Exploring and modelling the effects of agricultural land management and climate change on agroecosystem services in the Eastern Cape, South Africa

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Abstract

The aims of this study were to evaluate the impacts of agricultural land management strategies and climate change on irrigated maize production in the Eastern Cape, South Africa. To achieve these aims, the study was guided by two overarching research questions, subsequently broken down into more specific questions. The first research question examined the reasons behind farmers' current agricultural land management practices, the values they assigned to different agroecosystem services, their perceptions of climate change and the adaptation strategies they used to address challenges associated with agricultural crop production and climate change. To answer these questions, a survey of conventional farmers in the Eastern Cape was carried out. The survey targeted farmers who used fertilisers and irrigation water in their day to day farming. Results showed that farmers recognised the different benefits that agroecosystems provided even though they were not familiar with the term 'ecosystem services.' Farmers assigned a high value to food provisioning compared to other agroecosystem services and managed their farms for maximum crop yields or maximum crop quality. Fertiliser and irrigation water management decisions were based on multiple factors such as cost, availability of farming equipment and crop yield or crop quality considerations. Survey results showed that while most farmers were able to state the amount of fertiliser used per growing season, the majority of farmers did not know the amount of water they used per growing season. From the farmers' survey it was recommended that extension services and agricultural education programmes be strengthened in the region to increase farmers' knowledge on effective agricultural land management strategies that support sustainable intensification.

The second research question investigated the effects of agricultural land management strategies and climate change on crop yields in the Eastern Cape. This investigation was done in three steps. First, a crop model, the Environmental Policy Integrated Climate (EPIC) model was calibrated and validated using limited field data from maize variety trials carried out at the Cradock Research Farm in the Eastern Cape. Calibration and validation results proved satisfactory with model efficiencies (Nash Sutcliffe, NSE) greater than 0.5 for both calibration and validation. It was concluded that limited data from field trials on maize that only included grain yield and agricultural land management dates can be used for the calibration of the EPIC model to simulate maize production under South African conditions.

In the second step, the calibrated model was applied to simulate different irrigation and fertiliser management strategies for maize production in the Eastern Cape. Different irrigation and Nitrogen (N) fertiliser levels were compared to find optimal irrigation and N fertiliser management strategies that would increase maize yields while minimising environmental pollution (nitrate leaching). Model outputs were also compared to the average yields obtained in the field trials (baseline) and to maize yields reported by farmers in the farmers' survey. Results showed that improved management of irrigation water and N fertiliser could improve farmers' maize yields from approximately 7.2 t ha^{-1} to approximately 12.2 t ha^{-1}, an increase of approximately 69%. Results also revealed a trade-off between food provision and nitrate leaching. Simulations showed that increasing N fertiliser application under sufficient irrigation water levels would increase maize yields, however, this would be accompanied by an increase in N leaching.

Lastly, the EPIC model was then applied to simulate the effects of future climate change on irrigated maize production in the Eastern Cape. For these simulations, the model was driven by statistically downscaled climate data derived from three General Circulation Models (GCMs) for two future climate periods, (2040-2069) and (2070-2099), under two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5. Future maize yields were compared to the baseline (1980-2010) maize yield average. All three climate models predicted a decline in maize yields, with yields declining by as much as 23.8% in RCP 8.5, 2070-2099. Simulations also predicted increases in average daily maximum and minimum temperatures for both the two future climate periods under both RCPs. Results also indicated a decrease in seasonal irrigation water requirements. Nitrate leaching was projected to significantly increase towards the end of the century, increasing by as much as 373.8% in RCP 8.5 2070-2099. Concerning farmers' perceptions of climate change, results showed that farmers were aware of climate change and identified temperature and rainfall changes as the most important changes in climate that they had observed. To adapt to climate change, farmers used a variety of adaptation strategies such as crop rotations and intercropping. Apart from challenges posed by climate change, farmers also faced other challenges such as access to markets and access to financial credit lines, challenges that prevented them from effectively adapting to climate change. The study therefore recommended that appropriate and adequate strategies be designed to help farmers in the region offset the projected decrease in maize production and increase crop yields while minimising negative environmental impacts.

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List of Abbreviations

ACRU	Agricultural Catchments Research Unit
BCC	Beijing Climate Centre
AgMERRA	Agricultural Modern-Era Retrospective Analysis for Research and Applications
ARC	Agricultural Research Council
BMP	Best Management Practice
CICES	Common International Classification of Ecosystem Services
CIP	Climate Information Portal
CERES	Crop Environment Resource Synthesis
DSSAT	Decision Support System for Agrotechnology Transfer
EPIC	Environmental Policy Integrated Climate Model
ES	Ecosystem Services
FAO	Food and Agriculture Organisation
GCMs	General Circulation Models
GFDL	Geophysical Fluid Dynamic Laboratory
GIS	Geographic Information System
HI	Harvest Index
HSWD	Harmonised World Soil Database
IIASA	International Institute for Applied Systems Analysis
IPCC	Intergovernmental Panel on Climate Change
MEA	Millennium Ecosystems Assessment
MIROC	Model for Interdisciplinary Research on Climate
N	Nitrogen
NSE	Nash-Sutcliffe Efficiency

P	Phosphorus
PBIAS	Percent Bias
PES	Payments for Ecosystem Services
PHU	Potential Heat Units
RCM	Regional Climate Model
RCPs	Representative Concentration Pathways
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
SWB	Soil Water Balance
TEEB	The Economics of Ecosystems and Biodiversity
WA	Biomass to Energy Ratio
WSFY	Water-limited Harvest Index
WUE	Water Use Efficiency

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Dennis Junior Choruma

Signature: __________________________

9 March 2020

Date: __________________________

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Chapter 1: **Introduction**

This chapter gives an introduction to the overall study (section 1.1). Section 1.2 provides the rationale for the research. Next, the research questions are presented in section 1.3 and the research objectives described in section 1.4. Section 1.5 shows the flow diagram for the study and section 1.6 gives a general description of the study area. Lastly, section 1.7 provides an outline of the remaining chapters of the thesis.

1.1 Introduction

Ecosystems generate a variety of benefits for humans such as food, fresh water, medicines and timber. The term 'ecosystem services' (ES) is used to describe these benefits, whether direct or indirect (Costanza et al., 1997). To meet rising food needs from a growing human population, man has transformed natural ecosystems into highly managed ecosystems such as farmlands and pastures, and their ecosystem services used intensively (DeFries et al., 2004; Foley et al., 2005). Efforts to sustain economic growth while simultaneously conserving the natural environment (Sustainable Intensification, SI) present important policy and land management challenges, particularly for countries where land and water resources are already stressed. SI involves increasing crop production levels from the same area of land while reducing the negative environmental impacts of agricultural production and increasing the provision of environmental services (Cook et al., 2015). In this study, the focus is on increasing maize production while minimising leaching of N fertiliser to water bodies. The focus is on maize since maize is an important staple crop in the Eastern Cape whose production has been associated with the overutilization and pollution of groundwater in the study area (Goldblatt, 2011).

Growing concerns about climate change (Calzadilla et al., 2014; Godsmark et al., 2019; Nkhonjera, 2017), biodiversity loss (Lukey et al., 2017; Nattrass and Conradie, 2018; Orimoloye et al., 2018), and the poor management of natural resources such as water and agricultural lands (Kuschke and Geyer, 2016; Maherry et al., 2010; Tredoux et al., 2009) indicate that there is still a limited understanding of the links between natural systems, land management and ecosystem services. The focus of this study is on how agricultural land management and climate change affect the supply of ecosystem services in agriculture (from here on referred to as agroecosystem services).

Appropriate agricultural land management practices could avoid further ecosystem degradation while safeguarding the continued provision of agroecosystem services. However, to guide sustainable agricultural land management practices, detailed information about the present and possible future impacts of agricultural land management strategies on agroecosystem services is required (Petz, 2014). Although significant efforts have been made to improve the quantification of ecosystem services and to understand how they contribute to human well-being (Crossman et al., 2013), several knowledge gaps still exist about how ecosystems generate services, how to quantify ecosystem services trade-offs and how changes in land management affect the provision of ecosystem services, particularly within managed ecosystems such as farmlands (Carpenter et al., 2009; de Groot et al., 2010; Villamagna et al., 2013). The continued degradation of ecosystems provides evidence that further research is required to gain a better understanding of the social, economic and biophysical aspects of ecosystems and the feedback loops that exist between them (Barbier et al., 2011; TEEB, 2008).

Agricultural land management influences the processes that drive ecosystem function and efforts to maximise one ecosystem service (e.g. crop production) may result in a loss or depletion of other ecosystem services (e.g. biodiversity). Barbier et al., (2008) proposes that appropriate agricultural land management plans can only be developed when the true value of an ecosystem and its services is known. Therefore, to avoid setting unrealistic targets for sustainable intensification, a better understanding of the interactions between the biophysical ecosystem processes, ecosystem services and the effects of alternative agricultural land management practices on the ecosystem as a whole is necessary. Further, it is also important to develop modelling tools that synthesise information to support decision making concerning agricultural land management and predict the effects of alternative agricultural land management systems on ecosystem services supply (Nelson and Daily, 2010; Vigerstol and Aukema, 2011). Understanding the effects of agricultural land management on ecosystem services provision is vital in developing policies that promote sustainable intensification. Central to this understanding is compiling and analysing empirical evidence and information to support agricultural land management decisions so that agricultural land management is not grounded in poorly verified assumptions (ICSU et al., 2008).

Previous studies have suggested that empirical information about the ability of ecosystems to provide several ecosystem services at the same time is disjointed and a robust scientific basis for incorporating ecosystem services into land-use decisions is still lacking (Ehrlich et al., 2012; Nelson and Daily, 2010). Further, ecosystem services research has traditionally followed disciplinary lines mostly either in Economics (Barbier et al., 2011; Costanza et al., 1997; Gallai et al., 2009) or Environmental Science (Swinton, Lupi, Robertson, & Hamilton, 2007; Lakerveld, 2012). However, it is now becoming widely recognised that natural resources issues are trans-disciplinary, often occurring at the intersection of complex natural and social systems (Berkes, Colding, & Folke, 2003; Daily et al., 2009; Pagiola, 2008). If sustainable intensification is to be realised, there is a need for holistic and inter-disciplinary approaches to understanding and quantifying ecosystem services provision under alternative agricultural land management strategies and different social-ecological contexts.

In South Africa, most agricultural ecosystems are a collection of natural (grassland and forests) and human-modified (farmlands and forest plantations) systems (Korner et al., 2005). As such, the provision of agroecosystem services is governed not only by biophysical ecosystem processes but also by the way humans manage them (Schroter et al., 2005) Factors such as climate change, modify the ability of ecosystems to provide ecosystem services and can thus alter ecosystem functioning. At the same time, farmers can modify the ability of ecosystems to provide services through agricultural land management practices that maximise crop yields and profits. For example, the main goal of a farmer, located upstream of a river, when growing vegetables might be to sell their produce and make a profit and not necessarily to maintain downstream water quality. This has important implications for agricultural policymaking as failure to take into account, different stakeholders' objectives and the values they assign to different ecosystem services may result in a mismatch between policy and observed outcomes. A situation which in turn may lead to conflicts between stakeholders and further ecosystems mismanagement. Consequently a more integrated assessment of ecological and social issues in agricultural land management is required when developing sustainable agricultural systems (Lescourret et al., 2015).

Similar to global environmental challenges, current environmental challenges in South Africa suggest that the full impact of agricultural land management practices on ecosystems and ecosystem services as a whole is still not well understood. This is reflected by a general decline in ecosystem services supply in many parts of the country. Problems such as eutrophication

(Branch et al., 2013; Matthews, 2014), salinization of irrigated lands (le Roux et al., 2007; van Rensburg et al., 2011) and stream-flow reductions from commercial forest plantations (Everson et al., 2014; Scott et al., 1998) have become more frequent over the last few years. Population growth, increasing water scarcity and climate change currently threaten the ability of agricultural systems in South Africa to provide ecosystem services. Currently, it is not yet clear whether current agricultural land management practices in these landscapes will be able to meet future food demands without further compromising water resources and other ecosystem services, all under the backdrop of climate change.

To address these challenges and increase crop production, several studies in South Africa have used field experiments to investigate the links between agricultural land management and ecosystem services. For example, studies have been conducted to investigate the effects of different fertiliser levels on crop yields (Fanadzo et al., 2009; Lusiba et al., 2017; van Averbeke et al., 2007), irrigation scheduling and crop yields (Mavimbela and van Rensburg, 2015; Olivier and Singels, 2015), non-point source pollution from agriculture (Schulz and Peall, 2000; Walsh and Wepener, 2009) and the effects of forest plantations on catchment water availability (Albaugh et al., 2013; Scott and Lesch, 1997). Field experiments offer a reliable method of establishing causal relationships between agricultural land management practices and real-world observed measurements (Durr et al., 2016; Liang et al., 2016). However, field experiments are often expensive, time-consuming and labour intensive. In addition, they are difficult to interpret as differences between treatments may not show for several years (Cabelguenne et al., 1990).

Alternatively, a computer-based modelling approach can provide reasonably reliable results in a short time and save considerable resources in developing agricultural land management strategies when compared to traditional field experiments alone (Santhi et al., 2005; Zhao et al., 2016). Models can thus be used as complementary tools to field experiments as data from field experiments will still be required to run and evaluate model performance. Computer modelling is increasingly becoming a useful tool to address the complex interactions in agroecosystems that lead to agroecosystem services supply (Bagstad et al., 2013; Boumans et al., 2015; Turner et al., 2016). Computer models have the advantage that they can be applied to test a range of alternative agricultural land management strategies and evaluate a range of policy scenarios within a short time (Costanza et al., 2017).

While computer-based models provide a number of advantages, a major drawback is that most of the models currently in use in agricultural land management mainly focus on biophysical ecosystem processes. As a result, most of the agricultural models lack an adequate representation and consideration of different agricultural stakeholders' objectives and goals in ecosystem services production. Yet, stakeholders decisions and motivations are critical elements that may influence the outcomes of agroecosystem services (Webber et al., 2014). To assure relevancy, Costanza et al., (2017) explain that stakeholders should be actively involved in both model and policy development that concerns the provision of ecosystem services. Also, for model results to be used with confidence, ideally, models should be calibrated and validated with observed field data in the region of interest before being used as decision support tools in land management (Daggupati et al., 2015). Nevertheless, computer models are a useful decision support tool and are increasingly being used in agroecosystem services management in South Africa.

To have a better understanding of the complex interactions between agricultural land management and agroecosystem services, several studies in South Africa have used computer models to explore the links between agricultural land management practices, biophysical ecosystem processes and ecosystem services. The most frequent model applications have been in the fields of hydrology (Hughes, 2009; Perry, 2015; Warburton et al., 2013), crop management (Kollongei and Lorentz, 2015; Zinyengere et al., 2015), rainfall/runoff yield modelling (Hughes and Slaughter, 2016; Lorentz et al., 2012), hydrological responses of catchments to climate change (Warburton et al., 2013) and the effects of forest plantations on catchment water yield (Everson et al., 2014; Govender and Everson, 2005; Gush et al., 2002). However, few studies have looked at integrated modelling at the farm level to investigate the links between biophysical agroecosystem processes, motivations for farmers' management practices, and ecosystems services supply (Oosthuizen et al., 2016). Yet, farming decisions are often taken at the farm level where farmers are the key managers of agroecosystems and ultimately responsible for implementing sustainable agricultural land management strategies and ensuring food security, while protecting and conserving vital ecosystem processes, structure and function.

In view of the above challenges in South Africa, several questions can be asked? (a) What are the effects of different agricultural land management strategies and climate change on agroecosystem services delivery in South African agroecosystems? (b) What tools can be used to quantify the effects of agricultural land management on agroecosystem services, especially in data-scarce and semi-arid areas such as South Africa? (c) How do farmers as key stakeholders in agricultural land management perceive and value the benefits derived from agroecosystems? These questions are especially relevant for semi-arid areas such as the Eastern Cape of South Africa, where declining soil productivity and increasing water scarcity due to low rainfall and frequent droughts have led to the increased use and over-application of fertilisers and irrigation water, which in turn have led to a general deterioration of ground and surface water quality in the commercial farming areas (Goldblatt, 2011). Therefore, the objectives of this study were to (i) simulate the effects of agricultural land management strategies and climate change on agroecosystem services (ii) evaluate the values farmers assign to different agroecosystem services and (iii) evaluate farmers' perceptions of climate change in relation to agricultural land management strategies and agroecosystem services.

To achieve the above-mentioned objectives, the study used an ecosystem services approach that takes into account the social and biophysical aspects of agricultural production in the Eastern Cape. First, a survey of conventional farmers in the Eastern Cape was conducted to evaluate their motivation for the adoption of current agricultural land management practices and the values they assigned to different ecosystem services generated on their farmlands. In this context, 'values' corresponds to general assessments about ES that are seen as desirable by farmers (Dietz et al., 2005; Lamarque et al., 2014). The study focused on conventional as well as commercial farmers in the Eastern Cape as they are key decision-makers responsible for managing agricultural land and food production in the area. In this study, conventional farmers were defined as farmers who regularly used inputs such as synthetic fertilisers and irrigation water combined with farming technologies such as sprinkler and drip irrigation systems in their day to day farming. Commercial farmers are a type of conventional farmer defined as farmers who are in the farming business to produce crops and livestock for sale, usually with the use of chemical fertilisers and pesticide. In this study, 'farmers' referred to both conventional and commercial farmers.

Second, a crop model, the Environmental Policy Integrated Climate (EPIC) model is presented. The EPIC model was applied to simulate the provision of agroecosystem services under different agricultural management strategies. This provides a useful tool to analyse ecosystem trade-offs from different agricultural land management practices and explore combinations of irrigation and fertiliser management strategies that promote sustainable intensification of crop production systems. Finally, the EPIC model was applied to evaluate the impacts of climate change on future maize yields in the Eastern Cape using statistically downscaled climate data from three driving General Circulation Models (GCMs) under two Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5.

The present study contributes to the current debate on sustainable agricultural intensification and how agricultural systems in Africa can be better managed sustainably, indicating tools and approaches that can be used to quantify agroecosystem services. The study contributes to the policy arena by clarifying the implications of farmers' decisions and policy options on sustainable intensification of agroecosystems and the services they provide.

1.2 Agroecosystems as social-ecological systems

Agroecosystems can be described as social-ecological systems linking people with nature. The social aspects of agroecosystems include structures such as farmers, extension agents and researchers and processes such as agricultural land management regimes, policy regimes, institutional arrangements, learning and consultations. The ecological aspects include structures such as soil, water and air and processes such as nutrient and water cycles and organic matter decomposition. Therefore the evaluation of ES within different SES is influenced not just by the ecological properties of the ecological subsystems but also by the sociocultural and institutional contexts of the social subsystem as well (Tallis and Polasky, 2009). The SES framework provides guidance on how to assess the social and ecological dimensions that contribute to sustainable resource use and resource management (Ostrom, 2009). The SES approach explicitly recognises the connections and feedbacks linking human and natural systems (Leslie et al., 2015) and therefore can be used in the key processes of generating knowledge and the formulation of sustainable governance solutions (Quintas-Soriano et al., 2018). However, few studies in South Africa have addressed how farmers' perceptions of ES link to the biophysical properties and ecosystem functions of the ecosystems on which ES are based, or the extent to which ES are affected by socio-cultural context and human interests. (Cebrian 2017). Therefore, this study employed an ES approach under an SES framing to explore and model the effects of agricultural land management practices and climate change on agroecosystem services

1.3 Rationale

In South Africa, few studies have looked at integrated modelling at the farm level to investigate the links between farmers' motivations with regard to crop production decisions at the farm scale, ecosystem services and climate change (Oosthuizen et al., 2016). Farmers remain the key decision-makers at the farm level, and thus integrating their views into modelling processes is key to the sustainable management of agroecosystems.

To date, most South African fertiliser and irrigation water recommendations are based on soil types and land systems (FAO, 2005). These recommendations are determined by yield responses from fertiliser and water field trials and seldom consider environmental impacts. During the past few years, field studies have been conducted in South Africa to evaluate the impacts of nutrient management on crop productivity and water use (FAO, 2005; Kgonyane, 2010). Most irrigation and fertiliser management recommendations have been developed from such field studies. Although field trials are reliable in assessing crop nutrient and water needs, field experiments are often time-consuming, labour intensive and expensive to carry out on a regular and long-term basis. Further, field trials also have a limited ability to explore future crop and water needs under different climate scenarios. There is, therefore, a need for modelling studies that consider the impacts of agricultural management strategies on crop yields and the environment (CCA, 2013). Hence, scenario modelling can be a useful tool to complement field trials in agricultural and management planning (Mason et al., 2017). Thus, in South Africa, there is an urgent need to develop integrated modelling approaches that test the effectiveness of irrigation and fertiliser management practices in increasing yields and minimising water pollution under present and future climate scenarios, while incorporating farmers' perceptions, motivations and views in such integrated modelling approaches.

Maize is an important staple food in South Africa constituting a significant proportion of the South African diet. In addition, maize is an important feed source for the beef and dairy industry in South Africa. Prolonged periods of drought, erratic rainfall and declining soil fertility in most production areas have negatively impacted maize production. Efforts to increase maize production in provinces such as the Eastern Cape using chemical fertiliser and irrigation water have significantly contributed to groundwater pollution (Maherry et al., 2010), eutrophication (Matthews, 2014; Sibande, 2013) and salinization of irrigated lands (Aza-Gnandji1 et al., 2013). Further climate change is projected to have negative impacts on crop production and water availability in the Eastern Cape. Previous studies on maize production in the Eastern

Cape have mainly focused on maize production without fully considering the underlying motivations for farmers' management practices. Yet, farmers' motivations for adopting certain management practices have a direct effect on both maize yields and the environment. It is therefore important to find strategies that increase maize yields in the Eastern Cape while minimizing environmental pollution from agriculture and at the same time help farmers adapt to the anticipated negative impacts of climate change.

1.4 Research questions

Detailed information about the impact of agricultural land management on agroecosystem services is important to guide land policy and agricultural land management decisions. However, empirical evidence about the effects of alternative agricultural land management on ecosystem services is generally limited in South Africa. To contribute knowledge to this gap, this study addresses the following research questions:

1. *What are the motivations behind the Eastern Cape farmers' current irrigation and Nitrogen (N) fertiliser management practices and what values do they assign to different agroecosystem services?*
2. *How can a crop model be calibrated with limited field data for evaluation of alternative agricultural land management strategies and climate impact studies?*
3. *How can maize production in the Eastern Cape be optimised through improved irrigation and N fertiliser management strategies and what are the trade-offs between increasing maize production and minimising the potential risk of water pollution from N leaching?*
4. *What are farmers' perceptions of climate change and what are the impacts of future climate change on maize yields in the Eastern Cape?*

1.5 Research objectives

This study aims to explore agricultural land management strategies, specifically irrigation and fertiliser management, to increase maize production in the Eastern Cape while minimizing water use and environmental impacts (nitrogen leaching). The thesis contributes to the scientific discussion regarding the effects of agricultural land management on ecosystem services supply and the use of biophysical crop models and field data 0to evaluate ecosystem services provision. The specific objectives are as follows;

1. To explore motivations for farmers' management practices and values assigned to agroecosystem services in the Eastern Cape, South Africa.
2. To calibrate and validate the EPIC model for maize growth and yield simulation using limited field-scale data under South African conditions.
3. To quantify the effects of agricultural land management strategies and climate change on selected agroecosystem services at the farm scale.
4. To evaluate farmers' perceptions of climate change and compare current and future maize yields under different future climate scenarios.

1.6 Study flow diagram

This study used an ecosystem services-based modelling approach combining a survey of farmers' current agricultural land management practices and computer modelling to compare different irrigation and fertiliser management strategies and evaluate the impacts of climate change on maize yield in the Eastern Cape. Figure 1.1 shows the flow diagram for the study.

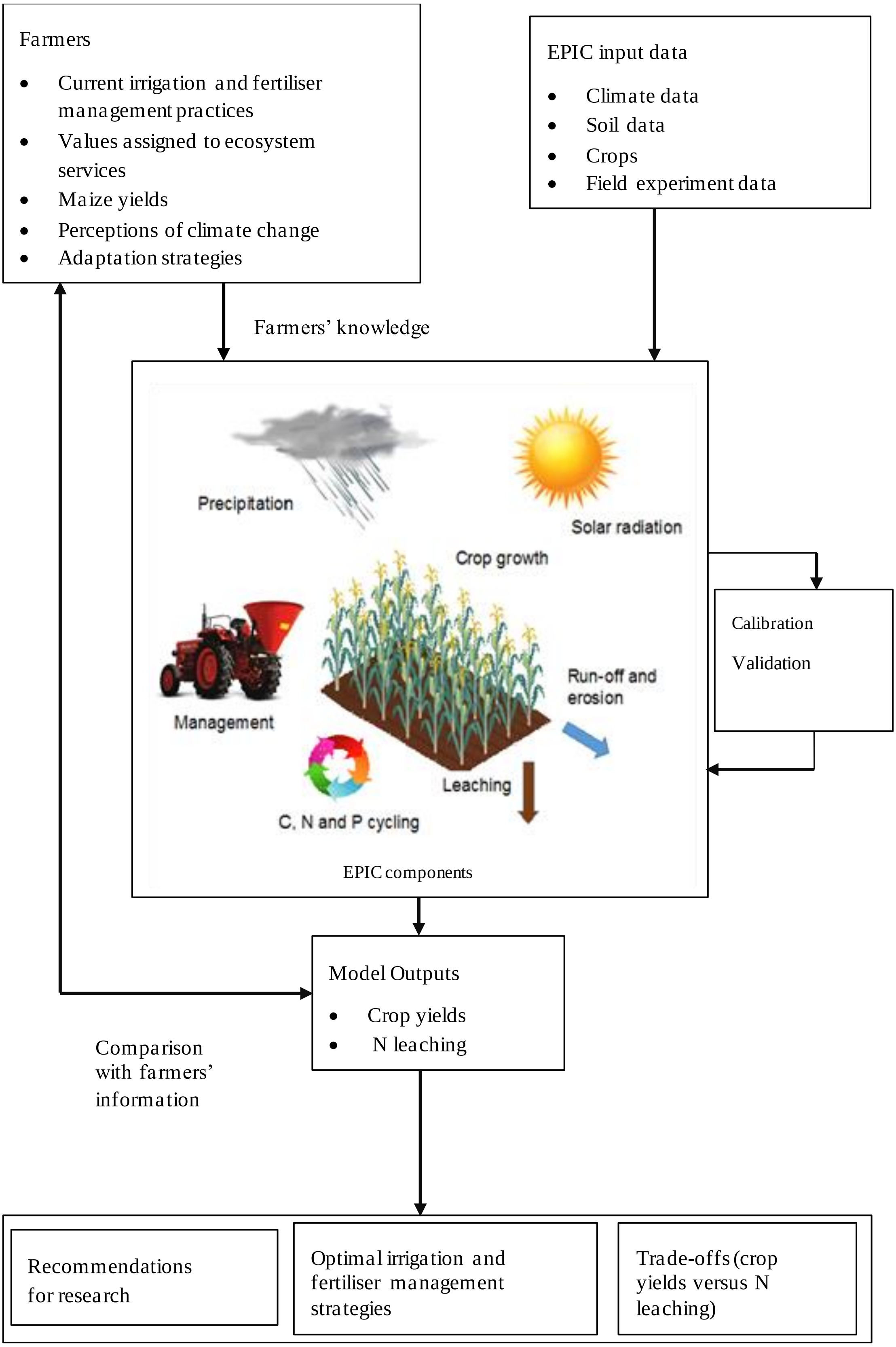

Figure 1.1. Flow diagram used in the study showing EPIC components and inputs.

1.7 General study area description

Field experiments used in the calibration and validation of the EPIC model were carried out at the Cradock Research farm. Cradock is situated in the Great Fish River Valley in the Eastern Cape Province, South Africa (32°13′ 11.09″ S, 25° 41′ 11.86″ E, elevation 849 m) (Figure 1.2). The Eastern Cape exhibits a bimodal rainfall pattern, with a winter rainfall zone in the west, and a summer rainfall zone in the east. In the north, east and along the coastal belt, summer seasonality encourages C4 grass production. In the semi-arid central and western regions, C3 grasses and shrubs predominate, favouring sheep and goat production. The northern areas generally have a high altitude and little water, which result in semi-arid conditions that characterise regions such as the Karoo. To the south, water is more available due to several rivers that pass through the area from surrounding mountains. Conditions inland are usually drier and hotter with lower rainfall levels compared to the coastal area. In summer, average temperatures range from 16º to 26ºC while winter temperatures range from 7º to 20º C. Winter months fall between April and August while summer temperatures are usually highest between November and April.

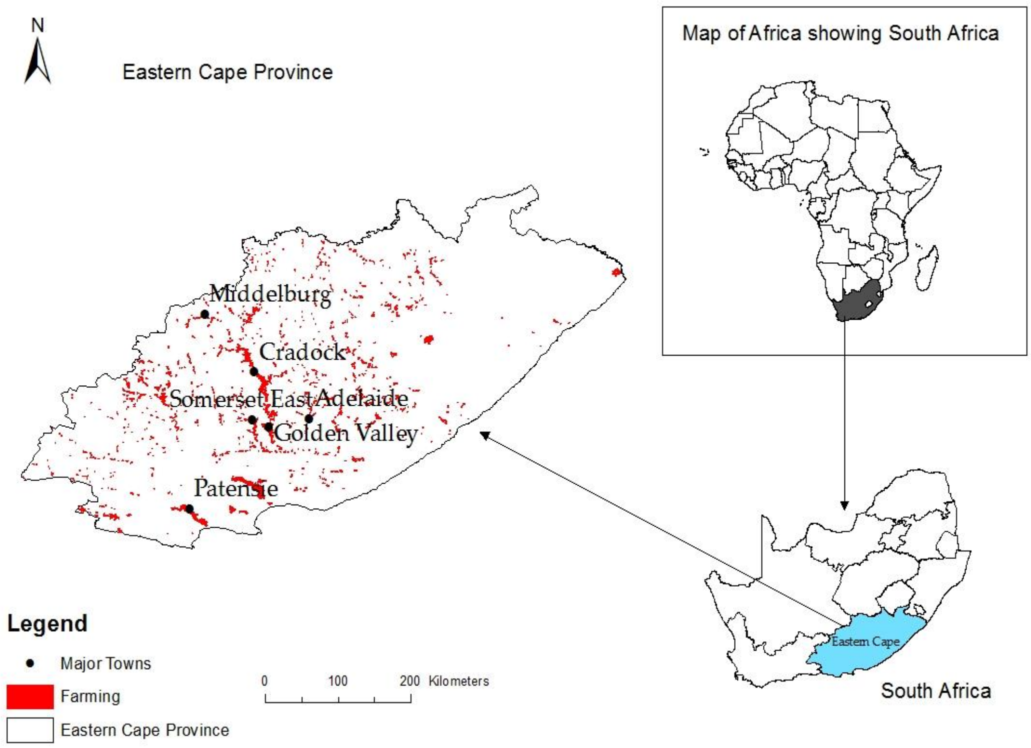

Figure 1.2 Map showing the location of Cradock in the Eastern Cape, South Africa

Agriculture in the Eastern Cape is dominated by both commercial (intensive beef and dairy, cereal, vegetable and fruit farming) in the south-western parts, and subsistence farming in the north-eastern regions. This study focuses on farmers who use inputs of chemical fertilisers and/or irrigation water in their day to day farming and agricultural land management practices related to Nitrogen fertiliser and irrigation water management. Nitrogen and water availability have been found to be the major constraints to agricultural production in sub-Saharan Africa (Mueller et al., 2012) and the mismanagement of irrigation and fertiliser has been blamed for many environmental problems in South Africa (Goldblatt, 2011).

In recent years, the government has encouraged the production of cereals such as maize in order to utilize all available arable land in the Eastern Cape and increase food security (Province of the Eastern Cape, 2014). The main source of water in the Cradock area is the Great Fish River. Most farms are privately owned and most conventional farms including commercial farms are distributed in towns situated along or close to the Great Fish River or its tributaries. Due to low soil fertility in the area, many conventional farmers practise the application of chemical fertilisers and pesticides to improve crop productivity (Goldblatt, 2011). Lucerne is also grown in the area as a feed source for cattle.

River ecosystems are under pressure, particularly in the semi-arid western parts of the province where there are high demands on limited water resources. Currently, the Eastern Cape faces high levels of soil degradation, particularly in commercial farmland areas (Goldblatt, 2011; Hamann and Tuinder, 2012). Pressure on groundwater in the western parts of the province is high with the main use of water in the province being irrigation, which accounts for almost two-thirds of water resources required in the Eastern Cape (Hamann and Tuinder, 2012).

1.8 Thesis Outline

This thesis proceeds as follows. In Chapter 2, a literature review of the concept of sustainable intensification is given. This includes a discussion of the concept of ecosystem services, the framework applied in this study and the tools that can be used in analysing and quantifying ecosystem services trade-offs in agriculture.

Chapter 3 describes a survey of the Eastern Cape conventional farmers' current agricultural management practices and the values they assign to different ecosystem services within farmlands. This chapter offers insights into the motivation for farmers' adoption of certain agricultural management strategies and as well as the values they assign to different agroecosystem services. This chapter contributes to the basis of developing current and future agricultural land management scenarios using computer models as well as agricultural land management strategies that are likely to be adopted by farmers.

Chapter 4 describes the set-up, calibration and validation of the EPIC model under South African conditions. Limited data from a field experiment on maize variety trials in the Eastern Cape are used to calibrate and validate the EPIC model to simulate maize yield in the Eastern Cape. This chapter demonstrates the utility and importance of calibrating computer models in the region of interest before application. The chapter describes a stepwise field-scale calibration procedure for the EPIC model under South African conditions.

In Chapter 5 the calibrated and validated EPIC model is applied to the case study area to evaluate different irrigation and fertiliser management strategies. Different combinations of irrigation water and N fertiliser levels are simulated and evaluated to explore best combinations of N fertiliser and irrigation water levels that maximise crop yields and minimise fertiliser and water losses from the farms into the environment.

In Chapter 6 the EPIC model is applied to simulate the effects of future climate change on maize yields in the Eastern Cape. Statistically downscaled climate data from three General Circulation Models (GCMs) are used to drive model simulations under two different future Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5, for two future time periods, 2040-2069 and 2070-2099. Model outputs on future maize yield and N leaching are then compared to the baseline period (1980-2010). In this chapter, the results of farmers' perceptions of climate change and their climate change adaptation strategies are also presented.

Chapter 7 presents a synthesis of the main findings from previous chapters. Recommendations are given and conclusions summarised. The chapter concludes with suggestions for future research.

Chapter 2: **Literature Review**

This chapter begins with an introduction (section 2.1) and reviews literature on the following topics: the concept of sustainable intensification (section 2.2); agriculture in a changing environment (section 2.3); strategies to increase crop yields (section 2.4); tools to evaluate agricultural land management (section 2.5); tools for predicting climate change (section 2.6) Lastly, section 2.7 provides a synthesis of the literature and highlights the need for an ecosystem services approach to agricultural land management.

2.1 Introduction

Balancing the need to produce more food and fibre for a growing population with environmental objectives is a key concern for global scientific and policy debates on sustainable agriculture. Based on projections from the Food and Agriculture Organisation (FAO) food production will need to increase by more than double by the year 2050 to meet the food needs of an estimated world population of just over 9 billion (FAO, 2003). A significant challenge in food security discussions is how to meet the rising demand for food while minimising environmental degradation (Royal Society, 2008). Sustainable intensification (SI) has developed as one major pathway for concurrently improving agricultural outputs and environmental conditions (Fish et al., 2014).

A great number of studies exist elaborating the theory and practice of sustainable land use (Fish et al., 2014) including the modelling of multifunctional landscapes in a variety of agricultural settings (e.g. Rossing et al., 2007) as well as the political and behavioural aspects of agricultural production (e.g.Wilson, 2007). In this study, the focus is on how an ecosystem services (ES) approach might aid in decision and policy-making concerning the crop production aspects of SI. Research with the idea of ES, whose origins are rooted in nature conservation and environmental sustainability, and the companion concepts of ecosystems approach and ecosystems assessment to decision-making is emerging to be an interdisciplinary issue increasingly bringing together once separate research disciplines (Burkhard et al., 2010).

One key framework for conceptualising and approaching the SI challenge is an ES perspective. Fish et al., (2014) explain that the ES approach is one way of describing the environmental resources that support and interact with agricultural production systems. Consequently, the study describes the types of approaches that would be relevant using an ES perspective to link crop production with environmental sustainability objectives. The necessity to frame issues of SI through ecosystem services-oriented references other than those based on wholly economic valuations of ecosystem services is highlighted in this review.

2.2 The concept of sustainable intensification

The term 'sustainable intensification' was introduced in the 1990s by Pretty (1997) to describe the need for increases in crop yields while protecting the environment and growing the economy in sub-Saharan Africa, where large crop yield gaps, especially cereals, have been reported (Struik and Kuyper, 2017). Since then, the definition of SI has changed and evolved over time (Garnett et al., 2013). For example, agricultural economists such as Ruben and Lee (2000) define SI as the simultaneous increase in returns to land and labour and the maintenance of soil nutrient balances. Pretty et al. (2011) and Firbank et al. (2013) redefined SI as producing more output per unit land while reducing environmental impacts and increasing contributions to natural capital and flow of environmental services. However, a widely cited definition is the definition by the Food and Agriculture Organisation (FAO), which defines SI as producing more food and fibre from the same area of land, while conserving resources, reducing negative environmental impacts and enhancing the natural capital flow of ES (FAO, 2011). While the definition by FAO is limited in that it emphasises the crop production aspect of agriculture and does not consider the whole range of factors involved in crop production such as access to markets and labour, in this study, the definition by FAO is adopted because of its explicit link to the concept of ES.

Godfray and Garnett (2014) argue that SI is not only about increasing food volume but also about improving the efficiencies in food production relative to environmental resources and impacts. In this respect, Godfray and Garnett (2014) seek to separate debates of SI with general targets for global food production arguing that while some increases in production to meet demand will be required, the issue of how to reconcile production with productivity is best approached through an understanding of local capacities and circumstances. This is because while agricultural systems face many similar challenges, differences in soil, climate and agricultural land management practises make individual systems unique. Adopting agricultural solutions developed in other regions without adapting them to local contexts may not necessarily bring about the desired results.

In South Africa, particularly in the Cradock region, as the effects of extended drought periods continue, farming in a water-constrained environment may no longer be a short-term challenge but rather a long-term challenge that requires a shift in the way water is managed in agricultural production. Since irrigated agriculture already accounts for more than 60% of total water usage in the province it is unlikely that farming will receive a higher allocation of water in the future. A business-as-usual approach to water usage will no longer be sufficient. The use of models such as the EPIC model can help develop optimal agricultural water management strategies that save water while maintaining crop yields. Developing optimal agricultural land management practices through an ES approach will help in ensuring that the focus is not only on crop production but also on the efficient use of scarce water resources and maintaining the integrity of the environment.

2.2.1 A brief history of the ecosystem services concept

The continued degradation of natural resources such as land and water has led to the development of new approaches to better understand how ecosystem changes affect human-well-being (Mastrangelo et al., 2015). One increasingly popular approach is the ecosystem services (ES) approach, which dates back to the 1970s when the economic benefits of natural processes and ecosystems to society were recognised (de Groot, 1987; Westman, 1977). However, a clear concept of ecosystem services in the scientific literature was only published in the 1990s (Daily, 1997; de Groot, 1992). The term 'ecosystem services' is therefore relatively young and as such, its definition has been heavily debated in the literature (Costanza et al., 2008; Fisher et al., 2009).

Ecosystem services definitions have mostly varied depending on the emphasis given to ecological components or economic use (Braat and de Groot, 2012). Daily (1997), defined ecosystem services as the conditions and processes through which natural ecosystems and the species that make them up, sustain and fulfil human life. Costanza et al., (1997) defined ES as the benefits humans derive directly or indirectly from ecosystem functions. However, the most frequently used definition of ES is that by the Millennium Ecosystem Assessment (MEA) which defined ES as the benefits people obtain from ecosystems (MEA, 2005). Although research on ES has grown considerably since the MEA report was published, the ES framework is still not integrated into many policies and agricultural management decisions such as which climate change adaptation strategies to prioritise (Seppelt et al., 2011).

One criticism of the MEA and related definitions is their lack of differentiation between intermediate and final ES (Johnston and Russell, 2011). Intermediate ES are frequently defined as those services with little or no direct benefits to people and comprise of the biophysical structures and processes that maintain ecosystems in a favourable state for the delivery of final ES (correspond roughly to the regulating and supporting ES categories) (MEA, 2005). Final ES are described as those services that benefit people explicitly and can be accounted for in biophysical or monetary terms through measures such as crop yield output per season (provisioning ES) or the number of lake visitors per year (cultural ES) (Lamothe and Sutherland, 2018). The lack of a clear distinction between intermediate and final ES can lead to double counting of different ES since some ES can be counted twice. Such errors can lead to sub-optimal decisions in land management (Briner, 2012). For example, water flow is classified as a regulating service, with the generation of hydropower as an output of the process. If economic values were attributed to both water flow and hydropower, this could lead to double valuation (Ojea et al., 2012).

Ecosystem services classifications have also been equally varied because of the specific biophysical and socio-cultural contexts in which they are defined or the scientific discipline of the researcher (Gómez-Baggethun and Ruiz-Pérez, 2011). For the scope of this thesis, the MEA classification of ES is adopted. The Millennium Ecosystem Assessment report (MEA, 2005) classifies ES into four broad categories: (1) provisioning services – biotic resources derived from ecosystems that can be removed such as food and timber; (2) regulatory services – services that help to sustain an environment suitable for human life such as water purification and flood regulation; (3) cultural services – these are mostly human-centred and refer to ecosystem components that are sources of inspiration for art, culture and spirituality; (4) supporting services – these are services that support the other three categories but are not a direct service to people for example nutrient cycling and soil formation.

Given the debate regarding the definition of ES some authors have suggested narrower definitions of ES. For example, Boyd and Banzhaf, (2007) define ES as the final components of nature, directly enjoyed, consumed or used to yield human well-being. The Economics of Ecosystems and Biodiversity (TEEB) report defined ES as the direct and indirect contributions of ecosystems to human wellbeing (TEEB, 2010). Haines-Young and Potschin, (2012), in their

Common International Classification of Ecosystem Services (CICES) report added to TEEB's definition that ES arise from the interaction of biotic and abiotic processes. The varying definitions of ES indicate that a universally acceptable definition of ES is highly unlikely as definitions largely depend on the reason and view-point of the assessment. Costanza et al., (2008) argue that a universal definition will be elusive but definitions can be fine-tuned according to the research context. The MEA meant to communicate general findings, CICES aimed to develop an ecosystem accounting approach and TEEB concentrated on economic valuation of ES, hence the variation in the definitions. In this thesis, the definition by TEEB which describes ES as outcomes of ecosystems and as contributions to human wellbeing is adopted and the ES considered are food provision and water quality protection within an agroecosystem context.

According to Norgaard, (2010), the ES approach has been promoted in sub-Saharan Africa due to its claimed merits in developing countries. For example, given the focus of the ES approach on the linkages between the economic, ecological and social aspects of ES supply, the ES approach can help in tackling the twin challenges of poverty and environmental degradation. Africa currently faces challenges such as high levels of poverty, increasing water scarcity, biodiversity loss, ecosystem degradation and low resilience to natural disasters and increased vulnerability to climate change (Economic Commission for Africa, 2012). The ES concept is proposed as a borderline object for sustainability science facilitating the integration of disciplines that have been traditionally separate, for example, ecology and human behaviour (Abson et al., 2014). In addition, the ES approach is also seen to be flexible enough to be applied in different social-ecological contexts, thereby allowing the production of knowledge relevant to local contexts (Opdam, 2009). Importantly, Daw et al., (2016) argue that, because the ES approach focuses on the ecological, social and economic aspects of ES supply, the concept can aid in tackling the challenges of poverty and environmental degradation. The ES approach is, therefore, ideal for producing policy-making knowledge in countries such as South Africa where agriculture forms a significant and important part of the economy.

In South Africa, the initial studies exploring the concept of ES took place in 2005 (van Jaarsveld et al., 2010), the same year the MEA 2005 report was published. Since then several ES studies have been conducted in South Africa. The majority of these studies have mainly focused on biodiversity conservation (e.g. Cumming and Maciejewski, 2017; Egoh et al., 2011). Studies have also focused on mapping ES using a variety of methods including

Geographical Information Systems (Anderson et al., 2017; Turpie et al., 2017) or focused on economic valuation of ecosystems, mostly at the national scale (Davenport et al., 2012; Mudavanhu et al., 2017) or local knowledge regarding ES (Shackleton and Shackleton, 2018).

With regard to ES research, Mthembu et al., (2019) provided a review of the advantages of intercropping in agricultural systems to increase small-scale farmers' food security in the Kwa-Zulu Natal area. However, the study by Mthembu et al., (2019) only provided a qualitative review of how intercropping can improve multiple ecosystem services supply. Of note, however, is the Working for Water Programme, which begun in 1995 and has grown to be one of the biggest conservation programmes in South Africa (Turpie et al., 2008), focusing on biodiversity conservation through the clearing of invasive alien species. While ES research in South Africa has grown since 1995, few studies have focused on farmers agricultural land management with regard to multiple ES supply and farmers' motivation for adopting specific agricultural management practices in light of current and potential future climate realities.

2.2.2 Sustainable intensification and the concept of ecosystem services

Studies examining the relationship between SI for increased food security, particularly crop production and ES, remains weakly developed (Fish et al., 2014). However, of note is the study by Bommarco et al., (2013) who argue for an approach to the SI of agriculture based on the notion of ecological intensification (EI). Ecological intensification describes the processes by which service-providing organisms are utilised in agricultural systems to increase yield levels while decreasing negative environmental impacts (Cassman, 1999; Doré et al., 2011). The essence of the argument by Bommarco et al., (2013) is that ES are the features of agricultural systems that need to be conserved if increases in food production are to be balanced with environmental stability. However, it is important to note that for SI to work, it will require managing the entire food production system in a sustainable manner and not just crop production.

Swinton et al., (2007) explain that agriculture both provides and receives ES that go beyond the provision of food. Food provision is therefore not against the environment but rather one of a range of intertwining services provided by the environment, which supports and enhances life. While farmers may value food provisioning services above other ES (Smith and Sullivan, 2014), the provision of food is underpinned by the delivery of other ES (Fish et al., 2014). For example, invertebrate pollination, nutrient cycling, soil fertility, water provision are all ES that contribute to food provision either directly or indirectly (Swinton et al., 2007; Zhang et al., 2007). The challenge of SI, therefore, is about ensuring that ES generated from agricultural landscapes can sustain the requirements for food production, while at the same time maintaining and sustaining the integrity of the environment. This study contributes to research that attempts to understand what motivates farmers decision-making concerning agricultural land management strategies and how these management strategies can be improved to increase crop yields while minimising environmental pollution.

2.2.3 A Framework for studying ecosystem services

A framework provides structure to the research and enables better comparison and validation of model outcomes (Bockstaller and Girardin, 2003). The current debate in ES research is around how ES actually flow and the questions whether all ES can be characterised in a similar way and how to differentiate between actual and potential service delivery (Spangenberg et al., 2014; Villamagna et al., 2013). In response to the question of how ES flow, Potschin and Haines-Young, (2011) developed the ES 'cascade-model' to explain the flow of ES from the ecological base to society. Nassl and Löffler, (2015) argue that the ES cascade model has proved to be a useful idea to define the basic elements of ES supply. The cascade model represents ES as part of a production chain that links the biophysical components of an ecosystem to socio-economic and cultural gains in human well-being (Nassl and Löffler, 2015). In the cascade model, the service is placed between the ecosystem and human well-being, implying that no service is provided without ecosystems and no service is used without humans (Potschin and Haines-Young, 2011; Spangenberg et al., 2014).

Despite the cascade model proving to be useful, it has been criticised for neglecting societal influence by under-representing societal feedback mechanisms and the influence of land use and agricultural land management on ES (Spangenberg et al., 2014; van Oudenhoven et al., 2012). Consequently, several researchers such as Spangenberg et al., (2014) and Bastian et al., (2012) have further modified the ES cascade model. Of note, has been the addition of a 'value' step to distinguish between ecosystem properties and ecosystem functions and the incorporation of feedback loops such as the influence of society on ES supply to the original unidirectional flow of ES. Spangenberg et al., (2014) argue that the cascade model can be greatly improved by acknowledging human involvement within each cascade step. Agricultural management plays a key role in the delivery of ES and the use of the ES concept may help gain useful insights into what motivates farmers to adopt certain agricultural land management strategies and how sustainable agricultural land management strategies that are likely to be adopted by farmers can be developed. In this study, the cascade model was modified to show how farmers' management practices influence the provision of agroecosystem services and how the values they assign to different agroecosystems may influence the way farmers manage agroecosystems. Figure 2.1 shows the adapted cascade model used in this study. The double arrows show two-way interactions while the curved arrows show the stepwise flow of ES. Along with monetary values, people can express the importance they attach to benefits using moral, aesthetic or spiritual criteria. And it is in relation to these values that people and societies choose to take steps to adjust or manage the pressures on ecosystems and ultimately the benefits they deliver to society. In the model, this feedback is what is shown by the arrow running from the benefits and values box back to the left-hand side of the cascade model.

In this study, the ES idea was used as a way of studying the biophysical and social aspects of agroecosystems. The cascade model is used as a tool for representing important elements in the crop production system linking ecosystems and people, two important factors critical to sustainable intensification and the supply of ES. This study applied a biophysical crop model (EPIC) in combination with a survey of farmers to gain useful insights into the links between farmers' motivations for agricultural land management strategies and how these agricultural land management strategies can be improved in a way that minimises negative environmental impacts and contribute to sustainable food production systems. In the adapted model, the focus of this study is indicated by the shaded bold arrow.

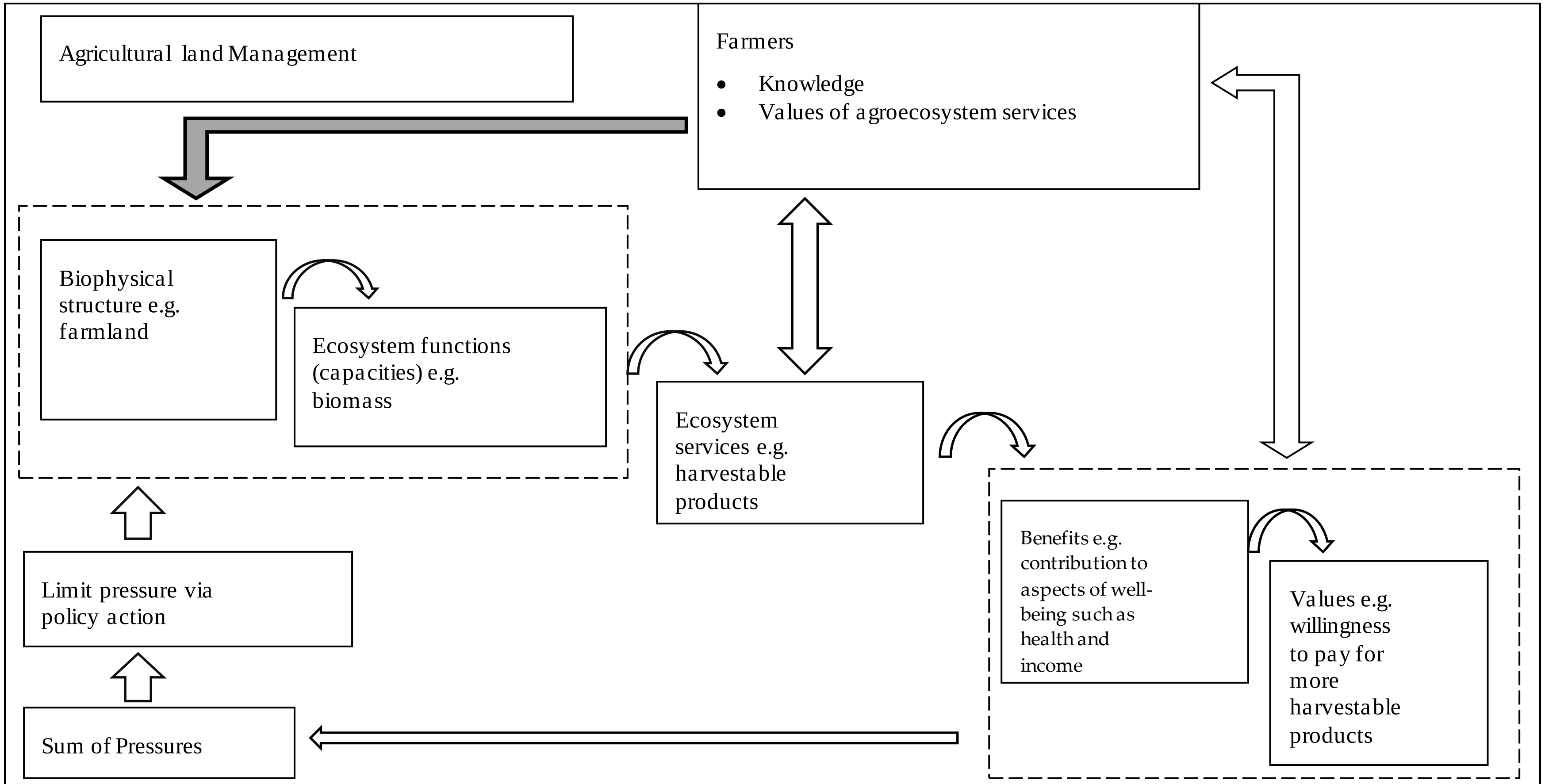

Figure 2.1. Adapted cascade model showing the links and feedback loops between farmers' values and knowledge, agricultural land management practices and ES supply based on Potschin and Haines-Young, (2011) and de Groot et al., (2010). The shaded arrow indicates the focus of this thesis**.**

2.2.4 Trade-offs and synergies between ecosystem services

In a human-managed ecosystem such as agriculture where multiple ES can be produced, the decision on which agroecosystem services to maximise can affect other agroecosystems directly or indirectly. For example, a decision on changing from agricultural land to a commercial forest plantation may not only affect provisioning services from crop production to carbon sequestration but may also affect other sectors (water sector) and people (downstream farmers). In the context of this study, a trade-off may occur when a farmer decides to increase fertiliser application to increase crop production. A trade-off is when an increase in one objective or variable leads to a decrease in another (Stevenson and Lindberg, 2010). While the farmer's decision to increase fertiliser application can bring about an increase in crop yield, the increase in N application can be accompanied by an increase in the potential amount of N fertiliser lost through leaching and runoff if the fertiliser application if not properly managed. A key outcome of this study is to demonstrate how trade-offs and synergies work and explore ways to minimise decisions and agricultural land management practices that enhance trade-offs, while currently promoting decisions and agricultural land management strategies that enhance synergies. The use of modelling tools through an ES approach that advocates for managing agroecosystems for multiple agroecosystem services supply can be useful in identifying optimal agricultural land management strategies that reduce trade-offs between agroecosystem services supply.

