Development and simulation of sensor-based irrigation control strategies for cotton using the VARIwise simulation framework

Alison C McCarthy[1*], Nigel H Hancock[2] and Steven R Raine[3]

* corresponding author

National Centre of Engineering in Agriculture
Faculty of Engineering and Surveying
University of Southern Queensland
West Street
Toowoomba, Queensland 4350
Australia

[1] Telephone: 61 7 4631 2189
Email: mccarthy@usq.edu.au
Facsimile: 61 7 4631 1870

[2] Telephone: 61 7 4631 2552
Email: hancockn@usq.edu.au
Facsimile: 61 7 4631 1870

[3] Telephone: 61 7 4631 1691
Email: raine@usq.edu.au
Facsimile: 617 4631 2526

Abstract

Feedback control systems offer opportunities to accommodate spatial and temporal differences in crop water requirement and to improve the automated irrigation of field crops via real-time data from in-field plant, soil-water and evaporation sensing. This paper describes two sensor-based strategies applied to irrigation control, 'Iterative Learning Control' (ILC) and custom-designed 'Iterative Hill Climbing Control' (IHCC), implemented in the control simulation and evaluation framework 'VARIwise'. Simulation of an irrigated cotton crop using soils and merged 1999-2004 weather data of SE Queensland, Australia, and represented by the performance of the well-validated cotton growth and production model OZCOT, permitted the relative performance of differing sensor data types and availability to be evaluated (both as alternatives and in combination) in meeting the requirement to optimise either crop yield or water use efficiency. These simulations indicated that ILC would perform better at maintaining soil-water deficit, whilst IHCC would be better at maximising crop yield when plant and soil sensors were utilised in combination. This work demonstrates that the optimal choice of field sensor(s) and control strategy will be a function of the irrigation objective and the spatial and temporal availability and type of field measurements.

Research highlights

- Two site-specific sensor-based irrigation strategies were simulated in VARIwise
- Iterative Learning Control (ILC) produced highest yield with soil-water data input
- Iterative Hill Climbing Control (IHCC) performed best with soil-and-plant data input

- Both sensor-based strategies were superior to the industry-standard strategy

Keywords

Variable-rate irrigation, centre pivot, lateral move, scheduling, automation, OZCOT

1. INTRODUCTION

Irrigation application and crop water use efficiencies can be improved by scheduling the irrigation of crops using physical and agronomic principles (Evans 2006). The irrigation management strategy determined using these principles may be automatically implemented using a control system. Irrigation control strategies can use historical or real-time quantitative measurements of the crop, weather and soil, either singly or in combination, to automatically adjust the irrigation application.

Irrigation is traditionally applied uniformly over an entire field, although not all plants in the field may require the same amount of water at any given time. In these cases, differential irrigation application to meet the plant requirements at different positions in the field may improve operational performance. However, 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' (Smith et al. 2009; McCarthy et al. 2010). Site-specific irrigation is enabled for centre pivot and lateral move irrigation machines through commercially available variable-rate hardware (e.g. Design Feats, Zimmatic, Valley). These systems adjust the irrigation application within the field by varying the speed of the machine and/or pulsing solenoid valves on each dropper. According to the choice of water outlet– sprinkler head or Low-Energy Precision Application (LEPA) sock – differential application may be achieved at the <1 m^2 scale.

The performance of an irrigation control system will be limited by: (i) the attributes that are measured in the field; (ii) the spatial resolution of the sensor data for both static sensors (e.g. soil-water probes) and on-the-go sensors (e.g. infrared thermometers measuring foliage temperature); and (iii) the temporal resolution of these data inputs. However the performance delivered by the control system may also be affected by unexpected environmental conditions (e.g. mid-irrigation and spatially-varied rainfall) or exceptional operational changes (e.g. crop damage or a capacity constraint of the irrigation machine such that it cannot deliver the optimal irrigation volumes in time). It may be expected that adaptive irrigation control systems have differing robustness to these operating conditions, data availability and system constraints (Warwick 1993).

In principle at least, adaptive control systems automatically and continuously re-adjust the controller to obtain the desired performance of the system (Warwick 1993). Their application to irrigation can potentially improve crop development and/or water use efficiency. In addition, adaptive control strategies may be used to accommodate the differing levels of data quality and availability normally found in irrigation practice, i.e. utilise the various combinations of weather, soil and plant data available (McCarthy et al. 2011a). Potentially optimal adaptive control strategies that determine irrigation volume and timing may be identified by simulating alternate adaptive control strategies in a simulation framework.

The objective of this paper is to determine the potential efficacy of 'sensor-based' adaptive control (as introduced in section 3 below) for the practical irrigation of cotton. A companion paper, McCarthy et al. (2013), reports the implementation and performance of model-based adaptive control strategies: refer section 3 below.

2. CONTROL SIMULATION FRAMEWORK 'VARIwise'

A simulation framework 'VARIwise' was created to develop, simulate, evaluate and also implement (as a machine controller) uniform and site-specific irrigation control strategies for centre pivot and lateral move irrigation machines. Full details are presented in McCarthy et al. (2010): a simplified schematic is presented in Figure 1.

Insert Figure 1 here

Within VARIwise, the field is divided into cells of minimum area 1 m^2 to accommodate spatial variability. The software 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 various levels of control strategies for variable-rate irrigation at different spatial scales; and
- requires a crop model integrated within VARIwise. In the simulation mode this model provides feedback data which permit evaluation of any control strategy implemented.

The well-established cotton growth model OZCOT (Wells and Hearn 1992) has been utilised by VARIwise for the present study. The OZCOT model combines a temperature-driven model of fruit dynamics with a soil-water balance model, and original sub-models for: fruiting, leaf area generating, boll growth and elementary nitrogen (Wells and Hearn 1992). The model was developed and validated for different soil types from agronomic experiments over a period of 30 years covering a range of Australian cotton growing regions (Hearn 1994). OZCOT's capacity to simulate yield, fruiting dynamics, nitrogen uptake and water use has been validated in the Ord Valley, Western Australia, for summer grown cotton during the 1960s and 70s (Hearn 1994). The model responds to different climatic situations, crop physiological characteristics, agronomic variables and management decisions, but does not account for the effects of insect pests, diseases, weeds and soil nutrient limitations other than nitrogen. The model does not simulate the effects of climate and management on fibre quality. The OZCOT model requires the parameters listed in Table 1 to be written into input files. After the OZCOT model has been executed, an output file is produced that contains estimates of the soil-water, fruit load and vegetation indices for each day of the predicted cotton season.

Insert Table 1 here

3. ADAPTIVE CONTROL STRATEGIES

Adaptive control strategies applicable to irrigation may be either: (i) 'sensor-based', for which the (simulated) irrigation application is directly adjusted according to the measurement response; or (ii) 'model-based', which use a calibrated soil and plant model for irrigation management. These strategies differ fundamentally in their data requirements and their use of the crop model. The focus of this paper is the relative performance of two candidate sensor-based irrigation control strategies: as noted above, a companion paper, McCarthy et al. (2013), reports the implementation and performance of model-based strategies.

By definition, sensor-based strategies can be implemented with a range of input variables chosen to provide feedback for control. This paper reports a simulation study to determine the appropriate input variable/s for each control strategy; and comment on the relative utility of each strategy.

Following a review of candidate adaptive control strategies (McCarthy et al. 2011b), the two sensor-based adaptive control strategies implemented in VARIwise are 'Iterative Learning Control' (ILC) and 'Iterative Hill Climbing Control' (IHCC). The two strategies are described below, and their implementation set out in the section following. In summary, these strategies refine the estimate of each successive irrigation volume applied by:

[ILC] – iteratively adjusting the irrigation volume applied in each cell of the field using the incremental response, i.e. the OZCOT-determined plant growth arising from the change in *particular field sensor information* which has resulted from the previous water application, in each cell; or

[IHCC] – similarly adjusting the irrigation volumes, but based on *multiple sensor increment information*, using a range of irrigation volumes applied within a group of homogenous cells.

3.1 Iterative Learning Control

Iterative Learning Control (ILC) can be used to control repetitive processes, e.g. robot arm manipulators, repetitive rotary systems, and factory batch processes, where the process model is imperfectly known (Ahn et al. 2007). An irrigation system may be interpreted as a repetitive process because the irrigation machine iteratively passes over the field throughout the crop season; and, given the complexity of variable plant growth, is certainly imperfectly described from the control perspective. Hence, in principle, classical ILC can be used to improve the system performance by eliminating the effects of any unknown but repeating disturbance (Korovessi and Linninger 2006). Applied to irrigation, an unknown feature of the crop response model that reoccurs as a consequence of irrigation may be regarded as a 'repeating disturbance'.

ILC requires that the process controlled by the strategy is reset to the same initial conditions after each iteration (Korovessi and Linninger 2006). Again, applied to 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.

The variables soil-water, leaf area index, square count or boll count may be used as feedback to measure the system performance for a cotton irrigation control system ('squares' are flower buds; and 'bolls' are the seed pods which contain the cotton fibre of the cotton plant). For example, for soil-water-based ILC a controller may target a particular soil-water deficit throughout the season (and the data may be used to calibrate the model). However, to be valid for feedback control, these measurements must be taken only after a suitable delay following irrigation to ensure the soil or crop has responded to the irrigation application.

Moore and Chen (2006) demonstrated an ILC strategy for a centre pivot irrigation machine to determine site-specific irrigation application volumes using soil-water as the feedback variable. The strategy was evaluated in simulations using a soil model with one dimensional flow. This soil model assumed constant crop water use irrespective of the crop stage, crop conditions and the daily and sub-daily weather dynamics. Hence, the model was reset to the same initial conditions after a fixed time delay and irrigation events were scheduled at regular time intervals.

