TOWARDS EVALUATION OF ADAPTIVE CONTROL SYSTEMS FOR IMPROVED SITE-SPECIFIC IRRIGATION OF COTTON

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ABSTRACT

Irrigation application in cotton crops is traditionally discharged at a constant rate for an entire field. However, not all plants in a crop may require the same amount of water due to the stochastic nature of the crop response and the spatial variability of environmental factors within the field. Control strategies are required to effectively manage spatially and temporally varied irrigation applications under large mobile irrigation machines (LMIMs, e.g. centre pivots and lateral moves) in real-time. We demonstrate that a decision-making framework for the site-specific irrigation of cotton should consist of a generic control scheme that integrates multi-dimensional irrigation scheduling strategies and is robust with respect to data gaps and deficiencies. These strategies may be based on historical (mapped) soil and application data, current and recent environmental (e.g. meteorological) data and measured plant-response data. A review of potential control strategies has been conducted and the development of a framework to evaluate these strategies is reported.

INTRODUCTION

The Australia cotton industry accounted for 10% of the total water used in Australia during 2004-2005 (ABS 2006). Approximately 4% of irrigated cotton crops in Australia are currently irrigated by large mobile irrigation machines and this is expected to increase to approximately 30% by 2020.

Irrigation application in cotton crops is traditionally held constant over an entire field. However, infield irrigation requirements in cotton may be spatially and temporally variable due to soil type, topography, difference in variety, crop condition (e.g. disease and water stress) and meteorological conditions (e.g. spatial variations in rainfall). Spatial and temporal variability of crop factors within a field can have a significant influence on agricultural production (Zhang et al. 2002) by reducing yield and quality of produce (Raine et al. 2005).

Control strategies that improve the spatial and temporal precision of irrigation application generally involve monitoring plant features and applying an irrigation amount based on sensor data. Control strategies that use physical and agronomic principles to vary irrigation applications have been shown to improve the efficiency of water use by 15 to 44% (Evans 2006). However, a range of methods can be used to determine irrigation requirements.

Farmers traditionally use historical data and/or qualitative measurements of crop status, weather and/or soil to decide the irrigation application amounts and timing. These measurements generally include irrigation history information, observed crop wilt and colour, climate (hot or dry) and rainfall, and soil appearance.

Figure 1 illustrates a generic decision-making process that uses the full range of these data and can be applied to both traditional and spatially varied irrigation management at a range of time scales. In traditional irrigation, the ‘decision support system’ is the farmer who decides on the irrigation amount; ‘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.

An irrigation control strategy can use historical data and/or quantitative measurements of crop status, weather and soil, either singularly or in combination, to automatically adjust the irrigation application. In contrast, an ‘adaptive’ control strategy uses these data to locally ‘modify’ the control, as required, to account for temporal and spatial variability in the field. In this sense, Figure 1 also illustrates the conceptual components of an adaptive control system for variable-rate irrigation application.

