Site-specific irrigation using automated control and machine vision for horticulture crops in Queensland and New Zealand

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Abstract
The spatial variability in soil properties across irrigated broadacre fields in Australia can be up to 500%. Currently irrigation for these fields is typically applied uniformly. Manual monitoring and processing soil moisture and crop measurements to implement site-specific irrigation and optimise water productivity is labour-intensive and expensive. A control system which automatically determines and delivers irrigation and fertiliser requirements has been developed to identify spatial irrigation requirements, and only apply water when and where it is needed. This system consists of: (i) sensors that measure weather, soil and plant response; (ii) a control system that automatically analyses the sensor data and determines irrigation and fertiliser requirements; and (iii) actuation hardware that applies site-specific irrigation and fertiliser requirements. This paper details the evaluation of irrigation control strategies in horticulture crops for centre pivot irrigation sites in Kalbar, Queensland and Palmerston North, New Zealand.

Keywords
Image analysis, centre pivot, spatial variability, VARIwise.

Introduction
There can be over 500% variability in soil properties and irrigation requirements within a single field. However, irrigation is traditionally applied uniformly over a field. This can lead to overwatering in some areas of a field and under-watering other areas, and reduced yield over the field. Variable-rate irrigation hardware is commercially available that enables site-specific application of irrigation from centre pivot and lateral move irrigation machines. However, uptake of this technology has been low because of difficulty in manual development and uploading of irrigation prescription maps that define the variations in irrigation applied over the field.

Adaptive control systems can automatically determine and deliver irrigation requirements to reduce water and labour costs. Current irrigation control strategies are typically either sensor- or model-based. Sensor-based strategies directly use measurements (e.g. soil moisture or stress from canopy temperature) to make irrigation decisions. For example, a sensor-based control strategy using soil-water data applies irrigation to fill the soil-water deficit when the soil-water reaches a set threshold. Automated wireless sensor networks can collect spatial soil moisture sensor data.

Model-based control strategies determine irrigation application and/or timing using a crop and/or soil-water model calibrated using infield measurements. Automated wireless sensor networks can collect spatial soil moisture sensor data and machine vision cameras can collect spatial plant growth and fruiting information. Crop production models typically simulate daily predictions of height, cover and fruiting or yield parameters (e.g. pod size and number of peas, root volume for carrots). The calibration procedure for model-based control involves iterative adjustment of input parameters to minimise the error between the simulated outputs and measurements. Therefore, plant measurements of height, cover and fruiting/yield are required for calibration. Machine vision cameras can collect spatial plant growth and fruiting information. 'VARIwise' software simulates these sensor- and model-based adaptive control strategies to determine site-specific irrigation requirements (McCarthy et al. 2010).

Simulations were conducted to compare the sensor-based and model-based control strategy with an industry standard grower's treatment. This involved: (i) identifying spatial variability in carrot and pea fields to identify homogeneous zones; (ii) collecting weather, soil and plant field for each zone; (iii) calibrating crop production model using available data; and (iv) simulating performance of control strategies and grower's treatment implemented over one season. The performance of each irrigation treatment was then compared.

Methods - Field sites

Two field sites were selected for collecting soil, plant growth and fruiting data as detailed in Table 1. These datasets were used for model calibration in VARIwise and simulation of the sensor-based and model-based irrigation control strategies.

Table 1. Site information for horticulture sites

Location	Crop	Seasons	Weather data source	Sowing density (plants/ m²)	Soil type	Distance of cameras along machine (m)	Manual data collection days
Kalbar	Carrots	30 May 2015 - 26 Oct 2015	Environdata Weather Master 2000	80	Brown clay loam	80, 106, 125, 165, 180, 210, 225	7/7, 20/7, 7/8, 14/8, 22/8, 5/9, 26/9, 2/10, 10/10
Palmerston North	Peas (Ashton and Massey)	18 Oct 2016 - 9 Jan 2017	CliFlo station 21963	80	Sandy loam	52, 56	16/11, 23/11, 30/11, 7/12, 17/12, 21/12, 26/12, 4/1

The Kalbar carrot site was irrigated using a five span centre pivot, whilst the Palmerston North pea site was irrigated by a two span centre pivot. Each field was divided into two management zones according to electrical conductivity maps and soil sampling. The locations of these zones are shown in Figure 1. For both sites, Zone 1 was sandier then Zone 2. Measurements were spatial interpolated using simple kriging at a grid size of 20 m.

