IMPROVEMENTS TO THE FUNCTIONALITY OF THE MYCANESIM® IRRIGATION SCHEDULING ADVICE SYSTEM FOR SUGARCANE

by

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DECLARATION 2 - PUBLICATIONS

1. Paraskevopoulos, AL and Singels, A. 2012. Oral presentation. A review of weather-based irrigation scheduling decision support systems. *Combined Congress, Potchefstroom, North West University, Jan 2012.*

2. Paraskevopoulos, AL and Singels, A. 2013. Integrating weather based crop modelling and soil water monitoring technologies to provide improved decision support for sugarcane irrigation management. *86th Annual Congress of the South African Sugar Technologists' Association, Durban, South Africa, 6 - 8 August 2013.*

3. Paraskevopoulos, AL and Singels, A. 2014. Integrating soil water monitoring technology and weather based crop modelling to provide improved decision support for sugarcane irrigation management. *Computers and Electronics in Agriculture*, 105, 44-53.

4. Paraskevopoulos, AL and Singels, A. 2014. Poster presentation. Optimising sugarcane irrigation scheduling with limited water: a simulation study. S*outh African National Council on Irrigation and Drainage Symposium, Glenburn Lodge, Gauteng, 18 - 20 November 2014.*

5. Paraskevopoulos, AL, Singels, A and van Niekerk, H. 2012. Oral presentation. Integrating weather based crop modelling and soil water monitoring technologies to provide improved decision support for sugarcane irrigation management. *South African National Council on Irrigation and Drainage Symposium, Alpine Heath Resort, Drakensberg, 20 - 23 November 2012.*

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ABSTRACT

MyCanesim® is a web-based crop simulation system that can be used for irrigation scheduling and yield estimation. Two shortcomings of the system identified were that 1) advised irrigation amounts could exceed seasonal water limitations imposed on farmers and 2) simulations are only accurate if farmers follow the recommended irrigation actions and if simulated and actual available soil water content are similar. These can be addressed by incorporating algorithms for optimal scheduling of limited water, and by making use of soil water content measurements in model simulations. The objectives of this study were to 1) evaluate the performance of different optimization algorithms that schedule limited water and 2) determine the accuracy of irrigation scheduling advice and cane yield estimates with and without adjustment of simulations with soil water content records.

Four irrigation scheduling algorithms were tested against a baseline algorithm, using 960 hypothetical scenarios consisting of different water supply, climate and cropping situations. These were: (a) Crop stage, which accounts for the yield sensitivity to water deficit as it varies with growth stage; (b) Stress level, which evaluates different soil water depletion levels for determining irrigation dates; (c) Prorata, which reduces irrigation throughout the growing season in proportion to the seasonal allocation shortfall; and (d) Water satisfaction, which iteratively schedules irrigation events on the day with the largest water demand. Algorithms increased simulated yields over the baseline by between 4.7 and 8.6 t/ha on average and operated at computational running times of between 1 and 40 s. The stress level algorithm was recommended for inclusion into MyCanesim®, since it had both a high yield improvement (8.5 t/ha) and quick operational time (2.5 s).

Soil water measurements from capacitance probes for thirteen fields in Mpumalanga were integrated through an automated process into the MyCanesim® system. The improvements in the accuracy of irrigation scheduling advice and yield estimates by the integrated system were assessed retrospectively. The integrated system resulted in more accurate irrigation scheduling advice (by 2 days) than weather-based scheduling alone.

These two improvements to MyCanesim® should allow sugarcane farmers to achieve higher irrigated water use efficiency and yields because of more accurate irrigation scheduling advice and yield estimates for full and restricted irrigation water supply.

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GLOSSARY

Acronym	Key Concept	Definition	Units
	Growing season	The period from the start of the crop to the harvest date.	Days
	Growth stage	A period within the growing season during which the crop behaves in a certain way.	Days
	Historical weather sequence	A time series of daily historic weather data, covering the period of a growing season.	
	Irrigation schedule	A program of irrigation dates and amounts for a given period.	
	Irrigation scheduling algorithm	An algorithm that generates a schedule of irrigation dates and amounts over the entire growing season.	
	Irrigation scheduling strategy	A set of rules that determined the dates and amounts of irrigation.	
	Rainfall classification	A way of grouping past rainfall data sequences into classes according to total rainfall over those periods.	
	Stressed crop	A crop that suffers yield loss due to having insufficient or too much soil water during some portion of the growing season.	
ADL	Allowable depletion level	The available soil water content (*ASWC*) at which an irrigation event will be triggered if there are no other constraints.	mm

$ALLOC_{\mathrm{cumd}}$	Cumulative daily allocation	The total amount of water available for irrigating the crop since the start of the crop until day *d*.	mm
$ALLOC_{stage\ s}$	Stage allocation	The total amount of water available for irrigating the crop for a particular growth stage *s*.	mm
$ALLOC_{season}$	Seasonal allocation	The total amount of water available for irrigating the crop over the entire growing season.	mm
ASWC	Available soil water content	The amount of water in the soil available to the plant, above the wilting point.	mm
$ASWC_{probe}$	*ASWC* generated from capacitance probe data	*ASWC* derived from *SWI* readings from capacitance sensors.	mm
AWS	Automatic weather station	A set of sensors, data loggers and transmitters for monitoring, storing and transmitting meteorological data.	
CR	Conversion ratio	A calibration factor used to convert *SWI* to *ASWC*.	mm/%
DNI	Date of next irrigation	The date when the next irrigation event is due.	
ET_0	Reference grass evapotranspiration	The rate of evapotranspiration from a large area covered by green grass, 8 to 15 cm tall, which grows actively, completely shades the ground and which is not short of water. (FAO, 2015 and Allen *et al.* 1998)	mm
ET_A	Actual evapotranspiration	Evapotranspiration of a crop under given conditions. The crop may or may not be stressed and have a partial canopy.	mm

Ecref	Sugarcane reference evapotranspiration	The potential evapotranspiration for an unstressed sugarcane crop with a full canopy. (McGlinchey and Inman-Bamber, 1996)	mm
ET_P	Potential evapotranspiration	Evapotranspiration of a crop at its given stage of development and with adequate water.	mm
GA	Genetic algorithm	A problem solving method that recombines and mutates current solution candidates to form new ones until a satisfactory solution has been found.	
GDD	Growing degree days	A thermal time measurement of plant age.	^{0}C days
FTP	File transfer protocol	A method of transferring files across the internet.	
FC_{SWI}	Soil water index field capacity	*SWI* reading from capacitance probes when soil water content is at field capacity.	%
$Isched_{cumd}$	Cumulative irrigation amount	The total amount of irrigation that has been scheduled and applied from the start of the crop to the current day *d*.	mm
$Isched_{cumseason}$	Cumulative irrigation amount for the season	The total amount of irrigation that has been scheduled and applied from the start of the crop to the harvest day.	mm
I_d	Daily irrigation amount	Irrigation amount on day *d*.	mm
IR_{cumd}	Cumulative irrigation requirement	The total amount of irrigation that a crop would need in order to avoid	mm

		water stress, from the start of the crop to the current day *d*.	
$IR_{cumseason}$	Cumulative irrigation requirement for the season	The total amount of irrigation that a crop would need in order to avoid water stress, from the start of the crop to the harvest date of the crop.	mm
IWUE	Irrigated water use efficiency	The increase in cane yield per unit of irrigation applied.	(t/ha/100mm)
K_C	Crop coefficient	Used to convert from ET_0 to the potential *ET* for a specific crop *C*.	
K_y	Yield response factor to water	The proportionality factor between relative yield loss and relative reduction in evapotranspiration, for a given growth stage or for the entire season.	unitless
PBS	Probe-based simulation	Simulation based on a combination of weather data and correction of soil water with $ASWC_{probe}$.	
R_d	Daily rainfall total	Rainfall total on a day *d*.	mm
SMS	Short message service	A method of text communication via cellular device.	
SWC	Soil water content	Generic term used to refer to some measure of soil water status.	mm or cm^3/cm^3
SWD	Soil water deficit	The difference between *TAM* and *ASWC*.	mm
SWI	Soil water index	A measure of soil water content as indicated by a capacitance probe (aggregated over all sensor readings).	%
TAM	Maximum plant available soil water.	The maximum amount of water in the soil that the plant can access when the roots occupy the full profile.	mm

WBS	Weather-based simulation	Simulation based only on weather data and not on data from soil or plant based sensors.	
WSI_d	Water satisfaction index	An index reflecting the availability of water to the plant. It is calculated from daily rainfall, daily irrigation and daily ET_P records.	unitless
Y_A	Simulated cane yield	Simulated fresh stalk mass of the sugarcane crop, under given conditions, with or without water stress.	t/ha
Y_D	Simulated dryland cane yield	Simulated fresh stalk mass from a dry land crop.	t/ha
Y_I	Simulated irrigated cane yield	Simulated fresh stalk mass from an irrigated crop under specified irrigated conditions.	t/ha
Y_M	Simulated maximum cane yield	Simulated fresh stalk mass of a sugarcane crop that can be achieved under given conditions and with no water stress.	t/ha
Y_{obs}	Observed yield	Yield derived from cane deliveries to the mill from a specific field.	t/ha
Y_{opt}	Optimal yield	Simulated potential yield for a given field given its specific soil properties, irrigation system and weather conditions.	t/ha
Yswc	$ASWC_{probe}$ based simulated yield	Simulated yield for a given field using $ASWC_{probe}$ to correct simulated soil water content.	t/ha
ΔY_s	Simulated stage yield increment	The increase in simulated stalk fresh mass over a given growth stage *s*.	t/ha

1. INTRODUCTION

1.1 Introduction

Irrigation scheduling is the process of deciding the timing, quantity and frequency of water application to a crop. Leib *et al*. (2002) defined scientific irrigation scheduling as the use of physical measurements to estimate crop water use and soil water status to inform these decisions. The main goals of irrigation scheduling are: to improve yield, conserve water, prevent groundwater pollution (Martin *et al*., 1990), to improve crop quality, avoid leaching of nutrients and avoid introducing crop stress through over or under-irrigation (Jensen *et al.*, 1970). Irrigation scheduling often aims to maintain available soil water content (*ASWC*) within a predetermined range, in order to achieve the aforementioned goals (Olivier and Singels, 2004).

Irrigation scheduling methods can be classified as weather-based, soil-based or plant-based. This study focused on weather-based methods. Weather-based irrigation scheduling decision support systems (*ISDSS*) rely on rainfall and potential evapotranspiration (ET_P) data obtained from a network of weather stations. Weather-based *ISDSS* can also provide estimates of yield by simulating crop growth.

One example of a weather-based *ISDSS* is MyCanesim® (Singels and Smith, 2006), which has been in existence since 2004. This system was developed by the South African Sugarcane Research Institute (*SASRI*) for farmers and researchers to make use of the Canesim® sugarcane model (of which various aspects are described by Singels *et al.,* 1998; Singels and Donaldson, 2000; and Singels and Bezuidenhout, 2002) for yield estimation and irrigation scheduling decisions. The MyCanesim® system provides irrigation scheduling advice *via* a website, cell phone, e-mail and/or fax (Singels and Smith, 2006).

After its initial development, MyCanesim® was used to provide real-time irrigation scheduling advice to a group of small-scale farmers in Pongola. This service was initiated in May 2005 and was extended to 50 farmers by 2008. Two shortcomings and recommendations for the improvement of MyCanesim® identified during this project (Singels and Smith, 2008) were as follows:

(a) It was possible for the imposed seasonal water limitations to be exceeded when following prescribed irrigation scheduling advice. Hence a method, or irrigation scheduling algorithm, was required which would provide sound irrigation advice, while taking seasonal water allocations into account. It was therefore decided to investigate, develop and compare algorithms for the optimal scheduling of limited water and to include one of these in MyCanesim®.

(b) Farmers mostly do not capture their irrigation records through the MyCanesim® web interface, mainly due to a lack of time, computer resources and or skills on their part (the majority of users are small scale farmers). MyCanesim®'s implied assumption that farmers always follow the prescribed schedule may therefore lead to actual and simulated soil water balances being different when farmers deviate from recommendations.

The use of soil water content measurements from soil water sensors, which form part of soil-based irrigation scheduling methods (Evett and Heng, 2008), were identified as a possible solution to this problem. In this study, such measurements were used to correct simulated soil water content, thus implicitly recording farmer irrigation activities. Consequent improvements to the accuracy of irrigation scheduling and yield forecasting were investigated.

Based on these shortcomings, the following research questions were addressed in this study:

(a) Which limited water optimization algorithm, amongst those reviewed, achieves the highest yield and irrigation water use efficiency (*IWUE*)?
(b) Will integrating *A*S*WC* records with a weather-based simulation model provide more accurate irrigation scheduling advice and yield forecasts?

The two main objectives of the study were therefore to:

(a) research and develop algorithms for scheduling limited water. The theoretical performance of several algorithms should be compared by determining the simulated yield increase over that of a baseline. The *IWUE* and computation time of each algorithm should also be evaluated. The algorithms should be tested using historical data.

(b) determine the accuracy of irrigation scheduling advice and simulated cane yields with and without adjustment to simulations of the crop soil water balance by means of measured *ASWC*, for thirteen fields in Mpumalanga.

The study is divided into three main sections (Chapters 2, 3 and 4), followed by a general discussion and conclusions (Chapter 5). Chapter 2, the literature review, focuses on various *ISDSS* and what features they offer, on irrigation scheduling under limited water supply and on soil water monitoring technology, thus providing scope for both general and specific future improvements to MyCanesim®. Chapter 3 addresses the first research question. For each algorithm, simulated yields generated under various hypothetical conditions and water supply scenarios were compared to that of a baseline algorithm. Chapter 4 addresses the second research question. Chapter 5 reviews the degree to which the research questions were answered, highlights important considerations and gives recommendations and ideas for future work.

1.2 References

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2. LITERATURE REVIEW

2.1 Introduction

Irrigation scheduling methods can be classified as weather-based, soil-based or plant-based. Jones (2004) and Stevens *et al.* (2005) reviewed the different irrigation scheduling methods and related technologies. Weather-based methods rely on estimations of evapotranspiration (*ET* in mm) from the crop (Penman, 1948 and Monteith, 1965; Priestley and Taylor, 1972; Diak *et al.*, 1998), which can be potential, (ET_P), *i.e.* what would be evapotranspired from a non-stressed crop, or actual (ET_A), what a crop actually evapotranspires. The ET_P experienced by a short, well-watered grass crop (ET_0) is related to a specific crop ET_P by a coefficient K_C. Soil-based methods, which give an indication of soil water content, include capacitance sensors (Evett and Heng, 2008) and the wetting front detector (Stirzaker *et al*. 2007). Plant methods include stalk elongation rate *e.g.* growth transducers (Inman-Bamber, 1995; Smit *et al.*, 2005) and the difference between canopy and air temperatures *e.g.* infra-red thermometers (Raschke, 1960, cited by Jones 2004; Jones, 1999). There are many more examples that can be found in the literature. This study focuses primarily on weather-based *ISDSS*.

With advances in telecommunication and internet services, many new weather and web-based *ISDSS* have been created over the last 20 years. For example, PlanteInfo of Denmark (Thysen and Detlefsen, 2006); NDAWN for the USA (Akyuz *et al.*, 2008); IMO of Oregon, USA (Hillyer and Sayde, 2010); WaterSense of Australia (Inman-Bamber *et al.,* 2005); and finally MyCanesim® of South Africa, are all examples of recently created *ISDSS*. Each system offers unique features to their client-base, which includes farmers, extension specialists and scientists.

The various means of communication, such as short message service (*SMS*), e-mail, websites and remote logins, like file transfer protocol (*FTP*), have facilitated the fast and easy access of data. Services, such as evapotranspiration estimations (Marek *et al*., 1996; CIMIS, 2011) and water balance and crop models (Annandale *et al.*, 1999; Lecler, 2000; Inman-Bamber *et al.*, 2007), have been made more accessible (Thysen and Detlefsen, 2006) to farmers.

The aim of this chapter is to report on a review of weather based *ISDSS,* to identify useful features and approaches in providing irrigation scheduling advice and to understand the state of such systems. Recommendations for improving the services of MyCanesim® will be made.

2.2 Irrigation Scheduling Decision Support Services and Systems

An *ISDSS* helps farmers to decide when and how much to irrigate. Four types of *ISDSS* are reviewed, namely irrigation information services (*IIS*), desktop and online model based *ISDSS* and soil water probe based *ISDSS*.

2.2.1 Irrigation information services

Table 2.1 summarizes key aspect of *IIS*s reviewed. The services reviewed in this section do not simulate farmers' fields or maintain a soil water balance, but give estimations of *ET*. In some cases, users need to estimate K_C values themselves. In other cases, these are provided. In the most advanced form, timing between irrigation events is given. Irrigation scheduling information is provided by a variety of different media. Some services deliver information related to crop growth, in addition to that of irrigation scheduling.

Table 2.1 Comparison of various *IIS* that provide generic information to support irrigation scheduling.

Variable[1]	**Explanation and further details of service**	**Media used**	**Reference**
ET_0		Internet-based bulletin board, e-mail, fax, a webpage	Marek *et al.*, 1996; AgriLifeExtension, 2011; Smith and Munoz, 2002
ET_0, K_C values	K_C factors were determined from field visits.	Website, *FTP*, consultants	CIMIS 2011; Smith and Munoz, 2002
ET_0 – rain	The service provided irrigation requirement and took into account short-term weather forecasts.	Fax	Hideshima *et al.*, 1996
ET_P	Crop-specific ET_P information was provided for several crops and planting dates.	Radios, newspapers, consultants	Salazar *et al.*, 1996
Ecref		Website	Singels *et al.*, 1999b
ET_P, temperature	ET_P was calculated as a function of crop type, crop start date and daily temperature.	Publication and website	Werner, 1996
GDD, physiological growth stage , K_C values		Internet-based bulletin board	Marek *et al.*, 1996
Irrigation intervals, delays for rain	Intervals depend on crop start date, time of year and were developed from long-term ET_P.	Tables on handouts, or electronic sheets *via* e-mail	Olivier *et al.*, 2009

[1]Refer to glossary for a list of terms and definitions

2.2.2 Crop model based desktop ISDSS

These systems use a crop model and soil water balance simulation model to generate information that can be used to make irrigation scheduling decisions. They operate on the user's computer and require field specific data to be entered. Table 2.2 lists the systems researched.

Systems that described their irrigation scheduling component in greater detail were studied more deeply (Table 2.3). Notable features are grouped according to the categories of, the operating engine, inputs and the outputs. MyCanesim®, although web-based, is nevertheless included for comparison.

The most popular features of these systems were: 1) the provision of irrigation scheduling advice (timing and amounts) and 2) the display of the soil water balance on a graph (both included in MyCanesim®). Features that MyCanesim® lacked include:

(a) The use of soil water measurements to correct simulations. Five *ISDSS* had this feature, but the automation of the collection of soil water data were not developed;
(b) The ability to cater for an irrigation strategy which changes during the season;
(c) An algorithm for optimising the irrigation schedule when seasonal water supply is limited; and
(d) The linking of the *ISDSS* to a *GIS* system, which adds a strong visual element.

The development of these features into MyCanesim® would result in a more versatile and powerful irrigation scheduling service.

Table 2.2 List of crop model based desktop *ISDSS* and degree of crop coverage.

Name	**Crop Coverage**	**Reference**
AquaCrop	Many crops	Steduto *et al.*, 2009; Raes *et al.*, 2011
Arkansas Irrigation Scheduling Program	Soybeans	Tacker *et al.*, 1996
BEWAB[1]	A few crops	Bennie *et al.,* 1988, cited by Singels *et al.,* 2010
Calex Cotton	Cotton, else not clear	Plant *et al.*, 1992
CANEGRO[1]	Sugarcane	Inman-Bamber, 1991
CanePro[1]	Sugarcane	McGlinchey, 2011
EPIC-PHASE	Maize, else not clear	Cabelguenne *et al.*, 1997
GISAREG, based on ISAREG (Pereira *et al.*, 2003)	Many crops	Fortes *et al.*, 2005
GWK[1]	A few crops	Stevens *et al.*, 2005
IrrigRotation	Many crops	Rolim and Teixeira, 2008
Irricheck[1]	Many crops[2]	Stevens *et al.*, 2005
Mehran Model	Wheat, cotton else not clear	Lashari *et al.*, 2010
MODERATO	Not clear	Bergez *et al.*, 2001
PUTU[1]	Many crops[2]	De Jager *et al.*, 1987; Stevens *et al.*, 2005
PRWIN[1]	Not clear	Stevens *et al.*, 2005
SCHED	Cabbage and squash	Ells *et al.*, 1993
SimISP	Potatoes	Singh *et al.*, 1993
SQR Canesim[1]	Sugarcane	SQR-Canesim manual, Vers. 2004
SWATRE	Potatoes, else not clear	Wesseling and van den Broek, 1988
SWB[1]	Many crops[2]	Annandale *et al.*, 2005
VINET1	Grapes	Stevens *et al.*, 2005
WISE	Not clear	Leib *et al.*, 2001
ZIMSched1	Sugarcane	Lecler, 2000

[1] Model developed in South Africa
[2] Includes sugarcane

Table 2.3 Features of crop model desktop based *ISDSS* that are used for irrigation scheduling.

S = single-crop, M = multi-crop, Y = yes, N = no, U = unclear and NM = not mentioned in paper.

Application / Feature	**Aqua-Crop**	**Cane-Pro**	**GISA-REG**	**SQR-Canesim**	**MODE-RATO**	**My-Canesim®**	**SWB**	**WISE**	**ZIM-Sched**	**Count of ISDSS with this feature**
Multi-crop / single-crop[1]	M	S	M	S	S	S	M	M	S	
Schedules limited seasonal water optimally[1]	NM	U	NM	N	NM	N	NM	NM	NM	0/9
Accounts for within field soil water spatial variability[1]	N[5]	U	NM	N	Y	Y	NM	NM	Y	3/9
Caters for flexible irrigation strategies *e.g.* for summer versus winter[1]	NM	U	NM	N	Y	N	Y	Y	Y	4/9
Weather data downloaded from weather stations automatically[2]	U[5]	U	NM	N	NM	Y	N	Y	Y	3/9
Makes use of soil water measurements[2]	U	Y	NM	Y	NM	N	Y	Y	Y	5/9
Uses a *GIS* system for visualisation[3]	N[5]	U[5]	Y	N	NM	N	U[5]	NM	N	1/9
Allows for control of irrigation pumps[3]	NM	Y	NM	N	NM	N	Y	NM	NM	2/9
Reports on physiological growth stage[3]	Y	Y[4]	Y	Y[4]	Y	Y[4]	Y	NM	NM	7/9
Recommends irrigation timing and amounts[3]	Y	Y	U	Y	Y	Y	Y	Y	Y	8/9
Displays *ASWC* on a graph[3]	Y	Y	Y	Y	NM	Y	Y	Y	Y	8/9

[1] Engine features
[2] Input features
[3] Output features
[4] Canopy cover only
[5] Under research for further development

2.2.3 Crop model based online ISDSS

Online *ISDSS* provide the benefits of a crop/water-balance model, whilst having a centralised data storage facility. Similar to the desktop applications of Section 2.2.2, these systems require the user to enter field inputs and to learn how to identify useful information from the outputs. Each *ISDSS* will be discussed under the headings of engine, inputs, outputs and technology used. Four systems were reviewed, namely PlanteInfo (Thysen and Detlefsen, 2006); NDAWN (Akyuz *et al*., 2008), IMO (Hillyer and Sayde, 2010) and WaterSense (Inman-Bamber *et al*., 2005).

PlanteInfo

PlanteInfo, an internet-based *ISDSS* for crop production, was launched in Denmark in 1996 (Jensen *et al*., 2000; Thysen and Detlefsen, 2006). By 2005, 334 farmers and 56 advisers were using the system. PlanteInfo is able to simulate the growth of all the major crops in Denmark, namely beet, pea, potato, maize, wheat, rape and grass (Thysen and Detlefsen, 2006). Root depth, phenological stage and leaf area index (*LAI*) are modelled. Crop development stages (*e.g.* elongation, filling and ripening for wheat) can be entered or calculated according to thermal time. A soil water balance is simulated for individual fields. Two soil horizons, each with their own depth and drainage properties, are modelled.

The system uses data from a network of 40 automatic and manual stations and 400 rainfall stations in Denmark. This is done with the aid of the Danish Meteorological Institute, who also provide weather forecasts. Medium-range climatic forecasts are obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). The processing of data from *AWS's* and manual stations takes one hour and three hours, respectively.

PlanteInfo has a simple interface for new users and a more advanced interface for experienced users. There is an input form for each variable, allowing one variable to be captured for all fields on one form. The developers of PlanteInfo felt that it was more user-friendly not to request all variables for an individual field on a single form. Rainfall data can be based on local rainfall records or from a nearby weather station. User-recorded rainfall data are captured into PlanteInfo, *via* a calendar type entry form.

