Innovative coupling of Hydrological modelling for IWRM: Linking catchment functioning with socio-economic conditions in the Olifants.

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Declaration

I declare that this thesis is my own unaided work. It is being submitted to the Degree of Doctor of Philosophy to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.

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Abstract

Computerised integrated models from science contribute to better informed and holistic ex-ante integrated assessments of multifaceted policies and technologies. This view has lead to considerable effort being devoted to developing integrated models to support decision-making under Integrated Water Resources Management (IWRM). Nevertheless, an appraisal of previous and ongoing efforts to develop such decision support systems shows that attempts to address the hydro-socio-economic effects on livelihoods have been deficient and fragmented. To date, no universal standard integration method or framework is in use. Existing integrated models application failures have pointed to the lack of stakeholder participation. In an endeavour to close this gap, this thesis focuses on an integrated model development with prediction capability, ICHSEA, developed in Avenues script language in ArcView 3.3, to take advantage of the mapping capability of ArcView. This model couples existing hydrology (SWAT), agronomy (PARCHED-THIRST) and socio-economic (OLYMPE) models to link livelihoods of resource-constrained smallholder farmers to water resources availability at catchment level in the semi-arid Olifants subbasin, South Africa. These three models were calibrated and validated using observed data and local stakeholder participation, prior to coupling in the integrated model. All the models performed well in representing the study conditions, as indicated by the statistical performance. The integrated model is generally applicable to any catchment. The study methodology was inspired by the need to enhance rural livelihoods and to close the gap of stakeholder involvement in building and applying integrated models to ensure acceptability and application in decision-making. Over 20 years, the predicted impacts of untied ridges and planting basins versus conventional rainfed tillage on surface runoff reduction were 14.3 % and 19.8 %, respectively, and about 41─46 % sediment yield reduction in the catchment. At 90 % confidence interval, family savings improved from US$ 4─US$ 270 under conventional rainfed to US$ 233─US$ 1 140 under supplemental irrigation. These results underscore the economic and environmental benefits that could be achieved by adopting the new crop management practices. A relationship between

maize crop evapotranspiration and family savings under different crop management strategies was also derived for five farm typologies in the catchment.

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Chapter 1: Introduction

1.1 Background of the research

In 1996 the World Food Summit set a goal of halving the number of food insecure people from 800 million in 1995 to 400 million by 2015 (Inocencio et al., 2003), now one of the Millennium Development Goals (United Nations, 2007, 2005, 2004). Though agriculture still accounts for at least 70 % of the world's total land usage (Pereira et al., 2002), it is unlikely that this goal will be achieved before 2030 in several continents (Inocencio et al., 2003) according to the International Food Policy Research Institute (IFPRI).

South Asia and Sub-Sahara Africa (SSA) regions with about 60 % of the world's food insecure people are the worst affected by food insecurity and malnutrition (Inocencio et al., 2003). A study conducted by International Water Management Institute (IWMI) shows that all African countries are projected to either be physically or economically water scarce in 2025, prompting total cereal imports into Africa of more than 10 % (Oxfam, 2005; Inocencio et al., 2003). In these water scarce regions in SSA, total cereal imports are projected to triple from 9 Mt/year in 1990 to 29 Mt/year in 2020 (Rosegrant et al., 2005; Inocencio et al., 2003).

Furthermore, physically water scarce countries, such as South Africa and North African countries with more than a quarter of the world's population residing within them, are projected to have inadequate water resources to meet both their domestic and food production water needs in 2025 (Saverimuttu and Rempel, 2005; Inocencio et al., 2003). From a study on food projections, Forum for Agricultural Research in Africa (FARA) estimates that coping with food needs of about 3 % population increase requires agricultural production to increase by an annual rate of 6 % to achieve food security in SSA by 2015 (Rosegrant et al, 2005; Inocencio et al., 2003). This steep increase in agricultural production necessitates agricultural intensification and possible increase in agricultural water demand.

With the rapidly growing world urban populations (e.g. from 23 % in 1980 to 34 % in 1999) (World Bank, 2000), agriculture will have to compete with higher-value municipal and industrial needs. This will result in reduced water allocations to agriculture that aggravates the problem of food insecurity and reliance on rainfed production. An estimated 60 % of the world's cereal production grown under rainfed conditions remains vulnerable to sufficiency of temporal and spatial variability of rainfall, especially in semi-arid regions (IWMI, 2000 cited in Inocencio et al., 2003). Hence, the challenge is to feed the growing population under increasing water scarcity and reduced irrigation water supply.

To increase food production under water scarcity, it is argued that there is growing awareness to adopt a multi-disciplinary integrated research approach on rainfed agriculture production (CAWMA, 2007) and eco-system (Martínez-Santos et al., 2009; Matthews, 2006). These studies require to be complemented by climatology, hydrology and socio-economic studies. The aims of these studies should be to analyse the natural dynamics and assess possible strategies to make semi-arid regions less vulnerable to present and future changing climate (Sattler et al., 2009; Rivington et al., 2007; Krol et al., 2006; Krol et al., 2001).

In addition, several studies (Rockström et al. 2001; Rockström, 2001, 1999; Rockström and Falkenmark, 2001; WFS, 1996) showed that current rainfed agricultural productivity could be increased three to five times by improved soil water management and rainwater harvesting techniques. Rockström and Falkenmark (2001) further report that there seems to be no hydrological limitations, even in semi-arid areas, to achieve five to ten times higher yields than experienced at present (0.5–1 t/ha yields).

There is overwhelming evidence of water scarcity in South Africa with a total population of 46.6 million. Eberhard (2003) indicated that 11.2 million people had access to inadequate water, while 18.1 million had no sanitation (Statistics SA, 2006; Eberhard, 2003) in the year 2001. The water availability per capita per year in South Africa is about 1100 m^3, less than 1700 m^3 (Falkenmark, 1998) indicating that the country is water stressed and will experience occasional or local water problems (Eberhard, 2003). The growing rural and urban populations, higher intensive cultivation, industrialisation, and, of late, environmental reserve concerns (NWA, 1998), have all combined to put pressure on South Africa's water resources (Ray and Gül, 2000).

Furthermore, South African irrigation farming covers 10 % (1.3 million ha) of cultivated land and accounts for about 62 % of the national water use (DWAF, 2004a). This irrigated agriculture produces a quarter of the agricultural output (de Lange et al., 2005), whereas rainfed agriculture that covers about 90 % of the cultivated land produces about three quarters of agricultural output (IPTRID, 2000). Similarly, Olifants River subbasin has over 100,000 ha of irrigation land that accounts for more than 50 % of water consumption in the subbasin (DWAF, 2004a). This irrigation water consumption is affected by ecological water needs.

The need to satisfy ecological water reserve (NWA, 1998) will result in a reduction in available water resources for existing uses by 15–20 % at national level (Inocencio et al., 2003). Therefore, satisfying the ecological water reserve leaves little scope for new large-scale irrigation development in the country and in the Olifants River subbasin in particular. Moreover, Olifants River subbasin is a closing one, as much of its water resources have been developed (DWAF, 2004a; Vörösmarty et al., 2000). Hence, there are water transfers into the Olifants subbasin. These water transfers from the Inkomati, Usutu, Mhlatuze and Upper Vaal catchments for power generation are estimated at 172 Mm^3/a (DWAF, 2004a). Magagula et al. (2006) estimated the transfers at 241 Mm^3/year, showing increased water transfers. Hence, water resource development through the construction of new infrastructure will be very expensive and is unlikely to be affordable by irrigation farmers.

As water availability shrinks, water transfers from the irrigated agricultural sector are expected, resulting in increased crop area under rainfed. Therefore, to maintain food production, rainfed crop productivity should be increased to stabilise farm incomes. Rainfed productivity increase is among the basic principles of new agricultural policy in South Africa (DWAF, 2004a) and internationally (CAWMA, 2007).

It follows from the above worrisome Olifants River subbasin and B72A catchment situations that poverty reduction (Merrey et al., 2005) and achieving food security (United Nations, 2007) are formidable challenges. These challenges are overcome by increased agriculture water productivity and access to water by the rural poor to reduce poverty, under enabling agricultural policies (Walker, 2002). However, questions that relate to the impacts of techniques that increase water productivity and food-related policies on catchment food production, environment and livelihoods through the year 2025 remain unanswered.

It is against this background that B72A catchment of the Olifants River subbasin was selected in this study to apply model integration. This study seeks to contribute to better understanding of blue and green water availability in the catchment and further develop a decision support system that can be used to evaluate alternative agricultural water management strategies.

The research is funded by WaterNet under the Challenge Programme for Water and Food (CPWF). The overall goal of the CPWF research project is "to contribute to improved rural livelihoods of poor smallholder farmers through the development of an IWRM framework for increased productive use of green and blue water flows and risk management for drought and dry-spell mitigation at all scales in the Limpopo basin"

In the next section, problem and purpose statements are described. Next, research objectives guiding the study are presented. In addition, the relevance and limitations of the study are described followed by organization of the thesis.

1.2 Problem statement

At the United Nations Conference on Water in the Mar del Plata in 1977 (United Nations, 2004), Integrated Water Resources Management (IWRM) approach was recommended to address the multiple competing water resources uses in a catchment or basin . These multiple competing uses are driven by management strategies that are either endogenous to the catchment (i.e. increases in demands for a particular service), or exogenous to the catchment such as requirements for compliance with standards imposed at a higher management level (Forsman et al., 2003).

In line with the IWRM approach developments, public engagement processes have been adopted to incorporate multiple values and interests in water resources decision-making processes. The merging of these trends has led water resources planners to embrace the use of transparent and readily understood computer models. These models aid consensus building across competing values and interests when making water resources decisions. Furthermore, user-friendly and credible integrated models that enable stakeholders to analyse scenarios in a rational way to aid decision-making in highly contested catchments, such as the Olifants subbasin, can be invaluable in sustainable catchment water management for improved livelihoods.

The Olifants River that lies in the Limpopo Basin, has a total catchment area of 54, 563 km^2 and flows from the highly populated Gauteng Province of South Africa into Mozambique. Thus, the Olifants River subbasin (an IWMI Benchmark Basin) stretches through the Northern Province (the poorest in South Africa), at river basin (catchment) level. Its water resources are largely committed (DWAF, 2004a) and its river flow frequently ceases. Zero flow was initially experienced in 1968 (DWAF, 1990). These zero-flows affect the diversity of fauna and flora including conservation areas in the Olifants subbasin. In addition, plans to revitalise small irrigation schemes in the Olifants subbasin, including B72A catchment would further increase agricultural water demand, which currently uses more than 50 % and 58 % water in the Olifants subbasin and B72A catchment, respectively (DWAF, 2004a).

Furthermore, Olifants subbasin's geographic position, the prevailing wind systems, including tropical cyclones from Indian Ocean, has a strong influence on its climate. The precipitation is seasonal and erratic (i.e. high frequency of dry spells), falling as intense thunderstorms during the warmer summer months, at times resulting in floods. During the last floods in February 2000, the flow at the Olifants River mouth peaked at 3,800 m^3/s (DWAF, 2004a), although the river is known to have zero flow during short periods as it enters the Kruger National Park. Still, a severe drought occurs practically every decade.

Furthermore, rainfall in the Olifants subbasin varies from 400–1000 mm per annum with coefficient of variation of about 0.6, whilst actual evapotranspiration varies from 1600–2000 mm (DWAF, 2002). The uneven distribution of water across the subbasin, coupled with increasing competition for the available water resources between users, has led to tensions and occasional water disputes between individuals and communities (Ashton, 2000).

There is painfully clear evidence of universal water stress, as people use unprotected water sources and long water queues at a community standpipes (Figure 1.1). With drinking water so scarce, agricultural water availability is even more scarce. In addition, pervasive poverty, unequal water allocations and inadequate water supply for many black rural communities, especially those in the former homelands in the Olifants subbasin is evident. The manifestations of poverty include food insecurity, lack of access to resources, declining environmental quality (through cultivation of high sloping areas prone to erosion) (Ntsheme, 2005), external economic shocks, social problems and lack of local community participation in decision-making. The presence of land degradation in the catchment due to overgrazing and poor agricultural practices (Figure 1.2) () gives rise to high sediment loads and consequently pollutes the rivers. This release of sediment-laden water to maintain the base flow resulted in fish deaths in the Kruger Park (DWAF, 2002).

The South African Water Law (NWA, 1998) has brought practical changes in water use and sharing among different users to protect catchment quality. The Department of Water Affairs and Forestry (DWAF) circulated a draft position paper for water allocation reform, "*Towards a Framework for Water Allocation Planning*" from January 2005. The thrust of the position paper was to consolidate the National Water Act on ensuring a balance between efficiency, sustainability and equity needs in water allocations (NWA, 1998). An inclusive water allocation strategy must be guaranteed for all, especially to meet the basic human needs of rural poor who have been previously disadvantaged.

Studies related to hydrology including water quality and allocation decision-making (Arranz and McCartney, 2007; McCartney et al., 2005) in the Olifants subbasin were hampered by lack of properly distributed spatial inputs such as rainfall and topography (BKS, 1998) and were deficient in addressing the socio-economic aspects of the community. In addition, these studies did not analyse water (blue and green) problems in agriculture in relation to food security in a holistic manner, but only as individual components (DWAF, 2004a).

In an endeavour to fulfil the holistic analyses of water problems, the worldwide-accepted IWRM approach was selected. This IWRM approach has unquestionably become mainstreamed in South African Water Law (NWA, 1998) and worldwide. There is conviction that IWRM can provide sustainable water security for every citizen including the rural poor into the 21st century. However, the effective field implementation of IWRM remains a major challenge. In South Africa, several studies highlighted a wide consensus on the need for multidisciplinary water resources management based on IWRM, but the required methodologies are lacking (Ntsheme, 2005; van Delden et al., 2004; Prasad, 2004; Ringler, 2001).

Given the water scarcity in the Olifants subbasin and B72A catchment in particular, an integrated water management approach is of extensive interest. Furthermore, water for irrigation as a means of rural development and poverty relief will therefore have to be sourced largely through re-allocation from existing users. In addition, water demand management, especially in the agricultural sector, which is the biggest user, is one of the possible solutions being considered by DWAF.

Furthermore, irrigation water demand could be reduced if rainfall under rainfed agriculture is efficiently harnessed for crop use or supplemental irrigation is practiced. Methods to utilise rainfall efficiently under rainfed agriculture include in-field rainwater harvesting crop-water management techniques. However, the socio-economic (i.e. farm family food security and profitability) and hydrological responses (i.e. streamflows and sediments) to supplemental irrigation water allocation and crop-water management related policy changes are important but unknown. This knowledge gap motivated the development of practical and user-friendly decision aid tools to assess the impacts and tradeoffs of alternative agricultural water allocations and crop-water management scenarios on smallholder farmers' food security at catchment level.

The decision support tool in this study context is computer based and attempts to model blue and green water management in a holistic manner by linking hydrological, agronomic and socio-economic models into an integrated modelling framework for sustainable catchment management. The study builds a tool to bring together water, food security, land and people in the B72A quaternary catchment.

Possible users of the tool are stakeholders with administrative interests in catchment water planning and food production. These include the Department of Water Affairs (DWA) and the Catchment Management Agencies (CMAs). CMAs are expected to use the tool in the development of Catchment Management Strategies including decisions on water licensing and best catchment management practices that need to consider hydrological, environmental, economic and social aspects of the catchment.

Figure 1.1 Evidence of universal water stress in the B72A quaternary catchment.

Figure 1.2 Hillside cultivation evidenced by field patches on the mountains.

1.3 The purpose statement

The purpose of this research was to explore and better understand how water allocation to agriculture and improved on-farm crop-water management options affect rural people's livelihoods and streamflows in the B72A catchment of Olifants subbasin, South Africa. In particular, this study was interested in the representative smallholder farmers' farm-based livelihoods at quaternary catchment level. The study was guided by the following hypothesis and research objectives.

1.4 Hypothesis

A computerised modelling framework that integrates hydrology and socio-economic aspects is a useful tool for assessing water availability for agricultural production, which is important for comprehensive understanding of the implications of new policies and technologies that achieve food security in the Olifants subbasin.

1.5 Research objectives

This section describes the overall and specific objectives of the study.

1.5.1 Overall objective

The main objective of the study is to develop and test an integrative modelling framework that enables a better understanding of the linkage between water resources and socio-economic aspects for enhanced agricultural water availability and productivity in B72A quaternary catchment, Olifants subbasin. This study intends to bring together Water, Food, Land, People and Finance in a holistic manner for improved rural livelihoods.

1.5.2 Specific objectives

a) To evaluate: (i) water resource availability (ii) maize crop water management and (iii) agricultural water use and allocation in the B72A catchment.

b) To define impact parameters that influence the physical, economic and social conditions in the B72A catchment.

c) To review available technical decision support models that address impact parameters defined in (b) and assess them for possible application in this work.

d) To develop a modelling framework that links water resources and socio-economic factors in order to understand agricultural water availability and productivity impacts on food production and livelihood.

e) To conceptualise scenarios in (a) in collaboration with farmers and extension officers and test them using an integrative modelling tool developed in (d). Scenario identied include (1) how much land can be brought under supplementary irrigation from ex-field rainwater harvesting in the catchment using water available during the growing season? (2).

What improvement in family livelihood savings or balance is realised when

- In-field rainwater harvesting in the form of ridges is applied
- In-field rainwater harvesting in the form of planting basins is applied
- Agricultural input/outputs market price variations are imposed through policy

f) To assess impacts in the B72A catchment using the parameters defined in (b).

The significance of the study is described in the next section.

1.6 Significance of the study

The computer based decision support tool provides a comprehensive set of hydrology and socio-economic criteria against which various water resource and crop-water management alternatives can be commonly compared. The study's endeavour to link hydrology and socio-economic aspects including participation of local stakeholders is encouraged in a number of policy related documents. These documents include Promotions of the Administration Justice Act (Act 3 of 2000, Section 3), National Water Act (NWA, 1998), Water Services Act of 1997 and National Water Resources Strategy (DWAF, 2004a).

In addition, the study supports the implementation of IWRM approach that has been articulated at a number of international meetings such as the United Nations Millennium Summit in 2000 and the World Summit on Sustainable Development in 2002 (DWAF, 2004a). These sentiments are echoed in the policy objectives of the New African Partnership for Development and the South African Vision for Water, Life and the Environment in the 21st century (DWAF, 2004a).

Furthermore, this study contributes towards the Hydrology for the Environment, Life and Policy (HELP) program crafted by the United Nations Educational Scientific and Cultural Organization (UNESCO) and the World Meteorological

Organisation (WMO) in which Olifants subbasin is one of the 25 basins that have submitted applications for inclusion in the HELP initiative world wide (Endreny et al, 2003). These basins under HELP initiative are expected to have unresolved hydrologic questions that are connected to climate, food production, pollution and human health, environment and water sharing conflicts.

Use of this computer based decision support tool will assist to better identify blue and green water management alternatives for improved food security and livelihoods from socio-economic objectives together with hydrological and environmental objectives for informed decisions. Furthermore, the tool will support the adoption of widely acceptable and sustainable catchment management strategies.

In the next section, the knowledge and information gained from the study on both quantitative and qualitative aspects is described.

1.7 The knowledge and information obtained from the study

Overall, the study contributes to new knowledge by developing and testing a methodology of linking hydrology and socio-economic aspects in water resources management. This study also contributes to bridging the information and knowledge gaps in ongoing attempts to reconcile productivity, efficiency and equity in water resources allocation and management in the Olifants subbasin and B72A catchment in particular. However, the study can be applied to other catchments where necessary data is available.

In addition, the study facilitates mutual trust building among low-level stakeholders through discourse in the development and use of the decision support tool. There are few research tools, which both researchers and farmers can use together to analyse problems and develop scenarios, and this study has contributed in closing this gap.

1.8 Limitations

There are several limitations in the current integrated model structure and components. Firstly, the current model is not capable of considering agricultural production decisions that are non-seasonal. The crop considered to vary in the production systems is maize, though other crop production systems can be analysed. Other major limitations in the model structure and components include key hydrological issues, such as lack of assessment of crop management options impact on water quality. Only sediments loads are presented in the model. These issues are not considered by the integrated model and require further consideration in future developments of the model.

1.9 Definition of terms

This section describes the five terms often referred to in this study. These terms are water resources, livelihoods, integrated modelling, policy-making and rainwater harvesting.

Water resource refers to water in its various forms of liquid, vapour and solid, and in various locations (atmosphere, surface and subsurface), which have potential value to human (United Nations, 2006). Water, in its three forms; green, blue and virtual (white) is essential to society's well-being and to sustainable economic growth. In this study catchment water resources are captured and used as rain (green water) in rainfed agriculture (Rockström et al., 2004; Rockström et al., 2002), runoff in rivers and reservoirs together with groundwater from boreholes and springs (blue water). Collection and realiability of hydrological input data for decision making is important for sustainable community water management decisions. Plants, animals, ecosystems and humans are sensitive to fluctuations in the storage, fluxes, and quality of available water resources. In turn, these storage, fluxes and quality are sensitive to climate change (e.g. manifested through rainfall variations). Therefore, the thrust of this study was to develop appropriate catchment management strategies, based on IWRM principles that incorporate sustainable use of green and blue water resources, which enables poor rural people to reduce risk of food deficits due to water scarcity, and to manage water for improved livelihoods.

Several authors have defined livelihood differently. In general, it refers to present and future people's economic and social network means of living (Hoadley and Limpitlaw, 2004; Avila, 2003; Chambers and Conway, 1992). It includes the activities people carry out to sustain themselves, the assets (human, financial, social, physical and natural) they own, and the linkages between their means of living, institutions and physical environment (Avila, 2003; DFID, 1999). Ellis and Mdoe (2003) argue that livelihood strategies and poverty reduction are linked. Poverty is the state of being poor (i.e. people living on less than US$ 1/capita/day) with lack of the means to provide material needs (Tunhuma, 2006). Poverty at rural community level, can be manifested through lack of sophistication, low literacy levels, use of unprotected water sources, lack of sanitation facilities that hinder development. Consequently, poverty reduction is achieved by providing sustainable livelihood strategies that are influenced by relative income levels (Ellis, 1999). Conversly, Carter (1999) argues that access to safe water and adequate shelter are better indicators of poverty and human possibility than income or expenditure-based measures, which do not capture the differences in intra-household inequality.

From the literature surveyed, an assessment is integrated when it draws a set of cause–effect interactions from physical and socio-economic fields, and communicates knowledge from diverse disciplines with the purpose to inform effective policy decision-making and exposing trade-offs (Martínez-Santos et al., 2009; Jakeman et al., 2008; Greiner, 2004; Pope et al., 2004). Integrated modelling is one of the techniques that include computer tools (van der Sluijs, 2002) used to process data and effectively inform policy-making.

Policy-making involves the process by which individuals and groups with diverse interests and goals negotiate to arrive at a mutually acceptable course of action (Marnicio and Rubin, 1988) or solution to a problem based on available knowledge and their perceptions. Collectively, the context, knowledge and goals of the various groups, and the tasks they perform to achieve goals, combine to influence the final policy decision. Two principal activities associated with policy-making are policy analysis and policy synthesis (Marnicio and Rubin, 1988). Policy analysis entails separating a problem into modules for detailed assessment, whereas policy synthesis entails assembling problem or solution components to form a whole.

Two classes of rainwater harvesting systems include systems that collect roof runoff for household use and systems that use in-field or adjoining catchment to provide supplemental irrigation for agriculture. Hence, the spatial scale of runoff collection varies from in-situ practices such as ridges and planting basins presented in this study that manage rainfall on farm land (water conservation) to external systems collecting runoff from catchment outside the cultivated area (ex-field). Rainwater harvesting system has three components: a watershed area to produce runoff; a storage facility (soil profile, surface reservoirs or groundwater aquifers) and a target area for beneficial use of the harvested rainwater (agriculture, domestic or other purposes).

This study focuses on rainwater harvesting for smallholder farming system crop production. The rainwater not captured when it falls goes to waste at a small scale such as field, but not at a larger scale such as a catchment. The benefits of rainwater harvesting for crop use include (Lancaster, 2006) ability to farm in areas with no alternative water supply, reduced topsoil loss, improved plant growth and improved groundwater recharge. Several rainwater management strategies improve crop yields and green water productivity by maximising plant water availability in the root zone (Critchley and Siegert, 1991).

In sum, water resources (quality and quantity) management impacts on livelihoods and in turn livelihoods impact on water resources were presented. Improved water resources management through rainwater harvesting combined with integrated modelling and supporting policies is likely to result in improved livelihoods and reduction in poverty.

1.10 Organisation of the thesis

The thesis comprises eight chapters (Figure 1.3). The first chapter gives the introduction of the study. In this chapter, the background and the problem and purpose statements are described followed by objectives. This is followed by significance of the study, knowledge and information obtained from the study, limitations and definitions of important terms. Lastly, the thesis organisation is presented. In the second chapter, the study area context at subbasin and catchment level is presented. In the third chapter, detailed literature review of hydrological, agronomic and socio-economic models is described. Furthermore, this chapter presents the definition of integrated models, why integrated models have been developed, examples of integrated models applications and points out the gaps in existing research. In the last section of this chapter, sensitivity and uncertainty analysis methods are described.

In the fourth chapter, methodology and integration conceptual framework are described. Included in this chapter is the description of the activities carried out during field data collection and how collected sample data were analysed. In the fifth chapter, results and discussions on field experiments and survey data are presented. In addition, the results from hydrology, agronomic and socio-economic modelling are presented.

In the sixth chapter, a case study on the application of socio-economic and agronomic models in the simulation of smallholder farming systems to enable the assessment of farm system resilience and adaptive capacity is presented. In the seventh chapter, application of the developed integrated model tool (ICHSEA) to study catchment is presented. Each chapter concludes with a summary. Finally, chapter eight furnishes the conclusions and recommendations arising from the study findings.

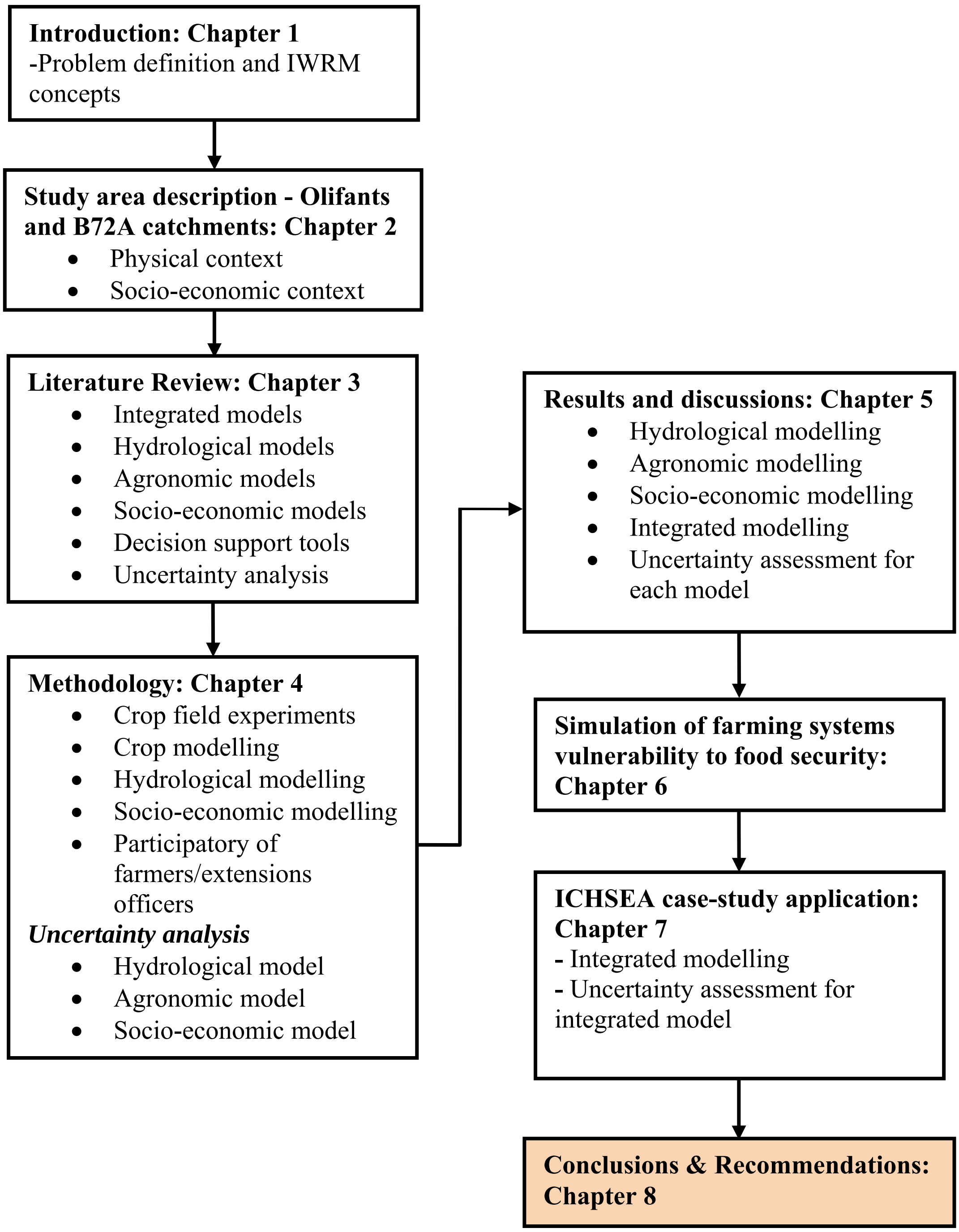


Figure 1.3 Research flow.

Chapter 2: Study Area Context

This chapter describes the location, physical and socio-economic characteristics of the study area in a transboundary Limpopo Basin that moulds the problems experienced by communities. Firstly, the physical context is described, followed by socio-economic context for both the Olifants subbasin and the pilot quaternary catchment, B72A. Under the socio-economic context, demographic pressure, access to water, agriculture production systems and institutions with water management interests are described. Knowing socio-economic context such as demographic composition, availability and access to water resources is important for planning management interventions. Finally, the chapter concludes with a summary of the study area.

2.1 Olifants Subbasin

This section briefly describes the characteristic of the Olifants subbasin in the Limpopo Basin where the quaternary catchment under study, B72A, is located. A quaternary catchment is a subdivision of a secondary catchment (B7 in this study) and is the lowest drainage area for water management in South Africa. The quaternary catchment is delineated based on topography and labelled from the top, down to the catchment outlet of each particular water management area.

In South Africa, Olifants subbasin is a primary catchment and is referred to as a Water Management Area (WMA). The Olifants River (total length of 770 km) originates from the east of Johannesburg and passes through three provinces of South Africa (Gauteng, Mpumalanga and Limpopo Province), before flowing through the Kruger National Park, where it joins the Letaba River before flowing into Mozambique and ends at the confluence with the Limpopo River (DWAF, 2004a) (see Figure 2.1. Olifants subbasin is a tributary subbasin to the Limpopo Basin shared by South Africa, Botswana, Zimbabwe and Mozambique. It is one of the largest subbasins of Limpopo Basin, with total area of 54, 563 km^2 and receives an average rainfall of 630 mm per year (DWAF, 2004a). However, the rainfall is characterised by considerable spatial and temporal variability that leads to seasonal dry spells and water shortages, prompting annual water transfers of 241 Mm^3 into the catchment (Magagula et al., 2006). Furthermore, overcrowding and insecure land ownership in the communal farming areas (such as the Shingwedzi, Selati, and Middle Olifants) are primary sources of land degradation in the subbasin. This land degradation feature is an important driver of poverty within the Olifants subbasin and is associated with declining indices of per capita agricultural production. Mapedza et al. (2008) reported that food security is a constant problem in the subbasin, with an estimated million people currently relying on food aid. Further signs of poverty stress in the subbasin are a high dependency ratio, with 32 % of more than half a million households in the subbasin without an income and lacking full sanitation coverage (Magagula et al., 2006). Only 54 % of households use pit latrine, while 14 % of the households have no sanitation facilities (Magagula et al., 2006).

In addition, there are a number of important ecological and conservation areas within the Olifants subbasin. The most well known conservation area is the Kruger National Park, located in the Lower Olifants subbasin. To ensure water supply to these areas and other users in a closing Olifants subbasin[1] (Magagula et al., 2006; DWAF, 2004a), with water deficit of about 181 Mm^3/year (Magagula et al., 2006), requires prudent water management. However, the term closing basin, is derived strictly from a catchment dam-development point of view that looks at potentially available surface water resources, while neglecting groundwater and water resources that could be made available through efficient water use. Magagula et al. (2006) noted that the apparent deficit does not mean that the actual water use exceeds supply, but that the needs for the ecological reserve are not fully met. The planned water resources development of the Rooipoort and the De Hoop Dams as well as the raising of the Flag Boshielo Dam will supply an additional 239 Mm^3/year (DWAF, 2004a), to the closing Olifants subbasin. Two water availability indicators were reported for the subbasin.

[1] Closing Basin is when all the available water in a catchment is used by the various sectors and there is no longer any potential for development.

The first indicator is the GINI-coefficient that measure water use inequality. The GINI-coefficient for the entire South Africa was estimated at 57.8 in 2001 by the World Bank (Magagula et al., 2006), while for the Olifants subbasin it was 85. A GINI-coefficient of 50 indicates equality, while higher figures indicate inequality of water use by users. The second indicator is the Water Poverty Index (WPI) that was estimated to be 27.1 for the subbasin in 2001. This low figure of WPI indicates that the subbasin is under water stress when compared to the national WPI for the same period that was estimated at 52.2.

The Olifants subbasin's rainfall variation, socio-economic context and its semi-aridness drew an interest in studies related to water management and poverty reduction. Other subbasin characteristics of population density and Water Poverty Index (WPI) are shown in Figure 2.2 and 2.3, respectively. The location of former homelands[2], which are densely populated areas, is shown in both Figure 2.2 and 2.3.

Magagula et al. (2006) reported highly skewed population distribution in the Olifants subbasin (Figure 2.2). An estimated 60 % of the population (3.2 million in 2005) live in the former homelands that cover 26 % of the subbasin area, while the other 40 % occupies the remaining 74 % of land. In addition, the subbasin has low literacy levels, with 33 % of the 49 % school going age population, without formal education (Magagula et al., 2006). Furthermore, only about 6 % of the population have education higher than Grade 12, which is the highest school grade for university entry.

Furthermore, Olifants subbasin was selected under the HELP initiative (Endreny et al., 2003) and is one of IWMI's benchmark river basins, serving as a field laboratory for carrying out research and capacity building in partnership with a range of local, national and international collaborators. These collaborators include ministries of water and agriculture, research organizations, universities,

[2] Homelands/Bantustans: areas set aside by the former apartheid regime for occupation by Africans. These areas were economically non-viable and existed entirely on grants from the South African government. The former apartheid government created 6 "self governing territories" (SGT's): Gazankulu, Kangwane, Kwandabele, Qwaqwa, Lebowa, Kwazulu and 4 "independent states" (TBVC's): Transkei, Bophuthatswana, Venda, Ciskei (South Africa, 1998). The *Subdivision of Agricultural Land Act, 70 of 1970* was the main instrument to implement such zoning regulations.

NGOS, and local communities. In the current study, Olifants subbasin has been denominated as a benchmark river basin of the Challenge Program on Water and Food (CPWF). This offers additional chances for synergies and inter-linkages with a wide range of CPWF research projects in the subbasin.

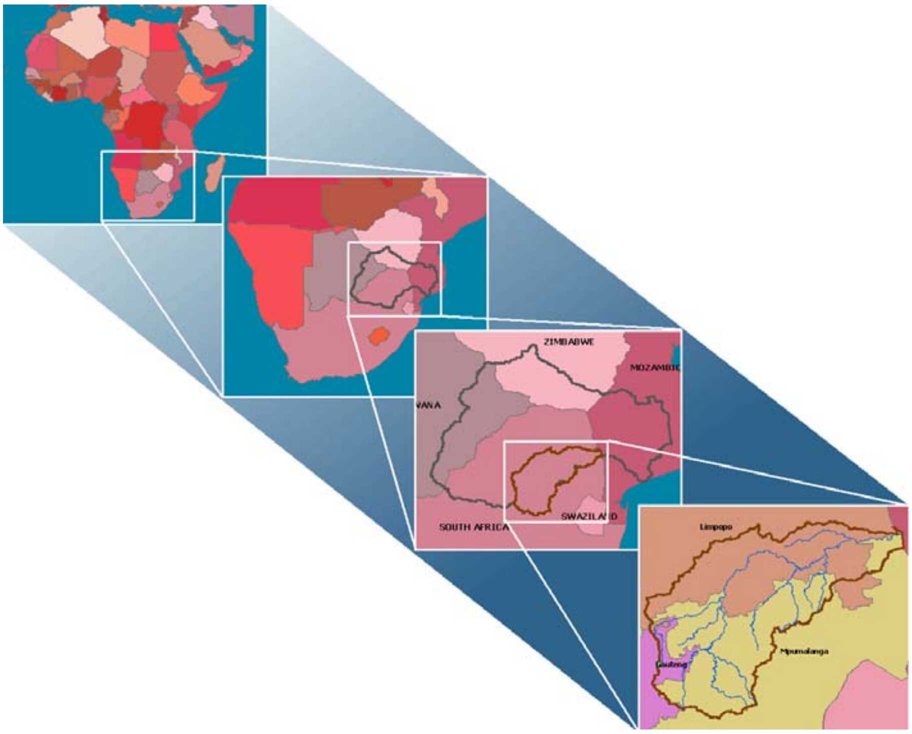


Figure 2.1 Location of the Olifants Water Management Area in South Africa and in the Limpopo Basin (Magagula et al., 2006).

Water management areas are the defining units for the Department of Water Affairs and Forestry (DWAF) and form the basis for the water management strategy in South Africa.

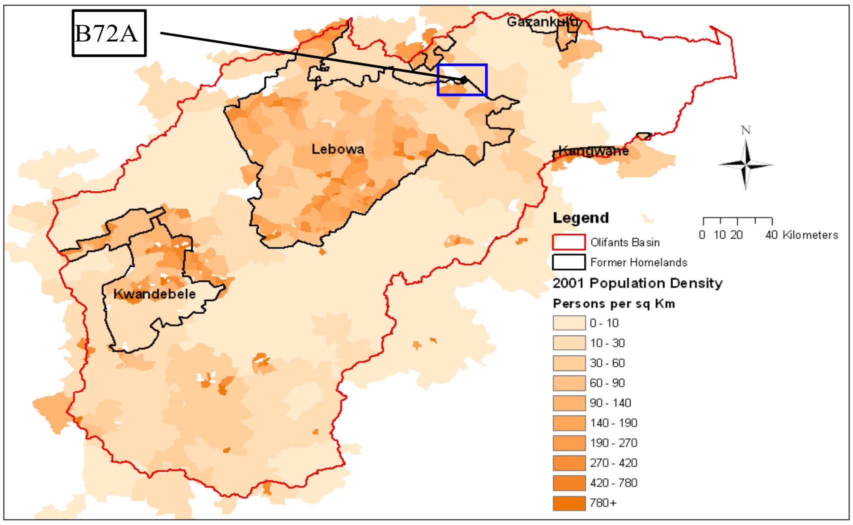


Figure 2.2 Olifants subbasin population density (Magagula et al., 2006). Data Source: Statistics SA, 2001.

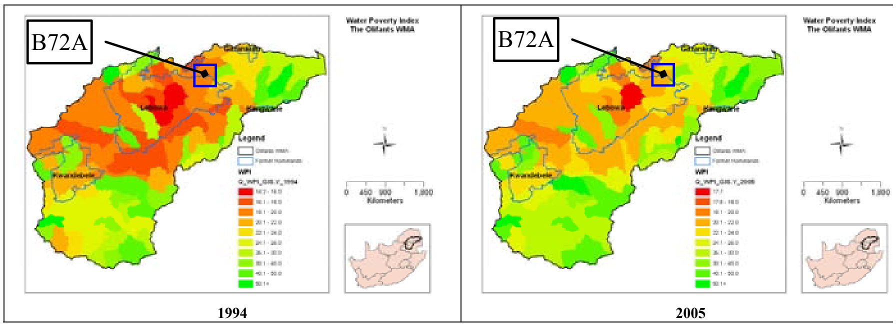


Figure 2.3 Temporal quaternary WPI maps for the period 1994 and 2005 (Magagula et al., 2006).

The B72A quaternary catchment WPI improved from 17.2 (1994) to 21.5 (2005) as shown in Figure 2.3. However, some quaternary catchments, especially those in the former homelands remain at low water poverty, indicating high levels of water poverty.

2.2 B72A quaternary catchment

2.2.1 Physical Context

The pilot quaternary catchment, B72A, with an area of 534 km^2 and located in the lower Olifants subbasin was chosen in the current study (Figure 2.4). The catchment is situated about 60 km south of Tzaneen in the Limpopo province. This catchment falls under Maruleng local municipality, in Mopani district municipality and is part of the Ga-Sekororo and Letsoalo Tribal Authorities (Mapedza et al., 2008). The main rivers in the catchment are Malomanye and Makhutsi rivers. A large percentage of the catchment (80 %) falls under the former Lebowa homeland (Figure 2.2). Some of the catchment priorities are promoting sustainable development for poverty alleviation and introducing technologies to optimise water use efficiency.

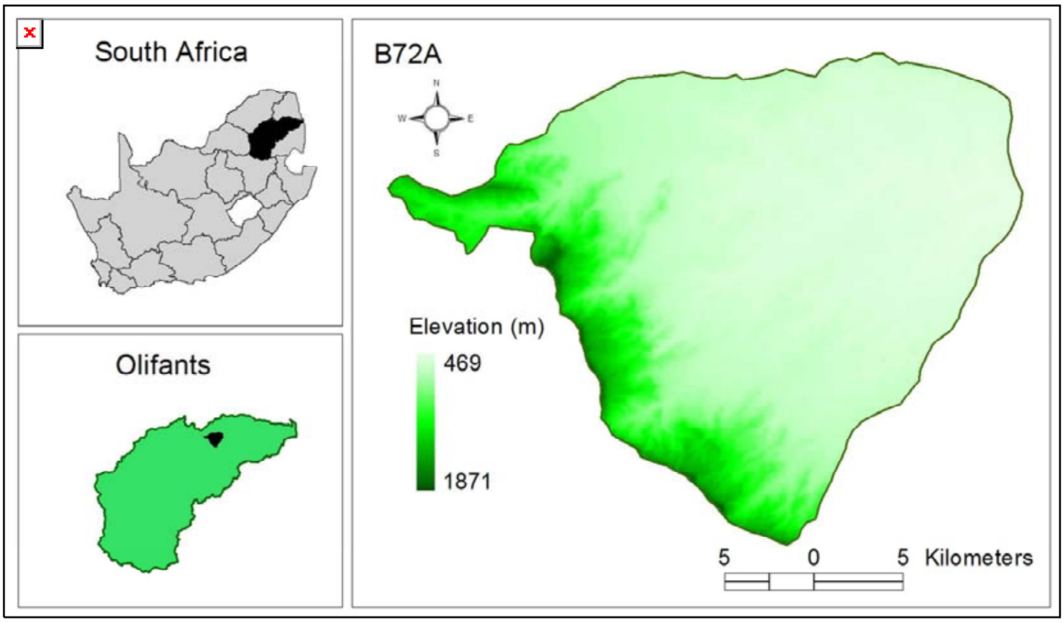


Figure 2.4 The location of B72A quaternary catchment.

2.2.2 Topography

The topography of the basin varies widely with altitudes ranging between 1871m at highest point in the upper part of the catchment and 469 m at the lower part of the catchment (Figure 2.4).

2.2.3 Climate

The climate of the catchment is largely controlled by the movement of air-masses associated with the Inter-Tropical Convergence Zone. Hence, the area experiences seasonal rainfall that largely occurs during the summer months, from October to April. The annual rainfall variation in the quaternary catchment is shown in Figure 2.5, while Figure 2.6 shows the monthly averages (12 years) of climatic data. The mean annual rainfall is 603 mm; with potential evapotranspiration rates above 1500 mm (actual evapotranspiration is around 840 mm) and the average maximum temperature of 27 ^{0}C (DWAF, 2004a). Groundwater recharge occurs in only three months of the year from December to March (Figure 2.6).

Annual rainfall varies from more than 700 mm in the mountains (western part of the catchment) (Figure 2.4) to less than 400 mm in the Eastern plain. In the central plain, the annual rainfall varies between 500–700 mm.

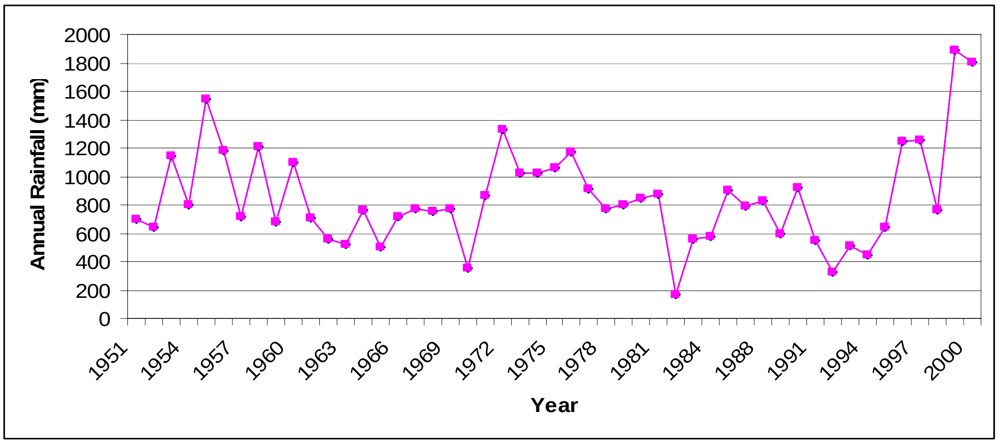


Figure 2.5 Annual rainfall variations in B72A catchment. (Mean = 603 mm, n = 50 years).

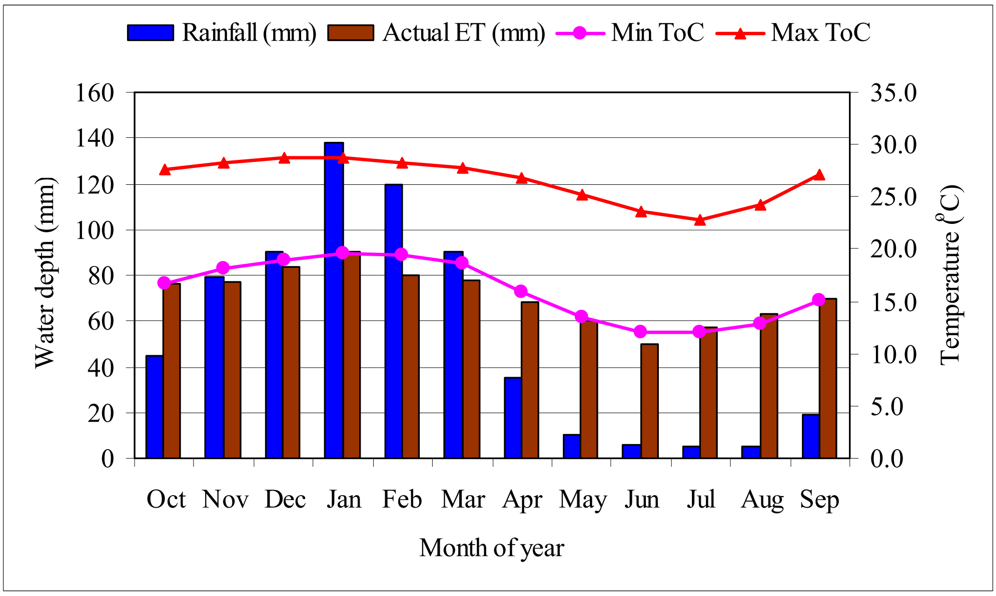


Figure 2.6 Mean monthly variation (n = 12 years) climatic data in B72A catchment.

2.2.4 Geology and Soils

In the central plain between Makhutsi and Malomanye rivers gneiss dominates and the soils are deep clay and sandy, whereas in the central plain, south of Malomanye River, there is harmony granite and free draining sandy soils (Mapedza et al., 2008).

These soils (sandy loam and loamy sand) are poor and susceptible to erosion (Mapedza et al., 2008; Rasiuba, 2007; Ntsheme, 2005). In addition, the soil depth is shallow, within range of 0.2–0.23 m (Ntsheme, 2005). Agricultural productivity is hampered by poor soil nutrients and low clay content (less than 11 %) (Rasiuba, 2007) that results in reduced soil water holding capacity for crop growth especially during dry spells. Deep clay soils are found close to the mountains.

2.2.5 Vegetation

Land uses in the catchment include nature reserve (top of Drakensberg Mountains), gaming and extensive cattle farming. Furthermore, human settlements, small-scale irrigation and rainfed farming, and commercial farming are present.

2.3 Socio-economic context

2.3.1 Demographic dynamics and economics

The total rural population in the B72A catchment is estimated at 56,000 inhabitants (Statistics SA, 2001), mainly Sepedi people. An average household in the catchment has five people (Magombeyi and Taigbenu, 2008). There is a high population density, characteristic of former homelands and a high level of poverty and unemployment. More than 80% of the population depends on agriculture to provide part of their food requirements and partly on remittances, pensions and welfare subsidies from the South African government (Mapedza et al. 2008; DWAF, 2004b).

In sum, population growth and agricultural change are inevitable and will exert more pressure on water supply that prompts changes in water management, allocation and use. Knowing the demographic composition, density and the socio-economic context of the catchment is important for development plans.

An estimated 46 % of the province's economically active population is unemployed and the Human Development Index (HDI) at provincial level is 0.47 (Mapedza et al., 2008). This high unemployment maybe attributed to low literacy levels in the catchment. Statistics SA (2001) estimated that 36 % of the population has no formal education and of the 27 % that reached secondary school, only 10 % have completed their secondary education. Of those that completed secondary education, only 5 % have attained tertiary education. The high unemployment has lead to the perception that the quality of livelihoods in rural areas is lower than in urban areas, resulting in most youths migrating to urban areas in anticipation of better living conditions (Mapedza et al., 2008; Nyalungu, forthcoming).

Furthermore, there is a high percentage (64 %) of female-headed households, and high HIV/AIDS prevalence (Mapedza et al., 2008), which impact on agricultural production. An immense disparity in distribution of wealth and standards of living among different parts of the quaternary catchment and subbasin equally exists, as consequences of development priorities of the former apartheid government. The majority of the population, in the former homelands has derived little or no benefit from the substantial development of water resources in the catchment.

2.3.2 Water resources availability

The estimated mean annual runoff in B72A quaternary catchment is 8.25 Mm^3 (Ncube, 2006). The main source of water for domestic uses is groundwater from boreholes and springs and streams. Diverse water users and land uses that characterise the quaternary catchment are likely to ignite conflicts due to water shortages.

Water resource availability is evidently going to be the key restraining component in efforts to improve the water poverty situation in the Olifants subbasin (Magagula et al., 2006) and B72A catchment. However, increased water use efficiency in both rainfed and irrigated agriculture, and ground-surface water conjunctive use could reduce these water shortages. A summary of the Olifants subbasin and B72A catchment characteristics is shown in Table 2.1.

Table 2.1 Comparison of Olifants subbasin and B72A quaternary catchment.

Characteristic	Olifants	B72A
Population (million)	3.2 (2005)	0.056
Household without income (%)	32	-
Catchment area (km^2)	54, 563	534
Location	25° & 26.5° South Latitude, 28.5° & 24.8° East Longitude	24 ° and 24 .42° South latitude
Mean Annual rainfall (mm)	630	603
Mean Runoff (Mm^3/a)	2040 (yield = 629)	8.25
Altitude (m)	300–2300	469–1871

Characteristic		Olifants	B72A
Access to water (%)	In and at dwellings	42	15.5
	Communal standpipes	30	70 (20% supplied by tanker, 20% boreholes)
	Unprotected sources	28	14.5
Water use (%)	Domestic	15.3	30
	Industrial	9.6	12
	Irrigation	57.7	50
	Other	17.4	8
Water deficit (Mm^3/a)		181 (2001)	Not known
GINI-coefficient		85	-
Water poverty index (WPI)		27.1 (National =52.2)	21.5 (2005)

Notes:

1. Source of water access and use in B72A: SWELL survey done by World Vision South Africa in collaboration with International Water Management Institute (IWMI) in 10 villages in November 2006.
2. Water Poverty Index measures the impact of water scarcity and water provision on human populations using a scale from 0 to 100, where a low score indicates high water poverty. It is comprised of five component indices: resources, access, capacity, use, and environment, each with various sub-indices (Merry and van Koppen, 2007). The WPI enables the identification of those communities where poverty maybe closely attached to water stress and enable prioritisation.
3. A GINI-coefficient of 50 indicates equality, while higher figures indicate inequality of water use by users.
4. Inocencio et al. (2003) estimated Olifants subbasin water deficit at 196 Mm^3 inclusive of transfers.
5. Mean (n = 95 years) annual rainfall for B72A was calculated from three stations (636707W, 636794W and 637070W) in the catchment.

2.3.3 Access to water and sanitation

There are several water users in B72A catchment including domestic, fishery, agriculture, conservancy, and the need to satisfy in-streamflow requirements into

Mozambique. At household level, water use ranges from 10 litres per person per day to more than 100 litres per person per day (Mapedza et al., 2008), depending on the type of access, the size and wealth status of the family and the village. However, there is generally poor access to water services and sanitation in the catchment. An estimated one third of the population's water access is below Reconstruction and Development Programme standard (Mapedza et al., 2008), that requires a community standpipe to be located at less than 200 m from a homestead. In addition, an estimated 33 % of households have no sanitation facilities, while the rest use pit latrines.

2.3.4 Rules for water allocation and distribution

An effective allocation and use of available resources is required in the water scarce B72A quaternary catchment. Firstly, there is provision for environmental water use and basic human needs water use, below which one does not need a permit to use the water (General authorizations and schedule one for small uses). Secondly, there is compulsory licensing mainly targeting the commercial farmers and other bulky water users. For instance, under commercial farmers, all agricultural water users or their representatives are required to provide details of their cropping patterns over the past two years to enable an estimate of their registered water requirements. Furthermore, tradable water allocations among the users can also be implemented (DWAF, 2004a). To ensure equity, the Department of Water Affairs (DWA) has embarked on water abstraction re-allocation and verification of water permits in the entire Olifants subbasin (DWAF, 2004a).

There is no payment for irrigation water under smallholder irrigation schemes. Therefore, tensions and conflicts of sharing available water resources are inevitable and many of the farmers eventually lose interest of farming (Liebrand, 2006).

2.3.5 Agriculture production systems

This section presents both crop and livestock production systems in the study area. Furthermore, game farming is also presented, but not discussed here, since it falls under commercial farming.

Three levels of farmers exist in the B72A quaternary catchment as shown in (Table 2.2). These are large-scale commercial farmers, emerging farmers, and small-scale farmers (Figure 2.7). The small-scale farmers include hillside, rainfed and supplemental irrigation farmers.

A. Large-scale commercial farming

Large commercial farms, which provide employment to the local population, are located in the northern part of the catchment. At national level, commercial agriculture provides substantial employment, especially in rural areas, to about 940 000 seasonal and contract farm workers and the figure adds up to at least 1.3 million households depended on full or part-time farm employment (DA, 2001, 2005). Agriculture contributes about 8 % to South Africa's total exports.

These commercial farms produce mainly for national and international markets. Crops grown include maize (*Zea mays L*), tomatoes and fruit trees such as mangoes and oranges. A few farmers are into game ranging. Initially around 1970s, there were about 26 farmers, but now only 12 remain due to the land re-allocation under the current government (Liebrand, 2006; Ntsheme, 2005). The farmers use both surface and groundwater, with half of the farmers relying entirely on boreholes and other half using a combination of borehole and river water. The irrigation methods used are centre pivot, drip and occasionally flood irrigation. The farmers indicated that the boreholes run dry yearly and hence it was not possible to meet all their water demands. Their production constraints are water shortage, national and international market price fluctuations and high minimum wages for farm labour (Liebrand, 2006).

B. Emerging farmers

The emerging farmers, who own more than 5 ha are a result of land re-allocation exercised by the government after buying land from the commercial farmers to address the historical land imbalances. An example of that gesture was the resettling of 300 Black farmers on 140 ha of land in Calais, Ga-Sekororo in 2001. A further 900 families were recently re-allocated land in the quaternary catchment (Nesamvuni et al., 2002). These emerging farmers practice medium-scale farming and are working towards commercialization. Crop productions by these farmers include maize, sugar beans, chillies, tomatoes and fruits trees. The farmers use both boreholes and surface water supplied by a dam on the Selati River (Ntsheme, 2005).

C. Small-scale farming

The small-scale or smallholder farmers include hillside, rainfed and supplemental irrigation farmers. These farmers mainly produce for family subsistence and their land sizes are generally, less than two hectares. They are involved in crop production of sorghum, maize, tomatoes, beans, groundnuts, sweet potatoes and vegetables. Generally, maize planting starts in October/November to take advantage of rainfall. In March/April, harvesting is completed and in irrigation fields, plots are prepared for winter vegetables, which are sold locally. More details for each smallholder type are discussed next.

D. Hillside farmers

The hillside farmers practice both dry land and livestock raring of cattle, goats, donkeys, pigs and poultry. However, about 75 % of these farmers are into maize, beans and groundnuts cultivation. Most of these farmers own less than 2ha and started farming in the hillsides in 1995. The reasons for ploughing in the hills are shortage of cropland on the low-lying areas, higher rainfall than in the low-lying areas, fertile soils since they have not been under cultivation for many years and the need to occupy land that formerly belonged to their ancestors. These hillside farmers practise the slash and burn system to prepare their land (Ntsheme, 2005), but do not practise in-field rainwater harvesting. However, they use contouring, log barriers and stone barriers as methods of conserving soil and soil moisture. In spite of these soil conservation structures, gullies and signs of erosion are evident in the fields. The estimated yields are decreasing over years and presently, are less than 3 t/ha. The causes of yield decrease were due to seasonal erratic and unevenly distributed rainfall, labour shortage and crop destruction by baboons.

E. Rainfed farming

The majority of the smallholder farmers practise rainfed farming. Female-headed families form a greater proportion of these farmers. In addition, about 50 % of the rainfed farmers are above 50 years old and have no formal education. Their field sizes are 1–1.5 ha and the soil is not very fertile (Ntsheme, 2005). An estimated 18 % of the farmers neither use manure or fertilisers, except ploughing back crop residues in the soil. Some of these rainfed farmers practice rainwater harvesting on a small scale, mainly for drinking purposes and small home gardens. Their maize (main crop) yields are less than 2 t/ha and are diminishing each year due to lower rainfall and frequent dry spells. Shortage of draft power, erratic rainfall and destruction of crops by livestock are some of the factors that constrain their crop production.

F. Smallholder Irrigation farmers

The irrigation schemes were initially established in 1956, with each family allocated 1 ha of land (Liebrand, 2006; Ntsheme, 2005). Government irrigation committees controlled the allocation of water and helped with the farming inputs and produce marketing. Under the new government in 1994, individuals farming in the schemes were selected to manage the schemes and that led to the collapse of these irrigation schemes. Currently, the government through the provincial Department of Agriculture is rehabilitating the schemes under the program Rehabilitation of Small Irrigation Schemes (RESIS). Female farmers, who have attained grade seven or lower and some with no formal education, form about 60 % of farmers in the irrigation schemes (Ntsheme, 2005). These irrigation farmers use tractor for ploughing and hoe for weeding. They all use artificial fertilisers and organic manure, while a few make use of pesticides. Their water allocation is time bound. Each farmer is allocated four irrigation hours per day per week, with excess irrigation water stored in night storage dams (Figure 2.8).

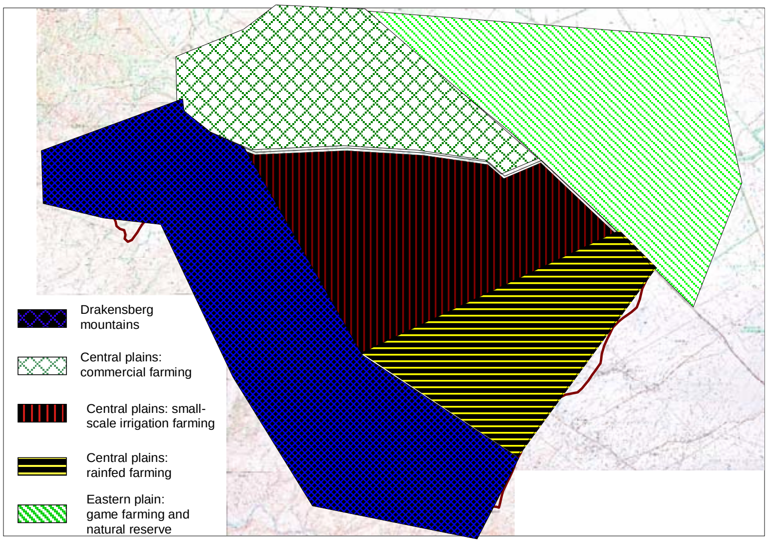


Figure 2.7 Agricultural areas in B72A quaternary catchment (Mapedza et al., 2008).

Figure 2.8 A lined irrigation channel leading to a night storage dam from an irrigation field.

Table 2.2 Types of farmers in B72A quaternary catchment

Farmer type	% of type	% of cultivated land	% blue water use
Commercial	0.4	27	63
Emerging	9.5	10	12
Rainfed and Hillside	80.1	59	-
Smallholder irrigation	10.0	4	25

(Source: Liebrand, 2006; Ntsheme, 2005)

Livestock statistics

The 2005 livestock statistics from Mertz Agricultural veterinary indicate that there are 14 043 cattle in the quaternary catchment under communal grazing only (Ntsheme, 2005). Cattle under commercial farming are not included. Game farming is also present under commercial farming (Liebrand, 2006).

With only 8.6 % of rainfall being available as surface water (DWAF, 2002), rainfed farming and small irrigation are important for farmers' food security. Hence, crop water productivity need to be improved (more production per drop of water) in the context of limited land and water resources for improved rural livelihoods in the area (CAWMA, 2007).

Irrigation methods

The source of water for small-scale irrigation schemes are springs in the mountain, which feeds, into rivers. The water is conveyed from the river source through lined and unlined canals to the schemes where it is distributed in the field by flood irrigation. Night storage dams are used to store water in some irrigation schemes (e.g. Sofaya scheme). However, in other schemes, these dams have heavily silted and no longer hold enough water for use during dry periods. Recently, drip kits were donated to the farmers but are not in use because the borehole and overhead tank to achieve enough head have not been completed.

Furthermore, these small-scale irrigation schemes are in a poor state of operation, with some requiring rehabilitation, farmer training programs and support services.

In addition, there is need for establishing effective institutional arrangement to manage the irrigation schemes and increase water use efficiency.

2.3.6 Constraints to agricultural production

Major risks to agriculture in the area relate to fluctuation in weather conditions (low and erratic rainfall), resulting in high variability of crop yields (Magombeyi and Taigbenu, 2008), crop damage by livestock, lack of formal credit facilities, unfavourable market arrangements (Fabre, 2006), lack of resources for cultivation and purchase of mineral fertilizers (Kgonyane and Dimes, 2007). To realize farm level goals of sufficient family income and food and sustainable farming, continuous adaptation by the farming systems to changing aforementioned external conditions is required.

The agricultural policy identified five principal challenges of success of these irrigation schemes, which are rehabilitation of irrigation schemes, development of new irrigation water sources, increased water use efficiency and farmer training programmes.

The water and land management institutions found in the study area are described in the next section.

2.3.7 Institutions

This section briefly describes the institutions related to water and agricultural management in the study area. Two levels of institutions are distinguished, the high and low levels.

Encouraging progress in terms of high-level water resources institutions comprises two aspects (DWAF, 2006). The first aspect was the establishment of three main water management areas, Limpopo, Luvuvhu/Letaba, and Olifants, managed by Mpumalanga Province. These water management area institutions will take over catchment management currently being executed by Department of Water Affairs (DWA). Secondly, Water User Associations have been established in the Olifants subbasin. Catchment management agencies' responsibilities include monitoring (water quality and quantity), controlling and / or implementing the catchment development plans, policy developing and educating the public to ensure a high level of awareness amongst water users, action groups and politicians. Detailed responsibilities of the catchment management agencies are presented in DWAF (2006).

Other institutions in the catchment include non-governmental organisations (NGOs). One example of an NGO in the catchment is the World Vision South Africa. This NGO has established a drought management committee in the catchment that holds meetings on monthly basis for assessing food situation and planning. Government can support this initiative by forming similar drought management committees in other quaternary catchments in the Olifants subbasin.

To sum up, there is a top-down approach in the management of water resources at community level that needs blending with the bottom-up approach to involve the local stakeholders in planning and to inform sustainable policies. The shift from central to local scale in water resources management, including distribution is critical to supporting the main founding concepts of IWRM principles that incorporate sustainable use of green and blue water (NWA, 1998).

The water distribution and management in the catchment remains in charge of several institutions, and sometimes there is duplication of roles. Water management structures in the area include the Department of Water Affairs (DWA) regional office. This regional office implements policy, strategy and regulatory work decided at the head office. In addition, the local municipality is responsible for the supply of domestic water to rural and urban areas, including the free basic water of 25 ℓ/capita/day as required by the National Water Act.

Furthermore, the Department of Agriculture is involved in both land and water management aspects for agricultural purposes. Other water management related institutions at local level are water user committees, tribal control, ward and village committees. The water user associations for commercial farmers are strong and knowledgeable in water related issues, while no formal water user associations exist for the smallholder farmers (Ntsheme, 2005).

In sum, there are several institutions involved in water management in B72A catchment. DWA, which is the regular, is also a service provider body. This creates conflicts of interest and render water management complex. In addition, villagers struggle to comprehend the regulations of several existing water and land management bodies and this has resulted in a weakened catchment management structure. The inclusion of local community in water related decision-making will likely improve the management of water resources in the catchment.

2.4 Summary

The chapter briefly described physical and socio-economic aspects of Olifants subbasin and then proceeded to a more detailed description of the pilot quaternary catchment, B72A.

The B72A quaternary catchment is representative of the Olifants subbasin because of its water scarcity, diverse water users and land uses including the high poverty levels and unemployment in former homelands. Three farming systems in the area are commercial, emerging and small-scale. The majority of farmers falls under small-scale farming and rely much on farm production together with other sources of income, such as pensions, social grants and off-farm employment. Maize crop, which provides staple food is grown by more than 80 % of the small-scale farmers. This maize crop is constantly under risk from erratic rainfall and dry spells, thereby affecting grain yield and subsequently smallholder food security.

Improvement of smallholder farmers' livelihood in a catchment characterised by water scarcity and frequent dry spells requires innovative maize production techniques. These innovative techniques need to be employed and evaluated in a holistic manner from food production to income realised from crop sales. Water management practices such as in-field and ex-field rainwater harvesting techniques that reduce the effect of dry spells need exploration. As the potential for irrigated agriculture is limited in the catchment, increases in agricultural production need to be achieved through improved rainfed cropping systems.

Furthermore, it is difficult to manage and coordinate the activities of all water and land management institutions in the quaternary catchment due to the asymmetry between political and water management boundaries. In addition, there is overlapping, duplication of activities and use of a top-down approach by the institutions. Thus, there is need to involve the lowest local stakeholders in planning and decision-making activities to inform sustainable catchment policies.

In sum, B72A quaternary catchment is a suitable test site for the CPWF program that is focusing on catchments of greatest poverty and encouraging effective use of scarce water resources to improve food security. The over commitment of the available water resources in the test catchment is likely to have a serious impact on the livelihoods of people and environment in the near future if a holistic management approach is not implemented.

In the next chapter, literature review on several model components that build the integrated model is presented. Furthermore, important aspects of decision-making, sensitivity and uncertainty analysis are described.

Chapter 3: Literature Review

3.1 Review of hydrological models

The field of hydrology focuses on the terrestrial part of the hydrological cycle, which involves the occurrence, transport and composition of water stocks and fluxes below and on the earth's surface (RNAAS, 2005). Hydrology is an interdisciplinary science (mathematics, fluid mechanics, soil mechanics, meteorology, etc.) that attempts to understand how the hydrological cycle interacts with the geosphere, atmosphere and biosphere. Hence, hydrological research plays an important role in helping to solve global problems, such as water scarcity and food insecurity under interdisciplinary research. As such, it provides the scientific knowledge and the predictive or descriptive models in the form of black box, process and conceptual models for decision support in the development of methodologies and policies of sustainable water resource management. The model variants of black box, process and conceptual models form the basis of hydrological model classification described in the next section.

3.1.1 Hydrological model classifications

The rainfall-runoff models range from very simple black box schemes to complex, differential, distributed models (Tan et al., 2004). Thus, rainfall-runoff models can be classified in terms of how hydrological processes are represented, the time and space scale that are used and what methods are used to solve model equations (Singh, 1995). The main features for distinguishing the approaches are the nature of basic algorithms (empirical, conceptual or process-based), whether a stochastic or deterministic approach is taken to define input or parameters and whether the spatial representation is lumped or distributed (Melone et al., 2005).

Distributed, semi-distributed and lumped models are model classes based on spatial variability representation (Melone et al., 2005). A lumped model spatially averages (Burnash, 1995) catchment model parameters and takes no account of the spatial distribution of the inputs or parameters thus treating the catchment as a single unit, whereas distributed and semi-distributed models take an explicit account of spatial variability of processes, input, boundary conditions, and/or watershed characteristics (Sahoo et al., 2006). These watershed characteristics include distribution of topography, soil types, vegetation types, geology and spatial variability in meteorological conditions.

Furthermore, lumped models are applicable to gauged catchments, whereas distributed and semi-distributed models are applicable to ungauged catchments. Lumped models do not furnish an adequate and reliable forecast (Melone et al., 2005); therefore, they are unsuitable for application in the current study. Moreover, the lack of observed data prevents formulation of fully distributed models giving rise to semi-distributed models in which the input quantities are allowed to vary in space by dividing the basin into a number of subbasins that are subsequently treated as single units (Melone et al., 2005; Boyle et al, 2001).

Additionally, lumped models are based on simple input/output mathematical relationships of catchment variables, while a distributed model includes the description of basic processes involved in the runoff formation and movement (Melone et al., 2005). Hence, lumped models use the black box approach in which empirical functions relate output to input, whereas process (distributed and semi-distributed) models use theoretical equations to solve hydrological processes (Tan et al., 2004). However, the number of parameters and variables in a distributed model is much higher than that of a lumped model for the same watershed (Muleta and Nicklow, 2005b).

Furthermore, simple lumped models or parametric models perform well when the observations data are reliable and adequate, but their reliability beyond the observations range may be uncertain (Melone et al., 2005). Hence, conceptual models are generally preferred. Melone et al. (2005) argue that fully distributed physically based models are conceptual because they must use average variables and parameters at grid or element scales greater than the scale of variation of the processes modelled (Beven, 1989).

A stochastic model has random variables represented by a probability distribution determining a range of output sets, each with a certain probability of occurrence

(Melone et al., 2005). Nevertheless, a stochastic model with the random variables replaced by their mean values could be considered as a deterministic model. A deterministic model constantly produce identical results for the same input parameters, while a stochastic model produces a different model result with each new run using input variables selected at random from a probability distribution (Zoppou, 2001).

In addition, a stochastic model has the advantages of representing heterogeneity when the explicit spatial or temporal detail is not known and variable uncertainty (Nilsen and Aven, 2002) inclusion into the model, though for large and complex problems the solutions are cumbersome (Zoppou, 2001). Krzysztofowicz et al. (1993), argue that the inclusion of uncertainty analysis in stochastic models is important in accounting for risks in decision-making to increase economic benefits of model forecasts.

In addition to the conceptual or empirical classification, catchment models can be classified as either event or continuous process driven. Event models are short-term models used for simulating a few or individual storm events and they form the basis for design of storm water infrastructure and as operational models (Melone et al., 2005). The major limitation to the use of event models is the problem of unknown initial conditions (e.g. initial soil moisture) that can not be measured and may affect the forecasts in real time (Melone et al., 2005). Continuous models simulate a catchment's overall water balance over a long period (monthly or seasonally) taking account of all runoff components with provision for soil moisture redistribution between storm events (Melone et al., 2005; Zoppou, 2001). These continuous models form the basis for water resources planning.

Thus, the use of any hydrological model depends on the availability of input data, time to process input, model type, structure and support to new users, modelling skill and project requirements and study objectives (Sahoo et al., 2006; Melone et al., 2005).

The objective of this section is to conduct a comparative review of existing rainfall-runoff models appropriate to semi-arid environments, with a focus on assessing their potential for integration with crop-yield and socio-economic models in a Graphical User Interface (GUI).

3.1.2 Model screening criteria

The hydrological model screening followed a loosely multi-objective model choice approach (Duckstein et al., 1982) to identify the most suitable model focused on crucial multi-criterion attributes that hydrological models for the study were required to possess. These attributes include availability of input data requirements (in terms of time and cost constraints of the project), being implemented on a daily time step, readily available and modifiable computer code. In addition, the prospect model should have an adequate level of technical acceptability and economical viability. For instance, a history of satisfactory validation in semi-arid environments (similar to those encountered in South Africa), as well as a history of satisfactory application of the model computer codes involved. The source code must be available to potential users. Furthermore, the prospect model should be capable of copying and distribution, and either be in the public domain or flexible in its licensing requirements.

The scope of model review and screening relied upon sources in the technical literature. Hence, model software copies were neither acquired nor subjected to independent evaluation. In the next sections, hydrological model reviews, not organised alphabetically by model name, are presented .

3.1.3 Comparison of SWAT with other Models

From the literature survey on SWAT comparisons with Dynamic Watershed Simulation Model (DWSM) (Borah et al., 2004) and Hydrologic Simulation Program-Fortran (HSPF) model (Bicknell et al., 1997), Borah and Bera (2004) concluded that SWAT is most promising. Furthermore, SWAT streamflow predictions were more consistent than HSPF (van Liew et al., 2003), hence better suited for assessment of the long-term climate impacts on surface water resources.

In another study, MIKE-SHE (Refsgaard and Storm, 1995) model predicted the overall variation of river flow slightly better than SWAT (El-Nasr et al., 2005). Srinivasan et al. (2005) found that SWAT estimated flow more accurately than the Soil Moisture Distribution and Routing (SMDR) (Cornell University, 2003) model. The above comparisons indicate SWAT as robust hydrological model, further justifying its application in the current study.

3.1.4 Interfaces SWAT with other Models

Innovative interfacing of SWAT with other environmental and/or economic models have been performed to expand the range of scenarios, such as impacts of groundwater withdrawal on the costs incurred from different choices of management practices. Examples of SWAT interfaces with other models are presented next.

SWAT and the MODFLOW groundwater model called SWATMOD, has been used to evaluate water rights and abstraction rate management on stream and aquifer responses (Menking et al., 2003). Galbiati et al. (2006) further interfaced SWAT with QUAL2E and MODFLOW to create the Integrated Surface and Subsurface model (ISSm) to predict water and nutrient interactions between the stream system and aquifer accurately. In another study, Muleta and Nicklow (2005a) interfaced SWAT with a genetic algorithm and a multi-objective algorithm to perform multi-objective evaluations of conservation programs on cropping system management options. A farm economic model was interfaced with the Agricultural Policy Extender (APEX) model (Williams and Izaurralde, 2006) and SWAT to simulate the economic and environmental impacts of manure management scenarios. They concluded that appropriate pasture nutrient management, lead to significant reductions in nutrient losses into receiving water bodies. In addition, Weber et al. (2001) interfaced SWAT with the ecological model ELLA and the Proland economic model to investigate the streamflow and habitat impacts of increasing grassland area. Other reported studies that interfaced SWAT with other models include Lemberg et al., (2002) and Whittaker et al., (2003).

SWAT was chosen for application in the current study for three main reasons: 1) it is robust interdisciplinary watershed model, 2) High international scientific acceptance shown by over 250 published peer-reviewed articles across the world and in particular Africa that report SWAT applications (Gassman et al., 2007; van Liew et al., 2007) and 3) The high possibility of interfacing the SWAT model with other models to expand the range of scenarios to be analysed and open source status of the SWAT code.

Furthermore, SWAT is chosen because it is a physically based model, easy to calibrate due to the automatic calibration module in the model. In addition, SWAT can be applied at different spatial scales and to ungauged catchments, as required by the current study, without losing the physical interpretation of the model and parameters. However, no information of the SWAT model application in in-field rainwater harvesting practices was found. Hence, the SWAT crop component was not used but the hydrology component in the current study.

In addition, hydrological information presented in this section (Table 3.1 and 3.2) provides planners and managers with an overview of modelling approaches that have been used to simulate water quantity in hydrological processes. In particular, it provides water managers and modellers with a comprehensive summary to appreciate the capabilities, limitations and assumptions made in various hydrological models.

Table 3.1 **Reference, input and output characteristics of hydrological models**

Model name	Reference	Inputs	Outputs
SIMHYD	Chiew et al., 2002; Tan et al., 2004	Average rainfall, potential evapotranspiration, Daily air temperature, daily river flows	Streamflow, interflow and baseflow
TOPographic MODEL (TOPMODEL)	Beven and Kirkby, 1979; Brasington and Richards, 1998)	DEM, rainfall, length of river network and catchment area.	Stream flows, soil moisture variations, water table depths, subsurface flow and groundwater recharge.
Hydrological Simulation Program – FORTRAN (HSPF)	Ward and Benaman, 1999; Bicknell et al., 1997	DEM, stream geometry, soils (type, depth, bulk density, and saturated conductivity), land use/land cover maps and meteorological data (precipitation, solar radiation, wind velocity, potential evapotranspiration, and air and dew point temperatures)	Stream flows, soil moisture budget, groundwater flow, interflow, surface flow and
MIKE Systéme Hydrologique Européen (SHE)	Ward and Benaman, 1999; Abbott and Refsgaard, 1996	Topography, soils, land-use type, aquifer hydraulic conductivities, Manning's roughness coefficient, drainage time constant, weather data (dry bulb and wet bulb temperature, dew temperature, relative humidity, wind velocity, sunshine hours, and cloud cover).	Stream flows and soil-water budget
Precipitation-Runoff Modelling System (PRMS)	Ward and Benaman, 1999	Soil type characteristics, moisture deficit at field capacity and wilting point, slope, aspect, elevation, solar radiation, vegetation type, land use, sediment concentration (mass/volume), surface roughness, detachment rate of sediment, daily maximum and minimum air temperature, hydraulic conductivity of the transmission zone and daily precipitation.	Stream flows, annual and monthly summaries of precipitation, interception, changes in water-balance relationships, flow regimes, flood peaks and volumes, soil-water relationships, sediment yields and groundwater recharge, inflows and outflows of groundwater and subsurface reservoirs.
Semi-Distributed Land-Use Runoff Process (SLURP)	Droogers and Kite, 2001; Kite et al., 2001; Kite, 1998)	DEM, land cover, soil type, recorded stream flow and climatic data (precipitation, temperature, radiation, wind and humidity) (Droogers and Kite, 2001; Romero, 2000).	Stream flows, soil evaporation, crop evapotranspiration, changes in canopy storage, soil moisture and groundwater.
Agricultural Catchments Research Unit (ACRU)	Schulze, 1983; (Smithers and Schulze, 2004	Temperature, reference potential evaporation, water demands, soils, vegetation and climatic information.	Stream flows, peak discharge, baseflow, reservoir yield analysis, sediment yield, irrigation water demand, soil-water budgets, crop yield and effective rainfall.
Hydrologiska Byråns	Melone et al., 2005; Lindstrom et al., 1997	land use, precipitation, air temperature and	Stream flows and soil-water budget

Model name	Reference	Inputs	Outputs
Vattenbalansavdelning (HVB)		potential evapotranspiration	
Water Resources Simulation Model (WRSM) 2000	Pitman et al., 2006	Land use/cover, rain files (contains monthly rainfall time series) and flows files with monthly river flows	Stream flows, groundwater outflows and net catchment runoff, monthly water demands on a route and reservoir storage state
Identification of unit Hydrographs And Component flows from Rainfall, Evapotranspiration and Streamflow (IHACRES)	Croke and Jakeman, 2004; Dye and Croke, 2003	Daily precipitation and temperature and forest cover	Stream flows and soil-water budget
Simulator for Water Resources in Rural Basins (SWRRB)	Ward and Benaman, 1999; Arnold and Williams, 1995	Daily/monthly precipitation, air temperature and solar radiation. Subbasin area, soil data, main channel width, slope, length, Manning's n, and effective hydraulic conductivity, runoff curve number and fraction of each subbasin that flows into ponds or reservoirs, with specific volume and spillway data for each.	Stream flows and soil-water budget and sediment yields
Soil and Water Assessment Tool (SWAT 2005)	Neitsch et al., 2001a; Arnold et al., 1998; Arnold and Williams, 1995	Terrain data, DEM, land use, soil survey, reservoir and aquifer characteristics, geographical coordinates and climatic data (daily precipitation, maximum and minimum air temperature, solar radiation data, relative humidity and wind speed data, are derived from measured records and/or climatic generator).	Stream flows and soil-water budget, crop yields and/or biomass, percolation and channel losses, shallow and deep aquifer flows and generation of climatic data.

Table 3.2 Comparison of hydrological models for application in the study

Model name	GIS- based	Application	Area applied	Advantages	Disadvantages
SIMHYD	no	Estimate high daily flows for flood risk assessment	Not in Africa but in semi-arid or humid basins located in USA, Australia	- require less quantity of hydrologic and meteorological data; more flexible	- does not consider the influence of uneven spatial distribution of precipitation on flow
TOPMODEL	yes	Flood-frequency analyses, streamflow generation, scaling in hydrology and water table estimation	Sweden, UK (Yorkshire)	- require less quantity of hydrologic and meteorological data	-lumped model
HSPF	yes	hydrological studies, land use management and flood control,	Turkey, USA	- simulate an infinite variety of landuse combinations;	- substantial input data requirements for setup and

Model name	GIS- based	Application	Area applied	Advantages	Disadvantages
		pollutant transport and to predict the impacts of future climatic conditions		appropriate for linkage to more complex hydrodynamic water models	calibration; can be used to model water rights or ownership
MIKE SHE	yes	Surface and groundwater management, pollutant loading and soil erosion under different climatic conditions	Europe (e.g. Sweden), USA (McMichael et al., 2006; Sahoo et al., 2006); none in semi-arid areas	-comprehensive, user-oriented GIS-based modelling system -can use autocalibration	- underlying physical formulation has presented problems resulting in overestimation of base flows; inadequacies in depicting rapid flow variations through macropores (Ward and Benaman, 1999).
SIMHYD	no	Estimate high daily flows for flood risk assessment	Not in Africa but in semi-arid or humid basins located in USA, Australia	- require less quantity of hydrologic and meteorological data; more flexible	- does not consider the influence of uneven spatial distribution of precipitation on flow
PRMS		Evaluates impacts of of precipitation, climate and land use on streamflow and sediment yields	no information available on application in semi-arid areas	- easily modified or coupled with other models and few parameters than those of the HSPF model	- limitations on the portability of the FORTRAN code
SLURP	yes	Investigate irrigation in basin-wide water management and water availability options and climate variability (agricultural and non-agricultural water uses)	Canada, Turkey (Kite et al., 2001; no information available on application in semi-arid areas	-well adapted to using both remotely sensed and ground truth data; simulate the behaviour of a watershed continuously.	-making Aggregated Simulation Area (ASA) as small as possible cause difficulties in data preparation and management; number of ASAs determination can be based on modeler experience
ACRU	yes	Water budgeting, crop yield modelling, reservoir yield simulation and irrigation water demand/supply, optimum water resource utilisation, resolving conflicting demands with risk analysis	Southern Africa (including South Africa), Germany (Herpertz, 1994) and USA	- integration of water demand and supply; caters for several levels of information availability; has a good formulation of both hydrology and sediment mechanics	- requires substantial amount of input data, especial spatially variable inputs; lacks robust application in semi-arid areas; software availability and model support is difficult
		Runoff simulations	Nordic countries, Sweden, Italy, Latin America and few in Africa	-relatively few inputs required	- lack of application in semi-arid environments

Model name	GIS- based	Application	Area applied	Advantages	Disadvantages
			(Love et al., 2009)		
WRSM	yes	Water resources planning	South Africa only	-relatively few inputs required	- its monthly time-step, misses the impacts of 7–14-day dry spells.
IHACRES		impacts assessment such as to assess changes in streamflows following a change of land-use	USA	- requires minimal and simple input data; model is relatively easy to set up and calibrate because of few parameters	- Simplicity of the model presents a weakness, as catchment processes are not well represented; model performance is constrained by inadequate rainfall data for big catchments.
SWRRB		impacts assessment of sedimentation, crop growth, nutrients and pesticides	USA	-	- lacks application experience in the semi-arid catchments typical of South Africa

3.1.5 Summary

The important features of twelve hydrological models, which represent a wide range of methodology approaches, capabilities, spatial and temporal resolution, advantages and disadvanatages were described and are summarised in Table 3.1and Table 3.2.

There are different approaches in hydrological modelling considering the scale and complexity of the model, because of different perspectives and scientific approaches. Based on the different modelling approaches, different models were developed to address specific objectives. Hence, several hydrological models with their applications were described and evaluated based on current study criterion, presented under model screening section. This evaluation criterion included modelling approach such as distributed physically-based, model robustness, advantages and disadvantages and successful applications of model worldwide especially in semi-arid areas. Based on the comparison shown in Table 3.1and on the subjective review of the author, it was felt that SWAT model is the most appropriate hydrological model for application to the problem in this study, hence, was selected.

3.2 Crop growth simulation models

The object of increasing food production to achieve food security in agriculture depends on effective use of available resources, while appreciating uncertainties associated with the physical and socio-economic environments. Issues such as climate change, climate variability, soil carbon sequestration and nutrient status, food security and environmental sustainability, have become important in shaping the crop management options for improved agricultural production. These issues triggered the development of two types of crop modelling tools (Spitters, 1990) that provided predictions of crop production in relation to climate, genotype, soil and management factors, whilst addressing long-term resource management issues in farming systems.

3.2.1 Types of crop growth models

Two main types (Spitters, 1990) of crop growth models are discussed: (a) regression models, describing the growth course with some empirical function (e.g. Richards function, polynomials). Therefore, these models are site specific and are not easily transferrable from site to site. (b) Mechanistic models, explaining the growth course from the underlying physiological processes in relation to the environment. Hence, these models are transferrable easily from site to site. Examples of the two types of crop models are presented next.

Firstly, the simple regression model such as Light INTerception and UtiLization simulator (LINTUL) simulates dry matter production based on crop light interception and constant utilisation efficiency and dry matter distribution based on a harvest index (de Wit, 1997; Spitters, 1990). Secondly, more detailed mechanistic model, Simple and Universal CROp growth Simulator (SUCROS) simulates crop growth from photosynthesis and respiration, and allocates the daily dry matter increments based on rate of CO_2 assimilation (photosynthesis) of the canopy which is a function of the development stage of the crop (Spitters, 1990). In the following section, mechanistic models are presented.

Crop growth models

Crop production studies are traditionally carried out by using conventional experimental-based agronomic approach (Stewart et al., 2006; Jame and Cutforth, 1996). Under this approach, crop production functions are derived from statistical analysis without referring to the underlying biological or physical principles involved. This approach poses a weakness of not understanding the crop system.

The application of the knowledge-based systems approach to agricultural management through dynamic crop growth simulation models has enhanced current knowledge of plant growth and development (Jame and Cutforth, 1996). After calibration, validation and verification using observed field data, the crop growth models can be used to predict crop responses to different environments that either are a result of global change or induced by agricultural management and to test alternative crop management options (Jame and Cutforth, 1996).

Computer crop simulation models of the soil-plant-atmosphere system contributes to both furthering the understanding of the processes that determine crop yield responses and predicting crop yield performance, resource use and environmental externalities for different management options and climatic conditions (Ko et al., 2009; Jame and Cutforth, 1996). In semi-arid areas, soil and water conservation techniques aimed at preventing runoff, or harvesting runoff from unplanted areas have long been proposed as key management techniques to increase yields and reduce year-to-year variability (Jame and Cutforth, 1996). Several crop models developed and applied in agricultural production include (not necessarily in alphabetical order):

- EPIC (Erosion Productivity Impact Calculator). Ko et al. (2009) gave a different acronym for the model as Environmental Policy Integrated Climate (EPIC).
- APSIM (Agricultural Production Systems Simulator)
- SWAP (Soil-Water-Atmosphere-Plant)
- CATCHCROP model
- PERFECT (Productivity Erosion and Runoff Functions to Evaluate Conservation Techniques)
- DSSAT (Decision Support System for Agro-technology Transfer)
- CropSyst (Cropping System Simulation Model)
- PARCHED-THIRST (Predicting Arable Resource Capture in Hostile Environments During The Harvesting of Incident Rainfall in Semi-arid Tropics)

The following sections briefly outline each crop model's structure and provide details on model inputs and outputs (Table 3.3). Advantages and disadvantages, and applications in different countries of the models are presented where appropriate. Finally, crop model applicability to the current study is assessed and reported (Table 3.4). The assessment uses Multi-Criteria Decision (MCDA), to mediate among many criteria, based on the historic wide application and testing of the model in similar environment to the study area (South Africa), capability of the model to simulate rainwater harvesting systems and accessibility of the model (code licensing and portability to various platforms.

Table 3.3 Reference, input and output characteristics of crop models

Model name	Reference	Inputs	Outputs
EPIC	Ko et al., 2009; Adejuwon, 2004; Bernardos et al., 2001; Sharpley and Williams, 1990; Williams et al., 1983, 1984, 1989; Kiniry et al., 1992	Weather (recorded and generated), soil characteristics, topography, land-use, crop varieties, management options. Weather data include precipitation, maximum and minimum air temperature (^oC), solar radiation (MJ/m^2), relative humidity (%) and wind speed (m/s).	Soil water balance, crop yields, and economics of fertiliser use and crop values.
APSIM	Stewart et al., 2006; Grenz et al., 2006; Smith et al., 2005; Robertson et al., 2005; Whitbread and Ayisi, 2004; Chivenge et al., 2004; Keating et al., 2003; Huth et al., 2003; Keating et al., 2003; Shamudzarira and Robertson, 2002; Carberry et al., 2002; Inman-Bamber and Muchow, 2001; Thorburn et al. 2000; Robertson et al., 2000; McCown et al., 1995; Carberry and Abrecht, 1991; Jones and Kiniry, 1986; Jones et al., 1998; Muchow and Keating, 1997; Keating et al., 1997; Dimes and Freebairn, 1996; Steiner et al., 1987)	Daily weather data (minimum and maximum temperature, radiation, and rainfall), soil characteristics (water lower limit, drained upper limit and saturated volumetric water contents), cultivar and crop management actions.	Soil water balance, crop water uptake, competition in intercrops or crop-weed mixtures, soil erosion, mineralisation of nitrogen and soil organic matter.
SWAP 2.0	Droogers and Kite, 2001; Van Dam et al., 1997; Van Diepen et al., 1989	Climatic data, irrigation day, crop type and soil characteristics	Soil water balance, transpiration, evaporation, drainage, irrigation, percolation and runoff, crop yield and yield per unit water.
CATCHCROP	Perez et al., 2002	Rainfall and temperature data, soil characteristics and fertiliser use	Soil water balance, crop yields and irrigation demands per crop-type unit area
PERFECT	Matthews et al., 2000		
DSSAT	Jones et al., 2003; Jame and Cutforth, 1996; Ritchie et al., 1998	Climatic data, soil properties, crop type, cultivar and management options	Soil water balance, crop growth period, average growth rates and the amount of assimilate partitioned to the economic yield components of the crop.
CropSyst Model	Stöckle et al, 2003; Stöckle et al., 1994; Donatelli et al, 1997; Abraha and Savage, 2008	Weather data, soil characteristics, crop characteristics, water stress characteristics and crop management options including crop rotation, cultivar selection, irrigation, nitrogen fertilisation, pesticide applications, soil and irrigation water salinity, tillage	Soil water balance, soil-plant nitrogen budget, crop phenology, crop canopy and root growth, biomass production, crop yield, residue production and decomposition, soil erosion by water, and pesticide fate.

Model name	Reference	Inputs	Outputs
		operations, and residue management (Donatelli et al, 1997).	
PARCHED-THIRST (Version PTv 2.4)	Young et al., 2002; Mzirai et al., 2001; Young and Gowing, 1996; Bradley and Crout, 1996; Stephens and Hess, 1999	Daily agro-meteorological data and soil properties	Soil water balance, crop yields, and economics of fertiliser use and crop values.

Table 3.4 Comparison of crop models for application in the study

Model name	Application	Area applied	Advantages	Disadvantages	Remarks
EPIC	Soil erosion on crop production; crop growth for annual and perennial plants; as a decision-support tool for different management strategies	USA (Santos et al., 2000), Argentina; Asia, South America and Europe (Ko et al., 2009; Bernardos et al., 2001; Williams et al., 1983, 1984, 1989).	- Computationally efficient and capable of computing the effects of management decisions; simulate the fate of agricultural pesticides	-Tend to overestimate low yields (Ko et al., 2009; Warner et al., 1997); no subsurface flow nor simulation of sediments (Arnold and Williams, 1995).	Not selected no rainwater harvesting
APSIM	Economic and ecological outcomes of management practice in the face of climatic risk; crop yields in response to weather, genotype; on-farm production and resource decision-making; research and education activities	Australia (Keating et al., 2003); Africa (Whitbread et al., 2009; Chikowo et al., 2008 (Probert et al., 1995). Netherlands (Asseng et al., 2000) and Turkey (Grenz et al., 2006).	- Extensively tested in different environments and performed well	- Can not address pastures and animal production; deficiencies in simulating impacts of waterlogging, frost and pests; does not capture in-field and ex-field rainwater harvesting	Not selected no rainwater harvesting
SWAP 2.0	study soil-water-atmosphere-plant relationships; water balance and crop yield	Netherlands and other parts of the world (Droogers and Kite, 2001), but not in Africa	- Simple crop yield algorithm computes the crop yield in input data scarce areas	- No mention of application in the tropics and Africa; its handling of rainwater harvesting is not discussed	Not selected due to its lack of application in Africa and no rainwater harvesting
CATCHCROP				-not GIS based	Not selected, lack wide use

Model name	Application	Area applied	Advantages	Disadvantages	Remarks
PERFECT	Study management practices such as crop/fallow sequences, tillage techniques, soil ameliorant and erosion.	UK, and Semi-arid Tropics and Sub-tropics (Freebairn et al., 1991)	-Relatively simple to set up	- no application in Africa found	Not selected due to its non-application in Africa
DSSAT	Investigate conservation practices, influence of crop residue cover and tillage on soil surface properties and crop, environmental impact and farming risk	Not specified	Not specified	- Unable to explore rainwater harvesting techniques and lack wide application and testing in Africa.	Not selected due to its non-application in Africa
CropSyst Model	Research tool, policy analysis of productivity and environmental impact- soil erosion by water, and pesticide fate crop yield, residue decomposition,	South Africa (Abraha and Savage, 2006)	- GIS based; has a user-friendly interface, has climate generator that can be used anywhere in the world	- does not simulate rainwater harvesting systems and crop diseases and pests, over-estimated soil-water content in the upper layers (Abraha and Savage, 2008)	Not selected due to its weakness in simulating soil-water content and no rainwater harvesting
PARCHED-THIRST (Version PTv 2.4)	Technology transfer both from researchers to the farmers,	Arid and semi-arid areas, Tanzania (Tumbo et al., 2003; Hatibu et al., 2002)	- Has climate generator, relatively easy data input, output, cater for rainwater harvesting, innovative user-interface to reduce user-learning overheads, developed in Microsoft Visual Basic v 5.0 for easier use in code in integration with other models.	-Not GIS based -does not simulate nutrients applied to the soil	Selected due to user-friendly interface, capture to different rainwater harvesting techniques, supplementary irrigation found in the arid and semi-arid areas such as South Africa

3.2.2 Summary

A review of several crop growth models and their applications to different contexts was presented. The crop growth model choice should address the objectives of the study. In some cases, crop models can be used in combination with other tools or models to enhance decisions for improved livelihoods. In the current study, PARCHED-THIRST model is selected for application according to the study objectives.

Crop growth models applications (Whitbread et al., 2009) include among others, adding value to field experimentation and direct engagement with farmers for mutual learning. In addition, calibrated and validated crop models support exploring cropping systems constraints and opportunities with researchers and extension staff and generating of decision support information for policy-makers.

Literature surveyed (Abraha and Savage, 2008; Abraha and Savage, 2006; Stöckle et al., 2003; Matthews et al., 2000; Mzirai et al., 2001; McCown et al., 1994; Keating et al., 1997) indicates huge benefits in enhancing rural livelihoods through crop modelling that provide potential ways of improving current farming systems. However, some studies (Matthews and Stephens, 2002; Stephens and Hess, 1999; Hess et al., 1997) have reported limited uptake and use of crop simulation modelling results in addressing food security problems in developing countries. This limited uptake of crop simulation results was attributed to lack of competent local users (Whitbread et al., 2009) and the challenge to communicate model results in simple ways that have meaning to farmers. Hence, there is need for training in crop model use.

Furthermore, crop models support timely, strategic and tactical agricultural management decisions (e.g. use of a model to quantify the expected yield responses sufficient to justify the adoption of a new or improved technology) not only for the current climatic variability, but also for the anticipated climatic changes (Jame and Cutforth, 1996) that obtained from the weather generator. Despite the several benefits from crop models presented, crop models have their limitations.

One of the crop models limitations is their inability to account for leaf damage that affects leaf area index, caused by insects, pests and diseases and herbicide applications. In addition, studies have indicted the difficulty in practice to modify and implement the plant or soil-water in the way shown by the simulations (Jame and Cutforth, 1996). Lastly, while most crop models could be well calibrated and applied to different environments, variables and parameters uncertainty due to the dynamic nature of the environment (weather, soil conditions) remains, hampering the reproduction of the field conditions and credibility of the simulation results (Wang et al., 2005). This variable and parameter uncertainty problem is addressed by sensitivity and uncertainty analysis of model inputs and outputs presented later in the study.

3.3 Socio-economic models

The call for sustainable farming has triggered the development and use of socio-economic models in support of decision-making and trade-offs made by farmers depending on the understanding of their farming systems. The premise of decision support research is grounded in the opinion that managers are incapable of holistically understanding every facet of a problem or solution when designing best practices based on knowledge of the environment. Therefore, there is need for farming models in the form of simulations and expert systems to bridge this gap.

The purpose of this section is to identify socio-economic models that have been developed and applied to support farm decision-making and consequently, select a suitable model for application in the current study.

This section will start by presenting the need for different forms of decision aid tools, expert versus simulation approaches. Next, different socio-economic models identified from literature, their inputs and outputs data requirements and contexts are presented. The last section presents a summary and an evaluation of the socio-economic models to select the most appropriate model for application in the current study.

3.3.1 Expert Systems versus simulation models

An expert system can be defined as an artificial intelligence application or a computer program that uses knowledge base of human expertise (judgement and behaviour*)* to aid in solving problems (FODC, 2003). Expert Systems support a decision maker by mimicking an expert person's reasoning, knowledge and experience, including the use of computer information systems and models, to solve complex problems even where knowledge is incomplete and uncertain for constructing simulation models. Despite its earlier high hopes, expert systems technology has found application only in areas where information can be reduced to a set of computational rules, such as insurance underwriting (McCown, 2002). Therefore, the expert system is not considered further in the current study, but simulation modelling.

System simulation is the mimicking of the operation of a real system in such a way as to produce a set of results or outputs, based on a set of known and/or assumed inputs (Haan, 1985). EPA (2003) defined simulation as the execution of a model, represented by a computer program that gives information about the system being investigated. Simulations often deliberately emphasise one part of reality at the expense of other parts. Although simulations do not solve or optimise problems, Plant and Stone (1991) argue that they are required to provide invaluable information in decision-making, especially in farm management.

The invaluable information obtained from farm modelling technology is essential for several reasons, including (Plant and Stone, 1991):

- Farm management is becoming much more intensive and demanding in terms of time and the scarce expertise, making the development of computer-assisted management tools imperative.
- It is not practical for farmers to learn purely from experience
- Farmers manage farms holistically. Expert Systems can be more comprehensive where farmer knowledge is incomplete and uncertain for constructing simulation models.

- Expert Systems can support a decision-maker by provision of heuristics or rules of thumb for new farm situations. These rules of thumb take the place of a systems-level understanding of all the complex interactions affecting crops and livestock and change as agriculture changes and new technologies emerge.

In addition, there have been several attempts to simulate the socio-economic aspects of farmers under farm modelling in the past. Although several farm simulation models have been developed, none of these models have been coupled or directly linked to the hydrological driver, which is the water availability in a catchment. Consequently, the single discipline models have failed to provide a holistic answer to the impacts of catchment management. A gap this study fills especially in semi-arid South Africa.

3.3.2 Input-price inflation model

A study in Oklahoma and Kansas traced the impact of input-price inflation on farm output, prices received by farmers, the parity ratio, gross receipts, costs and net income among 500 wheat farmers (Quance and Tweeten, 1971). Quance and Tweeten (1971) traced the macro effects of an increment in prices paid by farmers for all purchased inputs through the farm economy. The study showed that, a rise in input prices by 10 % reduced net income by 2.3 % in the short-term (1–2 years) and by 1.2 % in the long-term (many years) (Quance and Tweeten, 1971). These results assumed supply elasticity of 0.1 in the short-term and 0.8 in the long-term, the demand elasticity of –0.3 in the short-term and –1.0 in the long-term and the production elasticity of 0.62 (Quance and Tweeten, 1971).

The study concluded (Quance and Tweeten, 1971) that the input-price inflation impact is not large because higher input prices restrain use of inputs and hence restrain output. With an elastic demand, less output means more revenue. Nevertheless, input price gains, reaching 4 % annually, inflate production costs to the point where they considerably exceed additional receipts causing net farm income to decline sharply.

3.3.3 Decision support system (DSS) for viticulture

In the vineyard case study, Gertosio (1988) designed a decision support system (DSS) for viticulture cooperatives facing vineyard restructuring problems due to the rapid evolution of their legislative and economical environment. The restructuring included modification of the regulations concerning the wine production and the consumer's general behaviour for wine-drinking. To help the managers and farmers to define a socially acceptable restructuring strategy, the DSS modelled the vineyard to determine the strategy impacts, according to several future economic views. The DSS permitted each decision-maker (farmer) to conceive the evolution of farm income during ten subsequent years.

In sum, the viticulture DSS was not selected for application in the current study as it addressed farm income only.

3.3.4 Dynamic farm simulation software, GRANJAS

Berdegue et al. (1989) applied dynamic farm simulation software, GRANJAS to analyse the technological innovations impacts in the form of new agricultural practices and inputs to improve the crop yields and productivity for the Chilean peasant families. The new agricultural developments included the intensification of the crop subsystem and intensification of both crop and livestock production (Berdegue et al., 1989). These technological innovations meant to enhance farm productivity and living standards of the local peasant families.

The key results were that crop subsystem utilizes most of the capital and labour (82 % of total labour) resources, while livestock production, which base on the extensive use of the land, utilizes little capital or labour inputs (Berdegue et al., 1989). In addition, total crop net income (US$/ha) was over 4.5 times greater than the average off-farm wages earned, suggesting that the crop subsystem is the driving component of the farming system, while livestock production plays a stabilizing role (Berdegue et al., 1989). This GRANJAS model demonstrated to be a useful tool in searching for development strategies at the farm level by detecting the impact of the suggested innovations in terms of production (grain yield, labour productivity), resource (labour and inputs) requirements and income results (gross margin).

In sum, the GRANJAS model was not selected for application in the current study as it only addressed agricultural technological aspects.

3.3.5 Farmers and livestock management model

In a study related to livestock management, Mainland (1994) constructed a DSS model for farmers and advisors that is capable of modelling and evaluating different managerial strategies of a dairy herd, while taking into account the practical circumstances (weather cycles, herd potential, quality of land and managerial ability) of the farmers. This study found that, for different farm structures, the method of managing the dairy herd in order to achieve the highest gross margin varies markedly (Mainland, 1994). The study concluded that the difficulty in profitably managing the dairy farm requires an assessment of a multitude of decisions (through DSS) that take account the various constraints and managerial capabilities in calculating the outcome of different production strategies quickly.

In sum, the farmer livestock management model was not selected for application in the current study as it simulated livestock and farmers decisions only.

3.3.6 Interactive simulation model, FRAME

FRAME (Hendy and Thorne, 1995), an interactive simulation model based on quantitative treatment of energy and protein transactions in ruminant livestock has been applied in both temperate (Nepal) and tropical (Malawi) areas and produced acceptable results. This FRAME model predicted live weight changes of draught oxen and goats resulting from feeding decisions simulated in a dynamic way, depending on the farmers' feed availability, production objectives and feeding practices (Hendy and Thorne, 1995). The model use input data that describes feed quality and availability to predict the effects of different feed allocation strategies across animal types in mixed-species livestock holdings. In these livestock holdings, feed is in short supply, as in resource-poor farmers in the tropical countries (Hendy and Thorne, 1995). The FRAME model results in improved utilisation of resources along with the increase in animal productivity and household income.

In sum, the FRAME model was not selected for application in the current study as it addressed livestock issues only.

3.3.7 Model of an Integrated Dryland Agricultural System (MIDAS)

MIDAS (Model of an Integrated Dryland Agricultural System), a whole-farm linear programming model in profit maximising with a joint emphasis on biology and economics was developed in Western Australia (Pannell, 1996, 1997). The model has been applied for research prioritization, extension, policy analysis, education and provision of a database for other uses (Pannell, 1997). Extension use focused on general messages for groups of farmers, rather than for individual farmers (Pannell, 1996, 1997). The major strengths of MIDAS include (Pannell, 1996):

- Joint emphasis on biology and economics benefits analysis from a given change in the farming system (Kingwell et al., 1993). This strength also exists in the Olympe model presented later;
- Ability to address a range of farm issues in a profit-maximizing framework such as allocation of land to alternative enterprises and the impact of limited finance on the optimal farm strategy;
- Capacity to represent risk averse attitudes of farmers and
- Capacity to identify optimal tactical adjustments to the farm strategy in response to observed weather patterns.