3.2 Iterative Hill Climbing Control

A drawback of the ILC strategy is the potentially inefficient system identification, and particularly so when applied to irrigation which has a 'learning increment' of typically several days. This is a result of only one irrigation volume being evaluated in each cell during each irrigation event. As an alternative, adaptive spatially-varied identification may be more rapidly achieved by utilising site-specific combinations of plant, soil and weather data in different sub-areas of the field, i.e. using aggregates of cells having similar properties. Likewise, adaptive system identification may be incorporated into an irrigation control system to account for the slow speed of crop dynamics and the low frequency of irrigation events. To meet these requirements and circumvent these limitations, an alternative, multi-dimensional approach was developed, as follows.

The technique is designated 'Iterative Hill Climbing Control' (IHCC), in which 'hill climbing' involves changing the state of the system into one that is closer to the goal in the direction of steepest gradient (Russell and Norvig 1995). IHCC provides faster optimisation than ILC alone because it permits the evaluation of both:

- a range of inputs to the system at each irrigation event (i.e. multi-dimensional ILC); and
- a range of irrigation volumes on different cells in the field (within the particular sub-area) at each irrigation event.

As noted, IHCC involves grouping cells with similar properties in the field and applying different irrigation volumes to designated 'test cells' within each group of cells. 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.

4. IMPLEMENTATION OF SENSOR-BASED CONTROL STRATEGIES IN VARIwise

The ILC and IHCC strategies were implemented in VARIwise to calculate the optimal irrigation application volumes for each cell. For the ILC strategy, the irrigation volumes are determined from previous irrigation applications and measured responses. For the IHCC strategy, the volumes to apply are determined by evaluating the response to a range of irrigation volumes previously applied to test cells within representative homogenous areas of the field. Homogenous areas within fields are referred to as a management 'zone' in this paper and zone boundaries may be determined using soil properties, crop or variety differences, topography or management constraints.

The implementation of the control strategies within VARIwise involves six steps described in the following sections. Of necessity, the procedures differ for the ILC and IHCC strategies. In particular, the procedure for the calculation of irrigation volumes is fundamentally different (sections 4.6 and 4.7, respectively).

4.1 Select control areas

The ILC and IHCC strategies require different spatial resolutions for irrigation application. ILC can be used to determine irrigation applications to each individual cell; however, for IHCC the field must be divided into a number of zones.

The identification of zones for the IHCC strategy can be undertaken automatically by VARIwise using a measured field property (e.g. soil property). In this case, the property data assigned to each cell in the field is sorted in ascending order and then grouped into the user-specified number of evenly-sized zones. A small number of cells (i.e. a group of 'test cells') are then selected in each zone to evaluate different irrigation applications. The application of the various irrigation volumes to the test cells results in differential soil-water and crop responses. Hence, test cell responses are only indicative of the response in each zone for one irrigation event and the IHCC strategy requires the selection of new test cells in each zone for each irrigation. In VARIwise, this is achieved by a simple increment of the test cell number along with a requirement that the replacement cell still lies within the same zone and has not previously been used as a test cell.

4.2 Determine day of first irrigation

The number of days until the first irrigation in each cell or zone is calculated by dividing the plant available water capacity (*PAWC*) of the soil by the daily crop water use or daily crop evapotranspiration (ET_c). This procedure is described in McCarthy et al. (2010).

4.3 Calculate first irrigation volume

For ILC and IHCC non-test cells, the first irrigation application volume is calculated by aggregating the daily ET_c since the crop was sown. The daily ET_c is calculated as evapotranspiration obtained from the weather data, i.e. via reference (potential) evapotranspiration ET_o, and the appropriate crop coefficient, K_c, as published for each crop and growth stage, following the standard methodology of FAO 56, Allen et al. (1998).

For IHCC test cells, the irrigation volume applied to each test cell is similarly determined using the ET_o since the crop was sown, but with a range of crop coefficients imposed. 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 $\underline{K_c}$ = 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).

4.4 Check 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. In a field implementation, the currently-available datasets are kriged (i.e. spatially interpolated) across the field to ascribe a value to each cell in the field. This is because sensor data may be unavailable due to sensor failures or the installation of sensors being impractical (large numbers of infield sensors are often obstructive to growers).

4.5 Determine day of next irrigation

The irrigation events are scheduled when the crop has reached a user-specified cumulative crop water use 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-water 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 cumulative crop water use is determined as the sum of the daily crop evapotranspiration (calculated using the weather data).
- If soil data input is used but update data are not available, plus weather data are not available or not used, then the cumulative crop water use is calculated using historically averaged weather data.

Since the crop water use may not be uniform across the field due to spatial variability, the irrigations are initiated when an arbitrary proportional of the cells in the field have reached the user-specified cumulative crop water use (e.g. 15%).

4.6 Calculate irrigation volumes – ILC

For ILC the irrigation volume applied to each cell in the field is calculated using a common ILC algorithm (Ahn et al. 2007) which calculates the required system input (the irrigation volume to be applied) u_{k+1} at the forthcoming iteration, i.e. the (k+1)-th irrigation, according to:

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

where:

u_k = the system input (irrigation volume) on the previous iteration (k-th irrigation)

γ = the learning gain (a scalar factor)

$y_k(\Delta)$ = the *measured* system output (i.e. sensor data value, kriged as necessary) after delay Δ; and

$y_d(\Delta)$ = the *desired* system output (i.e. *desired* sensor data value) after delay Δ

in which the delay in measurement after each irrigation Δ permits the crop to respond to that irrigation (typically one day for the sensing of soil-water change; longer for the sensing of a plant growth variable). In all cases the response delay Δ must be less that the interval between irrigations. The learning gain γ is chosen by iteration as a compromise between slow learning (low γ) and instability in the predicted u_{k+1} values (high γ).

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-water) or always decrease when the irrigation volume applied decreases (e.g. soil-water 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. A negative learning gain is used where soil-water is the controlled variable. In this case, the soil-water variable is calculated by subtracting the desired deficit from the full point (field capacity) of the soil. However, conversely for cotton, the 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 of equation (1) calculates the volume to apply at the next irrigation event using measured field data and the desired value based on a single measured variable y. However, because more than one soil or plant measured variable may be applicable, an expanded ILC algorithm was implemented to accommodate for multiple variables. In this case, optimisation may be achieved by either one, or a combination, of the following (Liu et al. 2001):

i. assigning a weighting to each optimisation objective (variable y_i) and constructing a weighted sum of all the objectives, and/or
ii. optimising each objective separately to explore trade-offs

where the separate optimisation objectives are driven by difference between the measured and desired variable values, $y_{i,k}$ and $y_{i,d}$ respectively.

The multi-objective optimisation option (i) requires subjective selection of the weights for each objective; however the separate-objective option (ii) requires an additional decision-making procedure to determine which objective optimisation results in the desired performance for both objectives. The present VARIwise implementation for sensor-based irrigation optimisation aims to evaluate the effect of using multiple data inputs and the multi-objective optimisation option (i) was presumed sufficient with each objective equally weighed. Hence, the multi-objective ILC algorithm is:

$$u_{k+1} = u_k + \gamma \sum_{i=1}^{n} (w_i \times (y_{i,k}(\Delta) - y_{i,d}(\Delta))) \qquad (2)$$

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

4.7 Calculate irrigation volumes – IHCC

A performance index (PI) is calculated for each test cell in each zone. In VARIwise, the data used to determine the PI is 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:

$$PI = \frac{Current\ value(t)}{Maximum\ value(t)} \qquad (3)$$

For cotton, the LAI data should not simply be maximised as this would result in excessive vegetative growth rather than reproductive growth. Hence, the PI for LAI can be calculated and compared to the reported LAI for an optimal crop. For data that correspond to an optimal time series data set, the performance index is:

$$PI = \left| \frac{Target\ value(t) - Current\ value(t)}{Target\ value(t)} \right| \qquad (4)$$

where t represents the day of the data collection.

Multiple data variables may be incorporated into the PI by applying weights to the performance index of each data type and summing the weighted indices. For example, if leaf area index and square count are used with respective weights of 0.2 and 0.8, the total PI would be:

$$PI = 0.2 \times P_{LAI} + 0.8 \times P_{square/boll\ count} \qquad (5)$$

The PI for each test cell can be evaluated to determine the crop coefficient 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 would be obtained by finding the maximum point of a quadratic equation fitted through points plotted on a PI versus crop coefficient graph.

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:

$$PI = \sum_{i=1}^{n} k_i \, PI_i \qquad \text{where} \quad \sum_{i=1}^{n} k_i = 1 \qquad (6)$$

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 of Allen et al. (1998).

After the crop has consumed a user-defined cumulative crop water use, 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.

4.8 Practical considerations

For centre pivot and lateral move machines, the machine capacity and application volumes affect the time taken to traverse the field, and hence the timing of irrigation applications to each cell. To minimise the impact of travel time, the irrigation application to individual cells is limited to an arbitrary maximum volume (e.g. 25 mm) and the amount of water applied to individual cells is adjusted by the travel time and the daily crop water use.

5. CASE STUDY – EVALUATION OF SENSOR-BASED CONTROL STRATEGIES WITH COTTON

This section reports a case study using VARIwise to compare the performance of the ILC and IHCC strategies when different field sensor data (e.g. soil, plant and weather) were available, both singly or in combination. These strategies were also compared with the yield and water use performance produced for the equivalent crop irrigated according to an industry-standard irrigation management strategy.

5.1 Simulated crop, growing conditions and crop model

The case study involved simulations of a whole season cotton crop grown on the Darling Downs, Australia with parameters as outlined in Table 1. The sowing data, soil properties and weather pattern was characteristic of cotton growing regions in Australia. The soil and plant parameters of the cotton model OZCOT were kept within the boundary values defined by Wells and Hearn (1992).

The spatial variability in soil parameters in each cell and the zones applied for the IHCC strategy are shown in Figure 2. In the simulated field, the plant available water capacity (PAWC) ranges from 60 to 200 mm. This was selected to ensure the control strategies could deal with the different soil types that often exist within fields. The spatial variability in PAWC across irrigated broadacre fields in Australia can be 30 to 500% (Wong et al. 2006; Rab et al. 2009) because of differences in soil texture and root distribution.

