Simulation of irrigation control strategies for cotton using Model Predictive Control within the VARIwise simulation framework

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Abstract

Model-based irrigation control strategies applied to irrigation make decisions (on water application and/or timing) using a crop and/or soil production model. Decisions are made with respect to an optimisation objective which, for irrigation, can be either short-term (e.g. achieving/maintaining a set soil-water deficit) or predicted end-of-season (e.g. maximising final yield) by predicting how the crop will respond at the end of the season. In contrast, sensor-based irrigation strategies rely on achieving a performance that is measurable during the crop season to provide the feedback control, and may not necessarily optimise overall crop performance. Model-based control potentially avoids this limitation.

This paper describes the application of Model Predictive Control (MPC) methodology to the feedback control of irrigation via a model-based irrigation strategy implemented in the irrigation control simulation framework 'VARIwise'. The requirement to also accommodate spatial and temporal differences in crop water requirement across a heterogeneous field is met by defining management 'zones' according to differing soil and crop properties across the field and separately applying the control algorithm for each of these zones.

Case studies were conducted to evaluate MPC for a centre pivot irrigation machine-irrigated cotton crop (under typical Australian growing conditions) with: (i) different in-season performance objectives (maintaining soil-water deficit; maximising square count); (ii) different predicted end-of-season performance objectives (maximising yield; maximising water use efficiency); and (iii) maximising yield with different field data inputs for model calibration. The model predictive control strategy produced significantly higher simulated yields and water use efficiency than an industry-standard irrigation management strategy; and (in most but not all situations) direct sensor-based adaptive control strategies.

Research Highlights

- Model Predictive Control was simulated for site-specific irrigation in 'VARIwise'
- MPC accommodated both short-term (in-season) and long-term performance objectives
- MPC delivered the best performance when optimising crop yield
- MPC resulted in higher (simulated) yield than sensor-based strategies
- MPC required extensive data to accurately calibrate crop model

Keywords

Variable-rate irrigation, centre pivot, lateral move, scheduling, irrigation automation, Model Predictive Control

1. INTRODUCTION

The development of the control simulation framework ‘VARIwise’ has enabled the evaluation of site-specific, spatially-variable irrigation control strategies on field crops (McCarthy et al. 2010a). VARIwise permits spatially and temporally varied simulation and accommodates sub-field scale variations in all input parameters down to metre-scale zone size. Simulations of ‘sensor-based’ strategies showed potential improvements in yield and water use efficiency (McCarthy et al. 2013). These strategies compared the field measurements with a desired response (e.g. soil-water deficit) and adjusted the irrigation volume applied according to the difference.

1.1 Model Predictive Control (MPC) applied to irrigation

In contrast, an alternative 'advanced process control' approach to irrigation uses crop production models to aid the irrigation decision making process. These 'model-based' control strategies use the available field measurements to calibrate the crop model. The model is then repeatedly executed to determine the optimal irrigation volume and timing that will achieve the desired performance objective (e.g. predicted end-of-season yield).

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

From the control perspective, the 'process model' evolves during the growth of the crop such that the control must be adaptive. This requirement means that the model used by the MPC strategy must be continuously re-calibrated using the currently available field data. The plant growth and soil-water dynamics in the cotton model OZCOT (Wells and Hearn 1992) implemented within VARIwise, can be accurately calibrated (McCarthy et al. 2011. The calibrated OZCOT model has also been found to accurately simulate yield (Richards et al. 2001). Using one season's field experiment data McCarthy et al. (2011) found that OZCOT was most effectively calibrated (and therefore able to predict the soil and crop response to irrigation application) using full data input, whilst for situations where only two data inputs were available, the simulations suggested that either weather-and-plant or soil-and-plant inputs were preferable.

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

1.2 MPC and crop production models

The performance objectives set for MPC applied to irrigation can range from a short-term objective such as achieving a preset soil-water deficit following each irrigation to a 'whole season' objective such as maximising predicted end-of-season yield.

In addition, crop production models (such as OZCOT for cotton, discussed below) have sophisticated prediction capabilities which may be utilised in the implementation of MPC. For example, a performance objective to maximise the number of plant fruiting sites during growth should maximise potential predicted end-of-season yield. This additional crop response capability typically requires measurements of the plant to calibrate the crop production model according to the measured plant growth parameters (e.g. fruiting), which in turn requires infield plant sensors to provide calibration data. To maximise uptake of the site-specific irrigation control system by growers it is desirable to minimise the sensor requirements. A reduction in measurements could be achieved by using only the data types that are more influential in the model calibration or by reducing the spatial or temporal resolution of data. However, the data used to calibrate the model should still enable sufficient accuracy of the model. An insufficient range of measurements to calibrate the model used by MPC will influence the accuracy of the model and the model's ability to predict irrigation and crop performance.

Hence, this paper aims to:

- identify the optimal combination of performance objective and data input combination amenable to practical MPC strategies; and also
- explore the impact of different control horizon lengths (period of time for forecasting future events) on the performance of MPC.

The strategies simulated in this paper explore the viability of the use of MPC in the simulation of a 'realistic' irrigation situation with spatial and temporal variation across a heterogeneous field. Accordingly, this paper details the implementation of the MPC methodology in VARIwise and, for the example of cotton grown in Australia, presents results for a range of simulations having different performance objectives. The results are presented as three case studies, A, B and C, which, in order, evaluate the potential of MPC to optimise:

A. short-term responses of square count or soil-water;
B. predicted end-of-season crop yield or water use efficiency with (i) low and high soil nitrogen content, and (ii) crop seasons with and without rainfall; and
C. predicted end-of-season crop yield with different combinations of sensory input data to calibrate the model.

A comparison is then made between the MPC strategies and simulations of 'sensor-based' strategies for adaptive irrigation control (McCarthy et al. 2013).

2. IMPLEMENTATION

The simulation framework 'VARIwise' (McCarthy et al. 2010a) was created to develop, simulate and evaluate site-specific irrigation control strategies for centre pivot and lateral move irrigation machines on non-uniform (spatially and temporally varied) fields. The framework enables evaluation of strategies with different sensor data availability (both spatial and temporal); for example, the performance of the control strategies with spatial gaps in measured response is explored in McCarthy et al. (2010b). In addition, the framework can provide evaluation of different irrigation system capacity constraints and when supplied with real-time weather and/or other field data, the framework will provide direct machine actuation.

For the simulation (and management) of cotton irrigation, the cotton production model OZCOT (Wells and Hearn 1992) was used by VARIwise and was automatically and continuously calibrated according to the currently available weather, soil and plant data. Details are set out in McCarthy et al. (2011). To illustrate the VARIwise configuration used to evaluate MPC a general schematic is presented in Figure 1, in which the central blocks and data flows are explained in the following sections.

Insert Figure 1 here

The MPC algorithm predicts how much each output (e.g. soil-water, fruit load) will deviate from a time series trajectory within the prediction horizon. A MPC cost function $J(k)$ is calculated for each possible set of input actions in the current time step k using a least squares algorithm of the following form (Maciejowski 2002):

$$J(k) = \sum_{i=1}^{C} \sum_{j=1}^{N} \{w_j[r_j(k+i) - x_j(k+i)]\}^2 \qquad (1)$$

where:

$J(k)$	=	cost function at instant k
C	=	length of prediction/control horizon
N	=	number of system outputs
w_j	=	weighting coefficient for output j
$r_j(k+i)$	=	predicted value of jth output at future instant $k+i$
$x_j(k+i)$	=	target value of jth output at future instant $k+i$

The control action that minimises the cost function (i.e. that produces the smallest deviation in performance from the desired trajectory) is implemented. This optimisation is repeated at each sample time step to update the optimal input trajectory after a feedback update. Hence, this MPC algorithm calculates the sequence of control action adjustments over a specified future time interval.

In an irrigation context, the system outputs used to calculate the cost function will typically have different units and magnitudes, and the same percentage change in variables of different units and magnitudes may cause unintentional bias toward variables that are generally larger in magnitude. For example, a particular percentage difference in soil-water will produce a larger cost function than the same percentage difference in leaf area index. Hence, the MPC algorithm was modified (equation 2) to calculate a performance index that represents a percentage difference in the predicted outputs rather than a least squares objective function (equation 1). The control action that maximises the performance index *PI*(*k*) is then implemented in each time step, and is calculated using the equation:

$$PI(k) = \sum_{i=1}^{C} \sum_{j=1}^{N} w_j \left[\frac{r_j(k+i) - x_j(k+i)}{x_j(k+i)} \right] \qquad (2)$$

The MPC methodology was implemented to determine irrigation timing and site-specific irrigation volumes on a daily basis by means of the following four-step procedure:

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

The details of each step in relation to the following case studies are set out below. This procedure is independently applied to each ‘management zone’, where each zone in the field is defined according to differing soil and crop properties across the heterogeneous field.

