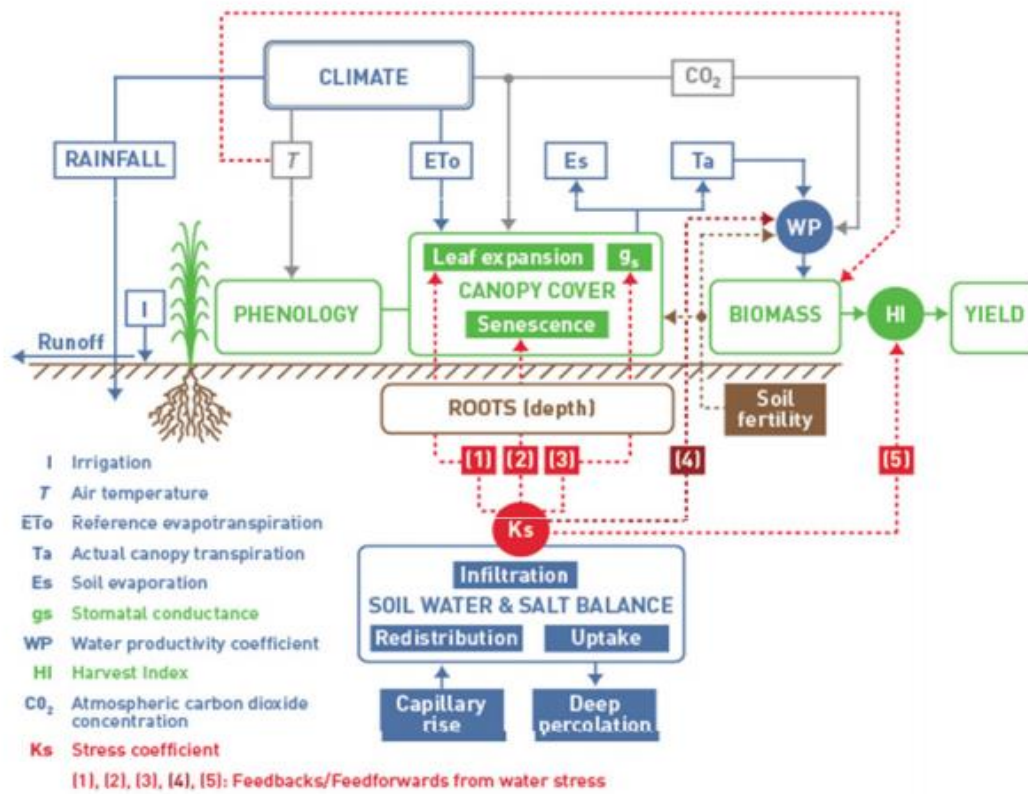
According to Steduto et al. (2009) (Figure 2.3), the progress is established by the AquaCrop's ability to:

1. separate evapotranspiration (ET) to soil evaporation (E) as well as crop transpiration (Tr).
2. approximate Tr and E
3. consider final yield (Y) as a role of biomass (B) and harvest index (HI). Hence, the differentiation of functional relations is enabled between the environment and HI, and between the environment and B,
4. separate reactions to water stress into the below, four, isolated parts –
  - a. canopy growth
  - b. canopy senescence
  - c. Tr
  - d. HI

The above changes led to the below AquaCrop's equation:

$$B = WP \times \Sigma Tr \dots$$

(2)



**Figure 2.3:** Representation of the structural relationships in the Soil-Plant-Atmosphere Continuum by AquaCrop (Raes et al., 2009)

Raes et al. (2009) noted that when crops are affected by water stress, the crops limit canopy enlargement. Instead, they allow early canopy senescence and close the stomata. Also, a continuation of water stress further affects the harvest index and water productivity. Therefore, it is important to consider the magnitude of the canopy in AquaCrop because of the three reactions to water stress at the canopy level. Furthermore, according to Steduto et al. (2009), the contextual model of AquaCrop’s crop element is developed by five key reactions to water stress.

### 2.2.6 Advantages and limitations of the models

A limitation of AquaCrop is that the model is distributed only as a compiled software package (Raes et al., 2018). This constrains applicability, particularly for interdisciplinary policy analysis where a user may want to link AquaCrop directly with other models or adapt the code for the specific purposes of their study (Foster et al., 2017). Furthermore, regardless of the extensive documentation of AquaCrop procedures (Raes et al., 2018; Raes et al., 2009; Steduto

et al., 2009), lack of open access to the source code limits transparency by making it tough for a user to reproduce model calculations and assess in full the influence of internal model structure on simulation outputs (Ince et al., 2012; Peng, 2011). Presently, AquaCrop is not envisioned to simulate perennial tree crops or vines (Hsiao et al., 2009; Steduto et al., 2012), yielding response to water and biomass partitioning processes are significantly more complex and less well understood.

One of the benefits of the AquaCrop model is that it offers simplicity as an imperative feature for its end users, unlike the other cereal crop development models such as DSSAT. This is because there is no advanced skill requirement needed to calibrate and work with it. Also, there are minimal input parameters required (Heng et al., 2009). Often the integrated default input variables are sufficient and do not require additional fitting. When additional variables are needed, they are mostly intuitive and can easily be determined using simple methods (Raes et al., 2009; Steduto et al., 2009). The simplicity of the SIMPLE model makes it suitable for many different crops for which there is limited information and data available, particularly for the noncommon cereals and legumes, also fruits and vegetables (Zhao et al., 2019).

Zhao et al. (2019) stated that due to its simplicity, the SIMPLE model has limitations. For instance, there is a lack of soil-crop nutrient dynamics. A main limitation of SIMPLE is the lack of phenology sensitivity to vernalization and photoperiod, which can be important in some crops and cultivars, such as carrots. Additionally, there is no consideration of the impacts of diffused light on RUE in the SIMPLE model. Some main effects of crop management practice are also not included, such as sowing density (partly only via maximum light interception) or sowing depth, impacting growth and yield. SIMPLE assumes a fixed harvest index, which can be considered a limitation in some terminal drought environments (Moser et al., 2006).

DSSAT includes a pest module that permits users to input field observations and scouting data on insect populations or damage to different plant parts, disease severity on different plant tissues, and physical damage to plants to simulate the impacts of identified pests and diseases on growth and yield (Jones et al., 2003). Contrary to this, the SIMPLE model does not consider the impacts of diseases, pests, and frost. Moreover, the model is unable to simulate excessive moisture effects on crop growth. The utilisation of basic crop physiology makes this model also suitable for being used as a teaching tool. The SIMPLE model can be utilised to assess future climate effects, particularly for crops not available in other model platforms (Zhao et al., 2019). In DSSAT, improved application programmes are incorporated for seasonal, spatial,

sequence and crop rotation analyses. The economic risks and environmental impacts associated with irrigation, climate change and variability, fertilizer, soil carbon sequestration, nutrient and precision management are assessed by DSSAT analyses (DSSAT, 2021).

### 2.2.7 Lessons, challenges and gaps

Figure 2.2 shows that the production of maize has been high over the years in comparison to millet and sorghum. In previous studies, maize's focus has been given to it as it is considered mainstream or an important crop. This has been the case because the production of maize has been high due to demand, as people consumed this crop more than other crops. According to Muza (2017) and SAGIS (2019), there is an increase in demand for maize, and other cereal crops, considering the increased incidence of severe climate events. Sorghum and millet have been identified as neglected and underutilized cereal crops as their production has been declining over the years. Based on the literature reviewed in this thesis, it is noted that sorghum and millet, as neglected and underutilized cereal crops, can be used to balance the equation of food demand and supply and reduce food and nutrition insecurity by improving dietary diversity. Thus, information is required regarding its production, agronomy, and eco-physiological responses to varying climate and environmental conditions.

Crop models are vital tools in decision-making, assessing the impacts of climate change/variability and management practices on productivity and environmental performance of alternative cropping systems, and promoting better and sustainable agriculture (Amanullah et al., 2007; Kadiyala et al., 2015; Xiong et al., 2014). No study has been performed to assess the performance of AquaCrop, DSSAT and the SIMPLE model in predicting yield and water use of selected NUS. Moreover, to assess the performance of these three crop simulation models in simulating the impacts of climate change and irrigation regimes on yield and water use of the selected NUS. Thus, the purpose of this thesis was to address the questions of which model is best suited for modelling NUS's yield and water use, climate change impacting NUS and irrigation as a management practice for NUS.

Before using crop models, users must familiarize themselves with the model's intended use and limitations and be aware of the uncertainties associated with the results incorporated into the decision-making processes (Willcock et al., 2016). Several challenges are encountered in crop simulation modelling (Kephe et al., 2021; Silva & Giller, 2021). These challenges include lack of available data in crop model input format, poor access to necessary data for model calibration and validation, difficulties in using data from climate change models and scenarios

and complexities in methodologies used for crop simulation. There is also a case when a suitable crop simulation model is chosen, and data limitations hinder some of the models' effective role for projections (Kephe et al., 2021). Although most crop models can simulate water- and nitrogen-limited yields under different management practices (e.g. amount, time and efficiency of application), little progress has been made in simulating phosphorus and potassium limitations and the interactions between these factors (Silva and Giller, 2021).

Most models are virtually untested or poorly tested, and hence their usefulness is unproven (Rauff & Bello, 2015). Thus, calibration and evaluation of models become a requirement. An intensely calibrated and evaluated model can be used to effectively conduct research that would, in the end, save time and money and significantly contribute to developing sustainable agriculture that meets the world's needs for food (Rauff & Bello, 2015). Primarily, parameterizing consists of the correspondence of observed canopy cover concerning the simulated canopy cover. Subsequently, the model's calibration is conducted by comparing the observed and simulated yield and/or biomass (Mabhaudhi, 2012). Accordingly, researchers observed that parameterizing the model is site-specific. Additionally, there should be tests for fundamental calibrated parameters under different soils, climates, cultivars, irrigation methods, and field management. The testing would be an essential basis for ensuring accuracy and ensuring advanced reliability of the simulated findings (de la Casa et al., 2013; Farahani et al., 2009), this is as cited by Greaves & Wang (2016). Evaluating the goodness of the appropriateness of AquaCrop, DSSAT and the SIMPLE model results in contrast to the experimental field measurements can be conducted via utilising the coefficient of determination ( $R^2$ ), root mean square error (RMSE) alongside its systematic (RMSEs) and unsystematic (RMSEu) parts, as well as Willmott's coefficient of agreement ( $d$  index) (Mabhaudhi et al., 2014b).

### **2.3 Conclusion**

Despite the large diversity of cereals, research has been biased towards major cereals. Ironically, the minor cereals are indigenous to semi- and arid tropics and are more adaptable to water-scarce conditions. There is a need to increase the cereal basket by adding minor cereal. This will also act as a buffer when major cereals are not successful due to drought. Crop simulation models are used as alternative means for rapidly assessing water-limited crop yield over a wide range of environmental and management conditions. Generally, crop simulation models are utilised to project how climate change, cultivar selection, management options, soil

type, and weather might affect future agriculture and study choices for adaptation by policymakers and local stakeholders. Over the last five decades, research teams have produced hundreds of crop models differentiated by the crops covered, the targeted regions, the temporal and spatial scales, the approach (statistical or process-based), the input data required and the output variables. Various statistical, mechanistic, deterministic, stochastic, dynamic, and static models assess and predict crop growth and yield. DSSAT, AquaCrop and the SIMPLE model are tools that differ in their degree of complexity and/or simplicity. Comparing these different models can help reveal the uncertainties of crop growth and yield predictions and identify suitable models for a specific study. In several cases, the model users are not familiar with their application's model limitations and specificities, which creates problems when identifying suitable models for a specific study. Thus, the limitations and opportunities of the models studied were reviewed.

## **CHAPTER 3: CALIBRATION OF AQUACROP, DSSAT AND THE SIMPLE MODEL**

### **3.0 Introduction**

Neglected and underutilised species (NUS) play a crucial role in food security and nutrition. Furthermore, NUS also plays a major role in income generation for the rural resource-poor households and sustainable production in marginal environments (Magbagbeola et al., 2010; Mal, 2007). However, due to the lack of data on growth and yield responses to the environment and different management strategies, current efforts for mainstreaming NUS have not matched those for commercially important crops. To bridge the gap in NUS research, numerous computer-based tools such as crop simulation models (CSMs) are presently being used in generating the much-needed data in crop research (Ewert et al., 2011). These tools are effective since they minimize the need for expensive and time-consuming field experiments. While crop simulation models as decision support tools offer users and policy makers data for best management practices, their uptake and use are low. One major reason for this is huge uncertainties related to model structure and parameters (Palosuo et al., 2011), such as various models requiring large data input and complexity. Further to this, it is uncertain whether the current ensemble of models is suited for modelling NUS. Due to the lack of data on NUS to parameterize and calibrate, many researchers have been calling for the development and use of simpler but equally robust models (Babel et al., 2019; Mabhaudhi et al., 2014a, 2019; Roberts et al., 2017; Zhao et al., 2019).

Currently, the most common crop models implemented in NUS studies are DSSAT (Jones et al., 2003) and AquaCrop (Steduto et al., 2009), which differ in their degree of complexity. Compared to AquaCrop, DSSAT is a more complex model due to its relative input requirement of more site-specific and crop variety-associated data (Babel et al., 2019). There are simpler models, such as the SIMPLE Model (Zhao et al., 2019). Although the SIMPLE model has been described as simple by several researchers (Manschadi et al., 2021; Soltani et al., 2020; Zhao et al., 2019), no published studies predict the growth, yield and resource use of any NUS. However, there is an ongoing debate on whether a model's simplicity may be appropriate to depict crop responses under observed climate and management options (Palosuo et al., 2011; Zhao et al., 2019). The argument is between using simple models to simulate crop growth and yield or focusing on complex models requiring a high level of expertise and data. This is important with the current drive for sustainable intensification in climate change using

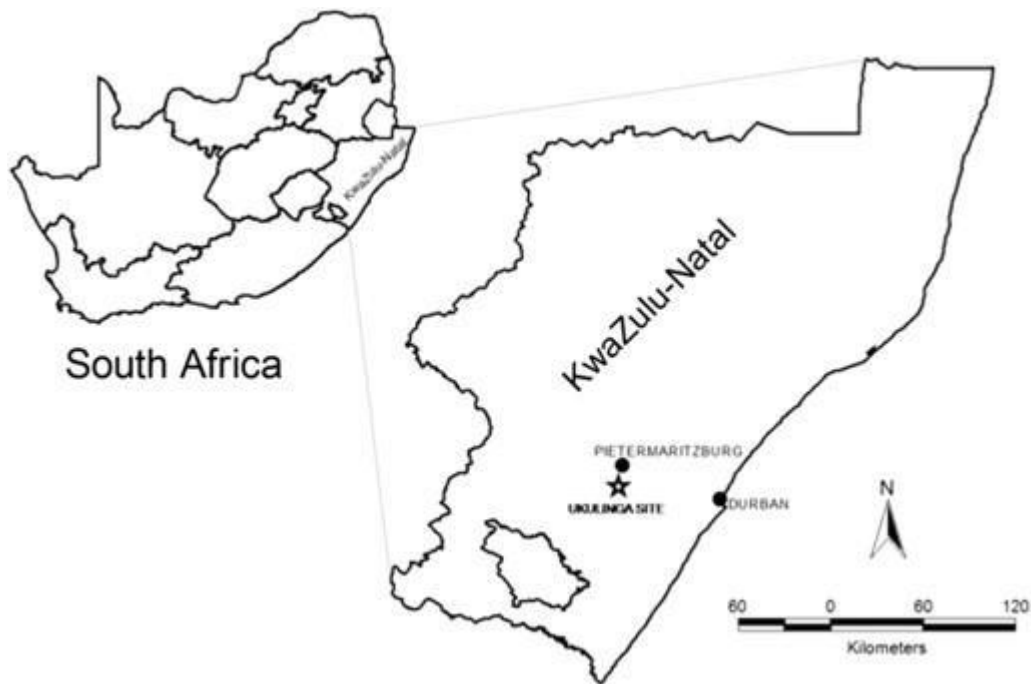
neglected and underutilised crops. As such, there is a need to assess the appropriateness of using models with varying complexity. Thus, this study compares the performance of three crop simulation models, namely, AquaCrop, DSSAT, and the SIMPLE model, in predicting yield, biomass, and water use of neglected and underutilized cereal crops. It is hypothesised that there is no significant difference in the performance of AquaCrop, DSSAT and the SIMPLE model in estimating/predicting yield, biomass and water use of neglected and underutilized cereal crops regardless of model complexity.

### **3.1 Materials and methods**

Simulations for maize, sorghum and millet were performed using AquaCrop Version 6.1, DSSAT version 4.7.5 and SIMPLE version 1.1. For a detailed description of models, refer to Section 2.2.4 in the literature review. These models required climate data inputs, crop characteristics, soil characteristics, and a description of management practices to run simulations. Data was sourced from the Ukulinga Research Farm. Maize was used as a base crop since it is a commercially important crop compared to millet and sorghum, which are identified as generally underutilised (*cf.* Section 2.2.1).

#### **3.1.1 Study site**

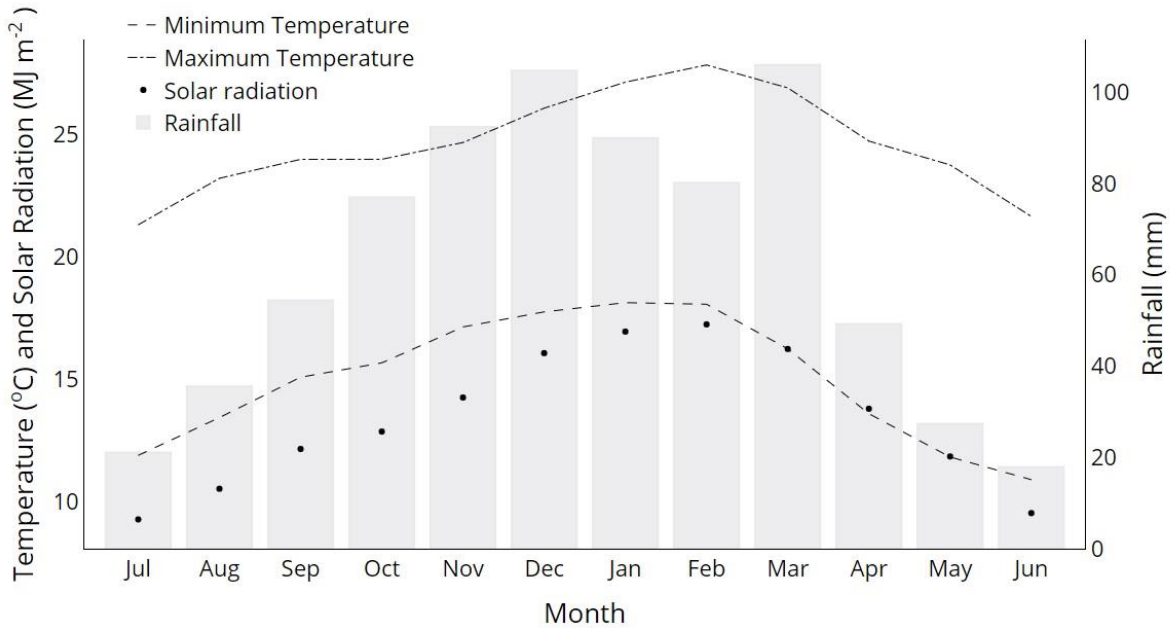
This study used climate and soil data from the Ukulinga Research Farm to create input data files for AquaCrop, DSSAT and SIMPLE models. Ukulinga Research Farm is situated in Pietermaritzburg in the subtropical hinterland of KwaZulu-Natal Province, South Africa (Figure 3.1) and represents a semi-arid environment. The farm is mainly used for training and research by the University of KwaZulu-Natal (UKZN) (Everson et al., 2012). The farm lies 29°37' S, 30°16' E with an elevation of approximately 775 m above sea level. Rain falls mostly in summer, between September and April. Rainfall distribution varies during the growing season (Swemmer et al., 2007), with the bulk of the rain falling in November, December, early January, and March (Figure 3.2). Occasionally light to moderate frost occurs in winter (May – July). Chibarabada et al. (2020) reported that Ukulinga receives an average annual rainfall of 694 mm, mainly during the summer months (mid-October to mid-February). During the summer months, average maximum temperatures are between 26 °C and 28 °C, while minimum temperatures can be as low as ten °C. The landform at Ukulinga is a colluvial fan, and soils are derived from marine shales.



**Figure 3.1:** Geographical view of Ukulinga Research Farm (Everson et al., 2012)

### 3.1.2 Climate description

The daily climate data were obtained from an automatic weather station (AWS) located at the Ukulinga Research farm. The AWS is part of the Agricultural Research Council-Institute for Soil, Climate and Water (ARC-ISCW) network of automatic weather stations. The climate data for all models comprised of rainfall (mm), minimum and maximum air temperature ( $^{\circ}\text{C}$ ), solar radiation ( $\text{MJ}\cdot\text{dy}^{-1}$ ) and reference evapotranspiration ( $\text{ET}_0$ ).  $\text{ET}_0$  was based on the FAO Penman-Monteith equation from full daily weather datasets described by (Allen et al., 1998).  $\text{ET}_0$  was calculated using FAO's  $\text{ET}_0$  calculator (Raes et al., 2009) using air temperature, solar radiation, wind speed and relative humidity from the meteo-station. For DSSAT and the SIMPLE model,  $\text{ET}_0$  was calculated by using the Priestley & Taylor (1972) approach. This approach was used because it is simple and requires less data. For AquaCrop, a default file of the mean annual  $\text{CO}_2$  concentration of 369.41 ppm as a reference in 2000 and 390 ppm in 2020, measured at the Mauna Loa Observatory in Hawaii, was used. DSSAT and the SIMPLE model also used this atmospheric  $\text{CO}_2$  concentration as input data for simulations. To calculate growing degree days (GDD), AquaCrop used daily minimum and maximum temperature. Temperature is equally important in both DSSAT and the SIMPLE model for phenological development and crop growth.



**Figure 3.2:** Long-term climate data for Ukulinga Research Farm from 2004-2019 obtained from a nearby weather station

### 3.1.3 Soil description

According to Chimonyo et al. (2016), the dominant soils at Ukulinga are chromic luvisols (FAO soil classification), and these are generally characterised as shallow brown acidic soils with low to moderate fertility. The soil textural class of the Ukulinga Research farm soil profile was classified as clay to clay-loam (USDA Taxonomic System) with an effective rooting depth of 0.6 m and three horizons (Table 3.1). In creating the soil file, there were no stresses (water, soil fertility, and soil salinity) being considered. The Soil file (.SOL) for AquaCrop and SIMPLE model was created using Ukulinga Research farm soil data. In DSSAT, the clay loam soil file embedded in the model was selected to resemble the Ukulinga soils best. Details of the actual soil parameters used in each model were presented in Table 3.1 and Table 3.2.

**Table 3.1:** Soil water properties from the experimental site at Ukulinga Research Farm (Mabhaudhi, 2012)

Depth (m)	Bulk density (g/cm <sup>3</sup> )	Permanent wilting point (mm/mm)	Field capacity (mm/mm)	Total available water (mm/mm)	Saturation (mm/mm)	Saturated hydraulic conductivity (mm/day)
0.60	1.20	283.00	406.00	123.00	481.00	25

The soil physical characteristics such as the soil texture, bulk density and porosity are considered (Table 3.2).

**Table 3.2:** The soil file from Ukulinga Research Farm

<b>Parameters</b>	<b>Units</b>	<b>Value s</b>	<b>AquaCro p</b>	<b>DSSA T</b>	<b>SIMPL E</b>
Upper horizon depth	cm	30	X	X	
Lower horizon depth	cm	10	X	X	
Number of soil horizons	-	3	X		
Sand content	%	33	X	X	
Silt content	%	33	X	X	
Clay content	%	34	X	X	
Bulk density	g/cm 3	1.20	X	X	
Organic carbon	%	2.90		X	
Organic nitrogen	%	0.24		X	
pH	-	4.51		X	
Saturated water content	%	46.73	X	X	
Field capacity	mm	46.32	X	X	
Wilting point	mm	23.03	X	X	
Plant available water-holding capacity	mm‡	233	X		X
Runoff-curve number	-	75	X	X	X
Deep drainage	-	0.27	X	X	X
Total pore space	mm	36	X	X	
Saturated hydraulic conductivity	cm/h *	25	X	X	
Maximum rooting depth	mm	1	X	X	X

**X denotes that the input was used in the model**

**\*For AquaCrop, units are mm/d; ‡ For SIMPLE, units are mm/m**

### 3.1.4 Crop file

The creation of crop files entailed matching phenology (GDD) and yield potential on pre-existing cultivars across the models. The study used cultivars described by Akumaga et al. (2017), Hadebe et al. (2017) and Bello & Walker (2016) for maize, sorghum and pearl millet, respectively (Table 3.3). The cultivars' characteristics are described below (Table 3.3) and in the sections below.

**Table 3.3:** Provincial potential, observed and mean simulated yield for maize, millet, and sorghum

Crops	Crop type (maturity)	Provincial potential yield (t/ha)	Observed yield (t/ha)
Maize	early to medium	<sup>1</sup> 8 - 11 (9.50)	<sup>4</sup> 5.51
Sorghum	medium to late	<sup>2</sup> 4	<sup>5</sup> 5.31
Pearl millet	early to medium	<sup>3</sup> 4.3 - 5.6 (4.95)	<sup>6</sup> 6.83

<sup>1</sup> Arathoon & Mtumtum (2013) <sup>2</sup> GAIN Report (2019) <sup>3</sup> GRAINSA (2021) <sup>4</sup> Akumaga et al. (2017) <sup>5</sup> Hadebe et al. (2017) <sup>6</sup> Bello & Walker (2016)

#### 3.1.4.1 AquaCrop model crop file

The AquaCrop model comprises two crop parameters: conservative and non-conservative (cultivar specific) parameters (Raes et al., 2009). Conservative parameters were used as presented in the model because they do not change substantially with time, management practices, geographic location or climate (Raes et al., 2009). Additionally, conservative parameters are assumed not to change with cultivars unless shown otherwise. In this study, the tuning of non-conservative parameters was not required because maize, sorghum, and pearl millet were calibrated in the AquaCrop model. Hence, crop parameters used in this study are similar to those used to calibrate the crops in the selected studies where they were obtained (Table 3.4).

#### 3.1.4.2 DSSAT model crop file

In the DSSAT model, the coefficients for a specific crop species are stored in three different files, namely cultivar (.CUL), ecotype (.ECO) and species (.SPE). Cultivar coefficients are for a single cultivar (traits differ among cultivars), ecotype coefficients are common to a group of cultivars and species coefficients are common to all cultivars (crop specific traits) (Jones et al., 2003). Hence, maize, sorghum and millet cultivars were selected in DSSAT. Cultivars chosen for maize, sorghum and millet were 2500-2600 GDD, PIONEER 8333 and BJ104, respectively (Table 3.5), as they best described the cultivars used by (Akumaga et al., 2017) (Hadebe et al.,

2017) and (Bello & Walker, 2016). The cultivars were selected based on their similarity with the GDD of crops used in the AquaCrop model.

#### 3.1.4.3 SIMPLE model crop file

The SIMPLE model included nine species parameters to specify crop types and four cultivar parameters characterizing cultivar differences. Species parameters were derived from accepted values in the literature (Zhao et al., 2019). Only cultivar parameters were calibrated within a reasonable range, but cultivar parameters are kept constant for the same cultivar when grown in different years or locations. The SIMPLE model calibrated only maize; however, it is not the cultivar used in this study (Table 3.6). Maize is one of the crops used in this study, and it is a cereal crop like sorghum and millet. Thus, calibrated maize values for species parameters (CO<sub>2</sub>\_RUE and S\_Water) simulated maize, millet, and sorghum results. I50A and I50B were not readily available for cultivar parameters; hence, these were calculated as I50A (thermal time for flowering\*50%) and I50B (thermal time for the start of senescence\*50%).

**Table 3.4:** Crop parameters of maize, sorghum, and pearl millet for AquaCrop model

<b>Crop parameters</b>	<b>Pearl millet</b>	<b>Sorghum</b>	<b>Maize</b>
Base temperature (°C) below which crop development does not progress	8	8	8
Upper temperature (°C) above which crop development no longer increases with an increase in temperature	32	30	30
Soil water depletion factor for canopy expansion (p-exp) - Upper threshold	0.30	0.15	0.14
Soil water depletion factor for canopy expansion (p-exp) - Lower threshold	0.65	0.70	0.72
Shape factor for water stress coefficient for canopy expansion (0.0 = straight line)	3	3	2.9
Soil water depletion fraction for stomatal control (p - sto) - Upper threshold	0.70	0.70	0.69
Shape factor for water stress coefficient for stomatal control (0.0 = straight line)	3	6	6
Soil water depletion factor for canopy senescence (p - sen) - Upper threshold	0.75	0.70	0.69
Shape factor for water stress coefficient for canopy senescence (0.0 = straight line)	3	3	2.70
Sum (ET <sub>o</sub> ) during stress period to be exceeded before senescence is triggered	0	0	0
Soil water depletion factor for pollination (p - pol) - Upper threshold	0.92	0.80	0.80
Vol% for Anaerobiotic point (* (SAT - [vol%]) at which deficient aeration occurs *)	10	5	5
Soil fertility stress at calibration (%)	50	50	50
Crop coefficient when canopy is complete but prior to senescence (K <sub>cb,x</sub> )	1.10	1.07	1.03
Decline of crop coefficient (%/day) as a result of ageing, nitrogen deficiency, etc.	0.15	0.30	0.30
Minimum effective rooting depth (m)	0.30	0.30	0.30
Maximum effective rooting depth (m)	1.75	0.60	1
Shape factor describing root zone expansion	18	13	13
Maximum root water extraction (m <sup>3</sup> water/m <sup>3</sup> soil.day) in top quarter of root zone	0.05	0.03	0.08
Maximum root water extraction (m <sup>3</sup> water/m <sup>3</sup> soil.day) in bottom quarter of root zone	0.01	0.01	0.02
Effect of canopy cover in reducing soil evaporation in late season stage	60	50	50
Soil surface covered by an individual seedling at 90 % emergence (cm <sup>2</sup> )	5	3	6.50
Number of plants per hectare	55556	44444	53333
Canopy growth coefficient (CGC): Increase in canopy cover (fraction soil cover per day)	0.24	0.13	1.30
Maximum canopy cover (CC <sub>x</sub> ) in fraction soil cover	0.95	0.89	0.96

Canopy decline coefficient (CDC): Decrease in canopy cover (in fraction per day)	0.10	1.70	1.06
Calendar Days: from sowing to emergence	4	14	7
Calendar Days: from sowing to maximum rooting depth	45	97	65
Calendar Days: from sowing to start senescence	80	98	91
Calendar Days: from sowing to maturity (length of crop cycle)	120	140	120
Calendar Days: from sowing to flowering	39	70	67
Length of the flowering stage (days)	20	77	30
Crop determinacy linked with flowering	1	1	1
Excess of potential fruits (%)	50	50	50
Building up of Harvest Index starting at flowering (days)	50	70	56
Water Productivity normalized for ET <sub>o</sub> and CO <sub>2</sub> (WP*) (gram/m <sup>2</sup> )	32	33.70	33.70
Water Productivity normalized for ET <sub>o</sub> and CO <sub>2</sub> during yield formation (as % WP*)	100	100	100
Reference Harvest Index (HI <sub>o</sub> ) (%)	30	45	40
Possible increase (%) of HI due to water stress before flowering	10	4	0
Coefficient describing positive impact on HI of restricted vegetative growth during yield formation	10	1	7
Coefficient describing negative impact on HI of stomatal closure during yield formation	8	3	3
Allowable maximum increase (%) of specified HI	15	25	15

**Table 3.5:** Cultivar coefficients of maize, sorghum, and millet for the DSSAT model

<b>Cultivar coefficients</b>		<b>Maize (2500- 2600 GDD)</b>	<b>Sorghu m (PIONE ER 8333)</b>	<b>Millet (BJ104)</b>
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8øC) during which the plant is not responsive to changes in photoperiod.	160.00	325.00	120.00
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered 12.5 hours).	0.75		
P2O	Critical photoperiod or the longest day length (in hours) at which development occurs maximum. At values greater than P2O, the rate of development is reduced.		15.50	13.40
P2R	Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O.		30.00	145.09
PANTH	Thermal time from the end of tassel initiation to anthesis (degree days above TBASE)			
P3	Thermal time from to end of flag leaf expansion to anthesis (degree days above TBASE)		152.50	
P4	Thermal time from anthesis to beginning grain filling (degree days above TBASE)		81.50	
P5	Thermal time (degree days above a base temperature of 8øC) from beginning of grain filling (3-4 days after flowering) to physiological maturity.	780.00	540.00	340.00
G1	Scaler for relative leaf size.		11.00	0.60
G2	Maximum possible number of kernels per plant.	750.00	6.00	
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).	8.50		
G4	Scaler for partitioning of assimilates to the panicle (head).			1.00
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	49.00	49.00	43.00
GT	Tillering coefficient, equivalent to G1, but on tillers			
G5	Potential grain size, mg			
AX	Leaf surface area (cm <sup>2</sup> /leaf) of largest leaf.			

