UNIVERSITY OF SOUTHERN QUEENSLAND

# Improved irrigation of cotton via real-time, adaptive control of large mobile irrigation machines

A Dissertation submitted by

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# Abstract

Improving the efficiency of water use in agriculture is increasingly essential to maintain the profitability and sustainability of farms. This involves applying only the minimum necessary irrigation water to maintain or improve the yield of individual plants. Improving cotton yield involves management of flower/fruit production in relation to vegetative growth. The cotton industry represents a significant proportion of agricultural production and water use in Australia.

Irrigation control strategies can be used to improve site-specific irrigation. These control strategies generally require weather, plant and/or soil data to determine irrigation volumes and/or timing that improve crop water use efficiency while maintaining or improving crop yield. In this dissertation the difficulties in applying standard control theory to irrigation control are reviewed, in particular that the system, the growing crop, varies with time and does not have fully-defined dynamics. Hence, as the plant response and environmental conditions fluctuate throughout the season, control strategies which accommodate temporal and spatial variability in the field and which locally modify the control actions (irrigation amounts) need to be 'adaptive'. Such irrigation control systems may then be implemented on large mobile irrigation machines, both 'lateral move' and 'centre pivot' configurations, to provide automatic machine operation.

This dissertation presents the specification and creation of a simulation framework 'VARIwise' to aid the development, evaluation and management of spatially and tem-

porally varied site-specific irrigation control strategies. The cotton model OZCOT has been integrated into VARIwise to provide feedback data in the control strategy simulations. VARIwise can accommodate sub-field scale variations in all input parameters using a 1 $m^2$ cell size, and permits application of differing control strategies within the field, as well as differing irrigation amounts down to this scale.

An automatic model calibration procedure was developed for VARIwise to enable real-time input of field data into the framework. The model calibration procedure was accurately implemented with measured field data and the calibrated model was then used to evaluate the effect of using different types of data in an irrigation control system. With the field data collected, the model was most effectively calibrated using the full set of plant, soil and weather data, while either weather-and-plant or soil-and-plant input provided adequate inputs to the control system if only two inputs were available.

A literature review of control systems identified three adaptive control strategies that are applicable to irrigation, namely: (i) Iterative Learning Control (ILC) which involves applying irrigation volumes to cells in the field calculated by comparing the desired and measured value of the input variable for control (e.g. soil moisture deficit); (ii) iterative hill climbing control which involves applying test irrigation volumes to test cells in the field to determine the application that produced the best crop response and applying that volume to the remainder of the field; and (iii) Model Predictive Control (MPC) which involves using a calibrated crop model to evaluate various irrigation applications and timings to determine which irrigation decision to implement.

The three control strategies were implemented and simulated in VARIwise to evaluate their respective robustness to limitations in data availability and system constraints. These strategies effectively adapted to temporal changes in weather conditions and spatially variable soil properties. For the set of field conditions simulated in VARIwise, the ILC, iterative hill climbing and MPC controllers produced their highest yield and water use efficiency with soil data, weather-and-plant data, and the full data input, respectively. MPC was most sensitive to spatially sparse input data but performed well with spatially variable rainfall and limited machine capacity. ILC was least sensitive to spatially sparse input data and variable rainfall, whilst iterative hill climbing control was most sensitive to spatially sparse input data and variable rainfall. Hence, in situations of high data input MPC should be implemented, whilst in situations of low data input ILC should be implemented. Iterative hill climbing control was most sensitive to limited irrigation machine capacity.

It is further concluded that cotton yield and irrigation water use efficiency may be significantly improved using adaptive control systems; and that adaptive control systems can adjust the irrigation application and improve the irrigation performance despite various data availability limitations and irrigation hardware constraints.

# Certification of Thesis

I certify that the ideas, experimental work, results, analyses, software and conclusions reported in this dissertation are entirely my own effort, except where otherwise acknowledged. I also certify that the work is original and has not been previously submitted for any other award, except where otherwise acknowledged.

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| Signature of Supervisors | Date |

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# List of Publications

The following articles have been published or submitted for publication about the research contained within this dissertation.

*JOURNAL*

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*CONFERENCE*

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MCCARTHY, A.C., Hancock, N.H. and Raine, S.R. (2010d) 'Simulation of adaptive site-specific irrigation control performance with spatially variable rainfall', *National Conference, Irrigation Association Limited*, 8-10 June, Sydney.

MCCARTHY, A.C., Hancock, N.H. and Raine, S.R. (2009) 'Exploration of data requirements for adaptive control of irrigation scheduling', *CIGR International Symposium of the Australian Society for Engineering in Agriculture*, 13-16 September, Brisbane, Australia. 8pp.

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Smith, R.J., Raine, S.R., MCCARTHY, A.C. and Hancock, N.H. (2007) 'Managing spatial and temporal variability in irrigated agriculture through adaptive control', *Society for Engineering in Agriculture 2007 National Conference: Agriculture and Engineering: Challenge Today, Technology Tomorrow*, 23-26 September, Adelaide, Australia. 12pp. [keynote]

*POSTER*

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# Chapter 1

# Introduction

## 1.1 Background

Australian agriculture accounted for 65% of the nation's water consumption in 2004-2005 (ABS 2006). In the same period, the cotton industry consumed 14.7% of the total water used in Australian agriculture (CA 2010). The gross value of the Australian cotton industry was $908 million, 10% of the total gross value of agricultural production in Australia during 2004-05 (ABS 2006).

A total of 84% of the Australian cotton crop in 2005-2006 was grown using irrigation (CA 2010). More than 94% of irrigated cotton in Australia is grown using furrow irrigation (Raine & Foley 2002), a gravity method of irrigation. The remainder of the irrigated cotton crop is grown using large mobile irrigation machines (LMIMs) (4%) and drip irrigation (less than 2%) (Raine & Foley 2002). However, LMIMs are rapidly being adopted and are expected to represent 30% of the irrigation within the Australian cotton industry by 2020. The two types of LMIMs are centre pivot and lateral move irrigation machines. These irrigation machines are self-propelled sprinkler irrigation systems, where centre pivots rotate around a pivot point at the centre of the irrigated area and lateral moves travel in a continuous straight path across a rectangular field.

Drip irrigation involves localised watering of plants in the field through pipes (e.g. Burt et al. 2000). Cotton farmers aim to apply a quantity of irrigation that will replenish the soil moisture to the desired level. However, farmers use many different methods to manage irrigations. For example, some farmers may irrigate when the soil moisture is low, while other farmers may irrigate on fixed intervals or when a neighbour who is thought to be a good manager is watering (Kranz et al. 1992; Evans 2006).

Irrigation scheduling methods that are based on physical and agronomic principles can improve the efficiency of water use by 15 to 44% (Evans 2006) while maintaining or increasing crop yields. These irrigation scheduling methods conventionally base the irrigation requirements on soil moisture and atmospheric measurements or calculations (Jones 2004). Many decision support systems are reported in the literature that help farmers decide when to irrigate and how much water to apply (e.g. McCown et al. 1995; Prajamwong et al. 1997; Mateos et al. 2002; Thysen & Detlefsen 2006; Richards et al. 2008). These decision support systems use models that simulate on-farm irrigation water demands; for example, HydroLOGIC is a commercial irrigation scheduling software package that uses a cotton crop model (OZCOT) to simulate how cotton grows and develops in response to its environment (Richards et al. 2008). Data requirements include measurements collected by the farmer (e.g. soil moisture deficit, fruit load and leaf area index) and weather information. Decision support systems have been developed to determine the irrigation application and timing of other crops including peanuts (Paz et al. 2007), maize (Ko et al. 2009), sugarcane (Chopart et al. 2007) and dry beans (Heinemann et al. 2000).

Automatic irrigation scheduling is a natural progression from decision support systems. Automatic irrigation control systems in the currently available literature are usually applied to drip and micro-irrigation systems, and initiate the irrigation based on real-time sensor data. The duration of the irrigation event is either a fixed period of time (Luthra et al. 1997; Evett et al. 2002*a*) or a calculated period of time corresponding to the crop's needs as indicated by the sensor data (Smajstrla & Locascio 2000; Dukes & Scholberg 2005). For example, Evett et al. (2002*a*) developed a system for centre pivots which uses infrared thermometers to evaluate crop canopy temperatures every minute during the day. Irrigation decisions are made every night based on the number of minutes in the day that the canopy temperature is above a threshold value. Similar irrigation control strategies have also been applied to greenhouse crops (e.g. Zhang et al. 1996; Testezlaf et al. 1997; Prenger et al. 2005; Kia et al. 2009).

Irrigation scheduling traditionally aims to apply water uniformly across a field. However, not all plants across the field require the same amount of water due to the stochastic nature of the crop response and the spatial variability of environmental factors within the field. Sources of spatial variability include plant genetics, soil type and topography. Irrigation non-uniformity and overwatering may result in waterlogged soils, and cause a reduction in crop water uptake and yield. Similarly, underwatering may result in poorly developed crops.

The spatial optimisation of irrigation application, both to reduce water use and increase yield, involves the application of water only to particular points on the field. There is also temporal variability in crop fields since crops require different amounts of water throughout the season depending on crop age, weather, pests and diseases. LMIMs are an appropriate irrigation application method for precision irrigation. This is because LMIMs are characterised by high-frequency irrigation application directly to plants. Considerable work is reported in the literature toward the development of variable-rate applicators for LMIMs (e.g. King & Wall 2005), some of which include a wireless sensor network (e.g. Pierce et al. 2006; Coates & Delwiche 2008) and irrigation system self-monitoring capabilities (e.g. Chávez et al. 2010*a*; Chávez et al. 2010*b*).

Control systems have been used to determine precision irrigation application in real-time using measured soil data (e.g. Capraro et al. 2008; Kim & Evans 2009; Kim et al. 2009; Park et al. 2009) and plant data (e.g. Peters & Evett 2008). The site-specific irrigation strategies using soil data typically involved filling the soil water profile, whilst the strategy using plant data involved adjusting irrigation volumes applied according to measured crop stress. However, a control strategy that uses data from only one sensor may not result in effective irrigation application as it optimises only one variable. Optimal strategies will need to consider multidimensional issues (e.g. crop response, crop age, target yield and management constraints). Hence, the development and implementation of a real-time control strategy may require: (i) the identification of appropriate control strategies; and (ii) the evaluation of the performance of these strategies with respect to the data availability and control requirements.

## 1.2 Research aim

*This research aims to develop and implement a real-time control methodology which utilises both historical mapped data and real-time sensor input to improve the spatial and temporal precision of irrigation applications through increased water use efficiency and/or crop yield.*

The methodology is realised in the form of a decision-making framework. The decision-making framework is an intelligent learning system including a set of databases which accumulates historical data. Consequently, decisions on varying the water applications may be based on both present sensed and historical recorded data. Predictive tools (e.g. meteorological forecast information) are also incorporated.

## 1.3 Dissertation outline

This dissertation consists of ten chapters. The development and evaluation of a software framework 'VARIwise' is central in seven chapters (3 to 9 inclusive). This framework permits the development, simulation and evaluation of site-specific irrigation control strategies for LMIMs. The relationship between the chapters is set out in Figure 1.1.

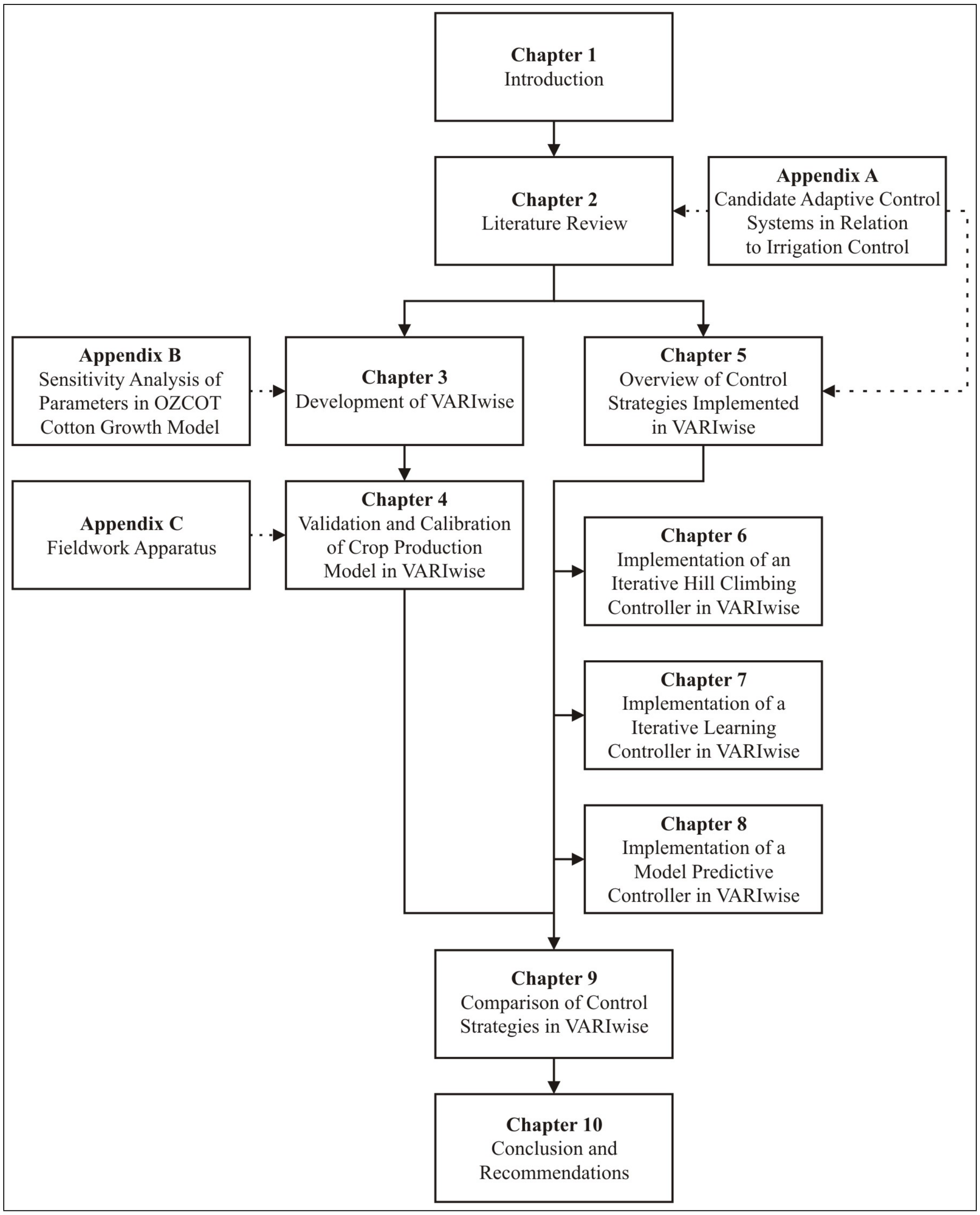



Figure 1.1: Block diagram of dissertation outline

- **Chapter 2** reviews irrigation management, measurement and management of spatial and temporal variability in a field, and adaptive control strategies and their applicability to irrigation. The literature review led to the research objectives.

- Simulation software (VARIwise) was developed to simulate and evaluate site-specific irrigation control strategies for large mobile irrigation machines. **Chapter 3** describes the development of the software including the input of measured field data, the incorporation of variable-rate application, a crop growth model and a model calibration procedure, and the implementation of alternative irrigation strategies. The operation of the software is illustrated using a case study of industry standard irrigation strategies.

- Fieldwork was conducted to demonstrate the model calibration procedure of Chapter 3. **Chapter 4** describes the fieldwork conducted and presents a comparison of the measured field data and data predicted by the calibrated model. The calibrated crop model within VARIwise was also used to conduct a preliminary exploration of data requirements for adaptive irrigation control to identify the relative significance of the various sensor variables (i.e. plant, soil and weather). This involved comparing the simulated control strategies with different input data combinations.

- A broad literature review of control systems, presented in Appendix A, identified strategies that are applicable to irrigation. **Chapter 5** sets out an overview of these control systems and develops a methodology for their comparison.

- **Chapter 6** describes the implementation of an iterative learning controller in VARIwise and illustrates the operation of the controller with a case study.

- **Chapter 7** details an iterative hill climbing controller in which test irrigation volumes are applied to the field to evaluate the crop response to different irrigation volumes. The implementation of this controller is described and an example case study is given.

- A model predictive controller was implemented in VARIwise using a calibrated model to determine optimal irrigation volumes and timing. **Chapter 8** details the implementation of the model predictive controller and provides a case study to demonstrate the capabilities of the controller.

- Finally, these three adaptive control strategies implemented in VARIwise were evaluated with sensor and irrigation machine constraints that are practical in a field situation. **Chapter 9** sets out the simulation results and a comparison of the strategies using various spatial and temporal resolutions of input data and irrigation machine capacities (which limits the amount of water that can be delivered).

- **Chapter 10** summarises conclusions about the application of adaptive control to LMIMs in relation to the research objectives. Further work recommended includes fieldwork to demonstrate the irrigation strategies integrated in VARIwise, extension of VARIwise to incorporate surface irrigation capability and the replacement of a static crop production model with a self-learning model.

# Chapter 2

# Literature Review

There is a need to identify and/or develop control strategies that can incorporate a range of factors, including crop response, target yield and management constraints, to improve the performance and precision of irrigation application (Chapter 1). These control strategies should seek to minimise water and fertiliser losses and environmental impacts, and maximise crop production returns. In this dissertation, such control strategies are referred to as optimal control strategies.

## 2.1 Spatial and temporal variability – significance, measurement and management

### 2.1.1 Spatial and temporal variability

Spatial and temporal variability of crop factors within a field can have a significant influence on agricultural production (Zhang et al. 2002) by reducing yield and quality of produce (Raine et al. 2007). For example, Bramley & Hamilton (2004) reported a tenfold variation of yield within Australian vineyards in any given year. In-field spatial variability is also dynamic within each growing season and between growing seasons;

hence, temporal variability exists. Spatially variable crop factors include soil properties, field topography and management practices (Zhang et al. 2002).

Soil properties that are spatially variable within fields include fertility (e.g. nitrogen content), texture (e.g. clay and loam), physical properties (e.g. moisture content and electric conductivity), chemical properties (e.g. pH, salinity and organic matter) and depth (Zhang et al. 2002). Variability of soil properties within a field has been found to affect the yield of a variety of crops (Cox et al. 2003 for soybean; Vrindts et al. 2003 for wheat; Johnson & Richard 2005 for sugarcane; Nyiraneza et al. 2009 for corn; Ping et al. 2008 for cotton). For example, Cox et al. (2003) reported that areas in a soybean field with high clay content had higher yield than areas with lower clay content. Similarly, when the application of water volume or water quality (e.g. salinity) is non-uniform in the field, soil properties may be an important factor in causing spatial variability in crop yield (Sadler et al. 2000).

There is often spatial variability of topographic factors within fields. In-field elevation differences can result in ponding of lower elevation areas (Sadler et al. 2000). In this case, ponded areas may be wetter than areas at higher elevations and hence may require less water.

Crop characteristics that are spatially variable within a field include crop density, height, stress, biophysical properties, structure, type and genetics (Zhang et al. 2002). Where crops of different types are planted within the same field, the crops will require different irrigation application amounts (Perry et al. 2002). However, genetic variations and differences in planting dates are also often found.

The management practices of farm managers may contribute to the variability of the field by impacting on the level of nutrients, compaction and acidity of the soil. Examples of management practices contributing to spatial variability include tillage practices, fertiliser and pesticide application, crop seeding rates, crop rotation and irrigation patterns (Brase 2006).

Meteorological conditions (e.g. rainfall, temperature and sunlight) can affect the crop yield. For example, the climatic conditions during the pre-harvest and drilling stages of the season may significantly alter soil structure and thus affect the crop yield (Landers & Steel 1994). Wind damage, and infestations of weeds, insects and disease, are also spatially variable and often have a significant effect on agricultural production (Zhang et al. 2002).

This review provides evidence that spatial and temporal variability of soil properties, topographic factors and crop characteristics exists within a field and that this variability can significantly affect crop production; hence, in-field variability needs to be addressed for irrigation management. The following sections describe the measurement and management of variability.

### 2.1.2 Measurement of variability

Sensing of field crops to determine irrigation requirement typically involves determining or estimating the crop water requirement. These sensors may measure the atmospheric conditions, soil water content or plant response.

#### 2.1.2.1 Weather measurement

Atmospheric demand is often used to estimate the daily crop water use and crop water requirement for irrigation management (White & Raine 2008). Daily crop water use (i.e. crop evapotranspiration or $ET_c$) is calculated using a crop coefficient ($K_c$) and a reference evapotranspiration ($ET_o$) (Equation 56 of Allen et al. 1998) as follows:

$$ET_c = K_c \times ET_o \tag{2.1}$$

where $ET_o$ is obtained from atmospheric measurements and $K_c$ is selected using Allen et al. (1998) which details crop coefficients for a range of crop types and growth stages. The atmospheric measurements are typically obtained from a nearby weather station that provides atmospheric measurements for a single point.

This equation can be utilised to determine site-specific irrigation volumes and consider spatial variability by adjusting the $K_c$ value according to spatially varying properties across the field. Allen et al. (1998) details the adjustments that can be made to $K_c$ according to a range of factors (e.g. crop cover, soil texture and planting date); however, $K_c$ values are not typically available for specific crop varieties and management conditions (e.g. deficit irrigation) (White & Raine 2008).

Atmospheric measurements may also be used to determine irrigation timing. This involves estimating the readily available water ($RAW$) in the soil which is the amount of water that a plant can extract from the effective root zone before the crop suffers water stress. The $RAW$ is typically affected by the soil texture and the maximum acceptable crop stress. The number of days between each irrigation event can be determined using the following equation (White & Raine 2008):

$$\text{Days} = \frac{RAW + \text{Effective rainfall}}{ET_c} \tag{2.2}$$

where effective rainfall is the rainfall that is used by the plant in the plant root zone.

Forecast meteorological data can also be used in an irrigation control system to estimate the timing and volumes of future irrigation events. For example, if a high probability of rain is forecast then the irrigation event may be deferred.

#### 2.1.2.2 Soil measurement

Irrigation can be more accurately managed using soil moisture status (Jones 2004). Measuring soil moisture can detect a soil water shortage or excess water application that can result in waterlogging, both of which may reduce crop yield. Soil moisture measurement involves sensing either **soil moisture content** or **soil water potential**. Soil moisture content is measured either:

1. directly from soil samples taken from the field which involves finding the percentage of water by either mass or volume of the sampled soil sample; or
2. indirectly using properties of the water in the soil with various sensors which may involve using neutron probes that measure the number of neutrons reflected by hydrogen in the soil water, or capacitance probes and time domain reflectometry (TDR) sensors that measure the electrical properties of the soil water (e.g. Marshall et al. 1996).

These sensors are often wireless and stream data multiple times an hour (e.g. Sentek 2009 for capacitance probes; SMEC 2009 for TDR sensors). Dukes & Scholberg (2005) used soil moisture content measurements from TDR sensors across a field in an automatic control system to initiate and terminate irrigation events in a subsurface drip irrigation system. The indirect method of soil moisture sensing may be utilised in an irrigation control system as multiple sensors can be located across the field taking point measurements at a high temporal resolution; however, the direct method of soil moisture measurement is not applicable to irrigation control as a large number of samples may be required and this would interfere with the crop growth from the crop roots being cut and the changes in infiltration and drainage behaviour (Marshall et al. 1996).

Soil water potential sensors measure the force with which water is held in the soil and estimate the energy that plants require to apply to extract water from the soil. The soil moisture can then be estimated because the energy required to extract water increases as the soil dries (Marshall et al. 1996). A prototype real-time wireless tensiometer and temperature sensor array has been developed by Vellidis et al. (2008) which consists of twenty sensors which transmit wireless data once every hour and may be integrated into a site-specific irrigation control system. These soil sensors take point measurements in the field and may be located across a field for input to a precision irrigation control system.

#### 2.1.2.3 Plant measurement

Plant response to irrigation water may be measured in addition to, or instead of, soil measurements in an irrigation control system (Jones 2004): this involves measuring **plant water status** and/or **plant response**. The water status of crop tissue can be determined from measurements of visible wilting and leaf and stem pressure, while the physiological plant response can be determined from measurements of growth rate and stomatal conductance (which is the speed at which water evaporates from plant pores) (Jones 2004). Stomatal conductance is often estimated from sap-flow sensors and thermal image systems. Sap-flow sensors measure the change in sap temperature with an increase in temperature (White & Raine 2008) whilst thermal imaging systems which involves measuring canopy temperature to indicate crop stress.

In-field plant response sensing systems have been developed using transducers to measure growth rate and indicate plant stress of young olive trees (Moriana & Fereres 2002), plum trees (Intrigliolo & Castel 2004) and lemon trees (Ortuño et al. 2009); these sensors are located on specific plants across the field taking point measurements. A camera-based vision approach to plant sensing has been developed at the University of Southern Queensland and involves autonomously measuring internode distances of cotton plants to indicate crop growth and water stress (McCarthy et al. 2009); this sensor was developed to be on-the-go or mounted on the gantry of the irrigation machine or a farm vehicle taking proximal measurements.

Infrared thermometers have been used to estimate water evaporation, and hence crop stress, and then to determine irrigation application and timing. For example, Peters & Evett (2008) mounted sixteen infrared thermometers on the gantry of a centre pivot irrigation machine and used the temperature-time-threshold method to adjust the irrigation. The temperature-time-threshold method involves monitoring the canopy temperature and making irrigation decisions every night based on the number of minutes in the day that the canopy temperature is above a threshold value.

#### 2.1.2.4 Conclusions

The usefulness of weather data in a precision irrigation control system may be limited because the crop coefficient may not be adjusted to reflect the spatial variability in the field and the weather data are typically obtained for a single location (and the spatial variability of the atmospheric conditions would not measured). However, weather data input would be appropriate in the absence of soil and plant data to estimate the crop water status.

The soil and plant sensors described in this section provide measurements at different temporal and spatial scales depending on the characteristics of the sensor. For example, soil moisture sensors can collect data every hour throughout the crop season at a small number of sampling points in the field, while sensors mounted on an irrigation machine can collect data every few days at a high spatial resolution. Hence, a control system to optimise the spatial and temporal plant responses to irrigation applications will be required to be able to integrate data from a variety of sensors at differing temporal and spatial scales.

### 2.1.3 Management of variability

The **spatial variability** within a field can be managed using data acquired from the sensors described in Section 2.1.2. This involves dividing the field into sub-areas, called management zones, which are more homogeneous in properties of interest than the field as a whole (Doerge 1998; Zhang et al. 2002). The field may be divided into management zones according to variations in soil moisture or crop type across the field. Sadler et al. (1998) report that variation may occur over distances as short as ten metres; hence, management zones with a width and/or length of less than ten metres may be required to manage spatial variation of soil and plant properties. Methods have been developed to analyse field variability maps, including topographical features, electrical conductivity and NDVI (Normalised Difference Vegetation Index) images, to define the locations and sizes of the management zones (Fraisse et al. 2001; Ferguson et al. 2003; Jaynes et al. 2005; Li et al. 2008).

The management zones in a field generally vary from year-to-year and often within a crop season (Plant 2001). At the same time, sensor data are often obtained at different temporal scales as described in Section 2.1.2. Hence, a control strategy that achieves optimal irrigation must be able to account for the **temporal variability** of the field, as well as incorporate data obtained at a variety of temporal scales.

The **stochastic nature** of the crop response must also be considered to manage spatial variability. This involves sampling a set of plants in each management zone to obtain accurate measurements as there is often spatial variability within each management zone. Every point in the field may not be sampled by all in-field sensors. Hence, it is often necessary to estimate values for the unsampled locations to produce a map of variability of the soil, crop or disease factors to represent the entire field (Stewart et al. 2005); this is called spatial interpolation. Kriging is a method of spatial interpolation for data points on a regular grid using irregularly spaced data (Wackernagel 2003).

### 2.1.4 Variable-rate technology

Sadler et al. (2000) identified the variable-rate sprinkler as the most critical hardware required to implement site-specific irrigation using LMIMs. There have been three approaches in the literature for implementing variable-rate sprinklers:

1. Either individual or groups of sprinklers are pulsed on and off using solenoid valves to create time-proportional control. Applicators have been developed and implemented in research applications by the Washington State University (Perry et al. 2002; Perry et al. 2003), the United States Department of Agriculture and Agricultural Research Service (USDA-ARS) in Fort Collins, Colorado (Fraisse

et al. 1995; Evans et al. 1996), Clemson University (Han et al. 2009) and WMC Technology Limited in New Zealand (Bradbury & Ricketts 2009). A commercial variable-rate system 'Farmscan' has been commercialised by Computronics Corporation Limited in Perth, Western Australia (http://www.farmscan.net.au/).

2. Multiple manifolds of different-sized nozzles are used in combinations to create a stepwise range of rates. This approach has been used by the University of Idaho (McCann & Stark 1993; McCann et al. 1997; King & Wall 2005) and the USDA-ARS group in Florence, South Carolina (Camp & Sadler 1994; Camp et al. 1998; Wall et al. 1996; Omary et al. 1997; Sadler et al. 2000; Sadler et al. 2002).

3. A concentric pin is inserted into the sprinkler nozzle to reduce the cross sectional area of the nozzle. The pin is then cycled in and out with the duty cycle required to achieve the desired time-averaged flow rate (King & Kincaid 1996; King et al. 1997).

Variable application volumes can also be achieved to a limited extent by varying the speed of the LMIM. This approach does not vary the irrigation application along the length of the lateral; rather, it varies the irrigation application only in the traverse direction. However, variable-rate sprinklers and machine speed control may both be implemented on a single irrigation machine (e.g. Han et al. 2009).

Variable-rate application is often used in conjunction with Low-Energy Precision Application (LEPA) socks. LEPA socks apply water at low pressure, either within the crop canopy or directly onto the soil surface, to reduce evaporation from the crop canopy and soil surface (Foley 2004). Any of the variable-rate sprinkler approaches described above can be applied to LEPA systems (White & Raine 2004).

### 2.1.5 Conclusions

In-field spatial and temporal variability of soil and crop properties exists and can affect agricultural production. Sensors that measure or estimate soil moisture content, soil water potential, plant water status and plant response have been developed which can quantify this variability but each sensor typically collects data at different spatial and temporal resolutions. To manage the variability, the field should be divided into management zones of approximately homogeneous properties. In cases of data unavailability in each zone of the field, the spatial resolution of the data may be effectively increased by spatially interpolating the available data and ascribing an estimated value to each zone. Technology has also been developed to apply site-specific irrigation via lateral move and centre pivot irrigation machines. These in-field soil and plant sensors and variable-rate applicators can be utilised for variability measurement and management to determine and implement irrigation management schemes and this is reviewed in the following section.

## 2.2 Irrigation management

Cotton has an average irrigation requirement of 6.3 ML/ha and in 2006-2007 the average yield of Australian cotton was 7.9 bales/ha; hence the average irrigation water use efficiency was 1.3 bales/ML (CA 2010). Current irrigation management practices often involve replenishing the soil moisture if irrigation water is available. However, the efficiency of the water used may be improved by either one, or a combination, of the follow: (i) reducing system losses (e.g. evaporation, deep drainage and runoff); (ii) reducing water logging to increase crop growth rates; and (iii) reducing crop evapotranspiration during non-critical periods of the crop season by deficit irrigating the crop (i.e. not completely replenishing the soil moisture) (Raine & Foley 2002).

### 2.2.1 Existing decision support systems

As discussed in Section 1.1, many decision support systems have been developed to assist farmers and agronomists with deciding irrigation timing and volumes to apply. These often involve entering soil moisture and climate data collected by the farmer into soil, crop growth and/or hydrological models which simulate crop development in response to different irrigation amounts. Decision support systems have also been automatically implemented on irrigation systems (e.g. Luthra et al. 1997; Smajstrla & Locascio 2000; Evett et al. 2002*a*; Dukes & Scholberg 2005).

### 2.2.2 Existing irrigation control strategies

Considerable work is reported in the literature toward the development of automatic irrigation application systems for lateral move and centre pivot irrigation machines to achieve site-specific irrigation (e.g. King & Wall 2005; Pierce et al. 2006; Coates & Delwiche 2008; Chávez et al. 2010*a*; Chávez et al. 2010*b*). Site-specific irrigation volumes applied using these applicators are typically determined using a predetermined irrigation prescription map; however, King & Wall (2005) utilised digitised remote images of the field to withhold water from non-cropped areas.

Control systems have been used to determine spatially-variable irrigation application using measured soil data (e.g. Moore & Chen 2006; Capraro et al. 2008; Kim & Evans 2009; Kim et al. 2009; Park et al. 2009) and plant data (e.g. Peters & Evett 2008):

- The system developed by Kim et al. (2009) divided the field into five areas based on a soil electrical conductivity map and the irrigation volume applied to each area was proportional to the soil water deficit measured using two time domain reflectometry sensors in each area. The irrigation events were triggered when the deficit of any of the soil sensors reached mid-range.
- Park et al. (2009) developed a model predictive controller that determined spatially variable irrigation volumes (applied by changing the machine speed of a centre pivot) to maintain soil moisture. This controller predicted soil moisture responses and irrigation applications using real-time weather data and a soil model calibrated using soil moisture measured with capacitance probes.
- Capraro et al. (2008) reported a closed-loop neural network-based irrigation controller for drip irrigation in which a soil model was developed using a neural

network and soil moisture data gathered during a sequence of irrigation events. The soil model was then used to estimate the irrigation application to regulate soil moisture.

- Another controller for variable-rate centre pivot irrigation using soil moisture data feedback was conceptualised by Moore & Chen (2006). In this case, an iterative learning controller adjusted the irrigation application flow rate to control the water or concentration of nutrients in the soil.

- Peters & Evett (2008) used crop stress as the indicator of irrigation requirement via an array of infrared thermometers mounted on a centre pivot irrigation machine which permitted the adjustment of the irrigation application for each of 48 areas of the field.

The majority of these control strategies are one-dimensional (using only soil or plant data input for irrigation management). However, local microclimate, plant genetics and pest infestations in the crop may result in one area having a different optimal yield relative to another area of the field, and if the control strategy aims for uniform yield across the field then the yield cannot be maximised.

The control systems described above respond (and adjust the irrigation control) only if the need to change control settings is manifest in the sensed variables. Soil data feedback has been utilised in the majority of the irrigation control systems currently in the literature (as discussed above), whilst weather data feedback has been used to manage irrigations under limited water supply (e.g. Rao et al. 1992) and plant data feedback has been utilised for automatic irrigation control (e.g. Peters & Evett 2008). However, soil and weather sensors may not provide the most accurate indication of crop status; rather, the plant may be the best indicator of water availability (e.g. Kramer & Boyer 1995; Wanjura & Upchurch 2002; Jones 2004). This is because the plants essentially integrate the atmospheric and soil factors that affect plant water status.

### 2.2.3 Conclusions

Control strategies have been developed for site-specific irrigation and often use soil information as feedback. However, plant data may be more useful in an irrigation control system to indicate crop water status. Because of the relatively short time constant associated with the evaporative demand (and hence transpiration response) of plants, an irrigation control system using plant growth data should enable input of parameters with appropriately short time constants as well as data with long time constants. A parameter with a short time constant is weather (which affects sub-daily dynamics of crop response), whilst a parameter with a long time constant is the change in soil water status. Hence, it is likely that the incorporation of measured plant, soil and weather data will normally be required for an optimal irrigation control system.

## 2.3 Control systems

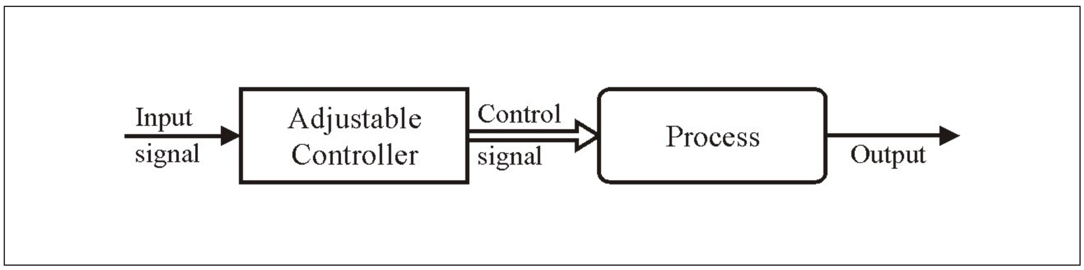
Using a control strategy to improve the spatial and temporal precision of irrigation application involves monitoring the weather, soil and/or plant features and adjusting the irrigation application and/or timing based on sensor data. An overview of types of control strategies and control strategies potentially applicable for use in a precision irrigation control system follows.

### 2.3.1 Overview of control systems

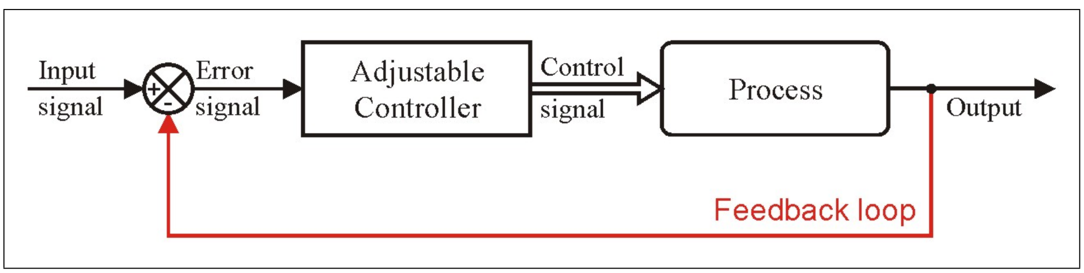
A control system is a device or system that maintains or alters the operation of a process. The whole system consists of: (i) the process being controlled[1]; (ii) the sensing system (to measure the process response if feedback is required); and (iii) the controller (which incorporates both the software and hardware required to control the process).

[1] The process being controlled is generally referred to as a plant; however, due to the possible confusion between a plant in the control sense and a plant in a cotton crop, a plant in the control sense will be referred to as a process.

Control systems may be either open-loop or closed-loop: an open-loop control system uses known relationships between the process input and output to adjust the controller parameters (Figure 2.1(a)), whilst a closed-loop control system measures the output of the process and adjusts the controller parameters to minimise the ‘error signal’ which is the difference between the input and the measured output (Figure 2.1(b)).




(a)




(b)

Figure 2.1: Block diagrams of: (a) open-loop control system; and (b) closed-loop control system

Open-loop control systems are sensitive to unwanted signals that are not considered when the controller parameters are adjusted since the output of the process is not monitored (e.g. Nise 2004). These unknown signals are called ‘disturbances’ and can corrupt the process input and output as follows:

1. By a disturbance on the process output; for example, if an irrigation application volume is calculated using soil moisture measurements and there is an unexpected soil moisture decrease since the calculation was performed, more water than calculated should have been applied to the crop; or

2. By a disturbance on the process input; for example, noise in the controller’s commands will also drive the process and corrupt the process output with the

effect of noise.

Figure 2.2 illustrates the block diagram of an open-loop control system with disturbances on the process input (labelled ‘Disturbance 1’) and output (labelled ‘Disturbance 2’).

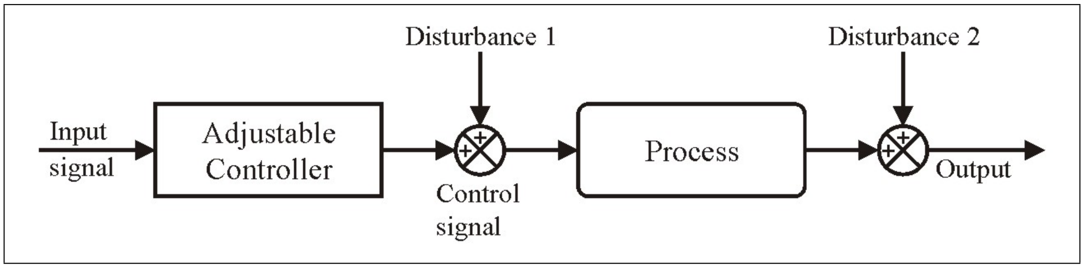



Figure 2.2: Block diagram of open-loop control system with disturbances on the process input and output (adapted from Nise 2004)

### 2.3.2 Limitations of conventional control systems

Much of standard control theory (developed for electrical and chemical applications, for example) assumes that a system does not vary with time and has fully-defined dynamics (e.g. Zaknich 2005). However, these assumptions are not valid for many agricultural systems for the following reasons:

- Crop growth, pests and weather, for example, vary within and between crop seasons and these alter the optimal irrigation amount to be applied to the plants. A conventional control system that is designed to apply an amount of irrigation required for optimal cotton growth under particular conditions (and with the implicit assumption that the conditions do not change) will tend to cause inaccurate determination of irrigation requirement and possible deterioration of crop health as time passes and with changes in the crop growth and/or atmospheric conditions.

- Determination of the appropriate *local* irrigation amount may require differing local irrigation strategies as a result of sub-field variations. However, large mobile irrigation machines typically apply irrigation to the entire field during each irrigation event and hence the irrigation timing may not equally benefit all the areas of the field. Sub-areas of the field may also have temporally variable irrigation requirements. The range of possible environmental variations would be difficult to fully define and hence control with conventional control systems.

- Conventional control systems typically require the process being controlled to be described using 'state equations' which describe the mathematical relationship between the variables. As reviewed in Section 2.1.1 the complex interactions in the soil-plant-atmosphere system suggest that only a simplified system could be reliably represented by state equations. A change in crop and/or soil properties would also influence the irrigation requirement and state equations that describe how the irrigation application, plant growth, soil water status and weather conditions interact.

Faced with this situation there are three options (e.g. Warwick 1993):

1. Continue with the existing control system design. This may result in the sub-optimal irrigation of the crop and potential deterioration of system performance, as noted.

2. Manually redesign the control system to account for the new conditions. This option is labour-intensive since it involves gathering data about the new conditions and then designing a new control system. The control system would also have to be redesigned every time the conditions changed.

3. Use a controller which can be automatically and continuously retuned to retain the desired performance of the system. This controller is able to adapt its parameters to compensate for changing conditions and does not require manual redesigning (Warwick 1993).

The adaptive control option described above in item 3 offers improvements to the performance of irrigation control systems. A controller that is adaptive can change the controller parameters to maintain control performance throughout the cotton crop season with the varying properties of the soil-plant-atmosphere system. A control system with an adaptive structure is called an adaptive control system.

### 2.3.3 Overview of adaptive control systems

The generally accepted definition of adaptive control is a system that automatically adjusts one or more controller parameters based on sensor feedback from the process to maintain the desired performance. Many other definitions are given in the literature which seek to differentiate adaptive control techniques from non-adaptive control techniques but there appears to be no generally-accepted system of classification (e.g. Ogata 1990; Mosca 1995; Filatov & Unbehauen 2000).

Conventional adaptive control systems feature two loops (Antsaklis et al. 1996): (i) an ordinary feedback loop that monitors the controlled variables to compensate for system uncertainties and disturbances on the controlled variables; and (ii) an adaptation loop that takes measurements of the system performance, and changes the adjustable controller parameters to compensate for variations in parameters, operating conditions, process dynamics and disturbances, to maintain an optimal system performance (Landau et al. 1998). A generic adaptive control system can be described on a structural level as follows, with reference to Figure 2.3:

1. The conventional feedback loop provides the primary reaction for system uncertainties and disturbances using constant and known controller parameters (Landau et al. 1998).

2. The adaptation loop tunes the adjustable controller by:

   (a) continuously and automatically measuring the dynamic characteristics of the process (Ogata 1990), i.e. block performance measurement;

(b) comparing the dynamic characteristics with the desired performance to measure the performance index[2], i.e. the block 'Comparison-Decision' with 'Desired performance' input; and

(c) adjusting the controller parameters (i.e. block adaptation mechanism) to optimise the performance of the system by:

i. modifying the adjustable controller parameters (parameter adaptation), i.e. arrow labelled 'Controller parameters';

ii. generating an additional signal for auxiliary control (signal adaptation), i.e. arrow labelled 'Auxiliary control'; and/or by

iii. changing the structure of the controller (sliding mode control) (Åström & Wittenmark 1989).

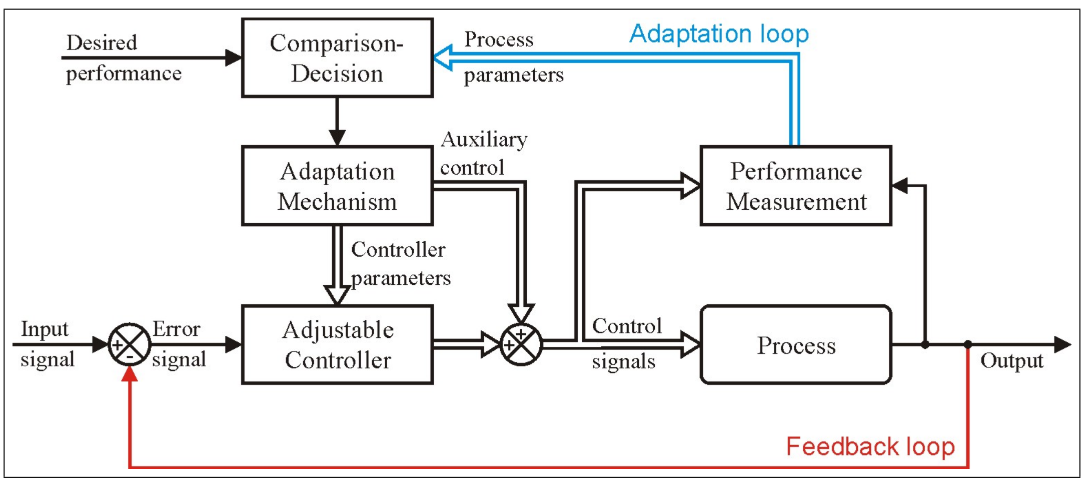



Figure 2.3: Block diagram of generic adaptive control system (adapted from Landau et al. 1998)

There is often a third loop in adaptive control systems, called a supervisory loop, that evaluates whether the conditions of the system are appropriate for a correct operation of the adaptation loop (Landau et al. 1998): for clarity this loop has been omitted from Figure 2.3.

[2]The performance index is a quantitative measure of the performance of the control system using the inputs, states, outputs and known disturbances (Landau et al. 1998). The performance index can be calculated using any characteristic that emphasises important control objectives (Ogata 1990). For example, for a control system that aims to optimally apply irrigation to crops, a performance index that is quantified between zero and one and is closer to one indicates that the system is reaching the maximum water use efficiency.

Methods of adaptive control include open-loop, model-reference, model-identification and intelligent adaptive control systems. All have potential relevance to the present project but as the literature is considerable their description and comparison is set out in Appendix A. From this review it is concluded that five control techniques are applicable to the irrigation of cotton. These are:

- **Dual adaptive control** which uses perturbation signals to learn more about the system and may be applied to irrigation to evaluate the response of the crop to different irrigation volumes (Section A.3.1)
- **Extremum adaptive control** which is used to achieve the optimal process output (e.g. maximise boll production of cotton) (Section A.3.4)
- **Iterative learning control** which would involve adjusting the irrigation volume applied depending on the error between the measured process output and desired process output after the previous irrigation (Section A.3.5)
- **Model predictive control** which would use field data to calibrate a plant and soil model and then use the calibrated model to determine the optimum irrigation timing and volume (Section A.3.6)
- **Variable structure control** which would ensure that the control system is robust to data gaps (Sections A.4.1 and A.4.3)

### 2.3.4 Adaptive control system design

The development and evaluation of an effective control system for irrigation application involves the consideration of design principles. Typical design principles identified by Ogata (1990) include robustness, stability and optimality:

1. Stability is a primary requirement of control systems (e.g. Krstić et al. 1995) and characterises how a system reacts to disturbances (Hangos et al. 2001). A system is stable if the signals remain bounded (Isermann et al. 1992); however, stability

is a difficult property to evaluate in adaptive control systems due to its dynamic nature (Friedland 1996).

2. Robustness can be interpreted as stability under system disturbances (de Silva 2000). The robustness of a control system denotes the insensitivity to parameter changes, model errors (in model-based control) and disturbances (in input and control signals) (de Silva 2000). Robust control systems are able to account for uncertainty in the process parameters to guarantee the stability of the system (Landau et al. 1998).

3. The output of a control system should converge to the optimal value. Achieving optimality in control systems relies on optimisation techniques (Ogata 1990) and optimisation generally consists of searching the space of variable controller parameters as a function of the performance index to determine where the performance index is optimal (Ogata 1990).

### 2.3.5 Conclusions

Adaptive control strategies offer improvements to site-specific irrigation management. Control strategies for irrigation should be adaptive to maintain performance with the naturally varying properties of the soil-plant-atmosphere system throughout a crop season.

Typical control system design principles are stability, robustness and optimality. These principles have varying levels of significance in the design of an adaptive control system for irrigation application. Control systems are traditionally designed with the greatest emphasis on stability (Åström 1990). However, in the design of a control system for site-specific irrigation application, it is anticipated that the most critical characteristic of the system is robustness. This is because in a field implementation there may be deficiencies in spatial and temporal data collection, or constraints on the irrigation machine capacity or water availability.

Optimality is the next most important principle in the design of an irrigation control strategy. To optimise irrigation control, a performance index is typically optimised and the sensed variable/s used to calculate the performance index varies according to the strategy employed. For example, the irrigation applied may be optimised using daily measured data and for cotton this may involve determining the irrigation that maximises the square count ('squares' are flower buds on a cotton plant) or boll count after an irrigation event. Alternatively, predicted end of season characteristics (i.e. yield, water use efficiency) may be maximised using a process model.

Of the control design principles, stability is the least significant principle in an irrigation control system. This is because the soil-plant-atmosphere system has slow dynamics compared with typical control processes (which are executed in less than a second) and the system will not become unstable rapidly.

## 2.4 Development of research objectives

The literature reviewed in the foregoing sections substantiates the view that non-constant irrigation application may be required across a field to improve irrigation water use and crop yield. Multiple variable spatial factors (e.g. genetic variation, field topography, soil properties, plant health) and variable temporal factors (e.g. weather and crop stage) have been identified. Considerable work is reported in the literature toward the development of automated variable-rate irrigation applicators, in-field spatial sensors, wireless sensors and sensors mounted on the gantry of irrigation machines (Sections 2.1.4 and 2.1.2). However, no integrated or generic approach is reported.

Site-specific irrigation control strategies in the current literature typically use either soil or plant data (Section 2.2). Plant data input alone may not be useful for control because of the relatively slow speed of crop dynamics; however, plant data input may be integrated in a control system with parameters which have short time constants (e.g. weather) and those which have long time constants (e.g. change in soil water status).

The review of control options for improving irrigation management identified a number of control strategies potentially applicable to irrigation (Section 2.3 and Appendix A). These strategies require various levels of data input and have different levels of operational complexity and robustness. It is clear that the identification of the optimal control strategies for variable-rate irrigation would be more appropriate in a simulation environment rather than in field trials given the range and complexity of the control options available. Simulation models may also be used to evaluate the various irrigation control options under a range of environmental and crop management conditions; in contrast field testing would be limited to the evaluation of one control system under a limited set of field and seasonal characteristics. It follows that average cotton performance cannot be directly compared to simulated control strategy performances because the irrigation performance of each season will differ depending on the weather profile, crop variety and in-field variability.

The evaluation of the control strategies can only effectively be conducted using a simulation model and software platform that allows for:

- the inclusion of field-scale variations in input parameters (e.g. crop response, crop age, target yield and management constraints);
- the input of data at a range of temporal scales;
- the ability to apply the control strategies to uniform and variable-rate irrigation (i.e. with different levels of output control); and
- the ability to apply the various levels of control strategies for variable-rate irrigation at different spatial scales.

The simulation model/s used in the software platform should also be calibrated to enable the control strategies to be accurately simulated and compared. The calibrated model could then be used to evaluate which types of data are most useful for irrigation control by comparing strategies which use different combinations of data input.

The literature review has led to the research aim stated in Section 1.2, namely to develop and implement a real-time control methodology which utilises both historical mapped data and real-time sensor input to improve the spatial and temporal precision of irrigation applications. A software platform with an integrated crop production model must be developed to evaluate the various site-specific irrigation control options under a range of spatially and temporally varied conditions and targets. The platform must incorporate adaptive control systems which are able to adapt their parameters to compensate for the changing process conditions that occur in irrigation systems. Optimal irrigation control systems may be identified by comparing the various irrigation control systems that are simulated.

Specific research objectives are therefore:

1. To develop and refine a software platform for simulating and evaluating irrigation control strategies (Chapter 3 and Appendix B).

2. To validate and demonstrate calibration of the model in the software platform (Chapter 4 and Appendix C).

3. To identify and implement appropriate irrigation control strategies for improving the performance of irrigation applications (Chapters 5 to 8 inclusive and Appendix A).

4. To evaluate the benefits and limitations of the various control options with respect to data input requirements and the level of output control available (Chapter 9).

# Chapter 3

# Development of VARIwise

## 3.1 Concept and overview

Superior, and hopefully optimal, irrigation control strategies for differing crop requirements, sensory inputs, temporal and spatial scale requirements and constraints on the irrigation machine and water availability may be identified by comparing adaptive control strategies. The conceptual components of an adaptive control system for variable-rate irrigation are illustrated in Figure 3.1.

Adaptive irrigation control strategies (Figure 3.1) can use both historical data and real-time quantitative measurements of crop status, weather and soil, either singularly or in combination, to locally adjust the irrigation application, as required, to account for temporal and spatial variability in the field. It should be noted that in Figure 3.1, the 'decision support system' embodies the control strategy; 'actuation' is the action of adjusting the irrigation volume and/or timing; and 'application' is the resulting physical amount and timing of water and fertiliser applied to the crop. By integrating a range of control strategies in VARIwise and using different combinations of sensor variables, the user may then explore: (i) optimal control strategies for irrigation; (ii) temporal and spatial scale requirements for irrigation control; and (iii) the utility of additional

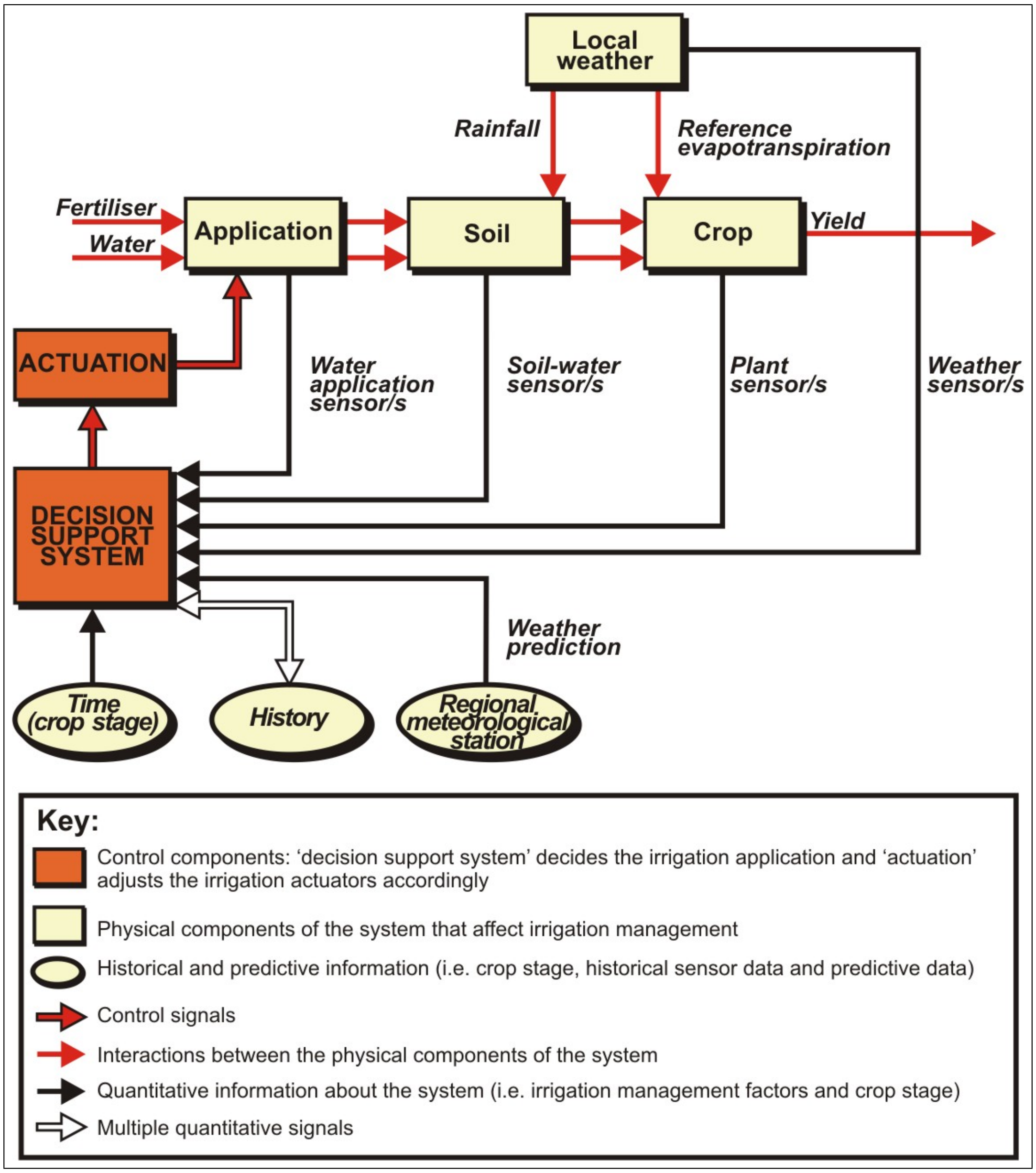



Figure 3.1: Conceptual adaptive control system for variable-rate irrigation – the basis of the simulation framework VARIwise

sensory input.

A general-purpose irrigation framework is required to develop, simulate and evaluate alternative site-specific irrigation control strategies incorporating multiple sensor variables. The software framework, named VARIwise[1], was conceived and developed and

[1]The name VARIwise is not an acronym and was chosen because the framework considers infield **variability** of the crop conditions to make irrigation decisions (which could be described as **wise**).

this chapter details its design and structure.

## 3.2 Software design specification

The framework must: (i) simulate and evaluate alternate irrigation control strategies to determine optimal strategies; and (ii) enable optimised control strategies to be executed in real-time and provide data outputs of irrigation volume and/or timing in an appropriate form for control actuation.

For both control strategy simulation and real-time control, the framework must enable data input for a range of field conditions in which weather, soil and plant data are available at various spatial and temporal scales. Smith et al. (2009) discuss the various conditions and the capabilities of simulation software for adaptive irrigation control.

The framework should accommodate data entry as text, images or numerical values. These data may be respectively obtained from daily Australian Bureau of Meteorology SILO patched point environmental data (QNRM 2009); obtained from aerial and in-field photos or EM38 maps; or entered directly into the software. The minimum resolution of the imported images should correspond to the spatial scale specified for the field in the framework: if the field is divided into 10 $m^2$ cells, then the pixels in the image should cover a maximum of 10 $m^2$. Image file formats should include all commonly used formats, including TIFF, JPEG and BMP. Data collected at particular sampling points across the field or otherwise imported may be at various spatial resolutions. For example, data may be available at a high spatial resolution from a soil electromagnetic (EM38) survey, or, in contrast, data may only be available at widely-separated point measurements from in-field soil moisture probes. It follows that the framework must be able to interpolate sparse spatial data to estimate field data at a higher spatial resolution.

For some sensor variables, only one reading may be available for the whole field and the presumption that this value is constant across the field may be questionable. For control strategy simulations, a single-point field-scale response may be insufficient to thoroughly evaluate irrigation control strategies at a high spatial resolution. Therefore, the framework should be able to impose additional variation (data 'noise') on chosen input datasets to estimate the spatial distribution across the field and permit the simulation of a wider variety of input conditions, in particular the effect of unmeasured variability. For example, in Australia, cotton is grown in areas dominated by unstable cumulonimbus storms which cause highly variable in-field rainfall (with a spatial scale of 10 to 100 m). A local weather station would only measure rainfall for a single nearby point, and imposing spatial variability on the rainfall data would enable the variability to be evaluated in simulation experiments.

Most soil and crop responses are highly dynamic; an example of this is the sub-daily changes in plant water use changes associated with the evaporative demand of plants. Hence, the framework should be able to handle input data at any temporal scale. It follows that for control strategy simulation, the crop production models utilised must have an appropriately short time resolution. However, the temporal scale of the framework simulation is limited by the characteristics of the model and currently most crop production models provide daily output only. In this situation, the simulation inputs must be averaged daily as the model outputs are determined daily. The performance of the control strategies may also be evaluated using data collected at different time steps.

Either simulated or measured in-field data should be utilised to provide feedback to the controller. Hence, the framework must be able to accumulate databases for all field data, simulation results and irrigation/fertigation applications, and retain these databases for use as historical input data in subsequent crop seasons. The simulation results of the control strategy output should be saved and graphically displayed over the crop season.

## 3.3 Software development

The framework, 'VARIwise', with the capabilities outlined above, was developed using Borland Delphi 6 (http://www.embarcadero.com/products/delphi/). Borland Delphi has the capability to create software frameworks that build databases and web applications, conduct image processing and statistical analysis, and execute mathematical functions and external applications (including crop models). VARIwise has the following major functional characteristics:

1. the ability to input whole-of-field data;
2. division of the field into variably sized cells;
3. creation, accumulation and management of spatial databases;
4. simulation of natural variability;
5. incorporation of variable-rate application;
6. incorporation of crop model/s (e.g. soil moisture response, plant response);
7. calibration of crop model/s;
8. implementation of control strategies; and
9. display of control strategy output.

The transfer of data between these functional areas is illustrated in Figure 3.2. The following Sections 3.3.1 to 3.3.3 describe processes within the framework which can be applied to both physical and simulation environments.