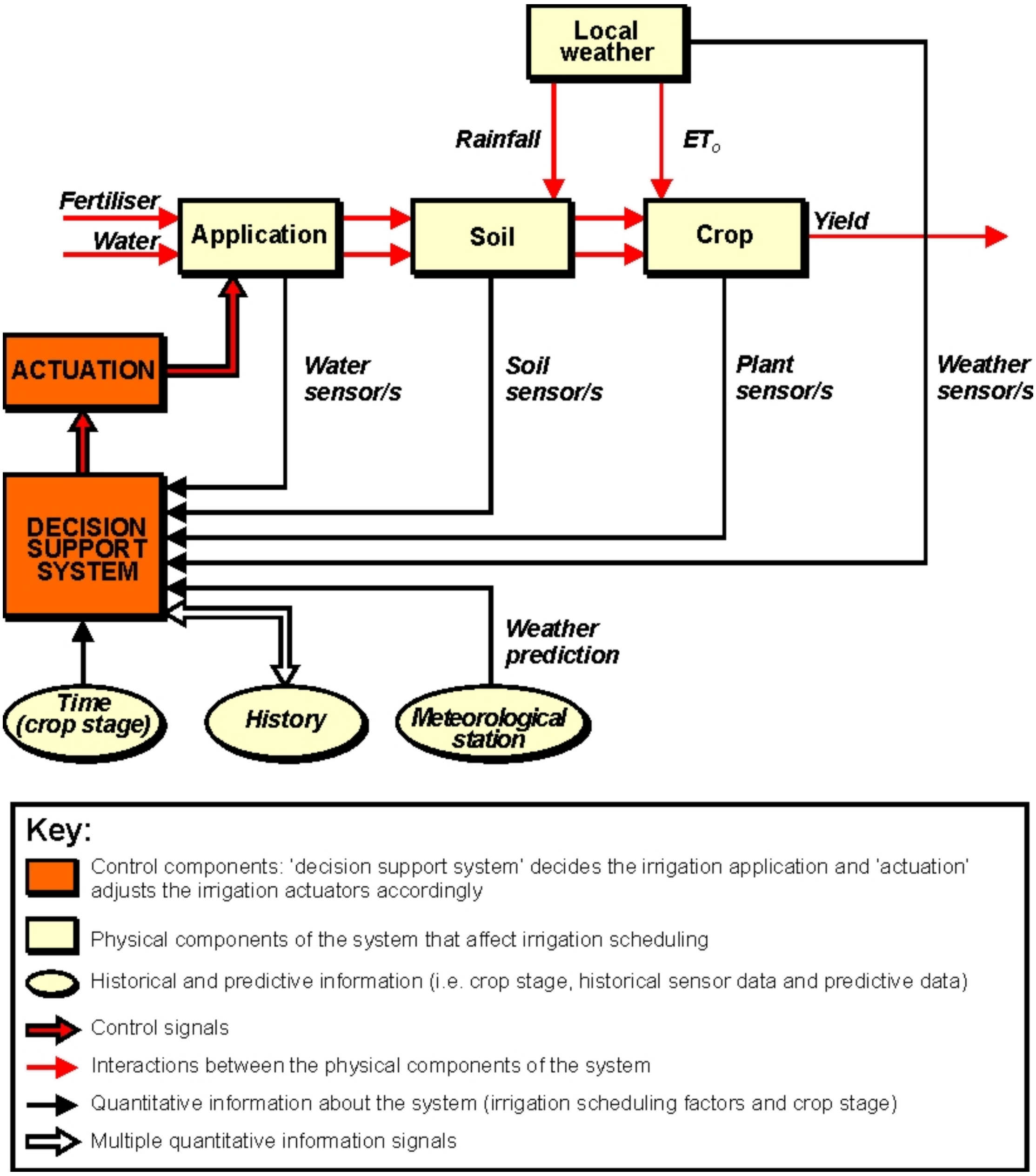

Figure 1: Conceptual adaptive control system for variable-rate irrigation application

ADAPTIVE CONTROL

A control system is a system that controls the operation of a process. For irrigation, a control system would attempt to optimise the crop response. This may be achieved by compensating for the spatial and temporal variability in the field by varying the irrigation application amount and timing. Control systems consist of a process being controlled, a controller and a measurement system (for feedback control). Control systems with feedback are called closed-loop control systems. These systems measure the output of the process (e.g. plant-response data) and adjust the control parameters based on the difference between the input and the measured output.

Much of standard control theory assumes that the process and input-output responses do not vary with time once identified. However, the characteristics of many processes vary with time in real-world situations. For example, many characteristics of an irrigated system vary within and between crop seasons (e.g. crop growth, pests and weather) and these alter the optimal irrigation amount to be applied to the plants. An option to improve the performance of these control systems is to use adaptive control. Adaptive control systems automatically and continuously retune the controller to retain the desired performance of the system (e.g. Warwick 1993). This involves choosing and implementing a scheme to appropriately modify the adaptive control parameters, generate additional signals for auxiliary control and/or change the architecture of the controller, to compensate for the changing conditions.