ALL	Leaf longevity (degree days) of the most longevous leaf.			
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**Table 3.6:** Crop parameters of maize, sorghum, and pearl millet for SIMPLE model

	<b>Crop parameters</b>	<b>Maize</b>	<b>Sorghum</b>	<b>Millet</b>
Tsum	Cumulative temperature requirement from sowing to maturity (°C d)	1419	1648	1337
HI	Potential harvest index.	0.40	0.45	0.30
I50A	Cumulative temperature requirement for leaf area development to intercept 50% of radiation (°C d)	402	420	234
I50B	Cumulative temperature till maturity to reach 50% radiation interception due to leaf senescence (°C d)	546	588	480
Tbase	Base temperature for phenology development and growth (°C)	8	8	8
Topt	Optimal temperature for biomass growth (°C)	30	30	32
RUE	Radiation use efficiency (above ground only and without respiration) (g MJ <sup>-1</sup> m <sup>-2</sup> ).	4.20	3.20	4
I50maxH	The maximum daily reduction in I50B due to heat stress (°C d)	100	100	100
I50maxW	The maximum daily reduction in I50B due to drought stress (°C d)	12	12	12
MaxT	Threshold temperature to start accelerating senescence from heat stress (°C)	44	44	48
ExtremeT	The extreme temperature threshold when RUE becomes 0 due to heat stress (°C)	50	50	50
CO <sub>2</sub> _RUE	Relative increase in RUE per ppm elevated CO <sub>2</sub> above 350 ppm.	0.01	0.01	0.01
S_Water	Sensitivity of RUE (or harvest index) to drought stress (ARID index).	1.50	1.50	1.50

### 3.1.5 Management file

In AquaCrop, DSSAT and SIMPLE model, the three crops were sown as a direct planting method. The planting period for simulation in all three models ranged from 10/2004 – 04/2019, and the planting dates chosen were 25 October for maize, 15 October for sorghum and 01 October for pearl millet. These dates represented the recommended planting dates for KZN for the different cereal crops. However, AquaCrop started simulation one day after planting. The optimal planting date was based on Department of Agriculture, Forestry and Fisheries (DAFF) recommendations and historical weather data at Ukulinga. The plant population for maize, sorghum and pearl millet were 53333, 44444 and 55556 plants/ha, respectively, in all the models. Management practices undertaken were made similar for AquaCrop, DSSAT and SIMPLE models. Due to the SIMPLE model having only irrigation as a management variable, all three models are considered irrigation solely as a management practice, which is investigated in chapter five. The assumption was that all the models were weed and stress-free (water, soil fertility, and soil salinity).

### 3.1.6 Model evaluation statistics

The methods of assessing and comparing the performance of models have been discussed widely (Bellocchi & Rivington, 2009; Kobayashi & Salam, 2000; Wallach et al., 2006; Willmott, 1981). There is provision for an indication of uncertainties in model simulations attributable to using various crop models (representing different complexity) and model user groups (representing different application skills) by showing outcomes from the three individual models, comparing observed data (from the individual studies) with those of model outputs aids in evaluating the reliability and accuracy of simulations. As such, we extracted data for observed yield from the articles used for model calibration. Arathoon & Mtumtum (2013), GAIN Report (2019) and GRAINSA (2021) were also used for the provision of provincial potential yield for the three crops. The provincial data was used to benchmark the yield potentials for each crop and each model's performance. The calibrated parameters were used to simulate outputs of the three models, including grain yield, aboveground biomass, and evapotranspiration (water use). Since AquaCrop, DSSAT, and the SIMPLE model does not calculate WPWP directly, simulated outputs of water use (WU in mm) and yield (Y in kg ha<sup>-1</sup>) were used to determine water productivity (WPWP in kg mm<sup>-1</sup> ha<sup>-1</sup>) as follows:

$$WP_s = \frac{Y \text{ (kg/ha)}}{WU \text{ (mm)}} \quad (1)$$

(Molden, 1997) defined water productivity as ‘crop production’ per unit ‘amount of water used’. Various statistical indicators used in assessing and comparing the performance of models were used in this study. Descriptive statistics such as means, standard deviations, line graphs, F-test and box and whisker plots were used to analyse outputs. For the F-test, when a p-value was less than 0.05, the results were statistically significant, and when a p-value was greater than 0.05, the results were statistically insignificant. Box and whisker plots can show stability and general distribution of the sets of data. A Mann-Kendall trend test was used to test whether statistically significant decreasing or increasing yield, biomass, WU and WP trend for maize, millet and sorghum.

$H_0$ : No trend in yield, biomass, WU and WP for maize, millet and sorghum

$H_a$ : Trend is present in yield, biomass, WU and WP for maize, millet and sorghum

A P-value < 0.05 indicates a trend, and if  $\tau$  is +ve, increasing trend, and if  $\tau$  is -ve decreasing trend. Additionally, other statistical indicators used were root mean square error (RMSE; Eq. 2), normalized root mean square error (NRMSE; Eq. 3), coefficient of determination ( $R^2$ ; Eq. 4), mean bias error (MBE; Eq. 5), and index of agreement (IA; Eq. 6) developed by Willmott (1981). The RMSE was taken to measure the relative average difference between the model estimates and measurements: it describes the average absolute deviations between the simulated and observed values.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2} \quad (2)$$

Where N is the number of the estimate–observation pairs,  $P_i$  is the model prediction, and  $O_i$  is the observed value of the model i.

$$NRMSE = \frac{RMSE}{\bar{O}} \quad (3)$$

where  $\bar{O}$  is the average observation value

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \quad (4)$$

MBE was taken as an indicator of under- or over-estimation, i.e., the direction and magnitude of bias.

$$MBE = N^{-1} \sum_{i=1}^N (P_i - O_i) \quad (5)$$

IA was used as a more general indicator of model efficiency.

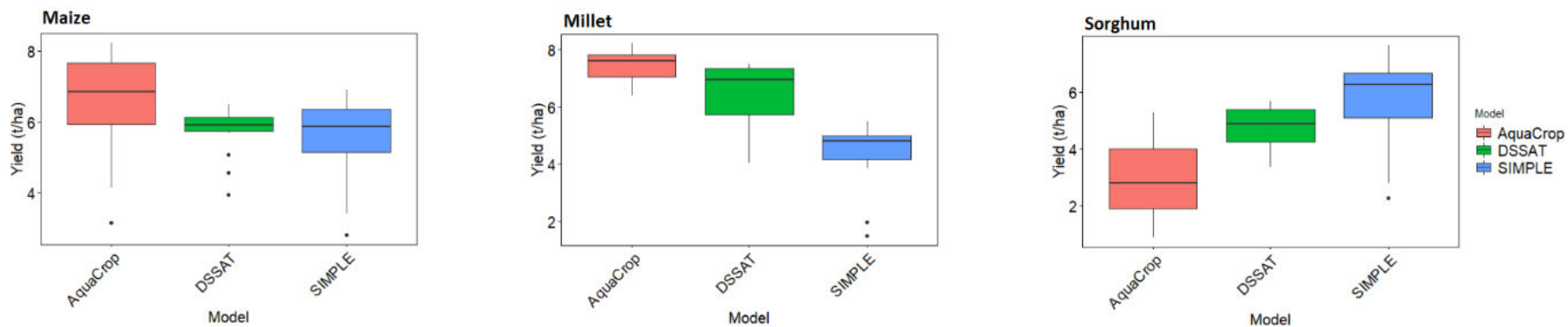
$$IA = 1 - \frac{NxMSE}{PE} \quad (6)$$

Where  $PE = \sum_{i=1}^N (|\dot{P}| + |\dot{O}|)(1^2)$  and where  $\dot{P} = P_i - \bar{O}$  and  $\dot{O} = O_i - \bar{O}_i$  and  $\bar{O}$  is the mean of the observed variable. The main objective of the study was to evaluate model performance. Also, there were limited data points to run all statistic tests; hence, statistical analysis was not done for the individual crops but considered maize, millet, and sorghum as sub-factors. However, in this study, all the three models were compared against each other (i.e., AquaCrop vs DSSAT, SIMPLE vs DSSAT and AquaCrop vs SIMPLE) because observed data was not available.

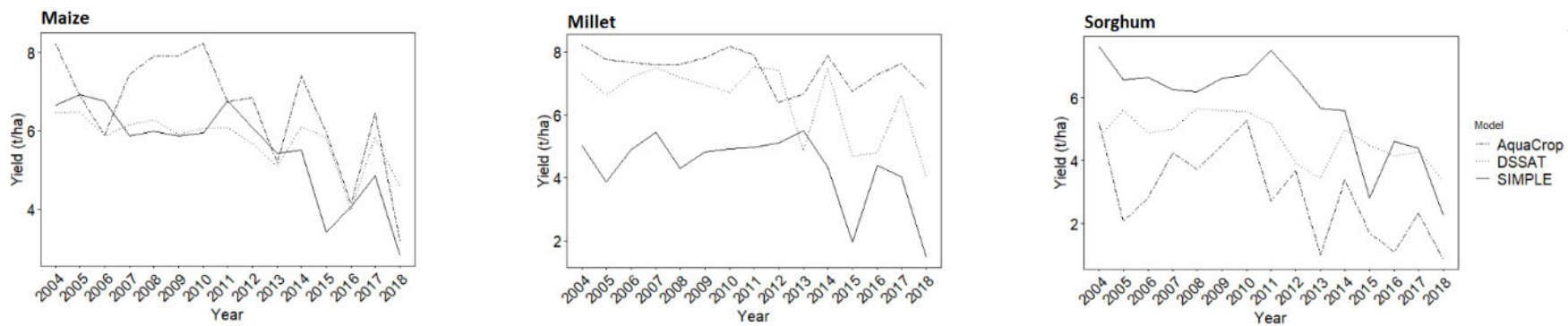
## 3.2 Results

### 3.2.1 Yield

The highest mean yield was simulated by the AquaCrop model for maize (6.55 t/ha) and millet (7.47 t/ha). Meanwhile, for sorghum, SIMPLE simulated the highest mean yield of 5.74 t/ha. Yield simulations in AquaCrop had wider box plots for maize and sorghum, suggesting more yield variability. This was in line with the large standard deviation ( $\pm 1.48$  t/ha) observed for maize under AquaCrop. DSSAT had the shorter box plots suggesting less yield variability for both these crops. Contrary to this, for millet, greater yield variability was observed under DSSAT, while the least variability was observed under the SIMPLE model (Figure 3.3). The DSSAT yield simulation for millet showed the most deviation from the mean by  $\pm 1.21$  t/ha than other models. For sorghum yield simulated by the SIMPLE model, the highest standard deviation was  $\pm 1.59$  t/ha (Figure 3.3). Across the simulation years, the Mann-Kendall trend analysis showed a significant ( $P < 0.05$ ) and positive trend (0.30) in yield for sorghum and a negative trend (-0.40 and -0.63) for maize and millet, respectively.



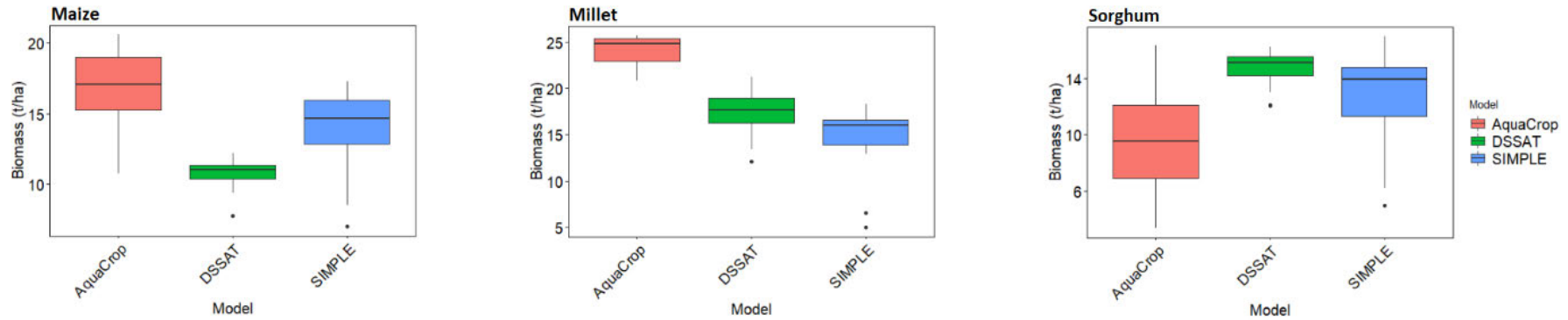
**Figure 3.3:** Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE



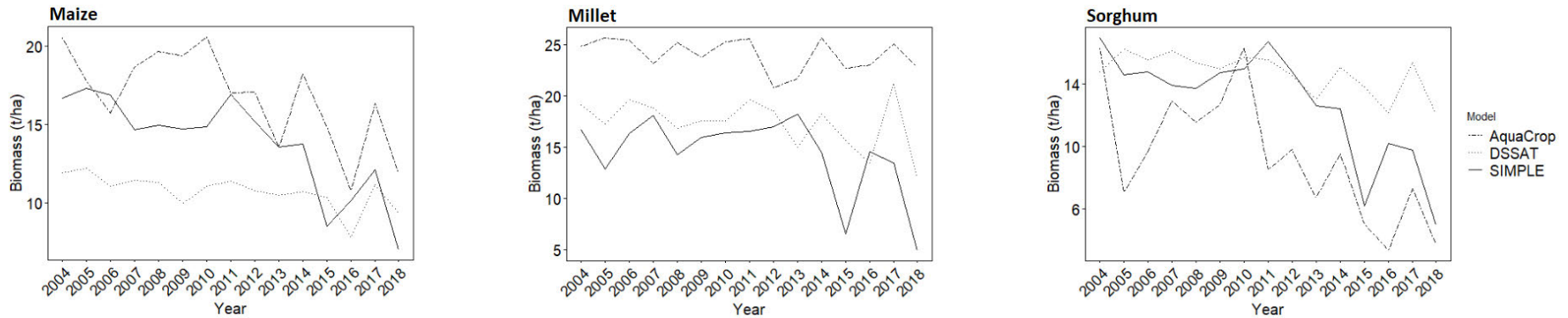
**Figure 3.4:** Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018

### 3.2.2 Biomass

The calculated mean for biomass showed that AquaCrop simulations attained the highest value for maize (16.78 t/ha) and millet (24.08 t/ha), and DSSAT for sorghum (14.69 t/ha). In Figure 3.5, the wider box plots shown by the AquaCrop model across maize and sorghum indicated more variation in biomass. For millet, the variation in biomass was similar across the three models. Compared to other models, DSSAT showed less variability in biomass for maize and sorghum, as shown by thinner box plots. Analysing simulated biomass results showed large standard deviations for maize (3.11) and millet in SIMPLE (3.87) and sorghum (4.03) in AquaCrop (Figure 3.5). Overall, the Mann-Kendall trend analysis did not detect a trend in biomass for sorghum. Overall significant ( $P < 0.05$ ) and a negative trend was observed in simulated biomass for maize ( $\tau = -0.66$ ) and millet ( $\tau = -0.37$ ). Figure 3.6 showed a negative trend for biomass from 2007-2011 in AquaCrop, while no clear trend was observed with biomass simulated with DSSAT and SIMPLE.



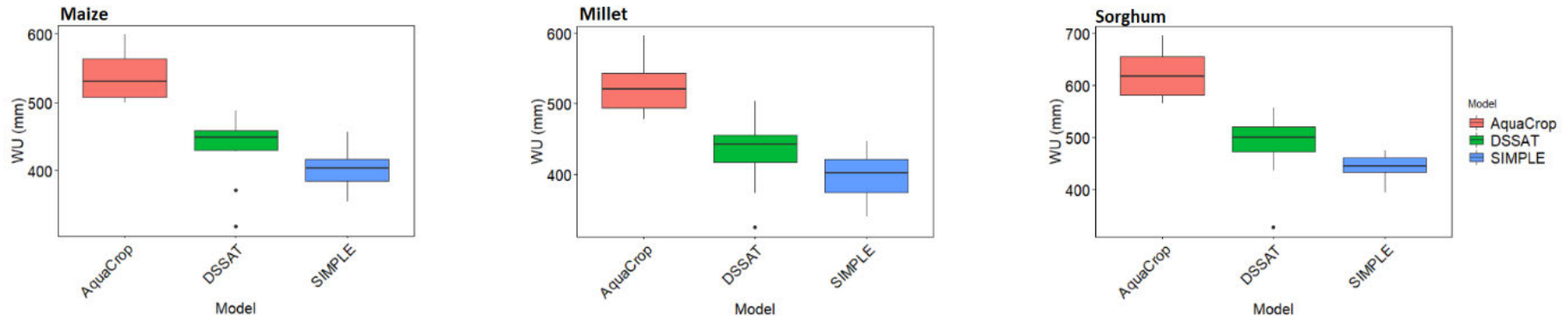
**Figure 3.5:** Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE



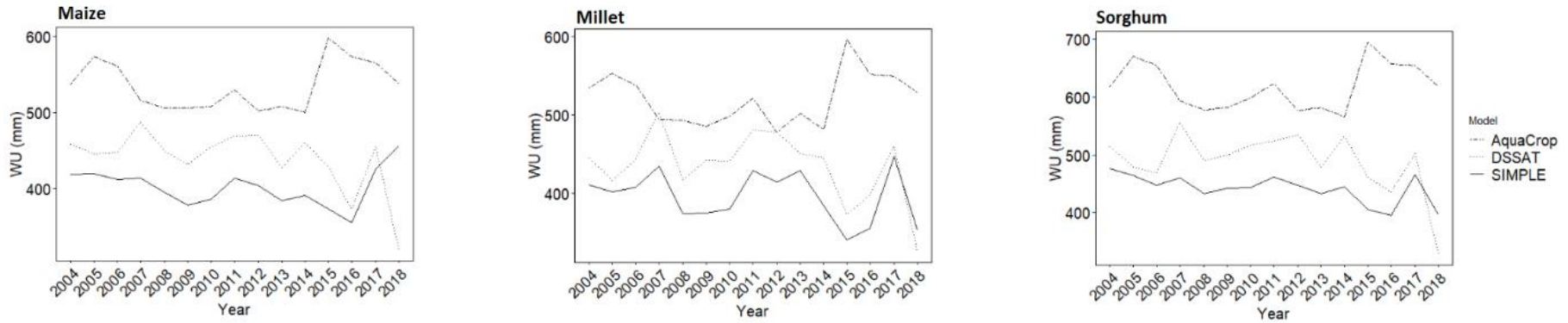
**Figure 3.6:** Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018

### 3.2.3 Water productivity

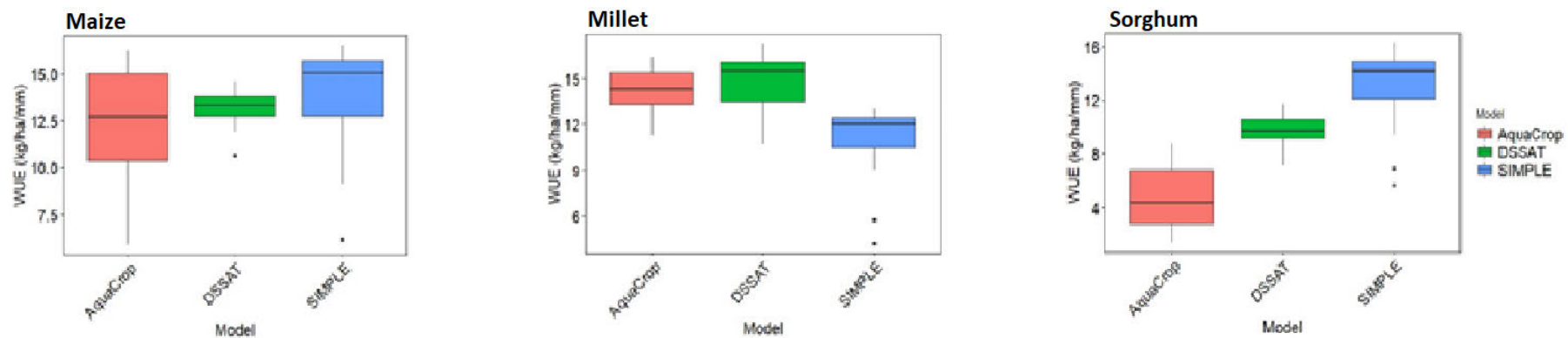
The calculated mean for WP showed that SIMPLE simulations attained the highest value for maize (13.77 t/ha) and sorghum (12.89 t/ha), and DSSAT for millet (14.78 t/ha) (Figure 3.9). This observation was not consistent with the yield trends where the AquaCrop model simulated higher yield for maize and millet while, for sorghum, SIMPLE simulated the highest mean yield. The wider box plots shown by the AquaCrop model across maize and sorghum suggested more variability in WP. Whereas for millet, more variability in WP was observed under DSSAT. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for maize and sorghum. This is consistent with the observed low variability in yield (Figure 3.9). The standard deviation calculated for WP infers that there was a high degree of standard deviation for millet (3.21) and sorghum (2.65) under the SIMPLE model and maize (3.16) under AquaCrop. The WP trend across all three models was consistent for maize from 2004-2018 (Figure 3.10). The Mann-Kendall trend analysis showed a significant ( $P < 0.05$ ) and negative trend in WP of  $\tau = -0.45$  for millet and a positive trend in WP of  $\tau = 0.42$  for sorghum.



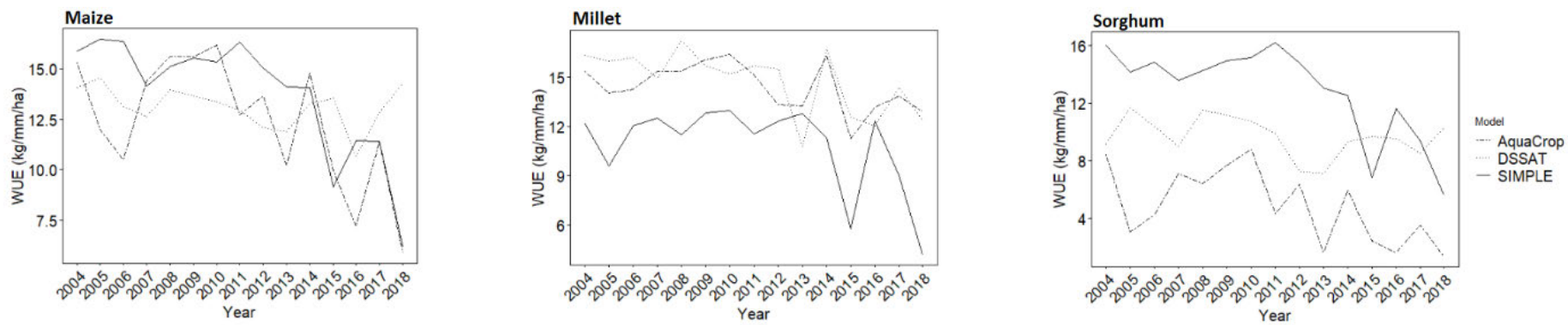
**Figure 3.7:** WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE



**Figure 3.8:** WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018



**Figure 3.9:** WP for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE



**Figure 3.10:** WP for maize, millet and sorghum simulated by AquaCrop, DSSAT and SIMPLE from 2004-2018

### 3.2.4 Model performance

Provincial potential, observed and mean simulated yield were compared (Table 3.7) using statistical indicators. Based on MBE, AquaCrop underestimated the yield by 0.22 t/ha, whereas in the case of DSSAT, the underestimation is observed to be 0.24 t/ha and 0.69 t/ha for SIMPLE when comparing the observed yield and simulated yield. Moreover, a higher coefficient of determination ( $R^2$ ) is observed in AquaCrop (0.99) compared to DSSAT (0.92) and the SIMPLE (0.51) model (Table 3.8). Taking into consideration the provincial potential yield as a comparative factor, the three models underestimated yield. The statistical comparison of observed and provincial potential yield showed an overestimated yield of 0.27 (Table 3.8).

**Table 3.7:** Provincial potential, observed and mean simulated yield for maize, millet, and sorghum

Crops	Crop type (maturity)	Provincial potential yield (t/ha)	Observed yield (t/ha)	Simulated yield (t ha <sup>-1</sup> )		
				Aqua Crop	DSSA T	SIMP LE
Maize	early to medium	<sup>1</sup> 8 - 11 (9.50)	<sup>4</sup> 5.51	6.55 (1.49)	5.75 (0.70)	5.52 (1.24)
Sorghum	medium to late	<sup>2</sup> 4	<sup>5</sup> 5.31	7.47 (0.57)	6.45 (1.21)	4.33 (1.16)
Pearl millet	early to medium	<sup>3</sup> 4.3 - 5.6 (4.95)	<sup>6</sup> 6.83	2.97 (1.47)	4.72 (0.77)	5.74 (1.59)

<sup>1</sup> Arathoon & Mtumtum (2013) <sup>2</sup> GAIN Report (2019) <sup>3</sup> GRAINSA (2021) <sup>4</sup> Akumaga et al. (2017) <sup>5</sup> Hadebe et al. (2017) <sup>6</sup> Bello & Walker (2016)

**Table 3.8:** Statistical comparison of the observed, provincial potential and simulated yield for AquaCrop, DSSAT and the SIMPLE model

Model performance	$R^2$	D-index	RMSE	NRMSE	MBE
Observed vs AquaCrop	0.99	-3.15	2.62	0.45	-0.22
Observed vs DSSAT	0.92	-18.13	1.39	0.24	-0.24
Observed vs SIMPLE	0.51	0.62	0.85	0.14	-0.69
Potential vs AquaCrop	0.03	0.27	2.87	0.47	-0.49
Potential vs DSSAT	0.003	-0.06	2.59	0.42	-0.51
Potential vs SIMPLE	0.27	0.36	2.35	0.38	-0.95
Observed vs Potential	0.06	-0.28	2.66	0.45	0.27

Except for NRMSE and the rest of the statistical indicators for yield, results suggested a satisfactory agreement between AquaCrop-DSSAT and DSSAT-SIMPLE. There was a positive correlation for all the three models being compared against each other. The correlations ( $R^2$ ) between AquaCrop-DSSAT, AquaCrop-SIMPLE and DSSAT-SIMPLE were 0.95, 0.58 and 0.78, respectively. There were slight differences in model agreement across the different statistical indicators. For instance, good agreement was observed for yield simulated by AquaCrop-DSSAT ( $D^2 = 0.77$ ). RMSE and NRMSE of 2.48 t/ha and 0.44 t/ha, respectively, for the comparison of AquaCrop and SIMPLE showed a higher deviation in this combination when compared with other comparisons in this study (Table 3.9).

There was a positive correlation in biomass for all the three models compared against each other. The comparison between AquaCrop and the SIMPLE model showed the highest  $R^2$  of 0.98, and the comparison between DSSAT and SIMPLE had the lowest  $R^2$  of 0.07. Biomass was simulated well in the agreement of 0.42 for AquaCrop-DSSAT, 0.31 for AquaCrop-SIMPLE and 0.22 for DSSAT-SIMPLE. However, due to the high value of AI for AquaCrop and DSSAT, it was evident that this comparison was in more agreement with simulating biomass. Biomass was overestimated in AquaCrop comparison to SIMPLE by 1.03 t/ha, similarly with the comparison between DSSAT and SIMPLE by 0.80 t/ha. Meanwhile, AquaCrop underestimated biomass in comparison to DSSAT by 0.80 t/ha. RMSE and NRMSE of 6.14 t/ha and 0.37 t/ha, respectively, for the comparison of AquaCrop and SIMPLE, showed a higher deviation in this combination than other comparisons in this study (Table 3.9).

The results showed a perfect coefficient ( $R^2 = 1$ ) in water use simulated by AquaCrop-SIMPLE. The same positive relationship of  $R^2 = 0.99$  was observed for the comparison of AquaCrop-DSSAT and DSSAT-SIMPLE. AI as a statistical indicator showed that there was an agreement for water use simulated by AquaCrop-DSSAT (0.27), AquaCrop-SIMPLE (0.14) and DSSAT-SIMPLE (0.54). There was an underestimation of water use for AquaCrop-DSSAT (-96.61 t/ha), AquaCrop-SIMPLE (-132.87 t/ha) and DSSAT-SIMPLE (-36.26 t/ha). RMSE and NRMSE of 146.59 t/ha and 0.26 t/ha, respectively, for the comparison of AquaCrop and SIMPLE, showed a higher deviation in this combination than other comparisons in this study. The least deviations (RMSE = 40.95 and NRMSE = 0.09) for water use were observed for the DSSAT-SIMPLE comparison (Table 3.9).

**Table 3.9:** Statistical comparison of simulated output variables for AquaCrop, DSSAT and the SIMPLE model

<b>Output variables</b>	<b>Model Comparison</b>	<b>R<sup>2</sup></b>	<b>D-index</b>	<b>RMSE</b>	<b>NRMSE</b>	<b>MBE</b>
Yield	AquaCrop-DSSAT	0.95	0.77	1.26	0.22	-0.80
	AquaCrop-SIMPLE	0.58	-1.44	2.48	0.44	1.03
	DSSAT-SIMPLE	0.78	-5.06	1.37	0.24	0.80
Biomass	AquaCrop-DSSAT	0.16	0.42	6.04	0.36	-6.06
	AquaCrop-SIMPLE	0.98	0.31	6.14	0.37	-2.98
	DSSAT-SIMPLE	0.07	0.22	2.71	0.19	3.08
Water use	AquaCrop-DSSAT	0.99	0.27	105.79	0.19	-96.61
	AquaCrop-SIMPLE	1.00	0.14	146.59	0.26	-132.87
	DSSAT-SIMPLE	0.99	0.54	40.95	0.09	-36.26

### 3.3 Discussion

AquaCrop, DSSAT and SIMPLE were able to simulate yield, biomass and water use for selected NUS. However, the performance of the three models was observed to be statistically different across the simulated years and for the different crop species. The statistical indicators ( $R^2$  and MBE) for observed yield compared with simulated yield suggest that yield, biomass, and WU simulated by AquaCrop across the selected NUS was more satisfactory than when DSSAT and the SIMPLE model did simulations. High yield and biomass variability simulated for maize and sorghum under AquaCrop and millet under DSSAT could suggest that both these models were more sensitive to input parameters, and this sensitivity was crop-specific. Moreover, in line with the statement by Manschadi et al. (2021), different simulated results in this study could be attributed to secondary data, different types of parameters, number of parameters, model types and algorithms. Similar to a study conducted by Timsina et al. (2008), the crop, soil, and climate inputs have a degree of uncertainty associated with them due to random errors and bias in their measurement and calibration. Also, the three models used in the study were calibrated using secondary data from different sources; hence the simulated and observed results are different. The disadvantage of using secondary data is that there is a high likelihood that not all parameters were captured that were used in calibrating the models. Hence, when interpreting and extrapolating the model results, due consideration should be given to uncertainties arising from model structure, model parameters and inputs, and the experimental data used for model calibration, validation, and application (Timsina et al., 2008).

On the other hand, AquaCrop and the SIMPLE model were calibrated, which means that the confidence in results for these models was improved, as the need to use default input values was minimised. The SIMPLE model used maize values embedded in the model for species parameters ( $CO_2\_RUE$  and  $S\_Water$ ) of the three crops; DSSAT used default files for the soil and crop data, suggesting confidence in results was low compared to AquaCrop and the SIMPLE model. Nevertheless, scientific processes and coefficients in AquaCrop, DSSAT and the SIMPLE model can never be complete, leading to uncertainties in model predictions (Timsina et al., 2008). This is the case as perfect modelling can never be attained for real systems because models abstract reality.

The results indicate that AquaCrop, with a water-driven growth engine, is better than DSSAT and the SIMPLE model, with a solar energy-driven growth engine for biomass and yield simulation. DSSAT and the SIMPLE model differs from AquaCrop by calculating biomass

accumulation based on RUE rather than normalized water productivity (WP\*) (cf. Section 2.2.5.3). (Albrizio & Steduto, 2005) showed high variability in RUE values but failed to normalize RUE by vapour pressure deficit to reduce climate variability. The conclusion made was that the robustness of RUE to simulate biomass in crop models was constrained. The follow-up studies also indicated that calculating biomass through WP\* was more robust than RUE (Albrizio & Steduto, 2005; Steduto et al., 2007; Steduto et al., 2009) which agrees with the findings of this study.

In this study, AquaCrop was the only model previously calibrated for sorghum using soil and climate data for Ukulinga Research Farm. For DSSAT and the SIMPLE model, current simulations are done for climatic and soil conditions that might have been similar in agro-ecological classification but differed based on the year that the studies were performed. According to Asseng et al. (2013), conducting model calibration and validation before comparison provides more robust and reliable results. Furthermore, there must be good quality data sets to which researchers have full confidence for calibration and validation. Furthermore, previous model comparisons have shown that minimal calibration of crop models can lead to a high degree of uncertainty of yield estimates (Asseng et al., 2013; Palosuo et al., 2011; Rötter et al., 2012). Also, providing more detailed data for model calibration did not necessarily result in high model performance when applied to new situations.

A large number of input parameters resulted in large and confounding impacts on overall outputs. According to Babel et al. (2019), the performance of a model in any specific site depends on the fine-tuning of the parameters and sound validation under a range of conditions. This study confirms that DSSAT requires relatively more site-specific and crop variety-associated data, in which default files were used to accommodate the unavailability of data. In contrast, AquaCrop is a simpler model with lesser soil and crop management data required as an input. Meanwhile, SIMPLE is a model which requires fewer input requirements in comparison to AquaCrop and DSSAT. There is limited data availability for NUS to parameterize complex models fully. The similarity in the performance of simpler models (i.e. SIMPLE and AquaCrop) and complex models (DSSAT) suggests less complex models can be adopted to advance modelling of neglected and underutilized cereal crop productivity. Nonetheless, even with simpler models, there is still a need for some input parameters to use in modelling NUS. Thus, standards and protocols for data collection must be formulated to attain the required quantity and quality.

### **3.4 Conclusion**

Three crop simulation models—AquaCrop (v 6.1), DSSAT (v 4.7.1) and SIMPLE (v 1.1)—were evaluated for their comparative performance for maize, millet and sorghum at Ukulinga Research Farm in Pietermaritzburg, South Africa. AquaCrop, DSSAT and the SIMPLE model simulated yield, biomass and water use for selected NUS. The presented results are based on several assumptions, and the predictions by the three models may be affected by a degree of uncertainty. These assumptions may have affected results and bias conclusions regarding yield, biomass, water use, and WP estimates. Further, the interactions between weather, soil characteristics, plant growth dynamics, and management alternatives may have affected simulation results. Despite the potential limitations, the AquaCrop, DSSAT and SIMPLE model can be used as decision support tools to assist farmers in producing NUS. However, AquaCrop was the better suitable model for simulating yield, biomass, and water use for selected NUS based on the statistical differences. Further, the model can be used, and the results of this study extrapolated to other areas with similar climatic and soil environments in South Africa where crop, soil, weather, and management data are available.