2.1 Step 1: updating measured and forecast weather data

For each day of the crop season, the meteorological data input file for the integrated crop model was updated to include the previous day’s weather and the updated weather forecast for the farm’s location. In a field implementation of MPC, the ‘previous day’s weather’ could be obtained from an on-site weather station and the ‘updated weather forecast’ could be obtained from the Bureau of Meteorology. However, to simulate the performance of MPC for a whole season (where there was no field implementation) both ‘previous day’s weather’ and ‘updated weather forecast’ had to be obtained from historical data.

Because of the high variability of Australian climate and the difficulty in picking a ‘typical’ year, an artificial daily meteorological dataset was created by averaging the day-on-day data of the five years (1999 to 2004 inclusive) appropriate to the location of Dalby (Latitude -28.18°N E, Longitude 151.26°), a major cotton-growing region of south-east Queensland, Australia, and this dataset was used for all simulations. Daily data comprised maximum and minimum temperature, solar radiation and rainfall, and was sourced from Australian Bureau of Meteorology SILO patched point environmental dataset (QNRM 2009). SILO is an enhanced climate database containing Australian climate data from 1889.

Forecast weather data, to be used predictively during the simulations, was created by imposing a Gaussian distribution of variability on the daily values of the five-year-averaged dataset using standard deviations of ±5°C, ±5°C, ±5 W.hr/m^2 and ±50% for maximum temperature, minimum temperature, daily solar radiation and rainfall, respectively; i.e. for any given day, the forecast one, two and three days ahead, then values for each variable randomly generated within each distribution by taking that day's values as the mean. For each day, only three days of the forecast weather data were used. This is because the two Australian short-term numerical weather prediction models forecast three and seven days ahead and are combined to improve the prediction accuracy (Ebert 2001). The three-day forecast would be more accurate than one model on its own because both models could predict weather to three days. A three-day forecast would ensure short-term prediction accuracy in the predictions, particularly as regards rainfall in south-east Queensland, Australia, where the summer rainfall is dominated by frontal bands of isolated cumulo-nimbus storms.

2.2 Step 2: calibrating the crop model – 'actual' and 'reference' models

The crop model OZCOT is utilised by VARIwise and can be automatically and continuously calibrated according to the 'currently' available weather, plus soil and plant data, using the procedure set out in McCarthy et al. (2011). The procedure for calibrating the production/growth model OZCOT in a real-time implementation, i.e. for actual irrigation machine control, involves automatically and iteratively adjusting the parameters used to predict soil water status and plant growth until the difference between the predicted and sensed variables reached a minimum. For the cotton model OZCOT, the plant variables (leaf area index, boll count, square count), soil variables (soil moisture content and plant available water capacity) and weather variables (daily minimum and maximum temperature, rainfall and solar radiation in weather input file) are interdependent. The plant behaviour can be calibrated by adjusting parameters in a crop properties file, whilst the soil moisture behaviour was calibrated by adjusting parameters in a soil properties file. These parameters were adjusted between the minimum and maximum values of the corresponding parameters in the predefined soil properties and crop variety parameter profiles. The parameters adjusted in the crop properties file included squaring rate (the rate of new flower buds being produced), growth rate of leaf area and plant population constant; whilst the parameters adjusted in the soil properties file were the initial soil moisture content and drained upper limit in each soil layer.

A **'reference' model, labelled 'RefModel',** is used to provide the crop growth prediction scenario for MPC. However, for the present case studies there was no measured field data input to calibrate the model. To overcome this, *a second OZCOT model of the cotton crop was used* in place of 'actual' field conditions. This model is referred to as the **'actual crop' model, labelled 'AcModel'** and the parameters were different to those in RefModel to emulate RefModel not exactly following the field conditions. In a field implementation the AcModel is not required as field measurements would be used. AcModel was then used to calibrate RefModel (Figure 1).

The crop and soil properties of AcModel were obtained from the user-specified soil and plant measurements (and these varied between simulations, as set out below). Within RefModel the crop variety was specified by the user at commencement. Likewise the soil properties of RefModel were user-specified, with the addition of areal variation in available soil-water imposed via a Gaussian distribution of variability having a standard deviation of ±25 mm (water depth equivalent).

2.3 Step 3: optimising irrigation volumes for each zone

Optimal irrigation volumes were determined by iteratively simulating the daily application of sixteen different irrigation volumes at 1 mm increments between 0 and 15 mm on each zone in the field. For each irrigation volume applied (for management zone *k*), a performance index *PI*(*k*) was calculated using equation (2). For variables that are maximised to achieve the optimal irrigation strategy (e.g. square count, yield, crop water use efficiency), the target value is taken to be the maximum realistic commercially attainable value (e.g. 15 bales/ha for cotton yield, 3 bales/ML for crop water use efficiency).

The predicted process outputs used to calculate the PI were taken one day after the irrigation application. The optimal irrigation volume for each zone was the irrigation volume with the highest PI; however, if more than one irrigation volume had the same PI then a water-efficient approach was taken and the optimal irrigation volume was the lowest quantitative volume that achieved the maximum PI. The irrigation volume was then calculated for each zone in the order in which the irrigation machine was to pass over the field.

2.4 Step 4: optimising the timing (day) of the next irrigation

The optimal day for the next irrigation event was determined using the calibrated RefModel. This involved performing the irrigation volume optimisation of the previous step for an arbitrary number of days (i.e. to a fixed horizon) and contained the assumption that the irrigation event could occur on only one of the days. The maximum horizon length was set to three days since three days of predictive weather were used.

The sixteen irrigation volumes tested on each zone depend on the irrigation day being tested. This is because, unless rainfall occurs, it was assumed that the crop water requirement (and hence irrigation application volume) increases for each day the irrigation event is delayed. For the first day irrigation volumes of 0 to 15 mm were tested with increments of 1 mm; for the second day 0 to 31 mm were tested with increments of 2 mm; and for the third day 0 to 47 mm were tested with increments of 3 mm.

A PI is calculated for each irrigation day by summing the individual PI values for each zone. The day with the highest total PI is taken to be the optimal day for the next irrigation event. The irrigation event is scheduled if the first day in the horizon had the highest PI and there are a minimum number of zones requiring irrigation greater than 0 mm. This ensures that the irrigation application is practical and irrigations are not initiated for only a small number of zones in the field. The threshold, i.e. the minimum proportion of zones requiring irrigation, was arbitrarily selected to be 15% for the case studies presented.

2.5 Subsequent iteration

After the optimal irrigation action – which may, of course, be a 'nil irrigation' action – was determined for the user-specified first day, the procedure described in the four subsections above was repeated every day throughout the crop season, with the irrigation events ending on a day specified by the user.

3. MPC CASE STUDY A: optimisation of short-term responses using different combinations of daily input data

The MPC strategy was evaluated with daily input data to predict and control irrigation applications to achieve either a short-term soil (e.g. deficit) or plant growth (e.g. leaf area index) target. A range of combinations of input variables for control were used to determine which input data stream was most useful for MPC.

3.1 Methodology for Case Study A

The field was automatically divided into 44 zones, each of area approximately 0.3 ha, and the irrigations occurred daily. This number of zones enabled the simulations to be executed in a timely manner with spatially variable soil properties across the field. The MPC strategy was evaluated for ten combinations of data input (Table 1). The input data combinations represent the data used both as input variables to calibrate RefModel and the variables used for control. For the simulations using both soil and plant data, the weighting on each variable was set to be 0.5. The strategies with soil data input aimed for soil-water deficit equal to 10% of the plant available water capacity in each zone.

Insert Table 1 here

In each simulation, the RefModel (to be calibrated) used the Siokra V16RR cotton variety with the underlying variability in plant available water capacity (PAWC) and starting soil-water deficit as set out in Figure 2. The starting soil-water deficit map was generated by assigning a starting soil-water deficit value of 30 mm across the field and imposing a Gaussian distribution of variability with standard deviation ±10 mm on each zone. The PAWC map was generating by assigning PAWC values of 60, 150 and 200 mm on three zones of the fields, spatially interpolating the PAWC using ordinary kriging and by similarly imposing a Gaussian distribution of variability with standard deviation ±10 mm on each zone. The PAWC ranges from 60 to 200 mm in the simulated field to ensure the control strategies could deal with the different soil types that often exist within fields.

Insert Figure 2 here

The measured crop response (AcModel) used the Sicot 73 cotton variety and soil variability map of Figure 2. Siokra V16RR is a “Roundup Ready” late-maturing cotton variety, whilst Sicot 73 is a full season cotton variety with high yield potential (CSD 2009). The prediction horizon was one day and it was practical for irrigation events to occur daily.