Apart from trade-offs, synergies between agroecosystem services can occur. Synergy is when an increase in the provision of one ecosystem service has a positive effect on the provision of other ES and in this case, it is a win-win scenario (Jax et al., 2013; Raudsepp-Hearne et al., 2010). For example, studies have suggested the possibility of a synergistic relationship between timber production and recreation i.e. in some cases people prefer managed forests compared to unmanaged forests (e.g. Gundersen and Frivold, 2008; Ribe, 1989). Other studies have also suggested insignificant trade-offs between biodiversity conservation in landscapes and the provision of other non-market ES such as clean air (Hooper et al., 2005). An examination of yields from agricultural systems globally suggests that on average, agricultural systems that conserve multiple ES through practices like crop diversification and conservation tillage perform just as much as intensive high input systems (Badgley et al., 2007), suggesting that it may be possible to maintain other agroecosystem services while enhancing food provision. To this end, Baulcombe et al., (2009) suggest that achieving SI will depend on the management of multiple ecosystem processes rather than the use of high inputs.

To minimise unintended agricultural land management consequences, farmers and land managers need to have a complete understanding of the benefits and losses arising from their decisions concerning natural resources and consequently the delivery of ES. It is also equally important to take into account the biophysical and social implications of agricultural land management strategies as trade-offs affect different ES and different groups of beneficiaries with different interests and objectives (Howe et al., 2014). For example, converting agricultural land to commercial forest land may affect not only water quality but also related sectors such as agriculture and downstream water users.

While information from the different academic disciplines can be used to provide information on trade-offs resulting from alternative agricultural land management strategies, studies by (Martín-López et al., 2014) show that different trade-offs are revealed depending on the research domain they are addressed by. This has implications for policy as a particular approach may favour the enhancement of one ecosystem service but may have unintended consequences on other ES. An interdisciplinary approach may help avoid such challenges and properly inform decision making. Several studies have advocated for methods that combine knowledge from different research disciplines in order to properly inform decision making in agricultural systems (de Groot et al., 2010; Hooper et al., 2005; MEA, 2005). This thesis combines knowledge from the social sciences (survey) and from the agricultural sciences (crop modelling) to gain insights into possible trade-offs between alternative agricultural land management strategies.

Climate change will also add to the complexity of decision making at the farm level. Due to the often delayed feedback loops and abrupt changes associated with climate change and agricultural systems, it is difficult to ascertain whether current management strategies will be effective under future climates and whether trade-offs between agroecosystem services will be lessened or magnified in the future (Eitzinger et al., 2018). This uncertainty renders changes in the climate system difficult to predict and makes the decision-making process for both farmers and policy-makers a difficult task. Using a modelling approach such as the one adopted in this study can help understand what agroecosystem services trade-offs may be magnified or diminished under future climate scenarios and therefore help develop BMPs that will minimise such trade-offs and promote synergies.

2.3 Agricultural production in a changing environment

Climate change is projected to have significant impacts on global crop production and water availability (Godfray et al., 2010). Increased atmospheric carbon dioxide, changing rainfall patterns, increased crop damage due to pests and disease and extreme weather events under future climate conditions are likely to affect ES such as water availability that are key to crop production, increasing the complexity of implications of ES trade-off and synergies (IPCC, 2014). The climate projections by the IPCC indicate that crop production will be negatively affected in semi-arid countries such as South Africa (IPCC, 2014).

In South Africa, climate change is expected to negatively impact future agricultural production through shifts in precipitation pattern, duration and frequencies, changes in temperature and the increasing frequencies of extreme events such as droughts (Calzadilla et al., 2014; Zwane and Montmasson-Clair, 2016). Many regions in South Africa are already facing challenges such as increasing water scarcity, environmental degradation and frequent droughts – all of which have significant impacts on food production. In 2015 the lowest annual rainfall since 1904 triggered a drought that reduced the national maize harvest by 14% relative to the 2011-2015 average, and by an extra 25% in 2016, an increasing loss of 35% in two years (Devereux and Waidler, 2017). This occasion highlighted the fact that South Africa's future capability to meet food requirements through agricultural production may well be undermined by climate change unless innovative mechanisms are deployed both at the farm and policy levels.

Climate change will add to the complexity of making agricultural land management decisions as it is not clear which trade-offs or synergies will be enhanced due to the uncertainty associated with projected climate change impacts. Improved agricultural land management that uses an ES approach can act as a mitigation strategy to counteract the negative impacts of climate change on ES supply. The Intergovernmental Panel on Climate Change, IPCC, (2014) estimates that adopting agricultural management practices such as improved irrigation and fertiliser management could improve crop yields under future climate conditions by 15-18% of the current yield levels compared to a business as usual scenario. However, adoption of agricultural land management will largely depend on farmers' decision-making processes and their perceptions of climate change. Therefore, understanding farmers perceptions of climate change is a key precondition to developing adaptation strategies likely to be adopted by farmers as farmers' perceptions of climate change can ultimately influence their adoption of climate change adaptation strategies. Walthall et al., (2013) point out that since agricultural systems are human-dominated, the vulnerability of agriculture to climate change depends not only on the biophysical effects of climate change but also on the responses taken by humans to lessen those negative effects.

To maintain agricultural productivity in the face of climate change, South African farmers, especially cereal farmers producing major staple crops such as maize and wheat, need to respond with effective adaptation strategies. At the farmer level, which is the main focus of this thesis, potential production adaptations include modifying agricultural inputs such as fertiliser, crop rotations and harvesting methods, reducing or eliminating tillage, utilizing drought-tolerant, corn hybrids, as well as diversifying into different types of crops expected to be more resilient to new weather patterns (Walthall et al., 2013). However, in order to develop agricultural land management and climate adaptation strategies that are effective currently and, in the future, it is important to have an understanding of the possible effects of alternative agricultural land management strategies as well as the effects of future climate scenarios on agricultural systems.

2.4 Strategies to increase crop yields as an agroecosystem provisioning service

Studies such as those by Folberth, (2013), van der Velde et al., (2014) and Pastori et al.,(2017) in sub-Saharan Africa indicate that increases in crop yields can be achieved in four major ways: (a) expanding irrigated areas, (b) improved nutrient and water management, (c) genetics and breeding of improved cultivars and (d) improved pest and disease control. In this thesis, the focus is on improved nutrient and water management as this is what is commonly practiced in the Eastern Cape of South Africa. Further, data on the other three strategies are sparse for the Eastern Cape.

In South Africa, the expansion of land under irrigation will be difficult due to limited land suitable for crop production. Already, less than 14% of South Africa's land is suitable for dryland agriculture with only about 3% regarded as high potential arable land (Collett, 2013; Simpson et al., 2019). Further, the limited amount of land available and other competing land uses such as bioenergy production and biodiversity conservation will make the expansion of irrigated agriculture in South Africa difficult. Improved agricultural land management strategies, coupled with increased resource-use efficiency and an improved farmers' agricultural knowledge base, will be required to produce more crops with the same area of available land. Crop yields can be improved by developing drought tolerant, disease tolerant and high yielding crop cultivars through traditional breeding and genetic engineering (Datta, 2013; Gill et al., 2014; Passioura, 2006). However, improved crop cultivars will only produce to their maximum yields under good environmental conditions such as the right amount of nutrients and water, conditions that are scarcely found naturally in agricultural fields in South Africa.

Further, controversy regarding the possible harmful effects of genetically modified crops restricts their widespread adoption. Apart from genetic engineering and use of improved crops, agricultural Best Management Practices (BMPs) such as irrigation management and crop nutrient management have the potential to significantly improve crop yields (Ali and Talukder, 2008; Passioura, 2006). Use of BMPs can also improve the water quality of surrounding water bodies by reducing nutrient leaching and run-off from farmlands (van Gaelen, 2016).

Several studies have demonstrated the usefulness of various management practices to improve crop yields and water quality. Wang and Xing (2016), who analysed the effects of irrigation and fertilization on tomato fruit yield and quality, concluded that irrigation and nutrient management was a significant factor in increasing crop yield. Similarly, efficient pesticide use shows great potential as a study by Oerke, (2006) found that global crop losses due to pests can vary between 50% and 80% if no pest control is applied. The management of water, nutrients and pesticides are the three major factors affecting crop growth and productivity. Conversely, excess nutrients and pesticides applications can negatively affect environmental quality. The use of improved irrigation and nutrient management strategies in the Eastern Cape have the potential to improve crop production in the Eastern Cape while minimising environmental water pollution.

2.4.1 Agricultural best management practices

Irrigation and crop nutrient BMPs can be described as a variety of agricultural practices that are meant to reduce nutrient leaching and runoff from farms while maintaining or increasing agricultural productivity. Sharpley et al., (2006) define agricultural (BMPs) as the water and soil conservation practices including social and cultural actions, which have been recognised as effective and practical ways to conserve water and soil on the farm. Best Management Practices can include maintaining riparian buffers between a farmer’s field and a nearby stream. Structural BMPs such as grassed waterways and wetlands are strategies used on the farm site to reduce pollutants using processes of filtration and infiltration (Liu et al., 2019).

Non-structural BMPs such as nutrient management strategies are used to improve crop yields while reducing pollutants at the source.

Although BMPs have been developed for agriculture, most of them are voluntary and farmer adoption remains low (Gillespie et al., 2007; Liu et al., 2013; Paudel et al., 2008). Non-adoption of BMPs, especially those developed by the government, often reflects practical concerns by farmers such as lack of compatibility of the proposed strategies with existing farm management practices, as well as contextual mismatches (Page and Bellotti, 2015; Yapa and Mayfield, 1978). Martinho (2019) argues that to promote, implement and encourage the adoption of BMPs, it is fundamental to involve stakeholders, particularly farmers. Martinho (2019) further stresses that without farmers involvement, there is the risk of low adoption by farmers, indicating that, understanding the factors that influence farmers' adoption of BMPs is fundamental to developing effective BMPs that are likely to be adopted by farmers (Liu et al., 2018).

Even though BMPs often include irrigation and crop nutrient management approaches, it is critical to select the appropriate management approach for an area (Getahun and Keefer, 2016; Sharpley et al., 2006). Evaluating the effectiveness of a specific BMPs such as fertilisation by field trials or by collecting monitoring data is both expensive, time-consuming and labour intensive (Özcan et al., 2017). In this thesis, nutrient and irrigation management, as well as adaptation strategies to climate change, were considered and modelled as part of a suite of BMPs at the farm scale.

2.5 Tools to develop and evaluate agricultural management practices

2.5.1 Field experiments

Field experiments present a way of evaluating the efficiency of crop management practices. The efficiency of agricultural land management strategies is usually evaluated by carrying out research on representative plots with experimental designs that involve replication and randomisation (Mason et al., 2017). Results from the field experiment analysis can be used to determine yields and impacts on environmental quality, including water resources resulting from a particular management strategy. Field experiments have the advantage that they can be implemented on many field sites with better representations of soil and climate variability. The disadvantages, however, are that field-based evaluations of agricultural land management strategies are often expensive and time-consuming. Also, field experiments are limited in terms of predicting the long-term effects of agricultural land management strategies under different climate conditions (Dechmi and Skhiri, 2013; Wu et al., 2015). As a result, the transferability of results from field experiments in space and time is limited. To overcome these limitations in the use of field experiments, crop simulation models are useful tools to complement field experiments in the development and evaluation of agricultural BMPs

2.5.2 Simulation models

Increasingly, computer simulation models are being used as a complementary approach to field experiments that can be used to simulate the effects of different agricultural land management practices on agricultural productivity and the environment. Simulation models have the advantage that they can be used to test alternative agricultural land management strategies at a lower cost and less time than field experiments. In addition, simulation models can be used to investigate the effects of climate change on agriculture (Challinor et al., 2009) under various climate change scenarios.

Physically-based models such as the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1989) describe the interactions between water, carbon and nitrogen cycles, vegetation growth and management practices. As a result, models such as EPIC constitute good tools for exploring the effects of farm management practices on crop yields as well as environmental qualities in relation to current and predicted future climate conditions (Ferrant, 2014). Physically-based models describe the system based on well-known physical principles and laws. As a result, physically-based models can be used to study various system inputs, transformation, and outputs. While other models in South Africa exist such as the Agricultural Catchments Research Unit (ACRU) model (Schulze and Arnold, 1984) and the Soil Water Balance (SWB) model (Annandale et al., 2005), they have been developed from hydrological models and lack a robust crop growth and fertiliser management component compared to EPIC (Williams et al., 1984).

Care must be taken, however, when using physically-based models. As physically-based models are only an approximation of real-world phenomena, several uncertainties are associated with the use of physically-based models. Model uncertainty can arise from inaccurate input data (e.g. soil and weather data) or model structure uncertainty (Fengmei et al., 2011). Uncertainty can be reduced, for example, by using the right model for the scale it was meant for and avoiding the use of inaccurate data for model calibration and validation

(Mulla et al., 2006). Different models inherently have their own weaknesses and strengths and it is important to select the model that is appropriate for the context and study objective.

In this study, the biophysical crop model Environmental Policy Integrated Climate Policy (EPIC) model (Williams et al., 1989) is used to simulate the effects of irrigation management, N fertiliser management and climate change on maize yield in the Eastern Cape. The model simulates approximately eighty crops with one crop growth model using unique parameter values for each crop. It contains a variety of crop management options including fertilization, irrigation and pesticide fate. EPIC operates on a daily time step and can be used for long term assessments spanning hundreds of years (Balkovič et al., 2014). It has been used for crop production studies (Folberth et al., 2013; van der Velde et al., 2014) and water resource studies (Forster et al., 2000; Intarapapong et al., 2002; King and Balogh, 2009). Studies in Africa have also found the model to be effective in simulating crop growth and crop management scenarios under resource-limited conditions (van der Velde et al., 2014; Worou et al., 2015). Additionally, soil nitrogen and phosphorus biogeochemistry models are incorporated into the EPIC model (Xu et al., 2014). The model is therefore well suited for simulating nutrient and irrigation management practices in agricultural systems.

Crop simulation models such as the EPIC model have several parameters and a significant problem arises in obtaining parameter values. For crop model results to be used with confidence it is therefore important to calibrate and validate the models in the area of interest. Calibration and validation are also critical to improve the accuracy of predictions in climate change studies (Jagtap and Jones, 2002). However, a major constraint to calibration and validation of crop simulation models is that the amount of experimental data for calibration is in general, limited because experimentation on crop systems is lengthy and is costly in terms of labour, time and equipment (Wallach, 2006). Klein, (2013) further explains that another important aspect is that the greater the number of parameters, the greater the risk of reproducing observations without a correct representation of the processes involved. Therefore, the number of parameters that have to be calibrated needs to be reduced in order to prevent computational problems (Confalonieri et al., 2016; Tremblay and Wallach, 2004; Wallach, 2011).

A significant challenge, therefore, in modelling agroecosystem services is to develop approaches that are complex enough to accurately represent the system, but simple enough to be understood and parameterised with limited data (Tallis and Polasky, 2009). While biophysical models are able to use secondary data obtained from various sources making them applicable when primary data are limited (Petz, 2014), a significant criticism of biophysical models has been their inadequate representation of the social aspects of ecosystems. For example, many crop models are unable to account for the influence of farmers' socio-economic constraints such as access to markets and credit lines on farmers management decisions (Webber et al., 2014). Combining a modelling framework with survey data or interviews can triangulate result and increase confidence if the findings support each other or add knowledge that broadens the understanding of potential adaptation or management strategies (Nuijten, 2011).

Thomas et al., (2011) argue that with regards to simulating management options, looking at farmers current management and adaptation practices should inform modellers. Combining the predictive poor of models with farmers' knowledge or perception can give rise to potential synergies (Webber et al., 2014). For example, qualitative outputs from crop models can triangulate qualitative information gathered from farmers. Studies by (Howden et al., 2007) emphasised the need for crop modelling studies to capture the reality in which management decisions are made and be linked to action research with farmers on the ground. Few studies in South Africa have combined the use of surveys and crop modelling to develop agricultural land management and adaptation strategies based on farmers' motivations for management practices and perceptions of climate change. Therefore, this study will use a biophysical model, EPIC, together with a social survey to investigate ways to optimise agricultural land management practices that promote SI, enhance the delivery of agroecosystem services while ensuring the protection of environmental integrity and evaluate the possible impacts of climate change on maize production in the Eastern Cape.

2.6 Tools for predicting climate change

To predict future climate conditions, General Circulation Models (GCMs) have been developed to project future climates based on greenhouse gas emissions and complex earth-atmosphere interactions (Mqadi, 2005). However, GCMs typically run at 250 km^2 resolutions, designed to simulate climate variables such as temperature and rainfall at the global or continental scale. The coarse resolution severely limits the application of GCMs to support decision making at the local scale (Mason 2011, Ramirez 2012). An increasingly popular approach is downscaling GCM climate data to finer resolutions typically 50 km^2 to produce downscaled climate data that are more representative of local-scale conditions

Downscaling is often reported as a method of making crop climate model outputs more relevant to farmers (Challinor et al., 2018). Methods such as dynamic downscaling and statistical downscaling have been developed for downscaling climate data, with each method having particular advantages and disadvantages (Wilby and Wigley, 1997). The majority of these methods involve using statistical methods or principles of physics to generate small scale data sets (Tadross et al., 2005; Ziervogel et al., 2014). While downscaling is often combined with bias correction whereby the output of climate models is corrected towards observations, it is impossible to eliminate all bias associated with downscaling. Downscaling techniques thus potentially add uncertainty to climate modelling.

Climate change impact studies in South Africa have grown over the last decades as technological advances in computer modelling have progressed. Modelling studies in agriculture have looked at the impact of climate change on different crops in South Africa. These included studies by Oosthuizen et al., (2016) assessing the impacts of climate change on several crops in different farming regions in South Africa while Haverkort et al., (2013) conducted a study on the effects of climate change on crop yield and land and water use efficiencies. Both studies used crop simulation models. Also, Walker and Schulze, (2006), focused on assessing sustainable maize production under different management and climate scenarios KwaZulu-Natal, South Africa. The study by Walker and Schulze, (2006), did not consider farmers motivations for using certain agricultural land management practices or perceptions of climate change, both factors which affect farmers adoption of BMPs for present and future climate scenarios. Therefore, this study will focus on farmers' motivations for agricultural land management strategies and perceptions of climate change. The study will combine a survey of farmers and crop modelling to integrate the knowledge from farmers and scientists to develop new insights into how sustainable intensification can be achieved in the Eastern Cape for current and future climate scenarios.

Although the EPIC model was developed by the US Department of Agriculture for use in the United States, the model has been successfully applied in the study of erosion, water pollution, and crop growth and production globally. However, it is yet to be introduced for field-scale studies in South Africa. The wide use of the EPIC model globally makes it an ideal model for comparison with locally developed models such as the ACRU model. Model inter-comparison is important to compare model performance against other models and reduce uncertainties associated with model structure (Bao et al., 2016). EPIC is able to simulate the growth of many crops with the same data file (Adejuwon, 2004). This represents an advantage over other crop models in simulating the productivity of crop farming systems in the Eastern Cape in which multi- and intercropping systems rather than mono-cropping are dominant. Hence, the same run of the model could result in outputs including yields of both the main crop and cover crops.

EPIC also provides for analysing trade-offs between plant growth and environmental impacts. For example, EPIC can be used to approximate the extent to which N fertiliser can be leached into nearby rivers and stream networks. This is of growing concern in the Eastern Cape as N meant for crops is lost to the environment with harmful negative environmental effects. Further, EPIC can analyse options of sustainable agriculture including soil irrigation water management, crop nutrient management and climate change impacts. The application of the EPIC model in the Eastern Cape can, therefore, help in informing policymakers and local government on the potential of agricultural systems in the Eastern Cape to contribute to meeting climate and food security targets in both the Eastern Cape and in South Africa.

2.7 Synthesis

Sustainable intensification has received a growing popularity as a framework to address the challenge of meeting the food demands of a growing population. While the origins of the concept go as far back as 20 years, presently the term is a contested one, with controversies coming primarily from the use of the term by different actors with different interests, values and scope of issues that it can address in the food system. Most discussions on sustainable intensification have focused on the technical aspects of sustainable intensification while neglecting the social and political considerations which are important because the implementation of the sustainable intensification concepts needs to be determined in different contexts with local stakeholders rather than external agents.

Food security does not only include crop production but encompasses the whole farm production system including aspects such as livestock production and access to markets. An integrated approach which takes into account the social-ecological and economic aspects of food production is required. Sustainable intensification is a useful guiding principle for addressing crop production in the total food production system. Successful actions in managing agroecosystem services supply in agriculture will depend on strong supporting policies and effective BMPs together with developing knowledge and capacity in farming communities to evaluate potential benefits.

While agroecosystems provide a variety of services essential to human wellbeing, maximising crop provisioning services can result in trade-offs with other agroecosystem services that support crop production. An ecosystem services approach to agricultural land management can reduce these trade-offs to produce win-win outcomes. The use of agricultural BMPs in agricultural land management is key to achieving SI and reducing the negative environmental impacts of agriculture. The challenge to produce more food while minimising negative environmental impacts will be magnified in the face of climate change. However, the use of technologies such as computer models can help find agricultural land management strategies that increase yields while minimising environmental pollution both for present and future climate scenarios.

In addition to the use of computer models, finding the most sustainable agricultural land management strategies will require a better understanding of the factors influencing farmers' decisions and the whole range of challenges farmers might be facing in farming. Further, contextualization and increased stakeholder involvement during model development and discussion of results are also required to make modelling results relevant and practical to end-users such as farmers.

The maintenance of ES, the long-term productivity and stability of agroecosystems requires a paradigm shift in agriculture that moves away from managing agroecosystems for single ES (food) to managing agroecosystems for multiple ES through more efficient use of soil, water and abiotic resources on farmlands. Coupled with an ES approach, the concept of SI can be used to help shift food production systems from managing farmlands for single ES (food provision) to multiple ES.

Increasing crop production in a sustainable manner at the farm level will require optimising irrigation efficiency and nutrient management for each individual farmer or field. Increasing future crop yields and minimising the impacts on water resources will take place in a rapidly changing world where the population is growing, agricultural land is scarce and society has to deal with the burden of water pollution from agricultural runoff. From an agricultural standpoint, sustainable intensification based on an ES approach can provide a way of thinking through the requirements for increasing food production while minimising environmental degradation (O'Higgins and Al-Kalbani, 2015).

Chapter 3: **Exploring Farmers' Management Practices and Values of Ecosystem Services in an Agroecosystem Context – A Case Study from the Eastern Cape, South Africa**

Section 3.1 provides a concise introduction to the chapter, while section 3.2 gives a brief summary of the key definitions, assumptions and the conceptual framework used in the chapter. Section 3.3 outlines the selection of farmers for the survey and the survey method; section 3.4 discusses how the data was analysed; section 3.5 discusses the results of the survey. Section 3.6 is a discussion of the results and finally, section 3.7 gives the conclusion highlighting the key findings from the study and their implications.

The following paper has been published as part of this chapter:

Choruma, D.J and Odume, O.N (2019) Exploring Farmers' Management Practices and Values of Ecosystem Services in an Agroecosystem Context – A Case Study from the Eastern Cape, South Africa, *Sustainability*, 11, 6567, doi:10.3390/su11236567.

3.1 Introduction

Agroecosystems provide a variety of benefits to humans, such as food, fibre, timber, and recreation. These benefits, whether direct or indirect, are defined as ES and contribute significantly to the wellbeing of human societies (TEEB, 2010). In agroecosystems, the supply of ES depends not only on the biophysical processes that regulate ecosystem function (e.g., climate, soil) but also on the way humans manage the ecosystem and related decision-making processes. In addition, challenges including climate change, increasing resource needs from a growing population have a significant effect on the ability of agroecosystems to continue generating ES. For example, based on projections from the Food and Agriculture Organisation (FAO), food production is expected to double by 2050 to meet the needs of an estimated world population of 9 billion (FAO, 2017). However, achieving this increase in food production while simultaneously maintaining the integrity of the environment within an agroecosystem presents a significant challenge, particularly in areas where land and water resources are already limited.

Historically, the food needs of society have been met through agricultural expansion and the intensive use of inputs, such as chemical fertilisers and pesticides, to boost crop production. However, competing land uses such as the expansion of urban areas now makes it difficult for agriculture to expand into new areas and the expected food demand will have to be met through increased agricultural productivity (Lipper et al., 2014). The overuse of agricultural inputs, such as chemical fertilisers and irrigation water, has had negative impacts on the environment often causing problems such as eutrophication of water bodies and salinisation of soils, respectively. In addition, climate change threatens the sustainability of agricultural systems through changes in factors influencing crop production such as temperature and precipitation. To increase food security, farmers are increasingly expected to increase agricultural productivity while minimising land degradation through improved farm management and, at the same time, manage the risks associated with climate change and extreme weather through tools such as agricultural insurance (Fusco et al., 2018; Porrini et al., 2019).

To help achieve sustainable intensification (SI) in agricultural systems, the use of agricultural ‘best management practices’ (BMPs) has gained interest in agricultural research (Kroll and Oakland, 2019; Mulla et al., 2006). Best Management Practices (defined earlier in Chapter 2, Section 2.5.1) such as integrated irrigation and fertiliser management, can minimise the negative impacts of agriculture on the environment while maintaining agricultural productivity. This is in contrast to extractive agricultural intensification practices such as over-application of chemical fertilisers that can lead to environmental problems such as eutrophication and significantly undermine sustainable intensification efforts (Zhang et al., 2007). In practice, BMPs are therefore meant to enhance the provision of multiple agroecosystem services while maintaining the integrity of the environment. Hence, the use of BMPs is central to the principle of sustainable intensification (Haas et al., 2017) and crucial to guiding agroecosystems management towards the goal of SI.

While BMPs are meant to enhance the supply of multiple agroecosystem services, the final decision to adopt BMPs rests with the farmer. Although BMPs have been developed for agriculture, farmer adoption of BMPs remains low (Paudel et al., 2008; Shen et al., 2013). This low adoption of BMPs often reflects practical concerns by farmers such as lack of compatibility of proposed management strategies with prevailing contexts – whether biophysical, financial and otherwise (Page and Bellotti, 2015). This study suggests that a better understanding of the reasons behind farmers' management practices and the values they assign to ES is needed to develop effective BMPs that contribute towards the realisation of SI goals.

At the farm scale, farmers remain the key decision-makers in agricultural land management and therefore, play an essential role in sustainable agricultural intensification (Mehdi et al., 2018; Purushothaman et al., 2013). Complementary approaches, such as climate-smart agriculture (Jagustovic et al., 2019; Lipper et al., 2014) that have the potential to increase food security while minimizing land degradation, all depend on farmers taking a central and active role in agricultural land management. Several studies have shown that farmers’ decisions are complicated, driven by personal factors (e.g., farming traditions) as well as external factors (e.g., markets) (Enström and Eriksson, 2018; Karali et al., 2011). Vanclay (2004) further adds that, while farmers are influenced by the resources they possess to manage their lands (e.g. machinery), they are also motivated by the social and traditional farming practices of the farming community. In such cases, trade-offs often exist between the agroecosystem services that are biophysically necessary to maintain crop production and those valued by farmers in a particular socio-cultural and farming context (Eide et al., 2014; Ribaudo et al., 2010).

As already argued in Chapter 2, the existence of trade-offs suggests an important link between valued and desired agroecosystem services and the way farmers manage their farms. For example, farmers assigning a higher value to food provisioning services over other ES may implement measures that enhance food provisioning (e.g., high fertiliser use), whereas farmers valuing cultural services, may adopt measures that favour cultural services outputs (e.g., biodiversity conservation). The values farmers assign to different agroecosystem services have important implications for SI as failure to take into account farmers' values of different agroecosystem services may result in mismatches between agricultural land management policies and farmers' practices at the farm scale. In turn, the mismatch between policy and practice may lead to further agroecosystem degradation and low adoption of BMPs that may impede the realisation of SI.

In South Africa, current challenges such as declining crop yields due to low soil fertility and agricultural water pollution indicate that there is still an incomplete understanding of how management practices affect agroecosystem services at the farm scale. However, studies exploring the links between farmers' values of ES and their local land management practices are scarce. The few studies on conventional farmers have focused mainly on enhancing crop varieties (Dlamini, 2014; Oosthuizen, 2005), improving irrigation and on-farm water use efficiency (Njoko and Mudhara, 2017; Singels et al., 2010) or determining crop fertiliser requirements (FAO, 2005; Van Der Laan et al., 2012). However, if the goal of SI is to be realised, it is critical to explore the reasons behind farmers' agricultural land management strategies and whether the values farmers assign to agroecosystem services influence the way they manage their farms. Such exploratory studies can contribute new perspectives and insights that can inform agricultural land management policies and strategies aimed at optimising agricultural production in a sustainable manner.

Therefore, the objective of this chapter was to explore the motivations for farmers' agricultural land management strategies and the values they assigned to agroecosystem services at the farm scale. This Chapter thus fulfils objective 1 of this study: "To explore motivations for farmers' agricultural land management practices and the values assigned to agroecosystem services in the Eastern Cape, South Africa". The results in this chapter can provide useful insights into farmers' decision-making and help develop strategies to increase crop production while minimising environmental degradation and enhancing the sustainable delivery of multiple agroecosystem services at the farm scale.

3.2 Key definitions, assumptions, and conceptual framework

3.2.1 Classification of ecosystem services

As already described in Chapter 2, various classifications of ES exist. For this study, the MEA classification of ES is adopted. The MEA classifies ES into provisioning, regulatory cultural and supporting services. Dietze et al., (2019), explain that in literature, although various definitions and classifications of ES exist, the concept of ES is well known by scientists but not by practitioners such as farmers.

3.2.2 Sources of information for farmers

One way of understanding why farmers adopt certain management practices is to identify sources of information farmers use when making farm-related decisions. Several studies have shown that farmers rely on a variety of sources of information (Licht and Martin, 2007; Radhakrishna et al., 2003) to manage their farms. Such studies investigating farmers' sources of information in the Eastern Cape are few. Knowledge of farmers' sources of information in the Eastern Cape could be helpful in developing alternative agricultural land management strategies and policies that promote SI. Several authors have argued that the concept of ES is well known to scientists but less known to practitioners such as farmers (Dominati et al., 2010; Koschke et al., 2014) while the literature on farmers' sources of information when making agricultural land management decisions is limited (Dietze et al., 2019). This study, therefore, focuses on farmers' sources of information when making farm management-related decisions.

3.2.3 Consideration of agricultural land management practices and ecosystem services

Schuler, (2016) explains that provisioning agroecosystem services are viewed as the most important ES for farmers as they form the basis of farmers' livelihoods and income sources. However, studies show that agroecosystem services are interrelated (Lescourret et al., 2015) and maximising the provision of a single ecosystem service may lead to a decline in other ES and ultimately the degradation of the agroecosystem as a whole. This study focuses on agricultural land management practices related to irrigation and fertiliser as they are directly related to increasing crop production through additional inputs of nutrients and water. Inorganic fertilisers combined with irrigation can maximise crop yields but, if not well-managed, they can have negative impacts on scarce water resources especially water quality (Bennett et al., 2009). On the other hand, organic fertilisers can increase the carbon content of the soil, improve soil structure thereby promoting the creation and conservation of soil organic matter (Tilman et al., 2002). In the Eastern Cape, crop production is mostly affected by soils with declining nutrient availability, low rainfall, and frequent droughts (Goldblatt, 2011). To increase soil productivity, farmers often use fertilisers combined with irrigation water.

3.2.4 Ecosystem services flow in agroecosystems

The cascade model presented in Chapter 2 was modified to include the role of farmers in agroecosystems management and agroecosystem services supply. The modification was necessary to account for the social dimension of farming processes as numerous authors have criticised the cascade model for neglecting social factors in influencing the flow of ES.

In the adapted framework (Figure 3.1), it is assumed that farmers' agricultural land management decisions are influenced by both the knowledge they have on agricultural land management and the values they assign to agroecosystem services and external drivers such as climate, government policies and the political context within which such decisions are made. Knowledge in the framework refers to farmers' understanding of how agroecosystems provide benefits to society and the effects of their agricultural land management practices on such agroecosystem services. Values here refer to the importance farmers assign to different agroecosystem services within an agroecosystem context, while external drivers could be biophysical, e.g. climate, soils; and socio-economic, e.g. government policies, desired income, and profit from farming. There are also feedback loops between biophysical drivers and socio-economic drivers, for example, prolonged droughts can influence the development of policies on water usage which in turn, can significantly affect the way farmers manage their farms. Decisions refer to the desired action chosen among alternatives after taking into consideration the knowledge and values about agroecosystem services in addition to the influence of external drivers (Lamarque et al., 2014).

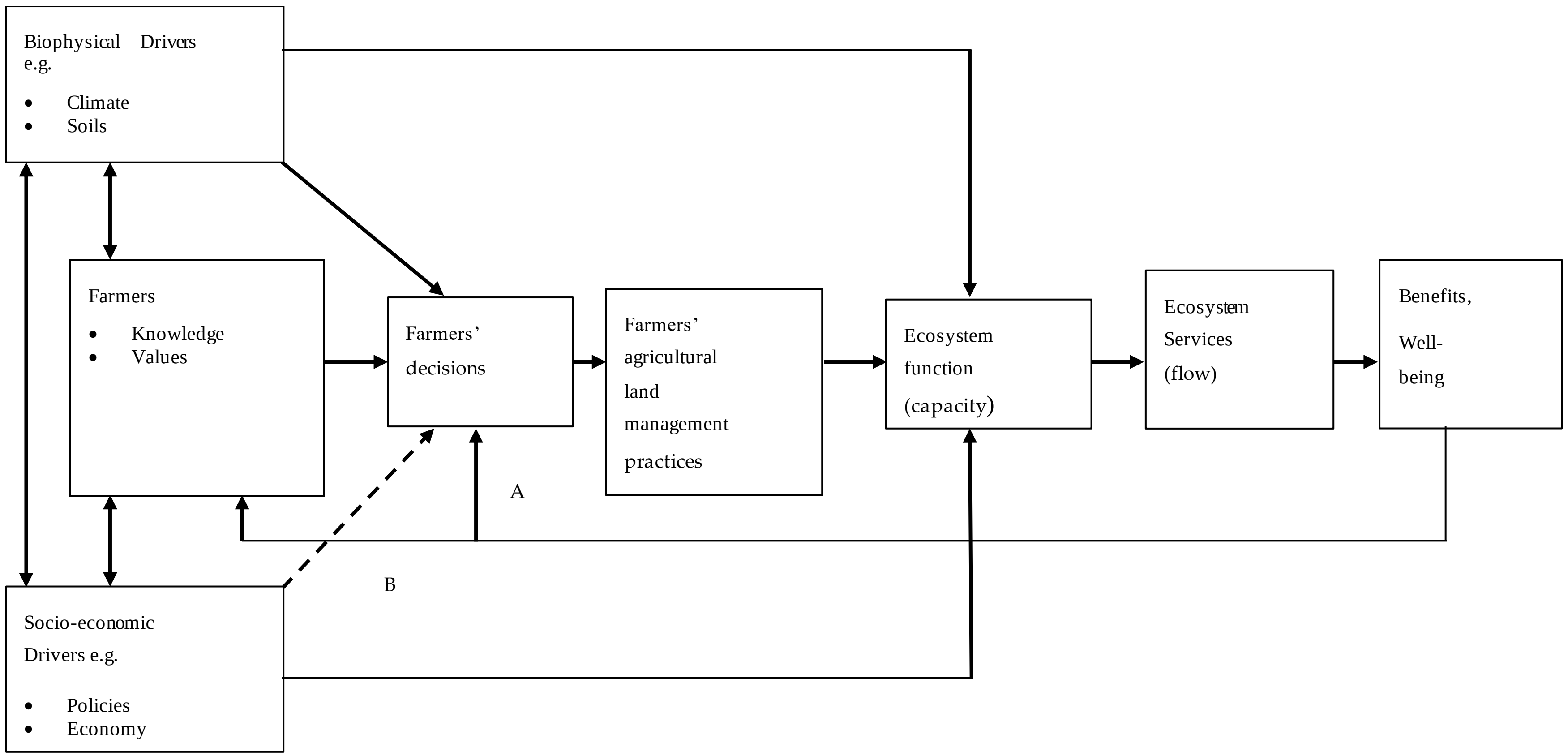

Figure 3.1. Adapted 'ecosystem services cascade' showing how farmers' agricultural land management practices affect the flow of ES. The framework shows the links and feedback between farmers' values and knowledge, management practices, and agroecosystem services. Benefits and values from ES can have direct effects (**A**) and indirect effects (**B**) on farmers' decisions. The model is adapted from Potschin and Haines-Young, (2011) and Lamarque et al., (2014).

3.3 Materials and methods

3.3.1 Study area

The study was carried out in the Cradock town of the Eastern Cape described in Chapter 1, section 1.7. Most subsistence farming occurs in rural areas while commercial crop farming is mostly concentrated around 'farming' towns (towns in which agriculture is the major economic activity). The Cradock area has maize, pasture, dairy, and beef producing farmers while nearby towns such as Somerset produce beetroot, carrots, and most vegetables (Nelson Mandela Bay Tourism, 2017). In the inland areas of the Karoo, the harsh climate limits agriculture to livestock farming. The increased use of fertiliser and irrigation water in the area to maintain agricultural productivity has led to a general deterioration of environmental water quality in commercial farming areas (Goldblatt, 2011).

3.3.2 Farmers selection

The study targeted farmers in the major farming towns in the Eastern Cape (Cradock, Somerset East, Middleburg, Golden Valley, and Adelaide). The targeted farmers were either the farm owners or farm managers who managed the farm on behalf of the farm owner. The towns were selected due to their close proximity to the Great Fish River where water from the river is used to irrigate farmlands. Crops are irrigated with water transferred from the river to farms through a series of canals and pipes (The Water Wheel, 2004).

Purposive sampling (Gakuubi and Wanzala, 2012; O'Keeffe et al., 2015; Shortall et al., 2017) was used in this study to select farmers that used inputs such as fertilisers and irrigation water regularly. Although random sampling procedures are considered more rigorous and accurate than non-probabilistic sampling methods, there may be instances where it is not feasible or practical to apply a random sampling method (Khapayi and Celliers, 2016). At the time of carrying out this research, there were, and still are, ongoing political debates in South Africa on issues of land reform and land redistribution. As a result, many farmers that were contacted were not willing to participate in a study involving giving out information concerning details of their farm enterprises.

To overcome this challenge, farmers' organisations in the Eastern Cape (Agri Eastern Cape, Great Fish River Water Users Association and Eastern Cape Farmers Group) were approached to identify farmers that would be willing to participate in the study. Ten farmers were initially identified and then contacted via email and also asked to identify other farmers that would be willing to participate in the survey. Through this snowballing sampling process (Babbie and Mouton, 2001), an additional 21 farmers were identified. An online version of the survey questionnaire was developed and the link attached to a request letter, which was shared via email with the identified farmers. Additionally, the survey link was shared on the online social networking platform of the Eastern Cape Farmers Group, after approval from the farmers' platform administrators, inviting farmers to complete the survey following (Page and Bellotti, 2015). This was done to accommodate farmers who were not identified beforehand but would be agreeable to participating in the survey. This meant that farmers also had the option to self-select and participate in the study.

The survey was conducted from January to April 2019. A period of two months after April was given to allow feedback from online/e-mail participants. During this two-month period, regular follow-ups were carried out to encourage participation. According to Babbie and Mouton (2001), the longer a respondent delays replying, the less likely he or she will be to do so. Therefore, at the end of the two-month period, it was assumed that no more responses would be received. The study was conducted in accordance with the Declaration of Helsinki, and the questionnaire and research design approved by the Rhodes University Research Ethics Committee (Ethics approval no. SCI2018/007).

3.3.3 Questionnaire development and survey

The survey questionnaire, adapted from Mack et al., (2017) and Smith and Sullivan, (2014) (see questionnaire in Appendix A), consisted of both open and closed-ended questions to elicit responses that could be analysed qualitatively and quantitatively. For closed-ended questions, respondents were allowed to add to the existing categories (Babbie, 2013; De Vaus, 2013). The questions were formulated and presented in sections according to the following aspects: (1) agricultural management practices; (2) the values assigned to different agroecosystem services by farmers; and (3) demographic information. For the sections on ES and payments for ecosystem services (PES), a brief description and explanation of the terms were given at the beginning of the section (see questionnaire in Appendix A). At the end of the questionnaire, participants were given the room to express any comments they had regarding agricultural land management practices and agroecosystem services.

For quality assurance, the questionnaire was pre-tested in focus groups with postgraduate students at Rhodes University, who had a background in agriculture and survey research methods. Only students who had gone for internships for more than a year in farms in the

Eastern Cape were chosen for the test group. These students were deemed knowledgeable about the type of farming practices in the Eastern Cape. Feedback from the group was incorporated to improve unclear and misleading/confusing wording.

3.4 Data analysis

3.4.1 Thematic analysis

Open-ended questions such as reasons for the type of fertilisers and irrigation methods were analysed using thematic analysis. The questions were developed with the intention of getting insights into why farmers used particular management practices and the values they assigned to ES. Thematic analysis is a technique for classifying recurrent and emerging themes (Ritchie and Lewis, 2003) and establishing a framework for presenting the meaning of collected data. The method is flexible and can be modified according to the needs of the study. The method can also be used for both explorative and deductive studies. Thematic analysis was chosen because the method can be used to produce an insightful analysis that answers the research question based on the data collected from key informants, in this case, farmers.

The data were compiled in Microsoft Excel 2016 and each question and response coded, grouped, and ranked. The thematic analysis method used in this study was based on a 6-step framework developed by Braun and Clarke, (2006). The six steps were as follows; Step 1 involved becoming familiar with the data by reading and re-reading the transcripts and writing down ideas and early impressions from the data. Step 2 involved generating initial codes relevant to the research objectives. Codes could also be modified during the coding process. In this study, open coding was used, meaning that there were no pre-set codes but codes were developed during the coding process. New codes were created while some codes were also modified. Step 3 involved searching for themes and combining codes into prospective or potential themes and collecting all data relevant to each prospective theme. Step 4 comprised of reviewing codes, modifying and developing codes from the preliminary themes generated in Step 2. All data relevant to each theme was gathered. Step 4 also included checking whether the themes made sense with respect to the research context and if the data supported the themes. Step 5 involved defining themes by generating names of the themes and clear definitions. The final step, Step 6, involved producing the report for analysis.

3.5 Results

3.5.1 Profile of farmers

A total of 48 farmers participated in the study and completed the questionnaire, the number having been limited by project resources and a low willingness to participate in the survey by commercial farmers. From the 31 farmers identified through the snowballing process, 14 farmers filled out and returned the questionnaire through email representing a 45% response rate. For the online questionnaire, 34 complete responses were returned.

The basic characteristics of farmers who participated in the survey are summarised in Table 3.1. The average farming experience was 12 years and the average age of respondents was 46 years. Of the 48 farmers who participated, 56% had a university degree, 40% had completed a diploma or technical vocation training and 4% had a high school education only. The farmed area managed ranged between 2 hectares to 2000 hectares with an average of 246 hectares per farm. Most farms greater than 300 hectares were skewed towards beef and dairy cattle production. The majority of farmers were mixed farmers (70%) having both crops and livestock whilst 24% were 'crops only' farmers and 6% 'livestock only' farmers. There were 75% of farmers who engaged in cereal farming, mostly wheat, and maize, 31% who grew legumes on their land and 23% who engaged in fruit and citrus farming.

Table 3.1: Demographic information of farmers showing the age, gender, education, and type of farming (n = 48)

Summary of farmers' demographic information		**Total (n = 48)**
Mean age (years)		46
Gender (%)	Male Female	70 30
Education (%)	University degree Diploma and Technical college High school and lower	56 40 4
Crop type (%)	Cereals Fruits and citrus Vegetables Legumes	75 23 58 31
Livestock (%)	Beef cattle Dairy cattle Poultry Sheep and goats	38 17 52 54

Farm size (%)	Small < 5 hectares Medium 5–100 hectares Large > 100 hectares	25 52 23
Farm type (%)	Crop only Livestock only Mixed	24 6 70

3.5.2 Sources of information when making farm management decisions

The survey results show that the majority of farmers consulted other farmers when making farm decisions. Other noteworthy sources of information were the Internet, Farmer Organisations and Agricultural magazines. The least cited source of information was books (2%). Figure 3.2 shows a summary of the sources of information farmers used when making farm decisions.

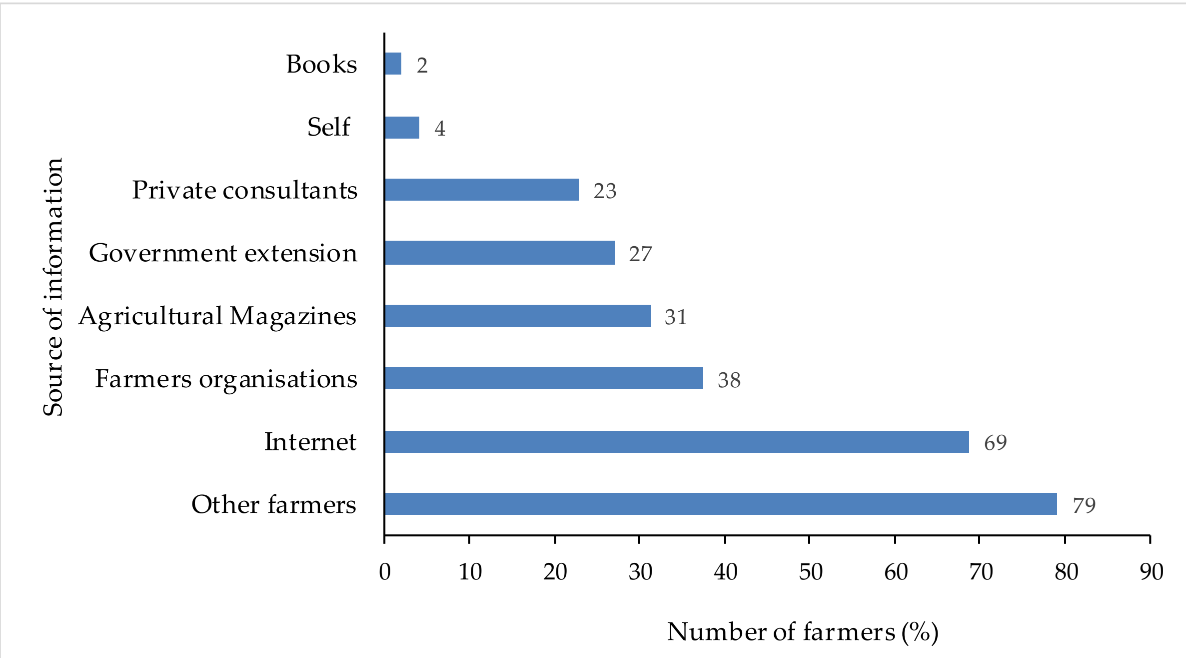

Figure 3.2. Sources of information used by farmers when making farm management-related decisions. Farmers had multiple sources of information hence percentages do not add up to 100.

3.5.3 Irrigation and fertiliser management practices

Irrigation Management

A total of 83% of farmers irrigated their land with the rest relying on rainfall. Irrigation scheduling was primarily determined by farmer experience (58%) and plant appearance or need (47%) (Table 3.2). Regarding irrigation methods, farmers applied irrigation via overheard sprinklers (58%), drip (33%), or surface irrigation (20%). Thematic analysis identified four main themes farmers cited as reasons for their choice of irrigation method, which included available irrigation equipment, water-saving, saving money, and crop type (Table 2). For example, one of the farmers responded:

"*I use Sprinklers for better germination on direct-seeded crops, drip to avoid disease on some crops*."

Another farmer indicated that:

"*Cannot afford drip system*."

Table 3.2. Survey of irrigation scheduling and reasons for the use of particular irrigation methods by farmers (n = 40). Respondents were asked open-ended questions about how they scheduled irrigation and the motivations for the adoption of specific irrigation methods.

How do you schedule irrigation? (n = 40)	**Respondents (%)[1]**
Experience	58
Plant need	47
Set schedule	10
Sensors	2
Reasons for type of irrigation method used (n = 40)	**Respondents (%)[1]**
Crop type	43
Saves money	30
Saves water	23
Available irrigation equipment	20
Environmental considerations	10

[1] Farmers could choose more than one option; hence percentages do not add up to 100.

With regard to income and irrigation type, farms with higher income mainly used sprinkler irrigation systems (Figure 3.3). there were more farms with smaller incomes using drip irrigation compared to farms with higher income. The highest number of farmers using surface irrigation was recorded in the category in which farm income was less than 50,000 Rands per annum.

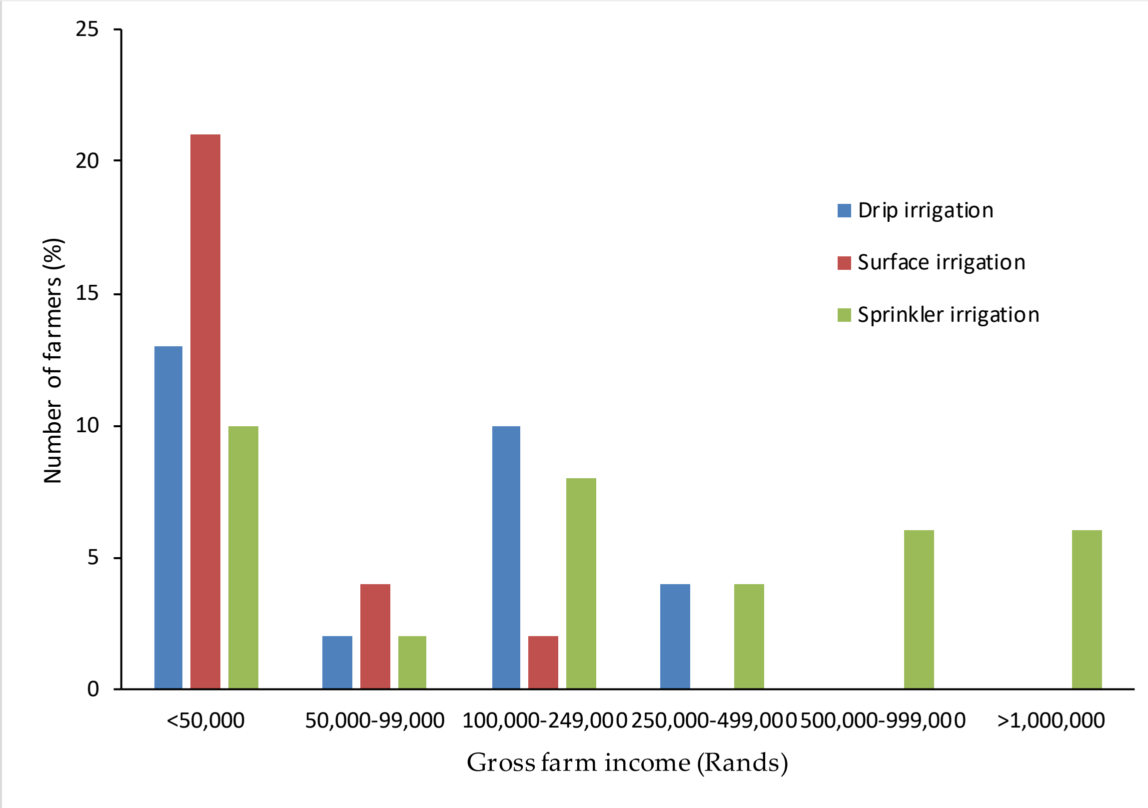

Figure 3.3. Type of irrigation used by farmers in the different income groups.

Fertiliser Management

Concerning fertiliser type, 44% of farmers used a combination of both inorganic and organic fertilisers, while 26% used inorganic fertilisers only, and 30% used organic fertilisers only. The most common method of fertiliser application was broadcast (60%). Fertiliser application in liquid form was reported by 26% of respondents while controlled release accounted for 11%. Only one farmer cited that they used aerial spraying. Fertiliser application timing was based mostly on farmers' experience, plant appearance, and soil testing (Table 3.3).

The most recurrent themes cited for the type of fertiliser used were crop yield or crop quality (53%) and the cost of fertiliser (47%). Other reasons for using a particular fertiliser included environmental considerations and recommendations from soil tests (Table 3). One farmer indicated that:

"Organic fertiliser is good for the environment, but I don't get it in sufficient amounts so I also use chemical fertilisers which I can readily buy."

The ease with which inorganic fertiliser can be applied featured as a recurring theme as echoed by one of the respondents:

"Inorganic fertilisers are easy to apply and increase yields."

Table 3.3. Survey of fertiliser management strategies given to farmers (n = 47). Respondents were asked open-ended questions on how they scheduled fertiliser application timing and the reasons they practised particular methods of fertiliser application.