## **CHAPTER 4: MODELLING OF CLIMATE CHANGE IN AQUACROP, DSSAT AND THE SIMPLE MODEL**

### **4.0 Introduction**

Although the South African (SA) government has identified agriculture as a plausible sector to aid rural development, youth employment, and rural poverty reduction, current crop yields are low. Within rural production systems, crop yields are challenged by worsening land degradation, especially declining soil fertility (Badu-Apraku & Fakorede, 2017; Rippke et al., 2016; Ukeje, 2004), and low water productivity (WP) (Mabhaudhi et al., 2018; Nouri et al., 2019; O’Leary et al., 2018). An increase in drought frequency is anticipated as climate changes, which is expected to affect agriculture severely. Based on estimations of changes in climate from the year 2012 to 2050, it is shown that there will be substantial warming (5-8°C) over the interior (DEA, 2016). The south and west regions will experience drier conditions, wetter conditions experienced by the eastern regions (DEA, 2016). Climate change impacts on agriculture will negatively affect rural resource-poor farmers or households, who already reside and farm on marginal lands (Hassan, 2006).

The utilisation of neglected and underutilised crops (NUS), also referred to as indigenous and traditional crops, can be employed as an alternative agricultural food source as a strategy to adapt to climate risk. However, researchers sparsely give NUS's attention regarding improving agronomic practices and improving their genetic potential. Noticeably, people in South Africa have developed some interest in these crops (Mabhaudhi et al., 2014a). Neglected and underutilised crops are adapted to a wide range of ecological niches and can tolerate both abiotic and biotic stress, mainly heat and water stress (Mabhaudhi, 2012). The use of NUS to reinstate them as alternative food crops require information about their growth and development.

More work is still required to be performed to bolster available quantitative information that describes the crop's eco-physiological responses to water stress and its suitability for production under projected climate change (Bello & Walker, 2016; Mabhaudhi et al., 2014b). Thus, for this purpose, the viable option would be the utilisation of crop models. Crop models are useful tools for approximating crop yields (Azam-Ali et al., 2001) and the comprehensive synthesis of quantitative understanding of physiological processes and evaluating crop management options (Sha et al., 2021). Without the presence of extensive, and in some instances, costly agronomic trials, the utilisation of crop models may aid to generate such

information (Mabhaudhi et al., 2014a). It was hypothesised that climate change modelled by AquaCrop, DSSAT and the SIMPLE model would predict similar impacts on yield, biomass and water use of selected cereal NUS. Thus, the study aimed to evaluate the performance of AquaCrop, DSSAT and SIMPLE in simulating the impacts of climate change on maize, millet and sorghum.

#### **4.1 Materials and methods**

Model simulations for maize, sorghum and millet were done using AquaCrop Version 6.1, DSSAT version 4.7.5 and SIMPLE version 1.1. Chapter 2 Section 2.2.4 in the literature review detailed the description of these models. These models required climate data inputs, crop characteristics, soil characteristics, and a description of management practices to run simulations. These inputs were attained from the Ukulinga Research Farm. Due to incomplete instructions for using the Gridcell Weather option in SIMPLE, the Weather option as climate file was used for simulations. The limitation of using Weather was that it could only read data until 2020 (present). Thus, to attain outputs from 2021-2099, climate data for these years had to be recorded under 1921-1999. The next sections present detailed procedures that were followed in completing this study.

##### **4.1.1 Study site**

This study used climate and soil data from the Ukulinga Research Farm to create input data files for AquaCrop, DSSAT and SIMPLE models. Ukulinga Research Farm (29°37'S; 30°16'E; 750 meters above sea level) is classified as a subtropical climate with a low risk of frost occurrence. The average annual rainfall is 694 mm, which is received mainly during the summer months (mid-October to mid-February) (Chibarabada et al., 2020). During the summer months, average maximum temperatures are between 26°C and 28°C, while minimum temperatures can be as low as 10°C. The soil was characterised as clay and was 0.6 m deep. Ukulinga is located within quaternary catchment U30D and quinary sub-catchment 4718. Briefly, a quaternary is a fourth level division of a primary catchment. Each quaternary catchment is then further subdivided into three quinary sub-catchments based on altitude. For detailed explanations, the reader is referred to Schulze et al. (2011).

##### **4.1.2 Climate data**

A quaternary catchment represents a fourth-level division of a primary drainage basin. There are 1946 quaternary catchments in southern Africa, originally delineated by the former

Department of Water Affairs and Forestry (DWAF). Each quaternary catchment has then been subdivided into three quinary sub-catchments according to altitude criteria (Schulze et al., 2010; Schulze & Horan, 2007), which produced a total of 5838 quinaries. Hence, each quaternary was sub-delineated into an upper, middle, and lower quinary of unequal area (but of similar topography) using "natural breaks" in altitude by applying the Jenks' optimisation procedure (Schulze & Horan, 2007, 2010).

The Ukulinga climate files for AquaCrop, DSSAT and SIMPLE were developed using the historical quinary climate database for South Africa (Schulze, 2011). Ukulinga research farm is located within quinary sub-catchment 4697 of quaternary catchment U30J (Schulze et al., 2011). In addition to historical data, the study also used downscaled future climate projections for the Ukulinga quinary. The climate projections were developed by the Council for Scientific and Industrial Research (CSIR) (Table 4.1) using output from six global climate models (GCMs) from the CMIP5 archive that was forced by Representative Concentration Pathway 8.5 (RCP 8.5). The climates produced under RCP 8.5 were used as they represent the most extreme scenarios. These six GCMs were selected based on their ability to reasonably represent the El Nino-Southern Oscillation (ENSO) phenomenon for the region.

Various downscaling approaches can be applied, and dynamical downscaling was applied in this study. The climate projections were dynamically downscaled to improve spatial resolution to 0.5° (~50 km) using the CCAM regional climate model developed by the Commonwealth Scientific and Industrial Research Organisation, CSIRO (McGregor, 2005; McGregor & Dix, 2001, 2008). After that, a multiple-nudging strategy was followed to obtain a downscaling to 0.1° (~10 km) resolution using CCAM in stretched-grid mode over South Africa (see Mabhaudhi et al., 2018a). Climate scenarios were then extracted for the gridded pixel that overlapped quinary sub-catchment 4697. For application in crop modelling at a local scale, it is necessary to correct systematic and localised biases in rainfall and temperature projections produced by the climate models. Compared to observed rainfall data from the historical quinary climate database for sub-catchment 4697, the downscaled climate projections were found to have a substantially larger number of rain days, with many rain days having minimal rainfall depths (i.e., < 0.10 mm). Therefore, as described and assessed by Cannon et al. (2015), a quantile delta mapping method was applied to bias correct the climate scenarios using a multiplicative factor for rainfall and an additive factor for temperature.

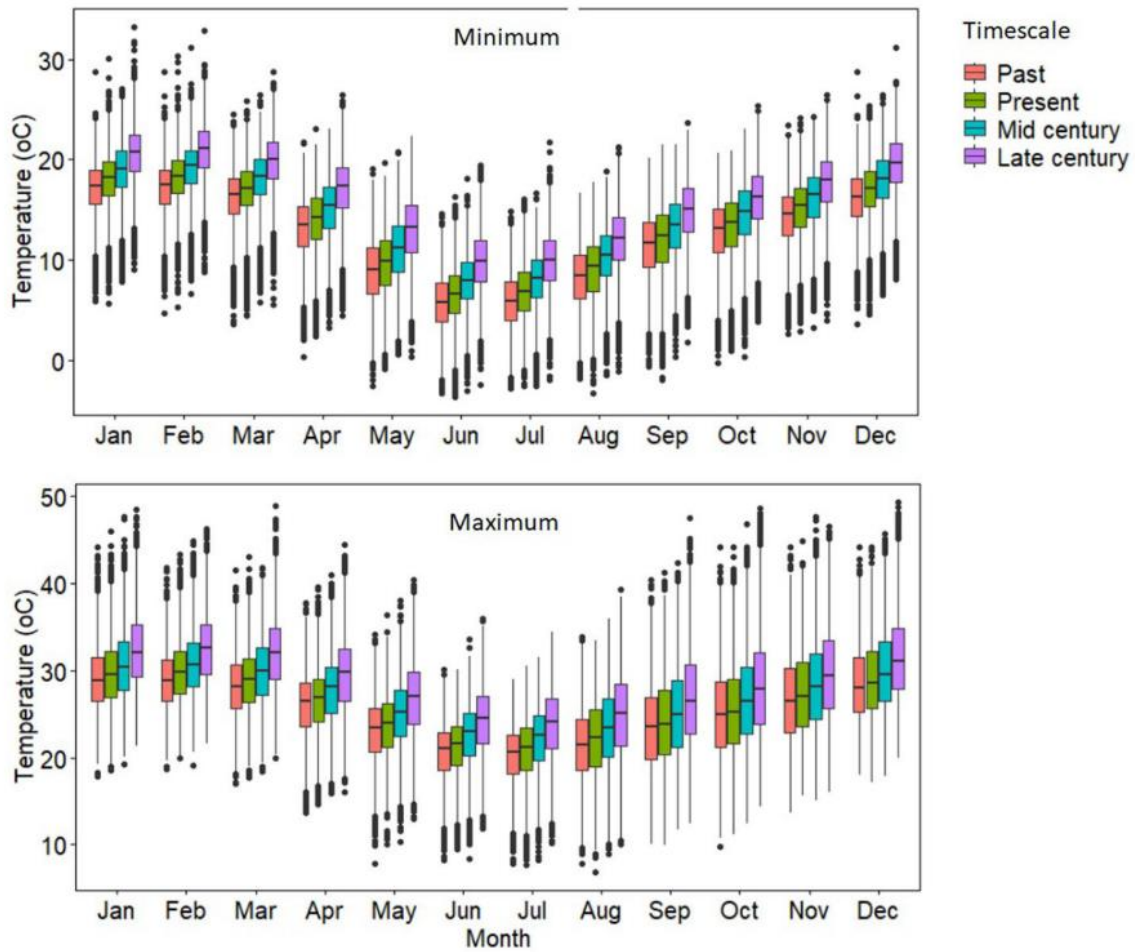
The bias-corrected climate data provide daily rainfall and temperature scenarios for a continuous period from 1961 to 2100. Daily reference crop evaporation ( $ET_0$ ) estimates were then computed as described for the historical data set (Schulze et al., 2011). Solar radiation for each GCM for Ukulinga was then calculated as described by Schulze & Chapman (2007). The climate database, therefore, satisfied climate file input requirements for AquaCrop, DSSAT and the SIMPLE model and was used to develop projections (as climate files - .CLI) for the past (1961–1991), present (1995–2025), mid-century (2030–2060) and late-century (2065–2095) periods. Throughout the analysis, the 'present' timescale was regarded as the baseline.

**Table 4.1:** Global climate models used in this study (Chimonyo et al., 2020)

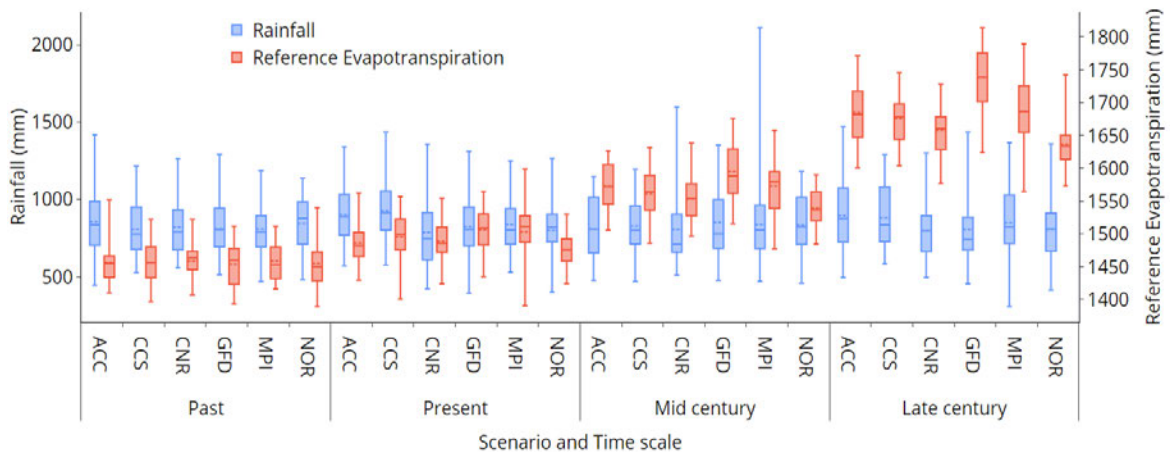
Abbreviation	Earth System Models	Institute	Horizontal resolution
ACC	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation, Australia (CSIRO), and Bureau of Meteorology, Australia (BOM)	$1.250 \times 1.875^\circ$
CCS	CCSM4	National Centre for Atmospheric Research (NCAR), USA	$0.9424 \times 1.250^\circ$
CNR	CNRM-CM5	Centre National de Recherches Meteorologiques, Meteo-France, France	$1.4005 \times 1.4065^\circ$
NOR	NorESM1-M	NorESM (Norwegian Earth System)	$1.250 \times 0.940^\circ$
GFD	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	$2.000 \times 2.500^\circ$
MPI	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	$1.8653 \times 1.875^\circ$

#### 4.1.2.1 Climate trends

Based on results from Chimonyo et al. (2020), Ukulinga is projected to have a warmer future (mid-and late-century) with the mean maximum temperature increasing by 4.5 °C relative to the baseline maximum temperature of 24 °C (Figure 4.1). The six GCMs project an increase in mean minimum temperatures in the future (mid-and late-century) that ranges from 2.0–4.8°C from a minimum baseline temperature of 13°C (Figure 4.1). In general, all GCMs showed that the mean annual precipitation (MAP) was fairly constant relative to the baseline. Variations were, however, observed across the simulated periods (Figure 4.2). For the late-century period, data showed that ACC and CCS predict a 10.6 and 8.3 % increase in MAP, respectively, while slight reductions of 3.5 and 2.5 % are predicted by CNR and NOR, respectively. However, the more extended box and whisker plots for ACC predict increased inter-annual variability of mean rainfall (750 mm) (Figure 4.2). In all instances, projected  $ET_o$  was observed to be higher (35 %) than projected rainfall and is set to increase in the future (mid and late century) (Figure 4.2). In this regard, the rainfall:  $ET_o$  ratio is projected to decrease in the near future.



**Figure 4.1:** Distribution of average monthly minimum (a) and maximum (b) temperature data for the different timescales (past, present, mid-and late-century) from the combined six GCMs



(ACC, CCS, CNR, GFD, NOR and MPI) used in this study (Chimonyo et al., 2020)

**Figure 4.2:** Rainfall data represents four different timescales (past, present, mid-and late-century) as simulated by the six GCMs (ACC, CCS, CNR, GFD, NOR and MPI) used in the study. The mean annual rainfall represents the average yearly rainfall calculated from observed rainfall data between 2004 and 2019 (Chimonyo et al., 2020)

#### 4.1.3 Soil description

The soil textural class of the Ukulinga Research Farm soil profile was classified as clay, with 0.6 m soil depth. Input parameters of the soil included volumetric water content at field capacity (FC) and permanent wilting point (PWP) as well as the saturated hydraulic conductivity (Ksat). Soil physical and hydraulic properties were obtained from the classification and characterisation of experimental site soils by Mabhaudhi (2012). Soil hydraulic and physical properties were used to develop a soil (.SOL) file in the model. Soil files were created using site-specific soil data presented in Table 3.1 and Table 3.2.

#### 4.1.4 Crop file

In AquaCrop and the SIMPLE model, the study used cultivars described by Akumaga et al. (2017), Hadebe et al. (2017) and Bello & Walker (2016) for maize, sorghum and pearl millet, respectively. Within the DSSAT crop file, we used the maize cultivar “2500-2600 GDD”, millet “BJ104” and sorghum “PIONEER8333” as it best described the crops used in terms of days to maturity and yield potential.

#### 4.1.5 Management file

In Aquacrop, DSSAT and SIMPLE model, when simulating for the three crops, sowing as a direct planting method was selected. The planting periods for simulation in all three models were past (1961–1991), present (1995–2025), mid-century (2030–2060) and late-century (2065–2095). Throughout the analysis, the 'present' timescale was regarded as the baseline. The planting dates chosen for simulation in all three models were 25 October for maize, 15 October for sorghum and 01 October for pearl millet. The optimal planting date was based on Department of Agriculture, Forestry and Fisheries (DAFF) recommendations and historical weather data at Ukulinga. However, AquaCrop started simulation one day after planting. The plant population for maize, sorghum and pearl millet were 53333, 44444 and 55556 plants/ha, respectively, in all the models. There were no management practices, specifically irrigation, taken into consideration.

#### 4.1.6 Statistical analysis

The three models used the six GCMs as climate input data by the three models in simulating the impacts of climate change on selected NUS. Simulation outputs for yield, biomass, WU and WP [yield (kg) per water evapotranspired (m<sup>3</sup>)] were then subjected to F-test analysis using

the R software (version 4.0.2). The F-test analysis was used to determine a significant difference in outputs for maize, millet and sorghum across models, GCMs, timescale. A p-value of less than 0.05 indicated statistically significant results, and a p-value greater than 0.05 indicated statistically insignificant results. Descriptive statistics such as means, standard deviations, and box and whisker plots were used to evaluate climate change impacts on yield, biomass, WU and WP for maize, sorghum, and millet. Box and whisker plots, coupled with standard deviations, can show stability and general distribution of data sets. A wider box indicates more variations across the median value of the dataset.

A Mann-Kendall trend test was used to perceive statistically significant decreasing or increasing yield, biomass, WU, and WP trends in maize, millet, and sorghum data.

$H_0$ : No trend in yield, biomass, WU and WP for maize, millet and sorghum

$H_a$ : Trend is present in yield, biomass, WU and WP for maize, millet and sorghum

A P-value  $< 0.05$  indicates a trend, and if  $\tau$  is +ve, increasing trend, and if  $\tau$  is -ve decreasing trend. The present (1995–2025) was used to describe the baseline to compare climate change impacts. The performance of individual GCMs was also evaluated using a similar statistical approach.

## **4.2 Results**

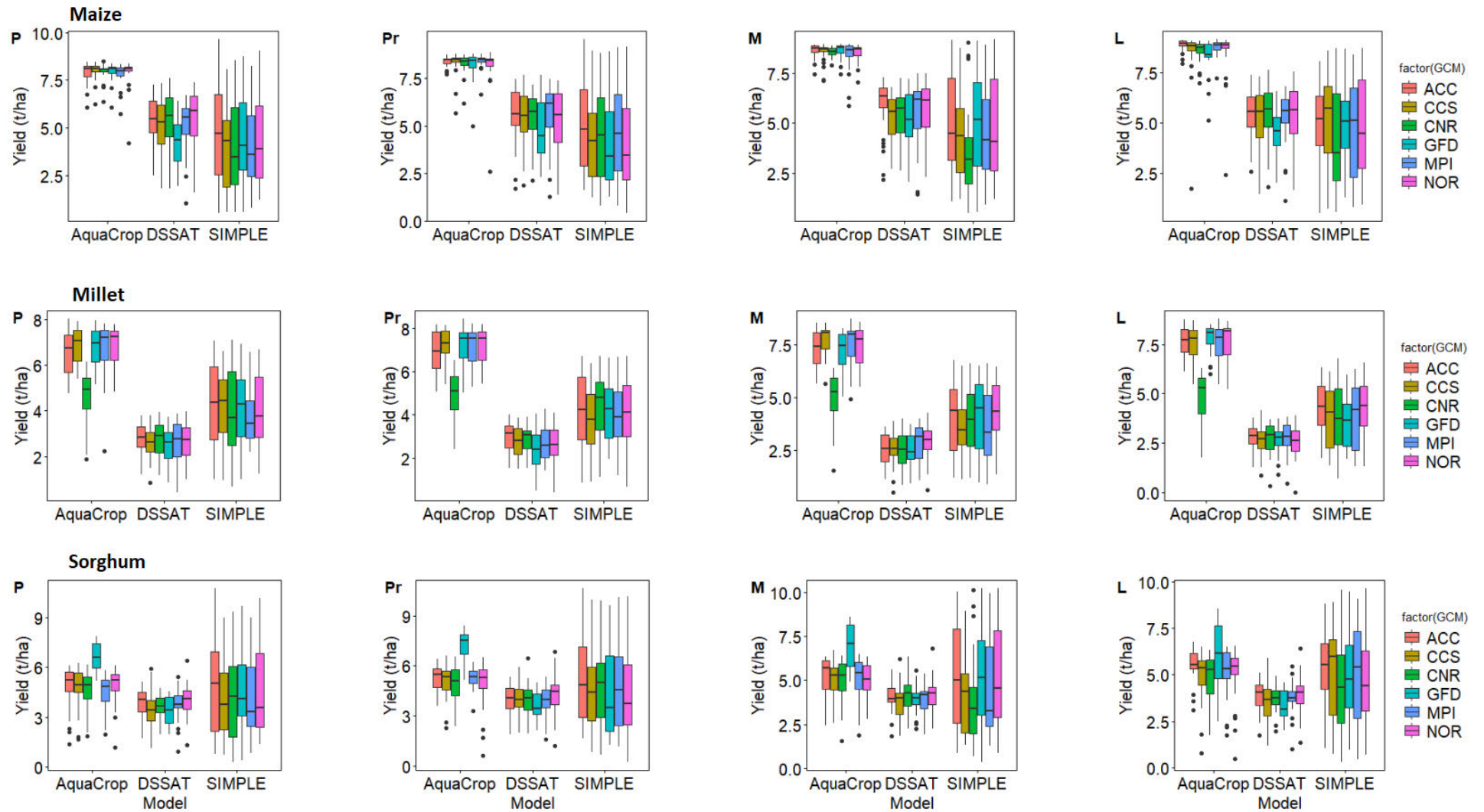
Coupled with AquaCrop 6.1, DSSAT 4.7.5 and SIMPLE 1.1, dynamically downscaled and bias-corrected climate projections for six GCMs forced by RCP 8.5 were used to simulate maize, millet and sorghum yields over the past, present, mid-, and late-centuries. The aim was to evaluate AquaCrop, DSSAT and SIMPLE's performance in simulating the impacts of climate change on yield, biomass, WU and WP of maize, millet, and sorghum.

### **4.2.1 Yield**

Across models, there were highly significant ( $P < 0.05$ ) differences for maize, millet, and sorghum yield. Yield simulations across all the crops under the SIMPLE model had wider box plots suggesting more yield variability. Contrary to this, DSSAT had the shorter box plots suggesting less yield variability, however only for millet and sorghum. Maize yield was less variable in AquaCrop (Figure 4.3). AquaCrop showed the highest simulated mean yield for maize (8.34 t/ha), millet (6.86 t/ha) and sorghum (5.28 t/ha) (Figure 4.3). SIMPLE simulated the lowest mean yield for maize (4.50 t/ha). Meanwhile, DSSAT simulated the lowest mean

yield for millet (2.68 t/ha) and sorghum (3.84 t/ha). Across all the time scales, it was observed that AquaCrop simulated the highest yield, the SIMPLE model and DSSAT simulated the lowest yield across the GCMs, which were inconsistent. This highest value of 8.88 t/ha was observed in the late-century period for ACC in maize, and the lowest value of 2.45 t/ha was observed in the present-century period for GFD in millet.

The results showed no significant ( $P > 0.05$ ) differences across the GCMs for maize yield; an average of 6.04 t/ha with a standard deviation of 2.33 t/ha was observed. Highly significant differences ( $P < 0.05$ ) across GCMs were observed for millet ( $4.52 \pm 2.12$  t/ha) and sorghum ( $4.59 \pm 1.82$  t/ha). Across the time scale, there were significant differences ( $P < 0.05$ ) in maize and sorghum yield and no significant ( $P > 0.05$ ) differences in millet yield. The observed trend for simulated maize yield was past ( $5.76 \pm 2.25$ ) < present ( $6.02 \pm 2.37$ ) < late ( $6.17 \pm 2.33$ ) < mid-century ( $6.21 \pm 2.35$  t/ha). The observed trend for simulated millet yield was past ( $4.37 \pm 2$ ) < present ( $4.55 \pm 2.08$ ) < mid- ( $4.56 \pm 2.22$ ) < late-century ( $4.60 \pm 2.29$  t/ha). The observed trend for simulated sorghum yield was past ( $4.38 \pm 1.82$ ) < late ( $4.62 \pm 1.80$ ) < present ( $4.69 \pm 1.85$ ) < mid-century ( $4.70 \pm 1.88$  t/ha). Across the past, present, mid-, and late-century periods, the Mann-Kendall trend analysis showed a significant ( $P < 0.05$ ) and positive ( $\tau = 0.05$ ) trend in yield for maize. On the other hand, no trend was detected in millet and sorghum yield.

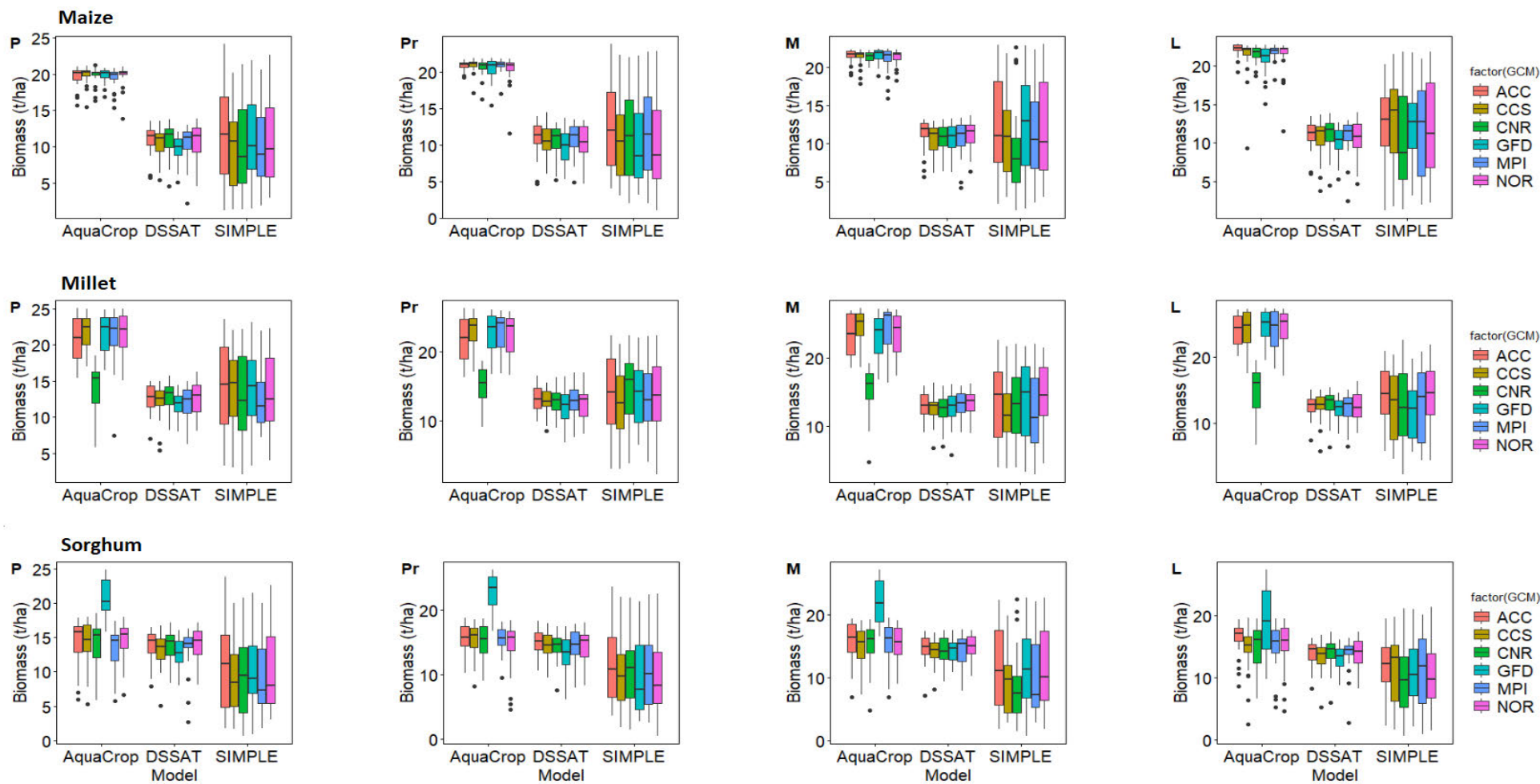


**Figure 4.3:** Simulated yield ( $t\ ha^{-1}$ ) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CCS, CNR, GFD, NOR and MPI)

#### 4.2.2 Biomass

Across models, there were highly significant ( $P < 0.05$ ) differences for maize, millet and sorghum biomass (Figure 4.4). In Figure 4.4, the wider box plots shown by the SIMPLE model across maize, millet and sorghum deduced more variation in biomass. Compared to other models, DSSAT showed less variability in biomass for millet and sorghum, as shown by thinner box plots. Meanwhile, less variations in maize biomass were observed in simulations by AquaCrop. AquaCrop showed the highest simulated mean biomass for maize (20.84 t/ha), millet (21.68 t/ha) and sorghum (16.04 t/ha). SIMPLE simulated the lowest mean biomass for sorghum (10.38 t/ha). Meanwhile, DSSAT simulated the lowest mean biomass for millet (12.63 t/ha) and maize (10.67 t/ha). Across the GCMs and time scales. It was observed that AquaCrop simulated the highest yield, the SIMPLE model and mostly DSSAT simulated the lowest yield for maize, millet and sorghum. The highest value of 24.83 t/ha was observed in the late-century period for GFD in millet, and the lowest value of 8.46 t/ha was observed in the mid-century period for CNR in sorghum.

There were no significant ( $P > 0.05$ ) differences across the GCMs for maize biomass. However, highly significant ( $P < 0.05$ ) differences were observed for millet and sorghum biomass. Across the GCMs, biomass trends for maize showed a gradual increase towards the late century compared to the baseline. The observed trend for simulated maize biomass was late (14.72) > mid (14.53) > present (14.10) > past-century (13.66 t/ha). The observed trend for simulated millet biomass was mid-century (16.16) > late (16.11) > present (15.97) > past-century (15.35 t/ha). The observed trend for simulated sorghum biomass was mid (13.80) > present (13.73) > late (13.52) > past-century (12.86 t/ha). The observed trend was consistent with the observed increase in future yield. The Mann-Kendall trend analysis did not detect a trend in biomass for millet and sorghum. A significant ( $P < 0.05$ ) and positive ( $\tau = 0.05$ ) trend was observed in biomass for maize.