### 3.3.1 Ability to input whole-of-field data

Data entry screens are provided to input farm, field and crop data. Data inputs required for the farm database include GPS location; for the field database include irrigation type and dimensions of the computational 'cells' ('cells' refer to sub-areas of the field);

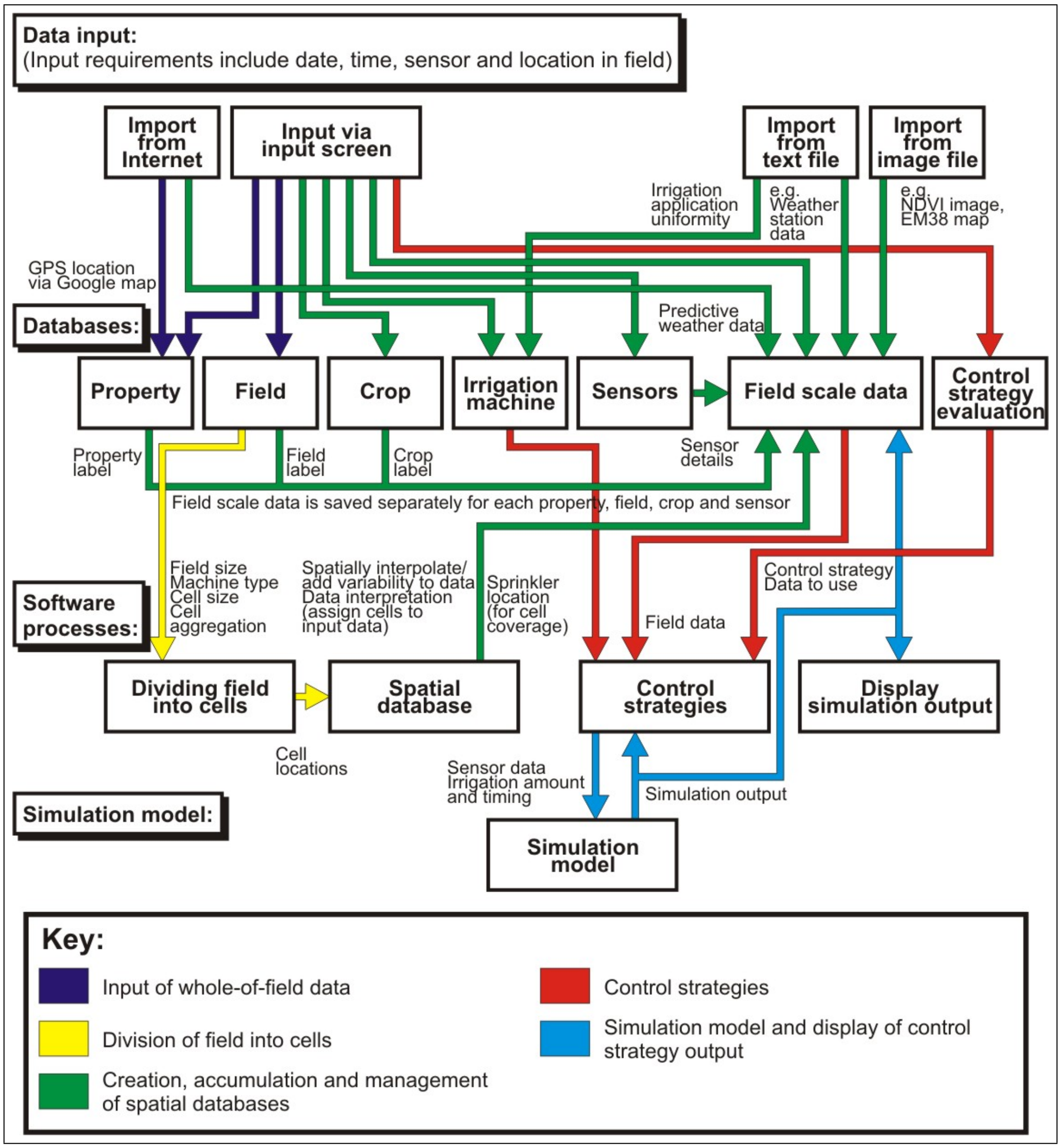


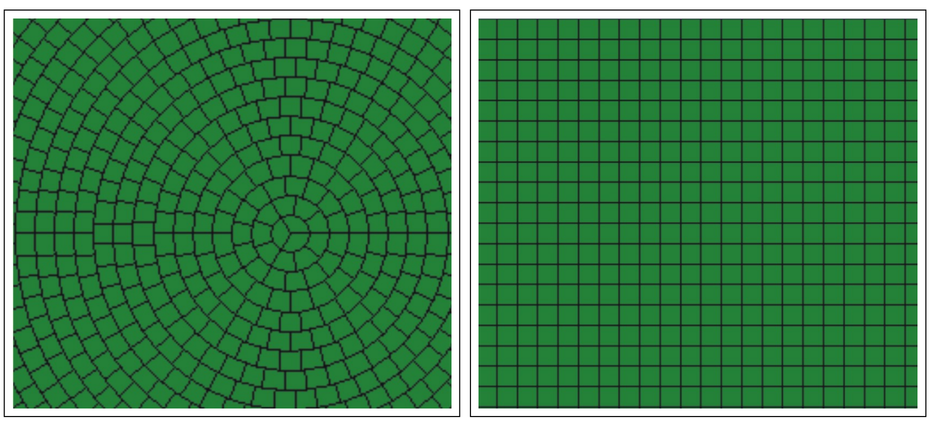

Figure 3.2: Block diagram for VARIwise software

and for the crop database include a crop label to distinguish between crop seasons on each field. Databases are also created for irrigation machine and sensor details. One database is created for each of the following: farms, field, crops, irrigation machines and sensors.

SILO climate datasets are automatically obtained from the Internet via the SILO website (http://www.nrw.qld.gov.au/silo/ppd/PPD$_$frameset.html). Edit boxes on the website are automatically entered with the GPS location of the farm. The SILO station details closest to the GPS location are saved and used to automatically download the latest weather details from SILO via the HydroLOGIC software (Richards et al. 2008). Seven day forecast weather is also automatically downloaded from a weather website (Elders weather website, http://www.eldersweather.com.au/) for the location entered in the farm details database.

### 3.3.2 Division of field into cells

The field is automatically divided into cells according to the dimensions and number of cells specified in the field information. The cell size is also automatically adjusted to fit evenly across the irrigation machine. Cells approximately 1 m wide and 1 m long for a centre pivot-irrigated and lateral move-irrigated field are displayed in Figure 3.3(a) and 3.3(b), respectively.



(a) (b)

Figure 3.3: VARIwise cells for field irrigated by: (a) centre pivot; and (b) lateral move irrigation machines

A high level of control in centre pivot and lateral move irrigation application can be achieved using a Low-Energy Precision Application (LEPA) sock (as discussed in Section 2.1.4). For example, for a machine irrigating a cotton crop, LEPA socks may be positioned 1 to 2 m apart; hence, in VARIwise the smallest controllable area has been assumed to be 1 m$^2$. If LEPA socks are not used on an irrigation machine, then irrigation decisions can be simulated at spatial scales larger than 1 $m^2$ and in these cases, the cells are automatically aggregated.

### 3.3.3 Creation, accumulation and management of spatial databases

Creating spatial databases in VARIwise requires the following characteristics of the data collection: farm label, field label, crop label, data type, sensor type, measurement units, location in the field, and date and time of measurement. Data types include nitrogen applied, soil moisture, leaf area index, plant height, temperature, rainfall and humidity. A new database file is automatically created for each unique combination of these characteristics; for example, the filename for a database containing soil moisture content data measured with an Enviroscan probe is shown in Figure 3.4. The databases created within the software are shown in Table 3.1.

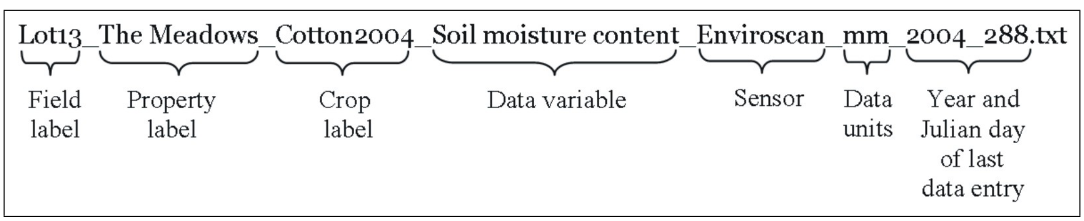



Figure 3.4: Example filename of spatial database in VARIwise

Field-scale measurements are entered into VARIwise either manually or imported from a data file (as text or .csv files) or image file (as BMPs or JPEGs). Input of an image requires a legend and the measurement that corresponds to the minimum and maximum legend values. For an RGB image, the data values are obtained for each cell by comparing the colour value on the image to the corresponding RGB values in a legend for the image.

The pattern of irrigation application as measured using standard catch can tests (in accordance with ASABE Standard S436.1, ASABE 2007) for a particular irrigation machine can be imported into VARIwise (commonly as a .csv file) and is automatically saved to the irrigation machine database. The application uniformity for two machines is illustrated in Figure 3.5.

Table 3.1: Databases within VARIwise

| **Type of database** | **Input method** | **Database entries** |
|---|---|---|
| *Static (unchanging) databases:* | | |
| Farms | Input screen/ Google Maps via an embedded web browser in VARIwise | Label, GPS location |
| Fields | Input screen | Label, irrigation type, dimensions of computational cell, number of cells to aggregate |
| Crops | Input screen | Label |
| Irrigation machines | Input screen | Dimensions, tower positions, machine capacity, irrigation application uniformity |
| Sensors | Input screen | Type of sensor, data type, units, time intervals of measurement |
| Field-scale databases ($i$) | Input screen | A new database ($i$=*1,2,3,...*) is created for each of the following variables: irrigation applied, sowing date, defoliation date/s, harvest date, crop variety, plant available water capacity |
| Control strategy evaluation databases ($j$) | Input screen | Each database ($j$=*1,2,3,...*) contains the following data for each control strategy evaluated: type of control strategy, input variable/s to use, whether machine speed is constant or variable, temporal and spatial scale of data input |
| *Temporally-modified databases:* | | |
| Field-scale databases ($k$) | (As appropriate:) Input screen/ text file/ image file (e.g. aerial or ground photos, EM38 map)/ Internet (e.g. SILO weather dataset (QNRM 2009) using GPS location in property file) | Each database ($k$=*1,2,3,...*) contains one variable, for example: management details (nitrogen application), plant measurements (boll counts), soil measurements (soil moisture, electrical conductivity), weather measurements (solar radiation, temperature, rainfall), other (yield) |

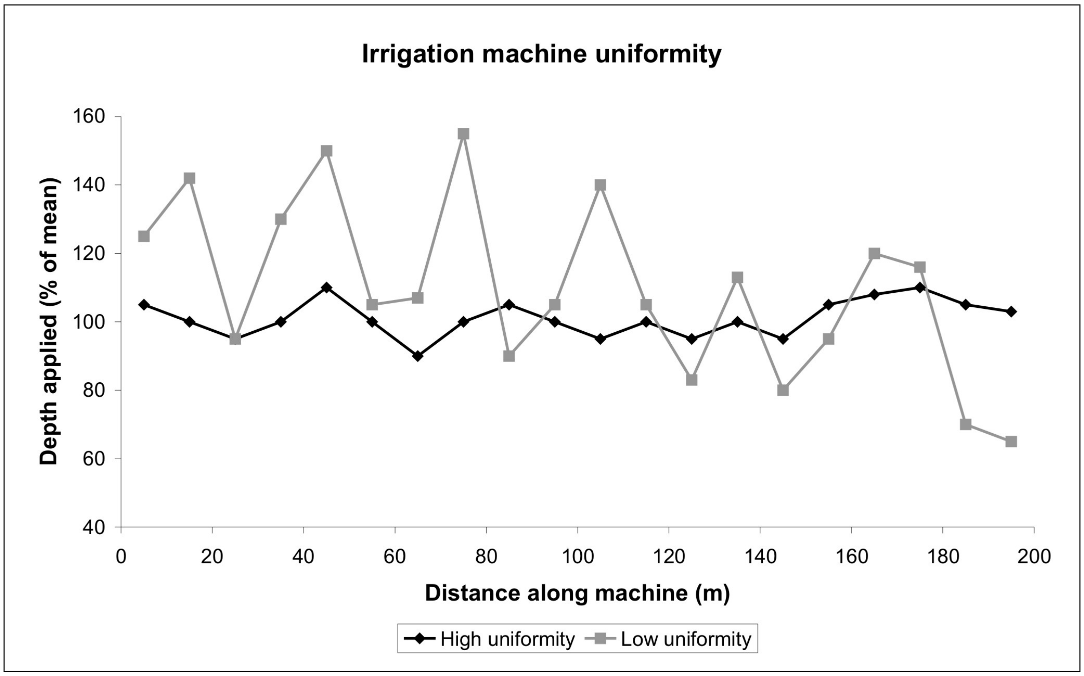



Figure 3.5: Examples of centre pivot uniformity distributions (obtained from Raine et al. 2008)

### 3.3.4 Simulation of natural variability

Imposing artificial variability upon the input parameters may be useful to conduct simulation experiments for control strategy evaluation. However, when the framework is operated in real-time control mode using measured field data, there is no benefit in introducing additional variation into the data. For simulation experiments, spatial variability may be imposed to single-point field data values to account for local variations (anticipated, but not directly measured) by one of two methods in the present implementation of VARIwise, namely:

1. For field-scale data representing a sub-area or (strictly) just a point in the field, any statistical distribution of variability or variability according to an imported map may be imposed. For example, given a single value of measured rainfall, the rainfall value ascribed to each cell may be chosen either randomly (to recognise rain gauge catch uncertainty) and/or as a gradient across the field to recognise the

spatial distribution of an individual storm. The random variation is generated in VARIwise using a random number generator component for Delphi 6 (AM-Random, http://www.esbconsult.com) and can impose statistical distributions including Gaussian, gamma and Weibull distributions.

2. Unknown point-scale field data may be estimated by interpolating the spatial measured data using 'ordinary kriging' (e.g. Güyagüler & Horne 2003). Kriging is a method for estimating the value of a property at an unsampled point location (e.g. Webster & Oliver 2001); and ordinary kriging uses linear interpolation (where its estimates are weighted linear combinations of the available data) without prior knowledge of the mean, and assumes that the local mean may not be closely related to the population mean (e.g. Scott 2000). Kriging may be used to estimate the soil moisture at unsampled locations in the field using data from in-field soil moisture probes. The ordinary kriging algorithm estimates the value $Z^*(u)$ at point $u$ using a weighted average of the known values and has the following general form (Güyagüler & Horne 2003):

$$Z^*(u) = \sum_{i=1}^{n} w_i \cdot Z(u_i) \tag{3.1}$$

where $u$ is the location of the unknown data point, $Z^*(u)$ is the estimated value at location $u$, there are $n$ measured data values $Z(u_i)$, $i$=1,...,$n$ and $w_i$ is the kriging weight of the variable at each location. This algorithm also requires that the weights sum to unity:

$$\sum_{i=1}^{n} w_i = 1 \tag{3.2}$$

The optimal weight of the variable at each known data point is determined using:

$$\begin{bmatrix} w_1 \\ \vdots \\ w_n \\ \lambda \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \dots & \gamma_{1n} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma_{n1} & \dots & \gamma_{nn} & 1 \\ 1 & \dots & 1 & 0 \end{bmatrix}^{-1} \begin{bmatrix} \gamma_{1u} \\ \vdots \\ \gamma_{nu} \\ 1 \end{bmatrix} \tag{3.3}$$

where $\gamma_{lm}$ is the 'semivariance' between the data points $l$ and $m$ which corresponds to the distance between these points, and $\lambda$ is the Lagrange multiplier which ensures that the sum of the weights is unity and that the solution is unbiased. In VARIwise, a linear semivariance may be used which corresponds to the simple Pythagorean distance between the data points, $a$ unknown and $b$ known:

$$\gamma_{lm} = k\sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \tag{3.4}$$

in $(x, y)$ space where $k$ is a constant. Alternatively the semivariance may correspond to the spatial variability of other input data in the field (e.g. electrical conductivity soil variability map).

Simulated variability may also be imposed on kriged data as described in (1) above.

Database files for the data modified to include variability are saved in VARIwise in the same format as the original data. However, the filename also contains:

- the text string *Variability*,
- the type of variability added (i.e. statistical probability distribution or kriging), and
- the parameters for the variability introduced (for a Gaussian distribution a required parameter is the standard deviation of the variability).

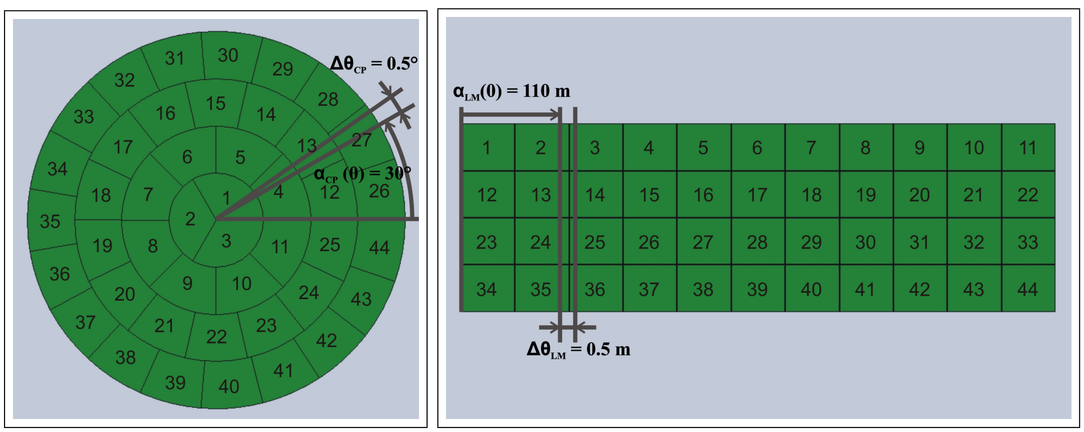
### 3.3.5 Incorporation of variable-rate application

In the VARIwise framework, variable-rate irrigation in both control strategy simulations and real-time control is achieved by adjusting the output of individual outlets (to sprinklers or LEPA socks). The irrigation applied by the machine also depends on the pump flow rate and travel speed of the machine and a variable-rate irrigation machine with fixed pump flow rate or travel speed may not be able to deliver the optimal irrigation volumes, even with outlets that are fully open. This can be rectified by either reducing the machine speed or increasing the pump flow rate and then adjusting the other outlets as required.

In VARIwise, the irrigation machine speed is adjusted according to the irrigation volumes applied to the cells currently covered and the machine capacity specified in the machine database. This method of adjustment is consistent with that of the commercial variable-rate irrigation system Farmscan (http://www.farmscan.net.au/). An irrigation machine capacity may be specified in L/s or ML/day to determine when the cells are irrigated (i.e. how many days are required to irrigate the field) and the maximum irrigation volume that can be applied.

When the field is irrigated in either the simulation or real-time environment, the irrigation volume is determined for the cells in the order that the cells would be irrigated by the irrigation machine passing over the field. During each irrigation event, the centre pivot irrigation machine traverses the field in the direction specified by the user, while the lateral move irrigation machine applies irrigation in the direction specified by the user for the first pass of the field. Following each irrigation event, the machine remains at the end of the field from the previous irrigation until the next irrigation event is initiated; hence, the direction that the machine travels to apply irrigation alternates for each irrigation event.

The original position of the irrigation machine in the field before each irrigation is specified by the user as an angle relative to a radius of the centre pivot irrigation machine (denoted by $\alpha_{CP}(0)$ in Figure 3.6(a)) and as a distance along the field for a lateral move irrigation machine (denoted by $\alpha_{LM}(0)$ in Figure 3.6(b)). The position of the irrigation machine is iteratively incremented by $\Delta\theta$ which is an angle for a centre pivot and a distance along the field for a lateral move. At each incremented position the irrigation volume is determined for the new cells covered by the machine. In Figure 3.6(a) the initial position of the centre pivot is 30° from the east direction and the incremented angle around the field is 0.5°, whilst in Figure 3.6(b) the initial position of the lateral move is 110 m from the edge of the field (with the machine travelling down the field in to the right of the page) and the incremented distance is 0.5 m.




(a) (b)

Figure 3.6: Movement of irrigation machine over field (with assigned cell numbers displayed) for: (a) centre pivot; and (b) lateral move

With each increment of the irrigation machine position, the irrigation volumes are calculated for all the newly-covered cells being irrigated by the machine. The new position of the machine ($\alpha(n)$ at position $n$) is determined using the previous position $\alpha(n-1)$ and the increment distance $\Delta\theta_{LM/CP}$, i.e.:

$$\alpha_{LM/CP}(n) = \alpha_{LM/CP}(n-1) + \Delta\theta_{LM/CP} \tag{3.5}$$

In Figure 3.6(a) the cells covered at angle $\alpha_{CP}(0) + \Delta\theta_{CP}$ are 1, 4, 13 and 27, whilst in

Figure 3.6(b) the cells covered at position $\alpha_{LM}(0) + \Delta\theta_{LM}$ are 3, 14, 25 and 36. The irrigation machine speed required to supply the calculated volume of water to the cells covered by the machine is calculated as follows:

$$s(n) \quad = \quad d \times \frac{mc}{v(n)} \tag{3.6}$$

where the $s(n)$ is the speed of the irrigation machine at position $n$ in m/day, $d$ is the total distance that the irrigation machine travels during the irrigation in metres (i.e. the circumference of the field for a centre pivot and the field length for a lateral move), $mc$ is the irrigation machine capacity in mm/day and *v(n)* is the average irrigation application at position $n$. The time taken to irrigate the field is accumulated as the machine passes over the field and used to adjust the irrigation timing of the cells. For the lateral move this is calculated using:

$$T_{LM}(n) \quad = \quad T_{LM}(n-1) + \frac{\Delta\theta_{LM}(m)}{s(n)} \tag{3.7}$$

where $T_{LM}(n)$ is the accumulated time for the irrigation event in days at increment $n$. For the centre pivot the accumulated time $T_{CP}(n)$ is calculated by converting the increment angle $\Delta\theta_{CP}$ to a distance travelled around the circumference of the field, i.e.:

$$T_{CP}(n) \quad = \quad T_{CP}(n-1) + 2\pi L \frac{\Delta\theta_{CP}}{360 \times s(n)} \tag{3.8}$$

where $L$ is the length of the centre pivot irrigation machine in metres.

### 3.3.6 Incorporation of crop model/s

When VARIwise is used to generate or evaluate irrigation strategies, a growth model appropriate to the crop and agricultural system will normally be utilised. This model generates synthetic field data which become inputs to the control system. Infield spatial and temporal differences may be represented by calibrating the model using *measured* spatial and temporal data: this will also allow for local real-time parameterisation of the model and may also improve the overall performance of the model. It is likely the calibration procedure will vary according to the model. Crop models are typically tested by comparing measured and predicted data averaged across the field over multiple years. While some crop models have been evaluated for their ability to represent spatial and temporal differences (e.g. Florin 2008; Oliver et al. 2010; Moore et al. 2010), the real-time calibration of cotton crop models using measured spatial and temporal differences has not be evaluated.

The full range of input data required for the evaluation of irrigation control strategies includes crop growth and fruit development (e.g. for cotton); plus soil moisture and weather data. For cotton this dataset may be obtained using the crop growth model OZCOT which is a cotton fruiting model (Hearn & Roza 1985) coupled with a soil water balance sub-model (Ritchie 1972) and sub-models for leaf area generation, boll growth and nitrogen uptake (Wells & Hearn 1992). The fruiting model captures the basic pattern of cotton growth and fruit development and is driven by temperature (i.e. day degrees[2]), solar radiation, water stress, water logging and nitrogen stress. The soil water balance model calculates the total soil moisture using the difference between the water uptakes (rainfall, irrigation) and water losses (soil evaporation, transpiration, deep drainage, surface runoff). Soil evaporation is estimated using the atmospheric evaporative demand and the capacity of the soil to transmit water to the surface, whilst transpiration is estimated using the leaf area index (Ritchie 1972). OZCOT also calculates runoff using the USDA Soil Conservation Service procedure (USDA 1986). However, OZCOT cannot predict the variation in erosion due to rainfall intensity and runoff rates and would require further development to account for these aspects.

Spatial customisation/calibration for OZCOT involves adjustment of parameters in

[2]Day degrees are a measure of thermal time and indicate the amount of heat available to the crop. Day degrees can be calculated by obtaining the average daily temperature in excess of a base temperature (taken as 12°C for cotton) assuming that crop development is negligible below the base temperature (Wells & Hearn 1992).

the soil properties and crop variety files (which describe the rate of boll and vegetative growth and are listed in Section B.1): these may be adjusted iteratively based on the error between the modelled data and measured data on the measurement days. OZCOT can automatically (and internally) correct any deviations between the modelled output and soil and plant measurements (entered into observation input files) by customising soil moisture and crop parameters used for predictions (Richards et al. 2008). However, this method of parameter calibration could only be used for during one crop season as OZCOT is only run for one year at a time and hence observations from only one year may be entered.

The interfacing (i.e. input and output data requirements) of crop growth models typically varies between each model; hence the incorporation of each model into VARIwise must be specifically programmed. The model OZCOT has been incorporated into VARIwise and was obtained as a stand-alone model from the simulation software HydroLOGIC (Richards et al. 2008). However, it is anticipated that other models will be able to be integrated into VARIwise due to the generic nature of the software structure.

Most crop production models operate at a daily time step (e.g. OZCOT): for these models the simulation inputs must be averaged daily and the outputs are determined daily. For simulation experiments, it would be useful to evaluate control strategies with input data at different temporal and spatial scales. This is achieved in VARIwise by only using the model output data at user-specified temporal intervals (i.e. every $n$ days) for irrigation decisions. The irrigation decision made then depends on data input specified by the user (i.e. the combination of plant, soil and weather data input), but in practice this is often further constrained by the data actually available. Table 3.2 sets out the data input combinations employed according to the data that are available. For example, the user may specify that the irrigation application be determined using a combination of plant height and soil moisture data. If plant data input is not available, soil moisture data input alone is used to determine the irrigation by applying the volume that will fill the soil deficit.

A strategy using only weather data input determines the irrigation application by es-

Table 3.2: Data inputs used for control when all data inputs specified in left hand column are not available

| **User-specified input variable/s for control** | **Input variable/s for control with unavailable data** | | |
|---|---|---|---|
| | **No plant data** | **No soil data** | **No weather data** |
| Weather | N/A | N/A | Averaged weather |
| Soil | N/A | Averaged weather | N/A |
| Plant | Averaged weather | N/A | N/A |
| Weather AND soil | N/A | Weather | Soil |
| Weather AND plant | Weather | N/A | Plant |
| Soil AND plant | Soil | Plant | N/A |
| Weather AND soil AND plant | Weather AND soil | Weather AND plant | Soil AND plant |

timating the crop evaporation and transpiration (i.e. evapotranspiration) following the method of Allen et al. (1998), whilst a strategy using only plant data input determines the irrigation application that maximises the reproductive growth and/or maintains the vegetative growth. Weather input is required for the operation of most crop models; hence, when weather input is unavailable, approximate climate data input for the time of the year is used in the model (i.e. 'averaged weather' in Table 3.2). Averaged weather input was used to provide the model with the minimal weather information that could be generated, enable the model to operate and enable the robustness of the strategy to limited weather input to be evaluated. The averaged weather dataset was generated using SILO climate datasets for the cropping period in the previous five years and calculating the daily average maximum and minimum temperature, solar radiation and rainfall such that each day in the season has the same weather conditions.

In this thesis the data combinations in the left hand column of Table 3.2 are referred to as 'data hierarchies' and a lower data hierarchy would be used by a control strategy in cases of data unavailability. The combinations of input variables in Table 3.2 are presented in the order of increasing data hierarchy (moving down the table) as more variables are included. It is expected that the usefulness of the input data would also increase for each row in Table 3.2 as plant data input is considered superior to soil moisture content to evaluate the plant water status and soil data input is considered superior to weather data input to estimate soil (and plant) water status.

The spatial resolution of the field data input may also be evaluated in the simulation environment by emulating sensors/measurements only being available in particular cells of the field. In VARIwise the user may select the cells in the field which have available data and the model output is then only obtained for these cells. The field data are then kriged across the field to improve the spatial resolution of the data and to enable irrigation decisions to be made for all the cells in the field.

Actual field data replace the crop model as controller inputs when VARIwise is used as part of a decision support system in a field implementation (Section 3.4). However, data from the crop model may be used in a field implementation to predict the crop response for an irrigation control strategy (if required). Data from the output of the crop model are saved to the corresponding VARIwise database files.

*Implementation of OZCOT in VARIwise*

The procedure for updating VARIwise database files for a control strategy simulation is dependent on the constraints of the crop model used. For example, for OZCOT (a cotton production model which is routinely used for cotton irrigation management in Australia; Richards et al. 2008), the irrigation applied is entered as equivalent rainfall and measured data input variables include soil moisture, leaf area index, cotton boll count and temperature.

OZCOT characterises the soil type based on the plant available water capacity, rather than the readily available water over the cotton plant's rooting depth, assumed to be 1.2 metres. Plant available water capacity is the quantity of water held in the soil between the nominal soil water potential of -10 kPa (field capacity) and -1500 kPa (permanent wilting point) and is expressed in millimetres depth of soil water (Scott 2000). At permanent wilting point, the plant can no longer extract water from the soil and will wilt and die. In contrast, readily available water is the amount of water that a plant can easily extract from the effective root zone before suffering water stress.

The HydroLOGIC software (a graphical user interface for OZCOT) provides a set of predefined soil property files that contain the drained upper limit (DUL), starting soil moisture and depth in each soil layer. The files are defined by the overall plant availability water capacity and starting moisture content. HydroLOGIC also provides predefined crop property input files which contain crop growth parameters for a range of cotton varieties. The input and output variables of OZCOT are listed and described in Section B.1.

A simulation is executed for each cell and irrigation event which requires measured data input from the VARIwise databases to be transferred to the necessary model input files. For OZCOT this involves four steps, namely:

1. Weather details to the OZCOT weather input file (including irrigation application determined by the control strategy which is entered as rainfall).

2. Management details (including seed depth, row spacing, plant stand and crop variety) to the OZCOT agronomy input file and crop variety input file.

3. Soil measurements (specifically measured plant available water capacity and soil moisture) to the OZCOT soil input file and the OZCOT observations input file.

4. Plant measurements (including measured boll counts and leaf area index) to the OZCOT observations input file.

### 3.3.7 Calibration of crop model/s

The model/s incorporated in VARIwise are automatically calibrated using weather, soil and plant data entered into VARIwise. Because the data may be spatially and/or temporally variable, the cells are calibrated separately when there is new data input. The general calibration procedure involves iteratively adjusting the parameters used to predict soil water status and plant growth until the difference between the predicted and sensed variables reaches a minimum.

Both the parameters that require adjustment and the method of adjusting the parameters are likely to be different for each model. For the cotton model OZCOT, the plant variables (leaf area index, boll count, square count), soil variables (soil moisture content and plant available water capacity) and weather variables (daily minimum and maximum temperature, rainfall and solar radiation in weather input file 'met.inp') are interdependent. The plant behaviour is calibrated by adjusting parameters in a crop properties file 'variety.inp', whilst the soil moisture behaviour is calibrated by adjusting parameters in a soil properties file 'soilw.inp'. These parameters were adjusted between the minimum and maximum values of the corresponding parameters in the predefined soil properties and crop variety parameter profiles. The parameters adjusted in the crop properties file include squaring rate (the rate of new flower buds being produced), growth rate of leaf area and plant population constant; whilst the parameters adjusted in the soil properties file are the depth of each soil layer and drained upper limit in each soil layer.

To automate the calibration procedure of OZCOT in VARIwise, all possible combinations of soil and crop parameter values may be evaluated. However, there are two parameters in the soil properties file for each layer of soil and 39 parameters in the crop properties file. Simulating all of the possible combinations of parameters would be time-consuming. For example, with three layers of soil there would be $3^{33} \approx 5.0 \times 10^{16}$ possible combinations of parameters to evaluate for three possible states of each parameter. Hence, only the parameters with the greatest effect on the OZCOT model outputs are adjusted in the calibration procedure.

The parameters most useful for the calibration procedure were identified from a sensitivity analysis (Appendix B). Parameters in the input files were iteratively adjusted and a sensitivity index was calculated after each adjustment to indicate the difference between the measured and simulated soil moisture, leaf area index, square count and boll count. The soil parameters were the most influential input parameters, whilst the most useful parameters in the crop properties file (i.e. the parameters that caused the greatest variation in the output) were identified as the following:

- Rate of squaring in 'thermal time', i.e. squares/plant/day-degree
- Respiration constant

- Ratio of leaf area per site for the cotton cultivar

A genetic algorithm was implemented in VARIwise to automatically refine these three plant parameters and all of the soil parameters. Ten possible states were assumed for each parameter to reduce computing time. A Borland Delphi V6 component was utilised (SoftTech Design, http://www.softtechdesign.com) to perform the optimisation in which the parameter combinations were evaluated by: (i) executing the crop model with the specified parameters; and (ii) calculating a fitness function using the error between the simulated and measured field data on the measurement days. The parameter combinations with the highest fitness functions were used to create the next population of parameter combinations to be evaluated. The optimisation was terminated after either 500 generations or when there was a maximum difference of 5% between the desired and modelled data, whichever occurred first.

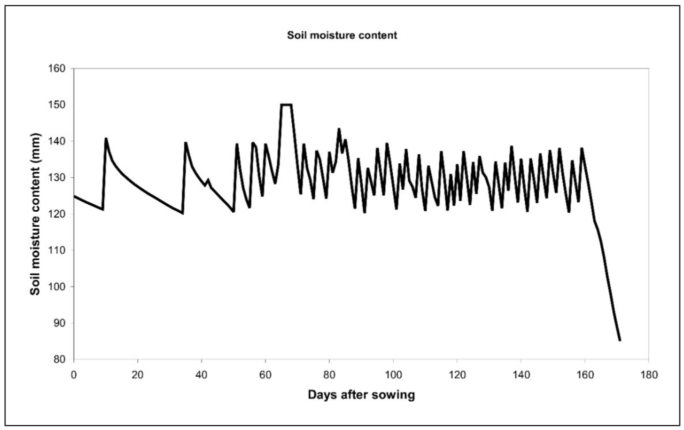
### 3.3.8 Implementation of control strategies

VARIwise is formulated to impose low (ideally zero) constraints on the control strategies that can be implemented in either simulation or physical (machine control) applications. The control strategies implemented in VARIwise typically require a performance index ($PI$) to be calculated to indicate how well the crop and/or soil responded to the previous irrigation volume applied. As noted in Section 2.3.5, the variables used to calculate the $PI$ depend on the strategy employed, the data available and the irrigation objectives of the user. For example, for the cotton model OZCOT, daily measured sensed variables that may be targeted or maximised are soil moisture content, leaf area index, square count and boll count. This is achieved by comparing the desired value of the variable with a value measured after an irrigation event. Alternatively, variables predicted by the model (e.g. crop yield) may be optimised. Irrigation Water Use Index (IWUI) and Crop Water Use Index (CWUI) may also be calculated for use in the $PI$ calculation to optimise water use. IWUI is the ratio of the crop yield (e.g. bales of cotton) to the irrigation water applied (ML), whilst CWUI is the ratio of crop yield (e.g. bales) to the total water used by the crop (ML) (BPA 1999). To calculate the CWUI, the total water used by the crop is determined from the modelled or measured change in soil moisture (depending on whether the strategy is implemented in the simulation or field environment).

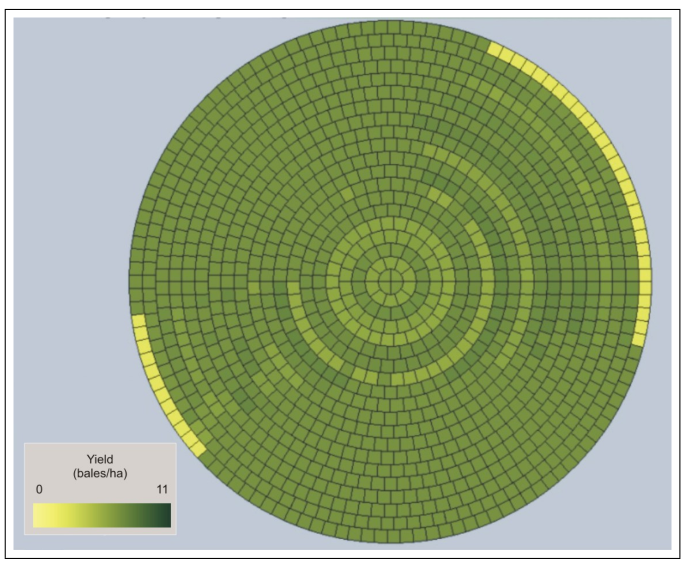
The irrigation control systems developed may also account for runoff and water intensity (to differentiate between low-pressure irrigation application and high-intensity storm rainfall). Runoff may be an additional variable to be monitored and minimised, whilst water application intensity may be measured indirectly via the crop response caused by the change in soil properties (from the irrigation/rainfall). However, total water used and crop performance are more indicative of the overall irrigation performance, and as noted in Section 3.3.6, OZCOT does not currently have the capability to account for water application intensity. Similarly, the control strategies may be multivariate and optimise both other crop management practices (e.g. nitrogen application and sowing date). However, this is outside the scope of this research.

### 3.3.9 Display of control strategy output

All sensor variables and control strategy outputs are retained in databases and can be viewed in the software by the user for each cell throughout the crop season as either: (i) tables of values; (ii) plotted graphs; or (iii) animated field maps. Examples of outputs (i) and (ii) are shown in Figure 3.7.




(a)




(b)

Figure 3.7: Example simulation output for soil moisture deficit-triggered irrigation: (a) graph of soil moisture during crop season in one cell; and (b) yield map for last day of season

## 3.4 Real-time implementation of VARIwise for irrigation machine control

It is intended that VARIwise will be used as part of a decision support system in real-time field implementations. This may involve mounting a computing system on a lateral move or centre pivot irrigation machine that transmits control actions to variable-rate irrigation hardware. VARIwise may also be interfaced with input data sources including an automatic weather station, wireless sensor networks of soil sensors, on-the-go real-time plant sensors, soil and plant stress field observations from the irrigation manager or agronomist, and flow meters for machine water applications.

Using execution run-time measurements it is estimated that computing the irrigation application and/or timing for a cell takes two seconds (time in Borland Delphi 6 on an Intel Core 2 Quad Q9400 (2.66 GHz) processor with Windows Vista operating system). For a field with 1000 cells and a computation time for each cell of two seconds, the irrigation control strategy would require approximately 33 minutes to determine the irrigation application to the cells over the crop season. An irrigation event would take over four hours for an irrigation machine moving at a typical maximum speed of two metres per minute over a field that is 600 metres in length. Hence, VARIwise should enable real-time identification and implementation of irrigation control strategies on a lateral move or centre pivot irrigation machine.

## 3.5 A VARIwise demonstration of industry standard irrigation strategies

To demonstrate the operation of the software, a case study is presented for two industry standard irrigation strategies, both of which have been simulated in VARIwise using synthetic data.

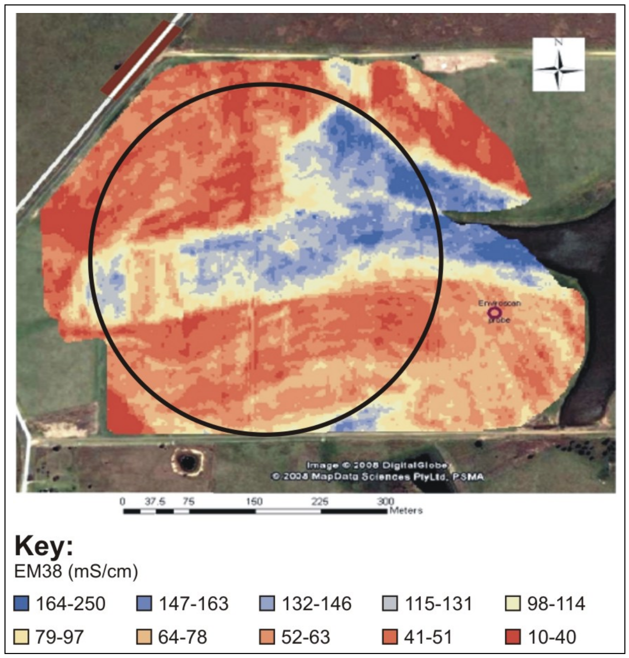
**Strategy A: Fixed irrigation strategy** in which the dates and amounts for the irrigation events are defined by the user.

**Strategy B: Soil moisture deficit-triggered irrigation strategy** in which the irrigation amount and soil moisture deficit triggering the irrigation are defined by the user.

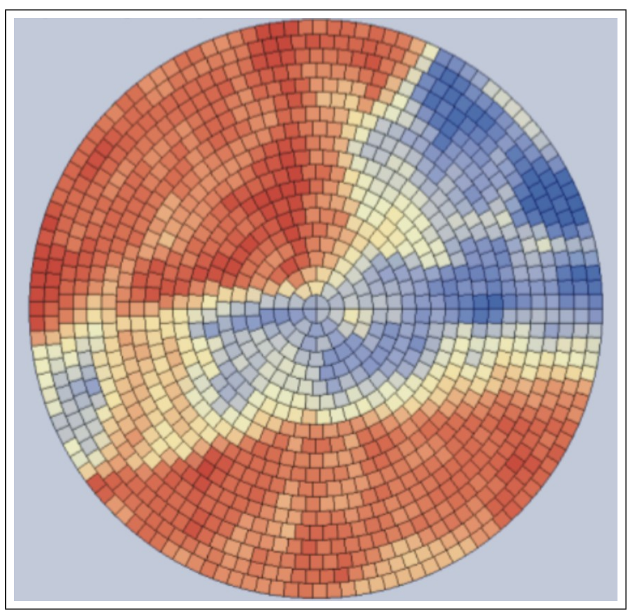
### 3.5.1 Methodology

In a simulation, cotton was sown on a 400 m diameter centre pivot-irrigated field on 4 October and was irrigated until 14 March of the following year. The nitrogen content of the soil was 120 kg/ha at the start of the season and a cell size of 100 $m^2$ was specified. Both the low and high uniformity irrigation machine application data of Figure 3.5 were utilised for the fixed irrigation strategy (20, 40 or 60 mm applied every six days), and only the low uniformity data were used for the soil moisture deficit-triggered irrigation strategy. These two irrigation strategies were simulated using the Sicot 73 crop variety. A daily weather profile for the site (with GPS location -28.18°N 151.26°E) was obtained from an Australian Bureau of Meteorology SILO dataset (QNRM 2009) for 2004/2005 which had a hot summer with the majority of the rainfall late in the crop season. The spatially varied soil properties (i.e. plant available water capacity) provided the underlying in-field variability (Figure 3.8).

For the soil moisture deficit-triggered irrigation strategy, irrigation events (in which 20 mm was applied) were triggered when a 30 mm soil moisture deficit was predicted (using the OZCOT model) in the three cells shown in Figure 3.9.




(a)



(b)

Figure 3.8: EM38 map: (a) to be imported into VARIwise; and (b) with electrical conductivity values assigned to each cell of the VARIwise simulation for the area circled in (a)

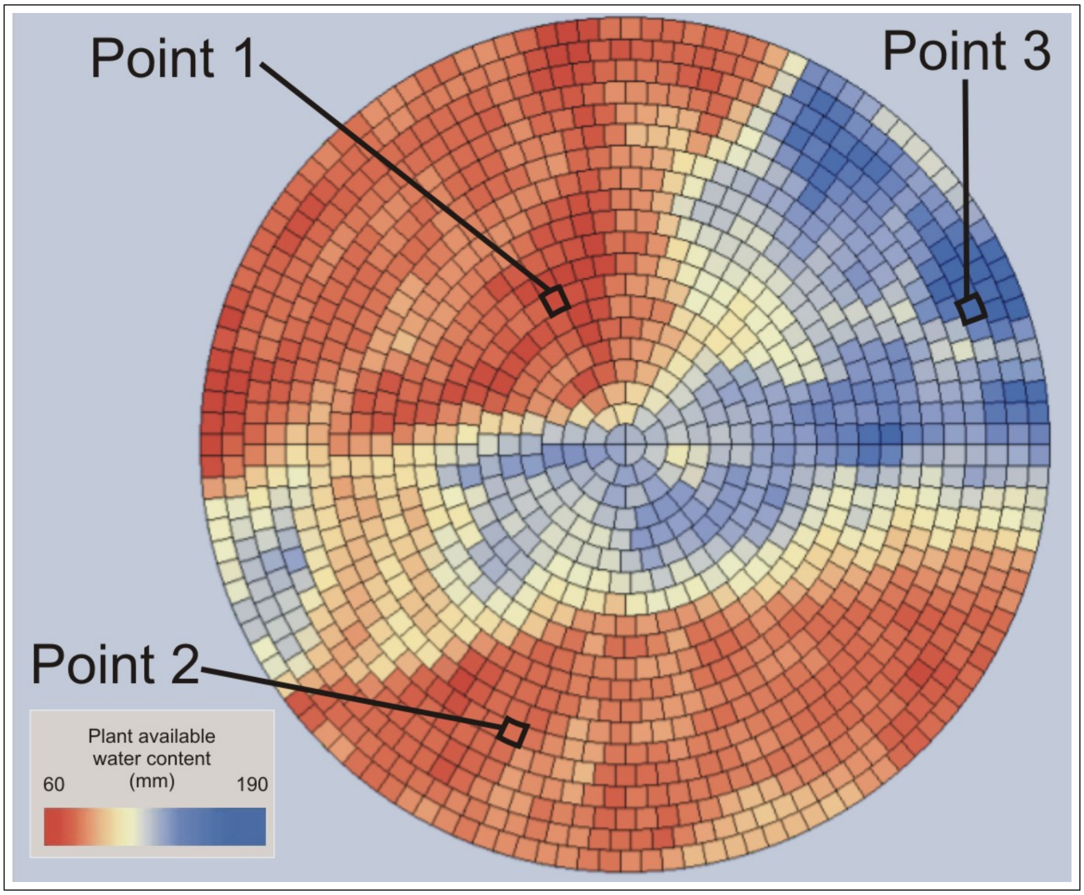



Figure 3.9: Trigger points for soil moisture deficit-triggered irrigation strategy in VARIwise

### 3.5.2 Results

The simulation output using two irrigation strategies 'A' and 'B' are shown in Figures 3.10 and 3.11 respectively. 'IWUI' is the Irrigation Water Use Index defined as the ratio of the crop yield (bales) to the irrigation water applied (ML) (BPA 1999).

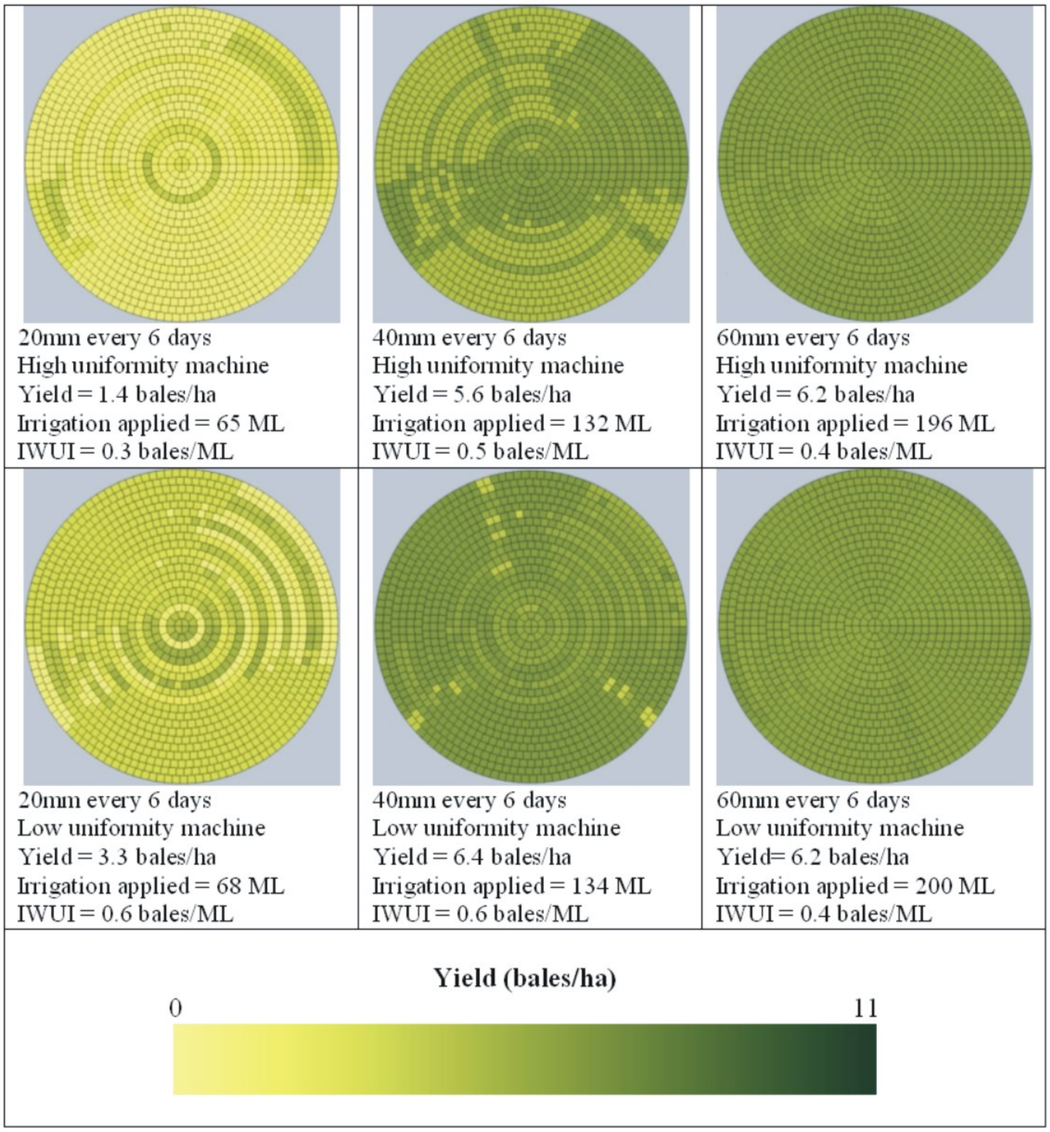



Figure 3.10: Yield output of the fixed irrigation strategy ('A') (the displayed legend is for the yield maps in Figures 3.10 and 3.11)

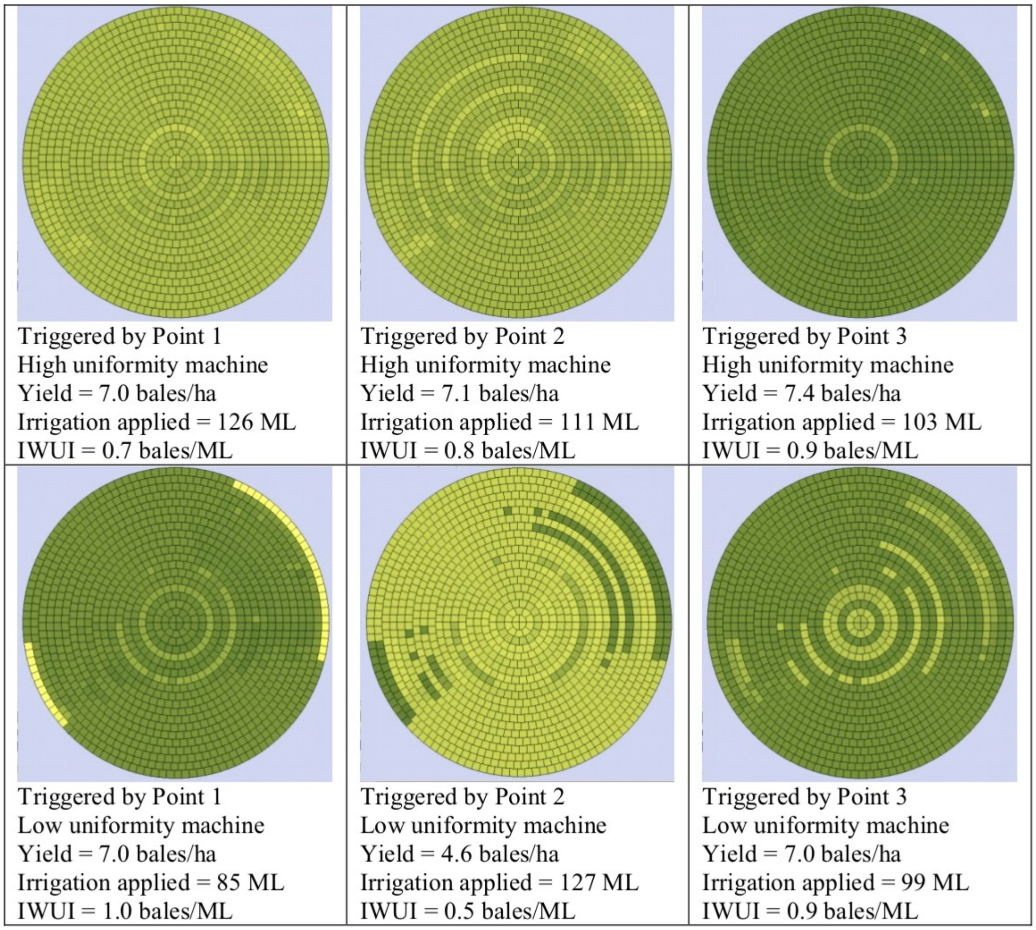



Figure 3.11: Yield output of the soil moisture deficit-triggered irrigation strategy ('B') (where the legend for the yield maps is shown in Figure 3.10)

Inspection of these results indicates:

- That for the fixed irrigation strategy 'A', the yield generally improved when the irrigation volume was increased.
- That for the soil moisture deficit-triggered irrigation strategy 'B', the location of the trigger point used to initiate irrigation events significantly affected the yield. The spatial variability of the yield was a function of the non-uniformity of the irrigation machine and the relationship between the location of the trigger point and the machine.

- That the uniformity of the machine affected the simulated yield for both 'A' and 'B': a low uniformity machine which applied large volumes of irrigation in some areas of the field resulted in higher yields.

## 3.6 Conclusion

The simulation framework VARIwise has been created to aid the development, evaluation and management of spatially and temporally varied site-specific irrigation control strategies. The input, database and output can provide resolutions of 1 $m^2$ (cell size) and sub-daily time steps, and the framework accommodates crop models according to crop type and alternative control strategies. A case study for the irrigation of cotton demonstrated that VARIwise:

- accommodates field-scale variations in input parameters
- successfully incorporates a standard cotton plant model (OZCOT); and
- permits desktop evaluation of irrigation control strategies.

# Chapter 4

# Field Calibration of the OZCOT Growth Model Within VARIwise

As introduced in Section 3.3.6, VARIwise requires a growth/production model appropriate to the crop under irrigation to provide both feedback and prediction in irrigation control strategies. The cotton growth model OZCOT is currently integrated in VARIwise.

Model calibration may be required to represent the spatial and temporal differences in each cell (as noted in Section 3.3.6). A model calibration procedure was developed for the OZCOT model (as described in Section 3.3.7) which involved iteratively adjusting the parameters in the soil and plant input files to minimise the error between the measured and simulated data.

A calibrated model can also be used to reliably conduct other simulations for the same set of field conditions under which the calibration data were collected. A possible exploratory simulation experiment using the calibrated model includes an evaluation of the relative significance of the sensed variables in an irrigation control system. Current irrigation control strategies commonly use only a single data input (e.g. soil, as noted in Section 2.2). Hence, using the calibrated model, the data inputs to an irrigation control system may be refined by evaluating (in simulation) the usefulness of additional sensory input to an irrigation control system. These simulations also indicate which data input combinations should be utilised if only limited data are available.

A programme of fieldwork was designed to collect weather data and to measure soil and plant response to irrigation and use the measured responses to calibrate the model. To maintain a modest field experiment, three irrigation treatments were applied and with three replicates of each treatment (i.e. nine plots were measured with three plots for each irrigation treatment). This chapter describes the fieldwork that was conducted to collect field data for model calibration and the simulations that were used to evaluate the relative significance of each sensor variable.

## 4.1 Objectives

This fieldwork aimed to demonstrate and utilise a calibrated crop model, specifically:

1. to demonstrate calibration of the refined model; and
2. to evaluate the relative significance of the sensor variables.

## 4.2 Site and equipment

Sicot 70BRF variety cotton was planted under a lateral move irrigation machine at Dalby, Queensland (with GPS location -27.21°N 151.20°E and altitude 373 m) on 15 October 2008. Urea was broadcast on the cotton crop on 14 October 2008 and the soil nitrogen content was estimated to be 120 kg/ha by the farm's agronomist.

Variable-rate nozzles were developed to adjust the irrigation applications along the irrigation machine (described in Appendix C.2). The additional sensors used in the trial were an automatic weather station (EasiData Mark 4, Environdata, Warwick

QLD); EM38 (Geonics Ltd., Ontario, Canada) electrical conductivity equipment; and Enviroscan (Sentek Pty Ltd., Adelaide SA) capacitance soil moisture sensors collecting data for five depths (10 cm, 20 cm, 30 cm, 40 cm and 50 cm).

Leaf area index (LAI) is the vegetative growth variable used in the cotton growth model currently integrated in VARIwise (OZCOT). However, measurement of LAI typically requires destructive sampling. Since experimental relationships between LAI and plant height have been developed for cotton (e.g. ASCE 1996; Richards et al. 2002), the plant height was measured and used to estimate LAI. A plant height sensor was developed for this fieldwork and is detailed in Appendix C.1.

## 4.3 Experimental procedure

### 4.3.1 Fieldwork

The field experiment involved collecting weather data (evaporative potential), soil moisture and plant height for three irrigation application treatments with three replicates. The three irrigation treatments applied are detailed in Table 4.1 and were labelled low, medium and high irrigation volumes relative to the commercial practice application determined from a soil moisture probe. A layout of the field trial and measurement locations is set out in Figure 4.1.

Table 4.1: Irrigation volumes applied to the low, medium and high irrigation treatments

| **Date** | **Irrigation applied in each treatment (mm)** | | |
|---|---|---|---|
| | **Low** | **Medium** | **High** |
| 9 January 2009 | 40 | 50 | 60 |
| 16 January 2009 | 50 | 50 | 50 |
| 28 January 2009 | 40 | 50 | 60 |
| 4 February 2009 | 20 | 30 | 40 |

Three irrigations were applied prior to the field trial. Measurements were taken for three controlled irrigation events (on 9 January, 28 January and 4 February 2009) and for one uncontrolled irrigation event (on 16 January 2009 where the medium irrigation treatment was applied to all plots). There were two rainfall events during the trial (7.6 mm and 16.2 mm on 23 and 25 January 2009, respectively). The irrigation volumes applied were varied using variable-rate nozzles and a horizontal EM38 electrical conductivity survey was conducted on the field one week after cotton was sown to choose a trial area which was as uniform as possible. The EM38 map of the field trial area is shown in Figure 4.1 and indicates electrical conductivity within the narrow range 110-136 mS/m.

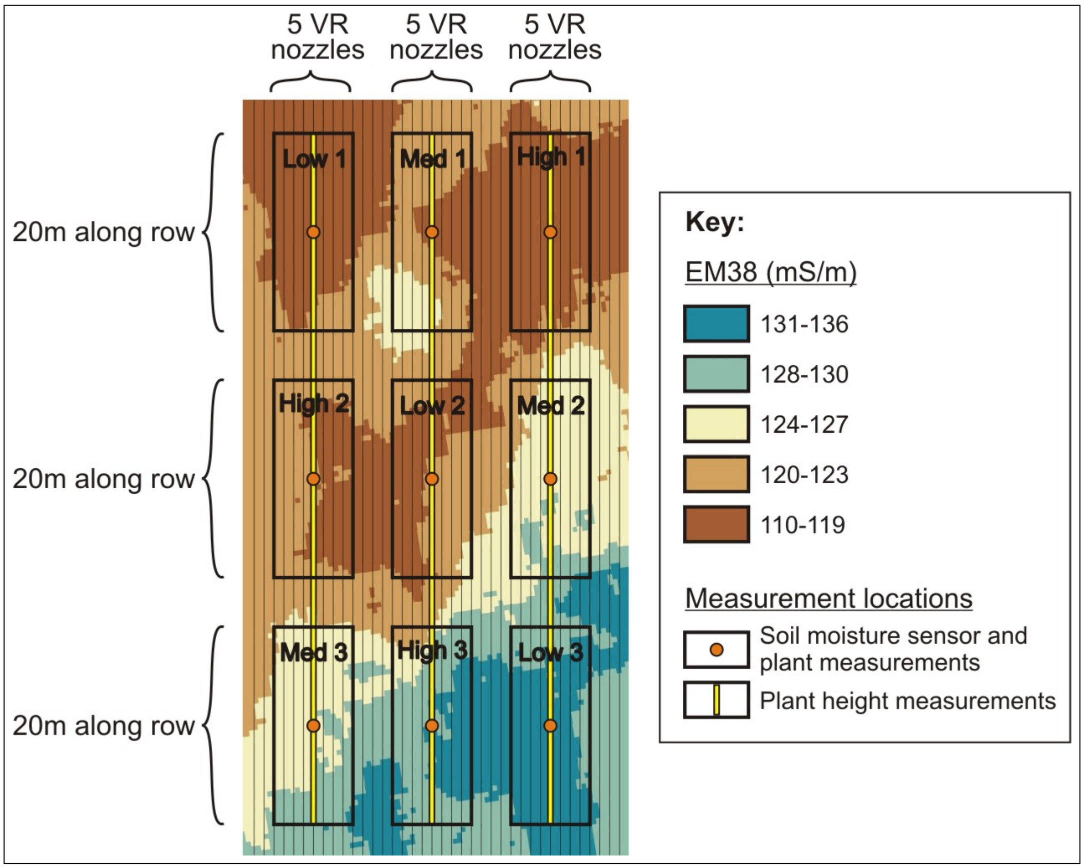



Figure 4.1: Field trial layout showing three replicates of low, medium and high application controlled via variable-rate nozzles overlaid on an EM38 electrical conductivity map of the trial area (the dark areas at top and centre are lowest quintile; those at bottom are highest quintile)

Field data were collected between December 2008 and February 2009 and involved measuring weather data using the weather station; measuring soil response using soil moisture sensors; measuring vegetative growth using a plant height sensor; and manually counting the number of cotton squares ('squares' are flowers on cotton plant) and bolls on ten cotton plants in each plot of Figure 4.1.

### 4.3.2 Data processing

Weather data were entered directly into the OZCOT model via a meteorological data file. The soil data required adjustment before further use because the Enviroscan soil moisture probes measure soil capacitance rather than volumetric soil moisture content. Site-specific calibration equations for converting capacitance to soil moisture content were not available for the trial area. The plant height dataset was converted to a leaf area index dataset for comparison with the modelled data using the experimental relationship developed by Richards et al. (2002) for cotton:

$$\mathrm{LAI} = 0.00347 \times \mathrm{Height} - 0.0352, \quad \mathrm{R}^2 = 0.914 \tag{4.1}$$

### 4.3.3 Model calibration

The soil and plant parameters of the OZCOT model were calibrated following the procedure in Section 3.3.7. Only the parameters which were identified in the sensitivity analysis as having a significant effect (Section 3.3.7) were adjusted in this calibration procedure. The calibrated model output and measured data were compared on the measurement days to evaluate the performance of the calibration.

## 4.4 Measured data and data processing

The measured field data required validation and pre-processing before being used to calibrate the OZCOT model: validation ensures that the measured data are sensible and within expected boundaries, whilst pre-processing ensures the collected data are in the correct format for input into the OZCOT model. This section presents the measured field data and details the validation of the measured weather data; the adjustment of the raw measured soil data to estimate soil moisture content; and the conversion of plant height to leaf area index to comply with the input requirements of the OZCOT model.

### 4.4.1 Weather data

Daily evapotranspiration was calculated using FAO56 (Allen et al. 1998) and data obtained from the in-field weather station and then compared to Australian Bureau of Meteorology SILO patched point environmental data (QNRM 2009) for the Dalby Airport (Figure 4.2). A daily $ET_o$ of 8 to 10 mm/day is typical for summer in Dalby (BOM 2009). Since the maximum daily $ET_o$ value calculated by the weather station was 5.1 mm/day, the weather station dataset was not considered to be accurate; this was most likely caused by an inaccurate solar radiation sensor. Hence, the SILO dataset was used for further data analysis.

