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Field evaluation of automated site-specific irrigation for cotton and perennial ryegrass using soil-water sensors and Model Predictive Control

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ABSTRACT

Variable-rate irrigation technology can reduce water use in centre pivot and lateral move irrigation systems through application of irrigation according to spatially varied soil-water profiles. However, filling the profile may not maximise yield because of variations in crop response and water requirements with crop stage. For example, cotton crops produce optimal yield under slight water stress during early stages. An irrigation strategy 'Model Predictive Control' has been implemented that accounts for changes in crop water requirements at different growth stages using biophysical crop models. This strategy involves automatically and iteratively executing the biophysical crop model APSIM parameterised with local soil and weather information, with different irrigation depths, to identify which combination maximises yield with the minimum depth of water application. This strategy has potential to address spatial and temporal variations in crop water requirements but has not previously been evaluated for variable-rate irrigation in the field. This paper reports field trials conducted over four cotton (*Gossypium hirsutum* L.) seasons and two perennial ryegrass (*Lolium. perenne* L.) seasons to evaluate the accuracy of the yield prediction of the biophysical model and compare field performance of irrigation strategies: uniform irrigation and variable-rate irrigation using a fixed underlying map, soil-water sensors and Model Predictive Control. Yield was most accurately predicted using on-site weather data and field soil core information, with $R^2 = 0.733$ and RMSE = 153.9 kg/ha for cotton, and $R^2 = 0.336$ and RMSE = 295.3 kg/ha for ryegrass. For cotton, Model Predictive Control led to 4.9% more yield with 5.6% reduction in water application, mainly through reduced water after peak bloom and/or open boll physiological stages. For grazed ryegrass, the Model Predictive Control strategy led to 8.5% more yield with 5.4% reduction in water application, potentially caused by reduced applications after grazing events. Further work includes evaluating the Model Predictive Control strategy with control of irrigation event timing under a broader range of field conditions to identify parameters to provide greatest economic return, and to refine biophysical models for improved performance of optimisation in the strategy.

1. Introduction

Irrigation is traditionally considered as uniform applications over entire fields; however, fields often have spatial variability in crop water requirements. This can lead to overwatering in some areas of a field and under-watering in other areas, and reduced yield over the field. Variable-rate irrigation (VRI) hardware is commercially available and enables site-specific application of irrigation by centre pivot and lateral move irrigation machines and costs $500-$1500/ha ($AU) depending on manufacturer and configuration. The commercial feasibility of VRI depends on field variability, crop type and potential water savings and yield improvements (El Chami et al., 2019; Sharma and Irmak, 2020). VRI can achieve water savings of up to 25% while maintaining yield (Hedley and Yule, 2009) through irrigation according to spatially variable water holding capacities, crop water use, or crop types; leaving capacity in the soil for capture of rainfall in soils with high water holding capacities and in regions with high in-season rainfall; and reducing or stopping irrigation in areas of fields that are uncropped or susceptible to overwatering or ponding (e.g. inner spans of the machine, areas in field prone to run-off, around water troughs, laneways, ditches) (Peters and Flury, 2017). In dairy (cattle) pastures, the reduced water in laneways would also reduce maintenance costs and cow lameness due to the drier

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laneways.

Approaches have been developed to automate development of VRI prescription maps aiming to match the spatial irrigation requirements over the field's cropped areas. Existing irrigation prescription map development processes available both commercially, and those developed in research, typically aim to fill the spatially variable soil-water profile. Commercial prescription map development processes may be: manual using software available with VRI hardware (e.g. Valley365, FieldNET); semi-automated using yield, elevation, or electrical conductivity maps through precision agriculture software (e.g. Precision Cropping Technologies); or automated using soil-water balance approaches from satellite imagery (e.g. Prospera). Research tools that automate prescription map development are based on soil-water sensors (El-Naggar et al., 2020); soil-water balance models using ETc from FAO56 (Barker et al., 2019) or biophysical models (Thorp et al., 2017); crop water stress indices from canopy thermometers (O'Shaughnessy et al., 2020; Vories et al., 2020) or satellite imagery (Veysi et al., 2017).

Irrigating to fill the soil-profile may not maximise key grower targets (i.e. yield or profit, Cammarano et al., 2012). At the same time, irrigating to fill the soil-profile may not minimise environmental impacts, e.g. reduce runoff and drainage (Gillies and Smith, 2015), nutrient leaching (Vogeler et al., 2019), or greenhouse gas emissions (Li et al., 2022a). However, optimising yield is a consideration to improve efficiency and positively impact the environment through production on less land. Thorp et al. (2017) found that reducing early season irrigation led to increased yield, possibly by encouraging cotton root growth and increasing capacity for water uptake and resilience to water shortage during reproductive development. A yield-driven strategy for irrigation management may provide yield improvements in addition to reported water savings. Automated irrigation strategies are reported that combine control systems with yield predictions from biophysical models to determine irrigation requirements that maximise yield. For example, a 'Model Predictive Control' (MPC) approach is reported that uses iterative execution of a biophysical model for cotton (*Gossypium hirsutum* L.) with different irrigation depths and timings to identify the irrigation management that maximises yield using the software 'VARIwise' over a prediction horizon (McCarthy et al., 2010, 2014). This strategy has potential to be automatically parameterised from online weather and soil data sources based on geo-referenced information. This would enable the strategy to be implemented autonomously in the background without the need for a skilled model operator.

The MPC strategy has potential to adapt irrigation application depths throughout the season to the temporal variations in crop water requirements caused by different crop growth stages. Simulation studies have reported little value in temporally adapting irrigation strategies for soybean crops (Kelly et al., 2023). However, there is potential for adaptive strategies to benefit other crops including cotton and grazed pasture. For example, cotton crops produce optimal yield under slight water stress during early stages, while grazed crops may require lower irrigation depths initially after grazing events. There is also potential to extend the strategies from cotton (*Gossypium hirsutum* L.) to grazed pasture. In Australia, VRI is most widely adopted in the pasture industry (e.g. perennial ryegrass (*Lolium. perenne* L.)) for reducing irrigation in laneways and existing water bodies in the field. Implementation of MPC would require use of a biophysical model that enabled ryegrass simulation. This may be achieved using the Agricultural Production Systems sIMulator (APSIM, Holzworth et al., 2014) which is modular in design and embeds models to simulate multiple crop types including cotton (OZCOT, Wells and Hearn, 1992) and pasture (AgPasture, Thornley, Johnson, 2000 as implemented in SGS/DairyMod/EcoMod, Johnson, 2008). The models predict final yield and daily values of crop height, cover, and fruiting or development parameters (e.g. open boll counts, dry matter).

No studies have been reported on the performance of yield-driven model-based strategies in the field. The use of biophysical models for guiding management decisions requires that the model accurately reflect field conditions, particularly yield for cotton and pasture growth for ryegrass. The cotton model OZCOT in APSIM is generally reported to predict yield and fruiting parameters with strong correlations (R^2=0.7–0.9; Yang et al., 2014, Shukr et al., 2021, Li et al., 2022b). Similarly, the pasture growth model AgPasture integrated in APSIM is reported to predict pasture growth with strong correlations (R^2=0.7–0.8; Li et al., 2011). However, the models can have lower correlations if they do not adequately capture the complexity of the physiological or soil processes. For example, for newer cotton varieties not captured in biophysical models, the fruiting development predicted by OZCOT is reported to be delayed compared with field assessments (Richards et al., 2001; Yeates et al., 2009). The model accuracy may also be reduced if row configurations are not standard (Milroy et al., 2004). For example, 1 m row spacing is most common in Australian cotton but growers may use 1.5 m row spacing in seasons with limited water. In addition, low accuracies have been reported for the daily simulated soil-water from AgPasture model because the temporal dynamics simulated were not present in sensor measurements (R^2=0.1 for APSIM; Harrison et al., 2018). This suggested that APSIM may be better suited for predicting parameters which have smaller fluctuations over time (e.g. yield).

Crop biophysical models require parameterisation to accurately reflect field conditions. This includes soil properties (drained upper limit, lower limit, saturated and starting soil-water content, bulk density), daily weather data (maximum and minimum temperature, solar radiation and rainfall) and crop variety features (e.g. leaf area growth rate and fruit size development rate relative to day degrees). The soil property drained upper limit is equivalent to the field capacity and crop lower limit is equivalent to the wilting point (Wigginton et al., 2012). APSIM uses these properties to calculate the plant available water capacity which is the maximum amount of water that can be stored in the soil profile and that is available to plants. This can be a major cause of spatial yield variability (He et al., 2022) due to irrigation mis-management. Apparent electrical conductivity from electromagnetic responses have been used to assess spatial variability and identify sampling locations for soil properties to parameterise APSIM. In addition, apparent electrical conductivity has been used to assess the spatial variability in soil texture, soil-water and salt content (e.g. Vories et al., 2020; Rodríguez-Pérez et al., 2011; Hedley et al., 2013). In fields with large variations in topography, digital elevation models could be used to calculate Topographic Wetness Indices and assess spatial variability (Priori et al., 2013). Therefore, in a field trial electrical conductivity or elevation mapping could be conducted to identify sampling locations. However, some soil properties (i.e. soil texture) influential on crop development and productivity are not incorporated into APSIM (Vogeler et al., 2022). Soil texture can influence crop development and yield, for example due to rapid root penetration in soils with lighter soils with higher sand and silt content (Vories et al., 2020; Vories et al., 2021). Therefore, the soil properties could be compared with strategy performance to identify their influence.

Soil water holding and texture properties can be estimated from online soil databases (e.g. APSoil in Australia) or assessed using infield soil sampling. Weather data from onsite weather stations are expected to be more accurate than regional weather information (e.g. Bureau of Meteorology stations and SILO simulations in Australia), particularly with significant spatial variations in rainfall over short distances in Australia, but can be expensive (~AU$10 000). Crop variety parameters for a range of varieties are often included with the models, but can be calibrated if parameters for the planted variety are not available (e.g. Thorp et al., 2017). A validation of model performance is required to ensure the weather and soil inputs are sufficient for model parameterisation, to assess need for parameter calibration, and to provide recommendations for field data requirements.

Field trials are required to compare MPC with uniform irrigation, and VRI using fixed historical maps and soil-water deficit, to evaluate yield and efficiency differences. Field trials that compare VRI strategies commonly involve small plot trials with at least two replicates of each strategy (e.g. different deficit treatments) across soil types (e.g. Hedley et al., 2011; Barker et al., 2018). Implementing VRI trials require catch-can data to ensure accurate applied irrigation depths. Plot-based trials provide accurate performance comparison between strategies as the replicates are within the same paddock and soil type. These can be assessed from yield, irrigation applied, and physiological indicators. Cotton physiological features that could be assessed include canopy cover and open boll counts, potentially measured at broad spatial scales using UAVs and image analysis algorithms. Existing image analysis algorithms involve segmentation to detect plant or open boll pixels based on colour thresholds, where canopy cover is estimated from the ratio between green and all pixels (Kumar and Miklavcic, 2018), and open boll area is estimated from the ratio between white pixels and all pixels (Yeom et al., 2018). Ryegrass yield could be assessed using dry matter yield assessments. For example, a calibrated C-Dax Rapid Pasture Meter (Agricultural Solutions, Ltd, Palmerston North, New Zealand) is commonly used to assess paddocks at a commercial scale and as an alternative pasture biomass ground truth to cuts and plate meters (e.g. Insua et al., 2019; Chen et al., 2021).