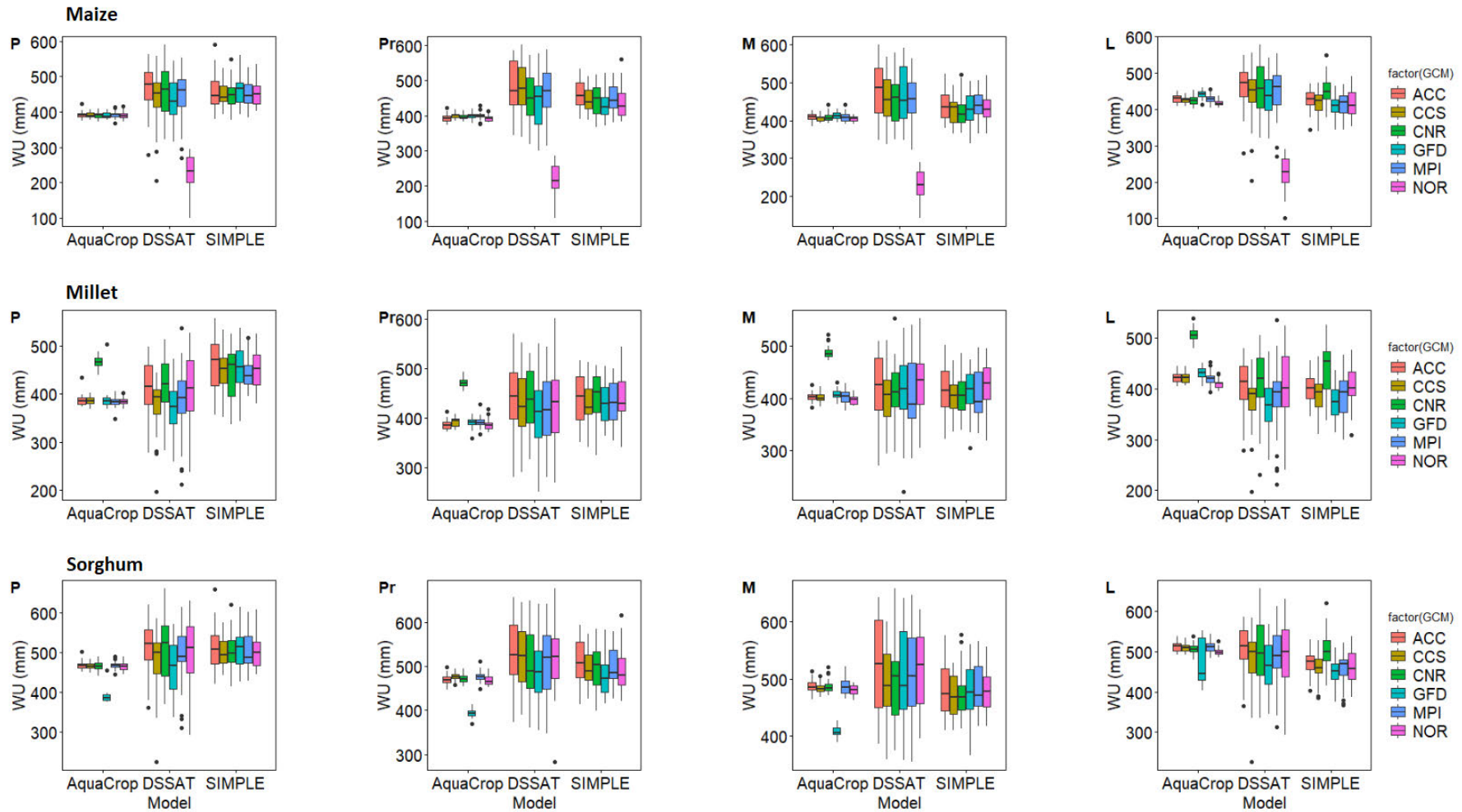


**Figure 4.4:** Simulated biomass ( $t\ ha^{-1}$ ) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CCS, CNR, GFD, NOR and MPI)

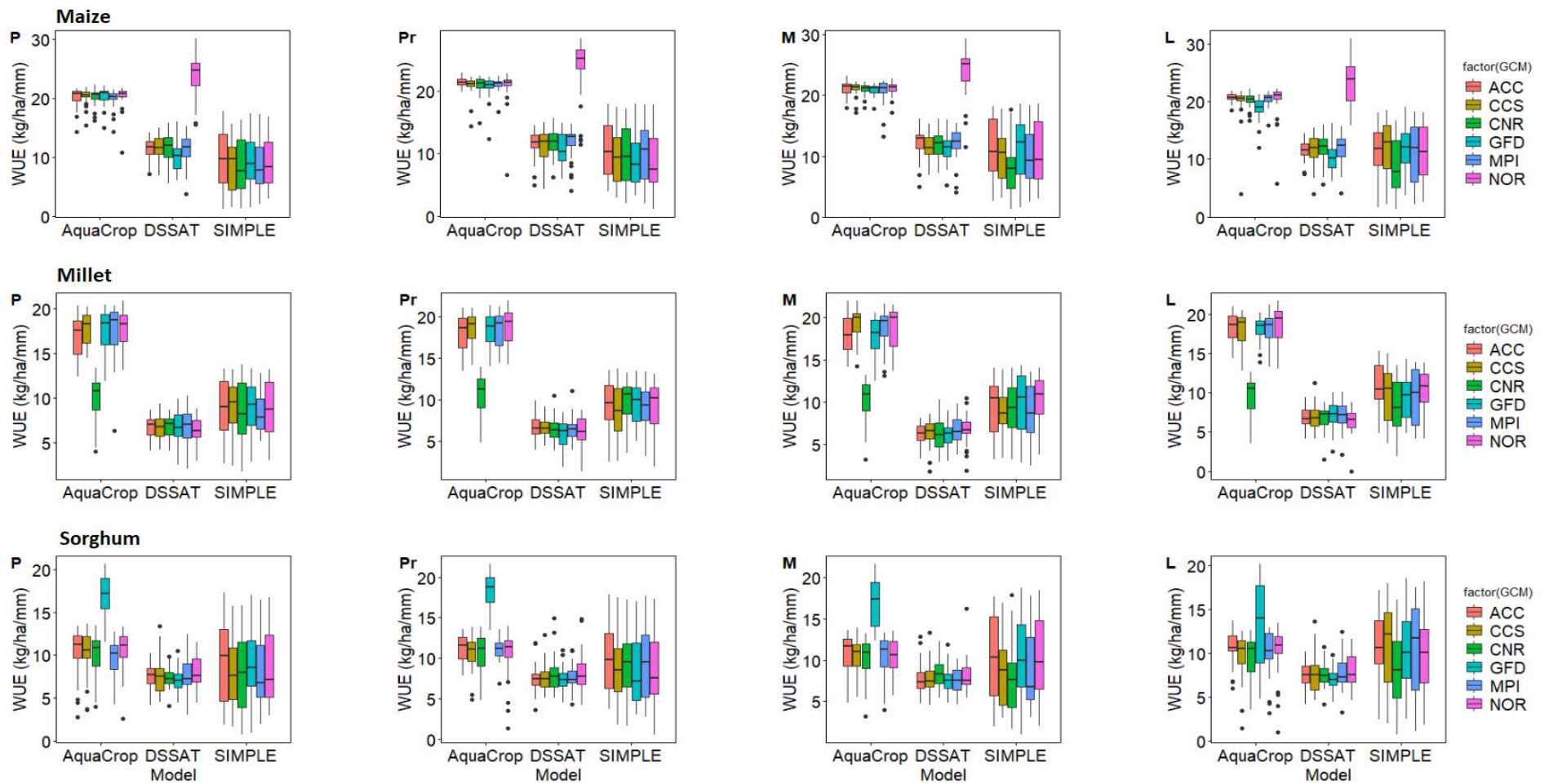
### 4.2.3 WU and WP

Highly significant ( $P < 0.05$ ) differences were observed in WU and WP for maize, millet, and sorghum across models. Results representing WU simulated by the DSSAT model showed wider box plots for maize, millet and sorghum, suggesting more variability. Thinner box plots were observed for WU simulated by the AquaCrop model across all the species suggesting less variability in WU (Figure 4.5). However, GFD simulated by AquaCrop showed a wider box plot in the late century for sorghum. The wider box plots shown by the SIMPLE model across maize, millet and sorghum suggested more variability in WP. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for millet and sorghum. While in WP for maize, less variations were observed in AquaCrop (Figure 4.6). Inconsistent results were observed in WP and WU for maize, millet, and sorghum across GCMs and models. It was depicted that the highest WP was observed under DSSAT for maize (24 kg/ha/mm) and the lowest under DSSAT for millet (5.89 kg/ha/mm). It was observed that the highest WP for GCMs was under NOR (18.04 kg/ha/mm) for maize and the lowest under CNR (8.49 kg/ha/mm) for millet. ACC predicted the highest water use (440.88 and 499.30 mm) for maize and sorghum, respectively, and CNR predicted the highest water use (445.78 mm) for millet. Meanwhile, the lowest water use predicted was under GFD (403.59 and 459.71 mm) for millet and sorghum, respectively, and NOR (354.53 mm) for maize.

There were no significant ( $P > 0.05$ ) differences in WU for maize and sorghum, while significant ( $P < 0.05$ ) differences were observed for millet across the time scale. Contrary to WU, it was observed that there were no significant ( $P > 0.05$ ) differences in WP for millet and maize, while sorghum was significantly ( $P < 0.05$ ) different. The Mann-Kendall trend analysis showed a significant ( $P < 0.05$ ) and positive ( $\tau = 0.03$ ) trend in WU of 0.03 for sorghum. Meanwhile, in WP, a significant ( $P < 0.05$ ) and positive ( $\tau = 0.03$ ) trend was observed for maize. Additionally, the trend analysis did not detect a trend in WU for maize and millet, in WP for millet and sorghum.



**Figure 4.5:** Simulated water use (mm) by AquaCrop, DSSAT and SIMPLE for maize, millet, and sorghum during four different time scales (past (P), present (Pr), mid-century (M) and late-century (L)) obtained from the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI)



**Figure 4.6:** Calculated water productivity ( $\text{kg ha}^{-1} \text{mm}^{-1}$ ) for maize, millet, and sorghum across the six GCMs (ACC, CSS, CNR, GFD, NOR and MPI) in each timescale (past (P), present (Pr), mid-century (M) and late-century (L)) for AquaCrop, DSSAT and SIMPLE model

### 4.3 Discussion

Observing the past to late century, the median value of climate change projections for minimum and maximum temperatures for Ukulinga showed a consistent warming trend across all months. This suggests an increased probability of hot nights and longer and more frequent heatwaves, especially for maize. Furthermore, this may result in a faster accumulation of heat units and a reduction in growth duration and accumulation of photosynthesis and increased night-time respiration, resulting in reduced crop yield (Schlenker & Roberts, 2009). The warming trend across the selected timescales is consistent with projected trends for South Africa (Mangani et al., 2018).

AquaCrop, DSSAT and the SIMPLE model with varying complexity simulated yield, biomass and WU for maize, millet, and sorghum under changes in climate over time. There is limited data available for selected NUS to parameterize complex models fully. Thus, simpler models can be adopted to advance modelling on NUS as a similar performance is observed between simpler and complex models. Millet is generally sensitive to low temperatures at the seedling stage and flowering. High daytime temperatures are needed for the grain to mature. It germinates well at soil temperatures of 23 to 30 °C (DAFF, 2011). Maize is a warm-weather crop and is not grown in areas where the mean daily temperature is less than 19 °C or the mean of the summer months is less than 23 °C. The critical temperature detrimentally affecting yield for maize is approximately 32 °C (du Plessis, 2003). Sorghum is a warm-weather crop requiring a temperature of 27 to 30 °C for optimum growth and development. However, the temperature can be as low as 21 °C, without a dramatic effect on growth and yield (DAFF, 2010). Compared to maize, millet and sorghum are better adapted to high temperatures (DAFF, 2011), and thus, may be more resilient to projected increases in temperature (Choudhary et al., 2019).

The increase and reduction in MAP observed suggests an increase in the probability of extreme weather events such as drought and floods. The trend showed a reduction in rainfall across timescales in all GCMs. This indicates a reduction in future rainfall for the site relative to the baseline. Water availability for crop production will, therefore, be negatively affected. This suggests that it is imperative to identify crops with low levels of water use that could be introduced into the environment. The increase in  $ET_0$  is consistent with the projected increase in minimum and maximum temperature and suggests increased crop water stress (Zhao et al., 2017). Differences in simulated WU across the GCMs could be that each climate model has

been developed based on its assumptions and unique mathematical representations of physical climate system processes, providing different climate projections (Confalonieri et al., 2016).

Similar to work done by Roberts et al. (2017), this study presented a framework for comparing crop models that can improve prediction, clarify differences between models, and ultimately improve assumptions used in crop modelling and ascertain potential impacts of climate change. AquaCrop, DSSAT and the SIMPLE model responded differently to changes in climate change. AquaCrop showed the least variation in yield and biomass for maize, millet, and sorghum; this suggests that AquaCrop was not as sensitive to pick up changes in weather variables compared to DSSAT. The results across the time scales, GCMs and models, verify that the climate change effect is substantial and may be difficult to capture entirely using simple process-based models (Roberts et al., 2017). The assessments of possible effects of climate change are based on estimations. This is the case since crop models are not universal; they must choose the most appropriate model according to their objectives. Crop models cannot give accurate projections because of an inadequate understanding of natural processes and computer power limitation (Rauff & Bello, 2015).

There are differences in output components reported, and this may be due to yearly differences in climatic conditions of the Ukulinga Research Farm. To improve the predictive capacity of the models under a wide range of environmental conditions, there is a need for a better understanding and description of the fundamental processes in the various crop-soil-atmosphere sub-systems (i.e., associated modules or routines). This was illustrated in the current study for modelling yield and WU under different temperatures and rainfalls. The results simulated by AquaCrop, DSSAT and the SIMPLE model showed high yield for maize and sorghum under the mid-century period and millet under the late-century period. This suggests that under the continuous variability in climate, these crops will be better suited for production in periods in which the greatest improvement in yield is attained. Although the yield for sorghum was greater in the present century than in the late century, it was still evident that the trend results for maize, millet and sorghum were consistent with the increased probability of extreme weather events as drought and floods (Schulze, 2011). High yield, biomass and WP variability were observed under the SIMPLE model across the GCMs, suggesting more sensitivity to climate variability. The high sensitivity of the SIMPLE model implies that it is less robust and simulates less stable outputs (Silvestro et al., 2017).

AquaCrop, DSSAT and the SIMPLE model produced different crop performance predictions under a future climate, reflecting different biological or physical mechanisms at work within the model structures. These models cannot be correct, and taking the mean of an ensemble of models may or may not improve the accuracy of predictions. The argument for ensemble modelling approaches has more traction in modelling global and regional weather systems. There is more fundamentally chaotic nature of global circulation models (Tebaldi & Knutti, 2007), but Keating (2020) was unconvinced that the same case applied in farming systems simulation. Keating (2020) suggested that directing energy into understanding why differences in model performance under climate change arise and gathering data and evolving model structures or calibration would be a more useful way forward. Modelling the impacts of climate change and adaptation and mitigation options are essential. However, there are many limitations in the models' capabilities and understanding of these impacts and options. Furthermore, uncertainties exist on the parameters and input factors required to run the models used in this study. There is a need to address these uncertainties (Keating, 2020) explicitly and know which factors data collection and calibration efforts should concentrate on (Silvestro et al., 2017).

#### **4.4 Conclusion**

Even though the AquaCrop, DSSAT and SIMPLE model simulation results for sorghum showed a higher increase in yield for the present century compared to the late century, it can still be concluded that the yield and biomass of maize, millet and sorghum will increase in response to projected climate change as yield improvements were observed to be great in the mid-century for all the species. Additionally, projected climate change is expected to increase WP for maize, millet, and sorghum across the three models. AquaCrop, DSSAT and the SIMPLE model responded differently to changes in climate change; thus, the hypothesis is accepted. However, the dissimilar responsiveness of the three models suggests that AquaCrop is the better suitable model for simulating the impacts of climate change on selected NUS.

## **CHAPTER 5: THE PERFORMANCE OF AQUACROP, DSSAT AND THE SIMPLE MODEL UNDER DIFFERENT IRRIGATION REGIMES**

### **5.0 Introduction**

There is a need to increase food production to alleviate malnutrition and food insecurity and cater for the growing population. However, in South Africa (SA), agricultural production is limited by water availability; this is in a semi-arid country whose water profile is rapidly moving from water-scarce to water-stressed (Singels et al., 2010). The annual mean rainfall for SA fluctuates around 500 mm, far below the world's mean of 860 mm per annum (Hardy et al., 2011). There is an uneven distribution of rainfall, with approximately 50% of the rain falling on 15% of the land (Hardy et al., 2011), stored in dams and later used for irrigation. A gradual decrease in rainfall by 2050 is projected within southern Africa (Cretat et al., 2011; Dai, 2013; Engelbrecht et al., 2009; Fraser et al., 2013) and will cause longer periods of droughts, floods when it does rain, and flick thunderstorms. Agricultural production and livelihoods in regions where rainfall variability is an issue, like SA, can be sustained only if priority is given to improving water productivity and enhancing the efficiency of water procurement (Cai et al., 2011). Technologies and strategies to improve water productivity and manage variable rainfalls are available (Mabhaudhi et al., 2019).

The inefficiencies detected in the irrigation process (Morillo et al., 2015; Wellens et al., 2013) have driven tools to facilitate farmers with irrigation scheduling. Thus, there is a need for practical decision-support tools to assess irrigation practices and the resulting yield. Greaves & Wang (2016) reported that irrigation strategies focusing on increasing agricultural water productivity, such as irrigation coupled with crop simulation modelling to investigate multiple alternatives, have a pivotal role in sustainable water development. Crop simulation models are ideally suited for the evaluation of irrigation strategies where there are various alternatives. Crop simulation models provide a low-cost means of investigating various management options (Dourado-neto et al., 1998; Rauff & Bello, 2015). Generally, the crop model applications in the impact assessment studies include huge uncertainties related to model structure and parameters (Palosuo et al., 2011). Moreover, in several cases, the model users are not familiar with the model limitations and the specificities of their application (Wolf et al., 1996). This leads to the recommendation of using multi-model estimates instead of relying on a single-model outcome (Palosuo et al., 2011). Furthermore, comparing various models for a specific site is the conventional method to identify a suitable model for its application.

Impact assessments of future climate change have been carried out across scales (Ewert et al., 2005; Rosenzweig & Parry, 1994; Semenov et al., 1996; Tao et al., 2009). In such studies, Global Climate Models (GCMs) outputs have been directly linked with crop models (e.g. DSSAT, AquaCrop), which are based on physiology (Ahmadzadeh et al., 2018; Ullah et al., 2019). Linking GCMs with crop models has been proposed as the next step to manage better increased seasonal rainfall variability in dry agricultural regions (Hansen & Blay-palmer, 1996; Tao et al., 2009; White et al., 2011). It was hypothesised that irrigation modelled by AquaCrop, DSSAT and the SIMPLE model had impacts on yield, biomass and water use for selected NUS. Therefore, the objective of this study was to evaluate the effect of irrigation on yield and water use of selected NUS across AquaCrop, DSSAT and the SIMPLE model under the mid-century period.

## **5.1 Materials and methods**

Numerous studies have reported that rainfall variability is set to increase in the near future. As we are in the present century (1995-2025), there is a need to establish the best management strategies for the future (mid-century period) to improve water productivity with available resources. Thus, there is the forecasting of agricultural productivity under different irrigation strategies in this study. AquaCrop, DSSAT and the SIMPLE model was used for climate change impact assessment for mid-century (2030–2060). The data of mid-century climate (2030–2060) and climate scenarios under RCP 8.5 were used to create weather files in the three models. According to Olfert et al. (2011), applying multiple GCMs due to the variability of climate projections between models is encouraged. The RCP and GCM used here have been described in Section 4.1.2.

The soil file was generated using soil details of Ukulinga Research Farm. Soils at the research farm have been described as shallow clayey to clayey loam (USDA taxonomic system). With medium-fertility (Mabhaudhi et al., 2013). Soils are derived from marine shales, and the landform is a colluvial fan and is classified as predominantly chromic luvisols. Soils are generally shallow and acidic with low to moderate fertility. Based on the profile pit description, the soil has an effective rooting depth of 0.6 m (Chimonyo et al., 2019). The soil file was created using information presented in Table 3.1 and Table 3.2. In this study, there was the use of cultivars best described by Akumaga et al. (2017), Hadebe et al. (2017) and Bello & Walker (2016) for maize, sorghum and pearl millet, respectively (Table 3.3). AquaCrop, DSSAT and

the SIMPLE model required different crop parameters to simulate outputs for the selected cereal crops, and these are discussed in Section 3.1.4.1, 3.1.4.2 and 3.1.4.3.

### 5.1.1 Management file

In Aquacrop, DSSAT and the SIMPLE model, the three crops (maize, millet, and sorghum) were simulated for the mid-century (2030–2060). The planting dates and plant population used are similar to those described in Section 4.1.4. Firstly, crops were grown under rainfed conditions, then under irrigation as a management practice. AquaCrop, DSSAT and the SIMPLE model takes into consideration the aspect of irrigation.

The SIMPLE model only requires the irrigation date and amount to simulate crop response to irrigation as a management practice (Zhao et al., 2019). Meanwhile, in DSSAT, irrigation can be applied on specific dates with specified irrigation amounts and methods or controlled by the plant's available water (Jones et al., 2003). AquaCrop can run simulations in different irrigation modes. The default mode is 'rainfed cropping', in which irrigation is not considered. In the other modes, (i) the irrigation water requirement can be determined, (ii) an existing irrigation schedule can be assessed, or (iii) an irrigation schedule can be automatically generated (FAO, 2017a). The methods chosen for use was irrigation scheduling in AquaCrop and the one in which irrigation can be applied on specific dates with specified irrigation amount and methods in DSSAT. These methods made it possible to have similar irrigation inputs across the three models; hence, they were chosen for this study. In AquaCrop, when generating irrigation schedules, the irrigation method needs to be specified since it affects the simulation of the soil water balance (FAO, 2017a). Thus, a sprinkler was selected as an irrigation method. It was not required to select the irrigation method in DSSAT, and the SIMPLE model does not have the irrigation method as a parameter under its inputs. Irrigation amounts of 10 and 20 mm were frequented every 7 and 14 days until maturity in AquaCrop, DSSAT and the SIMPLE model for maize, millet, and sorghum.

### 5.1.2 Statistical analysis

The three models used the ACC, CCS, CNR, GFD, MPI and NOR mid-century period data as climate input in simulating the effects of irrigation on selected NUS. Simulation outputs for yield, biomass, WU and WP [yield (kg) per water evapotranspiration ( $\text{m}^3$ )] were then subjected to F-test statistical analyses using the R software (version 4.0.2). When a p-value was less than 0.05, the results were statistically significant, and when a p-value was greater than 0.05, the

results were statistically insignificant. Descriptive statistics such as means, standard deviations, and box and whisker plots were used to evaluate the effects of irrigation on yield, biomass, WU and WP for maize, sorghum, and millet. Box and whisker plots, coupled with standard deviations, can show stability and general distribution of data sets. A wider box indicates more variations across the median value of the dataset. A Mann-Kendall trend test was used to perceive statistically significant decreasing or increasing yield, biomass, WU, and WP trends in maize, millet, and sorghum data.

$H_0$ : No trend in yield, biomass, WU and WP for maize, millet and sorghum

$H_a$ : Trend is present in yield, biomass, WU and WP for maize, millet and sorghum

A P-value < 0.05 indicates a trend, and if  $\tau$  is +ve, increasing trend, and if  $\tau$  is -ve decreasing trend.

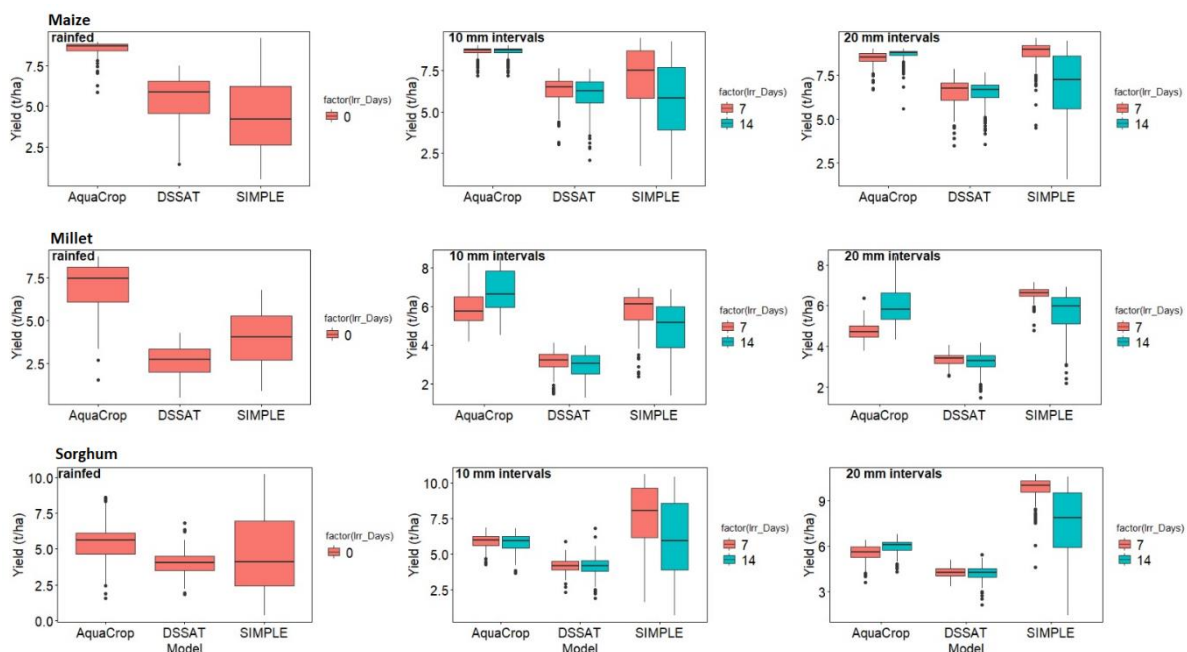
## 5.2 Results

### 5.2.1 Yield

Across models, there were highly significant ( $P < 0.05$ ) differences for maize, millet, and sorghum yield (results not presented). Regardless of the irrigation intervals, yield simulations across all the crops under the SIMPLE model had wider box plots suggesting more yield variability. Contrary to this, DSSAT had the shorter box plots suggesting less yield variability, however only for millet and sorghum. Maize yield was less variable in AquaCrop (Figure 5.1). AquaCrop showed the highest simulated mean yield for maize (8.57 t/ha) and millet (6.10 t/ha). Meanwhile, the SIMPLE model simulated the highest mean yield for sorghum (7.15 t/ha). Across time, there were no significant ( $P > 0.05$ ) differences in millet yield. On the contrary, significant ( $P < 0.05$ ) differences in maize and sorghum yield were observed (results not presented). Throughout the 2030-2060 period, the Mann-Kendall trend analysis did not detect a maize and millet yield trend. However, a significant ( $P < 0.05$ ) and positive ( $\tau = 0.04$ ) trend was observed for sorghum. The results showed no significant ( $P > 0.05$ ) differences across the GCMs for maize and millet yield (results not presented). For sorghum yield, a significant difference was observed across GCMs (results not presented).

Compared with the rainfed simulations, the results showed an increase in yield for all the crops due to irrigation. Further increases in yield were observed because of an increase in irrigation amount from 10 to 20 mm. It was observed that yield for maize was 6.21, 7.07 and 7.63 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Yield for millet was observed as

4.56, 4.91, and 4.93 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Yield for sorghum was observed as 4.70, 5.62, and 6.20 t/ha for rainfed, 10 mm and 20 mm of irrigation, respectively. Overall, there was a reduction in crop yield for all species when irrigation frequency was changed from 7 to 14 days. The highest reduction was observed for sorghum [0.61 t/ha (10.9%)] followed by maize [0.58 t/ha (8.21%)] and then millet [0.02 t/ha (4.07%)]. Figure 5.1 depicts that the greatest improvements in maize and sorghum yield were observed under the SIMPLE model when an irrigation amount of 20 mm was applied every seven days. Indifferent to maize and sorghum, the highest yield was observed under AquaCrop when millet was rainfed.



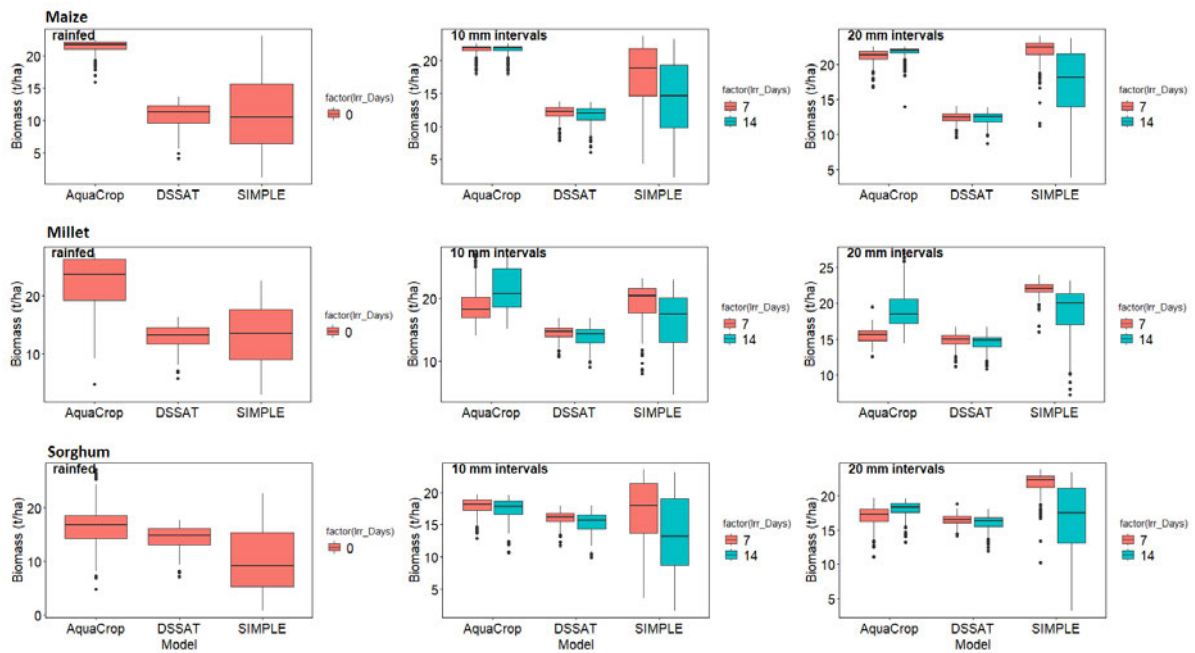
**Figure 5.1:** Yield for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

### 5.2.2 Biomass

Highly significant ( $P < 0.05$ ) differences were observed for maize, millet, and sorghum biomass across the models (results not presented). In Figure 5.2, the wider box plots shown by the SIMPLE model across maize, millet and sorghum show that there was more variation in biomass. Compared to other models, DSSAT showed less variability in biomass for millet and sorghum, as shown by thinner box plots. Meanwhile, fewer variations in maize biomass were observed in simulations based on AquaCrop. The results showed no significant ( $P > 0.05$ ) differences across the GCMs for maize and significant differences for millet and sorghum

biomass (results not presented). The average biomass for the GCMs ranged from 16.12-16.88 t/ha for maize with ACC yielding the highest results, 16.61-17.50 t/ha for millet with NOR yielding the highest results and 15.81-16.83 t/ha for sorghum with NOR yielding the highest results. Across time, there were no significant differences ( $P>0.05$ ) in maize and millet biomass. Contrary to this, highly significant ( $P<0.05$ ) differences in sorghum biomass over time were observed (results not presented). Across the 2030-2060 period, Mann Kendall trend analysis showed a significant ( $P<0.05$ ) and positive trend for millet ( $\tau = 0.02$ ) and sorghum ( $\tau = 0.04$ ) biomass. Then, for maize, no trend in biomass was detected. Similar to yield results, there were inconsistencies observed in biomass across time for all the crops.

An increase in biomass for all the species is observed due to irrigation. Further increases in maize, millet and sorghum yield were observed because of an increase in irrigation amount from 10 to 20 mm. The biomass for maize was observed to be 14.53, 16.49 and 17.78 t/ha for rainfed, 10 and 20 mm in irrigation, respectively. The most significant increase of 9% in biomass was with sorghum, and the least significant increase of 0.63% was with millet for 10 and 20 mm, respectively. A reduction in biomass across all crop species for irrigation frequency increased from 7 to 14 days. Results showed that the reductions were, 8.33% (1.37 t/ha) in maize, 0.87% (0.15 t/ha) in millet and 9.26% (1.5 t/ha) in sorghum. Figure 5.2 depicts that the SIMPLE model biomass output showed the highest maize (21.88 t/ha), millet (22 t/ha), and sorghum (21.71 t/ha) for the irrigation amount of 20 mm frequented every after seven days. Nonetheless, results further showed that high millet biomass was attained when the crop was rainfed (no irrigation) in AquaCrop.



**Figure 5.2:** Biomass for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

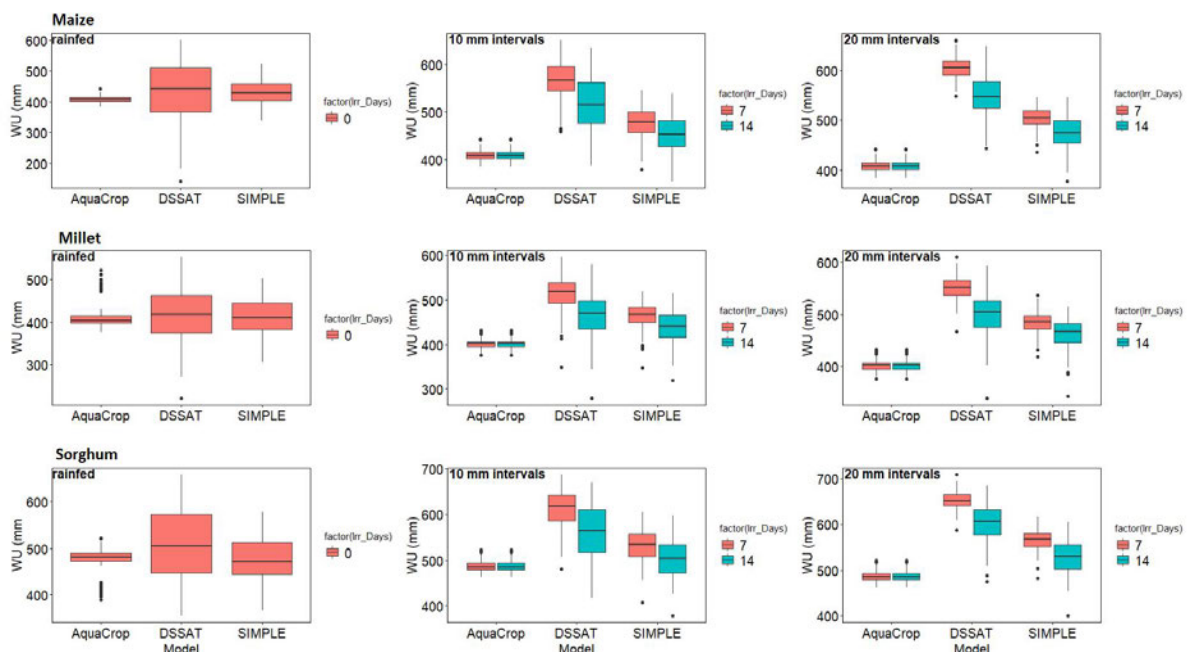
### 5.2.3 WU and WP

Across models, there were highly significant ( $P < 0.05$ ) differences in WU and WP for maize, millet, and sorghum (results not presented). The results showed fluctuations of WU and WP for maize, millet, and sorghum across the years. The response in WU for maize, millet and sorghum were significantly ( $P < 0.05$ ) different. However, with WP, there were no significant ( $P > 0.05$ ) differences for all the crops (results not presented). The Mann-Kendall trend analysis did not detect a trend in WU for maize and WP for maize and millet. A significant ( $P < 0.05$ ) and a positive trend was observed in WU for millet ( $\tau = 0.04$ ) and sorghum ( $\tau = 0.05$ ). In WP, a significant ( $P < 0.05$ ) and positive ( $\tau = 0.04$ ) trend was also observed but only for sorghum. The wider box plots shown by the SIMPLE model across maize, millet and sorghum suggested more variability in WP. Compared to other models, DSSAT depicted thinner box plots suggesting less variability in WP for millet and sorghum. While in WP for maize, less variations were observed in AquaCrop (Figure 5.4).

