VARIwise: a general-purpose adaptive control simulation framework for spatially and temporally varied irrigation at sub-field scale

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Abstract

Irrigation control strategies may be used to improve the site-specific irrigation of cotton via lateral move and centre pivot irrigation machines. A simulation framework 'VARIwise' has been created to aid the development, evaluation and management of spatially and temporally varied site-specific irrigation control strategies. 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.

In this paper the motivation and objectives for the creation of VARIwise are discussed, the structure of the software is outlined and an example of the use and utility of VARIwise is presented. Three irrigation control strategies have been simulated in VARIwise using a cotton model with a range of input parameters including spatially variable soil properties, non-uniform irrigation application, three weather profiles and two crop varieties. The simulated yield and water use efficiency were affected by the combination of input parameters and the control strategy implemented.

Keywords

Variable-rate irrigation, centre pivot, lateral move, management, automation

1. Introduction

Managing the irrigation of crops using physical and agronomic principles has been shown by Evans (2006) to improve efficiency of water use by 15 to 44%. The irrigation application determined using these principles may be automatically implemented on a lateral move or centre pivot irrigation machine. Irrigation control strategies can use historical data or quantitative measurements of crop status, weather and soil, or some combination of these, to automatically adjust the irrigation application. However, irrigation is traditionally applied uniformly over an entire field, although not all plants in a crop may require the same amount of water at any given time. It follows that differential application of water (and possibly fertiliser, applied via fertigation) will be required according to plant requirements at different locations in the field.

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 (Zaknich 2005). However, these assumptions are not valid for many agricultural systems. For example, crop growth, pests and weather vary within and between crop seasons and these alter the optimal irrigation amount to be applied to the plants. For every change in conditions a standard feedback control system would have to be manually redesigned and this is labour-intensive. Furthermore, determination of the appropriate local irrigation amount may require differing local irrigation strategies (e.g. as a result of varying soil properties). Hence, control strategies which accommodate temporal and spatial variability in the field and which locally modify the control actions (irrigation/fertigation amounts) need to be 'adaptive' (McCarthy et al., 2008; Smith et al., 2009).

Adaptive control systems automatically and continuously re-adjust ('retune') the controller to retain the desired performance of the system (e.g. Warwick 1993). Similarly, adaptive control strategies may be used to accommodate the various levels of data complexity normally found in irrigation (i.e. for the various combinations of plant, soil and weather data depending on data availability). By comparing adaptive control strategies, we may identify superior and hopefully optimal control strategies for irrigation, sensor variable requirements, and temporal and spatial scales requirements. The conceptual components of an adaptive control system for variable-rate irrigation are illustrated in Figure 1.

{Insert Figure 1 here}

Adaptive irrigation control strategies (Figure 1) can use both historical data and real-time quantitative measurements of crop status, weather and soil, either singly 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 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.

Considerable work is reported in the literature toward the development of variable-rate applicators for lateral move and centre pivot irrigation machines to achieve site-specific irrigation (e.g. King and Wall 2005), some of which include a wireless sensor network (e.g. Pierce et al. 2006; Coates and Delwiche 2008) and irrigation system self-monitoring capabilities (e.g. Chávez et al. 2009a; Chávez et al. 2009b). The evaluation of these applicators typically consisted of a predetermined irrigation prescription map; however, King and Wall (2005) utilised digitised remote images of the field to withhold water from non-cropped areas. Commercial irrigation control systems also commonly apply pre-determined, spatially-varied irrigation volumes derived from historical data (e.g. field maps) when indicated by sensed data (e.g.

Dukes and Perry (2006) evaluated the commercial ‘Farmscan’ variable-rate irrigation system).

Control systems have been used to determine spatially-variable irrigation application using measured soil data (e.g. Capraro et al. 2008; Kim and Evans 2009; Kim et al. 2009; Park et al. 2009) and plant data (e.g. Peters and 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 that was remotely sensed in each area (i.e. no irrigation was applied if the soil water deficit was at a minimum). The irrigation events were triggered when the deficit of any of the five 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 and a soil model calibrated using measured soil moisture. 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 and 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 and Evett (2008) used crop stress as the indicator of irrigation requirement via an array of infrared thermometers mounted on the centre pivot 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 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 has been utilised in the majority of the irrigation control systems currently in the literature (as discussed above), whilst weather data has been used to manage irrigations under limited water supply (e.g. Rao et al. 1992) and plant data has been utilised for automatic irrigation control (Peters and 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 and Boyer 1995; Wanjura and Upchurch 2002; Jones 2004). This is because the plants essentially integrate the atmospheric and soil factors that affect plant 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 (e.g. weather which affects sub-daily dynamics of crop response) as well as data with long time constants (e.g. change in soil water status). Hence, it is likely that the incorporation of multiple sensed variables (i.e. plant, soil and weather data) will normally be required for an optimal irrigation control system.

A general-purpose irrigation simulation framework is required to develop, simulate and evaluate alternative site-specific irrigation control strategies incorporating multiple sensor variables. This paper reports the development of a framework, 'VARIwise', for site-specific irrigation and illustrates its capability using a case study on the irrigation of cotton.

2. Specification of a Variable-rate Irrigation System Simulation/Control Framework

The framework must: (i) simulate alternate irrigation control strategies to determine optimal strategies; and (ii) enable optimised control strategies to be executed in real-time and provide data outputs (i.e. irrigation volume and/or timing) in an appropriate form for control actuation. Optimal adaptive control strategies to decide irrigation volume and timing may be identified by simulating and evaluating adaptive control strategies using a framework. For both control strategy simulation and real-time control, the framework must enable data input for a range of field conditions in which data (e.g. weather, soil type, irrigation machine type) is 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 (e.g. daily Australian Bureau of Meteorology SILO patched point environmental data; QNRM 2009) or images (e.g. aerial and in-field photos or EM38 maps) as well as numerical values. The minimum resolution of the imported images should correspond to the spatial scale specified for the field in the framework (e.g. 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. Certain data collected across the field or otherwise imported may be at a high spatial resolution (e.g. from an electromagnetic soil moisture (EM38) survey), whereas others may only be available as widely-separated point measurements (e.g. 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 data reading may be available for the whole field (e.g. rainfall) and the presumption that this value is constant across the field may be questionable. For control strategy simulations, single-point field scale data 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 data sets 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 in the rainfall data would enable the variability to be evaluated in simulation experiments.

Most field data is highly dynamic (e.g. plant water use changes throughout the day); hence, the framework should be able to handle input data at any temporal scale. It follows that for control strategy simulation, crop production models appropriate for these variables must have appropriately short time steps. However, the temporal scale of the framework simulation is limited by the characteristics of the model and currently most crop production models operate at a daily time step. In this situation, the simulation inputs must be averaged daily as the model outputs are determined daily. Temporal variability of the data (i.e. data collected at different time steps) may also be evaluated for different control strategies.

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. Software Development

A framework, 'VARIwise', with the capabilities outlined above, has been 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 (e.g. simulation 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 simulation model/s (e.g soil moisture response, plant response);

(7) implementation of control strategies; and

(8) display of control strategy output.

The transfer of data between these functional areas is illustrated in Figure 2. The following sections 3.1 to 3.5 describe processes within the framework which can be applied to both physical and simulation environments.

{Insert Figure 2 here}

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); 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.

3.2 Division of the 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(a) and (b), respectively.

{Insert Figure 3 here}

A high level of control in centre pivot and lateral move irrigation application can be achieved using a Low-Energy Precision Application (LEPA) sock: LEPA socks apply water at low pressure within the crop canopy or directly onto the soil (e.g. Foley 2004). 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 m². If LEPA socks are not used on an irrigation machine, then irrigation decisions can be simulated at spatial scales larger than 1 m² and in these cases, the cells are automatically aggregated.

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 4. The databases created within the software are shown in Table 1.

{Insert Figure 4 here}

{Insert Table 1 here}

Field-scale data is 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 5.

{Insert Figure 5 here}

3.4 Simulation of natural variability

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

(1) For field-scale data (e.g. rainfall) representing a sub-area or (strictly) just a point in the field, any statistical distribution of variability (e.g. Gaussian, gamma, Weibull) 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 (e.g. to recognise the spatial distribution of an individual storm).