In addition, a follow up model to address uncertainty MUDAS (Model of an Uncertain Dryland Agricultural System) was developed and presented (Pannell, 1997).

In sum, MIDAS model was not selected for application in the current study, though the model addressed biophysical, social and economic issues. The model's main limitation for application in the current study is its optimising approach.

3.3.8 Interactive crop management options software, Decible

Rossing et al. (1997) used model-based (interactive software 'Decible') explorations at field and farm levels in the diagnosis and design of sustainable farming systems to improve input use efficiency and yield. Decible simulates the effects of crop management options on yield, gross margin, protein content and soil mineral nitrogen at harvest for specific fields. These crop management options are described by a set of decision rules, representative for a farmer or proposed by researchers and extension officers (Rossing et al., 1997).

The information on whole-farm crop and soil management practices (timing of operations, labour requirements and equipment used) gathered through surveys is used.

An example of a decision aid from the simulation tool is "if the wheat crop is in the development stage 30, and calculated workability of the soil is sufficient, then apply nitrogen dressing calculated according to the balance sheet method" (Rossing et al., 1997). The generic decision rules are made specific for a particular crop and year.

Rossing et al. (1997) concluded that the diagnostic surveys and modelling studies enabled the exploration of sustainable production potential, identification of constraints and assessment of opportunities for improvement in the current farm practices.

In sum, Decible model was not selected for application in the current study, as the software is not in public domain.

3.3.9 Biophysical crop and livestock simulation model

Thornton and Herrero (2001) outlined a framework for the integration of detailed biophysical crop and livestock simulation models. The integrated model potential applications include studying mixed crop–livestock farming systems in the tropics to satisfy farm household's consumption needs and other economic considerations.

The nature of crop–livestock interactions in smallholder farming systems makes their integration difficult (Thornton and Herrero, 2001). One of the difficulties is how to take the outputs from detailed biophysical models and place them in an appropriate farm household context. This difficulty requires an integration of modelling with local farmers' objectives in the targeted farming systems, an approach feasible with OLYMPE model (Le Bars and Le Grusse, 2008; Le Grusse et al., 2006). Consequently, the crop-livestock system proposed by Thornton and Herrero (2001) became a powerful tool to analyse diversity of farming systems and in impact assessment studies by satisfying the following:

1. Describe and quantify the interactions between the farming system's components. In addition, use minimum data sets for parameterisation and validation
2. Represent the farmer's current and alternative management practices on land use and other resources under different weather conditions and both medium-term and long-term periods
3. Provide insight into the trade-offs (economic, environmental and social) involved in using different farm resources
4. Translate model outcomes into operational support for seasonal farm management. For example, in the case of livestock, the model should be able to provide herd, grassland and feeding management strategies, while for crops, issues such as planting density and manure/fertiliser applications maybe important
5. Integrate data from different scales.

Thornton and Herrero (2001) noted that the reasons why farm households manage their farm systems in a particular way have received little attention. It is believed that this omission is one reason for the lack of technology adoption in crop and livestock systems. From this study by Thornton and Herrero (2001), household management decisions have been difficult to study and require a greater input from the social sciences such as the use of participatory methods for data collection and technological dissemination (Le Bars and Le Grusse, 2008; Le Grusse et al., 2006; Thornton and Herrero, 2001).

Thornton and Herrero (2001) further argue that the farming systems characterisation studies sometimes overlook the temporal scale (short and long-term) in understanding of the farming dynamics. Hence, most researchers tend to concentrate on the time scales of the biological or economic processes — for example, a crop–growing cycle, seasonally fluctuating prices of inputs and outputs, and market conditions. Nevertheless, the longer time scales that farm households may use for setting up management goals for the farm system in their decision-making process and household stage of development (Nicholson and Thornton, 2001), have not received a fair treatment (Thornton and Herrero, 2001).

From the literature survey, much effort has concentrated on the farm operational decisions (such as how to supplement cows feed, how to fertilise crops and supplement water, etc.) and on identifying strategies for the operational decisions (Thornton and Herrero, 2001). Thus, strategic or tactical planning problems (and solutions), their relationship to farm family objectives and the way farmers manage their farm systems are less well studied, despite the fact that these are crucial aspects to consider for increased technology adoption from model simulations.

In sum, the integrated biophysical crop and livestock simulation model was not selected for application in the current study, as the software is not in public domain.

3.3.10 Simulation and optimisation model

The use of simulation and optimisation models in farming reported by Loevinsohn et al. (2002) working with Chilean farmers who were considering different farm management futures experienced data availability problems. The data required to model specific systems of interest to farmers were often not available when needed (Loevinsohn et al., 2002).

Furthermore, Loevinsohn et al. (2002) argued that simulation and optimisation models are likely to score poorly on the ability of farmer groups to use decision aids independently, unless farmers can readily access the necessary expertise at local institutions. Conversely, this is not a problem for models that inform strategic rather than operational decisions, because they are needed less frequently. Loevinsohn et al. (2002) concluded that relevance, transparency, flexibility and usability—features that help farmers learn about their changing farm systems and adapt their management accordingly—should appear in the design stage of methods and not be relegated to a later dissemination phase.

In sum, the simulation and optimisation model in farming was not selected for application in the current study, since the model uses the optimisation approach.

3.3.11 FARMSCAPE

FARMSCAPE (Farmers', Advisers', Researchers', Monitoring, Simulation, Communication And Performance Evaluation) is an industry-supported decision support system (DSS), developed for dryland farmers in Australia (Carberry et al., 2002). This DSS was build for grains/cotton industry and is used by farmers, advisers and researchers learning together about crop and soil management by conducting on-farm experiments and holding simulation-aided discussions (Carberry et al., 2002). Four applications of FARMSCAPE are benchmarking crop performance, scenario exploration of the risk of strategic management options, tactical planning and crop yield forecasting. The involvement by growers in the FARMSCAPE project ensured research activities and outcomes align with participants' expectations.

The DSS simulation outputs consist of seasonal yields and gross margins for the past and current climate record and for the alternative management practices. The most valuable improvement FARMSCAPE brought to farmers was the substitution of gut feel, general principles and data by real data, specific to individual farms' characteristics. However, the drawback of FARMSCAPE team was working with the most successful farmers only (the top 10 %), who were most interested in working collaboratively with researchers (Carberry et al., 2002).

The key messages from FARMSCAPE research team that have emerged from the FARMSCAPE program include (Carberry et al., 2002):

- Decision support and simulation as a way of learning, especially when farmers are contemplating a change in their current crop management practices is most effective in a participatory process that combines the strengths of practical knowledge and scientific knowledge
- Farmers are most interested in simulation when their Farm advisers are appropriate candidates with high-level knowledge for delivering simulation model results as decision support. However, the challenge was how to cost effectively transfer sufficient capability to these farm advisers to enable them to utilise and interpret results from the FARMSCAPE approach and associated crop model, Agricultural Production Systems Simulator (APSIM) in their business systems.

From the literature survey, FARMSCAPE has successfully explored the economic impacts of alternative cropping options. There is now interest to expand (to incorporate natural resource management, weed management and agroforestry systems) and replicate the FARMSCAPE approach in other regions (Carberry et al., 2002).

In sum, FARMSCAPE model was not selected for application in the current study because of software availability restrictions and it was only tested with farmers in Australia.

3.3.12 Model for Economic, Social and Environmental Evaluation of Land use (ECOSAUT).

Model for Economic, Social and Environmental Evaluation of Land use (ECOSAUT, it is a Spanish acronym) is an integrated catchment multi-criteria linear-programming optimisation model to evaluate the best land use or management alternative for improving an environmental service and the socio-economic conditions of the catchment habitants over a maximum of a 10-year period (Quintero et al., 2006). This ECOSAUT model is built based on the interdependencies between decision variables and decision alternatives in a catchment (Table 3.5). Decision variables correspond to the constraints established by the system's biological and economic capacities, farmer considerations, or regional policies, while decision alternatives refer to activities that are carried out in the system to maintain its functioning.

In addition, ECOSAUT model was developed in South America (Colombia) using experiences from the Andean watersheds in Colombia, Ecuador and Peru (Quintero et al., 2006). This model represents an agro-ecological system in which activities or processes relating to biophysical and socio-economic constraints have an impact on farmers' net income and environmental externalities. An externality is the beneficial (positive externality) or damaging (negative externality) effect caused on a third party (not involved in the initial decision) by the decision of another party or parties (Quintero et al., 2006).

The ECOSAUT method compares the advantages and disadvantages of different crop management practices; and evaluates current and potential scenarios of land use (e.g., infiltration ditches and live barriers), environmental externalities, generation of employment, and benefits from economic and social chains for society, thus clarifying policy conflicts and trade-offs (Quintero et al., 2006).

Furthermore, ECOSAUT inputs include basic biophysical information from watershed analyses by the Soil and Water Assessment Tool (SWAT) (USDA, 1999), socio-economic information. Additionally, estimates of the impact of climatic events such as frosts and droughts on productivity from surveys and field studies are required (Quintero et al., 2006). Outputs from the ECOSAUT model are land use area, erosion per land cover type, total erosion, runoff generated per land cover, labour use per activity, labour wage, net income and sources of income. Optimal solutions from the model are trade-offs between the interests of actors and the meeting of multiple constraints to improve living conditions and stimulate private and public investment to finance them (Quintero et al., 2006).

ECOSAUT application by decision-makers answers questions such as, what is the best technological alternatives for specific homogenous areas in the watershed, what is the impact of decisions by farmers in the upper, central and lower regions of the watershed have among each other and what would be the cost (or shadow price) of the environmental services (Quintero et al., 2006). These services costs constitute indicative prices (as no environmental service market exists) that can be used in negotiations to formulate and adopt specific policies or in schemes to pay for environmental services (Tognetti and Johnson, 2008; Quintero et al., 2006).

Table 3.5 Interdependence between decision variables and decision alternatives in the ECOSAUT model (Quintero et al., 2006).

DECISION VARIABLE	DECISION ALTERNATIVES									
	CROP ROTATIONS WITH OR WITHOUT SOIL CONSERVATIIONS	PERMANENT FOREST (HA)	PERMANENT PASTURES, WITH OR WITHOUT GREEN MANURES	USE OF CONCENTRATES FOR LIVESTOCK	NUMBER OF COWS	EXTRACTION OF SEDIMENTS FROM CANALS OR LAKE (TONS)	ENVIRONMENTAL INCOME (SALE OF ENVIRONMENTAL SERVICES)	POLLUTION BY WASTEWATERS (NITROGEN, PHOSPHOURS (TON/SEMESTER OR YEAR	LABOUR PURCHASE AND SALE	BANK LOANS
Net income (no. of years)	X	X	X	X	X	X	X		X	X
Cash flows	X	X	X	X	X	X	X		X	
Availability of land	X	X	X							
Erosion per landuse (ton/semester or year	X	X	X			X				
Water released to water resources per landuse (m^3/ha/semester or year)	X	X	X		X		X			
Nitrogen released to water resources per landuse (m^3/ha/semester or year)	X	X	X	X	X	X		X		
Phosphorus released to water resources per landuse (m^3/ha/semester or year)	X	X	X	X	X	X		X		
Labour per landuse (no. of work days per semester or year)	X	X	X						X	
Timber production, plantations (t/ha)		X								
Timber production native forests (t/ha)		X								
Energy production for livestock (Mega calories per kg per ha)	X		X	X	X					
Protein production for livestock (kg of dry matter per ha)	X		X	X	X					
Milk production (ton per cow per semester or year)					X					
Meat production (ton per cow per semester or year)					X	X				

From the literature studied, it can be concluded that the ECOSAUT model is a tool capable of integrating and allowing, among other things, the ex-ante evaluation of the impact of changes in land use on hydrologic externalities and the socio-economic status of a catchment's inhabitants. The model further estimates the trade-offs between criteria for income, productivity, sustainability and risks to permit understanding of the best management options (Quintero et al., 2006).

Despite the strengths of ECOSAUT model, it was disqualified for use in current study due to its huge data requirements and optimisation approach.

3.3.13 DYnamic Nutrient BALances (DYNBAL).

Using the DYnamic Nutrient BALances (DYNBAL) simulation model, Tittonell et al. (2007a) analysed the relative contribution of different management options (i.e. planting dates, weeding, operational resource and labour allocation decisions) and soil fertility between fields on diverse crop yields observed within smallholder farms of Sub-Saharan Africa. Consequently, the variation in soil nutrients provided an important insight into the highly variable investments and management strategies by smallholder farmers (farm sizes of 0.5 to 2.0 ha) observed from the study area. In addition, if conditions for investment are unfavourable, many different management strategies (but not necessarily many different decisions) lead to similar results in terms of productivity and sustainability of the farm system (Tittonell et al., 2007a).

In another study, Tittonell et al. (2007b) discusses the application of inverse modelling techniques using multi-objective shuffled complex algorithm and a crop/soil dynamic simulation model for optimisation of resource allocation strategies and trade-offs analysis of farm systems to increase food production and reduce soil erosion. The study concluded that feasible solutions at farm scale are affected by farm characteristics, which in turn varies across farms of different social status and is affected by location-specific factors (e.g. landscape, markets).

In sum, the two models (Tittonell et al., 2007a; Tittonell et al., 2007b) were not selected for application in the current study, as they use optimisation approach.

3.3.14 NUANCES-FarmSim.

The modelling framework NUANCES-FarmSim (with sub-modules for crops, livestock and organic manure) simulates all biophysical processes taking place on the farm (Africa NUANCES, 2007). For each of the farm components there is a model; NUANCES-Field for the crops grown on different fields of a farm, NUANCES-LivSim for individual livestock type on the farm and NUANCES-HeapSim for the management of organic material on the farm, i.e. residues and manure from fields and animals respectively. This NUANCES-FarmSim model use input data available from IMPACT database to run simulations over a 10-year period (Africa NUANCES, 2007).

The detailed characterisation data for all monitored farm locations is entered into the IMPACT database. For each monitored farm, information required include household members, labour use, crops cultivated, livestock kept, input and output of each cropping and livestock system including management of these systems (Africa NUANCES, 2007). The analysis tool of IMPACT provides flows and balances in terms of cash, labour, nutrients and self-sufficiency in protein and energy.

In addition to exploration of technological innovations impacts of different farm types, runs for each farm type maybe performed without changing current farmers' strategies to describe farm development over time. The study showed that the better-endowed farm types are self-sufficient over time, while the less endowed farm types are not self-sufficient (Africa NUANCES, 2007).

In sum, the NUANCES-FarmSim was no selected for application in the current study, as family food needs are not addressed.

3.3.15 Database and a simulation tool of farming systems, OLYMPE Model

The Olympe model (version 1.34) development was a joint effort by Institut National de la Recherche Agronomique (INRA), Institut Agronomique Méditerranéen de Montpellier (IAMM) and Centre de Coopération Internationale en Recherche Agronomique pour le Dévelopment (Cirad) in France (Attonaty et al., 1999, 2005). Olympe model is composed of a database and a simulation tool of farming systems. It has been adapted for use in the tropics (Le Bars et al., 2005).

This Olympe software (Le Bars et al., 2005) builds the economic and technical aspects (crop management) of the farms' operations as well as externalities (soil erosion) to enable analysis of farming systems and their relationships with the surrounding physical and economic environment. However, Olympe model does not allow the strategies and courses of action of the various stakeholders to be represented (Attonaty et al., 1999; 2005), although it is designed to work interactively with either individual or groups of farmers. These farmers' interactions under different model applications are governed by formalised rules for decision-making.

Examples of Olympe model applications include (Le Bars and Le Grusse, 2008; Le Bars and Snoeck, 2007; Le Grusse et al., 2006; Attonaty et al., 2005; 1999):

- Evaluation of the robustness of farming systems and economic impacts under technical management options, climatic and economic (prices and markets) uncertainties (Figure 3.1).
- Assessment of positive (carbon sequestration) or negative (pollution) environmental impacts of land use options.

Furthermore, Olympe model setting up involves the development of a farming systems database structured into several modules in collaboration with farmers in each typology (Figure 3.1). These farm typologies are derived from socio-economic surveys of the farmers and secondary data in the study area. The Olympe database module defines the categories of inputs (land, fertilisers, seeds, labour and water) and of outputs (crops and livestock products) including externalities (water pollution and soil erosion) for use by subsequent modules. The next step involves the simulation of the farming systems.

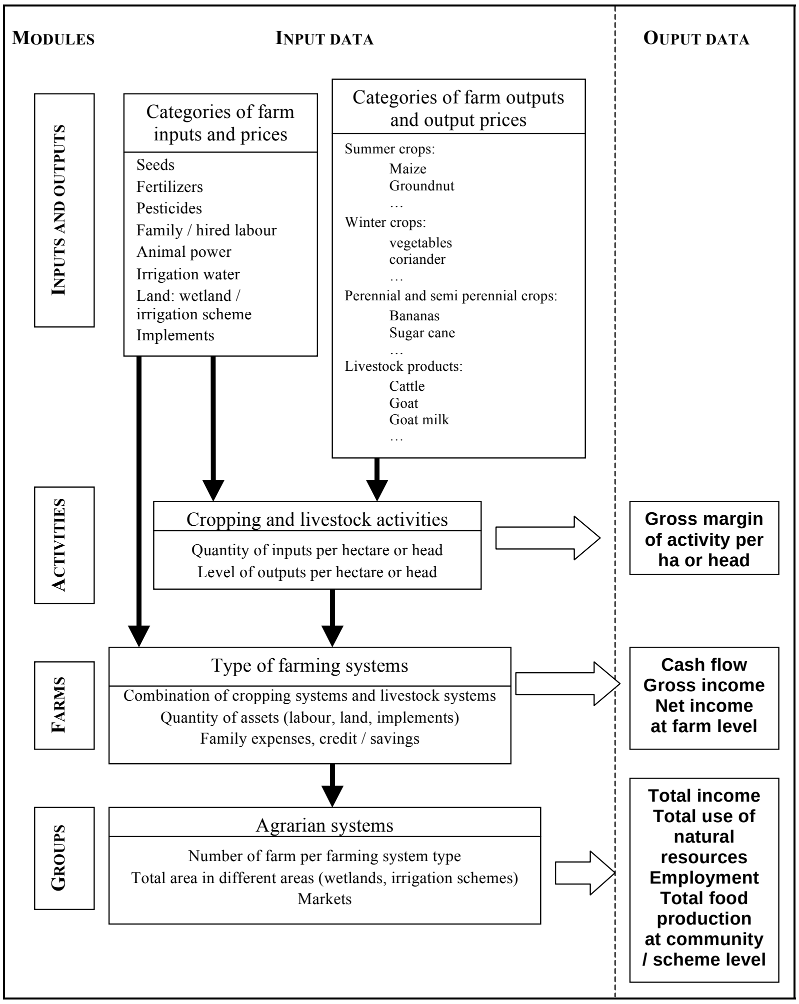


Figure 3.1 Flow chart for the Olympe model showing the different modules (Attonaty et al., 2005).

In addition, Olympe model has been linked to other models and field experiments to enhance the farm simulations, an attribute strongly required in current study. Le Grusse et al. (2006) developed a decision support system model by coupling Olympe and CropSyst (Cropping Systems) (Stöckle et al., 2003) models (Figure 3.2) in collaboration with local stakeholders. This DSS model facilitated collective decision-making (participative modelling) on acceptable solutions to irrigation water consumption and nitrate losses at farm and basin level.

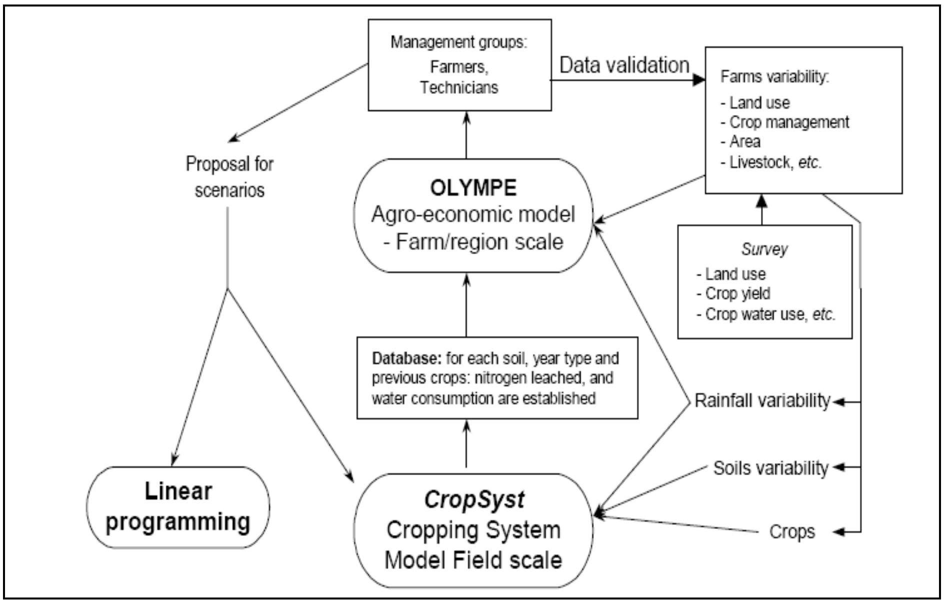


Figure 3.2 Model framework of bio-economic modelling representing farming and cropping operations (Le Grusse et al., 2006).

Furthermore, in Tunisia, Le Bars and Le Grusse (2008) built a negotiation framework involving farmers, dam managers and water allocation administrators concerning farm production choices resulting from water availability using a simulation gaming with Olympe model. Consequently, the study showed that global models and simulation games with stakeholders complement each other and can be used sequentially to a specific decision problem. In addition, Penot et al. (2004) reports other case studies on Olympe model applications carried out in Indonesia, Reunion Island, France, and North and West Africa that compared several technical agricultural pathways with changes in prices and subsidies. From these case studies, several advantages of Olympe model were noted.

Some of the Olympe model advantages are its easiness to understand, possibility of all stakeholders involvement in the model setup to simulation, shows results on the computer without delay and the input and output data are easy to see (Penot et al., 2004; Le Grusse et al., 2006). The literature on Olympe model training workshops showed that, after a short training (less than 4 days) period, farm advisers and students could use the model (Le Grusse et al., 2006; Le Bars and Le Grusse, 2008). Hence, the Olympe model has been widely applied in conjunction with other decision aid tools including stakeholders' participation.

Importance of participatory methods

The participatory methods (Vogel et al., 2007; Castelletti and Soncini-Sessa, 2006) provide active roles to stakeholders in the planning process, decision-making and implementation of management strategies. Hence, are regarded as the most effective approaches to ensure and assess agricultural sustainability (Vohland and Barry, 2009; Qiu et al., 2007; Le Grusse et al., 2006). However, there are several limitations associated with participatory methods.

Le Grusse et al. (2006) warn of the main limitation of participatory methods stemming from their qualitative nature and their apparent lack of rigour, structure, or systematic procedure for analysing and interpreting stakeholder contributions. A second limitation of participatory methods is that there are few research tools, in which both researchers and farmers can use together to diagnose problems and develop scenarios (Vohland and Barry, 2009; Le Grusse et al., 2006). A third limitation, participatory methods are time-consuming exercises that need careful coordination to have representative context results (Qiu et al., 2007; Le Grusse et al., 2006). The opportuities gained through participatory consultations include farmers seeing themselves as social change agents and increased feelings of programme ownership as reported by Castelletti and Soncini-Sessa (2006). The evaluation process created an environment for the community (farmers), extensions and NGOs to do something together, to create new knowledge for possible use in their farming activities. The lack of stakeholder participation in model building (i.e., the researchers tend to superimpose their existing mental and simulation models) may be a cause for non-adoption of models among practitioners. On one hand, the researchers feel their integrity is negatively affected by collaborating with practitioners,while on the other hand, stakeholders feel their legitimate concerns are not addressed (Vogel et al., 2007).

Although other models and methodologies exist for determining agriculture production and socio-economic interrelationships, the current study under CGIAR Challenge Program on Water and Food, PN17 project chose Olympe model because it:

- Creates a database on the farm systems operations
- Models agro-ecological systems and relate them to complex problems in natural resource management to seek answers. For example, Olympe model can evaluate the consequences of changes in input/output per crop, a change in a crop schedule and crop management
- Implements ex-ante analyses of the impacts of landuse changes or management practices under the production functions in a catchment.
- Builds into the farm system simulations unknown factors to assess the consequences of unforeseen internal or external farm system events (price fluctuations, climatic factors, changing market trends) on the project outputs
- Accomplishes analyses of impact over 10 years to evaluate changes in externalities, which cannot be perceived over short periods, as changes in externalities are associated with biophysical processes that slowly develop over time, such as erosion and changes in soil properties
- Accomplish the performance of both the environmental and socio-economic variables in a farm system in an integrated manner. Thus, evaluate not only environmental sustainability, but also help to stabilise or increase rural incomes from alternative management options
- Identify easily variables that describe a farm system’s functioning such as water use and cash flows
- Is an explorative tool rather than an optimisation model that sorts for one solution and require huge data
- Allow participatory of farmers and other stakeholders in the database and scenario construction to provide legitimacy to the model results

- Presence of a module in the model to link or integrate the model outputs to other software
- Is relatively easy to understand with few days of training
- Readily available support from the model developers to complement the training workshops offered in the study area under PN17 project.

3.3.16 Comparison of Olympe to other models

Olympe model is different from the other model approaches in that it considers a whole farming system (livestock, crops, tree plantation, management options and environmental externalities) and simulates for 10 consecutive years, adequate for policy impact analysis and for capturing the cyclic weather conditions such as droughts. Family expenses and incomes apart from the farming system are captured in the Olympe model making the model an appropriate tool to analyse total (farm plus non-farm income and food contribution) household food security. These strengths further supported the selection of Olympe model for adaptation and application in the current study.

From the literature survey, ECOSAUT and Olympe models both use outputs (catchment water and sediment yield, and nutrient loss) from the SWAT model, but there is no direct connection to the SWAT model. In addition, Olympe and ECOSAUT are similar in that they focus on understanding the causal relationship between land use (production systems) and associated technologies and their effects on the socio-economic and environmental conditions in a catchment (Le Grusse et al., 2006; Quintero et al., 2006). Understanding this causal relationship (which is the thrust of the current study) is important because most environmental conflicts in catchments arise from protests of those affected by sedimentation, water deficits during dry years, increased floods and reduced portability of water (Quintero et al., 2006).

In sum, Olympe model provides a forecast of the consequences on production and cash of the different farming scenarios under market and climatic perturbations considered by the farmers or the authorities. These Olympe model features fit well to the objectives of the current study. Therefore, the Olympe model was selected for application in the current study.

3.3.17 Summary

The summary of the models properties and areas of application are shown in

Table 3.6. It is important to note that the models presented do not simulate human behaviour but evaluate the conequences of those behaviour.

Table 3.6 Summary of the models properties and area of application. A yes indicates presence of the feature, while a no indicates otherwise.

Parameter	Models								
	MUDAS	FARM SCAPE	GRANJAS	NUANCES-FARMSIM	DYNBAL	FRAME	DECIBLE	ECOSAUT	OLYMPE
Time step									
Seasonal	yes	yes	yes	yes	yes	yes	yes	yes	yes
Input									
Crop	yes	yes			yes	yes	yes		
Crop and livestock	no	no	yes	yes	no	no	no	yes	yes
Output									
Production	yes	yes	yes	yes	yes	yes	yes	yes	yes
Income	yes	no	yes	yes	no		yes	yes	yes
Other features									
Participatory modelling with farmers	no	no	no	no	no	no	no	no	yes
Possible coupling with other models	yes	no	no	yes yes	no	no	no	no	yes

Challenges in crop model results application

McCown, (2002) reports numerous disappointing failures of attempts to introduce scientific models into practice, though not technically related. Rather, failures were practical and resulted in partial or complete failure to implement research findings. The focus of intervention management practice using models shifted to the social process of implementation to ensure model results acceptability and credibility. The challenge was to overcome (1) lack of engagement of researchers beyond the technical phase and (2) the marginalisation of local stakeholders/farmers in DSS or model planning conducted for use by them. This has been the focus of the current study, through the setup and use of Olympe and ICHSEA interface models with farmers in the study area.

In sum, from the literature surveyed, several farm simulation models have been developed and were briefly described. The models' strengths and weaknesses were presented and the final model selected for application in the current study, Olympe, described in detail. The main weakness of the models was lack of stakeholder participation in the modelling process that affected model credibility.

However, none of these models have been coupled dynamically or linked directly to the farm production driver, which is the water availability in a catchment. Consequently, the models have failed to provide a holistic answer to the impacts of catchment or crop management options. A gap the current study aims to fulfil by integrating the Olympe model with hydrology and agronomic models. Decision support tool and simulation (achieved by participatory modelling with Olympe) as learning aids are most effective in a participatory process that combines with the strengths of local practical knowledge and scientific knowledge (Carberry et al., 2002).

3.4 Model integration

This section presents a variety of developed integrated models and their applications across the world to support decision-making under policy and negotiations. Firstly, integration is defined; reasons for integration and the types of integration found in policy support studies are described. Next, the advantages and disadvantages of each form of integration are briefly presented. The last section discusses the limitations and important characteristics of integrated assessment models that overcome their limitations, drawing experience from past successes and failures of their applications. The objective of this section to draw experience from past integrated models for possible application into the development of the integrated model in this study.

3.4.1 Definition of integration and Integrated Assessment Model (IAM)

The term "integration" in the modelling literature can relate to several aspects including the integration of issues, disciplines, methods, models, scales of consideration and stakeholder interests in participatory activities (Greiner, 2004).

From the literature surveyed, an assessment is integrated when it draws a whole set of cause–effect interactions and communicates knowledge from diverse disciplines that go beyond the research result of a single discipline with the purpose to inform effective policy and decision-making and exposing trade-offs (Martínez-Santos et al., 2009; Jakeman et al., 2008; Greiner, 2004; Pope et al., 2004). Furthermore, other studies define integrated assessment as an interdisciplinary process of human, economic and resource-base (Janssen et al., 2009b; van Ittersum et al., 2008; Matthews et al., 2005), including participation of stakeholders (Rotmans and Dowlatabadi, 1998).

In addition, Ekasingh and Letcher (2008) define hard and soft systems integration methods in integrated modelling. Hard systems methods address situations where the problem is well defined and there is a definite solution, whereas soft system methods address problems that are difficult to define and there is no single right answer or perspective to take in resolving these problems. Hence, these soft systems address social problems, while the hard systems address the biophysical problems.

Additionally, Integrated Assessment and Modelling (IAM) is defined by Parker et al. (2002) as one of the techniques to process data and effectively inform policy-making. van der Sluijs (2002), argue that IAM include computer tools models used in a broader participatory assessment process, besides the complete integrated assessment methodology. Under IAM, quantitative sub-models representing different aspects of a sub-system that originate from different disciplines (social, economic and environmental) and operate on different spatial and temporal scales are combined into an interacting whole to answer specific objectives (Pope et al., 2004; Bland, 1999).

Several forms of IAM, depending on the objectives of the modelling exercise were found in literature. Pope et al. (2004) contrast Environmental impact assessment (EIA)–driven integrated assessment that identifies mitigation measures through which adverse impacts are minimised to acceptable levels, compared with baseline conditions, while Objectives–led integrated assessment ensures a desirable vision specified by integrated environmental, social and economic objectives. In addition, McIntosh et al. (2008), contrast predictive (explorative and evaluation) and goal-oriented (policy optimisation) modelling to provide potential link between biophysical and social processes within an IAM. Other forms of use are reported in van der Sluijs, (2002).

The reasons for integrated model development and implementation are associated with the growing complexity of societal issues that need comprehensive studies (Rotmans and Van Asselt, 2002). Hence, IAM aims to facilitate the re-use of discipline specific models and provide methods to link different models to enhance complex systems management (van Ittersum et al., 2008; Parker et al., 2002; Parson, 1995). Furthermore, integrated modelling assessment supports sustainability and aims at conveying innovative and sometimes counterintuitive insights into issues of interest, considering both exogenous and endogenous forces (Jakeman et al., 2008; Greiner, 2004).

Based on its useful traits, IAM has emerged in the last 10 years, as an important potential tool to inform policy decisions (Sharma and Norton, 2005), though several application problems have been identified.

The identified problems in the applications of Integrated Assessment Models (IAMs) are reported in Sharma and Norton (2005). Firstly, there has been inadequate incorporation of the consequences of sequential policy decisions. Secondly, policy decisions, taken repeatedly over time, lead to shifts in social systems and values that are not included in the IAMs. Thirdly, new information obtained after policy actions are taken may change the set of action choices that are available for making future decisions. In addition, van der Sluijs (2002) argues that IAMs are limited due to their inability to display both the crucial assumptions that underlie the model and the various forms of uncertainties in their outputs. Some of these uncertainties are addressed by stakeholder participation. Lastly, incorporation of institutions, as formal and informal rules of a society is lacking in most integrated assessment tools, despite their behavioural influence on the targeted actors (van Ittersum et al., 2008; Spangenberg et al., 2002).

3.4.2 DSS and how do they relate to integrated assessment model

Decision support systems (DSSs), are defined as computer-based systems that provide information by means of forecasting models and access to databases in order to support a decision-maker in complex and un-structured or partially structured management problems (Martínez-Santos et al., 2009; Gilmour et al., 2005; Tremblay et al., 2004; Turban, 1995). Unstructured problems refer to unclear and complex problems for which there is no single standard solution. The DSSs are developed from simulation, probabilistic and optimization models in combination with deterministic or stochastic approaches (Antonopoulou, 2003). In a normal operating environment, software programs, databases, and graphic interfaces are their main technological characteristics.

Furthermore, in agriculture, Antonopoulou (2003) classified DSSs as Integrated DSSs (IDSS), with capabilities to handle most agricultural activities, while Conventional DSSs cover agricultural activities mainly at control and operational level. Most of these agricultural DSSs are designed to answer questions and assist farmers in crop selection and management, including datasets of crop and livestock, soil and management elements. These DSSs aim to increasing problem understanding, identifying opportunities, reducing agricultural financial and environmental impacts in strategic or operational management and policy analysis (Borges et al., 2009; McIntosh et al., 2008; Castelletti and Soncini-Sessa, 2006; Antonopoulou, 2003). Hence, the usefulness of a DSS can be evaluated on different aspects.

These aspects include the alternatives provided by the DSS, improvements the DSS makes with the existing state of affairs and its human decision-making process improvements (Antonopoulou, 2003). In addition, decision-makers can perform sensitivity and uncertainty analysis to test the robustness of alternative management options in terms of risks. Under this risk analysis, multi-criteria decision analysis, weights and local context preference rules (such as low cost and effectiveness of identified options) help to increase confidence on identified strategies. In addition, confidence is gained by interfacing with the DSS end-users to solicit the preferred communication systems during DSS development (McIntosh et al., 2008), verification and validation (Sojda, 2007). Detailed steps for integrated model development are described in Zülch et al. (2002).

In sum, from the literature surveyed, both integrated (assessment) models and decision support systems seem to focus on assisting the human decision-making process. Therefore, in this study, an integrated model used to support decision-making is a decision support system tool.

3.4.3 Why integration?

There are several reasons for the increase in integrated model development, though their development is still at infancy (Gilmour et al., 2005). These reasons include increasing complexity of environmental and societal issues that demands comprehensive studies (Rotmans and Van Asselt, 2002; Rizzoli et al., 2008). In addition, there is need to relate science to policy-making (Jame and Cutforth, 1996) and integration of knowledge derived from a wide range of disciplines both natural and socio-economic systems to ensure sustainability. RNAAS (2005) argue that such integrated or coupled models should not only portray the impact of the socio-economic system on the water cycle, e.g. through land use and water management strategies, but also establish the response of the socio-economic system to hydrological events, such as floods and droughts.

An example from agriculture is that, the form and magnitude of crop and livestock systems responses to climate change in semi-arid areas will not be determined simply by the altered climate and carbon-dioxide concentration, but by localised individual farmers' biophysical conditions and the capacity for mitigation management will depend on the resources available to farmers (Rivington et al., 2007). Therefore, to draw conclusion about climate change impacts on farming systems, it is crucial to integrate the analysis of the biophysical processes and their influence on land use productivity, with socio-economic drivers and assess downstream effects (Rivington et al., 2007).

Furthermore, an attempt by past research to provide analytical tools and databases to assess the impacts of policies and innovations in agriculture faced fragmentation in modelling tools and lacked integrated approach (Van Ittersum et al., 2008; van Ittersum and Brouwer, 2009). Overcoming this challenge of fragmentation require integration of the numerous components that interact to effect plant growth, farm profitability and environmental quality (Jame and Cutforth, 1996). Therefore, integrated assessment and modelling has been proposed to improve the management of complex systems (Van Ittersum et al., 2008; Parker et al., 2002; Jame and Cutforth, 1996). Bland (1999) was probably the first one to use integrated modelling in the context of agricultural systems and only recently has the number of articles using this concept increased (Borges et al., 2009; Sattler et al., 2009; Van Ittersum et al., 2008; Rivington et al., 2007; Pacini et al., 2003).

3.4.4 Challenges in constructing integrated models

The challenges in constructing integrated models remain as there is need to link together dissimilar scientific knowledge domains (include different spatial and temporal scales, differing computer languages and model conceptual limitations) (Rizzoli et al., 2008) and to strike a balance between complexity and simplicity. In addition, the cross-disciplinary nature of integrated models makes them susceptible to different types and sources of uncertainty that propagate or accumulate as the individual models are executed (Rotmans and Van Asselt, 2002).

Furthermore, the integrated model end users are often implicitly identified, resulting in the development of integrated models that cannot be used outside the environments for which they were developed. Nonetheless, should integrated models be used outside their validated scope, meaningless outputs and inappropriate interpretations of the modelling results can ensue (Rizzoli et al., 2008). Moreover, there is no standard integration methodology on how to integrate various disciplines (Rotmans and Van Asselt, 2002). Hence, several integrated models have been developed to address specific objectives, although their applicability is restricted by lack of participation of end users in model construction and on how the problem is perceived, formulated and solved.

In sum, literature warns that an integrated model is as good as its weakest part of the whole model chain (Rotmans and Van Asselt, 2002). Hence, improvements should focus on these weak portions of the model chain. In the context of the current study, the development of an integrated model would address green and blue water policy issues, examine inter-policy impacts and facilitate the balancing of the socio-economic and hydrology model components.

In the next section, the types of model integration are described.

3.4.5 Types of integration

Literature surveyed (Rotmans and Van Asselt, 2002) showed that there are multiple integration strategies that include vertical, horizontal, loose and tight coupling. The two common approaches discussed in this section are loose and tight coupling.

Loose coupling

Loose coupling/integration strategy involves linking existing disciplinary models on an input-output basis. The advantage of this integration strategy is the easy in linking the different models. However, this loose coupling strategy may lead to an irresolvable mix-up of models and processes that hinders insight into the dynamic behaviour of the overall system. In addition, loose coupling strategy is based on linear linking of subsystems rather than integrating them, hence is limited in capturing many non-linear (stochastic) interactions and feedbacks inherent in reality (Rotmans and Van Asselt, 2002).

Tight coupling

Tight coupling/integration strategy involves developing a suite of simplified models called metamodels from the more complex or expert models. The advantage of this tight coupling strategy is harmonization of scale and more advanced spatial and temporal resolution aggregation of the discipline models. Additionally, the strategy allows feedback interactions between dissimilar systems, based on one conceptual model. However, this tight coupling strategy is a simplified system.

In the next section, examples of integrated models applications in decision-making exercises are described. These examples were drawn from South Africa and other parts of the world.

3.4.6 Examples of IAM/ DSS

In this section, diverse integrated model applications related to water and agricultural management and their policy issues are described. There are several examples of successful applications of integrated models in scenario analysis (ex-ante), especially in forest ecology, water, agriculture and climate change. These examples are briefly described next.

In an integrative effort to protect estuaries (Perissinotto et al., 2004) the South African Water Research Commission funded a multi-disciplinary study incorporating river mouth dynamics, physico-chemical conditions, nutrient conditions, phytoplankton and microphytobenthos, zooplankton, fish and birds to come up with measures for reserve determinations for estuaries using biological communities' responses (Borja et al., 2008).

Janssen et al. (2009a) describes the successful integration of System for Environmental and Agricultural Modelling; Linking European Science and Society (SEAMLESS) (Therond et al., 2009; van Ittersum and Brouwer, 2009; van Ittersum et al., 2008), integrated database and models. SEAMLESS was used to assess agricultural policies or technological innovations and environmental policy options contribution to sustainable development in 25 European Union member states' agricultural systems and the rest of the world at multiple scales. The database contains data on cropping patterns, production, farm structural data, soil and climate conditions, current agricultural management and policy information.

Furthermore, SEAMLESS-IF (Integrated Framework) is designed with stand-alone APES, FSSIM-AM, FSSIM-MP and SEAMCAP components that can either be re-used as stand-alone models or linked in SEAMLESS-IF to assess new policy proposals (van Ittersum et al., 2008). The use of Open Modelling Interface (OpenMI) (www.openmi.org; van Ittersum et al., 2008) allows the smooth technical linkages of components, even though they have been developed and programmed in different languages. SEAMLESS-IF is based on the concept of component-based modelling which breaks up larger models into discrete and re-usable components (van Ittersum et al., 2008).

Additionally, Sharma and Norton (2005), propose the use of Markov decision processes (MDPs) and partially observed Markov decision processes (POMDPs), where the choice of action is represented by a probability function as a policy decision aid tool for integrated assessment. Markov decision processes have been used to successfully model a wide variety of complex problems in the field of operations research and planning of highway maintenance in the policy and environment arenas.

Furthermore, the RAINS integrated model (Regional Acidification INformation and Simulation) (Sharma and Norton, 2005; van der Sluijs, 2002; Hordijk and Kroeze, 1997; Alcamo et al., 1990), focused on reducing SO_2 and NO_x emissions in Europe that causes acid rain. RAINS model played a major role in the international acid deposition negotiations framework of the United Nations Convention on Long-Range Transboundary Air Pollution and became an annex to the United Nations SO_2-protocol (van der Sluijs, 2002). In 2005, Schöpp et al. (2005) performed an uncertainty analysis of emission estimates in the RAINS and concluded that uncertainty in the activity data dominates the future emission estimates. In addition, an Integrated Model to Assess the Greenhouse Effect (IMAGE) (Rotmans, 1990) (IMAGE 2.0 latest version) focused on developing greenhouse reference and policy emission scenarios evaluations by the Intergovernmental Panel on Climate Change (IPCC) (Sharma and Norton, 2005). IMAGE 2.0, includes three modules: Energy-Industry, Terrestrial Environment and Atmosphere-Ocean, and has global coverage and the spatial resolution varies across modules (van der Sluijs, 2002; Hordijk and Kroeze, 1997; Alcamo, 1994).

Furthermore, Huime et al. (1995) reported an Evaluation of Strategies to address Climate change by Adapting to and Preventing Emissions (ESCAPE) model applied in Europe. This climate-change assessment model comprises four linked modules (including IMAGE 2.0). The ESCAPE model enabled the generation of future scenarios and impact assessment of greenhouse gas emissions on global climate and sea level through an energy-economic model. In addition, the ESCAPE model was improved to a new integrated climate change assessment model, Model for the Assessment of Greenhouse gas Induced Climate Change (MAGICC) that can easily be incorporated into other integrated frameworks (Huime et al., 1995).

Another IAM is the dynamic integrated climate-economy (DICE) (Nordhaus, 1992) model, which calculates the optimal amount of carbon tax required to be imposed in order to mitigate global warming due to greenhouse gas emissions. In addition, the TARGETS model (Tool to Assess Regional and Global Environmental and Health Targets for Sustainability) (Rotmans and de Vries, 1997) used in Netherlands, integrates several sub-models that allow participants to change the major assumptions on economic, environmental and societal processes and explore different trends such as those for population growth or energy efficiency (van der Sluijs, 2002). PoleStar was also developed in Stockholm, Sweden for the examination of economic, resource and environmental information of a region (van der Sluijs, 2002).

In another study, an integrated modelling framework, Land Allocation Decision Support System (LADSS) was developed in collaboration with stakeholders for the simulation of whole-farm systems resources, including soil, crop and livestock components (Rivington et al., 2007). The core of this integrated modelling framework components is the ORACLE relational database. The framework components are CropSyst, LSM (livestock systems model) and RST (resources scheduling tool). Detailed presentation of the framework for farm-scale decision-support systems (DSS) is found in Sibbald et al. (2000). This LADSS framework enabled the assessment of farm system resilience and adaptive capacity. The study concluded that issues of quantification and communication of uncertainty are central to the success of the integrated methodology framework.

Furthermore, Deybe (1998) applied Multi-Level Analysis Tool for the Agricultural sector (MATA) DSS model to evaluate the impact of policies in the agricultural sector on farmers' production and urban food consumption after the devaluation of 50 % of the Franc of the African Financial Community (FCFA) in Burkina Faso. The three modules of MATA are production aspects, consumers' behaviour and economic context and the parameters for policy simulation. Additionally, Borges et al. (2009) applied linear programming model in a modular DSS framework, Common Agricultural Policy (CAP) to assess the impact of changes in prices and in agricultural policy on land use patterns and on forestry.

Furthermore, Hengsdijk et al. (1998) applied a predictive quantitative systems analysis approach using linear programming as an integrating technique in rural agricultural production to support effectiveness of policy instruments and questions with various time and spatial scales in Mali. This quantitative systems analysis (Penning de Vries et al., 1992) approach emphasizes the need to think openly about entire agricultural production systems to identify trade-offs among conflicting objectives at different spatial scales. In addition, van der Sluijs (2002) and Welp (2001) report application of integrated assessment models on global climate in combination with focus groups discussions, role-plays and gaming within a European research project on energy and climate policy, Urban LifestYles, SuStainability and Integrated Environmental ASsessment (ULYSSES). The computer models used in the project included IMAGE (Alcamo, 1994) and TARGETS (Rotmans and Penning de Vries, 1997). ULYSSYES was tested in seven urban regions throughout Europe (van der Sluijs, 2002). Two examples of role-plays and gaming are *Storm* or *Corona* that have been developed in the Netherlands (Welp, 2001).

In another DSS study, DSS for Agricultural Resource Management (DSSARM), farmers' indigenous knowledge in agriculture is partially incorporated by crop scientists who work closely with the farmers (Ekasingh and Letcher, 2008). In addition, Bartolini et al. (2007) evaluated the economic, social and environmental impacts of irrigated agriculture and water policy scenarios on the sustainability of five irrigated farming systems in Italy using multi-attribute linear programming models.

Furthermore, Krol et al. (2006) presented the Semi-Arid Integrated Model (SIM) in North-east Brazil to describe the dynamic relationships between its main components of climate, water availability, agriculture and socio-economic components. SIM is built in a modular way, consisting of modules from the Water Availability, Vulnerability of Ecosystems and Society (WAVES) program. The schematic diagram for model integration is shown in Figure 3.3. Furthermore, Krol and Bronstert (2007) developed an integrated model to assess the influence of climatic variability on land and water resources utilisation to raise awareness about the impacts of water variability. This integrated model was applied in North-east Brazil as well, characterised by water scarce and a high proportion of people depending on natural resources.

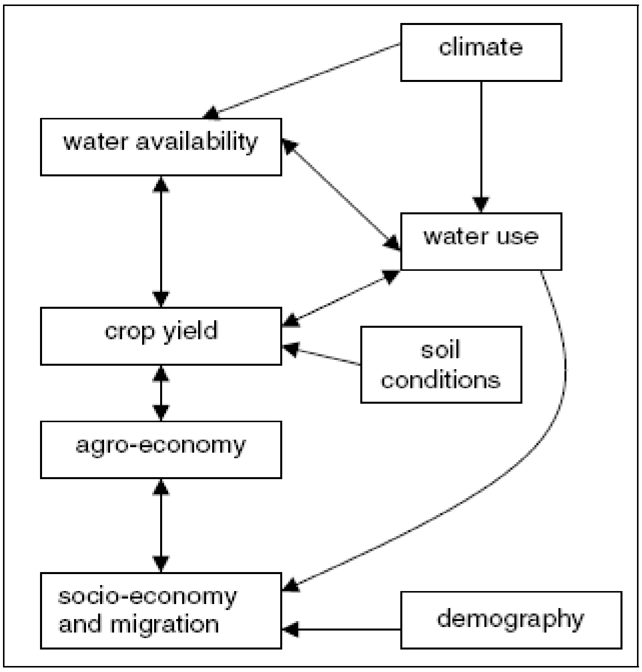


Figure 3.3 Schematic diagram for SIM integration (Krol et al., 2006). The double arrows indicate feedback effects, while one-directed arrow indicates a one-way effect.

In addition, a study in the river Elbe considered integrative framework components consisting of the cycle of problem setting, criteria selection, scenario definition including policy measures, multi-criteria and multi-stakeholder analysis of alternatives (Krol et al., 2006). The impacts were estimated using input–output linkages of chains of the partly integrated models.

Another widely adopted integrated framework for model integration and re-use reported by Rizzoli and Young (1997) is Dynamic Environmental Effects Model (DEEM) to support multi-disciplinary modelling of terrestrial, aquatic, and atmospheric processes. In another study involving GIS and model integration in USA, the TERRA (Terrestrial Ecosystem Regional Research and Analysis) investigate the use of the Modular Modeling System (MMS) (Rizzoli and Young, 1997).

Furthermore, Rudner et al. (2007) developed the Integrated Grid Based Ecological and Economic (INGRID) landscape model to simulate the ecological effects of dry grasslands management schemes and associated costs in order to serve as decision support tool for nature conservation agencies in Central European agricultural systems. Based on data exchange, the model framework integrates (see Figure 3.4) static and dynamic modules regarding abiotic and biotic state variables, economic aspects, processes and interactions into a spatially explicit landscape model. However, further developments of the INGRID landscape model envisaged include integration of population dynamic models or economic models for pasture management, inclusion of an expert module and sensitivity analyses (Rudner et al., 2007).

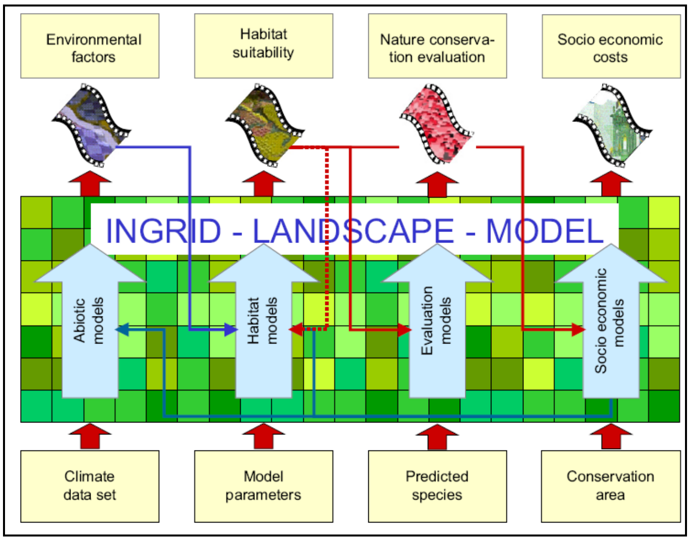


Figure 3.4 INGRID landscape model framework (Source: Rudner et al., 2007).

Furthermore, in municipal solid waste landfills management, a landfill dynamic simulation program MODUELO 2 has been developed and successfully applied in Spain for environmental impact assessment of leachate that can pollute surface and groundwater resources (de Cortázar and Monzón, 2007). Additionally, Sattler et al. (2009) presented a bio-economic modelling system, Multi-Objective Decision support system for Agro-ecosystem Management (MODAM) (Zander and Kächele, 1999) that evaluates single agricultural production practices by means of environmental (abiotic and biotic), economic and social indicators. The model was developed in Germany and the study concluded that the interface between agricultural activities and the resulting environmental implications is still lacking.

Additionally, PALM framework integrated human and biophysical models to simulate resource flows in rural community (Matthews, 2006). PALM represents an amalgamation of both ‘rule based’ plus continuous flow modelling paradigm and is a fully integrative model. The components integrated are CENTURY model (for organic matter decomposition), DSSAT model (for nitrogen dynamics, crop growth, soil processes) and household data (income, labour, food stores and cash). In addition, Avila-Foucat et al. (2009) linked ecological and economic models to identify optimal management strategies for catchment areas in which changes in nutrients loads affects abundance of economically important fish species in Mexico. The study concluded that agriculture expansion would be beneficial to the catchment as well as downstream to a certain limit, beyond which fisheries as well as eco-tourism would be negatively impacted.

In addition, Krysanova et al. (2007) reported a process-based ecohydrological spatially semi-distributed model SWIM (Soil and Water Integrated Model) (Krysanova et al., 1998) developed in Germany from SWAT and MATSALU models for climate and land use change impact assessment. The SWIM model integrates hydrological processes, vegetation/crop growth, erosion and nutrient dynamics in river basins. In addition, using GAMS language, Donaldson et al. (1995) combined a crop growth model (EPIC) (Williams et al., 1990) with an economic recursive linear programming model to identify the effects and risks of policy-related price changes on farmers' resource allocation in two European catchments. Under recursive approach, conditions prevailing in period T_n determine the choices without reference to their future consequences, whereas in period T_{n+1} the results are influenced by the period T_n conditions.

Furthermore, Rötter et al. (2007) investigated and presented the results of an Integrated Resource Management and Land use Analysis (IRMLA) Project in the Philippines. The IRMLA aimed to assess agricultural policy measures and innovative production systems from field to provincial scale. In addition, Abaza and Hamwey, (2001) integrated economic, environmental, and social assessment tools to provide policy impacts of trade liberalisation (globalisation of markets) on sustainable resources use and social welfare for sustainable development.

Furthermore, Martínez-Santos et al. (2009) report of participatory integrated assessment using groundwater flow model and Bayesian belief networks (BBNs) (Newton et al., 2007) in a conflictive setting of aquifer exploitation in Spain. In addition, Bland, (1999) reports an IAM application in a major irrigated region of Australia, Murray-Darling Basin Irrigation Futures Framework (MDBIFF). This model framework links biophysical, production, and socio-economic models to assess the impacts on the regional economy and environment caused by changes to water markets, land use and drainage schemes.

The MedAction Policy Support System (PSS) in the Mediterranean watersheds incorporates socio-economic and physical processes in a coupled manner (Matthies et al., 2007). Under this PSS project, it was noted that the end-user perception and acceptance of the DSS tool is important for successful implementation. Hence, this aspect was incorporated into the current study. In addition, an EU (EU, 2000) project under Water Framework Directive (EU-WFD), MULti-sectoral, INtegrated and Operational (MULINO) (Giupponi, 2007), combines socio-economic and environmental modelling components with an emphasis on the DSS credibility evaluation by end-users (Matthies et al., 2007).

In a more comprehensive approach to basin water resources DSS, De Kort and Booij (2007) and Schlüter and Rüger (2007) presented DSS uncertainty management by Monte Carlo uncertainty analysis. The combined assessment of uncertainties is new and of high relevance in the field of environmental policy decision-making (van Ittersum and Brouwer, 2009). Hence, uncertainty management was included in the current study.

3.4.7 Requirements of DSS for use in a participatory assessment process.

There are several conditions that the integrated models that support decision-making need to satisfy for them to be used in participatory decision-making. These conditions include providing results in a reasonable time-frame (van der Sluijs, 2002) and be used interactively with stakeholders to foster creative generation and exploration of rival problems (Jakeman et al., 2008; van der Sluijs, 2002). This extension to peer community enriches the model assessments and implementation, thus establishing social and scientific credibility (McIntosh et al., 2008). However, issues of community influence and power relations (Rivington et al., 2007; McIntosh et al., 2008) could affect the involvement of peer community. In addition, integrated assessment model must incorporate learning by doing and be easily updated to reflect advances in understanding if they are to capture the dynamics of socio-economic and ecological parameters (Jakeman et al., 2008; Sharma and Norton, 2005).

In sum, DSS need to be scientifically credible by having a sound structure, be transparent (Jakeman and Letcher, 2003), validated and peer reviewed. In addition, social credibility of the DSS requires the DSS developers to establish trust with end-users, clients and stakeholders (McIntosh et al., 2008).

3.4.8 Limitations of IAMs

Sharma and Norton, (2005) argue that many IAMs are uni-dimensional as they cover climatic change issues only based on monetary terms as the decision criteria. This approach assumes that all socio-economic and environmental issues can be evaluated in monetary terms and that actors have fixed preferences that does not change as their knowledge about processes advances. Furthermore, many IAMs ignore complex links and feedbacks among environmental systems, social, structural changes in political and economic systems (Martínez-Santos et al., 2009). Participatory modelling or multi-agent systems and companion modelling which are capable of dealing with social and political aspects and further help in model validation and uncertainty analysis (Ekasingh and Letcher, 2008) can address the social and political systems. In addition, Sharma and Norton (2005), cite the lack of extreme (low and high) events evaluation in IAMs, the absence of a strong political will and ill-suited institutional arrangements as limitations of integrated models.

3.4.9 Summary

In this section, integrated Assessment model (IAMs) was defined and briefly reviewed. Next, application examples of DSS tools and the issue of public participation in policy-making or negotiations were described. The conditions desirable for success and credibility of Integrated Assessment Models (IAMs) to better support decisions were highlighted. Finally, the limitations of IAMs with regard to their use in policy-making were identified. Based on these identified limitations from literature survey, the current integrated model design envisages overcoming some of them, including stakeholder participation and uncertainty analysis. A summary of the surveyed integrated models and their area of application are shown in Table 3.7. A blank means variable not available, while a yes indicates availability.

From literature surveyed, computer-based integrated model as a decision aid tool, represent a robust and flexible planning tool by providing information from natural and social sciences in development of successful catchment management strategies. In these integrated model interfaces (no agreed standardised integration interface or framework yet) are employed to enable communication among models written in different programming languages. However, the complexity nature of DSS tools makes their validation and verification difficult (Matthies et al., 2007). Hence, the need for DSS users to have an in-depth understanding of assumptions and limitations of integrated DSS components.

Furthermore, the development and application of such integrated model tools is still at infancy (Gilmour et al., 2005) and sometimes face implementation challenges. Reasons for implementation failure of integrated frameworks are largely due to a variety of factors that may range from the absence of a strong political will to ill-suited institutional arrangements. Common to all DSS studies is the need to involve adequately local authorities, managers and other stakeholders in strategic assessment to enhance credibility of DSS. Other DSS limitations include their assumption that all socio-economic and environmental issues can be evaluated in monetary terms, and that end users have fixed preferences. Furthermore, many DSS ignore the complex links and interactions between environmental systems, human social and economic systems that are susceptible to uncertainty.

The quantification and communication of uncertainty in DSS are central to the success of integrated models or DSS tools. Therefore, there is need to devote significant effort within DSS simulation modelling to cost-effectively improve the quality of input, calibration and validation data sets and to make efforts to quantify the uncertainties in simulation model outputs (Rivington et al., 2007).

To sum up, apart from the negative (pollution and competition of water users) human impact on water resources, positive impacts may be achieved through holistic and sustainable water management, supported by robust policies derived with the help of DSS. Despite significant development of IAMs, much needs to be done in order to achieve better integration and to enhance their usefulness through stakeholder iterative participation for making informed policy decisions.

Table 3.7 Summary of the surveyed integrated models and their area of application.

Model name	Socio-economic	Stakeholder inclusion	Climate change	Uncertainty analysis	Policy			Place applied	Reference
					Agriculture	Techonology	Environmental		
ECMD							yes	South Africa	Perissinotto et al., 2004
SEAMLESS					yes	yes	yes	EU & world	Therond et al., 2009; van Ittersum and Brouwer, 2009; Janssen et al., 2009a,b
MDPs and POMDPs							yes	–	Sharma and Norton, 2005
RAINS			yes	yes			yes	UN and EU	van der Sluijs, 2002; Hordijk and Kroeze, 1997; Alcamo et al., 1990
IMAGE			yes				yes	–	Rotmans, 1990
ESCAPE			yes				yes	EU	Huime et al., 1995
MAGICC			yes				yes	EU	Huime et al., 1995
DICE			yes				yes	–	Nordhaus, 1992
TARGETS	yes						yes	Netherlands	Rotmans and de Vries, 1997
PoleStar	yes						yes	Sweden	van der Sluijs, 2002
LADSS		yes		yes	yes			–	Rivington et al., 2007; LADSS, 2005
MATA	yes				yes			Africa-Burkina Faso	Deybe, 1998
CAP	yes				yes			–	Borges et al., 2009
PQSA-LP	yes				yes			Africa-Mali	Hengsdijk et al., 1998
ULYSSES	yes	yes	yes				yes	EU	Welp, 2001
DSSARM	yes	yes			yes			–	Ekasingh and Letcher, 2008
ESEIA	yes				yes		yes	Italy	Bartolini et al., 2007
SIM	yes	yes	yes		yes		yes	Brazil	Krol et al., 2006
TERRA			yes				√	USA	Rizzoli and Young, 1997
INGRID	yes				yes	yes	yes	EU	Rudner et al., 2007
MODUELO							yes	Spain	de Cortázar and Monzón, 2007
MODAM	yes				yes	yes	yes	Germany	Sattler et al., 2009 ; Zander and Kächele, 1999

Model name	Socio-economic	Stakeholder inclusion	Climate change	Uncertainty analysis	Policy			Place applied	Reference
					Agriculture	Techonology	Environmental		
PALM	yes				yes	yes		—	Matthews, 2006
SWIM			yes		yes		yes	Germany	Krysanova et al., 1998
EPIC-LP	yes				yes			EU	Donaldson et al., 1995
IRMLA					yes	yes		Philippines	Rötter et al., 2007
MDBIFF	yes				yes	yes	yes	Australia	Bland, 1999
PSS	yes	yes			yes			Mediterranean	Matthies et al., 2007
MULINO	yes	yes	yes				yes	EU	Giupponi, 2007

Notes:

1. PQSA-LP = Predictive Quantitative Systems Analysis using Linear Programming
2. ESEIA = economic, social and environmental impacts assessment
3. ECMD = Estuary community and mouth dynamics
4. — = not stated
5. From the table only two (RAINS and LADSS) studies attempted to include uncertainty analysis and only one (LADSS) include both uncertainty analysis and stakeholder participation. Hence, the focus of the current study is to contribute to methodology of integration including both stakeholder participation and uncertainty analysis.

3.5 Sensitivity and uncertainty analysis

Increased use of physics based models on water resources management emphasise the importance of integrated approaches that call for analysis and quantification of model predictions while recognising uncertainties in model descriptions and operating environments (Mezic and Runolfsson, 2008; Refsgaard et al., 2007; Brown et al., 2005). The uncertainty of a parameter comes from either natural phenomena or lack of knowledge about a parameter (Ju, 2008). This parameter uncertainty affects model outputs and consequently affects policy related decision-making.

This section presents definition, sources and methods of uncertainty and sensitivity analysis. In addition, management of uncertainty in integrated models and implications of uncertainty results in policy related decision-making are presented. The section concludes with a summary.

3.5.1 Definition of uncertainty

There are several definitions of uncertainty proposed, depending on the field of study. Uncertainty is defined as a worst-case distance in the space of output measures from a certain system (Helton et al., 2006). Shirmohammadi et al. (2006) consider uncertainty as "the estimated amount by which an observed or calculated value may depart from the true value." In atmospheric sciences, uncertainty, also referred to as predictability, is defined in terms of relative entropy between uncertain and certain measures, while in reliability studies it is defined in terms of distance between cumulative distribution functions (Mezic and Runolfsson, 2008). Furthermore, Refsgaard et al. (2007) adopt a subjective definition of uncertainty as the degree of confidence that a decision-maker has about possible outcomes from a model analysis. However, a person can be confident about the outcome but has misjudged the information, consequently the judgement will be wrong. All the definitions positioned uncertainty in the context of model uncertainty, as related to deviations between the real world and its simplified representation in models. As when analysing complex systems in real life, compliance between the model assumptions and the properties of the system being analysed never exists in an absolute sense (Brown et al., 2005; Nilsen and Aven, 2002).

3.5.2 Error and uncertainty

Oberkampf et al. (2002) differentiate error and uncertainty in modelling. Error is defined as a recognisable inaccuracy in any phase of modelling or simulation that is not due to lack of knowledge (uncertainty). For example, the error maybe viewed as acceptable for requirements of the analysis or because of prohibitive computational cost to correct it. In addition, an error can be either acknowledged (errors introduced by analyst and the analyst has some idea of the magnitude and impact of such errors) or unacknowledged (are inaccuracies not recognized by analyst such as blunders or mistakes from human errors). Double-checking of the system (e.g. computer code) by either the analyst or other people such as model reviewers can pick up these errors.

From the literature, uncertainty of the output is often calculated in terms of the variance of its probability distribution (Mezic and Runolfsson, 2008; Helton and Oberkampf, 2004). Uncertainty treatment relevant for the decision-making process involves identification, characterisation, communication and interpretation of uncertainty to interested parties (Van Asselt and Rotmans, 2002).

3.5.3 Types of uncertainty

The literature surveyed distinguishes between bounded uncertainty (often denoted as statistical uncertainty), where all possible outcomes are assumed known and unbounded uncertainty, where some or all possible outcomes are unknown (Walker et al., 2003). In the event that outcomes are known but not the probabilities, scenario analysis can be applied (Refsgaard et al., 2007; Walker et al., 2003).

Often, uncertainty is classified into two subtypes: reducible (epistemic) and irreducible (aleatory) (Mezic and Runolfsson, 2008; Refsgaard et al., 2007; Helton and Oberkampf, 2004; Oberkampf et al., 2002). Firstly, epistemic uncertainty arises from a lack of knowledge about quantities that have fixed but poorly known values. An example of epistemic uncertainty is uncertainty in initial conditions that can be reduced by improved and longer time series of field measurements (Mezic and Runolfsson, 2008; Refsgaard et al., 2007). Bayesian probability method is often employed for epistemic uncertainty, although fuzzy set theory and evidence theory promise to better perform in future (Oberkampf et al., 2002).

Secondly, an aleatory uncertainty arises from the inherent stochasticity (Oberkampf et al., 2002; Helton, 1994) behaviour of the system under study, such as weather or climate variability. Other studies referred an aleatory uncertainty as objective uncertainty (Natke and Ben-Haim, 1996), or primary uncertainty (Koopmans, 1957), or external uncertainty or random uncertainty (Van Asselt and

Rotmans, 2002). An example of an aleatory uncertainty could be possible accidents that could occur at a nuclear plant. The lack of knowledge with respect to variables required in the characterisation of the frequency, evolution or consequences of individual potential accidents contributes to the aleatory uncertainty (Helton and Oberkampf, 2004; Oberkampf et al., 2002).

Furthermore, uncertainties in the model forms (structural uncertainties) are estimated by use of alternative suitable models and determine how well they match experimental data (Hanson, 1999). Structural uncertainties lead to rapid growth in the model uncertainties when the model is used beyond the range of available experimental or observed data. This use beyond observed data space is referred to as model extrapolation. To avoid the rapid growth of uncertainties, experiments should be conducted to collect data that fills out the physical operating regime of the intended use of the simulation model results. In common modelling approach, using observed data to calibrate a simulation model for a given site partially remove modelling uncertainties associated with both structure of the model and parameter estimates (Arabi et al., 2007).

Mezic and Runolfsson (2008) and Helton and Oberkampf (2004) further made a distinction between a priori and a posteriori uncertainty. A priori uncertainty is any joint uncertainty (epistemic or aleatory) captured in an inputs description of the system, whereas a posterior uncertainty is any joint uncertainty that is inherent to the process dynamics and observations and captures the state of knowledge about the parameters (Hanson, 1999). Often uncertainties and errors from different sources are reported in terms of root mean-square deviation and confidence interval.

3.5.4 Sources of uncertainty

The sources of uncertainties based on extensive screening of the scholarly literature (Rotmans and Van Asselt, 2002) are presented in Figure 3.5. Epistemic uncertainty (lack of knowledge) is reducible through improvement in the modelling and measurement processes, whereas aleatory uncertainty (inherent variability) is always irreducible.

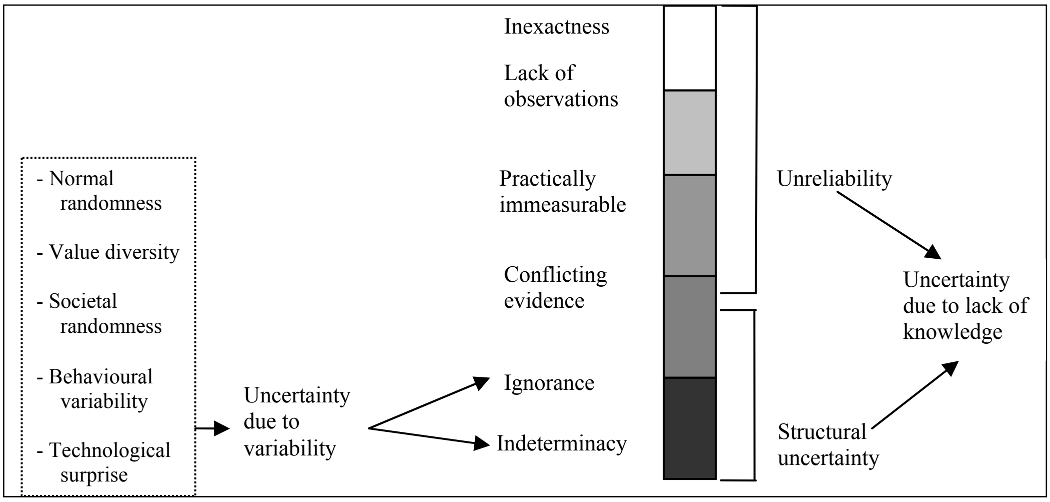


Figure 3.5 Sources of uncertainties (Rotmans and Van Asselt, 2002).

3.5.5 Error analysis

Models, being simplified representations of reality, produce output with errors. These model output errors are compounded by errors in input data. For instance, spatial data have errors due to measurements, digitisation, or interpolation (Hartkamp et al., 1999). How these errors interact when systems are interfaced or coupled is poorly understood. Hartkamp et al. (1999) noted that an error could increase because of aggregation of models or data. For example, aggregated soil data led to a 100 % error in model outputs (De Roo et al., 1989). Hence, error analysis, reliability and model outputs quality has become increasingly important as models are used to aid decision-makers for informed decision-making (Hartkamp et al., 1999).

In addition, error analysis is related to uncertainty analysis. Therefore, there is an increasing need to perform uncertainty analysis and report on how much confidence should be placed on the model outcomes or results of the analysis to make informed decisions (Helton et al., 2006). Contrary to traditional practices of performing uncertainty analysis after model set-up, calibration and validation Refsgaard et al. (2007) and Walker et al. (2003) recommended executing uncertainty analysis as an on-going task from problem definition and identification of modelling objectives through to decision-making process.

Several methods that have been developed to assessing and reporting uncertainty in individual and coupled models are presented in the next section.

3.5.6 Methods for uncertainty assessment

Several methodologies for assessing uncertainty have been reported in scientific literature (Refsgaard et al., 2007; Gilmour et al., 2005; Fieberg and Jenkins, 2005; Van der Sluijs et al., 2004; Oberkampf et al., 2002; Van Asselt and Rotmans, 2002; Sobol, 2001). A number of uncertainty analysis application examples including missile flight (Oberkampf et al., 2002), water policy and land use (Gilmour et al., 2005), wildlife conservation (Fieberg and Jenkins, 2005) and climate change (Van Asselt and Rotmans, 2002) were identified from literature. Presented in this section briefly, are selected commonly applied methods.

Data uncertainty engine (DUE)

Data uncertainty is an important input when assessing uncertainty of model outputs. Data uncertainty is represented by specific probability density functions (pdfs) developed under different simplifying assumptions (e.g. Gaussian; second-order stationarity and degree of temporal and spatial autocorrelation). The data uncertainty engine (DUE) software tool developed within the HarmoniRiB project (Refsgaard et al., 2007) can be downloaded from the project website http://www.harmonirib.com.

Error propagation equations

From literature surveyed, error propagation equations (Box 1) are widely used in the experimental and measurement sciences to estimate error propagation in calculations. The error propagation equations are only valid if the following conditions are met (Refsgaard et al., 2007): (1) the uncertainties have Gaussian (normal) distributions; (2) the uncertainties for non-linear models are relatively small: the standard deviation divided by the mean value is less than 0.3; and (3) the uncertainties have no significant covariance. As the above assumptions rarely hold, the error propagation equations are often used for preliminary screening analysis.

Box 2.1Error propagation equations (Refsgaard et al., 2007)

The error propagation equations for the most common operators are (σ is the standard deviation):

Addition and subtraction: $z = x + y + \ldots$ or $z = x - y - \ldots$

$$\sigma_z = \sqrt{\left(\sigma_x^2\right) + \left(\sigma_y^2\right) + \ldots} \qquad 2.1$$

Multiplication by an exact number: $z = cx$

$$\sigma_z = C\,\sigma_x \qquad 2.2$$

Multiplication and division: $z = xy$ or $z = x/y$

$$\frac{\sigma_z}{z} = \sqrt{\left(\left(\frac{\sigma_x}{x}\right)^2 + \left(\frac{\sigma_y}{y}\right)^2 + \ldots\right)} \qquad 2.3$$

Expert elicitation

Expert elicitation involves the direct quantification of uncertainty through a structured process to elicit subjective experts' judgements and represent them as a 'subjective' probability density functions (PDF) (Refsgaard et al., 2007). These probability density functions reflect the expert's degree of belief. This expert elicitation method is widely used to quantify uncertainties in cases where there are no or insufficient empirical data available to infer on uncertainty. Detailed methodology is found in Refsgaard et al. (2007). However, the main limitations are the subjectivity of the results that are sensitive to the selection of experts and the way different expertise is presented thereof.

Extended peer review

Extended peer review (Helton and Oberkampf, 2004), usually used for semi-structured problems, involves stakeholders' participation in the modelling process through their reasoning, observations, perspectives and imaginations that are normally unbounded by scientific rationality. Areas of improvement include problem formulation that results in highest order of magnitude of uncertainty in final model predictions (Helton and Oberkampf, 2004; Linkov and Burmistrov, 2003).

Furthermore, extended peer review method contributes local knowledge on elusive local conditions to determine most pertinent data to better match real-life contexts (Refsgaard et al., 2007; Helton and Oberkampf, 2004). The main strengths of extended peer review are quality assurance and a holistic approach followed by allowing the use of extra local knowledge from non-scientific sources essential for integrated management. However, main limitations are difficulty for stakeholders to understand the abstract problem concepts and the selection of representative stakeholders to avoid bias (Refsgaard et al., 2007).

Stakeholder involvement

Similar to extended peer review, the stakeholder approach attempts to involve stakeholders in the whole modelling process from problem formulation to decision-making in an effort to better managing complex environmental problems (Vogel et al., 2007). Van der Sluijs et al. (2004) gives a detailed guide on application of the stakeholder involvement method. The principal strengths of the stakeholder involvement are promotion of public accountability and support of subsequent management options. However, the method suffers from stakeholders' subjectivity.

Inverse modelling (parameter estimation)

Inverse modelling estimates parameter values by minimising an objective function, defined as a summation of squared deviation between the calibration field data and simulated output data (Refsgaard et al., 2006). Free software tools that support inverse modelling and some universal optimization routines such as PEST and UCODE can be downloaded from the internet (Refsgaard et al., 2007; Poeter and Hill, 1998). The main limitation of this parameter uncertainty technique is that the model calibration is based on a single model structure, resulting in incorrectly allocating model structure uncertainties to model parameter uncertainties (Refsgaard et al., 2007). Consequently, the estimated parameter uncertainties will inadequately compensate for the model structure uncertainty, when the model is used for prediction (model extrapolation) of conditions beyond the calibration data space (Refsgaard et al., 2006).

Inverse modelling (predictive uncertainty)

The inverse modelling method uses either regression algorithm or semi-analytical solution in which the regression algorithm is used to compute either a predictive uncertainty interval for the output variable or uncertainty in the difference between a reference case and a scenario simulation (Refsgaard et al., 2007). The method gives an objective estimate of the predictive uncertainty given the applied model structure. The main limitations of the method include the assumptions on linearity, normally distributed residuals and use of data for which observations exist. Consequently, the uncertainties of interpolated and or extrapolated variables compared to field observations cannot be measured by the inverse modelling method.

Multiple model simulation

Multiple model simulation addresses uncertainty about model structure (conceptual uncertainty) often considered the main source of uncertainty in model predictions resulting from modellers' interpretation of scenarios and approximations (Refsgaard et al., 2007; Refsgaard et al., 2006; Linkov and Burmistrov, 2003). Instead of performing predictions using a single model, the assessment is carried out using different models for the same system. For instance, in groundwater flow modelling, the application of different conceptual models based on different geological interpretations from different geologists constitutes multiple model simulation (Selroos et al., 2001). The main strength of alternative model structures simulations is the increased robustness of the model predictions, though it is difficult to determine adequacy of number of sampled models.

Numeral, unit, spread, assessment and pedigree (NUSAP)

The numeral, unit, spread, assessment and pedigree (NUSAP) approach is a multidimensional uncertainty assessment method that supports an analysis and diagnosis of uncertainty in policy-making (Refsgaard et al., 2007; Refsgaard et al. 2006; Rotmans and Van Asselt, 2002). The NUSAP complements quantitative analysis (numeral, unit, spread) with expert judgement of reliability (assessment) and systematic multi-criteria evaluation of a given knowledge base (pedigree) such as model assumptions and problem framing (Refsgaard et al., 2007; Refsgaard et al., 2006). Detailed NUSAP steps are presented (Refsgaard et al., 2007; Rotmans and Van Asselt, 2002). The main strength of NUSAP is its integration of qualitative and quantitative uncertainty. However, NUSAP method is based on experts' subjective judgements from existing knowledge. In addition, the method does not address uncertainty in relationships between different variables, and it is a time-consuming effort.

Uncertainty matrix

The uncertainty matrix method consists of sources of uncertainty in rows and types of uncertainty in columns (Refsgaard et al., 2007). The importance of each uncertainty to the problem under study is incorporated by subjective weighting factors concurred by modellers, experts and stakeholders. Hence, the main strength of the method is the provision of a platform for a structured dialogue among modellers and other stakeholders. Furthermore, the matrix provides a framework to track all sources of uncertainty throughout the modelling processes. However, similar to NUSAP, stakeholder involvement, extended peer review and expert elicitation, the method is qualitative. Therefore, it is subjective to experts' judgements.

Scenario analysis

A scenario is something that could or may happen in the future based on past events with an associated arbitrary probability space (Helton et al., 2000). Brown et al. (2005) argue the importance of scenarios where probabilities cannot be determined. Conventionally, it is an approach in which uncertainties are systematically addressed to provide ideas about the different future prospects (Van Asselt and Rotmans, 2002; Helton, 1994). Scenarios can be surprise-free as in trend scenarios that extend foreseen developments or they can include surprises to assess the best and worst cases of system behaviour (Van Asselt and Rotmans, 2002). The main limitations of this approach are that the quantitative scenarios are limited to aspects of reality that can be quantified while qualitative scenarios are sensitive to experts selected (subjectivity).

Monte Carlo analysis

Monte Carlo simulation is a statistical technique for stochastic model calculations and analysis of error propagation in calculations (Shirmohammadi et al., 2006; (U.S.EPA, 2000). Its purpose is to delineate out the structure of the model output distributions by taking random draws from the input distribution functions and parameters of the model and mapping the resulting output distributions. The general five steps of executing a Monte Carlo simulation are presented (Helton, 1993). Literature surveyed indicate that Monte Carlo analysis based methods form the most common approach for propagating uncertainty in mathematical and computational models (Mezic and Runolfsson, 2008; Oughton et al., 2008; Refsgaard et al., 2007; Halpern et al., 2006; Shirmohammadi et al., 2006; Muleta and Nicklow, 2005b; Helton et al., 2005; USEPA, 2000; Heuvelink, 1998; Helton, 1993; IAEA, 1989).

Monte Carlo analysis requires the analyst to specify probability distributions of all inputs and parameters, and the correlations between them. Assignment of input ranges and specification of associated probability distribution functions (PDFs) is the most difficult and subjective stage in application of Monte Carlo analysis

(Muleta and Nicklow, 2005b). The reasons are that many model parameters are not directly measurable, and even if measurable, it would be cost prohibitive to collect numerous, random samples of inputs to ascertain their 'true' PDFs and ranges (Muleta and Nicklow, 2005b). Furthermore, inputs maybe correlated, and ignoring correlations and co-variance in input distributions could lead to substantial under- or over-estimation of uncertainty in model outcome (Refsgaard et al., 2007). However, Monte Carlo approach has several advantages.

The advantages of the Monte Carlo approaches include conceptual simplicity; ease of implementation, applicability to wide scale of data and the full stratification over the range of each input variable to facilitate the identification of nonlinearities, thresholds and discontinuities. In addition, the method can generate uncertainty analysis results without the use of intermediate models and there are various routines for sensitivity analysis that can be incorporated into Monte Carlo method. Despite these positive properties, the Monte Carlo method suffers from slow convergence rate in many problems resulting in prohibitive and very heavy computations (Helton et al., 2005; Helton, 1993). Helton et al. (2005) recommends Latin hypercube sampling for use in analyses of complex systems with small sample sizes.

Other Monte Carlo forms for uncertainty and sensitivity analysis include the popular sampling-based procedures (Helton et al., 2005). From literature, free software packages exist that perform the Monte Carlo analysis such as @ risk and SimLab (Refsgaard et al., 2007).

Improvements to Monte Carlo analysis techniques

There are several improvements to Monte Carlo analysis techniques. These improvements include Latin hypercube sampling, Markov chain Monte Carlo technique, Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Freer, 2001), Adjoint differentiation and Polynomial Chaos method. Some of these techniques are briefly described in this section.

The Latin hypercube sampling, with more efficient sampling (Muleta et al., 2007; Muleta and Nicklow, 2005b; Helton et al., 2000), is more precise for generating random samples than the Monte Carlo sampling, because the full range of the probability distribution is sampled more evenly (Xu et al., 2008; Xu and Gertner, 2007). This is achieved by first stratifying the range of each variable into N disjoint intervals of equal probability and then drawing one random value from each interval to form an input sample to run the model.

The Markov chain Monte Carlo technique (Hanson, 1999) provides a way to generate a sequence of random parameter vectors drawn from an arbitrary target Probability Density Function alleviating the need to approximate the posterior by a Gaussian distribution (Hanson, 1999). The covariance matrix maybe obtained directly by computing the second moments of the Markov chain Monte Carlo.

Adjoint differentiation can be very helpful in making the Monte Carlo methods more efficient by saving computational time (Hanson, 1999; Helton, 1993). An alternative analytical method to uncertainty propagation is Polynomial Chaos methods also known as stochastic Finite Elements (Mezic and Runolfsson, 2008; Ghahem and Red-Horse, 1999). The method is based on expansions of the uncertain quantities of terms prescribed in the random basis functions. From the literature survey, it has been demonstrated that for certain problems Polynomial Chaos can be faster than Monte Carlo methods.

3.5.7 Sensitivity analysis

Sensitivity analysis refers to the determination of the contributions of the uncertainty in individual model inputs to the uncertainty in model predictions (Xu and Gertner, 2007; Helton et al., 2006; Fieberg and Jenkins, 2005; Muleta and Nicklow, 2005b; Schouwenberg et al., 2000). From literature review, there are a number of techniques available for sensitivity analysis but can all be classified into two groups: local and global sensitivity analysis methods (Iooss and Ribatet, 2008; Saltelli, et al., 2008; Xu and Gertner, 2007; Fieberg and Jenkins, 2005; Muleta and Nicklow, 2005b; Sobol, 2001).

The local sensitivity analysis techniques examine the local response of the output(s) by varying input parameters or set of assumptions one at a time while holding other parameters at base-case values (Helton, 1993). Local sensitivity analysis techniques such as differential analysis (Helton, 1993) are most applicable if a model's output space is linear or approximates a hyperplane. Differential analysis use Taylor series to approximate the model under consideration.

Once the model under consideration is approximated, the series is used to replace the original model in uncertainty and sensitivity studies. Additional information on differential analysis is available in a number of references (Xu and Gertner, 2007; Helton, 1993; Ronen, 1988; Lewins and Becker, 1982). Though widely used, local sensitivity methods often fail to produce meaningful results when the model under deliberation is non-linear, when input variables are subject to different orders of uncertainty or correlated (Da Veiga et al., 2008; Fieberg and Jenkins, 2005). To overcome these limitations, global sensitivity is applied.

Global sensitivity techniques examine the global response (averaged over the variation of all the parameters) of the model output(s) by exploring a finite (or even an infinite) region (Iooss and Ribatet, 2008; Fieberg and Jenkins, 2005). Apart from being real-valued quantities, input variables can also take the form of a function used to represent more complex entities such as flow fields or alternative models, loosely or tightly linked together (Helton et al., 2006; Helton et al., 2000; Helton, 1993).

Global sensitivity techniques for non-linear models include Fourier Amplitude Sensitivity Test (FAST), fractional factorial design (Saltelli et al., 1995), Plackett-Burman technique, Morris One-at-a-time method, response surface method, sampling-based methods and McKay's method based on one-way ANOVA (Refsgaard et al., 2007; Xu and Gertner, 2007; Muleta and Nicklow, 2005b; Beres and Hawkins, 2001; Helton et al., 2000; Helton, 1993). The above methods are more complex but use less computational effort, compared to the local sensitivity analysis approach (Iooss and Ribatet, 2008; Helton, 1993).

In addition, the mapping of inputs to outputs can then be explored based on examination of scatter plots, regression analysis and correlation analysis to determine which input uncertainties dominate the output uncertainties (Refsgaard et al., 2007; Helton, 1993). Additionally, mapping also provides an extensive check that the models in the system are correctly implemented (Helton and Oberkampf, 2004; Helton et al., 2000). The main strength of sensitivity analysis is identification of appropriate and targeted investment of resources to reduce uncertainty in analysis results (Xu and Gertner, 2007). For example, it can help to decide if there is need to focus on the correlated variations (Da Veiga et al., 2008) among specific parameters (if the correlated contribution dominates) or the parameter itself (if the uncorrelated contribution dominates).

3.5.8 Uncertainty in integrated models

Uncertainty is a key issue in integrated modelling for two reasons (Walker et al., 2003; Rotmans and Van Asselt, 2002). Firstly, integrated models do cover a wide variety of uncertainties that originate from a range of different types and sources. Secondly, integrated models are intended to capture an entire set of cause-effect relations involved in a specific problem. Hence, integrated models are prone to accumulation of uncertainties.

Uncertainty thus has both an ontological (variability: concerning the general properties of objects) and an epistemological (lack of knowledge: concerning the human ability to know) dimension (Rotmans and Van Asselt, 2002). Uncertainty is thus more than just the absence of knowledge.

Uncertainty about model completeness is the most fundamental and crucial for the quality of the integrated model (epistemological uncertainties), and is addressed in the model validation phase. However, complete validation is impossible in case of complex systems due to inherent uncertainty associated with ignorance and indeterminacy of the system. The other type of uncertainty is model operation uncertainties (Rotmans and Van Asselt, 2002). These model operation uncertainties occur partly due to the hidden flaws in the technical equipment such as numerical errors and bugs in hardware and software, but most importantly due to accumulation of uncertainties propagated through the model. Uncertainty about model form constitutes uncertainty pertaining to model structure, uncertainties about the functional relationships and uncertainties with regard to the choice of algorithms (methodological uncertainties). The parameters, inputs and initial conditions form uncertain model quantities (technical uncertainties) (Rotmans and Van Asselt, 2002).

3.5.9 Uncertainty management in integrated modelling

The aim of uncertainty analysis in integrated modelling is to evaluate to what extent particular uncertainties impact upon the model outputs and conclusions. Recent literature recommends executing uncertainty analysis throughout the modelling process from problem formulation to decision-making, contrary to the conventional practice of performing uncertainty analysis as a final step in the model cycle.

Furthermore, from the literature survey, approaches currently used for uncertainty analysis in integrated modelling include sensitivity analysis, probability-based methods, formal scenario analysis, hedging-oriented methods, validation, NUSAP approach and pluralistic uncertainty management. Detailed treatment of the different approaches is presented in literature (Refsgaard et al., 2007; Rotmans and Van Asselt, 2002; Van Asselt and Rotmans, 1999; Helton, 1993). In the following section, only probability-based method is briefly described.

Probability-based method

Probability-based method gives an indication of the likelihood of outputs such as the 95-percentile dependent on the (subjective) likelihood attached to uncertain model inputs or parameters by analysts or group of experts (Rotmans and Van Asselt, 2002). Probability distribution of inputs or parameters and consequently outputs are required to apply probability calculus. The common probabilistic method used is the Bayesian approach (Rotmans and Van Asselt, 2002). The main limitation of probability-based methods is that they exclusively address uncertainty in model quantities and ignore uncertainty in model structure.

In addition, combinations of the aforementioned uncertainty analysis methods are widely applied in integrated modelling. For example, hedging-oriented methods are combined with probability-based methods (Rotmans and Van Asselt, 2002), whereas sensitivity analysis is often used to filter out important parameters that will be subjected to probability-based uncertainty analysis. Although several method combinations are feasible, literature warns the lack of holistic methods to address all the facets of uncertainties.

Furthermore, Rotmans and Van Asselt (2002) strongly argue that uncertainty analysis lacks a tool-kit that holistically addresses salient technical, methodological and epistemological uncertainties in an adequate manner. Long-time series or measurements that are more accurate will evoke a better understanding of the level of variability and possible states of the systems under study. Nonetheless, a significant part of the salient uncertainties (variability) inherent in integrated models such as indeterminacy and ignorance remain. For instance, uncertainties in human behaviour as well as in the policies, on how to influence them are inherent and unresolved by more measurements. Measurements will therefore, not wholly solve the problem of uncertainty in integrated models (Rotmans and Van Asselt, 2002). What is required is to communicate the uncertainty to the best of the available knowledge to decision-makers.

3.5.10 Communicating uncertainty

In this approach, uncertainty in model quantities and model structure are ranked according to their contribution to total uncertainty. Furthermore, the uncertainty is communicated by different interpretations according to different perspectives (Rotmans and Van Asselt, 2002). To assess the most significant uncertainties, which are often due to subjectivity and disagreement among experts, multiple perspectives can be introduced.

A perspective is defined as a coherent description of the perceptual screen through which (groups of) people interpret the world and its social dimensions, and which guides their actions on the system of interest. Rotmans and Van Asselt (2002) advocates for a typology (Cultural theory) of perspectives to arrive at a limited set of perspective-based interpretations of uncertainties. This practically means that model inputs, quantities and relationships can be interpreted in alternative ways (world viewpoint and management approach) according to the qualitative description of the perspectives.

The different qualitative description of perspectives include the Egalitarian world viewpoint - risk-aversive attitude, Individualists world viewpoint - risk-seeking and Hierarchists viewpoint - risk-accepting attitude (Rotmans and Van Asselt, 2002). Using the perspective-based description makes subjectivity in integrated models explicit, and enhances the reflexivity of integrated assessors. However, the scheme is rigidity and cannot fully accommodate a variety of real world perspectives. Hence, different approaches should be used in complementary to address different types and sources of uncertainty in different ways. The challenge is to develop procedures that allow combinations of the available methods to communicate the results of uncertainty evaluation in an understandable and useful manner to decision-makers, stakeholders and the public.

In the next section, practical implications of uncertainty analysis in decision-making are described. Communication of uncertainty provides a mechanism for describing realistic outcomes.

3.5.11 Practical implications of uncertainty analysis

Socio-economic and environmental changes and their associated uncertainties continue to pose a challenge for decision-makers in water management. The ability to quantify uncertainty impacts creates flexibility in the management decision process and provides a mechanism for describing realistic outcomes (Shirmohammadi et al., 2006). For example, in some cases, decision-makers may be willing to take greater risks if such risk is associated with larger potential pay-offs, while in other cases the decision-makers can demand that a decision be based on the greatest amount of certainty in results. In decision-making under uncertainty, risk is often used to evaluate the robustness of management options (Xu et al., 2008). This risk depends on the probability of encountering undesired consequences and the nature of the undesirable consequences.

From literature survey, practical implications of uncertainty research in supporting policy-making turn out to be very sensitive to different assumptions about uncertainty. For example, the uncertainty about the parameters of a model may lead to cautious policy; introduction of extreme uncertainty about the shocks in the model implies that very aggressive policy rules may be optimal, stemming from policy-makers' fears of particularly dire long-run deviations. On the contrary, focusing on the real time data uncertainty in models leads to the attenuation of the optimal policy rule.

In conclusion, robust policy rules are very sensitive to different assumptions made about the structure of uncertainty. Hence, to design a robust policy rule in practice, it is necessary to combine different sources of uncertainty in a coherent structure and carefully quantify the uncertainty (Onatski and Williams, 2002). Although this exercise requires significant effort, results are far more rewarding for informed decision-making (Arabi et al., 2007; Isukapalli and Georgopoulos, 2001).

The magnitude of uncertainty in a strategy is a key factor in its acceptance as the cost of implementation of management actions such as the Total Maximum Daily Load (TMDL) program may significantly increase with larger uncertainty estimates. Hence, the best decision is the one most robust to uncertainty, specifically, the one guaranteed to give acceptable outcomes under the greatest degree of uncertainty (known as the precautionary principle) (Halpern et al., 2006; Shirmohammadi et al., 2006).

3.5.12 Summary

In this section, uncertainty and sensitivity analysis were defined and types of uncertainty presented. Furthermore, uncertainty analysis methods, uncertainty management in integrated models, communicating uncertainty and making decisions under uncertainty were presented.

The methods reported in literature are quantitative (statistical) and qualitative. However, the best method choice for any problem depends on a number of factors such as nature of the model, the type of uncertainty and sensitivity analysis results desired, the cost of modifying and/or evaluating the model, available input data quality and number of parameters. This suggests that no one approach dominates regardless of the model under consideration.

Furthermore, a more detailed description for the quantitative Monte Carlo analysis was presented, as it is the most applicable method to problems that need quantitative uncertainty analysis. Hence, Monte Carlo method was selected for application in the current study.

Uncertainties exist from diverse sources. These sources include model structure (since models are a simplification of the reality), model technical aspects (e.g. temporal and spatial resolution and bugs in software), model inputs, behavioural and societal variability, value diversity, technological surprise, ignorance and indeterminacy. These sources of uncertainty cannot be totally removed or quantified but can be managed reasonably with existing methods and tools such as the Monte Carlo method. Paradoxically, uncertainty can persist in situations where a lot of information is available because new information can either decrease or increase uncertainty by revealing the presence of uncertainties that were previously unknown or were underestimated.

It can be concluded that the ability to quantify uncertainty impacts creates flexibility in decision-making process in identifying robust policy rules. However, robust policy rules are very sensitive to different uncertainty structure assumptions. The magnitude of uncertainty associated with a management option or policy determines its acceptance, as costs are likely to increase as uncertainty increases. In addition, uncertainty analysis, though it requires much effort (Isukapalli and Georgopoulos, 2001) to incorporate in models and sometimes difficult to understand by decision-makers, it is increasingly being applied to enhance decision-making rather than just depending on model outputs, without reporting their reliability and confidence. Hence, uncertainty analysis was incorporated in the current study DSS development. Under the current study, impacts of crop diseases on crop yield not captured in the PARCHED-THIRST model can not be improved, while collection of more or longer time series of observed climatic (rainfall, temperature, humidity, wind speed, solar radiation) and physical (streamflows, soil and landcover properties), and checking its quality, may reduce the errors in the data. However, for climatic data there is always residual uncertainty in the data even after removing errors, due to the inherent uncertainty associated with it.

Chapter 4: Methods

In this chapter, the various construction phases contributing to the development of an integrated model that included field surveys, on-farm field experiments, construction of farm typologies in the studied area are presented. Later, models setup, calibration and validation of crop, hydrology and socio-economics models using data from field surveys and experiments are presented and then some key linkage aspects concerning the development of an integrated model from existing crop, hydrology and socio-economic models are briefly presented. This is followed by a description on uncertainty and sensitivity analysis on the integrated model. Possible scenario testing of technical and socio-economic aspects using the integrated model is also presented. Finally, the chapter concludes with a methodology summary.

4.1 Socio-economic farm surveys and construction of farm typology

This section describes the construction of farm typologies from socio-economic surveys carried out in the study area. The farm typologies are important in identifying farming constraints and opportunities in the study area context.

The initial step in the research was to use two socio-economic surveys applied to eight villages (Enable, Metz, Makgaung-Hafanie, Madeira, Ga-Sekororo, Sofaya, Tickyline and Worcester) to investigate land (rainfed and irrigated) production systems and family food security in the B72A quaternary catchment of the Olifants River Basin. These eight sample villages endeavoured to cover a range of biophysical conditions and smallholder farm types present in the B72A quaternary catchment. The two socio-economic surveys were designed and carried out in 2005 with the help of two MSc students (Nyalungu, forthcoming; Malajti, forthcoming). The detailed surveys are presented in Mapedza et al. (2008).

These surveys adopted a stratified and random sampling technique in farmer selection in the eight villages of the study area. The total sample size was 159 farmers. These farm surveys later provided inputs to the socio-economic model. Data collected in the surveys included rainfed and irrigated cropland area, livestock, non-farm production activities, types of crops grown, prices of agriculture inputs and outputs, family food security, family demography and household assets. This information collected from the surveys formed the basis for grouping similar farms. These groups of similar farms became the farm typologies.

The farm typologies were identified using multivariate analysis techniques (principal component analysis, correspondence analysis and cluster analysis) applied to the survey data to identify the most differentiating combinations of variables and their statistical relationships. Principal component analyses based on correlations among variables and inertia of data, and cluster analyses based on eight factorial coordinates were applied sequentially to establish eight preliminary farm typologies (Mapedza et al., 2008). These eight typologies were further re-grouped in this study to five farm typologies, which were later used as input into the socio-economic model. The cluster analysis intended to gather farms within relatively homogeneous groups in order to account for heterogeneity between (groups of) farms.

A hierarchical cluster algorithm (Ward method) (Ward, 1963) was applied to the sample and the number of clusters was derived based on the dendrogram. Indicators, such as farmland size, family size, cropping intensities, land to labour ratio, number of livestock units, total family balance, off-farm employment (Bezabih and Harmen, 1992), and input intensities (fertiliser, seeds) were used to differentiate the farming systems. Analysis of variance (ANOVA) and *F*-test of the different farming systems indicators and variables established heterogeneity between the farm groups.

Furthermore, group discussions and informal interviews with farmers, representatives of irrigation schemes and smallholder farmers' organisations, key non-governmental organisations (NGOs) personnel working with farmers, extension officers and field observations complemented the information from the surveys. This information from group discussions was further used in the validation of the five farm typologies (see Appendix A for an extract from field discussions on validation). Additional information on the prices of agricultural inputs/outputs was obtained through direct interviews of local shops in the study area in 2008. In addition to the above data sources, on-farm experimentations from 2005–2008, aimed at unearthing technical and social constraints in agricultural production systems augmented information used for farming systems classification. The on-farm experimentations are presented in the next section.

4.2 Field experimentation

This section describes collaborative on-farm experimental plots setup for the maize crop with farmers and their extension officers, under different production systems in the study area. Maize is the main crop grown and usually under monoculture, since it provides staple food in the area. The production systems considered were conventional rainfed, which served as the control, rainfed plus supplementary irrigation, in-field rainwater harvesting (ridges and planting basins/chololo pits).

These maize production systems experiments were conducted from 2005 to 2008. The first year 2005/2006 involved monitoring the crop yield and water balance of the smallholder farmers under their normal or conventional cropping practices (Rasiuba, 2007). In the following season, 2006/2007, studies to compare rainfed plus supplementary and complete rainfed agriculture were executed. In the 2007/2008, two in-field water-harvesting techniques in duplicates (ridges and planting basins) were tested and compared to conventional practices.

Furthermore, a local maize variety suitable for semi-arid climate, SNK 2147 with 110–130 days to maturity was sowed in all the field plots and every year. For each treatment or production system studied and for each year, the conventional treatment served as the control, since the aim was to compare conventional rainfed cropping systems with improved soil-water crop management options. There are about seven months fallow period in rainfed fields (May to November) before planting in November-December. In fields with access to supplementary or full irrigation water, the fallow period is at most a month.

The maize production system under supplemental irrigation is presented first, followed by in-field rainwater harvesting. However, the sites experimental setup for both supplemental irrigation and in-field rainwater harvesting are described in Table 4.1.

Table 4.1 Description of experimental sites characteristics.

Treatment	Area m^2	Planting date	2005/6	2006/7	2007/8	Fertiliser application kg-N/ha	Tillage operations
Conventional Tillage (CT) Rainfed	700	Dec 1 Nov 25	√	√	√	None	Plough by oxen or donkeys drawn plough and then seeding the maize during ploughing. Straws were removed after harvesting
Supplementary and Rainfed, with control treated with 14kg-N/ha	700	Nov 25	√	√	√	14	Similar to conventional, but a tractor was used for ploughing. Addition of supplemental irrigation from a weir during dry spells and fertiliser application in 2007/2008 only
In-field RWH: Ridges	671	Nov 25			√	None	After ploughing with oxen or donkeys, ridges about 0.2 m high and 0.9 m apart were made and maize seeded on the ridges at 0.4 m intervals. No fertiliser application
Planting basins/pits	100	Nov 25			√	None	Involved digging basins/pits 0.22 m in diameter and 0.3m in depth, spaced at 0.6 m within rows and 0.9 m between rows.

Figure 4.1 Conventional tillage

Figure 4.2 Ridges ready for maize sowing at experimental site.

Figure 4.3 Planting basins also known as chololo pits in West Africa.

Description of planting basins

Chololo pits are called by different names in West Africa and Southern Africa. Chololo pit, a modification of the zai pit, was named after the village where they were invented in Tanzania (Mati, 2005). This chololo pit technique has been adopted in Southern Africa from West Africa where they have been practised for centuries. Chololo pit is smaller in diameter than the zai pit, but both use the same principles (Mati, 2005) of impounding rainwater, conserving soil moisture and fertility for the crop in the pit. The dimensions of the chololo pit are 0.22 m in diameter and 0.3 m in depth. The pits are spaced at 0.6 m apart within rows and 0.9 m between rows. Rows must run along a contour. One to four seeds are sowed per hole (in this study, three seeds were sowed per chololo pit). The leaves that fell into the pits provide mulch that could help to reduce the soil water evaporation rate.

4.2.1 Field experiment under supplemental irrigation

Controlled plot experiments were conducted in collaboration with three smallholder farmers with two replicates per farm to determine various parameters for the water balance model. The experimental field layout consisted of quarter-hectare plots, with two equal smaller runoff plots of dimensions 4 m × 2 m in each test plot. The farmers were initially taught on daily field data capturing of rainfall, soil-moisture, runoff and irrigation water volume. The seasons studied were 2005/2006, 2006/2007 and 2007/2008.

In the irrigated plots, water was supplied by gravity-fed furrow irrigation system from a weir built across a stream. The supplemental irrigation was assumed not to cause field runoff. In addition, as the furrow is lined and the weir is close to the field (about 1 km), water losses were assumed negligible. Irrigation scheduling was left at the discretion of the farmers, but measured by a calibrated 90^0 V-notch weir located in the furrow. The periods, and times of irrigation were recorded over the course of each irrigation application and growing season to estimate water applied to the field.

The farmers scheduled irrigation times by a combination of two methods i.e. by intuition (when the maize crop showed signs of moisture stress) and calendar days since the last rainfall or irrigation (Shock et al., 2007). All plots were planted on the same day and farmers agreed on the same farm management strategies. Fertilisation treatment of 14 kg-N/ha per season (based on affordability and potential maize yields above average (0.5 t/ha) as recommended by ICRISAT from studies in the area (Kgonyane and Dimes, 2007) was applied in both rainfed and supplemental irrigation plots after the first weeding, except for the 2006/2007 rainfed plot because of little rainfall at Sofaya site.

The first weeding was done 28 days after sowing. Soil moisture levels at 200 mm depth were measured on a daily basis during the growing season at 12 positions diagonally across the field using a hydrosense neutron probe (Campbell Scientific, Inc., 2001). Daily rainfall and runoff were also recorded from each field. Manual rain gauges measured daily rainfall, while runoff was measured from underground collection containers in series, down slope of the runoff plots. In addition, soil micronutrients were analysed towards the harvest in 2007/2008 season. The plots were harvested by hand and the grain yield recorded.

Meteorological data for the study area were obtained from the nearest meteorological station, Tours Weather Station located at 24^0 05′ 55″ East latitude and 30^0 15′ 30″ South longitudes. In the absence of solar radiation from the station, extraterrestrial radiation and maximum sunshine hours were used in calculating solar radiation based on Trnka et al (2005) formula. The study area is located in between 24^0 00′ and 24^0 25′ 00″ South latitude, and by interpolation, maximum sunshine hours and extraterrestrial radiation were obtained. Furthermore, the field data collected were used in the calculation of the field water balance.

Water balance model under supplemental irrigation

Using data on precipitation, supplemental irrigation, soil moisture and runoff, a seasonal root zone soil-water balance over a daily temporal scale for three cropping seasons (2005/2006, 2006/2007 and 2007/2008) was constructed from Equation (3.1) (Zhang et al., 2006; Walker and Ogindo, 2003):

$$D = (P + I) - (R + E_c + \Delta S) \qquad (4.1)$$

where D is the deep drainage beyond the 1 m (Ali et al., 2007; Zand-Parsa et al., 2006) root zone (mm/d), P is the daily precipitation (mm), I is the irrigation water to the plot (mm/d), R is the runoff from the field (mm/d), E_c is the evapotranspiration (mm/d) and ΔS is the change in soil-water content (soil moisture at harvest minus soil moisture at sowing) in the root zone (mm/d). D was determined as a residual in Equation 4.1.