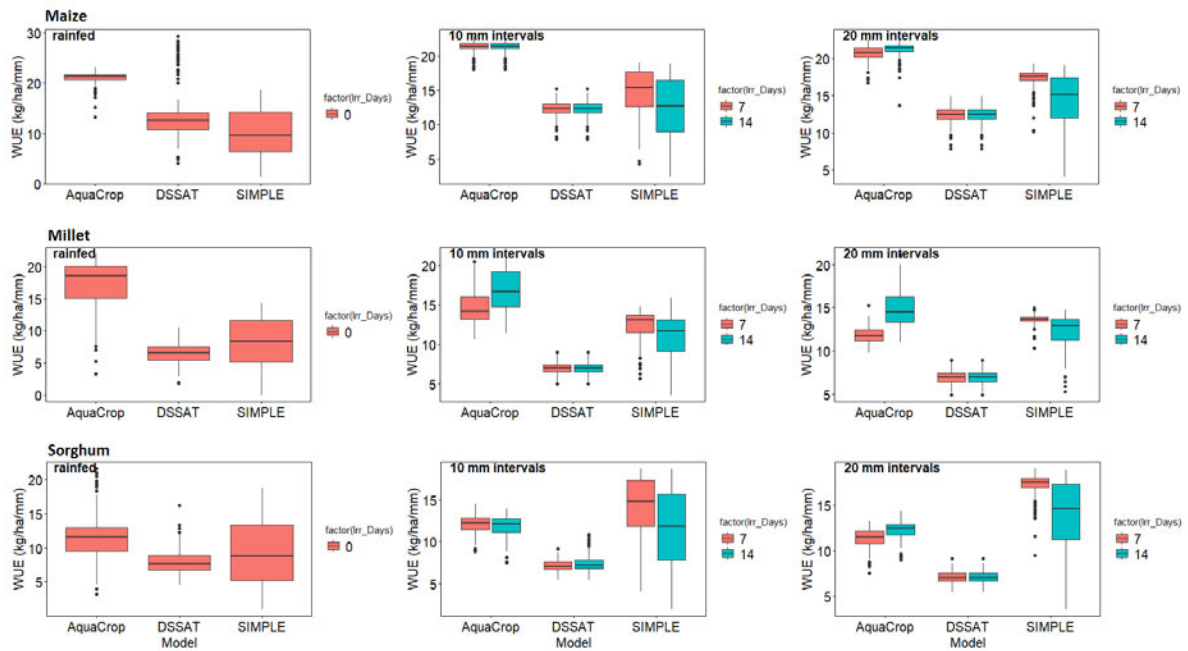
ACC predicted the highest water use (475.67 and 536.53 mm) for maize and sorghum, respectively, and CNR predicted the highest water use (453.79 mm) for millet. Meanwhile, the lowest water use predicted was under GFD (442.47 and 523.66 mm) for millet and sorghum,

respectively, and NOR (458.13 mm) for maize. The highest WP for GCMs was observed under ACC (15.90 kg/ha/mm) for maize and the lowest under CNR (10.43 kg/ha/mm) for sorghum. Inconsistencies of WU and WP were observed for maize, millet, and sorghum across GCMs and models. It was observed that the highest WU was observed under DSSAT for maize (530.73 mm), millet (487.90 mm) and sorghum (586.36 mm) (Figure 5.3). It was also observed that WU generated by AquaCrop remained constant for different irrigation amounts and days. It was depicted that the highest WP was observed under AquaCrop for maize (21 kg/ha/mm) and millet (15.10 kg/ha/mm), the SIMPLE model for sorghum (13.37 kg/ha/mm).

WP increased due to irrigation and an increase in irrigation amount, consistent with yield and WU. The results showed an increase in WP for maize and sorghum. The observed increase was due to an increase in water availability. Contrarily, there was a reduction in WP for millet due to an increase in irrigation amount. There was a reduction in WP for maize and sorghum, resulting from an increase in irrigation frequency of 7 to 14 days. Contrary, there was an increase in WP for millet resulting from an increase in irrigation frequency. Figure 5.4 depicts that the highest WP for maize (21.26 kg/ha/mm) was observed for AquaCrop than other models, irrigating with 10 mm every after seven days. Then, the highest WP for millet (16.85 kg/ha/mm) was observed for AquaCrop irrigating with 10 mm every 14 days. However, compared to irrigation, rainfed millet showed the highest WP of 17.13 kg/ha/mm simulated by AquaCrop. Lastly, the SIMPLE model output showed the highest sorghum (17.24 kg/ha/mm) WP for the irrigation amount of 20 mm frequented every after seven days (Figure 5.4).



**Figure 5.3:** WU for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under no irrigation (0 mm) and irrigation (10 and 20 mm)



**Figure 5.4:** WP for maize, millet and sorghum simulated by AquaCrop, DSSAT and the SIMPLE model under rainfed and irrigation (10 and 20 mm)

### 5.3 Discussion

Overall results show that AquaCrop, DSSAT and the SIMPLE model was sensitive enough to simulate changes in yield due to added irrigation. Results imply that these models are suited for modelling the effects of irrigation management for the selected species. Numerous studies report that models become sensitive to a certain crop more than other crops. Thus, this further suggests that the SIMPLE model, DSSAT and AquaCrop could be used to predict biomass and yield with a high degree of reliability under various irrigation management strategies and specific to selected crops. Hence, these models are valuable tools to aid in decision-making for effective irrigation management strategies. The inconsistencies in yield and biomass across the mid-century period are attributed to changes in climate over time. Applying a higher amount of irrigation resulted in higher yield, biomass, and water use simulated by the three models. Additionally, irrigating more frequently resulted in higher yield, biomass, and water use. Hence, the simulation of different water management scenarios indicated that optimal irrigation management significantly improved the irrigation water use by adjusting the irrigation water

applied. Nonetheless, AquaCrop is particularly well suited to simulating yield, biomass, and water use for selected NUS in different irrigation scheduling conditions.

There were reductions in yield by reducing irrigation frequency, suggesting dry periods, which implies that a shorter irrigation interval is more appropriate than a longer irrigation interval. WP with maize and millet is inconsistent with the relationship between these crops with yield and biomass. The reduction observed in WP for maize and millet is attributed to high amounts of water lost through unproductive means; Chimonyo & Mabhaudhi (2019) also reported this matter. Improvement in yield is more related to transpiration, and more water allows for carbon dioxide to be absorbed and oxygen to be transpired; hence improved yield is associated with improved water use, which is evident in this study. Water productivity (WP), which is the net benefits accrued per unit of water consumed (Molden et al., 2003), offers greater spatial and temporal stability and is a true efficacy parameter of the crop production process (Halsema & Vincent, 2012). The soil factors mainly drive the irrigation module, but each model interprets how the algorithm within the soil factors influences the soil water balance. Furthermore, the soil profile differs even if it is in the same area. The crop models consider only one point measured; hence, the models need more developments to accommodate this limitation.

For irrigation conditions in this study, the accuracy of DSSAT and the SIMPLE model with the Priestley-Taylor/Ritchie method for ET simulation was acceptable and close to AquaCrop. This suggests that the absence of relative humidity and wind speed among the model inputs does not limit the performance of DSSAT and the SIMPLE model under non-water stress conditions. Precise estimation of evapotranspiration (ET) constitutes the main basis for irrigation management (Qiu et al., 2019; Ran et al., 2017). In addition, better ET algorithms should demonstrate better performance in multiple aspects of the crop model simulation, not just in the ET simulation itself (Dejonge & Thorp, 2017; Thorp et al., 2019). A study conducted by Toumi et al. (2016) to validate AquaCrop showed that the precision rate for daily ET simulation was reliable overall.

The findings of this study are not in agreement with (Rogers & Alam, 1998), who verified that sorghum needs about 450–550 mm of water per growing season. Although the presented results support the potential of the AquaCrop, DSSAT and the SIMPLE model to incentivize farmers to enhance their irrigation practices, the soil properties must still be considered to ensure production while improving environmental sustainability (Malik & Dechmi, 2019). Overall, the three models can be used as a tool to develop the best irrigation management options for

increased yield and WP for maize, millet, and sorghum under variability in rainfall and temperatures. There is limited data availability for NUS to parameterize complex models fully. Simpler models (i.e., requiring lesser inputs) performed equally as well as the complex models in this study, suggesting that going forward, the less complex models can be adopted to advance modelling on NUS.

The observed yield variations across the models show different models produce different outputs even when the same parameter values are used. High yield, biomass and WP variability under the SIMPLE model could suggest more sensitivity to climate variability. However, it could also mean that it could not capture soil water dynamics within the soil plant atmosphere continuum. This might be related to the limited number of input data. The application of “ensemble” model predictions is an interesting development in crop-soil modelling (Wallach et al., 2018), but whether this is useful development or a distraction remains to be seen. Crop-soil models are predominately deterministic – given the same inputs, they generate the same predictions. The variability in soil and weather inputs generates variability in model predictions (Keating, 2020). The level of development for different crop modules in models is different. This study shows that GCMs behave differently because different schools of knowledge produce them, and different institutes use different algorithms to establish the GCMs. Hence, dissimilar behaviour in GCMs is always expected.

#### **5.4 Conclusion**

The AquaCrop, DSSAT and SIMPLE model were used as a research tool to estimate climatically driven yield, biomass, and water use for selected NUS in different irrigation scheduling conditions for the Ukulinga Research Farm. Applying more irrigation and irrigating more frequently resulted in higher yield, biomass and water use for maize, millet and yield generated by AquaCrop, DSSAT and the SIMPLE model. Thus, the hypothesis is accepted, and it can be concluded that the AquaCrop, DSSAT and SIMPLE model can be a useful decision support system to assist farmers in irrigation scheduling and applying an optimum amount of irrigation water. This can eventually help increase WP and make efficient use of variable rainfalls in South Africa. AquaCrop generated high yields for maize and millet, and the SIMPLE model for sorghum when irrigated implies that these models are better suited for modelling the effects of irrigation management for the selected species.

## **CHAPTER 6: GENERAL DISCUSSION, CONCLUSION AND RECOMMENDATIONS**

### **6.1 Discussion and conclusion**

The fact that AquaCrop, DSSAT and SIMPLE are successfully used to simulate crop yields, biomass, and WU by modelling climate change and irrigation may imply that the system of these models can be widely applicable. With relatively comparable results (i.e., yields disagreement and yield variability) to DSSAT and SIMPLE model, AquaCrop was observed as the better suitable model for simulating yield, biomass and WU under climate change impacts and irrigation management. This may be attributed to the crop or cultivar, soil and climate inputs used in this study being previously used in the AquaCrop calibration study conducted by Hadebe et al. (2017). The performance of a model in any site depends on the fine-tuning of the parameters and sound validation of the model under a wide range of conditions and crops (Babel et al., 2019). As AquaCrop, DSSAT and the SIMPLE model were not calibrated and validated for climate change and different irrigation management before their comparison, and this suggests that results are not robust and reliable. To overcome this challenge and get meaningful results, Folberth et al. (2012) suggested that it is essential to calibrate crop growth parameters to local conditions or use parameters from local field studies when applying large-scale crop growth models specifically for low yield regions as South Africa before their application. Hence, it is recommended that there must be calibration for all the models using inputs specific to Ukulinga Research Farm or SA.

A related concern has been an over-reliance on the notion of “validation” (Keating, 2020). The model has predictive power over a particular independent dataset, and hence it is “validated” and can be deployed elsewhere without question (Jones et al., 2017; Keating & Thorburn, 2018). A more appropriate view is that these models are evolving hypotheses of how key plant-soil-environment relations interact, always subject to continuing refinement and always “wrong” at some level but still potentially “useful” in carefully established circumstances. Keating (2020) was most comfortable with the validation process was continuously exposing the model to new datasets that “stress test” its performance in new directions. Exploring the key individual functions (plant development, growth and yield, water and nitrogen dynamics in both plant and soil is fundamental to ensuring models “get the right answers for the right reasons”. Any evolution of model structure, functional forms, or calibration must perform across the entire model testing database – not just on one new dataset.

A comparison of multiple crop simulation models serves the purpose of identifying the reasons for systematic model errors. When an error has been identified, steps can be taken to improve model performance based on better analysis of the processes involved (Akinseye et al., 2017). As found from the study, some aspects of the models were satisfactory (e.g., yield and biomass), but there was also a clear indication that model improvements should be sought for the parts that present high significant error (e.g., water use). These errors could be attributed to three possible sources: (i) model structure, (ii) bad parameterization/calibration or (iii) quality of field trial data. The use of crop models for the objectives of this study depends on the accuracy and reliability of their predictions of water consumption and grain yield under the given environment and management systems, so testing the models under a wide range of environments and cropping practices is continuously needed (Anothai et al., 2013).

The detail involved in a crop model is intricately linked to the model's end-use and precision. Even when a judicious choice of model is made, aspects of model limitations, challenges involved in simulation, and challenges in data acquisition must be borne in mind such that modelling studies are put in the proper perspective and successful applications are achieved. The very nature of both climate change and the agrarian system is complex (Faures et al., 2013). This means that insufficiencies in input data in each area pose a significant challenge to the accuracy and reliability of the models' outputs. The needs of models, such as DSSAT and APSIM, which are very robust tools for crop production projections, need complete climatic and phenological data to be effective. In South Africa, however, there is the challenge that the trials carried out are more focused on attainable yields and less attention paid to other data that are vital to these models. Hence, there is a shortage of information, especially regarding planting dates, emergence dates, flowering, maturity and biomass, and grain yields. Most of the data always found reports on a percentage to the milestone in the crop phenological state. Such data cannot be fed into any model because it meets the required input data format. It will then require the modeller to use assumptions that can be biased (Kephe et al., 2021). There is a need to integrate methods such assumptions can be based with minimal room for error.

This thesis aimed to compare models of varying complexity to simulate growth and yield for selected NUS accurately. The assumption is that there is limited data availability for NUS to parameterize complex models fully. Simpler models (i.e., with fewer input requirements) performed equally as well as the complex models, suggesting that going forward, the less complex models can be adopted to advance modelling on NUS. Following Jones et al. (2016, 2017), this study has shown that some analyses can be performed which are needed to advise

a farmer, but the availability of input data for agricultural systems models remains a major limitation. It is important to formulate necessary steps in collecting data inputs for crop simulation models. Worth noting is that the ease with which such data can be obtained will depend on the user's expertise and familiarity with the proposed data collection methods. Methods of data collection involve qualitative and quantitative approaches, using both primary and secondary data sources. The methods used as input data sources range from grey literature review, field trials, controlled environment (greenhouse) experiments, remote sensing, models, software, and geographic information systems (Kephe et al., 2021).

## **6.2 Recommendations**

- Experimental data were lacking for the calibration process for maize, millet and sorghum. Thus, there needs to be additional fieldwork carried out to fine-tune AquaCrop, DSSAT and the SIMPLE model for local growing conditions for selected species. Furthermore, initiatives such as AgMIP should aim to improve the quality of data collected, especially for datasets utilized for model calibration.
- Performing sensitivity analysis for the modelling outputs on different calibration and test years could be useful in future modelling studies.
- Further improvements are required for the structure and algorithm of the SIMPLE model. Additionally, there should be the availability of complete instructions to run the SIMPLE model.
- Future studies focusing on southern African climate change should consider utilising the CO<sub>2</sub> values from Cape Point instead of the Hawaii Mauna Loa Observatory values.
- GCMs were biased towards a lower MAP and higher MAT. Thus, in future studies, bias correction should be considered to improve confidence in the ability of climate models to predict the future climate.

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## 8. APPENDIX

### 8.1 Analysis of results for chapter 3

```
> summarySE(data=Maize_results, "Yield", groupvars = c("Model"),  
conf.interval = 0.95)
```

	Model	N	Yield	sd	se	ci
1	AquaCrop	15	6.552667	1.4884674	0.3843206	0.8242858
2	DSSAT	15	5.750000	0.7036436	0.1816800	0.3896648
3	SIMPLE	15	5.522000	1.2438604	0.3211634	0.6888269

```
> summarySE(data=Maize_results, "Yield", groupvars = c("Year"),  
conf.interval = 0.95)
```

	Year	N	Yield	sd	se	ci
1	2004	3	7.106667	0.96126653	0.55498749	2.3879184
2	2005	3	6.760000	0.24331050	0.14047538	0.6044168
3	2006	3	6.163333	0.49963320	0.28846336	1.2411577
4	2007	3	6.483333	0.84109056	0.48560386	2.0893848
5	2008	3	6.716667	1.03500403	0.59755985	2.5710925
6	2009	3	6.556667	1.16345749	0.67172250	2.8901886
7	2010	3	6.740000	1.29201393	0.74594459	3.2095405
8	2011	3	6.523333	0.39310728	0.22696059	0.9765326
9	2012	3	6.196667	0.60011110	0.34647431	1.4907586
10	2013	3	5.223333	0.17616280	0.10170764	0.4376127
11	2014	3	6.330000	0.97555113	0.56323471	2.4234033
12	2015	3	5.060000	1.43930539	0.83098335	3.5754328
13	2016	3	4.046667	0.09073772	0.05238745	0.2254050
14	2017	3	5.706667	0.80214296	0.46311746	1.9926336
15	2018	3	3.510000	0.92601296	0.53463383	2.3003437

```
> summarySE(data=Millet_results, "Yield", groupvars = c("Model"),  
conf.interval = 0.95)
```

	Model	N	Yield	sd	se	ci
1	AquaCrop	15	7.466000	0.5659228	0.1461206	0.3133976
2	DSSAT	15	6.452667	1.2102684	0.3124899	0.6702243
3	SIMPLE	15	4.334000	1.1605097	0.2996423	0.6426689

```
> summarySE(data=Millet_results, "Yield", groupvars = c("Year"),
conf.interval = 0.95)
```

	Year	N	Yield	sd	se	ci
1	2004	3	6.833333	1.6460964	0.9503742	4.089130
2	2005	3	6.083333	2.0038546	1.1569260	4.977851
3	2006	3	6.583333	1.4782535	0.8534700	3.672185
4	2007	3	6.840000	1.2219247	0.7054786	3.035429
5	2008	3	6.356667	1.7928841	1.0351221	4.453771
6	2009	3	6.520000	1.5406817	0.8895130	3.827265
7	2010	3	6.596667	1.6229705	0.9370225	4.031682
8	2011	3	6.790000	1.5955877	0.9212130	3.963659
9	2012	3	6.300000	1.1576269	0.6683562	2.875705
10	2013	3	5.663333	0.9124326	0.5267932	2.266608
11	2014	3	6.553333	1.9202170	1.1086378	4.770083
12	2015	3	4.456667	2.3828624	1.3757463	5.919358
13	2016	3	5.483333	1.5614843	0.9015234	3.878942
14	2017	3	6.083333	1.8375074	1.0608854	4.564621
15	2018	3	4.120000	2.6708987	1.5420441	6.634880

```
> summarySE(data=Sorghum_results, "Yield", groupvars = c("Model"),
conf.interval = 0.95)
```

	Model	N	Yield	sd	se	ci
1	AquaCrop	15	2.966667	1.4743941	0.3806869	0.8164923
2	DSSAT	15	4.720667	0.7704217	0.1989220	0.4266453
3	SIMPLE	15	5.740000	1.5861949	0.4095538	0.8784055

```
> summarySE(data=Sorghum_results, "Yield", groupvars = c("Year"),
conf.interval = 0.95)
```

	Year	N	Yield	sd	se	ci
1	2004	3	5.856667	1.5543916	0.8974284	3.861323
2	2005	3	4.743333	2.3739068	1.3705757	5.897111
3	2006	3	4.770000	1.9265773	1.1123099	4.785883
4	2007	3	5.173333	1.0186920	0.5881421	2.530571
5	2008	3	5.190000	1.2983451	0.7495999	3.225268
6	2009	3	5.570000	1.0701402	0.6178457	2.658376
7	2010	3	5.853333	0.7729381	0.4462560	1.920085
8	2011	3	5.130000	2.4005624	1.3859654	5.963328
9	2012	3	4.743333	1.6548817	0.9554464	4.110954
10	2013	3	3.353333	2.3507091	1.3571825	5.839485
11	2014	3	4.653333	1.1357963	0.6557523	2.821475
12	2015	3	2.993333	1.4099764	0.8140502	3.502575
13	2016	3	3.280000	1.9179155	1.1073091	4.764366
14	2017	3	3.666667	1.1588932	0.6690873	2.878850
15	2018	3	2.160000	1.2474374	0.7202083	3.098806

```
> summarySE(data=Maize_results "Biomass" groupvars = c("Model"),
conf.interval = 0.95)
```

	Model	N	Biomass	sd	se	ci
1	AquaCrop	15	16.78467	2.996970	0.7738142	1.6596664
2	DSSAT	15	10.72133	1.088734	0.2811098	0.6029206
3	SIMPLE	15	13.80333	3.106005	0.8019670	1.7200482

```
> summarySE(data=Maize_results, "Biomass", groupvars = c("Year"),
conf.interval = 0.95)
```

	Year	N	Biomass	sd	se	ci
1	2004	3	16.370000	4.306832	2.4865505	10.698763
2	2005	3	15.753333	3.076854	1.7764227	7.643330
3	2006	3	14.526667	3.065295	1.7697489	7.614615
4	2007	3	14.903333	3.616661	2.0880799	8.984283
5	2008	3	15.280000	4.190358	2.4193043	10.409426
6	2009	3	14.660000	4.690032	2.7077912	11.650685
7	2010	3	15.470000	4.798135	2.7702046	11.919228
8	2011	3	15.106667	3.210457	1.8535581	7.975217
9	2012	3	14.336667	3.218949	1.8584611	7.996313
10	2013	3	12.516667	1.789814	1.0333495	4.446144
11	2014	3	14.216667	3.783548	2.1844323	9.398854
12	2015	3	11.223333	3.267190	1.8863133	8.116151
13	2016	3	9.566667	1.568577	0.9056183	3.896561
14	2017	3	13.206667	2.755673	1.5909885	6.845471
15	2018	3	9.410000	2.405390	1.3887524	5.975319

```
> summarySE(data=Millet_results, "Biomass", groupvars = c("Model"),
conf.interval = 0.95)
```

	Model	N	Biomass	sd	se	ci
1	AquaCrop	15	24.07800	1.585845	0.4094633	0.8782114
2	DSSAT	15	17.39867	2.472670	0.6384407	1.3693191
3	SIMPLE	15	14.44333	3.866303	0.9982750	2.1410870

```
> summarySE(data=Millet_results, "Biomass", groupvars = c("Year"),
conf.interval = 0.95)
```

	Year	N	Biomass	sd	se	ci
1	2004	3	20.23000	4.206317	2.428518	10.449070
2	2005	3	18.62000	6.491849	3.748071	16.126646
3	2006	3	20.48333	4.620350	2.667560	11.477585
4	2007	3	20.04000	2.745742	1.585255	6.820802
5	2008	3	18.82000	5.722202	3.303715	14.214739
6	2009	3	19.14333	4.110405	2.373144	10.210813
7	2010	3	19.75667	4.828192	2.787558	11.993893
8	2011	3	20.60000	4.599185	2.655341	11.425008
9	2012	3	18.81333	1.940550	1.120377	4.820593
10	2013	3	18.34667	3.350244	1.934264	8.322467
11	2014	3	19.47667	5.709696	3.296495	14.183672
12	2015	3	15.00000	8.121379	4.688880	20.174624
13	2016	3	17.03000	5.265093	3.039803	13.079215
14	2017	3	19.95667	5.956294	3.438868	14.796254
15	2018	3	13.28333	8.965770	5.176390	22.272208

```
> summarySE(data=Sorghum_results, "Biomass", groupvars = c("Model"),
conf.interval = 0.95)
```

	Model	N	Biomass	sd	se	ci
1	AquaCrop	15	9.37600	4.030854	1.0407620	2.2322125
2	DSSAT	15	14.68667	1.341442	0.3463588	0.7428658
3	SIMPLE	15	12.75200	3.528630	0.9110884	1.9540903

```
> summarySE(data=Sorghum_results, "Biomass", groupvars = c("Year"),
conf.interval = 0.95)
```

	Year	N	Biomass	sd	se	ci
1	2004	3	16.006667	1.0989237	0.6344639	2.729878

```

2 2005 3 12.630000 4.8921263 2.8244705 12.152715
3 2006 3 13.343333 3.1866179 1.8397947 7.915998
4 2007 3 14.303333 1.6621171 0.9596238 4.128928
5 2008 3 13.553333 1.9111340 1.1033938 4.747520
6 2009 3 14.136667 1.2504533 0.7219495 3.106298
7 2010 3 15.656667 0.6952937 0.4014280 1.727205
8 2011 3 13.583333 4.4212253 2.5525956 10.982933
9 2012 3 13.043333 2.8023086 1.6179136 6.961320
10 2013 3 10.770000 3.5223288 2.0336175 8.749950
11 2014 3 12.346667 2.7807253 1.6054525 6.907705
12 2015 3 8.360000 4.7639374 2.7504606 11.834277
13 2016 3 8.573333 4.5967960 2.6539614 11.419074
14 2017 3 10.813333 4.1192516 2.3782510 10.232788
15 2018 3 6.953333 4.4616850 2.5759551 11.083440

```

```

> summarySE(data=Maize_results "WU" groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WU      sd      se      ci
1 AquaCrop 15 534.6667 31.93669 8.246019 17.68595
2 DSSAT    15 438.2000 42.05982 10.859799 23.29195
3 SIMPLE   15 401.8000 25.17425 6.499963 13.94103

```

```

> summarySE(data=Maize_results "WU" groupvars = c("Year")
conf.interval = 0.95)

```

```

      Year N      WU      sd      se      ci
1 2004 3 471.3333 60.11933 34.70991 149.3447
2 2005 3 479.3333 82.07517 47.38612 203.8860
3 2006 3 473.3333 77.91234 44.98271 193.5450
4 2007 3 472.3333 52.55790 30.34432 130.5611
5 2008 3 450.0000 55.50676 32.04684 137.8864
6 2009 3 438.6667 64.25989 37.10046 159.6304
7 2010 3 449.3333 61.13373 35.29558 151.8646
8 2011 3 471.0000 58.02586 33.50124 144.1442
9 2012 3 458.6667 49.97333 28.85211 124.1406
10 2013 3 440.0000 62.86493 36.29509 156.1652
11 2014 3 450.3333 55.13922 31.83464 136.9734
12 2015 3 466.6667 117.13383 67.62725 290.9766
13 2016 3 433.3333 121.25318 70.00556 301.2096
14 2017 3 481.6667 73.51417 42.44343 182.6193
15 2018 3 437.3333 110.19226 63.61953 273.7327

```

```

> summarySE(data=Millet_results, "WU", groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WU      sd      se      ci
1 AquaCrop 15 520.2000 33.86359 8.743542 18.75303
2 DSSAT    15 434.4667 44.49858 11.489484 24.64249
3 SIMPLE   15 395.4667 32.64499 8.428900 18.07819

```

```

> summarySE(data=Millet_results, "WU", groupvars = c("Year"),
conf.interval = 0.95)

```

```

      Year N      WU      sd      se      ci
1 2004 3 463.0000 63.92965 36.90980 158.81005
2 2005 3 457.0000 83.43261 48.16984 207.25809
3 2006 3 462.6667 67.67816 39.07400 168.12187

```

```

4 2007 3 477.0000 37.51000 21.65641 93.18000
5 2008 3 428.0000 60.25778 34.78985 149.68862
6 2009 3 434.0000 55.43465 32.00521 137.70730
7 2010 3 439.3333 59.51750 34.36245 147.84968
8 2011 3 476.6667 46.09049 26.61036 114.49513
9 2012 3 456.6667 36.95042 21.33333 91.78992
10 2013 3 460.6667 37.44774 21.62046 93.02535
11 2014 3 436.6667 49.03400 28.30979 121.80721
12 2015 3 436.3333 139.25636 80.39970 345.93197
13 2016 3 435.0000 103.58089 59.80245 257.30919
14 2017 3 485.3333 55.51877 32.05377 137.91626
15 2018 3 402.3333 110.58632 63.84704 274.71164

```

```

> summarySE(data=Sorghum_results, "WU", groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WU      sd      se      ci
1 AquaCrop 15 617.7333 40.07933 10.348438 22.19519
2  DSSAT 15 488.0000 54.39932 14.045843 30.12534
3  SIMPLE 15 441.1333 25.06240 6.471083 13.87909

```

```

> summarySE(data=Sorghum_results, "Year", groupvars = c("Year"),
conf.interval = 0.95)

```

```

      Year N      WU      sd      se      ci
1 2004 3 536.0000 73.51190 42.44212 182.6137
2 2005 3 537.3333 115.10575 66.45633 285.9385
3 2006 3 523.3333 113.60164 65.58794 282.2021
4 2007 3 536.3333 68.64644 39.63304 170.5272
5 2008 3 500.3333 73.05021 42.17556 181.4668
6 2009 3 508.0000 70.34202 40.61199 174.7393
7 2010 3 519.3333 78.05340 45.06415 193.8954
8 2011 3 536.3333 81.20550 46.88402 201.7256
9 2012 3 519.6667 65.36309 37.73740 162.3709
10 2013 3 498.0000 76.29548 44.04921 189.5285
11 2014 3 514.3333 62.40459 36.02931 155.0216
12 2015 3 521.0000 153.26774 88.48917 380.7382
13 2016 3 496.0000 140.92906 81.36543 350.0872
14 2017 3 541.0000 100.35437 57.93962 249.2941
15 2018 3 447.3333 151.66190 87.56204 376.7491

```

```

> summarySE(data=Maize_results "WP", groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WP      sd      se      ci
1 AquaCrop 15 12.35867 3.163580 0.8168329 1.7519324
2  DSSAT 15 13.12400 1.029700 0.2658675 0.5702291
3  SIMPLE 15 13.76800 2.989972 0.7720074 1.6557912

```

```

> summarySE(data=Maize_results "WP", groupvars = c("Year"),
conf.interval = 0.95)

```

```

      Year N      WP      sd      se      ci
1 2004 3 15.090000 0.9230926 0.5329478 2.293089
2 2005 3 14.346667 2.2476061 1.2976560 5.583363
3 2006 3 13.316667 2.9354613 1.6947894 7.292090
4 2007 3 13.726667 0.9671780 0.5584005 2.402603

```

```

5 2008 3 14.906667 0.8473685 0.4892284 2.104980
6 2009 3 14.933333 1.1119502 0.6419848 2.762238
7 2010 3 14.970000 1.4547508 0.8399008 3.613801
8 2011 3 13.996667 2.0326420 1.1735464 5.049363
9 2012 3 13.580000 1.4809119 0.8550049 3.678789
10 2013 3 12.056667 1.9653074 1.1346708 4.882094
11 2014 3 14.043333 0.7600219 0.4387989 1.887999
12 2015 3 10.883333 2.3549168 1.3596119 5.849938
13 2016 3 9.753333 2.2471389 1.2973863 5.582203
14 2017 3 11.870000 0.8400595 0.4850086 2.086824
15 2018 3 8.780000 4.7825098 2.7611833 11.880413

```

```

> summarySE(data=Millet_results, "WP", groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WP      sd      se      ci
1 AquaCrop 15 14.41467 1.474555 0.3807285 0.8165813
2 DSSAT 15 14.77933 1.934065 0.4993734 1.0710494
3 SIMPLE 15 10.87000 2.646631 0.6833573 1.4656556

```

```

> summarySE(data=Millet_results, "WP", groupvars = c("Year"),
conf.interval = 0.95)

```

```

      Year N      WP      sd      se      ci
1 2004 3 14.646667 2.1652329 1.2500978 5.378737
2 2005 3 13.193333 3.2595910 1.8819257 8.097273
3 2006 3 14.170000 2.0864563 1.2046161 5.183045
4 2007 3 14.260000 1.5400000 0.8891194 3.825572
5 2008 3 14.703333 2.9309612 1.6921912 7.280911
6 2009 3 14.873333 1.7883605 1.0325104 4.442534
7 2010 3 14.860000 1.7317332 0.9998166 4.301864
8 2011 3 14.133333 2.2356729 1.2907664 5.553719
9 2012 3 13.733333 1.6257409 0.9386219 4.038564
10 2013 3 12.266667 1.3326040 0.7693793 3.310372
11 2014 3 14.806667 3.0255137 1.7467812 7.515793
12 2015 3 9.870000 3.5908773 2.0731940 8.920234
13 2016 3 12.530000 0.5716642 0.3300505 1.420093
14 2017 3 12.410000 2.9386902 1.6966536 7.300111
15 2018 3 9.863333 4.8845095 2.8200729 12.133794

```

```

> summarySE(data=Sorghum_results, "WP", groupvars = c("Model"),
conf.interval = 0.95)

```

```

      Model N      WP      sd      se      ci
1 AquaCrop 15 4.886667 2.557509 0.6603460 1.4163013
2 DSSAT 15 9.707333 1.370367 0.3538273 0.7588841
3 SIMPLE 15 12.894667 3.210151 0.8288574 1.7777224

```

```

> summarySE(data=Sorghum_results, "WP", groupvars = c("Year"),
conf.interval = 0.95)

```

```

      Year N      WP      sd      se      ci
1 2004 3 11.220000 4.174254 2.410007 10.369423
2 2005 3 9.646667 5.825808 3.363532 14.472108
3 2006 3 9.840000 5.306421 3.063663 13.181880
4 2007 3 9.926667 3.317172 1.915170 8.240313
5 2008 3 10.760000 3.977348 2.296323 9.880281
6 2009 3 11.293333 3.641323 2.102319 9.045548

```

```

7 2010 3 11.586667 3.275368 1.891034 8.136464
8 2011 3 10.156667 5.959147 3.440515 14.803342
9 2012 3 9.503333 4.634925 2.675975 11.513793
10 2013 3 7.296667 5.716610 3.300486 14.200847
11 2014 3 9.303333 3.285367 1.896807 8.161303
12 2015 3 6.350000 3.669918 2.118828 9.116582
13 2016 3 7.616667 5.272887 3.044303 13.098577
14 2017 3 7.163333 3.160021 1.824439 7.849928
15 2018 3 5.780000 4.426025 2.555367 10.994856