Potential efficiency improvements have been identified for VRI of cotton and grazed ryegrass pasture using MPC and biophysical modelling to meet temporal and spatial crop water requirements. This has not previously been evaluated for grazed pasture or in field trials. In this study, the objectives were to: (a) evaluate the ability of biophysical model APSIM to accurately predict yield in VRI cotton and grazed ryegrass pasture scenarios; and (b) investigate the field performance of automated VRI strategies for cotton and ryegrass that aim to maximise yield, as well as improve irrigation water use, compared with standard grower practices and strategies based on filling the soil-water profile. Performance was based on crop development parameters, yield and irrigation water use indices.

2. Materials and methods

2.1. Irrigation control strategies

Four irrigation control strategies were selected for evaluation in the field. The strategies were implemented on the days the grower was irrigating as detailed below:

- *Uniform* – Flat irrigation rate with no sprinkler flowrate alterations. This represented a standard commercial practice to irrigate the field uniformly with the irrigation application depth set by the grower on the irrigation machine control panel.

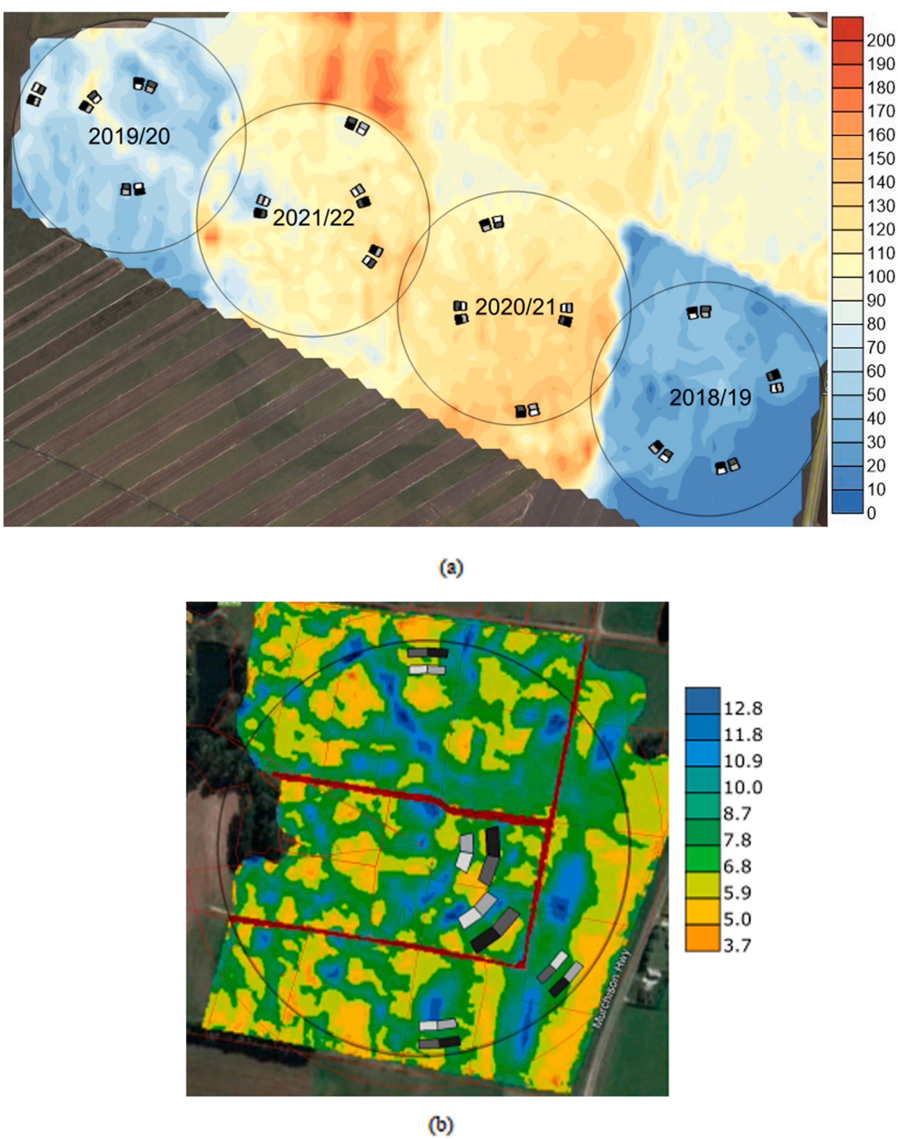


Fig. 1. Field variability maps for field sites for: (a) cotton in 2018/19, 2019/20, 2020/21 and 2021/22 where the legend is for vertical apparent electrical conductivity (dS/m); and (b) ryegrass in 2020/21 and 2021/22 where the legend is for the Topographic Wetness Index, red lines indicate paddock boundaries and maroon areas indicate presence of laneways. The grey circular outlines indicate the locations of the centre pivot irrigation machines which were 404 m long at the cotton sites and 280 m long at the ryegrass site. The uniform irrigation ('Uniform') plots are white, variable-rate irrigation using fixed map ('VRI-Fixed') plots are light grey, variable-rate irrigation using soil-water sensors ('VRI-SW') plots are dark grey and variable-rate irrigation using Model Predictive Control ('VRI-MPC') plots are black.

- *VRI from fixed map ('VRI-Fixed')* – Fixed variable-rate irrigation map with variability based on apparent electrical conductivity or elevation maps (Fig. 1). This represented a standard VRI practice where irrigation depths were scaled depending on underlying variability (e.g. from apparent electrical conductivity or elevation map) between 70% and 100%.
- *VRI from soil-water (SW) sensors ('VRI-SW')* – Apply irrigation depths to replenish the soil-water profile. These were calculated as the difference between the soil-water content at field capacity and averaged soil water content over the three sensors. The drained upper limit was measured from infield soil sampling.
- *VRI from MPC maximising yield ('VRI-MPC')* – The MPC strategy of McCarthy et al. (2014) was implemented to maximise predicted final yield. The model was parameterised from on-site weather data, soil properties and management information. The MPC strategy was implemented in VARIwise to compare the predicted yield at multiple irrigation depths ranging from 0 mm (i.e. no irrigation) to the flat rate irrigation depth of the irrigation machine (i.e. the irrigation depth configured during commercial operations). Yields were predicted with multiple irrigation depths at intervals of 5 mm in this range. For example, for an irrigation machine with flat rate irrigation depth of 15 mm, with four irrigation depths were simulated: 0, 5, 10 and 15 mm. The irrigation depths implemented were those that produced the highest predicted yield (lint yield for cotton and dry matter for perennial ryegrass). If two irrigation depths produced the same predicted yield, the lower irrigation depth was selected to be applied.

This trial focussed on comparing the performance of the irrigation strategies to determine spatial application depths, rather than determining the timing of the irrigation events, as the trials were conducted on commercial farms where the timing was controlled by the grower. Further trials may involve using the strategies to irrigate based on soil moisture, environmental impacts, rainfall forecast and estimated grazing dates for pasture.

VARIwise was updated from programmatic execution of the cotton model OZCOT (McCarthy et al., 2010) to APSIM version 7.10 build r4200. This involved developing software to generate an APSIM simulation file containing the soil and management parameters, calling the APSIM executable, and then reading the generated APSIM output file.

2.2. Field site selection

Trial sites selected were: (a) a seven-span centre pivot irrigated cotton field with a deep epicalcareous self-mulching black vertosol (Anon, 2022) over four seasons near Yargullen, Queensland, Australia; and (b) a five-span centre pivot irrigated perennial ryegrass pasture field with a deep red mesotrophic haplic ferrosol (Masters, 2012) over two seasons near Elliott, Tasmania, Australia (Table 1). Some paddocks in the ryegrass site were on steep slopes that contained slump features or hummocky patterns due to vegetation clearance and subsequent mass movement (Moreton, 1999).

The seven-span centre pivot used for four consecutive cotton seasons was towed between cotton fields each season. At the cotton site a flat rate application depth of 15 mm was applied until early vegetative growth ceased, and 30 mm depth was applied for the rest of the season, while the ryegrass machine had a flat rate application depth of 15 mm. The irrigation machine at the cotton site always irrigated in a clockwise direction, while the irrigation machine at the perennial ryegrass site irrigated in both clockwise and anti-clockwise directions, as it was part-circle.

The VRI hardware on the cotton machine was Valley VRI-iS® (Anon, 2022) which enabled individual sprinkler control, whilst the VRI hardware on the ryegrass machine was Valley VRI zone control which enabled control of 30 zones along the machine. AgSense® (AgSense, 2017) was installed on both machines to enable remote control of the machines and upload of the VRI maps. In this trial, the system was implemented to only reduce irrigation application depths such that the uniform irrigation strategy would apply the highest irrigation depth.

Table 1
Cotton and ryegrass field site details for evaluation of VRI strategies.

Crop	Season	Variety	Planting date for cotton; start of irrigation season for ryegrass	Harvest date for cotton; end of irrigation season for ryegrass	Date of variability mapping
Cotton	2018/19	Sicot 748B3F	18 October 2018	1 May 2019	21 August 2018
	2019/20	Sicot 748B3F	21 November 2019	30 June 2020	18 September 2019
	2020/21	Sicot 748B3F	5 November 2020	20 May 2021	14 August 2021
	2021/22	Sicot 748B3F	2 November 2021	03 May 2022	18 August 2021
Perennial ryegrass	2020/21	Perennial ryegrass dominant pasture*	1 November 2020	20 April 2021	2017
	2021/22		24 November 2021	30 April2022	

* ~90–95% perennial ryegrass with remainder weeds, clover, fescue and cocksfoot and some variation between paddocks in elevation ('slump' features) and weeds (dock clumps)

The accuracy of the angular position of the irrigation machine was verified by monitoring the application from test VRI maps over landmarks in the field (flags of the cotton site and laneways and fences for the ryegrass site), and the angle was offset as required. This was conducted for both directions of machine travel for the ryegrass site.

The irrigation machine uniformity and VRI performance were verified in catch can trials for both irrigation machines. This field process was used to identify uniformity in irrigation along the machine, and ensure the VRI hardware (nozzles and speed control) were accurately applying irrigation depths, and these depths were consistent in each direction of machine travel for the ryegrass site. At the cotton site, grids of catch cans were installed at the centre of Spans 2–7 with three rows of five catch cans along the machine at 1.5 m spacing, following the methodology of O'Shaughnessy et al., (2013). At the ryegrass site, grids of catch cans were installed in Span 5 with two rows of 20 catch cans at 1.7 m spacing parallel with the machine, and two rows of 31 catch cans at 1.7 m spacing perpendicular with the machine. Fixed VRI prescription maps were uploaded for the VRI application. For the cotton site, the root mean square error (RMSE) between prescribed and measured applied depths was 2.6 mm with an average applied irrigation depth of 28.0 mm, whilst for the ryegrass site the RMSE between prescribed and measured applied depths was 2.7 mm with an average applied depth of 12.3 mm. This is consistent with the reported performance of VRI systems (e.g. RMSE <3.0 mm,mm, O'Shaughnessy et al., 2013).

The variability in soil types was assessed in each field to select locations for replicates of treatments across the fields (four in the cotton trials and five in the ryegrass trials). The cotton fields were surveyed using a DUALEM-1S that records electromagnetic responses (i.e. electrical conductivity) to 50 cm and 150 cm depths (Fig. 1). The average measured electrical conductivity differed for each cotton field, potentially because of a difference in soil-water content each time the survey was conducted. The ryegrass field was surveyed using elevation mapping to determine a Topographic Wetness Index where smaller indices indicated steeper slope and higher indices indicated areas with potential for runoff (Fig. 1). Plot locations in ryegrass trials were positioned between machine towers, were contained within a paddock without laneways, and were approximately homogeneous with minimal overland flow to ensure water infiltrated where it was applied.

