AN ECONOMIC ANALYSIS OF SALINITY MANAGEMENT WITH EVOLUTIONARY ALGORITHMS IN VAALHARTS

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AN ECONOMIC ANALYSIS OF SALINITY MANAGEMENT WITH EVOLUTIONARY ALGORITHMS IN VAALHARTS

by BERHANE OKUBAY HAILE

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DECLARATION

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DEDICATION

This thesis is dedicated to my lovely wife, Meley Yacob; my beautiful daughters, Lidya, Melat, and Aida; and my late sibling Miss Regat Okubay.

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"Contribution to knowledge is possible by being committed not by promising."

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1-yr M-W	one-year maize-wheat
1-yr M-P	one-year maize-peas
ADC	Area dependent cost
CARA	Constant absolute risk aversion
CE	Certainty equivalent
CRRA	Constant relative risk aversion
CZ	Capillary zone
DAP	Days after planting
DARA	Decreasing absolute risk aversion
DRL	Drainage loss
DUL	Drain upper limit of each soil layer
E	Evaporation
EA	Evolutionary algorithm
EC	Electrical conductivity
ET	Evapotranspiration
GA	Genetic algorithm
GEN	Generation counter for evolutionary algorithms
GET-OPTIS	Global evolutionary technique for optimal irrigation-scheduling
GSL	Growing season length
GWK	Griekwaland-Wes Korporatief
HI	Harvest index
INF	Inflow
IR	Irrigation
LP	Linear programming
LPM	Lower partial moment
LWSR	Layer water supply rate
MAS	Margin above specified costs
MATLAB	Matrix laboratory programming language
Max T	Long-term maximum temperature
Min T	Long-term minimum temperature
OPH	Off-peak available hour
OTF	Outflow water
PD	Parameterised distribution

PEH	Peak available hour
PLD	Planting date
POD	Point of delivery
PWSR	Profile water supply rate
RAC	Risk-aversion coefficient
RF	Rainfall
SALMOD	Salinity and leaching model for optimal irrigation development
SC	State-contingent
SL	Salt leached
STH	Standard available hour
SWAMP	Soil water management program
SWAMP-ECON	Soil water management program economic model
SWAP	Soil water atmosphere and plant
SWB	Soil water balance
T	Transpiration
TQ	Target yield
TVIEC	Total variable irrigation electricity cost
VIS	Vaalharts Irrigation Scheme
WP	Water productivity
WTU	Water-table uptake
WUA	Water-user Associations
WUE	Water-use efficiency
YDC	Yield dependent cost

ABBREVIATIONS RELATED TO SOFTWARE PACKAGES

HYDRUS	Software package for simulating water, heat, and solute movement in two- and three-dimensional variably-saturated media.
ENVIRO-GRO	A program that simulates subsurface variably-saturated water flow, solute transport, root water uptake, nitrogen uptake, and relative yield for agricultural applications.
SALTMED	A systems approach to a sustainable increase in irrigated vegetable crop production in salinity-prone areas of the Mediterranean region.
UNSATCHEM	Software package for simulating water, heat, carbon dioxide and solute movement in one-dimensional variably-saturated media.

LIST OF UNITS AND SYMBOLS

UNITS

h	Hour
ha	Hectare
kg ha^{-1}	Kilogram per hectare
kg salt ha^{-1} mm^{-1}	Kilogram per hectare per millimetre
km	Kilometre
km^2	Square kilometre
kpa	KiloPascal
kw	Kilowatt
kVAr	KiloVar
m	Metre
m s^{-1}	Metre per second
mg L^{-1}	Milligram per litre
mm	Millimetre
mm day^{-1}	Millimetre per day
mS m^{-1}	Millisiemens per metre
^oC	Degrees centigrade
ZAR	South African currency (Rand)
ton	Tonnes
USD	United States dollar

SYMBOLS

r_a	Absolute risk aversion coefficient
$ta_{i,t}$	Active energy charge for time slot t
T_A	Actual transpiration or water uptake
θ_a	Air dry volumetric soil water content
a_j	Alternative risky prospect j
aC_c	Area-dependent cost for crop c
ρ	Area days under the relative daily transpiration requirement line
r	Arrow-Pratt coefficient of relative risk aversion
λ	Arrow-Pratt coefficient of risk aversion
Z_x	Combination of state-contingent output given vector input x
Ct	Cost of production using different inputs
k'	Counter for index
ψ_P	Critical leaf water potential where plant water stress sets in
ξ	Crop parameter
ς	Crop-specific parameter needed to calculate potential transpiration
X^n	Current generation schedules
$f_{(i)}$	Daily root distribution coefficient
d_i	Day i during the simulation period
Z_{WT}	Depth of the water table
EC_e	Electrical conductivity of a saturated extract
EC_{IR}	Electrical conductivity of irrigation
EC_{RF}	Electrical conductivity of rainfall
EC_{WT}	Electrical conductivity of water table
n_{el}	Elite size
B_n	Elitist set
ϖ	Empirical coefficient to calculate evaporation from bare soil
eop	End of optimisation
c	Field crop
fec	Fixed electricity cost
Z_f	Height between the middle of layer and the water-table surface

$k(h)$	Hydraulic conductivity function
Y	Income from crop production
x_i	Input i
b''	Intercept (mm) of the drainage curve
v_i	Irrigation depth in day i
$kVar$	Kilovar
kW	Kilowatt
Lr	Labour hour requirement
o_L	Lost solutions individual
ψ_m	Matric potential
n_{max}	Maximum generation
q_m	Maximum upward capillary flux
v_{max}	Maximum volume of water that can be applied
$E(Y)$	Mean of income distribution
d_{min}	Minimum time between two irrigations
v_{min}	Minimum volume of water that can be applied
NIR_W	Net irrigation weekly
nac	Network access charge
$dc_{i,t}$	Network demand charge
$\beta(z)$	Normalised root distribution function
DS	Number of days after the soil has been saturated
t	Number of days between each rain and/or irrigation event (time)
A'	Number of days until the end of the establishment stage
D'	Number of days until the end of the physiological maturity phase
C'	Number of days until the end of the reproductive development phase
B'	Number of days until the end of the vegetative growth phase
N	Number of inputs
M	Number of outputs
ι	Number of soil layers
π	Osmotic head
ψ_o	Osmotic potential
Q	Output amount
τ	Parameter describing the decline in hydraulic conductivity above the water table

c_2'	Parameter that converts EC to total dissolved salts
c_3'	Parameter that converts total dissolved salts to osmotic potential
DC	Parameter that determines the fraction of salt removed from a layer
c_1'	Parameter to convert EC to salt content
n_P	Population size
E_P	Potential evaporation
ET_P	Potential evapotranspiration
T_P	Potential transpiration rate
Z^+	Positive integer number
h	Pressure head
Pr_W	Price of irrigation water
p_{cr}	Probability of crossover
p_m	Probability of mutation
p_{SF}	Probability of shortfall
p_s	Probability of states of nature
γ	Random number
$tra_{i,t}$	Reactive energy charge
R	Real number
α	Reduction function
ET_o	Reference evapotranspiration
a'	Relative crop water requirement at the end of phase A'
d'	Relative crop water requirement at the end of phase D'
$rc_{i,t}$	Reliability charge for time slot t
θ_r	Residual volumetric soil water content
Lv	Rooting density
$rl_{(i)}$	Rooting depth
φ_s	Saturated hydraulic conductivity
MAS_s	SC margin above specified cost for crop c
S_{IR}	Schedule for irrigation
S_{TS}	Set of solution for tournament
Ω	Sets of states of nature
SC_ι	Silt plus clay percentage of each soil layer

a''	Slope (mm day^{-1}) of the drainage curve
F_{sr}	Specific soil-root conductance coefficient
σ	Standard deviation
$Pr_{s(c)}$	State-contingent crop prices
y_s	State-contingent net return
r_s	State-contingent revenue
S	States of nature
η_{IRS}	System efficiency
ζ_{IRS}	System flow rate
A_c	Area of irrigation-system size
Z_ℓ	Thickness of a soil layer
elC_c	Total electricity costs for crop c
LC_c	Total labour costs for crop c
RMC_c	Total repair and maintenance costs for crop c
ψ_t	Total soil water potential
WC_c	Total water costs for crop c
n_{TS}	Tournament size
T_R	Transpiration requirement
$U\left(a_j\right)$	Utility of alternative risky prospect of a_j
σ_d	Variance for irrigation time
σ_v	Variance for irrigation volume
$\phi_{(\iota)(i)}$	Volume of water percolating from specific layer in a specific day
θ_ι	Volumetric soil water at the start for every layer
θ_{fc}	Volumetric soil water content at field capacity
θ_{PWP}	Volumetric soil water content at permanent wilting point
θ_s	Volumetric soil water content at saturation
θ_o	Volumetric soil water content where $\psi_m = \psi_P$
θ_t	Volumetric soil water content where $\psi_t + \psi_o = \psi_P$
wL	Wage labour for irrigation
W_{soil}	Water content of soil profile during the drainage period
yC_c	Yield dependent cost for crop c

$EU(a_j)$	Expected utility of a_j
$(w_1,...,w_N)$	Input prices
$T(x,Q)$	Technology of production

ABSTRACT

The main objective of this research was to develop a bio-economic salinity management model to evaluate the stochastic efficiency, water-use efficiencies and environmental impact of optimal irrigation-scheduling practices while taking cognisance of irrigation-water quality, soil conditions, irrigation-technology constraints, crops and stochastic weather.

A bio-economic salinity management simulation model was developed in MATLAB through the integration of the **S**oil **WA**ter **M**anagement **P**rogram (SWAMP), by combining electricity-cost calculations with enterprise budgets to evaluate the impact of current irrigation schedules used by irrigators. The resulting SWAMP-ECON model was linked to an evolutionary algorithm to determine the benefits of following an optimised irrigation-scheduling strategy for each field crop. The model was also extended to model inter-seasonal allocation of water between two consecutive crops grown on the same field, to evaluate changes in the irrigation schedule of the first crop to manage the impact of soil salinity on the second crop. Risk was included in the analyses through the use of a state-general characterisation, where decisions are made without any knowledge of which state will occur. The models were applied to a case study farm in Vaalharts Irrigation Scheme with a 30.1 ha centre-pivot irrigation-system. The farm is characterised by Bainsvlei soil type and a shallow water table close to or below the root zone. The scenarios considered to run the model were two water qualities (low and high), two irrigation-system delivery capacities (10 mm day^{-1} and 12 mm day^{-1}), and three field crops (maize, wheat, and peas) with different salinity-tolerance levels. The field crops constitute the crops grown for intra-seasonal and one-year inter-seasonal applications. Stochastic efficiency, low water-use efficiencies and environmental-impact indicators were calculated to interpret results of irrigation-management options for achieving economic and environmental sustainability.

The results show that the farmer's existing irrigation schedules for the field crops in the study were over-irrigation strategies characterised by low water-use efficiencies, which are the direct result of farmers ignoring the contribution of the shallow water table to crop water-use. Over-irrigation resulted in large amounts of drainage water releasing between 11 000 and 26 600 kg ha^{-1} of salt into the environment. Decreasing water quality increases the risk of failing to reach potential production levels of the more salt-sensitive crops (maize and peas), however, the impact on expected margin above specified costs was low. Peas is the most profitable enterprise, followed by maize, and then wheat. On average, the expected margin above specified costs for peas, maize, and wheat, respectively, is ZAR 448 370, ZAR 321 909 and ZAR 245 885. The conclusion is that the current irrigation strategy is inefficient, has a large impact on the environment and presents the opportunity to improve profitability through better irrigation-scheduling practices that acknowledge the contribution of the shallow water table.

Results of the optimised irrigation schedules show significant increases in expected margin above specified costs, associated risk exposure, water-use efficiencies and water productivity, as well as decreases in environmental impact due to a reduction in the amount of salt leached (SL). The main contributing factor to the results is the fact that the amount of irrigation water could be reduced because the shallow water table contributed 40% to 62% to crop water-use evapotranspiration, depending on crop type, water quality, and irrigation-system delivery capacity scenario selected. The largest benefits were observed for the highly salt-tolerant crop (wheat), because no leaching was necessary to manage salt levels. Consequently, a large salt build-up in the soil was observed. Decreasing water quality, compared to good quality water, impacted more negatively on MAS, risk exposure and the extent of drainage losses by the more salt-sensitive crops. Irrigation-system delivery capacity did not affect water-application rates significantly, but the results show that it is easier to manage electricity costs with the larger capacity by using a time-of-use electricity tariff. The conclusion is that the benefit of an optimised irrigation strategy is considerable, though careful consideration should be given to the trade-off between decreasing water applications and increasing salinity levels in the soil. Results of the inter-seasonal optimised irrigation-scheduling strategy water-use show that the leaching needs to increase during the production of the first crop to reduce the starting soil-salinity level when the follow-up crop is planted, especially when the second crop is sensitive to high salinity levels. Low WUE, WP and profitability are the consequences, taking the follow-up crop into account. In conclusion, a risk-neutral farmer should only consider increasing the water applied to the first crop (e.g. maize) if the plan is to plant a salt-sensitive crop (e.g. peas) in the second season. In both the intra-seasonal and the inter-seasonal applications, a risk-averse decision-maker will use more irrigation water to reduce the variability of outcome.

The main recommendation from this research is that alternative institutional arrangements should be considered to ensure that irrigators do not lose their water-use entitlements if the water that is not used is deemed a non-productive use. A scheme-level hydrology analysis is necessary to determine the impact on the water table if all water-users start mining the water table. Future research should focus on extending the model to include the long-term problem of salinity and enhancing the model to deal with state-specific applications of water to crops as new information becomes available to farmers about a state of nature.

Key words: stochastic efficiency, water-use efficiency, water productivity, environmental impact, evolutionary algorithms, salinity, simulation, irrigation schedule, production risk, optimisation

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The South African agricultural sector is expected to play a crucial role in meeting the food and fibre demands of an increasing population. These demands are estimated to increase to meet the expected two percent per year growth of population from approximately 50.8 million population reported in 2011 (South Africa Yearbook, 2013/14; Statistics South Africa, 2012). The sector is also recognised as a key contributor to the sustainable development of South Africa's economy, and rural development. For instance, reports show that about three percent and seven percent of gross domestic product and formal employment, respectively, comes from primary agriculture (South Africa Yearbook, 2013/14). The agricultural sector should not only increase productivity to feed more mouths, but also produce high-quality food, which will be demanded due to the expected improvement of living standards caused by economic growth. Field crops, such as maize, wheat, barley, sorghum, peas and groundnuts, are some examples of the important crops that will help the sector to achieve food security, rural development, employment, and generation of foreign currency (Van Rensburg, De Clercq, Barnard and Du Preez, 2011). As reported in South Africa Yearbook (2013/14), during the period of collecting reviews for the study, field crops alone contributed around 28.3% of the total value of agricultural production.

Since the major production area of field crops in South Africa is located in arid and semi-arid regions, irrigation has been used to sustain production. These parts of the country experience highly variable and unpredictable rainfall, with high evapotranspiration (ET). The average annual rainfall in South Africa is about 464 mm (South Africa Yearbook, 2013/14; Van Rensburg *et al.*, 2011). Hence, irrigation has been a way to meet crop water requirements. To be profitable and sustainable the irrigation sector is dependent on efficient management of scarce natural resources, such as soil and water (Alexandratos and Bruinsma, 2012; Turral, Svendsen and Faures, 2010). Statistics show that 1.5 million ha of land is under irrigation in the country (South Africa Yearbook, 2013/14; DAFF, 2012). Currently, the sector is using about 60% of the country's scarce water resources (DWA, 2013).

South Africa is a water-scarce country, i.e. the water resource is under tremendous pressure (Armour, 2007, DWA, 2013; Goldblatt, 2010; Grové, 2006, 2008), which has significant implications for irrigated agriculture due to the increasing demand for water by other sectors (Goldblatt, 2010). In fact, in the past few decades irrigated agriculture has been operating under water laws that relate to the way water is allocated between competing uses, and proper management (Grové, 2008). The first document that was published to form a foundation for the White Paper on a National Water Policy (DWAF, 1997) was the Water Law Principles (DWAF, 1996). The National Water Policy's main objectives include achieving equitable access to water and ensuring sustainable and efficient use of water for optimal social and economic development. To achieve the goals of the policy, a legal framework known as the National Water Act (Act 36 of 1998) was issued with comprehensive provisions for the protection, use, development, conservation, management and control of water resources. Recently a new document, known as National Water Resources Strategy 2, was released, which builds on the first National Water Resources Strategy 1 that had been published in 2004 as a legal requirement of the National Water Act. The strategy provides a means to develop the National Water Conservation and Demand Management Strategy, with the aim of conserving and managing water resources. The water law endorses the use of more efficient irrigation-systems that suit specific soil, crop and weather conditions. In addition, the National Water Resources Strategy 2 suggests that low quality water could be one of the factors that limits irrigated agriculture's contributions to food security and, together with poor management, contributes to environmental degradation of surface and groundwater resources (DWA, 2013). Consequently, the sector must design strategies to achieve greater efficiency in the use of scarce water (Tesfhuney, 2012; Goldblatt, 2010; Grové, 2008), adapt sustainable production methods, and cope with the adverse effects of climate change (Calzadilla, Rehdanz and Tol, 2011; Schütze and Schmitz, 2010).

In large irrigation schemes salinity has become one of the serious threats to sustainable production of field crops, as well as to the well-being of the environment (Akhbari and Grigg, 2014; Borg, 1989, DWA, 2013). The practice of using long-term irrigation to alleviate the impact of rainfall shortage and variability in arid-regions is associated with problems of salinity and waterlogging of soils, which are poorly drained or characterised by having shallow water tables present within or just below the potential root zone (DAFF, 2012; Domínguez, Tarjuelo, De Juan, López-Mata, Breidy and Karam, 2011; Matthews, Grové, Barnard and Van Rensburg, 2010). For instance, Goldblatt (2010) reports that about 260 000 ha of irrigated land in South Africa has been affected by salinisation, of which 15 000 ha of land is in a serious condition.

Even though irrigation farmers are aware of the importance of considering salinity, few of them manage soils with shallow water tables differently from freely drained soils. Usually farmers irrigate according to crop water requirements and do not consider the water table as a source of water (Van Rensburg, Barnard, Bennie, Sparrow and Du Preez, 2012), despite evidence that shows a shallow water table can contribute between 30 to 60% to crop water-use, depending on soil type and depth (Ayars, Christen, Soppe and Meyer, 2006). As a result, over-irrigation occurs frequently in the presence of shallow water tables within or just below the potential root zone, thereby preventing onsite problems of salt accumulation and decreases in crop yield. However, offsite problems of surface and groundwater degradation due to excessive drainage and leaching are not prevented. Furthermore, over-irrigation wastes valuable freshwater resources and leaches essential nutrients from the root zone. Hence, there is a trade-off between the amount of water applied to the field, salt accumulation in the soil profile, and leaching. Sound irrigation-scheduling (timing and amount) is of the utmost importance when managing crop water-use under salinity conditions.

The question, however, is not whether irrigation farmers should practice appropriate irrigation-scheduling to manage salinity and water-use. Rather, the question is how to develop a sound irrigation strategy in light of declining water quality and rising electricity tariffs. Developing an irrigation strategy that will maximise profits and at the same time minimise environmental impact is particularly challenging and complex. Farmers risk aversion behaviour combined with lack of information forces them to ignore shallow water table as source water for growing crops. Farmers need to integrate information on irrigation water salinity, soil-water salinity, soil-water content and salt balances, crop water requirements, sensitivity of crops to salinity, irrigation technology, available irrigation hours and economic factors, to devise a proper irrigation-scheduling strategy to manage salinity economically. Furthermore, the dynamic and stochastic environment in which irrigation decisions are made adds to the complexity of salinity management decisions.

1.2 PROBLEM STATEMENT AND OBJECTIVES

Irrigation farm managers are currently unsure how to manage salinity economically through their choices of irrigation technology, irrigation-scheduling practices, crops with different salinity-tolerance levels and soils, because of the unavailability of an integrated bio-economic model that can evaluate the interaction between these choices on profitability indicators.

Developing management strategies for managing salinity economically requires quantification of the relationship between changes in soil-salinity levels and expected crop yield. A popular method to relate crop yield to the soil-water salinity level is the steady state Maas and Hoffman (1977) threshold and gradient functions for various crops. When the soil-water salinity level exceeds the soil-crop salinity threshold the crop cannot extract the required water from the soil, and crop growth is suppressed due to the osmotic effect that occurs as the total water potential in the soil is lowered. Ehlers, Barnard, Dikgwatlhe, Van Rensburg, Ceronio, Du Preez and Bennie (2007) confirmed the thresholds and gradients for South African conditions, and the information has been used by several researchers to evaluate alternative salinity management strategies economically.

Armour and Viljoen (2002) evaluated the short-run profitability and financial feasibility of alternative salinity management options over a season. These researchers considered alternative crops, irrigation-systems with different leaching capacities and the installation of artificial drainage as alternative management options. The Salinity and Leaching Model for Optimal Irrigation Development (SALMOD) that was used to evaluate the management alternatives is composed of a simulation module and an optimisation module. The simulation module calculates the economic parameters for all the management option combinations that are included in the optimisation module. The biophysical soil-salinity interrelationships are simplified through the use of the steady-state Maas and Hoffman (1977) crop-yield relationship and the necessary leaching fractions required to achieve a specific target yield when water quality is deteriorating. The optimisation module uses linear programming (LP) to maximise the gross margin above specified cost of the management alternatives, minus the amortised cost of investments. The researchers found that the benefits from leaching more as water quality deteriorates, to obtain a 100% yield, outweighs the costs of leaching until return flows become constraining. In follow-up research Armour and Viljoen (2007) investigated the long-term effects of salt build-up on the sustainability of irrigation farming. They emphasise a better understanding of the dynamic changes in salinity over time in order to assess the sustainability of irrigation farming. Including dynamics into the optimisation framework they had developed in 2002 posed problems and in 2007 Armour and Viljoen had to resort to economic simulation. The simulation model uses the same methodology that Armour and Viljoen (2002) had used to quantify the impact of soil salinity on crop yields.

Matthews *et al.* (2010) developed a nonlinear programming model to evaluate the trade-off between allocating water for production or leaching management. In contrast to the research by Armour and Viljoen (2002), which used discrete activities to represent alternative management options, Matthews *et al.* (2010) incorporated the Maas and Hoffman salinity crop yield function directly into the programming model through the use of data envelopment analysis. Results show that leaching is profitable, irrespective of water-supply conditions.

All of the above research studies followed a steady-state approach. The main focus of the steady-state approach is the quantification of the necessary leaching requirement to achieve a target yield when salinity is a problem (Letey and Feng, 2007). The steady-state assumption implies that the salt concentration and soil-water content are constant over time, because the relationship is based on the whole season. With seasonal relationships the intra-seasonal dynamics that influence the timing and quantity of irrigation amounts are assumed away. Matthews *et al.* (2010) caution against using seasonal production and leaching function models that ignore the timing of water applications, arguing that daily water and salt balances are necessary to manage salinity practically. Recently, Venter (2015) used daily water budget calculations to demonstrate the importance of the timing of irrigation events to manage electricity costs to accommodate time-of-use electricity tariffs. Managing salinity dynamically throughout the season will certainly complicate decision-making and increase the need for information on which decisions could be based.

The advancement of knowledge about physical-chemical-biological interactions that occur in the soil-water-plant matrix and the availability of high-speed computers have resulted in simulation models that can model the impact of salinity management on crop yield more realistically. These simulation models have proven to be more useful in evaluating salinity management options than the steady-state approach (Letey and Feng, 2007). One such model is the **S**oil **WA**ter **M**anagement **P**rogram (SWAMP) developed by South African researchers (Barnard, Van Rensburg, Bennie and Du Preez, 2013; Barnard, Bennie, Van Rensburg, and Du Preez, 2015; Bennie, Strydom, and Vrey, 1998). The model uses daily water and salt balances to simulate the effect of changing osmotic potential on crop yield without the use of the well-known Maas and Hoffman salinity threshold and slope parameters (Barnard *et al.*, 2015). Thus, the model is especially suited for evaluating the impact of irrigation-scheduling on crop yield when salinity is a problem.

South African literature on the economics of salinity management clearly shows the inability of the adopted modelling approaches to incorporate dynamic interactions between irrigation management, soil salinity and crop yields that are necessary to develop salinity management options that are economically and environmentally sustainable. Simulation models provide ways to simulate the impact of salinity management options on crop yields more accurately. Typically these models are too complex to be represented within a mathematical programming environment. As an alternative, crop-simulation models could be supplemented by economic modules to simulate the economic impacts of alternative management options. Recently Schütze and Schmitz (2010) and Schütze, De Paly and Shamir (2012) demonstrated that these models could be optimised through the use of evolutionary algorithms (EA).

The main objective of this research is to develop a bio-economic salinity management model to evaluate the stochastic efficiency, water-use efficiency (WUE) and environmental impact of optimal irrigation-scheduling practices while taking cognisance of irrigation water quality, soil conditions, irrigation-technology constraints, crops and stochastic weather.

The specific objectives of the research are as follows:

Sub-objective 1: To develop a bio-economic salinity management simulation model (SWAMP-ECON) to evaluate the stochastic efficiency, WUE and environmental impact of existing irrigation schedules.

Achieving Sub-objective 1 entails the development and integration of an economic module with SWAMP to evaluate existing irrigation schedules based on satisfying crop-water demand through irrigation applications. Special care was taken to ensure that the interrelationship between irrigation-system delivery capacity, timing of irrigation events and available time-of-use electricity hours were modelled correctly. The development and model integration were done in matrix laboratory (MATLAB) (Gdeisat and Lilley, 2013; MathWorks, 2013).

Sub-objective 2: To develop an optimal solution procedure to optimise irrigation schedules simulated with SWAMP-ECON in order to evaluate the benefit of optimal irrigation-scheduling in terms of stochastic efficiency, WUE and environmental impact within a season.

To achieve Sub-objective 2 an EA was developed to optimise the irrigation decisions within a season for a single crop irrigated with a centre-pivot with a known irrigation water delivery capacity. The EA is based on the Global Evolutionary Technique for OPTimal Irrigation-scheduling (GET-OPTIS) (Schütze and Schmitz, 2010; Schütze *et al.*, 2012). Using EA to schedule irrigation is complicated, because it is likely that impractical irrigation schedules will be generated, considering the hours necessary to apply the irrigation amount. Special routines were developed to ensure the feasibility of irrigation schedules for a given centre-pivot irrigation-system delivery capacity.

Sub-objective 3: To extend the model developed under Sub-objective 2 to evaluate the stochastic efficiency, WUE and environmental impact of optimal irrigation and salinity management within an inter-seasonal setting where two crops are grown successively on the same soil.

In order to achieve Sub-objective 3 the SWAMP-ECON model was extended to include two crops grown in succession. Continuous changes in the water and salt balances were modelled through the inclusion of a fallow period between the two crops. The continuous calculations enable the user of the model to evaluate whether a medium-run (two seasons) outlook necessitates changes to irrigation schedules in the short run.

A state-contingent (SC) approach (Chambers and Quiggin, 2000) was used to incorporate stochastic weather events while developing the models to achieve the three specific objectives.

1.3 DESCRIPTION OF THE STUDY AREA

A research model was applied to a representative field of a farm located in one of the largest and oldest irrigation schemes, Vaalharts Irrigation Scheme (VIS), in South Africa. The main attributes of the irrigation scheme, such as geographical location, land type and geology of the scheme, climate, soil, crops, water quality, water-users association (WUA), and irrigation-systems relevant to the study will be presented in the following sub-sections.

1.3.1 Geographical location

Developed as part of a major initiative of the government of South Africa during the so-called great depression of the 1930s, VIS (27°38'33"E, S24°48'69"S) covers around 370 km^2 (DAFF, 2012; Kruger, Van Rensburg and Van Den Berg, 2009). The irrigation scheme is located geographically between the provinces of Northern Cape and North-West. Sourcing most of its water from the Vaal River, VIS is located east of the Harts River and surrounded from the south by the Vaal River (DAES, 2008; Otieno and Adeyemo, 2011; Van Rensburg *et al.*, 2012). The Orange-Riet Irrigation Scheme, which is located mostly in the Free State province (Figure 1.1), with similar soil properties, climate, and geology, surrounds Vaalharts from the south.

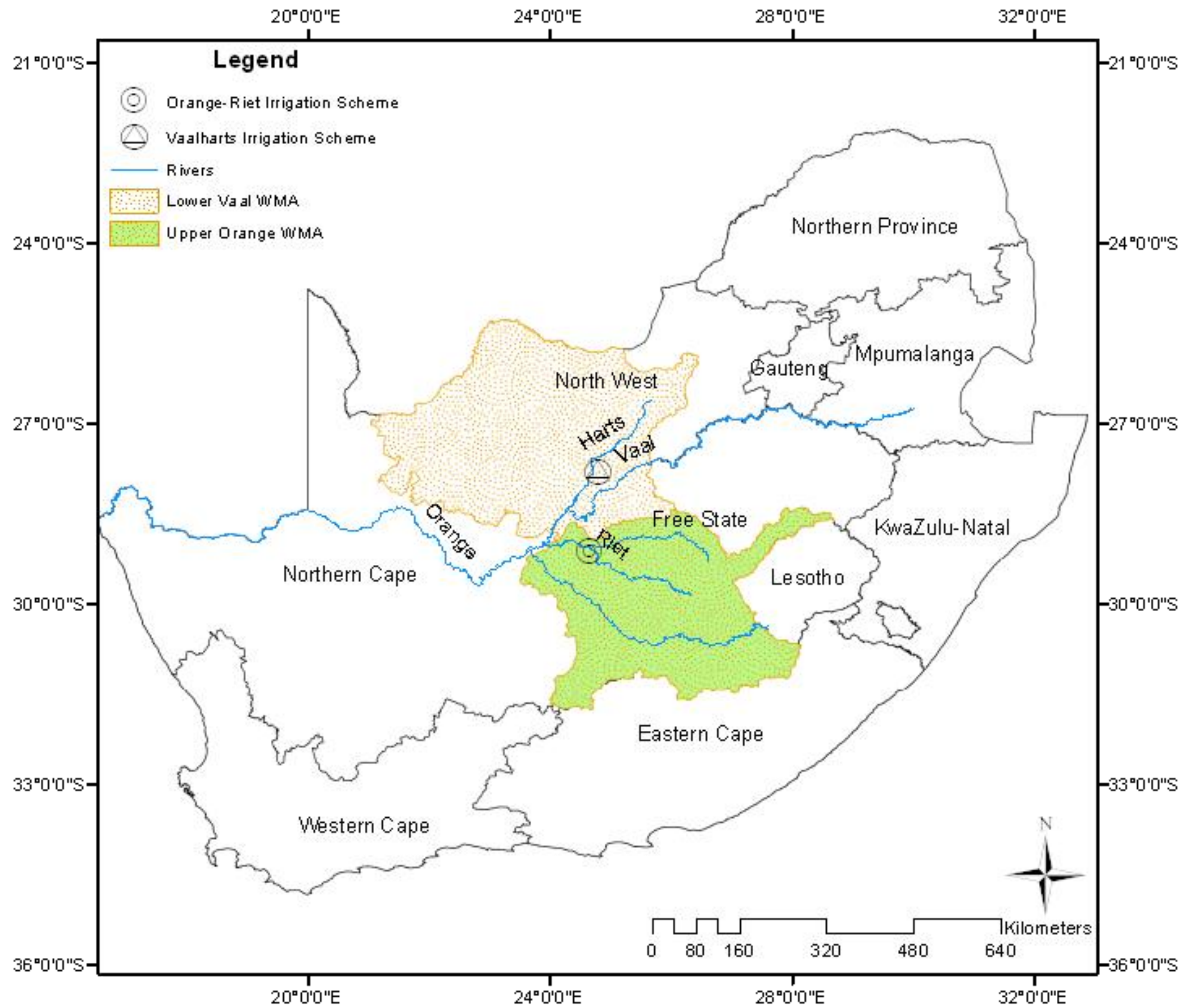


Figure 1.1: Map showing the location of Vaalharts Irrigation Scheme within the Lower Vaal Water Management Areas, South Africa (Van Rensburg *et al.*, 2012)

Water is diverted from Vaalharts Weir ($24^{o}55^{'}30^{''}$E, $28^{o}06^{'}54^{''}$S), which is fed from Bloemhof Dam, via concrete-lined canals measuring a total of 1 176 km (Verwey and Vermeulen, 2011), to Vaalharts. The infrastructure facilitates major agricultural activity, contributing to the economy of the country and fulfilling a significant role in providing food security (Armour, 2007; Van Rensburg *et al.*, 2011; Verwey and Vermeulen, 2011); approximately 39 820 ha is irrigated (Grové, 2006; Otieno and Adeyemo, 2011). At present there are about 1 040 registered irrigation farmers, of whom 47% and 53% are estimated to be commercial and emerging farmers, respectively. In operation for nearly 81 years, the irrigation scheme also supplies water to six municipalities and nine other industrial freshwater-users. The land holdings in the scheme vary from 25 to 75 ha in field size, with an approximate total of 1 250 plots (DAES, 2008; Verwey and Vermeulen, 2011). Furthermore, it is estimated that around 50% of the soils is drained artificially, as shallow water tables within or just below the potential root zone is present extensively throughout the scheme (Van Rensburg *et al.*, 2012).

1.3.2 Land type of the scheme

Vaalharts is located between two plateaus on the east and west sides of the glacial Harts River Valley (Van Rensburg *et al.*, 2012) at an altitude ranging from 1 050 to 1 175 m above sea level (DAES, 2008; Verwey and Vermeulen, 2011). Draining towards the Harts River, around 70% of the scheme has a slope less than 1%, enabling the scheme to be categorised as flat land (Verwey and Vermeulen, 2011). Hence, the fields in the scheme are suitable for various irrigation methods, such as flood, sprinkler, and micro-irrigation (Armour, 2007; DAFF, 2012). The scheme is grouped in Drainage Area C, Quaternary sub-catchments C31F, C32D, C33A, and C33B (DAES, 2008). The geology of the Vaalharts, with Pre-Cambrian igneous basement, is predominantly sedimentary of Karoo age (Van Rensburg *et al.*, 2012). The valley is of the Archean Ventersdorp Super Group type, composed of Archaean Kraaipan Group sediments and volcanic rock with various ages and mineral contents.

1.3.3 Climate

A number of researchers (DAES, 2008; DAFF, 2012; Van Rensburg *et al.*, 2012; Verwey and Vermeulen, 2011) categorise the climate of Vaalharts as being semi-arid, with very hot summers and cool winters. Some of the climate variables for Vaalharts are shown in Table 1.1. The average annual rainfall, which usually occurs from October to March, is 427 mm per year. The long-term maximum temperature during these months is above 25 ºC with mean minimum temperature ranging from 11 ºC to 16 ºC. In the coolest months the maximum temperature is around 18 ºC, with long-term mean minimum temperature of below zero ºC. The atmospheric evaporative demand is 1 647 mm with an aridity index of 0.26. The wind speed in the valley is between 3.5 to 5.6 m s^{-1}, usually in a north-northwest direction (DAES, 2008).

Table 1.1: Long-term mean maximum (Max T) and minimum temperature (Min T), reference evapotranspiration (ET_o), and rainfall per month at VIS (raw data courtesy of ARC-ISCW, Pretoria)

Month	Mean Min T (ºC)	Mean Max T (ºC)	Mean Rainfall (mm)	Mean ET_o (mm)
January	17	32	71	200
February	16	31	83	150
March	14	30	63	139
April	10	27	37	117
May	5	22	21	86
June	1	19	5	69
July	1	20	3	74
August	3	22	4	98
September	7	26	9	136
October	11	28	34	172
November	14	31	49	195
December	16	32	48	211
Mean	10	27	-	-
Total	-	-	427	1647

1.3.4 Soil

From the early stages of its development, Vaalharts has been one of the irrigation schemes that is rich in terms of soil survey studies. Mainly grouped as Kalahari Sand deposited through alluvial process, the soil in the valley are Hutton, Kimberley, Hutton/Mispath, Dundee and Katspruit/Kroonstad, and Plooyesburg forms (DAES, 2008; Van Rensburg *et al.*, 2012; Verwey and Vermeulen, 2011). The majority of the area has deep sandy to sandy loam soils of Hutton form and deep sandy loam to sandy clay soils of the Hutton and Kimberley forms, i.e. the soils comprise mainly 75% sand, 10% silt and 10% clay (DAES, 2008).

1.3.5 Crops

Vaalharts is well known for its variety and large-scale production of field crops (maize, wheat, groundnuts, peas, potatoes, etc.), pastures such as lucerne and teff, and small areas of perennials (vineyards, pecans, citrus and olives) (Van Rensburg *et al.*, 2011; Van Rensburg *et al.*, 2012; Verwey and Vermeulen, 2011). The scheme not only contributes to local markets, but also to markets in the United States, Europe, and Japan, to which it exports groundnuts, citrus and olives (DAES, 2008).

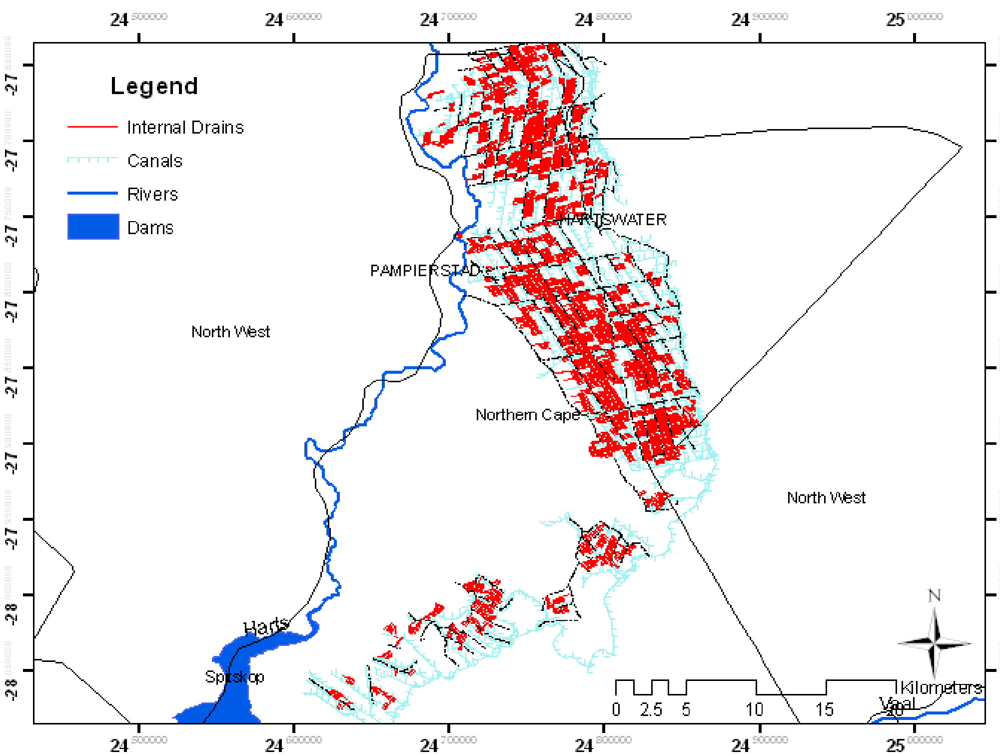
The field crops selected for study are wheat (*Triticum aestivum* L.), maize (*Zea mays* L.) and peas (*Pisum sativum* L.). Wheat is highly salt tolerant (600 mS m^{-1}), followed by maize (350 mS m^{-1}) and peas (105 mS m^{-1}), i.e. peas are very sensitive to salt accumulation in the potential root zone (Ehlers *et al.*, 2007).

1.3.6 Water quality

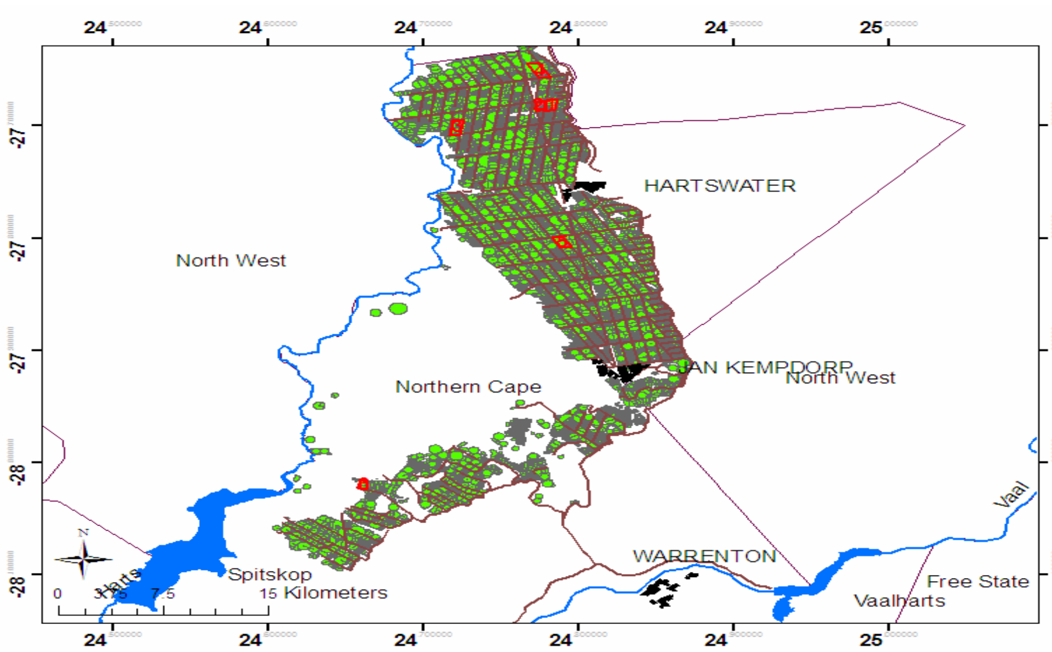
Management of water for irrigation should not only be concerned with the quantity of water available, but also with the quality aspect of the water. The VIS has been the focus of a number of studies (Armour, 2007; Van Rensburg *et al.*, 2011; Van Rensburg *et al.*, 2012; Verwey and Vermeulen, 2011) that assessed the irrigation water quality and its potential impacts on crops, soils, and ecosystems. The quality of irrigation water has a negative effect on the health of irrigation-systems through processes such as corrosion and scale deposits (DAES, 2008) and plant growth, which ultimately affect the quantity and quality of yields and soil properties, and which could degrade water resources (Van Rensburg *et al.*, 2012). Parameters that are mostly used to measure water quality include electrical conductivity (EC) and sodium absorption ratio.

Currently, as shown in Figure 1.2(a), almost 50% of the soils in the scheme is artificially drained (Van Rensburg *et al.*, 2012). These drainage systems are used to discharge most of the leachate and excess water back in to the Harts River (DAES, 2008; Van Rensburg *et al.*, 2012). Some farmers recycle and/or mix the drainage water with good quality water and re-use it to grow crops (Van Rensburg *et al.*, 2012). Sprinkler and micro-irrigation are predominantly used – the current extent is depicted in Figure 1.2(b). The remaining flood irrigation-systems are continuously being replaced with more efficient systems (Verwey and Vermeulen, 2011).

As mentioned briefly in Section 1.3.1, the main source of water for Vaalharts is the Vaal River (DAES, 2008; Van Rensburg *et al.*, 2011). The Vaal River, originating 200 km west, passes through Johannesburg, a densely populated city with massive mining and other industries, and Armour (2007, citing Du Preez *et al.*, 2000) refers to concerns that the river could be receiving polluted return flows that could affect the quality of the water. The concern is supported by Van Rensburg *et al.* (2012), who list factors that could aggravate the problem of water quality for crops, soils and downstream users. These points include importation of salts via irrigation, the presence of highly mineralisable Dwyka shales and tillite stratum underlying the scheme, rising water tables caused by over-irrigation due to flood irrigation, and leakage of canals and storage facilities due to old age. From the early 1970s up to 1994, the government supported the installation of subsurface artificial drainage systems to mitigate the problem to some extent. In later years the investment in drainage systems was undertaken by the irrigators themselves.



(a)



(b)

Figure 1.2: Map of Vaalharts Irrigation Scheme showing the distribution of the internal drainage systems installed (Van Rensburg *et al.*, 2012)

Van Rensburg *et al.* (2011) highlight the impact of discharging drain water to the Harts River. The water received by Vaalharts is classified as relatively good quality irrigation water (C2S1), with a mean long-term EC of 47 mS m^{-1}. However, the water that drains from the area becomes highly deteriorated, to C3S1 level of irrigation water quality, due to the addition of salt load in the drain water. This has a potential implications for downstream irrigators and water-users (Armour, 2007; Matthews *et al.*, 2010). For instance, Van Rensburg *et al.* (2012) report that, by the time the water reaches at Spitskop Dam, the EC reaches around 126 mS m^{-1}.

1.3.7 Water-user associations and irrigation-systems

Although a recent change in water legislation in South Africa will see the restructuring of the Catchment-based Water Management Areas from 19 to 9, WUA will continue to play a critical role in ensuring that water is protected, used, developed, conserved, managed and controlled in a sustainable and equitable manner for the benefit of all (DWA, 2013). The WUA of the VIS works to manage the water resource and to include all property of anyone that has a water-user right, in terms of Article 22 (1) of the National Water Act (Act 36 of 1998) (Van Rensburg *et al.* 2012). In this regard Van Rensburg *et al.* (2012) point out that WUAs manage the supply of irrigation water to the farms and the infrastructure for water conveyance and drainage, while the farmer has the sole authority regarding the fate of irrigation water on his/her farm.

1.4 OUTLINE OF THE STUDY

This research thesis is organised in five chapters, which include the Introduction (Chapter 1) and the Summary, conclusions and recommendations for further studies.

In Chapter 2 the theoretical framework of the study will be provided. This chapter starts with a detail discussion of traditional and SC risk modelling to include production risk in the study. Then, the basic features of SWAMP will be described, as the procedure to replace the state transformation function needed in a SC approach by state crop growth simulation model. Lastly, a discussion will be presented about EAs that are used as optimisation models to solve the main problem of the study.

Chapter 3 will present the data and procedures followed to develop the bio-economic salinity management model, which could be applied for intra-seasonal and inter-seasonal applications. Then, Chapter 4 will present the results of the stochastic efficiency, WUE and environmental-impact indicators of the field crops in relation to short-term and medium-term planning scenarios. The summary, conclusions and recommendations will form the last chapter in the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Chapter 2 consists of three sections. The first section discusses the parameterised distribution (PD) and SC approaches as tools to analyse risk in agriculture. The second section presents the SWAMP, i.e., a simulation model for crop yield estimation as influenced by the matric and osmotic potential of the soil water. Before the discussion is concluded, a special optimisation procedure known as EA will be presented.

2.2 MODELLING UNCERTAINTY IN AGRICULTURE

2.2.1 Introduction

Farm production is naturally risky and faces many sources of uncertainty (Crean, Parton, Mullen and Jones, 2013; Moss, 2010) – actually, there is no other sector in the economy that faces such extreme volatility (Hardaker, Huirne and Anderson, 1997; Kaiser and Messer, 2011; Quiggin and Chambers, 2006; Rasmussen, 2003; Rasmussen, 2011). The reason is the dependence of agriculture on many uncontrollable factors, such as weather conditions, plant diseases and pest infestations (Kaiser and Messer, 2011; Kaiser and Boehlje, 1980). Farmers also face many other types of risk that cannot be controlled or predicted accurately, including price, production and finance (Hardaker, Lien, Anderson and Huirne, 2015; Kaiser and Messer, 2011). Agricultural production, therefore, exhibits characteristics of stochastic production.

Literature provides a number of approaches to modelling risk and risk preferences in agriculture (Serra, Stefanou and Lansink, 2010). The approaches are grouped into two, namely PD (e.g. stochastic production functions) and SC, which have been put forward to deal with problems of production under uncertainty in agricultural activities (Hurley, 2010; Quiggin and Chambers, 2006; Shankar, 2013). Until recent years, the analysis of production under uncertainty has been dominated by the PD approach (Hardaker *et al*., 2015). In the next section the expected utility hypothesis as related to uncertainty will be discussed.

2.2.2 Expected utility hypothesis

The expected utility hypothesis is the fundamental theory used to help farmers make decisions under risk (Chavas, 2008; Kaiser and Messer, 2011; Rasmussen, 2011; Rasmussen and Karantininis, 2005; Serra *et al*., 2010). These classical approaches are commonly used for the problem of optimising production under risk/uncertainty (Anderson, Dillion and Hardaker, 1977; Just and Pope, 2003; Kaiser and Messer, 2011; Rasmussen, 2006). In order for a well-defined function to exist, the decision-makers' risk preferences must satisfy three axioms, which are sufficient conditions for the expected utility hypothesis to hold true (Kaiser and Messer, 2011). Then, the expected utility hypothesis, or Bernoulli's principle, defines a utility function on risky prospects $U(y)$, which assigns a single real number utility value for each prospect, and has the following properties:

(1) If a_1 is preferred to a_2, then $U(a_1)>U(a_2)$, and vice versa, for all a_1 and a_2 in a, where a_1 and a_2 are risky alternatives.

(2) The utility of a risky prospect (a_j) is equal to the expected utility of its outcome, i.e. $U(a_j)=E\left[U(a_j)\right]$.

(3) The utility value of each risky prospect is assigned an arbitrary origin and unit of scale.

The expected utility hypothesis is, in its basic form, relatively general. To model uncertainty in the decision process, this approach usually specifies maximisation of expected utility as the major choice criterion (Hardaker *et al*., 1997; Kaiser and Messer, 2011; Quiggin, 2001). Therefore, the optimal act, a_j^* from maximising the expected utility (Hazell and Norton, 1986) is given by:

$$EU(a_j^*)=Max_j\, U(a_j^*) \qquad 2.1$$

Hence, the expected utility hypothesis ranks alternatives based on the probability of the state of nature occurring, and relative preferences regarding outcomes as represented in the utility function (Boisvert and McCarl, 1990; Haile, 2003). To use the expected utility hypothesis successfully, the utility function must be elicited (Anderson *et al*., 1997; Rasmussen, 2006).

2.2.2.1 Elicitation of utility function

The functional form that represents an individual's behaviour can be selected; this functional form also determines the risk preferences of the decision-makers (Rasmussen, 2006). The challenge is that there is no standard (or common) functional form that suits all decision-makers' preferences. Many researchers have attempted to find an appropriate functional form and estimate its parameters (Grové and Oosthuizen, 2010; Rasmussen, 2011). A number of successful attempts to elicit individual utility functions have been reported in the literature (e.g., Anderson *et al*., 1977; Rasmussen, 2006). Although eliciting a utility function for all practical problems involving uncertainty is not always achievable, many researchers choose a functional form that is computationally easy (Hazell and Norton, 1986).

To apply the expected utility approach to problems of optimisation under risk, assumptions about the utility functions have been limited to those that permit the decision problem to be formulated as a quadratic programming problem. A famous application is a functional form in which the expected utility model framework takes the form of the negative exponential function (Grové and Oosthuizen, 2010; Rasmussen, 2006), which expresses a quadratic utility function by assuming a normally distributed income, Y , and is expressed as:

$$U(Y) = 1 - e^{-\lambda Y} \qquad 2.2$$

Where $\lambda(\lambda > 0)$ is the Arrow-Pratt coefficient of absolute risk aversion. It assumes constant absolute risk aversion (CARA), which is not regarded as a desirable property (Hardaker *et al*., 1997; Rasmussen, 2006). Then, maximising expected income (wealth) is equivalent to maximising:

$$W(Y) = E(Y) - (\lambda / 2)V(Y) \qquad 2.3$$

Where $E(Y)$ and $V(Y)$ are the mean and variance of the income distribution. Other desirable functional forms are logarithmic (see Equation 2.4), have decreasing absolute risk aversion (DARA) (Rasmussen, 2006) and the power function (see Equation 2.5) (Grové and Oosthuizen, 2010; Rasmussen, 2006):

$$U(Y) = ln(Y) \qquad 2.4$$

$$U(Y) = (1 / (1 - r))Y^{(1-r)} \qquad 2.5$$

Where r is the Arrow-Pratt coefficient of relative risk aversion, i.e. $r = Y\lambda$. Similar to the logarithmic function, the power function also has DARA and constant relative risk aversion (CRRA). In addition, the quadratic function $V(Y) = Y - bY^2$ has been used extensively in risk analysis, since it implies an expected profit and variance utility function (E-V utility function), i.e. $W(Y) = E(Y) - hV(Y) - h\left[E(Y)\right]^2$. It is important to note that agricultural producers are generally risk-averse, and they try to minimise the risk for a given level of expected outcome (Grové and Oosthuizen, 2010).

2.2.2.2 Challenges to expected utility modelling

The expected utility hypothesis has been the procedure that has found wide application for solving problems of risk/uncertainty (Boisvert and McCarl, 1990; Chambers and Quiggin, 2000; Chavas, 2008; Kaiser and Messer, 2011; McCarl and Spreen, 1997). However, the expected utility model has experienced severe criticism in the past few decades (Crean *et al*., 2013). First, the expected utility model formulated to deal with production under risk/uncertainty was severely criticised by Chambers and Quiggin (2000), and their stand has been supported by a number of studies (e.g. Chavas, 2008; Rasmussen, 2006; Shankar, 2013). These researchers claim the expected utility model fails to provide an accurate representation of individual risk preferences. The main problem is that the traditional approach does not consider the interaction between the uncontrolled (uncertain) variables and the decision variables controlled by the decision-maker (Chavas, 2008; Rasmussen, 2003). Secondly, on the basis of empirical research, Just and Pope (2003) assert that risk studies have failed to identify risk behaviour clearly enough, or in the context of models that are broad enough, to convince the bulk of risk researchers. A detailed discussion with good examples that support the arguments that the majority of risk studies were not successful is provided in the review research paper of Just and Pope (2003).

Since risk is an important consideration in agricultural decision-making, researchers are constantly investigating better alternative approaches to presenting and quantifying risk. Hence, the literature suggests a variety of techniques for analysing production under uncertainty, and these approaches will be discussed in Section 2.2.3.

2.2.3 Techniques to characterise risk in decision-making

According to Chambers and Quiggin (2000) there are two approaches to risk modelling: the PD approach and the SC approach. The two approaches are discussed next.

2.2.3.1 Parameterised distribution formulation

Simply defined, risk means decision-makers do not use resources as efficiently as they would have if they had had information about conditions in the coming season (Crean *et al*., 2013); risk implies uncertain future income consequences as a result of current choices made. Chambers and Quiggin (2000) categorise all competing approaches to production under uncertainty in which decisions are modelled as choices between random variables indexed by input (effort) levels, or between probability distributions over a finite set of possible outcomes, often confusingly referred to as states, as the PD approach.

According to the expected utility theory, maximising expected utility is the ultimate target of choices made in uncertain situations (Grové and Oosthuizen, 2010; Kaiser and Messer, 2011). Hurley (2010) lists three major components of expected utility: the possible outcomes (income), the likelihood of possible outcomes, and the utility of possible outcomes. Using these three components Hurley (2010) defines expected utility based on a PD approach as (Equation 2.6):

$$EU(x)=\int_{\underline{c}}^{\bar{c}} U(c) f(c|x) dc \qquad 2.6$$

Where c is a continuous random variable, bounded by $\bar{c}$ from above and $\underline{c}$ below to represent a set of mutually exclusive outcomes; x refers to an individual's choice over alternative activities that affect the distribution of outcomes; $U(c)$ is the utility outcome c; and $f(c|x)$ is an individual's subjective perception about the likelihood of outcome, c, given the choice of x.

For the past several decades, the PD approach has been the main tool used to determine optimal input use in production under uncertainty (Kaiser and Messer, 2011). The most popular PD approach is the one proposed by Just and Pope (1978), namely, the stochastic production approach, of which the main idea is to derive the first-order conditions for optimisation and use the implicit function theorem to describe comparative static responses to changes in parameters, such as average price level (Shankar, 2013). The specification enables inputs to increase or decrease the risk of production. However, even if the error function is expanded to include relative effects of each input, the assumptions used to parameterise the model imply that the inputs used did not change (Moss, 2010).

Several researchers have criticised the PD approach to risk analysis (Rasmussen, 2011). The main problem is that the PD approach typically fails to consider the interaction between the uncontrolled (uncertain) variables and the decision variables controlled by the farm manager. Hence, some authors (Hurley, 2010; Just and Pope, 2003) discuss other modelling approaches (such as prospect theory, SC approaches, adding psychological variables) that have the potential to explain anomalies observed. However, these new modelling approaches have not been investigated with data on decision-making observed in agriculture. The SC approach developed by Chambers and Quiggin (2000) is envisaged to be the right tool to analyse risk in agriculture. This approach analyses production uncertainty using the tools of conventional production theory (Hardaker *et al*., 2015).

2.2.3.2 State-contingent approach

The SC approach is a theory that has been revived by Chambers and Quiggin (2000). This approach is more general than the conventional stochastic production model for describing and analysing production under uncertainty (Crean *et al*., 2013; Rasmussen, 2003; Shankar, 2013). Debreu (1952) and Arrow (1953) are credited with originally developing this model; they developed a simple idea of SC commodities in the context of general equilibrium theory. Using the modern approach to producer and consumer theory, Chambers and Quiggin (2000) show that the SC approach, with a dual approach to production economics, adds a new dimension to modelling risk. In the SC approach, the likelihood that a state of nature will occur determines the outcome associated with input decisions. The approach characterises individuals' perceptions according to the occurrence of the state of nature, rather than variation in the outcome variable. Accordingly, Hurley (2010) expresses the SC expected utility as follows:

$$EU(x)=\int_{\underline{s}}^{\bar{s}} U\left(c\left(x|s\right)\right)f\left(s\right)ds \qquad 2.7$$

Where S is a continuous random variable bound by $\bar{s}$ from above and $\underline{s}$ below to represent a mutually exclusive set of SC outcomes; $c\left(x|s\right)$ is the level of outcome from choice x given state of nature s. $f\left(s\right)$ is the decision-maker's subjective beliefs about the likelihood of state of nature s.

If the SC approach is used to model risk, then the farm manager is capable of responding to different states of nature (e.g. weather) by adjusting the input levels in every state. This capability is measured in Equation 2.7 by the term $U\left(c\left(x|s\right)\right)$, in which the utility U is conditional on input choice in a given state of nature s. Hence, the SC approach gives the farm manager the capability to respond actively to uncertainty – exploitation of the opportunity offered by uncertainty is possible. Implying that when the SC approach is used the decision-maker is able to respond to differences in the states (e.g. rainfall) by changing input levels in every state. On the other hand, the $f\left(s\right)ds$ term represents the likelihood of chance outcomes within a SC framework; implying that a farm manager's choices cannot affect the likelihood of chances (Matthews, 2014). In the next section, the theory underlining SC approach will be discussed.

2.2.4 State-contingent theory

SC theory proposes presenting production under uncertainty as a multi-output technology, with a set of possible states of nature expressing uncertainty. The theory is essentially a new way of quantifying the relationship between inputs and outputs in the presence of production uncertainty. Therefore, it provides researchers with an alternative and better means to consider all problems of uncertainty in a new dimension (Crean *et al*., 2013). Accordingly, the relationship that is exhibited between inputs and outputs in a given production process depends solely on the state of nature that finally eventuates, instead of the relationship being fixed across states (Chavas, 2008). This means that decision-makers choose from a set of technologies rather than a single expected season (Quiggin and Chambers, 2006). Hence, the theory emphasises that problems involving uncertainty should be formulated in the form of SC production function for all states of nature (Chambers and Quiggin, 2002). Once the SC production functions have been expressed, then all the techniques and principles of marginality established for non-stochastic production economics could be implemented to decision-making processes under the occurrence of uncertainty (Hardaker *et al*., 2015; Quiggin, 2001; Rasmussen, 2011). Accordingly, the SC approach to production requires only the derivation of the appropriate marginal conditions to determine the optimal choices for a range of formulations (Hardaker *et al*., 2015).

The SC theory establishes the foundational criteria that apply for decision-making under uncertainty (Rasmussen, 2011). Defining the appropriate states of nature and production technology, and establishing optimality conditions for alternative input classification, are the essential steps of applying the theory to practical problems under uncertainty. A brief discussion of states of nature, production technology, and classifications of SC inputs are discussed in the following sections.

2.2.4.1 State of nature and production technology

The general SC approach to production decision-making under uncertainty proposed by Chambers and Quiggin (2000) is based on N inputs, M distinct outputs, and S possible states of nature. To reduce the complexity and to increase understanding of the approach, Rasmussen (2003) presents the concepts of the approach by assuming the production of only one output, Q. Sets of states of nature (Ω) are needed to describe the uncertain production conditions (Equation 2.8). From these sets of states of nature, "nature" selects the state of nature independently of the decisions made by the decision-maker.

$$\Omega=\{1,2,...,s,...,S\} \qquad 2.8$$

Let $x=(x_1,...,x_N)$ be an input vector with corresponding input prices $w=(w_1,...,w_N)$. The cost computation, Ct , in the approach is done as shown in Equation 2.9. Note that nature picks the state of nature after the farm manager has already committed his/her production decision on the amount of input, x , to apply.

$$Ct = (W')x \qquad 2.9$$

Subjective probabilities (p_s) that nature will pick the s[th] state of nature ($s = 1,...,S$) are required about the decision-maker's belief regarding the occurrence of a given state of nature s (Equation 2.10).

$$p_s = (p_1,...,p_s,...,p_S) \qquad 2.10$$

Following the SC approach, the decision-maker chooses the *ex ante* input-output combination (x , Q), and there will be an *ex post* output, which is represented as Q_s . The relationship that exists between committed inputs and the realised outputs in a given state of nature is formulated best using a production technology as shown in Equation 2.11. Hence, depending on the state of nature realised, the production of output in a given state s (Q_s) is captured by a transformation function (Equation 2.11), in which Q denotes a vector of SC outputs $(Q_1,...,Q_S)$. The output in a state of nature s (Q_s) is calculated as shown in Equation 2.12.

$$T(x,Q) = 0 \qquad 2.11$$

$$Q_s = max\{Q_s : T(x,Q) \leq 0\} \qquad \forall s \in \Omega \qquad 2.12$$

Hence, depending on the state of nature, there is a specific (i.e. SC) production technology (function). This point illustrates that *ex post* only one state of nature occurs. If a SC output price is given as Pr_s , then revenue (r_s) and net return (y_s) are computed as shown in Equation 2.13 and Equation 2.14. The net return is the difference between revenue and cost.

$$r_s = z_s Pr_s \qquad \forall s \in \Omega \qquad 2.13$$

$$y_s = r_s - Ct \qquad \forall s \in \Omega \qquad 2.14$$

Then, utility for the farm decision-maker is captured as shown in Equation 2.15. It is assumed that the utility is a non-decreasing function EU of the SC vector of net returns $y = (y_1,...,y_S)$.

$$EU = EU_s(y_1,...,y_s) \qquad 2.15$$

According to the SC approach, various inputs in the production process are decided prior to the occurrence of the state of nature. Hence, the total combination of inputs is the same in every state of nature, while outputs are related only to the specific state of nature that occurs later, which implies that a decision-maker's selection of a certain combination of inputs over another has the same meaning as looking forward over the season and selecting one output matrix over another. Such ability demonstrates that the decision-maker makes an economic choice to control the degree of variability in outputs, giving the decision-maker some opportunity to control it (Crean *et al*., 2013).

2.2.4.2 Classification of state-contingent inputs

The SC approach to uncertainty can be applied in an optimisation framework using the criteria for optimal production developed by Rasmussen (2003), provided that a production function is defined for each state of nature. The SC production functions can be used to derive the transformation curve (Rasmussen, 2011). Provided appropriate SC production functions for a random variable could be formulated, the principles of expected utility theory can be used to aid decision-making for irrigated land (Hurley, 2010; Quiggin and Chambers, 2006). In addition, deriving criteria for input use depends on having an exact form of the utility function for the decision-maker under consideration (Rasmussen, 2011).

Deriving criteria for a risk-averse farm manager is usually difficult, because formulating the exact utility function for this type of decision-maker is not straightforward (Rasmussen, 2011). For a risk-neutral farm manager, a linear utility function can be used to derive criteria for optimal input use without difficulty. For a risk-averse farm manager, specific criteria cannot be provided. However, it is possible to drive conditions that show whether a risk-averse decision-maker will use more or less input than a risk-neutral decision-maker – Rasmussen (2003) developed optimal input-use criteria that are based on these descriptions. Classification of states of nature as "good" and "bad" is a critical step in developing criteria. A subjective approach, which depends on the decision-maker's risk preference, is used to define a "good" or "bad" state of nature.

Using the conditions of a risk-neutral decision-maker as the benchmark, Rasmussen (2003) compares the actions of risk-averse and risk-neutral decision-makers. The definitions of "good" and "bad" states of nature require assumptions about utility functions. Let's consider a risk-neutral decision-maker who optimises production using the input vector x_n. The decision-maker will have a utility of $EU_s(y_1,...,y_s)=p_1y_1+...+p_sy_s$ as a result of the SC outcome y_s, where p_s represents subjective probability for state of nature s. On the other hand, let $EU_s(y_1,...,y_s)$ be the utility function for a risk-averse decision-maker. Rescaling, as in Equation 2.16, is required, since the scale of the utility function is arbitrary.

$$\sum_{s=1}^{s} EU_s \left\{ y_1(x_n),...,y_s(x_n) \right\} \equiv 1 \qquad 2.16$$

This implies that the sum of the derivatives of $EU(y)$ with respect to y_s at the point $y(x_n)$ is equal to one. Using the scaling of the utility function shown in Equation 2.16, Rasmussen (2003) provides a definition of "good" and "bad" states of nature, shown in Equation 2.17 and Equation 2.18 respectively.

$$EU_s(y_1,...,y_s) < p_s \qquad 2.17$$

$$EU_s(y_1,...,y_s) > p_s \qquad 2.18$$

As such, a good state is defined as a state where a SC net income of ZAR 1 provides a lower marginal utility than the probability of the state of nature under consideration. On the other hand, in a bad state the SC net income of ZAR 1 gives a higher marginal utility than the probability of the state.

If the decision-maker is risk-neutral, Rasmussen (2003) defines the neutral state of nature as (Equation 2.19):

$$EU_s(y_1,...,y_s) = p_s \qquad 2.19$$

It is important to note that a specific input may yield different responses (output) to input-use decisions in different states of nature. Different inputs must be differentiated to drive optimality conditions (Rasmussen, 2003). The following section will present the optimality conditions for state-general, state-specific and state-allocable inputs. Rasmussen (2011) demonstrates the different procedures to be applied to optimise the input use in each of these input types.

2.2.4.2.1 State-general inputs

The first group of inputs, known as state-general inputs, require no specific assumptions placed on input use. Because the decision about how much input to use is made prior to knowing the state of nature, these inputs are referred as non-state-specific inputs by Chambers and Quiggin (2000). Hence, by definition, a state-general input is an input that influences production of an agricultural product in one or more, possibly all, states of nature. These inputs are applied with the aim of an overall increase in output, irrespective of the state of nature that prevails. A state-general input, x_n, can be formally defined as:

$$\frac{\partial f_s(x)}{\partial x_n} \neq 0 \qquad \text{for one or more states } (s \in \Omega) \text{ for some (relevant) level of } x_n. \qquad 2.20$$

Fertiliser use in grain production is a good example of a state-general input. Assume maize is the grain that is produced under two prevailing states of nature with the production of Q_1 in a "wet" year and the production of Q_2 in a "dry" year. The production functions in each state of nature and the transformation function for the maize production are shown in Figure 2.1. The transformation function is constructed using the production functions for each state of nature. It is important to note that the amount of maize production in one state of nature ("wet" year) is completely independent of the maize production in another state of nature ("dry" year), and depends solely on the amount of fertiliser x_n used in the farm land.

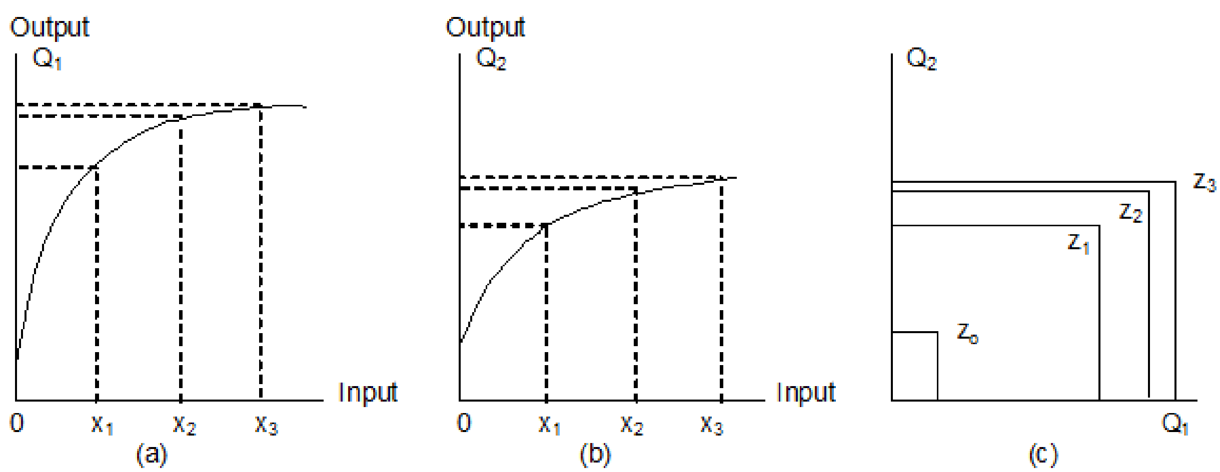


Figure 2.1: Deriving product transformation curve (c) using production functions (a and b) for state-general input use in a wet (Q_1) and dry (Q_2) state of nature

Suppose we consider four different levels of fertiliser input $(0, x_1, x_2, and\ x_3)$. Figure 2.1(a) illustrates graphically the maize production function ($Q_1 = f(x)$) in the "wet" year; while the maize production function ($Q_2 = f(x)$) is represented by Figure 2.1(b). The two states of nature use the same amount of fertiliser to produce maize yield and the input amount is decided before the state is known. However, maize yield achieved will differ between the states due to the state of nature effect, although the same quantity of fertiliser input is applied. A transformation function (Figure 2.1(c)) can be derived using these two production functions for the given four levels of fertiliser use, which shows four combinations of SC output (z_0, z_1, z_2, z_3). The derivation of the transformation function is possible, because the amount of fertiliser applied is the same regardless of the state of nature. Note that the amount of fertiliser that must be applied is decided on before the state is known. Rasmussen (2011) shows how to derive the transformation function for each fertiliser level by determining a slope for the transformation function. The rate of substitution is determined by calculating how much more of product Q_2 can be produced if one less of product Q_1 is produced. It should be clear that the concept rate of substitution is a situation involving either/or, and no substitution of Q_2 by Q_1 exists – this is because decisions cannot be changed after the state of nature is known, because the production decision had been made in advance (Matthews, 2014).

2.2.4.2.2 State-specific inputs

A state-specific input can be considered as a special case of a state-general input. An input applied to influence production of an output in only one state of nature is known as a state-specific input. Accordingly, the formal definition of a state-specific input x_n is (Rasmussen, 2003):

$$\frac{\partial f_t(x)}{\partial x_n} > 0 \text{ and } \frac{\partial f_s(x)}{\partial x_n} = 0 \text{ for } s \neq t \text{ for some (relevant) level of } x_n . \quad 2.21$$

Where $f_t(x)$ is the production in an alternative state of nature.