The maize crop actual evapotranspiration was estimated by Equation (4.2) (Chow et al., 1988; Allen et al., 1998; Moroizumi et al., 2009):

$$E_c = K_s K_c E_0 \qquad (4.2)$$

where E_c is the actual evapotranspiration (mm/d), K_s is the water stress condition, K_c is the maize crop coefficient, and E_0 is the reference evapotranspiration (mm/d). E_0 was calculated by the FAO Penman-Monteith equation (as a function of net radiation, air temperature, wind speed and vapour pressure). K_c values for maize from SAPWAT program were used according to the maize growth stages.

SAPWAT is a computer program based on FAO, Penman-Monteith method (FAO, 2002) developed to estimate crop water requirements (not a crop growth model) only for areas within South Africa (van Heerden and Crosby, 2002). It uses local climate, irrigation systems and planting dates that represent the general production patterns found in the area. The K_s value was evaluated by Equation (4.3) (Moroizumi et al., 2009; Chow et al., 1988):

$$K_s = 1 \qquad \text{for } \theta \geq \theta_t$$

$$= \frac{\theta - \theta_{wp}}{\theta_t - \theta_{wp}} \qquad \text{for } \theta_{wp} \leq \theta < \theta_t \qquad (4.3)$$

where θ is the soil water content at any day and θ_{wp} is the soil water content at the wilting point (9.5 % in this study). The value of θ_t was calculated from Equation (4.4) (Moroizumi et al., 2009):

$$\theta_t = \theta_{fc} - p(\theta_{fc} - \theta_{wp}) \qquad (4.4)$$

where θ_{fc} is the field capacity water content (20.7 % in this study). A value of p= 0.43 for maize was adopted based on Allen et al. (1998) (θ_t = 15.9 % in this study).

The crop water use efficiency or productivity (W_P) was calculated from the ratio of yield (kg/ha) to seasonal water evapotranspired (mm) (Zhang et al., 2006; Grove, 2006; DFID, 2003; Rockström et al., 1998; van der Zel and Bosch, 1993). Crop water productivity W_p was defined as:

$$W_p = Y/E_c \qquad (4.5)$$

where W_p represents the crop water productivity ($\frac{kg}{m^3}$), Y is grain yield of maize and E_c is the evapotranspiration during the year.

Marginal supplementary irrigation water productivity (MSIWP) was calculated from the ratio of change in yield to change in irrigation water applied (assuming no irrigation water loss to deep drainage), with other inputs held constant (Ali et al., 2007).

In the next section, other important experimental setups under exclusive rainfed cropping system and in-field rainwater harvesting are presented.

4.2.2 Field experiment under in-field rainwater harvesting

In this section, the maize grain yield performance under both ridges and planting basins in-field rainwater harvesting techniques, were evaluated and compared to conventional cropping practices.

The test plots were duplicates, with one control for each technique. Test plot dimensions were 6 m by 13 m. The daily rainfall was measured using a manual rain gauge on site, which was emptied daily. Runoff was also captured after storms and soil moisture content was measured once every three days on several points in the test plot by a hydrosense probe as described under supplementary irrigation experiment. Weather records were collected from Tours Weather Station more than 5 km from the field site. Hence, recorded weather data may differ to some extent from that at the site.

In addition, labour requirements for land preparation and sowing for each cropping system (conventional, ridges and planting basins) were also compared. The planting basins are also known as chololo pits in West Africa.

In the next section, the field data collected were used in the calculation of the field water balance under ridges, planting basins and conventional cropping systems.

Water balance model under in-field rainwater harvesting plots

This section presents the water balance components of the three cropping system practices of ridges, planting basins and conventional. These water balance components include crop evapotranspiration, precipitation, runoff, drainage and changes in soil moisture storage.

Crop evapotranspiration (E_c) was calculated as a residual from Equation (4.1), without irrigation component (Equation 4.6):

$$E_c = P - (R + D + \Delta S) . \qquad (4.6)$$

where P is precipitation, R is runoff, D is deep drainage below root zone and ΔS is change in soil moisture (harvest soil moisture minus sowing soil moisture).

D was determined based on soil moisture content and the soil hydraulic conductivity using Darcy's equation (Reshmidevi et al., 2008; Stephens, 2000). Van Genuchten's (1980) Equation (4.7) was used to estimate *D* as an approximation to the soil hydraulic conductivity:

$$K(\theta) = K_{ST}(\theta^*)^{0.5}\left[1-(1-(\theta^*)^{1/m})^m\right]^2 \qquad (4.7)$$

$$m = 1 - \frac{1}{n} \qquad (4.8)$$

where $\theta^* = \dfrac{\theta - \theta_r}{\theta_s - \theta_r}$ is reduced volumetric water content,

θ is the soil moisture content at any time step (%), θ_s is the volumetric water content of saturated soil (%), θ_r is the residual volumetric soil water content (%), K_{ST} is the saturated soil hydraulic conductivity, $K(\theta)$ is the unsaturated soil hydraulic conductivity and λ is the index of the pore distribution. For the sandy loam soil (in this study), λ = 7.5 n = 1.9, θ_r = 6%, θ_s = 45.3 % (Miyazaki, 2006).

In the next section, maize crop modelling is presented. The model input data were obtained from site characteristics and results of field experiments presented in earlier sections.

4.2.3 Soil sampling and testing

Integrated soil samples from 0–300mm soil depth were taken from each field and analysed for soil organic C, total N, available P, exchangeable bases and pH following standard methods for tropical soils (Anderson and Ingram, 1993). Duplicate samples were tested for each parameter. The test results are presented in chapter 5.

4.3 Agronomic model

The preceding section describes the setup, calibration and validation of Predicting Arable Resource Capture in Hostile Environments During the Harvesting of

Incident Rainfall in the Semi-arid Tropics (PARCHED-THIRST) (Mzirai et al., 2001) crop model using experimental data. As previously indicated, PARCHED-THIRST model was selected from several crop models surveyed because its data requirements are easily met and it is capable of simulating rainwater harvesting systems.

4.3.1 Agronomic model setup

Measured field values of weather parameters combined with meteorological data from the Tours Weather Station, crop management and soil properties were used for setting up the PARCHED-THIRST model. In addition, PARCHED-THIRST Climate Generator was used to extend the available historical data, in order to provide for long-term simulation. Soil moisture at planting in the experimental plots was taken as the initial soil moisture in the crop model. The season-end soil moisture values were employed as initial values in all subsequent simulations and water balance was carried over between years.

Furthermore, the soil saturated hydraulic conductivity was determined from the PARCHED-THIRST soil classification tool. Weeds were allowed for in the crop model and weeding was set at 28 days and 60 days after planting. Other soil properties used for setting up the PARCHED-THIRST model are shown in Table 4.2 (Rasiuba, 2007).

After satisfying all the data requirements, the PARCHED-THIRST model was executed and the simulated daily soil moisture variation and maize grain yield compared to observed values. Further adjustment of the initial model parameters was required to match observed values, under model calibration. Therefore, the simulated soil-water in each layer to the 200 mm soil depth was accumulated at a daily time step and compared with the daily soil-water values from the probe.

Table 4.2 Soil properties used for setting up the PT model.

Site	Organic matter g/kg	Bulk density g/cm^3	Sand	Silt	Clay	Soil Type
			%			
Enable	0.12	1.32	81	18.9	0.1	loamy sand
Sofaya	0.13	1.45	55	35	10	sandy loam
Worcester	0.13	1.40	69	26	5	sandy loam
Ha-fanie	0.06	1.30	16.7	20.6	0	loamy sand

4.3.2 Agronomic model calibration and validation

The general parameterisation strategy was to derive model parameters directly or indirectly from collected field data. Where measurements were not available, published data was employed. The model was calibrated in an iterative manner (Godwin et al., 1989) by modifying the crop genetic coefficients to match observed phenology (e.g. time to maturity) and grain yield. Furthermore, predicted soil moisture was also calibrated for all treatments to match observed field values during and at end of the growing season.

Data for the first two seasons, 2005/2006 and 2006/2007 were used for calibration, under supplementary irrigation cropping system, while the last season data, 2007/2008 was used for the model validation. For the cropping systems under both ridges and planting basins, observed data for 2007/2008 was used for calibration. To evaluate model performance, statistical methods discussed in the next section were employed.

The accuracy of the model predictions after calibration and validation was measured by computing the percentage error in crop yield prediction.

Furthermore, the root mean square error (RMSE) and coefficient of efficiency (E_f) were used to evaluate the predicted against the observed daily soil-water. The formulae for the performance measures are presented under model evaluations section. Crop parameters that resulted in the least RMSE and E_f close to one (one indicates perfect agreement) between the simulated and observed soil-water and yields were retained. For this study, the calibrated crop parameters are presented under Chapter 5.

Furthermore, once the PARCHED-THIRST model was calibrated satisfactorily and tested, it was applied to evaluate alternative crop-soil management practices for the study area in terms of their production potentials and impacts on the environment. However, even after calibration crop models, and any other model, still has some limitations. These limitations are presented briefly in the subsequent sub-section.

4.3.3 Limitations of the crop models

The simulated soil-water values are dependent on the correct choice of soil parameter inputs and the observed values are influenced by soil variability, distortion of soil structure, and lack of full contact between the soil and probe rods. Hence, even the observed field values have some associated uncertainty. The crop model simulations do not account for leaf damage that is caused by insects, pests and diseases (Jame and Cutforth, 1996). Any leaf damage affects leaf area index and consequently the plant growth.

In sum, setting of experimental plots in duplicates, training of farmers in field data collection of rainfall, soil-moisture content, supplemental irrigation flow measurements were completed. PARCHED-THIRST model was calibrated using experimental data and subsequently used for simulating and quantifying changes in maize crop productivity under different climatic conditions and soil-water conservation and crop management practices. Crop management practices include identifying best planting dates.

In the next section, hydrological modelling approach to quantify catchment blue and green water availability is presented. Rainfed agriculture depends on green water, whereas supplementary and full irrigation depends on blue water availability.

4.4 Hydrological model

This section briefly describes hydrological modelling in both four adjacent quaternary catchments (B72E, F, G and H) (Ncube, 2006) to B72A and the B72A quaternary catchment by use of the SWAT model, selected from the literature review presented in Chapter 3. The hydrological model produces daily streamflows given daily observations of climatic data and bio-physical data. Model data requirements, setup, calibration, validation are presented in this section.

4.4.1 Data availability and analysis

The rainfall, other climatic data, topographic, streamflows, land use and soil types were obtained from different sources. The best available land use and soil types for year the 2000 were re-classified to match the SWAT model landuse classification and the database edited accordingly. The different soil classes were defined in the user's soil database using data from the Agricultural Research Institute: Institute of Soil Water and Climate (ARC) and the ACRU model datasets which has generic information for South Africa (Schulze and Smithers, 2003). The following soil series and profile numbers for the land types were used in the catchment (Ncube, 2006):

Ab54= Hutton Hu16 (Profile P949)

Ae126= Hutton doveton Hu27 (Profile P1482)

Ae127= Hutton shorrocks Hu36 (Profile P954)

Fa347= Hutton musinga Hu26 (Profile P950)

Fb186= Hutton shorrocks Hu36 (Profile P987)

Lc157= Rock

The available water moisture was obtained from the ACRU soils dataset for South Africa (Schulze and Smithers, 2003) for the respective land types, while bulk density, saturated hydraulic conductivity, Soil Conservation Services (SCS) grouping, erosion hazards and soil albedo values were obtained from tables in Schulze (1995). Rainfall data from three rainfall stations in the area was obtained from a database by Lynch (2004). Other climatic data were obtained from the South African Weather Services meteorological stations. The two meteorological stations (Tours and Lekgalametse) close to the study site span the period 1966–1980 without missing data were used. In addition, a 20 m×20 m Digital Elevation Model (DEM) was obtained from Ncube (2006).

Furthermore, Department of Water and Forestry (DWAF) now Department of Water and Environmental Affairs provided the daily streamflows data at four gauging stations (DWAF, 2006) in adjacent catchments (B72E, F, G and H) with similar physical and climatic characteristics as the study area. The similarity of B72A catchment with adjacent catchments was computed from the Bray-Curtis coefficient, using landuse and soil types (Table 4.3). The Bray-Curtis coefficient (*BC*) is given by (Cheng, 2004; Bloom, 1981; Bray and Curtis, 1957) as:

$$BC_{jk} = 100\left(1 - \frac{\sum_{i=1}^{p}\left|y_{ij} - y_{ik}\right|}{\sum_{i=1}^{p}\left(y_{ij} + y_{ik}\right)}\right) \qquad (4.9)$$

where BC_{jk} is the similarity (%) between the j^{th} and k^{th} sites, and y_{ij} represents the abundance for the i^{th} species in the j^{th} site and p is number of parameters considered to similar among the catchments.

Table 4.3 Proportions of different land uses and soil types in adjacent and B72A catchments.

Catchment	SWAT landuse/cover type						
	Forest mixed	Forest evergreen	Range – brush	Range – grass	Agriculture	Arid	Residential
B72E, F, G and H (Ncube, 2006)	0.3	0.03	0.25	0.04	0.25	0.12	0.01
B72A	0.04	0.14	0.55	0.07	0.09	0.10	0.01
	SWAT Soil type						
	Ab54	Ae127	Fa347	Fb176	Lc157	Ae126	Fb186
B72E, F, G and H (Ncube, 2006)	0.09	0.6	0.13	0	0.04	0.12	0.02
B72A	0.07	0.38	0.16	0.34	0.04	-	-

This result showed that spatial similarity between the adjacent and B72A catchments exist, as indicated by land use/cover and soil types, with Bray-Curtis coefficient of 52% and 67%, respectively.

Hence, flow gauge B7H008 (rainfall gauge 0637271W) at the main outlet of four adjacent quaternary catchments was used to get the best parameters of the four catchments grouped to one catchment. These best parameters were then transferred to ungauged B72A quaternary catchment. The transferred best parameters were subsequently validated in the B72A catchment using observed streamflow series in subbasin number 10 of 407 days (15/06/2007 to 15/08/2008).

4.4.2

4.4.3 Hydrological model setup

The B72A study catchment was divided into ten sub-catchments, with areas less than 130 km^2 according to the stream threshold area definition. The lower the stream threshold area, the more streams and sub-catchments are defined. Equal dominance of 5 % for both landuse and soil type were used to create Hydrologic Response Unit (HRU) for each sub-catchment. The simulation options applied were the curve number method, Penman-Monteith method for evaporation, Muskingum channel routing and a first order Markov Chain.

4.4.4 Screening of model parameters

Using the sensitivity tool (van Griensven et al., 2002) incorporated in SWAT, with and without observed streamflows, the 27 sensitive model parameters related to hydrology processes were identified and ranked from the four adjacent quaternary catchments. The sensitivity tool used observed streamflow data from 1966–1976 at the main outlet of the four quaternary catchments. This sensitivity tool is based on the LH-OAT (Latin Hypercube – One-factor-At-a-Time) method (van Griensven et al., 2002). The first 13 ranked sensitive parameters were calibrated. Detailed sensitivity analysis methodology is presented in van Griensven et al. (2002). After sensitivity analysis, model calibration and validation for the four catchments were executed based on streamflows data.

4.4.5

4.4.6 Hydrological model calibration and validation

This section describes the SWAT model calibration and validation based on streamflow data (Flow gauge B7H008) at the main catchment outlet to four adjacent quaternary catchments to B72A catchment. Thus, use of similarity measures to transfer parameters from gauged to ungauged catchments was applied. The sensitive parameters identified under sensitivity analysis were used in model calibration and validation.

The 13 sensitive parameters from sensitivity analysis were used in the autocalibration, another tool incorporated in SWAT model (van Griensven et al., 2002). The ranges of the parameters were manually set based on the available data and literature sources of studies in similar catchments. The split sample in time approach was applied (van Griensven et al., 2002) in which one half of the flow data set were used to calibrate the model and the second half of the flow time series used to evaluate the calibration data set. Hence, calibration time series were from 1966–1976, while the validation series were from 1977–1980. This split sample in time approach represents the minimum criteria over which a model must pass to be considered suitable for further application in ungauged B72A catchment. However, using these flows for calibration, with land use covers for year 2000 (best available) presents non-stationarity and uncertainty in the model

(Beven, 2000). He further argues that field process studies are by their nature unique in both space and time, hence, they cannot be repeated under exactly the same boundary and initial conditions (Beven, 2000). Hence, the reasonable assumption of parameter stationarity (landuse/cover) was applied (Ainsworth et al., 2008).

Generally, a model performs worse during validation period than during the calibration period. However, if a model performs well during calibration and validation periods, the model is an acceptable representation of the natural system it intends to represent (van Griensven et al., 2002).

The evaluation criteria for measuring the simulation performance of the hydrological model were based on the streamflow data. These criteria were root mean square error (RMSE), model efficiency (ME), mean relative error (MRE), Nash-Sutcliff Coefficient of Efficiency (E_f), and mean cumulative error (MEC). These statistical criteria are described, later in the model evaluation section.

In the next section, socio-economic modelling using Olympe model is described.

4.5 Socio-economic modelling

This section briefly describes the socio-economic modelling using Olympe model selected from the literature review. The Olympe calculates the result of gross margin and potential family savings given crop yield and family food requirements. This model is based on a unit representative farm analysis as level of decision-making, which can be aggregated to regional level.

The model was applied to simulate smallholder farming systems performance in relation to providing food security under agricultural market-price and climatic variations. The indicators of farm family food security included both gross margins (income minus variable costs) and net family balance/savings (total family income (total farm gross margin + non-farm income) minus family needs). Each family, with an average of five members (Magombeyi and Taigbenu, 2008) is assumed to require 500 kg of maize each year. This food requirement is based on minimum recommended daily dietary requirement of 2 261 kilocalories per person in South Africa (Bonti-Ankomah, 2001).

4.5.1 Socio-economic model setup

The setting up of the socio-economic model, Olympe involved use of the five farm typologies constructed from interview surveys (Nyalungu, forthcoming; Malatji, forthcoming). In addition, detailed interviews on agricultural input/output prices were executed in local shops to fill any data requirements in Olympe model. Furthermore, crop production systems required in Olympe model for each farm typology were established from the PARCHED-THIRST crop model after calibration, using agriculture inputs and yields from interview surveys.

Using the identified five farm typologies data, Olympe model was set-up to simulate two 10-year horizons, though the model is capable of simulating up to 100 years. The two 10-year simulation period were considered adequate to evaluate policy impacts and is likely to cover the cyclic high and low rainfall years and markets perturbations. The maximum simulation period considered in the current study was 20 years. The unit of analysis in this study is the farm, as supported by Rivington et al. (2007). They argue that decision-making is best studied at the whole-farm scale, which represents the interface between biophysical processes and human intervention through management.

4.5.2 Socio-economic model calibration and validation

In this section, Olympe model calibration and validation through participatory method is presented. The model was calibrated using one year (2005/2006) of data from surveys. The survey data was complemented with field observations in the same period. The initial Olympe model results after calibration were presented to randomly selected farmers from each farm typology together with extension officers in the area for discussion and validation.

In these discussion and validation sessions, either the participants agreed or modified model input data to match their contexts, thereby verifying the Olympe model setup. Model validation through participatory method has been reported as a powerful tool in several socio-economic modelling studies (Le Bars and Le Grusse, 2008; Rivington et al., 2007; Penot et al., 2004; Attonaty et al., 1999).

In the next section, the most common statistical methods of evaluating model performance are presented. Model performance evaluation is an important aspect of modelling before a model can be applied with confidence to solve site-specific problems. A criteria based on the statistical methods is used as a yardstick to accept or reject model results.

4.6 Models performance evaluation

In this section, statistical methods used in any of the models presented in this study are briefly described and the general performance criteria for good or bad performance stated.

To evaluate model performance, six statistical criteria (Moriasi et al., 2007) were used: (i) coefficient of determination, R^2 (ii) root mean square error (*RMSE*), Equation 4.10 (iii) mean relative error (*MRE*), Equation 4.11; (vi), model efficiency (*ME*), Equation 4.12 and (v) mean cumulative error (*MCE*), Equation 4.13. Furthermore, the coefficient of efficiency (Nash and Sutcliffe, 1970), E_f, Equation 4.14, and percent bias (*PBIAS*) (Gupta et al., 1999), Equation 4.15 are employed. The acceptable performance levels of the statistical methods are also discussed.

The RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \quad (4.10)$$

where n is the number of values, S_i and O_i are the simulated and observed values, respectively.

$$MRE(\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{S_i - O_i}{O_i} \times 100 \quad (4.11)$$

$$ME = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \quad (4.12)$$

where S_i is the i^{th} simulated value, O_i is the i^{th} observed value, $\bar{O}$ is the average observed value, and n is the number of data pairs.

$$MCE = 1 - \left| \sqrt{\frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} O_i}} - \sqrt{\frac{\sum_{i=1}^{n} O_i}{\sum_{i=1}^{n} S_i}} \right| \tag{4.13}$$

$$E_f = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{4.14}$$

$$PBIAS = \left[\frac{\sum_{i=}^{n} (O_i - S_i) * 100}{\sum_{i=1}^{n} O_i} \right] \tag{4.15}$$

where O_i is observed streamflow at time step i, $\bar{O}$ is average observed streamflow during the evaluation period, S_i is the simulated streamflow at time step i. $\bar{O}$ was calculated for each evaluation period, for instance the calibration and validation periods. The ME is similar to E_f.

The coefficient of determination (R^2) describe the degree of co-linearity between simulated and observed data. R^2 ranges from zero to one, with higher values indicating less error variance. Typically values of R^2 greater than 0.5 are satisfactory (Moriasi et al., 2007). *ME* values are equivalent to the coefficient of determination (R^2), if the values fall close to the 1:1 line of simulated and observed data. However, *ME* is generally lower than R^2 when the predictions are biased, and can be negative.

Furthermore, *RMSE* and *MRE* values of zero indicate a perfect fit and values less than half the standard deviation of observed values are regarded as low and an acceptable level of performance (Moriasi et al., 2007). The E_f coefficient ranges from $-\infty$ to 1, where 1 represents a perfect fit (Nash and Sutcliffe, 1970). Values between zero and one are generally acceptable performance levels. Stehr et al. (2008) reports that E_f values below 0.36 are unsatisfactory. However, values less than zero are undesirable as they indicate that the mean observed value is a better predictor than the simulated value (Moriasi et al., 2007).

Furthermore, the PBIAS (Gupta et al., 1999) measures the average tendency of the data to be larger or smaller than the corresponding observed data and has the ability to indicate clearly poor model performance. Although optimum *PBIAS* value is zero, low values are acceptable as they indicate accurate model simulations. Stehr et al. (2008) indicate that $PBIAS \leq 20$ % are considered good, 20 % $\geq PBIAS \leq$ 40% are satisfactory with $PBIAS \geq 40$ % being unsatisfactory. In addition, positive values indicate model underestimation, while negative values indicate model overestimation bias (Moriasi et al., 2007). For further details on error indices methods see, Moriasi et al. (2007).

To sum up, in this section, statistical methods for evaluation of model performance were presented and criterion for acceptable and unacceptable performance levels discussed. It should be noted that some of the methods are very sensitive to extreme values (outliers), such as R^2, while some are less sensitive to those values, such as the E_f.

4.7 Integrated model framework

In this section, an integrated conceptual framework (Figure 4.4) that couples the three different models after their individual calibration and validation is presented. The three coupled models are hydrology, agronomy (crop growth) and socio-economic.

The Innovative Coupling of Hydrologic and Socio-Economic Aspects model (ICHSEA) couples SWAT (hydrology; Neitsch et al., 2001a, 2001b; Arnold et al., 1993), PARCHED-THIRST (crop growth; Young et al., 2002) and OLYMPE (socio-economics; Penot and Deheuvels, 2007). The ICHSEA interface was developed in Avenues script language in ArcView 3.3, to take advantage of the mapping capability of ArcView.

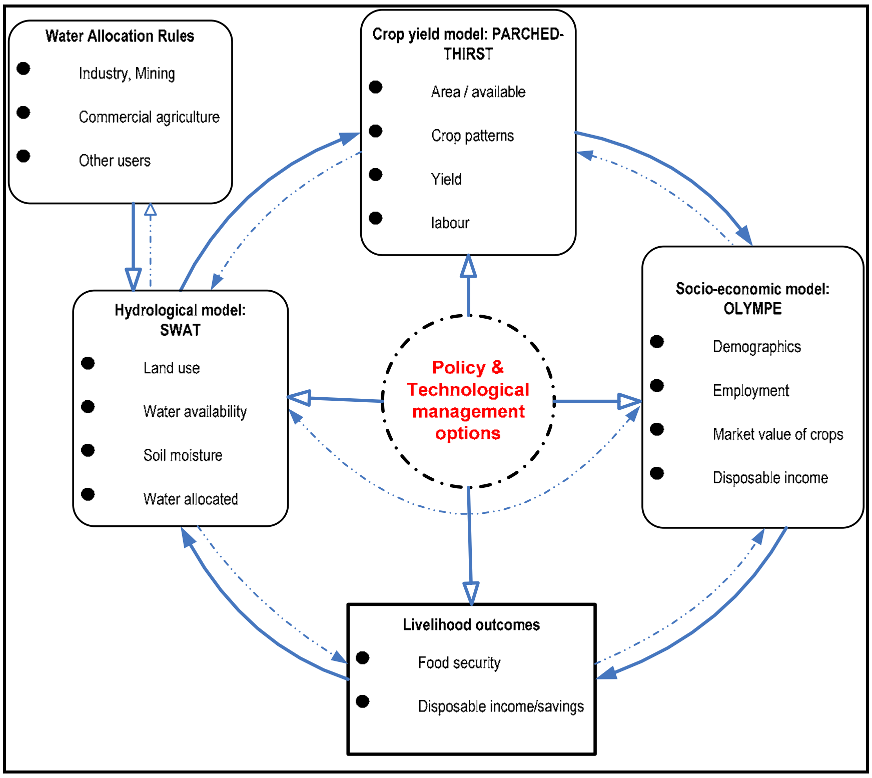


Figure 4.4 ICHSEA integrated conceptual model framework.

The solid arrows represent the forward linkage, while the broken arrows represents the feedback between models.

The Soil Water Assessment Tool (SWAT) model (Neitsch et al., 2001a, 2001b; Arnold and Fohrer, 2005) is a physically-based, continuous time semi-distributed hydrologic scale model that predicts the impact of land management practices on water, sediment, and agricultural chemical yields in watersheds. In addition, PARCHED-THIRST is a process-based model, which combines the simulation of hydrology with crop growth and yield in rainwater harvesting systems. OLYMPE model is composed of a database of farming systems and a simulation tool to enable analysis of farming systems and their relationships with the physical and economic environment.

4.7.1 Outline of the ICHSEA model integration interface

In ICHSEA, SWAT is executed first (Figure 4.5) to generate streamflow from rainfall, soil, landuse and other climatic data. This is followed by activation of the ICHSEA interface, an extension in ArcView, where the other two models can be executed. These model sequences of execution avoid opening two ArcView programs simultaneously. When ICHSEA and SWAT are executed simultaneously, SWAT overrides the ICHSEA.

Furthermore, the generated streamflow series, together with rainfall subsequently serve as the primary input into PARCHED-THIRST where rainfed, full or supplemental irrigation crop management options are simulated to give crop yields. The changes in landuse or crop type and area (e.g. as a result of different soil-water conservation or rainwater harvesting practices) in PARCHED-THIRST are feedback into SWAT under agriculture landuse to re-calculate the runoff and sediments generated. Using the re-calculated runoff, PARCHED-THIRST crop yields are re-calculated to take effect of the changed conditions.

These crop yields subsequently serve as input into the OLYMPE model where crop gross margin, family food needs, non-farm income, farm family potential savings and other socio-economic parameters are calculated. If family savings are inadequate, the farmer may decide to change crop or crop management practices, which will be captured in SWAT and consequently in PARCHED-THIRST, completing the sub-models dynamic feedbacks. Simulations can be repeated until the modeller is satisfied with the results. It is important to note that OLYMPE model does not simulate the human behaviour (studies argue that one can never represent it in models),but the consequence of those actions.

After getting satisfactory results, a modeller can move to the next step. In the next step, results module in the interface is activated to pull out the results from the ICHSEA project folder or from any specified folder containing the model results. These results are presented as maps, excel graphs and tables. Changes to any of the three models require a re-run of all the models to satisfy the dynamic feedbacks.

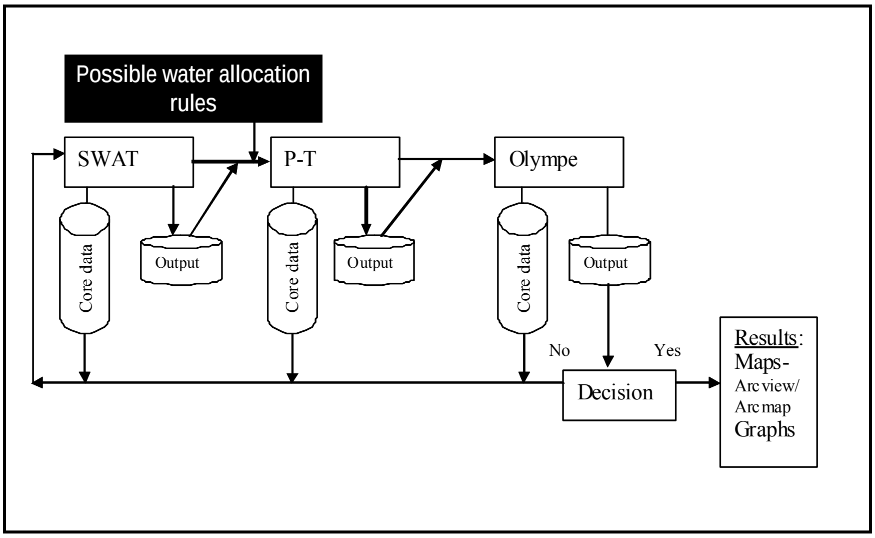


Figure 4.5 ICHSEA Coupling Model Architecture. P-T is PARCHED-THIRST crop model. SWAT is Soil and Water Assessment Tool. Each model has core data, which can be changed during scenarios.

Description of the model chain

The model chain consists of three models (Figure 4.5). The first model is SWAT and calculates streamflow and sediments. Possible water allocation rules to share the generated streamflows can come from the Department of Water and Environmental Affairs in South Africa, but currently 25% of the water is used by smallholders (Ntsheme, 2005). The second model, PARCHED-THIRST calculates seasonal crop yield. The last model, Olympe calculates farm gross margin and potential yearly family savings. The conversion module or the interface, ICHSEA converts outputs (flow, sediments, crop yield) from one model into suitable input for the next/other model. The interface links all the three models.

4.7.2 Calibration and Validation of the integrated model (ICHSEA)

DSS scenarios validation and verification was achieved through objective discussions with farmers and extension officers in the study area as recommended by Sojda (2007). This approach was employed since, DSS are generally complex and future oriented. Hence, the DSS have little observed evidence to allow direct comparison of the systems' predictions.

4.7.3 Interchageability of models

Model interchangeability is dependent on the interconnection of models and is not always a straightforward process. Hydrology model changeability can be possible if the alternative hydrology model produces daily flows in dbf or excel format. In addition, alternative crop growth model should run at daily time step and have daily input weather files in excel or csv format. The alternative socio-economic model is also changeable if it has seasonal input/output data and files are in excel format. Furthermore, it has to calculate gross margin for different crop and livestock systems, total farm and non-farm family income and family food requirements.

4.7.4 Auto-correlation of parameters in the integrated model

An equation to define the relationships between input parameters and the final integrated model output was derived using non-linear multi-regression in Statistical Package for Social Scientists (SPSS). For correlated parameters, one of the parameters was dropped from the overall relationship equation. For instance, total family income is related to gross margin. Hence, gross margin was dropped from the relationship equation.

In the next section, important integrated model parameters and their sensitivity analysis are described, followed by a description of uncertainty analysis of the sensitive integrated model parameters.

4.7.5 Sensitivity analysis

Indicators and measure of sensitivity are presented in this section.

The sensitivity of the integrated model was analysed in terms of the sensitivity of five economic, social and biophysical indicators. Sensitivity analysis considered essential drivers of the model results to be the expected rainfall, streamflow diversion for supplementary irrigation, crop yields, crop gross margin, non-farm income and family food requirements. These indicator parameters are used to decide on crop area, crop management options and food security by household decision-makers. The indicators were evaluated for each year of the simulation and final sensitivity of the model was then measured using the methods described next.

Local sensitivity analysis

The sensitivity analysis was performed by estimating the rate of change in the output of a model with respect to changes in model inputs. Varying parameters so that they are both larger and smaller by p (i.e., varying by ± p) instead of just (+p) allows to calculate the local nonlinearity of the effect of varying a parameter on the model results. A ranking of sensitivity results was used to provide a first-order determination of the most influential parameters to be included in the detailed uncertainty analysis.

Alternative method of scatter plots

An alternative method of scatter plots was used to determine the most important parameter of the integrated model. This was achieved by graphing the 5000 Monte Carlo samples of each of the four input parameters against the 5000 simulations of the model result and comparing the four graphs to identify a parameter with the most distinct trend. The most important parameter to the overall uncertainty in the model result is the one showing most distinct trend.

4.7.6 Uncertainty analysis

Monte Carlo method

Uncertainty analysis involved the propagation of uncertainties and natural variability in a model's inputs to calculate the uncertainty and variability in the model outputs. Monte Carlo method, selected from surveyed literature, was used to assess the integrated model uncertainty.

A basic spreadsheet was used to run a Monte Carlo simulation, and then later programmed. Using a spreadsheet the generation of multiple trials is implemented by propagating a basic formula as many times as the number of iterations required by the model. In Monte Carlo analysis, each time a result is calculated, all input parameters are varied within their uncertainty limits, each randomly and independent of the others.

Furthermore, inputs required for Monte Carlo simulations were the (subjective) probability distributions and uncertainty bounds for each parameter. To come up with these (subjective) probability distributions and uncertainty bounds, professional judgment after reviewing the available literature and data were used.

Uniform distribution was assumed for all the input parameters according to the Central Limit Theorem (Anderson, 1976). Input ranges were determined from observed data, and the upper and lower bounds were increased and decreased by 50 %, respectively, to account for surprise events. Normally, input ranges should be based on both qualitative and quantitative information available for a parameter (USEPA, 2000). The simple random sampling technique, widely used in Monte Carlo methods for generating random samples from parameter distributions was used.

The contributions of the uncertainty and variability of each model input to the uncertainty and variability of the model predictions were explicitly quantified.

In addition, the results of uncertainty analysis were presented in probability density function (PDF) and cumulative distribution function (CDF) plots showing the probability that the value of a random variable is less than a specific value. The location of the mean is indicated on both curves. These PDF and CDF plots displays: fractiles, including the median, probability intervals and confidence intervals.

Furthermore, a summary table of the relevant data such as minimum, maximum, mean, standard deviation accompany the CDF plots. Contribution of each of the four parameters to total uncertainty on final output, in this study, family savings is achieved by summing 5 %, median and 95 % values of the input parameters to get total uncertainty under error propagation. Other error propagation equations are presented in the next sub-section.

Variance propagation

Many studies have used variance and its components for uncertainty analysis (Schouwenberg et al., 2000; Hammonds et al., 1994; IAEA, 1989; Martz and Waller, 1982). The analytical approach, variance propagation, often (Hammonds et al., 1994) used for uncertainty analysis of simple equations, (IAEA, 1989; Martz and Waller, 1982) was used. For an additive model, the mean value of the result is equal to the sum of the mean values of the model parameters (Equation 4.16); the variance of the result, assuming statistical independence among the parameters, is equal to the sum of the variances of the parameters (Equation 4.17) (IAEA, 1989).

$$\mu_R = \sum_{i=1}^{p} \mu_i \qquad (4.16)$$

$$\sigma^2{}_R = \sum_{i=1}^{p} \sigma^2{}_i \qquad (4.17)$$

where μ_R is mean of the result, σ_R is variance of the result, i is the i^{th} parameter and p is the number of parameters in the model.

Nevertheless, the error propagation method has its limitations. Firstly, errors in spatial information such as soil and land use maps, and were not investigated. Secondly, the model structure is assumed correct, and the analysis only studies how input uncertainty propagates through the model.

In sum, a detailed sensitivity and uncertainty analyses of the integrated modelling tool were presented. This section described the indicators and measures of both sensitivity and uncertainty used. Lastly, error propagation based on both mean and variance was presented to assess total model uncertainty.

The next section presents scenarios analysed using the integrated model. The integrated model structure is assumed correct, and the analysis only studies how input uncertainty propagates through the model. In this study, coupled model and integrated model are used interchangeably. The integrated model becomes a decision support tool when used to aid decision-making.

4.7.7 Scenarios examined

In this section, possible scenarios to be answered by the integrated model, with time horizon of 10 years are presented. The scenarios represent how the integrated model might be used to generate useful information for management and policy support. These scenarios were initially identified by the researcher and then discussed with the farmers and extension officers for relevance in the study catchment.

In these scenario analyses, farmers are considered as entrepreneurs who must ensure that their enterprises are economically successful over the long-term to provide certain standards of living for their families (e.g. food security) and at the same time avoid environmental degradation. Scenarios analysed included providing answers to the following:

1. How much land can be brought under supplementary irrigation from ex-field rainwater harvesting in the catchment using water available during the growing season?

2. What improvements in family livelihood savings or balance is realised when

- In-field rainwater harvesting in the form of ridges is applied
- In-field rainwater harvesting in the form of planting basins is applied
- Agricultural input/outputs market price variations are imposed through policy

The data coming from the scenario analysis were fed into the models, once they were constructed and validated. Scenarios are intended to represent combined agriculture and water policy future impacts on food security and environment.

4.7.8 Model assumptions and limitations

In this section, model assumptions and limitations are described. These model aspects are important to model users in developing confidence and credibility in their use and in model developers. The key to developing this confidence is openness and transparency about underlying model assumptions and limitations (McIntosh et al., 2008). The assumptions and model limitations of ICHSEA are presented next.

Assumptions

The impact of national inflation on prices received by farmers through a shift in the output demand curve is ignored in this study. Only the impact of general inflation through higher real input prices is considered- and is simply called input-price inflation. In addition, the behavioural relationships of farm households are assumed stable during the simulation period. Furthermore, model structure is assumed to be correct, and the uncertainty analysis only studies how input uncertainty propagates through the model. Under ICHSEA application the land split of bush landuse to agricultural landuse is preformed using SWAT land-split tool to cater for the low resolution of GIS land covers used that could not capture the small fields of smallholder farmers.

Limitations

Firstly, errors in spatial information such as soil and land use maps were not investigated. Secondly, the current model is incapable of considering non-seasonal production decisions. Thirdly, the crop model simulations do not account for leaf damage that is caused by insects, pests and diseases. Fourthly, major limitations exist in the model structure and components, including key hydrological issues. The coupled model lack of water quality impacts assessment, as opposed to erosion. In addition, exclusion of groundwater systems, extraction significantly limits the usefulness of the biophysical model in assessing the downstream impacts of changes in agricultural development and management practices.

In sum, assumptions and limitations of the integrated model were presented. These two features of the model are important in establishing credibility of the model and correctly interpreting the model outputs for decision-making, while recognising their limitations.

In the next section, application of the integrated model through ICHSEA interface at quaternary catchment scale is described.

4.8 Application of ICHSEA

In this section, the application of ICHSEA in B72A catchment is presented to illustrate model interactions in the interface. The applications of ICHSEA interface are based on the crop and soil-water management techniques that were tested under the field experiments. Questions of relevance here include what are the effects of changes to crop and soil-water management techniques to surface water runoff, sediment loads, crop yields and potential effects on smallholder farmer food-security in the catchment? Next, brief descriptions of the model application are presented.

4.8.1 Application of integrated model to B72A catchment

The systematic application of the integrated model to B72A is shown in Appendix B as a brief manual on how to make a run from the integrated model. Technological alternatives impact on family food security evaluated were limited to alternative in-field and ex-field rainwater harvesting techniques and to manual and animal traction cultivation maize crop.

4.9 Summary

In this chapter, the field experimental sites and setup were presented. The practices investigated were conventional exclusive rainfed, supplemental irrigation, in-field rainwater harvesting using both ridges and planting basins. Next, using the data from experimental sites, a crop model was setup. In addition, using survey data, the main farm type differentiating factors were identified through factorial analysis and principal component. The resulting initial eight farm typologies were re-grouped into five farm typologies. Furthermore, steps to setup a hydrology model were presented. Using outputs from the surveys, crop model and hydrology model, a socio-economic model, Olympe setup was presented.

The three models (SWAT, PARCHED-THIRST and Olympe) were subsequently coupled through ICHSEA interface using their inputs/outputs into an integrated model to support decision-making in agriculture policy and crop management. Furthermore, to calibrate and validate the coupled model, participation of farmers and extension officers in small groups discussions on the coupled model inputs and results was required. These local stakeholders had been previously involved in validation of farm typology and the socio-economic model.

In addition, coupling of models introduces uncertainties that propagate through them. Hence, sensitivity and uncertainty analysis methods for the coupled models were described to evaluate the reliability of model simulations. The possible uses of the coupled model in policy and management problems were presented under scenarios. These scenarios intend to evaluate the effects of change in agricultural systems to food security and environment as in streamflow left after supplementary irrigation water diversion and sediments generated. No one tool or model by itself can possibly be adequate to capture these impacts, thus calling for development of integrated models.

In the next chapter, results and discussions of farm typologies, field experiments, standalone and coupled models applications are presented. The coupled model is applied to a case study in B72A catchment in Olifants sub-basin.

Chapter 5: Results and Discussions

5.1 Construction of farm typology

This section presents the farming system typologies, constructed from field surveys in the study area.

Five farming systems (A–E) (see Figure 5.1) were identified in the B72A quaternary catchment in the Olifants River Basin in South Africa that feature diverse cropping and livestock systems. The farming systems' main characteristics such as resource availability, input costs and minimum farm incomes are presented in Table 5.1. In addition, these farming systems depend on a combination of factors such as environmental conditions (land quality and rainfall), and capital endowments affected by the socio-economic conditions of the farmers. Hence, the different farming systems experience different constraints that influence their technological innovations adoption. Off-farm incomes substantially complement incomes from limited agricultural land and influence the intensity of farming activities. A larger proportion (> 60 %) of the farms were female-headed with limited off-farm activities, therefore had more limited resources than male-headed farms.

In addition, the most significant variables that distinguish between farming typologies appeared to be the number of hired workers, the asset endowment (measured by an asset index, see Table 5.1 notes), the number of livestock units, the sources of income, the level of both crop income and total family income, the fertiliser use per hectare and the crop diversity. Land area and the proportion of income from irrigated crop in the agricultural income, as well as the seed costs per hectare did not significantly differ across farming types.

It is noted that farming systems evolve with time (Landais, 1998; Perret, 1999) and as such, farming systems presented in this section are likely to change in the future. However, the catchment farm typology presented is unique since farm surveys in Olifants subbasin are not available at a geographic scale finer than the provincial one.

Table 5.1 Farming systems in the B72A quaternary catchment, Olifants River Basin. Data was derived from field surveys from 2005–2006.

Variables	Av	STD	Type A	Type B	Type C	Type D	Type E	F-Stat	F-Test
Family Characteristics									
Age of farmer	**54.4**	14.1	49	52	57	50	67	3	**
Family members working on farm	**2.02**	1.99	2.67	1.90	1.94	1.80	1.33	0.82	no
Number of hired workers	**0.81**	1.12	1.17	0.85	0.49	2.40	0.67	8.90	***
Family labour/ha	**3.40**	6.2	4.6	5.3	2.5	1.3	0.8	2.07	*
Total labour/ha	**4.50**	6.6	6.5	6.1	3.3	4.3	1.5	2.12	*
Assets									
Household asset index	**1.27**	1.11	1.25	0.80	1.32	2.20	3.33	7.11	***
Land area (ha)	**1.30**	1.54	0.94	1.01	1.54	1.21	2.03	1.40	no
Livestock Units	**2.61**	3.59	1.20	1.12	3.23	3.99	12.1	11.1	***
Source of Income									
% Employment Income	**21%**	32%	73%	4%	15%	0%	91%	59.8	***
% Off farm Income	**3%**	14%	1%	4%	2%	21%	0%	4.87	***
% Livestock Income	**2%**	6%	0%	0%	4%	1%	1%	4.72	***
% Crops Income	**38%**	37%	12%	88%	18%	67%	4%	103	***
% Remit & grants	**5%**	14%	3%	0%	9%	0%	0%	3.17	**
% Pensions income	**31%**	35%	12%	4%	52%	11%	5%	27.1	***
Irrigation income /crop income	**54%**	38%	44%	49%	58%	67%	59%	1.03	no
Annual Crop income (US$)	**383**	430	219	613	295	596	325	5.85	***
Total family income (US$/year)	**1 925**	2 288	2 803	752	1 838	1 553	14 1	66.2	***
Agricultural Practices									
Fertiliser (N.P.K) costs US$/ha	**9**	7	5	11	4	21	4	4.01	***
Seed costs US$/ha	**8**	6	2	7	4	11	18	0.89	no
Vegetables diversity	**2.25**	1.67	1.3	2.4	2.2	3.9	3.7	5.72	***

Notes:

1. Sample size (N) = 159 farmers, with 60 % of the farmers being females.
2. 1 US$ = 9 ZAR (2008).
3. Av = Average
4. Ratio N=3: P=2: K=1
5. *** F test significant at 99 %, **; F test significant at 95 %, no: not significant at 90 %

6. Type A: Subsistence farmers with external jobs; Type B: Resource-constrained rainfed farmers; Type C: Social grants supported rainfed farmers; Type D: Intensive, diversified irrigation farmers and Type E: Rich, salaried entrepreneurs - very extensive farmers.
7. Off-farm income refers to income from self jobs such as hawking, craft work, brewing beer and excludes salaried employment
8. The household asset index was calculated from standardised scores (0–5) based on the type, size, construction material of the house (s) at the homestead, farming implements and in-house items such as cooking stoves, furniture etc.
9. Vegetable diversity was calculated based on the number of vegetable crops grown by the farmer.

Five farm typologies identified in the catchment are briefly presented in the next sections.

5.1.1 Type A: Subsistence farmers with external jobs

The type A farmers acquire most of their income (> 70 %) from employment outside farming but none from government grants. Agriculture supplements the family food requirements and fertiliser (N.P.K) usage is below average (80 kg/ha). In addition, these farmers grow both maize and vegetables, and their livestock units (1.2) are below average (2.61) (Table 5.1).

5.1.2 Type B: Resource-constrained rainfed and irrigation farmers

The type B farmers are younger than the average age of farmers (54 years), with low levels of assets. The farmland size is below average and manpower/ha is the highest. These farmers realise far below average total family income with farming forming the main activity to support family needs. An estimated 88 % of their family income comes from agriculture with half the income contributed by irrigation agriculture (Table 5.1). They possess below average (1.12) livestock units (mainly goats).

5.1.3 Type C: Social grant supported rainfed farmers

The type C farmers are supported by the government through social grants, not necessarily used for farming activities and pensions that contribute 52 % towards stabilising the total family income. Farming for family subsistence purpose is the main interest of these farmers. The total (family plus hired) manpower/ha of 3.3 capita/ha and fertiliser/ha (N.P.K) use of 33 kg/ha are below the average values of 4.5 capita/ha and 80 kg/ha respectively. In addition, their cropping system is undiversified as they practice low levels of irrigation. However, they own above average (2.6) livestock units (Table 5.1.

5.1.4 Type D: Intensive, diversified irrigation farmers

The type D farmers derive most (67 %) of their income from farming with diversified crops and livestock units. Income from farming is used to buy large quantities of inputs such as fertilisers (190 kg/ha) and seeds. Their farmland size is slightly below average (1.3 ha). Additionally, the small cultivated area and high inputs, and high irrigation income support intensive farming activities for these farmers. These farmers are younger than the average age (54 years) (Table 5.1). Hence, they are likely to be receptive to innovations.

5.1.5 Type E: Rich, salaried entrepreneurs – very extensive farmers

The type E farmers obtain most of their income (> 90 %) from non-agricultural employment. They represent a small proportion of the famers in the area and are the richest farmers, with highest asset index (3.3) and livestock units (12.1). However, their crop income is only 4 %, while the average for all farms in the area is 38 %.

In addition, the farmers own the largest (2.0 ha) pieces of land, but the land is not fully utilised because household heads are engaged in other activities. With an average farmer age greater than 67 years, these farmers are old, labour constrained and reluctant to engage in crop production. Additionally, the farmers practice vegetable farming mostly for family consumption and rarely sell their produce. Maize cropping is not very important, as these farmers are investors in livestock production, shown by highest livestock units (Table 5.1).

A brief comparison of the farm typologies is described in the next section.

5.1.6 Comparisons of farm typologies

The bulk of the family income for farm Types A, B, C, D and E come from employment (73 %), crops (88 %), pensions (52 %), crops (67 %) and employment (91 %) respectively. Farm Type E is least vulnerable. This is expected, since employment (a buffer in drought years) contributes most to family income and an accumulated high levels of assets including livestock, provides a second buffer compared to other farm types (Table 5.1). This observation is supported by Duvernoy (2000), who reported cattle as a common way of accumulating wealth and as a symbol of status by farmers. The above farm typology results maybe useful in several projects.

The farm typology results maybe useful to focusing development projects within limited budget on needy areas of farming systems to achieve profitable and environmentally sustainable farming. For instance, the different levels of fertiliser usage can be used to assess the level of farm crop management with respect to soil nutrients, potential pollution to the environment. However, the approach has its drawbacks (Duvernoy, 2000). A farm typology is based on a sample of farms and thus, only represents the diversity of farms in that area. In addition, typologies are based on precise data obtained by in-depth interviews, which are very expensive and difficult to obtain for large regions.

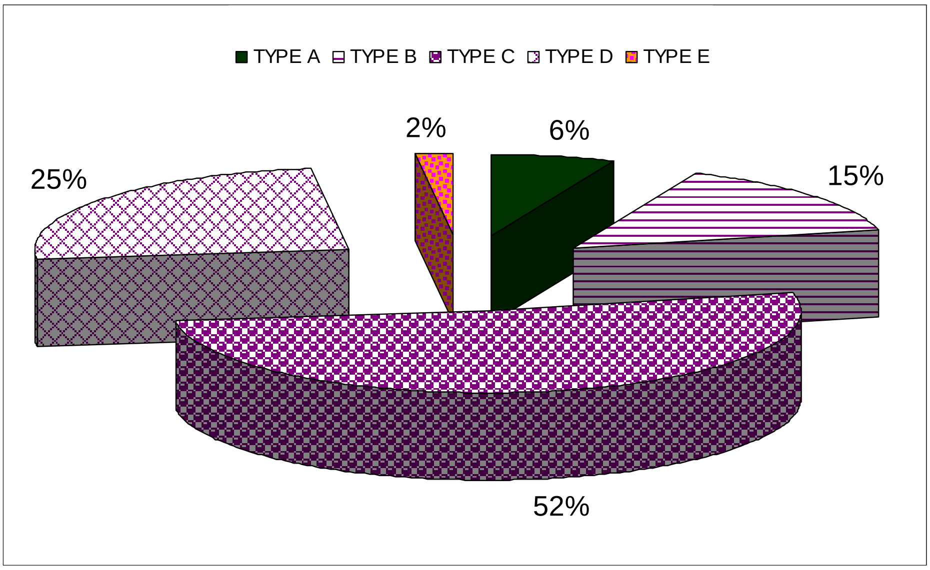


Figure 5.1 Proportion of farm typologies in the B72A quaternary catchment from farmer sample.

In sum, farm systems typologies were presented, as a means of classification to enable grouping of farms from a point of view relevant to the objectives of the study. Their main characteristics, such as resource availability, input costs and minimum farm incomes were presented. From the classifications, farm Type E with highest livestock units and employed off-farm is the least vulnerable to food security. This result concurs with the finding of Carter (1999) in South Africa. The results of this research maybe used to focus development projects on specific localities according to the funding priorities. For instance, from the survey, women constituted more than 60 % of the farm household heads and were the most vulnerable households. Therefore, programmes that uplift women will make greatest impact in the study area. In addition, farm typology enhances understanding of farm household systems and their behaviour under different production conditions and periods. Although soil moisture is the main variable under investigation in this study, plant nutrients from fertiliser application play a significant role in crop yield enhancement, provided enough soil moisture is available.

The typology building exercise became an important input in the socio-economic modelling of farming systems performed later in the study.

5.2 Soil physical and chemical parameter levels

Soil physical and chemical parameter analysis in 2007/2008 (sampled on 25/07/2009, after harvest) are shown in Table 5.2. Nutrients soil test used to evaluate fertility, measure the soil nutrients that are expected to become plant-available and do not measure total amounts of nutrients in the soil. Hence, measurements of total nutrient content are not useful indicators of sufficient nutrients for plant growth, because only small portion of the nutrients are available to the plant.

Compared to rating guidelines by Marx et al. (1999) of low nutrient levels (nitrate: < 10 ppm, phosphate: < 20 ppm, potassium: < 150 ppm, calcium: < 1000 ppm and magnesium: < 60 ppm), phosphate levels in the study site in

2007/2008 are lower than recommended levels for maize. Hence, phosphate is the limiting nutrient in the soil. In addition, macronutrients (nitrogen, phosphorus, potassium) levels for 2005/2006 (sampled on 23/07/2008, after harvest) were low (Marx et al., 1999), suggesting that less than 50–75 % (Hanlon, 2001) of the potential crop yield is expected regardless of the improvement of other important parameters such as water and weeding. However, the 2007/2008 soil nutrient status showed an improvement from the 2005/2006 season (Rasiuba, 2007).

Sofaya site nutrient levels have increased from the 2005/2006 season levels with an improvement in soil pH. For Enable and Worcester sites there is a generally an increase in the nitrate and phosphorous levels, suggesting an improved soil nutrient status for improved crop yields. These nutrients improvement maybe attributed to both crop residues and residues burning during land preparation.

Table 5.2 Soil test results of seasons 2007/2008 and 2005/2006.

Site	P (mg/kg)	K (mg/kg)	Mg (mg/kg)	Ca (mg/kg)	NO^-_3 (mg/kg)	Organic C (%)	pH
Enable	26.2 (3)	96 (117)	98 (343)	1985 (3489)	4.9 (0.83)	0.86 (1.21)	8.15 (7.2)
Sofaya	11.2 (2.4)	207 (100)	311 (284)	2090 (1927)	12.3 (0.56)	1.33 (1.26)	6.02 (5.1)
Worcester	21.2 (0)	154 (145)	356 (428)	6098 (3505)	7.8 (0.62)	1.79 (1.32)	8.34 (5)

Notes:

1. Values in brackets are for soil tests after harvesting in 2005/6.
2. P is phosphate, K is potassium, Ca is calcium, Mg is magnesium and organic C is organic carbon.
3. ppm is equivalent to mg/kg.
4. The parameters were tested using following methods: Ammonium Acetate (Extractable cations), Walkey-Black (Organic Carbon), Bray-1 (Extractable Phosphorus) and method after Kamphake (Nitrogen nitrate). Atomic Absorption Spectrometer with nitric acid digestion were used to test potassium, calcium and magnesium.

The results of the field water balance under supplementary irrigation are presented in the next section.

5.3 Field water balance under supplementary irrigation

5.3.1 Rainfall

The rainfall events for 2005/2006, 2006/2007 and 2007/2008 seasons at the three study sites are presented in Table 5.3. The seasonal rainfall during the three seasons for maize varied from 238 to 1422 mm (Table 5.3). The 2006/2007 and 2007/2008 seasons were very dry below the long-term average (603 mm) (except for Sofaya site in 2007/2008), while 2005/2006 season received above normal rainfall.

Table 5.3 Rainfall and raindays during the maize growing period for the study sites.

Variable	Enable			Sofaya			Worcester		
	2005/6	2006/7	2007/8	2005/6	2006/7	2007/8	2005/6	2006/7	2007/8
Raindays (> 0.5 mm)	30	33	16	30	28	25	28	30	12
Raindays (> 10 mm)	25	11	14	21	15	8	21	8	6
Raindays (days)	30	33	16	30	28	25	28	30	12
Total rainfall (mm)	1112	403	361	1422	388	611	1072	303	238

Note:
A rainday is a day in which more than 0.5 mm of rainfall is received.

Cumulative rainfall from the three sites during the experiments is presented in Figure 5.2–Figure 5.4. Generally, at all the three sites in 2005/6 season, rainfall was low during the first half of the growing period and high during the last half of the season. In contrast to the 2005/6 season, the 2006/7 and 2007/8 seasons had high rainfall during the first quarter and very low rainfall during the last three quarters of the maize crop growing period. Consequently, the frequency of dry spells in low rainfall seasons increased compared to wet seasons (e.g. 2005/6), resulting in complete crop failure under conventional tillage practices.

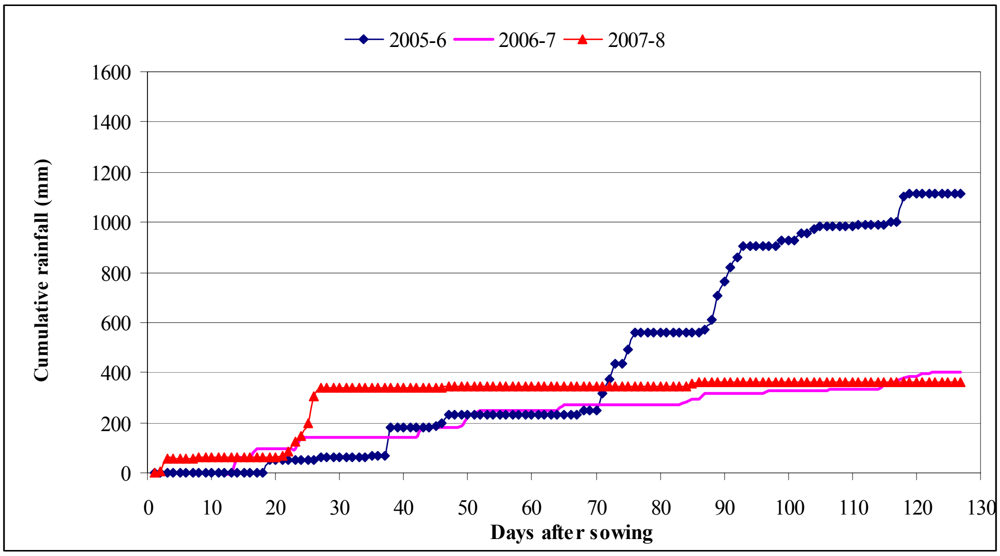


Figure 5.2 Cumulative rainfall during maize growing season from November to March at Enable site.

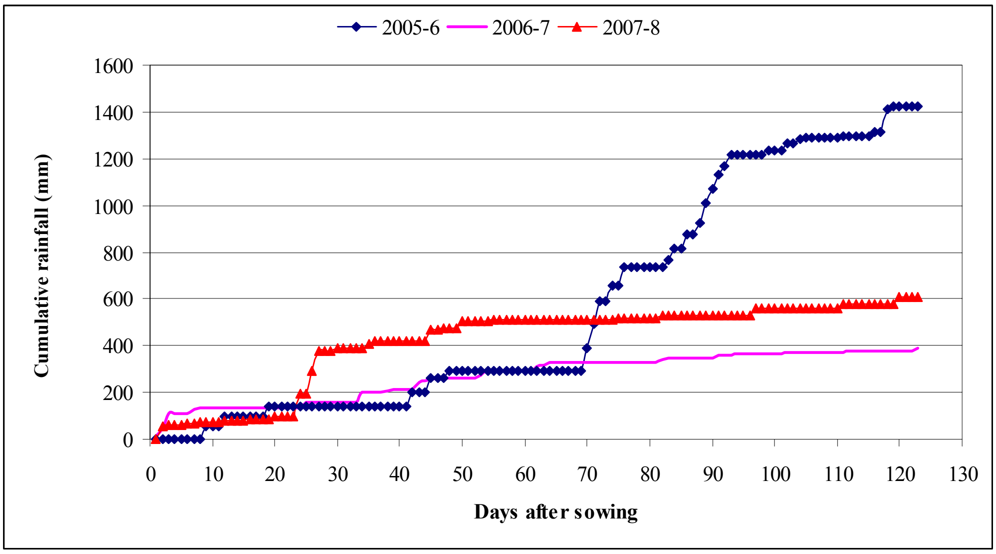


Figure 5.3 Cumulative rainfall during maize growing season from November to March at Sofaya site.

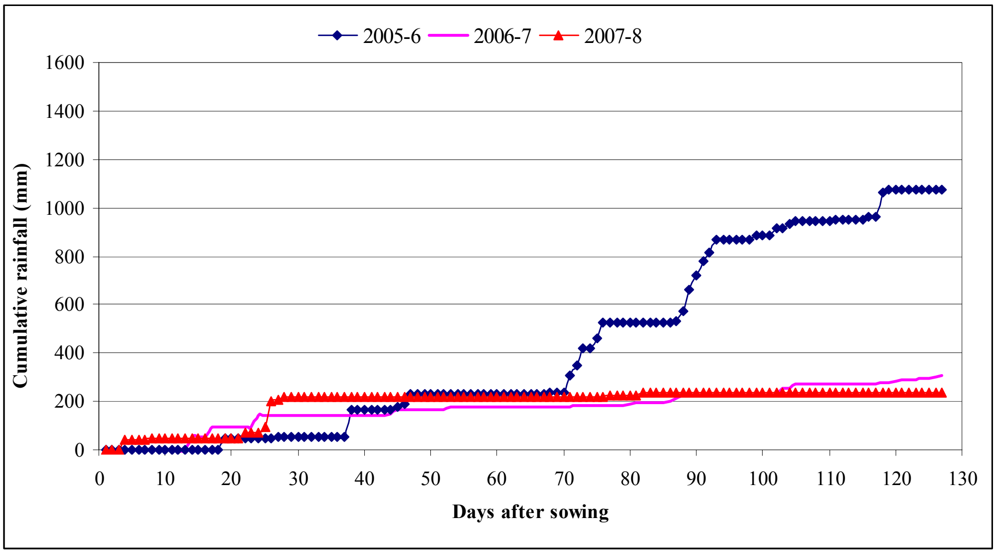


Figure 5.4 Cumulative rainfall during maize growing season from November to March at Worcester site.

5.3.2 Water balance and yield under supplementary irrigation

Water balance components, maize grain yield and water use efficiencies (kg dry matter grain per mm rainfall) for the study sites are shown in Table 5.4. The average evapotranspirations (E_C) under rainfed and supplementary irrigation for the three seasons were 344 mm and 431 mm respectively. These observed E_C values are less than the general maximum (500–800 mm) required by a medium maturity maize crop for maximum yields (FAO, 2002).

Table 5.4 Water balance components, water productivity, irrigation water productivity, marginal irrigation water productivity and yield reduction from the study area.

Production system	Season	P (mm)	I (mm)	ΔS (mm)	R (mm)	D (mm)	E_C (mm)	Grain yield (kg/ha)	W_P (kg mm^{-1} ha^{-1})	M_{SIWP} (kg mm^{-1} ha^{-1})
Rainfed with Supplementary Irrigation	2005/ 2006	1422	48	120	540	364	446	2000	4.5	16.7
	2006/ 2007	388	112	-54	82	56	416	1450	3.5	9.8
	2007/ 2008	611	96	-87	293	71	430	1700	4.0	11.9
Control – Exclusive Rainfed	2005/ 2006	1422	0	120	557	349	396	1200	3.0	0
	2006/ 2007	388	0	-66	105	42	307	350	1.1	0
	2007/ 2008	611	0	-30	257	56	328	556	1.7	0

The variation of grain yield with evapotranspiration (Figure 5.5) for exclusive rainfed and rainfed plus supplemental irrigation showed a strong correlation. This implies that the yield potential of maize increases as the E_C and seasonal rainfall increases.

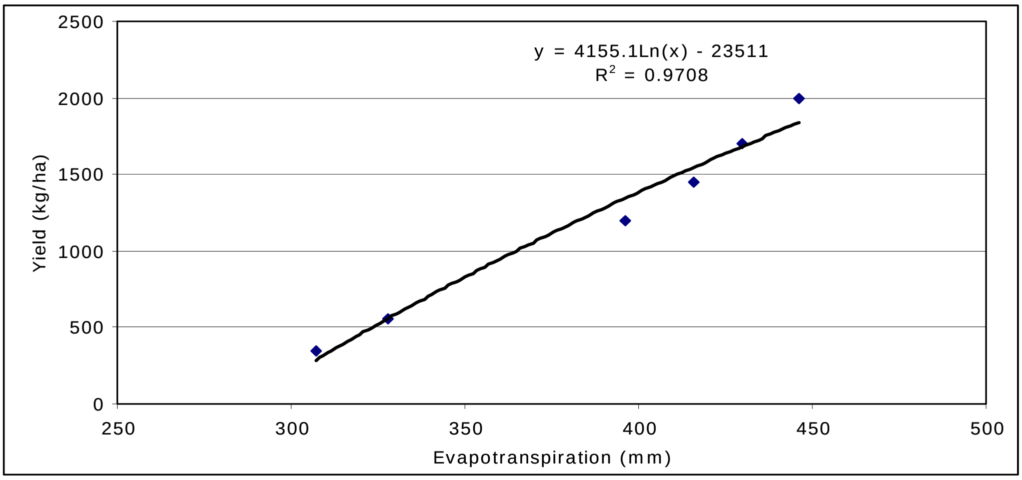


Figure 5.5 Correlation of yield variation with evapotranspiration in the study plots (n = 6).

Maximum grain yields in fields with supplementary irrigation ranged from 1.45 to 2 t/ha, while yields in exclusive rainfed fields ranged from 0.35 to 1.2 t/ha (Table 5.4). Earlier researchers working on maize in South, East and West Africa (Oweis and Hachum, 2003; Rockström et al., 1998) reported similar results. The variation in yields is attributed to several factors that include crop genetics and seasonal weather conditions.

The seasonal rainfall (Figure 5.3) and its erratic distribution throughout the growing season depicted by soil moisture changes in rainfed plots (Figure 5.8 – Figure 5.10) affected maize yield. A good correlation of yield difference between rainfed and supplementary irrigation practices with rainfall during the crop growing period (Figure 5.6) indicated that lack of soil water during critical crop growing stages reduced maize grain yield.

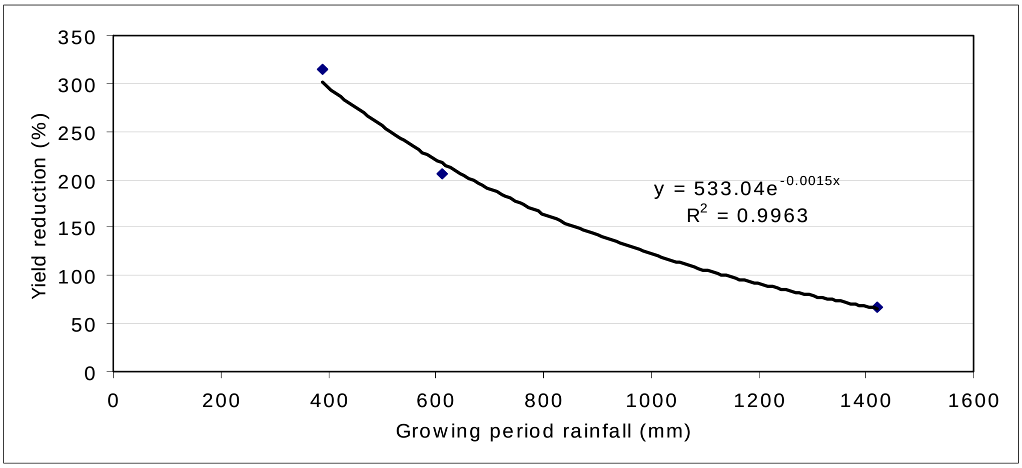


Figure 5.6 Correlation of yield reduction under rainfed compared to supplemental irrigation during the growing seasons from 2005 to 2008.

Supplemental irrigation during dry spells with fertilisation of 14 kg-N/ha increased yields on average by 196 % (Table 5.4). Fox and Rockström (2000) reported similar result of 180 % yield increase in semi-arid Burkina Faso. In addition, during the low rainfall seasons 2006/2007 and 2007/2008 the grain yield reduction without supplemental irrigation ranged from 206 % to 314 %, while for the wettest year (2005/2006) the yield reduction was 67 % . These different yield reductions with rainfall quantity indicate significant yield improvements under supplemental irrigation are realised during drier seasons than wet ones. Hence, there was high potential maize yield in 2005/2006 season due to more favourable high and evenly distributed rainfall. For this reason, the yield gap between exclusive rainfed and supplemental irrigation practices was smaller compared to drier seasons (2006/2007 and 2007/2008).

Furthermore, the correlation of surface runoff and deep drainage beyond the 1 m root zone with rainfall during the crop growing period at study site is shown in Figure 5.7.

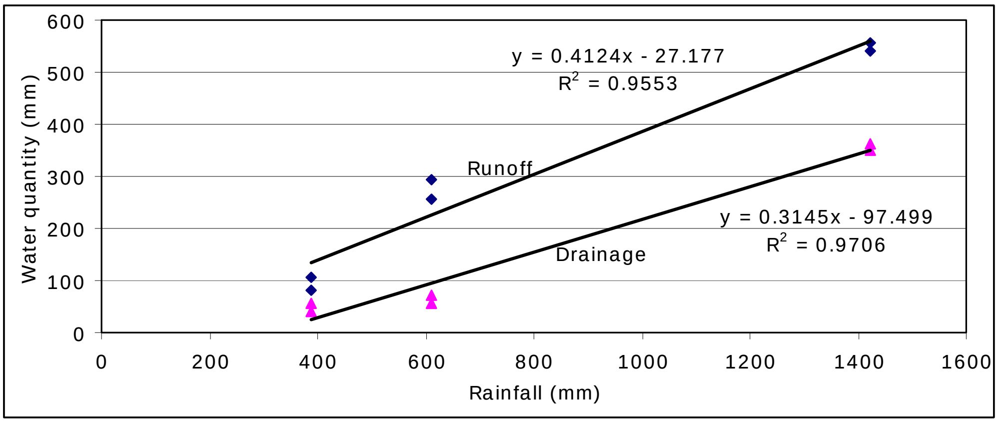


Figure 5.7 Correlation of surface runoff and deep drainage beyond the 1 m root zone with rainfall during the crop growing period.

Surface runoff and drainage (Figure 5.7) from the field soil profile showed a strong linear relationship with seasonal rainfall. These results indicate the great potential for surface runoff water harvesting and groundwater recharging at study site as the quantity of rainfall increases. Runoff generated was high as the rainfall events occurred in pockets (Figure 5.3) of 2–4 consecutive days, which allowed little time for infiltration.

These high runoff field results signify a significant scope for improving water productivity in rainfed farming through supplemental irrigation from local runoff harvesting, especially when combined with soil fertility management as reported in other parts of Africa (Fox and Rockström, 2000; Rockström, 1999). In wet years, the yield improvement under supplemental irrigation is reduced when compared to dry years.

5.3.3 Soil moisture and grain yield variation

The available soil moisture throughout the growing period has a significant effect on yields. In some days the volumetric soil moisture content fell below the permanent wilting point of the sandy loam soil of 9.5 % volumetric soil water content (Mzirai et al. 2001), causing severe crop water stress. In addition, the sub-soil acidity (pH < 5) in the study site could have further restricted water uptake by the crop roots (Robertson et al., 2003).

Despite high annual rainfall of 1422 mm in 2005/2006 season, the crop suffered from periods of water shortage, during the vegetative stage (18–32 days after sowing), early in 2005/2006 (Figure 5.8) and flowering stage (50–70 days after sowing). DS = intra-seasonal long dry spells during the crop growing period, dashed horizontal lines indicate average soil field capacity (F.C = 20.7 %) and the permanent wilting point (P.W.P = 9.5 %) (Figure 5.8–Figure 5.10). Furthermore, in 2006/2007 season (Figure 5.9), crop water stress at soil moisture contents less than 15.9 % (Moroizumi et al., 2009) occurred in the vegetative and grain filling stages, while in 2007/2008 (Figure 5.10) crop water stress was experienced from flowering through to grain filling (80–100 days after sowing) (FAO, 2002; Rockström et al., 1998).

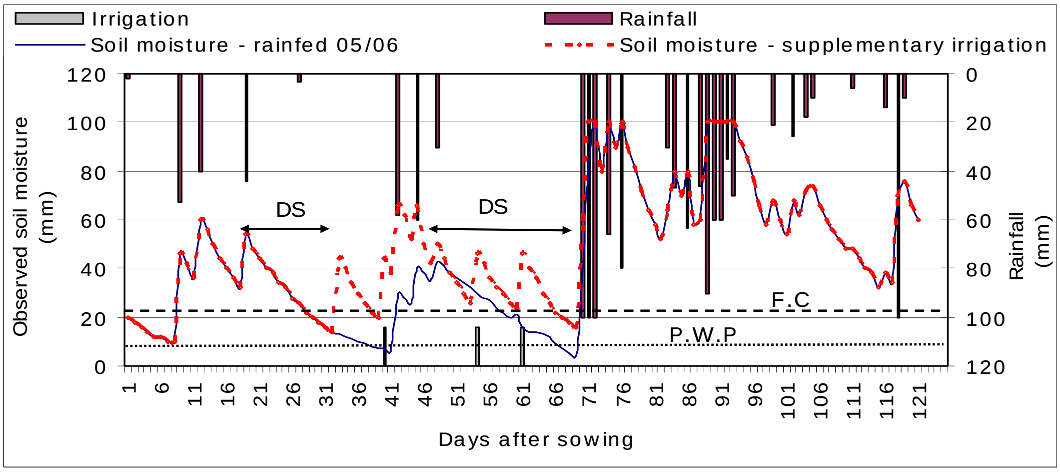


Figure 5.8 Rainfall, irrigation and soil moisture changes monitored under rainfed and supplemental irrigation agriculture 2005/2006 season.

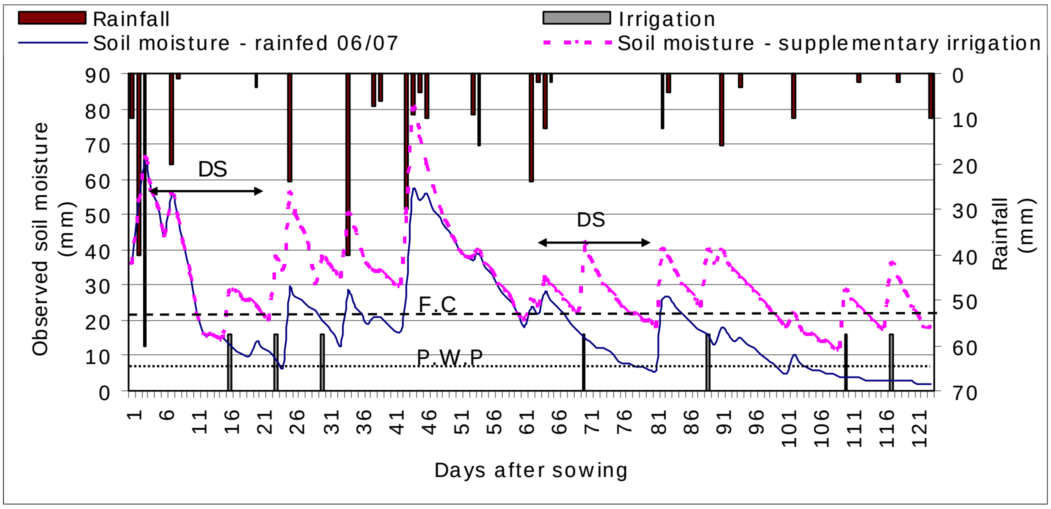


Figure 5.9 Rainfall, irrigation and soil moisture changes monitored under rainfed and supplemental irrigation agriculture 2006/2007 season.

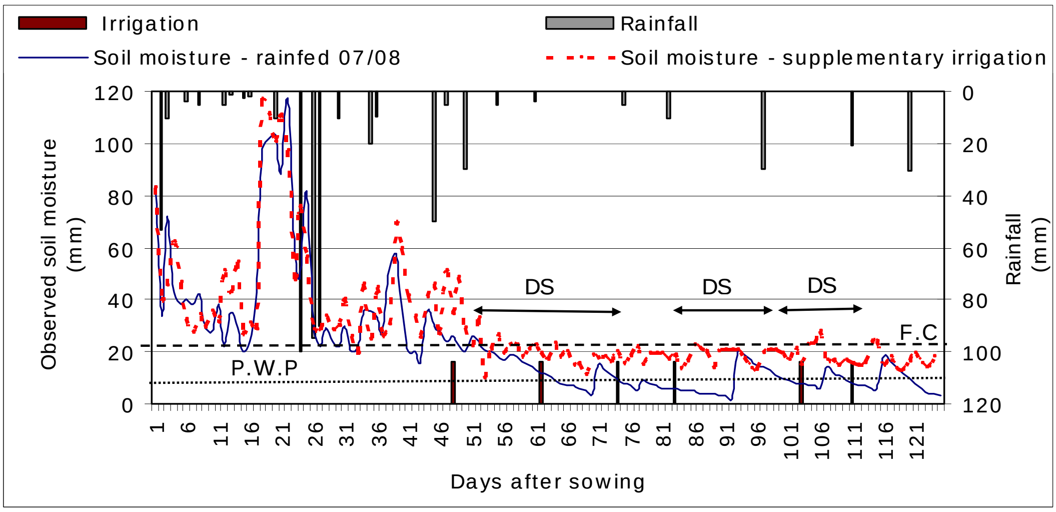


Figure 5.10 Rainfall, irrigation and soil moisture changes monitored under rainfed and supplemental irrigation agriculture for 2007/2008 season.

In addition, at least two dry spells were experienced during the crop growing period in each season. Dry spells that were greater than 10 days resulted in volumetric soil moisture levels falling below 5 %, and triggering crop water stress. These soil moisture deficits adversely affected plant growth and yield under rainfed plots due to increased total resistance in the soil-plant system resulting in reduced photosynthesis and growth (FAO, 2002).

In 2006/2007 the maize grain yield drastically reduced to 350 kg/ha because the soil moisture stress experienced in the early growth stages (12–25 days after sowing) could have reduced the crop leaf area index and radiation use efficiency which have direct bearing on dry matter accumulation in plants (Ali et al., 2007; Rockström et al., 2002). Hence, field soil moisture at a specific (daily or 7-day) time step could be a useful indicator in soil and crop management.

Soil moisture levels from the hydrosense moisture probe could be used to determine the onset of crop-water stress for the efficient utilisation of irrigation and precipitation (Abraha and Savage, 2008). Based on the observed soil moisture values, supplemental irrigation application was late in some days, as the soil-water was close to permanent wilting point on the day of water application. However, Katerji et al. (2008) in their synthesis on indicators of crop water status, demonstrated that soil water status, assessed through criteria like soil water content or soil water potential constitutes an imperfect parameter to characterise real crop water status. Instead, they recommend the use of leaf water potential or pre-dawn leaf water potential in order to schedule irrigation water supply. With improved timely and adequate supplemental irrigation application coupled with soil nutrient management, farmers could ensure minimum crop-water stress, thereby enhancing families' food and income availability.

5.3.4 Marginal irrigation water productivity (M_{SIWP})

The M_{SIWP} is an indicator for assessing the performance of supplementary irrigation management methods, to ascertain whether higher crop yields surpass cost of supplying additional water (Rockström et al., 2002). The M_{SIWP} ranged from 9.8–16.7 kg mm^{-1} ha^{-1} (average of 12.8 kg mm^{-1} ha^{-1}) for 2005/2006, 2006/2007 and 2007/2008 seasons respectively (Table 4.4). The results are higher than 2.5–7.6 kg mm^{-1} ha^{-1} reported in Burkina Faso (Rockström et al., 2002) but on the lower side when compared to 15–62 kg mm^{-1} ha^{-1} reported elsewhere under supplemental irrigation (Tingem et al., 2008; Li et al., 2003). With the current (2008) price of maize grain at South Africa Rand (ZAR) 2.00/kg, on average 1 m^3 of irrigation water applied timely can produce ZAR 2.56 equivalent to US$ 0.28 (using 2009 exchange rate of 9 ZAR = 1 US$) worth of maize. The monetary return per m^3 of supplemental irrigation water is five-fold higher than the cost of 1 m^3 water under full irrigation of ZAR 0.5/m^3. These values demonstrate the huge gains to be substantiated with timely and adequate supplemental irrigation to bridge dry spells, provided the water is available.

5.3.5 Evapotranspiration water productivity (W_P)

Shifting from exclusive rainfed agriculture to supplemental irrigation agriculture in the study area increased average crop evapotranspiration water productivity (W_P) from 1.1 to 4.5 kg mm^{-1} ha^{-1} (or 309 % increase) (Table 5.4). The corresponding average yield increase was from 800 kg/ha to 1144 kg/ha. This yield improvement can be attributed to timely supplemental irrigation water application to crops to avoid severe water stress and increased soil-water availability for the plant. These W_P field results are comparable to an average grain yield increases of 1.5 kg mm^{-1} ha^{-1} for rainfed to 3.5–10 kg mm^{-1} ha^{-1} for supplemental irrigation (Rockström et al., 2002). In addition, results from Burkina Faso reported tripling yields from 460 kg/ha to 1400 kg/ha by combining supplemental irrigation and fertiliser application (Rockström et al., 2002).

In contrast, for seasons with severe dry spells, such as 2006/2007 season in Ga-Sekororo area, a complete crop failure for all treatments lacking dry spell mitigation measures such as supplemental irrigation was experienced. Consequently, the results indicate that water harvesting for dry spell mitigation can play a critical role in mitigating the risk of crop failure during cropping seasons characterised by severe and high frequency dry spells.

To sum up, the daily soil moisture from water balance can be used to estimate the impact of dry spells during the crop growing season. Use of supplemental irrigation can help bridge the intra-seasonal dry spells in semi-arid tropics, thereby increasing crop yields. Furthermore, huge benefits of supplementary irrigation are realised when rainfall is below average and unevenly distributed throughout the season. However, the rainfall has to be adequate to generate streamflows or runoff that is harvested to provide the required supplemental irrigation water.

With the water productivity for rainfed agriculture lower than supplemental irrigation, the results demonstrate the great opportunities that exist for upgrading rainfed agriculture and ensuring food security in rural communities through timely and adequate supplemental irrigation to bridge and manage dry spells. The sources for supplemental irrigation water supply can be diverse, with ex-field rainwater harvesting from a river weir being one of them. Appropriate rainwater harvesting techniques should be employed to harness huge amounts of surface runoff generated in the study area.

Furthermore, low soil nutrients that characterise the study area can be overcome through better soil fertility management with the overall result of higher water productivity. Improvement of the limiting soil phosphate nutrient in the study site is required to enhance crop yield. There is need to investigate the levels of nutrients at which supplemental irrigation perform best and improve supplemental irrigation water application efficiency.

In the next section, field water balance under in-field rainwater harvesting techniques is presented.

5.4 Field water balance under in-field rainwater harvesting

The maize crop water balance components, yields and combined land preparation and sowing costs of each technique from Enable and Worcester sites within the B72A catchment of the Olifants subbasin are shown in Table 5.5.

Precipitation during the crop growing period (2007/2008) was very low at both sites, and the rainwater harvesting (RWH) treatments made the difference between zero yield and yields of 585 and 335 kg ha^{-1} at Worcester and Enable, respectively. Yields from chololo pits at Worcester were higher than yields from untied ridges at Enable, despite the lower rainfall at Worcester. Furthermore, there was much greater soil drying in the chololo pits at Worcester than in the other treatments, reflecting better crop-water extraction efficiency and crop growth at that site. These good yield results (yield tripling) under chololo pits have also been reported in East Africa (Mati, 2005). Besides affecting the crop yield component, the rainwater harvesting treatments also affect the proportions of rainfall that goes to field runoff and drainage.

From the field water balance, the two rainwater harvesting treatments reduced runoff, and increased deep drainage slightly. The chololo pits reduced runoff by 100 % in small to moderate rainfall events as reported by Magombeyi et al. (2009) and Botha et al. (2003). These chololo pits work by forming small water harvesting reservoirs in the field, allowing moisture retention to last longer, resulting in more evapotranspiration water available to the crop. This phenomenon is shown at Worcester site (Table 5.5) by higher evapotranspiration than the rainfall received. Another factor that could contribute to this phenomenon is the availability of abundant initial soil moisture at sowing in the chololo pits.

The chololo pits required much more labour for the combined land preparation and sowing activities than ridges treatment and conventional tillage practice. Subsequently, chololo pits cost almost five times as much to implement than conventional tillage practice (Table 5.5). Ridges required about one third of the labour of the chololo pits, and at about one-third the cost, were also more labour demanding and expensive than conventional tillage practice. Nonetheless, the chololo pits and ridges techniques produced grain yield in a low rainfall year when conventional method produced no grain yield. However, the cost of chololo pits in the first year differs from the subsequent years costs.

Table 5.5 Maize water balance components, grain yield and cost of in-field rainwater harvesting techniques in comparison to conventional tillage practices in B72A catchment, Olifants subbasin.

Water balance components	Study sites for 2007/2008 season			
	Worcester		Enable	
	Chololo pits	Conventional	Ridges	Conventional
Precipitation (P, mm)	268	268	361	361
Soil moisture change between harvest and sowing (ΔS, mm)	-111	-36	-24	-17
Runoff (R, mm)	21	69	46	129
Drainage (D, mm)	22	11	19	8
Crop evapotranspiration (E_c, mm)	336	224	320	241
Maize crop grain yield (kg/ha)	585	0	335	0
Grain yield per unit crop evapotranspiration (kg/ha/mm of E_c)	1.74	0	1.05	0
Labour requirement (person days/ha)	43	10	15	10
*Cost (US$/ha)	168	35	58	35

Notes:

1. *ZAR = South Africa Rand (1 US$ = ZAR 9 in 2008).
2. Conventional tilled land is land that is ploughed, levelled and maize seeds sowed in lines 0.9 m apart and 0.40 m within rows. The planting lines are made by simple hoe or by ox-drawn plough or tractor.
3. Person days/ha are the days spend in land preparation and sowing of maize seeds per hectare.
4. Chololo pits (in East and West Africa) are also known as planting basins in Southern Africa

It was noted that the planting basins required the highest labour in the initial year, but decreases in subsequent years as same pits from the previous seasons are used, with little maintenance. In addition, the labour for chololo pits/ planting basins preparation can be spread over the dry period prior to planting season, thereby avoiding high labour demands when the rainy season commences. This has the advantage that the farmers sow at the right time and avoid waiting or paying for draught power, increasing their chances of high yields. Hence, farmers have developed interest in these two techniques.

Farmers have shown enthusiasm for the ridges and chololo pits techniques as they capture and store soil water for crops for longer periods than conventional methods, with a number of them successfully adopting the chololo pits in their small vegetable gardens (Figure 5.11). Adoption of chololo pits in gardens reduced the frequency and labour required to irrigate the vegetables, leaving time for farmers to perform other activities. However, the two techniques have their drawbacks besides the labour requirements.

Figure 5.11 Adaptation of the chololo pits technique in small vegetable gardens at Worcester site.

During high rainfall seasons, leaching and water logging could adversely affect crop yield in both ridges and chololo pits treatments. On sandy soils, both techniques have some limitations due to poor soil structure that result in low soil water holding capacity. Furthermore, breaching of ridges was noticed in huge storms, requiring constant maintenance of the ridges during the growing period. Although the study has shown a potential for increased RWH, its effectiveness depends on rainfall patterns (requires forecasts studies), soil type, crops and other agricultural practices like planting date and density, and mulching. Further work is required to identify conditions where chololo pits/ planting basins are likely to be beneficial and to develop associated crop management guidelines.

Policy implication of the results

The results indicate that policies that target in-field rainwater harvesting such as planting basins and ridges improve crop yields in semi-arid areas and thereby improve rural livelihoods. Field rainwater harvesting committees, headed by women who are the most vulnerable groups in the study area maybe established to support knowledge sharing and labour planning on field rainwater harvesting techniques through extension services. In addition, supplemental irrigation committees can be established to advise on the possible sources and application of supplemental irrigation. The sources of supplemental irrigation should include weirs across streams and rainwater harvesting tanks that store runoff water. Most importantly, small hand pumps should be installed on these tanks for easy access of water from these rainwater-harvesting tanks.

In sum, two important in-field RWH techniques (ridges and planting basins) that maybe applied in semi-arid areas to enhance rainfed agriculture were presented. In general, maize productivity under conventional practices is low compared to the one under RWH techniques. The reason for low crop productivity is the low rainwater storage capacity under conventional practices. New technologies on rainwater harvesting are appropriate and beneficial to farmers only if it is acceptable and affordable to farmers who are able to incorporate it into their existing systems. Acceptability comes from the use of appropriate testing techniques that includes on-farm trials presented in this chapter. However, suitable conditions for application of rainwater harvesting technologies need further study, if improved rainfed yields are to be achieved.

In the next section, a discussion of how the field experimental results were used to set up a crop growth and yield simulation model for the study site for different treatments is presented. The calibration, validation and subsequent crop model application in simulations are important to go beyond (extrapolation) the experimental observations as presented in the next section.

5.5 Agronomic model

This section describes the crop model, PARCHED-THIRST setup, calibration and validation based on experimental field data such as soil moisture and crop yield. Satisfactory calibration and validation enables the crop model to be used for extrapolation of experimental results.

5.5.1 Agronomic model calibration and validation

Calibrated maize crop parameters and genetic coefficients used in PARCHED-THIRST model at Enable, Sofaya and Worcester sites are presented in Appendix A, Table A1. These parameters and coefficients were calibrated based on field-measured grain yield and maturity dates during the 2005–2008 growing seasons.

The graphs (Figure 5.12–5.19) shown in the subsequent section provide a seasonal visual comparison (distribution and agreement) of simulated and measured essential data and a first overview of model performance. The first season yield and soil moisture variation to a soil depth of 200 mm were used for calibration, while the second and third season yields and soil moisture were used for validation of the model.

The statistical coefficients of performance achieved from the comparisons are reasonably good for both soil water and yield (Figure 5.12–5.19) for all the sites. Therefore, the PARCHED-THIRST model was able to simulate the soil water variation during the growing period and resultant crop yield with an acceptable precision. Hence, PARCHED-THIRST model can be applied in crop management and yield prediction purposes for the tested crop production systems in the study area with confidence. In addition, the weather generator incorporated in PARCHED-THIRST would further improve crop management by ensuring efficient extrapolation beyond field experiments.

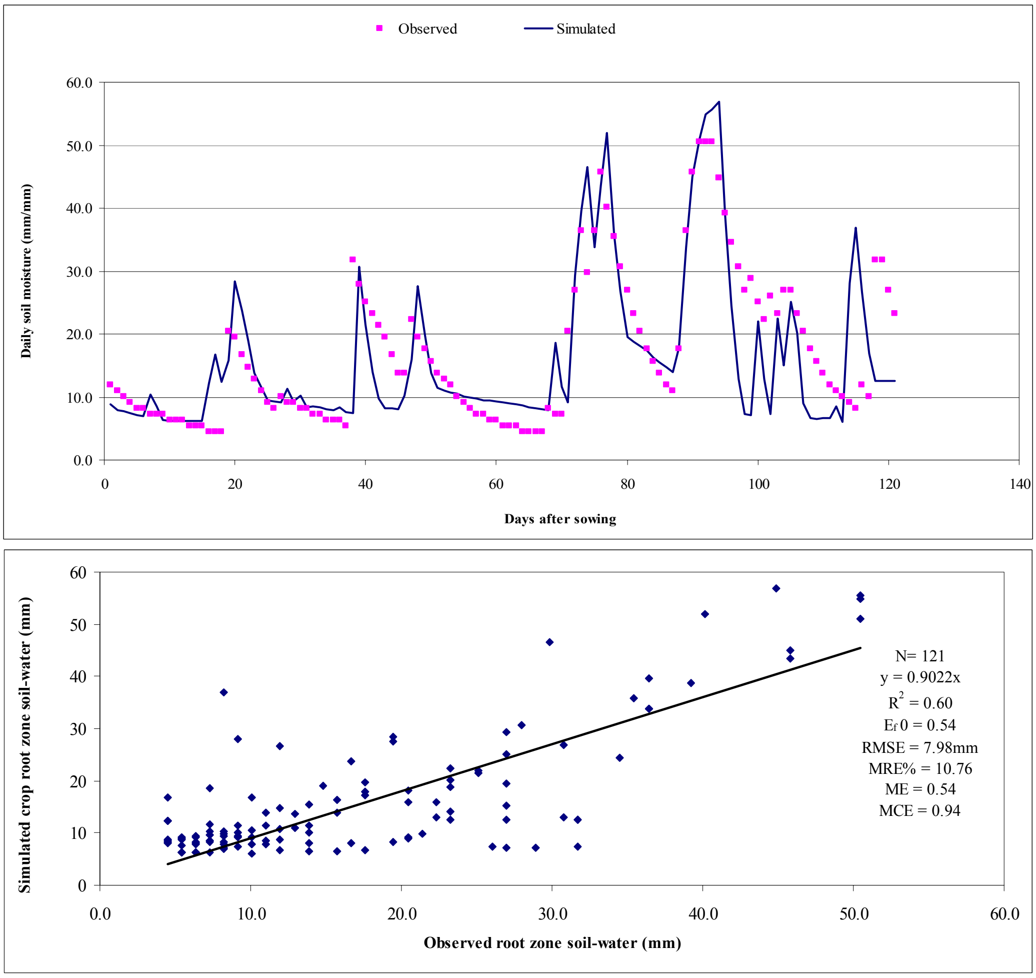


Figure 5.12 Variation of observed and simulated (after calibration) crop root zone soil-water with days after sowing for maize crop at Enable site under exclusive rainfed practice in 2005/2006 season.

The soil-water variation was overestimated (Figure 5.12) for all values by the model under rainfed practice at Enable site.

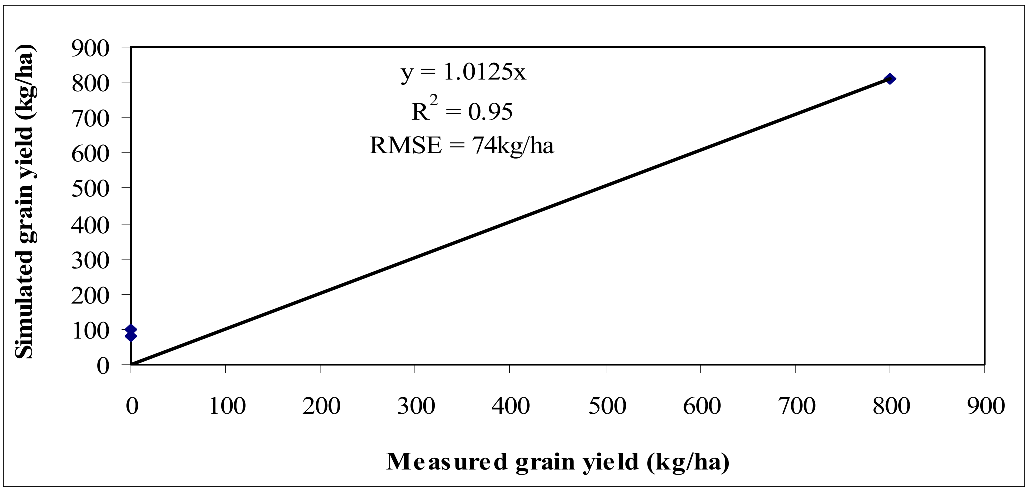
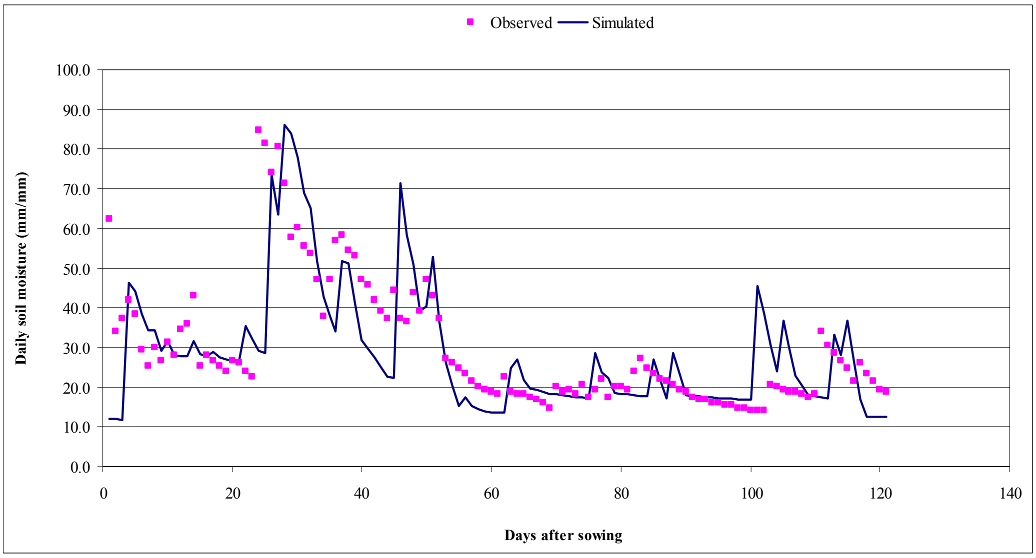


Figure 5.13 Measured versus simulated grain yield at Enable site.



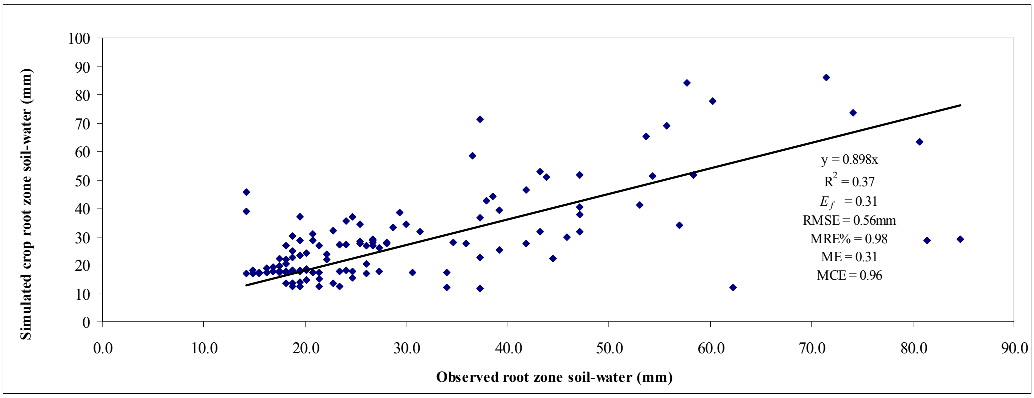
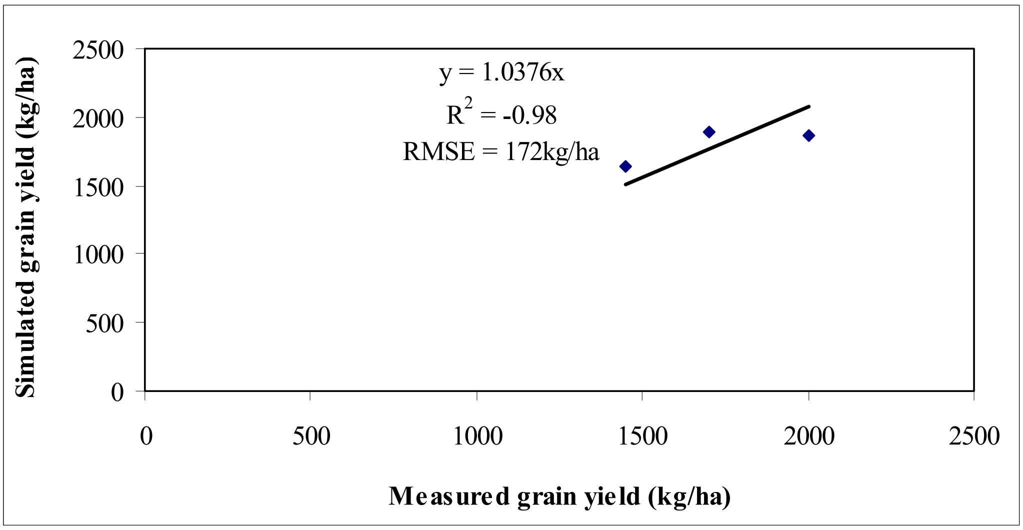
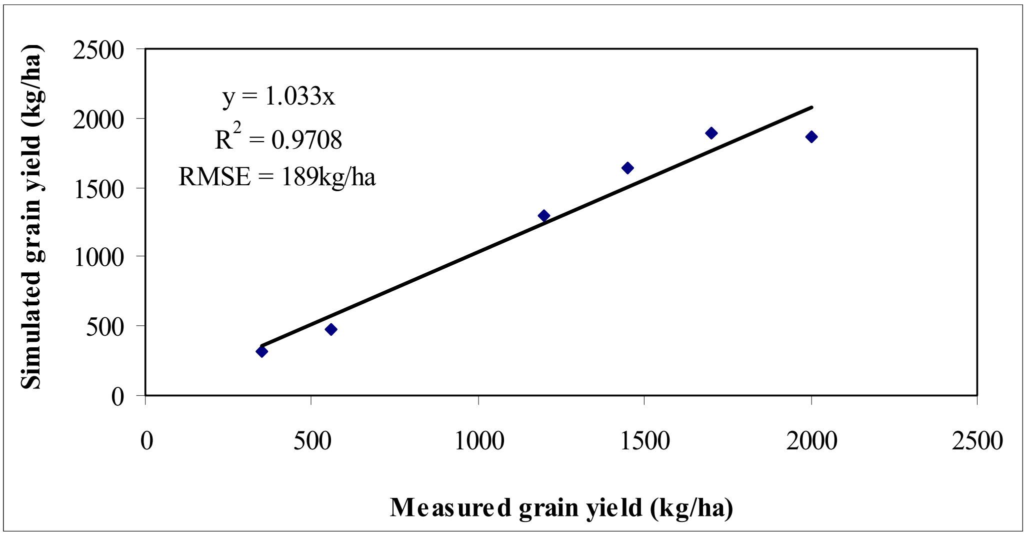


Figure 5.14 Variation of observed and simulated (after calibration) crop root zone soil-water with days after sowing for maize crop at Sofaya site under rainfed and supplemental irrigation practice in 2007/2008 season.

The soil-water variation was overestimated (Figure 5.14) for all values by the model under supplemental irrigation practice at Sofaya site.



(a)



(b)

Figure 5.15 Measured versus simulated grain yield at Sofaya site: (a) under supplemental and (b) under both exclusive rainfed and supplemental irrigation.

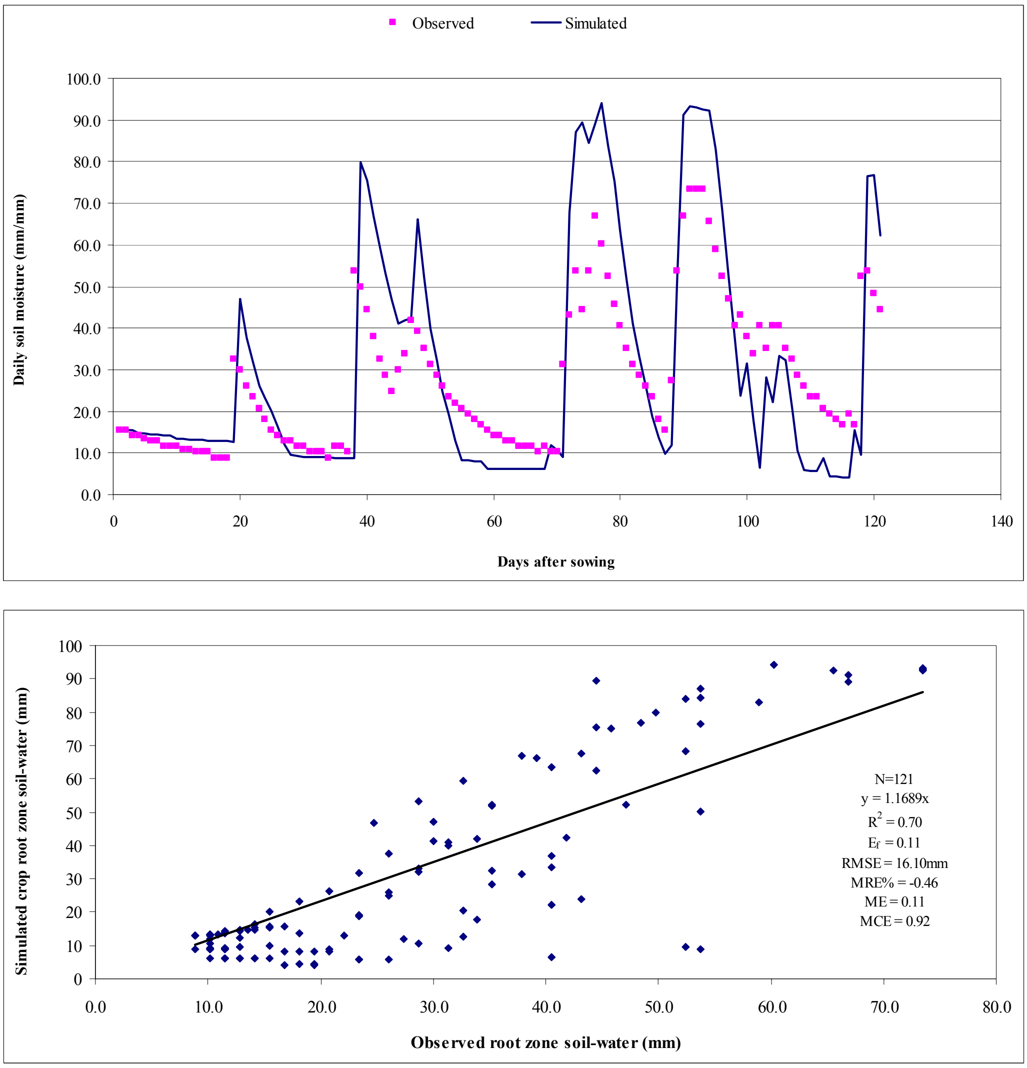


Figure 5.16 Variation of observed and simulated (after calibration) crop root zone soil-water with days after sowing for maize crop at Worcester site under exclusive rainfed practice in 2005/2006 season.