Insert Figure 2 here

Averaged weather input was used when sensed weather data was not an input. This provided the model with the minimum set of weather information that could be generated which would enable the model to operate. The averaged weather dataset was generated using SILO (QNRM 2009) 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 had the same weather conditions.

A daily weather profile was obtained 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 (Figure 3) was used as the weather data input for simulations that include weather in the input data combination, whilst the same weather profile (Figure 3) was averaged daily and used as the weather data input for simulations without weather in the input data combination.

Insert Figure 3 here

5.2 Determination of the industry-standard (baseline) irrigation schedule

An industry-standard irrigation management strategy was implemented as a baseline for the performance of the adaptive control strategies. This strategy applied a uniform irrigation treatment across the field where irrigation events were initiated when the soil-water deficit reached a set amount in one point in the field. The soil-water deficit was taken in the cell with the lowest plant available water capacity, as this is the most limiting soil (Figure 2(a)). In this simulation, 25 mm was applied to the whole field when the soil-water deficit had reached 30 mm in the cell with sandy soil.

5.3 Adaptive control implementation

The robustness of the irrigation control strategy to sensed data availability was evaluated by simulating the strategies using different combinations of data input (McCarthy et al. 2011a). This indicated the control inputs that are most appropriate to each control strategy. The simulations used the same underlying crop model but different combinations of input variables for control. For example, the simulation evaluating the importance of sensed soil data to the ILC strategy involves adjusting the irrigation volume according to the error between the desired soil-water and the measured soil-water after each irrigation event.

An optimal time series dataset is required for each input variable to compare with the measured output and calculate the next irrigation volume u_{k+1}. The leaf area index (LAI) for an optimal cotton crop is shown in Figure 4. The dataset was obtained from OZCOT for a high yielding simulation and the curve was smoothed using exponential smoothing with a smoothing factor of 0.85. For this case study, a 12.6 ha centre pivot irrigated field was automatically divided into 1266 cells of area 100 m² (with cell dimensions of 10 m wide and 10 m long).

Insert Figure 4 here

5.3.1 Methodology – ILC

The ILC strategy was simulated using the five applicable input data combinations (Table 2). 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 reached a 40 mm soil-water deficit. 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.

Insert Table 2 here

Simulations for ILC were conducted in VARIwise using the agronomic factors in Table 1 and the underlying soil variability in Figure 2(a). The desired LAI time series set of Figure 4 was used. This cell size was selected to enable timely execution of the simulations and accommodate substantial in-field spatial variability of soil properties. The following values were used for the ILC parameters defined in Section 4.6:

- the learning gain (γ) was unity;
- the irrigations were initiated after 40 mm of crop water use; and

- the time delay (Δ) between the irrigation event and the parameter measurement depended on the data input.

5.3.2 Methodology – IHCC

Using weather, soil and plant input data, there are six possible combinations of data input for IHCC (Table 3). As with ILC, weather-only input is not applicable for control as the weather data 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 maintain a soil-water deficit equal to 10% of the plant available water capacity in each cell following each irrigation event.

Insert Table 3 here

For IHCC strategies there must be 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 three zones and five test cells requires 15 test cells for each irrigation event. Because these test cells must be replaced with new test cells after every irrigation event, a minimum of 300 cells are required for a season with 20 irrigation events. The field of 1266 cells was automatically divided into three zones (Figure 2(b)) and five test cells were used in each zone.

The underlying soil variability of Figure 2(a) was implemented. 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.

5.4 Performance of control strategies

5.4.1 Performance using an industry-standard irrigation management strategy

An industry-standard irrigation schedule was implemented with field properties as per Table 1 and involved applying 25 mm between 14 October 2004 and 14 March 2005 when the soil-water deficit in a sandy cell reached 30 mm. The final yield was 9.1 ± 1.9 bales/ha with CWUI of 0.9 bales/ML_{total} (total water in ML) and IWUI of 1.4 bales/$ML_{irrigated}$ (irrigation applied in ML) (Figure 5). 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). The total volume of water applied to the crop (including rainfall) was 10.2 ML/ha, whilst the irrigation applied to the crop was 6.8 ML/ha. Variations reported in the average yield values are standard deviations of yield across the field (Figures 5 and 6). The applied water and yields produced by the simulations are consistent with local typical experience.

Insert Figure 5 here

5.4.2 Performance using ILC

Figure 6 sets out the simulated outputs of the ILC strategies using the data input combinations described in Table 3. The simulated irrigation applied, soil-water 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 7(a) and 7(b)). The ILC strategy produced the highest yield and water use efficiency with soil-water input (simulation #1).

Insert Figure 6 here

Insert Figure 7 here

ILC produced lower yields with leaf area index input (simulations #2, #3 and #5) than with soil-water input (Figure 6). The irrigation volumes applied were higher throughout the crop season for ILC targeting leaf area index than soil-water deficit (Figure 7). 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 for this crop. The leaf area index 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-water deficit (Figure 8(b)); hence, ILC with leaf area index input could not adapt to the difference in soil-water for different soils. The leaf area index was also generally lower for ILC targeting leaf area index than ILC maintaining soil-water deficit (Figure 9). This suggests that leaf area index is a less effective indicator of irrigation requirement than soil-water deficit for ILC. The additional input of plant data to the soil simulation

(simulation #4) also reduced the simulated yield and water use efficiency (compared with simulation #1).

There were differences between the simulated and desired soil-water deficit for the strategy targeting soil-water deficit (#simulation 1, Figure 8(a)). These were likely caused by the plant physiological response varying to each irrigation event during the crop season, while the ILC relies on process repetition to refine the irrigation volume and assumes that the crop conditions essentially 'reset' before the next irrigation event.

Insert Figure 8 here

Insert Figure 9 here

5.4.3 Performance using IHCC

The simulations described in Table 3 produced the yields and water use efficiencies in Figure 10. IHCC produced reasonable yields and water use efficiencies for all data input combinations. The highest yield was simulated using the soil-and-plant input (simulation #9), whilst the lowest yields were simulated using plant-only input (simulation #7) and weather-and-plant input (simulation #8). The IHCC strategy that maximised square/boll count (simulation #9) resulted in a higher maximum square count than the strategy that attempted to maintain a fixed soil-water deficit (simulation #6) (Figure 9). The simulations using plant input in combinations with weather or soil data (simulations #8-10) produced higher yields than those only using only soil data input (simulations #6). This suggests that square count indicated the plant status more accurately than soil response. The soil-and-plant strategy that targeted a soil-water deficit and maximised square/boll count (simulation #9) performed better than simulations that maximised square/boll count (simulation #10). This is because the first squares form approximately 60 days after sowing, and the strategy requires soil-water indicate crop water requirement during this early stage.

Insert Figure 10 here

Insert Figure 11 here

IHCC with soil-and-plant input (simulation #9) applied less irrigation water than that with plant-only (simulation #7). This is because the fruit load input does not accurately identify the irrigation timing or volume of water to be applied and tends to over-irrigate during wet periods of the crop season (eg. 63 to 86 days after sowing, Figure 11). Including the soil data improves the accuracy of the application volume determination and hence, the efficiency of water application was higher using soil data in combination with the plant data.

The spatial variability observed in the simulated yield (Figure 10) was higher when a single sensor input (simulations #6 and #7) was used compared to a multi-sensor combinations. Spatial variability in yield was caused by both differences in the soil properties and the 'test' irrigation volumes being applied to various cells across the field. The irrigation volumes applied to the clay loam and clay cells were generally larger than those applied to the sand cells (Figure 11). The higher soil-water storage capacity on these soils was found to produce larger crops which then resulted in larger irrigation deficits at irrigation. It was also noted that the soil-water deficit at irrigation in the sand, clay loam and clay cells was generally closer to the target deficit (6 mm, 10 mm and 19 mm, respectively) using weather-and-soil input (Figure 11(a)) than using weather-and-plant input (Figure 11(b)).

Deviations from the desired soil-water deficit were also 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. 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 between zones where the zone division is jagged and therefore less certain. Hence, the location of the test cells is important for the irrigation optimisation.

6. DISCUSSION

The Iterative Learning Control strategy generally produced higher crop water use efficiency performance indices than the Iterative Hill Climbing Control strategy. The highest crop and irrigation water use efficiencies were achieved using ILC with soil-water data (simulation #1), whilst the highest irrigation water use efficiency using IHCC was achieved when soil-and-plant data (simulation #9) was used. Similar yields were obtained for the IHCC strategy with soil-and-plant input (simulation #9, 12.4 ± 1.6 bales/ha) and the ILC strategy with soil-only input (simulation #1, 12.2 ± 1.5 bales/ha).

ILC adjusted the irrigation volume to achieve the desired soil-water deficit following the irrigation event for the different soil types in the field. The IHCC strategy was less effective at maintaining a target soil-water deficit than the ILC strategy (Figure

8). With soil-only input, IHCC produced an average yield and crop water use efficiency (simulation #6, 11.2 ± 1.8 bales/ha and 1.0 bales/ML_{total}, respectively) lower than those of the ILC strategy with soil-input (simulation #1).

The IHCC strategy can optimise parameters (e.g. through maximising square/boll counts) and targeting temporally-variable soil/crop responses, whilst the ILC strategy can only target temporally-variable soil/crop responses (e.g. soil-water deficit). Hence, leaf area index was selected for ILC and fruit load was selected for IHCC. ILC performed poorly with plant data (i.e. leaf area index) input. This suggests that IHCC may be more appropriate for weather-and-plant data input, whilst ILC may be preferable with soil-input only. However, the case study indicates that leaf area index input was not appropriate for ILC because of its lack of sensitivity to irrigation volume application. For the ILC strategy, there was no benefit in using multiple combinations of soil, plant or weather data.

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 rapidly to the new system state in dry periods following the rainfall.