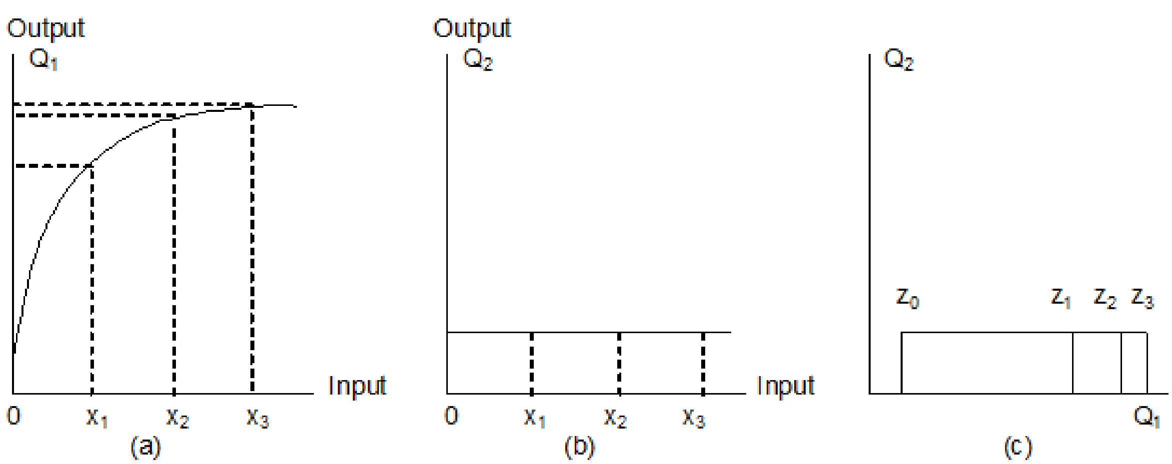


Figure 2.2: Derivation of product transformation curve (c) using production functions (a and b) for state-specific input use in a wet (Q_1) and dry (Q_2) states of nature

Let's assume a spray can provide protection against fungal infection during maize production. Though maize production takes place in either a "wet" year (Q_1) or "dry" year (Q_2), the fungicide is only effective in a "wet" state of nature. The farm manager applies the spray beforehand without knowing which state of nature will occur. The maize production functions for each state of nature and the associated transformation function for the state-specific spray input is shown in Figure 2.2.

Accordingly, Figure 2.2(a) represents the production function for maize ($Q_1 = f(x)$) in the "wet" state of nature due to the application of the fungicide. If the state of nature is "wet", then an increase in the application of fungal spray will correspond with an increase in maize production. On the other hand, if the state of nature is dry, the application of the fungal spray will have no effect on the level of maize output, as shown in Figure 2.2(b). Figure 2.2(c), which represents the transformation function for the state-specific input, is derived by combining the production functions for the two states of nature. The four levels of fungal spray $(0, x_1, x_2, \text{and } x_3)$ correspond to SC maize output levels (z_0, z_1, z_2, z_3). The transformation function demonstrates that application of fungicide spray will have no effect on the level of maize production in the case of a dry state of nature (Rasmussen, 2011).

2.2.4.2.3 State-allocable inputs

A state-allocable input is an input that may influence output in two or more states of nature and can be allocated to different states of nature. State-allocable input therefore avoids the problem of inefficiency that could arise due to the assumption of free disposability. Besides, it is possible to consider a state-allocable input as the sum of two (or more) state-specific inputs. The farm manager makes *ex ante* decisions on state-allocable inputs. Rasmussen (2003) provides a formal definition of a state-allocable input, x_n, as:

$$\frac{\partial f_s(x)}{\partial x_{ns}} \text{ for two or more states } (s \in \Omega) \text{ for some (relevant) level of } x_n \qquad 2.22$$

Where x_{ns} is the amount of input x_n allocated (*ex ante*) to the s^{th} state of nature.

A good example is the available amount of labour a farm producer has to either improve an irrigation-system or improve a drainage system, both of which will ultimately affect maize production. If the state of nature is a "wet" year (Q_1) labour allocated to improve the drainage system will increase yield, since draining water will reduce the occurrence of water logging of the soil (Chambers and Quiggin, 2000). On the other hand, if the state of nature is a "dry" year (Q_2) labour allocated to improve the irrigation-system will result in increased maize production by reducing water stress on the crop. It is assumed that an improvement will have no effect if the opposite state of nature unfolds after the decision has been made. That is, improving drainage will have no effect during a “dry” season, and improving the irrigation-system will have no effect during a “wet” year. The production functions and transformation function for the case of state-allocable input is given in Figure 2.3.

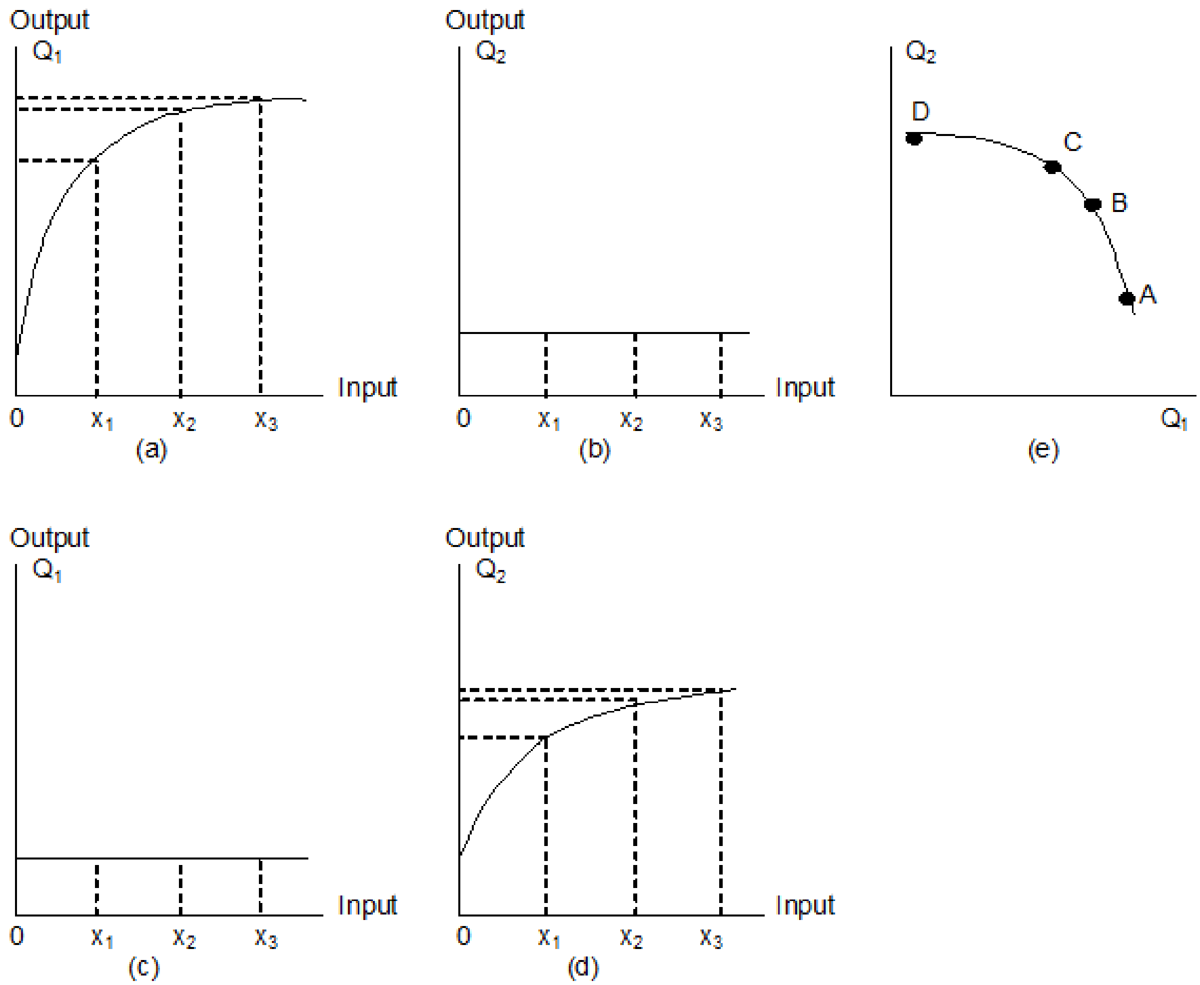


Figure 2.3: Derivation of product transformation curve (e) using production functions for state-allocable input use in a “wet” (Q_1) and “dry” (Q_2) states of nature

As discussed above, assume we have labour that should be used to improve either the drainage system or the irrigation-system. First, assume the farm manager decides to improve the drainage system. If the state of nature is “wet” (Q_1), then the farmer can achieve a higher maize output if excess water is drained from the root zone (Figure 2.3(a)). However, if the state of nature is “dry” (Q_2), the farmer's allocation of labour to improve the drainage system will have no effect on maize output level (Figure 2.3(b)). On the other hand, the farmer may decide to allocate the available labour to improve irrigation-systems. Figure 2.3(c) depicts the production function of maize if a "wet" year prevails – the improved irrigation will have no effect on the level of maize output. If a "dry" year is the state that unfolds after the decision making process, then there will be an increase in maize yield due to the improved irrigation-system (Figure 2.3(d)). The resulting transformation function, shown in Figure 2.3(e), shows all possible allocations of labour to improve maize production. Point A in Figure 2.3(e) shows the SC output that can be achieved if the farmer allocates all the labour available to improving the drainage system. The opposite SC output, i.e., allocating all labour to improving the irrigation-system, is represented by Point D. All other allocations of labour between the two types of investment are represented along the transformation curve as Points B and C. The transformation curve, therefore, shows the possibility of substitution between SC outputs for state-allocable inputs (Rasmussen, 2011).

2.2.4.2.4 Representation of optimal input choice

Consider a single input, namely, fertiliser, and assume that fertiliser input is a continuous decision variable that requires the determination of the optimal input level. To obtain the optimal input level of fertiliser, it is essential to estimate SC production functions, measuring the impact on yield of different fertiliser rates contingent upon the state of nature that unfolds. In principle, at least, it may be possible to estimate SC production functions for several states. But, to explain the procedure and to simplify the approach required, a graphical approach could be followed for only two states of nature ("wet" and "dry" years).

Choosing a negative exponential utility function with a coefficient of absolute risk aversion r_a, iso-utility contours can be obtained for a risk-averse decision-maker. There are two production functions, $Q_1 = f(x)$ and $Q_2 = f(x)$, for the "wet" and "dry" year, respectively. With the right assumptions about price of crop, price of input, other variable costs and area, it is possible to convert the two production functions into net revenue functions for each of the two states of nature and to copy the results into state space, as shown in Figure 2.4. Let's assume that the locus of net revenue values depicted in Figure 2.4 is similar to a production possibility set of two outputs. Then, the optimal input level is located at the point of tangency between the iso-utility contour and the locus of net revenue functions (see Optimum point in Figure 2.4) (Hardaker *et al*., 2015).

In real irrigation problems, a number of states and more than one decision variable (inputs) are involved in the decision-making process. Hence, the SC approach to production involves the optimal choices for a range of SC functions (Hardaker *et al*., 2015). The optimisation process requires us to derive the appropriate marginal conditions using a mathematical approach. Besides, the optimisation problem requires defining an appropriate objective function. Deriving the appropriate marginal conditions to obtain the optimal choices for a range of formulations for an optimisation problem in an SC approach using mathematical programming applications is provided in Rasmussen (2003; 2011).

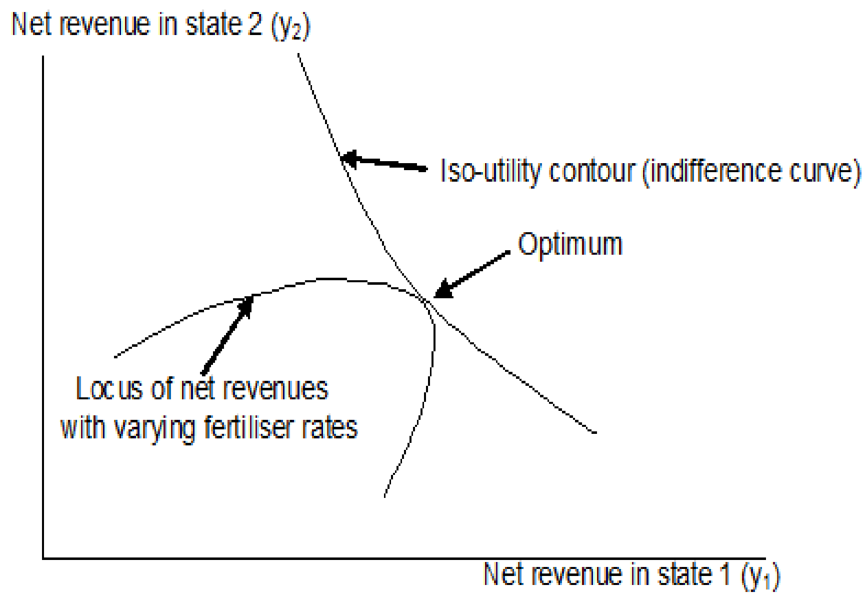


Figure 2.4: Representation of optimal choice of an input in state space

2.2.4.3 Discussion and conclusions

In recent years a number of researchers in the field of risk analysis have reached the conclusion that the PD approach does not allow the decision-maker to explore uncertainty appropriately in order to benefit from the opportunities that uncertainty offers to the decision-maker (Hurley, 2010; Just and Pope, 2003; Rasmussen, 2011). However, the SC approach, as an alternative approach to risk modelling, has the advantage over the PD approach in that it explicitly considers the interaction between controllable inputs and uncontrollable inputs (the uncertain states of nature). Basically, the two types of approaches differ in the means of characterising the outcome distribution. In the SC approach, state of nature is the basis for characterising the distribution of the outcome variable, whereas, in the PD approach, choice of the input variable is the basis for characterising the distribution of the outcome variable. Hence, the state of nature, not the individual choices, determines the likelihood of a chance outcome when using the SC approach. As explained by Quiggin (2001), the SC approach maps a set of states of nature to a set of outcomes, whereas the PD approach usually intermingles probabilities of state of nature with the technology of production, which creates confusion that should not be ignored. In comparison, production under uncertainty can be modelled more realistically with the SC approach than the PD approach, because the SC approach can handle factors external to the decision-maker better.

It is important to note that most literature on the application of the SC approach to optimisation problems use transformation functions to aid decision-making under uncertainty (Rasmussen, 2011). However, Hardaker *et al*. (2015) demonstrate that the application of the SC approach to optimisation can be done without the use of transformation functions. Accordingly, the researchers point out that SC production functions can be used directly to quantify the distribution of risk over states of nature. Hence, by using only SC production functions, it is possible to characterise the risk of the outcome variable contingent on state of nature, and to incorporate the SC functions in an optimisation framework to determine risk-efficient input decisions using a direct expected utility-maximisation approach.

The empirical application of the SC approach, however, poses a number of challenges to characterising risk using SC production functions (Griffiths and O'Donneli, 2004; Rasmussen, 2006). The challenges are related to identifying the possible S states, choosing the S functional forms of the production functions, and estimating them. In the ideal case the data set (output levels for all levels of input use) should include observations of all S states, as is required for estimation of the SC production functions (Chavas, 2008; Quiggin and Chambers, 2006; Rasmussen, 2007; Shankar, 2013). However, data sets for real farms are aggregated and do not have observations for all states of nature (Quiggin and Chambers, 2006). In such cases, Monte Carlo simulation could be used to generate an artificial, uncertain production environment based on Cobb Douglas production functions by using SC parameters (Rasmussen and Karantininis, 2005). An important fact that helps to identify states of nature is the point stressed by Rasmussen (2006), that typical SC variables, such as sunshine, rainfall and temperature, are not independent variables. For practical purposes, Matthews (2014) and Rasmussen (2011) suggest combining state variables and assuming that a production year could be taken to represent a state of nature.

The next section will present transient-state soil-salinity models to simulate the impact of salinity on yield of crops, soil salinity, and salt return flows.

2.3 TRANSIENT-STATE SOIL-SALINITY CROP MODELLING

Steady-state mathematical models are based on the assumption that the soil water content and salinity at given points in time and space will remain constant and generally require constant continually flow (Letey and Feng, 2007; Letey, Hoffman, Hopmans, Grattan, Suarez, Corwin, Oster, Wu and Amrhein, 2011). Steady-state models provide an unrealistic representation of real-life situations where dynamic interactions between water and salt balances determine crop growth (Letey *et al*., 2011). Hence, transient-state mathematical models that allow for most or all of the variables encountered in the field and that determine soil salinity and plant response due to irrigation being time dependent, are preferred. In general, transient-state mathematical models allow for water and salt flow in irrigated water table soils, and the corresponding response of different crops to matric and osmotic stress, due to variable rainfall, irrigation, evaporation, transpiration and WTU. Some transient-state models will also allow for the chemistry of major dissolved ions in soil water to provide an approach to account for cation exchange, mineral dissolution and precipitation. The effect of salinity, sodicity and pH on hydraulic conductivity and hence water flow can also be simulated.

Literature provides numerous transient-state models to choose from, which include ENVIRO-GRO (Feng, Meiri and Letey, 2003), SWAP (Van Dam, Groenendijk, Hendricks and Kroe, 2008), HYDRUS (Šimůnek, Van Genuchten and Šejna, 2008), UNSATCHEM (Suarez and Šimůnek, 1997), SALTMED (Ragab, Malash, Abdel Gawad, Arsian and Ghaibeh, 2005), SWB (Annandale, Benade, Jovanovic, Steyn and Du Sautoy, 1999) and SWAMP (Barnard *et al*., 2015; Bennie *et al*., 1998). The aim of this section is not to provide a comprehensive review of all transient-state models, but rather show some of the general approaches adopted by these models and highlight differences between the SWAMP and some of the popular models mentioned above. The SWAMP model receives special attention, because it is a locally developed model that has been validated in the research area (Ehlers *et al*., 2007; Van Ransburg *et al*., 2012).

A transient-state model can be characterised by the way it models soil water flow, plant yield and transpiration, and salt flow. The next sub-section will focus on these points.

2.3.1 Soil water flow

Soil water flow models can be grouped into two, namely, simple and complex, depending on the degree of complexity followed in modelling the soil profile. Complex transient-state models (e.g. ENVIRO-GRO, SWAP, HYDRUS, UNSATCHEM, and SALTMED) consider the soil profile to be continuous, and to simulate water flow, while simultaneously considering crop water uptake functions, following the basic equations for hydraulic and hydrodynamic behaviour of water through a porous soil medium. These models are capable of simulating downward water movement and upward flow of water due to capillary rise from a shallow water table. They depend on numerical solutions to solve Richard's equation for soil water flow (Barnard *et al*., 2015; Van Rensburg *et al*., 2012) and require water retention ($\alpha(h)$) and hydraulic conductivity functions ($k(h)$) for a specific soil. The parameters that normally describe these functions include the saturated hydraulic conductivity (φ_s), residual (θ_r) and saturated volumetric soil water content (θ_s), and empirical ς, ξ and α parameters.

On the other hand, simple soil water models (e.g. SWAMP and SWB) have a fixed number of soil layers and a cascading (tipping bucket) approach to water movement or redistribution of rainfall and irrigation. These models require parameters such as initial volumetric soil water content (θ_{Start}) of each soil layer, the volumetric soil water content at field capacity (θ_{fc}, drain upper limit or upper limit of plant available water), and permanent wilting point (θ_{pwp}, lower limit of plant available water) (Barnard *et al*., 2015).

2.3.2 Plant modelling

2.3.2.1 Growth and yield

Some of the transient-state models (e.g. SWAP, SALTMED, and SWB) use a plant-growth subroutine, in various degree of complexity, to estimate growth and yield of field crops and to allow for some or all of the growth-defining and growth-limiting factors. However, SWAMP is one of the transient-state models that do not simulate plant growth per se. The model simulates water uptake and then relates the seasonal uptake to seasonal potential uptake to calculate the relative yield. Plant characteristics and climatic factors are the only factors that determine the potential uptake, which refers to non-limiting water supply from the soil profile. The potential uptake is the product of potential transpiration (T_P) rate and a normalised root distribution function ($\beta(z)$), of which a variety of functions can be chosen to represent it (Barnard *et al*., 2015).

2.3.3 Potential evaporation and transpiration

Most of the transient-state models compute the potential evapotranspiration (ET_P) using crop factors and a reference evapotranspiration (ET_O), which is a hypothetical clipped cool-season grass with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1} and an albedo of 0.23. The reference surface closely resembles an extensive surface of green, well-watered grass of uniform height, actively growing and completely shading the ground. The approach of FAO 56 (Allen, Pereira, Raes and Smith, 1998) is adopted to compute ET_O using routinely measured weather data, such as air temperature, global radiation, wind speed and relative humidity. Then, most of the transient models separate ET_P into potential evaporation (E_P) and potential transpiration (T_P) by using either the leaf area index or soil cover. However, SWAMP simulates T_P using a different approach, as proposed by De Wit (1958), in which T_P is related to maximum biomass production with a crop-specific parameter (ς) and the mean ET_O over the growing season. The approach requires information to be provided on the potential seed yield of the crop. Then, the potential seed yield of the crop is used to compute maximum biomass production using a harvest index (HI).

2.3.3.1 Actual transpiration and root water uptake

Although models like SWAP can also allow for a microscopic approach to root water uptake, most of the transient-state models follow a macroscopic approach. In macroscopic approach water uptake is averaged over a large number of roots (Barnard *et al*., 2015 citing Skaggs *et al*., 2006). Generally, in using the macroscopic approach, the sink terms for water uptake in Richards's equation are computed from the potential uptake and a dimensionless water stress response (reduction) function, usually known as Type II formulations (Barnard *et al*., 2015 citing Cardon and Letey, 1992). The formulations are empirical functions that relate water uptake by the crop based on a response to water potential. In general, a dimensionless water stress response function (α, reduction function) must be defined for matric and osmotic stress, where h is the pressure head and π the osmotic head. Either a piecewise linear or alternative smooth S-shaped reduction function can be used to compute $\alpha(h)$, using adjustable parameters to reduce water uptake according to critical pressure heads. For $\alpha(\pi)$ the Maas and Hoffman threshold and slope parameters (Maas and Hoffman, 1977) can be used for the same piecewise linear or alternative smooth S-shaped reduction functions (Barnard *et al*., 2015). Either an additive or a multiplicative approach can be used to combine matric and osmotic stress. The salinity threshold and slope parameters for $\alpha(\pi)$ should, however, be used with caution, because determining these parameters from literature remains a challenge. According to Skaggs *et al*. (2006), as summarised by Barnard *et al*. (2015), “this is because crop salt tolerance information (salinity threshold and slope) serves only as a guideline. Absolute tolerance will vary, depending on climate, soil conditions and agronomic practices. Additionally, because studies fail to report environmental and agronomic factors affecting yield, crop salt tolerance determined with this insufficient data will be biased. An added difficulty is that parameters for these reduction functions are parameterised at local total potential heads, while salinity threshold and slope parameters express salt tolerance at a time and root zone average soil salinity".

SWAMP does not depend on the well-known Maas and Hoffman (1977) threshold and slope parameters for the piecewise linear or S-shaped reduction functions. Water uptake due to osmotic stress is simulated with an algorithm that computes the water supply of a rooted soil layer. Soil-root conductance, relative soil water content, rooting density and the soil-root hydraulic gradient are some of the parameters that determine the supply of water. The crop will not be stressed, provided there is an adequate supply of water. Reduction in water uptake can occur if the demand from the crop (potential transpiration) is not satisfied due to a decrease in soil water content and/or increases in soil salinity.

2.3.3.2 Salt transport

The convection-dispersion equation is the procedure applied to calculate salt transport in complex soil water models. Generally, salt uptake by plants is assumed to be negligible. However, in a simple model like SWAMP, the cascading approach to salt transport is the basic principle followed: leaching curves (Barnard *et al*., 2015) are used to determine the relationship between the fraction of salt removed per unit soil depth and volume of percolation per unit soil depth. Soil texture and sodicity status will determine the empirical leaching curves to be used in these models (Barnard *et al*., 2015; Van Rensburg *et al*., 2012).

2.3.4 Discussion and conclusions

SWAMP is a simple, local model that can be used to simulate water and salt flow within a soil profile that is due to rainfall, irrigation, evaporation, transpiration, drainage and WTU. SWAMP is capable of estimating the consequent effect of matric and osmotic stress on crop yield dynamically over the growing season. It does not depend on the Maas and Hoffman (1977) parameters to model osmotic stress, and requires easily obtainable inputs (initial and boundary conditions). Estimating crop yields as affected by salinity and water stress is highly dependent on the transient state of water and salt balances, as well as the interaction between these balances. Consequently, estimating SC production functions using the output of SWAMP may not capture the necessary detail of the transient state necessary to optimise irrigation decisions under saline water conditions. Hence, it could be difficult to develop and solve a mathematical programming model that retains the necessary complexity to optimise irrigation decisions under saline water conditions while considering the transient-state model.

Alternatives to mathematical programming methods to optimise irrigation salinity management options while retaining the complexity of transient-state models are explored in the following sections.

2.4 PARADIGM SHIFT IN IRRIGATION OPTIMISATION

Optimisation is a well researched and recognised tool in operational research for assisting irrigation-management decision-making (Elsayed, Sarker and Essam, 2014; Haupt and Haupt, 2004; Spall, 2003; Sarker and Ray, 2009) and improve problem understanding (Maier, Kapelan, Kasprzyk, Kollat, Matott, Cunha, Dandy, Gibbs, Keedwell, Marchi, Ostfeld, Savic, Solomtatine, Vrugt, Zecchin, Minsker, Barbour, Kuczera, Pasha, Castelleti, Giuliani and Reed, 2014). Maier *et al*. (2014) point out clearly that decision-making is not an easy task, as it is highly subjective and dependent upon the decision-makers' views of what constitute good decisions. Optimisation helps to determine better management strategies, develop better designs and operational regimes, calibrate simulation models better, and solve conflicting interests among divergent stakeholders in irrigation-related issues (Maier *et al*., 2014). Haupt and Haupt (2004) define optimisation as the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment, to find the minimum or maximum output or result. Optimisation could be applied to simple problems as well as to many naturally complex real-world problems (Elsayed *et al*., 2014; Louati, Benabdallah, Lebdi and Milutin, 2011).

A multitude of optimisation methods for solving real irrigation problems are reported in the literature (Haq and Anwar, 2010; Maier *et al*., 2014). In general, the available optimisation tools can be grouped roughly into two groups, namely, conventional and computational intelligence techniques (Haupt and Haupt, 2004). The conventional methods include useful tools, such as LP (Armour and Viljoen, 2002; Viljoen, Dudley and Gakpo, 2000), dynamic LP (Grové, 2008; Haile, Grové and Oosthuizen, 2003), nonlinear programming (Matthews *et al*., 2010; Venter, 2015). The main focus of conventional optimisation tools is the attainment of optimal solutions. Solving problems requires the mathematical representation of the problem within a constrained optimisation framework. Optimality conditions are applied to determine the optimal level of decision variables. However, detailed representation of complex irrigation-scheduling problems results in non-linearities and discontinuous functions (Venter, 2015), which complicate the application of optimality conditions to achieve global optimal solutions. Consequently, conventional methods cannot guarantee global or near-global solutions, since such problems are often difficult and tedious to solve, as they exhibit non-linearity, high dimensionality, and multimodality (Elsayed *et al*., 2014; Kerachian and Karamouz, 2007; Maier *et al*., 2014; Sivanandam and Deepa, 2008). Hence, computational intelligence techniques, such as EAs, genetic algorithms (GA), and simulated annealing (Farmani, Abadia and Savic, 2007; Haupt and Haupt, 2004; Kerachian and Karamouz, 2007; Maier *et al*., 2014; Schütze *et al*., 2012), are suggested for solving very complex irrigation-optimisation problems.

A computational intelligence technique suggested for irrigation problems is EA (Elsayed *et al*., 2014). EAs are natural optimisation tools that could achieve near-global and/or optimal solutions (Nicklow, Reed, Savic, Dessalengne, Harrell, Chan-Hiton, Karamouz, Minsker, Ostfeld, Singh and Zechman, 2010; Spall, 2003). Over the past years EAs have been explored more and more to find solutions for both real irrigation problems and theoretical problems (Elsayed *et al*., 2014; Johns, Keedwell and Savic, 2014; Maier *et al*., 2014; Nicklow *et al*., 2010). EA could be formulated as an optimisation procedure with an objective function (fitness function) that may have one or a number of constraints that determine the feasible space to be searched (Sivanandam and Deepa, 2008). The popularity of EA as a tool for dealing with irrigation problems is due partly to the increase in computational power available in recent years (CarrilloCobo, Camacho Poyato, Montesinos and Rodriguez Diaz, 2014; Fernández Garcia, Rodriguez Diaz, Camacho Poyato and Montesinos, 2013). These tools have a number of advantages over traditional optimisation tools. Specific advantages include the simplicity of the approach in terms of operators and mathematical procedures used, its robust response to changing circumstances, the fact that it can use simulation models in easy steps, its flexibility, its suitability for parallel computing, its ability to achieve near-optimal or optimal solutions, and its applicability to a variety of complex problems (Maier *et al*., 2014; Nicklow *et al*., 2010; Sarker and Ray, 2009). The field of EA is still in the process of rapid development; it is gaining in complexity and exhibiting various degrees of desirability (Cai, McKinney and Lasdon, 2001; Sivanandam and Deepa, 2008).

Maier *et al*. (2014), in their recent review of EA, emphasise that the main objective of optimisation should be to explore the best alternative irrigation management strategies for investigating problems, rather than using optimisation solely to achieve optimal solutions to problems. In fact, a number of recent research papers (see Elsayed *et al*., 2014; Johns *et al*., 2014; Rajkumar and Thompson, 2002; Rana, Khan and

Rahimi, 2008) agree with Maier *et al*. (2014) that the most important goal of optimisation should be improvement of a solution – searching for the optimum is less important for practical complex systems facing irrigation decision-makers. Hence, these facts show that there is a paradigm shift in optimisation, from using conventional optimisation procedures to achieve an optimal solution, to using evolutionary techniques to obtain near-optimal or optimal solutions – this is the result of viewing the goal of optimisation to achieving better solutions to real-world problems (Spall, 2003), especially in situations that represent very complex problems.

The next section will discuss EA as a tool of optimisation for highly complex irrigation problems.

2.5 EVOLUTIONARY ALGORITHMS

Of the several optimisation procedures described in the literature, EA (also known as evolutionary computations) is one of the techniques that has been used extensively to address the problem of competing demand for scarce fresh water resources (Garg and Dadhich, 2014; Geerts and Raes, 2009; Maier *et al*., 2014; Schütze *et al*., 2012). Therefore, this section is devoted to a brief literature review in relation to the advancement of knowledge about EA.

2.5.1 Evolutionary algorithms in irrigation problems

2.5.1.1 Overview of evolutionary algorithms

EAs are a group of stochastic search and optimisation methods that mimic the fundamental principles of natural selection and natural genetics (Nicklow *et al*., 2010; Sivanandam and Deepa, 2008), and which rely heavily on "survival of the fittest", as espoused by Darwinist theory (Anwar and Haq, 2013; Rana *et al*., 2008). In natural selection, according to Rana *et al*. (2008), stronger individuals are likely to be the winners in an environment where several species compete for scarce natural resources. Hence, in EA, the strongest offspring in a given generation have a greater chance to survive and reproduce (Anwar and Haq, 2013; Lehmann and Finger, 2014; Sivanandam and Deepa, 2008). In fact, natural selection, as emphasised in a number of research papers (such as Haq and Anwar, 2010; Nicklow *et al*., 2010; Spall, 2003), is the main procedure used to explain why parents with suitable attributes of chromosomes could be replaced by offspring that have the highest probability of adapting to their dynamic environment and to survive, compared to offspring of individuals (parents) with less suitable attributes of chromosomes. In nature, natural selection works very well, and it served to stimulate researchers in the field of optimisation to simulate natural evolution to solve decision problems (Nicklow *et al*., 2010; Spall, 2003).

In their recent position paper, Maier *et al*. (2014) categorise EA as a member of the metaheuristic optimisation tools available for researchers and decision-makers. Maier *et al*. (2014), citing Zufferey (2012), define metaheuristic "as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space in which learning strategies are employed to structure information to achieve efficiently near-optimal solutions". Complete randomness as applied to operation procedures is a key feature of metaheurisitc optimisation tools (Spall, 2003). Further, Maier *et al*. (2014) classify metaheuristic into two groups. The first group is characterised by population-based algorithms. Examples are GA, evolutionary strategies, and ant colony optimisation. The second group includes simulated annealing, tabu search, and local search methods that are mainly single-point-based methods. These kinds of optimisation tools are a means to challenge and solve non-linear problems (Karamouz, Zahraie, Kerachian and Eslami, 2010).

As it is one of the most well-established metaheuristic natural optimisation procedures (Maier *et al*., 2014), the family of EA comprises a number of different algorithms (Elsayed *et al*., 2014). Spall (2003) groups evolutionary strategies, evolutionary programming, and GA that were independently developed in the 1960s and 1970s together as the components of modern EA. Highly inspired by achievements in the field of observation of natural phenomena (Nicklow *et al*., 2010; Sarker and Ray, 2009), EAs employ randomised operators of biological evolutions, such as crossover, selection, and mutations, in the process of natural optimisation as a response to competition for natural resources (Nicklow *et al*., 2010; Sivanandam and Deepa, 2008). These vital operators give existence to new generations of individuals (solutions) who compete to survive via a selection process, which is guided by a problem-specific fitness function (Nicklow *et al*., 2010).

2.5.1.2 Basic steps in evolutionary algorithm optimisation

Although the various categories of EA use a variety of steps in their search for optimal solutions (Spall, 2003), the basic steps in the optimisation process in all EA, following Maier *et al*. (2014), can be summarised as shown in Figure 2.5:

1. Problem formulation (i.e. selection and definition of decision variables, objectives, and constraints);
2. Selection of decision variables and constraints;
3. Evaluation of objectives and constraints for the selected decision variable values, which is generally done using one or more simulation models;
4. Selection of an updated set of decision variable values based on feedback received from the evaluation process using some search methodology;
5. Repetition of Points 3 and 4 until the selected stopping criterion has been satisfied; and
6. Passing the optimal solutions into an appropriate decision-making process.

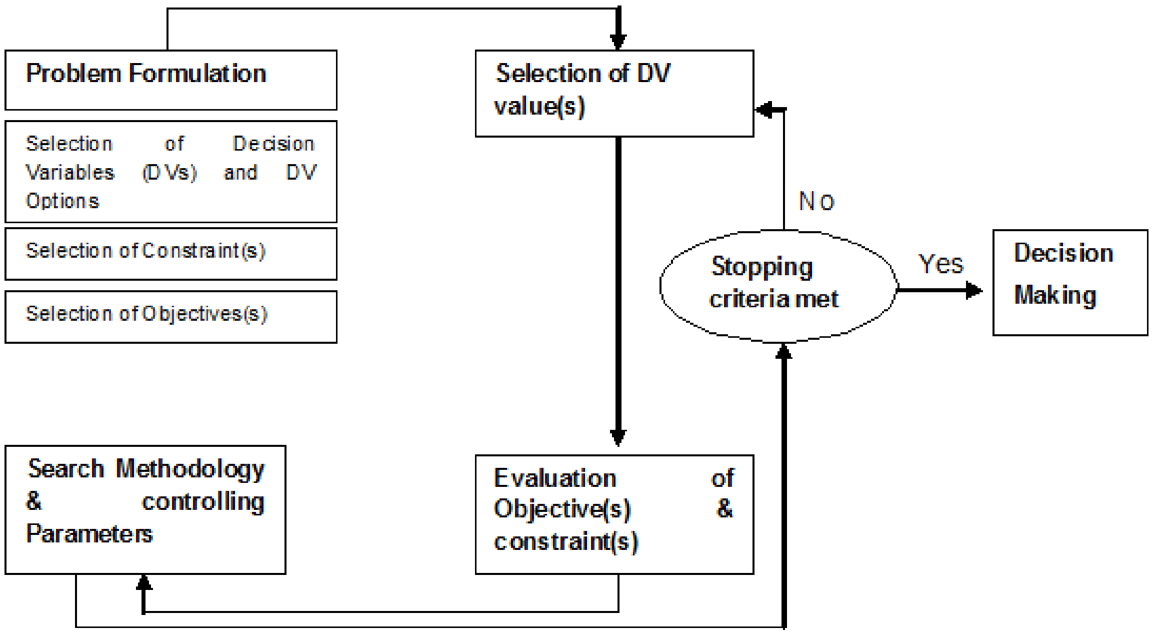


Figure 2.5: Schematic representation of steps in EA optimisation. The square shapes represent the steps and the oval shapes represent a decision point (Source: Maier *et al*., 2014)

2.5.1.2.1 Constraint handling

Many problems of irrigation may be formulated with constraint(s) forced upon them (Elsayed *et al*., 2014; Johns *et al*., 2014). The addition of constraint(s) to the mathematical formulation of water-related problems compounds the complexity of the search space of EA for finding optimal or near-optimal solutions (Nicklow *et al*., 2010). Consequently, how to incorporate constraint(s) in EA is a much-researched area and there are a number of ways to handle the challenge. The first, and a much-used approach, is to add the constraint(s) into the fitness function using a penalty function, in which the value obtained through the penalty function identifies the solutions' distance from feasibility (Anwar and Haq, 2013; Elsayed *et al*., 2014; Johns *et al*., 2014; Nicklow *et al*., 2010). An objective function with penalty function added is often called a fitness function (Anwar and Haq, 2013; Haupt and Haupt, 2004). Elsayed *et al*. (2014) distinguish two types of penalty function, namely, static and dynamic. Static penalty is the most common penalty function, and it refers to a penalty factor that remains constant throughout the EA application. In contrast, in dynamic penalty the penalty factor varies over time, enabling the tightening of the constraints as the EA population develops. The second method of including constraint(s) involves the use of a repair algorithm (Haq and Anwar, 2010; Nicklow *et al*., 2010). This approach is also known as hybrid algorithms, in which EA are used in association with other optimisation techniques to improve the solution (Nicklow *et al*., 2010). The method is very popular in many combinatorial optimisation problems, where an infeasible solution is repaired through the iterative modification of individual decision variables

(Haq and Anwar, 2010; Johns *et al*., 2014). Another method uses an indirect representation, where the genes do not code for variables directly, but uses a heuristic that determines the phenotype, given the genotype achieved by the algorithms (Johns *et al*., 2014). The approach is most common in non-irrigation applications of EA and involves the use of specialised mating and mutation operators (Nicklow *et al*., 2010). The last means outlined by Nicklow *et al*. (2010) is using multi-objective formulations, where constraints are reorganised as objectives.

In the next sub-section, GA, which are a type of EA, will be discussed.

2.5.2 Genetic algorithms in irrigation problems

2.5.2.1 Overview of genetic algorithms

GAs are the most popular of the EAs (Louati *et al*., 2011; Nicklow *et al*., 2010; Sivanandam and Deepa, 2008) and have found a number of applications in irrigation problems over the past two decades (Elsayed *et al*., 2014). As per literature (Haq, Anwar and Clarke, 2008; Johns *et al*., 2014; Michalewicz, 1996; Schütze *et al*., 2012), GAs are basically a type of adaptive heuristic optimisation search algorithm that is capable of achieving global or near-global optimal solutions provided they are applied to the right problem (Akhbari and Grigg, 2014; Schütze *et al*., 2012). Haq *et al*. (2008) describe heuristics as an approximate algorithm or inexact procedure, because the solution obtained through these methods may not be an optimal one. GAs were initially introduced as optimisation techniques by John Holland (Holland, 1975; Spall, 2003).

GAs are most commonly applied for function optimisation (Spall, 2003). Well known for their being approximate in applications, there is the need for such algorithms to be evaluated to show their effectiveness. Parameter tuning and configuration are critical for GA to run efficiently (Van Vuuren, Van Rooyen, Van Zyl and Van Dijk, 2005). According to Haq *et al*. (2008), in evaluating these procedures, the most important points to be considered include:

- Solution quality: how close a solution comes to the optimum;
- Computational complexity: the time required to obtain the solution; and
- Robustness: how well the algorithm performs over a range of problems.

GAs use a population of potential solutions in the search for optimal or near-optimal solutions in the state space, using only a fraction of the number of possible potential solutions (Rana *et al*., 2008; Van Vuuren *et al*., 2005). These characteristics of these natural optimisation tools distinguish them from conventional optimisation approaches, which commonly use one solution at a time to look for the optimal solution (Anwar and Haq, 2013). In their search for the best solution, GAs consider multiple initial solutions to the problem under consideration simultaneously and improve these candidate solutions at each iteration to get a new set of candidate solutions, till a possible global optimum solution is achieved (Ines and Droogers, 2002; Johns *et al*., 2014; Sarker and Ray, 2009). In the final generation of a solution, GA do provide multiple solutions that are close to the optimal solutions, creating an opportunity for decision-makers to see a number of alternatives for their decision-making process (Louati *et al*., 2011).

In GA, the potential solution to a problem could be represented using a set of parameters that are recognised as genes or chromosomes (Anwar and Haq, 2013; Michalewicz, 1996). Each chromosome represents a solution to the problem and could be evaluated to determine how well it solves the problem (Michalewicz, 1996; Mitchell, 1996). The evaluation is usually referred to in the literature as the goodness of the chromosomes for solving the problem. The goodness of a chromosome ("fitness function") is closely related but not necessarily identical to the value of the objective function (Anwar and Haq, 2013; Maier *et al*., 2014; Sivanandam and Deepa, 2008) and it is used as a test to pass on good solutions to the next generation (Johns *et al*., 2014; Karamouz *et al*., 2010).

The literature mentions a variety of GAs; however, the basic characteristics of these GAs are the same (Karamouz *et al*., 2010). One of the explanations for why we have different varieties of GA is the way GAs are coded to represent decision variables (Karamouz *et al*., 2010; Spall, 2003). The coding of GA is very important for their application; the coding could be achieved using binary or real coding, distinguishing the tool as binary and real GA (Spall, 2003). Real coding is very useful to large and complex problems that enable the GA to attain optimal solutions with more accuracy and reasonable solution time (Karamouz *et al*., 2010). Good literature is available on types of GA and the methodology of coding and decoding (Haupt and Haupt, 2004; Spall, 2003).

2.5.2.2 The basic concepts and methodology of genetic algorithms

To find optimal or near-optimal solution, GAs use simple operators, such as random selection, crossover, and mutation, on a population of solutions (Anwar and Haq, 2013; Elsayed *et al*., 2014; Louati *et al*., 2011; Karamouz *et al*., 2010). Methodologically, GA work to produce a progressive improvement of individual solutions, with the aim being to create new individuals from old generations (Sivanandam and Deepa, 2008). Improving the solution is done by evaluating the individual solutions (chromosomes) at each iteration to find a better solution to the given problem through providing better chances to more fit solutions to reproduce, than to solutions that are poor in quality (Anwar and Haq, 2013). Evaluation of solutions is done using a fitness function, which is used as a measure to differentiate among solutions (Spall, 2003). This process of improving the solution is repeated in a number of iterations and, gradually, the population solutions evolve toward the optimal solution (Akhbari and Grigg, 2014; Rana *et al*., 2008).

The basic methodologies of GA can be summarised in five steps and are represented in the flow chart shown in Figure 2.6.

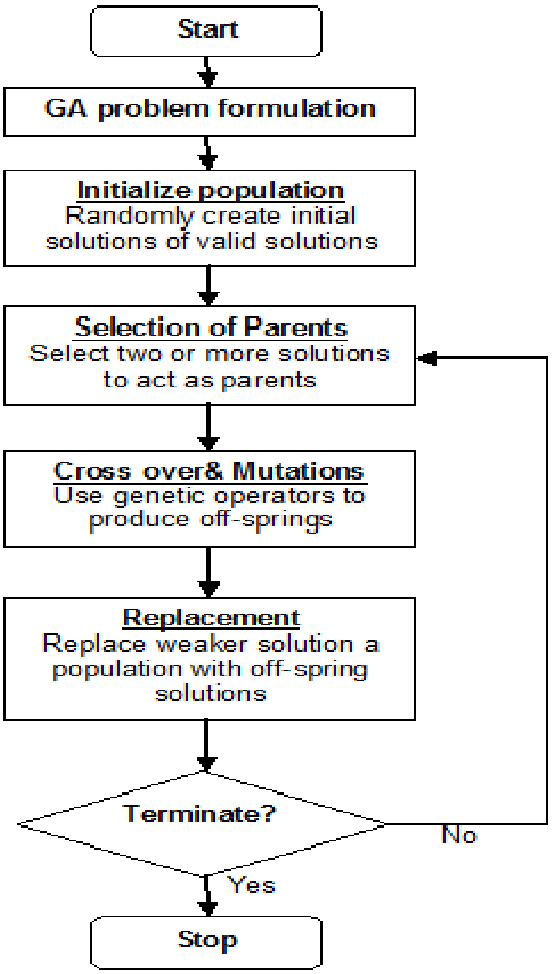


Figure 2.6: Flow chart of the basic methodology of genetic algorithms (Source: Van Vuuren *et al*., 2005)

As shown in Figure 2.6, the first step is the creation of the initial population using random procedures or perturbing an input chromosome. Anwar and Haq (2013) point out that the size of the population depends on the nature of the problem. The most important point to consider when generating an initial population is that the members must be as diverse as possible, regardless of the method of initialising them (Rajkumar and Thompson, 2002). The second step is to use a fitness function to numerically evaluate the performance of each possible solution chromosome. The next step is exploitation or natural selection, in which the chromosomes with better fitness scores are chosen one or more times into a mating subset in a random fashion. Chromosomes with unsatisfactory fitness scores are discarded from the population. The fourth step involves exploration, which involves recombination and mutation operators. Here, if the selected parents are permitted to mate, a recombination operator is employed to mix desired genes between the parents to produce one or more offspring. If they are not allowed to mate, the parents are placed into the next generation unchanged. After this step, the population is complete with newly created chromosomes, and the last step involves the repeated iteration of steps two through four, continuing for a fixed number of generations or until a stopping criterion is met. It is important to note that GAs, as emphasised by Kerachian and Karamouz (2007), guarantee that the probability of the new solution being better than the one before is higher.

2.5.2.3 Operators and parameters

The success and performance of GA depends on the design of its search operators as well as their appropriate integration (Elsayed *et al*., 2014; Nicklow *et al*., 2010; Van Vuuren *et al*., 2005). A GA uses a number of fundamental operators and parameters as main search tools (Spall, 2003). The key operators include parent selection, crossover, mutation, replacement, and termination. Some of the essential parameters are discussed in brief in the following sub-sections.

2.5.2.3.1 Selection of parent(s)

In the production of a new-offspring solution, the selection of parent solutions from the existing population is an important step in the process of GA. To conduct the procedure, high probability of selection is allocated to every member of the solution that satisfies the fitness function conditions well (Maier *et al*., 2014; Van Vuuren *et al*., 2005), the selected solution will be used as parent to generate the next population of solutions (Karamouz *et al*., 2010). The literature provides a number of selection methods, of which the most popular for irrigation research problems are roulette wheel, uniform random, and tournament selection (Van Vuuren *et al*., 2005). A thorough, detailed discussion of a number of available parent-selection techniques can be found in number of GA papers, such as that of Sivanandam and Deepa (2008), Nicklow *et al*. (2010), and Karamouz *et al*. (2010). Specifically, discussion of the weaknesses and strengths of the various selection methods can be found in the work of Nicklow *et al*. (2010).

2.5.2.3.2 Crossover (recombination)

Van Vuuren *et al*. (2005) point out that crossover is the component that differentiates GAs from other EAs. The aim of crossover is to produce offspring that share some characteristics of the selected parent solutions (Anwar and Haq, 2013; Elsayed *et al*., 2014). Cross-mating to the fitter individuals takes place according to certain criteria (Mitchell, 1996; Spall, 2003). According to the criteria, the genes of the parents are mixed and recombined (crossover), for the production of new chromosomes in the new generation (Elsayed *et al*., 2014). This process of crossover combines the best traits of the solution chromosomes of the parents to generate the new offspring (Haupt and Haupt, 2004; Sivanandam and Deepa, 2008). In the crossover process the probability of crossover, or crossover rate parameter, is often used; it is defined as the probability of choosing an individual of the population as a parent for the creation of the crossover pool (Haq and Anwar, 2010). Depending on the nature of the irrigation problem to be optimised, various techniques of crossover are employed to guide the GA to a better solution (Van Vuuren *et al*., 2005; Spall, 2003). Some of the techniques of crossover available to researchers include single or multiple crossover, uniform random crossover, and arithmetic crossover (Spall, 2003). Van Vuuren *et al*. (2005) and Sivanandam and Deepa (2008) provide detailed discussions of most of the crossover techniques available for GA. It is important to note that the literature on crossover currently does not provide a single crossover method that is superior to others (Kerachian and Karamouz, 2005).

2.5.2.3.3 Mutation

Crossover is essential for finding a new population of solution. However, crossover might pose the risk of the loss of some critically useful genetic materials in the process (Kerachian and Karamouz, 2005). Hence, various research papers (such as Maier *et al*., 2014; Nicklow *et al*., 2010) suggest using a mutation operator. Mutation is a diversity operator that prevents GA from converging quickly or trapping in “local optima” (Elsayed *et al*., 2014; Karamouz *et al*., 2010; Spall, 2003). In mutation, some of the chromosomes in the solution population are allowed to mutate (change) randomly, mimicking the natural evolution process and enabling the chromosomes of new offspring to differ from those of the parents (Haupt and Haupt, 2004), thereby helping the GA to avoid intelligently premature convergence (Elsayed *et al*., 2014). According to Haupt and Haupt (2004) and Van Vuuren *et al*. (2005) mutation could be performed on a bit-by-bit basis for binary encoding (or on a gene-by-gene basis for non-binary encoding), where each bit is altered by a small probability. The small probability used is termed the mutation rate and it refers to the probability of a given gene mutating (Cai *et al*., 2001; Haq and Anwar, 2010).

2.5.2.3.4 Replacement

In GA, the appropriate strategy to replace chromosomes in the population with newly generated offspring chromosome is crucial (Van Vuuren *et al*., 2005). It is not always advisable to replace only the weakest member of the chromosomes, as this might lead to quick convergence (Spall, 2003). Van Vuuren *et al*. (2005) list some of the replacement strategies as weakest replacement strategy, in which the member in the population with lower fitness value than the offspring is replaced; first weaker strategy, in which the first member found in the population with a lower fitness than the offspring is replaced; and random replacement strategy, where a random member of the population is replaced.

2.5.2.3.5 Termination criteria

Once appropriate selection, crossover and mutation operators and a replacement strategy for a population member has been designed, the process of GA is iterated and better and better chromosomes accumulate until an appropriate termination criterion is reached (Anwar and Haq, 2013; Haq and Anwar, 2010; Van Vuuren *et al*., 2005; Spall, 2003). Although a number of termination criterion procedures are quoted in the literature, Maier *et al*. (2014) point out that determining exactly which termination or convergence criteria are most appropriate for solving real-world irrigation problems remains a challenge. Usually, researchers use a simple technique to stop the algorithm process after a fixed number iterations or generations, although it is often very difficult to know how many iterations are enough for a specific problem (Anwar and Haq, 2013; Van Vuuren *et al*., 2005). Other means of termination criteria could be based on insignificant further improvement in the fitness values of the individuals (convergence), a certain predefined percentage of the amount of variation of individuals between different generations, or a predefined value of fitness being achieved (Anwar and Haq, 2013).

The main aim of termination criteria is to avoid early convergence in the algorithm. The right termination criterion is only achieved through process of experimentation (Nicklow *et al*., 2010; Van Vuuren *et al*.; 2005). Spall (2003) emphasises that the issue of convergence is critical to the selection of the right termination criterion. Hence, GAs need to be formulated carefully and tested thoroughly (Haq *et al*., 2008; Nicklow *et al*., 2010). Van Vuuren *et al*. (2005), citing South, Wetherill, and Tham (1993), mention fitness scaling, increasing the population size, adding non-random chromosomes to the initial population and increasing the mutation rate, as some of the methods that could help GA avoid local optimum and attain better termination criteria.

2.5.2.3.6 Parameter values

Careful decision-making is required to determine which values to use for the various parameters needed for implementing and controlling the GA search for optimal solution. Some of the key algorithm parameters that need decision-making when formulating GA include the size of the initial population, probability of crossover, probability of mutation, number of generations, and tournament size (Akhbari and Grigg, 2014; Goldberg, 1989; Johns *et al*., 2014; Nicklow *et al*., 2010). The selection of values for these parameters highly determines the quality of solution achieved (Johns *et al*., 2014; Maier *et al.*, 2014) and most research papers use the values suggested in the work done by Goldberg (1989) and De Jong (1975) for GA. However, Johns *et al*. (2014) point out that a conclusive approach to parameter selection for any irrigation problem has to be found, although a large amount of research related to parameter allocation to GA or EA could be located in a number of research reports.

2.5.3 Application of evolutionary and genetic algorithms in irrigation problems

A number of interesting research papers describing the successful application of EA and/or GA to both single and multi-objective water-management problems are available (Akhbari and Grigg, 2014; Elsayed *et al*., 2014).

2.5.3.1 International applications

Using EA and/or GA to solve irrigated-water-management problems has gained momentum over the last couple of decades, although there are many issues that must still be resolved to improve the tools for application to complex, real irrigation problems (Maier *et al*., 2014; Nicklow *et al*., 2010). Some of the successful applications of EA and/or GA internationally in the area of water management problems include optimising management decisions in potato production in the context of various irrigation policy scenarios (Lehmann and Finger, 2014), irrigation-scheduling problems (Anwar and Haq, 2013; Haq and Anwar, 2010; Schütze *et al*., 2012), salinity-related problems (Rajkumar and Thompson, 2002; Rana *et al*., 2008), minimising water and energy consumption (Fernández Gracia *et al*., 2013; Moradi-Jalal, Rodin and Mariño, 2004), problems of irrigation related to climate change (Carrillo Cobo *et al*., 2014; Schütze and Schmitz, 2010), water allocation policies (Kumar, Raju and Ashok, 2006; Sadati, Speelman, Sabouhi, Gitizadeh and Ghahraman, 2014), crop-planning problems (Farmani *et al*., 2007; Sarker and Ray, 2009), and water-distribution network design (Johns *et al*., 2014).

On-farm irrigation problems have been the focus of attention for a considerable number of researchers over many decades. Some of the critical problems include irrigation investment decisions, waterlogging and salinity, deficit-irrigation management, crop-pattern planning, management of water and energy, and irrigation-scheduling. Inherently, addressing some of the programming problems (e.g. irrigation investment and salinity) exhibit long-term decision problems. Rajkumar and Thompson (2002) developed GA for the complex nonlinear salinity-intrusion problem in the Sacramento-San Joaquin River Delta system. Their binary coded GAs, which were used to optimise an artificial neural network, deals with environmental problems in a river ecosystem. However, their model does not address the long-term nature of salinity impact, and it was applicable to a watershed area instead of being a study of the impact of salinity on farmland and crops. Within the watershed scale model, Akhbari and Grigg (2014) recently modelled the impact on irrigated farms of competition for scarce water caused by water allocation to environmental uses; they used multi-objective GA and Soil and Water Assessment Tool (Douglas-Mankin, Srinivasan and Arnold, 2010) to simulate river flow and salinity. Another indirect application to increase production of crops using GA is demonstrated by Rana *et al*. (2008), who attempted to manage salinity problems through minimising the capillary up-flow rates from the water tables. The GA model was aimed at optimising pumping operations of a surface drainage scheme, based on the principles of the spatio-temporal variation in groundwater dynamics of the Murray Irrigation Area of Australia. Their model, which found application in managing waterlogging and salinisation through cost-effective operation of the tube wells, uses a modular groundwater optimiser, which is characteristically a simulation optimisation algorithm of MODFLOW and MT3D (McDonald and Harbaugh, 2003). The GA model aims to achieve a minimum of 2 m groundwater depth below the top surface of the soil profile. Although the model is excellent for managing the groundwater table, it does not model the complex interaction that exists between the soil, plants, and the atmosphere, which affects field crop growth.

The literature is not rich in terms of application of GA to irrigation problems in the context of long-term planning. The available applications mostly focus on irrigation-basin management as applied to surface and groundwater management. For instance, Cai *et al*. (2001) developed a hybrid genetic algorithm and linear programming model for sustainable water management problems in irrigation-dominated basins in an attempt to provide an optimal plan to satisfy demand that arises from different sectors, as well demand from field crops. A pure GA within the scope of water-quality management in reservoir-river systems, known as Stochastic Varying Chromosome Length Genetic Algorithm with Water Quality Constraints, was demonstrated by Kerachian and Karamouz (2007) to optimise long-term reservoir operation and waste-load allocation, and they proposed a plan to minimise salinity of the supplied water to downstream rivers and salt build-up in the reservoir. Recently, Karamouz *et al*. (2010) applied a multi-period GA to optimise the crop pattern; in an allocation problem they considered surface and groundwater sources of irrigation water. Even though their model deals with conjunctive water-use management, the model attempts to use the production function to estimate the production amount of agricultural crops and the impact of deficit irrigation. The production function in their model uses the popular Doorenbos and Kassam (1979) production function model. Karamouz *et al*. (2010) followed a similar approach to Ghahraman and Sepaskhah (2004), using allocated water and crop water demand instead of actual and potential ET. All the above-mentioned applications of GA demonstrate the importance of long-term planning in solving irrigation problems, but fail to address on-farm irrigation problems that are as important as problems that relate to irrigation-basin management.

Considering the extreme pressure currently being experienced by the agricultural sector to be more water efficient in response to increased competition for the available, scarce water supply from other sectors (Mushtaq and Moghaddasi, 2011; Turral *et al*., 2010), irrigation-scheduling is being intensively researched as a means of saving water (Schütze *et al*., 2012). Using an efficient and applicable GA model to address on-farm irrigation-scheduling problems was proposed by Schütze *et al*. (2012). The GA model by Schütze *et al*. (2012) is an open-loop optimisation model, and is defined by Schütze *et al*. (2012), citing Shani, Tsur, and Zemel (2004), as an optimisation tool that is based on forecasts generated by simulation or analytical functions of the water balance and crop production of an irrigation-system for a whole growing period in advance. The model is applied to address intra-seasonal irrigation-scheduling under limited seasonal water supply. Schütze *et al*. (2012) modelled irrigation-scheduling by formulating the search space using only actual irrigation events (i.e. dates and amounts of water applied) in the form of a mixed integer nonlinear optimisation problem, which is basically an a *priori* unknown number of decision variables.

The simulation-optimisation model (Schütze *et al*., 2012) is a tailored evolutionary optimisation tool that can make a significant contribution to the study of deficit irrigation on irrigated farms. This model is specialised, since the irrigation-scheduling problem needs to be as realistic as possible. Using the knowledge of different crop-yield responses at different stages of the growth period, the decision-maker must decide when and how much water to apply during the growing season of the field crop (Ghahraman and Sepaskhah, 2004). The model was formulated with an objective function to maximise the crop yield and a number of constraints that relate to limited water resource, timing of irrigation, and irrigation depths. To solve the MINLP, Schütze *et al*. (2012) used an EA structure that deviates from other standard operators of EA in terms of defining the selection, crossover, and mutation operators. As explained by Schütze *et al*. (2012), the main differences include, first, that there is a change in the order in which the individual operators are achieved; and secondly, Schütze *et al*. (2012) added an extra reconstruction step to ensure that the offspring solution was feasible and complied with the constraints in the optimisation problem. To attain feasible solutions they applied fundamental knowledge about irrigation-scheduling, which advise irrigation in advance, rather than too late, to meet the future requirements of crops. After successfully modelling the EA operators, Schütze *et al*. (2012) applied the model to the management of deficit-irrigation-systems in combination with a neuro-dynamic programming technique to come up with optimal irrigation policy. However, their model is used to solve the problem of intra-seasonal irrigation-scheduling for a single crop and incorporates neither the interaction that exists among multiple crops nor intra-season and inter-season problems of irrigation-scheduling facing irrigation farmers.

2.5.3.2 South African applications

Although EAs are finding popularity internationally, the application of these tools to water-management problems essentially related to irrigated agriculture in South Africa is still in its infancy (Van Vuuren *et al*., 2005). Van Vuuren *et al*. (2005) report that EA and/or GA have great potential to be applicable in many South African sectors that use water. The meagre literature that is reported about the application EA in the country refers to optimising water-distribution systems (Ndiritu, 2005; Van Dijk, Van Vuuren and Van Zyl, 2008); optimal pipe diameter (Van Vuuren, 2002); reservoir system optimisation to maximise yield (Ndiritu, 2003), and prediction of stream flow using EA (Oyebode, Adeyemo and Otieno, 2014).

2.5.4 Discussion and conclusions

EA are powerful stochastic search algorithms with several practical applications for problems relating to irrigation management. EA and/or GA could be applied to complex nonlinear irrigation problems to find optimal/near-optimal solutions for cases where a conventional optimisation approach fails. Hence, EAs have the potential to link the SWAMP crop-growth model in an optimisation framework while retaining the complexity of SWAMP under saline water conditions. EAs are generally problem-specific in their applications. In an irrigation-schedule optimisation problem application involving saline irrigation water-use, the EA must be tailor made to obtain optimal or near-optimal solutions.

To solve real irrigation-optimisation problems using EA/GA, a researcher needs to use computers. The computer could be used in two ways. First, readymade EA/GA computer codes can be used. These days a number of software tools, such as Evolver (Palisade Corporation, 2010), GAlib (Wall, 1996), GPdotNET (Bahrudin, 2015), Matlab Tool box (Mathworks, 2013), Java GAs Package (Meffert, 2016), and GeneHunter (Lewinson, 2007) are available to solve a variety of problems. Another option applied by many researchers is writing their own code using software packages such as MATLAB and GAMS to come up with a better solution time and to improve application of various operators of EA/GA options for specific problem applications. A software language that is gaining popularity among academics, research institutions, and industrial enterprises in various fields, such engineering, science, and economics, is MATLAB. MATLAB is a multi-paradigm numerical computing environment and fourth-generation programming language. Developed by MathWorks, MATLAB is capable of matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C^{++}, Java, Fortran and Python (Mathworks, 2013; Gdeisat and Lilley, 2013).

2.6 CONCLUSIONS AND IMPLICATIONS FOR THIS RESEARCH

From the review of literature in this chapter, the following conclusions and implications for the research could be made.

- If a farm business is exposed to production risk, the SC approach to production uncertainty can be used to improve the modelling of risk. As such SC approach provide two advantages over PD approach in risk modelling. First, there is no need to quantify probability assessment of output risk. Secondly, application of SC approach is possible independently of the risk preferences of the farmer.
- The practical application of the SC approach requires the estimation of SC production functions. To retain the water and salt flow within a transient-state model, SC crop-growth models could be used in place of SC production functions.

- The SWAMP model can be used to simulate the impact of saline water on crop yield and soil salinity for South African irrigation lands with reasonable accuracy.
- To determine the optimal irrigation schedule that provides optimal water-use and salt management, the SWAMP model should be optimised. The optimisation of SWAMP needs at least three steps. First, the optimisation procedures require that an economic module is integrated to the SWAMP model. The addition of the economic model is essential to consider the impact of economic factors in addition to biophysical factors, to determine the best irrigation strategies. Second, the modelling of salinity to include production risk using the SC approach for all states of nature will increase solution time and complexity of the model, since the application requires SC crop-growth models. Hence, to solve the optimisation problem within a reasonable solution time a sound procedure is required to reduce the states of nature to be considered in the risk analysis. Lastly, the optimisation of SWAMP requires an EA as a solution procedure. Furthermore, the successful optimisation of SWAMP requires the development of a tailor made EA for the saline irrigation water management.
- In the context of South Africa, the development of EA to find optimal irrigation-scheduling that would establish better water-use and soil-salinity management when salinity is an issue in irrigated farms, will help to fill the gap in the application of EA.

CHAPTER 3

DESCRIPTION OF METHODOLOGY AND DATA

3.1 INTRODUCTION

Hazell and Norton (1986) emphasise that any data that is used should apply, as accurately as is possible, to the irrigated farm business being studied. The model and the data needs are based on a case farm in the VIS in South Africa. Data for the empirical study were obtained from various sources, among which were research projects of the Department of Agricultural Economics and Department of Soil, Crop, and Climate Sciences at the University of the Free State, the National Department of Agriculture of the Republic of South Africa, Griekwaland-Wes Korporatief (GWK) enterprise budget, field trips, abstracts of agricultural statistics published by the National Department of Agriculture, Eskom, and from consulting done by South African Irrigation Institute (SABI) accredited irrigation-system designers in relation to the centre-pivot design and parameters required to compute energy-related costs.

In this chapter the methodologies developed and used to study the effect of low quality water on crop yield, soil salinity, and the environment will be presented. The first section will present the conceptual framework used to link SWAMP, GA, and the economic decision model. Then, the optimisation procedure that was developed to optimise irrigation-scheduling, namely, the special GA, will be presented. The third section will present methods of calculating the fitness function. The discussion is based on the algorithms that constitute the SWAMP model and the economic model linked to SWAMP. Then, a section will be devoted to the procedure followed to extend the irrigation-schedule optimisation model to the inter-seasonal water-management situation. Next, the strategy followed to select the baseline irrigation strategy will be discussed. The last section will present the scenarios followed for model application.

3.2 CONCEPTUAL MODEL LINKING AND SOLUTION PROCEDURES

The conceptual framework followed to develop the SWAMP-ECON model is shown in Figure 3.1, which presents the design followed to link the SWAMP model, the economic model and the special EA model to obtain an optimal irrigation schedule. The optimal irrigation schedule is the schedule that leads to optimal water-use and salt management at field level. The schematic design is an illustration of the simulation-optimisation approach developed to solve the problem of salinity when saline water is used for irrigation in the presence of a shallow water table and/or freely draining soil.

The simulation-optimisation procedure starts with the initialisation of a set of random irrigation schedules, which could be for single or double cropping and for intra-seasonal or inter-seasonal application, respectively. The initialisation process requires inputs such as population size (n_P), minimum amount of water (v_{min}) and maximum amount of water (v_{max}) that can be applied by the irrigation-system, and the minimum interval between two consecutive irrigations (d_{min}). The process of initialisation generates n_P potential solutions, known as population. In the process of initialisation, each potential solution has to be a feasible solution in terms of the irrigation-system delivery capacity. The solution generated has to fit the system delivery capacity within the irrigation interval in such a way as to minimise energy use. So the *Fix irrigation schedule* process ensures the feasibility of a solution and requires system efficiency (η_{IRS}), system flow rate (ζ_{IRS}), and the area of the irrigation (system size) (A_c) as inputs. If the solution generated is feasible, then it does not change when applied to the process of simulating yield. However, if the solution generated is not feasible, then it needs to be processed by the *Fix irrigation schedule* process to fit the irrigation-system capacity.

Once a feasible irrigation schedule has been generated, it is passed to the SWAMP crop-growth model to simulate yield under matric and osmotic stresses. If the growing season being considered is for a single crop (intra-seasonal), then the irrigation schedule is used in the SWAMP model to generate SC yields for a single crop. However, if two growing seasons (inter-seasonal model application) are being considered, the irrigation schedule has a chromosome that represents the combined irrigation schedules of two crops. Therefore, an *Allocate irrigation schedule to crops* process is required to separate the irrigation-schedule solution with chromosome length that defines the two crops from an irrigation schedule representing each crop. The process needs growing-season length (GSL_c) to be defined for each crop as input. The potential irrigation-schedule solutions obtained via the process *Allocate irrigation schedule to crops* can be used as input in the SWAMP model defined for each crop. For both the intra-seasonal and inter-seasonal applications, the SWAMP model requires water-quality parameters defined by EC, soil and crop parameters (see detail in Section 3.4.1), and parameters that describe the states of nature, namely, rainfall (RF) and reference evapotranspiration (ET_O). Since the application is to include production risk using an SC approach, the SWAMP model is used as SC growth models for S states of nature. The SC growth models use the same potential irrigation schedule to generate SC yields for a given crop c for state s. Thus, the irrigation input is treated as a state general input.

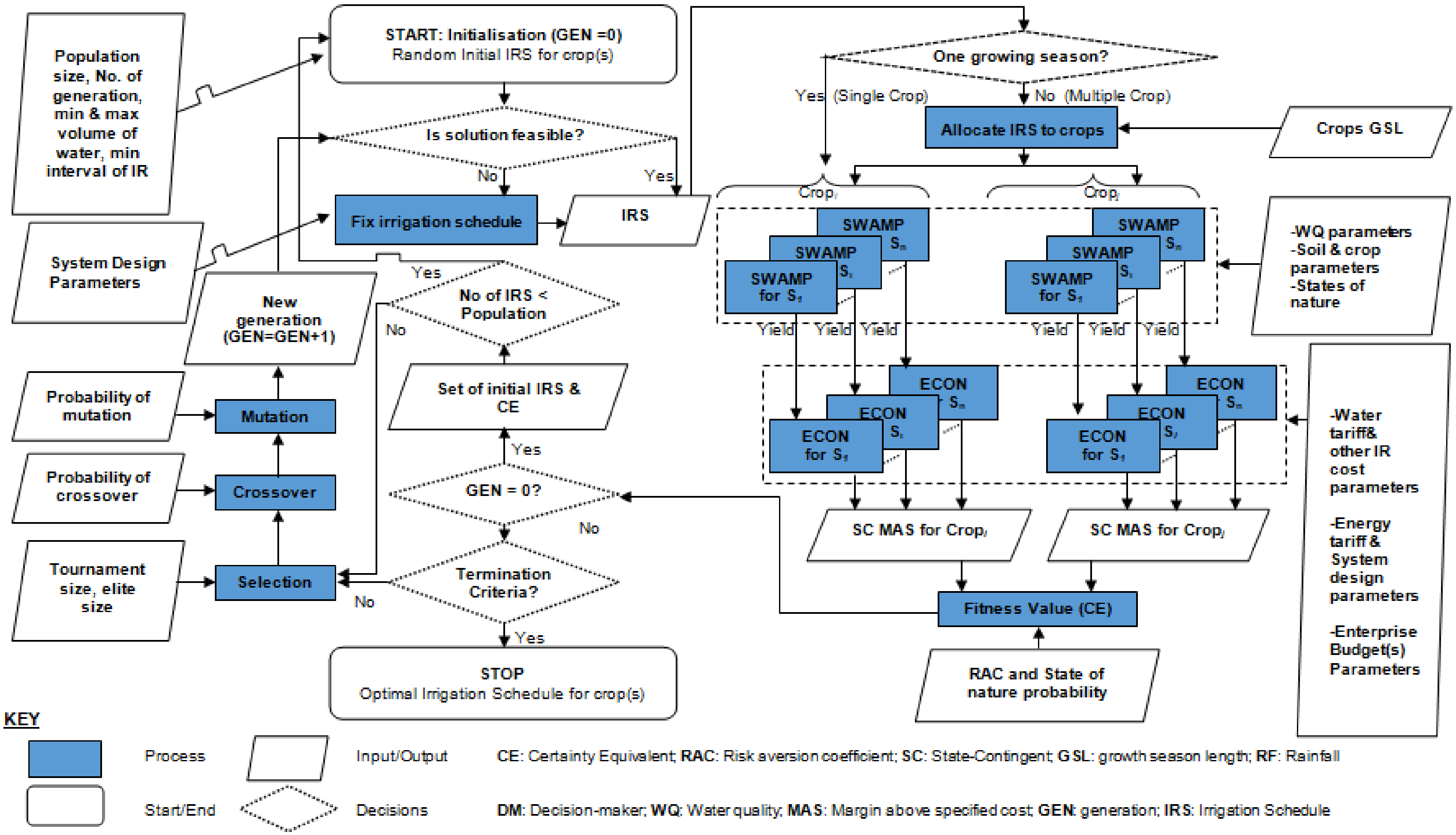


Figure 3.1: Schematic representation of the SWAMP-ECON genetic algorithm model for a case study farm in the Vaalharts Irrigation Scheme

Hence, depending on the number of states of nature considered, SC yields are simulated using the same potential irrigation-schedule solution for all states of nature. The SC yields are used as inputs in the economic model to compute revenue and yield-dependent production costs, which are expressed as functions of crop yield. The SC yields will vary, but will have the same irrigation costs because the same irrigation schedule is used to simulate yields in each state of nature. The states of nature production processes will have different yield-dependent costs, but the same area-dependent costs. Therefore, the economic model generates SC margins above specified costs, which are important for calculating the fitness function for each potential irrigation schedule. The fitness-value calculation is based on a CE calculation, which requires absolute risk aversion coefficient (r_a) (RAC) and states of nature probabilities ($p_S = \{p_1,...,p_s,...,p_S\}$). The SWAMP and the economic model constitute an inner loop within the GA model, which is defined over the S states of nature. Therefore, each initial potential irrigation schedule will have its own fitness value.