```

## 8.2 Analysis of results for chapter 4

```

> ddply(Maize, .(Time), summarise, mean=mean(Yield), sd=sd(Yield))
  Time    mean    sd
1    1 5.755663 2.252668
2    2 6.015968 2.366982
3    3 6.205520 2.349447
4    4 6.167079 2.334748
> ddply(Millet, .(Time), summarise, mean=mean(Yield), sd=sd(Yield))
  Time    mean    sd
1    1 4.371864 1.998401
2    2 4.552025 2.082640
3    3 4.562783 2.223108
4    4 4.599409 2.294360
> ddply(Sorghum, .(Time), summarise, mean=mean(Yield), sd=sd(Yield))
  Time    mean    sd
1    1 4.380287 1.818707
2    2 4.688118 1.849784
3    3 4.698226 1.878317
4    4 4.615125 1.800947
> ddply(Maize, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
  Model    mean    sd
1 AquaCrop 8.336210 0.7016133
2   DSSAT 5.268844 1.4361679
3   SIMPLE 4.503118 2.3510503
> ddply(Millet, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
  Model    mean    sd
1 AquaCrop 6.863230 1.3250613
2   DSSAT 2.684261 0.7686987
3   SIMPLE 4.017070 1.5644618
> ddply(Sorghum, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
  Model    mean    sd
1 AquaCrop 5.280403 1.3175715
2   DSSAT 3.836761 0.9122409
3   SIMPLE 4.669153 2.5594463
> ddply(Maize, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))
  GCM    mean    sd
1 ACC 6.311398 2.203044

```

```

2 CCS 5.995591 2.319461
3 CNR 5.927742 2.435934
4 GFD 5.871210 2.329352
5 MPI 6.068333 2.315413
6 NOR 6.042070 2.370083
> ddply(Millet, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))
  GCM    mean    sd
1 ACC 4.689973 2.148221
2 CCS 4.632984 2.266347
3 CNR 3.861245 1.531258
4 GFD 4.601263 2.261078
5 MPI 4.607366 2.276423
6 NOR 4.736290 2.224662
> ddply(Sorghum, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))
  GCM    mean    sd
1 ACC 4.764059 1.819084
2 CCS 4.391720 1.675809
3 CNR 4.340968 1.740583
4 GFD 5.019597 2.132954
5 MPI 4.464543 1.790961
6 NOR 4.591747 1.769697
> ddply(Maize, .(Time Model,GCM), summarise, mean=mean(Yield), sd=sd(Yield))
  Time  Model GCM    mean    sd
1     1 AquaCrop ACC 7.914194 0.5240215
2     1 AquaCrop CCS 7.991935 0.4426769
3     1 AquaCrop CNR 7.916774 0.4961007
4     1 AquaCrop GFD 7.950323 0.4630802
5     1 AquaCrop MPI 7.806452 0.5698921
6     1 AquaCrop NOR 7.932903 0.7477486
7     1     DSSAT ACC 5.398387 1.2661019
8     1     DSSAT CCS 5.100968 1.3864856
9     1     DSSAT CNR 5.322258 1.5080312
10    1     DSSAT GFD 4.300323 1.1864414
11    1     DSSAT MPI 5.106774 1.3734637
12    1     DSSAT NOR 5.440645 1.5511263
13    1   SIMPLE ACC 4.660968 2.7026473
14    1   SIMPLE CCS 3.980323 2.2090714
15    1   SIMPLE CNR 4.038387 2.5569397
16    1   SIMPLE GFD 4.540968 2.3605259
17    1   SIMPLE MPI 3.984516 2.1694574
18    1   SIMPLE NOR 4.214839 2.1481447
19    2 AquaCrop ACC 8.387419 0.2494122
20    2 AquaCrop CCS 8.314194 0.6133828
21    2 AquaCrop CNR 8.286452 0.4800108
22    2 AquaCrop GFD 8.206129 0.7068035
23    2 AquaCrop MPI 8.399355 0.3795694
24    2 AquaCrop NOR 8.142581 1.0843830
25    2     DSSAT ACC 5.607742 1.4130645

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26	2	DSSAT	CCS	5.393548	1.4946294
27	2	DSSAT	CNR	5.380968	1.3746281
28	2	DSSAT	GFD	4.729355	1.6001624
29	2	DSSAT	MPI	5.594194	1.5894187
30	2	DSSAT	NOR	5.256129	1.7428228
31	2	SIMPLE	ACC	5.009355	2.4132301
32	2	SIMPLE	CCS	4.215161	2.1389372
33	2	SIMPLE	CNR	4.457097	2.4763322
34	2	SIMPLE	GFD	4.150968	2.4716598
35	2	SIMPLE	MPI	4.671935	2.4481836
36	2	SIMPLE	NOR	4.084839	2.6183148
37	3	AquaCrop	ACC	8.620645	0.3540521
38	3	AquaCrop	CCS	8.558065	0.4546751
39	3	AquaCrop	CNR	8.581613	0.2450999
40	3	AquaCrop	GFD	8.632581	0.3712947
41	3	AquaCrop	MPI	8.428710	0.7306880
42	3	AquaCrop	NOR	8.528387	0.4397128
43	3	DSSAT	ACC	5.835484	1.3678739
44	3	DSSAT	CCS	5.225484	1.2717412
45	3	DSSAT	CNR	5.360000	1.3238932
46	3	DSSAT	GFD	5.213871	1.3496559
47	3	DSSAT	MPI	5.568387	1.4898705
48	3	DSSAT	NOR	5.660645	1.3919769
49	3	SIMPLE	ACC	5.134839	2.4793008
50	3	SIMPLE	CCS	4.323226	2.2272395
51	3	SIMPLE	CNR	3.586452	2.2301159
52	3	SIMPLE	GFD	5.072903	2.4805526
53	3	SIMPLE	MPI	4.589355	2.3475589
54	3	SIMPLE	NOR	4.778710	2.4972848
55	4	AquaCrop	ACC	8.878710	0.2807934
56	4	AquaCrop	CCS	8.490323	1.3134902
57	4	AquaCrop	CNR	8.570323	0.5279424
58	4	AquaCrop	GFD	8.321290	0.8482639
59	4	AquaCrop	MPI	8.750323	0.3747220
60	4	AquaCrop	NOR	8.459355	1.2684530
61	4	DSSAT	ACC	5.316774	1.1988700
62	4	DSSAT	CCS	5.151290	1.5601832
63	4	DSSAT	CNR	5.427742	1.4069511
64	4	DSSAT	GFD	4.469355	1.1687028
65	4	DSSAT	MPI	5.284516	1.3126255
66	4	DSSAT	NOR	5.307419	1.4977182
67	4	SIMPLE	ACC	4.972258	1.8405809
68	4	SIMPLE	CCS	5.202581	2.2250992
69	4	SIMPLE	CNR	4.204839	2.6001562
70	4	SIMPLE	GFD	4.866452	1.8421284
71	4	SIMPLE	MPI	4.635484	2.3871822
72	4	SIMPLE	NOR	4.698387	2.2969677

> ddply(Millet, .(Time,Model,GCM), summarise, mean=mean(Yield), sd=sd(Yield))

Time	Model	GCM	mean	sd
1	1	AquaCrop ACC	6.525484	0.9376099
2	1	AquaCrop CCS	6.877097	0.7702216
3	1	AquaCrop CNR	4.630000	1.1318598
4	1	AquaCrop GFD	6.742903	0.8389604
5	1	AquaCrop MPI	6.771935	1.1774051
6	1	AquaCrop NOR	6.816774	0.8448684
7	1	DSSAT ACC	2.759032	0.6835562
8	1	DSSAT CCS	2.553871	0.6660915
9	1	DSSAT CNR	2.832903	0.7376910
10	1	DSSAT GFD	2.523871	0.7265887
11	1	DSSAT MPI	2.617419	0.9170822
12	1	DSSAT NOR	2.663871	0.7776875
13	1	SIMPLE ACC	4.226774	1.8134008
14	1	SIMPLE CCS	4.099032	1.5906358
15	1	SIMPLE CNR	3.940968	1.9541859
16	1	SIMPLE GFD	4.183226	1.6510267
17	1	SIMPLE MPI	3.813226	1.2636676
18	1	SIMPLE NOR	4.115161	1.7098828
19	2	AquaCrop ACC	6.911290	1.0128170
20	2	AquaCrop CCS	7.241290	0.8050538
21	2	AquaCrop CNR	4.990323	1.1227006
22	2	AquaCrop GFD	7.230968	0.8453021
23	2	AquaCrop MPI	7.262258	0.8370413
24	2	AquaCrop NOR	7.251613	0.8187515
25	2	DSSAT ACC	2.966452	0.7320407
26	2	DSSAT CCS	2.791935	0.6801246
27	2	DSSAT CNR	2.762581	0.6741660
28	2	DSSAT GFD	2.445484	0.8667827
29	2	DSSAT MPI	2.688387	0.8163377
30	2	DSSAT NOR	2.660000	0.8700345
31	2	SIMPLE ACC	4.205806	1.5857969
32	2	SIMPLE CCS	3.874516	1.4997441
33	2	SIMPLE CNR	4.451290	1.3992182
34	2	SIMPLE GFD	4.142258	1.4486148
35	2	SIMPLE MPI	3.931935	1.5631238
36	2	SIMPLE NOR	4.128065	1.5208296
37	3	AquaCrop ACC	7.292258	0.8829032
38	3	AquaCrop CCS	7.781613	0.6926524
39	3	AquaCrop CNR	4.982032	1.1626004
40	3	AquaCrop GFD	7.195806	0.9383950
41	3	AquaCrop MPI	7.484839	1.0239820
42	3	AquaCrop NOR	7.464194	0.9117996
43	3	DSSAT ACC	2.576452	0.7300710
44	3	DSSAT CCS	2.602903	0.7711039
45	3	DSSAT CNR	2.587097	0.8242135
46	3	DSSAT GFD	2.545484	0.7468728
47	3	DSSAT MPI	2.844839	0.8225484

```

48 3 DSSAT NOR 2.887097 0.8751883
49 3 SIMPLE ACC 4.020323 1.7117622
50 3 SIMPLE CCS 3.715161 1.2477069
51 3 SIMPLE CNR 3.873548 1.4669277
52 3 SIMPLE GFD 4.197742 1.7053303
53 3 SIMPLE MPI 3.726129 1.7200420
54 3 SIMPLE NOR 4.352581 1.4574452
55 4 AquaCrop ACC 7.683871 0.7440864
56 4 AquaCrop CCS 7.570323 0.8490563
57 4 AquaCrop CNR 4.863548 1.2255925
58 4 AquaCrop GFD 7.800323 0.6934574
59 4 AquaCrop MPI 7.659032 0.8153092
60 4 AquaCrop NOR 7.687742 0.9313528
61 4 DSSAT ACC 2.776452 0.6521633
62 4 DSSAT CCS 2.628065 0.7339320
63 4 DSSAT CNR 2.781290 0.7866543
64 4 DSSAT GFD 2.626774 0.6868789
65 4 DSSAT MPI 2.726129 0.8127143
66 4 DSSAT NOR 2.573871 0.8126774
67 4 SIMPLE ACC 4.335484 1.3851085
68 4 SIMPLE CCS 3.860000 1.5966527
69 4 SIMPLE CNR 3.639355 1.8632891
70 4 SIMPLE GFD 3.580323 1.2982796
71 4 SIMPLE MPI 3.762258 1.6462720
72 4 SIMPLE NOR 4.234516 1.3488608

```

```
> ddply(Sorghum, .(Time,Model,GCM), summarise, mean=mean(Yield), sd=sd(Yield))
```

```

  Time  Model GCM    mean    sd
1     1 AquaCrop ACC 4.787742 1.2756768
2     1 AquaCrop CCS 4.755484 1.1899799
3     1 AquaCrop CNR 4.630000 1.1318598
4     1 AquaCrop GFD 6.584516 0.8892688
5     1 AquaCrop MPI 4.365161 1.1450993
6     1 AquaCrop NOR 4.936129 1.0197930
7     1 DSSAT ACC 3.827742 0.8869187
8     1 DSSAT CCS 3.548065 1.0677029
9     1 DSSAT CNR 3.673226 0.6581610
10    1 DSSAT GFD 3.351613 0.7867024
11    1 DSSAT MPI 3.757097 0.9077672
12    1 DSSAT NOR 4.039032 0.9847685
13    1 SIMPLE ACC 4.916129 3.0012161
14    1 SIMPLE CCS 4.114839 2.3248654
15    1 SIMPLE CNR 4.210968 2.7702700
16    1 SIMPLE GFD 4.744516 2.5571466
17    1 SIMPLE MPI 4.221935 2.3929862
18    1 SIMPLE NOR 4.380968 2.3184612
19    2 AquaCrop ACC 5.222581 0.7833176
20    2 AquaCrop CCS 5.093871 0.9797880
21    2 AquaCrop CNR 4.990323 1.1227006

```

22	2	AquaCrop	GFD	7.150968	0.9647603
23	2	AquaCrop	MPI	5.264839	0.6192192
24	2	AquaCrop	NOR	4.906774	1.3548515
25	2	DSSAT	ACC	3.991290	0.9063728
26	2	DSSAT	CCS	4.027742	0.9363465
27	2	DSSAT	CNR	3.984516	0.9070312
28	2	DSSAT	GFD	3.641290	0.8305410
29	2	DSSAT	MPI	3.890645	0.9368064
30	2	DSSAT	NOR	4.238065	1.1829298
31	2	SIMPLE	ACC	5.261935	2.7037535
32	2	SIMPLE	CCS	4.424839	2.3352514
33	2	SIMPLE	CNR	4.790645	2.5591651
34	2	SIMPLE	GFD	4.307097	2.5945818
35	2	SIMPLE	MPI	4.810968	2.6923600
36	2	SIMPLE	NOR	4.387742	2.7201896
37	3	AquaCrop	ACC	5.289677	1.0271952
38	3	AquaCrop	CCS	5.051613	1.0050642
39	3	AquaCrop	CNR	4.981935	1.1622232
40	3	AquaCrop	GFD	6.947419	1.1684319
41	3	AquaCrop	MPI	5.055161	1.2749794
42	3	AquaCrop	NOR	5.098065	0.9548592
43	3	DSSAT	ACC	4.061935	0.8045720
44	3	DSSAT	CCS	3.793226	0.9405757
45	3	DSSAT	CNR	4.162258	0.8852145
46	3	DSSAT	GFD	3.906774	0.7505571
47	3	DSSAT	MPI	3.863871	0.8836541
48	3	DSSAT	NOR	4.203548	0.9193822
49	3	SIMPLE	ACC	5.210000	2.9602658
50	3	SIMPLE	CCS	4.249032	2.2008822
51	3	SIMPLE	CNR	3.806774	2.3291005
52	3	SIMPLE	GFD	5.280323	2.8196081
53	3	SIMPLE	MPI	4.543548	2.8127431
54	3	SIMPLE	NOR	5.062903	2.7741307
55	4	AquaCrop	ACC	5.489355	0.8885191
56	4	AquaCrop	CCS	4.922258	1.3114768
57	4	AquaCrop	CNR	4.863548	1.2255925
58	4	AquaCrop	GFD	6.124839	1.6744310
59	4	AquaCrop	MPI	5.109032	1.2594611
60	4	AquaCrop	NOR	5.108387	1.4000478
61	4	DSSAT	ACC	3.762903	0.8365931
62	4	DSSAT	CCS	3.608710	1.0616583
63	4	DSSAT	CNR	3.716129	0.6640767
64	4	DSSAT	GFD	3.343548	0.7261384
65	4	DSSAT	MPI	3.770968	0.8099027
66	4	DSSAT	NOR	3.918065	1.0239415
67	4	SIMPLE	ACC	5.347419	1.9616999
68	4	SIMPLE	CCS	5.110968	2.4482121
69	4	SIMPLE	CNR	4.281290	2.6759817

```

70  4  SIMPLE GFD 4.852258 2.1682754
71  4  SIMPLE MPI 4.921290 2.6718891
72  4  SIMPLE NOR 4.821290 2.4578985
> ddply(Maize, .(Time), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Time    mean    sd
1    1 13.65505 5.671609
2    2 14.10332 6.037400
3    3 14.52697 6.118045
4    4 14.72097 5.962880
> ddply(Millet, .(Time), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Time    mean    sd
1    1 15.34668 5.354590
2    2 15.96758 5.479034
3    3 16.15911 5.980924
4    4 16.11188 6.290235
> ddply(Sorghum, .(Time), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Time    mean    sd
1    1 12.86251 4.776137
2    2 13.72672 4.949894
3    3 13.79131 4.999427
4    4 13.52407 4.577395
> ddply(Maize, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Model    mean    sd
1 AquaCrop 20.84430 1.457895
2   DSSAT 10.66774 2.105735
3   SIMPLE 11.24269 5.886638
> ddply(Millet, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Model    mean    sd
1 AquaCrop 21.67605 4.366281
2   DSSAT 12.62766 2.055865
3   SIMPLE 13.38523 5.200094
> ddply(Sorghum, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Model    mean    sd
1 AquaCrop 16.03573 4.015641
2   DSSAT 14.01696 2.316725
3   SIMPLE 10.37577 5.687590
> ddply(Maize, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 14.81153 5.789368
2 CCS 14.18328 5.895616
3 CNR 13.93306 6.207288
4 GFD 14.15298 5.906648
5 MPI 14.26086 5.932518
6 NOR 14.16774 6.023601
> ddply(Millet, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 16.47414 5.716403
2 CCS 16.31761 6.073423
3 CNR 13.57418 3.997017

```

```

4 GFD 16.20401 6.054969
5 MPI 16.16828 6.260307
6 NOR 16.63968 5.815892
> ddply(Sorghum, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 13.81804 4.336464
2 CCS 12.87105 4.282606
3 CNR 12.80583 4.656381
4 GFD 15.03742 6.086892
5 MPI 13.08194 4.591008
6 NOR 13.24263 4.503811
> ddply(Maize, .(Time Model,GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Time  Model GCM    mean    sd
1     1 AquaCrop ACC 19.730000 1.2697743
2     1 AquaCrop CCS 19.890968 1.1282032
3     1 AquaCrop CNR 19.801613 1.0850011
4     1 AquaCrop GFD 19.896452 0.9061146
5     1 AquaCrop MPI 19.497419 1.2717363
6     1 AquaCrop NOR 19.870645 1.2933572
7     1     DSSAT ACC 11.016452 1.8825843
8     1     DSSAT CCS 10.642258 1.8239878
9     1     DSSAT CNR 10.868710 2.2144296
10    1     DSSAT GFD  9.810968 1.7296134
11    1     DSSAT MPI 10.512903 2.3507661
12    1     DSSAT NOR 10.708387 2.4033742
13    1   SIMPLE ACC 11.653871 6.7549368
14    1   SIMPLE CCS  9.947419 5.5227795
15    1   SIMPLE CNR 10.095484 6.3919970
16    1   SIMPLE GFD 11.350000 5.9023707
17    1   SIMPLE MPI  9.960645 5.4226008
18    1   SIMPLE NOR 10.536774 5.3705390
19    2 AquaCrop ACC 20.920000 0.6263652
20    2 AquaCrop CCS 20.849677 1.0751542
21    2 AquaCrop CNR 20.710323 1.0688264
22    2 AquaCrop GFD 20.525484 1.3556126
23    2 AquaCrop MPI 20.939355 0.8730633
24    2 AquaCrop NOR 20.445484 1.8455692
25    2     DSSAT ACC 11.049032 2.1875730
26    2     DSSAT CCS 10.559032 2.1482184
27    2     DSSAT CNR 10.639032 2.2198789
28    2     DSSAT GFD  9.760323 2.3277034
29    2     DSSAT MPI 10.863548 2.1595672
30    2     DSSAT NOR 10.127419 2.5937129
31    2   SIMPLE ACC 12.520968 6.0343662
32    2   SIMPLE CCS 10.538387 5.3441726
33    2   SIMPLE CNR 11.144194 6.1912076
34    2   SIMPLE GFD 10.376452 6.1760055
35    2   SIMPLE MPI 11.678065 6.1232025

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36 2 SIMPLE NOR 10.212903 6.5441614
37 3 AquaCrop ACC 21.522903 0.8723004
38 3 AquaCrop CCS 21.345484 1.0490117
39 3 AquaCrop CNR 21.427742 0.6032894
40 3 AquaCrop GFD 21.549032 0.8992566
41 3 AquaCrop MPI 21.118065 1.5487036
42 3 AquaCrop NOR 21.334194 0.9935317
43 3 DSSAT ACC 11.214194 1.9927967
44 3 DSSAT CCS 10.564516 1.9365293
45 3 DSSAT CNR 10.516774 2.0400202
46 3 DSSAT GFD 10.630000 1.8809891
47 3 DSSAT MPI 10.779032 2.2422479
48 3 DSSAT NOR 11.117419 1.8541880
49 3 SIMPLE ACC 12.491613 6.4976689
50 3 SIMPLE CCS 10.806129 5.5695396
51 3 SIMPLE CNR 8.965806 5.5722466
52 3 SIMPLE GFD 12.681613 6.1995527
53 3 SIMPLE MPI 11.472903 5.8676822
54 3 SIMPLE NOR 11.948065 6.2427203
55 4 AquaCrop ACC 22.141935 0.7785689
56 4 AquaCrop CCS 21.303548 2.4351339
57 4 AquaCrop CNR 21.448065 1.1416024
58 4 AquaCrop GFD 20.904516 1.7201101
59 4 AquaCrop MPI 21.767419 0.8818804
60 4 AquaCrop NOR 21.322903 2.2275760
61 4 DSSAT ACC 11.049032 1.7689797
62 4 DSSAT CCS 10.747742 2.2302567
63 4 DSSAT CNR 11.066452 2.0674518
64 4 DSSAT GFD 10.186452 1.7559889
65 4 DSSAT MPI 10.953871 2.1340004
66 4 DSSAT NOR 10.642258 2.2780792
67 4 SIMPLE ACC 12.428387 4.5973247
68 4 SIMPLE CCS 13.004194 5.5595136
69 4 SIMPLE CNR 10.512581 6.4993523
70 4 SIMPLE GFD 12.164516 4.6067420
71 4 SIMPLE MPI 11.587097 5.9713138
72 4 SIMPLE NOR 11.746452 5.7427232

```

```
> ddply(Millet, .(Time,Model,GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

```

Time Model GCM mean sd
1 1 AquaCrop ACC 20.79774 2.943440
2 1 AquaCrop CCS 21.68355 2.371753
3 1 AquaCrop CNR 14.15516 3.116281
4 1 AquaCrop GFD 21.38806 2.705516
5 1 AquaCrop MPI 21.40097 3.636423
6 1 AquaCrop NOR 21.66806 2.765260
7 1 DSSAT ACC 12.61516 1.866722
8 1 DSSAT CCS 12.25452 2.157226
9 1 DSSAT CNR 12.74871 2.052557

```

10	1	DSSAT	GFD	11.73935	1.785258
11	1	DSSAT	MPI	11.94452	2.473622
12	1	DSSAT	NOR	12.68710	2.205282
13	1	SIMPLE	ACC	14.08774	6.045935
14	1	SIMPLE	CCS	13.66419	5.302462
15	1	SIMPLE	CNR	12.94323	6.273292
16	1	SIMPLE	GFD	14.03419	5.417414
17	1	SIMPLE	MPI	12.71258	4.210243
18	1	SIMPLE	NOR	13.71548	5.697947
19	2	AquaCrop	ACC	21.81839	3.213902
20	2	AquaCrop	CCS	22.95677	2.600093
21	2	AquaCrop	CNR	14.98903	3.047330
22	2	AquaCrop	GFD	22.91419	2.660359
23	2	AquaCrop	MPI	22.96935	2.790613
24	2	AquaCrop	NOR	22.79548	2.706496
25	2	DSSAT	ACC	13.35258	1.762317
26	2	DSSAT	CCS	12.87452	1.923925
27	2	DSSAT	CNR	12.78806	1.666924
28	2	DSSAT	GFD	12.06581	2.283930
29	2	DSSAT	MPI	12.88742	2.156247
30	2	DSSAT	NOR	12.56097	2.203953
31	2	SIMPLE	ACC	14.01968	5.288142
32	2	SIMPLE	CCS	12.91548	5.000257
33	2	SIMPLE	CNR	14.83419	4.662449
34	2	SIMPLE	GFD	13.80903	4.825895
35	2	SIMPLE	MPI	13.10484	5.209843
36	2	SIMPLE	NOR	13.76065	5.069875
37	3	AquaCrop	ACC	23.40710	3.069102
38	3	AquaCrop	CCS	24.56355	2.306389
39	3	AquaCrop	CNR	15.12303	3.352300
40	3	AquaCrop	GFD	23.01161	3.220983
41	3	AquaCrop	MPI	24.11065	3.443235
42	3	AquaCrop	NOR	23.52548	2.996784
43	3	DSSAT	ACC	12.92548	1.937297
44	3	DSSAT	CCS	12.78323	1.971611
45	3	DSSAT	CNR	12.56226	2.155680
46	3	DSSAT	GFD	12.63355	2.286729
47	3	DSSAT	MPI	13.22935	1.896233
48	3	DSSAT	NOR	13.37742	1.925793
49	3	SIMPLE	ACC	13.40000	5.705744
50	3	SIMPLE	CCS	12.38355	4.160497
51	3	SIMPLE	CNR	12.90903	4.891545
52	3	SIMPLE	GFD	13.99097	5.683474
53	3	SIMPLE	MPI	12.42032	5.732686
54	3	SIMPLE	NOR	14.50742	4.856589
55	4	AquaCrop	ACC	24.13871	2.329008
56	4	AquaCrop	CCS	24.30774	2.768871
57	4	AquaCrop	CNR	14.91871	3.560576

```

58 4 AquaCrop GFD 24.83194 2.376348
59 4 AquaCrop MPI 24.40452 2.871808
60 4 AquaCrop NOR 24.34548 3.011879
61 4 DSSAT ACC 12.67645 1.702632
62 4 DSSAT CCS 12.55903 1.972934
63 4 DSSAT CNR 12.78968 2.224670
64 4 DSSAT GFD 12.09742 1.719426
65 4 DSSAT MPI 12.29548 2.415680
66 4 DSSAT NOR 12.61581 2.118162
67 4 SIMPLE ACC 14.45065 4.612543
68 4 SIMPLE CCS 12.86516 5.323003
69 4 SIMPLE CNR 12.12903 6.211507
70 4 SIMPLE GFD 11.93194 4.328314
71 4 SIMPLE MPI 12.53935 5.487112
72 4 SIMPLE NOR 14.11677 4.497123

```

```
> ddply(Sorghum, .(Time,Model,GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

```

  Time  Model GCM      mean      sd
1     1 AquaCrop ACC 14.351290 3.353701
2     1 AquaCrop CCS 14.169355 3.226773
3     1 AquaCrop CNR 14.155161 3.116281
4     1 AquaCrop GFD 20.795484 2.801855
5     1 AquaCrop MPI 13.281935 3.184135
6     1 AquaCrop NOR 14.580968 2.715039
7     1 DSSAT ACC 13.860000 2.227525
8     1 DSSAT CCS 13.198065 2.317370
9     1 DSSAT CNR 13.781613 2.429450
10    1 DSSAT GFD 12.753226 1.892225
11    1 DSSAT MPI 13.485161 2.919329
12    1 DSSAT NOR 14.028065 2.310891
13    1 SIMPLE ACC 10.923871 6.669920
14    1 SIMPLE CCS  9.143871 5.167456
15    1 SIMPLE CNR  9.358065 6.156090
16    1 SIMPLE GFD 10.541935 5.682291
17    1 SIMPLE MPI  9.380968 5.317844
18    1 SIMPLE NOR  9.736129 5.151369
19    2 AquaCrop ACC 15.640968 2.386915
20    2 AquaCrop CCS 15.440968 2.465523
21    2 AquaCrop CNR 14.989032 3.047330
22    2 AquaCrop GFD 22.634839 3.014977
23    2 AquaCrop MPI 15.569677 1.954254
24    2 AquaCrop NOR 14.464194 3.770387
25    2 DSSAT ACC 14.895806 2.033906
26    2 DSSAT CCS 14.505161 2.143231
27    2 DSSAT CNR 14.376452 2.049328
28    2 DSSAT GFD 13.298387 2.710749
29    2 DSSAT MPI 14.493226 2.546806
30    2 DSSAT NOR 14.589355 2.640341
31    2 SIMPLE ACC 11.691613 6.008859

```

```

32  2  SIMPLE CCS  9.833548 5.189521
33  2  SIMPLE CNR 10.647742 5.686596
34  2  SIMPLE GFD  9.571613 5.764476
35  2  SIMPLE MPI 10.690323 5.982714
36  2  SIMPLE NOR  9.748065 6.045344
37  3 AquaCrop ACC 15.911613 3.027833
38  3 AquaCrop CCS 15.073226 3.102647
39  3 AquaCrop CNR 15.123548 3.352070
40  3 AquaCrop GFD 21.981290 3.463350
41  3 AquaCrop MPI 15.411290 3.442497
42  3 AquaCrop NOR 15.490645 2.687444
43  3   DSSAT ACC 14.686129 2.142777
44  3   DSSAT CCS 14.100645 2.112455
45  3   DSSAT CNR 14.309032 2.186180
46  3   DSSAT GFD 14.250323 1.847361
47  3   DSSAT MPI 14.435806 2.428984
48  3   DSSAT NOR 14.907742 2.007374
49  3  SIMPLE ACC 11.578065 6.577425
50  3  SIMPLE CCS  9.440000 4.891997
51  3  SIMPLE CNR  8.459677 5.177020
52  3  SIMPLE GFD 11.733548 6.266377
53  3  SIMPLE MPI 10.098710 6.248491
54  3  SIMPLE NOR 11.252258 6.166734
55  4 AquaCrop ACC 16.420323 2.518430
56  4 AquaCrop CCS 14.741290 3.594164
57  4 AquaCrop CNR 14.918710 3.560576
58  4 AquaCrop GFD 18.986452 5.401438
59  4 AquaCrop MPI 15.266452 3.626640
60  4 AquaCrop NOR 15.458710 3.719830
61  4   DSSAT ACC 13.974839 1.975429
62  4   DSSAT CCS 13.449355 2.407160
63  4   DSSAT CNR 14.036129 2.394797
64  4   DSSAT GFD 13.117742 1.788869
65  4   DSSAT MPI 13.933548 2.563719
66  4   DSSAT NOR 13.941290 2.309243
67  4  SIMPLE ACC 11.881935 4.359285
68  4  SIMPLE CCS 11.357097 5.440650
69  4  SIMPLE CNR  9.514839 5.946394
70  4  SIMPLE GFD 10.784194 4.818221
71  4  SIMPLE MPI 10.936129 5.935966
72  4  SIMPLE NOR 10.714194 5.461020
> ddpIy(Maize, .(Time), summarise, mean=mean(WU), sd=sd(WU))
  Time    mean    sd
1     1 418.7115 70.84783
2     2 421.9086 72.77868
3     3 421.8674 65.68061
4     4 420.3530 64.64105
> ddpIy(Millet, .(Time), summarise, mean=mean(WU), sd=sd(WU))

```

```

Time      mean      sd
1      1 414.6326 55.65929
2      2 422.0412 53.78650
3      3 414.4749 46.83086
4      4 408.4283 51.97649
> ddply(Sorghum, .(Time), summarise, mean=mean(WU), sd=sd(WU))
Time      mean      sd
1      1 483.0323 59.33651
2      2 489.4516 59.99955
3      3 486.2545 54.48999
4      4 486.4247 53.09878
> ddply(Maize, .(Model), summarise, mean=mean(WU), sd=sd(WU))
Model      mean      sd
1 AquaCrop 405.9624 17.43170
2  DSSAT 417.7460 107.71790
3  SIMPLE 438.4220 40.71292
> ddply(Millet, .(Model), summarise, mean=mean(WU), sd=sd(WU))
Model      mean      sd
1 AquaCrop 413.6398 36.10213
2  DSSAT 406.4126 66.38193
3  SIMPLE 424.6304 48.49791
> ddply(Sorghum, .(Model), summarise, mean=mean(WU), sd=sd(WU))
Model      mean      sd
1 AquaCrop 472.1962 35.75303
2  DSSAT 500.0242 76.74009
3  SIMPLE 486.6519 46.23817
> ddply(Maize, .(GCM), summarise, mean=mean(WU), sd=sd(WU))
GCM      mean      sd
1 ACC 440.8844 53.71212
2 CCS 431.5081 49.98121
3 CNR 433.9651 52.62712
4 GFD 429.1828 49.63189
5 MPI 434.1882 50.55660
6 NOR 354.5323 98.64039
> ddply(Millet, .(GCM), summarise, mean=mean(WU), sd=sd(WU))
GCM      mean      sd
1 ACC 416.8011 48.71860
2 CCS 404.5054 45.35012
3 CNR 445.7849 54.77365
4 GFD 403.5941 50.83623
5 MPI 405.2876 52.43711
6 NOR 413.3925 49.26885
> ddply(Sorghum, .(GCM), summarise, mean=mean(WU), sd=sd(WU))
GCM      mean      sd
1 ACC 499.3038 53.06454
2 CCS 486.1237 50.03364
3 CNR 491.6532 54.03773
4 GFD 459.7124 64.57921

```

5 MPI 490.8602 54.08506

6 NOR 490.0914 55.99275

```
> ddply(Maize, .(Time,Model,GCM), summarise, mean=mean(WU), sd=sd(WU))
```

	Time	Model	GCM	mean	sd
1	1	AquaCrop	ACC	391.7097	9.111142
2	1	AquaCrop	CCS	391.3226	8.009940
3	1	AquaCrop	CNR	391.2258	9.379800
4	1	AquaCrop	GFD	389.7742	8.712863
5	1	AquaCrop	MPI	391.2903	9.747456
6	1	AquaCrop	NOR	389.5806	10.414010
7	1	DSSAT	ACC	464.1935	66.016371
8	1	DSSAT	CCS	439.9355	73.773498
9	1	DSSAT	CNR	457.5806	78.086181
10	1	DSSAT	GFD	430.0645	64.652886
11	1	DSSAT	MPI	448.0323	67.390644
12	1	DSSAT	NOR	227.1613	48.054897
13	1	SIMPLE	ACC	458.8710	49.120085
14	1	SIMPLE	CCS	450.8710	35.717169
15	1	SIMPLE	CNR	451.1613	41.332067
16	1	SIMPLE	GFD	459.0000	42.354850
17	1	SIMPLE	MPI	451.6129	36.314990
18	1	SIMPLE	NOR	453.4194	38.055025
19	2	AquaCrop	ACC	393.1935	10.140412
20	2	AquaCrop	CCS	399.7419	8.115696
21	2	AquaCrop	CNR	396.8710	9.218611
22	2	AquaCrop	GFD	399.2903	8.881417
23	2	AquaCrop	MPI	399.7419	10.152070
24	2	AquaCrop	NOR	392.8710	8.597449
25	2	DSSAT	ACC	482.3871	71.038805
26	2	DSSAT	CCS	477.8710	63.992573
27	2	DSSAT	CNR	454.4839	72.297474
28	2	DSSAT	GFD	441.0968	71.802672
29	2	DSSAT	MPI	471.9355	70.226270
30	2	DSSAT	NOR	219.0645	44.127796
31	2	SIMPLE	ACC	458.9355	40.271525
32	2	SIMPLE	CCS	446.4516	36.811990
33	2	SIMPLE	CNR	441.9032	43.735077
34	2	SIMPLE	GFD	430.5161	41.500900
35	2	SIMPLE	MPI	449.6774	40.282657
36	2	SIMPLE	NOR	438.3226	45.608031
37	3	AquaCrop	ACC	409.3226	9.403500
38	3	AquaCrop	CCS	405.7097	8.038215
39	3	AquaCrop	CNR	408.1935	10.508471
40	3	AquaCrop	GFD	413.6129	9.035771
41	3	AquaCrop	MPI	408.6452	12.103852
42	3	AquaCrop	NOR	404.5484	7.311355
43	3	DSSAT	ACC	478.4194	71.995266
44	3	DSSAT	CCS	454.2258	62.369175