3.2 Case Study A – Results and discussion

Table 2 sets out the numerical results of the MPC Case Study A, whilst Figure 3 illustrates the spatial variability of the yield for each simulation of the case study. The performance of the control strategies are compared based on the average and variability of the yield, irrigation applied, Irrigation Water Use Index (IWUI) and Crop Water Use Index (CWUI) across the zones in the field. The variability reflects differences in yield response according to spatially variable irrigation application.

The strategies that use weather-soil-and-plant data to calibrate and target a fixed soil-water (simulation #19) and maximise square/boll count (simulation #20), are also compared using the simulated soil-water deficit (Figure 4) and simulated square count (Figure 5) throughout the crop season.

Insert Table 2 here

Insert Figure 3 here

Insert Figure 4 here

Insert Figure 5 here

The simulated yield and water use efficiency increased as more data streams were included in the input data combination. This is shown in Table 2 as the single-input simulations produced the lowest yields and water use efficiencies (simulations #11 and #12) while the three simulations having three data inputs (simulations #18, #19 and #20) performed better than all of the five simulations having two data inputs (simulations #13 to #17 inclusive).

The data combinations with soil data and no plant data (simulations #11 and #13) resulted in higher yields than those with plant data and no soil data (simulations #12 and #14). This result suggests that if only one data input is available then soil data input is most effective for calibrating RefModel and for irrigation control. The simulations using combinations of soil and plant data input to determine the irrigation volumes (simulations #15 and #18) generally produced lower yields and water use efficiencies than those using only plant data input to determine the irrigation volumes (simulations #17 and #20) with the same data available for RefModel calibration. For example, for the strategies with soil and plant data available to calibrate RefModel, a higher yield was simulated when the strategy maximised the square/boll count (simulation #17) than when the strategy attempted to both maintain soil-water and maximise square count (simulation #15). Hence, in this case there was no obvious benefit in the using multiple variables to determine the application volumes.

The MPC strategy accurately maintained the soil-water deficit threshold during low rainfall periods of the crop season for simulation #19 (63 to 85 days after sowing, Figure 4(a)). For the MPC strategy that maximised square/boll count (simulation #20), the soil-water deficit was always higher than the soil-water deficit threshold that was approximately maintained in simulation #19 throughout the crop season (Figure 4(b)). The soil-water deficit was also lowest in the sand zone (with the lowest plant available water capacity) and highest in the clay zone (with the highest plant available water capacity) throughout the crop season for the strategy optimising square count. This indicates that to maximise the square count, the soil-water deficit should be reduced in proportion with the plant available water capacity of the soil.

The highest yield was achieved using weather-soil-and-plant input and maximising square count (simulation #20). The square count was higher throughout the crop season for this simulation compared with that for MPC maintaining soil-water deficit (simulation #19) (Figure 5). Hence, the implemented MPC strategy successfully increased the simulated square count and improvements in yield (by 14%) and crop water use efficiency (by 30%) were observed by maximising square count instead of targeting soil-water.

4. MPC CASE STUDY B: optimisation using a predicted end-of-season yield or water use efficiency target

The MPC strategy uses RefModel to forecast the response of cotton crop with specific environmental conditions and soil and crop properties; hence, the irrigation volume/timing may be adjusted to achieve a desired predicted end-of-season output, in this case a final yield or water use efficiency. This is in contrast to Case Study A in which the MPC strategy used daily input data (e.g. square count, soil-water) to predict the best short-term response to a range of irrigation volumes.

4.1 Methodology for Case Study B

The field was automatically divided into 44 zones as per the previous case study and the irrigations could occur daily. The MPC strategy was evaluated for crop seasons with and without rainfall and with two levels of initial nitrogen content (120 kg/ha and 250 kg/ha). The same weather dataset was used for both these sets of simulations; however the daily rainfall was set to zero for the simulations without rainfall. In the simulations with rainfall there was high rainfall during days 63 to 85 after sowing.

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

4.2 Case Study B – Results and discussion

The simulation results are displayed in Table 3 and Figure 6 and the spatially varied irrigation volumes applied are compared with different in-season rainfall and starting nitrogen content at commencement (Figure 7 and Figure 8, respectively).

Insert Table 3 here

Insert Figure 6 here

Insert Figure 7 here

Insert Figure 8 here

For each set of field conditions (i.e. starting nitrogen content and in-season rainfall), the simulated yield was highest for the MPC strategy that optimised yield (simulations #21, #23, #25 and #28). Similarly, the strategies optimising IWUI (simulations #27 and #30) and CWUI (simulations #26 and #29) produced the highest respective IWUI and CWUI of the simulations with the same field conditions. This indicates that MPC strategy could adjust the irrigation application to improve either yield or water use efficiency.

Increasing the starting nitrogen content significantly improved the simulated yield and water use efficiency. This is shown in Table 3 as the yield for the no-rainfall simulation with the higher nitrogen content of 250 kg N/ha (e.g. 17.9 bales/ha for simulation #23) was nearly double that of the simulation with the lower nitrogen content of 120 kg N/ha (e.g. 9.0 bales/ha for simulation #21). Since the irrigation volumes applied were similar for these two simulations (Figure 8), the CWUI and

IWUI of the higher nitrogen content simulations were also nearly double that of the lower nitrogen content simulations. Hence, nitrogen application had a significant effect on the final yield without greatly affecting the irrigation volume required to be applied.

Rainfall significantly affected the simulated yield and CWUI (Table 3). Table 3 shows that the yields, irrigation applications and CWUI of simulations #21-#24 (without rainfall) are higher than those of simulations #25-#30 (with rainfall). This suggests that the crop is easier to control with less rainfall in the season. The difference in yield and CWUI is most noticeable for simulations with high nitrogen content (e.g. simulation #28 with rainfall and simulation #23 without rainfall) because the simulated yields are higher and the differences between the yields are more apparent. It follows that during the period of the crop season with high rainfall (63 to 86 days after sowing), lower irrigation volumes were applied compared to the periods of no rainfall (87 to 105 days after sowing) (Figure 7).

The rainfall did not generally affect the IWUI for the simulated set of field conditions (e.g. simulation #21 with no rainfall versus simulation #25 with rainfall). This is because more rainfall caused both the yield and irrigation application (which are used to calculate the IWUI) to decrease by approximately the same proportion.

5. MPC CASE STUDY C: optimisation using a predicted end-of-season target, with limited calibration data

The MPC simulations of the Case Study B assumed that the full data input of weather, soil and plant information was available for RefModel calibration. However, all three data streams may not be available in a field implementation. Case Study C evaluates the usefulness of different data streams to calibrate RefModel in a MPC strategy with a predicted end-of-season target.

5.1 Methodology for Case Study C

The seven possible input data combinations (Table 2) were separately evaluated as input for RefModel calibration. The datasets were obtained daily from the cotton model Sicot 71B and used to calibrate the Siokra V16RR cotton model. The field and weather conditions were as used in the earlier case studies, the MPC strategy optimised yield and the irrigations occurred daily.

5.2 Case Study C – Results and discussion

Table 4 and Figure 9 set out a comparison of an MPC strategy that maximises yield with different combinations of input data to calibrate RefModel. The use of more information in the input data combination generally increased the average yield and water use efficiency (Table 4). Table 4 shows that MPC performance with all three input variables (simulation #37/#28) was superior to that with any two variables (simulations #34-#36); and similarly performance with two input variables was superior to that with any single input variable alone, except plant input (simulation #33) versus soil-and-plant input (simulation #36). This suggests that the MPC calibration performs better with soil data input than plant data input.

Insert Table 4 here

Insert Figure 9 here

The lowest yields and water use efficiencies were simulated with only weather data input (e.g. simulations #31). This is because the weather data (without field-specific soil or crop data) provides no information to adequately parameterise the crop model used by the MPC strategy. This could lead to insufficient model calibration and sub-optimal irrigation volumes being determined. The irrigation water use efficiency was higher using the weather and plant combination (simulation #35) than using the full data input (simulation #37/#28): this is because the yield was maximised rather than the water use efficiency in this case study.

6. GENERAL DISCUSSION

A Model Predictive Control strategy was successfully implemented in VARIwise. The controller uses currently available field data to calibrate the OZCOT cotton production model and then evaluates a range of irrigation volumes and timings in each zone. The controller then implements the site-specific irrigation volumes on the day that achieves the highest water use efficiency or yield averaged over the field, as user specified.