Once a set of initial solutions, with their respective fitness values, have been initialised, then the solutions will be used as a new set of solutions to start the GA optimisation procedure. So, each new solution will go through three steps of GA operators to obtain an irrigation schedule that improves the fitness value. The first is a selection operator, which uses a tournament selection procedure. The process requires a tournament size (n_{TS}) and elite size (n_{el}) to be defined to select best parents to create offspring. The parents that are selected produce a new offspring through a crossover operator using the specified probability of crossover (p_{cr}) as an input. Lastly, to prevent early convergence, a mutation operator is performed to achieve a diversity of solutions. The mutation operator requires a probability of mutations as input (p_m). Finally, all the irrigation schedules generated through the GA operators will form a set of newly generated solutions that go to the process of SWAMP simulation and economic model one by one to calculate their respective fitness values for each new irrigation schedule to improve the solutions to the next level of new generation by using the GA operators. The process of creating better solutions to improve the fitness values will continue from one generation to the next generation until termination criteria have been fulfilled. At the end of the optimisation, a near-optimal irrigation schedule is selected from the set of irrigation schedules created through the whole process of optimisation.

In the next sections the detail of the simulation-optimisation procedure developed will be discussed.

3.3 EVOLUTIONARY ALGORTIHM FOR INTRA-SEASONAL IRRIGATION-SCHEDULING

An irrigation farmer cannot attain maximum crop yield when irrigation is constrained by quantity and quality of irrigation water. The irrigation schedule chosen during the entire growing period of a field crop has a significant impact on yield, salinity of soils and drainage. Formulating optimisation problems to achieve optimal irrigation-scheduling is very challenging; the main reason, as explained by Schütze *et al.* (2012), is that the number of decision variables (e.g. the number of irrigations) is *a priori* unknown, resulting in an irrigation-scheduling-problem formulation that could be either a high-dimensional nonlinear or a mixed-integer optimisation problem.

In this study, as discussed in Section 3.2, a simulation-optimisation approach is basically followed to achieve optimal water-use and salinity management. The impact of different irrigation schedules on a field crop is simulated by the SWAMP model. In actual application, the simulation model is treated as a function that converts input parameters into output performance measures. The function is usually considered as a black box in the optimisation algorithms (Schütze *et al.*, 2012). To overcome the difficulty of modelling irrigation-schedule optimisation, the tailor-made EA proposed by Schütze *et al.* (2012), GET-OPTIS, was adapted with some modifications to address the main research problem of the study. The GET-OPTIS method optimisation was selected because the model has proven to be more reliable than heuristic and general EA (Schütze *et al.*, 2012). The model developed in this study is called SWAMP-ECON. The SWAMP-ECON that has been developed is capable of solving deterministic as well as stochastic optimisation problems while using saline irrigation water.

The formulation of the EA procedure followed for intra-seasonal crop modelling by SWAMP-ECON will be presented next with reference to the schematic representation shown in Figure 3.1.

3.3.1 Defining initial irrigation-schedule solutions

3.3.1.1 Define parameters for model

The SWAMP-ECON model starts by declaring the parameters required to operate the EA, SWAMP and economic decision model. The inputs and parameters for the model are coded as shown in Appendix A. These parameters are essential for running the optimisation process. The SWAMP model needs parameters to be defined for crop type, soil type, soil initial and boundary conditions, and inputs for crop, water quality, and type of modelling to consider (e.g. intra- or inter-seasonal optimisation). The economic decision model requires parameters such as system efficiency (η_{IRS}), system flow rate (ζ_{IRS}), area planted (A_c), growth-season length of a given crop (GSL_c), off-peak available hour (OPH), standard available hour (STH), peak available hour (PEH), absolute risk-averse coefficient (r_a), number of states of nature and their respective probability (p_s), energy tariffs, enterprise budget parameters, water tariffs, and other costs to be defined. The parameters defined for the EA section are population size (n_P), number of maximum generation (n_{max}), end of optimisation (eop), tournament size (n_{TS}), elite size (n_{el}), variance for irrigation time (σ_d), variance for irrigation volume (σ_v), probability of crossover or combination (p_{cr}), probability of mutation (p_m), minimum interval between two consecutive irrigation events (d_{min}), minimum water depth applied (v_{min}) and maximum water depth applied (v_{max}). The EA section of the model uses some of the parameters needed in the economic model, which include η_{IRS}, ζ_{IRS}, A_c, GSL, OPH, STH and PEH.

3.3.1.2 Initialisation of random solutions

Intra-seasonal optimisation needs initial irrigation schedules to be defined for a crop grown over a single growing season. The set of initial solutions need to be initialised randomly one by one. The GA parameters required to initialise random solutions are n_P, v_{min} and v_{max}. An initial irrigation schedule could be formulated as shown in Equation 3.1, where S_{IR} represents the irrigation schedule for the growing season under consideration, comprising $i=1,...,n$ irrigation events $s_{IR(i)}$ each represented by the date d_i and the irrigation depth v_i. It is important to note that the number of irrigation events (n) of $s_{IR(i)}$ is not fixed *a priori* and is a decision variable in the model (Schütze *et al.*, 2012). The first step in the initialisation process is to determine the number of irrigation events (Equation 3.2). The number of irrigation events required for an irrigation schedule is obtained by approximating a random number (γ) generated (between 0 and 1), which is then multiplied by 100 to an integer and adding a value of one to the result (see Appendix B(1)). The process generates n irrigation events, which take a value [2,101], which are distributed along the crop-growing season.

$$S_{IR} = \left\{ s_{IR(i)} \right\}_{i=1,\dots,n} = \left\{ (d_1, v_1), \dots, (d_i, v_i), \dots, (d_n, v_n) \right\} \quad n \, and \, d \in Z^+, \quad v_i \in R \qquad 3.1$$

$$n = \left\{ 1 + a \quad where \quad a = \gamma * 100 \quad and \quad a \in Z^+ \right. \qquad 3.2$$

Once the number of irrigation events in a season is known, the specific days on which irrigation must take place must be generated. The days associated with each irrigation event are generated using a random number multiplied by 100, which is then approximated to an integer number (Equation 3.3). Hence, a vector of days is created to represent all irrigation events, which need to be sorted from the lowest to higher dates representing the dates of growing seasons of the crop.

$$d_i = \left\{ a = \gamma_i * (100) \quad where \quad a \in Z^+ \quad \forall i \in n \right. \qquad 3.3$$

Next, Equation 3.4 is used to generate the volume of water to be applied on a specific date d_i for an irrigation event of an irrigation schedule. The formula ensures that the volume of water for each of the n

irrigation events ($s_{IR(i)}$) that specify a potential solution are generated. The volume of water for an irrigation event is bounded by a lower and upper limit of water that can be applied by the pivot. The volume of water that can be applied to a field within a season should be equal or above zero (Equation 3.5). The MATLAB code to generate the volume of water and date for the irrigation event is shown in Appendix B(1).

$$v_i = \{\gamma_i * (v_{max} - v_{min}) + v_{min} \qquad \forall i \in n \tag{3.4}$$

$$\sum_{i=1}^{n} v_i \geq 0 \tag{3.5}$$

All the randomly generated irrigation events for an irrigation schedule should be feasible solutions in terms of the irrigation-system delivery capacity. The gap between any irrigation events should be enough to apply the volume of water in the previous irrigation event before continuing to apply the next volume of water. A feasible solution is achieved using a reconstruction algorithm, which is discussed next.

3.3.1.3 Reconstruction

Reconstruction of a solution is done in three steps. The first step of the reconstruction process uses the date and volume of water of each of the n irrigation events ($s_{IR(i)}$), d_{min}, v_{min} and v_{max} as inputs. The d_{min} is an input that describes the minimum time between two irrigation events, which must be set below the difference of the two irrigation events (Equation 3.6). The *fixschedule* function, which also uses a *killminwater* function coded in MATLAB (Appendix B(2)), is applied to restructure the irrigation events in terms of date and volume. The *fixschedule* function takes the volume of water generated for the first irrigation event as it is. However, for the remaining irrigation events, i.e. $i \geq 2$ *and* $i \in n$, the volume of water generated for an irrigation event must be checked against the associated date generated for the irrigation event, because there is a possibility that more than one irrigation events might have the same date of application. The function keeps the volume of water generated for the specific irrigation event under consideration if the difference between the date of the current irrigation event and the previous irrigation event is greater or equal to d_{min}. In contrast, if the difference between the date of the current irrigation event and the previous irrigation event is less than d_{min}, the water volume generated for the current irrigation event under consideration should be added to the previous irrigation event's volume of water, because the date for the current irrigation event and the date for the previous irrigation event are the same. Once all the irrigation events are restructured by the *fixschedule* function, the *killminwater* function overtakes the process of restructuring the irrigation events. It simply removes any irrigation event that is below v_{min}. Overall, the first step of the reconstruction process results in irrigation events with volume of water not below v_{min} with their respective, appropriate dates of application.

$$|d_i - d_{i-1}| \geq d_{min} \tag{3.6}$$

Where d_i refers to date of irrigation event i.

However, to minimise irrigation cost, there must be a large enough time gap between irrigation events for the volumes of water applied per irrigation event, depending on the system delivery capacity. Therefore, a second step of reconstruction is needed to make sure that there is enough of a time gap between two consecutive irrigation events, such that it is possible to apply the volume of water in the first irrigation event to minimise energy cost before applying the water of the next irrigation event. The function *fixIrrSystem_Capacity* shown in Appendix B(3) was coded to achieve further refinement of the irrigation events for an irrigation schedule. The inputs S_{IR}, d_{min}, η_{IRS}, ζ_{IRS}, A_c, GSL_c, v_{min}, v_{max} and OPH are needed by the function. The function assumes that the volume of water of an irrigation event could be applied on the day of the irrigation event and the next day if the need arises to optimise OPH so as to minimise irrigation cost.

Accordingly, three parameters, namely, count-day (cD), added-day (aD) and interval between two irrigation events (Dff), which are calculated endogenously, are defined to achieve the correct adjustment of dates of irrigation events to fit the irrigation-system delivery capacity. The count-day parameter can take the value of 0 or 1, depending on the volume of water of an irrigation event. For an irrigation event the algorithm uses Equation 3.46 to compute the pumping hours (PH) (see Section 3.4.2.1.6) required using inputs of v_i, η_{IRS}, ζ_{IRS}, and A_c. Then, it compares the calculated PH with that of the OPH available on the day of the specific irrigation event being considered. If the PH is less than OPH then the cD parameter is set to 0. It means the volume of water can be applied within the same date that specifies the event without affecting irrigation cost. If the opposite is true, then cD will take the value of 1, implying the volume of water of an irrigation event needs to be applied in two days (i.e. on the date that specifies the irrigation event plus the next day). On the other hand, the aD parameter can take any integer value and refers to the number of days that must be added to the day of the current irrigation event to provide enough of a time gap for the volume of water in the previous irrigation event to be applied within two days, so as to use the off-peak hours available in the second day. The aD is always calculated by considering the number of days that are added to the previous event, as well as the cD values of the previous event. Furthermore, it measures the time gap that should exist between the current event and the next event. Adjustment to the dates of irrigation events of an irrigation-schedule starts with the first event. For the first event, the aD parameter is set as 0, because there is no need to add days to it. The date of the first event is kept as it is. The cD for the event is calculated before the next event is considered. To adjust the events ($i \geq 2$ *and* $i \in n$), other than the first, it is necessary to consider the days added to the previous event (aD_{i-1}), which could be 0 or greater than 0 ($aD_{i-1} \in Z^{+}$).

When aD_{i-1} is equal to 0, three possibilities arise to adjust the date of an irrigation event.

- In the first situation, the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) is less than d_{min}. In this situation, the date of the current event is kept as it is ($d_i = d_i$). The volume of water is kept as it is and only changes if it is greater than v_{max}. Then cD_{i-1} calculated is carried forward as it is and aD_i is 0 because days added to d_i is 0.
- In the second situation, the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) is equal to d_{min}. For this case, the date of the current event is adjusted by adding cD_{i-1}, i.e. $d_i = d_i + cD_{i-1}$, for all d_i less than the GSL_c. Again, the volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is carried forward and $aD_i = cD_{i-1}$. In the case where d_i is greater or equal to the GSL_c, then date of the irrigation event is set to equal $d_i = GSL_c$, and the volume of water cannot exceed the irrigation-system delivery capacity. In addition, aD_i is equal to 0 because it is impossible to have date of irrigation that exceeds the growing-season length.
- In the last situation, the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) is greater than d_{min}. The date of the current event is kept as it is, i.e. $d_i = d_i$, for all d_i less than the GSL_c. Again, the volume of water is kept as it is and only changes if it is greater than v_{max}. New cD_i calculated is carried forward and $aD_i = 0$. In the case where d_i is greater than or equal to the GSL_c, then date of the irrigation event is set to equal $d_i = GSL_c$, and the volume of water cannot exceed the irrigation-system delivery capacity. The aD_i is set as 0.

When aD_{i-1} is greater than 0, adjusting the date of an irrigation event is done based on the following possibilities.

- In the first situation, the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) minus the date added to it (aD_{i-1}) is less than d_{min}. In this situation, the date of the current event is $d_i = d_i + aD_{i-1}$. The volume of water is kept as it is and only changes if it is greater than v_{max}. Then, the cD_{i-1} calculated is carried forward as it is and $aD_i = aD_{i-1}$ since the date of current and previous event is the same.

- In the second situation the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) minus the date added to it (aD_{i-1}) is equal to d_{min}. For this case, the date of the current event is adjusted by adding the sum of aD_{i-1} and cD_{i-1}, i.e. $d_i = d_i + aD_{i-1} + cD_{i-1}$, for all d_i less than the GSL_c. Again, the volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is carried forward and $aD_i = aD_{i-1} + cD_{i-1}$. For an irrigation event with d_i greater or equal to the GSL_c, the date of the irrigation event is set as $d_i = GSL_c$, and the volume of water cannot exceed the irrigation-system delivery capacity. In addition, aD_i is set as 0.
- In the last situation, the difference between the date of the current event (d_i) and the date of previous event (d_{i-1}) minus the date added to it (aD_{i-1}) is greater than d_{min}. In this case, a parameter that measures the time gap available between the current event and the previous events is defined. The parameter is named difference day (Dff) and is calculated as $Dff = d_i + (d_{i-1} - aD_{i-1}) + 1$. The Dff parameter could be 0 or greater than 0. If Dff is 0, then it means there is not enough of a time gap and the current event's date should be adjusted. Therefore, the date of the current event is adjusted by adding the sum of aD_{i-1} and cD_{i-1}, i.e. $d_i = d_i + aD_{i-1} + cD_{i-1}$, for all d_i less than the GSL_c. The volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is carried forward and $aD_i = aD_{i-1} + cD_{i-1}$. However, the function considers the possibility of equating the added day parameter to 0 if Dff parameter is greater than 0. If Dff parameter is greater than 0, then it is important to consider a further three cases. The first case involves the Dff parameter being greater than 0 and the days added to the previous event equal to Dff (i.e. $aD_{i-1} = Dff$). Then, the date of the current irrigation event is adjusted by adding cD_{i-1} ($d_i = d_i + cD_{i-1}$) for all d_i less than the GSL_c. This means that the current event date should be adjusted only if the count-day parameter calculated for the previous event is 1. The volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is carried forward and $aD_i = cD_{i-1}$. In the second case, the Dff parameter is greater than 0 and the days added to the previous event are fewer than Dff (i.e. $aD_{i-1} < Dff$). Then, the date of the current event is kept as it is. The volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is carried forward and $aD_i = 0$. The third case involves a Dff parameter greater than 0 and the days added to the previous event greater than Dff (i.e. $aD_{i-1} < Dff$). Then, the date of the current event is adjusted as $d_i = d_i + (aD_{i-1} - Dff) + cD_{i-1}$. This implies that consideration must be given to the gap that exists between the current and previous irrigation events. The volume of water is kept as it is and only changes if it is greater than v_{max}. Then new cD_i calculated is

carried forward and $aD_{i-1} = (aD_{i-1} - Dff) + cD_{i-1}$. For an irrigation event with d_i greater or equal to the GSL_c, the date of the irrigation event is set as $d_i = GSL_c$, and the volume of water cannot exceed the irrigation-system delivery capacity. Moreover, aD_i is set as 0.

The last step of the reconstruction procedure is coded as the function *scheduletodayarray* (Appendix B(4)). The algorithms uses the inputs S_{IR} and GSL_c. The function ultimately provides the irrigation dates and volumes arranged as an irrigation schedule assigned for the growing length of the crop. Hence, the overall process of reconstruction provides a feasible irrigation schedule ready to be used in the fitness-function calculation.

3.3.2 Solving the irrigation-scheduling problem

A feasible irrigation schedule that is composed of n irrigation events is used as an input by the SWAMP simulation model to generate SC yields that are used in the economic model to generate SC gross margins above specified cost. The SC margins above specified costs are used to compute a fitness value for the irrigation schedule generated (see Section 3.4). The process will continue until the complete n_P amount of potential solution, with its respective fitness value, has been generated. Hence, the GA has a population of solutions to start the next generation of solutions. The process of improving the solutions is done using GA operators discussed in the next sub-sections, and the objective of the optimisation is to obtain an optimal irrigation-schedule solution that maximises the CE (Equation 3.7).

$$S_{IR}^{*} = arg\ max CE\left(S_{IR}\right) = arg\ max CE\left(\left\{\left(d_i, v_i\right)\right\}\right)_{i=1,\ldots,n} \qquad 3.7$$

3.3.2.1 Selection

The first operator to be employed on each irrigation schedule is the natural-selection procedure. The method of selection employed is tournament selection combined with an elitism procedure. The elitism procedure ensures that best solutions are not lost and, in combination with tournament selection, will form a set of best schedules to be included in the next generation in their unchanged form. The selection process needs inputs such as schedule S_{IR} (containing n_j irrigation events i at a date d_i with volume v_i), n_{TS}, current generation of schedules X^n and elitist set B_n. The code for the selection operator is presented in Appendix B(5).

The algorithm for the tournament selection is performed for each individual in the current generation as follows. The process starts by calculating the index of the new solution to form the set of new generation from the index of previous generation under consideration. Assume a generation-counter parameter (GEN) will be the counter that measures generation reached by the EA. Because the initialised solution is now the current solution to start the EA, the generation counter will be 1 in the beginning (i.e. GEN=0) (for a later generation the generation counter will be GEN=GEN + 1). Now, let's define a parameter k', which is calculated as $k' = GEN * n_P + 1$ to be used to formulate the index of the new generation solutions. For instance, if GEN=1 and $n_P = 30$ then $k' = 31$. The index of the first solution in the first generation will be calculated as $new\,index = k' + currentindex - n_P$. Hence, if the first solution is taken, then the new index will be 31 (31+30-30) because the individual solution index is set from 0 to $n_P - 1$. For the second solution it will be 32, for the third solution it will be 33, and so on until the 60th solution is formulated. For the GEN= 2, then the index will be 61, 62,..., 90. The process will continue until the termination criteria have been fulfilled. To select the parents of the next generation, a solution (e.g. the first solution in GEN=0 is to derive the 31th solution in GEN=1) will be one participant of a tournament selection process with a set of $n_{TS} - 1$ ($S_{TS} = \{S^1, ..., S^{n_{TS}-1}\}$) randomly chosen competitors of the same current schedule solutions X^n (e.g. for GEN=1 it will be X^0). The $n_{TS} - 1$ is the tournament size. The criteria to win or lose the tournament involve evaluation of the fitness value. The procedure uses a parameter o_L to count the loss of a solution that takes the value 0 or 1. The set of solutions formed in the tournament process is known as competitors. The individual solution under consideration will compete with all the competitors. If it is better than all the competitors in terms of fitness value then it is retained in the set of new best schedules (i.e. B_n) and proceeds unchanged to the next generation setting the parameter loss to be $o_L = 0$. This means there is no lost solution and it is not needed to do a crossover and mutation procedure to form new offspring. However, if the current solution loses to any of the competitors, then the best competitor is selected. Then, a new individual is generated from the best competitor by applying the crossover, mutation, and reconstruction operators. The parameter loss will be $o_L = 1$, indicating that a new offspring must be produced. The winning competitor will be the mother parent to produce an offspring that needs to mate with a partner, which should be selected by a crossover process. The tournament selection is performed for the whole set of the current schedule individuals through iteration.

3.3.2.2 Crossover

The next operator of the EA that is performed after the selection process, is crossover. The crossover code is as shown in Appendix B(6). The inputs required for the crossover are mother and father parent irrigation schedules and p_{cr}. The crossover process for each set of individual solutions is initiated if the parameter o_L is equal to 1, i.e. there is a solution to be replaced from crossover because an individual competitor has won the tournament in the selection process. The parameter p_{cr} is used to select a mate by comparing it to a random number. If $p_{cr} < \gamma$, then a mate is chosen randomly from the set of current solutions, otherwise the solution will be kept as it is. The chosen mate, provided that $p_{cr} < \gamma$, is then again put under tournament competition similar to the tournament selection procedure discussed in Section 3.3.2.1. The best competitor will be the partner (father parent) for crossover to the mother parent selected during the selection process in Section 3.3.2.1. Then, the chromosomes of both parents will be used to produce an offspring using the *mate* function presented in Appendix B(6). The crossover operators are specially designed, since the number of irrigation events can vary between the two parent individuals (Schütze *et al.*, 2012). Then, crossover may undergo a mutation process, depending on p_m, which preserves the relationship between the irrigation time and volume of the schedules of the two parents. Hence, the *mate* function determines each irrigation event for the offspring schedule from the set of union of the parents' irrigation schedules with a certain probability p_{cr}. The crossover, provided that the parameter o_L is equal to 1, is performed for the whole set of the current solution individuals through iteration.

3.3.2.3 Mutation

The crossover process that gives a new solution offspring needs to be readjusted before it undergoes the mutation process, in terms of date d_i with the appropriate volume of water v_i to produce a meaningful schedule. The code named *dayarraytoschedule* function shown in Appendix B(7) is used to rearrange the schedule appropriately. The function needs the new offspring schedule S_{IR} as an input. Once the schedule has been arranged properly, then the mutation process is applied to obtain diversity of solution. The mutation process is coded as *mutate* function that uses the schedule S_{IR}, mutation rates σ_d and σ_v for irrigation date d_i and volume v_i to control the mutation to fit different crops (Appendix B(8)). The function randomly changes the date and volume of water by adding a normally distributed random value, which has to be generated for each variable to be mutated. The procedure gives a mutated offspring solution and needs rearrangement before it undergoes a reconstruction procedure described in Section 3.3.1.2. The code is presented in Appendix B(9) and the function is defined as *re_arrange_scheduleforIRR*. Now, the overall process results in a new offspring solution that replaces the individual solution in the current set of schedule solutions. The process of mutation is undertaken for the whole set of current irrigation schedules through iteration.

3.3.2.4 Termination

Each schedule solution that has been created through the four steps of selection, crossover, mutation, and reconstruction that belong as start-up generation for the EA will be used in the simulation model to compute their respective fitness values. Therefore, through an iteration process fitness value is calculated for the whole set of solutions and will form the current new generation of solutions. Then, the algorithms iterate until a certain desired degree of convergence is reached using a combination of criteria, such as the maximum generation limit and a desired amount of fitness value. The criteria used in this research involves terminating the EA if there is no improvement in the fitness value for a certain number of consecutive generations (e.g. 30 generations) compared to the maximum fitness value of an individual schedule thus far created through EA process.

3.3.2.5 Setting the values for the parameters of the genetic algorithms

The SWAMP-ECON model requires EA parameters that were obtained using the literature, as well as trial and error. A population size of 50 schedules was used in the study. The probabilities for combination (crossover) and mutation were set to be equal to 0.33 and 0.95, respectively. An elitism procedure with a tournament size of $n_{TS} = 5$ was used for the natural-selection process. Values of $\sigma_d = 1.5$ (day) and $\sigma_v = 0.5$ (mm) were applied as variance for irrigation dates and volumes, respectively. The minimal irrigation interval was set to one day for solving the SWAMP-ECON. The maximum generation was set at 100.

Next, the calculation of the fitness function for an irrigation schedule will be presented. The fitness value is the criterion implemented by the EA to evaluate the performance of the irrigation schedule generated through the iteration process of the EA algorithms to improve the solution from one generation to another generation.

3.4 FORMULATION OF FITNESS FUNCTION

An irrigation-schedule solution generated through the process of initialisation at the beginning of the EA or later through the operators of the EA is used by the SWAMP simulation model to simulate yield for each state of nature. The SC yields and the irrigation schedule are used in the economic model to calculate the SC margins above specified costs, which are used as inputs to calculate a fitness value. Hence, this section will describe the methodology of the SWAMP as well as the economic model used in the study.

3.4.1 Soil Water Management Program (SWAMP) model

When a farmer uses low quality water for irrigation, SWAMP provides a better balance between simplicity, accuracy, and robustness to simulate crop yield and soil salinity, than most complex transient-state models. Barnard *et al.* (2015), citing Smith and Smith (2009), classify SWAMP based on its inputs, output and scope as a quantitative and deterministic model. In SWAMP, daily changes in water content of a multi-layer (ℓ) soil and seasonal influence on crop yield are determined from daily simulations of evaporation, root water uptake, WTU through capillary rise and percolation and daily measurements of rainfall and irrigation. The model can be applied to cropping systems with a fallow period, freely drained soils and where a water table is present within or just below the potential root zone. This section will present the initial and boundary conditions, algorithms and parameters required by SWAMP.

3.4.1.1 Initial and boundary conditions

SWAMP requires initial and boundary conditions, i.e. input variables, which are easily obtainable. Hence, the model can easily be used for practical irrigation problems. These inputs are different from information needed by the various algorithms that require calibration, i.e. model parameters. The input variables include: planting date (PLD); growing season length for crop (GSL_c, days); actual or target yield (TQ, kg ha^{-1}); harvest index HI; mean atmospheric evaporative demand over growing season (ET_o, mm day^{-1}) expressed as reference ET of a clipped cool-season grass; if present the depth of the water table (Z_{WT}, mm); number of soil layers (ℓ), soil layer thickness (Z_ℓ, mm), and silt-plus-clay percentage of each layer (SC_ℓ, %); volumetric soil water content at the start of growing season for every layer (θ_ℓ, mm mm^{-1}); date and amount of rainfall (RF_i, mm) and irrigation (IR_i, mm); EC of layer ℓ at the start of the season ($EC_{e(\ell)}$, mS m^{-1}); mean EC of irrigation water during season (EC_{IR}, mS m^{-1}), and mean EC of water table during the growing season (EC_{WT}, mS m^{-1}). The values used for simulation are provided in Section 3.4.1.4.

3.4.1.2 Description of the SWAMP model

The first detailed description of the SWAMP model is available in Bennie *et al.* (1998). The main mathematical algorithms for the sub-routines that simulate water stress in combination with salt stress are available in Barnard *et al.* (2015). In this section, the fundamental algorithms in SWAMP will be described.

3.4.1.2.1 Infiltration

It is assumed that the rainfall and irrigation rate will not exceed the infiltration capacity of the soil. Hence, infiltration is not modelled by the model, i.e. rainfall and irrigation water are infiltrated in a single event on a daily basis into the first soil layer.

3.4.1.2.2 Water budget (redistribution)

The net effect of convection and dispersion is assumed to simulate water flow in SWAMP. The cascading principle forms the basis of calculating the redistribution of water from the top of the soil profile downwards. It is assumed that water will fill each soil layer only to the drained upper limit (DUL, mm) of the specific layer. Any excess water will drain to the layer below, provided it exceeds the deficit of the next specific layer to fill it to the DUL level. Using the DUL of each soil layer, the redistribution of water starts by calculating the effective rainfall and irrigation (EF, mm) that infiltrates the first layer of the soil on day i using Equation 3.8 while run-off and run-on are assumed to be negligible.

$$EF_{RF(i)+IR(i)} = RF_{(i)} + IR_{(i)} \qquad 3.8$$

Where RF and IR refer to rainfall (mm) and irrigation (mm) on a specific day respectively.

In each layer, the water deficit (DF, mm) is computed from the difference in DUL and the simulated volumetric soil water content (θ) of each soil layer on daily basis, according to Equation 3.9. It is assumed that, when there is a rainfall and/or irrigation event, the EF flows into (INF, mm) the first soil layer (Equation 3.10).

$$DF_{(\ell)(i)} = \left(\theta DUL_{(\ell)} - \theta_{(\ell)(i)}\right)\left(Z_{(\ell)}\right) \qquad 3.9$$

$$INF_{(\ell=1)(i)} = EF_{RF(i)+IR(i)} \qquad 3.10$$

Where $Z_{(\ell)}$ is the thickness (mm) of each soil layer.

Once the first layer is filled to its DUL, then excess water flows from it to the next layer. The process of flow will continue until a soil layer is reached where the INF is less than the DF, as described in Equation 3.11.

$$INF_{(\ell)(i)} = INF_{(\ell-1)(i)} - DF_{(\ell-1)(i)} \qquad 3.11$$

The overall amount of applied water (AP, mm) retained in a specific soil layer is assumed to be equal to the DF when the INF into this particular layer is larger than the DF, as stated in Equation 3.12. But, if the INF is lower than DF then the AP is set equal to the INF into the layer under consideration

(Equation 3.13). The calculation of the outflow (OTF, mm) from any specific layer is done according to Equation 3.14.

$$AP_{(\ell)(i)} = DF_{(\ell)(i)} \qquad \text{when} \quad INF_{(\ell)(i)} > DF_{(\ell)(i)} \qquad 3.12$$

$$AP_{(\ell)(i)} = INF_{(\ell)(i)} - OTF_{(\ell)(i)} \qquad \text{when} \quad INF_{(\ell)(i)} < DF_{(\ell)(i)} \qquad 3.13$$

$$INF_{(\ell+1)(i)} = OTF_{(\ell)(i)} = INF_{(\ell)(i)} - DF_{(\ell)(i)} \qquad 3.14$$

In summary, the fundamental Equations 3.8 to 3.14 illustrate the cascading principle used to calculate the daily water budget in each soil layer (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012).

3.4.1.2.3 Evaporation

The Ritchie Equation (as described in Equation 3.15) is used to estimate cumulative evaporation from a bare soil surface (E_{Bare}, mm) during irrigation and/or rainfall events using an empirical coefficient (ϖ) and the number of days between rainfall and/or irrigation events (t). The evaporation from covered soil surfaces (E_{crop}, mm) is calculated with Equation 3.16 by reducing E_{Bare} by a factor equal to 1 minus the fractional shading of the soil (FB).

$$E_{Bare} = \varpi\left(t\right)^{0.5} \quad \text{where} \quad E_{Bare} = E_{Bare} - E_{Bare(i-1)} \qquad 3.15$$

$$E_{Crop} = E_{Bare}\left(1 - FB_{(i)}\right) \quad \text{where} \quad E_{Crop(i)} = E_{Crop} - E_{Crop(i-1)} \qquad 3.16$$

3.4.1.2.4 Potential transpiration or transpiration requirements

SWAMP uses Equation 3.17 to determine the seasonal potential transpiration (T_P), which is dependent only on climatic conditions and crop characteristics. The parameters required to calculate T_P are the mean atmospheric evaporative demand over the growing season (ET_O), a crop-specific parameter (ς), and a maximum biomass production parameter (Q_m, kg ha^{-1}).

$$T_P = ET_O\left(\frac{Q_m}{\varsigma}\right) \qquad 3.17$$

The T_P is used to compute the seasonal transpiration requirement (T_R) for a specific input target seed yield (Equation 3.18), where a total biomass production term (Q_a, kg ha^{-1}) is used for that specific target yield (Stewart *et al.*, 1977).

$$T_R = T_P - \left[T_P \left(1 - \frac{Q_a}{Q_m} \right) \right] \qquad 3.18$$

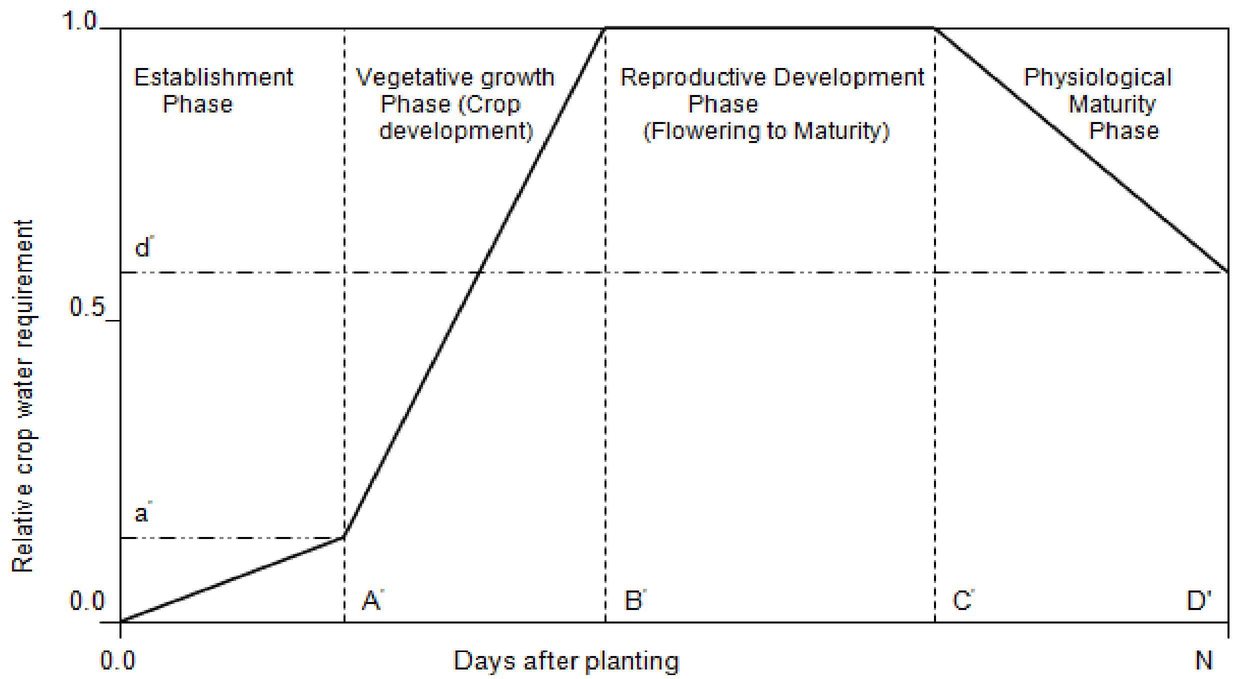


Figure 3.2: A hypothetical graph for estimating daily relative crop water requirements in a given growing season (Bennie *et al*., 1998)

Daily estimations of transpiration requirements are obtained from the seasonal transpiration (T_R) with Equation 3.19. The seasonal transpiration uses a generated growth curve equation for computing the relative daily T_R ($T_{R\ Rel}$). The parameter needs inputs on days after planting (DAP). Parameters A', B', C', and D' represent the number of days until the end of establishment, vegetative growth, reproductive development and physiological maturity, respectively. Parameters a' and d' represent the relative crop-water requirement at the end of phases A' and D', respectively, while ρ is the area under the relative daily T_R line (Figure 3.2).

$$T_{R(i)} = T_{R\,Rel(i)}\left(\frac{T_R}{\rho}\right) \qquad 3.19$$

$$T_{R\,Rel(i)} = \left(\frac{a'}{A'}\right)(DAP) \qquad when \quad DAP \le A'$$

$$T_{R\,Rel(i)} = a' + \left(\frac{1-a'}{B'-A'}\right)(DAP - A') \qquad when \quad A' < DAP \le B'$$

$$T_{R\,Rel(i)} = 1 \qquad when \quad B' < DAP \le C'$$

$$T_{R\,Rel(i)} = 1 - \left[\left(\frac{1-d'}{D'-C'}\right)(DAP - C')\right] \qquad when \quad C' < DAP \le D'$$

3.4.1.2.5 Root density

Multiplying the default root growth rate parameter for the crop under consideration by the days after planting until onset of the reproductive-growth stage is used to calculate the increase in rooting depth and total length per unit surface area ($rl_{(i)}$, mm mm^{-2}) during the growing season of the crop. Then, the rooting density (Lv, mm roots mm^{-3} soil), which is the distribution of roots among the soil layers, is calculated with Equation 3.20, where $f_{(i)}$ represents the daily root-distribution coefficient (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012).

$$Lv_{(\ell)(i)} = \frac{rl_{(i)}\left[\left(1 - Exp\left(-f_{(\ell)(i)}Z_{(\ell)}\right)\right) - \left(1 - Exp\left(-f_{(\ell-1)(i)}Z_{(\ell-1)}\right)\right)\right]}{Z_{(\ell)}} \qquad 3.20$$

3.4.1.2.6 Actual transpiration

Demand and supply components characterise the water-flow system of water uptake by plant roots in SWAMP. Daily estimated evaporation (E) and potential transpiration requirement (T_R) constitute the demand aspect while the supply component is simulated as in Equation 3.21 and is determined by conditions in the soil-root system (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012).

$$PWSR_{(i)} = \sum_{\ell=1}^{n} LWSR_{(\ell)(i)} \qquad 3.21$$

Where $PWSR_{(i)}$ refers to the daily profile water-supply rate and $LWSR_{(\ell)(i)}$ represents the layer water-supply rate on a specific day. The unit of measurement is in mm day^{-1} for both parameters.

Equation 3.22 is used to determine $LWSR_{(\ell)(i)}$, where F_{sr} is the soil-root conductance coefficient (mm^2 d^{-1} kPa^{-1}), Lv the root density (mm roots mm^{-3} soil), ψ_m the matric potential (-kPa), ψ_P the critical leaf-water potential where plant water stress sets (-kPa), θ the simulated daily volumetric soil-water content (mm mm^{-1}) and θ_o the volumetric soil water content (mm mm^{-1}) where ψ_m = ψ_P, which is determined with Equation 3.23 (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012). Accordingly, the formula for calculating $LWSR_{(\ell)(i)}$ is:

$$LWSR_{(\ell)(i)} = F_{sr}\, ln\left(\frac{\theta_{(\ell)(i)}}{\theta_{o(\ell)(i)}}\right)\left(\pi Lv_{(\ell)(i)}\right)^{0.5}\left|\psi_{m(\ell)(i)} - \psi_P\right| Z_{(\ell)} \qquad 3.22$$

Daily simulated θ in combination with calculated volumetric soil water content of the specific soil layer at 1500 kPa (θ_{1500}), volumetric soil-water content of the specific layer at 10 kPa (θ_{10}) and υ (calculated using Equation 3.24) are used to determine daily matric potential (ψ_m) with Equation 3.23.

$$\psi_m = 1500\left(\frac{\theta_{1500(\ell)}}{\theta_{(\ell)(i)}}\right)^{\nu_{(\ell)}} \qquad 3.23$$

$$\nu_{(\ell)} = -\frac{-5.0056}{ln\dfrac{\theta_{1500(\ell)}}{\theta_{10(\ell)}}} \qquad 3.24$$

The $PWSR$ and T_R may be used in simulating the actual transpiration (T_A, mm day^{-1}). Actually, when $PWSR$ for a specific day is greater than T_R for that day, actual transpiration will be equal to the transpiration requirement (T_R). The daily transpiration rate is distributed among the soil layers by multiplying the relative water-supply rate from each layer as shown in Equation 3.25. However, if the $PWSR$ of a specific day is equal or less than T_R for that day, daily actual transpiration will be equal to $PWSR$. Equation 3.25 determines the water uptake from a specific rooted soil layer. The calculated T_A can be used to simulate yield, replacing seasonal transpiration T_R, by rearranging Equation 3.18 to obtain the actual biomass estimation, which gives the expected yield when it is multiplied with HI of the specific crop (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012).

$$T_{A(\ell)(i)} = \left(T_{R(i)}\right)\left(\frac{LWSR_{(\ell)(i)}}{PWSR_{(i)}}\right) \qquad 3.25$$

3.4.1.2.7 Water-table uptake

One of the capabilities of the SWAMP model is calculating water-table uptake (WTU, mm) from shallow water tables located within or just below the potential root zone. The details of the process are explained in Ehlers *et al.* (2003), and it is simulated by relating the maximum upward flux (capillary fringe) from a water table to a specific height above the water table. Equation 3.26 relates the maximum upward flux (q_m, mm day^{-1}) from each layer within the capillary zone (CZ), where τ is an empirical parameter relating the decline in hydraulic conductivity above the water table, Z_f height between the middle of the layer and the water-table surface, and φ_s the saturated hydraulic conductivity (mm day^{-1}). If the T_A of a specific layer is less than q_m for that layer, the sum of daily uptake ($T_{A(i)}$) from each layer within the capillary fringe is considered as WTU. However, if $q_m < T_A$ for the specific layer then the WTU is equal to q_m. SWAMP is capable of water-uptake simulation in both constant and falling water tables (Barnard *et al.*, 2015; Van Rensburg *et al.*, 2012).

$$q_{m(\ell=CZ)} = (\varphi_s)\left(Exp^{\tau}\right)(Z_f) \qquad 3.26$$

3.4.1.3 Water supply under osmotic stress

Barnard *et al.* (2015) explored the SWAMP model to simulate water supply under osmotic stress and the impact on crop yield by adding additional inputs and parameters and defining adaptations to algorithms of SWAMP presented in Section 3.4.1.2. The added inputs include the EC of a saturation extract of each layer at the beginning of the season ($EC_{e(\ell)}$), mean EC of the water table (EC_{WT}), mean EC of the irrigation water (EC_{IR}), and mean EC rainfall (EC_{RF}) required for the season. The fundamental principle followed by Barnard *et al.* (2015) is to quantify daily changes in the salt content (kg ha^{-1}) of a soil layer from simulations of water and salt added to, and lost from, the specific layer. The parameters added are c_1', c_2', and c_3'. Parameter c_1', which converts EC to salt content (kg salt ha^{-1} mm^{-1}), is multiplied by the relevant volume of water (mm) with the corresponding EC to calculate the amount of salt added to or lost from a specific layer. Parameters c_2' and c_3' were defined to convert EC to total dissolved salts (mg L^{-1}) and to convert total dissolved salts to osmotic potential (ψ_o), respectively. It is important to note that the extended model of Barnard *et al.* (2015) does not simulate salt added due to fertilisers, and assumes the salt removed by field crops to be negligible.

SWAMP follows the cascading principle to salt flow in soil layers. Main salt addition to first soil layers comes from irrigation and rain, while salt addition to the layer beneath will be equal to salt removed from the layer above until percolation to the layer beneath is 0 (Barnard *et al.,* 2015). In brief, the main adaptations followed by Barnard *et al.* (2015) and Van Rensburg *et al.* (2012) include the need to compute the osmotic potential (ψ_o, -kPa) and the modification required to compute $LWSR_{(\ell)(i)}$. Accordingly, consideration of matric and osmotic potential is needed to compute total potential in saline soils. Hence, Barnard *et al.* (2015) and Van Rensburg *et al.* (2012) replace the matric potential (ψ_m) in Equation 3.22 with the total soil potential (ψ_t, -kPa). In addition, in the same Equation 3.22, θ_o was replaced by θ_t. The total soil potential is obtained by adding matric and osmotic potentials. The ψ_o is computed as (Equation 3.27):

$$\psi_{o(\ell)(i)} = \left[\frac{EC_{e(\ell)(i)}(c_2')(c_3')}{\theta_{(\ell)(i)}} \right] \theta_{s(\ell)} \qquad 3.27$$

Where $EC_{e(\ell)(i)}$ is simulated EC of daily saturated soil extract in a specific layer; and θ_s is saturated soil-water content of a specific layer.

Using these discussed adaptations, changes were made to Equation 3.22 to obtain an equation to compute $LWSR_{(\ell)(i)}$, which includes the impact of increasing salinity and decreasing osmotic potential on the supply of a rooted soil layer. The formula to calculate $LWSR_{(\ell)(i)}$ is Equation 3.28:

$$LWSR_{(\ell)(i)} = F_{sr}\, ln\left(\frac{\theta_{(\ell)(i)}}{\theta_{t(\ell)(i)}} \right) \left(\pi Lv_{(\ell)(i)} \right)^{0.5} \left| \psi_{t(\ell)(i)} - \psi_P \right| Z_{(\ell)} \qquad 3.28$$

Where θ_t represent the volumetric lower limit of plant-available water under matric and osmotic stress. If a saline soil is considered, θ_t is the volumetric soil water content where $\psi_m + \psi_o = \psi_P$.

3.4.1.4 Model inputs and parameters (data)

This section will present all the inputs and parameters needed by SWAMP to use the crop-growth model to simulate SC yields to model production risk using the SC approach.

3.4.1.4.1 Selection of field crops

To produce field crops sustainably in the VIS using saline irrigation water requires an evaluation of the complex interactions that exist among various factors, such as topographical, meteorological, biological, edaphic (soil and water-related) and anthropogenic (management) conditions. To attain a profitable and sustainable farm under irrigation-induced salinity, it is important to include the economic factors in biophysical models.

The field crops selected for the study are maize (*Zea mays* L.), wheat (*Triticum aestivum* L.), and peas (*Pisum sativum* L.). These crops were selected because they are commonly grown in the area and have different levels of salt tolerance. It is assumed that sound agronomic practices are followed, with conventional land-preparation practices that comprise either burning or baling of crop residues to remove excessive amounts of plant residue, followed by disking and/or ploughing, and/or ripping before planting. Furthermore, to manage disease and soil fertility, double cropping is very common in VIS. Double cropping involves the harvesting of two successive crops per year (Van Rensburg *et al*., 2012). The modelling of double cropping is achieved by including short off-season periods (fallow) during the year and both seasons are assumed to comprise a yearly state of nature (Figure 3.3).

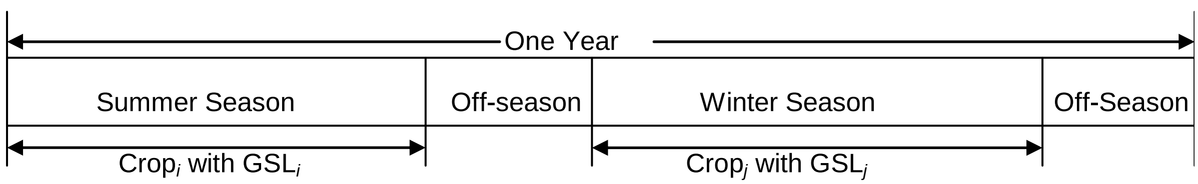


Figure 3.3: Schematic representation modelling double cropping in Vaalharts Irrigation Scheme

As discussed in Section 3.4.1.1, the initial and boundary conditions for simulating yield for the three field crops are required. Parameters such as PLD, GSL_c, TQ, and HI are assumed to be the same for each state of nature (Table 3.1). The TQ and HI are used by SWAMP to calculate the transpiration requirement under matric and osmotic stress.

Table 3.1: Inputs used in SWAMP to simulate the effect of osmotic stress on water uptake and yield of three field crops in a representative farm at Vaalharts Irrigation Scheme for Bainsvlei soils

Inputs	Maize	Wheat	Peas
Planting date*	December 10	July 5	July 15
Crop growth length (days)	141	151	131
Target seed yield (kg ha^{-1})	15 254	7 500	4512
Harvest index	0.58	0.50	0.48

*The planting dates are assumed to be the same for each state of nature in the model.

3.4.1.4.2 Inputs for initial and boundary conditions

If production risk is to be modelled correctly, parameters, such as RF, ET_o, and p_s, should be determined for each state of nature. Because the SWAMP growth model is used to simulate a SC yield for each element of states of nature, determining the number of states of nature to include in the SC approach is critical. SWAMP needs daily rainfall and mean ET_o as inputs for each field crop for a given growing season. Hence, modelling production risk under declining water quality requires that values of daily rainfall and mean ET_o for each state of nature defined in the model are assigned. However, a procedure must be designed to include manageable states of nature, so as to reduce computation time.

Table 3.2: Seasonal rainfall (RF), mean reference evapotranspiration (ET_o), and state of nature probability (p_s) for field crops considered in intra-seasonal analysis

Crop	Parameters	States of nature						
		S_1	S_2	S_3	S_4	S_5	S_6	S_7
Maize	Rainfall (mm)	237	259	222	539	417	134	358
	Mean ET_o (mm day^{-1})	5.3	5.3	5.6	4.8	4.6	5.8	5.2
	Probability (p_s)	3/17	2/17	3/17	1/17	3/17	1/17	4/17
Wheat	Rainfall (mm)	102	245	178	180	145	94	45
	Mean ET_o (mm day^{-1})	4.9	4.9	4.7	4.6	4.8	5.2	5.1
	Probability (p_s)	1/17	2/17	1/17	1/17	6/17	3/17	3/17
Peas	Rainfall (mm)	90	141	166	127	141	91	45
	Mean ET_o (mm day^{-1})	5.0	5.0	4.7	4.6	4.8	5.2	5.1
	Probability (p_s)	1/17	2/17	1/17	1/17	6/17	3/17	3/17

A cluster-analysis procedure was followed on 20-year weather data (from 1980 to 1999) for VIS to determine the number of states of nature to consider for SC risk modelling. Since the reference year was assumed to start from the planting of the maize crop (summer season), the data were reduced to 17 years. The parameter considered in the cluster analysis to define the states of nature is rainfall for the growing season of the field crops. For the intra-seasonal model (single-crop case), states of nature were derived by running a separate cluster analysis by distinguishing the crop as being a summer (maize) crop or a winter crop (wheat and/or peas). Hence, seven states of nature were defined for each crop based on seasonal rainfall. Maize has its own states of nature, defined by rainfall and ET, with their respective probabilities of states of nature. Wheat and peas may differ in terms of rainfall and ET values for the states of nature, while the two crops have the same probabilities of states of nature, since both crops are winter crops that can be represented by the same states of nature. Table 3.2 summarises the values of the parameters RF , ET_o , and p_s . In general, rainfall received in summer is relatively good compared to rain in the winter season. Rainfall during the winter season is not only low, but also highly skewed to the right of the growing season for most of the states of nature (see Appendix F).

In contrast, a single cluster analysis was performed to determine the states of nature for an inter-seasonal model (double cropping), because all the crops are grown within the same year. Each crop could vary in terms of rainfall and ET values for the states of nature while having the same probabilities of states of nature (Table 3.3). In both the intra-seasonal and inter-seasonal cases, the probabilities for states of nature were determined by using the dendrogram produced from the cluster analysis. Hence, the probability of a state of nature is calculated by dividing the numbers of years included within a cluster group by the total number of years of the data used in the cluster analysis.

Table 3.3: Seasonal rainfall (RF), mean reference evapotranspiration (ET_o), and state of nature probability (p_s) for field crops grown in consecutive seasons (inter-seasonal)

Crop	Parameters	States of nature						
		S_1	S_2	S_3	S_4	S_5	S_6	S_7
Maize	Rainfall (mm)	237	259	222	539	417	134	358
	Mean ET_o (mm day^{-1})	5.3	5.3	5.6	4.8	4.6	5.8	5.2
	Probability (P_s)	3/17	2/17	3/17	1/17	3/17	1/17	4/17
Wheat	Rainfall (mm)	102	71	180	194	43	68.8	148
	Mean ET_o (mm day^{-1})	4.9	5.2	4.6	4.3	3.9	5.1	5.0
	Probability (P_s)	3/17	2/17	3/17	1/17	3/17	1/17	4/17
Peas	Rainfall (mm)	90	57	127	179	19	69	69
	Mean ET_o (mm day^{-1})	5.0	5.3	4.6	4.3	4.0	5.0	5.1
	Probability (P_s)	3/17	2/17	3/17	1/17	3/17	1/17	4/17

3.4.1.4.3 Soil information

The soil type and parameters of the soil should also be defined. The soil considered in the study was a 2 m deep, red, and fine sandy loam soil, which is known as Bainsvlei Amalia soil (Soil Classification Working Group, 1991). The Bainsvlei soil has silt and clay percentages that qualify the soil as a Plinthustalf (Soil Survey Staff, 2003). For the purpose of the study it was assumed that there are 16 soil layers. The Z_ℓ , SC_ℓ percentage, and θ at the start of the season for every layer are shown in Table 3.4. The measured initial volumetric soil-water content given in Table 3.4 are for Bainsvlei soil, which has a shallow water table, at 1200 mm depth.

SWAMP model can calculate crop WTU using the information Z_ℓ. Crop WTU from 0 to 600 mm soil layer depth was calculated as the difference between the drain upper limit and the daily simulated soil-water content (where rain and/or irrigation contribute to soil moisture). In contrast, crop WTU from the 600 to 2 000 mm soil layer depth was replaced through capillary rise from the water table. Lastly, but not least, the SWAMP model requires inputs for EC of the irrigation water, water table, and soil extract at the start of the season. The EC inputs measure the salt stress to simulate yield osmotic stress. Different scenarios of water quality were considered for the study area (see Section 3.7).

Table 3.4: Thickness, silt-plus-clay percentage, and initial volumetric soil-water content for Bainsvlei soil for a representative irrigation farm in Vaalharts Irrigation Scheme

Soil layer (ℓ)	Thickness of soil layer (Z_ℓ, mm)	Silt plus clay content (SC_ℓ, %)	Volumetric soil water content at the start of season (θ_ℓ, mm mm^{-1})	Depth (mm)
1	315	10.4	0.1180	315
2	285	18.0	0.1840	600
3	100	18.0	0.3060	700
4	100	18.0	0.3110	800
5	100	18.0	0.3160	900
6	100	18.0	0.3230	1000
7	100	18.0	0.3310	1100
8	100	18.0	0.3400	1200
9	100	18.0	0.3860	1300
10	100	18.0	0.3860	1400
11	100	18.0	0.3860	1500
12	100	24.0	0.3860	1600
13	100	24.0	0.3860	1700
14	100	24.0	0.3860	1800
15	100	24.0	0.3860	1900
16	100	24.0	0.3860	2000

Source: Ehlers *et al.* (2003)

3.4.1.4.4 Derivation of other parameters

The drained upper limit for each soil layer needed to be calculated (see Equation 3.34), which requires prior calculation of a number of parameters. Hence, using information on Z_ℓ and SC_ℓ percentage, the weighted DUL of the root zone (DUL_{rz}, mm) is calculated using Equation 3.29:

$$W_{Soil} = -a'' \ln DS + b'' \qquad 3.29$$

Where W_{soil} is the water content of the soil (mm) during the drainage period, a'' is the slope (mm day^{-1}), DS is the number of days after the soil has been saturated and b'' is the intercept (mm).

Van Rensburg *et al.* (2012) extended the concept of Equation 3.29 to specify the drainage curve for either a bare or cropped soil (Equation 3.30 and Equation 3.31, respectively) to calculate the DUL_{rz}. The calculated DUL_{rz} is then used in Equation 3.32 to simulate soil profile soil water moisture drain upper limit ($\theta_{soil}DUL$), which is used to calculate water content of each soil drained upper limit ($W_\ell DUL$) (Equation 3.33).

$$DUL_{rz(Bare)} = b'' - a'' \ln\left(\frac{a''}{E_{(i)}}\right) \qquad 3.30$$

$$DUL_{rz(Crop)} = b'' - a'' \ln\left(\frac{a''}{T_{R(i)}}\right) \qquad 3.31$$

$$\theta_{Soil}DUL = \frac{DUL_{rz(Bare\ or\ Crop)}}{\sum_{\ell=1}^{n} Z_\ell * SC_\ell} \qquad 3.32$$

$$W_\ell DUL = \theta_{Soil}DUL * \left(Z_\ell * SC_\ell\right) \qquad 3.33$$

Finally, the drain upper limit for each soil layer is calculated as:

$$DUL_\ell = \frac{W_\ell DUL}{Z_\ell} \qquad 3.34$$

Table 3.5: Model parameters and equations to calculate unmeasured parameters in SWAMP to simulate the effect of osmotic stress for three field crops in a representative farm in Vaalharts Irrigation System for Bainsvlei soils

	Parameters and equations	Means of obtaining the parameters	Maize	Wheat	Peas
Redistribution	a'' =18.73 mm day^{-1} b'' =535.54 mm	Measured values (Barnard *et al.*(2015) citing Barnard *et al.* (2010))	same values	same values	same values
Evaporation	$Z_{(\ell=1)}=Exp\left[3.4244\left(SC_{(\ell=1)}\right)^2+5.7193\right]$ $\theta_{a(\ell=1)}=0.0012\left(SC_{(\ell=1)}\right)+0.006$ $FB_i=\left(\frac{FB_m}{100}\right)\left(T_{R(Rel)(i)}\right)$ $FB_m=(FB_1)(Q_a)+FB_2$ when $Q_a \le FB_3$ $FB_m=1$ when $Q_a > FB_3$ FB_m is fractional cover $\varpi_{(i)}=0.087(Z_{(\ell=1)})(\theta_{(\ell=1)(i)}-\theta_{a(\ell=1)})+1.36$	FB_1 (default) FB_2 (default) FB_3 (default) (kg ha^{-1})	0.013 12 7 000	0.0170 15 5 000	0.045 10 2 000
Potential transpiration	ς (crop specific)	Default	220	110	71
	Q_m (max biomass (kg ha^{-1}))	Default	26 300	15 000	9 400
	A' : End of establishment phase (days)	Measured (Ehlers *et al.*, 2003)	20	65	60
	B' : End of vegetative growth phase (days)	>>	60	110	100
	C' : End of reproductive development phase (days)	>>	65	130	110
	D' : End of physiological maturation phase (days)	>>	141	151	131
	a' : Relative crop water requirement at the end of phase A'	>>	0.1	0.2	0.25
	b' : Relative crop water requirement at the end of phase D'	>>	0.05	0.5	0.5
	$\rho=(A'*a')/2+\left((B'-A')*a'+\left((B'-A')*(1-a')\right)/2\right)$ $+(C'-B')+\left(\left((D'-C')*(1-d')\right)\right)/2+(D'-C')*d'$				
Root density*	$rl_{(i)}=L_m*T_{R(Rel)(i)}*\left(\frac{FB_m}{1}\right)$	Default L_m (root length index, mm mm^{-2})	9.4	9.8	2.7
	$f(i)=\frac{2.303}{(0.7)(RPR)(i)}$	Default RPR (root penetration rate, mm day^{-1})	23.5	19	12.7
Actual transpiration	$\theta_{10(\ell)}=0.0345(SC_{(\ell)})^{0.611}$ $\theta_{1500(\ell)}=0.00385\left(SC_{(\ell)}\right)+0.013$	SC_ℓ is silt-plus-clay (%)(measured)			
	ψ_p (critical leaf water potential, kpa)	Default	1 800	2 400	1 500
	RGP (days)	Default	85	105	120
	Rm (root maximum)	Default	2 000	2 000	1 500
	F_{sr} (soil root conductance, mm^2 day^{-1} kpa^{-1})	Determined with an iteration subroutine as described in Barnard *et al.* (2015)	0.000024	0.000025	0.000068
Water-table uptake	$\varphi_s=2925.8\,exp^{-0.1218(SC_{\ell=CZ})}$ $\tau=0.0003(SC_{\ell=CZ})-0.011$	$SC_{\ell=CZ}$ is silt-plus-clay (%) of layer k in CZ			

Table 3.5 provides all the other parameters that need to be calibrated in SWAMP. These parameters and equations are used to calculate the unmeasured parameters (defaults) that are needed to simulate redistribution, evaporation, transpiration, capillary rise and water supply from the various soil layers for the three field crops. As discussed in Section 3.4.1.3, values of 0.075, 7.5, and 0.072 were set for c_1', c_2', and c_3', respectively, for the new, added parameters when osmotic stress had to be modelled by SWAMP. As demonstrated by Barnard *et al.* (2015), calculating the fraction of salt removed as a function of percolation for the proper simulation of osmotic stress on field crops needs a parameter DC for every soil layer. The DC is determined as shown in Equation 3.35, where $\phi_{(\ell)(i)}$ in the equation is the volume of water percolating from the specific layer and g = 0.2673(SC_ℓ) - 12.346.

$$DC_{(\ell)(i)} = 0.94\left(1 - exp^{g\left(\frac{\phi_{(\ell)(i)}}{z_\ell}\right)}\right) \tag{3.35}$$

3.4.1.5 Coding and validations

Barnard *et al*. (2015) already calibrated and validated the SWAMP model for South African irrigation farms using saline water for irrigation. However, the available SWAMP model that considers water stress (assuming salinity of the water to be 0) was coded in C^{++}. On the other hand, the main features of the SWAMP model, which include matric and osmotic stresses, were coded using a Micro-Excel model, while some parameters (e.g. default values, Lv and q_m) as inputs from the values derived from the SWAMP model were coded in C^{++}. The objective of coding in the study was to code the whole SWAMP model in MATLAB to facilitate smooth integration of SWAMP and the EA because the EA was coded in MATLAB. Hence, it was essential to code the main algorithms and parameter equations correctly to simulate the impact of saline water quality on yield of field crops as well as soil salinity. All the algorithms and parameter equations presented and discussed in Section 3.4.1 were available in Micro-Excel codes (Barnard *et al*., 2015). The outputs of the SWAMP model coded in MATLAB were validated by using the outputs of the Micro-Excel version of the SWAMP crop growth model for a given scenario for all three crops. Appendix C presents the main codes of the SWAMP algorithms using MATLAB (Gdeisat and Lilley, 2013).

3.4.2 Economic model (ECON)

An economic model was linked to the SWAMP growth model so as to evaluate the effect of an irrigation schedule on yield, as well as the economic impact of the irrigation schedule on production costs. This section will discuss the methods followed to link the economic model to SWAMP as well as the data used for the different inputs.

3.4.2.1 Description of the ECON model

3.4.2.1.1 Fitness function (objective function)

The EA algorithm has a fitness function that helps the model to evaluate performance of a potential irrigation-schedule solution. The objective function of the model maximises the CE of an irrigation schedule. Equation 3.36 shows the objective function used in the SWAMP-ECON model:

$$Max\ CE = Max\left(-ln\left(\sum_{s=1}^{n} p_s * e^{(-r_a * GM_s)}\right) / r_a\right) \tag{3.36}$$

Where r_a is the absolute RAC and GM_s is the SC gross margin for crop c for state s.

The SC gross margin is calculated as the margin above specified costs for a specified crop and specified state s as shown in Equation 3.37. The gross margin above specified costs is calculated by subtracting the SC yield-dependent costs, area-dependent costs and irrigation-dependent costs from the SC production revenue. The margin above specified cost is calculated by assuming prices to be constant, with the exclusion of electricity costs.

$$MAS_s = r_{c(s)} - YDC_{c(s)} - ADC_c - IDC_c \tag{3.37}$$

Where $r_{c(s)}$ is production income for crop c for state s; $YDC_{c(s)}$ is the yield-dependent costs for crop c for state s (ZAR); ADC_c is the area-dependent cost for crop c (ZAR); and IDC_c is the irrigation-dependent cost for crop c (ZAR). All costs and incomes are given in South African rand (ZAR).

The sections that follow describe the procedures adopted to calculate each of the components of the gross margin in state s that are needed in the fitness function in more detail.

3.4.2.1.2 State-contingent production revenue

The SC revenue of a field crop is a function of the yield, area of crop planted and price of the crop. In the SC approach the price of the crop is assumed to be constant for states of nature. The following formula shows the procedure used to calculate SC revenue of a crop for a given state of nature $s \in \Omega$.

$$r_{c(s)} = Q_{c(s)} * Pr_c * A_c \tag{3.38}$$

Where $Q_{c(s)}$ is the yield of the crop for a specific state of nature; Pr_c is the constant price of the crop (ZAR); and A_c represents the area of the crop planted.

In calculating $r_{c(s)}$, the crop price and the area of crop planted are inputs in the model, while the crop yield is endogenously determined in the model for each state of nature. In the model, for an irrigation schedule SC yields are simulated, the simulated yields are used in the calculation of SC revenues. Hence, the model provides a set of SC revenues ($r_{c(1)},...,r_{c(S)}$) that will be used to compute the margin above specified cost.

3.4.2.1.3 State-contingent yield-dependent costs

The SC yields simulated from the SWAMP model are associated to have SC yield-dependent costs. The SC yield-dependent cost for each state of nature is calculated as:

$$YDC_{c(s)} = Q_{c(s)} * yC_c * A_c \qquad 3.39$$

Where yC_c is the yield-dependent cost (ZAR ha^{-1}). In calculating the total yield cost, it is assumed that there is a linear relationship between inputs and outputs.

3.4.2.1.4 Area-dependent costs

Area-dependent costs include all input costs, which will change according to the area planted. Because the area planted in the model is assumed to be constant, the area-dependent costs will be the same for all states of nature. Equation 3.40 shows the procedure to calculate the area-dependent costs for a crop.

$$ADC_c = aC_c * A_c \qquad 3.40$$

Where aC_c is the area-dependent cost (ZAR ha^{-1}).

3.4.2.1.5 Irrigation-dependent costs

Irrigation-dependent cost is calculated as a function of irrigation water applied. The applied water determines the pumping hours required, which will have an implication on irrigation-dependent cost. The formula to calculate the irrigation-dependent cost is:

$$IDC_c = elC_c + LC_c + RMC_c + WC_c \qquad 3.41$$

Where: elC_c is total electricity costs for crop c (ZAR); LC_c is total labour costs for crop c (ZAR); RMC_c is total repair and maintenance costs for crop c (ZAR); and WC_c is total water costs for crop c. (ZAR). Since the same irrigation schedule is considered in simulating yield for all states of nature in the model, the irrigation-dependent cost will be the same for all states of nature. The irrigation-dependent costs (IDC_c) require the calculation of electricity costs, labour costs, repair and maintenance costs and water costs.

The elC_c calculation is composed of variable and fixed electricity costs. The type of electricity tariff used determines the total electricity costs. The Ruraflex tariff options include a fixed cost and variable cost for the irrigation water applied. Fixed costs are constant throughout the month and have to be paid irrespective of energy consumption, while the variable costs depend on the amount of electricity consumed to apply water to the field. Management (hours pumped), electricity tariffs and irrigation-system design (kW) are the parameters that determine the amount of the variable electricity costs. The elC_c is calculated as:

$$elC_c = \sum_{i,t}(ta_{i,t} + rc_{i,t} + dc_{i,t}) * kW * PH_{i,t} + \sum_{i,t} tra_{i,t} * kvar * PH_{i,t} + fec \qquad 3.42$$

Where $ta_{i,t}$ is active energy charge on day i in time slot t (ZAR kWh^{-1}); $rc_{i,t}$ is reliability energy charge (ZAR kWh^{-1}); $dc_{i,t}$ is demand energy charge (ZAR kWh^{-1}); kW is kilowatt (kW); $PH_{i,t}$ is pumping hours on day i in time slot t (h); $tra_{i,t}$ is reactive energy charge on day i in time slot t (ZAR kVARh^{-1}); $kVar$ is kilovar; and fec is fixed electricity cost (ZAR).

The elC_c calculation is composed of three components. The first part involves the active-energy electricity-tariff calculation, which depends on active, reliable and demand energy charge components for electricity tariffs. The sum of the three components for a specific day multiplied by the kW requirement of an irrigation-system and the pumping hours determines the amount of active-energy electricity tariff. The calculation of the kW requirement depends on the irrigation-system layout and design, while the pumping hours (PH) are influenced by irrigation management and the limits that are placed on irrigation hours during the irrigation cycle when using time-of-use electricity tariffs. The second component is the reactive energy charge, which is calculated as the product of reactive energy charge on day i in time slot t, the $kVar$ and PH of an irrigation-system on day i time slot t. The $kvar$ and kW are provided as inputs in the model. The last component is the fixed electricity cost and it is an input in the model. The fixed electricity cost depends on the type of electricity tariff.

The formulae proposed by Meiring (1989) were used to calculate the labour-cost component of irrigation-dependent costs (IDC_c). Equation 3.43 shows the formula to calculate labour cost, where Lr is labour hours needed per 24 hours irrigation for a given size centre-pivot (h), following data proposed by Meiring (1989) as a basis, and wL represents labour wage (ZAR h^{-1}). The labour requirement is assigned a value of 0.58 labour h^{-1}. Following the Department of Labour (2014), the model was solved with a minimum wage of ZAR 12.41 h^{-1}. For a centre-pivot irrigation-system, the labour cost is considered to be variable since the number of labour hours required is affected by the number of hours the system is operated. The size of the irrigation-system and type of activity being performed affect the amount of labour needed per operating hour. The labour demand for every 24 hours the system is operated is calculated within the model. Therefore, the total labour hours is calculated by multiplying labour demand, labour hours, and the labour wage.

$$LC_c = \left(\sum\nolimits_{i,t} \frac{PH_{i,t}}{24} \right) * Lr * wL \qquad 3.43$$

Equation 3.44 shows the calculation of the repair and maintenance cost component of irrigation-dependent costs IDC_c (Meiring,1989). It is assumed that the use of the pump during the growing season affects the repair and maintenance cost of the pump. The irrigation-system's design is one of the factors that is considered in calculating the repair and maintenance tariff (RM). It is expressed as a percentage per 1 000 hours pumped. The repair and maintenance tariff is expressed as an input in the model:

$$RMC_c = \left(\sum\nolimits_{i,t} PH_{i,t} \right) * RM \qquad 3.44$$

Where RM is repair and maintenance tariff per 1000 h pumped for an irrigation-system (ZAR h^{-1}).

The last component of the irrigation-dependent costs is IDC_c, water cost, which is calculated as:

$$WC_c = \left(\sum\nolimits_{c,i} IR_{c,i} \right) * A_C * Pr_w \qquad 3.45$$

Where $IR_{c,i}$ is irrigation for crop c on day i (mm) and Pr_w is the water price (tariff) (ZAR mm^{-1}).

The water tariff needed in the calculation of water cost is the total payments made by an irrigator for the irrigation services provided to him/her. The water tariff is based on volume, which is a fixed rate per unit of water received. The water tariff is an input in the model.