```

45 3 DSSAT CNR 448.4516 61.055624
46 3 DSSAT GFD 469.2258 73.571149
47 3 DSSAT MPI 460.2581 65.309503
48 3 DSSAT NOR 234.1935 36.022603
49 3 SIMPLE ACC 439.1613 38.106952
50 3 SIMPLE CCS 426.6129 33.937862
51 3 SIMPLE CNR 424.1613 38.963313
52 3 SIMPLE GFD 432.8065 38.100236
53 3 SIMPLE MPI 441.6129 34.314892
54 3 SIMPLE NOR 434.4516 38.144321
55 4 AquaCrop ACC 428.8387 11.045653
56 4 AquaCrop CCS 425.7742 8.624421
57 4 AquaCrop CNR 424.1613 10.921223
58 4 AquaCrop GFD 440.6774 11.288304
59 4 AquaCrop MPI 429.3871 11.937832
60 4 AquaCrop NOR 417.6129 7.723028
61 4 DSSAT ACC 459.5484 58.026338
62 4 DSSAT CCS 442.6129 70.942548
63 4 DSSAT CNR 457.0968 73.411786
64 4 DSSAT GFD 436.1935 58.545947
65 4 DSSAT MPI 447.9032 66.662011
66 4 DSSAT NOR 223.9677 45.149739
67 4 SIMPLE ACC 426.0323 27.428068
68 4 SIMPLE CCS 416.9677 33.639742
69 4 SIMPLE CNR 452.2903 39.678872
70 4 SIMPLE GFD 407.9355 28.008255
71 4 SIMPLE MPI 410.1613 34.820585
72 4 SIMPLE NOR 419.1935 37.197150

```

```
> ddply(Millet, .(Time,Model,GCM), summarise, mean=mean(WU), sd=sd(WU))
```

```

Time Model GCM mean sd
1 1 AquaCrop ACC 386.4516 11.601261
2 1 AquaCrop CCS 385.7419 7.818643
3 1 AquaCrop CNR 467.1613 10.779910
4 1 AquaCrop GFD 388.4194 22.842613
5 1 AquaCrop MPI 383.5484 10.984349
6 1 AquaCrop NOR 385.1613 9.077800
7 1 DSSAT ACC 411.4839 56.613821
8 1 DSSAT CCS 377.7742 54.599579
9 1 DSSAT CNR 415.9677 62.918722
10 1 DSSAT GFD 370.0000 54.051210
11 1 DSSAT MPI 382.2258 73.573867
12 1 DSSAT NOR 408.0323 67.538376
13 1 SIMPLE ACC 459.5161 53.531842
14 1 SIMPLE CCS 447.6129 45.172763
15 1 SIMPLE CNR 445.8710 55.061022
16 1 SIMPLE GFD 452.6129 54.906392
17 1 SIMPLE MPI 443.6774 33.473758
18 1 SIMPLE NOR 452.1290 39.919704

```

19	2	AquaCrop	ACC	386.5806	10.019229
20	2	AquaCrop	CCS	392.9032	9.554597
21	2	AquaCrop	CNR	472.2581	11.427942
22	2	AquaCrop	GFD	391.6774	10.100782
23	2	AquaCrop	MPI	391.8710	11.546260
24	2	AquaCrop	NOR	386.1613	10.705440
25	2	DSSAT	ACC	445.4839	70.174483
26	2	DSSAT	CCS	422.5484	73.286124
27	2	DSSAT	CNR	438.4839	64.019721
28	2	DSSAT	GFD	408.8387	70.771980
29	2	DSSAT	MPI	416.4194	73.931849
30	2	DSSAT	NOR	427.6129	75.811906
31	2	SIMPLE	ACC	440.4516	47.431943
32	2	SIMPLE	CCS	428.8387	40.769349
33	2	SIMPLE	CNR	445.3871	46.560124
34	2	SIMPLE	GFD	431.4516	43.552909
35	2	SIMPLE	MPI	432.2581	43.676056
36	2	SIMPLE	NOR	437.5161	45.104228
37	3	AquaCrop	ACC	402.9355	8.294317
38	3	AquaCrop	CCS	401.4194	9.204253
39	3	AquaCrop	CNR	487.2903	11.773398
40	3	AquaCrop	GFD	406.9032	9.064049
41	3	AquaCrop	MPI	402.8387	13.515662
42	3	AquaCrop	NOR	396.9677	7.503261
43	3	DSSAT	ACC	419.4516	63.122547
44	3	DSSAT	CCS	403.7742	49.953118
45	3	DSSAT	CNR	411.7742	56.999245
46	3	DSSAT	GFD	409.9355	68.737149
47	3	DSSAT	MPI	409.5484	72.276708
48	3	DSSAT	NOR	430.2258	56.644923
49	3	SIMPLE	ACC	420.3226	46.173143
50	3	SIMPLE	CCS	405.9032	33.056875
51	3	SIMPLE	CNR	407.4516	37.700432
52	3	SIMPLE	GFD	410.6129	42.135241
53	3	SIMPLE	MPI	409.9032	48.111229
54	3	SIMPLE	NOR	423.2903	37.967700
55	4	AquaCrop	ACC	421.8710	10.032421
56	4	AquaCrop	CCS	421.3871	10.236137
57	4	AquaCrop	CNR	506.5806	11.831523
58	4	AquaCrop	GFD	431.0645	11.713057
59	4	AquaCrop	MPI	420.2581	12.449813
60	4	AquaCrop	NOR	409.9032	8.780109
61	4	DSSAT	ACC	407.8065	52.927258
62	4	DSSAT	CCS	378.5484	52.944524
63	4	DSSAT	CNR	410.4194	65.406816
64	4	DSSAT	GFD	365.7419	50.467130
65	4	DSSAT	MPI	382.0645	72.603460
66	4	DSSAT	NOR	399.7419	66.729787

```

67 4 SIMPLE ACC 399.2581 29.999964
68 4 SIMPLE CCS 387.6129 35.187761
69 4 SIMPLE CNR 440.7742 50.690374
70 4 SIMPLE GFD 375.8710 34.712862
71 4 SIMPLE MPI 388.8387 44.197358
72 4 SIMPLE NOR 403.9677 41.215275
> ddpIy(Sorghum, .(Time,Model,GCM), summarise, mean=mean(WU), sd=sd(WU))
  Time  Model GCM  mean  sd
1     1 AquaCrop ACC 467.8710 10.512665
2     1 AquaCrop CCS 466.5161  8.632771
3     1 AquaCrop CNR 467.1613 10.779910
4     1 AquaCrop GFD 387.9677 14.654883
5     1 AquaCrop MPI 467.2903 10.558389
6     1 AquaCrop NOR 464.8710 11.485475
7     1  DSSAT ACC 511.2581 68.412459
8     1  DSSAT CCS 474.4516 78.011896
9     1  DSSAT CNR 502.1935 83.240383
10    1  DSSAT GFD 464.5484 70.057043
11    1  DSSAT MPI 490.2581 72.840450
12    1  DSSAT NOR 501.4516 88.982335
13    1 SIMPLE ACC 511.8065 54.774337
14    1 SIMPLE CCS 501.9677 38.245247
15    1 SIMPLE CNR 501.2581 50.660285
16    1 SIMPLE GFD 507.4194 48.613972
17    1 SIMPLE MPI 502.0645 43.569053
18    1 SIMPLE NOR 504.2258 41.463003
19    2 AquaCrop ACC 470.0000 11.153475
20    2 AquaCrop CCS 476.0000  9.110434
21    2 AquaCrop CNR 472.2581 11.427942
22    2 AquaCrop GFD 393.2581  9.172305
23    2 AquaCrop MPI 476.4839 11.503249
24    2 AquaCrop NOR 468.4516 10.417417
25    2  DSSAT ACC 533.0968 76.634350
26    2  DSSAT CCS 525.9677 69.825250
27    2  DSSAT CNR 502.9355 79.043842
28    2  DSSAT GFD 488.5484 76.435523
29    2  DSSAT MPI 515.4516 85.149218
30    2  DSSAT NOR 518.8387 80.089990
31    2 SIMPLE ACC 508.9032 48.018993
32    2 SIMPLE CCS 496.5161 39.115104
33    2 SIMPLE CNR 493.2258 49.771953
34    2 SIMPLE GFD 479.3871 46.448306
35    2 SIMPLE MPI 498.7742 44.526928
36    2 SIMPLE NOR 492.0323 48.582908
37    3 AquaCrop ACC 487.8387 10.421442
38    3 AquaCrop CCS 484.2258  8.636009
39    3 AquaCrop CNR 487.2903 11.773398
40    3 AquaCrop GFD 408.8710  9.646215

```

```

41  3 AquaCrop MPI 487.8710 14.219100
42  3 AquaCrop NOR 481.1613  7.874418
43  3   DSSAT ACC 522.4516 82.033667
44  3   DSSAT CCS 490.1613 65.816460
45  3   DSSAT CNR 492.9677 69.944018
46  3   DSSAT GFD 510.3548 77.640431
47  3   DSSAT MPI 509.0968 79.897165
48  3   DSSAT NOR 515.4839 72.893013
49  3  SIMPLE ACC 485.7742 45.579754
50  3  SIMPLE CCS 470.2258 35.533749
51  3  SIMPLE CNR 473.0000 39.734116
52  3  SIMPLE GFD 478.8710 44.913800
53  3  SIMPLE MPI 484.9355 43.454908
54  3  SIMPLE NOR 482.0000 41.922945
55  4 AquaCrop ACC 512.4839 12.824120
56  4 AquaCrop CCS 509.0000  9.715966
57  4 AquaCrop CNR 506.5806 11.831523
58  4 AquaCrop GFD 477.9677 54.869229
59  4 AquaCrop MPI 512.2258 14.800247
60  4 AquaCrop NOR 499.0645  9.646884
61  4   DSSAT ACC 506.2903 59.337000
62  4   DSSAT CCS 478.2903 74.828779
63  4   DSSAT CNR 498.1613 80.525398
64  4   DSSAT GFD 468.5806 63.716965
65  4   DSSAT MPI 490.0323 71.863984
66  4   DSSAT NOR 489.7097 85.667261
67  4  SIMPLE ACC 473.8710 29.289067
68  4  SIMPLE CCS 460.1613 35.298817
69  4  SIMPLE CNR 502.8065 47.686070
70  4  SIMPLE GFD 450.7742 32.709540
71  4  SIMPLE MPI 455.8387 43.591358
72  4  SIMPLE NOR 463.8065 40.029505

> ddply(Maize, .(Time), summarise, mean=mean(WP), sd=sd(WP))
  Time    mean    sd
1    1 14.18568 6.219178
2    2 14.62007 6.302498
3    3 14.99504 6.112482
4    4 14.83219 5.749920

> ddply(Millet, .(Time), summarise, mean=mean(WP), sd=sd(WP))
  Time    mean    sd
1    1 10.56389 5.001023
2    2 10.89919 5.322861
3    3 10.98394 5.409551
4    4 11.07179 5.184395

> ddply(Sorghum, .(Time), summarise, mean=mean(WP), sd=sd(WP))
  Time    mean    sd
1    1  9.080735 3.729492
2    2  9.618100 3.856373

```

```

3   3 9.668351 3.830881
4   4 9.455179 3.632758
> ddply(Maize, .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 20.555228 1.740672
2   DSSAT 13.432164 5.354066
3   SIMPLE  9.987339 4.687769
> ddply(Millet, .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 16.817056 3.746628
2   DSSAT  6.570484 1.567388
3   SIMPLE  9.251573 3.024096
> ddply(Sorghum, .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 11.360860 3.465554
2   DSSAT  7.708051 1.739585
3   SIMPLE  9.297863 4.569048
> ddply(Maize, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM      mean      sd
1 ACC 14.44645 5.430196
2 CCS 13.97333 5.687684
3 CNR 13.73409 5.919203
4 GFD 13.70970 5.562188
5 MPI 14.04132 5.645951
6 NOR 18.04457 7.081540
> ddply(Millet, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM      mean      sd
1 ACC 11.291559 5.280228
2 CCS 11.392930 5.536306
3 CNR  8.493038 2.907681
4 GFD 11.281747 5.350092
5 MPI 11.300833 5.526628
6 NOR 11.518118 5.616839
> ddply(Sorghum, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM      mean      sd
1 ACC  9.495753 3.386220
2 CCS  8.983817 3.253271
3 CNR  8.761801 3.241186
4 GFD 11.150914 5.149416
5 MPI  9.029516 3.380306
6 NOR  9.311747 3.329396
> ddply(Maize, .(Time,Model,GCM), summarise, mean=mean(WP), sd=sd(WP))
  Time  Model GCM      mean      sd
1     1 AquaCrop ACC 20.226129 1.5656579
2     1 AquaCrop CCS 20.436452 1.3012009
3     1 AquaCrop CNR 20.246774 1.3725946
4     1 AquaCrop GFD 20.417097 1.4294875
5     1 AquaCrop MPI 19.965484 1.6012700

```

6	1	AquaCrop	NOR	20.373548	1.9834911
7	1	DSSAT	ACC	11.542903	1.7962761
8	1	DSSAT	CCS	11.482258	2.1717746
9	1	DSSAT	CNR	11.565161	2.6201080
10	1	DSSAT	GFD	9.993226	2.4551136
11	1	DSSAT	MPI	11.305484	2.6154475
12	1	DSSAT	NOR	23.653226	3.9719948
13	1	SIMPLE	ACC	9.750645	5.0157113
14	1	SIMPLE	CCS	8.563871	4.3155677
15	1	SIMPLE	CNR	8.600323	5.0210839
16	1	SIMPLE	GFD	9.592581	4.4073015
17	1	SIMPLE	MPI	8.598065	4.2374642
18	1	SIMPLE	NOR	9.029032	3.9367172
19	2	AquaCrop	ACC	21.340968	0.7571013
20	2	AquaCrop	CCS	20.800645	1.5423898
21	2	AquaCrop	CNR	20.896774	1.4082125
22	2	AquaCrop	GFD	20.560000	1.8231420
23	2	AquaCrop	MPI	21.018710	0.9590125
24	2	AquaCrop	NOR	20.737419	2.8163901
25	2	DSSAT	ACC	11.495806	2.0897763
26	2	DSSAT	CCS	11.189677	2.5013949
27	2	DSSAT	CNR	11.725484	2.0898514
28	2	DSSAT	GFD	10.552903	2.5067192
29	2	DSSAT	MPI	11.659677	2.5275119
30	2	DSSAT	NOR	23.457419	5.0702833
31	2	SIMPLE	ACC	10.619677	4.4472460
32	2	SIMPLE	CCS	9.169355	4.0752570
33	2	SIMPLE	CNR	9.682258	4.7565756
34	2	SIMPLE	GFD	9.266129	4.7827347
35	2	SIMPLE	MPI	10.088710	4.6446943
36	2	SIMPLE	NOR	8.899677	4.9417638
37	3	AquaCrop	ACC	21.080645	1.1311114
38	3	AquaCrop	CCS	21.095806	1.1140161
39	3	AquaCrop	CNR	21.042258	0.9501253
40	3	AquaCrop	GFD	20.875484	0.8971653
41	3	AquaCrop	MPI	20.665806	2.0641750
42	3	AquaCrop	NOR	21.088710	1.1762135
43	3	DSSAT	ACC	12.183871	2.4600023
44	3	DSSAT	CCS	11.440000	2.1753482
45	3	DSSAT	CNR	11.867097	2.2439388
46	3	DSSAT	GFD	11.072258	2.1987886
47	3	DSSAT	MPI	11.965806	2.6447631
48	3	DSSAT	NOR	23.995806	3.8903803
49	3	SIMPLE	ACC	11.373226	4.8222079
50	3	SIMPLE	CCS	9.855161	4.5471499
51	3	SIMPLE	CNR	8.165161	4.2791455
52	3	SIMPLE	GFD	11.343226	4.8994200
53	3	SIMPLE	MPI	10.131290	4.6497281

```

54 3 SIMPLE NOR 10.669032 4.9267368
55 4 AquaCrop ACC 20.713226 0.7562204
56 4 AquaCrop CCS 19.974194 3.1619032
57 4 AquaCrop CNR 20.214516 1.2941480
58 4 AquaCrop GFD 18.883871 1.9302412
59 4 AquaCrop MPI 20.401935 1.1589691
60 4 AquaCrop NOR 20.269032 3.1184166
61 4 DSSAT ACC 11.506774 1.8973058
62 4 DSSAT CCS 11.471290 2.6496462
63 4 DSSAT CNR 11.846129 2.5766382
64 4 DSSAT GFD 10.214839 2.3435555
65 4 DSSAT MPI 11.734839 2.6104417
66 4 DSSAT NOR 23.450000 4.2029736
67 4 SIMPLE ACC 11.523548 4.0267510
68 4 SIMPLE CCS 12.201290 4.7725261
69 4 SIMPLE CNR 8.957097 5.1207781
70 4 SIMPLE GFD 11.744839 3.9976050
71 4 SIMPLE MPI 10.960000 5.2245127
72 4 SIMPLE NOR 10.911935 4.7084140
> ddpIy(Millet, .(Time,Model,GCM), summarise, mean=mean(WP), sd=sd(WP))
  Time  Model GCM      mean      sd
1     1 AquaCrop ACC 16.870000 2.280820
2     1 AquaCrop CCS 17.809677 1.832797
3     1 AquaCrop CNR  9.935484 2.519092
4     1 AquaCrop GFD 17.410968 2.327256
5     1 AquaCrop MPI 17.620000 2.971887
6     1 AquaCrop NOR 17.695161 2.138577
7     1 DSSAT ACC  6.672903 1.331911
8     1 DSSAT CCS  6.710645 1.371763
9     1 DSSAT CNR  6.750645 1.262680
10    1 DSSAT GFD  6.834839 1.794846
11    1 DSSAT MPI  6.730000 2.005024
12    1 DSSAT NOR  6.455484 1.305125
13    1 SIMPLE ACC  8.900645 3.118952
14    1 SIMPLE CCS  8.930000 3.004504
15    1 SIMPLE CNR  8.470968 3.601368
16    1 SIMPLE GFD  8.978710 2.842998
17    1 SIMPLE MPI  8.482903 2.276572
18    1 SIMPLE NOR  8.890968 3.182417
19    2 AquaCrop ACC 17.854194 2.412108
20    2 AquaCrop CCS 18.421935 1.952065
21    2 AquaCrop CNR 10.590323 2.472421
22    2 AquaCrop GFD 18.445806 1.988248
23    2 AquaCrop MPI 18.519355 2.001289
24    2 AquaCrop NOR 18.788387 2.163500
25    2 DSSAT ACC  6.691935 1.546886
26    2 DSSAT CCS  6.590323 1.109806
27    2 DSSAT CNR  6.340645 1.541685

```

28	2	DSSAT	GFD	5.891290	1.611804
29	2	DSSAT	MPI	6.421290	1.514018
30	2	DSSAT	NOR	6.153226	1.668461
31	2	SIMPLE	ACC	9.303548	2.784162
32	2	SIMPLE	CCS	8.834194	2.879815
33	2	SIMPLE	CNR	9.816452	2.489673
34	2	SIMPLE	GFD	9.405806	2.593709
35	2	SIMPLE	MPI	8.893226	2.948383
36	2	SIMPLE	NOR	9.223548	2.850895
37	3	AquaCrop	ACC	18.092581	2.138375
38	3	AquaCrop	CCS	19.398710	1.804330
39	3	AquaCrop	CNR	10.244194	2.451486
40	3	AquaCrop	GFD	17.680645	2.267787
41	3	AquaCrop	MPI	18.561613	2.384046
42	3	AquaCrop	NOR	18.806452	2.296485
43	3	DSSAT	ACC	6.103226	1.316901
44	3	DSSAT	CCS	6.378387	1.624742
45	3	DSSAT	CNR	6.244194	1.785721
46	3	DSSAT	GFD	6.160000	1.330839
47	3	DSSAT	MPI	6.904516	1.624943
48	3	DSSAT	NOR	6.653226	1.810859
49	3	SIMPLE	ACC	9.282581	3.301032
50	3	SIMPLE	CCS	9.017419	2.504883
51	3	SIMPLE	CNR	9.316774	2.959156
52	3	SIMPLE	GFD	9.951935	3.450485
53	3	SIMPLE	MPI	8.802581	3.230342
54	3	SIMPLE	NOR	10.111935	2.822851
55	4	AquaCrop	ACC	18.218387	1.776133
56	4	AquaCrop	CCS	17.983226	2.102031
57	4	AquaCrop	CNR	9.596452	2.403753
58	4	AquaCrop	GFD	18.099355	1.601630
59	4	AquaCrop	MPI	18.218065	1.828722
60	4	AquaCrop	NOR	18.748387	2.206149
61	4	DSSAT	ACC	6.792581	1.351730
62	4	DSSAT	CCS	6.895806	1.648959
63	4	DSSAT	CNR	6.677419	1.510146
64	4	DSSAT	GFD	7.187097	1.696361
65	4	DSSAT	MPI	7.071290	1.723618
66	4	DSSAT	NOR	6.380645	1.608376
67	4	SIMPLE	ACC	10.716129	2.960461
68	4	SIMPLE	CCS	9.744839	3.519130
69	4	SIMPLE	CNR	7.932903	3.525489
70	4	SIMPLE	GFD	9.334516	2.787048
71	4	SIMPLE	MPI	9.385161	3.392722
72	4	SIMPLE	NOR	10.310000	2.673274

```
> ddply(Sorghum, .(Time,Model,GCM), summarise, mean=mean(WP), sd=sd(WP))
```

	Time	Model	GCM	mean	sd
1	1	AquaCrop	ACC	10.270000	2.807413

2	1	AquaCrop	CCS	10.214839	2.621590
3	1	AquaCrop	CNR	9.935484	2.519092
4	1	AquaCrop	GFD	16.994516	2.336451
5	1	AquaCrop	MPI	9.360000	2.508051
6	1	AquaCrop	NOR	10.633548	2.248645
7	1	DSSAT	ACC	7.464194	1.408682
8	1	DSSAT	CCS	7.489032	2.059539
9	1	DSSAT	CNR	7.377097	1.138257
10	1	DSSAT	GFD	7.214839	1.346167
11	1	DSSAT	MPI	7.685806	1.913983
12	1	DSSAT	NOR	8.077097	1.659215
13	1	SIMPLE	ACC	9.173548	5.004966
14	1	SIMPLE	CCS	7.949355	4.069454
15	1	SIMPLE	CNR	8.006129	4.800609
16	1	SIMPLE	GFD	9.029032	4.314306
17	1	SIMPLE	MPI	8.153226	4.104459
18	1	SIMPLE	NOR	8.425484	3.848884
19	2	AquaCrop	ACC	11.125161	1.734518
20	2	AquaCrop	CCS	10.703871	2.066451
21	2	AquaCrop	CNR	10.590323	2.472421
22	2	AquaCrop	GFD	18.170000	2.339813
23	2	AquaCrop	MPI	11.056129	1.359288
24	2	AquaCrop	NOR	10.499032	2.938501
25	2	DSSAT	ACC	7.543871	1.734915
26	2	DSSAT	CCS	7.676129	1.732651
27	2	DSSAT	CNR	8.050323	2.160789
28	2	DSSAT	GFD	7.458065	1.356179
29	2	DSSAT	MPI	7.552581	1.564314
30	2	DSSAT	NOR	8.197742	2.405675
31	2	SIMPLE	ACC	9.993871	4.428917
32	2	SIMPLE	CCS	8.663226	4.083736
33	2	SIMPLE	CNR	9.340968	4.394035
34	2	SIMPLE	GFD	8.630645	4.468946
35	2	SIMPLE	MPI	9.331613	4.565330
36	2	SIMPLE	NOR	8.542258	4.570885
37	3	AquaCrop	ACC	10.860968	2.176011
38	3	AquaCrop	CCS	10.427419	2.055260
39	3	AquaCrop	CNR	10.244194	2.451486
40	3	AquaCrop	GFD	16.988065	2.806778
41	3	AquaCrop	MPI	10.402258	2.726966
42	3	AquaCrop	NOR	10.600645	2.014151
43	3	DSSAT	ACC	7.894194	1.857900
44	3	DSSAT	CCS	7.780000	1.925149
45	3	DSSAT	CNR	8.507097	1.804631
46	3	DSSAT	GFD	7.764839	1.686798
47	3	DSSAT	MPI	7.614194	1.579373
48	3	DSSAT	NOR	8.233226	1.987973
49	3	SIMPLE	ACC	10.314839	5.179880

50	3	SIMPLE	CCS	8.794194	4.074766
51	3	SIMPLE	CNR	7.793226	4.065811
52	3	SIMPLE	GFD	10.617419	5.037151
53	3	SIMPLE	MPI	9.020000	4.901923
54	3	SIMPLE	NOR	10.173548	4.978994
55	4	AquaCrop	ACC	10.736129	1.856220
56	4	AquaCrop	CCS	9.694839	2.613981
57	4	AquaCrop	CNR	9.596452	2.403753
58	4	AquaCrop	GFD	13.290323	4.764874
59	4	AquaCrop	MPI	10.014839	2.582839
60	4	AquaCrop	NOR	10.251613	2.858907
61	4	DSSAT	ACC	7.425806	1.438082
62	4	DSSAT	CCS	7.560968	2.097531
63	4	DSSAT	CNR	7.538387	1.305001
64	4	DSSAT	GFD	7.120323	1.154136
65	4	DSSAT	MPI	7.757097	1.856490
66	4	DSSAT	NOR	8.010323	1.759696
67	4	SIMPLE	ACC	11.146452	3.832794
68	4	SIMPLE	CCS	10.851935	4.865764
69	4	SIMPLE	CNR	8.161935	4.647080
70	4	SIMPLE	GFD	10.532903	4.224289
71	4	SIMPLE	MPI	10.406452	5.222623
72	4	SIMPLE	NOR	10.096452	4.532898

### 8.3 Analysis of results for chapter 5

```
> ddply(Maize, .(Year), summarise, mean=mean(Yield), sd=sd(Yield))
```

	Year	mean	sd
1	2030	7.058367	1.769739
2	2031	7.125300	1.767238
3	2032	6.682167	2.087393
4	2033	7.340089	1.685475
5	2034	7.357456	1.673307
6	2035	7.237033	1.742881
7	2036	7.548056	1.462008
8	2037	7.167133	2.001215
9	2038	7.103133	1.917348
10	2039	7.331011	1.426433
11	2040	6.912822	1.954871
12	2041	6.865444	2.237818
13	2042	6.982044	2.067407
14	2043	7.309278	1.662117
15	2044	7.294367	1.430938
16	2045	7.085911	1.882333
17	2046	7.330967	1.747947

```

18 2047 7.254267 1.621922
19 2048 7.065433 1.962206
20 2049 6.986167 2.047042
21 2050 6.880667 1.922644
22 2051 7.360111 1.845023
23 2052 7.485856 1.675329
24 2053 6.500278 2.204681
25 2054 6.920667 2.082100
26 2055 7.136011 1.875157
27 2056 7.683033 1.361181
28 2057 7.032189 1.797498
29 2058 6.658067 2.206945
30 2059 7.086956 1.747491
31 2060 6.918556 1.974071
> ddply(Millet, .(Year), summarise, mean=mean(Yield), sd=sd(Yield))
  Year    mean    sd
1  2030 4.950644 1.695893
2  2031 4.884867 1.737472
3  2032 4.673789 1.829091
4  2033 4.865378 1.686742
5  2034 4.894722 1.741457
6  2035 4.975322 1.731026
7  2036 4.874711 1.550186
8  2037 4.891833 1.682188
9  2038 4.787756 1.776233
10 2039 5.038689 1.484072
11 2040 4.692200 1.901707
12 2041 4.824533 1.867880
13 2042 4.766200 1.879068
14 2043 4.881989 1.607453
15 2044 4.876356 1.658228
16 2045 4.917389 1.735695
17 2046 4.869989 1.630679
18 2047 4.827278 1.696109
19 2048 4.590356 1.894970
20 2049 4.878100 1.753855
21 2050 4.939667 1.635927
22 2051 4.979167 1.557681
23 2052 4.906144 1.680282
24 2053 4.858889 1.866533
25 2054 4.778933 1.865134
26 2055 4.867267 1.780748
27 2056 4.795522 1.568628
28 2057 4.855389 1.661201
29 2058 4.737211 1.973340
30 2059 4.840267 1.784413
31 2060 4.766122 1.946861
> ddply(Sorghum, .(Year), summarise, mean=mean(Yield), sd=sd(Yield))

```

```

      Year      mean      sd
1  2030  5.526756  1.990221
2  2031  5.674711  2.225306
3  2032  5.179522  1.988702
4  2033  5.739544  2.034820
5  2034  5.779744  1.955392
6  2035  5.831300  1.925857
7  2036  6.111633  2.183346
8  2037  5.898489  2.294831
9  2038  5.746889  2.243890
10 2039  5.788033  2.018406
11 2040  5.355011  1.757885
12 2041  5.605133  2.284300
13 2042  5.432911  2.200514
14 2043  5.884667  2.041535
15 2044  5.770967  1.857441
16 2045  5.608122  2.058855
17 2046  5.840533  2.254727
18 2047  5.780422  2.027947
19 2048  5.638067  2.132625
20 2049  5.737589  2.144566
21 2050  5.481856  1.915069
22 2051  6.112967  2.266587
23 2052  6.096356  2.130353
24 2053  5.183422  1.958819
25 2054  5.380867  2.278302
26 2055  5.827256  2.063726
27 2056  6.147633  2.192907
28 2057  5.499578  1.875602
29 2058  5.126756  2.155111
30 2059  5.690678  1.902414
31 2060  5.324700  1.941723
> ddply(Maize, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
      Model      mean      sd
1 AquaCrop  8.572652  0.5784727
2   DSSAT  6.163475  1.0564970
3   SIMPLE  6.621825  2.3694176
> ddply(Millet, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
      Model      mean      sd
1 AquaCrop  6.098137  1.251866
2   DSSAT  3.070694  0.629228
3   SIMPLE  5.375042  1.437696
> ddply(Sorghum, .(Model), summarise, mean=mean(Yield), sd=sd(Yield))
      Model      mean      sd
1 AquaCrop  5.711232  0.7750179
2   DSSAT  4.153368  0.6149682
3   SIMPLE  7.148508  2.7546369
> ddply(Maize, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))

```

```

      GCM      mean      sd
1 ACC 7.258445 1.765399
2 CCS 7.069153 1.885967
3 CNR 6.950166 1.994739
4 GFD 7.158942 1.860993
5 MPI 7.157247 1.822369
6 NOR 7.121951 1.793167
> ddply(Millet, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))
      GCM      mean      sd
1 ACC 4.837983 1.792750
2 CCS 4.925832 1.759852
3 CNR 4.692720 1.637306
4 GFD 4.797729 1.748250
5 MPI 4.862531 1.790340
6 NOR 4.970948 1.669584
> ddply(Sorghum, .(GCM), summarise, mean=mean(Yield), sd=sd(Yield))
      GCM      mean      sd
1 ACC 5.752729 2.142741
2 CCS 5.569895 2.040956
3 CNR 5.484551 1.963254
4 GFD 5.860247 2.168946
5 MPI 5.583961 2.110748
6 NOR 5.774832 2.066492
> ddply(Maize .(Irr) summarise, mean=mean(Yield), sd=sd(Yield))
      Irr      mean      sd
1  0 6.205520 2.349447
2 10 7.068285 1.793347
3 20 7.627248 1.401544
> ddply(Millet, .(Irr), summarise, mean=mean(Yield), sd=sd(Yield))
      Irr      mean      sd
1  0 4.562783 2.223108
2 10 4.909581 1.713321
3 20 4.928921 1.439548
> ddply(Sorghum, .(Irr), summarise, mean=mean(Yield), sd=sd(Yield))
      Irr      mean      sd
1  0 4.698226 1.878317
2 10 5.624843 1.883320
3 20 6.203634 2.193627
> ddply(Maize .(Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
      Irr_Days      mean      sd
1          0 6.205520 2.349447
2           7 7.635839 1.402392
3          14 7.059694 1.789961
> ddply(Millet, .(Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
      Irr_Days      mean      sd
1          0 4.562783 2.223108
2           7 4.927331 1.447294
3          14 4.911171 1.706800

```