7. CONCLUSION

Two sensor-based irrigation control strategies, ‘Iterative Learning Control’ (ILC) and custom-designed ‘Iterative Hill Climbing Control’ (IHCC) were simulated in the software VARIwise for a cotton crop ‘grown’ with the soils and merged 2004-2009 weather data of south-east Queensland, Australia, and represented by the performance of the well-validated cotton growth and production model OZCOT. These strategies used the crop water use to determine irrigation timing and soil and/or crop response to determine irrigation application volume. The simulations indicated that there was no significant difference between the highest yield achieved by the ILC strategy using soil-water data and the IHCC strategy using soil and plant sensor data. Both strategies produced higher simulated yields and water use efficiencies than an industry-standard irrigation management strategy.

The optimal sensor combination and control strategy that should be used in the field will depend on the crop and water availability. Where sensor data availability is non-limiting then the simulated IHCC strategy using plant and soil sensors produced higher yield than the ILC strategy. However, where sensor data availability is limited then the results indicate that an ILC strategy would be preferable to optimise irrigated water use efficiency. Valid field validation remains a challenge (unless there are multiple fields and irrigation machines) but further work will involve field evaluations to compare the simulated and measured control strategy performance.

Acknowledgements

The authors are grateful to the Australian Research Council and the Cotton Research and Development Corporation for funding a postgraduate studentship for the senior author.

References

Ahn, H.-S., Moore, K. L. and Chen, Y. (2007) *Iterative learning control: robustness and monotonic convergence for interval systems*. Communications and Control Engineering, Springer, London.

Allen, R., Perera, L., Raes, D. and Smith, M. (1998), *Crop evapotranspiration: guidelines for computing crop water requirements*, Technical report, FAO Irrigation and Drainage Paper 56.

BPA (1999) *Determining a framework, terms and definitions for water use efficiency in irrigation*, Barrett Purcell and Associates, Land and Water Resources Research and Development Corporation, Canberra, Australia.

Evans, R. (2006) *Irrigation technologies*. Sidney, Montana. Viewed 19 June 2007, http://www.sidney.ars.usda.gov/.

Gibb, D., Neilsen, J. and Constable, G. (2004) Cotton growth responses to water stress. In: 'WaterPAK - a guide for irrigation management in cotton', Australian Cotton Cooperative Research Centre and Cotton Research and Development Corporation, Narrabri, Australia, chapter 3.1, pp. 117-126.

Hearn, A.B. (1994) OZCOT: A simulation model for cotton crop management. *Agricultural Systems* **44**:257-299.

Korovessi, E. and Linninger, A. (2006) *Batch processes*. Taylor and Francis Group, Florida.

Liu, G., Yang, J.-B. and Whidborne, J. (2001) *Multiobjective optimisation and control*. Engineering Systems Modelling and Control, Research Studies Press Ltd.

McCarthy, A.C., Hancock, N.H. and Raine, S.R. (2010) VARIwise: a general-purpose adaptive control simulation framework for spatially and temporally varied irrigation at sub-field scale. *Computers and Electronics in Agriculture* **70**(1):117-128.

McCarthy A.C., Hancock, N.H. and Raine, S.R. (2011a) Real-time data requirements for model-based adaptive control of irrigation scheduling in cotton. *Australian Journal of Multi-disciplinary Engineering* **8**:2 pp189-206.

McCarthy A.C., Hancock, N.H. and Raine, S.R. (2011b) Advanced process control of irrigation: the current state and an analysis to aid future development. *Irrigation Science*. doi: 10.1007/s00271-011-0313-1.

McCarthy A.C., Hancock, N.H. and Raine, S.R. (2013) Simulation of irrigation control strategies for cotton using Model Predictive Control within the VARIwise simulation framework. *Submitted to Computers and Electronics in Agriculture*

Moore, K. and Chen, Y. (2006) Iterative learning control approach to a diffusion control problem in an irrigation application. *In*: 'IEEE International Conference on Mechatronics and Automation', LuoYang, China, pp. 1329-1334.

QNRM (2009) *Queensland Natural Resources and Mines enhanced meteorological datasets*. Viewed 4 March 2008, http://www.longpaddock.qld.gov.au/silo/.

Rab, M.A., Fisher, P.D., Armstrong, R.D., Abuzar, M., Robinson, N.J. and Chandra, S. (2009) Advances in precision agriculture in south-eastern Australia. IV. Spatial variability in plant-available water capacity and its relationship with yield in site-specific zones, *Crop and Pasture Science* **60**:885-900.

Richards, Q.D., Bange, M.P. and Johnston, S.B. (2008) HydroLOGIC: an irrigation management system for Australian cotton, *Agricultural Systems* **98**(1):40-49.

Rochester, I. (2006) Efficient use of nitrogen fertilisers. *The Australian Cottongrower* **27**(7):48-50.

Rochester, I., Ceeney, S., Maas, S., Gordon, R., Hanna, L. and Hill, J. (2009) Monitoring nitrogen use efficiency in cotton crops. *The Australian Cottongrower* **30**(2):42-43.

Russell, S. and Norvig, P. (1995) *Artificial intelligence: a modern approach*. Prentice Hall, New Jersey.

Smith, R., Raine, S., McCarthy, A. and Hancock, N. (2009) Managing spatial and temporal variability in irrigated agriculture through adaptive control. *Australian Journal of Multi-disciplinary Engineering* **7**(1):79-90.

Warwick, K. (1993) *Adaptive control*. In: S. Tzafestas, ed., ‘Applied control’, Electrical and Computer Engineering, Marcel Dukker Inc, New York, chapter 9, pp. 253-271.

Wells, A. and Hearn, A. (1992) OZCOT: a cotton crop simulation model for management. *Mathematics and Computers in Simulation* **33**:433-438.

Wong, M., Oliver, Y., Robertson, M. and Wittwer, K. (2006) Technologies to estimate plant available soil-water storage capacities at high spatial resolution, *In*: 13th Australian Agronomy Conference, 10-14 September, Perth, Western Australia.

Figures and Tables

Table 1: Agronomic factors used in cotton model OZCOT for control strategy simulations (where HydroLOGIC is a user interface for OZCOT, Richards et al. (2008))

Agronomic factor	Value	Source
Sowing data	4 October 2004	Nil
Plant stand	12 plants/m	Default in HydroLOGIC
Seed depth	5 cm	Default in HydroLOGIC
Row spacing	1 m	Default in HydroLOGIC
Available nitrogen	250 kg/ha (for maximum yield)	Rochestor (2006); Rochester et al. (2009)
Previous crop	Other	Nil
Defoliation dates	Determined by OZCOT	Nil
Harvest date	Determined by OZCOT	Nil
Cotton variety	Sicot 73	Nil
Plant available water capacity	As per Figure 1	Nil
Starting soil-water	Plant available water capacity	Nil
Weather data	As per Figure 2	Nil
Machine type	Centre pivot	Nil
Field size	400 m diameter	Nil
Machine capacity	15 mm/day	Nil
End of irrigation period	14 March 2005	Nil

Table 2: Simulations conducted to compare interactions between control strategies (labelled by ID#) and input variables for Iterative Learning Control.

ID #	**Input variables for control**	**Weather data input**	**Irrigation calculation**	
			Irrigation volume	**Irrigation timing**
1	Soil	Averaged SILO data	Maintain soil-water deficit	Change in soil-water
2	Plant	Averaged SILO data	Target leaf area index	Change in ET_c
3	Weather AND plant	SILO data	Target leaf area index	Change in ET_c
4	Soil AND plant (A)	Averaged SILO data	Maintain soil-water deficit and target leaf area index	Change in soil-water
5	Soil AND plant (B)	Averaged SILO data	Target leaf area index	Change in soil-water

Table 3: Simulations conducted to compare interactions between control strategies (labelled by ID#) and input variables for Iterative Hill Climbing Control. N

ID #	Input variables for control	Weather data input	Irrigation calculation	
			Irrigation volume	**Irrigation timing**
6	Soil	Averaged SILO data	Maintain soil-water deficit	Change in soil-water
7	Plant	Averaged SILO data	Maximise square/boll count	Change in ET_c
8	Weather AND plant	SILO data	Maximise square/boll count	Change in ET_c
9	Soil AND plant (A)	Averaged SILO data	Maintain soil-water deficit and maximise square/boll count	Change in soil-water
10	Soil AND plant (B)	Averaged SILO data	Maximise square/boll count	Change in soil-water

Table 4: Performance of the industry-standard irrigation strategy for homogeneous and spatially variable field

Infield soil properties	**Average yield (bales/ha)**	**Average water applied (ML_{total}/ha)**	**Average irrigation applied ($ML_{irrigated}$/ha)**	**CWUI (bales/ ML_{total})**	**IWUI (bales/ $ML_{irrigated}$)**
Sand	5.8	9.0	6.0	0.6	1.0
Clay loam	10.0	8.7	5.8	1.1	1.7
Clay	10.7	9.5	6.3	1.1	1.7
Spatial variable	9.1 ± 1.9	10.2	6.8	0.9	1.4

Table 5: Performance of the ILC strategies with different data input combinations for homogenous and spatially variable fields

Control strategy ID #	Infield soil properties	Average yield (bales/ha)	Average water applied (ML_{total}/ha)	Average irrigation applied ($ML_{irrigated}$/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
1	Sand	10.0	9.0	5.8	1.1	1.7
	Clay loam	12.7	8.8	5.7	1.4	2.2
	Clay	12.9	8.5	5.5	1.5	2.3
	Spatially variable	12.2 ± 1.5	11.3	7.3	1.1	1.7
2	Sand	7.4	15.0	9.7	0.6	0.8
	Clay loam	7.5	15.9	10.3	0.5	0.7
	Clay	8.5	15.8	10.2	0.7	0.8
	Spatially variable	8.3 ± 1.6	16.5	10.3	0.5	0.8
3	Sand	8.5	12.2	7.9	0.7	1.1
	Clay loam	8.2	14.4	9.3	0.6	0.9
	Clay	9.1	14.1	9.1	0.6	1.0
	Spatially variable	8.9 ± 1.9	12.6	8.0	0.7	1.1
4	Sand	9.7	8.8	5.7	1.1	1.7
	Clay loam	11.4	10.6	6.9	1.1	1.7
	Clay	12.7	11.3	7.3	1.1	1.7
	Spatially variable	10.2 ± 1.4	11.1	7.7	0.9	1.3
5	Sand	9.5	9.3	6.0	1.0	1.6
	Clay loam	10.9	11.1	7.2	1.0	1.5
	Clay	11.9	11.6	7.5	1.0	1.6
	Spatially variable	9.9 ± 2.0	12.8	7.9	0.8	1.3