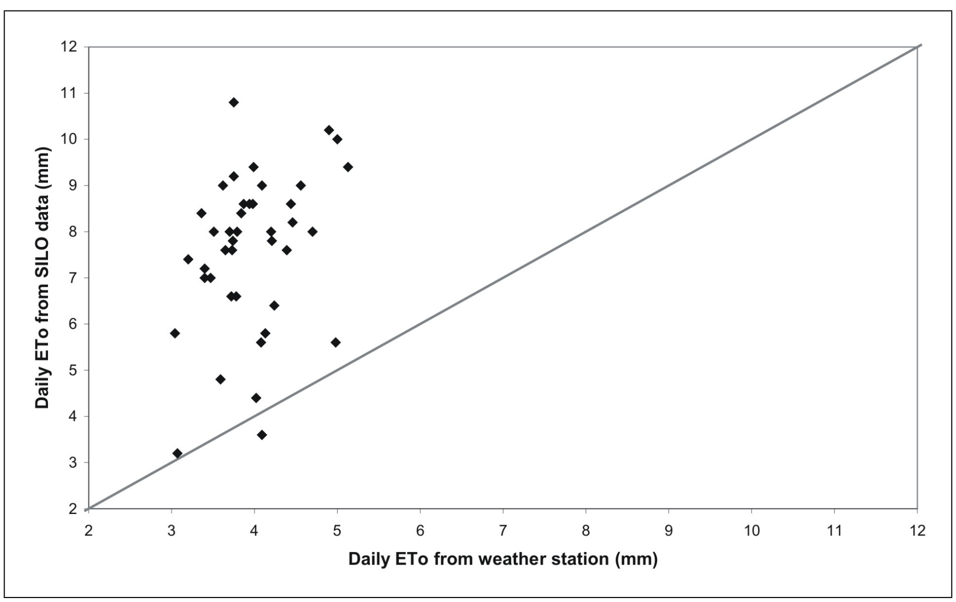



Figure 4.2: Comparison of daily $ET_o$ measured using in-field weather station with daily $ET_o$ from SILO data and 1:1 line

### 4.4.2 Soil data

Raw soil capacitance measurements from the Enviroscan sensors provide the pattern of the soil water trends. The Enviroscan software used a generic algorithm to estimate volumetric soil moisture for the measured capacitance (Figures 4.3, 4.4 and 4.5). However, since the OZCOT model requires measurements of the soil moisture content, the soil dataset required adjustment to estimate the actual volumetric soil moisture content.

The required adjustment (in calibration) for the soil dataset was determined by comparing the applied irrigation volume with the change in the soil moisture calibrated with the generic algorithm that occurred at each irrigation event, which is the method of Pendergast & Hare (2007). For example, in Figure 4.3 the first 40 mm irrigation event caused the estimated soil moisture to increase by 150 mm. Each soil reading was then divided by the average amount of overestimation over all irrigation events. For this field trial, the average overestimation of the Enviroscan sensors was 145±8% throughout the field trial. This is consistent with overestimation (of up to 100%) that is reported in the literature for Enviroscan sensor measurements of soil near saturation (e.g. Evett et al. 2002*b*; Jabro et al. 2005). The adjusted soil moisture graph was created by dividing the soil dataset by 2.45.

Figure 4.6 illustrates the change in estimated soil moisture content and calibrated soil moisture content (after adjustment of the raw data) versus irrigation volume applied. Quadratic curves were also fitted through each of these datasets (Figure 4.6): quadratic fits were used because the soil moisture plateaus as the change in soil moisture content approaches the field capacity with higher irrigation application.

The measured soil moisture content was sporadic between 22 and 27 January and missing after 27 January for replicates 3, 2 and 1 of the low, medium and high irrigation treatments, respectively: this was caused by a faulty battery. Hardware faults also caused the missing data before 8 January for replicate 2 of the low irrigation treatment.

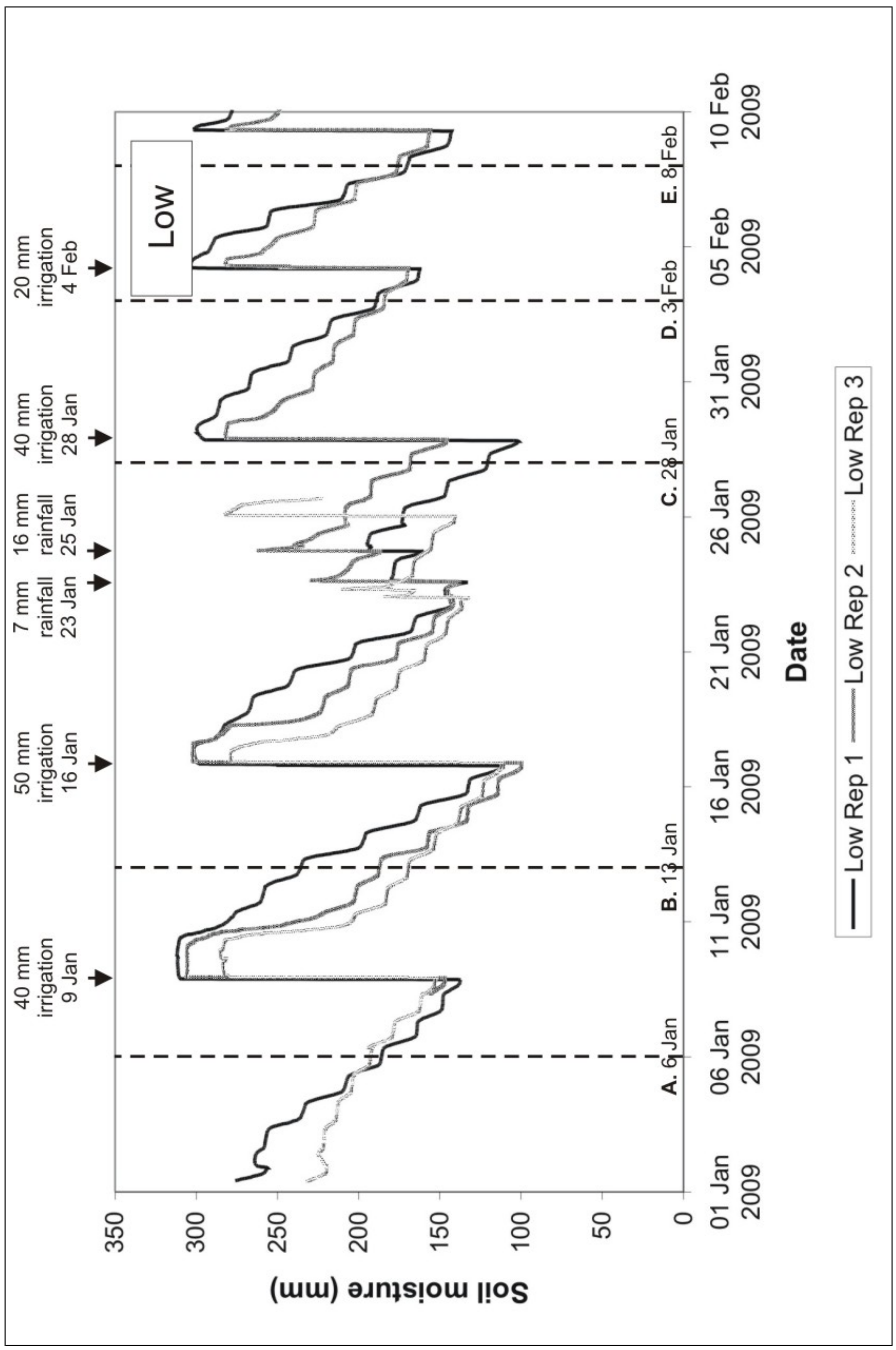



Figure 4.3: Soil moisture estimated by the generic Sentek algorithm during the trial period for low irrigation treatments

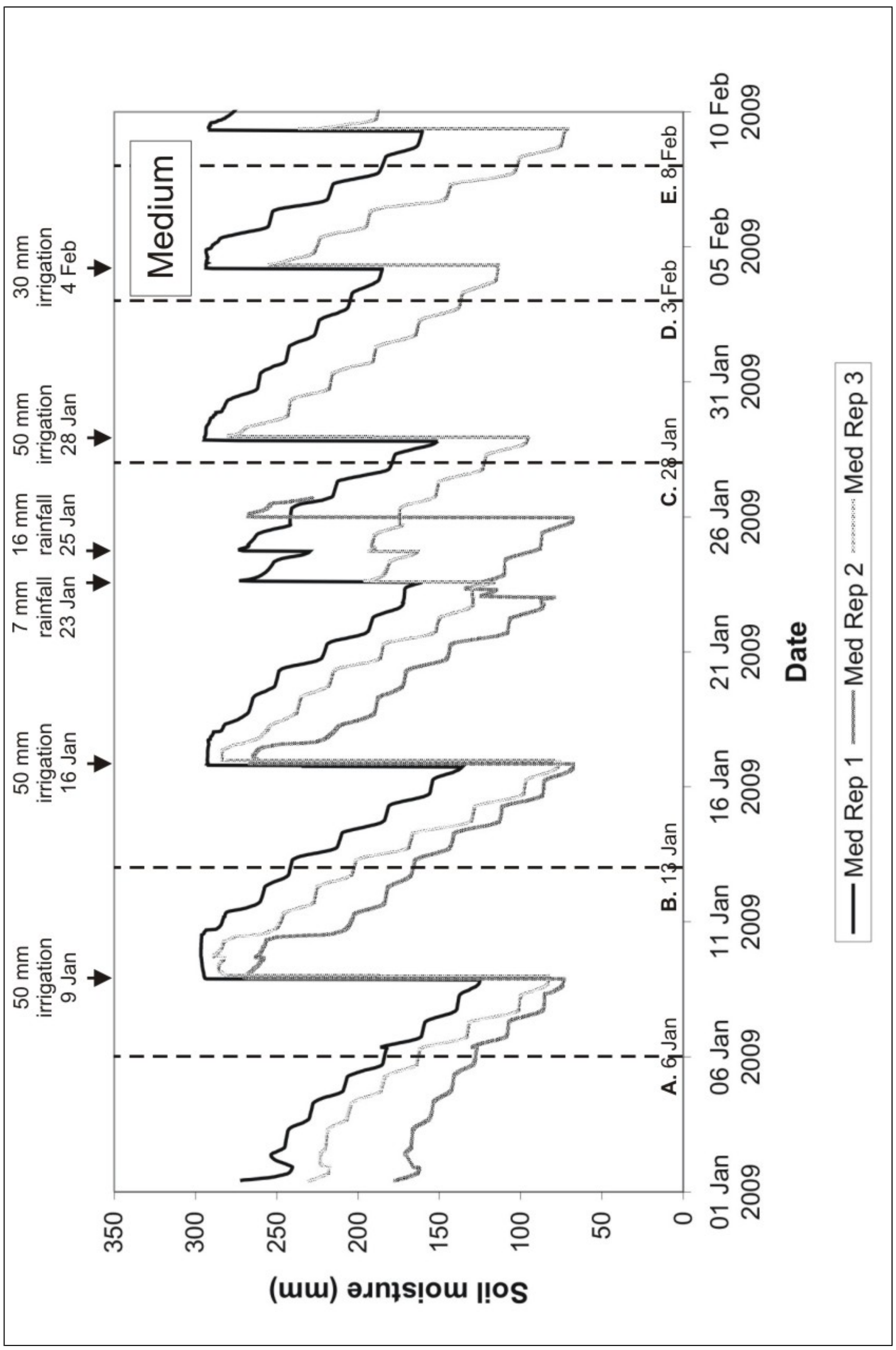



Figure 4.4: Soil moisture estimated by the generic Sentek algorithm during the trial period for medium irrigation treatments

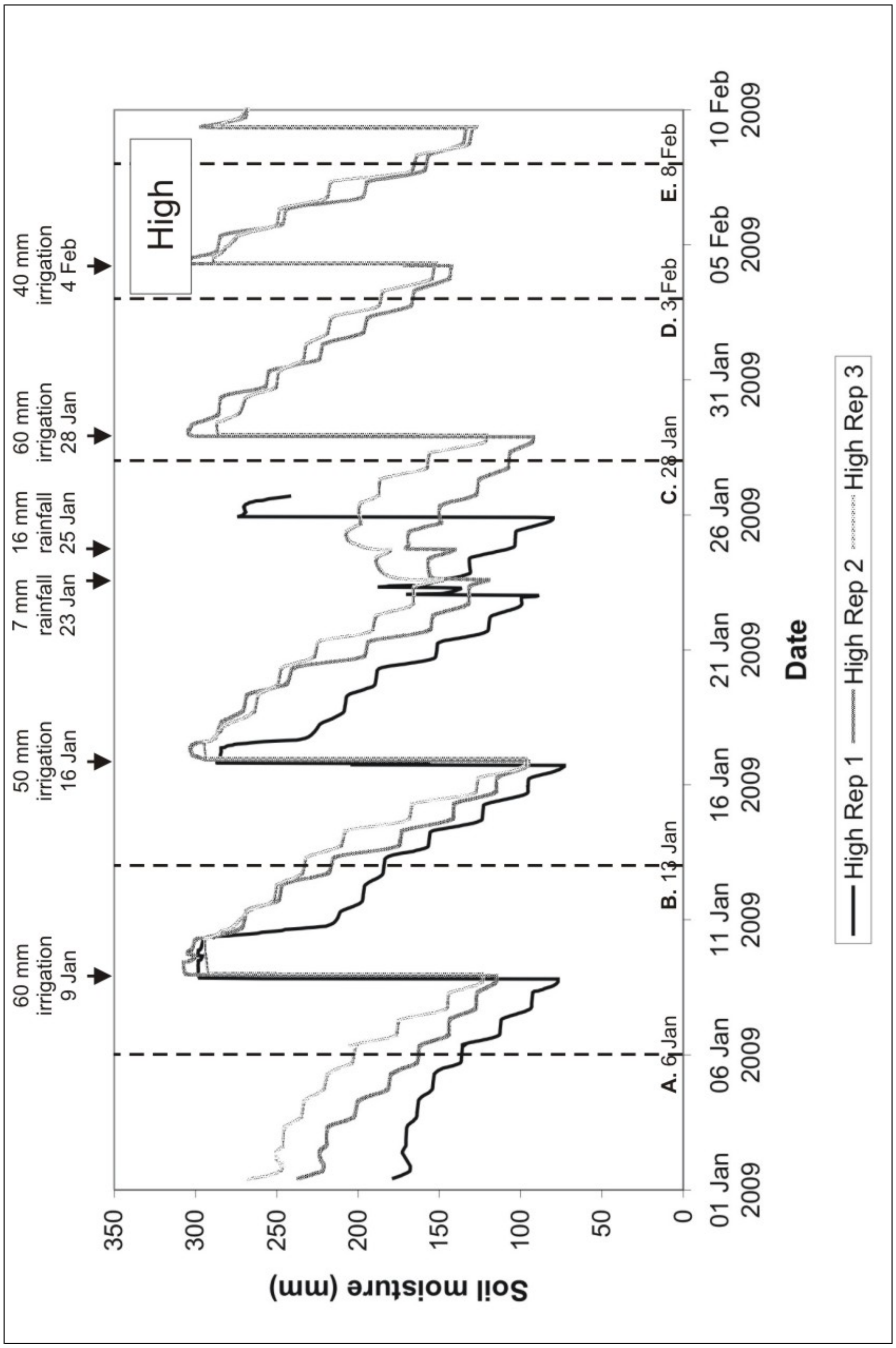



Figure 4.5: Soil moisture estimated by the generic Sentek algorithm during the trial period for high irrigation treatments

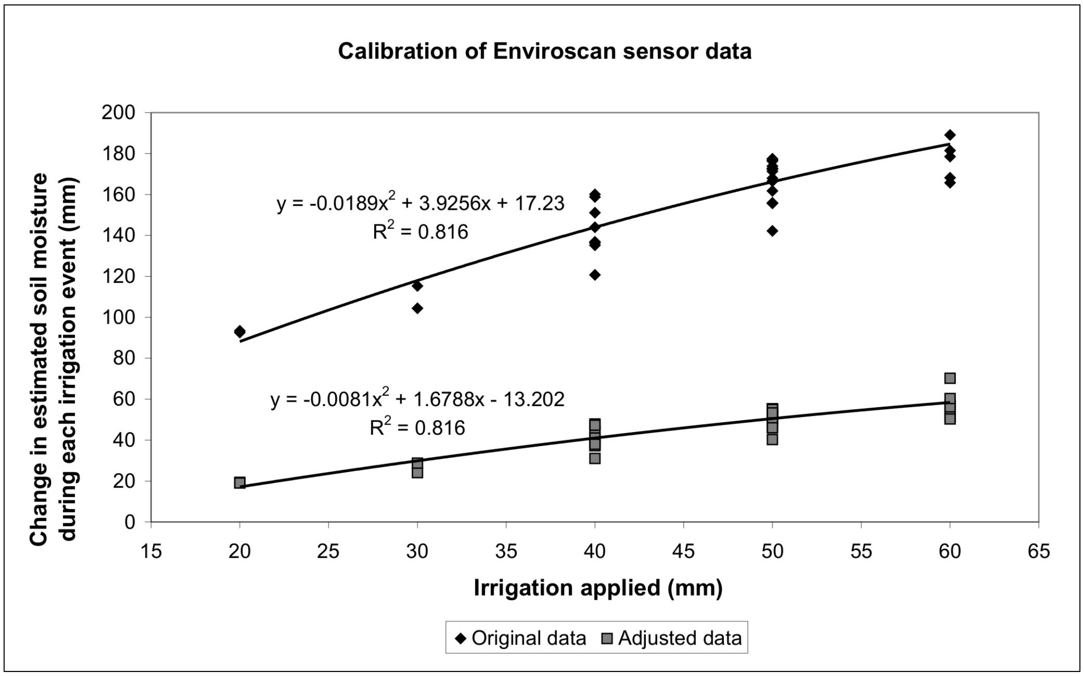



Figure 4.6: Calibration of Enviroscan sensor data

This adjustment accounts for the relative changes in soil moisture content throughout the crop season, but does not account for the quantitative soil moisture content values with respect to the field capacity and refill point of the soil. Hence, the soil moisture curves were also adjusted such that the maximum soil moisture content aligned with the soil field capacity. In this fieldwork, the field capacity was assumed to be 265 mm (as determined by the farm's agronomist) and the soil moisture readings were adjusted accordingly.

The calibrated graphs are shown in Figures 4.7, 4.8 and 4.9. These graphs illustrate the change in total soil moisture that occurred during each irrigation event and the dynamics of the daily crop water use. The plant measurement days (A. to E.) are also displayed on the graphs.

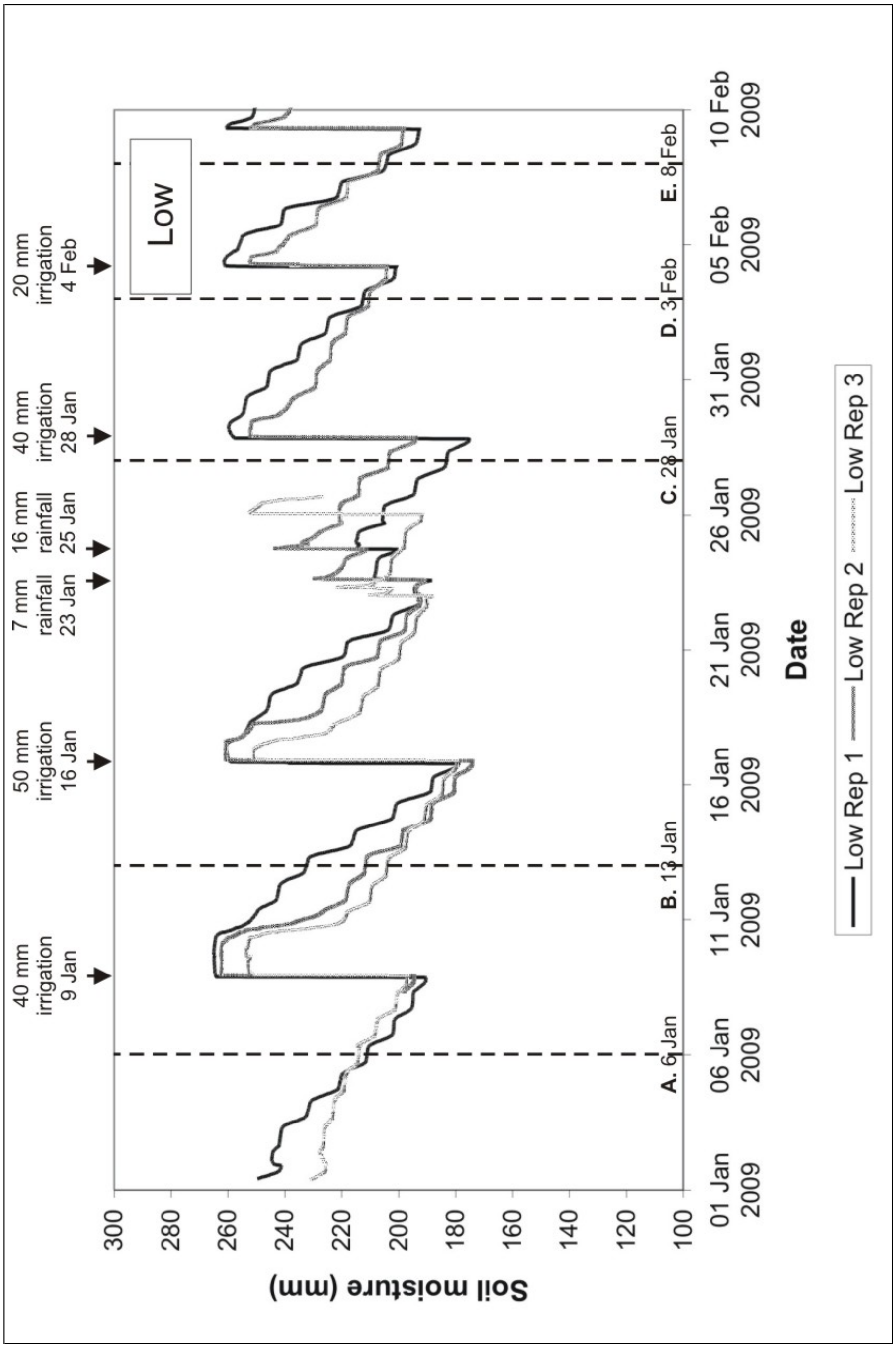



Figure 4.7: Adjusted soil moisture during the trial period for low irrigation treatments

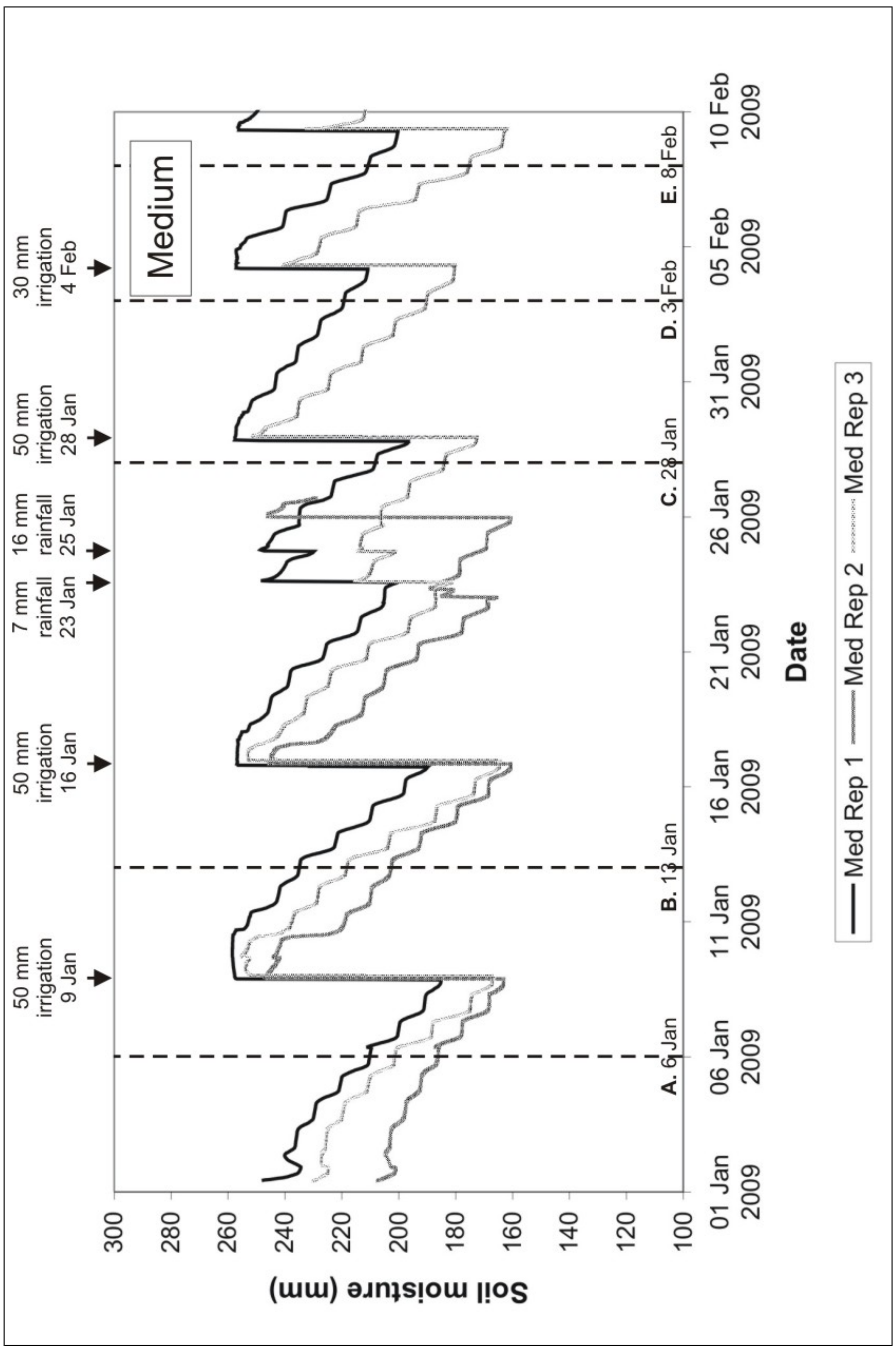



Figure 4.8: Adjusted soil moisture during the trial period for medium irrigation treatments

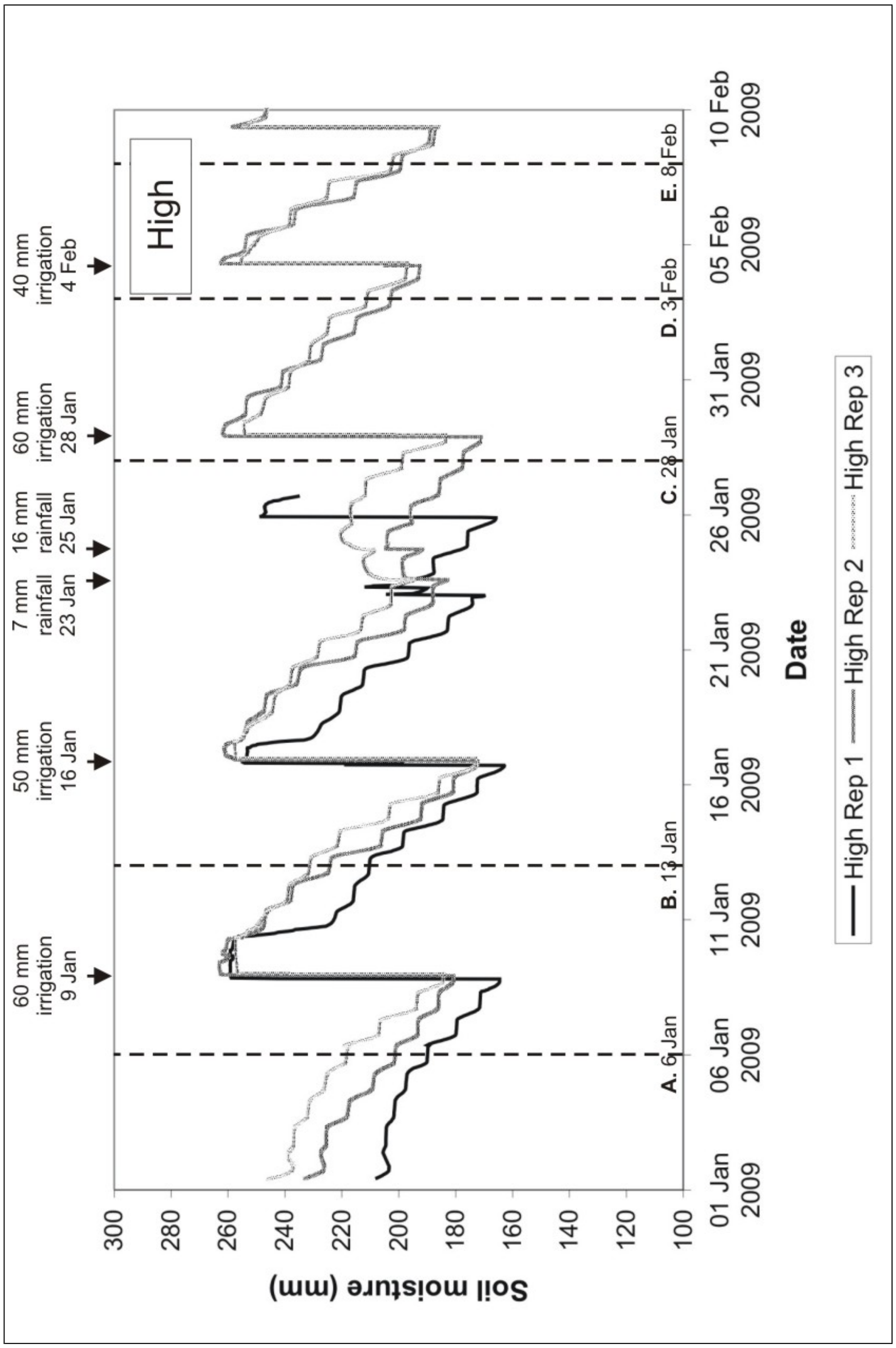



Figure 4.9: Adjusted soil moisture during the trial period for high irrigation treatments

The soil water response varies within each set of replicates indicating that there is either variability between sensors or spatial variability in the soil properties. For example, following the irrigation event on 9 January the maximum soil moisture content plateaus at a different value for each sensor. There is also spatial variability in the daily crop water use as illustrated by the soil moisture extraction curves during the period 9 to 16 January: this is most likely caused by the difference in soil water holding properties at each probe and/or variations in water requirements of individual plants.

The adjustment procedure effectively improved the accuracy of the soil dataset as the change in the adjusted soil moisture content during each irrigation event was closer in magnitude to the applied irrigation (Figures 4.6, 4.7, 4.8 and 4.9). However, there was some variation in the irrigation applied at the sensors in each replicate, possibly because of wind drift and deflection of the irrigation water within the crop canopy.

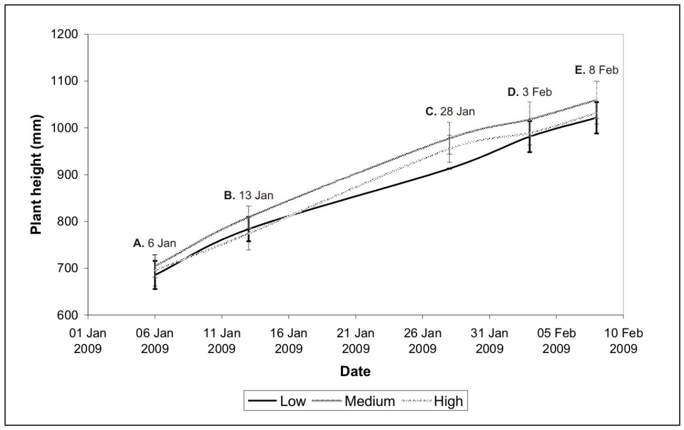
### 4.4.3 Plant data

Measured plant height, square count and boll count data are illustrated in Figures 4.10(a), 4.10(b) and 4.10(c), respectively. The plant height trends were similar for all three irrigation treatments (Figure 4.10(a)) and the plant heights in each irrigation treatment were not significantly different (at the 95% significance level) on the plant measurement days, with the exception of the plant height in the low irrigation treatment plots on 28 January. This change in plant height occurred after the second irrigation event of the field trial (where the first event was a low treatment and second event was a standard treatment) and two rainfall events (7 mm and 16 mm on 23 and 25 January, respectively). The lower plant height on 28 January was likely caused by the first low irrigation treatment of the season and the effect of this treatment was delayed for approximately two weeks. This suggests evaluations of the crop response to irrigation in an irrigation control system require a time delay between the irrigation application and measurement of the vegetative growth response.

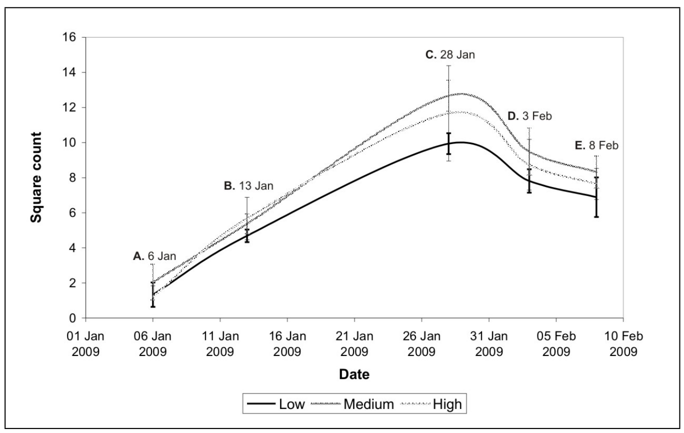
There was no significant difference (at the 95% significance level) in the square counts between the irrigation treatments on the measurement days. This is illustrated in Figure 4.10(b) as the trends of the square count are similar for the three irrigation treatments and there are large variations in the square counts between the replicates. This large variation is common in agronomic field trials and highlights the difficulties of identifying production responses within plant populations.

The medium and high irrigation treatments produced the highest change in square count over the field trial period (Figure 4.10(b)). Hence, more squares were grown on the plants with higher irrigation volumes applied.

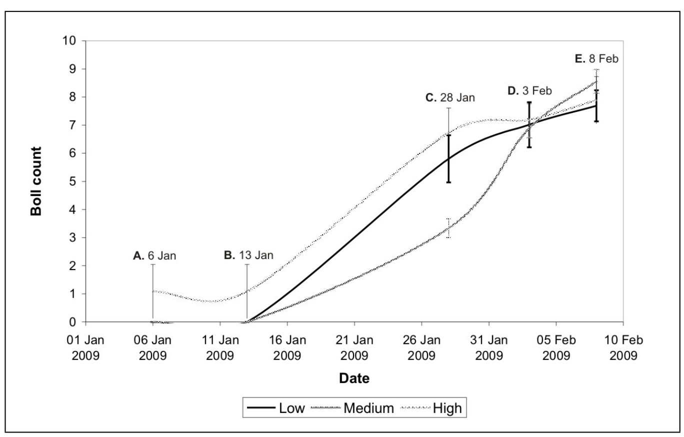
There were large variations in the boll counts in the low and high irrigation treatment plots (Figure 4.10(c)); however, the boll counts in these treatment plots followed similar trends. The boll counts in the low and high irrigation treatment plots increased the most between 13 and 28 January, whilst the boll counts within the medium irrigation treatment plot increased the most (and at a higher rate than in the low and high treatment plots) between 28 January and 3 February. There was a significant difference (at the 95% significance level) in boll counts between the medium irrigation treatments and the low and high irrigation treatments on 28 January. Hence, the irrigation treatment affected the rate at which the bolls were produced from squares. Underwatering in the low irrigation treatment plots and overwatering in the high irrigation treatment plots may have caused the lower rate of boll production in these plots.




(a)




(b)




(c)

Figure 4.10: Average and standard error of: (a) plant height; (b) square count; and (c) boll count on the measurement days for the low, medium and high irrigation treatments

## 4.5 Model calibration

Analyses are presented in this section with respect to the fieldwork objective 1, to demonstrate the model calibration (Section 4.1). Comparison of the measured field data and the output of both the uncalibrated and calibrated models on the measurements days with the same input conditions are presented.

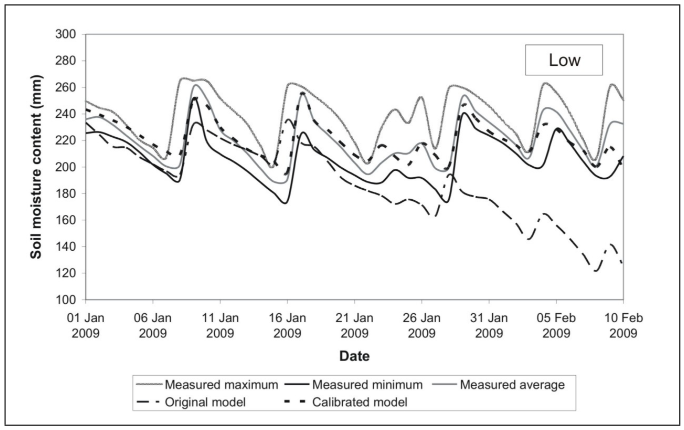
### 4.5.1 Comparison of soil data from fieldwork and calibrated model

Figure 4.11 displays the soil moisture that was both measured in the field trial and generated by the OZCOT model for each irrigation treatment. The modelled soil moisture was generated in OZCOT by entering the SILO weather data and irrigation application volumes into the weather file and the average plant available water capacity (of 265 mm) into the soil input file. Because the modelled soil moisture lies outside the measured minimum and maximum soil moisture range for each irrigation treatment, the soil moisture component of OZCOT was calibrated following the procedure of Section 3.3.7. The differences between the measured and modelled datasets may have occurred for the following reasons:

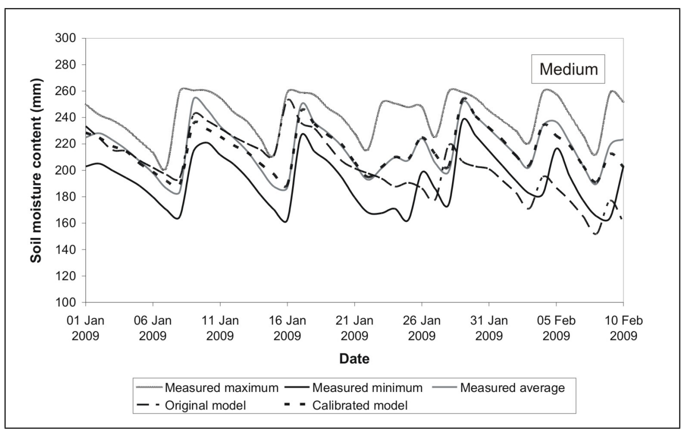
- the climate dataset was obtained from a nearby weather station and not from an onsite weather station (which was faulty);
- the plant available water capacity was estimated by the agronomist at the other end of the field to the fieldwork conducted;
- the soil nitrogen content was estimated by the agronomist and not measured; and
- the plant available water capacity, starting soil moisture and crop variety of the fieldwork did not correspond to any of OZCOT's predefined profiles.

The original pre-calibration dataset was generally within the minimum and maximum measured soil moisture until 18 January for the low irrigation treatment (Figure 4.11(a)) and until 28 January for the medium and high irrigation treatments (Figures 4.11(b) and 4.11(c), respectively. The modelled dataset was closer to the measured dataset for the medium and high treatments than for the low treatments. This indicates that the irrigation volumes applied in the low irrigation plots were higher than the desired volume.

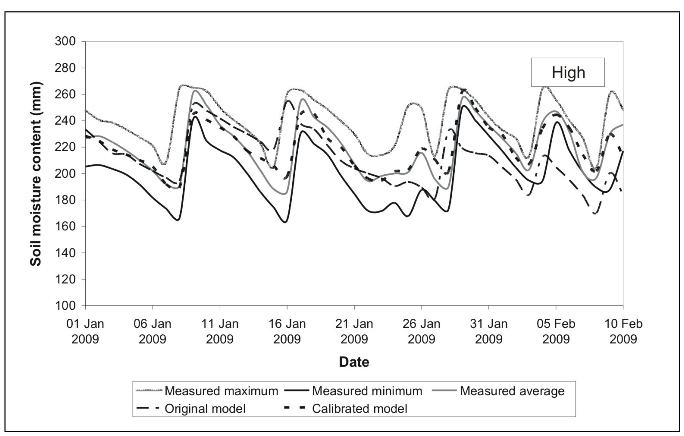
The modelled and measured irrigation volumes applied did not generally occur simultaneously. This is because the model could not apply the irrigation at a particular time of the day as it operates using a daily time step. For example, the irrigation event on 28 January occurred in the evening but the model applied the irrigation at noon on the day specified (Figures 4.7, 4.8 and 4.9).




(a)




(b)




(c)

Figure 4.11: Comparison of model output, both original and calibrated, with minimum, maximum and average measured soil moisture curves for: (a) low irrigation treatments; (b) medium irrigation treatments; and (c) high irrigation treatments

Following the calibration of the soil and plant parameters of the model, the modelled soil moisture was generally within the minimum and maximum measured soil moisture and close to the average measured data. This indicates that the OZCOT model could be calibrated to reflect the measured soil moisture content of the three simulated irrigation treatments.

The calibrated modelled soil moisture is plotted against the measured soil moisture in Figure 4.12. There was no significant difference between the gradient of the soil data (i.e. modelled soil moisture divided by measured soil moisture) and unity, and between the intercept of the curve and zero. Hence, the soil component of the OZCOT model was accurately calibrated using the measured soil moisture data.

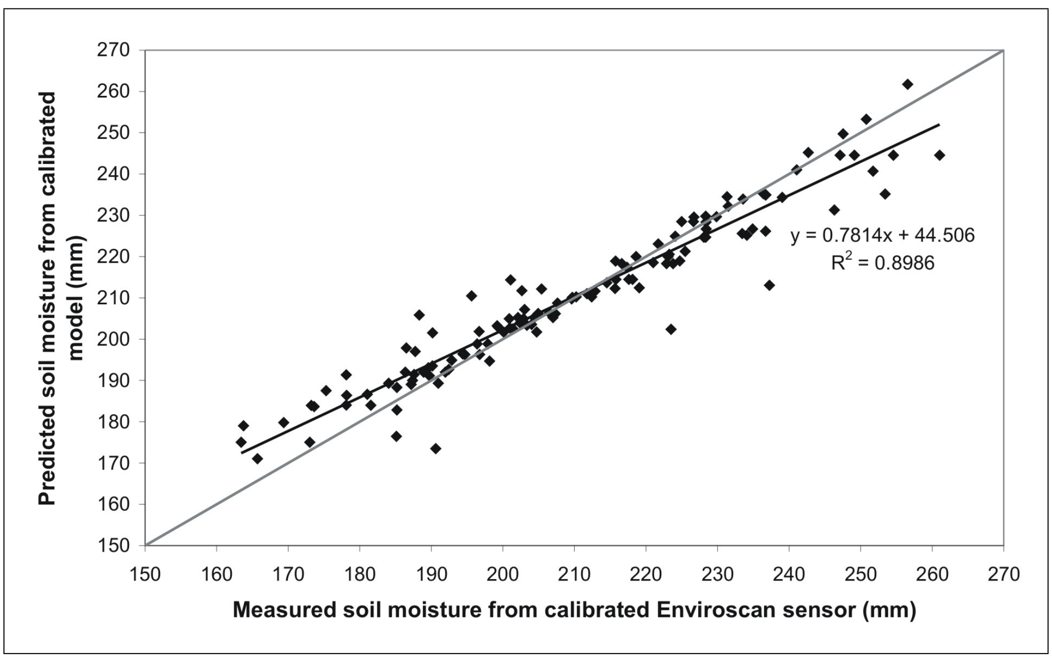



Figure 4.12: Comparison of soil moisture data from Enviroscan probe, from calibrated model and 1:1 line

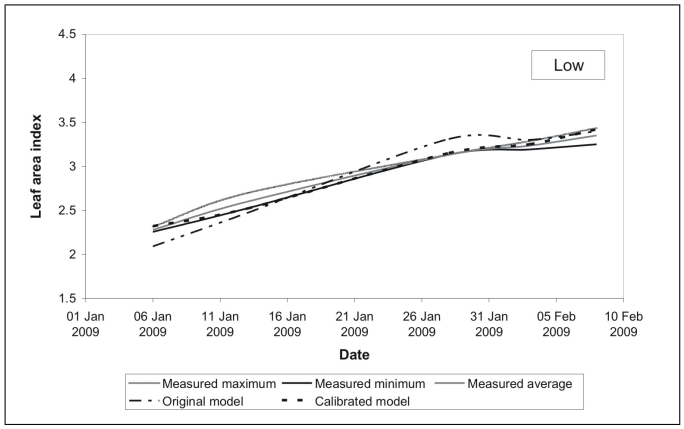
### 4.5.2 Comparison of plant data from fieldwork and calibrated model

Comparisons of the measured plant dataset and the original and calibrated model datasets are displayed in Figures 4.13, 4.14 and 4.15. The model was calibrated with plant and soil data simultaneously following the procedure of Section 3.3.7. A comparison of the measured and calibrated model datasets is shown in Figure 4.16.

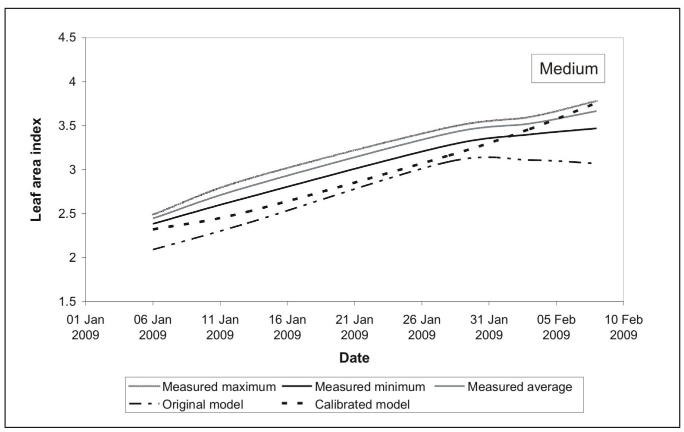
The leaf area index predicted with the uncalibrated model did not generally lie within the minimum and maximum measured leaf area index for any of the irrigation treatments (Figure 4.13). Following calibration, the leaf area index in the low irrigation plot generally followed the average measured leaf area index (Figure 4.13(a)), whilst the leaf area index in the high irrigation plot generally followed the minimum measured leaf area index (Figure 4.13(c)).

In the medium irrigation plots, the leaf area index simulated using the calibrated model was only within the measured range after 31 January (Figure 4.13(b)). Following calibration, the simulated leaf area index dataset was closer to the measured region. However, this calibration was less effective than for the low and high irrigation treatments. Hence, the calibration improved the accuracy of the model but the OZCOT model may not be able to accurately represent all the field conditions on a daily basis throughout the crop season.

For all three irrigation treatments and throughout the field trial period, the square count simulated with the uncalibrated model was significantly different to the measured square count (Figure 4.14). Following calibration, the model produced square counts that stayed within the minimum and maximum measured square counts with the exception of a brief period above the maximum measured value in the high irrigation treatment between 9 and 11 January (Figure 4.14(c)).




(a)

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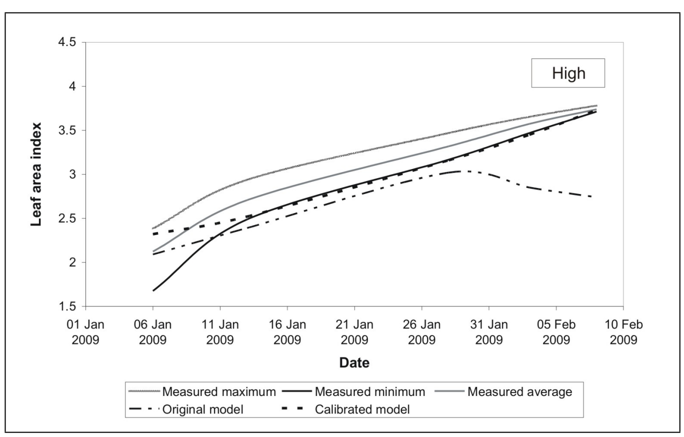
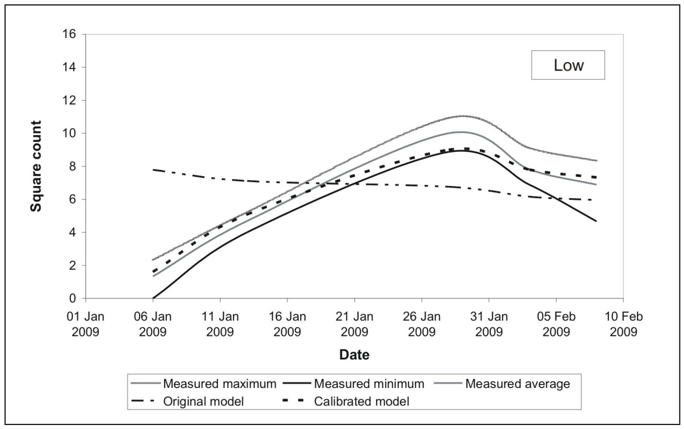
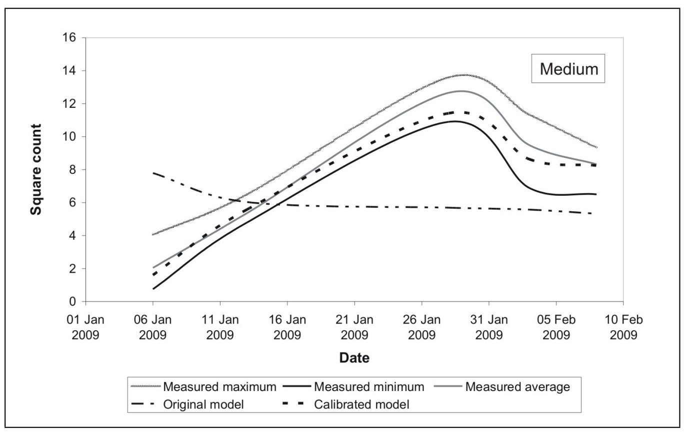



(c)

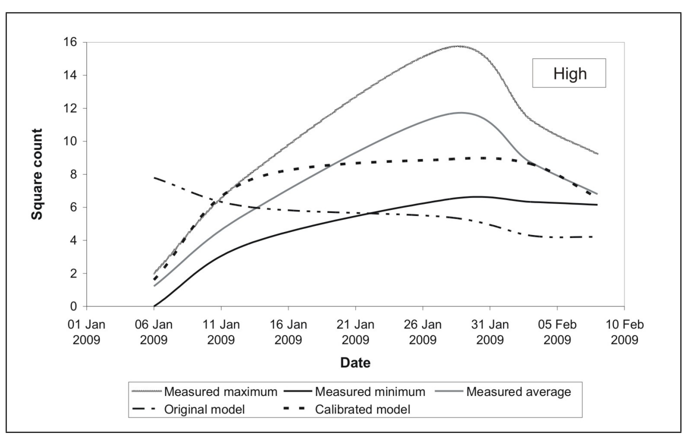
Figure 4.13: Comparison of model output, both original and calibrated, with minimum, maximum and average measured leaf area index for: (a) low irrigation treatments; (b) medium irrigation treatments; and (c) high irrigation treatments




(a)




(b)




(c)

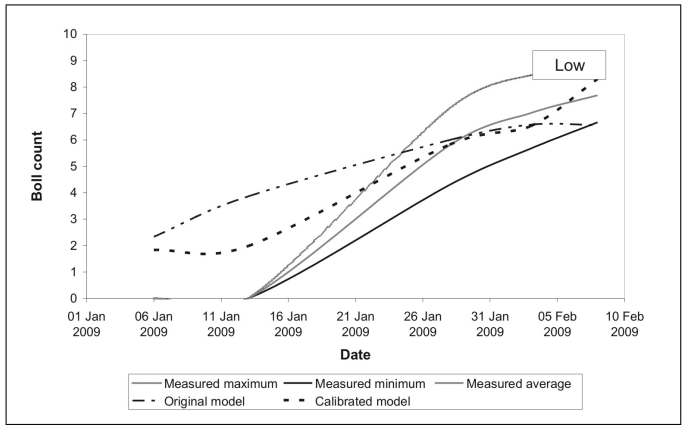
Figure 4.14: Comparison of model output, both original and calibrated, with minimum, maximum and average measured square counts for: (a) low irrigation treatments; (b) medium irrigation treatments; and (c) high irrigation treatments

The boll counts simulated with the uncalibrated model were generally outside the minimum and maximum measured boll count (Figure 4.15). Following the model calibration, the simulated boll count stayed closer to the average measured boll count. The simulated boll count was within the minimum and maximum measured boll counts after 22 January for the low irrigation treatment (Figure 4.15(a)) and after 1 February for the medium irrigation treatment (Figure 4.15(b)). The ability to calibrate the boll count only at the end of the field trial period indicates that temporal data are required to fine tune the model as the season progresses. The boll count was within the minimum and maximum measured boll count throughout the field trial period for the high irrigation treatment (Figure 4.15(c)).

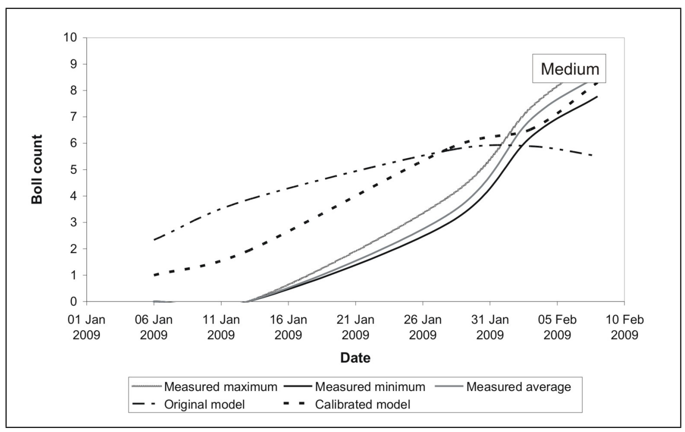
The average modelled and measured leaf area index, square counts and boll counts for all irrigation treatments are compared in Figures 4.16(a), 4.16(b) and 4.16(c), respectively. There was no significant difference between unity and the gradient for any of the plant data (i.e. the modelled plant response divided by the measured plant response with an intercept at the origin), and between the intercept of the curves and zero. Hence, the OZCOT model was able to accurately calibrate the leaf area index, square count and boll count.

### 4.5.3 Conclusions

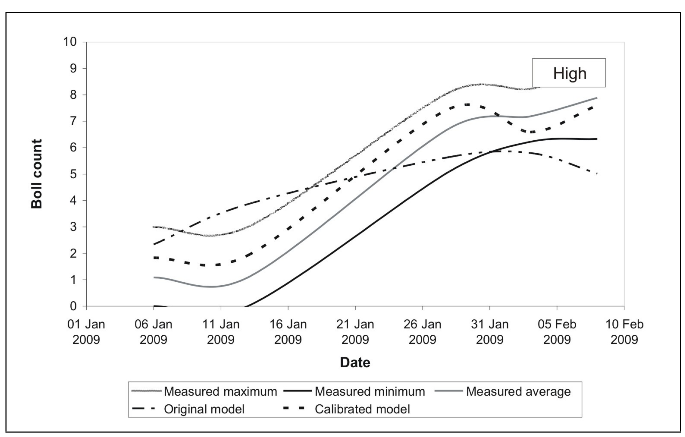
The cotton growth model OZCOT (pre-calibration) did not accurately predict the daily soil moisture content, leaf area index, square count or boll count of the cotton crop for the field conditions and irrigation treatments of the field work conducted. However, following calibration of the model using the measured field data (and the calibration procedure of Section 3.3.7), there was no significant difference between the modelled data and measured soil moisture and plant response data on the measurement days. Hence, the OZCOT model was successfully calibrated even with only the most influential input parameters (identified in Section 3.3.7) being adjusted.




(a)

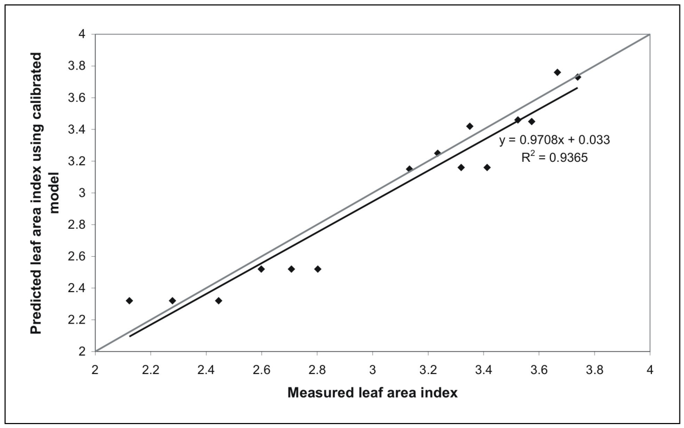



(b)

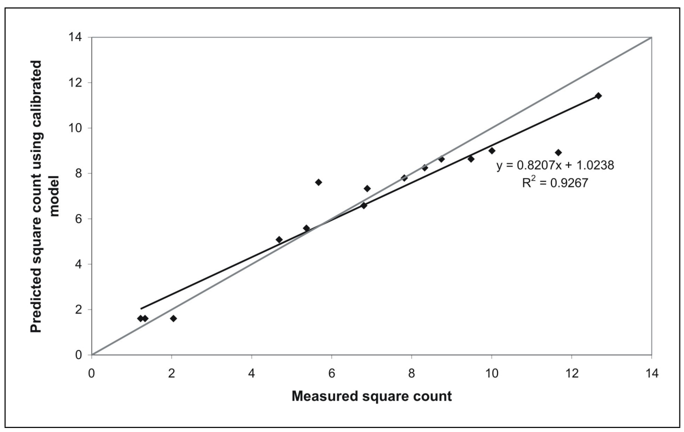



(c)

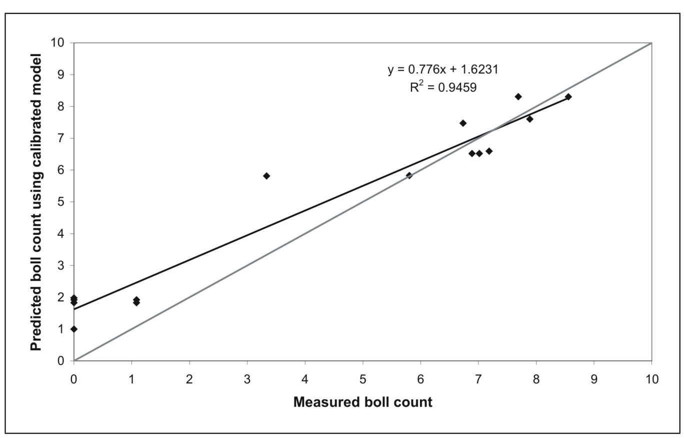
Figure 4.15: Comparison of model output, both original and calibrated, with minimum, maximum and average measured boll counts for: (a) low irrigation treatments; (b) medium irrigation treatments; and (c) high irrigation treatments




(a)




(b)




(c)

Figure 4.16: Measured data versus data from calibrated model for: (a) leaf area index; (b) square counts; and (c) boll counts

## 4.6 Exploration of data requirements for adaptive irrigation control

Plant, soil and weather data input, either singularly or in combination, will normally be required for an optimal irrigation control system to determine irrigation applications. In situations of data unavailability, some combinations may not be possible; however, particular input data combinations may be more useful than others. Identification of the relative significance of particular input data streams, or combinations of input data, will also potentially refine the usefulness of additional sensors.

The section reports work towards the fieldwork objective 2, to evaluate the relative significance of the sensor variables (Section 4.1). The model (that was calibrated in VARIwise) was used to evaluate the relative significance of each sensed variable as a control input for the cotton crop detailed in Section 4.3.1.

### 4.6.1 Methodology

The relative significance of each sensor variable was explored by simulating an irrigation control strategy for each type of input data, singularly and then in combination (Table 4.2). There were three individual sources of data input (i.e. weather, soil and plant) and four possible combinations of the data sources.

For all input data combinations simulated, the calibrated model (from Section 4.5) was used and the input data combination indicated the 'real-time' data that were entered into OZCOT 'observation' files to further align the calibrated model with the measured data. The real-time data entered were soil moisture content for the soil data and leaf area index, square count and boll count for the plant data.

The input data combinations were simulated with three sets of starting field conditions, each defined from soil and plant measurements of the three irrigation treatments of the field trial. The field trial data measured before the first irrigation in the trial period (on

9 January 2009) were averaged for the three low, medium and high irrigation treatment replicates (Figure 4.1) and entered as the starting real-time data into the observation files. The starting conditions of the low, medium and high irrigation treatments are referred to as plots 1, 2 and 3, respectively. In plot 3 the soil moisture and plant height were initially the lowest of the plots, whilst in plots 1 and 2 the soil moisture and plant height were initially similar to each other. Measured data after the start of the trial period were not entered because the irrigation applied in the evaluation of the input data combinations would not be the same as in the field trial.

The simulated irrigations were applied on the same days as the actual irrigation events in the field trial. The irrigation volumes that were applied depended on the input data combination as follows:

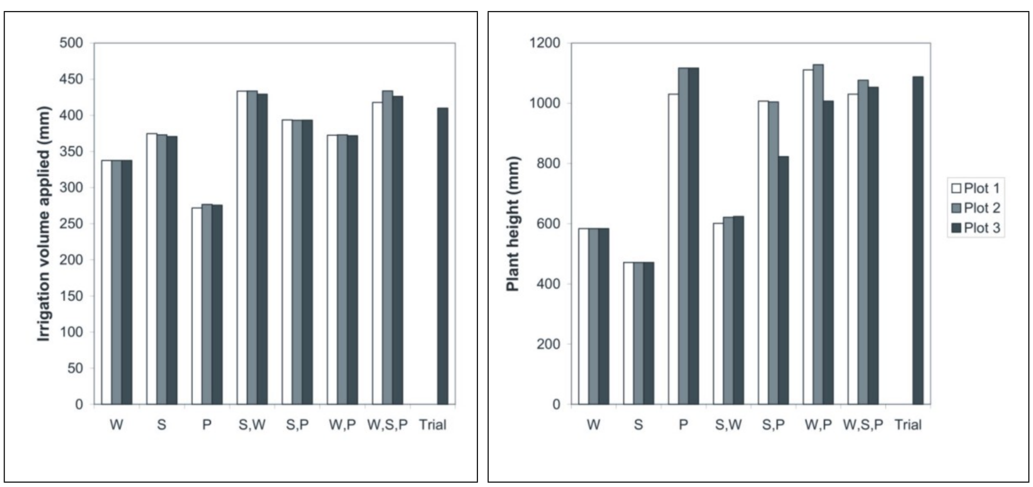
- When soil data input was used, the volume applied was the simulated soil water deficit.
- When weather data input was used (and soil data input was not used), the volume applied was the total crop evapotranspiration ($ET_c$ calculated from daily weather data (SILO) and crop factor) since the previous irrigation.
- When neither weather data nor soil data input were used, the volume applied was the total $ET_c$ since the previous irrigation, where the daily $ET_c$ was estimated using SILO weather data input that was averaged over the trial crop season.