Three alternative optimisation possibilities were identified and explored, and the conclusions for each, and their comparison, are as set out below. In each case the MPC strategy performed successfully in the (simulated) task of controlling an automatic irrigation machine applying spatially-varied irrigation amounts. For convenience, Table 5 gathers together the particular simulation outputs referred to in this section. Table 5 also compares results of MPC with two sensor-based control strategies, namely Iterative Learning Controller (ILC) and Iterative Hill Climbing Controller (IHCC), simulated on fields with PAWC varying between 60 and 200 mm with 1266 zones, and the same weather profile and crop variety (as detailed in McCarthy et al. 2013). These sensor-based strategies refine the estimate of each successive irrigation volume applied by:

[ILC] – iteratively adjusting the irrigation volume applied in each zone 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 zone; 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 zones.

Insert Table 5 here

The performance of the MPC strategy was also compared with an industry-standard irrigation strategy (first line of Table 5). This strategy applied a uniform irrigation treatment (25 mm) across the field and initiated irrigation events when the soil-water deficit reached a set amount (30 mm) in one point in the field (in the cell with sandy soil). The soil-water deficit was taken in the cell with the lowest plant available water capacity, as this is the most limiting soil. To ensure validity of the comparison this simulation was executed using the same weather conditions and spatially variable plant available water capacity and starting soil-water, and crop variety as the reference model. The nitrogen content was set to 250 kg/ha.

The MPC strategy was evaluated with different combinations of input data (section 3 above). The predicted yield and water use efficiency were highest when the strategy maximised the square count and calibrated the model using all three streams of data input (weather, soil and plant, simulation #20). The yield and water use efficiency were also higher than those of the industry-standard irrigation management strategy (McCarthy et al. 2013), and also ILC (simulation #1) and IHCC (simulation #9) with either weather-soil-and-plant, weather-and-soil or weather-and-plant data input available (likewise refer McCarthy et al. 2013). However, the MPC (optimising daily input data) performed worse than the ILC and IHCC where there was only either soil input (simulation #11) or weather-and-plant (simulation #14) input data available.

The controller successfully adjusted the irrigation to improve the yield, CWUI or IWUI, as appropriate (Section 4). The yield was higher with high nitrogen content (e.g. simulation #28) than with low nitrogen content (simulation #25) and with no rainfall during the crop season (simulation #23) compared with high rainfall (simulation #28). This is because the control strategy could better control the water applied in response to the other environmental factors. The simulated average yields and water use efficiencies were significantly higher than the industry-standard irrigation management strategy, ILC strategy (simulation #1) and IHCC strategy (simulation #9) (McCarthy et al. 2013).

MPC was evaluated with different combinations of input data available to calibrate the model (Section 5). The controller performed best with input of weather-soil-and-plant data (simulation #28), but still produced higher yields and water use efficiencies with weather-and-soil (simulation #34) or weather-and-plant (simulation #35) input than the irrigation-standard irrigation management strategy, and ILC (simulation #1) and IHCC (simulation #9) case studies (McCarthy et al. 2013).

Higher yields and water use efficiencies were produced for MPC optimising predicted end-of-season data (simulation #28) than for MPC using daily input data to maximise square count (simulation #20). However, both of these control strategies required either the full data input, weather-and-soil or weather-and-plant data input to obtain yields higher than the ILC or IHCC strategies.

7. CONCLUSION

The Model Predictive Control strategy implemented in the control simulation software VARIwise performed successfully in the task of controlling an automatic irrigation machine applying water to a simulated cotton crop grown in typical conditions for south-east Queensland, Australia. In all simulations the MPC strategy specified 'sensible' irrigation amounts typical of irrigation practice in this region. Simulations using the MPC strategy indicated that the MPC strategy could be successfully used to either maximise crop yield, or crop and irrigation water use efficiencies.

The MPC strategy produced significantly higher yield and crop water use efficiency than the sensor-based strategies for the same (simulated) field conditions (similarly simulated in VARIwise and reported in McCarthy et al. 2013). However, MPC required weather-soil-and-plant, weather-and-soil or weather-and-plant information to accurately calibrate the crop model. This indicates (for cotton grown as stated) that whilst the MPC-based strategies are potentially superior, sensor-based strategies may be more appropriate for field implementations where there is limited data availability.

Finally, we note here that direct field evaluation is particularly challenging, because direct comparison requires replicated plots having the same soil types and distributions, and with simultaneous operation such that each experiences the same weather conditions. In principal at least, an alternative to achieve such a comparison would be to determine variability of soil properties under an irrigation system, *a priori*, and then define plots of the same soil type such that the irrigation application could be adjusted according to different MPC strategies, and in comparison with industry-standard control (e.g. calculated using evapotranspiration or soil-water).

Field evaluations would enable the sensing and control hardware requirements and performance of autonomous, adaptive control strategies to be compared with industry-standard irrigation. These control strategies would determine irrigation application and timing using a black-box control system based on sensed inputs and sends control signals to irrigation actuation hardware. This will potentially lead to the optimisation of irrigation water use and yield under different climate scenarios and water availability situations.

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Figures and Tables

Table 1: Simulations (identified by ID #) conducted to compare interactions between control strategies and input variables for Model Predictive Control. N/A indicates non-applicable and SILO indicates use of historical climate data. (Simulations #1 to #10 not tabulated here are those undertaken for sensor-based control, McCarthy et al. (2013).)

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

Table 2: Performance of the model predictive control strategy with variable-rate irrigation machine for different input data combinations (yield maps of simulations #11-#20 are in Figure 3)

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

Table 3: Performance of the model predictive control strategy with variable-rate irrigation machine for different weather data inputs, starting nitrogen contents and optimised variables (yield maps of simulations #21-#30 are in Figure 6)

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

Table 4: Performance of the model predictive control strategy optimising yield for crop season with rainfall and 250 kg/ha of available nitrogen for different input data combinations, where simulation #37[1] is a duplication of simulation #28 for comparison (yield maps of simulations #31-#37 are in Figure 9)

ID #	**Input variable for control**	**Average yield (bales/ha)**	**Average water applied (ML_{total}/ha)**	**Average irrigation applied ($ML_{irrigated}$/ha)**	**CWUI (bales/ ML_{total})**	**IWUI (bales/ $ML_{irrigated}$)**
31	Weather	5.6 ± 1.1	9.9	7.2	0.6	0.8
32	Soil	9.1 ± 1.0	9.0	5.9	1.0	1.5
33	Plant	10.0 ± 1.3	9.2	6.0	1.1	1.7
34	Weather AND soil	12.2 ± 1.7	8.3.	5.2	1.5	2.3
35	Weather AND plant	12.4 ± 1.4	8.1	5.0	1.5	2.5
36	Soil AND plant	9.4 ± 0.8	9.2	6.0	1.0	1.5
37[1]	Weather AND soil AND plant	14.3 ± 0.5	9.3	6.2	1.5	2.3

Table 5: Control strategy simulation outputs where the initial nitrogen content is 250 kg/ha and there is rainfall during the crop season unless otherwise noted.

ID #	**Control strategy**	**Input variable for control**	**Average yield (bales/ha)**	**Average water applied (ML_{total}/ha)**	**Average irrigation applied ($ML_{irrigated}$/ha)**	**CWUI (bales/ ML_{total})**	**IWUI (bales/ $ML_{irrigated}$)**
N/A[A]	Industry-standard	Nil	9.1 ± 1.9	10.2	6.8	0.9	1.4
1[A]	ILC	Soil	12.2 ± 1.5	11.0	7.3	1.1	1.7
9[A]	IHCC	Soil AND plant	12.4 ± 1.6	12.2	8.1	1.0	1.5
11	MPC (daily input)	Soil	5.2 ± 2.4	9.4	6.4	0.5	0.8
14	MPC (daily input)	Weather AND plant	6.4 ± 1.0	5.3	2.2	1.2	2.9
20	MPC (daily input)	Weather AND soil AND plant	12.1 ± 0.7	9.4	6.3	1.3	1.9
23	MPC (end- of-season input)[1]	Weather AND soil AND plant	17.9 ± 0.9	6.6	6.6	2.7	2.7
25	MPC (end- of-season input) [2]	Weather AND soil AND plant	8.4 ± 0.4	9.0	5.9	0.9	1.4
28/ 37	MPC (end- of-season input)	Weather AND soil AND plant	14.3 ± 0.5	9.3	6.2	1.5	2.3
34	MPC (end- of-season input)	Weather AND soil	12.2 ± 1.7	8.3	5.2	1.5	2.3
35	MPC (end- of-season input)	Weather AND plant	12.4 ± 1.4	8.1	5.0	1.5	2.5

[A] From McCarthy et al. 2013
[1] Crop season has no rainfall
[2] Initial nitrogen content is 250 kg/ha
Abbreviations: ILC is Iterative Learning Control, IHCC is Iterative Hill Climbing Control and MPC is Model Predictive Control