The soil-water variation for maize crop tended to be overestimated for the high soil-water values and underestimated for the low values under exclusive rainfed practice at Worcester site (Figure 5.16).

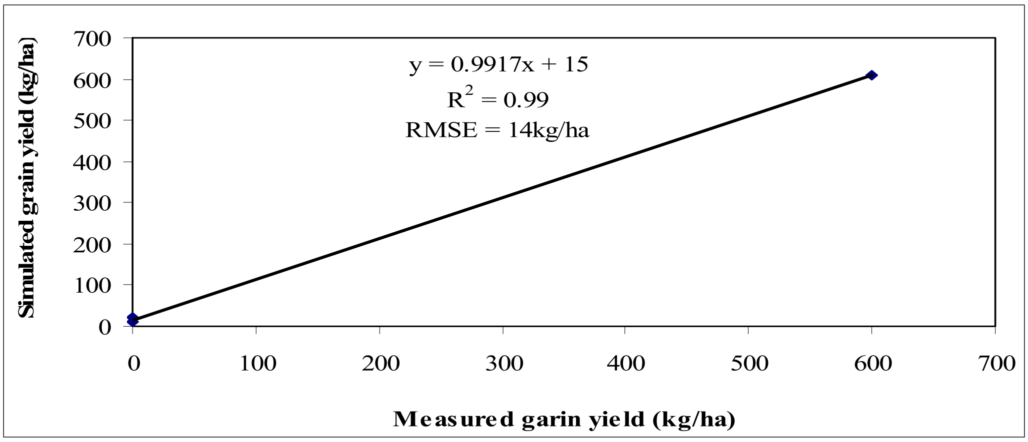


Figure 5.17 Measured versus simulated grain yield at Worcester site.

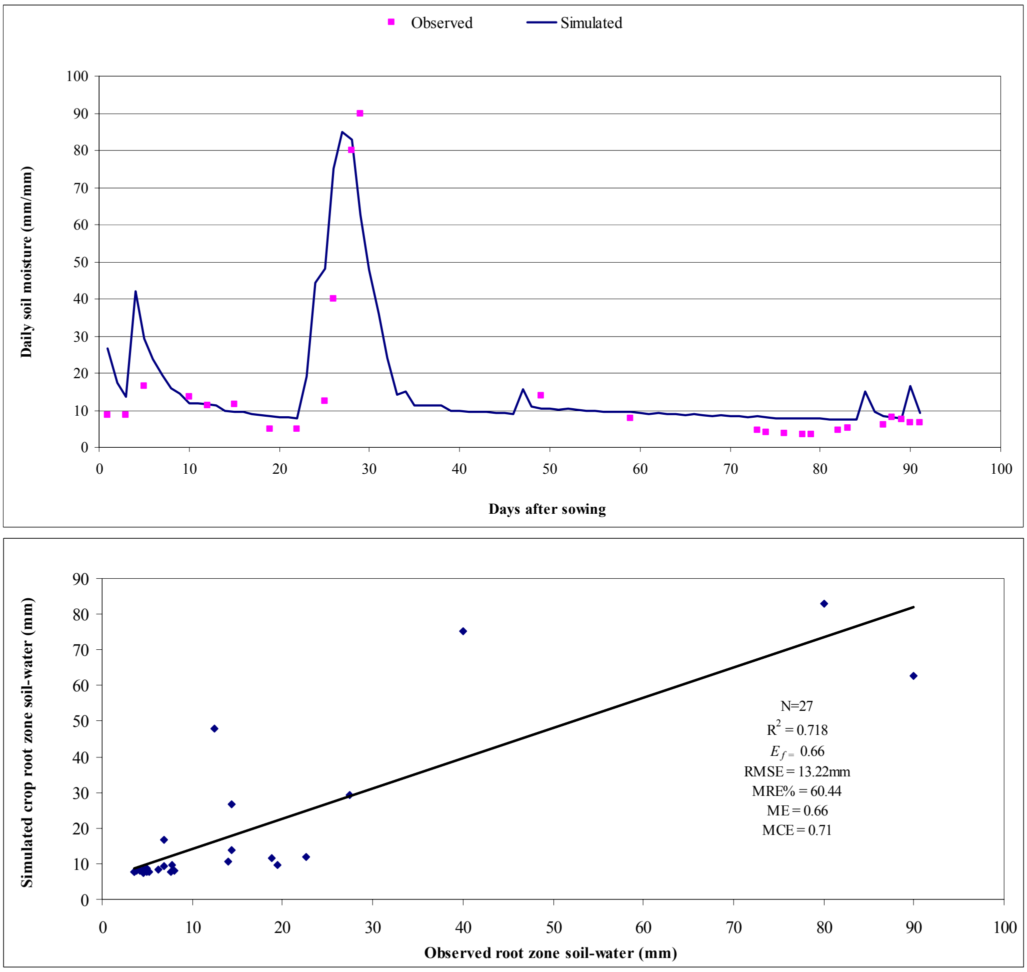


Figure 5.18 Variation of observed and simulated (after calibration) crop root zone soil-water with days after sowing for maize crop at Enable site under ridges practice in 2007/2008 season.

The soil-water variation was overestimated for all values by the model under ridges practice at Enable site (Figure 5.18). The observed and simulated yields were 335 kg/ha and 320 kg/ha respectively, giving an error of 4.5 %.

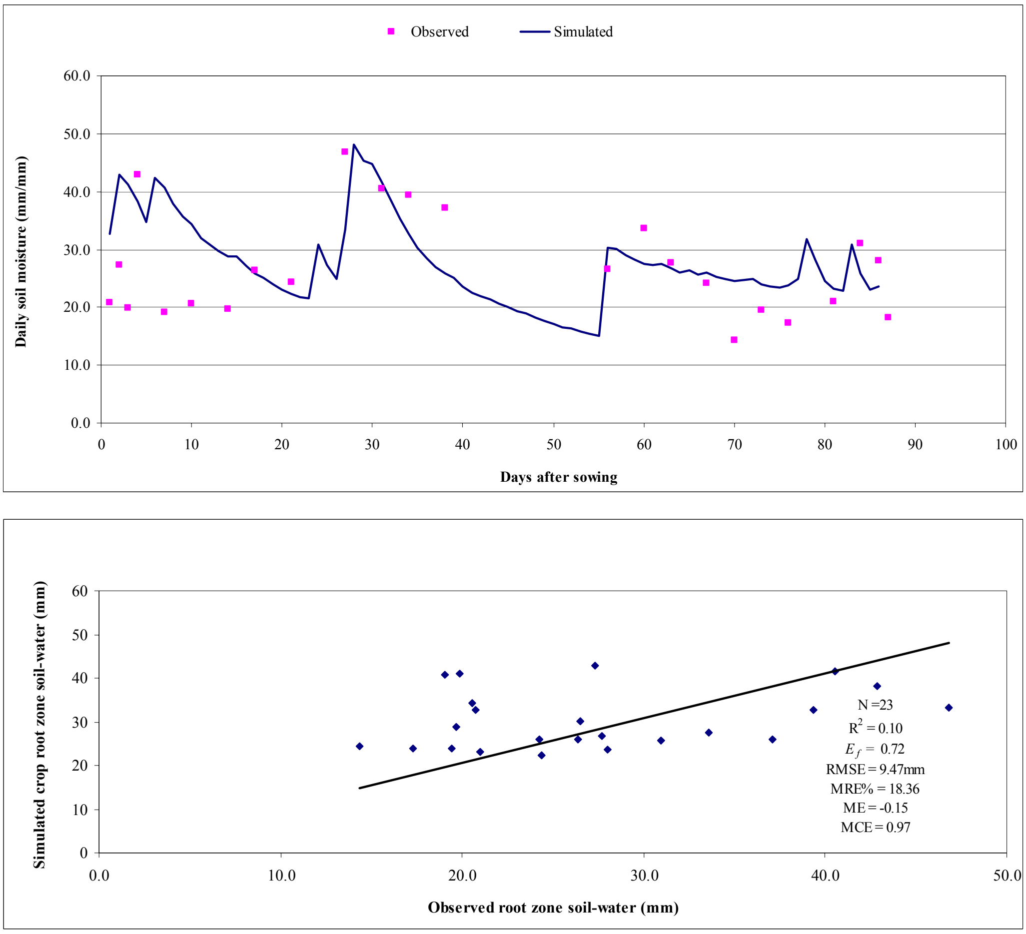


Figure 5.19 Variation of observed and simulated (after calibration) crop root zone soil-water with days after sowing for maize crop at Worcester site under chololo/ planting basins practice in 2007/2008 season.

The soil-water variation for maize crop tended to be overestimated for the low soil-water values and underestimated for the high values under chololo/planting basins practice at Worcester site. The observed and simulated yields were 585 kg/ha and 590 kg/ha respectively, giving an error of –0.9 %. The discrepancy between observed and simulated yields can be attributed to biotic or abiotic factors that PARCHED-THIRST model fails to simulate.

5.5.2 Reasons for difference of simulated and observed variables

There are several reasons why simulated and observed values differ. Firstly, the inherent model assumptions are responsible for the difference. Secondly, the soil-water values are dependent on the correct choice of soil physical and chemical parameter inputs. In addition, observed values are influenced by soil spatial variability, distortion of soil structure and lack of full contact between the soil and probe rods when taking field measurements. Furthermore, the model simulations do not account for leaf damage due to insects, pests and diseases that affects leaf index and consequently affect the crop yield (Abraha and Savage, 2008). The above constitute the uncertainty in the crop model yield and soil-water results.

5.5.3 Planting dates

Semi-arid areas are characterised by low and erratic rainfall with variable start date and duration for the growing season that greatly impact crop yields. Using the calibrated and validated PARCHED-THIRST model for the three sites, the variation of simulated yields and planting dates, based on availability of water are shown in Figure 5.20–Figure 5.23. The rainy seasons are considered to start on the same day each year, 25th October for the three experimental sites.

The targeted yields (at least 0.5 t/ha, after allowing harvesting yield losses) adequate to feed an average family of five people in the study area formed the basis for selecting suitable planting dates. The suitable planting dates for Sofaya site, under supplemental irrigation are from 15th of November to 15th of January (Figure 5.20), whereas for Enable site under exclusive rainfed agriculture are from 29th November to 15th of January (Figure 5.21). In addition, the planting dates for Worcester site are from 10th of December to 15th of January (Figure 5.22), whereas those for the overall catchment are from 15th of November to 15th of January (Figure 5.23). Extending of sowing dates reduces the supplemental irrigation demand (Oweis and Hachum, 2001) by taking advantages of more rainfall and reduced frequency of dry spells as the season progresses. However, planting very late under rainfed practice, after 15th January is not advisable as rainfall might stop before crop maturity and livestock that freely graze after 1st of June may destroy the crop before maturity.

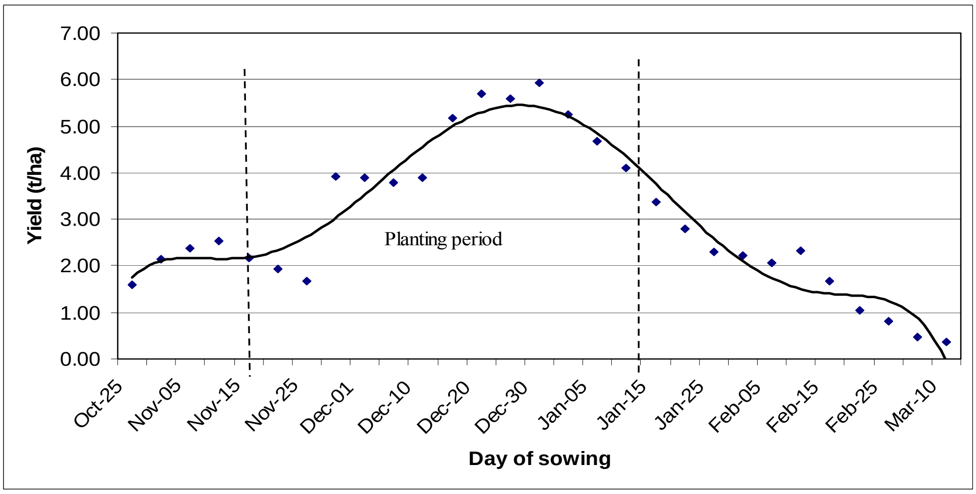


Figure 5.20 Relationship of planting dates and maize yields at Sofaya site in B72A catchment. The correlation coefficient, $R^2 = 0.93$).

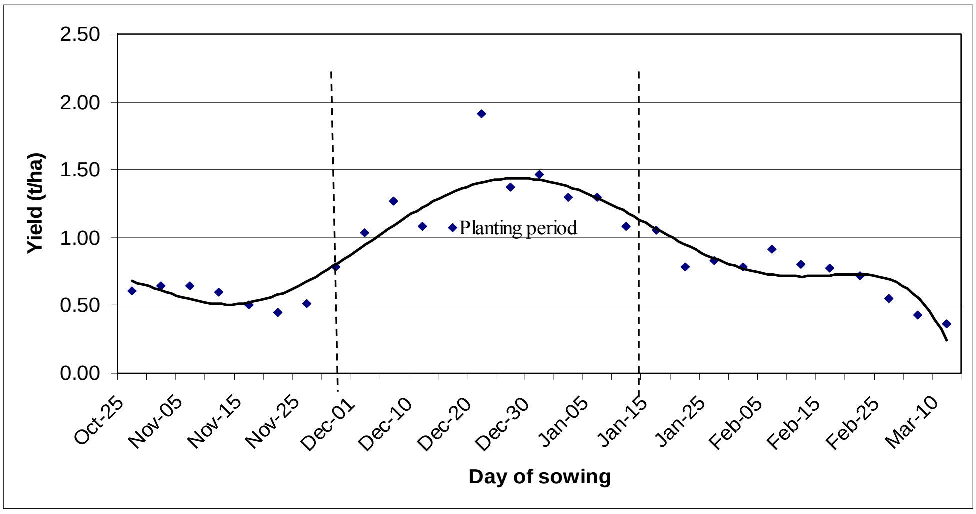


Figure 5.21 Relationship of planting dates and maize yields at Enable site in B72A catchment. The correlation coefficient, $R^2 = 0.84$).

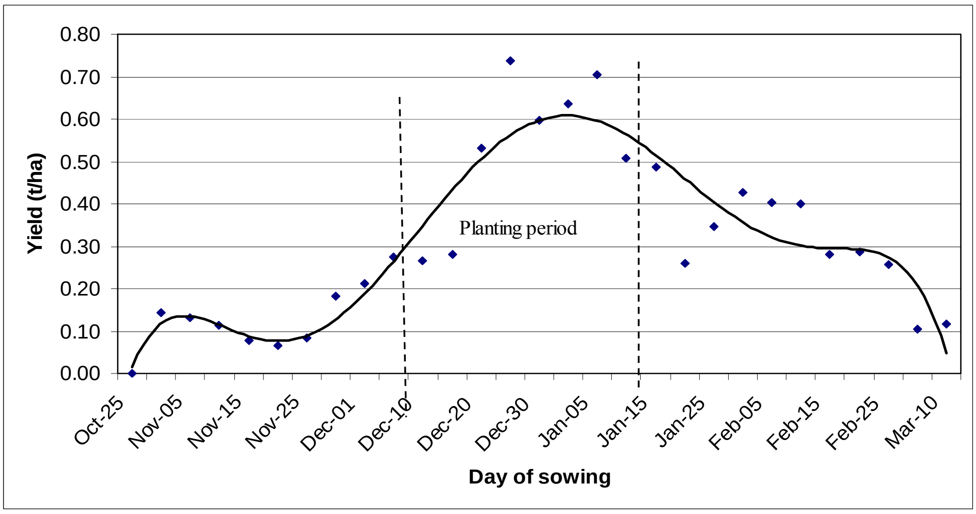


Figure 5.22 Relationship of planting dates and maize yields at Worcester site in B72A catchment. The correlation coefficient, $R^2 = 0.86$).

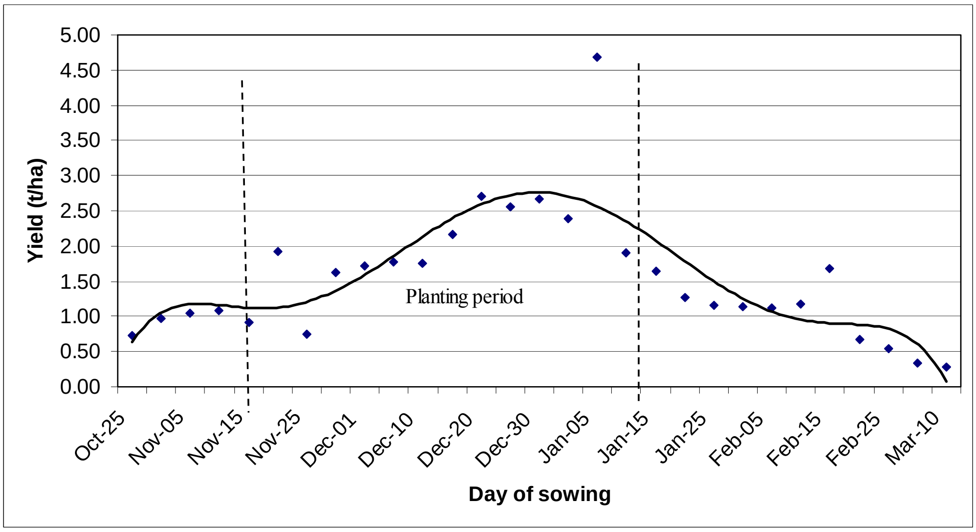


Figure 5.23 Relationship of planting dates and maize yields in B72A quaternary catchment. All the three sites combined. The correlation coefficient, $R^2 = 0.67$).

In sum, the analysis above suggests that for better maize yields the best planting dates for B72A catchment are from second week of November to second week of January based on 2005–2008 seasons. Although planting between 20 December and early January appears to give the highest yields, there is a potential danger of rains ending early and crop failing to reach maturity.

Therefore, 28 November to 20 December planting window in the catchment is a good period.

Although planting dates shown are dependent on water availability, every season farmers need to decide on when to plant considering the real time circumstances. These circumstances include the availability of labour, seeds, the perceived moisture status of the soil and the perceived likelihood of continued rains based on knowledge of historical climate pattern.

The variation of yield with planting dates among the different sites presented suggests that the crop model can be useful in predicting suitable planting dates of a particular location based on climate and physical characteristics to ensure improved rainfed agriculture yields. However, the amount of data (three seasons) used to reach this conclusion is very limited to make any significant conclusion.

In sum, PARCHED-THIRST crop model calibration and validation using field data was presented and its performance assessed based on soil-water and crop yield. PARCHED-THIRST model reasonably simulated the soil-water variation and crop yield for different crop management techniques in all the experimental sites with an acceptable precision shown by statistical performance. Hence, the model was applied to simulate yield responses from various in-field water harvesting and supplemental irrigation scenarios. The best maize planting dates, based on climatic and physical characteristics for B72A catchment are from second week of November to second week of January. However, other socio-economic factors affect the real time planting dates, such as availability of labour and seeds.

Furthermore, the PARCHED-THIRST crop model was now suitable to be coupled with the other models (socio-economic and hydrology) to form an integrated model described later.

In the next section, hydrological model setup, sensitivity analysis, calibration and validation are discussed.

5.6 Hydrology modelling

This section describes the simulations and performance of the hydrological model in the study site, SWAT selected from the literature survey. The model was auto-calibrated using long-time streamflow series from adjacent catchments. The calibrated parameters were then applied in B72A catchment, based on catchment topography, land use (Figure 5.24) and soils (Figure 5.25) similarity. The flows were validated against one-year flow series in one of the subcatchments in B72A. The similarities of the catchments are noted from both Figure 5.24 and Figure 5.25.

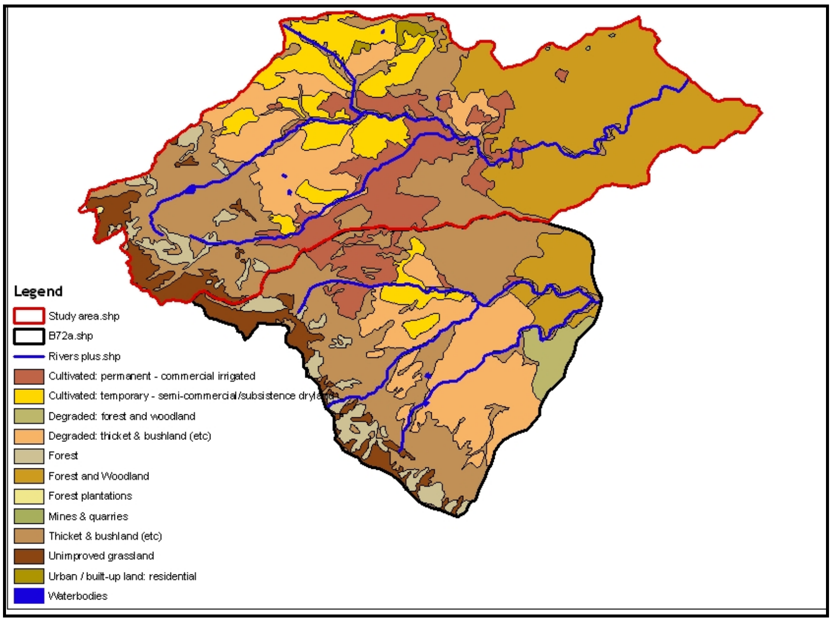


Figure 5.24 Land uses in B72A and adjacent catchment

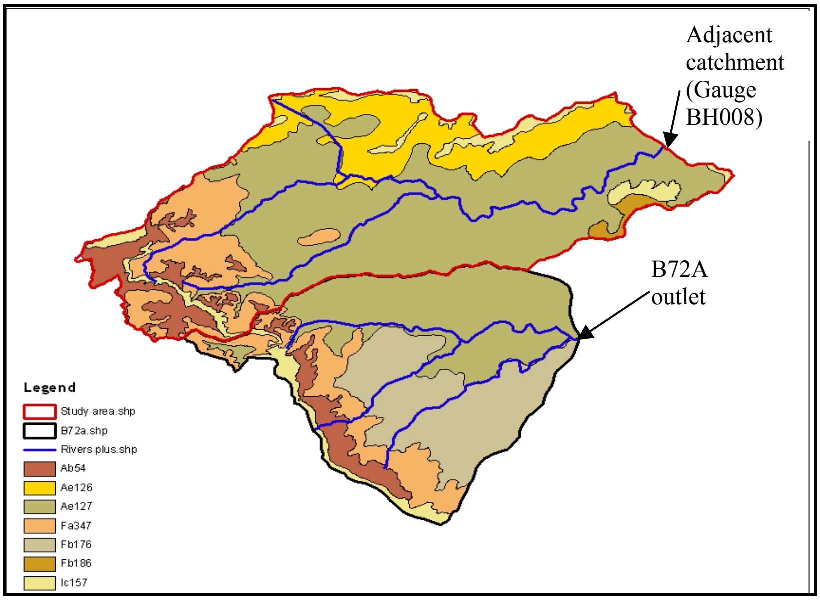


Figure 5.25 Soil types in B72A and adjacent catchment.

A reasonable fit for the calibration period was obtained using 13 parameters in adjacent quaternary catchments (Table 5.6). SWAT model performed better during calibration (Figure 5.26) than validation period (Figure 5.27). This phenomenon can be attributed to high flows that were represented well in the calibration period, but the model failed to represent low discharges under validation period, shown by the magnitude of maximum flows in both calibration and validation periods.

Table 5.6 SWAT parameters used in auto-calibration of streamflows in B72A catchment.

Parameter name	Parameter description	Value
Slsubbsn	Average slope leng	127.39
Sol_K	Saturated hydraulic conductivity (mm/hr)	28.10
Revapmn	Threshold water depth in the shallow aquifer for revaporation (mm)	415.07
Canmx	Maximum canopy storage (mm)	9.50
Slope	Average slope stepness (m/m)	0.100
Esco	Soil evaporation compensation factor (-)	0.10
Ch_K2	Channel effective hydraulic conductivity (mm/hr)	146.00
Surlag	Surface runoff lag time (days)	4
CN2	Initial SCS curve number II value (-)	50.08
Biomix	Biological mixing coefficiency (-)	0.40
Gwqmn	Threshold water in the shallow aquifer for flow (mm)	5000
Alpha_Bf	Baseflow alpha factor (days)	0.0
Sol_Awc	Available water capacity of the soil layer (mm H_2O/mm soil).	0.5

Notes:

SCS = Soil Conservation Service

(-) = dimensionless

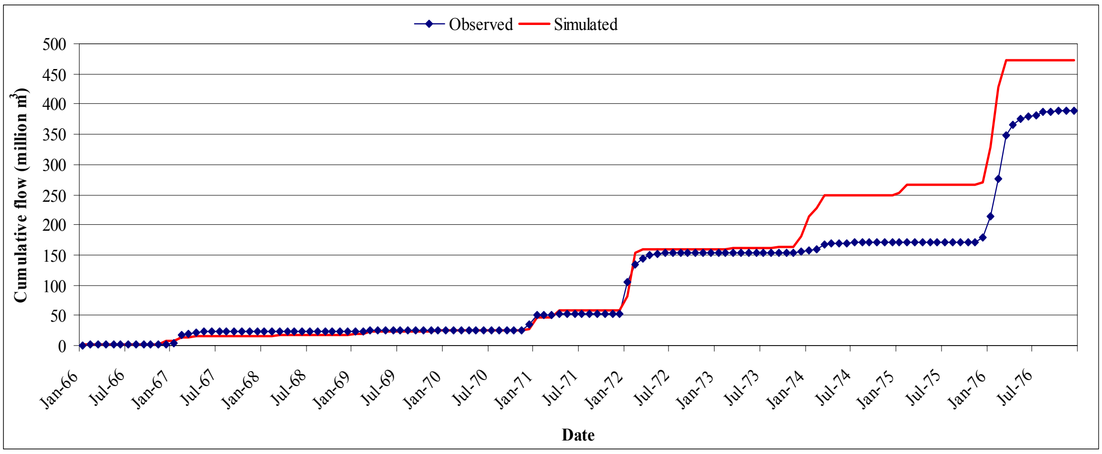


Figure 5.26 Cumulative mass-curves of simulated and observed streamflows at calibration period (1966–1976) at adjacent catchment to B72A catchment.

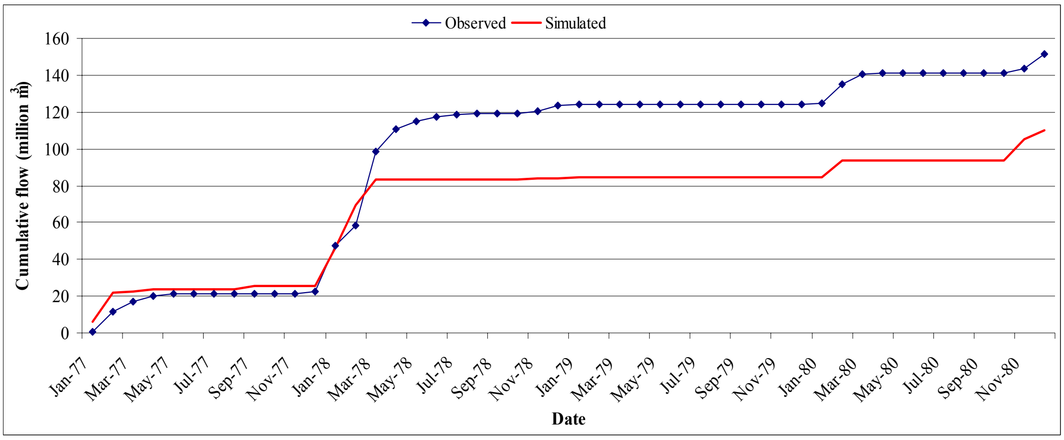


Figure 5.27 Cumulative mass-curves of simulated and observed streamflows during calibration period (1977–1980) at an adjacent catchment to B72A catchment.

The statistical performances of SWAT model under both calibration and validation periods are presented in Table 5.7.

Table 5.7 Summary statistics on calibration and validation periods of SWAT model in B72A catchment

Statistical indicator	Period			
	Calibration		Validation	
	Observed	Simulated	Observed	Simulated
RMSE (Mm^3/month)	6.90		6.29	
E_f	0.52		0.36	
MEC	0.81		0.68	
PBIAS (%)	53.43		72.21	
Maximum	73.0	100.0	40.0	23.0
Median	0.00	0.00	0.00	0.00

The model performed well for some statistical indicators. The best model performances obtained E_f coefficients of 0.52 and 0.36 for calibration and validation periods, respectively. This performance is adequate to apply the model in simulations as the E_f coefficients are not below 0.36 (Stehr et al., 2008). However, the PBIAS was positive in both calibration and validation periods, indicating that the model typically underestimates the runoff. One possible explanation is the inadequate rainfall stations coverage in the catchment (only three rainfall stations data were used). These results indicate the importance of climatic data as the main forcing input in hydrological modelling. Hence, in future studies spatially variable rainfall data should be obtained from methods with high spatial capabilities such as co-kriging rather than the Thiessen polygons used in SWAT.

Using the parameters from the adjacent catchment presented in Table 5.6,the SWAT model was set up for B72A catchment. Further validation by comparing the model simulations with just over a year series of observed flows in one of the subcatchments in B72A catchment is presented in Figure 5.28. This comparison just provides an indication of the model performance because of the short period of streamflow series used.

The model efficiency performance was low *with* E_f coefficient of 0.1. Other criteria were MCE (0.68), RMSE (0.02 m^3/s) PBIAS (27.4 %) and MRE (60 %). A RMSE close to zero indicates a perfect fit, while PBIAS values of less than 40 % are satisfactory (Stehr et al., 2008). However, the MRE and MCE were high. Based on the satisfactory performance levels of PBIAS and RMSE, the SWAT model was applied to simulate the water resources availability in B72A catchment under the integrated model.

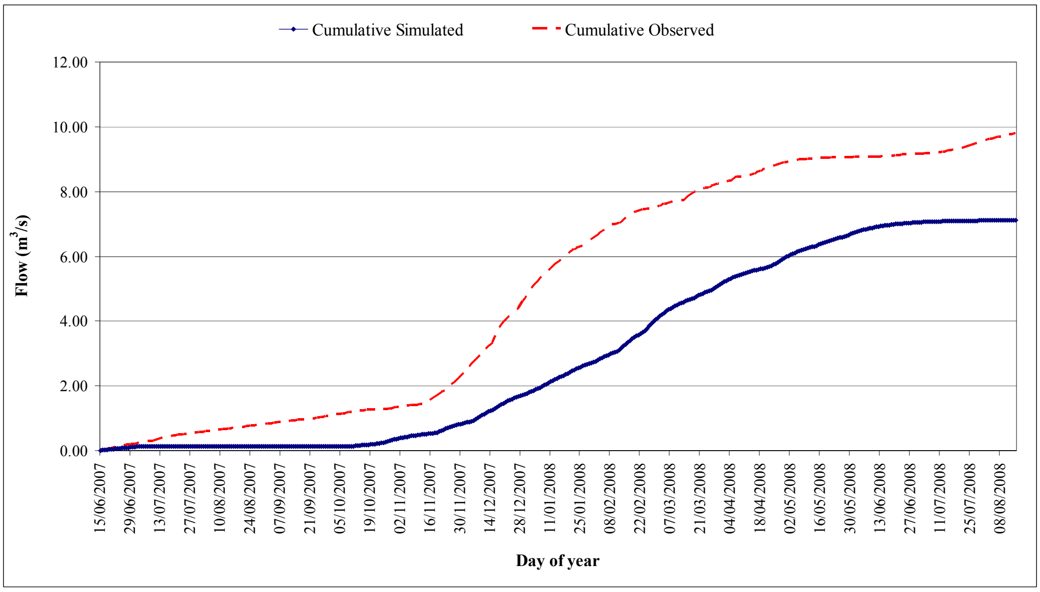


Figure 5.28 Cumulative mass-curves of simulated and observed streamflows for further validation of SWAT model in B72A catchment.

SWAT model performance under local poor data conditions in the B72A catchment confirms its potential applicability in assessing the impacts of climate changes in data scarce areas. The calibrated and validated SWAT model became an important input into the integrated model development discussed later in this study. However, the model show streamflows under estimation (Figure 5.28), which can result in the model indicating water stress, whereas the catchment might not be stressed.

In the next section, socio-economic model, Olympe is setup, calibrated, validated and applied to simulate smallholder farmers in B72A catchment. The model was selected for application from the extensive literature survey on socio-economic models presented in Chapter 3.

5.7 Socio-economic modelling

This section describes the Olympe model setup, calibration and validation. A case study in farming system simulation that employed Olympe model and crop model, PARCHED-THIRST, is presented in the next chapter. The model was applied to simulate smallholder farming systems performance in relation to providing food security under agricultural market-price and climatic variations.

5.7.1 Socio-economic model setup

The Olympe model setup data from the farm typologies constructed from farm surveys served as the main input data. Detailed Olympe model calibration and validation through group discussions with farmers and extension officers are presented separately in the next chapter.

5.8 Summary

In this chapter, results and discussions on several aspects on surveys, experimental studies and modelling were presented. The five identified farm typologies (A–E) with vulnerable women being the majority of farm household heads were presented. These farm typologies enhance understanding of farm household systems and their behaviour under different production conditions and periods. The results showed that type E farm typology with highest livestock units and employed off-farm is the least vulnerable to food security. In addition, programmes that uplift women livelihoods will make greatest impact in the study area. Furthermore, the five farm typologies together with their production characteristics served as important inputs in the setting up of the socio-economic model, Olympe. Olympe model enabled the simulations of the five farming systems.

Furthermore, experimental results showed that supplemental irrigation practice performed better than exclusive rainfed agriculture, with greatest average yield increase (196 %) being realised in drier seasons. In addition, in-field rainwater harvesting techniques (ridges and planting basins) performed better than conventional practices, with highest yields realised under planting basins with as little in-season rainfall as 268 mm. However, planting basins require more labour and costs compared to ridges and conventional crop practices. To ensure timely planting and avoiding peak labour demands, it is possible to spread planting basins preparation over the season before or just after first rainfall event.

Using experimental data, PARCHED-THIRST crop model, was setup for conventional, supplemental irrigation, ridges and planting basins maize crop practices. The crop model was subsequently calibrated and validated prior to application in crop growth simulation exercises. The crop model provides the rural community with the technical knowledge to enable them to plan and manage their agricultural activities more efficiently. For instance, the crop model can provide the best maize planting dates, based on climatic and physical characteristics. For B72A catchment, the planting dates are from second week of November to second week of January. However, other socio-economic factors that affect the real-time planting dates, such as availability of labour and seeds are not captured in the crop model.

Crop models and any other model still have some limitations after calibration. These limitations include inherent crop model assumptions, failure to simulate biotic or abiotic factors such as leaf damage due to insects, pests and diseases that affects leaf index and consequently affect the crop yield. Despite these model limitations PARCHED-THIRST model reasonably simulated the soil-water variation and crop yield for different crop management practices in all the experimental sites with an acceptable precision, shown by statistical performance. Furthermore, agricultural policies that target in-field rainwater harvesting such as planting basins and ridges improve crop yields in semi-arid areas, thereby improving rural livelihoods. Although detailed impacts of nutrients on crop yield where not investigated, it should be appreciated that nutrients also play a major role in enhancing crop water unptake (Barron and Okwach, 2005; Wade et al., 1998).

In addition, results on the hydrology model showed that the streams are ephemeral, no dams to store high streamflows and there is water scarcity in the area. Hence, construction of farm dams and small reservoirs will regulate streamflows and enable supply of supplemental irrigation. The SWAT was able to simulate reasonably streamflows in the study area shown by acceptable statistical performance.

Both the crop and hydrology models were able to represent the study site conditions after calibration and validation. This suggests that these two models were now suitable to be coupled with together and with other models to form an integrated model for the study site to enhance decision-making.

Chapter 6: Application of Olympe and PARCHED-THIRST models in farm systems modelling

6.1 Background

Food security and sustainable farming (FAO, 1996) have been the focus of a number of domestic (DWAF, 2004a) and international policy initiatives such as the Millennium Development Goals (United Nations, 2007, 2005, 2004). This has been triggered by population growth and the consequent increase in food demand (UNDP, 2006; Weibe, 2002). However, challenges remain with more than 800 million people undernourished, mostly smallholder farmers from Africa and Asia (Weibe, 2002).

For many of these smallholder resource-constrained farmers, food security depends on farm production and income from agriculture (World Bank, 1986). Bonti-Ankomah (2001) defined family food security as access by all family members at all times to adequate, safe and nutritious food for a healthy and productive life. Thus, smallholder farmer food security consists of the ability to produce own sufficient food through agriculture and access to disposable cash to purchase food items at markets.

Smallholder farmer systems in the Olifants River Basin of South Africa are characterised by low yields and high risks of crop failure, thereby posing a grave threat to family food security. Their performance with respect to food production and farm profitability is poorly understood. Therefore, to address the food security threats at farm level in the Olifants River Basin and in particular, B72A catchment where agriculture substantially contributes to the total family income requires an improved understanding of the dynamic links between farming practices, land, economics and food security.

Furthermore, farmers in B72A catchment are at high risk of crop failure due to continued trend in erratic and uneven distribution patterns of precipitation during the growing season (Magombeyi and Taigbenu, 2008; Berry et al., 2006; Botha et al., 2003; Stern et al., 1982). Besides climatic threats to food security, Bonti-

Ankomah (2001) and Graves et al. (2007) argue that socio-economic factors have a greater influence on food security at farm level. They noted that a country's ability to produce sufficient food does not necessarily guarantee food security if strong social welfare nets do not support families unable to produce or buy enough food.

An improved understanding of how agricultural production affects food security through its impacts on both food supplies and family incomes, and how food security in turn influences farmers' decisions about farming is effectively achievable by simulation modelling (Penot et al., 2004; Matthews et al., 2000). Although these simulation studies have been performed to improve farming practices (Le Bars and Le Grusse, 2008; Tittonell et al., 2007a, 2007b; Tittonell et al., 2005; Carberry et al., 2002; Keating and McCown, 2001; Matthews et al., 2000; Pannell, 1996; Berdegue et al., 1989), several failures in farm technology adoptions were attributed to poor understanding of farming systems and the context of farmers (Biggs, 1995).

Furthermore, from the literature surveyed, farming practices simulation with farmers has not been applied in South Africa and not much in Southern Africa. Hence, studies like this help to understanding local farming systems performance under hazards and farmers' strategies in different contexts (biophysical and socio-economic). This enables timely improvement and better adoption of technology innovations and consequently improves family food security.

The purpose of this chapter is to ascertain the effect of climate-induced risks and fluctuating farm input/output prices on farm gross margin and food security for five smallholder farming systems in B72A catchment in Limpopo Province of South Africa. Through a biophysical model, PARCHED-THIRST and a socio-economic farm systems simulation model, OLYMPE, the performance of identified farming practices based on maize yield, gross margin and total family balance over a 10-year period were evaluated.

The results of this study are useful to smallholder farmers and extension officers in providing quantitative information on profitability of alternative farm enterprises or management strategies necessary to improve current farming systems. Farming systems in need of technology investments are identified and projections of food productions under threats explored for planning purposes. This chapter results feeds into a broader integrated model, ICHSEA applied in chapter seven.

6.2 Framework for the assessment of smallholder farming system risk

The five identified farming systems under the homestead apply different agricultural management practices that give rise to different crop yields. Different crops yields and family food needs (dependent on number, composition) are compared. The excess crop yield, above family needs, maybe sold to get disposable cash to buy other services. In the case of food needs exceeding available yield, the farmer has to augment the family food supply from other sources of income. Depending on levels of food production, disposable income and new knowledge of the farmers, they can change crop management practices in the next season to increase chances of high crop yield and disposable income. Hence, there is a cyclic relationship shown in the framework in Figure 5.1 that formed the basis for evaluating risk of farmers to meeting food security under climate and market (maize grain, maize seed and fertiliser) shocks.

It is noted that feedbacks between the different components can occur within the framework and will be better captured in the integrated model interface (ICHSEA) presented in the next chapter.

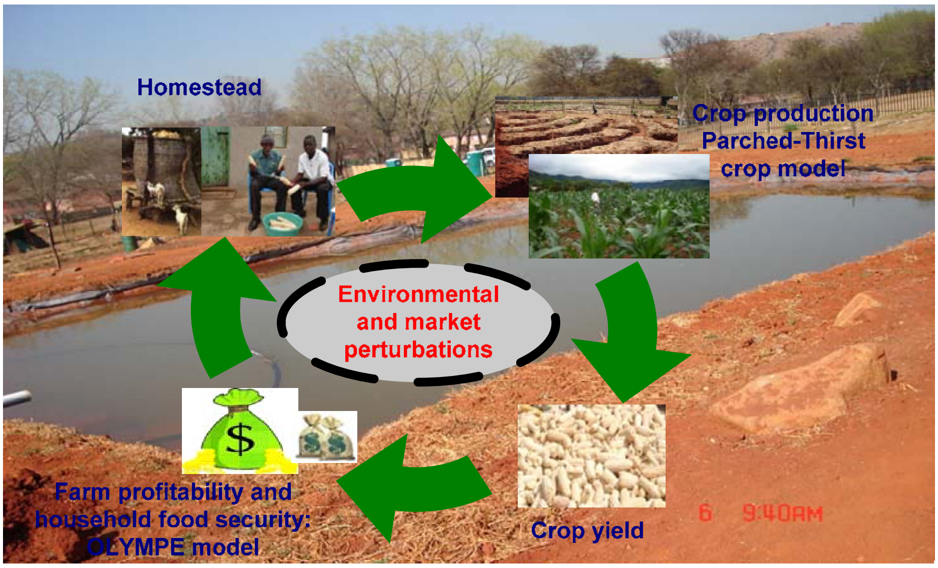


Figure 6.1 Framework for assessing smallholder farming system risk to climate and market shocks.

6.3 Methods

The main method employed to evaluate farming systems production performances is the OLYMPE model. Determination of the profitability of different farming systems comprised three steps, that is: 1) using identified farm typologies to define the typical farming systems in the socio-economic model, Olympe 2) applying a biophysical model, PARCHED-THIRST to determine yields for farming systems, and 3) employing Olympe to determine the financial effects under different scenarios (climate and market prices) at farm-scale. Detailed descriptions of the OLYMPE and PARCHED-THIRST models features were presented in the literature review sections and will not be repeated here.

6.3.1 Maize crop yield modelling

The relationships between rainfall and crop yields for each farm typology (crop production functions) required for the farm simulations were deduced from observed data on maize crop yield, evapotranspiration and rainfall over three years (2005—2008) presented in Chapter 5. The observed data were extrapolated using PATCHED-THIRST crop model (Mzirai et al., 2001), calibrated for the study area.

6.3.2 Indicators used for farming systems performance assessment.

Performance evaluations of different farming systems based on annual gross margin (gross income at farm gate prices less variable costs) were carried out. The gross margin (output from Olympe) excludes farm's fixed costs, therefore does not measure farm profit. The total net income is shown in Equation 6.1.

Net farm income + non-farm income = Total family income (6.1)

where net farm income is the combined variable and fixed costs subtracted from the total farm output.

Fixed costs remain constant irrespective of the level of output produced, such as depreciation of equipment, rent etc. Variable costs vary directly with the level of output, for example costs of fertiliser, seed and insecticide. The total family income less total family expenses gives the total family balance. The cost of maize grain proportion consumed by the family was accounted for in the family expenses account.

The ability of a farming system to maintain a stable positive gross margin under adverse market prices and climate conditions such as droughts and floods is the farm resilience.

6.3.3 Labour and return-expense ratio calculations from Olympe outputs

The ratio of total farm output to number of available workers gives returns on labour. The available family labour used was based on an average throughout the whole year. The ratio of total farm outputs to total expenses estimates returns per unit expense.

6.3.4 Minimum recommended household food expenditure.

A threshold for family income was calculated based on the minimum recommended daily dietary requirement of 2 261 kilocalories per person in South Africa (Bonti-Ankomah, 2001), and extrapolated to the family unit by the number and composition of family members (Dogliotti et al., 2005). Thus, the minimum per capita expenditure to meet this recommended dietary intake in South Africa was US$ 32 (2006) per month. The food expenditure for the farm family was adjusted to 2008 prices by an average (2005–2008) yearly food consumer price index of 10 % in South African rural areas (Nkgasha et al., 2008). Accordingly the minimum annual food expenditure for a farm family of five persons (Magombeyi and Taigbenu, 2008) in the study area was therefore estimated at US$ 2 542 (2008), assuming that household expenditure grew by the yearly inflation rate.

6.3.5 Scenarios tested

Two types of scenarios were tested. The first set of scenarios compares the maize productions under two different crop-water management practices and their subsequent impact on economic farming system performance. The two management practices are current practices and improved crop water management practices (Figure 6.2 in the form of chololo pits. Both practices were tested under average climatic conditions and severe drought/flood conditions using the simulated 10-year rainfall series. The second set of simulations, analyses the impacts of inputs (fertiliser and seed) and output (maize grain and livestock) price variation on farm performances separately and in combination.

In the all scenarios, impacts of the main crop, maize, were analysed, while the other crops were kept at the base-year (2008) production levels and prices. The 10-year simulation period ensures coverage of low and high price variations, and different climatic years, but these years are not necessarily the next 10 real years. The detailed scenario descriptions and simplifying assumptions are described in the next sections and summarised in Table 5.1.

6.3.6 Maize yield variation under different production practices.

Current crop management practices involve ploughing, levelling and sowing the maize seeds, while planting basins involve the digging of pits (of 0.22 m diameter, 0.3 m depth, spaced at 0.6 m within rows and 0.9 m between rows) and planting two to three maize seeds per pit (Mati, 2005). The planting basin technique captures and stores more rainfall than the current crop management practice resulting in more water to the crop roots and possibly higher yields.

Using 10-year (2009—2018) rainfall generated from PATCHED-THIRST model weather generator, maize yield varied within the range (7—249 %) and (76—576 %) of the long-term average yield of 0.5 t/ha in the area for current and planting basins practices, respectively. The planting basins improved the yields by more than fivefold in above average (600 mm) rainfall years, while in below average rainfall seasons maize yield stabilised to about 76 % (Figure 6.2) of long-term average yield, which is better than the current practice. This suggests that the risk of current crop management practices is higher compared to the improved technology of planting basins in the area.

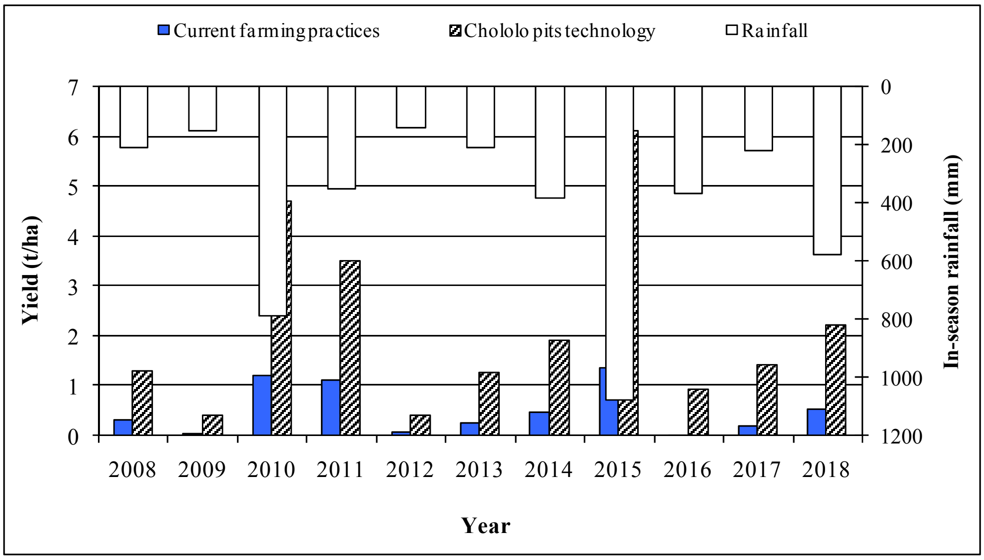


Figure 6.2 Maize yield variation under current and *chololo pits/* planting basins crop management. The average (n = 10 years) yield is 0.5 t/ha and 2 t/ha for current and planting basins practices, respectively.

6.3.7 Maize and fertiliser price variations

The yearly variations in market prices of maize grain, fertiliser (top dressing and basal (N=3: P=2: K=1)) and maize seeds were estimated for the simulation period (2009—2018) based on the historic trends observed during the period 1990—2008 (NAMC, 2008; OECD-FAO, 2008; SAFEX, 2008). The choice to analyse input of fertiliser was based on its largest (39.3 %) contribution to total variable farm input costs in the region (NAMC, 2008). Short-term (less than a year) price variability is not included in this study.

Four scenarios of maize price were considered: current trend, high price, low price and OECD-FAO outlook (OECD-FAO, 2008). The high and low price series scenarios were derived from Monte Carlo simulation (van der Sluijs et al., 2004) using Microsoft Excel (Wittwer, 2004) based on historical prices. The highest historical grain price (US$ 190/tonne) was taken as the lower bound for maize high-price scenario, while the upper bound was taken as twice the highest historical value (with the assumption that the prices doubles). Under the low-price scenario, the upper and lower bounds prices were taken as the lowest historical price (US$ 91/tonne) and twice the lowest historical price, respectively.

In addition, the maize grain price-variation is defined in relation to the current price US$ 228/tonne (2008) paid for maize grain to farmers without an increase in its quality or quantity. The maize grain price range is 40—98 % for the low price scenario, 84—121 % for the current price trend, and 88—157 % for high price variation (Figure 6.3a). The OECD-FAO outlook price variation is not discussed further as the price variation lies between the low and high price scenarios. The maize price hikes are attributed to raising fuel prices and decreased production.

Annual fertiliser and maize seed price variation scenarios under current trend and high price are presented in Figure 6.3b. The lower price bound was the 2008 price, while the upper bound was three and half times the 2008 price for high fertiliser and maize seed price variations. The fertiliser price variation ranges are 100—267 % of the 2008 price of US$ 0.46/kg for the current price trend and 88—157 % for high price variation for the 10-year simulation period. The maize seed price variation ranges are 54—76 % of the 2008 price of US$ 0.83/kg for the current price trend, and 96—192 % for high price variation for the 10-year simulation period.

Different fertiliser producers tend to release new improved fertiliser types and various package sizes on the market for trials by farmers. Consequently, it is difficult to monitor the fertiliser prices due to continuous injection of new products into the market. Therefore, the fertiliser and maize seed price fluctuations depicted in Figure 6.3b only provides a general trend (NAMC, 2008). The high price fertiliser variation is analysed.

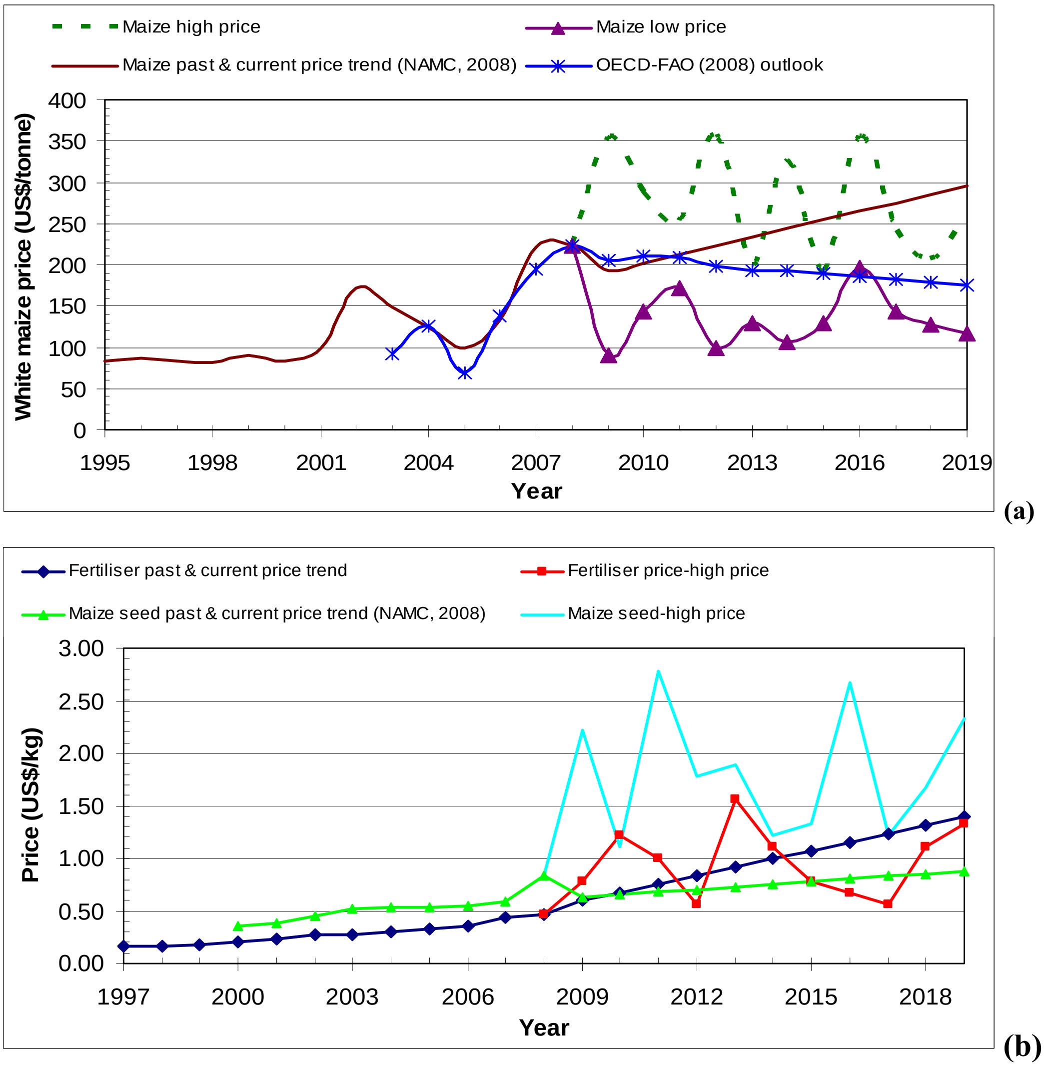


Figure 6.3 (a) Annual maize price variation scenarios under current trend, high price, low price and OECD-FAO (2008) outlook; (b) Maize seed and fertilizer price scenarios for current trend and high prices.

In a more holistic approach a combined scenario of input and output price variation was tested. Under this scenario, farm outlook is assessed assuming crop management under planting basins technique and maize grain, fertiliser and maize seed prices following the current trend.

The production behaviour of each farm typology was explained by the socio-economic farm characteristics derived from surveys. The economic values were based on 2008 exchange rate, 1US$ was equivalent to ZAR 9 (SAFEX, 2008). A summary of the scenarios is presented in Table 6.1Table 6.1.

6.3.8 Assumptions on scenarios

Under the different maize production scenarios, it was assumed that changes in maize yields are only due to changes in productivity of the land. In this study, maize yields changed because of new technology developments in water, land and crop management. Furthermore, there is an increase of maize production without maize yield quality changes under the planting basins technology. Farm labour, soil quality and crop area place limits on farm production, and were assumed to remain constant over the simulation period.

Under maize-price variation scenario, other factors (costs of inputs, labour, productivity) were kept at base-year level (2008). Fertiliser-price variation simulations were applied without changes in fertiliser quantities or quality and other input costs were kept at the base-year level. For all the simulations, the crop mix of each farm typology was assumed to remain constant, while physical conditions at farm scale are assumed spatially homogeneous. This meant that adaptations of farmers to changes in their economic environment, such as through crop type change were not considered. Finally, number of family members and grazing availability on farm is assumed to remain constant over the simulation period.

Table 6.1 Summary of scenarios tested.

Variables	Scenarios										
	1	**2A**	**2B**	**2C**	**3A**	**3B**	**3C**	**4A**	**4B**	**5**	**6**
Yields											
- Current management practices and average long-term yield	X				X	X	X	X	X	X	
- Current management practices and climate variability		X									
- Improved management practices and climate variability			X								X
- Current and improved practices and extreme drought/flood conditions				X							
Maize grain price											
- 2008 price	X	X	X	X				X	X	X	
- Long term current trend					X						X
- Low price						X					
- High price							X				
Fertilizer and maize seed price											
- 2008 price	X	X	X	X	X	X	X			X	
- Long term current trend								X			X
- High price									X		
Cattle price variation										**X**	

6.4 Results

6.4.1 Farming system performance under average historical maize yields (Scenario 1).

The annual farm gross margin under historic (past 5 years) yields varies from – US$ 902 to US$ 481 (Figure 6.4a) and the total family balance variation was from – US$ 218 to US$ 10 857 (Figure 6.4b). Farm Types B and C performed very poorly as indicated by their negative gross margin, implying variable production costs exceed the gross farm income and own production is insufficient to adequately support the household. Therefore, the farm is economically unsustainable in low yield years as 2008 (Figure 6.2) and are deteriorating their assets. Therefore, this farm types are highly vulnerable to food insecurity. However, farm Type C, had a positive total family balance (US$ 1 098) because most of the family income (73 %) is realised from employment outside farming, implying that the agricultural component of the production system is not sustainable.

Farm Type B experienced a negative (–US$ 100) total family balance, implying food shortage by this amount. Hence, Type B farmer has to source income outside farming to secure family food. The negative total family balance could be a stimulus to farm Type B to change to better farming practices to mitigate against crop failure or take up employment elsewhere. Farm Type E had the highest gross margin mainly from sales of high livestock units (Table 5.1Table 5.1). The Figures 6.4a and 6.4b reveal that the farm Type E and Type A with the highest and second highest total family balance (Figure 6.4b), respectively, are most resilient to crop failure than other farm types as they do not depend much on crop production. The results from farm Type E suggest that gross margin from livestock production is more stable than from crop production (in other farm Types) especially in dry years.

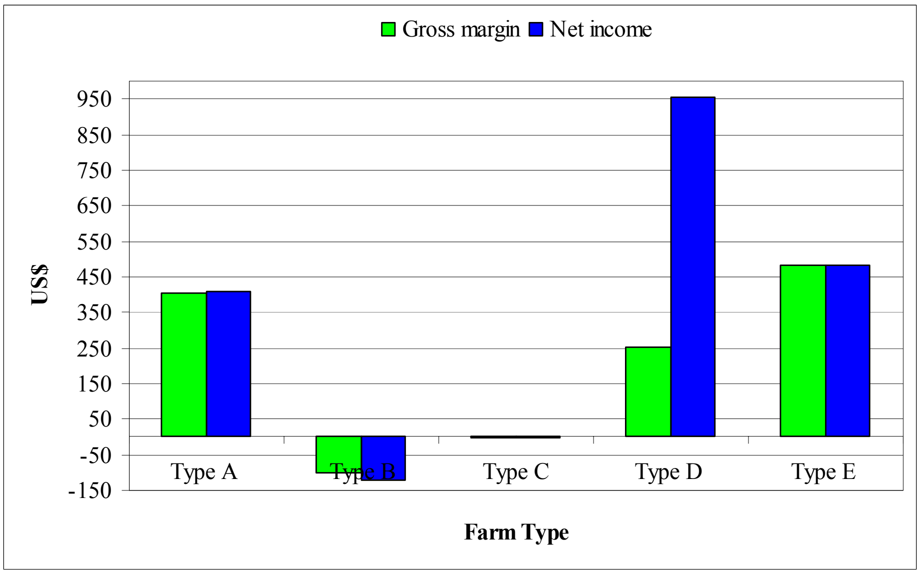


Figure 6.4 (a) Average (5 years) annual farm gross margin and net income

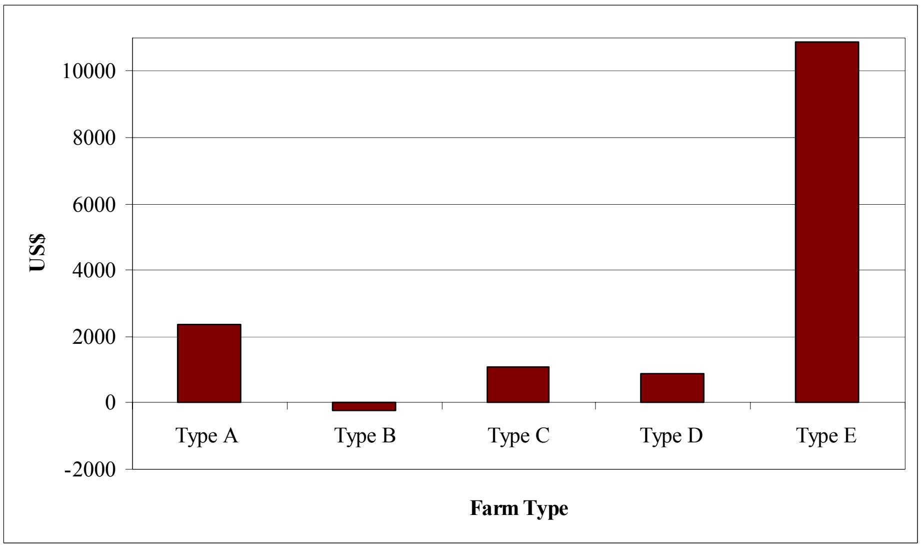


Figure 6.5 (b) Average annual (5 years) total family balance.

Manpower required (mandays) for farm activities including the available labour and return-expense ratios (Table 6.2) were calculated from OLYMPE model results and farm systems characteristics (Table 5.1). Available family labour was based on a yearly average because family labour is seldom accurate. Farm Type E, the livestock keepers showed the highest return on labour (US$ 363/capita.year) followed by Type D (US$ 233/capita.year) and Type C (US$ 173/capita.year).

The gross margins were US$ 430/ha, –US$ 100/ha, –US$ 0.44/ha, US$ 209/ha and US$ 238/ha for farm Types A, B, C, D and E, respectively. Farm Type A had the highest gross margin/ha because of the small cultivated area (Table 6.2). In addition, the return-expense ratios ranged from 0.8 for farm Type B to 3 for Type E. Farm Type E had the highest return-expense ratio, followed by farm Type A (1.9) and farm Type D (1.4), with diversified crops and a small number of livestock units. High return-expense ratios are desirable as they indicate that expenses are low relative to the revenue they produced. However, when these ratios are too high, one cannot tell whether it is because of a combination of low revenues and low expenses.

In sum, farm Types B and C had the lowest labour return and lowest return-expense ratio, implying farm diversification and intensification could be attractive strategies to resuscitate the two farming systems. However, the object of choosing a crop management technique can be decided based on family labour availability. If the available labour is exceeded, it becomes important to know when and by how much additional labour cost is required.

Table 6.2 Base year labour and indicator ratios for the farm types calculated from OLYMPE model results and typology characteristics (Table 5.1).

Variable	Farming systems				
	Type A	Type B	Type C	Type D	Type E
Labour Requirement/season (hours)	259	284	416	363	53
Farm size (ha)	0.94	1.01	1.54	1.21	2.03
Total workers available (family + hired)	7	6	3	4	2
Hired workers	1	1	0	3	1
Used labour/season (h/ha)	276	281	270	300	26
Shortage of labour	No	No	No	Yes	No
Total farm expenses (US$)	429	472	519	680	244

Variable	Farming systems				
	Type A	Type B	Type C	Type D	Type E
Total farm outputs (US$)	833	371	518	934	727
Farm gross margin (US$)	405	-100	-1	253	482
Farm gross margin (US$/ha. season)	430	-100	0	209	238
Return on labour (US$/capita. season)	119	62	173	233	363
Return-expense ratio	1.9	0.8	1.0	1.4	3

6.4.2 Farming systems comparisons under different maize production practices (Scenarios 2).

Farming system performance under current crop management practices (Scenario 2a).

The Figures 6.5a and 6.5b show scenario of gross margin and total family income variation under current crop management.

Type B farmer performed worst, with gross margin range of (–US$ 180— US$ 434), while Type E performed best, with gross margin range of US$ 478— US$ 896. Farmer Type D performed second best with gross margin range of US$ 148 — US$ 828 (71—394 %) and total farm margin (75—139 %) of 2008 figures. The negative gross margin is indicative of unprofitable farming and own production is insufficient to adequately support the household. Hence, the farmer has to look elsewhere to meet the shortfall in order to satisfy the family needs. The gross margin under Type E farmer is not affected much by the variability in maize yields. Taking 2008 as the base-year, the observed farm Type E gross margin variation (99—184 %) and total family balance only varied by 1 % (103—104 %). Similarly, farmer Type A had gross margin variation (88—138 %) and total family balance variation of (98—101 %). The different response to current production practices by farm Types A and E is attributed to the stable income from high number of livestock units under farm Type E (Table 5.1).

Livestock was less affected compared to crop production by the erratic distribution of rainfall and dry spells responsible for poor yields in the study area, except in extreme drought conditions. Type A and B had the highest variability of gross margin and total family balance (–118—150 %). The variation of gross margin and annual family income depicts a similar trend. However, it was noted that farmer Type D was no longer second best (Figure 6.5b) in terms of total family balance, but farmer Type A, because of the large contribution of employment (73 %) to family income.

The results indicate a possibility for farm-based households to realise higher total annual family income than households with full-time employed members in above average rainfall years. The drastic drop in gross margin in 2009 (Figure 6.5a) was due to a severe drought (Table 6.2) or a major disaster such as floods that cause enormous damages to crop and livestock production. All farmers recovered in the subsequent year, but it might sometimes take 2—3 years to recover from such devastating disasters because of resource limitations to rehabilitate damaged infrastructure.

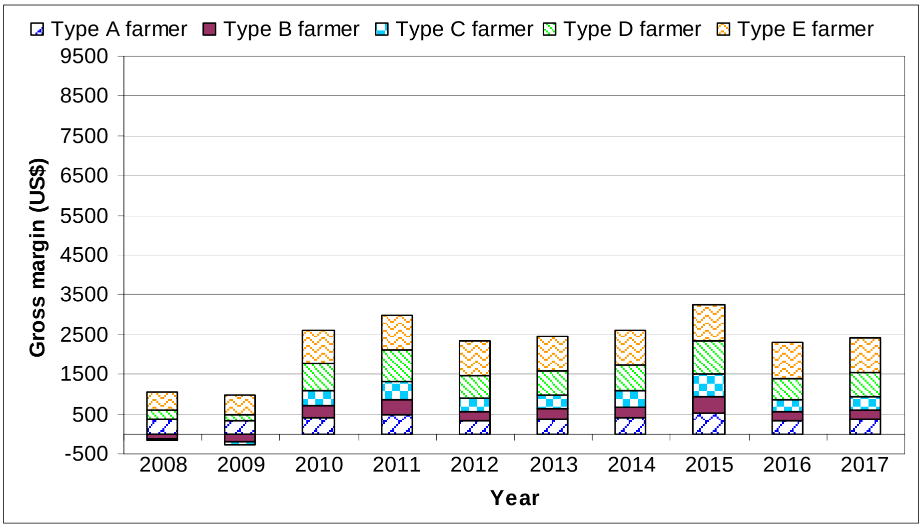


Figure 6.6 (a) Projected annual gross margin under current maize crop management and rainfall variation.

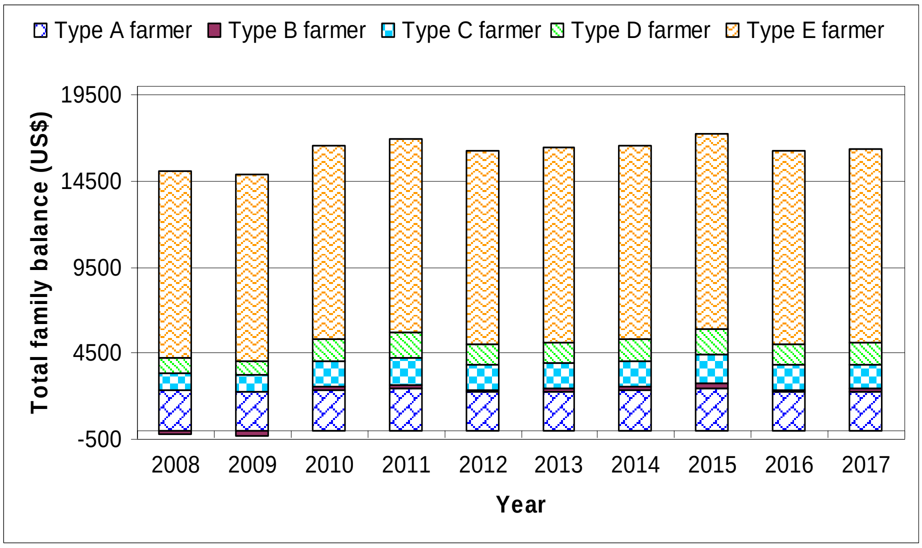


Figure 6.7 (b) Projected total family balance under current maize crop management and rainfall variation.

Farming system performance under planting basins (Scenario 2b).

Figures 6.6a and 6.6b show gross margin and total family balance for maize productions under planting basins crop management scenario. The annual yield variation under planting basins was presented in Figure 6.2. The variations based on 2008 figures were: Type A farm gross margin (76—192 %), total family balance (98—119 %); Type B (–177—412 %), total family balance (–218—699 %); Type C (–18—815 %), total family balance (86—186 %); Type D gross margin (55—368 %), total family balance (82—205 %). Type E farm gross margin variation (98—209 %) and total family balance (100—104 %) remained significantly unchanged from the current management results (Figures 6.5a and 6.5b).

Farm Type B performed worst under this scenario, as shown by the negative gross margin (Figures 6.6a) and negative total family balance in the first two years of simulation (Figure 6.6b). The planting basins outperformed the current crop management practices in the study area, even during the severe drought year of 2009. Furthermore, planting basins consistently reduced variability of farms' gross margin and total family balance during the 10-year simulation period.

Hence, planting basins can significantly improve food security provided a threshold rainfall amount is received.

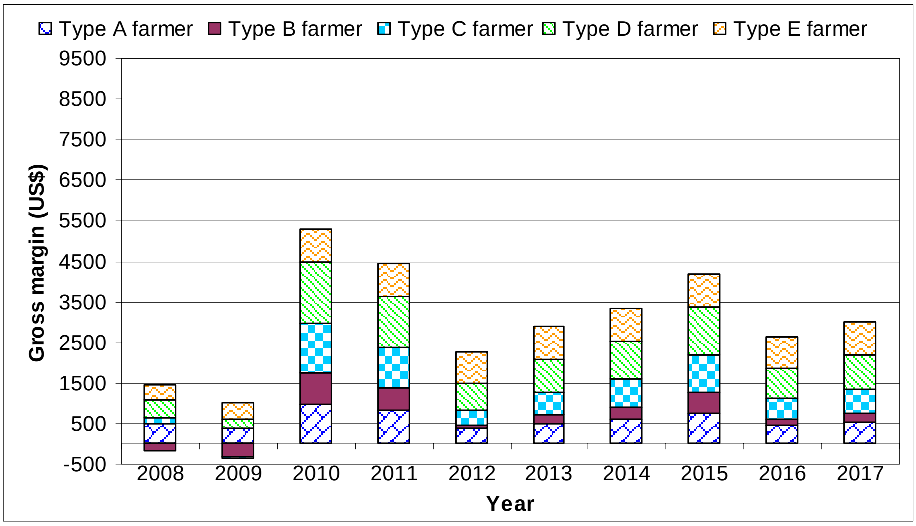


Figure 6.8 (a) Simulated farm gross margin under *chololo pits/* planting basins technology and rainfall variation.

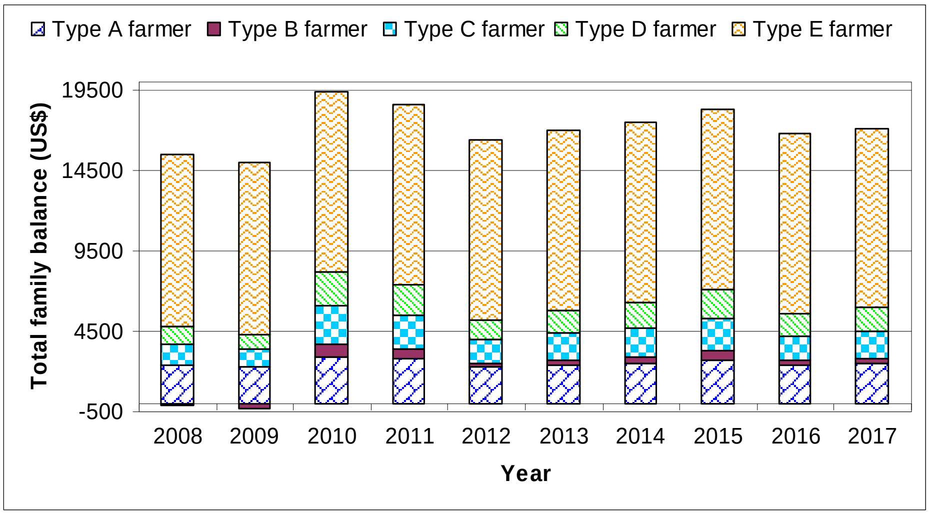


Figure 6.9 (b) Projected farm total family balance under planting basins technology and rainfall variation.

6.4.3 Farming system performance under severe drought/flood (Scenario 2c).

The scenario of farmers under a severe drought/ flood in the year 2009, when no maize grain was harvested is shown in Figures 6.7a and 6.7b. The scenario was of interest as the Limpopo River Basin, where Olifants River is a sub-basin, is under constant threat from El Nino conditions, such as the 2000 cyclone. The effect of the flood reduced crop yield to below 20 % of the average long-term yield (0.5t/ha) and in some areas complete crop failure was noticed.

A sharp drop in gross margin was observed (Figure 6.7a) and a decrease in total family balance (Figure 6.7b) in the cyclone year (2009) for all the farm types, with farm Type B most affected (gross margin (–US$ 359) and total family balance (–US$ 291). The gross margin declined by 55 % and 22 % compared to base line (2008) figures for Type A (US$ 405) and Type E (US$ 483) farmers, respectively. Farm Types C and D had negative gross margin of –US$ 428 and –US$ 33, respectively. Despite having negative gross margins, farm Types C and D had positive total family balance of US$ 670 and US$ 612, respectively due to additional farm family income from pensions, remittances and grants.

Furthermore, farm Types B, C and D showed negative gross margin as expenses exceeded sales. Farm Type C had the largest negative gross margin value (–US$ 428), implying that the farmer had the largest loss on the farm enterprise, hence, was unable to meet family food requirements. The total family balance declined by 9 %, 732 %, 38 %, 31 %, and 1 % for farm Types A, B, C, D and E, respectively. The percentage decline in total family balance represents the contribution of maize grain production to the total family food security.

The results indicate the importance of supplementing the total farm balance from other sources outside farming such as employment. This appears to be a viable livelihood strategy in drought/flood-prone Olifants catchment. Farm Types A and E realise > 70 % family income from employment, while social welfare grants from government serves as safety nets for rural resource-constrained farmers (Table 5.1).

Under farm Types E and D, livestock consistently stabilised farm gross margin. However, farm Types E and D revealed susceptibility to extreme events such as floods and extended droughts that could destroy livestock or reduce price of livestock units due to poor health. Therefore, in extreme events, such as floods, all the farmers have trouble feeding their families from farm production. Farmers without regular income from employment suffered the most and had to rely on pensions, off-farm income activities, remittances and social welfare grants (Table 5.1). In addition, social support from government and donors as either food or cash enables food market access by the farmers.

The order of vulnerability of farm types to severe drought starting with the most vulnerable is B, C, D, A and E. Farm Type B is most vulnerable because it derives about 88 % (Table 5.1) of total family income from crops. When compared to other shocks in a farming systems, severe drought/flood results in the most decrease in gross margin and total family income, partly due to loss of production for own consumption.

The loss of production triggers increased expenditure in buying food from the market and consequently, price hikes of maize grain at local and regional level. OECD-FAO (2008) and OECD (1999) argue that the supply-side affected by production shortfalls in cereals by exporting countries set a stage for global rapid price hikes in the last three years as global stock levels slumped. Similarly, timing of Asian monsoon rains impact price variability of agricultural commodities (OECD, 1999).

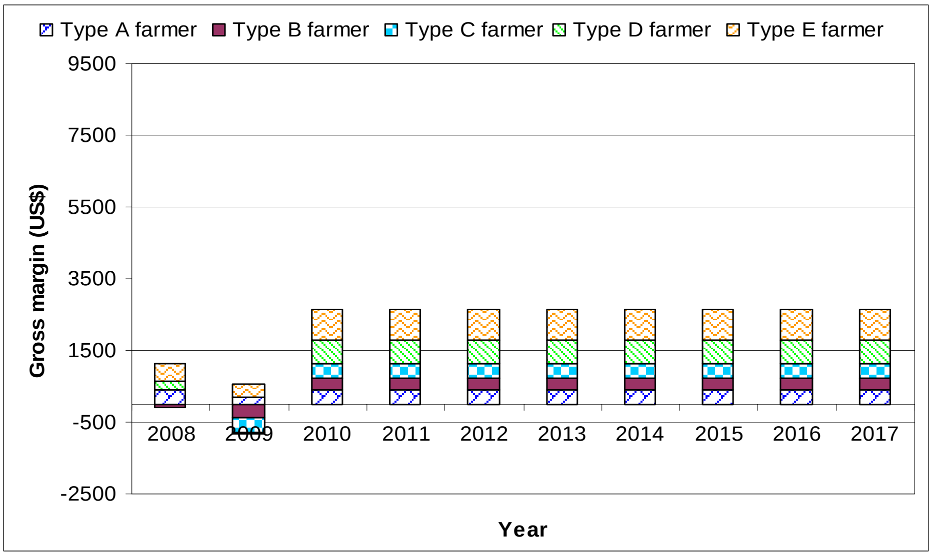


Figure 6.10 (a) Projected annual farm gross margin under low maize production.

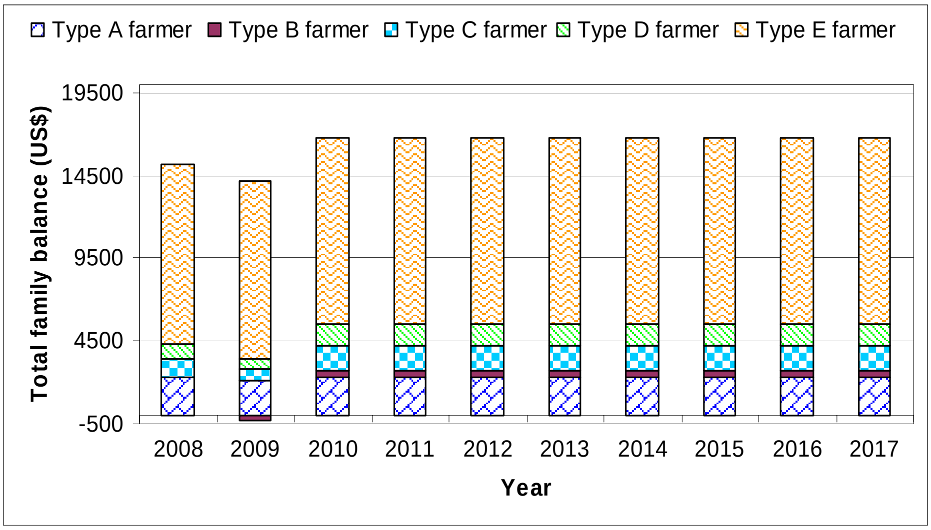


Figure 6.11 (b) Projected farm total family balance under low maize production.

6.4.4 Farming system performance under maize grain price variation.

Farming system performance under current maize grain price trend (Scenario 3a).

The gross margin and total family balance variation under current price trend of maize (Figure 6.3a) are shown in Figures 6.8a and 6.8b. The farm Type A gross margin variation is (96—105 %) and farm Type B (–113—318 %) of the 2008 base line figures. Farm Type D showed highest variation (98—149 %) in total family balance, while farm Types A (99—101%) and E (100—111%) were not significantly impacted by maize price variation compared to farm Types B and C which rely mostly on crop production. Farm gross margin showed a similar trend to total family balance.

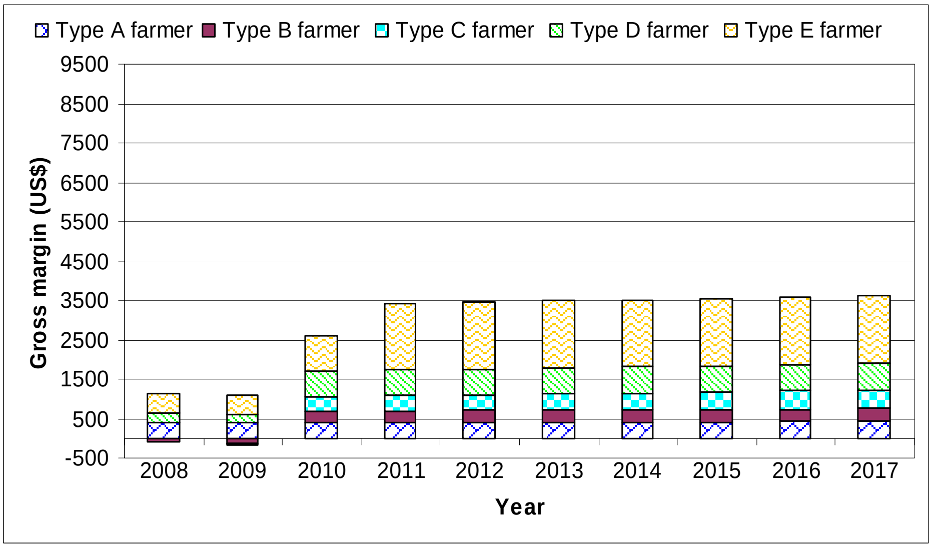


Figure 6.12 (a) Projected annual farm gross margin under current trend maize price variation.

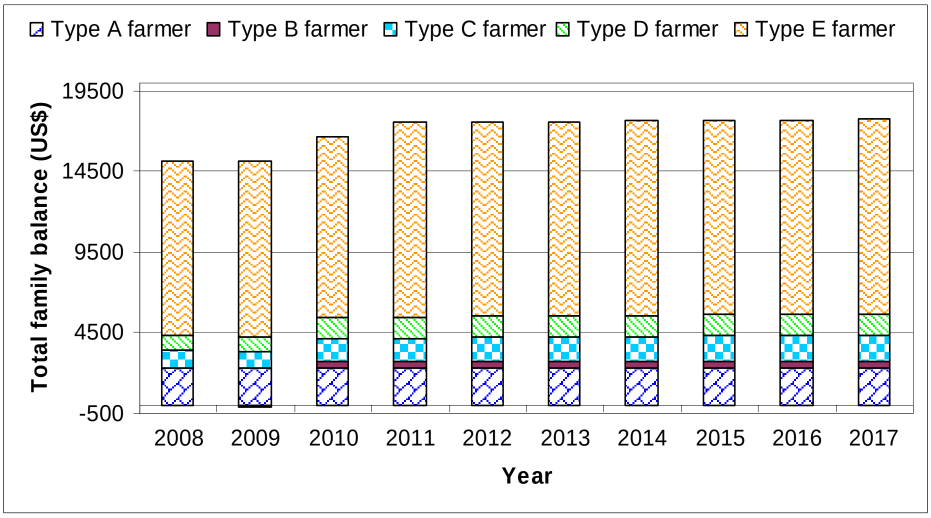


Figure 6.13 (b) Projected farm total family balance under current trend maize price variation.

Farming system performance under low maize grain price variation (Scenario 3b).

The gross margin and total family balance variation under low maize price scenario (Figure 6.3a) are presented in Figures 6.9a and 6.9b. The low price scenario mostly affected farmer Types B and C. Farmer Type C derive 52 % of total family balance from pensions and farmer B derive 88 % from agriculture.

Farmer Type D performed best on gross margin because of its crop diversification (Table 5.1) that compensated for low maize prices. These results suggest that crop diversification can reduce vulnerability to family food security.

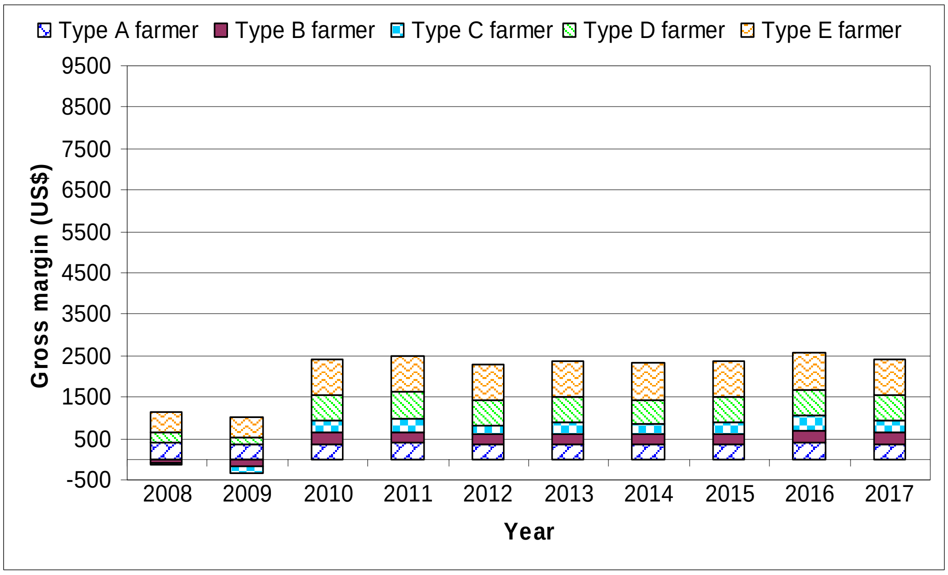


Figure 6.14 (a) Projected annual gross margin under low maize price variation.

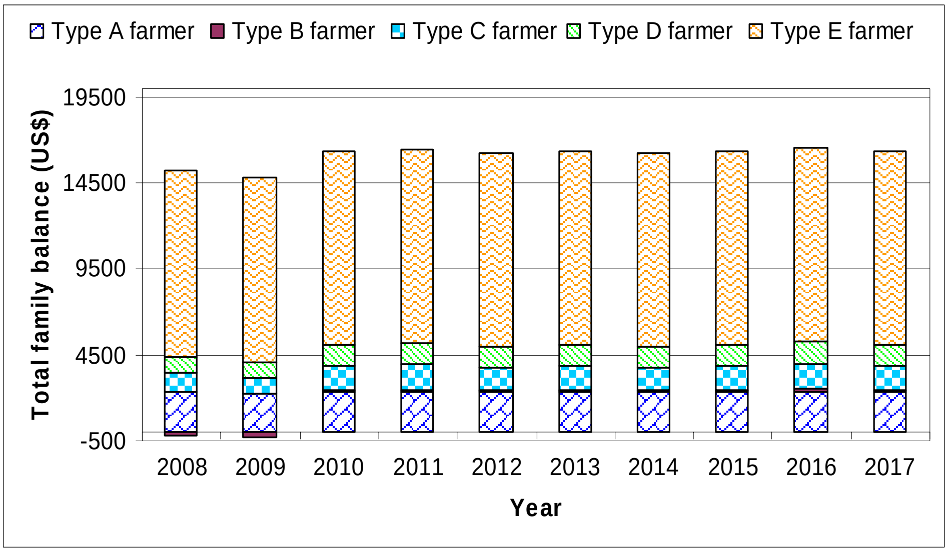


Figure 6.15 (b) Projected total family balance under low maize price variation.

Farming system performance under high maize grain price variation (Scenario 3c).

The gross margin and total household balance variation under high price of maize (above US$ 228) (Figure 6.3a) are shown in Figures 6.10a and 6.10b. Least variation (10—29 %) in gross margin (Figure 6.10a) for farm Type A was noted compared to the 2008 figures. Farm Types B and C total family balance varied (–72—154 %). Farm Types B and C were the most affected as they experienced negative gross margin and total family balance (Figures 6.10a and 6.10b). Therefore, farm Types B and C are most susceptible to maize price inflation shocks, while farm Types D and E are the most resilient to maize price inflation shocks.

In addition, farm Type D is the second most resilient because of its diversification and intensive farm practices (Table 6.2), with the income stabilised by other crops such as vegetables, groundnuts and sugar beans. High livestock units (12.09) (Table 5.1) that were liquidated to provide cash, made farm Type E the most resilient to maize price shocks. The negative gross margin under farm type A indicates family food insecurity and requires the farmer to source extra cash elsewhere to secure family food requirements.

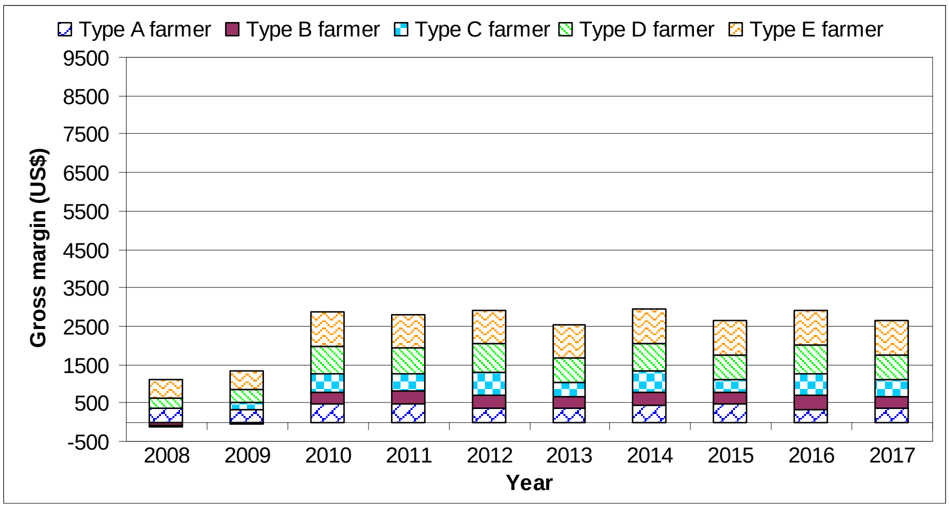


Figure 6.16 (a) Projected annual gross margin under high maize price variation.

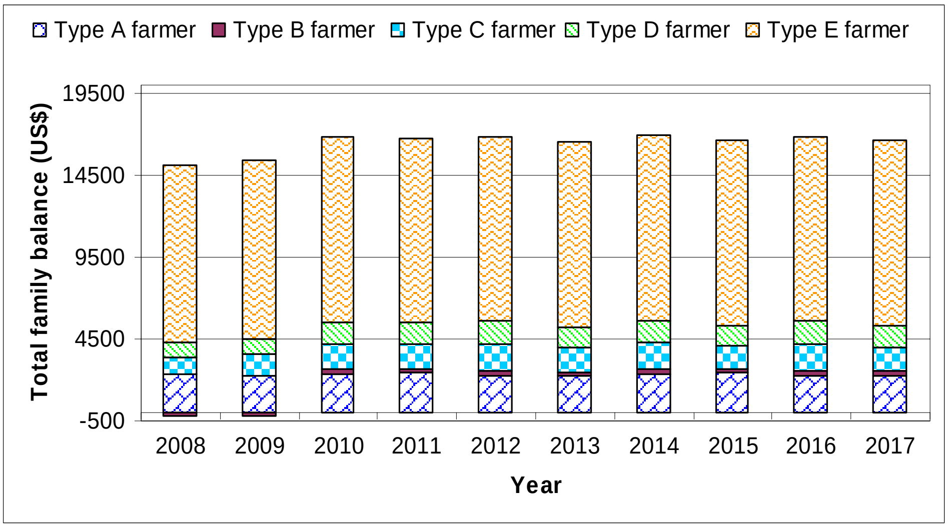


Figure 6.17 (b) Projected annual total household balance under high maize price variation.

6.4.5 Farming system performance under fertiliser price variations.

Farming system performance under current trend fertiliser price variation (Scenario 4a).

The fertiliser price variation under current trend and high prices was presented (Figure 6.3b). The results of the current trend fertiliser price variation scenario are shown in Figures 6.11a and 6.11b. Farm Type D, with highest quantity of fertiliser use (190 kg/ha) (Table 5.1) showed highest variation (100—260 %) and (100—145 %) in gross margin and total family balance (Figures 6.11a and 6.11b), respectively. In addition, farm Types A, B, C and E showed (100 %), (–100—305 %), (–183—605 %) and (100—184 %) change in gross margin compared to 2008 figures. Farm Types B and C were most affected as they apply fertiliser in irrigated plots that produce half of their annual income, while farm Type A was not affected because of its low fertiliser usage (Table 5.1).

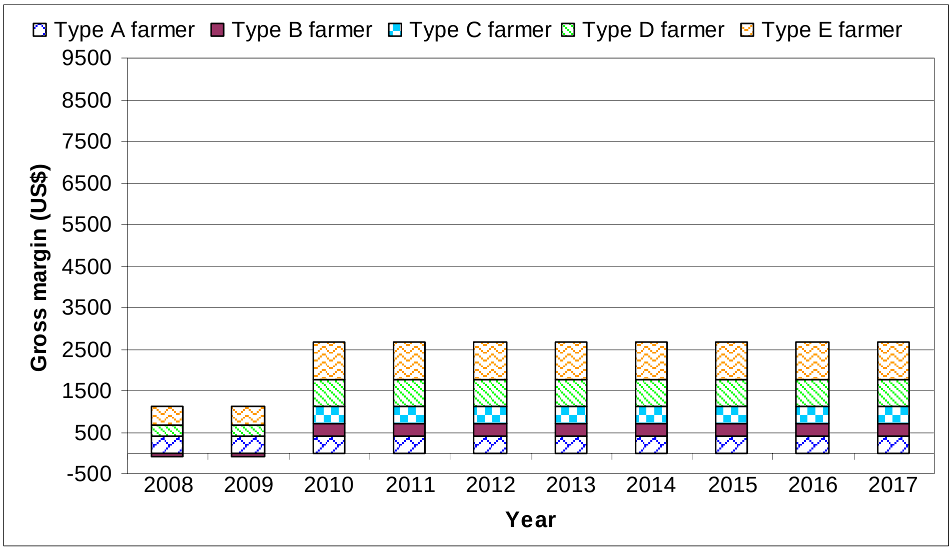


Figure 6.18 (a) Projected annual gross margin under current trend of fertiliser price.

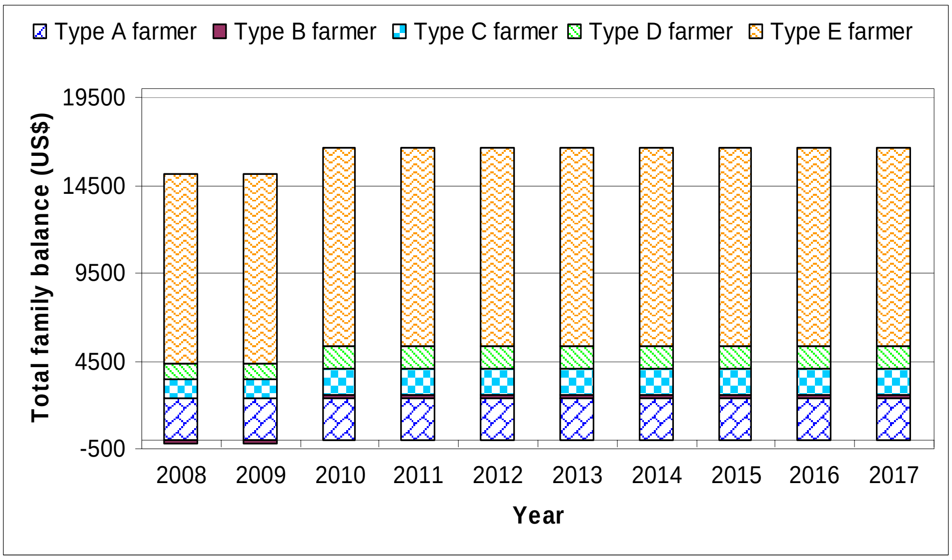


Figure 6.19 (b) Projected annual total family balance under current trend of fertiliser prices.

Farming system performance under high fertiliser price variation (Scenario 4b).

Comparing the scenarios of fertiliser under current price trend (Figures 6.11a and 6.11b) and high prices (Figures 6.12a and 6.12b), it was noted that in both scenarios the fertiliser price variation (Figure 6.3b) did not affect gross margin and total family balance for farm Type A. The percentage change in total family balance for farm Type A was the same for the two scenarios, suggesting insignificant effects of fertiliser price changes on total family balance.

This result supports the practice of smallholder farmers who tend to reduce fertiliser application as prices rise. The decline in gross margin and total family balance in 2008 to 2009 is related to severe reduction or excessive rainfall. The impact of fertiliser prices changes for the farmers is insignificant because they use small quantities of fertilisers, except for farm Types D and B that use 190 kg/ha and 95 kg/ha fertiliser, respectively (Table 5.1). For these two farm types, the gross margin varied by 160 % for Type D farmer and 205 % for Type A, relative to 2008 gross margin values. Consequently, the total family balance for Type D and B changed by 45 % and 37 %, respectively.

These changes in fertiliser price maybe driven by policy. For instance, developments in the bio-fuel markets had a noticeable influence on fertiliser prices as they influence the international demand for fertilisers, and hence the availability of fertiliser inputs material. An agricultural policy that ensures the poorest rural farmers have access fertiliser at reasonable prices will enhance agricultural production.

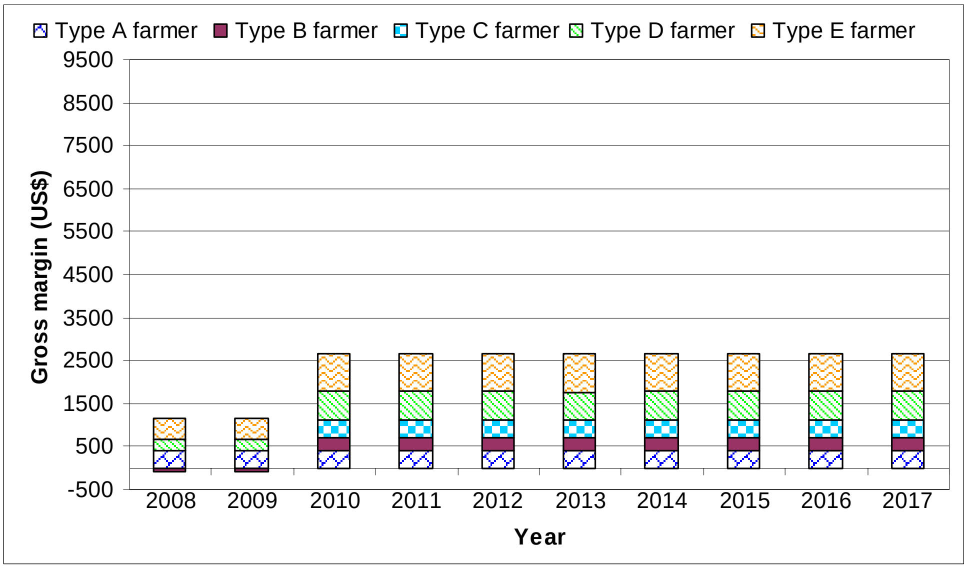


Figure 6.20 (a) Projected annual gross margin under high fertilizer prices

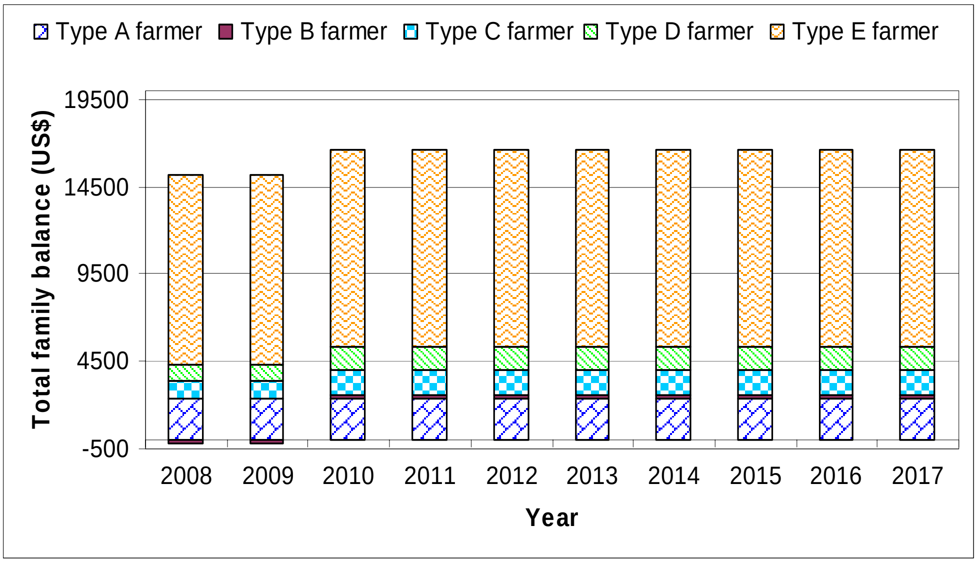


Figure 6.21 (b) Projected annual total family balance under high fertiliser prices.

6.4.6 Farming system performance under cattle price variation (Scenario 5).

The price per beast was varied from US$ 333—US$ 778 (US$ 556 as the base price). The gross margin (Figure 5.13a) varied according to the following ranges for farm Types A (80—151 %), B (–1 336—734 %), C (–108 350—17 958 %), D (–114—889 %) and E (80—488 %) compared to 2008 figures. The total family balance varied according to the following ranges Type A (14—39 %), B (–600—36 %), C (–9—119 %), D (32—251%) and E (4—22 %) compared to 2008 figures.

The gross margin is highest under the cattle price variation scenario compared to the other scenarios related to the maize crop. Farm Type E (with the highest livestock units of 12) is only the farm type able to satisfy the minimum family food requirements (Figure 6.13a). Farmer Type A will experience food shortages from 2011 (Figure 6.13b).

The results show that even for the richest farmers (highest number of livestock) the family food requirements cannot be met by agriculture alone (Figure 6.13a). This suggests the need for farmers to engage in other off-farm activities to broaden and supplement their farming livelihood strategies.

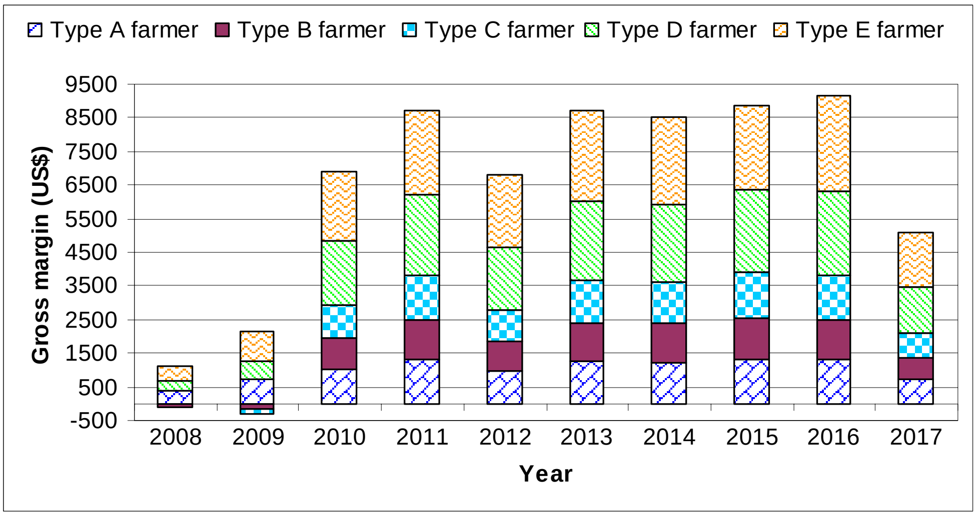


Figure 6.22 (a) Projected annual gross margin under cattle price variation scenario.

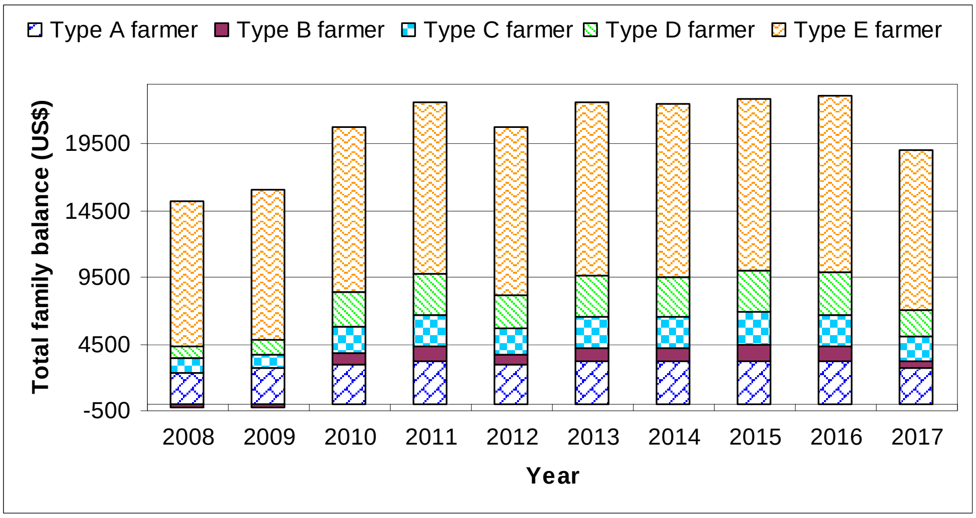


Figure 6.23 (b) Projected annual farm balance under cattle price variation scenario.

6.4.7 Combined planting basins, fertiliser and maize price variations under current trend (Scenario 6).

The combined effect of planting basins technology, fertiliser and maize under current price trend variation is presented in Figures 6.14a and 6.14b. The gross margin (Figure 6.14a) varied according to the following ranges for farm Types A (74—177 %), B (–930—6001 %), C (–51—782 %), D (52—344 %) and E (98—188 %) compared to 2008 figures. The total family balance (Figure 5.14b) varied according to the following ranges for Types A (95—116 %), B (–240—719 %), C (83—176 %), D (82—184 %), E (100—104 %) compared to 2008 figures.