(2) Interpolating spatial data points (e.g. soil moisture) 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 (i.e. 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). 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 (e.g. standard deviation).

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). To compensate for the change in water application hydraulics required by variable-rate irrigation, either one or both of two parameters (i) machine speed and (ii) pump flow rate, may be changed. For (i) the required machine speed is estimated in VARIwise using the machine capacity (specified in the machine database) and the total irrigation depth applied by the machine at one time. Option (ii) is not considered further in this paper.

3.6 Incorporation of simulation model/s

When VARIwise is used to generate or evaluate irrigation strategies, a simulation model appropriate to the crop and agricultural system will normally be utilised to generate synthetic field data which become inputs to the control system. Because simulation models are typically tested by comparing measured and predicted data averaged across the field over multiple years, such models are generally not calibrated or tested for their ability to appropriately represent measured spatial and temporal differences. Therefore calibrating the model using *measured* spatial and temporal data will allow for local real-time parameterisation of the model and may also improve the overall performance of the model (although it is beyond the scope of the present paper to further develop this conjecture). We note also that it is likely the calibration procedure will vary according to the model.

The input data required for complete evaluation of irrigation control strategies include crop growth (e.g. leaf area index), fruit development (for cotton), soil moisture and weather data. For cotton this data set may be obtained using the crop simulation model OZCOT which is routinely used for cotton irrigation management in Australia (Richards et al., 2008). OZCOT is a cotton fruiting and leaf area growth model (Hearn & Da Roza 1985) coupled with a soil water balance sub-model (Ritchie 1972) and nitrogen uptake sub-model (Wells and Hearn 1992). The fruiting model captures the basic pattern of cotton growth and fruit development and is driven by weather data (e.g. day degrees) and soil properties (e.g. soil water deficit). The soil model calculates the components of the soil water balance, i.e. soil evaporation is estimated using the atmospheric evaporative demand and the capacity of the soil to transmit water to the surface, and transpiration is estimated using the leaf area index (Ritchie 1972). Spatial customisation/calibration for OZCOT involves adjustment of parameters in the soil properties and crop variety files (which describe the rate of boll and vegetative growth): these may be adjusted iteratively based on the error between the modelled data and measured data on the measurement days.

The interfacing (i.e. input and output data requirements) of crop simulation 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. Again, further work here is beyond the scope of this paper.

Actual field data replaces the simulation model as controller inputs when VARIwise is used as part of a decision support system in a field implementation. However, data from the simulation 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 simulation model is saved to the corresponding VARIwise database files.

The procedure for updating VARIwise database files for a control strategy simulation is dependent on the constraints of the simulation model used. For example, for OZCOT the irrigation applied is entered as equivalent rainfall and measured data input variables include soil moisture, leaf area index, cotton boll count and temperature.

A simulation is executed for each cell and irrigation event and 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 (including measured plant available water content 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.

3.7 Implementation of control strategies

VARIwise is formulated to impose minimal (ideally zero) constraints on the control strategies that can be implemented in either simulation or physical (machine control) applications. For the purpose of illustration, this paper uses simulated data to demonstrate the following control strategies which are presently implemented in VARIwise:

Strategy A: Fixed irrigation schedule in which the dates and amounts for the irrigation events are defined by the user;

Strategy B: Soil moisture deficit-triggered irrigation schedule in which the irrigation amount and deficit triggering the irrigation are defined by the user; and

Strategy C: Self-optimising irrigation management which involves, firstly, the system inputs (i.e. irrigation application) changing iteratively such that the system output (i.e. plant and soil measurements and yield) is closer to the goal; and then, secondly, using 'hill climbing' to improve the irrigation decision. '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).

Hill climbing is typically implemented in processes which are repeatedly executed and evaluated in a small amount of time (e.g. within seconds). Therefore, direct application of this method to irrigation would not be efficient due to the different time scales (i.e. irrigations occurring days apart). However, the efficiency of hill climbing may be improved by using 'test cells' to evaluate a range of inputs to the system (i.e. at each irrigation event); and test cells may be selected in each area of the field with homogenous properties. For soil, the areas of homogenous properties may be determined from an EM38 map, and in this paper each such area is referred to as a 'zone'. Hence, the self-optimising irrigation strategy involves the following procedure:

Step 1. The field is automatically divided into zones of homogenous properties according to input data. For example, an EM38 electromagnetic survey imported into VARIwise for the irrigated area of the field as shown in Figure 6(a) can be used to derive a soil moisture map shown in Figure 6(b). Figure 7 shows a field divided into two zones using this EM38 map.

{Insert Figure 6 here}

{Insert Figure 7 here}

Step 2. A small number of cells (i.e. a group of 'test cells') are selected in each zone to evaluate different irrigation applications.

Step 3. 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. 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: (i) 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 data set; and (ii) crop coefficient (*Kc*) estimated from Table 12 of 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 crop coverage which changes during the growing season and 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:

$$Days = \frac{RAW\ (mm) + Effective\ rainfall\ (mm)}{ETc\ (mm/day)}$$

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 zone in the field (defined in step 1) 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).

Step 4. 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 (ET_O) and the crop coefficient) since the crop was sown. In each test cell, the crop coefficient used to estimate the crop water use is offset from the crop coefficient used to calculate the irrigation applied to the non-test cells. For example, for K_C = 0.35 and five test cells, the crop coefficients might be chosen as 0.07, 0.21, 0.35, 0.49 and 0.63 for each test cell, respectively (i.e. multiples of 0.14 on either side of the mean, 0.35).

Step 5. Before the next irrigation is applied (in this case, a fixed number of days), the crop response to the previous irrigation is evaluated. 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.

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 (e.g. optimal LAI data obtained from OZCOT as shown in Figure 8). For data that follows an optimal time series data set (e.g. Figure 8), the performance index is:

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

where t represents the day of the data collection.

{Insert Figure 8 here}

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:

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

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:

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

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 (e.g. Figure 9).

{Insert Figure 9 here}

Step 6. After a preset time interval, the non-test cells are irrigated with an amount calculated using the crop coefficient corresponding to the maximum performance index of the test cells from the previous irrigation and the aggregated reference evapotranspiration since the previous irrigation. The irrigation amounts applied to the test cells are calculated using crop coefficients offset (as step (4) above) from the optimal coefficient of the previous irrigation.

VARIwise automatically selects new test cells in each zone after every irrigation to ensure that the response of the test cell is indicative of the rest of the zone. This is achieved by a simple increment of the cell number (e.g. right-hand spiral for a centre pivot irrigated field) provided that the replacement cell still lies in the required zone.

Step 7. Steps 5. and 6. are repeated for each irrigation event.

By integrating a range of control strategies – the three above and others which may be added – 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 usefulness of additional sensors.

3.8 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; (iii) or animated field maps. Examples of these outputs are shown in Figure 10.

{Insert Figure 10 here}

4. Case study on the Irrigation of Cotton

Simulations of the three control strategies introduced in Section 3.7 are compared in this case study with various input conditions.

4.1 Case study inputs

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. Nitrogen application was 120 kg/ha at the start of the season and a cell size of 100 m² was specified. Both the low and high uniformity irrigation machine application data of Figure 5 were utilised for the fixed irrigation schedule, and only the low uniformity data was used for the soil moisture deficit-triggered irrigation schedule. These two irrigation schedules were simulated using the Sicot 73 crop variety and a weather profile ('Weather Profile 1'). The self-optimising irrigation strategy was evaluated for two crop varieties (Sicot 73 and Sicot 71B) and under the three weather profiles in which Weather Profile 1 is hot and wet late in the crop season, Weather Profile 2 is hot and wet early in the crop season, and Weather Profile 3 is hot early in the crop season with limited rainfall, and with respective GPS locations of -28.18°N 151.26°E, -29.50°N 149.90°E and -30.09°N 145.94°E. Daily weather profiles for these sites were obtained from Australian Bureau of Meteorology SILO data (QNRM 2009) for 2004/2005.