Table 6: Performance of the IHCC strategy with different data input combinations for homogenous and spatially variable fields

Control strategy ID #	Infield soil properties	Average yield (bales/ha)	Average water applied (ML_{total}/ha)	Average irrigation applied ($ML_{irrigated}$/ha)	CWUI (bales/ ML_{total})	IWUI (bales/ $ML_{irrigated}$)
6	Sand	9.9	8.8	5.7	1.1	1.7
	Clay loam	12.3	9.0	5.8	1.4	2.1
	Clay	12.6	9.3	6.0	1.4	2.1
	Spatially variable	11.2 ± 1.9	11.1	7.9	1.0	1.4
7	Sand	9.0	7.6	4.9	1.2	1.8
	Clay loam	10.9	7.9	5.1	1.4	2.1
	Clay	11.1	8.5	5.5	1.3	2.0
	Spatially variable	10.9 ± 2.5	11.9	7.7	0.9	1.4
8	Sand	9.2	7.4	4.8	1.2	1.9
	Clay loam	11.2	7.6	4.9	1.5	2.3
	Clay	11.4	11.6	5.1	1.0	2.2
	Spatially variable	11.0 ± 1.8	11.2	7.5	1.0	1.5
9	Sand	10.0	8.8	5.7	1.1	7.5
	Clay loam	12.4	9.1	5.9	1.4	2.1
	Clay	12.7	9.4	6.1	1.4	2.1
	Spatially variable	12.4 ± 1.6	12.6	8.1	1.0	1.5
10	Sand	10.1	8.8	5.7	1.4	1.8
	Clay loam	12.4	9.1	5.9	1.4	2.1
	Clay	12.7	9.6	6.2	1.3	2.0
	Spatially variable	11.4 ± 1.8	11.6	7.3	1.0	1.6

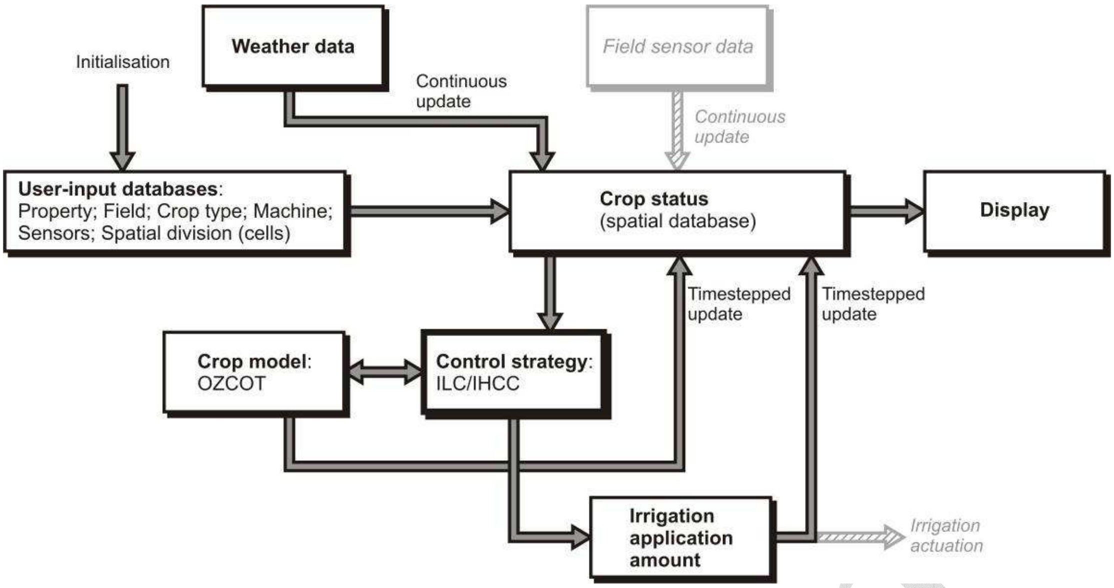
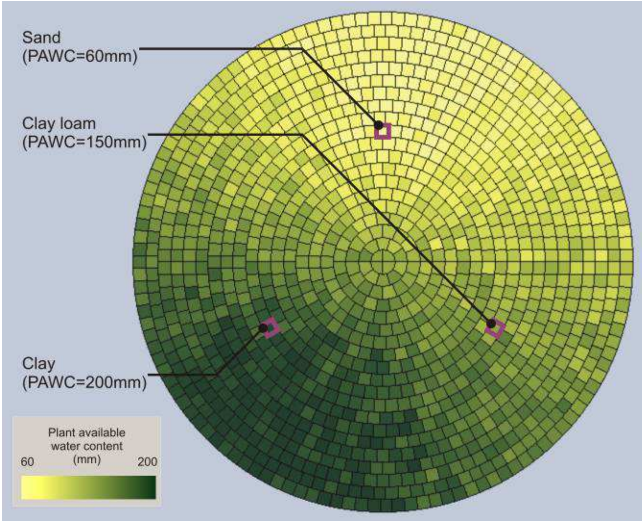
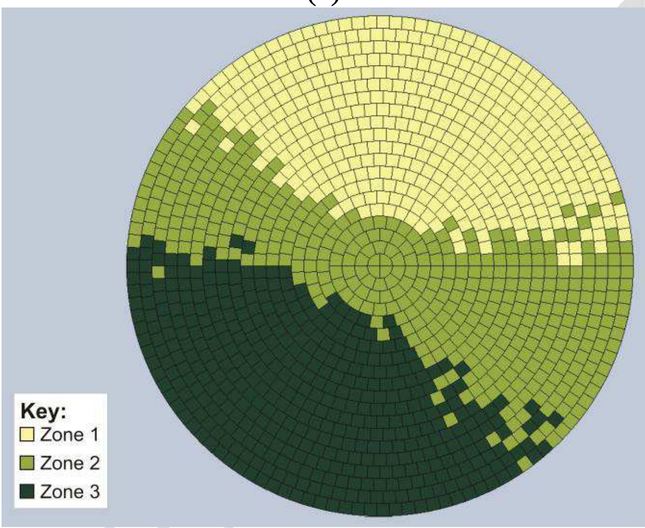


Figure 1: The simulation framework VARIwise configured to evaluate (in simulation mode) the sensor-based adaptive control strategies. The items shown in grey/hatched are not implemented but would be present in a field evaluation.) This diagram is adapted from the full VARIwise flowchart presented as Figure 2 of McCarthy et al. (2010).



(a)



(c)

Figure 2: Soil variability for: (a) industry-standard, ILC and IHCC strategy simulation; and (b) the cells assigned to each zone using the soil variability data of Figure 2(a)

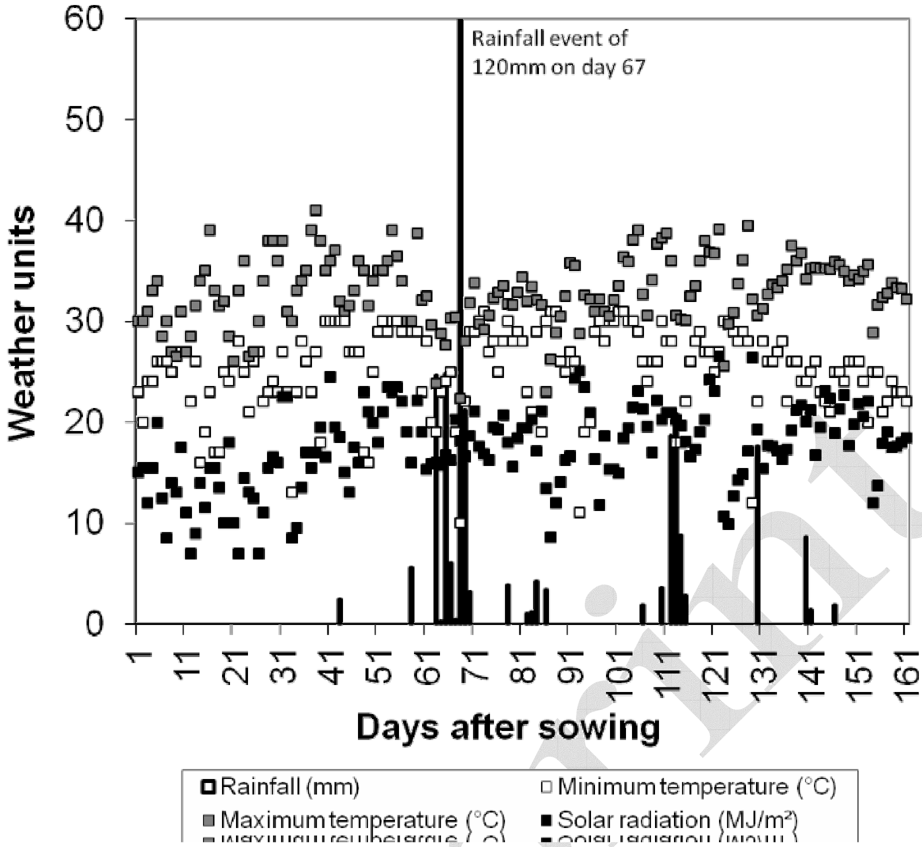


Figure 3: Weather profile used in industry-standard irrigation management and iterative learning, iterative hill climbing control strategies