The results show high variability in gross margin compared to total family balance. Farm Types B and C could hardly secure enough food for their families in 2008—2009, indicated by negative gross margin. Farm Type E maintained a stable gross margin as livestock prices are unlikely to decrease in the future.

Additionally, total family balance for farm Types D and C remained the same throughout the 10-year simulation period, with farm Type B having the lowest total family balance. As reported by Weibe (2002) that farmer's best choice between two techniques is driven by their cumulative returns over a period. Based on total family balance, only farm Types A and E are likely to meet their family food requirements.

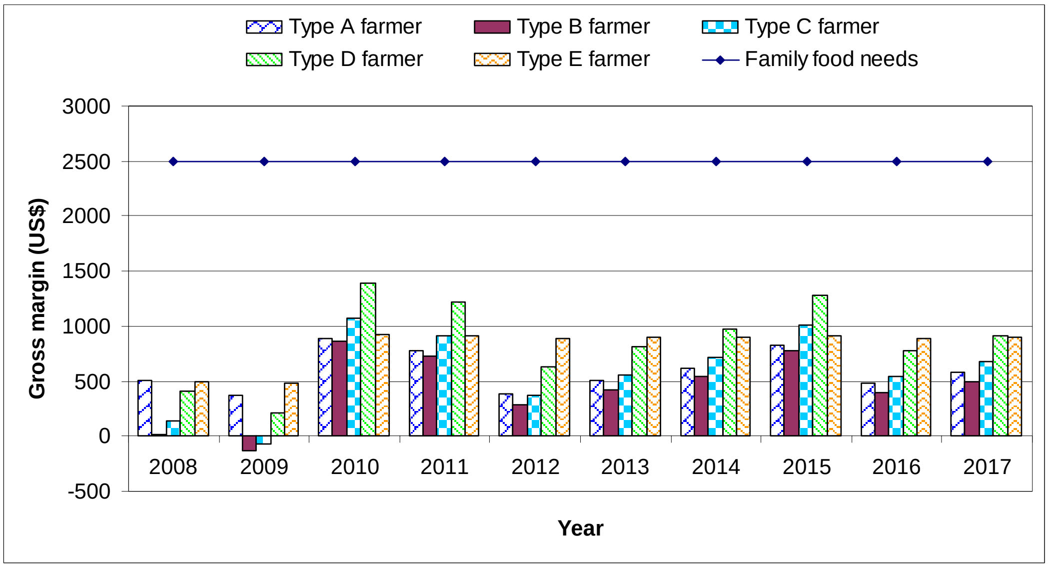


Figure 6.24 (a) Projected annual gross margin under combined scenario of planting basin technology, future rainfall variation, current trend in fertiliser and maize grain prices.

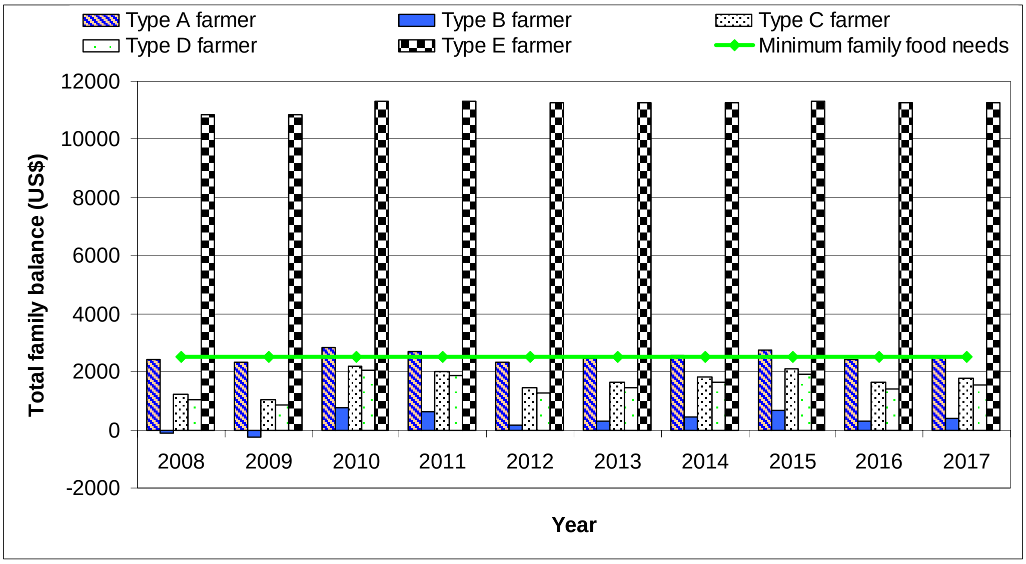


Figure 6.25 (b) Projected annual total family balance under combined scenario of planting basin technology, future rainfall variation, current trend in fertiliser and maize grain prices.

In sum, farm Types C and D can be combined to into one typology as they respond in a similar way to shocks as indicated by similar total family balance. From the combined scenario tested, farm Types A and E showed variation of 19 % and 4 % in total family balance from baseline figures, indicating that these farm typologies are not directly affected by agricultural production changes at farm level. Furthermore, the farm Types A and E have maintained positive gross margin and total family balance in all scenarios. This can be explained by the high contribution (73—91 %) of employment to total family income. Hence, farm Types A and E are the most resilient to agricultural shocks.

6.5 Discussions

The socio-economic-agronomic model presented in this chapter is considered a useful instrument for assessing the resilience of different farming systems (farm typologies) based on farm returns, family food needs and total family income. For a realistic modelling at farm level, different categories of family farms (typologies), based on finance, resource endowments and farming practices were identified. Furthermore, the strengths and weaknesses of the different farming systems were considered to provide an insight into the highly variable farm investments and management strategies that are often observed in smallholder farmers.

The cultivated area (0.9—2 ha) for the farm typologies are comparable to four smallholder farm typologies (based on resource endowments and objective of farming) of farm sizes 0.5, 0.9, 1.2 and 2.8 ha, found in western Kenya (Africa NUANCES, 2007). Mono-cropping farming systems present more risks for the farmer compared to livestock system and mixed (crop and livestock) farming systems.

It is noted that relationships and trends are more important than absolute figures, as the modelled scenarios reflect indicative maize price variations that assume a certain distribution and historical trends. In addition, data and variables used in constructing the farming systems were obtained from experimental observations validated in consultation with experts, extension officers and farmers and interview surveys (Wossink et al., 1992), the forecasts by the model should be considered indicative, as input variables might differ from actual future values.

The results showed that the level of farm vulnerability and risk mitigation is strongly affected by farm resource endowment, in particular livestock units, crop management techniques, fraction of the area irrigated, farm area and labour availability per hectare. Farm vulnerability reduction and risk mitigation can be achieved by the introduction of livestock (cattle, goats, and sheep) into the farming systems to act as a buffer to mitigate climatic and market price shocks. With the PARCHED-THIRST model unable to account for feedback between low rainfall that results in reduced grazing/fodder and livestock production, it was not possible to completely capture farm type E's vulnerability to low rainfall in OLYMPE model. However, livestock is not affected by dry spells to the same extend as crop production. If externalities of the farming systems were evaluated the results could be different.

An important characteristic of farm Type B is the presence of abundant family labour of 5.3 people/ha (Table 5.1). Since preparation of planting basins is labour intensive in the first year, with most of the farm activities done by hand (irrigation, weeding, planting and harvesting) farm Type B is most suited to adapt this technique.

The increased gross margin and total family balance under planting basins technique supports changing from current cropping practices to one that more efficiently capture and conserve soil water. Planting basins improve the family food production and generate more income thereby promoting food security at farm level. Nevertheless, Dogliotti et al. (2005) argue that in a well-supplied internal market, an increase in production would aggravate competition among local farmers, which adversely affects resource-constrained farmers such as farm Type B.

In addition, extreme events such as severe droughts and cyclones drastically reduce farm income through production shortfalls and consequent maize price rise resulting in family food insecurity. In reality, farmers may take longer, two or more years to recover from such hazards.

It should be noted that rural households supplement their food expenditure by own production and spend less cash on buying food. These households are therefore more vulnerable to food insecurity and malnutrition during poor yield years. From the above discussion, there are indications that farming system Type B is not a viable system in the study area, as farm returns fall below family needs and its income is the most affected by weather-related shocks.

Furthermore, households need other goods and services other than food to meet basic needs. The non-food items acquired from farm profits after satisfying the family food needs were captured in the family expenses accounts in OLYMPE model. Other countries have made a rough estimate of the non-food component as one-third of the food component. In South Africa, approximately half of the food expenditure is spent on non-food items (Casale and Desmond, 2007; Bonti-Ankomah, 2001).

Maize price increases enhance the purchasing power and farm production of smallholder farmers given favourable weather conditions (Koch and Rook, 2008). From literature surveyed, it is still not clear how increases in food prices such as maize grain because of production shortfalls and increases in petroleum prices will influence long-term regional food security. In addition, inflation dynamics differ across regions in a way that significantly affects the transmission of commodity price shocks (OECD, 1999). In the long-term, high food prices could boost domestic production in developing countries and improve food security. However, these positive gains would depend on sound economic policies and new technology adoption by developing countries at appropriate levels to improve crop productivity.

In the wake of global bio-fuel agenda, maize prices jumped to above US$ 200/tonne in the last three years. Unlike some countries, South Africa has provided social safety net by restricting the use of certain food commodities, in particular maize, for bio-fuels production to enhance the food security for the poor (Koch and Rook, 2008). Social protection, argued by the African Union, if provided from on-budget resources in developing countries could offer sustainable means for increasing purchasing power and creating a long-term production stimulus for resource-constrained smallholder farmers (OECD, 1999). However, social protection can result in increased world market price variability, which affects producers, and consumers in countries open to trade (OECD, 1999).

The study had its limitations. These include not dealing with the impacts that maize production increase would have at regional level or basin scale. The results from the different farm typologies can be extended to a regional scale by summing the total number of farmers that fall under each farm typology to find impacts of technological innovations or policy changes at an aggregate level. At the farm aggregation level factors such as climate, market prices or regional infrastructure are considered exogenous and not directly affected by the farm system functioning. This assumption loses its validity when a collection of individual farms plays a key role in a feedback process of change at a larger geographical scale. Hence, factors at the regional scale will have a feedback effect on the decisions made at farm scale and vice versa. Some attempts to deal with this cyclic interaction between farm and regional scales are discussed in Wossink et al. (1992).

Policy implications drawn from the study include:

- Promoting planting basins and ridges in suitable conditions (rainfall, slope and soil) as a means of in-field rainwater harvesting technique
- Raising smallholder crop diversification levels to mitigate risk of a single crop failure
- Assistance for labour intensive soil water conservation structures could be subsidised initially by government and NGOs, be gender sensitive and enable the poorest farmers who are unable to employ labour to gain from an improved soil water conservation technique.
- Encouraging mixed farm productions (crop and livestock), with livestock serving as a buffer to bolster livelihoods in drought/flood years. Livestock herds need to be controlled to avoid land degradation.

Nonetheless, the above policies have their limitations, as the farmers need to save money to invest in livestock, need of sufficient pasture and access to markets to sell the crops and livestock productions at viable prices. In addition, in-field rainwater techniques required huge labour in the first year, though it can be spread over a year, before sowing.

To sum up, the model presented above is useful to:

- Supporting decisions by farmer on whether or not to shift from sole crop production into crop and livestock production,
- Policy-makers seeking to encourage mixed and crop diversified farming productions together with soil-water management practices.

Despite the technically feasible solutions derived from the model, policy-makers should consider the costs to farmers and society of recommending or requiring uptake of the farming methods (i.e. economic efficiency).

6.6 Summary

A farming simulation model for smallholder farmers was presented. The bio-economic simulation combined an agronomic model (PARCHED-THIRST) with a socio-economic model (OLYMPE), providing a realistic portrayal of agricultural reality. Farm risks evaluation through scenarios related to markets, crop management techniques and weather hazards on maize production were presented and are summarised in Table 6.3. The results demonstrate the great opportunities that exist to upgrading farming systems in the B72A quaternary catchment in Olifants subbasin, especially rainfed agriculture by use of planting basins to ensure food security and profitable farming in rural communities. With the larger proportion of the farmers being females, the establishment of water conservation committees led by females to implement the planting basins and other in-field rainwater harvesting techniques will greatly improve food security for women and the community.

Furthermore, the order of vulnerability to severe droughts and food insecurity, starting with the most vulnerable, is farm Type B, C, D, A and E. No farming systems except Type E could satisfy the recommended minimum food requirements for an average family size of five persons. The results indicate that fams with regular jobs and livestock are food secure under a range of scenarios. However, livestock cause severe land degradation, as has happened in South Africa (Ntsheme, 2005) and southern Africa, if the livestock numbers are not controlled. Consequently, this strategy should be handled with caution. The study suggests that integrating livestock (cattle, goats) production into diversified crop production systems results in a better and more resilient farming scheme than farm productions solely based on crops. Nonetheless, PARCHED-THIRST model was unable to account for feedback between low rainfall that results in reduced grazing/fodder and livestock production, which could reduce the reported farming resilience.

Table 6.3 Summary of average gross margin and family balance results of scenarios tested

VARIABLE	FARM TYPE	SCENARIOS									
		2a	**2b**	**2c**	**3a**	**3b**	**3c**	**4a**	**4b**	**5**	**6**
	A	389	593	382	406	371	397	405	409	1029	595
Average gross margin/year (US$)	B	208	234	198	226	185	248	224	224	808	440
	C	297	589	281	330	209	394	322	322	898	594
	D	558	859	549	579	527	609	578	578	1797	862
	E	800	731	797	1375	805	808	807	807	2034	820
Average family balance/year (US$)	A	2327	2531	2321	2345	2309	2336	2343	2347	2967	2533
	B	102	311	275	303	79	141	118	118	702	334
	C	1395	1687	1379	1428	1307	1492	1420	1420	1996	1692
	D	1203	1504	1194	1224	1172	1254	1223	1223	2442	1507
	E	11174	11105	11171	11750	11179	11183	11181	11181	12409	11194

In addition, livestock provides a buffer or farm savings (stabiliser) against market and climatic shocks, especially dry spells. While, new technologies such as planting basins may help increase maize vproductivity, land and possibly labour availability may affect the production response. Thus, technology innovations and policies should articulate solutions to poor yields and livestock farming in the Olifants subbasin. Nonetheless, there is no universal farming solution to improve the performance of all the farm types as they face different socio-economic challenges. Therefore, results from this chapter increase the knowledge of important perturbations that cause food insecurity in the absence of social safety nets.

To sum up, the findings show that the OLYMPE combined with a crop model could be a suitable tool for farm production risks assessment and better targeting of agricultural policies by planners and policy-makers from a small to a larger scale, provided adequate model input data are available. Further research should involve iterative discussions and testing of the potential management practices that enhance crop yields by farmers, extension officers and other stakeholders with the aid of the OLYMPE model.

Chapter 7: Case study: Application of ICHSEA decision support system for smallholder crop management in B72A catchment of the Olifants Subbasin, South Africa.

Agricultural development in the Olifants subbasin of the Limpopo River Basin, South Africa is severely constrained by low and erratic rainfall, high temperature, decreasing soil fertility and limited farmer access to productivity increasing options. Availability of new and technically feasible farm production systems, supported by appropriate policies is generally assumed to improve production for enhanced food security, especially in smallholder rainfed agriculture. However, local farmers, water management institutions including agriculture institutions have been slow to build both technical and policy related capacity and adapt to new crop management practices under both climate and market variability. Climate change compounded by political and socio-economic changes have challenged the viability of traditional decision-making norms typically guided by experience and rules of thumb to sustain rural livelihoods.

In the design and selection of decisions related to effective agricultural policy and technological interventions (Figure 7.1), integrated systems modelling has proved to be a useful tool (RNAAS, 2005; Loevinsohn et al., 2002; Parker et al., 2002; Sibbald et al., 2000). In addition, the need for a comprehensive approach to coordinated policy-making continues to be recognised internationally through major UN Conferences (Abaza and Hamwey, 2001). It is on this basis that a study was carried out to develop an integrated model, ICHSEA, comprising hydrology, agronomy and socio-economic models in the B72A quaternary catchment in the Olifants subbasin, northern part of South Africa as part of the Challenge Programme Water and Food Project PN17.

ICHSEA (Innovative coupling of hydrological and socio-economic aspects) model interface was developed to simulate farmer's gross margin and food security through family balance response to changes in agricultural practices and crop product prices that may be policy driven. This ICHSEA model formed the main driver of the proposed decision support system (DSS) that evaluates policy and weather related impacts on identified farming systems in the quaternary catchment.

The main objective of this chapter is to illustrate the application of ICHSEA tool to support the exploration of rainfed agriculture strategies that improve the productivity and production of maize crop to meet family food security (in terms of both food production and monetary gains), while satisfying downstream water requirements including the environment. Climate change is likely to increase the occurrence and intensity of water-related natural disasters thus, creating stress on both human and environmental development. By employing an integrated approach through ICHSEA, this chapter explores some of the ways to reducing human vulnerabilities. The chapter further examines the recent developments in smallholder farmer crop risk reduction strategies presented in Figure 7.1; in an effort to aid farmers understand the production aspects of the agriculture systems they manage.

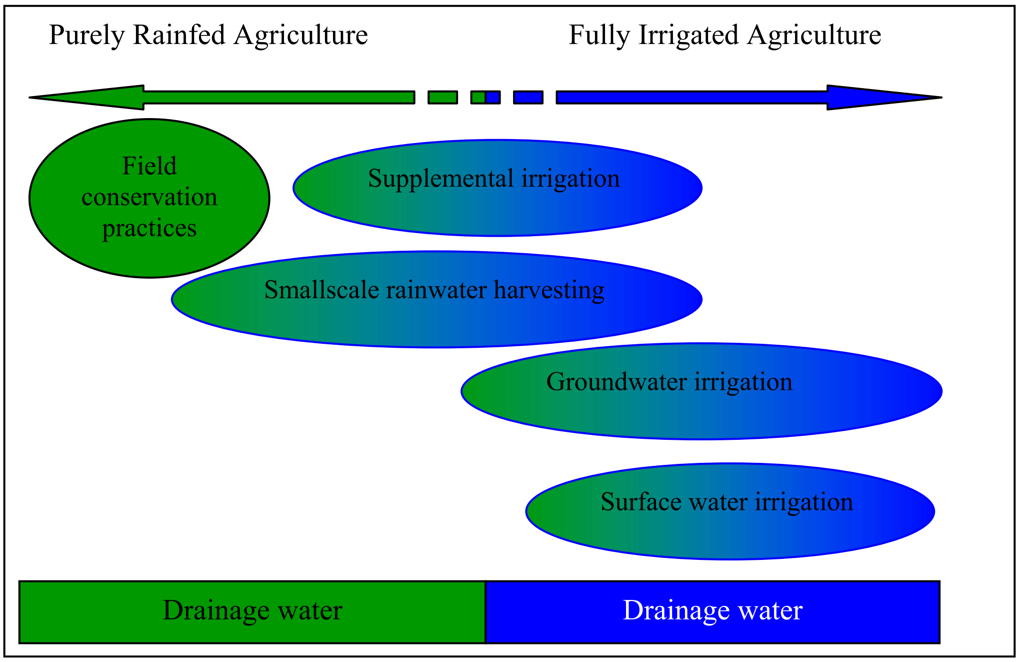


Figure 7.1 Diverse agricultural water management options along the green and blue water spectrum (CAWMA, 2007).

The continuum of water management practices (Figure 7.1) starts with green water in fields, grazing and forestry areas that are entirely dependent on rainwater. Field conservation practices focus on storing water in the soil, while surface and groundwater is added to enhance high value crop and livestock productions.

This chapter presents brief descriptions of ICHSEA model framework and a methodology on how to run a simulation using ICHSEA interface. An application example of B72A catchment to assess the impacts of four crop management and maize grain market price variation scenarios under smallholder farming systems demonstrates the potential applications of ICHSEA model.

The B72A catchment has an estimated eleven thousand smallholder farmers, with an average land size of 1.3 ha per farm family (Table 5.1). Important characteristics of the integrated model, sensitivity and uncertainty, including their implications in decision-making are discussed. The chapter concludes with a summary.

7.1 Model framework

The ICHSEA model framework, showing model connections is shown in Figure 7.2. The suite of models comprises hydrology, agronomy and socio-economic models. The integrated model time-step is one year, but each model runs on a temporal resolution appropriate for the process modelled, ranging from daily to yearly. Detailed descriptions of these individual models were presented in Chapter 3, while the full description of the ICHSEA model, its assumptions and source data for model construction are presented in Chapter 4. The importance of hydrological model in the integrated model is briefly described in the next paragraph.

As hydrology studies the processes that determine the absorption and movement of water in and on the earth's surface, it is of high importance to agriculture and the environment. In addition, the hydrological model component was more appropriate rather than rainfall for the integrated model as water resources cannot be assumed as stationary in time where landcover changes are inevitable, since rainfall-runoff relationships are primarily driven by the interaction of climate, landcover and soil. A stable land use/cover status is generally elusive, especially for catchments in developing countries. Based on the above argument, an understanding of the influence of land use/cover due to different crop management options on hydrology was required. Consequently, a hydrological model was considered as the driver of the ICHSEA integrated model framework. However, an equally important feature for farming system is nutrient availability under water availability (Zand-Parsa et al., 2006; Aina et al., 1991), as farm yields are much higher with added fertiliser or nutrient and households that use fertiliser (from farm surveys) appears to be having a better wellbeing. Simulation of nutrient impacts on yield was not considered inthis study, but only under experimental field conditons.

Firstly, a physically based distributed hydrological model (SWAT) was used to generate surface runoff and sediments in the catchment. This model uses hydrological response unit method that assumes similar hydrological response from similar land use, soil and topography given the same meteorological conditions in an area. The agriculture land, not presented in the initial landcover because of low-resolution data, was incorporated in SWAT land use using the SWAT land use split tool by changing a percentage of range bush landcover into agriculture land (Figure 7.3). Secondly, the crop growth model, PARCHED-THIRST, may or may not (depending on user choice) use a portion of streamflows generated from SWAT to supplement rainfed crop water requirements in the simulation of crop yields under different crop management strategies in the catchment.

The proportion of catchment streamflow yield diverted for smallholder supplemental irrigation is 25 % as shown in Table 2.2 (Liebrand, 2006; Ntsheme, 2005) was based on the overall current water use and allocation of 60 % in agriculture sector in the catchment (DWAF, 2004a). However, this simple water allocation model attempts to mimic irrigation water allocation processes in the catchment and can be varied according to user's objectives. These streamflows are not used in crop yield simulations in the crop model under exclusive rainfed agricultural practices. Finally, using crop yield from the crop model, a socio-economic model, Olympe simulated the resultant family food security in terms of farm gross margin and family savings, referred also in this study as family balance. The balance is the excess money after meeting family needs including food. In addition, Olympe model shows sustainability of the farming system in the catchment based on providing enough food for the family and having extra family balance for buying other services or to save for use under poor yield years. Other sustainability factors on environment are assessed by the hydrological model as streamflows and sediment loads in the river after implementation of different crop management options. The criteria of the indicators selected paid attention to both the agricultural effects and functions for the development of agriculture, farmer and rural areas. Although Qiu et al. (2007) reported 35 possible indicators for sustainable agriculture that include agricultural assets, levels of nutrient use, age of farmers, total income from farming, agriculture productivity, use of water for irrigation, agricultural employment and area of farmland. They stressed the need for the indicators to meet three criterion of environmentally friendly, economically viable and socially acceptable. In this study the indicators used are given equal weight, hence , there is no one overarching sustainability indicator.

The linking of these three models (SWAT, PARCHED-THIRST and Olympe) presented challenges that were resolved by the interface. These challenges include different languages, time steps and software platforms that these models were originally executed. However, the interface was developed with flexibility to add substitute models as required, as long as the substitute models conform to ICHSEA time steps and input/output file format. A screen shot of ICHSEA interface is shown in **Figure 7.4**Figure 7.4.

The ICHSEA tool was developed in Avenues language using scripts in ArcView 3.3. Clicking the radio buttons shown in Figure 7.4 under main tasks and subtasks in the interface, directs the user on execution steps to complete each task.

Figure 7.2 ICHSEA Model framework.

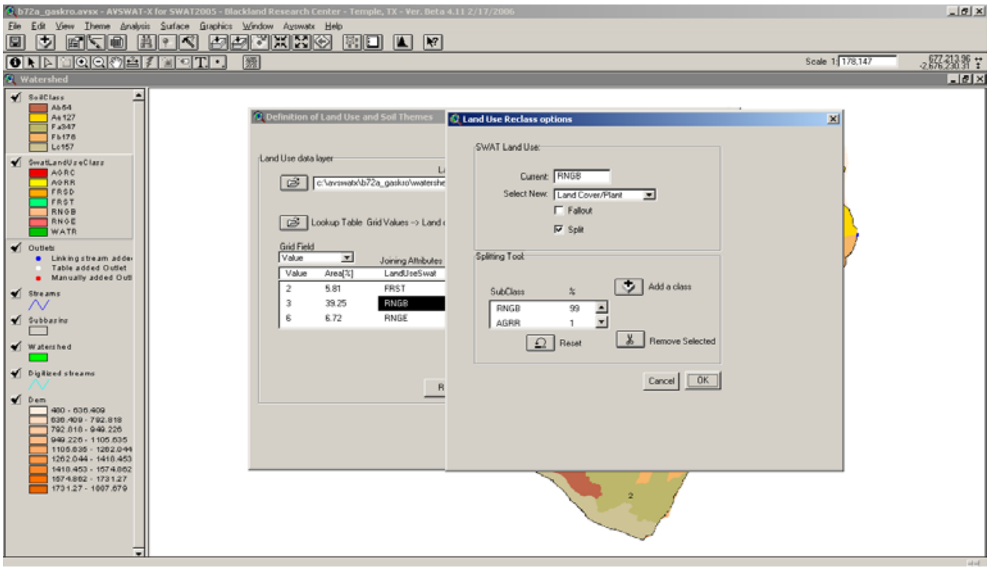


Figure 7.3 Land split tool in SWAT used to incorporate agriculture land around smallholder homesteads in the current land use.

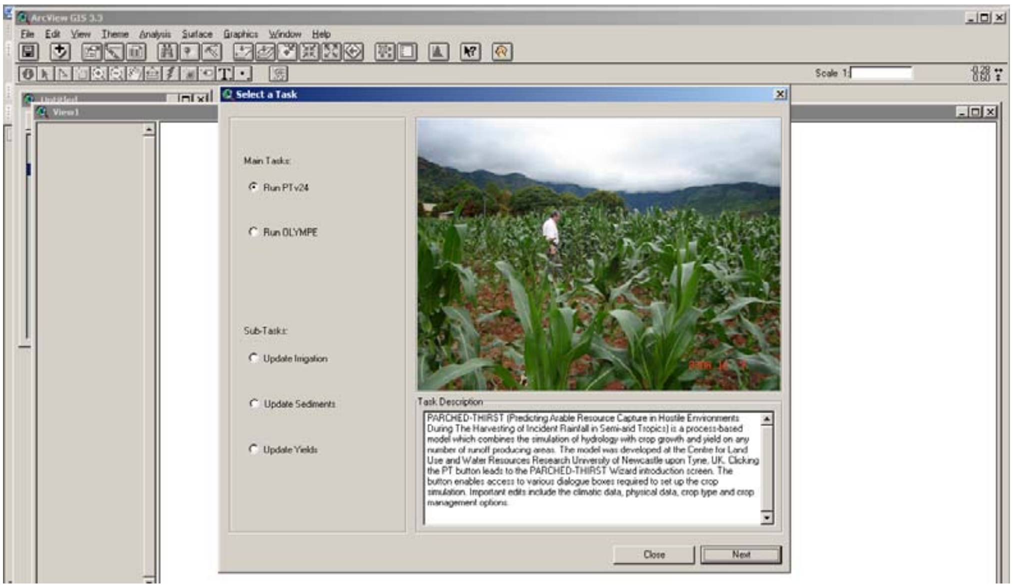


Figure 7.4 Screen shot of the ICHSEA interface.

7.2 Methodology

The methodology is based on the following steps: (1) selection of relevant farming systems. The farming systems, A–E presented in Chapters five and six were used; (2) definition of agricultural and water management scenarios that affect smallholder farmers; (3) simulation of impacts of different scenarios on farm performance based on grain yield, gross margin, family balance and catchment stream outflow; (4) aggregation of the results for each farming system in all the subcatchments in the study area; and (5) sensitivity and uncertainty analysis of results for the five farming systems.

7.2.1 Model validation

The integrated model system was evaluated at three levels. Firstly, verification of individual model components was based on historic data calibration and validation, prior to models coupling. Furthermore, testing and peer review of the component models, hydrological, crop and socio-economic models presented in the literature in Chapter 3, provided confidence in the model applications. Secondly, soft validation (Letcher et al., 2005) of both individual and complete integrated system through farmers and extension officers field discussions of model capabilities and results (Figure 7.5). In addition, local agricultural managers (government) and non-governmental organisation field officers were consulted. Sojda (2007) and Letcher et al. (2005) argue for the soft validation approach, due to several degrees of freedom in the integrated model that are not captured when model validity is tested against a single time series or even multiple time series. In addition, the time series are usually not available.

Figure 7.5 Field group discussion sessions held with farmers.

Under soft validation, the integrated model results discussions (Figure 7.5) were followed by entering contributions of the participants in the computer and running the model. The model results were further discussed and fine-tuned to match closely the reality in the catchment.

7.2.2 Sensitivity tests and uncertainty analysis

Scatter plots were used to find the most sensitive parameters. Scatter plots involved plotting of family balance against variables that affect it, one at a time. Monte Carlo method, using random sampling was used to propagate the uncertainty in the model parameters to produce a probability distribution of model predictions. A more detailed description of sensitivity analysis is provided under Chapter 4.

7.2.3 Scenario analysed

Three crop management scenarios were assessed. These scenarios form part of the techniques presented in Figure 7.1 that are recommended for upgrading rainfed agriculture in arid and semi-arid areas (CAWMA, 2007).

Scenario A: Current rainfed management practices in the catchment

The current practice involves ploughing and planting in rows on a flat surface under conventional rainfed agriculture.

Scenario B: Rainfed management practice combined with maize price variation.

The maize price varied from 43–130 % of the basis grain price of US$ 205/tonne according grain price projections by NAMC (2008). Impact of the maize price variation on family balance was investigated.

Scenario C: Untied ridges

Ridge:furrow ratio of 30:30 cm was used, with crops planted in the furrow. The ridges served as micro rainwater harvesting catchment. Ridges practice was represented in SWAT model, to asses the effects of the practice on downstream water availability. Studies under ridges practice by Wang et al. (2007) reported surface runoff reduction of 29 %, while Wang et al. (2008) reported surface runoff reductions of 36–39 % in semi arid areas.

Scenario D: Planting basins

The planting basins also known as "chololo" pits in Tanzania are holes about 25 cm deep and 30 cm in diameter, being spaced at 60 cm within the rows and 90 cm between rows. The rows are set up roughly on the contour. The soil from the pits is put on the lower side of the pit, forming a half-moon shape to increase runoff harvesting into the pit. Planting basins were represented in SWAT model, to asses the effects of the practice on downstream water availability and to give feedback from crop management and landcover changes in PARCHED-THIRST into the hydrological model.

Furthermore, basin tillage practice was reported to reduce runoff by at least 50 % compared to conventional planting system (Morin et al., 1984).

Estimation of CN values for infield rainwater harvesting techniques

The hydrological model was first calibrated to represent the existing conventional tillage practices (CN = 85, from Chapter 5). This was followed by adjustment (reduction) of the calibrated CN values to reflect the impacts of infield rainwater harvesting (Rawls and Richardson 1983).

To derive the CN value from observed storm rainfall and runoff data (obtained under field experiments), a trial and error procedure was required (Hoesein et al., 1989), as rainfall intensity-duration data for the area was not available. Equations 7.1and 7.2 (SCS, 1972) were applied for the trial and error approach:

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \qquad (7.1)$$

$$S = \frac{25400}{CN} - 254 \qquad (7.2)$$

Where Q is the total runoff depth for the storm event (mm), P is the depth of rainfall (mm), CN (-) is the runoff curve number for the land, S (mm) is the hydrological response potential. CN is considered to be a function of soil type, land use, cover, and antecedent runoff condition (Elhakeem and Papanicolaou, 2009; Hoesein et al., 1989). This gave CN values of 73 and 58 for untied ridges and planting basins, respectively. These values were comparable to those obtained from the rainfall-runoff-CN values chart by Rawls and Richardson (1983) of 65 and 55, for untied ridges and planting basins, respectively, for observed storm depth of 110mm that produces runoff of 46 mm and 21 mm under untied ridges and planting basins, respectively.

Scenario E: Supplementary irrigation

Under supplemental irrigation practice, the streamflow diversions were deducted from total streamflow and the net streamflow is presented to show the impact of streamflow diversions for supplemental irrigation on downstream water availability. The potential supplemental irrigation area in the catchment was estimated based on supplementing rainfall to meet current water use of 3000 m^3/ha.season for maize crop. Seasonal water availability for supplemental irrigation was obtained by summation of daily streamflow diversions.

Impact assessment

Firstly, a base case scenario under exclusive rainfed maize agricultural practice (land and water use) was executed to generate the values of baseline indices to provide the reference point for assessment of other scenarios. The indicators applied to interpret model output and variables tested included total farm gross margin (US$), family balance (US$), yearly streamflow volume (million cubic meters) and sediments. Estimation of sediments was based on the assumption that if the model correctly predicted streamflows then it must indicate the sediment loss trend. Several studies have indicated that both sediment yield and runoff are highly sensitive to effective hydraulic conductivity (Pandey et al., 2007), while López-Tarazón et al. (2010) found that sediment variables (e.g., total load and concentration) were significantly correlated with total rainfall and rainfall over the previous days. López-Tarazón et al. (2010), also concluded that sediment loads observed were in response to different precipitation amounts.

In addition, evapotranspiration water productivity defined as the ratio of crop water evapotranspired to corresponding yield was calculated to compare the impact of different crop management practices. The yield refers to both total above ground dry matter yield and marketable crop yield. In this study, the marketable grain yield was used for two important reasons. Firstly, significant variation in the ratio of grain yield to total dry biomass for maize occurs in response to water deficits (Katerji et al., 2008), a characteristic found in semi-arid environments. Secondly, the marketable yield signifies the potential economical value that contributes directly to smallholder farmer food security.

Crop evapotranspiration for water productivity calculations was determined by PARCHED THIRST crop model. Conversely, Katerji et al. (2008) reported on vast literature that pointed to the deficiency of crop production simulation models to calculate correctly daily evapotranspiration.

7.3 Results

The style and format for presenting ICHSEA model results were carefully considered to provide useful and effective input to both technical users and policy-makers in the decision-making process. Therefore, detailed results are presented for the technical users, whereas only a summary of the main results are presented for the policy-makers. This section presents the summary results from the different models in Figure 7.6. However, the detailed results are presented in this section to show the full capability of the ICHSEA tool.

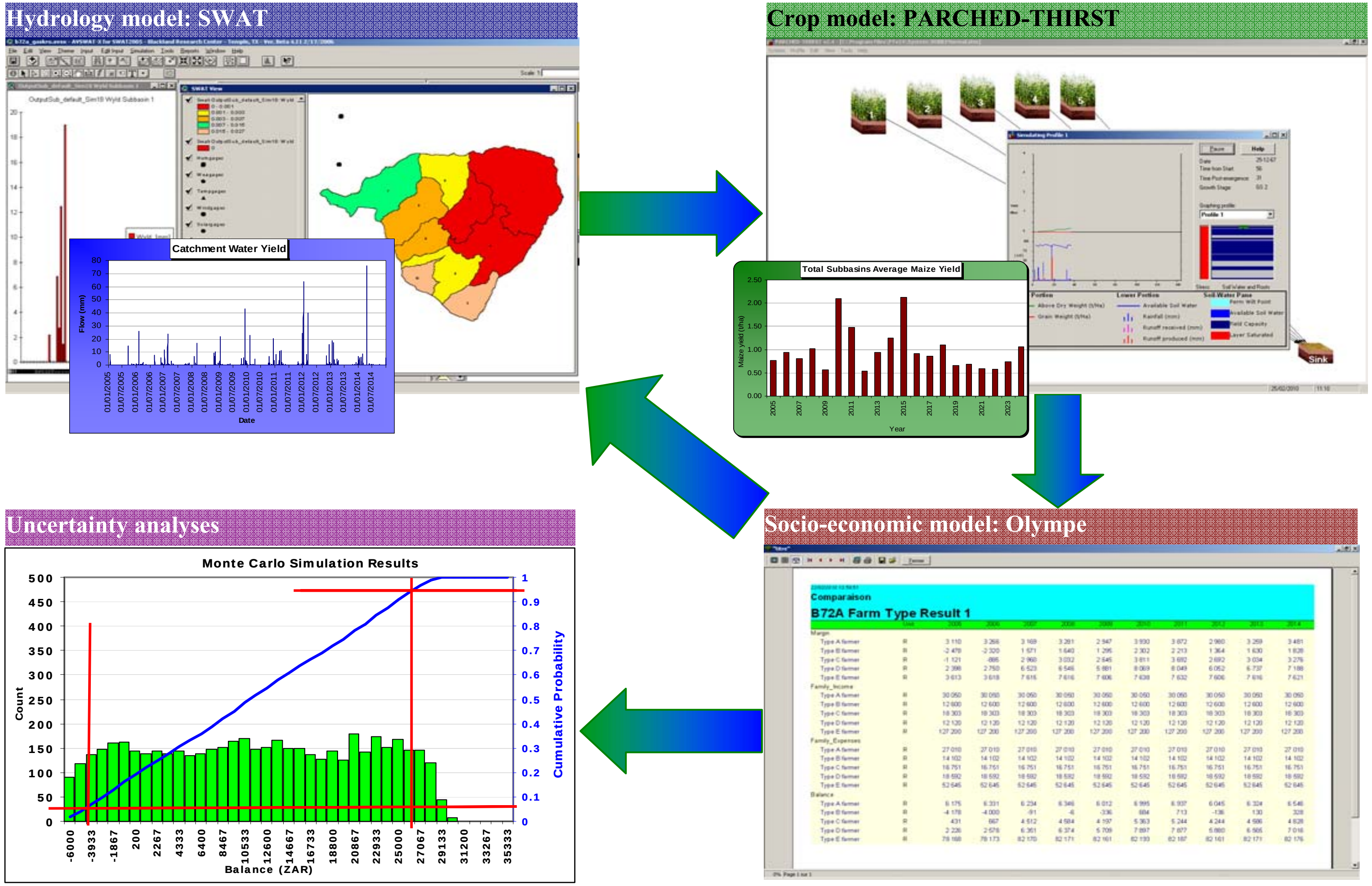


Figure 7.6 Summary of the ICHSEA results for policy-makers at quaternary catchment scale.

The streamflows at quaternary catchment outlet under conventional rainfed, ridges, planting basins and supplemental irrigation practices are shown Figure 7.7. Although annual streamflows are presented to show the impacts of different practices on streamflows, it should be noted that these annual flows were derived from aggregated daily-simulated flows. The daily impacts on streamflows were elicited from the daily flows. Planting basins practice showed the highest streamflows reduction compared to the ridges and conventional rainfed practices (Figure 7.7). In addition, significant streamflows reduction occurred under ridges practice compared to conventional rainfed practice (Figure 7.7).

In addition to runoff reduction due to increased soil surface roughness, crops under ridges and planting basins cause an increase in the height and biomass of vegetation, leading to an increased rainfall interception, root depth and soil porosity (Weatherhead and Howden, 2009) that may decrease runoff rates.

The annual sediments generated under the four crop management practices are presented in Figure 7. The average annual sediment losses for these practices were conventional rainfed (395 t/year), supplemental irrigation (260 t/year), ridges (233 t/year), and planting basins (211 t/year). In year 2014, there is a spike in sediment load, under conventional rainfed (Figure 7.8), which can be ascribed to the existing conventional conservation practices CN values not precisely accounted in the model (Pandey et al.,2008). Another reason could be the phenomenon inherent in erosion models of over-estimating sediment loads in small events, while under-estimating in large events (Pandey et al.,2008; Nearing, 1998; Ghidey et al., 1995). The results indicate the benefits gained under planting basins by reducing sediment loads, minimising land degradation and nutrient loss. However, these benefits depend on the hydroclimatic and geomorphologic characteristics of the basin, together with the availability of sediment within the catchment (López-Tarazón et al., 2010). Sediments reduce water availability in streams and dams by siltation and increase the cost of treating portable water. Therefore, runoff and sediment yield estimations are necessary for developing catchment management plans that involve soil and water conservation measures.

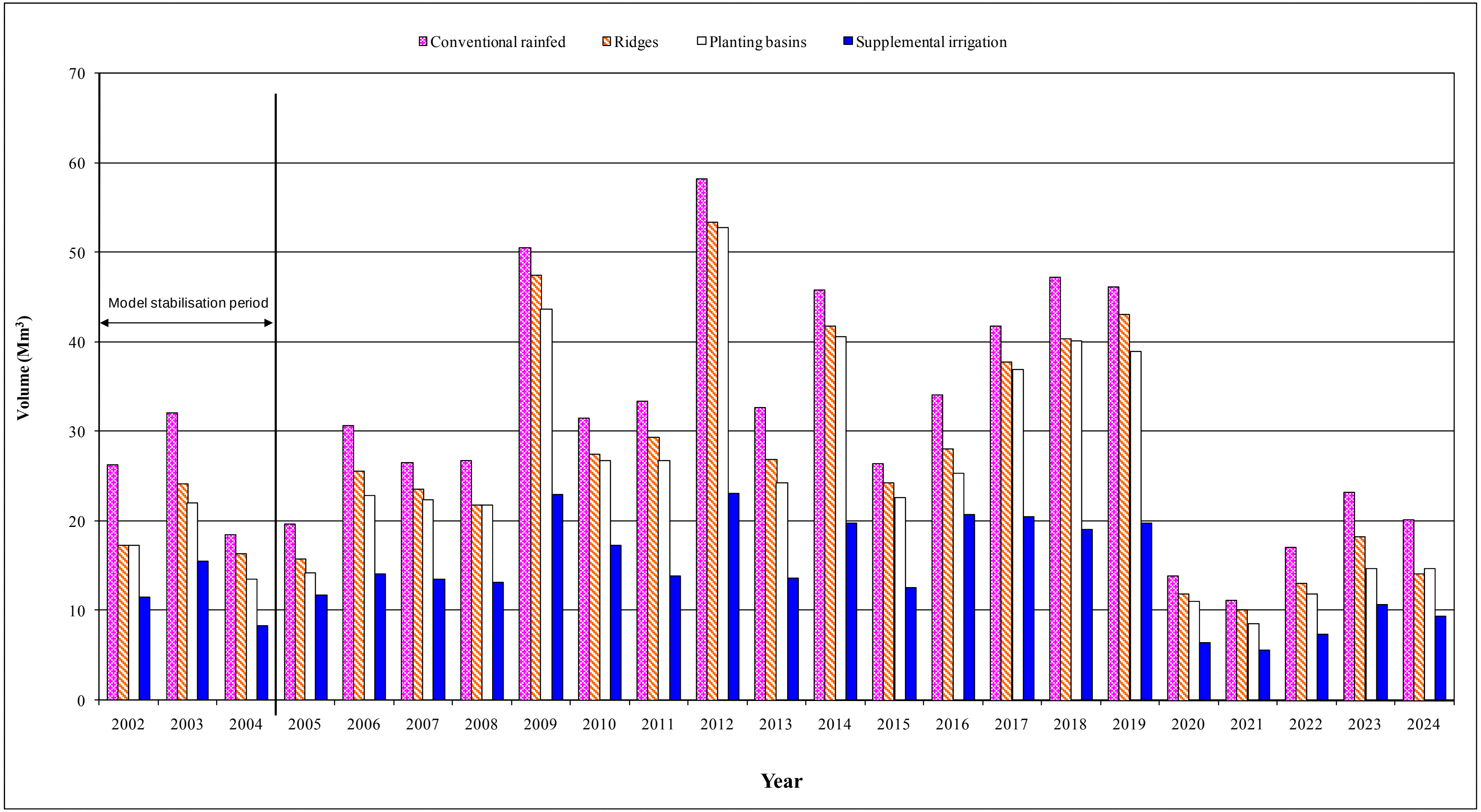


Figure 7.7 Annual volumes out of B72A from 2005 to 2024 under rainfed, untied ridges, planting basins and supplemental irrigation practices.

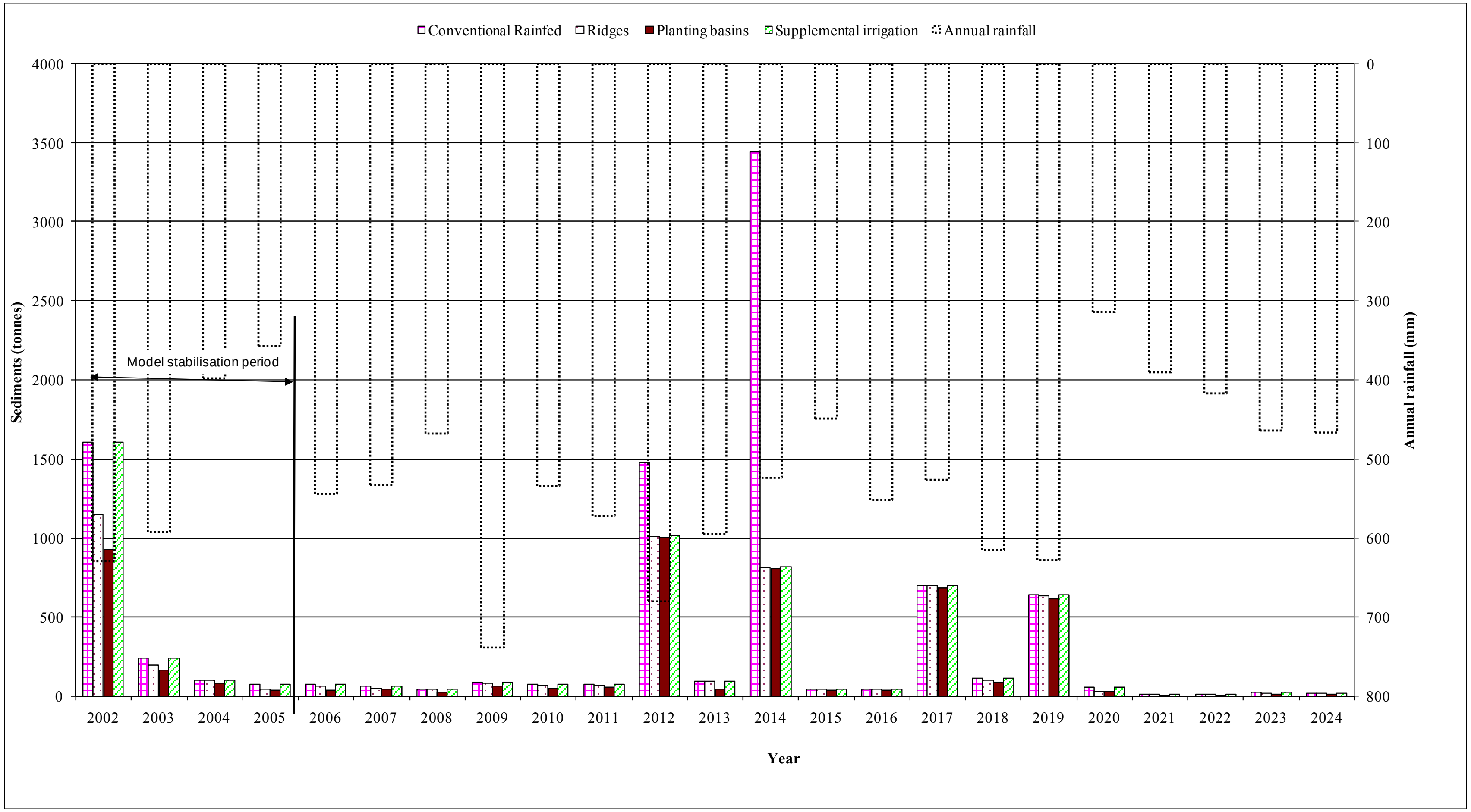


Figure 7.8 Annual sediments out of B72A from 2005 to 2024 under rainfed, untied ridges, planting basins and supplemental irrigation practices.

The mean annual streamflows for the period 2005–2024 were conventional rainfed (31 Mm^3), untied ridges (26.6 Mm^3), planting basins (24.9 Mm^3) and supplemental irrigation (14.4 Mm^3) as shown in Figure 7.7. The mean annual flow is estimated at 31 Mm^3 (58 mm) is 78 % of naturalised flow of 74 mm from WR2005 (Middleton and Bailey, 2005). The annual streamflow reductions were 14.3 %, 19.8 % and 53.8 % for untied ridges, planting basins and supplemental irrigation practice, respectively. The catchment shows drier conditions for the simulation period 2015–2024 (28.1 Mm^3; mean rainfall of 482mm) shown by reduced streamflows and consequently, reduced irrigation water abstraction when compared to the 2005–2014 (33.3 Mm^3; mean rainfall of 555mm) period (Figure 7.7). The annual rainfall standard deviation for 2005–2014 and 2015–2024 was 106mm and 99mm, respectively. Indicating a more uniform rainfall distribution under 2015–2024 than 2005–2014. In wet periods or seasons (2005–2014), the streamflow reduction is minimal due to both reduced supplemental demand because of high rainfall and abundant streamflows.

The potential supplemental irrigation area and sum of diverted supplemental irrigation in the study area is shown in Figure 7.9. The graph shows high correlation of potential supplemental irrigation with streamflow diverted. These results indicate that high rainfall supports large potential supplemental irrigation area because of high generated streamflows and reduced field water demands due to high rainfall. The potential supplemental irrigation area is important to plan for enhanced smallholder farmer food security and storage facilities to improve the reliability of irrigation water supply.

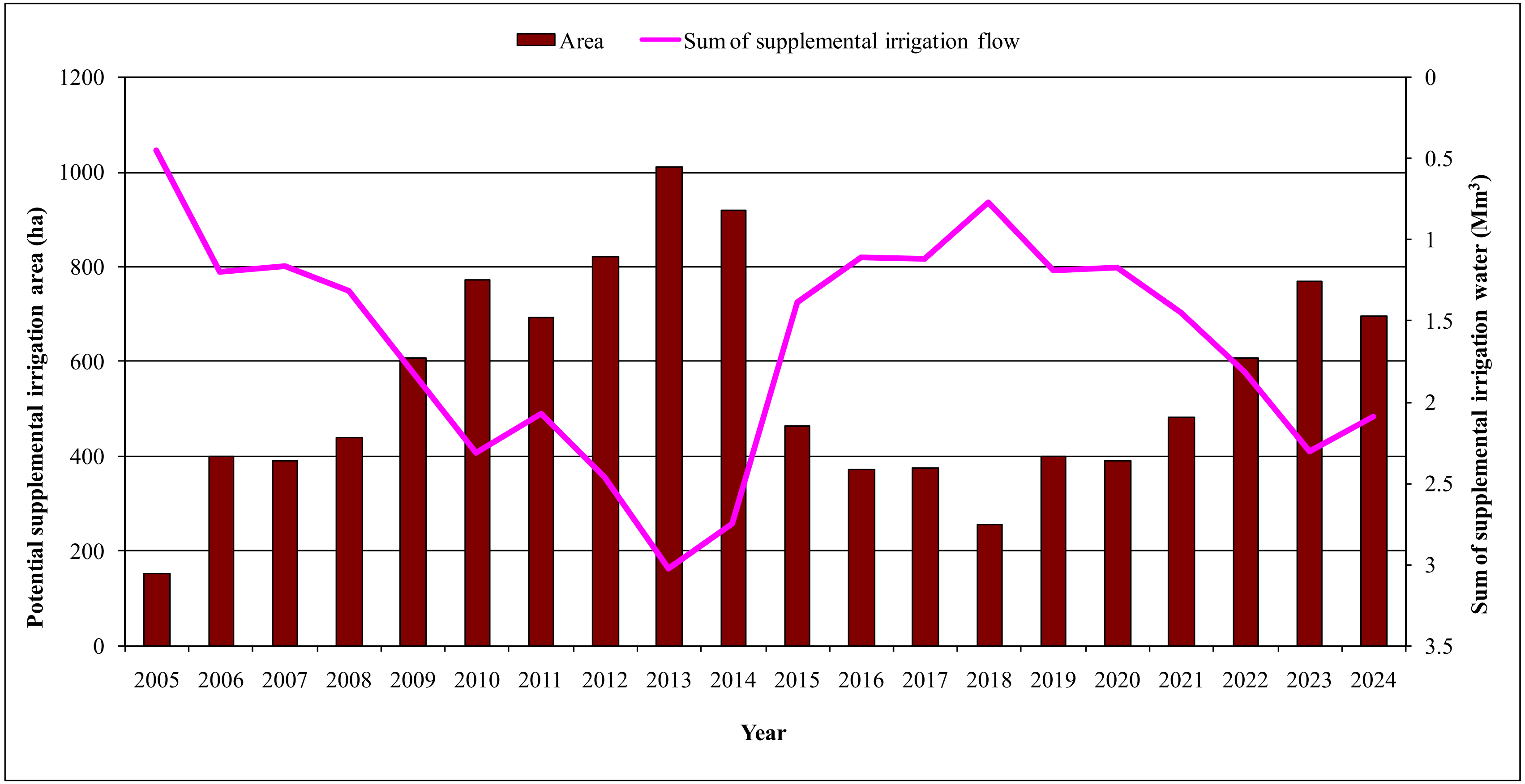


Figure 7.9 Potential supplemental irrigation area and sum of diverted supplemental irrigation water from November to April for the period 2005 to 2024.

7.3.1 Crop yields

The following sections provides an overview of agricultural production systems performance under untied ridges, planting basins and supplemental irrigation practices in comparison to average rainfed maize yields of 0.67 t/ha and 1.22 t/ha for farm types B and D, respectively. The 0.67 t/ha grain yield is adequate to supply yearly maize grain requirements of 500 kg for an average family of five in B72A catchment (Magombeyi and Taigbenu, 2008). For illustration of the crop yield results, farm type B, the most-resource-constrained and farm type D, an intensive and diversified farm (Table 5.1), were selected. Crop yields and their deviation from average rainfed yield for other farm types (A, C and E) are presented in Appendix C.

Rainfed practice

The farm family food requirements for farm type B are not satisfied in 14 years out of the 20 years simulated (crudely, representing a 70 % chance of food insecurity) due to low crop yields (Figure 7.10). There is no grain shortage for farm type D (Figure 7.11), though the yield is below average (1.22 t/ha) in 15 years out of the 20 years simulated. This result is attributed to the more intensive crop management practices including higher fertiliser use under farm type D compared to farm type B (Table 5.1) that improves crop growth response and water productivity. The minimal variation of deviation from the mean maize yield shown under farm type B in Figure 7.10 indicates the risk averse of the smallholder resource-constrained farmers who tend to maintain stable yields, even at low levels to barely meet family needs. In addition, their farming systems fail to maximise crop productivity in good rainfall years as high proportion of rainfall is lost as surface runoff as presented under experimental results in Chapter 5.

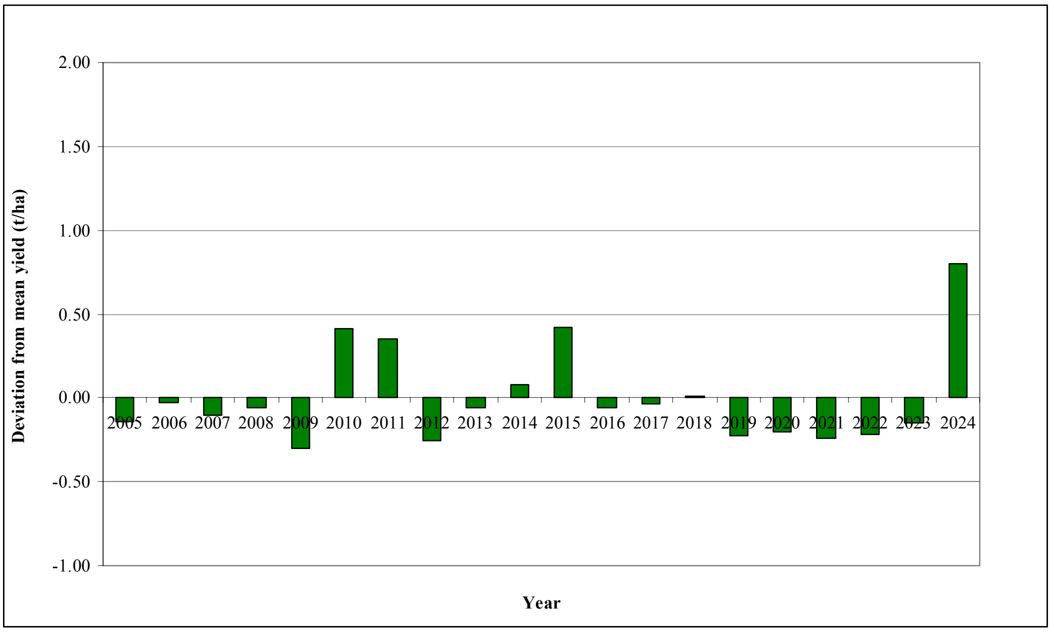


Figure 7.10 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type B under conventional rainfed crop management scenario using 20 years of simulated data.

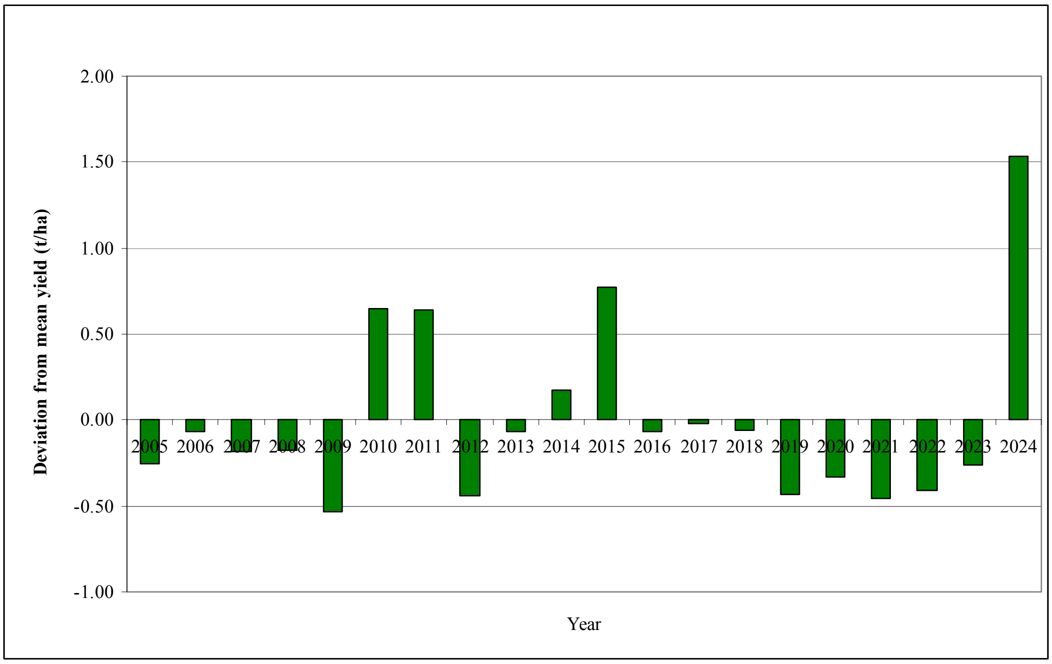


Figure 7.11 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type D under conventional rainfed crop management scenario using 20 years of simulated data.

Untied ridges practice

The yield performance under untied ridges practice for both farm types B (Figure 7.12) and D (Figure 7.13) show huge improvements in maize yields compared to conventional tillage practice (Figure 7.10 and Figure 7.11). With the doubling of maize yields under farm type B, the family grain shortage was reduced more than twice to 5 years in 20 years simulated (Figure 7.12), while farm type D (Figure 7.13) showed even more surplus maize grain compared to rainfed practice (Figure 7.11). However, with proper storage facilities, the surplus yields realised in good rainfall years are enough to cushion farm type B in dry years. These results suggest an improved crop water use efficiency under ridges practice by concentrating rainfall to the crop root zone, thereby making more water available to the plant compared to rainfed practice that generate more field runoff.

The potential water productivity improvement under untied ridges (Figure 7.13) for farm type D, that appeared to be more water use efficient under conventional rainfed practice shown in Figure 7.11, is minimal compared to farm type B. This minimal water productivity improvement is due to the limited unbeneficial rainfall reduction under farm type D that could be capitalised to increase water productivity.

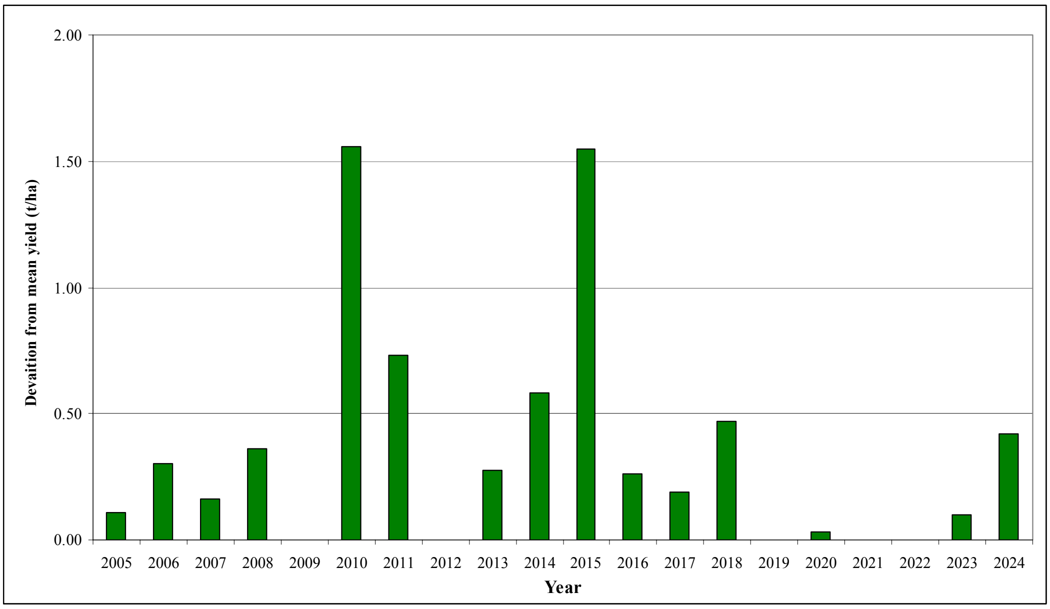


Figure 7.12 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type B under untied ridges crop management scenario using 20 years of simulated data.

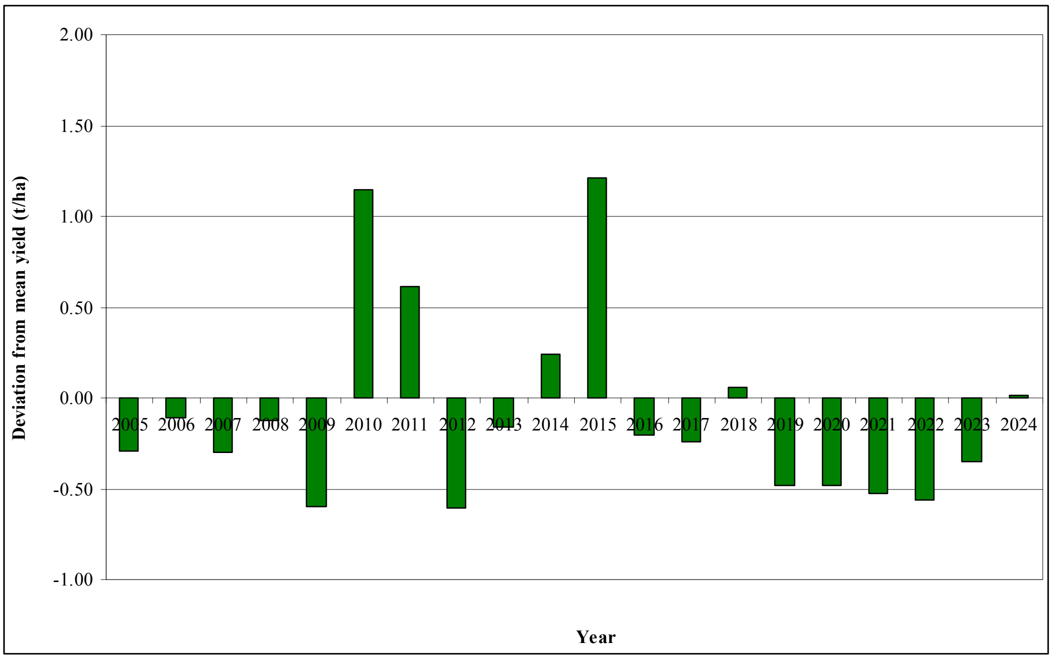


Figure 7.13 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type D under untied ridges crop management scenario using 20 years of simulated data.

Planting basins practice

Planting basins practice showed highest yield improvements and stabilisation compared to both untied ridges and conventional rainfed practices for both farm types B (Figure 7.14) and D (Figure 7.15). There is yearly surplus food production under farm type B, shown in Figure 7.14 for all the 20 years simulated, indicating superiority of planting basins in securing reliable food security over both rainfed and untied ridges practices. These increased yields under planting basins indicate that planting basins harvest more rainfall and retain more soil moisture for longer periods, mitigating against reasonable dry spell periods of crop water stress than both untied ridges and conventional rainfed practices. This aspect was demonstrated under on-farm experimental results in Chapter 5.

Untied ridges and planting basins practices help to harvest and concentrate (regulate) runoff flow, to increase water infiltration and soil water storage to bridge short dry spells, in addition to reducing soil and nutrient losses. However, the application of various rainwater harvesting practices is site-specific and depends on local rainfall characteristics, construction materials and tools, site conditions and labour cost. The labour and construction costs for the different treatments presented in Table 5.5 showed that planting basins practice required the highest labour cost compared to conventional and untied ridges practices in the first year. In addition, the untied ridges system is most suitable in gentle slopes to avoid frequent breaching of ridges during rainfall storms, especially in marginal rainfall areas. To avoid ridge breaching, lateral movement of water along the furrows towards any low points that may exist in the field should be controlled, if possible prevented.

However, untied ridges and planting basins practices fail under longer dry spell periods leading to complete crop failure and discouraging farmer investment in fertiliser use. These longer dry spells can be mitigated by supplemental irrigation practice, discussed in the next section.

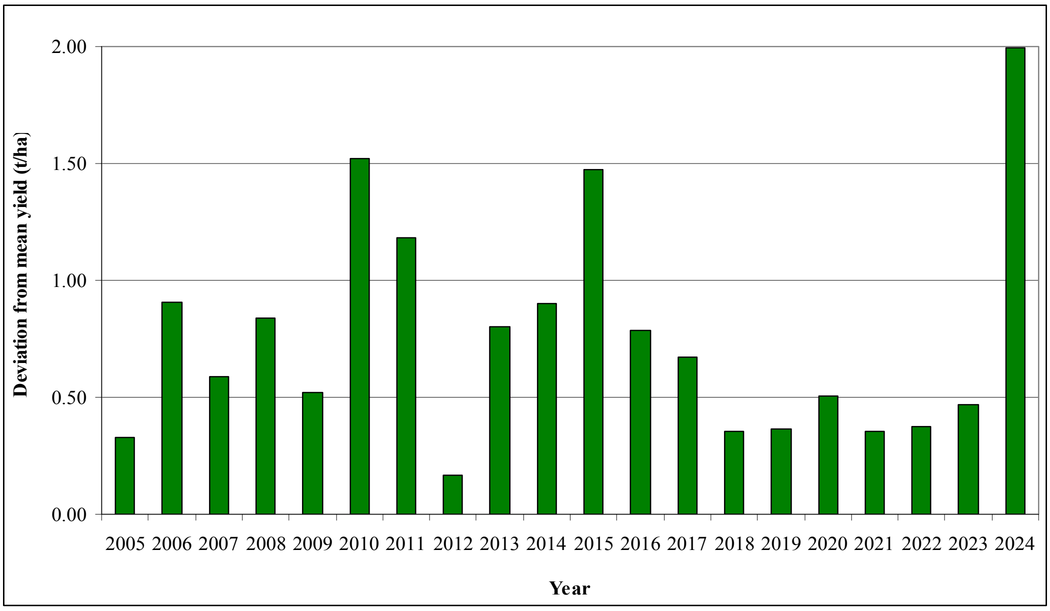


Figure 7.14 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type B under planting basins crop management scenario using 20 years of simulated data.

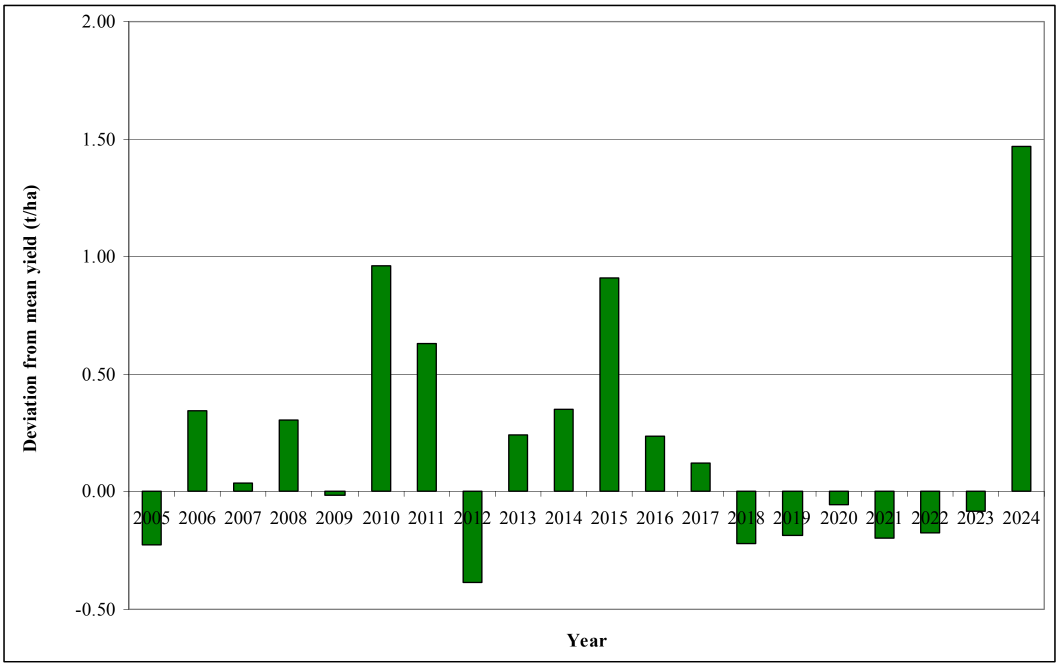


Figure 7.15 Seasonal mean maize grain yields deviation from mean rainfed yield for farm type D under planting basins crop management scenario using 20 years of simulated data.

Average maize crop yields

A summary of the crop yields under different crop management options including supplemental irrigation practice per farm type are shown in Table 7.1. Detailed seasonal yield results and corresponding socio-economic results are presented in Appendix D. The average maize yields for the 20 years of simulation under rainfed practice (Table 7.1) are lower than 1.8 t/ha, while supplemental irrigation practice yields (Table 7.1) are comparable to 2.9 t/ha found in Ghana (Yangyuoru et al., 2003). In addition, crop yields under supplemental irrigation practice are at least four-fold higher than rainfed practice, while crop yields under planting basins practice are at least two-fold higher than rainfed practice. The results demonstrate huge yield gains from implementing supplemental irrigation practice in semi-arid regions. However, the feasibility of supplemental irrigation practice in the study area depends on a number of issues such as availability of water, proximity of the field to the source of water such as a river, dam, or rainwater harvesting tank, maintenance of conveyance structures and water allocation.

Table 7.1 Average farm yields under different crop management practices

Practice	Year	Farm type average yield				
		A (t/ha)	B (t/ha)	C (t/ha)	D (t/ha)	E (t/ha)
Rainfed	2005–2014	0.64	0.65	0.63	1.19	0.34
	2015–2024	0.67	0.68	0.65	1.24	0.35
Ridges	2005–2014	0.77	1.05	1.05	1.20	1.12
	2015–2024	0.69	0.95	0.95	1.06	1.00
Planting Basins	2005–2014	1.39	1.44	1.44	1.44	1.44
	2015–2024	1.34	1.40	1.40	1.40	1.40
Supplemental irrigation	2005–2014	2.17	2.76	2.73	2.73	2.73
	2015–2024	2.29	2.90	2.88	2.88	2.88

It is noteworthy that all farm types were better off in terms of yield, independent of the technology used (Table 7.1) during the periods 2005–2014 and 2015–2024. Although the 2015–2024 period was drier than the 2005–2014 period, its rainfall distribution was more uniform (standard deviation of 99mm) than the 2005–2014 (standard deviation of 106mm). Uniform rainfall distribution enhances crop yield as fewer and shorter dry spells are experienced during the crop growing period.

Water productivity

The analysis of water use efficiency also known as water productivity at the field scale consists of finding correlations between the crop yields and a number of site parameters that affect water use efficiency variability. Excluding experimental errors related to the determination of crop yield and soil moisture used to calibrate the crop model, the water use efficiency variability (Figure 7.16–Figure 7.20) is attributed to four main sources: (1) crop management practices: water and fertiliser applied to crops; (2) plant: phenological stage sensitivity to water stress (Katerji et al., 2008); (3) biotic stress due to weeds; (4) environment: soil type and texture affect water use efficiency.

Loam soils (Katerji et al., 2008) are favourable to high plant water use efficiency due to easier water extraction by well-developed high-density plant roots. Climatic changes (IPCC, 2001) affect carbon-dioxide levels and temperature and consequently the evaporative demand. There is new evidence that carbon-dioxide does not always translate into more efficient water productivity at field to basin scale (Ainsworth et al., 2008). Temperature increase under climate change shorten the crop maturity period that reduces water consumption and increase daily evapotranspiration due to the increase of vapour pressure deficit, as a result of the increase in temperature (Katerji et al., 2008). In practice, the different factors responsible for water use efficiency variability act both jointly and independently.

Other factors such as maize variety and biotic stress due to diseases and insects (Katerji et al., 2008) can contribute to variability in water use efficiency. However, these two factors were excluded in this study as the same maize variety was used in simulations and due to lack of impact data from field observations. Molden and Oweis (2007) argue that the date of sowing, crop density and several cycles of mono-cropping can affect water use efficiency. In fact, the crop density was different for the different crop management practices investigated in this study as shown in Appendix A, Table A1.

The non-linear relationship between water productivity (WP) and maize grain yields for farm types B and D under conventional rainfed practice is presented in Figure 7.16. The water productivity for maize decreased gradually with a reduction in seasonal rainfall and distribution (not shown), but increased as a lesser amount of evapotranspiration water is used to obtain more crop yield (Figure 7.16).

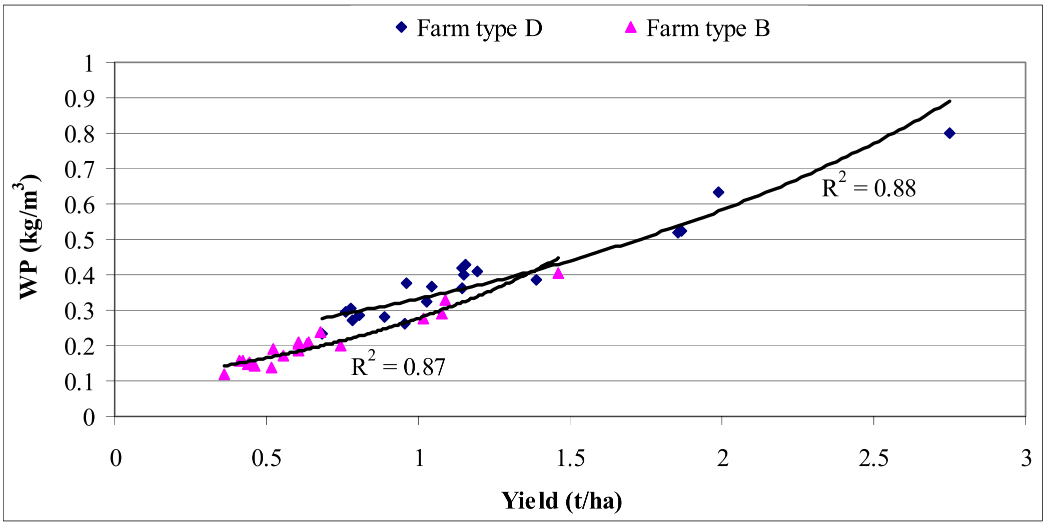


Figure 7.16 Nonlinear relationship between water productivity (WP) and maize grain yields for farm types B and D under conventional rainfed practice, n = 20 years for each farm type.

Farm type B tend to use more water but obtain less crop yield than farm type D for the same crop yield (Figure 7.16), indicating that rainfall is effectively used under farm type D compared to farm type B. The maize yield under farm type D is higher than that of farm type B for the same amount of evapotranspired water (Figure 7.16). This difference in crop yield is explained by the different crop management practices such as quantity of applied nitrogen fertiliser (Table 5.1). Farm type D uses higher fertiliser quantities than farm type B (Table 5.1) that increase maize crop water productivity and crop yield.

Under untied ridges practice for both farm types B and D (Figure 7.17), there is more than doubling of water productivity (200–280 %) due to increased crop yields compared to conventional rainfed practice (Figure 7.16). Furthermore, planting basins practice for both farm types B and D (Figure 7.18) showed about 35 % improvement in water productivity compared to untied ridges (Figure 7.17). Under supplemental irrigation practice water productivity increases, (essentially linearly) as maize yield increases (Figure 7.19), with both farm types B and D equally performing. Despite highest yields (at least 2 t/ha) obtained under supplemental irrigation practice (Figure 7.19), its average water productivity is about 20 % less compared to that under untied ridges practice (Figure 7.17). In

Figure 7.18 (untied ridges) and Figure 7.19 (planting basins), water use efficiency is the same, whereas in different in Figure 7.17. This result can be ascribed to more water availability under these two practises to the extend that water availability is no longer limiting the crop growth, but nutrient availability. Despite additional nutrients playing a major role in crop water use efficiency, it was out of scope under this study.

There is increasing water productivity as one moves from conventional rainfed, supplemental irrigation, untied ridges to planting basins practices.

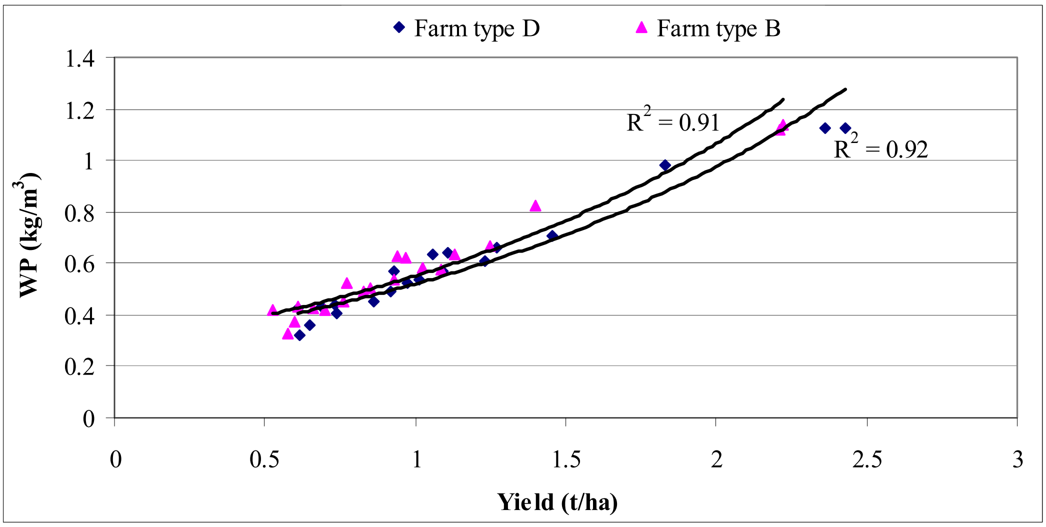


Figure 7.17 Nonlinear relationship between water productivity (WP) and maize grain yields for farm types B and D under untied ridges practice, n = 20 years for each farm type.

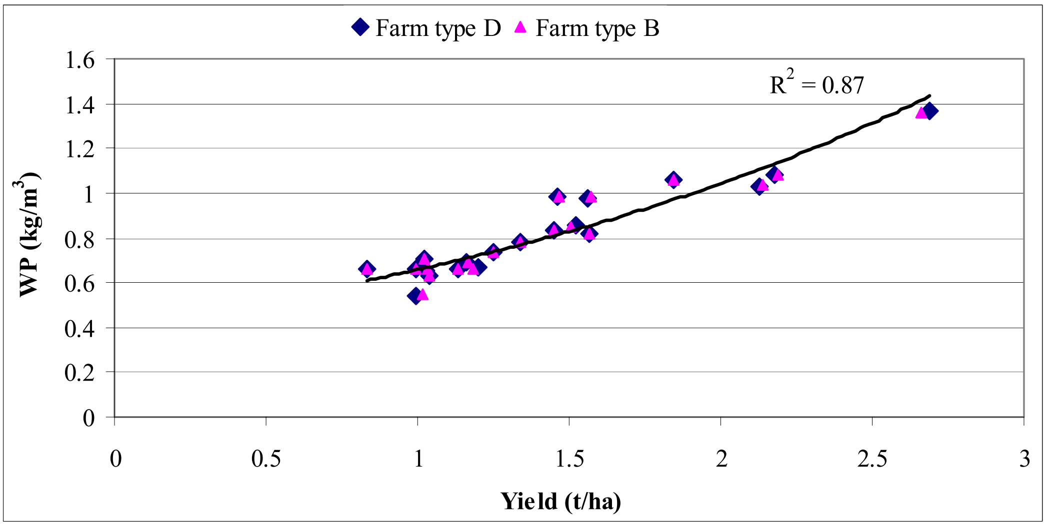


Figure 7.18 Nonlinear relationship between water productivity (WP) and maize grain yields for farm types B and D under planting basins practice, n = 40 years.

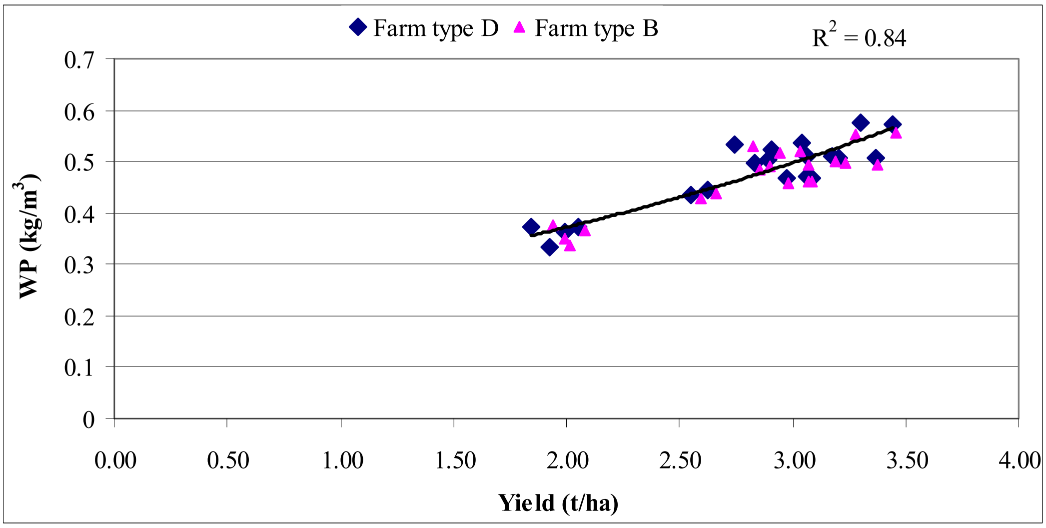


Figure 7.19 Nonlinear relationship between water productivity (WP) and maize grain yields for farm types B and D under supplemental irrigation practice, n = 40 years.

The values in Figure 7.16–Figure 7.19 are not fundamentally different, and seem to be following a generic curve, as presented by Rockström and Barron (2007). In addition, the exponential relationship of water productivity and crop yields concurs with findings by Rockström et al. (2007). They argue that the vapour shift towards productive transpiration in smallholder farming systems with yields less than 3 t/ha implies a non-linear relationship between water productivity and crop yield as presented in Figure 7.16–Figure 7.19 for different seasonal rainfall amounts and distribution in the current study.

The potential for water productivity improvement for farm type D that appeared more water use efficient, under untied ridges is minimal because of limited unbeneficial water depletion that could be capitalised to increase water productivity. Significant supplemental irrigation water productivity improvement could be achieved by reducing excessive irrigation supplies at farm level that contributed to increased deep percolation and evaporation losses from model simulation results (not shown). Water productivity improvement strategies for farm types B and D should be directed towards the factors that enhance crop yield, such as control of pests and diseases (Mdemu et al., 2009), weed control, use of better crop varieties, correct crop-sowing time and correct use of fertiliser input.

Average long-term water productivity

The conventional rainfed crop water productivity (Figure 7.20) for farm type B (0.21 kg/m^3) was lower than that for farm type D (0.39 kg/m^3). Farm type E had the lowest water productivity of 0.1 kg/m^3 followed by farm type C (0.2 kg/m^3) as shown in Figure D1 of Appendix D. The difference in evapotranspiration water productivity between farm types B and D was due to differences in crop yield and water management practices that are influenced by water availability. Low water productivity under farm type B reflects poor soil water management practices. Furthermore, average crop evapotranspiration water productivity under untied ridges, planting basins and supplemental irrigation practices was 0.60, 0.82 and 0.47 kg/m^3, respectively, for both farm types B and D.

Different crop management practices for different farm types in B72A catchment lead to variation of maize water productivity as presented in Figure 7.20. The water productivity under planting basins practice is more than twice that of rainfed practice, but just less than twice that of supplemental irrigation practice as presented in Figure 7.20. Hence, reduction of water supply or deficit irrigation under supplemental irrigation improves water productivity.

The supplemental irrigation water productivity of 0.47 kg/m^3 in the current catchment-wide simulation is comparable to the results obtained at plot scale (0.35–0.4 kg/m^3) presented in Table 5.4. Three reasons are attributed to the discrepancy observed. Firstly, water was applied when the soil moisture was close to permanent wilting point at plot scale, as in deficit irrigation. Deficit irrigation that deliberately and systematically under irrigates crops leads to higher water productivity (Sepaskhah and Akbari, 2005). Secondly, is the issue of scale. Different soil qualities in the catchment could have enhanced water productivity compared to gains realised under one soil type at plot scale. Thirdly, the different climatic conditions over the catchment also contributed to increased water productivity at catchment scale.

The results obtained under rainfed (0.21–0.39 kg/m^3) and supplemental irrigation (0.47 kg/m^3) maize practices are comparable to those found by Rockström et al. (2002) of 0.15 kg/m^3 for rainfed and 0.35–1.0 kg/m^3 for supplemental irrigation practice. Furthermore, the rainfed practice results fall within reported values under semi-arid areas in South Africa (0.14 kg/m^3) (Durand, 2006), Cameroon (0.12 kg/m^3), Burkina Faso (0.11–0.34 kg/m^3), Kenya (0.11–0.34 kg/m^3) (Barron and Okwach, 2005) and slightly lower than results from Tanzania (0.4–0.7 kg/m^3) (Mdemu et al., 2009). However, as expected the values are lower than those found in the Mediterranean region (France, Lebanon, Turkey, Italy and Spain) of 0.82–2.15 kg/m^3 (Katerji et al., 2008) due to latitude effect (Molden and Oweis, 2007) that affects climate as one moves away from the equator.

The water use efficiency results presented, refer to maize production in the farm, hence, do not reflect the overall farm family water use efficiency, as other water uses, such as livestock watering and other crops that influence household income, wellbeing and wealth were not considered under current study scope.

Under plant phenological stage sensitivity to water stress, Katerji et al. (2008) found that during critical stages corresponding to flowering stage, a moderate water deficit leads to a severe crop yield reduction and considerable variation of water productivity. In practice, this water productivity comparison knowledge presented for different crop management practices can be useful in identifying of practices that are more resilient to dry spells compared to conventional rainfed practice in semi-arid areas. Studies to identifying soil water conservation methods that can bridge these phenological sensitive stages are required for improved smallholder farming system resilience to weather vagaries, including sensitivity to dry spells and to climate change.

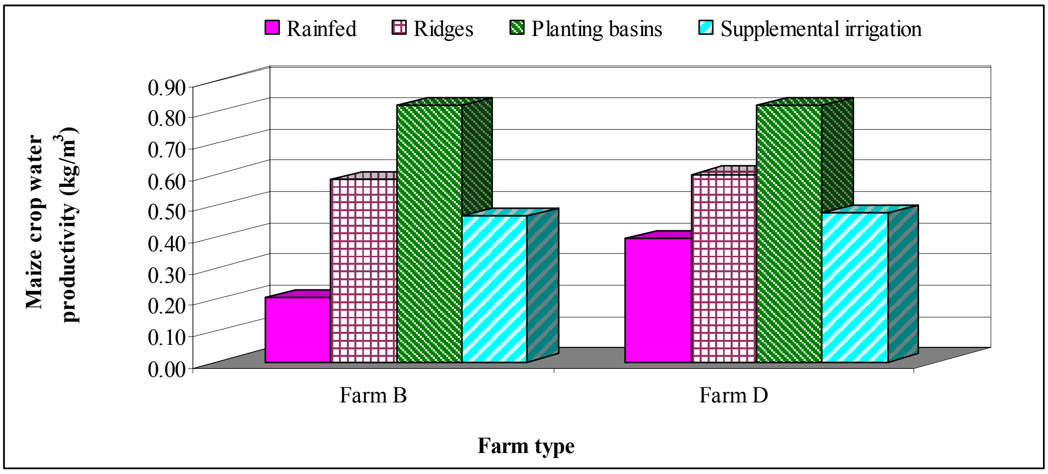


Figure 7.20 Potential average (n = 20 years) water use efficiency of rainfed, untied ridges, planting basins and supplemental irrigation in B72A catchment.

7.3.2 Gross margin and family balance

The percentage exceedence of gross margin and family balance for farm types B and D calculated using Weibull formula are shown in Figure 7.21 and Figure 7.22, respectively. The lines of best fit shown in Figure 7.21 account for about 89 % and 93 % of the gross margin variability for farm types B and D, respectively. Under family balance, the lines of best fit account for about 92 % and 94 % of the variability for farm types B and D, respectively as shown in Figure 7.22.

The two plots of gross margin and family balance indicate that different relationships exist between farm types B and D. Farm type B has less gross margin and family balance compared to farm type D. For 80 % of the time the seasonal gross margin was at least US$ 100 for farm type B, while it was at least US$ 400 for farm type D. The lower gross margin for farm type B compared to farm type D is due to lower crop maize yields. Subsequently, 80 % of the time the seasonal family balance was at least US$ 25, for farm type B (Figure 7.22), while for farm type D it was at least US$ 600. These results show that farm type B is struggling to provide for family food and hardly have substantial yearly savings to provide a buffer in bad years, whereas farm type D, with higher family balance is more food secure. This result is confirmed by both negative gross margin (Figure 7.21) and family balance (Figure 7.22) experienced by farm type B. A summary of the gross margin and family balance under different crop management options per farm type are shown in Table 7.2.

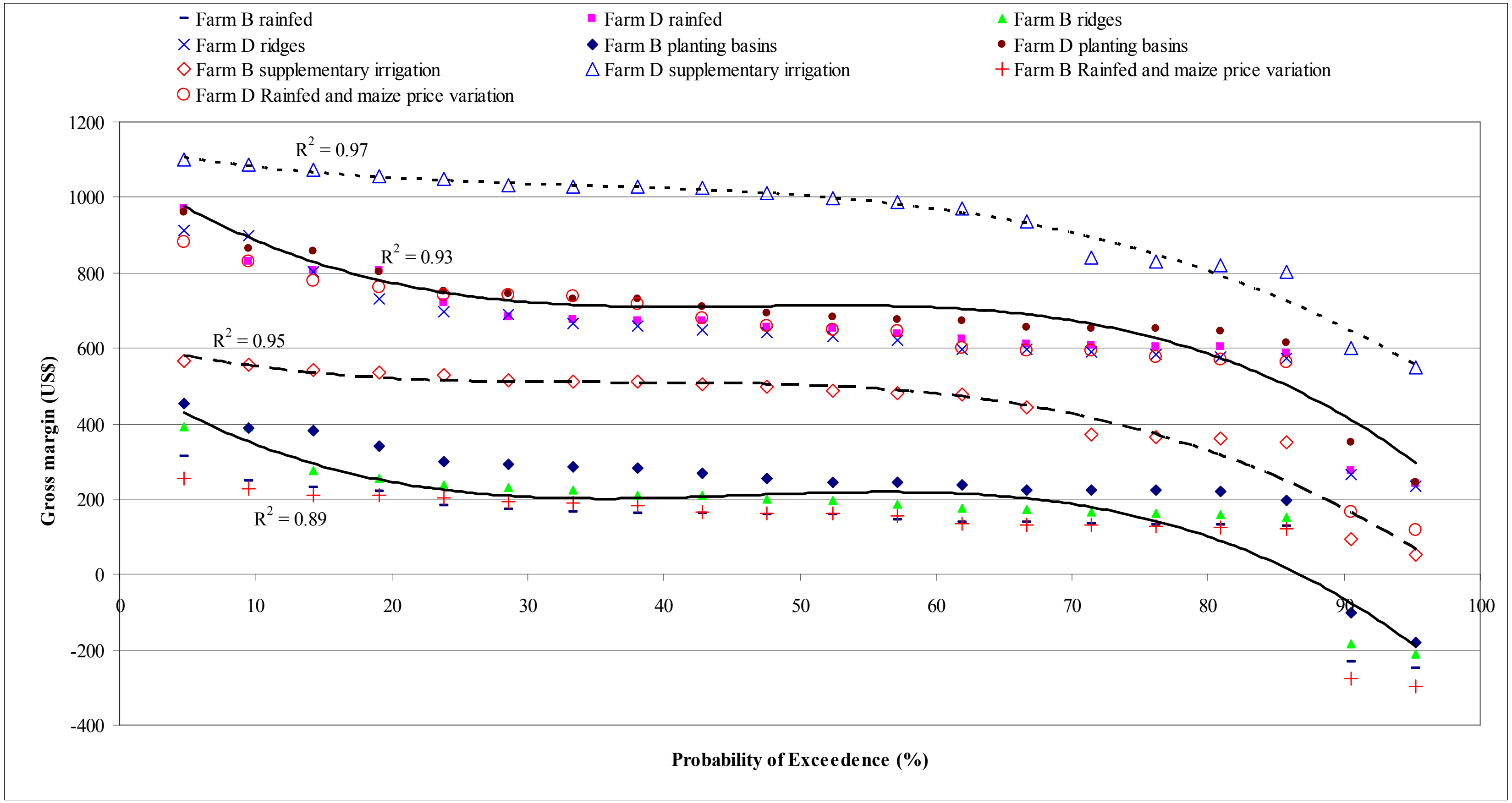


Figure 7.21 Percentage exceedence of gross margin per selected farm types B and D under different crop management scenarios using 20 years of simulated data.

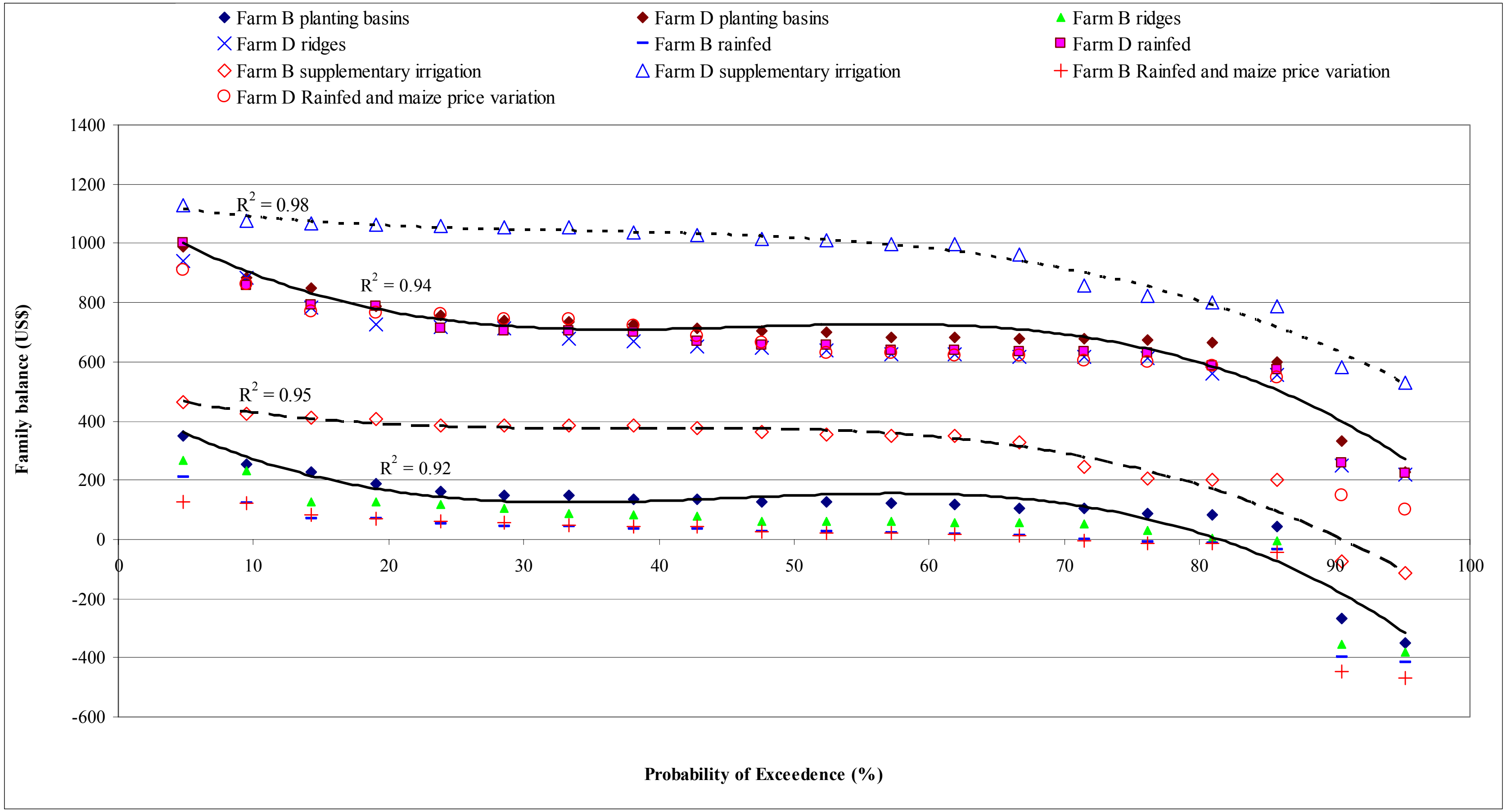


Figure 7.22 Percentage exceedence probability of family balance per selected farm types B and D under different crop management scenarios using 20 years of simulated data.

The farm gross margin or profit indicator is one of the key indicators of the long-term farm sustainability (Table 7.2). In addition, the results in Table 7.2 show that in the second 10 years of simulation (2015–2024) all the farms preformed better compared to the first 10 years (2005–2014). The improvement in gross margin is attributed to increased crop yields due to better rainfall distribution that results in fewer and shorter dry spells. The coefficients of variation for rainfall were 0.18 and 0.2, for 2015–2024 and 2005–2014 periods, respectively. If farm financial returns are consistently negative, then the farming system is unsustainable, unless supplemented by other sources of income. For instance, farmers often survive even with negative farm profit by accepting certain under-remuneration from a production practice and adjust to the shortage by sourcing supplemental income off-farm or they may be drawing income from their assets and are highly vulnerable.

The typical aggregated results of gross margin and family balance under planting basins for each of the ten subbasins in the B72A catchment are presented in Table D11 in Appendix D. The estimated numbers of farmers in each subbasin are also presented in Appendix D. There is no agriculture being practiced under subbasin 2.

Table 7.2 Average gross margin and family balance per farm type for different simulation periods.

Practice	Year	Farm type gross margin and family balance (US$)									
		Farm A		Farm B		Farm C		Farm D		Farm E	
		Gross margin	Family balance	Gross margin	Family balance	Gross margin	Family balance	Gross margin	Family balance	Gross margin	Family balance
Rainfed	2005-2014	333	639	90	-69	231	387	602	585	682	8137
	2015-2024	338	735	173	59	316	471	692	720	762	8217
Rainfed and maize price variation (NAMC, 2008)	2005-2014	322	629	77	-82	195	350	571	553	681	8137
	2015-2024	337	735	173	59	316	471	690	718	762	8217
Ridges	2005-2014	350	657	146	-13	306	461	604	586	688	8144
	2015-2024	340	738	213	99	369	524	658	686	767	8223
Planting Basins	2005-2014	427	733	201	42	374	529	648	631	691	8147
	2015-2024	420	817	276	162	447	602	721	749	771	8226
Supplemental irrigation	2005-2014	524	830	387	228	599	754	887	869	702	8158
	2015-2024	538	936	487	373	706	862	996	1024	783	8239

7.3.3 Sensitivity

In addition to carrying out complex model simulations, there is need to determine and report how sensitivity and uncertainties affect the model's ability to predict the behaviour of the physical system under study. The results of sensitivity analysis using scatter plots are presented in this section.

The scatter graphs of dependent variable, family balance and independent variables, of in-season rainfall and crop yield for farm types B (Figure 7.23–Figure 7.27) and D (Figure 7.28–Figure 7.32) show similar trend on all the parameters, indicating how their life strategies are similarly affected by both in-season rainfall and crop yields. The persistent outliers shown in Figures 7.23, 7.26 and 7.29 are ascribed to seasons where different yields are realised from the same seasonal rainfall amount. This is possible under different crop management and rainfall distribution situations. Rainfall and crop yield variables show a non-linear relationship with the family balance (Figure 7.27), whereas gross margin show a high correlation with family balance for both farm types B (Figure 7.25) and D (Figure 7.30). This high correlation is expected as gross margin was incorporated in the family balance calculations. Hence, the gross margin was excluded in the development of relationship equation between family balance, in-season rainfall and crop yield.

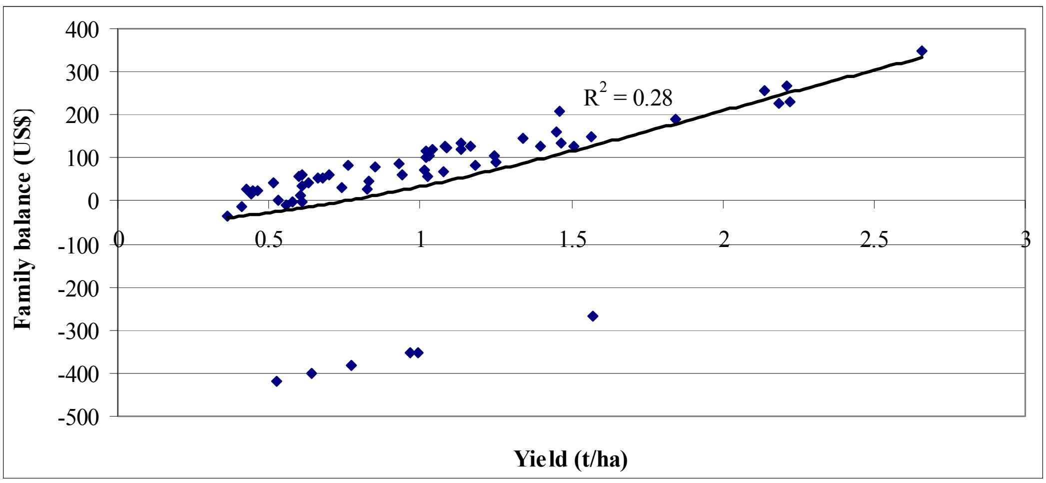


Figure 7.23 Correlation of family balance and maize grain yield for farm type B

The relationship between family balances with in-seasonal rainfall was very weak compared to crop evapotranspiration, based on the magnitude of correlation coefficient (R^2). However, a stronger relationship between family balance/ savings and evapotranspiration as anticipated was found under farm types C (R^2 = 0.70) (Appendix E), B (R^2 = 0.69) (Figure 7.24) and D (R^2 = 0.64) (Figure 7.28). This stronger relationship is due to farmers' high dependence on crop production to support their family food and income (Table 5.1). The spread of data points in the 150 to 200mm region (Figure 7.24 and Figure 7.28), result in large family balance. This is expected, as in this evapotranspiration range , yields are highly variable due to the intra-seasonal rainfall distribution that result in either poor or good yields in some seasons. A strong relationship was not found in the dry years, where zero yields were experienced leading to high negative family balance under farm type A and C. In addition, there is no strong relationship of family balance and evapotranspiration under farm types A (R^2 = 0.46) and E (R^2 = 0.43) (see Appendix E for farm type A, C and E Figures), due to their high reliance on employment income, as they depend on more than 71 % employment income as shown in Table 5.1.