The spatially varied soil properties (i.e. plant available water content) produced the underlying variability for the simulations presented in this case study (Figure 6). For the soil moisture deficit-triggered irrigation schedule, 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 11.

{Insert Figure 11 here}

For the self-optimising irrigation strategy, the field was automatically divided into two zones (Figure 7) using the EM38 map imported into VARIwise (Figure 6) and five test cells. The target LAI derived from a VARIwise simulation of soil moisture deficit-triggered irrigation with the highest yield (triggered by Point 3 in Figure 11) was used and is shown in Figure 8.

The performance index was calculated using leaf area index and square count with respective weights of 0.2 and 0.8. This data was obtained from the OZCOT model one day before the next scheduled irrigation event. Irrigations were applied every six days following the first scheduled irrigation event.

4.2 Case study output and discussion

The simulation output using three alternative control strategies is shown in Figures 12, 13 and 14 in which 'IWUI' denotes Irrigation Water Use Index and is the ratio of the crop yield (bales) to the irrigation water applied (ML) (BPA 1999). The simulations demonstrated the effect (on yield and irrigation water use index) of the fixed irrigation schedule and machine uniformity (Figure 12), the location of the trigger point used for soil moisture deficit-triggered irrigation schedule (Figure 13) and the variable-rate, self-optimising irrigation strategy (Figure 14). Inspection of these results indicates:

- For the fixed irrigation schedule, the yield generally improved when the irrigation volume was increased.
- The uniformity of the machine affected the simulated yield: a low uniformity machine which applied large volumes of irrigation in some areas of the field resulted in higher yields.
- For the soil moisture deficit-triggered irrigation schedule, 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.
- The simulated yield for the self-optimising irrigation strategy was higher than the fixed and soil moisture deficit-triggered irrigation schedules under the same input conditions and when the weather and crop properties were varied. The spatial variability of the yield was caused by the spatial variability of the soil properties and the 'test' irrigation volumes being applied to various cells across the field.

The irrigation strategies and input conditions simulated in VARIwise in this case study show significant differences in yield and water use. These differences demonstrate the potential value of VARIwise as a variable-rate irrigation simulation framework and for further investigations of adaptive irrigation control strategies.

It is intended that VARIwise will be used as part of a decision support system in real-time field implementations, i.e. a computing system would be mounted on a lateral move or centre pivot and transmit control actions to variable-rate irrigation hardware. VARIwise could be interfaced with input data sources including an automatic weather station, wireless sensor networks of soil sensors, on-the-go plant sensors, field observations from the irrigation manager or agronomist (e.g. plant stress) and flow meters for machine water applications. It is anticipated that computing the irrigation application and/or timing for one cell would take 2 seconds (which is the execution time for an algorithm in Borland Delphi 6 on an Intel Core 2 Quad Q9400 (2.66 GHz) processor and Windows XP operating system), enabling real-time implementation on a lateral move or centre pivot moving at 2 metres per minute.

Future work will involve comparing the irrigation control strategies and management constraints (e.g. limited water situations), comparing the simulation results with field data, integrating measured field data with in-built simulation models, and exploring the data requirements for irrigation control and the optimal spatial scales and time steps for measurements (e.g. soil moisture, LAI, weather). For the field evaluations, data would be collected by an agronomist from in-field sensors.

5. 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 simulation 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, a standard cotton plant model (OZCOT) and evaluation of adaptive control strategies which have the potential to improve yield and irrigation water use index. Further work in VARIwise will entail an analysis of the control strategy outputs and exploration of the strategies using input data with various spatial scales and time steps.

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Table caption

Table 1: Databases within VARIwise

Figure captions

Figure 1: Conceptual adaptive control system for variable-rate irrigation – the basis of the simulation framework VARIwise

Figure 2: Flow chart for VARIwise software

Figure 3: VARIwise cells for field irrigated by a: (a) centre pivot; and (b) lateral move

Figure 4: Example filename of spatial database in VARIwise

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Figure 6: EM38 map: (a) to be imported in VARIwise; and (b) with electrical conductivity values assigned to each cell for the area circled in (a)

Figure 7: Zones for self-optimising irrigation strategy in VARIwise derived from the soil electrical conductivity data of Figure 6(b)

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Figure 11: Trigger points for soil moisture deficit-triggered irrigation schedule in VARIwise

Figure 12: Output of the fixed irrigation schedule for Weather Profile 1 and Sicot 73 and legend for yield maps in Figures 12-14

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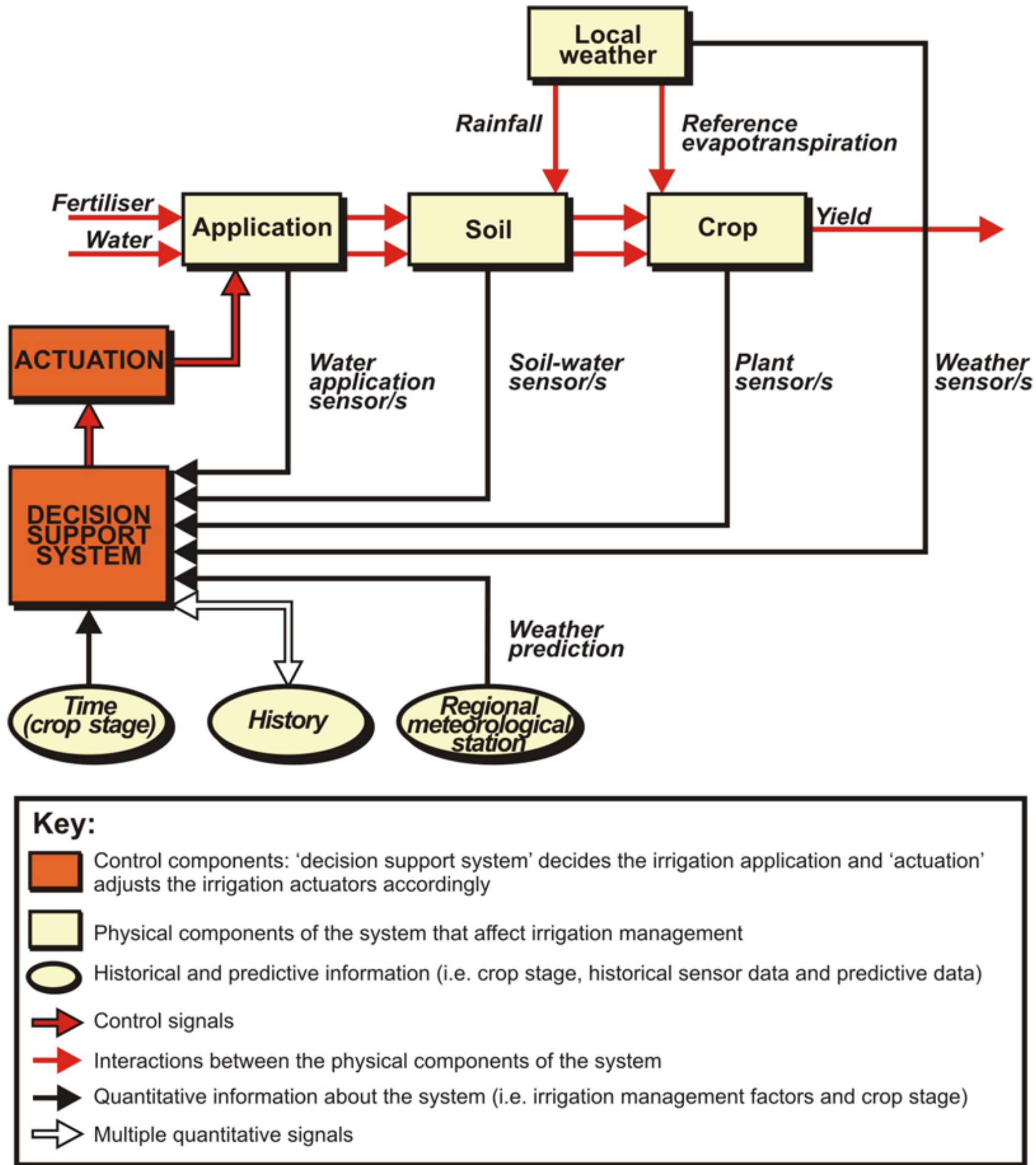
Figure 14: Output of the self-optimising irrigation strategy with variable-rate irrigation machine (where legend for yield maps is in Figure 12)