How do you schedule fertiliser application timing? (n = 47)	**Respondents (%)**[1]
Experience	70
Plant appearance need	60
Soil testing	45
Supplier recommendations	38
Consultant/extension	21
Other farmers	6
Reasons for type of fertiliser used (n = 47)	**Respondents (%)**[1]
Crop yield/crop quality	53
Cost/cheap/save money	47
Environmental considerations	23
Soil test recommendations	2

[1] Farmers could choose more than one option; hence percentages do not add up to 100.

3.5.4 Ecosystem services

Knowledge of agroecosystem services

After a brief explanation of the concept of ES, farmers were asked if they had ever come across the term ES before the present study. A total of 77% of farmers indicated that they had never heard of the term, while only 23% reported they had heard the term. Farmers were then asked to indicate how frequently they thought croplands provided eleven selected agroecosystem services or benefits to society. The selected agroecosystem services included provisioning, regulatory, supporting, and cultural services (Table 3.4). The provision of food was ranked highest as the benefit that croplands always provided followed by '*farmlands are pleasing to look at*' i.e. aesthetic. Provision of fuel was cited as the least frequent agroecosystem service farmlands provided.

Table 3.4. Farmers' responses to the question, how frequently do you think farmlands provide the following agroecosystem services to society?

	Number of farmers (%)		
Ecosystem service	**Always provided**	**Sometimes provided**	**Never provided**
Provide food	75	25	0
Farmlands are pleasing to look at	65	23	13
Provide medicine	60	15	25
Provide clean air	48	46	6
Provide recreation	44	56	0
Reduce soil erosion	25	58	17
Maintain species diversity	17	58	25
Provide fuel	13	69	19
Regulate local climate	10	73	17
Provide fresh water	8	60	31
Reduce flooding	8	73	19

Values of agroecosystem services from agriculture

Farmers were asked to rank how valuable to them the benefits croplands provided were. Table 3.5 shows the results of how farmers ranked agroecosystem services according to the perceived value they derived from the agroecosystem services. Food provisioning was valued higher than all the other agroecosystem services followed by the provision of clean air. The provision of fuel was cited as the least valuable agroecosystem service coming from agroecosystems.

Table 3.5. Values assigned to different agroecosystem services by farmers.

	Number of farmers (%)		
Ecosystem service	**Very valuable**	**Moderately valuable**	**Not valuable**
Provide food	88	10	2
Provide clean air	83	17	0
Reduce soil erosion	67	31	2
Provide fresh water	58	35	6
Are pleasing to look at	54	42	4
Reduce flooding	54	38	8
Maintain species diversity	50	31	19
Provide recreation	42	29	29
Regulate local climate	42	48	10
Provide medicine	38	42	4
Provide fuel	21	48	31

Payments for ecosystem services

Eighty-six percent (86%) of the farmers specified that they would be prepared to participate in a conservation program that offered payments for improving agroecosystem services on their farmlands, whilst 4% said that they would not be willing to participate and 10% were not sure if they would be willing to participate in a PES scheme at the time of the survey. Concerning who should be responsible for maintaining agroecosystem services from farmlands, 50% of the farmers indicated that society should be responsible, while 50% thought it was the responsibility of farmers.

3.6 Discussion

3.6.1 Farmers' management practices

An examination of the study participants showed that they were mostly crop farmers, livestock farmers, and mixed farmers, which was judged to be representative of the range of farmers in Cradock and the surrounding towns. (Jordaan, (2017), personal communication). A spatial analysis of the responses revealed representation of the main farming towns around Cradock, including the town of Cradock. The Eastern Cape, and in particular the Cradock, area has been predominantly a livestock producing region due to its semi-arid climate. These conditions are generally not ideal for cereal production compared to the warmer and traditional cereal producing areas such as Kwa-Zulu Natal (ARC, 2017). However, the production of cereals such as maize has gained interest in recent years due to government efforts to increase grain production in the Eastern Cape (Nelson Mandela Bay Tourism, 2017). This explains why there are more farmers engaged in both livestock and crop farming compared to single enterprises.

Concerning fertiliser management, farmers mainly considered fertilisers that enhanced crop appearance or crop quality or led to increased yields when choosing fertilisers. The most common reason for using organic fertilisers on vegetables was to improve the quality of vegetables while inorganic fertilisers were preferred for cereals to ensure maximum grain yield. Studies have shown that consumers have a higher preference for organically produced vegetables as consumers perceive them to be healthier than conventionally produced vegetables (Peck et al., 2006; Rembialkowska, 2000; Vukasovič, 2016). This may explain why farmers used organic fertilisers for vegetables, to improve the quality of vegetables, and inorganic fertiliser for cereals, where quality may be less important compared to yield.

Studies have also shown that the long-term application of chemical fertilisers can lead to soil acidification, nutrient imbalances and groundwater pollution through leaching (Lin et al., 2019)while the long-term additions of organic manure can have beneficial effects on grain yield, soil quality and the environment (Liu et al., 2010) To promote sustainable agricultural practices, farmers in the region may need more education on how ES are interlinked and how maximizing the provision of one ecosystem service may, in the long run, lead to a general decline of all ES from a given parcel of land. However, since farmers consider profits, farmers may need incentives for them to seriously consider the environmental implications of fertiliser choices and not focus only on economic goals.

The broadcast method was a common fertiliser application method as it provides an easy and convenient way of applying solid fertilisers such as nitrogen compounds and manure. However, in a study by Khan et al., (2007), comparing fertiliser application methods, the broadcast method was found to be less efficient than other methods such as ring application and fertigation, with fertiliser being easily washed away as leachate or lost in runoff. The use of this method indicates that farmers are losing part of their fertilisers through this application method and this affects crop yields and farmers' income, undermining SI.

While inorganic fertilisers provide a quick source of nutrients for the crop, organic fertilisers work over a longer time period, releasing nutrients when the soil is warm and moist, which tends to correspond with the plants' times of greatest need for nutrients. Organic fertilisers are less prone to leaching compared to inorganic fertilisers and continue to improve the soil structure and texture through the addition of organic matter long after the plants have taken the nutrients they need. So, while inorganic fertiliser is cheaper in the short term, it adds less to the soil in the long term.

Several studies have shown that while organic farming systems are more environmentally sustainable, they produce lower yields compared to conventional systems (Cavigelli et al., 2009; Seufert et al., 2012). This difference in yield between conventional and organic systems may discourage farmers who are 'maximum yield-oriented' from converting to organic farming systems. A review by (Fess and Benedito, 2018), comparing organic farming systems versus conventional farming systems concluded that, despite the lower yields in organic systems, the environmental benefits including microbial diversity, soil building, carbon sequestration and reduced leaching could far outweigh the yield benefits from conventional systems. In the long term, the adoption of organic management practices may enhance the farming system sustainability and minimise water pollution in the region due to the limited use of chemical fertilisers and reduced reliance on production methods that are energy-intensive highly influences the sustainability of organic-based farming systems. In South Africa, changing customer preferences towards more healthy foods and increased environmental awareness has led to an increase in the demand for products produced using sustainable production methods However barriers to the development of organic farming systems such as high certification fees and a lack of an active organic farming policy and legislation still exist in South Africa.

With regard to irrigation management, the most cited method of irrigation, overhead sprinklers, has been shown to be less efficient compared to drip irrigation when it concerns water-saving (Albaji et al., 2010; Rodrigues et al., 2013). Given that South Africa is a water-stressed country and agriculture already accounts for approximately 70% of water withdrawals in South Africa, it is important to prioritise water saving in the agriculture sector. While drip irrigation might be the logical choice because of its higher efficiency in saving water, farmers' responses showed that besides water-saving, the choice of irrigation method was also dependent on what irrigation equipment was available to the farmer, the cost of maintaining the irrigation system and what irrigation system the farmer could afford. This calls for the development of innovative and local strategies in the agricultural sector to save water that consider farmers' socio-economic status and knowledge on irrigation management. For example, the efficiency of surface irrigation systems can be improved by levelling fields and collecting and re-using runoff. Demonstrating this information to farmers through farmer field schools might be useful to farmers who cannot afford the most efficient irrigation system and encourage them to manage their existing irrigation systems more efficiently.

Although the irrigation and fertiliser methods being used by farmers in this study vary in their efficiency of use, none of the fertiliser and irrigation application and scheduling methods are 100% efficient and all result in fertiliser and water loss from the growing area. Results of the present study also indicate that most farmers manage fertiliser and irrigation separately using methods such as experience and plant observation, which may not be entirely accurate in determining crop irrigation and fertiliser scheduling. However, fertiliser and irrigation management closely interact in determining crop yields (Mack et al., 2017). Farmers must manage both inputs carefully to achieve high yields and make a profit on their investments while reducing the impact of water and nutrients use on ecosystems and ES. Using the appropriate amounts of fertiliser and water at the right time is key to improving yields and minimizing negative environmental impacts. However, the results of this study show that farmers may not be practising this balanced application of fertiliser and water due to financial capacity, logistic constraints or lack of appropriate knowledge simultaneously managing irrigation water and fertiliser.

In this study, farmers mentioned experience as an important knowledge source for scheduling irrigation and fertiliser management practices. A literature review by Ritter et al., (2017), came to the conclusion that farmers often used knowledge from their farming experience more than knowledge from education. The review went further to suggest that this experience included information learned from exchanges and discussions between farmers themselves. This is also in agreement with the results of this study as the major source of information for farmers was from other farmers. Events such as farmer field school or farm tours organised by Farmers' Organisations or government agencies such as the Eastern Cape Rural Development could provide a platform for researchers and government officials to introduce and discuss the concepts of sustainable intensification and ES with farmers. These discussions could help fill the gap between scientific information and farming practices by bringing together theory and practice in a practical and all-inclusive manner for all stakeholders. Ground-level support from extension officers and dialogue between farmers and scientists are conducive for the implementation of effective and sustainable fertiliser and irrigation management practices.

With regard to sources of information, results show that most farmers obtain their information for making farm-related decisions from other farmers. The results of other studies with farmers have shown that the majority of farmers also get their information when making farming decisions from other farmers (Khapayi and Celliers, 2016; Marra et al., 2012). The Internet and Farmer's Organisations were also important sources of information in this study. Research shows that internet use in South Africa is on the rise, especially through mobile phones, with more people being able to access a variety of information on their mobile smartphones (Salahuddin and Gow, 2016). Studies by Lu and Chang, (2016) and Phillips et al., (2018), have demonstrated that farmers are increasingly using social media platforms including Facebook for knowledge exchange to support on-farm decisions. This is in agreement with the results of this study in which the majority of farmers indicated the use of the internet as a source of information for making decisions. This suggests that potential for engaging farmers in policy and agricultural land management discussions may entail outreach through internet platforms such as online farmer groups and electronic agricultural magazines or through Farmers' Organisations which have online platforms as these sources seem to be popular with farmers.

Interestingly, government extension accounted for less than half of the farmers as a source of information. Several studies in South Africa have highlighted challenges currently being faced by government extension services such as lack of skilled manpower and financial support in extension and conservation (Davis and Terblanché, 2016; Khapayi and Celliers, 2016). Studies by Mnkeni et al., (2010), at the Zanyokwe and Tugela Irrigation Schemes in the Eastern Cape, highlighted that extension officers lacked basic technical skills in crop husbandry and irrigation management and could not fully support farmers. There is, therefore, an opportunity for the government to work with farmers to increase awareness of the ES concept. Efforts to work with farmers and invest more resources in building capacity of extension services should be prioritised so that government extension specialists are able to fully support farmers in developing and adopting strategies that improve crop yields while protecting the environment at the same time.

3.6.2 The concept of ecosystem services in practice

Researchers and policymakers are increasingly using the ES concept to deal with natural resources management. However, this does not seem to be the case at the farming community level. In this study, 77% of farmers were not familiar with the term ES. This is in agreement with studies by Bernués et al., (2016) in which more than 70% of the survey respondents were not familiar with the term. Although farmers were not familiar with the term ES, the results of this study show that farmers were knowledgeable about ES without calling them ES. By ranking (always, sometimes, or never) the selected ES that agriculture provided, farmers demonstrated knowledge and understanding of what ES were, even if they did not specifically use the term ES. This is similar to studies by Lamarque et al., (2014) and Koschke et al., (2014), in which farmers were knowledgeable about ES without calling them ES. In a similar study, Smith and Sullivan, (2014), highlighted that poor familiarity with the term ES is a reflection of different exposure levels towards the concept of ES with a low awareness at the farming community level, while there is a high level of awareness at the research level. For management purpose, the result suggests the relevance of bridge the research-practice interface, as academic concepts such as ES may only be taken up in practice if practitioners are deeply involved in their formulation and evolution.

3.6.3 Consideration of ES in agricultural farming practices

Food provisioning was considered as the most important ES for farmers because it is the source of livelihoods and income for farmers. This is supported by studies by Logsdon et al., (2015), who found that farmers placed a higher value on the provision of food compared to other ES such as climate regulation. This shows that farmers typically manage agricultural lands for food provision and economic reasons and not necessarily for the provision of other ES. While this may be obvious, farmers may not be aware that ES are interlinked with other ES such as pollination supporting crop production. Crop production, therefore, relies on the maintenance of other agroecosystem services. An approach in which farms are managed for optimising a single agroecosystem service reflects a poor understanding of the interlinkages between different ES, and may also accelerate environmental degradation and hence the ecological base supporting the continued supply of the valued and desired ES. For example, climate regulation was not highly valued compared to provision of food. However, climate regulation and agricultural production are highly interlinked (Dietze et al., 2019) with the majority of greenhouse gas emissions coming from agricultural land uses such as deforestation and the application of chemical fertilisers and manure on farmlands (FA0, 2016). Farmers, therefore, need information and a greater understanding of the different types of ES and how they are related to farming. One way of increasing farmers' knowledge of ES would be through the use of funding or regulatory instruments that enhance the provision of ES related information to farmers.

From an SI and ES point of view, farmers are critical stakeholders responsible for agroecosystems management and ES supply. While farmers may manage agroecosystems for the sole purpose of food provision, food provision is just one of a variety of interconnected ES supplied by agroecosystems. Swinton et al., (2007) explain that agriculture supplies and receives ES that range well beyond the provision of food. Previous research has demonstrated that when farmlands are managed for maximum food production, other ES may decline and ultimately lead to a decline in overall agricultural productivity (Pilgrim et al., 2010), highlighting an urgent need to adopt an ES approach to managing agroecosystems. Such an approach would ideally involve managing farmlands for the concurrent delivery of multiple agroecosystem services.

3.6.4 Research findings in relation to policy and practice implications

In this study, the majority of farmers indicated a willingness to participate in conservation programs that would offer payments to improve ES management. The implication for sustainable intensification and land management policy development is that farmers may require ongoing financial payments 'on behalf of society' to manage ecosystems in a more sustainable way for present and future generations. Other studies such as those by Hanslip et al., (2008) and Xiong and Kong, (2017) have demonstrated that farmers are generally willing to receive payments to manage agroecosystems more efficiently. Payments for ES (PES), while beyond the scope of this study, have been the focus of several studies (Bryan and Crossman, 2013; Engel et al., 2008; Prager et al., 2011).

For example, The Regional Integrated Silvopastoral Ecosystem Management Project in Costa Rica, has been assessing the use of PES to encourage the adoption of silvopastoral practices in Costa Rica (Pappagallo, 2018). Results show that in the project's first two years, the area of degraded pasture fell by two thirds, while pastures with high tree density increased considerably. Also, by 2007 the project appeared to have been successful in persuading farmers to increase significantly the use of practices that generate higher levels of ecosystem services. The environmental benefits associated with the project included a 71% increase in carbon sequestered, increases in bird and butterfly species and a modest increase in forested area. The production of milk increased by 10% and farm income also increased by 115%. (Pappagallo, 2018)

Although not a cure-it-all solution to address ecological problems in agriculture, PES can be a useful policy tool to enhance agroecosystem services management in agricultural landscapes. The results of this study provide further evidence to motivate the implementation of such policies in South Africa. Farmers' willingness to participate in PES programs is an indication to policymakers to develop PES programs and incentives for farmers to manage their farmers in a more efficient and sustainable manner. However, further studies would be required to ascertain whether such PES programmes would be economically feasible and how such PES programmes could be structured and managed. The Eastern Cape government should also consider the potential use of subsidies and tax instruments as mechanisms to encourage farmers to adopt sustainable practices and overcome financial constraints.

3.7 Conclusion

Farmers have a variety of reasons (e.g. costs, crop yield) when choosing agricultural land management practices and assign different values to different agroecosystem services which in turn, influence the way they manage their farms. While farmers can identify the range of ES provided by farmlands, most farmers in the Eastern Cape are not familiar with the term ES yet. To achieve sustainable management of croplands in South Africa and increase the adoption of sustainable agricultural land management practices in by farmers requires: (1) a common language between researchers, policymakers and farmers, (2) a knowledge of the factors that motivate farmers when choosing farm management strategies, and (3) the values and importance farmers assign to different agroecosystem services. The study presents a preliminary study that offers insights into some of the important factors related to farmers' decision making and how this affects the provision of agroecosystem services. Future studies should investigate the amount or types of PES that would be attractive to farmers as well as test farmers' knowledge on the interrelationships between multiple ES.

Chapter 4: **Calibration and Validation of the EPIC model for Maize Production in the Eastern Cape, South Africa**

This Chapter addresses the calibration and validation of the EPIC model before it is applied to simulate different irrigation and fertiliser management strategies in Chapter 5 and the effects of future climate change in Chapter 6. Section 4.1 gives an introduction to the study. Section 4.2 describes the materials and methods used in the study including the calibration procedure used. Section 4.3 presents the calibration and validation results and section 4.4 is a discussion of the results. Finally, section 4.5 provides a conclusion highlighting the implications of the results regarding the use of field data for calibration of the EPIC model.

The following paper has been published as part of this chapter:

Choruma D.J., Balkovic, J., Odume, O.N. (2019) Calibration and Validation of the EPIC model for Maize Production in the Eastern Cape, South Africa. Agronomy 9(9), 494; doi.org/10.3390/agronomy 909049

4.1 Introduction

A key area of interest in agronomic research is to find agricultural land management strategies that maximize food production without degrading land and water resources. To develop such strategies, field experiments have been used to investigate the impacts of different management strategies on crop yields and the environment (Greer and Pittelkow, 2018; Tian et al., 2018; Zhou et al., 2019). Field experiments are sources of reliable data for establishing causal relationships between agricultural land management practices and real-world observed measurements (Durr et al., 2016; Liang et al., 2016). However, field experiments are often expensive, time-consuming, and labour-intensive.

Crop growth simulation models are alternative methods that offer a quicker and less expensive way of investigating the effects of agricultural land management practices on crop yields and the environment. A modelling approach can provide reasonably reliable results in developing agricultural land management strategies, provided the models are calibrated and validated using reliable observed field data (Arnold et al., 2012; Zhao et al., 2016). For example, crop models have been applied to refine management practices, such as fertiliser application and water usage at the farm and plot scales (Khan and Walker, 2015). Further, crop models have been used to test the effectiveness of alternative agricultural land management practices under varying climate change scenarios. However, to yield meaningful results, it is prudent to calibrate crop models in the region of intended use before their application (Folberth et al., 2012).

Model calibration is the procedure where model parameters are fine-tuned to increase the agreement between model simulations and real-world observations (Xiong et al., 2013). Calibration is important to increase model accurateness and decrease model prediction uncertainty (Daggupati et al., 2015). Calibration is done by judiciously choosing model parameter values, adjusting them within recommended ranges, for example, from literature or expert opinions, and comparing the simulated outputs with observed data for a given set of conditions (Arnold et al., 2012). A successful calibration would be when the model reproduces observed data within a satisfactory degree of accuracy and precision for the intended model use (James and Burges, 1982; Moriasi et al., 2007). Once calibrated and validated, the model can be reasonably applied in the area of interest. Calibrated crop growth models can, therefore, be useful tools to complement field experiments and support decision making for sustainable agricultural land management.

The Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1984), originally developed in the United States of America (USA), is a process-based, field-scale model with a daily time scale. It simulates the chemical processes occurring in the soil–water–plant interaction under different agricultural management regimes (Williams et al., 2015). The main components of EPIC are weather simulation, crop growth, carbon and nutrient cycling, tillage, soil erosion, and hydrology (Balkovič et al., 2013). Globally, the model has been applied to study crop yield responses to nutrients and water management (Folberth et al., 2013; Zhang et al., 2018), irrigation management and scheduling (Ko et al., 2009; Rinaldi, 2001), soil erosion (van Zelm et al., 2018), and climate change impacts on crop yields (Lychuk et al., 2017; Xiong et al., 2016). However, the majority of these studies have been conducted at the global and regional scales using a Geographic Information Systems (GIS) modified version of the EPIC model, Global-EPIC (GEPIC), with few studies conducted in South Africa.

In Africa, studies using EPIC have mostly been performed in West Africa (Adejuwon, 2004; Gaiser et al., 2010; Worou et al., 2012) where soil and weather conditions differ from the semi-arid conditions in South Africa. Studies that have applied EPIC in South Africa have been at the sub-Saharan scale (Folberth et al., 2012; van der Velde et al., 2014) where combined data from provincial statistics have been used to calibrate models due to data scarcity issues (Singels et al., 2010; Zinyengere et al., 2015). The application of the EPIC model at the regional scale in Africa implies that field-scale conditions, such as local heterogeneity in climate, soil, and farm management practices, are difficult to incorporate, potentially resulting in high levels of uncertainties in model results (Arunrat et al., 2018; Therond et al., 2011). The use of field-scale data can greatly increase model accuracy and reduce uncertainty in model predictions, particularly if results are to guide local decision-making processes. To date, information on field-scale calibration and validation studies using EPIC in South Africa are limited. In South Africa, the models that have been applied widely in the field of agricultural management have been the Agricultural Catchments Research Unit (ACRU) model (Kollongei and Lorentz, 2015; Schulze and Arnold, 1984), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003) and the Soil Water Balance (SWB) model (Annandale et al., 2005). However, the majority of these models have mostly been hydrological models that have been adapted for agricultural water management and lack a robust crop growth and fertiliser management component compared to EPIC, which was specifically developed for agricultural management (Williams et al., 1984). Therefore, using limited field data (maize grain yield and management practices) from the Cradock Research Farm in the Eastern Cape, this Chapter addresses the second objective of this study: “To calibrate and validate the EPIC model for maize growth and yield simulation using limited field-scale data under South African conditions.” A global EPIC-based modelling framework

4.2 Materials and methods

4.2.1 Study Site

Field studies for calibration of the EPIC model were carried out at the Cradock Research Farm in the Eastern Cape, South Africa. The Cradock Research Farm is situated within the Great Fish River valley catchment (Figure 4.1), where intensive irrigation and commercial farming are practised. Soils and climate within the research farm are representative of the broader catchment. The soil is classified as a fine-loamy mollic ustifluvent (Soil Survey Staff, 2014) of alluvial origin, characterized by high sand and silt contents of the alluvial and colluvial material derived from Beaufort sediments in the Eastern Cape. Table 4.1 shows the general characteristics of the soil profile used in the study. Cradock has an average annual rainfall of 341 mm with most of the rainfall occurring in February and March (late summer). Cradock is mostly a farming town, situated along the Great River Fish River where water from the river is used for irrigation purposes.

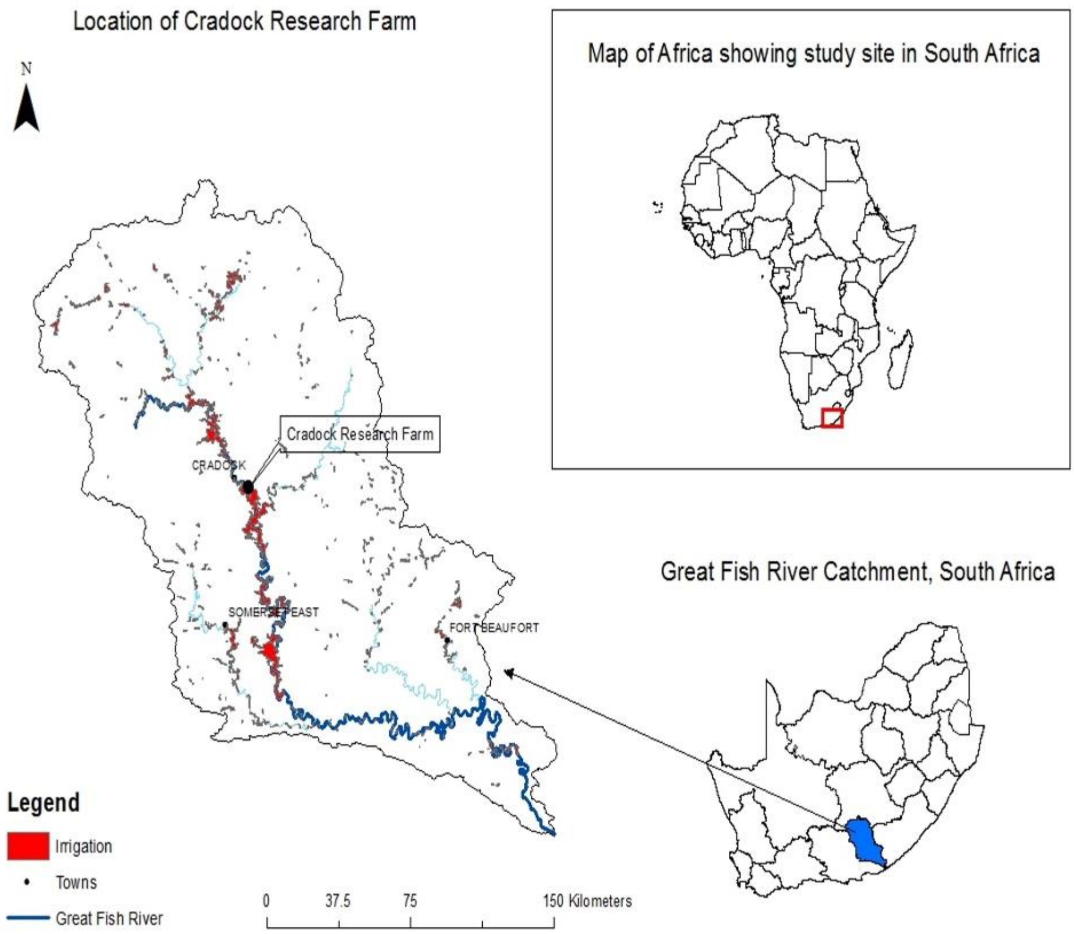

Figure 4.1. Map of Africa showing South Africa and the location of the Cradock Research Farm within the Great Fish River System.

Table 4.1. Selected soil properties and depths of the soil profile used as input into the Environmental Policy Integrated Climate (EPIC) model at Cradock Research Farm.

Soil Parameters	**Soil layer number**	
	1	**2**
Bulk density (g cm^{-3})	1.48	1.52
Clay (%)	20.4	15.1
Sand (%)	52.8	42.5
Silt (%)	26.8	42.4

pH (water)	6.5	6.5
Soil organic carbon (%)	0.91	0.2
Cation exchange capacity (cmol (+) kg^{-1})	14.3	13.4

4.2.2 Field experiment

Field trials on maize were carried out at Cradock Research Farm for the Agricultural Research Council (ARC) by the Cradock research manager from 1999 to 2003. The field trials were carried out to evaluate the potential yield and cultivar stability of different high-yielding maize hybrid cultivars under the semi-arid conditions of the Eastern Cape. Two maize hybrid cultivars, CRN 3760 and PHB 30H22, were chosen for the modelling study as they had complete records for grain yield and agricultural management for the period 1999 to 2003. The maize varieties selected for the modelling study were grown on two independent fields with similar soils at the Cradock Research Farm but managed according to the same irrigation and fertiliser regime. A randomized block design (RBD) (Clewer and Scarisbrick, 2001), with three replications, was used throughout. Plant population was at 50,000 plants per hectare with a row spacing of 0.9 m.

A standard management plan developed by ARC was used to schedule agricultural management practices, including irrigation amount and timing, fertiliser amount, and planting densities. Irrigation type was flood irrigation with the crop receiving a maximum of 600 mm irrigation water per growing season. Nitrogen fertiliser was applied at a rate of 195 kg N ha^{-1} $season^{-1}$. Soil tillage was done using a power plough, and common weed and pest control were carried out as needed. Table 4.2 shows the typical irrigation and fertiliser amounts used during the trial period. This agricultural management plan was used throughout the trial period from 1999 to 2003. During the trial period, the same management practices were performed around the same time each year with only minor changes according to prevailing local weather conditions.

It should be noted that although agricultural management practices were recorded during the trial period, most variables that would be useful in evaluating model performance, such as soil organic carbon contents, leaf area index, and nitrogen content in grain, were not recorded during the trial period. Only the final grain yield was recorded, and this limited the observed data that could be compared with model outputs.

Table 4.2. Summary of agricultural land management plan used for both field sites during the five years of the trial period.

Date[1]	Operation	Type	Amount
22 October	Planting	Maize	50 000 plants ha^{-1}
22 October	Fertiliser application	Superphosphate	476 kg ha^{-1}
22 October	Fertiliser application	Ammonium sulfate	330 kg ha^{-1}
22 October	Fertiliser application	Calcium sulfate	120 kg ha^{-1}
22 October	Irrigation	Furrow	75 mm
15 November	Fertiliser application	Ammonium sulfate	300 kg ha^{-1}
26 November	Irrigation	Furrow	75 mm
10 December	Fertiliser application	Ammonium sulfate	300 kg ha^{-1}
17 December	Irrigation	Furrow	75 mm
28 December	Irrigation	Furrow	75 mm
18 January	Irrigation	Furrow	75 mm
8 February	Irrigation	Furrow	75 mm
19 February	Irrigation	Furrow	75 mm
11 March	Irrigation	Furrow	75 mm
5 June	Harvesting	Manual	11 tonnes $hectare^{-1}$ (average)

[1]The dates given in the table are not fixed for each year. They indicate the approximate times of year each management activity was carried out during the trial period.

4.2.3 Model description

The EPIC model simulates approximately 80 crops with the model using unique parameter values for each crop (Williams et al., 2015). In the crop growth routine, crop yield is estimated as a function of the potential and water-limited harvest index (HI, WSYF), biomass to energy ratio (WA), planting density (PD), photosynthetic active radiation (PAR), and vapor pressure deficit (VPD) (Xiong et al., 2016). Potential biomass is adjusted to actual biomass through daily stress caused by extreme temperature, water, and nutrient stress or inappropriate aeration. Values of context-specific parameters such as potential heat units accumulated by a crop from its sowing to maturity (PHU), harvest index (HI) and optimum temperature (OT) need to be adjusted according to the region and context in which the model is to be applied. A further description of the EPIC model components is given in Appendix B.

4.2.4 Data sources

Daily weather data for the Eastern Cape, which included precipitation, maximum and minimum temperature, solar radiation, and relative humidity for the years 1980–2010 were obtained from the publicly available AgMERRA (Ruane et al., 2015) climate dataset at 0.5 × 0.5 arc-degree spatial resolution. Soil data (bulk density, cation exchange capacity, texture, and electrical conductivity) were obtained from records of previous soil analyses done at the Cradock Research Farm. However, some soil parameters required to set up the EPIC model were missing, and these were obtained from the Harmonized World Soil Database (HSWD) (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009). The missing soil parameters in the EPIC soil file were then adjusted with values from the HSWD based on expert opinion (Jordaan, 2017). Agricultural management data, such as fertiliser application, irrigation amount, and planting and harvesting dates during the trial period, were obtained from the Cradock Research Farm manager (ARC, 2017).

Initial PHUs were estimated from long term (1980–2010) daily maximum and minimum temperature values and optimal temperature for maize growth using the PHU calculator at Purdue University, Indiana, USA. Base (minimum temperature for plant growth) and OT were set to 8 °C and 25 °C, respectively, according to values in the ARC Maize production guideline (ARC, 2017). The number of days from planting to maturity were obtained from the maize hybrid variety producer (Pannar Quality Seeds, 2018). Planting and harvesting dates recorded during the trial period were also used as inputs. Together, the long-term maximum and minimum temperature data, base and optimum temperature, as well as the number of days from planting to maturity were used to estimate the potential heat units required from planting to maturity based on the following heat unit formulas:

Equation 1

$$Daily\ Heat\ Unit = \frac{maximum\ temperature + minimun\ temperature}{2} - threshold\ Temperature$$

Equation 2

$$PHU = Daily\ Heat\ Units\ \times Number\ of\ days\ from\ planting\ to\ harvest$$

Based on this calculation, initial potential heat units were set to 2340 and the duration of the growing season set to 180 days.

Annual grain yield and management practices including tillage, fertilization, sowing, planting, irrigation, and harvesting dates were recorded on site. Data for the period 1999–2003 from one field site were used to calibrate the model while data from the second field site were used for model validation. The agricultural management plan provided by the Cradock Farm manager was used as input for fertiliser application timing, irrigation scheduling, and planting and harvesting times. Based on the management plan, the corresponding crop operation schedules, including tillage, fertiliser application, irrigation timing, planting, and harvesting dates were designed in EPIC's Operations Schedule file for each site.

4.2.5 Model setup

The EPIC-IIASA modelling framework (Balkovič et al., 2014) was used in this study. Obtained data sets were converted to simulation grids at a resolution of 5 × 5 arc-min. The modelling scheme was set up by combining available GIS layers on soil, relief, and weather (Balkovič et al., 2013; Xiong et al., 2013). The model was constructed for the whole of the Eastern Cape and divided into homogenous response units according to physical properties given by the intersection of site properties, such as elevation and soil texture. Subsequently, a zone raster was defined, consisting of homogenous simulation units and weather grids upon which the model was run (Balkovič et al., 2014). For this study, the simulation grid in which Cradock was located was chosen for model simulations. One soil profile adjusted for soil properties experienced in the study area (see Section 2.1) was therefore used to run the simulations in the model. The Priestly–Taylor method for potential evapotranspiration (PET) was used in the model for estimation of PET. The Priestly–Taylor method was chosen because it gave PET values close to previously reported values for PET in the region compared to other methods of estimating PET (Schulze and Maharaj, 2007).

The model was run for 31 years from 1980 to 2010, corresponding to the length of the weather records. Simulated crop yields were compared to observed yields from the period 1999 to 2003 with the initial 19 years serving as a warm-up period for equilibrating soil functions, water erosion, as well as soil nutrient depletion. Irrigation and fertiliser application were set to manual scheduling and input into the operations schedule file based on dates recorded during the field trials (Table 4.2).

4.2.6 Model calibration and validation

Parameters identification

During calibration, few adjustments were made to the default parameters to reflect local crop cultivars and site conditions. Earlier studies in semi-arid conditions by Wang et al., (2005), Causarano et al., (2010), and Folberth, (2013) have found simulated crop yields to be sensitive to (i) potential heat units (PHU, Equation 2); (ii) planting density (PD), the number of plants per unit area; (iii) biomass to energy ratio (WA), defined as the potential growth per unit of intercepted photosynthetically active radiation; (iv) harvest index (HI) or ratio of economic yield to above-ground biomass; and (v) microbial decay rate. These parameters were selected for calibration to adjust simulated yields to correspond to observed yields as closely as possible. The choice of parameters to calibrate was based mainly on observed available data and also on suggestions from EPIC developers following (Rinaldi et al., 2011).

Calibration procedure

Calibration was done according to the steps in Figure 4.2 adapted from (Xiong et al., 2013).

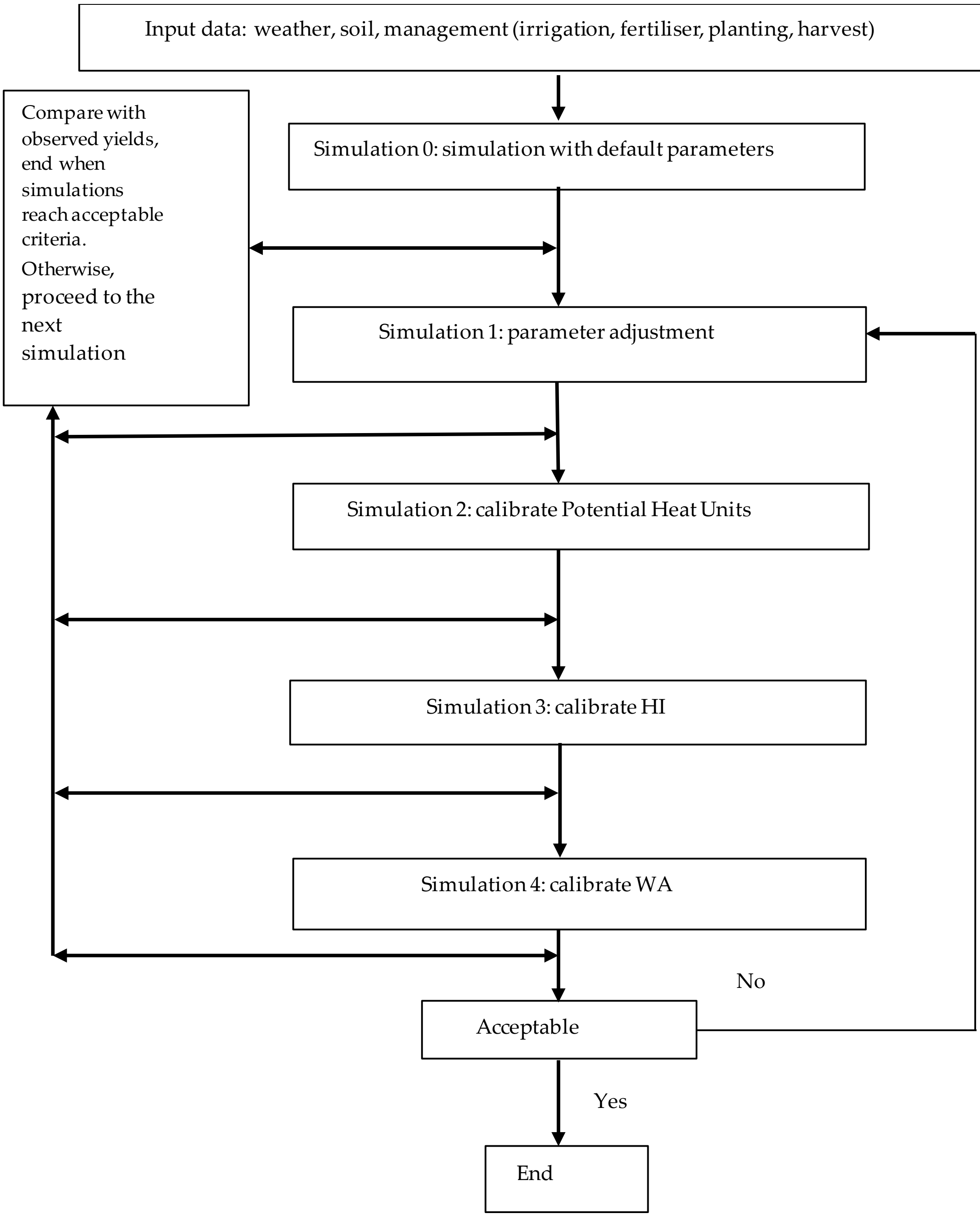

Figure 4.2 Steps followed in the calibration process (adapted from Xiong et al., (2013)

Simulation 0: Simulation with default parameters

The default maize crop parameter dataset (provided with EPIC version 0810) was used as the starting basis to establish a modified parameter set for maize yield simulation. The default maize parameters were modified using data from the calibration period (1999–2003) and values from literature to account for the local context. The modified parameter set was then used to run a simulation for the period 1980 to 2010. HI and WA were set to their default values of 0.5 and 40 kg ha^{-1} MJ^{-1} m^2, respectively. PHUs were set to 2340 according to calculations using the growing season length and the maximum and minimum temperatures. Irrigation and fertiliser application were both set to manual and input into the operations schedule file according to the management records obtained from the Cradock Station manager. Planting and harvesting dates were also taken from management records. Planting density was set to 5 plants per square meter based on management records.

Simulation 1: Parameter adjustment

Model parameters influencing soil organic carbon and crop growth were adjusted based on literature, site history (Jordaan, 2017), and expert knowledge (Balkovic, 2018). Interviews with Mr. G. Jordaan, the Cradock Farm Manager, were conducted in April 2017. Mr Jordaan provided soil and farm management data. Consultations with J. Balkovic, the lead researcher using the EPIC model at the International Institute of Applied Systems analysis (IIASA) were conducted in June 2017 at IIASA, Austria. The value that gave the lowest root-mean-square error (RMSE, Equation 3) between observed yields and simulated yields was selected as the final calibration value. Table 4.3 shows the parameters adjusted and the values before and after calibration. The microbial decay rate coefficient Parm (20) was set to 1 after values reported in previous EPIC modelling frameworks, such as EPIC-BOKU (Folberth et al., 2016). The microbial decay rate coefficient impacts carbon mineralization, which affects crop yield (Wang et al., 2005). Century slow humus transformation rate (Parm 47) and exponential coefficient in equation expressing tillage effect on residue decay rate (Parm 52) affect carbon dynamics and must be estimated to simulate nitrogen supply correctly. The minimum HI under water stress (WSFY) was set to 0.01 from 0.4, which gives a stronger weight to water stress in the model's calculation of HI (Folberth et al., 2012).

Table 4.3. Crop and carbon cycle-related parameters, default values, suggested parameter ranges, and calibrated values in the EPIC model.

Parameter	Symbol	Default value	Calibrated value	Suggested range	Source
Crop parameters					
Potential heat units	PHU	2340	2480	1000–2900	(Williams et al., 1989)
Minimum harvest index	WSFY	0.40	0.01	0.01–0.40	(Williams et al., 2015)
Harvest index	HI	0.5	0.5	0.45–0.60	(Kiniry et al., 1995)
Biomass to energy ratio	WA	40	40	30–45	(Sinclair and Muchow, 1999)
Carbon cycle parameters					
Microbial decay rate coefficient	Parm (20)	0.1	1.00	0.5–1.5	(Wang et al., 2005)
Slow humus transformation rate	Parm (47)	0.000548	0.00068	0.00041–0.00068	(Causarano et al., 2007)
Tillage effect on Residue decay rate	Parm (52)	5	6.20	5–15	(Steglich et al., 2018)
Exponential coefficient in potential water use root growth distribution	Parm (54)	5	2.5	2.5–7.5	(Williams et al., 2015)

Simulation 2: PHU adjustment

PHUs were adjusted in steps of 5 to match observed yields as closely as possible. The PHUs that gave the lowest RMSE between observed and simulated yields were selected as the final calibrated PHU.

Simulation 3: HI adjustment

HI has been shown to vary across locations and management practices (Worou et al., 2015). In the HI adjustment simulation, HI was adjusted from 0.4 to 0.8 in steps of 0.05 to explore the effects of varying HI on crop yields.

Simulation 4: WA adjustment

WA is used in the model for converting energy to biomass. Different values of WA were changed by steps of 5 to explore the influence of WA on crop growth. WA has been shown to significantly affect crop yield and should be one of the last parameters to be adjusted (Williams et al., 2015).

4.2.7 Statistical analyses

To evaluate model efficiency in predicting observed yields, the following statistics were computed: Root-mean-square error (RMSE), the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE) and percent bias (PBIAS) as respectively indicated in the equations below.

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Equation 3

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(s_i - o_i)^2\right]^{\frac{1}{2}}$$

Equation 4

$$R^2 = \frac{[\sum(O_i - O_{mean})\,(S_i - S_{mean})]^2}{\sum(O_i - O_{mean})^2 \sum(S_i - S_{mean})^2}$$

Equation 5

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - O_{mean})}$$

Equation 6

$$PBIAS = \frac{\sum_{i=1}^{n} 100(O_i - S_i)}{\sum_{i=1}^{n} O_i}$$

Where n is the sample number, O_{mean} and S_{mean} are the observed mean and simulated mean values, respectively. Oi and Si are the observed and predicted values of the ith observation (i = 1 to n), respectively. For RMSE, values closer to zero imply a good fit between observed and simulated yields (Bao et al., 2016). A value of zero for RMSE means that the model predicts the observations with perfect accuracy. The coefficient of determination, R^2, ranges from 0 to 1, with higher values indicating less error variance (Moriasi et al., 2007). NSE ranges from negative infinity to 1. A value of NSE equal to 1 represents a perfect model fit, and negative NSE values indicate that the mean observed value is a better predictor than the simulated value (Moriasi et al., 2007). PBIAS measures the tendency of simulated data to be larger or smaller than the observed data. It has an optimal value of 0, with positive values indicating underestimation and negative values indicating overestimation (Gupta et al., 1999). Differences in mean values between observed and simulated values were evaluated using the Student's *t*-test in Excel 2016. Model performance was considered satisfactory if $R^2 \geq 0.6$, PBIAS $\leq$ +/−25% and NSE $\geq$ 0.4 following (X. Wang et al., 2012).

4.3 Results

4.3.1 Model calibration

Simulation with default parameters

The simulation with default parameters showed an overall underestimation of observed yields with PBIAS = 17.6, $r^2 = 0.02$, RMSE = 3.65 t ha^{-1}, and NSE = −3.3. Simulated yields ranged from 7 tonnes per hectare (t ha^{-1}) to 8.3 t ha^{-1} while observed yields ranged from 9 t ha^{-1} to 14 t ha^{-1}. The model underestimated crop yields for all years, as shown in Figure 4.3.

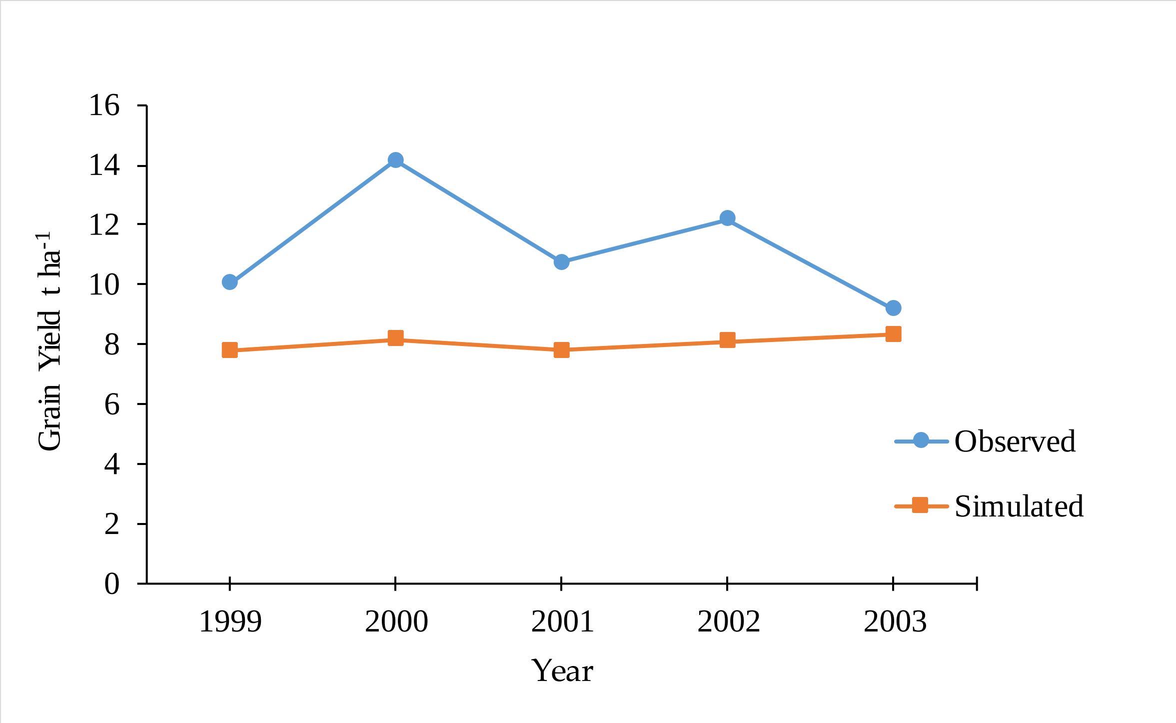


Figure 4.3 Simulation with default parameters showing the simulated yields for the weather period with observed data.

Parameter adjustment

Adjusting the parameters Parm 20, Parm 47, Parm 52, Parm 54 and WSFY improved RMSE from 3.65 t ha^{-1} in the default simulation to 1.28 t ha^{-1}. Model efficiency, as expressed by NSE improved from negative values to 0.47. Further parameters adjustment did not improve model simulations. The calibrated parameter values are summarized in Table 4.3.

PHU calibration

The initial PHU calculated from long-term weather records gave a RMSE of 1.86 t ha^{-1} between the observed and simulated yields. Increasing PHU value improved model simulations with the PHU value of 2480 giving the lowest RMSE value of 1.17 t ha^{-1}. Further adjustments of PHU above 2480 did not yield any improvement of RMSE. Following up on the parameter adjustment in the previous section, calibrating PHU brought model simulations within the criteria set for satisfactory model calibration (R^2 > 0.6 and PBIAS < +/−25%) and further calibration of the crop parameters HI and WA was not performed. In this calibration simulation with PHU = 2480, simulated crop yields ranged from 10 t ha^{-1} to 12 t ha^{-1} while observed yields ranged from 9 t ha^{-1} to 14 t ha^{-1} (Figure 4.4).

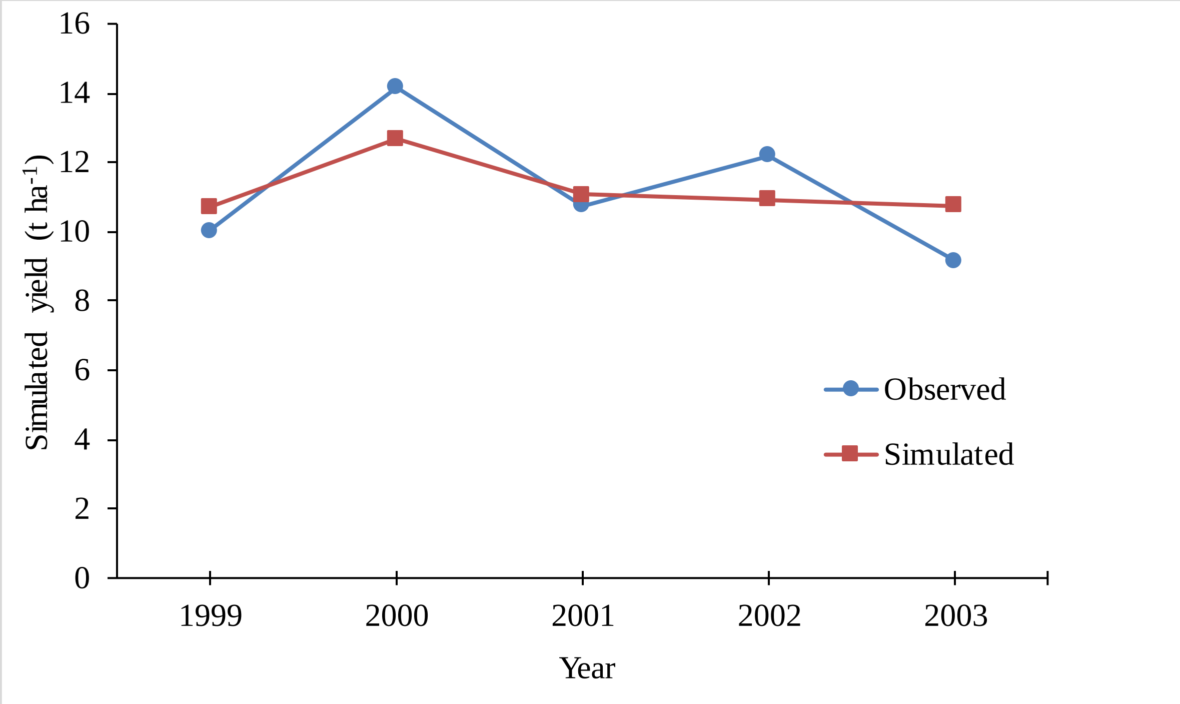


Figure 4.4. Comparison of observed yields in tonnes per hectare (t ha^{-1}) and simulated yields for the period with observed data after initial potential heat units (PHUs) calibration of the model.

Final PHU calibration results showed a coefficient of determination (R^2) between simulated and observed yields of 0.76 (Figure 4.5). A Nash - Sutcliffe efficiency of 0.56 and a PBIAS = 0.31% were considered satisfactory and did not require further efforts in calibrating HI and WA in the model. RMSE decreased from 3.65 t ha^{-1} in the default simulation to 1.17 t ha^{-1} in the PHU calibrated simulation (Table 4.4). Model output showed that maize yield was mostly constrained by water and N fertiliser stress. There was no stress due Phosphorus (P) indicating the crop had adequate P fertiliser.

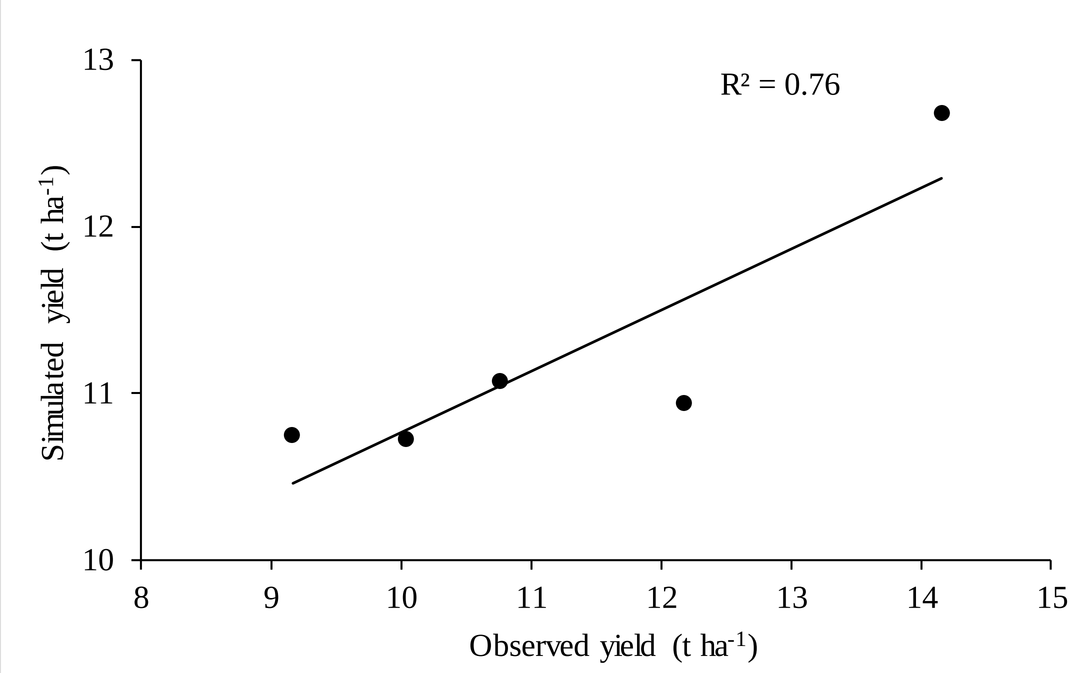


Figure 4.5. Linear regression of simulated crop yields in tonnes per hectare (t ha^{-1}) on observed maize yields with the calibrated maize crop file.