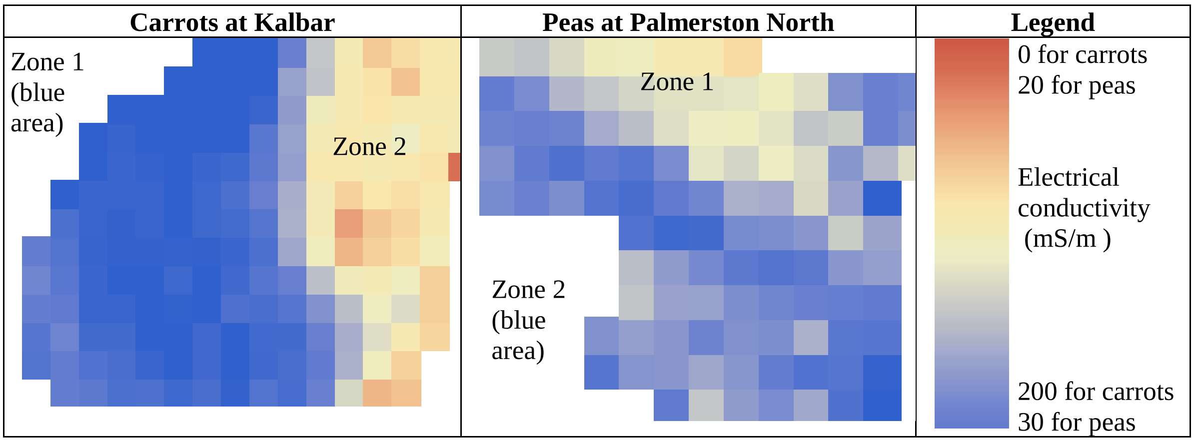

Figure 1. Spatial variability maps for electrical conductivity and location of management zones.

Methods - Irrigation strategies

Two irrigation control strategies were simulated for each field and compared with the grower's treatment as follows: (i) sensor-based control where irrigations were triggered from the soil-water deficit; and (ii) model-based control maximising water use efficiency. For the 2016/17 pea trial, no irrigation was applied because of high rainfall. Therefore the model calibrated using the 2016/17 data was also used to simulate the 2015/16 low rainfall season. For the carrot crop 16 mm was applied on 14 July, 11 August, 23 August and 12 September. For option (i), irrigations were triggered when the soil-water deficit was below 20 mm. For option (ii), the model-based control strategy of McCarthy et al. (2010) was implemented where the model was iteratively executed with different irrigation volumes and timings to identify the combination that maximised irrigation water use index (kg yield/ML).

Methods - Sensor calibration

Cover and flower counts for model calibration were measured using a machine vision system installed on the irrigation machines. The cameras on the irrigation machine were smartphones with an App installed to capture and upload images and GPS location at a set time interval. As no irrigations were applied at the Palmerston North site in 2016/17, dry runs of the irrigation machine on the manual data measurement days enabled image data collection. For the other sites, machine vision data was collected on the irrigation days.

Image analysis algorithms (automated colour and shape thresholding) were developed to estimate canopy cover, and pea flower and pod counts. In each zone, manual measurements were collected for plant height and cover, and node, flower and pod counts in three replicate plots. Carrot canopy cover and root size and mass were measured in two replicate plots.

Methods - Model calibration

The carrot crop was simulated using the APSIM 'carrots4' module and the pea crop was simulated using the APSIM 'fieldpeas' module. Base parameters for pea variety 'parvie' were used because it is a similar variety to those planted at the Palmerston North site. The collected weather and soil data were entered into the model for each zone via the weather file and soil properties. The plant parameters were calibrated following the procedure of McCarthy et al. (2011) to minimise the error between the simulated and manual observations on the measurement days. Table 2 shows the parameters adjusted and values before and after calibration

Table 2. Calibrated APSIM plant parameters for carrot and pea simulations.

Crop	Parameter	Units	Influenced output	Parameter before calibration	Parameter after calibration
Carrots	Root Front Velocity	mm/day	Root height	10	1.5
	Emergence Partition Fraction	m^2/ m^2	Root mass	0.1	0.06
	Initial leaf area	m^2/ m^2	Canopy cover	0.000049	0.0075
Peas	Plant canopy height	mm	Height	50 800	120 930
	Stem rate increase	mm/day	Height	0 10	0 17
	Maximum change in leaf area	$m^2/ m^2/day$	Canopy cover	30000 30000	15000 15000
	Minimum change in leaf area	$m^2/ m^2/day$	Canopy cover	20000	5000
	Initial leaf area	m^2/ m^2	Canopy cover	1000	22000

Results - Model calibration

Figure 2 compares the canopy cover variability for the two sites. The model was calibrated using the management, weather, soil, and plant measurements collected for the two zones. For carrots, the average error before calibration was 54.9 cm for root depth and 13.8 g for root mass, and after calibration was 2.7 cm for root depth and 10.7 g for root mass. Figure 3 shows that for peas, the average error before calibration was 8.1% for cover, 11.4 cm for height and 8.1 nodes, whilst after calibration was 2.8% for cover, 3.5 cm for height and 2.8 nodes.