So called ‘classical’ methods of adaptive control include gain scheduling and model-reference adaptive control. Gain scheduling is used in operating conditions where there are rigid, pre-defined relationships between some measurable variables characterising the environment (e.g. soil moisture) and the process dynamics (e.g. crop health) (Bell & Griffin 1969). After the process is measured, the control variables corresponding to the measured conditions are used to adjust the controller. Model-reference adaptive control systems use a reference model of the ideal system to control the process. Models which can be used include crop or soil-water hydraulic models. The input to the reference model is also the input to the physical process (i.e. irrigation amount). In this case, the control parameters are adjusted based on the difference between the measured output of the process (i.e. the sensor values) and the output of the reference model (Åstrom & Wittenmark 1994). It is hypothesised that the irrigation of cotton can be optimised by repeatedly using the feedback in a closed-loop control strategy to adjust the irrigation application amount and timing.

DECISION SUPPORT AND CONTROL IN IRRIGATION

The inadequate development of control and decision support systems for implementing precision agriculture decisions has been identified as a major stumbling block to the adoption of precision agriculture (McBratney et al. 2005). Site-specific irrigation control systems are reported in the literature (see below), but they do not make irrigation decisions based on multi-dimensional issues (e.g. crop response, crop age and management constraints).

PRIOR WORK

Automatic controllers currently reported for spatially varied irrigation often use map-based (historical) data rather than real-time data from on-the-go sensors (e.g. CC 2002). Sensor-based irrigation systems are potentially more accurate than map-based systems due to the real-time nature of the data. Sensor-based control systems in the literature have been used to initiate irrigation events and determine irrigation amounts without accounting for spatial variability. The duration of the irrigation event is either a fixed period of time (e.g. Dukes & Scholberg 2004 for drip irrigation; and Evett et al. 2006 for centre pivot irrigation) or a calculated period of time corresponding to the crop’s needs as indicated by the sensor data (e.g. van Bavel et al. 1996 for drip irrigation). However, two automated site-specific sensor-based irrigation control systems have been reported in the literature for LMIMs (Evans et al. 2007; and Moore & Chen 2006). The system developed by Evans et al. (2007) forms a soil map based on soil moisture data calibrated with neutron probes and a weather station. Irrigation and fertiliser amounts determined by the soil map are transmitted to the sprinklers. Another controller for variable-rate centre pivot irrigation using feedback of soil moisture data was conceptualised by Moore and Chen (2006). This learning controller adjusts the irrigation application flow rate to control the water or concentration of nutrients in the soil.

It follows that these control systems respond (and adjust the irrigation control) only if the changing control requirements are manifest in the sensed variables (i.e. soil moisture and weather data). However, soil and weather sensors may not give the most accurate indication of crop status. Kramer and Boyer (1995) suggest that the plant, rather than the soil, may be the best indicator of water availability. This is because the plants automatically integrate the atmospheric and soil factors that affect plant water status. Hence, the incorporation of plant, soil and weather data (as per Figure 1) should be investigated for an optimal irrigation control system for cotton (although all of the incorporated variables may not be necessary for particular irrigation control). Other issues to be considered for irrigation control include crop age and management constraints. The design of a generic control system has commenced that is able to incorporate multiple dimensions of sensed variables.

ROBUSTNESS

In agricultural environments, cost and practicality requirements commonly mean that some input data may be unavailable. For example, it is common that only one soil moisture sensor is used in a field despite the wide range of soils being present. In this case, another irrigation scheduling method may be required for data-deficient areas of the field which uses data from another sensor (e.g. evapotranspiration and on-the-go plant sensors). Hence, to ensure the control system is robust to data availability, the control system developed should be capable of incorporating data from plant, soil and weather sensors. Depending on the data available in different areas of the field, a different irrigation scheduling method may be used which requires plant, soil and weather data, either singularly or in combination. Such a control system would be robust to data gaps and deficiencies, while maintaining a minimum level of control performance.