The main output of the system *via* a webpage is the soil water status for the current and coming five days of every field. This output is based on weather forecasts. The system does not recommend irrigation actions. Fields are grouped together on a single report, one field per line. Soil water deficit (*SWD*) is shown both numerically and graphically and is colour-coded to indicate its severity. It is possible to sort and filter the table. Several other variables are displayed, namely root development, *LAI*, evaporation from the soil (*E)*, transpiration from the crop (*T)* and ET_P.

The application is coded in the Statistical Analysis Software package (SAS, Cary, North Carolina, USA) and uses SAS Graph and JavaScript. The platform-specific user-interfaces (cell phone, desktop) are linked to a common database.

North Dakota Agricultural Weather Network (NDAWN) irrigation advice service

The NDAWN irrigation scheduling application can be found at http://ndawn.ndsu.nodak.edu. The system was described by Akyuz *et al*. (2008). A spreadsheet version of the model used in the system is described by Steele *et al.* (2010). By 2008, the system had 40 users and over 200 fields registered.

The NDAWN system uses a soil water balance model (water profit and loss system). The three soil types occupying the largest area of the field are modelled as cohorts. A multi-layered root zone that increases linearly in depth with time, is simulated (Scherer, 2011). Although the crop canopy is not simulated, ET_0 can be determined from radiation and temperature using the Jensen and Haise Equation (1963; cited by Steele *et al.*, 2010). ET_P was determined using K_C curves developed by Stegman *et al*. (1977; cited by Steele *et al.*, 2010), based on days after emergence of the crop. Actual evapotranspiration (ET_A) is then calculated by the model from ET_P and the crop water stress.

Weather data are downloaded daily from an *AWS* network. The user selects his field from aerial photographs from a *GIS*-type interface and enters the crop type, planting date and emergence date. Soil properties, such as slope and rooting depth, are downloaded from a database of the United States Department of Agriculture-Natural Resource Conservation Services (USDA-NRCS). Irrigation data are captured by the farmer.

The system displays ET_A and the *SWD* for the various soil types in each field in a table. A *GIS*-based aerial photograph of the field indicates the sub-field boundaries.

The system was built from open source software. JQuery and Yahoo User Interface (YUI) (Yahoo, Sunnyvale, California, USA) manages the web pages. OpenLayers was used for the *GIS* interactions. A PostgreSQL database was used to store *GIS* shape files and PostGIS, an extension to PostgreSQL, was used to create the layered soil maps

Irrigation Management Online (IMO)

IMO (Hillyer and Sayde, 2010) was developed by Oregon State University and the Natural Resources Conservation Service (NCRS). By 2010, the system was undergoing its fourth year of field trials. The system consists of three components: 1) the Irrigation Efficiency Model (IEM), 2) the web-based advisory system and 3) an Excel-based economics module.

The IEM component provides yield estimates based on estimations of *ET*. To achieve this, weather data from several automatic North American *AWS* networks are downloaded daily into the system. The yield calculations are based on the method of Doorenbos and Kassam (1979) though the IMO developers intend to integrate the new FAO AquaCrop model (Steduto *et al*., 2009) into their system. Soil water measurements are combined with reference *ET* values to calculate *ASWC.*

The second component is the web advisory system which takes into account the water needs for the whole farm and provides an optimum schedule for each field. The system can provide irrigation scheduling advice under a limited water supply scenario. Three different future weather scenarios, namely high, average and low *ET* scenarios are generated.

The economics module calculates profits, based on yield income and cost of irrigation. The module downloads yield and irrigation amounts from the simulation scenarios.

System inputs are facilitated through a series of wizards, which explain what is required at each step. User inputs include: the irrigation efficiency, a soil water allowable depletion level (*ADL*), a target refill level and the daily farm irrigation capacity.

System outputs such as irrigation dates and amounts and *ASWC* are provided for each field on graphs. The system advises on the gross daily and seasonal irrigation requirements and indicates when the farm-level irrigation capacity would be exceeded by the irrigation schedule.

The IEM component of the system is programmed in C# (Microsoft Corporation) and uses MODCOM. The Economic spreadsheet is programmed in VBA in Excel (Microsoft Corporation).

WaterSense

WaterSense is a tool developed for sugarcane in the Childers and Bundaberg regions in Australia (Inman-Bamber *et al*., 2005). WaterSense is the combination of two previous systems called WaterBalance (Inman-Bamber *et al*., 2007) and CaneOptimizer, based on the APSIM model for sugarcane (Keating *et al.*, 2003). WaterBalance was developed for irrigation scheduling under conditions where water supply would easily meet the *ET* demand and calculated ET_0. CaneOptimizer was developed for restricted water conditions (Inman-Bamber *et al*., 2007) and calculated canopy cover and the soil water balance. The algorithm used by WaterSense to schedule under limited water is given in Section 2.3.2. Essentially, it finds the optimal irrigation trigger (plant stress level) at which the limited water supply produces the highest yield.

Field data inputs include: the nearest *AWS*, irrigation records, plant and harvest dates, soil type and the annual water allocation. The user specifies a maximum *ADL* when scheduling with an unlimited water supply.

The user is presented with graphs of canopy cover (%), a stress index (%), the advised dates and amounts of irrigation, the *SWD* at different depths in the soil profile and expresses the daily yield increment as a percentage of the unstressed value (Inman-Bamber *et al*., 2007). The user also receives e-mail feedback summarising his inputs, yield estimates, past irrigation and future irrigation dates (Inman-Bamber, 2005). Future irrigation events are shown as cumulative frequency distributions, since many historical weather sequences are used as substitutes for future scenarios.

The model is written in VB.net (Microsoft Corporation,) and the data is stored in an SQL Server database (Microsoft Corporation,). The website is written in ASP.net (Microsoft Corporation) (Inman-Bamber, 2011).

2.2.4 Soil water probe based ISDSS

A number of companies offer irrigation scheduling services through the use of capacitance probes. In South Africa, these include Aquacheck, DFM, Probe Schedule and Irricheck™. Typically, services from these companies will include installation and maintenance of probes, as well as provision of a software interface which gives soil water sensor outputs and irrigation scheduling recommendations. In some cases agronomic support is also offered to help farmers to interpret such data. The features of a few of these services are now discussed.

Aquacheck (www.aquacheck.co.za) started in 1997. Soil water data may be delivered or collected using general packet radio service (*GPRS*), radio frequency (*RF*) or hand held devices either to a central server or to the local computer. The data can then be viewed using the CropGraph desktop program, mobile or web interface (www.aquacheckweb.com). Data is converted to mm values by agents and agronomists, who also choose the soil water irrigation trigger levels. No forecasts appear to be made. The software recommends current irrigation amounts equal to the current *SWD*. Soil water data and precipitation can be graphed (Figure 2.1). Sensor measurements can be reported individually or as a weighted average over all depths. The software also reports on root zone (weighted average of top sensor readings) and buffer zone (weighted average of lower sensor readings) soil water status.

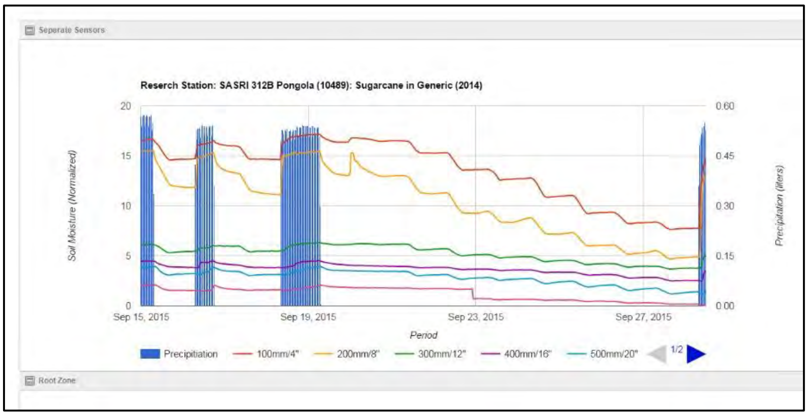

Figure 2.1 Aquacheck separate sensors graph (available at www.aquacheckweb.com).

Probe Schedule (www.probeschedule.com) offers a software service in conjunction with various probe vendors such as HydraWize. Data from probes are transferred to a central server using *GPRS*. The data are made available *via* apps and notifications for smart phones or *via* a website. An in house agronomist determines the allowable depletion level (*ADL*) in soil water status terms used by the software for each field. Each farm has its own dashboard listing the current soil water status of each probe over three depths, allowing the farmer to quickly determine his next irrigation action. Soil water deficits (and hence irrigation requirements) are given in numbers and colour is employed to indicate the severity of the deficit (red – dry, green – sufficient, blue – overly wet). Graphs of soil water status data are also available and *ET* is projected. The software provides links to other useful websites that provide current wind conditions and short term rainfall forecasts.

Irricheck™ (www.irricheck.co.za) provides irrigation scheduling advice through the use of data from capacitance probes as well as a network of weather stations. Probes are connected to *GPRS* receivers and transmitters, which collect data half hourly. Soil water data are stored on a cloud database and are used to determine crop water requirements, which depend on the phenological stage of the crop. Software interfaces are available *via* apps for smart phones and through a website. Weather forecasts (max and min temp, wind speed and cloud cover) are provided. Advice includes the status of the top and bottom soil layers (too dry, ok, too wet) and irrigation dates and amounts are recommended. Rainfall for each of the last four days as well as estimated actual transpiration and evaporation over the past week are reported on. The service is backed by a team of agricultural and irrigation specialists and agents.

2.2.5 The MyCanesim® system

MyCanesim® (http://portal.sasa.org.za, 2011) is a web-based crop simulation system that can be used for irrigation scheduling or research investigations. Because this system forms the basis of this research, it will be described in more detail, compared to the previous systems in Section 2.2.3.

System description

MyCanesim® is a centralised model based *ISDSS* and consists of several components (Singels and Smith, 2006). Data (rainfall, temperature, solar radiation, humidity and wind) from 42 automatic weather stations, are downloaded at 8am each day. Both ET_0 and *Ecref* are calculated, the data quality is checked and patched data are stored in an Oracle database. Data processing takes approximately 2 hours. A daily time step crop model (Canesim®) simulates the water balance, canopy cover and yield with or without irrigation. Canesim®'s water balance algorithms are described by Singels *et al.* (1998), the canopy development by Singels and Donaldson (2000) and the sucrose and yield formation by Singels and Bezuidenhout (2002). In Canesim, the accumulation of biomass is a function of the amount of radiation intercepted by the crop as well as crop water status. The partitioning of biomass to stalks depends on the development stage of the crop.

A program called IrrigationSMS determines the irrigation advice. For irrigation systems which move to different cohorts in the same field, the scheduling takes into account three cohorts, as well as the anticipated *ET* on each cohort for the remainder of the irrigation cycle (Singels and Paraskevopoulos, 2010). A program called the IrrigationController allows the system administrator to update harvest dates and capture irrigation events. A web-based user-interface allows users to manage fields. An e-mail-*SMS* gateway called SMS-Impi delivers the text messages and the program Canesim®-SMS-Reply responds to *SMS* feedback from farmers, which indicates whether irrigation advice is followed or not.

Inputs for the Canesim® model

The MyCanesim® website allows the user to enter various types of data into the system through the field, irrigation and rainfall forms, respectively. Field data can be divided into crop, soil, irrigation scheduling data and personal information. The field data input page requires the following information:

(a) Crop parameters (row spacing, trash layer, plant or ratoon type crop, plant and harvest dates);
(b) Soil parameters (maximum/total soil water available to the plant in the root zone (*TAM* in mm) and the drainage rate for water in excess of the *TAM*);
(c) Irrigation scheduling parameters (irrigation type, irrigation cycle lengths, fixed irrigation amount, depletion level, refill level and timing of irrigation, whether every fixed number of days or need-based); and
(d) Personal information for receiving the irrigation scheduling advice by *SMS* or e-mail.

Local rainfall and irrigation data can be entered into the system. A current limitation, however, is that such data are not used for the real time scheduling advice, but only for exploratory simulations.

Outputs of the MyCanesim® system

Typically, large-scale farmers and extension staff would receive irrigation advice by e-mail, fax or website downloads, while small-scale farmers would receive advice by *SMS* (Singels, 2007). Three reports are provided to large-scale farmers. The first, the Irrigation Advice and Current Estimates Report, contains: (a) the current recommended irrigation actions; (b) the future recommended actions; (c) the estimated dry-off dates; (d) the current simulated yields; (e) the cumulative rain; and (f) the cumulative irrigation up to the current date for each field. The second report *viz* the Field Properties and Final Estimates Report, provides: (a) the start and harvest dates; (b) the estimated yield; (c) the cumulative rain; and (d) the cumulative irrigation at harvest. The third, for users who are interested in detailed information, downloadable from the web interface (available in Excel 2003 format), provides daily values of irrigation, rainfall, yield, crop water stress and canopy cover.

The *SMS* advice is currently only available in *isiZulu* and consists of: (a) the recommended current irrigation action; (b) the current yield; (c) the expected yield at harvest; and (d) the drying off advice. Users receive an *SMS* whenever there is a recommended change in irrigation action. An *SMS* is also received on Wednesdays, confirming the current irrigation recommendation.

Drawbacks of the MyCanesim® system

Two major drawbacks of MyCanesim® which were identified in recent projects were that: (a) the irrigation scheduling rules do not take into account restricted water allocations and hence farmers can be advised to irrigate more than they are allowed; and (b) the information on actual irrigation and actual soil water status are not utilised. Hence, the simulated soil water balances can be different from the actual soil water balances in a field, leading to incorrect advice (Singels, 2011). In order to address the first problem, methods for optimising yield with a limited water allocation for a single field will later be examined. The second issue can be addressed by utilizing data from soil water sensors to correct simulated soil water content.

Technology on which MyCanesim® is built

The web-based user-interface is driven by an Oracle Portal server (Oracle Corporation, Redwood Shores, California, USA), which allows forms to be generated by procedures on the Oracle 10g Database. The IrrigationSMS program, which generates the advice, as well as IrrigationController for the system administrator, were written in C#, in Microsoft.Net Visual Studios 2008 (Microsoft Corporation). The Canesim® model was written in the Oracle procedural language, PL/SQL (Singels and Smith 2006).

2.2.6 Comparison of online ISDSS reviewed: highlighting key features

From the previous sections, it may be asked what the differences between the online *ISDSS* are and what makes each one unique. Hence, some sort of comparison is in order. In Table 2.4 the various features of the online *ISDSS* just reviewed have been extracted and listed. The table can serve as a starting checklist and reference for future developments of any *ISDSS*.

Table 2.4 Engine[1], input[2] and output[3] features of the online *ISDSS*. The presence of each feature is indicated by a Y. Refer to glossary for a list of terms and definitions.

Engine: Application/ Feature[1]	**Plante-Info**	**NDAWN**	**IMO**	**Water-Sense**	**My-Canesim®**
Multi-crop (M) / single-crop (S)[1]	M	M		S	S
Crop simulation model[1]	Y	Y		Y	Y
Thermal time[1]	Y				Y
Soil water balance[1]	Y	Y	Y	Y	Y
Growing root zone[1]		Y			
Spatial variability of soils[1]		Y			
Irrigation uniformity[1]			Y		
Optimizes use of limited water[1]			Y	Y	
Multiple possible future weather scenarios[1]			Y		
Considers fields conjunctively[1]			Y		
Economics accounted for[1]			Y		
Short-term weather forecasts[2]	Y				
Automatic update of weather data[2]	Y	Y	Y	Y	Y
Crop data[2]	Y	Y		Y	Y
Soil data[2]	Y	Y	Y	Y	Y
Irrigation scheduling info (*e.g.* cycles, amounts)[2]			Y		Y
User irrigation and precipitation records[2]	Y				
Management allowable depletion level[2]			Y		Y
Management stress threshold[2]				Y	
Irrigation allocation[2]			Y	Y	
GIS database used[2]		Y			
Yield estimate[3]	Y		Y	Y	Y
Potential growth rate of non-stressed cane[3]				Y	
Current and future *ASWC*[3]	Y		Y	Y	Y
Stress index[3]	Y				Y
SWD[3]		Y			
Simulated ET_A[3]		Y			Y
Current and future irrigation actions[3]				Y	Y
Total daily farm irrigated water use[3]			Y		
Graphs *e.g.* of *ASWC*[3]	Y		Y	Y	Y
Grouping of fields in outputs[3]	Y				Y
Non-internet-based media used[3]					Y

2.2.7 A special case of an ISDSS

IrriSatSMS (Hornbuckle *et al.*, 2009) is an *ISDSS* which does not fit into any of the above categories. It uses a soil water balance to simulate farmers' fields, but there is no graphical interface for the users. The system calculates daily water budgets, based on irrigation, rainfall and ET_0 data for its registered fields. IrriSatSMS downloads rainfall and ET_0 data from an *AWS* network on a daily basis. Users can upload rainfall and irrigation data *via SMS*. Crop factors (K_C values) are determined from canopy cover, which is derived from normalised difference vegetation index (*NDVI*) values from satellite imagery. From these data, IrriSatSMS calculates and sends *ASWC* values *via SMS* to users each day. Novel features include the use of *NDVI* images and the reporting of *ASWC via SMS*.

2.3 Irrigation Scheduling Under a Limited Water Supply

In South Africa irrigation demand can often exceed water supply (Rossler, 2013). Hence, there is a need to optimize the scheduling of limited water. Reasons for water being restricted include limited rainfall, degradation of sources and competition between sectors (Pereira *et al.*, 2002). In this thesis, the optimal scheduling of irrigation with limited water is considered on a per field basis and not over several fields in an area *i.e.* optimization is considered in time, over a cropping season and not spatially.

Several approaches used to schedule irrigation under a limited water supply will be reviewed with respect to: (a) the model used; (b) the crop; (c) the method used to optimize; and (d) the method of forecasting necessary for operational use of each approach.

2.3.1 Physiological growth stage approach

In the approach of Rao *et al*. (1988b), a crop water balance model with a growing root zone was developed to determine the weekly *ET* deficit for cotton. Since the model did not grow biomass, a yield-water production function, based on that of Doorenbos and Kassam (1979), was used to calculate the yield deficit of each physiological growth stage:

$$1 - \frac{Y_i}{Y_{M_i}} = K_i\left(1 - \frac{ET_{Ai}}{ET_{Pi}}\right) \qquad \text{Equation 2.1}$$

where, for the ith physiological growth stage of the crop,

Y_i is the actual yield in t/ha,

Y_{Mi} is the potential, unstressed yield in t/ha,

K_i is the yield-response factor,

ET_{Ai} is the actual ET in mm experienced by the crop for stage i, and

ET_{Pi} is the potential ET in mm that could have been experienced, if there was no stress.

This calculation is done for each physiological crop stage and the final, seasonal ratio of $\frac{Y}{Y_M}$ is determined from the ratios at each stage (Rao *et al.,* 1988a).

The water balance model is separated into the physiological stages and takes the initial *ASWC* and assigned water allocation as inputs for each stage. How rooting depth was accounted for is not clear, but may be fixed at the start of each physiological stage.

The approach of Rao *et al*. (1988b) optimized the use of limited allocated water, by finding the optimal apportioning (which maximized yield) of the allocated water to the different physiological crop stages, rather than determining the optimal daily schedules. Hence, this is a broad approach of optimization. Optimizing the division of water into growth stages required testing all possible permutations of such divisions. Every physiological stage is simulated with every possible apportionment of water.

Each combination of initial *ASWC* and water apportionment can be simulated for each physiological growth stage, independent of the other stages. These simulations can then be recombined to represent the simulation of the crop for the entire season. This process is an example of dynamic programming (Bellman, 1954), since each unit of a solution to the problem is used many times, but only simulated once. In this way, every possible cropping scenario can be simulated quickly. For example, if there are 10 possible initial *ASWC* amounts (10 mm to 100 mm in steps of 10mm), 10 possible apportionments (100 mm to 1000 mm in steps of 100 mm) and four possible physiological stages, there are 400 base simulations from which any growing season can be constructed. The algorithm then chooses the crop and apportionment which maximized yield. Using this example, the number of possible combinations of apportionments of water to stages is large, namely 10x10x10x10 = 10000 permutations for four stages, but can be reduced upon eliminating impossible combinations. The large number of permutations is referred to as the "curse of dimensionality" by Paudyal and Manguerra (1990).

The approach of Rao *et al.* (1988b) was adapted to run operationally to provide real time advice (Rao *et al.,* 1992). Historic data was used up to the current date. Thereafter, long-term weekly average ET_P was used to forecast the ET_P and the rainfall was selected from the 25% long-term average percentile for the given week. Irrigation was scheduled on a weekly basis. The model would recalculate its schedules at the start of the new week. Within each crop stage, water is used until it runs out. Hence, there is a need for further optimization, especially if growth stages cover a long period of time.

Prasad *et al.* (2006) and Ghahramani and Sepaskhah (2004) gave similar methods of optimising a seasonal irrigation schedule with a limited water supply for a single field. Prasad et al. (2006) extended this approach to optimise water usage for a field across multiple crops and seasons.

2.3.2 Stress level approach

Inman-Bamber *et al*. (2005) developed an *ISDSS* system called WaterSense, based on the APSIM-sugarcane model **(**Keating *et al.*, 2003), to optimize the use of a limited water supply. Their approach, unlike that of Rao *et al.* (1988b), involved the optimization of a daily irrigation schedule. The steps in their algorithm were:

(a) Simulate the crop up to the current date with available weather and irrigation data;
(b) Simulate at least 400 future crop scenarios, using 40 historical weather sequences from the current date onwards. Ten different stress levels are used as irrigation triggers, with the proviso that the total irrigation of each scenario may not exceed the specified water allocation. Stress was quantified as the ratio between actual and potential photosynthesis (simulated); and
(c) For each weather sequence, identify the simulated crop scenario that had the highest yield. The median next irrigation date of these 40 best scenarios is taken as the recommended next irrigation date.

2.3.3 Evolutionary algorithms approach

De Paly and Zell (2009) introduced a new approach of finding an optimal irrigation schedule for a crop with a limited water allocation, based on evolutionary algorithm techniques. They used a water balance model and yield-water production functions similar to Rao *et al.* (1988b). They tested their model for maize on historical data. A daily optimal irrigation schedule was found (Schutze *et al.,* 2005), rather than an apportionment of water to stages. However, it is important to note that their techniques apply generically to any model that can determine yield in some way.

De Paly and Zell (2009) tested the following techniques: (a) genetic algorithms (*GA's*), as demonstrated by Sivanandam and Deepa, (2008); (b) particle swarm optimization, as demonstrated by Kennedy and Eberhart (1995); and (c) differential evolution, as demonstrated by Storn and Price (1996). These techniques have been shown to solve many types of optimization problems that cannot be solved by other means. These techniques fall under the class known as evolutionary algorithms, since potential solutions to the problem evolve during its solving. As an example of these techniques, a *GA* approach for finding an optimal irrigation schedule is described.

Sivanandam and Deepa, (2008), Michalewicz (1992) and Bolboaca *et al*. (2010) described the basics of *GA*s. The simplest form of a *GA* involves the representing of solutions to a problem in the form of sequences of binary bits (1s or 0s), usually of equal length. The sequences are evaluated by a fitness (also known as objective) function (*Y*), to see how "good" the solution is. The overall objective will be to find the specific sequence which maximises the fitness function. The sequences are modified through an iterative process to find better solutions to the problem.

In the case of an irrigation scheduler, an irrigation sequence I = 1001001...001 could represent an irrigation schedule for a season, with 1 indicating an irrigation event and 0 indicating no irrigation and the length of the sequence being 365 bits for each of the 365 days of the season. The *GA* would operate on these irrigation sequences, using crossover and mutation operations, in order to improve them.

The process of finding fitter irrigation sequences involves four steps. The first step involves the selection of irrigation sequences with good fitness (those that achieve high yields), which will be used to create a new set of potentially fitter sequences. The original sequences are said to be parents, the new ones children and a new generation of sequences is said to be formed. The second step is the selection of pairs of parents and a crossover point, where portions of two sequences are interchanged at the crossover point to create pairs of children. The third step is the mutation of sequences, by randomly flipping a bit from 0 to 1 or *vice versa e.g.* flip the last bit of 1001...111 to obtain 1001...110. The final step is the evaluation of the fitness of the new child sequences and then selecting the next generation. By modifying the sequences in this way, the average fitness of each new generation can be improved.

An important theoretical result for *GAs* is the schema theorem, as derived in Michalewicz (1992). It states that small subsequences of bits that tend to yield good fitness will occur more frequently in sequences, as the population grows from generation to generation.

In the case of the work of De Paly and Zell (2009), the fitness function is represented by a yield calculated by a crop simulation model. Such a model should have a fast execution time. For real time irrigation scheduling, a technique of forecasting rainfall is necessary, in order to accurately predict the need for irrigation water. De Paly and Zell (2009) did not discuss how they would forecast weather or run their model operationally. In this approach, it is also possible that sequences may allow more water than the allocation (*e.g.* through crossover). A fitness penalty function can be introduced that penalises such cases (subtracts yield), which causes the genetic algorithm to favour those sequences which adhere to the allocation.