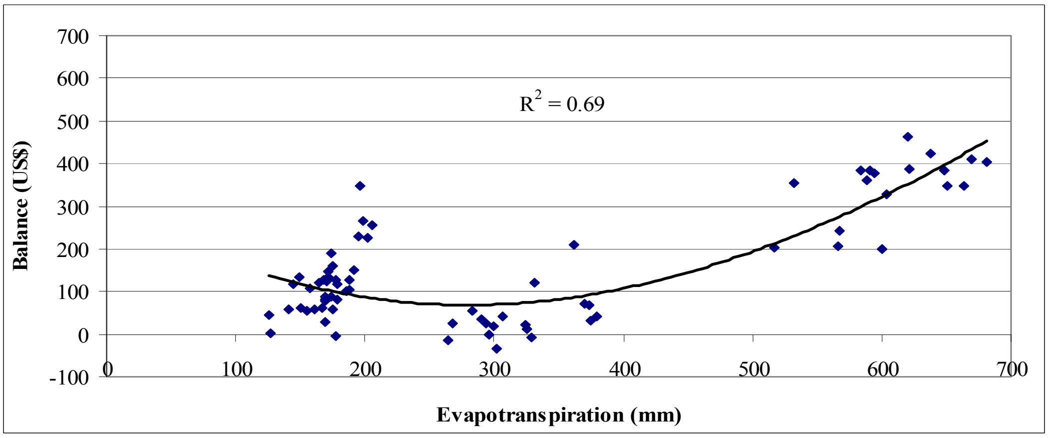


Figure 7.24 Correlation of family balance and evapotranspiration for farm type B

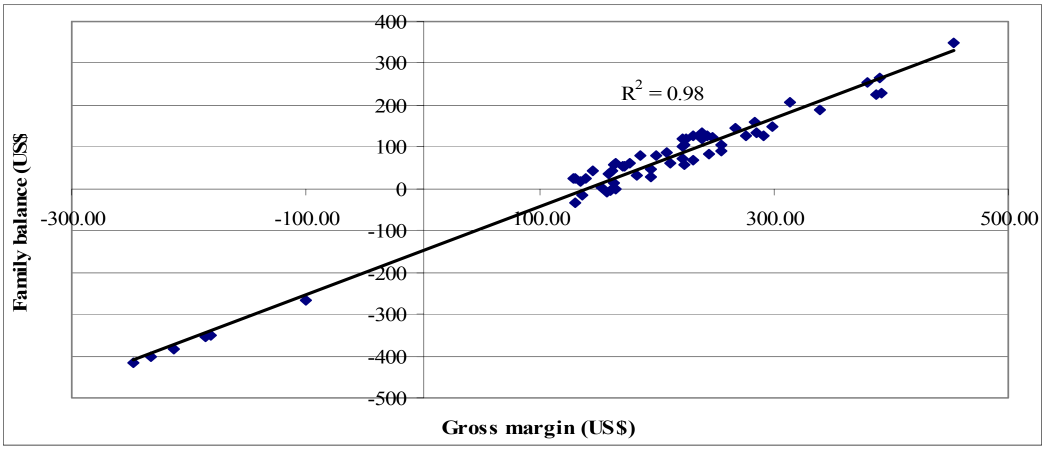


Figure 7.25 Correlation of family balance and gross margin for farm type B.

A threshold gross margin of US$ 140 is required to supplement other family income sources under farm type B (Figure 7.25), for a family to break even. Gross margin above this threshold, results in family savings or balance for farm type B. This family balance may be used for other family service needs besides food.

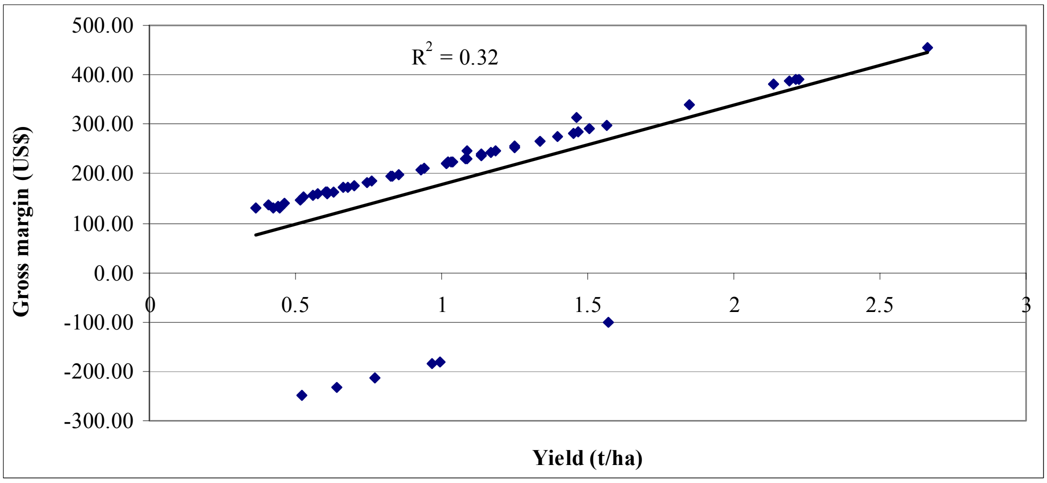


Figure 7.26 Correlation of gross margin and maize grain yield for farm type B.

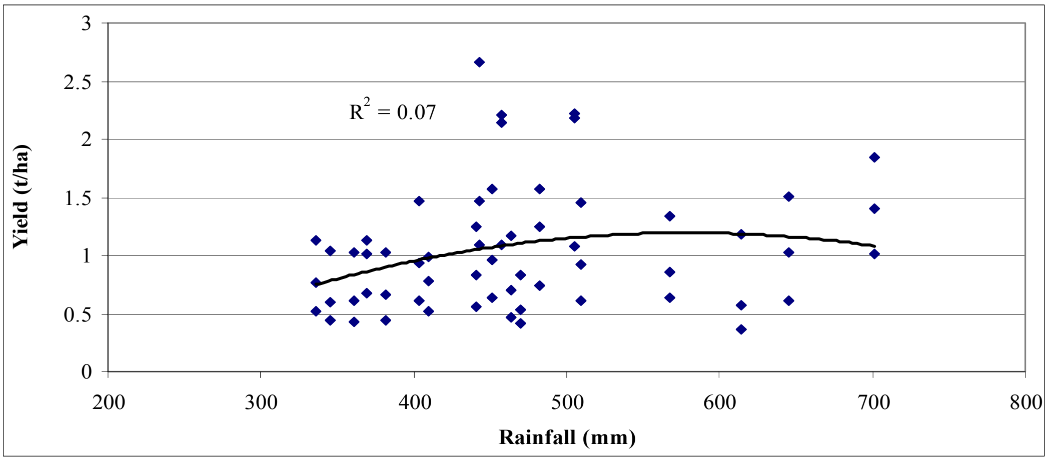


Figure 7.27 Correlation of maize grain yield and rainfall for farm type B.

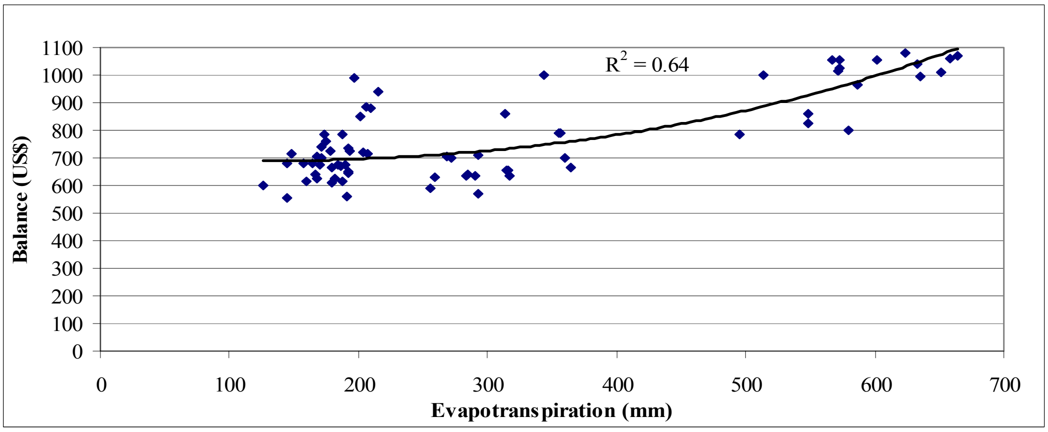


Figure 7.28 Correlation of family balance and evapotranspiration for farm type D.

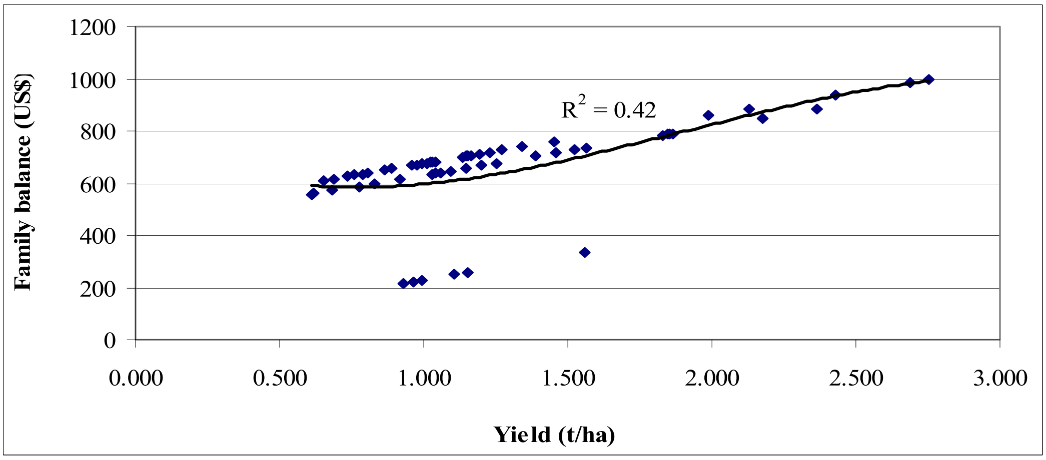


Figure 7.29 Correlation of family balance and maize grain yield for farm type D.

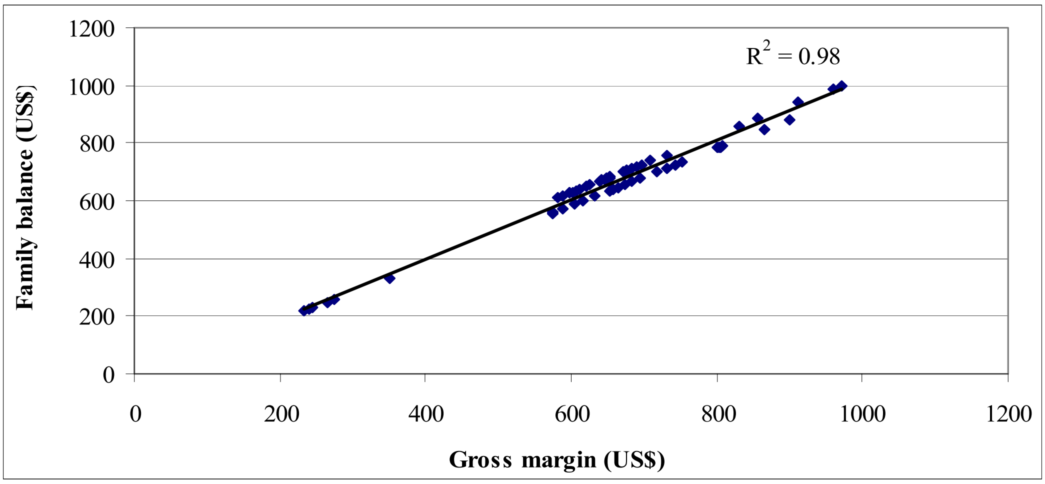


Figure 7.30 Correlation of family balance and gross margin for farm type D.

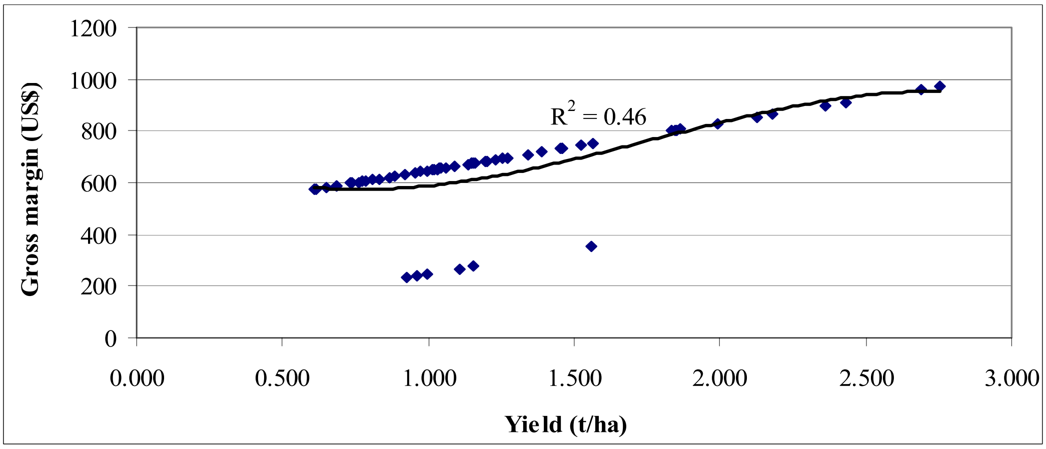


Figure 7.31 Correlation of maize grain yield and rainfall for farm type D.

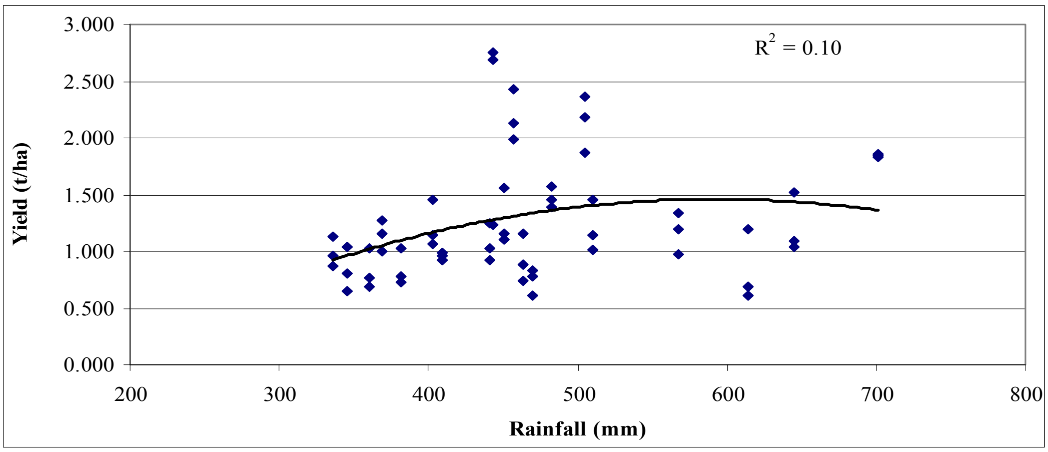


Figure 7.32 Correlation of gross margin and maize grain yield for farm type D.

The goal of sensitivity analysis is to determine relationships between the uncertainty associated with individual elements of input parameters (seasonal rainfall and yield) and the uncertainty associated with individual elements of output parameters (family balance) (Helton et al., 2005). Based on examination of scatter plots and correlation analysis the dominant variables influencing the uncertainty in the model family balance predictions were identified to be crop yield followed by in-season rainfall. Soil nutrients (both native and external (fertilisers), though not evaluated in this study, have been reported to affect crop yield and crop water use efficiency (Barron and Okwach, 2005; Bennie and Hensley, 2001), In addition, sensitivity analysis provides an extensive check that the models in the system are correctly implemented for instance by identifying correlated (e.g. family balance and gross margin) and uncorrelated (e.g. yield and rainfall) parameters (Helton and Oberkampf, 2004; Helton et al., 2000). Through sensitivity analysis appropriate and targeted investment of resources in crop yield and rainfall data collection to reduce uncertainty in analysis of family balance outputs can be achieved. Sensitivity results demonstrate that the users should attach certainty on model outputs relative to the levels of parameter sensitivity impact demonstrated in the sensitivity analysis (Xu and Gertner, 2007).

Crop yield and rainfall

The relationship of crop yield and rainfall is non-linear due to many factors that could not be isolated in on-farm experimental observations. These factors include rainfall distribution, intensity and amount, length of dry spells, temperature variations and impact of initial soil moisture at planting (a fixed date of planting was selected for all the simulations). Crop yields vary from one farming season to another and the crop yield output for a particular period or year is a function of favourable climatic factors such as rainfall, sunshine and temperature, humidity, soil fertility, topography and crop management practice. These climatic factors differ for each season.

Reliability of rainfall, particularly at critical stages of crop development, accounts for much of the variation in agriculture's potential including crop yield. Inter-annual and intra-seasonal rainfall variability is a major challenge to rainfed farmers. Humidity and wind speed combine to influence crop water needs. Crop water needs are higher when it is dry than when it is humid, and crops grown in windy climates use more water than those in calm climates (Brouwer and Heibloem, 1986). Hence, there was lack of controls relative to the range of explanatory variables due to the exposure of experimental fields to the weather variability.

Therefore, the complete impact of rainfall distribution was missed from short period experimental fields' results that were subsequently used to calibrate the crop model. Some studies found similarly non-linear relationships between crop yield and rainfall (Yenesew and Tilahun, 2009). A more subtle approach is to draw a relationship between grain yield and evapotranspiration. Stronger relationships between maize grain yield and evapotranspiration than with in-season rainfall were noted (not shown). However, a more explanatory variable (water productivity) derived from crop yield and evapotranspiration is presented in Figure 7.20.

In sum, the high dependence on rainfall, coupled with low input use and degraded soils increase vulnerability of farmers to weather vagaries in the semi-arid study catchment. The difference in evapotranspiration water productivity between farm type B and D and between different practices was mainly due to differences in harvested crop yield. Average crop yields under supplemental irrigation and planting basins practices were about four and two times higher, respectively, compared to conventional rainfed practice.

The maize crop evapotranspiration water productivity of the studied farm types is comparable to literature results reported under semi-arid climates. Furthermore, evapotranspiration water productivity estimates have shown two important applications. Firstly, as diagnostic tool to identify the level of water-use efficiency of a crop management system (farm type) or practice under study. Secondly, to provide insight into the alternative opportunities (such as planting basins and supplemental irrigation) for better crop water management to enhance crop water productivity.

Water productivity can potentially be enhanced in the study catchment by improving the agronomic practices to rainwater harvesting techniques, such as ridges and planting basins and to supplemental irrigation water management in areas were surface water is available. The need for site-specific crop production improvement practices is emphasised. Improving water productivity in agriculture reduces the competition for scarce blue water resources, mitigate environmental degradation and enhance food security by producing more food per drop of water. The saved water can be released to other uses.

In addition, the quality and representativeness of climate data used in the crop and hydrological models is fundamental in the capability of the models, whether used separately or within a decision support system, to make credible estimates. Overall, the water productivity improvement strategy is critical for sustainable food security for smallholder farmers, especially in semi-arid areas characterised by high population growth, low and unevenly rainfall distribution and under potential climate changes.

Statistical distribution checks of parameters and sensitivity analysis

A distribution check of the input and output variables (number of data points for each variable, n = 60) gave coefficients of kurtosis and skewness presented in this section. Kurtosis is a relative measure of the shape compared to the shape of a normal distribution, while skewness is a measure of asymmetry. The normal distribution has both kurtosis and skewness of zero. Positive kurtosis indicates a relatively peaked distribution, while a negative kurtosis indicates a relatively flatter distribution than a normal distribution. In addition, positive skewness indicates a distribution with an asymmetric tail extending to more positive values, while negative skewness indicates a distribution with an asymmetric tail extending to values that are more negative.

For farm type B, kurtosis coefficients were rainfall (0.042), crop yield (1.17) and family balance (2.98), while skewness coefficients were rainfall (0.827), crop yield (1.17). Kolmogorov-Smirnov statistical goodness of fit to a normal distribution was rainfall (0.142), crop yield (0.122) and family balance (-0.233) for farm type B. For farm type D, kurtosis coefficients were rainfall (0.042), crop yield (1.07) and family balance (1.99), while skewness coefficients were rainfall (0.827), crop yield (1.25). Kolmogorov-Smirnov statistical goodness of fit to a normal distribution was rainfall (0.142); crop yield (0.201) and family balance (0.176) for farm type D. Both kurtosis and skewness coefficients indicate that the independent parameters, crop yield and rainfall do not follow a perfect normal distribution. The practical use of the coefficients presented above is to indicate distributions of input variables to use under uncertainty analysis by Monte Carlo analysis.

Correlation analysis to measure the statistical association among random variables based on samples (n = 60 data points for each variable) was executed. A widely used measure is the linear correlation coefficient or Pearson's correlation coefficient. Calculating the correlation between each generated input parameter and the output (family balance) can show important parameters that contribute most to errors. Based on the magnitudes of the correlation coefficients, errors in crop yield were most important than those in rainfall (Table 7.3). This result concurs with the scatter plots and regression models presented earlier. The practical implication of this result is to analyse the important parameters in uncertainty analysis and to determine the extent to which their uncertainty can be reduced through investments in field investigations and development of better crop and rainfall simulation models.

Table 7.3 Correlations between variables, for farm types B and D.

Parameter		Farm type B			Farm type D		
		Family Balance	Rainfall	Yield	Family Balance	Rainfall	Yield
Pearson Correlation	Family Balance	1.00	0.12	0.53	1.00	0.18	0.63
	Rainfall	0.12	1.00	0.21	0.18	1.00	0.27
	Yield	0.53	0.21	1.00	0.63	0.27	1.00
Sig. (1-tailed)	Family Balance		0.18	0.00		0.08	0.00
	Rainfall	0.18		0.06	0.08		0.02
	Yield	0.00	0.06		0.00	0.02	

Relationship equations for farm types B and D family balance with rainfall and maize grain yield under rainfed, ridges and planting basins were estimated using product equation, as the variables are not normally distributed from statistical kurtosis coefficients. However, according the Central Theorem (USEPA, 2000), whatever distributions are assigned to input variables, the output always tend to be normally distributed. For the three rainfed practices combined, a nearly perfect linear fit found to the data from ICHSEA model is represented by the regression models of the form $y = y(x) = f(x_i x_j)$ in Equations 7.3 and 7.4 for farm types B and D, respectively.

The correlation coefficients (R^2) were 0.86 (Equation 7.3) and 0.90 (Equation 7.4) for farm types B and D, respectively, suggests a very strong relationship between family balance and predictors of rainfall and crop yield.

Family balance: $F_{B:\ Farm\ B} = 154.07\ X - 190.24$ (7.3)

Family balance: $F_{B:\ Farm\ D} = 221.52\ X - 252.24$ (7.4)

where $X = Yield^{0.5} \times Rainfall^{0.1}$ (t/ha mm)

The non-linear dependence of farm family balance on rainfall and crop yield shows that poverty is indeed multidimensional and highly related to physical climate, crop management practices and environment. However, the study did not exhaust all the possible poverty dimensions and conditions that affect livelihood and incomes, such as health, market access, access to safe water, adequate shelter information, age of farmers, and education (Qiu et al., 2007; Carter, 1999). Depletion of environmental resources such as soil and water can indeed make some categories of people be trapped in the poverty cycle even under economic growth at country level. The relationships presented in this section are used in the error propagation analysis presented in the next section.

7.3.4 Uncertainty propagation

The results of 5000 Monte Carlo simulations using the model Equations 7.1 and 7.2 to propagate the uncertainty in the model parameters for each farm type to produce a probability distribution of model predictions are presented in this section. Important prerequisites for any uncertainty and sensitivity analysis are the assumptions that statistical distributions for the input values are correct and that the model sufficiently captures the critical processes taking place in the system under investigation (Loucks and Van Beek, 2005). However, these assumptions are rarely satisfied. A random value is sampled from the probability distribution for each uncertain model parameter. A uniform type of distribution according to widely accepted rule of thumb (Ju, 2008) was assumed for the rainfall and grain yield parameters.

The probability distributions graphs derived from 5000 Monte Carlo runs by varying rainfall and maize crop yield parameters simultaneously shows cumulative distribution functions (CDFs) and statistical measures for the 5^{th} , 50^{th} (median) and 95^{th} percentile confidence interval are shown in Figure 7.33 Figure 7.38 for different crop management practices. The areas between 5^{th} and 95^{th} give the 90 % confidence interval for the family balance.

Uncertainties associated with each parameter can be quantified and ranked according to their importance to the overall results of family balance, providing an aide in prioritising data collection and research efforts. In this study crop yield is more important than in-season rainfall, because for the same rainfall amount different yields can be obtained depending on management practices employed.

The 90 % confidence interval (US$ 4–US$ 270) of family balance under combined practices of rainfed, ridges and planting basins for farm type B is presented in Figure 7.33.

The family balance is reduced to US$ 4–US$ 132 at 90 % confidence interval under maize price variation presented in Figure 7.34. These results indicate family balance reduction by almost half due to the impact of maize price variation (43–130 % of the basis price of US$ 205/tonne). However, under supplemental irrigation practice, family balance increased to US$ 233–US$ 429 at 90 % confidence interval as presented in Figure 7.35. This result indicates increased and more reliable family savings to be gained under supplemental irrigation compared to conventional rainfed, ridges and planting basins practices. However, these gains can only be realised where water supply to provide supplemental irrigation is available.

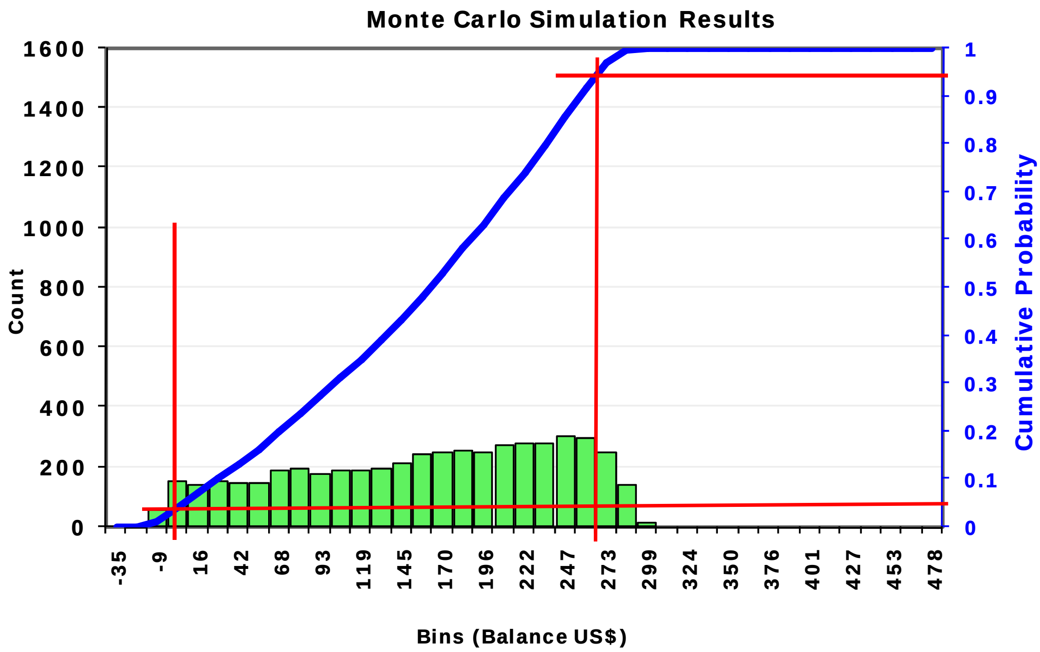


Figure 7.33 Family balance cumulative probability distribution curve under combined practices for farm type B.

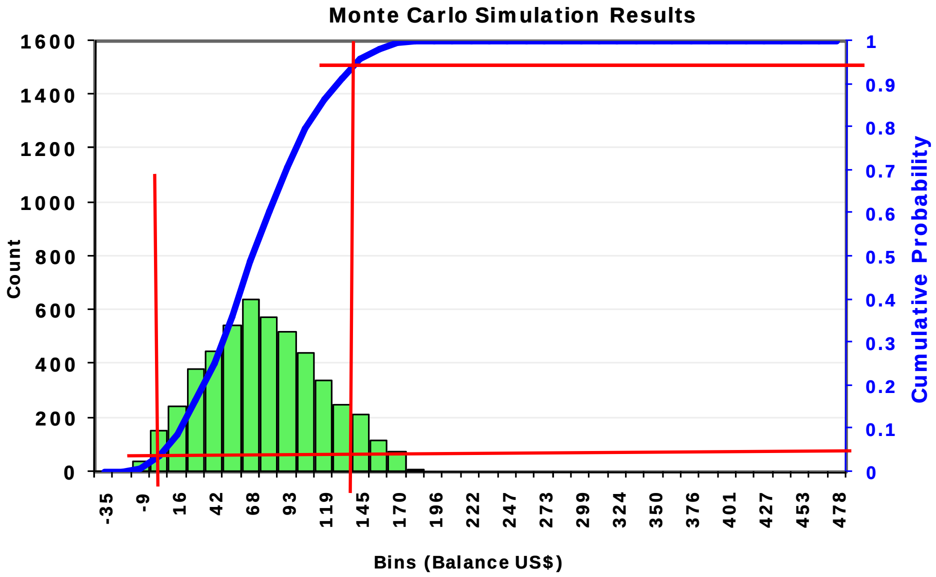


Figure 7.34. Family balance cumulative probability distribution curve under rainfed practice with maize price variation for farm type B.

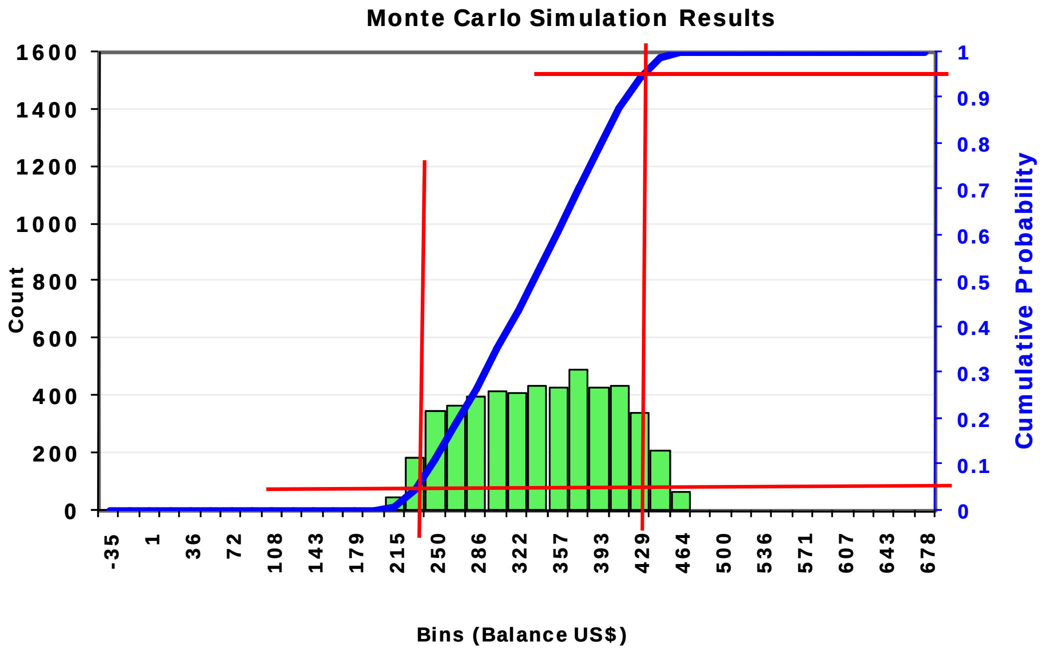


Figure 7.35 Family balance cumulative probability distribution curve under supplemental irrigation practice for farm type B.

A similar trend to farm type B is shown under farm type D. The 90 % confidence interval (US$ 600–US$ 900) of family balance under combined practices of rainfed, ridges and planting basins for farm type D is presented in Figure 7.36.

The family balance slightly increased to US$ 600–US$ 960 at 90 % confidence interval under maize price variation presented in Figure 7.37. This increase in family balance is explained by higher (almost twice) yields (Table 7.1) obtained under farm type D compared to farm type B. However, under supplemental irrigation practice, family balance increased to US$ 900–US$ 1 140 at 90 % confidence interval as presented in Figure 7.38.

In sum, resource-constrained farm type B is more vulnerable to maize price variations than the more intensive and diversified (Table 5.1) farm type D due to lower maize yields. Farm types A and C presented in Appendix E (Figures E1 and E2) responded similar to farm type B under combined practices and maize price variation scenario, while farm type E was not affected by maize price variation as it produces low yields and rely very much (91 %) on employment income (Table 5.1). All the farm types showed an increase in family balance under supplemental irrigation practice. Based on the performance measure of maximising family balance for enhanced food security and poverty reduction supplemental irrigation is the best strategy for smallholder farmers. However, the feasibility of wide adoption of this strategy is limited by water scarcity and possible cost of infrastructure.

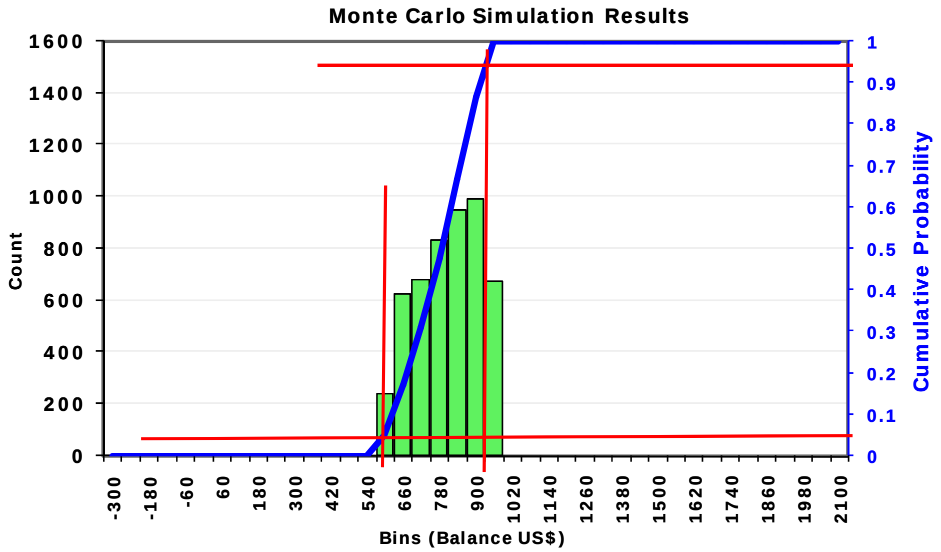


Figure 7.36 Family balance cumulative probability distribution curve under combined practices for farm type D.

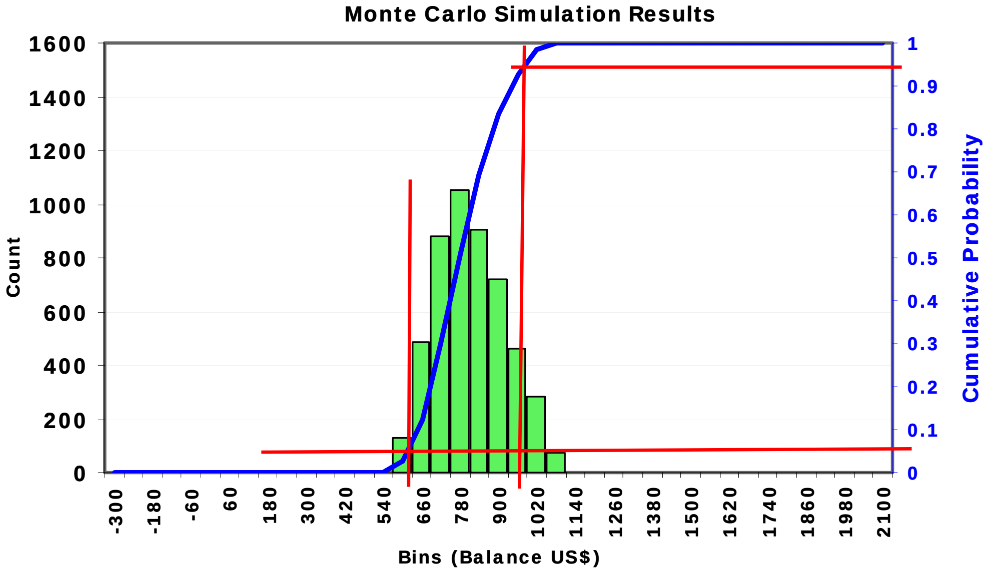


Figure 7.37. Family balance cumulative probability distribution curve under rainfed practice with maize price variation for farm type D.

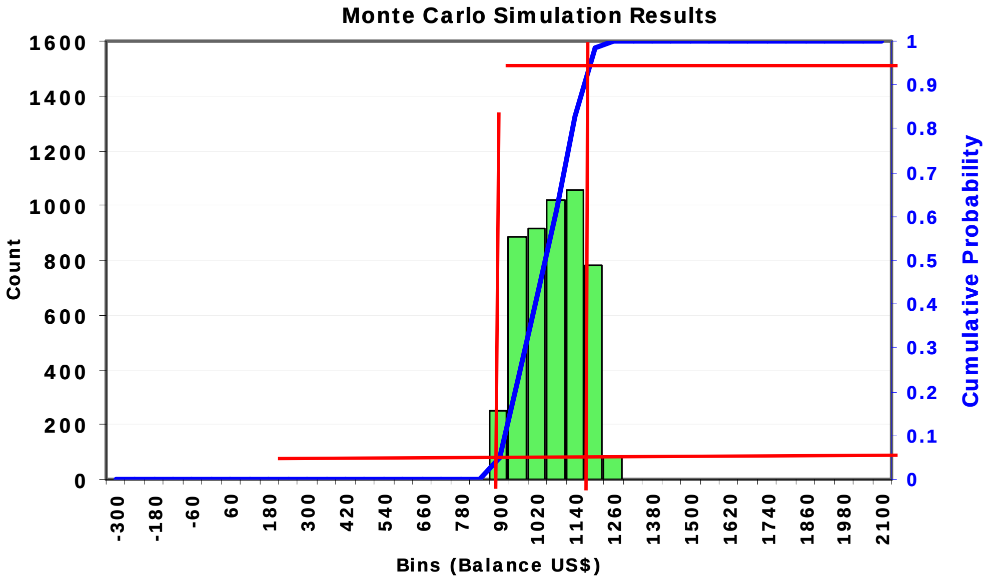


Figure 7.38 Family balance cumulative probability distribution curve under supplemental irrigation practice for farm type D.

The combined uncertainty calculated for different scenarios per farm type from uncertainty propagation equation after Refsgaard et al. (2007) are presented in Table 7.4. The contribution of crop yield to total uncertainty under combined practices is twice that of rainfall, indicated by ratio of standard deviation to mean (Table 7.4). This result confirms earlier sensitivity analysis results that indicated that the crop yield had a higher correlation with family balance than rainfall.

Similarly, under maize price variation, the contributions to family balance uncertainty, starting with the highest contributor, are crop yield, rainfall and maize price variation (Table 7.4). However, under supplemental irrigation practice supplemental irrigation water supply contributes most to uncertainty followed by rainfall and then crop yield (Table 7.4). This result is in agreement with on-farm results and indicates that supplemental irrigation in semi-arid areas is very important as it bridges crop water stress that results in low crop yields under rainfed practice.

Generally, a reduction in the magnitude of uncertainty in family balance is noted in Table 7.4 as input parameters were increased from two to three, under the three scenarios. This reduction in uncertainty is in conformity with finding of Loucks and Van Beek (2005) who warned that, while adding new parameter or model detail can reduce uncertainty, increasing model complexity, especially if the parameter added is based on processes difficult to measure can increase uncertainty in model results (Özkaynak et al., 2009). This reduction in uncertainty as a third parameter is added indicate that the two initial parameters of rainfall and crop yield partly captured the causes of family balance variation. Therefore, the family balance model could be improved by including additional predictors such as market price variations. Secondly, the added parameter variations were well understood, for instance through the hydrological model used to simulate the streamflows.

Table 7.4 Combined uncertainties under different scenarios per farm type.

Scenario/ practice	Equation form	Farm type	Mean					Standard deviation				Combined uncertainty
			Rainfall (R mm)	**Yield (Y t/ha)**	**Maize price (P US$)**	**Sum streamflow (F m^3)**	**F.balance (US$)**	$\sigma_{Rainfall}$	σ_{Yield}	σ_{Price}	$\sigma_{Streamflow}$	$\sigma_{F.Balance}$ **(US$)**
Combined practices	F.balance = *f* (R*Y)	A	521.13	1.44			779.81	106.04	0.65			383.62
		B	515.44	1.51			150.36	105.18	0.67			73.06
		C	518.99	1.53			616.41	105.41	0.67			297.56
		D	518.30	1.68			776.11	105.14	0.62			325.51
		E	520.48	1.45			8226.28	105.45	0.72			4443.95
Maize price variation under rainfed	F.balance = *f* (R*Y* P)	A	519.90	0.99	212.07		733.33	106.04	0.38	31.25		338.59
		B	518.91	0.91	211.59		71.51	105.50	0.32	31.63		30.74
		C	518.26	0.87	211.76		523.81	105.59	0.30	31.44		221.60
		D	520.11	1.73	212.86		785.56	105.47	0.60	31.59		334.99
		E	516.02	0.47	212.65		8218.38	104.89	0.16	31.47		3436.92
Supplemental irrigation	F.balance = *f* (R*Y* F)	A	520.16	2.24		5302819	894.24	105.70	0.54		1790761	413.24
		B	519.18	2.70		5290158	336.26	106.72	0.44		1812390	145.26
		C	518.52	2.65		5248728	832.07	104.54	0.47		1819572	364.54
		D	516.49	2.64		5281535	1044.11	105.19	0.46		1794093	451.85
		E	521.22	2.64		5271220	8237.57	105.88	0.46		1810927	3589.59

Notes:

1. σ = Standard deviation; R= rainfall; Y = Yield and F = sum of streamflow/season
2. F.balance = family balance or family savings after satisfying family food requirements

Models being simplified representations of the reality produce output with errors. The uncertainty analysis showed how much uncertainty there is in the model output (uncertainty analysis) and where the uncertainty comes from (sensitivity analysis). The sources of uncertainty identified were context and framing uncertainty due to natural environment, socio-economic and political issues; inputs uncertainty due to system data and driving forces; model uncertainty due to structure, technical and parameters. Not all of these uncertainties were addressed, but stakeholder involvement and Monte Carlo analysis for statistical uncertainty were used in the study to provide an indication of the reliability of the resulting calculations in decision-making.

In addition, there is need to report the confidence that should be placed on the results of the model analysis to make informed decisions. The magnitude of uncertainty is a key to management practice or policy acceptance as the cost of implementation of management practices such as the planting basins or supplemental irrigation may significantly increase with larger family balance uncertainty estimates. In this study, supplemental irrigation is the best strategy based on both increased food production and family balance/savings at 90 % confidence, although its feasibility depends on other factors.

The main limitation of the parameter uncertainty techniques presented in this chapter is that the model calibration is based on a single model structure for each of the three models coupled in this study. Therefore, errors in the model structure (conceptual uncertainty), often considered to be main source of uncertainty in model predictions (Refsgaard et al., 2007; Refsgaard et al., 2006) are incorrectly allocated to model parameter uncertainties.

In addition, the estimated parameter uncertainties inadequately compensate for the model structure uncertainty, when the model is used for prediction of conditions beyond the calibration base (model extrapolation) (Refsgaard et al., 2006). This problem is addressed by using different models of the same system of interest (multiple model simulation) and determines how well the models match experimental data.

The model structure uncertainty analysis was not assessed for two reasons. Firstly, due to time constraints. Secondly, the integrated models have been widely used and ascertained to be stable and performed well under different environments from extensive literature survey presented in Chapter 3.

Caution was exercised to reduce epistemic uncertainty by collecting and using long-term series of climatic data from the study area. More knowledge was gained through in-field experiments for at least three consecutive years, physical and chemical soil tests, field observations and discussions with farmers and extension officers. Nevertheless, no matter how much effort is invested in quantifying and reducing uncertainties in model results, individual or coupled, uncertainties will remain due to inherent nature of the systems and the simplifications of reality in models.

7.3.5 Integrated model validation

A key element of designing the ICHSEA interface was presenting of preliminary model runs and results to local farmers and extension officers in the form of groups discussions (Figure 7.5). In these group discussions, participants evaluated the results and were consulted for changes and refinement to the input data. This exercise enabled blending of ideas between the researcher (model developer), potential end users' requirements and management options that were finally accommodated in the integrated model. As argued by Abaza and Hamwey (2001), stakeholder participatory involvement has huge short- and long-term benefits that outweigh costs, time and resources invested in participation. For instance, it provides a clearer recognition of stakeholder concerns allowing the model developer, end users and policy-makers to address them.

However, power relations among the stakeholders could affect the validation discussions. Giving stakeholders the opportunity to contribute and challenge model assumptions before results are reported also creates a sense of ownership of the modelling process that makes model results difficult to reject in the future. The ICHSEA model will continue to be validated in future to incorporate future developments and additional data availability. Improved ICHSEA model validation is likely to improve its predictive capacity, although Rotmans and Van Asselt (2002) argue that the interpretative and instructive value of an integrated model is far more important than its predictive capability, which is rather limited.

In addition, when running the ICHSEA model interface, information about how parameters and inputs flows, and failed communications among models is provided. This type of scrutiny addresses the need to debug logical errors as part of verification as described for expert systems and models (Sojda, 2007). For example, an error would be detected if a step in the sequence of model execution is omitted or when models being coupled refer to different simulation periods.

7.3.6 Future developments and limitations of the current model

Overall, the sensitivity analysis of the model demonstrates the capability of providing some of the trade-offs associated with crop management changes in blue and green water resource availability, use and management. However, this integrated model application demonstrates some limitations such as incapability to simulate farm production decisions that are non-seasonal. Standardised Monte Carlo analysis can be can be used so that the mean and variance of input parameters are adjusted to be uncorrelated to ensure that the signal from one is not confused with signal from another (Loucks and Van Beek, 2005).

7.4 Summary

This chapter illustrated the application of integrated model, ICHSEA in B72A catchment in northern South Africa encompassing five farm types by evaluating the impact of different climatic conditions on the performance indicators based on catchment stream outflows, sediment load, food security and disposable income. It then discusses the sensitivity and uncertainty analysis of the model results to give confidence to the model results and to enhance decision-making.

The results presented in this chapter are a first attempt at integrated assessment of smallholder farmer livelihoods at catchment level. The component models were individually calibrated using available observed data before coupling into an integrated model that was evaluated through group discussions with local stakeholders. These discussions with local stakeholders made clear the contradictory objectives and expectations between the researcher and local stakeholders that necessitated finding a common ground. However, issues of influence and empowerment (McIntosh et al., 2008; Rivington et al., 2007) can affect the stakeholder participation process.

The individually calibrated model statistical performance results were presented in Chapter 5. Where inadequate observed streamflow data was encountered, robust method of validating the hydrological model results using adjacent gauged catchments was successfully performed through the use of physical characteristics similarity measures, to transfer parameters from gauged to ungauged catchments (Burn and Boorman, 1993). However, extrapolation of hydrological parameter values to other catchments may be highly uncertain as uniqueness of a particular catchment may not unequivocally be represented by a set of calibrated parameters (Beven, 2000).

The developed ICHSEA model runs on 10-year timeframes to enable a holistic assessment of smallholder farmer livelihoods and streamflows (environmental) in response to different catchment management practices and weather cycles. For instance, from the five scenarios tested in this chapter, supplementary irrigation practice had the greatest influence on both food security and environment (streamflows), thus creating a potential policy conflict if environmental streamflows are to be satisfied. Therefore, the current revitalisation of smallscale irrigation systems programme by the Department of Agriculture to improve and stabilise rural food security in the Olifants subbasin need to recognise the environment as a legitimate user and reach acceptable trade-offs.

Furthermore, farmers can more than double their maize production in wet years and stabilise production in dry years by moving from conventional rainfed practice to planting basins practice, an in-field rainwater harvesting technique. Rainwater harvesting increases the water available to the crop root zone, leaving less proportion allocated to runoff that becomes blue water in rivers and affect recharge. These impacts of rainwater harvesting require further studies (Ncube et al., 2009).

The potential crop area estimates to be placed under supplemental irrigation provided are based on current maize crop water use of 3000 m^3/ha.season. If there is an improvement of water productivity, for instance to 2000 m^3/ha.season, the potential areas may be increased.

Furthermore, climate change could lead to important future modifications of agricultural practices including the wide adoption of rainwater-harvesting techniques, sowing and yielding date, supplemental irrigation practice and crop variety choice. Hence, rainwater harvesting and supplemental irrigation practices are important to prepare smallholder agriculture systems to face these future climate changes.

Low water productivity values for maize in the current study are attributed to low crop yield due to poor crop timing, excessive water application, especially under supplemental irrigation practice and poor field crop management. The best planting dates (Chapter 5) are from first to second weeks of December, but 25 November was used in the modelling to be consistent with the current planting dates practice.

The correct determination of evapotranspiration or transpiration is crucial for accurate water productivity investigations. Crop water productivity could be enhanced by improving field crop management practices such as correct crop planting dates that lead to shorter crop season, proper supply of supplemental irrigation water, improved seeds and correct micro-dosing of nitrogen fertiliser, depending on farmer affordability. Nitrogen application greatly improves water use efficiency (Katerji et al., 2008), but it is important to maintain available phosphorus in the soil so that the response to nitrogen and applied supplemental irrigation or rainfall is not constrained.

The yearly family balance benefit of US$ 600–US$ 1 140 at 90 % confidence brought about by supplemental irrigation warrant investment in increasing storage capacity or constructing a dam in the catchment. Dam construction is one of the main strategies to reduce water shortages in the dry period (June to October) and to carry water availability from wetter years to drier years. The size of the dam will depend on the estimated MAR (31 Mm^3) of the catchment. For instance, a dam with a storage capacity of 10 % (3.1 Mm^3) of MAR can be constructed. A dam of this capacity at 75 % irrigation water supply (about 200 mm/ha) provides supplemental irrigation to above 775 ha and can benefit more than 1 550 families with half a hectare each. Since the yield for the half-hectare field is above one tonne under supplemental irrigation, food security for these families is likely to be satisfied. Bohle (2004) argues that while, food insecurity can be chronic and transitory, it should be integrated more systematically into broader issues of 'human security'. In this study food security in relation to maize production and market prices variation has been explored.

The results presented in this chapter are important for supporting decision-making and planning by extension officers and catchment water managers for poverty alleviation in smallholder farming communities.

Policy implications

The findings of this study have important policy implications for farmers, extension services and future studies. Despite farmers adapting to the climatic variation, the government needs to help the adaptation process. This help involves making available the necessary resources such as mechanical equipment to dig planting basins and providing small and more efficient supplemental irrigation infrastructure systems, especially in the drier and low-lying areas of B72A catchment and other parts of the country to counteract low soil moisture and high temperatures during intra-seasonal dry spell periods. Nevertheless, water resource constraints would limit opportunities to use supplemental irrigation as a counter to low soil moisture and climate change.

To ease water constraints and enhance productivity, there is need to move from conventional rainfed to in-field and ex-field rainwater harvesting techniques that encourage infiltration and conserve soil moisture for longer periods after a rainfall event. Technological and social attitude changes, towards accepting and implementing in-field water harvesting technology potentially increase rainfed crop yields and reduce supplemental irrigation water demand. These changes are enhanced by policies that encourage food self-sufficiency in this semi-arid at both catchment and country scales. This conclusion concurs with literature that highlighted lack of appropriate policies and strategies for minimising the risk and upgrading the rainfed agriculture systems (green water), unlike blue water.

Furthermore, the inclusion of sensitivity analysis showed non-linearity interactions between the models, particularly between the crop yield and hydrologic component (rainfall). Both sensitivity and uncertainty analysis through Monte Carlo analysis added confidence in the application of the integrated model in decision-making by providing model users with risks of family balance to different crop management practices. However, Standardised Monte Carlo analysis can be can be used to enhance uncertainty analysis (Loucks and Van Beek, 2005).

Reflection on ICHSEA development

The integration of multiple existing models to reduce modelling effort into an integrated model, ICHSEA was successful. ICHSEA model led to quick assessment of the impacts of different crop management scenarios on livelihoods of smallholder farmers in wider physical and socio-economic contexts. Hence, it is important to at this stage to highlight that the OLYMPE model does not simulate the social human behaviour, but simulate the consequences of human actions or decisions. The suite of management actions developed in this integrated system were limited to water availability management in rainfed crop fields that has a great impact in reducing potential yields in arid and semi-arid areas. Additionally, the model can be a useful tool for discussion and negotiation processes.

In addition, ICHSEA model was able to address key scientific questions such as, what is the intra-seasonal, inter-annual and decade-scale variability in stocks and fluxes of green and blue water and how they impact rural livelihoods under diverse crop management options? These questions indirectly address impacts of climate change and variability indicating the flexibility of the ICHSEA model.

Based on the easy-to-use interface and the user contributions during the calibration and validation processes, ICHSEA model interface could become an accepted and credible instrument for supporting sustainable smallholder crop water management and policymaking. However, limitations of the model should be recognised to avoid misuse.

The limitations of the model include, few data used for validation of the hydrological model, as the main quaternary catchment outlet is ungauged. Secondly, the calculation of the potential supplemental irrigation area was based on summation of potential daily-diverted flows to get total amount of water available for supplemental irrigation. Hence, potential supplemental irrigation area is restricted by growing period seasonal water volume. In addition, externalities of nutrients such as fertiliser are unaccounted for in the model. However, the farmers do not use much fertiliser under maize production because of high costs. Further studies can tackle this aspect.

Chapter 8: Conclusions and Recommendations

8.1 Conclusions

Most natural resource systems involve highly complex interactions of soil, plant, weather and management components that are difficult to describe quantitatively. Thus, improved management of these natural resources demand integrated, flexible and easy to use modelling tools (DSS) that are able to simulate the quantitative and qualitative aspects of the system. These simulations enable better understanding of problems such as smallholder farmer food insecurity and support different crop management scenarios thought to be critical to improved water resource management. The ridges and planting basins that fall under the conservation agriculture are promoted as a potential solution to increasing crop water productivity to ensure food security of smallholder farming families in sub-Saharan Africa.

This chapter presents the methodological steps and main findings with regard to assessment of socio-economic and environmental implications of various crop water management practices and the development of an integrated model to provide decision support for smallholder farmers. The findings are mainly based on the case study carried out in water scarce B72A quaternary catchment of the Olifants subbasin, South Africa. The contributions to knowledge, possible improved methods of data collection and methodology approach that could have been used in the study and limitations of the study are presented. Finally, suggestions for further research are presented.

The purpose of this thesis is to link smallholder farmers' livelihoods and food security to their agricultural production systems in semi-arid and water scarce B72A quaternary catchment of the Olifants subbasin. The main objective of the research is to develop an integrated modelling tool to serve as a decision support system to assist in smallholder agriculture policy understanding and crop management practices in semi-arid and water scarce catchments. The general objective of the research is to understand how smallholder cropping systems in

B72A quaternary catchment of the Olifants subbasin affect both crop yields and livelihood of smallholder farmers.

For an enhanced understanding of farm household systems and their behaviour, the methodology involved construction of farm typologies. These typologies served as input into the socio-economic modelling of farming systems under different climatic and market perturbations. The performance evaluation indicators of the farming systems were based on providing enough food for the family and the savings after satisfying the family food requirements. The socio-economic model was calibrated using the first three years of data and later validated by discussion with farmers and extension officers.

The socio-economic model, together with crop model PARCHED-THIRST were then applied to identified five farm typologies. The crop model was calibrated based on three years of on-farm experimental data and other observed data. The simulations showed that farm type B, which rely on more than 80 % farm income is most vulnerable, while farm type E, with highest livestock units and rely on 91% employment income is least vulnerable. Furthermore, farm type D with diversified crops performed better compared to farm type B in satisfying its family food requirements.

Based on the successful results of farming systems modelling that combined crop growth and socio-economic models, a hydrology model was included to complete the integrated model to support decision-making by extension officers and other institutions with interest in catchment agriculture and water management. To achieve this integration, avenues script language, under ArcView 3.3 was applied. This integrated model scenarios were validated by group discussions (Vogel et al., 2007) with the farmers and agricultural extension officers as there was lack of a comprehensive database, common to integrated models (Sojda, 2007). After validation, the integrated model was applied in the simulation of different crop management practices, initially tested in on-farm trials and the resultant streamflows, sediments, farm gross margin and family savings were presented.

Under the integrated model, individual models of hydrology, agronomy and socio-economic were setup and calibrated. For the hydrology model, the representative flow gauge B7H008 (rainfall gauge 0637271W) at the main outlet of four quaternary catchments (B72E, F, G and H) was used to get the best simulation parameters of the four catchments. These best parameters were then transferred to ungauged B72A quaternary catchment, based on physical catchment characteristic similarity (Burn and Boorman, 1993) for water resources availability simulations. The transferred best parameters were validated in B72A using observed 407 days (15/06/2007 to 15/08/2008) streamflow series in subbasin 10, and showed good performance indicated by statistical criterion.

However, the limitation of the transfer methods is that they are dependent on the availability and representativeness of the source gauge's flow data. An additional limitation is that sensitivity analysis results used to obtain the best parameters in adjacent catchments are not necessarily transferable between different catchments as demonstrated by Ncube (2006). Furthermore, calibrations of a simulation model for a given catchment, besides destroying the physically based nature of the model, it reduces modelling uncertainties associated with both structure of the model and parameter estimates. Arabi et al. (2007) contend that even with the best model structure, parameter estimation contains residual uncertainty that propagates into model predictions and the evaluation of crop management practices effectiveness.

Furthermore, the integrated model scenarios were validated by participatory approach, through several focus groups discussion with local farmers, non-governmental organisations with interest in farming and food security and extension officers. The combination of qualitative and quantitative data in the integrated model development, calibration and validation provided a robust approach and model credence in estimating the impact of crop management, weather and market price variations to smallholder farmers' livelihoods.

A number of feedback loops between the three models were included. However, the user is still responsible for specifying links between component modules, and ensures their correctness with respect to objective and logic.

Based on the crop management practices investigated in on-farm experiments, scenarios were generated. These scenarios were rainfed (base scenario), untied ridges, planting basins, supplemental irrigation and maize price variation under base scenario. Therefore, by executing the model under various crop management practices, the model predicted how annual farm gross margin of the representative five farm typologies is affected by changes in productivity resulting from changes in crop management practices. Hence, it is important to at this stage to highlight that the OLYMPE model does not simulate the social human behaviour, but simulate the consequences of human actions or decisions. Land use change, known to have less impact than its management (Schulze, 2003) (e.g. crop management practices presented in this study) may have significant hydrological response impact by either enhancing or retarding infiltration, and thereby increasing or decreasing streamflow generation.

Results from on-farm experiments show that the current crop water use and productivity under conventional rainfed agriculture are 344 ET- mm/ha and 0.11kg/m^3, respectively. The average yield under rainfed of 0.7 t/ha is low and needs improvement. Thus, the performance evaluation based on yield and water productivity of four crop management practices for five farm types were evaluated. Under in-field crop water management practices, planting basins produced best results on food security compared to untied ridges and conventional rainfed tillage practices. However, supplemental irrigation performed best compared to these in-field rainwater harvesting practices, because of its capability to bridge longer dry spells.

In addition, the estimated mean annual runoff from B72A catchment was 31 Mm^3/year, while blue water use by agriculture (both smallscale and commercial farmers) is estimated at 58 % of the catchment yield. Department of Water and Environmental Affairs slash this agriculture allocation to 20–30 % in poor rainfall years.

Furthermore, results from model simulation showed that supplemental irrigation practice resulted in highest streamflow reduction (54 %) followed by planting basins (19.8 %) and untied ridges (14.3 %) practices. The average yield performance under conventional rainfed, ridges, planting basins and supplemental irrigation practices under different climatic conditions for 20 years was presented.

The conventional rainfed practice average yields were farm A (0.66 t/ha), farm B (0.67 t/ha), farm C (0.64 t/ha), farm D (1.22 t/ha) and farm E (0.35 t/ha). The average conventional rainfed evapotranspiration (ET) for all the farmers was 310 mm. For untied ridges practice, average yield was 0.73 t/ha (ET = 140 mm) for farm A and 1 t/ha (ET = 175 mm) for the rest of the farm types. The average yields under planting basins practice for each farm type was about 1.4 t/ha (ET = 169 mm), while for supplemental irrigation practice the average yields were 2.2 t/ha for farm type A and 2.8 t/ha for farm types B, C, D and E. The difference in yield of farm A from other farms is due to weeding practices. The results indicate the importance of both supplemental irrigation and rainwater harvesting to increase yields and water productivity and thereby enhance food security.

Though supplemental irrigation practice had highest average yield (2.8 t/ha), its water productivity (0.47 kg/ m^3) was lower than that of planting basins practice (0.82 kg/ m^3) with an estimated yield of 1.4 t/ha. Hence, in semi-arid areas, where physical and economic access to supplemental irrigation is low, planting basins should be encouraged because of their high water productivity and yield that is more than sufficient to ensure grain food security for an average farm family of five.

The use of supplemental irrigation should be encouraged in the lower drier parts of the catchment and controlled as it results in highest streamflow reductions (53 %) that affect both the environment and downstream users compared to planting basins (19.8 %), untied ridges (14.3 %) and conventional rainfed. Supplemental irrigation is only useful for risk mitigation, when rainfall is unevenly distributed, thus when it has a greater yield impact. The yield impact is even amplified when supplemental irrigation is combined with affordable micro-dosing (14 kg/ha) (Kgonyane and Dimes, 2007) of nitrogen fertiliser as presented in Chapter 5. The annual average potential area that can be put under supplemental irrigation for the 20-year simulation period is 530ha, with a maximum of 1000 ha and minimum of 152 ha. The average potential area can only support 1000 families (about 10% of smallholder families in the catchment), assuming each gets 0.5ha, this result indicates potential improvement in crop yield and consequently livelihoods from supplemental irrigation in the water scarce catchment.

The use of in-field and ex-field rainwater harvesting raised water productivity that is the physical grain yield quantity derived from the use of a given quantity of water. However, these methods require construction labour probably more than the conventional rainfed practice.

Land preparation labour requirements show that planting basins preparation requires the highest labour in the first year at a cost of US$ 168/ha, but can be spread out before rainfall season, while for untied ridges and conventional rainfed practices is US$ 58/ha and US$ 35/ha, respectively.

Annual sediment losses were highest under conventional rainfed practice (395 t/year) compared to supplemental irrigation practices (260 t/year), untied ridges (233 t/year) and planting basins (211 t/year). However, the sediments assessment has limitations due to lack of control data to calibrate and validate. Therefore, the actual quantity impacts of the sediments might have been missed. The aim of achieving policy trade-offs to meet farm family food security must balance the competing demands of food production, sediments reduction and streamflows in a manner acceptable to diverse stakeholders.

Conversely, reaching a trade-off to meeting family food security is further complicated by grain market price variations that diminish or enhance food security (scenario B). High grain market price favour food security, while low grain prices reduce it. Therefore, attractive rural market policies are required to compliment the improvement in crop production or even stimulate production for enhanced smallholder farmer food security. This result concurs with findings by Fabre (2006) in the study area and CAWMA, (2007) that recommends integration of rainwater harvesting practices and markets to reduce food security risk of smallholder farmers.

Furthermore, results show that gross margin and family balance vary for different farm typologies. The results indicate increased household gross margin and family balance with the application of both ex-field and in-field rainwater harvesting practices. These results indicate potential crop management options for improved farm production and income with socio-economic support to use effectively both green and blue water.

The strongest relation between water availability and farmer livelihood balance (savings) was found under farm types B and D and C because they rely much on income from agriculture. However, no relationship was found in dry years under conventional rainfed due to diverse sources of income that come into play to supplement agriculture production and negative family balances. Under farm types A and E, no strong relationship was found as they rely on more than 73 % employment income. Hence, most resource-constrained farmers in semi-arid areas who depend on food and income derived from crop yields are greatly impacted by variations in rainfall. However, with supplemental irrigation to mitigate dry spells, an estimated 10 % of the households in the catchment can benefit.

However, the need to connect unlike disciplines of scientific knowledge (including different spatial and temporal scales) and to strike a balance between complexity and simplicity pose challenges in constructing integrated models. Hence, several specific integrated models have been developed with no overall integrated concept or theory of how to integrate various disciplines. In addition, because of the cross-disciplinary character of integrated models, they include many different types and sources of uncertainty that propagate or accumulate as the individual models are executed. Hence, policymakers need to be aware that uncertainty is central to policymaking (Rotmans and Van Asselt, 2002) and the final policy-making decision should be made under an acceptable uncertainty depending on available knowledge.

In South Africa, there is little experience of developing decision support systems (DSS) to enhance the efficiency and effectiveness of smallholder farming system crop management planning in the face of unreliable and uneven rainfall distribution characteristic of semi-arid areas (Perissinotto et al., 2004).

The integrated modelling of the B72A quaternary catchment that provided catchment decision support systems proved the general suitability of coupled catchment models to strategic IWRM planning and decision-making. ICHSEA DSS was designed to assist in identifying patterns, problems (e.g., low yields and streamflow reduction), opportunities and eventually in making decisions on smallholder farming systems at both individual and catchment scale.

This thesis demonstrated that the proposed model approach in the framework of a DSS is able to anticipate the impacts of changes in smallholder farming system crop management options and or input/output market prices on food security in rural areas. Using 20 years of climatic data, the thesis further showed that such an integrated DSS model may be used for exploring policy impacts of climate variations on smallholder farming systems. In addition, by employing an integrated approach, this thesis explored some of the ways of better reducing smallholder farmer vulnerabilities and evaluates developments in smallholder farmer crop risk reduction strategies.

To evaluate farmer risk, the integrated model takes advantage of the integrated functionality of explorative simulation to estimate the gross margin and family balance of conventional rainfed and improved agricultural management activities for each policy or crop management scenario investigated. From several scenarios on the impact of changes in policy and or market prices on maize crop, policy-makers may select better policies suited for specific objectives and farm typology. This approach provided valuable information leading to the conclusion that crop management options such as rainwater harvesting techniques substantially improve food production and water productivity even under both low and uneven rainfall distribution and have a substantial impact on farm income and family food security. Thus, the implementation of untied ridges, planting basins and supplemental irrigation practices lead to different levels of advancement in smallholder farmer food security.

There are different pathways out of poverty and securing food security. The implementation of low-cost crop water management techniques that can be widely adopted by even resource-constrained farmers such as those presented in this thesis under farm type B, can be viewed as a stepping stone in obtaining quick gains in sustainable farming (FAO, 1996), food security and disposable family income. This contributes to achieving one of the Millennium Development Goals on hunger and poverty reduction (United Nations, 2007, 2005; DWAF, 2004a). These gains are enhanced under favourable institutions and market conditions. Furthermore, the implementation of low-cost techniques to harvest and efficiently use unreliable and erratic rainfall in semi-arid areas should be viewed as an integrated system with the physical environment and markets for sustainable and balanced benefits.

As an educational tool, ICHSEA model that integrates all of the relevant components of smallholder farmer food insecurity problem enables individuals to explore those components (hydrology, agronomy and socio-economic) that are unfamiliar to them. In this regard, ICHSEA enables the role and contribution of each separate research effort, such as hydrological modelling, on-farm field experiments, crop modelling, farm surveys, focus group discussions, socio-economic modelling and incorporation of uncertainty analysis to the overall program of smallholder livelihoods improvement to be expressed. Furthermore, ICHSEA consolidated and handled the acquisition of scientific information and captured the current level of understanding in each research effort that emerged from the specific discipline research areas.

Furthermore, ICHSEA integrated model development fulfilled the activities associated with policymaking, which are policy understanding in a wider context and policy synthesis (Marnicio and Rubin, 1988) presented in Chapter 1. This was achieved by detailed analysis of problem components (e.g. water availability, crop yield, farm income and socio-economic aspects related to farmer resource levels) through specific discipline models and then synthesising by coupling the model components to form a whole. The model coupling was achieved with minimally sufficient level of complexity to ensure that the model results are credible to both technical users and policy-makers and responsive to the information needs of the general question being examined of smallholder farmer livelihood improvement through farming.

However, a good understanding of the technical and the non-technical characteristics of the policy problem and its context are important; as the technical models at best provide only one of many inputs to a policy decision. Agricultural policy is never established solely based on model simulations results. It it possible that the ICHSEA model may remain a research tool, due to its technical and data intensive nature, with the researcher being the key interpreter of model outputs to farmers and policy makers involved in various policy actions.

I conclude that the integrated model is a useful tool in understanding, communicating complex scientific issues to a wide audience and provide a useful breakdown and synthesis to complex issues that are not solved by individual models. Hence, it has proven to be an invaluable and credible tool in the decision-support spheres especially with the involvement of low-level stakeholders throughout problem formulation and models validation.

Implications

The purpose of the integrated model is to understand the implications of current crop management options and how improved alternative crop management options enhance food security in the catchment. The model was able to represent both different crop management and farm types. Most resource-constrained, farm type B is risk averse that makes it difficult for them to try new crop management practices. Managing and predicting the diverse livelihood strategies of resource-constrained smallholder farmers is very challenging as their socioeconomic context is at least as diverse as their biophysical environment.

While several applications of holistic integrated models are found in literature, most of them lacked validation by targeted end users. The success of ICHSEA can most probably be attributed to its systematic approach both in addressing local stakeholder involvement and the actual decision-making on viable crop management practices using robust models. This exercise contributes to wiser decision, governance and investments. However, the effectiveness of ICHSEA to address these concerns is still at infancy, and can be pursued in future studies.

The underlying causal relationships for the different crop management practices have been represented correctly in the integrated model. Using this integrated model, changes to crop management practices and crop market prices were investigated and resulted in management practices that improved crop production and food security, though under uncertainty. To acknowledge the limitations of existing knowledge of hydrological systems and other two models used in this thesis, results of farm balance were reported as a range of possible values through cumulative probability curves, instead of reporting single-valued predictions.

Quantifying the uncertainty effects of input variables provided an indication of the reliability of the resulting calculations. Using conventional error propagation theory, crop yield contributed most to uncertainty in family savings or balance. However, GIS data can contain systematic errors that error propagation cannot address effectively. This shortcoming can be addressed in future studies under probability modelling.

The conclusions and implications of this study are considered valid within B72A catchment and applicability to any arid or semi-arid catchment facing challenges of increasing rural food security through smallholder agricultural production is possible after integrated model calibration with catchment specific data.

There are several areas that this thesis has made significant contribution. These areas include methodological and data related contributions and are described in the next section.

8.2 Contributions to knowledge

The main contribution of this thesis to knowledge development is the development and testing a methodology of coupling different existing models developed in different languages and platforms into an integrated model system to serve as a decision support system for rural smallholder farmers in both blue and green agricultural water resources management. The integrated model system components are hydrology, agronomy and socio-economic models. Hence, the thesis used known and existing individual models in a new way by coupling them to work as one system.

The thesis further contributes to the methodology of enhanced rainfed and supplemental irrigation agricultural technologies development, specifically by means of local on-farm trials in collaboration with local farmers. The methodology presented provides a practical guide to appropriate methodologies that could be adopted in the design of rainwater harvesting crop management techniques in on-farm trials. This contribution provides a practical guide that forms an integral part of farming systems research and extension as asserted by (Jones, 1986). Additionally, the thesis serves to convince the researchers that scientifically valid data for successful development of new and improved agricultural technologies can be obtained from on-farm trials with the collaboration of local farmers. Hence, it is vital for them to establish close working relationships with both local extension officers and farmers, and to learn from their knowledge and experience that is invaluable to both problem and solution definitions of the study area.

In addition, the research contributes towards an integrated approach to provide a holistic assessment of the consequences related to agricultural technology and policy changes (e.g., market price changes under conventional rainfed practice in scenario B). Data related contributions on crop yield, soil chemical and nutrient characteristics, rainfall, soil moisture variation during the growing season and eliciting local knowledge of the catchment through stakeholder participation in data collection and models validation were made.

Furthermore, the research has advanced and provided new insights into the non-linear relationship of rural food security with rainfall and maize crop yield. A non-linear relationship equation was developed. This non-linear relationship results from the diverse crop management practices and livelihoods strategies rural smallholder farmers engage to sustain family food requirements. These diverse livelihood strategies are related to the resource endowments of the farmers as shown from farm surveys. Consequently, different types of farmers produce different crop yields from the same amount of rainfall. Hence, the thesis found that crop yields, which are highly dependent on crop management options, are more important in determining food security than the amount of rainfall received (impact of rainfall distribution was not analysed). This conclusion concurs with pertinent literature argument that there seems to be no hydrological limits in maize rainfed agriculture to obtaining five to ten times higher yields than experienced at present (0.5–1 t/ha) (Rockström and Falkenmark, 2001).

Improved data collection techniques and methodology approach that could have been applied.

The best available techniques within budget limitations were used to collect data. However, the resolution of data collected in the study area would have been improved with the use of automatic rain gauges to capture the rainfall intensity that would have been used to explain the yearly variation of yields and water productivity for the different farm types in the catchment. The need to take moisture at different depths to the maximum maize root depth using access tubes on Time-domain reflectometer (TDR)-soil moisture or use of lysimeters could have improved the water balance results.

Furthermore, there was need for larger runoff measuring plots with installed automatic runoff measuring tipping buckets. The runoff plots used were small to accommodate the potential maximum runoff volume generated from highest rainfall intensity in the study area. The use of sapflow meters could have improved the estimation of crop transpiration that was determined from crop evapotranspiration residual in the water balance. Tight coupling approach could have been used instead of loose coupling to better simulate non-linear problems. However, the innovation trade-off of several feedbacks achieved under current loose coupling sufficed to address the non-linear problems.

Nonetheless, the model developed in this thesis has some limitations. These limitations that are presented in the next section.

8.3 Limitations and further study

This study shows some limitations in the current integrated model structure and its components. Firstly, the integrated model is not capable of considering agricultural production decisions that are non-seasonal and cannot provide real-time recommendations or predictions. Secondly, the crop considered to vary in the production systems is maize, though other crop production systems can be analysed. Thirdly, the crop model simulations do not account for leaf damage that is caused by insects, pests and diseases that affects leaf index and consequently affect the crop yield. Fourthly, the coupled model lacks water quality impact assessment of crop management practices, as opposed to erosion.

In addition, exclusion of groundwater systems extraction significantly limits the usefulness of the biophysical model in assessing the downstream impacts of changes in agricultural development and management practices. Sixthly, the reported potential supplemental irrigation areas are potential in terms of water availability and not in terms of soils or feasibility of using the land for agriculture. Except for the subbasins with agriculture, that shows the actual potential area available for supplemental irrigation. Seventhly, errors in spatial input data such as climatic, soil and land use maps that could lead to under- or overestimations of streamflows were not investigated, but precautions to reduce the errors through checking data quality and use of long time series was considered adequate.

Finally, the integrated model components were calibrated based on historical data that may result in failure of the models to simulate future extreme conditions. In addition, hydrological model validation was based on one-year daily flows in a subcatchment in the B72A catchment, other than the main catchment outlet. Depending on the availability of data in future, it is recommended to perform a daily calibration and validation on the B72A catchment outlet to get most accurate results representing the actual conditions over the catchment. With advancement of data production in future, weather data and physical characteristics such as land use and soil GIS covers at a finer resolution can be updated.

Two areas require consideration in future developments of the ICHSEA model. Firstly, a possible future scenario is relaxing the statistical independence assumption among parameters such as rainfall, crop yield and family balance in sensitivity and uncertainty analysis. As a result, statistically dependent criteria including correlation should be incorporated into the models. Standardised Monte Carlo analysis to ensure that the signal from one parameter is not confused with signal from another (Loucks and Van Beek, 2005) may be employed. Secondly, performance of the different rainwater harvesting methods under different rainfall regimes and intensity needs further study to explain fully the seasonal variation in water productivity.

In sum, assumptions and limitations of the integrated model were presented. These two features of the model are important in establishing credibility of the model and correctly interpreting the model outputs for decision-making, while recognising model limitations.

The purpose of the research was to evaluate water resources availability, maize crop water use and to develop an integrated model for better understanding of smallholder food security and crop production practices. This purpose was achieved as briefly presented under each objective in the following sections:

a) To evaluate: (i) water resource availability (ii) maize crop water management and (iii) agricultural water use and allocation in the B72A catchment.

The mean annual flow is estimated at 31 Mm^3 (58 mm) that is 78 % of naturalised flow of 74 mm from WR2005 (Middleton and Bailey, 2005). Approximately 58 % of the water in the catchment is used for irrigation to irrigate 18.83 km^2 of agriculture land, most of it commercial and emerging farmers. Current evapotranspiration water use under conventional rainfed and supplemental irrigation practices are 344 mm and 431 mm, respectively.

b) To define impact parameters that influences the physical, economic and social conditions in the B72A catchment.

The impact parameters identified were rainfall (climate), soil, crop yield (food production), other income sources besides agriculture such as pensions, social grants and employment, farmer age (from farm surveys), sediments and streamflows.

c) To review available technical decision support models that address impact parameters defined in (b) and assess them for possible application in this work.

No decision support tool was found suitable to address the current objectives, hence there was need to develop a new model framework that captured the identified impact parameters.

d) To develop a modelling framework that links water resources and socio-economic factors in order to understand agricultural water availability and productivity impacts on food production and livelihood.

An explanation of the new modelling framework was presented in Chapter 4, including the construction of farm typologies. The model framework functions and applications were presented in Chapter 7 through a case study.

e) To conceptualise scenarios in (a) and test them using an integrative modelling tool developed in (d)

To test the integrated model, conceptualisations of five scenarios were presented in Chapter 7. These scenarios included crop management practices and market price perturbations of maize grain that could be triggered by both policy and demand changes.

f) To assess impacts in the B72A catchment using the parameters defined in (b).

Under these scenarios, performances of different farm typologies were evaluated based on the impact parameters identified under objective b that included rainfall, streamflow, sediment, crop yield, farm gross margin and family balance/savings. These are just a few indicators, from several indicators that could be used (Qiu et al., 2007). In the analysis crop yield had more weight than seasonal rainfall. However, the indicators are given equal weight towards sustainability of food security, due to their forward and backward interactions.

In conclusion, this thesis has addressed the naturally multi-disciplinary linkage between resource-constrained smallholder farmers' crop management practices, streamflows to their socio-economic aspects, in the form of food production and security. Hence, the integrated model served as an evaluation tool for quantifying impacts of crop management practices and policy changes consequences on rural food security in the context of Integrated Water Resources Management (IWRM). It is hoped that ICHSEA tool has made significant contribution towards the development of tools that practitioners including agricultural institutions could use to identify the real constraints to improved rural livelihoods in semi-arid developing countries.

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APPENDIX A: Maize crop genetic coefficients from calibration at different experimental sites and field validation of farm typologies.

Appendix: A

Table A1 Genetic coefficients of maize crop under different experimental sites.

Parameter		Enable rainfed	Sofaya sup. irrig.	Worcester rainfed	Enable ridges	Worcester chololo pits
Profile	Slope (%)	3	3	3	3	3
	Area (ha)	0.5	0.5	0.5	0.5	0.5
Topography	Bund height (cm)				25	40
Maximum ponded days		0	0	0	0	2
Critical ponding depth (cm)		0	0	0	0	10
Reduction in evaporation (%)		0	0	0	0	20
Weeds	1st weeding-day	30	30	30	30	30
	2nd weeding-day	60	60	60	60	0
	3rd weeding-day	0	0	0	0	0
	Max. water uptake (mm/mm/d)	20	24	20	30	2
	Root advancement (mm/d)	35	5	12	27	2
	Max depth (mm)	1500	1500	1000	1500	600
Soil	Texture	Loamy sand	Sandy loam	Sandy loam	Loamy sand	Sandy loam
	Sand fraction	0.8	0.54	0.69	0.8	0.69
	Silt fraction	0.18	0.33	0.26	0.18	0.26
	Clay fraction	0.02	0.13	0.05	0.02	0.05
	Organic matter fraction	0.012	0.013	0.013	0.012	0.013
	Bulk density (g/cm^3)	1.38	1.41	1.4	1.38	1.4
	Cation exchange	0	0	0	0	0
	Initial water content (mm)	11.5	10	11.5	10	10
	Fertility (t/ha/day)	0.1	0.1	0.1	0.1	0.1
	Strength a	0.000015	0.000015	0.000015	0.000015	0.000015
	Strength b	3	3	3	4	3
	Drainage rate	1	1	1	1	1
	Micropore distribution	900	10	10	500	10
	Micropore flow rate	1	0.4	0.4	1	0.4
Plant density/ha		40000	30000	40000	40000	30000
Cultivar		Maize-1 Enable rainfed.cul	Maize-1 Sofaya.cul	Maize-1 Worcester rainfednorm.cul	Maize-1 Enable rainfed.cul	Maize-1 Worcester rainfednorm.cul
Length of growth stage 1		380	380	375	380	375

Parameter		Enable rainfed	Sofaya sup. irrig.	Worcester rainfed	Enable ridges	Worcester chololo pits
(thermal time)						
Length of growth stage 2 (thermal time)		625	650	645	625	645
Length of growth stage 3 (thermal time)		659	657	657	659	657
Size	Specific leaf area, stage 1 (m^2/kg)	12	14	10	15	14
	Specific leaf area, stage 2 (m^2/kg)	23	25	25	25	25
	Max. leaf area of single plant in sparse canopy (m^2)	0.35	0.5	0.3	0.25	0.3
Roots	Max. daily extension (mm/d)	4	5.5	2	5	3
	Max. depth (mm)	1200	1000	1200	1000	1100
Grain	Conversion factor	2	2	1	2	1
	Max. grain weight (g)	0.34	0.44	0.28	0.39	0.15
Temperature (^oC)	Base	8	8	8	8	8
	Maximum	38	38	38	38	38
	plateau	24	24	24	24	24
	Start of thermal denaturation	45	45	45	45	45
Other	Light extinction	0.47	0.47	0.47	0.47	0.47
	Wilting point (m)	45	45	45	45	45

Notes:

All genetic coefficients of maize were estimated by using phenology and growth data from experiments conducted from 2005-2008 in B72A quaternary catchment.

A2: An extract from field discussion

Interview and discussion with local staff from the Department of Agriculture on farm typologies validations.

1. Mr. Mthembula

Position: Deputy Manager, Department of Agriculture (Metz)

2. Ms Moriri

Position: Crop Scientist, Department of Agriculture - Metz

Type A: Confirmed as existing in the study area by the deputy manager.

Type B: Confirmed as existing in the area and are the poorest.

Type C: Social grant supported farmers/pensioners are above 60 years and have been confirmed. However, since the age in the table is an average the majority of the farmers might be over 60 years.

Mr Mthembula highlighted that the type C farmer is difficult to convince to use the grants/pensions they receive to invest into farming. The main reason given was the need for farmers to support other close family members including grandchildren and those in sick. Hence, it is difficult for them to spare any money for farming.

They even depend on seed from previous years. Most of the type C farmers were said to be rainfed farmers.

Type D: The farmers were confirmed to exist in the area and were associated with villages like Ballon and Mkutsi CPA (Community Property Associations) and these are mainly emerging farmers with pieces of land greater than 5ha.

Type E: The type E farmers were confirmed to exist in the area and mainly from retired teaching professionals. Some of these farmers buy a bakkie and sell fruits, which gives them huge income.

The farmer proportions by type from statistical analyses and expert opinion from the Department of Agriculture senior staffs are shown in Table 1. The comparison was done to establish whether the statistical classifications was a reasonable estimate or not of the existing farmer types in the study area.

Table 1. Farmer type proportions in the study area

Farm type	Typology from statistics (%)	Mathembula (%)	Moriri (%)	Comment
A	6	11 (Enable, Lorraine, Ballon)	15	Relative proportion in agreement with Moriri
B	15	51 (whole Maruleng)	20	Relative proportion in disagreement with Moriri
C	52	23 (whole Maruleng)	40	Same as above
D	25	13 (Ballon, Oaks, Willows)	23	Same as above
E	2	2 (scattered)	2	In agreement statistical classification

Notes:

1. The associated villages where the type of farming is wide spread are shown in brackets.
2. Moriri is crop scientist working with farmers on the ground, while Mr Mathembula is the deputy manager. Hence, we relied more on the crop scientist's expert opinion on farm proportions than those constructed by the deputy manager.

The farmer proportions show a great difference for type B and C from Mr Mathembula's expert opinion. Actually, it is a switch between their proportions compared to statistical results.

The deputy manager further gave the Department of Agriculture's farm classification as:

- < 0.5ha household/backyard farming
- < 2ha subsistence
- < 5ha smallholder farmers
- > 5ha emerging farmers

However, we felt this classification was only based on farm area and did not consider the social aspects of the farmers.

APPENDIX B: ICHSEA manual to run an integrated model to evaluate different crop management practices

Appendix B

Part A: Run SWAT model to generate streamflows from 2005-2024.

Click start and select programs, select ESRI then ArcView GIS 3.3 (Figure 1).

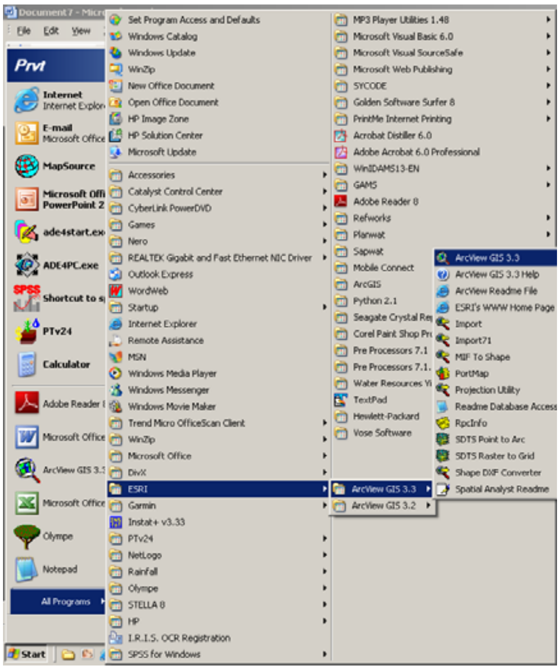


Figure 1

Clicking on ArcView GIS 3.3 displays Figure 2.

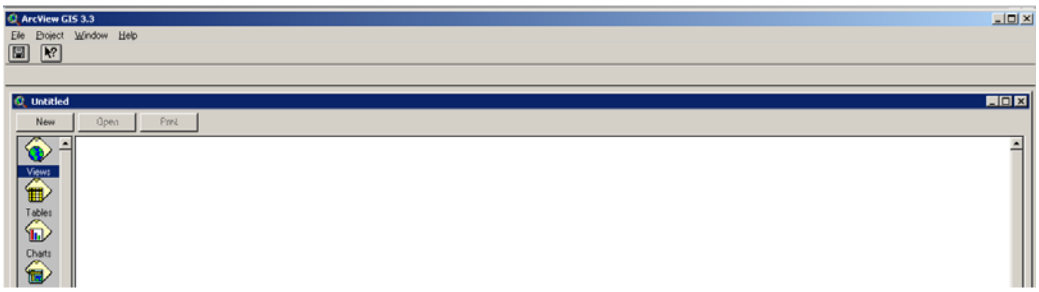


Figure 2

Click on **File** and select **Extensions** (it takes few seconds to load the extensions). Then select **AVSWATX Extendable** (Figure 3).

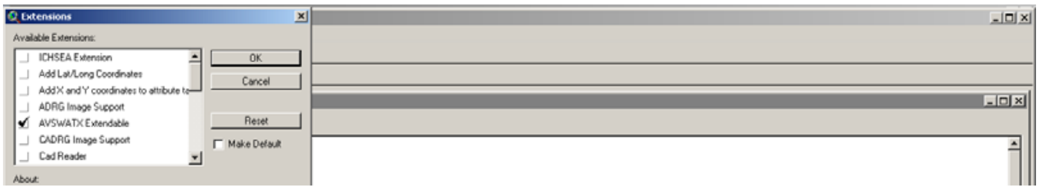


Figure 3

Click **Ok** to display Figure 4.

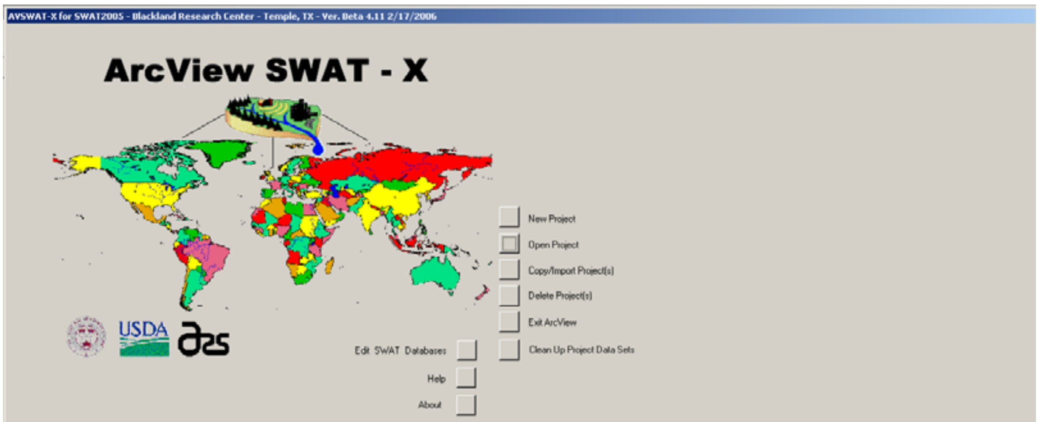


Figure 4

Click **Open Project(s)** and select **b72a_gaskro.avsx** (Figure 5)**.**

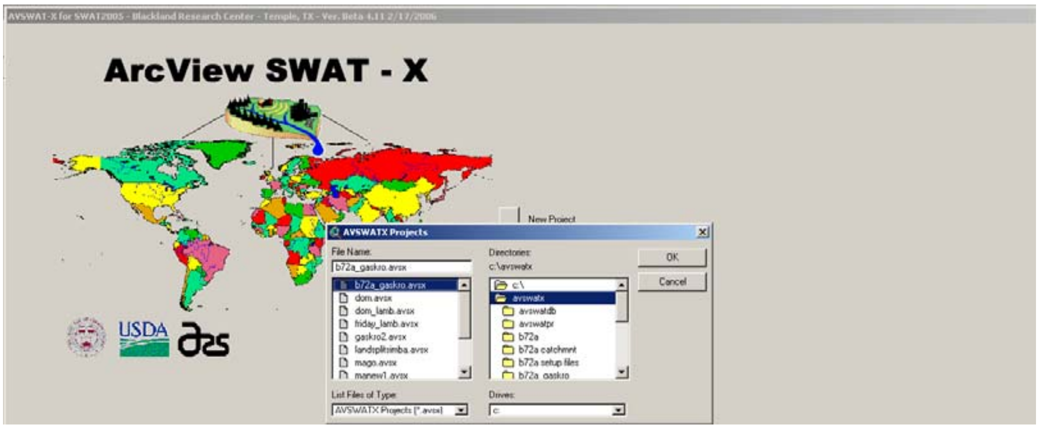


Figure 5

Click **Ok** to display Figure 6.

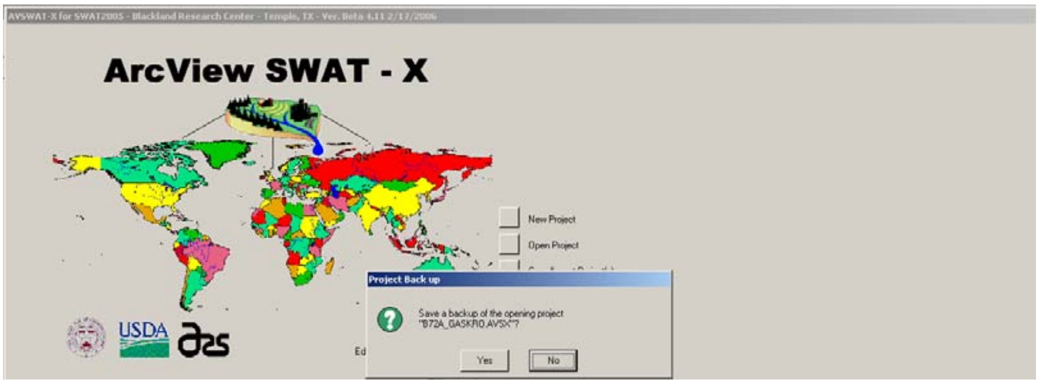


Figure 6

Click **No** (Figure 6) to display Figure 7.

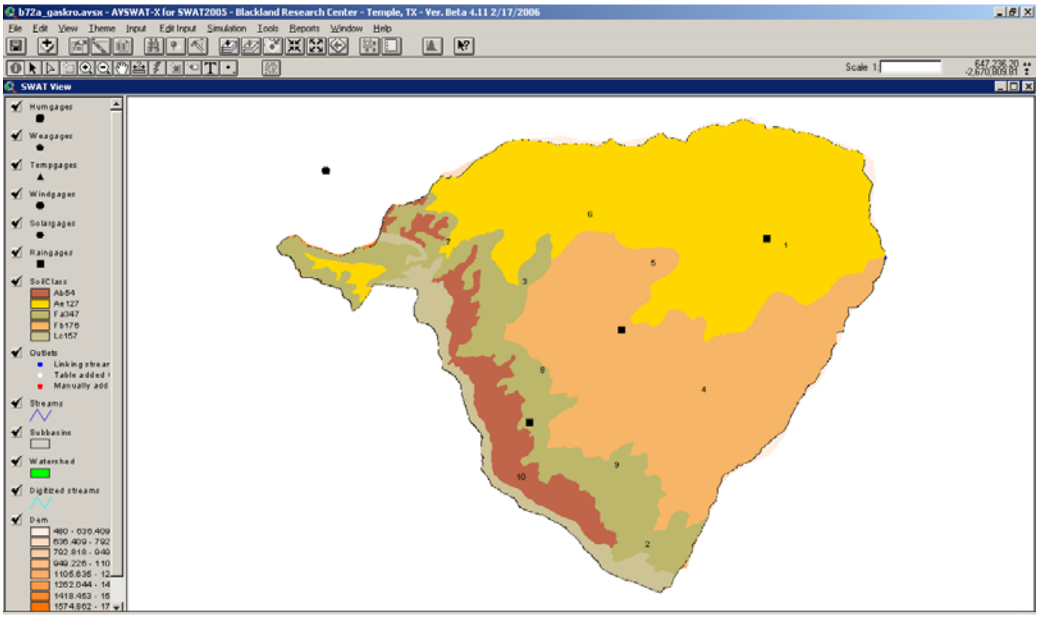


Figure 7

Click on Simulation and select Run SWAT (Figure 8).

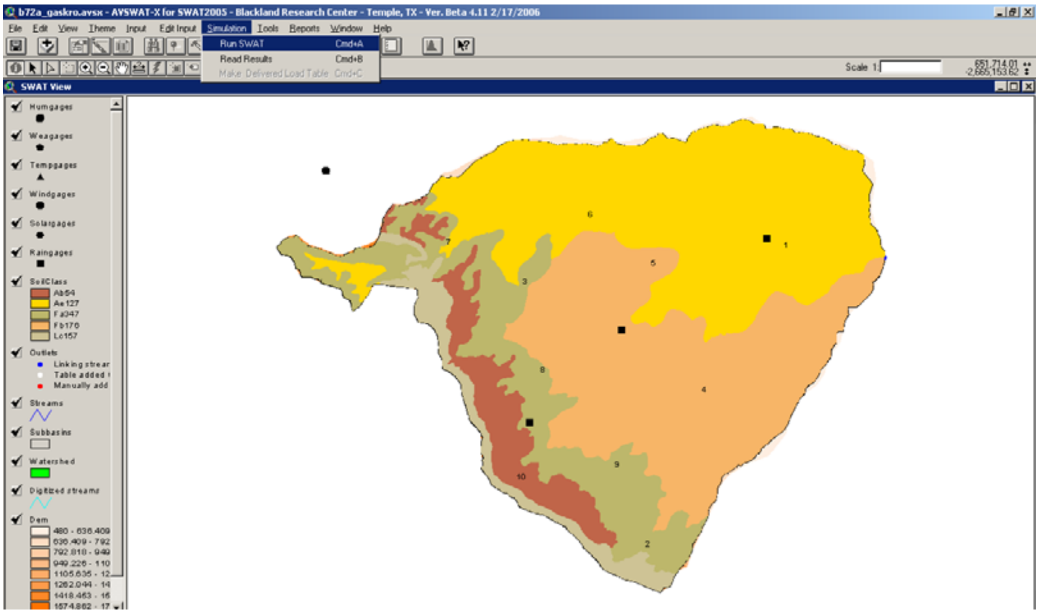


Figure 8

Click on **Run SWAT** to display Figure 9. Edit the window for the correct start date of simulation and end date to simulate the first 10 years (Figure 9). For the second 10 years of simulation, start date is changed to 1 January 2015 and end date to 31 December 2024.

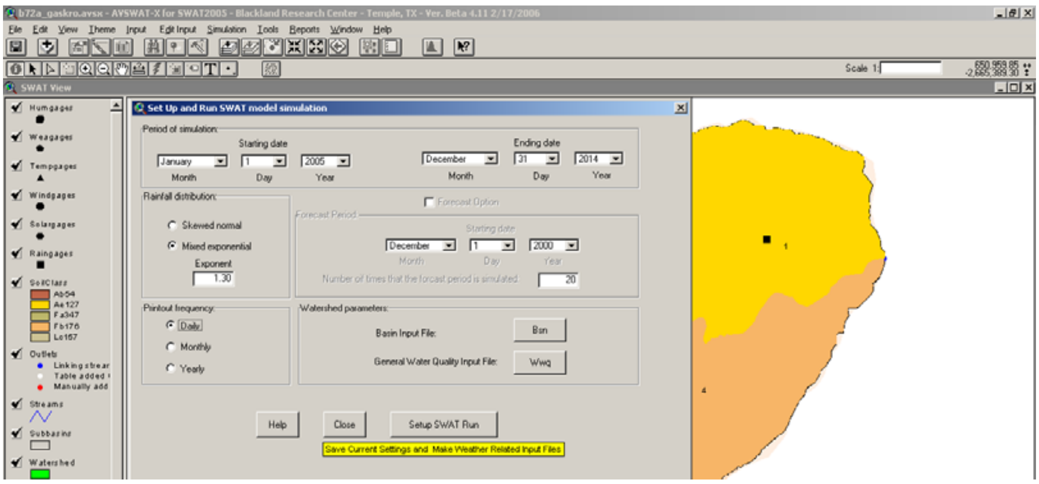


Figure 9

Click **Setup SWAT Run.** The model takes few seconds to execute this task and it displays Figure 10.

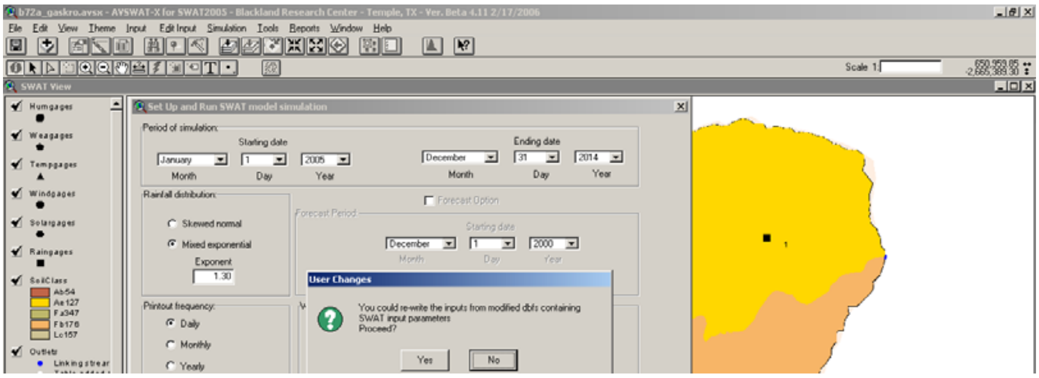


Figure 10

Click **No** if no inputs were changed, as in this example. Click **Yes** to display Figure 11. Click on each input that was edited and click **Ok** when finished.

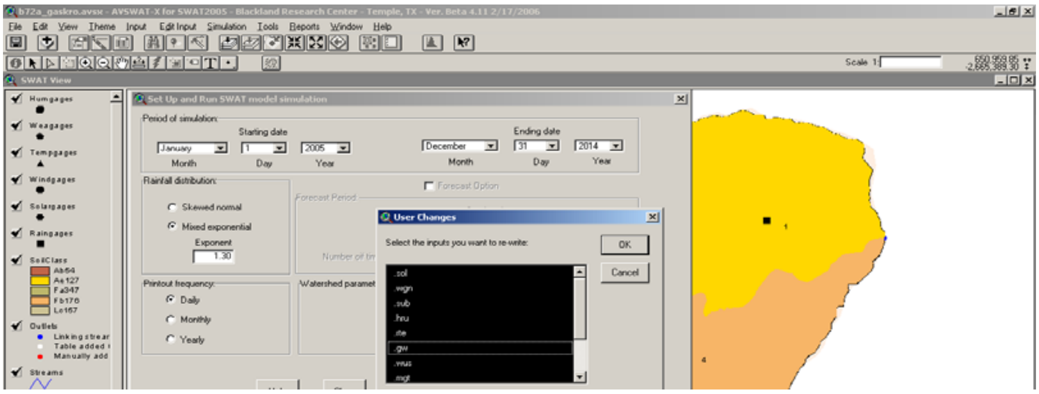


Figure 11

Click **Ok** to update the inputs. When the update process is complete, Figure 12 is displayed. Click **Ok**.

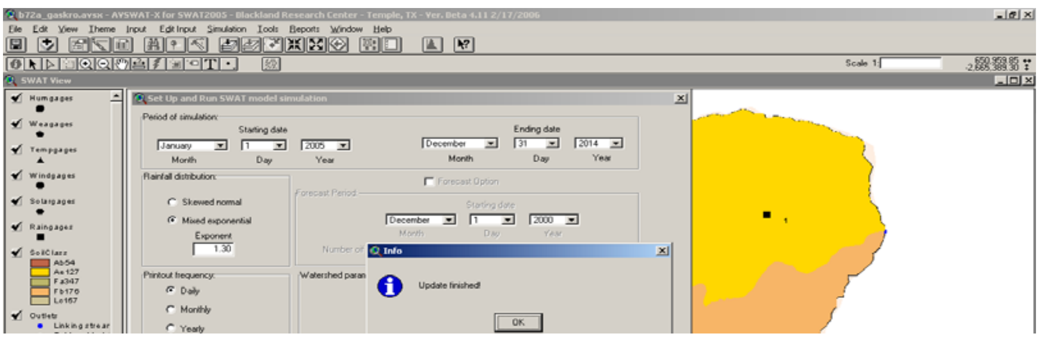


Figure 12

Click **Run SWAT** (Figure 13).

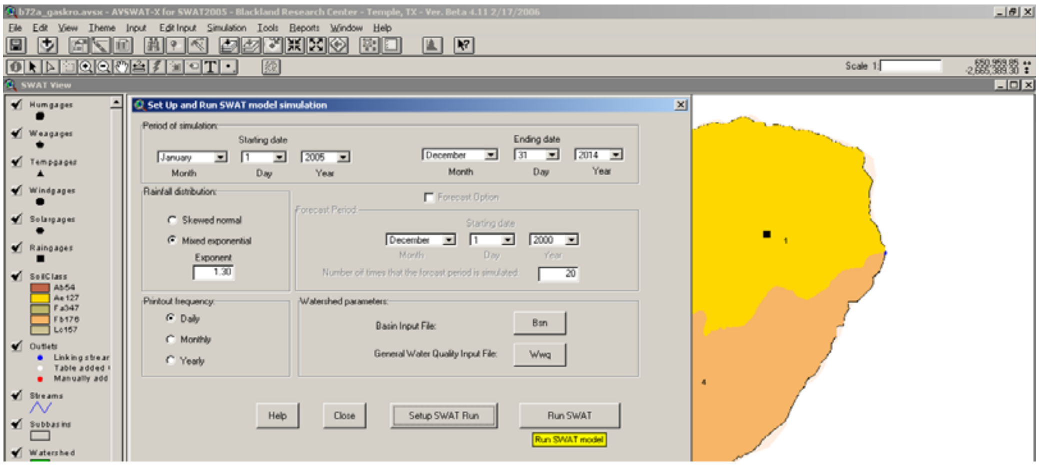


Figure 13

Click on **Run SWAT** to commence the simulation process (Figure 14).

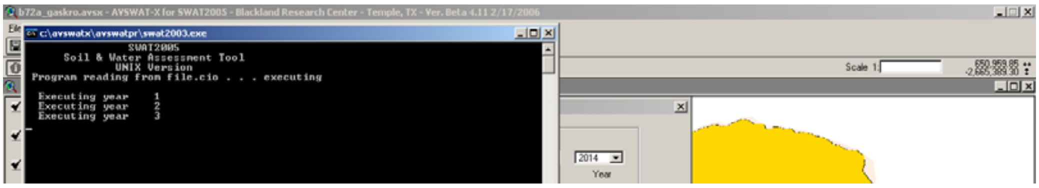


Figure 14

When the simulation is successfully or unsuccessfully completed, a message is displayed (Figure 15).

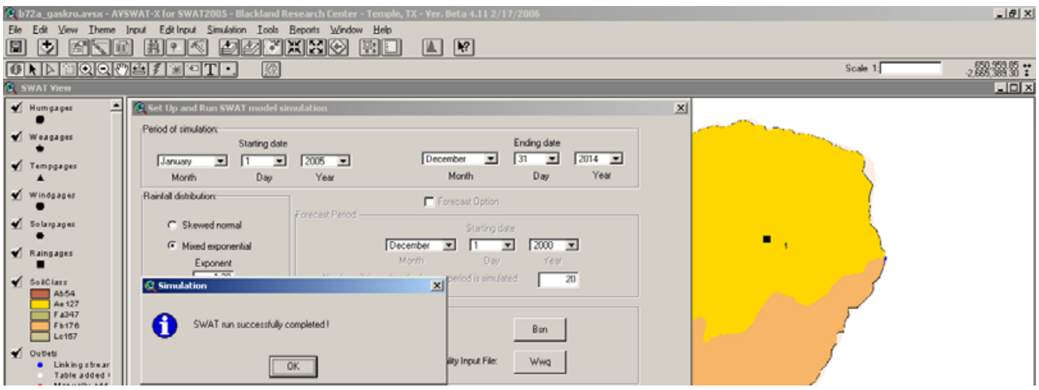


Figure 15

Click **Ok** to display Figure 16.