Table 4.4. Model evaluation statistics before and after calibration showing Nash–Sutcliffe efficiency (NSE), root-mean-square error percentage (RMSE), and percent bias (PBIAS).

	Observed Mean Yield (t ha^{-1})	Simulated Mean Yield (t ha^{-1})	NSE	RMSE (t ha^{-1})	PBIAS
Before calibration	11.26	8.05	-3.34	3.65	28.55
After calibration	11.26	11.23	0.56	1.17	0.31

4.3.2 Model validation

In the validation site, observed maize yields ranged from 9 t ha^{-1} to 14 t ha^{-1} while simulated yields ranged from 10 t ha^{-1} to 12 t ha^{-1}. The model slightly overestimated maize yields for three out of the five validation years. The year 2000 had exceptionally high observed yields (14.01 t ha^{-1}), which were under-simulated by the model. The year 2003 had low observed yields, which were overestimated by the model (Figure 4.6).

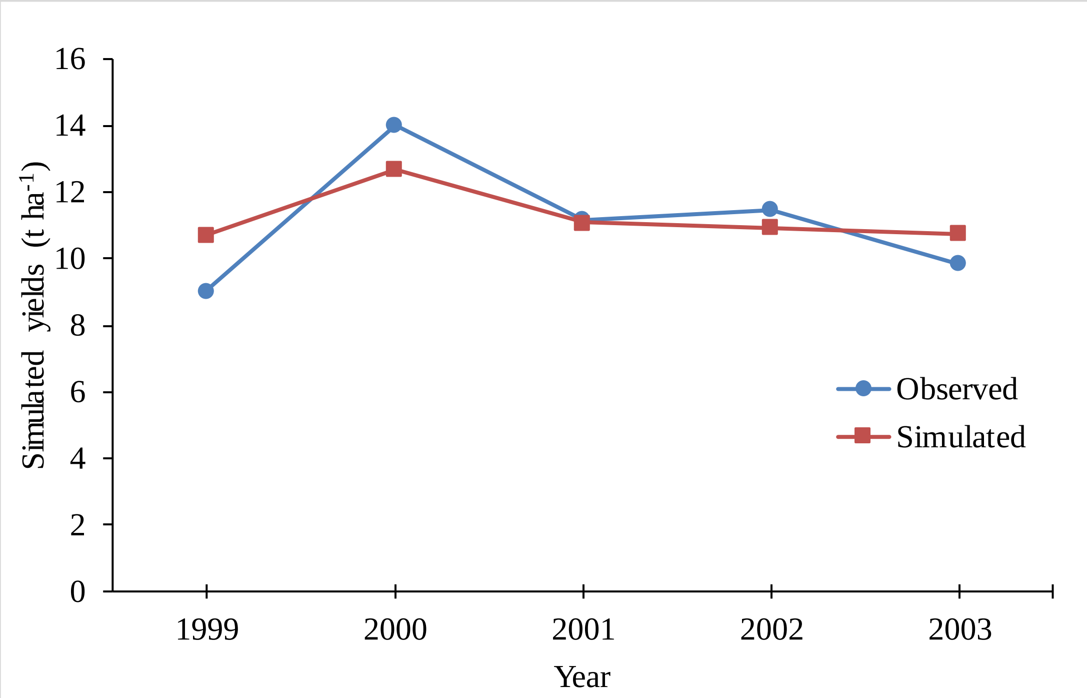


Figure 4.6. Comparison of observed yields in tonnes per hectare (t ha^{-1}) and simulated yields in the validation simulation with the calibrated model.

The coefficient of determination, R^2, between observed and simulated yields was 0.85, as shown in Figure 4.7. Model performance was satisfactory with NSE = 0.61, RMSE = 1.06 t ha^{-1}, and PBIAS = −1.02. Table 5.5 shows a summary of the model statistics for the validation site. A Student's *t*-test comparing the observed and simulated mean grain yields showed that the observed mean yield was not significantly different from the simulated mean yield (p = 0.9) at the 95% significance level.

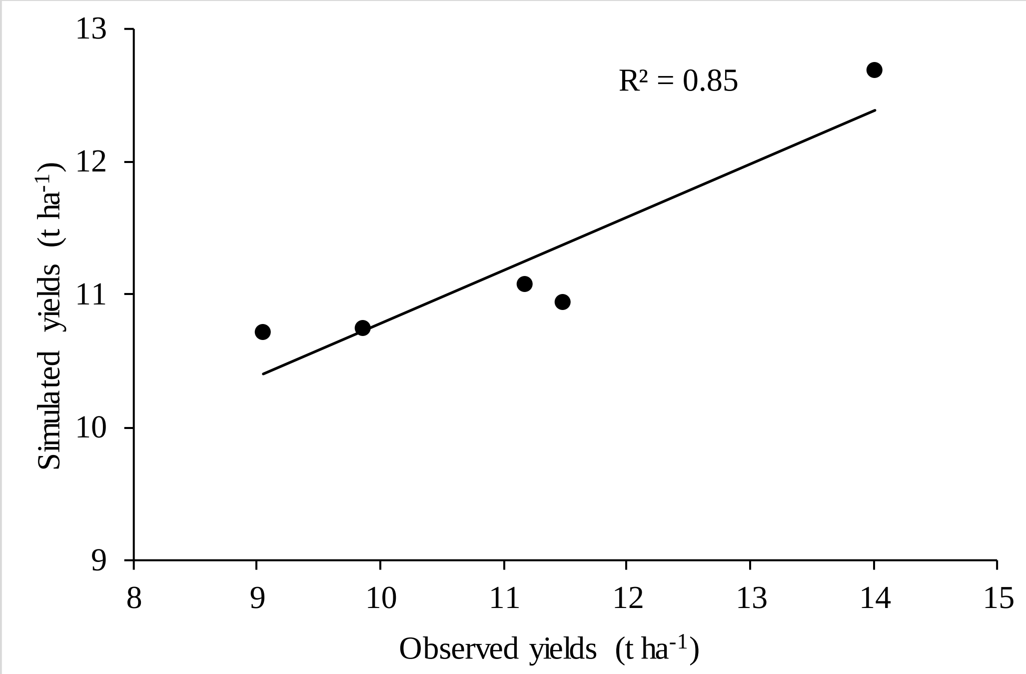


Figure 4.7. Linear regression of simulated crop yields (t ha^{-1}) on observed maize yields for the validation period.

Table 4.5. Mean simulated and observed maize grain yield in tonnes per hectare (t ha^{-1}), Nash–Sutcliffe Efficiency (NSE) and root-mean-square error (RMSE) and PBIAS for the validation simulation.

	Observed Mean Yield (t ha^{-1})	Simulated Mean Yield (t ha^{-1})	NSE	RMSE (t ha^{-1})	PBIAS
Validation	11.12	11.23	0.61	1.06	-1.02

4.4 Discussion

In this current study, the EPIC crop model was evaluated for its possible use as a decision support tool in irrigation and fertiliser management of crops in a semi-arid condition in South Africa. The success of crop growth simulation models depends on the real-world accuracy of simulating crop yields and other variables of importance. The calibration results of this study displayed a reasonable agreement between observed and simulated crop yields.

Effective parameter estimation is essential in accurately reproducing field conditions. Wang et al., (2005) considered that, although the majority models might be effectively used in many environments, uncertainty about many of the parameters persists, and their estimation is important in obtaining useful model results. In this study, the simulation with default parameters gave a poor agreement between observed and simulated yields, indicating the necessity for calibration. However, adjusting parameters related to carbon dynamics using site history and expert knowledge greatly improved model simulations, demonstrating the importance of calibration with site-specific parameters and giving weight to Niu et al., (2009) and Xiong et al., (2013) assertions that detailed data on a local scale can improve the reliability and accuracy of model simulations. Model uncertainty can thus be reduced by using site-specific data.

Adjusting PHU improved crop yield simulations to values nearer to observed yields. This improvement in model simulations is in agreement with studies by Xiong et al., (2013) and Angulo et al., (2013), which showed that refinement of PHUs to the specific region could significantly improve the agreement between simulated and observed yields. PHU is directly linked to the growth of biomass and its allocation to final yield, hence the significant effect of PHU adjustment on crop yields. The results of the present study showed that simulated yields were closest to observed yields when PHU was 2480. This value is within the range of PHUs reported in the literature for maize. For example, experiments conducted in the USA by Williams et al., (1989), showed that the PHUs required for the maturity of maize vary between 1000 and 2900. The Agricultural Research Council's maize information guide states that maize normally takes 120 days from planting to maturity, but this value is generally for the warmer traditional maize-growing areas in South Africa, such as Kwa-Zulu Natal (du Plessis, 2003). The Cradock region is relatively cooler compared to other maize growing areas, which may explain the long duration of the growing season.

By default, the potential HI of maize for the EPIC model is set to 0.5, which is typical for improved high yield maize varieties (Gaiser et al., 2010). The value of 0.5 was taken as the final calibrated value and is the same as the HI values used by Balkovič et al., (2013) and Kiniry et al., (1997). The biomass to energy ratio (WA) is a known parameter influencing crop yields (Wang et al., 2005). During PHU calibration, a RMSE of 1.17 t ha^{-1} and PBIAS = 0.31 between observed and simulated yields were observed, indicating that no further adjustment of WA and HI were needed as acceptable criteria set for model performance had been satisfied. The default value of 40 kg ha^{-1} MJ^{-1} m^2 was therefore adopted as the final calibration value. This value is the same as that used by Wang et al., (2011) and Balkovič et al., (2013). WA increases yield through biomass changes and should be adjusted last based on experimental data as it can significantly change the rate of crop growth and final crop yield (Williams et al., 2015). The HI value of 0.5 is also close to values reported in studies in nine states in the USA (Kiniry et al., 1997) and the value of 0.48 reported by (Wang et al., 2005).

Although the model simulated observed yields correctly, in some years the model overestimated low yields. This is in agreement with studies by Martin, (1993) and Warner et al., (1997) that found that EPIC tended to overestimate low yields. Kiniry et al., (1995) indicated that overestimation of plant available water at field capacity could cause EPIC to overestimate yields in dry years and suggested measuring the maximum depth of water extraction using local cultivars. However, this was beyond the scope of the present study. In 2003, when low maize yields were observed, management records show that the 2003 trials suffered heavy weed infestations. While EPIC successfully simulates water and fertiliser effects on plant growth, currently the model does not accurately account for the competition from weeds (Ko et al., 2009). This may explain why the model over-simulated the lower yields observed in 2003. Although EPIC has a pest damage factor, it is only represented as an estimate rather than a detailed process in the model (Williams et al., 2015).

4.5 Conclusion

The results of the study suggest that limited data from field trials on maize that only include grain yield and agricultural management dates can be used for the calibration of the EPIC model under the semi-arid conditions of South Africa. The evaluation of the EPIC model with observed independent field trial data was reasonably accurate, given the limited data available for model evaluation. However, it is important to calibrate parameters related to carbon dynamics and PHUs according to local conditions as soil and carbon-related parameters, and site-specific PHUs can significantly improve model simulation results. Further studies using the calibrated model that evaluate different crop management options, such as deficit irrigation and fertiliser application timing, should be carried out in the Eastern Cape. Field trials on maize and other crops are also carried out across many sites in South Africa by seed producers to evaluate the stability and potential yield of crop varieties under different weather and soil conditions. Availability of such datasets presents opportunities for the calibration and validation of crop models before their application. Crop model users should make an effort to work with researchers who carry out field trials on crop varieties to ensure collection of detailed data needed for model calibration and validation that are not usually collected by seed producers.

Chapter 5: **Application of the EPIC Model to Simulate the Effects of Different Irrigation and Fertiliser Levels on Maize Yield in the Eastern Cape, South Africa**

This chapter addresses the application of the calibrated EPIC model to simulate different irrigation and fertiliser management strategies. Section 5.1 gives an introduction to the study. Section 5.2 describes the materials and methods used in the study as well as the description of the scenarios used for the study. Section 5.3 presents the results of the scenario simulations; section 5.4 is a discussion of the results of the scenario simulations; section 5.5 provides a discussion of the study limitations and lastly, section 5.6 concludes the study highlighting the importance of combining farmer surveys and development of agricultural management strategies using crop models.

This chapter will be submitted to the journal *Agricultural Water Management*.

5.1 Introduction

Several management factors such as crop pest and disease control influence crop yields. However, water and Nitrogen (N) availability remain the two most important agricultural management factors critical for crop production (Mueller et al., 2012) particularly in the Eastern Cape where water is scarce and most soils are degraded (Goldblatt, 2011). Previous research has shown that the major reasons for persistent low yields in South Africa are soil degradation and soil mineral nutrient (e.g. nitrogen (N) and phosphorus (P)) depletion (Folberth et al., 2012). This is especially true for maize fields where nitrogen (N) is the most limiting nutrient (Sipaseuth et al., 2007) and farmers often over-fertilise with N to ensure maximum yields, (Gaudin et al., 2015; Liu et al., 2012), a situation which often leads to further soil degradation and environmental water quality deterioration.

Continuous removal of crop residues from cultivated areas and inadequate soil nutrient replacement, either through inorganic fertilisers or organic fertilisers, have led to soil nutrient reduction in many parts of South Africa. Similarly, low water availability has also been identified as a significant yield-limiting factor in most semi-arid regions like South Africa (Hammad et al., 2018; Yin et al., 2014). Frequent droughts and unpredictable rainfall patterns present a high possibility of yield losses in semi-arid regions (FAO, 2008). Consequently, the projected increase in food demand will require more efficient use of water and N to increase crop yields. In addition to this, climate change, growing water scarcity and increasing N fertiliser prices in South Africa will require even more prudent approaches to N and water resources use.

The efficient or balanced management of water and nitrogen (whether from inorganic or organic sources) at the farm scale has been shown to significantly increase crop yields while minimizing environmental degradation (Folberth et al., 2013; van der Velde et al., 2014). In this context, efficient management means applying water and N fertiliser at the right timing, in the right quantities, at the right placement and right source (fertiliser). In irrigated cropping systems, water application closely interacts with the efficient use of N, with the relationship being described as co-limitation. Co-limitation means that the crop response to N and water is greater than its response to each factor in isolation (Sadras, 2004). This implies that management strategies aimed at increasing food production while minimising N losses should rely on optimising N and water simultaneously rather than separately. However, studies have shown that the majority of farmers do not practice this balanced application of irrigation and fertiliser due to several reasons such costs, equipment available and a lack of adequate knowledge on irrigation and fertiliser management For example in a study by Fanadzo et al., (2010), on conventional small-scale farmers in the Eastern Cape, lack of adequate knowledge on balanced irrigation and N fertiliser application was a significant factor affecting crop yields. The increase in cases of eutrophication (Maherry et al., 2010; Sibande, 2013) and groundwater pollution (Maherry et al., 2010; Tredoux and Talma, 2006) attributed to nutrient (N and P) rich run-off in most commercial farming areas in South Africa suggests that the majority of large-scale commercial farmers may also not be practicing the balanced application of fertilisers and water. A study by Kollongei and Lorentz, (2015) in the Mkabela catchment in KwaZulu-Natal identified nutrient-rich agricultural runoff from sugarcane fields as a major source of non-point source pollution in the catchment. A common practice by commercial farmers is to apply enough N fertiliser (often excess) to ensure that it is not limiting without due concern about potential environmental consequences (Dreschel et al., 2015).

Irrigated agriculture can improve the sustainability of cropping systems while simultaneously increasing food production (FAO, 2003). However, when water and fertiliser are applied in excess, N in leachates and return flow may contaminate water bodies (Isidoro et al., 2006). For example, in South Africa, nutrient-rich runoff from agricultural fields has been blamed for problems such as eutrophication and algal blooms (Goldblatt, 2011; Maherry et al., 2010; Pearce and Schumann, 2001). Further, excess N losses from agricultural fields represent economic losses to the farmers an N meant for crops is lost to the environment. To develop N and irrigation water strategies that increase food production while minimising environmental degradation, field experiments have been used to test the effects of different management strategies on crop yields and the environment. Field experiments have the advantage that they can be implemented on many field sites with better representations of soil, which is a vital component of crop growth. However, as already argued in previous chapters, field experiments are often time-consuming, labour-intensive and expensive to carry out on a regular and long-term basis.

Crop growth simulation models offer a quicker and less expensive method of investigating the effects of different agricultural management strategies on crop yields and the environment. Simulation models can offer reasonably reliable results when developing agricultural management strategies for sustainable intensification. For example, crop models have been used to determine irrigation requirements at the field level (Alexandrov and Hoogenboom, 1999; Guerra et al., 2005) and optimize the allocation of fertiliser and water among crops during the growing season (Bryant et al., 1992; Cabelguenne et al., 1999). However, for results to be applied with confidence, the models should first be calibrated and validated in the area of interest using observed data. Once calibrated and validated, the crop models can then be applied with reasonable accuracy to assess the effects of irrigation and fertiliser combinations on crop yields and derive optimal irrigation water and fertiliser quantities that maximize crop productivity while minimizing environmental degradation.

In South Africa, interest is growing in applying simulation models to assess fertiliser and irrigation water use management strategies in crop production. For example, Kgonyane (2010) used the Agricultural Production Systems Simulator (APSIM) model to simulate maize response to low inputs of nitrogen and phosphorus for dry regions. Fessehazion et al., (2014) used the SWB model to generate irrigation calendars and simulate water dynamics for ryegrass growth. However, the majority of fertiliser recommendations are still based on field experiments (ARC, 2017; FAO et al., 2005). While interest has grown in crop simulation modelling, the majority of modelling studies have investigated water and N management separately. Yet, irrigation and fertiliser management are closely linked, interacting to determine crop yields and N losses to the environment. There is, therefore, a need to develop location-specific agricultural management strategies to concurrently optimise water and nitrogen fertiliser use at the farm scale. Therefore, the objective of this chapter was to apply the calibrated EPIC model (chapter 4) to simulate the impacts of different irrigation water and N fertiliser levels on maize yield and identify the optimal N fertiliser and irrigation management strategies for maximising grain yield and minimising N leaching risk. As mentioned in Chapter 4, Section 4.1, maize yields were constrained by N fertiliser and water. Further, consultations with the Cradock Manager revealed that the major factors limiting crop yields in the Cradock area and surrounding areas were N and water. An assessment on the mineralogy and soil fertility status of soils in the Eastern Cape by (Mandiringana et al., 2007) found that the majority of soils from the commercial farming areas had medium to high levels of Phosphorus while soils from the rural areas generally had low levels of Phosphorus. Therefore, in this study, the focus was on irrigation water and N fertiliser management.

5.2 Materials and methods

In summary, the EPIC crop model was used to assess the impacts of different irrigation water and fertiliser strategies on maize yield using limited historical data from a field trial on maize cultivar stability carried out at the Cradock Research Farm in South Africa. Grain yield data from two independent fields at the Cradock Research Farm were used to calibrate and validate the model and statistics used to evaluate model performance. Further details of the calibration and validation study are described in Chapter 4. After successful calibration and validation, the EPIC model was then applied at the same location to simulate the impacts of different irrigation and fertiliser management strategies on grain yield and to identify optimal strategies for maximising maize production and minimising leaching risk. The following output variables were analysed for the different scenarios: economic yield (YLD, in t ha^{-1}), Water use efficiency (WUEF) was calculated as (YLD/ET) in kg ha^{-1} mm^{-1}, with ET as growing season evapotranspiration in mm and N lost in percolate (PRKN). A description of the study site and crop modelling is given below.

5.2.1 Site description

The Cradock Research Farm (32° 13' 11.09" S, 25° 41' 11.86" E, elevation 849 m) is located within the Great Fish River valley catchment (Figure 4.1), where intensive irrigation and commercial farming are practised. Soils and climate within the research farm are representative of the broader catchment. The soil is classified as a fine-loamy mollic ustifluvent (Soil Survey Staff, 2014), characterized by high sand and silt contents of alluvial and colluvial material derived from Beaufort sediments in the Eastern Cape. Further details of the general soil characteristics are described in Chapter 4. Cradock has an average annual rainfall of 341 mm with the majority of the rainfall occurring in February and March (late summer).

5.2.2 Model description

A detailed description of the EPIC model is given in Chapter 4. Here, only the plant growth and N transport and transformation components are briefly described. Detailed descriptions of other EPIC components and specific relationships can be found in (Williams et al., 1989).

EPIC transports soil NO_3-N through surface runoff and percolation and lateral sub-flow. The amounts of NO_3-N transported is estimated as the product of the volume of water flow and NO_3-N concentration at specific soil layers. When water is evaporated from the soil, NO_3-N is moved upwards into the topsoil. Mineralisation, immobilization, volatilization, nitrification, and de-nitrification are N transformations simulated by the EPIC model. These transformations are important as they determine the final amount of N that will be available for uptake by crops and that will be potentially lost to the environment.

EPIC uses a single routine for simulating all the crops considered. In this module, each crop has unique values for the model parameters and crop yield is estimated as a function of the harvest index (HI), biomass to energy ratio (WA), planting density (PD), radiation use efficiency (RUE), photosynthetic active radiation (PAR) and vapour pressure deficit (VPD) (Xiong et al., 2016). Potential biomass is adjusted to actual biomass through daily stress caused by extreme temperature, water and nutrient stress. Annual crops grow from planting date to harvest date or until the accumulated heat units equal the potential heat units for the crop.

5.2.3 Model inputs

Site-specific inputs included precipitation, maximum and minimum temperature, solar radiation, and relative humidity derived from the AgMERRA climate data set. Soil data (bulk density, cation exchange capacity, texture, and electrical conductivity) were obtained from records of previous soil analyses done at the Cradock Research Farm. Some soil data parameters required to set up the EPIC model were missing and these missing parameters were obtained from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009). The soil parameters in the EPIC soil file were then adjusted with values from the HSWD based on expert opinion.

Prior to application of the EPIC model, a survey of farmers' current irrigation and fertiliser management practices using a questionnaire, was conducted in the Eastern Cape. The survey study, presented in Chapter 3, was used to find out farmers' current farm management practices and the reasons behind particular management practices. During the survey, data on maize farmers' yields, type of irrigation used, and irrigation water amount per maize growing season were collected. Data on farmers' irrigation strategies, N fertiliser management and average maize yield were collected for comparison with simulated agricultural land management scenarios and maize yield outputs to determine whether farmers' irrigation and water management strategies could be improved. In this chapter, only crop yields, fertiliser and irrigation management practices concerning maize production are presented.

5.2.4 Model set-up

The global based EPIC-IIASA modelling framework described in Chapter 4 was used to run crop management simulations. To compare simulated yields, N fertiliser and irrigation management strategies with the baseline yields and agricultural management strategies, the irrigation and fertiliser amounts used during the field trials on maize (Chapter 4) were taken as the 'baseline' scenario. Model outputs were further compared to the average yields and N fertiliser and water levels reported by farmers in the survey (Chapter 3) to determine whether there was room for improvement in farmers' N fertiliser and irrigation water management strategies. Farmers' irrigation and water management strategies were not simulated due to lack of data on farmers' actual management practices dates such as planting, harvesting and fertiliser application dates. However, reported yields, irrigation water and N fertiliser amounts were compared to simulated model outputs from different irrigation and N fertiliser level scenarios. In the baseline scenario, Nitrogen (N) containing fertiliser was applied at a rate of 195 kg N ha^{-1} and Phosphorus (P) containing fertiliser applied at a rate of 95 kg P ha^{-1}. N fertiliser was applied three times during the growing season and P fertiliser applied once at planting. Irrigation water was applied at a depth of 75 mm per irrigation event using flood irrigation eight times during the growing season to give a total of 600 mm irrigation water per maize growing season. Further details of the management plan used in the field trials on maize are given in Chapter 4.

In the EPIC model, irrigation scheduling can be manual and fixed according to user dates or applied automatically by the model based on plant water stress levels. In simulation scenarios where irrigation water is adequate (sufficient for crop and not a limiting factor), irrigation was set to automatic. Setting irrigation to 'automatic' in the model applied irrigation water automatically to ease water stress if water deficit limited plant growth by more than 10% on a given day (Liu et al., 2007). The minimum interval between automatic irrigation applications was set to 5 days. Similarly, in scenarios where fertiliser was adequate, the model was set to automatic fertiliser application. With this setting, the model applies fertiliser automatically based on crop stress. In the scenarios, 'adequate' represents the cases were irrigation water or fertiliser is not limited and is applied automatically in the model. Since Phosphorus (P) was not limiting, the application of P was done automatically in the model simulations except in the simulations with baseline fertiliser application, where phosphorus application was set at 95kg P ha^{-1} according to levels and dates applied in the field trials on maize. Other general management operations carried out by the model in the scenarios were soil tillage using a power plough before planting and common weed and pest control which were carried out as needed.

5.2.5 Irrigation and fertiliser management scenarios

The management scenarios used in the study are presented in Table 5.1. Scenarios were designed to cover a range of possible N fertiliser and irrigation water combinations. The different N fertiliser and irrigation water combinations were then simulated with the calibrated model. Phosphorus was applied automatically as it was assumed not a limiting factor based on simulations from Chapter 4. Rain-fed only scenarios were included in the simulations as some farmers in the Eastern Cape do not use irrigation and rely on rainwater for crop production.

Table 5.1. Fertiliser and irrigation management scenarios used in the study. Each scenario represents a combination of fertiliser and irrigation water supply levels.

Scenario	Description	Abbreviation
I	Baseline fertiliser supply (195 kg N ha $^{-1}$) and baseline irrigation water (600 mm.)	FbIRb
II	'Rain-fed' only with baseline fertiliser	FbR
III	'Rain-fed' only with adequate fertiliser	FaR
IV	Baseline fertiliser and adequate irrigation	FbIRa
V	Adequate fertiliser and baseline irrigation	FaIRb
VI	Adequate fertiliser and adequate irrigation	FaIRa
VII	Fertiliser supply at different levels with baseline irrigation	FvIRb
VIII	Fertiliser supply at different levels with adequate irrigation	FvIRa
IX	Adequate fertiliser supply and varying irrigation levels at fixed dates according to the field experiment	FaIRv

1) Fertiliser (F) and irrigation (IR) water supply (b = baseline, a = adequate, v = varying levels, r = rain fed)

To assess maize yield responses to improved irrigation and n fertiliser inputs, two groups of scenarios were set. Scenarios I to VI were set for combinations of baseline and adequate supply of irrigation water and N fertiliser. Scenarios VII to IX. For N fertiliser, the adequate level was set to 200 kg ha^{-1}, which represents the currently highest application rates in high input countries (Folberth, 2013). For irrigation, the maximum, applicable amount was set to 2000 mm, corresponding to adequate water supply following (Folberth et al., 2012). A brief description of the individual scenarios is given next.

Scenario I represented the management practices used in the field trials on maize used to calibrate the EPIC model. This is the baseline scenario. Scenario II represented a 'rain-fed only' scenario with the baseline fertiliser (195 kg N ha^{-1}) while Scenario III represented a 'rain-fed only' scenario with an adequate N fertiliser value of 200 kg N ha^{-1} as suggested by (Folberth et al., 2013). Scenario IV considered the effects on maize yield of baseline fertiliser with an adequate irrigation water supply and scenario V considered the effects on maize yield of adequate fertiliser supply with baseline irrigation water supply (600 mm). Scenario VI considered the 'high production' scenario with no limits on both fertiliser and irrigation water. In this scenario, the model was set to automatic irrigation and automatic fertilization. Under these fertiliser and irrigation water settings, the maize crop obtains sufficient nitrogen and water and has no N and water stress. Scenarios VII considered the effects of combinations of different fertiliser levels and adequate fertiliser level with baseline irrigation on maize yield. N supply levels were set at 10, 30, 50, 70, 100, 130, 150, 170, 195, 200, and 250 kg N ha -1. Scenario VIII considered the effects of different fertiliser levels as set in Scenario VII with adequate water supply. Scenario VIII focused on N fertilization that has been identified as the main limitation in restricting maize yield production where water is available (Breman et al., 2001). Scenario IX considered the effects on maize yield of different irrigation water amounts with baseline fertiliser. Irrigation water supply levels were set at 25% (150mm), 50% (300mm), 75% (450mm), 125% (750mm), 150% (900mm) and 200% (1200mm) of baseline irrigation. Analysis of survey results revealed that most farmers used sprinkler irrigation in contrast to flood irrigation used in the field experiment. The irrigation setting was therefore changed to sprinkler irrigation in the scenarios to reflect current farming practices.

5.3 Results

5.3.1 Farmers survey

A total of 54% of the farmers who participated in the survey on management practices were maize farmers. Concerning maize yields, maize yields reported by farmers ranged from 2 t ha^{-}

^{1} to 15 t ha^{-1} with an average maize yield of 7.2 t ha^{-1}. Regarding the method of irrigation, the majority of maize farmers (56%) used sprinkler irrigation followed by flood irrigation (25%) and then drip irrigation (19%) (Figure 5.1). The amount of irrigation water applied ranged from 400 mm to 500 mm with an average of 500 mm per irrigation season. However, 44% of maize farmers did not know the total amount of irrigation water they applied each season. Farmers mainly scheduled irrigation water and fertiliser application based on plant appearance and farming experience.

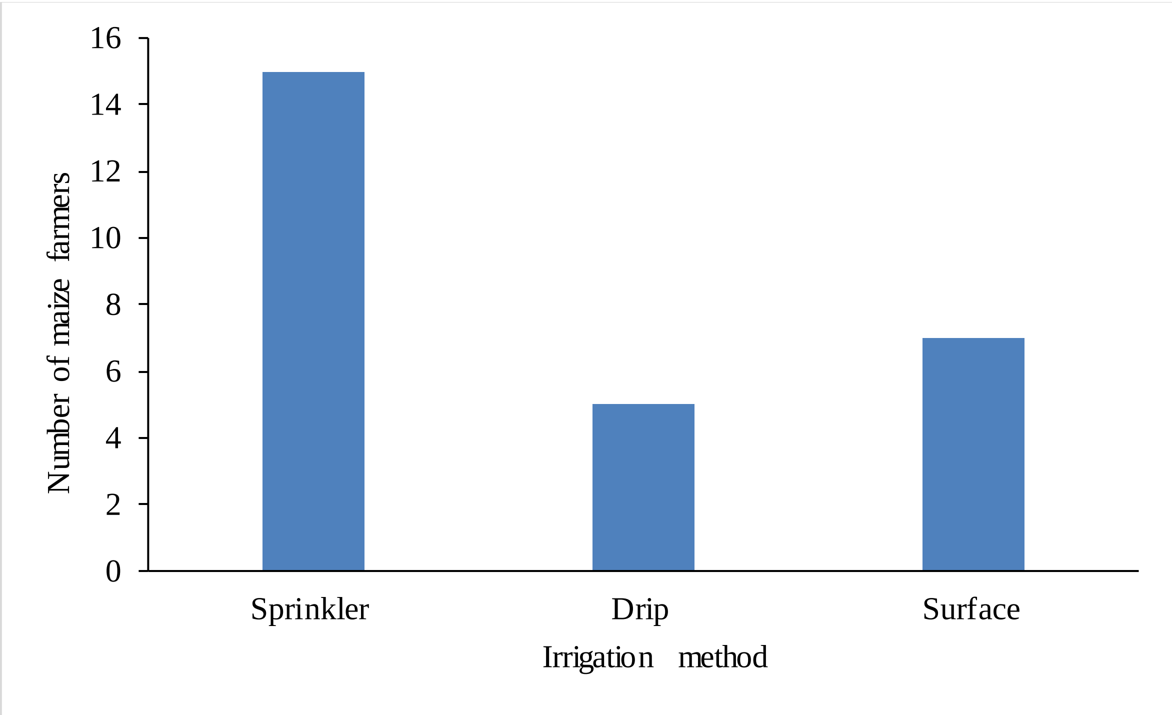


Figure 5.1. Number of maize farmers applying a particular irrigation method for maize

Fertiliser type applied ranged from Ammonium nitrate (AN), ammonium sulphate (AS), urea and Compound D with the most frequent form of fertiliser applied being AN. The amount of AN applied by maize farmers per maize growing season ranged from 150 kg AN ha^{-1} to 450 kg AN ha^{-1} with an average AN application of 224 kg AN ha^{-1}.

5.3.2 Grain yield under 'rain-fed' and irrigation scenarios

A summary of the simulated impacts of different fertiliser and irrigation strategies on maize yields is shown in Figure 5.2. The lowest yields were simulated under the 'rain-fed' only scenarios (II-FbR and III-FaR) with an average maize yield of 0.8 t ha^{-1}. Increasing fertiliser amount in the second rain-fed only scenario (III-FaR) did not result in any further increases in maize yield. Water deficit was the main constraint in both the ‘rain-fed’ only scenarios with an average water stress days (WS) value of 126 days. With irrigation, crop yields were higher compared to the ‘rain-fed’ only scenarios. In scenario V (FaIRb) maize yield was similar to the baseline scenario maize yield (I-FbIRb) at 11.2 t ha^{-1}. In Scenario IV (FbIRa) maize yield was 11.4 t ha^{-1}, 1.79% higher than yields in the baseline scenario. The average maize yield in the scenario with adequate nutrients and adequate water (VI-FaIRa) was 12.2 t ha^{-1}. This scenario gave the highest yield for all simulations.

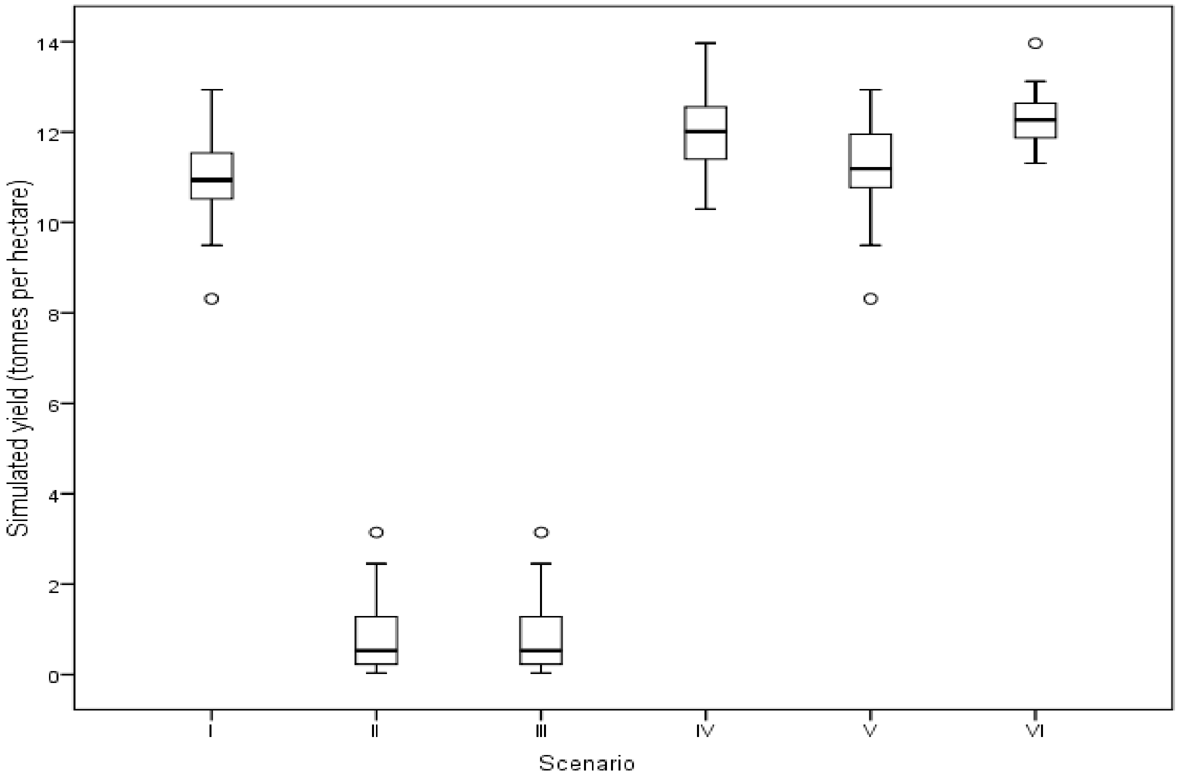


Figure 5.2. Simulated crop yield under different management scenarios. The Roman numerals refer to the scenarios described in Table 5.1. In the box plot, the solid middle line in the box represents the median maize yield and the circles represent outliers.

Concerning the scenarios with different fertiliser levels, VII-FvIRb and VIII-FvIRa, the N fertiliser increases to different levels while irrigation is set to baseline or field experiment level (600mm) and ‘adequate irrigation level’ (automatic irrigation) respectively. Under both scenarios, yields increased linearly with additional N supply from 0 to approximately 150 kg N ha^{-1} levelled off at maximum application rates of 155 to 165 kg N ha^{-1} with no further yield increases beyond 165 kg N ha^{-1} (Figure 5.3). The greatest incremental yield increase occurred between 30 and 130 kg N ha^{-1} and beyond 130 kg N ha^{-1}, yield response to additional N fertiliser slowed down. Yields for scenario VIII were higher than yields for scenario VII for the same fertiliser levels as shown in Figure 5.3.

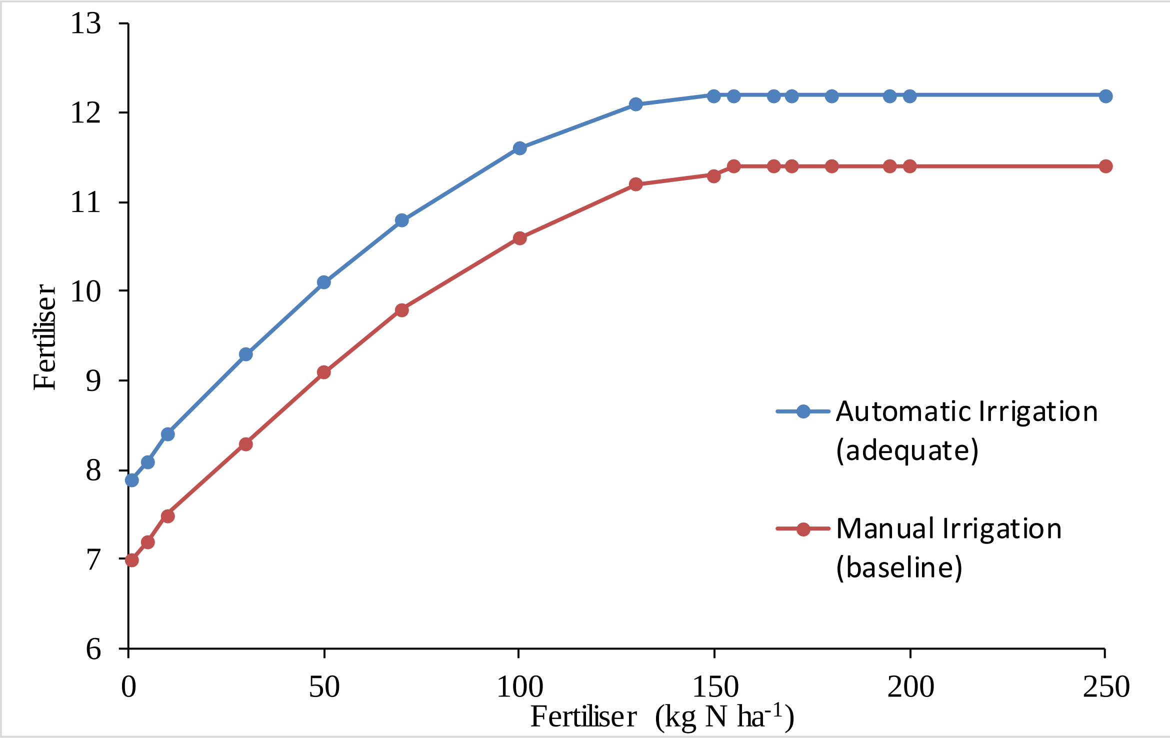


Figure 5.3. Relationship between yield (t ha^{-1}) and N fertiliser amount (kg N ha^{-1}) for scenarios VIII with adequate water and scenario VII with baseline irrigation water level.

In scenario (IX), with adequate fertiliser and fixed irrigation dates, the relationship between grain yield and applied irrigation water was of a second-order nature (Figure 5.4). Additional water amounts resulted in a relatively higher yield. A maximum yield of 11.4 t ha^{-1} was obtained at an irrigation level of 750 mm and the minimum yield of 0.8 t ha^{-1} at 0 mm. Grain yield increased with additional amounts of water up to 750 mm where further additions of irrigation water did not result in increases in grain yield.

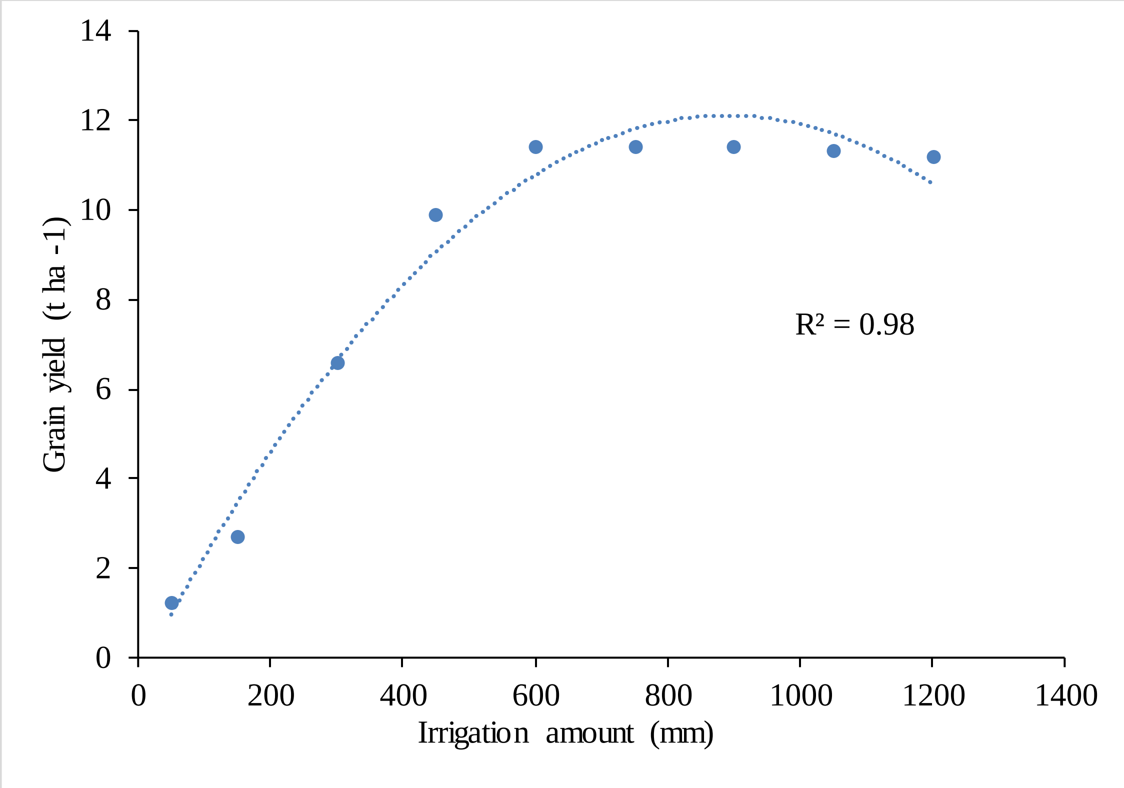


Figure 5.4 Relationship between irrigation water applied and grain yield

5.3.3 N leaching

Under sufficient water and varying N fertiliser levels (VIII-FvIRa), N leaching increased with increasing N fertiliser applied (Figure 5.5). At N fertiliser applications below 50 kg N ha^{-1}, N leaching was less than 10 kg N ha^{-1}, however, above 160 kg N ha^{-1} application, N fertiliser leaching significantly increased, with N fertiliser applications above 200 kg N ha^{-1} resulting in N leaching values greater than 50 kg N ha^{-1}. Figure 5.6 shows that as grain yield increased, nitrate leaching also increased. Grain yield levels off at 11.4 t ha^{-1} corresponding to an N leaching rate of 29 kg N ha $^{-1}$. Beyond 11.4 t ha^{-1} there were no further increases in grain yield while N leaching increases indicating economic losses of N fertiliser and potential environmental water pollution.

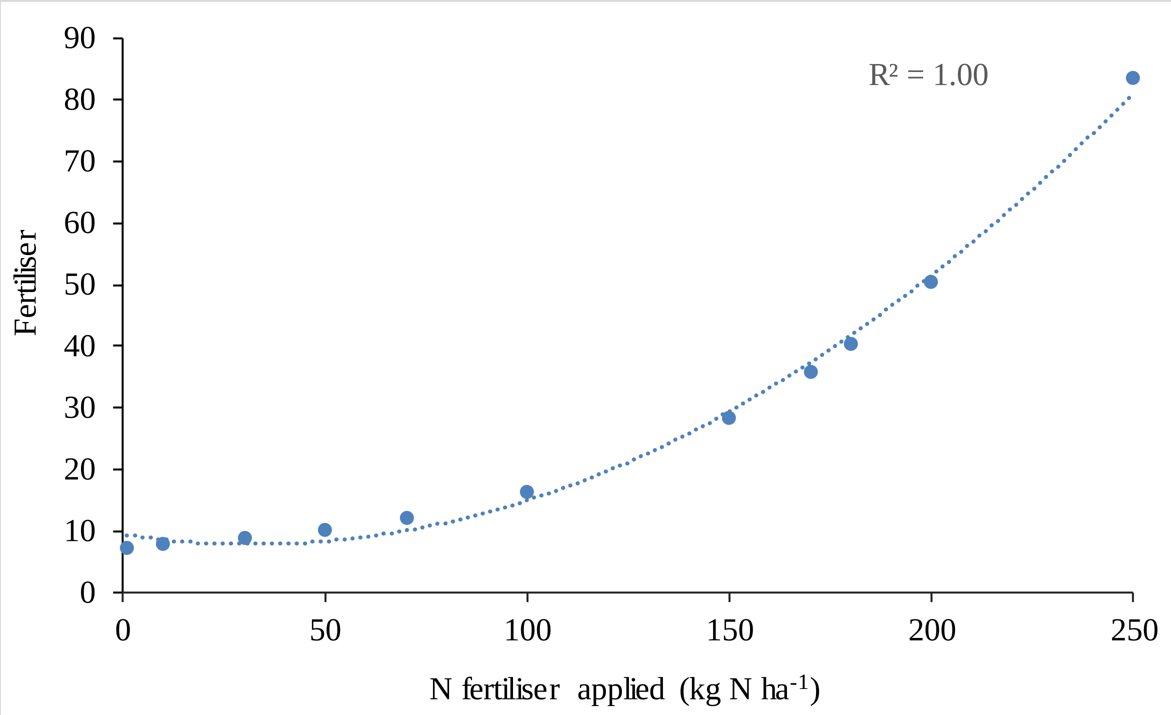


Figure 5.5 Relationship between fertiliser amount applied (N kg ha^{-1}) and amount of Nitrogen leached (kg ha^{-1}).

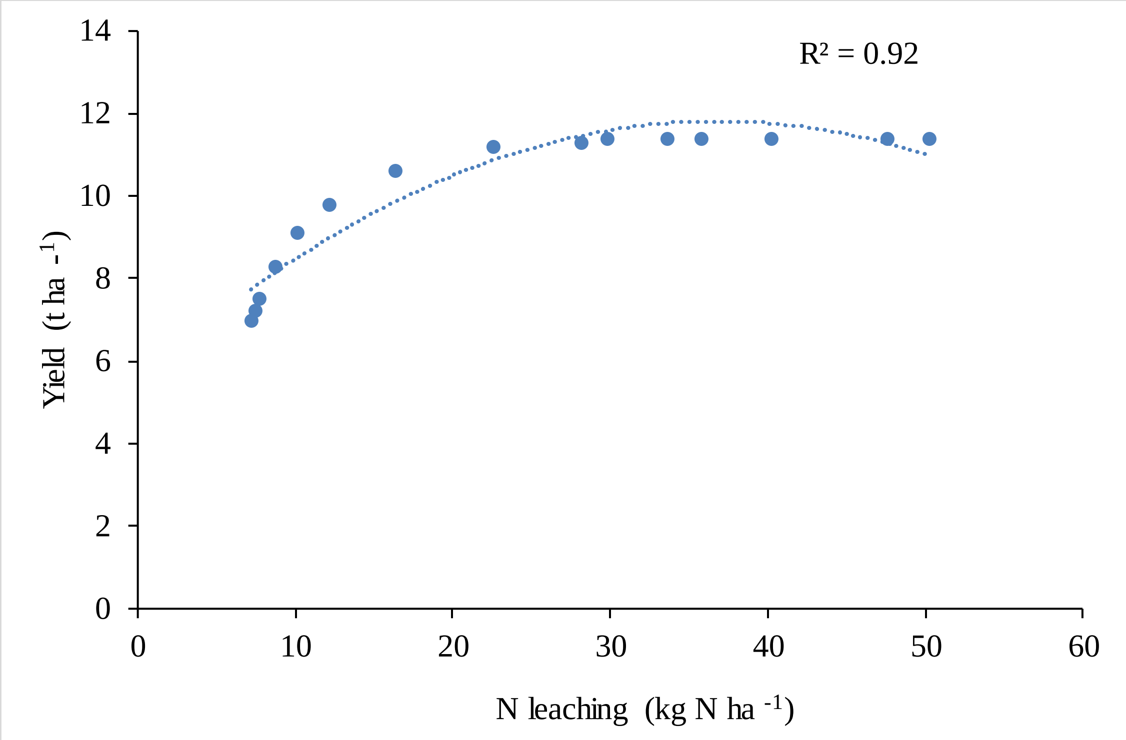


Figure 5.6 Relationship between grain yield (t ha^{-1}) and N leaching (kg N ha^{-1})

In the scenario with different irrigation water levels and adequate fertiliser (IX-FaIRv), increasing the amount of irrigation water increased average water use efficiency (WUEF) up to a maximum WUEF of 19.74 kg ha^{-1} mm^{-1} at 750 mm irrigation water level (Figure 5.6). Average WUEF increased by 85% from 10.68 kg ha^{-1} mm^{-1} at 0 mm to 19.72 kg ha^{-1} mm^{-1} at 600 mm. Between 600 mm and 750 mm irrigation water level, WUEF increased by only 0.9%. Beyond an irrigation water level of 750 mm, there were no further increases in WUEF.

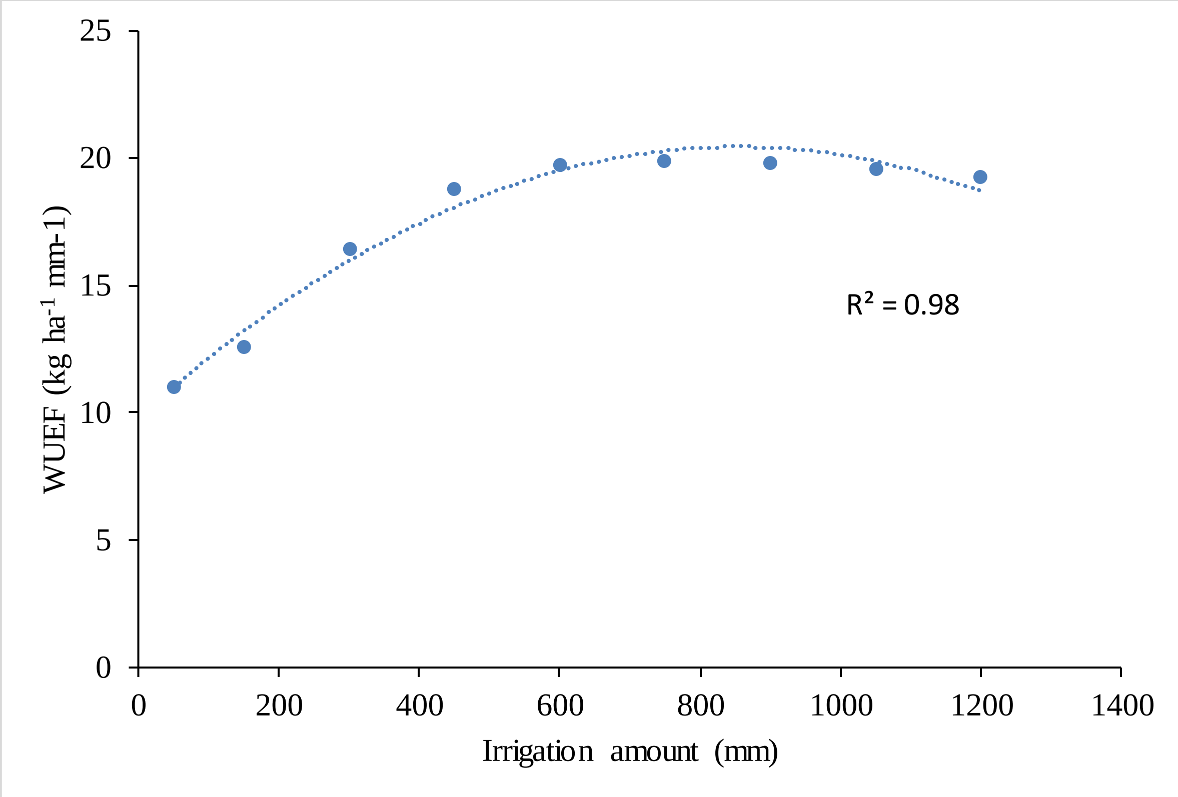


Figure 5.7. Relationship between irrigation amount (mm) and water use efficiency (kg ha^{-1} mm^{-1}).