Soil cores were collected in the sampling locations with results in Tables 2 and 3 for cotton and ryegrass, respectively. At the cotton site, two replicates of samples were collected using a 35 mm diameter hydraulic soil sampling rig. The cores were divided into 30 cm sections to a 90 cm depth. At the ryegrass site, three replicates of samples were collected using a steel ring with 72.5 mm internal diameter and 61 mm height which was hammered into the profile at each depth. These samples were analysed to characterise parameters required for APSIM (bulk density, drained upper limit, lower limit, saturated water content) using predicted van Genuchten soil water retention curve parameters with RETC (Schaap et al., 2001) a retention curve development software that quantifies the hydraulic functions of unsaturated soils (Simunek et al., 2007). Soil water characteristics from the online soil database APSoil (www.apsim.info) were also obtained for comparison. The plant available water capacity was calculated for each sampling location (Table 2) as the difference between drained upper limit and crop lower limit (Wigginton et al., 2012). Soil texture was assessed using the hydrometer analysis method of Gee and Bauder (1986).

The soil properties were compared with the underlying soil variability maps to ground truth the soil differences. Electrical conductivity and Topogaphic Wetness Indices were extracted from the maps for the cotton and ryegrass sites, respectively. This involved averaging measurements within 15 m of each sampling location for comparison with soil properties at the same sampling location. From Table 2, for each cotton season, the higher electrical conductivity corresponded with higher plant available water capacity, silt and clay content, and lower sand content and bulk density. Therefore, the electrical conductivity map indicated variation in water holding capacity and soil texture. From Table 3, for the ryegrass site, the higher Topographic Wetness Index corresponded with higher plant available water capacity, slump features and clay content, and lower sand and silt content.

Trial plots were assigned in each site and replicated with dimensions of size and spacing to ensure that the irrigation strategies were applied independently without overlap from adjacent management zones. The plots were positioned to align with the VRI management zones and areas irrigated with each strategy were at least 20 m wide and 30 m considering sprinkler throw distance. If the management zones were larger than 20 m wide, the plots were the width of the management zone. Higgins et al. (2016) recommended a minimum management zone size of 23 m for the Valley section control VRI system used at their ryegrass site. VRI prescription maps were generated following the xml file format required for AgSense, and uploaded on days of irrigation.

The dates of irrigation events were determined by the onsite managers and growers. The irrigation events were occasionally stopped before the whole field was irrigated because of rainfall. This would have led to variations in irrigation applied depths between the replicates of the plots in the uniform irrigation plots.

For the cotton sites, soil nitrate and ammonium nitrogen tests were conducted before the initial nitrogen application each season. The grower applied approximately 250 N kg/ha before planting and 60 N kg/ha as a side-dressing before flowering. Nitrogen would not have been a limiting factor for the irrigation sites as the average nitrogen requirement for cotton over a season to achieve high yields is about 250 N kg/ha (Smith and Welsh, 2018), with 60–70% applied upfront and 30–40% applied as a side dressing prior to flowering (Baird, 2022).

2.3. Data collection

Weather data was collected at each site and season to provide minimum and maximum daily temperature, rainfall and solar radiation for APSIM simulations. Automatic weather stations (AWS) were installed at the sites (Environdata Weathermaster 2000 at the cotton site, and Environdata Weather Maestro with Middleton solar sensors at the ryegrass site). Weather data were obtained from the closest Australian Government's Bureau of Meteorology (BoM through ftp://ftp.bom.gov.au/) weather station (Oakey Airport for cotton site, and Wynyard Airport for ryegrass site). Interpolated regional weather station datasets from 'SILO', a Queensland Government database containing continuous daily climate data for Australia since 1889 (through https://www.longpaddock.qld.gov.au/silo/), were obtained for comparison with the onsite AWS data.

Table 4 provides a summary of the weather data from on-site weather stations. There were large variations in rainfall between the weather stations, as expected, which were caused by the large spatial variation in rainfall. The solar radiation was lower from the SILO station than the AWS and BoM, which would lead to underestimation of the daily crop water use and yield. The temperature was generally lower from the AWS than BoM. At both cotton and ryegrass sites, this may have been caused by the BoM stations being located at airports which have differences in land use compared with the farm sites and enclosed conditions leading to microclimates (Johnston, 2020).

Soil moisture was monitored at the centre of the VRI-SW plots using soil-water sensors. At the cotton sites, ICT International MP406 standing wave sensors which have an accuracy of $\pm$ 1% (Anon, 2022) were installed at depths of 30, 60 and 90 cm. At the ryegrass site, EnviroPro EP100GL-04 capacitance probes which have an accuracy of $\pm$ 2% (EnviroPro, 2022) were installed with sensors at 10 cm intervals to 40 cm. The soil-water measurement at each depth was logged every 15 minutes throughout the season. The soil-water sensor data was calibrated using the approach of Pendergast and Hare (2007) by: (i) scaling the data such that the change in soil moisture matched the known irrigation depth applied; and (ii) adjusting the soil-water curve such that the maximum soil-water content measured equalled the soil field capacity.

Manual plant measurements were collected in the VRI-SW plots of the cotton site to assess the model accuracy. These measurements were for the same five plants in the centre of each plot. Plant stand was assessed in each replicate after emergence, and canopy width and square, green boll and open boll counts were measured weekly. Yield was assessed in all plots at harvest from lint collected by hand from 1 m^2 in the centre of each plot. The lint was weighed and a cotton turnout percentage was 40% from the same cultivar in previous commercial gin operations.

For the ryegrass sites, grazing dates were required to record harvesting events in APSIM. Grazing dates were manually recorded by observing pasture in images collected by oblique cameras in the VRI-SW and VRI-MPC plots of each replicate. In the 2021/22 season, the grazing events were verified using GPS trackers on the cattle at the ryegrass site. The plots were monitored weekly to compare in-season crop growth patterns between irrigation strategies. The centre of each ryegrass plot was assessed weekly using a C-Dax Pasture Meter pulled by a quadbike to measure the height of pasture swards and estimate dry matter yield. The calibration provided by the onsite field staff to convert pasture height from the C-Dax to dry matter is shown in Eq. 1. This calibration was conducted with a rising plate meter at the site.

$$Dry\ matter\left(\frac{kg}{ha}\right) = \frac{Pasture\ height\ (cm) - 15.675}{4.685} \tag{1}$$

The centre of each cotton plot was monitored weekly using a DJI Phantom 4 UAV to assess canopy cover and open bolls. The UAV mission was developed using Litchi software. Top view images were captured approximately 3 m from the ground while the UAV was hovering so there was no thrust or propeller wind on the crop canopy (Fig. 2). Image analysis algorithms were implemented to extract fractional canopy cover using plant segmentation (Kumar and Miklavcic, 2018) and open boll area that extracts ratio of white pixels to all pixels (Yeom et al., 2018).

The image analysis outputs for canopy cover and open boll area were compared with the measured canopy width and open boll counts, respectively, to verify accuracy for indicating in-season crop growth (Fig. 3). The open boll area analysis was focussed on the images

Table 2

Soil properties in each zone and trial for layers '1′, '2′ and '3′ where layer 1 is 0–30 cm, layer 2 is 30–60 cm and layer 3 is 60–90 cm. ECa_1 and ECa_2 are the electrical conductivity measured in the vertical (0–50 cm) and horizontal (50–150 cm) orientations, respectively. Soil data sources were online database of soil water characteristics (APSoil) and infield core samples. Different fields were used for each cotton season. Entries with '-′ indicate soil properties not available from source.

Source	Zone	Plant available water capacity (mm)	ECa_1 (dS/m)	ECa_2 (dS/m)	Bulk density (Mg/m^3)			Lower limit (m/m)			Drained upper limit (m/m)			Particle size sand (%)			Particle size silt (%)			Particle size clay (%)		
					1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
2018/19																						
	1	154	39.2	108.5	0.95	0.94	0.97	0.26	0.250	0.232	0.424	0.422	0.404	8.70	6.05	12.54	12.73	19.87	20.66	78.57	74.07	66.79
Cores	2	151	23.9	54.9	1.03	1.00	0.99	0.220	0.236	0.217	0.386	0.406	0.385	20.72	9.90	25.13	14.60	19.21	13.01	64.68	70.89	61.86
	3	152	32.9	89.2	0.96	1.00	1.03	0.240	0.240	0.206	0.413	0.407	0.373	8.93	13.92	25.54	20.65	13.34	15.93	70.42	72.74	58.53
	4	154	47.5	117.1	0.93	0.91	0.97	0.253	0.258	0.241	0.426	0.430	0.411	0.88	5.91	11.68	24.74	16.97	16.40	74.37	77.12	71.92
Online	All	222	-	-	1.00	1.05	1.05	0.270	0.280	0.280	0.530	0.520	0.520	-	-	-	-	-	-	-	-	-
2019/20																						
	1	161	85.1	140.6	0.94	1.05	1.10	0.213	0.181	0.170	0.393	0.361	0.345	11.92	11.61	17.45	31.52	39.39	35.38	56.56	49.00	47.17
Cores	2	170	100.0	185.6	0.92	0.96	0.95	0.211	0.200	0.175	0.396	0.383	0.371	6.54	11.91	9.01	39.74	35.89	48.28	53.72	52.19	42.71
	3	159	36.8	61.9	1.00	1.33	1.06	0.187	0.145	0.172	0.373	0.306	0.354	6.71	18.24	13.09	44.68	38.87	40.59	48.61	42.89	46.31
	4	159	48.8	84.5	0.98	1.21	1.13	0.219	0.158	0.173	0.397	0.333	0.347	6.36	8.02	12.81	34.06	47.01	38.12	59.58	44.97	49.07
Online	All	209	-	-	1.04	1.06	1.08	0.254	0.305	0.305	0.529	0.519	0.511	-	-	-	-	-	-	-	-	-
2020/21																						
	1	162	111.5	124.4	0.93	0.96	1.02	0.231	0.240	0.205	0.413	0.416	0.386	0.74	0.82	2.59	38.40	31.19	41.80	60.87	67.99	55.61
Cores	2	153	127.1	159.3	1.11	1.18	1.20	0.212	0.177	0.169	0.388	0.347	0.339	0.58	10.14	12.18	33.01	38.12	38.39	66.40	51.74	49.43
	3	151	133.2	183.0	1.07	1.11	1.12	0.226	0.224	0.212	0.396	0.389	0.379	1.97	8.08	8.60	29.31	21.61	26.59	68.72	70.30	64.81
	4	149	166.4	219.0	1.15	1.19	1.15	0.217	0.202	0.209	0.384	0.367	0.375	0.80	6.35	6.47	30.80	30.78	28.94	68.39	62.87	64.59
Online	All	222	-	-	1.04	1.05	1.05	0.270	0.280	0.280	0.530	0.520	0.520	-	-	-	-	-	-	-	-	-
2021/22																						
	1	151	92.8	117.2	1.01	1.24	1.32	0.194	0.165	0.137	0.377	0.324	0.300	7.79	24.80	19.05	40.39	26.79	41.09	51.82	48.41	39.85
Cores	2	158	146.5	182.2	1.05	1.07	1.21	0.169	0.185	0.164	0.355	0.360	0.328	9.92	13.12	20.49	45.33	35.46	31.67	44.75	51.41	47.84
	3	146	135.3	188.7	1.04	1.26	1.36	0.199	0.176	0.156	0.375	0.335	0.306	10.61	16.31	24.19	34.23	29.74	29.21	55.16	53.95	46.60
	4	139	51.2	85.4	1.23	1.43	1.45	0.176	0.147	0.127	0.338	0.298	0.275	16.18	16.62	26.89	30.64	38.60	36.46	53.17	44.78	36.64
Online	All	209	-	-	1.04	1.06	1.08	0.254	0.305	0.305	0.529	0.519	0.511	-	-	-	-	-	-	-	-	-

Table 3
Soil properties in each zone and trial for layers '1′ and '2′ for perennial ryegrass where layer 1 is 0–10 cm and layer 2 is 10–30 cm. Soil data sources were online database of soil water characteristics (APSoil) and infield core samples. The same field was used for both ryegrass seasons. Entries with '-' indicate soil properties not available from source. Slump features are described objectively and manually assigned a severity level from 0 to 4 in brackets. Observations of pasture composition are noted. Zones 1 and 2 had sand, silt and clay particle sizes (%) of approximately 30.5, 22.5 and 47.5%, whilst zones 3-5 had sand, silt and clay particle sizes (%) of approximately 25.0, 20.0 and 55.0%.