### 4.6.2 Results

The results displayed in Figure 4.17 compare the simulated irrigation volumes and plant data for the seven input data alternatives. The simulation results are also compared with the measured field dataset for the high irrigation treatment plots (displayed in the last row of Table 4.2) rather than the low and medium irrigation treatments which were deficit treatments.

Table 4.2: VARIwise simulation output at the end of the trial period on 8 February 2009 for all seven combinations of input data and the three plot starting conditions, followed by the irrigation application in the field trial and final measured plant data

| **Input data** | **Observation file data input during trial** | | | **Irrigation volume calculation** | **Plot starting conditions** | **Irrigation volume applied (mm)** | **Final LAI** | **Final plant height (mm)** | **Final square count** | **Final boll count** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Plant data** | **Weather data** | **Soil data** | | | | | | | |
| Weather (only) | Nil | Daily SILO | Nil | Cumulated ETc | 1 | 337 | 1.99 | 584 | 4 | 8 |
| | | | | | 2 | 337 | 1.99 | 584 | 4 | 8 |
| | | | | | 3 | 337 | 1.99 | 584 | 4 | 8 |
| Soil (only) | Nil | Averaged SILO | Measured daily | Modelled soil water deficit | 1 | 375 | 1.60 | 471 | 3 | 5 |
| | | | | | 2 | 373 | 1.60 | 471 | 3 | 5 |
| | | | | | 3 | 371 | 1.60 | 471 | 3 | 5 |
| Plant (only) | Measured daily | Averaged SILO | Nil | Cumulated ETc | 1 | 272 | 3.54 | 1030 | 3 | 6 |
| | | | | | 2 | 277 | 3.84 | 1117 | 3 | 7 |
| | | | | | 3 | 277 | 3.84 | 1117 | 4 | 8 |
| Soil and weather | Nil | Daily SILO | Measured daily | Modelled soil water deficit | 1 | 434 | 2.05 | 601 | 3 | 7 |
| | | | | | 2 | 434 | 2.12 | 621 | 3 | 7 |
| | | | | | 3 | 430 | 2.13 | 624 | 3 | 7 |
| Soil and plant | Measured daily | Averaged SILO | Measured daily | Modelled soil water deficit | 1 | 394 | 3.46 | 1007 | 6 | 4 |
| | | | | | 2 | 393 | 3.45 | 1004 | 5 | 4 |
| | | | | | 3 | 393 | 2.82 | 823 | 2 | 4 |
| Weather and plant | Measured daily | Daily SILO | Nil | Cumulated ETc | 1 | 373 | 3.82 | 1111 | 12 | 6 |
| | | | | | 2 | 373 | 3.88 | 1128 | 11 | 7 |
| | | | | | 3 | 372 | 3.46 | 1007 | 11 | 6 |
| Weather, soil and plant | Measured daily | Daily SILO | Measured daily | Modelled soil water deficit | 1 | 418 | 3.54 | 1030 | 6 | 8 |
| | | | | | 2 | 434 | 3.70 | 1076 | 6 | 8 |
| | | | | | 3 | 426 | 3.62 | 1053 | 5 | 8 |
| Measured weather, soil and plant | Nil | Nil | Nil | As for trial | 3 | 410 | 3.74 | 1088 | 7 | 8 |




(a) (b)

Figure 4.17: (a) Irrigation volume applied and (b) final cotton plant height for seven combinations of data input for low, medium and high irrigation treatment plots (W, S and P denote weather, soil and plant data input, respectively).

The simulated performance of the control strategies with data input from single sensors were poorly correlated to the control strategy with full data input (Table 4.2). This is demonstrated by the low irrigation application volumes of Figure 4.17(a) and plant height of Figure 4.17(b) for the weather-only (W), soil-only (S) and plant-only (P) simulations compared with the irrigation volumes and plant height with full data input. Hence, data input from a single sensor gave a poor correlation to the measured dataset.

Of the single data input options, the soil-data-only option gave the best correlation to the simulated irrigation volume applied with full data input but a poor prediction of the simulated plant data with full data input, whilst the plant-data-only option alone gave the best correlation to the simulated plant data with full data input but a poor prediction of the irrigation volume applied. Therefore if only one sensor input can be provided then either plant or soil data input should be used depending on the desired crop performance.

Of the data input combinations with two data sources, the soil-and-plant and weather-and-plant combinations gave the most accurate prediction of the simulation with full data input for both the irrigation applied (Figure 4.17(a)) and plant height (Figure 4.17(b)). This indicates that plant data input is required to calibrate the plant growth and fruit development in the OZCOT model and either weather or soil data input is required to calibrate the crop water use within OZCOT.

The soil-and-plant combination gave the most accurate prediction of the irrigation volume applied in the trial (within 4%), whilst the weather-and-plant combination gave the most accurate prediction of the measured plant height (within 1%). However, the weather-and-soil data combination gave a poor correlation to both the irrigation volume applied and the plant measurements. The incorporation of all three sensors gave the best correlation to the simulated data with full data input (within 4% of irrigation volume and 3% of plant height).

In plot 3 (with the lowest starting soil moisture and plant height), the irrigation volume applied (Figure 4.17(a)) and plant height (Figure 4.17(b)) were generally the lowest of the three treatment plots. This is because a smaller plant will generally have lower transpiration than a larger plant and therefore consume less water. Similarly, in plots 1 and 2, the irrigation volume and plant height (and hence the crop water use) were generally higher than in plot 3.

A simulation using all the measured field data as real-time data inputs and irrigation events as per the field trial gave the same results as the measured field data (Table 4.2). This is because the model was calibrated to fit the measured field data.

### 4.6.3 Conclusion

Control strategies were implemented that utilised different input data combinations - weather (evaporative demand), soil moisture and plant height, individually and in combination.

From the simulations of these strategies the following observations were made:

- Single sensor data input produced inaccurate results as regards prediction of plant growth and irrigation volume applied.
- If only a single data input is available, the soil-data-only input strategy most closely replicated the simulation with full data input.
- If only two data sources are available, the soil-and-plant or weather-and-soil combination strategies most closely replicated the simulation with full data input.
- The strategy with full data input produced the same soil moisture and plant response as the measured field data.

The OZCOT model was successfully aligned to the measured field data using the calibrated model and full 'real-time' data input to the observations input file. However, given the limited duration of this single set of field trials, these conclusions are regarded as illustrative rather than definitive.

## Chapter 5

# Adaptive Irrigation Control Strategies Implemented in VARIwise – Overview and Establishment

### 5.1 Holistic irrigation control – general observations

From a control perspective, the irrigation system comprises the machine (as water-delivery actuator) plus the crop being grown as characterised by the local plant response to water applied. Although the individual plants which constitute the crop are nominally identical, it is to be expected that individual plant responses will not be the same due to their differing (local) soil/water conditions and the growth history at each position in the field (Zhang et al. 2002). Furthermore, as plant response is a function of plant age, the combination of these phenomena indicate that unique system identification is not possible and adaptive approaches must be adopted.

Limitations of sensing hardware and irrigation machines, and dynamics of the crop, present difficulties in applying classical control approaches to the process of irrigation. Five areas of difficulty are identified and described in the following sections.

### 5.1.1 Slow speed of crop dynamics

The plant growth that occurs in response to an irrigation application may not be measurable for days after the irrigation (and commonly too small to be reliably measurable before the next irrigation event). However, as noted in Chapter 2, plant response may provide a better indication of water requirement than soil and weather sensors (e.g. Kramer & Boyer 1995; Wanjura & Upchurch 2002; Jones 2004). Hence, ideally, an irrigation control system should incorporate plant data with soil water status to ensure the availability of appropriate feedback information before the subsequent irrigation event.

Likewise, the very slow response militates against the successful use of simple feedback control: classical feedback control systems are typically implemented in processes which are repeatedly executed and evaluated within milliseconds. And similarly, direct application of many commonplace system identification strategies is not efficient due to the different time scales in irrigation, again because irrigations occur days apart and the crop's response to the irrigation is only reliably measurable after a number of days.

### 5.1.2 In-field variability sensing

Datasets required by an irrigation control system include weather (which indicates the crop's evaporative demand), soil moisture status and plant growth and health (stress). Soil moisture content, on-the-go water status and plant growth sensors that enable data measurement at a high spatial resolution have been developed (e.g. Vellidis et al. 2008, Peters & Evett 2008; McCarthy et al. 2009, respectively). As noted in Chapter 2, natural spatial variability of rainfall is often another unquantified variable.

### 5.1.3 Characteristics of the irrigation machine

A fundamental irrigation system constraint is the irrigation machine capacity, which is defined as the maximum amount of water that can be applied to the field (litres per second). This translates into the depth of irrigation (millimetres) according to machine speed of movement. In turn the speed at which an irrigation machine traverses a field of given area determines the frequency of irrigation applications; for example, an irrigation machine with a capacity of 12 mm/day requires 2.5 days to apply irrigation water to a depth of 30 mm to the field.

It is also significant that the irrigation machine as a water delivery actuator may not apply the desired irrigation volume. The irrigation outlets may require calibration to ensure the measured application corresponds to the desired irrigation output. The irrigation pattern from the sprinklers is also influenced by environmental factors including wind drift and evaporation losses.

### 5.1.4 Fundamental resource constraints

In practice, the volume of irrigation water available for irrigation is almost always limited by the fixed amount of water allocated to the grower. In turn, this may constrain the volume of irrigation water that can be applied to the field during each irrigation event. Hence, an irrigation control system must use the currently available water in the most efficient manner. This involves using the water to either: (i) fully irrigate a small area of the field chosen from plant condition (and grow the remainder of the crop in the field with either reduced or no irrigation); or (ii) irrigate the whole field and increase the time between irrigation events and/or apply the minimum volume to maintain the crop.

### 5.1.5 Unknown process dynamics

Classical control practice often assumes that the dynamics of the process – in this case the soil-plant-atmosphere system – are, or at least may be, fully defined. Crop production models, which relate growth to environmental factors, are available (e.g. OZCOT for cotton, Wells & Hearn 1992); however they require a calibration procedure to be reliably used to predict the response of a particular crop to irrigation. As set out in Section 3.3.7, the model may be calibrated by iteratively adjusting crop and soil parameters until the crop model output converges to the measured dataset (measured and modelled data from a cotton model are shown in Figure 4.11). A calibrated model might be used in a model predictive controller for irrigation management (Appendix A.3.6) and to provide feedback data in evaluations of control strategies in the simulation environment.

## 5.2 Development of irrigation strategies

An adaptive control system implemented on an irrigation machine must be robust to intermittent data availability and accommodate spatial variability. Control systems applicable to irrigation were identified in Section 2.3.3 (from Appendix A). These control systems have different model and input data requirements, optimisation methods and computational complexities. An overview of these systems and the formulation of the control strategies for the irrigation environment follow.

For the irrigation strategies presently implemented in VARIwise (Chapters 6, 7 and 8), two simplifying assumptions have been made. These are that unlimited water is available and that the irrigation is applied as desired. The strategies also would not be programmed to avoid waterlogging to enable the strategies to adapt to the crop response.

### 5.2.1 Iterative learning control

Iterative learning control was identified (Appendix A) as being applicable to irrigation. This strategy involves varying the irrigation application according to the error between the measured process output and desired process output after the previous irrigation. Because this strategy assumes the initial conditions are reset after each iteration, the irrigation events would be initiated when the crop water use since the previous irrigation event reaches a threshold value. The crop conditions would then be approximately the same before each irrigation event is initiated.

The iterative learning control strategy can consider the irrigation machine capacity by increasing the irrigation volume applied to cells according to the additional crop water use (measured from soil moisture sensors or estimated from weather data) between the irrigation initiation and when the irrigation is actually applied. Iterative learning control also requires data input from each cell in the field; hence, measured field data must be kriged in situations of sparse input data to increase the spatial resolution of the input data (as per Chapter 3).

Variable structure control concepts (Appendix A.4.3) may be applied to iterative learning control to ensure that the control system is robust to data gaps and deficiencies. This involves adjusting the irrigation decision method depending on the input data available. For example, if soil data input is not available in one area of the field then plant or weather data input is used to determine the irrigation timing and/or volume.

### 5.2.2 Iterative hill climbing control

A drawback of the iterative learning control strategy is the potentially inefficient system identification. This is because there are a limited number of irrigation events that occur during a crop season and only one irrigation volume is being evaluated in each cell during each irrigation event. Adaptive spatially-varied identification may be achieved by utilising site-specific combinations of plant, soil and weather data in different sub-areas of the field. Likewise, adaptive system identification may be incorporated into an irrigation control system to account for the slow speed of crop dynamics and the frequency of irrigation events. To meet these requirements and circumvent the limitations set out above, an alternative approach is proposed.

The efficiency of control systems may be improved for irrigation by evaluating a range of inputs to the system at each irrigation event. This would be implemented for an irrigation control system by applying and evaluating a range of irrigation volumes on different cells in the field. This is similar to the dual adaptive control concept where perturbation signals are used to learn more about the process (Appendix A.3.1). This method has been adapted to irrigation and named 'iterative hill climbing control'. 'Hill climbing' involves changing the state of the system into one that is closer to the goal in the direction of steepest gradient (Russell & Norvig 1995). This strategy involves the following process:

1. The field is divided into zones according to a pre-measured variability map.
2. 'Test cells' are selected in each zone to evaluate different irrigation volumes.
3. Test irrigation volumes are applied to each test cell.
4. Before the next irrigation is applied the crop response to the previous irrigation volume is evaluated. A performance index is calculated for each test cell in each zone to evaluate the response of the soil and/or plant to the irrigation volume. Using plant data in the performance index calculation may involve maximising the square count and this is similar to the extremum adaptive control concept (Appendix A.3.4). The irrigation volume that was applied to the test cell with the highest performance index is then applied to the whole zone.
5. Steps 3 and 4 are repeated for each irrigation event. New test cells are also selected in each zone after each irrigation event to ensure that the response of a test cell is indicative of the rest of the zone.

The performance of the iterative hill climbing control strategy would be affected by the number of zones in the field and the number of test cells in each zone. For example, if a large number of test cells are used in each zone then more test cell 'experimentation' will be conducted which would improve the performance of the optimisation but also increase the required number of cells in the zone as new test cells are selected for each irrigation event and there must be sufficient tests cells for the crop season. This would in turn reduce the possible number of zones in the field and provide less spatial discrimination for the irrigation application since the strategy does not consider the spatial variability within each zone in the field.

As per the iterative learning controller, the irrigation machine capacity may be considered by increasing the irrigation application according to the crop water consumed since the irrigation was initiated. The strategy should also be robust to data gaps by using lower hierarchies of data (defined in Section 3.3.6) if a data stream input is unavailable. The irrigation events would be initiated at regular intervals.

Spatial data unavailability is generally not important for iterative hill climbing control as data input is only required for the test cells. However, if field measurements of a test cell are missing, kriging the available data would not show the response of the test cells to the test irrigation volumes. Hence, kriging is not appropriate for iterative hill climbing control and if critical data input is missing the control procedure will fail.

### 5.2.3 Model predictive control

Model predictive control is applicable to irrigation as it involves using a calibrated model to evaluate a range of inputs and implement the input with the best performance (Appendix A.3.6). For irrigation, model predictive control would involve using field data to calibrate a crop and soil model (e.g. OZCOT) and then using the calibrated model to determine the optimum irrigation timing and volume. Fieldwork has demonstrated that OZCOT may be calibrated using weather, soil and plant data (Chapter 4).

The irrigation machine capacity can be accommodated by increasing the irrigation applications that are evaluated to account for the additional crop water use since the irrigation was initiated.

The model predictive controller requires an accurate process model that is calibrated using the available weather, soil and plant data throughout the crop season to determine the irrigation volumes and/or timing. In contrast, for a field implementation the iterative learning and iterative hill climbing controllers do not require a process model as they use measured field data to directly adjust the irrigation applied.

Because model predictive control uses a model's simulations to determine irrigation application, variables that are not directly measured (e.g. final crop yield and water use efficiency) may potentially be controlled and optimised. In contrast, the iterative learning and iterative hill climbing control strategies determine irrigation applications using measurements of soil and/or crop response to target the desired soil and/or crop response.

## 5.3 'Case study' methodology for comparing control strategies

The performance of an irrigation control system will be limited by the attributes that are measured in the field, the spatial resolution of the sensor data for both static sensors (e.g. soil moisture probes) and on-the-go sensors (e.g. infrared thermometers) and the temporal resolution of the input data. The control system performance may also be affected by spatially variable rainfall or an irrigation machine with a capacity constraint such that it cannot deliver the optimal irrigation volumes in time. Adaptive irrigation control systems have differing robustness to these data availability and system constraints. VARIwise case studies are presented in Chapters 6, 7 and 8 to compare the adaptive control strategies with different input data types and in Chapter 9 to evaluate the robustness of the strategies with particular system constraints.

There are seven possible combinations of data input which could be used for irrigation control (Table 3.2), namely:

1. Weather only
2. Soil only
3. Plant only
4. Weather AND soil
5. Weather AND plant
6. Soil AND plant
7. Weather AND soil AND plant

The data inputs used for irrigation control were compared by simulating the strategies using different combinations of data input. This will indicate the control inputs that are most appropriate to each control strategy. This comparison also differs from the evaluation conducted in Chapter 4 which used the seven combinations of data input to limit the data available to the model and hence the cotton model accuracy. In contrast, the simulations to compare the adaptive irrigation control strategies use the same underlying crop model but only use the input variables for control. Hence, the simulation evaluating the input of soil data to the iterative learning controller involves adjusting the irrigation volume according to the error between the desired soil moisture and the measured soil moisture after each irrigation event. The implementation of this strategy in the simulation environment does not involve manipulating the crop model.

The adaptive control strategies were also evaluated for different spatial and temporal scales of input data and for limitations on the irrigation machine capacity. The simulations that have been conducted to evaluate these features for each control strategy are summarised in Table 5.1: the results for the spatial data resolution evaluation are presented in Chapters 6, 7 and 8 according to the strategy, and the data resolution and irrigation machine capacity evaluations are presented in Chapter 9.

Table 5.1: Simulations conducted with each control strategy to compare interactions between control strategies and sensor and irrigation machine restrictions

| **Evaluated feature** | **Input variable for control** | **Method of data input usage** |
|---|---|---|
| Spatial resolution of input data | One point | Use input data for one point over field |
| | Three points | Use input data kriged for each cell |
| | Ten points | |
| Spatial variability of rainfall | No variation | Use constant rainfall in each cell |
| | ±20% variation | Use rainfall with random variability imposed in each cell |
| | ±50% variation | |
| Temporal resolution of input data | Fifteen days | Use input data combination that is lower in data hierarchy than current combination |
| | Six days | |
| | Three days | |
| Irrigation machine capacity | 5 mm/day | Limit daily irrigation machine application |
| | 10 mm/day | |
| | 15 mm/day | |

The case study simulations of Chapter 9 only constrain one input at a time. For example, for simulations which have data available only at only particular points in the field, data are available at these points every day.

## 5.4 Agronomic parameters

As noted in the previous section, the following three chapters set out simulation case studies to demonstrate and evaluate the operation of the adaptive control strategies. In each, the simulated outputs of the cotton model OZCOT were used as data feedback to the control system. OZCOT requires the input of the parameters (Table 5.2) via agronomic, soil properties and crop variety input files. Chapter 3 describes the method used to enter the parameters into these input files. The values of the parameters were fixed as the values of Table 5.2 for all the control system case studies to ensure valid comparison.

Table 5.2: Agronomic factors used in cotton model OZCOT for control strategy simulations

| **Agronomic factor** | **Value** | **Source** | **Method of fixing** |
|---|---|---|---|
| Sowing date | 4 October 2004 | Nil | Automatically entered into agronomic factors file |
| Plant stand | 12 plants/m | Default in HydroLOGIC | Automatically entered into agronomic factors file |
| Seed depth | 5 cm | Default in HydroLOGIC | Automatically entered into agronomic factors file |
| Row spacing | 1 m | Default in HydroLOGIC | Automatically entered into agronomic factors file |
| Available nitrogen | 250 kg/ha (for maximum yield) | Rochester (2006); Rochester et al. (2009) | Automatically entered into agronomic factors file |
| Previous crop | Other | Nil | Automatically entered into agronomic factors file |
| Defoliation dates | Determined by OZCOT | Nil | Automatically entered into agronomic factors file |
| Harvest date | Determined by OZCOT | Nil | Automatically entered into agronomic factors file |
| Cotton variety | Sicot 73 | Nil | Automatically entered into crop variety file |
| Plant available water content | As per Figure 5.1 | Nil | Automatically entered into soil properties file |
| Starting soil moisture content | 50 mm | Nil | Automatically entered into soil properties file |
| Weather data | As per Figure 5.2 | Nil | Automatically entered into weather file |
| Machine type | Centre pivot | Nil | Fixed in VARIwise |
| Field size | 400 m diameter | Nil | Fixed in VARIwise |
| Cell dimensions | Set by user input | Nil | Fixed in VARIwise |
| Machine capacity | 15 mm/day | Nil | Fixed in VARIwise |
| Initial machine position | 0° | Nil | Fixed in VARIwise |
| End of irrigation period | 14 March 2005 | Nil | Fixed in VARIwise |

## 5.5 Case study scenario

This section presents a VARIwise case study of a cotton crop irrigated using a fixed irrigation strategy and for comparison with the adaptive control strategy simulations presented in Chapters 6, 7 and 8. A cell width and radial length of 50 metres were specified and the field was automatically divided into 44 cells each of area approximately 0.3 ha. The underlying soil variability map (Figure 5.1) was created by:

1. specifying the plant available water capacity (PAWC) for three points in the field;
2. spatially interpolating the soil data for the other cells (using kriging procedure); and
3. adding a Gaussian random variation with a standard deviation of ±5% to the spatial data.

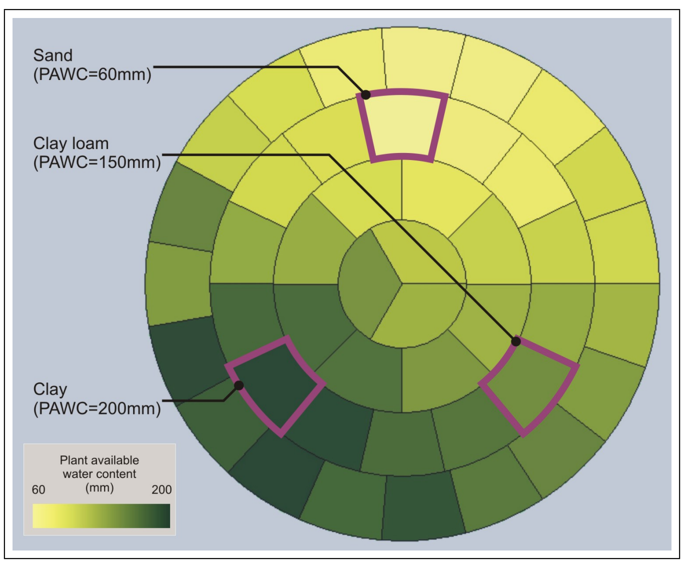



Figure 5.1: Soil variability for fixed strategy to compare with adaptive control strategy results

The weather profile in Figure 5.2 was used as the weather data input for simulations that include weather in the input data combination, whilst the same weather profile (Figure 5.2) was averaged daily and used as the weather data input for simulations without weather in the input data combination. A daily weather profile was obtained

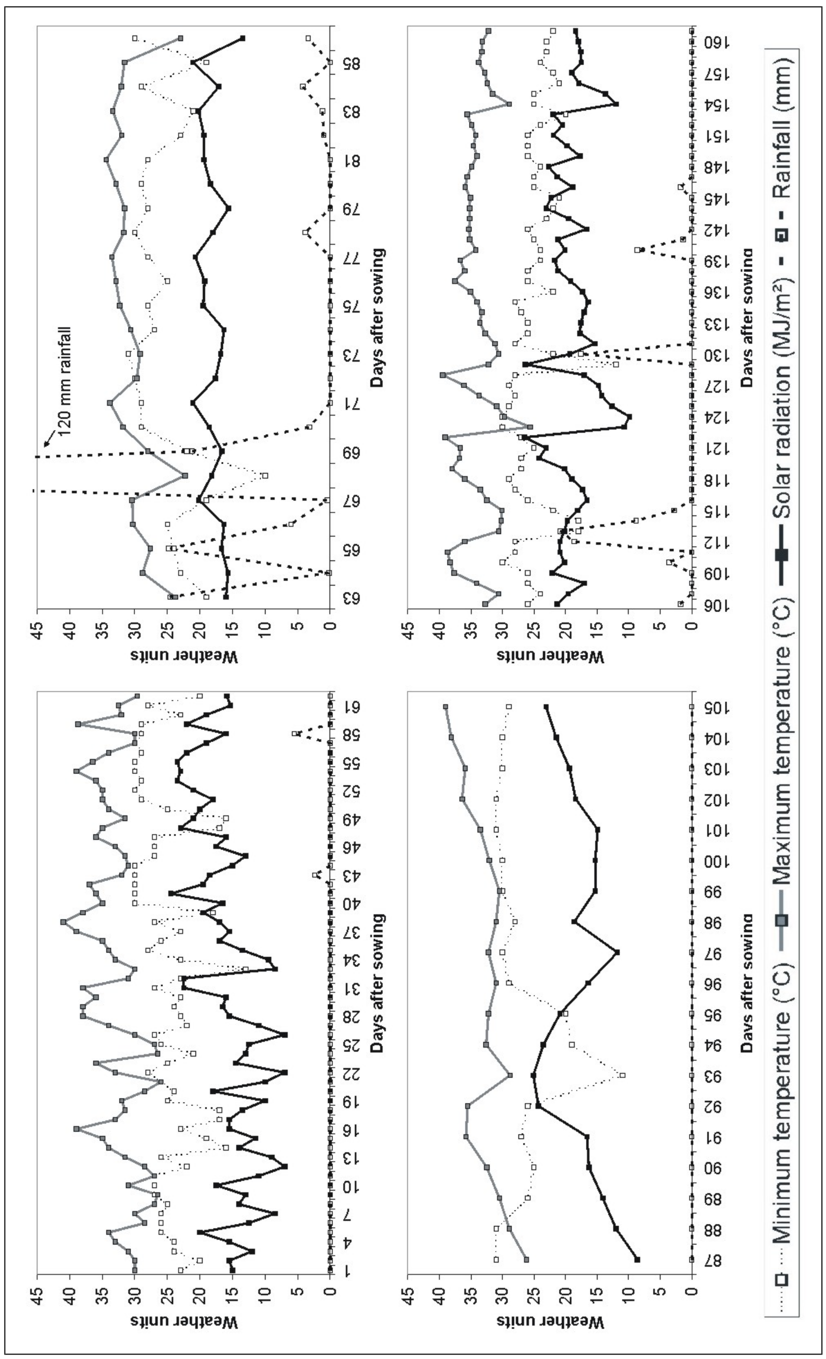



Figure 5.2: Weather profile used in iterative learning, iterative hill climbing and model predictive control strategies

for the GPS location -28.18°N 151.26°E from an Australian Bureau of Meteorology SILO dataset (QNRM, 2009) for 2004/2005. The weather profile is relatively hot and wet, late in the crop season. The weather profile was separated into four graphs in Figure 5.2 for clarity based on the rainfall during the crop season: there is low rainfall in the periods 1-61 and 87-105 days after sowing (shown in the two graphs on the left of Figure 5.2), whilst there rainfall during in the periods 63-86 and 106-161 days after sowing (shown in the two graphs on the right of Figure 5.2). Graphs of simulated outputs are presented with the same divisions in Chapters 6, 7 and 8.

A fixed irrigation schedule was implemented with field properties as per Table 5.2 and involved applying 30 mm every two weeks between 14 October 2004 and 14 December 2004 and 20 mm every week between 14 December 2004 and 14 March 2005. The final yield was 6.2 ± 2.1 bales/ha with CWUI of 0.9 bales/ML$_{total}$ (total water in ML) and IWUI of 1.5 bales/ML$_{irrigated}$ (irrigation applied in ML) (Figure 5.3). The total volume of water applied to the crop (including rainfall) was 7.2 ML/ha, whilst the irrigation applied to the crop was 4.1 ML/ha. Variations reported in the average yield for this simulation and those in the case studies in this thesis are standard deviations.

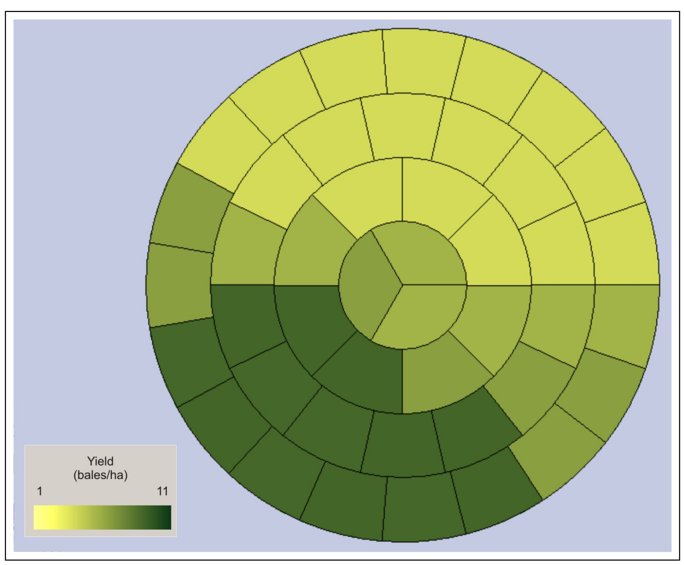



Figure 5.3: Yield map for fixed strategy to compare with adaptive control strategy results with 6.2 ± 2.1 bales/ha

# Chapter 6

# Implementation of an Iterative Learning Controller in VARIwise

Iterative Learning Control (ILC) can be used to control repetitive processes (e.g. robot arm manipulators, repetitive rotary systems, factory batch processes) (Ahn et al. 2007). An irrigation system may be interpreted as a repetitive process as the irrigation machine iteratively passes over the field throughout the crop season. Classical ILC is used to improve the system performance by eliminating the effects of any repeating disturbance (Korovessi & Linninger 2006). Hence, the process controlled by the ILC controller must be reset to the same initial conditions after each iteration. For irrigation, each iteration of ILC is an irrigation event and the conditions may be approximately reset by scheduling the irrigations after a set amount of crop water use.

Soil moisture, leaf area index, square count or boll count may be used as feedback to measure the system performance for a cotton irrigation control system. These measurements should be taken after a time delay to ensure the soil or crop has responded to the irrigation water. A controller using soil moisture may target a particular soil moisture deficit throughout the season (this may be interpreted as a method of calibrating the model).

Moore & Chen (2006) demonstrated an ILC controller for a centre pivot irrigation machine using a soil model and soil moisture as the feedback variable. This soil model did not consider the water use of the crop caused by the crop stage, crop conditions and the daily and sub-daily weather dynamics. This enabled the model to reset to the same initial conditions after a fixed time delay and irrigation events to be scheduled at regular time intervals. The Moore & Chen (2006) ILC controller applied a constant irrigation volume for the first four irrigation events to allow the system to come to a steady state.

## 6.1 Implementation

An ILC controller was implemented in VARIwise to calculate the optimal irrigation application volumes for each cell. Determining the timing and application volumes for ILC irrigations involves the following procedure:

1. Determine day of first irrigation
2. Calculate first irrigation volume
3. Check data availability
4. Determine day of next irrigation
5. Determine subsequent irrigation volumes

### 6.1.1 Determining day of first irrigation

The number of days until the first irrigation is determined by dividing the readily available water ($RAW$) of the soil by the daily crop water use (Section 2.1.2.1). The $RAW$ is the fraction of the total available water (specified by the user as a soil property) that can be extracted from the effective root zone before the crop suffers water stress (Chapter 8 of Allen et al. 1998) and this fraction ('depletion fraction') is estimated using

Table 22 of Allen et al. (1998). The daily crop water use is estimated by calculating the crop evapotranspiration ($ET_c$) from:

1. Weather data (i.e. reference evapotranspiration ($ET_o$) and effective rainfall) entered by the user or obtained in the framework from an Australian Bureau of Meteorology dataset; and
2. Crop coefficient ($K_c$) estimated from Table 12 (Allen et al. 1998) using the sowing date entered by the user, i.e. $ET_c = K_c \times ET_o$ (Equation 56 of Allen et al. 1998).

The crop coefficient indicates the transpiration and crop coverage[1] which changes according to crop stage during the growing season and also affects soil evaporation (Allen et al. 1998). For example, from Table 12 of Allen et al. (1998) (which has been incorporated into VARIwise), crop coefficient estimates for cotton grown under typical irrigation management are $K_c = 0.35$ during the initial crop stage (0 to 30 days after sowing), $K_c = 0.35$ linearly increasing to 1.2 during the plant development stage (31 to 80 days after sowing), $K_c = 1.2$ during the mid-season stage (81 to 135 days after sowing) and $K_c = 0.7$ during the late season stage (136 days after sowing until the end of the crop season). The interval from commencement to the first irrigation is estimated to be:

$$\text{Days} = \frac{RAW + \text{Effective rainfall}}{ET_c} \tag{6.1}$$

where the effective rainfall is calculated on a daily time step basis taking into account the soil moisture deficit.

The day calculated for the first irrigation may be different for each cell in the field since the soil properties, and hence the readily available water content, are spatially variable. In this situation, the field is irrigated according to the most limiting cell condition (i.e. on the earliest date calculated).

[1]More precisely the effect of bulk stomatal resistance

### 6.1.2 Calculating first irrigation volume

The first irrigation application volume is calculated by aggregating the daily crop water use (calculated using weather data ($ET_o$) and the crop coefficient) since the crop was sown.

### 6.1.3 Checking data availability

In the simulation environment the model output data are obtained for the cells and days specified by the user. This enables the performance of the control strategy to be evaluated with input data at different spatial and temporal resolutions. The currently available field dataset is kriged (i.e. spatially interpolated) spatially across the field to ascribe a value to each cell in the field.

### 6.1.4 Determining day of next irrigation

The irrigation events are scheduled when the crop has used a user-specified amount of water since the previous irrigation event. The method of calculating the crop water use depends on the datasets available, thus:

- If soil data input is used in the control strategy and update data are available, the crop water use is determined using the change in soil moisture since the previous irrigation.
- If soil and weather data inputs are used in the control strategy but update soil data are not available and update weather data are available, the crop water use is determined as the daily crop evapotranspiration (calculated using the weather data) and the cumulated crop water use since the previous irrigation.
- If soil data input is used but update data are not available, plus weather data are not available or not used, then the crop water use is determined using histori-

cally averaged weather data and the cumulated crop water use since the previous irrigation.

Since the crop water use may not be uniform across the field due to spatial variability, the irrigations are initiated when an arbitrary number of the cells have reached the set crop water use. The irrigation events should also be scheduled at approximately the same time of day to reduce the effects of the sub-daily evaporative demand. In the simulation environment and for a model that simulates at a daily time step, sub-daily changes are not considered.

### 6.1.5 Determining subsequent irrigation volumes

The irrigation volume applied to each cell in the field is calculated using an ILC algorithm. A typical ILC algorithm (Ahn et al. 2007) has the form:

$$u_{k+1}(t) = u_k(t) + \gamma(y_k(t+\Delta) - y_d(t+\Delta)) \tag{6.2}$$

where:

| | | |
|---|---|---|
| $u_k(t)$ | = | the system input on iteration (i.e. irrigation) $k$ |
| $\gamma$ | = | a learning gain |
| $y_k(t+\Delta)$ | = | the system output after delay $\Delta$ |
| $y_d(t+\Delta)$ | = | the desired response after delay $\Delta$ |

The ILC algorithm assumes that the refined input is adjusted in the same direction as the difference between the measured and desired value for a positive learning gain and that the refined input is adjusted in the opposite direction to the difference between the measured and desired value for a negative learning gain. For example, when the desired value is less than the measured value (and the difference is negative) and the learning gain is positive, then the irrigation volume applied is less than the previous irrigation volume. Hence, this algorithm may only be used for variables which either always increase when the irrigation volume applied increases (e.g. soil moisture content) or always decrease when the irrigation volume applied decreases (e.g. soil moisture deficit). An applicable plant variable may be leaf area index since vegetative growth typically increases with increased water application and hence would require a positive learning gain. However, square and boll counts are not applicable for ILC as cotton reproductive growth is maximised when the plant is under mild water stress (Gibb et al. 2004).

For each irrigation event and cell, the ILC algorithm may be used to calculate the volume to apply at the next irrigation event using measured field data and the desired value for the corresponding variable. Because this form of the algorithm only considers one measured variable, the ILC algorithm was revised to account for multiple variables. This may be achieved by either one, or a combination, of the following (Liu et al. 2001):

- Assigning a weighting to each objective and constructing a weighted sum of all the objectives
- Optimising each objective separately to explore trade-offs

The multi-objective optimisation option 1 requires subjective selection of the weights for each objective; however option 2 requires an additional decision-making procedure to determine which objective optimisation results in the desired performance for both objectives. This implementation aims to evaluate the effect of using multiple data inputs; hence multi-objective optimisation option 1 would be sufficient if each objective were equally weighed. The revised multi-objective ILC algorithm has the form:

$$u_{k+1}(t) = u_k(t) + \gamma \sum_{i=1}^{n} (w_i \times (y_{i,k}(t+\Delta) - y_{i,d}(t+\Delta))) \tag{6.3}$$

where $n$ variables are used in the control strategy and $w(i)$ is the weighting of the $i$th variable for the control strategy (where all weightings must sum to unity).

An optimal time series dataset is required for each input variable to compare with the measured output and calculate the next irrigation volume. The leaf area index for an optimal cotton crop is shown in Figure 6.1. This dataset was obtained from OZCOT for the highest yielding soil moisture deficit-triggered irrigation strategy (Figure 3.11 in Section 3.5.2) and the curve was smoothed using exponential smoothing with a smoothing factor of 0.85. The maximum leaf area index achieved (approximately 1.8) in this strategy was lower than many irrigated cotton crops reported in the literature (e.g. Richards et al. 2002). This may be because this strategy was deficit irrigated which led to higher flowering and yields than well watered plants which often have excessive vegetative growth and a high LAI (which leads to low flowering and yields).

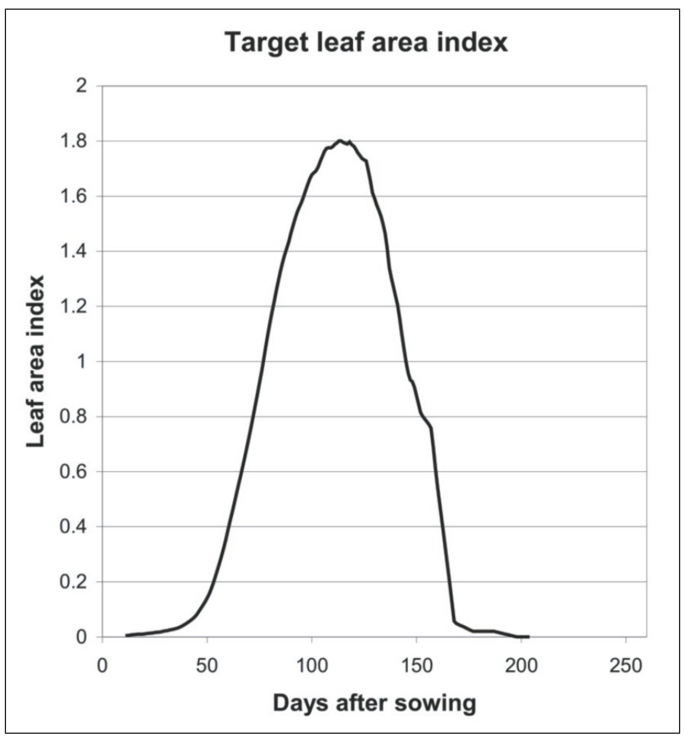



Figure 6.1: Target leaf area index used for iterative learning control strategy for cotton in VARIwise (Wells & Hearn 1992)

To use soil moisture content as the controlled variable, the desired response is to target a user-specified soil moisture deficit throughout the crop season: this would require a negative learning gain. To keep the sign of the learning gain consistent with that of the leaf area index (i.e. positive), the desired soil moisture content is used as the controlled variable and is calculated by subtracting the desired deficit subtracted from the full point (field capacity) of the soil.

The irrigation machine capacity affects the time taken to traverse the field and, hence, the time that irrigation is applied to each cell. To account for the machine capacity, the irrigation application is increased by the measured or estimated daily crop water use to compensate for each day of the additional crop water use between the initiation of the irrigation event and the day that the machine passes each cell. The irrigation volume applied to each cell is limited to an arbitrary maximum volume (e.g. 60 mm) to ensure that the volumes are practical and in line with industry standard irrigation applications via lateral moves and centre pivots.

## 6.2 Case study: optimisation using daily input data

### 6.2.1 Methodology

A case study was conducted for ILC using the five applicable input data combinations (Table 6.1). For the simulations with two input data variables, the weightings on each variable were chosen to be 0.5. Irrigations were initiated when 15% of the cells had consumed 40 mm of water. The simulations using soil data input adjusted the irrigation volume to achieve a deficit of 10% of the plant available water capacity in each cell following each irrigation event. The data for feedback in the control strategy were obtained from the OZCOT model on different days depending on the data type: the soil dataset was obtained one day after the previous irrigation event, whilst the plant dataset was obtained one day prior to next scheduled irrigation event.

Simulations for ILC were conducted in VARIwise using the agronomic factors in Table 5.2. The field was automatically divided into 44 cells, each of area approximately 0.3 ha, as per the fixed irrigation simulation in Chapter 5 and the underlying soil variability in Figure 5.1 was implemented. For this case study, the following values were used for the ILC parameters defined in Section 6.1:

- the learning gain ($\gamma$) was unity;
- the irrigations were initiated after 40 mm of crop water use; and
- the time delay ($\Delta$) between the irrigation event and the parameter measurement depended on the data input. For soil data input the time delay was one day and for plant data input the time delay was the number of days until the next irrigation because plant response is not immediate.

Table 6.1: Simulations conducted to compare interactions between control strategies and input variables for Iterative Learning Control. N/A indicates that the input is not applicable; Nil[1] indicates that the weather-only data option is not applicable to ILC because weather information does not indicate the crop response to an irrigation application; Nil[2], Nil[3] and Nil[4] indicate that the input variable combination is duplicated in simulations #1, #4 and #5, respectively. These duplications occur because soil data input is used (if available) instead of weather data input to determine the crop water use.

| **ID #** | **Input variable/s for control** | **Weather data input** | **Irrigation calculation** | |
|---|---|---|---|---|
| | | | **Irrigation volume** | **Irrigation timing** |
| Nil[1] | Weather | N/A | N/A | N/A |
| 1 | Soil | Averaged SILO data | Target soil moisture deficit | Change in soil moisture |
| 2 | Plant | Averaged SILO data | Target leaf area index | Change in crop evapotranspiration |
| Nil[2] | Weather AND soil | SILO data | Target soil moisture deficit | Change in soil moisture |
| 3 | Weather AND plant | SILO data | Target leaf area index | Change in crop evapotranspiration |
| 4 | Soil AND plant (A) | Averaged SILO data | Target soil moisture deficit and target leaf area index | Change in soil moisture |
| 5 | Soil AND plant (B) | Averaged SILO data | Target leaf area index | Change in soil moisture |
| Nil[3] | Weather AND soil AND plant | SILO data | Target soil moisture deficit and target leaf area index | Change in soil moisture |
| Nil[4] | Weather AND soil AND plant | SILO data | Target leaf area index | Change in soil moisture |

### 6.2.2 Results and discussion

Table 6.2 and Figure 6.2 set out the simulated outputs of the ILC controller using the data input combinations described in Table 6.1. The simulated irrigation applied, soil moisture content and leaf area index in the sand, clay loam and clay cells are compared for the strategies with plant-only input (simulation #1) and soil-only input (simulation #2) (Figure 6.3). The ILC strategy produced the highest yield and water use efficiency with soil moisture input (simulation #1).

Table 6.2: Performance of the iterative learning control strategy with variable-rate irrigation machine for different input data combinations where CWUI and IWUI are defined in Section 3.3.8

| ID # | Input variable for control | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|
| 1 | Soil | 10.7 ± 1.7 | 9.9 | 6.5 | 1.1 | 1.6 |
| 2 | Plant | 7.3 ± 2.4 | 7.1 | 4.0 | 1.0 | 1.8 |
| 3 | Weather AND plant | 7.6 ± 2.9 | 8.1 | 5.0 | 0.9 | 1.5 |
| 4 | Soil AND plant (A) | 9.0 ± 2.7 | 9.0 | 5.9 | 1.0 | 1.5 |
| 5 | Soil AND plant (B) | 8.5 ± 2.2 | 9.8 | 6.7 | 0.9 | 1.3 |

ILC produced lower yields with leaf area index input (simulations #2, #3 and #5) than with soil moisture input. The irrigation volumes applied using leaf area index input were low at the start of the crop season (until 80 days after sowing, Figure 6.3(b)) and following this the irrigation volumes increased (because of the difference between the measured and target LAI, Figure 6.5(b)) until the maximum application (60 mm) was applied. The leaf area index was not affected by the irrigation volumes until later in the season: this indicates that the leaf area index is not proportionally related to irrigation application and that the leaf area index input is not effective to determine the crop water requirements (Figure 6.3(b)). The LAI measurement also may not have detected whether the plant was actively transpiring or stressed.

The irrigation volumes applied using leaf area index also exceeded the soil moisture deficit (Figure 6.3(b), Figure 6.4(b)); hence, ILC with leaf area index input could not adapt to the soil moisture content. This suggests that leaf area index is a less effective indicator of irrigation requirement than soil moisture deficit for ILC. The addition of plant data input to the soil simulation (simulation #4) also reduced the simulated yield and water use efficiency.

Rainfall significantly affected the ILC performance. From Figure 6.4 and for the soil-input only simulation (simulation #1), high rainfall during the 62 to 86 days after sowing period kept the deficit near-zero following each irrigation event. During the dry period (87 to 105 days after sowing) the soil moisture deficit after each irrigation event was generally higher than during the high rainfall period and approached the desired values (6 mm, 10 mm and 19 mm for the sand, clay loam and clay cells, respectively). Any error between the simulated and desired soil moisture deficit was caused by irrigations occurring before or after the crop of the graphed cells had consumed the set amount of water. This is because the irrigations were initiated after 15% of the cells had consumed the set amount of water, rather when any specified cells in the field had consumed the set amount of water. Hence, ILC could approximately maintain soil moisture deficit in low rainfall situations. Rainfall during the period 106 to 130 days after sowing reduced the deficit to zero (and possibly caused waterlogging) and following this period, the deficits were maintained closer to the desired deficits. The irrigation events occurred more frequently during 106 to 160 days after sowing because the cotton crop consumed more water during this growth stage. Rainfall may also have affected the refinement of the irrigation volume as the LAI measurement that was used to adjust the irrigation volume was actually the response to both the specific irrigation volume applied and any rainfall that had occurred since the previous irrigation event.

The ILC controller generally applied high volumes of water during each irrigation event; hence, the machine took up to four days to apply the irrigation to the whole field because of the 15 mm/day machine capacity. Higher volumes of irrigation were also applied to the clay cells than the sand and clay loam cells (Figure 6.3). This is because irrigation events took several days to complete and more irrigation was applied to the clay cell which could hold more water and hence was better able to withstand a delay associated with the machine rotation.

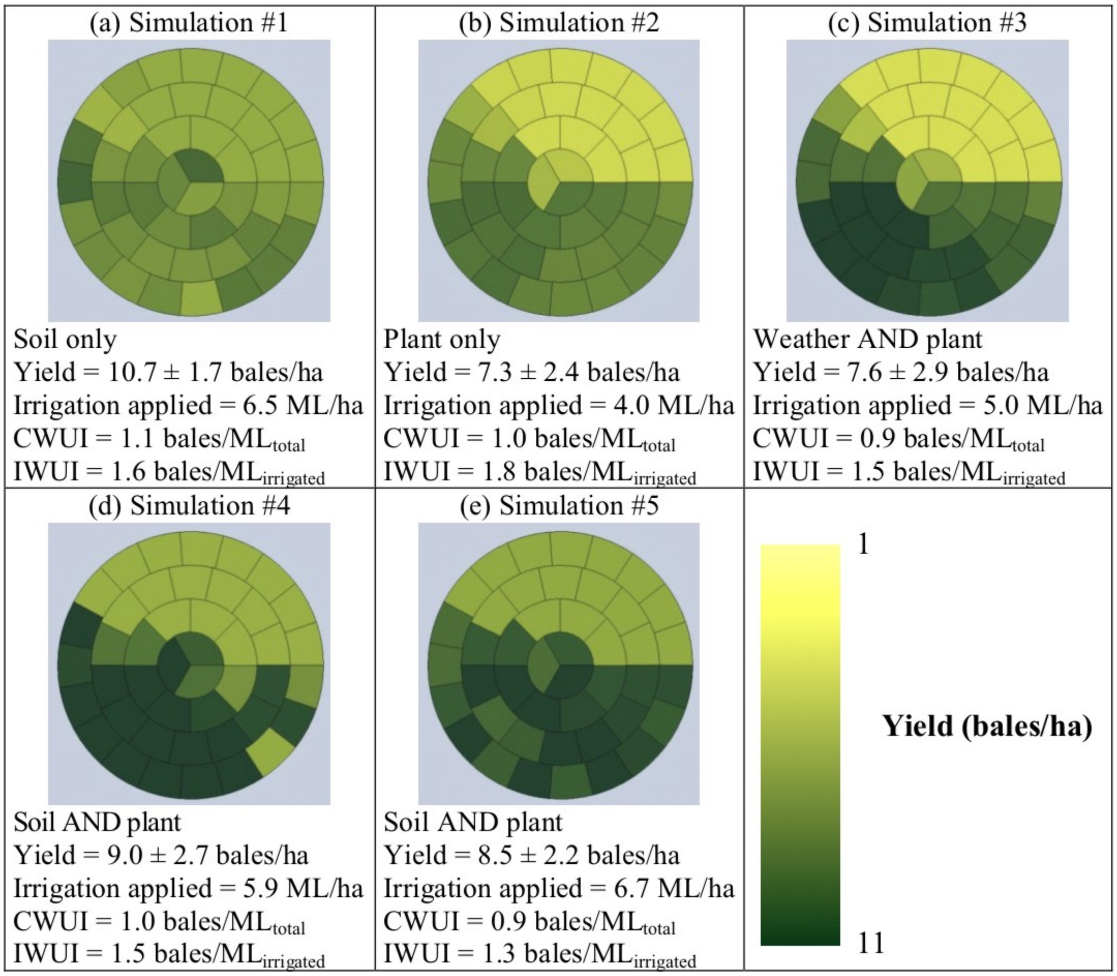
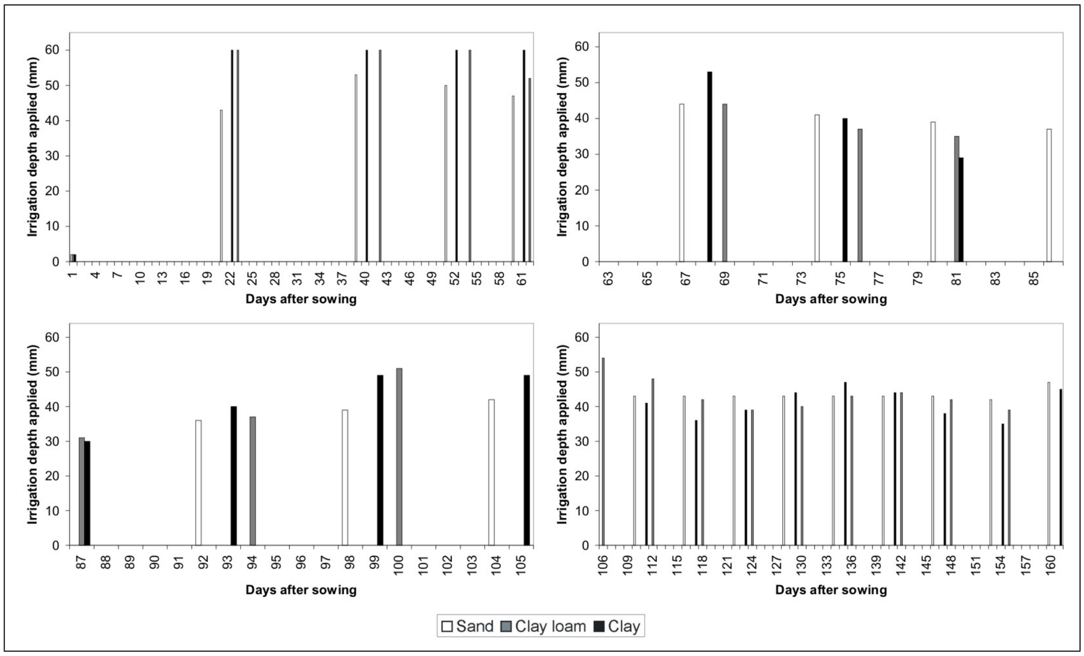
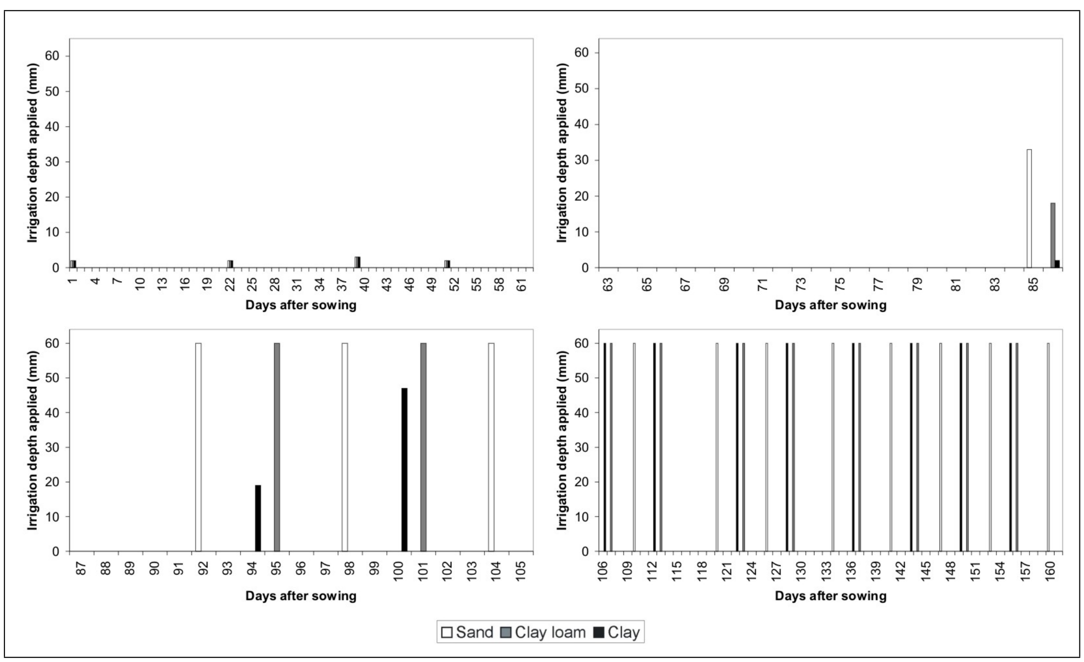



Figure 6.2: Yield output of iterative learning control strategy with variable-rate irrigation machine and legend for yield maps (numerical data for simulations #1-#5 are shown in Table 6.2)

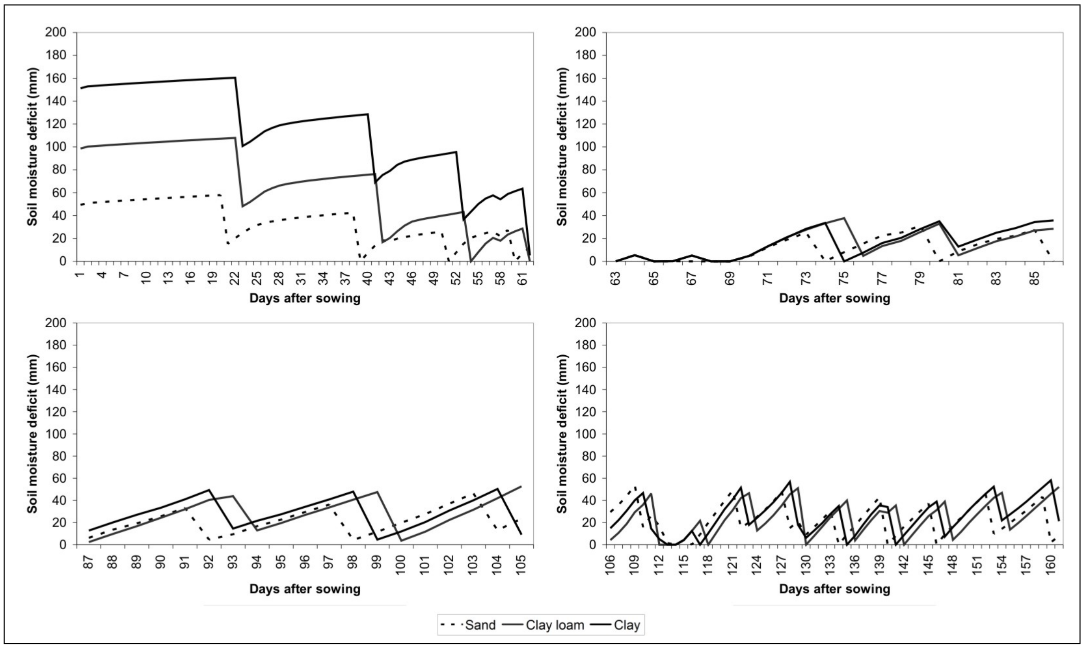



(a)

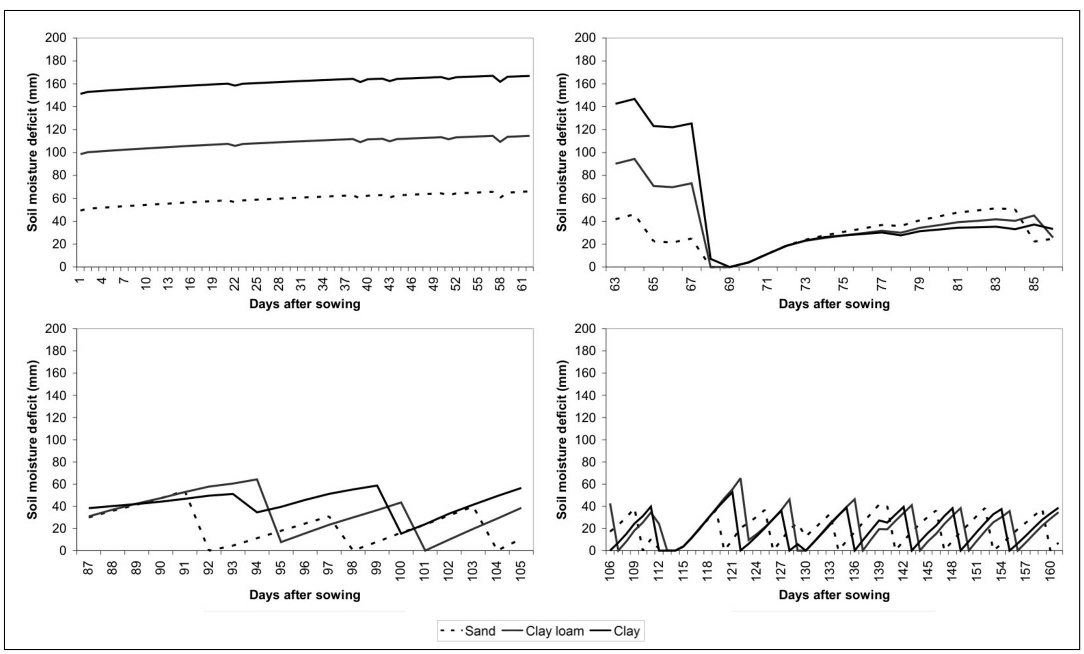



(b)

Figure 6.3: Irrigation volumes applied to sand, clay loam and clay cells for strategies that target: (a) soil moisture deficit (simulation #1); and (b) leaf area index (simulation #2)

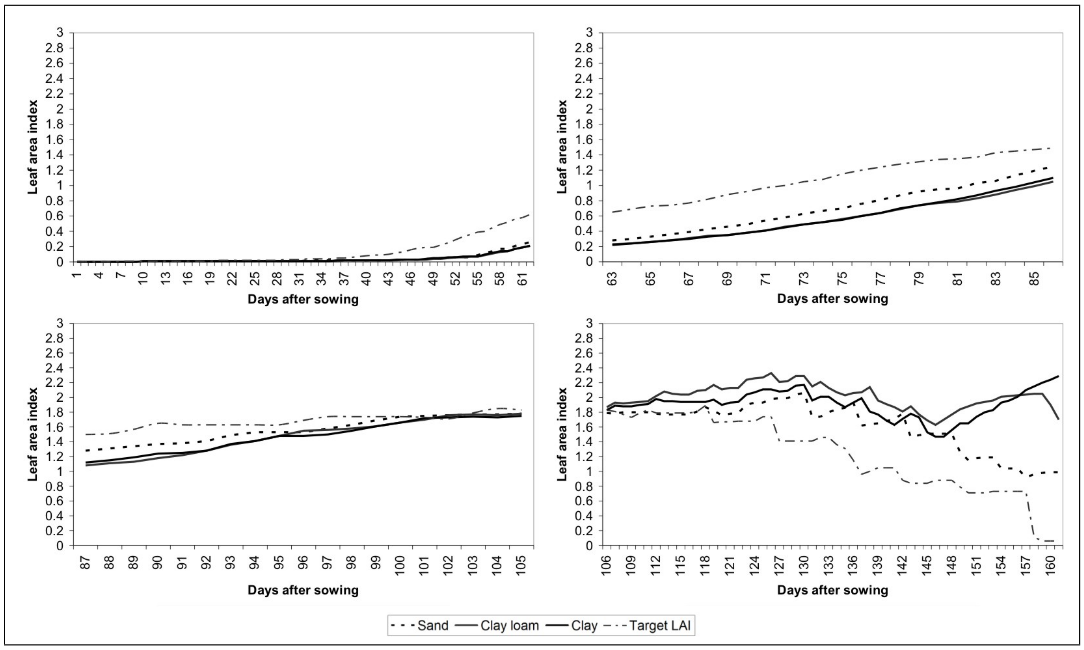



(a)

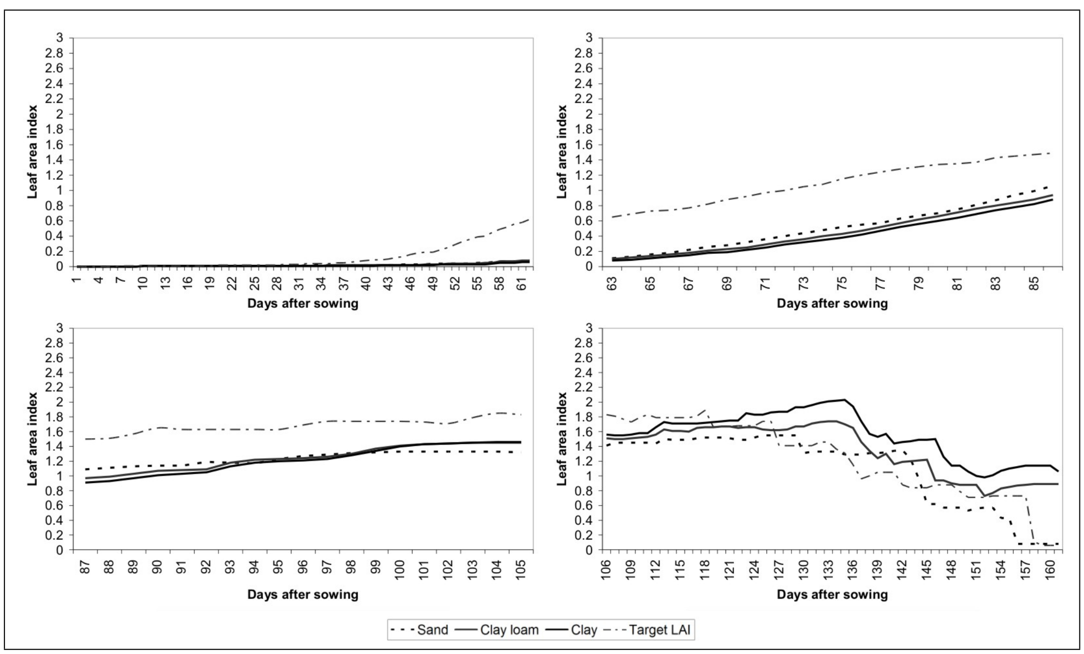



(b)

Figure 6.4: Simulated daily soil moisture deficit in sand, clay loam and clay cells for strategies that target: (a) soil moisture deficit (simulation #1); and (b) leaf area index (simulation #2)




(a)




(b)

Figure 6.5: Simulated daily leaf area index in sand, clay loam and clay cells for strategies that target: (a) soil moisture deficit (simulation #1); and (b) leaf area index (simulation #2)

## 6.3 Irrigation conclusions

An ILC strategy was implemented in VARIwise which calculated the irrigation volume to apply to each cell in the field using the difference between measured response and the desired response. The strategy was evaluated for five combinations of data input in the simulation environment which used modelled data as feedback.