2.4 Soil Water Monitoring Technology for Irrigation Scheduling with Emphasis on Capacitance Probes

Weather-based crop models are good at estimating evapotranspiration (*ET*) and future irrigation needs over large areas (Akyüz *et al.*, 2008; Busch *et al.*, 2009; Inman-Bamber *et al.*, 2005; Thysen and Detlefsen, 2006) while electronic soil water sensors are able to provide good estimates of soil water status at a given point (Farina and Bacci, 2005), provided sensor output is appropriately interpreted (Paige and Keefer, 2008). Synergy can be obtained by combining these technologies to enhance their usefulness for irrigation management because the predictive power of weather-based models (e.g. the ability to forecast irrigation requirements and yield) can be combined with the accuracy of field based sensors for estimating soil water status. Soil water sensors are now reviewed, focusing on capacitance probes and then on efforts to integrate simulation models with soil water probe data. The objective of the study is to provide background in support of using data from such sensors to improve the accuracy of irrigation scheduling in MyCanesim®.

2.4.1 Overview

Soil-based methods for scheduling irrigation can be divided into three categories (Stevens *et al*., 2005): soil water potential methods, soil water content (*SWC*) methods and the wetting front detector.

Soil water potential is a measure of the suction (negative pressure in units of kPa) required to extract water from the soil. Soil water potential instruments include tensiometers, gypsum blocks, granular matrix sensors and thermocouple sensors (Stevens *et al*., 2005).

Some examples of commonly used soil water content methods include:

(a) The gravimetric method, which requires sampling, drying and weighing of soil samples. The difference between wet and dry mass gives the *SWC*;

(b) Neutron water meters, which measure the number of slow neutrons (count/standard count) passing through the soil (Reinders *et al*., 2010). This number is dependent on *SWC*;

(c) Capacitance sensors, also known as frequency domain reflectometers (*FDR*) and time domain reflectometers (*TDR*), which measure the soil dielectric permittivity determined mainly by the *SWC* (Reinders *et al*., 2010); and

(d) Other technology for measuring *SWC* such as ground penetrating radar and the dual-probe heat-pulse method (Frangi *et al*., 2009).

The wetting front detector was described by Stirzaker *et al*. (2007). As free water drains through the soil after a wetting event, it eventually reaches the funnel of the instrument where it is accumulated and causes a float to appear on the surface, providing an indication that the wetting front has penetrated to the depth of the funnel. Using two sensors in conjunction at different depths is recommended for irrigation scheduling.

2.4.2 Capacitance soil water probes

Technology

Capacitance soil water probes estimate the *SWC* of a field by measuring the soil water dielectric permittivity, which is a measure of how the soil and the water it holds affect a surrounding or neighbouring alternating electric field (Gardner *et al.*, 1998). The permittivity of the soil has a real and complex part. The real part is called the apparent permittivity (ϵ). The ϵ of air is 1, of dry soil is 5 and of water is 80, thus changes in ϵ in soil are mostly affected by changes in *SWC* (Paige and Keefer, 2008). By measuring the change in frequency of the oscillating electric field of the probe, ϵ can be measured.

Probes are generally sensitive to temperature, but they can be designed to be insensitive to temperature changes between 10°C and 30°C (Vera *et al.*, 2009). Capacitance probes are only sensitive to changes in *SWC* in a small radius around the probe and are sensitive to disturbances during installation – hence the use of slurry to make them fit tightly in the soil (van Niekerk, 2010).

Calibration to estimate volumetric soil water content

More than 60 years of work has been done on the correlation between ϵ and *SWC* (Starr and Paltineanu, 1998). There are various equations for relating ϵ to volumetric *SWC* (θ), for example Topps Equation (Topp *et al.,* 1980 as cited by Pumpanen and Illvesniemi, 2005):

$$\theta = a\epsilon^3 + b\epsilon^2 + c\epsilon + d \qquad \text{Equation 2.2}$$

and Ledieu's Equation (Ledieu J *et al.*, 1986 as cited by Pumpanen and Illvesniemi, 2005):

$$\theta = a\sqrt{\varepsilon} - b \qquad \text{Equation 2.3}$$

where a, b, c and d are constants that should be determined for the soil involved.

Starr and Paltineanu (1998) found a non-linear relationship between θ and the frequency at which the capacitance field oscillates, while Vera *et al.* (2009) used a scaled voltage to determine θ. Gardner *et al*. (1998) related θ to ϵ using soil properties such as bulk density and texture.

Results in research on the ability of capacitance probes to accurately measure θ differ. Paige and Keefer (2008) cited several examples showing that capacitance probes measured θ sufficiently accurately for research purposes. In contrast, Evett *et al.* (2009) and Evett *et al.* (2012) found that capacitance probes produced large errors in measuring θ and recommended that the probes not be used for precision measurement. Vera *et al.* (2009) found that capacitance probes responded well to both small and large changes in θ and are therefore useful for research. Zerizghy *et al*. (2013) found that they were accurate enough for measuring soil water evaporation. There is general consensus that capacitance probes need to be calibrated after being installed if the user wants accurate measurements of θ, because their calibration is affected by soil properties such as bulk density and texture (Paige and Keefer, 2008). Factory calibrations alone are insufficient for accurate measurement of θ (Leib *et al.*, 2003 and Pumpanen and llvesniemi, 2005).

Suitability for irrigation scheduling

Typically, capacitance probes that are used for irrigation scheduling are calibrated for a theoretical field at factory level. Factory calibrations typically involve taking a reading from the probe in air and a reading in water (Leib *et al.*, 2003). Thus, ε is related to a soil water index (*SWI*) ranging from 0 to 100, which would then be linearly related to the actual *SWC* of the field. Leib *et al*. (2003) suggested that factory calibrated probes can still be used for irrigation scheduling if appropriate scheduling trigger levels are chosen. Probes can be calibrated from factory settings to *SWC* from night-time (when *ET* is assumed zero) irrigation or rainfall.

Irrigators make scheduling decisions based on the spatial average *SWC* of a field, so probes should be placed where the *SWC* is most representative of the average *SWC* of the field (Evett *et al.*, 2009). Vera *et al.* (2009) stated that probes should be placed in the zone with the highest root density and be used as biological sensors as well as soil water sensors. Having sensors at several depths in the soil will better reflect the true *SWC* (Leib *et al.*, 2003) and can help explain the flow of water in the soil (Starr and Paltineanu, 1998).

Capacitance probes are easily adapted to continuous real-time monitoring (Vera *et al.*, 2009). Capacitance probes thus have the advantage over the gravimetric method in that readings can be taken automatically and on a regular, frequent basis. Capacitance probes do not have the risk of radiation that neutron probes have.

Other uses

Probes can highlight "breaking points" in the soil, where the slope of extraction patterns change (e.g. the stress point or drainage), or can indicate more or less profuse root activity (Starr and Paltineanu, 1998) and consequent root depth. Probes are also useful for estimating the total available moisture (*TAM*), for developing irrigation scheduling strategies and for seeing how water lower in the profile is used.

2.4.3 Integration with weather-based crop and soil water balance simulation models

Very little work has been published on the integration of probe and model technology, especially for enhancing irrigation scheduling and general irrigation management. Holloway-Phillips *et al.* (2008) proposed a framework for "fusing" soil water models and in situ soil water sensors to predict soil water extraction and the date of the next irrigation. Real time data from sensors could be used to "enhance or calibrate" simulations of the soil water balance to support irrigation management.

The Soil Water Balance (SWB) crop model system developed by Annandale *et al*. (2005) has the capability to store measured soil water data in its database for comparison with simulated values. Neutron water meter data or converted volumetric soil water data can be uploaded manually into the SWB database and can be used to correct the simulated soil water content.

Thomson and Ross (1996) developed a system to use data from soil water potential sensors to adjust soil water balance parameters in a crop model for scheduling irrigation in peanuts. Sensor data were fed manually into the modelling database and used to automatically adjust soil and rooting parameters in order to improve the accuracy of soil water balance simulations and irrigation advice.

It is clear that there is scope for integrating probe technologies into models and that soil water sensor data can add a new dimension to crop model simulation and irrigation scheduling.

2.5 Discussion and Conclusions

2.5.1 Approaches to providing irrigation scheduling advice

In this review, two general approaches to providing irrigation scheduling advice were found: (a) the generic information provided by *IIS*; and (b) field-specific information provided by model based *ISDSS*. The *IIS* provide easily obtainable *ET* and/or other data, which requires further work by the farmer to make irrigation scheduling decisions. Field-specific *ISDSS*, on the other hand, simulate the soil water balance and recommend irrigation when a chosen soil water depletion level is reached. They provide more detailed and precise information than *IIS* and have advanced features, such as the ability to test whether irrigation systems will meet the long-term demand of *ET* minus rainfall. Users need more time to master these systems, although complexity can be hidden, as in the case of MyCanesim®, which gives simple *SMS* advice and does not require the user to operate the model (Smith *et al.*, 2005). The level of detail in the information provided could be tailored for individual users.

Model based *ISDSS* can be implemented online or locally on desktops. The online systems store code and data centrally, as opposed to locally on the desktops, thus providing better protection and requiring easier maintenance and upgrading. A possible drawback of online systems is that they can become too slow when a large number of users use it simultaneously.

The effort taken to generate, retrieve and apply useful information from these two approaches (generic vs field-specific), as well as the improvement in irrigation water use efficiency (*IWUE)* and yield should be compared.

2.5.2 Useful features of ISDSS

Three aspects of the ISDSS will be discussed namely the engine (calculation method); inputs and outputs.

From the useful operating features of ISDSS listed in Table 2.4, the ability to allow flexible scheduling rules (different rules for different times of the year or stages of the crop) was most relevant for the study. For example, a farmer may speed up a centre pivot in summer and slow it down in winter, applying less or more water per event. The *ISDSS* must thus be able to smoothly transition from the summer strategy to the winter one. Flexible irrigation strategies may also need to be tested ahead of their implementation.

The accuracy and relevance of irrigation advice and yield forecasts can be enhanced by correcting simulations with field measurements of soil water content, irrigation and canopy cover. For example *NDVI* data from satellites can be used to estimate canopy cover and crop coefficients (Hornbuckle *et al.*, 2009), which can be used to correct the simulated canopy cover, thus improving transpiration estimates and the consequent irrigation schedule and yield forecast.

The organization of input is crucial for the ease of use of ISDSS. Two approaches are used, namely: (a) the grouping of inputs by type for multiple fields in one form; and (b) the grouping of several input types for a given field in one form. The former reinforces the nature of a given input and allows the farmer to see how that input varies for his farm, whilst the latter gives an overview of the field.

The type of information that is generated by the systems, the presentation format and the medium of dissemination, can play important roles in determining the success of the systems in changing irrigation practices.

Irrigation information includes various forms of *ET, SWC, SWD,* a crop water stress index and recommended irrigation amounts and dates. *SWC* information empowers the farmer to make his own irrigation scheduling decision and possibly allows him to consider factors which are not accounted for by the system. A crop water stress index can be used as an additional scheduling criteria, possibly improving the accuracy of scheduling. Future recommended irrigation dates can be useful when planning irrigation operations. Recommended irrigation dates and amounts are useful for farmers who want to be simply told what to do. They may not have the time to do their own calculations, or they do not understand how to determine their own schedules.

In addition, yield and quality predictions are useful in allowing the farmer to plan financially *e.g.* for harvesting and transport purposes. The simulation of both a stressed and non-stressed version of each crop will help the farmer ascertain growth and final yield losses. The provision of an economic output that weighs costs (electricity and water) against benefits (yields), while taking all fields into account simultaneously, can help farmers make better irrigation decisions.

Graphs are a powerful way of bringing messages across. They allow for much more information to be presented at once than could be done in a table. A useful feature is to allow a farmer to hover his cursor over a graph curve to be shown the numeric value at that point.

Another powerful way of conveying information is the spatial representation of field data *via* maps. In this way, farmers receive a whole farm perspective at a glance. Maps of fields could be used to indicate the degree of key variables, *e.g.* dark greens could represent lush, well-watered crops and brown could be used for water stressed crops. Different variables, such as *ET*, yield and canopy cover, could be displayed on different maps.

2.5.3 Scheduling with limited water

Three approaches of optimizing the irrigation schedule under a limited water supply on a single field over time were reviewed, namely the crop stage approach (Rao *et al.*, 1998b; 1), the stress-based approach (Inman-Bamber *et al.*, 2005; 2) and the *GA* approach (De Paly and Zell, 2009; 3). The common objective of all these approaches was to maximise crop yield for a given seasonal allocation of irrigation water. Aspects of interest to this study taken from these approaches are: the method of calculating yield response to water, the method of calculating the soil water balance, the method of selecting weather data to represent the future and the optimisation approach.

A simple empirical approach was used to determine yield from water use in two of the study cases, namely that of a stage based production function driven by the ratio of ET_A *to* ET_P (approaches 1, 3). In the case of approach (2), a sophisticated process-based yield model with a daily time step was used. The first approach may have a shorter simulation time, whereas the second approach may generate more accurate yields.

The calculation of the soil water balance model was done to occur at either weekly (1) or daily (2) time steps. A weekly/coarser time step captures less of the dynamics of the system and relies more on assumptions, but requires less inputs. Also, a weekly/coarser time step water balance allows for long term average rainfall and *ET* to be used to represent the future (see Rao *et al*., 1992), which would not be realistic for a daily water balance. In that case, multiple simulatSteele
ions using different historical daily weather sequences to represent the future, may be used to capture the uncertainty of rainfall (2). Sequences with a higher probability of occurrence (as indicated by climate forecasts) may be selected.

Optimisation of the irrigation schedule was done in two ways. Multiple irrigation schedules were evaluated iteratively (1, 2, 3) and/or a set of rules were used to build the optimal schedule (2). The time resolution of the optimized schedule also differs. Stage based optimisation may be faster and offer a broad perspective on optimal water application, while daily based optimisation allows for more detailed scheduling. The performance of the different approaches need to be compared, which will be the subject of chapter 3.

2.5.4 Capacitance soil water balance monitoring

There are many different types of soil monitoring technology, of which capacitance probes are one. Capacitance probes have the advantages over the gravimetric method and neutron probes in that they offer automatic logging and are not radioactive. The literature disagrees about the suitability of capacitance probes for measuring θ accurately, but suggests they can used for irrigation scheduling even with just factory calibrations. For scheduling irrigation, probes should be placed at a location where they are representative of the average *SWC* of the field, as well as where roots are active. Sensors at several depths should be used. Not much work has been done in incorporating the data from soil water probes into models and discovering related benefits, so there is scope for new research in this area.

To ensure compatibility with simulation systems, soil water data processing and data integration should be automated as far as possible. The option to correct simulations with soil water records may enhance the relevance and accuracy of irrigation advice, as well as estimates of crop performance (*e.g.* yield).

2.5.5 Conclusions

This chapter described the most pertinent features of ISDSS and approaches to providing decision support for irrigation scheduling which are relevant to this study. Based on this it is recommended that the following features be considered for inclusion and testing in MyCanesim®:

(a) A system output report, per field, for *ASWC*, daily rainfall and next irrigation date and amount;
(b) A spatial representation of a farm to enhance the reporting of the system;
(c) A method for optimizing the scheduling under limited water allocation;
(d) Functionality to integrate field measurements (*ASWC*, irrigation and canopy cover) with simulations of water balance and crop growth, in order to improve the accuracy of real time advice;
(e) Functionality to allow flexible scheduling rules to enable more powerful strategizing and to accommodate farmers who change practices throughout a season; and
(f) Functionality for simultaneously considering the demand for water by all fields, especially when water supply is limited, and providing irrigation scheduling advice accordingly.

The next two chapters focus on introducing features (c) and (d) (for *ASWC* only) into MyCanesim® and assessing potential benefits.

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3. ALGORITHMS FOR SCHEDULING LIMITED IRRIGATION WATER

3.1 Introduction

One of the drawbacks of the MyCanesim® sugarcane yield and irrigation scheduling system is that the advised irrigation total for a twelve month crop can exceed the seasonal water allocation ($ALLOC_{season}$) imposed by the relevant Water User Associations. Irrigation scheduling algorithms are needed to provide sound irrigation advice that, apart from minimising water stress and water wastage, also maximise yields, adhere to the $ALLOC_{season}$ within the constraints of the irrigation system and which execute in a reasonable amount of time. In the literature review, three scheduling algorithms were identified for possible use in MyCanesim®, namely:

(a) The physiological growth stage or crop stage algorithm (Rao *et al.*, 1988a,b, and Rao *et al.,* 1992). This algorithm simulates the water balance and yield contribution for different growth stages using various allocations of irrigation water for each stage (stage allocation, $ALLOC_{stage}$). The algorithm finds a set of stage simulations that produces the highest yield at harvest, while adhering to the $ALLOC_{season}$.

(b) The stress level algorithm (Inman-Bamber *et al.*, 2005 and Inman-Bamber *et al.*, 2007), which uses a water balance and yield model to evaluate the impact of irrigation schedules derived from applying different allowable depletion levels (*ADL*). The operator enters their choice of *ADL* values that should be applied before the algorithm is run.

(c) Genetic algorithms (De Paly and Zell, 2009), which simulate yield from various sets of daily irrigation schedules covering the entire growing season. These schedules are represented using binary strings (1 for a day with irrigation and 0 for a day with no irrigation) and then use the crossover and mutation processes to find new irrigation schedules, which may achieve higher yields. Due to the large number of simulations required to execute the genetic algorithm, this component was left out of the study.

Four additional scheduling algorithms were evaluated namely:

(d) The prorata algorithm, which schedules irrigation so that the cumulative irrigation total at the current date *d* in the season does not exceed a specified fraction of the long-term average cumulative irrigation requirement on that day. That fraction is the seasonal allocation divided by the long-term average seasonal irrigation requirement.

(e) An advanced version of the prorata algorithm that allows a variance to the cap on to-date water use. The extent of the variance declines as the season progresses and is cancelled when the to-date water use reaches a specified percentage of the seasonal allocation.

(f) The water satisfaction algorithm, which schedules irrigation on the day in the growing season where the ratio of water supply (rainfall plus irrigation) to water demand (potential evapotranspiration (ET_P)) is the lowest. Preference for irrigation is given to growth stages that show a greater yield response to water, all else being equal.

(g) A baseline algorithm where irrigation was scheduled whenever the *ASWC* reached the base *ADL* of 50% of maximum plant available moisture (*TAM*), provided that the to-date cumulative irrigation total does not exceed $ALLOC_{season}$. If $ALLOC_{season}$ is reached before the end of the growing season, irrigation is ceased.

3.2 Methods

3.2.1 Simulation test cases

In order to compare the performance of algorithms, crop yield and soil water balance simulations were performed using historical weather data. The algorithms had access to the weather record of the entire growing season. Nine hundred and sixty (960) hypothetical crop scenarios were simulated per algorithm. These scenarios were constructed as follows: data was used from four weather stations, each in a different sugarcane milling region (Komati, Malelane, Pongola and Umfolozi). Two crop cycles were selected, April and October, representing a late summer/early autumn harvest and a late winter/early spring harvest.

Since the irrigation scheduling algorithms may perform differently under different rainfall conditions, three classifications of rainfall season (low, medium and high total rainfall) per weather station and crop cycle were simulated. The low, medium and high rainfall seasons were selected as follows: for each weather station and crop cycle (April or October start and harvest), seasonal rainfall totals for historical weather sequences were ranked from smallest to largest. Complete weather sequences with rainfall totals closest to the 17%, 50% and 83% percentile rankings (*i.e.* the median low, normal and high rainfall sequences) were chosen to represent dry, average and wet years (Table 3.1). Weather sequences that had missing data were excluded and replaced with the closest available percentile year. Only three sequences were chosen per site to keep the number of simulations manageable.

Properties of two hypothetical soils (*TAM*s of 80 mm and 120 mm and well drained) were used as simulation input. Two fixed irrigation amounts (8 mm and 40 mm) were chosen with an irrigation cycle of 1 day. The assumed irrigation system was drip, so as to avoid confounding effects of canopy interception on simulated crop water use and yield. The default *ADL* was set to 70% of *TAM* (meaning that only 30% of TAM was depleted before irrigation was triggered) for 8 mm fixed irrigation scenarios (to avoid water stress) and to 50% of *TAM* for 40 mm fixed irrigation scenarios (to avoid water stress, minimize water wastage through runoff and deep percolation and maximize rainfall efficiency). The initial *ASWC* value was set to 50% of *TAM* for each scenario. Ten different $ALLOC_{season}$, ranging from 100 mm to 1000 mm in steps of 100 mm, were investigated. Crop input parameters represented a ratoon crop of cultivar NCo376 at row spacing of 1.5 m.

Table 3.1 Selected twelve month weather sequences for each weather station and crop cycle. Three types of sequences were chosen for each station, namely a dry, average and wet rainfall scenario. Rainfall totals and percentile rankings [3,4] for the specified twelve month periods are indicated.

		April crop cycle			**October crop cycle**		
Weather Station	**Classification**	**Start year**	**Twelve month rainfall total (mm)[1]**	**Percentile (%)[3]**	**Start year**	**Twelve month rainfall total(mm)[2]**	**Percentile (%)[4]**
Amanxala - Komati Mill	Dry year	2004	462	18.8	2000	430	18.8
	Average year	2009	713	50.0	2011	685	50.0
	Wet year	2005	944	87.5	2005	944	87.5
Malelane – Mhlati	Dry year	2004	382	15.4	2007	393	23.1
	Average year	2009	569	53.8	2003	646	53.8
	Wet year	2010	900	84.6	2009	757	84.6
Pongola – SASRI	Dry year	1997	558	12.5	2004	586	18.8
	Average year	2007	654	50.0	2003	695	50.0
	Wet year	2006	827	87.5	2009	758	87.5
Mtubatuba – Dangu	Dry year	2002	501	21.4	2002	578	21.4
	Average year	2003	886	50.0	2009	825	50.0
	Wet year	2004	980	71.4	2011	1073	85.7

[1] Rainfall total from 1 April to 31 March the subsequent year
[2] Rainfall total from 1 October to 30 September the subsequent year
[3,4] Percentile ranking (ascending) of the rainfall total for the specified season, based on a ranking of all twelve month seasons for the specified station.

3.2.2 Theory and implementation of algorithms

Crop Stage Algorithm

The crop stage scheduling algorithm was described in the literature review (Rao *et al.*, 1988b). In the implementation of the algorithm in this study, the simulated crop growing season (12 months) was divided into eight stages of equal duration (45 days). Using eight stages instead of the four used by Rao *et al.* (1988b) allowed more flexibility in scheduling of $ALLOC_{season}$, which should result in better solutions. Nine possible $ALLOC_{stage}$ of irrigation were tested for at each stage, ranging from 0 to 320 mm in steps of 40 mm. The maximum $ALLOC_{stage}$ of 320 mm was chosen since it was divisible by the 40 mm and 8 mm fixed irrigation depths and it was unlikely that a stage would use more than 320 mm. Steps of 40 mm were used because of divisibility by the fixed irrigation depths. While the $ALLOC_{stage}$ was varied for a specific growth stage, the remainder of the $ALLOC_{season}$ was distributed evenly between the remaining growth stages. Within a given stage, irrigation was scheduled using ADL = 50% of TAM and until the $ALLOC_{stage}$ was exhausted. This implies that there may have been water deficits and stress in some stages if water was exhausted before the end of the 45 day period.

The final step was the recombination process. All possible combinations of sequences of crop stages were assessed by comparing the sum of $ALLOC_{stage}$ with $ALLOC_{season}$ and evaluating the sum of yields. The optimal irrigation schedule was chosen from the combination that had the highest simulated yield and for which the sum of $ALLOC_{stage}$ did not exceed the $ALLOC_{season}$. Simulated yield at harvest was recalculated by simulating the crop as a whole using the chosen optimal irrigation schedule.

Stress Level Algorithm

The stress level scheduling algorithm (Inman-Bamber *et al.,* 2005) schedules using a predetermined set of $ADLs$ and constraining seasonal total irrigation ($Ischedcum_{season}$) season below the seasonal allocation ($ALLOC_{season}$).

This approach is best explained by an example. Let us assume that the algorithm has already determined the first n optimal irrigation events through n rounds of testing. In test round n +

1, it determines optimal irrigation event *n + 1* as follows: starting after the *nth* irrigation event, schedule irrigation and simulate crop growth using a given *ADL* value, till the end of the simulated season and ceasing irrigation when the $ALLOC_{season}$ is exhausted. This is repeated for every *ADL* value. The algorithm then picks the *n + 1*th irrigation event from the *ADL* value that simulated the highest yield. This procedure is then repeated for event *n + 2* and subsequent events, until the end of the growing season. Thus the algorithm explores the use of different *ADL* for different periods and evaluates simulated yield response to water stress imposed during different periods in the season.

Implementation: simulations were conducted for six different *ADL*s, ranging from 10% to 60% of *TAM* in steps of 10%. Each simulation consisted of two parts, namely the first part for which an irrigation schedule had already been determined and the second part which explored the impact of irrigation triggered by a given *ADL* and the remainder of the $ALLOC_{season}$ on simulated yield. Next irrigation dates were determined iteratively from the simulations that produced the highest yields. This process was repeated until the $ALLOC_{season}$ was exhausted and no more irrigation could be scheduled. Finally, the crop was re-simulated with the chosen set of irrigation events and the simulated yield recorded in the database.