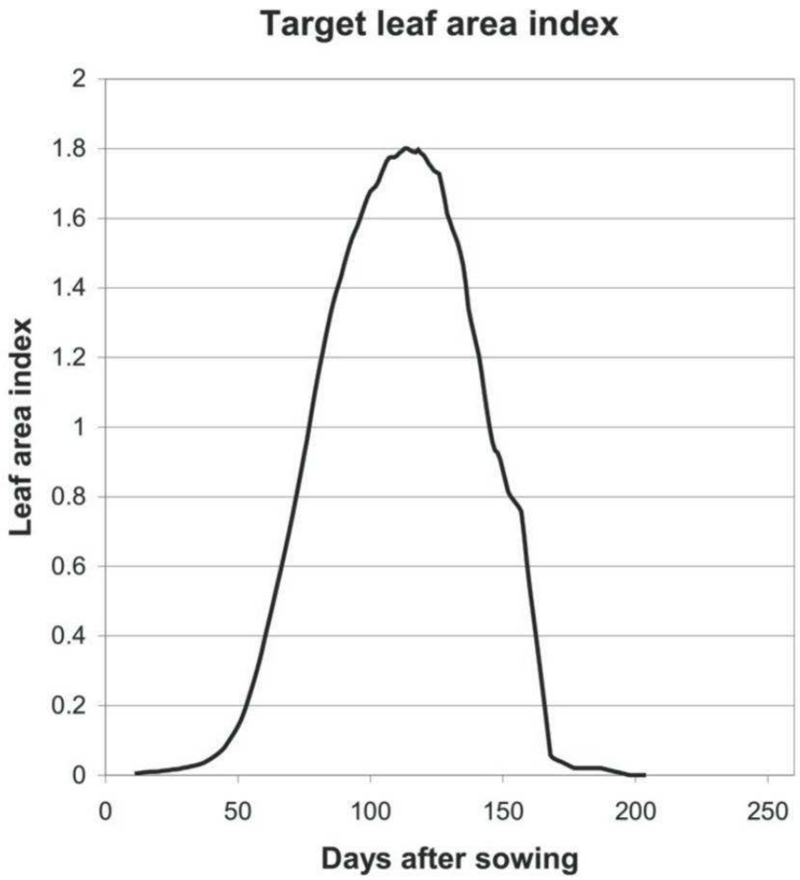


Figure 4: Target leaf area index used for iterative learning control strategy for cotton in VARIwise (Wells and Hearn 1992)

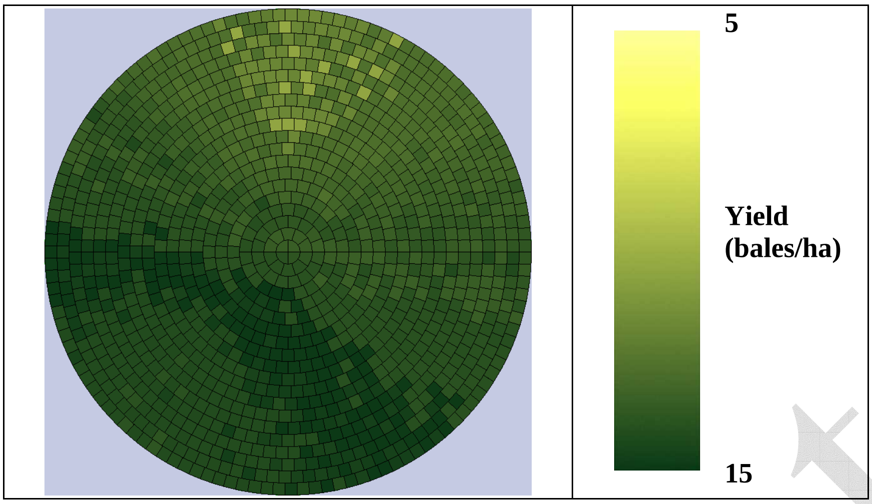


Figure 5: Yield map for industry-standard irrigation management strategy for comparison with adaptive control strategy results (average 9.1 ± 1.9 bales/ha)

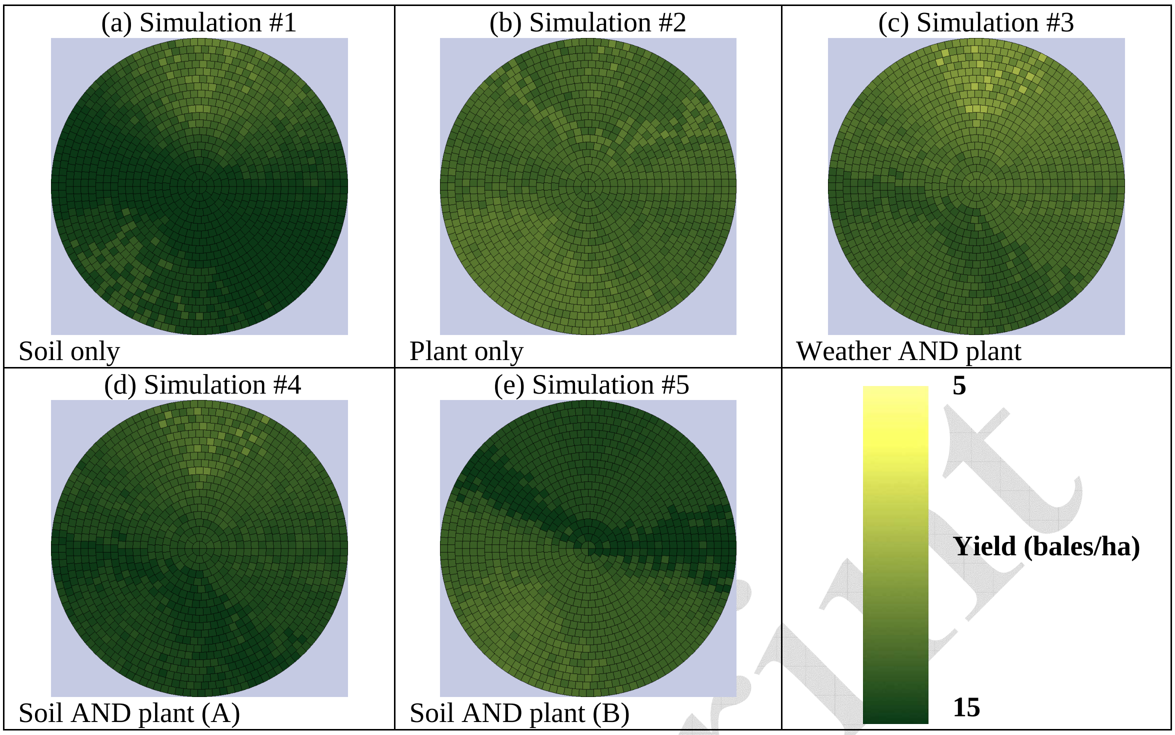
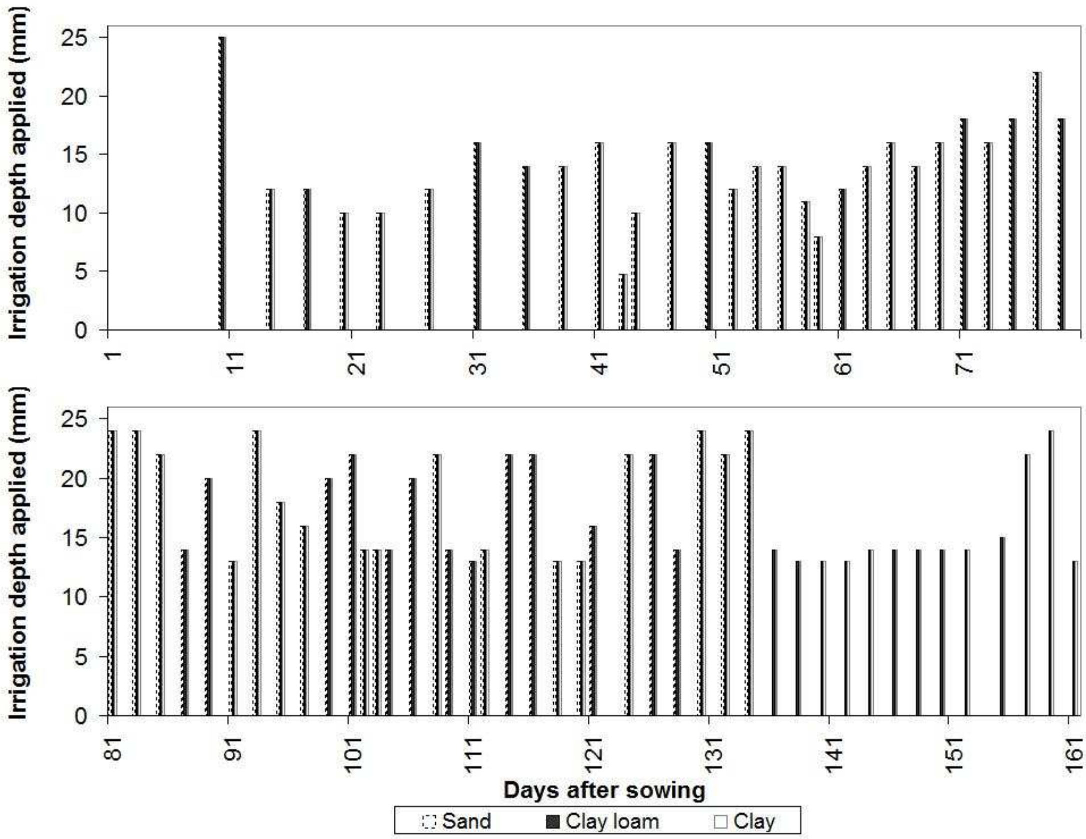
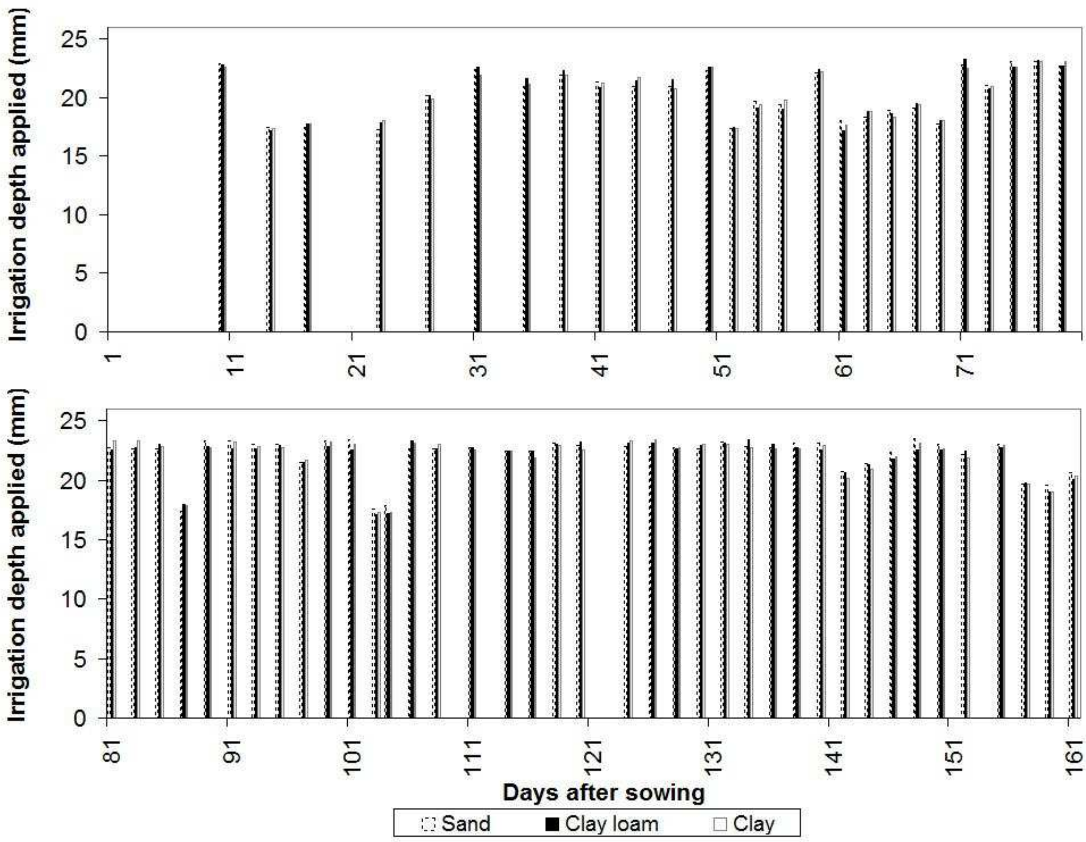