ILC adjusted the irrigation volume to achieve the desired soil moisture deficit following the irrigation event for the different soil types in the field. Leaf area index input was not appropriate for ILC because of its lack of sensitivity to irrigation volume application. The irrigation refinement was most effective during dry periods of the season as rainfall was a (non-repeating) disturbance in the control system; however, ILC adapted to the new system state in dry periods following the rainfall.

Chapter 9 sets out further evaluations of iterative learning control with various system constraints.

# Chapter 7

# Implementation of an Iterative Hill Climbing Controller in VARIwise

The literature review of control systems (Section 5.2 and Appendix A) led to the development of the 'iterative hill climbing controller' (Section 5.2.2). This control system involves iteratively changing the irrigation application on different cells in the field, designated 'test cells', selected in each area of the field, where each area has homogeneous properties. The responses of the test cells are compared to determine which irrigation volume resulted in the response closest to the desired response. This enables the control system to identify appropriate input options within a single irrigation event without using a process model.

By evaluating multiple volumes over multiple cells, the iterative hill climbing controller may converge to the optimal irrigation volumes faster than Iterative Learning Control (ILC) (Chapter 6) which evaluates only one irrigation volume per cell within each irrigation event. This is beneficial for an irrigation system due to the slow rate at which the effect of any particular irrigation input has to be evaluated – typically irrigations occur several days apart. This is different to typical feedback control applications which provide opportunity for actuation responses on timescales measured in seconds (and often milliseconds).

## 7.1 Implementation

An iterative hill climbing controller has been implemented in VARIwise to determine the optimal irrigation volumes to apply to the field. The volumes to apply are determined by evaluating the previous irrigation volumes applied to test cells representative of homogeneous areas of the field. The areas of homogeneous properties may be determined from a soil property or EM38 electromagnetic map if soil data input is used to manage the field, and each such area is referred to as a 'zone' in this chapter. Homogeneous areas may also be identified according to crop or variety differences, topography or management constraints. The iterative hill climbing control strategy involves the following procedure:

1. Divide field into zones
2. Select 'test cells'
3. Determine day of first irrigation
4. Calculate first irrigation volume
5. Check data availability
6. Determine day of next irrigation
7. Calculate the 'Performance Index'
8. Determine subsequent irrigation volumes

### 7.1.1 Division of field into zones

The field is automatically divided into a user-specified number of zones, where each zone has approximately the same number of cells. The cells are assigned to each zone based on the sensed value of the variable of interest. This is achieved by sorting the values of the data input (e.g. plant available water capacity) assigned to each cell in the field in ascending order and then grouping the values into the user-specified number of evenly-sized zones.

### 7.1.2 Selection of 'test cells'

A small number of cells (i.e. a group of 'test cells') are selected in each zone to evaluate different irrigation applications. After the application of the test irrigation volumes, the soil water status, and hence the response to irrigation, of the plants in the test cells would differ from the plant response in the remaining cells of the zone because of the different irrigation volumes applied. If the same test cells are used for subsequent irrigations, the irrigation volume that achieves the desired response in the test cells may not correspond to the volume that achieves the desired response in the remaining cells. Therefore, test cell responses are only indicative of the response in each zone for one irrigation event. Hence, VARIwise automatically selects new test cells in each zone after every irrigation. This is achieved by a simple increment of the cell number on a right-hand spiral for a centre pivot irrigated field; and the next cell along the field for a lateral move irrigated field provided that the replacement cell still lies in the required zone.

### 7.1.3 Determining day of first irrigation

The day of the first irrigation is determined using the procedure of the ILC controller (Section 6.1.1).

### 7.1.4 Calculating first irrigation volume

The first irrigation application is calculated for the non-test cells in each zone by aggregating the daily crop water use (calculated using weather data (evapotranspiration, $ET_o$) and the crop coefficient) since the crop was sown.

The irrigation volume applied to each test cell is determined using the $ET_o$ since the crop was sown and a range of crop coefficients. These crop coefficients are offset from the zone crop coefficient (which is the crop coefficient used to calculate the irrigation volumes applied to the non-test cells). The crop coefficient offsets used are specified by the user as a percentage of the zone crop coefficient. For example, using a zone crop coefficient of $K_c = 0.35$, five test cells and an offset of 40%, the crop coefficients would be 0.07, 0.21, 0.35, 0.49 and 0.63 for each test cell, respectively (i.e. multiples of 40% on either side of the median crop coefficient, 0.35).

### 7.1.5 Checking data availability

The available field data inputs are checked using the procedure of the ILC controller (Section 6.1.3).

### 7.1.6 Determining day of next irrigation

The iterative hill climbing controller initiates the irrigation events at a fixed interval specified by the user (e.g. every five days). This is in contrast to the ILC controller which assumed that the system was essentially reset after each irrigation event and hence the irrigations were initiated after a set crop water use (Section 6.1.4).

### 7.1.7 The 'Performance Index'

A Performance Index ($PI$) is generally a quantitative measure of the performance of the control system and can be calculated using any characteristic that emphasises important control objectives (as introduced in Section 2.3.3). In VARIwise, the data used to determine the $PI$ are specified by the user, and for a cotton crop appropriate parameters are leaf area index (LAI) and 'square count' ('squares' are flower buds on a cotton plant). The type of data specified affects how the $PI$ is calculated.

To optimise cotton yield, the $PI$ can be calculated as the ratio of the current boll or square count to the maximum count of the test cells using:

$$PI = \frac{\text{Current value}(t)}{\text{Maximum value}(t)} \tag{7.1}$$

where $t$ represents the day of the data collection.

For cotton, the leaf area index data should not simply be maximised as this would result in excessive vegetative growth rather than reproductive growth. Hence, the $PI$ for leaf area index can be calculated and compared to the reported leaf area index for an optimal crop. An optimal leaf area index dataset obtained from OZCOT is shown in Figure 6.1. For data that follows an optimal time series data set, the performance index is calculated by comparing the current value with a target value at time ($t$) as follows:

$$PI = \left| \frac{\text{Target value}(t) - \text{Current value}(t)}{\text{Target value}(t)} \right| \tag{7.2}$$

Multiple data variables may be incorporated into the $PI$ by applying weights ($k_i$) to the performance index of each data type ($PI_i$) and summing the weighted indices (where there are $n$ data inputs). Hence, the general form for the $PI$ calculation with multiple data variables and weights is:

$$PI = \sum_{i=1}^{n} k_i PI_i \tag{7.3}$$

$$\text{where } \sum_{i=1}^{n} k_i = 1$$

### 7.1.8 Determining subsequent irrigation volumes

The relationship between the $PI$ for the test cells can be evaluated to calculate the optimal crop coefficient (and hence, application volume) to be used for the ‘non-test’ cells in the next irrigation. The crop coefficient used for the next irrigation corresponds to the maximum $PI$: this is obtained by calculating the maximum point of a quadratic equation fitted through points plotted on a $PI$ versus crop coefficient graph (e.g. Figure 7.1). Although the dataset of Figure 7.1 suggests a non-symmetrical $PI$/crop coefficient relationship, the fitting of a higher-order polynomial was not considered to be justified for these sparse datasets. The crop coefficient that corresponds to the maximum point of the fitted quadratic is only used if it is within the range of crop coefficients tested. If the maximum point of the quadratic lies outside this range, then the crop coefficient for the test cell with the highest $PI$ is selected as the optimal crop coefficient. If all the test cells have the same $PI$ then the crop coefficient is estimated from Table 12 (Allen et al. 1998).

After the user-defined fixed time interval, the non-test cells are then irrigated with an amount calculated using the aggregated $ET_o$ and the optimal crop coefficient. The volumes applied to the new test cells are calculated using the user-defined offset percentage applied to the optimal crop coefficient identified for the previous irrigation.

As per ILC, the irrigation volumes applied are increased, as appropriate, to compensate for the additional water use in each cell between the initiation of the irrigation event and the machine passing over the cell. The maximum irrigation volume applied is limited to 60 mm to ensure the application is practical.

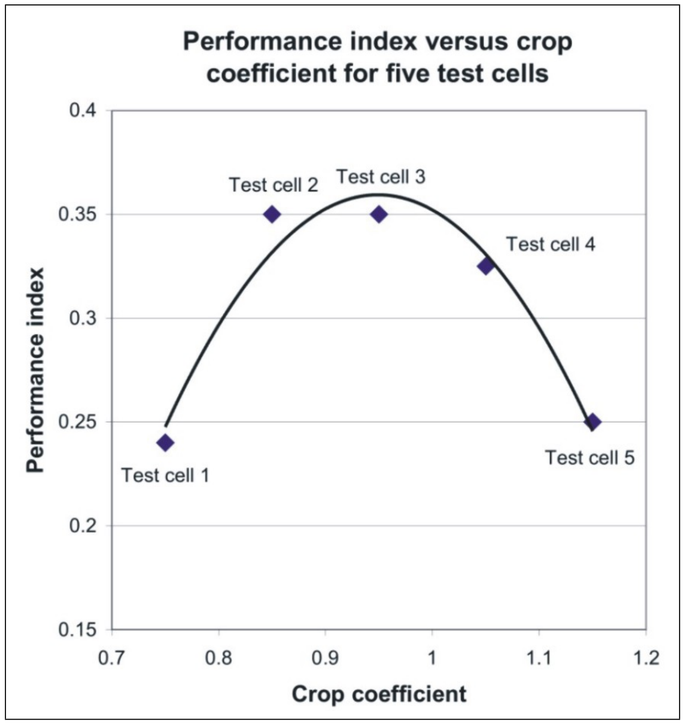



Figure 7.1: VARIwise determination of maximum $PI$ using a quadratic fit to the available data points

## 7.2 Case study: optimisation using daily input data

### 7.2.1 Methodology

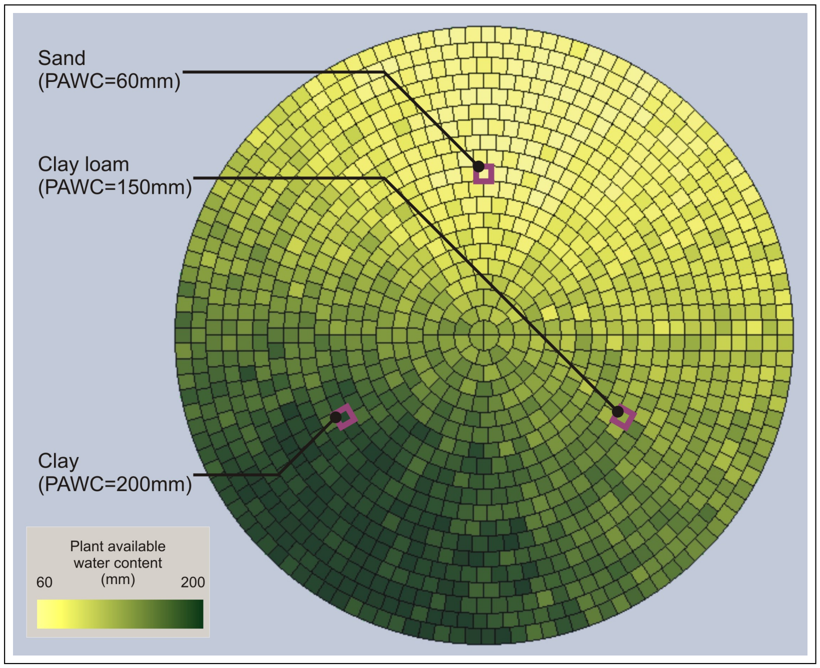
Using weather, soil and plant input data, there are six possible combinations of data input for the iterative hill climbing controller (Table 7.1). As per ILC, weather-only input is not applicable for control as the weather data input does not provide a measure of the crop response. For the simulations with two input variables, the weighting on each variable was set to be 0.5. The simulations using plant data to determine the irrigation application used square count as the input variable for control. This is because squares form earlier in the crop season than bolls (and can be controlled earlier in the crop season). Square count was used instead of leaf area index to maximise the reproductive growth of the cotton plant (which should maximise the final yield) rather than manage the vegetative growth. The strategies with soil data input aimed to target a fixed soil moisture deficit equal to 10% of the plant available water capacity in each cell following each irrigation event.

Table 7.1: Simulations conducted to compare interactions between control strategies and input variables for iterative hill climbing control

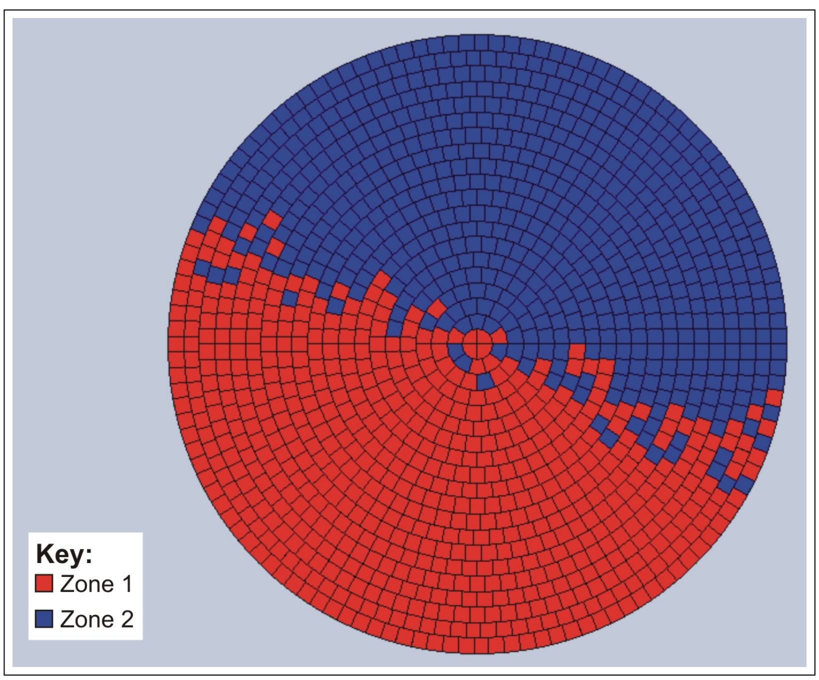
| **ID #** | **Input variables for control** | **Weather data input** | **Irrigation calculation** |
|---|---|---|---|
| Nil | Weather | N/A | N/A |
| 6 | Soil | Averaged SILO data | Target soil moisture deficit |
| 7 | Plant | Averaged SILO data | Maximise square/boll count |
| 8 | Weather AND soil | SILO data | Target soil moisture deficit |
| 9 | Weather AND plant | SILO data | Maximise square/boll count |
| 10 | Soil AND plant | Averaged SILO data | Target soil moisture deficit and maximise square/boll count |
| 11 | Weather AND soil AND plant | SILO data | Target soil moisture deficit and maximise square/boll count |

Many more cells in the field are required for iterative hill climbing control than for ILC (which used 44 cells in the case study in Section 6.2). This ensures that there are sufficient cells in the field for the test cells to be replaced after each irrigation event in the crop season. For example, a field with two zones and five test cells requires ten test cells for each irrigation event. Because these test cells must be replaced with new test cells after every irrigation event, a minimum of 200 cells are required for a season with 20 irrigation events. For this case study, a 12.6 ha centre pivot irrigated field was automatically divided into 1266 cells of area 100 m$^2$ (with cell dimensions of 10 m wide and approximately 10 m long).

The underlying soil variability (Figure 7.2(a)) was created in VARIwise by the same procedure as the fixed irrigation simulation in Section 5.5. The field was automatically divided into two zones (Figure 7.2(b)) and five test cells were used in each zone. The feedback data were obtained from the OZCOT model one day after the previous irrigation event for soil responses and one day before the next scheduled irrigation event for plant responses. The irrigations were initiated every five days.




(a)




(b)

Figure 7.2: (a) Soil variability map for iterative hill climbing control strategy simulation; (b) the cells assigned to each zone using the soil variability data of Figure 7.2(a)

### 7.2.2 Results and discussion

The simulations described in Table 7.1 produced the yields and water use efficiencies in Table 7.2. Iterative hill climbing control produced reasonable yields and water use efficiencies for all data input combinations. The simulated yield was identical for both single input options (i.e. soil-only input, simulation #6; and plant-only input, simulation #7); hence, the soil-and-plant strategy (simulation #8) performed equally well because targeting a soil moisture deficit (for the soil-only option) and maximising square count (for the plant-only option), without weather data input, both provided useful input to the strategy. However, the IWUI was higher with plant-only input than with soil-only input. This is because square count more accurately indicated the plant status than soil response. Hence, using plant data provided more water efficient determination of irrigation application.

Table 7.2: Performance of the iterative hill climbing control strategy with variable-rate irrigation machine for different input data combinations

| ID # | Input variable/s for control | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|
| 6 | Soil | 9.8 ± 1.6 | 12.8 | 9.7 | 0.8 | 1.0 |
| 7 | Plant | 9.8 ± 1.6 | 12.0 | 8.9 | 0.8 | 1.1 |
| 8 | Weather AND soil | 9.8 ± 1.5 | 12.3 | 9.2 | 0.8 | 1.1 |
| 9 | Weather AND plant | 10.9 ± 1.5 | 10.2 | 7.2 | 1.0 | 1.5 |
| 10 | Soil AND plant | 9.9 ± 1.6 | 11.7 | 9.5 | 0.8 | 1.0 |
| 11 | Weather AND soil AND plant | 10.6 ± 1.5 | 11.9 | 9.6 | 0.8 | 1.1 |

The highest yield was simulated using the weather-and-plant input (simulation #9), whilst the lowest yield was simulated using either the soil-only input (simulation #6) or plant-only input (simulation #7). The spatial variability of the yield (Figure 7.3) was caused by the spatial variability of the soil properties and the ‘test’ irrigation volumes being applied to various cells across the field.

From Figure 7.4, the iterative hill climbing controller with weather-and-plant data input applied less irrigation water than that with plant-only. This is because if the weather dataset was not available, the strategy irrigates the field during the wet periods of the crop season (63 to 86 days after sowing). Hence, the application of water was more efficient using weather data in the combination.

The irrigation volumes applied to the clay loam and clay cells were greater than those applied to the sand cells (Figure 7.4). This is because additional irrigation was applied to the clay loam and clay cells to compensate for the water used between the start of the irrigation event and the day that the irrigation machine reached these cells.

The soil moisture deficit in the sand, clay loam and clay cells was closer to the desired deficit (6 mm, 10 mm and 19 mm, respectively) using weather-and-soil input (Figure 7.5(a)) than using weather-and-plant input (Figure 7.5(b)). Deviations from the desired soil moisture deficit were caused by the test cells not being representative of all the cells in the zone, causing the 'best' response of the test cells to be inaccurate and the irrigation application of the whole zone to be inappropriate. In this case study, the field is divided into two zones with both the clay and clay loam cells located in the same zone; hence, these cells are treated the same despite a 50 mm difference in plant available water capacity. In contrast, ILC treated each cell separately and attempted to target a fixed soil moisture deficit in each individual cell. It follows that the square count may not be maximised in each cell of the field because of the differences in properties of the test cells and non-test cells. Deviations may also have been caused by test cells being inappropriately chosen at the border of the zones where the zone division is jagged. Hence, the location of the test cells is important for the irrigation optimisation. However, the iterative hill climbing control strategy that maximised square count resulted in a higher maximum square count than the strategy that attempted to maintain a fixed soil moisture deficit (Figure 7.6).

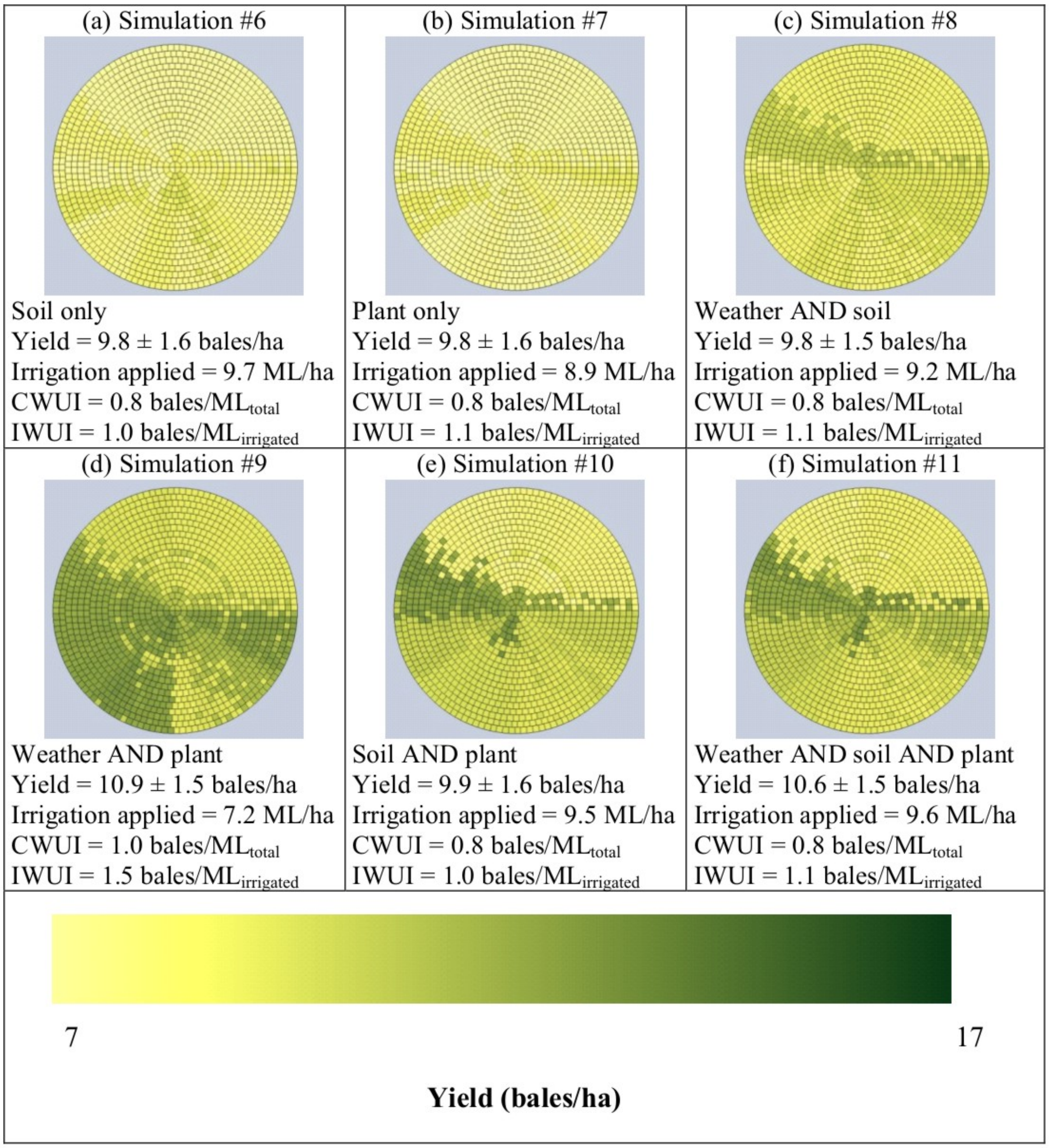
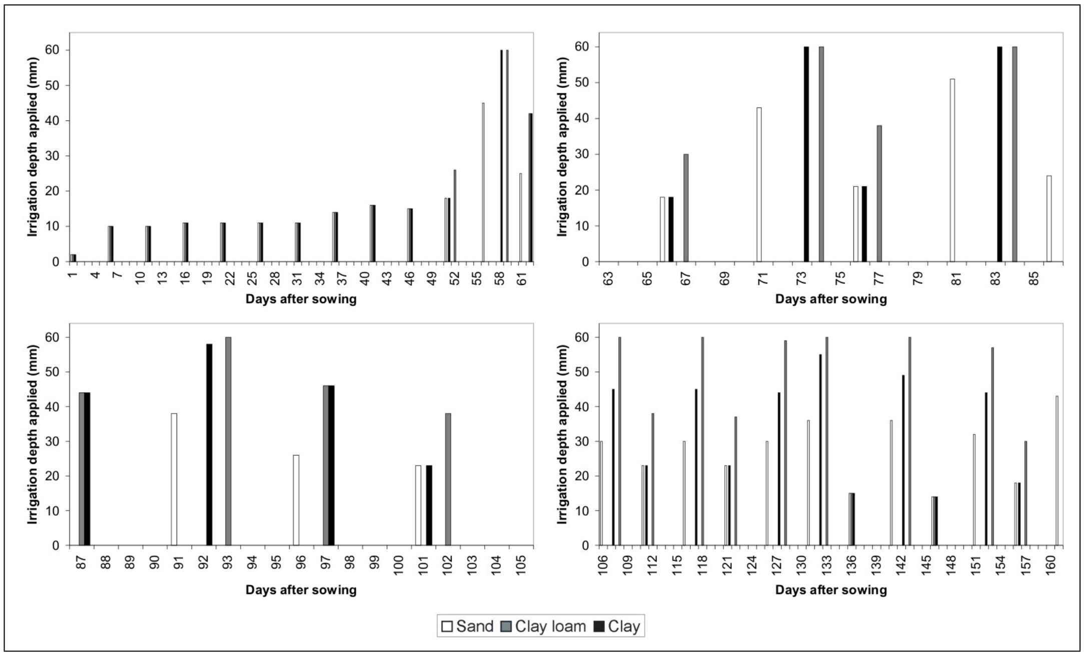
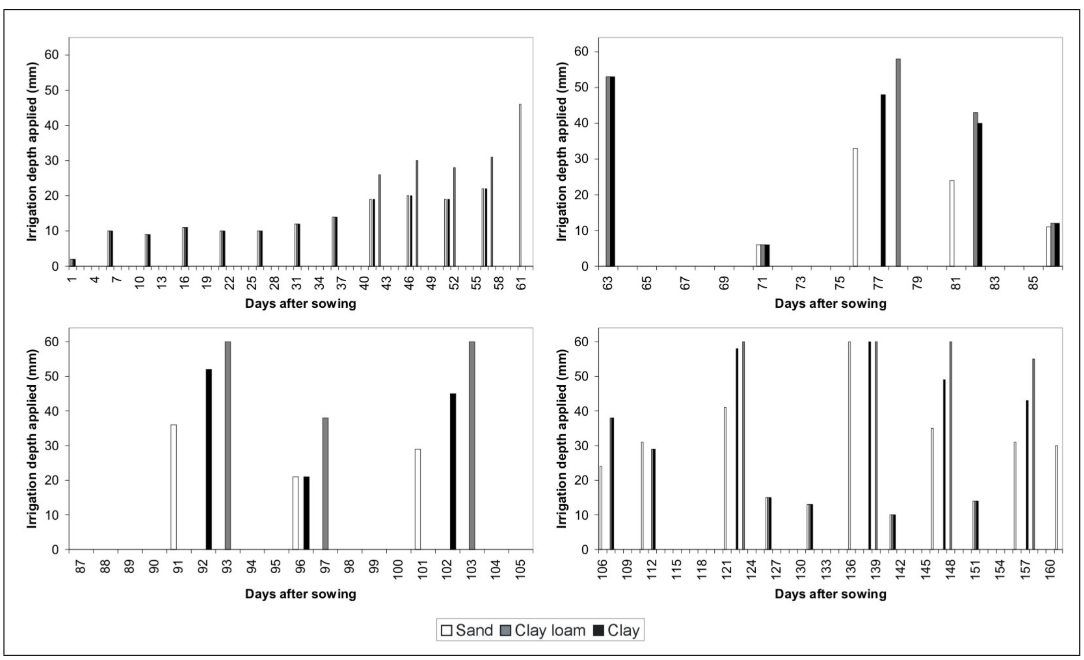



Figure 7.3: Yield output of iterative hill climbing control strategy with variable-rate irrigation machine and legend for yield maps (numerical data for simulations #6-#11 are shown in Table 7.2)

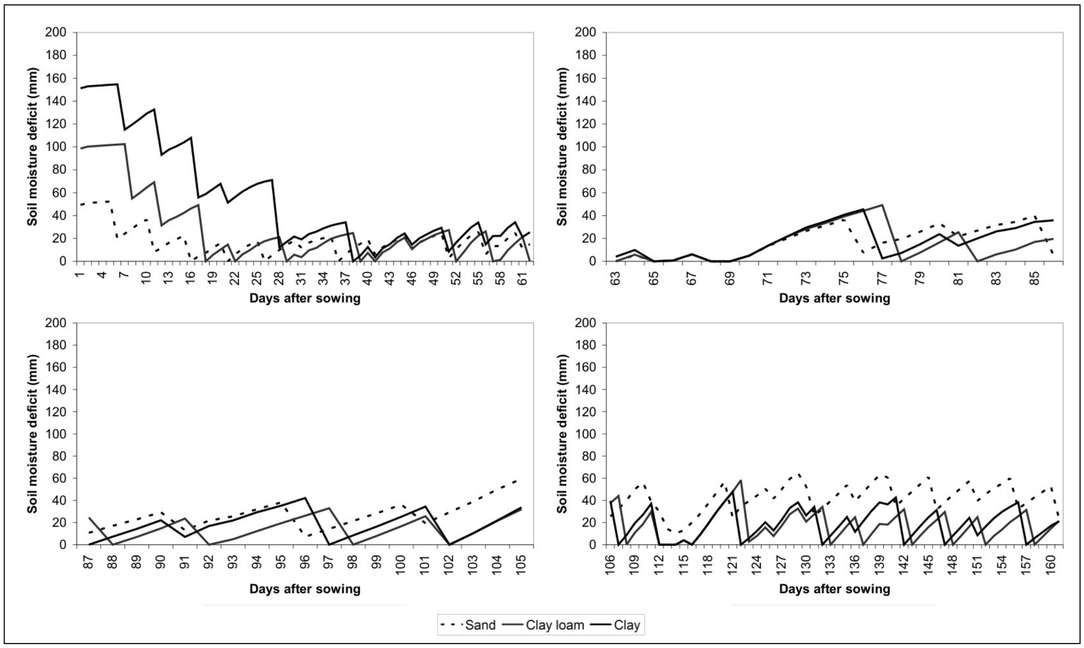



(a)

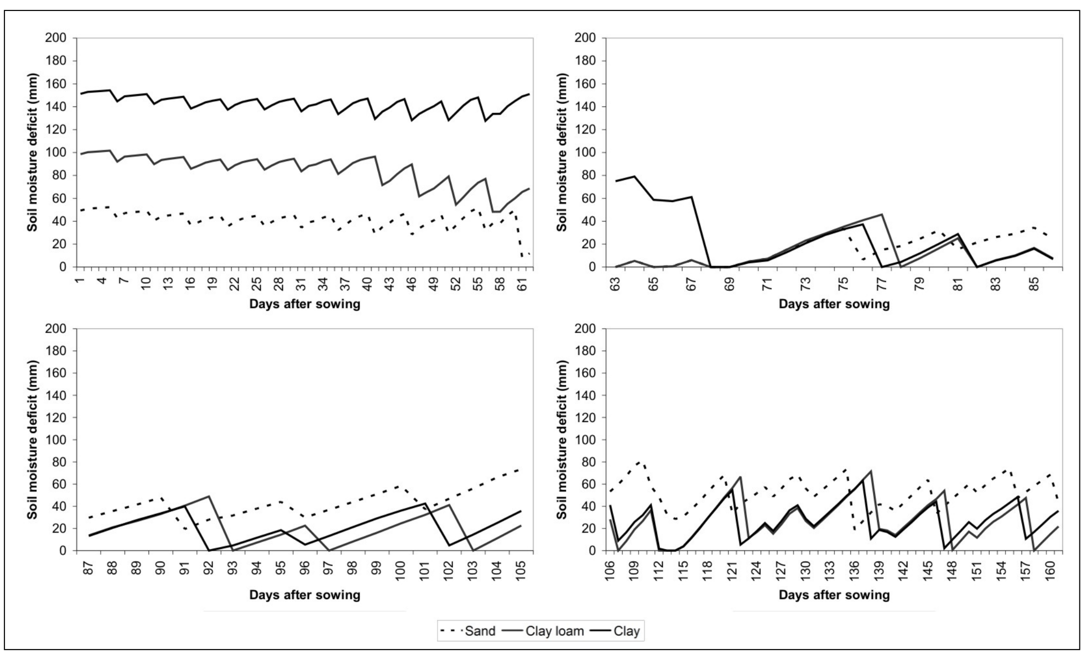



(b)

Figure 7.4: Irrigation volumes applied to sand, clay loam and clay cells for strategies that maximise square count: (a) without weather data (simulation #7); and (b) with weather data (simulation #9)

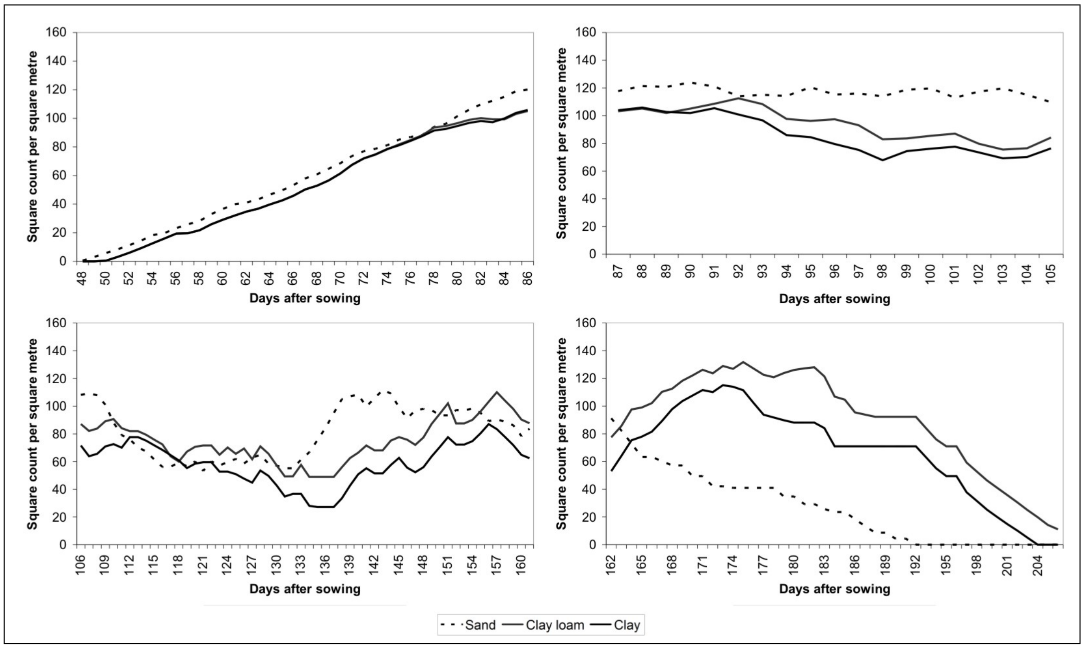



(a)

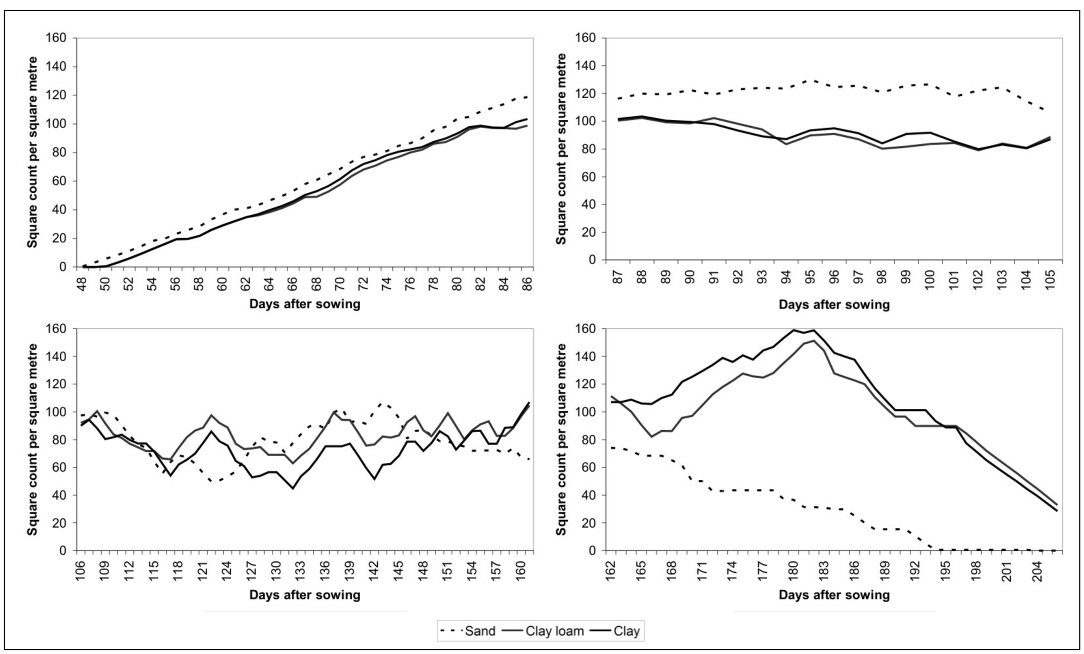



(b)

Figure 7.5: Simulated daily soil moisture deficit in sand, clay loam and clay cells for strategies that (in combination with input weather data): (a) target soil moisture deficit (simulation #8); and (b) maximise square count (simulation #9)




(a)




(b)

Figure 7.6: Simulated daily square count in sand, clay loam and clay cells for strategies that (in combination with input weather data): (a) target soil moisture deficit (simulation #8); and (b) maximise square count (simulation #9)

### 7.2.3 Comparison with iterative learning control strategy

There was no significant difference between the simulated yield or crop water use efficiency of the iterative hill climbing controller with weather-and-plant input (10.9 $\pm$ 1.5 bales/ha, 1.0 bales/$ML_{total}$) and the ILC controller with soil-only input (10.7 $\pm$ 1.7 bales/ha, 1.1 bales/$ML_{total}$). However, with soil-only input, the iterative hill climbing controller produced an average yield and crop water use efficiency (9.8 $\pm$ 1.6 bales/ha and 0.8 bales/$ML_{total}$, respectively) lower than those of the ILC controller and ILC performed poorly with plant data input. This suggests that iterative hill climbing control may be more appropriate for weather-and-plant data input, whilst ILC may be preferable with soil-input only. The iterative hill climbing strategy was less effective at maintaining a soil moisture deficit than the ILC controller.

## 7.3 Irrigation conclusions

An iterative hill climbing control strategy was implemented in VARIwise which involved iteratively evaluating a range of irrigation volumes on 'test cells' in zones of the field to determine the volume that improved the crop response. The controller produced the highest yield and crop water use efficiency with weather-and-plant input. The iterative hill climbing strategy was able to determine irrigation volumes and adapt to the field conditions to increase the square count.

# Chapter 8

# Implementation of a Model Predictive Controller in VARIwise

Model Predictive Control (MPC) involves using a model to predict the optimal input signal at each time step over a finite fixed horizon (Kwon & Han 2005). Only the first optimal control action is implemented after each time step. MPC is applicable to irrigation since a soil-plant-atmosphere model may be used to evaluate the application of various irrigation volumes on a fixed number of consecutive days; for example, the model may be used to, firstly, determine the best irrigation volume to apply on each cell for each of the next three days; and, secondly, determine which day resulted in the best overall performance. The future process outputs used to evaluate the irrigation scheme may be predicted daily with measurements of square/boll count, leaf area index or soil moisture content. Alternatively, the simulated final crop yield or water use efficiency may be used to evaluate the various irrigation schemes.

The requirement that the control be adaptive means that (at least) the model used by the MPC controller must be continuously re-calibrated using the currently available field data. The plant growth and soil water dynamics in the cotton model (OZCOT) can be accurately calibrated as demonstrated in Chapter 4. The calibrated OZCOT model has also been found to accurately simulate yield (Richards et al. 2001).

Park et al. (2009) developed two MPC systems for centre pivot irrigation which both used measured soil and weather inputs to calibrate a soil model. Their first implementation used the calibrated model to determine the irrigation volumes which would fill the soil profile for irrigation events on fixed days; whereas their second implementation used the calibrated model to determine the irrigation timing for a fixed irrigation volume application which would fill the soil profile. Neither implementation incorporated the crop growth response.

This chapter details the implementation of the MPC strategy in VARIwise and presents three MPC case studies which optimise:

- daily square count or soil moisture content (Section 8.2);
- final crop yield or water use efficiency with low and high nitrogen content and in crop seasons with and without rainfall (Section 8.3); and
- final crop yield with different combinations of input data to calibrate the model (Section 8.4).

## 8.1 Implementation

MPC was implemented to determine irrigation timing and site-specific irrigation volumes in both the simulation and field environments with the following procedure:

1. Update measured and forecast weather data
2. Calibrate crop model
3. Optimise irrigation volume for each cell
4. Optimise day of next irrigation

### 8.1.1 Updating measured and forecast weather data

For each day of the crop season, the meteorological data input file for the integrated crop model is updated to include the previous day's weather and the updated weather forecast for the farm's location. The procedure for updating the weather data is different in the simulation and field environments for MPC. This is because the weather data input is not available in real-time in the simulation environment; rather, the whole crop season may be simulated within hours (depending on the number of cells).

For a field implementation in Australia, the previous day's weather input was obtained from an Australian Bureau of Meteorology SILO patched point environmental dataset and a seven day predictive weather dataset was obtained from the Elders weather website as per Section 3.3.1. This weather dataset consists of maximum and minimum temperature, solar radiation and rainfall. Only three days of the predictive weather data were used due to the potential unreliability of the forecast data past this time period. After the three day period, the weather data in the input file were taken as the average of the daily weather data for the crop season so far and no rainfall data were entered during this period. Because only three days of predictive weather data were used, the maximum forecast period for the MPC system was also three days. For MPC implemented in the simulation environment, the weather input was automatically obtained for the farm's location and starting at the crop's sowing date and for the following year using, for example, the Australian Bureau of Meteorology SILO patched point environmental dataset.

In the present case studies, predictive weather data were generated by adding a Gaussian distribution of variability to the obtained weather dataset on the corresponding days. Standard deviations of $\pm 5°C$, $\pm 5°C$, $\pm 5$ W.hr/m$^2$ and $\pm 50\%$ were specified for the maximum temperature, minimum temperature, daily solar radiation and rainfall, respectively. The weather data for the remaining days of the crop season were created as per the field implementation which involved averaging each day's weather over the crop season. The weather data file was updated after each day had been simulated.

### 8.1.2 Calibrating the crop model – ‘actual’ and ‘reference’ models

The integrated crop model was automatically and continuously calibrated according to the currently available weather, soil and plant data using the procedure set out in Section 3.3.7. The procedure for calibrating the cotton model OZCOT in a real-time implementation involves automatically adjusting the parameters in the crop variety and soil properties input files to minimise the error between the model output and measured data on the measurement days. However, in the simulation environment there is no measured field data input to calibrate the model. To overcome this, models for two different cotton crops have been used: one as the ‘reference’ model that evaluates the irrigation volumes, and the second as the ‘actual’ model that describes the actual field conditions and was then used to calibrate the reference model. The crop and soil properties of the actual model were obtained from the user-specified soil and plant measurements, whilst the crop variety of the reference model was specified by the user in the simulation details. The soil properties of the reference model were automatically generated by adding a Gaussian distribution of variability with a standard deviation of ±25 mm to the user-specified soil measurements.

### 8.1.3 Optimising irrigation volumes for each cell

Optimal irrigation volumes were determined by iteratively simulating the daily application of sixteen different irrigation volumes at 1 mm increments between 0 and 15 mm on each cell in the field. For each irrigation volume applied, a *PI* was calculated following the procedure of the iterative hill climbing control strategy (Section 7.1.7). The predicted process outputs used to calculate the *PI* were taken one day after the irrigation application. The optimal irrigation volume for each cell was the irrigation volume with the highest *PI*; however, if more than one irrigation volume had the same *PI* then a water-efficient approach was taken and the optimal irrigation volume was the lowest quantitative volume that achieved the maximum *PI*. The irrigation volume was then calculated for each cell in order of the machine passing over the field (as per ILC and iterative hill climbing control).

### 8.1.4 Optimising day of next irrigation

The optimal day for the next irrigation event is determined using the calibrated model. This involves performing the irrigation volume optimisation of the previous step for an arbitrary number of days (a fixed horizon) and assumes that the irrigation event occurs on only one of the days. The length of the fixed horizon is specified by the user. However, the maximum horizon length was set to three days since three days of predictive weather were used.

The sixteen irrigation volumes tested on each cell depend on the irrigation day being tested because, unless rainfall occurs, the crop water requirement increases as each day passes. For the first day 0 to 15 mm were tested with increments of 1 mm; for the second day 0 to 31 mm were tested with increments of 2 mm; and for the third day 0 to 47 mm were tested with increments of 3 mm.

A $PI$ is calculated for each irrigation day by summing the individual $PI$ values for each cell. The day with the highest total $PI$ is taken to be the optimal day for the next irrigation event. An irrigation event is only scheduled if the irrigation day with the highest $PI$ has a minimum number of cells requiring irrigation to ensure that the irrigation system is practical and irrigations are not initiated for only a small number of cells in the field. The minimum number of cells requiring irrigation was arbitrarily selected to be 15% for the case studies presented. Hence, irrigation events were initiated if the first day in the horizon has the highest $PI$ and more than 15% of the cells require irrigation greater than 0 mm.

After the optimal irrigation action has been determined for the current day, the procedure described in this section is repeated every day throughout the crop season. The irrigation events end on a day specified by the user.

## 8.2 MPC case study: optimisation using daily input data

The MPC controller was evaluated with a range of data input combinations to determine which input data stream was most useful for MPC. Daily input data were used to predict and evaluate the response of the soil and/or crop to a range of irrigation volumes.

### 8.2.1 Methodology

As per the ILC controller simulations, the field was automatically divided into 44 cells, each of area approximately 0.3 ha, and the irrigations occurred daily. The MPC controller was evaluated for ten combinations of data input (Table 8.1). The input data combinations represent the data used both as input variables to calibrate the model and the variables used for control. For the simulations using both soil and plant data, the weighting on each variable was set to be 0.5. The strategies with soil data input aimed for soil moisture deficit equal to 10% of the plant available water capacity in each cell.

In a simulation, the reference model (to be calibrated) used the Siokra V16RR cotton variety with the underlying soil variability as set out in Figure 8.1. The measured crop response used the Sicot 73 cotton variety and soil variability map of Figure 5.1. Siokra V16RR is a Roundup Ready late maturing cotton variety, whilst Sicot 73 is a full season cotton variety with high yield potential (CSD 2009). The prediction horizon was one day and irrigation events could occur daily.

### 8.2.2 Results and discussion

Table 8.2 sets out the numerical results of the MPC case study, whilst Figure 8.2 illustrates the spatial variability of the yield for each simulation of the case study. The strategies that use weather-soil-and-plant data to calibrate and target a fixed soil mois-

Table 8.1: Simulations conducted to compare interactions between control strategies and input variables for Model Predictive Control

| ID # | Input variables for control | Weather data input | Irrigation calculation |
|---|---|---|---|
| Nil | Weather | N/A | N/A |
| 12 | Soil | Averaged SILO data | Target soil moisture deficit |
| 13 | Plant | Averaged SILO data | Maximise square/boll count |
| 14 | Weather AND soil | SILO data | Target soil moisture deficit |
| 15 | Weather AND plant | SILO data | Maximise square/boll count |
| 16 | Soil AND plant (A) | Averaged SILO data | Target soil moisture deficit and maximise square/boll count |
| 17 | Soil AND plant (B) | Averaged SILO data | Target soil moisture deficit |
| 18 | Soil AND plant (C) | Averaged SILO data | Maximise square/boll count |
| 19 | Weather AND soil AND plant (A) | SILO data | Target soil moisture deficit and maximise square/boll count |
| 20 | Weather AND soil AND plant (B) | SILO data | Target soil moisture deficit |
| 21 | Weather AND soil AND plant (C) | SILO data | Maximise square/boll count |

ture (simulation #20) and maximise square count (simulation #21), are also compared using the simulated soil moisture deficit (Figure 8.3) and square count (Figure 8.4) throughout the crop season.

The simulated yield and water use efficiency increased as more data streams were included in the input data combination. This is shown in Table 8.2 as the single-input simulations produced the lowest yields and water use efficiencies (simulations #12 and #13) while the simulations with three data inputs (simulations #19-#21) performed better

Table 8.2: Performance of the model predictive control strategy with variable-rate irrigation machine for different input data combinations (yield maps of simulations #12-#21 are in Figure 8.2)

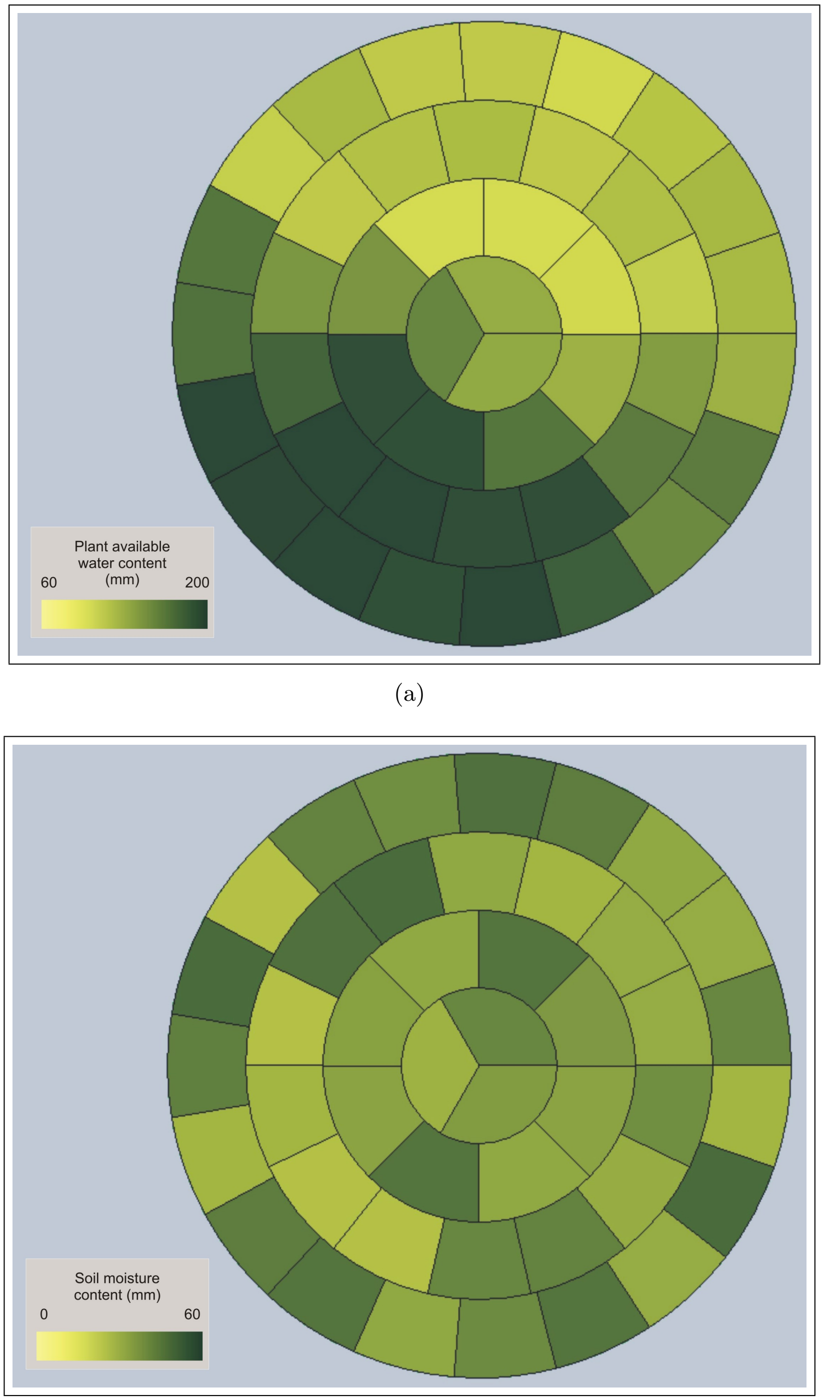
| **ID #** | **Input variable for control** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ $\mathbf{ML}_{total}$)** | **IWUI (bales/ $\mathbf{ML}_{irrigated}$)** |
|---|---|---|---|---|---|---|
| 12 | Soil | 5.2 ± 2.4 | 9.4 | 6.4 | 0.5 | 0.8 |
| 13 | Plant | 2.9 ± 2.1 | 4.6 | 1.5 | 0.6 | 1.9 |
| 14 | Weather AND soil | 7.4 ± 1.5 | 9.2 | 6.2 | 0.8 | 1.2 |
| 15 | Weather AND plant | 6.4 ± 1.0 | 5.3 | 2.2 | 1.2 | 2.9 |
| 16 | Soil AND plant (A) | 7.8 ± 1.9 | 8.8 | 5.7 | 0.9 | 1.4 |
| 17 | Soil AND plant (B) | 7.3 ± 2.1 | 9.5 | 6.4 | 0.8 | 1.1 |
| 18 | Soil AND plant (C) | 8.2 ± 2.7 | 9.0 | 5.9 | 0.9 | 1.4 |
| 19 | Weather AND soil AND plant (A) | 10.8 ± 1.6 | 8.8 | 5.7 | 1.2 | 1.9 |
| 20 | Weather AND soil AND plant (B) | 10.6 ± 1.9 | 10.2 | 7.1 | 1.0 | 1.5 |
| 21 | Weather AND soil AND plant (C) | 12.1 ± 0.7 | 9.4 | 6.3 | 1.3 | 1.9 |

than the simulations with two data inputs (simulations #14-#18).

The data combinations with soil data and no plant data (simulations #12 and #14) resulted in higher yields than those with plant data and no soil data (simulations #13 and #15). Hence, if only one data input is available then soil data input is most effective for calibrating the model and for irrigation control. The simulations using combinations of soil and plant data input to determine the irrigation volumes (simulations #16 and #19) generally produced lower yields and water use efficiencies than those using only plant data input to determine the irrigation volumes (simulations #18 and #21) with the same data available for model calibration. For example, for the strategies with soil and plant data available to calibrate the model, a higher yield was simulated when the strategy maximised the square count (simulation #18) than when the strategy attempted to both maintain soil moisture and maximised square count (simulation #16). Hence, in this case there was no benefit in the using multiple variables to determine the application volumes.

The MPC controller accurately maintained the soil moisture deficit during low rainfall periods of the crop season for simulation #20 (63 to 85 days after sowing, Figure 8.3(a)). For the MPC controller that maximised square count (simulation #21), the soil moisture deficit was always higher than the soil moisture deficit that was approximately maintained in simulation #20 throughout the crop season (Figure 8.3(b)). The soil moisture deficit was also lowest in the sand cell (with the lowest plant available water capacity) and highest in the clay cell (with the highest plant available water capacity) throughout the crop season for the strategy optimising square count. This indicates that to maximise the square count, the soil moisture deficit should be reduced in proportion with the plant available water capacity of the soil.

The highest yield was achieved using weather-soil-and-plant input and maximising square count (simulation #21). The square count was higher throughout the crop season for this simulation compared with that for MPC maintaining soil moisture deficit (simulation #20) (Figure 8.4). Hence, the implemented MPC controller successfully increased the simulated square count and improvements in yield (by 14%) and crop water use efficiency (by 30%) were observed by maximising square count instead of maintaining soil moisture deficit.