Prorata Algorithm

The prorata algorithm presumes that yield losses due to water deficit will be minimized by spreading the available irrigation over the growing season in proportion to the long term average irrigation requirement. The prorata algorithm restricts the to-date irrigation total of a crop from exceeding the to-date allocation ($ALLOC_{cumd}$) which is calculated as the product of the long term average to-date irrigation requirement (expressed as fraction of the long term average irrigation requirement) and the seasonal allocation ($ALLOC_{season}$).

Irrigation is scheduled so that:

$$Ischedcum_d \leq (1+\delta)ALLOCcum_d = (1+\delta)\frac{ALLOC_{season}}{\overline{IRcum_{season}}} \times \overline{IRcum_d} \quad \text{Equation 3.1}$$

where

$Ischedcum_d$ = the cumulative irrigation for the crop on day *d* in mm,

$ALLOCcum_d$ = the cumulative irrigation allocation since the start of the crop on day *d* in mm,

$ALLOC_{season}$ = the seasonal irrigation allocation in mm,

$\overline{IRcum_{season}}$ = the long-term average cumulative irrigation requirement at the end of the season in mm,

$\overline{IRcum_d}$ = the long-term average cumulative irrigation requirement on day *d* in mm, and

δ = a fraction which allows irrigation water to be used more quickly (δ >0) or more slowly (δ <0), called the tolerance factor.

$$\delta = \delta_0 \times \left(1 - \frac{Ischedcum_d}{\beta \times ALLOC_{season}}\right);\ \ and\ \delta = 0\ if\ \frac{Ischedcum_d}{\beta \times ALLOC_{season}} \geq 1 \qquad \text{Equation 3.2}$$

where

δ_0 = a base increase or reduction in allowed cumulative irrigation (as a fraction), and

β = the fraction of $ALLOC_{season}$ at which δ becomes 0,

And

$$\overline{IRcum_d} = \frac{1}{n}\sum_{i=1}^{n} IRcum_{d,i} \qquad \text{Equation 3.3}$$

where

$\overline{IRcum_d}$ = the long-term cumulative irrigation requirement for the crop on growing day *d* in mm, generated by simulating and averaging the irrigation demand for many seasons,

$IRcum_{d,i}$ = the cumulative irrigation requirement for season *i* on day *d*; where there are *n* number of such seasons.

$\overline{IRcum_d}$ (and hence and $\overline{IRcum_{season}}$) were calculated for a given cropping situation (given site, soil, crop cycle and irrigation system). $IRcum_{d,i}$ were determined by scheduling irrigation events when *ASWC* reached *ADL* = 50% of TAM. $\overline{IRcum_d}$ was pre-calculated using long-term weather data in C# and stored in the Oracle database for use in different crop situations.

An example of how the algorithm schedules irrigation is shown in Figure 3.1.

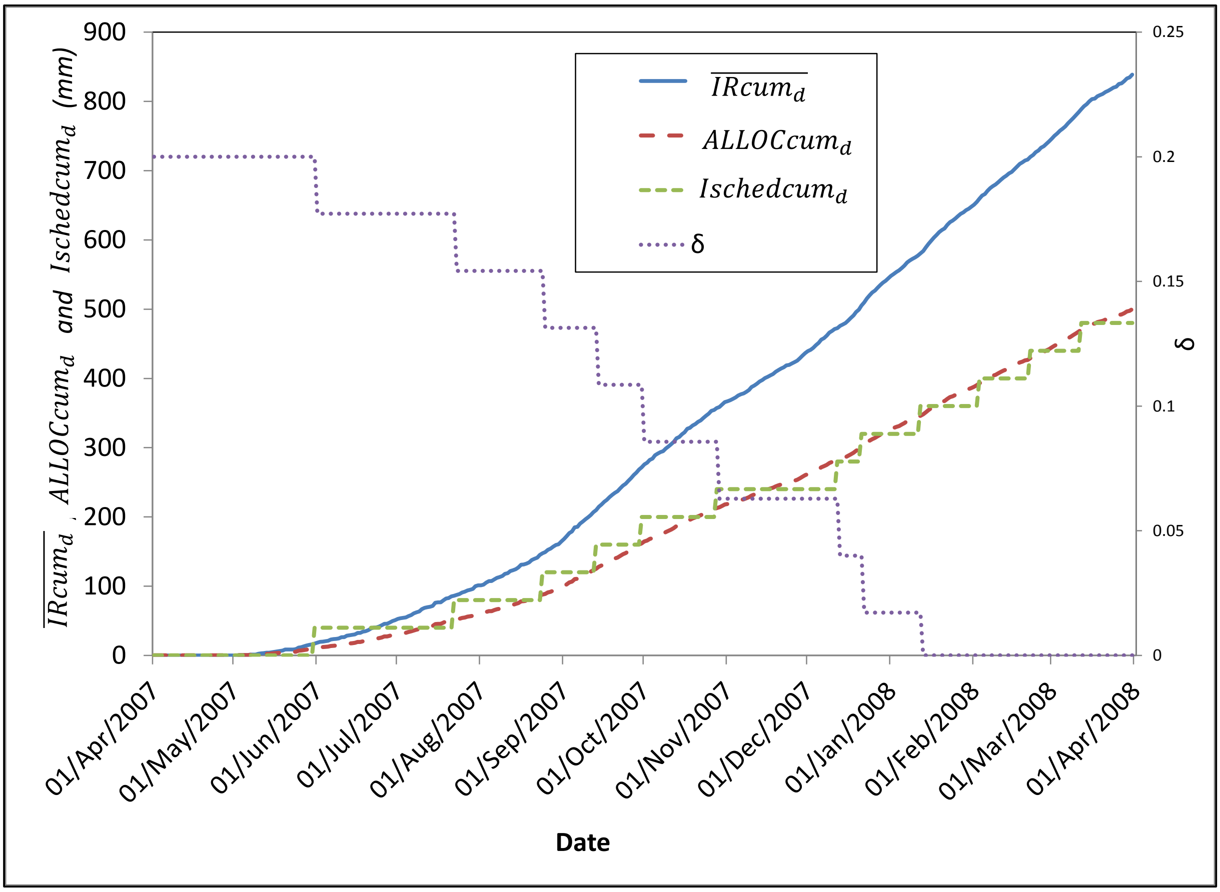

Figure 3.1 The long-term average cumulative irrigation requirement ($\overline{IRcum_d}$), the pro-rata cumulative allocation ($ALLOCcum_d$) and the cumulative scheduled irrigation ($Ischedcum_d$) for a seasonal irrigation allocation ($ALLOC_{season}$) of 500 mm. The value of δ is also plotted as it decreases from 0.2 to 0 as $Ischedcum_d$ approaches β (= 0.7) of $ALLOC_{season}$ (see Equation 3.2). The example was for a hypothetical twelve month Pongola crop started in April 2007 with a long term average seasonal irrigation requirement of 839 mm.

Two versions of the algorithm were implemented. The basic version used δ_0 = 0 in Equation 3.2, while the advanced version tested each of $\delta_0 \in$ {-0.2, 0, 0.2}. The value of 0.2 was used because it was considered a mild alteration of the δ = 0. β (Equation 3.3) was chosen to be 0.7, so that, for the last 30% of the $ALLOC_{season}$, there would be adequate irrigation water left to support the remaining stalk growth.

In the advanced version of the algorithm, δ decreases linearly in absolute value as the cumulative irrigation for the crop increases, becoming 0 when the cumulative irrigation equals

β multiplied by the *ALLOC_{season}*. Flexibility is thus given to the algorithm to use more (or less) water early in the season than the standard version. This flexibility is tightened as the percentage depletion of the seasonal allocation approaches β.

Water Satisfaction Algorithm

The water satisfaction algorithm is built on the assumption that the yield response to irrigation depends on growth stage and the irrigation requirement on a given day. The irrigation requirement is calculated on the principle that long periods without rainfall and with high *ET*, have high irrigation demand and conversely. The algorithm compares a time integration of rainfall plus irrigation with a time integration of *ET* to determine which day has the greatest demand for water (Equation 3.4). Irrigation, rainfall and *ET* are evaluated over the entire growing period. The sensitivity of sugarcane to water deficits during different growth stages is also taken into account.

The water satisfaction index (*WSI*) on a day *d* of the growing season was defined as:

$$WSI_d = K_{y,d} \frac{\sum_{e=1}^{e=final\ day}(|d-e|+1)^{\alpha} \times (R_e + I_e)}{\sum_{e=1}^{e=final\ day}(|d-e|+1)^{\alpha} \times (ET_{p,e})} \qquad \text{Equation 3.4}$$

where

d	= the day *d* in the growing season which is being evaluated,
$K_{y,d}$	= a water stress sensitivity factor for day *d,*
e	= any day in the growing season,
α	= the time difference scaling constant,
R_e	= the rainfall on day *e* in mm,
I_e	= the irrigation amount on day *e* in mm, and
$ET_{P,e}$	= the potential evapotranspiration on day *e* in mm.

WSI_d is large when *d* is distant from high values of rain and irrigation water and close to high values of *ET*, and conversely. Thus the maximum WSI_d represents the day that is most water needy. When $\alpha<1$ it reduces the impact of larger values of $|d - e| + 1$ on WSI_d and places more emphasis on the rain, irrigation and ET_P amounts on day d. The value of $|d - e| + 1$ represents the number of days or time distance between days d and e and is used to determine how far away a wetting event or evapotranspiration event is from the current day d. Values for $K_{y,d}$ and $\propto$ should be calculated by experimentation.

The algorithm iteratively schedules irrigation on the day with maximum WSI taking into account previously scheduled irrigation events until $ALLOC_{season}$ has been depleted.

Parameterisation

Values for $K_{y.d}$ were determined by evaluating Canesim® simulated yield using irrigation schedules generated by the water satisfaction algorithm using four sets of tentative $K_{y,d}$ values. These four sets were designed to reflect the varying sensitivity of crops to water deficit as growing season progresses (Figure 3.2). The $K_{y,d}$ values within a set were varied in stepwise fashion from month to month only, but a continuous variation could have been used instead.

A distinction was made between the stalk growth phase, when the crop is relatively sensitive to water deficits and the shoot emergence and tillering phase when the crop is less sensitive (Pene and Edi, 1999). It was therefore necessary to estimate the time when the stalk growth phase commences. This was done by assuming that the crop requires a thermal time (base10) of 1100 ^{o}Cd (Jones, 2013). The onset of stalk growth was rounded to the closest end of the month (4 months for April crops and 3 months for October crops at all sites)

Four possible sets of parameters were tested in a simulation trial to determine a best set of $K_{y,d}$ values (Figure 3.2). Each parameter set consisted of twelve values representing the twelve months of the year, to be applied in calculating WSI_d.

The $K_{y,d}$ sets 1, 2 and 3 have $values < 1$ in the first 4 (April) or first 3 (October) months of the growing period (tillering stage). This implies that the water satisfaction algorithm will give preference to scheduling irrigation in later months i.e. during stalk elongation, all else being equal. Parameter set 4 has $K_{y,d} = 1$ for all months, implying no preference for scheduling during any specific period. Each set of $K_{y,d}$ parameters was tested, by applying them on the 960 scenarios described in section 3.2.1. and feeding the resultant irrigation schedule to the Canesim® model for simulating yield at harvest.

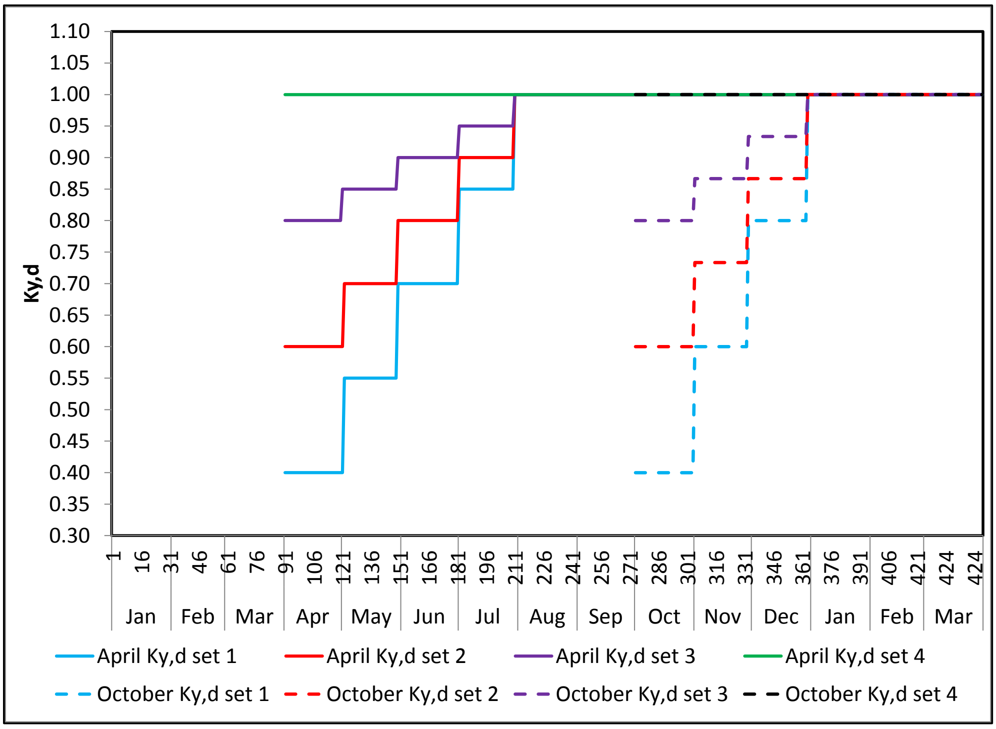

Figure 3.2 Water stress sensitivity factor ($K_{y,d}$) parameter sets tested for use in the water satisfaction algorithm for two crop cycles (April, October) for different months of the year.

The $K_{y,d}$ parameters sets 1, 2 and 3 achieved similar simulated yields irrespective of region or crop cycle. Parameters sets 1, 2, 3 and 4 achieved the best yields in 53, 53, 63 and 12 cases out of 80, respectively. Parameter set 4 performed the best at the highest allocation of 1000 mm. Therefore it was decided to choose $K_{y,d}$ values from parameter set 3 for allocations between 100 mm to 900 mm and from set 4 (i.e. $K_{y,d}$ = 1 for all d) for allocations over 900 mm. *TAM*, irrigation amount and rainfall class had no effect on the relative performance of the algorithms.

It was also necessary to choose a value for $\propto$ in Equation 3.4. Using $K_{y,d}$ parameter set 3 in the above simulation experiment, values of 1, 0.5, 0.2 and 0.1 were tested for $\propto$. From 960 test simulations, average simulated yields were calculated for different regions, crop cycles and seasonal allocations. Out of the 80 resultant cases, the values of 1, 0.5, 0.2 and 0.1 achieved the highest yields 7, 23, 21 and 29 times respectively. The $\propto = 0.5$, $\propto = 0.2$ and $\propto = 0.1$ values performed very similarly. Since $\propto = 0.1$ achieved the highest yields in 29 out of 80 cases as opposed to the next best of 23, it was decided to use the value of $\propto = 0.1$ in the main part of the study. *TAM* had no effect on the order of performance of the algorithms. For the large fixed irrigation amount (40mm), the value of $\propto = 1$ performs better than $\propto = 0.1$ on $ALLOC_{season}$ of 400 mm or less. Rainfall class had no effect on the algorithm performance.

Thus, a suitable set of parameters was chosen for Equation 3.4 for use in comparison against the other algorithms.

3.2.3 Summary

Table 3.2 summarises the differences in approaches with regards to the scheduling aspects and the optimisation rule of the algorithms described thus far. The majority of algorithms use a crop model to calculate the optimal irrigation schedule. The exception is the water satisfaction algorithm, which nevertheless needs some information about yield and crop water stress relations at different growth stages to improve its accuracy. Two algorithms (crop stage, stress level) generated a multitude of irrigation schedules and chose the schedule that maximised yield, while the other two algorithms (prorata, water satisfaction) applied a special set of rules in forming a single optimal schedule. The former algorithms would run slowly (as seen in the following section), while the latter would run quickly. The direct objective of the majority of algorithms was to maximise yield, except for the water satisfaction algorithm which attempted to minimise the cumulative water deficit across the growing season.

In order to code these scheduling algorithms into procedures, flowcharts describing the main processes involved were developed. These flowcharts were translated into C# procedures and linked to an Oracle database. The procedures made use of the Canesim® sugarcane yield and water balance model, either in calculation or in simulating the optimal irrigation schedule, which is coded in Oracle PLSQL. Canesim® was programmed to use a flexible *ADL* (which could vary through the growing season) for scheduling irrigation which helped with the implementation of the scheduling.

Table 3.2 Comparison of various strategies employed by the different scheduling algorithms.

Strategy/Algorithm	**Crop stage**	**Stress level**	**Prorata**	**Water satisfaction**	**Baseline**
Model used to calculate schedule	Canesim®	Canesim®	Canesim®	Simple yield response factor model, based on Canesim®	Canesim®
Scheduling rule	ADL^1 = 50%, non-exceedence of $ALLOC_{stage}{}^2$	ADL^1 varied, non exceedence of $ALLOC_{season}{}^3$	ADL^1 = 50%, non-exceedence of prorata allocation	When water is most needed, non exceedence of $ALLOC_{season}{}^3$	ADL^1 = 50%, non-exceedence of $ALLOC_{season}{}^3$
Number of irrigation schedules formed and tested	Many	Many	One	One	One
Was weather data directly analysed during scheduling?	No – done indirectly through model	No – done indirectly through model	Yes – historical water requirement derived	Yes – rain and ET data used in formula	No – done indirectly through model
Was the crop divided into different growth stages?	Yes	Indirectly through Canesim®	Indirectly through Canesim®	Yes	Indirectly through Canesim®
Optimisation objective	Maximise $\sum \Delta Y_S{}^4$	Maximise $Y_a{}^5$	Maximise $Y_a{}^5$	Maximise seasonal WSI^6	None

[1] ADL = allowable depletion level
[2] $ALLOC_{stage}$ = irrigation allocation for a growth stage
[3] $ALLOC_{season}$ = irrigation allocation for the growing season
[4] ΔY_S = yield increment for a growth stage
[5] Y_a = actual yield achieved by the crop
[6] WSI = Water satisfaction index

3.2.4 Evaluation of algorithms.

Algorithms were ranked according to their performance in terms of simulation computation time, simulated cane yields and irrigated water use efficiency (*IWUE),* taking into account the conditions under which these were achieved. *IWUE* is defined as (Olivier and Singels, 2004):

$$IWUE = (100)\frac{Y_I - Y_D}{Icum_{season}} \qquad \text{Equation 3.5}$$

where

$IWUE$ is the simulated irrigated water use efficiency in t/ha/100mm,

Y_I is the simulated irrigated yield in t/ha,

Y_D is the simulated dryland yield in t/ha, and

$Icum_{season}$ is the total simulated applied irrigation for the crop, in mm.

Algorithms are deemed to perform better if they have shorter computation time, or achieve higher yields and/or *IWUE*.

3.3 Results and Discussion

3.3.1 Algorithm computation times

The average computation time of each algorithm is given Table 3.3, with the fastest possible time (and hence the standard for comparison) being that of the baseline algorithm (0.41 s). Of the algorithms under investigation, the prorata and water satisfaction algorithms were the fastest, with computation running times close to that of the baseline. The stress level algorithm was the slowest. The computation time of the crop stage and prorata algorithms was not affected by the fixed irrigation amount, while it was affected for the water satisfaction and stress level algorithms. It was decided not to simulate the 8 mm irrigation amount for the stress level algorithm because a) it took too long to simulate a single scenario and b) the large numbers of simulation results caused the local database to crash. This reduced the overall number of scenarios for the stress level algorithm from 960 to 480.

Algorithm computation times could be reduced when it is required to optimise the timing of the next irrigation event only (call this the operational computation time) (see Table 3.3). This is true of the stress level algorithm, which needs to iterate only once over its set of exploratory ADLs to determine the date of the next irrigation event. The prorata algorithm, which requires a single comparison of $Ischedcum_d$ against $ALLOCcum_d$ (Equation 3.1) on each day of the simulation, has the same computation time as the baseline algorithm. The crop stage and water satisfaction algorithms require optimisation over the entire growing period in order to optimise the timing of the next irrigation event and hence their computation time is not reduced.

Table 3.3 The number of Canesim® simulations, average computation time (full season[1]) and approximate operational computing time (next event only[2]) and required for optimising the irrigation schedule of a hypothetical crop for different algorithms for a 400 mm seasonal allocation.

Algorithm	**Conditions for optimisation**	**Number of simulations (n)**	**Average computation time[1] (s)**	**Approximate operational computation time[2] (s)**
Baseline		1	0.41	
Crop stage	8 stages with 7 allocations each	56	32.75	32.75
Crop stage	8 stages with 9 allocations each	72	41.25	41.25
Stress level	6 stress levels, 8 mm irrigation amount	300	147.0	2.46
Stress level	6 stress levels, 40 mm irrigation amount	60	25.0	2.46
Water satisfaction		0	1.83	1.83
Prorata basic		1	0.99	0.41
Prorata advanced		1	2.96	2.96

3.3.2 Algorithm performance as determined by yield

Algorithm performance was assessed on the increase in simulated yield and $IWUE$ over that of the baseline algorithm. Yield results (Table 3.4) are discussed first, followed by a brief discussion on $IWUE$, as $IWUE$ results were similar to those of yields. Selected results are also shown in Figures 3.3 to 3.6 and further numerical results are provided in Appendices A1-A3.

The ranking of the overall performance of the algorithms was: (1) crop stage, (2) stress level (3) advanced prorata, (4) water satisfaction and (5) prorata with average yield increases over the baseline of 8.6, 8.5, 5.7, 5.5 and 4.7 t/ha respectively. The average simulated yield increases achieved by the crop stage and stress level algorithms were significantly higher than those achieved by the three other algorithms in most cases (Table 3.4). Yield increases for these two algorithms did not differ significantly from each other for almost every comparison performed (Table 3.4). The other three algorithms differed significantly from each other in certain cases only (Table 3.4). The effect of region, rainfall class, crop cycle, allocation, *TAM* and irrigation amount on algorithm performance and ranking is now discussed.

Region

Performance ranking of the algorithms was not affected by region (Figure 3.3, Figure 3.4, Table 3.4). The average simulated yield increases achieved over the baseline by the crop stage and stress level algorithms were significantly higher than those achieved by the other algorithms.

Table 3.4 Summary of the simulated yields increases (t/ha) over that of the baseline algorithm achieved by each algorithm as averaged over different scenario inputs. Significant differences were determined using the Fisherman's protected least significant difference test (in the case of more than one comparison) or using the two sample unpaired Student's t-test (for one comparison). Standard deviations of the yield increases are shown and different letters indicate significant differences between means (p<0.05). Each scenario input block was analysed separately. Upper case letters apply to individual rows and lower case letters apply to individual columns within each scenario input block.