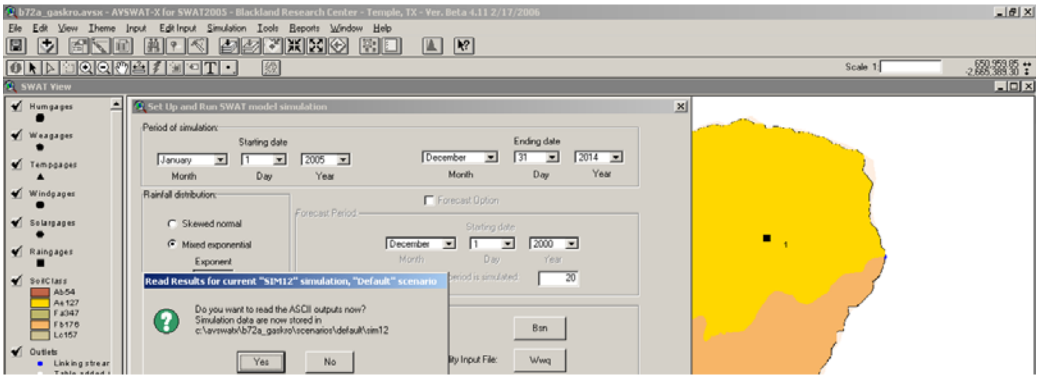


Figure 16

Click **Yes** to view the output (Figure 17).

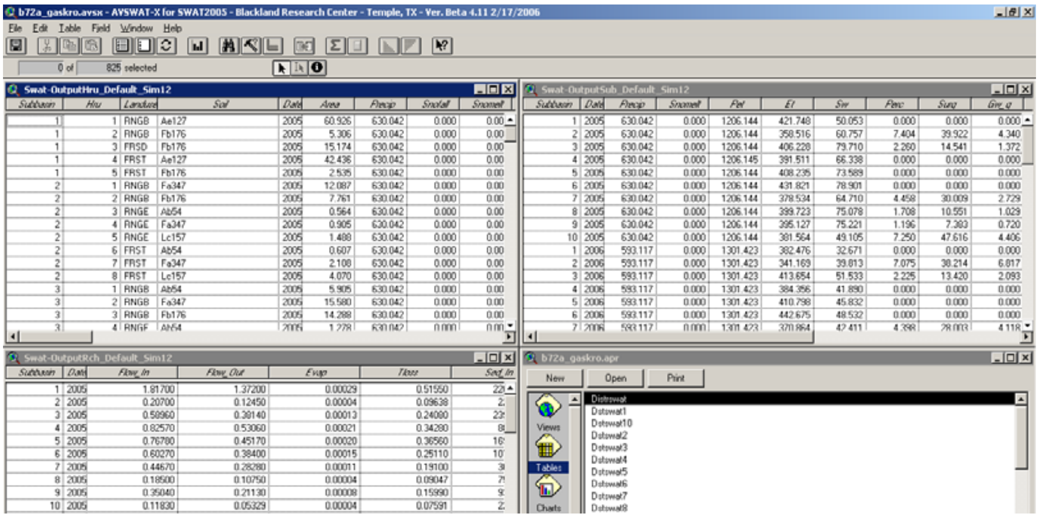


Figure 17

By clicking **Yes**, the output is written in dbf format under **tablesout** folder in C:\AVSWATX\b72a_gaskro\scenarios\default\sim**12****tablesout** in the latest **SimX** (Figure 18) and is ready for use by the ICHSEA interface. Where **X** is the latest number depending on prior simulations that have been executed.

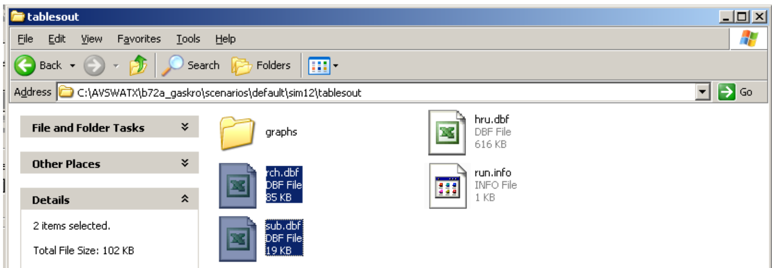


Figure 18

Click on **Views** and then click **Open** (Figure 19).

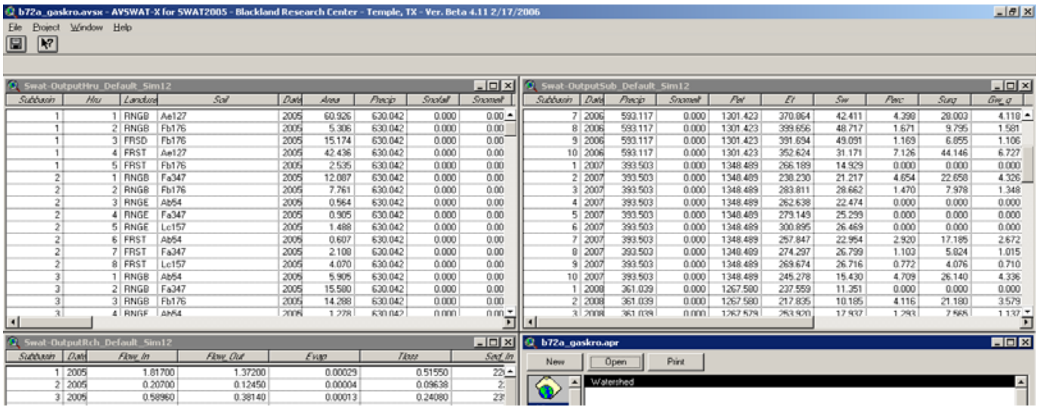


Figure 19

Click on **AVSWATX** and select **SWAT view** (Figure 20).

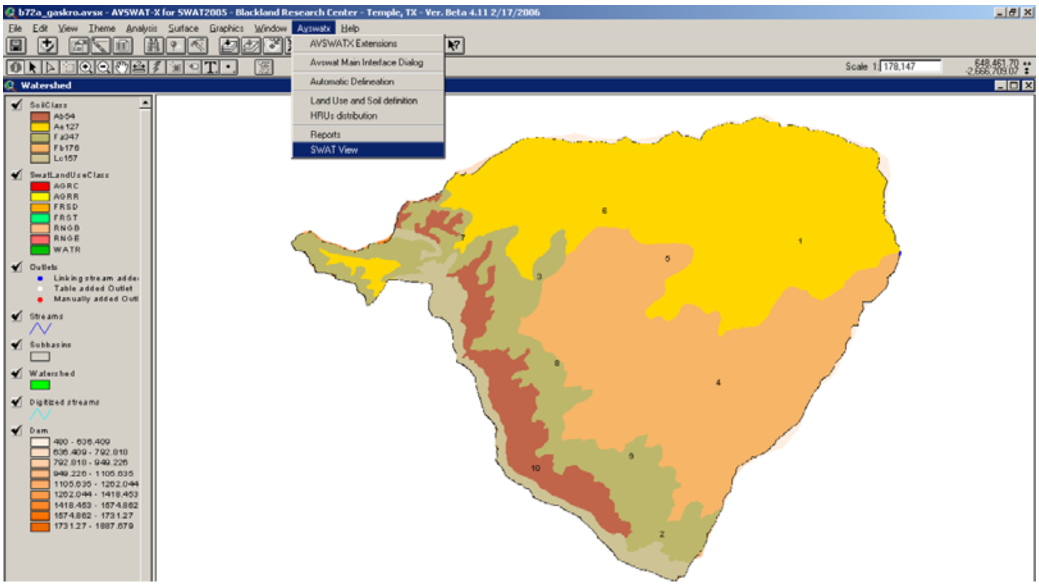


Figure 20

Click on **Simulation** and select **Run SWAT** (Figure 21). Repeat the editing of dates and steps described above to make a new run using the start date as 1 January 2015 and end date as 31 December 2024. Repeat the steps above to complete a run and view the results. After viewing the results, **Save** the project and close the ArcView, as flows to be used by the ICHSEA interface are already saved in C:\AVSWATX\b72a_gaskro\scenarios\default\sim**13\tablesout.** Sim13 can be Sim**X+1**, depending on the last simulation number, Sim**X**.

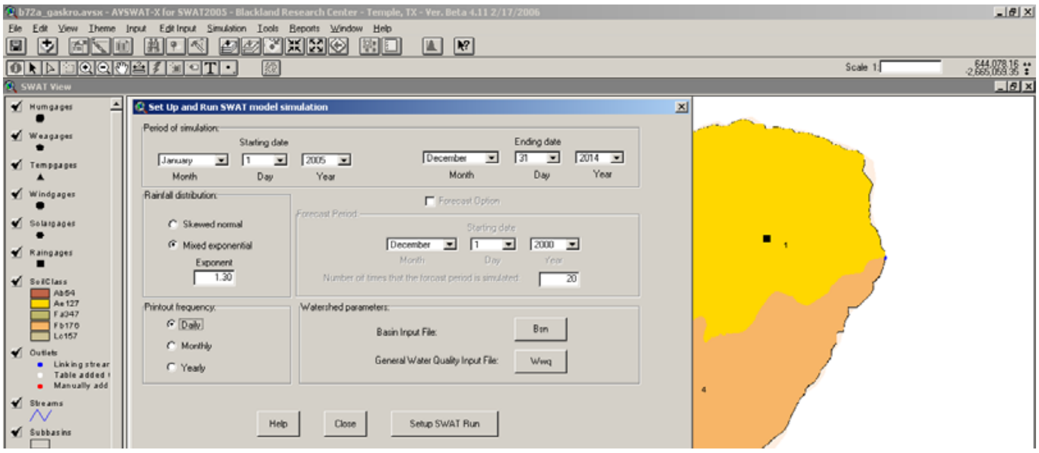


Figure 21

Part B: Run the PARCHED-THIRST for the yields from 2005-2024.

Getting started:

Go to **Start** and click on **ArcView** to open the ArcView window (Figure 22).

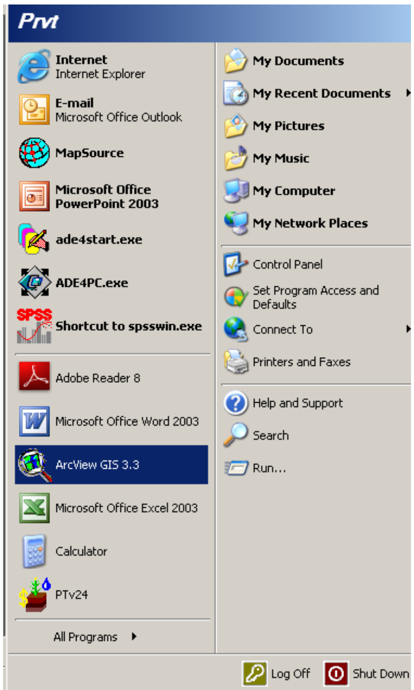


Figure 22

Click on **ArcView** icon to Open the ArcView window and maximize the window (Figure 23).

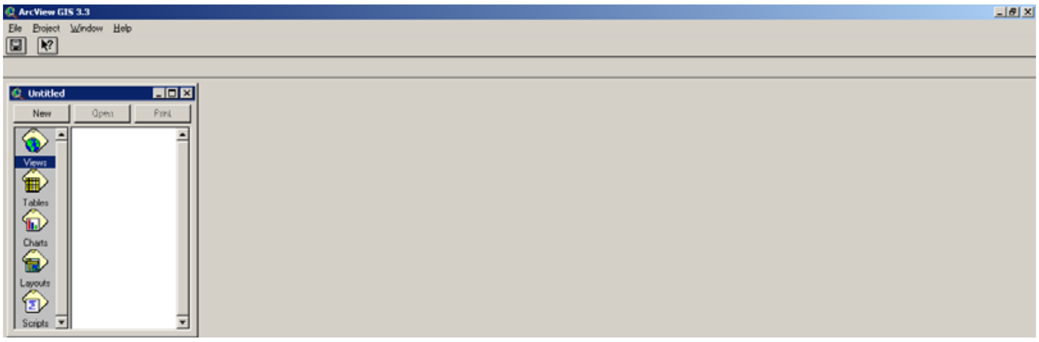


Figure 23

Go to **File** and select **Extensions**. Click on the **Extensions** button (Figure 24).

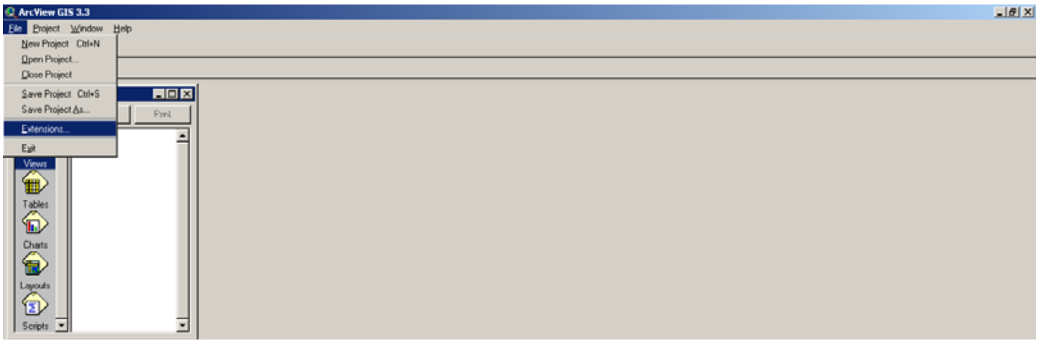


Figure 24

Clicking on **Extensions** button opens the dialogue box (Figure 25). Tick on the **ICHSEA Extension** and click **Ok**.

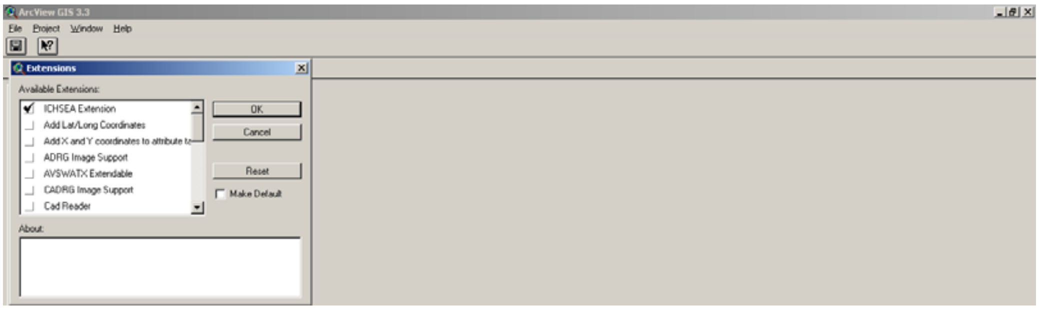


Figure 25

Clicking **Ok**, displays Figure 26.

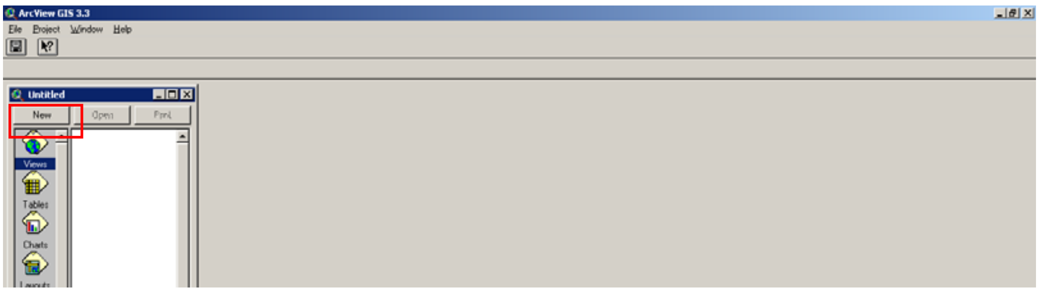


Figure 26

Click on **New** to open the ICHSEA interface button shown by a **dog head** on the screen. Maximize the **View 1** window (Figure 27).

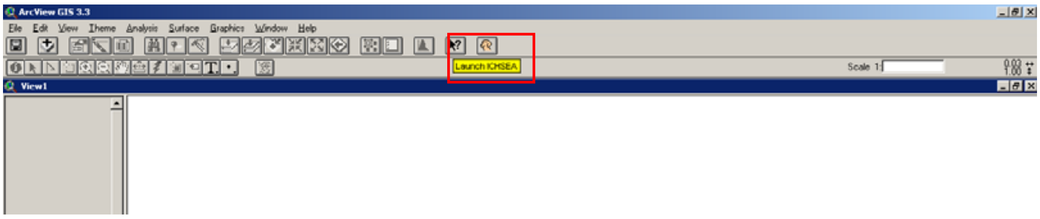


Figure 27

Click the **dog head** to open the ICHSEA extension main interface screen and select **Run PTv24** under **Main Tasks** (Figure 28).

Note: The hydrological model must be executed prior to loading the ICHSEA extension or just before loading the **Main tasks** (e.g. Clicking on **PTv24** button on the ICHSEA interface). Or one can open another **ArcView** window to run the hydrological model, SWAT. If another **ArcView** window is not opened and SWAT model is executed, the ICHSEA extension is disconnected and the SWAT model will take precedence over the ICHSEA extension.

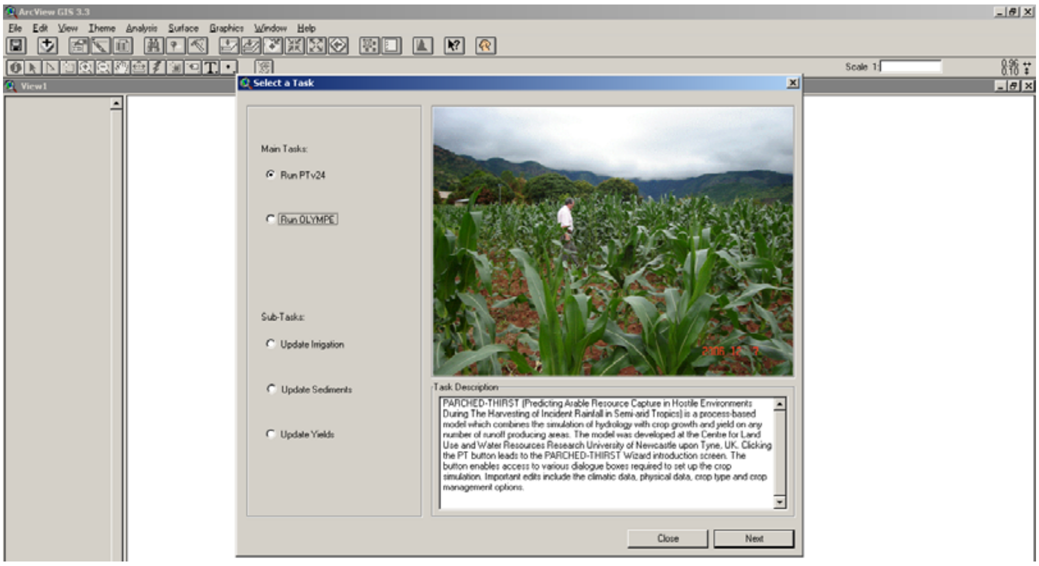


Figure 28

Click **Next** button to open the PARCHED-THIRST crop model and select **Experienced Users** (Figure 29).

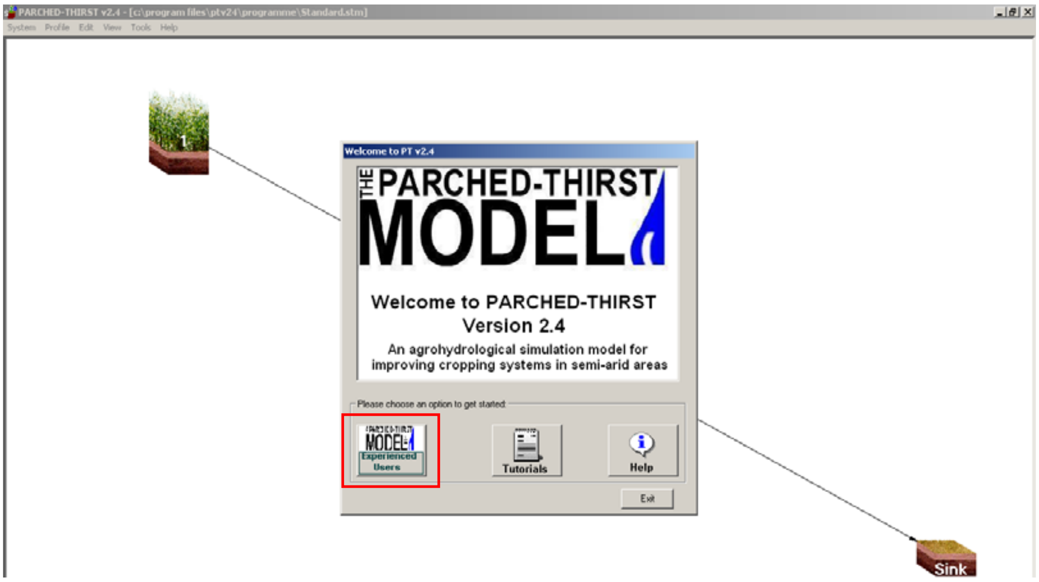


Figure 29

Click **Experienced Users** button to display Figure 30.

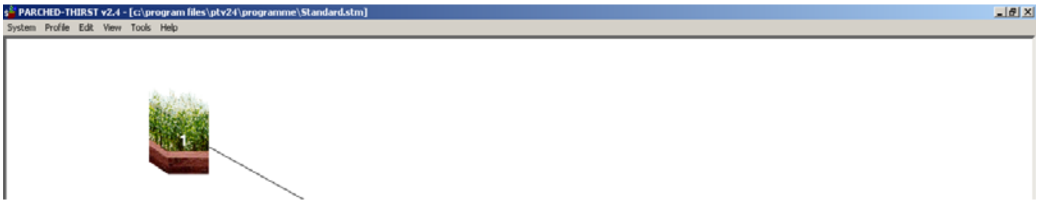


Figure 30

Click on **System** and select **Open** to select a crop system of interest to open (Figure 31).

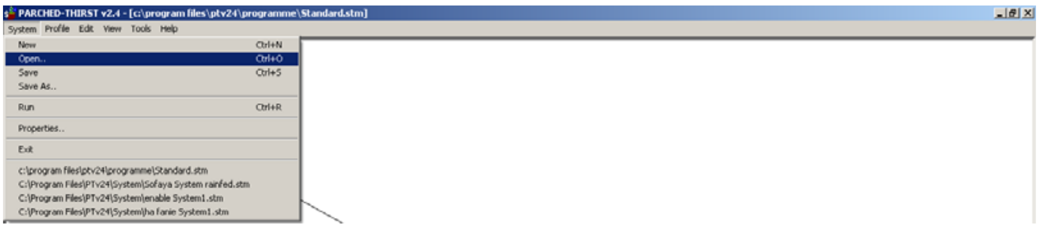


Figure 31

Click **Open** to display the systems that are available in the PTv24 model and select **SUBB1 Rainfed.stm**, for conventional rainfed agriculture in subbasin 1 out of 10 subbasins in the study area (Figure 32).

SUBB1 Ridges.stm is for ridges practice, **SUBB1 Planting basins** is for planting basins practice and **SUBB1 SuppIrrigation** is for supplemental irrigation practice. Hence, depending on the practice of interest one of these practices can be selected for evaluation in subbasin 1 to subbasin 10 of the B72A quarternary catchment.

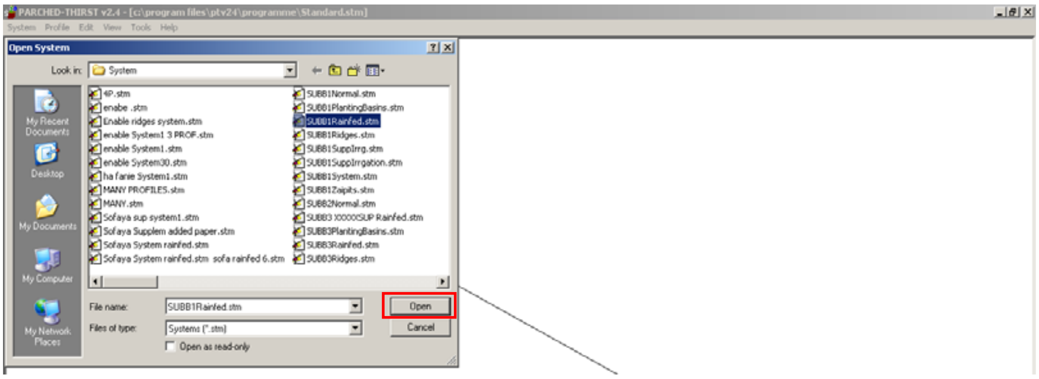


Figure 32

Click on **Open** button (Figure 32), to open the system profiles (Figure 33). The five profiles shown in the diagram are the five different farm types found in the study area. Hence, each profile is representative of each farm type. Profile 1 represents farm Type A field; Profile 2 represents farm Type B field; Profile 3 represents farm Type C field; Profile 4 represents farm Type D field and Profile 5 represents farm Type E field.

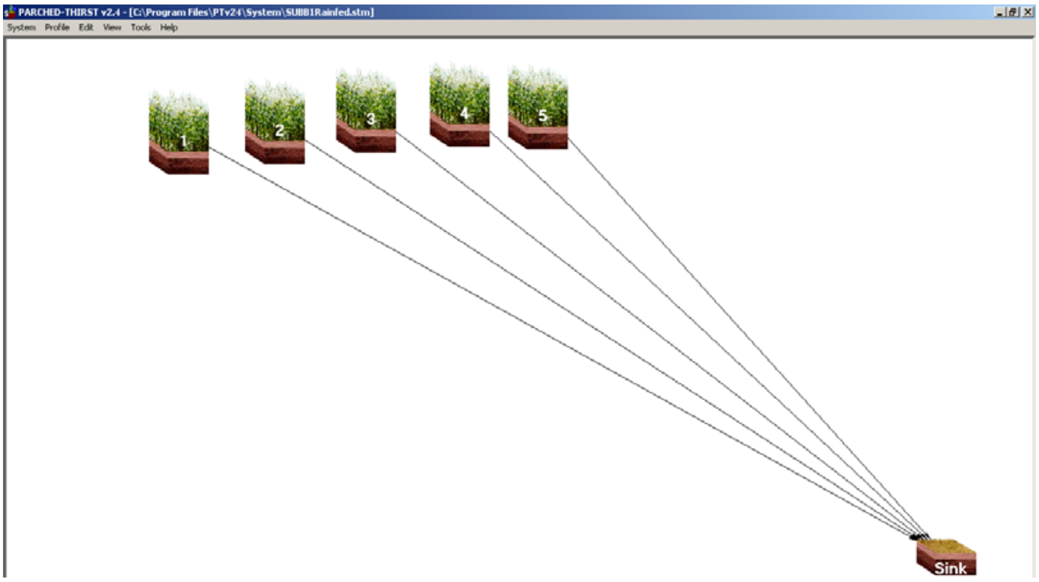


Figure 33

Click on **System** and select **Properties** (Figure 34).

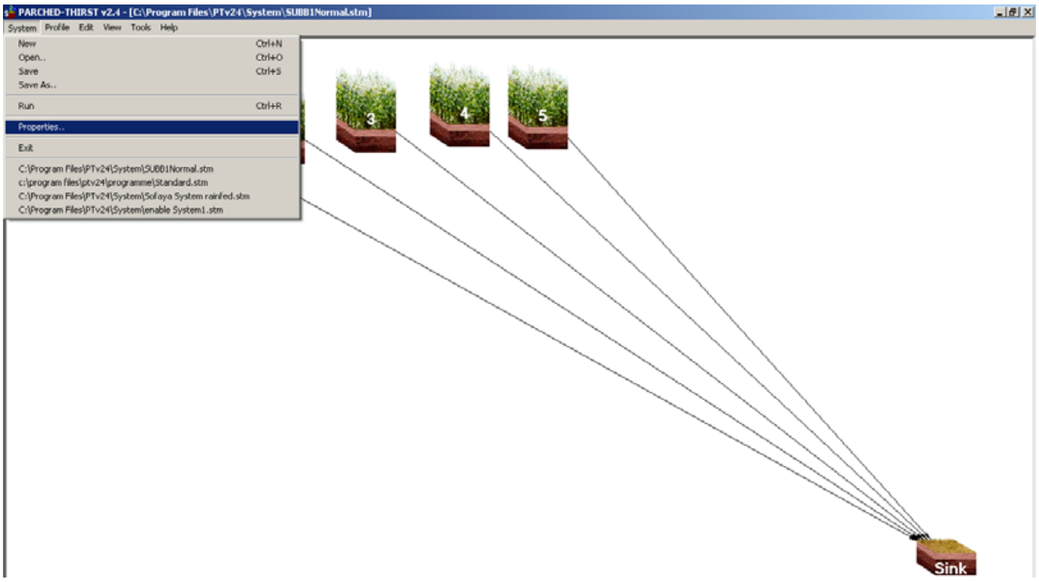


Figure 34

Click on **Properties** to display Figure 35.

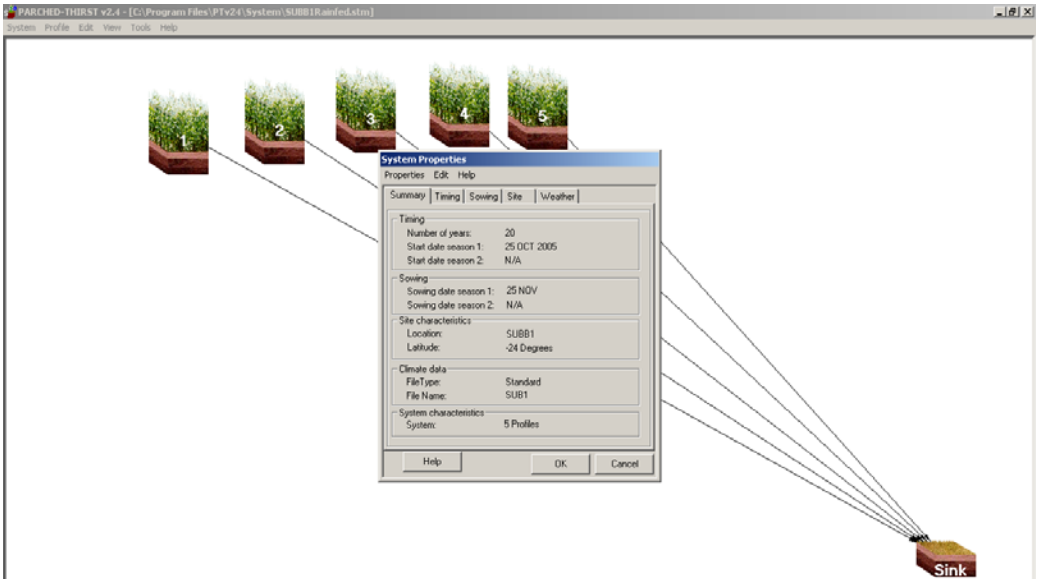


Figure 35

Click on **Weather** to display Figure 36.

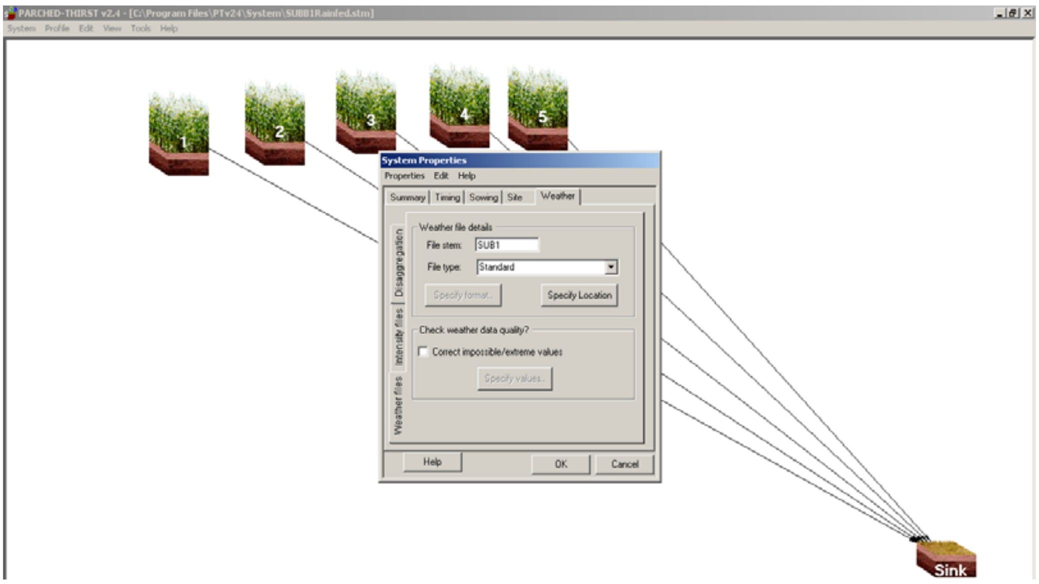


Figure 36

Click on **Specify Location** and click **Ok** (Figure 37). The screen will prompt you to select the **Weather file** to be used in the crop-yield simulation and the **start year**.

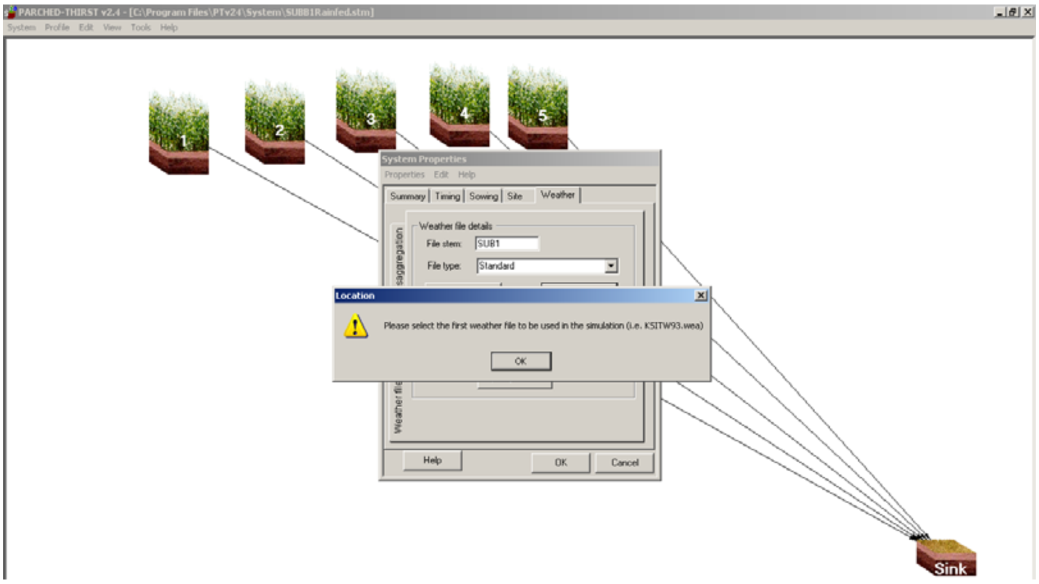


Figure 37

Click **Ok** to display Figure 38. If an incorrect weather folder is displayed. Change to the correct folder by following the path: C:\ICHSEA PROJECT\PT Model\ICHSEA Weather

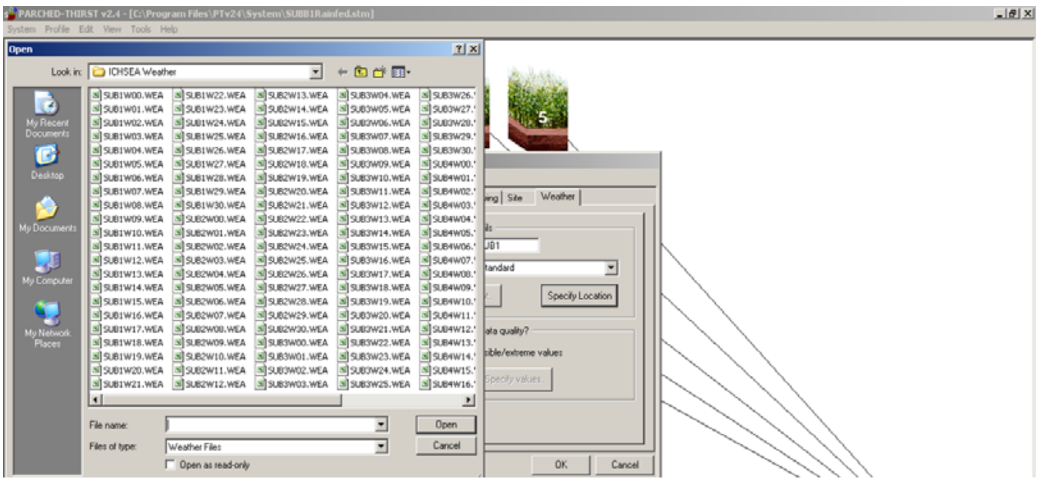


Figure 38

Click **Start year** of simulation under SUB1 weather files (e.g. SUB1W05.WEA in this example) and then click **Open** (Figure 39).

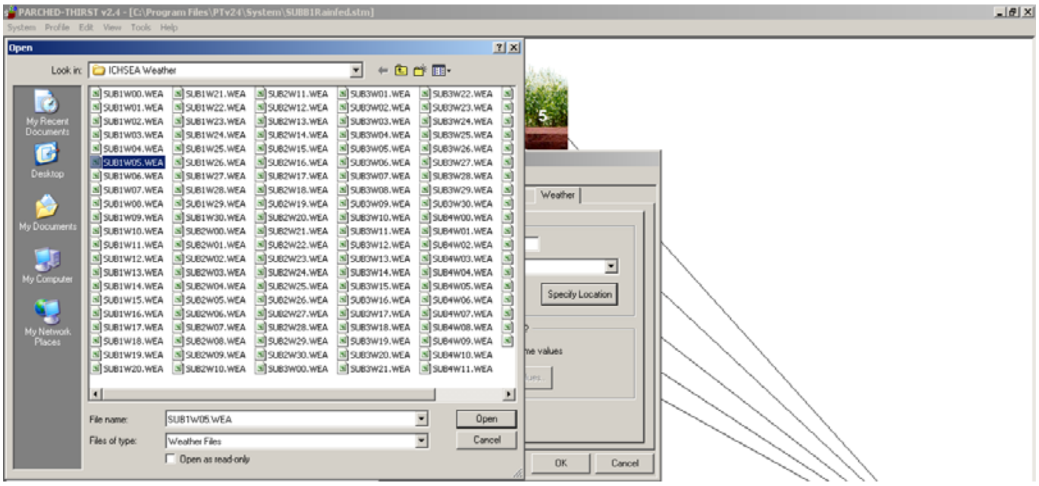


Figure 39

Click **Ok** (Figure 40).

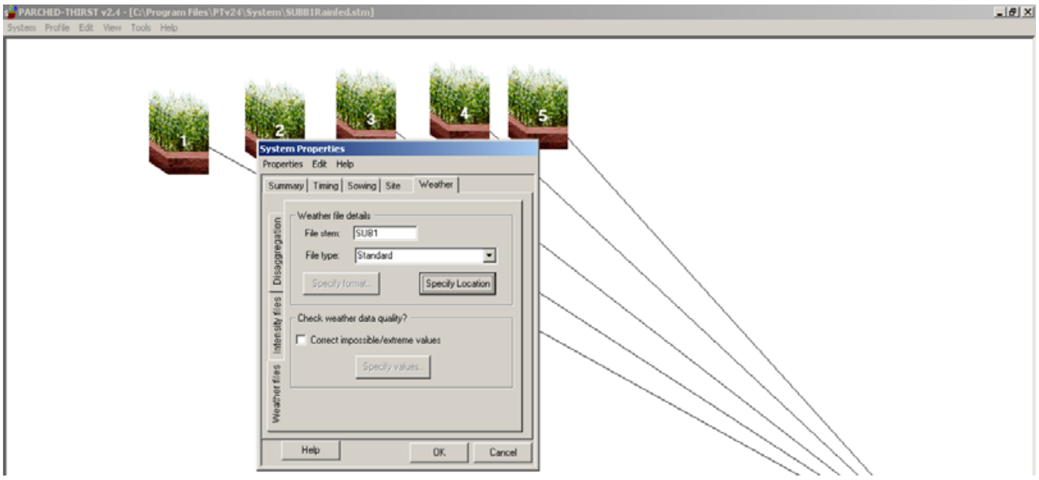


Figure 40

Click on **Site** to display Figure 41.

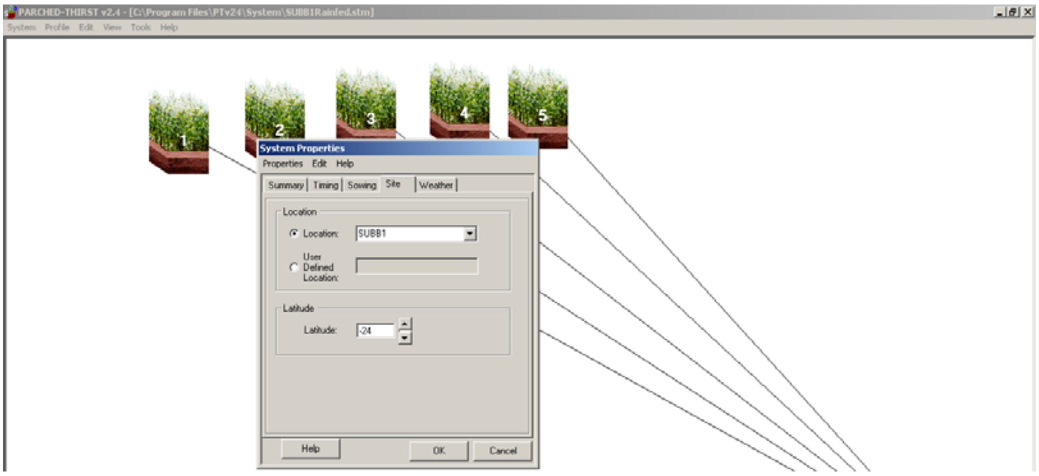


Figure 41

Check whether the **Location** (SUBB1) and **Latitude** (-24 for Southern Hemisphere) are correct. If not correct, click on **User Defined Location** and type four letters to represent the location name. The latitude can also be changed using the up and down arrows keys. In this example, the latitude should be set at -24.

Click **Sowing** to display Figure 42.

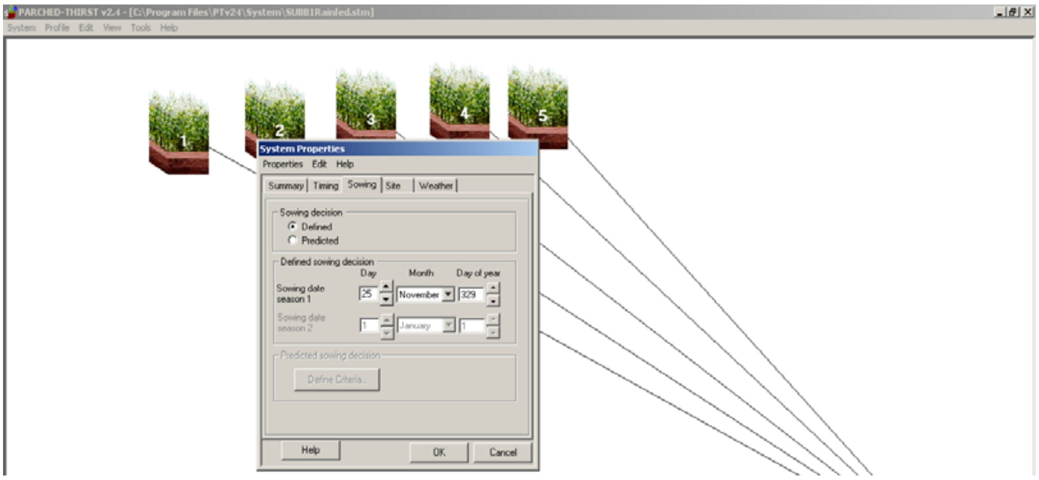


Figure 42

Adjust the planting day and month according to your planting date and select **Defined** under the **Sowing decision** buttons. **Predicted** can be used where the planting commences when a certain moisture criterion is satisfied (Figure 43). To use predicted, click on **Predicted** and then click **Define criteria**. Use the arrows to select the soil moisture content required at planting and click **Ok**. This means that the crop is planted on the day the planting soil moisture is satisfied. However, in this example, under **Sowing decision** select **Defined**.

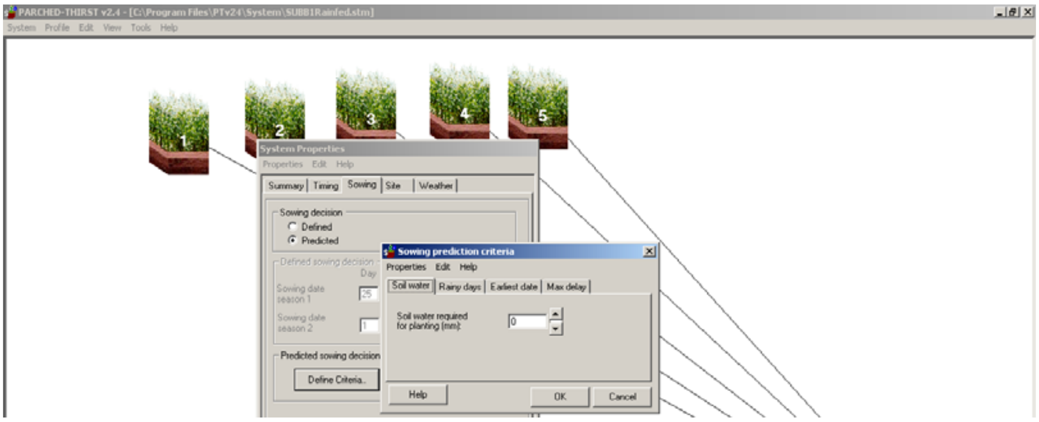


Figure 43

Click **Timing** to display Figure 44.

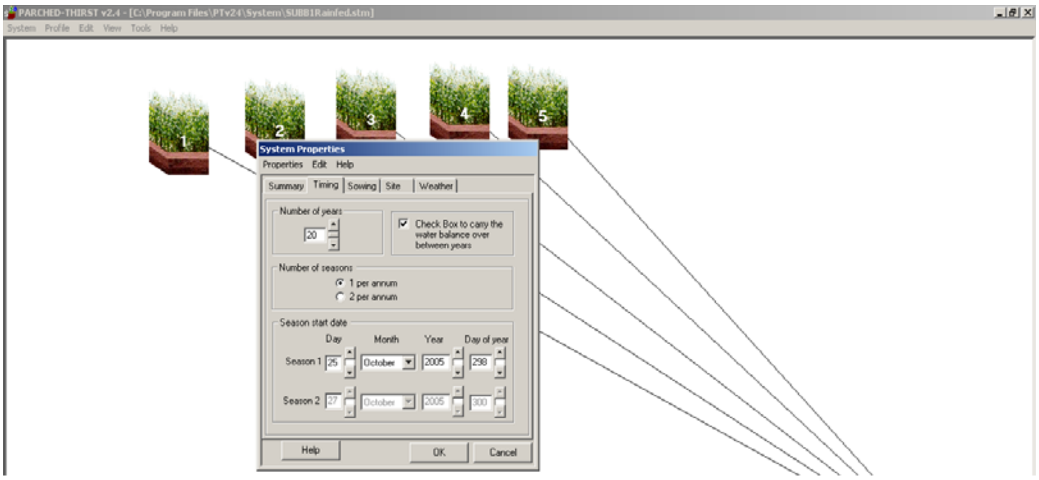


Figure 44

Select the **Number of simulation years** (20 years), **Number of seasons** (number of seasons =1) and the **Season start date** (25 October 2005). Note that the number of simulation years selected in Figure 44 window should be the same as those used in the SWAT model simulation.
Click **Ok** after making the necessary changes (Figure 44).

Click **Summary** to display the **System Properties** as a summary (Figure 45).

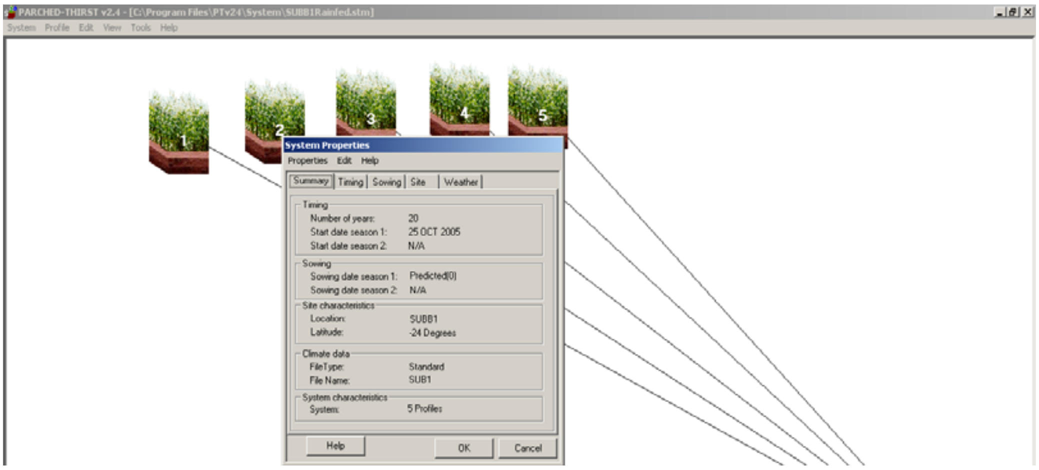


Figure 45

Check the **System Properties**. If satisfied with the properties, click **Ok**. If not, **edit** as required by clicking on the **Timing**, **Sowing**, **Site** and **Weather** buttons. When finished, click **Ok** to display Figure 46.

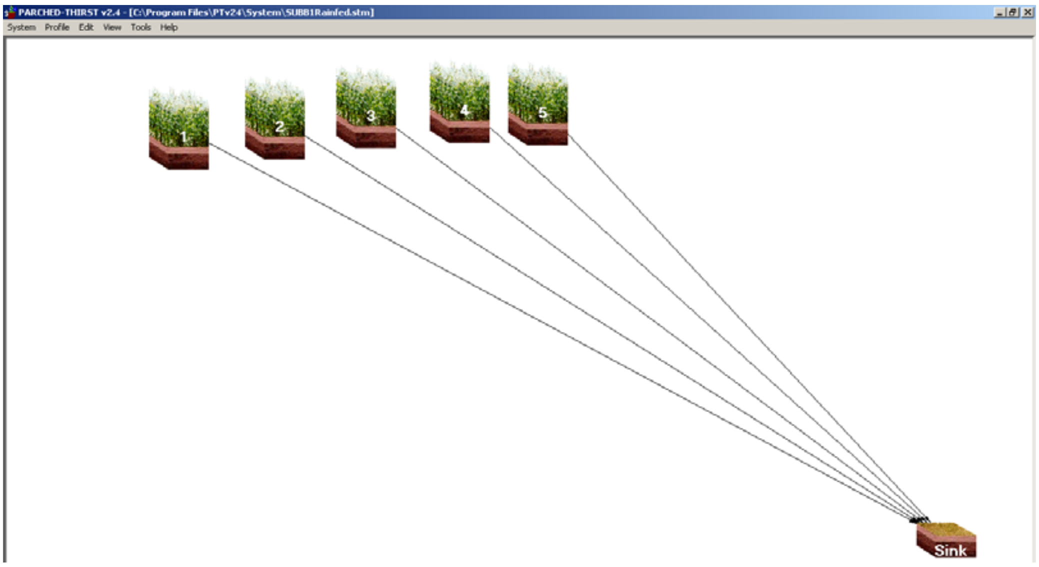


Figure 46

Click **System** and select **Run** (Figure 47).

Figure 47

Click **Run** to display Figure 48. Change the folder to C:\ICHSEA PROJECT\PT Model\PT ICHSEA OUTPUT and edit file name to **SUBB1 RAINFEDSimulationSummary.csv** (Figure 48). One can use another file name as long as there is SUBB1 and type of agriculture practice to show that the yields are for subbasin1 under rainfed practice in the study area.

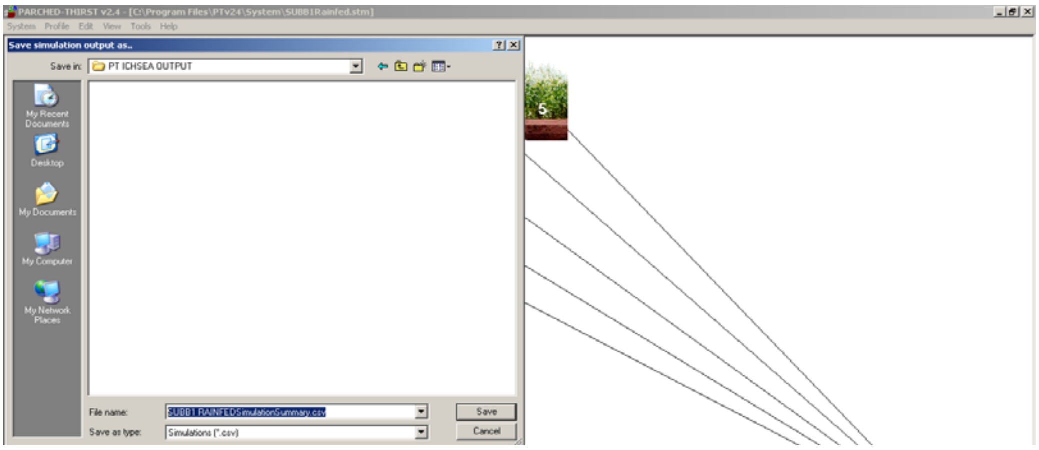


Figure 48

Click **Save (**Figure 48).

Clicking **Save** displays Figure 49.

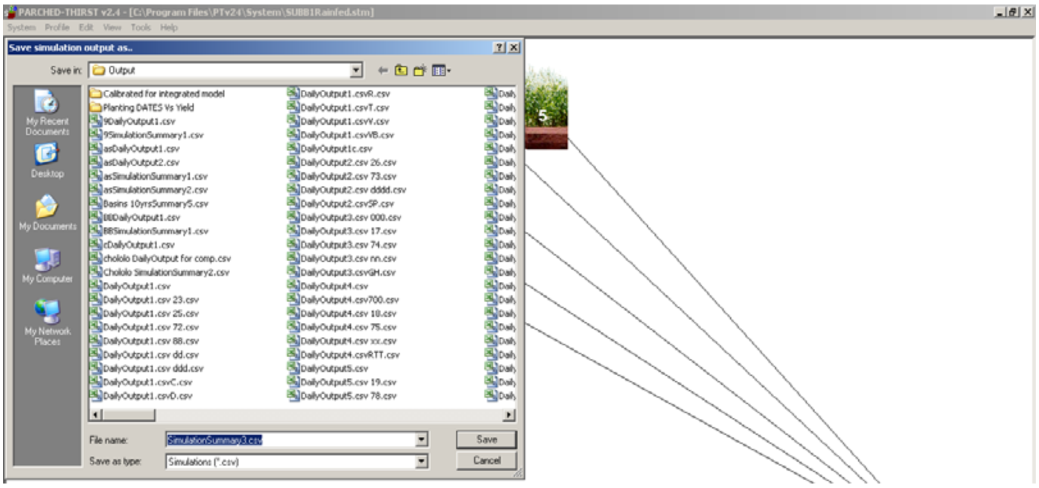


Figure 49

Edit the **File name** to **SUBB1 RAINFEDDailyOutput.csv** to save daily simulations results (Figure 50).

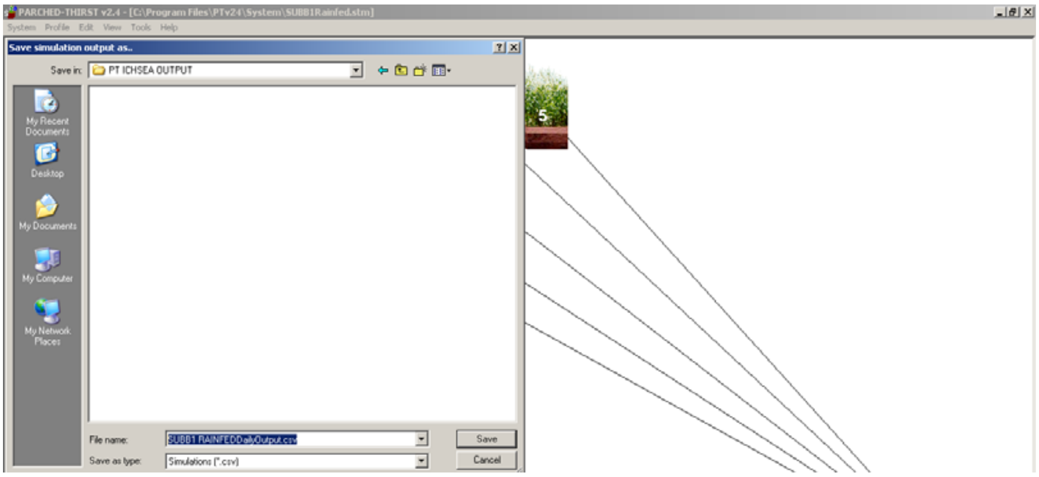


Figure 50

Click **Save** to display Figure 51. The window will ask whether you would like to view runtime graphs. Click **Yes** to view the graphs or **No** to avoid display of simulations graphs.

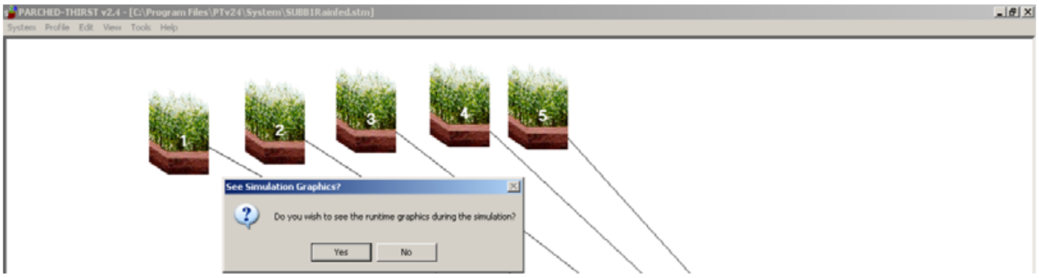


Figure 51

Click **Yes** to display Figure 52 and under **Speed of simulation**, select **Fast**.

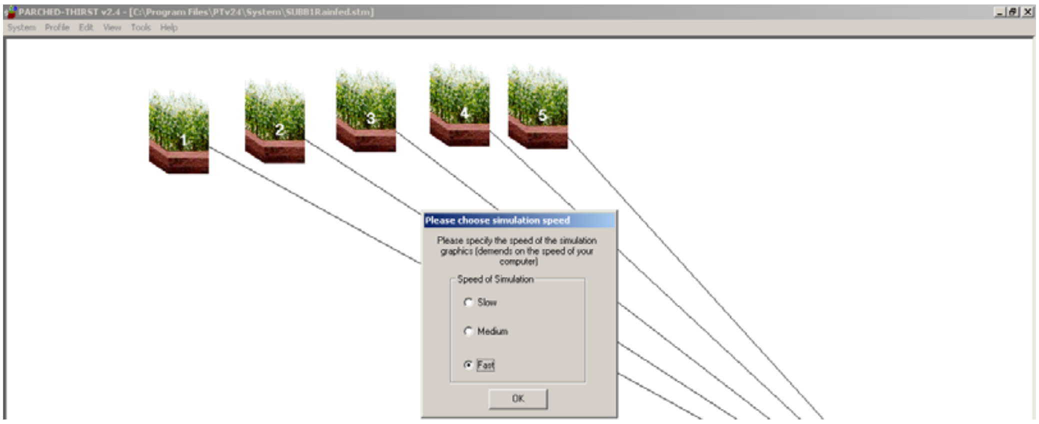


Figure 52

Click **Ok** to start the simulation process (Figure 53).

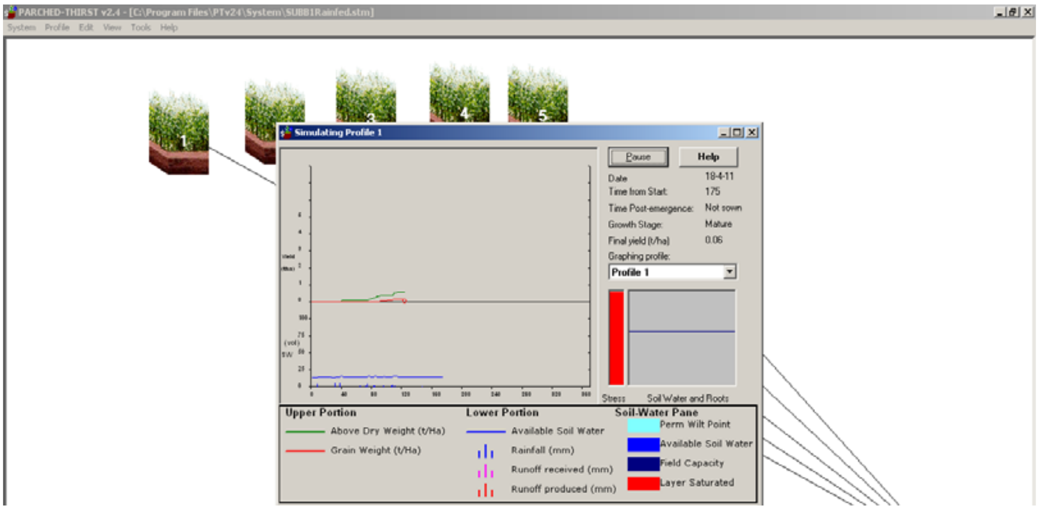


Figure 53

When the simulation is complete, Figure 54 is displayed.

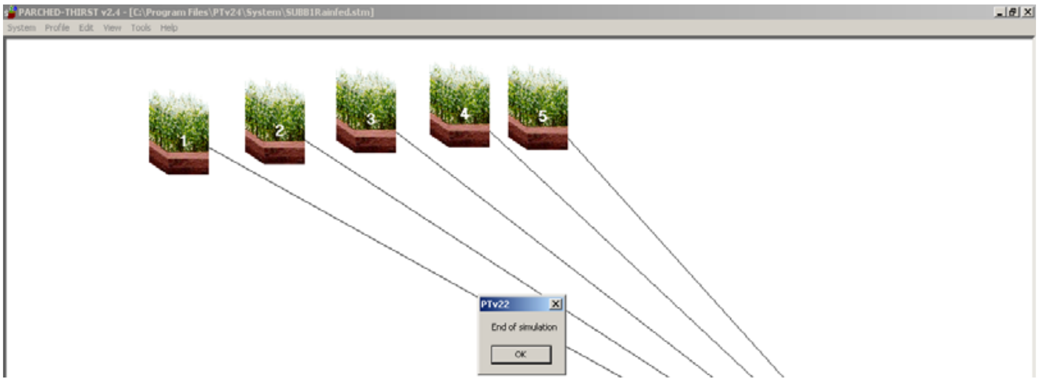


Figure 54

Click **Ok** to display Figure 55.

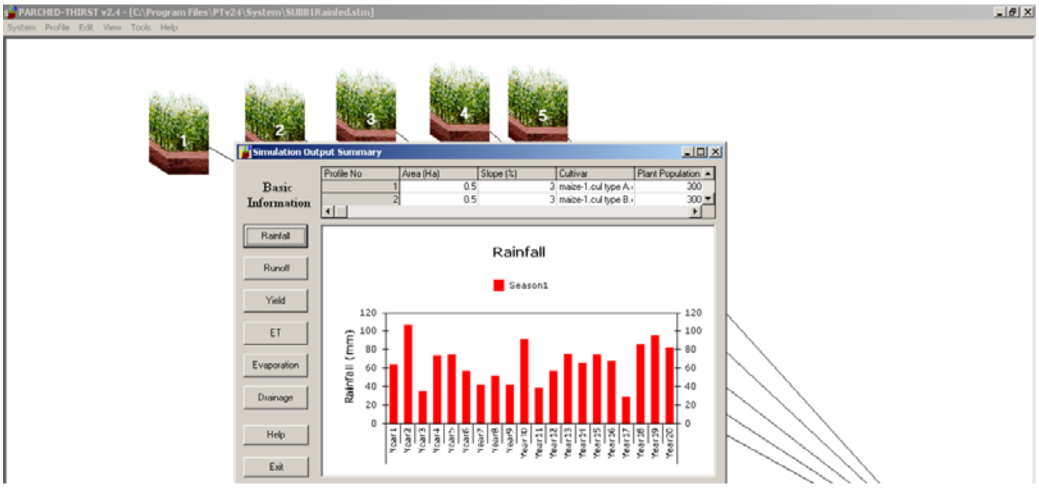


Figure 55

Close the **simulation output summary** window to display Figure 56. The simulation for **SUB1** (subbasin 1) is complete.

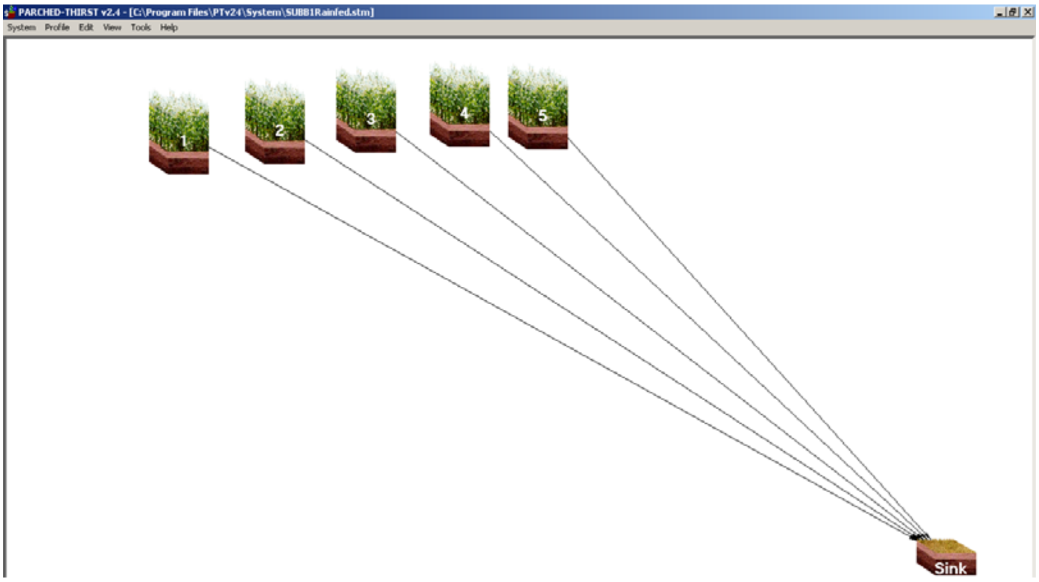


Figure 56

The next step is to simulate **SUB2, SUB3, ……SUB10** (subbasin2 – subbasin10, where there is agriculture only. In this catchment example, there is no crop production in **SUB2**. Hence, SUB2 is not simulated). This requires repeating the steps explained above for **SUB1** rainfed simulation.

To open **SUB3Rainfed.stm**, click on **System** and select **Open.** Then select **SUB3Rainfed.stm** (Figure 57).

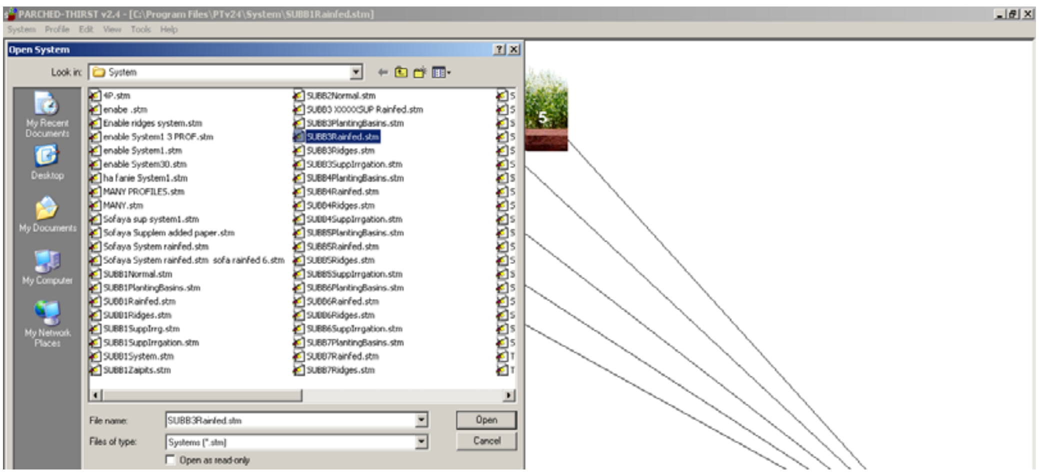


Figure 57

Click **Open** to display Figure 58.

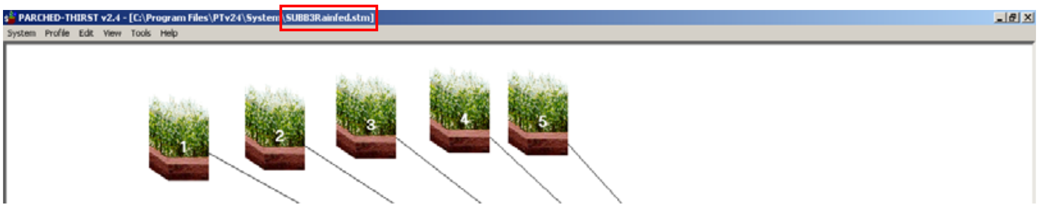


Figure 58

Open **SUB4Rainfed.stm** system the same way as **SUB3Rainfed.stm** system (Figure 59).

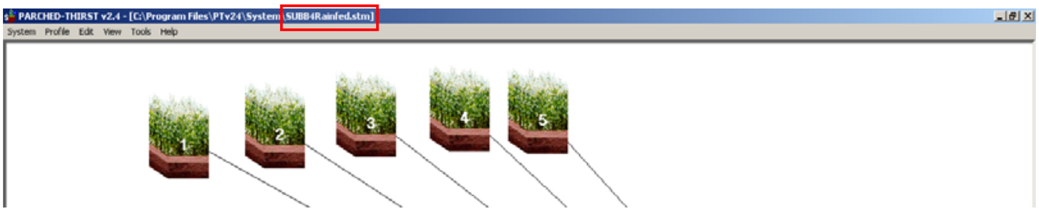


Figure 59

After running PARCHED-THIRST to get maize yields for the simulation period 2005–2024, under a crop management practice of interest, there is need to load the crop yield results into the Olympe model.

Part C: Loading the PARCHED-THIRST results into Olympe model

The maize crop yields are loaded into Olympe model using the **Quantities** button under **Hazards** in the Olympe main interface. The steps to achieve this loading of crop yields into Olympe are described in the next section.

Copy maize crop yields from the PARCHED-THIRST **summary output** files located in C:\ICHSEA PROJECT\PT Model\PT ICHSEA OUTPUT.
Open Olympe model and click on **Quantities** under **Hazards** (Figure 60).

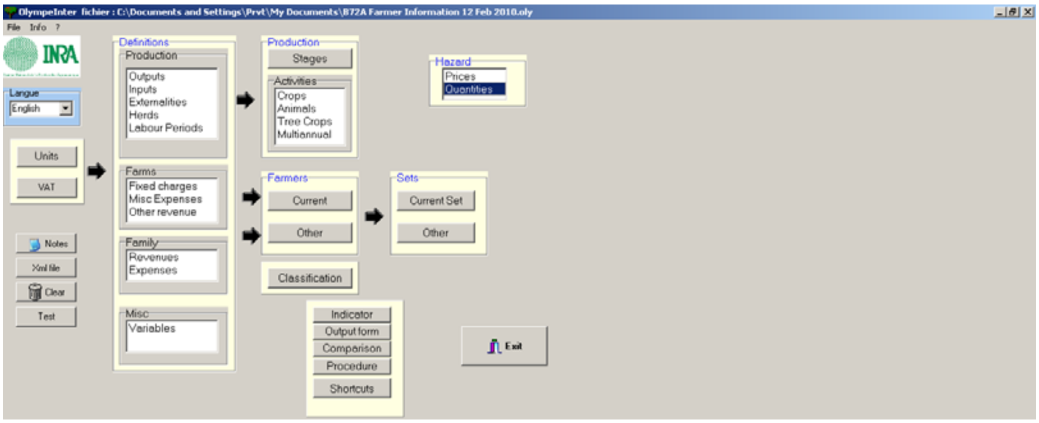


Figure 60

Click on **Quantities** to display Figure 61.

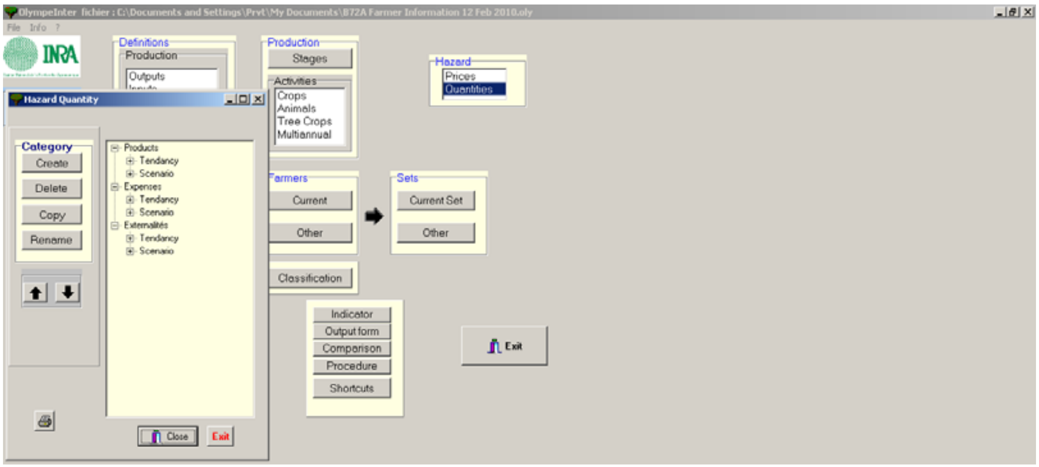


Figure 61

Click on **Tendancy** under **Products** to display Figure 62 and select **Yields Rainfed Farmer A 2005 2024.** The selection of the **Yields Rainfed Farmer A** ensures the yields from rainfed practice under farm type A are used. If a different practice is required, correct selection should be made at this stage for the Olympe model to use the correct yields.

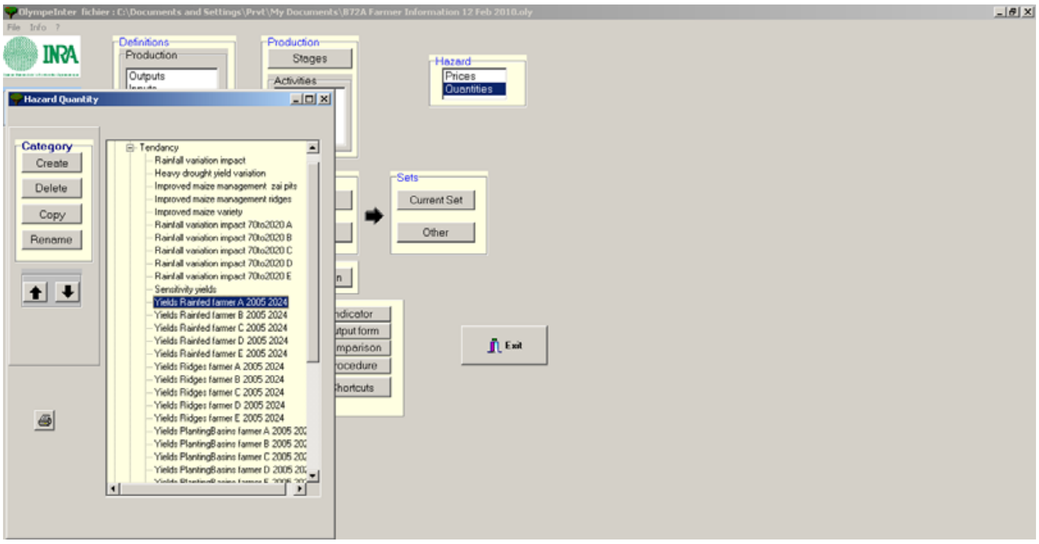


Figure 62

Double click on **Yields Rainfed Farm A 2005 2024** and select the **Value** button to display Figure 63. The **Precision** button should indicate **2**, for 2 decimal places (Figure 63).

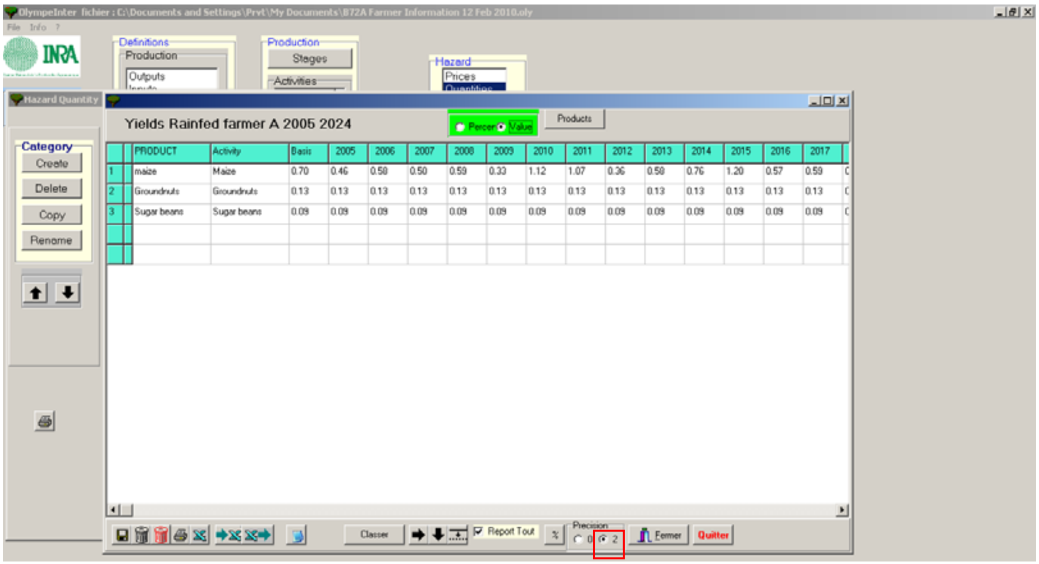
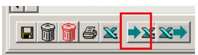


Figure 63

Click on the Excel  button to send the table to Excel format shown in Figure 64.

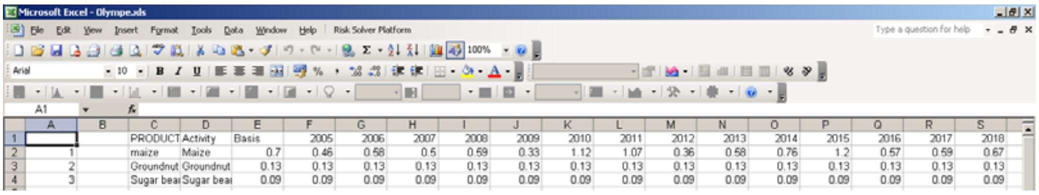


Figure 64

Paste the yields from PARCHED-THIRST **summary output file** into a new Excel file (there is no need to save this new file). From **Edit** select **Paste special** and then **Transpose** (Figure 65).

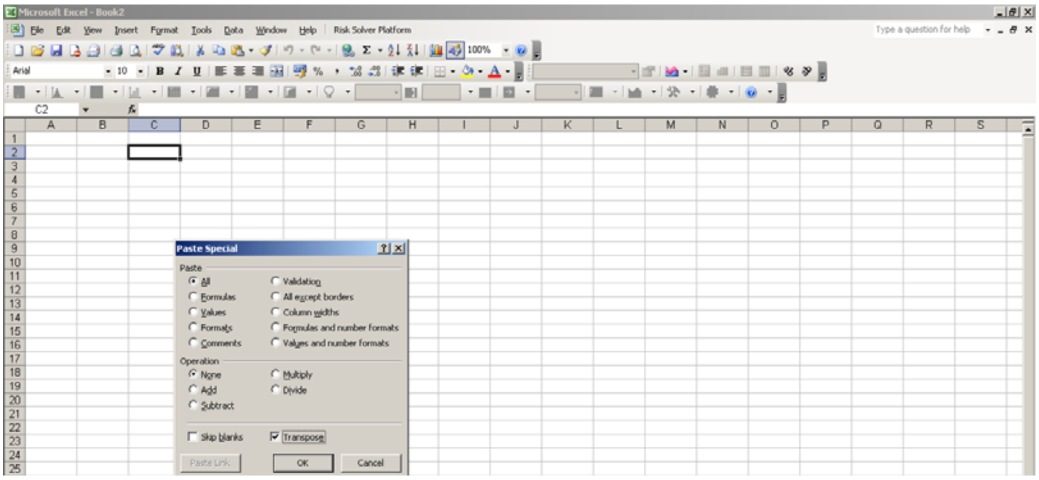


Figure 65

Click **Ok** to display PARCHED-THIRST yields in a row format (Figure 66).

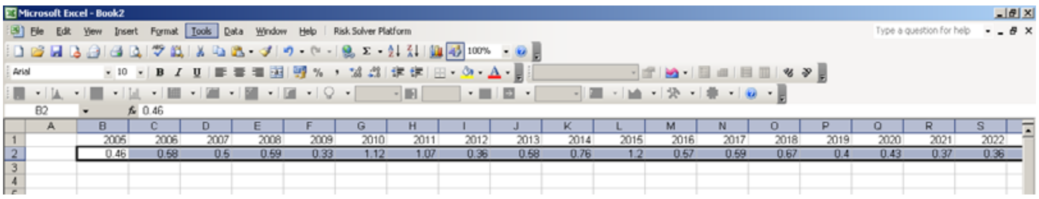


Figure 66

Copy the PARCHED-THIRST yields in the row format and paste in **Olympe.xls** file (Figure 67), making sure the yields are pasted in the **maize** crop row from the start year, 2005. The start year should correspond with the start year of maize yield simulation from the PARCHED-THIRST model and streamflow simulations from SWAT model.

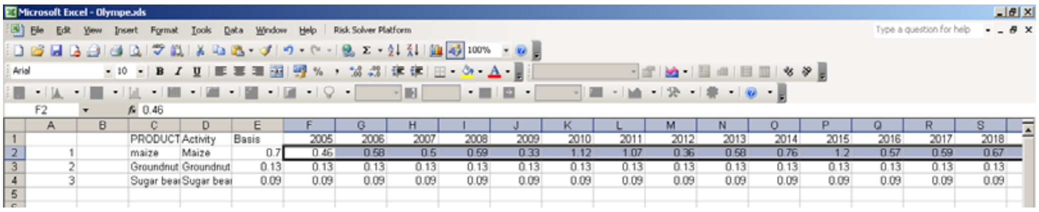


Figure 67

Click **File** and select **Save** (Figure 68). The other crops yields are left unchanged as they should be kept at **base year** values.

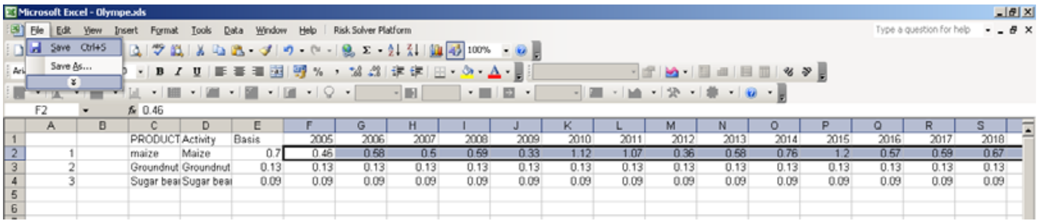
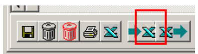


Figure 68

Close the **Olympe.xls** file.

Go to Olympe interface and click the second **Excel** button  to pull the maize yield figures saved in **Olympe.xls** into the Olympe interface as shown in Figure 69. The yield data for Farmer A is now loaded in the Olympe interface database. What is left is to assign the loaded yields to farmer A under **Farmers** section in Olympe interface.

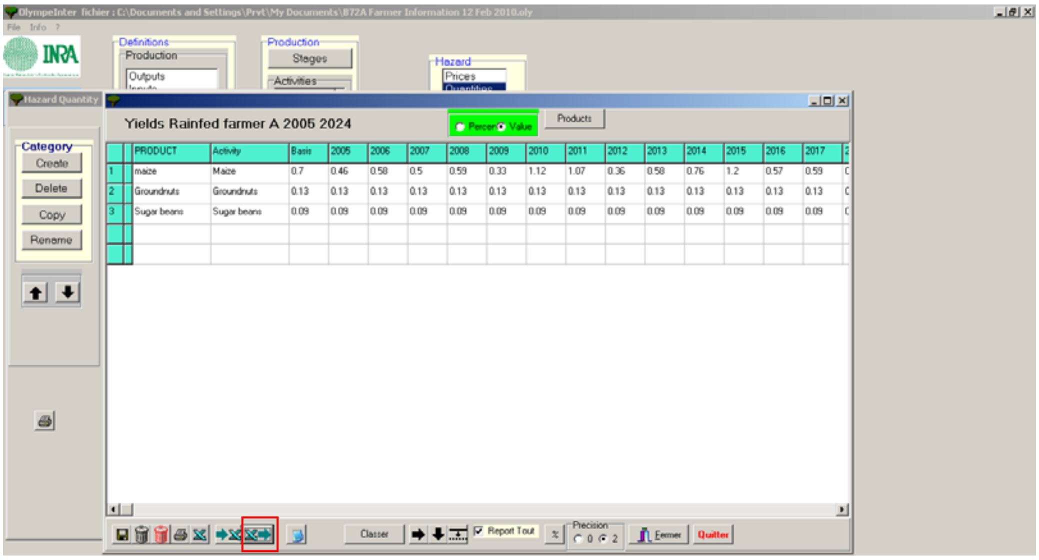


Figure 69

Close the table by clicking on **fermer** button (Figure 70).

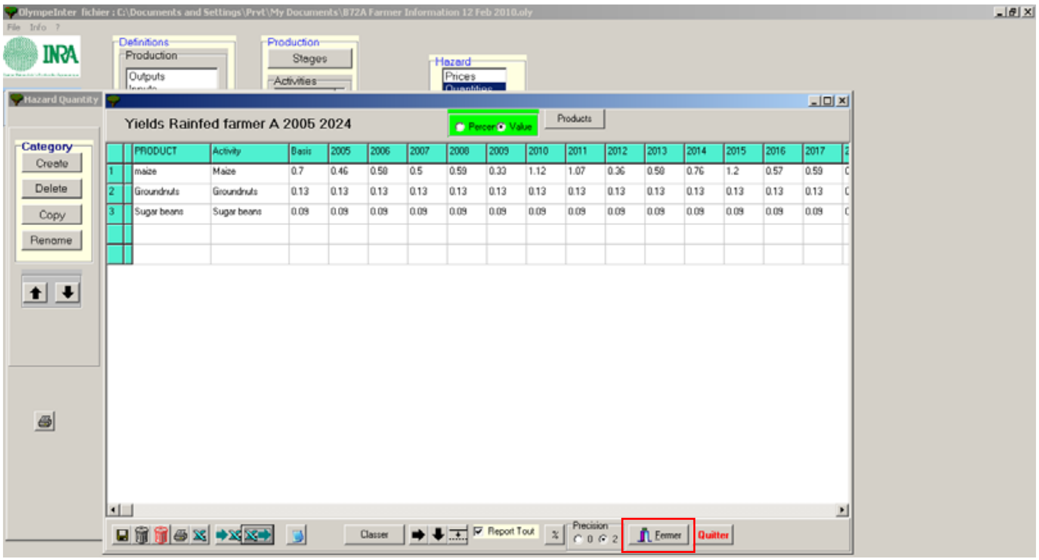


Figure 70

Clicking on **fermer** button displays back Figure 61 (Figure 71). Select the next farmer, **Farmer B** and load the yields from PARCHED-THIRST following the same procedure described above. Repeat this procedure until the **Rainfed yields** for **farm types C, D** and **E** are loaded into Olympe.

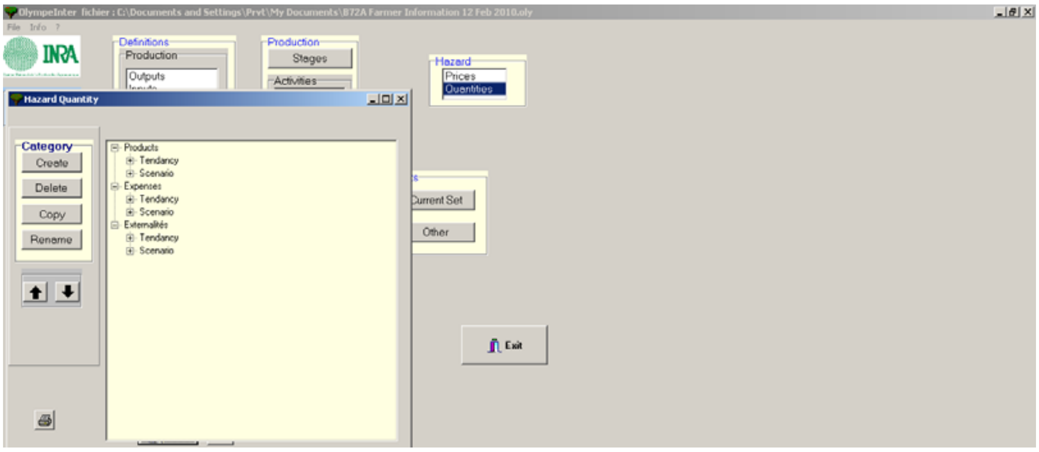


Figure 71

For example, continue to select **Yields Rainfed farmer B 2005 2024** (Figure 72).

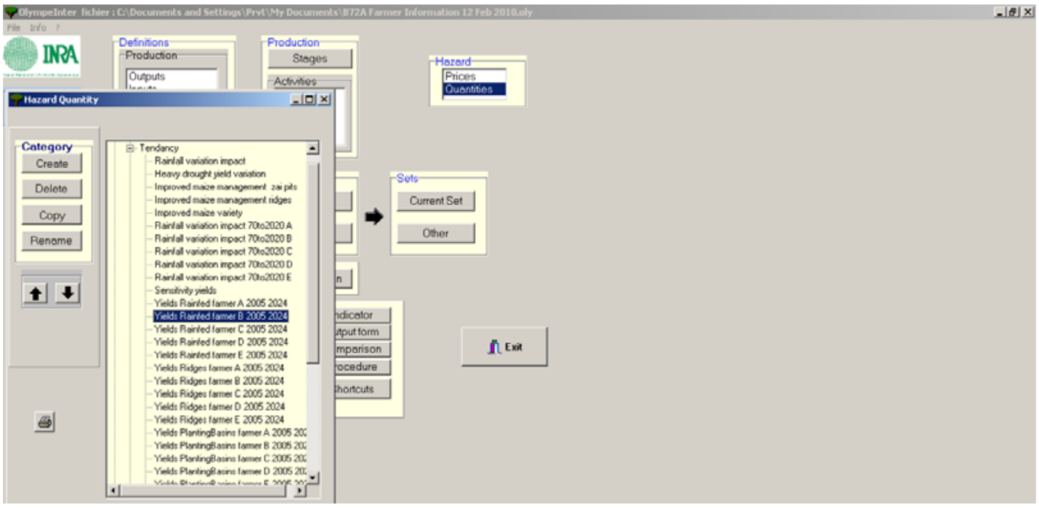


Figure 72

After completion of loading the **Rainfed** maize yields for each farm type, proceed to view the results and compare the five farm types.

Viewing of Results

Go to the Olympe main interface by clicking **start** and selecting the **Olympe** program  (Figure 73).

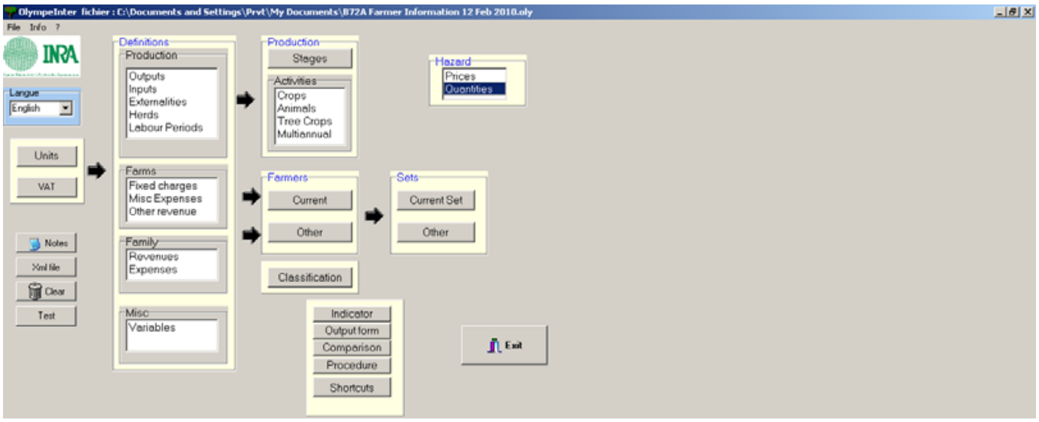


Figure 73

Under **Farmers**, click **Other** to display Figure 74.

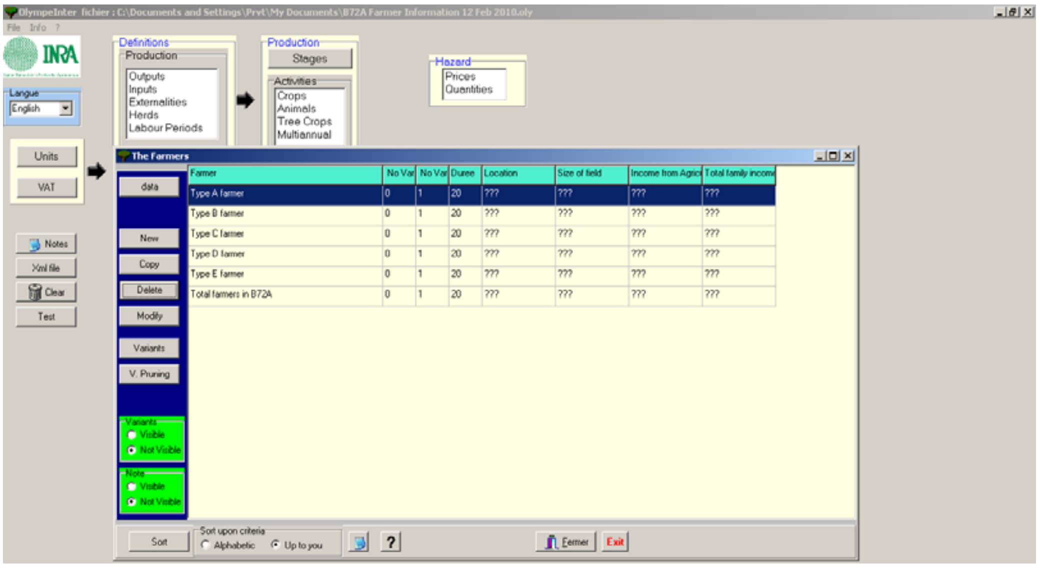


Figure 74

Select any of the five farmer types (A–E) and click on **Data** button to display Figure 75.

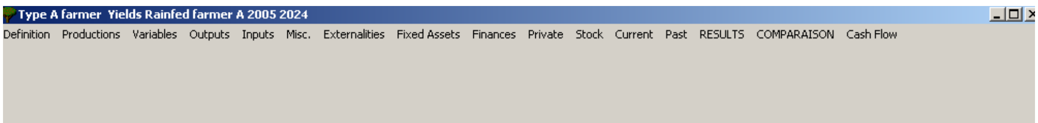


Figure 75

Click on **Definition** to display Figure 76.

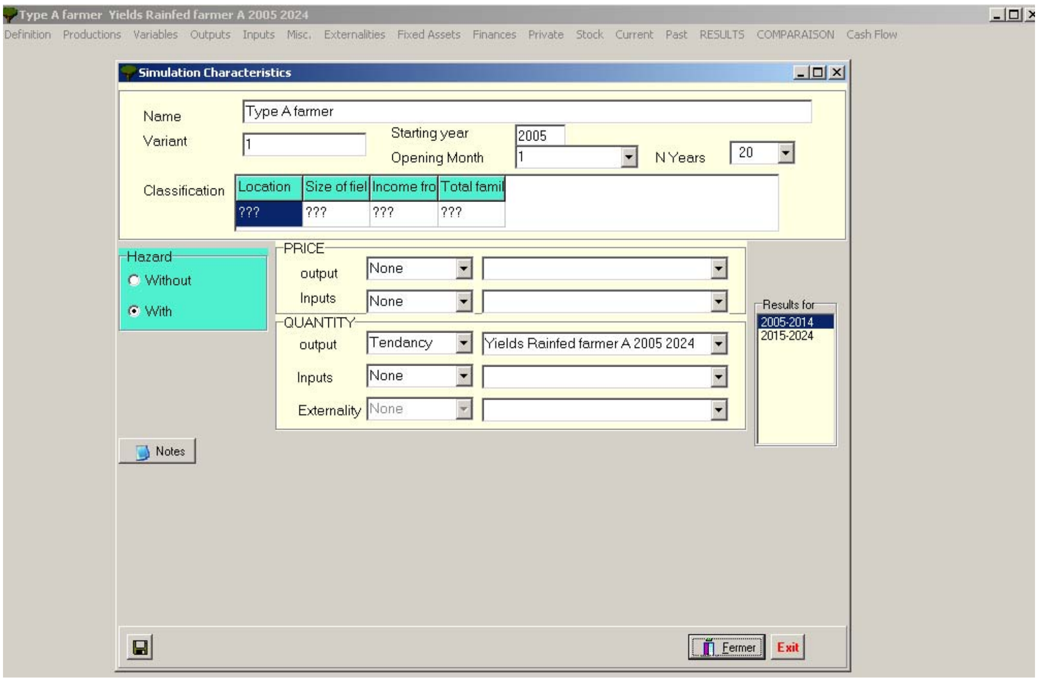


Figure 76

Check to ensure heading: **Quantity** is showing **Output: Tendency**. Select **Yields Rainfed farmer A 2005 2024** as shown in Figure 77.

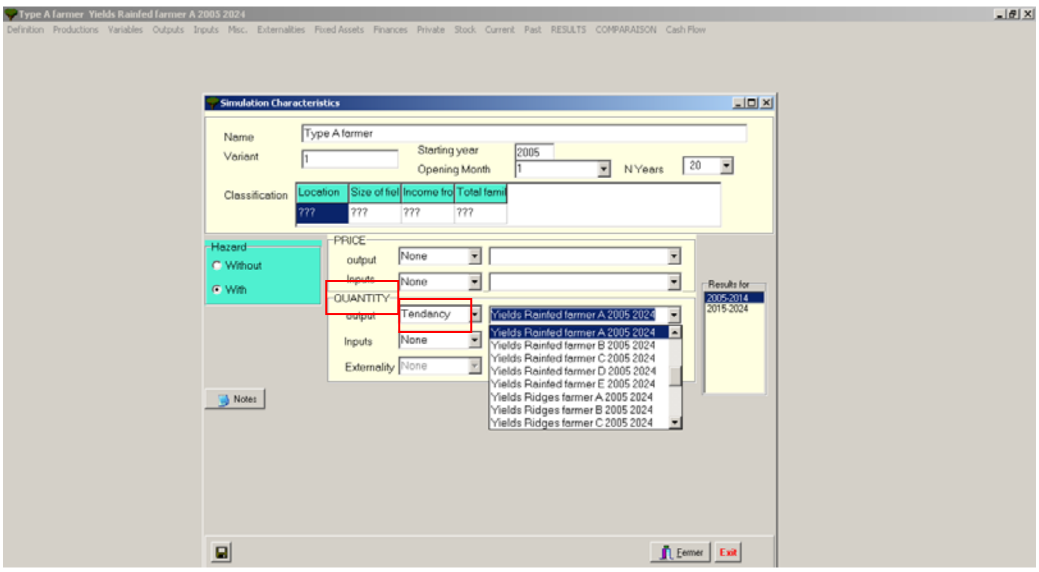


Figure 77

Click the period **2015–2024** to display Figure 78.

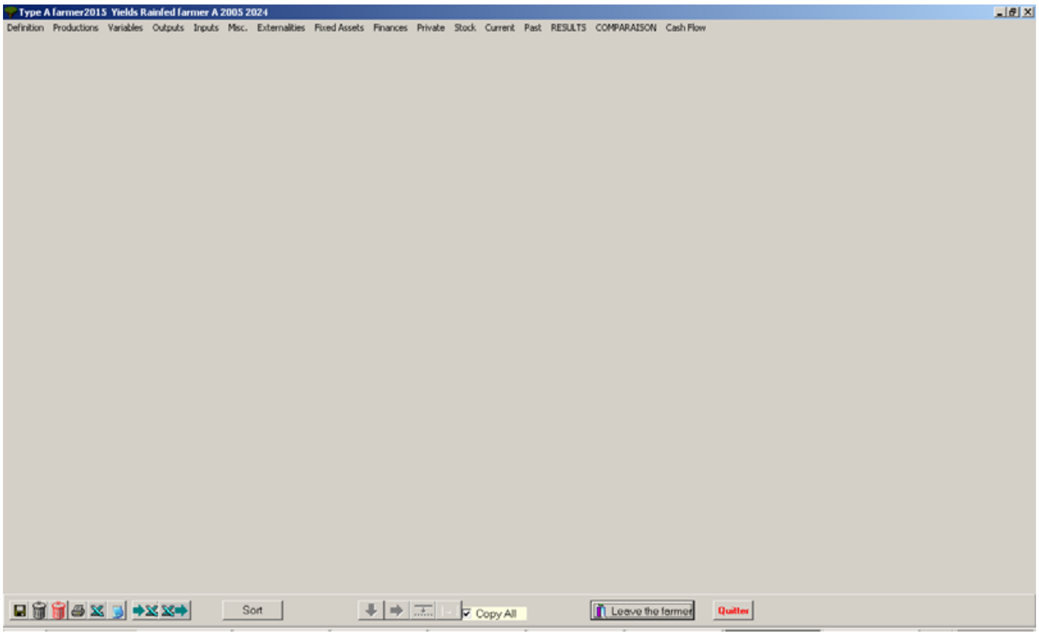


Figure 78

Click on **Definition** and select **Yields Rainfed farmer A 2005 2024** as shown in Figure 79. The two previous steps ensure that the scenario uses the yield series for the two periods 2005–2014 and 2015–2024 that were loaded under **Hazards** as one series from 2005–2024 in the main interface.

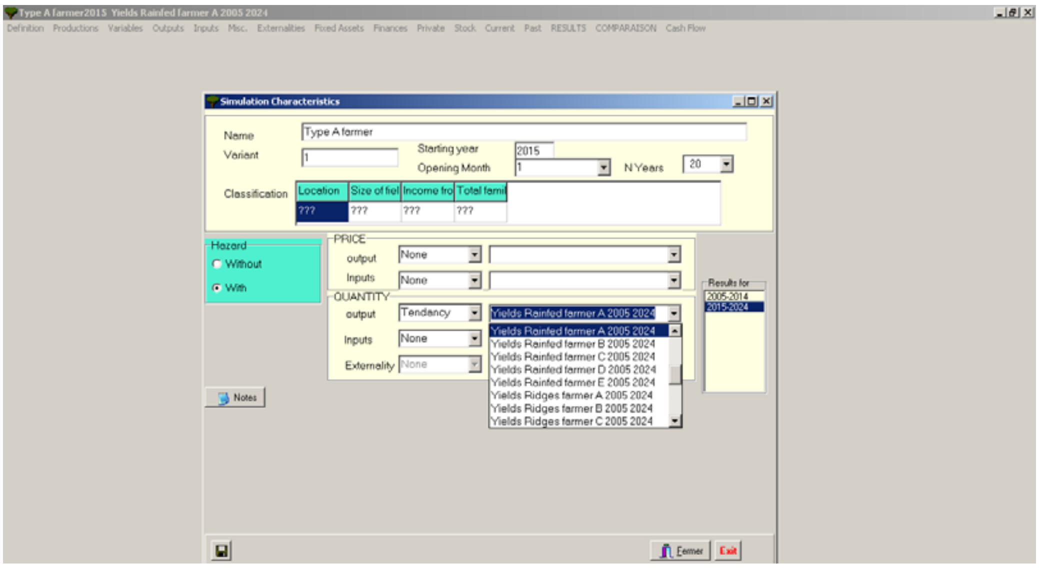


Figure 79

Check that all the farmer types have **Yields Rainfed X 2005 2024** under **Quantity**: **Tendancy**. For example, for farm type B, it should be **Yields Rainfed B 2005 2024** and for type C, it should be **Yields Rainfed C 2005 2024.**

Close the **Simulation characteristics** window. Choose any of the five farm types and click **Data** to display Figure 80. In this example, type A farmer was selected.

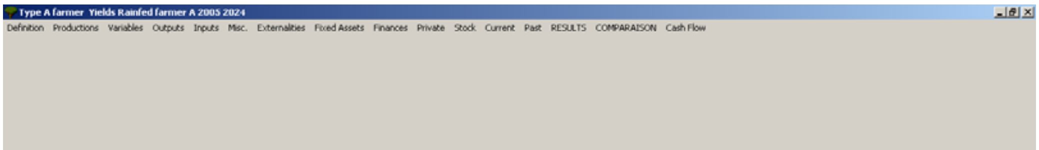


Figure 80

Click on **Results** to display Figure 81.