Figure 6: Yield maps and average yield and irrigation outputs of iterative learning control (ILC) strategy with variable-rate irrigation machine and legend for yield maps for simulations specified in Table 2


Irrigation depth applied (mm)
Days after sowing
Sand
Clay loam
Clay

(a)


Irrigation depth applied (mm)
Days after sowing
Sand
Clay loam
Clay

(b)

Figure 7: Irrigation volumes applied to sand, clay loam and clay cells for ILC strategies that target: (a) soil-water deficit (simulation #1); and (b) leaf area index (simulation #2)

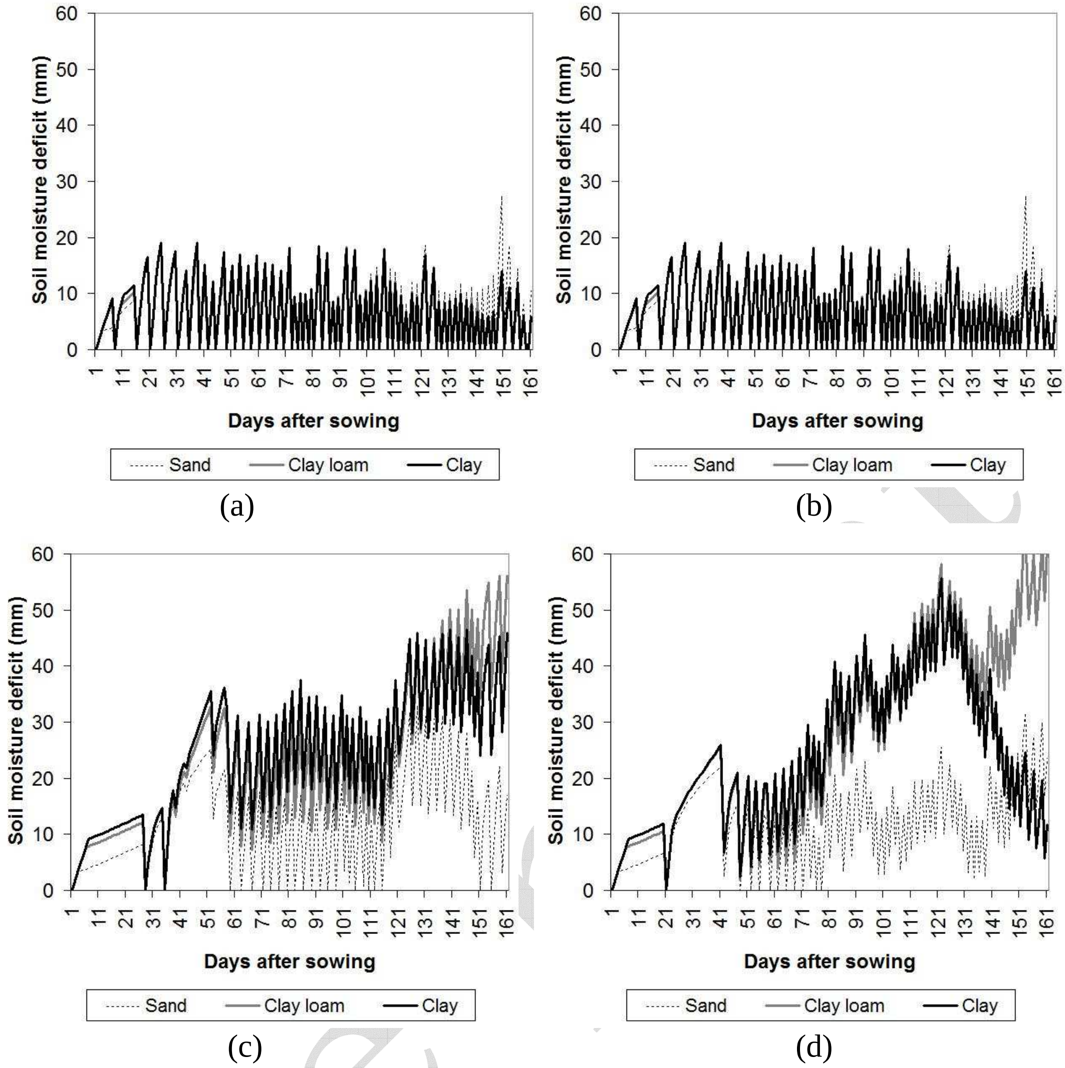
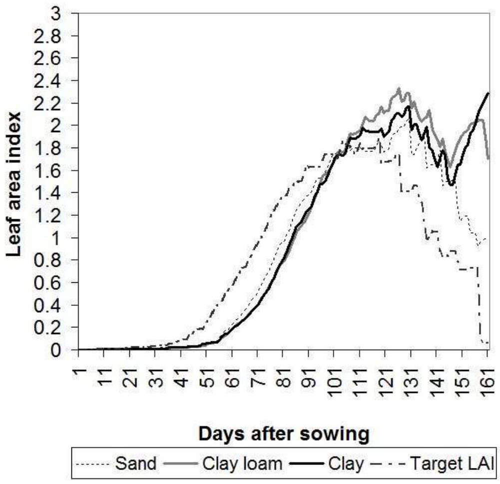
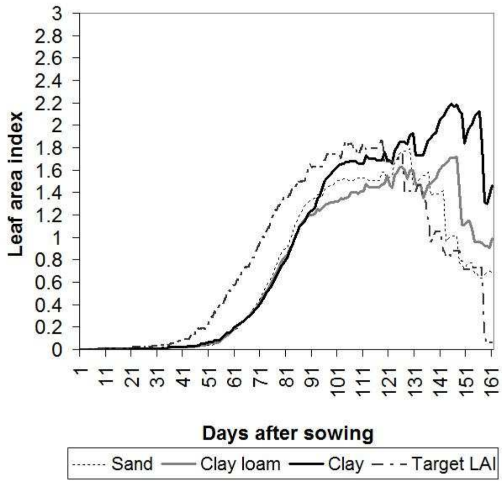
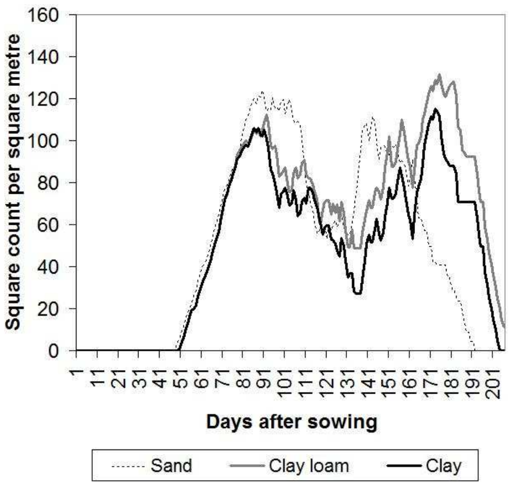


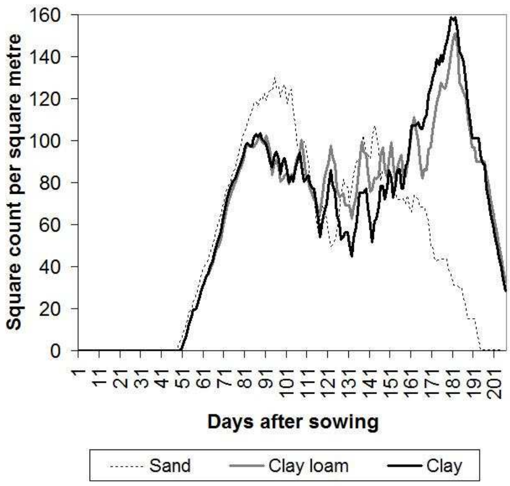
Figure 8: Simulated daily soil-water deficit in sand, clay loam and clay cells for ILC strategies that target: (a) soil-water deficit (simulation #1); and (b) leaf area index (simulation #2); and IHCC strategies that: (c) target soil-water deficit and maximise square/boll count (simulation #8); and (d) maximise square/boll count (simulation #9)