Inputs		Yield increase (t/ha) for each algorithm				
Scenario input	**Input value**	**Crop Stage**	**Stress Level**	**Water Satisfaction**	**Prorata**	**Advanced Prorata**
Station	Komati	9.7 ±8.2 ^{A,a}	9.7 ±6.9 ^{A,a}	6.6 ±10.9 ^{B,a}	3.8 ±6.3 ^{C,c}	5 ±6.6 ^{C,bc}
	Malelane	8.4 ±6.5 ^{A,b}	8.5 ±6.3 ^{A,a}	4.9 ±8.3 ^{B,bc}	4.8 ±6.6 ^{B,b}	6.0 ±7 ^{B,b}
	Pongola	9.6 ±7.1 ^{A,ab}	9.2 ±6.3 ^{A,a}	6.4 ±8.2 ^{B,ab}	6.1 ±5.6 ^{B,a}	7.2 ±5.8 ^{B,a}
	Umfolozi	6.6 ±6.4 ^{A,c}	6.5 ±5.6 ^{A,b}	4.2 ±7.2 ^{B,c}	3.9 ±4.9 ^{B,bc}	4.6 ±5.1 ^{B,c}
ALLOC-season (mm)	100	5.8 ±3.2 ^{A,e}	5.1 ±1.9 ^{A,de}	3.7 ±3.1 ^{B,d}	5.0 ±3.3 ^{A,cd}	5.7 ±3.2 ^{A,c}
	200	9.8 ±4.5 ^{A,cd}	7.9 ±3.4 ^{B,c}	4.8 ±4.7 ^{C,d}	4.8 ±4 ^{C,d}	5.7 ±4.1 ^{C,c}
	300	11.2 ±5.9^{A,bc}	10.5 ±4.9^{A,b}	11 ±7.3 ^{A,ab}	6.4 ±4.9 ^{B,bc}	7.6 ±5.2 ^{B,b}
	400	14.5 ±7.7^{A,a}	13.5 ±6.6^{AB,a}	12 ±9.3 ^{B,a}	7.2 ±6.6 ^{C,b}	8.5 ±7.1 ^{C,b}
	500	14.3 ±7.6^{A,a}	14.2 ±6 ^{A,a}	12.2 ±9.3^{AB,a}	8.8 ±7.1 ^{C,a}	10.5 ±7.5^{BC,a}
	600	12.5 ±6.7^{A,b}	12.5 ±6.1^{A,a}	9.8 ±8.7 ^{AB,b}	7.3 ±6.8 ^{C,b}	8.4 ±7B ^{C,b}
	700	9.3 ±5.6 ^{A,d}	10.4 ±5.6^{A,b}	7.4 ±7.4 ^{B,c}	6.2 ±5.5 ^{B,bcd}	7.4 ±5.7 ^{B,b}
	800	5.1 ±4.9 ^{A,e}	5.9 ±5 ^{A,d}	0.4 ±6.5 ^{C,e}	2.0 ±4.5 ^{B,e}	2.9 ±4.4 ^{B,d}
	900	2.4 ±3.9 ^{A,f}	3.5 ±4.2 ^{A,e}	-2.9 ±4.9 ^{C,f}	0.3 ±3.1 ^{B,f}	1.0 ±3.2 ^{B,e}
	1000	0.7 ±2.7 ^{A,g}	1.2 ±2.6 ^{A,f}	-3.0 ±3.6 ^{C,f}	-1.2 ±2.3^{B,g}	-0.7 ±2 ^{B,f}
Crop cycle	April	7.6 ±5.9 ^{A,b}	7.5 ±5 ^{A,b}	2.9 ±6.5 ^{C,b}	3.0 ±5 ^{C,b}	3.9 ±5 ^{B,b}
	October	9.5 ±8.2 ^{A,a}	9.4 ±7.4 ^{A,a}	8.2 ±10 ^{B,a}	6.3 ±6.3 ^{C,a}	7.5 ±6.8 ^{B,a}
Soil TAM (mm)	80	9.8 ±7.6 ^{A,a}	9.3 ±6.7 ^{A,a}	6.2 ±9.3 $^{BC, a}$	5.6 ±6.2 ^{C,a}	6.7 ±6.5 ^{B,a}
	120	7.3 ±6.5 ^{A,b}	7.6 ±6 ^{A,b}	4.9 ±8.2 ^{B,b}	3.8 ±5.5 ^{C,b}	4.7 ±5.8 ^{B,b}
Rainfall class	High Rain	8.6 ±7.1 ^{A,a}	8.3 ±6.5 ^{A,a}	5.6 ±8.5 ^{B,a}	3.8 ±5.6 ^{C,b}	4.6 ±5.8 ^{BC,b}
	Med Rain	8.8 ±8.2 ^{A,a}	8.3 ±7.3 ^{A,a}	6.2 ±9.9 ^{B,a}	5.0 ±6.4 ^{C,a}	6.1 ±6.8 ^{BC,a}
	Low Rain	8.3 ±6 ^{A,a}	8.9 ±5.4 ^{A,a}	4.8 ±7.8 ^{C,a}	5.3 ±5.7 ^{C,a}	6.4 ±5.9 ^{B,a}
Irrigation amount (mm)[1]	8	9 ±7.3 ^{A,a}		6.5 ±9.2 ^{B,a}	5.0 ±5.9 ^{C,a}	5.7 ±6.2 ^{BC,a}
	40	8.1 ±7 ^{A,b}	8.5 ±6.4 ^{A}	4.5 ±8.3 ^{C,b}	4.3 ±6 ^{C,a}	5.6 ±6.3 ^{B,a}
Average[2]	450	11.9 ±6.7^{A}	11.5 ±5.9^{A}	9.5 ±8.3 ^{B}	6.8 ±6 ^{D}	8.0 ±6.4 ^{C}
Average[3]	550	8.6 ±7.2 ^{A}	8.5 ±6.4 ^{A}	5.5 ±8.8 ^{B}	4.7 ±5.9 ^{C}	5.7 ±6.2 ^{B}

[1] - The stress level algorithm (*SL*) was not simulated using the 8 mm fixed irrigation amount

[2] - The average was taken over the 200 mm to 700 mm allocation range

[3] – The average was taken over the 100 mm to 1000 mm allocation range

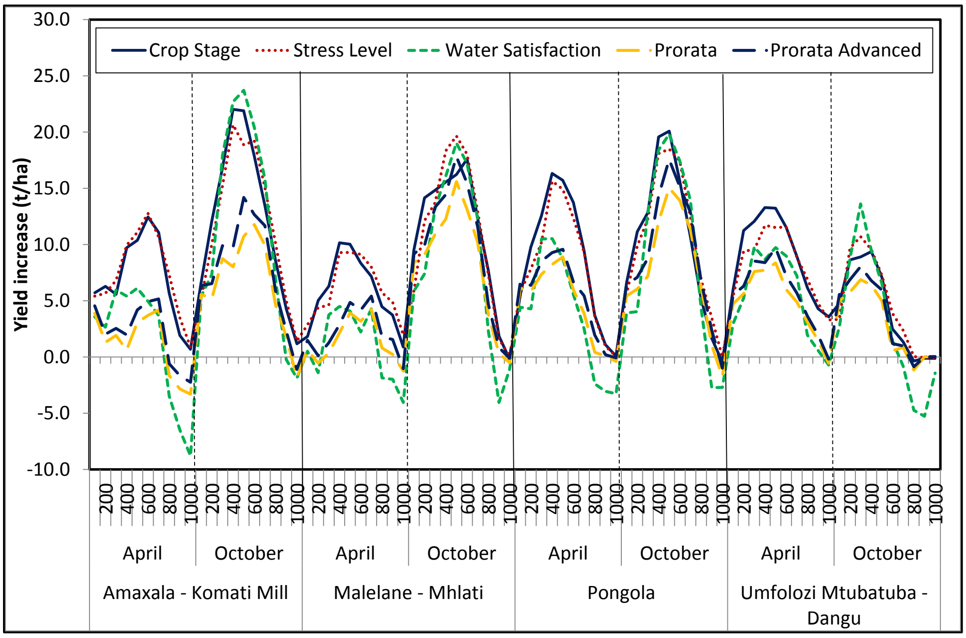

Figure 3.3 Increase in simulated yield over the baseline algorithm using different irrigation scheduling optimisation algorithms. Average values are shown for different seasonal allocations (mm), crop cycles and regions (80 values per algorithm).

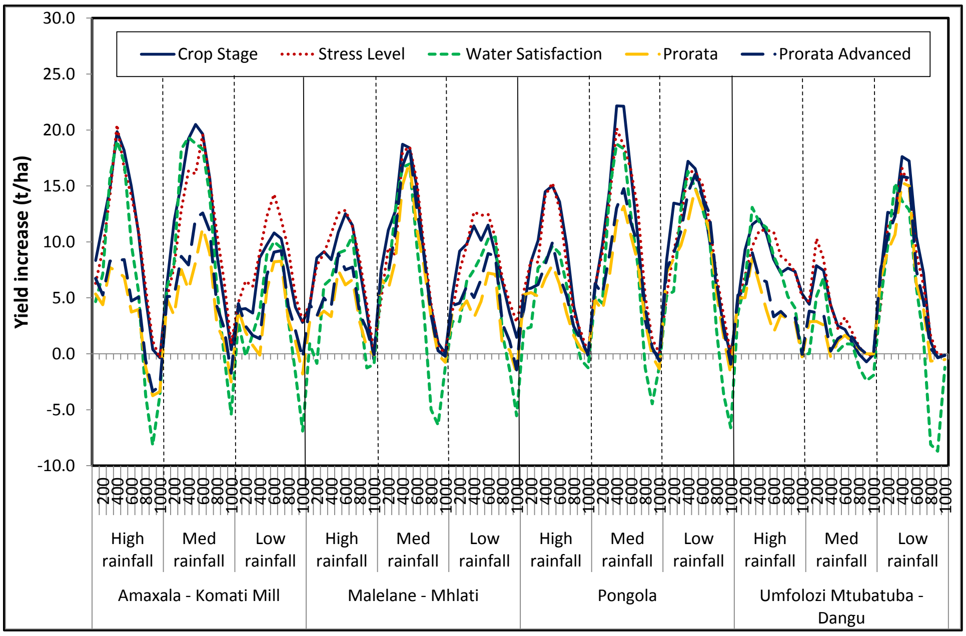

Figure 3.4 Increase in simulated yield over the baseline algorithm using different irrigation scheduling optimisation algorithms. Average values are shown for different seasonal allocations (mm), rainfall classifications and stations/regions (120 values per algorithm).

Allocation

Algorithm performance rankings remained similar as before, except that, for $ALLOC_{season}$ between 300 mm and 600 mm, the water satisfaction algorithm performed as well as the crop stage and stress level algorithms (there were no significant differences, Table 3.4).

Yield increases were significantly different across $ALLOC_{season}$ (Table 3.4). Simulated yield increases achieved by the scheduling algorithms were small for the 100 mm $ALLOC_{season}$ (5 t/ha), were highest at the 500 mm and 600 mm $ALLOC_{season}$ (12 t/ha) and then declined as the $ALLOC_{season}$ increased to 1000 mm (-0.6 t/ha). In some cases, simulated yields achieved by some algorithms were lower than the baseline for the 800 mm to 1000 mm $ALLOC_{season}$, for example, the case of the water satisfaction and prorata algorithms (Figures 3.3 to 3.7). The good performances of the algorithms for the intermediate $ALLOC_{season}$ levels stresses the importance of using optimization under $ALLOC_{season.}$ of this magnitude. At the higher $ALLOC_{season,}$ it becomes sufficient to schedule according to the normal *ADL* rule. The results confirm that the best impact of optimization is achieved with intermediate allocations because although the shortfall is large, the limited but substantial irrigation supply can make a difference to yields if applied optimally. When allocations are very low, less impact is gained because there the supply is too limited, while optimization of allocations close to the seasonal demand brings little benefit because the crop mostly has adequate water.

Crop cycle

The algorithms performed significantly better for October crop cycles than April crop cycles (Table 3.4), suggesting a severe underperformance by the baseline algorithm for October crop cycles. This is confirmed by the fact that the algorithms achieved similar absolute yields for April and October cycles (except for the water satisfaction algorithm which consistently performed worse for April than for October cycles), whereas the baseline achieved higher absolute yields for April than October cycles (4 t/ha on average) (Appendix A1). This was true for all regions and rainfall classes, except for Umfolozi.

Investigation was made into why baseline simulations achieved lower yields for October crop cycle than for April crop cycles. Rainfall distribution is strongly seasonal with most of it occurring in summer in the study areas (Figure 3.5). The baseline algorithm irrigates primarily at the start of the crop. Thus, for April crops, the baseline irrigates through the dry months, with rain covering crop water requirements near the end. For an October crop, the baseline algorithm exhausts the allocation during the initial wet months and leaves a long dry period towards the end of the crop, resulting in a low yield.

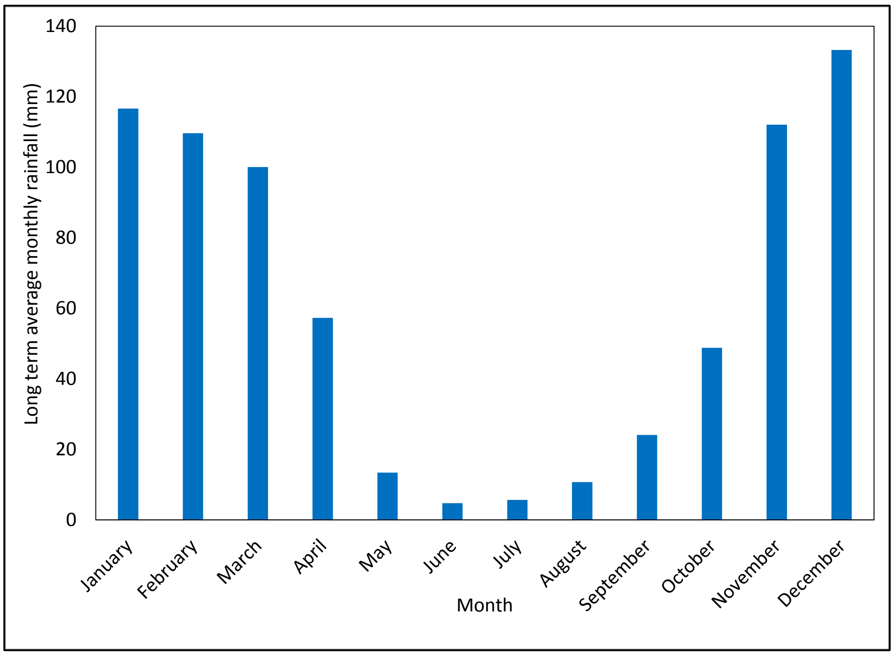

Figure 3.5 Long term average monthly rainfall for the Amanxala - Komati Mill weather station. Rainfall is higher in the summer months than in winter months.

Further investigation was made into why the water satisfaction algorithm specifically performed better for October crop cycles than April crop cycles. The algorithm, as it is formulated in this study, allocates water to periods with a water deficit but prioritizing later growth stages over earlier growth stages. This works well for October cycles when the early growth stages received a lot of rain. It does not work as well for the April cycles because the earlier growth stages occur during periods of low rainfall (Figure 3.5).

Maximum plant available soil water (TAM)

Performances were significantly better for the scenarios with the 80 mm *TAM* (Table 3.4) than for those with the 120 mm *TAM*. This makes sense because, for the simulated soils with the 120 mm *TAM,* less water is wasted through runoff and drainage and therefore there is more buffering capacity for erroneous irrigation practices, while in the case of the 80 mm *TAM,* more precise irrigation scheduling is required. *TAM* appears to play no role on the ranking of algorithms.

Irrigation amount

The performance ranking of the algorithms remained as before (apart from the fact that the stress level algorithm was not simulated on the 8 mm fixed irrigation amount due to excessively high simulation numbers) (Table 3.3). Average yield increases were slightly higher for the 8 mm irrigation amount than those of the 40 mm amount, though in general the differences were not statistically significant (Table 3.4). These results imply that it is not necessary to consider *TAM* and irrigation amount when deciding which algorithm to program into MyCanesim®.

Rainfall class

Algorithm performance rankings remained as mentioned previously. There were no significant differences between simulated yield increases across rainfall classes (crop stage and stress level algorithms, Table 3.4). The prorata algorithms performed worse on average for the high rainfall scenarios than for the medium and low rainfall scenarios (Table 3.4). This is due to the algorithm holding back water during the first part of the growing season and then not using up the full allocation due to adequate rainfall later. The other algorithms are more flexible as to when they can irrigate and therefore perform better in high rainfall seasons.

Figures 3.4, 3.6 and 3.7 give results in more detail than Table 3.4. Examining region by rainfall class (Figure 3.4) showed that algorithms generally performed better for the medium rainfall class (for both April and October crop cycles) except for the Umfolozi region where the low rainfall class gave better yield improvements. Algorithms showed better performances for April crop cycles for medium and low rainfall classes (Figure 3.6). This can be attributed to the baseline algorithm performing better in high rainfall scenarios - there is less room for improving the irrigation schedule by the optimisation algorithms. The crop stage and stress level algorithms were consistently the best performers in each rainfall class. Although the water satisfaction algorithm seemed to perform better than the advanced prorata algorithm in the high and medium rainfall classes, (Figure 3.4, Figure 3.6), there were no significant differences in these cases (Table 3.4).

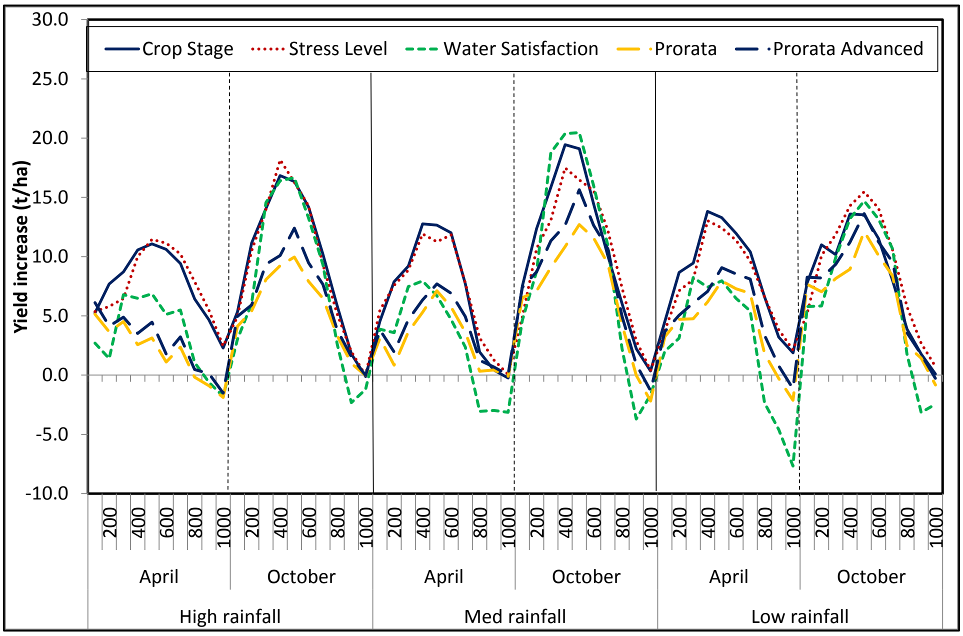

Figure 3.6 Increase in simulated yield over the baseline algorithm using different irrigation scheduling optimisation algorithms. Average values are shown for different seasonal allocations, crop cycles and rainfall classifications (60 values per algorithm).

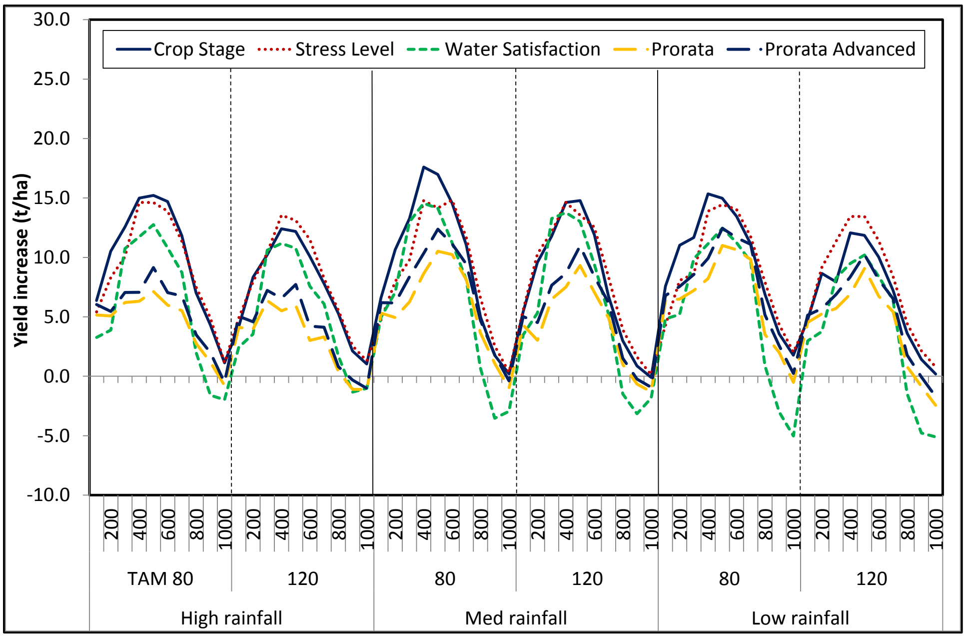

Figure 3.7 Increase in simulated yield over the baseline algorithm using different irrigation scheduling optimisation algorithms. Average values are shown for different seasonal allocations, total available moistures (*TAM*) and rainfall classifications (60 values per algorithm).

3.3.3 Algorithm performances as determined by irrigated water use efficiency (IWUE)

The crop stage algorithm achieved a significantly higher *IWUE* over that of the stress level algorithm in 11 out of 24 cases (all other cases did not differ significantly) (Table 3.5). The *IWUE* increases of these two algorithms were significantly higher than those of the other three algorithms in the majority of cases (Table 3.5).

The reason for the *IWUE* increases of the crop stage algorithm being significantly higher than those of the stress level algorithm can mostly be attributed to higher yields. There were cases when the crop stage algorithm was able to use less than the full $ALLOC_{season}$, but still achieve simulated yields similar to those of the stress level algorithm (see the 900 mm and 1000 mm $ALLOC_{season}$ cases in Table 3.4, Table 3.5).

3.3.4 Optimising of future irrigation events

In this study irrigation scheduling algorithms were evaluated using historical weather data. In practice, when applying the algorithms operationally, this will not be the case. In order to optimize the timing of future irrigation events, consideration should be given on how to represent future weather.

An example is now given, proposed by Inman-Bamber *et al.* (2007) using a simple rainfall categorical forecast of low (below normal), medium or high (above normal) rainfall for the rest of the growing season. Suppose that the forecast status is that the above normal rainfall category is likely to occur. Future irrigation could be scheduled by substituting future weather data with data from all past seasons with above normal rainfall total for the relevant period. The median or average next irrigation event can be chosen as the next official irrigation date. This needs to be evaluated using historical weather data.

Regarding the use of short term rainfall forecasts, Singels *et al.* (1999a) found that for supplementary irrigation conditions, there was no improvement to profitability and only a 3% saving in irrigation in the majority of cases. Therefore it is recommend not to make use of short term rainfall forecasts, but to rather assume zero rainfall over the next week or two when determining irrigation scheduling advice.

Table 3.5 Summary of the simulated irrigated water use efficiency (*IWUE)* increases (t/ha/100mm) over that of the baseline algorithm achieved by each algorithm as averaged over different scenario inputs. Significant differences were determined using the Fisherman's protected least significant difference test (in the case of more than one comparison) or using the two sample unpaired Student's t-test (for one comparison). Different letters indicate statistically significant differences between means ($p<0.05$). Each scenario input was analysed separately. Upper case letters apply to individual rows and lower case letters apply to individual columns within each scenario input block.

Inputs		***IWUE* increase (t/ha/100mm) for each algorithm**				
Scenario input	**Input value**	**Crop stage**	**Stress level**	**Water satisfaction**	**Prorata**	**Advanced Prorata**
Station	Komati	$3.1^{A,a}$	$2.7^{A,a}$	$2.0^{B,a}$	$1.5^{C,a}$	$1.8^{BC,a}$
	Malelane	$2.9^{A,a}$	$2.4^{A,a}$	$1.3^{C,b}$	$1.5^{BC,a}$	$1.8^{B,a}$
	Pongola	$3.2^{A,a}$	$2.8^{AB,a}$	$1.8^{D,a}$	$2.0^{CD,a}$	$2.3^{BC,a}$
	Umfolozi	$2.6^{A,a}$	$2.2^{AB,a}$	$1.0^{D,b}$	$1.6^{C,a}$	$1.9^{BC,a}$
ALLOC-season (mm)	100	$7.7^{A,a}$	$6.4^{B,a}$	$4.2^{C,a}$	$5.3^{B.a,}$	$6.2^{B,a}$
	200	$4.9^{A,b}$	$4.0^{B,b}$	$2.4^{C,b}$	$2.3^{C,b}$	$2.7^{C,b}$
	300	$4.2^{A,c}$	$3.8^{A,bc}$	$2.9^{B,bc}$	$2.1^{C,bc}$	$2.6^{BC,bc}$
	400	$3.6^{A,d}$	$3.4^{AB,cd}$	$3.0^{B,bc}$	$1.8^{C,c}$	$2.1^{C,c}$
	500	$3.1^{A,d}$	$3.0^{AB,d}$	$2.5^{BC,c}$	$1.8^{D,c}$	$2.1^{CD,c}$
	600	$2.2^{A,e}$	$2.1^{A,e}$	$1.6^{B,d}$	$1.2^{B,d}$	$1.4^{B,d}$
	700	$1.6^{A,f}$	$1.5^{A,f}$	$0.6^{C,e}$	$0.9^{B,d}$	$1.1^{B,d}$
	800	$0.9^{A,g}$	$0.7^{AB,g}$	$-0.2^{D,f}$	$0.4^{C,e}$	$0.5^{BC,e}$
	900	$0.7^{A,g}$	$0.4^{B,gh}$	$-0.7^{C,fg}$	$0.3^{B,e}$	$0.3^{B,e}$
	1000	$0.5^{A,g}$	$0.2^{B,h}$	$-1.1^{C,g}$	$0.2^{B,e}$	$0.2^{B,e}$
Crop cycle	April	$2.5^{A,b}$	$2.2^{B,b}$	$0.9^{D,b}$	$1.1^{CD,b}$	$1.4^{C,b}$
	October	$3.3^{A,a}$	$2.8^{B,a}$	$2.1^{D,a}$	$2.15^{CD,a}$	$2.5^{BC,a}$
Soil TAM (mm)	80	$3.3^{A,a}$	$2.6^{B,a}$	$1.7^{D,a}$	$1.9^{CD,a}$	$2.2^{C,a}$
	120	$2.6^{A,b}$	$2.4^{A,a}$	$1.3^{C,b}$	$1.4^{BC,b}$	$1.7^{B,b}$
Rainfall class	High Rain	$2.8^{A,a}$	$2.5^{A,a}$	$1.4^{B,a}$	$1.5^{B,a}$	$1.8^{B,a}$
	Med Rain	$3.1^{A,a}$	$2.5^{B,a}$	$1.6^{C,a}$	$1.6^{C,a}$	$2.0^{C,a}$
	Low Rain	$2.8^{A,a}$	$2.6^{A,a}$	$1.5^{C,a}$	$1.8^{BC,a}$	$2.0^{B,a}$
Irrigation amount (mm)[1]	8	$3.2^{A,a}$		$1.8^{B,a}$	$1.5^{B,a}$	$1.7^{B,b}$
	40	$2.7^{A,a}$	2.5^{B}	$1.2^{D,b}$	$1.7^{C,a}$	$2.1^{B,a}$
Average[2]	450	3.3^{A}	3.0^{B}	2.2^{C}	1.7^{D}	2.0^{C}
Average[3]	550	2.9^{A}	2.5^{B}	1.5^{D}	1.6^{D}	1.9^{C}

[1] - The stress level algorithm (*SL*) was not simulated using the 8 mm fixed irrigation amount

[2] - The average was taken over the 200 mm to 700 mm allocation range

[3] – The average was taken over the 100 mm to 1000 mm allocation range

3.4 Conclusions

Simulated yield performances as well as computation time needs to be considered when choosing the most effective limited water irrigation scheduling algorithm for use in MyCanesim®. In what follows, consideration is first given to choosing an algorithm for irrigation scheduling, for the purposes of maximising actual yields. Secondly, consideration is given to choosing an algorithm which only forecasts yield, for planning purposes. As will be seen, the algorithms are not the same, since the computation time for scheduling the next irrigation event is much less in some cases than that for scheduling over the whole season and hence a slow algorithm that achieves large yield benefits maybe be chosen in the former case.