Source	Zone	Plant available water capacity (mm)	Topographic Wetness Index	Bulk density (Mg/m^3)		Lower limit (m/m)		Drained upper limit (m/m)		Slump features	Pasture composition
				1	2	1	2	1	2		
	1	84	5.9	1.04	1.06	0.301	0.220	0.333	0.356	Flat (1)	Dock clumps
	2	150	7.1	0.89	1.02	0.257	0.221	0.374	0.333	Flat (0)	Uniform
Cores	3	150	6.7	1.04	1.06	0.257	0.264	0.328	0.321	Slump features (3)	Uniform
	4	156	10.5	1.01	1.02	0.199	0.244	0.352	0.316	Slump features (4)	Cocksfoot clumps
	5	161	9.5	0.94	1.01	0.261	0.236	0.358	0.314	Some slope (2)	Uniform
Online	All	90	-	1.45	1.45	0.210	0.210	0.360	0.360	-	-

Table 4
Summary of weather parameters from the on-site automatic weather station (AWS) and regional weather stations Bureau of Meteorology (BoM) and 'SILO' over the four cotton and two ryegrass seasons. The interquartile range indicates the spread of the data.

		Solar radiation (MJ/m^2)			Minimum temperature (°C)			Maximum temperature (°C)			Rainfall (mm)		
		AWS	BoM	SILO	AWS	BoM	SILO	AWS	BoM	SILO	AWS	BoM	SILO
Cotton 2018/19	**Median**	25.7	23.6	23.7	15.4	17.0	17.0	30.8	31.0	31.2	0.0	0.0	0.0
	Interquartile range	8.8	9.1	8.8	5.1	4.9	4.7	6.3	6.4	6.3	0.0	0.0	0.0
	Maximum	35.2	31.5	34.5	21.3	22.5	22.3	39.9	40.0	40.3	41.4	22.2	34.0
	Minimum	7.6	4.9	6.5	2.3	5.2	5.4	20.5	21.0	21.2	0.0	0.0	0.0
Cotton 2019/20	**Median**	21.3	21.1	19.1	16.1	17.2	17.6	29.3	30.0	30.3	0.0	0.0	0.0
	Interquartile range	11.9	11.4	11.3	8.1	8.6	8.2	7.0	6.4	6.9	0.0	0.0	0.0
	Maximum	35.1	31.5	32.7	22.1	23.1	23.3	38.1	40.7	40.9	97.6	115.2	68.1
	Minimum	4.1	4.6	4.9	-0.4	-0.4	0.4	13.2	13.2	13.3	0.0	0.0	0.0
Cotton 2020/21	**Median**	21.0	21.1	18.7	14.3	16.4	16.4	29.0	29.3	29.7	0.0	0.0	0.0
	Interquartile range	10.5	10.9	10.3	6.7	6.4	6.0	6.2	6.6	6.8	0.2	0.2	0.1
	Maximum	32.5	31.5	30.9	22.2	22.8	22.7	40.1	40.3	40.7	41.2	48.8	31.4
	Minimum	3.3	3.9	5.0	2.1	-0.5	0.4	16.1	17.0	16.8	0.0	0.0	0.0
Cotton 2021/22	**Median**	21.0	22.1	14.8	14.8	16.5	10.5	27.7	28.1	18.6	0.0	0.0	0.1
	Interquartile range	8.8	9.3	9.9	4.9	4.1	4.4	4.5	4.5	3.2	0.2	0.6	0.7
	Maximum	32.3	31.4	30.3	22.0	23.3	17.4	37.4	38.1	29.0	150.8	88.8	93.2
	Minimum	2.0	1.2	4.4	5.3	6.5	3.7	19.3	20.2	11.7	0.0	0.0	0.0
Ryegrass 2020/21	**Median**	19.5	18.6	14.2	10.4	10.3	12.1	19.3	19.7	20.0	0.0	0.0	0.0
	Interquartile range	12.9	12.3	9.4	4.8	5.9	5.1	3.8	3.1	3.7	0.8	0.6	0.7
	Maximum	33.5	32.0	31.7	16.9	18.3	17.9	31.6	32.2	26.5	101.4	99.8	44.6
	Minimum	1.3	1.3	3.1	1.5	-1.2	5.2	11.9	13.3	14.6	0.0	0.0	0.0
Ryegrass 2021/22	**Median**	20.7	19.7	14.2	12.3	11.8	12.1	20.9	21.1	20.0	0.0	0.0	0.0
	Interquartile range	14.3	13.6	9.4	5.0	5.6	5.1	4.3	3.8	3.7	0.4	0.2	0.7
	Maximum	33.5	31.9	31.7	18.4	19.2	17.9	28.3	28.3	26.5	33.6	26.4	44.6
	Minimum	2.0	1.9	3.1	5.2	2.6	5.2	15.2	16.0	14.6	0.0	0.0	0.0

collected at defoliation as these would be most correlated with the open boll counts. There were very strong correlations between the measured canopy width and canopy cover detected by UAV image analysis (R^2=0.897), and the measured open bolls and open boll area detected by UAV image analysis (R^2=0.718). The lower coefficient of determination for open boll area was expected, as not all open bolls were visible from the top view of the plant.

2.4. Model and irrigation performance evaluation

The accuracy of APSIM with weather and soil data from different sources was evaluated to confirm whether on or off-field data sources were required. In APSIM, the weather source was programmatically updated by referring the APSIM model to a text file containing the weather data from the specified source, while the soil data source was programmatically updated in the APSIM xml file used to run the model. No other parameters were varied for this evaluation. Potential weather sources compared include regional weather stations BoM and SILO and the on-site automatic weather station (AWS). Potential soil data sources include infield core samples and soil-water characteristics obtained from online database APSoil. APSIM outputs from parameterised simulations were compared with field measurements using coefficients of determination (R^2) and root mean square error (RMSE). Cotton field measurements compared include square counts, green and open boll counts (per m^2), canopy cover (%), soil moisture (mm) and lint yield (kg/ha), whilst ryegrass field measurements compared include height (mm), dry matter (kg DM/ha) and soil moisture (mm). For both crops, soil moisture measurements were obtained from the infield sensors. For cotton, canopy cover was obtained from the daily infield camera images, and square and boll counts and lint yield were obtained from manual measurements, whilst for ryegrass, height and dry matter were obtained from weekly-fortnightly C-Dax sensor data.

The irrigation strategies were implemented for each whole ryegrass season, and from approximately 40 days after sowing for each cotton season. The irrigation strategies were evaluated from measured end of season yield, total irrigation applied, irrigation water use index (IWUI), gross production water use index (GPWUI) and weekly crop growth features. Yield was interpreted as lint yield for cotton and dry matter yield for ryegrass. Irrigation applied was calculated from applied irrigation depths in the VRI maps. IWUI was calculated as the ratio between yield and total irrigation applied. GPWUI was calculated as the ratio between yield and total water used by the crop, which was the sum of

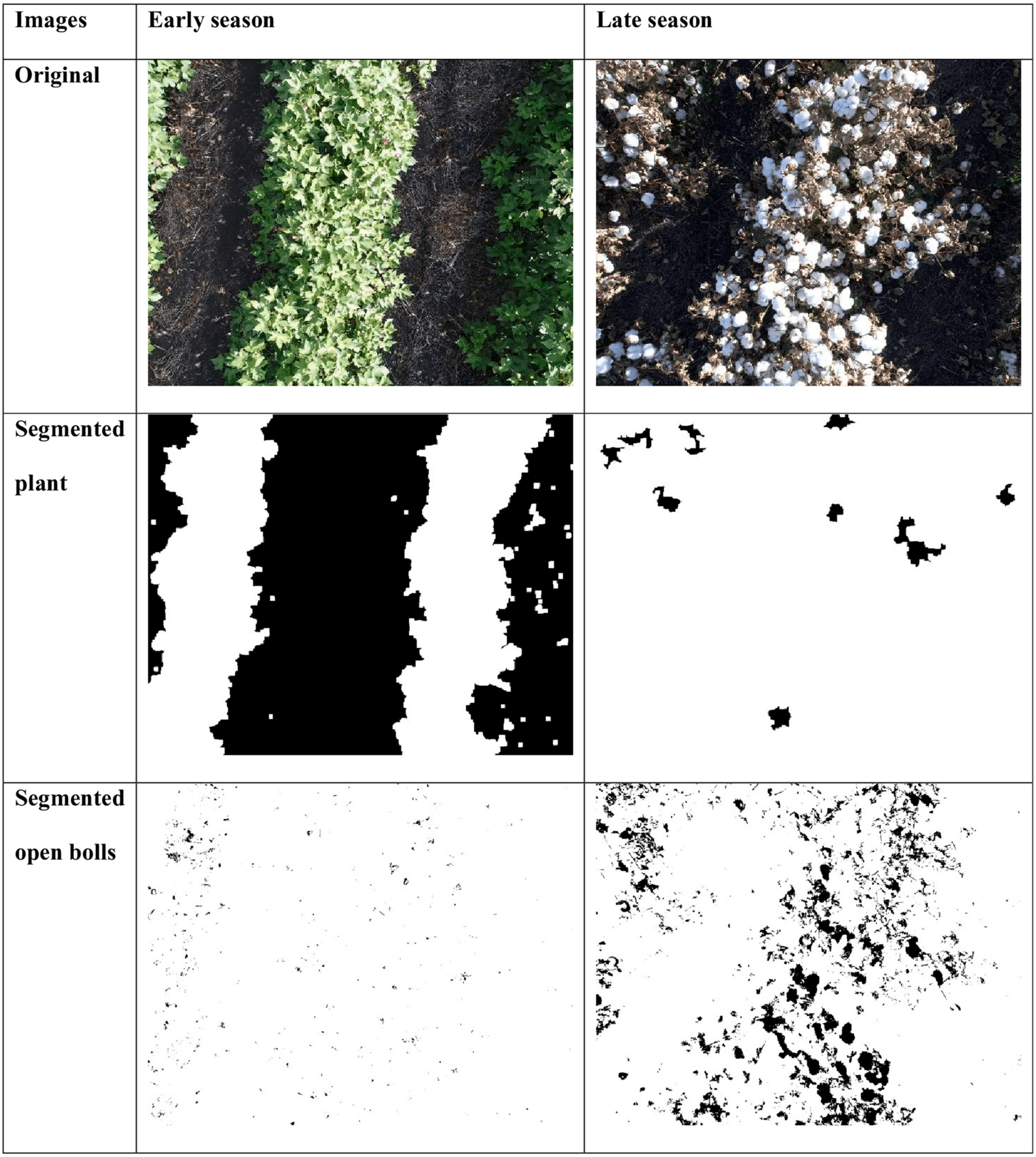
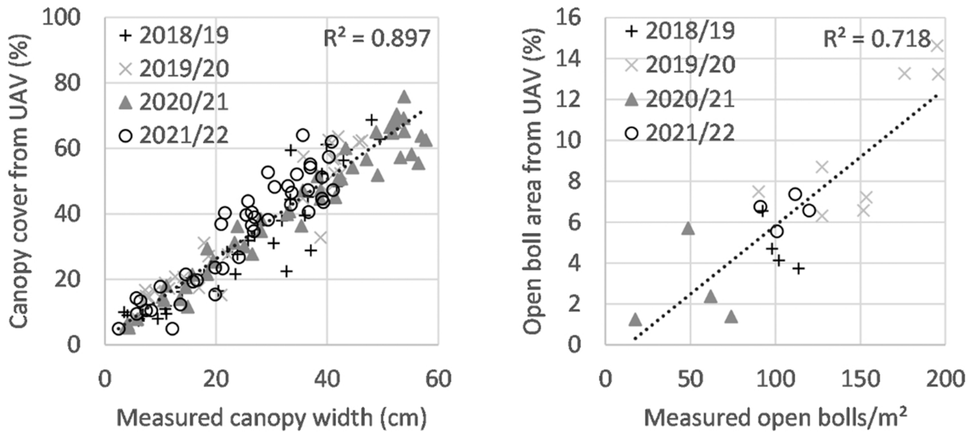


Fig. 2. Sample infield image analysis for evaluation of in-season growth and boll development differences in irrigation strategies using segmented plant and open bolls. Black pixels in segmented images indicate presence of detected plant or open boll pixels.

the soil moisture change, effective irrigation applied and effective rainfall. The soil moisture change was the difference between the start and end simulated soil moisture over the season. Effective irrigation applied was calculated assuming 90% efficiency in the irrigation application (Smith et al., 2014). Multiple approaches are reported for calculating effective rainfall (e.g. Ali and Mubarak, 2017). For this application, effective rainfall was calculated from the rainfall recorded by the onsite automatic weather station, where for ryegrass, the first 2 mm and over 25 mm were ineffective, and for cotton, the first 3 mm was ineffective and only 70% of the remaining rainfall was effective.