3.4.2.1.6 Pumping hours

An irrigation event is described by date d_i and volume of water v_i. The formula proposed by Burger *et al*. (2003) is used to calculate the pumping hours required by the irrigation-system to supply v_i as:

$$PH_i = \frac{\frac{v_i}{\eta_{IRS}} * A_c * 10}{\zeta_{IRS}} \qquad 3.46$$

Where η_{IRS} is system efficiency (%) and ζ_{IRS} is the flow rate ($m^3\ h^{-1}$).

The irrigation amount is generated by the model, while the flow rate and system efficiency are input parameters in the model. The calculated PH_i could be allocated to the three time-of-use tariff structures (off-peak, standard, and peak) in a way that minimises energy cost and takes advantage of Eskom's time-of-use electricity tariffs. In allocating the irrigation hours calculated, two basic main constraints are implemented. The first constraint is to restrict the allocated time-slot hours not to exceed the amount of available time-use slots in a specific day (Equation 3.47).

$$DPH_{i,t} \le thc_{i,t} \qquad 3.47$$

Where $thc_{i,t}$ is the available irrigation hours within each irrigation cycle on day i in timeslot t (h).

The second constraint involves that the available off-peak hours on day (d_i) and the next day (d_{i+1}) must be exploited to minimise energy cost. To achieve minimisation of energy cost it was assumed that the generated volume v_i of an irrigation event could be applied that specific day (d_i) and possibly the next day (d_{i+1}) so as to use its off-peak hours available. The second constraint was implemented in three successive sub-constraints defined for each time slot. The sub-constraints involve the calculation of the parameter difference in days between two consecutive irrigation events ($diff = d_{i+1} - d_i$) and the parameter transfer hours to the next day (tPH). The constraint for the allocation of the off-peak time slot irrigation hour is:

$$DPH_{i,OP} = \begin{cases} \text{if } diff = 0 & \text{then} \quad DPH_{i,OP} = PH_i \\ \text{if } diff > 0 \text{ and } PH_i \le OPH_i & \text{then} \quad DPH_{i,OP} = PH_i \\ \text{if } diff > 0 \text{ and } PH_i > OPH_i & \text{then} \quad DPH_{i,OP} = OPH_i \\ & \quad tPH = a = PH_i - OPH_i \end{cases} \qquad 3.48$$

Where OPH_i is the available off-peak hours in day i and OP refers the time slot for off-peak hours.

Equation 3.48 insures that the allocation of irrigation must be done first to the off-peak time slot and cannot exceed the available off-peak hours on that specific day. Any excess irrigation hour (tPH) is transferred to the next day off-peak time slot (OPH_{i+1}). Therefore, if tPH is less than the available off-peak hour of the next day then the next day off-peak time slot irrigation allocation ($DPH_{i+1,OP}$) will be equal to the amount transferred (i.e. $a = tPH$). If the opposite is true, then $DPH_{i+1,OP}$ will be equal to the available off-peak hour of the next day while the difference between tPH and the available off-peak hour of the next day is transferred, to be allocated to the standard time slot of day d_i. Once the allocation of irrigation hours has been done for off-peak hours, then the allocation of the irrigation hours to the standard time-use slot is done, based on what happens after the allocation of the off-peak time slot of the next day. Hence, the constraint for allocating the standard time slot is:

$$DPH_{i,ST} = \begin{cases} \text{if } a < OPH_{i+1} & \text{then } DPH_{i,ST} = 0 \\ \text{if } a > OPH_{i+1} \text{ and } a - OPH_{i+1} < STH_i & \text{then } DPH_{i,ST} = a - OPH_{i+1} \\ \text{if } a > OPH_{i+1} \text{ and } a - OPH_{i+1} > STH_i & \text{then } DPH_{i,ST} = STH_i \\ & tPH = b = \left(a - OPH_{i+1}\right) - STH_i \end{cases} \quad 3.49$$

Where STH_i is the available standard hours in day i and ST refers the time slot for standard hours.

According to Equation 3.49, the allocation of irrigation hours to the standard time slot on day d_i will take place only if the next day's (d_{i+1}) available off-peak hours are fully consumed. It also calculates the number of irrigation hours that may have to be transferred to the next day, before the start of allocation of irrigation hours to the peak time slot on day d_i. Therefore, if tPH is less than the available standard hour of the next day, then the next day standard time slot irrigation allocation ($DPH_{i+1,ST}$) will be equal to the amount transferred (i.e. $b = tPH$). If the opposite is true, then $DPH_{i+1,ST}$ will be equal to the available standard hour of the next day, while the difference between tPH and the available standard hour of the next day is transferred, to be allocated to the peak time slot of day d_i. The constraint for allocation of irrigation hours to the peak time slot is:

$$DPH_{i,PE} = \begin{cases} \text{if } b < STH_{i+1} & \text{then } DPH_{i,PE} = 0 \\ \text{if } b > STH_{i+1} \text{ and } b - STH_{i+1} < PEH_i & \text{then } DPH_{i,PE} = b - STH_{i+1} \\ \text{if } b > STH_{i+1} \text{ and } b - STH_{i+1} > PEH_i & \text{then } DPH_{i,PH} = PEH_i \\ & \text{and } DPH_{i+1,PE} = \left(b - STH_{i+1}\right) - PEH_i \end{cases} \quad 3.50$$

Where PEH_i is the available peak hours in day i and PE refers the time slot for peak hours.

According to Equation 3.50, the allocation of irrigation hours to the peak time slot on day d_i will take place only if the next day's (d_{i+1}) available standard hours are fully consumed. Hence, irrigation hours remaining in the next day's standard time slot will be allocated to the peak time slot of day d_i and d_{i+1}, depending on the number of hours transferred.

3.4.2.1.7 Coding the economic model

The codes for the economic model are presented in Appendix D. The main output parameters needed to analyse results from the output of the SWAMP and economic model were coded as shown in Appendix E. The codes in Appendix E give the printout for the outputs of the SWAMP and ECON model.

3.4.2.2 Model inputs and parameters

3.4.2.2.1 Choice of risk-aversion coefficient

For a risk-averse decision-maker, it was required to determine the r_a in order to estimate the CE used to define the fitness function of the GA. The estimation is based on the maximum risk aversion of 2.5 usually reported in applied MOTAD studies (Grové, 2008; Matthews, 2014). The risk-aversion coefficient was calculated as:

$$r_a = \frac{2.5}{\sigma} \qquad 3.51$$

Where r_a is the RAC and σ is the standard deviation.

The standard deviation is computed from the gross margin above specified cost of each crop for each state of nature obtained from the risk-neutral optimisation gross-margin results (i.e. from outcomes of the seven states of nature). Risk-aversion coefficient was computed for all the alternatives of the risk-neutral analysis using Equation 3.51. Then, the risk-aversion coefficient with the smallest value of all the crop alternative scenarios was taken as the risk-aversion coefficient to be used in the risk-averse optimisation so as to avoid over estimating the risk associated for smaller variability in gross-margin. As such, the values 0.00018 and 0.00015 were selected as RAC for the single crop and double-crop risk-averse scenarios respectively.

3.4.2.2.2 Economic input parameters

Enterprise budgets were prepared for all three crops (maize, wheat, and peas), as shown in Appendix G. Using the enterprise budgets, economic inputs required for the economic model for each crop were determined. These inputs include price of output (Pr_c), yield-dependent cost (yC_c) and area-dependent cost (aC_c). The computation of yield and area-dependent costs for the three field crops is based on Griekwaland-Wes Korporatief's input cost guide for November 2014 (GWK, 2014). In the calculation of yield-dependent costs, a linear relationship was assumed to exist between yield and inputs to produce the crop. Table 3.6 shows the crop prices, and area and yield-dependent parameters for maize, wheat, and peas.

Table 3.6: Economic input parameters and maximum and target yield for maize, wheat, and peas for a representative irrigated farm in Vaalharts Irrigation Scheme

	Maize	Wheat	Peas
Crop price (ZAR ton^{-1})	2 150	3 205	6 000
Yield-dependent costs (ZAR ton^{-1})	833.3	1202.5	1199.2
Area-dependent costs (ZAR ha^{-1})	8 473	5 717.7	5361.2
Maximum yield (ton ha^{-1})	17.4	9.4	7.6

Source: GWK (2014)

3.4.2.2.3 Irrigation-dependent parameters

The economic model needs electricity-tariff parameters to be defined. The tariffs and charges in Eskom's booklet for the period 2014 to 2015 were applied to calculate electricity costs for a representative farm in VIS. Eskom tariff options for irrigation include Ruraflex and Land rate (Eskom, 2014/15). However, in this study only the electricity tariff option of Ruraflex applicable to VIS was considered for calculating electricity cost of an irrigation schedule. The Ruraflex charges considered in the research are shown in Table 3.7. Accordingly, the charges for the active energy ($ta_{i,t}$) and network-access charges (fixed charge) (nac) are based on the assumption that the representative farm uses the less than or equal to 300 km transmission zone and a voltage of greater or equal to 500 V and less than or equal to 22 kV. For the same farm, a voltage smaller than 500V was the basis for selecting the reliability ($rc_{i,t}$) and network demand charge ($dc_{i,t}$). Because wheat and peas are irrigated during the high season, a reactive energy charge ($tra_{i,t}$) is assigned to these crops only. The charge for service and administration is based on the less than or equal to 100 kVA. Active energy will have the greatest effect on variable costs in the case of Ruraflex. Ruraflex's active energy has components of low and high season time-of-use tariffs. In addition, Ruraflex includes a reactive energy charge during the high season as well as an administration charge.

The water tariff (Pr_w) is based on the VIS's WUA, which is based on a volume-based charge with an allocation of 9 140 $m^3ha^{-1}year^{-1}$. The tariff per millimetre water applied is calculated by dividing the tariff by the water allocation and it has the value ZAR 0.714 mm^{-1}.

Table 3.7: Variable and fixed electricity tariffs for the Ruraflex electricity tariff structure for a representative irrigated farm land in Vaalharts Irrigation Scheme, 2014/15

Variable Electricity Cost Tariffs			
Active Energy Charge (c kWh^{-1})	High (June-August)	Off-peak	37.25
		Standard	68.61
		Peak	226.48
	Low (September-April)	Off-peak	32.25
		Standard	50.84
		Peak	73.88
Reliability Service Charge (c kWh^{-1})			0.29
Network Demand Charge (c kWh^{-1})			18.8
Reactive Energy Charge (c $kVArh^{-1}$)	High (June-August)		6.35
	Low (September-April)		0
Fixed Electricity Cost Tariffs			
Network Access Charge (ZAR $kVA^{-1}month^{-1}$)			12.10
Service Charge (ZAR $Account^{-1}day^{-1}$)			12.99
Administration Charge (ZAR POD^{-1}* day^{-1})			3.69

*POD: Point of Delivery

Source: Eskom (2014/15)

3.4.2.2.4 Irrigation-system design parameters

Field observation showed that the most widely used centre-pivot irrigation-systems in VIS are irrigation-systems with delivery capacities of 10 mm day^{-1} and 12 mm day^{-1}. The centre-pivot considered for the study is able to cultivate 30.1 ha of land. It is assumed that centre-pivot irrigation-systems are designed for a 750 m main pipeline at a static height of 12 m. Table 3.8 shows the essential parameters and their values considered in the study to calculate electricity-related irrigation costs. The parameter flow rate is dependent on the size of the pivot and the designed capacity of the centre-pivot irrigation-system.

Table 3.8: Irrigation-system design parameters for an irrigated farm for centre-pivot with small sizes and two system delivery capacities

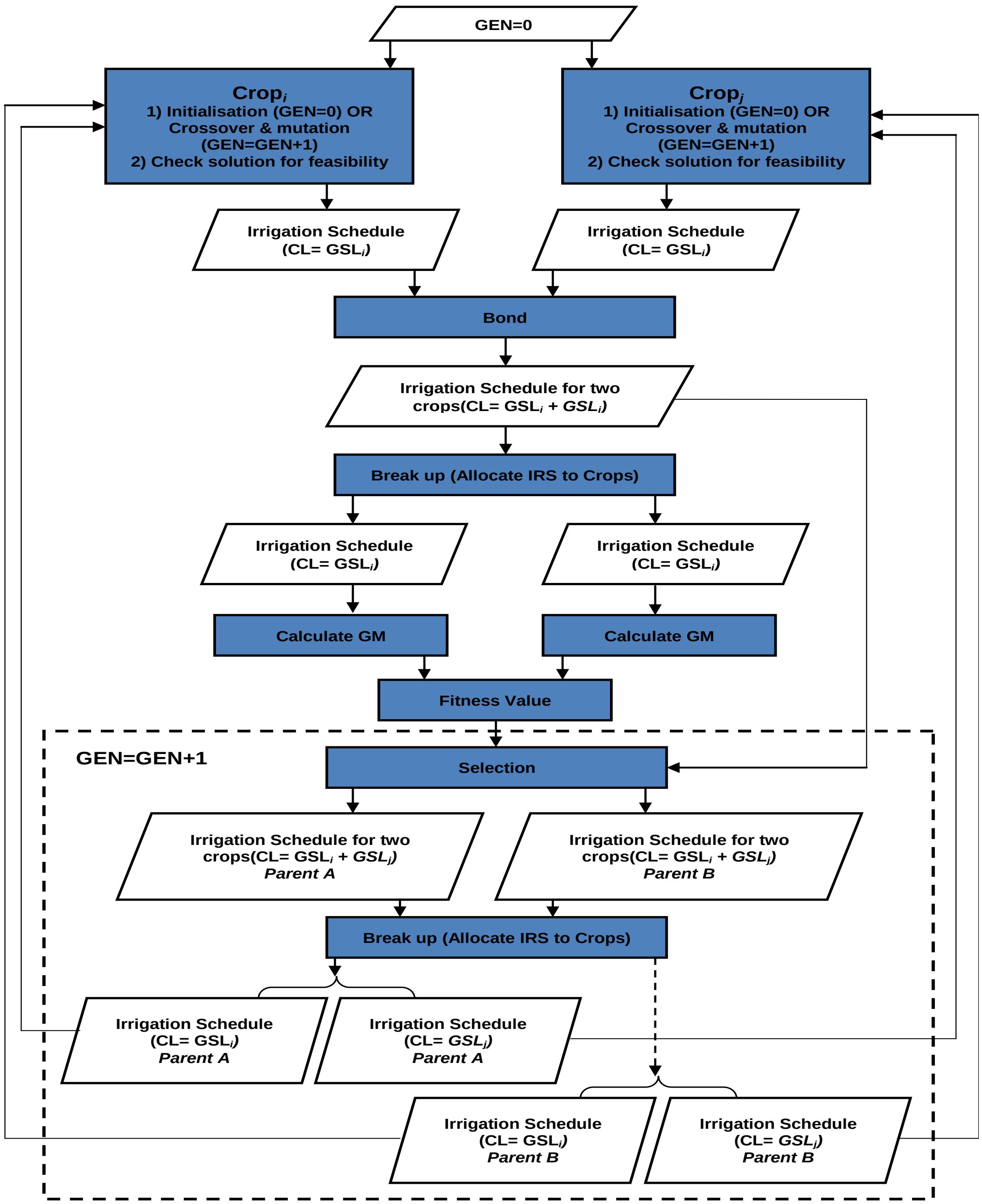
Design Parameters	Centre-pivot Size (30.1ha)	
	Irrigation-system Delivery Capacity	
	10 (mm day^{-1})	12 (mm day^{-1})
Flow rate (m^{3}h^{-1})	125.5	150.5
Pressure (m)	22.4	24.1
Static head (m)	12	12
Efficiency of pump (fraction)	0.755	0.755
Kilovar (kVAr)	13.5	14.1
Kilovolt-ampere (kVA)	50	50
kW Pump	21.8	24.9
Repair	0.43	0.41

Source: Myburgh (2014)

3.5 EXTENDING TO INTER-SEASONAL WATER MANAGEMENT

The inter-seasonal optimisation problem refers to a cropping system involving two crops (a summer crop and a winter crop) that are planted in consecutive growing seasons in a given year. The principle followed to model inter-seasonal optimisation is similar to that of the intra-seasonal optimisation discussed in Sections 3.3 and 3.4, but extended to handle two crops. The extension to a two-crop case was achieved by formulating two simple algorithms, which were integrated into the model of intra-seasonal optimisation. In addition, the calculation of SC margins above specified costs was extended to a two-crop case. The two algorithms were formulated to bond irrigation schedules of crops, and break up bonded irrigation schedules, back to irrigation schedules for individual crops.

In addition to Figure 3.1, Figure 3.4 is to used explain the method followed to extend the intra-seasonal model to an inter-seasonal model. Bonding and break-up algorithms play crucial roles in modelling inter-seasonal crop production. It is assumed that the same intra-seasonal irrigation-schedule optimisation procedure could be applied to each crop while performing bonding or break-up algorithms to extend the model to inter-seasonal scheduling. The bond algorithm (see Appendix B(10)) is a process that creates an irrigation schedule with a chromosome length equal to the sum of the growing-season length of two crops ($GSL_i + GSL_j$). A chromosome that accounts for both crops is important, since the irrigation schedule that is represented in Equation 3.1 for the single-crop case is now assumed to be the irrigation schedule for the whole year (two seasons), which optimises the total output of the farm from the production of the two crops. The break-up algorithm (*Allocate Irrigation Schedule to Crops*) is an algorithm (see Appendix B(11)) that splits the irrigation schedule for the whole year into two, based on the GSL, to identify the irrigation schedule for each crop.



CL = chromosome length

Figure 3.4: Schematic design to extend to inter-seasonal irrigation schedule optimisation

Hence, the schematic flow chart in Figure 3.4 shows how the extension to a two-crop case is done. At initialisation stage (GEN = 0), initialisation of an irrigation schedule is done for each crop by following the procedure described for the intra-seasonal procedure (Section 3.3.2.2). Then, the bonding procedure is performed to create an irrigation schedule that represents the two crops with chromosome length equal to the sum of the GSL for each crop. To calculate the fitness value of a solution, the break-up algorithm is required to divide the irrigation schedule that represents the whole year (i.e. for two crops) into individual crop-irrigation schedules. The allocated irrigation schedule for the crops is needed to calculate the SC gross margin for each crop, which is, eventually, essential for calculating the fitness value associated with the irrigation schedule that represents the two crops. The calculation of SC margin above specified cost for the intra-season schedule is done as shown in Equation 3.52 for the inter-seasonal schedule. The calculated SC margin above specified cost is used in place of Equation 3.36 to maximise the CE for the production of two crops. The generation of an irrigation schedule for two crops and calculating the corresponding fitness value will be done for all members of the set of solutions that have a member size of the population size (n_P).

$$MAS_s = \sum_{c=1}^{2} r_{c(s)} - YDC_{c(s)} - ADC_c - IDC_c \qquad 3.52$$

The portion of the flow chart that is presented within the rectangular broken line box in Figure 3.4 is the procedure followed to do EA operators for two crops grown inter-seasonally. An irrigation schedule for two crops, with its corresponding fitness value, will be the new-generation solution to starting the EA operators to improve the solution. The selection operator is introduced by applying the elitism and tournament selection approach as discussed for the intra-seasonal irrigation-schedule case. The selection process creates two mating parents. Then, each parent schedule for the two crops is broken up into individual crop schedules to create two parents (mother and father chromosomes) for each crop. Then, crossover and mutation are performed for each crop on the parent chromosomes to create an offspring schedule for each crop. The resulting offspring irrigation schedules for each crop are combined to create an irrigation schedule for the two crops. Fitness calculation can be performed on the combined irrigation schedule as discussed before, similar to the initialisation-schedule case.

3.6 DEVELOPMENT OF IRRIGATION STRATEGY FOR FARMERS

It is important to quantify the irrigation strategy applied by farmers to supply water to field crops, so as to evaluate the impact of their irrigation strategy on crops, soil salinity, and the environment. Most irrigation farmers in the VIS supply water to meet crop-water requirements. The assumptions followed, in line with expert opinions in the area, are that the farmers irrigate every week to compensate for ET loss of water from the soil – their strategy is based on their experience of farming in their field. Hence, an approach was developed in the study to propose a best average irrigation strategy for farmers to use for the different field crops under investigation, taking into consideration the centre-pivot's delivery capacity.

In the absence of measured field data, developing an irrigation strategy for farmers is not an easy task when production risk has to be modelled. The states of nature in this study are defined in terms of rainfall and reference evapotranspiration (ET_o). Selecting an irrigation strategy for farmers becomes complicated when rainfall in different states of nature is included in the analysis. To overcome the problem, a two-step optimisation procedure was followed to determine the best average irrigation strategy across states of nature. The procedure developed was used to determine current farmers' irrigation strategies for three field crops, namely, maize, wheat, and peas, irrigated for a centre-pivot irrigation-system with specified delivery capacity.

The first optimisation procedure involves taking the potential transpiration and evaporation of the specific crop simulation data for each state of nature determined from the SWAMP model using a random irrigation schedule (Section 3.4.1), states of nature rainfall, and constraints on net irrigation for each week. The calculation of weekly net irrigation for each state of nature is achieved in three steps. The first step involves using the simulated daily potential transpiration and evaporation to determine the weekly ET required in the growing season for the crop corresponding to each state of nature. In the second step, weekly net irrigations for a crop for a given state of nature are calculated as shown in Equation 3.53. Weekly net irrigations are calculated using a minimum condition for weekly states of nature rainfall, which is the sum of daily rainfall within the specified week. The minimum weekly state of nature rainfall was assumed to be 10 mm day^{-1}. If the weekly rainfall in a given state of nature observed is below the minimum weekly state of nature rainfall, then it is assumed that the farmers ignore the rainfall in determining the irrigation schedule in that specific week for that specific state of nature.

$$NIR_{W(s)} = \begin{vmatrix} 0 & \text{if } RF_{W(s)} \geq ET_{W(s)} \\ ET_{W(s)} & \text{if } RF_{W(s)} < RF_{min} \\ ET_{W(s)} - RF_{W(s)} & \text{if } RF_{W(s)} \leq RF_{min} \end{vmatrix} \qquad 3.53$$

Where $NIR_{W(s)}$ is the weekly net irrigation for a given state of nature; RF_W is the weekly rainfall for a given state of nature; $ET_{W(s)}$ is the weekly ET of the crop for a given state of nature; and RF_{min} is the minimum rainfall.

In the last step, then, the weekly net irrigation for a given state of nature determined by Equation 3.53 is refined further by setting a minimum condition for the irrigation amount (IR_{min}). The minimum irrigation amount condition is set at a value of 5 mm day^{-1} that can be applied in the specified week. Equation 3.54 is the formula used to calculate the weekly net irrigation for a given state of nature.

$$NIR_{W(s)} = \begin{cases} 0 & \text{if } NIR_{W(s)} = 0 \\ IR_{min} & \text{if } NIR_{W(s)} \leq IR_{min} \\ NIR_{W(s)} & \text{if } NIR_{W(s)} > IR_{min} \end{cases} \qquad 3.54$$

The calculated weekly net irrigation for each state of nature is used to determine the best average weekly net irrigation. The optimal weekly best average irrigation strategy for farmers is achieved by defining an objective function that minimises the sum of total deviation, as shown in Equation 3.55. The decision variable for the objective function is weekly best average irrigation strategy for farmers (AIR_W).The optimisation was solved using an Excel solver with an evolutionary tool.

$$Minimise\, d = \sum_{W}^{m} \sum_{s}^{n} \left(NIR_{W(s)} - AIR_W \right)^2 \qquad 3.55$$

Subject to:

$$IR_{min} \leq AIR_W \leq 7 * \zeta_{IRS} \qquad 3.56$$

$$AIR_W \geq 0 \qquad 3.57$$

The second optimisation procedure was needed to distribute the weekly best average irrigation strategy to the daily irrigation schedule, based on minimising the irrigation electricity cost. A model was constructed in Excel with all the parameters needed to consider electricity-tariff use and the centre-pivot irrigation-delivery capacity. Using the Excel solver, the optimal weekly best average irrigation strategy was redistributed by minimising the irrigation cost.

3.7 APPLICATION TO INTRA-SEASONAL AND INTER-SEASONAL SCHEDULING

The following alternative scenarios were established to run the optimisation model:

- Three crops, namely, maize, wheat and peas, were considered for the intra-seasonal scheduling, while a maize-wheat and maize-peas type of double cropping was considered for the inter-seasonal scheduling.
- The soil in the irrigation field was characterised as exhibiting a shallow water table, which is assumed to be constant throughout the growing season.

- The salinity condition of the field was quantified by measuring the electrical conductivity of the irrigation water, the water table, and the soil extract. Two water-quality scenarios, good and low, were considered to run the optimisation model. The good-quality-water scenario is based on the current condition of the VIS. The low-quality-water scenario was set at a higher level of EC than the good water quality EC, of 75, 225, and 150 (mS m^{-1}) for irrigation, water table, and soil extract to characterise good quality water, respectively, whereas, EC of 225, 375, and 300 (mS m^{-1}) for irrigation, water table, and soil extract to characterise low quality water, respectively. The EC s of the irrigation water and water table are assumed to be constant throughout the growing season while the EC of the soil extract (EC_e) represents the condition at the start of the growing season.
- Two irrigation-systems with delivery capacities of 10 mm day^{-1} and 12 mm day^{-1} were selected to evaluate the impact of centre-pivot delivery capacity on achieving optimal water-use and salinity management.

The SWAMP-ECON was successfully solved and stochastic efficiency, WUE and environmental impact indicators were used to interpret results for the intra- and inter-seasonal applications of field crops in the study area.

CHAPTER 4

RESULTS, DISCUSSIONS AND CONCLUSIONS

4.1 INTRODUCTION

In this chapter, all methodologies presented in Chapter 3 are applied to model, in an economical way, the management of water and salinity for a case study farm in VIS, which is characterised as having Bainsvlei soil with a shallow water table close to or below the root zone. The centre-pivot considered could irrigate 30.1 ha of farmland. Scenarios considered were designed to model the interaction that exists between a farmer's options, such as centre-pivot irrigation-system delivery capacity, irrigation-scheduling strategies, field crops with different salinity-tolerance levels, and different irrigation-water qualities. Profitability, WUE, water productivity (WP) and environmental indicators were used to interpret results. The electricity-tariff system used in the model was the Ruraflex tariff option, which demonstrates the impact of electricity energy charge on profitability. First, the intra-season results and findings of stochastic efficiency, WUE, WP and environmental impact of the farmer's existing irrigation-scheduling will be presented for maize, wheat and peas. Next, the farmer's irrigation strategy will be compared with an optimal irrigation schedule to determine the benefits of optimal irrigation-scheduling. Finally, the model results for the optimal irrigation schedule within an inter-seasonal setting will be discussed, where the water-use of two crops are optimised simultaneously to determine the importance of considering the follow-up crop when making decisions on current crop irrigation schedules.

4.2 CURRENT IRRIGATION PRACTICES FOR INTRA-SEASONAL FIELD CROPS

The farmer's irrigation schedules for three field crops, obtained using the procedure described in Section 3.6, were used as irrigation inputs in the SWAMP-ECON model to simulate yields, evaporation, transpiration, WTU, percolation, salt build-up, SL, and economic parameters for each state of nature. Irrigation schedules considered were for two irrigation-system delivery capacities for maize, wheat and peas, respectively. The irrigation schedules considered were derived from knowledge that farmers irrigate crops to fulfil the water requirements of crops during the growing season. The farmer's average best irrigation strategy across states of nature was derived using an optimisation procedure (see Section 3.6) for all three field crops, taking into consideration the centre-pivot's delivery capacity. The results of the analyses of the current farmer's irrigation-scheduling for intra-seasonal cropping are presented in this section.

4.2.1 Stochastic efficiency (profitability)

Table 4.1 shows the expected margin above specified costs (MAS), lower partial moment (LPM) indicators and expected yields for the farmer's existing irrigation-scheduling for three field crops for a case study farm in the VIS. Maize is grown in the summer season, which has relatively better rainfall, while wheat and peas are grown in the winter season. Wheat is salt tolerant while maize and peas are moderately salt tolerant and salt sensitive, respectively.

As shown in Table 4.1, peas is the most profitable enterprise, followed by maize and then wheat, irrespective of the water quality and irrigation-system delivery capacity considered. Hence, the profit ranking remains the same regardless of the water quality and irrigation-system delivery capacity scenarios considered for the irrigation strategy the farmer designed for each field crop in the study. On average,[1] the expected MAS for peas, maize and wheat, respectively, is ZAR 448 370, ZAR 321 909 and ZAR 245 885.

A comparison of the two water-quality scenarios in Table 4.1 show that there was a slight decrease in the expected MAS of maize and peas, while the expected MAS for wheat remained unchanged when using low quality water for both irrigation-system delivery capacities. The slight decreases in MAS when using low quality water were ZAR 2 185 and ZAR 2 283 for maize and peas, respectively, for the 10 mm day^{-1} irrigation-system, while slight decreases, of ZAR 2 368 and ZAR 1 330 for maize and peas, respectively, were observed for the 12 mm day^{-1} irrigation-system. The decreases in MAS observed for the field crops as a result of the use of low quality water were generally less than one percent for the two crops for both irrigation-system delivery capacities. Thus, the impact of water-quality changes seems small. The farmer's irrigation strategy amount was designed on the assumption that the farmer ignores irrigation water quality, thereby the same irrigation electricity costs result for the two quality-water scenarios for a given irrigation-system delivery capacity. Consequently, the small changes in crop yield explain the differences in MAS between the two water qualities for maize and peas. Because maize and peas are moderately salt tolerant and salt-sensitive crops, respectively, they each show a slight decrease in expected yield when low quality water is used, compared to the expected yield that might be achieved by using good quality water. This is because these two crops experience some stress in very bad states of nature (see Appendix H). Considering the average of the irrigation-system delivery capacity, the decreases in expected yield due to using low quality water are 57 kg ha^{-1} and 14 kg ha^{-1} for maize and peas, respectively. In general, maize and peas showed a less than 0.5% decrease in expected relative yield when using low quality water, compared to the expected relative yield obtained by using good quality water.

[1]Calculation based on expected MAS for both water qualities and irrigation-system delivery capacities.

Table 4.1: Expected MAS, LPM indicators and expected crop yields for the farmer's irrigation strategy using centre-pivot (30.1 ha)

		Parameter	Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡
Pivot Delivery Capacity	10 (mm day^{-1})	Expected MAS (ZAR)	322 381 (0)	245 190 (0)	448 774 (0)	320 196 (6 269)	245 189 (0)	446 491 (3 373)
		ρ_{SF}	0	0	0	0.35	0	0.94
		Expected shortfall (ZAR)	0	0	0	2 615	0	3 415
		Expected yield (kg ha^{-1})	15 242 (0)	7 446 (0)	4 473 (0)	15 187 (158)	7 446 (0)	4 457 (24)
		Expected YR††	0.999	0.993	0.991	0.996	0.993	0.988
	12 (mm day^{-1})	Expected MAS (ZAR)	323 713 (0)	246 581 (0)	449 773 (0)	321 345 (6 863)	246 581 (0)	448 443 (1 768)
		ρ_{SF}	0	0	0	0.35	0	0.94
		Expected shortfall (ZAR)	0	0	0	2365	0	1329
		Expected yield (kg ha^{-1})	15 242 (0)	7 446 (0)	4 473 (0)	15 182 (173)	7 446 (0)	4 464 (12)
		Expected YR††	0.999	0.993	0.991	0.995	0.993	0.989

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

‡Numbers in bracket are standard deviations; ††YR is relative yield (actual/potential)

Even though the expected MAS for maize and peas was not affected to a great extent by irrigation-water quality changes, the risk caused by being unable to manage irrigation-water applications to avoid water and osmotic stress increased greatly. The two indicators that are used to quantify the impact of water quality deterioration on production risk are shortfall probability and expected shortfall. Shortfall probability is defined as the cumulative probability of failing to achieve the potential MAS in some states of nature considered as a result of using good or low quality water for irrigation. Expected shortfall is calculated as the expected negative deviations from potential MAS in the presence of production risk. Accordingly, wheat is not affected by production risk caused by low quality water, as the farmer's irrigation strategy enables the crop to cope with the impact of matric and osmotic stress in all states of nature. However, peas is the most vulnerable crop, followed by maize, for both irrigation-system delivery capacities. Peas show 94% shortfall probability when water quality is low, with a shortfall of ZAR 3 415 and ZAR 1 329 expected for the 10 mm day^{-1} and 12 mm day^{-1} irrigation-system delivery capacities respectively. Although the shortfall probability for peas was very high, the expected shortfalls observed for the irrigation-systems were very small compared to the expected MAS. The second-most-vulnerable crop is maize, because it showed a 35% shortfall probability, that is, a shortfall of ZAR 2 615 and ZAR 2 365 expected for the 10 mm day^{-1} and 12 mm day^{-1} irrigation-system delivery capacities respectively. Although the risk of not realising potential yields for maize and peas was high, the impact on MAS was fairly small.

Besides, a comparison of the expected MAS for the two irrigation-system delivery capacities shows that the 12 mm day^{-1} irrigation-system resulted in slightly higher expected MAS for all three crops, regardless of water quality scenario. The increases in expected MAS were ZAR 1 332 (maize), ZAR 1 391 (wheat) and ZAR 999 (peas) for good quality water, while increases in expected MAS to the value of ZAR 1 149 (maize), ZAR 1 392 (wheat) and ZAR 1 952 (peas) were observed for low quality water. The increases in expected MAS for the field crops can be explained by the differences in total variable irrigation electricity cost (TVIEC) of the two irrigation-system delivery capacities for both water qualities. Table 4.2 shows the distribution of the pumping hours for time slots of energy tariff time use, total irrigation hours and TVIEC of the three field crops that resulted from following the farmer's respective irrigation strategies for both irrigation-system delivery capacities. Because the same irrigation strategy was used by the farmer for a given field crop irrespective of the water-quality scenario, the number of total irrigation hours and amount of TVIEC for a given crop and irrigation-system delivery capacity were the same for both water qualities. No distinction between water qualities therefore exists in terms of TVIEC.

Table 4.2: Total irrigation hours, total variable electricity cost and total irrigation cost based on Ruraflex and total irrigation cost of the farmer's irrigation strategy for three field crops using centre-pivot (30.1 ha)

Parameter	Irrigation-system Delivery Capacity					
	10 mm day^{-1}			12 mm day^{-1}		
	Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡
OPH (h)	973 (79%)	958 (72%)	1 055(66%)	905 (88%)	871 (78%)	911 (68%)
STH (h)	254 (21%)	347 (26%)	450 (25%)	118 (12%)	237 (21%)	390 (29%)
PEH (h)	0	27 (2%)	84 (3%)	0	5 (0.4%)	40 (3%)
Total Irrigation Hours	1 227	1 332	1 589	1 023	1 113	1 341
TVEC (ZAR)	15 663	18 823	21 988	14 352	17 410	20 817
TIRC (ZAR) ††	26 667	31 503	36 237	25 334	30 111	35 238

‡Numbers in brackets are percentages that represent contribution to the total irrigation hours

††TIRC = Total irrigation cost

The reason why the TVIEC for the 12 mm day^{-1} irrigation-system was lower than the 10 mm day^{-1} irrigation-system is twofold. Firstly, irrigation-systems with higher delivery capacities allow the irrigator to apply the same amount of water in a shorter period of time. The use of the 12 mm day^{-1} irrigation-system reduced the total irrigation hours by approximately 16%. Secondly, the ability to apply the same amount of water in a shorter time period allows the irrigator to manage the distribution of the hours among the time-of-use electricity tariff time periods. Use of the higher irrigation-system delivery capacity results in small changes in the distribution of hours, favouring the use of more of the lower-tariff hours, such as off-peak and standard hours, by reducing the use of peak hours as much as possible for all field crops. Using the 12 mm day^{-1} irrigation-system lowers the TVIEC observed for the 10 mm day^{-1} irrigation-system slightly, by ZAR 1 311 (maize), ZAR 1 413 (wheat) and ZAR 1 171 (peas) for both water qualities. Hence, it was the decrease in TVIEC that contributed to the small increase in expected MAS for each field crop when using the 12 mm day^{-1} irrigation-system delivery capacity.

From the profitability analyses, it can be concluded that decline in water quality did not affect the profitability of any of the field crops significantly, because the farmer's irrigation strategy allowed the crops to achieve close to the potential yield in all states of nature. Changing the irrigation-system delivery capacity to a higher level did consistently increase the MAS for all the field crops. Besides, although the impact on expected MAS was low, using low quality water resulted in an increase in risk caused by not realising the potential of the moderately and very salt-sensitive crops.

Sub-section 4.2.2 will discuss the impact of the farmer's irrigation strategy on water-use management indicators.

4.2.2 Water-use management

Table 4.3 shows expected cumulative values of simulated parameters for evaporation, transpiration, drainage loss and WTU, as well as calculated values for expected cumulative rainfall, cumulative irrigation, soil moisture at the start of the growing season, change in soil-water content observed at the end of the season, WUE, and WP for the farmer's irrigation strategy designed for each field crop.

WUE and WP indicators[2] are used to evaluate the performance of the farmer's irrigation schedule while considering the quality aspect of the irrigation. WUE is defined as the ratio of the amount of water transpired by a crop to the amount of water supplied to the crop through rainfall, irrigation and WTU. Two methods of WP calculation were applied to determine the impact of total water-use and applied water independently. WP of total water-use (WP_{TWU}) was calculated as the ratio of grain produced to total water-use by a field crop. On the other hand, WP of water applied (WP_{WA}) was calculated as the ratio of grain produced to water supplied to the crop through rainfall and irrigation. The WP_{TWU} and WP_{AW} are used to determine the effect of irrigation-induced drainage and avoiding excess irrigation on grain yield, respectively, independently.

[2]WUE and WP treated as two different terms in this study.

As mentioned before, the irrigation strategy of the farmer in the study does not consider water quality and, hence, the same cumulative irrigation amount was assumed for both water qualities for an irrigation-system delivery capacity scenario. On the other hand, the two irrigation-system delivery capacities use the same amount of cumulative irrigation, but may differ in terms of the timing and amount of water applied for a field crop. The cumulative irrigation amounts for maize and wheat are ~512 mm and ~591 mm, respectively, for both centre-pivot irrigation-system delivery capacities. But, the cumulative irrigation amounts for peas are 663 mm and 671 mm for the 10 mm day^{-1} and 12 mm day^{-1} irrigation-systems, respectively. The slight difference in the cumulative irrigation amounts for peas under the two systems is due to the fact that the 10 mm day^{-1} irrigation-system delivery capacity was too low to deliver the crop's total water requirement in some of the weeks of the growing season of the crop. As a result, peas received slightly less irrigation under the 10 mm day^{-1} irrigation-system.

Table 4.3 shows that the irrigation strategy the farmer followed for each field crop resulted in huge water-use inefficiency, regardless of the irrigation-system delivery capacity or water quality scenario considered. The expected WUEs are ~58%, ~65% and ~63% for maize, wheat and peas, respectively, indicating that a significant amount of the water supplied (RF + IR + WTU) was lost from the soil profile through processes of evaporation and drainage, in addition to transpiration by the crop. Depending on the field-crop type, 35% to 42% of the water supplied to the crop may be lost through evaporation and/or drainage processes. Important to note is that inefficiencies in water-use may be accompanied with low WP too. The expected WP indicators in Table 4.3 were low due to the low expected WUE of the farmer's irrigation strategy for a field crop. The expected WP indicators were approximately the same for a field crop regardless of the irrigation-system delivery capacity and/or water-quality scenario considered. Accordingly, the expected WP_{TWU} are equal to approximately 14.5 kg ha^{-1} mm^{-1}, 7.2 kg ha^{-1} mm^{-1} and 4.3 kg ha^{-1} mm^{-1} for maize, wheat and peas, respectively. Similarly, the expected WP_{AW} are equal to 19 kg ha^{-1} mm^{-1}, 10 kg ha^{-1} mm^{-1} and 6 kg ha^{-1} mm^{-1} for maize, wheat and peas, respectively.

The low WUE and WP in Table 4.3 were the result of excess application of irrigation water, because the irrigation strategy followed by the farmer did not consider the role of the shallow water table as a source of water to the crop's ET. However, the simulation result of SWAMP-ECON shows that the shallow water table could contribute significantly to ET in all the three field crops. In addition, it is clear that changing the irrigation-system delivery capacity and/or the water quality scenario did not significantly change the cumulative expected WTU contribution to ET of a field crop under the farmer's irrigation strategy. The WTU may range from 40% to 49%, depending on the crop type, with salt-sensitive crops (maize and peas) exhibiting WTU towards the lower range, while the salt-tolerant crop (wheat) has a WTU close to the upper range. Further, the result of the farmer's irrigation strategy shows that there was a build-up of soil moisture at the end of the growing seasons of all the field crops, regardless of the water-quality scenarios of both irrigation-system delivery capacities. The expected soil moisture build-up at the end of the growing season was ~3% for maize and wheat, while it was ~2% for peas, regardless of the water qualities of either irrigation-system delivery capacities.

Table 4.3: Summarised expected parameters for soil-water balance, WUE and WP for the farmer's irrigation strategies for field crops using centre-pivot (30.1 ha)

	Parameter	Irrigation Water Quality					
		Good Quality Water*			Low Quality Water**		
		Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡
Pivot delivery capacity: 10 ($mm\ day^{-1}$)	W_{Start} (mm)	591	591	591	591	591	591
	RF (mm)	309 (100)	131 (59)	113 (39)	309 (100)	131 (59)	113 (39)
	IR (mm)	512	590	663	512	590	663
	E_{Soil} (mm)	163 (13)	128 (7)	158 (4)	163 (13)	130 (7)	160 (4)
	T (mm)	622 (41)	671 (25)	651 (27)	620 (38)	671 (25)	648 (24)
	DRL (mm)	269 (114)	226 (61)	223 (53)	271 (110)	233 (58)	236 (45)
	WTU (%)	40.4 (0.5)	47.5 (1)	40.8 (0.7)	40.3 (1.1)	48.8 (1.5)	42.8 (1.7)
	ΔW_{Soil} (%)	2.9 (0.9)	2.9 (0.5)	2.0 (1.2)	2.9 (1.0)	2.9 (0.5)	2.0 (1.1)
	WUE (%)	58	65	63	58	64	62
	WP_{TWU} ($kg\ ha^{-1}\ mm^{-1}$)	14.5	7	4	14.4	7.2	4.3
	WP_{AW} ($kg\ ha^{-1}\ mm^{-1}$)	19	10	6	19	10	6
Pivot delivery capacity: 12 ($mm\ day^{-1}$)	W_{Start} (mm)	591	591	591	591	591	591
	RF (mm)	309 (100)	131 (59)	113 (39)	309 (100)	131 (59)	113 (39)
	IR (mm)	511	591	671	511	591	671
	E_{Soil} (mm)	158 (12)	123 (7.2)	145 (2)	158 (12)	125 (7)	147 (2)
	T (mm)	622 (41)	671 (25)	651 (27)	619 (38)	671 (25)	649 (26)
	DRL (mm)	275 (114)	231 (62)	242 (51)	277 (108)	237 (58)	254 (44)
	WTU (%)	40.4 (0.6)	47.2 (1)	40.5 (0.6)	40.4 (1.1)	48.4 (1.6)	42.4 (1.7)
	ΔW_{Soil} (%)	2.8 (0.9)	2.9 (0.5)	2.0 (1.2)	2.7 (1)	2.9 (0.5)	2.0 (1.1)
	WUE (5%)	58	65	62	58	64	61
	WP_{TWU} ($kg\ ha^{-1}\ mm^{-1}$)	14.4	7.3	4.3	14.4	7.2	4.2
	WP_{AW} ($kg\ ha^{-1}\ mm^{-1}$)	19	10	6	19	10	6

*Characterised by EC_{IR}= 75 mS m^{-1}; EC_{WT}= 225 mS m^{-1}; EC_e= 150 mS m^{-1}

**Characterised by EC_{IR}= 225 mS m^{-1}; EC_{WT}= 375 mS m^{-1}; EC_e= 300 mS m^{-1}

‡Number brackets is standard deviation for the parameter

ΔW_{Soil} is change in soil water content at end of the growing season; W_{Start} is the initial soil moisture

Water-use efficiency (WUE) = T/(RF+IR+WTU); $WP_{Total\ Water\text{-}use}$ = Grain yield/(RF+IR); $WP_{Applied\ Water}$ = Grain yield/(ET+DRL)

In conclusion, the water-use of the farmer's irrigation strategy was not optimal as it resulted in huge inefficiencies, as indicated by low WUE and WP for the field crops under investigation. The low WUE of the farmer's irrigation strategy was accompanied by high leaching, which has the potential to provide high crop yields, even when water quality deteriorated. Clearly, there is potential to save water by managing irrigation better, so as to increase WUE and WP. However, it is important to note that there is a trade-off between increasing WUE and reducing leaching – it may be necessary to leach salts from the soil profile to maintain good crop yields.

From an environmental viewpoint, a high level of leaching is of great concern. In the next sub-section, the impact of the farmer's irrigation strategy on drainage, soil salinity and salt return flows will be presented.

4.2.3 Environmental impact

Table 4.4 shows the change in salt build-up at the end of the growing season, expected cumulative SL during the growing season and salt-leaching efficiency of drainage water for the strategy the farmer followed to grow three field crops for a case study field in VIS. The irrigation schedule followed significantly determines the soil salinity at field level as well as the salt return flows to downstream users. In the simulation application of SWAMP-ECON for the farmer's irrigation strategy, the soil profile was assumed to have an initial salt level of 8 304 kg ha^{-1} and 16 608 kg ha^{-1} for the good quality water and low quality water, respectively. The initial salt level of the low quality water was higher, because the EC of the soil extract for the low quality water at the start of the season was assumed to be double that of the EC amount of the soil extract with good quality water at the start of the season. The aim of doubling the initial salt level was to determine the impact that soils that already have high salt levels have on the field crops. The good quality water was based on the current situation of water quality in VIS. The EC for irrigation, water table and soil extract was doubled (i.e. from the case of good quality water) to formulate the low quality water scenario and to evaluate the impact of low quality water on crops, soil and the environment.

Table 4.4 shows that the farmer's irrigation strategy for each field crop caused significant leaching of salt from the soil to the environment, thereby decreasing the salt-content level of the soil profile tremendously by the end of the growing season. Saline irrigation return flows do cause externalities for downstream users. The decrease in salt-content level in the soil profile at the end of the season ranges from 43% to 53%, while the amount of expected cumulative SL ranges from 11 000 to 26 600 kg ha^{-1} depending on the combination of crop type, water quality and irrigation-system delivery capacity scenario chosen. Generally, as shown in Table 4.4, changing the irrigation-system delivery capacity does not cause significant differences in the amount of salt being leached from the soil profile, as the expected cumulative SL for each crop is similar for the two irrigation-system delivery capacities. However, changing the water from good to low quality water did significantly increase the amount of salt being leached from the soil profile of all three crops. In general, using low quality water for the strategy chosen causes the expected cumulative SL to increase by more than double amount from the expected cumulative SL amount that may occur by using good quality water for all three crops under both irrigation-system delivery capacities – this is because there is increase in salt-leaching efficiency when lower quality water is used for irrigation.

Table 4.4: Summarised expected environmental indicators of field crops for the farmer's irrigation strategy using centre-pivot (30.1 ha)

		Parameter	Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡
Pivot delivery capacity	10 (mm day^{-1})	S_{Start} (kg ha^{-1})	8 304	8 304	8 304	16 608	16 608	16 608
		ΔS_{Soil} (%)	-47.9 (23)	-48.3 (20)	-48.8 (18)	-45.0 (24)	-44.2 (22)	-44.0 (20)
		Expected SL (kg ha^{-1})	11 098 (1 577)	12 764 (1 395)	12 297 (1 327)	23 096 (3 247)	26 596 (3108)	26 349 (2 852)
		SLE (kg ha^{-1} mm^{-1})	41	56	55	85	114	112
	12 (mm day^{-1})	S_{Start} (kg ha^{-1})	8 304	8 304	8 304	16 608	16 608	16 608
		ΔS_{Soil}(%)	-52.4 (22)	-48.0 (20)	-48.3 (21)	-50.1 (23)	-43.2 (22)	-43.2 (23)
		Expected SL (kg ha^{-1})	11 467 (1 504)	12 721 (1 474)	12 280 (1 530)	23 935 (3 140)	26 383 (3 200)	26 297 (3 440)
		SLE (kg ha^{-1} mm^{-1})	42	55	51	86	111	104

*Characterised by EC_{IR}= 75 mS m^{-1}; EC_{WT}= 225 mS m^{-1}; EC_e= 150 mS m^{-1}

**Characterised by EC_{IR}= 225 mS m^{-1}; EC_{WT}= 375 mS m^{-1}; EC_e= 300 mS m^{-1}

‡Numbers in brackets are standard deviations

S_{Start} is salt level at the start of the season; ΔS_{Soil} is change in soil salt content at the end of season

SLE is salt-leaching efficiency (SLE= (S_{Final}-S_{Start})/DRL)

The conclusion is that the farmer's irrigation strategy for a field crop significantly decreases the soil salinity at farm level while it releases huge amounts of salt to downstream users as return flows. The effect of releasing salt into the environment is compounded when the water-used for irrigation in the farmer's irrigation strategy is of low quality. The release of huge amounts of salt as return flow has the potential to cause externalities to downstream water-users.

4.2.4 Discussions and conclusions

The main conclusion is that the farmer's irrigation strategy, which is based on the principle that irrigators irrigate to meet the crop's water requirement, is an over-irrigation strategy, because the farmer strategy did not consider the contribution of a shallow water table close to or below the plant root zone as a source of water supply. As a result, the expected WUE and WP indicators were low. A large potential exists for farmers to improve their profitability if they acknowledge the shallow water table as a source of water, thereby indirectly creating an opportunity to increase expected WUE and WP. Cognisance should be taken that the extensive leaching of salts caused by over-irrigation resulted in lower soil salinity levels that did not have any meaningful impact on the profitability of the three field crops. Using low quality water increased the risk of failing to manage irrigation water applications sufficiently to avoid water and osmotic stress, especially for the salt-sensitive crops (maize and peas); however, the impact was small. Care should therefore be taken when developing an irrigation strategy to increase the use of the water from the shallow water table; the strategy will necessarily have an impact on the amount of SL, which may lead to higher salinity levels, which, in turn, may impact crop production negatively. Careful consideration of the trade-off between increasing WUE and reducing leaching and the impact thereof on profitability and risk is necessary to develop an irrigation strategy that considers the shallow water table as a source of water supply in the presence of low quality water.

4.3 OPTIMAL IRRIGATION STRATEGIES FOR INTRA-SEASONAL FIELD CROPS

The SWAMP-ECON model was applied to find an optimal irrigation schedule for each of the three field crops (maize, wheat and peas), in order to evaluate the impact of the achieved optimal irrigation schedules on water and salt management at field level and the environment by considering the water-quality aspect of irrigation. The initial soil moisture at the beginning of the season, initial salt content at the beginning of the season for the two water qualities, and the rainfall in each state of nature for each crop were kept the same as that of the farmer's irrigation strategy. The SWAMP-ECON model was solved using 40 personal computers to save time in running the trials for all the possible combinations of scenarios. The model was solved using MATLAB version R2013a. The personal computers used were Dell with Intel (R) Core (TH) i3-32 processor (CPU) and installed memory (RAM) of 8.00GB. The runtime of the intra-seasonal application of SWAMP-ECON model in a single personal computer could range from 45 minutes to 8 hours, depending on the combination of crop type, water quality and irrigation-system delivery capacity scenario selected. It was observed that the better the water quality, the longer the computer runtime was for the model, as the simulation-optimisation procedure developed had to compare a greater number of alternative irrigation schedules to optimise profit.

A characteristic of EA is that it provides different near-optimal solutions every time the model is rerun, even though the conditions (scenarios) of the model are unchanged. As a result, some or most of the initial population solutions provided to the model as start-up generation solutions are different for each run of the model. In this study eight trial solutions for each possible combination of crop type, water quality and irrigation-system delivery capacity were compared to select the best near-optimal solution from among near-optimal solutions. The model was solved for risk-neutral and risk-averse decision-makers. Results of analyses of optimised irrigation schedules for intra-seasonal cropping of the crops under study are presented in this section.

4.3.1 Stochastic efficiency of optimised irrigation schedules

The main purpose of Table 4.5 is to compare the stochastic efficiency of an optimised irrigation strategy of a risk-neutral decision-maker with a farmer's irrigation strategy for each field crop under study. The section named optimal irrigation strategy in Table 4.5 shows expected MAS, LPM indicators, expected yields, expected relative yields and TVIEC of three field crops that result from a field crop's near-optimal irrigation-scheduling. The section on the right side shows deviations for the mentioned parameters from the farmer's irrigation practice. Detailed cost-related data are provided in Appendix I.

As shown in Table 4.5, significant increases in expected MAS for all three field crops could be achieved by following the near-optimal irrigation-scheduling of a risk-neutral decision-maker, compared to the farmer's irrigation practice for each field crop regardless of the water quality and the irrigation-system delivery capacity scenario selected. Consider the good quality water scenario with an irrigation-system delivery capacity of 10 mm day^{-1}. For the mentioned scenario the expected profit from producing maize, wheat and peas increased, respectively, by ZAR 14 190, ZAR 23 123 and ZAR 10 931 when following the optimised irrigation-scheduling strategy instead of the farmer's irrigation strategy for each field crop. It is obvious that changes in expected yield cannot explain the gain in expected profit, because the yield decreased by 91 kg ha^{-1}, 25 kg ha^{-1}, and 34 kg ha^{-1} for maize, wheat and peas, respectively. Most of the increase in MAS is caused by each field crop's near-optimal irrigation-scheduling solution being able to reduce the TVIEC by ZAR 10 429, ZAR 14 795 and ZAR 9 835 for maize, wheat and peas, respectively, compared to under the farmer’s respective irrigation strategies. Reduction in TVIEC was possible because the optimisation considers the shallow water table as a source of water for each field crop's ET. Consequently, less water needs to be applied to ensure that soil water salinity levels do not increase beyond the threshold salinity levels that affect crop yields negatively. Wheat shows the highest decrease in TVIEC due to its higher salt tolerance than the other two crops.

Using low quality water instead of good quality water significantly decreases the increase in profit that is possible for each field crop due to optimisation of irrigation-scheduling, instead of using the farmer's irrigation strategy under both irrigation-system delivery capacities. For instance, decreases in the increase in profit from using low quality water instead of good quality water are ZAR 5 680 (14 190 - 8 510), ZAR 7 911 (23 123 - 15 212) and ZAR 6 654 (10 931 - 4 277) respectively for maize, wheat, and peas under the 10 mm day^{-1} irrigation-system. Using low quality water increases the TVIEC cost of the three crops by ZAR 4 638 (10 429 - 5 791), ZAR 4 200 (14 795 - 10 595) and ZAR 6 938 (9 835 - 2 897) respectively. This is because the optimised strategy applies more irrigation water to maintain a sound level of salinity in the soil profile, so as to minimise its effect on the field crop's yield as the water quality deteriorates. As a result the crop yields under good quality water and low quality water were very similar, but yields are achieved at higher irrigation costs if the water quality is low.

Table 4.5: Expected MAS, LPM indicators, expected yields and expected relative yields of three field crops with optimal irrigation strategy (assuming a risk-neutral decision-maker) and deviations from farmer's irrigation practice when using centre-pivot irrigation-system (30.1 ha)

		Parameter	OPTIMAL IRRIGATION STRATEGY (RISK-NEUTRAL)						DEVIATIONS FROM FARMER'S IRRIGATION PRACTICE					
			Irrigation Water Quality						Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡	Maize^	Wheat^	Peas^	Maize^	Wheat^	Peas^
Pivot Delivery Capacity	10 (mm day^{-1})	Expected MAS (ZAR)	336 571 (13 680)	268 313 (2 389)	459 705 (7 317)	328 706 (13 769)	260 401 (3 546)	450 768 (3 913)	14 190 (4.4)	23 123 (9.4)	10 931 (2.4)	8 510 (2.7)	15 212 (6.2)	4 277 (1.0)
		ρ_{SF}	0.35	0.35	0.41	0.35	0.41	0.94	0.35 (-×)	0.35 (-×)	0.41 (-×)	0 (0)	0.41 (-×)	0 (0)
		Expected shortfall (ZAR)	3 589	1 514	4 923	3 767	3 294	3 562	3 589 (-×)	1 514 (-×)	4 923 (-×)	1 152 (44)	3 294 (-×)	147 (4.3)
		Expected yield (kg ha^{-1})	15 151 (345)	7 421 (40)	4 439 (51)	15 150 (347)	7 405 (59)	4 455 (27)	-91 (-0.6)	-25 (-0.3)	-34 (-0.8)	-37 (-0.2)	-41 (-0.6)	-2 (0.0)
		Expected YR††	0.993	0.989	0.984	0.993	0.987	0.987	-0.006 (-0.6)	-0.004 (-0.4)	-0.007 (-0.7)	-0.003 (-0.3)	-0.006 (-0.6)	-0.001 (-0.1)
		TVIEC (ZAR)	5 234	4 028	12 153	9 873	8 228	19 091	-10 429 (-67)	-14 795 (-79)	-9 835 (-45)	-5 791 (-37)	-10 595 (-56)	-2 897 (-13)
	12 (mm day^{-1})	Expected MAS (ZAR)†	336 983 (12 705)	268 815 (1 109)	461 943 (3 442)	329 632 (14 909)	260 701 (1 708)	450 980 (4 979)	13 270 (4.1)	22 234 (9.0)	12 170 (2.7)	8 287 (2.6)	14 120 (5.7)	2 537 (0.6)
		ρ_{SF}	0.24	0.35	0.35	0.35	0.41	0.82	0.24 (-×)	0.35 (-×)	0.35 (-×)	0 (0)	0.41 (-×)	-0.12 (-13)
		Expected shortfall (ZAR)	3 199	638	1 653	4 092	1 254	3 157	3 199 (-×)	638 (-×)	1 653 (-×)	1 724 (73)	1 254 (-×)	1 828 (137)
		Expected yield (kg ha^{-1})	15 161 (320)	7 435 (18)	4 462 (24)	15 138 (376)	7 425 (28)	4 451 (34)	-81 (-0.5)	-11 (-0.1)	-11 (-0.2)	-44 (-0.3)	-21 (-0.3)	-13 (-0.3)
		Expected YR††	0.994	0.991	0.989	0.992	0.990	0.987	-0.005 (-0.5)	-0.002 (-0.2)	-0.002 (-0.2)	-0.003 (-0.3)	-0.003 (-0.3)	-0.001 (-0.2)
		TVIEC (ZAR)	5 041	4 079	12 388	8 726	8 504	18 000	-9 311 (-65)	-13 331 (-77)	-8 430 (-40)	-5 626 (-39)	-8 905 (-51)	-2 818 (-14)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

‡Numbers in brackets are standard deviations; ^Numbers in brackets are changes expressed in percentages

×Blank spaces indicated not applicable as division by zero is undefined

††YR is relative yield calculated as Yield actual/Yield potential

Comparison of the two irrigation-system delivery capacity scenarios in Table 4.5 shows that the 12 mm day^{-1} irrigation-system delivery capacity slightly decreases the increase in profit that can be achieved by near-optimal irrigation-scheduling of each of the three field crops compared to the 10 mm day^{-1} irrigation-system delivery capacity for both water quality scenarios, except for peas when the water quality is good. For instance, when good quality water is used, the decreases in increase in profit observed are ZAR 920 (maize) and ZAR 889 (wheat), while peas show an increase in profit that amounts to ZAR 1 239. The reason why peas behaves differently when water quality is good might be due to the GA solution for the higher irrigation-system delivery capacity, which results in slightly better yield of peas than under the lower irrigation-system delivery capacity. This might result in slightly better revenue from peas under the higher irrigation-system delivery capacity. On the other hand, when water quality is low, all three field crops show decreases in increase in profit, amounting to ZAR 223 (maize), ZAR 1 092 (wheat) and ZAR 1 740 (peas), from using the 12 mm day^{-1} irrigation-system delivery capacity rather than the lower irrigation-system delivery capacity. In general, the increases in profit that can be achieved by optimisation instead of using the farmer's irrigation strategy seem to be higher when using the lower irrigation-system delivery capacity.

The optimised irrigation-scheduling strategy of a field crop obtained by assuming a risk-neutral farmer significantly increases the risk of failing to achieve the potential MAS for each field crop in the study, compared to the farmer's irrigation strategy for both irrigation-system delivery capacities for each crop when considering good quality water (Table 4.5). As a result, the expected shortfall also increases. When the water quality is good, increases in the probability of a shortfall ranged from 24 percentage points for maize irrigated by the 12 mm day^{-1} irrigation-system, to as high as 41 percentage points for peas irrigated by the 10 mm day^{-1} irrigation-system. The crops were able to achieve their potential MAS by following the farmer's irrigation strategy for each crop when water quality was good. The increases in expected shortfall ranged from ZAR 638 for wheat irrigated by the 12 mm day^{-1} irrigation-system to as high as ZAR 4 923 for peas irrigated by the 10 mm day^{-1} irrigation-system. On the other hand, when low quality water is used, wheat shows a large increase in risk, which is reflected in increases in both exposure to risk and expected shortfall, while the other two field crops show increases only in extent of risk. For both irrigation-system delivery capacities the increases in risk for wheat are 41 percentage points, while the increases in extent of risk (expected shortfall) are ZAR 3 294 and ZAR 1 254 for the 10 and 12 mm day^{-1} irrigation-systems respectively. The extent of risk increases observed for maize and peas range from ZAR 147 for peas irrigated by the 10 mm day^{-1} irrigation-system, to ZAR 1 724 for maize irrigated by the 12 mm day^{-1} irrigation-system. There is an exception for peas irrigated by the 12 mm day^{-1} irrigation-system, for which decreases in probability of shortfall were observed. In general, the reason why the optimised irrigation strategy for each crop shows increases in either the risk of failing to meet the potential expected MAS or extent of the risk is that the farmer's irrigation strategies for the crops are over-irrigation strategies. If a farmer follows an over-irrigation strategy, the variability of MAS for a field crop is either avoided, or exists to a lesser extent, depending on the crop type and water quality scenario selected. However, optimised irrigation-scheduling allows some variability to exist, because the irrigation strategy is designed to minimise water-use by allowing lower MAS in some unfavourable states of nature.

In addition, comparison of the two irrigation-system delivery capacities shows that some reduction in risk could be achieved by using the 12 mm day^{-1} irrigation-system delivery capacity instead of the lower irrigation-system delivery capacity, depending on the crop type and water-quality scenario considered. When the water quality is good, wheat shows a reduction of risk only, to the extent of ZAR 876. Interesting is the fact that the 12 mm day^{-1} irrigation-system, when compared to the 10 mm day^{-1} irrigation-system, decreases exposure to risk as well as the extent of the risk for the more salt-sensitive crops (maize and peas). The effect is most profound for peas (most sensitive to salt build-up), for which the probability of shortfall decreased by six percentage points (0.41 - 0.35) while the extent of risk (expected shortfall) for the crop reduced by ZAR 3 270 (4 923 - 1 653) when using good quality water. On the other hand, when the water quality is low, wheat again shows a reduction in extent of risk only, to the value of ZAR 2 040, while peas shows reduction in both exposure to risk (12 percentage points) and extent of risk (ZAR 405). The exposure to risk for maize was the same for both irrigation-systems, while the extent of risk might show a slight increase, to the amount of ZAR 325, when water quality is low. The reason why the higher irrigation-system delivery capacity could reduce the risk compared to that observed in the lower irrigation-system delivery capacity relates to the fact that more water could be supplied in a short period of time under the former capacity, which results in an increased ability to leach salts from the soil.

In conclusion, significant improvement in profitability is achieved by following optimal irrigation-scheduling (considering a risk-neutral decision-maker) instead of the farmer's existing irrigation strategy for a field crop. The improvement in stochastic efficiency is associated with huge risk exposure, but with lower expected shortfall. In addition, low quality water does significantly decrease the profitability that could be achieved by optimisation compared to the case using good quality water. The impact of changing irrigation-system delivery capacity on stochastic efficiency is small, as both irrigation-system delivery capacities considered are very close. Further, it can be noted that the better the salt-tolerance of a field crop, the higher will be the expected benefit from optimisation of irrigation-scheduling of each field crop in the study.

The next sub-section will consider the impact of following the optimised irrigation-scheduling of a field crop on water-use management, soil salinity and the environment.

4.3.2 Water-use management of optimised irrigation schedules

The section named optimal irrigation strategy in Table 4.6 presents the expected cumulative IR; simulated expected cumulative DRL, WTU and SL; and calculated expected WUE and WP due to each field crop's near-optimal irrigation-scheduling for a risk-neutral decision-maker. The section on the right-hand side shows deviations from the parameters of the farmer's irrigation strategy. The assumptions about the states of nature and the water-quality scenarios for each field crop were kept the same as that of the farmer's strategy. Only key output parameters were used to compare the optimal irrigation-scheduling strategy with the farmer's irrigation-scheduling strategy. The full soil-water balance results are provided in Appendix J. The discussion focuses on the 10 mm day^{-1} irrigation-system, and the 12 mm day^{-1} irrigation-system will be used to show the impact of changing irrigation-system delivery capacities on water-use management.

One of the critical targets of optimising irrigation-scheduling is improving WUE of field crops in the presence of scarce water resources. Accordingly, Table 4.6 confirms that a large increase in expected WUE for each field crop could be achieved by following near-optimal irrigation-scheduling, compared to the farmer's irrigation strategy for both water qualities and irrigation-system delivery capacities. When considering good quality water for irrigation, increases in expected WUE are 23 (maize), 34 (wheat) and 19 (peas) percentage points for a field irrigated by the 10 mm day^{-1} irrigation-system. Improvement in expected WUE was possible because each crop's optimised irrigation-scheduling considers the contribution of the shallow water table as a source of water to meet some of the ET demand of a field crop, while the farmer's irrigation strategy for each crop does not. For the above example, the near-optimal irrigation-scheduling strategy for each field crop resulted in a 46% (maize), 62% (wheat) and 46% (peas) expected cumulative WTU. In addition, the simulation-optimisation approach not only considered the contribution of the shallow water table, but also increased the expected cumulative WTU compared to the farmer's irrigation-scheduling strategy, except for peas when the water quality is low. If good quality water is irrigated according to the 10 mm day^{-1} irrigation-system, Table 4.6 shows that increases in expected cumulative WTU are 5 (maize), 4 (wheat) and 2 (peas) percentage points. The exceptional case of peas when low quality water is used might relate to the fact that peas is a highly salt-sensitive crop. Hence, when an over-irrigation strategy is followed for peas, as in the case of the farmer's irrigation strategy, the simulation tends to use more water, thereby leaching salt from the soil profile while increasing the expected cumulative WTU. However, the simulation-optimisation model simulates the expected cumulative WTU by considering various complex variables, such as water quality, energy tariffs and salinity-tolerance level of the crop. In general, the ability of the simulation-optimisation procedure to consider the contribution of a shallow water table to a field crop's ET leads to a significant reduction in expected irrigation amount applied for each field crop, thereby significantly reducing expected cumulative DRL as well. Hence, for the example above, compared to the farmer's irrigation strategy, the water saving due to optimisation was 342 mm (maize), 458 mm (wheat) and 280 mm (peas), while expected cumulative DRL was minimised by 205 mm (maize), 219 mm (wheat) and 200 mm (peas). Therefore, optimisation of irrigation-scheduling of a field crop for a risk-neutral farmer is associated with better expected WUE, thereby creating an opportunity to save large amounts of scarce water resources.

Within a given water-quality scenario, the greatest increase in expected WUE due to optimised irrigation-scheduling in comparison to the farmer's irrigation-scheduling of each field crop was achieved by wheat regardless of the irrigation-system delivery capacity. For instance, if good quality water is applied using the 10 mm day^{-1} irrigation-system delivery capacity, the increase in expected WUE for wheat as a result of implementing optimised irrigation-scheduling is 34 percentage points, which is higher by 11 and 15 percentage points than the increase in expected WUE observed for both maize and peas, respectively. Wheat has the highest salt-tolerance level. As a result, less water is required to drain salts from the soil profile in order to achieve good crop yields. Consequently, water savings are highest for wheat, thereby increasing the expected WUE. Again considering the above example, the increase in water saving for wheat is 458 mm, which is 116 mm (458 - 342) and 178 mm (458 - 280) higher than the water saving achieved for maize and peas, respectively. The result magnifies the importance of the salinity-tolerance level of the field crop when determining an optimised irrigation-scheduling strategy. Therefore, the higher the salt-tolerance level of the field crop, the higher will be the water saving achievable by following optimised irrigation-scheduling for a field crop derived for a risk-neutral farmer.

Table 4.6 also shows the impact of deteriorating water quality on expected WUE. Using low quality water significantly decreases the expected increase in WUE that could be achieved by following near-optimal irrigation-scheduling compared to the farmer's irrigation strategy for both irrigation-system delivery capacities. For example, if the 10 mm day^{-1} irrigation-system delivery capacity is used to optimally irrigate the field, the decreases in the increase in expected WUE as a result of using low quality water are 11 (23 - 12), 10 (34 - 24) and 13 (19 - 6) percentage points for maize, wheat, and peas respectively, compared to the good quality water scenario. This is because more salts need to be leached as the salinity (salt level) of the irrigation water increases. Therefore, the simulation optimisation needs to apply more water to maintain the soil salinity below the threshold level above which expected yields for the crop might start to decline when low quality water is used for irrigation. Consequently, Table 4.6 shows that using low quality water instead of good quality water results in a significant decrease in the amount of water that could be saved in cultivating each field crop through optimised irrigation-scheduling instead of the farmer's irrigation strategy for both irrigation-system delivery capacities, thereby decreasing expected WUE. For the 10 mm day^{-1} irrigation-system with low quality water, the amount of water conserved as a result of following optimised irrigation-scheduling was 194 mm (maize), 328 mm (wheat) and 77 mm (peas). Therefore, compared to the water saving achievable when using good quality water, the decrease in water saving when using low quality water is 148 mm (342 -194), 130 mm (458 - 328) and

203 mm (280 - 77) for maize, wheat and peas, respectively. In addition, it should be noted that the contribution of a shallow water table decreases as the water quality deteriorates. For the example above, for instance, using low quality water instead of good quality water decreases the expected cumulative WTU by 5 (maize) (46% - 41%), 8 (wheat) (62% - 54%) and 6 (peas) (46% - 40%) percentage points. In conclusion, using deteriorating quality water to irrigate field crops significantly reduces the improvement in expected WUE achievable due to optimisation of irrigation-scheduling of a field crop, compared to using the farmer's irrigation-scheduling.

On the other hand, a comparison of the two irrigation-system delivery capacities shows a slight decrease in expected WUE for the crops grown in winter (wheat and peas) when using the higher irrigation-system delivery capacity for both water qualities (see the section optimal irrigation strategy in Table 4.6). For instance, when the water quality is good, the decrease in expected WUE from using the higher irrigation-system delivery capacity are two and three percentage points for wheat and peas, respectively. Decrease in expected WUE is due to the fact that the near-optimal expected irrigation amounts for wheat and peas show slight increases under the higher irrigation-system delivery capacity. Considering good quality water, for instance, expected cumulative irrigation increased by 15 mm (147 - 132) and 37 mm (420 - 383) for wheat and peas, respectively. In general, the changes in expected WUE that could be gained for the field crops studied by selecting a certain irrigation-system delivery capacity is not large when optimal management is achieved.