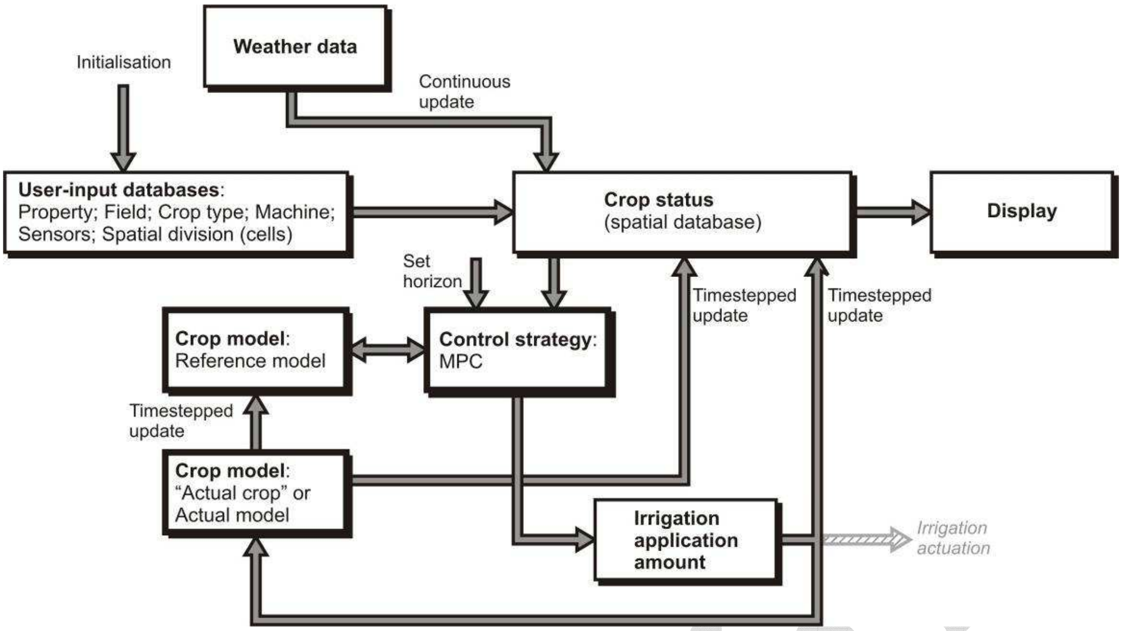
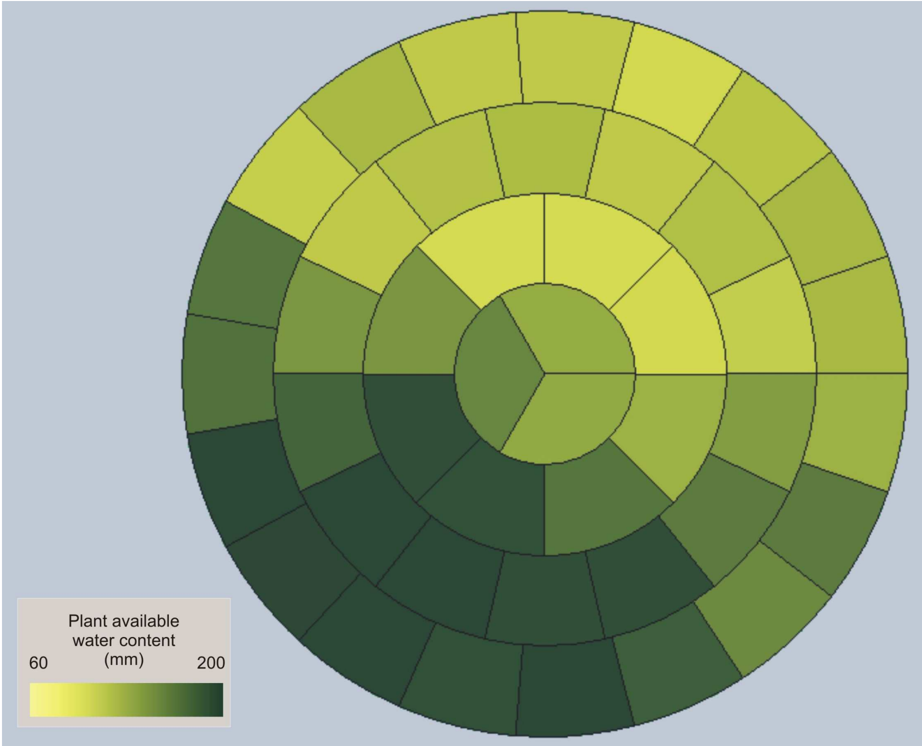


Figure 1: The simulation framework VARIwise configured to evaluate (in simulation mode) the model-based adaptive control strategy Model Predictive Control (MPC). In this mode, the block 'AcModel' (also an OZCOT formulation) has replaced the field data measurements which would normally update 'RefModel'. (This diagram is adapted from the full VARIwise flowchart presented as Figure 2 of McCarthy et al. 2010.)



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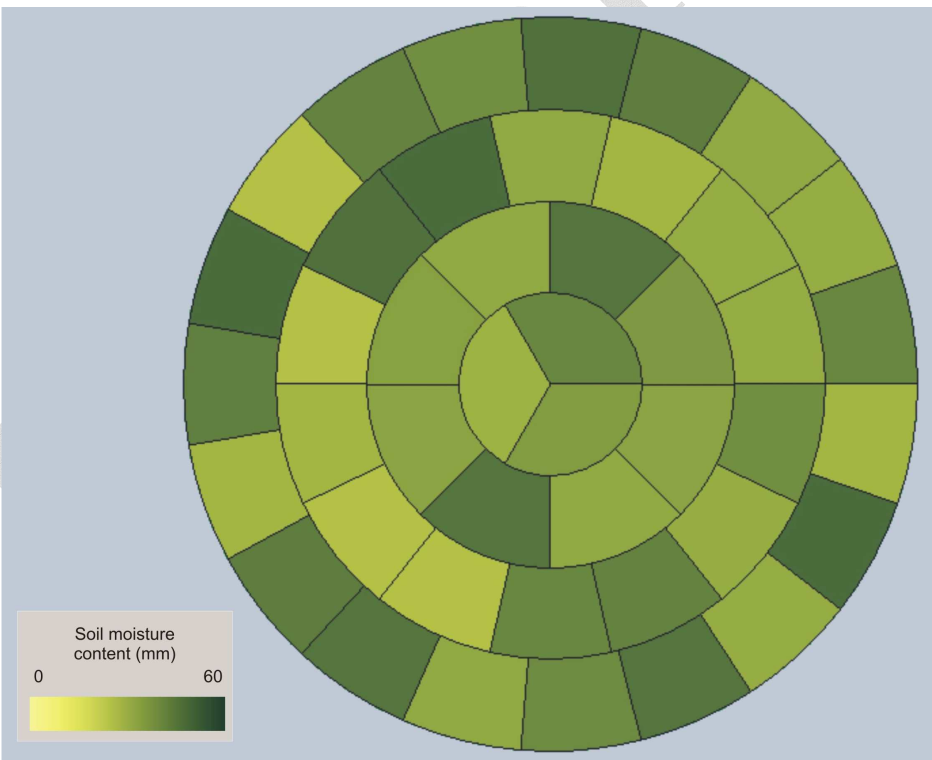


(b)

Figure 2: Soil variability as calibrated in model predictive control implementation: (a) plant available water capacity; and (b) soil-water on sowing date