The percentage differences in irrigation applied, yield and IWUI were compared with the uniform and VRI (fixed) irrigation strategies. Variations over fields were evaluated using standard deviations. Ryegrass yield was assessed from the average daily dry matter growth and dry matter yield. The average daily dry matter growth was calculated from a weighted average of positive changes in biomass between C-Dax samples. The dry matter yield was calculated by multiplying the average daily dry matter growth with the number of days between the first and last C-Dax samples in the irrigation season (155 days in 2020/21 and 133 days in 2021/22).



(a) (a)

Fig. 3. Comparison of field measurements collected manually and estimated using automated analysis of unmanned aerial vehicle (UAV) imagery: (a) canopy cover; and (b) open boll area. Trendlines are shown in each figure for all seasons.

The weekly crop growth was assessed using the UAV for cotton and C-Dax for ryegrass to compare with changes in irrigation depths applied. The differences for each strategy in irrigation application depths, yield, IWUI and growth parameters, were also compared with the plant available water capacity, soil texture and/or elevation parameters (for ryegrass) to identify impacts from soil or slope properties on the performance in each field and season.

3. Results and discussion

3.1. Prediction accuracy

Table 5 presents the accuracy of APSIM for cotton simulation using weather and soil data from different sources. APSIM most accurately predicted lint yield using weather data from on-site AWS and soil data from infield soil cores, with R^2= 0.733 and RMSE= 153.9 kg/ha using infield cores and R^2= 0.749 and RMSE= 191.9 kg/ha using APSoil. Weather data source had a greater influence on simulation accuracy of lint yield than soil data source, with input from BoM being slightly more accurate than from SILO. From Table 3, the largest difference in weather parameters between weather data sources was for rainfall which may have caused this variation in simulation performance.

APSIM most accurately predicted lint yield and canopy cover, and least accurately predicted soil-water content and fruiting parameters across weather and soil data inputs. The low accuracies in soil-water content may have been caused by the model not accurately reflecting the differences in water use or evaporation due to the row configuration being 1.5 m rather than 1 m which is generally used for Australian cotton. In addition, soil-water was measured daily and the model may have been unable to accurately reflect daily fluctuations as measured. The lower prediction accuracies for square and boll counts may have been caused the delay in the APSIM-simulated fruit development compared with the field measurements as reported in the literature. The soil texture information not being incorporated into APSIM may have contributed to inaccurate rate of soil-water extraction which led to differences in fruit development. However, APSIM may have represented soil texture information through the soil water related parameters.

Table 6 presents the accuracy of APSIM for grazed ryegrass pasture simulation using weather and soil data from different sources to evaluate the most suitable data source for parameterisation. APSIM was most accurate using AWS or BoM weather data and soil core information, with accuracy of dry matter being R^2= 0.336–0.355 and RMSE= 295.3–331.1 kg/ha using infield cores and R^2= 0.353–0.364 and RMSE= 301.1–336.4 kg/ha using APSoil. For ryegrass, soil data source had a greater influence on simulation accuracy than weather data source, with similar performance across the different weather stations. This contrasts with cotton simulations where weather data source was more influential than soil data source. This may be caused by less variation in weather measurements, particularly solar radiation, between weather stations for the ryegrass site compared with the cotton site. APSIM could more accurately simulate height and dry matter than

Table 5
Prediction accuracy (coefficient of determination, R^2, and root mean square error, RMSE) for cotton simulations with regional weather stations ('SILO' and 'BoM') and on-site weather station ('AWS') and soil data sources (online soil database APSoil and infield soil core) for soil-water content, canopy cover, yield and square, green boll and open boll counts.

Weather data source	Soil data source	Soil-water content (mm)		Canopy cover (%)		Square count/m		Green boll count/m		Open boll count/m		Lint yield (kg/ha)	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
SILO regional station	Online database	0.010	46.6	0.368	13.2	0.196	26.0	0.096	25.5	0.048	3.5	0.554	338.9
	Infield cores	0.030	40.0	0.427	11.9	0.257	23.2	0.104	24.1	0.039	4.2	0.393	361.0
Closest Bureau of Meteorology (BoM) station	Online database	0.119	52.7	0.838	8.2	0.168	25.2	0.408	25.3	0.543	15.2	0.469	329.8
	Infield cores	0.103	47.7	0.864	7.0	0.301	20.6	0.452	21.8	0.546	14.6	0.477	221.1
On-site automatic station (AWS)	Online database	0.114	52.0	0.800	9.1	0.223	25.0	0.452	25.4	0.585	13.2	0.749	191.9
	Infield cores	0.098	47.4	0.822	8.5	0.243	23.8	0.468	22.8	0.563	13.1	0.733	153.9

Table 6
Prediction accuracy (coefficient of determination, R^2, and root mean square error, RMSE) for ryegrass simulations with regional weather stations ('SILO' and 'BoM') and on-site weather station ('AWS') and soil data sources (online soil database APSoil and infield soil core) for soil-water content, height and dry matter ('DM') assessments.

Weather data source	Soil data source	Soil-water content (mm)		Height (mm)		Dry matter (kg DM/ha)	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
SILO regional weather station	Online database	0.223	10.6	0.341	16.0	0.321	283.2
	Infield cores	0.252	4.9	0.351	15.8	0.359	301.5
Closest Bureau of Meteorology weather station	Online database	0.068	12.3	0.366	16.1	0.364	336.4
	Infield cores	0.307	5.4	0.356	16.0	0.355	331.1
On-site automatic weather station	Online database	0.035	8.4	0.356	17.3	0.353	301.1
	Infield cores	0.285	8.5	0.331	17.3	0.336	295.3

soil moisture.

APSIM most accurately predicted dry matter and height and least accurately predicted soil-water content across weather and soil data inputs. As for the cotton simulations, the low accuracies in predicted soil-water content may have been caused by the highly fluctuating nature of soil-water data over short time spans that is not well represented in the model. Overall, the coefficients of determination were lower for ryegrass simulations (overall highest R^2=0.366) compared with cotton simulations. This may be caused by slight variations in accuracy around grazing events.

3.2. Irrigation strategy performance – cotton

Table 7 and Fig. 4 compare the performance of the uniform irrigation and VRI strategies in field trials for cotton, whilst Fig. 5 compares the irrigation applied by each strategy. During the 2018/19 season, the irrigation machine had insufficient system capacity to deliver the crop's water requirements because of high temperatures and low rainfall. This

Table 7
Average and standard deviation of yield of cotton, total irrigation applied, irrigation water use index, gross production water use index and maximum canopy cover and open boll area of irrigation strategies over each season. The strategies compared are uniform irrigation ('Uniform'), variable-rate irrigation using fixed map ('VRI-Fixed'), variable-rate irrigation using soil-water sensors ('VRI-SW') and variable-rate irrigation using Model Predictive Control ('VRI-MPC'). The days after sowing that the maximum canopy cover and open boll area occurred are also shown. The average and standard deviation of these values over the four replicates are shown. The effective rainfall was 196, 229, 228 and 396 mm for the 2018/19, 2019/20, 2020/21 and 2021/22 seasons, respectively.

Strategy	Season	Yield (kg/ha)	Irrigation applied (ML/ha)	Irrigation water use index (bales/ ML)	Gross production water use index (bales/ ML)	Maximum canopy cover (%)	Days after sowing to maximum canopy cover	Maximum open boll area (%)	Days after sowing to maximum open boll area
Uniform	2018/19	1958.3 ± 74.9	3.3 ± 0.0	2.6 ± 0.1	1.8 ± 0.1	58.8 ± 3.4	91 ± 3	5.8 ± 0.4	156 ± 0
	2019/20	2969.2 ± 139.3	3.7 ± 0.1	3.6 ± 0.2	2.3 ± 0.1	83.0 ± 3.5	123 ± 10	11.7 ± 0.8	177 ± 0
	2020/21	1977.6 ± 60.5	2.9 ± 0.1	3.0 ± 0.2	1.5 ± 0.1	66.5 ± 3.1	114 ± 4	6.3 ± 0.2	156 ± 4
	2021/22	1640.8 ± 35.2	2.2 ± 0.1	3.3 ± 0.1	1.0 ± 0.0	54.1 ± 2.5	90 ± 7	6.1 ± 0.4	179 ± 0
	Average	**2136.5 ± 77.5**	**3.0 ± 0.1**	**3.1 ± 0.1**	**1.6 ± 0.1**	**65.6 ± 3.1**	**104 ± 6**	**7.5 ± 0.5**	**167 ± 1**
VRI-Fixed	2018/19	1709.7 ± 181.7	3.2 ± 0.1	2.4 ± 0.2	1.6 ± 0.2	60.4 ± 4.3	97 ± 5	5.5 ± 0.8	156 ± 0
	2019/20	3010.4 ± 120.8	3.6 ± 0.1	3.7 ± 0.1	2.3 ± 0.1	81.2 ± 3.9	130 ± 8	11.9 ± 0.7	177 ± 0
	2020/21	2041.7 ± 16.8	2.7 ± 0.1	3.3 ± 0.2	1.6 ± 0.0	66.1 ± 3.3	117 ± 0	6.5 ± 0.2	159 ± 0
	2021/22	1586.2 ± 124.2	1.9 ± 0.1	3.7 ± 0.3	1.0 ± 0.1	54.1 ± 3.9	95 ± 8	6.1 ± 0.6	179 ± 0
	Average	**2087 ± 110.9**	**2.9 ± 0.1**	**3.3 ± 0.2**	**1.6 ± 0.1**	**65.4 ± 3.9**	**110 ± 5**	**7.5 ± 0.6**	**168 ± 0**
VRI-SW	2018/19	1910.2 ± 35.2	3.3 ± 0.0	2.5 ± 0.1	1.7 ± 0.0	60.6 ± 3.8	90 ± 2	5.5 ± 0.2	156 ± 0
	2019/20	3020.7 ± 146.0	3.6 ± 0.1	3.7 ± 0.2	2.3 ± 0.2	82.7 ± 3.6	123 ± 10	12 ± 0.9	177 ± 0
	2020/21	2010.3 ± 13.4	2.8 ± 0.1	3.2 ± 0.1	1.6 ± 0.0	65.5 ± 3.2	114 ± 4	6.1 ± 0.1	159 ± 0
	2021/22	1672.3 ± 60.9	1.8 ± 0.1	4.1 ± 0.3	1.1 ± 0.1	55.2 ± 2.0	83 ± 2	6.7 ± 0.2	179 ± 0
	Average	**2153.4 ± 63.8**	**2.9 ± 0.1**	**3.4 ± 0.2**	**1.7 ± 0.1**	**66.0 ± 3.2**	**102 ± 4**	**7.6 ± 0.3**	**168 ± 0**
VRI-MPC	2018/19	1803.5 ± 73.4	3.2 ± 0.1	2.5 ± 0.1	1.7 ± 0.1	56.5 ± 2.1	91 ± 3	5.0 ± 0.4	156 ± 0
	2019/20	3023.3 ± 159.3	3.3 ± 0.1	4.1 ± 0.2	2.5 ± 0.1	85.1 ± 3.0	116 ± 10	12.0 ± 0.9	177 ± 0
	2020/21	2055.5 ± 105.4	2.5 ± 0.1	3.7 ± 0.3	1.7 ± 0.1	69.9 ± 3.2	117 ± 0	6.5 ± 0.5	154 ± 5
	2021/22	1684.8 ± 56.0	1.8 ± 0.1	4.1 ± 0.4	1.1 ± 0.1	56.0 ± 2.5	88 ± 7	6.7 ± 0.2	179 ± 0
	Average	**2141.8 ± 98.5**	**2.7 ± 0.1**	**3.6 ± 0.2**	**1.7 ± 0.1**	**66.9 ± 2.7**	**103 ± 5**	**7.5 ± 0.5**	**166 ± 1**