Irrigated agriculture will be more profitable provided the improvement in the expected WUE of a field crop achieved by implementing optimised irrigation-scheduling is accompanied by improvement in expected WP. Accordingly, Table 4.6 shows that significant increases in both expected WP indicators could be attained by following near-optimal irrigation-scheduling instead of the farmer's irrigation strategy for both water qualities and irrigation-system delivery capacities. An exception is for peas, where neither expected WP indicators show any change, or only slight change that might be negligible, when using the low quality water. Assuming good quality water is supplied for the 10 mm day^{-1} irrigation-system, for example, increases in expected WP_{TWU} are 5 kg ha^{-1} mm^{-1} (35%), 4 kg ha^{-1} mm^{-1} (50%) and 2 kg ha^{-1} mm^{-1} (40%), while increases in expected WP_{AW} are 13 kg ha^{-1} mm^{-1} (68%), 18 kg ha^{-1} mm^{-1} (180%) and 3 kg ha^{-1} mm^{-1} (50%) for maize, wheat and peas, respectively. The significant decreases in expected cumulative DRL and the lower irrigation amount that are associated with the optimised irrigation-scheduling of a field crop, compared to the respective irrigation strategies of the farmer, contribute to the improvements observed in expected WP_{TWU} and expected WP_{AW}. Again, assuming good quality water is supplied under the 10 mm day^{-1} irrigation-system, the decreases in expected cumulative DRL are 205 mm (maize), 219 mm (wheat) and 200 mm (peas), which ultimately result in an increase in WP_{TWU} for each field crop. Therefore, applying an optimised irrigation-scheduling strategy for a field crop makes it possible to improve WP.

In addition, Table 4.6 shows that, under a given water-quality scenario, maize has the highest increase in expected WP_{TWU} and wheat has the highest increase in expected WP_{AW} as a result of following optimised irrigation-scheduling instead of the farmer's irrigation-scheduling for both irrigation-system delivery capacities. For instance, assuming good quality water is supplied using the 10 mm day^{-1} irrigation-system, a 5 kg ha^{-1} mm^{-1} (35%) increase in expected WP_{TWU} was observed for maize, while an 18 kg ha^{-1} mm^{-1} (180%) increase in expected WP_{AW} was observed for wheat. The reason why maize shows the highest expected WP_{TWU} might be due to the huge rainfall event that occurred in one of the states of nature during the end of the growing season for maize. Consequently, the improvement in expected WP_{TWU} for maize, compared to the other two crops, due to optimised irrigation-scheduling becomes high. On the other hand, the reason why wheat shows the highest increase in expected WP_{AW} is that the crop is highly salt tolerant compared to the other two crops. Consequently, as discussed earlier, wheat has the highest expected cumulative WTU, thereby enabling the farmer to save the greatest amount water by growing wheat instead of the other two crops.

The results also show the effects of using deteriorating quality water on both WP indicators. Compared to irrigating the field with good quality water, irrigation with low quality water decreases the increase in both expected WP indicators that could be achieved for each field crop by following optimised irrigation-scheduling instead of the farmer's irrigation strategy for both irrigation-system delivery capacities. When using the 10 mm day^{-1} irrigation-system, for example, the decreases in the increase in expected WP_{TWU} as a result of using low quality water instead of good quality water, are 2 kg ha^{-1} mm^{-1} (5 - 3), 2 kg ha^{-1} mm^{-1} (4 - 2) and 1.6 kg ha^{-1} mm^{-1} (2 - 0.4) for maize, wheat, and peas, respectively. On the other hand, using the same irrigation-system delivery capacity, the decreases in the increase in expected WP_{AW} from using low quality water compared to good quality water are 8 kg ha^{-1} mm^{-1} (13 - 5), 9 kg ha^{-1} mm^{-1} (18 - 9) and 3 kg ha^{-1} mm^{-1} (3 - 0) for maize, wheat, and peas, respectively. As water becomes more saline, the increases in expected cumulative DRL for each field crop explain the observed decreases in the increase in expected WP_{TWU}. For the example considered above, for instance, the expected cumulative DRL increased by 74 mm (138 - 64), 46 mm (53 - 7) and 99 mm (122 - 23) for maize, wheat, and peas respectively. On the other hand, the reason given earlier for expected WUE of each field crop decreasing as water quality deteriorates, increases in the amount of expected cumulative irrigation required for each field crop as water quality declines explains the decreases in the increase in expected WP_{AW}. For the above example, for instance, increases in expected cumulative irrigation amount due to using low quality water, compared to use of good quality water, are 148 mm (maize), 130 mm (wheat) and 203 mm (peas). Therefore, deteriorating water quality negatively affects both expected WP indicators. Changing the irrigation-system delivery capacity might cause slight changes in both expected WP indicators, either decreases or increases, depending on the water quality and crop type, but the changes are not large, as the two systems are very close in delivery capacity.

Table 4.6: Summarised cumulative expected IR, DRL, WTU, WUE, WP and SL of three field crops under optimal irrigation strategy (assuming a risk-neutral decision-maker) and respective deviations by the strategy from the farmer's irrigation practice using centre-pivot (30.1 ha)

		Parameter	OPTIMAL IRRIGATION STRATEGY (RISK-NEUTRAL)						DEVIATIONS FROM FARMER'S IRRIGATION PRACTICE					
			Irrigation Water Quality						Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡	Maize^	Wheat^	Peas^	Maize^	Wheat^	Peas^
Pivot Delivery Capacity	10 (mm day^{-1})	IR (mm)	170	132	383	318	262	586	-342 (-67)	-458 (-78)	-280 (-42)	-194 (-38)	-328 (-56)	-77 (-12)
		DRL (mm)	64 (81)	7 (16)	23 (20)	138 (98)	53 (33)	122 (41)	-205 (-76)	-219 (-97)	-200 (-90)	-133 (-49)	-180 (-77)	-114 (-48)
		WTU (%)	46 (4.5)	62 (6.2)	46 (4.4)	41 (1.7)	54 (4)	40 (2.3)	6 (14)	15 (31)	5 (13)	1 (2)	5 (11)	-3 (-7)
		WUE (%)	81	99	82	70	88	68	23 (40)	34 (52)	19 (30)	12 (21)	24 (38)	6 (10)
		WP_{TWU} (kg ha^{-1} mm^{-1})	19.6	10.5	5.6	17.1	9.6	4.7	5 (35)	4 (50)	2 (40)	3 (19)	2 (33)	0.4 (9)
		WP_{AW} (kg ha^{-1} mm^{-1})	32	28	9	24	19	6	13 (68)	18 (180)	3 (50)	5 (26)	9 (90)	0 (0)
		Expected SL (kg ha^{-1})	2 869 (2 311)	573 (1 251)	2 486 (1 574)	12 059 (4 851)	9 547 (5153)	16 952 (3 127)	-8 229 (-74)	-12 191 (-96)	-9 811 (-80)	-11 037 (-48)	-17 049 (-64)	-9 397 (-36)
	12 (mm day^{-1})	IR (mm)	178	147	420	307	290	599	-333 (-65)	-444 (-75)	-251 (-37)	-204 (-40)	-301 (-51)	-72 (-11)
		DRL (mm)	70 (83)	10 (17)	37 (26)	133 (98)	57 (35)	134 (39)	-205 (-75)	-221 (-96)	-205 (-85)	-144 (-52)	-180 (-76)	-120 (-47)
		WTU (%)	46 (4.2)	61 (6)	44 (4)	41 (2)	53 (4)	40 (2)	6 (14)	14 (29)	4 (9)	1 (1)	5 (10)	-2 (-6)
		WUE (%)	81	97	79	71	86	67	20 (40)	30 (49)	20 (27)	10 (22)	20 (34)	10 (10)
		WP_{TWU} (kg ha^{-1} mm^{-1})	19.4	10.5	5.5	17.3	9.4	4.7	5 (35)	3 (44)	1 (28)	3 (20)	2 (31)	1 (12)
		WP_{AW} (kg ha^{-1} mm^{-1})	31	27	8	25	18	6	12 (63)	17 (170)	2 (33)	6 (32)	8 (80)	0 (0)
		Expected SL (kg ha^{-1})	3 173 (2 275)	928 (1 192)	3 835 (2 289)	11 909 (4 825)	9 374 (4 833)	16 634 (2 827)	-8 294 (-72)	-11 793 (-93)	-8 445 (-69)	-12 026 (-50)	-17 009 (-64)	-9 663 (-37)

*Characterised by EC_{IR}= 75 mS m^{-1}; EC_{WT}= 225 mS m^{-1}; EC_e= 150 mS m^{-1}; **Characterised by EC_{IR}= 225mS m^{-1}; EC_{WT}= 375 mS m^{-1}; EC_e= 300 mS m^{-1}

‡Numbers in brackets are standard deviations; ^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU); Water productivity ($WP_{\text{Total water-use}}$) = Grain yield/(ET+DRL); Water productivity ($WP_{\text{Applied water}}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix J

In conclusion, compared to the farmer's existing irrigation strategy, the optimised irrigation-scheduling of a field crop provides the farmer with the opportunity to increase expected WUE and WP for the crop. This is because the simulation-optimisation model considers the contribution of a shallow water table that is close to or below the plant root zone as a source water supply. Consequently, optimised irrigation-scheduling, compared to the farmer's irrigation strategy, helps the farmer to save water, as well as minimise expected cumulative DRL. Besides, differences in increase in expected WUE and WP achievable due to optimisation of irrigation-scheduling among the field crops studied show that the farmer should manage the different crops differently when water quality is an issue, based on their salinity-tolerance levels. If the farmer’s desire is to improve WUE and WP, then the farmer must plant highly salt-tolerant field crops. Further, using declining water quality for field crop production significantly decreases the increase in expected WUE and WP that could be gained for a field crop by following optimised irrigation-scheduling instead of the farmer's irrigation-scheduling. On the other hand, changes in expected WUE and WP that could be achieved by changing the irrigation-system delivery capacity are not large.

The impact of optimal water-use should also be analysed from the perspective of soil salinity build-up and salt return flows to the environment. Hence, the next sub-section will discuss the environmental impact of following sound irrigation-scheduling based on the simulation-optimisation model.

4.3.3 Environment impact of optimised irrigation schedules

Declining water quality has become a concern for irrigated agriculture, because scarce fresh water resources are increasingly being threatened by expanding industrial and agricultural activities, increasing urbanisation, population growth, and climate change. Hence, when the water-used for irrigation deteriorates in quality, the benefits of optimised irrigation-scheduling for field crops should not be evaluated from maximisation of profit and WUE perspectives only, but should also consider minimisation of environmental impact due to salt return flows on downstream users. Hence, the key indicators presented in Table 4.6 will be used in this sub-section to show the impact of optimisation on salinity management in light of declining water quality. The discussion focuses on the 10 mm day^{-1} irrigation-system, and the 12 mm day^{-1} irrigation-system will be used to show the environmental impact of changing irrigation-system delivery capacities.

As shown in Table 4.6, significant opportunity is created to decrease the expected cumulative SL during the production of each field crop under study by following a near-optimal irrigation-scheduling instead of the farmer's irrigation-scheduling for both water qualities and irrigation-system delivery capacities. If good quality water is applied to the field using the 10 mm day^{-1} irrigation-system delivery capacity, for example, then decreases in expected cumulative SL achieved are 8 229 kg ha^{-1}, 12 191 kg ha^{-1} and 9 811 kg ha^{-1} for maize, wheat, and peas, respectively. As explained earlier in the discussion on expected WUE, minimising expected cumulative DRL by the simulation-optimisation procedure contributes to a decrease in expected cumulative SL for each field crop under optimised irrigation-scheduling instead of the farmer's irrigation-scheduling. For the above example, for instance, decreases in expected cumulative DRL are 205 mm (maize), 219 mm (wheat) and 200 mm (peas), thereby significantly decreasing expected cumulative SL to the environment. However, reduced expected cumulative SL means salt build-up at farm level. Besides, under a water-quality scenario, wheat shows the highest decrease in expected cumulative SL compared to the other two crops, because it has the highest decrease in expected cumulative DRL compared to the other crops (e.g. for the above example, wheat has 209 mm decrease in expected cumulative DRL). This demonstrates that leaching is not essential for the low quality water scenario designed in the study when the crop is highly salt tolerant. It should be noted that maize sometimes shows higher than or comparable expected SL to peas, because there was a large rainfall event close to the end of the growing season of maize in one of the states of nature considered in the model. Otherwise, the trend is that the higher the salt-tolerance level of the crop, the lower will be the SL from the soil profile.

Moreover, compared to the case of using good quality water to irrigate field crops, using low quality water results in an optimised irrigation-scheduling strategy for each field crop that significantly increases the expected cumulative SL for both irrigation-system delivery capacities (see the section optimal irrigation strategy in Table 4.6). For instance, if low quality water is applied using the 10 mm day^{-1} irrigation-system, the expected cumulative SL are 12 059 kg ha^{-1}, 9 547 kg ha^{-1} and 16 952 kg ha^{-1} for maize, wheat and peas, respectively. Compared to using good quality water, the increases in expected cumulative SL from using low quality water are 9 190 kg ha^{-1} (12 059 - 2 869), 8 974 kg ha^{-1} (9 547 - 573) and 14 466 kg ha^{-1} (16 952 - 2 486) for maize, wheat and peas, respectively. As explained earlier, the required increases in drainage that accompany the use of more saline water to irrigate the field crops contribute to the observed increase in expected cumulative SL when using low quality water. For the above example, for instance, using low quality water instead of good quality water increases the expected DRL by 74 mm (maize), 46 mm (wheat) and 99 mm (peas). Consequently, as the water quality deteriorates, more salts need to be drained from the soil profile to ground water or watercourses.

However, it can be noted that the decrease in expected cumulative SL that could be achieved for each field crop by following optimised irrigation-scheduling instead of the farmer's existing irrigation strategy is higher when using low quality water than good quality water for both irrigation-systems, except for peas when using the lower irrigation-system delivery capacity (see the right-hand side section in Table 4.6). Compared to the good quality water scenario, using low quality water with the 10 mm day^{-1} irrigation-system prevents the release of 2 808 kg ha^{-1} (11 037 - 8 229) and 4 858 kg ha^{-1} (17 049 - 12 191) expected cumulative SL for maize and wheat, respectively, under the optimised irrigation-scheduling instead of the farmer's irrigation-scheduling - this is because the reduction in expected cumulative SL as a result of minimisation of expected DRL is higher when using low quality water than when good quality water is used. Each mm drained water leaches more salts when water quality is low than when water quality is good. So, the advantage of minimising drainage would be higher when water quality is low than when it is good. For the above example, for instance (i.e. the lower irrigation delivery capacity), the decreases in expected cumulative DRL achieved by following optimised irrigation-scheduling instead of the farmer's irrigation strategy were 133 mm and 180 mm for maize and wheat, respectively. These decreases achieved in expected cumulative DRL would result in a greater reduction in expected cumulative SL than the reduction in expected cumulative SL that could be obtained because of the decrease in expected cumulative DRL achieved when water quality is good. On the other hand, the reason for the exception observed for peas could be related to the slightly lower irrigation amount allocated in the farmer's irrigation strategy for this crop when using the lower irrigation-system delivery capacity (see Section 4.2.1). Overall, the reduction in expected cumulative SL that could be achieved for a field crop when following optimised irrigation-scheduling is high when using low quality water, compared to good quality water. Besides, indirectly, the result also demonstrates that more salt-build up is tolerated by following optimised irrigation-scheduling when the water quality is good, than by either irrigation-system delivery capacity. It is not wise to leach large amounts of salt from the soil if the water quality is good.

Comparison of the two irrigation-system delivery capacities shows that the impact of each field crop's optimised irrigation-scheduling on the environment differs, depending on the quality of the water-used to irrigate the field (see the section optimal irrigation strategy in Table 4.6). If the water quality is good, the 10 mm day^{-1} irrigation-system leaches less salt to the environment than the 12 mm day^{-1} irrigation-system for all three field crops. The opposite is true when the water quality is low for all three field crops. For instance, assuming the water quality for irrigation is low, the expected SL is 11 909 kg ha^{-1} (maize), 9 374 kg ha^{-1} (wheat) and 16 634 kg ha^{-1} (peas) when using the higher irrigation-system delivery capacity. If the above case is compared with the results of expected SL for a lower irrigation-system delivery capacity, the decrease in expected cumulative SL is 150 kg ha^{-1} (12 059 - 11 909), 173 kg ha^{-1} (9 547 - 9 374) and 318 kg ha^{-1} (16 952 - 16 634) for maize, wheat and peas, respectively. So, if the farmer is concerned about salt flow to the environment when low quality water is used, it is better to use the higher irrigation-system delivery capacity. The opposite is true if the water quality is low and the farmer wants to achieve less soil salinity build-up on the farm. However, if the water quality is good, the farmer's needs to make the opposite decision to the situation encountered when the water quality is low.

In conclusion, because expected cumulative DRL was minimised due to optimised irrigation-scheduling, compared to the farmer's existing irrigation-scheduling, the reduction in drainage-induced salt returns to the environment was large. In addition, the field crops chosen for cultivation have significant implications for the amount of expected cumulative SL from the soil, because there is a direct proportional relationship between the salt-tolerance level of the crop and the amount of expected cumulative SL from the soil.

Reducing the amount of expected cumulative SL by optimised irrigation-scheduling is beneficial from an environmental perspective, because its impact on downstream water-users will be low. However, less leaching means on-site salt build-up, i.e., increase in soil salinity. This creates a great concern for the farmer, because on-site salt build-up in one season might affect the expected yield of the crop to be cultivated in the next season, depending on the salt-tolerance level of the crop. Hence, it is essential to recognise the trade-off that exists between leaching salt from the soil and soil salinity build-up from an inter-season dimension as well.

Farmers are generally risk-averse, and the next section will discuss the changes observed in all three indicators for a risk-averse decision-maker.

4.3.4 Impact of risk aversion on optimal irrigation strategy

Irrigation is generally a mechanism for coping with production risk, and which helps to reduce the variability of yield that might arise due to low and unpredictable rainfall in dry or semi-arid regions. Optimisation is an essential tool for designing strategies for better water-use and salinity management via sound irrigation-scheduling. The near-optimal irrigation-scheduling of each field crop derived for a risk-neutral farmer under different scenarios of water quality and irrigation-system delivery capacities might be too risky for an irrigation farmer who is risk-averse to adopt. Hence, this section analyses differences between risk-neutral and risk-averse decision-makers in terms of the impacts of their respective optimal irrigation strategies on water-use and salinity management. The aim was to determine if risk-averse behaviour has an impact on optimal irrigation-scheduling, considering the quality of water-used for irrigation.

4.3.4.1 The effect of risk aversion on stochastic efficiency (profitability)

The results of a comparison of the stochastic efficiency of a risk-averse decision-maker and that of a risk-neutral farmer are presented in Table 4.7. In Table 4.7, the section named optimal irrigation strategy shows the CE, LPM indicators, expected yields and expected relative yields of three field crops under a near-optimal irrigation strategy assuming a risk-averse decision-maker. The section on the right side of Table 4.7 shows deviations of the mentioned parameters from optimised irrigation-scheduling of field crops for a risk-neutral decision-maker.

As demonstrated by Table 4.7, for the RAC considered in the study, the decreases in CE observed by following each field crop's near-optimal irrigation strategy derived for a risk-averse farmer, compared to a risk-neutral farmer, are small, regardless of the water quality and irrigation-system delivery capacity scenarios considered. On average,[3] compared to a risk-neutral case, the slight decreases in CE due to the risk-averse behaviour considered in the study are ZAR 2 949 (maize), ZAR 1 905 (wheat) and ZAR 613 (peas). Because the centre-pivot size is 30.1 ha, the increases in risk premium the risk-averse farmer will experience per hectare are not really large (less than ZAR 100 on average for any of the crops). The reason why there are slight decreases in CE for each field crop relate to the fact that the optimised irrigation-scheduling for the risk-averse farmer discounts the variability of the MAS in the farmer's decision. As a result, a risk-averse decision-maker uses more water, which slightly increases the irrigation costs, compared to the case of a risk-neutral farmer. On average,[4] compared to the risk-neutral case, the increases in TVIEC due to risk-averse behaviour considered in the study are ZAR 3 436 (maize), ZAR 1 403 (wheat) and ZAR 766 (peas). Depending on the water quality and irrigation-system delivery capacity selected, probability of shortfall decreases by a maximum of 29 (maize), 6 (wheat) and 12 (peas) percentage points. In addition, depending on the crop type, water quality and irrigation-system delivery capacity selected, the reduction in extent of risk (expected shortfall) could range between ZAR 450 and ZAR 4 100. When expressed in percentage changes, the decrease in extent of risk ranges between 17% and 92% for a risk-averse farmer compared to the case for risk-neutral decision farmer. SWAMP simulates expected yield in the presence of matric and osmotic stress based on predefined potential yield. Hence, a risk-averse farmer will try to minimise gross-margin risk by trying to achieve the potential yield, as long as the cost associated with achieving it is low. Compared to the risk-neutral case, the slight increases in expected yield observed for the risk-averse farmer proves that the farmer was applying more water (see Table 4.8). On average, the increases in expected yield due to following the optimised irrigation-scheduling strategy compared to the case of a risk-neutral farmer are 83 kg ha^{-1} (maize) and 11 kg ha^{-1} for both wheat and peas. Therefore, a farmer with risk-averse behaviour would choose an irrigation strategy with a greater quantity of water, so as to reduce his/her marginal risk as far as possible.

In conclusion, risk-averse behaviour induces a farmer to follow a water management strategy that increases the irrigation costs so as to reduce the variability of net return from producing a field crop. However, the decreases in CE observed in this study are not large, because the RAC considered was for less risk-averse decision-maker.

[3]Average calculated by considering CE for both water qualities and irrigation-system delivery capacities for a field crop.

[4]Average calculated by considering TVIEC for both water qualities and irrigation-system delivery capacities for a field crop.

Table 4.7: CE, lower partial moment indicators, expected yields and expected relative yields of three field crops with optimal irrigation strategy (assuming a risk-averse decision-maker) and deviations from risk-neutral optimal irrigation strategy using centre-pivot (30.1 ha)

		Parameter	OPTIMAL IRRIGATION STRATEGY (RISK-AVERSE♯)						DEVIATIONS FROM OPTIMAL IRIGATION STRATEGY (RISK-NEUTRAL)					
			Irrigation Water Quality						Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡	Maize^	Wheat^	Peas^	Maize^	Wheat^	Peas^
Pivot Delivery Capacity	10 (mm day^{-1})	CE (ZAR)	334 216 (1 819)	268 203 (1 051)	459 438 (2 226)	325 435 (1 207)	256 314 (1 355)	450 341 (112)	-2 355 (-0.7)	-110 (0.0)	-267 (0.1)	-3 271 (-1.0)	-4 087 (-1.6)	-427 (0.1)
		ρ_{SF}	0.06	0.35	0.35	0.06	0.35	0.82	-0.29 (-83)	0 (0)	-0.06 (-15)	-0.29 (-83)	-0.06 (-15)	-0.12 (-13)
		Expected shortfall (ZAR)	442	771	1 014	299	1 335	359	-3147 (-88)	-743 (-49)	-3909 (-79)	-3468 (-92)	-1959 (-59)	-3203 (-90)
		Expected yield (kg ha^{-1})	15 231 (45)	7 433 (17)	4 461 (15)	15 234 (30)	7 430 (22)	4 467 (17)	80 (0.5)	12 (0.2)	22 (0.5)	84 (0.6)	25 (0.3)	12 (0.3)
		Expected YR††	0.998	0.991	0.990	0.999	0.991	0.991	0.005 (0.5)	0.002 (0.2)	0.006 (0.6)	0.006 (0.6)	0.004 (0.4)	0.004 (0.4)
		TVIEC (ZAR)	8 263	4 457	13 991	13 557	11 400	20 158	3 028 (58)	429 (11)	1 838 (15)	3 684 (37)	3 171 (39)	1 067 (6)
	12 (mm day^{-1})	Expected MAS (ZAR)	334 638 (1 704)	268 562 (1 130)	461 135 (2 015)	325 808 (1 300)	257 530 (1 056)	450 029 (4 716)	-2 345 (-0.7)	-253 (-0.1)	-808 (-0.2)	-3 824 (-1.2)	-3 171 (-1.2)	-951 (-0.2)
		ρ_{SF}	0.06	0.35	0.35	0.06	0.35	0.71	-0.18 (-75)	0 (0)	0 (0)	-0.29 (-83)	-0.06 (-15)	-0.11 (-13)
		Expected shortfall (ZAR)	415	826	1 073	321	771	2 615	-2784 (-87)	188 (29)	-580 (-35)	-3771 (-92)	-483 (-39)	-542 (-17)
		Expected yield (kg ha^{-1})	15 231 (42)	7 432 (19)	4 466 (14)	15 234 (32)	7 433 (17)	4 455 (29)	70 (0.5)	-3 (0.0)	4 (0.1)	96 (0.6)	8 (0.1)	4 (0.1)
		Expected YR††	0.999	0.991	0.990	0.999	0.991	0.987	0.005 (0.5)	0 (0)	0.001 (0.1)	0.007 (0.7)	0.001 (0.1)	0 (0)
		TVIEC (ZAR)	7 797	4 043	12 988	13 001	10 550	17 559	2 756 (55)	-36 (-1)	601 (5)	4 275 (49)	2 046 (24)	-441 (-2)

♯RAC= 0.00182744; *characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}; **characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

‡Numbers in brackets are standard deviations; ^Numbers in brackets are changes expressed in percentages

×Blank spaces indicated not applicable as division by zero is undefined

††YR is relative yield calculated as Yield actual / Yield Potential

Therefore, the impact of the water management strategy chosen by a risk-averse farmer also affects the WUE. These changes are discussed in next sub-section.

4.3.4.2 The effect of risk aversion on water-use management

The section named optimal irrigation strategy in Table 4.8 presents the expected cumulative IR; simulated expected cumulative DRL, WTU and SL, and calculated expected WUE and WP due to each field crop's near-optimal irrigation-scheduling for a risk-averse decision-maker. The section on the right-hand side shows deviations of the mentioned parameters from the farmer's irrigation strategy.

Table 4.8 demonstrates that following a near-optimal irrigation strategy derived for risk-averse behaviour defined in this study, compared to a risk-neutral farmer, might slightly decrease the expected WUE of each field crop, depending on the crop type, water quality, and irrigation-system delivery capacity scenarios considered. On average,[5] the decreases in expected WUE, expressed in percentage points, are 7.8 (maize), 4 (wheat) and 1.5 (peas). The observed decreases in expected WUE could be explained by the fact that the risk-averse behaviour considered in the study induces the risk-averse farmer to use more irrigation water than the risk-neutral farmer. On average, the increases in expected cumulative irrigation due to the risk-averse compared to risk-neutral behaviour are 116 mm (maize), 47 mm (wheat) and 25 mm (peas). In addition, the contribution of a shallow water table decreases slightly for the risk-averse farmer – by less than five percentage points – compared to the risk-neutral farmer. This means the risk-averse farmer needs to increase the expected cumulative irrigation to meet the ET demand of a field crop fully. The exceptional cases, i.e., no change in expected WUE, occur because the change in the expected cumulative irrigation observed between the two decision-makers is very low. Besides, in some cases, the application of water by a risk-averse farmer may be lower than that in a risk-neutral case. For example, for peas, the optimised irrigation amount for the risk-averse farmer is 8 mm lower than for the risk-neutral farmer when using the higher irrigation-system delivery capacity. Such kinds of situations arise because the solutions being compared are from near-optimal solutions. In conclusion, the risk-averse behaviour in the study lowers the expected WUE for each field crop.

[5]Averages computed by considering the water qualities and irrigation-system delivery capacities.

Table 4.8: Summarised expected IR, DRL, WTU, WUE, WP and SL of three field crops with optimal irrigation strategy (assuming a risk-averse decision-maker) and deviations from that of risk-neutral optimal irrigation strategy using centre-pivot (30.1 ha)

		Parameter	OPTIMAL IRRIGATION STRATEGY (RISK-AVERSE♯)						DEVIATIONS FROM OPTIMAL IRIGATION STRATEGY (RISK-NEUTRAL)					
			Irrigation Water Quality						Irrigation Water Quality					
			Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
			Maize‡	Wheat‡	Peas‡	Maize‡	Wheat‡	Peas‡	Maize^	Wheat^	Peas^	Maize^	Wheat^	Peas^
Pivot Delivery Capacity	10 (mm day^{-1})	IR (mm)	265	147	438	446	365	620	95 (56)	15 (11)	55 (14)	128 (40)	103 (39)	34 (6)
		DRL (mm)	105 (97)	9 (18)	40 (26)	224 (117)	64 (36)	144 (42)	41 (64)	2 (29)	17 (74)	86 (62)	11 (21)	22 (18)
		WTU (%)	42 (2.6)	61 (6.1)	43 (4)	40 (0.9)	51 (3.8)	39 (1.6)	-4 (-9)	-1 (-2)	-3 (-7)	-1 (-2)	-3 (-6)	-1 (-3)
		WUE (%)	74	97	78	62	80	66	-7 (-9)	-2 (-2)	-4 (-5)	-8 (-11)	-8 (-9)	-2 (-3)
		WP_{TWU} (kg ha^{-1} mm^{-1})	18.1	10.5	5.4	15.2	8.9	4.6	-1.5 (-8)	0 (0)	-0.2 (-4)	-1.9 (-11)	-0.7 (-7)	-0.1 (-2)
		WP_{AW} (kg ha^{-1} mm^{-1})	27	27	8	20	15	6	-5 (-16)	-1 (-4)	-1 (-11)	-4 (-17)	-4 (-21)	0 (0)
		Expected SL (kg ha^{-1})	4 642 (2 625)	1 010 (1 434)	3 641 (2 113)	19 510 (4 923)	9 945 (4 740)	18 531 (2 988)	1 773 (62)	437 (76)	1 155 (46)	7 451 (62)	398 (4)	1 579 (9)
	12 (mm day^{-1})	IR (mm)	271	146	437	452	360	591	93 (52)	-1 (-1)	17 (4)	145 (47)	70 (24)	-8 (-1)
		DRL (mm)	117 (98)	11 (17)	44 (30)	227 (114)	64 (37)	127 (39)	47 (67)	1 (10)	7 (9)	94 (71)	7 (12)	-7 (-5)
		WTU (%)	42 (2.2)	61 (6)	42 (3.6)	40 (0.8)	51 (3.8)	40 (2)	-4 (-9)	0 (0)	-2 (-5)	-1 (-2)	-2 (-4)	0 (0)
		WUE (%)	74	97	79	62	80	67	-7 (-9)	0 (0)	0 (0)	-9 (-13)	-6 (-7)	0 (0)
		WP_{TWU} (kg ha^{-1} mm^{-1})	17.9	10.5	5.4	15.2	8.8	4.6	-1.5 (-8)	0 (0)	-0.1 (-2)	-2.1 (-12)	-0.6 (-6)	-0.1 (-2)
		WP_{AW} (kg ha^{-1} mm^{-1})	26	27	8	20	15	6	-5 (-16)	0 (0)	0 (0)	-5 (-20)	-3 (-17)	0 (0)
		Expected SL (kg ha^{-1})	5 165 (2 675)	1 240 (1 349)	3 948 (2 199)	18 608 (4 671)	11 118 (5 242)	17 271 (3 094)	1 992 (63)	312 (34)	113 (3)	6 699 (56)	1 744 (19)	637 (4)

♯RAC= 0.00182744; *characterised by EC_{IR}= 75 mS m^{-1}; EC_{WT}= 225 mS m^{-1}; EC_e= 150 mS m^{-1}; **characterised by EC_{IR}= 225 mS m^{-1}; EC_{WT}= 375 mS m^{-1}; EC_e= 300 mS m^{-1}

‡Numbers in brackets are standard deviations; ^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU); Water productivity ($WP_{\text{Total water-use}}$) = Grain yield/(ET+DRL); Water productivity ($WP_{\text{Applied water}}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix J

Slight decreases in both WP indicators could also result from following each field crop's optimised irrigation-scheduling derived for risk-averse behaviour defined in the study, compared to risk-neutral behaviour for both water qualities and irrigation-system delivery capacities. On average, the slight decreases in WP_{TWU} are 1.7 kg ha^{-1} mm^{-1} (maize), 0.3 kg ha^{-1} mm^{-1} (wheat) and 0.1 kg ha^{-1} mm^{-1} (peas), while the decreases in WP_{AP} are 5 kg ha^{-1} mm^{-1} (maize), 2 kg ha^{-1} mm^{-1} (wheat) and 0.25 kg ha^{-1} mm^{-1} (peas). Slight increases in expected cumulative DRL, which are the indirect consequence of the risk-averse grower's tendency to use more irrigation water, contribute to the decreases in WP_{TWU} observed. Slight decreases in WP_{AW} are directly related to the use of more irrigation water by the risk-averse farmer. Therefore, the result demonstrates that risk-averse behaviour negatively impacts WP.

In conclusion, risk-averse behaviour negatively impacts expected WUE and WP, as the farmer uses more irrigation water.

4.3.4.3 The effect of risk aversion on the environment

The irrigation strategy followed by a risk-averse farmer should not only be evaluated in terms of the possible changes to profitability and WUE indicators, but also in terms of possible changes it might have on salinity management. Table 4.8 shows that significant increases in expected cumulative SL can be observed if each crop's optimised irrigation-scheduling for risk-averse farmer behaviour as defined in the study is compared to the case of a risk-neutral farmer, regardless of the water quality and irrigation-system delivery capacity scenarios considered. On average,[6] the increases in expected cumulative SL are around 7 451 kg ha^{-1} (maize), 398 kg ha^{-1} (wheat) and 1 579 kg ha^{-1} (peas). As pointed out earlier, risk-averse farmers are inclined to use more water, so their profitability would be less variable. Consequently, the risk-averse farmer's choice of an optimised irrigation-scheduling strategy that is associated with the application of more water would cause more expected cumulative DRL than the irrigation strategy followed by a risk-neutral farmer, thereby increasing the expected cumulative SL from the soil profile. On average, the increases in expected cumulative DRL are 67 mm (maize), 5 mm (wheat) and 10 mm (peas).

In conclusion, risk-averse behaviour increases the salt return flows to downstream users because risk-averse farmers follow an over-irrigation strategy. Consequently, the salt build-up at farm level would be less than the case under the irrigation strategy followed by a risk-neutral farmer.

[6]Averages calculated by considering both water qualities and irrigation-system delivery capacities.

4.3.5 Discussions and conclusions

The main conclusion is that the SWAMP-ECON model successfully integrated factors, such as irrigation water quality, soil condition (i.e. presence of a shallow water table), irrigation technology constraints, salt-tolerance level of field crops, energy prices, input prices, output prices, and stochastic weather, to design optimised irrigation-scheduling strategies for field crops. The optimised irrigation-scheduling strategies achieved for the field crops selected for this study enable irrigation farmers to improve their profitability, WUE and WP, because the model successfully considers the contribution of a shallow water table close to or below the plant root zone as source of water. It is essential to note that the improvement of profitability was possible at the expense of invulnerability to production risk. In addition, the model minimises drainage, which essentially lowers salt return flows to the environment. The improvements achievable regarding profitability, WUE, and amount of SL might vary, depending on the risk attitude of the decision-maker. Generally, risk-neutral farmers show the highest improvement in stochastic efficiency, WUE and lowering environmental impact. However, these farmers might have the highest soil salinity at farm level. However, risk-averse farmers exhibit lower levels of the mentioned indicator than risk-neutral farmers, because they tend to use more water. Hence, the irrigation strategy chosen by risk-averse farmers will reduce variability in profitability while slightly increasing irrigation-related costs.

Irrigation provides the opportunity to harvest agricultural produce two to three times per year, depending on the type of crops that could be planted in different seasons. The next section will present the type of water-use management changes that might result in the first crop when inter-seasonal cropping is considered.

4.4 OPTIMAL IRRIGATION STRATEGIES FOR INTER-SEASONAL CROPPING SYSTEMS

Consideration of intra-seasonal field crop production does not provide a complete picture of the influence of water quality on achieving better water-use and salinity management at field level, or the impact of salt return flows on the environment when farmers use cropping systems. Cropping systems are commonly applied by irrigation farmers for various reasons. Some of the reasons include protecting natural resources (soil, water, air, and nutritive substances), controlling pests and diseases, and controlling other variables (e.g. to improve water infiltration). Hence, cropping systems practiced by farmers should be environmentally friendly, while at the same time increasing the production of field crops and taking into account crop particularities.

The SWAMP-ECON model was implemented for one-year cropping systems to gain greater knowledge on how to manage water and salinity at farm level and reduce the impact on the environment by return salt flows. The assumption followed in one-year cropping system optimisation is that a risk-neutral farmer plants maize in the summer season, while he/she has the option to plant wheat or peas in the following winter season. Hence, the crop rotations considered were one-year maize-wheat and maize-peas. The states of nature considered for both crop rotations were the same as that of maize in single-season optimisation. The initial soil moisture and salt content at the beginning of the season for maize in both crop rotations was assumed to be the same as that of intra-seasonal optimisation for maize. On the other hand, for the crops that follow maize (i.e., wheat or peas), the irrigation water quality remains the same, while initial soil moisture and salt content in each soil layer would take the end values of the first short fallow period that follows maize. Depending on the crop rotation chosen, and water quality and irrigation-system delivery capacity scenarios selected, the runtime of the inter-seasonal application of the SWAMP-ECON model may range from one and a half hours to 11 hours.

The objective of the inter-seasonal application was to determine how the water-use and salinity management of the field crop planted in the summer season (in this study, maize) will be affected by the salinity tolerance level of the crop planted in the next season in the case where water quality is an issue in irrigation. Assuming a risk-neutral farmer, the results that demonstrate the possible changes in water and salinity management that may occur for maize as a result of following inter-seasonal optimised irrigation-scheduling, compared to that of the case in intra-seasonal optimisation for the crop, will be presented first. Then, the result for maize for inter-seasonal optimisation for a risk-neutral farmer compared to that of inter-seasonal optimisation of a risk-averse farmer will be presented at a defined RAC. Because the results for the two irrigation-system delivery capacities were very similar, only the results for the 12 mm day^{-1} irrigation-system will be used for discussion in this chapter. The full results for the lower irrigation-system delivery capacity is provided in Appendices K and L. Hence, in the following sub-sections, the possible changes observed for maize double cropping in stochastic efficiency, WUE, and environmental indicators will be discussed.

4.4.1 Changes in stochastic efficiency (profitability)

Table 4.9 shows the deviations in profitability indicators of maize grown in one-year cropping systems compared to maize grown in intra-season with optimised irrigation-scheduling designed for a risk-neutral decision-maker. The results are for the 12 mm day^{-1} irrigation-system delivery capacity.

In comparison to intra-seasonal optimisation of irrigation-scheduling for maize, Table 4.9 shows that following a risk-neutral farmer's optimised irrigation-scheduling strategy for maize in one-year crop rotation will slightly decrease the expected MAS for both water qualities when using the 12 mm day^{-1} irrigation-system delivery capacity. On average,[7] the decreases in expected MAS are ZAR 2 166 and ZAR 4 352 for maize in one-year maize-wheat (1-yr M-W) and one year maize-peas (1-yr M-P) cropping

[7] Calculation based on CE for both water qualities.

systems, respectively. These decreases occur because the optimised irrigation-scheduling for maize in one-year crop rotations is associated with slight increases in TVIEC. On average,[8] the increases in TVIEC are ZAR 510 and ZAR 2 975 for maize in 1-yr M-W and 1-yr M-P cropping systems, respectively. Therefore, the decreases in expected MAS in the first season crop (i.e., maize, in this study) show that the water-use management of the crop grown in the first season definitely considers the matric and osmotic stresses that might be encountered by the crop to be planted in the next season.

With a given water quality, in comparison to intra-seasonal optimisation of irrigation-scheduling for maize, the result shows that the decrease in expected MAS due to following a risk-neutral farmer's optimised irrigation-scheduling strategy for maize grown in inter-season is slightly higher for maize in 1-yr M-P than maize in 1-yr M-W cropping systems. For instance, when good quality water is applied using the 12 mm day^{-1} irrigation-system, the decreases in expected MAS for maize in the 1-yr M-P cropping system was ZAR 5 325, which is ZAR 3 563 (5 325 - 1 762) higher than the decrease observed for maize in a 1-yr M-W cropping system. The reason is the fact that the maize in the 1-yr M-P crop rotation was associated with optimised irrigation-scheduling that had higher TVIEC than the case of maize in the 1-yr M-W crop rotation. For the above example, for instance, the TVIEC for the maize in the 1-yr M-P crop rotation was ZAR 3 554, which is ZAR 3 026 (3 554 - 528) higher than the increase observed for maize in the 1-yr M-W cropping system. This shows that the salt-tolerance level of the crop that follows maize in the second season affects the amount of decrease in expected MAS that might occur for maize involved in the first season of the one-year crop rotation.

Moreover, as shown in Table 4.9, maize in the 1-yr M-W crop rotation shows a slight increase in risk exposure, while maize in the 1-yr M-P crop rotation shows a slight decrease in risk exposure for both water qualities under a risk-neutral farmer's optimised irrigation-scheduling strategy for maize in one-year crop rotation, compared to intra-seasonal optimised irrigation-scheduling for maize. For example, if low quality water is applied using the 12 mm day^{-1} irrigation-system delivery capacity, maize in the 1-yr M-W crop rotation shows increases in both exposure to risk (10 percentage points) and extent of risk (ZAR 847). The reason is that the increase in water-use by maize in the 1-yr M-W crop rotation did not lead to an increase in expected yield for the crop, thereby increasing the variability of net return for the crop. Although not very large, in the above example, maize shows a decrease in expected yield amounting to 21 kg ha^{-1}. On the other hand, in the above example, maize in the 1-yr M-P crop rotation shows a decrease in extent of risk (ZAR 976), because the optimised water-use designed allows for an increase in expected yield (23 kg ha^{-1}) for the crop, thereby enabling the farmer to lower the variability in net returns.

[8]Calculation based on TVIEC for both water qualities.

Table 4.9: Deviation of the profitability indicators of maize grown in crop rotation compared to that of maize cultivated in intra-season with optimal irrigation strategy (risk-neutral) using 12 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS FOR MAIZE GROWN IN CROP ROTATION FROM SINGLE MAIZE OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water*		Low Quality Water**	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ Expected MAS (ZAR)	-1 762 (-0.5)	-5 325 (-1.6)	-2 569 (-0.8)	-3 378 (-1.0)
Δ ρ_{SF}	0.1 (46)	0.0 (0)	0.2 (51)	-0.2 (-49)
Δ Expected shortfall (ZAR)	847 (27)	-916 (-29)	1711 (42)	-931 (-23)
Δ Expected Yield (kg ha^{-1})	-21 (-0.1)	23 (0.2)	-43 (-0.3)	24 (0.2)
Δ Expected YR††	-0.002	0.001	-0.002	0.002
Δ TVIEC (ZAR)	528 (11)	3 554 (71)	492 (6)	2 396 (28)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

††YR is relative yield calculated as Yield actual/Yield potential

In conclusion, a risk-neutral decision-maker chooses an optimised irrigation-scheduling strategy for maize in a one-year crop rotation that might slightly reduce the expected MAS for maize, compared to a single optimisation case for the crop. This is because the simulation-optimisation model has to consider the expected MAS from the crop in the second season so as to maximise the overall profitability of the crop rotation.

The next sub-section will discuss the changes that might occur in the same one-year cropping system considered above, from a water-use management perspective.

4.4.2 Changes in water-use management

Table 4.10 compares the deviations in the WUE indicators and environmental indicators for maize grown in one-year cropping systems to that of maize grown in intra-season, with optimised irrigation-scheduling designed for risk-neutral decision-makers. The results in Table 4.10 are for the 12 mm day^{-1} irrigation-system delivery capacity. The data for that of the 10 mm day^{-1} irrigation-system delivery capacity is provided in Appendix L.

Table 4.10 shows that the extent of decreases in expected WUE for maize that might result from following maize's optimised irrigation-scheduling strategy for risk-neutral farmers in the one-year cropping system, compared to the crop's intra-seasonal optimised case (risk-neutral), depends on the salinity-tolerance level of the field crop that follows in the second season. If the crop rotation is the 1-yr M-W (i.e. the second season crop is highly salt tolerant), then the decreases in expected WUE for maize observed were very small for both water qualities. On the other hand, if the crop rotation is the 1-yr M-P (i.e. the second season crop is salt sensitive), then the decreases in expected WUE for maize were significant for both water qualities. For instance, if good quality water is used, the decreases in expected WUE for maize were two and 10 percentage points for the 1-yr M-W and 1-yr M-P cropping systems, respectively. The decreases in expected WUE for maize occurred because the inter-seasonal application of the model increased the amount of expected cumulative irrigation required for maize in the first season, compared to intra-seasonal optimisation of irrigation-scheduling for the crop. Depending on the salt-tolerance level of the second season field crop, the inter-seasonal application of the SWAMP-ECON model considers the interaction that exists among various complex variables, to determine optimised irrigation strategies for both crops in the cropping system. Among the variables are the matric and osmotic stresses experienced by both crops in the different seasons, soil-moisture level and salt level at the end of the growing season of maize, amount of salt that could be leached and soil moisture level during the first off-season period (i.e. between maize and wheat or peas), and soil-moisture level and salt level at the end of the growing season of the second-season crop. For instance, again considering good quality water, the increases in expected cumulative irrigation for maize were 18 mm and 125 mm for the 1-yr M-W and 1-yr M-P cropping systems, respectively. Accordingly, the increase in expected cumulative irrigation for maize in the 1-yr M-W cropping system is not large; consequently, not much difference in expected WUE resulted, compared to intra-seasonal optimisation of maize. However, the increase in expected cumulative irrigation for maize in the 1-yr M-P cropping system is significant and, consequently, the difference in expected WUE is large compared to the case of intra-seasonal optimisation of maize. The large increase in expected cumulative irrigation for maize grown in the 1-yr M-P cropping system occurs because some salt should be drained, as the second crop to be planted is peas. Therefore, significant decreases in WUE for maize in a one-year crop rotation could occur, provided the crop that follows in the second season is very salt sensitive.

Sound information about WP indicators for maize grown in inter-seasonal rotation provides the farmer with critical information for evaluating the impact of following optimised irrigation-scheduling on his/her agricultural productivity per drop of water. Accordingly, Table 4.10 compares the decreases in both expected WP indicators that occur from following maize's optimised irrigation-scheduling strategy for a risk-neutral farmer in one-year cropping systems to the crop's intra-seasonal optimised case (risk-neutral) for both water qualities. However, the decreases in both expected WP indicators are worth considering for maize grown in the 1-yr M-P cropping system. For the maize cultivated in the 1-yr M-W cropping system the decreases in both expected WP indicators were almost negligible. For instance, if good quality water was supplied, the decreases in expected WP_{TWU} and WP_{AW} for maize grown in the 1-yr M-P cropping system were 2 kg ha^{-1} mm^{-1} and 19 kg ha^{-1} mm^{-1}, respectively. The increases in expected cumulative DRL and IR for maize grown in the 1-yr M-P cropping system, compared to intra-seasonal maize optimisation, contribute to the observed decreases in expected WP_{TWU} and WP_{AW} for maize, respectively. Therefore, significant decreases in WP indicators for maize in a one-year crop rotation could occur, provided the crop that follows in the second season is very salt sensitive.

Table 4.10: Deviations in the expected cumulative IR, DRL, WTU, SL, and expected WUE and WP of maize in crop rotation compared to that of maize in intra-season cultivated with optimal irrigation strategy (a risk-neutral decision-maker) using the 12 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION FROM SINGLE MAIZE OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water*		Low Quality Water**	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ IR (mm)	18 (10)	125 (70)	17 (6)	89 (29)
Δ DRL (mm)	-2 (-3)	45 (64)	-2 (-2)	45 (34)
Δ WTU (%)	-1 (-2)	-4 (-9)	0 (0)	-1 (-2)
Δ WUE (%)	-2 (-2)	-10 (-12)	-1 (-1)	-6 (-8)
Δ WP_{TWU} (kg ha^{-1} mm^{-1})	-0.2 (-1)	-2 (-10)	-0.2 (-1)	-1.3 (-8)
Δ WP_{AW} (kg ha^{-1} mm^{-1})	-1 (-3)	-6 (-19)	-1 (-4)	-3 (-12)
Δ Expected SL (kg ha^{-1})	-61 (-2)	2 423 (76)	-580 (-5)	3 019 (25)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU)

Water productivity ($WP_{Total\ water\text{-}use}$) = Grain yield/(ET+DRL);Water productivity ($WP_{Applied\ water}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix J

In conclusion, assuming a risk-neutral farmer, inter-seasonal application of the SWAMP-ECON model demonstrates that appropriate changes are required in the water-use management of the first-season crop if the crop planted in the second season is a very salt-sensitive crop (i.e. 1-yr M-P cropping systems). These changes do reduce the expected WUE and WP of the first crop (maize). However, if the cropping system is 1-yr M-W (i.e. salt tolerant crop planted in the second season) only minor changes in the water-use management are required, resulting in no significant impact on the expected WUE and WP of the first crop (maize).

It also critical to consider the changes in water-use management due to inter-seasonal application from an environmental perspective. Hence, the next sub-section will discuss cropping system optimisation from an environmental impact perspective.

4.4.3 Changes in environmental impact

If more saline water is used for irrigation, determining irrigation-scheduling for the first crop in a one-year cropping system while ensuring sound environmental status (both from soil salinity build-up and salt return flows) presents the greatest challenge to irrigation farmers. Maize is moderately salt sensitive. So, in a one-year cropping system, it was assumed that the farmer has the option to plant wheat (salt tolerant) or peas (very salt sensitive) in the second season. Table 4.10, which was presented in the previous sub-section, will be used to identify the appropriate irrigation-scheduling that should be followed by a risk-neutral farmer so as to achieve an environmentally friendly one-year cropping system.

Table 4.10 shows that significant increases in expected cumulative SL for maize result if maize's optimised irrigation-scheduling strategy for a risk-neutral farmer is followed in a one-year cropping system, compared to the crop's intra-seasonal optimised case (risk-neutral), provided the second-season crop is salt sensitive (peas) for both water qualities. For instance, if the water quality was good, increases in expected cumulative SL for maize in the 1-yr M-P cropping system, compared to maize grown in intra-seasonal, was 2 423 kg ha^{-1}. This implies that the risk-neutral farmer had to leach more salt, because he/she was expecting to plant a very salt-sensitive crop in the next season. The expected cumulative rainfall that occurred during the short off-season period between maize and peas was very low (see Appendix L), forcing the farmer to use more irrigation water for maize, consequently increasing the expected cumulative DRL during the first season. For the above example, increases in expected IR for maize was 125 mm, which resulted in 45 mm increase in expected cumulative DRL for maize. However, if the crop in the second season was going to be wheat, the optimised irrigation-scheduling for maize did not increase the expected cumulative SL during the first season compared to maize grown in single-season scheduling. The reason is that wheat that would be planted in the second season is salt tolerant and, therefore, enabling the crop to easily tolerate the salt build-up of the first season. Of course, there was slight increase in expected cumulative IR in the 1-yr M-W crop rotation as well, but the extra volume of water was used to conserve the soil moisture in the soil for the next crop, instead of for draining salt (see Appendix J). In conclusion, compared to 1-yr M-W, the 1-yr M-P crop rotation will have greater environmental impact in the first season, but less soil salinity build-up in the soil profile.

4.4.4 Impact of risk aversion on inter-seasonal optimal irrigation strategy

In this sub-section, the results of inter-seasonal one-year cropping system optimisation for a risk-averse farmer will be presented. The aim is to determine if risk-averse and risk-neutral farmers manage water and salinity differently. Hence, the inter-seasonal optimisation for 1-yr M-W and 1-yr M-P were run using an RAC of 0.00015 under the same condition as that of the risk-neutral farmer.

4.4.4.1 The effect of risk aversion on stochastic efficiency (profitability)

Table 4.11 shows the deviations in the profitability indicators of maize grown by following a risk-averse farmer's inter-seasonal optimised irrigation-scheduling compared to that of risk-neutral farmer's inter-seasonal optimised irrigation-scheduling for the 12 mm day^{-1} irrigation-system delivery capacity. The table shows differences in stochastic efficiency between risk-neutral and risk-averse decision-makers.

For the assumed RAC in the study, Table 4.11 shows that the decreases in CE observed by following the near-optimal irrigation strategy derived for the risk-averse farmer, compared to the risk-neutral farmer for maize cultivated in one-year cropping systems, are not significant regardless of the water quality. On average,[9] compared to the risk-neutral case, the slight decreases in CE due to the risk-averse behaviour considered in the study were ZAR 5 116 and ZAR 2 805 for maize grown in 1-yr M-W and 1-yr M-P cropping systems, respectively. This average decrease is so small, because, when the decrease is expressed per hectare for the 30.1 ha centre-pivot, the increase in risk premium experienced by the risk-averse farmer is very small (less than ZAR 150). The reason why there were slight decreases in CE for maize relates to the fact that the crop's inter-seasonal optimised irrigation-scheduling strategy derived for the risk-averse farmer would use more irrigation water, which is associated with slight increases in irrigation costs compared to the case of the risk-neutral farmer. On average,[10] compared to the risk-neutral case, the increases in TVIEC due to risk-averse behaviour considered in the study were ZAR 5 413 and ZAR 2 858 for maize grown in 1-yr M-W and 1-yr M-P cropping systems, respectively. In conclusion, the optimised irrigation-scheduling strategy obtained for the defined risk-aversion behaviour in the study for maize cultivated in a one-year cropping system did not decrease the CE significantly compared to the case of the risk-neutral decision-maker.

On the other hand, the result shows that the farmer with the defined risk-aversion behaviour would choose an optimised irrigation strategy for maize cultivated in an inter-seasonal system that significantly decreases his/her gross-margin risk, compared to the case of risk-neutral farmer, for both water qualities. The decreases in gross-margin risk were achieved by decreasing both the exposure to risk (probability of

[9] Calculation based on CE for both water qualities.

[10] Calculation based on TVIEC for both water qualities.

shortfall) and expected shortfall. Depending on the water quality and the type of one-year crop rotation selected, the decreases in probability of shortfall may range between 12 and 47 percentage points, while the decreases in expected shortfall may range between ZAR 1 900 and ZAR 5 510. The risk-averse farmer was able to lower the risk for maize grown in the one-year cropping system, compared to the risk-neutral farmer, by using more irrigation water. Using more irrigation water helps the farmer to lower the variability of his/her net returns. As can be seen from the changes in expected yield, the farmer with the defined risk aversion was targeting the potential yield, because the cost associated with doing so is low. Depending on the water quality and the type of one-year crop rotation selected, the increases in expected yield range between 50 kg ha^{-1} and 140 kg ha^{-1}. In conclusion, a farmer with risk-averse behaviour would choose an irrigation strategy with greater quantity of water for the first crop grown in the intra-seasonal cultivation, so as to reduce variability in net return.

Table 4.11: Deviations in the profitability indicators of maize grown by following risk-averse farmer's inter-seasonal optimised irrigation-scheduling from that of risk-neutral farmer using a 12 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-AVERSE$^{\sharp}$) FROM THAT OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water*		Low Quality Water **	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ CE (ZAR)	-2 897 (-1)	-3 104 (-1)	-7 335 (-2)	-2 506 (-1)
Δ ρ_{SF}	-0.29 (-83)	-0.18 (-75)	-0.47 (-89)	-0.12 (-67)
Δ Expected shortfall (ZAR)	-3 617 (-89)	-1 906 (-86)	-5 506 (-95)	-2 858 (-90)
Δ Expected Yield (kg ha^{-1})	91 (0.6)	50 (0.3)	139 (0.9)	72 (0.5)
Δ Expected YR††	0.006	0.004	0.009	0.005
Δ TVIEC (ZAR)	3 610 (65)	2 752 (32)	7 217 (78)	2 963 (27)

$^{\sharp}$RAC =0.000145442; *characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

††YR is relative yield calculated as Yield actual/Yield Potential

Overall, the risk-averse farmer chooses to apply more water for the first crop in inter-seasonal cultivation, significantly reducing the variability of net return for the crop, with no significant decrease in the CE for the crop compared to the risk-neutral case.

4.4.4.2 The effect of risk aversion on water-use management

Table 4.12 shows the deviations in WUE and environmental impact indicators for maize grown by following the risk-averse farmer's inter-seasonal optimised irrigation-scheduling compared to that of the risk-neutral farmer's inter-seasonal optimised irrigation-scheduling for the 12 mm day^{-1} irrigation-system. The table was prepared to show changes in WUE and environmental impact for risk-neutral and risk-averse decision-makers.

Table 4.12 demonstrates that implementing an optimised irrigation-scheduling strategy for maize cultivated in inter-seasonal rotation by the risk-averse farmer defined in the study, compared to the risk-neutral farmer, significantly decreases the expected WUE for maize for both water qualities. On average, the decreases in the expected WUE for maize were 12 and 6.5 percentage points for maize cultivated in 1-yr M-W and 1-yr M-P cropping systems, respectively. Comparing increases in the amount of cumulative IR expected by the risk-averse farmer and the risk-neutral farmer for maize grown in the first season explains the observed decreases in expected WUE for maize. On average,[11] increases in the amount of expected cumulative IR for maize are 189 mm and 103 mm for maize cultivated in 1-yr M-W and 1-yr M-P cropping systems, respectively, because of the risk-averse behaviour considered in the study. Decreases in WUE for maize are higher when maize is grown in the 1-yr M-W than for the 1-yr M-P crop rotation. The decrease in expected WUE for maize in the 1-yr M-W crop rotation was negligible for the risk-neutral farmer, while a significant decrease occurred for maize cultivated in the 1-yr M-P crop rotation for the same decision-maker (see Section 4.4.2). In conclusion, risk-averse behaviour will result in significant decreases in WUE for maize grown in inter-seasonal cultivation, because the farmer will be obliged to follow an over-irrigation strategy.

The result also shows that slight decreases in both expected WP do occur under the optimised irrigation-scheduling strategy for maize cultivated according to inter-seasonal cultivation for risk-averse behaviour defined in the study compared to the risk-neutral farmer case for both water qualities. On average,[12] decreases that amount to 2.5 kg ha^{-1} mm^{-1} and 1.5 kg ha^{-1} mm^{-1} in expected WP_{TWU} are observed for maize cultivated in 1-yr M-W and 1-yr M-P crop rotations, respectively. The increases observed in expected cumulative DRL for maize cultivated in a one-year cropping system contribute to the decrease in expected WP_{TWU} for maize in both crop rotations. On average,[13] increases amount to 108 mm and 77 mm in expected DRL observed for maize cultivated in 1-yr M-W and 1-yr M-P crop rotations respectively. In addition, on average, decreases amounting to 6.5 kg ha^{-1} mm^{-1} and 3.5 kg ha^{-1} mm^{-1} in expected WP_{AW} were observed for maize grown in 1-yr M-W and 1-yr M-P crop rotations, respectively.

[11]Calculation based on the expected cumulative IR for both water qualities.

[12]Calculation based on WP for both water qualities.

[13] Calculation based on expected cumulative DRL for both water qualities.

The increases observed in expected cumulative IR for maize grown in a one-year crop rotation explain the decrease in expected WP_{AW} for maize in both crop rotations. In conclusion, risk-averse behaviour will decrease the WP indicators of the first crop grown in inter-seasonal cultivation compared to the crop grown in intra-seasonal cultivation.

Table 4.12: Deviations in the WUE and environmental impact indicators of maize grown by following the risk-averse farmer's inter-seasonal optimised irrigation-scheduling compared to that of risk-neutral farmer using a 12 mm day^{-1} centre-pivot system (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-AVERSE$^{\sharp}$) FROM THAT OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water *		Low Quality Water**	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ IR (mm)	121 (62)	101 (33)	256 (79)	106 (27)
Δ DRL (mm)	54 (79)	63 (55)	162 (123)	90 (51)
Δ WTU (%)	-4 (-8)	-1 (-2)	-2 (4)	0 (-0.5)
Δ WUE (%)	-9 (-11)	-7 (-10)	-15 (-22)	-6 (-10)
Δ WP_{TWU} (kg ha^{-1} mm^{-1})	-2 (-10)	-1 (-9)	-3 (-20)	-2 (-10)
Δ WP_{AW} (kg ha^{-1} mm^{-1})	-6 (-19)	-4 (-14)	-7 (-29)	-3 (-15)
Δ Expected SL (kg ha^{-1})	1 990 (64)	2 432 (44)	12 968 (115)	6 738 (45)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1};$^{\sharp}$RAC =0.000145442

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU); Water productivity ($WP_{Total\ water\text{-}use}$) = Grain yield/(ET+DRL)

Water productivity ($WP_{Applied\ water}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix L

Overall, the risk-averse behaviour assumed in the study decreases the expected WUE and WP for maize grown in the first season of a one-year cropping system, because the farmer uses more irrigation water than the risk-neutral farmer. The strategy decreases the matric and osmotic stress that would be encountered by the crop that follows the first-season crop. The implication of the observed strategy for the environmental impact on downstream users will be presented in the next sub-section.

4.4.4.3 The effect of risk aversion on environmental impact

As shown in Table 4.12, significant increases in expected SL for maize occurred as a result of applying an optimised irrigation-scheduling strategy to maize in inter-seasonal cultivation by risk-averse farmers as defined in the study, compared to risk-neutral farmers, for both water qualities. On average,[14] the increases in expected SL for maize in the first season were 7 479 kg ha^{-1} and 4 585 kg ha^{-1} for maize cultivated in 1-yr M-W and 1-yr M-P crop rotations, respectively. The increases in expected SL for maize in the first season were the result of the increases in expected cumulative DRL for maize observed for the risk-averse farmer compared to the risk-neutral farmer. As explained in the previous sub-section, 4.4.4.2, on average, increases that amount to 108 mm and 77 mm in expected cumulative DRL for maize were observed for maize cultivated in 1-yr M-W and 1-yr M-P crop rotations, respectively. These drainage increases cause a significant amount of salt to be leached from the soil to downstream watercourses. Hence, a risk-averse decision-maker will be inclined to leach more salt in the first season with the aim of lowering the soil salinity level experienced by the crop that follows in the second season.

4.4.5 Discussions and conclusions

The main conclusion is that the SWAMP-ECON model was able to integrate crop types, water qualities, expected rainfall events for the field crops, as well as off-season periods, and the type of risk attitude, so as to design sound optimised irrigation-scheduling for the crops cultivated in crop rotation. The results show that both risk-neutral and risk-averse farmers should manage water and salinity during the first crop by considering the second crop's salt-tolerance level, compared to intra-seasonal cropping. Assuming the first-season crop is maize, a risk-neutral farmer would be forced to use more irrigation water if the next season's crop is very salt sensitive than if the next crop is salt sensitive. Overall, the profitability changes in the first crop are low for both 1-yr M-W and 1-yr M-P crop rotations. However, slight changes in WUE and WP are observed for maize cultivated in 1-yr M-P cropping systems. In comparison to 1-yr M-W crop rotation, more salt is leached in the first season in the 1-yr M-P cropping systems. On the other hand, a risk-averse farmer would be forced to use more irrigation water in the first season, regardless of the crop type that follows. Of course, by how much irrigation water needs to be increased is evaluated on the basis of the salt-tolerance level of the crop that is cultivated in the next season. Hence, in both cropping systems considered in the study, significant decreases in WUE and WP are observed for maize cultivated in the first season. Overall, inter-seasonal application of the simulation optimisation model provides the farmer with useful information on how to manage water and salinity in medium-term cropping systems.

[14] Calculation based on expected cumulative SL for both water qualities.

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 INTRODUCTION

Maximising profit from the production of a field crop grown in an intra- or inter-seasonal setting while minimising the environmental impact under salinity conditions requires the development of a sound irrigation strategy. In this research it is argued that current modelling approaches relating to the economics of salinity management in South Africa do not incorporate dynamic interactions among irrigation management, soil salinity and crop yields that are essential for developing salinity management options that are economically and environmentally sustainable. Hence, there is a need for an integrated bio-economic salinity management model that could evaluate the effects of interactions among farmers' choices of irrigation technology, irrigation-scheduling practices, and the effects of different salinity-tolerance levels of crops and soils on profitability indicators, taking into account stochastic weather.

The main objective of this research was therefore to develop a SWAMP-ECON to evaluate the stochastic efficiency, WUE and environmental impact of optimal irrigation-scheduling practices while taking cognisance of irrigation-water quality, soil conditions, irrigation-technology constraints, crops and stochastic weather. Much effort was devoted to modelling the complex interactions that exist among irrigation-water quality, soil conditions, irrigation-scheduling, salinity-tolerance levels of different crops, and production uncertainty. The model was applied to a case study in the VIS to demonstrate its applicability. The farm is characterised as having Bainsvlei soil and it was assumed that there is a constant shallow water table.

In this study, three sub-objectives were formulated to achieve the main objective. Next, a summary of and conclusions for each of the sub-objectives are discussed, and that is followed, in the final section, by recommendations.

5.2 MODELLING EXISTING IRRIGATION PRACTICES FOR FIELD CROPS

Sub-objective 1: To develop a SWAMP-ECON to evaluate the stochastic efficiency, WUE and environmental impact of existing irrigation schedules.

A bio-economic model is characterised by a biological component that is able to simulate the impact of management changes on the biological system of concern, and an economic component that quantifies the impact on profitability indicators. The development of SWAMP took place over several platforms and no unified model exists that can simulate the impact of alternative irrigation schedules on crop yield under saline conditions while taking into account a shallow water table. Therefore, it was, firstly, necessary to code the whole SWAMP salinity model in MATLAB to facilitate analysis. Next, an economic decision model was integrated into the biophysical salinity module to evaluate the impact of irrigation application on satisfying crop-water demand, in order to consider, in addition to biophysical constraints, economic incentives affecting decisions made by farmers. The SWAMP-ECON simulation model was used to evaluate the stochastic efficiency, WUE and environmental sustainability of the existing practices.

The SWAMP-ECON simulation model shows that the existing irrigation schedules that were followed for the field crops in the study were over-irrigation strategies that had different impacts on the stochastic efficiency, WUE and environmental impact indicators, depending on the crop type, irrigation-water quality, and irrigation-system delivery capacity scenarios considered. The stochastic efficiency analysis shows that peas is the most profitable enterprise, followed by maize and then wheat, irrespective of the water quality and irrigation-system delivery capacity considered. On average, the expected MAS for peas, maize, and wheat, respectively, is ZAR 448 370, ZAR 321 909 and ZAR 245 885. Decline in water quality had a slight effect only on the stochastic efficiency of moderate and very salt-sensitive crops (maize and peas respectively), thereby increasing the risk of failing to realise the potential gross MAS for these crops. Although the risk of not achieving potential crop yields for maize and peas when using low quality water was high, the impact on expected MAS was low. Increasing the irrigation-system delivery capacity did consistently increase the MAS for all the field crops, but the increase was not large. Furthermore, the farmer's irrigation strategy for a field crop resulted in considerable water-use inefficiency, regardless of the water quality and irrigation-system delivery capacity considered. Depending on the type of field crop considered, about 35% to 42% of the water supplied (RF + IR + WTU) to a field crop could be lost through evaporation and/or drainage processes. Losses occurred because the farmer did not consider the contribution of the shallow water table to the crop's ET. Depending on the crop type, water quality, and irrigation scenarios selected, a shallow water table could contribute from 40% to 49% to ET of a field crop for the over-irrigation strategy followed by the farmer. The expected WP results are low because the expected WUE for the existing farmer's irrigation strategies was inefficient. The over-irrigation strategy of the farmers showed in soil moisture build-up at the end of the growing season. An over-irrigation strategy for a field crop resulted in a decrease in the salt content of the soil profile at the end of the growing season, thereby releasing large amounts of salt return flows to downstream users. Depending on the crop type, water quality, and irrigation scenarios selected the salt content of the soil profile at the end of the season, compared to the start of the season, could be between 43% to 53% lower, while the expected SL could range between 11 000 to 26 600 kg ha^{-1}.

Three main conclusions could be reached from the application of the SWAMP-ECON simulation model. Firstly, from the profitability analysis, it can be concluded that decline in water quality does not affect the profitability of all field crops significantly, because the farmer's over-irrigation strategy enables the field crops to achieve close to their potential yield in all states of nature. In general, the degree of risk was not large enough, although the risk of not realising the potential MAS increased for salt-sensitive field crops. Secondly, the water-use of the farmer's irrigation strategy was not optimal due to the low expected WUE and WP for the field crops under investigation. Therefore, the farmer’s irrigation strategies for all three field crops were less efficient. Lastly, the farmer's existing irrigation strategy for field crops significantly decreases the soil salinity at farm level, while it releases a large amount of salt to downstream users, which might cause externalities. Considerable potential exists for farmers to improve their profitability if they acknowledge the shallow water table as a source of water. However, developing an appropriate irrigation-scheduling strategy that integrates the contribution of a shallow water table requires a careful evaluation of the trade-off between increasing WUE and reducing leaching, and the impact thereof on profitability and risk.

5.3 INTRA-SEASONAL MODELLING UNDER SALINE IRRIGATION WATER

Sub-objective 2: To develop an optimal solution procedure to optimise irrigation schedules simulated with SWAMP-ECON in order to evaluate the benefit of optimal irrigation-scheduling in terms of stochastic efficiency, WUE and environmental impact within a season.

The main purpose of Sub-objective 2 was to determine the benefit of optimal irrigation-scheduling compared to the farmer’s strategy. The SWAMP-ECON model was linked to GET-OPTIS (Schütze *et al*., 2012) to optimise irrigation schedules. GET-OPTIS was, however, developed further to include special routines to ensure the feasibility of irrigation schedules for a given centre-pivot irrigation-system delivery capacity. The resulting solution procedure proved to be a useful tool for optimising bio-economic crop simulation models under production uncertainty.

The results of the optimised irrigation schedule under risk neutrality show significant increases in expected MAS, WUE and WP for all three field crops under study compared to the farmer's existing irrigation schedule, regardless of the water quality and the irrigation-system delivery capacity scenario selected. The optimised irrigation-scheduling strategy reduces irrigation application and therefore TVIEC significantly, because the shallow water table could contribute 40% to 62% to ET, depending on the crop type, water quality and irrigation-system delivery capacity scenarios considered. Although the optimised irrigation schedules increase the producer's expected outcomes, the strategy also results in increased risk exposure. Optimised irrigation-scheduling could possibly lead to low MAS in some unfavourable states of nature, consequently resulting in variability of net return from field-crop production. On the other hand, the amount of expected cumulative SL from the soil decreases significantly for all three field crops, compared to the farmer's irrigation strategy, because irrigation applications are more effective. Thus, the optimisation procedure reduces degradation of the environment while it causes a build-up of salt in the soil profile.

For a given water quality scenario, the result shows that the highest increases in expected MAS, WUE and WP_{AW} were achieved for wheat by following the crop's optimised irrigation schedule derived for a risk-neutral farmer, irrespective of the irrigation-system delivery capacity. The decreases in TVIEC, expected cumulative IR and DRL for wheat caused greater increases in expected MAS, WUE and WP_{AW} than for maize and peas. Wheat is associated with the highest soil salinity build-up, since it releases lower amounts of salt into the environment than maize and peas. Therefore, the more salt tolerant the crop, the higher will be the increases in expected MAS, WUE and WP_{AW}.

Moreover, the results show that a reduction in water quality would significantly decrease the expected MAS, WUE and WP that could be achieved by following the optimised irrigation schedule for all three field crops, regardless of the irrigation-system delivery capacities selected. As irrigation water deteriorates, the optimisation procedure is forced to apply more water than would be necessary with good quality water. As a result, low soil-salinity levels are maintained, thereby minimising the effect of low quality water on crop yield. However, an increase in the amount of irrigation water applied increases TVIEC and expected cumulative DRL, thereby resulting in a lower expected MAS, WUE and WP than would be the case for a situation where water quality is good. As water quality deteriorates, the amount of salt that leaches into the environment increases significantly.