Table

Table 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, configuration of irrigation outlets, type of outlets (i.e. end gun, boombacks), pump flow rate, irrigation application uniformity
Sensors	Input screen	Type of sensor, data type, units, time intervals of measurement
Field-scale database (i)	Input screen	A new database ($i=1,2,3,\ldots$) is created for each of the following variables: sowing date, defoliation date/s, harvest date, crop variety, plant available water content
Control strategy evaluation database (j)	Input screen	Each database ($j=1,2,3,\ldots$) contains the following data for each control strategy evaluated: Type of control strategy, data variable/s to use, whether machine speed is constant or variable
Temporally-modified databases:		
Field-scale database (k)	(As appropriate:) Input screen/ text file/ image file (e.g. aerial or ground photos, EM map)/ Internet (e.g. weather data from SILO data set (QNRM, 2009) using GPS location in property database)	Each database ($k=1,2,3,\ldots$) 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, evapotranspiration *Other*: yield

Figures



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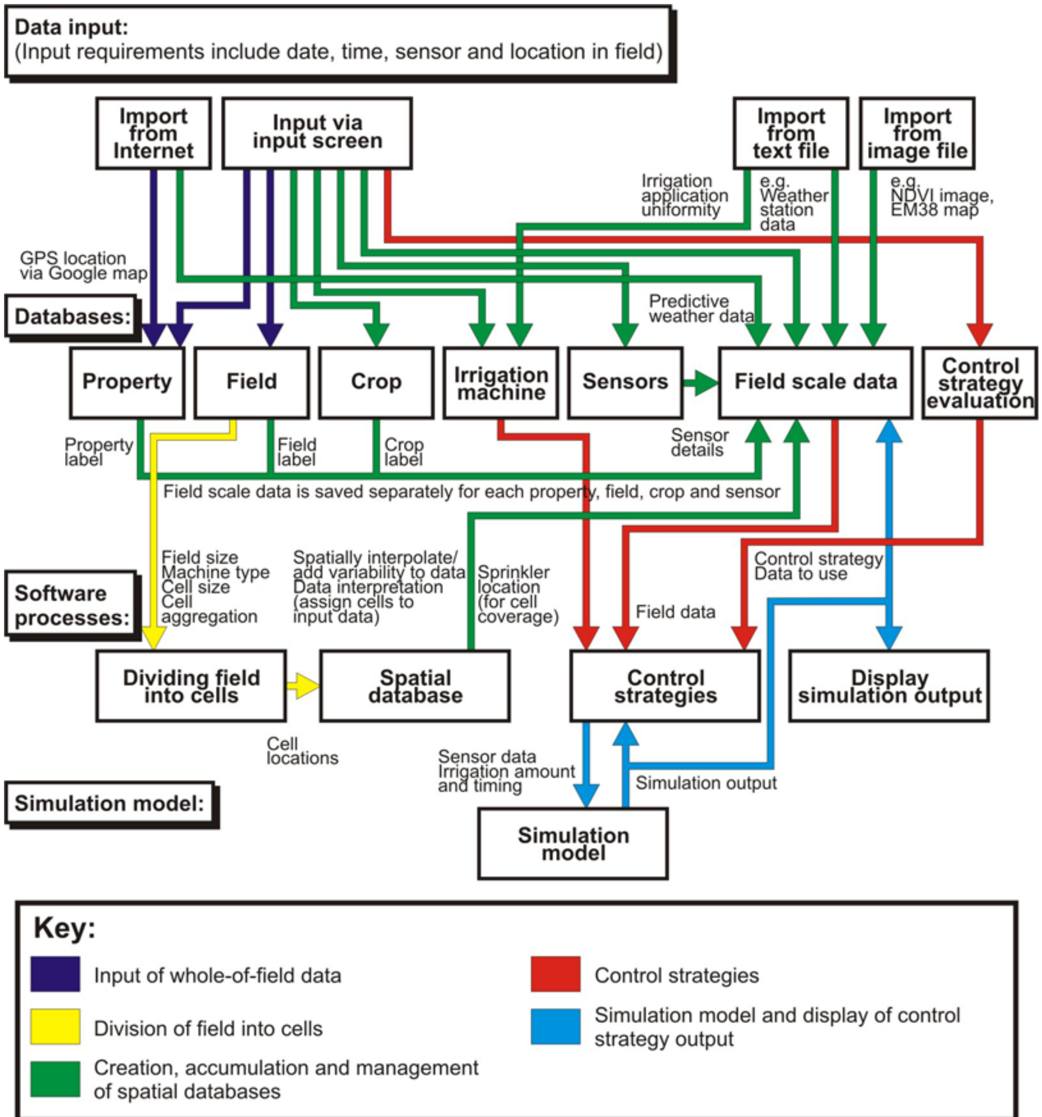

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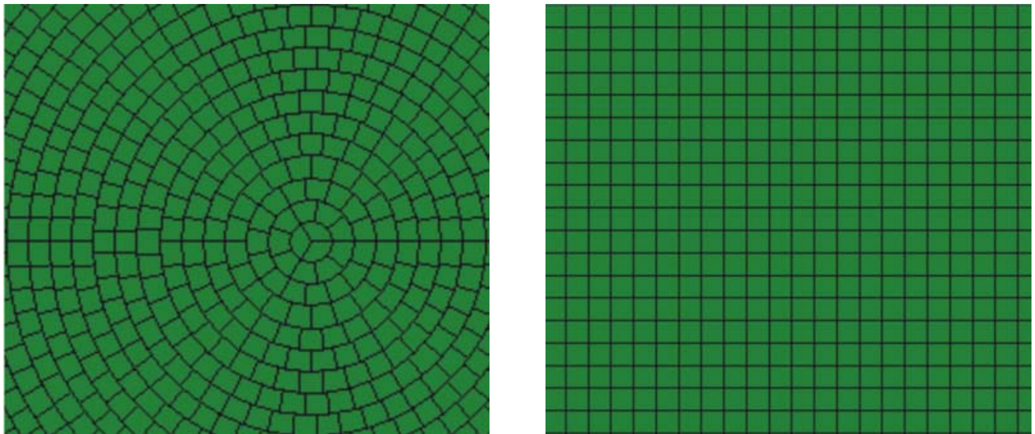


(a) (b)

Figure 3: VARIwise cells for field irrigated by a: (a) centre pivot; and (b) lateral move

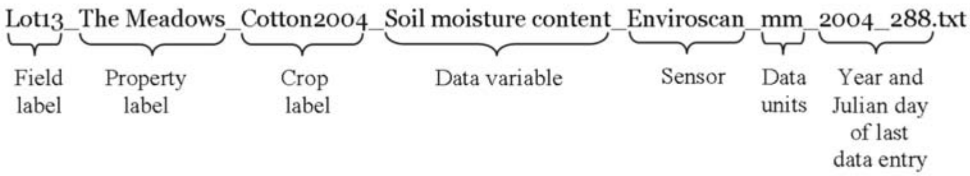
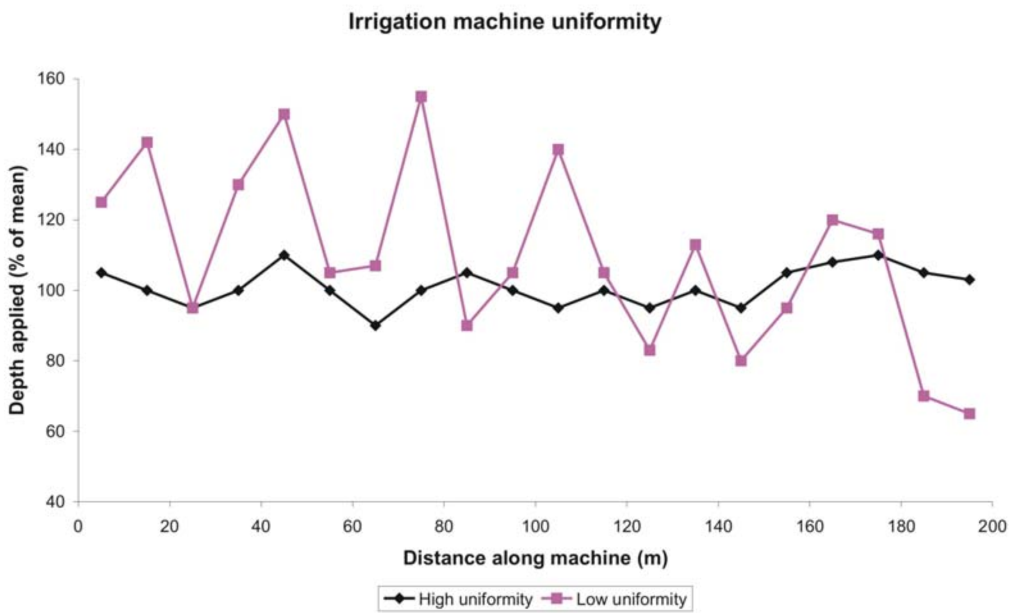