GENERIC DECISION SUPPORT FRAMEWORK

Our research to date has identified eight dimensions of data complexity (Table 1). These dimensions integrate data from the various sensors illustrated in Figure 1 into a framework for adaptive control. Each level of data complexity uses a different irrigation scheduling method with different sensor data requirements. When integrated with a feedback control strategy, each level can be used to determine the irrigation amount to apply and potentially the irrigation timing. After multiple passes of the crop, the control strategy may be used to optimise the irrigation application amount. By evaluating and comparing each level of data complexity, the data requirements for optimising irrigation control can be determined.

Table 1: Dimensions of data complexity in conceptual adaptive control system/s applied to irrigation

Level of data complexity	**Method**	**Possible sensors**
History-based	This involves irrigating the crop at certain stages in the season as per previous irrigations.	Historical plant, soil and weather data
Soil-based	The soil water potential or soil moisture content can be used directly to determine the irrigation requirements.	Soil moisture content, soil water potential
Weather-based	This control strategy uses data from weather station/s and other regional sources (e.g. Bureau of Meteorology). For example, evapotranspiration and solar radiation data from the weather station may be used in a water balance model (which involves balancing the water losses and uptakes of the plant root zone) to determine the irrigation schedule.	Weather station, predictive meteorological data
Soil- AND weather-based	Soil moisture data may be used to calibrate the water balance model and adjust the crop coefficient and readily available water values as required.	As for soil- and weather-based control
Plant-based	The current crop response is monitored. This control strategy would apply an irrigation amount based on the current crop response from plant-based sensing (e.g. McCarthy et al. 2007, 2008). This method involves applying an irrigation amount determined using a predefined relationship between the crop response and crop water requirement.	Plant size and shape (e.g. height, projected foliage cover, stem diameter, internode distance), plant stress (e.g. thermal, infrared or hyperspectral responses)
Iterative plant-based	The change in crop response since the previous irrigation is monitored. The previous irrigation amount applied is evaluated based on the current and previous crop response. The process is repeated for each irrigation until an optimal is reached.	As for plant-based control
Plant- AND weather-based	This control strategy may use the water balance model. Plant-based sensor data can be used to more accurately estimate the crop coefficient used in the crop evapotranspiration calculation.	As for weather- and plant-based control
Soil- AND plant- AND weather-based	All of the components in Figure 1 are used to control the irrigation. The soil data may be used to validate a water balance model.	As for soil-, weather- and plant-based control

Various control strategies (e.g. gain scheduling and model-reference adaptive control as previously mentioned) can be used at each level of data complexity. However, the appropriate control strategy to be used at each level of data complexity may only be determined by simulating the response of the crop and soil to the irrigation options. Hence, a framework (VARIwise) has been developed that divides the field into computational cells and enables the response of each cell to the application to be simulated.

We have chosen to evaluate the control strategies via simulations on a field at a resolution of 1 m^2. This is the smallest area controllable on a LMIM-irrigated field in practice. In this framework, the 1 m^2 field areas are referred to as computational cells. A 1 m^2 irrigation resolution can be achieved by a LMIM using a low-energy precision application (LEPA) sock. LEPA socks apply water at low pressure, either within the crop canopy or directly onto the soil surface, to reduce evaporation from the crop canopy and soil surface (e.g. Foley 2004). If sprinklers which apply water across a larger area are used on the LMIM, then irrigation decisions can be simulated at spatial scales larger than 1 m². In these cases, the computational cells are simply aggregated.

EVALUATION SOFTWARE

A framework is required to evaluate the potential control strategies and then determine the most appropriate control strategy at each level of data complexity. Since we currently know of no literature reporting the development of such a framework, the senior author has commenced development of software (VARIwise) for control strategy simulation and evaluation. The features of the software are outlined below.