The relationship between WUEF and grain yield showed a second-order relationship (Figure 5.7). WUEF increased as grain yield increased. Beyond 12.2 t ha^{-1}, there were no further increases in WUEF.

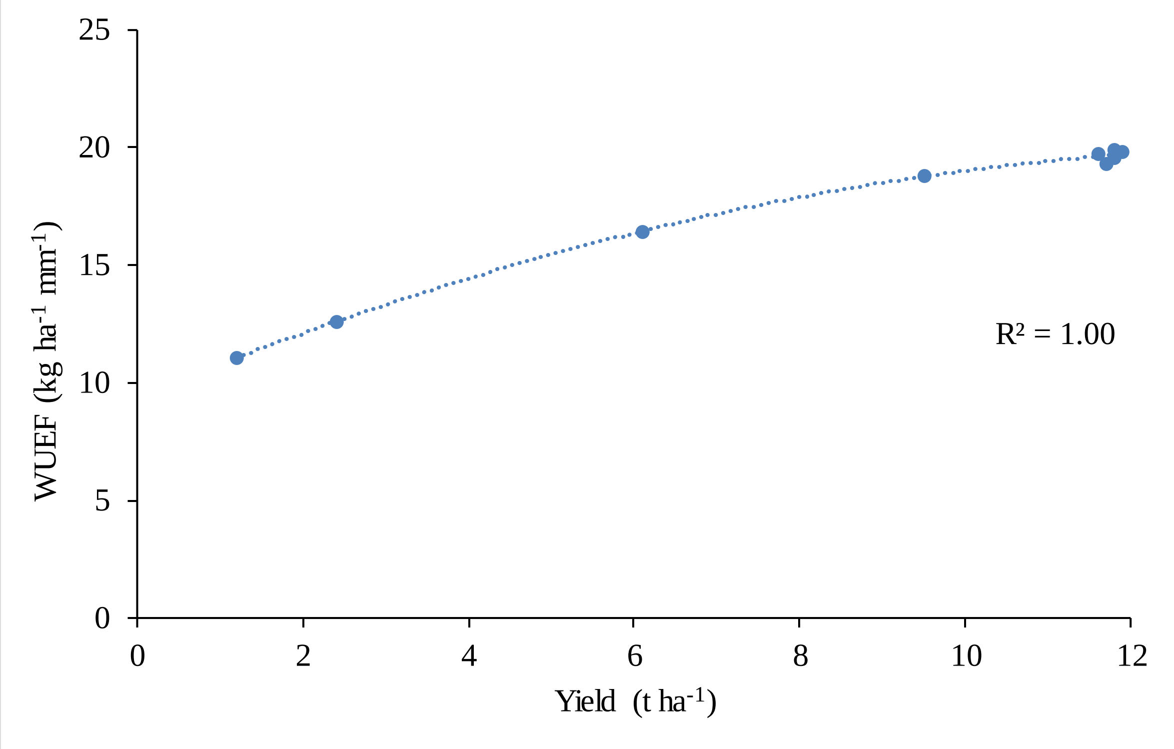


Figure 5.8. Relationship between yield (t ha^{-1}) and water use efficiency (kg ha^{-1} mm^{-1})

In summary, for the scenario in which irrigation water and N fertiliser were sufficient and the model applied irrigation water and N fertiliser when needed by the crop, the maximum potential yield simulated was 12.2 t ha $^{-1}$. This yield was achieved at an irrigation water amount of approximately 750 mm and an N fertiliser level of approximately 155 kg N ha^{-1}. In the scenarios with irrigation and N fertiliser applied according to fixed dates based on the management plan used in the field trials, the maximum potential yield simulated was 11.4 t ha^{-1}.

5.4 Discussion

Farmers' survey results show that most farmers apply fertiliser in the form of Ammonium nitrate which contains approximately 21% N by composition. In this study, farmers applied an average of 224 kg AN, which translates to approximately 52 kg N ha^{-1}. This N fertiliser application level is similar to surveys conducted by Fanadzo et al., (2010), who found that on average, farmers in the Zanyokwe Irrigation Scheme in the Eastern Cape applied approximately an average of 47.6 kg N ha^{-1} per maize growing season. The average grain yield of 7.2 t ha^{-1} achieved by farmers in the current study is less than the potential yield of 9 to 12 t ha^{-1} possible under irrigation in South Africa (du Plessis and Bruwer, 2003). The lower N application rates by farmers may explain the lower yields obtained by farmers compared to the field experiment. Simulations showed that between 0 and 150 kg N ha^{-1} maize yield increased linearly with additional fertiliser application. To achieve higher yields, farmers may increase current fertiliser application levels.

Survey results also revealed that the majority of farmers did not practice a balanced application of N fertiliser and irrigation water. Most farmers did not know the total amount of irrigation water they applied per season and applied water based on farming experience or plant appearance. This may lead to incorrect fertiliser and water application timing and hence lower yields. Several studies in South Africa have identified poor agricultural management practices as one of the major reasons for low yields in South African irrigated farming systems (Bembridge, 2000; Fanadzo et al., 2010). If significant efforts towards sustainable intensification and food security are to be made, it is important to optimise nitrogen and water to match crop requirements.

With regard to the scenario simulations, the ‘rain-fed’ only (Scenario II) simulation yield of 0.8 t ha-1 is comparable to studies by Ndhleve et al., (2017) in the Eastern Cape who found average farm maize yields below 1 t ha^{-1} for rain-fed farming systems. In the absence of irrigation, (Scenario III), increasing the amount of fertiliser did not increase maize yields demonstrating that in semi-arid conditions, water availability is a major constraint to sustainable intensification and hence, achieving food security. This result is similar to field trials conducted by Moeletsi et al., (2009) who found water deficiency as the main limiting factor for dryland maize production in South Africa. Low yields are usually typical of subsistence/small scale farmers who are unable to purchase irrigation equipment. Small scale farming can play a significant role in reducing the vulnerability of food-insecure households. Improving the productivity of small-scale farmers can help towards ensuring long-term food security in South Africa. The productivity of small-scale farmers can be improved by encouraging farmers to adopt sustainable intensification of food production through the use of improved agricultural land management strategies. This will involve the sustainable use of fertiliser and water saving technologies as well as increasing small-scale farmers’ access to markets so they can earn money to purchase improved farming equipment.

Comparing scenarios IV and V, higher yields were achieved when water was adequate (IV) rather than when fertiliser was adequate (V). This suggests that in this study, water supply may play a greater role in limiting crop yields compared to fertiliser. These results further support field studies by Moeletsi et al., (2009) who found that in semi-arid environments typical of South Africa, the major limiting factor in maize production was water supply. Studies by Mandiringana et al., (2007)showed that while most of the rural areas in the Eastern Cape had low soil fertility naturally, the commercial farming areas had a higher soil fertility compared to soils in the rural areas Given that agriculture already accounts for 70 % of water withdrawals in South Africa there is need to develop innovative technologies that save water in agriculture without reducing crop yields and food security. Planning for a sustainable agricultural future remains critical given that South Africa is already water-stressed, a situation which may get worse in the future due to the projected negative impacts of climate change on water resources.

In scenario VIII when the model was set to automatic irrigation and water applied as needed by the crop, the maximum yield simulated was 12.2 t ha^{-1}, which was achieved at 155 kg N ha-1. This is within range of possible yields attainable under irrigation in South Africa (du Plessis and Bruwer, 2003). The yield in this scenario is higher than the maximum yield of 11.4 t ha^{-1} simulated with fixed irrigation dates in scenario VII. This slightly higher maximum yield with automatic irrigation indicates that the fixed dates used in the field experiment may not be the optimum dates when water is needed by the maize crop. This mismatch between crop water needs and irrigation application my lead to lower grain yields and warrants further studies to determine exactly when the crop requires fertiliser and irrigation water application. Scenario VI with sufficient irrigation and fertiliser also had a maximum yield of 12.2 t ha^{-1} suggesting that irrigation water might play a more significant role when fertiliser is adequate.

Scenario IX showed a second-order relationship. Similar studies such as those by Bozkurt et al., (2006), Kipkorir et al., (2002) and Farré and Faci, (2009) have also reported non-linear relationships between grain yield and irrigation water. However, Payero et al., (2006) found a linear relationship between grain yield and irrigation water amount. According to Tolk and Howell, (2003), the relationship between maize yield and irrigation water applied is influenced by several factors such as climate, soil and irrigation practices. This variation in the relationship between yield and irrigation highlights the importance of investigating crop responses to irrigation under local growing conditions. Adopting irrigation and fertiliser management practices developed somewhere else might not bring about the desired yield increases and environmental goals.

The optimal seasonal irrigation water requirements of approximately 600 - 750 mm found in this study are similar to the results of Djaman et al., (2018) who carried out a study of irrigated maize under semi-arid conditions and found an average irrigation water requirement of 730 mm per maize growing season. (Trout et al., 2017) reported that irrigation water requirements for maize varied from 616 to 774 mm in semi-arid environments in the Great Plains of the United States. Similarly, the optimal fertiliser application level of approximately 150 kg N ha^{-1} found in this study corresponds to a level that is currently common in industrialised regions with high yields such as America and China (FAO et al., 2005). Studies by Folberth et al., (2012) have found a fertiliser application level of 150 kg N ha^{-1} close to adequate N supply in most part of sub-Saharan Africa.

Comparison of farmer survey results with sufficient irrigation scenarios simulation results shows that at an irrigation level of 750 mm farmers may increase N fertiliser application from 52 kg N ha^{-1} up to 155 kg N ha^{-1}. This would result in a yield increase of 69% from the current yield levels. From Figure 5.5 it can be deduced that at the current farmers' level of N fertiliser application of 50 kg N ha^{-1}, N leaching is approximately 10 kg N ha^{-1} while at the field experiment level of 195 kg N ha^{-1}, N-leaching is approximately 45 kg N ha^{-1}. This implies that if farmers increase the amount of fertiliser applied, grain yield will increase, however, the potential risk of nitrate leaching to water bodies will also increase. This presents a trade-off between different ES. Applying more N fertilisers to increase food provision will lead to increased risk of nitrate leaching which may reduce environmental water quality. This information can help decision-makers evaluate the consequences of certain agricultural management practices both economically and environmentally as well as choose optimal strategies that promote sustainable agricultural intensification.

The relationships between irrigation amount and crop yield with WUEF showed a positive correlation between grain yield and WUEF up to a certain yield and then levelled off. This relationship implies that increasing irrigation water, but only up to a certain level, will increase yield. Beyond this level, in this case, 750 mm, any additional water application will not result in further crop yield increases and would also be inefficient in terms of crop water use. This information is useful for farm managers and policymakers when making water management decisions based on WUEF and crop production. The values of WUEF found in this study are also similar to values by (Guo et al., 2010) in semi-arid Northern China that ranged from 11 to 20 kg ha^{-1} mm^{-1}.

With increasing rainfall variability, water scarcity and prevalence of droughts in the Eastern Cape of South Africa, there would be major local and regional water supply and demand consequences to consider if current 'rain-fed only' agricultural systems were to convert to irrigated agriculture to increase crop yields. For example, policymakers and the government would have to consider the implications of such a conversion on municipal and industrial water demand and supply in the Eastern Cape, which is already under pressure from other competing water uses such as municipal and industrial water use. It is unlikely that agriculture which already accounts for more than 60% of water withdrawals in the region would be allocated more water over municipal water requirements. This implies that to increase crop yields agricultural systems will be required to produce more food with limited water resources. Results of this study suggest that farmers can increase crop yields by improving N fertiliser and irrigation application timing.

The simulations at the farm-scale in this study show that the EPIC model can be used as a decision support tool for maize crops under different irrigation water and fertiliser amounts in the Eastern Cape. The capability of the EPIC model to simulate different irrigation and fertiliser management strategies without carrying out long and expensive field experiments makes it an effective research and application tool in agroecosystem services management. However, the results of the simulations must be taken in comparative and not absolute terms as the final crop yield is the result of several complex interactions in the soil-plant-atmosphere which can cause real-world values to vary from model simulation values, for example, pests and diseases can have a significant negative effect on crop yields if not managed well.

5.5 Study limitations

The study assumed no deficiencies in other macronutrients except N. However, in reality, this may not be the case with farmers' individual soils and farmers would need to have their soils assessed for any other nutrient deficiencies. It was also assumed that there were no deficiencies in soil micronutrients. According to Voortman et al., (2003), most soils in sub-Saharan Africa contain low amounts of micronutrients due to the chemical composition of the parent material and weathering over long time periods. While micronutrients are seldom a limiting factor under low input conditions, they can be a significant limiting factor under high input, intensive agriculture (Gaiser et al., 1999).

The automatic irrigation and fertilization option used in the model may lead to an overestimation of crop yields by assuming that local farmers have complete knowledge concerning water and fertiliser management. Irrigation and fertiliser timing can significantly affect crop yield and water use efficiency and would need further detailed data on water and fertiliser management to determine optimum dates for fertiliser and irrigation application timing based on crop growth stages. In addition, in the adequate water supply scenarios, the model assumed unlimited water supply but in practice, the irrigation water supply may be restricted by water authorities. Further research would also need to consider the potential yield implications due to seasonal restrictions in water abstraction for irrigation and priorities for maize against other crops such as vegetables. Despite these limitations, this study provides a useful assessment of the potential maize yield benefits and environmental consequences when considering different fertiliser and irrigation management strategies.

5.6 Conclusion

A previously calibrated and validated EPIC crop growth model was used to simulate the yield impacts of different fertiliser and irrigation regimes and compared to a researcher-led experiment and current farm management practices identified from a farmer survey of irrigation and fertiliser management practices. It can be concluded that the optimal management practices for irrigated maize production in the Cradock area are to irrigate the maize crop with approximately 600 to 750 mm water spread out over eight times in the irrigation season and to fertilise the soil at a rate of 155 to 160 N kg ha^{-1}. Implementation of this management strategy would increase maize yields by 69% from the current farmers' average maize yield of approximately 7.2 t ha^{-1} to approximately 12.2 t ha^{-1} while increasing irrigation water use by 20% (from approximately 500 mm to 600 - 750 mm). However, an amount of 35kg N ha^{-1} can be potentially lost through leaching and trade-offs between increasing crop yields and minimising nitrate leaching will have to be reached. There is room to improve farmers' current maize yields by improving nitrogen and irrigation water management. The study highlights the use of crop models in combination with knowledge of farmers' practices to develop practical irrigation and fertiliser management strategies that help to achieve the sustainable intensification of agricultural food production.

Chapter 6: **Evaluating Farmers' Perceptions of Climate Change and Future Impacts of Climate Change on Maize Production in the Eastern Cape, South Africa.**

This Chapter evaluates farmers' perceptions of climate change and the impact of future climate change on maize production in the Eastern Cape. Section 6.1 provides an introduction of the chapter and section 6.2 describes the materials and methods used in the study and the climate data used for the study. Statistically downscaled data from three driving GCMs are used to drive the simulation. This section also describes how the outputs of the climate scenarios were analysed; section 6.3 presents the results of the climate scenario simulations and the survey results concerning farmers' perceptions; section 6.4 is a discussion of the results of the climate scenario simulations including a discussion of farmers' perceptions of climate change, adaptation strategies and factors affecting farm production. Section 6.5 provides a discussion of the study limitations. Finally, section 6.6 concludes the study highlighting the fact that farmers face various challenges in farming that may hinder efforts to improve food security in South Africa.

6.1 Introduction

Climate change is anticipated to have a significant impact on the resilience of agricultural systems in South Africa. Based on projections by the Intergovernmental Panel on Climate Change (IPCC), increases in greenhouse gases particularly carbon dioxide (CO_2), will modify global climate by causing an increase in surface air temperature, altering rainfall patterns and increasing the frequency of extreme weather events (IPCC, 2007). While the increased temperature may boost the yields of some crops in some regions by increasing the rate of biomass accumulation (Ainsworth and long, 2005), the negative effects of climate change such as increased rainfall variability and droughts are expected to far outweigh the positive benefits associated with climate change (Webber et al., 2014).

It has become increasingly important to predict and evaluate the possible impacts of climate change on future crop yields in order to develop effective adaptation strategies and develop sustainable agricultural land management practices. An early understanding of the effects that climate change might have on crops may help farmers and decision-makers minimise agricultural production risks and take advantage of opportunities that may arise from climate change and thus increase food security. This knowledge of how future climate conditions may affect agricultural production is especially important in semi-arid regions such as South Africa where water scarcity and increasing frequencies of droughts are already limiting crop production (Goldblatt, 2011).

One way of predicting and evaluating the effects of future climate conditions on agricultural production is through the use of crop models and general circulation models (GCMs). Crop models have been used in agricultural research to simulate crop growth, soil water balance and nutrient management under different climate conditions (He et al., 2018; Uzoma et al., 2015), assess the effects of climate change on crop production and environmental risks (Basche et al., 2016; Wang et al., 2015), and explore potential adaptation strategies (Folberth, 2013). In South Africa, crop models have been applied in the fields of hydrology and agriculture. For example, Warburton et al., (2013) investigated the impacts of climate change on the hydrological response of catchments while Abraha and Savage, (2006) investigated the potential impact of climate change on maize yields in the KwaZulu Natal area. However, to predict future climate change impacts, crop models require future weather parameters including precipitation and rainfall as input.

General Circulation Models (GCMs) have been developed to project future climates based on different greenhouse gas scenarios and complex earth-atmosphere interactions. General Circulation Models are numerical models that use complex mathematical equations to simulate the earth's atmospheric processes and predict climate (Tang et al., 2016). Currently, GCMs project climate parameters at a resolution of approximately 250 km^2 (Ziervogel et al., 2008). While at this resolution, accurate prediction can be made at the global scale, the resolution is coarse at the local scale to support decision making and planning. To reduce the uncertainty involved with the use of GCMs, data from GCMs is usually downscaled either statistically or dynamically to produce local climate data or Regional Climate Models (RCMs) that reflect local conditions more accurately (Tadross et al., 2005). Statistical downscaling for example makes use of the quantitative relationships between the state of the larger-scale climatic environment and local variations sourced from historical data while dynamical downscaling makes use of the boundary conditions (e.g. surface pressure and wind) and principles of physics within an atmospheric circulation system to generate high-resolution datasets (Oosthuizen et al., 2016). However, dynamical downscaling is a computationally and technically expensive method, limiting the number of institutions employing the approach. Coupling specific local baseline climate data with GCM output provides a valuable way of reducing the uncertainty associated with climate projections. In this study, freely available climate data, statistically downscaled by the Climate Systems Analysis Group of Cape Town University (CSAG) to reflect local weather more accurately, were used for the climate simulations.

While it is evident in the literature that crop models are the primary tools to assess the impacts of climate change on crop productivity, the majority of crop models have the shortcoming that they cannot fully account for many of the drivers that affect crop productivity at the farm scale (Malawska et al., 2014; Rounsevell et al., 2012). For example, the majority of crop models cannot provide answers to the questions of how farmers' management behaviour could be changed to introduce new agricultural land management strategies (Wei et al., 2005). Webber et al., (2014) explain that perception of climate change is not the only factor leading to changed farm practices, but that farmers face a myriad of challenges such as access to markets, access to credit lines and extreme weather events such as droughts and flooding when making farm management-related decisions.

What is not evident from the literature, however, is how crop models should be used in informing climate change adaptations beyond the prediction of climate change impacts on crop yields (Webber et al., 2014). To inform climate change adaptation, it is important to understand the dynamics of farmers' decision-making processes at the farm scale in the face of both biophysical and economic uncertainty. While research on climate change impacts and farmers' views and responses have been conducted recently in South Africa (Findlater et al., 2019; Oduniyi and Tekana, 2019), few studies have combined the use of crop models and survey data on farmers' perceptions of climate change and the risk and adaptation management strategies implemented at the farm scale.

In South Africa, research groups such as the Council for Scientific and Industrial Research (CSIR) and the Climate Systems Analysis Group (CSAG) have developed downscaled future climate data for South Africa. However, despite the availability of this locally developed downscaled climate data, few climate change impact studies in South Africa have used downscaled climate data to assess the impacts of future climate change on crop yields (Ziervogel et al., 2014). Therefore, the objective of this chapter is to evaluate farmers' perceptions of climate change and compare current and future maize yields under different future climate scenarios. This chapter thus addresses objective four of the study. While the focus of this study was not on climate uncertainty, three climate models were compared to reduce the uncertainty of climate change projections associated with different models that could affect crop response. An understanding of farmers' current perceptions of climate change and the impacts of future climate change on maize can help to anticipate how farmers might adapt to and mitigate the impacts of future climate on crop yields. This understanding can also help in facilitating the development of sustainable adaptation strategies that farmers are likely to adopt and increase food security in the region.

6.2 Materials and methods

6.2.1 Study area

The biophysical data were collected from the Cradock Research Farm (Figure 1.2) in the Eastern Cape, South Africa (32° 13′ 11.09″ S, 25° 41′ 11.86″ E, elevation 849 m) as fully described in Chapter 1 section 1.6.

6.2.2 Model description

The EPIC model described in Chapter 4 was used for all climate scenarios simulations. Future climate data sets were used as weather input into the EPIC model to simulate crop yields under the different future climate data sets. The model was calibrated and validated for maize yield using data from field trials on maize carried out at the Cradock Research Farm. Further details and discussion of the calibration and validation experiment can be found in Chapter 4, section 4.2.6. Briefly, the model uses the concept of radiation use efficiency (RUE) by which a fraction of daily photosynthetically active radiation (fPAR) is intercepted by the crop canopy and converted to biomass (Lychuk et al., 2017). EPIC also requires other weather inputs such as precipitation, minimum and maximum temperature, wind speed and relative humidity. Biomass is reduced by stresses caused by shortages of radiation, water, nutrients and temperature extremes. The value of the most severe stress is used to reduce biomass accumulation, root growth, harvest index and crop yield (Rinaldi and de Luca, 2012).

6.2.3 Farmers' survey

To explore the perceptions of farmers on climate change, a survey was conducted on conventional farmers in the Eastern Cape. The climate change section was part of the survey from Chapter 3. The main questions in this section asked farmers whether they had noticed any changes in climate, whether climate change had affected crop production in any way and any other factors that had influenced farmers to change the type of crops grown on the farm. Farmers were also asked to explain the major challenges they were facing on their farm, whether they thought these were related to climate event and how they were mitigating their effects or adapting to such events.

6.2.4 Climate data

Future maize yield simulations were based on statistically downscaled climate input data from three General Circulation Models available from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). The climate data were downloaded from the Climate Systems Analysis Group (CSAG) Climate Information Portal (CIP) website (http://cip.csag.uct.ac.za). The data come from two main sources – the Computing Centre for Water Resources located at the University of KwaZulu-Natal and the South African Weather Services. The data were collated and quality controlled prior to being uploaded to the CIP (MacKellar et al., 2014). Due to inherent uncertainties in individual models, three GCMs were used to bracket a range of changes in global mean temperature and precipitation and consider a wide range of plausible future scenarios. The selected GCMs have been previously applied in climate change impact studies in South Africa and found to be representative of the region in terms of projection signal (see Lekalakala, (2017) for example). The driving GMCs chosen for this study were the BCC-CSM1.1, GFDL-ESM2M and MIROC-ES models (Table 6.1).

Table 6.1. List of driving GCMs and the model abbreviations used in this study.

No	Driving Regional Circulation Model	Source	Abbreviation of the model used in this study
1	BCC-CSM1.1	Beijing Climate Centre, China Meteorological Administration, China	BCC
2	GFDL-ESM2M	Geophysical Fluid Dynamic Laboratory, USA	GFDL
3	MIROC-ESM	Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	MIROC

For future greenhouse gas emission scenarios, two Regional Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5 for two future 30-year periods, from 2040-2069 and 2070- 2099, were chosen to compare two different possible climate scenarios depending on the level of greenhouse gas emissions. RCP 4.5 was developed by the GCAM modelling team at the Pacific Northwest National Laboratory's Joint Global Change Research Institute (JGCRI) in the United States. It is a stabilization scenario in which the total radiative forcing is stabilized shortly after 2100, without overshooting the long-run radiative forcing target level (Smith and Wigley, 2006; Wise et al., 2009). RCP 8.5 was developed using the MESSAGE model and the IIASA Integrated Assessment Framework by the International Institute for Applied Systems Analysis (IIASA), Austria. RCP 8.5 is characterized by increasing greenhouse gas emissions over time, representative of scenarios in the literature that lead to high greenhouse gas concentration levels (Riahi et al., 2011).

For the baseline simulation, weather data for 31 years from 1980 to 2010 for the Cradock Research Farm obtained from the AgMERRA (Ruane et al., 2015) data set was used as input into the EPIC model. Weather data included daily maximum and minimum temperature and rainfall. Management practices including planting dates, fertiliser and irrigation levels used during the maize cultivar evaluation trials were used as the baseline management practices being used in the area. In the future simulations, the three climate model simulations under RCP 4.5 and RCP 8.5 scenarios, for the two 30-year periods plus the baseline were simulated giving a total of 13 EPIC simulations.

It is important to note that, in the field experiment in Chapter 4, the maize crop was left to dry out in the field even though it had reached physiological maturity. However, the time from physiological maturity to actual harvest date was not recorded, only the final harvest date was given. Due to this lack of information on the actual time from physiological maturity to harvest, changes in the length of the growing season under future climate scenarios were not included in the data analysis.

6.2.5 Data analysis

Farmers' survey

Survey responses on climate change from the farmers' survey in Chapter 3 were analysed using thematic analysis to identify recurrent and emergent themes regarding farmer's perceptions on climate change, perceived impacts on crop production as well as mitigation and adaptation strategies at the farm scale.

Climate scenarios

The following model output variables for the simulations were analysed: biomass yield (YLDF in t ha^{-1}), seasonal irrigation water applied (IRGA, in mm), seasonal evapotranspiration (ETa, in mm) and N leaching (kg N ha^{-1}). Water Use Efficiency (WUE) in kg mm^{-1} was calculated as YLDF/ETa. The means of the output variables for the current scenario were compared to the means of the output variables for the future periods. Model variables were analysed using analysis of variance (ANOVA) computed using Statistical Package for Social Scientists (SPSS) version 21 software. For all ANOVA analyses, post hoc Tukey tests were used to determine the significant differences between treatments. To identify the sources variation between means, Tukey's HSD test was used. An independent samples t-test was performed to test for mean differences in the output variables between the two future periods, 2040-2069 and 2070-2099.

6.3 Results

6.3.1 Farmers' perceptions of the impacts of climate change

All 48 farmers responded that they had heard of the term 'climate change' and had a variety of responses on how climate change had affected their farming activities. For example, one of the farmers indicated that:

"*Rainfall patterns have changed, on average annual rainfall figures have fallen in the last 5 years ... it is not spread out over the growing season as before and although the season average does seem consistent, the number of rain days are less and concentrated towards the middle/end of the growing season. This leads to irregular growth patterns with dry/saturated periods. Leaching of fertilisers also occur and herbicide applications become more difficult to manage*"

Yet another farmer indicated that "*Yes, climate change has affected production. Dry pastures in the summer mean having to feed hay for a greater amount of time each year, which is more expensive*."

Thematic analysis revealed four major ways farmers thought climate change had affected their farming activities. Figure 6.1 shows the major observations made by farmers on how climate change had affected farm production.

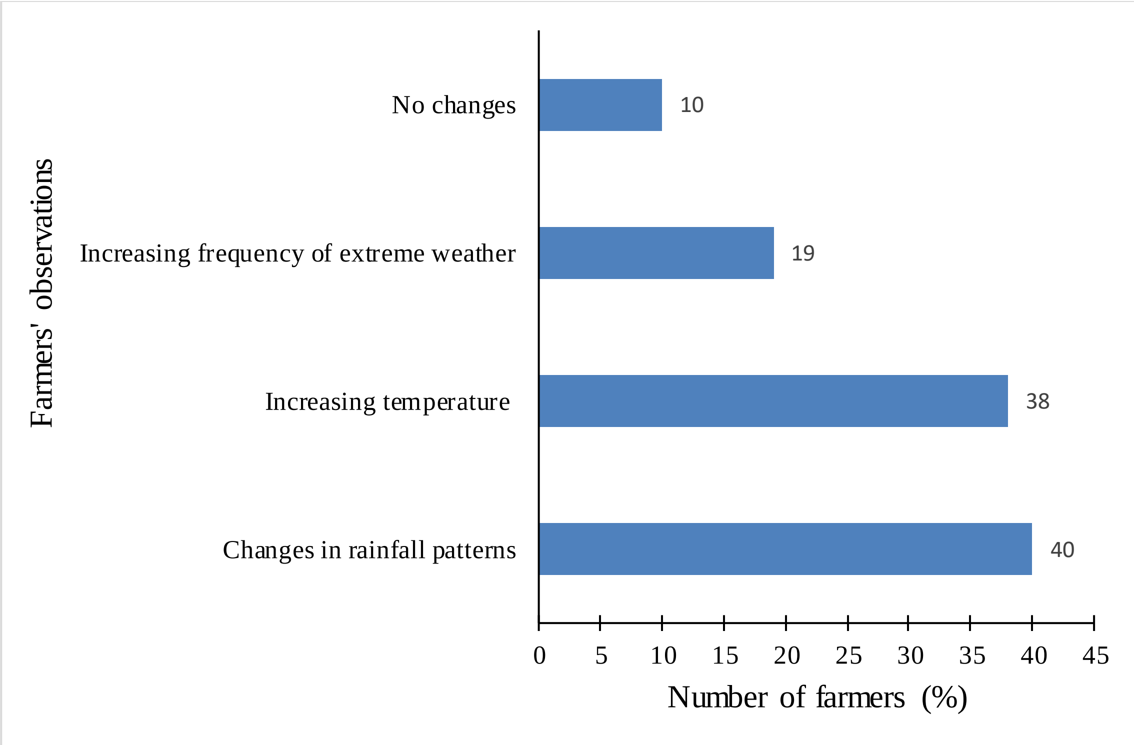


Figure 6.1 Farmer's perceptions of climate change

When farmers were asked how rainfall patterns had changed, the majority of farmers (75%) responded that the rainy season started late and 60% reported that the length of the growing season had decreased (figure 6.2). Regarding rainfall amount, 45% of farmers observed a decrease in rainfall amount and 40% observed an increase in rainfall amount. Regarding temperature changes, 80% of farmers reported that average temperatures had increased while only 5% reported that temperature had decreased.

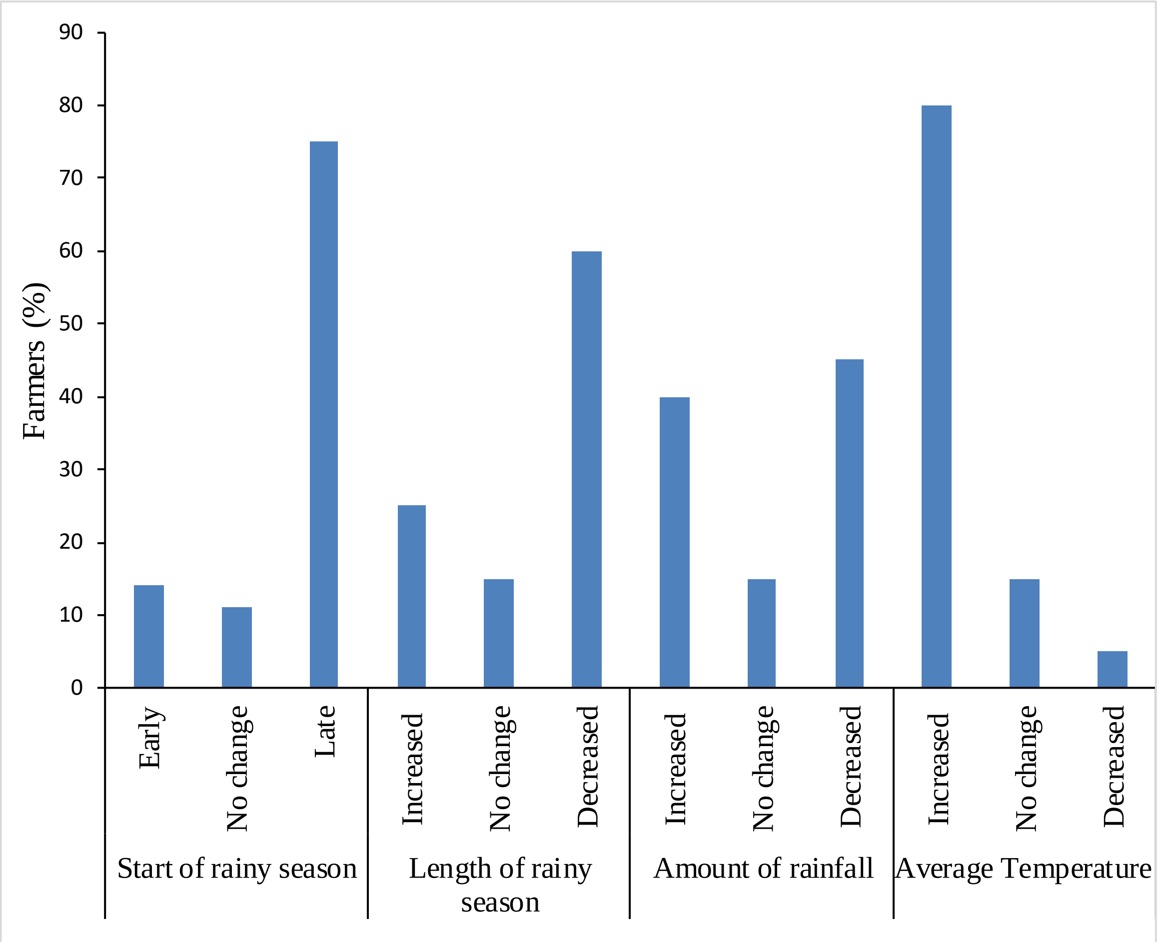


Figure 6.2 Farmers' perceptions of changes in rainfall and temperature

6.3.2 Effects of climate change on agriculture

Climate change is having an effect on agriculture in the Eastern Cape. Table 1 shows that 80% of the farmers agreed that climate change had a negative impact on crop yields while 20% did not agree. In addition, 83% of farmers cited that climate change had led to increased food costs. Results also revealed that 73% of farmers reported that climate change was responsible for the increase in land degradation while only 21% disagreed.

Table 6.2 Distribution of farmers by perceived effects of climate change (n = 48)

Farmers' perception of climate change	**Percentage** (n = 48)
Decrease in crop yields	
Strongly agreed	63
Agreed	17
No response	0
Disagree	13
Strongly disagree	7
Increase in food costs	
Strongly agreed	73
Agreed	10
No response	0
Disagree	13
Strongly disagree	4
Increased land degradation	
Strongly agreed	52
Agreed	21
No response	6
Disagree	17
Strongly disagree	4
Increase in crop and livestock pests and diseases	
Strongly agreed	58
Agreed	21
No response	0
Disagree	21
Strongly disagree	0

6.3.3 Climate change adaptation strategies being used by farmers

Farmers reported using a wide variety of strategies to adapt to climate change. Table 6.2 shows the strategies commonly being used by farmers to adapt to climate change.

Table 6.3. Adaptation strategies being used by farmers.

Adaptation strategies	**Percentage (%) ***
Crop-livestock diversification (e.g. crop rotation, mulching)	75
Intensification of farming (e.g. use of chemical fertilisers, pesticides)	83
Diversification of income-generating activities	35
No adaptation strategies	8

* n = 48, Farmers had multiple adaptation strategies

6.3.4 Barriers to climate change adaptation

The most-reported challenge farmers were facing was access to markets (83%) followed by access to loans and credit lines (73%). Other significant challenges farmers cited were access to education and extension support and climate and weather. Climate and weather challenges included an increased frequency of droughts. Figure 6.4 shows the major challenges cited by farmers when asked the question, what are the major challenges you are currently facing in your farming enterprise?"

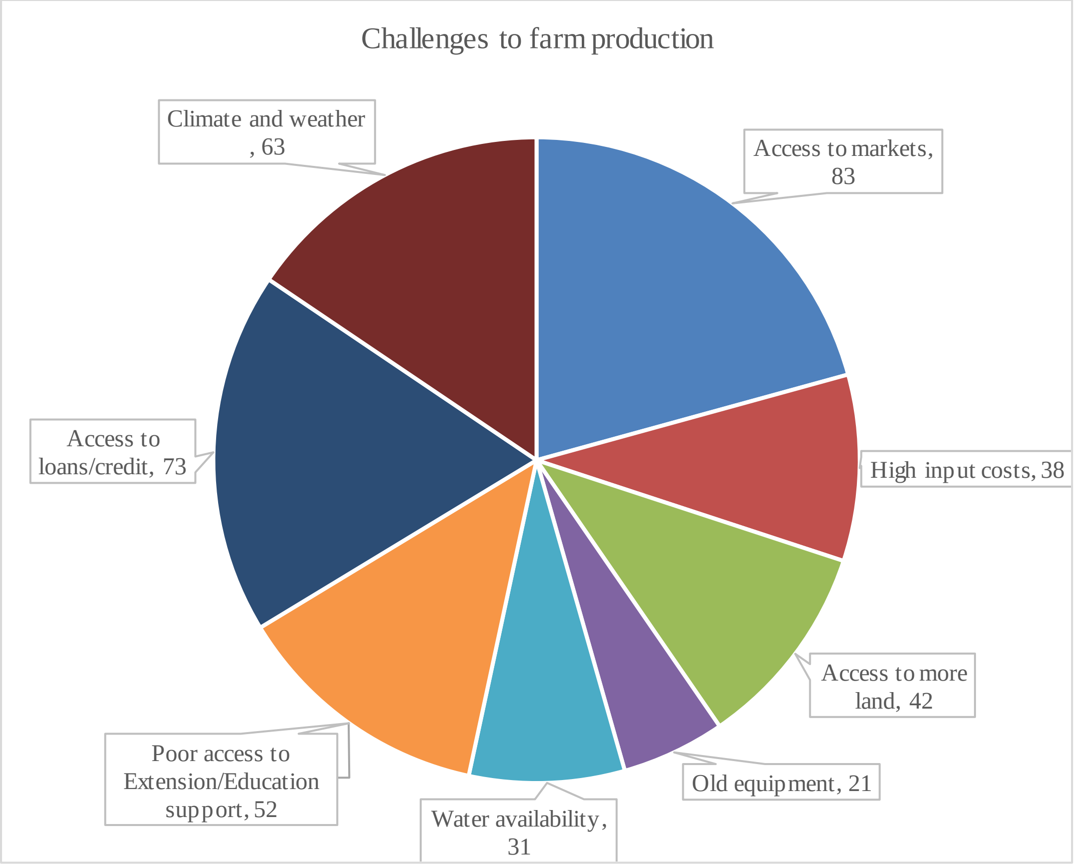


Figure 6.3. Challenges being faced by farmers in the Eastern Cape. Numbers indicate percentages of farmers

6.3.5 Climate data analysis

All three GCMs showed, for both scenarios, an increase in the average temperatures from March to October (Figure 6.4). The increase was more pronounced in the RCP 8.5 scenario and for the MIROC model were average temperatures in June and July were above 10°C and approximately 6.8°C higher than the baseline average for the two months. For the RCP 4.5 scenario, the increase in average temperature was lower compared to the RCP 8.5 scenario. The highest monthly average temperature in the RCP 4.5 scenario was 23.7°C in January and February for the model MIROC and approximately 21°C for the GFDL and BCC models. In the months from September to December, the temperatures were similar across the all three models.

An increase in winter rainfall was also observed from May to July for both RCPs with higher average rainfall values in RCP 8.5 (Figure 6.5). The MIROC model showed a different trend for rainfall for both the RCP 4.5 and RCP 8.5 scenarios with higher average monthly rainfall for the months September to December, showing peaks of about 70 mm in November (Figure 6.5). The baseline, BCC and GFDL scenarios also showed peaks in November in the RCP 8.5 scenario but having rainfall peaks lower than the MIROC model.

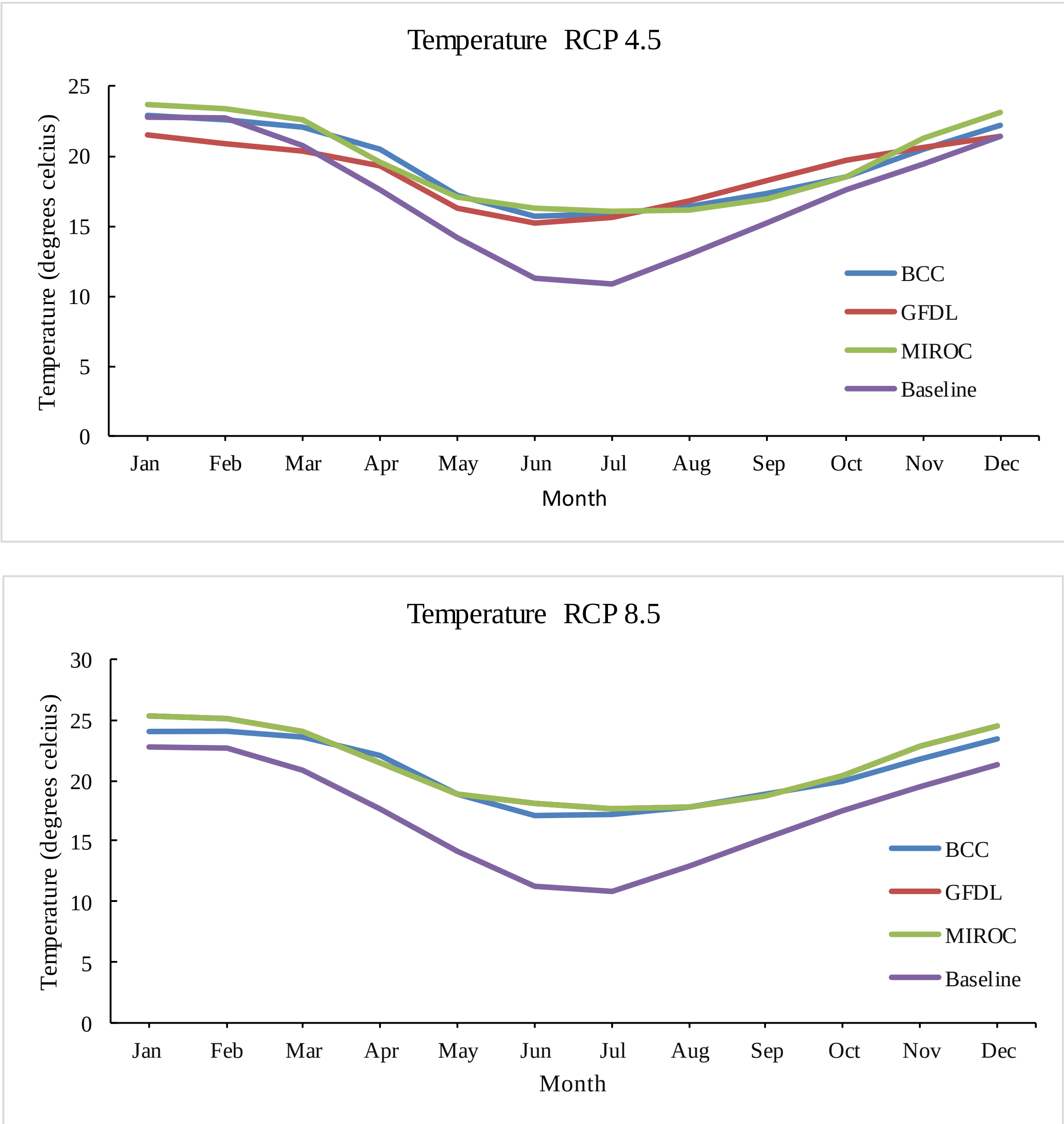
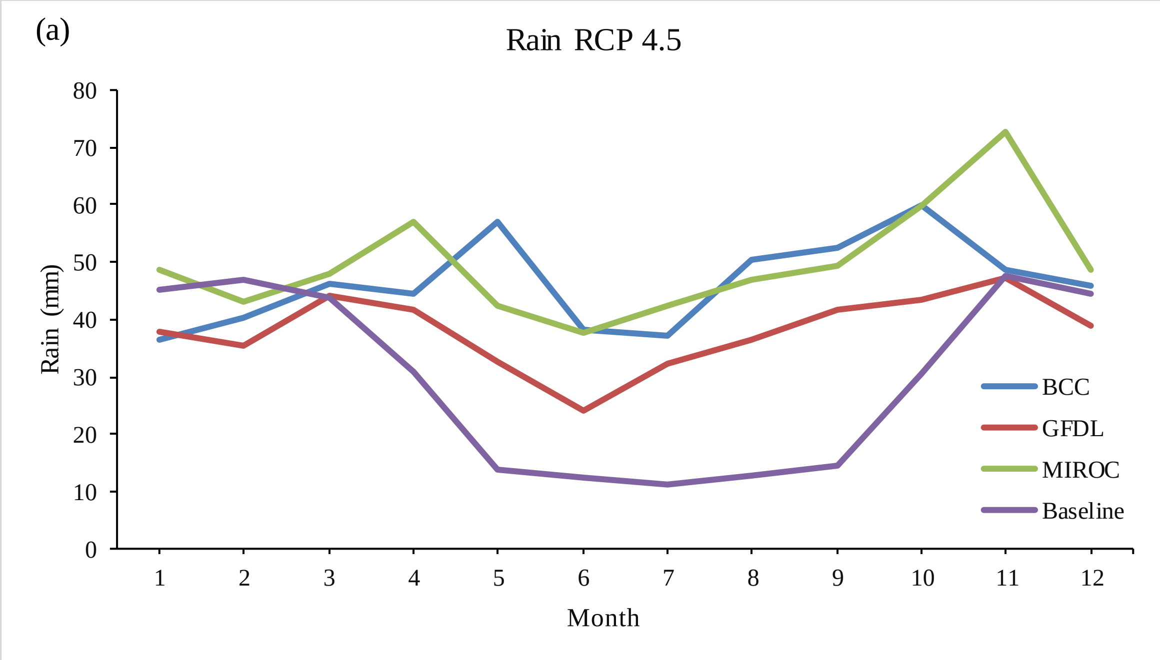


Figure 6.4 Monthly average (of the two 30-year future periods and 31 years of baseline data) temperatures for RCP 4.5 (a) and RCP 8.5 (b).



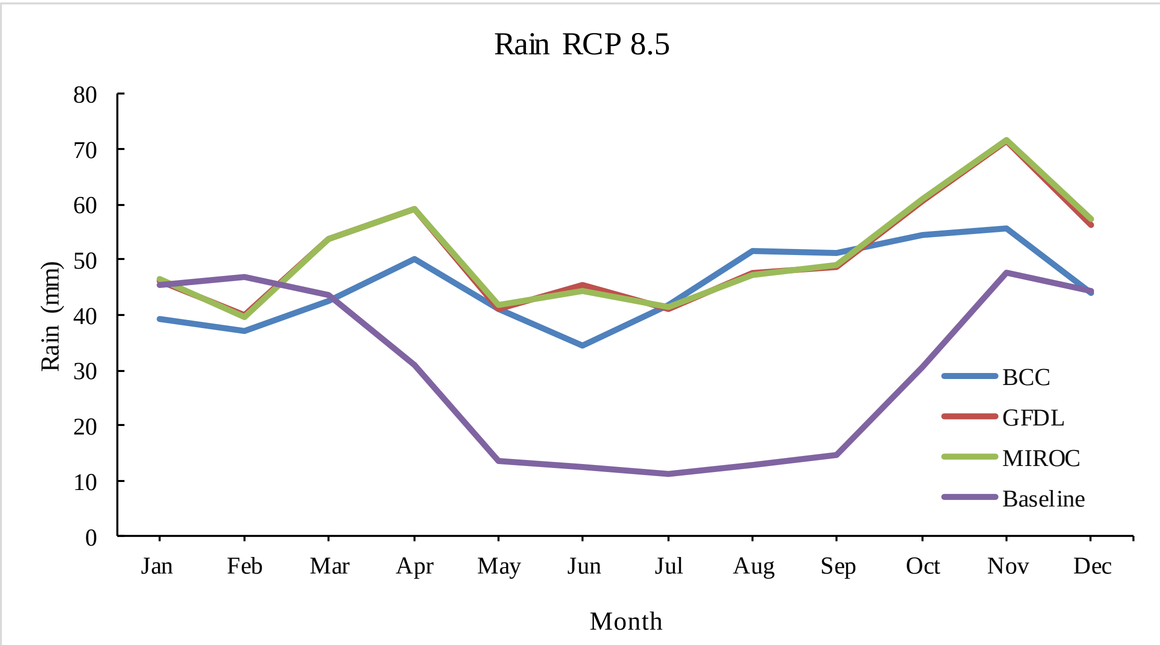


Figure 6.5 Monthly average (of the two 30-year future periods and 31 years of baseline data) rainfall for RCP 4.5 (a) and RCP 8.5 (b).

The climate model simulations that had the highest increase in temperature for the RCP 4.5 scenario were the MIROC model with a monthly percentage difference from the baseline of about 51% in July and the GFDL model with peaks of more than 40% in June and July for the period 2070 – 2099. (Figure 6.6). RCP 8.5 showed higher temperature differences from the baseline compared to RCP 4.5 for both climate models and future time periods. The highest percentage difference from the baseline in RCP 8.5 was given by the MIROC model reaching a peak of 71% in July.

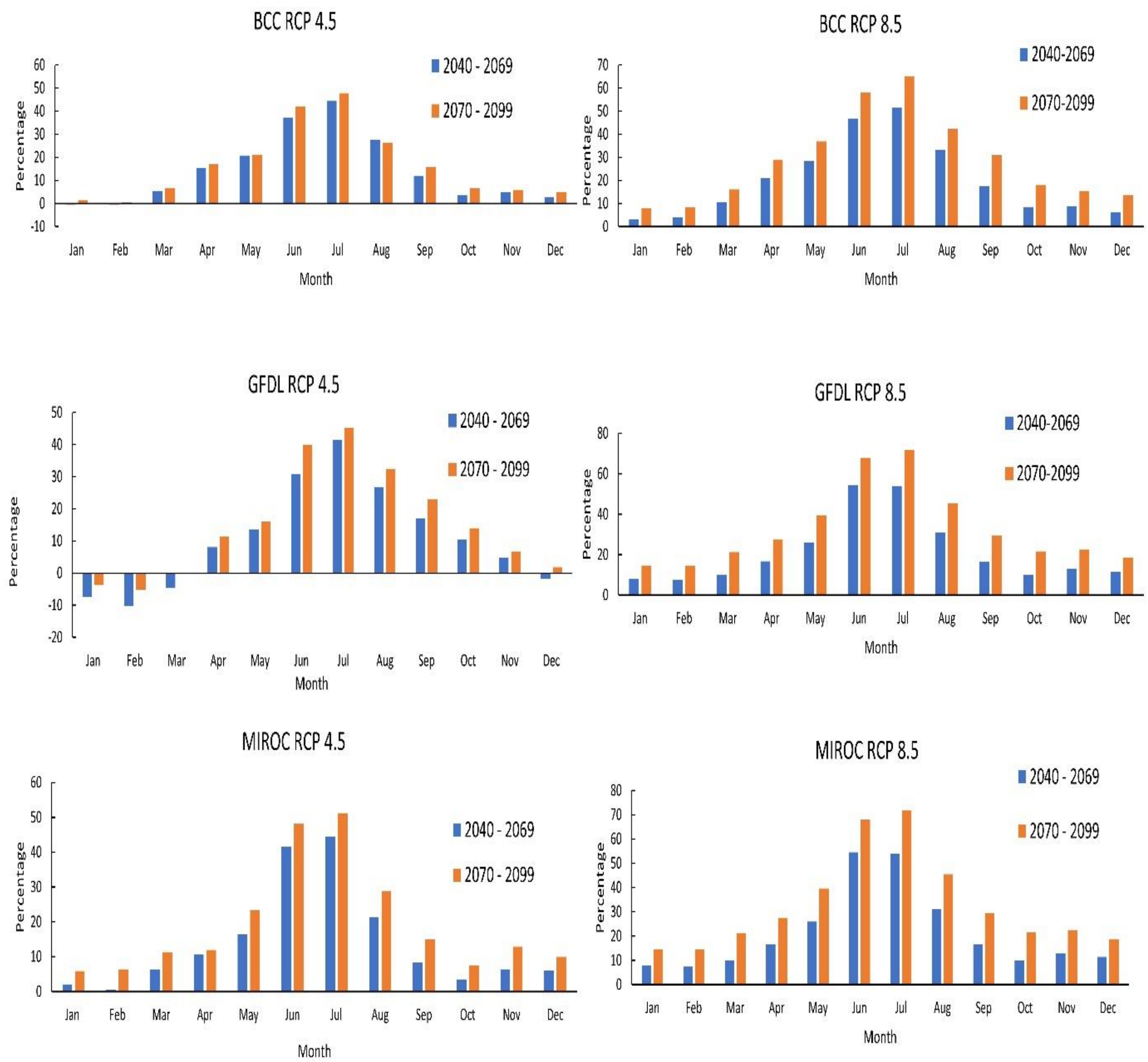


Figure 6.6. Percentage differences from the baseline of average monthly temperatures for the two thirty-year periods generated by the simulation and for the three climate models.