In this study, optimisation of the irrigation schedule was performed retrospectively for the entire growing season. All algorithms were able to achieve higher yields than those of the baseline by at least 4.7 t/ha on average, and show promise for improving yields under conditions of seasonal water restriction, especially under intermediate restrictions of around 50%. Algorithms that simulate large yield increases (crop stage, stress level) ran slowly, while algorithms which achieved lower yield increases (water satisfaction, prorata) ran faster. Yield differences between the crop stage algorithm and the stress level algorithm were marginal. However, for the purposes of providing irrigation advice to farmers, algorithm computation time (Table 3.3) required to optimise the timing of the next irrigation event and not necessarily that of the entire season, can be considered. In that case, the stress level algorithm runs quicker than the crop stage algorithm (Table 3.3) and is therefore recommended for inclusion in MyCanesim®.

Since the relatively slow stress level algorithm will be used to optimise the timing of the next irrigation event only, another algorithm is required for forecasting yield, the future soil water balance and future crop growth. A fast algorithm, either the prorata or water satisfaction algorithm, is recommended. The water satisfaction algorithm over-irrigates when the $ALLOC_{season}$ is greater than 700 mm and should not be considered in its current form. The water satisfaction algorithm should be improved to achieve better yields for higher $ALLOC_{season}$, by providing a feedback mechanism to indicate when over-irrigation has occurred. The water satisfaction algorithm should also be programmed to use effective rainfall rather than rainfall. The prorata algorithm can therefore suffice for yield forecasting.

3.5 References

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4. INCORPORATING SOIL WATER MONITORING TECHNOLOGY INTO MYCANESIM®

4.1 Introduction

A problem is created when farmers do not upload irrigation dates and amounts to MyCanesim® (Singels, 2007; Singels and Smith, 2006) because the simulated and actual soil water balance may differ when irrigation scheduling advice was not followed (noted in Singels and Smith, 2008). This implies that future scheduling advice may be inaccurate because it is based on an unrealistic simulated soil water status. Resetting simulated soil water status with data collected from soil water sensors may be a solution to this problem (Farina and Bacci, 2005; Paige and Keefer, 2008). In addition, accurate historical soil water content may also result in more accurate simulation of crop drought, water logging stresses (or lack thereof) and the consequent influence on crop growth, the recommended date of next irrigation, more accurate yield forecasts and more useful post-season irrigation performance analyses.

The main objective of this part of the study was to incorporate near real-time field records of soil water status into the weather-based sugarcane simulation system, MyCanesim®, and to evaluate its use for supporting irrigation management (as suggested by Holloway-Phillips *et al.,* 2008). The specific objectives were to:

(a) develop a procedure to convert the soil water index (SWI, in %) data from the probes to available soil water content ($ASWC_{probe}$, in mm);

(b) use $ASWC_{probe}$ to reset simulated $ASWC$ in MyCanesim®; and

(c) assess the usefulness of the integrated system by (1) evaluating the quality of irrigation scheduling advice and yield forecasts and by (2) using it to analyse agronomic performance on the study fields.

4.2 Methods

4.2.1 Trial sites and soil water monitoring

Thirteen sugarcane fields in Mpumalanga were selected for evaluating the integration of soil water sensor data into MyCanesim®. A map showing their locations is given in Figure 4.1. Details of the different sites and inputs used for simulations are given in Table 4.1.

Plant available water holding capacity (*TAM,* in mm) of soils was determined from effective rooting depth (*ERD,* in m) and clay content (*CC* as a fraction) following the method of Van Antwerpen *et al.*, (1994):

$$TAM = 1000 * ERD * (FC - WP) \qquad \text{Equation 4.1}$$

$$FC = \left(\frac{54.7 * CC}{24.53 + CC * 100}\right) \qquad \text{Equation 4.2}$$

$$WP = \left(\frac{91.94 * CC}{135.54 + CC * 100}\right) \qquad \text{Equation 4.3}$$

where

FC = volumetric field capacity in m^3/m^3, and

WP = volumetric wilting point in m^3/m^3.

Fields on farm F had continuous logging capacitance probes (probes from Aquacheck (Pty) Ltd, Durbanville, South Africa) installed on them prior to the 2011/12 cropping season. Aquacheck capacitance probes were installed on all the other fields listed in Table 4.1, some in November 2011 and some in March 2012. Probes had six sensors spaced at depth intervals of 100 mm (60 cm probes), or four sensors spaced at 100 mm intervals with two more at 600 and 800 mm (80 cm probes). When converting probe *SWI* data to Canesim® $ASWC_{probe}$ data, equal weightings were used for all sensors of a given probe, regardless of the sensor spacing. This reflected the assumed lower rooting density in the bottom two layers of a 80 cm root zone where sensors were spaced at 200 mm rather than 100 mm. Probes were installed as close as possible to the cane row or immediately next to drip emitters (in the case of drip irrigated fields) by inserting them in a vertical cavity created by a soil auger and filling any remaining space between the probe and the cavity wall with a slurry (van Niekerk, 2010). Details of probe depths and operational periods are provided in Table 4.2.

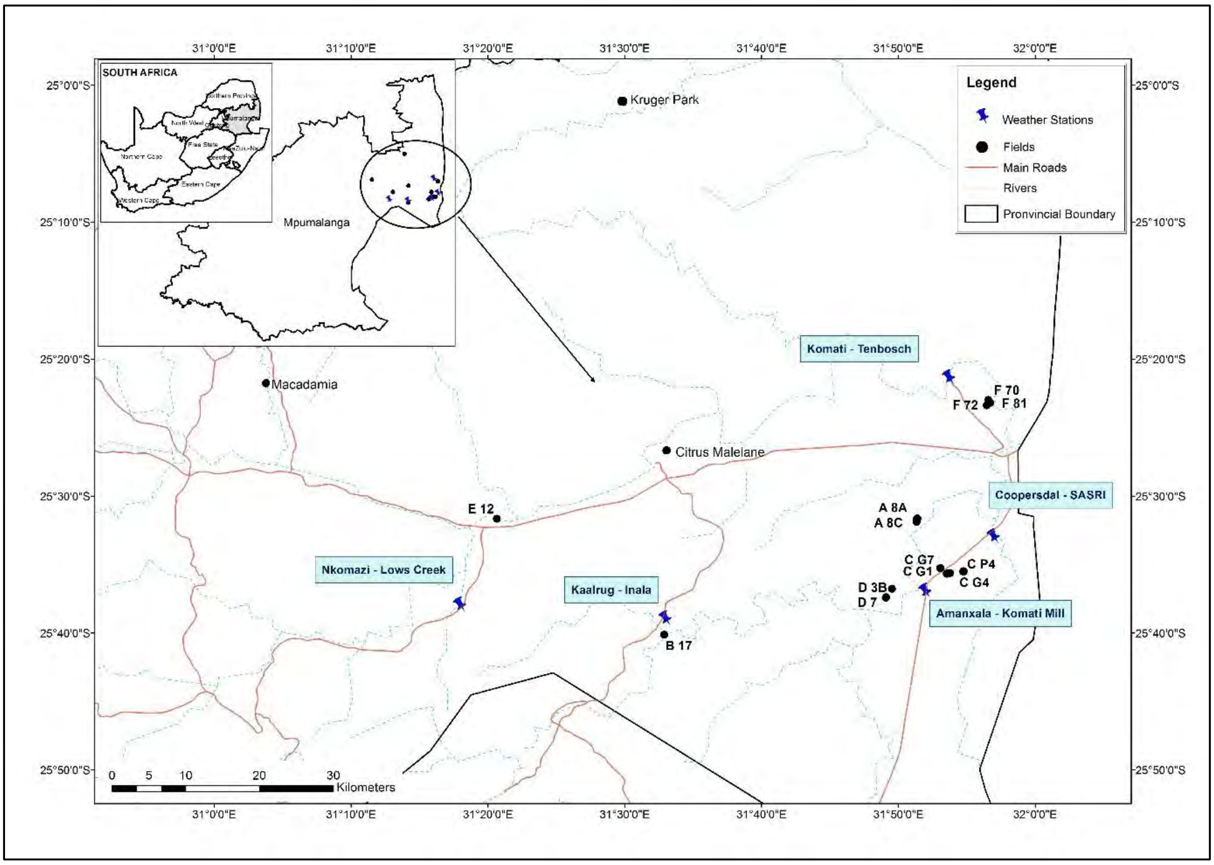

Figure 4.1 Map of locations of study fields in Mpumalanga. Locations include commercial (A, C, D, F) and small scale farms (B, E). (Courtesy of Ingrid Mthembu, SASRI.)

Table 4.1 Field details for different sites and simulation settings for the Canesim® sugarcane model. *TAM* is the maximum amount of water in the root zone available to the plant when the profile is at field capacity; Irrig. refers to irrigation, *SD* = surface drip, *OH* = overhead (centre pivot or dragline), *SSD* = sub-surface drip. Irrigation amount (Irrig. amnt.) is the design irrigation amount per event. *ADL* is the chosen allowable depletion level at which point an irrigation is triggered.

Farm code	Field name	Rooting depth (m)	Clay content (%)	TAM (mm)	Automatic weather station[a]	Vari ety	Row spacing (m)	Crop start date 2011	Crop harvest date 2012	Crop harvest date 2013	Irrig. syste m	Irrig. cycle (d)	Irrig. amnt. (mm)	ADL (mm)
A	8A	0.77	36	102	Coopersdal – SASRI	N25	1.1[c]	31/Jul/2011	29/Jun/2012	07/Jul/2013	SD	1	7	71
A	8C	0.75	45	96	Coopersdal – SASRI	N25	1.1[c]	31/Jul/2011	28/Jun/2012	11/Jul/2013	SD	1	7	70
B	17	0.68	71	61	Kaalrug – Inala	N25	0.95[c]	08/Sep/2011	25/Aug/2012	01/Nov/2013	OH SD	7 2	24 9	42 42
C	G1	0.72	39	93	Amanxala - Komati Mill	N19	1.5[b]	11/Jun/2011	14/Jun/2012	27/Jun/2013	SD	1	7	65
C	G4	0.72	38	94	Amaxnala - Komati Mill	N19	1.5[b]	24/Jun/2011	16/Jun/2012	23/Jun/2013	SD	1	7	65
C	G7	0.60	39	78	Amanxala - Komati Mill	N14	1.5[b]	08/Aug/2011	04/Jul/2012	No crop	OH	2	12	56
C	P4	0.70	41	90	Amanxala - Komati Mill	N32	0.9[c]	14/Oct/2011	14/Dec/2012	26/Nov/2013	SSD	1	7	63
D	3B	0.40	27	54	Amanxala - Komati Mill	N19	1.1[c]	12/May/2011	20/Jun/2012	02/Nov/2013	SD	1	6	36
D	7	0.72	36	80	Amanxala - Komati Mill	N19	1.4[b]	01/Jul/2011	08/Jun/2012	Ploughed out	OH	7	48	56
E	12	0.75	20	96	Nkomazi - Lows Creek	N32	0.95[c]	21/Jul/2011	21/Jul/2012	03/Aug/2013	SD	3	8	67
F	70	0.57	25	76	Komatipoort – Tenbosch	N36	0.95[c]	19/May/2011	21/May/2012	29/Jun/2013	SD	1	6	53
F	72	0.70	43	89	Komatipoort – Tenbosch	N23	1.5[b]	12/Sep/2011	23/Oct/2012	13/Sep/2013	OH	2	15	62
F	81	0.73	46	90	Komatipoort – Tenbosch	N36	0.95[c]	22/May/2011	26/May/2012	26/Jun/2013	SD	1	6	63

[a] Campbell Scientific Inc., North Logan, Utah

[b] Single line configuration

[c] Tram line configuration

4.2.2 System development

Soil water status data conversion

A method of converting the factory calibrated *SWI* data to $ASWC_{probe}$ for use in MyCanesim® was needed. The assumption was that the relationship between *SWI* and $ASWC_{probe}$ was linear and that the coefficients of linearity would differ from field to field as determined by sensor and soil properties.

Recorded soil water status of the root zone (the average *SWI* of all available sensors in the profile) was transformed to units of $ASWC_{probe}$ using two field specific calibration factors, namely (1) the *SWI* at field capacity (FC_{SWI} in %) and (2) a conversion ratio (*CR* in mm/%, defined as the amount of available soil water per unit of *SWI*):

$$ASWC_{probe} = TAM - CR(FC_{SWI} - SWI) \qquad \text{Equation 4.4}$$

where *TAM* is the available soil water content of the root zone at field capacity after drainage of free water (in mm). Values for FC_{SWI} were determined by investigating recorded drainage and extraction patterns after a wetting event. Significant wetting of an already wet root zone will increase *SWI* above the FC_{SWI}, causing rapid drainage and decline of *SWI* over time. As soon as the *SWI* reaches FC_{SWI}, drainage rate and decline in *SWI* would slow markedly, indicating the transition from rapid drainage of free water to extraction of water by plants, providing an indication of the value of FC_{SWI}. Values for *CR* were determined by comparing recorded extraction rates for dry days with MyCanesim® simulated extraction rates (assuming these are accurate) and adjusting *CR* values until these extraction patterns (average rates of decline in simulated and observed *ASWC*) matched. Values for *CR* can also be determined by comparing recorded responses to night-time wetting events of known amounts of water but this was not used here because reliable irrigation and local rainfall records were not available. Actual values determined for FC_{SWI} and *CR* are given in Table 4.2. Note that in most cases recalibration of FC_{SWI} and *CR* had to be done the second season and only in two cases (8C, P4) did one set of calibration factors apply to both seasons. Recalibration was required in cases where probes were re-installed in the second season or where irrigation systems were changed

(17). It should be noted that the calibration of the first season was sometimes based only on a partial data set (see Table 4.2).

Soil water data integration into MyCanesim®

Half-hourly *SWI* data were transferred from a central Aquacheck server to the MyCanesim® database and then converted to $ASWC_{probe}$. The $ASWC_{probe}$ value at 8:00 am is taken as the daily value that is displayed on soil water graphs (Figure 4.2). The user can also manually upload $ASWC_{probe}$ data into the database through the MyCanesim® web interface. Users need to specify whether they want simulated *ASWC* to be corrected with measured values or not. If the correct option is chosen, the simulated *ASWC* at the start of the day will be reset to the measured value, except on days when rainfall or irrigation exceeded 15 mm. This exception was required to avoid potential errors that could be caused by the uncertainty of whether the wetting event occurred before or after the reading of the 8:00am *SWI* value. The threshold value of 15 mm was chosen so that large wetting events would not be double counted causing larger errors, while smaller, more frequent irrigation events would not excluded.

Table 4.2 Details of soil water monitoring stations and values for soil water index conversion factors (see Equation 4.4).

Farm code	**Field name**	**Soil water sensor depth (cm)**	**Operational period 2011-2012**	**FC_{SWI} (%)**	**CR (mm/%)**	**Operational period 2012-2013**	**FC_{SWI} (%)**	**CR (mm/%)**
A	8A	80	09/November/2011 – 14/December/2011; 20/January/2012 – 29/June/2012	75.0	2.48	20/October/2012 – 03/July/2013	80.0	5.00
A	8C	80	09/November/2011 – 28/June/2012	83.0	3.23	20/July/2012 – 04/July/2013	83.0	3.23
B	17	60	07/December/2011 – 25/August/2012	75.0	3.43	20/October/2012 – 03/March/2013 24/April/2013 – 25/August/2013	84.0	3.00
C	G1	60	09/November/2011 – 11/June/2012	86.0	9.50	20/July/2012 – 27/February/2013 24/March/2013 – 03/June/2013	85.0	14.00
C	G4	60	16/March/2012 – 11/June/2012	86.0	8.64	09/August/2012 – 12/June/2013	88.0	15.00
C	G7	60	16/March/2012 – 03/July/2012	83.0	4.70	Fallow	NA	NA
C	P4	60	16/March/2012 – 11/December/2012	86.6	5.78	13/February/2013 – 06/November/2013	86.6	5.78
D	3B	60	09/November/2011 – 20/June/2012	85.0	1.29	11/July/2012 – 27/September/2012 14/October/2012 – 08/October/2013	77.0	2.00
D	7	60	09/November/2011 – 08/June/2012	64.0	4.00	Fallow	NA	NA
E	12	60	07/December/2011 – 12/July/2012	68.0	4.02	26/September/2012 – 11/July/2013	64.0	3.35
F	70	80	03/May/2012 – 12/May/2012	80.0	3.26	06/June/2012 – 14/June/2013	74.0	4.00
F	72	80	04/April/2011 – 15/September/2012	75.0	4.79	15/November/2012 - 10/September/2013	75.0	5.50
F	81	80	22/October/2011 – 06/November/2011; 16/November/2011 – 22/March/2012; 29/March/2012 – 12/May/2012	80.0	4.00	06/June/2012 – 20/June/2013	84.0	4.00

System outputs

The soil water graph, available on the MyCanesim® website, was modified to display values of $ASWC_{probe}$ (Figure 4.2). Online graphing was done using the freeware (available for non-commercial use) at http://www.highcharts.com. This package was chosen out of eleven freeware candidates because it could display multiple series on multiple axes, display values on mouse over events, allowed scrolling and zooming, could export graphs as images and was compatible with HTML and JavaScript. An example of the new soil water graph is shown in Figure 4.2.

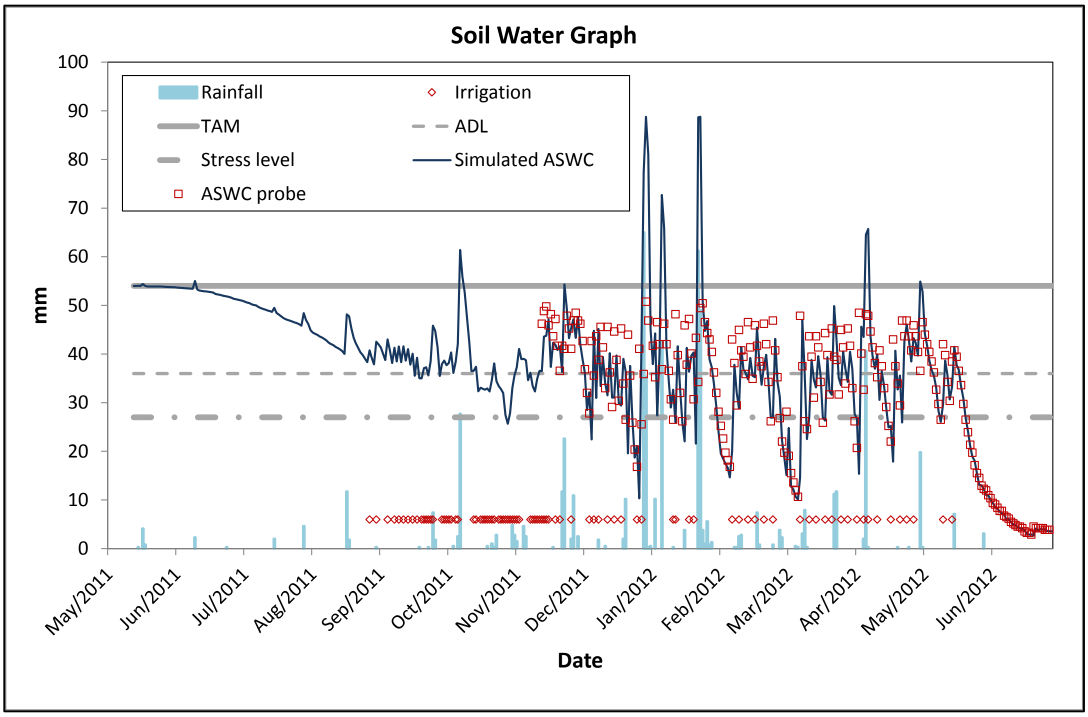

Figure 4.2 An example of MyCanesim® output: Daily values of simulated (blue line) and measured (red open squares) root zone available soil water content (*ASWC*), rainfall (blue bars) and irrigation (red open circles). The horizontal solid line indicates the *ASWC* at field capacity (*TAM*), the line with small dashes indicates the chosen allowable depletion level (*ADL*) and the line with mixed dot dash represents Canesim®'s stress point. In this specific example simulated *ASWC* was corrected with measured values ($ASWC_{probe}$).

The different programming and data components of the integrated MyCanesim® system are illustrated in Figure 4.3. Selected graphs of Canesim® simulations for the study fields as corrected by $ASWC_{probe}$ are given in Appendix B1.

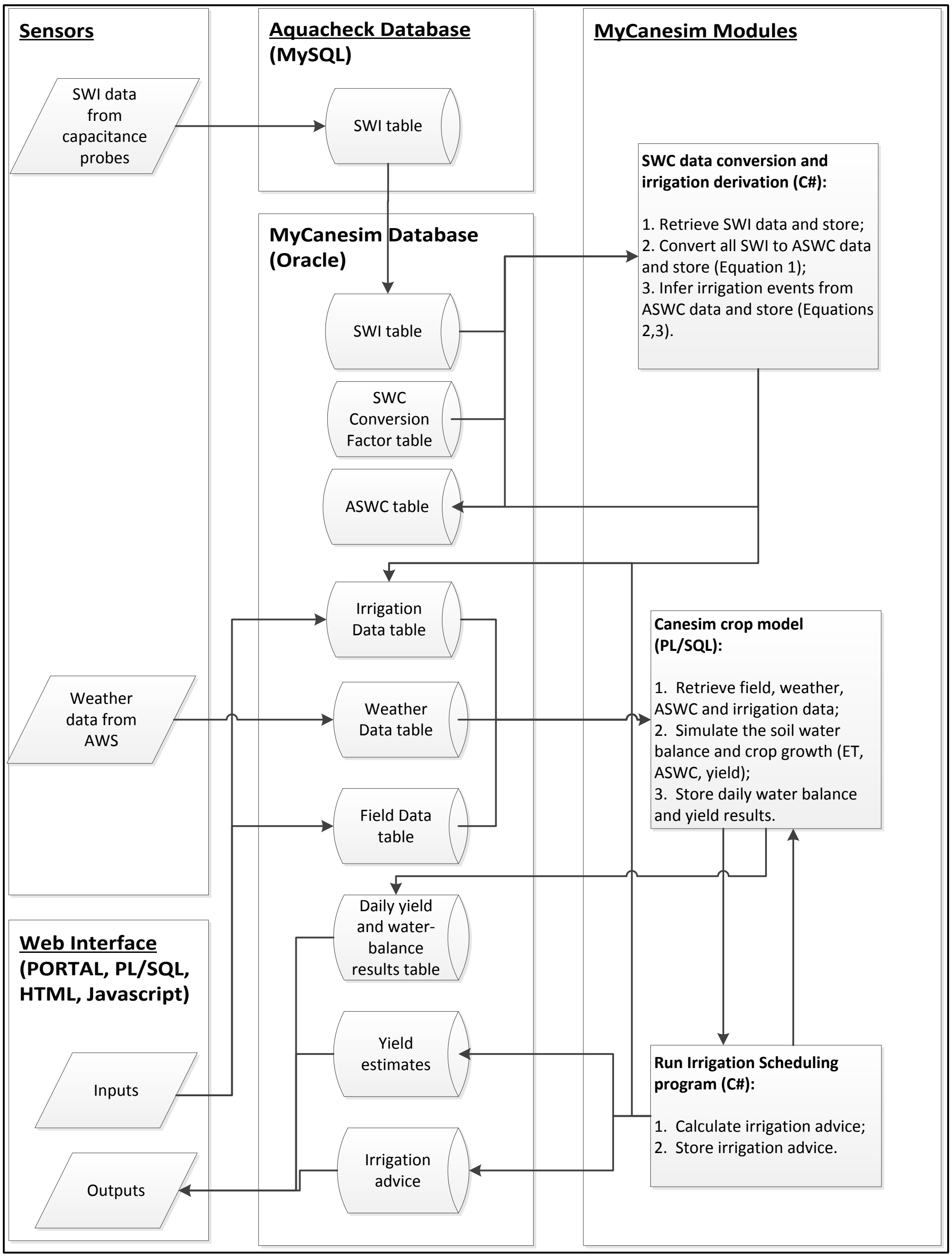

Figure 4.3 A flowchart summarizing components and data flow of the integrated MyCanesim® sugarcane simulation system. Software components include: MySQL database, Oracle PORTAL 11, Oracle PL/SQL 10.0.5 and Oracle database 10g (Oracle Corporation, Redwood Shores, California, www.mysql.com and www.oracle.com) and Microsoft Visual # 2010 (Microsoft, Redwood, Washington, www.microsoft.com). *SWI* refers to soil water index and *ASWC* refers to available soil water content.