(a)

(b)

Figure 8.1: Soil variability used for model that is calibrated in model predictive control system: (a) plant available water capacity; and (b) soil moisture content on sowing date

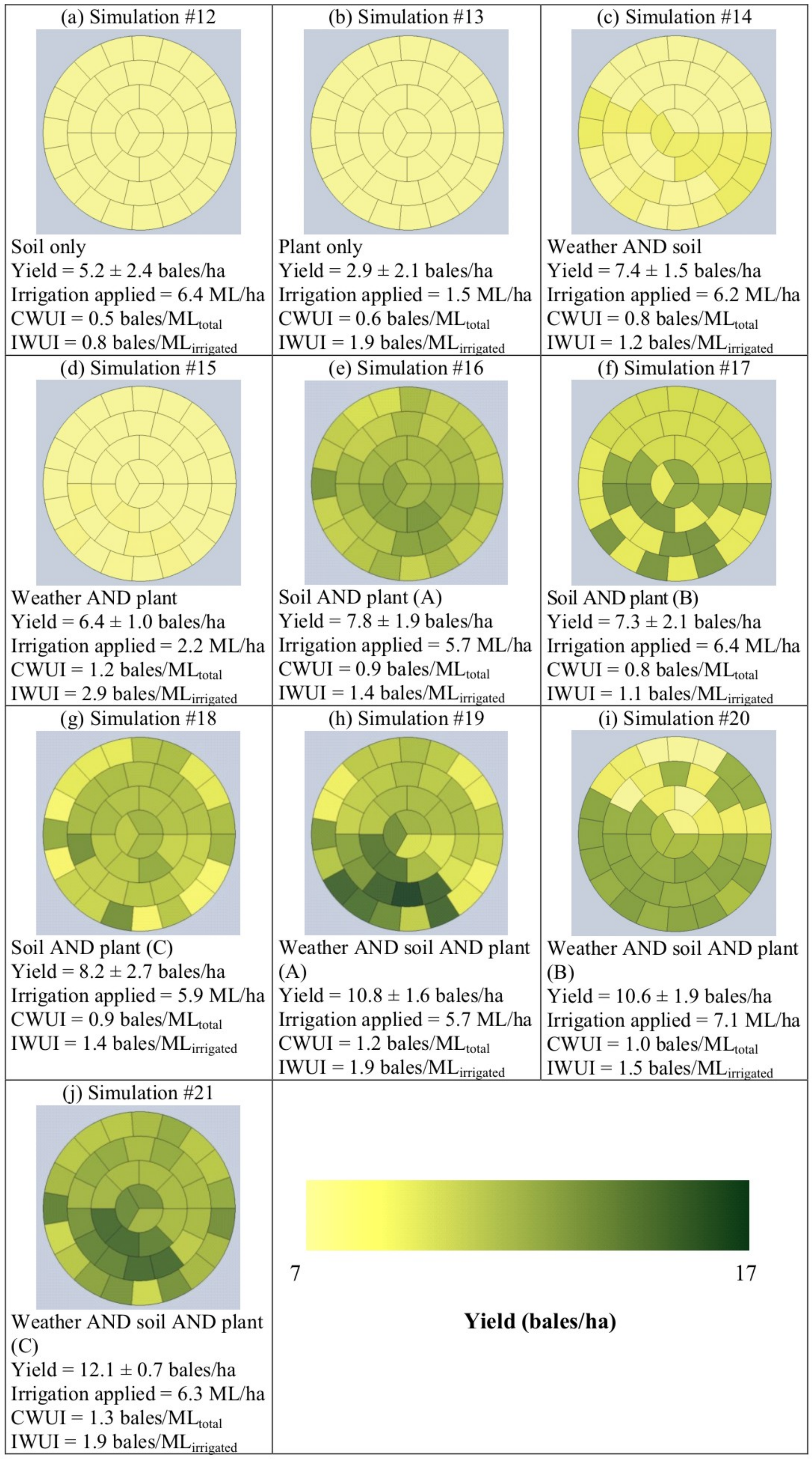
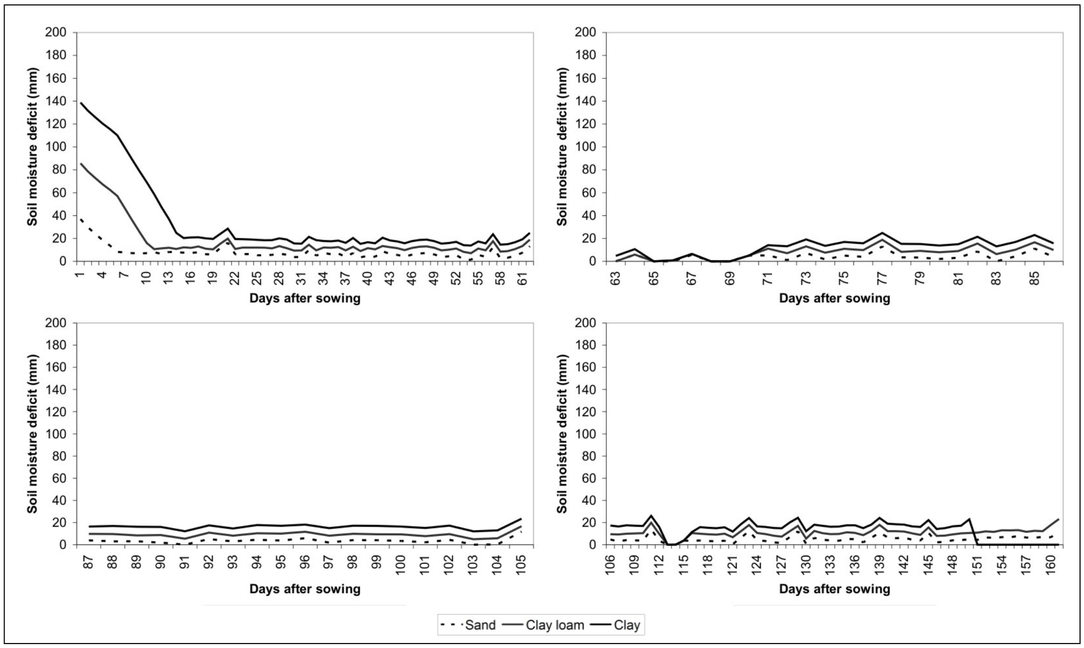
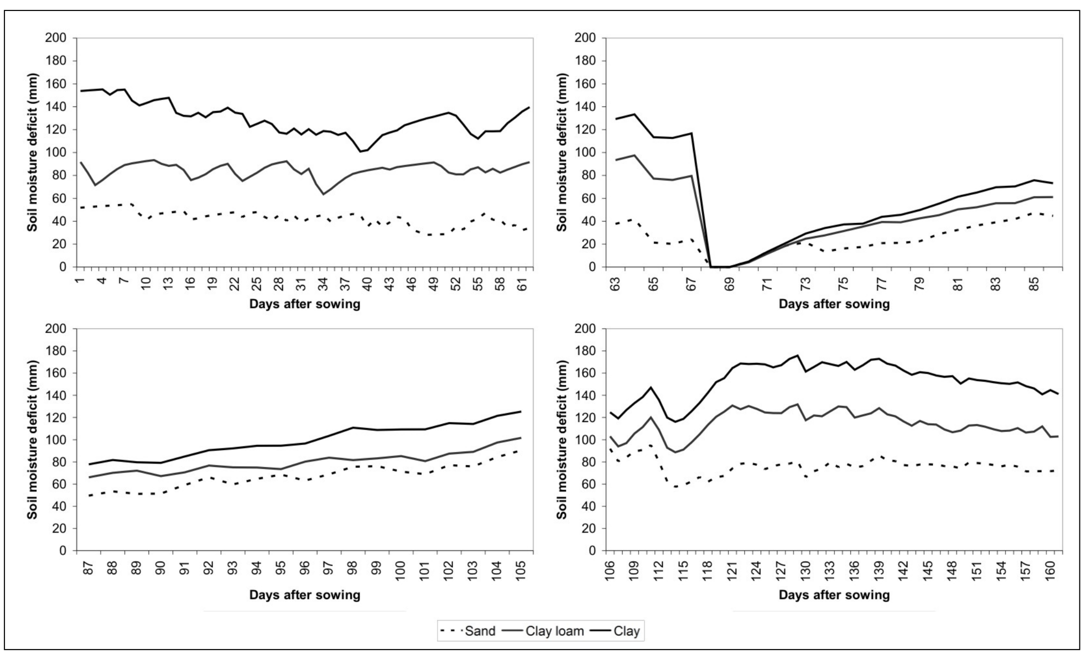



Figure 8.2: Yield output of model predictive control strategy for different combinations of data input and legend for yield maps (numerical data for simulations #12-#21 are in Table 8.2)

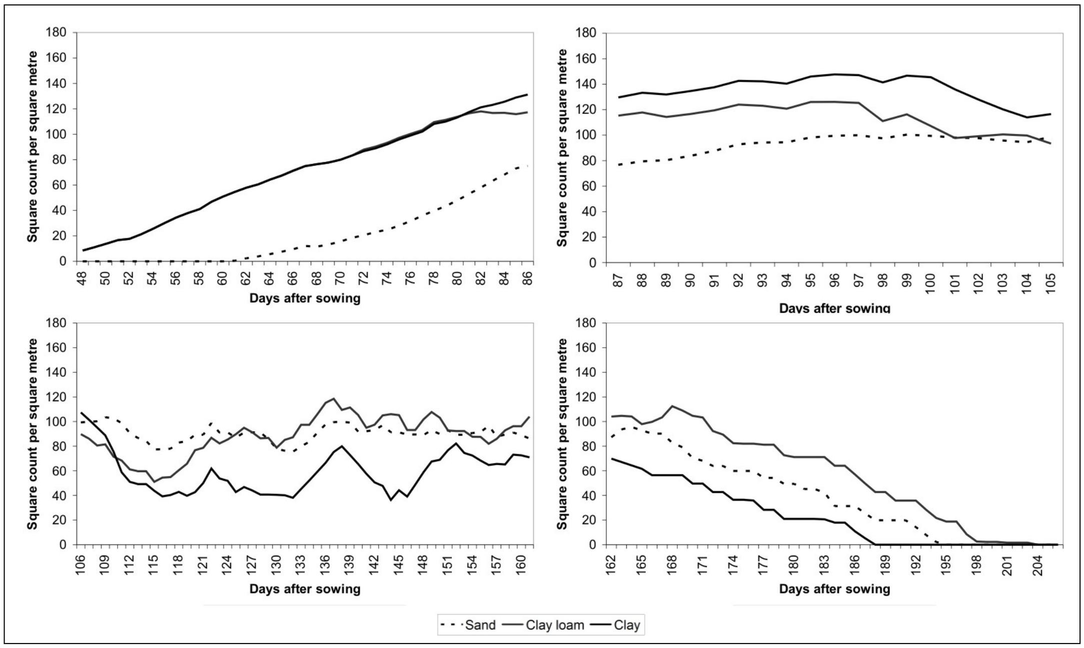



(a)

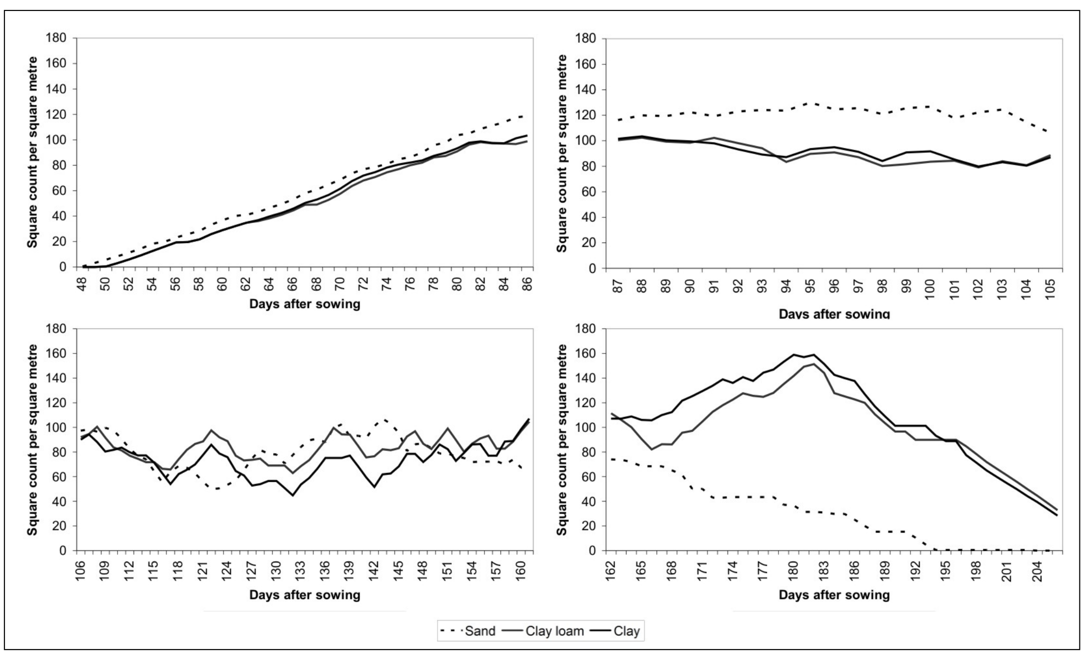



(b)

Figure 8.3: Simulated daily soil moisture deficit in sand, clay loam and clay cells for strategies that use weather, soil and plant data for model calibration and: (a) target soil moisture deficit (simulation #20); and (b) maximise square count (simulation #21)




(a)




(b)

Figure 8.4: Simulated daily square count in sand, clay loam and clay cells for strategies that use weather, soil and plant data for model calibration and: (a) target soil moisture deficit (simulation #20); and (b) maximise square count (simulation #21)

## 8.3 MPC case study: optimisation using final data

The MPC controller uses a calibrated crop model to forecast the state of the system; hence, the irrigation volume/timing may be adjusted to achieve a desired output, in this case a final yield or water use efficiency. This is in contrast to the case study of the previous section in which the MPC controller used daily input data (e.g. square count, soil moisture content) to predict the best response to a range of irrigation volumes.

### 8.3.1 Methodology

For a simulation, the field was automatically divided into 44 cells as per the previous case study and the irrigations could occur daily. The MPC controller was evaluated for crop seasons with and without rainfall and with two levels of initial nitrogen content (120 kg/ha and 250 kg/ha). The same weather dataset was used for both these sets of simulations. However, in one treatment the rainfall was set to zero while in the other treatments there was high rainfall during days 63 to 85 after sowing.

The MPC controller was used to optimise the predicted Irrigation Water Use Index (IWUI), Crop Water Use Index (CWUI) and yield assuming the machine capacity enabled the machine to traverse the field once every day. An algorithm maximising IWUI or CWUI may decide to apply no irrigation to minimise the irrigation volume but would also produce low yield. Hence, to ensure that the IWUI and CWUI optimisation would irrigate the crop, the minimum acceptable yield was arbitrarily set at 5 bales/ha in all optimisations. The soil moisture content across the field on the day of sowing was assumed to be 50 mm.

### 8.3.2 Results and discussion

The simulation results are displayed in Table 8.3 and Figure 8.5 and the irrigation volumes applied are compared with different in-season rainfall and starting nitrogen content at commencement (Figure 8.6 and Figure 8.7, respectively).

Table 8.3: Performance of the model predictive control strategy with variable-rate irrigation machine for different weather data inputs, starting nitrogen contents and optimised variables (yield maps of simulations #22-#31 are in Figure 8.5)

| ID # | Optimised variable | Rainfall (mm) | Initial nitrogen content (kg/ha) | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|---|---|
| 22 | Yield | 0 | 120 | $9.0 \pm 0.4$ | 6.8 | 6.8 | 1.3 | 1.3 |
| 23 | CWUI/ IWUI | 0 | 120 | $8.4 \pm 0.6$ | 5.2 | 5.2 | 1.6 | 1.6 |
| 24 | Yield | 0 | 250 | $17.9 \pm 0.9$ | 6.6 | 6.6 | 2.7 | 2.7 |
| 25 | CWUI/ IWUI | 0 | 250 | $17.3 \pm 1.2$ | 6.5 | 6.5 | 2.7 | 2.7 |
| 26 | Yield | 302 | 120 | $8.4 \pm 0.4$ | 9.0 | 5.9 | 0.9 | 1.4 |
| 27 | CWUI | 302 | 120 | $8.4 \pm 0.6$ | 8.1 | 5.0 | 1.0 | 1.7 |
| 28 | IWUI | 302 | 120 | $7.7 \pm 0.5$ | 7.5 | 4.4 | 1.0 | 1.8 |
| 29 | Yield | 302 | 250 | $14.3 \pm 0.5$ | 9.3 | 6.2 | 1.5 | 2.3 |
| 30 | CWUI | 302 | 250 | $13.3 \pm 1.0$ | 7.8 | 4.7 | 1.7 | 2.8 |
| 31 | IWUI | 302 | 250 | $12.5 \pm 0.3$ | 7.3 | 4.2 | 1.7 | 3.0 |

For each set of field conditions (i.e. starting nitrogen content and in-season rainfall), the simulated yield was highest for the MPC strategy that optimised yield (simulations #22, #24, #26 and #29). Similarly, the strategies optimising IWUI (simulations #28 and #31) and CWUI (simulations #27 and #40) produced the highest respective IWUI and CWUI of the simulations with the same field conditions. This indicates that MPC control strategy could adjust the irrigation application to improve either yield or water use efficiency.

Increasing the starting nitrogen content significantly improved the simulated yield and water use efficiency. This is shown in Table 8.3 as the yield for the no-rainfall simulation with the higher nitrogen content of 250 kg N/ha (e.g. 17.9 bales/ha for simulation #24) was nearly double that of the simulation with the lower nitrogen content of 120 kg N/ha (e.g. 9.0 bales/ha for simulation #22). Since the irrigation volumes applied were similar for these two simulations (Figure 8.7), the CWUI and IWUI of the higher nitrogen content simulations were also nearly double that of the lower nitrogen content simulations. Hence, nitrogen application had a significant effect on the final yield without greatly affecting the irrigation volume required to be applied.

Rainfall significantly affected the simulated yield and CWUI (Table 8.3). Table 8.3 shows that the yields, irrigation applications and CWUI of simulations #22-#25 (without rainfall) are higher than those of simulations #26-#31 (with rainfall). This suggests that the crop is easier to control with less rainfall in the season. The difference in yield and CWUI is most noticeable for simulations with high nitrogen content (e.g. simulation #29 with rainfall and simulation #24 without rainfall) because the simulated yields are higher and the differences between the yields are more apparent. It follows that during the period of the crop season with high rainfall (63 to 86 days after sowing), lower irrigation volumes were applied compared to the periods of no rainfall (87 to 105 days after sowing) (Figure 8.6).

The rainfall did not generally affect the IWUI for the simulated set of field conditions (e.g. simulation #22 with no rainfall and simulation #26 with rainfall). This is because more rainfall caused both the yield and irrigation application (which are used to calculate the IWUI) to increase by approximately the same proportion; hence, any effect of the rainfall was essentially cancelled.

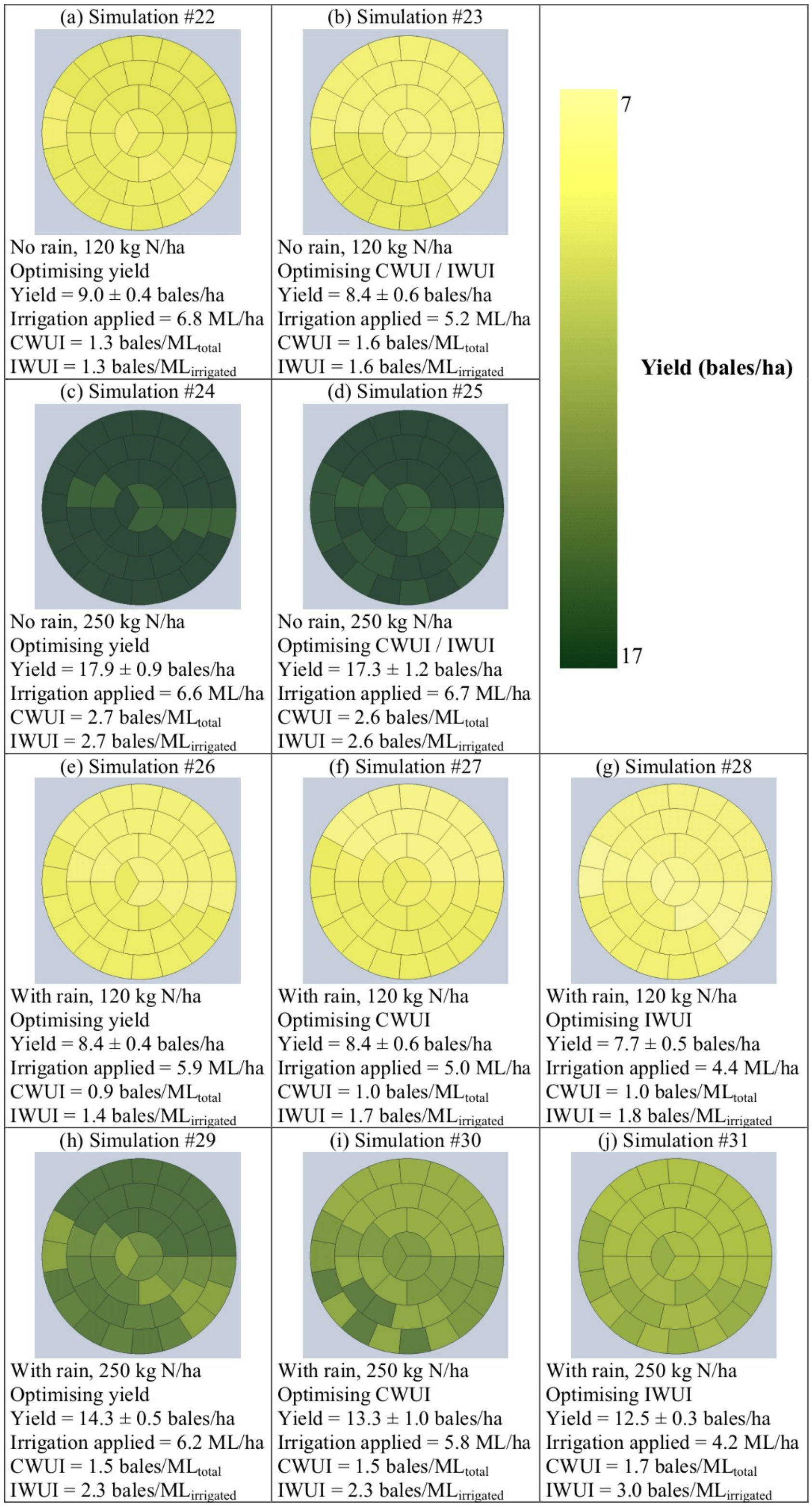
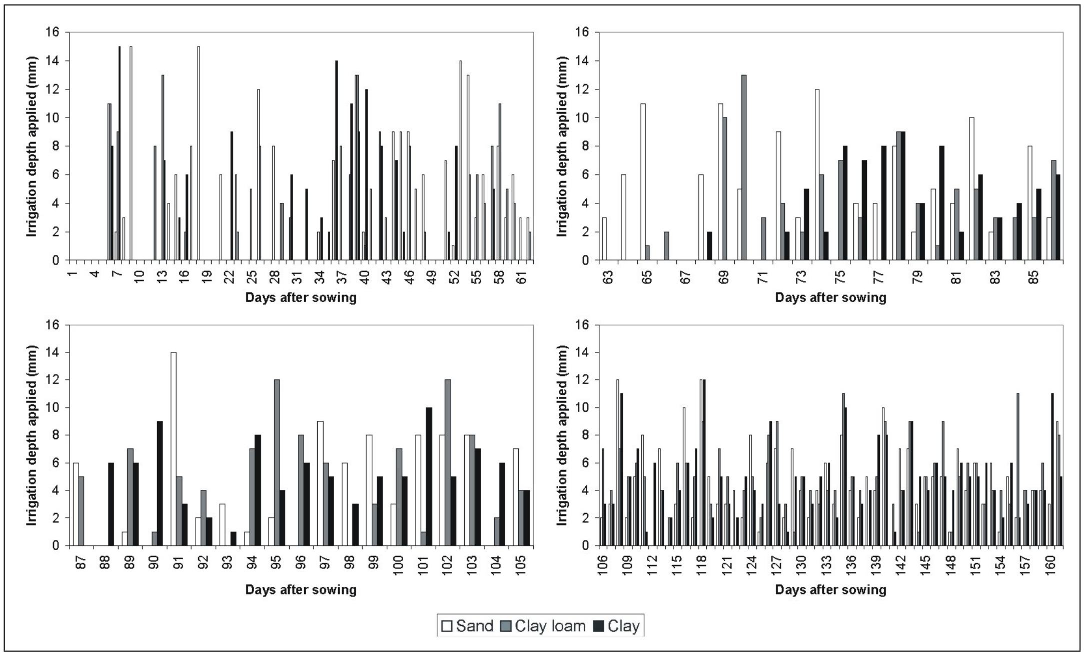
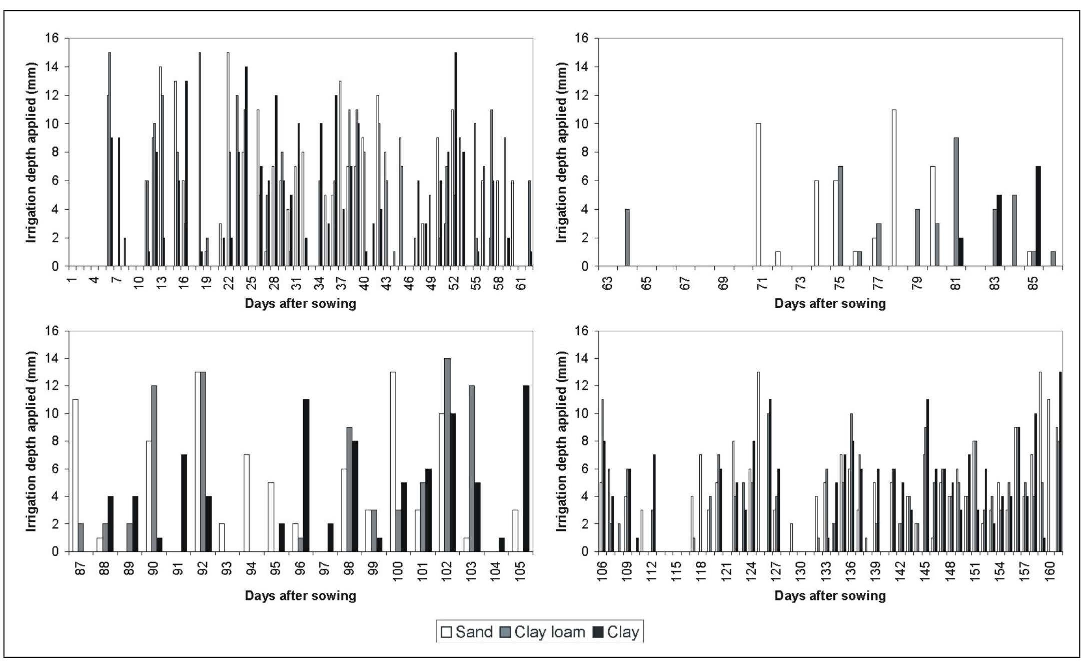



Figure 8.5: Yield output of model predictive control strategy with variable-rate irrigation machine and legend for yield maps (numerical data for simulations #22-#31 are in Table 8.3)

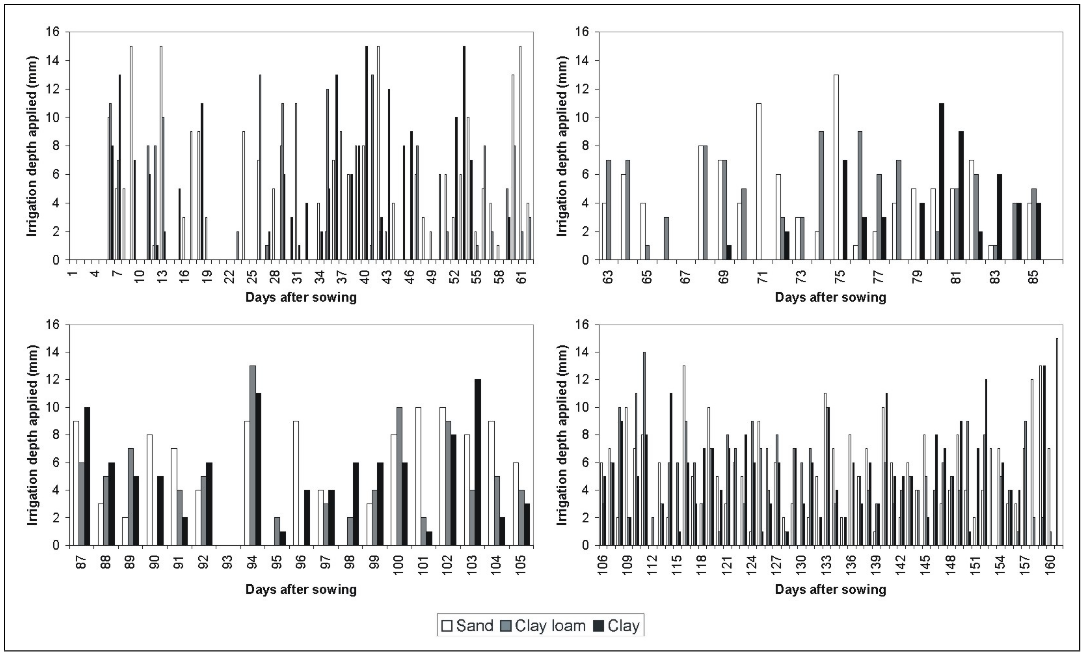



(a)

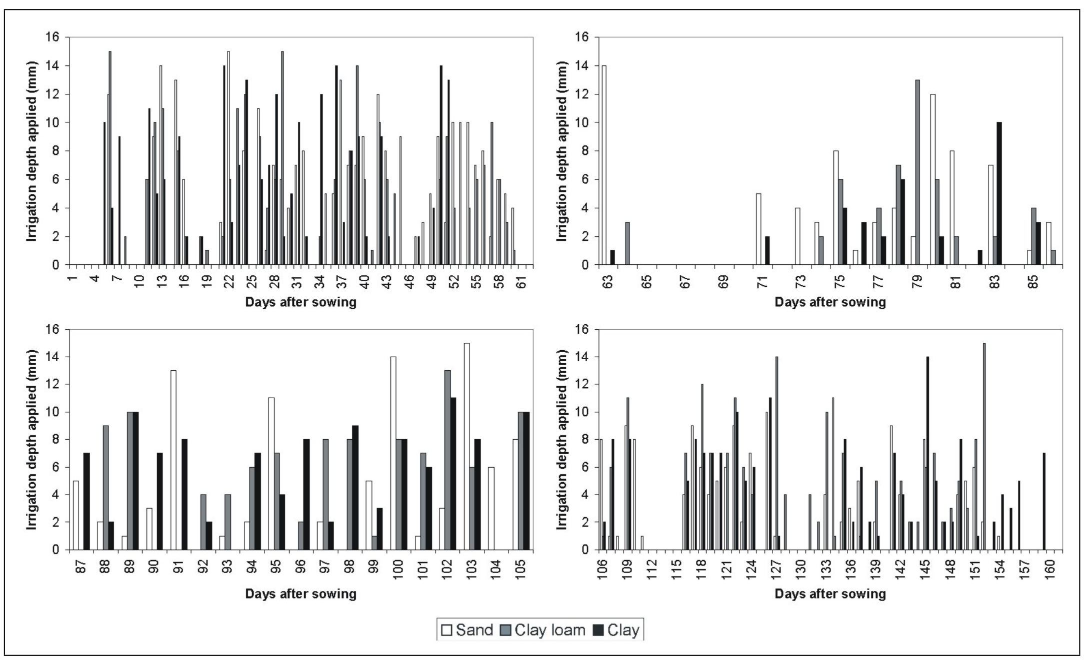



(b)

Figure 8.6: Irrigation volumes applied to sand, clay loam and clay cells for simulations #25 and #28 to evaluate effect of rainfall during crop season; the model predictive controller optimised IWUI with 250 kg/ha of available nitrogen and for crop season with: (a) no rainfall; and (b) 302 mm of rainfall as per Figure 5.2




(a)




(b)

Figure 8.7: Irrigation volumes applied to sand, clay loam and clay cells for simulations #26 and #29 to evaluate effect of nitrogen content; the model predictive controller optimised yield for crop season with no rainfall and available nitrogen of: (a) 120 kg/ha; and (b) 250 kg/ha

## 8.4 MPC case study: optimisation using final data, with limited calibration data

The MPC simulations of the previous section assumed that the full data input of weather, soil and plant information was available for model calibration; however, all three data streams may not be available in a field implementation. This section reports a case study to evaluate the usefulness of different data streams to calibrate the model in a MPC controller.

### 8.4.1 Methodology

The seven possible data combinations (Table 8.2) were separately evaluated as data input for model calibration. The datasets were obtained daily from the cotton model Sicot 71B and used to calibrate the Siokra V16RR cotton model. The field was divided into 44 cells, the MPC controller optimised yield and the irrigations occurred daily.

### 8.4.2 Results and discussion

Table 8.4 and Figure 8.5 set out a comparison of an MPC strategy that maximises yield with different combinations of input data to calibrate the model. The use of more information in the input data combination generally increased the average yield and water use efficiency (Table 8.4). Table 8.4 shows that MPC performance with all three input variables (simulation #29) was superior to that with any two variables (simulations #35-#37); and similarly performance with two input variables was superior to that with any single input variable alone, except plant input (simulation #34) versus soil-and-plant input (simulation #37). This suggests that the MPC calibration performs better with soil data input than plant data input.

The lowest yields and water use efficiencies were simulated with no weather data input (e.g. simulations #33 and #34). This indicates that for irrigation of cotton in this situation MPC is most sensitive to weather data input. The crop and irrigation water use efficiencies were higher using the weather and plant combination (simulation #36) than using the full data input (simulation #29): this is because the yield was maximised rather than the water use efficiency.

Table 8.4: Performance of the model predictive control strategy optimising yield for crop season with rainfall and 250 kg/ha of available nitrogen for different input data combinations (yield maps of simulations #32-#37 are in Figure 8.8)

| **ID #** | **Input variable for control** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ ML$_{total}$)** | **IWUI (bales/ ML$_{irrigated}$)** |
|---|---|---|---|---|---|---|
| 32 | Weather | 5.6 ± 1.1 | 9.9 | 7.2 | 0.6 | 0.8 |
| 33 | Soil | 9.1 ± 1.0 | 9.0 | 5.9 | 1.0 | 1.5 |
| 34 | Plant | 10.0 ± 1.3 | 9.2 | 6.0 | 1.1 | 1.7 |
| 35 | Weather AND soil | 12.2 ± 1.7 | 8.3 | 5.2 | 1.5 | 2.3 |
| 36 | Weather AND plant | 12.4 ± 1.4 | 8.1 | 5.0 | 1.5 | 2.5 |
| 37 | Soil AND plant | 9.4 ± 0.8 | 9.2 | 6.0 | 1.0 | 1.5 |
| 29 | Weather AND soil AND plant | 14.3 ± 0.5 | 9.3 | 6.2 | 1.5 | 2.3 |

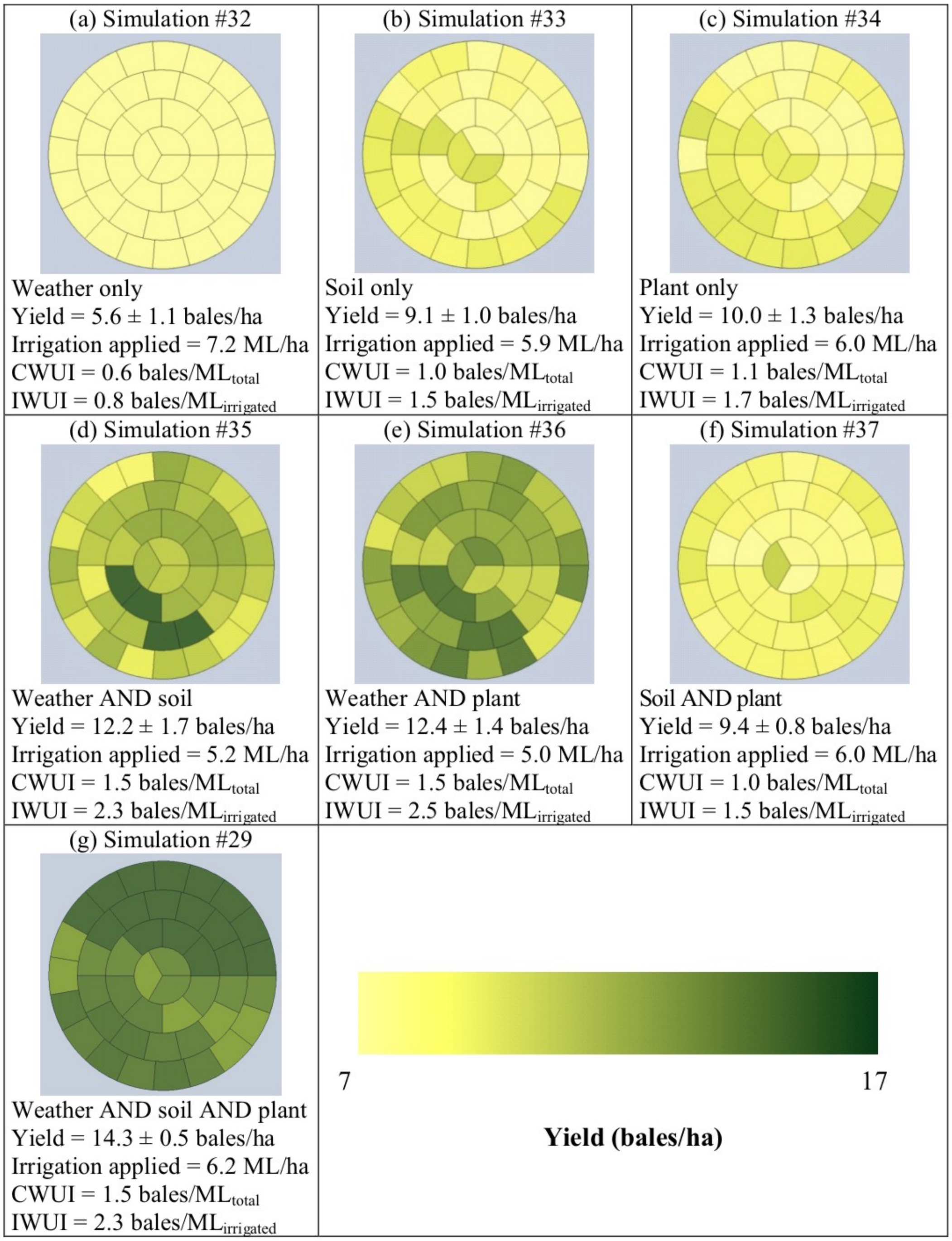



Figure 8.8: Yield output of model predictive control strategy with variable-rate irrigation machine and legend for yield maps (numerical data for simulations #32-#37 are in Table 8.4)

## 8.5 Irrigation conclusions

A model predictive controller was successfully implemented in VARIwise. The controller involved using the currently available field data to calibrate the OZCOT cotton model, evaluating a range of irrigation volumes and timings in each cell with the calibrated model and then implementing the irrigation decision with the highest water use efficiency or yield. Three alternative optimisation possibilities were identified and explored, and the conclusions for each, and their comparison, are in the following sections. For convenience, Table 8.5 gathers together the particular simulation outputs referred to in this section.

### 8.5.1 Optimisation on daily input data

The MPC controller was evaluated with different combinations of input data (Section 8.2). The predicted yield and water use efficiency were highest when the strategy maximised the square count and calibrated the model using all three streams of data input (weather, soil and plant, simulation #21). The yield and water use efficiency were also higher than those of the fixed irrigation strategy (first row of Table 8.5 and Section 5.5), ILC controller (simulation #1) and iterative hill climbing controller (simulation #9) with either weather-soil-and-plant, weather-and-soil or weather-and-plant data input available. However, the MPC (optimising daily input data) performed worse than the ILC and iterative hill climbing controllers where there was only either soil input (simulation #12) or weather-and-plant (simulation #15) input data available.

### 8.5.2 Optimisation on final data

The controller successfully adjusted the irrigation to improve the yield, CWUI or IWUI, as appropriate (Section 8.3). The yield was higher with high nitrogen content (e.g. simulation #29) than with low nitrogen content (simulation #26) and with no rainfall during the crop season (simulation #24) compared with high rainfall (simulation #29).

This is because the control strategy could better control the water applied in response to the other environmental factors. The simulated average yields and water use efficiencies were significantly higher than the fixed irrigation strategy, ILC controller (simulation #1) and iterative hill climbing controller (simulation #9).

Table 8.5: Control strategy simulation outputs referred to in this section where the initial nitrogen content is 250 kg/ha and there is rainfall during the crop season unless otherwise noted

| **ID #** | **Control strategy** | **Input variable for control** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ $ML_{total}$)** | **IWUI (bales/ $ML_{irrigated}$)** |
|---|---|---|---|---|---|---|---|
| N/A | Fixed | Nil | 6.2 ± 2.1 | 7.2 | 4.1 | 0.9 | 1.5 |
| 1 | ILC | Soil | 10.7 ± 1.7 | 9.9 | 6.5 | 1.1 | 1.6 |
| 9 | Iterative hill climbing control | Weather AND plant | 10.9 ± 1.5 | 10.2 | 7.2 | 1.0 | 1.5 |
| 12 | MPC (daily input) | Soil | 5.2 ± 2.4 | 9.4 | 6.4 | 0.5 | 0.8 |
| 15 | MPC (daily input) | Weather AND plant | 6.4 ± 1.0 | 5.3 | 2.2 | 1.2 | 2.9 |
| 21 | MPC (daily input) | Weather AND soil AND plant | 12.1 ± 0.7 | 9.4 | 6.3 | 1.3 | 1.9 |
| 24 | MPC (end of season input)[1] | Weather AND soil AND plant | 17.9 ± 0.9 | 6.6 | 6.6 | 2.7 | 2.7 |
| 26 | MPC (end of season input)[2] | Weather AND soil AND plant | 8.4 ± 0.4 | 9.0 | 5.9 | 0.9 | 1.4 |
| 29 | MPC (end of season input) | Weather AND soil AND plant | 14.3 ± 0.5 | 9.3 | 6.2 | 1.5 | 2.3 |
| 35 | MPC (end of season input) | Weather AND soil | 12.2 ± 1.7 | 8.3 | 5.2 | 1.5 | 2.3 |
| 36 | MPC (end of season input) | Weather AND plant | 12.4 ± 1.4 | 8.1 | 5.0 | 1.5 | 2.5 |

[1]Crop season has no rainfall

[2]Initial nitrogen content is 120 kg/ha

### 8.5.3 Optimisation on final data, with limited calibration data

MPC was evaluated with different combinations of input data available to calibrate the model (Section 8.4). The controller performed best with input of weather-soil-and-plant data (simulation #29), but still produced higher yields and water use efficiencies with weather-and-soil (simulation #35) or weather-and-plant (simulation #36) input than the fixed irrigation strategy, and ILC (simulation #1) and iterative hill climbing control (simulation #9) case studies.

### 8.5.4 Comparison of optimisation alternatives

Higher yields and water use efficiencies were produced for MPC optimising end of season data (simulation #29) than for MPC using daily input data to maximise square count (simulation #21). However, both of these controllers required minimum data input of either the full data input, weather-and-soil or weather-and-plant data input to maintain yields higher than the ILC or iterative hill climbing controllers.

# Chapter 9

# Evaluation of Adaptive Control Strategies in VARIwise

## 9.1 Overview

The three adaptive control strategies implemented in VARIwise, namely iterative learning control (ILC), iterative hill climbing control and model predictive control (MPC), were developed to be robust to temporal data gaps (by using a lower data hierarchy) and spatial data gaps (by estimating the response using spatial interpolation of the available data points). Unmeasured infield variability may also be estimated using other data sources in the field, for example, rainfall volumes could be estimated using the change in soil moisture content. Irrigation machine capacity constraints would reduce the maximum volume of irrigation applied by an irrigation machine in one day: this could change the irrigation timing and volumes required to keep up with the crop water requirements. The three control strategies have different characteristics for spatial discrimination of irrigation application and irrigation event initiation; hence, the method utilised to deal with these limitations depends on the control strategy.

The control strategies were evaluated in VARIwise with respect to spatial and temporal input data resolution and irrigation machine capacities. Three spatial and temporal input resolutions, two distributions of spatially variable rainfall, and three irrigation machine capacities were simulated in VARIwise for each adaptive control strategy as set out in Table 5.1 and reproduced here as Table 9.1. This enabled interactions between the control strategy characteristics and the data and irrigation input requirements to be determined.

Table 9.1: Simulations conducted with each control strategy to compare interactions between control strategies and sensor and irrigation machine restrictions

<table>
<tr><th>Section</th><th>Evaluated feature</th><th>Input variable for control</th><th>Method of data input usage</th></tr>
<tr><td rowspan="3">9.2</td><td rowspan="3">Spatial resolution of input data</td><td>One point</td><td>Use input data for one point over field</td></tr>
<tr><td>Three points</td><td rowspan="2">Use input data kriged for each cell</td></tr>
<tr><td>Ten points</td></tr>
<tr><td rowspan="3">9.3</td><td rowspan="3">Spatial variability of rainfall</td><td>No variation</td><td>Use constant rainfall in each cell</td></tr>
<tr><td>±20% variation</td><td rowspan="2">Use rainfall with random variability imposed in each cell</td></tr>
<tr><td>±50% variation</td></tr>
<tr><td rowspan="3">9.4</td><td rowspan="3">Temporal resolution of input data</td><td>Fifteen days</td><td rowspan="3">Use input data combination that is lower in data hierarchy than current combination</td></tr>
<tr><td>Six days</td></tr>
<tr><td>Three days</td></tr>
<tr><td rowspan="3">9.5</td><td rowspan="3">Irrigation machine capacity</td><td>5 mm/day</td><td rowspan="3">Limit daily irrigation machine application</td></tr>
<tr><td>10 mm/day</td></tr>
<tr><td>15 mm/day</td></tr>
</table>

The control strategies were evaluated with the agronomic factors of Table 5.2, and each with only one data input combination for feedback. The data input combinations used were selected based on the case studies presented in Chapters 6, 7 and 8 which compared each strategy with different combinations of input data. From these case studies, the optimal data input combination for the ILC, iterative hill climbing and MPC controllers were soil moisture deficit, weather-and-plant data and weather-soil-and-plant data, respectively, for the field conditions simulated.

## 9.2 Spatial resolution of input data

In a real-time field implementation of an irrigation control strategy, measured field data may not be available for each cell in the field. Simulations of the three adaptive irrigation control strategies were compared for this case study with data available at only particular points in the field.

### 9.2.1 Methodology

Simulations using three different spatial resolutions of input data were conducted in VARIwise, represented by having data available at one, three or ten cells in the field, respectively. For ILC, soil moisture was available for these cells; for iterative hill climbing control, plant information (square count) was available for these cells; whilst for MPC, soil moisture and plant information (leaf area index, square count and boll count) were available for these cells. Ten replicates at each spatial resolution have been simulated, in each case with the cells selected randomly across the field, i.e. thirty simulations for each of the three control strategies.

### 9.2.2 Results and discussion

Tables 9.2, 9.3 and 9.4 show the average and standard deviation of the simulated outputs for ten replications of simulations and the simulation with input from all sampling points. Within columns *across all three tables* the use of matching superscripts ($a$, $b$, ... $l$) indicates no significant difference (at the 95% significance level) within the replications.

The tables also show the average and standard error of each set of simulations for each different number of sampling points (rows with 'Average'); and within the *columns* the use of matching uppercase superscripts ($A$, $B$, ... $F$) indicates no significant difference (at the 95% significance level) between the sets of replications.

#### 9.2.2.1 Iterative learning controller performance

Table 9.2: Performance of the iterative learning control strategy with different numbers of sampling points

| **ID #** | **Number of sampling points** | **Rep** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ $\mathbf{ML}_{total}$)** | **IWUI (bales/ $\mathbf{ML}_{irrigated}$)** |
|---|---|---|---|---|---|---|---|
| 38 | | 1 | $10.9 \pm 1.1^a$ | 10.0 | $7.0^a$ | $1.09^a$ | 1.56 |
| 39 | | 2 | $10.3 \pm 1.5^a$ | 11.1 | $8.0^b$ | $0.93^b$ | 1.28 |
| 40 | | 3 | $11.1 \pm 0.9^b$ | 9.1 | $6.0^c$ | $1.22^c$ | 1.84 |
| 41 | | 4 | $9.3 \pm 1.9^c$ | 11.7 | $8.6^d$ | $0.80^d$ | 1.08 |
| 42 | One | 5 | $10.9 \pm 1.3^a$ | 10.0 | $6.9^a$ | $1.09^a$ | 1.57 |
| 43 | | 6 | $8.3 \pm 1.7^d$ | 12.7 | $9.5^e$ | $0.66^e$ | 0.87 |
| 44 | | 7 | $10.6 \pm 1.0^a$ | 9.8 | $6.7^a$ | $1.08^a$ | 1.59 |
| 45 | | 8 | $9.6 \pm 1.4^c$ | 11.4 | $8.4^d$ | $0.84^d$ | 1.15 |
| 46 | | 9 | $10.2 \pm 1.5^a$ | 11.5 | $8.4^d$ | $0.88^b$ | 1.21 |
| 47 | | 10 | $10.7 \pm 1.4^a$ | 11.1 | $8.0^b$ | $0.97^b$ | 1.33 |
| Nil | | Average | $10.2 \pm 0.3^A$ | $10.8 \pm 0.3$ | $7.8 \pm 0.3^A$ | $0.98 \pm 0.05^A$ | $1.36 \pm 0.09$ |
| 48 | | 1 | $11.2 \pm 0.9^b$ | 9.2 | $6.1^c$ | $1.21^c$ | 1.83 |
| 49 | | 2 | $10.5 \pm 0.8^a$ | 9.9 | $6.9^a$ | $1.06^a$ | 1.52 |
| 50 | | 3 | $10.5 \pm 1.0^a$ | 11.1 | $8.0^b$ | $0.95^b$ | 1.32 |
| 51 | | 4 | $10.7 \pm 1.7^a$ | 10.4 | $7.3^a$ | $1.03^a$ | 1.46 |
| 52 | | 5 | $10.4 \pm 0.7^a$ | 8.8 | $5.7^f$ | $1.19^f$ | 1.84 |
| 53 | Three | 6 | $10.4 \pm 0.7^a$ | 8.8 | $5.7^f$ | $1.19^f$ | 1.84 |
| 54 | | 7 | $10.4 \pm 0.7^a$ | 8.8 | $5.7^f$ | $1.19^f$ | 1.84 |
| 55 | | 8 | $11.2 \pm 0.9^e$ | 9.2 | $6.1^c$ | $1.21^f$ | 1.83 |
| 56 | | 9 | $10.4 \pm 0.7^a$ | 8.8 | $5.7^f$ | $1.19^f$ | 1.84 |
| 57 | | 10 | $10.7 \pm 1.7^a$ | 10.4 | $7.3^a$ | $1.03^a$ | 1.46 |
| Nil | | Average | $10.7 \pm 0.1^B$ | $9.5 \pm 0.2$ | $6.4 \pm 0.2^B$ | $1.12 \pm 0.03^B$ | $1.63 \pm 0.07$ |
| 58 | | 1 | $10.3 \pm 1.5^a$ | 10.4 | $7.3^a$ | $0.99^a$ | 1.41 |
| 59 | | 2 | $10.4 \pm 1.5^a$ | 10.5 | $7.5^a$ | $0.99^a$ | 1.39 |
| 60 | | 3 | $10.8 \pm 1.0^a$ | 9.9 | $6.8^a$ | $1.09^a$ | 1.60 |
| 61 | | 4 | $11.0 \pm 1.0^b$ | 9.8 | $6.7^a$ | $1.12^a$ | 1.65 |
| 62 | Ten | 5 | $11.0 \pm 1.0^b$ | 9.8 | $6.7^a$ | $1.12^a$ | 1.65 |
| 63 | | 6 | $10.6 \pm 1.3^a$ | 10.6 | $7.5^g$ | $1.00^a$ | 1.42 |
| 64 | | 7 | $11.1 \pm 1.1^b$ | 9.7 | $6.7^a$ | $1.14^a$ | 1.66 |
| 65 | | 8 | $10.9 \pm 1.2^a$ | 9.9 | $6.8^a$ | $1.10^a$ | 1.59 |
| 66 | | 9 | $10.8 \pm 1.0^a$ | 9.9 | $6.8^a$ | $1.09^a$ | 1.60 |
| 67 | | 10 | $11.3 \pm 1.2^b$ | 9.7 | $6.6^a$ | $1.16^f$ | 1.71 |
| Nil | | Average | $10.8 \pm 0.1^B$ | $10.0 \pm 0.1$ | $6.9 \pm 0.1^B$ | $1.09 \pm 0.02^B$ | $1.56 \pm 0.04$ |
| 1 | 44 (All) | N/A | $10.7 \pm 1.7^B$ | 9.9 | $6.5^B$ | $1.08^B$ | 1.64 |

The simulated yield and water use efficiency was generally consistently high using ILC and with all three scales of spatial data input (simulations #38-#67 of Table 9.2). ILC was sensitive to the location of the point used with a single data point input; this is illustrated by simulations #41, #43 and #45 which produced significantly lower yields than the other simulations. However, with three or ten data point inputs, ILC was less sensitive to the unmeasured spatial variability of the soil properties as a high crop yield was generally maintained (simulations #48-#67). This is because the soil moisture in the cells without measured data was estimated using the spatial interpolation procedure. Any error between the estimated soil moisture status and actual soil moisture status in the unmeasured cells did not generally affect the crop yield. This error would have caused the ILC algorithm to maintain a different soil moisture deficit to that specified (10% of plant available water capacity). However, this error did not cause the crop to be water stressed. The spatial variability of the yield was also low for all simulations (#38-#67).

As the number of sampling points in the field increased, the following general observations were made:

- the average yield increased;
- the irrigation volume applied decreased;
- the crop water use efficiency increased significantly between one and three points but not between three, ten and all points; this indicates that using three data inputs is as useful as all inputs for ILC; and
- the consistency of the average yield and irrigation applied across the field improved; this indicates that the crop yield and irrigation applied are less sensitive to the location of the input data points in the field as the number of data points increases.

#### 9.2.2.2 Iterative hill climbing controller performance

As the number of data points increased (Table 9.3), the following general observations were made:

- the simulated yields and crop water use efficiencies were more variable;
- the yield was underestimated for all treatments; and

Table 9.3: Performance of the iterative hill climbing control strategy with different numbers of sampling points

| **ID #** | **Number of sampling points** | **Rep** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ $\mathbf{ML}_{total}$)** | **IWUI (bales/ $\mathbf{ML}_{irrigated}$)** |
|---|---|---|---|---|---|---|---|
| 68 | One | 1 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 69 | | 2 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 70 | | 3 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 71 | | 4 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 72 | | 5 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 73 | | 6 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 74 | | 7 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 75 | | 8 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 76 | | 9 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| 77 | | 10 | $7.9 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.82^{d}$ | 1.11 |
| Nil | | Average | $7.9 \pm 0.3^{C}$ | $10.1 \pm 0.0$ | $7.0 \pm 0.0^{B}$ | $0.82 \pm 0.04^{A}$ | $1.11 \pm 0.03$ |
| 78 | Three | 1 | $10.2 \pm 0.8^{a}$ | 10.1 | $7.0^{a}$ | $1.01^{a}$ | 1.46 |
| 79 | | 2 | $8.0 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.79^{d}$ | 1.14 |
| 80 | | 3 | $8.0 \pm 0.9^{d}$ | 10.1 | $7.0^{a}$ | $0.79^{d}$ | 1.14 |
| 81 | | 4 | $10.8 \pm 1.1^{a}$ | 9.9 | $6.8^{i}$ | $1.09^{a}$ | 1.60 |
| 82 | | 5 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 83 | | 6 | $10.4 \pm 1.2^{a}$ | 9.7 | $6.6^{k}$ | $1.07^{a}$ | 1.57 |
| 84 | | 7 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 85 | | 8 | $10.2 \pm 0.9^{a}$ | 10.2 | $7.1^{i}$ | $1.00^{a}$ | 1.44 |
| 86 | | 9 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 88 | | 10 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| Nil | | Average | $7.5 \pm 0.8^{C}$ | $8.8 \pm 0.5$ | $5.8 \pm 0.5^{C}$ | $0.85 \pm 0.05^{A}$ | $1.31 \pm 0.06$ |
| 88 | Ten | 1 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 89 | | 2 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 90 | | 3 | $10.1 \pm 1.2^{a}$ | 9.5 | $6.4^{l}$ | $1.06^{a}$ | 1.57 |
| 91 | | 4 | $10.1 \pm 1.2^{a}$ | 9.5 | $6.4^{l}$ | $1.06^{a}$ | 1.57 |
| 92 | | 5 | $10.7 \pm 1.1^{a}$ | 9.9 | $6.9^{b}$ | $1.08^{a}$ | 1.55 |
| 93 | | 6 | $10.8 \pm 1.1^{a}$ | 9.9 | $6.8^{i}$ | $1.09^{a}$ | 1.60 |
| 94 | | 7 | $10.8 \pm 1.1^{a}$ | 9.9 | $6.8^{i}$ | $1.09^{a}$ | 1.60 |
| 95 | | 8 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 96 | | 9 | $4.8 \pm 1.1^{f}$ | 6.9 | $4.1^{j}$ | $0.69^{e}$ | 1.16 |
| 97 | | 10 | $10.4 \pm 1.2^{a}$ | 9.7 | $6.6^{k}$ | $1.07^{a}$ | 1.57 |
| Nil | | Average | $8.2 \pm 0.9^{D}$ | $8.6 \pm 0.5$ | $5.7 \pm 0.4^{C}$ | $0.95 \pm 0.07^{A}$ | $1.44 \pm 0.07$ |
| 9 | 44 (All) | N/A | $10.9 \pm 1.5^{B}$ | 10.2 | $7.2^{A}$ | $1.04^{A}$ | 1.52 |

- irrigation water use efficiency increased closer to that for the simulation with all input points.

The iterative hill climbing control strategy applied the same irrigation volume and resulted in the same yield for any chosen single point of data input (simulations #68-#77 of Table 9.3). This is because the control strategy determines the irrigation application using the standard crop coefficient for cotton (from Table 12 of Allen et al. (1998)) if the response of the 'test cells' to the test irrigation volumes is the same. When only one data point input is used for the field, the response of the test cells is not measured and is assumed to be constant across the field; hence, each test cell would have the same measured response.

The simulations with multiple data inputs (simulations #78-#97) were more variable than the simulations with one data point input. This is because the iterative hill climbing strategy determines the irrigation volume by evaluating the response of different irrigation volumes to 'test cells'. This strategy is only reliable if the randomly selected data points are also the test cells: this is unlikely as there are 1266 cells in the field and, in this case study, only 10 test cells are used for each irrigation and are relocated after each irrigation event. Hence, the strategy measures the spatially interpolated response of the general irrigation volume applied to the field, rather than the individual test cells. This suggests that the iterative hill climbing control strategy is not reliable with data available only at random data points.

#### 9.2.2.3 Model predictive controller performance

The MPC controller was simulated with the input of data from the same random data points in the field as the ILC and iterative hill climbing controllers (Table 9.4). As the spatial scale of input data reduced (i.e. the number of input data points increased), the following general observations were made:

- the crop and irrigation water use efficiencies increased but substantially below the maximum yield achieved with all data inputs;
- the irrigation volume application reduced; and
- as per ILC, the consistency of the average yield and irrigation applied across the field improved.

The MPC strategy performed poorly with data input from a limited number of sampling points in the field (simulations #98-#127) even though the maximum yield and irrigation water use efficiency using all field data points greatly exceeded those achieved by the other controllers. This indicates that the model was not accurately calibrated using the estimated values of soil moisture content and plant available water capacity. This may be caused by the random variability imposed in the soil properties across the field.

The location of the data points in the field affected the yield and water use efficiency and this effect was the greatest in the simulations of one data input in the field. For example, using one point of data input led to yields and water use efficiencies higher than several simulations using three or ten data points (simulation #104), while also leading to the lowest yield and water use efficiency of all the simulations (simulation #101). Hence, the location of the point in the field limits the performance of MPC.

There was no significant difference between the average yield or water use of the simulations using data from one and three points in the field (simulations #38-#57). However, the yield and water use efficiency of the simulations using data from ten points were greater than those of the simulations using data from one or three points. This indicates that the input of data from one or three points in the field does not provide sufficient spatial information to accurately calibrate the crop model and that more points would be needed to use this controller under field conditions. The highest average yield and water use efficiency was provided with input from all data points in the field.

The standard deviation of the yields for the simulations with ten data input points were higher those those with one or three data input points. This is because the number of cells with known properties – and hence accurately optimised yield – increased, leading to a more accurate spatial interpolation of the cell properties.

From the case study of Section 8.4, MPC performed significantly better when either only plant (simulation #34) or soil (simulation #33) data input was available in each cell of the field than when data were only available at a small number of random sampling points in the field (Table 9.4). This indicates that the spatial interpolation and estimation of the soil properties and crop response caused large inaccuracies in the

Table 9.4: Performance of the model predictive control strategy with different numbers of sampling points

| ID # | Number of sampling points | Rep | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|---|
| 98 | One | 1 | $4.1 \pm 0.8^g$ | 9.5 | $6.4^d$ | $0.45^g$ | 0.64 |
| 99 | | 2 | $3.1 \pm 1.3^h$ | 8.6 | $5.3^d$ | $0.41^h$ | 0.58 |
| 100 | | 3 | $2.5 \pm 1.2^i$ | 7.0 | $4.8^a$ | $0.36^i$ | 0.52 |
| 101 | | 4 | $2.0 \pm 1.0^j$ | 6.7 | $4.5^a$ | $0.30^j$ | 0.45 |
| 102 | | 5 | $5.1 \pm 0.8^f$ | 11.4 | $8.2^e$ | $0.46^k$ | 0.62 |
| 103 | | 6 | $5.2 \pm 0.7^f$ | 10.3 | $7.6^e$ | $0.50^l$ | 0.68 |
| 104 | | 7 | $5.8 \pm 1.4^k$ | 9.7 | $6.9^d$ | $0.60^m$ | 0.84 |
| 105 | | 8 | $4.4 \pm 0.7^l$ | 9.6 | $6.8^d$ | $0.46^k$ | 0.64 |
| 106 | | 9 | $5.7 \pm 1.9^k$ | 10.1 | $7.1^d$ | $0.56^n$ | 0.80 |
| 107 | | 10 | $2.3 \pm 1.1^i$ | 6.4 | $4.1^a$ | $0.36^i$ | 0.56 |
| Nil | | Average | $4.0 \pm 0.5^E$ | $9.2 \pm 0.5$ | $6.2 \pm 0.5^B$ | $0.42 \pm 0.03^C$ | $0.63 \pm 0.03$ |
| 108 | Three | 1 | $3.5 \pm 0.8^m$ | 7.7 | $4.9^a$ | $0.45^k$ | 0.71 |
| 109 | | 2 | $3.4 \pm 1.1^m$ | 8.5 | $5.7^b$ | $0.40^h$ | 0.59 |
| 110 | | 3 | $4.4 \pm 0.6^l$ | 9.0 | $6.2^b$ | $0.49^k$ | 0.71 |
| 111 | | 4 | $3.8 \pm 1.3^g$ | 9.1 | $6.3^b$ | $0.42^h$ | 0.60 |
| 112 | | 5 | $4.1 \pm 0.9^g$ | 9.0 | $6.2^b$ | $0.46^k$ | 0.66 |
| 113 | | 6 | $4.3 \pm 1.3^l$ | 8.4 | $5.7^b$ | $0.51^k$ | 0.76 |
| 114 | | 7 | $3.9 \pm 1.2^g$ | 8.4 | $5.6^b$ | $0.47^k$ | 0.70 |
| 115 | | 8 | $3.9 \pm 0.7^g$ | 8.8 | $6.0^b$ | $0.44^k$ | 0.64 |
| 116 | | 9 | $3.4 \pm 1.1^m$ | 8.5 | $5.7^b$ | $0.40^h$ | 0.59 |
| 117 | | 10 | $3.4 \pm 1.1^m$ | 99 | $5.1^a$ | $0.43^h$ | 0.67 |
| Nil | | Average | $3.8 \pm 0.1^E$ | $8.8 \pm 0.2$ | $5.7 \pm 0.2^B$ | $0.43 \pm 0.01^C$ | $0.67 \pm 0.02$ |
| 118 | Ten | 1 | $6.2 \pm 4.1^k$ | 8.8 | $5.9^c$ | $0.70^m$ | 1.05 |
| 119 | | 2 | $5.2 \pm 3.8^k$ | 8.1 | $5.3^m$ | $0.64^l$ | 0.98 |
| 120 | | 3 | $5.7 \pm 3.5^k$ | 7.9 | $4.9^m$ | $0.72^m$ | 1.16 |
| 121 | | 4 | $6.1 \pm 3.6^k$ | 8.8 | $5.8^j$ | $0.70^m$ | 1.05 |
| 122 | | 5 | $5.8 \pm 4.1^k$ | 7.7 | $4.9^m$ | $0.75^m$ | 1.18 |
| 123 | | 6 | $5.2 \pm 4.1^k$ | 7.7 | $4.7^m$ | $0.69^l$ | 1.11 |
| 124 | | 7 | $5.4 \pm 4.1^k$ | 8.3 | $5.5^m$ | $0.65^l$ | 1.98 |
| 125 | | 8 | $5.0 \pm 4.3^k$ | 8.0 | $5.3^m$ | $0.62^l$ | 0.95 |
| 126 | | 9 | $4.9 \pm 3.9^k$ | 7.2 | $4.3^n$ | $0.68^l$ | 1.14 |
| 127 | | 10 | $5.9 \pm 4.0^k$ | 8.7 | $5.7^j$ | $0.68^m$ | 1.03 |
| Nil | | Average | $5.5 \pm 0.1^F$ | $8.7 \pm 0.2$ | $5.3 \pm 0.2^C$ | $0.64 \pm 0.01^D$ | $1.00 \pm 0.02$ |
| 29 | 44 (All) | N/A | $14.3 \pm 0.5^G$ | 9.3 | $6.2^B$ | $1.54^E$ | 2.30 |

calibrated model. In contrast, when there was no soil input to the strategy (simulation #36 in Chapter 8), irrigation was determined using a model calibrated with the measured crop response in each cell and with the underlying randomly variable soil moisture properties of the reference model (Figure 8.1(b)) since there was no measured feedback soil data. This indicates that the soil variability in the field could be effectively estimated with measured plant response in each cell and with no soil moisture data.

#### 9.2.2.4 Comparison of control strategies

The ILC controller produced higher yields and water use efficiencies than the MPC controller with data input from a limited number of sampling points. This is because MPC determined the irrigation application using a model calibrated with kriged soil moisture and plant (square count, boll count and leaf area index) data. The errors in each data stream may have accumulated and significantly reduced the accuracy of the calibrated model. In contrast, ILC required the interpolation of only one data input (soil moisture content). The iterative hill climbing controller requires measurements in specific cells of the field (rather than randomly selected cells) for reliable operation.

## 9.3 Spatial variability of rainfall

The spatial variability of natural rainfall in Australian summer cropping areas is observed to be substantial on a scale of 10s to 100s of metres due to highly-localised cumulonimbus storms. Typically an automatic weather station or other data source will only provide rainfall data for a single point nearby, hence this variability is often unquantified and the effect on irrigation optimisation unknown. Using VARIwise, three adaptive irrigation control strategies were evaluated for performance and robustness to simulated spatial variability of rainfall.

### 9.3.1 Methodology

Rainfall was spatially varied by applying a Gaussian distribution of variability to the rainfall measurement ascribed to each cell of the field. The average value of the rainfall was obtained from the weather profile for Dalby, Queensland during 2004/2005 and two amounts of imposed variability, 20% and 50%, were evaluated. Ten replicates of each rainfall pattern were simulated for each control strategy.

For this case study, the iterative hill climbing control strategy was implemented with weather-soil-and-plant data input rather than weather-and-plant data input: this enables the strategy to consider the change in soil moisture as the effective rainfall in each cell while still maximising square count. If soil response was not used, this strategy could only estimate the rainfall depth from weather data collected at a single point which would be assumed to be constant in each cell.

### 9.3.2 Results and discussion

For each control strategy, Tables 9.5 and 9.6 show the average and standard deviation of the simulated outputs for ten replicate simulations plus the corresponding simulation with constant rainfall. Within columns the use of matching superscripts ($a$, $b$, ... $f$)

indicates no significant difference (at the 95% significance level). Tables 9.5 and 9.6 also show the average and standard error of each set of simulations with imposed variability of 20% and 50%, respectively (in rows with ‘Average’); and within the columns the use of matching superscripts ($A$, $B$, ... $D$) indicates no significant difference (at the 95% significance level) between the aggregates of the replications and the simulations with constant rainfall (simulations #1, #9 and #29).

Figure 9.1 displays the average and standard error of the simulated yield and crop water use efficiencies for the three strategies with constant rainfall and 20% and 50% variability in the rainfall.