6.3.6 Climate scenario simulation results

The simulation results displayed a common trend among all the three GCMs used in the RCPS (RCP 4.5 and RCP 8.5) to the baseline maize yields. There was a reduction in maize yield for

BCC and MIROC for both RCPS and the two future periods. Maize yield decreased by up to 20% RCP 8.5 2070-2099 (Table 6.4), WUE decreased buy up to 21.7 % in RCP 8.5 2070-2099 and seasonal irrigation amount decreased by up to 13% in RCP 8.5 2040-2069. However, N leaching increased in all future climate scenarios, increasing by as much as 375% in RCP 8.5 2070 – 2099. Table 6.3 shows the average values between the different scenarios and model outputs.

Table 6.4. Average model output values and mean comparison test for the different scenarios, climate models and future time periods

	Yield ($t\ ha^{-1}$)	Irrigation water used (mm)	WUEF ($kg\ ha^{-1}\ mm^{-1}$)	N leaching ($kg\ N\ ha^{-1}$)	Seasonal Et (mm)
Scenario					
Baseline	12.24^{A}±0.58	562.89^{A} ±82.53	24.13^{A} ±1.33	19.91^{B} ±24.17	907.78^{C} ±46.79
RCP 4.5	11.51^{B} ±1.10	541.09^{A} ±74.29	23.46^{A} ±1.96	36.79^{B} ±34.09	943.10^{A} ±39.08
RCP 8.5	10.20^{C} ±0.81	460.81^{B} ±61.86	22.40^{B} ±1.19	66.13^{A} ±53.58	918.84^{B} ±40.94
GCM					
BCC-ESM	10.89^{A}±1.17	509.23^{A}±66.43	23.24^{A}±2.34	49.22^{A} ±41.35	922.45^{A} ±32.91
GFDL	11.05^{A} ±1.32	510.82^{A} ±92.8	22.95^{B} ±1.33	47.34^{A} ±52.37	933.88^{A} ±45.78
MIROC	10.62^{A} ±0.95	481.52^{A} ±73.55	22.58^{BC} ±1.09	56.49^{A} ±48.18	936.34^{A} ±44.62
Period					
2040 - 2069	11.31* ±0.73	525.26*±68.77	23.37* ±0.76	39.35* ±34.14	938.76* ±36.59
2070 - 2099	10.39* ±1.33	475.82* ±81.78	22.48* ±1.33	62.78* ±55.77	922.62* ±45.13

Note: For Tukey's test, different superscript letters on means in the same column indicate significant difference at $p < 0.05$, the same superscript on means in the same column indicates no significant difference between means.

* indicates a significant difference at $\alpha = 0.05$ for independent samples t-test.

WUEF = Water Use Efficiency, Et = Evapotranspiration

Table 6.5. Percentage differences (Future – baseline) of EPIC simulations of future climate scenarios with respect to the baseline of maize.

Scenario and Period	Yield	Seasonal irrigation	Water Use Efficiency	N leaching
BCC				
RCP 4.5 2040-2069	-8.2	-5.4	-4.3	-26.4
RCP 4.5 2070-2099	-7.4	-5.9	-5.1	108.8
RCP 8.5 2040-2069	-10.7	-5.9	-7.0	148.4
RCP 8.5 2070-2099	-15.6	-8.0	-14.1	215.5
GFDL				
RCP 4.5 2040-2069	0.0	-1.9	0	17.4
RCP 4.5 2070-2099	-2.5	0.3	-2.8	39.4
RCP 8.5 2040-2069	-14.8	-13.6	-13.4	207.5
RCP 8.5 2070-2099	-20.8	-13.6	-21.7	375.4
MIROC				
RCP 4.5 2040-2069	-8.2	-13.2	-6.6	113.5
RCP 4.5 2070-2099	-13.1	-8.7	-12.1	178.8
RCP 8.5 2040-2069	-10.7	-12.9	-9.6	153.2
RCP 8.5 2070-2099	-23.8	-13.6	-22.7	373.8

6.3.7 BCC model

The second future period, 2070 – 2099 where the gap from the baseline was more highlighted, maize yield was on average equal to 10.3 t ha^{-1} for RCP 8.5 and 11.3 t ha^{-1} for RCP 4.5. RCP 8.5, 2070-2099 gave the largest yield difference from the baseline yield (Figure 6.7a). Seasonal irrigation amount showed a decreasing trend in the future periods compared to the baseline (Figure 6.7b). The decrease in seasonal irrigation amount was comparable between RCP 4.5 2040-2069, RCP 4.5 2070-2099 and RCP 8.5 5040-2099, with the three-time periods having similar seasonal irrigation requirements. RCP 8.5 2070-2099 had the largest seasonal irrigation requirement decrease compared to the baseline scenario with a seasonal irrigation amount 8% lower than the baseline. Future WUE also showed a decreasing trend from the baseline scenario for all future time periods (Figure 6.7c). The largest decrease in WUE was in RCP 8.5, 207-2099 which was 22.7% lower than the baseline WUE. N leaching increased in all future scenarios except in RCP 4.5, 2040-2099 where N leaching slightly decreased compared to the baseline scenario (Figure 6.7d). RCP 8.5, 2070-2099 had the largest increase in N leaching when compared to the baseline scenario.

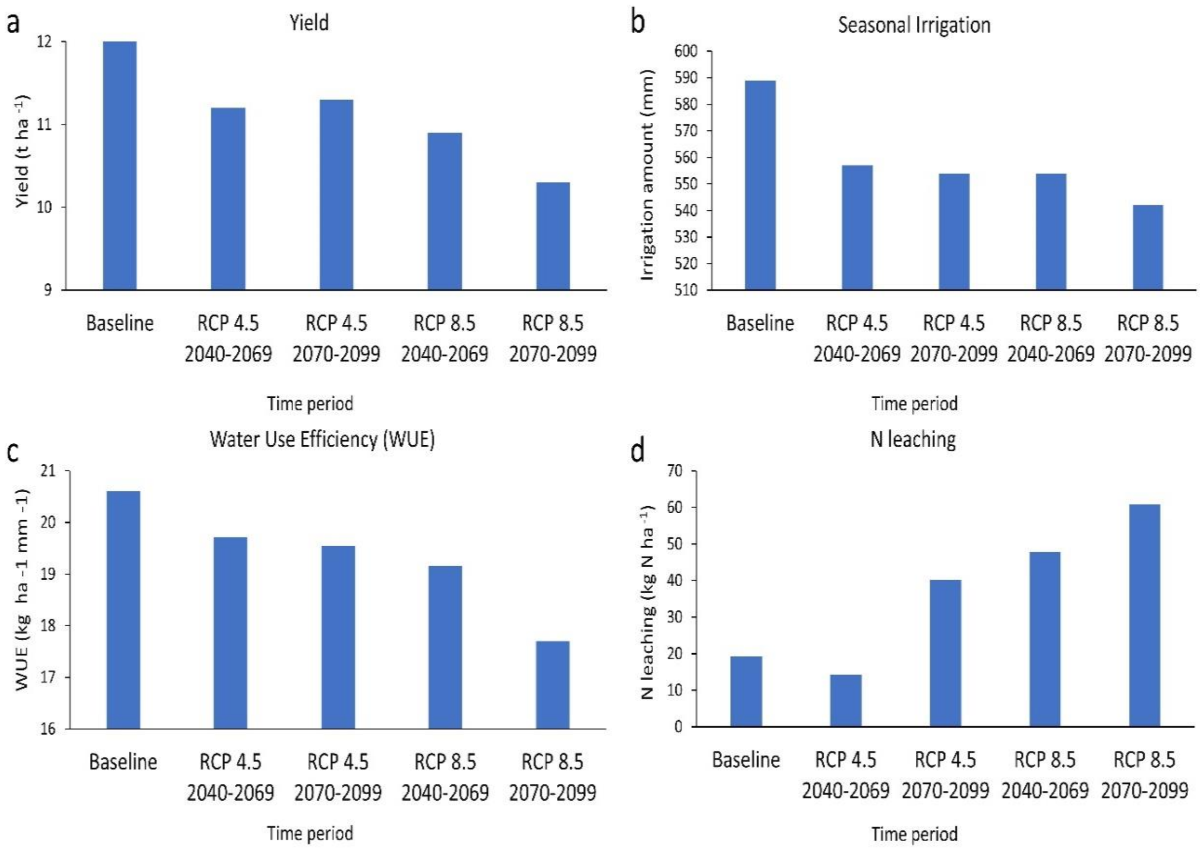


Figure 6.7. EPIC model outputs from the simulations using BCC-ESM climate data. Values were plotted and shown for the two 30-year periods compared to the baseline simulation.

6.3.8 GFDL model

For this model, crop yield was similar to the baseline scenario but yields slightly lower (Figure 6.8a). For RCP 4.5 and 8.5 there were only slight differences in yield in the two future periods for this scenario. The two future scenarios for RCP 8.5 showed lower yields compared to both RCP 4.5 and the baseline scenario. Seasonal irrigation was similar to the baseline period for the two future periods in RCP 4.5. However, both future periods for RCP 8.5 showed a marked decrease in seasonal irrigation amount compared to the baseline scenario. The largest decrease in seasonal irrigation compared to the baseline scenario was observed for the period 2040 – 2069 in RCP 8.5 (Figure 6.8b). WUE slightly decreased in the future climate scenarios ranging from 15.91 kg ha^{-1} mm^{-1} in RCP 8.5 2070-2099 to 20.61 kg ha^{-1} mm^{-1} in RCP 4.5, 2040-2069 compared to 20.61 kg ha^{-1} mm^{-1} in the baseline scenario (Figure 6.8c). N leaching increased in all future climate periods for all the scenarios compared to the baseline scenario (Figure 6.8d). RCP 8.5, 2070-2099 had the largest increase in N leaching with an average of 91.64 kg N ha^{-1}

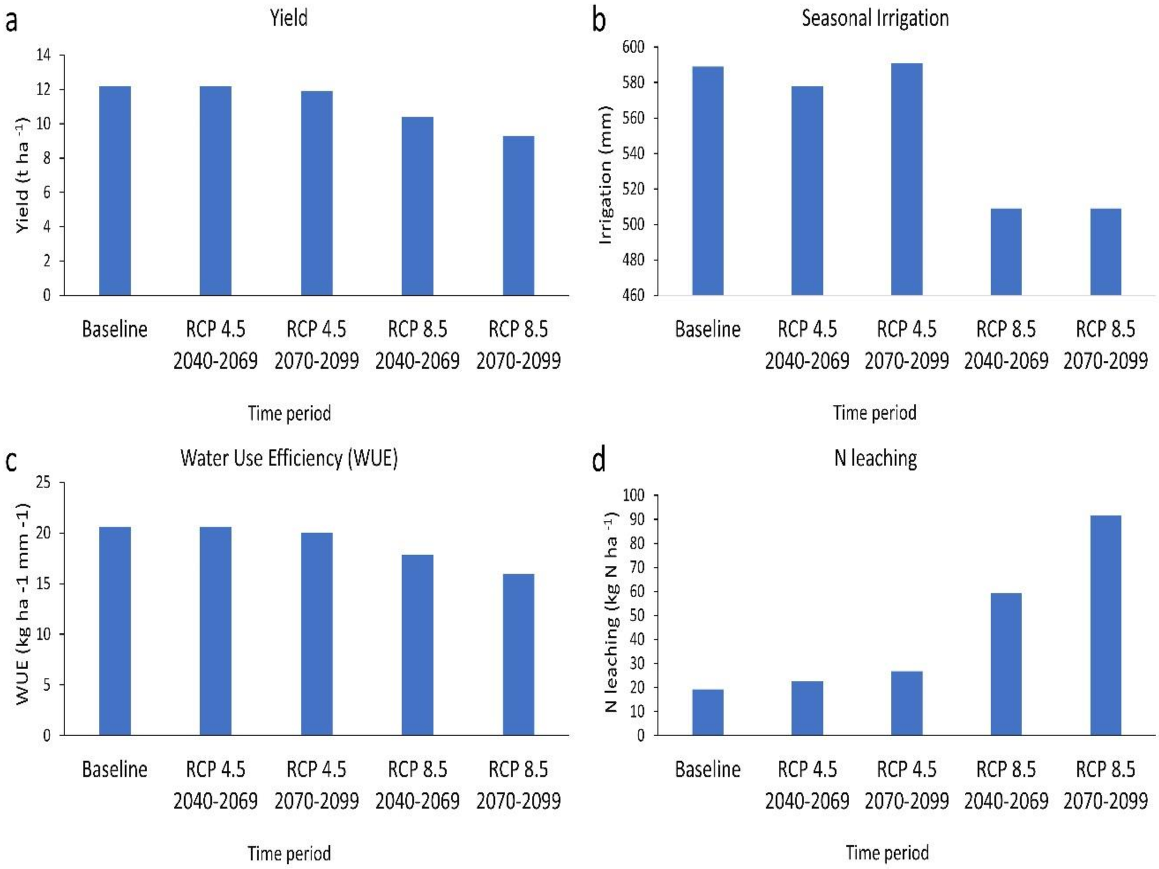


Figure 6.8. EPIC model outputs from the simulations using GFDL climate data. Values were plotted and shown for the two 30-year periods compared to the baseline simulation.

6.3.9 MIROC model

The MIROC model showed a similar trend of decreasing yield production for all the time period with respect to the baseline period. Maize yield decreased by up to 23% in RCP 8.5, 2070-2099 (Figure 6.9a). Seasonal irrigation also decreased significantly in the future time periods for all the RCPs. Seasonal irrigation amount decreased by up to 13% in RCP 4.5, 2040-

2069 and the two time periods for RCP 8.5 compared to the baseline period (Figure 6.9b). For WUE, the model simulated a slight decrease over time particularly in RCP 8.5, 2070-2099 (Figure 6.9c. N leaching increased for all future time periods compared to the baseline scenario. RCP 8.5 2070-2099 had the largest increase in N leaching compared to all the other time periods for all the three models (Figure 6.9d).

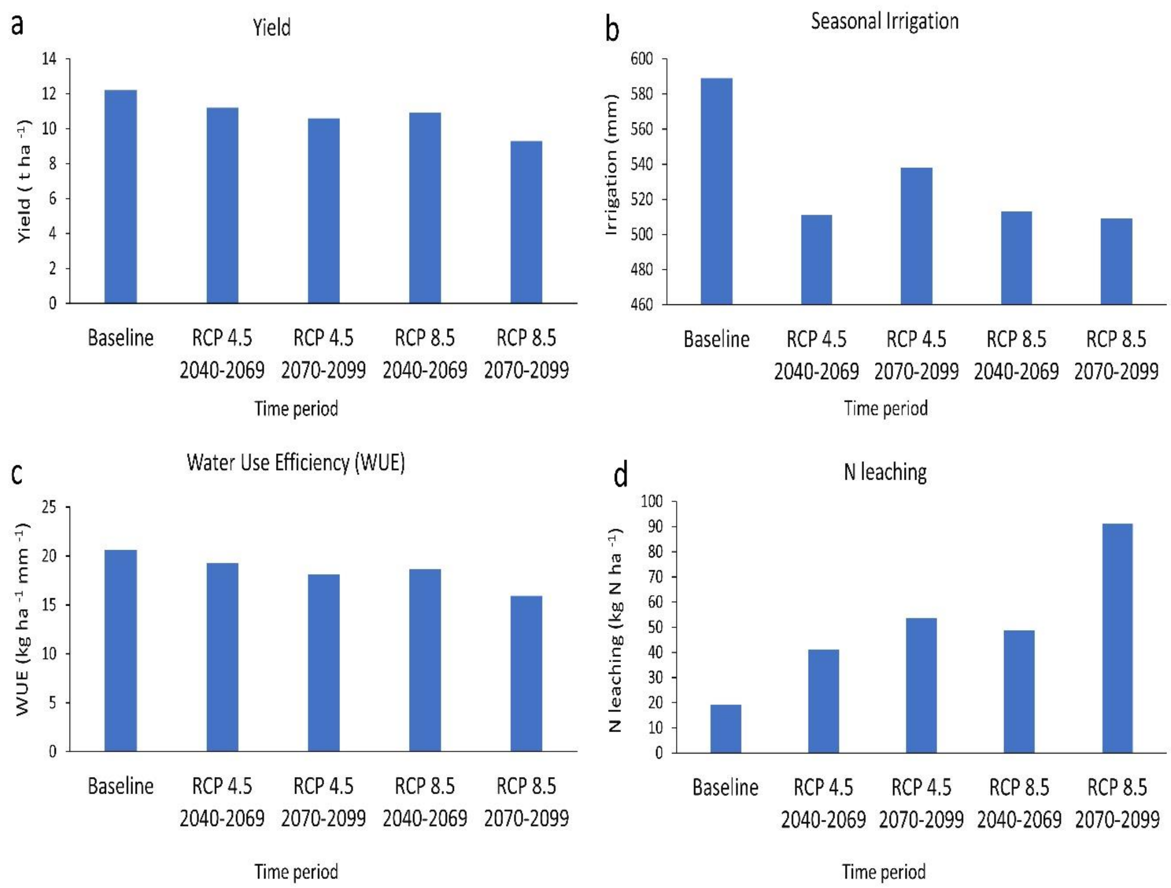


Figure 6.9. EPIC model outputs from the simulations using MIROC climate data. Values were plotted and shown for the two 30-year periods compared to the baseline simulation

6.4 Discussion

6.4.1 Farmers' perceptions of climate change

Results of the study show that farmers were aware of climate change as more than 80% percent of farmers who responded perceived a change in the climate. Farmers' major pieces of evidence of climate change were changes in temperature and changes in rainfall patterns. Several studies analysing climate and weather trends in South Africa have shown that average temperatures in South Africa have increased over the decades (Davis-Reddy and Vincent, 2017; Department of Environmental Affairs, 2013; Jury, 2018). A study by MacKellar et al., (2014) on observed and modelled trends for rainfall and temperature for South Africa found significant increases in temperature and rainfall variability in the Eastern Cape.

Most farmers who had perceived the impacts of climate change developed adaptation strategies. The main adaptation strategies identified by farmers included “crop-livestock diversifications”, “intensifying farming through the use of chemical fertilisers and pesticides” and “diversification of income-generating activities”. The different strategies employed by farmers indicates that framers are seeking to improve their farming systems through agrobiodiversity and ensure a minimum harvest for their own food security. In this study, most farmers practised mixed farming which included maize, a common staple crop in the area. Studies have shown that the yields of crops grown in association are often less affected by climate impacts.

6.4.2 Implications of farmers’ adaptation choices

Farmers’ choices of adaptation strategies can serve either to maximise profit or avoid farming losses in the face of climate change (Gebreeyesus, 2017). In this study, all the adaptation strategies used by farmers fit into these two purposes. The most cited strategy to cope with climate change was to intensify farming through the use of chemical fertilisers and pesticides. However many studies have highlighted the negative impacts of chemical fertilisers and pesticides on the environment, especially when they are applied in excess of crop requirement (Kumari et al., 2014). Given the increase in land degradation which ultimately underpins the production of food, it is important for farmers to shift to more sustainable farming practices like organic farming or integrated pest management as the long-term effects of high input agriculture include losses in biodiversity and soil and water pollution.

Crop diversification is the agricultural practice of growing more than one type of crop in a given area in the form of crop rotations or intercropping (Fadina and Barjolle, 2018). Diversified production systems are seen as one of the most ecologically feasible and cost-effective ways of reducing the uncertainties involved with climate change in agriculture (Makate et al., 2016). The results of this study show that many farmers already use this strategy to adapt to climate change in the Eastern Cape. Crop diversification can help in improving soil fertility through intercropping of cereals with nitrogen-fixing legumes, decreasing reliance on chemical fertilisers (Lin, 2011; Makate et al., 2016). In their study using data from over 500 smallholder farmers, Makate et al., (2016) found that adopting crop diversification strategies improved crop productivity, income and overall food security of farmers. Makate et al., (2016) concluded that crop production was a practical climate smart agricultural practice that significantly improved crop productivity in rural farming systems. Diversified cropping systems, in general, tend to be more agriculturally stable and resilient (Makate et al., 2016).

A crop diversification strategy which has proved effective in adapting to climate change and increasing food security simultaneously is agroforestry – the integration of trees with crop cultivation and livestock production. Trees provide climate mitigation and adaptation benefits through carbon sequestration and increase the resilience of agroecosystems by providing farmers with both income (sale of tree products e.g. fruits, timber) and increased productivity (through enhanced ES such as pollination and biodiversity) (Duguma et al., 2020). According to World Vision, (2019), grain yield can significantly increase when farmers incorporate trees within crop production systems. The inclusion of agroforestry practices in degraded lands such as those that make up the greater part of the Eastern Cape can lead to sustainable environmental and economic outcomes in agricultural production systems.

6.4.3 Barriers to effective climate change adaptation

Several studies in Africa have demonstrated several barriers that challenge the ability of farmers to adapt to climate change. The major barriers identified include access to credit, lack of information on climate change adaptation strategies, poor extension services and institutional factors (Assoumana et al., 2016; Juana et al., 2013; Sani et al., 2017). Juana et al., (2013) reported that the institutional factors that influence the adoption of new technologies are access to information via extension services (climate information and production technologies) and access to credit. Juana et al., (2013), further add that farmers who have substantial agricultural extension contacts have better chances of being aware of changing climatic conditions as well as adaptation measures in response to the changes in these conditions. This is confirmed by the findings of Sani et al., (2017) and Mnkeni et al., (2010) who came to the conclusion that lack of credit, poor access to markets, and lack of information about climate change and high cost of adaptation were the main climate change adaptation constraints.

6.4.4 Impacts of climate change on maize yield

Model ensemble results also predict a decrease in maize yield for all future scenarios with a more pronounces decreases in RCP 8.5 2070-2099. This decrease can be attributed to an increased temperature that would shorten the growth stage of the maize crop. Temperature influences the duration of growth through a faster accumulation of growing degree days. Several studies have shown that increases in temperature lead to an early maturing of crops, which allows for less time to accumulate biomass and form grain yield (Craufurd and Wheeler, 2009; Dominguez-Faus et al., 2013; Sacks et al., 2010). The projected decrease in maize yield in this study is in agreement with other studies in Southern Africa. For example, studies by Matarira et al., (1995) projected decreases in maize yield in Zimbabwe under both irrigated and rain-fed agriculture. In their study, they used the CERES model driven by GCMs (specifically the GFDL and the Canadian Climate Centre Model). Walker and Schulze, (2006), also studied the response of smallholder maize production in Potshini village, KwaZulu Natal, South Africa up to the late 21st century climates. Their study projected a decrease in average maize yields of approximately 30% but also showed that more efficient management of fertiliser and manure applications would be a viable management strategy to adapt to climate change.

Rainfall can also influence crop yield as water is key to crop growth and development. In this study, rainfall was predicted to decrease in the study area. This has implications for food production as rainfall is used to supplement irrigation in the study area. Further, rainfall is the ultimate source of irrigation water and a decrease in rainfall would lead to decreased flows in the Great Fish River, leading to further water shortages in an already water-scarce area. Further water shortages would have a significant impact on food production in the area as the Great Fish River supplies most of the irrigation water used by conventional farmers in the area. Previous studies by Mnkeni et al., (2010) and results from Chapter 5 have shown that without irrigation, rain-fed maize yields in the Eastern Cape are very low even when sufficient fertiliser is provided. In light of the predicted impacts of climate change in the study area, there is an urgent need for farmers to get financial and technical support to implement on-farm water adaptation strategies such as rainwater harvesting and the use field water conservation strategies such as mulching.

With regard to nitrate leaching, all future simulations predicted significant increases in N leaching. Generally, increases in temperature accelerate phenological development leading to a shorter growing period and less nutrient uptake. Without matching the amount of fertiliser applied to crop N needs, excess N can be lost to the environment through leaching. This indicates the need to make adjustments of fertilisation schemes under climate change conditions into consideration when developing future agricultural land management strategies aimed at maximising the use of N by plants and minimising N losses to the environment.

It is important to note that in the simulations, no adaptive agricultural land management strategies aimed at minimising the effects of climate change were considered. This is unlikely to be the case in practice. Agroecosystems are managed and farmers have a variety of possible adaptation options (Yang et al., 2014) as the results of the survey have shown. While the study did not show possible yield changes due to the implementation of climate change adaptation measures, the study does provide a clear picture on maize yield and N leaching if no climate change adaptation measures are taken. Increases in temperature and a decreased length of the rainfall season predicted in this study suggest that short term growing maize varieties and drought-tolerant maize varieties may be needed in the Eastern Cape if crop production is to be sustained.

The results of climate impact studies, however, should not be taken in absolute terms but rather as possible pathways for the future of agricultural production. Decision and policymakers should take into account other factors that may influence crop yield. In this study, the combined influence of other factors such as the development of pests and disease on crop yield was assumed to be fully controlled through appropriate management practices. The results of the study can be used by farmers and policymakers to plan how to adapt to the projected increases in temperature. It is important to develop adaptation strategies that take into account the projected increases in temperature and minimise N leaching. N leaching represents an economic loss to farmers (N fertiliser not utilised by plants) and a potential water pollutant. It is recommended that studies that test the effectiveness of adaptation strategies and current and future climate scenarios using the EPIC model be carried out in the region.

6.5 Limitations of the study

Downscaled climate projections unavoidably inherit uncertainties from general circulation models (GCMs). Sources of uncertainty arise from internal variability of the model, the greenhouse gas emission scenario used (RCPs), the statistical downscaling process and imperfections in the GCMs from which the downscaled data was derived. Other sources include using only one crop model (EPIC) to project the impacts of climate change on crop yield. Asseng, (2013) suggested that ensembles of many models could give a better estimate of yield than using one model, however, this was beyond the scope of this study.

Also, crop management such as fertilization was also assumed to be similar across the future time periods which may not be the case in reality as farmers act to adapt to changing farming conditions. In addition, one maize cultivar was considered in this study assuming different cultivars would give similar responses to the impacts of climate change as presented in Rurinda et al., (2015) and Araya et al., (2015). It is also important to note that in utilizing survey responses, reported adaptation strategies were analysed, rather than observed strategies.

6.6 Conclusion

Farmers are aware of climate change and use a variety of adaptation strategies such as crop rotations and intercropping to cope with climate change impacts. The most noticeable changes farmers have observed are increases in temperature and changes in rainfall patterns. Both factors will have a negative impact on crop production and lead to decreased yields in the absence of agricultural management interventions. Apart from challenges associated with climate change such as increased temperature, farmers face other challenges such as access to credit lines that prevent them from effectively adapting to climate change.

Future climate change will have a negative impact on maize production and environmental water quality in the Eastern Cape. Already farmers are observing increases in temperature and decreases in crop and pasture yields. Mitigating the future impacts of climate change is a crucial food security task in the study area. Models can help anticipate a range of possible impacts of climate change on crop production and help in planning appropriate agricultural land management responses that will contribute to sustainable food production and food security. A modelling approach combined with farmers' knowledge from surveys offers a way of gaining useful insights into challenges that farmers encounter when trying to adapt to the climate. The EPIC model can be considered a useful tool for exploring the future impacts of climate change on crop yields and the environment. Future studies using EPIC should test the effectiveness of various crop rotation and intercropping strategies based on farmers current crop rotation and intercropping strategies

Chapter 7: **Synthesis**

7.1 Summary

Overall, this study contributes to the wider adaptation of the ecosystem services (ES) approach for agricultural land management and policy decisions. de Groot et al., (2010) identified quantitative methods as essential to move the concept of ES from theory into practice. However, better engagement of key stakeholders such as farmers in agriculture is equally important and a prerequisite to effectively applying the ES concept to agricultural land management policy development and decision making.

The main objectives of this research were to evaluate (i) the reasons behind farmers' current agricultural land management strategies (ii) the values farmers assigned to ES (iii) farmers' perceptions of climate change and (iv) to quantify the effects of agricultural land management strategies and climate change on ES provision in the Eastern Cape Province of South Africa. To achieve these objectives, the study adopted a social-technical approach to exploring and modelling agroecosystem services at the farm scale, and within the Eastern Cape region.

First, a survey of Eastern Cape conventional farmers was carried out to find out their current management practices, the values they assigned to different agroecosystem services and their perceptions of climate change. Next, a crop growth model, the Environmental Policy Integrated Climate Model (EPIC), was then calibrated and validated for South African conditions using limited data from field variety trials on maize carried out at the Cradock Research Farm in the Eastern Cape. After satisfactory calibration and validation, the model was applied to simulate different irrigation and Nitrogen (N) fertiliser management strategies to find the optimum N fertiliser and irrigation water management strategies for maize production in the Eastern Cape. Finally, to assess the impacts of future climate change on maize production in the Eastern Cape, statistically downscaled climate data for the Cradock area, driven by three GCMs for two future periods, under two different emission scenarios (RCP 4.5 and RCP 8.5) were used as input into the EPIC model to simulate future maize yields.

7.2 Addressing the research objectives of the study

7.2.1 Objective 1: To explore motivations for farmers' management practices and values of ecosystem services in an agroecosystem context in the Eastern Cape, South Africa.

Farmers had several reasons for using particular types of fertilisers and irrigation methods. Fertiliser choices were mostly based on crop yield or crop quality considerations. Choice of irrigation was mostly based on the cost of irrigation equipment and irrigation equipment available. Further, results show that while most farmers knew the amount of fertiliser they used; they did not know the exact amount of irrigation water they used during the crop growing season. The assumption that science has readily available technologies that can be used to solve farmers' problems has been described by (Nederlof and Odonkor, 2006) as erroneous. The results of this study show that farmers use complex sets of criteria such as crop quality, labour availability and access to markets. It is not always the case that solutions that are technically sound will be adopted by farmers. Policymakers and extension support should take this into consideration when developing or recommending agricultural land management practices for farmers. Farmer uptake of recommended agricultural land management can only be understood if the farmers' socio-cultural context is taken into account (Nederlof and Odonkor, 2006).

Farmers in the Eastern Cape revealed that lack of access to markets was a major constraint to farming. The study revealed that besides access to markets, farmers also lacked access to credit which may prevent them from buying new equipment and using technology to adapt to climate change. Concerning sources of information, farmers mostly exchanged farming-related information between themselves. Other important sources were the internet and Farmer's Organisations. While farmers had access to extension services, extension services only accounted for 27% as sources of information for farmers. This calls for the government to renew and strengthen extension efforts in the region and also presents opportunities for researchers to work with government extension services to provide sound information to improve farmers' agricultural management practices and access to climate change adaptation information.

The use of information and communication technology (ICT) in agriculture, also known as e-agriculture, can help in providing farmers with correct information on agricultural land management strategies and climate change adaptation strategies. Internet-based social platforms and the use of smartphones can be used to reach farmers that are not easily accessible.

The use of e-agriculture can help sustainable intensification efforts through improved information and communication processes between farmers, researchers and government agricultural extension services.

With regard to the values farmers assigned to different ES, survey results show that even though most farmers had not heard the term ES they recognised the multiple benefits that ecosystems provided to people. Farmers assigned a high value to food provisioning ES compared to other supporting services such as climate regulation and managed their farms to achieve maximum production. This may indicate that other ES may not be well understood by farmers. An understating of the values key stakeholders assign to ES can improve the implementation of the ES framework in agricultural land management and policy in the Eastern Cape.

7.2.2 Objective 2: To calibrate and validate the EPIC model for maize growth and yield simulation using limited field-scale data under South African conditions

The calibration of crop models is important to improve the reliability of crop model simulation when developing improved agronomic management practices as default crop parameters can result in the low predictive capacity of crop models (Guillaume et al., 2011). Experimental data provide robust references for crop model calibration (Wallach et al., 2011) however, the availability of such experimental data is limited as field experiments are costly and time-consuming.

In this thesis, a calibration procedure that can be applied to data-limited catchments is presented. The method comprises of three successive steps: (i) simulation with default parameters (ii) soil parameters adjustment to reflect site soils, (iii) calibration of Potential Heat Units based on local cultivar maximum and minimum temperatures and base temperatures and (iv) calibration of crop parameters. The calibration procedure is also feasible, with low computational costs. However, Klein (2013), explains that parameter set that may perform well under present conditions may not do so under future conditions or different site conditions. This implies that the predictive power of model significantly decreases when used under different conditions from the site the model was calibrated, a view opposed to the other view that the validity of dynamic crop models is beyond the conditions for which they have been calibrated (Wallach et al., 2006). Further, the current climate is not representative of future climate. This highlights the importance of considering parameter uncertainties when using model outputs.

7.2.3 Objective 3: To quantify the effects of agricultural land management strategies and climate change on selected agroecosystem services at the farm scale.

Comparison of farmers reported yields with yield simulations under improved fertiliser and irrigation water management suggests that there is room for improvement to increase farmers' maize yields from an average of 7 t ha^{-1} to approximately 12 t ha^{-1}. Simulations revealed that by managing N fertiliser and irrigation water more efficiently, farmers' maize yields could be significantly improved. A strong relationship between crop yield and nitrogen fertiliser indicates that nutrient management is critical to maintaining productivity. This is in agreement with findings by Mueller et al., (2012) that the yield gap can be closed with appropriate nutrient management when water is not limiting. In the 'rain-fed' only simulations, increasing fertiliser did not increase maize yields indicating that in semi-arid regions, water availability plays a significant role in determining crop yields.

Further, simulation results also showed the existence of trade-offs between agricultural productivity and N leaching. This is in agreement with previous studies (see e.g. Power, 2010), that have demonstrated the existence of trade-offs between agricultural productivity and environmental impacts. In this study, increasing N fertiliser application increased maize yields but was accompanied by a corresponding increase in N leaching. Increasing fertiliser beyond approximately 155 kg N ha^{-1} did not result in any further increases in maize yields but rather increased the amount of N lost through leaching. This highlights the importance of matching N fertiliser applications to cropping needs to avoid both economic losses and negative environmental impacts.

Model simulations further showed that the trade-offs between increasing maize yields and minimising nutrient leaching can be expected to intensify with climate change, especially towards the end of the century. The establishment of catch crops to minimise N leaching has been broadly suggested in the literature. Studies on the use of catch crops have mostly been based on modelling (Constantin et al., 2012; Doltra et al., 2011) or field experiments (Askegaard et al., 2011). Farmers can be encouraged on the use of catch or cover crops such as cowpeas, oats or alfalfa to minimise N fertiliser losses through N leaching.

7.2.4 Objective 4: To evaluate farmers' perceptions of climate change and compare current and future maize yields under different future climate scenarios.

Survey results indicate that farmers in the Eastern Cape are aware of climate change and are able to describe the effects climate had on crop and pasture production. About 40% of farmers had observed changes in temperature and precipitation while 38% had noticed changes in crop and pasture yields and attributed these yield changes to climate change. These observations are consistent with several studies in South Africa that have shown general increases in temperature and rainfall intensity (Jury, 2018; MacKellar et al., 2014). The perceptions of climate change and adaptation choices made by farmers are important considerations in the design of adaptation strategies by policymakers (Waibel et al., 2018). Failure to take into account these perceptions may result in the development of adaptation strategies that may not be taken up by farmers. In this study, the majority of farmers already indicated the use of adaptation strategies such as crop rotations and intercropping. It would be useful for future studies to use models to test the effectiveness of adaptation strategies under current and future climate change.

EPIC simulation results revealed that under current crop management conditions, climate change will generally have a negative effect on maize yield. All three climate models showed a projected decline in maize yield mostly due to increased temperatures since a fully irrigated maize crop was used in the simulations. In addition, simulations showed that irrigation water requirements are likely to decrease on average due to the decreases in yield. While the decline in irrigation water requirements in the catchment due to water scarcity already being experienced in the catchment, this decrease in irrigation water requirement will be accompanied by a decrease in yields and water use efficiency. N leaching is also projected to increase in all scenarios with increases by as much as to 373% in the 2090s.

7.3 Agricultural land management and policy implications of the study

Improvement of agricultural land management practices and climate change adaptation strategies in the Eastern Cape will be necessary for both the current and future periods. This study has shown that maize yields in the Eastern Cape can be improved by managing N fertiliser and irrigation water in a more efficient manner. To improve crop productivity while minimising environmental impacts, there is need to encourage farmers to manage irrigation water and fertiliser simultaneously, ensuring that these inputs are provided to the crop at the right rate, from the right source, at the right placement and at the right timing. Irrigation efficiency could be improved by using drip irrigation, the use of sensors to detect soil moisture levels and regularly monitoring equipment and repairing leaks in irrigation systems. Fertiliser efficiency could be improved by using techniques such as precision agriculture, application of fertilisers in irrigation water, and micro-dosing techniques that have been tested in field trials.

If sustainable intensification is to be achieved, there is an urgent need to strengthen agricultural extension services in the region. The results of this study have shown that currently, extension support to farmers in the area is low. Improved extension support will play a critical role in providing farmers with technical information based on scientific principles that is necessary to adapt to climate change and sustainably increase crop yields. Such technical information can be provided to farmers through government training of extension workers. Extension workers should be trained on new technologies and techniques to improve agricultural land management as well as strategies to adapt to climate change. Extension workers form an important link between policymakers, researchers and farmers as they can serve as middlemen who can pass information about more efficient agricultural land management practices, climate change and market information. Extension workers should be given the capacity to regularly visit farmers and work closely with farmers in implementing sustainable agricultural land management practices and keeping good farm records that can be used to inform crop modelling studies. In addition, farmers' field schools can be used to provide information to groups of farmers. Results of this study have shown that farmers rely on information from other farmers. Using farmers field schools can be an effective way of spreading BMPs among farmers in the region. Farmers' field schools could be funded by other stakeholders in agriculture such as fertiliser and seed companies in collaboration with farmers organisations and government departments such as the Department of Agriculture.

The study demonstrated the usefulness of crop trial data in calibrating a crop model before its application, even though the data was limited. Organisations such as the ARC grain institute and SA Grain regularly carry out field trials on crops such as maize and wheat. However, these trials are mainly to test differences between crop varieties and not necessarily to inform crop modelling studies. Crop modellers could work with trial managers to design trials in which key parameters needed for model evaluation could also be measured. This can increase the quality of data available for model calibration and validation in South Africa. Limited data to calibrate models is often cited as one of the major challenges in the application of crop models in South Africa (Zinyengere et al., 2015).

Crop production is one aspect of sustainable intensification as other factors also contribute to the total food production system. The study showed that apart from addressing the challenges associated with climate change, farmers have to overcome a variety of challenges associated with farming. For example, many farmers responded that limited access to markets was a major constraint to farming. The government may subsidise farmers by providing easier access to credit or new and improved farming equipment. Access to credit will allow farmers to purchase agricultural inputs and will also encourage farmers to adopt more efficient agricultural land management strategies (e.g. adoption of drip irrigation systems) that contribute to sustainable intensification and increased food security. Government and conservation organisation should also increase the number of PES programmes that involve farmers in the Eastern Cape to encourage farmers to manage farms for the provision of multiple ES. Farmers in this study showed a willingness to participate in PES schemes however, studies should be conducted first to find out which ES should receive payments and at what level or form of payment.

7.4 Study limitations

The modelling approach used in this study faced several limitations mainly emerging from (i) the use of a crop model and (ii) climate modelling uncertainties while the farmers' survey was restricted by a limited sample size.

7.4.1 The use of a crop model

Crop modelling studies and climate impact studies can be useful sources of information do aid framers and policymakers in decision making and planning. However, it is important to consider the success of uncertainty that can be introduced into the study at different points (Klein, 2013). Sources of uncertainty are related to input data and model structure. These two sources of uncertainty are briefly described below

Input data

Uncertainties related to input data usually relate to errors in the soil and weather input data that may not be entirely representative of the study area. This is usually due to a lack of detailed site-specific data, which may warrant the use of global data sets generated by extrapolation. In this study, some soil parameters needed as input in the model were not measured in sufficient detail or completely not measured during the field experiments. The HWSD is the only publicly available source of information with sufficient detail on soil texture available in South Africa. The HSWD was used to complement the site-specific available soil data under the guidance of expert opinion on soil properties of the study site. The HSWD is quality controlled by FAO and IIASA (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009). With regard to weather data, the

AgMERRA database is quality controlled by NASA's Global Modelling and Assimilation Office (Rienecker et al., 2011), potentially reducing the uncertainty related to input data.

Model structure

Klein (2013) explains that model equations are all subject to variability and uncertainty. As a result, functional relationships between input and outputs can be subjective depending on the model used (Bao et al., 2016). Processes included in simulation models may not always be fully understood or well implemented. For example, Free Air Carbon Enrichment (FACE) experiments indicate productivity increases due to increased carbon dioxide levels but do not address important co-limitations arising from water and nutrient availability (Klein, 2013). The magnitude of crops responses to increased CO_2 levels is thus uncertain and the subject of current debates among researchers (Long et al., 2006; Parry et al., 2004). Biernath et al., (2011), argues that many crop models are currently unable to capture the complex underlying processes associated with CO_2 fertilization and are therefore unable to reproduce experimental results. In this study, the CO_2 effects were not considered due to lack of annual data on future CO_2 levels for the periods used in the scenarios. To reduce uncertainties associated with the model structure, the use of an ensemble of crop models has been suggested for example the AgMIP Project (Agricultural Model Inter-comparison and Improvement) (Rosenzweig et al., 2013), which compares the outputs of several models based on the same data sets. However, this was beyond the scope of the present study.

A limiting factor in crop production in Sub Saharan agricultural systems is insufficient availability of micronutrients such as zinc and molybdenum in soils (Folberth, 2013). According to Bationo et al., (1998), micronutrient deficiencies can render increased application of macronutrients ineffective. Available soil data did not include micronutrient elements and the EPIC version 0810 used in the study does not account for the role of micronutrients in plant growth. Phosphorus application rates were not also considered and assumed to be sufficient. However, in practice, this may vary between different farmers' fields.

7.4.2 Climate change modelling uncertainties

Results of climate change impacts are subject to several uncertainties due to incomplete knowledge about the underlying geophysical processes of global change (GCM uncertainties) and due to uncertain future scenarios (emission scenario uncertainties) (Folberth, 2013). Uncertainties in climate projections with respect to climate models can have significant impacts on crop model outputs (Ceglar et al., 2011; Klein, 2013). To reduce uncertainties associated with individual climate models, three different models under two contrasting climate scenarios were selected to capture the full range of changes in temperature and precipitation projected by the models. van der Linden and Mitchell, (2009) state that emission scenario uncertainties are less relevant until the middle of the 21st century hence the 2040-2069 scenario was chosen as the starting period for future climate simulations.

7.4.3 Survey limitations

The study was restricted by a limited sample size. Many farmers who had been contacted declined to participate in the study indicating that they were not comfortable revealing their farm business details such as the size of the farm, farm income and fertiliser practices. The limited sample size restricted the analysis of results to descriptive statistics. A limitation in the number of respondents might lead to limitations for quantitative analysis due to the number of cases and due to the absence of variance in the population. Case studies can provide insightful data and can be considered effective tools for research on limited sample sizes (Chetty, 1996) and as a suitable approach for theory building (Eisenhardt and Graebner, 2007). It is recommended that future studies engage a 'trusted' agent such as a Farmer's Organisations to assist with similar studies and minimise issues of mistrust between researchers and farmers.

7.5 Recommendations for future research

Future work with EPIC will involve testing the effectiveness of several adaptation strategies under different climate change scenarios. This should be done with the involvement of stakeholders particularly farmers (both commercial, emerging and smallholder farmers) who are ultimately responsible for taking up adaptation strategies. Future studies may also look at the effectiveness of different crop rotations, for example, maize-soybean or maize-alfalfa rotations under different future climate scenarios. In addition, future studies with farmers can test farmers' knowledge of the interrelationship of different ES in agroecosystems.

There are considerable uncertainties in the assessment of climate change impacts on crop yield using crop models. Besides the uncertainties arising from the use of GCMs, there are significant differences between projections of climate impacts on crop yields from different crop models using the same climate data sets. These differences are often due to differences in model set up, model parameterisation and model assumptions (Folberth, 2013). Reducing these uncertainties requires a combined effort from the crop modelling community in South Africa to compare EPIC outputs with other models such as the ACRU (Schulze, 1995) or AquaCrop (Raes et al., 2009) models. Such a joint effort will improve the reliability of crop models in the prediction of climate change impacts on crop yields and water use.

The modelling approach applied in this study has been applied to the Cradock area only. The model could be applied to other catchments since climate conditions and soil may significantly differ. Field trials are regularly carried out by the Agricultural Research Council in many parts of South Africa (Dlamini et al., 2015). Crop modellers should endeavour to work with crop variety trial managers to design field trials that capture comprehensive data that can be used for model calibration and validation. Partnerships between crop modellers, trial managers and seed producers can improve the availability of data for model calibration and validation. Models can then, in turn, be applied to simulate the performance of crop varieties under different soil and climate conditions. Extension and farmer support should also encourage detailed record-keeping of farm management practices by farmers. Detailed farm agricultural management records can be used for rigorous model calibration and validation.

In conclusion, the present study is one of the few studies that use a social-technical approach within an ES framing, combining insights from farmers practices, values and behaviour with those from an application of a technical model to shed light on important maize production parameters under present and future climate conditions. The study thus makes important contributions to the understanding of the complexity of interacting factors that may influence agroecosystem services at the farm scale.

References

Abraha, M.G., Savage, M.J., 2006. Potential impacts of climate change on the grain yield of maize for the midlands of KwaZulu-Natal, South Africa. Agric. Ecosyst. Environ. 115, 150–160. https://doi.org/10.1016/j.agee.2005.12.020

Abson, D.J., von Wehrden, H., Baumgärtner, S., Fischer, J., Hanspach, J., Härdtle, W., Heinrichs, H., Klein, A.M., Lang, D.J., Martens, P., Walmsley, D., 2014. Ecosystem services as a boundary object for sustainability. Ecol. Econ. 103, 29–37. https://doi.org/10.1016/j.ecolecon.2014.04.012

Adejuwon, J.O., 2004. Assessing the Suitability of the EPIC Crop Model for Use in the Study of Impacts of Climate Variability and Climate Change in West Africa.

Albaji, M., Shahnazari, A., Behzad, M., Naseri, A., BoroomandNasab, S., Golabi, M., 2010. Comparison of different irrigation methods based on the parametric evaluation approach in Dosalegh plain: Iran. Agric. Water Manag. 97, 1093–1098. https://doi.org/10.1016/J.AGWAT.2010.02.015

Albaugh, J.M., Dye, P.J., King, J.S., 2013. *Eucalyptus* and Water Use in South Africa. Int. J. For. Res. 2013, 1–11. https://doi.org/10.1155/2013/852540

Alexandrov, V., Hoogenboom, G., 1999. Crop Water Use as a Function of Climate Variability in Georgia, in: Hatcher, K.J. (Ed.), Proceedings of the 1999 Georgia Water Resources Conference : March 30-31, 1999. Institute of Ecology, University of Georgia, Athens, Georgia, pp. 425–428.

Ali, M.H., Talukder, M.S.U., 2008. Increasing water productivity in crop production—A synthesis. Agric. Water Manag. 95, 1201–1213. https://doi.org/10.1016/J.AGWAT.2008.06.008

Anderson, S.J., Ankor, B.L., Sutton, P.C., 2017. Ecosystem service valuations of South Africa using a variety of land cover data sources and resolutions. Ecosyst. Serv. 27, 173–178. https://doi.org/10.1016/j.ecoser.2017.06.001

Angulo, C., Rötter, R., Lock, R., Enders, A., Fronzek, S., Ewert, F., 2013. Implication of crop model calibration strategies for assessing regional impacts of climate change in Europe. Agric. For. Meteorol. 170, 32–46. https://doi.org/10.1016/j.agrformet.2012.11.017

Angus, J.F., Cunningham, R.B., Moncur, M.W., Mackenzie, D.H., 1980. Phasic development in field crops I. Thermal response in the seedling phase. F. Crop. Res. 3, 365–378. https://doi.org/10.1016/0378-4290(80)90042-8

Annandale, J.G., Steyn, J.M., Benadé, N., Jovanovic, N.Z., Soundy, P., 2005. Technology Transfer of the Soil Water Balance (SWB) model as a user friendly Irrigation Scheduling Tool.

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K.M., Kisekka, I., Martorano, L.G., 2015. Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. Agric. For. Meteorol. 214–215, 252–265. https://doi.org/10.1016/J.AGRFORMET.2015.08.259

ARC, 2017. Maize Information Guide. Pretoria, South Africa.

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., Van Griensven, A., Liew, M W Van, Kannan, N., Jha, M.K., Harmel, D., Member, A., Liew, Michael W Van, Arnold, J.-F.G., 2012. SWAT: Model Use, Calibration and Validation. Trans. ASABE 55, 1491–1508.

Arunrat, N., Pumijumnong, N., Hatano, R., 2018. Predicting local-scale impact of climate change on rice yield and soil organic carbon sequestration: A case study in Roi Et Province, Northeast Thailand. Agric. Syst. 164, 58–70. https://doi.org/10.1016/J.AGSY.2018.04.001

Askegaard, M., Olesen, J.E., Rasmussen, I.A., Kristensen, K., 2011. Nitrate leaching from organic arable crop rotations is mostly determined by autumn field management. Agric. Ecosyst. Environ. 142, 149–160. https://doi.org/10.1016/J.AGEE.2011.04.014

Asseng, S., 2013. Uncertainty in simulating wheat yields under climate change. Nat. Clim. Chang. 3, 627–632. https://doi.org/10.1038/ncliamte1916

Assoumana, B., Ndiaye, M., Der Puije, G. Van, Diourte, M., Gaiser, T., 2016. Comparative Assessment of Local Farmers' Perceptions of Meteorological Events and Adaptations Strategies: Two Case Studies in Niger Republic. J. Sustain. Dev. 9, 118. https://doi.org/10.5539/jsd.v9n3p118

Aza-Gnandji1, C.R., Xu, Y., Raitt, L., Levy, J., 2013. Salinity of irrigation water in the Philippi farming area of the Cape Flats, Cape Town, South Africa 39. https://doi.org/10.4314/wsa.v39i2.3

Babbie, E.R., 2013. The practice of social research. Wadsworth Cengage Learning.

Babbie, E.R., Mouton, J. (Johann), 2001. The practice of social research, South Afri. ed. Oxford University Press Southern Africa, Cape Town.

Badgley, C., Moghtader, J., Quintero, E., Zakem, E., Chappell, M.J., Avilés-Vázquez, K., Samulon, A., Perfecto, I., 2007. Organic agriculture and the global food supply. Renew. Agric. Food Syst. 22, 86–108. https://doi.org/10.1017/S1742170507001640

Bagstad, K.J., Semmens, D.J., Waage, S., Winthrop, R., 2013. A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosyst. Serv. 5, 27–39. https://doi.org/10.1016/j.ecoser.2013.07.004

Balasko, J.A., Smith, D., 1971. Influence of Temperature and Nitrogen Fertilization on the Growth and Composition of Switchgrass (Panicum virgatum L.) and Timothy (Phleum pratense L.) at Anthesis1. Agron. J. 63, 853. https://doi.org/10.2134/agronj1971.00021962006300060009x

Balkovic, J., 2018. International Institute of Applied Systems Analysis. Austria, Personal Communication.

Balkovič, J., Van Der Velde, M., Schmid, E., Skalsk, R., Obersteiner, M., Stürmer, B., Xiong, W., 2013. Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation. https://doi.org/10.1016/j.agsy.2013.05.008

Balkovič, J., van der Velde, M., Skalský, R., Xiong, W., Folberth, C., Khabarov, N., Smirnov, A., Mueller, N.D., Obersteiner, M., 2014. Global wheat production potentials and management flexibility under the representative concentration pathways. Glob. Planet. Change 122, 107–121. https://doi.org/10.1016/J.GLOPLACHA.2014.08.010

Bao, Y., Hoogenboom, G., McClendon, R., Vellidid, G., 2016. A comparison of the performance of the CSM-CERES-Maize and EPIC models using maize variety trial data. Elsevier.

Barbier, E., Koch, E., Silliman, B., 3 Sally D. Hacker, 4, Eric Wolanski,5 Jurgenne Primavera,6 Elise F. Granek,7 Stephen Polasky,8 Shankar Aswani, 9, Lori, A., 2009. Coastal ecosystem-based management with nonlinear in ecological functions and values. Zhongguo Renkou Ziyuan Yu Huan Jing/ China Popul. Resour. Environ.

Barbier, E.B., Hacker, S.D., Kennedy, C., Koch, E.W., Stier, A.C., Silliman, B.R., 2011. The value of estuarine and coastal ecosystem services, Ecological Monographs.

Basche, A.D., Archontoulis, S. V., Kaspar, T.C., Jaynes, D.B., Parkin, T.B., Miguez, F.E., 2016. Simulating long-term impacts of cover crops and climate change on crop production and environmental outcomes in the Midwestern United States. Agric. Ecosyst. Environ. 218, 95–106. https://doi.org/10.1016/J.AGEE.2015.11.011

Bastian, O., Haase, D., Grunewald, K., 2012. Ecosystem properties, potentials and services – The EPPS conceptual framework and an urban application example. Ecol. Indic. 21, 7–16. https://doi.org/10.1016/J.ECOLIND.2011.03.014

Bationo, A., Lompo, F., Koala, S., 1998. Research on nutrient flows and balances in west Africa: state-of-the-art. Agric. Ecosyst. Environ. 71, 19–35. https://doi.org/10.1016/S0167-8809(98)00129-7

Baulcombe, D., Crute, I., Davies, B., Dunwell, J., Gale, M., Jones, J., Ptetty, J., Sutherland, W., Toulmin, C., 2009. Reaping the benefits: science and the sustainable intensification of global agriculture., Manufacturing Chemist. The Royal Society, Policy document 11/09, London.

Bembridge, T.J., 2000. Guidelines for rehabilitation of small-scale farmer irrigation schemes in South Africa. Water Research Commission, Pretoria :

Bennett, E.M., Peterson, G.D., Gordon, L.J., 2009. Understanding relationships among multiple ecosystem services. Ecol. Lett. 12, 1394–1404. https://doi.org/10.1111/j.1461-0248.2009.01387.x

Berkes, F., Colding, J., Folke, C., 2003. Navigating Social-Ecological Systems: Building Resilience for Complexity and Change.