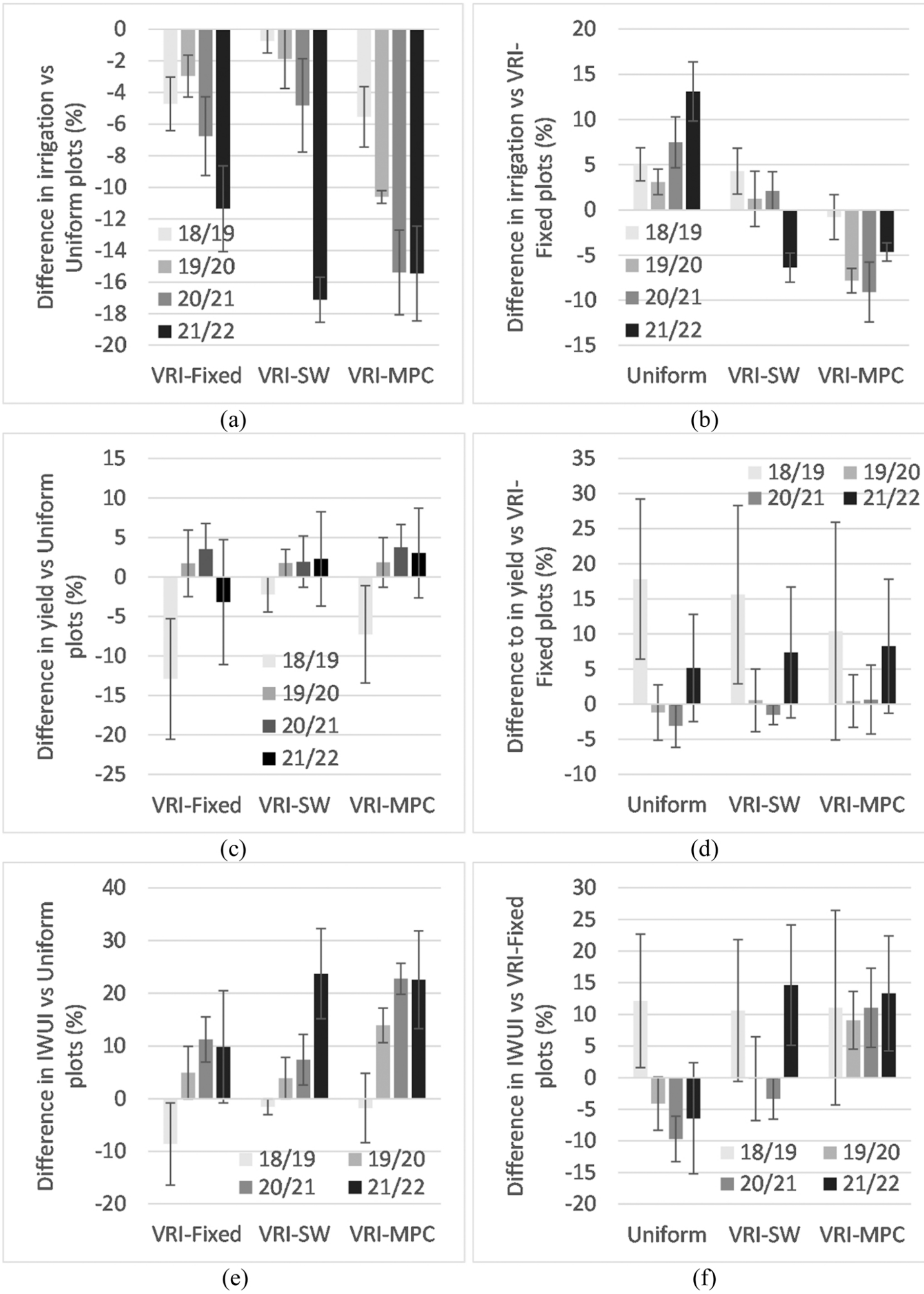


Fig. 4. Percentage differences in total irrigation applied by each strategy for each cotton season (2018/19–2021/22) compared with: (a) uniform irrigation ('Uniform'); and (b) variable-rate irrigation using fixed map ('VRI-Fixed'); lint yield compared with: (b) uniform irrigation; and (c) variable-rate irrigation using fixed map; and irrigation water use index (IWUI) compared with: (e) uniform irrigation; and (f) variable-rate irrigation using fixed map. The strategies compared are uniform irrigation ('Uniform'), variable-rate irrigation using fixed map ('VRI-Fixed'), variable-rate irrigation using soil-water sensors ('VRI-SW') and variable-rate irrigation using Model Predictive Control ('VRI-MPC').

led to the uniform irrigation strategy producing the highest yield in 2018/19. During the 2021/22 season, the crop yield was significantly lower because of two flood events and cooler temperatures, leading to similar performance across all strategies.

From Table 7, during the 2019/20 and 2020/21 cotton-growing seasons, the highest IWUI and GPWUI and lowest irrigation applied were achieved using the VRI-MPC approach, followed by VRI-SW, VRI-Fixed and uniform irrigation. From Fig. 4, over all seasons, compared with VRI-Fixed, VRI-MPC produced 4.9 % more yield with 5.6 % less water, VRI-SW produced 5.5 % more yield with the same water and uniform irrigation produced 4.7 % more yield with 7.2 % more water. Over 2019/20 and 2020/21, compared with VRI-Fixed, VRI-MPC produced 0.5 % more yield with 8.5 % less water, VRI-SW produced 0.5 % less yield with 1.7 % more water, and uniform irrigation produced 2.2 % less cotton yield with 5.3 % more water. There was no statistical difference in irrigation or yield between the strategies.

From Fig. 4, over all cotton-growing seasons, compared with uniform irrigation, VRI-MPC produced 0.3 % more yield with 11.7 % less water, VRI-SW produced 0.9 % more yield with 6.1 % less water and VRI-Fixed produced 2.7 % less yield with 6.4 % less water. Over 2019/20 and 2020/21, compared with uniform irrigation, VRI-MPC produced 2.8% more yield with 13.0 % less water, VRI-SW produced 1.8 % more yield with 3.3 % less water and VRI-Fixed produced 2.6 % more yield with 4.9 % less water. The difference in irrigation application between the Uniform and the VRI-Fixed plots was significant at the 0.05 level.

Overall, the strategies had a larger impact on irrigation applied rather than cotton yield. This suggests that with the water available, weather and management used from the trial site, the approximate maximum yield was achieved with all strategies. However, the VRI-MPC strategy reduced the irrigation applied to obtain this yield. This also indicates that the model optimisation used in VRI-MPC strategy can identify irrigation water savings without impacting yield. There is

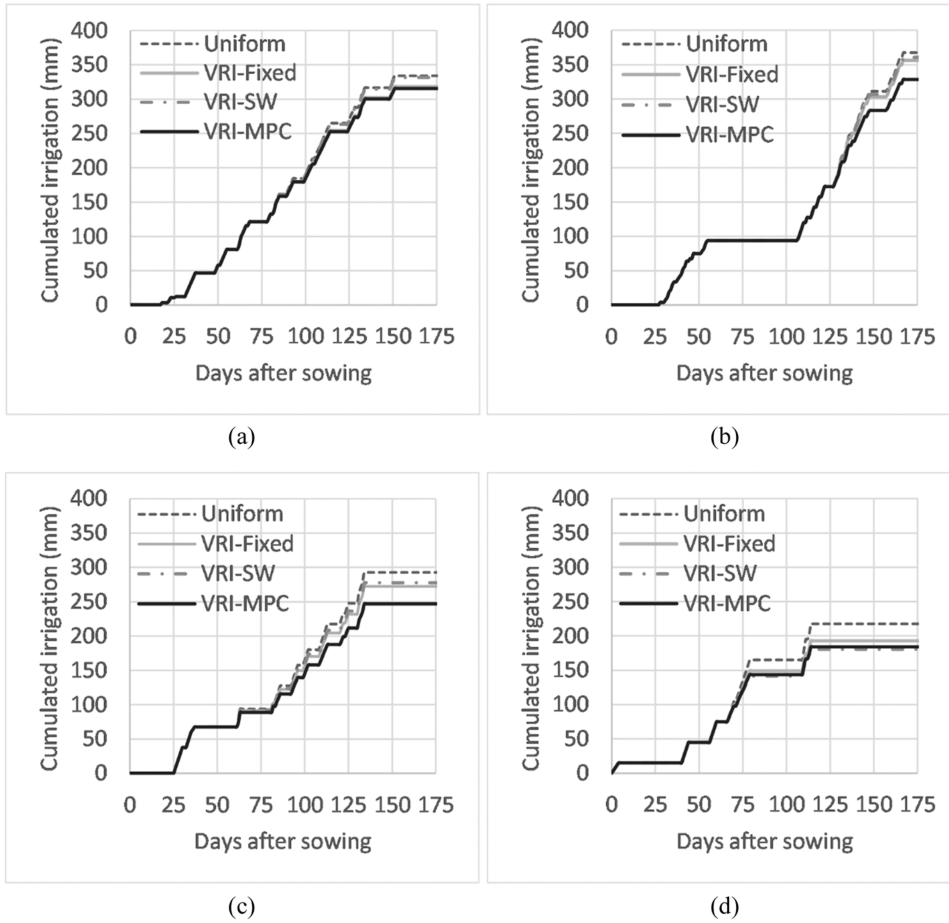


Fig. 5. Cumulated irrigation depth applied for each cotton season in: (a) 2018/19; (b) 2019/20; (c) 2020/21; and (d) 2021/22.

potential for different strategies to be applied depending on the market value of cotton and water. There is also potential for a similar model-based irrigation strategy to include consideration of environmental impacts.

From Fig. 5, in all seasons, similar irrigation depths were applied by all strategies until flowering. In the 2020/21 and 2021/22 seasons, irrigation applications were reduced after 80–100 days after sowing which was after peak bloom. Water stress during peak bloom to open bolls can cause young boll shedding but has less impact on yield than loss of early season bolls. In the 2018/19 and 2019/20 seasons, the VRI-MPC strategy also reduced irrigation applications at approximately 120 days after sowing, which coincided with boll opening. Less water applied during peak boll opening may hasten boll opening, improving defoliation and reducing regrowth leading to increased yield and fibre quality.