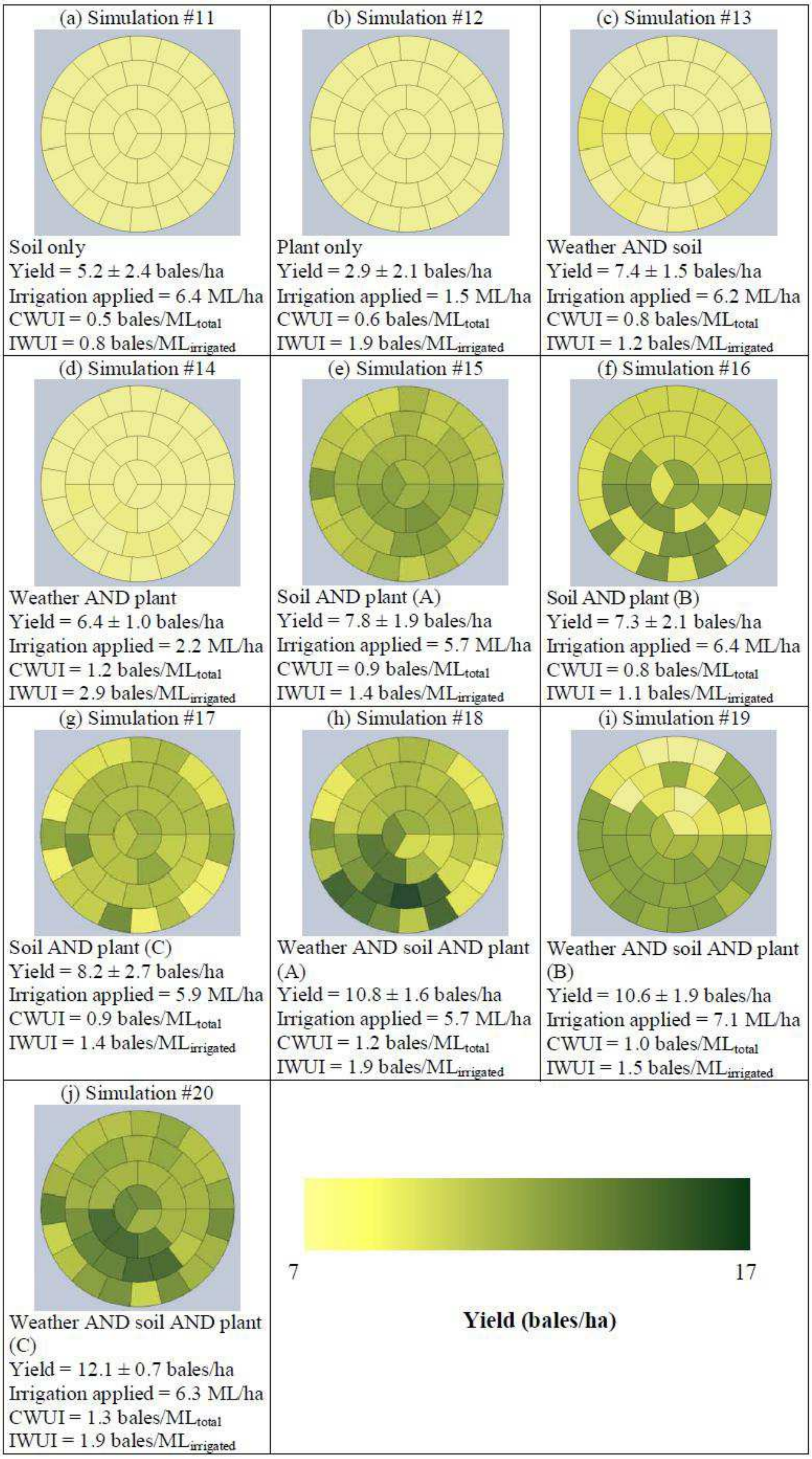
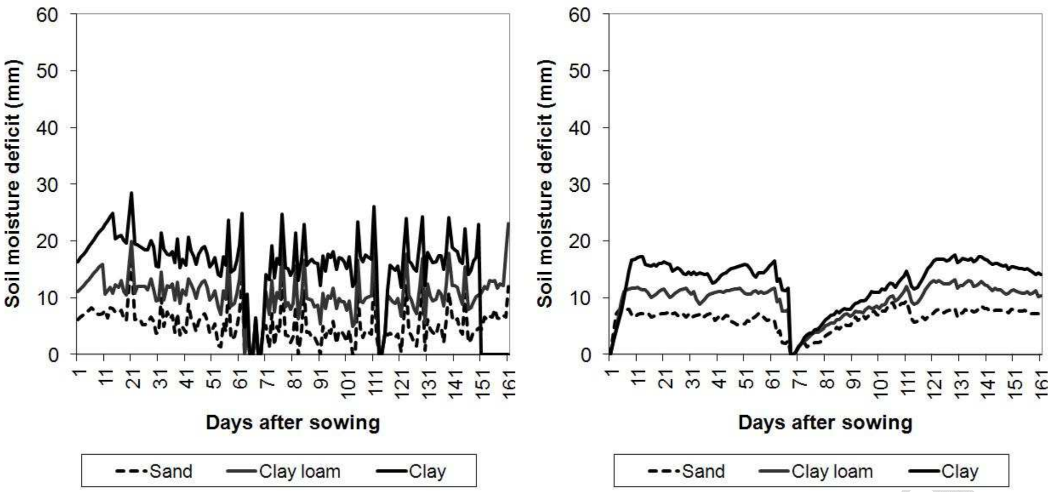
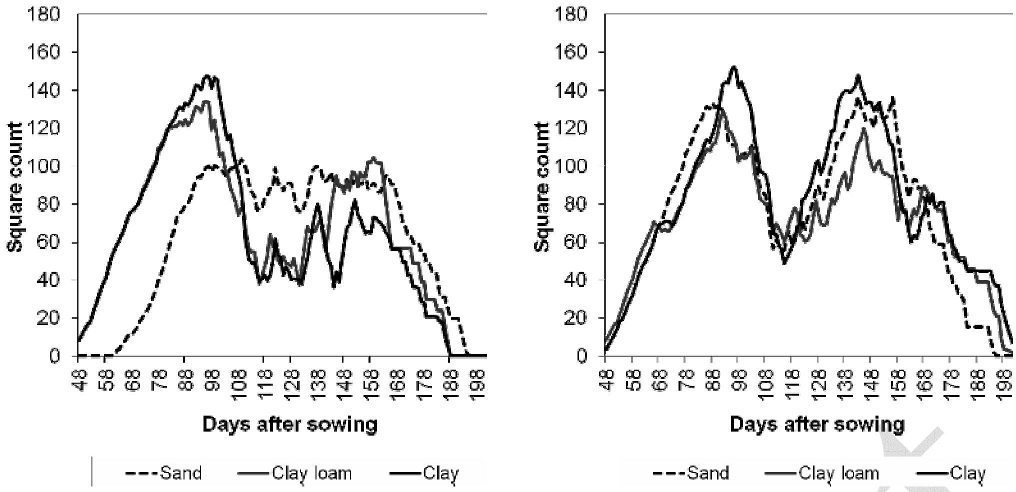


Figure 3: Yield maps and average yield and irrigation outputs of model predictive control strategy for different combinations of data input and legend for yield maps for simulations #11 to #20 (numerical data are set out in Table 2)



(a) (b)

Figure 4: Simulated daily soil-water deficit in sand, clay loam and clay zones for strategies that use weather, soil and plant data for model calibration (RefModel). Set (a): targeting fixed soil-water deficit (simulation #19); and set (b): maximising square/boll count (simulation #20)



(a) (b)

Figure 5: Simulated daily square count in sand, clay loam and clay zones for strategies that use weather, soil and plant data for model calibration (RefModel). Set (a): targeting fixed soil-water deficit (simulation #19); and set (b): maximising square count (simulation #20)