1. Software specifications

   The primary objective of the software is to provide a platform on which control strategies for variable-rate irrigation can be evaluated. To achieve this:
   - the field is divided into computational cells;
   - control strategies for each level of data complexity are implemented;
   - a generic scheme selects a level of data complexity that is used by computational cells in the field;
   - third party models are used in simulations including HydroLOGIC (CSIRO 2005) and WaterSCHED (QDPI 1993; and as described in Harris 2006) (and others as development progresses);
   - the crop's response to each control strategy is compared; and
   - the interface is user friendly.

2. Design, coding and testing of modules

   The software is organised into five modules which have the following functions:

   a) *Input LMIM data*

      Data inputs for lateral moves include the length of the LMIM and field: for centre pivots the data input is the length of the LMIM. The number of spans and sprinklers per span are other inputs. Future considerations for the LMIM specifications include endgun and boomback details.

   b) *Assign cell coordinates for the field*

      The field is divided into computational cells of approximately 1 m² area. The width of each cell is taken as the distance between each nozzle (normally 2 m for a LEPA sock). The cells can also be aggregated to form a coarse mesh to monitor and/or control larger areas of the field. Figure 2 displays an example VARIwise interface for a coarse mesh on a field irrigated by a centre pivot.

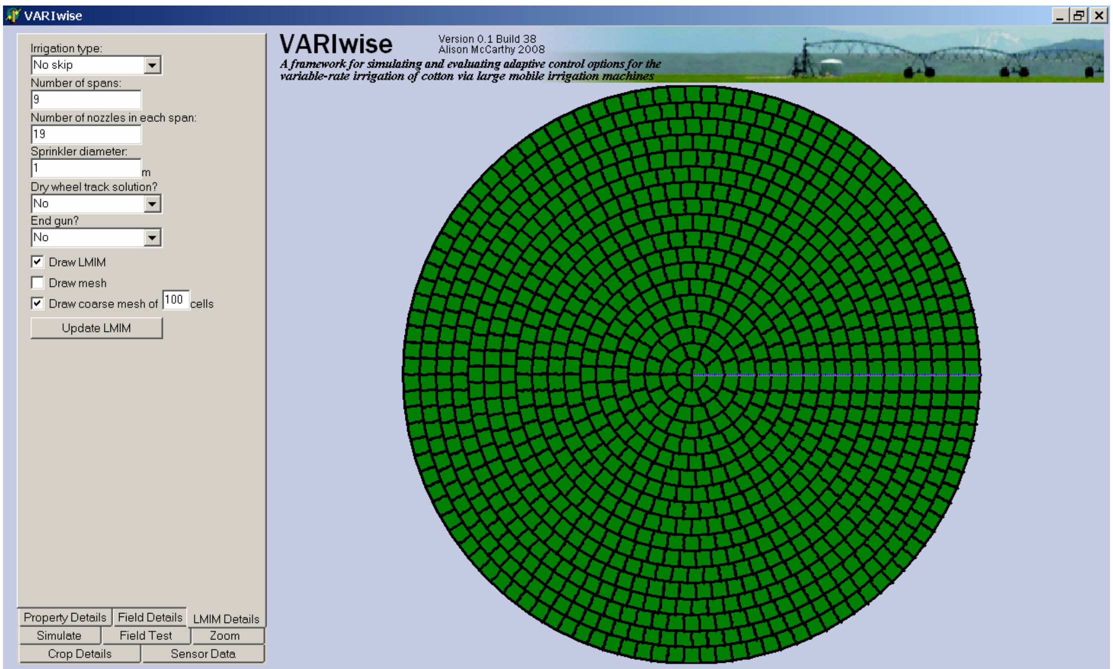

Figure 2: Example VARIwise interface showing a 400 m diameter centre pivot field with a coarse mesh

The software has a zoom capability (Figure 3) that enables responses in individual cells to be visually monitored. Individual cells in view can be selected and data corresponding to the selected cell can be specified or displayed.