From Table 7, the maximum cotton canopy cover and open boll area were similar across all strategies. There was less variation in the date of maximum boll area than maximum canopy cover. The VRI-Fixed strategy produced the highest maximum canopy cover which occurred slightly later than the other strategies. The VRI-SW strategy produced the highest maximum open boll area which occurred slightly later than the other irrigation strategies.

Figs. 6 and 7 compare the irrigation, cotton lint yield and maximum canopy cover and open boll area in each plot and strategy with the plant available water content and silt content, respectively. These show the yield and maximum canopy cover and open boll area being positively correlated with the plant available water capacity and silt content. This is because silty soils hold the most available water to plants, and soils with higher capacity store water and enable extraction of water better by crops during dry growing seasons. No strong correlations were observed between irrigation, yield or cotton development and bulk density, sand or clay content.

The performance of MPC may have been limited by the accuracy of APSIM. In particular, the delay in the simulated physiological responses may have led to the irrigation strategy inaccurately assessing growth stage and corresponding irrigation requirement. In addition, APSIM did not consider soil texture which was found to be highly influential on yield. There is potential for improvements in the performance of model-based management decisions with further development of the crop and soil prediction components in APSIM. The benefit of MPC may be larger in fields with more variation in soil properties which could be verified in further trials. There is potential for further work to identify guidelines for field selection with sufficient variability to implement the system.

3.3. Irrigation strategy performance - ryegrass

Table 8 and Fig. 8 compare the performance of the uniform irrigation and VRI strategies in field trials for ryegrass, while Fig. 9 compares the irrigation applied by each strategy. From Table 8, the highest IWUI and GPWUI for ryegrass and lowest irrigation applied were achieved using the VRI-MPC approach, followed by VRI-SW, VRI-Fixed and uniform irrigation. From Fig. 8, compared with VRI-Fixed, VRI-MPC produced 8.5% more dry matter yield with 5.4% less water, VRI-SW produced 7.4% less dry matter yield with 2.9% more water and uniform irrigation produced 6.2% more yield with 14.4% more water. The VRI-MPC strategy resulted in the highest water use efficiency, whilst the uniform irrigation strategy applied the most water. Compared with uniform irrigation, VRI-MPC produced 9.0% more dry matter yield with 16.9% less water, VRI-SW produced 9.2% less dry matter yield with 9.9% less water and VRI-Fixed produced 4.5% more dry matter yield with 12.4%

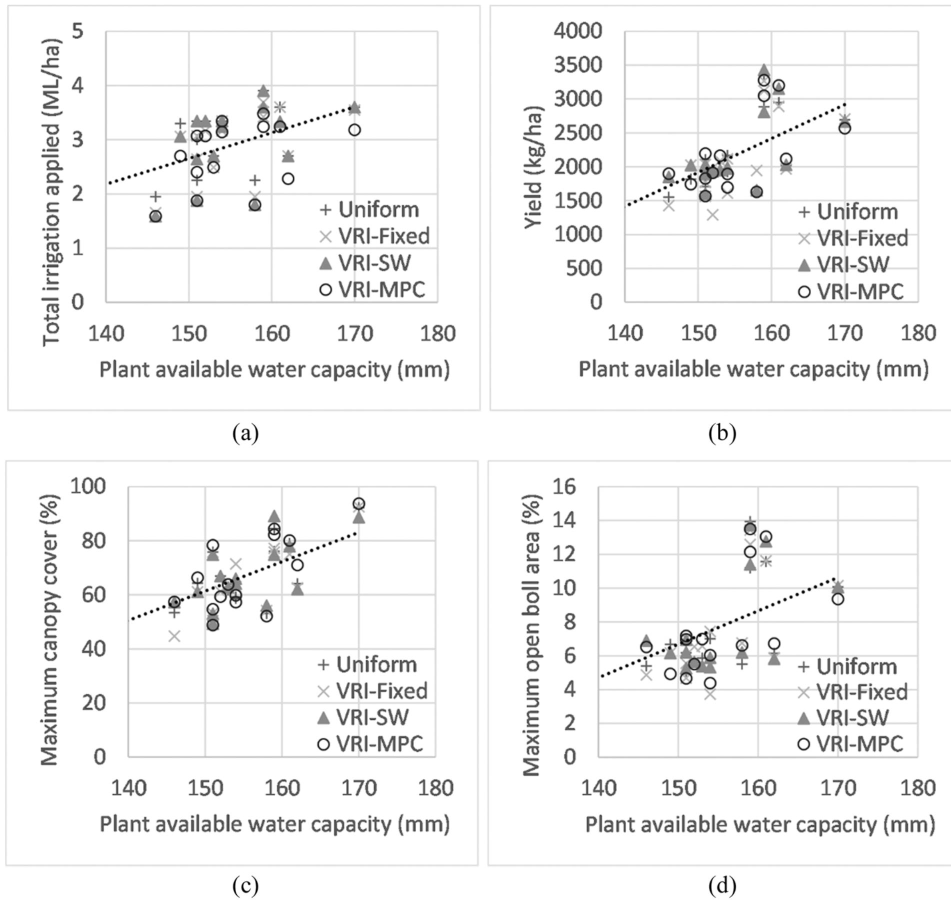


Fig. 6. Comparison of strategy performance with plant available water capacity in all cotton seasons for: (a) total irrigation applied; (b) cotton yield; (c) maximum canopy cover; and (d) maximum open boll area. Trendlines are shown in each figure for all seasons.

less water. All VRI strategies increased yield and applied less water than the uniform strategy, and VRI-MPC and VRI-SW strategies produced the largest yield improvements. There was no statistical difference in irrigation or yield between the strategies. The difference in irrigation application between the Uniform and the VRI-Fixed plots was significant at the 0.05 level.

From Fig. 9, the uniform strategy applied more water across all pasture growth stages. The VRI strategies applied lower irrigation depths from up to 5 days after grazing, after which the VRI-MPC strategy applied slightly less water compared with the other VRI strategies. It is expected the water savings using VRI-MPC occurred because water applications were reduced to coincide with the lower ryegrass water requirement after grazing. This reduced irrigation application, while still meeting the pasture's needs, may have led to less water saturation resulting in improved growth. It is also noted that the VRI-MPC could meet the crop's water needs despite the lower accuracies of APSIM simulations of ryegrass yield compared with cotton lint yield. This indicates that the model could extract relative rather than absolute yield responses to different volume water.

There were larger variations in responses between plots in the ryegrass than cotton trials. At the same time, the pasture grown slightly increased with higher Topographic Wetness Indices and slump features, potentially because in these locations the pasture was more protected which led to improved pasture cover. The pasture grown slightly decreased with higher sand and silt content, potentially because of the reduced water holding capacity of these soils which may have impacted the crop during dry periods of the season. However, thess trend were only slight because of low spatial variation in plant available water capacity between replicates. This suggests that the variations between plots were due to pasture compositions between paddocks (e.g. dock clumps) and/or slump features rather than water capacity.

From Table 8, the highest dry matter yield was achieved using the VRI-MPC strategy, followed by VRI-SW, Uniform irrigation and VRI-Fixed. The uniform irrigation strategy had the highest average daily pasture growth rate, possibly caused by rapid growth after grazing from the higher irrigation depths, but then a reduction in growth caused by overwatering in later stages leading to reduced harvested herbage.

The reported trial focussed on using the VRI techniques to adjust irrigation volumes on days of irrigation events at the commercial sites. There is potential for further productivity improvements if the strategies were applied to determine when to start irrigating, potentially based on soil moisture status, forecast rainfall and grazing events for pasture. In addition, the VRI-MPC strategy could be adapted to economic and environmental impact optimisation by linking with water, production costs, run-off or leaching parameters.

The performance of MPC may have been limited by the accuracy of APSIM for predicting daily soil dynamics over short time spans. This may have influenced the ryegrass simulations more than the cotton simulations because of the shorter seasons. This is because the grazed pasture had a harvest event at each grazing which was optimised, whilst the cotton had only one harvest event and target for optimisation. In a commercial field implementation, the system may be limited by the need for daily grazing information. This would require either cattle trackers, infield pasture sensors or manual data input which are not standard in current systems.

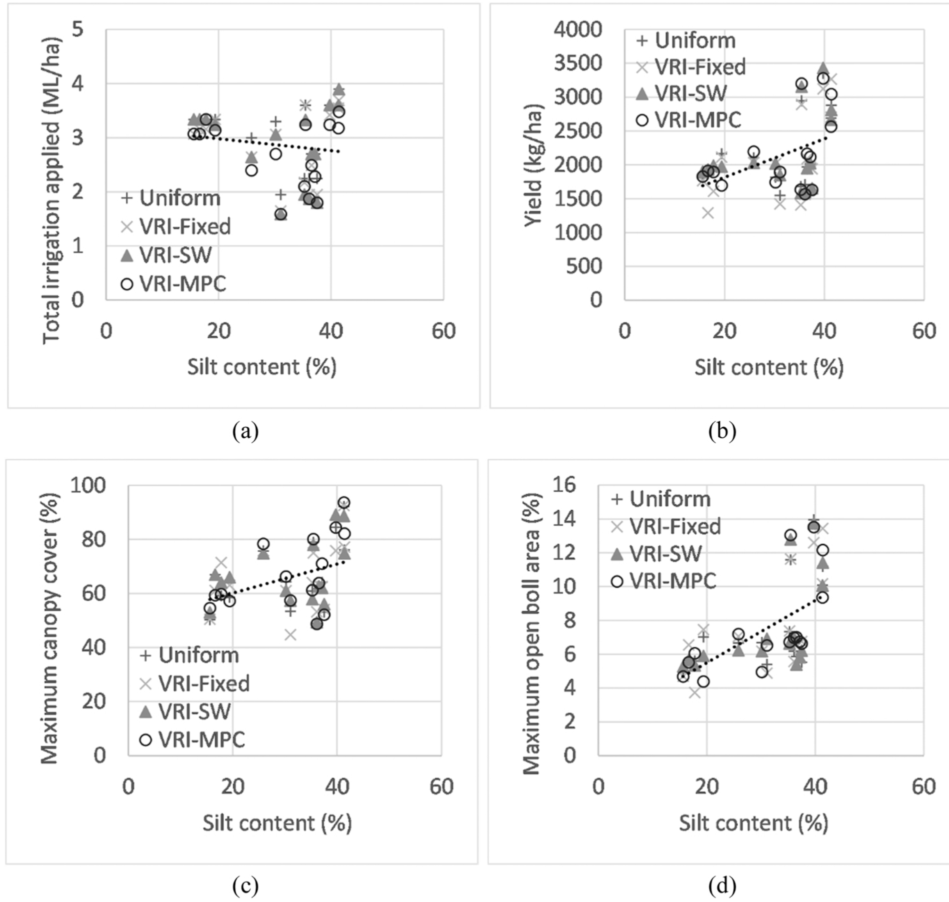


Fig. 7. Comparison of strategy performance with silt content in all cotton seasons for: (a) total irrigation applied; (b) cotton yield; (c) maximum canopy cover; and (d) maximum open boll area. Trendlines are shown in each figure for all seasons.

Table 8
Average and standard deviation of pasture dry matter ('DM') grown, total irrigation applied, irrigation water use index and gross production water use index of irrigation strategies over each season. The strategies compared are uniform irrigation ('Uniform'), variable-rate irrigation using fixed map ('VRI-Fixed'), variable-rate irrigation using soil-water sensors ('VRI-SW') and variable-rate irrigation using Model Predictive Control ('VRI-MPC'). The average and standard deviation of these values over the five replicates are shown. The effective rainfall was 290 and 187 mm 2020/21 and 2021/22 seasons, respectively. There was an average of 4.6 and 5.2 grazing events in the 2020/21 and 2021/22 seasons, respectively.