```

> ddply(Sorghum, .(Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Irr_Days    mean    sd
1         0 4.698226 1.878317
2         7 6.222848 2.205120
3        14 5.605629 1.863689
> ddply(Maize, .(Irr, Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Irr Irr_Days    mean    sd
1   0         0 6.205520 2.349447
2  10         7 7.368163 1.528693
3  10        14 6.768407 1.980122
4  20         7 7.903514 1.206845
5  20        14 7.350982 1.524068
> ddply(Millet, .(Irr, Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Irr Irr_Days    mean    sd
1   0         0 4.562783 2.223108
2  10         7 4.954176 1.518127
3  10        14 4.864986 1.888787
4  20         7 4.900486 1.373653
5  20        14 4.957357 1.503254
> ddply(Sorghum, .(Irr, Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Irr Irr_Days    mean    sd
1   0         0 4.698226 1.878317
2  10         7 5.916625 1.915961
3  10        14 5.333061 1.805179
4  20         7 6.529070 2.423852
5  20        14 5.878197 1.882920
> ddply(Maize, .(Model,Irr,Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Model Irr Irr_Days    mean    sd
1 AquaCrop  0         0 8.558333 0.4566315
2 AquaCrop 10         7 8.677973 0.3243592
3 AquaCrop 10        14 8.515005 0.9945347
4 AquaCrop 20         7 8.447522 0.4292107
5 AquaCrop 20        14 8.664425 0.3929843
6  DSSAT   0         0 5.477312 1.3684070
7  DSSAT  10         7 6.319124 0.8396689
8  DSSAT  10        14 6.033409 1.0449967
9  DSSAT  20         7 6.510156 0.8017706
10 DSSAT  20        14 6.477376 0.7469892
11 SIMPLE  0         0 4.580914 2.4053916
12 SIMPLE 10         7 7.107392 1.8237440
13 SIMPLE 10        14 5.756806 2.2549545
14 SIMPLE 20         7 8.752866 0.7637596
15 SIMPLE 20        14 6.911145 1.8933463
> ddply(Millet, .(Model,Irr,Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
  Model Irr Irr_Days    mean    sd
1 AquaCrop  0         0 7.033457 1.3232115
2 AquaCrop 10         7 5.927441 0.9250986
3 AquaCrop 10        14 6.772296 1.0571847

```

```

4 AquaCrop 20      7 4.750930 0.3940382
5 AquaCrop 20     14 6.006559 0.8894543
6 DSSAT 0        0 2.673978 0.7977301
7 DSSAT 10       7 3.158124 0.5282595
8 DSSAT 10     14 2.962720 0.6608750
9 DSSAT 20       7 3.351425 0.3199323
10 DSSAT 20     14 3.207220 0.5079761
11 SIMPLE 0       0 3.980914 1.5583004
12 SIMPLE 10      7 5.776962 0.9632958
13 SIMPLE 10     14 4.859941 1.3751456
14 SIMPLE 20      7 6.599102 0.2959802
15 SIMPLE 20     14 5.658290 1.0364867

```

```
> ddply(Sorghum, .(Model,Irr,Irr_Days), summarise, mean=mean(Yield), sd=sd(Yield))
```

```

      Model Irr Irr_Days      mean      sd
1 AquaCrop  0      0 5.403978 1.2941771
2 AquaCrop 10      7 5.880769 0.5015449
3 AquaCrop 10     14 5.782129 0.6016412
4 AquaCrop 20      7 5.531624 0.5518919
5 AquaCrop 20     14 5.957661 0.4482149
6 DSSAT 0      0 3.998602 0.8684887
7 DSSAT 10     7 4.180801 0.4897569
8 DSSAT 10    14 4.121280 0.7036825
9 DSSAT 20     7 4.285763 0.3336190
10 DSSAT 20    14 4.180392 0.5042518
11 SIMPLE 0      0 4.692097 2.6833312
12 SIMPLE 10     7 7.688306 2.0915316
13 SIMPLE 10    14 6.095774 2.5865274
14 SIMPLE 20     7 9.769823 0.8084842
15 SIMPLE 20    14 7.496538 2.1637162

```

```
> #Biomass###
```

```
> ddply(Maize .(Year), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

```

      Year      mean      sd
1 2030 16.34587 5.175597
2 2031 16.52107 5.258970
3 2032 15.42642 5.760619
4 2033 17.07361 5.044767
5 2034 17.17438 5.053063
6 2035 16.65972 5.160142
7 2036 17.81391 4.679876
8 2037 16.85928 5.648787
9 2038 16.50854 5.508448
10 2039 17.09978 4.490672
11 2040 15.93391 5.476425
12 2041 16.16966 6.070621
13 2042 16.17690 5.668701
14 2043 17.21462 4.941961
15 2044 16.81580 4.704229
16 2045 16.38086 5.432836

```

```
17 2046 17.16161 5.247152
18 2047 16.93322 4.972917
19 2048 16.43764 5.671609
20 2049 16.45562 5.737681
21 2050 16.18688 5.198629
22 2051 17.33226 5.479048
23 2052 17.69823 4.899649
24 2053 15.29107 5.697793
25 2054 16.05600 5.845684
26 2055 16.72580 5.176813
27 2056 17.86841 4.742281
28 2057 16.36381 5.143486
29 2058 15.66647 5.958279
30 2059 16.49741 5.052449
31 2060 16.11211 5.575137
```

```
> ddply(Millet, .(Year), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

```
  Year    mean    sd
1  2030 17.40673 3.892956
2  2031 17.00291 4.665654
3  2032 16.61829 4.822102
4  2033 17.18078 4.326677
5  2034 17.30504 4.634574
6  2035 17.62033 4.035770
7  2036 17.50584 3.530115
8  2037 17.31946 3.886050
9  2038 16.92972 4.342754
10 2039 17.77372 3.537366
11 2040 16.75076 4.872104
12 2041 17.19890 4.350181
13 2042 16.90027 5.003430
14 2043 17.24898 3.813311
15 2044 17.36687 3.931467
16 2045 17.33432 4.357769
17 2046 17.37914 3.467839
18 2047 17.17576 3.804265
19 2048 16.37138 4.993492
20 2049 17.41989 4.259281
21 2050 17.36007 3.995710
22 2051 17.45699 3.823534
23 2052 17.37184 3.792641
24 2053 17.05548 4.628510
25 2054 16.76602 5.213437
26 2055 17.07009 4.451770
27 2056 16.99690 3.693980
28 2057 17.11989 3.964444
29 2058 16.88516 4.642004
30 2059 17.00568 4.250500
31 2060 16.87236 4.982713
```

```
> ddply(Sorghum, .(Year), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

	Year	mean	sd
1	2030	16.11207	3.929019
2	2031	16.25809	4.226067
3	2032	15.20911	4.496874
4	2033	16.50610	3.939793
5	2034	16.63601	3.690395
6	2035	16.71709	3.705473
7	2036	17.55521	2.901464
8	2037	16.90174	3.794452
9	2038	16.32676	4.224716
10	2039	16.70948	3.381409
11	2040	15.50516	4.013689
12	2041	16.17464	4.588891
13	2042	15.57014	4.464589
14	2043	16.90921	3.446397
15	2044	16.59509	2.822511
16	2045	16.14077	4.055107
17	2046	16.76364	3.601415
18	2047	16.50514	3.760361
19	2048	16.03750	4.415701
20	2049	16.39976	4.222593
21	2050	15.91406	3.593085
22	2051	17.44197	3.556819
23	2052	17.38632	3.014078
24	2053	14.92146	4.560864
25	2054	15.54156	4.818303
26	2055	16.69774	3.868221
27	2056	17.54347	3.116690
28	2057	15.76319	3.628721
29	2058	14.92531	4.534730
30	2059	16.38278	3.517700
31	2060	15.50246	4.274745

```
> ddply(Maize, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

	Model	mean	sd
1	AquaCrop	21.44941	1.283270
2	DSSAT	11.84249	1.451180
3	SIMPLE	16.54302	5.941336

```
> ddply(Millet, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

	Model	mean	sd
1	AquaCrop	19.40917	3.814464
2	DSSAT	14.12207	1.568985
3	SIMPLE	17.93034	4.783148

```
> ddply(Sorghum, .(Model), summarise, mean=mean(Biomass), sd=sd(Biomass))
```

	Model	mean	sd
1	AquaCrop	17.36230	2.299956
2	DSSAT	15.67659	1.562948
3	SIMPLE	15.88559	6.121447

```

> ddply(Maize, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 16.87723 5.276400
2 CCS 16.51602 5.385455
3 CNR 16.12443 5.560309
4 GFD 16.84632 5.328565
5 MPI 16.71450 5.249829
6 NOR 16.59134 5.157111
> ddply(Millet, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 17.17380 4.447054
2 CCS 17.38920 4.259994
3 CNR 16.61374 4.014156
4 GFD 17.04081 4.323354
5 MPI 17.20394 4.531483
6 NOR 17.50166 3.993139
> ddply(Sorghum, .(GCM), summarise, mean=mean(Biomass), sd=sd(Biomass))
  GCM    mean    sd
1 ACC 16.48672 3.861809
2 CCS 16.05320 3.917938
3 CNR 15.81232 4.045830
4 GFD 16.83292 4.064037
5 MPI 16.15789 4.002722
6 NOR 16.50592 3.746926
> ddply(Maize, .(Irr), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr    mean    sd
1  0 14.52697 6.118045
2 10 16.48911 5.179507
3 20 17.77650 4.686116
> ddply(Millet, .(Irr), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr    mean    sd
1  0 16.15911 5.980924
2 10 17.34639 4.020836
3 20 17.45870 3.314498
> ddply(Sorghum, .(Irr), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr    mean    sd
1  0 13.79131 4.999427
2 10 16.21216 3.547214
3 20 17.66259 2.998035
> ddply(Maize, .(Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr_Days    mean    sd
1         0 14.52697 6.118045
2         7 17.81941 4.709990
3        14 16.44621 5.146719
> ddply(Millet, .(Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr_Days    mean    sd
1         0 16.15911 5.980924
2         7 17.47977 3.335417

```

```

3      14 17.32532 4.002797
> ddply(Sorghum, .(Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr_Days    mean      sd
1         0 13.79131 4.999427
2         7 17.68511 2.954822
3        14 16.18964 3.574011
> ddply(Maize, .(Irr, Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr Irr_Days    mean      sd
1   0         0 14.52697 6.118045
2  10         7 17.17477 4.813907
3  10        14 15.80346 5.439405
4  20         7 18.46405 4.516804
5  20        14 17.08896 4.755012
> ddply(Millet, .(Irr, Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr Irr_Days    mean      sd
1   0         0 16.15911 5.980924
2  10         7 17.50118 3.299724
3  10        14 17.19159 4.628940
4  20         7 17.45836 3.373558
5  20        14 17.45904 3.257395
> ddply(Sorghum, .(Irr, Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Irr Irr_Days    mean      sd
1   0         0 13.79131 4.999427
2  10         7 16.97723 2.959412
3  10        14 15.44710 3.906045
4  20         7 18.39299 2.777679
5  20        14 16.93218 3.034494
> ddply(Maize, .(Model,Irr,Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Model Irr Irr_Days    mean      sd
1 AquaCrop  0         0 21.38290 1.0303582
2 AquaCrop 10         7 21.68955 0.8074651
3 AquaCrop 10        14 21.38765 2.0786808
4 AquaCrop 20         7 21.11877 1.0729494
5 AquaCrop 20        14 21.66818 0.9270670
6  DSSAT   0         0 10.80366 1.9866592
7  DSSAT  10         7 12.06620 1.1161779
8  DSSAT  10        14 11.63059 1.4553768
9  DSSAT  20         7 12.39124 0.8470389
10 DSSAT  20        14 12.32075 0.9130712
11 SIMPLE  0         0 11.39435 6.0518926
12 SIMPLE 10         7 17.76854 4.5593151
13 SIMPLE 10        14 14.39215 5.6374599
14 SIMPLE 20         7 21.88213 1.9094244
15 SIMPLE 20        14 17.27794 4.7333309
> ddply(Millet, .(Model,Irr,Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
  Model Irr Irr_Days    mean      sd
1 AquaCrop  0         0 22.29024 4.4558574
2 AquaCrop 10         7 18.79485 2.6470074

```

```

3 AquaCrop 10      14 21.44583 3.3349988
4 AquaCrop 20      7 15.55610 1.0327235
5 AquaCrop 20     14 18.95881 2.4473837
6 DSSAT 0        0 12.91855 2.0284057
7 DSSAT 10      7 14.45212 1.1563795
8 DSSAT 10     14 13.86035 1.5449752
9 DSSAT 20      7 14.82194 0.9424620
10 DSSAT 20     14 14.55738 1.1477410
11 SIMPLE 0       0 13.26855 5.1941853
12 SIMPLE 10      7 19.25656 3.2110308
13 SIMPLE 10     14 16.26860 4.5600151
14 SIMPLE 20      7 21.99704 0.9866921
15 SIMPLE 20     14 18.86094 3.4549983
> ddply(Sorghum, .(Model,Irr,Irr_Days), summarise, mean=mean(Biomass), sd=sd(Biomass))
      Model Irr Irr_Days      mean      sd
1 AquaCrop  0        0 16.49860 4.003535
2 AquaCrop 10        7 17.86009 1.358334
3 AquaCrop 10     14 17.42309 1.729187
4 AquaCrop 20        7 16.98541 1.634941
5 AquaCrop 20     14 18.04433 1.188919
6 DSSAT 0        0 14.44828 2.117026
7 DSSAT 10        7 15.98651 1.067393
8 DSSAT 10     14 15.37199 1.530882
9 DSSAT 20        7 16.48291 0.776292
10 DSSAT 20     14 16.09325 1.079134
11 SIMPLE 0        0 10.42704 5.963261
12 SIMPLE 10        7 17.08509 4.647845
13 SIMPLE 10     14 13.54623 5.747929
14 SIMPLE 20        7 21.71066 1.796596
15 SIMPLE 20     14 16.65894 4.808296
> #WU###
> ddply(Maize, .(Year), summarise, mean=mean(WU), sd=sd(WU))
      Year      mean      sd
1 2030 472.4814 80.42394
2 2031 466.1601 77.90660
3 2032 461.6501 71.81950
4 2033 473.4891 79.02987
5 2034 475.3045 76.71545
6 2035 474.8315 77.31257
7 2036 478.5384 79.54800
8 2037 469.0419 80.44789
9 2038 471.8603 76.42527
10 2039 493.5012 76.50028
11 2040 465.7754 75.53649
12 2041 464.6977 76.24752
13 2042 463.8677 73.59467
14 2043 470.8895 71.88920
15 2044 469.2311 74.47092

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```

16 2045 473.3002 78.81299
17 2046 479.7209 76.23163
18 2047 473.8376 74.40854
19 2048 461.9600 69.33852
20 2049 476.9935 82.92526
21 2050 468.8303 66.67356
22 2051 478.7198 78.42574
23 2052 475.1725 70.02361
24 2053 453.8407 64.67239
25 2054 459.3165 67.75190
26 2055 477.1604 69.20813
27 2056 477.8966 71.65636
28 2057 454.4366 67.56162
29 2058 443.9924 61.43298
30 2059 459.0472 64.99523
31 2060 459.7582 67.94850

```

```
> ddply(Millet, .(Year), summarise, mean=mean(WU), sd=sd(WU))
```

```

  Year      mean      sd
1 2030 454.8758 57.91010
2 2031 445.6072 65.04141
3 2032 442.0721 59.07162
4 2033 450.2401 59.65744
5 2034 447.4460 56.72890
6 2035 449.9907 55.04617
7 2036 464.7439 59.31441
8 2037 455.6399 60.33973
9 2038 452.5479 61.20884
10 2039 464.2872 56.21492
11 2040 439.8359 56.42536
12 2041 443.9777 54.92214
13 2042 439.9606 55.72053
14 2043 455.7477 51.13280
15 2044 450.2826 57.74433
16 2045 446.8974 61.11011
17 2046 455.3670 49.75375
18 2047 449.5021 51.81487
19 2048 442.5996 52.85218
20 2049 453.2280 59.22707
21 2050 453.1167 48.68498
22 2051 451.0169 54.92903
23 2052 454.4818 51.04866
24 2053 434.1175 50.66419
25 2054 429.3711 58.46944
26 2055 459.7077 61.53080
27 2056 457.1304 53.49579
28 2057 443.7517 44.25392
29 2058 439.3002 50.95404
30 2059 438.0757 54.05355

```

```

31 2060 435.0055 51.46358
> ddpIy(Sorghum, .(Year), summarise, mean=mean(WU), sd=sd(WU))
  Year      mean      sd
1  2030 529.8229 67.52410
2  2031 525.5196 70.89039
3  2032 524.1522 64.83691
4  2033 528.6106 68.17773
5  2034 532.3790 66.93844
6  2035 537.1311 68.71021
7  2036 542.7976 72.27437
8  2037 534.7011 68.99929
9  2038 535.2662 68.53739
10 2039 551.7024 62.74557
11 2040 523.5785 64.58632
12 2041 523.9903 68.64815
13 2042 522.3764 62.04863
14 2043 534.8269 65.42504
15 2044 531.4350 63.61540
16 2045 532.5979 72.64595
17 2046 541.7211 64.00175
18 2047 535.4017 64.45140
19 2048 525.3370 58.54227
20 2049 539.4912 69.71873
21 2050 530.3668 56.52065
22 2051 540.8309 64.46969
23 2052 537.7025 57.99388
24 2053 512.9735 57.39070
25 2054 521.5553 68.67817
26 2055 543.7878 60.68694
27 2056 541.7188 62.67170
28 2057 518.3745 59.34183
29 2058 508.8263 57.84096
30 2059 526.9816 59.99589
31 2060 521.3584 60.01148
> ddpIy(Maize, .(Model), summarise, mean=mean(WU), sd=sd(WU))
  Model      mean      sd
1 AquaCrop 408.3387  9.817402
2   DSSAT 530.7291 85.305188
3   SIMPLE 468.5422 39.374344
> ddpIy(Millet, .(Model), summarise, mean=mean(WU), sd=sd(WU))
  Model      mean      sd
1 AquaCrop 404.7452 18.52455
2   DSSAT 487.9041 63.24867
3   SIMPLE 452.5048 39.97502
> ddpIy(Sorghum, .(Model), summarise, mean=mean(WU), sd=sd(WU))
  Model      mean      sd
1 AquaCrop 484.0376 17.92574
2   DSSAT 586.3556 70.32629

```

```

3   SIMPLE 522.2502 45.35937
> ddply(Maize, .(GCM) summarise, mean=mean(WU), sd=sd(WU))
  GCM    mean    sd
1 ACC 475.6728 70.43550
2 CCS 467.9433 69.42345
3 CNR 468.9700 70.84064
4 GFD 470.6608 66.28355
5 MPI 473.8477 68.98273
6 NOR 458.1253 93.47737
> ddply(Millet, .(GCM), summarise, mean=mean(WU), sd=sd(WU))
  GCM    mean    sd
1 ACC 449.2545 55.33859
2 CCS 446.1430 54.71503
3 CNR 453.7864 58.01948
4 GFD 442.4695 51.98902
5 MPI 447.1090 58.64642
6 NOR 451.5455 56.84105
> ddply(Sorghum, .(GCM), summarise, mean=mean(WU), sd=sd(WU))
  GCM    mean    sd
1 ACC 536.5286 64.62796
2 CCS 527.5057 63.76292
3 CNR 530.4449 64.92283
4 GFD 523.6551 66.12829
5 MPI 534.2265 64.79202
6 NOR 532.9261 65.12095
> ddply(Maize .(Irr) summarise, mean=mean(WU) sd=sd(WU))
  Irr    mean    sd
1  0 421.8674 65.68061
2 10 470.8911 65.44109
3 20 491.1835 75.08201
> ddply(Millet, .(Irr), summarise, mean=mean(WU), sd=sd(WU))
  Irr    mean    sd
1  0 414.4749 46.83086
2 10 447.1629 50.18670
3 20 466.5613 57.73848
> ddply(Sorghum, .(Irr), summarise, mean=mean(WU), sd=sd(WU))
  Irr    mean    sd
1  0 486.2545 54.48999
2 10 530.3274 57.49332
3 20 553.7482 65.21383
> ddply(Maize .(Irr_Days) summarise, mean=mean(WU), sd=sd(WU))
  Irr_Days    mean    sd
1         0 421.8674 65.68061
2         7 494.5251 77.31752
3        14 467.5496 61.51225
> ddply(Millet, .(Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Irr_Days    mean    sd
1         0 414.4749 46.83086

```

```

2      7 469.1828 58.96056
3     14 444.5415 47.54511
> ddply(Sorghum,.(Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Irr_Days    mean    sd
1         0 486.2545 54.48999
2         7 555.8424 66.23177
3        14 528.2332 55.35988
> ddply(Maize,.(Irr, Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Irr Irr_Days    mean    sd
1    0         0 421.8674 65.68061
2   10         7 483.0080 70.37016
3   10        14 458.7742 57.67700
4   20         7 506.0422 82.15235
5   20        14 476.3249 63.97953
> ddply(Millet,.(Irr, Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Irr Irr_Days    mean    sd
1    0         0 414.4749 46.83086
2   10         7 459.3871 52.67517
3   10        14 434.9388 44.36059
4   20         7 478.9785 63.18234
5   20        14 454.1441 48.70849
> ddply(Sorghum,.(Irr, Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Irr Irr_Days    mean    sd
1    0         0 486.2545 54.48999
2   10         7 543.1105 59.80919
3   10        14 517.5444 52.08031
4   20         7 568.5742 69.85160
5   20        14 538.9221 56.51250
> ddply(Maize .(Model,Irr Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Model Irr Irr_Days    mean    sd
1 AquaCrop  0         0 408.3387  9.838606
2 AquaCrop 10         7 408.3387  9.838606
3 AquaCrop 10        14 408.3387  9.838606
4 AquaCrop 20         7 408.3387  9.838606
5 AquaCrop 20        14 408.3387  9.838606
6  DSSAT   0         0 424.1290 105.854079
7  DSSAT  10         7 564.1978  40.118838
8  DSSAT  10        14 513.6591  55.450636
9  DSSAT  20         7 604.8645  20.152849
10 DSSAT  20        14 546.7952  40.214996
11 SIMPLE  0         0 433.1344  37.010710
12 SIMPLE 10         7 476.4875  30.451334
13 SIMPLE 10        14 454.3247  35.189025
14 SIMPLE 20         7 504.9233  19.989569
15 SIMPLE 20        14 473.8409  31.050571
> ddply(Millet,.(Model,Irr,Irr_Days), summarise, mean=mean(WU), sd=sd(WU))
  Model Irr Irr_Days    mean    sd
1 AquaCrop  0         0 416.3925 33.44753

```

```

2 AquaCrop 10      7 401.8333 10.41616
3 AquaCrop 10     14 401.8333 10.41616
4 AquaCrop 20      7 401.8333 10.41616
5 AquaCrop 20     14 401.8333 10.41616
6 DSSAT 0         0 414.1183 61.52053
7 DSSAT 10        7 512.0661 36.32070
8 DSSAT 10     14 464.1226 50.27276
9 DSSAT 20        7 550.2516 20.47065
10 DSSAT 20     14 498.9618 37.11589
11 SIMPLE 0         0 412.9140 41.14987
12 SIMPLE 10        7 464.2617 27.96454
13 SIMPLE 10     14 438.8604 36.26786
14 SIMPLE 20        7 484.8504 19.13397
15 SIMPLE 20     14 461.6373 28.80917
> ddply(Sorghum, .(Model,Irr,Irr_Days), summarise, mean=mean(WU), sd=sd(WU))

```

```

      Model Irr Irr_Days      mean      sd
1 AquaCrop  0         0 472.8763 30.65414
2 AquaCrop 10         7 486.8280 11.37292
3 AquaCrop 10     14 486.8280 11.37292
4 AquaCrop 20         7 486.8280 11.37292
5 AquaCrop 20     14 486.8280 11.37292
6 DSSAT 0         0 506.7527 74.80984
7 DSSAT 10        7 610.7538 40.08463
8 DSSAT 10     14 561.0172 58.81333
9 DSSAT 20        7 652.2586 18.62950
10 DSSAT 20     14 600.9957 40.36677
11 SIMPLE 0         0 479.1344 41.83337
12 SIMPLE 10        7 531.7497 33.45166
13 SIMPLE 10     14 504.7880 39.56947
14 SIMPLE 20        7 566.6362 21.23219
15 SIMPLE 20     14 528.9426 33.97261

```

```
> ##WP###
```

```
> ddply(Maize, .(Year), summarise, mean=mean(WP), sd=sd(WP))
```

```

      Year      mean      sd
1  2030 15.67334 5.007851
2  2031 15.89470 4.798997
3  2032 15.06723 5.450989
4  2033 16.00590 4.887226
5  2034 16.13537 4.467743
6  2035 15.90985 4.826748
7  2036 16.54456 4.404848
8  2037 16.04877 4.647916
9  2038 15.84822 4.854801
10 2039 15.66070 4.104763
11 2040 15.41341 5.112575
12 2041 15.37558 5.332652
13 2042 15.68275 5.103894
14 2043 16.17346 4.483178

```

```

15 2044 16.22045 4.230123
16 2045 15.56634 4.888631
17 2046 16.02026 4.647679
18 2047 16.01102 4.443507
19 2048 15.90517 5.009883
20 2049 15.46999 4.937873
21 2050 15.28371 5.079357
22 2051 16.18841 4.859923
23 2052 16.53278 4.359286
24 2053 14.66259 5.277203
25 2054 15.42349 4.975921
26 2055 15.53494 4.902093
27 2056 16.71293 4.124366
28 2057 15.96977 4.926270
29 2058 15.50105 5.154886
30 2059 15.95711 4.355967
31 2060 15.55456 4.866595

```

```
> ddply(Millet,.(Year), summarise, mean=mean(WP), sd=sd(WP))
```

```

  Year    mean    sd
1  2030 11.26508 4.517138
2  2031 11.18480 4.409351
3  2032 10.78793 4.554913
4  2033 11.06154 4.312024
5  2034 11.22616 4.419720
6  2035 11.45958 4.531482
7  2036 10.77782 3.863968
8  2037 11.13283 4.224155
9  2038 11.04199 4.423823
10 2039 11.10018 3.923780
11 2040 10.95623 4.683206
12 2041 11.16667 4.598310
13 2042 11.17151 4.507411
14 2043 11.11114 4.084851
15 2044 11.14562 4.154280
16 2045 11.25862 4.390620
17 2046 10.95389 4.028247
18 2047 11.00389 4.167158
19 2048 10.62010 4.539526
20 2049 11.08007 4.309651
21 2050 11.21453 4.242732
22 2051 11.32313 3.928553
23 2052 11.16664 4.095968
24 2053 11.35785 4.620292
25 2054 11.14528 4.408385
26 2055 10.80967 4.491495
27 2056 10.80474 3.950620
28 2057 11.17104 4.200138
29 2058 11.18195 4.747790

```

```

30 2059 11.45830 4.303777
31 2060 11.14370 4.616130
> ddply(Sorghum, .(Year), summarise, mean=mean(WP), sd=sd(WP))
  Year      mean      sd
1  2030 10.670063 3.709504
2  2031 10.996865 4.081052
3  2032  9.932974 3.811354
4  2033 10.947317 3.686923
5  2034 10.958431 3.513325
6  2035 11.068488 3.511319
7  2036 11.537905 4.060473
8  2037 11.264341 4.166451
9  2038 10.885491 4.096547
10 2039 10.723058 3.602307
11 2040 10.360291 3.189094
12 2041 10.829507 4.174279
13 2042 10.474533 4.032567
14 2043 11.257901 3.788298
15 2044 11.194824 3.533857
16 2045 10.588764 3.782889
17 2046 11.056881 4.025290
18 2047 11.048606 3.718128
19 2048 10.784005 4.217366
20 2049 10.833372 3.833818
21 2050 10.523968 3.590671
22 2051 11.588983 4.097541
23 2052 11.528990 3.944524
24 2053 10.086904 3.672785
25 2054 10.258397 4.231867
26 2055 10.851514 3.832476
27 2056 11.594049 4.038988
28 2057 10.767680 3.797586
29 2058 10.214768 4.018184
30 2059 11.100721 3.659946
31 2060 10.452396 3.571708
> ddply(Maize .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 21.00193 1.457639
2  DSSAT 12.56655 2.638345
3  SIMPLE 13.84589 4.315623
> ddply(Millet, .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 15.098076 3.149629
2  DSSAT  6.839302 1.018938
3  SIMPLE 11.380280 3.281587
> ddply(Sorghum, .(Model), summarise, mean=mean(WP), sd=sd(WP))
  Model      mean      sd
1 AquaCrop 11.833829 1.839678

```

```

2   DSSAT  7.350388 1.120718
3   SIMPLE 13.368878 4.502474
> ddply(Maize, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM    mean    sd
1 ACC 15.89812 4.572491
2 CCS 15.64141 4.873039
3 CNR 15.37028 4.961028
4 GFD 15.78210 4.657009
5 MPI 15.69420 4.699016
6 NOR 16.44262 4.964495
> ddply(Millet, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM    mean    sd
1 ACC 11.16592 4.279709
2 CCS 11.48092 4.310232
3 CNR 10.71519 3.882554
4 GFD 11.20425 4.062638
5 MPI 11.27701 4.255189
6 NOR 10.79203 5.006672
> ddply(Sorghum, .(GCM), summarise, mean=mean(WP), sd=sd(WP))
  GCM    mean    sd
1 ACC 10.86958 3.882579
2 CCS 10.66506 3.724613
3 CNR 10.43053 3.569107
4 GFD 11.39650 4.309202
5 MPI 10.60768 3.818979
6 NOR 11.13684 3.686759
> ddply(Maize, .(Irr) summarise, mean=mean(WP), sd=sd(WP))
  Irr    mean    sd
1  0 14.99504 6.112482
2 10 15.61507 4.687455
3 20 16.39938 4.025999
> ddply(Millet, .(Irr), summarise, mean=mean(WP), sd=sd(WP))
  Irr    mean    sd
1  0 10.42271 5.931189
2 10 11.47336 4.170211
3 20 11.08000 3.362795
> ddply(Sorghum, .(Irr), summarise, mean=mean(WP), sd=sd(WP))
  Irr    mean    sd
1  0  9.668351 3.830881
2 10 10.779660 3.561056
3 20 11.513744 3.989285
> ddply(Maize, .(Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr_Days    mean    sd
1         0 14.99504 6.112482
2         7 16.43340 4.009739
3        14 15.58105 4.695441
> ddply(Millet, .(Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr_Days    mean    sd

```

```

1      0 10.42271 5.931189
2      7 11.08018 3.334001
3     14 11.47318 4.193284
> ddply(Sorghum, .(Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr_Days      mean      sd
1      0  9.668351 3.830881
2      7 11.537328 4.003223
3     14 10.756076 3.540331
> ddply(Maize, .(Irr, Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr Irr_Days      mean      sd
1  0      0 14.99504 6.112482
2 10     7 16.07492 4.339243
3 10    14 15.15522 4.973048
4 20     7 16.79188 3.619167
5 20    14 16.00688 4.363417
> ddply(Millet, .(Irr, Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr Irr_Days      mean      sd
1  0      0 10.42271 5.931189
2 10     7 11.36390 3.679335
3 10    14 11.58282 4.609884
4 20     7 10.79647 2.924431
5 20    14 11.36354 3.731450
> ddply(Sorghum, .(Irr, Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Irr Irr_Days      mean      sd
1  0      0  9.668351 3.830881
2 10     7 11.171446 3.666277
3 10    14 10.387875 3.411140
4 20     7 11.903211 4.286089
5 20    14 11.124277 3.630824
> ddply(Maize, .(Model,Irr,Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Model Irr Irr_Days      mean      sd
1 AquaCrop  0      0 20.97478 1.2750869
2 AquaCrop 10     7 21.25965 0.8439408
3 AquaCrop 10    14 20.85613 2.4486411
4 AquaCrop 20     7 20.69272 1.0442672
5 AquaCrop 20    14 21.22637 1.0046939
6  DSSAT   0      0 13.75414 5.3068534
7  DSSAT  10     7 12.18310 1.1175506
8  DSSAT  10    14 12.18310 1.1175506
9  DSSAT  20     7 12.35620 1.1161711
10 DSSAT  20    14 12.35620 1.1161711
11 SIMPLE  0      0 10.25618 4.7566512
12 SIMPLE 10     7 14.78202 3.2854230
13 SIMPLE 10    14 12.42644 4.2629134
14 SIMPLE 20     7 17.32673 1.3161859
15 SIMPLE 20    14 14.43807 3.4357571
> ddply(Millet, .(Model,Irr,Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
  Model Irr Irr_Days      mean      sd

```

1	AquaCrop	0	0	17.130699	3.8318283
2	AquaCrop	10	7	14.744175	2.2189205
3	AquaCrop	10	14	16.849166	2.5668156
4	AquaCrop	20	7	11.823076	0.9249839
5	AquaCrop	20	14	14.943266	2.1434236
6	DSSAT	0	0	6.407258	1.5985796
7	DSSAT	10	7	6.947313	0.7783917
8	DSSAT	10	14	6.947313	0.7783917
9	DSSAT	20	7	6.947313	0.7783917
10	DSSAT	20	14	6.947313	0.7783917
11	SIMPLE	0	0	7.730161	4.4652650
12	SIMPLE	10	7	12.400204	1.7464034
13	SIMPLE	10	14	10.951994	2.6267668
14	SIMPLE	20	7	13.619007	0.5677717
15	SIMPLE	20	14	12.200033	1.8777179

```
> ddply(Sorghum, .(Model,Irr,Irr_Days), summarise, mean=mean(WP), sd=sd(WP))
```

	Model	Irr	Irr_Days	mean	sd
1	AquaCrop	0	0	11.587258	3.3868674
2	AquaCrop	10	7	12.084919	1.0552496
3	AquaCrop	10	14	11.888004	1.2990829
4	AquaCrop	20	7	11.365818	1.1394246
5	AquaCrop	20	14	12.243147	0.9533089
6	DSSAT	0	0	7.965591	1.8140687
7	DSSAT	10	7	7.107676	0.6376067
8	DSSAT	10	14	7.463323	1.1071131
9	DSSAT	20	7	7.107676	0.6376067
10	DSSAT	20	14	7.107676	0.6376067
11	SIMPLE	0	0	9.452204	4.7707182
12	SIMPLE	10	7	14.321743	3.3955162
13	SIMPLE	10	14	11.812297	4.3838765
14	SIMPLE	20	7	17.236139	1.2648201
15	SIMPLE	20	14	14.022007	3.5291179