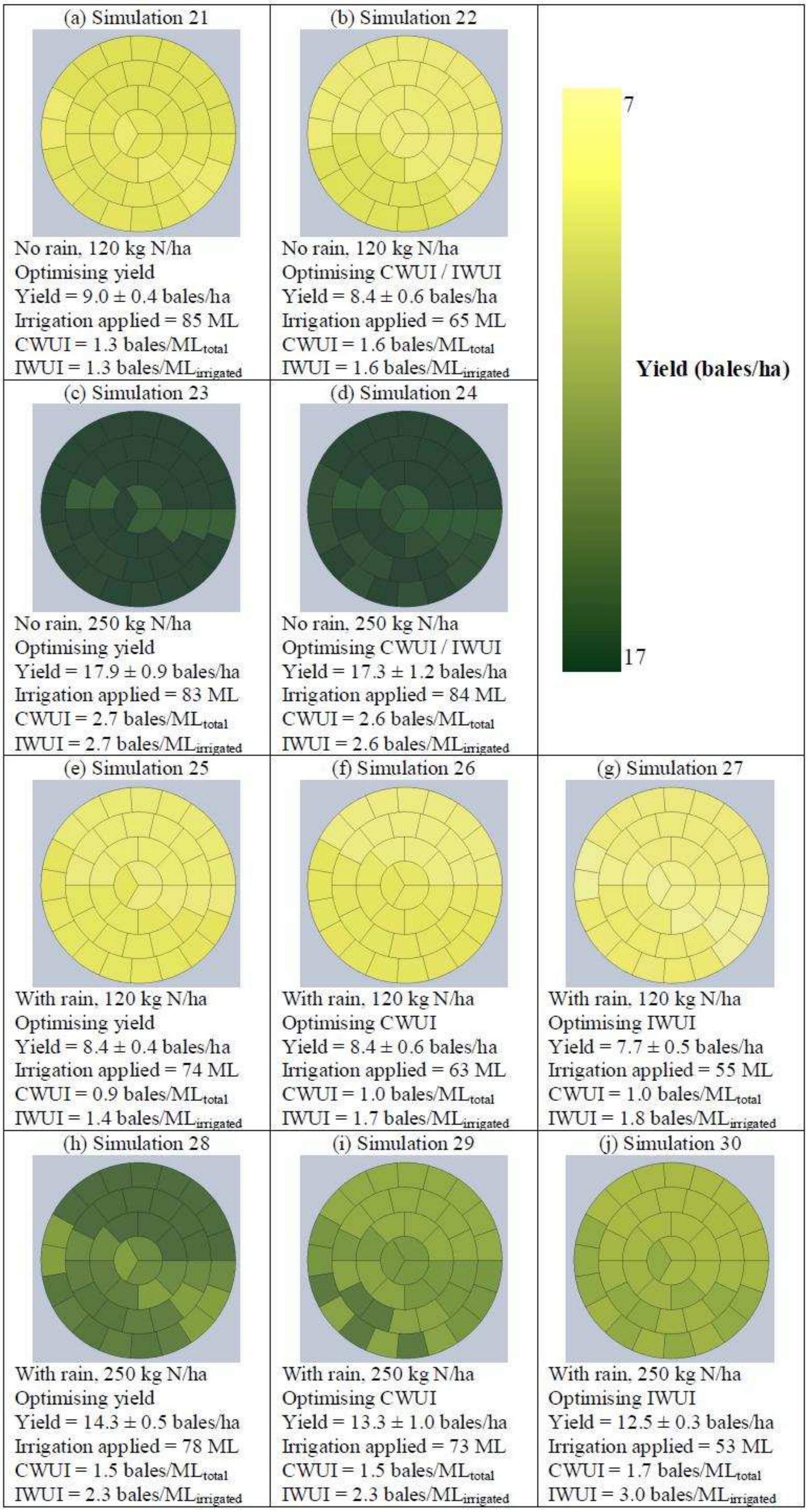
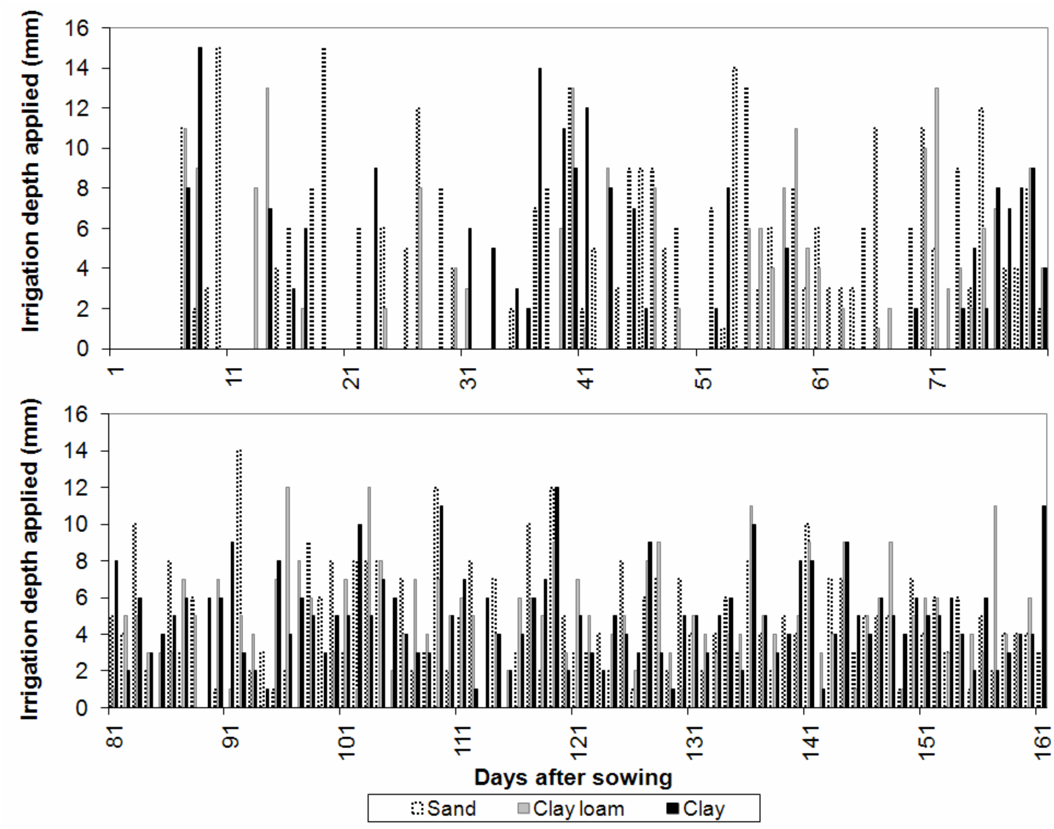


Figure 6: Yield maps and average yield and irrigation outputs of model predictive control strategy with variable-rate irrigation machine and legend for yield maps for simulations #21 to #30 (numerical data for simulations are presented in Table 3)



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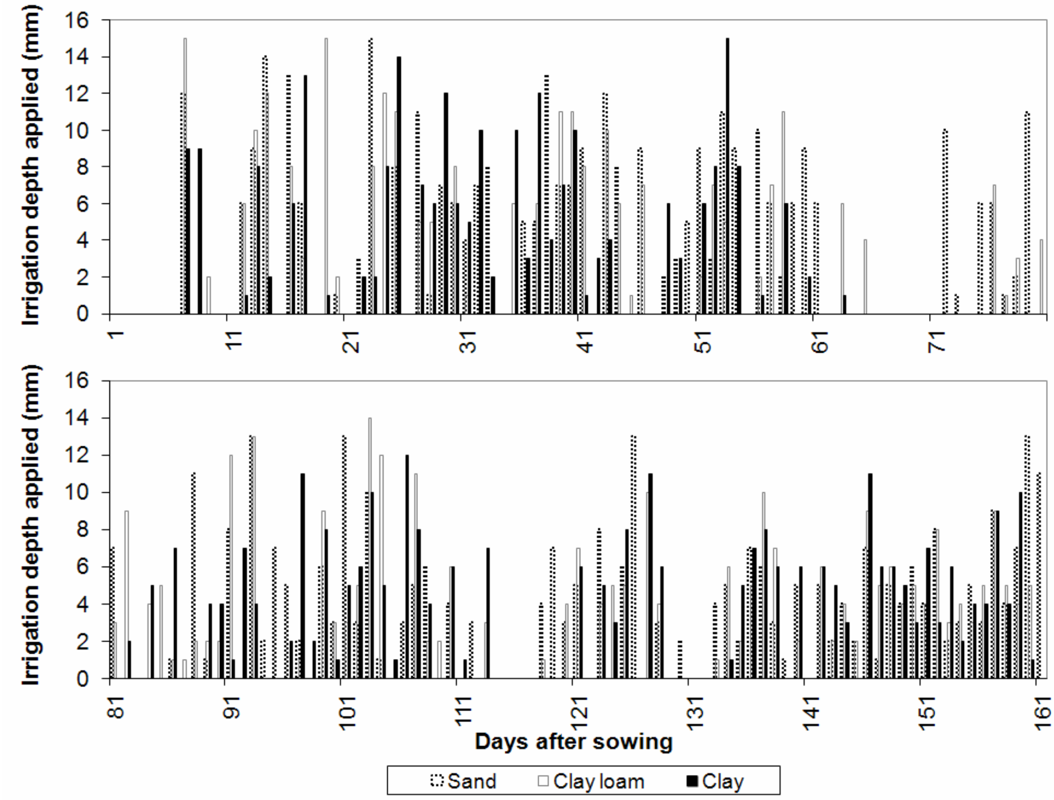
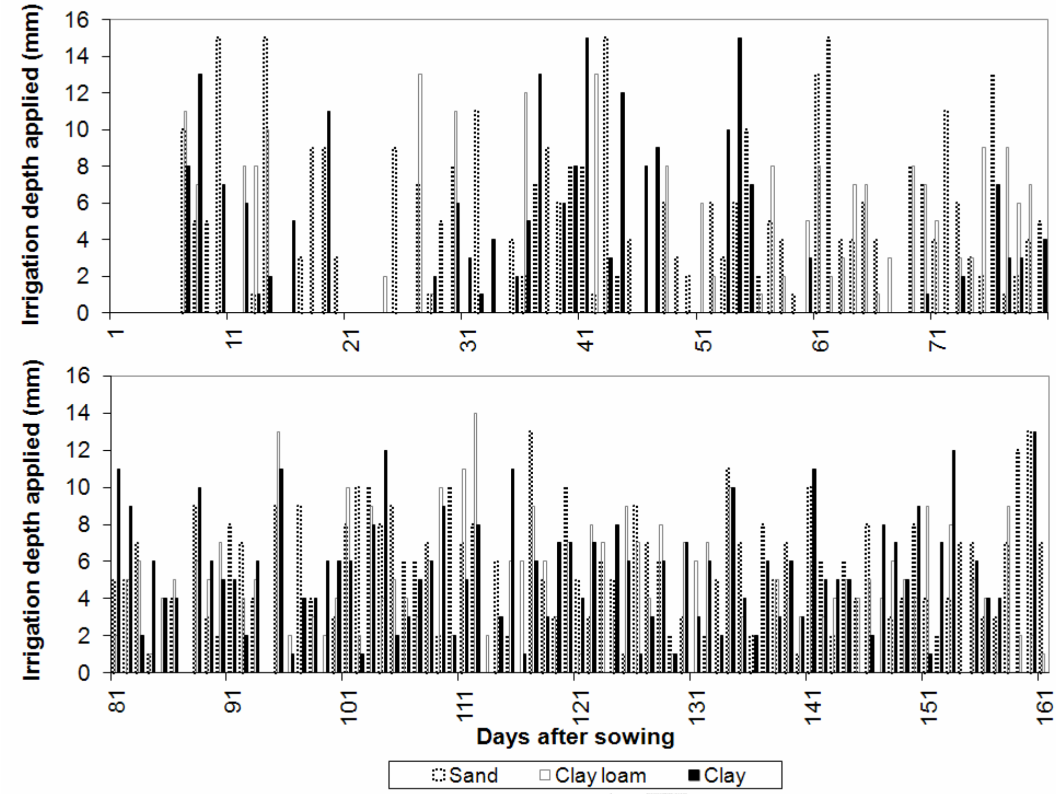
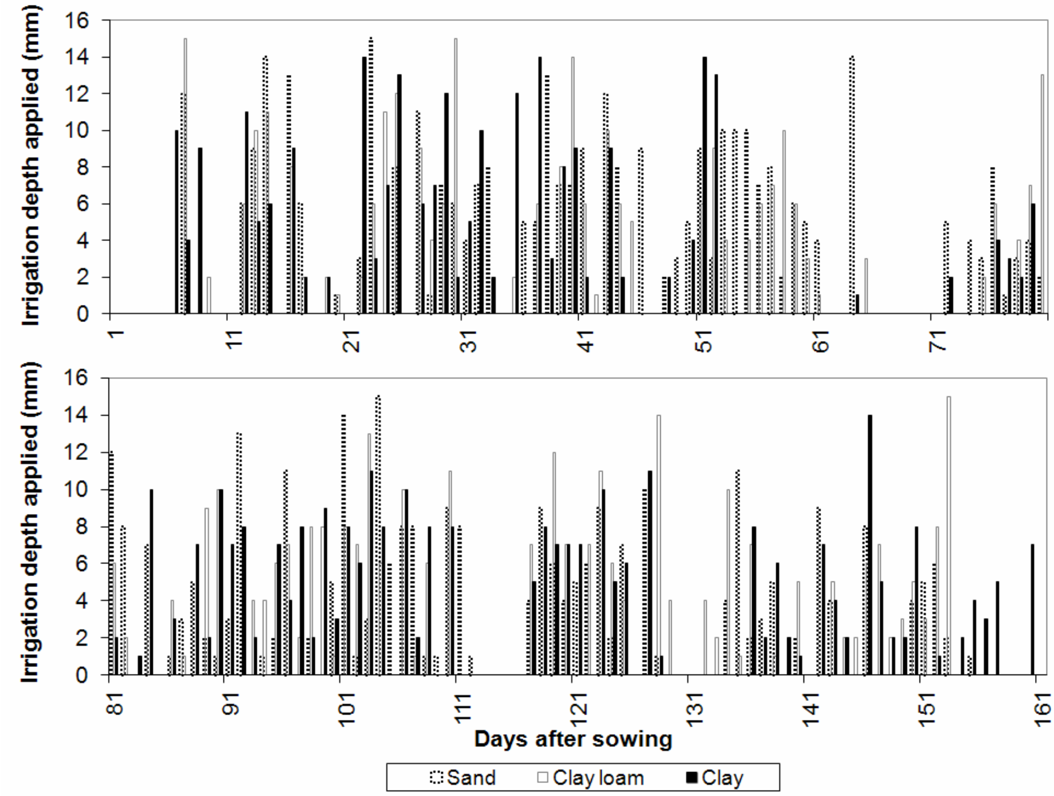