4.2.3 System evaluation

The usefulness of the integrated system was evaluated by (1) retrospectively assessing the improvement in the accuracy of irrigation scheduling advice and yield forecasts by probe-based simulation (*PBS*) over weather-based simulation (*WBS*) and (2) by using system outputs to analyse agronomic performance.

4.2.3.1 Irrigation scheduling advice

The MyCanesim® system provides tactical irrigation scheduling advice to farmers, by forecasting the date when the next irrigation is due (date of next irrigation, or *DNI*) based on simulated *ASWC* and the user-specified *ADL*. Correcting simulated *ASWC* with $ASWC_{probe}$ should improve the accuracy of irrigation scheduling advice, because the starting point of the *ASWC* projection is likely to be a more accurate reflection of reality than a simulation based on weather data and the assumption that the farmer followed previous advice. The error (in days) resulting from forecasting the *DNI* should reduce when correcting simulations with $ASWC_{probe}$.

To test this hypothesis, two approaches were used to simulate the soil water balance up to a hypothetical current date. Firstly, the soil water balance was simulated using weather data only (weather-based simulation, *WBS*). Secondly, $ASWC_{probe}$ was used to correct the soil water content (probe-based simulation, *PBS*).

For the subsequent irrigation management window (which extends from after the hypothetical current date until the actual *DNI* (DNI_{actual})), *WBS* was used to forecast the *DNI* for both simulation methods. The forecasted *DNI* were then compared with the DNI_{actual}, which was taken as the date when $ASWC_{probe}$ depleted to the chosen *ADL* (70% of *TAM*) in the management window. This process was repeated for each week of the growing period (for which $ASWC_{probe}$ data was available) to emulate an operational mode.

The accuracy of *DNI* forecasts was quantified by calculating the average difference (named the *DNI* bias, in units of days) and the average absolute difference (the *DNI* forecast error, days) between the predicted and actual *DNI*. The frequency with which *DNI* forecasts were a) early ($<DNI_{actual}$), b) on time ($= DNI_{actual}$) and c) late ($>DNI_{actual}$) was also calculated.

Where $ASWC_{probe}$ indicated that a farmer probably irrigated earlier than DNI_{actual}, the case was excluded from the analysis.

4.2.3.2 Yield forecasts

Correcting Canesim®'s simulated *ASWC* using measurements may also improve its yield forecasting accuracy, for similar reasons mentioned in the previous section.

To test this hypothesis, two types of yield forecasts were made. The first yield forecast ($Yield_{WBS}$) was obtained by using *WBS* only, with a full record of weather data. The second ($Yield_{PBS}$) was obtained using *PBS* up to a hypothetical current date and then completing the simulation up to crop harvest using *WBS.* This was done for each week of the growing season for which $ASWC_{probe}$ data was available.

Forecast accuracy was quantified by calculating the average difference (named the yield forecast bias, *YFB* in t/ha) and the average absolute difference (the yield forecast error, *YFE, in* t/ha) between the forecasted and observed yields *viz:*

$$YFB = \frac{1}{n}\sum(Y_f - Y_{obs}) \qquad \text{Equation 4.5}$$

$$YFE = \frac{1}{n}\sum|(Y_f - Y_{obs})| \qquad \text{Equation 4.6}$$

where *YFB* and *YFE* were calculated for *WBS* and *PBS* respectively.

The difference between the forecasted and observed yields (Y_{obs}) as a percentage of Y_{obs}, were also plotted (selected plots in Appendix B2) for each week of the simulated growing season.

It should be noted that for both the *DNI* and yield forecasts, actual weather data was used throughout simulations. In practice, future weather data is approximated through a substitute weather sequence from past records.

4.2.3.3 Reviewing agronomic performance

The potential value of integrating soil water monitoring data with weather-based simulations was demonstrated by inferring the agronomic performance, including the quality of irrigation management, for the different fields by comparing simulated yields using optimal irrigation (Y_{opt}), yields from *ASWC* corrected simulations (Y_{swc}) and actual yields (Y_{obs}). Criteria for inferring agronomic performance are given in Table 4.3.

Table 4.3 Knowledge gained by comparing yields from various simulations. Y_{opt} is the simulated yield using an optimal irrigation schedule; Y_{swc} is the yield from a simulation based on observed soil water records; and Y_{obs} is the actual yield achieved.

Comparison	Deduction
$Y_{obs} > 0.85\ Y_{opt}$	Good irrigation[2], good husbandry
$Y_{obs} < 0.85\ Y_{opt}$	Crop underperformance due to one or more limiting factors
$Y_{swc} > 0.85\ Y_{opt}$	Good irrigation[2]
$Y_{swc} < 0.85\ Y_{opt}$	Under/over-irrigation caused preventable drought/water logging stress
$Y_{obs} > 0.85\ Y_{swc}$	Good husbandry
$Y_{obs} < 0.85\ Y_{swc}$	Suboptimal husbandry

[1] – Yield differences above the 0.85 limit indicate good management performances. Canesim simulations assume ideal field management practices except for those of irrigation – the 0.85 accounts for the difference between the ideal and more achievable, practical situation.
[2] – Irrigation practices were evaluated accounting for the limitations of the existing irrigation system

The extent of water stress (drought stress and waterlogging) experienced is also an indication of the appropriateness of irrigation practices. Drought stress days were defined as days when *ASWC* was less than 40% of *TAM*, excluding the last 30 days of the season (when irrigation is typically intentionally withheld to promote sucrose accumulation). Water logged days were defined as days when *ASWC* was greater than 110% of *TAM*. The Canesim® model assumes that drought stress occurs when *ASWC* is below 50% of *TAM* and that waterlogging occurs when *ASWC* exceeds 100% of *TAM*. Thresholds of 40% and 110% of *TAM* were chosen in order to exclude days with slight drought and waterlogging stress. When the number of stress days exceeded 30, a typical dry-off period, this was considered to have had a significant impact on yield.

4.3 Results and Discussion

4.3.1 Irrigation scheduling advice

The Canesim® model was used to retrospectively simulate the soil water balance and crop growth of the case study fields, up to a hypothetical current date, using either *WBS* or *PBS* and the date of the next irrigation event (*DNI*) was forecast. The *DNI* forecast bias and error for *PBS* and *WBS*, as they differed from DNI_{actual}, were calculated.

Results are given in Table 4.4 and show that *PBS* enabled more accurate irrigation advice than *WBS*. This is evidenced by a lower average *DNI* forecast bias for both growing seasons, a lower *DNI* forecast error in 75% of cases for the 2011-2012 season and in 100% of cases for the 2012-2013 season. The DNI_{PBS} was on time in 66% of cases for the 2011-2012 season and in 71% of cases (more than double that of DNI_{WBS}) for the 2012-2013 season. In just three cases, the *DNI* forecast error was more for *PBS* than for *WBS* (fields 8A, 8C and 81 for 2011-2012).

The average DNI_{WBS} forecast errors for fields with low (≤ 80 mm) and high *TAM* (> 80 mm) values were 4.1 and 3.8 days respectively, while the DNI_{PBS} forecast errors were 0.7 and 1.8 days. Thus the improvement in accuracy of forecasts is greater in the case of low *TAM* soils than it is for high *TAM* soils, (3.4 days versus 2 days improvement). The three fields with the lowest *TAM* values (3B, 17 and 70) had the smallest DNI_{PBS} forecast bias and errors, as well as the highest frequency of on time *DNI* forecasts, for the 2011-2012 season (Table 4.4). These results suggest that *PBS* is more beneficial for soils with low TAM than high TAM values. This makes sense if one considers that the ratio between the error in days (when weather-based scheduling has led to inaccuracies in simulated *ASWC*) and the time taken to deplete the profile is larger for low *TAM* soils.

The average DNI_{WBS} forecast errors for drip irrigated fields and overhead irrigated fields, respectively, were 3.9 and 3.7 days, while the DNI_{PBS} forecast errors were only 1.6 and 1.0 days, respectively. Thus, the size of the *DNI* forecast errors is smaller for overhead irrigated fields than for drip and the degree of improvement in accuracy of forecasts is also slightly more for overhead than for drip. Fields 8A, G1 and 81, which are all drip irrigated, had the largest DNI_{PBS} forecast errors. These results suggest that *PBS* is more beneficial for overhead irrigated fields than drip. The reason for a greater improvement for overhead fields as opposed to drip fields is not clear.

Table 4.4 The bias, error and frequency of early, on time and late forecasts, of the date of next irrigation (*DNI*) for weather-based simulation (*WBS*) and probe-based simulation (*PBS*) for the 2011-2012 and 2012-2013 growing seasons; *TAM* is the total available moisture of the soil.

						DNI forecast bias		DNI forecast error		DNI forecast timing: Early		DNI forecast timing: On time		DNI forecast timing: Late		
Season	**Farm**	**Field**	**Soil TAM (mm)**	**Irrigation system**	**Irrigation amount (mm)**	**WBS (days)**	**PBS (days)**	**WBS (days)**	**PBS (days)**	**WBS (%)**	**PBS (%)**	**WBS (%)**	**PBS (%)**	**WBS (%)**	**PBS (%)**	**(n)**
2011	A	8A	102	SD	7	0.7	2.5	1.0	2.6	13.3	6.7	46.7	40.0	40.0	53.3	15
	A	8C	96	SD	7	0.9	1.3	0.9	1.3	0.0	0.0	42.9	71.4	57.1	28.6	14
	B	17	61	OH	24	3.2	-0.2	3.5	0.3	6.5	6.5	12.9	90.3	80.6	3.2	31
	C	G1	93	SD	7	-3.4	-2.0	3.4	2.8	80.0	40.0	20.0	20.0	0.0	40.0	5
	C	G4	94	SD	7	-4.0	-1.0	4.0	1.0	100.0	100.0	0.0	0.0	0.0	0.0	1
	C	G7	78	OH	12	0.0	-1.3	2.4	1.6	44.4	44.4	22.2	44.4	33.3	11.1	9
	D	3B	54	SD	6	0.4	0.1	0.4	0.1	0.0	0.0	70.6	94.1	29.4	5.9	17
	D	7	80	OH	48	3.3	-0.9	5.2	1.2	27.8	38.9	0.0	55.6	72.2	5.6	18
	E	12	96	SD	8	-0.7	0.3	1.8	1.2	38.5	23.1	23.1	53.8	38.5	23.1	13
	F	70	76	SD	6	8.7	0.6	8.9	0.6	7.1	0.0	28.6	78.6	64.3	21.4	14
	F	72	89	OH	15	0.0	-0.8	2.1	1.3	31.6	26.3	31.6	57.9	36.8	15.8	19
	F	81	90	SD	6	1.3	2.7	1.5	2.7	9.1	0.0	54.5	54.5	36.4	45.5	11
	Avg					0.9	0.1	2.9	1.4	18.6	15.0	30.5	65.9	50.9	19.2	
2012	A	8A	102	SD	7	2.3	1.4	2.9	1.4	28.6	0.0	28.6	57.1	42.9	42.9	7
	A	8C	96	SD	7	3.8	2.9	3.8	3.0	0.0	6.7	46.7	46.7	53.3	46.7	15
	B	17	61	SD	9	3.5	0.3	3.5	0.3	0.0	0.0	4.5	90.9	95.5	9.1	22
	C	G1	93	SD	7	5.0	0.5	5.0	0.5	0.0	0.0	39.4	87.9	60.6	12.1	33
	C	G4	94	SD	7	7.1	-0.1	7.3	0.3	10.0	20.0	40.0	70.0	50.0	10.0	10
	C	P4	90	SD	7	-8.7	-4.3	8.7	4.3	100.0	66.7	0.0	33.3	0.0	0.0	3
	D	3B	54	SD	6	1.2	-0.6	3.1	1.2	12.5	20.8	47.9	70.8	39.6	8.3	48
	E	12	96	SD	8	5.0	3.4	5.3	3.5	7.1	3.6	25.0	57.1	67.9	39.3	28
	F	70	76	SD	6	6.0	-0.3	6.1	0.4	3.3	13.3	33.3	80.0	63.3	6.7	30
	F	72	89	OH	15	2.8	0.1	5.1	0.7	46.2	23.1	15.4	61.5	38.5	15.4	13
	F	81	90	SD	6	2.6	1.6	2.9	1.9	14.3	7.1	42.9	57.1	42.9	35.7	14
	Avg					2.8	0.4	4.9	1.6	10.3	10.8	33.6	70.9	56.1	18.4	

4.3.2 Yield forecasts

Table 4.5 gives the yield forecast bias and errors from the two simulation methods. Selected diagrams showing the percentage differences between weekly (1) *WBS* and (2) *PBS* yield forecasts from the observed yields are given in Appendix B2.

PBS yield forecasts were more accurate than *WBS* forecasts in 16 out of 24 cases. However, the improvement in forecast accuracy, as measured by average forecast error, was small (1.5 t/ha).

Results show that *PBS* improves yield forecasts markedly over those of WBS when farmers deviate from an ideal irrigation schedule. For example, in the case of field 17, which was severely under irrigated in 2011-2012 (see Appendix B2 for a graph), the *PBS* yield forecast error was 8.7 t/ha less than that of *WBS*. Similarly for P4, which was severely over-irrigated in 2012-2013, the *PBS* yield forecast error was 7.7 t/ha less than for *WBS*. Therefore *PBS* is important in achieving accurate yield forecasts when irrigation management is poor. In contrast, *PBS* and *WBS*-based yield forecasts were similar for fields that were well irrigated (fields 8A, 8C, G1, G4, G7, P4, 3B, 12, 70, 72 in the 2011-2012 season, fields 8A, 8C, G1, G4,12, 70, 72, 81 in the 2012-2013 season).

For *WBS*, the yield forecast error for the 2012-2013 season was less than that for the 2011-2012 season. This suggests that farmers scheduled their irrigation closer to the ideal in 2012-2013.

The average *WBS* yield forecast errors for fields with low *TAM* soils was 25.6 t/ha and for high *TAM* soils was 15.6 t/ha respectively, while the *PBS* yield forecast errors were 22.7 and 14.9 t/ha. This result suggests that minor improvement is made to the accuracy of yield forecasts by *PBS* over those of *WBS*, but that yield forecasts are more accurate for low TAM soils than for high TAM soils, irrespective of correction of simulations by $ASWC_{probe.}$ This makes sense if one considers that it is easier to maintain *ASWC* in the ideal range for high *TAM* soils than for low and hence the yield forecast, which assumes ideal irrigation, is more likely to be met.

The average *WBS* yield forecast errors for drip irrigated fields and overhead irrigated fields respectively were 19.7 and 14.7 days, while the *PBS* yield forecast errors were 19.1 and 12.3 days respectively. Thus there is a small improvement in accuracy for overhead fields. The yield forecast error is smaller for overhead than for drip fields. This suggests that the irrigation regime for drip irrigated fields was further from the ideal, while for overhead fields it was closer.

Table 4.5 The bias and error of yield forecasts using weather-based simulation (*WBS*) and probe-based simulation (*PBS*) for different fields for the 2011-2012 and 2012-2013 growing seasons. *TAM* is the total available moisture of the soil. The percentage of days of the growing season for which soil water status data was available is also shown.

							Yield forecast Bias (t/ha)		Yield forecast Error (t/ha)	
Season	**Farm code**	**Field**	**Soil TAM (mm)**	**Irrigation system**	**Irrigation amount (mm)**	**Percentage available data (%)**	**WBS**	**PBS**	**WBS**	**PBS**
2011	A	8A	102	SD	7	59	27.8	26.4	27.8	26.4
	A	8C	96	SD	7	69	33.6	31.7	33.6	31.7
	B	17	61	OH	24	73	19.4	8.2	19.4	10.7
	C	G1	93	SD	7	57	17.6	16.2	17.6	16.2
	C	G4	94	SD	7	25	-3.7	-5.4	3.7	5.4
	C	G7	78	OH	12	33	9.0	8.0	9.0	8.0
	C	P4	90	SSD	7	26	25.0	24.2	25.0	24.2
	D	3B	54	SD	6	55	55.4	55.8	55.4	55.8
	D	7	80	OH	48	61	38.4	30.9	38.4	30.9
	E	12	96	SD	96	61	-1.0	4.8	1.0	5.0
	F	70	76	SD	76	61	9.4	8.0	9.4	8.0
	F	72	89	OH	89	83	12.2	12.7	12.2	12.7
	F	81	90	SD	90	88	18.2	15.8	18.2	15.8
	Avg					58	20.1	18.3	20.8	19.3
2012	A	8A	102	SD	7	62	16.0	16.1	16.0	16.1
	A	8C	96	SD	7	87	21.0	21.2	21.0	21.2
	B	17	61	OH	9	54	3.0	5.6	3.0	5.9
	C	G1	93	SD	7	71	12.0	10.8	12.0	10.8
	C	G4	94	SD	7	75	-17.0	-15.9	17.0	15.9
	C	P4	90	SSD	7	75	24.0	16.3	24.0	16.3
	D	3B	54	SD	6	73	62.0	57.0	62.0	57.0
	E	12	96	SD	8	72	-7.0	-7.7	7.0	7.7
	F	70	76	SD	6	92	-7.0	0.1	7.0	5.4
	F	72	89	OH	15	92	-6.0	-5.5	6.0	5.5
	F	81	90	SD	6	92	7.0	7.3	7.0	7.3
	Avg					77	10.7	10.3	16.9	15.7

For most fields, there was a decrease in the *PBS* yield forecast error from 2011-2012 to 2012-2013, presumably because more *SWI* data were recorded in 2012-2013.

4.3.3 Reviewing agronomic performance with output from the integrated system

Simulated yields using optimal irrigation (Y_{opt}) and yields from *ASWC* corrected simulations (Y_{swc}) were compared to actual yields (Y_{obs}) to assess field irrigation and management performances on the study fields for both seasons (Table 4.6). Fields that underperformed are identified and briefly discussed.

The analysis suggest that 2012 yields were limited well below potential for fields 8A, 8C, 17, 3B, 7 because Y_{obs} was less than 85% of Y_{opt}. Insufficient irrigation and preventable drought stress were inferred for fields 8C (excessive drying off identified) and 17 (irrigation system did not operate for long periods) as shown in Table 4.6. Fields G7 seemingly also experienced some drought stress as shown in Table 4.6. This was not reflected in the ratio of Y_{swc} to Y_{opt} because of limited *SWI* data.

For fields where Y_{obs} was less than 85% of Y_{swc}, that was taken as an indication of the presence of yield limiting factors other than insufficient irrigation, for example poor crop stand, weed competition, nutrient deficiency or pest and disease damage. This seemed to be the case for fields 8A, 8C, 3B, 7 (poor crop stand was observed in this field), 1 and 14, but this needs to verified through field visits. Water logging may have been a problem on fields G1, 7 and 81 as indicated by high numbers of water logged days (Table 4.6).

In 2013, yields were limited below potential for fields 8C, P4 and 3B (Y_{obs} < *85%* of Y_{opt}). For all three fields, the presence of limiting factors other than irrigation was identified as a contributing cause, based on the fact that Y_{obs} was less than 85% of Y_{swc}. All three fields also experienced periodic water logging, while field 3B had extended periods of drought stress.

Table 4.6 Simulated yield using optimal irrigation (Y_{opt}), observed yields (Y_{obs}) and yields using ASWC corrected simulations (Y_{swc}) expressed as percentages of the Y_{opt}, the number of drought stress days ($ASWC$<40%TAM, excluding the last 30 days), the number of water logged stress days ($ASWC$>110%TAM) and the percentage of days of the growing season for which soil water status data was available (SWI data) for each field for the 2011-2012 and 2012-2013 growing seasons.

Season	Farm code	Field Name	Y_{opt} (t/ha)	Y_{obs} / Y_{opt} (%)	Y_{swc} / Y_{opt} (%)	Y_{obs} / Y_{swc} (%)	Dryland yield (t/ha)	Stress days (drought)	Stress days (water logged)	SWI data availability (%)	Main conclusion from yield analysis[1]
2011	A	8A	116	76	95	81	41	23	13	59	Good irrigation[1] and good husbandry.
	A	8C	116	71	86	83	40	56	44	69	Good irrigation, suboptimal husbandry. Some water logging. Excessive drying off.
	B	17	89	78	62	126	25	187	17	73	Under irrigation, good husbandry, prolonged drought stress.
	C	G1	126	85	96	89	42	0	30	57	Good irrigation, good husbandry, some water logging.
	C	G4	123	102	97	105	39	0	23	25	Good irrigation, good husbandry.
	C	G7	113	92	97	94	35	45	8	33	Good irrigation, good husbandry, drought stress due to system limitations.
	C	P4	160				73				Not enough data.
	D	3B	135	59	93	64	33	2	10	55	Good irrigation, suboptimal husbandry.
	D	7	120	67	91	73	39	27	24	61	Good irrigation, suboptimal husbandry, some water logging.
	E	12	101	92	97	104	32	40	4	61	Good irrigation, good husbandry, some drought stress. .
	F	70	123	92	96	97	41	5	77	61	Good irrigation, good husbandry, water logging.
	F	72	153	93	100	93	46	8	23	83	Good irrigation, good husbandry.
	F	81	130	86	93	92	42	14	35	88	Good irrigation, good husbandry, some water logging.
2012	A	8A	115	86	98	88	61	13	63	62	Good irrigation, good husbandry, some water logging.
	A	8C	115	82	98	84	59	8	30	87	Good irrigation, suboptimal husbandry.
	B	17	112	97	65	150	57	141	69	54	Under irrigation, good husbandry, prolonged drought stress, some water logging.
	C	G1	123	90	91	99	77	83	16	71	Good irrigation, good husbandry, a long period of drought stress at the start of crop.
	C	G4	121	114	100	114	77	48	24	75	Good irrigation, good husbandry.
	C	P4	128	81	96	84	41	0	32	75	Good irrigation, suboptimal husbandry, water logging.
	D	3B	160	61	79	78	66	127	58	73	Under irrigation, suboptimal husbandry, excessive drying off, water logging.
	E	12	94	107	89	121	63	48	11	72	Good irrigation, good husbandry, mild drought stresses.
	F	70	110	105	111	95	49	132	15	92	Good irrigation, good husbandry, long period of drought stress at start of crop.
	F	72	111	105	99	107	32	0	30	92	Good irrigation, good husbandry.
	F	81	128	95	100	95	55	7	21	92	Good irrigation, good husbandry.

[1] – "Good irrigation" means good irrigation scheduling given the limitations of the existing irrigation system

4.4 Conclusions

The main objective of this part of the study was to incorporate near real-time field records of soil water status into the weather-based sugarcane simulation system, MyCanesim®, and to evaluate its use for supporting irrigation scheduling.

Irrigation scheduling advice accuracy determined from *PBS* improved over that from *WBS* for 19 out of 22 crops. *PBS* resulted in an improvement in the accuracy of the forecasted *DNI* over that of *WBS* by 1.5 and 3.3 days on average in the respective growing seasons. This demonstrated that the use of soil probe data greatly enhanced the ability of MyCanesim® to forecast *DNI*. Results also show that probe data was more useful for scheduling irrigation on low *TAM* soils than high *TAM* soils. Improvements in advice accuracy by *PBS* over *WBS* were greater for overhead irrigated fields than for drip irrigated fields.

PBS yield forecasts were also more accurate than those from *WBS* in 15 out of 24 cases. However, the *PBS* forecast error was only slightly less than that of *WBS*. Yield forecast accuracy was greatly enhanced by *PBS* over that of *WBS* when poor irrigation practices were followed.

A framework was developed for comparing Y_{swc}, Y_{opt}, (produced by the integrated system) and Y_{obs}, in order to assess the quality of irrigation practices and husbandry. The framework was useful for identifying fields which underperformed due to poor irrigation and could help farmers to adjust irrigation practices in consequent seasons.

The integrated system promises to provide greater benefit to farmers than the weather-based system alone, provided that probe output is reliable.