Results also show that use of a larger irrigation-system delivery capacity leads to a slight increase in the expected MAS, irrespective of field crop produced and water quality used. The improvement in expected MAS for all field crops was possible because the larger irrigation-system delivery capacity is capable of handling time-of-use for electricity better than the lower irrigation-system delivery capacity. In contrast, the two irrigation-system delivery capacities used in the study did not differ significantly in their water-use management, as their delivery capacities were very similar.

Comparing a risk-averse farmer to a risk-neutral farmer shows that a risk-averse farmer will increase the application of irrigation water to lower the variability of outcomes. A risk-averse farmer will increase the amount of irrigation water when faced with production uncertainty, because water is a risk-reducing input, that is, risk-averse farmers have an incentive to reduce their risk exposure. Consequently, in this study, slight decreases in CE were observed for farmers who used the irrigation schedule derived for the risk-averse irrigator, compared to the case of the risk-neutral farmer. On the other hand, the decrease in expected WUE and WP were 7.8 (maize), 4 (wheat) and 1.5 (peas) percentage points on average for the risk-averse irrigator. Furthermore, the expected cumulative DRL and the associated salts leached were higher for the risk-averse farmer.

Conclusions regarding the application of the simulation-optimisation procedure in an intra-seasonal cropping system include the following. Firstly, the salt-tolerance level of a field crop has a significant impact on the amount of water a risk-neutral farmer could save from implementing an appropriate irrigation schedule. The higher the salt tolerance of the field crop, the higher will be the amount of water saved when following an optimised irrigation schedule. The conclusion is that a farmer who wants to save scarce water resources can reduce water applied to salt-tolerant crops before changing irrigation practices of less salt tolerant crops. This reduction in water-use will also have the least impact on farmers' MAS, WUE and WP. Secondly, farmers faced with deteriorating water quality should increase their water-use to manage crop-yield risk. As water quality deteriorates, more water should be applied to maintain soil salinity below the threshold level, thereby reducing the negative impact of salinity on crop yield. However, using more water increases the negative impact on the environment. Next, choice of system capacity does not have a significant influence on producers' profitability, although the higher delivery capacity would manage the time-of-use of electricity, thereby reducing the TVIEC. The benefit that could be gained in terms of water-use and salinity management for the larger irrigation-system delivery capacity is very small and can be assumed to be negligible due to the similarity of the irrigation-system delivery capacities in the study. Therefore, the conclusion is that the choice of irrigation-system capacity will not impact the water-use and salinity management of farmers under the optimal irrigation schedule. The choice of system is purely based on profit and the need to manage electricity costs. Lastly, compared to a risk-neutral farmer, a risk-averse decision-maker should increase the application of irrigation to manage onsite soil salinity build-up, so as to lower the variability of net return from crop production. On the other hand, the optimised irrigation strategy followed for a field crop causes more environmental problems to downstream water-users, because the risk-averse farmer's optimal water-use releases more salt as return flows compared to a risk-neutral farmer.

5.4 INTER-SEASONAL MODELLING UNDER SALINE IRRIGATION WATER

Sub-objective 3: To extend the model developed under Sub-objective 2 to evaluate the stochastic efficiency, WUE and environmental impact of optimal irrigation and salinity management within an inter-seasonal setting where two crops are grown successively on the same soil.

The main aim of Sub-objective 3 was to determine how irrigation-scheduling for a field crop changes in the short term in view of inter-seasonal cropping systems. Consequently, two simple sub-routine algorithms were added to the intra-seasonal simulation-optimisation model to extend the model for inter-seasonal application. The first algorithm was simply called bond algorithms and it is used, basically, to extend the solution chromosome to include two crops. The second algorithm (named break-up algorithms) is used to split the solution chromosome into individual irrigation schedules for the two crops. Moreover, short-term off-season periods were included to model the inter-seasonal application for a more realistic evaluation of the daily water and soil balances throughout a year. Hence, the inter-seasonal model was used to evaluate 1-yr M-W and 1-yr M-P cropping systems.

For a given irrigation-system delivery capacity, the results of inter-seasonal and intra-seasonal application were compared to evaluate the possible changes that might occur in optimised irrigation-scheduling for maize because of inter-seasonal application. Generally, the result shows that following a risk-neutral farmer's optimised irrigation-scheduling strategy for maize in a one-year crop rotation will slightly decrease the expected MAS for maize compared to intra-seasonal optimisation for the crop regardless of the water qualities. However, the decreases in expected MAS for maize are large in 1-yr M-P compared to maize in 1-yr M-W cropping systems. The reason is that inter-seasonal optimisation of irrigation-scheduling for maize is associated with slight increases in TVIEC compared to intra-seasonal optimisation for the crop. More water needs to be applied in a one-year cropping system because of the need to drain some salt from the soil to reduce its effect on yield of the second crop in the next season. Although the decreases in expected MAS are not large, within a given water quality scenario, the decreases in expected MAS for maize due to a inter-seasonal optimised irrigation-scheduling strategy is slightly higher in 1-yr M-P than maize's expected MAS in a 1-yr M-W cropping system. In addition, a decrease in risk exposure in the production of maize results if the second crop that follows maize is peas. This shows that the salt tolerance of the field crop that follows maize affects the extent of the decrease in expected MAS for the first season crop (maize).

In addition, the result shows that following the risk-neutral farmer's optimised irrigation-scheduling strategy for maize in a one-year crop rotation will significantly decrease the expected WUE and WP compared to intra-seasonal optimisation for the crop, provided the second-season crop is peas for both water qualities. The decreases in expected WUE and WP for maize in a 1-yr M-P cropping system is explained by the fact that more water should be applied to grow maize when the second season crop is peas. Furthermore, for maize grown in a 1-yr M-P cropping system, significant increases in expected cumulative DRL was observed. Consequently, significant increases in expected cumulative SL occur for maize grown in 1-yr M-P cropping systems compared to maize grown in an intra-seasonal optimisation schedule. However, if the second-season crop is wheat, the decreases in expected WUE and WP are very small, while salt build-up in the first season could be tolerated by wheat.

Moreover, the result shows slight decreases in CE in maize's optimised irrigation-scheduling derived for the RAC considered in the study if a one-year cropping system is applied, compared to the case for a risk-neutral decision-maker. The result occurs regardless of the water quality and irrigation-system delivery capacity scenarios considered. However, the risk-averse irrigator will apply more irrigation water for maize in the one-year cropping system than the risk-neutral farmer. Consequently, the risk-averse farmer’s decision to apply more water leads to significant decreases in exposure to gross margin risk for maize grown in a one-year cropping system. On the other hand, the risk-averse behaviour results in optimised irrigation-scheduling for maize in the one-year cropping system that significantly decreases the expected WUE and WP for maize, compared to the case of risk-neutral farmer. The reason for the large decreases is that the risk-averse farmer is inclined to apply a large amount of irrigation for maize in inter-seasonal cultivation. As a result, the expected cumulative DRL shows significant increases too. Consequently, significant increases in expected cumulative SL are observed when following optimised irrigation-scheduling for maize grown in a one-year cropping system by the risk-averse irrigator considered in the study, compared to the case of risk-neutral farmer.

The main conclusions reached from the analysis of inter-seasonal one-year cropping systems are as follows. Firstly, risk-neutral farmers should consider increasing the irrigation amount supplied to the first-season crop (e.g. maize) only if the farmer is considering planting a salt-sensitive crop (e.g. peas) in the second season. It is not economically wise to drain salt in the first season if a highly salt-tolerant crop is envisaged to be planted next. The farmer should allow the salt to accumulate and wait for it to be leached by good rainfall, or consider leaching after some years, instead of following more frequent leaching practice. Secondly, compared to a risk-neutral farmer, a risk-averse decision-maker should increase the application of irrigation to manage on-site soil salinity build-up, so as to lower variability of net return from a one-year cropping system, irrespective of the type of crop that follows the first-season crop.

5.5 RECOMMENDATIONS

A number of important recommendations could be made from the main findings of this thesis. The presentation of the recommendations section will be done in two parts. The first section will present recommendations for water policy-makers to help them design appropriate strategies for using scarce water resources for sustainable economic development and environmental conservation. Next, recommendations for further research will be presented.

5.5.1 Water resource management recommendations

The sustainable use of water resources requires an understanding of all the complex social, economic, and environmental variables that determine the quantity and quality of water. Grové (2008) points out that a new generation of decision support models are required in South Africa to evaluate the effects of alternative water policies on economic efficiency of irrigation and to quantify the effect of irrigation farmers' actions on the amount of return flows within catchment areas, and beyond.

The model developed in this study was able to determine the impact of water quality on farm-level profitability and WUE. The VIS is known for its shallow water table, which moves downwards, but also moves laterally towards downstream watercourses. Should all the farmers upstream decide to mine the shallow water table, less water would return to the Harts River. This reduction in return flow would reduce water availability for farmers downstream. Moreover, the use of the shallow water table will not result in a water saving, since farmers will use any additional or available water to increase the cropping area. This increase in consumptive use of water will decrease the long-term water availability in the irrigation scheme. It is therefore necessary to conduct a hydrological study to evaluate the long-term use of the shallow water table in the area.

5.5.2 Recommendations for further research

- This research considered the inter-seasonal effect of salinity management; however, only two-season production systems were considered. It is recommended that a longer-term analysis be conducted to evaluate WUE and the environmental impact of salinity management decisions, especially under fluctuating water tables.
- Unlimited water supply was modelled in this study. However, water is a scarce resource and its use in agriculture is facing increasing competition from other sectors. Further procedures need to be incorporated into the model to consider irrigation-scheduling under limited water conditions.
- In this research the SWAMP model was used to generate SC gross MAS for each state of nature without directly estimating transformation functions. The approach provides a technique for applying the SC approach to practical irrigation problems. In the technique followed water is assumed to be a state-general input in which the optimal irrigation strategy will be the best average strategy irrespective of the state of nature that unfolds during the actual growing season. However, farmers could adjust their irrigation strategies by updating their information about the

actual state of nature they encounter during the growing season. Hence, the model should be enhanced to deal with state-specific applications of water to crops.

- Precision agriculture technology should be developed further to achieve food security and sustainable management of farm land and the environment. The success of precision agriculture depends on models that include various variables, such as non-uniform water distribution, spatial variability of soil-moisture content, crop-water stress, and crop cultivars that might affect the outcome under saline and deficit irrigation. Thus, more research is needed to expand the model to include the application of precision agriculture.
- Risk in agriculture could arise from a variety of sources, such as market risk and institutional risk, which were not incorporated in this study. However, such kinds of risk sources are important to the sustainable management of water and the environment and should be explored further by using bio-economic salinity simulation management models.
- There is a need for more research on ways to model sound irrigation-scheduling in light of worldwide climate change. Climate change would impact the type of crop that should be grown, the availability of water, as well as the quality of water.
- In this study no procedures were incorporated to include income, property and real estate taxes. Hence, implications of including these variables as decision variables on developing sound irrigation-scheduling under saline conditions should be part and parcel of future extension of this model.
- The optimised irrigation schedule relies on the use of the shallow water table. However, using a shallow water table can increase salt build-up in soils. Farmers should, therefore, carefully manage their soil-water and salt build-up, which increases farmers' information burden. Using crop-water requirements for irrigation management is not enough. Farmers require in-depth information on the water available in the soil, and about soil-salinity levels.

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PERSONAL COMMUNICATION

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APPENDICES

APPENDIX A

DECLARE INPUT PARAMETERS FOR SWAMP-ECON

```
%========== GENERAL PARAMETER DECLARATION FOR SWAMP-ECON ===========================
%This section presents general parameters declaration needed to run the optimisation model successfully for
%different alternatives.
%==================================================================================

%### DEFINING TIME HORIZONS -----------------------------------------------------------------------------------------------------

YEARS = 1;

%### ALTERNATIVE TO BE CONSIDERED ------------------------------------------------------------------------------------------

t_rota = {'winter'}; %'summer' OR 'winter' & refers to time of rotation
choose_rota = {'do_choose_fallow'}; %'do_choose_fallow' OR 'do_choose_peas'
Select_Y_rota = 1; %select year_gap of rotation or fallow
soilPcond = {'constaWT'}; %Choose 'freelyDrain' OR 'constaWT'

%### CROP ASSIGNMNET ------------------------------------------------------------------------------------------------------------

crop = {'maize','offseason1','wheat','offseason2','fallow','peas'};

case_rot = {'Rep_w_fallow','Rep_w_peas'}; %replace with: fallow or peas

%========== PARAMETER DECLARATION FOR SWAMP SECTION OF SWAMP-ECON ==================
% This section presents parameters declaration needed for the SWAMP section of the optimisation model.
%==================================================================================

%### WATER QUALITY PARAMETERS ASSIGNMENT ---------------------------------------------------------------------------

ECi = 75; %electrical conductivity of the irrigation water (mS m^-1)
ECwt = 225; %electrical conductivity of the water table (mS m^-1)

%### SOIL_TYPE ASSIGNMENT ---------------------------------------------------------------------------------------------------

soilType = {'bainsvlei'}; %Choose from: 'clovelly' or 'bainsvlei'

%### LOAD SOIL PARAMETERS FROM EXCEL FILE ----------------------------------------------------------------------------

[rSo_T,cSo_T] = size(soilType);

for I  = 1:cSo_T
if strcmp(soilType(i),'bainsvlei')
  [A,B] = xlsread('InitialSoilParameter.xlsx','bainsvlei','A3:F18');
elseif strcmp(soilType(i),'clovelly')
  [A,B] = xlsread('InitialSoilParameter.xlsx','clovelly','A3:F18');
else
  disp('the soil type is not in the list or misspelled');
end
end
```

```
%### LOAD Lv FOR MAZIE, PEAS, AND WHEAT ---------------------------------------------------------------------------------------

if strcmp(soilPcond,'constaWT')
%Water Table case
  [LvMaWT,Lvmm1] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Maize_WT','B2:Q142');
  [LvWhWT,Lvww1] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Wheat_WT','B2:Q152');
  [LvPeWT,Lvpp1] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Peas_WT','B2:Q132');
else

%Freely Drained case
  [LvMaFD,Lvmm] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Maize_FD','B2:Q142');
  [LvWhFD,Lvww] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Wheat_FD','B2:Q152');
  [LvPeFD,Lvpp] = xlsread('Peas_Maize_Wheat_SimuData.xlsx','Lv_Peas_FD','B2:Q132');
end

if strcmp(soilPcond,'constaWT')
% Assignment of Lv for each crop:CASE: Constant Water Table
for i_crop = 1:length(crop)
if strcmp(crop(i_crop),'maize')
  Lv.crop{i_crop} = LvMaWT;
elseif  strcmp(crop(i_crop),'offseason1')
  Lv.crop{i_crop} = 0;
elseif strcmp(crop(i_crop),'wheat')
  Lv.crop{i_crop} = LvWhWT;
elseif  strcmp(crop(i_crop),'offseason2')
  Lv.crop{i_crop}  = 0;
elseif  strcmp(crop(i_crop),'fallow')
  Lv.crop{i_crop} = 0;
elseif strcmp(crop(i_crop),'peas')
  Lv.crop{i_crop} = LvPeWT;
else
end
end
else % Assignment of Lv for each crop: Freely Drained
for i_crop = 1:length(crop)
if strcmp(crop(i_crop),'maize')
  Lv.crop{i_crop} = LvMaFD;
elseif  strcmp(crop(i_crop),'offseason1')
  Lv.crop{i_crop} = 0;
elseif strcmp(crop(i_crop),'wheat')
  Lv.crop{i_crop} = LvWhFD;
elseif  strcmp(crop(i_crop),'offseason2')
  Lv.crop{i_crop} = 0;
elseif  strcmp(crop(i_crop),'fallow')
  Lv.crop{i_crop} = 0;
elseif strcmp(crop(i_crop),'peas')
  Lv.crop{i_crop} = LvPeFD;
else
end
end
end

%### RE_NAME the GSL ---------------------------------------------------------------------------------------------------------

[GSL_N] = GrowthSeasonLength(crop,soilType);
%~~~~~~~~~Pre allocation
for ii_c = 1:length(crop)
if strcmp(crop(ii_c),'maize')
  crop_sgl(ii_c) = GSL_N.crop{ii_c};
elseif strcmp(crop(ii_c),'wheat')
  crop_sgl(ii_c) = GSL_N.crop{ii_c};
elseif  strcmp(crop(ii_c),'peas')
```

```
  crop_sgl(ii_c) = GSL_N.crop{ii_c};
else
end
end
Largest_GSL = max(crop_sgl);

%### LOAD DAILY DATENUMBER, RAINFALL, ETo INPUTS FROM EXCEL FILE -------------------------------------------

[RainFFF,EToooo] = xlsread('Rainfall_ETo.xlsx','RainandETo','H2:M7306');

%========= PARAMETER DECLARATION FOR ECON SECTION OF SWAMP-ECON ==================
%This section presents the general parameter declarations needed for the ECON section of the optimisation model.
%===============================================================================

%### RISK PARAMETRES ASSIGNMENT -----------------------------------------------------------------------------------------

%~Declare state of nature and risk parameters (here with rainfall and ETo)

risk_att = {'neutral'}; % select from: 'averse' or 'neutral'
RAC = 0.000182744; % Risk Aversion Coefficient

if and(YEARS == 1,Select_Y_rota == 1)
if strcmp(choose_rota,'do_choose_fallow')
if strcmp(t_rota,'winter') % maize
  state_n = 7;
  prob_s = [3/17, 2/17, 3/17, 1/17, 3/17, 1/17, 4/17];
else % wheat
  state_n = 7;
  prob_s = [1/17, 2/17, 1/17, 1/17, 6/17, 3/17, 3/17];
end
else% peas
  state_n = 7;
  prob_s = [1/17, 2/17, 1/17, 1/17, 6/17, 3/17, 3/17];
end

elseif and(YEARS == 1,Select_Y_rota > 1) % To run double crop: Maize == > Wheat
if strcmp(choose_rota,'do_choose_fallow')
  state_n = 7;
  prob_s = []; % To be defined when the model is ready for medium_term
end
else% To run double crop: all crops with rotations Maize\ wheat\ peas
  state_n = 7;
  prob_s = []; % To be defined based on double cropping model and long-term
end

%### CENTRE-PIVOT PARAMETERS -----------------------------------------------------------------------------------------------

Irr_S_design = {'Pivot_B'}; % Choose from:
%'Pivot_A' 8; 'Pivot_B' 10; %'Pivot_C' 12; %'Pivot_D' 14; 'Pivot_E' 8; 'Pivot_F' 10; 'Pivot_G' 12; 'Pivot_H' 14

%### DECLARE THE PIVOT PARAMETERS ------------------------------------------------------------------------------------
[IR_S_Cap,IR_S_Size,IR_S_FlowR,IR_S_Pres,IR_S_SHead,Eff_Pump,kVAr,kW,Repair] = ...
select_IR_S_design (Irr_S_design);
Pivot_eff = 1; %Pivot efficiency

%### IRRIGATION COST RELATED PARAMETERS ---------------------------------------------------------------------------

Labour_hr = 0.58;
Wage_Labour = 12.41; % ZAR h^-1
W_Tariffs = 0.714; % water-users association water tariffs ZAR mm^-1
Spray = 0; % spray losses (fraction)
```

```
%### DEFINE RELABILITY, NETWORK DEMAND CHARGE, AND NETWORK ACCESS CHARGE ---------------------

Voltage = {'L500V'}; % Choose: 'L500V' or 'GE500V_LE22kV'

[Reliability_sC,N_Demand_C] = reliability_demand_charge(Voltage);

%### DEFINE SERVICE CHARGE AND ADMINISTRATION CHARGE -------------------------------------------------------

Monthly_utilised_capacity = {'LE100kVA'}; % Choose:
%'LE100kVA'; 'GE100kVAandLE500kVA'; 'G500kVAandLE1MVA'; %'G1MVA'; 'Key_customers'

[Service_C,Admin_C] = service_admin(Monthly_utilised_capacity);

%### DEFINE THE TRANSMISSION ZONE AND VOLTAGE ----------------------------------------------------------------------
T_zone_Voltage = {'L300Km_GE500VandLE22kV'}; % Choose:
% 'L300Km_L500V'; 'L300Km_GE500VandLE22kV'; 'G300KmandLE600km_L500V';
% 'G300KmandLE600km_GE500VandLE22kV'; % 'G600KmandLE900km_L500V';
% 'G600KmandLE900km_GE500VandLE22kV'; 'G900km__L500V'; 'G900km__GE500VandLE22kV'

[N_Access_C] = network_accessC(T_zone_Voltage);

%### PRICES for YIELD of CROPS -----------------------------------------------------------------------------------------------------

[crop_price] = croppriceAssign(crop); %ZAR ton^-1

%### CROP PRODUCTION COSTS --------------------------------------------------------------------------------------------------

[IC_perHa,IC_yield,IC_yieldMax,max_yield] = crop_prod_cost(crop);

%========== PARAMETER DECLARATION FOR GA SECTION OF SWAMP-ECON =====================
% This section presents the parameter declarations needed for the GA section of the optimisation model.
%=================================================================================

%### DEFINING GA PARAMETERS -------------------------------------------------------------------------------------------------

numindi = 50;       %Population size
startgen = 0;       %Base generation (needed if an incomplete run is to be restarted)
startindi = 0;      %Base individual
endgen = 100;       %Number of generations (maximum number of iterations)
tournsize = 5;      %Tournament size
elite = 1;          %Elite (1 = steady state)
mateprob = 1/3;     %Crossover or recombination probability
wprob = 1.0;        %Adoption probability (mutation probability)
dvar = 0;           %Mutation parameter for variances dvar = 0 constant variances with dt & dw
dt = 1.5;           %Variance for irrigation time
dw = 0.5;           %Variance for irrigation volume
igens = 30;         %No. of generations after which an improvement must have happened
mindt = 1;          %Minimum distance double irrigation within ten days
minvol = 6;         %Minimum volume
maxvol = 15;        %Maximum volume
eop = 25;           %End of optimisation
```

APPENDIX B

MATLAB CODE FOR GA PART OF SWAMP-ECON

```
%-------- APPENDIX B (1) ------------------------------------------------------------------------------------------------------------------
%### GENERATE RANDOM DAYS AND WATER FOR CROP i
%Coded by B.O Haile, University of Free State

irrcount = 1+ceil(rand*100);
DAYS = sort(ceil(rand(irrcount,1)*100));
WATER = rand(irrcount,1)*(maxvol-minvol)+minvol;
d_cropi = DAYS;
w_cropi = WATER;

%-------- APPENDIX B (2) ------------------------------------------------------------------------------------------------------------------
%### RECONSTRUCTION STEP 1

function [days,water] = fixschedule(days,water,mindt,minvol,watervol)
%The function generates appropriate dates & water for an irrigation event.
%Format of Call:fixschedule(days,water,mindt,minvol,watervol) Source: Schütze et al. (2012)

if length(days)>1
lastday = days(1);
lastindex = 1;
for i = 2:length(days)
if days(i)-lastday<mindt
water(lastindex) = water(lastindex)+water(i);
water(i) = 0;
else
lastday = days(i);
lastindex = i;
end
end
end

while max(water)>1500 % consider daily border (actually should not be necessary however to be safe)
diff = (max(water)-1500)*length(water)/(length(water)-1);
[S I] = max(water);
water(I(1)) = water(I(1))-(diff+1);
water = water+diff/length(water);
end

while min(water(find(water>0)))<minvol % consider least quantity of water
[days water] = killminwater(days,water);
end
end

function [days,water] = killminwater(days,water)
%The function generates appropriate dates & water for an irrigation. (Source: Schütze et al. (2012))

goodpos = find(water>0);
if length(goodpos)>1
minw = min(water(goodpos));
killpos = find(water == minw);
water(killpos(1)) = 0;
```

```
killpos = find(water == 0);
water = water+minw/(length(goodpos)-1);
water(killpos) = 0;
end
return

%-------- APPENDIX B (3) --------------------------------------------------------------------------------------------------
%### RECONSTRUCTION STEP 2

function [days,water] = fixIrrSystem_Capacity(T_Hori,i_crop,OP_a_hrs,days,water,mindt,minvol,maxvol,
Pivot_eff,IR_S_Size, IR_S_FlowR,eos,IR_S_Cap)

%This function computes the irrigation schedules that are practical with the irrigation-system capacity. And
% assumes that water is going to be applied on that specific day and the next day at a minimum.
%Coded by B.O Haile

%Format of Call:
fixIrrSystem_Capacity(T_Hori,i_crop,OP_a_hrs,days,water,mindt,minvol,maxvol,Pivot_eff,IR_S_Size,IR_S_FlowR)

%Initialising the days to be added in the next irrigation event
lastday = days(1);
lastindex = 1;

if water(lastindex) == 0
count_day = 0;
water(lastindex) = water(lastindex);
elseif water(lastindex)>maxvol
water(lastindex) = rand*(maxvol-minvol)+minvol;
if ((water(lastindex)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(lastindex),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
elseif water(lastindex)>= minvol&& water(lastindex)<= maxvol
water(lastindex) = water(lastindex);
if ((water(lastindex)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= ...
OP_a_hrs(days(lastindex),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
else
water(lastindex) = 0;
count_day = 0;
end

add_day = 0;
ADD_D(lastindex) = add_day;
%-----------------------------------------------------------------------------------------------------------------------------
for i = 2:length(days)
if ADD_D(lastindex) == 0
if days(i)-lastday<mindt
days(i) = days(i);
water(i) = water(i);
%count_day = count_day;
add_day = 0;

lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;
elseif days(i)-lastday == mindt
if count_day == 0
```

```
days(i) = days(i);
add_day = 0;
else
days(i) = days(i)+count_day;
add_day = count_day;
end

%<<<<<< It is critical to know on what happens at the last i
if days(i)<eos
days(i) = days(i);
add_day = add_day;
water(i) = water(i);
elseif days(i) == eos
days(i) = eos;
add_day = 0;
if water(i)>IR_S_Cap
water(i) = IR_S_Cap;
else
water(i) = water(i);
end
else
days(i) = eos;
add_day = 0;
water(i) = 0;
end
%Calculate new count_day
if water(i) == 0
count_day = 0;
water(i) = water(i);
elseif water(i)>maxvol
water(i) = rand*( maxvol-minvol)+minvol;
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
elseif water(i)>= minvol&& water(i)<= maxvol
water(i) = water(i);
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
else
water(i) = 0;
count_day = 0;
end

lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;

else %case where it is>mindt
days(i) = days(i);
add_day = 0;
%<<<<<< It is critical to know on what happens at the last i
if days(i)<eos
days(i) = days(i);
add_day = add_day;
water(i) = water(i);
elseif days(i) == eos
days(i) = eos;
```

```
add_day = 0;
if water(i)>IR_S_Cap
water(i) = IR_S_Cap;
else
water(i) = water(i);
end
else
days(i) = eos;
add_day = 0;
water(i) = 0;
end
%Calculate new count_day
if water(i) == 0
count_day = 0;
water(i) = water(i);
elseif water(i)>maxvol
water(i) = rand*( maxvol-minvol)+minvol;
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
elseif water(i)>= minvol&& water(i)<= maxvol
water(i) = water(i);
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
else
water(i) = 0;
count_day = 0;
end

lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;

end
elseif ADD_D(lastindex)>0
if days(i)-(lastday-ADD_D(lastindex))<mindt
water(i) = water(i);
days(i) = days(i)+ADD_D(lastindex);
add_day = ADD_D(lastindex);
count_day = count_day;

lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;

elseif days(i)-(lastday-ADD_D(lastindex)) == mindt
if count_day == 0
 days(i) = days(i)+ADD_D(lastindex);
 add_day = ADD_D(lastindex);
else
 days(i) = days(i)+ADD_D(lastindex)+count_day;
 add_day = ADD_D(lastindex)+count_day;
end

%<<<<<< It is critical to know on what happens at the last i
if days(i)<eos
days(i) = days(i);
```

```
add_day = add_day;
water(i) = water(i);
elseif days(i) == eos
days(i) = eos;
add_day = 0;
if water(i)>IR_S_Cap
water(i) = IR_S_Cap;
else
water(i) = water(i);
end
else
days(i) = eos;
add_day = 0;
water(i) = 0;
end
% Calculate new count_day
if water(i) == 0
count_day = 0;
water(i) = water(i);
elseif water(i)>maxvol
water(i) = rand*( maxvol-minvol)+minvol;
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
elseif water(i)>= minvol&& water(i)<= maxvol
water(i) = water(i);
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
else
water(i) = 0;
count_day = 0;
end
lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;

else% case>mindt
diff_day = days(i)-(days(i-1)-ADD_D(lastindex))-1;

if diff_day == 0
if count_day == 0
days(i) = days(i)+ADD_D(lastindex);
add_day = ADD_D(lastindex);
else
days(i) = days(i)+ADD_D(lastindex)+count_day;
add_day = ADD_D(lastindex)+count_day;
end

elseif diff_day> 0
if ADD_D(lastindex) == diff_day
if count_day == 0
days(i) = days(i);
add_day = 0;
else
days(i) = days(i)+count_day;
add_day = count_day;
end
```

```
elseif ADD_D(lastindex)<diff_day
days(i) = days(i);
add_day = 0;
else
days(i) = days(i)+(ADD_D(lastindex)-diff_day)+count_day;
add_day = (ADD_D(lastindex)-diff_day)+count_day;
end
else
end
%<<<<<< It is critical to know on what happens at the last i
if days(i)<eos
days(i) = days(i);
add_day = add_day;
water(i) = water(i);
elseif days(i) == eos
days(i) = eos;
add_day = 0;
if water(i)>IR_S_Cap
water(i) = IR_S_Cap;
else
water(i) = water(i);
end
else
days(i) = eos;
add_day = 0;
water(i) = 0;
end
%Calculate new count_day
if water(i) == 0
count_day = 0;
water(i) = water(i);
elseif water(i)>maxvol
water(i) = rand*( maxvol-minvol)+minvol;
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
elseif water(i)>= minvol&& water(i)<= maxvol
water(i) = water(i);
if ((water(i)/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR<= OP_a_hrs(days(i),T_Hori).crop{i_crop}
count_day = 0;
else
count_day = 1;
end
else
water(i) = 0;
count_day = 0;
end
lastday = days(i);
lastindex = i;
ADD_D(lastindex) = add_day;
end

else % it can be negative but in case

end % ENDS: the added day case
end % ENDS: the i loop
end % ENDS: the function
```

%-------- **APPENDIX B (4)** --
% ### RECONSTRUCTION STEP 3 [Source: Schütze *et al*. (2012)]

```
functiondayarray = scheduletodayarray(days,water,eos)
% The function schedules to the day array the exact water with the exact date
% Format of Call: scheduletodayarray(days,water,eos) [Source: Schütze et al. (2012)]

dayarray = zeros(eos,1);
fori = 1:length(days)
if days(i)<= eos
dayarray(days(i)) = dayarray(days(i))+water(i);
end
end
return
```

%-------- **APPENDIX B (5**) --
%###SELECTION PROCESS [Source: Schütze *et al*. (2012)]

```
%[ Copy OLD generation to NEXT generation]
indistart = 0;
if generation == startgen
indistart = startindi;
end

offset = 0;
for indi = indistart:(numindi-1)

k = generation*numindi+1+offset;
element(k+indi,:) = element(k+indi-numindi,:);
lai(k+indi) = lai(k+indi-numindi);
if dvar> 0
 vari(k+indi,:) = vari(k+indi-numindi,:); % variance
end

% Do tournament selection
lost = 0;
for tround = 1:tournsize-1;
contenter = ceil(numindi*rand);
if lai(k-contenter)>lai(k+indi)
lai(k+indi) = lai(k-contenter);
element(k+indi,:) = element(k-contenter,:);

if dvar>0
vari(k+indi,:) = vari(k-contenter,:);
end

lost = 1;
else
end
end
end
```

%-------- **APPENDIX B (6**) ---
% ### CROSSOVER PROCESS [Source: Schütze *et al*. (2012)]

```
% MATE with someone?
% Only change if we have no elite selection or face a "losser"
if or(lost == 1,elite == 0);
if rand<mateprob % Consider recombination probability
mate = ceil(numindi*rand);
for tround = 1:tournsize-1; % tournament
contenter = ceil(numindi*rand);
```

```
if lai(k-contenter)>lai(k-mate)
mate = contenter;
end
end
element(k+indi,:) = mate(element(k+indi,:), element(k-mate,:), wprob);
% Variance (Assumed to be the same for all crops)
if dvar> 0 % if automatic control of mutation rates
vari(k+indi,1) = vari(k+indi,1)+rand*(vari(k-mate,1)-vari(k+indi,1));
vari(k+indi,2) = vari(k+indi,2)+rand*(vari(k-mate,2)-vari(k+indi,2));
end
end
else
 Do nothing
end
% Mate function
function dayarray = mate(element(k+indi,:), element(k-mate,:),wprob)
%The function recombines parent chromosomes to form an offspring.

dayarray = floor(rand(1,length(element(k+indi,:)))+dist).* element(k+indi,:)+
            floor(rand(1,length(element(k-mate,:)))+dist).* element(k-mate,:);

while and(sum(dayarray) == 0,find(dayarray> 0)> 1)
dayarray = floor(rand(length(element(k+indi,:)),1)+dist).* element(k+indi,:)+
            floor(rand(length(element(k-mate,:)),1)+dist).* element(k-mate,:) ;
end
return
```

%-------- **APPENDIX B (7**) ---

% ### ARRANGE SCHEDULE AFTER CROSSOVER [Source: Schütze *et al*. (2012)]

```
function [days,water] = dayarraytoschedule(dayarray)
days = [];
water = [];
k = 1;
for i = 1:length(dayarray)
if (dayarray(i)>0)
days(k) = i;
water(k) = dayarray(i);
k = k+1;
end
end
days = days;
water = water;
return
```

%-------- **APPENDIX B (8**) ---

%**###** MUTATION [Source: Schütze *et al*. (2012)]

```
%Mutate the solution
if dvar> 0 % if automatic control of mutation rates
% mutate variance for days
vari(k+indi,1) = vari(k+indi,1)*exp(dvar*exprnd(1));
if vari(k+indi,1)< 0 %Never happen but never say never using Matlab
vari(k+indi,1) = 0;
end
% mutate variance for water
vari(k+indi,2) = vari(k+indi,2)*exp(dvar*exprnd(1));
if vari(k+indi,2)< 0 % Never happen but never say never using Matlab
vari(k+indi,2) = 0;
end
end
```

```
%## do day array to schedule
[days,water] = dayarraytoschedule(dayarray);
if dvar>0
% ## mutate with individual variance
[days, water] = mutate(days,water,vari(k+indi,1)*1,...
vari(k+indi,2)*500,watervol,eos);
else
[days, water] = mutate(days,water,dt,dw,eos);
end

%The function mutate:

function [days,water] = mutate(days,water,sigmad,sigmaw,eos)

oldwater = water;
for i = 1:length(days)

days(i) = round(days(i)+normrnd(0,sigmad));
if days(i)<1
days(i) = 1;
end
if days(i)> (eos-3);
days(i) = (eos-3);
end

water(i) = round(water(i)+normrnd(0,sigmaw));
if water(i)<0
water(i) = 0;
end
end

if sum(water) == 0
water = oldwater;
else
end
return
```

%-------- **APPENDIX B (9**) ---

```
%### RE-ARRANGE SCHEDULE FUNCTION
% Coded: B.O.Haile

function [days,water] = re_arrange_scheduleforIRR_S(dayarray)

% The function identifies days and waters to be used to fit irrigation-systems capacity.

days = find(dayarray>0);
water = dayarray(find(dayarray>0));
end
```

%-------- **APPENDIX B (10**) ---

```
%### BONDING TWO CROPS
% ADD each water generated to account for two crops

water_for_crops = [w_crop1; w_crop2];
```

%-------- **APPENDIX B (11**) ---

```
% ### ALLOCATE IRRIGATION SCHEDULES TO CROPS

function [Irrig,IR_hrs,Total_Irrig,Total_IR_hrs] = generate_IR_fallow(indi,YEARS,...
crop,GSL_N,t_rota,element,Select_Y_rota,Pivot_eff,IR_S_Size,IR_S_FlowR)

% This function generates irrigation schedules from the generated solution for each crop with appropriate years.
```

```
% B.O.Haile: University of Free State, Department: AGEC, May 2015.
% Format of call:[IrrigIR_hrsTotal_IrrigTotal_IR_hrs] = generate_IR_fallow...
%                  (t_rota, YEARS,crop,GSL_N,Select_Y_rota,element,indi,Pivot_E,IR_S_Size,IR_S_FlowR)

ifstrcmp(t_rota,'summer')

%##Separating element into irrigation for each crop per year
count_r = 0;
for T_Hori = 1:YEARS

%--------------------REASSIGN GSL for the CROPS -------------------------------------------------------------------------------------
for aa = 1:length(crop) %      *****
if strcmp(crop{aa},'maize')
i_crop = aa;
eos = GSL_N.crop{i_crop};
N_GSL_C1 = eos;
end
end
for aa = 1:length(crop) %      *****
if strcmp(crop{aa},'wheat')
i_crop = aa;
eos = GSL_N.crop{i_crop};
N_GSL_C2 = eos;
end
end
% -----------------------------------------------------------------------------------------------------------------------------------------------

% Allocate and arrange schedule for maize (First Crop)
for aa = 1:length(crop) %****************************
if strcmp(crop{aa},'maize')
i_crop = aa;
end
end
if (rem(T_Hori,Select_Y_rota)~ = 0) %      since maize is replaced
          IRR = element(indi,1+N_GSL_C1*(T_Hori-1)+N_GSL_C2*(T_Hori-1)-...
           N_GSL_C1*count_r: N_GSL_C1*(T_Hori-1)+N_GSL_C2*(T_Hori-1)+N_GSL_C1-N_GSL_C1*count_r)';
else

end

%^^^^^^^^^^ Initialisation to sum total irrigation
if (rem(T_Hori,Select_Y_rota)~ = 0)
  T_IRRI = 0;
  T_IR_hr = 0;
else
  T_IRRI = [];
  T_IR_hr = [];
end

for i = 1: N_GSL_C1
if (rem(T_Hori,Select_Y_rota)~ = 0)
Irrig(i,T_Hori).crop{i_crop} = IRR(i);
Sum_Irr = T_IRRI+IRR(i);
T_IRRI = Sum_Irr;
IR_hrs(i,T_Hori).crop{i_crop} = ((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
TT_IR_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
Sum_IR_hr = T_IR_hr+TT_IR_hrs(i);
T_IR_hr = Sum_IR_hr;
else
end
end
Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
```

```
Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

% Allocate and arrange schedule for wheat (Second Crop)
for aa = 1:length(crop) %****************************
if strcmp(crop{aa},'wheat')
i_crop = aa;
end
end

if (rem(T_Hori,Select_Y_rota)~ = 0)
      IRR = element(indi, 1+N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)-...
N_GSL_C1*count_r: N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)+N_GSL_C2-N_GSL_C1*count_r)';
else
      IRR = element(indi, 1+N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)-...
N_GSL_C1*(count_r+1): N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)+N_GSL_C2-N_GSL_C1*(count_r+1))';
end

%^^^^^^^^^^^ Initialisation to sum total irrigation
T_IRRI = 0;
T_IR_hr = 0;
for i = 1: N_GSL_C2
Irrig(i,T_Hori).crop{i_crop} = IRR(i);
Sum_Irr = T_IRRI+IRR(i);
T_IRRI = Sum_Irr;
IR_hrs(i,T_Hori).crop{i_crop} = ((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
TT_IR_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
Sum_IR_hr = T_IR_hr+TT_IR_hrs(i);
T_IR_hr = Sum_IR_hr;
end
Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

% ## CONSIDER crop IN and OUT due to crop rotation
if (rem(T_Hori,Select_Y_rota)~ = 0)
rot_y = 0;
count_r = count_r+rot_y; %Occurrence of rotation
else
rot_y = 1;
count_r = count_r+rot_y; %Occurrence of rotation
end
end %ends YEARS
else % winter rotation

%## Separating element into irrigation for each crop
count_r = 0;
for T_Hori = 1:YEARS
%--------------------REASSIGN GSL for the CROPS-------------------------------------------------------------------------------------
for aa = 1:length(crop) %****************************************
if strcmp(crop{aa},'maize')
 i_crop = aa;
eos = GSL_N.crop{i_crop};
N_GSL_C1 = eos;
end
end
for aa = 1:length(crop) %****************************************
if strcmp(crop{aa},'wheat')
i_crop = aa;
eos = GSL_N.crop{i_crop};
N_GSL_C2 = eos;
end
end
%-------------------------------------------------------------------------------------------------------------------------------------------
```

```
%Allocate and arrange schedule for maize (First Crop)
for aa = 1:length(crop) %****************************
if strcmp(crop{aa},'maize')
i_crop = aa;
end
end

 IRR = element(indi,1+N_GSL_C1*(T_Hori-1)+N_GSL_C2*(T_Hori-1)-...
        N_GSL_C2*count_r: N_GSL_C1*(T_Hori-1)+N_GSL_C2*(T_Hori-1)+N_GSL_C1-N_GSL_C2*count_r)';

%^^^^^^^^^^^ Initialisation to sum total irrigation
T_IRRI = 0;
T_IR_hr = 0;
for i = 1: N_GSL_C1
Irrig(i,T_Hori).crop{i_crop} = IRR(i);
Sum_Irr = T_IRRI+IRR(i);
T_IRRI = Sum_Irr;
IR_hrs(i,T_Hori).crop{i_crop} = ((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
TT_IR_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
Sum_IR_hr = T_IR_hr+TT_IR_hrs(i);
T_IR_hr = Sum_IR_hr;
end
Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

% Allocate and arrange schedule for wheat (Second Crop)
for aa = 1:length(crop) %*****************************
if strcmp(crop{aa},'wheat')
i_crop = aa;
end
end
if (rem(T_Hori,Select_Y_rota)~ = 0) % since wheat is replaced
 IRR = element(indi, 1+N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)-...
        N_GSL_C2*count_r: N_GSL_C1*(T_Hori)+N_GSL_C2*(T_Hori-1)+N_GSL_C2-N_GSL_C2*count_r)';
else

end

%^^^^^^^^^^^ Initialisation to sum total irrigation
if (rem(T_Hori,Select_Y_rota)~ = 0)
T_IRRI = 0;
T_IR_hr = 0;
else
T_IRRI = [];
T_IR_hr = [];
end

for i = 1: N_GSL_C2
if (rem(T_Hori,Select_Y_rota)~ = 0) % since wheat is replaced
Irrig(i,T_Hori).crop{i_crop} = IRR(i);
Sum_Irr = T_IRRI+IRR(i);
T_IRRI = Sum_Irr;
IR_hrs(i,T_Hori).crop{i_crop} = ((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
TT_IR_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
Sum_IR_hr = T_IR_hr+TT_IR_hrs(i);
T_IR_hr = Sum_IR_hr;
else

end
end
Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;
```

```
%## CONSIDER crop IN and OUT due to crop rotation
if (rem(T_Hori,Select_Y_rota)~ = 0)
rot_y = 0;
count_r = count_r+rot_y; % Occurrence of rotation
else
rot_y = 1;
count_r = count_r+rot_y; % Occurrence of rotation
end

end % ends YEARS
end % ends t_rota
end % ends the function
```

APPENDIX C

MATLAB CODE FOR SWAMP SECTION OF THE MODEL

```
%======== ADDITIONAL INPUT DECLARATION FOR SWAMP ====================================
%This section presents the MATLAB code for inputs that are needed for SWAMP in addition to the inputs defined in
%Appendix A. Coded by Berhane O Haile, University of Free State
%==============================================================================

%### DEFINE THE STATE OF NATURE TO BE CONSIDER --------------------------------------------------------------------

s_nat = 1; % <<<<<<< Change the value for RISK_PROGRAMMING (i.e. take the value from 1, … , n)

%### LOAD OPTIMAL IRRIGATION SCHEDULE ----------------------------------------------------------------------------------
if strcmp(choose_rota,'do_choose_fallow')

  if strcmp(t_rota,'winter') % maize crop

     [OptSc,optss] = xlsread('Opt_Irr_Sch_MAIZE.xlsx','sheet1','C6:EM6');
  else % wheat crop
     [OptSc,optss] = xlsread('Opt_Irr_Sch_WHEAT.xlsx','sheet1','C6:EW6');
  end
  else % peas
     [OptSc,optss] = xlsread('Opt_Irr_Sch_PEAS.xlsx','sheet1','C6:EC6');
end

indi = 1;
element(indi,:) = OptSc(1,:); % the optimal irrigation schedule

%### PLANTING DATE ASSIGNMENT FOR THE CROPS ---------------------------------------------------------------------
% Planting date needs to be defined for each state of nature.
%~~Crop1 = wheat
        P_year_crop1 = 1981; % planting year for crop1
        P_month_crop1 = 12; % planting month for crop1
        P_date_crop1 = 10; % planting month for crop1
%~~Crop2 = wheat
        P_year_crop2 = 1982; % planting year for crop2
        P_month_crop2 = 07; % planting month for crop2
        P_date_crop2 = 05;   % planting month for crop2
%~~Crop3 = peas
        P_year_crop3 = 1982; % planting year for crop3
        P_month_crop3 = 07; % planting month for crop3
        P_date_crop3 = 15; % planting month for crop3

%### CUTTING UP MATRIX A TO FORM 5 INPUT VARIABLES FOR SOIL PROFILES -------------------------------------
Soil_L = A(:,1)'; %soil layer number count
Zadj_k = A(:,2)'; %adjusted thickness of layer
SC_k = A(:,3)'; %silt + clay content of layer
ThetaS_k = A(:,4)'; %Moisture at the start of the season for each layer
ECeS_k = A(:,5)'; %EC extract at the start of the season for each layer
Depth_k = A(:,6)'; %Depth of each layer

[mm,nn] = size(Soil_L);
Zavg = sum(Zadj_k)/length(Soil_L);
SCavg = sum(Zadj_k.* SC_k)/sum(Zadj_k);
```

```
KK = 0.31-(0.03*(SC_k(1).^0.5));

%### DEFINE CROP PARAMETERS ---------------------------------------------------------------------------------------------------

[Ya,Q,FBmax,GSL_N] = cal_YaQFBmax(crop,soilType);

%### LOAD DAILY DATENUMBER, RAINFALL, ETo INPUTS FROM EXCEL FILE --------------------------------------------
% <<<<<<< NB: Check here for state of nature consideration

[RainFFF,EToooo] = xlsread('Rainfall_ETo.xlsx','RainandETo','H2:M7306');
DateNumber = RainFFF(:,1); % Identifying datenumber
RainF_d_y = RainFFF(:,2); % Rainfall per given datenumber (mm)
ETo_d_y = RainFFF(:,3); % ETo per given datenumber (mm)
DoW_d_y = RainFFF(:,4); % Sets the days of the week (1 = Sun; 2 = Mon etc)
Season_d_y = RainFFF(:,5); % Season of the days for energy (1 = low 2 = high)

%### INDEXES ASSIGNMENT BASED ON PLANTING DATE FOR THE CROPS ----------------------------------------------

%~~~~~~~~ Identify crops based on planting date
[P_year,P_month,P_date] = Identify_PD(crop,P_year_crop1,P_month_crop1,...
                  P_date_crop1,P_year_crop2,P_month_crop2,P_date_crop2,...
                  P_year_crop3,P_month_crop3,P_date_crop3);

%~~~~~~~~ Identify date numbers for the crops in the rotation
[Start_PD_year,PD_number] = Identify_DateNo(YEARS,crop,P_year,P_month,P_date);

%~~~~~~~~ Identify the indexes of each growing days of the crops
[F_index] = Identify_indexCrops(YEARS,crop,soilType,DateNumber,PD_number);

%~~~~~~~~ Compute difference to get indexes of off_S1 and off_S2 & replace
%with fallow or winter peas
[Diff_OffS1,Diff_OffS2,Diff_fal_S,Diff_fal_W] = cal_DiffCrops...
                                                (YEARS,Start_PD_year,case_rot,GSL_N,F_index);

%### RAIN AND ETo ASSIGNMENT FOR EACH YEAR FOR THE CROPS ------------------------------------------------------

[Day_o_Week,Day_S_type,RainF,ETo,RainF_OffS1,RainF_OffS2,RainF_fallS,...
RainF_fallW] = Identify_RainETo(YEARS,crop,soilType,F_index,RainF_d_y,...
ETo_d_y,DoW_d_y,Season_d_y,case_rot,Diff_OffS1,GSL_N,Diff_OffS2,Diff_fal_S,...
Diff_fal_W);

%### DEFINE CROP PARAMETERS Tm & STR per YEAR -----------------------------------------------------------------------

% Preallocation is required

Largest_GSL = max(crop_sgl);
s = struct('preall',cell(1));
Tm = repmat(s,1,YEARS);
STR = repmat(s,1,YEARS);
TpMax = repmat(s,1,YEARS);
T_STR_pot = repmat(s,1,YEARS);
TRR = repmat(s,Largest_GSL,1);
TR = repmat(s,Largest_GSL,1);
FB = repmat(s,Largest_GSL,1);

% NB: The crop name can be changed to “wheat” or “peas” whenever it is needed
for T_Hori = 1:YEARS
for aa = 1:length(crop)      %*********************************************
if strcmp(crop{aa},'maize')
        i_crop = aa;
end
end
```

```
if strcmp(crop(i_crop),'maize')
  crop{i_crop} = 'maize';
  [FB1,FB2,FB3,m,Ym,A1,B1,C1,D1,a1,d1,Lm,RPR,PsiP,PD,GSL,Fert,RGP,FBtot, ...
  TY,HI,Fsr] = CropParameters(crop{i_crop},soilType);
  TTT = zeros(GSL,1);
  TR_New = zeros(GSL,1);

%~~~~~~~~seasonal maximum transpiration

Tm(T_Hori).crop{i_crop} = (Ym/m)* ETo(T_Hori).crop{i_crop};

%~~~~~~~~seasonal transpiration

STR(T_Hori).crop{i_crop} = Tm(T_Hori).crop{i_crop};

%~~~~~~~~Daily Transpiration,Lx,fx, and FB
for i = 1:GSL
if i <= A1
     TRR(i,T_Hori).crop{i_crop} = (a1/A1)*i;
elseif i > A1 && i <= B1
     TRR(i,T_Hori).crop{i_crop} = a1 + ((1-a1)/(B1-A1))*(i-A1);
elseif i >B1 && i<= C1
     TRR(i,T_Hori).crop{i_crop} = 1;
elseif i > C1 && i <= D1
     TRR(i,T_Hori).crop{i_crop} = 1-((1-d1)/(D1-C1))*(i-C1);
else
end
     TR(i,T_Hori).crop{i_crop} = TRR(i,T_Hori).crop{i_crop}*...
                          (STR(T_Hori).crop{i_crop}/Q.crop{i_crop});

if TRR(i,T_Hori).crop{i_crop}> 0
     FB(i,T_Hori).crop{i_crop} = (FBmax.crop{i_crop}/100)* TRR(i,T_Hori)...
                         .              crop{i_crop};
else
     FB(i,T_Hori).crop{i_crop} = 1-((1/((0.9999)+(0.0018)*(FBmax.crop{i_crop})...
                                       +(7.5698*(10.^-6))*((FBmax.crop{i_crop}).^2))));
end
     TTT(i,T_Hori) = TR(i,T_Hori).crop{i_crop};
     TR_New(i) = TTT(i,T_Hori);
end
     TpMax(T_Hori).crop{i_crop} = max(TR_New);
     T_STR_pot(T_Hori).crop{i_crop} = sum(TR_New);
end

end

%### DUL FOR EACH LAYER k ----------------------------------------------------------------------------------------------------------

ZSC = Zadj_k.* SC_k;
FZsum = sum(ZSC);

[ULPAWet,ThetaSoilULPAW,WkULPAW,ThetaULPAW_k,ULPAWe] = …
                                                   cal_DULandOth(a,b,crop,YEARS,KK,TpMax,ZSC,FZsum,Zadj_k);

%### OTHER SOIL PARAMETERS ASSIGNMNET ----------------------------------------------------------------------------
[ThetaSatu_k,Theta10,Theta1500,ThetaaA,C,Wsatu_k] = cal_OtherSoilPara(Soil_L,SC_k,Zadj_k);

[ThetaO] = cal_ThetaO(Soil_L,crop,soilType,Theta1500,C);

%### EFFECTIVE RAIN AND IRRIGATION ------------------------------------------------------------------------------------------
-
%NB: Only the code on how to calculate these parameters is provided here to save space.
```

```
%      FOR CROP CASE: Example: FOR MAIZE CROP

if strcmp(crop(i_crop),'maize')
for i = 1:GSL_N.crop{i_crop}
          Eff_RI(i,T_Hori).crop{i_crop} = Irrig(i,T_Hori).crop{i_crop}+RainF(i,T_Hori).crop{i_crop};
End
       end
%      FOR fallow CASE: Example: FOR offseason 1

for caseR = 1:length(case_rot)
if strcmp(case_rot{caseR},'Rep_w_fallow')
for i = 1:Diff_OffS1(1,T_Hori).case_rot{caseR}
              Eff_RI(i,T_Hori).crop{i_crop}.case_rot{caseR} = RainF_OffS1(i,T_Hori).case_rot{caseR};
end
end
end

%### ECin and Sin -----------------------------------------------------------------------------------------------------------------------------
%NB: Only the code on how to calculate these parameters is provided here to save space.

%      FOR CROP CASE: Example: FOR MAIZE CROP

if strcmp(crop(i_crop),'maize')
for i = 1:GSL_N.crop{i_crop}
if (Eff_RI(i,T_Hori).crop{i_crop} == 0)
           ECin(i,T_Hori).crop{i_crop} = 0;
else
           ECin(i,T_Hori).crop{i_crop} = (RainF(i,T_Hori).crop{i_crop}*2 + ...
                                         (Irrig(i,T_Hori).crop{i_crop}*ECi))/Eff_RI(i,T_Hori).crop{i_crop};
end
           Sin(i,T_Hori).crop{i_crop} = ECin(i,T_Hori).crop{i_crop}*0.075*Eff_RI(i,T_Hori).crop{i_crop};
end
end

%      FOR fallow CASE: Example: FOR offseason 1

for caseR = 1:length(case_rot)
if strcmp(case_rot{caseR},'Rep_w_fallow')
for i = 1:Diff_OffS1(1,T_Hori).case_rot{caseR}
if (Eff_RI(i,T_Hori).crop{i_crop}.case_rot{caseR} == 0)
             ECin(i,T_Hori).crop{i_crop}.case_rot{caseR} = 0;
else
             ECin(i,T_Hori).crop{i_crop}.case_rot{caseR} = (RainF_OffS1(i,...
             T_Hori).case_rot{caseR}*2)/Eff_RI(i,T_Hori).crop{i_crop}.case_rot{caseR};
end
             Sin(i,T_Hori).crop{i_crop}.case_rot{caseR} = ECin(i,T_Hori)...
             .crop{i_crop}.case_rot{caseR}*0.075*Eff_RI(i,T_Hori)...
             .crop{i_crop}.case_rot{caseR};
end
end
end

%### WATER BUDGET: CASCADING PRINCIPLE -------------------------------------------------------------------------------------
% NB: only for one crop (e.g. maize) is given here to save space. Otherwise, the same principle is used for other
%crops as well as fallow periods with little modifications.

for aa = 1:length(crop) %********************************************
if strcmp(crop{aa},'maize')
         i_crop = aa;
end
end
if strcmp(soilPcond,'freelyDrain') %#### <<<<<
```

```
      ThetaS_k = ThetaULPAW_k(T_Hori).crop{i_crop};
end
if  strcmp(crop(i_crop),'maize')
     crop{i_crop} = 'maize';
     [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP  ...
     FBtot TY HI Fsr] = CropParameters(crop{i_crop},soilType);
if T_Hori == 1
     [Theta L_water W_soil Shortage EffRainShort RainPerLayer MatricPot...
     DC Sp ECe SaltContent ECe_L_sum ECe_Mean Total_Theta OsmoticPot LWSR...
     PWSR T S_soil S SWT S_perco WTU S_WTU WTU_P S_Rain S_Irr Diff_Swtu_Sp ...
     c_day E_time Ecum Euncovered Ecovered Evapo] = WaterBudget_yesC_Y1...
     (T_Hori,GSL,Soil_L,i_crop,crop,ThetaS_k,Zadj_k,ThetaULPAW_k,Eff_RI,...
     Theta1500,C,ECeS_k,ThetaSatu_k,SC_k,Fsr,Lv,PsiP,TR,ECwt,RainF,Sin,...
     ThetaaA,FB,soilPcond,ECin,Wsatu_k);
else
     [Theta L_water W_soil Shortage EffRainShort RainPerLayer MatricPot...
     DC Sp ECe SaltContent ECe_L_sum ECe_Mean Total_Theta OsmoticPot LWSR...
     PWSR T S_soil S SWT S_perco WTU S_WTU WTU_P S_Rain S_Irr Diff_Swtu_Sp ...
     c_day E_time Ecum Euncovered Ecovered Evapo] = WaterBudget_yesC_Yothers...
     (T_Hori,GSL,Soil_L,i_crop,crop,ThetaS_k,Zadj_k,ThetaULPAW_k,Eff_RI,...
     Theta1500,C,ECeS_k,ThetaSatu_k,SC_k,Fsr,Lv,PsiP,TR,ECwt,RainF,Sin,...
     ThetaaA,FB,soilPcond,ECin,Wsatu_k,Theta_Link,ECe_Link);
end

     Theta = Theta;
     ECe = ECe;
     T_actual_new = zeros(GSL,1);
for i = 1:GSL
for k = 1:nn
        Theta_Link(k) = Theta(end,k,T_Hori);
        ECe_Link(k) = ECe(end,k,T_Hori);
        MOISTURE(i,k,T_Hori).crop{i_crop} = Theta(i,k,T_Hori);
        EC_SOIL(i,k,T_Hori).crop{i_crop} = ECe(i,k,T_Hori);
        MATRIC(i,k,T_Hori).crop{i_crop} = MatricPot(i,k,T_Hori);
        OSMOTIC(i,k,T_Hori).crop{i_crop} = OsmoticPot(i,k,T_Hori);
        TOTAL_THETA(i,k,T_Hori).crop{i_crop} = Total_Theta(i,k,T_Hori);

        EVAPO(i,T_Hori).crop{i_crop} = Evapo(i,T_Hori);
        TRANSP(i,T_Hori).crop{i_crop} = T(i,T_Hori);
        wtu(i,T_Hori).crop{i_crop} = WTU(i,T_Hori);
        PERCO(i,T_Hori).crop{i_crop} = EffRainShort(i,end,T_Hori);
        W_SOIL(i,T_Hori).crop{i_crop} = W_soil(i,T_Hori);
        S_RAIN(i,T_Hori).crop{i_crop} = S_Rain(i,T_Hori);
        S_IRR(i,T_Hori).crop{i_crop} = S_Irr(i,T_Hori);
        S_wtu(i,T_Hori).crop{i_crop} = S_WTU(i,T_Hori);
        S_PERCO(i,T_Hori).crop{i_crop} = S_perco(i,T_Hori);
        S_SOIL(i,T_Hori).crop{i_crop} = S_soil(i,T_Hori);
        ECe_M(i,T_Hori).crop{i_crop} = ECe_Mean(i,T_Hori);
        T_actual_new(i) = TRANSP(i,T_Hori).crop{i_crop};
end
end
     T_STR_actual(T_Hori).crop{i_crop} = sum(T_actual_new(1:end-1));
     Y_act(T_Hori).crop{i_crop} = (Ym-(Ym*(1-(T_STR_actual(T_Hori).crop{i_crop}...
                                   /T_STR_pot(T_Hori).crop{i_crop}))))* HI;
end
```

```
%========== DECLARATION OF FUNCTIONS FOR SWAMP ========================================
%This section presents the MATLAB code for functions that are needed for SWAMP.
%=====================================================================================

%---------- FUNCTION: IDENTIFYING THE APPROPRIATE DATES OF RAIN FALL ------------------------------------------

function [Diff_OffS1 Diff_OffS2 Diff_fal_S Diff_fal_W] = cal_DiffCrops...
                        (YEARS,Start_PD_year,case_rot,GSL_N,F_index)

%The function computes the difference between crops end and start of planting date to find out the length of the
% Off seasons and fallow periods.
%Format of call: calculate_DiffCrops(YEARS,Start_PD_year,case_rot,GSL_N,F_index)

for caseR = 1:length(case_rot)

if strcmp(case_rot{caseR},'Rep_w_fallow')
%N:B: Need to identify where they are located manually according to sequence of crop rotation
for T_Hori = 1:YEARS
      Year_Ref(T_Hori) = Start_PD_year(T_Hori).crop{3}; %assume it is winter crop

if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
       Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{3}-...
F_index(end+(GSL_N.crop{1}-GSL_N.crop{3}),T_Hori).crop{1}-1;
else
       Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{3}-...
F_index(end,T_Hori).crop{1}-1;
end

if (rem((Year_Ref(T_Hori)),4) == 0)
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end+...
            (GSL_N.crop{1}-GSL_N.crop{3}),T_Hori).crop{1}-F_index...
            (1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}-...
            ((F_index(end,T_Hori).crop{3}- F_index(1,T_Hori).crop{3})+1);
else
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end,T_Hori).crop{1}...
            -F_index(1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}...
            -((F_index(end,T_Hori).crop{3}- F_index(1,T_Hori).crop{3})+1);
end
else
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end+(GSL_N.crop{1}-...
              GSL_N.crop{3}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
             -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end,T_Hori).crop{3}-F_index(1,T_Hori).crop{3})+1);
else
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end,T_Hori).crop{1}...
            -F_index(1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}...
            -((F_index(end,T_Hori).crop{3}- F_index(1,T_Hori).crop{3})+1);
end
end

%If summer fallow( replace summer crop)
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
       Diff_fal_S(1,T_Hori).case_rot{caseR} = ((F_index(end+(GSL_N.crop{1}-...
            GSL_N.crop{3}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            + Diff_OffS1(1,T_Hori).case_rot{caseR};
else
       Diff_fal_S(1,T_Hori).case_rot{caseR} = ((F_index(end,T_Hori).crop{1}-...
          F_index(1,T_Hori).crop{1})+1)+ Diff_OffS1(1,T_Hori).case_rot{caseR};

end
```

```
%If winter fallow (replace winter crop)
if (rem((Year_Ref(T_Hori)),4) == 0)
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
        Diff_fal_W(1,T_Hori).case_rot{caseR} = 366-((F_index(end+(GSL_N.crop{1}...
         -GSL_N.crop{3}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1);
else
      Diff_fal_W(1,T_Hori).case_rot{caseR} = 366-((F_index(end,T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1);
end
else
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
        Diff_fal_W(1,T_Hori).case_rot{caseR} = 365-((F_index(end+(GSL_N.crop{1}...
         -GSL_N.crop{3}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1);
else
      Diff_fal_W(1,T_Hori).case_rot{caseR} = 365-((F_index(end,T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1);
end
end

end

else% replace winter crop wheat with winter peas
for T_Hori = 1:YEARS
    Year_Ref(T_Hori) = Start_PD_year(T_Hori).crop{6}; %assume it is winter crop

if ((GSL_N.crop{1}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{6})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end,T_Hori).crop{1}-1;

elseif ((GSL_N.crop{1}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{3})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end,T_Hori).crop{1}-1;

elseif ((GSL_N.crop{3}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{6})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end-(GSL_N.crop{3}-GSL_N.crop{1}),T_Hori).crop{1}-1;

elseif ((GSL_N.crop{3}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{1})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end-(GSL_N.crop{3}-GSL_N.crop{1}),T_Hori).crop{1}-1;

elseif ((GSL_N.crop{6}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{3})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end-(GSL_N.crop{6}-GSL_N.crop{1}),T_Hori).crop{1}-1;

elseif ((GSL_N.crop{6}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{1})>= 0)
      Diff_OffS1(1,T_Hori).case_rot{caseR} = F_index(1,T_Hori).crop{6}-...
         F_index(end-(GSL_N.crop{6}-GSL_N.crop{1}),T_Hori).crop{1}-1;

else
end


if (rem((Year_Ref(T_Hori)),4) == 0)
if ((GSL_N.crop{1}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{6})>= 0)
       Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end,T_Hori).crop{1}...
         -F_index(1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}-...
         ((F_index(end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}-...
         F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{1}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{3})>= 0)
       Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end,T_Hori).crop{1}...
         -F_index(1,T_Hori).crop{1})+1) -Diff_OffS1(1,T_Hori).case_rot{caseR}...
         -((F_index(end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}-...
```

```
            F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{3}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{6})>= 0)
           Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end-(GSL_N.crop{3}-...
            GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{6}),T_Hori).crop{6}- F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{3}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{1})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{6}),T_Hori).crop{6}- F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{6}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{3})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end-(GSL_N.crop{6}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end,T_Hori).crop{6}...
            -F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{6}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{1})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 366 -((F_index(end-(GSL_N.crop{6}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end,T_Hori).crop{6}...
            -F_index(1,T_Hori).crop{6})+1);
else
end

else
if ((GSL_N.crop{1}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{6})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end,T_Hori).crop{1}...
            -F_index(1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}...
            -((F_index(end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}...
            -F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{1}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{3})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end,T_Hori).crop{1}...
            -F_index(1,T_Hori).crop{1})+1)-Diff_OffS1(1,T_Hori).case_rot{caseR}...
            -((F_index(end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}...
            -F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{3}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{6})>= 0)
           Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{6}),T_Hori).crop{6}- F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{3}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}-GSL_N.crop{1})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end-(GSL_N.crop{3}...
            -GSL_N.crop{6}),T_Hori).crop{6}- F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{6}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}-GSL_N.crop{3})>= 0)
         Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end-(GSL_N.crop{6}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end,T_Hori).crop{6}...
            - F_index(1,T_Hori).crop{6})+1);

elseif ((GSL_N.crop{6}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-GSL_N.crop{1})>= 0)
          Diff_OffS2(1,T_Hori).case_rot{caseR} = 365 -((F_index(end-(GSL_N.crop{6}...
            -GSL_N.crop{1}),T_Hori).crop{1}-F_index(1,T_Hori).crop{1})+1)...
```

```
            -Diff_OffS1(1,T_Hori).case_rot{caseR}-((F_index(end,T_Hori).crop{6}...
            -F_index(1,T_Hori).crop{6})+1);
else
end

end
```

%---------- **FUNCTION: CALCULATE DUL FOR A SPECIFIC CROP** ---

```
function [ULPAWet,ThetaSoilULPAW,WkULPAW,ThetaULPAW_k,ULPAWe] = cal_DULandOth...
                                        (a,b,crop,YEARS,KK,TpMax,ZSC,FZsum,Zadj_k)
%This function computes the drained upper limit in the case of specific cropand when there is no crops.
%Format of call:cal_DULandOth(a,b,crop,T_period,KK,TpMax,ZSC,FZsum,Zadj_k)

for T_Hori = 1:YEARS
for i_crop = 1:length(crop)
if strcmp(crop(i_crop),'maize')
%DUL for root zone (soil profile)

  ULPAWet(T_Hori).crop{i_crop} = b-a.*(log(a/TpMax(T_Hori).crop{i_crop}));
  ThetaSoilULPAW(T_Hori).crop{i_crop} = ULPAWet(T_Hori).crop{i_crop}/FZsum;
  WkULPAW(T_Hori).crop{i_crop} = (ThetaSoilULPAW(T_Hori).crop{i_crop}).*ZSC;

%DUL for each soil layer
  ThetaULPAW_k(T_Hori).crop{i_crop} = ((WkULPAW(T_Hori).crop{i_crop})./Zadj_k);

elseif strcmp(crop(i_crop),'wheat')
%DUL for root zone (soil profile)
  ULPAWet(T_Hori).crop{i_crop} = b-a.*(log(a/TpMax(T_Hori).crop{i_crop}));
  ThetaSoilULPAW(T_Hori).crop{i_crop} = ULPAWet(T_Hori).crop{i_crop}/FZsum;
  WkULPAW(T_Hori).crop{i_crop} = (ThetaSoilULPAW(T_Hori).crop{i_crop}).*ZSC;
%DUL for each soil layer
  ThetaULPAW_k(T_Hori).crop{i_crop} = ((WkULPAW(T_Hori).crop{i_crop})./Zadj_k);

elseif strcmp(crop(i_crop),'peas')
%DUL for root zone (soil profile)
  ULPAWet(T_Hori).crop{i_crop} = b-a.*(log(a/TpMax(T_Hori).crop{i_crop}));
  ThetaSoilULPAW(T_Hori).crop{i_crop} = ULPAWet(T_Hori).crop{i_crop}/FZsum;
  WkULPAW(T_Hori).crop{i_crop} = (ThetaSoilULPAW(T_Hori).crop{i_crop}).*ZSC;
%DUL for each soil layer
  ThetaULPAW_k(T_Hori).crop{i_crop} = ((WkULPAW(T_Hori).crop{i_crop})./Zadj_k);

else
  ULPAWe(T_Hori).crop{i_crop} = b-a.*(log(a/KK));
  ThetaSoilULPAW(T_Hori).crop{i_crop} = ULPAWe(T_Hori).crop{i_crop}/FZsum;
  WkULPAW(T_Hori).crop{i_crop} = (ThetaSoilULPAW(T_Hori).crop{i_crop}).*ZSC;
  ThetaULPAW_k(T_Hori).crop{i_crop} = ((WkULPAW(T_Hori).crop{i_crop})./Zadj_k);
end
end
end
```

%---------- **FUNCTION: CALCULATE MOISTURE RELATED PARAMETERS** ---

```
function [ThetaSatu_k,Theta10,Theta1500,ThetaaA,C,Wsatu_k] = cal_OtherSoilPara(Soil_L,SC_k,Zadj_k)
%The function computes all the moisture related parameters of the soilprofile layers.
%Format of call:cal_OtherSoilPara(Soil_L,SC_k,Zadj_k)

[mm,nn] = size(Soil_L);

%Preallocating for speed
ThetaSatu_k = zeros(1,nn);
Theta10 = zeros(1,nn);
```

```
Theta1500 = zeros(1,nn);
ThetaaA = zeros(1,nn);
C = zeros(1,nn);
Wsatu_k = zeros(1,nn);

for k = 1:length(Soil_L)
   ThetaSatu_k(k) = (0.0029*SC_k (k))+ 0.316;
   Theta10(k) = (0.0345*(SC_k(k).^0.611));
   Theta1500(k) = (0.00385*SC_k(k))+ 0.013;
   ThetaaA(k) = 0.0012*SC_k(k)+ 0.006; % only for K = 1 needed
   C(k) = -5.0056 /(log(Theta1500(k)/Theta10(k)));
   Wsatu_k(k) = ThetaSatu_k(k)* Zadj_k(k);
end
```