Figure 4: Example filename of spatial database in VARIwise



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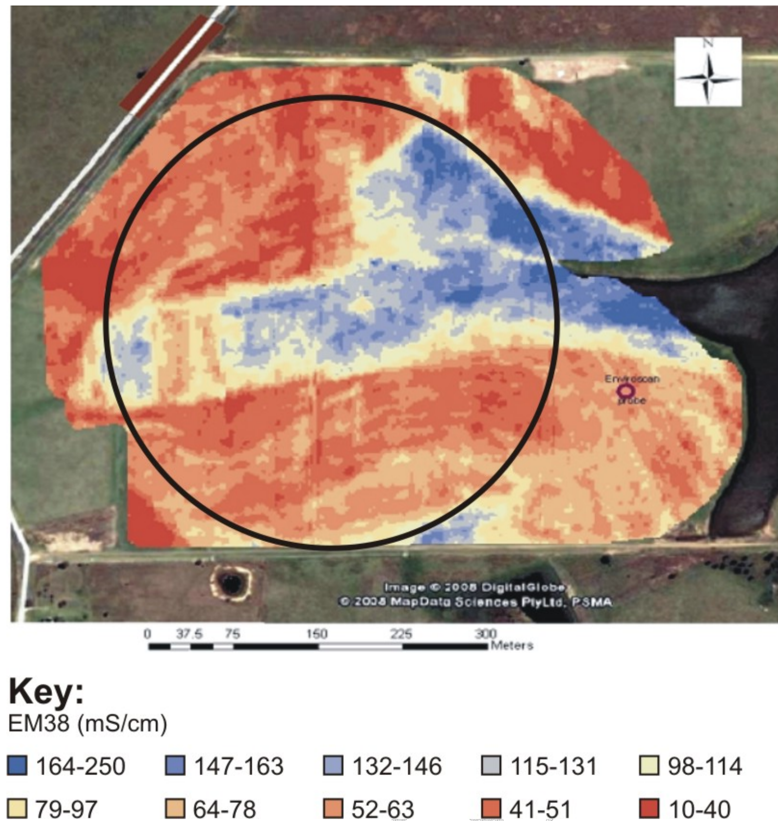
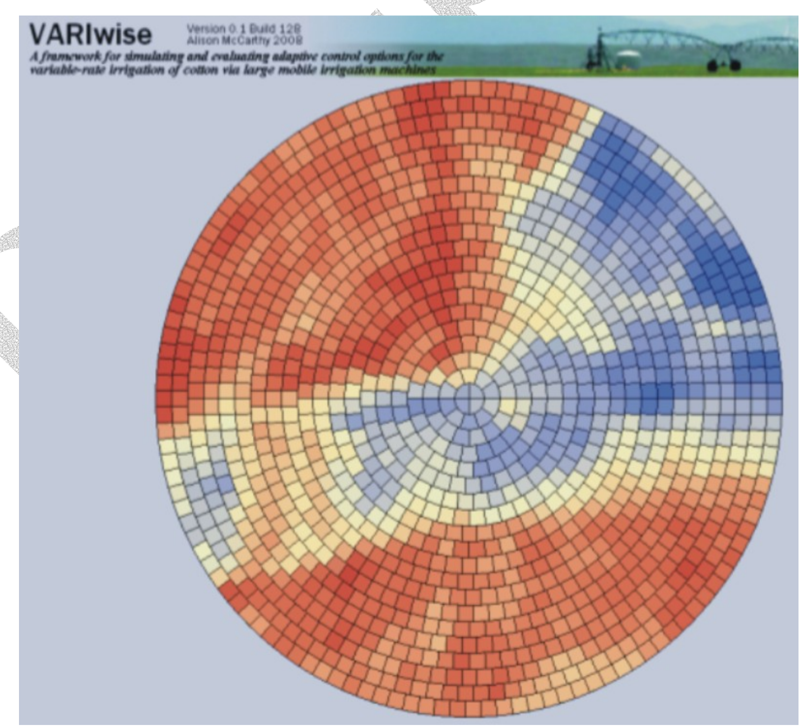


(a)



(b)

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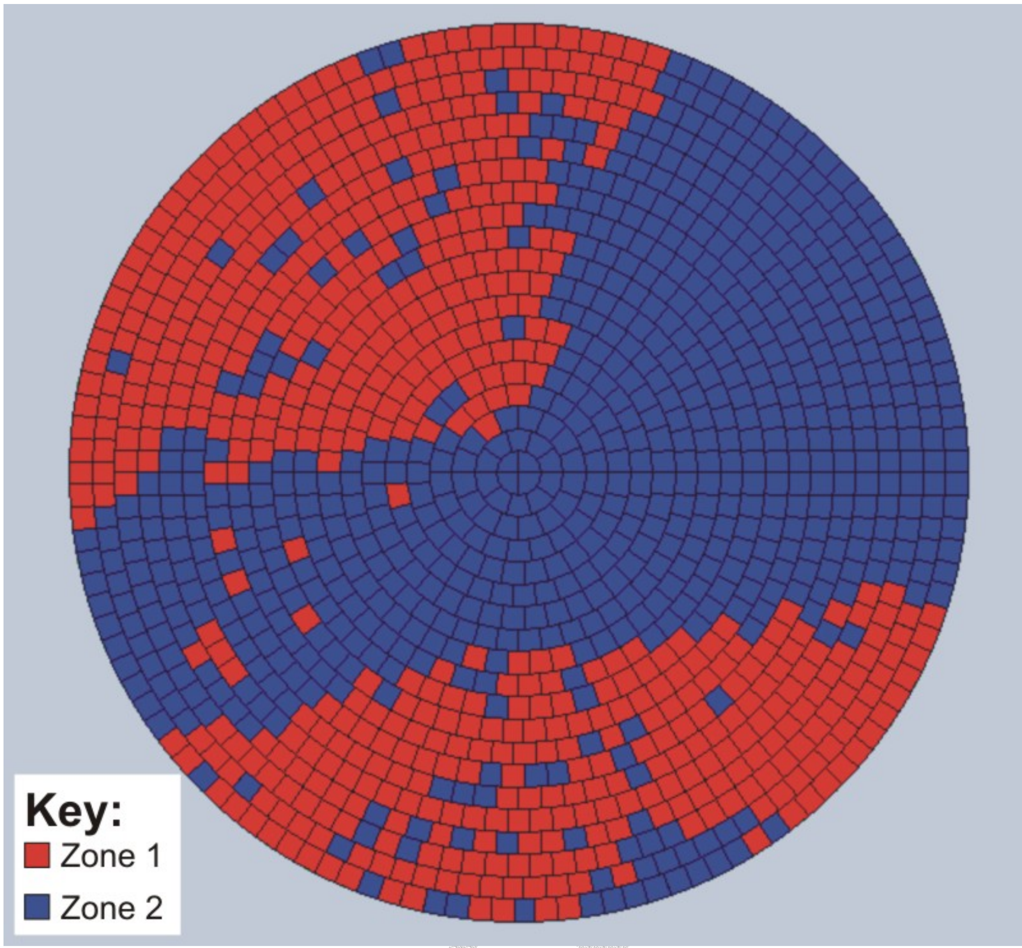