#### 9.3.2.1 Iterative learning control performance

The introduction of spatially variable rainfall did not significantly affect the performance of the ILC controller (simulations #128-#137 of Table 9.5 and #158-#167 of Table 9.6). This is because ILC accounts for the rainfall in each cell via soil moisture measurements which are used to vary the irrigation volume.

#### 9.3.2.2 Iterative hill climbing control performance

Both amounts of spatially variable rainfall significantly reduced the yield and water use efficiency of the iterative hill climbing controller (simulations #138-#147 of Table 9.5; and #168-#177 of Table 9.6), despite the effective rainfall being considered in each cell. Therefore, the crop coefficient optimisation was less effective with spatially variable rainfall than with constant rainfall. The iterative hill climbing strategy determines the irrigation volume in each cell using the same crop coefficient in all the cells of each zone. The spatially variable rainfall may have caused additional variation in the soil and/or crop properties of the cells and reduced the uniformity of the cell crop coefficients within the zones.

Table 9.5: Performance of the adaptive control strategies with spatially variable rainfall with ±20% standard deviation (replicates 1 to 10 for each strategy); plus the corresponding result for constant rainfall (#1, #9 and #29)

| ID # | Control strategy | Rep | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|---|
| 128 | Iterative learning control | 1 | $11.0 \pm 2.7^a$ | 9.4 | $6.2^a$ | $1.17^a$ | 1.77 |
| 129 | | 2 | $10.7 \pm 2.4^a$ | 9.5 | $6.4^a$ | $1.11^a$ | 1.66 |
| 130 | | 3 | $9.9 \pm 2.3^a$ | 9.4 | $6.2^a$ | $1.06^b$ | 1.59 |
| 131 | | 4 | $10.2 \pm 2.1^a$ | 9.2 | $6.3^a$ | $1.10^a$ | 1.62 |
| 132 | | 5 | $11.0 \pm 2.3^a$ | 9.5 | $6.4^a$ | $1.17^a$ | 1.74 |
| 133 | | 6 | $11.0 \pm 2.7^a$ | 9.6 | $6.3^a$ | $1.15^a$ | 1.74 |
| 134 | | 7 | $11.3 \pm 2.3^a$ | 9.5 | $6.4^a$ | $1.19^a$ | 1.77 |
| 135 | | 8 | $11.2 \pm 2.3^a$ | 9.5 | $6.3^a$ | $1.17^a$ | 1.77 |
| 136 | | 9 | $11.0 \pm 2.5^a$ | 9.5 | $6.4^a$ | $1.15^a$ | 1.74 |
| 137 | | 10 | $10.8 \pm 2.4^a$ | 9.7 | $6.5^a$ | $1.11^a$ | 1.67 |
| Nil | | Average | $10.8 \pm 0.2^A$ | $9.5 \pm 0.1$ | $6.3 \pm 0.1^A$ | $1.13 \pm 0.01^A$ | $1.71 \pm 0.02$ |
| 1 | | Nil | $10.7 \pm 1.7^A$ | 9.9 | $6.5^A$ | $1.08^A$ | 1.64 |
| 138 | Iterative hill climbing control | 1 | $10.7 \pm 1.5^a$ | 11.2 | $7.7^b$ | $0.95^c$ | 1.38 |
| 139 | | 2 | $9.9 \pm 1.3^a$ | 11.0 | $7.5^c$ | $0.90^c$ | 1.31 |
| 140 | | 3 | $10.0 \pm 1.4^a$ | 10.9 | $7.4^c$ | $0.92^c$ | 1.35 |
| 141 | | 4 | $10.0 \pm 1.4^a$ | 10.9 | $7.4^c$ | $0.92^c$ | 1.35 |
| 142 | | 5 | $9.9 \pm 1.3^a$ | 11.1 | $7.5^c$ | $0.90^c$ | 1.31 |
| 143 | | 6 | $10.0 \pm 1.4^a$ | 10.9 | $7.4^c$ | $0.92^c$ | 1.35 |
| 144 | | 7 | $10.7 \pm 1.5^a$ | 11.4 | $7.8^d$ | $0.94^c$ | 1.36 |
| 145 | | 8 | $9.9 \pm 1.3^a$ | 11.0 | $7.5^c$ | $0.90^c$ | 1.31 |
| 146 | | 9 | $10.2 \pm 1.4^a$ | 11.0 | $7.5^c$ | $0.92^c$ | 1.35 |
| 147 | | 10 | $10.0 \pm 1.4^a$ | 10.9 | $7.4^c$ | $0.92^c$ | 1.35 |
| Nil | | Average | $10.1 \pm 0.1^B$ | $11.0 \pm 0.1$ | $7.5 \pm 0.1^B$ | $0.92 \pm 0.01^B$ | $1.34 \pm 0.01$ |
| 9 | | Nil | $10.9 \pm 1.5^A$ | 10.2 | $7.2^C$ | $1.04^A$ | 1.52 |
| 148 | Model predictive control | 1 | $14.8 \pm 2.6^b$ | 9.5 | $6.4^e$ | $1.57^d$ | 2.32 |
| 149 | | 2 | $14.6 \pm 3.0^b$ | 9.3 | $6.3^e$ | $1.56^d$ | 2.32 |
| 150 | | 3 | $15.0 \pm 2.8^b$ | 9.3 | $6.3^e$ | $1.61^d$ | 2.39 |
| 151 | | 4 | $14.6 \pm 2.7^b$ | 9.5 | $6.4^e$ | $1.54^d$ | 2.28 |
| 152 | | 5 | $14.0 \pm 2.5^b$ | 9.5 | $6.5^e$ | $1.47^e$ | 2.16 |
| 153 | | 6 | $14.4 \pm 2.8^b$ | 9.5 | $6.4^e$ | $1.52^d$ | 2.23 |
| 154 | | 7 | $14.1 \pm 3.1^b$ | 9.3 | $6.2^f$ | $1.52^d$ | 2.28 |
| 155 | | 8 | $14.7 \pm 2.8^b$ | 9.4 | $6.3^e$ | $1.57^d$ | 2.34 |
| 156 | | 9 | $14.4 \pm 2.7^b$ | 9.5 | $6.5^e$ | $1.51^d$ | 2.23 |
| 157 | | 10 | $14.7 \pm 2.6^b$ | 9.3 | $6.3^e$ | $1.57^d$ | 2.33 |
| Nil | | Average | $14.9 \pm 0.2^C$ | $9.5 \pm 0.1$ | $6.3 \pm 0.1^A$ | $1.57 \pm 0.04^C$ | $2.37 \pm 0.05$ |
| 29 | | Nil | $14.3 \pm 0.5^C$ | 9.3 | $6.2^A$ | $1.54^C$ | 2.30 |

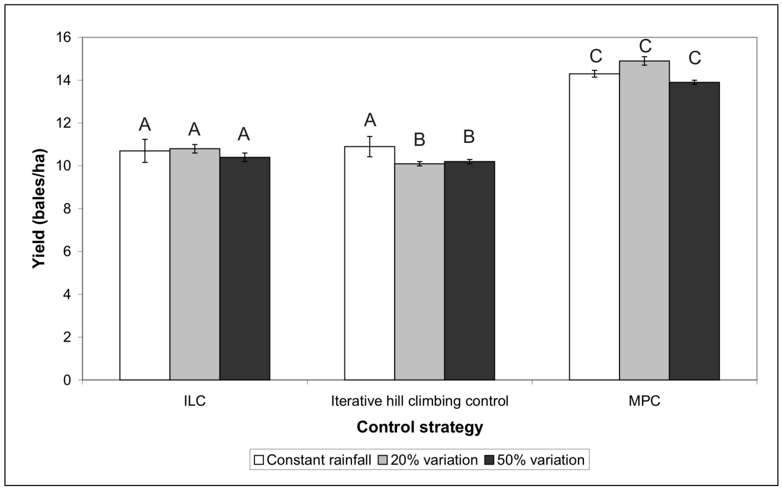
#### 9.3.2.3 Model predictive control performance

The MPC controller was generally not sensitive to spatially variable rainfall (simulations #148-#157 of Table 9.5; and #178-#187 of Table 9.6). This is because MPC considers the rainfall in each cell via soil moisture measurements that are used to calibrate the model. This model is then used to evaluate various irrigation timings and applications and determine which irrigation decision to implement.

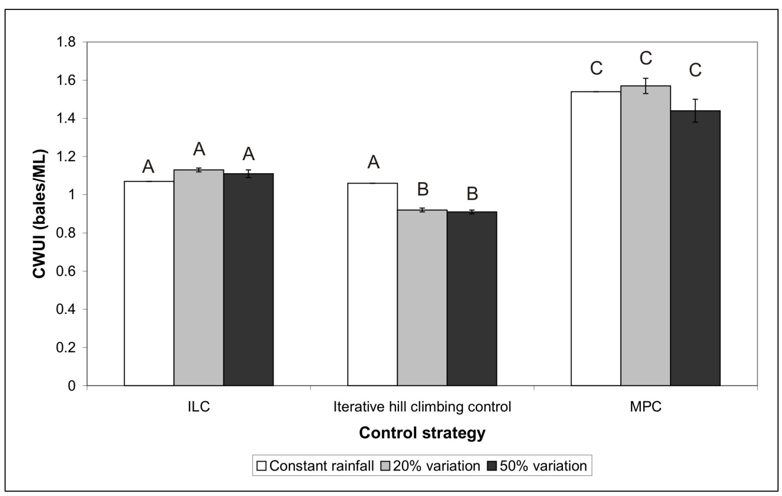
Table 9.6: Performance of the adaptive control strategies with spatially variable rainfall with ±50% standard deviation (replicates 1 to 10 for each strategy); plus the corresponding result for constant rainfall (#1, #9 and #29)

| ID # | Control strategy | Rep | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|---|
| 158 | Iterative learning control | 1 | $11.3 \pm 2.3^{a}$ | 9.4 | $6.3^{a}$ | $1.20^{a}$ | 1.79 |
| 159 | | 2 | $10.1 \pm 3.1^{a}$ | 9.4 | $6.3^{a}$ | $1.08^{b}$ | 1.61 |
| 160 | | 3 | $10.4 \pm 2.7^{a}$ | 9.4 | $6.3^{a}$ | $1.11^{a}$ | 1.64 |
| 161 | | 4 | $10.1 \pm 2.8^{a}$ | 9.3 | $6.2^{a}$ | $1.09^{b}$ | 1.62 |
| 162 | | 5 | $10.1 \pm 2.5^{a}$ | 9.3 | $6.3^{a}$ | $1.08^{b}$ | 1.61 |
| 163 | | 6 | $11.4 \pm 2.4^{a}$ | 9.4 | $6.3^{a}$ | $1.21^{a}$ | 1.81 |
| 164 | | 7 | $10.1 \pm 2.4^{a}$ | 9.3 | $6.3^{a}$ | $1.08^{b}$ | 1.61 |
| 165 | | 8 | $10.1 \pm 2.3^{a}$ | 9.4 | $6.3^{a}$ | $1.08^{b}$ | 1.61 |
| 166 | | 9 | $10.4 \pm 2.4^{a}$ | 9.4 | $6.3^{a}$ | $1.11^{a}$ | 1.66 |
| 167 | | 10 | $10.1 \pm 3.0^{a}$ | 9.4 | $6.3^{a}$ | $1.08^{b}$ | 1.61 |
| Nil | | Average | $10.4 \pm 0.2^{A}$ | 9.4 ± 0.1 | $6.3 \pm 0.1^{A}$ | $1.11 \pm 0.02^{A}$ | 1.66 ± 0.03 |
| 1 | | Nil | $10.7 \pm 1.7^{A}$ | 9.9 | $6.5^{A}$ | $1.08^{A}$ | 1.64 |
| 168 | Iterative hill climbing control | 1 | $10.7 \pm 1.6^{a}$ | 11.4 | $7.9^{d}$ | $0.90^{c}$ | 1.30 |
| 169 | | 2 | $9.9 \pm 1.3^{a}$ | 11.3 | $7.7^{d}$ | $0.91^{c}$ | 1.34 |
| 170 | | 3 | $10.0 \pm 1.4^{a}$ | 11.1 | $7.5^{c}$ | $0.91^{c}$ | 1.44 |
| 171 | | 4 | $10.0 \pm 1.5^{a}$ | 11.2 | $7.5^{c}$ | $0.92^{c}$ | 1.37 |
| 172 | | 5 | $9.9 \pm 1.4^{a}$ | 11.4 | $7.8^{d}$ | $0.83^{f}$ | 1.22 |
| 173 | | 6 | $10.0 \pm 1.5^{a}$ | 11.1 | $8.0^{d}$ | $0.92^{c}$ | 1.28 |
| 174 | | 7 | $10.7 \pm 1.6^{a}$ | 11.2 | $8.5^{d}$ | $0.92^{c}$ | 1.22 |
| 175 | | 8 | $9.9 \pm 1.4^{a}$ | 10.9 | $7.5^{c}$ | $0.91^{c}$ | 1.33 |
| 176 | | 9 | $10.2 \pm 1.5^{a}$ | 10.9 | $7.7^{c}$ | $0.94^{c}$ | 1.33 |
| 177 | | 10 | $10.0 \pm 1.4^{a}$ | 11.0 | $8.0^{d}$ | $0.95^{c}$ | 1.30 |
| Nil | | Average | $10.2 \pm 0.1^{B}$ | 11.2 ± 0.71 | $7.8 \pm 0.2^{C}$ | $0.91 \pm 0.01^{B}$ | 1.30 ± 0.02 |
| 9 | | Nil | $10.9 \pm 1.5^{A}$ | 10.2 | $7.2^{B}$ | $1.04^{A}$ | 1.52 |
| 178 | Model predictive control | 1 | $13.6 \pm 2.83^{b}$ | 9.7 | $6.6^{e}$ | $1.40^{e}$ | 2.06 |
| 179 | | 2 | $13.9 \pm 3.4^{b}$ | 9.5 | $6.5^{e}$ | $1.46^{e}$ | 2.14 |
| 180 | | 3 | $13.7 \pm 3.1^{b}$ | 9.6 | $6.6^{e}$ | $1.42^{e}$ | 2.09 |
| 181 | | 4 | $14.3 \pm 3.2^{b}$ | 9.5 | $6.5^{e}$ | $1.50^{e}$ | 2.21 |
| 182 | | 5 | $13.4 \pm 2.9^{b}$ | 9.6 | $6.5^{e}$ | $1.39^{e}$ | 2.06 |
| 183 | | 6 | $13.4 \pm 3.0^{b}$ | 9.6 | $6.6^{e}$ | $1.39^{e}$ | 2.03 |
| 184 | | 7 | $14.3 \pm 3.1^{b}$ | 9.5 | $6.5^{f}$ | $1.50^{e}$ | 2.20 |
| 185 | | 8 | $13.9 \pm 3.0^{b}$ | 9.5 | $6.5^{e}$ | $1.46^{e}$ | 2.14 |
| 186 | | 9 | $13.9 \pm 2.8^{b}$ | 9.6 | $6.6^{e}$ | $1.44^{e}$ | 2.11 |
| 187 | | 10 | $14.1 \pm 3.5^{b}$ | 9.5 | $6.4^{e}$ | $1.49^{e}$ | 2.20 |
| Nil | | Average | $13.9 \pm 0.1^{C}$ | 9.6 ± 0.1 | $6.5 \pm 0.1^{A}$ | $1.44 \pm 0.06^{C}$ | 2.13 ± 0.05 |
| 29 | | Nil | $14.3 \pm 0.5^{C}$ | 9.3 | $6.2^{A}$ | $1.54^{C}$ | 2.30 |

Marginally significant reductions in CWUI and IWUI were indicated with 50% variability of rainfall (Figure 9.1). This suggests there was a significant difference between the predicted and actual rainfall which caused the MPC strategy to determine irrigation volumes for inaccurate field conditions.




(a)




(b)

Figure 9.1: Control performance with constant and ±20% and ±50% variability in the rainfall for: (a) yield; and (b) crop water use efficiency; where error bars indicate the standard error and matching uppercase letters indicate no significant difference between the simulations

#### 9.3.2.4 Comparison of control strategies

The ILC and MPC controllers were not significantly affected by rainfall with 20% or 50% spatial variability. This is because both the ILC and MPC strategies determine the irrigation on an individual cell basis. However, the performance of the iterative hill climbing control strategy was significantly affected by rainfall with spatial variability because this strategy provides less spatial discrimination for the irrigation application than ILC and MPC and assumes that all the cells in each zone have the same crop coefficient. Hence, this strategy adapts poorly to spatially variable rainfall.

## 9.4 Temporal resolution of input data

In a field implementation, weather, soil and/or plant properties may not be measured daily because of the characteristics of the sensor or the measurement not being available due to sensor hardware failure. For example, on-the-go plant sensors may only revisit a particular cell to measure the plant parameters every few days. The three adaptive irrigation control strategies were evaluated in VARIwise for robustness with respect to temporal data availability. The temporal resolution of the input data affects which data input is used by the adaptive control strategies (as noted in Section 3.3.6).

### 9.4.1 Methodology

The control strategies were evaluated for three temporal resolutions of data input: fifteen, six and three days. Weather, soil and plant information was available for each cell in the field on intervals of the temporal resolutions beginning on the sowing date. With temporally unavailable data, the strategies adjusted their operation as follows:

- For ILC, if update soil measurements are not available then the weather dataset is used to calculate the crop evapotranspiration and estimate the soil moisture status.
- For iterative hill climbing control, if plant measurements are not available on the day before the scheduled irrigation event then the data input used depends on both the date of the latest plant measurement and the date of the previous irrigation event. Since the irrigation events occur every five days and the measurements are only available every three, six or fifteen days, plant measurements may not be available after each irrigation event to evaluate the response of the

test cells to the irrigation applied. Therefore, in this strategy:

- If plant measurements since the previous irrigation event are available then this data input is used,
- If plant measurements since the previous irrigation event are not available then the crop water use since the previous irrigation (estimated using soil moisture measurements and crop evapotranspiration) is applied to the field.

- For MPC the reference model is calibrated using the available data.

### 9.4.2 Results and discussion

Table 9.7 presents the results of simulations conducted to evaluate the performance of the strategies with data available at different time intervals. The results of the strategies with daily data input are also presented.

Table 9.7: Performance of the control strategies with different numbers of days between data input

| **ID #** | **Control strategy** | **Number of days between data input** | **Yield (bales/ ha)** | **Total water applied (ML/ha)** | **Irrigation applied (ML/ha)** | **CWUI (bales/ $ML_{total}$)** | **IWUI (bales/ $ML_{irrigated}$)** |
|---|---|---|---|---|---|---|---|
| 188 | Iterative learning control | Fifteen | 5.5 ± 2.3 | 6.8 | 3.3 | 0.8 | 1.7 |
| 189 | | Six | 6.4 ± 3.1 | 6.8 | 3.3 | 0.9 | 1.9 |
| 190 | | Three | 7.8 ± 2.8 | 7.6 | 4.1 | 1.0 | 1.9 |
| 1 | | One | 10.7 ± 1.7 | 9.9 | 6.5 | 1.1 | 1.6 |
| 191 | Iterative hill climbing control | Fifteen | 9.1 ± 1.7 | 9.8 | 6.7 | 0.9 | 1.4 |
| 192 | | Six | 9.3 ± 1.4 | 10.1 | 7.0 | 0.9 | 1.3 |
| 193 | | Three | 9.3 ± 1.4 | 10.1 | 7.0 | 0.9 | 1.3 |
| 9 | | One | 10.9 ± 1.5 | 10.2 | 7.2 | 1.0 | 1.5 |
| 194 | Model predictive control | Fifteen | 12.5 ± 1.9 | 8.8 | 5.8 | 1.4 | 2.2 |
| 195 | | Six | 12.5 ± 1.6 | 8.5 | 5.5 | 1.5 | 2.3 |
| 196 | | Three | 13.2 ± 1.9 | 8.6 | 5.5 | 1.5 | 2.4 |
| 29 | | One | 14.3 ± 0.5 | 9.3 | 6.2 | 1.5 | 2.3 |

#### 9.4.2.1 Iterative learning control performance

The ILC controller was sensitive to temporal data availability (simulations #188-#190): this is because ILC estimates the soil moisture content using weather data if the soil moisture is not measured on the day after each irrigation event. The inaccuracies in the soil moisture estimation would effectively cause the ILC controller to target a soil moisture deficit different to the desired deficit. ILC also assumes that each iteration of irrigation events is repetitive; hence, if daily soil moisture measurements are not available then the water consumed by the crop (that is used to determine irrigation timing) is estimated from the weather data rather than more accurately determined from the soil data.

The simulated yield and water use efficiencies of ILC increased with a reduction in the number of days between data collection. This is because more accurate data inputs were used to determine the soil moisture deficit and calculate the irrigation application. The irrigation application also increased with an increase in temporal resolution; this indicates that irrigations were initiated more frequently and/or higher volumes were applied when the irrigation decisions were made more accurately.

The irrigation water use efficiency was higher with data input every three days than every day for ILC (simulations #190 and #1). This is because less irrigation was applied with limited temporal data input (as noted above), whilst the yield remained high (but still lower than with data input every day).

#### 9.4.2.2 Iterative hill climbing control performance

For the iterative hill climbing controller, the average yield and water use efficiency were higher when data inputs were available every six days than every fifteen days (simulations #191 and #192). The iterative hill climbing control strategy performance was the same with data input every three and six days (simulations #192 and #193). Hence, the data feedback used were equally effective for the simulations with data available every six and three days, despite the data only being available for five out of six irrigation events for the simulations with data available at six day intervals.

#### 9.4.2.3 Model predictive control performance

As the number of days between data collection increased, the simulated yield and water use efficiencies of MPC reduced (simulations #194-#196). This is because the reference crop model used to evaluate the irrigation applications was calibrated with less data input and was thus less accurate.

#### 9.4.2.4 Comparison of control strategies

For all three control strategies, the simulated control performance generally improved when data were available more frequently. The ILC controller was most sensitive to temporal data availability, whilst the iterative hill climbing and MPC controllers were least sensitive to temporal data available. In contrast, ILC was least sensitive to sparse spatial data (Section 9.2.2.1), whilst the MPC controller was least sensitive to temporal data availability and most sensitive to sparse spatial data (Section 9.2.2.3). This indicates that daily model calibration is not required for the reference model of the MPC for the field conditions simulated.

## 9.5 Irrigation machine capacity

Irrigation machines are typically designed with the capacity to deliver the irrigation requirements of the crops that are likely to be grown on a particular field. However, inadequate irrigation machine capacity can significantly reduce the crop performance and yield potential if the irrigation machine is unable to supply the crop's irrigation requirements. The robustness of the three adaptive control strategies to limited irrigation machine capacities was evaluated in VARIwise.

The effect of limited machine capacities was also evaluated on fields irrigated via both lateral move and centre pivot irrigation machines. Lateral move irrigation machines may irrigate the driest part of the field (rather than the wettest part) following each irrigation event. This is in contrast to centre pivot irrigation machines for which the driest area in the field is normally in front of the machine (Foley & Raine 2001).

### 9.5.1 Scenario inputs

Centre pivot and lateral move irrigation machines of length 200 m were simulated in VARIwise. The lateral move irrigated field was 200 m wide (with the irrigation machine located across the field width) and 630 m long: these dimensions made the areas of the two fields approximately equal. The daily weather profile utilised in this case study (and in the previous case studies) is replicated in Figure 9.2 as it is of particular relevance for irrigation machines with low system capacities. This is because they typically rely on rainfall to increase the soil water more than machines with high system capacities.

The fields were divided into different numbers of cells depending on the irrigation machine type and control strategy used. Iterative hill climbing control requires many more cells than ILC and MPC to ensure there are sufficient cells in the field to select the new test cells after each irrigation event. Hence, the centre pivot irrigated field was divided into 44 cells for the ILC and MPC controllers (Figure 5.1) and 1266 cells for the iterative hill climbing controller (Figure 7.2(a)), whilst the lateral move irrigated

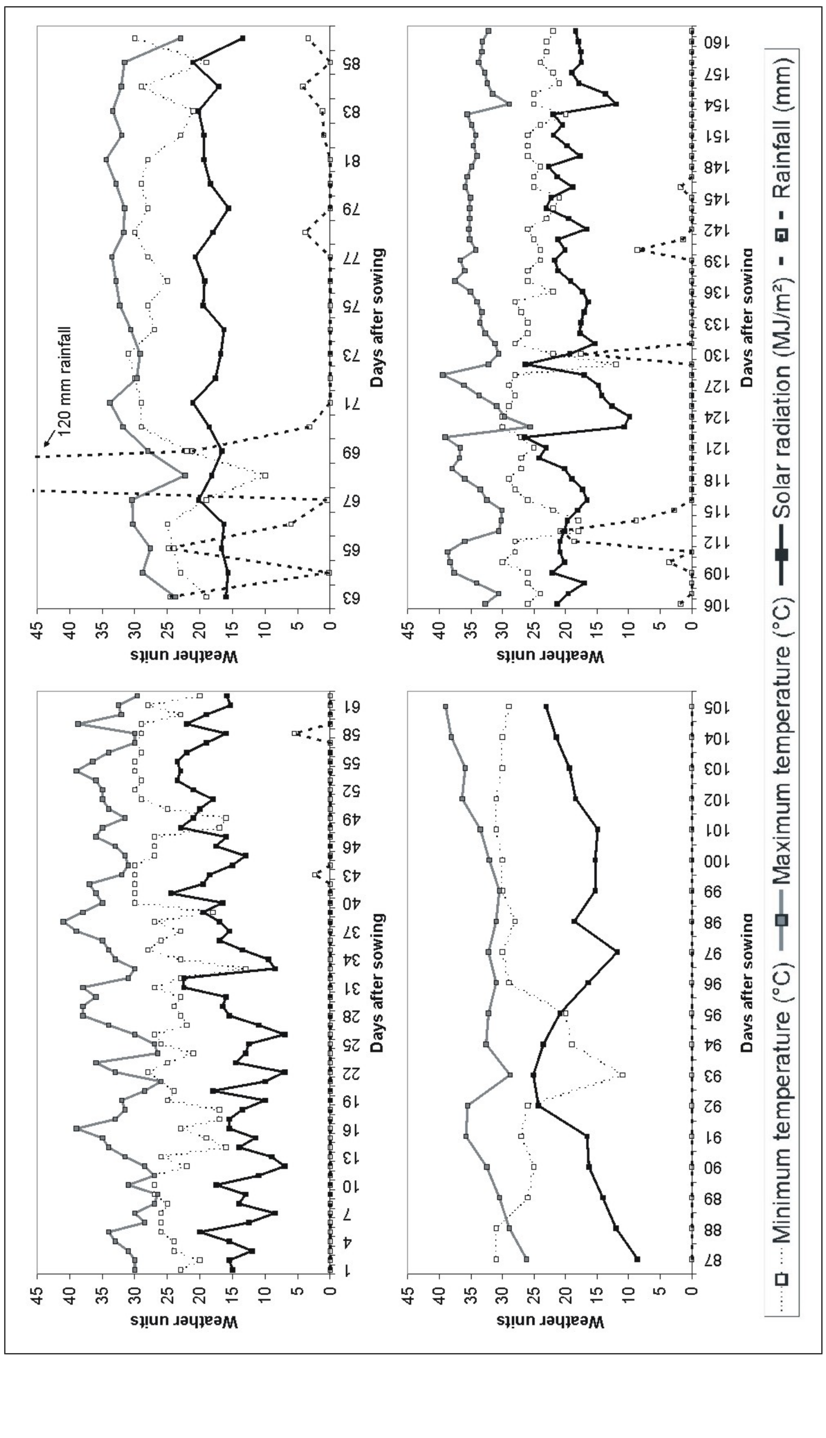



Figure 9.2: Weather profile used in iterative learning, iterative hill climbing and model predictive control strategies

field was divided into 44 cells for the ILC and MPC controllers (Figure 9.3(a)) and 1260 cells for the iterative hill climbing controller (Figure 9.3(b)).

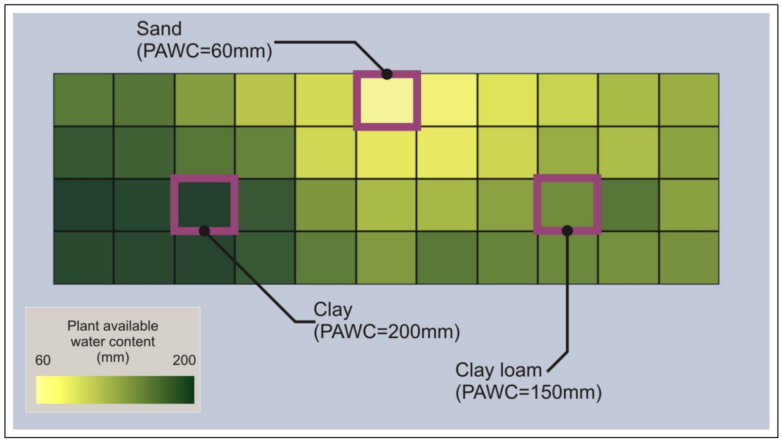
The centre pivot irrigation simulations utilised the same underlying soil variability maps as for the previous simulations in this thesis, i.e. Figure 5.1 for ILC and MPC and Figure 7.2(a) for iterative hill climbing control. The underlying soil variability maps were created in VARIwise for the lateral move irrigated field following the procedure described in Section 5.5 which has been reproduced here:

1. specifying the plant available water capacity (PAWC) for three points in the field;
2. spatially interpolating the soil data for the other cells (using kriging procedure); and
3. adding a Gaussian random variation with a standard deviation of $\pm 5\%$ to the spatial data.

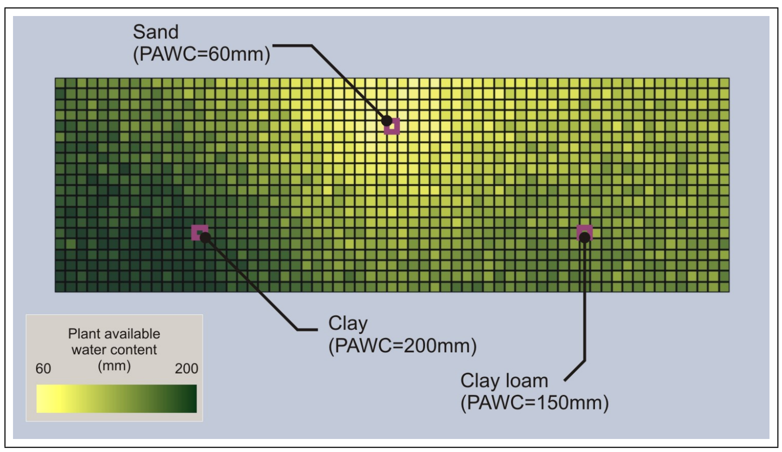
This procedure was used to create the soil variability maps for both the lateral move irrigated fields of ILC and MPC (Figure 9.3(a)) and iterative hill climbing control (Figure 9.3(b)). Both lateral move and centre pivot irrigated fields were divided into two zones for the iterative hill climbing control strategy and the cells that were allocated to each zone are illustrated in Figure 9.3(c) and Figure 7.2(b), respectively. Each zone of the centre pivot irrigated contained 633 cells, whilst each zone of the lateral move irrigated field contained 630 cells.

### 9.5.2 Methodology

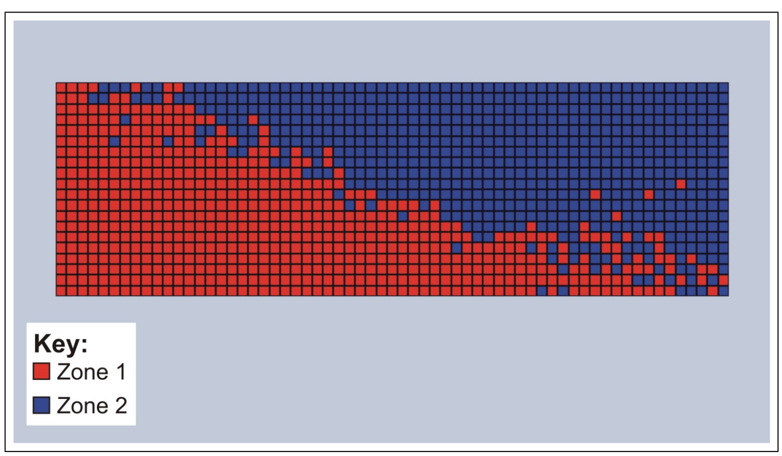
Simulations were conducted to compare the control strategies with three irrigation machine capacities (5, 10 and 15 mm/day) and two irrigation machine types (centre pivot and lateral move irrigation machines). The irrigation machine capacity was evaluated within VARIwise by, firstly, determining the irrigation volume to apply to the cells and, secondly, limiting the number of cells that were irrigated on each day according to the machine capacity and the irrigation applied to each cell (following the method described




(a)




(b)




(c)

Figure 9.3: PAWC variability maps of the lateral move irrigated fields that were simulated for: (a) iterative learning and model predictive control; and (b) iterative hill climbing control; and (c) zones for the iterative hill climbing control strategy simulated on the lateral move irrigated field derived from the PAWC variability data of Figure 9.3(b)

in Section 3.3.5). As noted in Section 3.3.5, the centre pivot irrigation machine applied irrigation in the one direction (in this case, anti-clockwise in Figure 5.1), whilst the lateral move irrigation machine applied irrigation moving left to right in Figure 9.3(a) for the first irrigation event and then alternating direction for each subsequent irrigation event (to emulate the machine continuously traversing the field from one end to the other).

### 9.5.3 Results and discussion

Table 9.8 presents the simulated performance of the three adaptive control strategies irrigated via centre pivot and lateral move irrigation machines with three irrigation machine capacities.

Table 9.8: Performance of the control strategies with different irrigation machine capacities and types

| ID # | Control strategy | Irrigation machine | Irrigation machine capacity (mm/day) | Yield (bales/ ha) | Total water applied (ML/ha) | Irrigation applied (ML/ha) | CWUI (bales/ $ML_{total}$) | IWUI (bales/ $ML_{irrigated}$) |
|---|---|---|---|---|---|---|---|---|
| 197 | Iterative learning control | Centre pivot | 5 | 9.1 ± 1.5 | 10.5 | 7.4 | 0.9 | 1.2 |
| 198 | | | 10 | 10.1 ± 3.0 | 9.7 | 6.7 | 1.0 | 1.5 |
| 1 | | | 15 | 10.7 ± 1.7 | 9.9 | 6.5 | 1.1 | 1.6 |
| 199 | | Lateral move | 5 | 10.2 ± 1.7 | 10.7 | 7.6 | 0.9 | 1.3 |
| 200 | | | 10 | 11.5 ± 1.0 | 10.7 | 7.6 | 1.1 | 1.5 |
| 201 | | | 15 | 11.7 ± 2.1 | 11.2 | 8.1 | 1.0 | 1.4 |
| 202 | Iterative hill climbing control | Centre pivot | 5 | 9.3 ± 3.5 | 7.9 | 4.9 | 1.0 | 1.6 |
| 203 | | | 10 | 9.8 ± 2.0 | 9.6 | 6.6 | 1.0 | 1.5 |
| 9 | | | 15 | 10.9 ± 1.5 | 10.2 | 7.2 | 1.0 | 1.5 |
| 204 | | Lateral move | 5 | 7.3 ± 1.6 | 8.2 | 5.1 | 0.9 | 1.4 |
| 205 | | | 10 | 11.1 ± 1.5 | 10.1 | 7.0 | 1.1 | 1.6 |
| 206 | | | 15 | 11.6 ± 2.2 | 10.3 | 7.2 | 1.1 | 1.6 |
| 207 | Model predictive control | Centre pivot | 5 | 11.7 ± 1.9 | 8.0 | 4.9 | 1.5 | 2.4 |
| 208 | | | 10 | 12.0 ± 1.8 | 8.7 | 5.6 | 1.4 | 2.2 |
| 29 | | | 15 | 14.3 ± 0.5 | 9.3 | 6.2 | 1.5 | 2.3 |
| 209 | | Lateral move | 5 | 12.4 ± 1.5 | 8.7 | 5.6 | 1.4 | 2.2 |
| 210 | | | 10 | 13.1 ± 1.1 | 8.6 | 5.6 | 1.5 | 2.4 |
| 211 | | | 15 | 14.5 ± 2.1 | 8.4 | 5.4 | 1.7 | 2.7 |

#### 9.5.3.1 Iterative learning control performance

The simulated yield and water use efficiency generally improved with an increase in the machine capacity for both the centre pivot and lateral move irrigated fields. However, the simulated yields for the machines with 5 mm/day capacity (simulations #197 and #199) were reasonably high despite the limited capacity, most likely because of the significant rainfall events during the season as shown in Figure 9.2. Higher irrigation volumes were applied less frequently to compensate for the low machine capacities: this is because the strategy increased the irrigation volume for each day since the irrigation event was initiated. The yield was also lower when a low capacity machine was used: this indicates that higher yields are produced when lower irrigation volumes are applied more frequently.

For the three simulated irrigation machine capacities, the final yield was higher for the lateral move irrigation machine (simulations #197, #198 and #1) than the centre pivot irrigation machine (simulations #199-#201). This suggests that the maximum yield possible for a field with the soil properties created for the lateral move simulations (Figure 9.3(b)) may be higher than that for the centre pivot simulations with the same weather and crop properties (i.e. the fields are not directly comparable). This is because the distribution of soil water holding capacities in the field were different for the lateral move and centre pivot simulations and this affected the amount of irrigation volume applied (e.g. sand cells require irrigation more frequently); hence the position of the irrigation machine in the field and the timing of the irrigation events were also different. This also indicates that ILC adapted to the irrigation machine dynamics (i.e. where the driest area of the field is at the other end of the field). This is because ILC initiates irrigation events after a percentage of the cells have consumed a set amount of crop use, and, in this case, the cells at the other end of the field would have consumed this crop water use first and caused the initiation of the irrigation events.

#### 9.5.3.2 Iterative hill climbing control performance

The iterative hill climbing controller produced higher average yields and water use efficiencies with higher irrigation machine capacities. However, the average yield was significantly lower using the lateral move with 5 mm/day machine capacity (simulation #204) than using the centre pivot at this machine capacity (simulation #202). This indicates that the low capacity irrigation machine could not deliver the irrigation requirement. The poor performance of the strategy with a 5 mm/day machine capacity was most likely caused by the fixed timing of the irrigations as the irrigation events were not initiated after a set crop water use and as frequently as required.

With 10 mm/day and 15 mm/day system capacities, the lateral move irrigated field (simulations #205 and #206) produced higher yields than the centre pivot irrigated field (simulations #203 and #9). As for ILC, this indicates that the lateral move irrigated field may have a higher yield potential than the centre pivot irrigated field because of the distribution of soil properties and the change in irrigation pattern (and hence timing). Higher yields may also have been produced because lower irrigation volumes were applied more frequently with the higher capacity machines.

The CWUI and IWUI were generally consistent for both the lateral move and centre pivot irrigation machines. Hence, the iterative hill climbing control could adapt to the irrigation application properties of the lateral move irrigation machine.

#### 9.5.3.3 Model predictive control performance

The simulated yield and water use efficiencies of the MPC controller generally reduced as the irrigation machine capacity reduced (simulations #29, #207-#211). For all irrigation machine capacities, the average yield and water use efficiency of the lateral move irrigated field was greater for the MPC controller than those of the centre pivot irrigated field. This indicates that the maximum yield possible for a field with the soil properties created for the lateral move simulations is higher than that for the centre pivot simulations with the same weather and crop properties. As for ILC and iterative hill climbing control, this is because the soil variability affected the amount of irrigation volume applied and hence the position of the irrigation machine in the field.

For both the lateral move and centre pivot irrigated fields, higher irrigation volumes and fewer irrigation events were applied for the lower irrigation machine capacities to compensate for the increased time required to apply irrigation and hence the increased crop water requirement. The lower yields of the low irrigation machine capacity simulation suggest that applying higher irrigation volumes produces lower yield than applying larger irrigation volumes.

MPC was successfully implemented for the lateral move irrigation machine. This is because MPC could initiate irrigations to avoid the soil drying out at the opposite end of the field (which is the driest area in the field).

#### 9.5.3.4 Comparison of control strategies

For all three control strategies and two irrigation machine types, the simulated yield and CWUI generally improved with an increase in machine capacity (Table 9.8). This is because an irrigation machine with a low machine capacity may not be able to deliver the irrigation volume required in time. The simulations indicated that applying smaller irrigation volumes produced higher yields than applying larger irrigation volumes. All three strategies successfully adapted to the irrigation application pattern of the lateral move irrigation machine.

The ILC and MPC adapted to the lower machine capacities better than the iterative hill climbing controller. This is because both ILC and MPC consider the day of irrigation in the irrigation optimisation procedure for each cell and then may apply less irrigation to enable more frequent irrigation events. MPC produced the highest yields and water use efficiencies for both the centre pivot and lateral move irrigated fields at all machine capacities. The significant rainfall events during the crop season may also have improved the response of the strategies to the lower irrigation machine capacities.

## 9.6 Conclusion

The three adaptive irrigation control strategies implemented in VARIwise were evaluated to compare their robustness and response to limitations on irrigation machine capacities, spatial and temporal data input, and spatially variable rainfall. These simulations led to the following conclusions:

1. the iterative learning control strategy is preferable in situations of sparse spatial data;
2. the iterative hill climbing controller requires data input in specific cells (and not randomly selected cells) of the field to maintain control performance;
3. iterative learning control and model predictive control are least sensitive to unquantified spatially variable rainfall and low irrigation machine capacities;
4. all three adaptive control strategies can adapt to irrigation application via lateral move irrigation machines; and
5. the model predictive control strategy outperforms the other strategies in situations of:
   (a) full data input;
   (b) high spatial data availability; and
   (c) low temporal data availability.

# Chapter 10

# Conclusion and Recommendations

A control/simulation framework 'VARIwise' was created to develop, simulate and evaluate adaptive irrigation control strategies. The cotton model OZCOT was integrated to enable feedback to the control strategies in the simulation environment. It has been demonstrated that the VARIwise framework can evaluate adaptive control strategies and determine site-specific irrigation volumes and/or timing to potentially improve the crop yield and/or water use efficiency of a simulated cotton crop. The framework may potentially be integrated as part of a real-time irrigation controller on a lateral move or centre pivot irrigation machine.

In this chapter, the achievement of the objectives (Section 2.4) is discussed and the recommended further work is described.

## 10.1 Achievement of objectives

The aim of this research was to develop and implement a real-time control methodology which utilises both historical mapped data and real-time sensor input to improve the spatial and temporal precision of irrigation applications through increased water use efficiency and/or crop yield. Of necessity this would be adaptive to changing conditions, both spatially across the field, and temporally with differing weather and seasonal factors.

*Objective 1. Develop and refine a software platform for simulating and evaluating irrigation control strategies*

A simulation framework 'VARIwise' has been created to aid the development, evaluation and management of spatially and temporally varied site-specific irrigation control strategies and the cotton model OZCOT has been integrated (Chapter 3). VARIwise accommodates sub-field scale variations in all input parameters using a 1 $m^2$ cell size, and permits application of differing control strategies within the field, as well as differing irrigation amounts down to this scale. An automatic model calibration procedure was developed in VARIwise.

*Objective 2. Validate and demonstrate calibration of the model in the software platform*

Fieldwork was conducted to demonstrate the automatic model calibration procedure in VARIwise (Chapter 4). The field experiment involved implementing three irrigation treatments with three replicates. Using measured soil and plant data from the fieldwork, the OZCOT model was accurately calibrated and the reliability of the modelled cotton growth variables improved under the same conditions as the fieldwork.

The calibrated model was used to evaluate the effect of using different data inputs in an irrigation control system. For the field conditions of the fieldwork, the model was most effectively calibrated using full data input (i.e. plant, soil and weather data). For a situation where only two data inputs were available, the simulations suggested that either weather-and-plant or soil-and-plant input were preferable.

*Objective 3. Identify and implement appropriate irrigation control strategies for improving the performance of irrigation applications*

Three control strategies applicable to irrigation were identified and developed (Chapters 2 and 5, and Appendix C). The control strategies were then implemented in VARIwise and are as follows:

1. **Iterative learning control** was implemented by using the error between the desired and measured value of the soil moisture deficit to adjust the irrigation volume of the next irrigation event (Chapter 6)

2. **Iterative hill climbing control** was implemented by: (i) dividing the field into groups of cells with homogeneous properties according to an input soil (e.g. EM38) variability map; (ii) selecting a small number of 'test cells' in each cell group to evaluate different irrigation amounts; (iii) applying different irrigation amounts to each test cell; and (iv) using the response of each test cell to the previous irrigation amount to decide the irrigation amount to apply to the non-test cells in each corresponding cell group (Chapter 7)

3. **Model predictive control** was implemented by using field data measurements of weather, soil and plant to calibrate a crop production model and an optimisation algorithm that uses the calibrated model to predict the optimal irrigation application timing and site-specific volumes (Chapter 8)

*Objective 4. Evaluate the benefits and limitations of the various control options with respect to data input requirements and the level of output control available*

The three integrated control strategies each required different combinations of input data to perform optimally and these were identified in case studies as follows:

1. the iterative learning control strategy maintained a soil moisture deficit in each cell;
2. the iterative hill climbing control strategy maximised the square count in each zone; and
3. the model predictive control strategy maximised the predicted final yield using the full data input to calibrate the crop model.

All three strategies outperformed the fixed irrigation strategy for yield and water efficiency: this demonstrates the potential benefits of adaptive control for irrigation management.

The limitations and constraints of the three adaptive irrigation control strategies were explored by simulating the strategies in VARIwise for various spatial and temporal scales, for spatially variable rainfall and also with respect to irrigation machine constraints (Chapter 9 with conclusions in Section 9.6). From these comparisons, it was concluded that:

1. the iterative learning control strategy is preferable in situations of sparse spatial data;
2. the iterative hill climbing controller requires data input in specific cells (and not randomly selected cells) of the field to maintain control performance;
3. iterative learning control and model predictive control are least sensitive to unquantified spatially variable rainfall and low irrigation machine capacities;
4. all three adaptive control strategies can adapt to irrigation application via lateral move irrigation machines; and
5. the model predictive control strategy outperforms the other strategies in situations of:
    (a) full data input;

(b) high spatial data availability; and

(c) low temporal data availability.

## 10.2 Recommended further work

### 10.2.1 Field implementation of VARIwise

Commercial variable-rate systems for lateral move and centre pivot irrigation machines typically apply pre-determined, spatially-varied irrigation volumes derived from predetermined maps and lack real-time control capability. VARIwise could be integrated with a commercial variable-rate system to determine the optimum rate and timing of applications, to identify and react to crop responses, and to optimise water use efficiency. This would also enable a field demonstration of an adaptive irrigation control strategy and comparison between the performance of the simulated and measured strategy.

### 10.2.2 Incorporate hydraulic and sprinkler models

A field implementation of VARIwise on a lateral move or centre pivot irrigation machine may require hydraulic and sprinkler models to be integrated. This is because variable-rate irrigation application via irrigation machines typically involves turning sprinklers on and off which causes fluctuations in machine performance. A hydraulic model would quantify and predict these fluctuations, determine pre-emptive control actions to compensate for them and adjust the irrigation volume applied along the machine accordingly. A sprinkler simulation model would predict the application patterns under various conditions (e.g. sprinkler spacing and wind) and adjust the irrigation application as appropriate. This model would require measurements of the depth of water being applied across the field.

### 10.2.3 Adapt VARIwise to furrow irrigation

The majority of cotton is grown using furrow irrigation in Australia. VARIwise may be adapted to manage furrow irrigation to determine irrigation timing, application depths and target efficiencies. This would be achieved by dividing the field into cells sufficiently small to accommodate the variability in soil properties and irrigation applications inherent in furrow systems. The control strategies would then prescribe irrigation volumes and/or timing to each cell in the field and aggregate them to give the target application for the furrow. Furrow irrigation control hardware would then implement the irrigation application to each furrow determined in VARIwise and, after the event, advise VARIwise of the depth applied to each cell plus measured soil and plant data. VARIwise then updates the input data and irrigation predictions in preparation for the next irrigation.

### 10.2.4 State space formulation of crop models

Classical control systems require the system process to be represented in the state space which involves defining the system as a set of input, output and state variables related by differential equations. For the irrigation of a field crop, a set of state space equations would relate the plant growth rate to input variables including solar radiation, temperature, soil moisture, soil nutrients available and pesticide applied. By formulating the soil-plant-atmosphere system in state space equations, a wider range of both classical and more advanced control systems could be applied to the irrigation (and fertigation) of agricultural field crops. This may also improve the performance of the adaptive control strategies and enable more precise definition of the desired system performance (e.g. whether to achieve the fastest plant growth, minimum water usage or optimal water conservation).

### 10.2.5 Dealing with other crops by incorporating a self-learning capability

The control strategies implemented in VARIwise are not cotton-specific and may be applied to any agricultural crop. In VARIwise, crop models are required to evaluate strategies in the simulation environment and as part of model predictive control. The integration of additional crop models in VARIwise is readily achievable but may involve programming specific to each crop model if the appropriate model does not have generic input and output data formats, although some crop models have been developed with a generic format (e.g. Wang et al. 2002). An update to a crop model may also require additional programming if there are changes in input and output data formatting. The need for this additional programming could be overcome by integrating a self-learning model in VARIwise to build/enhance models based on weather, soil and plant measurements, grower local knowledge and experience and final yield and water use. The software would then be easily transportable between crops and crop seasons to accumulate site-specific databases and models of measured data. The self-learning model would replace the crop production model in VARIwise.

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# Appendix A

# Candidate Adaptive Control Systems in Relation to Irrigation Control

This appendix contains an overview and initial evaluation of potentially useful control system designs as reported in the literature. The control systems have been grouped as:

1. Conventional adaptive control
2. 'Intelligent' adaptive control
3. Additional adaptive control approaches
4. Non-adaptive control alternatives

## A.1 Conventional adaptive control

### A.1.1 Open-loop adaptive control

Open-loop (feedforward) adaptive control systems (Isermann et al. 1992) are used in operating conditions where there are rigid, pre-defined relationships between some measurable variables characterising the environment and the process dynamics (Bell & Griffin 1969). These relationships may be obtained by determining the best irrigation volumes to apply on a field for a range of weather, soil and/or plant datasets. In an open-loop adaptive control system the variable/s are chosen in advance and stored for future reference, and for an irrigation system the stored variables would be the irrigation volume to apply in certain weather, soil and plant conditions. After the process is measured from weather, soil and plant sensors, the controller parameter/s corresponding to the measured conditions are used to adjust the controller. The remainder of this appendix describes methods of closed-loop (feedback) adaptive control.

### A.1.2 Model-reference adaptive control

Model-reference adaptive control systems involve using a static reference model of the ideal system to control a process. The reference model may be in the form of either equations or a simulation model. In model-reference adaptive control the input of the reference model is also the input of the process (Bell & Griffin 1969). The parameters of the controller are adjusted based on the error between the output of the process and the output of the reference model and requires the transfer function to be known (Åström 1995).

There are different methods of adjusting the controller parameters such that the desired closed-loop behaviour is attained: two methods are the MIT rule and the Lyapunov rule. The MIT rule is a *gradient descent* algorithm that iteratively changes the adjustable parameters and seeks the minimum performance index (if minimising the performance index produces the desired performance) (Anderson 2005). If the performance index is maximised, then the algorithm is called 'gradient ascent' or 'hill climbing'. An adaptive controller based on the MIT rule is not guaranteed to give a stable closed-loop system (Åström & Wittenmark 1994). In contrast, an adaptive controller based on the Lyapunov rule guarantees system stability for all inputs by eventually tracking the reference model with zero error (the Lyapunov rule is a method for deriving an error equation and parameter-adjusting design equations) (Chalam 1987).

### A.1.3 Model-identification adaptive control

A model-identification adaptive control system creates a dynamical reference model using measured input and output signals while the system is running; in contrast, a model-reference adaptive control system uses a static reference model. The controller parameters are calculated from the estimated process model (Isermann et al. 1992). Model-identification adaptive control systems often assume that the estimated model parameters are identical to the process parameters (Isermann et al. 1992); this is called a certainty equivalent adaptive controller. One of the most commonly reported model-identification adaptive control systems in the literature is the self-tuning regulator (e.g. Åström & Wittenmark 1989; Mosca 1995; Cheng 2003) which is a type of certainty equivalent adaptive controller. Alternatively, adaptive controllers may be 'cautious' if the uncertainties in the model parameters are estimated and used to apply a cautious action on the process in the form of smaller changes to the manipulated variables (Isermann et al. 1992).

### A.1.4 Discussion – utility of conventional adaptive control techniques for irrigation

The application of open-loop adaptive control systems to irrigation would be labour intensive because of the data collection required and the large number of possible variations of weather, soil and plant data that occur in the soil-plant-atmosphere system.

Hence, this system is considered inappropriate for irrigation control, and particularly so in Australia which has high environmental variability. Therefore, closed-loop control systems will be the focus for an irrigation control system.

Both model-reference adaptive control and model-identification adaptive control systems rely on a reference model to control the process. The model-reference adaptive control uses the model as the desired behaviour of the process and is compared with the measurement output of the process. Model-reference adaptive control would be appropriate as part of an irrigation control system assuming the transfer function of the soil-plant-atmosphere system is known. The control system could adjust the irrigation application to achieve the desired values of soil moisture content and leaf area index during the crop season. However, a transfer function for this process is unknown. Therefore, to apply model-reference adaptive control to irrigation, an alternative method of parameter adjustment that does not require the transfer function would have to be implemented.

Model-identification adaptive control systems use measured input and output data to create process models. Model-reference adaptive control may be applicable to irrigation if there is sufficient data available about the process to develop the model. With sufficient input data, the model-identification adaptive control would be able to accommodate more variations in the process than model-reference adaptive control. However, the model-reference adaptive control may be more appropriate than the model-identification adaptive control if a reliable model is available.

## A.2 'Intelligent' adaptive control

The conventional adaptive control systems that have been described in the previous section use reference models of the system dynamics to control the process. However, models may not be available or their construction may be computationally and labour intensive for systems that operate in an undefined environment, have unknown dynamics and/or have time-varying parameters (Karray & de Silva 1999). Novel control methods have been developed that do not require an explicit model of the process; rather, they apply knowledge of the process acquired in the past to similar situations in the present or future (Karray & de Silva 1999). The following sections describe adaptive control systems that are based on intelligent control techniques including neural networks, fuzzy logic and evolutionary (genetic) computing.

### A.2.1 Rule-based adaptive control

Rule-based systems store knowledge and procedures in the form of rules (Turban & Aronson 1998). These systems consist of a set of rules and a rule selector that decides which rule should be used based on the system performance. The system becomes adaptive when the rules used to adjust the controller are selected based on the monitored system performance, a library of identification algorithms and the experience gained during the operation of the system (Wang et al. 1995). An excitation signal may be injected into the system if necessary to identify the rule to be used.

### A.2.2 Knowledge-based expert adaptive control

Knowledge-based expert adaptive control systems are an extension of rule-based adaptive control systems (described in the previous section); however, they can contain data as well as rules. A knowledge-based expert system consists of: (i) a knowledge base (containing data and rules); (ii) an inference engine; and (iii) a user interface (Åström & Wittenmark 1989). The inference engine processes the rules according to a search algorithm to select the rule that satisfies the goals (Åström & Wittenmark 1989). The user interface enables expert knowledge and rules to be entered into the knowledge base, edited and/or browsed for the development of the system knowledge base. A knowledge-based expert adaptive control system contains several algorithms including excitation algorithms for rule identification and supervision algorithms, as well as tables for storing data in the knowledge base.

### A.2.3 Neural adaptive control

A neural network is a learning method that attempts to model the biological interconnections of neurons (nerve cells) in the human brain (e.g. Ng 2003). A neural network is composed of a group of parallel processing elements called nodes or neurons and weighted connections between the nodes (Karray & de Silva 1999). Each neuron has multiple inputs and a single output, and has two basic components: (i) a summer that adds the weights of the input signals together using a linear combination of the weighted input signals; and (ii) an activation function that transforms the summer output to a neuron output through a nonlinear function (Ng 2003). By adjusting the weights of the connections, the controller may be trained to approximate a nonlinear function representing the process dynamics (Karray & de Silva 1999). The nodes in a neural network are ordered into a set of layers. Neural networks use a variety of structures which characterise the organisation of the nodes from the input layer to the output layer and learning algorithms which train the network. These neural network features are described in detail by Fausett (1994).

In neural adaptive control, a neural network is often trained to adjust the adaptive controller parameters for a model-reference or model-identification adaptive control system using knowledge acquired from similar situations in the past (Wu et al. 1999). Neural networks can also be applied to other adaptive control systems including open-loop adaptive control. For example, a neural adaptive control system described by Mital & Chin (1996) has an open-loop architecture in which the difference between the desired and actual output of the process is applied to the input of both the controller and the neural network. The neural network provides a correction to the controller signal and is trained continually on-line. The neural network eventually takes over the control action after the process dynamics have been learned.

### A.2.4 Adaptive fuzzy control

Fuzzy logic is a type of logic in which the variables can have degrees of truth or falsehood and rules in the form of syntax are used to represent relationships between the controller input and output. The boundary of the rule areas is not sharp; rather, it is fuzzy and defined by a distribution function (Filippidis et al. 1999).

There are three primary processes in a fuzzy logic-based control system: (i) fuzzification; (ii) fuzzy inference engine; and (iii) defuzzification (Passino 1996). Fuzzification is the process of converting the numeric inputs into a form that can be used by the inference mechanism (Passino & Yurkovich 1998). This involves decomposing the system inputs and outputs into one or more sets using a 'membership function' (Ng 2003). In an ordinary set, each element either belongs or does not belong to a set; however, in a fuzzy set, elements can have partial membership (Ng 2003). The 'membership function' represents the grade of possibility that an element belongs to a particular fuzzy set (Filippidis et al. 1999). The fuzzy inference engine then uses information about the inputs (that were fuzzified in the previous step), decides which rules apply and determines the process input (Passino & Yurkovich 1998). Defuzzification then converts the conclusions reached by the fuzzy inference engine into a numeric input for the process (Wang et al. 1995).

An adaptive control system can use a fuzzy logic control methodology in any of the initialisation, validation or reasoning processes of the control system (Wang et al. 1995). For example, Warwick (1993) describes a direct adaptive fuzzy control system described in which the rules of controller parameter adjustment are modified if the performance index calculated using the error signal is sub-optimal. The error signal is filtered using an approximate model of the process since only part of the error signal that is used to determine the performance index is due to an incorrect control signal (Wang et al. 1995).

### A.2.5 Genetic adaptive control

Genetic algorithms are search-and-optimisation algorithms that are based on the evolution of a population toward a solution of a certain problem (Zuo 1997). Genetic algorithms begin with 'population' of possible solutions which are represented by 'chromosomes' (Ng 2003). Solutions from one population are selected to form a new population according to their fitness; the fitness of a solution represents how suitable each solution is for a given task (Filippidis et al. 1999). This evolving process is continuously repeated until a set of stop criteria is satisfied.

Porter & Passino (1998) describe several methods of applying genetic algorithms to adaptive control. For example, genetic model-based control involve using a genetic algorithm to determine which controller to use from a bank of candidate controllers.

### A.2.6 Hybrid control

Hybrid control systems combine the capabilities of different control techniques to improve the performance of the system (Wu et al. 1999). For example, neural networks and knowledge-based expert systems offer different capabilities for an adaptive control system. An irrigation control system may use an expert system to determine how much irrigation to apply, and a neural network to learn how to determine the irrigation amount. The neural network would subsequently take over the operation (Wu et al. 1999).

A hybrid control system that combines fuzzy logic and neural networks is popular in the literature (Jang 1997). Wu et al. (1999) describe an adaptive control system in which a neural network is used to tune a fuzzy rule base and associated membership functions of the fuzzy variables. This type of controller is advantageous in fuzzy logic control systems since deriving a fuzzy control strategy is often difficult and time-consuming (Wu et al. 1999).

### A.2.7 Discussion – utility of ‘intelligent’ adaptive control techniques for irrigation

The control methods described in this section involve using ‘intelligent’ techniques to develop a process model and/or adjust the controller parameters. The development of the model would require a full dataset of weather, soil and plant for different types of crops, crop seasons, soil types, crop stages and positions in the field (to account for the spatial and temporal variability in the field). Cotton models (e.g. OZCOT) which may be used to predict the crop behaviour are already available and may be calibrated for different areas of the field if required; hence, there is no need to create a custom model for cotton.

Learning how the controller parameters should be adjusted would require the algorithm to be ‘trained’ to determine the irrigation application timing and volumes for different weather, soil and crop conditions and to different parts of the field. As with conventional adaptive control (Section A.1.4) this task would involve gathering field data about the crop response to a range of irrigation schemes and would be computationally and labour intensive using currently available sensors. Therefore, intelligent control systems as described above are not considered further in this thesis.

## A.3 Additional adaptive control approaches

Other types of adaptive control include dual, self-oscillating and high-gain adaptive control. These are described in the following sections.

### A.3.1 Dual adaptive control

The conventional and intelligent adaptive control methods described previously in this Appendix are ‘nondual’. Nondual adaptive controllers only use current knowledge to control the process (Wittenmark 2002). In contrast, dual adaptive control systems experiment with the process to learn about its behaviour and to control it better in the future, as well as control the system using current knowledge (Isermann et al. 1992). This may be achieved by using both a standard control signal and a perturbation signal as inputs to the process.

Two types of dual adaptive controllers are optimal and sub-optimal controllers. Optimal dual adaptive controllers can only be performed numerically as they require the quality of future data and process properties to be known in advance, whilst sub-optimal dual adaptive controllers add a test signal to the process input signal and monitor the output to actively learn and optimise controller performance criterion (Isermann et al. 1992). Short-term deterioration in control performance is expected in sub-optimal dual adaptive control systems until the controller parameters are optimised.

### A.3.2 Auto-tuning

Auto-tuning is the automatic adjustment of conventional controller parameters (Åström & Wittenmark 1989). The tuning is based on an experimental phase in which test signals are added to the input signals (Åström & Wittenmark 1989). Examples of test signals are steps and pulses.

### A.3.3 Self-oscillating adaptive control

A self-oscillating adaptive system is a class of adaptive control related to model-reference adaptive control and auto-tuning. Self-oscillating adaptive control involves adjusting the controller parameters to minimise the error between the reference model output and measured output, but with perturbation signals continually exciting the system (Åström & Wittenmark 1994).

### A.3.4 Extremum adaptive control

Adaptive control systems typically involve adjusting the controller parameters such that the process output converges to a set point: this assumes that the set point is known. If the set point is the unknown optimum of a measured variable, extremum adaptive control may be utilised to find the 'extremum point' that maximises or minimises the variable, depending on which point is desired (Krstić et al. 1995). An extremum controller finds the optimum operating point and then tracks this point if it is varying (Åström & Wittenmark 1989).

### A.3.5 Iterative learning control

Iterative learning control involves refining the input to a system that operates repetitively with the same initial conditions at each iteration (Ahn et al. 2007). If the process conditions are the same each time the process operates, then any errors in the output response are repeated during each operation. These errors are recorded during operation and are used to determine the modifications to the system input for the next iteration (Korovessi & Linninger 2006).