%---------- **FUNCTION: CALCULATE THETA_O PARAMETERS** --

```
function [ThetaO] = cal_ThetaO(Soil_L,crop,soilType,Theta1500,C)
%This function computes the Theta0 of the specific layers.
%Format of call:cal_ThetaO(Soil_L,crop,soilType,Theta1500,C)

for k = 1:length(Soil_L)
for i_crop = 1:length(crop)
if strcmp(crop(i_crop),'maize')
   crop{i_crop} = 'maize';
   [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot .
   TY HI Fsr] = CropParameters(crop{i_crop},soilType);
   ThetaO(k).crop{i_crop} = Theta1500(k)/exp(log(abs(PsiP)/1500)/C(k));
elseif strcmp(crop(i_crop),'offseason1')
elseif strcmp(crop(i_crop),'wheat')
   crop{i_crop} = 'wheat';
   [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot .
   TY HI Fsr] = CropParameters(crop{i_crop},soilType);
   ThetaO(k).crop{i_crop} = Theta1500(k)/exp(log(abs(PsiP)/1500)/C(k));
elseif strcmp(crop(i_crop),'offseason2')
elseif strcmp(crop(i_crop),'fallow')
elseif strcmp(crop(i_crop),'peas')
   crop{i_crop} = 'peas';
   [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot .
   TY HI Fsr] = CropParameters(crop{i_crop},soilType);
   ThetaO(k).crop{i_crop} = Theta1500(k)/exp(log(abs(PsiP)/1500)/C(k));
else
end

end
end
```

%---------- **FUNCTION: CROP RELATED PARAMETERS** ---

```
function [Ya Q FBmax GSL_N] = cal_YaQFBmax(crop,soilType)
%This function computes the potenital yield (Ya), the scalar variable Q & FBmax for each crop and renames the
% GSL (growing season length)
%Format of call: cal_YaQFBmax(crop,soilType)

for i_crop = 1:length(crop)

if strcmp(crop(i_crop),'maize')
crop{i_crop} = 'maize';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
TY HI Fsr] = CropParameters(crop{i_crop},soilType);
Ya.crop{i_crop} = TY/HI;   % actual seed yield
Q.crop{i_crop} = (A1*a1)/2 + ((B1-A1)*a1 + ((B1-A1)*(1-a1))/2) + (C1-B1)+(((D1-C1)*(1-d1))/2 + (D1-C1)*d1);
```

```
GSL_N.crop{i_crop} = GSL;

%~~~~~~~~~Fractional cover for cropped field
if TY <= FB3
   FBmax.crop{i_crop} = (FB1*TY)+ FB2;
else
   FBmax.crop{i_crop} = 100;
end

elseif strcmp(crop(i_crop),'offseason1')

elseif strcmp(crop(i_crop),'wheat')
crop{i_crop} = 'wheat';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
TY HI Fsr] = CropParameters(crop{i_crop},soilType);
Ya.crop{i_crop} = TY/HI;   % actual seed yield
Q.crop{i_crop} = (A1*a1)/2 + ((B1-A1)*a1 + ((B1-A1)*(1-a1))/2) + (C1-B1)+(((D1-C1)*(1-d1))/2 + (D1-C1)*d1);

GSL_N.crop{i_crop} = GSL;

%~~~~~~~~~Fractional cover for cropped field
if TY <= FB3
FBmax.crop{i_crop} = (FB1*TY)+ FB2;
else
FBmax.crop{i_crop} = 100;
end

elseif strcmp(crop(i_crop),'offseason2')
elseif strcmp(crop(i_crop),'fallow')
else
crop{i_crop} = 'peas';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
TY HI Fsr] = CropParameters(crop{i_crop},soilType);
Ya.crop{i_crop} = TY/HI;   % actual seed yield
Q.crop{i_crop} = (A1*a1)/2 + ((B1-A1)*a1 + ((B1-A1)*(1-a1))/2) + (C1-B1)+(((D1-C1)*(1-d1))/2 + (D1-C1)*d1);

GSL_N.crop{i_crop} = GSL;
%~~~~~~~~~Fractional cover for cropped field
if TY <= FB3
FBmax.crop{i_crop} = (FB1*TY)+ FB2;
else
FBmax.crop{i_crop} = 100;
end
end
end
end
end
```

%---------- **FUNCTION: CALCULATE TIME PARAMETERS FOR FALLOW CASE** ---

```
function  [E_time] = calcu_E_time1_noC(i,T_Hori,i_crop,caseR,Eff_RI,ThetaULPAW_k,...
                          Theta,Zadj_k,c_day)

%This function computes E_time for field without field crop cases (bare soil) in the rotation.
%Format of call:calcu_E_time1_noC(i,T_Hori,i_crop,caseR,Eff_RI,ThetaULPAW_k,...
                  Theta,Zadj_k,c_day)

if Eff_RI(i,T_Hori).crop{i_crop}.case_rot{caseR} > 0
  E_time(i,T_Hori) = 1;
else
if (((ThetaULPAW_k(T_Hori).crop{i_crop}(1)-Theta(i,1,T_Hori))*Zadj_k(1)/c_day(i,T_Hori))^2) > 60

  E_time(i,T_Hori) = 60;
```

```
else
  E_time(i,T_Hori) = (((ThetaULPAW_k(T_Hori).crop{i_crop}(1)-Theta(i,1,T_Hori))*Zadj_k(1)/c_day(i,T_Hori)).^2);
end
end
end

%---------- FUNCTION: CALCULATE TIME PARAMETERS FOR CROP CASE -------------------------------------------------

function  [E_time] = calcu_E_time1_yesC(i,T_Hori,i_crop,Eff_RI,ThetaULPAW_k,Theta,Zadj_k,c_day)

%This function computes E_time for field crop cases.
%Format of call:calcu_E_time1_yesC(i,T_Hori,i_crop,Eff_RI,ThetaULPAW_k,Theta,Zadj_k,c_day)

if Eff_RI(i,T_Hori).crop{i_crop} > 0
   E_time(i,T_Hori) = 1;
else
if (((ThetaULPAW_k(T_Hori).crop{i_crop}(1)-Theta(i,1,T_Hori))*Zadj_k(1)/c_day(i,T_Hori))^2) > 60
  E_time(i,T_Hori) = 60;
else
  E_time(i,T_Hori) = (((ThetaULPAW_k(T_Hori).crop{i_crop}(1)-Theta(i,1,T_Hori))*Zadj_k(1)/c_day(i,T_Hori)).^2);
end
end
end

%---------- FUNCTION: CLALCULATE EVAPORATION FROM UNCOVERED SOIL -------------------------------------------

function [Euncovered] = calcu_Euncovered1(i,T_Hori)

%Format of call:calcu_Euncovered1(i,T_Hori)
  Euncovered(i,T_Hori) = 0.10;
end

function [Euncovered] = calcu_Euncovered(i,T_Hori,Ecum,E_time)

if ((Ecum(i,T_Hori)-Ecum(i-1,T_Hori)) <= 0) && (E_time(i,T_Hori) <= E_time(i-1,T_Hori))
  Euncovered(i,T_Hori) = Ecum(i,T_Hori);
else
if E_time(i,T_Hori) == E_time(i-1,T_Hori)
  Euncovered(i,T_Hori) = Ecum(i,T_Hori);
else
if (Ecum(i,T_Hori)-Ecum(i-1,T_Hori)) <= 0
  Euncovered(i,T_Hori) = 0;
else
  Euncovered(i,T_Hori) = Ecum(i,T_Hori)-Ecum(i-1,T_Hori);
end
end
end

%---------- FUNCTION: CLALCULATE EVAPORATION FROM COVERED SOIL ----------------------------------------------

function [Evapo] = calcu_Evapo(i,T_Hori,i_crop,Theta,ThetaaA,crop,Euncovered,Ecovered)

%This function computes evaporation from the first layer in the case of covered with field crop or uncovered with
% field crops.
%Format of call:calcu_Evapo(i,T_Hori,Theta,ThetaaA,crop,Euncovered,Ecovered)

if Theta(i,1,T_Hori)< ThetaaA(1)
  Evapo(i,T_Hori) = 0;

else
if strcmp(crop{i_crop},'offseason1')
  Evapo(i,T_Hori) = Euncovered(i,T_Hori);
```

```
elseif strcmp(crop{i_crop},'offseason2')
   Evapo(i,T_Hori) = Euncovered(i,T_Hori);
elseif strcmp(crop{i_crop},'fallow')
   Evapo(i,T_Hori) = Euncovered(i,T_Hori);
else
   Evapo(i,T_Hori) = Ecovered(i,T_Hori);
end
end
end

%---------- FUNCTION: CLALCULATE LWSR FOR A FIELD WITH NO CROP--------------------------------------------------

function [LWSR] = calcu_LWSR_noC(i,k,T_Hori,i_crop,Theta,Total_Theta,MatricPot,OsmoticPot,Lv,Zadj_k)
%This function computes the layer water supply rate for each day
%Format of call:calculating_LWSR(i,k,T_Hori,Fsr,Theta,Total_Theta,MatricPot,OsmoticPot,Lv,PsiP,Zadj_k)

Fsr = 0;
PsiP = 0;
LWSR(i,k,T_Hori) = Fsr*log(Theta(i,k,T_Hori)/Total_Theta(i,k,T_Hori))*...
                              (pi*Lv.crop{i_crop}).^0.5*abs((MatricPot(i,k,T_Hori)+OsmoticPot(i,k,T_Hori))-PsiP)*Zadj_k(k);

end

%---------- FUNCTION: CLALCULATE LWSR FOR A FIELD WITH CROP -------------------------------------------------------

function [LWSR] = calcu_LWSR_yesC(i,k,T_Hori,i_crop,Fsr,Theta,Total_Theta,MatricPot,OsmoticPot,Lv,PsiP,Zadj_k)
%This function computes the layer water supply rate for each day
%Format of call:calcu_LWSR_yesC(i,k,T_Hori,Fsr,Theta,Total_Theta,MatricPot,OsmoticPot,Lv,PsiP,Zadj_k)

LWSR(i,k,T_Hori) = Fsr*log(Theta(i,k,T_Hori)/Total_Theta(i,k,T_Hori))*...
                 (pi*Lv.crop{i_crop}(i,k)).^0.5*abs((MatricPot(i,k,T_Hori)+OsmoticPot(i,k,T_Hori))-PsiP)*Zadj_k(k);
end

%---------- FUNCTION: CLALCULATE MATRIC POTENTIAL ---------------------------------------------------------------------

function [MatricPot] = calcu_MatricPot(i,k,T_Hori,Theta,Theta1500,C)
%This function computes the matric potential for each soil layer in a givensoil profile per day.
%Format of call: calcu_MatricPot(i,k,T_Hori,Theta,Theta1500,C)

MatricPot(i,k,T_Hori) = 1500* (Theta1500(k)/Theta(i,k,T_Hori)).^C(k);

end

%---------- FUNCTION: CLALCULATE OSMOTIC POTENTIAL -------------------------------------------------------------------

function [OsmoticPot] = calcu_OsmoticPot(i,k,T_Hori,ECe,Theta,ThetaSatu_k)
%This function computes the osmotic potential of each soil layer per day.
%Format of call:calculating_OsmoticPot(i,k,T_Hori,ECe,Theta,ThetaSatu_k)

OsmoticPot(i,k,T_Hori) = ((ECe(i,k,T_Hori)*7.5*0.072)/Theta(i,k,T_Hori))*ThetaSatu_k(k);
end

%---------- FUNCTION: CLALCULATE TRANSPIRATION FROM COVERED SOIL --------------------------------------------
%This function computes the transpiration from uncovered soil.
%Format of call:calcu_T_noC(i,T_Hori,PWSR

function [T] = calcu_T_noC(i,T_Hori,PWSR)

if (PWSR(i,T_Hori) == 0)
T(i,T_Hori) = PWSR(i,T_Hori);
end
end
```

```
% --------- FUNCTION: CLALCULATE TRANSPIRATION FROM CROPPED FIELDS ------------------------------------------

function [T] = calcu_T_yesC(i,T_Hori,i_crop,TR,PWSR)
%This function computes actual transpiration for field crops.
%Format of call:calcu_T_yesC(i,T_Hori,i_crop,TR,PWSR)
if (PWSR(i,T_Hori)>= TR(i,T_Hori).crop{i_crop})
   T(i,T_Hori) = TR(i,T_Hori).crop{i_crop};
else
   T(i,T_Hori) = PWSR(i,T_Hori);
end
end

%---------- FUNCTION: DEFINING CROP PARAMETERS ---------------------------------------------------------------------------

function [FB1,FB2,FB3,m,Ym,A1,B1,C1,D1,a1,d1,Lm,RPR,PsiP,PD,GSL,Fert,RGP,...
                        FBtot,TY,HI,Fsr ] = CropParameters(crop,soilType)
% This function declares the crop parameters needed by the model (inputdata).
%Format of call:CropParameters(crop,soilType)

switch crop
case {'maize'}
       FB1 = 0.013;
       FB2 = 12;
       FB3 = 7000; %Kg per ha
       m = 220;    % crop specific parameter
       Ym = 26300; % maximum biomass production
       A1 = 20;
       B1 = 60;
       C1 = 65;
       D1 = 141;
       a1 = 0.1;
       d1 = 0.05;
       Lm = 9.4; %default root length index (mm per mm square)
       RPR = 23.53; %default root penetration rate (mm per d)
       PsiP = 1800; % critical leaf water potential (kpa)
       PD = 10; % Planting date the dd/mm/yy (DEC 10)
       GSL = 141; % growth seasonal length (days)
       Fert = 100; % kg per ha
       RGP = 85; % days
       FBtot = 100; %
       RootMax = 2000;
       [r,c] = size(soilType);

for i = 1:c
if strcmp(soilType(i),'clovelly')
  TY = 14654; % Target yield
  HI = 0.47; % Harvest Index (GY/BY) i.e. grain yield per biomass yield
  Fsr = 0.000019; %soil root conductance (mm square per d per kpa)
elseif strcmp(soilType(i),'bainsvlei')
  TY = 15254.00; % Target yield (potential yield)
  HI = 0.58; % Harvest Index (GY/BY) i.e. grain yield per biomass yield
  Fsr = 0.00002400; %soil root conductance (mm square per d per kpa)
else
disp('soil type not in the list');
end
end

case {'offseason1'}

case {'wheat'}
       FB1 = 0.0170;
       FB2 = 15;
```

```
      FB3 = 5000;
      m = 110;      % crop specific parameter
      Ym = 15000;   % maximum biomass production
      A1 = 65;
      B1 = 110;
      C1 = 130;
      D1 = 151;
      a1 = 0.2;
      d1 = 0.5;
      Lm = 9.8; %default root length index (mm per mm square)
      RPR = 19; %default root penetration rate (mm per d)
      PsiP = 2400; % critical leaf water potential (kpa)
      PD = 05; % Planting date the dd/mm/yy July 05
      GSL = 151; % growth seasonal length (days)
      Fert = 100; % kg per ha
      RGP = 105;% days
      FBtot = 100;
      RootMax = 2000;

[r,c] = size(soilType);

for i = 1:c
if strcmp(soilType(i),'clovelly')
  TY = 5678; % Target yield
  HI = 0.37; % Harvest Index(GY/BY) ie grain yield per biomass yield
  Fsr = 0.000044; %soil root conductance (mm square per d per kpa)

elseif strcmp(soilType(i),'bainsvlei')
  TY = 7500; % Target yield
  HI = 0.50; % Harvest Index
  Fsr = 0.00002460; %soil root conductance (mm square per d per kpa)
else
  disp('soil type not in the list');
end
end

case {'offseson2'}
case {'fallow'}
case {'peas'}
      FB1 = 0.045; %
      FB2 = 10;    %
      FB3 = 2000;  %Kg per ha
      m = 71;      % crop specific parameter
      Ym = 9400;   % maximum biomass production
      A1 = 60;
      B1 = 100;
      C1 = 110;
      D1 = 131;
      a1 = 0.25;
      d1 = 0.5;
      Lm = 2.7; %default root length index (mm per mm square)
      RPR = 12.7; %default root penetration rate (mm per d)
      PsiP = 1500; % critical leaf water potential (kpa)
      PD = 15; % Planting date the dd/mm/yy July 15
      GSL = 131; % growth seasonal length (days)
      Fert = 100; % kg per ha
      RGP = 120;%days
      FBtot = 100;%*****not provided now
      RootMax = 1500;

[r,c] = size(soilType);
for i = 1:c
```

```
if strcmp(soilType(i),'clovelly')
   TY = 4743;  % Target yield
   HI = 0.43;  % Harvest Index(GY/BY) ie grain yield per biomass yield
   Fsr = 0.000044; %soil root conductance (mm square per d per kpa)

elseif strcmp(soilType(i),'bainsvlei')
   TY = 4512;  % Target yield
   HI = 0.48; % Harvest Index
   Fsr = 0.00006800; %soil root conductance (mm square per d per kpa)
else
   disp('soil type not in the list');
end
end
otherwise
      disp('crop not in the list or misspelled')
end;
```

%---------- **FUNCTION: RE-DEFINING GROWTH SEASONL LENGTH PARAMETERS** --

```
function [GSL_N] = GrowthSeasonLength(crop,soilType)
%This function re-names the GSL (growing season length)
%Format of call: cal_YaQFBmax(crop,soilType)

for i_crop = 1:length(crop)

if strcmp(crop(i_crop),'maize')
crop{i_crop} = 'maize';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
                                        TY HI Fsr] = CropParameters(crop{i_crop},soilType);

GSL_N.crop{i_crop} = GSL;

elseif strcmp(crop(i_crop),'offseason1')

elseif strcmp(crop(i_crop),'wheat')
crop{i_crop} = 'wheat';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
TY HI Fsr] = CropParameters(crop{i_crop},soilType);

GSL_N.crop{i_crop} = GSL;

elseif strcmp(crop(i_crop),'offseason2')
elseif strcmp(crop(i_crop),'fallow')
else
crop{i_crop} = 'peas';
[FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
TY HI Fsr] = CropParameters(crop{i_crop},soilType);

GSL_N.crop{i_crop} = GSL;

end
end
end
```

%---------- **FUNCTION: IDENTIFYING DATE NUMBER TO APPROPRIATELY ASSIGN RAINFALL AND ETo**

```
function [Start_PD_year PD_number] = Identify_DateNo(YEARS,crop,P_year,P_month,P_date)
%This function identifies date numbers for the crops in the rotation aswell as the years of the starting period in each
%year assuming all sameconstant planting date every year.
%Format of call:Identify_DateNo(YEARS,crop,P_year,P_month,P_date)

for T_Hori = 1:YEARS
```

```
for i_crop = 1:length(crop)
%~~~~~~~~Convert the start of planting dates assuming constant PD each year
if strcmp(crop{i_crop},'maize')
   Start_PD_year(T_Hori).crop{i_crop} = P_year.crop{i_crop}+ T_Hori-1 ;
%Identify the date number for planting date considering leap year to the
%crop
if P_date.crop{i_crop} <= eomday(Start_PD_year(T_Hori).crop{i_crop},...
             P_month.crop{i_crop})
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop}...
          ,P_month.crop{i_crop},P_date.crop{i_crop});
else
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop}...
          ,P_month.crop{i_crop},P_date.crop{i_crop}-1);
end
elseif strcmp(crop(i_crop),'offseason1')

elseif strcmp(crop(i_crop),'wheat')
   Start_PD_year(T_Hori).crop{i_crop} = P_year.crop{i_crop}+ T_Hori-1 ;

%Identify the date number for planting date considering leap year to the
%crop
if P_date.crop{i_crop} <= eomday(Start_PD_year(T_Hori).crop{i_crop}...
             ,P_month.crop{i_crop})
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop}...
          ,P_month.crop{i_crop},P_date.crop{i_crop});
else
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop},...
          P_month.crop{i_crop},P_date.crop{i_crop}-1);
end
elseif strcmp(crop(i_crop),'offseason2')

elseif strcmp(crop(i_crop),'fallow')
else
   Start_PD_year(T_Hori).crop{i_crop} = P_year.crop{i_crop}+ T_Hori-1 ;

%Identify the date number for planting date considering leap year to the
%crop
if P_date.crop{i_crop} <= eomday(Start_PD_year(T_Hori).crop{i_crop}...
             ,P_month.crop{i_crop})
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop}...
          ,P_month.crop{i_crop},P_date.crop{i_crop});
else
    PD_number(T_Hori).crop{i_crop} = datenum(Start_PD_year(T_Hori).crop{i_crop},...
          P_month.crop{i_crop},P_date.crop{i_crop}-1);
end
end

end
end
```

%---------- **FUNCTION: IDENTIFYING THE INDEXES GROWING DAYS** --

```
function [F_index] = Identify_indexCrops(YEARS,crop,soilType,DateNumber,PD_number)

%This function identifies the indexes of each growing days of the crops foreach year so that it can identify the
%rainfall and ETo to take intoconsideration for the specific crop.
%Format of call: Identify_indexCrops(YEARS,crop,soilType,DateNumber,PD_number)


for T_Hori = 1:YEARS

for i_crop = 1:length(crop)
```

```
if strcmp(crop(i_crop),'maize')
  crop{i_crop} = 'maize';
  [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
  TY HI Fsr] = CropParameters(crop{i_crop},soilType);

  [r_index_DNo1, c_index_DNo1] = find(DateNumber == PD_number(T_Hori).crop{i_crop});
   Index(T_Hori).crop{i_crop} = r_index_DNo1;
for i = 1:GSL
if i == 1
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop};
else
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop}+ i-1;
end
end
elseif strcmp(crop(i_crop),'offseason1')

elseif strcmp(crop(i_crop),'wheat')
  crop{i_crop} = 'wheat';
  [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
  TY HI Fsr] = CropParameters(crop{i_crop},soilType);

  [r_index_DNo2, c_index_DNo2] = find(DateNumber == PD_number(T_Hori).crop{i_crop});
   Index(T_Hori).crop{i_crop} = r_index_DNo2;
for i = 1:GSL
if i == 1
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop};
else
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop}+ i-1;
end
end
elseif strcmp(crop(i_crop),'offseason2')

elseif strcmp(crop(i_crop),'fallow')

else
   crop{i_crop} = 'peas';
  [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
  TY HI Fsr] = CropParameters(crop{i_crop},soilType);

  [r_index_DNo3, c_index_DNo3] = find(DateNumber == PD_number(T_Hori).crop{i_crop});
   Index(T_Hori).crop{i_crop} = r_index_DNo3;
for i = 1:GSL
if i == 1
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop};
else
        F_index(i,T_Hori).crop{i_crop} = Index(T_Hori).crop{i_crop}+ i-1;
end
end
end
end
end
end
```

%---------- **FUNCTION: IDENTIFYING THE PLANTING DATES OF CROPS** --

```
function [P_year,P_month,P_date] = Identify_PD(crop,P_year_crop1,P_month_crop1,P_date_crop1,…
P_year_crop2,P_month_crop2,P_date_crop2,P_year_crop3,P_month_crop3,P_date_crop3)

%This function converts the input dates to be useful for automatic cropreferencing.
%Format of call:Identify_PD(crop,P_year_crop1,P_month_crop1,P_date_crop1,P_year_crop2,...
                P_month_crop2,P_date_crop2,P_year_crop3,P_month_crop3,P_date_crop3)
```

```
%~~~~~~~~Identify crops based on planting date
for i_crop = 1:length(crop)
if strcmp(crop{i_crop},'maize')
        P_year.crop{i_crop} = P_year_crop1;
        P_month.crop{i_crop} = P_month_crop1;
        P_date.crop{i_crop} = P_date_crop1;
elseif strcmp(crop{i_crop},'offseason1')

elseif strcmp(crop{i_crop},'wheat')
        P_year.crop{i_crop} = P_year_crop2;
        P_month.crop{i_crop} = P_month_crop2;
        P_date.crop{i_crop} = P_date_crop2;
elseif strcmp(crop{i_crop},'offseason2')

elseif strcmp(crop{i_crop},'fallow')
elseif strcmp(crop{i_crop},'peas')
        P_year.crop{i_crop} = P_year_crop3;
        P_month.crop{i_crop} = P_month_crop3;
        P_date.crop{i_crop} = P_date_crop3;
else
end
end
end
```

%---------- **FUNCTION: ASSIGNE THE RIGHT RAINFALL AND ETo**--

```
function [Day_o_Week,Day_S_type,RainF,ETo,RainF_OffS1,RainF_OffS2,RainF_fallS,...
   RainF_fallW] = Identify_RainETo(YEARS,crop,soilType,F_index,RainF_d_y,ETo_d_y,...
   DoW_d_y,Season_d_y,case_rot,Diff_OffS1,GSL_N,Diff_OffS2,Diff_fal_S,Diff_fal_W)

%This function assigns the appropriate rainfall,ETo, days of the week, and season as low and high energy tariifs for
%each cases of crop
%Format of call: Identify_RainETo_Summer
%(YEARS,crop,soilType,F_index,RainF_d_y,ETo_d_y,case_rot,Diff_OffS1,GSL_N,Diff_OffS2,t_rota,Diff_fal_S)

for T_Hori = 1:YEARS
for i_crop = 1:length(crop)
if strcmp(crop(i_crop),'maize')
   crop{i_crop} = 'maize';
   [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
   TY HI Fsr] = CropParameters(crop{i_crop},soilType);
   sumETo(T_Hori).crop{i_crop} = 0;
for i = 1:GSL
    Day_o_Week(i,T_Hori).crop{i_crop} = DoW_d_y(F_index(i,T_Hori).crop{i_crop},1);
    Day_S_type(i,T_Hori).crop{i_crop} = Season_d_y(F_index(i,T_Hori).crop{i_crop},1);
    RainF(i,T_Hori).crop{i_crop} = RainF_d_y(F_index(i,T_Hori).crop{i_crop},1);
    ETo_d(i,T_Hori).crop{i_crop} = ETo_d_y(F_index(i,T_Hori).crop{i_crop},1);
    sumETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}+ETo_d(i,T_Hori).crop{i_crop};
    ETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}/GSL;
end

elseif strcmp(crop(i_crop),'offseason1')
for caseR = 1:length(case_rot)
for i = 1:Diff_OffS1(1,T_Hori).case_rot{caseR}
if strcmp(case_rot{caseR},'Rep_w_fallow')
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
            RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index(end+...
                    (GSL_N.crop{1}-GSL_N.crop{3}),T_Hori).crop{1}+i,1);
else
            RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index(end,T_Hori).crop{1}+i,1);
end
else
```

```
if ((GSL_N.crop{1}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}-...
              GSL_N.crop{6})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end,T_Hori).crop{1}+i,1);
elseif ((GSL_N.crop{1}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}...
                -GSL_N.crop{3})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end,T_Hori).crop{1}+i,1);
elseif ((GSL_N.crop{3}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}...
                -GSL_N.crop{6})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end-(GSL_N.crop{3}-GSL_N.crop{1}),T_Hori).crop{1}+i,1);
elseif ((GSL_N.crop{3}-GSL_N.crop{6})>= 0) && ((GSL_N.crop{6}...
                -GSL_N.crop{1})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end-(GSL_N.crop{3}-GSL_N.crop{1}),T_Hori).crop{1}+i,1);
elseif ((GSL_N.crop{6}-GSL_N.crop{1})>= 0) && ((GSL_N.crop{1}...
                -GSL_N.crop{3})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end-(GSL_N.crop{6}-GSL_N.crop{1}),T_Hori).crop{1}+i,1);
elseif ((GSL_N.crop{6}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}...
                -GSL_N.crop{1})>= 0)
          RainF_OffS1(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
             (end-(GSL_N.crop{6}-GSL_N.crop{1}),T_Hori).crop{1}+i,1);
else
end
end
end
end

elseif strcmp(crop(i_crop),'wheat')
  crop{i_crop} = 'wheat';
  [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
  TY HI Fsr] = CropParameters(crop{i_crop},soilType);
  sumETo(T_Hori).crop{i_crop} = 0;
for i = 1:GSL
   Day_o_Week(i,T_Hori).crop{i_crop} = DoW_d_y(F_index(i,T_Hori).crop{i_crop},1);
   Day_S_type(i,T_Hori).crop{i_crop} = Season_d_y(F_index(i,T_Hori).crop{i_crop},1);
   RainF(i,T_Hori).crop{i_crop} = RainF_d_y(F_index(i,T_Hori).crop{i_crop},1);
   ETo_d(i,T_Hori).crop{i_crop} = ETo_d_y(F_index(i,T_Hori).crop{i_crop},1);
   sumETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}+...
                         ETo_d(i,T_Hori).crop{i_crop};
   ETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}/GSL;
end

elseif strcmp(crop(i_crop),'offseason2')
for caseR = 1:length(case_rot)
for i = 1:Diff_OffS2(1,T_Hori).case_rot{caseR}
if strcmp(case_rot{caseR},'Rep_w_fallow')
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
            RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
               (end,T_Hori).crop{3}+i,1);
else
            RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
               (end-(GSL_N.crop{1}-GSL_N.crop{3}),T_Hori).crop{3}+i,1);
end
else
if ((GSL_N.crop{1}-GSL_N.crop{3})>= 0) && ((GSL_N.crop{3}...
                 -GSL_N.crop{6})>= 0)
            RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
               (end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}+i,1);
elseif ((GSL_N.crop{1}-GSL_N.crop{6})>= 0) &&...
```

```
                    ((GSL_N.crop{6}-GSL_N.crop{3})>= 0)
              RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                 (end-(GSL_N.crop{1}-GSL_N.crop{6}),T_Hori).crop{6}+i,1);
elseif ((GSL_N.crop{3}-GSL_N.crop{1})>= 0) &&...
                    ((GSL_N.crop{1}-GSL_N.crop{6})>= 0)
              RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                 (end-(GSL_N.crop{3}-GSL_N.crop{6}),T_Hori).crop{6}+i,1);
elseif ((GSL_N.crop{3}-GSL_N.crop{6})>= 0) &&...
                    ((GSL_N.crop{6}-GSL_N.crop{1})>= 0)
              RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                 (end-(GSL_N.crop{3}-GSL_N.crop{6}),T_Hori).crop{6}+i,1);
elseif ((GSL_N.crop{6}-GSL_N.crop{1})>= 0) &&...
                    ((GSL_N.crop{1}-GSL_N.crop{3})>= 0)
              RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                 (end,T_Hori).crop{6}+i,1);
elseif ((GSL_N.crop{6}-GSL_N.crop{3})>= 0) &&...
                    ((GSL_N.crop{3}-GSL_N.crop{1})>= 0)
              RainF_OffS2(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                 (end,T_Hori).crop{6}+i,1);
else
end
end
end
end

elseif strcmp(crop(i_crop),'fallow')

for caseR = 1:length(case_rot)
if strcmp(case_rot{caseR},'Rep_w_fallow')
%~~~~~~~~~alternative summer fallow
for i = 1:Diff_fal_S(1,T_Hori).case_rot{caseR}
if i == 1
               RainF_fallS(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                      (1,T_Hori).crop{1},1);
else
               RainF_fallS(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                      (1,T_Hori).crop{1}+i-1,1);
end
end
%~~~~~~~~~aternative winter fallow
for i = 1:Diff_fal_W(1,T_Hori).case_rot{caseR}
if ((GSL_N.crop{1}-GSL_N.crop{3})<= 0)
               RainF_fallW(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                  (end+(GSL_N.crop{1}-GSL_N.crop{3}),T_Hori).crop{1}+i,1);
else
               RainF_fallW(i,T_Hori).case_rot{caseR} = RainF_d_y(F_index...
                  (end,T_Hori).crop{1}+i,1);
end
end
end
end

elseif strcmp(crop(i_crop),'peas')
   crop{i_crop} = 'peas';
   [FB1 FB2 FB3 m Ym A1 B1 C1 D1 a1 d1 Lm RPR PsiP PD GSL Fert RGP FBtot ...
   TY HI Fsr] = CropParameters(crop{i_crop},soilType);
   sumETo(T_Hori).crop{i_crop} = 0;
for i = 1:GSL
     Day_o_Week(i,T_Hori).crop{i_crop} = DoW_d_y(F_index(i,T_Hori).crop{i_crop},1);
     Day_S_type(i,T_Hori).crop{i_crop} = Season_d_y(F_index(i,T_Hori).crop{i_crop},1);
     RainF(i,T_Hori).crop{i_crop} = RainF_d_y(F_index(i,T_Hori).crop{i_crop},1);
     ETo_d(i,T_Hori).crop{i_crop} = ETo_d_y(F_index(i,T_Hori).crop{i_crop},1);
```

```
    sumETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}+...
                         ETo_d(i,T_Hori).crop{i_crop};
    ETo(T_Hori).crop{i_crop} = sumETo(T_Hori).crop{i_crop}/GSL;
end

else
end
end
end
end

%---------- FUNCTION: DEFINES ADDITIONAL SOIL PARAMETERS----------------------------------------------------------------

function [a,b] = SoilParameters (soilType,SCavg,Zadj_k)
%This functions assign values for a,b1,b needed to compute drainage curve.
%Format of call: SoilParameters (soilType,SCavg,Zadj_k)

[r,c] = size(soilType);
for i = 1:c
if strcmp(soilType(i),'clovelly')
     a = 28.94; % mm per d (measured taken from the articles)
     b = 476.86; % mm per d (measured taken from the articles)
elseif strcmp(soilType(i),'bainsvlei')
     a = 18.73; % mm per d (measured taken from the articles)
     b = 535.54; % mm per d (measured taken from the articles)
else
      disp('crop not in the list or misspelled')
end
end

%---------- FUNCTION: WATER BUDGET FOR SOIL PLANTED WITH CROP----------------------------------------------------

function [Theta,L_water,W_soil,Shortage,EffRainShort,RainPerLayer,MatricPot,...
         DC,Sp,ECe,SaltContent,ECe_L_sum,ECe_Mean,Total_Theta,OsmoticPot,LWSR,...
         PWSR,T,S_soil,S,SWT,S_perco,WTU,S_WTU,WTU_P,S_Rain,S_Irr,Diff_Swtu_Sp,...
         c_day,E_time,Ecum,Euncovered,Ecovered,Evapo] = WaterBudget_yesC_Y1...
         (T_Hori,GSL,Soil_L,i_crop,crop,ThetaS_k,Zadj_k,ThetaULPAW_k,Eff_RI,...
         Theta1500,C,ECeS_k,ThetaSatu_k,SC_k,Fsr,Lv,PsiP,TR,ECwt,RainF,Sin,...
         ThetaaA,FB,soilPcond,ECin,Wsatu_k)

% The function calculated water budget for soil covered with crop according to cascading priniciple. If it is fallow %period a similar function but with little modification to calculate certain parameters can be used. To save space, the %water budget for fallow period time is not provided in this appendix.

[mm,nn] = size(Soil_L);

for i = 1:GSL
%%%%%%%%%%%%%%%% Initialization
if i == 1
   PWSR(i,T_Hori) = 0;
   S_soil(i,T_Hori) = 0;
   W_soil(i,T_Hori) = 0;
   ECe_L_sum(i,T_Hori) = 0;

for k = 1:nn
%~~~~~~~~~~~~~~~~To link moisture with years
if strcmp(crop{i_crop},'maize')
if T_Hori == 1
          Theta(i,k,T_Hori) = ThetaS_k(k);
else
          Theta(i,k,T_Hori) = Theta_Link(k);
end
```

```
else
            Theta(i,k,T_Hori) = Theta_Link(k);
end
        L_water(i,k,T_Hori) = Theta(i,k,T_Hori).*Zadj_k(k);
        W_soil(i,T_Hori) = W_soil(i,T_Hori)+ L_water(i,k,T_Hori);

%~~~~~~~~~~~~~~~Defining DEFICIT
if (ThetaULPAW_k(T_Hori).crop{i_crop}(k)-Theta(i,k,T_Hori))*Zadj_k(k)< 0
          Shortage(i,k,T_Hori) = 0;
else
          Shortage(i,k,T_Hori) = (ThetaULPAW_k(T_Hori).crop{i_crop}(k)-...
                      Theta(i,k,T_Hori))*Zadj_k(k);
end

%~~~~~~~~~~~~~~~Defining INFLOW
if k == 1
if Eff_RI(i,T_Hori).crop{i_crop} <= 0
           EffRainShort(i,k,T_Hori) = 0;
else
           EffRainShort(i,k,T_Hori) = Eff_RI(i,T_Hori).crop{i_crop};
end
else
if EffRainShort(i,k-1,T_Hori)- Shortage(i,k-1,T_Hori)<= 0
           EffRainShort(i,k,T_Hori) = 0;
else
           EffRainShort(i,k,T_Hori) = EffRainShort(i,k-1,T_Hori)-Shortage...
                              (i,k-1,T_Hori);
end
end

%~~~~~~~~~~~~~~~Defining APPLIED WATER
if EffRainShort(i,k,T_Hori) == 0
         RainPerLayer(i,k,T_Hori) = 0;

else
if EffRainShort(i,k,T_Hori)< Shortage(i,k,T_Hori)
           RainPerLayer(i,k,T_Hori) = EffRainShort(i,k,T_Hori);
else
           RainPerLayer(i,k,T_Hori) = Shortage(i,k,T_Hori);
end
end
     [MatricPot1] = calcu_MatricPot(i,k,T_Hori,Theta,Theta1500,C);
      MatricPot(i,k,T_Hori) = MatricPot1(i,k,T_Hori);

%~~~~~~~~~~~~~~~~Defining DC and Sp
     DC(i,k,T_Hori) = 0.94*(1-exp(-11.52*((EffRainShort(i,k,T_Hori)-...
                  RainPerLayer(i,k,T_Hori))/Zadj_k(k))));
     Sp(i,k,T_Hori) = 0;

%~~~~~~~~~~~~~~~~Defining ECe and SaltContent
if strcmp(crop{i_crop},'maize')  % To link years with EC
if T_Hori == 1
             ECe(i,k,T_Hori) = ECeS_k(k);
else
             ECe(i,k,T_Hori) = ECe_Link(k);
end
else
             ECe(i,k,T_Hori) = ECe_Link(k);
end
     SaltContent(i,k,T_Hori) = ECe(i,k,T_Hori)*0.075*(ThetaSatu_k(k).*Zadj_k(k));
     ECe_L_sum(i,T_Hori) = ECe_L_sum(i,T_Hori)+ (ECe(i,k,T_Hori)*Zadj_k(k));
     ECe_Mean (i,T_Hori) = ECe_L_sum(i,T_Hori)/2000;
```

```
%~~~~~~~~~~~~~~~~~Defining Total_Theta
if strcmp(crop{i_crop},'maize')
        Total_Theta(i,k,T_Hori) = 0.003554939+(0.000089444*ECe(i,k,T_Hori))+(0.002556596*SC_k(k));
elseif strcmp(crop{i_crop},'wheat')
        Total_Theta(i,k,T_Hori) = 0.012185212 +(0.0000594449*ECe(i,k,T_Hori))+(0.002481094*SC_k(k));
elseif strcmp(crop{i_crop},'peas')
        Total_Theta(i,k,T_Hori) = 0.003862562 +(0.000102912*ECe(i,k,T_Hori))+(0.002474746*SC_k(k));
else
        Total_Theta(i,k,T_Hori) = 1; % Just to avoid 0 value but not needed for offseason case
end

      [OsmoticPot1] = calcu_OsmoticPot(i,k,T_Hori,ECe,Theta,ThetaSatu_k);
      OsmoticPot(i,k,T_Hori) = OsmoticPot1(i,k,T_Hori);

      [LWSR1] = calcu_LWSR_yesC(i,k,T_Hori,i_crop,Fsr,Theta,Total_Theta,MatricPot,...
            OsmoticPot,Lv,PsiP,Zadj_k);
      LWSR(i,k,T_Hori) = LWSR1(i,k,T_Hori);
      PWSR(i,T_Hori) = PWSR(i,T_Hori)+ LWSR(i,k,T_Hori);

      T(i,T_Hori) = 0;
      S_soil(i,T_Hori) = S_soil(i,T_Hori) + SaltContent(i,k,T_Hori);
end
      S_perco(i,T_Hori) = Sp(i,end,T_Hori);
      WTU(i,T_Hori) = 0;

for k = 1:nn
%~~~~~~~~~~~~~~~~~Defining S ()
if PWSR(i,T_Hori) == 0
         S(i,k,T_Hori) = 0;
else
         S(i,k,T_Hori) = TR(i,T_Hori).crop{i_crop}*(LWSR(i,k,T_Hori)/...
                  PWSR(i,T_Hori));
end
%~~~~~~~~~~~~~~~~~Defining SWT ()
if strcmp(soilPcond,'constaWT')
if k < 3
        SWT(i,k,T_Hori) = 0;
elseif k >= 3 && k < 9
        SWT(i,k,T_Hori) = S(i,k,T_Hori);
else
        SWT(i,k,T_Hori) = 0;
end
elseif strcmp(soilPcond,'freelyDrain')
        SWT(i,k,T_Hori) = 0;
else
end

%~~~~~~~~~~~~~~~~~Defining ECeT
      ECeT(i,k,T_Hori) =  ECe(i,k,T_Hori);

%~~~~~~~~~~~~~~~~~Other related calculations
      WTU(i,T_Hori) = WTU(i,T_Hori) + SWT(i,k,T_Hori);
      S_WTU(i,T_Hori) = WTU(i,T_Hori)*0.075*ECwt;
      WTU_P(i,T_Hori) = WTU(i,T_Hori)-EffRainShort(i,end,T_Hori);
      S_Rain(i,T_Hori) = 2*0.075*RainF(i,T_Hori).crop{i_crop};
      S_Irr(i,T_Hori) = Sin(i,T_Hori).crop{i_crop}-S_Rain(i,T_Hori);
      Diff_Swtu_Sp(i,T_Hori) = S_WTU(i,T_Hori)-S_perco(i,T_Hori);

end
      c_day(i,T_Hori) = 0.087.*Zadj_k(1).*(Theta(i,1,T_Hori)-ThetaaA(1))+ 1.16;

      [E_time1] = calcu_E_time1_yesC(i,T_Hori,i_crop,Eff_RI,ThetaULPAW_k,...
```

```
            Theta,Zadj_k,c_day);
      E_time(i,T_Hori) = E_time1(i,T_Hori);

      Ecum(i,T_Hori) = c_day(i,T_Hori).*(E_time(i,T_Hori).^0.5);

      [Euncovered1] = calcu_Euncovered1(i,T_Hori);
      Euncovered(i,T_Hori) = Euncovered1(i,T_Hori);

      Ecovered(i,T_Hori) = Euncovered(i,T_Hori)*(1-FB(i,T_Hori).crop{i_crop});

      [Evapo1] = calcu_Evapo(i,T_Hori,i_crop,Theta,ThetaaA,crop,Euncovered,Ecovered);
      Evapo(i,T_Hori) = Evapo1(i,T_Hori);

else
     PWSR(i,T_Hori) = 0;
     S_soil(i,T_Hori) = 0;
     W_soil(i,T_Hori) = 0;
     ECe_L_sum(i,T_Hori) = 0;

for  k = 1:nn

if strcmp(soilPcond,'constaWT')
if k == 1
      Theta(i,k,T_Hori) = Theta(i-1,k,T_Hori)+(RainPerLayer(i-1,k,T_Hori)/Zadj_k(k))...
              -(Evapo(i-1,T_Hori)/Zadj_k(k))-(S(i-1,k,T_Hori)/Zadj_k(k));
elseif k == 2
      Theta(i,k,T_Hori) = Theta(i-1,k,T_Hori)+(RainPerLayer(i-1,k,T_Hori)/Zadj_k(k))...
               -(S(i-1,k,T_Hori)/Zadj_k(k));
else
      Theta(i,k,T_Hori) = Theta(i-1,k,T_Hori); % due to water table
end
elseif strcmp(soilPcond,'freelyDrain')
if k == 1
      Theta(i,k,T_Hori) = Theta(i-1,k,T_Hori)+(RainPerLayer(i-1,k,T_Hori)/Zadj_k(k))...
              -(Evapo(i-1,T_Hori)/Zadj_k(k))-(S(i-1,k,T_Hori)/Zadj_k(k));
else
      Theta(i,k,T_Hori) = Theta(i-1,k,T_Hori)+(RainPerLayer(i-1,k,T_Hori)/Zadj_k(k))...
              -(S(i-1,k,T_Hori)/Zadj_k(k));
end
else
end
      L_water(i,k,T_Hori) = Theta(i,k,T_Hori)*Zadj_k(k);
      W_soil(i,T_Hori) = W_soil(i,T_Hori)+ L_water(i,k,T_Hori);

%~~~~~~~~~~~~~~~Defining DEFICIT
if (ThetaULPAW_k(T_Hori).crop{i_crop}(k)-Theta(i,k,T_Hori))*Zadj_k(k)< 0
        Shortage(i,k,T_Hori) = 0;
else
        Shortage(i,k,T_Hori) = (ThetaULPAW_k(T_Hori).crop{i_crop}(k)-...
                Theta(i,k,T_Hori))*Zadj_k(k);
end
%~~~~~~~~~~~~~~~Defining INFLOW
if k == 1
if Eff_RI(i,T_Hori).crop{i_crop} <= 0
        EffRainShort(i,k,T_Hori) = 0;
else
        EffRainShort(i,k,T_Hori) = Eff_RI(i,T_Hori).crop{i_crop};
end
else
if EffRainShort(i,k-1,T_Hori)- Shortage(i,k-1,T_Hori)<= 0
        EffRainShort(i,k,T_Hori) = 0;
else
```

```
          EffRainShort(i,k,T_Hori) = EffRainShort(i,k-1,T_Hori)-Shortage...
                              (i,k-1,T_Hori);
end
end
%~~~~~~~~~~~~~~~Defining APPLIED WATER
if EffRainShort(i,k,T_Hori) == 0
         RainPerLayer(i,k,T_Hori) = 0;

else
if EffRainShort(i,k,T_Hori)< Shortage(i,k,T_Hori)
         RainPerLayer(i,k,T_Hori) = EffRainShort(i,k,T_Hori);
else
         RainPerLayer(i,k,T_Hori) = Shortage(i,k,T_Hori);
end
end
       [MatricPot1] = calcu_MatricPot(i,k,T_Hori,Theta,Theta1500,C);
        MatricPot(i,k,T_Hori) = MatricPot1(i,k,T_Hori);

%~~~~~~~~~~~~~~~~Defining DC
     DC(i,k,T_Hori) = 0.94*(1-exp(-11.52*((EffRainShort(i,k,T_Hori)-...
                   RainPerLayer(i,k,T_Hori))/Zadj_k(k))));

%~~~~~~~~~~~~~~~~ Defining the target ECeT
if k == 1
if  ECin(i-1,T_Hori).crop{i_crop} > ECe(i-1,k,T_Hori)
            ECeT(i,k,T_Hori) = ECe(i-1,k,T_Hori);
else
            ECeT(i,k,T_Hori) = (DC(i-1,k,T_Hori)*ECin(i-1,T_Hori).crop{i_crop})...
                            + ((1-DC(i-1,k,T_Hori))*ECe(i-1,k,T_Hori));
end
else
if ECeT(i-1,k-1,T_Hori) > ECe(i-1,k,T_Hori)
            ECeT(i,k,T_Hori) = ECe(i-1,k,T_Hori);
else
            ECeT(i,k,T_Hori) = (DC(i-1,k,T_Hori)*ECeT(i-1,k-1,T_Hori))+ ...
                            ((1-DC(i-1,k,T_Hori))*ECe(i-1,k,T_Hori));
end
end
%~~~~~~~~~~~~~~~~Defining SWT ()
if strcmp(soilPcond,'constaWT')
if k < 3
         SWT(i,k,T_Hori) = 0;
elseif k >= 3 && k < 9
         SWT(i,k,T_Hori) = S(i-1,k,T_Hori);
else
         SWT(i,k,T_Hori) = 0;
end
elseif strcmp(soilPcond,'freelyDrain')
         SWT(i,k,T_Hori) = 0;
else
end

%~~~~~~~~~~~~~~~~ Defining Sp(i,k,T_Hori)  NB:Field crops case
if k == 1
if DC(i-1,k,T_Hori) == 0
          Sp(i,k,T_Hori) = 0;
else
          Sp(i,k,T_Hori) = SaltContent(i-1,k,T_Hori)-(ECeT(i,k,T_Hori)*0.075*Wsatu_k(k))...
                       + Sin(i-1,T_Hori).crop{i_crop} + (ECwt*0.075*SWT(i,k,T_Hori));
end
else
if DC(i-1,k,T_Hori) == 0
```

```
        Sp(i,k,T_Hori) = 0;
else
        Sp(i,k,T_Hori) = SaltContent(i-1,k,T_Hori)-(ECeT(i,k,T_Hori)*0.075*Wsatu_k(k))...
                   + Sp(i,k-1,T_Hori) + (ECwt*0.075*SWT(i,k,T_Hori));
end
end

%~~~~~~~~~~~~~~~~Defining saltcontent(i,k) NB:Field crops case
if k == 1
      SaltContent(i,k,T_Hori) = SaltContent(i-1,k,T_Hori)+ Sin(i-1,T_Hori).crop{i_crop}...
                         + (ECwt*0.075*SWT(i,k,T_Hori))- Sp(i,k,T_Hori);
else
      SaltContent(i,k,T_Hori) = SaltContent(i-1,k,T_Hori)+ Sp(i,k-1,T_Hori)...
                         + (ECwt*0.075*SWT(i,k,T_Hori))- Sp(i,k,T_Hori);
end

%~~~~~~~~~~~~~~~~Defining ECe(i,k)
      ECe(i,k,T_Hori) = SaltContent(i,k,T_Hori)/((Wsatu_k(k)*0.075));
      ECe_L_sum(i,T_Hori) = ECe_L_sum(i,T_Hori)+ (ECe(i,k,T_Hori)*Zadj_k(k));
      ECe_Mean(i,T_Hori) = ECe_L_sum(i,T_Hori)/2000;

%~~~~~~~~~~~~~~~~Defining Total_Theta
if strcmp(crop{i_crop},'maize')
      Total_Theta(i,k,T_Hori) = 0.003554939+(0.000089444*ECe(i,k,T_Hori))+...
                      (0.002556596*SC_k(k));
elseif strcmp(crop{i_crop},'wheat')
      Total_Theta(i,k,T_Hori) = 0.012185212 +(0.0000594449*ECe(i,k,T_Hori))+...
                      (0.002481094*SC_k(k));
elseif strcmp(crop{i_crop},'peas')
      Total_Theta(i,k,T_Hori) = 0.003862562 +(0.000102912*ECe(i,k,T_Hori))+...
                      (0.002474746*SC_k(k));
else
      Total_Theta(i,k,T_Hori) = 1; % Just to avoid 0 value but not needed for offseason case
end

      [OsmoticPot1] = calcu_OsmoticPot(i,k,T_Hori,ECe,Theta,ThetaSatu_k);
      OsmoticPot(i,k,T_Hori) = OsmoticPot1(i,k,T_Hori);

      [LWSR1] = calcu_LWSR_yesC(i,k,T_Hori,i_crop,Fsr,Theta,Total_Theta,MatricPot,...
            OsmoticPot,Lv,PsiP,Zadj_k);
      LWSR(i,k,T_Hori) = LWSR1(i,k,T_Hori);

      PWSR(i,T_Hori) = PWSR(i,T_Hori)+ LWSR(i,k,T_Hori);

      [T1] = calcu_T_yesC(i,T_Hori,i_crop,TR,PWSR);
      T(i,T_Hori) = T1(i,T_Hori);

      S_soil(i,T_Hori) = S_soil(i,T_Hori) + SaltContent(i,k,T_Hori);
end
      S_perco(i,T_Hori) = Sp(i,end,T_Hori);
      WTU(i,T_Hori) = 0;

for k = 1:nn
%~~~~~~~~~~~~~~~~Defining S ()
if PWSR(i,T_Hori) == 0
      S(i,k,T_Hori) = 0;
else
      S(i,k,T_Hori) = T(i,T_Hori)*(LWSR(i,k,T_Hori)/PWSR(i,T_Hori));
end
%~~~~~~~~~~~~~~~~Other related calculations
      WTU(i,T_Hori) = WTU(i,T_Hori) + SWT(i,k,T_Hori);
      S_WTU(i,T_Hori) = WTU(i,T_Hori)*0.075*ECwt;
```

```
    WTU_P(i,T_Hori) = WTU(i,T_Hori)-EffRainShort(i,end,T_Hori);
    S_Rain(i,T_Hori) = 2*0.075*RainF(i,T_Hori).crop{i_crop};
    S_Irr(i,T_Hori) = Sin(i,T_Hori).crop{i_crop}-S_Rain(i,T_Hori);
    Diff_Swtu_Sp(i,T_Hori) = S_WTU(i,T_Hori)- S_perco(i,T_Hori);
end
    c_day(i,T_Hori) = 0.087.*Zadj_k(1).*(Theta(i,1,T_Hori)-ThetaaA(1))+1.16;

    [E_time1] = calcu_E_time_yesC(i,T_Hori,i_crop,Eff_RI,E_time);
    E_time(i,T_Hori) = E_time1(i,T_Hori);

    Ecum(i,T_Hori) = c_day(i,T_Hori).*(E_time(i,T_Hori).^0.5);

    [Euncovered1] = calcu_Euncovered(i,T_Hori,Ecum,E_time);
    Euncovered(i,T_Hori) = Euncovered1(i,T_Hori);

    Ecovered(i,T_Hori) = Euncovered(i,T_Hori)*(1-FB(i,T_Hori).crop{i_crop});

    [Evapo1] = calcu_Evapo(i,T_Hori,i_crop,Theta,ThetaaA,crop,Euncovered,Ecovered);
    Evapo(i,T_Hori) = Evapo1(i,T_Hori);

end
end
end%Ends the function
```

APPENDIX D

MATLAB CODE FOR ECON SECTION OF THE MODEL

```
% ========= ADDITIONAL INPUT DECLARATION FOR ECON ===================================
%This section presents the MATLAB code for inputs that are needed for ECON (economic decision model) in
%addition to the inputs defined in Appendix A. Coded by Berhane O Haile, University of Free State
% ==============================================================================

%### DEFINING T_Hori ------------------------------------------------------------------------------------------------------------------

% NB: T_Hori is always defined as:

T_Hori = 1:YEARS

%### SEPARATE IRRIGATION PARAMETER TO INDIVIDUAL CROP CASES ------------------------------------------------

[Irrig,IR_hrs,Total_Irrig,Total_IR_hrs] = generate_IR_fallow(indi,YEARS,...
                                crop,GSL_N,t_rota,element,Select_Y_rota,Pivot_eff,IR_S_Size,IR_S_FlowR);

% OR could be used depending which crop is being used for crop rotation
[Irrig,IR_hrs,Total_Irrig,Total_IR_hrs] = generate_IR_peas(indi,YEARS,...
                               crop,GSL_N,element,Select_Y_rota,Pivot_eff,IR_S_Size,IR_S_FlowR);

%### CALL ELECTRIC ENERGY RELATED PARAMETERS ---------------------------------------------------------------------

[OP_a_hrs,Stand_a_hrs,P_a_hrs,OP_aeT,Stand_aeT,P_aeT,OP_reT, ...
          Stand_reT,P_reT] = generate_energy_par(RainFFF,crop,YEARS,soilType, case_rot,T_zone_Voltage);

%### ALLOCATE AVAILABLE IRRIGATION HOURS -------------------------------------------------------------------------------

%NB: Only for one crop case given as an example. If it needed to use it for different crops "for" could be used.
%Here, the example is for maize.

for aa =1:length(crop)
if strcmp(crop{aa},'maize')
        i_crop =aa;
end
end
for i = 1:GSL_N.crop{i_crop}
        ir_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
        op_a_hrs(i) = OP_a_hrs(i,T_Hori).crop{i_crop};
        stand_a_hrs(i) = Stand_a_hrs(i,T_Hori).crop{i_crop};
        p_a_hrs(i) = P_a_hrs(i,T_Hori).crop{i_crop};
end
      [A_OP_hrs,A_Stand_hrs,A_P_hrs] = alloc_IR_hrs(ir_hrs,op_a_hrs,stand_a_hrs,p_a_hrs);
for i = 1:GSL_N.crop{i_crop}
       Alloc_OP_hrs(i,T_Hori).crop{i_crop} = A_OP_hrs(i);
       Alloc_Stand_hrs(i,T_Hori).crop{i_crop} = A_Stand_hrs(i);
       Alloc_P_hrs(i,T_Hori).crop{i_crop} = A_P_hrs(i);
end
```

```
%### STATE CONTINGENT GROSS MARGIN CALCULATION--------------------------------------------------------------------

% The state contingent gross margin can be calculated as follow. Maize crop is used as an example.

for aa =1:length(crop)
if strcmp(crop{aa},'maize')
        i_crop = aa;
end
end
        [Revenue,T_Irrig_Cost] = cal_Revenue_IrrigCost(T_Hori,i_crop,...
          Y_act,crop_price,IR_S_Size,Alloc_OP_hrs,OP_aeT,...
          kW,Alloc_Stand_hrs,Stand_aeT,Alloc_P_hrs,P_aeT,OP_reT,...
          Stand_reT,P_reT,kVAr,Reliability_sC,N_Demand_C,Repair,...
          Labour_hr,Wage_Labour,spray,W_Tariffs,GSL_N,Total_IR_hrs,...
          Total_Irrig);

% ===> Area Dependent Cost
        AD_cost = IC_perHa.crop{i_crop}*IR_S_Size;
% ===> Yield Dependent Cost
        YD_cost = IR_S_Size*(Y_act(T_Hori).crop{i_crop}/1000)*IC_yield.crop{i_crop};
% ===> Total crop production cost
        T_Prod_Cost = AD_cost + YD_cost;
% ===> Present Value of Gross Margin
        PV_GM_C1 = (Revenue-T_Irrig_Cost-T_Prod_Cost)/(1+(i_rate/100)).^(T_Hori-1);

% Capture the income and the different costs
         Income(T_Hori).crop{i_crop} = Revenue;
        T_IR_cost(T_Hori).crop{i_crop} = T_Irrig_Cost;
        Area_DC(T_Hori).crop{i_crop} = AD_cost;
        Yield_DC(T_Hori).crop{i_crop} = YD_cost;

FitValue = PV_GM; % It can be arranged in a loop if more crops are considered for a state of nature

%### CERTAINTY EQUIVALENT CALCULATION------------------------------------------------------------------------------------

%NB: This section provides the codes to calculate CE. Simplified steps are outlined but not the whole modelled code
%to run the appropriate scenarios.

%~~~~~~~~~~~~ Step 1 needs to define parameters
   EU = 0; % Expected utility
  Sum_for_CE = 0; % prepare for Certainty Equivalent calculation

%~~~~~~~~~~~~ Step 2 needs to call the simulated yield for each crop

for s_nat = 1: state_n  % Defining the state of nature

    [Y_act] = NEW_SWAMP(YEARS,t_rota,choose_rota,Select_Y_rota,crop,...
        case_rot,soilPcond,ECi,ECwt,soilType,A,Lv,RainFFF,Irrig,s_nat);

if strcmp (risk_att, 'neutral') % for risk neutral farmer
        Expected_utility = FitValue* prob_s(s_nat);
        EU = EU + Expected_utility;

else% for risk averse farmer
        calcu_s_for_CE = prob_s(s_nat) * exp(-1*RAC*FitValue);
        Sum_for_CE = Sum_for_CE + calcu_s_for_CE;
end
end% ENDS the state of nature

%~~~~~~~~~ Step 3: CAPTURE the FITNESS FUNCTION for each individual solution
if strcmp (risk_att, 'neutral') % for risk neutral farmer
  Iai(indi) = EU; % Expected utility
```

```
else
  lai(indi) = -log(Sum_for_CE)/RAC; % CE of for risk-avese
end

% ========= FUNCTIONS DEFINED FOR ECON ============================================
%This section presents the MATLAB code for functions needed for the ECON model.
% ================================================================================

%------------- FUNCTION:  AVAILABLE HOURS DURING A WEEK ----------------------------------------------------------------

function [OP_a_hrs Stand_a_hrs P_a_hrs] = available_IR_hrs(D_o_W,T_Hori,i_crop)
%The function assign available Off-peak, Standard, and Peak hrs per each day for the irrigation period for each crop
%for the specified years.
%Format of Call: available_IR_hrs(Day_o_Week)

D_o_W = D_o_W';

for i = 1:length(D_o_W)
if D_o_W (i) == 1
   DoW = {'Sun'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;

elseif D_o_W (i) == 2
   DoW = {'Mon'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
elseif D_o_W (i) == 3
   DoW ={'Tue'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
elseif D_o_W (i) == 4
   DoW ={'Wed'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
elseif D_o_W (i) == 5
   DoW ={'Thu'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
elseif D_o_W (i) == 6
   DoW ={'Fri'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop} = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
elseif D_o_W (i) == 7
   DoW ={'Sat'};
   [Off_Peak Stand Peak] = daily_ET_IrrHrs(DoW);
   OP_a_hrs(i,T_Hori).crop{i_crop } = Off_Peak;
   Stand_a_hrs(i,T_Hori).crop{i_crop} = Stand;
   P_a_hrs(i,T_Hori).crop{i_crop} = Peak;
else
```

```
end
end
end

%------------- FUNCTION: CALCULATE REVENUE AND COST ------------------------------------------------------------------

function [Revenue,T_Irrig_Cost] = cal_Revenue_IrrigCost(T_Hori,i_crop,...
         Y_act,crop_price,IR_S_Size,Alloc_OP_hrs,OP_aeT,kW,Alloc_Stand_hrs,Stand_aeT,Alloc_P_hrs,…
         P_aeT,OP_reT,Stand_reT,P_reT,kVAr,Reliability_sC,N_Demand_C,Repair,Labour_hr,…
         Wage_Labour,spray,W_Tariffs,GSL_N,Total_IR_hrs,Total_Irrig)

%The function calculates the revenue and total irrigation cost for a crop in a specific year for the given irrigation
%schedule.

Revenue = Y_act(T_Hori).crop{i_crop} * crop_price.crop{i_crop}*IR_S_Size ;

Sum_active_E =0;
Sum_reactive_E =0;
for i = 1:GSL_N.crop{i_crop}

% ACTIVE ENERGY
 Active_E(i) = Alloc_OP_hrs(i,T_Hori).crop{i_crop}*(OP_aeT(i,T_Hori)...
        .crop{i_crop}/100)*kW + Alloc_Stand_hrs(i,T_Hori).crop{i_crop}...
        *(Stand_aeT(i,T_Hori).crop{i_crop}/100)*kW ...
        + Alloc_P_hrs(i,T_Hori).crop{i_crop}*(P_aeT(i,T_Hori).crop{i_crop}/100)*kW ;
  Sum_active_E = Sum_active_E + Active_E(i);

% REACTIVE ENERGY
 Reactive_E(i) = Alloc_OP_hrs(i,T_Hori).crop{i_crop}*(OP_reT(i,T_Hori)...
        .crop{i_crop}/100)*kVAr + Alloc_Stand_hrs(i,T_Hori).crop{i_crop}...
        *(Stand_reT(i,T_Hori).crop{i_crop}/100)*kVAr ...
        + Alloc_P_hrs(i,T_Hori).crop{i_crop}*(P_reT(i,T_Hori).crop{i_crop}/100)*kVAr ;

  Sum_reactive_E = Sum_reactive_E + Reactive_E(i);

end
% ===>Total active energy cost
  Total_actE = Sum_active_E;
% ===> Total reactive energy cost
  Total_reactE = Sum_reactive_E;
% ===> Reliability service charge
  Reliability = Total_IR_hrs(T_Hori).crop{i_crop}*(Reliability_sC/100)*kW;
% ===> Network demand charge
  Demand = Total_IR_hrs(T_Hori).crop{i_crop}*(N_Demand_C/100)*kW;
% ===> Repair and maintenance
  RandM = Total_IR_hrs(T_Hori).crop{i_crop}*Repair;
% ===>Labour cost
  Labour = (Total_IR_hrs(T_Hori).crop{i_crop}/24)*Labour_hr*Wage_Labour;
% ===>Water tariff cost
  Tariff = (Total_Irrig(T_Hori).crop{i_crop}/(1-spray))*W_Tariffs*IR_S_Size;
% ===> Total Irrigation dependent cost
  T_Irrig_Cost = Total_actE + Total_reactE + Reliability + Demand + RandM + Labour+Tariff;
end% ENDS: the function

%------------- FUNCTION: DEFINE PARAMETERS NEEDED FOR CROP COST ------------------------------------------------

function [IC_perHa,IC_yield,IC_yieldMax,max_yield] = crop_prod_cost(crop)

%This function assign the crop production cost for the field crops specified
%Format of Call: crop_prod_cost(crop)

for i_crop =1:length(crop)
```

```
if strcmp(crop(i_crop),'maize')
   IC_perHa.crop{i_crop} = 8473.0175; %R/ha
   IC_yield.crop{i_crop} = 833.26; %R/ton
   IC_yieldMax.crop{i_crop} = 15151.50679; %R/ha
   max_yield.crop{i_crop} = 17.39;  %ton/ha;

elseif strcmp(crop(i_crop),'wheat')
   IC_perHa.crop{i_crop} = 5717.744; %R/ha
   IC_yield.crop{i_crop} = 1202.48; %R/ton
   IC_yieldMax.crop{i_crop} = 10702.49708;
max_yield.crop{i_crop} = 9.37;  %ton/ha
elseif strcmp(crop(i_crop),'peas')
   IC_perHa.crop{i_crop} = 5361.210; %R/ha
   IC_yield.crop{i_crop} = 1199.20; %R/ton
   IC_yieldMax.crop{i_crop} = 8261.650077;
   max_yield.crop{i_crop} = 7.63 ; %ton/ha:
else
end
end
end

%------------- FUNCTION: DEFINING PARAMETERS NEEDED FOR CROP COST ---------------------------------------------

function [crop_price] =croppriceAssign(crop)
%This function assign the crop price for the field crops specified
%Format of Call: croppriceAssign(crop):
for i_crop =1:length(crop)
if strcmp(crop(i_crop),'maize')
   Price =2150; %R/ton
   crop_price.crop{i_crop} = Price/1000;  %R/kg

elseif strcmp(crop(i_crop),'wheat')
   Price =3205; %R/ton
   crop_price.crop{i_crop} = Price/1000;  %R/kg

elseif strcmp(crop(i_crop),'peas')
   Price = 6000; %R/ton
   crop_price.crop{i_crop} = Price/1000;  %R/kg
else
end
end
end

%------------- FUNCTION: DEFINING PARAMETERS ENERGY TARIFFS--------------------------------------------------------

function [OP_aeT,Stand_aeT,P_aeT,OP_reT,Stand_reT,P_reT] = electric_charge...
                                   (D_S_t,T_zone_Voltage,T_Hori,i_crop)
%This function assigns the electric energy tariffs based on time-of-useslot.
%Format of Call: electric_charge(D_S_t,T_zone_Voltage,T_Hori,i_crop)

[r,c] = size(T_zone_Voltage);

D_S_t =D_S_t';

for i =1:length(D_S_t)
if D_S_t(i) == 1
       Season_indi = {'Low'};
elseif D_S_t(i) == 2
       Season_indi = {'High'};
else
disp('Season not found')
end
```

```
  [rr,cc] = size(Season_indi);
for ii =1:c
%#### Active Energy Charge (c/kwh)
if strcmp(T_zone_Voltage(ii), 'L300Km_L500V')
for iii = 1:cc
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 32.58; %(c/kwh)
        Standard = 51.35; %(c/kwh)
        Peak = 74.62; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 37.63; %(c/kwh)
        Standard = 69.30; %(c/kwh)
        Peak = 228.74; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end
elseif strcmp(T_zone_Voltage(ii), 'L300Km_GE500VandLE22kV')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 32.25; %(c/kwh)
        Standard = 50.84; %(c/kwh)
        Peak = 73.88; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 37.25; %(c/kwh)
        Standard = 68.61; %(c/kwh)
        Peak = 226.48; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G300KmandLE600km_L500V')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 32.91; %(c/kwh)
        Standard = 51.87; %(c/kwh)
        Peak = 75.36; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 38.01; %(c/kwh)
```

```
            Standard = 69.99; %(c/kwh)
            Peak = 231.03; %(c/kwh)
            OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
            Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
            P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G300KmandLE600km_GE500VandLE22kV')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
            Off_Peak = 32.58; %(c/kwh)
            Standard = 51.34; %(c/kwh)
            Peak = 74.62; %(c/kwh)
            OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
            Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
            P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
            Off_Peak = 37.63; %(c/kwh)
            Standard = 69.29; %(c/kwh)
            Peak = 228.73; %(c/kwh)
            OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
            Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
            P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G600KmandLE900km_L500V')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
            Off_Peak = 33.24; %(c/kwh)
            Standard = 52.38; %(c/kwh)
            Peak = 76.12; %(c/kwh)
            OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
            Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
            P_aeT(i,T_Hori).crop{i_crop } = Peak;        %active EEC

elseif strcmp(Season_indi(iii),'High')
            Off_Peak = 38.38; %(c/kwh)
            Standard = 70.69; %(c/kwh)
            Peak = 233.34; %(c/kwh)
            OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
            Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
            P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G600KmandLE900km_GE500VandLE22kV')

for iii =1:cc
```

```
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 32.91; %(c/kwh)
        Standard = 51.87; %(c/kwh)
        Peak = 75.36; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 38.01; %(c/kwh)
        Standard = 69.98; %(c/kwh)
        Peak = 231.02; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G900km__L500V')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 33.57; %(c/kwh)
        Standard = 52.91; %(c/kwh)
        Peak = 76.87; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 38.76; %(c/kwh)
        Standard = 71.40; %(c/kwh)
        Peak = 235.67; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

else
disp('season not correct')
end
end

elseif strcmp(T_zone_Voltage(ii), 'G900km__GE500VandLE22kV')

for iii =1:cc
if strcmp(Season_indi(iii),'Low')
        Off_Peak = 33.24; %(c/kwh)
        Standard = 52.38; %(c/kwh)
        Peak = 76.12; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
        P_aeT(i,T_Hori).crop{i_crop} = Peak;         %active EEC

elseif strcmp(Season_indi(iii),'High')
        Off_Peak = 38.38; %(c/kwh)
        Standard = 70.69; %(c/kwh)
        Peak = 233.33; %(c/kwh)
        OP_aeT(i,T_Hori).crop{i_crop} = Off_Peak;    %active EEC
        Stand_aeT(i,T_Hori).crop{i_crop} = Standard; %active EEC
```

```
        P_aeT(i,T_Hori).crop{i_crop} = Peak;        %active EEC
else
disp('season not correct')
end
end
else

end
end

%#### Reactive Energy Charge (c/kVArh)
for iii =1:cc
if strcmp(Season_indi(iii),'Low')
        ReA_E_Cost = 0; %(c/kVArh)
        OP_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;   %reactive EEC
        Stand_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;%reactive EEC
        P_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;    %reactive EEC
elseif strcmp(Season_indi(iii),'High')
        ReA_E_Cost = 6.35; %(c/kVArh)
        OP_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;   %reactive EEC
        Stand_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;%reactive EEC
        P_reT(i,T_Hori).crop{i_crop} = ReA_E_Cost;    %reactive EEC

else
disp('season not correct')
end
end
end
end
```