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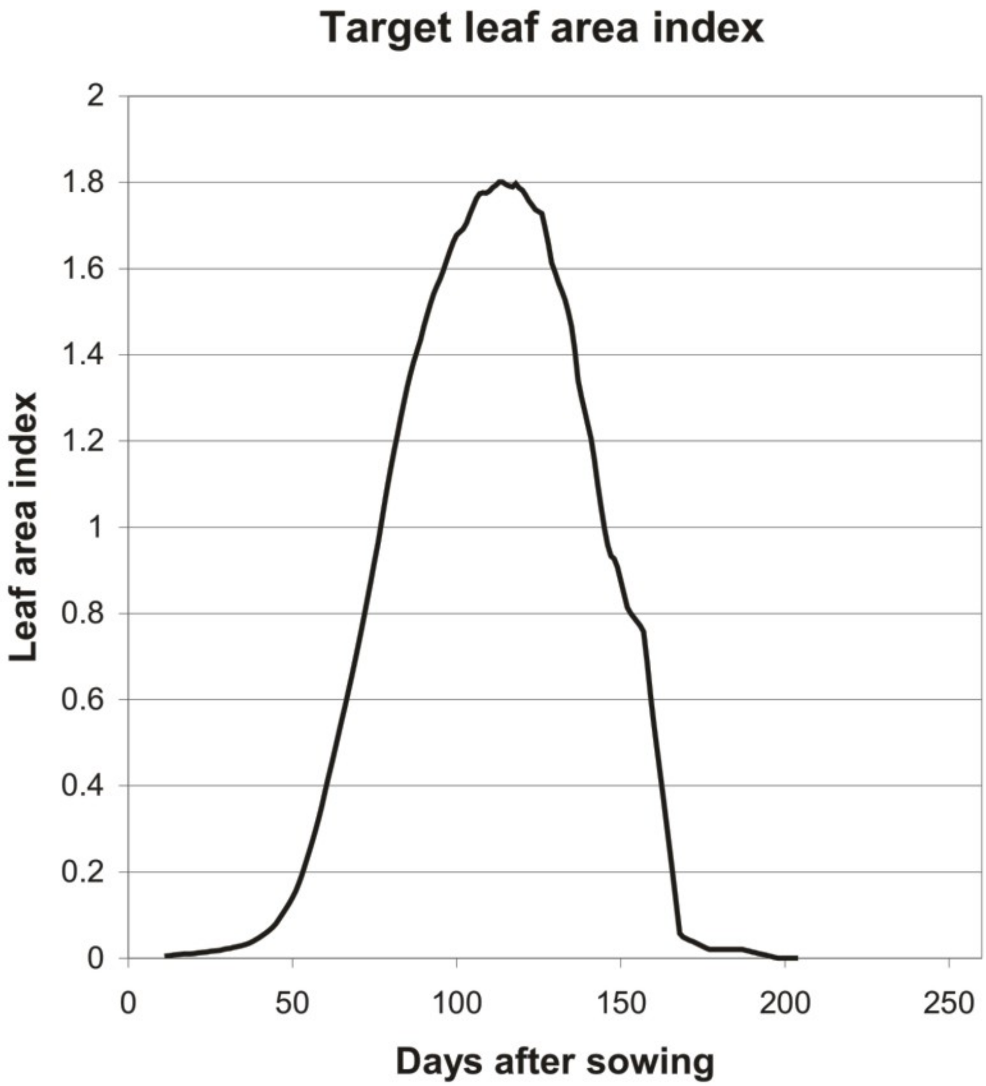

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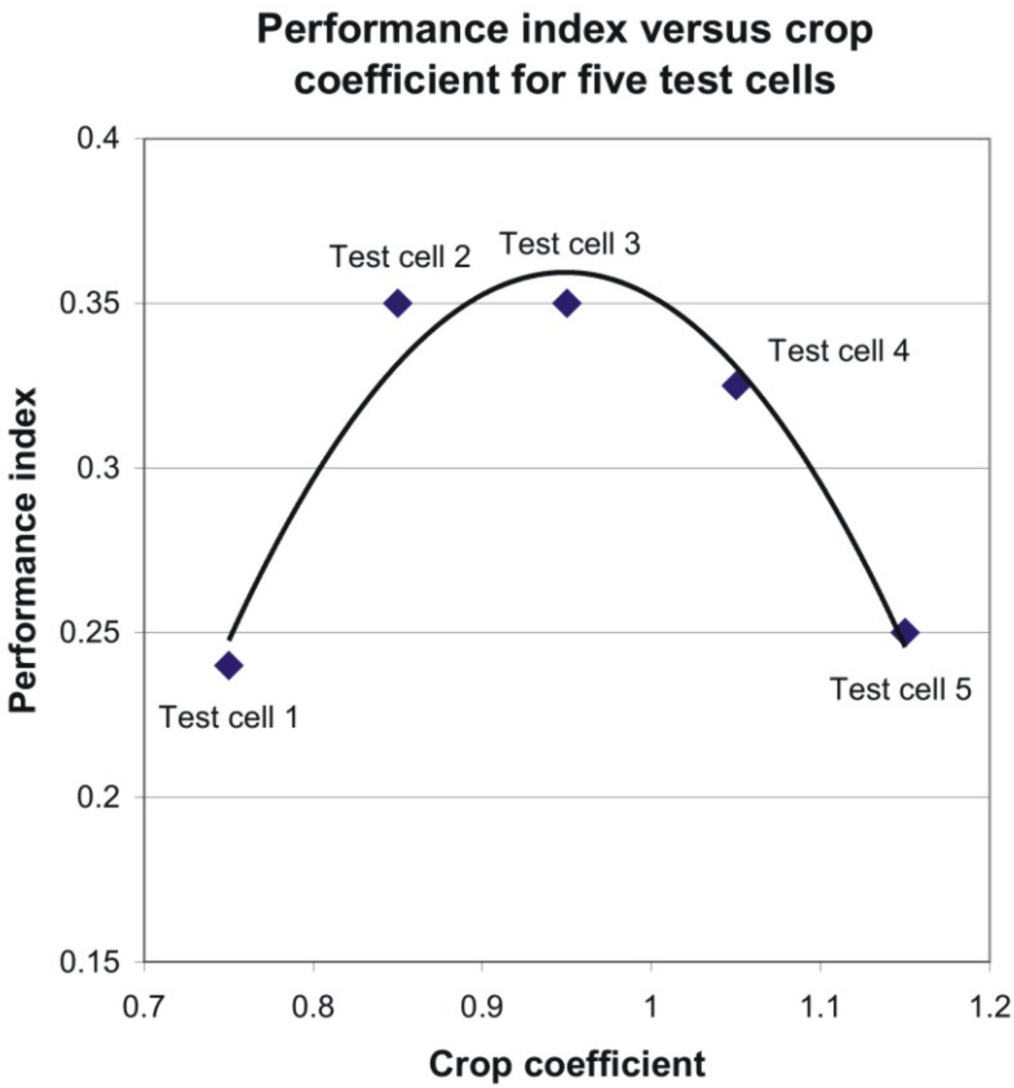
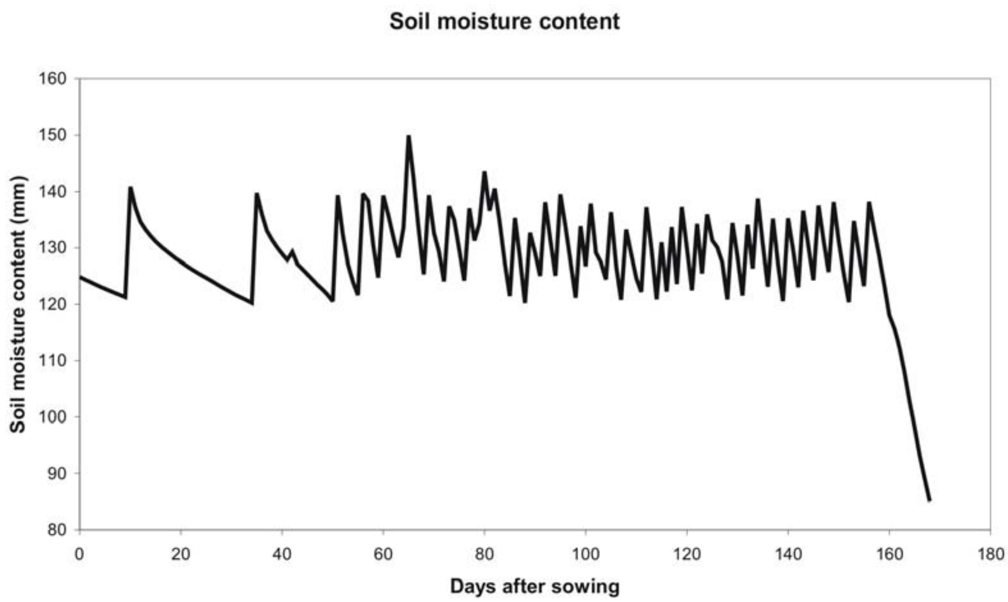
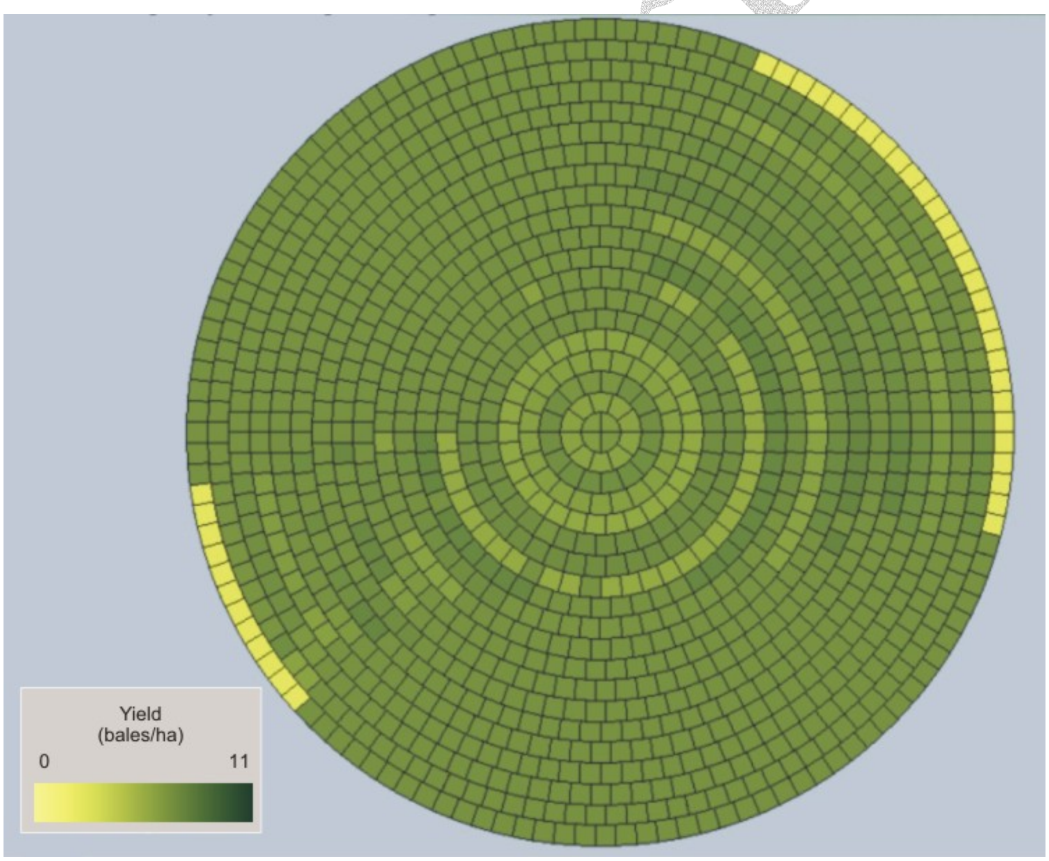