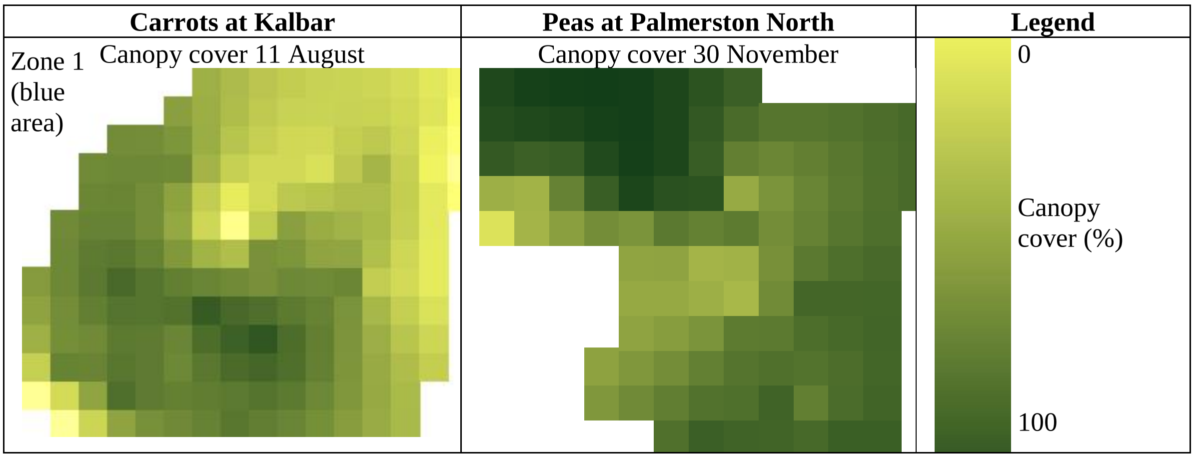

Figure 2. Spatial variability maps for canopy cover for carrot and pea crops.

Results - Control strategy simulation

Table 3 compares the three irrigation treatments using the calibrated pea and carrot model in VARIwise. Simulations were also conducted in the low rainfall 2015/16 season for peas in Palmerston North as the 2016/17 season did not require irrigation.

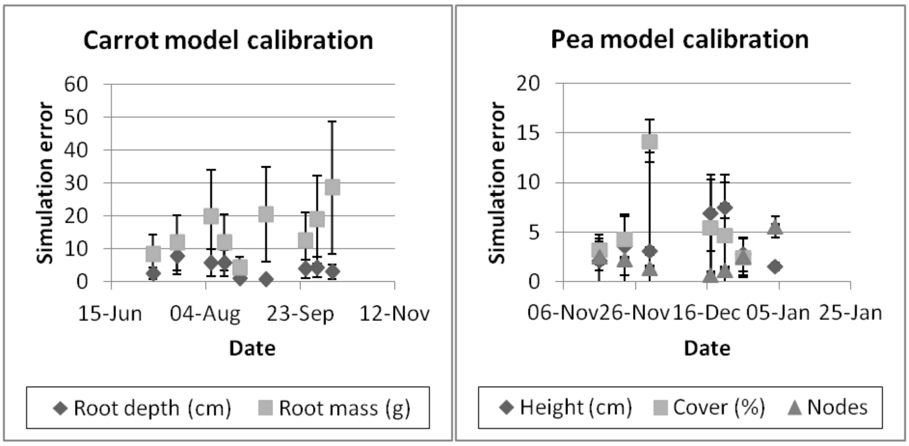

Figure 3. Relative error (%) in carrot and pea model simulation after calibration using crop data.

Table 3. Comparison of simulated irrigation control strategies for peas and carrots.

Season	Treatment	Max canopy cover (%)	Max height (cm) (canopy for peas, root for carrots)	Yield (t/ha)	Irrigation applied (ML/ha)
Peas 2016/17	Grower's treatment	71.3	65.9	3.5	0.0
	Soil-water deficit	72.1	67.2	3.6	0.6
	Model-based control	72.1	67.2	3.6	0.3
Peas 2015/16	Soil-water deficit	71.4	75.6	2.0	0.8
	Model-based control	71.7	76.1	2.1	0.7
Carrots 2016	Grower's treatment	76.5	24.7	31.2	0.6
	Soil-water deficit	72.4	28.7	33.4	0.6
	Model-based control	73.6	27.8	34.3	0.6

The following observations were made from these simulation results:

- For carrots, the control strategies produced slightly higher yield than the grower's treatment with the same total irrigation application.
- For peas, the control strategies applied more water than the grower's treatment with no significant improvement in yield at the 0.05 significance level.
- The pea canopy cover and height were larger for the soil-water deficit strategy and model-based control strategy than the grower's treatment.
- There was no significant difference in yield between the soil-water deficit and model-based strategy at the 0.05 significance level.
- The model-based control strategy applied less water than the soil-water deficit strategy in the 2016/17 pea crop and the same water for the 2015/16 pea crop and 2016 carrot crop.

Conclusion

A field data collection and simulation study was conducted to compare soil-water deficit triggered and model-based irrigation control strategies for carrots and peas. For carrots there was a slight yield improvement using model-based control or soil-water deficit triggered irrigation, whilst for peas there was no significant difference in yield using the control strategies.

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