%------------- **FUNCTION: DEFINING PARAMETERS SEPARATE IRRIGATION SCHEDULE FOR EACH CROP**---

```
function [Irrig,IR_hrs,Total_Irrig,Total_IR_hrs] = generate_IR_fallow(indi,YEARS,...
                            crop,GSL_N,t_rota,element,Select_Y_rota,Pivot_eff,IR_S_Size,IR_S_FlowR)

%This function generates irrigation schedules from the generated solutionfor each crop for the appropriate %years.
%Format of call:[Irrig IR_hrs Total_Irrig Total_IR_hrs] = generate_IR_fallow...
% (t_rota, YEARS,crop,GSL_N,Select_Y_rota,element,indi,Pivot_E,IR_S_Size,IR_S_FlowR)

%NB: A similar function but with slight modification is provided for crop rotation with Peas (It is named as
%generate_IR_Peas function).

if strcmp(t_rota,'summer')

%#### Separating element into irrigation for each crop per year
  count_r = 0;
for T_Hori = 1:YEARS

%--------------------REASSIGN GSL for the CROPS-----------------------------------------------------------------------------------------
for aa =1:length(crop) %*****
if strcmp(crop{aa},'maize')
          i_crop = aa;
eos = GSL_N.crop{i_crop};
          N_GSL_C1 = eos;
end
end
for aa =1:length(crop) %*****
if strcmp(crop{aa},'wheat')
           i_crop = aa;
eos = GSL_N.crop{i_crop};
           N_GSL_C2 = eos;
end
```

```
end
%--------------------------------------------------------------------------------------------------------------------------------------------

%Allocate and arrange schedule for maize (First Crop)
for aa =1:length(crop)          %****************************
if strcmp(crop{aa},'maize')
            i_crop =aa;
end
end

if (rem(T_Hori,Select_Y_rota)~ =0) %since maize is replaced
        IRR = element(indi,1 + N_GSL_C1*(T_Hori-1)+ N_GSL_C2*(T_Hori-1)-...
        N_GSL_C1*count_r: N_GSL_C1*(T_Hori-1)+ N_GSL_C2*(T_Hori-1)+N_GSL_C1 - N_GSL_C1*count_r)';
else

end

%^^^^^^^^^^^ Initialisation to sum total irrigation
if (rem(T_Hori,Select_Y_rota)~ = 0)
        T_IRRI =0;
        T_IR_hr =0;
else
        T_IRRI =[];
        T_IR_hr =[];
end

for i =1: N_GSL_C1
if (rem(T_Hori,Select_Y_rota)~ = 0)
Irrig(i,T_Hori).crop{i_crop} = IRR(i);
          Sum_Irr = T_IRRI+IRR(i);
          T_IRRI = Sum_Irr;
          IR_hrs(i,T_Hori).crop{i_crop} =((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
          TT_IR_hrs(i) =IR_hrs(i,T_Hori).crop{i_crop};
          Sum_IR_hr =T_IR_hr + TT_IR_hrs(i);
          T_IR_hr = Sum_IR_hr;
else
end
end
          Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
          Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

%Allocate and arrange shcedule for wheat (Second Crop)
for aa =1:length(crop)          %****************************
if strcmp(crop{aa},'wheat')
            i_crop =aa;
end
end

if (rem(T_Hori,Select_Y_rota)~ =0)
   IRR = element(indi, 1+ N_GSL_C1*(T_Hori)+ N_GSL_C2*(T_Hori-1)- ...
        N_GSL_C1*count_r: N_GSL_C1*(T_Hori)+ N_GSL_C2*(T_Hori-1)+ N_GSL_C2- N_GSL_C1*count_r)';
else
  IRR = element(indi, 1+ N_GSL_C1*(T_Hori)+ N_GSL_C2*(T_Hori-1)-N_GSL_C1*(count_r+1): N_GSL_C1...
       *(T_Hori)+ N_GSL_C2*(T_Hori-1)+N_GSL_C2- N_GSL_C1*(count_r+1))';
end

%^^^^^^^^^^^ Initialisation to sum total irrigation
        T_IRRI =0;
        T_IR_hr =0;
for i =1: N_GSL_C2
          Irrig(i,T_Hori).crop{i_crop} = IRR(i);
          Sum_Irr = T_IRRI+IRR(i);
```

```
            T_IRRI = Sum_Irr;
            IR_hrs(i,T_Hori).crop{i_crop} =((Irrig(i,T_Hori).crop{i_crop}...
                              /Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
            TT_IR_hrs(i) =IR_hrs(i,T_Hori).crop{i_crop};
            Sum_IR_hr =T_IR_hr + TT_IR_hrs(i);
            T_IR_hr = Sum_IR_hr;
end
            Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
            Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

%#### CONSIDER crop IN and OUT due to crop rotation
if (rem(T_Hori,Select_Y_rota)~ =0)
             rot_y = 0;
             count_r = count_r + rot_y;  % Occurrence of rotation
else
             rot_y = 1;
             count_r = count_r + rot_y;  % Occurrence of rotation
end

end%ends YEARS


else% winter rotation
%$$$
%#### Separating element into irrigation for each crop
  count_r =0;
for T_Hori = 1:YEARS

%---------------------REASSIGN GSL for the CROPS ----------------------------------------------------------------------------------------
for aa =1:length(crop) %****************************************
if strcmp(crop{aa},'maize')
              i_crop = aa;
eos = GSL_N.crop{i_crop};
              N_GSL_C1 = eos;
end
end
for aa =1:length(crop) %****************************************
if strcmp(crop{aa},'wheat')
                i_crop = aa;
eos = GSL_N.crop{i_crop};
                N_GSL_C2 = eos;
end
end
%---------------------------------------------------------------

%Allocate and arrange schedule for maize (First Crop)
for aa =1:length(crop)          %****************************
if strcmp(crop{aa},'maize')
              i_crop =aa;
end
end

   IRR = element(indi,1 + N_GSL_C1*(T_Hori-1)+ N_GSL_C2*(T_Hori-1)-...
        N_GSL_C2*count_r: N_GSL_C1*(T_Hori-1)+ N_GSL_C2*(T_Hori-1)+N_GSL_C1 - N_GSL_C2*count_r)';

%^^^^^^^^^^ Initialisation to sum total irrigation
          T_IRRI =0;
          T_IR_hr =0;
for i =1: N_GSL_C1
            Irrig(i,T_Hori).crop{i_crop} = IRR(i);
            Sum_Irr = T_IRRI+IRR(i);
            T_IRRI = Sum_Irr;
```

```
            IR_hrs(i,T_Hori).crop{i_crop} =((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
            TT_IR_hrs(i) = IR_hrs(i,T_Hori).crop{i_crop};
            Sum_IR_hr = T_IR_hr + TT_IR_hrs(i);
            T_IR_hr = Sum_IR_hr;
end
            Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
            Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

%Allocate and arrange schedule for wheat (Second Crop)
for aa =1:length(crop)          %****************************
if strcmp(crop{aa},'wheat')
              i_crop =aa;
end
end

if (rem(T_Hori,Select_Y_rota)~ = 0) %since wheat is replaced
   IRR = element(indi, 1+ N_GSL_C1*(T_Hori)+ N_GSL_C2*(T_Hori-1)- ...
          N_GSL_C2*count_r: N_GSL_C1*(T_Hori)+ N_GSL_C2*(T_Hori-1)+ N_GSL_C2- N_GSL_C2*count_r)';
else

end

%^^^^^^^^^^^ Initialisation to sum total irrigation
if (rem(T_Hori,Select_Y_rota)~ = 0)
             T_IRRI =0;
             T_IR_hr =0;
else
             T_IRRI =[];
             T_IR_hr =[];
end

for i =1: N_GSL_C2
if (rem(T_Hori,Select_Y_rota)~ = 0) %since wheat is replaced
           Irrig(i,T_Hori).crop{i_crop} = IRR(i);
            Sum_Irr = T_IRRI+IRR(i);
            T_IRRI = Sum_Irr;
            IR_hrs(i,T_Hori).crop{i_crop} =((Irrig(i,T_Hori).crop{i_crop}/Pivot_eff)*10*IR_S_Size)/IR_S_FlowR;
            TT_IR_hrs(i) =IR_hrs(i,T_Hori).crop{i_crop};
            Sum_IR_hr = T_IR_hr + TT_IR_hrs(i);
            T_IR_hr = Sum_IR_hr;
else

end
end
            Total_Irrig(T_Hori).crop{i_crop} = T_IRRI;
            Total_IR_hrs(T_Hori).crop{i_crop} = T_IR_hr;

%####CONSIDER crop IN and OUT due to crop rotation
if (rem(T_Hori,Select_Y_rota)~ = 0)
               rot_y = 0;
               count_r = count_r + rot_y;  %Occurrence of rotation
else
               rot_y = 1;
               count_r = count_r + rot_y;  %Occurrence of rotation
end

end%ends YEARS
end% ends t_rota
%$$$$
end%ends the function
```

```
%------------- FUNCTION: DEFINING PARAMETERS RELATED FOR ELECTRICITY COST----------------------------------

%~~~~~~~~~~~~ RELIABILITY AND DEMAND CHARGE

function [Reliability_sC,N_Demand_C] = reliability_demand_charge(Voltage)

%This function assigns reliability service charge and network demand chargefor energy:
%Format of Call: electric_charge(Day_S_type,T_zone_Voltage)

[r c] =size(Voltage);
for i =1:c
if strcmp(Voltage(i), 'L500V')
    Reliability_sC = 0.29;   % c/kWh reliability service charge
    N_Demand_C = 18.8;       % c/kWh network demand charge
elseif strcmp(Voltage(i), 'GE500V_LE22kV')
    Reliability_sC = 0.29;   % c/kWh reliability service charge
    N_Demand_C = 16.48;      % c/kWh network demand charge
else
disp('Choose voltage correctly')
end

end
end

%~~~~~~~~~~~~ SERVICE AND ADMINISTRATION CHARGE

function [Service_C,Admin_C] = service_admin(Monthly_utilised_capacity)

%This function assigns service charge and administration chargefor energy:
%Format of Call: electric_charge(Day_S_type,T_zone_Voltage)

[r c] =size(Monthly_utilised_capacity);
for i =1:c
if strcmp(Monthly_utilised_capacity(i), 'LE100kVA')
    Service_C = 12.99;     % R/Account/day
    Admin_C = 3.69;        % R/POD/day
elseif strcmp(Monthly_utilised_capacity(i), 'GE100kVAandLE500kVA')
    Service_C = 44.32 ;% R/Account/day
    Admin_C = 20.54  ;% R/POD/day
elseif strcmp(Monthly_utilised_capacity(i), 'G500kVAandLE1MVA')
    Service_C = 136.33  ;% R/Account/day
    Admin_C = 31.53   ;    % R/POD/day
elseif strcmp(Monthly_utilised_capacity(i), 'G1MVA')
    Service_C = 136.33  ;% R/Account/day
    Admin_C = 58.51   ;    % R/POD/day
elseif strcmp(Monthly_utilised_capacity(i), 'Key_customers')
    Service_C = 2671.9 ;% R/Account/day
    Admin_C = 58.51  ;% R/POD/day
else
disp('Choose Monthly_utilised_capacity correctly')
end

end

%------------- FUNCTION: DEFINING IRRIGATION-SYSTEM PARAMETERS----------------------------------------------------

function [IR_S_Cap,IR_S_Size,IR_S_FlowR,IR_S_Pres,IR_S_SHead,Eff_Pump,kVAr,kW,Repair] =...
                              select_IR_S_design (Irr_S_design)

%This system selects irrigation-system parameters for pivot that are neededfor further computations.
%Format of Call: select_IR_S_design (Irr_S_design)
```

```
[r,c] =size(Irr_S_design );
for i =1:c
if strcmp(Irr_S_design (i), 'Pivot_A')

      IR_S_Cap = 8;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 30.1 ;% Ha (Area)
      IR_S_FlowR = 100.5; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 21.1 ;%m (Centre pressure)
      IR_S_SHead = 12 ;%m (Static Head)
      Eff_Pump = 0.747;   % in % (efficiency of pump)
kVAr = 10.46416626;
kW = 16.2;
      Repair =0.2873554;

elseif strcmp(Irr_S_design (i), 'Pivot_B')
      IR_S_Cap = 10;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 30.1; % Ha (Area)
      IR_S_FlowR = 125.5; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 22.4; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.755;   % in % (efficiency of pump)
kVAr = 13.5104266;
kW = 21.8;
      Repair =0.433294;

elseif strcmp(Irr_S_design (i), 'Pivot_C')
      IR_S_Cap = 12;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 30.1; % Ha (Area)
      IR_S_FlowR = 150.5; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 24.1; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.775;   % in % (efficiency of pump)
kVAr =14.1114803;
kW = 24.9;
      Repair =0.413217;

elseif strcmp(Irr_S_design (i), 'Pivot_D')
      IR_S_Cap = 14;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 30.5; % Ha (Area)
      IR_S_FlowR = 178; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 22.9; %m (Centre pressure)
      IR_S_SHead = 12;  %m (Static Head)
      Eff_Pump = 0.784; % in % (efficiency of pump)
kVAr =16.77509305;
kW =29.6;
      Repair =0.413217;

elseif strcmp(Irr_S_design (i), 'Pivot_E')
      IR_S_Cap = 8;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 47.7; % Ha (Area)
      IR_S_FlowR = 158.9; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 22.9; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.778;   % in % (efficiency of pump)
kVAr =14.5648612;
kW =25.7;
      Repair =0.413217;

elseif strcmp(Irr_S_design (i), 'Pivot_F')
      IR_S_Cap = 10;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 47.7; % Ha (Area)
      IR_S_FlowR = 198.6; %m cube per hr (Irrigation-system flow rate)
```

```
      IR_S_Pres = 25.2; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.797;   % in % (efficiency of pump)
kVAr =24.43015028;
kW = 35;
      Repair =0.4443296;

elseif strcmp(Irr_S_design (i), 'Pivot_G')
      IR_S_Cap = 12;  % mm per day (Irrigation-system capacity)
      IR_S_Size = 47.7; % Ha (Area)
      IR_S_FlowR = 239; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 28; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.814;   % in % (efficiency of pump)
kVAr = 30.30738424;
kW = 45.1;
      Repair =0.4443296;

elseif strcmp(Irr_S_design (i), 'Pivot_H')
      IR_S_Cap = 14;  % mm per day (Irrigation-system capcity)
      IR_S_Size = 47.7; % Ha (Area)
      IR_S_FlowR = 278; %m cube per hr (Irrigation-system flow rate)
      IR_S_Pres = 31.1; %m (Centre pressure)
      IR_S_SHead = 12;%m (Static Head)
      Eff_Pump = 0.817;   % in % (efficiency of pump)
kVAr = 38.6609326;
kW = 53.4;
      Repair =0.4443296;
else
disp('Irr_S_design not in the list or misspelled')
end
end
end
-----------------------------------------------------------------------------------------------------------------------------------------------
```

APPENDIX E

MATLAB CODE FOR PRINTOUT OF SWAMP-ECON OUTPUTS

```
%========== OUTPUTS OF THE MODEL FOR FIELD CROPS =======================================
%This section presents the MATLAB codes that are useful to get a print out in Excel for the outputs of the SWAMP-
%ECON model for the field crops. It is used by changing the filename that identify each field crop.
%=====================================================================================

% Choose filename from: 'OUTPUT_MAIZE.xlsx'; 'OUTPUT_WHEAT.xlsx'; 'OUTPUT_PEAS.xlsx'

        filename = 'OUTPUT_MAIZE.xlsx';
for i = 1:GSL_N.crop{i_crop}
          dog(i) = i-1;
          IR(i) = Irrig(i,T_Hori).crop{i_crop};
          rain(i) = RainF(i,T_Hori).crop{i_crop};
          OP_HRS(i) = Alloc_OP_hrs(i,T_Hori).crop{i_crop};
          STAND_HRS(i) = Alloc_Stand_hrs(i,T_Hori).crop{i_crop};
          P_HRS(i) = Alloc_P_hrs(i,T_Hori).crop{i_crop};
          evap(i) = EVAPO(i,T_Hori).crop{i_crop};
          trans(i) = TRANSP(i,T_Hori).crop{i_crop};
          wwtu(i) = wtu(i,T_Hori).crop{i_crop};
          perc(i) = PERCO(i,T_Hori).crop{i_crop};
          w_soil(i) = W_SOIL(i,T_Hori).crop{i_crop};
          s_rain(i) = S_RAIN(i,T_Hori).crop{i_crop};
          s_irr(i) = S_IRR(i,T_Hori).crop{i_crop};
          s_WTU(i) = S_wtu(i,T_Hori).crop{i_crop};
          s_perc(i) = S_PERCO(i,T_Hori).crop{i_crop};
          s_soil(i) = S_SOIL(i,T_Hori).crop{i_crop};
          ece_mean(i) = ECe_M(i,T_Hori).crop{i_crop};
          tr(i) = TR(i,T_Hori).crop{i_crop};
for k = 1:nn
               moist(i,k) = MOISTURE(i,k,T_Hori).crop{i_crop};
               ec_soil(i,k) = EC_SOIL(i,k,T_Hori).crop{i_crop};
               matri(i,k) = MATRIC(i,k,T_Hori).crop{i_crop};
               osmoti(i,k) = OSMOTIC(i,k,T_Hori).crop{i_crop};
               tot_theta(i,k) = TOTAL_THETA(i,k,T_Hori).crop{i_crop};
end

end
          eto = ETo(T_Hori).crop{i_crop};
          yield = Y_act(T_Hori).crop{i_crop};
          revenue = Income(T_Hori).crop{i_crop};
          total_ir_c = T_IR_cost(T_Hori).crop{i_crop};
          area_dc = Area_DC(T_Hori).crop{i_crop};
          yield_dc = Yield_DC(T_Hori).crop{i_crop};

          system_cap = IR_S_Cap;
          ecirr = ECi;
          ecwtab = ECwt;

          combine_spe = [system_cap;ecirr;ecwtab];
          column_name = {'SYSTEM_CAP'; 'ECi'; 'ECwt'};
          xlRange = 'A4';
          xlswrite(filename,column_name,sheet,xlRange);
```

```
            xlRange = 'B4';
            xlswrite(filename,combine_spe,sheet,xlRange);

            combine_O1 = [eto,yield,revenue,total_ir_c,area_dc,yield_dc];
            column_name = {'ETo','YIELD','REVENUE','T_IR_COST','AREA_DC','YIELD_DC'};%@@
            xlRange = 'A1';
            xlswrite(filename,column_name,sheet,xlRange);
            xlRange = 'A2';
            xlswrite(filename,combine_O1,sheet,xlRange);

            combine_O2 = [dog',IR',rain',OP_HRS',STAND_HRS',P_HRS',evap',trans',wwtu',...
                    perc',w_soil',s_rain',s_irr',s_WTU',s_perc',s_soil',ece_mean',tr'];

            column_name = {'Days','IR','RF','OP_Hrs','S_Hrs','P_Hrs','E','T','WTU','D','W_SOIL','S_RAIN',...
'S_IR','S_wtu','S_D','S_SOIL','ECe_MEAN','TRp'}; %@@

            xlRange = 'G1';
            xlswrite(filename,column_name,sheet,xlRange);
            xlRange = 'G2';
            xlswrite(filename,combine_O2,sheet,xlRange);

            combine_O3 = [moist,ec_soil,matri,osmoti,tot_theta];
            column_name = {'LM1','LM2','LM3','LM4','LM5','LM6','LM7','LM8','LM9',...
'LM10','LM11','LM12','LM13','LM14','LM15','LM16','ECe1','ECe2','ECe3','ECe4','ECe5','ECe6','ECe7','ECe8',...
'ECe9','ECe10','ECe11','ECe12','ECe13','ECe14','ECe15','ECe16','MA1','MA2','MA3','MA4','MA5','MA6','MA7',...
'MA8','MA9','MA10','MA11','MA12','MA13','MA14','MA15','MA16','OS1','OS2','OS3','OS4','OS5','OS6','OS7',
'OS8','OS9','OS10','OS11','OS12','OS13','OS14','OS15','OS16','TotTheta1','TotTheta2','TotTheta3','TotTheta4',...'TotT
heta5','TotTheta6','TotTheta7','TotTheta8','TotTheta9','TotTheta10','TotTheta11','TotTheta12','TotTheta13',...
'TotTheta14','TotTheta15','TotTheta16'};
            xlRange = 'Z1';
            xlswrite(filename,column_name,sheet,xlRange);
            xlRange = 'Z2';
            xlswrite(filename,combine_O3,sheet,xlRange);


% ========= OUTPUTS OF THE MODEL FOR FALLOW PERIODS ==================================
%This section presents the MATLAB could that are useful to get a print out in Excel for the outputs of the SWAMP-
%ECON model for the fallow period. It is used by changing the filename that identify each fallow period.
% ======================================================================================

% Choose filename from: 'OUTPUT_OFFSEASON1.xlsx'; 'OUTPUT_OFFSEASON2.xlsx'
filename = 'OUTPUT_OFFSEASON1.xlsx';
fori = 1:GSL_Spe
           dog(i) = i-1;
           rain(i) = RainF_OffS1(i,T_Hori).case_rot{caseR};
           evap(i) = EVAPO(i,T_Hori).crop{i_crop};
           trans(i) = TRANSP(i,T_Hori).crop{i_crop};
           wwtu(i) = wtu(i,T_Hori).crop{i_crop};
           perc(i) = PERCO(i,T_Hori).crop{i_crop};
           w_soil(i) = W_SOIL(i,T_Hori).crop{i_crop};
           s_rain(i) = S_RAIN(i,T_Hori).crop{i_crop};
           s_irr(i) = S_IRR(i,T_Hori).crop{i_crop};
           s_WTU(i) = S_wtu(i,T_Hori).crop{i_crop};
           s_perc(i) = S_PERCO(i,T_Hori).crop{i_crop};
           s_soil(i) = S_SOIL(i,T_Hori).crop{i_crop};
           ece_mean(i) = ECe_M(i,T_Hori).crop{i_crop};
for k = 1:nn
                  moist(i,k) = MOISTURE(i,k,T_Hori).crop{i_crop};
                  ec_soil(i,k) = EC_SOIL(i,k,T_Hori).crop{i_crop};
                  matri(i,k) = MATRIC(i,k,T_Hori).crop{i_crop};
                  osmoti(i,k) = OSMOTIC(i,k,T_Hori).crop{i_crop};
                  tot_theta(i,k) = TOTAL_THETA(i,k,T_Hori).crop{i_crop};
```

```
end
end
          system_cap = IR_S_Cap;
          ecirr = ECi;
          ecwtab = ECwt;

          combine_spe = [system_cap;ecirr;ecwtab];
          column_name = {'SYSTEM_CAP'; 'ECi'; 'ECwt'};
          xlRange = 'A4';
          xlswrite(filename,column_name,sheet,xlRange);
          xlRange = 'B4';
          xlswrite(filename,combine_spe,sheet,xlRange);

          combine_O2 = [dog',rain',evap',trans',wwtu',perc',w_soil',s_rain',...
                 s_irr',s_WTU',s_perc',s_soil',ece_mean'];

     column_name {'Days','RF','E','T','WTU','D','W_SOIL','S_RAIN','S_IR','S_wtu','S_D','S_SOIL','ECe_MEAN'}; %

          xlRange = 'G1';
          xlswrite(filename,column_name,sheet,xlRange);
          xlRange = 'G2';
          xlswrite(filename,combine_O2,sheet,xlRange);

          combine_O3 = [moist,ec_soil,matri,osmoti,tot_theta];
          column_name = {'LM1','LM2','LM3','LM4','LM5','LM6','LM7','LM8','LM9',...
'LM10','LM11','LM12','LM13','LM14','LM15','LM16','ECe1','ECe2','ECe3','ECe4','ECe5','ECe6','ECe7','ECe8',...
'ECe9','ECe10','ECe11','ECe12','ECe13','ECe14','ECe15','ECe16','MA1','MA2','MA3','MA4','MA5','MA6','MA7',...
'MA8','MA9','MA10','MA11','MA12','MA13','MA14','MA15','MA16','OS1','OS2','OS3','OS4','OS5','OS6','OS7',...
'OS8','OS9','OS10','OS11','OS12','OS13','OS14','OS15','OS16','TotTheta1','TotTheta2','TotTheta3','TotTheta4',...'TotT
heta5','TotTheta6','TotTheta7','TotTheta8','TotTheta9','TotTheta10','TotTheta11','TotTheta12','TotTheta13',...
'TotTheta14','TotTheta15','TotTheta16'};
          xlRange = 'Z1';
          xlswrite(filename,column_name,sheet,xlRange);
          xlRange = 'Z2';
          xlswrite(filename,combine_O3,sheet,xlRange);
----------------------------------------------------------------------------------------------------------------------------------------
```

APPENDIX F

RAINFALL DISTRIBUTION FOR STATES OF NATURE

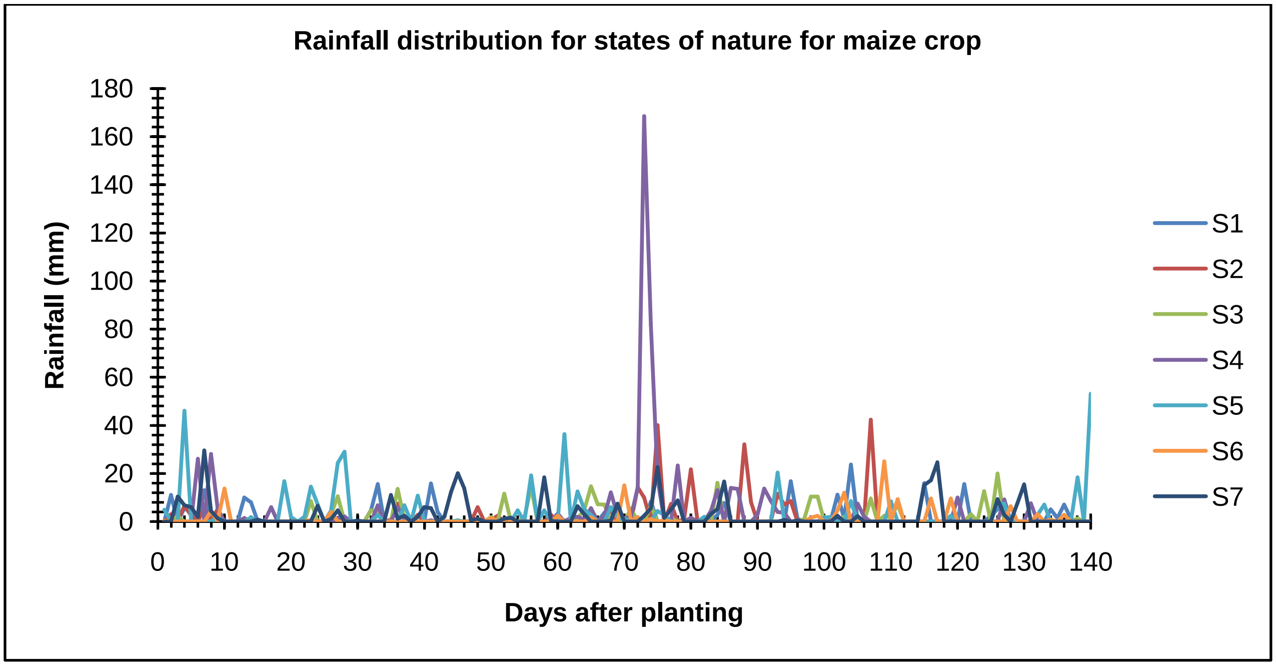


Figure F.1: Rainfall distribution for states of nature for maize

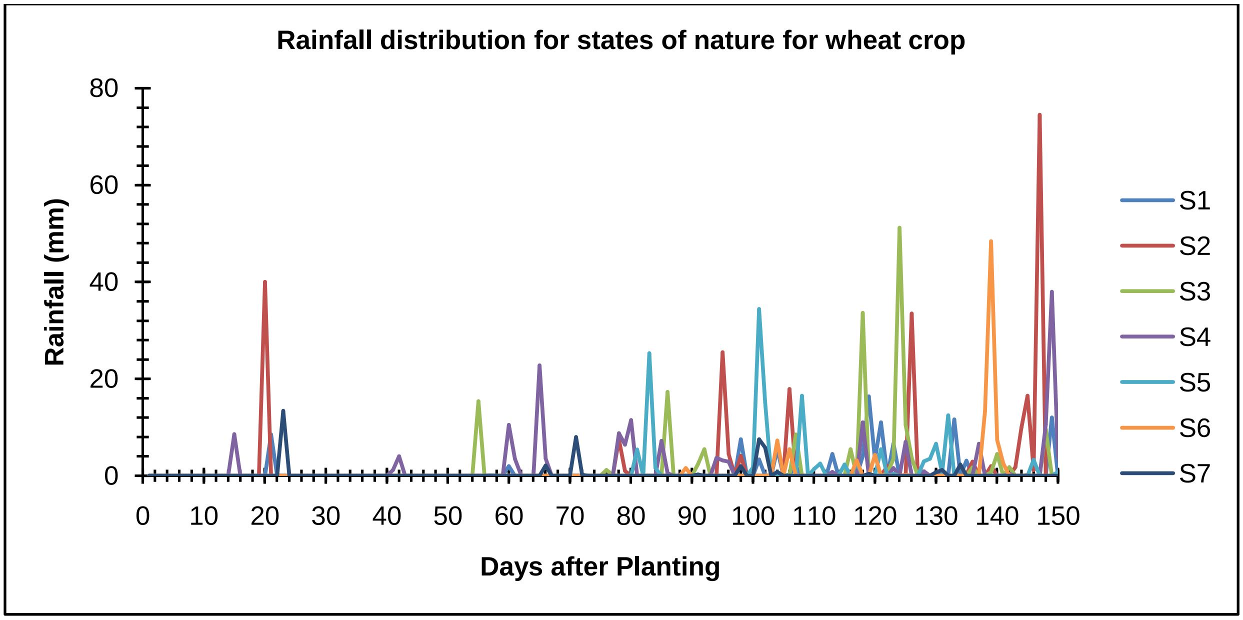


Figure F.2: Rainfall distribution for states of nature for wheat

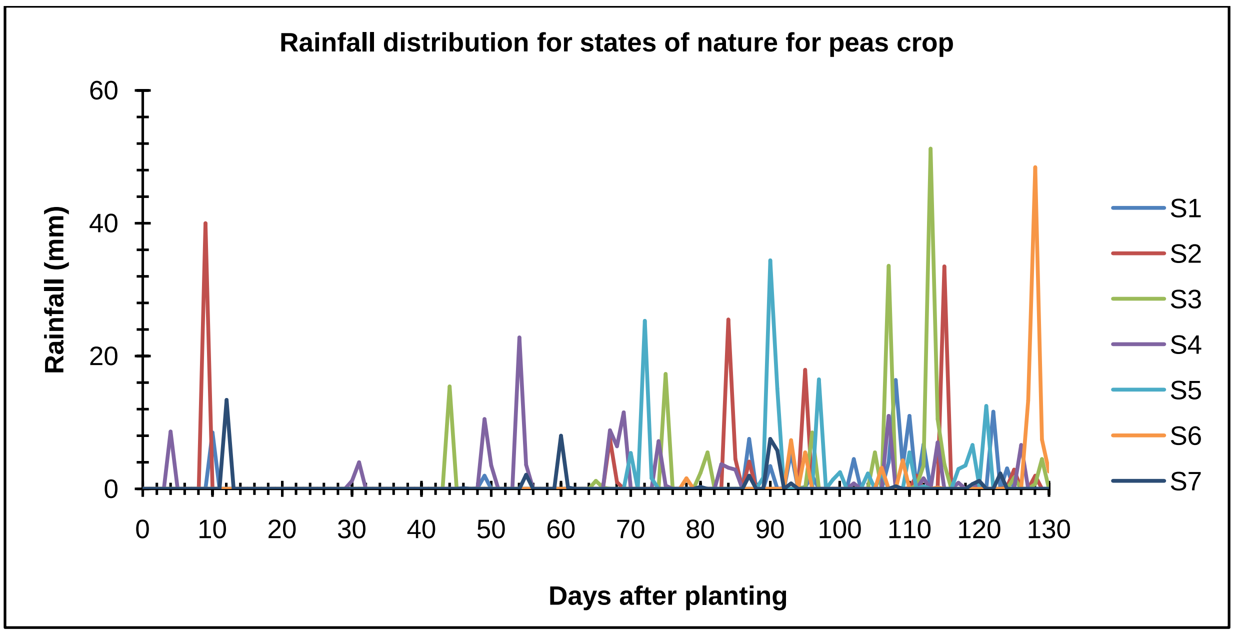


Figure F.3: Rainfall distribution for states of nature for peas

APPENDIX G

ENTERPRISE BUDGET FOR FIELD CROPS

Table G.1a: Crop enterprise budget for maize crop with a target yield of 13 ton ha^{-1} (2014)

INPUTS	PRODUCT	UNIT	AMOUNT	PRICE UNIT^{-1} (ZAR)	COST HA^{-1} (ZAR)
Yield Dependent Cost					
HEDGING	Safex	ton	13.00	150.00	1950.00
FERTILIZATION	N	kg	286.00	15.38	4398.68
	P	kg	52.00	31.60	1643.20
	K	kg	80.00	12.84	1027.20
	Ca	kg	10.00	28.27	282.70
	Mg	kg	10.00	50.83	508.30
	S	kg	25.00	5.00	125.00
INSURANCE	GWK	ton	13.00	2.10%	587.00
HARVESTING	Transport	ton	13.00	69.00	897.00
Area Dependent Costs					
FUEL	Diesel	litre	52	11.15	579.80
MICRO ELEMENTS	Sidi Seed	kg	0.125	105.86	13.23
	Sidi Zn	kg	2.00	65.53	131.06
	Sidi Maize	kg	2.00	63.83	127.66
	Sidi Boost	kg	2.00	65.53	131.06
	Speedfol	kg	1.00	33.27	33.27
	Sidi Moly	litre	1.00	91.09	91.09
	Marinure	litre	1.00	77.46	77.46
	Comcat	kg	0.2	525.85	105.17
	Anngro	litre	0.12	284.45	34.134
SEED	Seed	kernels	90000	0.036	3240.00
WEED CONTROL	Atrazine	litre	1.50	57.83	86.75
	Wenner	litre	1.00	104.77	104.77
PEST CONTROL	Curaterr	kg	20.00	61.93	1238.60
	Abacus	litre	1.60	360.56	576.90
	Duett	litre	1.00	254.69	254.69
	Abactien	litre	1.00	108.78	108.78
	Airplane	ha	2.00	150	300.00
HARVESTING	Combine	ha	1.00	850	850.00
MECHANIZATION	M & R	ha	1.00	400	400.00

Source: GRIEKWALAND-WES KORPORATIEF (2014)

Table G.1b: Crop enterprise budget for wheat crop with a target yield of 7.5 ton ha^{-1} (2014)

INPUTS	PRODUCT	UNIT	AMOUNT	PRICE $UNIT^{-1}$ (ZAR)	COST HA^{-1} (ZAR)
Yield Dependent Cost					
HEDGING	Safex	ton	7.50	150.00	1125.00
FERTILIZATION	N	kg	250.00	15.38	3845.00
	P	kg	48.00	31.60	1516.80
	K	kg	78.00	12.84	1001.52
	Ca	kg	15.00	28.27	424.05
	Mg	kg	10.00	50.83	508.30
	S	kg	16.00	5.00	80.00
INSURANCE	GWK	ton	7.50	5.40%	1298
HARVESTING	Transport	ton	7.50	69.00	517.50
Area Dependent Costs					
FUEL	Diesel	litre	59.00	11.15	657.85
MICRO ELEMENTS	Sidi Seed	kg	0.13	105.86	13.23
	Sidi Zn	kg	2.00	65.53	131.06
	Sidi Wheat	kg	2.00	62.69	125.38
	Sidi Boost	kg	3.00	65.53	196.59
	Speedfol	kg	1.00	42.67	42.67
	Marinure	litre	1.00	77.46	77.46
	Comcat	kg	0.40	525.85	210.34
	Anngro	litre	0.12	284.45	34.13
SEED	Seed	kg	100.00	12.00	1200.00
WEED CONTROL	Broxonil	litre	1.50	187.00	280.50
	MCPA	litre	0.50	60.00	30.00
PEST CONTROL	Bumper	litre	1.20	183.43	220.12
	Methomidaphos	litre	1.00	110.00	110.00
	Karate EC	litre	0.65	260.99	169.64
	Wetcit	litre	1.20	110.40	132.48
	CECECE 750	litre	0.80	176.01	140.81
	Ethaphon	litre	1.00	97.34	97.34
	Abamectien	litre	0.50	108.78	54.39
	Airplane	ha	3.00	150.00	450.00
HARVESTING	Combine	ha	1.00	800.00	800.00
MECHANIZATION	M & R	ha	1.00	543.75	543.75

Source: GRIEKWALAND-WES KORPORATIEF (2014)

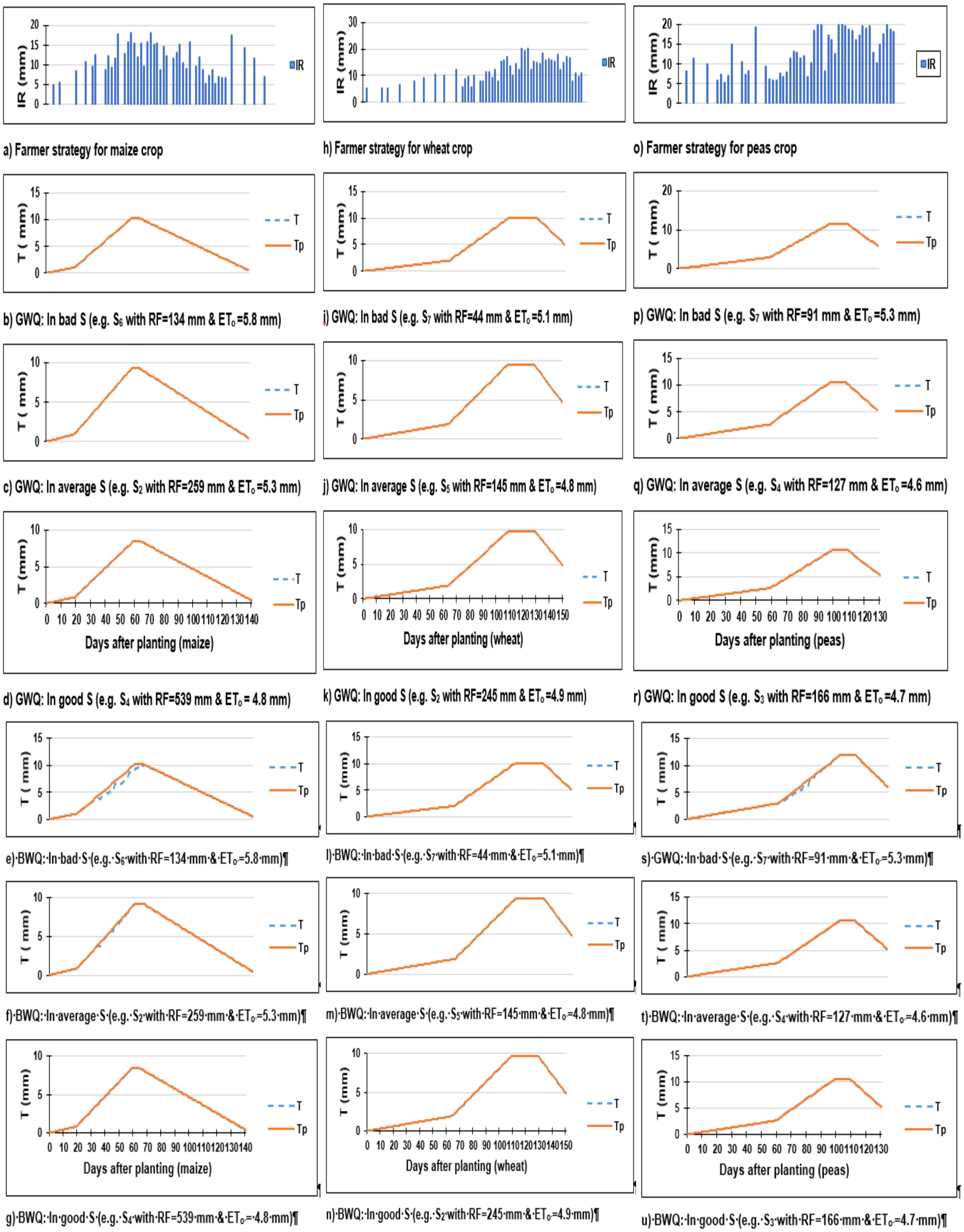
Table G.1c: Crop enterprise budget for peas crop with a target yield of 4 ton ha^{-1} (2014)

INPUTS	PRODUCT	UNIT	AMOUNT	PRICE $UNIT^{-1}$ (ZAR)	COST HA^{-1} (ZAR)
			Yield Dependent Cost		
PACKAGINIG	bags	ton	80.00	3.95	316.00
FERTILIZATION	N	kg	100.00	15.38	1538.00
	P	kg	30.00	31.60	948.00
	K	kg	80.00	12.84	1027.20
	Ca	kg	15.00	28.27	424.05
	Mg	kg	10.00	50.83	508.30
	S	kg	15.00	5.00	75.00
INSURANCE	GWK	ton	4.00	5.80%	1392.00
HARVESTING	Transport	ton	4.00	69.00	276.00
			Area Dependent Costs		
FUEL	Diesel	litre	45.00	11.45	515.25
MICRO ELEMENTS					
	Speedfol	kg	3.00	33.27	99.81
	Sidi Moly	liter	0.25	91.09	22.77
	Afrikelp	liter	1.00	77.46	77.46
	Comcat	kg	0.20	525.85	105.17
	Anngro	liter	0.12	284.45	34.13
					0.00
SEED	Seed	kg	120.00	7.70	924.00
	Entstof	gram	2.40	140.00	336.00
WEED CONTROL	Igran	litre	2.00	234.00	468.00
PEST CONTROL	Dithane	kg	2.50	66.81	167.03
	Karate	liter	0.30	260.99	78.30
	Topaz	liter	0.22	898.28	197.62
	Copperflo Plus	liter	2.50	42.00	105.00
	Lugbespuiting	ha	3.00	150.00	450.00
HARVESTING	Combine	ha	1.00	800.00	800.00
	Platsnyer	ha	1.00	290.00	290.00
MECHANIZATION	M & R	ha	1.00	382.77	382.77

Source: GRIEKWALAND-WES KORPORATIEF (2014)

APPENDIX H

SAMPLE STATES OF NATURE TRANSPIRATION AND POTENTIAL TRANSPIRATION FOR FARMER'S EXISTING IRRIGATION STRATEGY



a) Farmer strategy for maize crop

h) Farmer strategy for wheat crop

o) Farmer strategy for peas crop

b) GWQ: In bad S (e.g. S_6 with RF=134 mm & ET_o=5.8 mm)

i) GWQ: In bad S (e.g. S_7 with RF=44 mm & ET_o=5.1 mm)

p) GWQ: In bad S (e.g. S_7 with RF=91 mm & ET_o=5.3 mm)

c) GWQ: In average S (e.g. S_2 with RF=259 mm & ET_o=5.3 mm)

j) GWQ: In average S (e.g. S_5 with RF=145 mm & ET_o=4.8 mm)

q) GWQ: In average S (e.g. S_4 with RF=127 mm & ET_o=4.6 mm)

d) GWQ: In good S (e.g. S_4 with RF=539 mm & ET_o= 4.8 mm)

k) GWQ: In good S (e.g. S_2 with RF=245 mm & ET_o=4.9 mm)

r) GWQ: In good S (e.g. S_3 with RF=166 mm & ET_o=4.7 mm)

e) BWQ: In bad S (e.g. S_6 with RF=134 mm & ET_o=5.8 mm)

l) BWQ: In bad S (e.g. S_7 with RF=44 mm & ET_o=5.1 mm)

s) GWQ: In bad S (e.g. S_7 with RF=91 mm & ET_o=5.3 mm)

f) BWQ: In average S (e.g. S_2 with RF=259 mm & ET_o=5.3 mm)

m) BWQ: In average S (e.g. S_5 with RF=145 mm & ET_o=4.8 mm)

t) BWQ: In average S (e.g. S_4 with RF=127 mm & ET_o=4.6 mm)

g) BWQ: In good S (e.g. S_4 with RF=539 mm & ET_o=4.8 mm)

n) BWQ: In good S (e.g. S_2 with RF=245 mm & ET_o=4.9 mm)

u) BWQ: In good S (e.g. S_3 with RF=166 mm & ET_o=4.7 mm)

Figure H: Sample states of nature transpiration and potential transpiration for farmer irrigation strategy for field crops in a representative farm in VIS for 10 mm day^{-1} pivot irrigation-system (S is state of nature; GWQ is good quality water and BWQ is low quality water)

APPENDIX I

EXPECTED REVENUE AND COST DATA

Table I-1: Summarised economic parameters of a state-contingent production risk analysis for farmer's irrigation strategy using centre-pivot system (30.1ha)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)					
	Farmers Strategy					
	Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas
IRH (hrs)$^{+}$						
OPH	973	958	1074	973	958	1074
STH	254	347	414	254	347	414
PEH	0	27	71	0	27	71
Expected yield (kg ha^{-1})	15 242	7 446	4 473	15 187	7 446	4 457
Expected YR††	0.999	0.993	0.991	0.996	0.993	0.986
Revenue (ZAR)$^{+}$	986 363	718 291	807 844	982 796	718 291	803 718
IRC (ZAR)$^{+}$	26 667	31 503	35 461	26 667	31 503	35 461
ADC (ZAR)$^{+}$	255 038	172 104	161 372	255 038	172 104	161 372
YDC (ZAR)$^{+}$	382 278	269 495	161 461	380 895	269 495	160 636
Expected MAS (ZAR)	322 381	245 190	449 550	310 196	245 190	446 491
	SDC = 12 mm day^{-1} (Bainsvlei soil with constant water table)					
	Farmers Strategy					
	Good Quality Water			Low Quality Water		
	Maize	Wheat	Peas	Maize	Wheat	Peas
IRH (hrs)$^{+}$						
OPH	905	871	911	905	871	911
STH	118	237	390	118	237	390
PEH	0	5	40	0	5	40
Expected yield (kg ha^{-1})	15 242	7 446	4 473	15 182	7 446	4 464
Expected YR††	0.999	0.993	0.991	0.995	0.993	0.989
Revenue (ZAR)$^{+}$	986 363	718 291	807 844	98 2497	718 291	806 183
IRC (ZAR)$^{+}$	25 334	30 111	35 238	25 334	30 111	35 238
ADC (ZAR)$^{+}$	255 038	172 104	161 372	255 038	172 104	161 372
YDC (ZAR)$^{+}$	382 278	269 495	161 461	380 779	269 495	161 129
Expected MAS (ZAR)$^{+}$	323 713	246 581	449 773	321 345	246 581	448 443

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

$^{+}$ Calculation for centre-pivot size with 30.1 ha

SDC = system delivery capacity; IRH = irrigation hours

Table I-2: Summarised economic parameters of a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy‡ for a field irrigated with centre-pivot system (Intra-seasonal)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)											
	Risk Neutral						Risk Averse♯					
	Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas
IRH (hrs)+												
OPH	316	254	730	568	461	1 049	471	285	829	871	716	1 116
STH	92	62	189	194	167	355	165	67	222	198	144	371
PEH	0	0	0	0	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 151	7 421	4 439	15 150	7 405	4 455	15 231	7 433	4 461	15 234	7 430	4 467
Expected YR††	0.993	0.989	0.984	0.993	0.987	0.987	0.998	0.991	0.990	0.999	0.991	0.991
Revenue (ZAR)+	980 503	715 869	801 692	980 429	714 398	804 647	985 642	717 058	806 578	985 876	716 757	807 648
IRC (ZAR)+	8 888	6 865	20 384	16 707	13 859	31 685	13 958	7 616	23 404	23 142	19 244	33 483
ADC (ZAR)+	255 038	172 104	161 372	255 038	172 104	161 372	255 038	172 104	161 372	255 038	172 104	161 372
YDC (ZAR)+	380 006	268 586	160 232	379 978	268 034	160 822	381 998	269 032	161 208	382 089	268 919	161 422
Expected MAS/CE	336 571	268 313	459 705	328 706	260 401	450 768	334 216	268 203	459 438	325 435	256 314	450 341
	SDC=12 mm day^{-1} (Bainsvlei soil with constant water table)											
	Risk Neutral						Risk Averse♯					
	Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas
IRH (hrs)+												
OPH	305	270	717	519	465	971	438	270	746	729	628	1 013
STH	51	24	122	95	97	227	104	22	128	175	86	169
PEH	0	0	0	0	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 161	7 435	4462	15 138	7 425	4 451	15 231	7 432	4 466	15 234	7 433	4 455
Expected YR††	0.994	0.991	0.989	0.992	0.990	0.987	0.999	0.991	0.990	0.999	0.991	0.987
Revenue (ZAR)+	981 140	717 269	805 778	979 682	716 283	803 898	985 685	716 963	806 504	985 839	717 057	804 576
IRC (ZAR)+	8 866	7 238	21 414	15 324	14 737	30 873	13 621	7 181	22 380	22 715	18 287	30 260
ADC (ZAR)+	255 038	172 104	161 372	255 038	172 104	161 372	255 038	172 104	161 372	255 038	172 104	161 372
YDC (ZAR)+	380 253	269 111	161 048	379 688	268 741	160 672	382 015	268 997	161 193	382 075	269 032	160 808
Expected MAS/CE	336 983	268 815	461 943	329 632	260 701	450 980	334 638	268 562	461 135	325 808	257 530	450 029

‡ GA solution; ♯Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

+ Calculation for centre-pivot size with 30.1 ha

SDC= system delivery capacity; YR†† = relative yield calculated as (actual/potential)

Table I-3: Summarised economic parameters of a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy[‡] for a field irrigated with centre-pivot system (Inter-seasonal Maize-Wheat)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)							
	Risk Neutral				Risk Averse[♯]			
	Good Quality Water[*]		Low Quality Water[**]		Good Quality Water[*]		Low Quality Water[**]	
	Maize	Wheat	Maize	Wheat	Maize	Wheat	Maize	Wheat
IRH (hrs)[+]								
OPH	386	360	689	640	666	529	893	964
STH	134	95	259	190	173	160	257	239
PEH	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 171	7 379	15 135	7 412	15 240	7 430	15 226	7 441
Expected YR[††]	0.995	0.984	0.992	0.988	0.999	0.991	0.998	0.992
Revenue (ZAR)[+]	981 808	711 824	979 472	715 081	986 225	716 817	98 5351	717 842
IRC (ZAR)[+]	11 398	9 999	20 869	19 710	18 222	15 421	25 055	27 160
ADC (ZAR)[+]	255 038	172 104	255 038	172 104	255 038	172 104	255 038	172 104
YDC (ZAR)[+]	380 512	267 068	379 607	268 290	382 224	268 942	381 885	269 326
Expected MAS/CE	334 860	262 653	323 958	254 977	330 732	258 826	322 660	249 168
	SDC=12 mm day^{-1} (Bainsvlei soil with constant water table)							
	Risk Neutral				Risk Averse[♯]			
	Good Quality Water[*]		Low Quality Water[**]		Good Quality Water[*]		Low Quality Water[**]	
	Maize	Wheat	Maize	Wheat	Maize	Wheat	Maize	Wheat
IRH (hrs)[+]								
OPH	332	388	540	616	503	459	991	821
STH	60	21	107	137	132	93	169	90
PEH	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 140	7 381	15 095	7 403	15 231	7 431	15 234	7 445
Expected YR[††]	0.992	0.984	0.990	0.987	0.998	0.991	0.999	0.993
Revenue (ZAR)[+]	979 756	712 059	976 887	714 206	985 663	716 918	985 879	718 217
IRC (ZAR)[+]	9 781	10 141	16 181	20 427	16 000	14 489	28 896	23 382
ADC (ZAR)[+]	255 038	172 104	255 038	172 104	255 038	172 104	255 038	172 104
YDC (ZAR)[+]	379 717	267 157	378 605	267 962	382 006	268 980	382 090	269 467
Expected MAS/CE	335 221	262 657	327 063	253 713	332 324	260 112	319 728	253 262

[‡] GA solution; [♯]Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

[+] Calculation for centre-pivot size with 30.1 ha

SDC= system delivery capacity; YR[††] = relative yield calculated as (actual/potential)

Table I-4: Summarised economic parameters of a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy‡ for in a field irrigated with centre-pivot system (Inter-seasonal Maize-Peas)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)							
	Risk Neutral				Risk Averse♯			
	Good Quality Water*		Low Quality Water**		Good Quality Water*		Low Quality Water**	
	Maize	Peas	Maize	Peas	Maize	Peas	Maize	Peas
IRH (hrs)+								
OPH	669	745	774	1031	794	823	831	1 215
STH	176	295	169	327	244	321	253	402
PEH	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 194	4 455	15 100	4 448	15 239	4 470	15 221	4 472
Expected YR††	0.996	0.987	0.990	0.986	0.999	0.991	0.998	0.991
Revenue (ZAR)+	983 249	804 650	977 199	803 298	986 204	807 358	985 039	807 726
IRC (ZAR)+	18 360	23 786	20 390	30 658	22 667	26 223	23 663	37 072
ADC (ZAR)+	255 038	161 372	255 038	161 372	255 038	161 372	255 038	161 372
YDC (ZAR)+	381 071	160 823	378 726	160 552	382 216	161 364	381 764	161 437
Expected MAS/CE	328 780	458 669	323 046	450 715	326 271	458 350	323 178	447 839
	SDC=12 mm day^{-1} (Bainsvlei soil with constant water table)							
	Risk Neutral				Risk Averse♯			
	Good Quality Water*		Low Quality Water**		Good Quality Water*		Low Quality Water**	
	Maize	Peas	Maize	Peas	Maize	Peas	Maize	Peas
IRH (hrs)+								
OPH	516	724	699	979	712	860	885	1 138
STH	90	155	93	195	96	183	118	187
PEH	0	0	0	0	0	0	0	0
Expected yield (kg ha^{-1})	15 184	4 443	15 162	4 449	15 234	4 471	15 234	4 470
Expected YR††	0.995	0.985	0.994	0.986	0.999	0.991	0.999	0.991
Revenue (ZAR)+	982 636	802 363	981 202	803 538	985 846	80 7521	985 869	807 274
IRC (ZAR)+	15 107	22 735	19 633	30 413	20 028	27 237	24 864	34 295
ADC (ZAR)+	255 038	161 372	255 038	161 372	255 038	161 372	255 038	161 372
YDC (ZAR)+	380 833	160 366	380 277	160 600	382 077	161 397	382 086	161 347
Expected MAS/CE	331 658	457 889	326 254	451 152	328 554	457 485	323 748	450 184

‡ GA solution; ♯Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

+ Calculation for centre-pivot size with 30.1 ha

SDC= system delivery capacity; YR†† = relative yield calculated as (actual/potential)

APPENDIX J

EXPECTED SOIL-WATER BALANCE DATA

Table J-1: Summarised expected soil water and salt balance of a state-contingent production risk analysis for farmer's irrigation strategy using centre-pivot system (30.1ha)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)					
	Farmers Strategy					
	Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas
RF(mm)	309	131	113	309	131	113
IR (mm)	512	590	663	512	590	663
E_{Soil} (mm)	163	128	158	163	130	160
T (mm)	622	671	651	620	671	648
DRL (mm)	269	226	223	271	233	236
WTU (%)	40.4	47.5	40.8	40.3	48.8	42.8
ΔW_{Soil} (%)	2.9	2.9	2.0	2.9	2.9	2.0
ΔS_{Soil} (%)	-47.9	-48.3	-48.8	-45.0	-44.2	-44.0
SL (kg ha^{-1})	11 098	12 764	12 297	23 096	26 596	26 349
	SDC = 12 mm day^{-1} (Bainsvlei soil with constant water table)					
	Farmers Strategy					
	Good Quality Water			Low Quality Water		
	Maize	Wheat	Peas	Maize	Wheat	Peas
RF(mm)	309	131	113	309	131	113
IR (mm)	511	591	671	511	591	671
E_{Soil} (mm)	158	123	145	158	125	147
T (mm)	622	671	651	619	671	649
DRL (mm)	275	231	242	277	237	254
WTU (%)	40.4	47.2	40.5	40.4	48.4	42.4
ΔW_{Soil} (%)	2.8	2.9	2.0	2.7	2.9	2.0
ΔS_{Soil} (%)	-52.4	-48.0	-48.3	-50.1	-43.2	-43.1
SL (kg ha^{-1})	11 467	12 721	12 280	23 935	26 383	26 297

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

SDC= system delivery capacity

ΔW_{Soil} is change in soil water content at end of the growing season

ΔS_{Soil} is change in soil salt ; SL is salt leached from soil

Table J-2: Summarised expected water-use and salt build-up in a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy‡ for a field irrigated with centre-pivot system (30.1 ha) (Intra-seasonal)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)											
	Risk Neutral						Risk Averse♯					
	Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas
RF(mm)	309	131	113	309	131	113	309	131	113	309	131	113
IR (mm)	170	132	383	318	262	586	265	147	438	446	365	620
E_{Soil} (mm)	93	28	122	129	53	175	115	31	138	156	106	183
T (mm)	618	668	646	618	667	648	622	670	650	622	669	651
DRL (mm)	64	7	23	138	53	122	105	9	40	224	64	144
WTU (%)	45.8	62.0	45.8	40.8	54.3	39.6	42.2	61.2	43.0	39.9	50.5	39.4
ΔW_{Soil} (%)	-2.1	-3.6	0.6	-1.0	-2.3	2.3	-0.8	-3.0	1.1	0.1	-0.2	2.5
ΔS_{Soil} (%)	35.2	87.4	56.1	1.7	31.2	1.1	14.9	82.2	42.8	-30.5	35.1	-5.0
SL (kg ha^{-1})	2 869	573	2 486	12 059	9 547	16 952	4 642	1 010	3 641	19 510	9 945	18 531
	SDC = 12 mm day^{-1} (Bainsvlei soil with constant water table)											
	Risk Neutral						Risk Averse♯					
	Good Quality Water*			Low Quality Water**			Good Quality Water*			Low Quality Water**		
	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas	Maize	Wheat	Peas
RF(mm)	309	131	113	309	131	113	309	131	113	309	131	113
IR (mm)	178	147	420	307	290	599	271	146	437	452	360	591
E_{Soil} (mm)	93	30	131	124	60	173	111	30	140	152	112	186
T (mm)	618	670	649	617	669	647	622	670	650	622	670	648
DRL (mm)	70	10	37	133	57	134	117	11	44	227	64	127
WTU (%)	45.5	61.0	43.8	41.0	53.2	39.6	42.0	61.3	42.0	39.8	51.1	39.9
ΔW_{Soil} (%)	-2.1	-3.1	0.5	-0.8	-0.9	2.8	-1.3	-3.1	-0.6	1.5	-1.2	0.8
ΔS_{Soil} (%)	31.8	82.9	40.1	1.5	34.0	4.3	8.8	79.5	43.0	-25.2	28.3	0.1
SL (kg ha^{-1})	3 173	928	3 835	11 909	9 374	16 634	5 165	1 240	3 498	18 608	11 118	17 271

‡ GA solution

♯Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

SDC= system delivery capacity; RF is rainfall; IR is irrigation; T is transpiration; E_{Soil} is evaporation from soil; DRL is drainage loss

WTU is water table uptake contribution to T; ΔW_{Soil} is change in soil water content at end of the growing season

ΔS_{Soil} is change in soil salt; SL is salt leached from soil

Table J-3: Summarised expected water-use and salt build-up in a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy[‡] for a field irrigated with centre-pivot system (30.1 ha) (Inter-seasonal: Maize-Wheat)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)															
	Risk Neutral								Risk Averse							
	Good Water Quality				Bad Water Quality				Good Water Quality				Bad Water Quality			
	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2
RF(mm)	309	19	116	19	309	19	116	19	309	19	116	19	309	19	116	19
IR (mm)	217	0	190	0	396	0	360	0	350	0	287	0	479	0	502	0
E_{Soil} (mm)	104	24	51	10	147	25	124	11	136	24	102	10	160	24	182	10
T (mm)	619	0	638	0	617	0	641	0	622	0	642	0	621	0	643	0
DRL (mm)	77	5	4	2	173	5	22	5	146	5	7	2	242	5	95	5
WTU (%)	43.8	0.0	59.7	0.0	39.7	0.0	48.1	0.0	40.6	0.0	52.0	0.0	39.1	0.0	46.5	0.0
ΔW_{Soil} (%)	-0.5	-1.5	-0.4	1.1	2.0	-1.7	0.1	0.6	1.3	-1.7	-1.8	1.1	1.3	-1.6	-0.2	0.7
ΔS_{Soil} (%)	27.2	-3.3	76.6	-2.5	-12.8	-3.0	82.6	-4.3	0.9	-3.4	89.5	-2.4	-34.6	-3.4	77.7	-4.2
SL (kg ha^{-1})	3 464	273	418	375	15 424	357	3 902	944	6 052	224	717	300	20 606	271	10 769	666
	SDC=12 mm day^{-1} (Bainsvlei soil with constant water table)															
	Risk Neutral								Risk Averse							
	Good Water Quality				Bad Water Quality				Good Water Quality				Bad Water Quality			
	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2	Maize	OffS1	Wheat	OffS2
RF(mm)	309	19	116	19	309	19	116	19	309	19	116	19	309	19	116	116
IR (mm)	196	0	204	0	324	0	394	0	317	0	284	0	580	0	456	456
E_{Soil} (mm)	103	24	56	10	138	23	119	12	136	24	89	10	196	29	174	174
T (mm)	617	0	638	0	615	0	640	0	622	0	643	0	622	0	644	644
DRL (mm)	68	5	4	2	131	5	36	7	122	5	11	4	293	6	71	71
WTU (%)	44.7	0.0	58.6	0.0	40.7	0.0	47.0	0.0	41.5	0.0	52.7	0.0	39.4	0.0	47.8	47.8
ΔW_{Soil} (%)	-1.0	-1.5	0.0	1.1	-0.2	-1.5	3.5	0.0	0.9	0.9	0.0	0.7	3.9	-2.6	-1.1	-1.1
ΔS_{Soil} (%)	31.1	-3.5	72.8	-2.5	6.1	-3.1	49.1	-6.2	11.4	-3.5	76.9	-4.7	-46.2	-4.3	132.3	-4.7
SL (kg ha^{-1})	3 112	317	398	391	11 329	471	7 704	1 421	5 102	246	958	672	24 297	266	8 301	707

[‡] GA solution

[♯] Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

SDC= system delivery capacity; RF is rainfall; IR is irrigation; T is transpiration; E_{Soil} is evaporation from soil; DRL is drainage loss

WTU is water table uptake contribution to T; ΔW_{Soil} is change in soil water content at end of the growing season

ΔS_{Soil} is change in soil salt; SL is salt leached from soil

Table J-4: Summarised expected water-use and salt build-up in a state-contingent production risk analysis, risk-neutral and risk-averse decision makers cases, using optimal irrigation strategy[‡] for a field irrigated with centre-pivot system (30.1 ha) (Inter-seasonal: Maize-Peas)

Parameter	SDC = 10 mm day^{-1} (Bainsvlei soil with constant water table)															
	Risk Neutral								Risk Averse							
	Good Water Quality				Bad Water Quality				Good Water Quality				Bad Water Quality			
	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2
RF(mm)	309	19	79	59	309	19	79	59	309	19	79	59	309	19	79	59
IR (mm)	352	0	433	0	393	0	566	0	433	0	477	0	452	0	674	0
E_{Soil} (mm)	153	27	138	22	155	26	171	25	162	27	157	22	161	26	212	22
T (mm)	620	0	629	0	616	0	627	0	622	0	631	0	636	0	631	0
DRL (mm)	136	5	36	12	168	5	89	31	197	5	54	15	188	5	167	20
WTU (%)	42.1	0.0	41.4	0.0	39.7	0.0	38.9	0.0	40.4	0.0	41.1	0.0	39.6	0.0	39.5	0.0
ΔW_{Soil} (%)	2.2	-2.1	-4.4	4.5	1.5	-1.9	0.8	0.7	2.2	-2.1	-3.8	4.0	-0.7	-1.9	-0.7	3.1
ΔS_{Soil} (%)	-6.2	-3.8	65.8	-9.4	-12.1	-3.3	34.7	-16.2	-34.0	-3.3	95.6	-13.0	-11.6	-3.6	1.2	-16.3
SL (kg ha^{-1})	6 828	239	2 657	1 101	15 354	403	12 662	2 895	9 473	138	2 731	1 294	16 693	352	19 426	1 759
	SDC=12 mm day^{-1} (Bainsvlei soil with constant water table)															
	Risk Neutral								Risk Averse							
	Good Water Quality				Bad Water Quality				Good Water Quality				Bad Water Quality			
	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2	Maize	OffS1	Peas	OffS2
RF(mm)	309	19	79	59	309	19	79	59	309	19	79	59	309	19	79	59
IR (mm)	303	0	440	0	396	0	587	0	404	0	522	0	502	0	663	0
E_{Soil} (mm)	137	26	137	22	153	25	180	22	157	27	172	22	165	26	213	22
T (mm)	619	0	627	0	618	0	628	0	622	0	631	0	622	0	631	0
DRL (mm)	115	5	22	17	178	5	121	14	178	5	67	19	268	5	161	16
WTU (%)	42.3	0.0	40.3	0.0	39.8	0.0	39.3	0.0	41.1	0.0	39.8	0.0	39.8	0.0	39.4	39.8
ΔW_{Soil} (%)	0.6	-1.9	-1.7	3.7	0.2	-1.8	-2.1	4.3	1.9	-2.0	-2.5	3.2	0.5	-1.9	-1.8	0.5
ΔS_{Soil} (%)	5.6	-3.7	64.5	-12.7	-8.9	-3.6	11.2	-10.9	-18.3	-3.5	49.6	-14.1	-37.9	-3.6	21.6	-14.6
SL (kg ha^{-1})	5 596	263	2 058	1 677	14 928	391	16 774	1613	8 028	188	4 522	1 257	21 666	240	17 392	1 600

‡ GA solution

♯Risk aversion coefficient is 0.00182744

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 37 5mS m^{-1}; EC_e = 300 mS m^{-1}

SDC= system delivery capacity

ΔW_{Soil} is change in soil water content at end of the growing season

ΔS_{Soil} is change in soil salt

APPENDIX K

DEVIATIONS IN THE PROFITABILITY INDICATORS

Table K-1: Deviation of the profitability indicators of maize grown in crop rotation compared to that of maize cultivated in intra-season with optimal irrigation strategy (risk-neutral) using 10 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS FOR MAIZE GROWN IN CROP ROTATION FROM SINGLE MAIZE OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water*		Low Quality Water **	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ CE (ZAR)	-1 711 (-0.5)	-7 791 (-2.3)	-4 748 (-1.4)	-5 660 (-1.7)
Δ ρ_{SF}	0.00 (0)	-0.17 (-48)	0.18 (51)	0.18 (51)
Δ Expected shortfall (ZAR)	-799.0 (-22.3)	-1681.0 (-46.8)	454.0 (12.1)	1 846.0 (49.0)
Δ Expected Yield (kg ha^{-1})	20.0 (0.1)	43.0 (0.3)	-15.0 (-0.1)	-50.0 (-0.3)
Δ Expected YR††	0.002	0.003	-0.001	-0.003
Δ TVIEC (ZAR)	1 500.4 (28)	5 561.0 (106)	2 485.4 (25.2)	2 070.9 (21.0)

*characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

††YR is relative yield calculated as Yield actual/Yield Potential

Table K-2: Deviations in the profitability indicators of maize grown by following risk-averse farmer's inter-seasonal optimised irrigation-scheduling from that of risk-neutral farmer using a 10 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-AVERSE[♯]) FROM THAT OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water*		Low Quality Water **	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ CE (ZAR)	-4 128 (-1)	-2 509 (-1)	-1 298 (-0.4)	132 (0)
Δ ρ_{SF}	-0.29 (-83)	-0.12 (-67)	-0.47 (-89)	-0.47 (-89)
Δ Expected shortfall (ZAR)	-2 705 (-97)	-1 810 (-95)	-3 601 (-85)	-4 802 (-86)
Δ Expected Yield (kg ha^{-1})	69 (0.5)	45 (0.3)	91 (0.6)	121 (0.8)
Δ Expected YR[††]	0.004	0.003	0.006	0.008
Δ TVIEC (ZAR)	3 970 (59)	2 571 (24)	2 394 (19)	10 868 (91)

[♯]RAC =0.000145442 *characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

[††]YR is relative yield calculated as Yield actual/Yield Potential

APPENDIX L

DEVIATIONS IN WATER-USE EFFICIENCY INDICATORS

Table L-1: Deviations in the expected cumulative IR, DRL, WTU, SL, and expected WUE and WP of maize in crop rotation compared to that of maize in intra-season cultivated with optimal irrigation strategy (a risk-neutral decision-maker) using the 10 mm day^{-1} centre-pivot (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION FROM SINGLE MAIZE OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water *		Low Quality Water**	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ IR (mm)	47 (0.28)	182 (1.07)	78 (0.25)	75 (0.24)
Δ DRL (mm)	13 (0.2)	72 (0.13)	35 (0.25)	30 (0.22)
Δ WTU (%)	-2 (-4.3)	-4 (-8.7)	-1 (-2.4)	-1 (-2.4)
Δ WUE (%)	-3 (-3.7)	-14 (-17.3)	-5 (-7.1)	-5 (-7.1)
Δ WP_{TWU} (kg ha^{-1} mm^{-1})	-0.6 (-3.1)	-2.9 (-14.8)	-1 (-5.8)	-1 (-5.8)
Δ WP_{AW} (kg ha^{-1} mm^{-1})	-3 (-9)	-9 (-28)	-3 (-13)	-2 (-8)
Δ Expected SL (kg ha^{-1})	595 (21)	3 959 (138)	3 365 (28)	3 295 (27)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1}

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375 mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU); Water productivity ($WP_{\text{Total water-use}}$) = Grain yield/(ET+DRL);Water productivity ($WP_{\text{Applied water}}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix J

Table L-2: Deviations in the water-use efficiency and environmental impact indicators of maize grown by following risk-averse farmer's inter-seasonal optimised irrigation-scheduling from that of risk-neutral farmer using a 10 mm day^{-1} centre-pivot system (30.1 ha)

Parameter	DEVIATIONS OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-AVERSE$^{\sharp}$) FROM THAT OF MAIZE GROWN IN CROP ROTATION OPTIMISATION (RISK-NEUTRAL)			
	Irrigation Water Quality			
	Good Quality Water *		Low Quality Water**	
	1-yr (M-W)	1-yr (M-P)	1-yr (M-W)	1-yr (M-P)
	Maize^	Maize^	Maize^	Maize^
Δ IR (mm)	133	81	83	59
Δ DRL (mm)	69 (89)	61 (45)	69 (40)	20 (12
Δ WTU (%)	-3 (-7.8)	-2 (-3.8)	-1 (-2.2)	0 (-0.9)
Δ WUE (%)	-10 (-12)	-4 (-7)	-5 (-7)	-5 (-8)
Δ WP_{TWU} (kg ha^{-1} mm^{-1})	-2 (-11)	-1 (-7)	-1 (-8)	-1 (-9)
Δ WP_{AW} (kg ha^{-1} mm^{-1})	-6 (-20)	-2 (-11)	-2 (-8)	-2 (-9)
Δ Expected SL (kg ha^{-1})	2 588 (0.7)	2 645 (0.4)	5 182 (0.3)	1 339 (0.1)

*Characterised by EC_{IR} = 75 mS m^{-1}; EC_{WT} = 225 mS m^{-1}; EC_e = 150 mS m^{-1};$^{\sharp}$RAC =0.000145442

**Characterised by EC_{IR} = 225 mS m^{-1}; EC_{WT} = 375mS m^{-1}; EC_e = 300 mS m^{-1}

^Numbers in brackets are changes expressed in percentages

Water-use efficiency (WUE) = T/(RF+IR+WTU); Water productivity ($WP_{Total\ water\text{-}use}$) = Grain yield/(ET+DRL); Water productivity ($WP_{Applied\ water}$) = Grain yield/(RF+IR)

N.B: Data for T (transpiration) and RF (rainfall) are provided in Appendix J