Figure 9: VARIwise determination of maximum *PI* using a quadratic fit to the available data points



(a)



(b)

Figure 10: 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

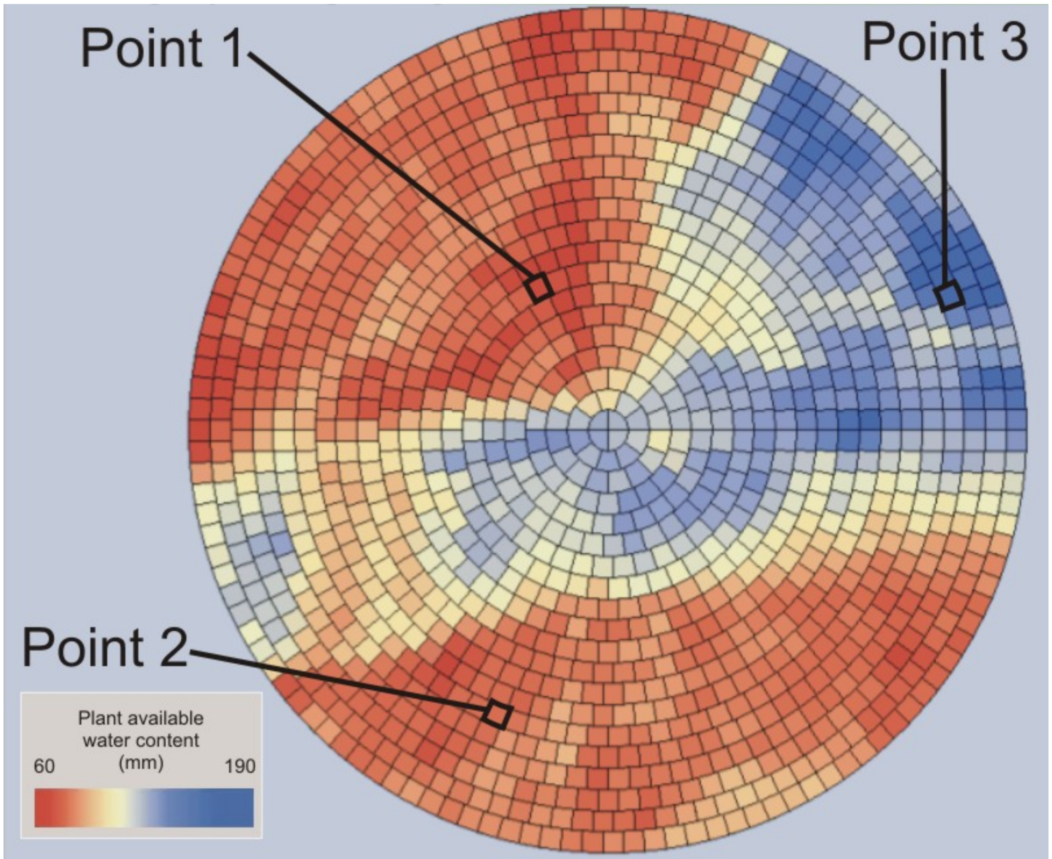


Figure 11: Trigger points for soil moisture deficit-triggered irrigation schedule in VARIwise