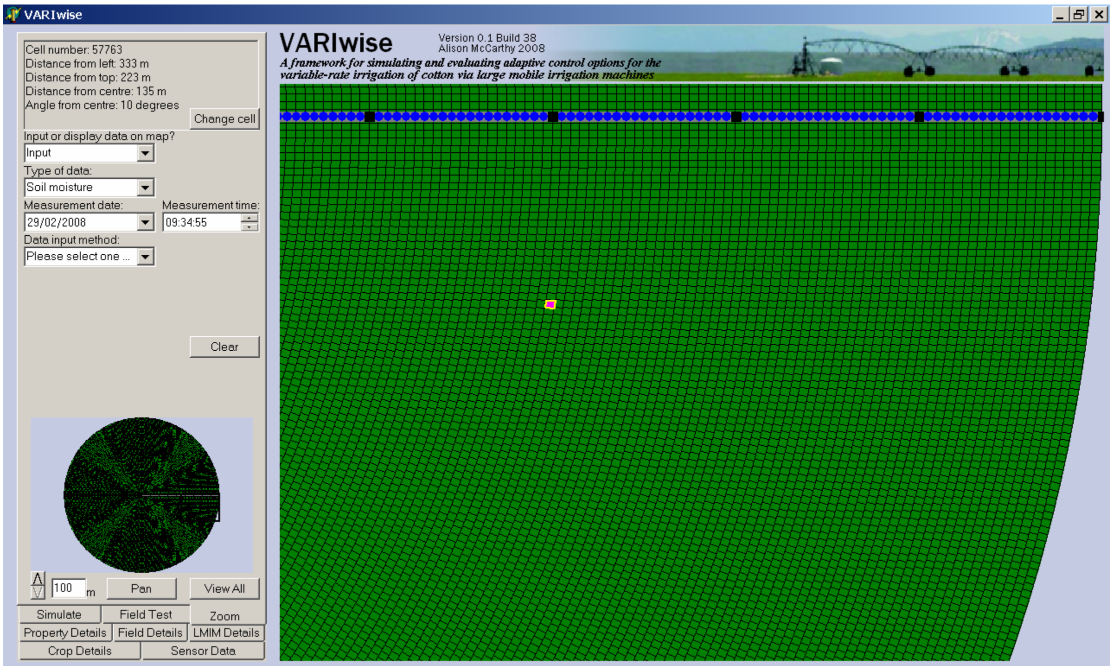

Figure 3: Example VARIwise interface showing a 100 m wide section of the field and the selection of an individual cell

c) *Input data*
The control system can use data from a range of sources. This includes manual measurements (e.g. a sensor reading or observation for a location in the field); website/s (e.g. predicted meteorological data); bitmap/s (e.g. NDVI image); text file/s (e.g. historical soil moisture readings); or sensor/s in real-time (e.g. weather station). These data each have a geographic location and timestamp, but may vary in spatial and/or temporal scale (i.e. valid for differing areas of the field and/or differing time periods). A database of the historical, real-time and predictive data is formed for each cell.

d) *Control strategies*
The control strategies included in this module are selected based on a comparison of the desired control performance features with properties of control strategies investigated in a literature review. Desired control performance features for precision irrigation application include input and output requirements. Optimisation methods, performance features and non-technical issues are also considered in the comparison of the control strategies. For example, stability and steady-state error are performance features involved in the design or selection of a control strategy, while operational complexity and manual data requirements are non-technical issues that may be considered in the selection of an appropriate control strategy.

e) *Simulation models*
This involves the software loading, entering data into and reading data from third party simulation models. Data from each cell that is stored in a database are entered into the corresponding model. Values obtained by the simulation model are used by VARIwise to estimate how the plant and soil data will change in response to the irrigation amount applied and timing.

3. Integration of modules
The modules described above are integrated such that the outputs of the simulation models can be compared for each control strategy tested. The performance of each level of data complexity is also compared to determine the input-output data requirements of a control system for the optimal irrigation of cotton.

CONCLUSIONS

Existing irrigation control systems that only optimise one variable may be sub-optimal. Eight levels of data complexity identified in this paper should be compared to determine the optimal control option and the most appropriate input-output requirements of an irrigation control system. The software (VARIwise) currently under development by the authors will be used to determine the appropriate control strategies for each level of data complexity.

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