Bernués, A., Tello-García, E., Rodríguez-Ortega, T., Ripoll-Bosch, R., Casasús, I., 2016. Agricultural practices, ecosystem services and sustainability in High Nature Value farmland: Unraveling the perceptions of farmers and nonfarmers. Land use policy

59, 130–142. https://doi.org/10.1016/J.LANDUSEPOL.2016.08.033

Biernath, C., Gayler, S., Bittner, S., Klein, C., Högy, P., Fangmeier, A., Priesack, E., 2011. Evaluating the ability of four crop models to predict different environmental impacts on spring wheat grown in open-top chambers. Eur. J. Agron. 35, 71–82. https://doi.org/10.1016/J.EJA.2011.04.001

Bockstaller, C., Girardin, P., 2003. How to validate environmental indicators. Agric. Syst. 76, 639–653. https://doi.org/10.1016/S0308-521X(02)00053-7

Bommarco, R., Kleijn, D., Potts, S.G., 2013. Ecological intensification: harnessing ecosystem services for food security. Trends Ecol. Evol. 28, 230–238. https://doi.org/10.1016/j.tree.2012.10.012

Boumans, R., Roman, J., Altman, I., Kaufman, L., 2015. The Multiscale Integrated Model of Ecosystem Services (MIMES): Simulating the interactions of coupled human and natural systems. Ecosyst. Serv. 12, 30–41. https://doi.org/10.1016/j.ecoser.2015.01.004

Boyd, J., Banzhaf, S., 2007. What are ecosystem services? The need for standardized environmental accounting units. Ecol. Econ. 63, 616–626. https://doi.org/10.1016/J.ECOLECON.2007.01.002

Bozkurt, Y., Yazar, A., Gençel, B., Sezen, M.S., 2006. Optimum lateral spacing for drip-irrigated corn in the Mediterranean Region of Turkey. Agric. Water Manag. 85, 113–120. https://doi.org/10.1016/J.AGWAT.2006.03.019

Braat, L.C., de Groot, R., 2012. The ecosystem services agenda:bridging the worlds of natural science and economics, conservation and development, and public and private policy. Ecosyst. Serv. 1, 4–15. https://doi.org/10.1016/J.ECOSER.2012.07.011

Branch, G.M., Bustamante, R.H., Robinson, T.B., 2013. Impacts of a ‘black tide’ harmful algal bloom on rocky-shore intertidal communities on the West Coast of South Africa. Harmful Algae 24, 54–64. https://doi.org/10.1016/J.HAL.2013.01.005

Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qual. Res. Psychol. 3, 77–101. https://doi.org/10.1191/1478088706qp063oa

Breman, H., Groot, J.J.R., van Keulen, H., 2001. Resource limitations in Sahelian agriculture. Glob. Environ. Chang. 11, 59–68. https://doi.org/10.1016/S0959-3780(00)00045-5

Briner, S., 2012. Provision of ecosystem goods and services by agriculture and forestry in mountainous regions of Switzerland. ETH ZURICH. https://doi.org/10.3929/ethz-a-007567387

Bryan, B., Crossman, N., 2013. Impact of multiple interacting financial incentives on land use change and the supply of ecosystem services. Ecosyst. Serv. 4, 60–72. https://doi.org/10.1016/j.ecoser.2013.03.004

Bryant, K.J., Benson, V.W., Kiniry, J.R., Williams, J.R., Lacewell, R.D., 1992. Simulating Corn Yield Response to Irrigation Timings: Validation of the Epic

Model. jpa 5, 237. https://doi.org/10.2134/jpa1992.0237

Burkhard, B., Petrosillo, I., Costanza, R., 2010. Ecosystem services – Bridging ecology, economy and social sciences. Ecol. Complex. 7, 257–259. https://doi.org/10.1016/j.ecocom.2010.07.001

Cabelguenne, M., Debaeke, P., Bouniols, A., 1999. EPICphase, a version of the EPIC model simulating the effects of water and nitrogen stress on biomass and yield, taking account of developmental stages: validation on maize, sunflower, sorghum, soybean and winter wheat. Agric. Syst. 60, 175–196. https://doi.org/10.1016/S0308-521X(99)00027-X

Cabelguenne, M., Jones, C., Marty, J., Dyke, P., 1990. Calibration and validation of EPIC for crop rotations in southern France. Agric. Syst. 33, 153–171.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R.S.J., Ringler, C., 2014. Climate change and agriculture: Impacts and adaptation options in South Africa. Water Resour. Econ. 5, 24–48. https://doi.org/10.1016/J.WRE.2014.03.001

Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., Defries, R.S., Díaz, S., Dietz, T., Duraiappah, A.K., Oteng-Yeboah, A., Pereira, H.M., Perrings, C., Reid, W. V, Sarukhan, J., Scholes, R.J., Whyte, A., 2009. Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment.

Cassman, K.G., 1999. Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture. Proc. Natl. Acad. Sci. U. S. A. 96, 5952–5959. https://doi.org/10.1073/pnas.96.11.5952

Causarano, H.J., Doraiswamy, P.C., Muratova, N., Pachikin, K., Mccarty, G.W., Akhmedov, B., Williams, J.R., 2010. Improved modeling of soil organic carbon in a semiarid region of Central East Kazakhstan using EPIC. https://doi.org/10.1051/agro/2010028

Causarano, H.J., Shaw, J.N., Franzluebbers, A.J., Reeves, D.W., Raper, R.L., Balkcom, K.S., Norfleet, M.L., Izaurralde, R.C., 2007. Simulating Field-Scale Soil Organic Carbon Dynamics Using EPIC. Soil Sci. Soc. Am. J. 71, 1174. https://doi.org/10.2136/sssaj2006.0356

Cavigelli, M.A., Hima, B.L., Hanson, J.C., Teasdale, J.R., Conklin, A.E., Lu, Y., 2009. Long-term economic performance of organic and conventional field crops in the mid-Atlantic region. Renew. Agric. Food Syst. 24, 102–119. https://doi.org/10.1017/S1742170509002555

CCA, 2013. Council of Canadian Academies | CCA | Water and Agriculture in Canada: Towards Sustainable Management of Water Resources.

Ceglar, A., Črepinšek, Z., Kajfež-Bogataj, L., Pogačar, T., 2011. The simulation of phenological development in dynamic crop model: The Bayesian comparison of different methods. Agric. For. Meteorol. 151, 101–115. https://doi.org/10.1016/j.agrformet.2010.09.007

Challinor, A.J., Ewert, F., Arnold, S., Simelton, E., Fraser, E., 2009. Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. J. Exp. Bot. 60, 2775–2789. https://doi.org/10.1093/jxb/erp062

Challinor, A.J., Müller, C., Asseng, S., Deva, C., Nicklin, K.J., Wallach, D., Vanuytrecht, E., Whitfield, S., Ramirez-Villegas, J., Koehler, A.-K., 2018. Improving the use of crop models for risk assessment and climate change adaptation. Agric. Syst. 159, 296–306. https://doi.org/10.1016/J.AGSY.2017.07.010

Chetty, S., 1996. The Case Study Method for Research in Small-and Medium-Sized Firms. Int. Small Bus. J. Res. Entrep. 15, 73–85. https://doi.org/10.1177/0266242696151005

Clewer, A.G., Scarisbrick, D.H., 2001. Practical statistics and experimental design for plant and crop science. Wiley.

Collett, A., 2013. The impact of effective (geo-spatial) planning on the agricultural sector. South African Surv. Geomatics Indaba 22-24 July 2013.

Confalonieri, R., Orlando, F., Paleari, L., Stella, T., Gilardelli, C., Movedi, E., Pagani, V., Cappelli, G., Vertemara, A., Alberti, L., Alberti, P., Atanassiu, S., Bonaiti, M., Cappelletti, G., Ceruti, M., Confalonieri, A., Corgatelli, G., Corti, P., Dell'Oro, M., Ghidoni, A., Lamarta, A., Maghini, A., Mambretti, M., Manchia, A., Massoni, G., Mutti, P., Pariani, S., Pasini, D., Pesenti, A., Pizzamiglio, G., Ravasio, A., Rea, A., Santorsola, D., Serafini, G., Slavazza, M., Acutis, M., 2016. Uncertainty in crop model predictions: What is the role of users? Environ. Model. Softw. 81, 165–173. https://doi.org/10.1016/j.envsoft.2016.04.009

Constantin, J., Beaudoin, N., Launay, M., Duval, J., Mary, B., 2012. Long-term nitrogen dynamics in various catch crop scenarios: Test and simulations with STICS model in a temperate climate. Agric. Ecosyst. Environ. 147, 36–46. https://doi.org/10.1016/J.AGEE.2011.06.006

Cook, S., Silici, B., Walker, S., 2015. Sustainable intensification revisted, World Agriculture. London. https://doi.org/10.7591/9780801466083-009

Costanza, R., De Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., Farber, S., Grasso, M., 2017. Twenty years of ecosystem services: How far have we come and how far do we still need to go? https://doi.org/10.1016/j.ecoser.2017.09.008

Costanza, R., de Groot, R., Farberll, S., Grassot, M., Hannon, B., Limburg, K., Naeem, S., O, R. V, Paruelo, J., Raskin, R.G., Suttonllll, P., 1997. The value of the world's ecosystem services and natural capital.

Costanza, R., Pérez-Maqueo, O., Martinez, M.L., Sutton, P., Anderson, S.J., Mulder, K., 2008. The Value of Coastal Wetlands for Hurricane Protection. AMBIO A J. Hum. Environ. 37, 241–248. https://doi.org/10.1579/0044-7447(2008)37[241:TVOCWF]2.0.CO;2

Craufurd, P.Q., Wheeler, T.R., 2009. Climate change and the flowering time of annual crops. J. Exp. Bot. 60, 2529–2539. https://doi.org/10.1093/jxb/erp196

Crossman, N.D., Burkhard, B., Willemen, L., Palomo, I., Drakou, E.G., Martín-Lopez, B., McPhearson, T., Boyanova, K., Egoh, B., Dunbar, M.B., Maes, J., 2013. A blueprint for mapping and modelling ecosystem services. Ecosyst. Serv. 4, 4–14.

https://doi.org/10.1016/J.ECOSER.2013.02.001

Cumming, G.S., Maciejewski, K., 2017. Reconciling community ecology and ecosystem services: Cultural services and benefits from birds in South African National Parks. Ecosyst. Serv. 28, 219–227. https://doi.org/10.1016/j.ecoser.2017.02.018

Daggupati, P., Pai, N., Ale, S., Douglas-Mankin, K.R., Zeckoski, R.W., Jeong, J., Parajuli, P.B., Saraswat, D., Youssef, M.A., 2015. A Recommended Calibration and Validation Strategy for Hydrologic and Water Quality Models. Trans. ASABE 58, 1705–1719. https://doi.org/10.13031/trans.58.10712

Daily, G.C., 1997. Nature's Services Societal Dependence on Natural Ecosystems. Island Press. https://doi.org/10.1017/9781108233194.003

Datta, A., 2013. Genetic engineering for improving quality and productivity of crops. Agric. Food Secur. 2, 2–4. https://doi.org/10.1186/2048-7010-2-15

Davenport, N.A., Shackleton, C.M., Gambiza, J., 2012. The direct use value of municipal commonage goods and services to urban households in the Eastern Cape, South Africa. Land use policy 29, 548–557. https://doi.org/10.1016/j.landusepol.2011.09.008

Davis-Reddy, C.L., Vincent, K., 2017. Climate Change Handbook for Southern Africa Climate, 2nd ed. CSIR, Pretoria, South Africa.

Davis, K.E., Terblanché, S.E., 2016. Challenges facing the agricultural extension landscape in South Africa, Quo Vadis? South African J. Agric. Ext. 44, 231–247. https://doi.org/10.17159/2413-3221/2016/v44n2a428

Daw, T.M., Hicks, C.C., Brown, K., Chaigneau, T., Januchowski-Hartley, F.A., Cheung, W.W.L., Rosendo, S., Crona, B., Coulthard, S., Sandbrook, C., Perry, C., Bandeira, S., Muthiga, N.A., Schulte-Herbrüggen, B., Bosire, J., McClanahan, T.R., 2016. Elasticity in ecosystem services: exploring the variable relationship between ecosystems and human well-being. Ecol. Soc. 21, art11. https://doi.org/10.5751/ES-08173-210211

de Groot, R.S., 1992. Functions of nature : evaluation of nature in environmental planning, management and decision making. Funct. Nat. Eval. Nat. Environ. planning, Manag. Decis. making.

de Groot, R.S., 1987. Environmental functions as a unifying concept for ecology and economics. Environmentalist 7, 105–109. https://doi.org/10.1007/BF02240292

de Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecol. Complex. 7, 260–272. https://doi.org/10.1016/J.ECOCOM.2009.10.006

De Vaus, D.A., 2013. Surveys in social research, Sixth. ed. Routledge.

Dechmi, F., Skhiri, A., 2013. Evaluation of best management practices under intensive irrigation using SWAT model. Agric. Water Manag. 123, 55–64. https://doi.org/10.1016/j.agwat.2013.03.016

DeFries, R., Foley, J., Asner, G., 2004. Balancing human needs and ecosystem function RS DeFries et al. Front Ecol Env. 2, 249–257.

Department of Environmental Affairs, 2013. Long-Term Adaptation Scenarios Flagship Research Programme (LTAS) for South Africa. Climate Change Implications for the Water Sector in South Africa., LTAS Phase Technical Report. Pretoria.

Devereux, S., Waidler, J., 2017. Why does malnutrition persist in South Africa despite social grants? (No. No.001), Food Security SA Working Paper Series.

Dietz, T., Fitzgerald, A., Shwom, R., 2005. Environmental Values. Annu. Rev. Environ. Resour. 30, 335–372. https://doi.org/10.1146/annurev.energy.30.050504.144444

Dietze, V., Hagemann, N., Jürges, N., Bartke, S., Fürst, C., 2019. Farmers consideration of soil ecosystem services in agricultural management - A case study from Saxony, Germany. Land use policy 81, 813–824. https://doi.org/10.1016/J.LANDUSEPOL.2018.11.003

Djaman, K., O'Neill, M., Owen, C., Smeal, D., Koudahe, K., West, M., Allen, S., Lombard, K., Irmak, S., 2018. Crop Evapotranspiration, Irrigation Water Requirement and Water Productivity of Maize from Meteorological Data under Semiarid Climate. Water 10, 405. https://doi.org/10.3390/w10040405

Dlamini, T.., 2014. An Economic Value of the National Cultivar Trials in South Africa. Pretoria.

Dlamini, T.S., Magingxa, L., Liebenberg, F., 2015. Estimating the economic value of the national cultivar trials in South Africa: A case for sorghum, sunflower, soybeans and dry beans, in: 2015 Fourth Congress, June 11-12, 2015. Italian Association of Agricultural and Applied Economics (AIEAA)., Ancona, Italy.

Doltra, J., Lægdsmand, M., Olesen, J.E., 2011. Cereal yield and quality as affected by nitrogen availability in organic and conventional arable crop rotations: A combined modeling and experimental approach. Eur. J. Agron. 34, 83–95. https://doi.org/10.1016/j.eja.2010.11.002

Dominati, E., Patterson, M., Mackay, A., 2010. A framework for classifying and quantifying the natural capital and ecosystem services of soils. Ecol. Econ. 69, 1858–1868. https://doi.org/10.1016/j.ecolecon.2010.05.002

Dominguez-Faus, R., Folberth, C., Liu, J., Jaffe, A.M., Alvarez, P.J.J., 2013. Climate Change Would Increase the Water Intensity of Irrigated Corn Ethanol. Environ. Sci. Technol. 47, 6030–6037. https://doi.org/10.1021/es400435n

Doré, T., Makowski, D., Malézieux, E., Munier-Jolain, N., Tchamitchian, M., Tittonell, P., 2011. Facing up to the paradigm of ecological intensification in agronomy: Revisiting methods, concepts and knowledge. Eur. J. Agron. 34, 197–210. https://doi.org/10.1016/j.eja.2011.02.006

Dreschel, P., Heffer, P., Magen, H., Mikkelsen, R., Wichelns, D., 2015. Managing Water and Fertilizer for Sustainable Agricultural Intensification, First edit. ed, International Fertilizer Industry Association. International Fertilizer Industry Association (IFA), Internatio- nal Water Management Institute (IWMI), International Plant Nutrition Institute (IPNI), and International Potash Institute (IPI), Paris, France.

du Plessis, J., 2003. Maize production. Department of Agriculture, Pretoria, South Africa.

du Plessis, J., Bruwer, D., 2003. Short Growing Season Cultivars. ARC – Grain Crops Institute. Potchefstroom, South Africa.

Duguma, L., Minang, P., Aynekulu, E., Carsan, S., Nzyoka, J., Bah, A., Jamnadass, R., 2020. From Tree Planting to Tree Growing : Rethinking Ecosystem Restoration Through Trees From Tree Planting to Tree Growing : Rethinking Ecosystem Restoration Through Trees 34. https://doi.org/http://dx.doi.org/10.5716/WP20001.PDF

Durr, C., Constantin, J., Wagner, M.-H., Navier, H., Demilly, D., Goertz, S., Nesi, N., 2016. Virtual modeling based on deep phenotyping provides complementary data to field experiments to predict plant emergence in oilseed rape genotypes. Eur. J. Agron. 79, 90–99. https://doi.org/10.1016/J.EJA.2016.06.001

Economic Commission for Africa, 2012. New and Emerging Challenges in Africa. Addis Ababa, Ethiopia.

Egoh, B.N., Reyers, B., Rouget, M., Richardson, D.M., 2011. Identifying priority areas for ecosystem service management in South African grasslands. J. Environ. Manage. 92, 1642–1650. https://doi.org/10.1016/j.jenvman.2011.01.019

Ehrlich, P.R., Kareiva, P.M., Daily, G.C., 2012. Securing natural capital and expanding equity to rescale civilization. Nature 486, 68–73. https://doi.org/10.1038/nature11157

Eide, M., Rusten, M., Male, R., Jensen, K.H.M., Goksøyr, A., 2014. A characterization of the ZFL cell line and primary hepatocytes as in vitro liver cell models for the zebrafish (Danio rerio). Aquat. Toxicol. 147, 7–17. https://doi.org/10.1016/j.aquatox.2013.11.023

Eisenhardt, K.M., Graebner, M.E., 2007. Theory Building From Cases: Opportunities And Challenges. Acad. Manag. J. 50, 25–32. https://doi.org/10.5465/amj.2007.24160888

Eitzinger, A., Binder, C.R., Meyer, M.A., 2018. Risk perception and decision-making: do farmers consider risks from climate change? Clim. Change 151, 507–524. https://doi.org/10.1007/s10584-018-2320-1

Engel, S., Pagiola, S., Wunder, S., 2008. Designing payments for environmental services in theory and practice: An overview of the issues. Ecol. Econ. 65. https://doi.org/10.1016/j.ecolecon.2008.03.011

Enström, M., Eriksson, J., 2018. Farmers' Behaviour in Risky Decision-making-A multiple case study of farmers' adoption of crop insurance as a risk management tool. Swedish University of Agricultural Sciences.

Everson, C.S., Clulow, A., Becker, M., Watson, A., Ngubo, C., Bulcock, H., Mengistu, M., Lorentz, S., Demlie, M., 2014. The long term impact of Acacia mearnsii on evaoporation, streamflow, low flows and ground water resources. Phase II: Understanding the controlling environmental variables and soil water processes over a full crop rotation.

FA0, 2016. The State of Food and Agriculture, Notes and Queries. Rome, Italy. https://doi.org/10.1093/nq/s8-IV.94.301-a

Fadina, A., Barjolle, D., 2018. Farmers' Adaptation Strategies to Climate Change and Their Implications in the Zou Department of South Benin. Environments 5, 15. https://doi.org/10.3390/environments5010015

Fanadzo, M., Chiduza, C., Mnkeni, P., 2009. Comparative response of direct seeded and transplanted maize (Zea mays L.) to nitrogen fertilization at Zanyokwe irrigation scheme, Eastern Cape, South Africa. African J. Agric. Res. 4, 689–694.

Fanadzo, M., Chiduza, C., Mnkeni, P.N.., Van der Stoep, L., Steven, J., 2010. Crop production management practices as a cause for low water productivity at Zanyokwe Irrigation Scheme. Water SA 36. https://doi.org/10.4314/wsa.v36i1.50904

FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009. Harmonized World Soil Database - Version 1.1. Rome, Italy and Laxenburg, Austria,.

FAO, 2017. The future of food and agriculture: Trends and challenges. Rome.

FAO, 2011. A policymaker's guide to the sustainable intensification of smallholder crop production., Save and Grow. Rome, Italy. https://doi.org/10.1007/978-3-319-45438-2_2

FAO, 2008. Water and the rural poor interventions for improving livelihoods in sub-Saharan Africa. FAO, Rome.

FAO, 2005. Fertilizer use by crop in South Africa. Rome, Italy.

FAO, 2003. World agriculture: towards 2015/2030 An FAO persepective. London.

FAO, Food and Agriculture Organisation, E., FAO, 2005. Fertilizer use by crop in South Africa. Rome.

Farré, I., Faci, J., 2009. Deficit irrigation in maize for reducing agricultural wateruse in a Mediterranean environment. Agric. Water Manag. 383–394.

Fengmei, Y., Pengcheng, Q., Jiahua, Z., Erda, L., Vijendra, B., 2011. Uncertainties in assessing the effect of climate change on agriculture using model simulation and uncertainty processing methods 56, 729–737. https://doi.org/10.1007/s11434-011-4374-6

Ferrant, S., 2014. Agro-hydrology and multi temporal high resolution remote sensing. Hydrol. Earth Syst. Sci. Discuss 11, 7689–7732. https://doi.org/10.5194/hessd-11-7689-2014

Fess, T.L., Benedito, V.A., 2018. Organic versus conventional cropping sustainability: A comparative system analysis. Sustain. 10. https://doi.org/10.3390/su10010272

Fessehazion, M., Annandale, J., Everson, C., Stirzaker, R., van der Laan, M., Truter, W., Abraha, A., 2014. Perfomance of Simple Irrigation Scheduling calenders based on average weather data for annual ryegrass. African J. Range Forage Sci. 31, 221–228. https://doi.org/10.2989/10220119.2014.906504

Findlater, K.M., Kandlikar, M., Satterfield, T., 2019. Misunderstanding conservation agriculture: Challenges in promoting, monitoring and evaluating sustainable farming. Environ. Sci. Policy 100, 47–54. https://doi.org/10.1016/j.envsci.2019.05.027

Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification among British farms. Agric. Ecosyst. Environ. 173, 58–65. https://doi.org/10.1016/J.AGEE.2013.04.010

Fish, R., Winter, M., Lobley, M., 2014. Sustainable intensification and ecosystem services: New directions in agricultural governance. Policy Sci. 47, 51–67. https://doi.org/10.1007/s11077-013-9183-0

Fisher, B., Turner, R.K., Morling, P., 2009. Defining and classifying ecosystem services for decision making. Ecol. Econ. 68, 643–653. https://doi.org/10.1016/J.ECOLECON.2008.09.014

Folberth, C., 2013. Modeling crop yield and water use in the context of global change with a focus on maize in sub-Saharan Africa. ETH ZURICH. https://doi.org/10.3929/ethz-a-010113683

Folberth, C., Elliott, J., Müller, C., Balkovic, J., Chryssanthacopoulos, J., Izaurralde, R.C., Jones, C.D., Khabarov, N., Liu, W., Reddy, A., Schmid, E., Skalský, R., Yang, H., Arneth, A., Ciais, P., Deryng, D., Lawrence, P.J., Olin, S., Pugh, T.A.M., Ruane, A.C., Wang, X., 2016. Uncertainties in global crop model frameworks: effects of cultivar distribution, crop management and soil handling on crop yield estimates. Biogeosciences Discuss. 1–30. https://doi.org/10.5194/bg-2016-527

Folberth, C., Gaiser, T., Abbaspour, K.C., Schulin, R., Yang, H., 2012. Regionalization of a large-scale crop growth model for sub-Saharan Africa: Model setup, evaluation, and estimation of maize yields. Agric. Ecosyst. Environ. 151, 21–33. https://doi.org/10.1016/J.AGEE.2012.01.026

Folberth, C., Yang, H., Gaiser, T., Abbaspour, K.C., Schulin, R., 2013. Modeling maize yield responses to improvement in nutrient, water and cultivar inputs in sub-Saharan Africa. Agric. Syst. 119, 22–34. https://doi.org/10.1016/j.agsy.2013.04.002

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global Consequences of Land Use. Science (80-.). 309, 570–574. https://doi.org/10.1126/SCIENCE.1111772

Forster, D.L., Richards, R.P., Baker, D.B., Blue, E.N., 2000. EPIC modeling of the effects of farming practice changes on water quality in two Lake Erie watersheds. J. Soil Water Conserv. 55, 85–90.

Fusco, G., Miglietta, P.P., Porrini, D., 2018. How Drought Affects Agricultural Insurance

Policies: The Case of Italy. J. Sustain. Dev. 11, 1. https://doi.org/10.5539/jsd.v11n2p1

Gaiser, T., de Barros, I., Sereke, F., Lange, F.-M., 2010. Validation and reliability of the EPIC model to simulate maize production in small-holder farming systems in tropical sub-humid West Africa and semi-arid Brazil. Agric. Ecosyst. Environ. 135, 318–327. https://doi.org/10.1016/J.AGEE.2009.10.014

Gaiser, T., Fadegnon, B., Cretenet, M., Gaborel, C., 1999. Long-term Experiments on a Tropical Acrisol: Evolution of Soil Properties and Maize Yield, in: Merbach, W., Körschens, M. (Eds.), Dauerdüngungsversuche Als Grundlage Für Nachhaltige Landnutzung Und Quantifizierung von Stoffkreisläufen. Umweltforschungszentrum Leipzig-Halle GmbH, Bericht.

Gakuubi, M., Wanzala, W., 2012. A survey of plants and plant products traditionally used in livestock health management in Buuri district, Meru County, Kenya. J. Ethnobiol. Ethnomed. 8, 39. https://doi.org/10.1186/1746-4269-8-39

Gallai, N., Salles, J.-M., Settele, J., Vaissière, B.E., 2009. Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. Ecol. Econ. 68, 810–821. https://doi.org/10.1016/j.ecolecon.2008.06.014

Garnett, T., Appleby, M.C., Balmford, a, Bateman, I.J., Benton, T.G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P.K., Toulmin, C., Vermeulen, S.J., Godfray, H.C.J., 2013. Sustainable Intensifi cation in Agriculture: Premises and Policies. Sci. Mag. 341, 33–34. https://doi.org/10.1126/science.1234485

Gaudin, A.C.M., Janovicek, K., Deen, B., Hooker, D.C., 2015. Wheat improves nitrogen use efficiency of maize and soybean-based cropping systems. Agric. Ecosyst. Environ. 210, 1–10. https://doi.org/10.1016/j.agee.2015.04.034

Gebreeyesus, K.., 2017. Impact of Climate Change on the Agro-ecological Innovation of Coffee Agroforestry Systems in Central Kenya. Montpellier, France.

Getahun, E., Keefer, L., 2016. Integrated modeling system for evaluating water quality benefits of agricultural watershed management practices: Case study in the Midwest. Sustain. Water Qual. Ecol. 8, 14–29. https://doi.org/10.1016/j.swaqe.2016.06.002

Gill, S.S., Gill, R., Tuteja, R., Tuteja, N., 2014. Genetic engineering of crops: A ray of hope for enhanced food security. Plant Signal. Behav. 9. https://doi.org/10.4161/psb.28545

Gillespie, J., Kim, S.-A., Paudel, K., 2007. Why don't producers adopt best management practices? An analysis of the beef cattle industry. Agric. Econ. 36, 89–102. https://doi.org/10.1111/j.1574-0862.2007.00179.x

Godfray, H.C.J., Garnett, T., 2014. Food security and sustainable intensification. Philos. Trans. R. Soc. B Biol. Sci. 369, 20120273. https://doi.org/10.1098/rstb.2012.0273

Godfray, J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Sci. Mag. 327.

Godsmark, C.N., Irlam, J., van der Merwe, F., New, M., Rother, H.-A., 2019. Priority focus areas for a sub-national response to climate change and health: A South African provincial case study. Environ. Int. 122, 31–51. https://doi.org/10.1016/J.ENVINT.2018.11.035

Goldblatt, A., 2011. Agriculture: Facts and Trends South Africa. World Wide Fund Nat. 2–26.

Gómez-Baggethun, E., Ruiz-Pérez, M., 2011. Economic valuation and the commodification of ecosystem services. Prog. Phys. Geogr. Earth Environ. 35, 613–628. https://doi.org/10.1177/0309133311421708

Govender, M., Everson, C.S., 2005. Modelling streamflow from two small South African experimental catchments using the SWAT model. Hydrol. Process. https://doi.org/10.1002/hyp.5621

Greer, K.D., Pittelkow, C.M., 2018. Linking Nitrogen Losses With Crop Productivity in Maize Agroecosystems. Front. Sustain. Food Syst. 2, 29. https://doi.org/10.3389/fsufs.2018.00029

Guerra, L.C., Hoogenboom, G., Hook, J.E., Thomas, D.L., Boken, V.K., Harrison, K.A., 2005. Evaluation of on-farm irrigation applications using the simulation model EPIC. Irrig. Sci. 23, 171–181. https://doi.org/10.1007/s00271-005-0105-6

Guillaume, S., Bergez, J.-E., Wallach, D., Justes, E., 2011. Methodological comparison of calibration procedures for durum wheat parameters in the STICS model. Eur. J. Agron. 35, 115–126. https://doi.org/10.1016/J.EJA.2011.05.003

Gundersen, V.S., Frivold, L.H., 2008. Public preferences for forest structures: A review of quantitative surveys from Finland, Norway and Sweden. Urban For. Urban Green. 7, 241–258. https://doi.org/10.1016/J.UFUG.2008.05.001

Guo, R., Lin, Z., Mo, X., Yang, C., 2010. Responses of crop yield and water use efficiency to climate change in the North China Plain. Agric. Water Manag. 97, 1185–1194. https://doi.org/10.1016/J.AGWAT.2009.07.006

Gupta, H.V., Sorooshian, S., Yapo, P.O., 1999. Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. J. Hydrol. Eng. 4, 135–143. https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135)

Gush, M., Scott, D., Jewitt, G., Schulze, R., Lumsden, T., Hallowes, L., Görgens, A., 2002. Estimation of Streamflow Reductions Resulting from Commercial Afforestation in South Africa.

Haas, M.B., Guse, B., Fohrer, N., 2017. Assessing the impacts of Best Management Practices on nitrate pollution in an agricultural dominated lowland catchment considering environmental protection versus economic development. J. Environ. Manage. 196, 347–364. https://doi.org/10.1016/J.JENVMAN.2017.02.060

Haines-Young, R., Potschin, M., 2012. Common International Classification of Ecosystem Services (CICES, Version 4.1) 1–17.

Hamann, M., Tuinder, V., 2012. Introducing the Eastern Cape : A quick guide to its history , diversity and future challenges A report by.

Hammad, H.M., Abbas, F., Ahmad, A., Farhad, W., Anothai, J., Hoogenboom, G., 2018. Predicting water and nitrogen requirements for maize under semi-arid conditions using the CSM-CERES-Maize model. Eur. J. Agron. 100, 56–66. https://doi.org/10.1016/j.eja.2017.10.008

Hanslip, M., Kancans, R., Maguire, B., 2008. Understanding Natural Resource Management from a Landholder's Perspective: Results of the Border Rivers-Gwydir survey 2007-08.

Haverkort, A.J., Franke, A.C., Engelbrecht, F.., Steyn, J.M., 2013. Climate Change and Potato Production in Contrasting South African Agro-Ecosystems. Effects on Land and Water Use Efficiences. Eur. Assoc. potato Res. 56, 67–84. https://doi.org/10.1007/s11540-013-9231-3

He, W., Yang, J.Y., Qian, B., Drury, C.F., Hoogenboom, G., He, P., Lapen, D., Zhou, W., 2018. Climate change impacts on crop yield, soil water balance and nitrate leaching in the semiarid and humid regions of Canada. PLoS One 13, e0207370. https://doi.org/10.1371/journal.pone.0207370

Hooper, D.U., Chapin, F.S., Ewel, J.J., Hector, A., Inchausti, P., Lavorel, S., Lawton, J.H., Lodge, D.M., Loreau, M., Naeem, S., Schmid, B., Setälä, H., Symstad, A.J., Vandermeer, J., Wardle, D.A., 2005. Effects of biodiversity on ecosystem functioning : A consensus of current knowledge. Ecol. Monogr. 75, 3–35. https://doi.org/10.1890/04-0922

Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. Proc. Natl. Acad. Sci. U. S. A. 104, 19691–6. https://doi.org/10.1073/pnas.0701890104

Howe, C., Suich, H., Vira, B., Mace, G.M., 2014. Creating win-wins from trade-offs? Ecosystem services for human well-being: A meta-analysis of ecosystem service trade-offs and synergies in the real world. Glob. Environ. Chang. 28, 263–275. https://doi.org/10.1016/J.GLOENVCHA.2014.07.005

Hughes, D.A., 2009. Simulating the hydrology and total dissolved solids (TDS) of an ephemeral river in South Africa for environmental water requirement determinations. River Res. Appl. 25, 850–860. https://doi.org/10.1002/rra.1188

Hughes, D.A., Slaughter, A.R., 2016. Disaggregating the components of a monthly water resources system model to daily values for use with a water quality model. Environ. Model. Softw. 80, 122–131. https://doi.org/10.1016/j.envsoft.2016.02.028

ICSU, UNESCO, UNU, 2008. Ecosystem Change and Human Well-being Research and Monitoring Priorities Based on the Findings of the Millennium Ecosystem Assessment. Paris.

Intarapapong, W., Hite, D., Reinschmiedt, L., 2002. Water Quality Impacts of Conservation Agricultural Practices in the Mississippi Delta. J. Am. Water Resour. Assoc. 38, 507–515.

IPCC, 2014. IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. Geneva, Switzerland.

Isidoro, D., Quílez, D., Aragüés, R., 2006. Environmental Impact of Irrigation in La Violada District (Spain). J. Environ. Qual. 35, 776. https://doi.org/10.2134/jeq2005.0065

Izaurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006. Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecol. Modell. https://doi.org/10.1016/j.ecolmodel.2005.07.010

Jagtap, S.S., Jones, J.W., 2002. Adaptation and evaluation of the CROPGRO-soybean model to predict regional yield and production. Agric. Ecosyst. Environ. 93, 73–85. https://doi.org/10.1016/S0167-8809(01)00358-9

Jagustovic, R., Zougmoré, R.B., Kessler, A., Ritsema, C.J., Keesstra, S., Reynolds, M., 2019. Contribution of systems thinking and CAS theory to climate-smart agriculture : an example from Ghana. Agric. Syste 65–75.

James, L.., Burges, S.J., 1982. Selection, Calibration, and Testing of Hydrologic Models. In: Hydrologic Modeling of Small Watersheds. ASAE Monograph, St. Joseph.

Jax, K., Barton, D.N., Chan, K.M.A., de Groot, R., Doyle, U., Eser, U., Görg, C., Gómez-Baggethun, E., Griewald, Y., Haber, W., Haines-Young, R., Heink, U., Jahn, T., Joosten, H., Kerschbaumer, L., Korn, H., Luck, G.W., Matzdorf, B., Muraca, B., Neßhöver, C., Norton, B., Ott, K., Potschin, M., Rauschmayer, F., von Haaren, C., Wichmann, S., 2013. Ecosystem services and ethics. Ecol. Econ. 93, 260–268. https://doi.org/10.1016/j.ecolecon.2013.06.008

Johnston, R.J., Russell, M., 2011. An operational structure for clarity in ecosystem service values. Ecol. Econ. 70, 2243–2249. https://doi.org/10.1016/j.ecolecon.2011.07.003

Jones, J.., Hoogenboom, G., Porter, C.., Boote, K.., Batchelor, W.., Hunt, L.., Wilkens, P.., Singh, U., Gijsman, A.., Ritchie, J.., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jordaan, G., 2017. Cradock Research Farm. South Africa, Personal Communication.

Juana, J.S., Kahaka, Z., Okurut, F.N., 2013. Farmers' Perceptions and Adaptations to Climate Change in Sub-Sahara Africa: A Synthesis of Empirical Studies and Implications for Public Policy in African Agriculture. J. Agric. Sci. 5, 121–135. https://doi.org/10.5539/jas.v5n4p121

Jury, M.R., 2018. Climate trends across south africa since 1980. Water SA 44, 297–307. https://doi.org/10.4314/wsa.v44i2.15

Karali, E., Rounsevell, M.D.A., Doherty, R., 2011. Integrating the diversity of farmers' decisions into studies of rural land-use change. Procedia Environ. Sci. 6, 136–145. https://doi.org/10.1016/J.PROENV.2011.05.014

Kgonyane, M.C., 2010. Low rates of Nitrogen and Phosphorus as fertilizer options for Maize (Zea Mays L. in drier regions. University of Limpopoo.

Khan, M., Walker, D., 2015. Application of Crop Growth Simulation Models in Agriculture with special reference to Water Management Planning, International Journal Of Core Engineering & Management (IJCEM.

Khan, S., Jan, N., Ulllah, I., Younas, M., Ullah, H., 2007. Evauation of various methods of fertilizer application in potato (Solanum tuberosum L.), Sarhad J. Agric.

Khapayi, M., Celliers, P.R., 2016. Factors limiting and preventing emerging farmers to progress to commercial agricultural farming in the King William's Town area of the Eastern Cape Province, South Africa. South African J. Agric. Ext. 44, 25–41. https://doi.org/10.17159/2413-3221/2016/v44n1a374

King, K.., Balogh, J.., 2009. Evaluation of an Agricultural Water Quality Model for Use in Golf Course Management. Am. Soc. Agric. Eng. 33–36.

Kiniry, J.R., Major, D., Izaurralde, R., Williams, J., Gassmann, P., Morrison, M., Bergentine, R., Zentner, R., 1995. EPIC model parameters for cereal, oilseed, and forage crops in the northern Great Plains region. NRC Res. Press 679–688.

Kiniry, J.R., Williams, J.R., Vanderlip, R.L., Atwood, J.D., Reicosky, D.C., Mulliken, J., Cox, W.J., Mascagni, H.J., Hollinger, S.E., Wiebold, W.J., 1997. Evaluation of Two Maize Models for Nine U.S. Locations. Agron. J. 89, 421. https://doi.org/10.2134/agronj1997.00021962008900030009x

Kipkorir, E.., Raes, D., Massawe, B., 2002. Seasonal water production functions and yield response factors for maize and onion in Perkerra, Kenya. Agric. Water Manag. 56, 229–240. https://doi.org/10.1016/S0378-3774(02)00034-3

Klein, T., 2013. Adapting agricultural land management to climate change: A regional multi-objective optimization approach. University of Bern, Switzerland. https://doi.org/10.1007/s10980-013-9939-0

Ko, J., Piccinni, G., Steglich, E., 2009. Using EPIC model to manage irrigated cotton and maize. Agric. Water Manag. 96, 1323–1331. https://doi.org/10.1016/J.AGWAT.2009.03.021

Kollongei, K.J., Lorentz, S.A., 2015. Modelling hydrological processes , crop yields and NPS pollution in a small sub-tropical catchment in South Africa using ACRU-NPS Modelling hydrological processes , crop yields and NPS pollution in a. Hydrol. Sci. J. 60, 2003–2028. https://doi.org/10.1080/02626667.2015.1087644

Korner, C., Ohsawa, M., Spehn, E., Berge, E., Bugmann, H., Groombridge, B., Hamilton, L., Hofer, T., Ivees, J., 2005. Ecosystems and human well-being : current state and trends : findings of the Condition and Trends Working Group of the Millennium Ecosystem Assessment. Island Press.

Koschke, L., Van der Meulen, S., Frank, S., Schneidergruber, A., Kruse, M., Fürst, C., Neubert, E., Ohnesorge, B., Schröder, C., Müller, F., Bastian, O., 2014. Do you have 5 minutes to spare? -The challenges of stakeholder processes in ecosystem services studies. Landsc. Online 37, 1–25. https://doi.org/10.3097/LO.201437

Kroll, S.A., Oakland, H.C., 2019. A Review of Studies Documenting the Effects of Agricultural Best Management Practices on Physiochemical and Biological Measures of Stream Ecosystem Integrity. Nat. Areas J. 39, 58. https://doi.org/10.3375/043.039.0105

Kumari, K., Kumar, K., Rao, C., 2014. Adverse Effects of Chemical Fertilizers and Pesticides on Human Health and Environment. J. Chem. Pharm. Sci. 150–151.

Kuschke, I., Geyer, J., 2016. Agriculture: Market Intelligence Report, GreenCape 1–55.

Lamarque, P., Meyfroidt, P., Nettier, B., Lavorel, S., 2014. How Ecosystem Services Knowledge and Values Influence Farmers' Decision-Making. PLoS One 9, 107572. https://doi.org/10.1371/journal.pone.0107572

Lamothe, K.A., Sutherland, I.J., 2018. Intermediate ecosystem services: the origin and meanings behind an unsettled concept. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 14, 179–187. https://doi.org/10.1080/21513732.2018.1524399

le Roux, P., du Preez, C., Strydom, M., van Rensburg, L., Bennie, A., 2007. Effect of irrigation on soil salinity profiles along the Lower Vaal River, South Africa. Water Sa 33.

Lekalakala, G., 2017. Options for Managing Climate Risk and Climate Change Adaptation in Smallholder Farming Systems of the Limpopo Province, South Africa. Georg-August-University Göttingen.

Lescourret, F., Magda, D., Richard, G., Adam-Blondon, A.-F., Bardy, M., Baudry, J., Doussan, I., Dumont, B., Lefèvre, F., Litrico, I., Martin-Clouaire, R., Montuelle, B., Pellerin, S., Plantegenest, M., Tancoigne, E., Thomas, A., Guyomard, H., Soussana, J.-F., 2015. A social–ecological approach to managing multiple agro-ecosystem services. Curr. Opin. Environ. Sustain. 14, 68–75. https://doi.org/10.1016/J.COSUST.2015.04.001

Leslie, H., Basurto, M., Nenadovic, L., Sievanen, K., Cavanaugh, J., Cota-Nieto, B., Erisman, E., Finkbeiner, G., Hinojosa-Arango, M., Moreno-Baez, S., Nagavarapu, S., Waver, H., Aburto-Oropeza, 2015. Operationalising the social-ecological systems framework to assess sustainability., in: Proceedings of the National Academy of Sciences.

Liang, H., Hu, K., Batchelor, W.D., Qi, Z., Li, B., 2016. An integrated soil-crop system model for water and nitrogen management in North China. Sci. Rep. 6, 25755. https://doi.org/10.1038/srep25755

Licht, M., Martin, R., 2007. Communication channel preferences of corn and soybean producers. J. Ext. 45.

Lin, B.B., 2011. Resilience in Agriculture through Crop Diversification: Adaptive Management for Environmental Change. Bioscience 61, 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Lin, Weiwei, Lin, M., Zhou, H., Wu, H., Li, Z., Lin, Wenxiong, 2019. The effects of chemical and organic fertilizer usage on rhizosphere soil in tea orchards. PLoS One 14, 1–16. https://doi.org/10.1371/journal.pone.0217018

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Sen, P.T., Sessa, R., Shula, R., Tibu, A., Torquebiau, E.F., 2014. Climate-smart agriculture for food security. Nat. Clim. Chang. 4, 1068–1072. https://doi.org/10.1038/nclimate2437

Liu, E., Yan, C., Mei, X., He, W., Bing, S.H., Ding, L., Liu, Q., Liu, S., Fan, T., 2010. Long-term effect of chemical fertilizer, straw, and manure on soil chemical and biological properties in northwest China. Geoderma 158, 173–180. https://doi.org/10.1016/j.geoderma.2010.04.029

Liu, H. long, Yang, J. yi, He, P., Bai, Y. lu, Jin, J. yun, Drury, C.F., Zhu, Y. ping, Yang, X. ming, Li, W. juan, Xie, J. gui, Yang, J. min, Hoogenboom, G., 2012. Optimizing Parameters of CSM-CERES-Maize Model to Improve Simulation Performance of Maize Growth and Nitrogen Uptake in Northeast China. J. Integr. Agric. 11, 1898–1913. https://doi.org/10.1016/S2095-3119(12)60196-8

Liu, J., Williams, J.R., Zehnder, A.J.B.B., Yang, H., 2007. GEPIC - modelling wheat yield and crop water productivity with high resolution on a global scale. Agric. Syst. 94, 478–493. https://doi.org/10.1016/j.agsy.2006.11.019

Liu, R., Zhang, P., Wang, X., Chen, Y., Shen, Z., 2013. Assessment of effects of best management practices on agricultural non-point source pollution in Xiangxi River watershed. Agric. Water Manag. 117, 9–18. https://doi.org/10.1016/j.agwat.2012.10.018

Liu, T., Bruins, R.J.F., Heberling, M.T., Liu, T., Bruins, R.J.F., Heberling, M.T., 2018. Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis. Sustainability 10, 432. https://doi.org/10.3390/su10020432

Liu, Y., Wang, R., Guo, T., Engel, B.A., Flanagan, D.C., Lee, J.G., Li, S., Pijanowski, B.C., Collingsworth, P.D., Wallace, C.W., 2019. Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. J. Hydrol. 577, 123965. https://doi.org/10.1016/J.JHYDROL.2019.123965

Logsdon, R.A., Kalcic, M.M., Trybula, E.M., Chaubey, I., Frankenberger, J.R., 2015. Ecosystem services and Indiana agriculture: farmers' and conservationists' perceptions. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 11, 264–282. https://doi.org/10.1080/21513732.2014.998711

Long, S.P., Ainsworth, E.A., Leakey, A.D.B., Nösberger, J., Ort, D.R., 2006. Food for thought: lower-than-expected crop yield stimulation with rising CO2 concentrations. Science 312, 1918–21. https://doi.org/10.1126/science.1114722

Lorentz, S.A., Kollongei, J., Snyman, N., Berry, S.R., Jackson, W., Ngaleka, K., Pretorius, J.J., Clark, D., Thornton-Dibb, S., Le Roux, J.J., Germishuyse, T., Görgens, A., 2012. Modelling Nutrient and Sediment Dynamics at the Catchment Scale.

Lu, Y.-T., Chang, Y.-H., 2016. Investigation of the internet adoption on senior farmers.

Eng. Comput. 33, 1853–1864. https://doi.org/10.1108/EC-08-2015-0259

Lukey, P., Cumming, T., Paras, S., Lloyd, S., 2017. Making biodiversity offsets work in South Africa – A governance perspective. Ecosyst. Serv. 27, 281–290. https://doi.org/10.1016/J.ECOSER.2017.05.001

Lusiba, S., Odhiambo, J., Ogola, J., 2017. Effect of biochar and phosphorus fertilizer application on soil fertility: soil physical and chemical properties. Arch. Agron. Soil Sci. 63, 477–490. https://doi.org/10.1080/03650340.2016.1218477

Lychuk, T.E., Hill, R.L., Izaurralde, R.C., Momen, B., Thomson, A.M., 2017. Evaluation of climate change impacts and effectiveness of adaptation options on crop yield in the Southeastern United States. F. Crop. Res. 214, 228–238. https://doi.org/10.1016/J.FCR.2017.09.020

Mack, R., Owen, J.S., Niemiera, A.X., Latimer, J., 2017. Virginia Nursery and Greenhouse Grower Survey of Best Management Practices. Horttechnology 27, 386–392. https://doi.org/10.21273/HORTTECH03664-17

MacKellar, N., New, M., Jack, C., 2014. Observed and modelled trends in rainfall and temperature for South Africa: 1960-2010. S. Afr. J. Sci. 110, 1–13. https://doi.org/10.1590/sajs.2014/20130353

Maherry, A., Tredoux, G., Clarke, S., Engelbrecht, P., 2010. State of Nitrate Pollution in Groundwater in South Africa. Pretoria.

Makate, C., Wang, R., Makate, M., Mango, N., 2016. Crop diversification and livelihoods of smallholder farmers in Zimbabwe: Adaptive management for environmental change. Springerplus 5. https://doi.org/10.1186/s40064-016-2802-4

Malawska, A., Topping, C.J., Nielsen, H.Ø., 2014. Why do we need to integrate farmer decision making and wildlife models for policy evaluation? Land use policy 38, 732–740. https://doi.org/10.1016/J.LANDUSEPOL.2013.10.025

Mandiringana, O.T., Mnkeni, P.N.S., Mkile, Z., van Averbeke, W., Van Ranst, E., Verplancke, H., 2007. Mineralogy and fertility status of selected soils of the Eastern Cape Province, South Africa. Commun. Soil Sci. Plant Anal. 36, 2431–2446. https://doi.org/10.1080/00103620500253514

Marra, A., Jensen, K., Clark, C., Menard, R., 2012. Information Sources and Farmers' Attitudes Toward Switchgrass Production as a Biofuel Feedstock. J. Ext. 50, 5–6.

Martín-López, B., Gómez-Baggethun, E., García-Llorente, M., Montes, C., 2014. Trade-offs across value-domains in ecosystem services assessment. Ecol. Indic. 37, 220–228. https://doi.org/10.1016/J.ECOLIND.2013.03.003

Martin, S., 1993. An evaluation of the EPIC model for soybeans grown in Southern Piedmont soils. Trans. ASABE.

Martinho, V.J.P.D., 2019. Best management practices from agricultural economics: Mitigating air, soil and water pollution. Sci. Total Environ. 688, 346–360. https://doi.org/10.1016/J.SCITOTENV.2019.06.199

Mason, N.W.H., Palmer, D.J., Romera, A., Waugh, D., Mudge, P.L., 2017. Combining field experiments and predictive models to assess potential for increased plant diversity to climate-proof intensive agriculture. Ecol. Evol. 7, 4907–4918. https://doi.org/10.1002/ece3.3028

Mastrangelo, M.E., Weyland, F., Herrera, L.P., Villarino, S.H., Barral, M.P., Auer, A.D., 2015. Ecosystem services research in contrasting socio-ecological contexts of Argentina: Critical assessment and future directions. Ecosyst. Serv. 16, 63–73. https://doi.org/10.1016/j.ecoser.2015.10.001

Matarira, C.H., Makadho, J.M., Mwamuka, F.C., 1995. Climate change impacts on maize production and adaptive measures for the agricultural sector. World Bank, Energy 3 4.

Matthews, M.W., 2014. Eutrophication and cyanobacterial blooms in South African inland waters: 10 years of MERIS observations. Remote Sens. Environ. 155, 161–177. https://doi.org/10.1016/J.RSE.2014.08.010

Mavimbela, S.S.W., van Rensburg, L.D., 2015. Effect of Water Regime and Runoff Strip Width on Soil Water Balance for an Integrated In-Field Rainwater Harvesting. Arid L. Res. Manag. 29, 141–166. https://doi.org/10.1080/15324982.2014.944245

MEA, 2005. Ecosystems and Human Well-being : Current State and Trends , Volume 1, Current. Island Press.

Mehdi, B., Lehner, B., Ludwig, R., 2018. Modelling crop land use change derived from influencing factors selected and ranked by farmers in North temperate agricultural regions. Sci. Total Environ. 631–632, 407–420. https://doi.org/10.1016/J.SCITOTENV.2018.03.014

Mnkeni, P., Chiduza, C., Modi, A.T., Stevens, J.B., 2010. Best Management Practices for Smallholder Farming on Two Irrigation Schemes in the Eastern Cape and Kwazulu-Natal Through Participatory Adaptive Research.

Moeletsi, M., Mellaart, E., Mpandeli, N., 2009. Crop water requirements analysis for maize trial sites in Makhado during 2007/08 season, in: International Conference on "Challenges and Opportunities in Agrometeorology. New Dehli, India, pp. 23–25.

Moriasi, D.N., Arnold, J.G., Liew, M.W. Van, Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations, Transactions of the ASABE.

Mqadi, L., 2005. Production Function Analysis of the Sensitivity of Maize Production to Climate Change in South Africa. University of Pretoria Pretoria.

Mthembu, B.E., Everson, T.M., Everson, C.S., 2019. Intercropping for enhancement and provisioning of ecosystem services in smallholder, rural farming systems in KwaZulu-Natal Province, South Africa: a review. J. Crop Improv. 33, 145–176. https://doi.org/10.1080/15427528.2018.1547806

Mudavanhu, S., Blignaut, J., Stegmann, N., Barnes, G., Prinsloo, W., Tuckett, A., 2017. The economic value of ecosystem goods and services: The case of Mogale's Gate Biodiversity Centre, South Africa. Ecosyst. Serv. 26, 127–136. https://doi.org/10.1016/j.ecoser.2017.06.005

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257. https://doi.org/10.1038/nature11420

Mulla, D.J., Birr, A.S., David, M., 2006. Evaluating the effectiveness of agricultural management practices at reducing nutrient losses to surface waters.

Nassl, M., Löffler, J., 2015. Ecosystem services in coupled social–ecological systems: Closing the cycle of service provision and societal feedback. Ambio 44, 737–749. https://doi.org/10.1007/s13280-015-0651-y

Nattrass, N., Conradie, B., 2018. Predators, livestock losses and poison in the South African Karoo. J. Clean. Prod. 194, 777–785. https://doi.org/10.1016/J.JCLEPRO.2018.05.169

Ndhleve, S., Nakin, M.D.V., Longo-Mbenza, B., 2017. Impacts of supplemental irrigation as a climate change adaptation strategy for maize production: a case of the Eastern Cape Province of South Africa. Water SA 43, 222. https://doi.org/10.4314/wsa.v43i2.06

Nederlof, S.E., Odonkor, E.N., 2006. Lessons from an Experiential Learning Process: The Case of Cowpea Farmer Field Schools in Ghana. J. Agric. Educ. Ext. 12, 249–271. https://doi.org/10.1080/13892240601062447

Nelson, E.J., Daily, G.C., 2010. Modelling ecosystem services in terrestrial systems. F1000 Biol. Rep. 2, 53. https://doi.org/10.3410/B2-53

Nelson Mandela Bay Tourism, 2017. Agriculture - Nelson Mandela Bay (Port Elizabeth) [WWW Document]. URL https://www.nmbt.co.za/agriculture_port_elizabeth.html (accessed 9.4.17).