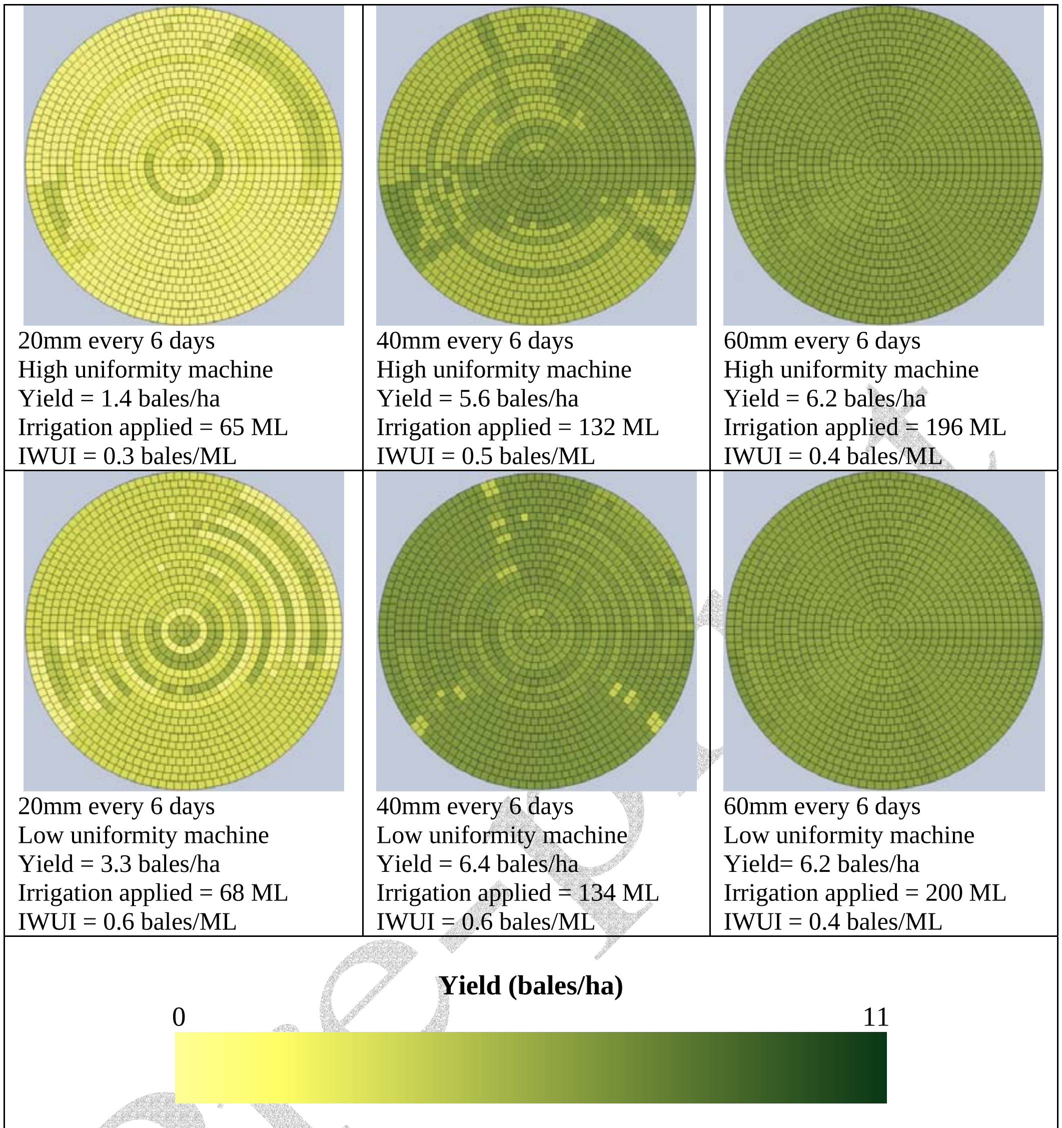


Figure 12: Output of the fixed irrigation schedule for Weather Profile 1 and Sicot 73 and legend for yield maps in Figures 12-14

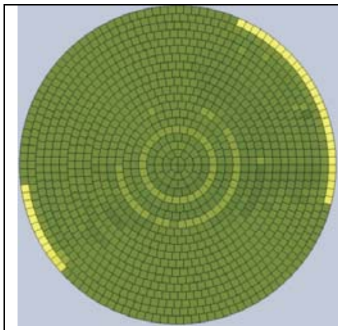
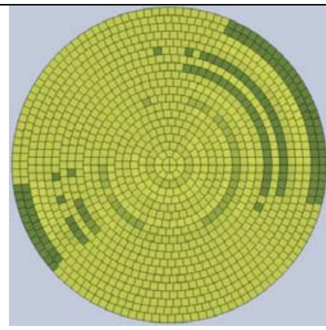
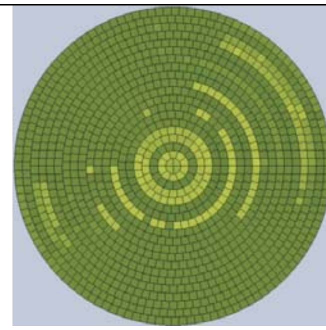
		
Triggered by Point 1 Low uniformity machine Yield = 7.0 bales/ha Irrigation applied = 85 ML IWUI = 1.0 bales/ML	Triggered by Point 2 Low uniformity machine Yield = 4.6 bales/ha Irrigation applied = 127 ML IWUI = 0.5 bales/ML	Triggered by Point 3 Low uniformity machine Yield = 7.1 bales/ha Irrigation applied = 99 ML IWUI = 0.9 bales/ML

Figure 13: Output of the soil moisture deficit-triggered irrigation schedule for Weather Profile 1 and Sicot 73 (where legend for yield maps is in Figure 12)

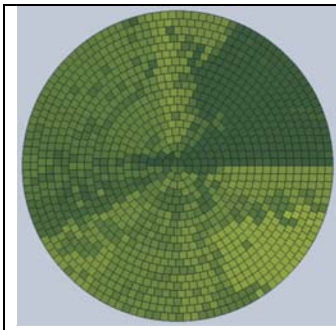
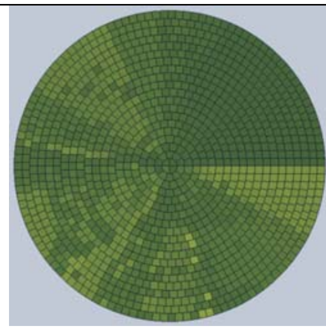
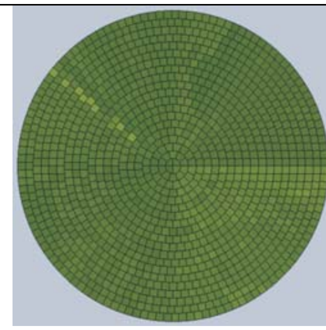
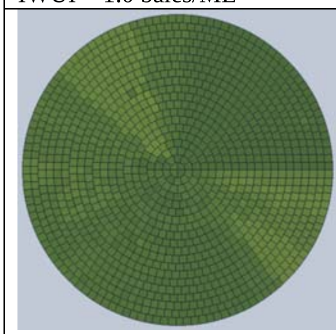
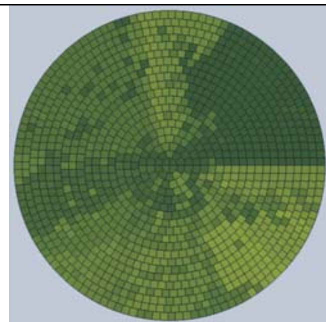
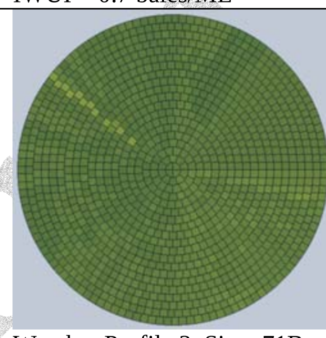
		
Weather Profile 1, Sicot 73 Yield = 9.3 bales/ha Irrigation applied = 116 ML IWUI = 1.0 bales/ML	Weather Profile 2, Sicot 73 Yield = 9.2 bales/ha Irrigation applied = 130 ML IWUI = 0.9 bales/ML	Weather Profile 3, Sicot 73 Yield = 8.4 bales/ha Irrigation applied = 162 ML IWUI = 0.7 bales/ML
		
Weather Profile 1, Sicot 71B Yield = 9.1 bales/ha Irrigation applied = 136 ML IWUI = 0.8 bales/ML	Weather Profile 2, Sicot 71B Yield = 9.3 bales/ha Irrigation applied = 116 ML IWUI = 1.0 bales/ML	Weather Profile 3, Sicot 71B Yield = 8.4 bales/ha Irrigation applied = 162 ML IWUI = 0.6 bales/ML

Figure 14: Output of the self-optimising irrigation strategy with variable-rate irrigation machine (where legend for yield maps is in Figure 12)