Strategy	Season	Pasture grown (t DM/ha)	Average daily growth rate (kg DM/ha)	Irrigation applied (ML/ha)	Irrigation water use index (t DM/ML)	Gross production water use index (t DM/ML)
Uniform	2020/21	11.3 ± 1	72.7 ± 6.2	4.2 ± 0.1	2.7 ± 0.2	1.3 ± 0.1
	2021/22	7.5 ± 0.7	56.3 ± 5.6	6.1 ± 0.3	1.2 ± 0.1	1.0 ± 0.1
	Average	9.4 ± 0.8	64.5 ± 5.9	5.2 ± 0.2	2.0 ± 0.2	1.2 ± 0.1
VRI-Fixed	2020/21	10.2 ± 1.6	65.6 ± 10.4	3.6 ± 0.0	2.8 ± 0.5	1.3 ± 0.2
	2021/22	8.4 ± 0.6	75.4 ± 16.7	5.4 ± 0.2	1.6 ± 0.2	1.2 ± 0.1
	Average	9.3 ± 1.1	70.5 ± 13.5	4.5 ± 0.1	2.2 ± 0.3	1.3 ± 0.2
VRI-SW	2020/21	9.6 ± 1	61.8 ± 6.3	3.5 ± 0.1	2.8 ± 0.3	1.3 ± 0.1
	2021/22	8.5 ± 0.8	64.0 ± 5.9	5.2 ± 0.2	1.7 ± 0.2	1.3 ± 0.1
	Average	9.0 ± 0.9	62.9 ± 6.1	4.3 ± 0.2	2.2 ± 0.3	1.3 ± 0.1
VRI-MPC	2020/21	11.2 ± 1.2	72.4 ± 7.6	3.5 ± 0.1	3.2 ± 0.3	1.5 ± 0.2
	2021/22	8.4 ± 0.4	75.7 ± 16.2	4.9 ± 0.2	1.7 ± 0.1	1.3 ± 0.1
	Average	9.8 ± 0.8	74.1 ± 11.9	4.2 ± 0.2	2.4 ± 0.2	1.4 ± 0.1

4. Conclusions

Field trials have been conducted over four cotton seasons and two perennial ryegrass seasons to evaluate the accuracy of the yield prediction of a biophysical model, and compare field performance of uniform and variable-rate irrigation strategies. The predicted yield from the

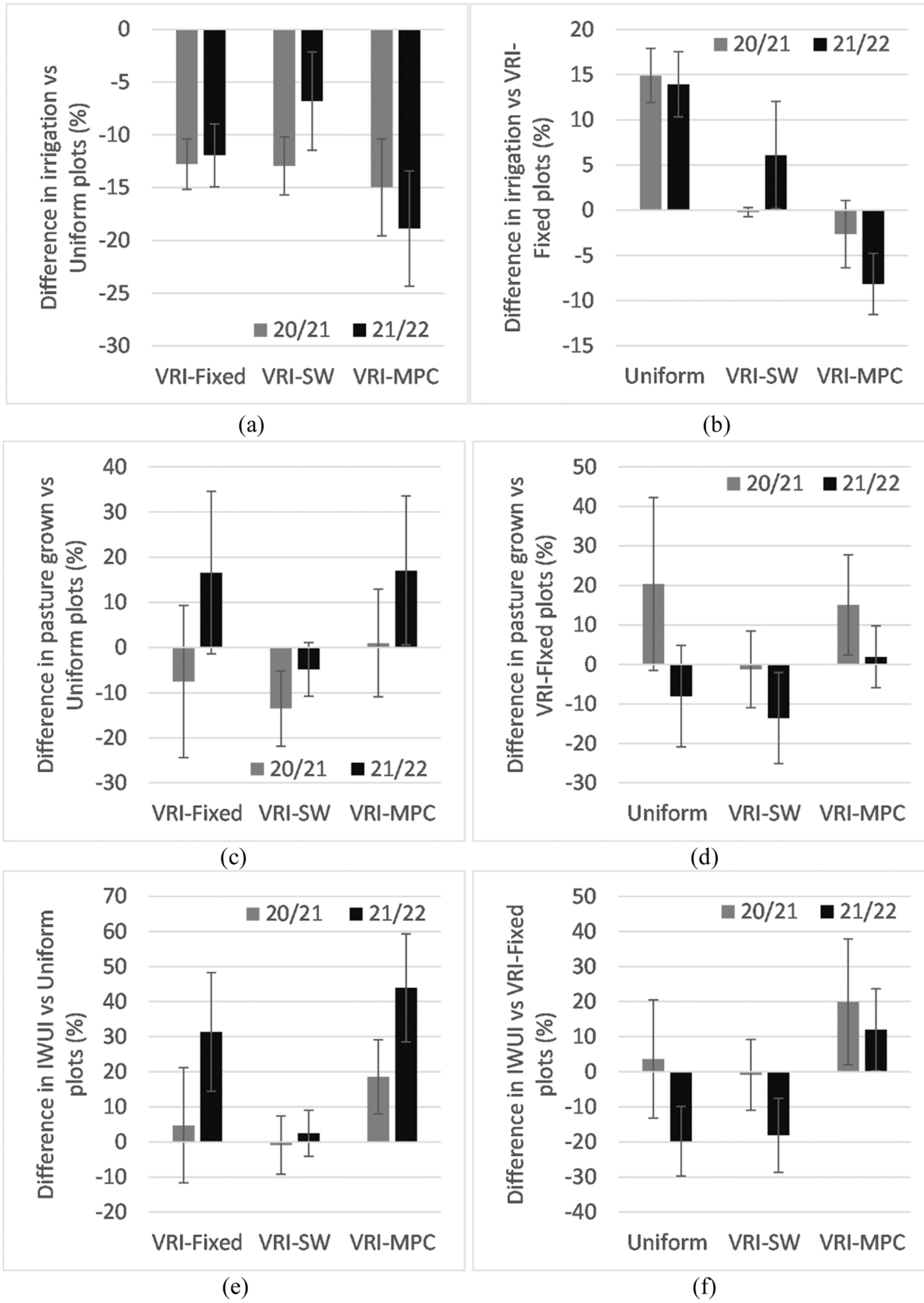


Fig. 8. Percentage differences in total irrigation applied to each ryegrass pasture season (2020/21–2021/22) compared with: (a) uniform irrigation ('Uniform'); and (b) variable-rate irrigation using fixed map ('VRI-Fixed'); pasture grown compared with: (c) uniform irrigation; and (d) variable-rate irrigation using fixed map; and irrigation water use index (IWUI) compared with: (e) uniform irrigation; and (f) variable-rate irrigation using fixed map. variable-rate irrigation using fixed map. The strategies compared are uniform irrigation ('Uniform'), variable-rate irrigation using fixed map ('VRI-Fixed'), variable-rate irrigation using soil-water sensors ('VRI-SW') and variable-rate irrigation using Model Predictive Control ('VRI-MPC').

biophysical crop model was most accurate using on-site weather data and soil core information with $R^2 = 0.733$ and RMSE = 153.9 kg/ha for cotton, and RMSE = 127.4 kg/ha for ryegrass for all season. From the cotton field trials, variable-rate irrigation strategies had a larger impact on irrigation applied rather than yield, with Model Predictive Control led to 4.9% more yield with 5.6% reduced water application compared with standard VRI. Water savings occurred through reduced water after peak bloom and/or open boll physiological stages. For grazed ryegrass, the Model Predictive Control strategy led to 8.5% more yield with 5.4% reduced water application compared with standard VRI, potentially caused by reduced application after grazing events. The performance of all strategies was affected by plant available water capacity for cotton and slope for ryegrass. There is potential for the strategy performance to improve with more accurate models for new varieties, soil texture and short time span dynamics (e.g. soil moisture). Further work includes evaluating the Model Predictive Control strategy with economic and/or environmental impact optimisation, controlling irrigation event timing, and under a broader range of soil properties and weather conditions to identify conditions that provide economic return using the strategy.

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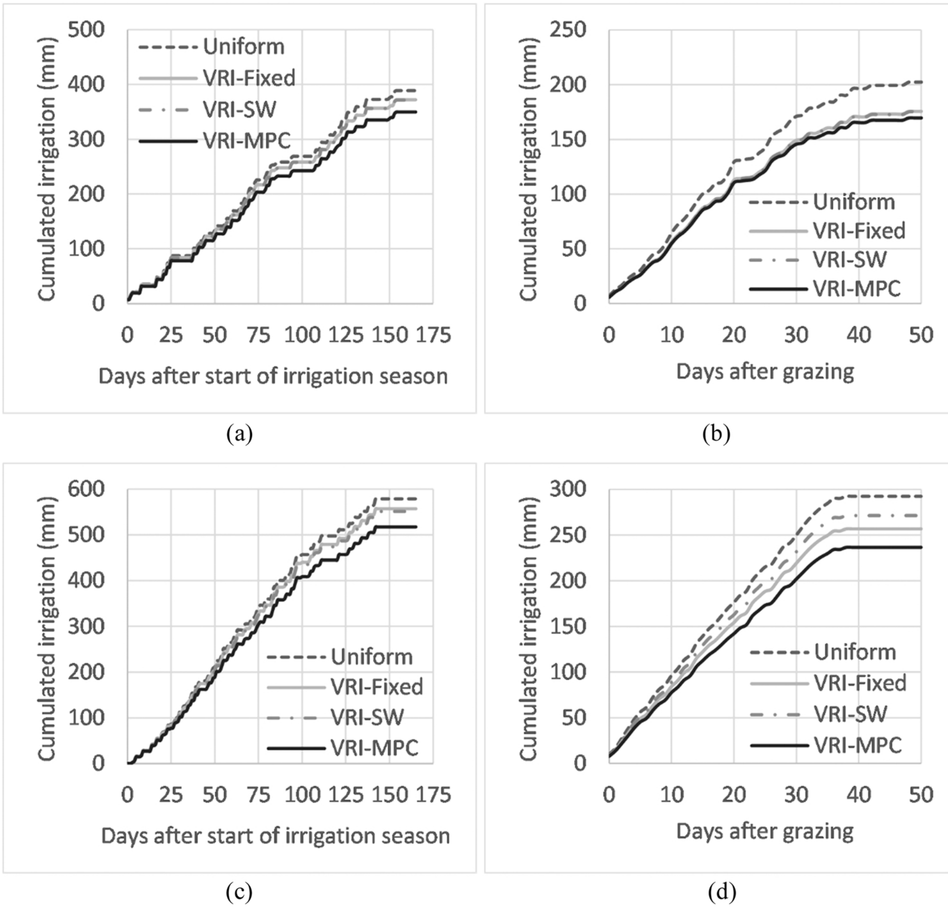

Fig. 9. Cumulated irrigation depth applied to perennial ryegrass in season 2020/21 since: (a) start of irrigation season; and (b) grazing; and in season 2021/22 since: (c) start of irrigation season; and (d) grazing where there were no irrigation events after 36 days after grazing. The strategies compared are uniform irrigation ('Uniform'), variable-rate irrigation using fixed map ('VRI-Fixed'), variable-rate irrigation using soil-water sensors ('VRI-SW') and variable-rate irrigation using Model Predictive Control ('VRI-MPC').

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The authors are unable or have chosen not to specify which data has been used.

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CRediT authorship contribution statement

Alison McCarthy: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Joseph Foley:** Conceptualization, Validation, Resources, Project administration, Funding acquisition. **Pieter Raedts:** Validation, Data curation, Investigation. **James Hills:** Conceptualization, Validation, Resources, Project administration, Funding acquisition.

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