(a) (b)





(c) (d)

Figure 9: Simulated daily leaf area index in sand, clay loam and clay cells for ILC strategies that target: (a) soil-water deficit (simulation #1); and (b) leaf area index (simulation #2); and square count for IHCC strategies that: (c) target soil-water deficit (simulation #6); and (d) maximise square/boll count (simulation #9)

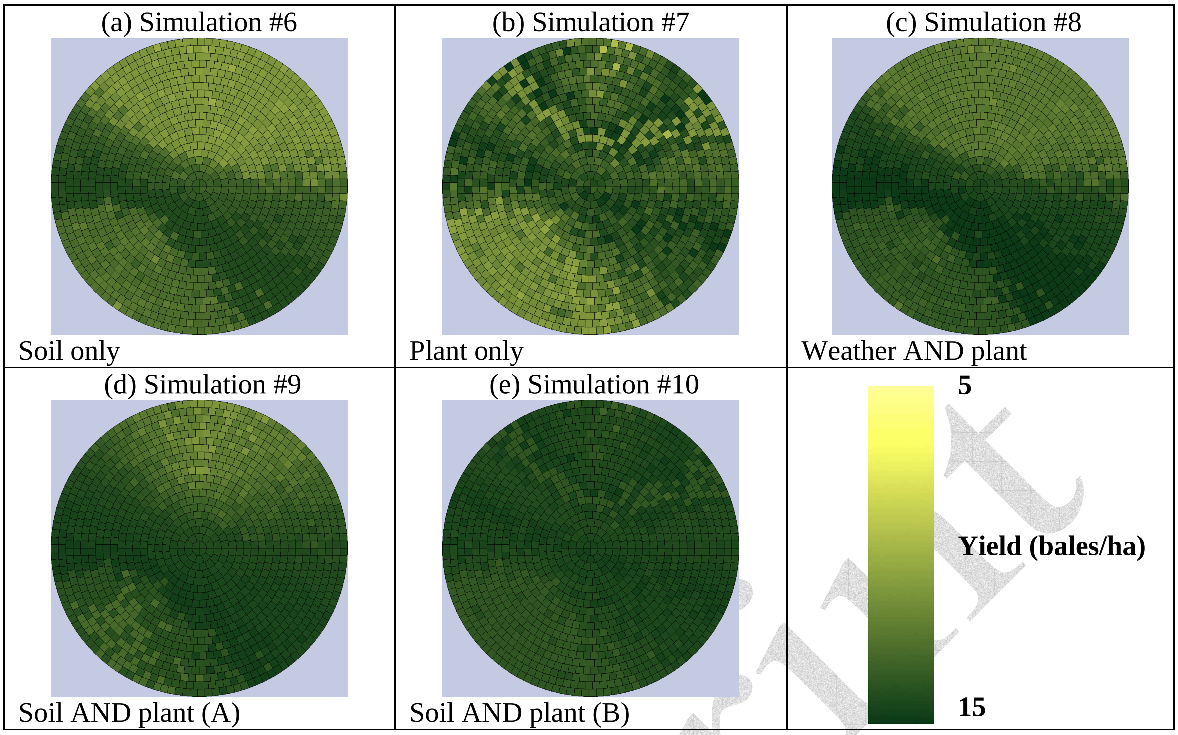
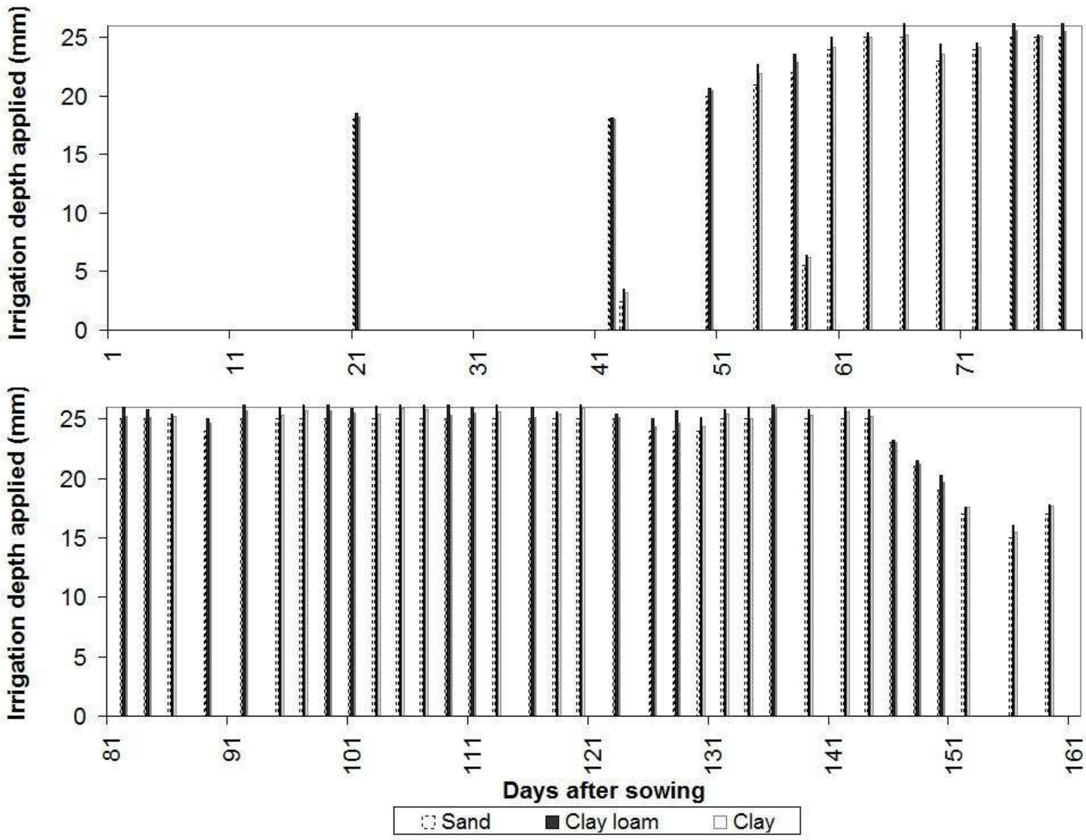


Figure 10: Yield maps and average yield and irrigation outputs of iterative hill climbing control (IHCC) strategy with variable-rate irrigation machine and legend for yield maps for simulations specified in Table 3


Irrigation depth applied (mm)
Irrigation depth applied (mm)
Days after sowing
Sand
Clay loam
Clay
(a)

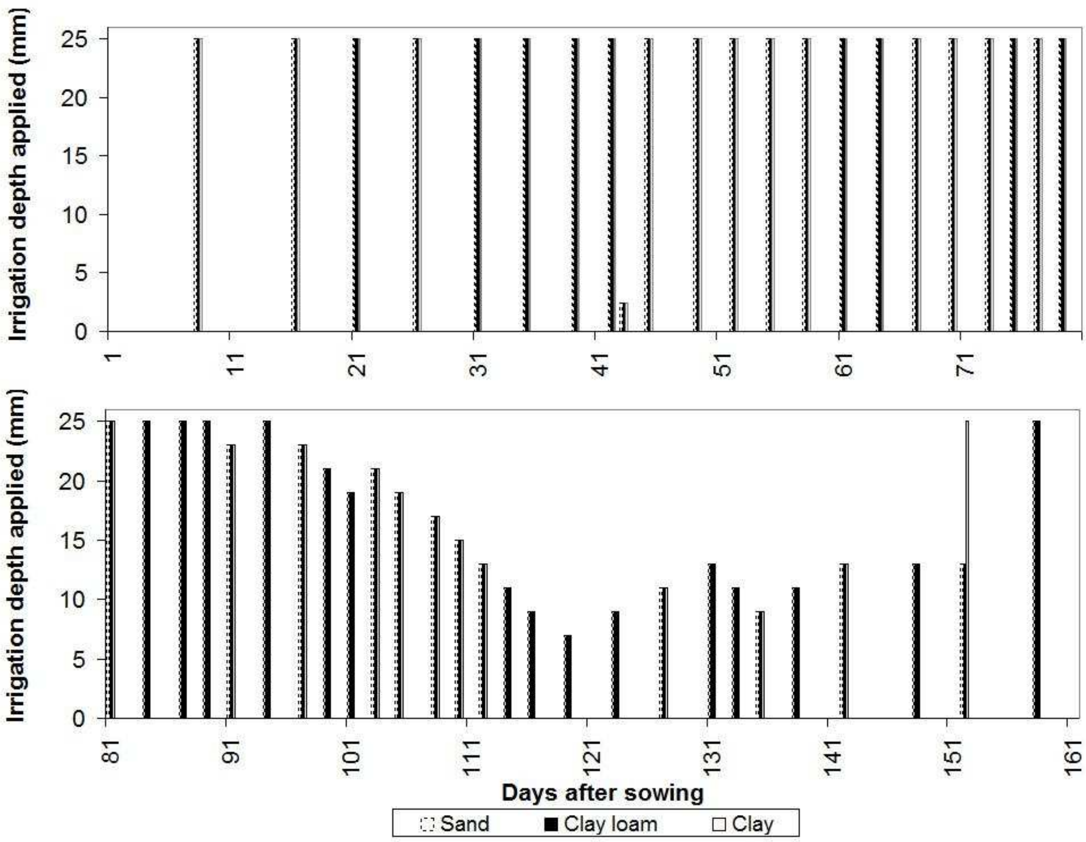

Irrigation depth applied (mm)
Irrigation depth applied (mm)
Days after sowing
Sand
Clay loam
Clay
(b)

Figure 11: Irrigation volumes applied to sand, clay loam and clay cells for IHCC strategies that maximise square/boll count and determine irrigation timing using: (a) weather data (simulation #7); and (b) soil-water content (simulation #9)