Niu, X., Easterling, W., Hays, C.J., Jacobs, A., Mearns, L., 2009. Reliability and input-data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the U.S. Great Plains. Agric. Ecosyst. Environ. 129, 268–276. https://doi.org/10.1016/j.agee.2008.09.012

Njoko, S., Mudhara, M., 2017. Determinant of farmers' ability to pay for improved irrigation water supply in rural KwaZulu-Natal, South Africa. Water SA 43, 229. https://doi.org/10.4314/wsa.v43i2.07

Nkhonjera, G.K., 2017. Understanding the impact of climate change on the dwindling water resources of South Africa, focusing mainly on Olifants River basin: A review. Environ. Sci. Policy 71, 19–29. https://doi.org/10.1016/J.ENVSCI.2017.02.004

Norgaard, R.B., 2010. Ecosystem services: From eye-opening metaphor to complexity blinder. Ecol. Econ. 69, 1219–1227. https://doi.org/10.1016/J.ECOLECON.2009.11.009

Nuijten, E., 2011. Combining research styles of the natural and social sciences in agricultural research. NJAS - Wageningen J. Life Sci. 57, 197–205. https://doi.org/10.1016/J.NJAS.2010.10.003

O'Higgins, T., Al-Kalbani, M.S., 2015. A Systems Approach to Environmental

Management : It’s not easy being Green. Dunedin Academic Press.

O’Keeffe, J., Buytaert, W., Mijic, A., Brozovic, N., Sinha, R., 2015. The use of semi-structured interviews for the characterisation of farmer irrigation practices. Hydrol. Earth Syst. Sci. Discuss. 12, 8221–8246. https://doi.org/10.5194/hessd-12-8221-2015

Oduniyi, O.S., Tekana, S.S., 2019. Adoption of agroforestry practices and climate change mitigation strategies in North West province of South Africa. Int. J. Clim. Chang. Strateg. Manag. 11, 716–729. https://doi.org/10.1108/ijccsm-02-2019-0009

Oerke, E.C., 2006. Crop losses to pests. J. Agric. Sci. 144, 31–43. https://doi.org/10.1017/S0021859605005708

Ojea, E., Martin-Ortega, J., Chiabai, A., 2012. Defining and classifying ecosystem services for economic valuation: the case of forest water services. Environ. Sci. Policy 19–20, 1–15. https://doi.org/10.1016/J.ENVSCI.2012.02.002

Olivier, F.C., Singels, A., 2015. Increasing water use efficiency of irrigated sugarcane production in South Africa through better agronomic practices. F. Crop. Res. 176, 87–98. https://doi.org/10.1016/j.fcr.2015.02.010

Oosthuizen, E., 2005. An Evaluation of Cultivar Stability in ARC Maize Trials over a Six year period. University of the Free State.

Oosthuizen, H., Schulze, R., Crespo, O., Louw, D., Tadross, M., Waagsaether, K., Arowolo, S., 2016. Modelling Impacts of Climate Change on selected South African Crop Farming sysytems.

Opdam, P., 2009. Groen-blauwe netwerken in duurzame gebiedsontwikkeling 1–50.

Orimoloye, I.R., Kalumba, A.M., Mazinyo, S.P., Nel, W., 2018. Geospatial analysis of wetland dynamics: Wetland depletion and biodiversity conservation of Isimangaliso Wetland, South Africa. J. King Saud Univ. - Sci. https://doi.org/10.1016/J.JKSUS.2018.03.004

Ostrom, E., 2009. A general framework for analysing sustsinsbility of social-ecologicsl systems. Science (80-.). 325, 419–422.

Özcan, Z., Kentel, E., Alp, E., 2017. Evaluation of the best management practices in a semi-arid region with high agricultural activity. Agric. Water Manag. 194, 160–171. https://doi.org/10.1016/J.AGWAT.2017.09.007

Page, G., Bellotti, B., 2015. Farmers value on-farm ecosystem services as important, but what are the impediments to participation in PES schemes? Sci. Total Environ. 515–516, 12–19. https://doi.org/10.1016/J.SCITOTENV.2015.02.029

Pannar Quality Seeds, 2018. Know the Maize Plant.

Pappagallo, L., 2018. Operationalizing payments for ecosystem services for pastoralists in rangeland settings. Ethiopia.

Parry, M.., Rosenzweig, C., Iglesias, A., Livermore, M., Fischer, G., 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Glob. Environ. Chang. 14, 53–67. https://doi.org/10.1016/J.GLOENVCHA.2003.10.008

Parton, W.J., Ojima, D.S., Cole, C. V., Schimel, D.S., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. Quant. Model. soil Form. Process. Proc. Symp. Minneapolis, 1992 147–167.

Passioura, J., 2006. Increasing crop productivity when water is scarce—from breeding to field management. Agric. Water Manag. 80, 176–196. https://doi.org/10.1016/J.AGWAT.2005.07.012

Pastori, M., Bouraoui, F., Aloe, A., 2017. Modeling the impact of water and nutrient management in African agriculture, African Journal of Water Conservation and Sustainability.

Paudel, K.P., Gauthier, W.M., Westra, J. V, Hall, L.M., 2008. Factors Influencing and Steps Leading to the Adoption of Best Management Practices by Louisiana Dairy Farmers. J. ofAgricultural Appl. Econ. 40, 203–222.

Payero, J.O., Melvin, S.R., Irmak, S., Tarkalson, D., 2006. Yield response of corn todeficit irrigation in a semi-arid climate. Agric. Water Manag. 101–112.

Pearce, M.W., Schumann, E.H., 2001. The impact of irrigation return flow on aspects of the water quality of the Upper Gamtoos Estuary, South Africa 27.

Peck, G., Andrews, P., Reganold, J., Fellman, J., 2006. Apple orchard productivity and fruit quality under organic, conventional, and integrated management. HORTSCIENCE 41, 99–107.

Perry, K.A., 2015. Application of the SWAT hydrological model in a small, mountainous catchment in South Africa.

Petz, K., 2014. Mapping and modelling the effects of land use and land management change on ecosystem services from local ecosystems and landscapes to global biomes. Wageningen.

Phillips, T., Klerkx, L., Mcentee, M., 2018. An investigation of social media's roles in knowledge exchange by farmers, in: European IFSA Symposium. Chania (Greece), p. 1.

Pilgrim, E.S., Macleod, C.J.A., Blackwell, M.S.A., Bol, R., Hogan, D. V., Chadwick, D.R., Cardenas, L., Misselbrook, T.H., Haygarth, P.M., Brazier, R.E., Hobbs, P., Hodgson, C., Jarvis, S., Dungait, J., Murray, P.J., Firbank, L.G., 2010. Interactions Among Agricultural Production and Other Ecosystem Services Delivered from European Temperate Grassland Systems. Adv. Agron. 109, 117–154. https://doi.org/10.1016/B978-0-12-385040-9.00004-9

Porrini, D., Fusco, G., Miglietta, P.P., 2019. Post-Adversities Recovery and Profitability: The Case of Italian Farmers. Int. J. Environ. Res. Public Health 16, 3189. https://doi.org/10.3390/ijerph16173189

Potschin, M., Haines-Young, R., 2011. Ecosystem services: Exploring a geographical perspective. Prog. Phys. Geogr. 35, 575–594.

https://doi.org/10.1177/0309133311423172

Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. Lond. B. Biol. Sci. 365, 2959–71. https://doi.org/10.1098/rstb.2010.0143

Prager, K., Reed, M., Scott, A., 2011. Encouraging collaboration for the provision of ecosystem services at a landscape scaleâ€"Rethinking agri-environmental payments. Land use policy 29, 244–249. https://doi.org/10.1016/j.landusepol.2011.06.012

Pretty, J., Toulmin, C., Williams, S., 2011. Sustainable intensification in African agriculture. Int. J. Agric. Sustain. 9, 5–24. https://doi.org/10.3763/ijas.2010.0583

Pretty, J.N., 1997. The sustainable intensification of agriculture. Nat. Resour. Forum 21, 247–256. https://doi.org/10.1111/j.1477-8947.1997.tb00699.x

Province of the Eastern Cape, 2014. Eastern Cape Vision 2030 Provincial Development Plan. Flourishing people in a thriving province ￼.

Purushothaman, S., Patil, S., Francis, I., König, H.J., Reidsma, P., Hegde, S., 2013. Participatory impact assessment of agricultural practices using the land use functions framework: case study from India. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 9, 2–12. https://doi.org/10.1080/21513732.2012.721005

Quintas-Soriano, C., Brandt, S., Running, K., Baxter, C., Gibson, D., Narducci, J., 2018. Social-ecological systems influence ecosystem service perception: a Programme on Ecosystem Change and Society (PECS) analysis. Ecol. Soc. 23.

Radhakrishna, R., Nelson, L., Franklin, R., Kessler, G., 2003. Information sources and extension delivery methods used by private longleaf pine landowners. J. Ext. 41.

Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., 2009. AquaCrop The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. Agron. J. 101, 438. https://doi.org/10.2134/agronj2008.0140s

Raudsepp-Hearne, C., Peterson, G.D., Bennett, E.M., 2010. Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. Proc. Natl. Acad. Sci. U. S. A. 107, 5242–5247. https://doi.org/10.1073/pnas.0907284107

Rembialkowska, E., 2000. The nutritive and sensory quality of carrots and white cabbage fromRembialkowska, E. (2000). The nutritive and sensory quality of carrots and white cabbage from organic and conventional farms. In IFOAM 2000: the world grows organic. Proceedings 13th Inter, in: IFOAM 2000: The World Grows Organic. Proceedings 13th International IFOAM Scientific Conference, Basel, Switzerland, 28 to 31 August, 2000. vdf Hochschulverlag AG an der ETH Zurich.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., Rafaj, P., 2011. RCP 8.5—A scenario of comparatively high greenhouse gas emissions. Clim. Change 109, 33–57. https://doi.org/10.1007/s10584-011-0149-y

Ribaudo, M., Greene, C., Hansen, L., Hellerstein, D., 2010. Ecosystem services from agriculture: Steps for expanding markets ☆. https://doi.org/10.1016/j.ecolecon.2010.02.004

Ribe, R.G., 1989. The aesthetics of forestry: What has empirical preference research taught us? Environ. Manage. 13, 55–74. https://doi.org/10.1007/BF01867587

Rienecker, M.M., Suarez, M.J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M.G., Schubert, S.D., Takacs, L., Kim, G.K., Bloom, S., Chen, J., Collins, D., Conaty, A., Da Silva, A., Gu, W., Joiner, J., Koster, R.D., Lucchesi, R., Molod, A., Owens, T., Pawson, S., Pegion, P., Redder, C.R., Reichle, R., Robertson, F.R., Ruddick, A.G., Sienkiewicz, M., Woollen, J., 2011. MERRA: NASA's modern-era retrospective analysis for research and applications. J. Clim. 24, 3624–3648. https://doi.org/10.1175/JCLI-D-11-00015.1

Rinaldi, M., 2001. Application of EPIC model for irrigation scheduling of sunflower in Southern Italy. Agric. Water Manag. 49, 185–196. https://doi.org/10.1016/S0378-3774(00)00148-7

Rinaldi, M., de Luca, D., 2012. Applications of EPIC model to assess climate impact on sorghum in southern Italy. Ital. J. Agron. https://doi.org/10.4081/ija.2012.e12

Rinaldi, M., Garofalo, P., Rubino, P., Steduto, P., 2011. Processing tomatoes under different irrigation regimes in Southern Italy: Agronomic and economic assessments in a simulation case study. Ital. J. Agrometeorol. 39.

Ritchie, J., Lewis, J., 2003. QUALITATIVE RESEARCH PRACTICE A Guide for Social Science Students and Researchers Edited by.

Ritter, C., Jansen, J., Roche, S., Kelton, D.F., Adams, C.L., Orsel, K., Erskine, R.J., Benedictus, G., Lam, T.J.G.M., Barkema, H.W., 2017. Invited review: Determinants of farmers' adoption of management-based strategies for infectious disease prevention and control. J. Dairy Sci. 100, 3329–3347. https://doi.org/10.3168/jds.2016-11977

Rodrigues, G.C., Paredes, P., Gonçalves, J.M., Alves, I., Pereira, L.S., 2013. Comparing sprinkler and drip irrigation systems for full and deficit irrigated maize using multicriteria analysis and simulation modelling: Ranking for water saving vs. farm economic returns. Agric. Water Manag. 126, 85–96. https://doi.org/10.1016/J.AGWAT.2013.05.005

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies. Agric. For. Meteorol. 170, 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011

Rossing, W.A.H., Zander, P., Josien, E., Groot, J.C.J., Meyer, B.C., Knierim, A., 2007. Integrative modelling approaches for analysis of impact of multifunctional agriculture: A review for France, Germany and The Netherlands. Agric. Ecosyst. Environ. 120, 41–57. https://doi.org/10.1016/j.agee.2006.05.031

Rounsevell, M.D.A., Robinson, D.T., Murray-Rust, D., 2012. From actors to agents in socio-ecological systems models. Philos. Trans. R. Soc. B Biol. Sci. 367, 259–269. https://doi.org/10.1098/rstb.2011.0187

Royal Society, 2008. Reaping the benefits: Science and the sustainable intensification of agriculture. London.

Ruane, A.C., Goldberg, R., Chryssanthacopoulos, J., 2015. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. Agric. For. Meteorol. 200, 233–248. https://doi.org/10.1016/J.AGRFORMET.2014.09.016

Ruben, R., Lee, D.R., 2000. Combining internal and external inputs for sustainable intensification. Policy document no. 65, Change.

Rurinda, J., van Wijk, M.T., Mapfumo, P., Descheemaeker, K., Supit, I., Giller, K.E., 2015. Climate change and maize yield in southern Africa: What can farm management do? Glob. Chang. Biol. 21, 4588–4601. https://doi.org/10.1111/gcb.13061

Sacks, W.J., Deryng, D., Foley, J.A., Ramankutty, N., 2010. Crop planting dates: An analysis of global patterns. Glob. Ecol. Biogeogr. 19, 607–620. https://doi.org/10.1111/j.1466-8238.2010.00551.x

Sadras, V.O., 2004. Yield and water-use efficiency of water- and nitrogen-stressed wheat crops increase with degree of co-limitation. Eur. J. Agron. 21, 455–464. https://doi.org/10.1016/J.EJA.2004.07.007

Salahuddin, M., Gow, J., 2016. The effects of Internet usage, financial development and trade openness on economic growth in South Africa: A time series analysis. Telemat. Informatics 33, 1141–1154. https://doi.org/10.1016/J.TELE.2015.11.006

Sani, S., Haji, J., Goshu, D., 2017. Climate change adaptation strategies of smallholder farmers :The case of Assosa District , Western Ethiopia. J. Environ. Earth Sci. 6, 9–15.

Santhi, C., Srinivasan, R., Arnold, J G, Williams, J.R., Arnold, Jeffrey G, 2005. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. https://doi.org/10.1016/j.envsoft.2005.05.013

Schroter, D., Cramer, W., Leemans, R., Prentice, I.C., Araújo, M.B., Arnell, N.W., Bondeau, A., Bugmann, H., Carter, T.R., Gracia, C.A., de la Vega-Leinert, A.C., Erhard, M., Ewert, F., Glendining, M., House, J.I., Kankaanpää, S., Klein, R.J.T., Lavorel, S., Lindner, M., Metzger, M.J., Meyer, J., Mitchell, T.D., Reginster, I., Rounsevell, M., Sabaté, S., Sitch, S., Smith, B., Smith, J., Smith, P., Sykes, M.T., Thonicke, K., Thuiller, W., Tuck, G., Zaehle, S., Zierl, B., 2005. Ecosystem Service Supply and Vulnerability to Global Change in Europe. Science (80-.). 310, 1333–1337. https://doi.org/10.1126/science.1115233

Schuler, S., 2016. Ecosystem services - an instrument of environmental and resource management in Germany ?: Conceptual foundations, ethical motives and participatory ... ibidem-Verlag, Stuttgart.

Schulz, R., Peall, S., 2000. Effectiveness of a Constructed Wetland for Retention of Nonpoint-Source Pesticide Pollution in the Lourens River Catchment, South Africa. Environ. Sci. Technol 35, 422–426. https://doi.org/10.1021/ES0001198

Schulze, R.., Arnold, H., 1984. Hydrological models for application to small rural catchments in Southern Africa : refinements and development. Pretoria.

Schulze, R., 1995. Hydrology and agrohydrology : a text to accompany the ACRU 3.00 agrohydrological modelling system. Water research Commission.

Schulze, R., Maharaj, M., 2007. A-Pan Equivalent Reference Potential Evaporation. In: Schulze, R.E. (Ed). 2007. Pretoria, RSA.

Scott, D., Le Maitre, D., Fairbanks, D., 1998. Forestry and streamflow reductions in South Africa: A reference system for assessing extent and distribution. Water SA 24.

Scott, D.F., Lesch, W., 1997. Streamflow responses to afforestation with EucaZypfus grundis and Pinus putuZu and to felling in the Mokobulaan experimental catchments, South Africa. J. J. Hydrol. 199, 360–377.

Seppelt, R., Dormann, C.F., Eppink, F. V., Lautenbach, S., Schmidt, S., 2011. A quantitative review of ecosystem service studies: approaches, shortcomings and the road ahead. J. Appl. Ecol. 48, 630–636. https://doi.org/10.1111/j.1365-2664.2010.01952.x

Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 485, 229–232. https://doi.org/10.1038/nature11069

Shackleton, S.E., Shackleton, R.T., 2018. Local knowledge regarding ecosystem services and disservices from invasive alien plants in the arid Kalahari, South Africa. J. Arid Environ. 159, 22–33. https://doi.org/10.1016/j.jaridenv.2017.07.001

Sharpley, A.N., Daniel, T., Gibson, G., Bundy, L., Cabrera, M., Sims, T., Stevens, R., Lemunyon, J., Kleinman, P., Parry, R., 2006. Best Management Practices To Minimize Agricultural Phosphorus Impacts on Water Quality. United States Dep. Agric. ARS-163.

Shen, C., Niu, J., Phanikumar, M.S., 2013. Evaluating controls on coupled hydrologic and vegetation dynamics in a humid continental climate watershed using a subsurface-land surface processes model. Water Resour. Res. 49, 2552–2572. https://doi.org/10.1002/wrcr.20189

Shortall, S., Sutherland, L., McKee, A., Hopkins, J., 2017. Women in Farming and the Agriculture Sector. Aberdeen.

Sibande, R.X., 2013. Costs of Eutrophication at the Vaal River System: An Integrated Economic Model. University of Pretoria.

Simpson, G.B., Badenhorst, J., Jewitt, G.P.W., Berchner, M., Davies, E., 2019. Competition for land: The water-energy-food nexus and coal mining in Mpumalanga province, South Africa. Front. Environ. Sci. 7, 1–12.

https://doi.org/10.3389/fenvs.2019.00086

Sinclair, T.., Muchow, R.., 1999. radiation Use Efficiency. Adv. Agron. 215–265.

Singels, A., Annandale, J.G., Jager, J.M. De, Schulze, R.E., Inman-Bamber, N.G., Durand, W., Rensburg, L.D. Van, Heerden, P.S. Van, Crosby, C.T., Green, G.C., Steyn, J.M., 2010. Modelling crop growth and crop water relations in South Africa: Past achievements and lessons for the future. South African J. Plant Soil 27, 49–65. https://doi.org/10.1080/02571862.2010.10639970

Sipaseuth, N., Attanandana, T., Yost, R., 2007. Nitrogen Fertilizer Response of Maize on Some Important Soils from DSSAT Software Prediction. Plant Soil 27, 21–27.

Smith, H.F., Sullivan, C.A., 2014. Ecosystem services within agricultural landscapes—Farmers' perceptions. Ecol. Econ. 98, 72–80. https://doi.org/10.1016/J.ECOLECON.2013.12.008

Smith, S., Wigley, T., 2006. Multi-Gas Forcing Stabilization with Minicam. Energy J. 27, 373–391.

Soil Survey Staff, 2014. Keys to Soil Taxonomy, 12th ed. Washington, DC.

Spangenberg, J.H., von Haaren, C., Settele, J., 2014. The ecosystem service cascade: Further developing the metaphor. Integrating societal processes to accommodate social processes and planning, and the case of bioenergy. Ecol. Econ. 104, 22–32. https://doi.org/10.1016/J.ECOLECON.2014.04.025

Steglich, E.M., Osorio, J., Doro, L., Jeong, J., Williams, J., 2018. Agricultural Policy Environmental Extender Model-User's Manual.

Stevenson, A., Lindberg, C., 2010. New Oxford American Dictionary. Oxford University Press. https://doi.org/10.1093/acref/9780195392883.001.0001

Struik, P.C., Kuyper, T.W., 2017. Sustainable intensification in agriculture: the richer shade of green. A review. Agron. Sustain. Dev. 37. https://doi.org/10.1007/s13593-017-0445-7

Swinton, S., Lupi, F., Robertson, P., Hamilton, S., 2007. Ecosystem services and agriculture: Cultivating agricultural ecosystems for diverse benefits. Ecol. Econ. 64, 245–252. https://doi.org/10.1016/J.ECOLECON.2007.09.020

Tadross, M., Jack, C., Hewitson, B., 2005. On RCM-based projections of change in southern African summer climate. Geophys. Res. Lett. 32, L23713. https://doi.org/10.1029/2005GL024460

Tallis, H., Polasky, S., 2009. Mapping and Valuing Ecosystem Services as an Approach for Conservation and Natural-Resource Management. Ann. N. Y. Acad. Sci. 1162, 265–283. https://doi.org/10.1111/j.1749-6632.2009.04152.x

Tang, J., Niu, X., Wang, S., Gao, H., Wang, X., Wu, J., 2016. Statistical downscaling and dynamical downscaling of regional climate in China: Present climate evaluations and future climate projections. J. Geophys. Res. 121, 2110–2129. https://doi.org/10.1002/2015JD023977

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93, 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

TEEB, 2010. The Economics of Ecosystems and Biodiversity: Mainstreaming the Economics of Nature: A synthesis of the approach, conclusions and recommendations of TEEB.

TEEB, 2008. The economics of ecosystems and biodiversity : an interim report. [European Communities].

The Water Wheel, 2004. The Great Fish River Valley.

Therond, O., Hengsdijk, H., Casellas, E., Wallach, D., Adam, M., Belhouchette, H., Oomen, R., Russell, G., Ewert, F., Bergez, J.-E., Janssen, S., Wery, J., Van Ittersum, M.K., 2011. Using a cropping system model at regional scale: Low-data approaches for crop management information and model calibration. Agric. Ecosyst. Environ. 142, 85–94. https://doi.org/10.1016/J.AGEE.2010.05.007

Thomas, D.S.G., Twyman, C., Osbahr, H., Hewitson, B., 2011. Adaptation to Climate Change and Variability: Farmer Responses to Intra-seasonal Precipitation Trends in South Africa. Adv. Glob. Chang. Res. 43, 155–178. https://doi.org/10.1007/978-90-481-3842-5_7

Tian, X., Li, C., Zhang, M., Wan, Y., Xie, Z., Chen, B., Li, W., 2018. Biochar derived from corn straw affected availability and distribution of soil nutrients and cotton yield. PLoS One 13, e0189924. https://doi.org/10.1371/journal.pone.0189924

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. 2 Tilman. Nature 418, 671–677. https://doi.org/https://doi.org/10.1038/nature01014

Tolk, J.A., Howell, T.A., 2003. Water use efficiencies of grain sorghum in three USAsouthern Great Plains soils. Agric. Water Manag. 97–111.

Tompsett, P.B., 1976. Factors Affecting the Flowering of Andropogon gayanus Kunth. Responses to Photoperiod, Temperature and Growth Regulators. Ann. Bot. 40, 695–705. https://doi.org/10.1093/oxfordjournals.aob.a085183

Tredoux, G., Engelbrecht, P., Israel, S., 2009. Nitrate in Groundwater. Why is it a Hazard and How to Control It? Rep. to Water Res. Comm. by CSIR, Nat. Reesources Environ. Stellenbosch 1–21.

Tredoux, G., Talma, A.S., 2006. Nitrate pollution of groundwater in southern Africa. Groundw. Pollut. Africa 15–36.

Tremblay, M., Wallach, D., 2004. Comparison of parameter estimation methods for crop models. Agronomie 24, 351–365. https://doi.org/10.1051/agro:2004033

Trout, T.J., Asce, F., Dejonge, K.C., 2017. Crop Water Use and Crop Coefficients of Maize in the Great Plains. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001309

Turner, K., Anderson, S., Gonzales-Chang, M., Costanza, R., Courville, S., Dalgaard, T., Dominati, E., Kubiszewski, I., Ogilvy, S., Porfirio, L., Ratna, N., Sandhu, H., Sutton, P.C., Svenning, J.-C., Turner, G.M., Varennes, Y.-D., Voinov, A., Wratten, S., 2016. A review of methods, data, and models to assess changes in the value of ecosystem services from land degradation and restoration. Ecol. Modell. 319, 190–207. https://doi.org/10.1016/j.ecolmodel.2015.07.017

Turpie, J.K., Forsythe, K.J., Knowles, A., Blignaut, J., Letley, G., 2017. Mapping and valuation of South Africa's ecosystem services: A local perspective. Ecosyst. Serv. 27, 179–192. https://doi.org/10.1016/j.ecoser.2017.07.008

Turpie, J.K., Marais, C., Blignaut, J.N., 2008. The working for water programme: Evolution of a payments for ecosystem services mechanism that addresses both poverty and ecosystem service delivery in South Africa. Ecol. Econ. 65, 788–798. https://doi.org/10.1016/J.ECOLECON.2007.12.024

USDA Soil Conservation Service, 1972. National Engineering Handbook, in: National Engineering Handbook. Washington DC, USA.

Uzoma, K.C., Smith, W., Grant, B., Desjardins, R.L., Gao, X., Hanis, K., Tenuta, M., Goglio, P., Li, C., 2015. Assessing the effects of agricultural management on nitrous oxide emissions using flux measurements and the DNDC model. Agric. Ecosyst. Environ. 206, 71–83. https://doi.org/10.1016/J.AGEE.2015.03.014

van Averbeke, W., Juma, K., Tshikalange, T., 2007. Yield response of African leafy vegetables to nitrogen, phosphorus and potassium: The case of Brassica rapa L. subsp. chinensis and Solanum retroflexum Dun. #. Water SA 33.

Van Der Laan, M., Annandale, J.G., Tesfamariam, E., du Preez, C., Benade, N., Bristow, K., Stirzaker, R., 2012. Modelling Nitrogen and Phosphorus Dynamics in Cropping Systems at the Field Scale.

van der Linden, P., Mitchell, J., 2009. ENSEMBLES: Climate Change and Its Impact: Summary of Research and the Results from the ENSEMBLES Project. Met Off. Hadley Centre, Exet. https://doi.org/10.1002/9781119941156.ch9

van der Velde, M., Folberth, C., Balkovič, J., Ciais, P., Fritz, S., Janssens, I.A., Obersteiner, M., See, L., Skalský, R., Xiong, W., Peñuelas, J., 2014. African crop yield reductions due to increasingly unbalanced Nitrogen and Phosphorus consumption. Glob. Chang. Biol. 20, 1278–1288. https://doi.org/10.1111/gcb.12481

van Gaelen, H., 2016. Evaluating agricultural management from field to catchment scale Development of a parsimonious agro-hydrological model. KU Leuven.

van Jaarsveld, A.S., Reyers, B., Scholes, R.J., 2010. The regional assessments of ecosystem services in Southern Africa. Presentation 1–25.

van Oudenhoven, A.P.E., Petz, K., Alkemade, R., Hein, L., de Groot, R.S., 2012. Framework for systematic indicator selection to assess effects of land management on ecosystem services. Ecol. Indic. 21, 110–122. https://doi.org/10.1016/J.ECOLIND.2012.01.012

van Rensburg, L., de Clercq, W., Barnard, J., du Preez, C., 2011. Salinity guidelines for irrigation: Case studies from Water Research Commission projects along the Lower Vaal, Riet, Berg and Breede Rivers. Water SA 37.

https://doi.org/10.4314/wsa.v37i5.11

van Zelm, R., van der Velde, M., Balkovic, J., Čengić, M., Elshout, P.M.F., Koellner, T., Núñez, M., Obersteiner, M., Schmid, E., Huijbregts, M.A.J., 2018. Spatially explicit life cycle impact assessment for soil erosion from global crop production. Ecosyst. Serv. 30, 220–227. https://doi.org/10.1016/J.ECOSER.2017.08.015

Vanclay, F., 2004. Social principles for agricultural extension to assist in the promotion of natural resource management. Aust. J. Exp. Agric. 44, 213. https://doi.org/10.1071/EA02139

Vigerstol, K.L., Aukema, J.E., 2011. A comparison of tools for modeling freshwater ecosystem services. J. Environ. Manage. 92, 2403–2409. https://doi.org/10.1016/J.JENVMAN.2011.06.040

Villamagna, A.M., Angermeier, P.L., Bennett, E.M., 2013. Capacity, pressure, demand, and flow: A conceptual framework for analyzing ecosystem service provision and delivery. Ecol. Complex. 15, 114–121. https://doi.org/10.1016/J.ECOCOM.2013.07.004

Voortman, R.L., Sonneveld, B.G.J.S., Keyzer, M.A., 2003. African land ecology: opportunities and constraints for agricultural development. AMBIO A J. Hum. Environ. 32, 367–373. https://doi.org/10.1639/0044-7447(2003)032[0367:ALEOAC]2.0.CO;2

Vukasovič, T., 2016. Consumers' Perceptions and Behaviors Regarding Organic Fruits and Vegetables: Marketing Trends for Organic Food in the Twenty-First Century. J. Int. Food Agribus. Mark. 28, 59–73. https://doi.org/10.1080/08974438.2015.1006974

Waibel, H., Pahlisch, T.H., Völker, M., 2018. Farmers' Perceptions of and Adaptations to Climate Change in Southeast Asia: The Case Study from Thailand and Vietnam, in: Lipper, L., McCarthy, N., Zilberman, D., Asfaw, S., Branca, G. (Eds.), Climate Smart Agriculture : Building Resilience to Climate Change. Springer International Publishing, Cham, pp. 137–160. https://doi.org/10.1007/978-3-319-61194-5_7

Walker, N.J., Schulze, R.E., 2006. An assessment of sustainable maize production under different management and climate scenarios for smallholder agro-ecosystems in KwaZulu-Natal, South Africa. Phys. Chem. Earth 31, 995–1002. https://doi.org/10.1016/j.pce.2006.08.012

Wallach, D., 2011. Crop Model Calibration: A Statistical Perspective. Agron. J. 103, 1144. https://doi.org/10.2134/agronj2010.0432

Wallach, D., Buis, S., Lecharpentier, P., Bourges, J., Clastre, P., Launay, M., Bergez, J.-E., Guerif, M., Soudais, J., Justes, E., 2011. Environmental modelling & software : with environment data news. Elsevier Science Ltd.

Wallach, D., Makowski, D., Jones, J.W., 2006. Working with dynamic crop models : evaluation, analysis, parameterization, and applications. Elsevier.

Walsh, G., Wepener, V., 2009. The influence of land use on water quality and diatom community structures in urban and agriculturally stressed rivers. Water Sa 35.

Walthall, C.L., Anderson, C.J., Baumgard, L.H., Takle, E., Wright-morton, L., 2013. Climate Change and Agriculture in the United States: Effects and Adaptation.Geological and Atmospheric Sciences Reports. 1. http://lib.dr.iastate.edu/ge_at_reports/1.

Wang, J., Wang, E., Yang, X., Zhang, F., Yin, H., 2012. Increased yield potential of wheat-maize cropping system in the North China Plain by climate change adaptation. Clim. Change 113, 825–840. https://doi.org/10.1007/s10584-011-0385-1

Wang, X., He, X., Williams, J.R., Izaurralde, R., Atwood, J.D., 2005. Sensitivity an Uncertainity Analysis of Crop Yields and Soil Organic Carbon Simulated with EPIC. Trans. ASAE 48.

Wang, X., Li, J., Naveed Tahir, M., De Hao, M., 2011. Validation of the EPIC model using a long-term experimental data on the semi-arid Loess Plateau of China. Math. Comput. Model. 54, 976–986. https://doi.org/10.1016/j.mcm.2010.11.025

Wang, X., Williams, J.R., Gassman, P.W., Baffaut, C., Izaurralde, R.C., Jeong, J., Kiniry, J.R., 2012. EPIC and APEX: Model Use, Calibration, and Validation. Trans. ASABE 55, 1447–1462. https://doi.org/10.13031/2013.42253

Wang, X., Xing, Y., 2016. Evaluation of the effects of irrigation and fertilization on tomato fruit yield and quality: a principal component analysis. Nature, Sci. Reports. https://doi.org/10.1038/s41598-017-00373-8

Wang, Z., Qi, Z., Xue, L., Bukovsky, M., Helmers, M.J., 2015. Modeling the impacts of climate change on nitrogen losses and crop yield in a subsurface drained field. Clim. Change 129, 323–335. https://doi.org/10.1007/s10584-015-1342-1

Warburton, M., Schulze, R., Jewitt, G., 2013. Hydrological responses to combined land-use and climate change in three diverse South African catchments. IAHS Publ.

Warner, G., Stake, J., Guillard, K., 1997. Evaluation of EPIC for a shallow New England soil: I. Maize yield and nitrogen uptake. Trans. ASABE.

Webber, H., Gaiser, T., Ewert, F., 2014. What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa? Agric. Syst. 127, 161–177. https://doi.org/10.1016/J.AGSY.2013.12.006

Wei, Y., Chen, D., Davidson, B., White, R., 2005. Bio-economic strategy to combat non-point pollution in China. Pedosphere 15, 156–163.

Westman, W.E., 1977. How Much Are Nature’s Services Worth? Science (80-.). 197, 960–964. https://doi.org/10.1126/science.197.4307.960

Wilby, R.L., Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. Prog. Phys. Geogr. Earth Environ. 21, 530–548. https://doi.org/10.1177/030913339702100403

Williams, J.., Gerik, T., Dagitz, S., Magre, M., Meinardus, A., Steglich, E., Taylor, R., 2015. Environmental Policy Integrated Climate Model - Users Manual Version 0810.

Williams, J.R., Jones, C.A., Dyke, P.T., 1984. A modeling approach to determining the relationship between erosion and soil productivity. Trans. ASAE Am. Soc. Agric. Eng. 27, 129–144.

Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC Crop Growth Model. Trans. ASAE 32, 0497–0511. https://doi.org/10.13031/2013.31032

Wilson, G.A. (Geoffrey A., 2007. Multifunctional agriculture : a transition theory perspective. CABI.

Wise, M., Calvin, K., Thomson, A., Clarke, L., Bond-Lamberty, B., Sands, R., Smith, S.J., Janetos, A., Edmonds, J., 2009. Implications of Limiting CO2 Concentrations for Land Use and Energy. Science (80-.). 324, 1183–1186. https://doi.org/10.1126/science.1168475

World Vision, 2019. FMNR 1983: Outstanding Practice in Agroecology. Factsheet 6.

Worou, O.N., Gaiser, T., Oikeh, S., 2015. Sensitive parameters for EPIC model evaluation and validity under soil water and nutrients limited conditions with NERICA cropping in West Africa. African J. Agric. Res. 10, 2286–2299. https://doi.org/10.5897/AJAR2014.9423

Worou, O.N., Gaiser, T., Saito, K., Goldbach, H., Ewert, F., 2012. Simulation of soil water dynamics and rice crop growth as affected by bunding and fertilizer application in inland valley systems of West Africa. Agric. Ecosyst. Environ. 162, 24–35. https://doi.org/10.1016/J.AGEE.2012.07.018

Wu, May, Ha, Miae, Ha, M, Wu, M, 2015. Simulating and evaluating best management practices for integrated landscape management scenarios in biofuel feedstock production Modeling and Analysis: Evaluating Best Management Practices for Biofuel Feedstock Production. Biofuels Bioprod. Bioref 9. https://doi.org/10.1002/bbb

Xiong, K., Kong, F., 2017. The Analysis of Farmers' Willingness to Accept and Its Influencing Factors for Ecological Compensation of Poyang Lake Wetland. Procedia Eng. 174, 835–842. https://doi.org/10.1016/J.PROENG.2017.01.230

Xiong, W., Balkovič, J., Van Der Velde, M., Zhang, X., Izaurralde, R.C., Skals, R., Lin, E., Mueller, N., Obersteiner, M., 2013. A calibration procedure to improve global rice yield simulations with EPIC. Ecol. Modell. 273, 128–139. https://doi.org/10.1016/j.ecolmodel.2013.10.026

Xiong, W., Skalský, R., Porter, C.H., Balkovič, J., Jones, J.W., Yang, D., 2016. Calibration-induced uncertainty of the EPIC model to estimate climate change impact on global maize yield. J. Adv. Model. Earth Syst. 8, 1358–1375. https://doi.org/10.1002/2016MS000625

Xu, M., Wang, Z., Duan, X., Pan, B., 2014. Effects of pollution on macroinvertebrates and water quality bio-assessment. Hydrobiologia 729, 247–259. https://doi.org/10.1007/s10750-013-1504-y

Yang, Yanmin, Liu, D.L., Anwar, M.R., Zuo, H., Yang, Yonghui, 2014. Impact of future climate change on wheat production in relation to plant-available water capacity in a semiaridenvironment. Theor. Appl. Climatol. 115, 391–410. https://doi.org/10.1007/s00704-013-0895-z

Yapa, L.S., Mayfield, R.C., 1978. Non-Adoption of Innovations: Evidence from Discriminant Analysis. Econ. Geogr. 54, 145. https://doi.org/10.2307/142849

Yin, G., Gu, J., Zhang, F., Hao, L., Cong, P., Liu, Z., 2014. Maize yield response to water supply and fertilizer input in a semi-arid environment of Northeast China. PLoS One 9, 1–6. https://doi.org/10.1371/journal.pone.0086099

Zhang, J., Balkovič, J., Azevedo, L.B., Skalský, R., Bouwman, A.F., Xu, G., Wang, J., Xu, M., Yu, C., 2018. Analyzing and modelling the effect of long-term fertilizer management on crop yield and soil organic carbon in China. Sci. Total Environ. 627, 361–372. https://doi.org/10.1016/J.SCITOTENV.2018.01.090

Zhang, W., Ricketts, T.H., Kremen, C., Carney, K., 2007. Ecosystem services and dis-services to agriculture. Ecol. Econ. 64, 253–260. https://doi.org/10.1016/J.ECOLECON.2007.02.024

Zhao, Z., Sha, Z., Liu, Y., Wu, S., Zhang, H., Li, C., Zhao, Q., Cao, L., Zhang, H., Zhang, H., Li, C., Li, C., Zhao, Q., Zhao, Q., Cao, L., Cao, L., 2016. Modeling the impacts of alternative fertilization methods on nitrogen loading in rice production in Shanghai. Sci. Total Environ. 566–567, 1595–1603. https://doi.org/10.1016/j.scitotenv.2016.06.055

Zhou, Z., Palmborg, C., Ericson, L., Dryler, K., Lindgren, K., Bergkvist, G., Parsons, D., 2019. A 60-years old field experiment demonstrates the benefit of leys in the crop rotation. Acta Agric. Scand. Sect. B — Soil Plant Sci. 69, 36–42. https://doi.org/10.1080/09064710.2018.1492010

Ziervogel, G., Cartwright, A., Tas, A., Adejuwon, J., Zermoglio, F., Shale, M., Smith, B., 2008. Climate change and adaptation in African agriculture. Training 4179, 53. https://doi.org/10.1002/cnm

Ziervogel, G., New, M., Archer van Garderen, E., Midgley, G., Taylor, A., Hamann, R., Stuart-Hill, S., Myers, J., Warburton, M., 2014. Climate change impacts and adaptation in South Africa. Wiley Interdiscip. Rev. Clim. Chang. 5, 605–620. https://doi.org/10.1002/wcc.295

Zinyengere, N., Crespo, O., Hachigonta, S., Tadross, M., 2015. Crop model usefulness in drylands of southern Africa: an application of DSSAT 32. https://doi.org/10.1080/02571862.2015.1006271

Zwane, M., Montmasson-Clair, G., 2016. Climate Change Adaptation and Agriculture in South Africa: a policy assessment. South Africa.

Appendices

Appendix A. Questionnaire on farmers' agricultural land management practices and values assigned to agroecosystem services in agriculture.

Thank you for taking the time to participate in this study. This survey is anonymous and results will only be used for academic purposes.

The farmer remains a significant shareholder in safeguarding our future food security as many decisions impacting food production are made at the farm level. The aim of this survey is to find out from farmers or land managers, the current agricultural management practices they are using and any other challenges they are facing in their farm business. Information will be used to recommend policies that are farmer oriented and suggest management practices that increase farmers' yields. Your input is greatly appreciated.

Please answer the questions to the best of your knowledge.

I understand that the survey is voluntary and I am free to stop participation at any moment. I confirm that the information I provide will be used to write research reports.
* Check all that apply.

I agree to participate ☐

Agricultural land management

1. In what province is your farm located? ___________________________________

2. What is the total size of your farm? ______________________________________

3. How long have you been farming or managing land? __________________________

4. Please check all the crops that you produce

Check all that apply.

- Maize ☐
- Lucerne ☐
- Vegetables ☐
- Citrus ☐
- Wheat ☐
- None ☐
- Other: ____

5. Please check all the livestock on your farm

Check all that apply.

- Beef cattle ☐
- Dairy cattle ☐
- Sheep ☐
- Goats ☐
- Poultry ☐
- None ☐
- Other: ____

6. Where do you get information when making farm decisions?

Check all that apply.

- Other farmers ☐
- Private Consultant ☐
- Government Extension ☐
- Internet ☐
- Agricultural Magazines ☐
- Farmers' Organisations ☐

Other: ____

7. Do you irrigate your crops?

Mark only one box.

Yes ☐ No ☐

8. If yes, what is your main source of irrigation water?

Check all that apply.

River/stream ☐

Groundwater ☐

Dam/Pond ☐

I do not irrigate ☐

Other:

____

9. What Irrigation methods do you use?

Check all that apply.

Surface ☐

Overhead ☐

Drip ☐

Sub-surface ☐

I do not irrigate ☐

Other:

____

10. What are your reasons for using those kinds of irrigation methods?

____

____

____

11. Do you apply fertilisers on your field?

Mark only one box.

Yes ☐

No ☐

12. If yes, what type of fertilisers do you apply?

Check all that apply.

Organic (animal or compost) ☐

Inorganic/Chemical (NPK, Ammonium compounds) ☐

Other: ____

13. What are your reasons for applying those particular fertilisers?

____

____

____

14. What methods do you use when determining fertiliser application rates?

Check all that apply.

Soil Analysis ☐

Crop yield considerations ☐

Past experience ☐

Private Consultant ☐

Extension Services ☐

Environmental Goals ☐

Other: ____

15. What methods do you use to apply fertiliser?

Check all that apply.

Liquid ☐

Controlled release ☐

Broadcast ☐

Arial or Spraying ☐

Other: ____

16. Why do you use those particular methods?

____

____

____

17. How do you make decisions on fertiliser application timing?

Check all that apply.

Plant appearance/need ☐

Fertiliser Label ☐

Supplier instructions ☐

Past experience ☐

Soil and plant testing ☐

Consultant ☐

Other: ____

18. What is the average yield per growing season for your main crops?

____

19. For the crops you have mentioned above, approximately how much fertiliser do you use per growing season?

____

____

20. Do you know how much irrigation water you use per growing season?

Mark only one box.

Yes ☐

No ☐

I do not irrigate ☐

21. If yes, approximately how much do you use for each crop?

____

22. What are the three biggest problems in the management of your farm?

____

____

____

Ecosystem Services

There is growing awareness that farmlands provide a variety of benefits to society, such as food provision, purifying water, renewing soil and providing a habitat for birds and animals. The term 'ecosystem services' is used to refer to these benefits.

23. How familiar are you with the term "ecosystem services"?

Check appropriate box

Very familiar	Somewhat familiar	Never heard the term before

24. How often do you think croplands provide the following benefits to society?

Check all that apply.

	Always	Sometimes	Never
provide food			
reduce soil erosion			
provide fuel			
provide recreation			
provide freshwater			

provide clean air			
reduce flooding			
provide medicines			
are pleasing to look at			
maintain species variety			
regulate local climate			

25. How valuable is this benefit to you?

Check all that apply.

Ecosystem Service	Very valuable	Medium value	Not valuable
provide food			
reduce soil erosion			
provide fuel			
provide recreation			
provide freshwater			
provide clean air			
reduce flooding			
provide medicines			
are pleasing to look at			

maintain species variety			
regulate local climate			

26. What are your biggest ecosystem concerns on the farm?

____

____

____

____

27. What aspects of your land are most important to you? Why?

____

____

____

____

30. Please check all the conservation/adaptation management practices used on your farm

Check all that apply.

- Nutrient Management ☐
- Irrigation management ☐
- Intercropping ☐
- No-till ☐
- Riparian buffer ☐
- Grassed waterways ☐
- Crop residues ☐
- Crop rotation ☐
- Cover crops ☐
- Filter strips ☐

Compost manure ☐

Rotational grazing ☐

None ☐

Other: ____

Payments for ecosystem services (PES)

Payments for ecosystem services are increasingly being used to help manage ecosystems more sustainably. PES are economic arrangements or incentives used to reward the conservation of ecosystem services. PES describe schemes in which the beneficiaries, or users, of ecosystem services, provide payments to the stewards, or providers, of ecosystem services. In practice, this often involves a series of payments to land managers in return for a guaranteed management action by the land managers likely to enhance the provision of ecosystem services. Payments are made by the beneficiaries of the ecosystem services in question, for example, by the government acting on behalf of society.

31. Would you be willing to implement conservation practices on your land if you knew how they would benefit your farm?

Mark only one box.

Yes ☐

No ☐

28. If there was a conservation program that offered you a payment for improving the quantity or quality of ecosystem services your land provides, would you consider participating?

Mark only one box.

Yes ☐

No ☐

Climate change

29. Have you heard of climate change?

Mark only one box.

Yes ☐ No ☐

30. If yes, has it affected your farm production in any way?

____

____

____

____

31. Have you, in any of the past years, changed the type of crops grown on the farm?

Mark only one box.

Yes ☐ No ☐

32. If yes, what has encouraged you to change the type of crops you grow?

Check all that apply.

	Large influence	Medium influence	No influence
Climate Change (weather)			
Technological advances			
Financial factors			
Government policies			
Markets (demand, access)			
Pests and diseases			
Advice from other farmers			

Advice from agronomists			

33. What have you noticed about rainfall in the past 10 to 20 years concerning the following (please tick appropriate box)

Start of rainy season

Early ☐

No change ☐

Late ☐

Length of rainy season

Increased ☐

No change ☐

Decreased ☐

Amount of rainfall

Increased ☐

No change ☐

Decreased ☐

Average temperature

Increased ☐

No change ☐

Decreased ☐

34. Are there any other factors that have made you change or consider changing the type of crops you grow?

____

____

____

____

35. What are some of the major challenges that are making it difficult for your farming practice to be profitable?

____

____

____

____

36. What one thing would be of most value to you in making your farming operation profitable?

Demography

37. Gender

Mark only one oval.

Female ☐

Male ☐

Other: ____________________

38. Age *

Check all that apply.

Less than 25 ☐

25 - 34 ☐

35 - 44 ☐

45 - 54 ☐

55 - 65 ☐

Above 65 ☐

39. Please check your highest level of education *

Mark only one box.

Primary school ☐

Secondary school ☐

Matriculation ☐

Diploma ☐

Technical/Vocational training ☐

University degree ☐

Other: ____

40. Please check your annual gross farm income *

Mark only one oval.

- Less than R 50 000 ☐
- R 50 000 - R 99 000 ☐
- R 100 000 - R 249 000 ☐
- R 250 000 - R 499 000 ☐
- R 500 000 - R 999 000 ☐
- Over R 1 000 000 ☐

41. Any other comments?

____

____

____

____

____

Thank you for your participation!

Appendix B. Further EPIC model description

The EPIC model was originally developed in America to investigate the relationship between soil erosion and soil productivity (Williams et al., 1989). The model simulates approximately eighty crops with one crop growth model using unique parameter values for each crop. It contains a variety of crop management options including fertilization, irrigation and pesticide fate. EPIC operates on a daily time step and can be used for long term assessments spanning hundreds of years (Balkovič et al., 2014). It has been used for crop production studies (Folberth et al., 2013; van der Velde et al., 2014) and water resource studies (Forster et al., 2000; Intarapapong et al., 2002; King and Balogh, 2009). Several studies have also found the model to be effective in simulating crop growth and crop management scenarios under resource-limited conditions (van der Velde et al., 2014; Worou et al., 2015). Additionally, soil nitrogen and phosphorus biogeochemistry models are incorporated into the EPIC model (Xu et al., 2014). The model is therefore well suited for simulating nutrient and irrigation management practices in agricultural systems. The major management and biophysical components of the EPIC model are briefly described below.

Crop growth and yield.

EPIC uses a single crop module capable of simulating the major agronomic crops, trees, and pastures. The model simulates about 100 different crops each with unique crop growth parameters. Crop specific parameters have been developed for the major crops and the user may create new crop parameters or adjust existing parameters as required. The model can also simulate crops grown in rotations and in particular cases, in mixtures (Forster et al., 2000).

The model is capable of simulating growth for both annual and perennial crops. Crop growth and development are based on the accumulation of heat units from planting to harvesting. Potential biomass production is based on light interception and assimilation. Potential increases in root and above-ground biomass are multiplied by plant growth-regulating factors to obtain the actual daily growth. Development of leaf area index (LAI) depends on crop-specific maximum LAI, inbound solar radiation, plant stress, and heat units (HU) (Williams et al., 1989). The height of the crop depends on crop-specific maximum crop height and HU. Based on a maximum harvest index (HI) and a minimum harvest index under water stress (WSFY), the model calculates the development of and actual HI over the growing season depending on HU and water stress. At harvest, the model calculates economic crop yield based on biomass and actual HI. Annual crops grow from planting to harvest date or until the accumulated heat units equal the potential heat units for the crop.

Phenological development and maturity

Plant development is accelerated by warm temperatures. High temperatures shorten the time to emergence (Angus et al., 1980), to antithesis (Tompsett, 1976) and grain filling period (Balasko and Smith, 1971). Phenological development and crop maturity are based on the heat unit accumulation approach. Heat units are based on the concept that the development of the plant is dependent upon the accumulated heat to which it was subjected during its developmental stages (Warburton et al., 2013) In general, the lower the temperature, the slower the rate of growth and development of the plant.

Weather

The model requires daily inputs of precipitation, maximum and minimum temperatures, solar radiation, relative humidity, and wind speed. The weather data can be based on measured data or generated stochastically. Historical daily weather data can be used directly in EPIC simulations when the length of historical daily weather is the same as the simulation period. When historical data is limited, historical daily weather data can be used to generate monthly weather data, which are used to generate EPIC weather input data for the entire simulation period (Williams et al., 2015).

Nutrient cycling

The model simulates nitrogen and phosphorus fertilization, crop uptake, transformations, and movement. The nutrient application can be automatic, based on crop stress levels or manual according to user-specified dates and amounts. Nutrients can be applied as mineral fertilisers, animal manure or in irrigation water (fertigation). Crop use of N is estimated using a supply and demand method. The daily crop demand for N is given by the difference between the ideal N content for the day and the crop N content (Williams et al., 1989).

Tillage

The user may select different tillage equipment according to local farming practices. characteristics of simulated tillage equipment can be changed in the model. Tillage equipment affects nutrient cycling and soil hydrology. Various crop rotations can be simulated with the generic crop growth routine used in EPIC. An extensive array of tillage systems and other management practices can also be simulated with the model (Williams et al., 2015).

Plant stresses

The growth of roots is constrained by soil temperature and aluminium toxicity depending on pH, organic carbon, base saturation, and a crop-specific aluminium tolerance factor. Development of above-ground biomass is limited mainly by nutrient (N and P), water temperature and aeration stress. Water and nutrient stresses are based on deficits compared to optimal supply on each day (Folberth, 2013). Air stress is calculated as a function of porosity, soil water content and critical aeration factor. The totals of the daily values for each stress factor over the growing season are referred to as stress days.

Hydrologic Cycle

Precipitation in the model is divided into runoff and percolation with runoff volume estimated using a modified routine based on the USDA Soil Conservation Service curve number method (USDA Soil Conservation Service, 1972). Runoff, percolation, lateral subsurface flow and snowmelt are simulated (Forster et al., 2000). The model allows the simulation of crop yields different Potential Evapotranspiration (PET) equations which allows reasonable model applications in different climatic regions (Balkovič et al., 2013). Seven options are provided to simulate water erosion and five options are available to simulate potential evapotranspiration. In this thesis the Hargreaves method for estimating PET was used.

Soil organic carbon

The EPIC model used in this study EPIC v810 uses N cycling and organic carbon routines based on the Century model (Parton et al., 1994). Based on the description by (Izaurralde et al., 2006), organic matter (OM) is split into different pools: microbial biomass, slow humus, passive humus metabolic and structural litter and standing dead residue and roots. C and N may exit the system through leaching, erosion, and volatilization (Folberth et al., 2012). Exchanges between the various pools depend on several factors including soil water content, temperature, tillage profile depth, and C/N rations if microbial processes are involved. To allow for equilibration of soil functions and OM pools. The effects of soil texture on organic matter stabilization are also modelled.