(b)

Figure 7: Irrigation volumes applied to sand, clay loam and clay zones for simulations #24 and #27 to evaluate effect of rainfall during crop season. The model predictive controller optimised IWUI with 250 kg/ha of available nitrogen and for crop season with: set (a) no rainfall; and set (b) 302 mm of rainfall



(a)



(b)

Figure 8: Irrigation volumes applied to sand, clay loam and clay zones for simulations #25 and #28 to evaluate effect of nitrogen content; the model predictive controller optimised yield for crop season with no rainfall and available nitrogen of: set (a) 120 kg/ha; and set (b) 250 kg/ha

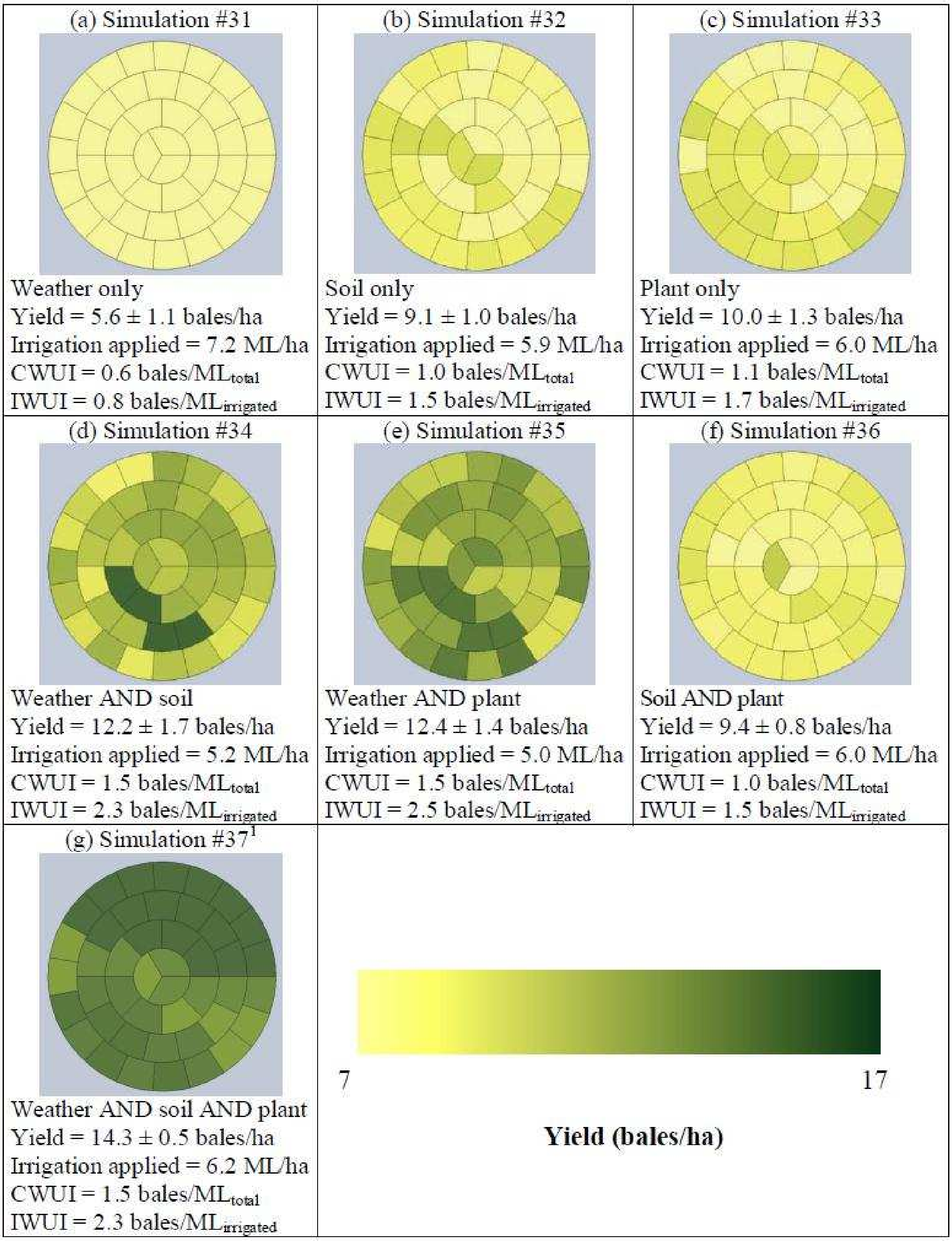


Figure 9: Yield maps and average yield and irrigation outputs of model predictive control strategy with variable-rate irrigation machine and legend for yield maps, where simulation #37[1] is a duplication of simulation #28 for comparison (numerical data for simulations #31-#37 are in Table 4)