### A.3.6 Model predictive control

Predictive control systems involve forecasting the output signal at each time step (Škrjanc & Matko 2000) by solving an open-loop control problem over a fixed horizon in the future (Camacho & Bordons 2004). Model predictive control systems use a model of the physical system to forecast the process output and an optimisation algorithm to determine which control action to take to achieve the desired performance (Mosca 1995). The model used for the optimisation may be updated by calibration using the currently available data and an automatic calibration procedure.

### A.3.7 Discussion – utility of additional adaptive control approaches for irrigation

Several concepts in non-conventional adaptive control systems are applicable to irrigation control systems. Dual adaptive control concepts may be utilised in an irrigation system by applying different irrigation volumes to one part of the field and comparing the response to each volume to determine the best irrigation volume. Auto-tuning and self-oscillating adaptive control systems also involve using perturbation signals to adjust the controller parameters.

Extremum adaptive control concepts may be used to optimise measured variables that are maximised and for cotton these variables could be square or boll counts. This control method could also be applicable to soil moisture content or leaf area index and may be achieved by comparing the measured variables with a time series dataset that describes the optimal behaviour of the sensed variable throughout the crop season.

Iterative learning control may be used for irrigation as it involves repeatedly applying and refining inputs to a process to achieve the desired system performance. An iterative learning control strategy utilised for irrigation may involve refining the irrigation volume applied to maintain a soil moisture deficit. Iterative learning control and model reference adaptive control (Section A.1.2) are similar in that they both adjust the process input using the error between the measured and desired process outputs. The main differences are: (i) that iterative learning control does not require the transfer function of the system; and (ii) that iterative learning control assumes that the process returns to the same initial state after each iteration to eliminate the effects of any disturbances.

For the irrigation of a crop, the same initial soil moisture content and rate of crop water use may not be achieved after each irrigation event in a crop season. This is because the crop water use is temporally variable and depends on the dynamic daily and sub-daily weather conditions, crop growth stage and crop condition. To help overcome the weather dynamics, the irrigations may be initiated after the crop has consumed a threshold water use (determined either from weather or soil moisture data).

A model predictive control system for irrigation would use field data to calibrate the crop model. The calibrated model would then be used to simulate different irrigation schemes and determine the optimal irrigation timing and volumes.

## A.4 Alternatives to adaptive control

There are types of non-adaptive control systems that can adjust the controller parameters to retain the desired performance of a process with parameter variations. These systems include robust control and optimal control and are described in the following sections.

### A.4.1 Robust control

A robust control system exhibits the desired performance of the system in the presence of process model uncertainties and changes in process dynamics (Dorf & Bishop 2001). Robust controllers respond faster to parameter variations than adaptive controllers; however, adaptive controllers can generally handle larger parameter variations (Åström & Wittenmark 1994). Landau et al. (1998) recommend that a robust controller be designed before an adaptive controller is designed, since robust control design generally improves the adaptation transients and overall performance of adaptive control systems.

### A.4.2 Optimal control

Optimal control is a branch of modern control theory that focusses on designing controllers which will achieve the best possible value of the performance index (Lewis 1995). The requirements of optimal control systems include: (i) a mathematical description of the model of the process so the prescribed outputs can follow the desired trajectory; (ii) a specification of the performance index; and (iii) a statement of the control and state boundary conditions and physical constraints on the control (Naidu 2002). Optimal control systems are mathematically intense because the solution depends on the optimisation of the unique process and performance index (Lewis 1995).

### A.4.3 Variable structure control

Variable structure control involves changing the control signal abruptly when the process deviates from the desired behaviour (Schilling 1990). In contrast, adaptive control involves gradually changing the controller parameters as the process dynamics change. Variable structure control can achieve robust control since the system is insensitive to process variations (Åström & Wittenmark 1989). Sliding mode control is a method of variable structure control which involves using different controllers in different parts of the state space of the system (Åström & Wittenmark 1989).

### A.4.4 Discussion

The control system should be robust to uncertainties caused by sensor inaccuracy, stochasticity of sensor measurements and incorrect irrigation volume application. A robust irrigation control system may use additional feedback from measurements of soil moisture content and water depth (via catch cans). In agricultural environments, cost and practicality requirements commonly mean that some input data may be unavailable in agricultural environments. For example, it is common that only one soil moisture sensor is used in a field despite the wide range of soils being present. In this case, another irrigation management strategy may be required for data-deficient areas of the field which uses data from another sensor. If no soil measurements are available, then the strategy may use evapotranspiration or on-the-go plant sensors to manage the irrigations. Hence, to ensure the control system is robust to data availability, a variable structure control system may be utilised which uses different sensor input depending on the data available in different areas of the field. Such a control system would be robust to data gaps and deficiencies, while maintaining a minimum level of control performance.

The optimal control system approach requires a mathematical description of the model of the process. Hence it is not applicable to this irrigation control system.

## A.5 Conclusion

The foregoing review of control systems has identified five control techniques that are applicable to the irrigation of cotton. These are:

- **Dual adaptive control** which uses perturbation signals to learn more about the system and may be applied to irrigation to evaluate the response of the crop to different irrigation volumes (Section A.3.1)
- **Extremum adaptive control** which is used to achieve the optimal process output of either maximising square/boll count for cotton or targeting a soil moisture content or leaf area index throughout the crop season (Section A.3.4)
- **Iterative learning control** which would involve adjusting the irrigation volume applied depending on the error between the measured process output and desired process output after the previous irrigation (Section A.3.5)
- **Model predictive control** which would use field data to calibrate a cotton and soil model and then use the calibrated model to determine the optimum irrigation timing and volume (Section A.3.6)
- **Variable structure control** which would ensure that the control system is robust to data gaps (Sections A.4.1 and A.4.3)

As noted, the selection of these techniques has focussed on cotton. Consideration of their wider applicability to irrigation of other crops is beyond the scope of this thesis.

# Appendix B

# Sensitivity Analysis of Parameters in OZCOT Cotton Growth Model

This appendix details the sensitivity analysis that was conducted to identify the most influential input parameters in the OZCOT growth model. The sensitivity analysis involved the following procedure:

1. Identifying the model input parameters and output variables
2. Executing the model with a range of input parameter values
3. Calculating a sensitivity index to quantify the difference in each output with the adjustment of each input parameter
4. Ranking the influence of each parameter on the model output

## B.1 OZCOT input parameters and output variables

The daily cotton growth and soil response simulated by the OZCOT model are defined by parameters in crop variety and soil properties input files and these parameters are described in Tables B.1 and B.2, respectively. There are 39 parameters in the crop variety input file, and three parameters for each layer of soil in the soil properties input file: these soil properties are the depth of each layer, drained upper limit and starting soil moisture. For this analysis, the starting soil moisture was assumed to be known (from the input data).

In Table B.1, the numbers 1 to 8 in the names of parameters 12-18 (FRUDD1-8), 20-27 (BLTME1-8) and 28-35 (WT1-8) correspond to the fruiting age class (Hearn & Roza 1985). In OZCOT, the age classes and the size of the fruit in each class are defined as follows:

1. Small squares (3.0-5.0 mm)
2. Medium squares (5.0-10.0 mm)
3. Large squares (>10.0 mm)
4. Flowers
5. Small bolls (<25 mm)
6. Medium bolls (25.0-37.5 mm)
7. Large bolls (37.5-42.5 mm)
8. Open bolls

Table B.1: Crop parameters in OZCOT input variety file

| ID | Parameter | Units | Abbreviation | Lower range | Upper range |
|---|---|---|---|---|---|
| 1 | Rate of emergence | mm/day degree | RATE_MERG | 0.08 | 1.20 |
| 2 | Thermal time between emergence and the appearance of the first square | day degrees | DDISQ | 306.4 | 511.2 |
| 3 | Tipping out[1] time | days | TIPOUT | 41.6 | 62.4 |
| 4 | Rate of squaring in thermal time | squares/ plant/day degree | SQCON | 0.01448 | 0.02844 |
| 5 | Respiration constant | Nil | RESPCON | 0.012744 | 0.027672 |
| 6 | Plant population constant | Nil | POPCON | 0.029064 | 0.043596 |
| 7 | Constant relating timing of cutout[2] to boll load[3] | Nil | FCUTOUT | 0.38312 | 0.64932 |
| 8 | Area of cotyledons | $mm^2$ | ACOTYL | 0.00042 | 0.00063 |
| 9 | Growth rate of leaf area with water stress if crop is not yet squaring | $mm^2/mm^2$ | RLAI | 0.008 | 0.012 |
| 10 | Maximum leaf area index growth rate per site | $mm^2$/site | DLDS_max | 0.096 | 0.144 |
| 11 | Ratio of leaf area per site | $mm^2$/site | FLAI | 0.416 | 1.044 |
| 12 | Thermal development requirements for each cotton fruiting stage | day degrees | FRUDD1 | 40 | 60 |
| 13 | | | FRUDD2 | 124 | 216 |
| 14 | | | FRUDD3 | 230 | 420 |
| 15 | | | FRUDD4 | 252 | 456 |
| 16 | | | FRUDD5 | 365 | 624 |
| 17 | | | FRUDD6 | 479 | 792 |
| 18 | | | FRUDD7 | 649 | 1051 |
| 19 | | | FRUDD8 | 824 | 1338 |
| 20 | Fraction of boll development completed in one day | Nil | BLTME1 | 0.000 | 0.000 |
| 21 | | | BLTME2 | 0.000 | 0.000 |
| 22 | | | BLTME3 | 0.000 | 0.000 |
| 23 | | | BLTME4 | 0.056 | 0.084 |
| 24 | | | BLTME5 | 0.168 | 0.252 |
| 25 | | | BLTME6 | 0.264 | 0.396 |
| 26 | | | BLTME7 | 0.440 | 0.660 |
| 27 | | | BLTME8 | 0.800 | 1.000 |
| 28 | Weighting of each age class in proportion to plant's carbohydrate requirement | Nil | WT1 | 0.00832 | 0.01248 |
| 29 | | | WT2 | 0.02176 | 0.03264 |
| 30 | | | WT3 | 0.11528 | 0.17292 |
| 31 | | | WT4 | 0.07904 | 0.11856 |
| 32 | | | WT5 | 0.40336 | 0.60504 |
| 33 | | | WT6 | 0.76936 | 1.15404 |
| 34 | | | WT7 | 0.80000 | 1.00000 |
| 35 | | | WT8 | 0.46280 | 0.69420 |
| 36 | Seed cotton per boll | g/boll | SCBOLL | 3.0 | 6.6 |
| 37 | Ratio of seed cotton per boll to seed cotton and burr per boll | g/g | FBURR | 0.984 | 1.476 |
| 38 | Percent of lint per boll | % | PCLINT | 32 | 52 |
| 39 | Proportion of any day's flowers that shed[4] | Nil | SHED | 0.0 | 1.0 |

[1] Tipping out involves the damage and removal of the growing tip of the cotton's main stem

[2] Cut out is a crop stage late in the cotton season prior to boll opening when vegetative growth ceases and young bolls abort

[3] Boll load is the maximum number of developing bolls retained (Hake et al. 1996)

[4] Shedding is a process that involves the loss of bolls when nutrients are missing or plants are stressed

Table B.2: Soil parameters in OZCOT input soil file

| **ID** | **Parameter** | **Units** | **Abbreviation** | **Lower range** | **Upper range** |
|---|---|---|---|---|---|
| 40 | Depth of layer 1 | cm | DP1 | 15 | 60 |
| 41 | Depth of layer 1 | cm | DP2 | 15 | 60 |
| 42 | Depth of layer 1 | cm | DP3 | 15 | 60 |
| 43 | Drained upper limit of layer 1 | mm/mm | DUL1 | 0.00264 | 1.00000 |
| 44 | Drained upper limit of layer 2 | mm/mm | DUL2 | 0.00264 | 1.00000 |
| 45 | Drained upper limit of layer 3 | mm/mm | DUL3 | 0.00264 | 1.00000 |

For the sensitivity analysis, the simulated response was analysed after each input parameter was adjusted between an appropriate minimum and maximum value. The lower and upper ranges of the input parameters were obtained from the minimum and maximum parameters of the existing input files of HydroLOGIC, respectively, and these ranges are shown in Tables B.1 and B.2. HydroLOGIC is an irrigation management software package that simulates cotton growth using the OZCOT model and contains pre-defined input files of various cotton varieties and soil types for OZCOT (Richards et al. 2008).

The range of parameter values utilised in the sensitivity analysis was extended to allow for a wider range of crop and soil properties, while keeping the parameters within a realistic range. For each parameter, the lower range utilised was 80% of the minimum value and the upper range utilised was 120% of the maximum value of the corresponding parameter in the input files.

The OZCOT model predicts various plant and soil response variables, namely:

1. Fruiting sites
2. Square count
3. Boll count
4. Open boll count
5. Leaf area index

6. Potential nitrogen uptake
7. Soil moisture content
8. Boll load
9. Fruit nitrogen
10. Carrying capacity of carbon
11. Carrying capacity of nitrogen
12. Soil moisture index
13. Vegetative nitrogen stress index
14. Fruit nitrogen stress index
15. Irrigation deficit
16. Lint

The output variables considered in this sensitivity analysis were soil moisture content, leaf area index, square count and boll count. These were selected because they are the most likely to be measured in a field experiment and used to calibrate the growth model.

## B.2 Input parameter combinations

For this sensitivity analysis, the effect of individual inputs (i.e. the first-order effects) on the simulated output was evaluated to rank the parameter importance. A one-at-a-time analysis was conducted which involved repeatedly varying one parameter at a time while fixing the other parameters (Hamby 1994) and evaluating the effect of changing each input parameter on the modelled outputs. The parameter input values that were evaluated were equally distributed between the lower and upper limits of input parameter (defined in Tables B.1 and B.2). For this analysis, twenty sampling points were chosen.

The one-at-a-time analysis was conducted for a range of field conditions. This is because if the analysis was only conducted for one particular combination of weather, plant and soil properties and irrigation treatment, the variation in the output may be dependent on the set of field conditions used. Hence, the analysis was conducted for three crop varieties and soil types, each with a different set of parameters which would be held fixed during the sensitivity analysis. Three irrigation treatments and weather profiles were also implemented for the sensitivity analysis.

Sand, clay loam and clay soils were implemented with plant available water capacities of 100 mm, 200 mm and 300 mm and initial soil moisture contents of 50 mm, 100 mm and 150 mm, respectively. The three crop varieties used were Delta Diamond, Sicot 70 and Siokra V16BR, whilst the three irrigation treatments implemented were weekly applications of 20, 30 or 40 mm. Daily weather profiles for GPS locations -28.18°N 151.26°E, -29.50°N 149.90°E and -30.09°N 145.94°E were obtained from Australian Bureau of Meteorology SILO data (QNRM, 2009) for 2004/2005. The cotton crop was sown on 4 October and irrigated until 15 March of the following year.

A total of 81 possible sets of field conditions were evaluated (with three weather profiles, three crop varieties, three soil types and three irrigation treatments), and 35640 simulations were conducted for the sensitivity analysis (with the 20 adjustments made to each of the 45 input parameters with 81 sets of field conditions). Daily simulated output was recorded for soil moisture content, leaf area index, square count and boll count for each simulation.

## B.3 Calculating the sensitivity index

A sensitivity index was calculated to quantify the influence of each parameter on the simulated outputs. As noted in the previous section, this analysis involved conducting simulations for a range of field conditions. The sensitivity of the parameters is also likely to vary according to the day in the crop season. Hence, to ensure that any variation in the simulated response was caused by the adjustment of an input parameter rather than the temporal variation of the crop response and/or a change in the weather, soil or plant properties, separate sensitivity indices were calculated for each set of field conditions and day of the crop season. The sensitivity index ($SI_{p,r,i}(t)$) was calculated (Hamby 1994) as follows:

$$SI_{p,r,i}(t) = \frac{D_{p,r,i,max}(t) - D_{p,r,i,min}(t)}{D_{p,r,i,max}(t)} \tag{B.1}$$

where $D_{p,r,i,max}(t)$ and $D_{p,r,i,min}(t)$ are the respective minimum and maximum simulated values of output $r$ (i.e. soil moisture content, leaf area index, square count and boll count) when the $p$th parameter is adjusted over its range and for the $i$th combination of field conditions and day $t$.

The sensitivity indices were combined to quantify the overall sensitivity of each simulated output to each input parameter. The first-order indices are commonly averaged to measure the overall sensitivity of the output to each input parameter (Braddock & Schreider 2006). Hence, the sensitivity indices for each field condition and day were averaged as follows:

$$\mu_{p,r} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{d} \sum_{t=1}^{d} SI_{p,r,i}(t) \right) \tag{B.2}$$

where $\mu_{p,r}$ is the mean sensitivity index, $N$ is the total number of field conditions (81 in this case) and $d$ is the number of days in the simulated crop season.

Averaging the daily sensitivity indices throughout the crop season would mask the temporal changes in the most significant parameters; however, it would also identify the parameters that were most significant over the entire crop season. The averaged sensitivity indices for each parameter in the OZCOT model are shown in Figures B.1, B.2, B.3 and B.4 for the simulated soil moisture, leaf area index, square count and boll count, respectively.

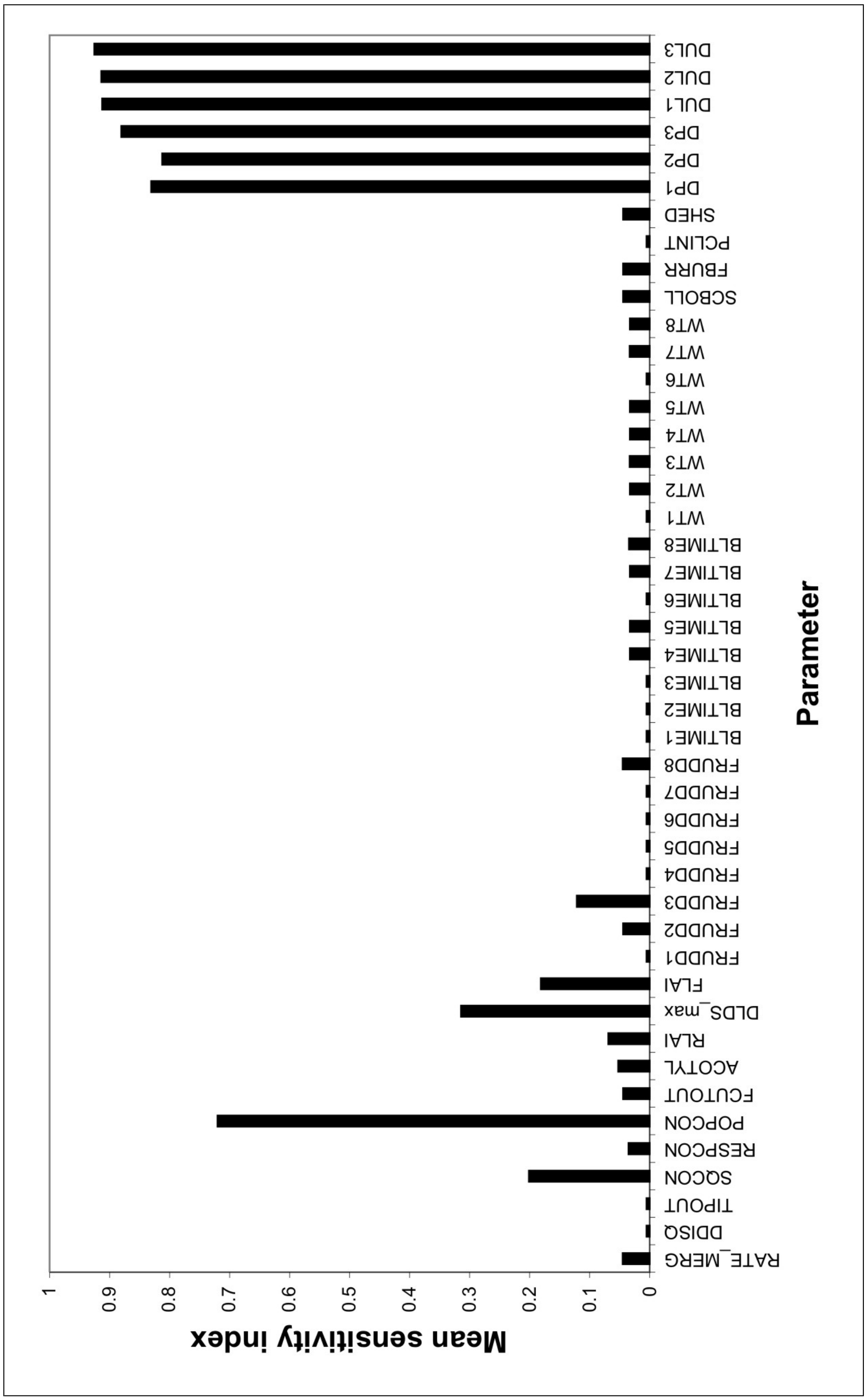


Figure B.1: Averaged sensitivity indices of simulated soil moisture response to OZCOT input parameters

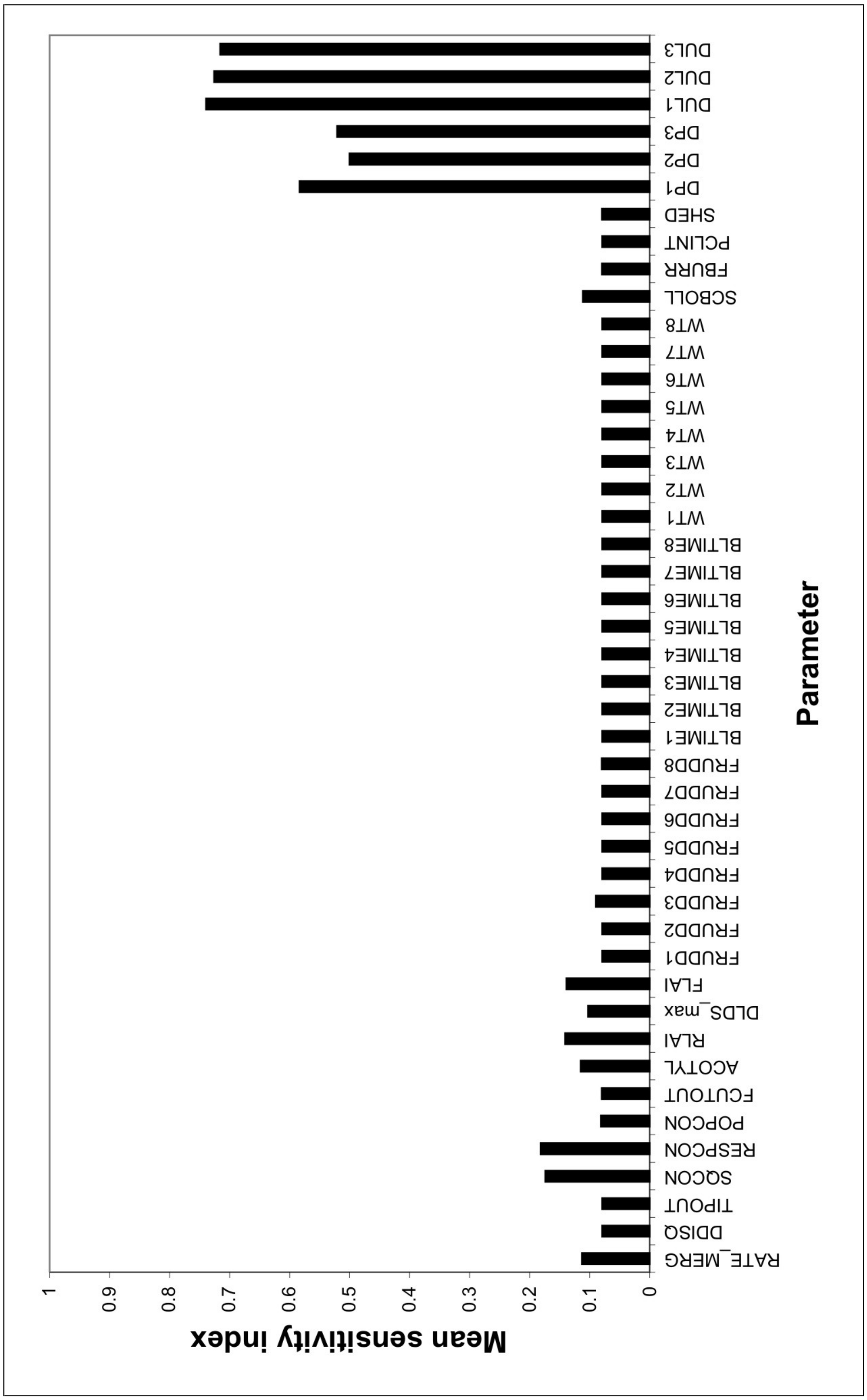


Figure B.2: Averaged sensitivity indices of simulated leaf area index response to OZCOT input parameters

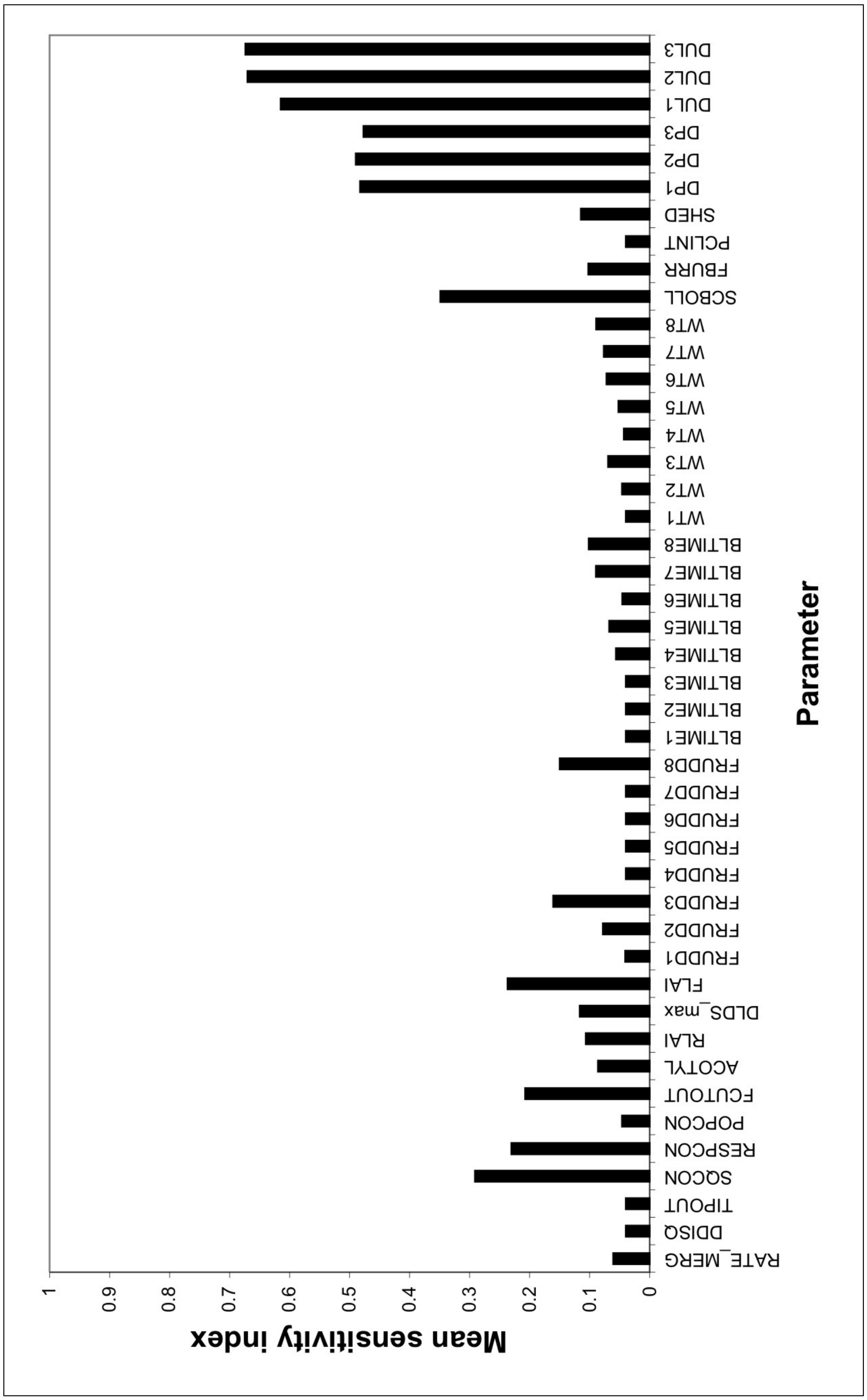


Figure B.3: Averaged sensitivity indices of simulated square count response to OZCOT input parameters

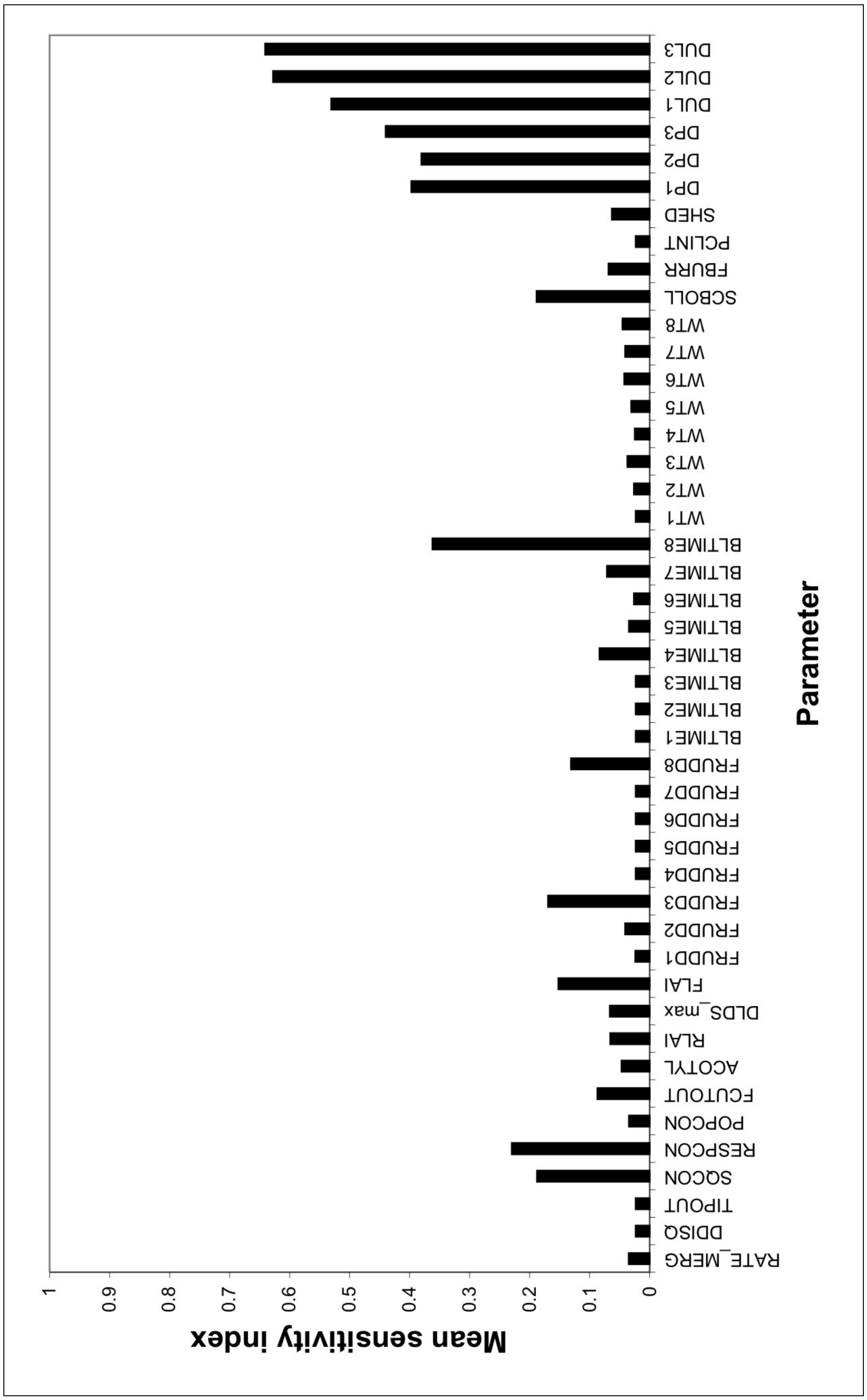


Figure B.4: Averaged sensitivity indices of simulated boll count response to OZCOT input parameters

## B.4 Ranking the input parameters

The averaged sensitivity indices for each simulated output and input parameter were assigned ranks from one (highest) to 45 (lowest) (Table B.3). From these rankings the following observations were made:

- The averaged sensitivity indices were significantly higher for the input soil parameters (depth of each layer, DP1-3, and drained upper limit in each layer, DUL1-3) than the input crop parameters for the four simulated outputs.
- For the simulated soil moisture content, the highest ranking crop parameters were the plant population constant (POPCON), maximum leaf area growth rate per site (DLDS_max), rate of squaring (SQCON) and ratio of leaf area per site (FLAI). These parameters would affect the plant spacing, vegetative growth and production of squares. This is consistent with the properties of crop water use and hence soil moisture content which are affected by both vegetative growth and fruit production.
- For the simulated leaf area index, the highest ranking crop parameters were the respiration constant (RESPCON), rate of squaring (SQCON), ratio of leaf area per site (FLAI) and growth rate of leaf area (RLAI). These parameters would affect both the plant's vegetative growth and fruit production. This is because the production of squares is linked to vegetative growth; for example, leaf area index reaches a maximum at peak flowering.
- For the simulated square count, the highest ranking crop parameters were the seed cotton per boll (SCBOLL), rate of squaring (SQCON), respiration constant (RESPCON) and ratio of leaf area per site (FLAI). As noted above, the production of squares is linked to vegetative growth; hence it is reasonable for the square count to be most influenced by parameters that relate to both vegetative growth and square and boll production.
- For the simulated boll count, the highest ranking crop parameters were the daily

boll development (BLTME8), respiration constant (RESPCON), rate of squaring (SQCON) and thermal requirements in the large squares stage (before flower buds open, FRUDD3). All of these parameters are related to boll and square development.

The ranks of the averaged sensitivity indices for each simulated output were summed to determine the overall ranking of each parameter (last two columns of Table B.3). The lowest summed rank was the most significant parameter for the simulated field conditions.

## B.5 Conclusion

In this sensitivity analysis, the most significant parameters were the depth of each soil layer (DP1-3) and drained upper limit in each soil layer (DUL1-3). The crop parameters were significantly less influential than the soil parameters and the next three lowest summed rankings were deemed to be the most influential crop parameters. Hence, the most significant crop parameters for the four simulated outputs were rate of squaring (SQCON), respiration constant (RESPCON) and ratio of leaf area per site (FLAI). These parameters influence both the vegetative and reproductive cotton growth throughout the crop season.

Table B.3: Means and ranks of the first-order sensitivity indices for each parameter in the OZCOT input files

| **Parameter** | **Soil moisture content** | | **Leaf area index** | | **Square count** | | **Boll count** | | **Sum of ranks** | **Overall rank** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Rank** | **Mean** | **Rank** | **Mean** | **Rank** | **Mean** | **Rank** | | |
| RATE_MERG | 0.009 | 14 | 0.03 | 13 | 0.02 | 29 | 0.009 | 30 | 86 | 21 |
| DDISQ | 0.003 | 36 | 0.016 | 28 | 0.012 | 36 | 0.006 | 36 | 136 | 33 |
| TIPOUT | 0.003 | 37 | 0.016 | 29 | 0.012 | 37 | 0.006 | 37 | 140 | 36 |
| SQCON | 0.083 | 9 | 0.096 | 8 | 0.144 | 8 | 0.075 | 9 | 34 | 7 |
| RESPCON | 0.007 | 16 | 0.101 | 7 | 0.115 | 9 | 0.103 | 8 | 40 | 8 |
| POPCON | 0.602 | 7 | 0.022 | 16 | 0.021 | 28 | 0.014 | 21 | 72 | 19 |
| FCUTOUT | 0.007 | 18 | 0.018 | 17 | 0.084 | 11 | 0.025 | 16 | 62 | 15 |
| ACOTYL | 0.013 | 13 | 0.042 | 12 | 0.028 | 22 | 0.013 | 24 | 71 | 18 |
| RLAI | 0.022 | 12 | 0.061 | 10 | 0.036 | 17 | 0.021 | 19 | 58 | 13 |
| DLDS_max | 0.199 | 8 | 0.047 | 11 | 0.044 | 15 | 0.022 | 18 | 52 | 12 |
| FLAI | 0.071 | 10 | 0.074 | 9 | 0.09 | 10 | 0.047 | 13 | 42 | 9 |
| FRUDD1 | 0.003 | 34 | 0.016 | 30 | 0.012 | 34 | 0.006 | 34 | 132 | 32 |
| FRUDD2 | 0.007 | 21 | 0.016 | 22 | 0.031 | 18 | 0.014 | 22 | 83 | 20 |
| FRUDD3 | 0.035 | 11 | 0.025 | 15 | 0.074 | 12 | 0.075 | 10 | 48 | 10 |
| FRUDD4 | 0.003 | 38 | 0.016 | 31 | 0.012 | 38 | 0.006 | 38 | 145 | 37 |
| FRUDD5 | 0.003 | 39 | 0.016 | 32 | 0.012 | 39 | 0.006 | 39 | 149 | 39 |
| FRUDD6 | 0.003 | 40 | 0.016 | 33 | 0.012 | 40 | 0.006 | 40 | 153 | 40 |
| FRUDD7 | 0.003 | 41 | 0.016 | 34 | 0.012 | 41 | 0.006 | 41 | 157 | 41 |
| FRUDD8 | 0.008 | 15 | 0.018 | 18 | 0.063 | 13 | 0.051 | 12 | 58 | 14 |
| BLTIME1 | 0.003 | 42 | 0.016 | 35 | 0.012 | 42 | 0.006 | 42 | 161 | 42 |
| BLTIME2 | 0.003 | 43 | 0.016 | 36 | 0.012 | 43 | 0.006 | 43 | 165 | 43 |
| BLTIME3 | 0.003 | 44 | 0.016 | 37 | 0.012 | 44 | 0.006 | 44 | 169 | 44 |
| BLTIME4 | 0.005 | 27 | 0.016 | 38 | 0.021 | 27 | 0.02 | 20 | 112 | 28 |
| BLTIME5 | 0.005 | 25 | 0.016 | 24 | 0.022 | 26 | 0.011 | 28 | 103 | 25 |
| BLTIME6 | 0.003 | 33 | 0.016 | 39 | 0.014 | 32 | 0.007 | 32 | 136 | 34 |
| BLTIME7 | 0.005 | 28 | 0.016 | 21 | 0.029 | 21 | 0.023 | 17 | 87 | 22 |
| BLTIME8 | 0.006 | 23 | 0.016 | 40 | 0.03 | 20 | 0.271 | 4 | 87 | 23 |
| WT1 | 0.003 | 35 | 0.016 | 41 | 0.012 | 35 | 0.006 | 35 | 146 | 38 |
| WT2 | 0.005 | 30 | 0.016 | 25 | 0.017 | 31 | 0.008 | 31 | 117 | 29 |
| WT3 | 0.006 | 22 | 0.016 | 23 | 0.027 | 23 | 0.012 | 27 | 95 | 24 |
| WT4 | 0.005 | 31 | 0.016 | 42 | 0.014 | 33 | 0.006 | 33 | 139 | 35 |
| WT5 | 0.005 | 26 | 0.016 | 26 | 0.019 | 30 | 0.01 | 29 | 111 | 27 |
| WT6 | 0.003 | 32 | 0.016 | 27 | 0.023 | 25 | 0.013 | 23 | 107 | 26 |
| WT7 | 0.005 | 24 | 0.016 | 43 | 0.026 | 24 | 0.013 | 26 | 117 | 30 |
| WT8 | 0.005 | 29 | 0.016 | 44 | 0.03 | 19 | 0.013 | 25 | 117 | 31 |
| SCBOLL | 0.007 | 19 | 0.029 | 14 | 0.16 | 7 | 0.063 | 11 | 51 | 11 |
| FBURR | 0.007 | 20 | 0.017 | 20 | 0.043 | 16 | 0.028 | 14 | 70 | 17 |
| PCLINT | 0.003 | 45 | 0.016 | 45 | 0.012 | 45 | 0.006 | 45 | 180 | 45 |
| SHED | 0.007 | 17 | 0.017 | 19 | 0.049 | 14 | 0.027 | 15 | 65 | 16 |
| DP1 | 0.816 | 5 | 0.443 | 4 | 0.259 | 5 | 0.194 | 6 | 20 | 4 |
| DP2 | 0.786 | 6 | 0.335 | 5 | 0.28 | 4 | 0.191 | 7 | 22 | 6 |
| DP3 | 0.873 | 4 | 0.322 | 6 | 0.236 | 6 | 0.205 | 5 | 21 | 5 |
| DUL1 | 0.909 | 3 | 0.575 | 1 | 0.385 | 3 | 0.291 | 3 | 10 | 3 |
| DUL2 | 0.911 | 2 | 0.55 | 2 | 0.457 | 2 | 0.403 | 2 | 8 | 2 |
| DUL3 | 0.923 | 1 | 0.529 | 3 | 0.462 | 1 | 0.417 | 1 | 6 | 1 |

# Appendix C

# Fieldwork Apparatus

This appendix comprises the sections listed below.

**Appendix C.1** contains details of the plant height sensor developed and used in the fieldwork (Chapter 4).

**Appendix C.2** contains details of the variable-rate nozzles developed for the fieldwork (Chapter 4).

## C.1 Plant height sensor

A plant height sensor was developed as part of the fieldwork detailed in Chapter 4. The plant height sensor consisted of an infrared distance sensor (Sharp Model GP2D12) mounted on a 1.7 m tall 45 mm box steel frame with four wheels (Figure C.1). The two pairs of wheels (1 mm and 0.5 m in circumference, respectively) were mounted on 25 mm box steel and 900 mm apart, and the front pair of wheels stabilised the unit. A plywood shade hood was used to reduce the light interference with the infrared sensors. The frame was manually pushed down the cotton rows in the field trial and 44 data points were collected in every metre at a travel speed of 1.5 m/s.

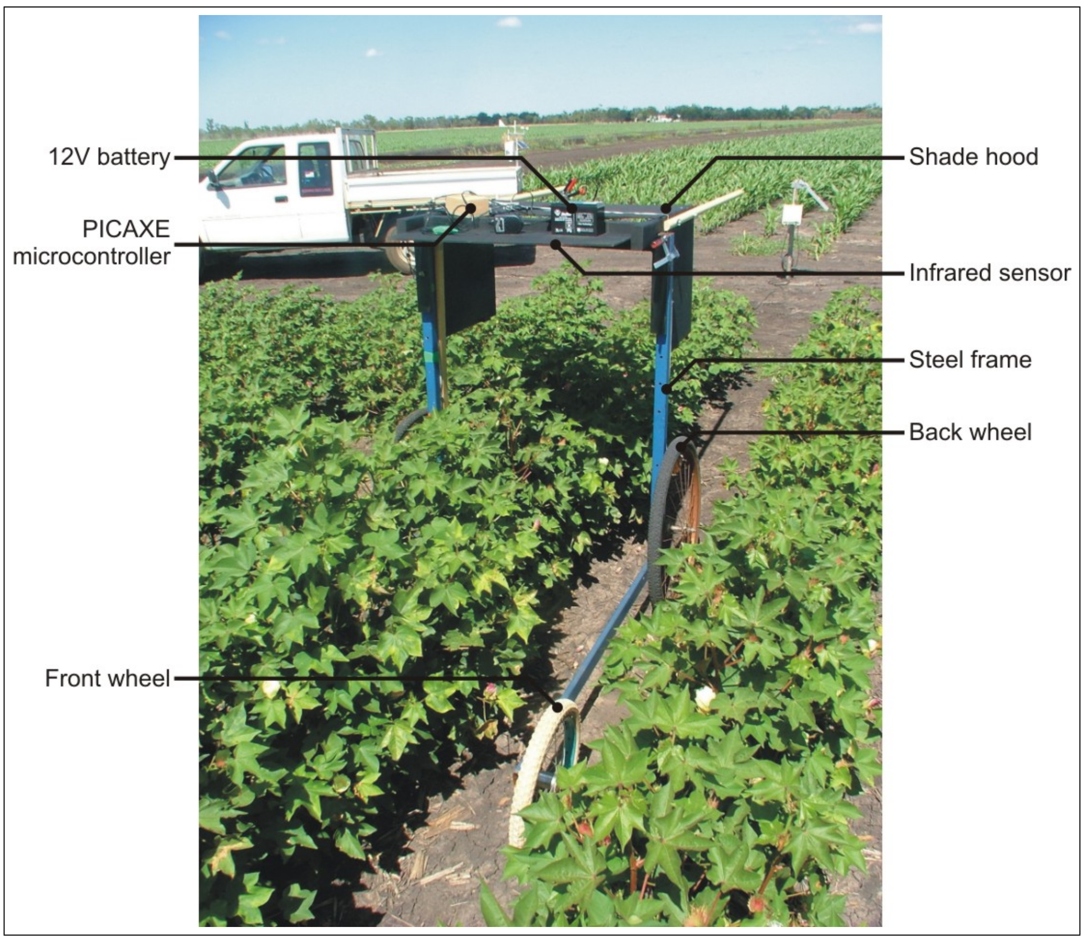


Figure C.1: Plant height sensor on cotton row in trial site

The distance that the unit had moved was determined using a reed switch mounted on the frame and a magnet on the 1 m circumference wheel: the reed switch opened when the magnet was near, i.e. every metre travelled. A PICAXE microcontroller was used to input the plant height and travel distance data (Figure C.2) and stream these datasets to software written in Borland Delphi 6 which saved the data to a database. In the data analysis, it was assumed that the travel speed was constant within each metre travelled.

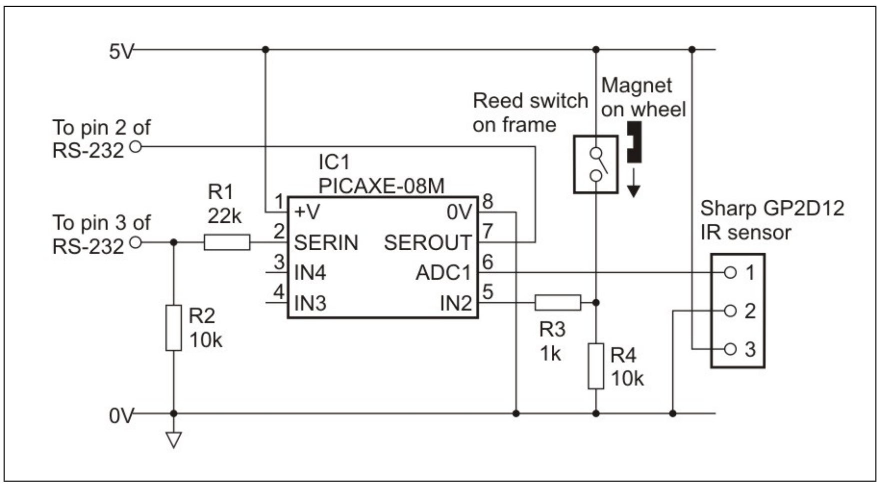


Figure C.2: Schematic diagram of plant height sensor circuit using infrared distance sensor (Sharp GP2D12) and reed switch to determine distance traversed in field

Plant height measured manually and using the sensor were compared to confirm the reliability of the height sensor (Figure C.3). There was an average standard deviation of 24 mm for ten replicate datasets measured using the plant height sensor along 75 metres of the field (Figure C.4).

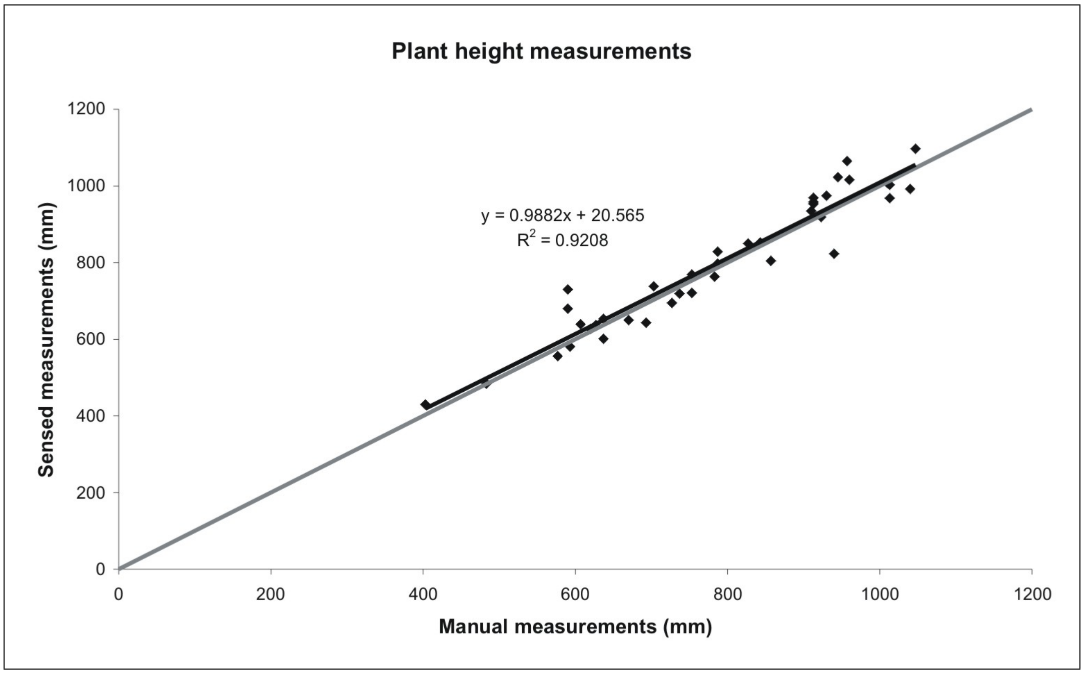


Figure C.3: Comparison of plant height measured manually and with sensor and 1:1 line

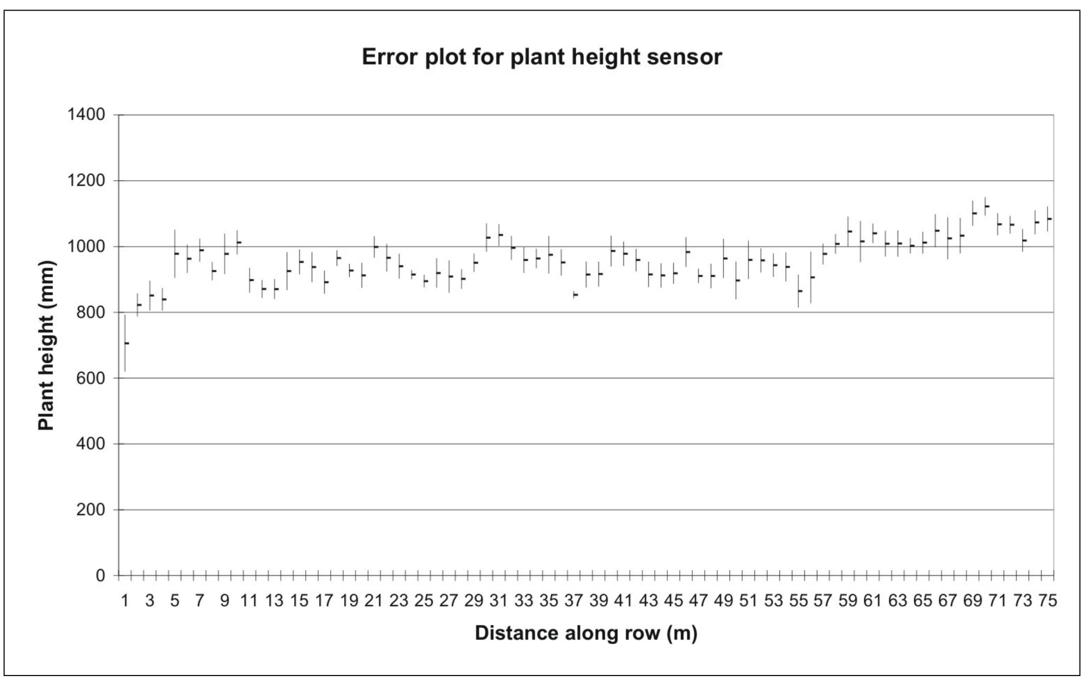


Figure C.4: Example variation in readings from plant height sensor for 10 replicates of 75 metres of the field (average standard deviation = 24 mm)

## C.2 Variable-rate nozzles

The irrigation applications were varied by adjusting the ball valve on the droppers of the sprinklers used to irrigate the trial area (Figure C.5). A servo was attached to each ball valve and a PICAXE microcontroller was used to adjust the servo position, i.e. the amount that the ball valve opened was controlled by adjusting the servo (Figure C.6). This method of variable-rate irrigation reduced the flow rate of the water through the nozzles. Hence, the spray pattern of the sprinklers was maintained for the three irrigation treatments.

The distance travelled by the irrigation machine was determined using a reed switch on the machine and a magnet on the tyre which was 1.4 m in circumference. This distance measurements were used to adjust the servo positions for the different irrigation treatments along the cotton rows. To achieve the high irrigation treatment, larger nozzles were installed on the sprinkler heads. The discharge of three irrigation treatments were verified with catch can data. Sixteen valves were manufactured and installed on the span of the irrigation machine over the trial site (Figure C.7).

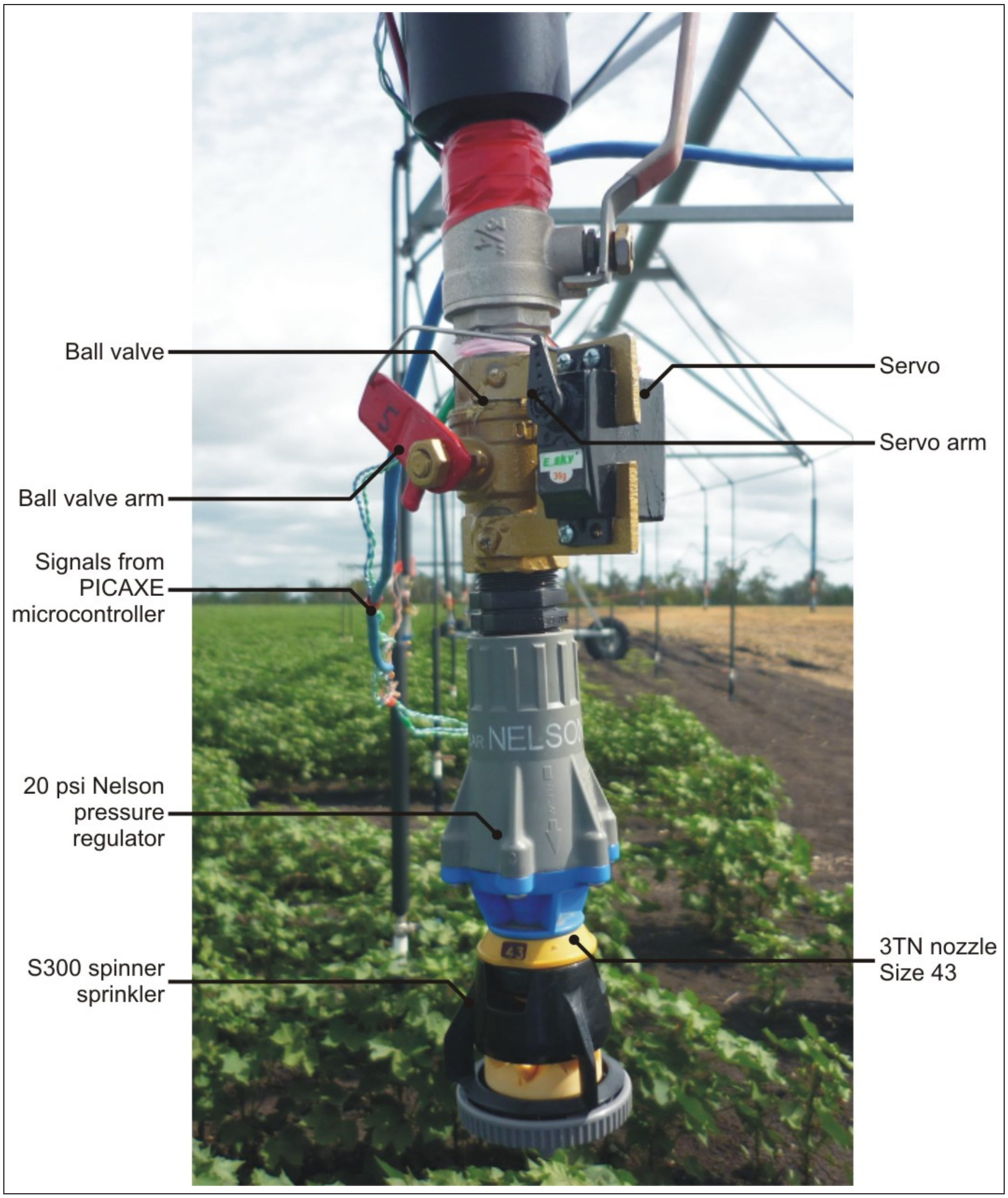


Figure C.5: Variable-rate nozzle constructed

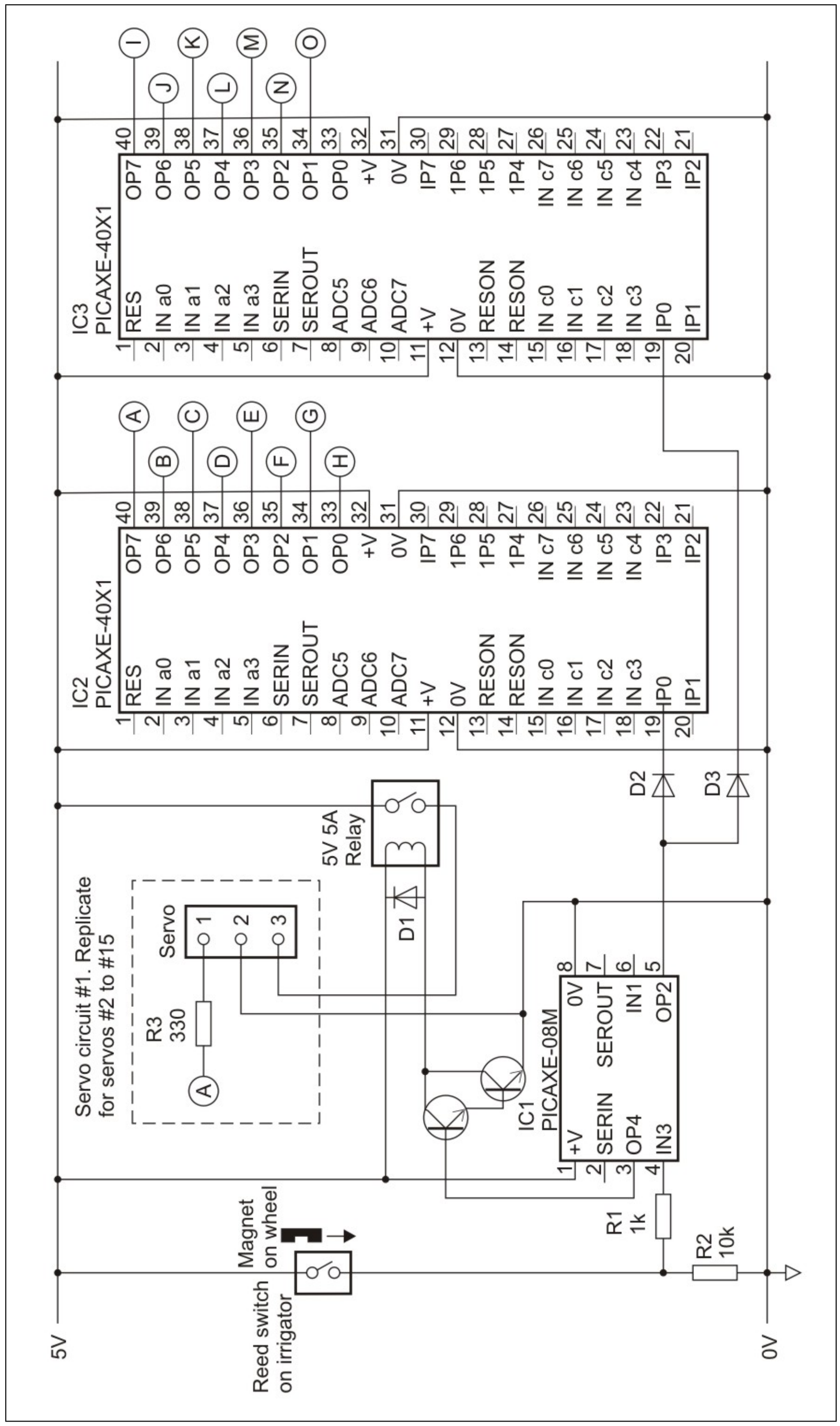


Figure C.6: Schematic diagram of variable-rate nozzles controller circuit using servos and reed switch attached to the irrigation machine to determine distance traversed in field

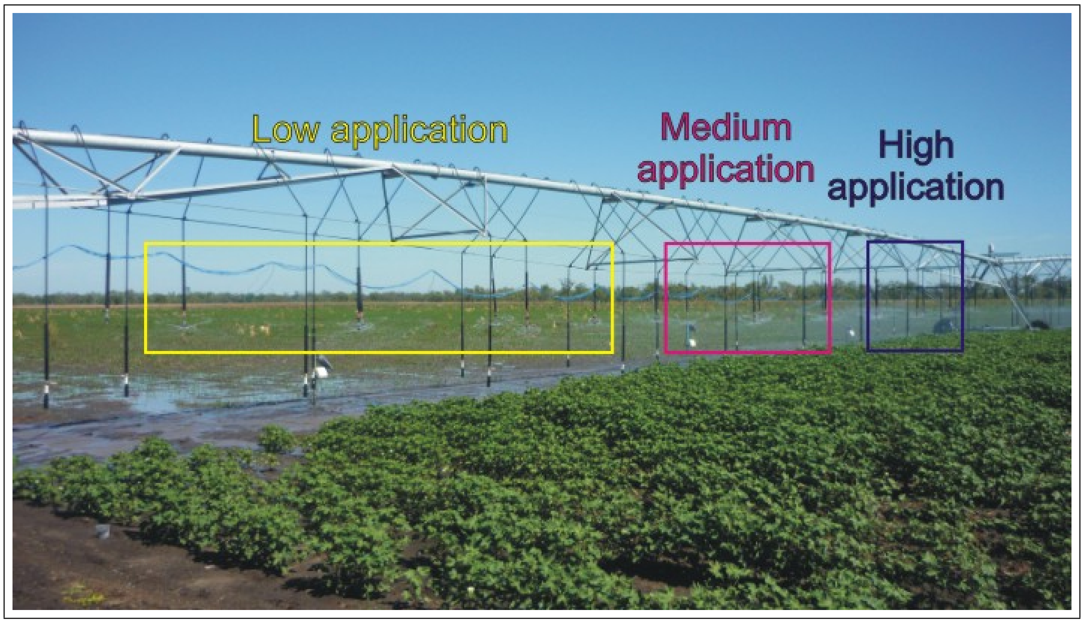


Figure C.7: Distribution of irrigation application on irrigation machine for low, medium and high irrigation treatments