4.5 References

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5. GENERAL DISCUSSION AND CONCLUSIONS

In this study two research questions were to be answered:

(a) Which limited water allocation optimisation algorithm achieves, theoretically, the highest yield and irrigation water use efficiency (*IWUE*)?

(b) Will integrating soil water records with a weather-based simulation model provide more accurate irrigation scheduling advice and yield forecasts?

How successfully each research question was answered in this study, the main findings and any considerations and recommendations for further research are discussed below.

5.1 Algorithms for Scheduling Limited Irrigation Water

Five irrigation scheduling optimisation algorithms were programmed and simulated on 960 test case scenarios. Two of the algorithms were based on literature, namely the crop stage and stress level algorithms. The water satisfaction, prorata and advanced prorata algorithms were developed in this study. Simulated cane yields were compared with those generated by the baseline algorithm, which scheduled irrigation according to the allowable depletion level (*ADL*) rule until the seasonal allocation was exhausted. The crop stage and stress level algorithms consistently achieved the highest yield benefit (8.6 and 8.5 t/ha higher, respectively, than the baseline on average) followed by the advanced prorata, water satisfaction and prorata algorithms (5.7, 5.5 and 4.7 t/ha yield benefit, respectively). The water satisfaction and prorata algorithms had the fastest computing times (1.83 and 0.99 s/season, respectively). However, a conclusion from Chapter 4 indicated that the stress level algorithm could also be run quickly (2.46 s/season) if it was used to schedule the next irrigation event only, instead of the entire season's events. Therefore the stress level algorithm was recommended for inclusion into Canesim®, for making the irrigation scheduling decision for the current day, while the prorata algorithm was recommended for yield forecasting and determination of the future irrigation schedule.

Soil type, climate and irrigation system had little effect on the performance ranking of algorithms, while crop cycle did have an effect. The water satisfaction algorithm generally performed as well as the crop stage and stress level algorithms for October crop cycles, but performed worse than these two algorithms for April crop cycles. This is because the water satisfaction algorithm tended to schedule irrigation in the later part of the season after stalk growth commenced, causing more water stress in the early part of the season for April crop cycles than for October crop cycles because of the typical seasonal rainfall distribution (dry from April to August, wet from September to March).

The highest yield benefits for all algorithms were achieved for seasonal allocations between 300 mm to 700 mm. The water satisfaction and prorata algorithms performed poorly (small positive or negative yield benefits) at seasonal allocations of more than 700 mm. In the case of the water satisfaction algorithm, this can be explained by the fact that it always scheduled the full allocation, causing simulated water logging stress in some cases, whereas the crop stage and stress level algorithms would only apply as much water as required by the crop to achieve maximum yield. The prorata algorithm scheduled irrigation in proportion to the long-term demand, reserving some irrigation for the end of the growing season. For seasons where irrigation deficits were above average early in the growing season and below average later on, the prorata algorithm caused unnecessary early season stress, reserving too much water for the late season that may not be required.

Although the optimisation algorithms showed great promise in improving yields over those of the baseline scenario, it is important to consider their feasibility for practical implementation. Issues that need to be considered are: availability of input data, the water restriction conditions in which they will operate and scope for their further use.

Knowledge of past water use, the current value of *ASWC*, future water availability, expected rainfall and an optimisation algorithm are necessary for scheduling irrigation optimally under limited water supply. The current value of *ASWC* may be measured or calculated; expected rainfall may be estimated from short and long-term climate forecasts and the optimisation algorithms can be applied to make an appropriate irrigation scheduling decision. Water availability for the remainder of the water year is, however, affected by water used to date. It is therefore necessary for irrigation records to be regularly captured into MyCanesim®. This is currently done manually, but the process could be automated using flow meters and/or rain gauges.

5.2 Incorporating Soil Water Monitoring Technology into MyCanesim®

A system was developed which integrated soil water records into soil water balance simulations. Soil water records were automatically downloaded on a daily basis using a combination of cellular and internet technology, from a service provider's database and stored in the local MyCanesim® database. Soil water status data were converted into units of available soil water content ($ASWC_{probe}$), using a linear conversion. The Canesim® crop model was adjusted to allow correction of simulated *ASWC* with $ASWC_{probe}$ data. Thus, crop growth simulations were affected by more accurate simulation of drought and soil water saturation stresses.

Tests were performed to evaluate the improvement in irrigation advice and yield forecast made by the integrated system. The forecast accuracy of the next date of irrigation (*DNI)* was improved by 2.4 days on average, which is considered a great improvement. The accuracy of yield forecasts was improved for cases where farmers deviated from an ideal irrigation schedule, but not otherwise.

Resetting simulations with $ASWC_{probe}$ thus improved the accuracy of irrigation scheduling advice which should limit under and over-irrigation, leading to increased simulated yields and *IWUE*. Another benefit of the integrated MyCanesim® system is that irrigation practices may be analysed post-season to guide future irrigation practices.

The practical feasibility and limitations of the use of soil moisture probes for irrigation scheduling needs to be considered. The placement of soil water probes may adversely affect irrigation practices in the case of drip irrigated fields, since the soil distribution of irrigation water may be irregular. The farmer may under-irrigate, on average, if the probe were located in the wettest position (for example underneath the emitter, as is current practice). Similarly, over-irrigation may occur when scheduling is based on data from probes located in the driest position (for example in the inter-row halfway between emitters). The wetting patterns of the irrigation system and soil should therefore be studied to locate the position of average wetness for probe location, or alternatively for improving probe calibration procedures.

5.3 Conclusions

The literature review described the most pertinent features and approaches of irrigation scheduling decision support systems (*ISDSS*). Several features were recommended for inclusion to MyCanesim®. These include:

(a) The optimization of the irrigation schedule under limited water supply in order to maximise yields;
(b) Prioritisation of fields for irrigation when water supply is limited.
(c) Adding functionality for integration of field measurements (*ASWC*, irrigation and canopy cover) with simulations of the water balance and crop growth, in order to improve the accuracy of real time advice; and
(d) Increasing the flexibility in the irrigation scheduling rules to enable better representation of irrigation practices (such as variable cycle times and irrigation amounts);
(e) The addition of a report which lists, per field, the daily available soil water content (*ASWC*) value of the morning, rainfall from the previous day and night and the recommended irrigation date and amount; and
(f) A spatial representation of the farm to enhance the reporting of the system.

Two of these improvements, points (a) and (c) in the former list, were researched in more detail and developed and tested using the Canesim® sugarcane model.

Five optimisation algorithms for irrigation scheduling were researched and their yields and *IWUE* determined under limited water supply for a large number of scenarios. Simulated yield ranking results were similar to those of *IWUE*, hence analyses focused on yield. All algorithms were able to improve on yields generated by the baseline algorithm (on average). Algorithms which had short computation times generally achieved lower simulated yields than algorithms that were more complex and took longer to run. The crop stage algorithm, which achieved the highest simulated yields and irrigated water use efficiency, was not recommended for inclusion in MyCanesim® due to the large number of investigative simulations required for optimisation. The stress level algorithm, which also achieved high simulated yields, was recommended for inclusion into MyCanesim® to provide irrigation advice, but was not recommended for MyCanesim® yield forecasting due to the long computation time required. The water satisfaction algorithm is not precise enough and, in its current form, tends to irrigate in excess of the crop requirement in some cases. The prorata algorithm runs quickly, achieves reasonable simulated yields and was recommended for inclusion into MyCanesim® for yield forecasting. Suitable algorithms have been found for MyCanesim® which may be used to provide irrigation advice under limited water supply. As the seasonal water allocation increases and approaches the irrigation requirement, the simple rule of irrigating at a well-chosen depletion level achieves yields close to potential, and optimisation provides little benefit.

Near real-time field records of soil water status were successfully integrated into the weather-based sugarcane simulation system, MyCanesim®, and evaluated for supporting irrigation scheduling. The evaluation of the system showed that the use of soil water probe data improved the accuracy of irrigation scheduling advice in the majority of test cases. Improvements in advice by probe-based scheduling (*PBS)* over weather based scheduling (*WBS)* were greater for soils with low *TAM* than soils with high *TAM* and greater for overhead irrigated fields than for drip irrigated fields. Yield forecast accuracy was greatly enhanced by *PBS* over that of *WBS* when poor irrigation practices were followed.

A framework for analysing yields based on optimal irrigation (Y_{opt}), $ASWC_{probe}$ corrected (Y_{swc}) (both simulations) and observed yields (Y_{obs}) was developed for assessing the quality of irrigation practices and husbandry. The analysis in this study suggested that yields were limited well below potential for six fields in 2012 and for three fields in 2013. The framework could help farmers to identify and address problematic irrigation practices and consequently achieve higher yields.

In summary, the optimisation algorithms showed potential for enabling more efficient use of limited water and increased cane yields when seasonal water restrictions are imposed. The automated integration of soil water status data into the MyCanesim® *ISDSS* lead to more accurate irrigation scheduling. Together these technologies promise to promote the sustainability of the irrigated sugarcane industry in South Africa.

5.4 Recommendations for Further Research

Recommendations concerning the limited water optimisation algorithms include the following:

(a) This study demonstrated theoretical yield improvements of the optimisation algorithms over the baseline algorithm. This theoretical results however, needs to be confirmed in practice.

(b) The optimisation algorithms could be used to discover general irrigation scheduling rules for cases of limited seasonal water supply. They could be applied to many historical weather scenarios to derive best average irrigation schedules for various $ALLOC_{season}$ and regions. Such work may aid long-term irrigation planning at a farm or catchment level.

(c) This study addressed the optimisation of the irrigation schedule of a single field over the growing season. In practice, farmers must optimise limited water over many fields and over shorter periods - a more complex optimization problem.

Recommendations concerning the integration of probe data into weather-based simulation models include the following:

(a) Auto-calibration of capacitance data to $ASWC$ is an attractive proposition. A computer program could detect the value of FC_{SWI} (Equation 4.4) by monitoring for a large change in the derivative of capacitance data a few days after a large rainfall or irrigation event. Also, an appropriate CR value (Equation 4.4) can be derived by matching the rate of depletion in $ASWC$ to simulated ET for fully canopied crops (to eliminate uncertainty of canopy simulations) over known dry periods. The program could refine conversion coefficients as more data becomes available for calibration and regenerate the $ASWC_{probe}$ data on a daily basis. The stress point and wilting point may also be inferred.

(b) A layered soil water balance model may be more suitable for integration with soil water capacitance probes, since such probes typically have sensors at several depths. An integrated layered system may enhance irrigation scheduling advice for the following reasons:

a. over-irrigation can be detected through accumulation of water in lower layers; and
b. temporary alleviation of drought stress could be simulated when the top layers receive adequate water.

APPENDIX A

A1 Aggregate Yields Achieved by the Optimisation Algorithms

Table A1.1 Summary of the simulated yields (t/ha) achieved by each algorithm averaged over different scenario inputs. The dryland yield (no irrigation), potential yield (no drought stress and with a limitless seasonal allocation ($ALLOC_{season}$)) and the algorithm that performed the best in terms of yield are also indicated. *CS* = Crop Stage and *SL* = Stress Level.

Inputs		Yields (t/ha) for each algorithm						Boundaries		
Scenario input	Input value	Crop Stage	Stress Level	Water Satisfaction	Pro-rata	Advanced Prorata	Base-line	Dry-land	Poten-tial	Best performing algo-rithm
Station	Komati	101.1	101.2	98.0	95.2	96.4	91.4	48.1	135.3	SL
	Malelane	102.5	102.6	99.1	99.0	100.1	94.1	40.1	139.6	SL
	Pongola	98.9	98.6	95.7	95.5	96.6	89.4	43.9	126.6	CS
	Umfolozi	103.4	103.3	101.0	100.7	101.3	96.8	52.3	127.5	CS
$ALLOC_{season}$ (mm)	100	55.8	54.9	53.6	54.9	55.6	49.9	46.1		CS
	200	70.1	68.9	65.1	65.1	66.0	60.3	46.1		CS
	300	79.4	78.6	79.2	74.6	75.8	68.2	46.1		CS
	400	93.0	92.7	90.5	85.7	87.0	78.5	46.1		CS
	500	101.8	101.4	99.7	96.3	98.0	87.5	46.1		CS
	600	112.0	112.6	109.4	106.9	108.0	99.6	46.1		SL
	700	118.2	118.8	116.3	115.1	116.2	108.9	46.1		SL
	800	125.2	126.0	120.4	122.0	122.9	120.0	46.1		SL
	900	128.4	129.1	123.1	126.3	127.0	126.0	46.1		SL
	1000	130.9	131.2	127.2	129.0	129.5	130.2	46.1		SL
Crop cycle	April	102.5	102.3	97.8	97.9	98.7	94.9	46.4	135.9	CS
	October	100.4	100.5	99.1	97.3	98.5	91.0	45.8	128.6	SL
Soil TAM (mm)	80	100.1	99.2	96.4	95.8	96.9	90.3	44.0	131.9	CS
	120	102.9	103.6	100.5	99.3	100.3	95.6	48.2	132.6	SL
Rainfall class	High Rain	104.8	104.7	101.7	99.9	100.8	96.1	53.6	132.2	CS
	Med Rain	105.2	104.9	102.6	101.4	102.5	96.4	50.6	130.5	CS
	Low Rain	94.5	94.7	91.0	91.5	92.6	86.2	34.1	134.1	SL
Irrigation amount (mm)[1]	8	101.9	[1]	99.4	97.9	98.6	92.9	46.1	132.5	CS
	40	101.0	101.4	97.4	97.3	98.6	92.9	46.1	132.0	SL
Average[2]	450	95.8	95.5	93.3	90.6	91.8	83.8	46.1	132.2	CS
Average[3]	550	101.5	101.4	98.4	97.6	98.6	92.9	46.1	132.2	CS

[1] - The stress level algorithm (*SL*) was not simulated using the 8 mm fixed irrigation amount

[2] - The average was taken over the 200 mm to 700 mm allocation range

[3] – The average was taken over the 100 mm to 1000 mm allocation range

A2 Aggregate Irrigated Water Use Efficiency (IWUE) Achieved by the Optimisation Algorithms

Table A2.1 Summary of the simulated *IWUE* (t/ha/100mm) achieved by each algorithm averaged over different scenario inputs. The *IWUE* of the crop that gave the potential yield (no drought stress and with a limitless seasonal allocation ($ALLOC_{season}$)) and the algorithm that performed the best in terms of *IWUE* are also indicated. *CS* = Crop Stage and *SL* = Stress Level.

Inputs		*IWUE* (t/ha/100mm) for each algorithm							
Scenario input	**Input value**	**Crop Stage**	**Stress Level**	**Water Satisfaction**	**Pro-rata**	**Advanced Prorata**	**Base-line**	**IWUE for potential yield**	**Best performing algorithm**
Station	Komati	10.3	10.1	9.2	8.7	9.0	7.2	8.27	CS
	Malelane	12.3	12.0	10.7	10.9	11.2	9.4	10.36	CS
	Pongola	11.1	10.7	9.6	9.8	10.1	7.8	8.9	CS
	Umfolozi	11.0	10.6	9.3	10.0	10.2	8.4	9.03	CS
ALLOC-season (mm)	100	12.1	11.0	8.5	9.7	10.5	4.4		CS
	200	12.0	11.4	9.5	9.4	9.8	7.1		CS
	300	11.9	11.6	10.6	9.8	10.2	7.7		CS
	400	11.7	11.7	11.1	9.9	10.2	8.1		CS, SL
	500	11.6	11.5	11.0	10.3	10.6	8.5		CS
	600	11.2	11.2	10.5	10.2	10.4	9.0		CS, SL
	700	10.8	10.8	9.9	10.2	10.4	9.2		CS, SL
	800	10.3	10.2	9.3	9.8	10.0	9.4		CS
	900	10.0	9.8	8.7	9.7	9.7	9.4		CS
	1000	9.8	9.3	8.1	9.5	9.5	9.3		CS
Crop cycle	April	11.1	10.9	9.5	9.7	10.0	8.6	9.17	CS
	October	11.2	10.8	10.0	10.0	10.3	7.8	9.11	CS
Soil TAM (mm)	80	11.3	10.6	9.7	9.8	10.1	8.0	9.12	CS
	120	11.0	11.1	9.7	9.9	10.1	8.4	9.16	SL
Rainfall class	High Rain	10.4	10.2	9.0	9.0	9.3	7.5	8.26	CS
	Med Rain	11.4	11.0	10.0	9.9	10.3	8.3	9.14	CS
	Low Rain	11.6	11.4	10.3	10.6	10.8	8.8	10.02	CS
Irrigation amount (mm)[1]	8	11.3		9.9	9.6	9.8	8.1	9.14	CS
	40	11.0	10.8	9.5	10.0	10.5	8.3	9.14	CS
Average[2]	450	11.5	11.4	10.4	10.0	10.3	8.3	9.14	CS
Average[3]	550	11.1	10.8	9.7	9.8	10.1	8.2	9.14	CS

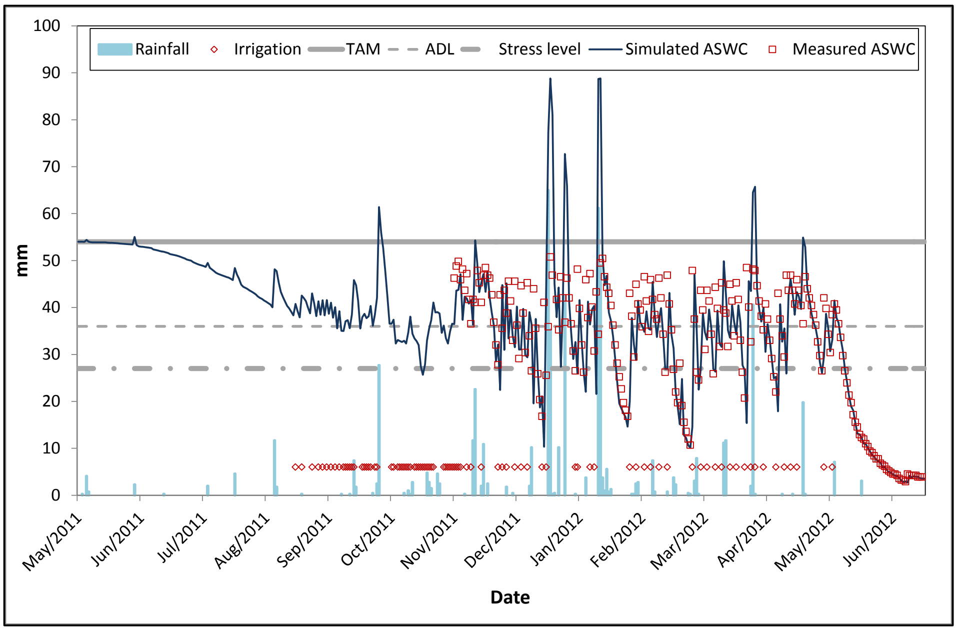
[1] – The stress level algorithm (*SL*) was not simulated using the 40 mm fixed irrigation amount

[2] – The average was taken over the 200 mm to 700 mm allocation range

[3] – The average was taken over the 100 mm to 1000 mm allocation range

APPENDIX B

B1 Examples of Soil Water Balance Graphs for Selected Monitored Fields



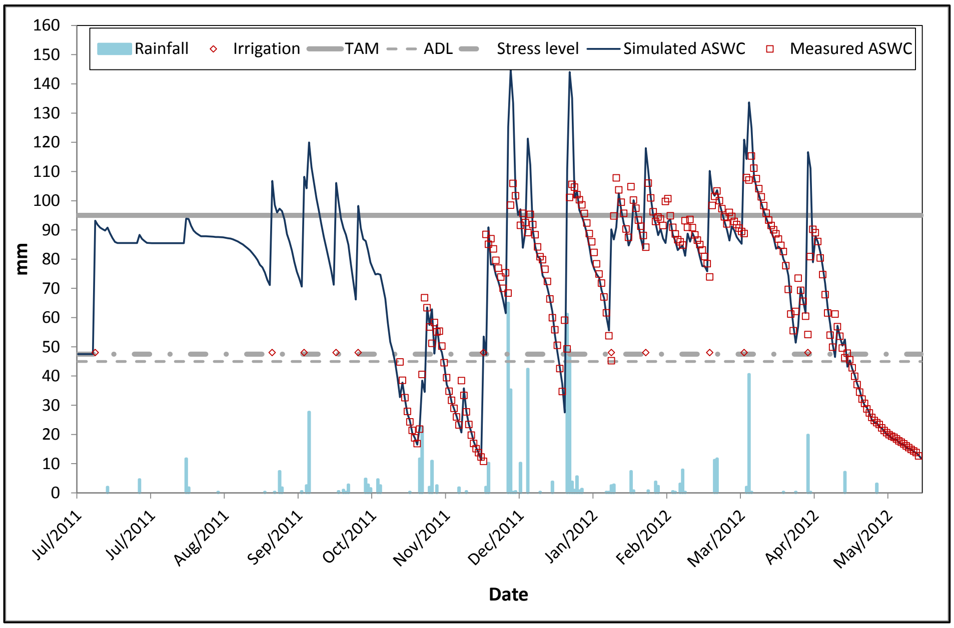
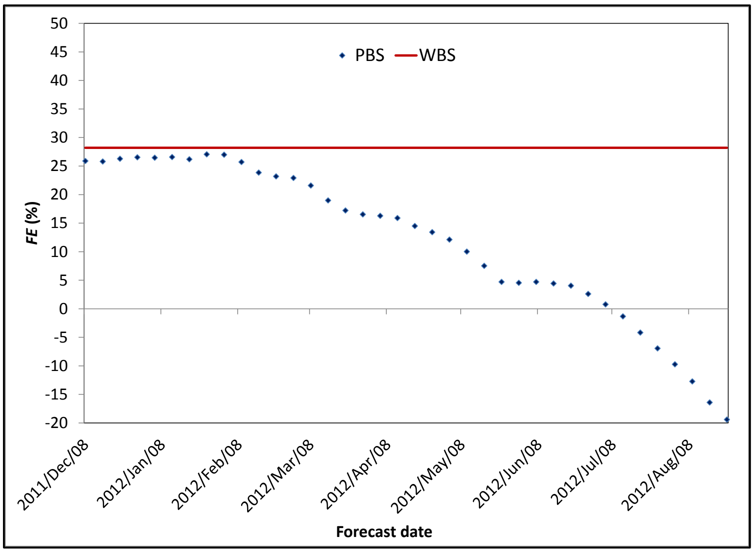


Figure B1.1 (top) and Figure B1.2 (bottom). The soil water balances for field 3B (top) and for field 7 (bottom) are shown, for the 2011-2012 growing season. Daily values of simulated (blue line) and measured (red open squares) root zone available soil water content (*ASWC*), rainfall (blue bars) and irrigation (red open circles). The horizontal solid line indicates the *ASWC* at field capacity (*TAM*), the line with small dashes indicates the chosen allowable depletion level (*ADL*) and the line with mixed dot dash represents Canesim®'s stress point. Simulated *ASWC* was corrected with measured values ($ASWC_{probe}$).

B2 Examples of Yield Forecast Error Graphs for Selected Monitored Fields



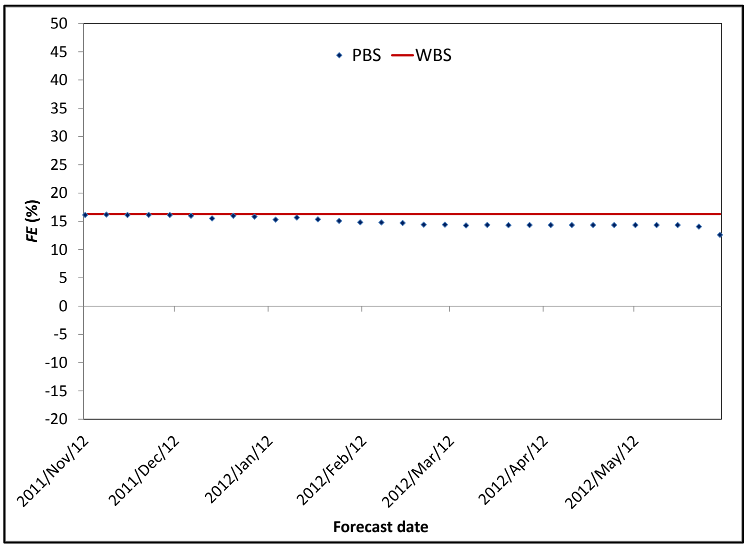


Figure B2.1 (top) and Figure B2.2 (bottom). The forecast error (*FE,* defined as the difference between the forecasted (Y_f) and observed yields (Y_{obs}) expressed as a percentage of Y_{obs}) for fields 17 (top) and G1 (bottom) for the 2011-2012 growing cycle, for weather-based simulation (*WBS*, solid brown line) and probe-based simulation (*PBS*, dots). In the case of field 17, yield forecast accuracy was dramatically improved by correcting the simulated soil water balance with probe data. In the case of field G1, the farmer irrigated in a near-optimal manner and the yield forecast accuracy was not improved by correcting the simulated soil water balance with probe data. The line y = 0 represents the observed yield. *PBS* Forecasts begin when probe data becomes available.