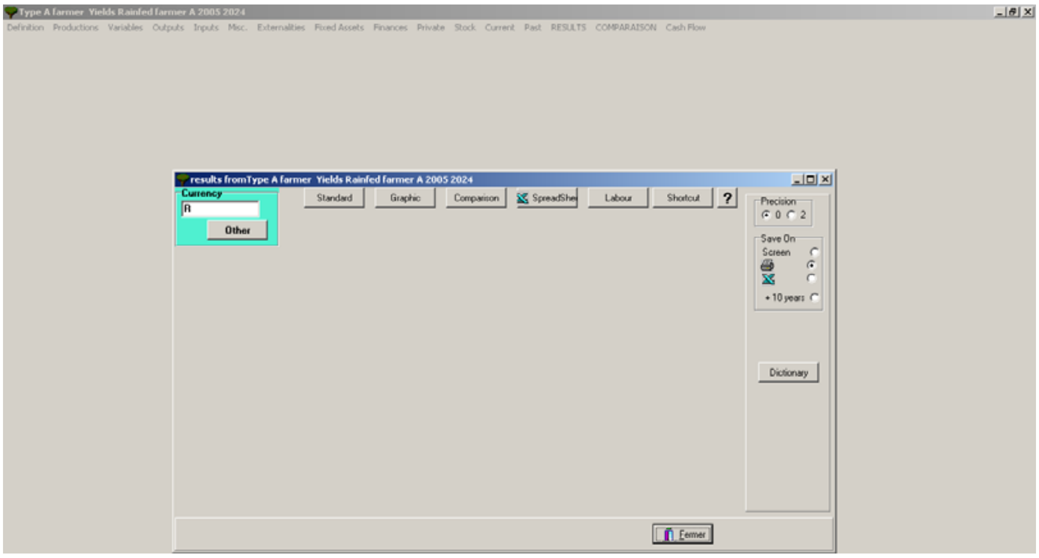


Figure 81

Select the **Excel** button under **Save On** (Figure 82).

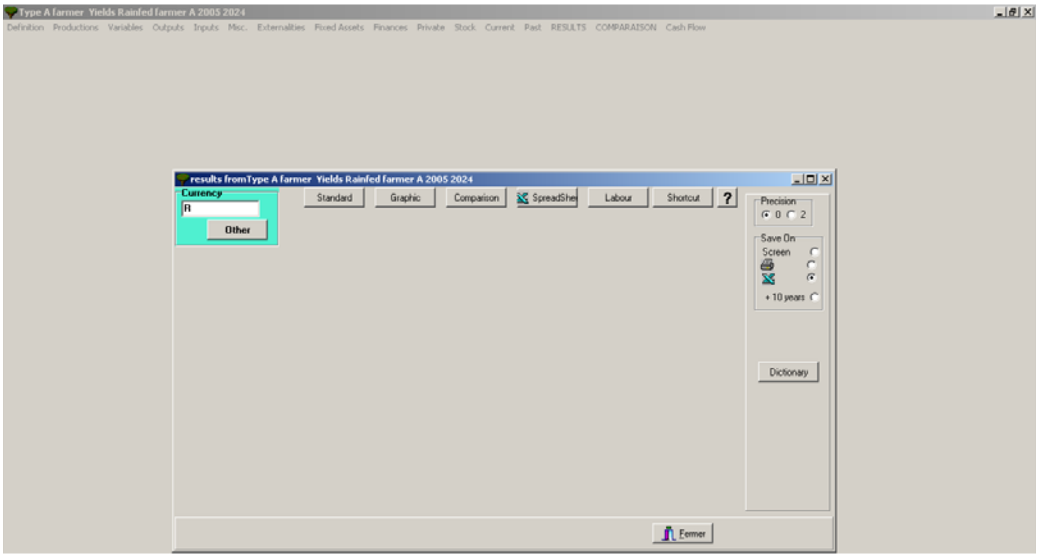


Figure 82

Click on **Comparison** button to display Figure 83 and select **one serie** button.

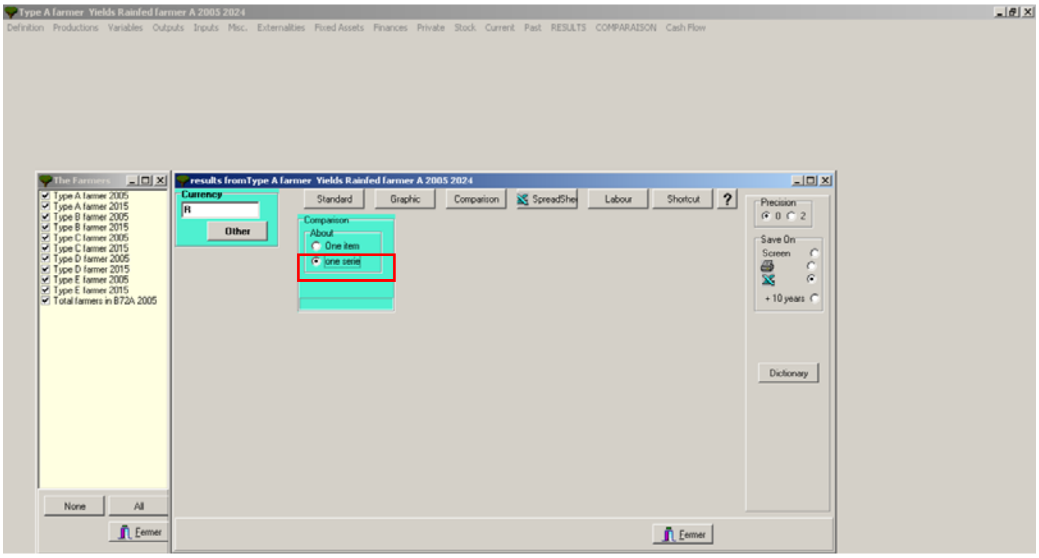


Figure 83

Select **B72A Farm Type Result 1** and unmark the **Total farmers in B72A 2005** as shown in Figure 84.

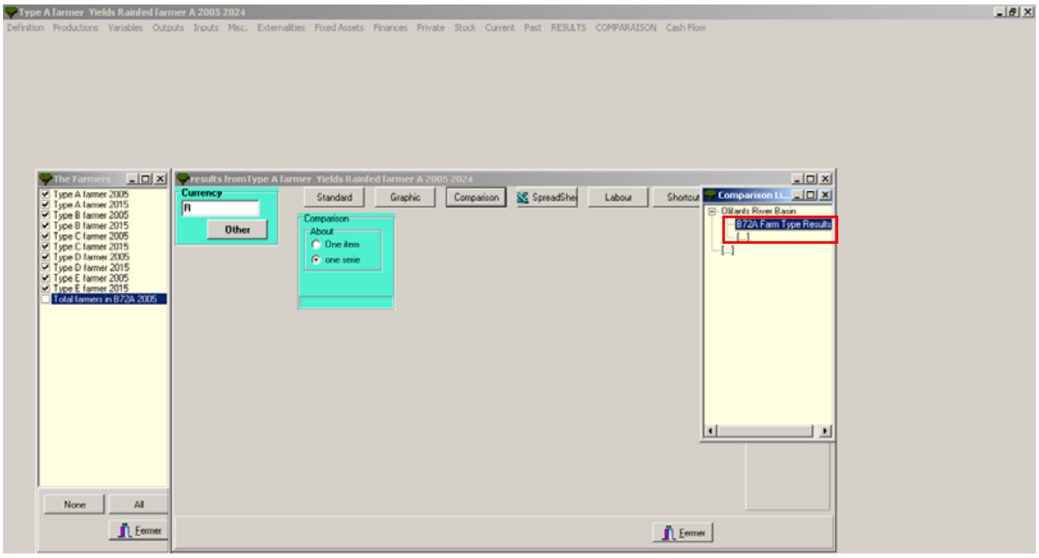


Figure 84

Double click on selected **B72A Farm Type Result 1** to display Figure 85.

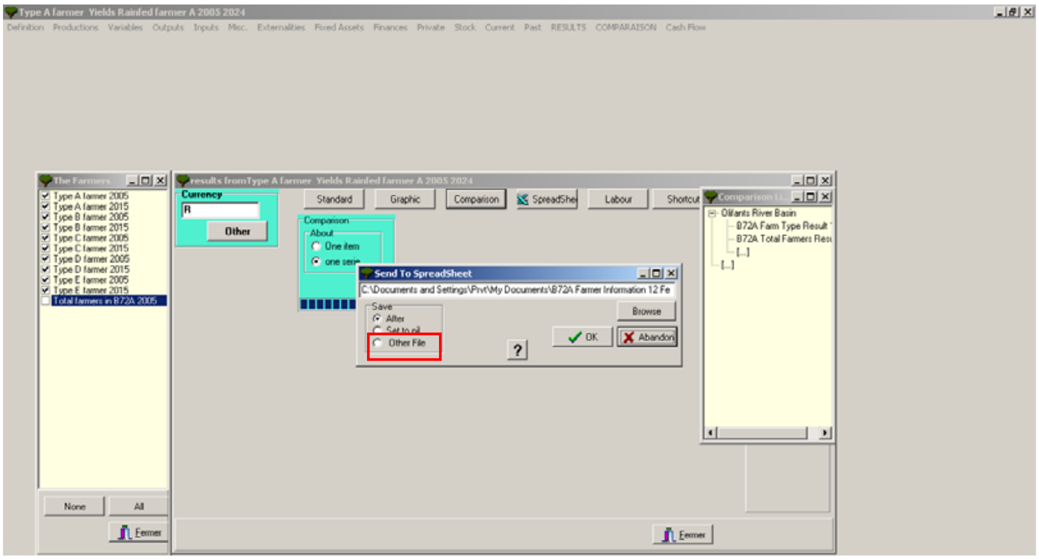


Figure 85

On **Send to Spreadsheet** window, under **Save**, select **Other File** and click **Ok**. Save the result file in C:\ICHSEA PROJECT\Olympe ICHSEA OUTPUT, under file name: **Rainfed 2005 2024 B72A Farmer Information** as shown in Figure 86.

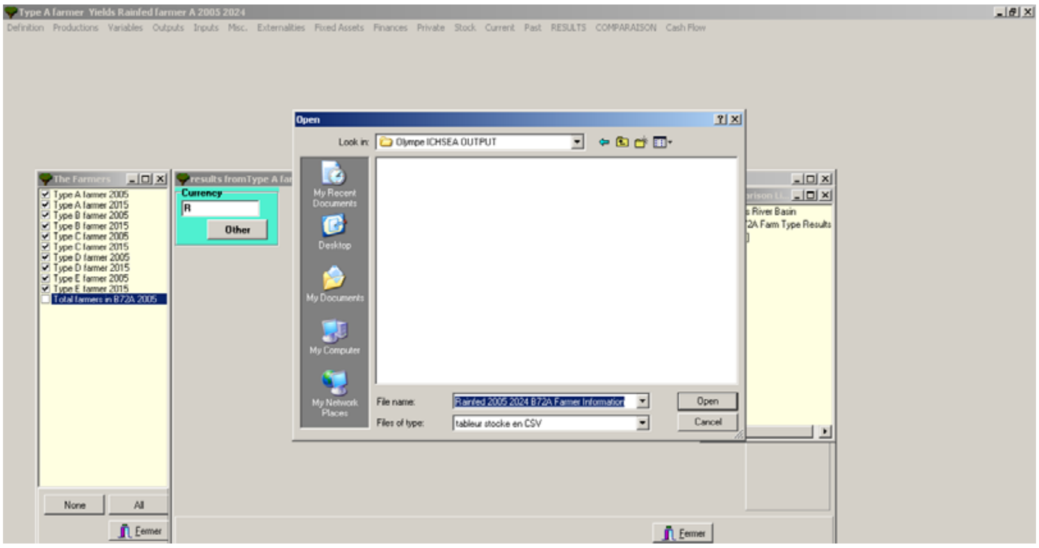


Figure 86

Click on **Open** to save **Rainfed 2005 2024 B72A Farmer Information** file in the C:\ICHSEA PROJECT\Olympe ICHSEA OUTPUT folder where it can be accessed at a later stage to display the results of the integrated model.

Open **Rainfed 2005 2024 B72A Farmer Information** file from C:\ICHSEA PROJECT\Olympe ICHSEA OUTPUT folder (Figure 87).

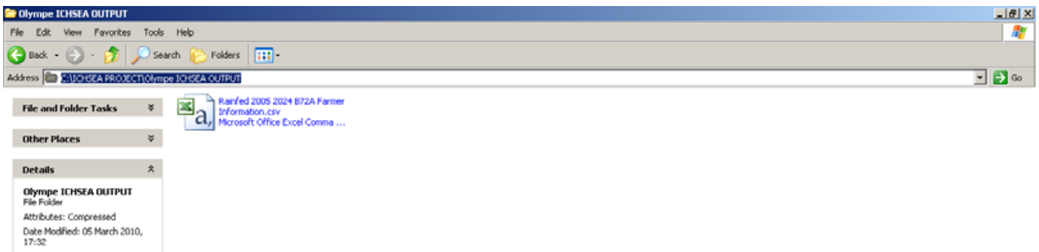


Figure 87

Double click on **Rainfed 2005 2024 B72A Farmer Information** file to display Figure 88. Click on **Data** and select **Text to columns.**

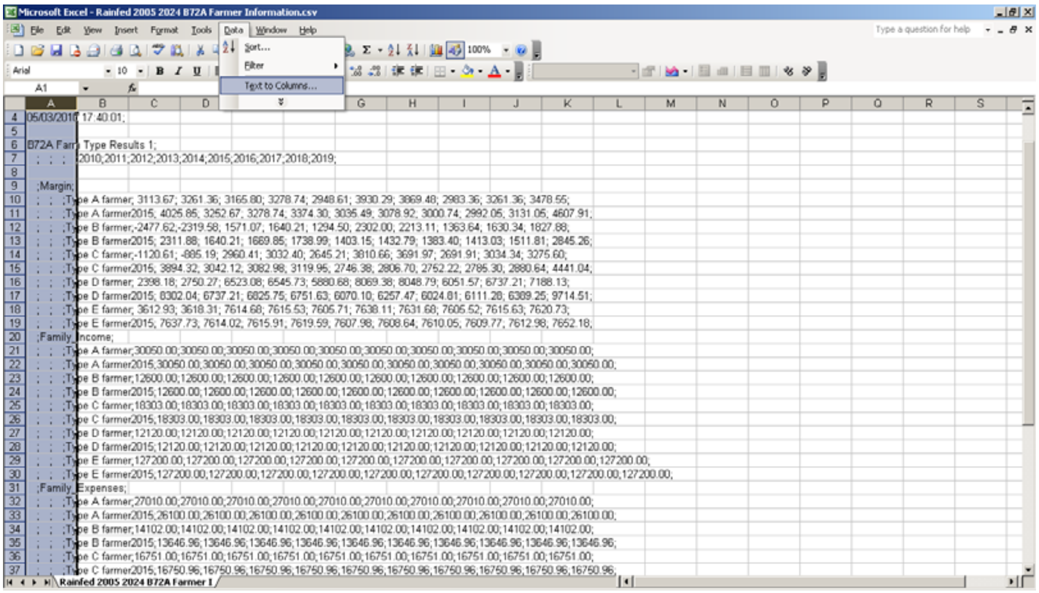


Figure 88

Select **Delimited** button and click **Next**. Select **Semicolon** as shown in Figure 89.

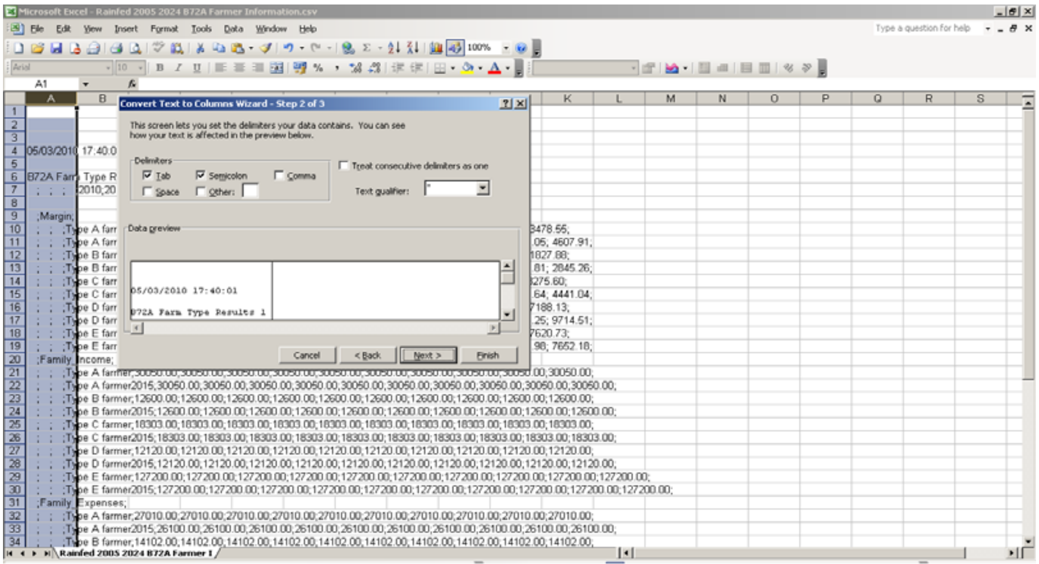
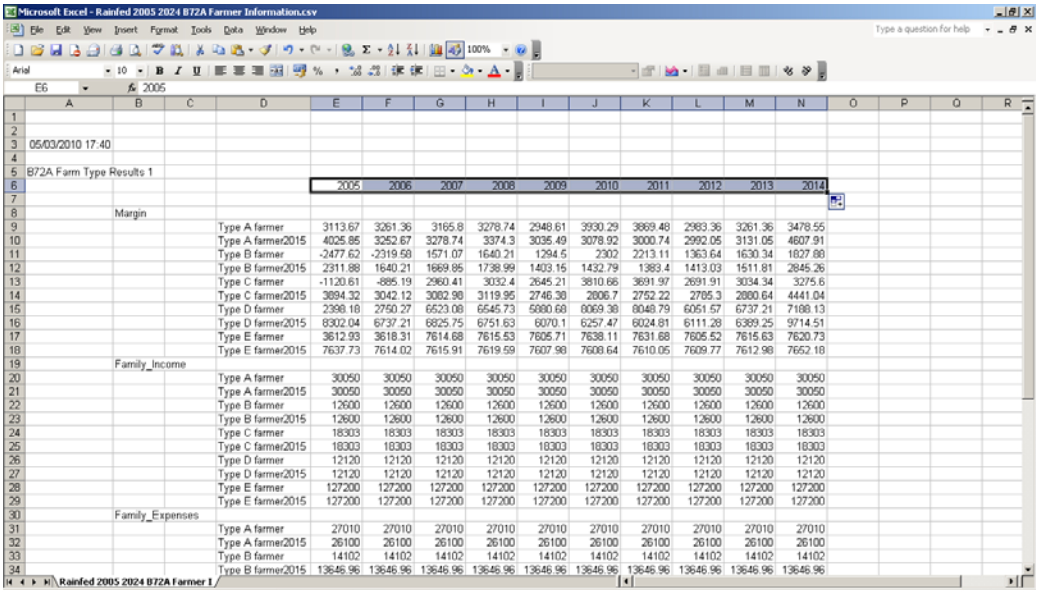


Figure 89

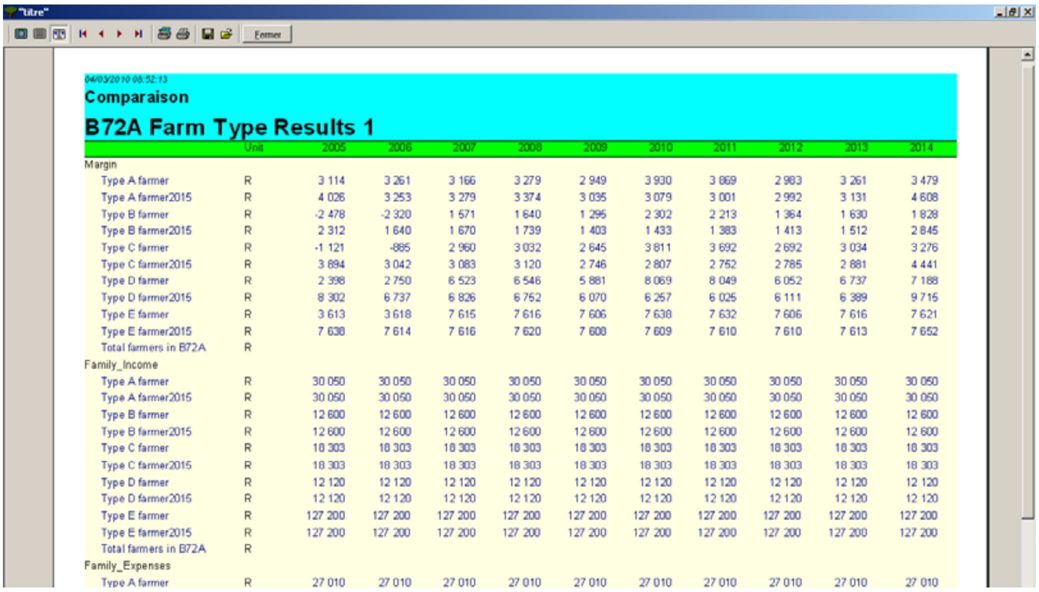
Click on **Finish** button to display Figure 90. Ensure that the start year is 2005, to conform to the start year of simulation in Olympe model.



		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Margin											
	Type A farmer	3113.67	3261.36	3165.8	3278.74	2948.61	3930.29	3869.48	2983.36	3261.36	3478.55
	Type A farmer2015	4025.85	3252.67	3278.74	3374.3	3035.49	3078.92	3000.74	2992.05	3131.05	4607.91
	Type B farmer	-2477.62	-2319.58	1571.07	1640.21	1294.5	2302	2213.11	1363.64	1630.34	1827.88
	Type B farmer2015	2311.88	1640.21	1669.85	1738.99	1403.15	1432.79	1383.4	1413.03	1511.81	2845.26
	Type C farmer	-1120.61	-885.19	2960.41	3032.4	2645.21	3810.66	3691.97	2691.91	3034.34	3275.6
	Type C farmer2015	3894.32	3042.12	3082.98	3119.95	2746.38	2806.7	2752.22	2785.3	2880.64	4441.04
	Type D farmer	2398.18	2750.27	6523.08	6545.73	5880.68	8069.38	8048.79	6051.57	6737.21	7188.13
	Type D farmer2015	8302.04	6737.21	6825.75	6751.63	6070.1	6257.47	6024.81	6111.28	6389.25	9714.51
	Type E farmer	3612.93	3618.31	7614.68	7615.53	7605.71	7638.11	7631.68	7605.52	7615.63	7620.73
	Type E farmer2015	7637.73	7614.02	7615.91	7619.59	7607.98	7608.64	7610.05	7609.77	7612.98	7652.18
Family_Income											
	Type A farmer	30050	30050	30050	30050	30050	30050	30050	30050	30050	30050
	Type A farmer2015	30050	30050	30050	30050	30050	30050	30050	30050	30050	30050
	Type B farmer	12600	12600	12600	12600	12600	12600	12600	12600	12600	12600
	Type B farmer2015	12600	12600	12600	12600	12600	12600	12600	12600	12600	12600
	Type C farmer	18303	18303	18303	18303	18303	18303	18303	18303	18303	18303
	Type C farmer2015	18303	18303	18303	18303	18303	18303	18303	18303	18303	18303
	Type D farmer	12120	12120	12120	12120	12120	12120	12120	12120	12120	12120
	Type D farmer2015	12120	12120	12120	12120	12120	12120	12120	12120	12120	12120
	Type E farmer	127200	127200	127200	127200	127200	127200	127200	127200	127200	127200
	Type E farmer2015	127200	127200	127200	127200	127200	127200	127200	127200	127200	127200
Family_Expenses											
	Type A farmer	27010	27010	27010	27010	27010	27010	27010	27010	27010	27010
	Type A farmer2015	26100	26100	26100	26100	26100	26100	26100	26100	26100	26100
	Type B farmer	14102	14102	14102	14102	14102	14102	14102	14102	14102	14102
	Type B farmer2015	13646.96	13646.96	13646.96	13646.96	13646.96	13646.96	13646.96	13646.96	13646.96	13646.96

Figure 90

To view the results on the screen, select the **Screen** button in Figure 82 and double click **B72A Farm Type Result 1** to display Figure 91. The **Type A farmer** line shows the results from 2005 to 2014 (first 10-year simulation period), while **Type A farmer2015** line shows the results from 2015 to 2024 (second 10-year simulation period).



	Unit	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Margin											
Type A farmer	R	3 114	3 261	3 166	3 279	2 949	3 930	3 869	2 983	3 261	3 479
Type A farmer2015	R	4 026	3 253	3 279	3 374	3 035	3 079	3 001	2 992	3 131	4 608
Type B farmer	R	-2 478	-2 320	1 571	1 640	1 295	2 302	2 213	1 364	1 630	1 828
Type B farmer2015	R	2 312	1 640	1 670	1 739	1 403	1 433	1 383	1 413	1 512	2 845
Type C farmer	R	-1 121	-885	2 960	3 032	2 645	3 811	3 692	2 692	3 034	3 276
Type C farmer2015	R	3 894	3 042	3 083	3 120	2 746	2 807	2 752	2 785	2 881	4 441
Type D farmer	R	2 398	2 750	6 523	6 546	5 881	8 069	8 049	6 052	6 737	7 188
Type D farmer2015	R	8 302	6 737	6 826	6 752	6 070	6 257	6 025	6 111	6 389	9 715
Type E farmer	R	3 613	3 618	7 615	7 616	7 606	7 638	7 632	7 606	7 616	7 621
Type E farmer2015	R	7 638	7 614	7 616	7 620	7 608	7 609	7 610	7 610	7 613	7 652
Total farmers in B72A	R										
Family_Income											
Type A farmer	R	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050
Type A farmer2015	R	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050	30 050
Type B farmer	R	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600
Type B farmer2015	R	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600	12 600
Type C farmer	R	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303
Type C farmer2015	R	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303	18 303
Type D farmer	R	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120
Type D farmer2015	R	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120	12 120
Type E farmer	R	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200
Type E farmer2015	R	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200	127 200
Total farmers in B72A	R										
Family_Expenses											
Type A farmer	R	27 010	27 010	27 010	27 010	27 010	27 010	27 010	27 010	27 010	27 010

Figure 91

After viewing the Olympe results. Go to the ICHSEA results module and click on **present summary results** to display catchment yield, average catchment yields, and the family balances. At present the uncertainty analysis from Monte Carlo is done outside the ICHSEA main interface. Future developments of the integrated model can be incorporate this aspect into the interface.

Software requirements:

Software and hardware requirements for the model

Arcview 3.3

Spatial Analyst

Pentium 4, 1GIG RAM, space 10GIG

Microsoft Office 2003 is recommended (with Excel and Word)

Microsoft Office 2007 is also suitable provided bdf files can be read.

The name of the user and the project are required

APPENDIX C: Crop yields and their deviation from average for farm types A, C and E

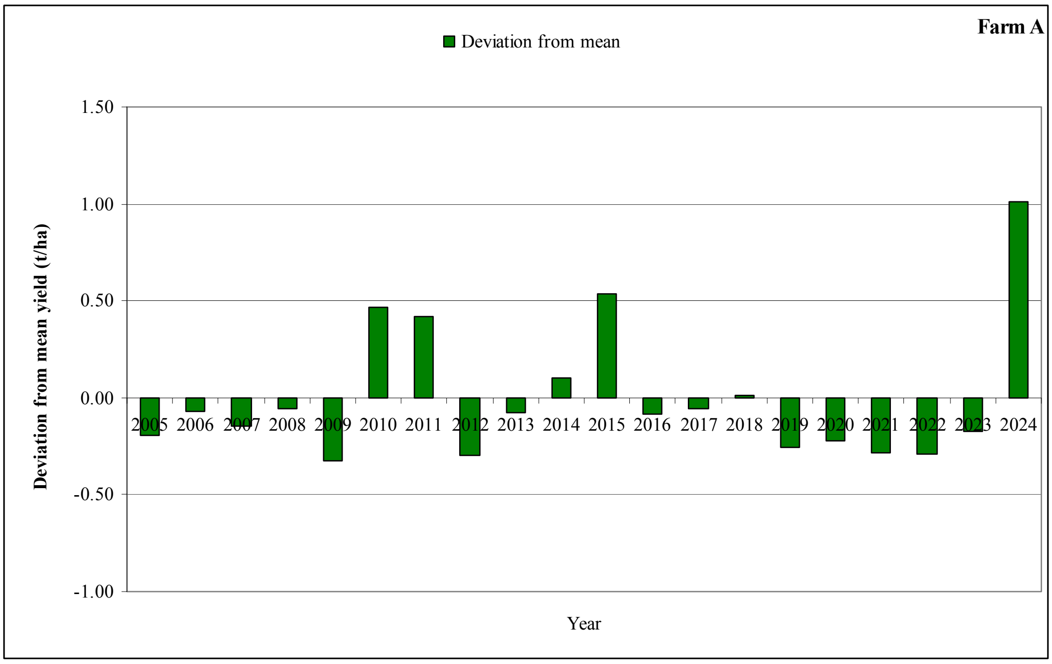


Figure C1 Seasonal maize grain yields for farm type A under conventional rainfed crop management scenario using 20 years of simulated data.

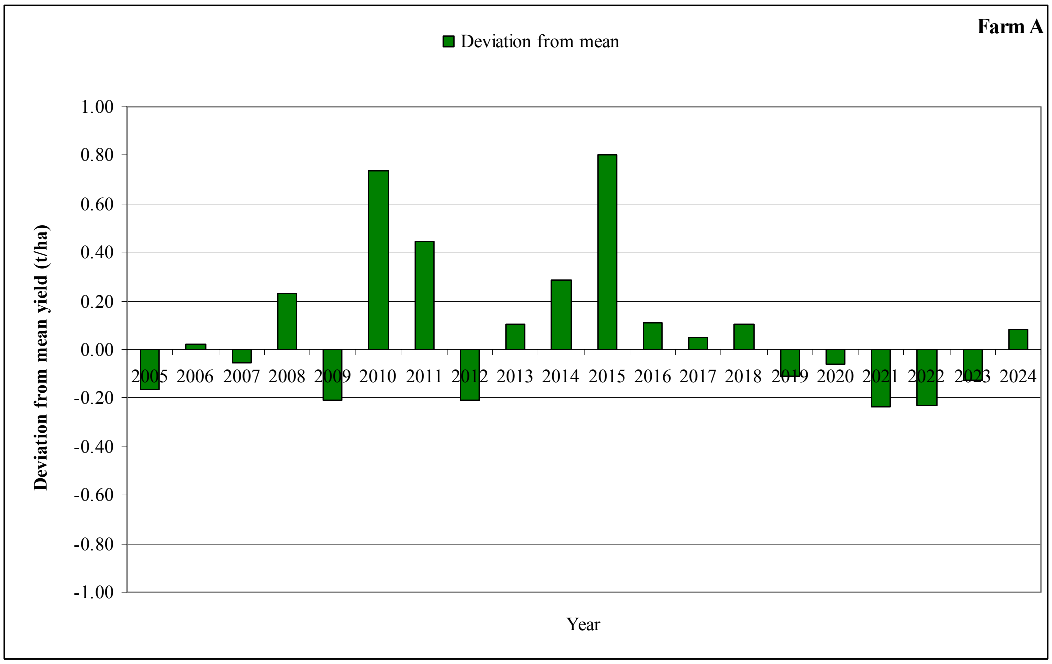


Figure C2 Seasonal maize grain yields for farm type A under untied ridges crop management scenario using 20 years of simulated data.

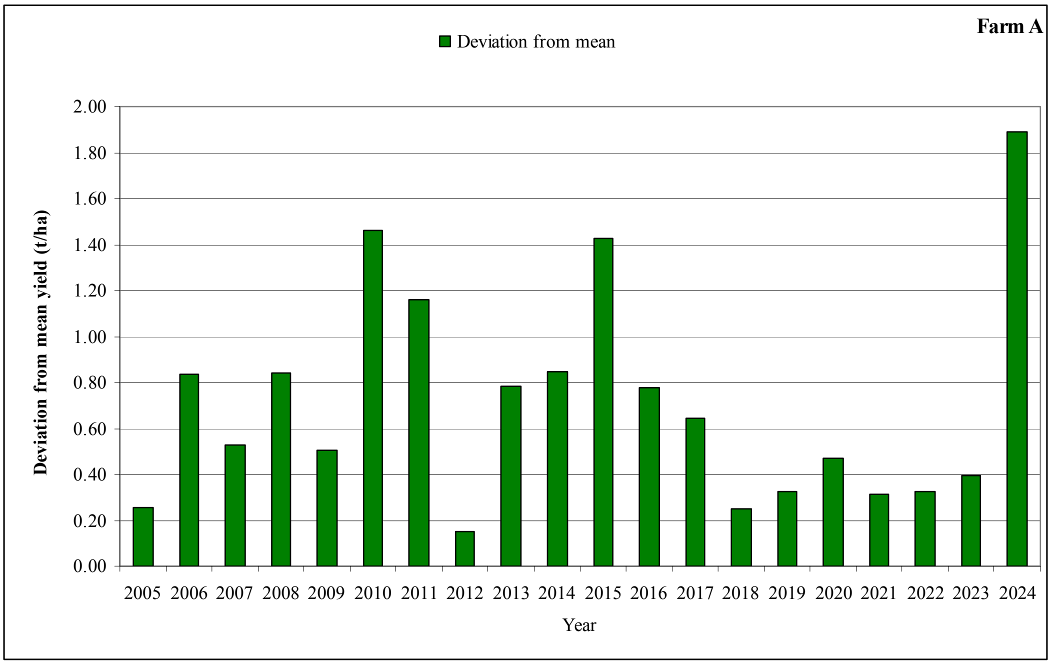


Figure C3 Seasonal maize grain yields for farm type A under planting basins crop management scenarios using 20 years of simulated data.

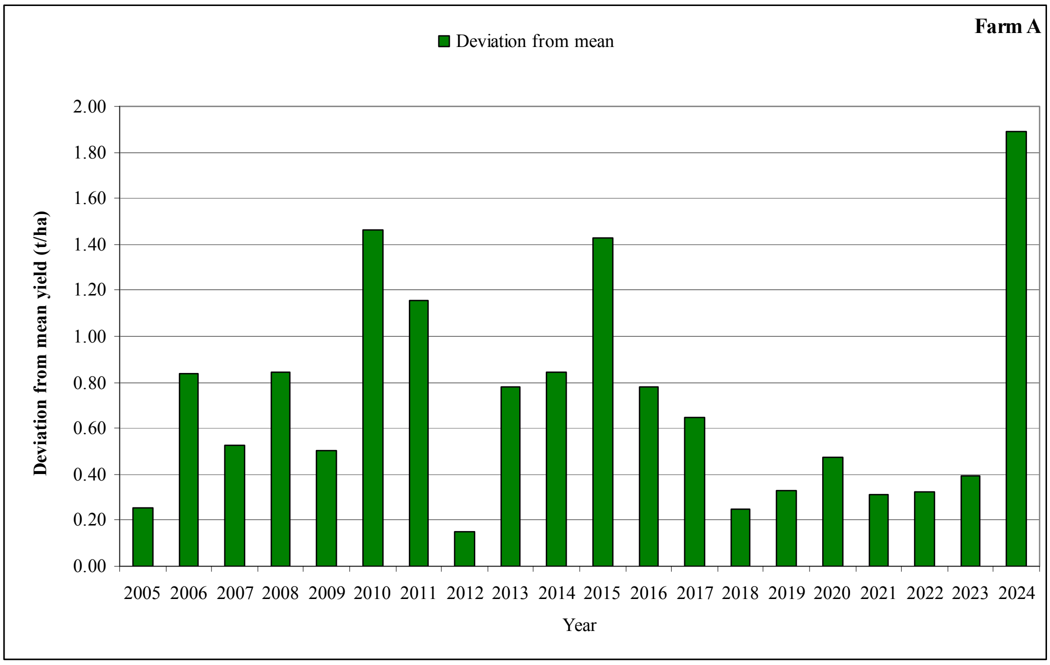


Figure C4 Seasonal maize grain yields for farm type A under supplemental irrigation crop management scenario using 20 years of simulated data.

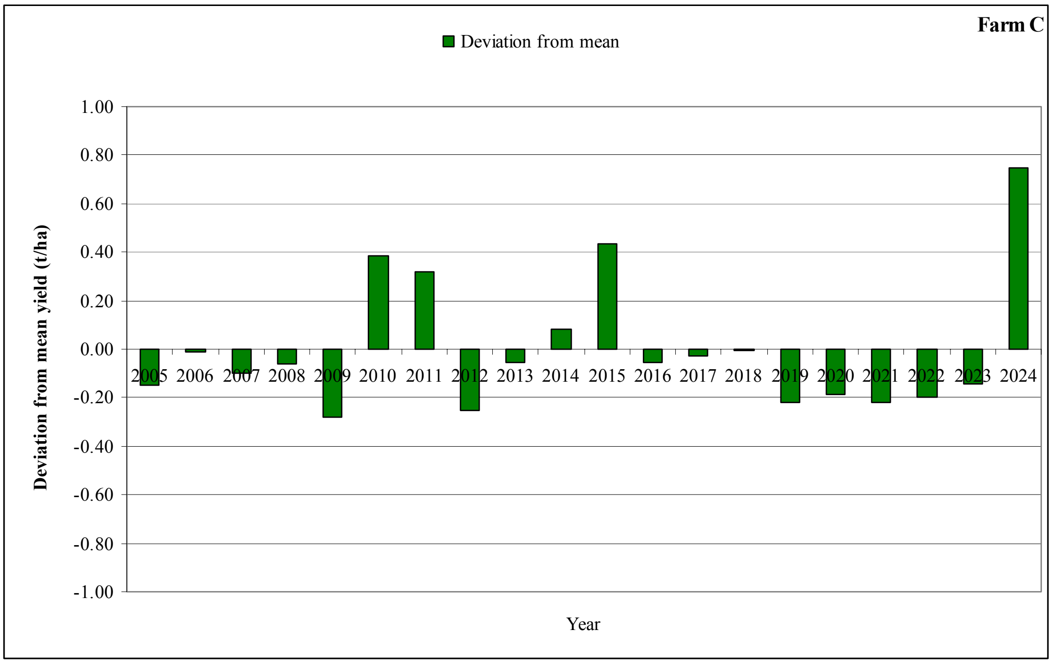


Figure C5 Seasonal maize grain yields for farm type C under conventional rainfed crop management scenario using 20 years of simulated data.

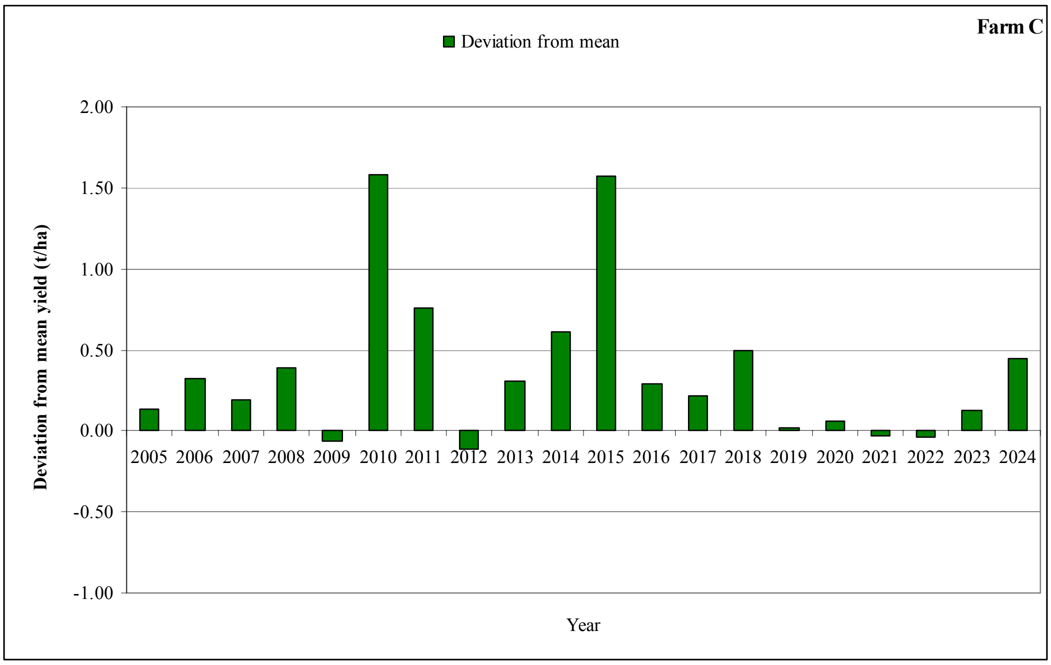


Figure C6 Seasonal maize grain yields for farm type C under untied ridges crop management scenario using 20 years of simulated data.

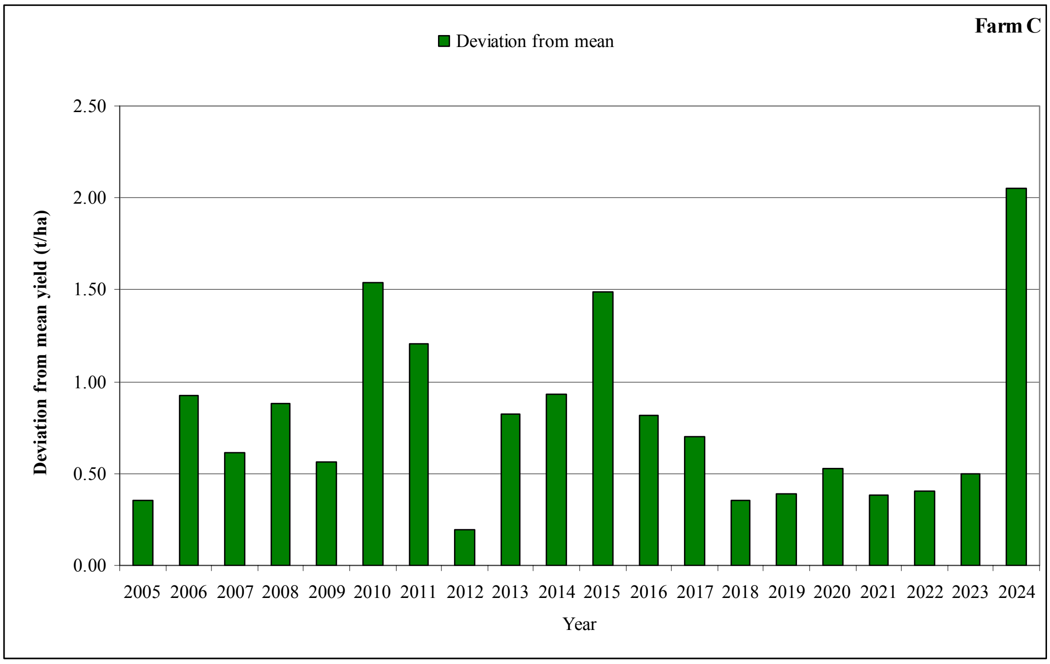


Figure C7 Seasonal maize grain yields for farm type C under planting basins crop management scenarios using 20 years of simulated data.

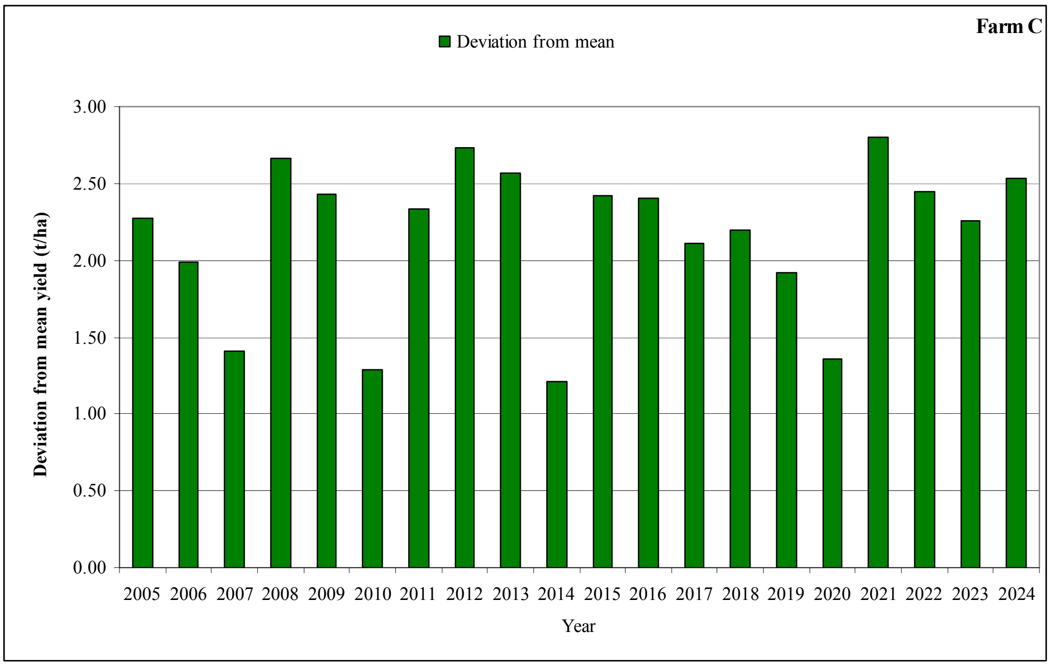


Figure C8 Seasonal maize grain yields for farm type C under supplemental irrigation crop management scenario using 20 years of simulated data.

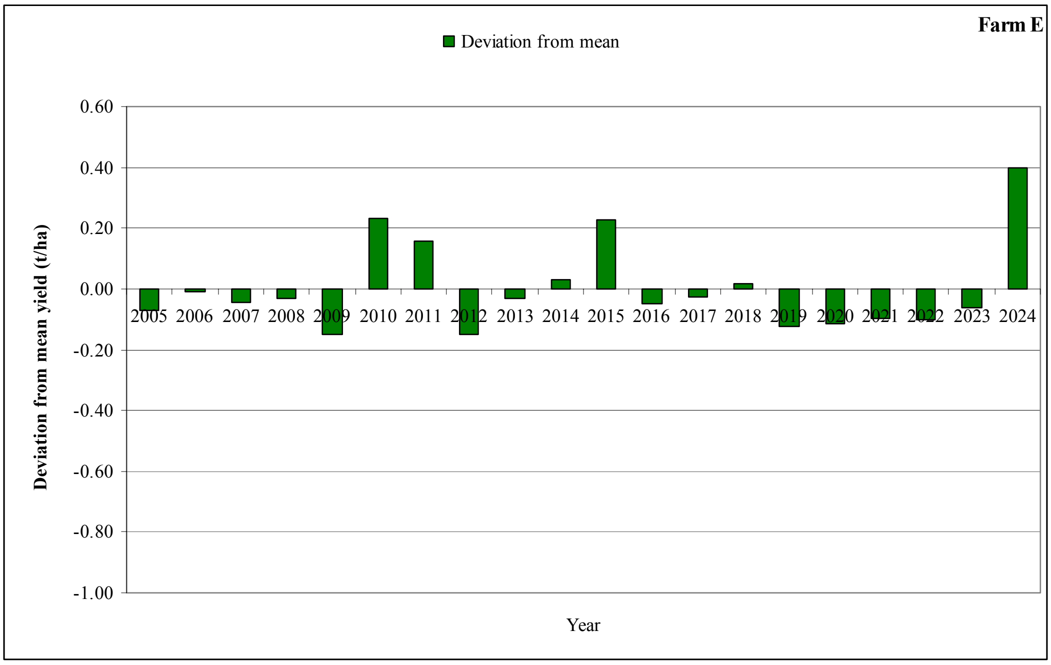


Figure C9 Seasonal maize grain yields for farm type E under conventional rainfed crop management scenario using 20 years of simulated data.

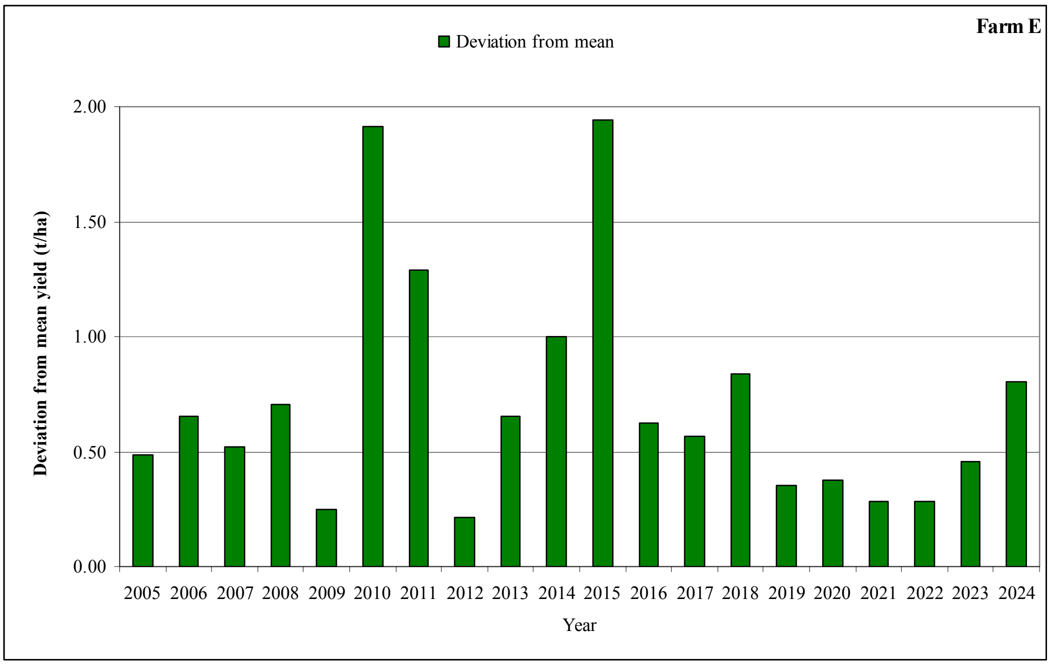


Figure C10 Seasonal maize grain yields for farm type E under untied ridges crop management scenario using 20 years of simulated data.

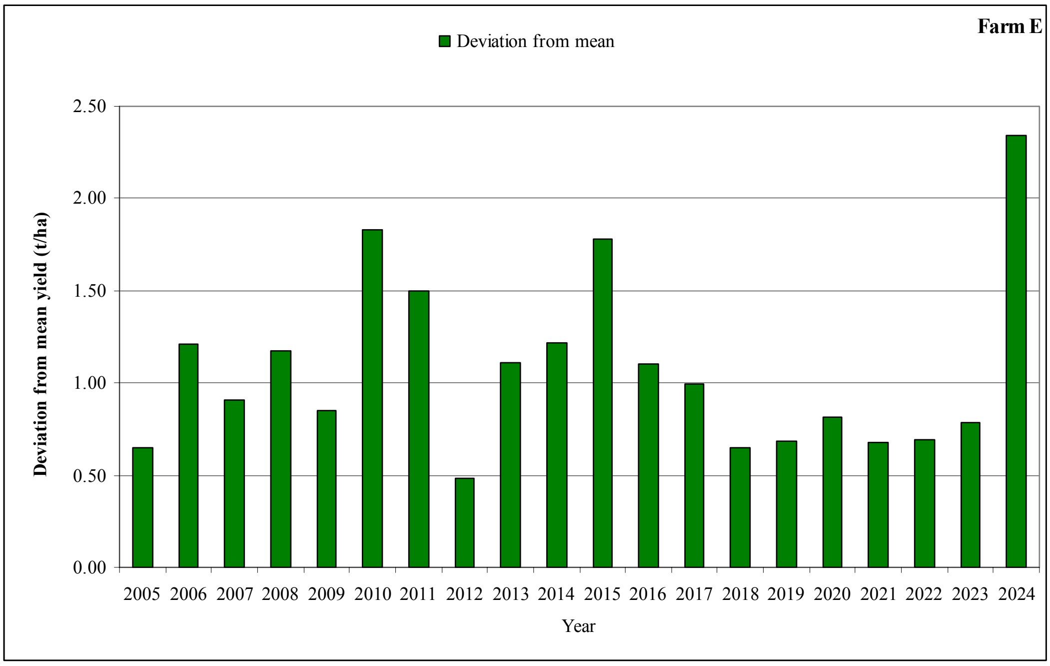


Figure C11 Seasonal maize grain yields for farm type E under planting basins crop management scenario using 20 years of simulated data.

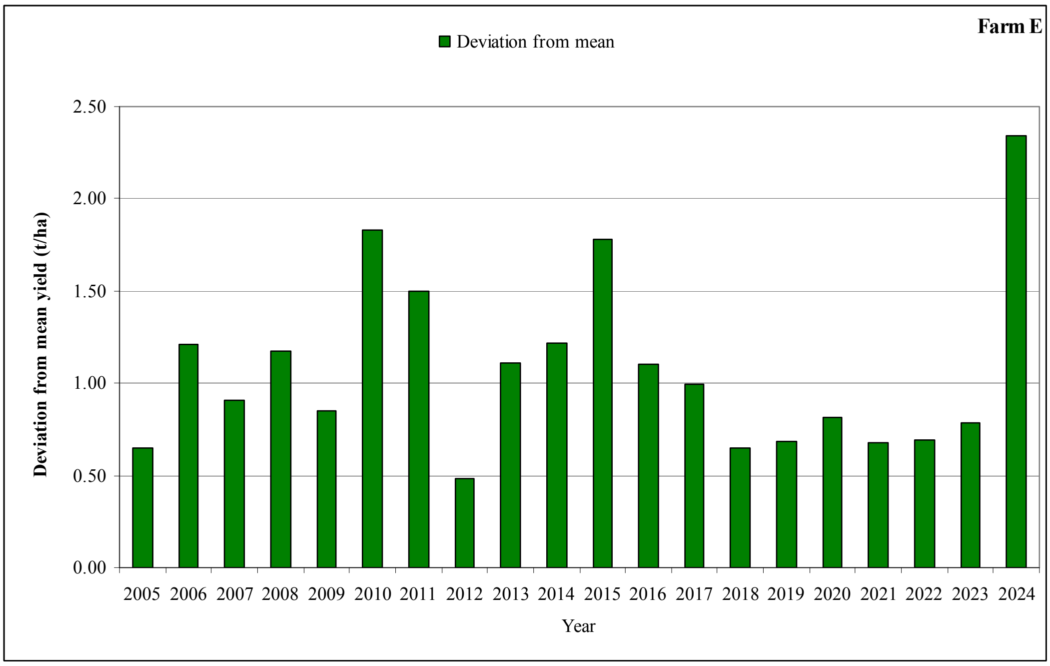


Figure C12 Seasonal maize grain yields for farm type E under supplemental irrigation crop management scenario using 20 years of simulated data.

Appendix D: Farmer Crop Yields Results and Olympe Results

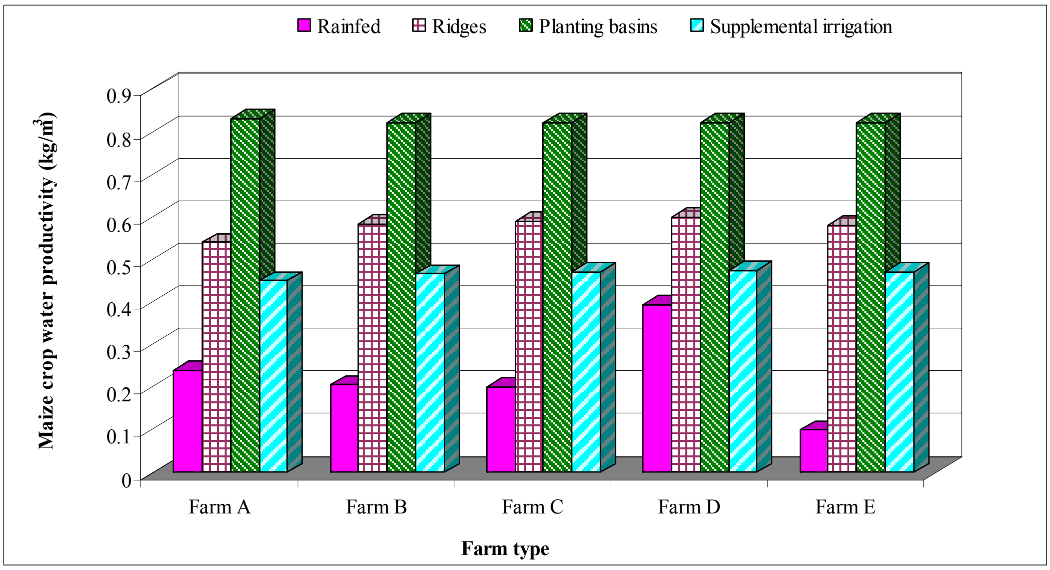


Figure D1 Potential average (n = 20 years) water use efficiency of rainfed, untied ridges, planting basins and supplemental irrigation in B72A catchment.

Table D1: Rainfed practice average yields in B72A catchment

Year	Farm A (t/ha)	Farm B (t/ha)	Farm C (t/ha)	Farm D (t/ha)	Farm E (t/ha)
2005	0.46	0.52	0.49	0.96	0.28
2006	0.58	0.64	0.63	1.15	0.34
2007	0.51	0.56	0.54	1.03	0.30
2008	0.60	0.61	0.58	1.04	0.31
2009	0.33	0.36	0.36	0.68	0.20
2010	1.12	1.08	1.02	1.86	0.58
2011	1.07	1.01	0.96	1.85	0.50
2012	0.35	0.41	0.39	0.78	0.20
2013	0.58	0.60	0.58	1.15	0.32
2014	0.76	0.74	0.72	1.39	0.38
2015	1.19	1.09	1.07	1.99	0.58
2016	0.57	0.61	0.59	1.15	0.30
2017	0.60	0.63	0.61	1.19	0.32
2018	0.67	0.68	0.63	1.15	0.36
2019	0.40	0.44	0.42	0.79	0.23
2020	0.43	0.46	0.45	0.89	0.23
2021	0.37	0.42	0.42	0.76	0.25
2022	0.36	0.45	0.44	0.81	0.25
2023	0.48	0.52	0.49	0.96	0.28
2024	1.66	1.46	1.38	2.75	0.75

Table D2: Ridges practice average yields in B72A catchment

Year	Farm A (t/ha)	Farm B (t/ha)	Farm C (t/ha)	Farm D (t/ha)	Farm E (t/ha)
2005	0.49	0.77	0.77	0.93	0.84
2006	0.68	0.97	0.97	1.11	1.00
2007	0.60	0.83	0.83	0.92	0.87
2008	0.89	1.02	1.02	1.09	1.05
2009	0.45	0.58	0.58	0.62	0.59
2010	1.39	2.22	2.22	2.36	2.26
2011	1.10	1.40	1.40	1.83	1.64
2012	0.45	0.53	0.53	0.61	0.56
2013	0.76	0.94	0.94	1.06	1.00
2014	0.94	1.25	1.25	1.46	1.34
2015	1.46	2.21	2.21	2.43	2.29
2016	0.76	0.93	0.93	1.01	0.97
2017	0.71	0.85	0.85	0.97	0.91
2018	0.76	1.13	1.13	1.27	1.19
2019	0.55	0.66	0.66	0.73	0.70
2020	0.60	0.70	0.70	0.74	0.73
2021	0.42	0.61	0.61	0.69	0.63
2022	0.43	0.60	0.60	0.65	0.63
2023	0.53	0.76	0.76	0.86	0.80
2024	0.74	1.08	1.08	1.23	1.15

Table D3: Planting basins practice average yields in B72A catchment

Year	Farm A (t/ha)	Farm B (t/ha)	Farm C (t/ha)	Farm D (t/ha)	Farm E (t/ha)
2005	0.91	0.99	0.99	0.99	0.99
2006	1.49	1.57	1.56	1.56	1.56
2007	1.18	1.25	1.25	1.25	1.25
2008	1.50	1.51	1.52	1.52	1.52
2009	1.16	1.18	1.20	1.20	1.20
2010	2.12	2.19	2.18	2.18	2.18
2011	1.81	1.85	1.85	1.85	1.85
2012	0.80	0.83	0.83	0.83	0.83
2013	1.44	1.47	1.46	1.46	1.46
2014	1.50	1.57	1.57	1.57	1.57
2015	2.08	2.14	2.13	2.13	2.13
2016	1.43	1.45	1.45	1.45	1.45
2017	1.30	1.34	1.34	1.34	1.34
2018	0.90	1.02	0.99	0.99	0.99
2019	0.98	1.03	1.03	1.03	1.03
2020	1.13	1.17	1.16	1.16	1.16
2021	0.97	1.02	1.02	1.02	1.02
2022	0.98	1.04	1.04	1.04	1.04
2023	1.05	1.14	1.14	1.14	1.14
2024	2.55	2.66	2.69	2.69	2.69

Table D4: Supplementary irrigation practice average yields in the B72A catchment

Year	Farm A (t/ha)	Farm B (t/ha)	Farm C (t/ha)	Farm D (t/ha)	Farm E (t/ha)
2005	2.46	2.95	2.91	2.91	2.91
2006	2.13	2.66	2.63	2.63	2.63
2007	1.39	2.08	2.05	2.05	2.05
2008	1.99	3.28	3.30	3.30	3.30
2009	2.65	3.07	3.06	3.06	3.06
2010	1.34	2.02	1.92	1.92	1.92
2011	2.41	2.98	2.97	2.97	2.97
2012	3.18	3.38	3.37	3.37	3.37
2013	2.90	3.23	3.20	3.20	3.20
2014	1.29	1.94	1.85	1.85	1.85
2015	2.47	3.07	3.06	3.06	3.06
2016	2.58	3.03	3.04	3.04	3.04
2017	1.89	2.82	2.75	2.75	2.75
2018	2.29	2.85	2.83	2.83	2.83
2019	2.03	2.59	2.55	2.55	2.55
2020	1.28	1.99	1.99	1.99	1.99
2021	2.67	3.46	3.44	3.44	3.44
2022	2.71	3.09	3.09	3.09	3.09
2023	2.31	2.90	2.89	2.89	2.89
2024	2.68	3.19	3.17	3.17	3.17

Table D5: Rainfed practice gross margin, family expenses, income and balance in B72A catchment

	Farm Type A (US$)				Farm Type B (US$)				Farm Type C (US$)				Farm Type D (US$)				Farm Type E (US$)			
Year	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**
2005	311	3005	2701	617	-248	1260	1410	-418	-112	1830	1675	43	240	1212	1859	223	361	12720	5265	7817
2006	327	3005	2701	633	-232	1260	1410	-400	-89	1830	1675	67	275	1212	1859	258	362	12720	5265	7817
2007	317	3005	2701	623	157	1260	1410	-9	296	1830	1675	451	652	1212	1859	635	761	12720	5265	8217
2008	328	3005	2701	635	164	1260	1410	-1	303	1830	1675	458	655	1212	1859	637	762	12720	5265	8217
2009	295	3005	2701	601	129	1260	1410	-34	265	1830	1675	420	588	1212	1859	571	761	12720	5265	8216
2010	393	3005	2701	700	230	1260	1410	68	381	1830	1675	536	807	1212	1859	790	764	12720	5265	8219
2011	387	3005	2701	694	221	1260	1410	71	369	1830	1675	524	805	1212	1859	788	763	12720	5265	8219
2012	298	3005	2701	605	136	1260	1410	-14	269	1830	1675	424	605	1212	1859	588	761	12720	5265	8216
2013	326	3005	2701	632	163	1260	1410	13	303	1830	1675	459	674	1212	1859	657	762	12720	5265	8217
2014	348	3005	2701	655	183	1260	1410	33	328	1830	1675	483	719	1212	1859	702	762	12720	5265	8218
2015	402	3005	2701	800	247	1260	1410	122	389	1830	1675	545	830	1212	1859	859	764	12720	5265	8219
2016	325	3005	2701	723	159	1260	1410	36	304	1830	1675	459	674	1212	1859	702	761	12720	5265	8217
2017	328	3005	2701	725	162	1260	1410	41	308	1830	1675	464	683	1212	1859	711	762	12720	5265	8217
2018	337	3005	2701	735	173	1260	1410	54	312	1830	1675	467	675	1212	1859	703	762	12720	5265	8217
2019	304	3005	2701	701	135	1260	1410	17	275	1830	1675	430	607	1212	1859	635	761	12720	5265	8216
2020	308	3005	2701	705	139	1260	1410	23	281	1830	1675	436	626	1212	1859	654	761	12720	5265	8216
2021	300	3005	2701	698	130	1260	1410	26	275	1830	1675	430	602	1212	1859	631	761	12720	5265	8217
2022	299	3005	2701	696	129	1260	1410	25	279	1830	1675	434	611	1212	1859	639	761	12720	5265	8216
2023	313	3005	2701	711	146	1260	1410	41	288	1830	1675	443	639	1212	1859	667	761	12720	5265	8217
2024	461	3005	2701	858	313	1260	1410	208	444	1830	1675	599	971	1212	1859	1000	765	12720	5265	8221
mini	295	3005	2701	601	-248	1260	1410	-418	-112	1830	1675	43	240	1212	1859	223	361	12720	5265	7817
max	461	3005	2701	858	313	1260	1410	208	444	1830	1675	599	971	1212	1859	1000	765	12720	5265	8221
mean	335	3005	2701	687	132	1260	1410	-5	273	1830	1675	429	647	1212	1859	652	722	12720	5265	8177
SD	43.2	0.00	0.00	65.4	135.5	0.00	0.00	147.7	136.2	0.00	0.00	136.2	164.3	0.00	0.00	172.3	123.2	0.00	0.00	123.2

Table D6: Ridges practice gross margin, family expenses, income and balance in B72A catchment

Year	Farm Type A (US$)				Farm Type B (US$)				Farm Type C (US$)				Farm Type D (US$)				Farm Type E (US$)			
	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance
2005	315	3005	2701	621	-213	1260	1410	-383	-63	1830	1675	92	233	1212	1859	216	366	12720	5265	7822
2006	338	3005	2701	645	-186	1260	1410	-354	-29	1830	1675	126	266	1212	1859	249	367	12720	5265	7823
2007	329	3005	2701	635	195	1260	1410	29	346	1830	1675	502	632	1212	1859	615	766	12720	5265	8222
2008	364	3005	2701	671	223	1260	1410	58	381	1830	1675	536	664	1212	1859	647	768	12720	5265	8223
2009	309	3005	2701	616	159	1260	1410	-4	303	1830	1675	458	576	1212	1859	558	764	12720	5265	8219
2010	427	3005	2701	733	392	1260	1410	230	591	1830	1675	746	899	1212	1859	882	778	12720	5265	8234
2011	390	3005	2701	697	275	1260	1410	125	446	1830	1675	602	801	1212	1859	784	773	12720	5265	8228
2012	309	3005	2701	616	153	1260	1410	3	294	1830	1675	449	575	1212	1859	557	764	12720	5265	8219
2013	348	3005	2701	655	211	1260	1410	61	366	1830	1675	522	658	1212	1859	640	767	12720	5265	8223
2014	371	3005	2701	678	254	1260	1410	104	420	1830	1675	575	732	1212	1859	714	770	12720	5265	8226
2015	435	3005	2701	832	390	1260	1410	266	589	1830	1675	744	912	1212	1859	940	778	12720	5265	8234
2016	349	3005	2701	746	209	1260	1410	87	364	1830	1675	519	649	1212	1859	677	767	12720	5265	8223
2017	342	3005	2701	739	198	1260	1410	78	351	1830	1675	506	642	1212	1859	670	767	12720	5265	8222
2018	348	3005	2701	746	238	1260	1410	119	400	1830	1675	555	697	1212	1859	725	769	12720	5265	8224
2019	322	3005	2701	719	171	1260	1410	54	317	1830	1675	473	597	1212	1859	626	765	12720	5265	8220
2020	328	3005	2701	725	177	1260	1410	60	324	1830	1675	479	598	1212	1859	626	765	12720	5265	8221
2021	306	3005	2701	703	164	1260	1410	60	308	1830	1675	464	589	1212	1859	617	764	12720	5265	8220
2022	307	3005	2701	704	163	1260	1410	58	307	1830	1675	462	582	1212	1859	610	764	12720	5265	8220
2023	320	3005	2701	717	186	1260	1410	81	335	1830	1675	490	622	1212	1859	650	766	12720	5265	8221
2024	346	3005	2701	743	231	1260	1410	127	392	1830	1675	547	690	1212	1859	718	769	12720	5265	8224
mini	306	3005	2701	616	-213	1260	1410	-383	-63	1830	1675	92	233	1212	1859	216	366	12720	5265	7822
max	435	3005	2701	832	392	1260	1410	266	591	1830	1675	746	912	1212	1859	940	778	12720	5265	8234
mean	345	3005	2701	697	180	1260	1410	43	337	1830	1675	492	631	1212	1859	636	728	12720	5265	8183
SD	37	0	0	55	146	0	0	155	155	0	0	155	163	0	0	168	124	0	0	124

Table D7: Planting basins practice gross margin, family expenses, income and balance in B72A catchment

Pbasins	Farm Type A (US$)				Farm Type B (US$)				Farm Type C (US$)				Farm Type D (US$)				Farm Type E (US$)			
Year	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**
2005	367	3005	2701	673	-182	1260	1410	-352	-24	1830	1675	131	246	1212	1859	228	367	12720	5265	7823
2006	439	3005	2701	746	-100	1260	1410	-268	75	1830	1675	230	351	1212	1859	333	372	12720	5265	7828
2007	401	3005	2701	707	255	1260	1410	89	421	1830	1675	576	693	1212	1859	676	770	12720	5265	8225
2008	440	3005	2701	746	291	1260	1410	126	468	1830	1675	623	743	1212	1859	726	772	12720	5265	8227
2009	398	3005	2701	704	245	1260	1410	82	412	1830	1675	567	684	1212	1859	667	769	12720	5265	8225
2010	517	3005	2701	823	387	1260	1410	225	583	1830	1675	738	865	1212	1859	848	777	12720	5265	8233
2011	479	3005	2701	786	339	1260	1410	189	525	1830	1675	680	804	1212	1859	786	775	12720	5265	8230
2012	354	3005	2701	660	195	1260	1410	45	347	1830	1675	502	615	1212	1859	598	766	12720	5265	8221
2013	432	3005	2701	739	285	1260	1410	135	457	1830	1675	613	732	1212	1859	715	771	12720	5265	8227
2014	440	3005	2701	747	299	1260	1410	149	476	1830	1675	631	752	1212	1859	735	772	12720	5265	8228
2015	512	3005	2701	910	380	1260	1410	255	574	1830	1675	729	856	1212	1859	884	777	12720	5265	8232
2016	432	3005	2701	829	283	1260	1410	161	456	1830	1675	611	731	1212	1859	759	771	12720	5265	8227
2017	415	3005	2701	813	267	1260	1410	146	436	1830	1675	591	710	1212	1859	738	770	12720	5265	8226
2018	366	3005	2701	764	222	1260	1410	102	376	1830	1675	531	646	1212	1859	674	767	12720	5265	8223
2019	376	3005	2701	773	224	1260	1410	106	382	1830	1675	537	652	1212	1859	680	768	12720	5265	8223
2020	394	3005	2701	791	243	1260	1410	127	405	1830	1675	560	677	1212	1859	705	769	12720	5265	8224
2021	374	3005	2701	771	222	1260	1410	118	380	1830	1675	536	651	1212	1859	679	768	12720	5265	8223
2022	376	3005	2701	773	225	1260	1410	120	384	1830	1675	539	654	1212	1859	682	768	12720	5265	8223
2023	384	3005	2701	782	238	1260	1410	134	401	1830	1675	556	672	1212	1859	700	769	12720	5265	8224
2024	570	3005	2701	967	454	1260	1410	349	672	1830	1675	828	960	1212	1859	988	782	12720	5265	8237
min	354	3005	2701	660	-182	1260	1410	-352	-24	1830	1675	131	246	1212	1859	228	367	12720	5265	7823
max	570	3005	2701	967	454	1260	1410	349	672	1830	1675	828	960	1212	1859	988	782	12720	5265	8237
mean	423	3005	2701	775	239	1260	1410	102	410	1830	1675	566	685	1212	1859	690	731	12720	5265	8186
SD	58.1	0.0	0.0	72.3	145.8	0.0	0.0	156.5	155.6	0.00	0.00	155.6	158.7	0.0	0.0	165.7	123.6	0.0	0.0	123.6

Table D8: Supplementary irrigation practice gross margin, family expenses, income and balance in B72A catchment

	Farm Type A (US$)				Farm Type B (US$)				Farm Type C (US$)				Farm Type D (US$)				Farm Type E (US$)			
Year	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**	**Gross margin**	**Family Income**	**Family Expenses**	**Balance**
2005	559	3005	2701	865	94	1260	1410	-76	311	1830	1675	466	600	1212	1859	583	384	12720	5265	7839
2006	519	3005	2701	825	54	1260	1410	-114	262	1830	1675	417	548	1212	1859	531	381	12720	5265	7837
2007	427	3005	2701	734	372	1260	1410	206	561	1830	1675	716	841	1212	1859	824	776	12720	5265	8232
2008	501	3005	2701	808	541	1260	1410	376	780	1830	1675	935	1073	1212	1859	1056	787	12720	5265	8242
2009	583	3005	2701	889	512	1260	1410	348	738	1830	1675	893	1029	1212	1859	1012	785	12720	5265	8240
2010	421	3005	2701	727	362	1260	1410	201	539	1830	1675	694	818	1212	1859	801	775	12720	5265	8231
2011	554	3005	2701	860	498	1260	1410	348	722	1830	1675	878	1012	1212	1859	995	784	12720	5265	8240
2012	649	3005	2701	955	555	1260	1410	405	792	1830	1675	947	1086	1212	1859	1069	788	12720	5265	8243
2013	613	3005	2701	920	534	1260	1410	384	762	1830	1675	918	1055	1212	1859	1038	786	12720	5265	8242
2014	414	3005	2701	720	352	1260	1410	202	525	1830	1675	680	803	1212	1859	786	775	12720	5265	8230
2015	560	3005	2701	958	511	1260	1410	387	738	1830	1675	893	1029	1212	1859	1057	785	12720	5265	8240
2016	574	3005	2701	971	506	1260	1410	384	734	1830	1675	889	1025	1212	1859	1053	785	12720	5265	8240
2017	489	3005	2701	886	476	1260	1410	356	683	1830	1675	838	970	1212	1859	999	782	12720	5265	8238
2018	538	3005	2701	935	481	1260	1410	362	698	1830	1675	853	987	1212	1859	1015	783	12720	5265	8238
2019	507	3005	2701	904	444	1260	1410	326	649	1830	1675	804	935	1212	1859	963	781	12720	5265	8236
2020	413	3005	2701	811	359	1260	1410	243	551	1830	1675	706	831	1212	1859	859	776	12720	5265	8231
2021	586	3005	2701	983	566	1260	1410	461	805	1830	1675	960	1100	1212	1859	1128	788	12720	5265	8244
2022	590	3005	2701	987	514	1260	1410	409	742	1830	1675	897	1033	1212	1859	1062	785	12720	5265	8241
2023	541	3005	2701	939	487	1260	1410	383	708	1830	1675	864	998	1212	1859	1026	783	12720	5265	8239
2024	587	3005	2701	984	528	1260	1410	423	757	1830	1675	913	1049	1212	1859	1078	786	12720	5265	8241
min	413	3005	2701	720	54	1260	1410	-114	262	1830	1675	417	548	1212	1859	531	381	12720	5265	7837
max	649	3005	2701	987	566	1260	1410	461	805	1830	1675	960	1100	1212	1859	1128	788	12720	5265	8244
mean	531	3005	2701	883	437	1260	1410	301	653	1830	1675	808	941	1212	1859	947	743	12720	5265	8198
SD	69	0	0	88	141	0	0	155	152	0	0	152	155	0	0	165	123	0	0	123

Table D9: Rainfed practice and maize price variation gross margin, family expenses, income and balance in B72A catchment

	Farm Type A (US$)				Farm Type B (US$)				Farm Type C (US$)				Farm Type D (US$)				Farm Type E (US$)			
Year	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance	Gross margin	Family Income	Family Expenses	Balance
2005	272	3005	2701	579	-298	1260	1410	-468	-263	1830	1675	-107	118	1212	1859	101	360	12720	5265	7815
2006	290	3005	2701	596	-277	1260	1410	-445	-212	1830	1675	-57	167	1212	1859	150	360	12720	5265	7816
2007	315	3005	2701	621	154	1260	1410	-12	288	1830	1675	443	646	1212	1859	629	761	12720	5265	8217
2008	326	3005	2701	632	161	1260	1410	-3	296	1830	1675	451	649	1212	1859	632	761	12720	5265	8217
2009	287	3005	2701	594	120	1260	1410	-43	227	1830	1675	382	564	1212	1859	547	760	12720	5265	8216
2010	374	3005	2701	681	210	1260	1410	48	339	1830	1675	494	761	1212	1859	744	763	12720	5265	8219
2011	377	3005	2701	683	210	1260	1410	60	345	1830	1675	501	778	1212	1859	761	763	12720	5265	8218
2012	297	3005	2701	603	135	1260	1410	-15	264	1830	1675	420	602	1212	1859	585	761	12720	5265	8216
2013	328	3005	2701	635	166	1260	1410	16	311	1830	1675	466	680	1212	1859	663	762	12720	5265	8217
2014	356	3005	2701	663	192	1260	1410	42	350	1830	1675	505	741	1212	1859	724	762	12720	5265	8218
2015	423	3005	2701	821	253	1260	1410	128	435	1830	1675	590	882	1212	1859	910	764	12720	5265	8220
2016	339	3005	2701	737	181	1260	1410	58	351	1830	1675	506	715	1212	1859	744	762	12720	5265	8217
2017	346	3005	2701	744	189	1260	1410	69	369	1830	1675	524	738	1212	1859	766	762	12720	5265	8218
2018	363	3005	2701	760	203	1260	1410	84	387	1830	1675	542	740	1212	1859	769	763	12720	5265	8218
2019	322	3005	2701	719	163	1260	1410	45	349	1830	1675	505	659	1212	1859	688	761	12720	5265	8217
2020	297	3005	2701	695	130	1260	1410	14	238	1830	1675	393	593	1212	1859	621	760	12720	5265	8216
2021	290	3005	2701	687	125	1260	1410	20	228	1830	1675	383	571	1212	1859	599	761	12720	5265	8216
2022	288	3005	2701	686	126	1260	1410	22	228	1830	1675	383	576	1212	1859	604	760	12720	5265	8216
2023	298	3005	2701	696	132	1260	1410	28	231	1830	1675	386	593	1212	1859	622	761	12720	5265	8216
2024	404	3005	2701	801	228	1260	1410	123	341	1830	1675	496	831	1212	1859	860	763	12720	5265	8219
min	272	3005	2701	579	-298	1260	1410	-468	-263	1830	1675	-107	118	1212	1859	101	360	12720	5265	7815
max	423	3005	2701	821	253	1260	1410	128	435	1830	1675	590	882	1212	1859	910	764	12720	5265	8220
mean	330	3005	2701	682	125	1260	1410	-11	255	1830	1675	410	630	1212	1859	636	722	12720	5265	8177
SD	42.3	0.0	0.0	68.4	146.1	0.0	0.0	158.3	178.8	0.0	0.0	178.8	189.3	0.0	0.0	198.1	123.7	0.0	0.0	123.7

Table D10 Number of farmers in subbasins by type

Farm type	Subbasin 1	Subbasin 2	Subbasin 3	Subbasin 4	Subbasin 5	Subbasin 6	Subbasin 7	Subbasin 8	Subbasin 9	Subbasin 10	Total
Total	**172**		**370**	**3445**	**1271**	**1509**	**590**	**2402**	**100**	**1459**	11318
A	10.32	0	22.2	206.7	76.26	90.54	35.4	144.12	6	87.54	679
B	25.8	0	55.5	516.75	190.65	226.35	88.5	360.3	15	218.85	1698
C	89.44	0	192.4	1791.4	660.92	784.68	306.8	1249.04	52	758.68	5885
D	43	0	92.5	861.25	317.75	377.25	147.5	600.5	25	364.75	2830
E	3.44	0	7.4	68.9	25.42	30.18	11.8	48.04	2	29.18	226

Note:
The numbers of farmers in each subbasin were apportioned according to the percentage of farmers in the village and according to area of village falling the subbasin.

Table D11a Typical Average Socio-economic results for the subbasins under planting basins practice

Year	Subbasin 1		Subbasin 2		Subbasin 3		Subbasin 4		Subbasin 5	
	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)
2005	8748	46313	0	0	18818	99628	175211	927613	64643	342234
2006	25000	62617	0	0	53779	134699	500722	1254157	184737	462709
2007	80825	118488	0	0	173867	254888	1618845	2373210	597257	875573
2008	88513	126218	0	0	190406	271515	1772831	2528023	654069	932690
2009	79311	117055	0	0	170612	251804	1588535	2344502	586075	864982
2010	107353	145130	0	0	230934	312199	2150183	2906822	793290	1072444
2011	97863	135944	0	0	210519	292438	1960098	2722835	723160	1004564
2012	68846	106928	0	0	148099	230019	1378924	2141660	508741	790145
2013	86845	124926	0	0	186817	268736	1739417	2502154	641741	923146
2014	89819	127900	0	0	193215	275134	1798988	2561725	663720	945124
2015	105918	147553	0	0	227846	317411	2121434	2955353	782683	1090350
2016	86608	128295	0	0	186308	275983	1734674	2569627	639991	948040

Year	Subbasin 1		Subbasin 2		Subbasin 3		Subbasin 4		Subbasin 5	
	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)
2017	83343	125077	0	0	179284	269060	1669283	2505167	615866	924257
2018	73513	115287	0	0	158138	248002	1472389	2309100	543224	851920
2019	74485	116299	0	0	160230	250178	1491871	2329356	550411	859394
2020	78322	120169	0	0	168484	258504	1568723	2406882	578765	887996
2021	74239	116391	0	0	159701	250376	1486947	2331202	548595	860075
2022	74775	116926	0	0	160853	251528	1497673	2341928	552552	864032
2023	77472	119623	0	0	166655	257329	1551691	2395945	572481	883961
2024	121666	163817	0	0	261722	352397	2436848	3281103	899052	1210532

Table D11b Typical Average Socio-economic results for the subbasins under planting basins practice

Year	Subbasin 6		Subbasin 7		Subbasin 8		Subbasin 9		Subbasin 10	
	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)
2005	76747	406319	30007	158866	122165	646771	5086	26926	74204	392856
2006	219329	549354	85755	214790	349125	874452	14535	36405	212062	531151
2007	709096	1039528	277248	406442	1128727	1654703	46991	68889	685601	1005084
2008	776546	1107340	303620	432956	1236093	1762645	51461	73382	750816	1070649
2009	695820	1026953	272057	401526	1107594	1634686	46111	68055	672764	992926
2010	941836	1273264	368246	497830	1499199	2026759	62415	84378	910629	1231075
2011	858574	1192673	335692	466320	1366664	1898476	56897	79037	830126	1153154
2012	604005	938103	236158	366787	961444	1493256	40027	62167	583991	907020
2013	761910	1096009	297897	428526	1212795	1744608	50491	72631	736665	1059693
2014	788004	1122102	308100	438728	1254331	1786143	52220	74361	761894	1084922

Year	Subbasin 6		Subbasin 7		Subbasin 8		Subbasin 9		Subbasin 10	
	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)	Gross margin (US$)	Balance (US$)
2015	929243	1294522	363322	506142	1479153	2060598	61580	85787	898453	1251629
2016	759833	1125564	297085	440081	1209488	1791653	50353	74590	734656	1088269
2017	731190	1097328	285886	429042	1163895	1746708	48455	72719	706962	1060969
2018	644945	1011446	252165	395463	1026612	1610002	42740	67028	623575	977932
2019	653478	1020319	255502	398932	1040195	1624126	43305	67616	631826	986511
2020	687142	1054277	268664	412209	1093780	1678180	45536	69866	664373	1019344
2021	651322	1021127	254659	399248	1036763	1625413	43162	67669	629741	987293
2022	656020	1025825	256496	401085	1044241	1632891	43474	67980	634283	991835
2023	679681	1049487	265747	410336	1081904	1670555	45042	69548	657160	1014712
2024	1067403	1437209	417341	561931	1699074	2287724	70736	95242	1032035	1389588

Appendix E: Correlation of family balance and evapotranspiration for different farm types and Family balance cumulative probability distribution curve under different practices

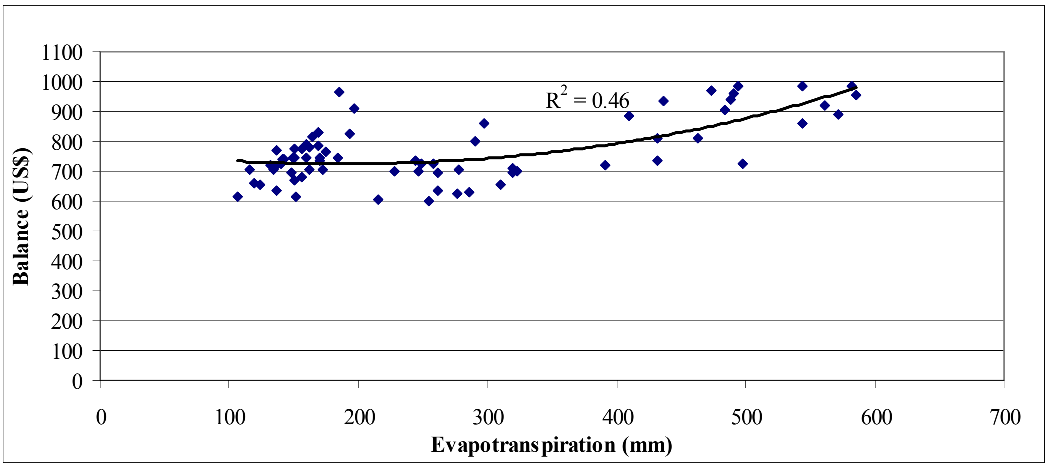


Figure E1 Correlation of family balance and evapotranspiration for farm type A.

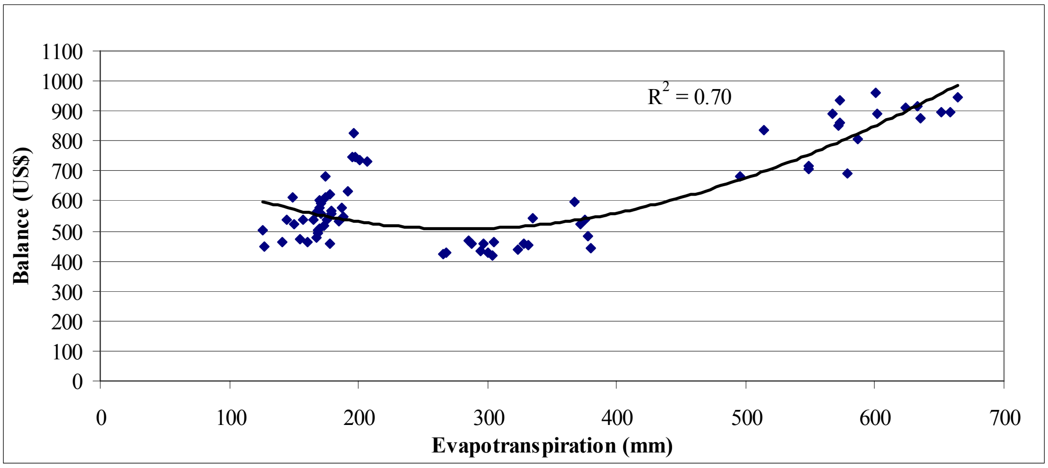


Figure E2 Correlation of family balance and evapotranspiration for farm type C.

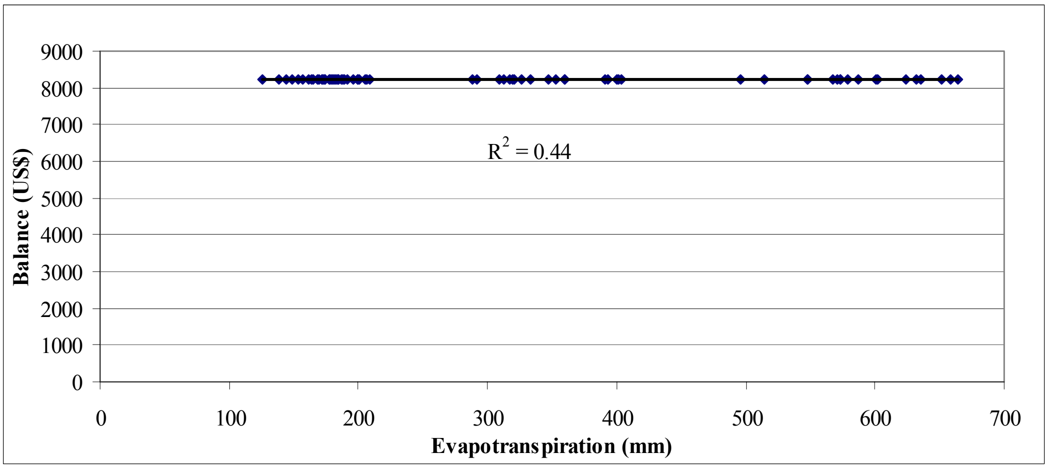


Figure E3 Correlation of family balance and evapotranspiration for farm type E.

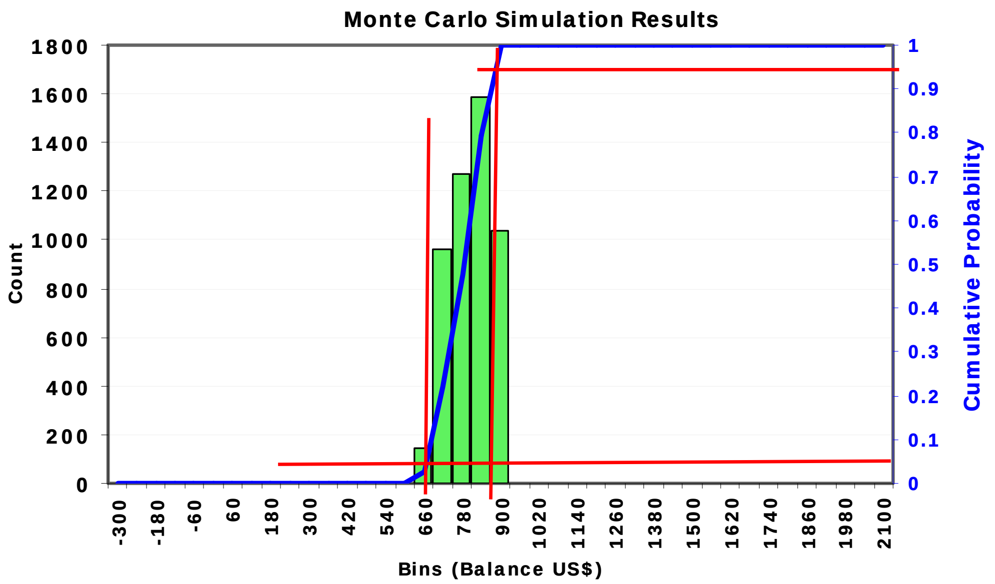


Figure E4 Family balance cumulative probability distribution curve under combined practices for farm type A.

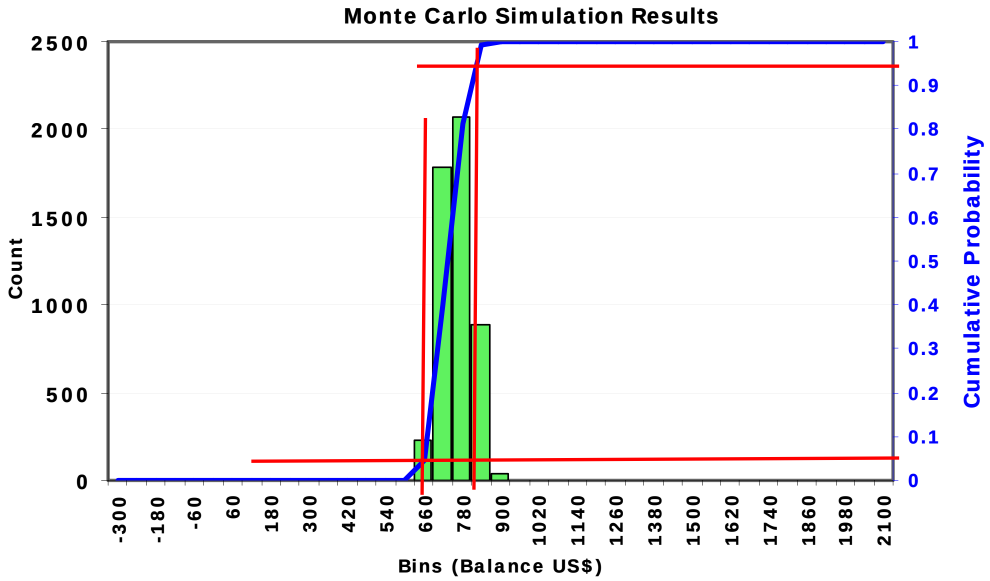


Figure E5 Family balance cumulative probability distribution curve under rainfed practice with maize price variation for farm type A.

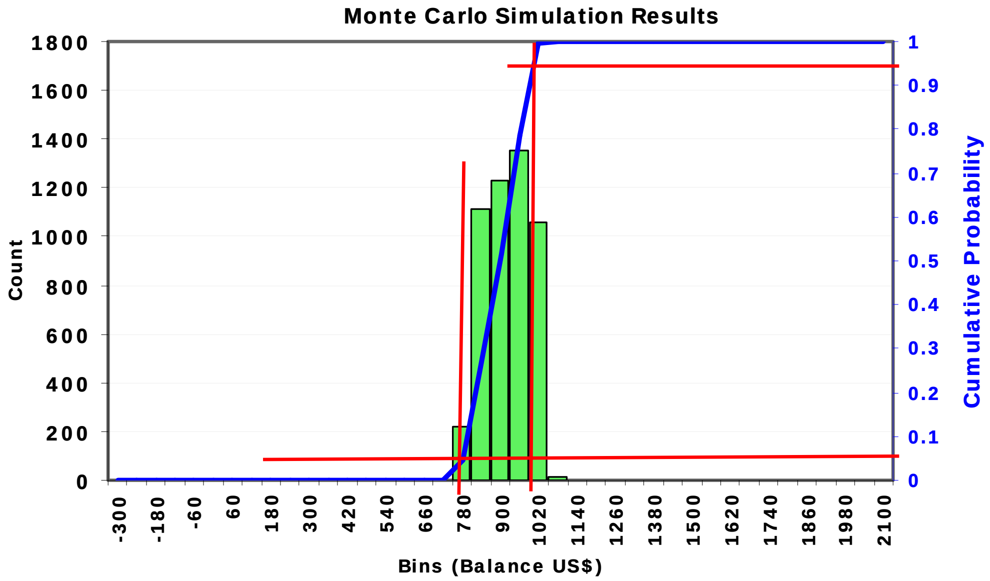


Figure E6 Family balance cumulative probability distribution curve under supplemental irrigation practice for farm type A.

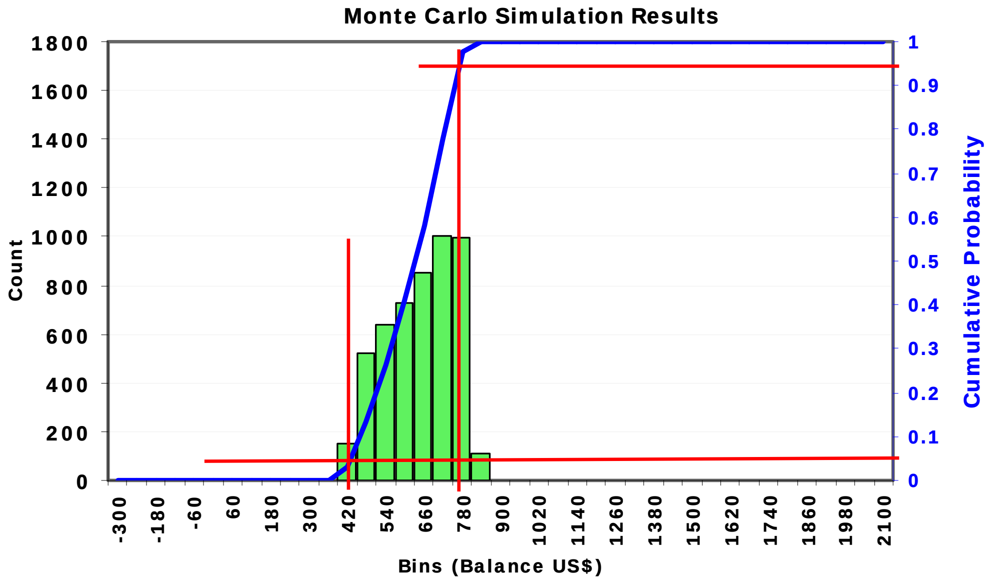


Figure E7 Family balance cumulative probability distribution curve under combined practices for farm type C.

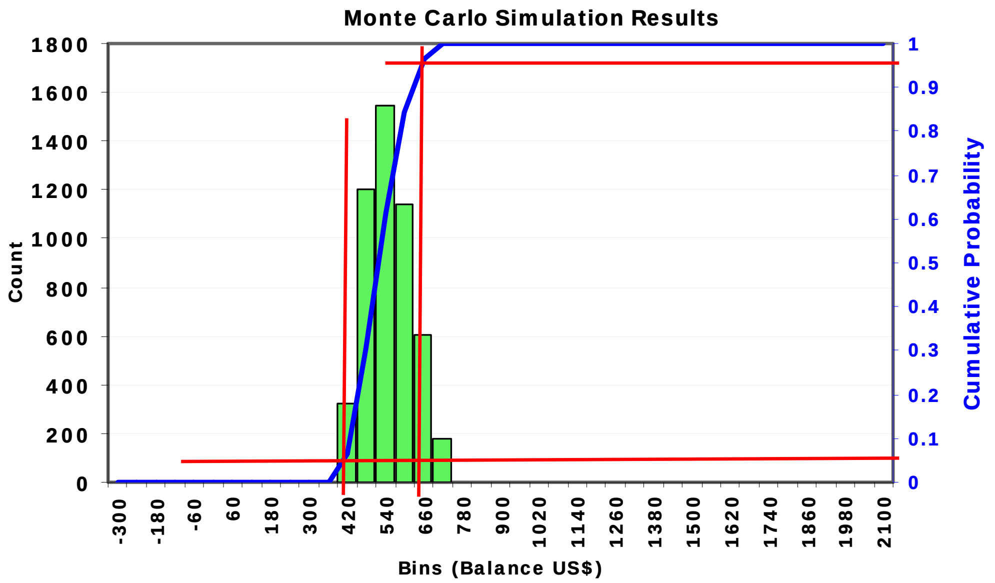


Figure E8 Family balance cumulative probability distribution curve under rainfed practice with maize price variation for farm type C.

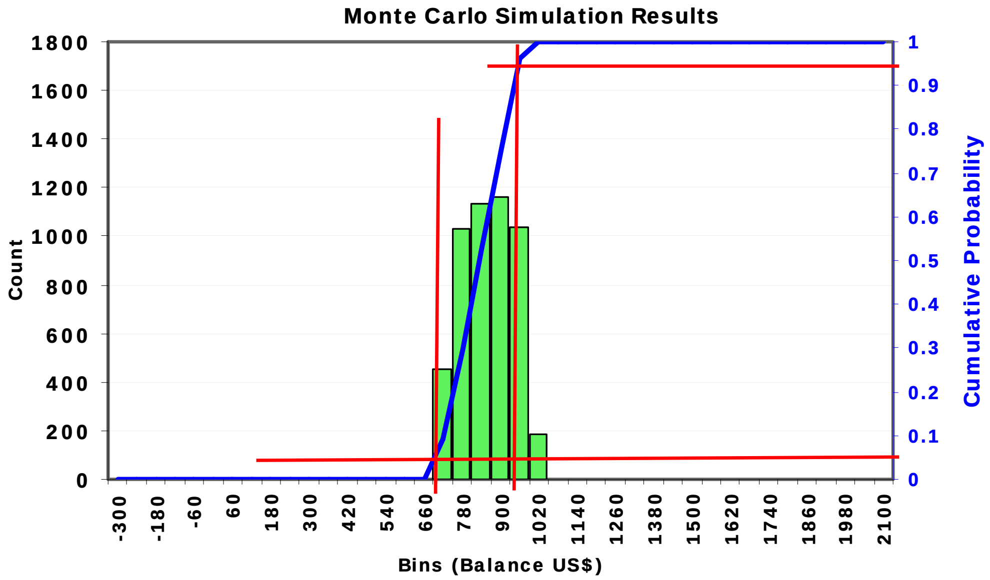


Figure E9 Family balance cumulative probability distribution curve under supplemental irrigation practice for farm type C.

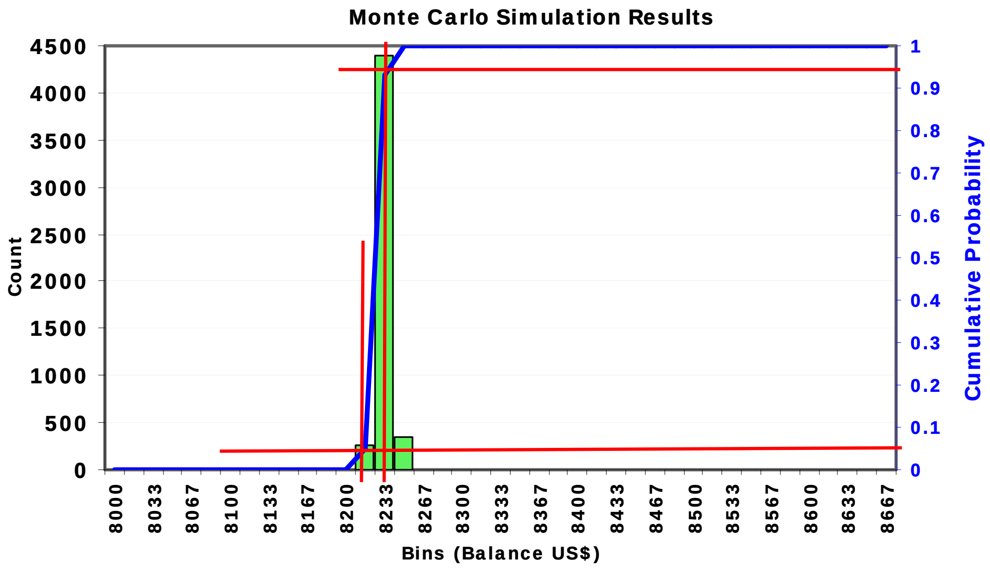


Figure E10 Family balance cumulative probability distribution curve under combined practices for farm type E.

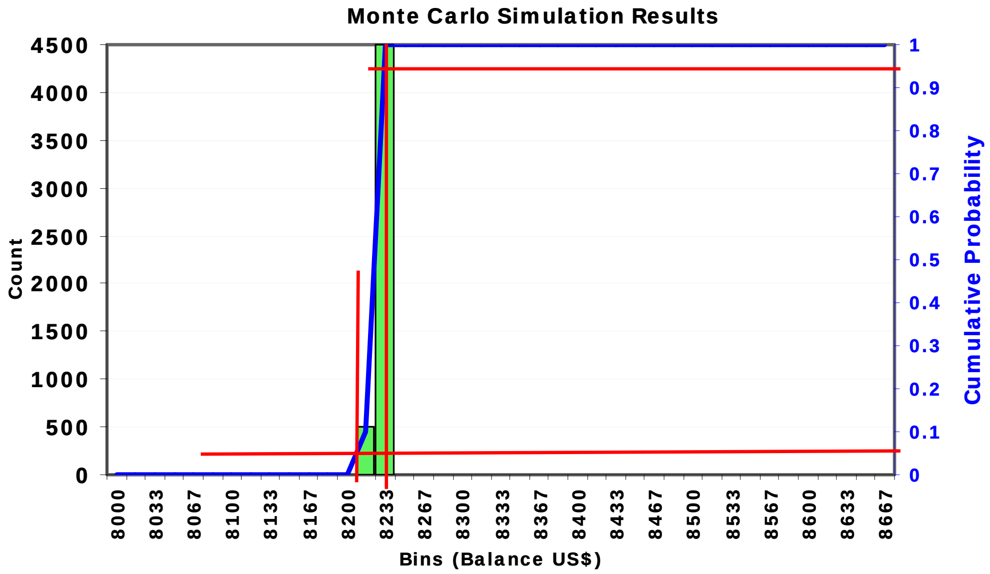


Figure E11 Family balance cumulative probability distribution curve under rainfed practice with maize price variation for farm type E.

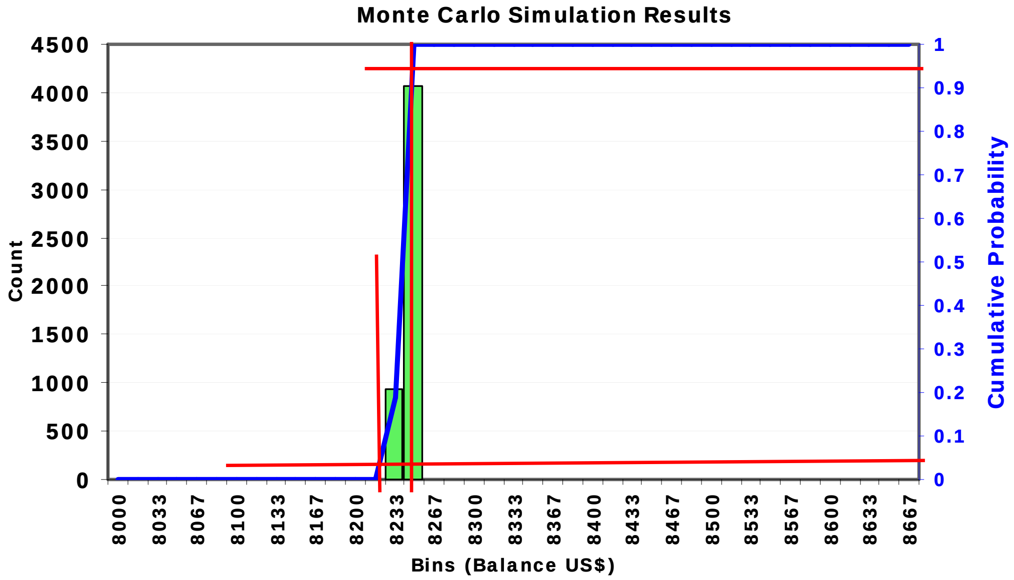


Figure E12 Family balance cumulative probability distribution curve under supplemental irrigation practice for farm type E.