Benchmarking cotton productivity

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Key findings

- Water use can be estimated easily with the (IrriSAT 2017) app.
- First flower, cut out and defoliation can be predicted.
- Cotton water productivity could be up to six bales per hectare below its potential.

Introduction

Water use efficiency is a key measure of cotton productivity (Boyce 2015). Crop water use is difficult to measure, but can be estimated using a web-based app (IrriSAT 2017). This app was developed for weather-based irrigation scheduling using a crop coefficient (Kc) estimated from satellite observations and reference crop evapotranspiration (ETo) estimated from scientific information for landowners (SILO) grids (Jeffery et al. 2001) Whole water use of cotton fields from the Murray Valley to Central Queensland was estimated for the 2014–15 and 2015–16 seasons.

Method

Modelling Kc from remotely sensed data

Estimating transpiration from satellite observations

The crop coefficient (Kc) is the ratio of crop evapotranspiration (ETc) to reference crop evapotranspiration (ETo) (Doorenbos & Pruitt 1977). ETo can be estimated from meteorological data; the Bureau of Meteorology has adopted the Penmann–Monteith equation (Monteith & Unsworth 1990) to calculate ETo. The normalised difference vegetation index (NDVI) can be used to estimate Kc using a linear relationship $Kc = 1.37 \times NDVI - 0.086$ (Trout, Johnson & Gartung 2008). The NDVI can be measured by satellite.

This study uses the NDVI of one or more of three satellites (Landsat 7, Landsat 8 or Sentinel 2). Mosaics of these data are produced in eight-day periods. The value of NDVI assigned to each mosaic was assumed to be observed on the first day of the observation window. The time series of these mosaics begins on 1 January each calendar year. When an observation window straddles the change of year, the same observations are used in the last window of the old year and the first period of the new year. Mosaics were populated in the following order:

1. Obtain cloud-free Sentinel 2 data
2. Obtain cloud-free Landsat 8 data
3. Obtain cloud-free Landsat 7 data.

Each mosaic could be a mix of two spatial resolutions: 10 m for the Sentinel 2 instrument and 30 m for the Landsat instruments. These satellites also have different spectral resolutions; the Sentinel 2 and Landsat 8 observe in similar spectral bands, while the spectral bands of the Landsat 7 instrument have different bandwidths.

Data acquisition

The satellite data is delivered as .csv files via a Google Earth engine interface and app (IrriSAT 2017). Fields of interest were drawn as polygons in the app or uploaded as .kml files (Figure 1). The Google Earth Engine App develops a time series of observations – one for each eight-day window. These observations are assumed to occur on the first day of each window. Each observation consisted of the percentage of the polygon visible to the satellite(s), the area-weighted minimum, mean and maximum Kc, and the lower and upper quartiles and median Kc of those visible polygons. The app also accesses reference crop evapotranspiration (ETo) from the BOM SILO grids (Jeffrey et al. 2001) and calculates crop evapotranspiration (ETc) $ETc = Kc \times ETo$.

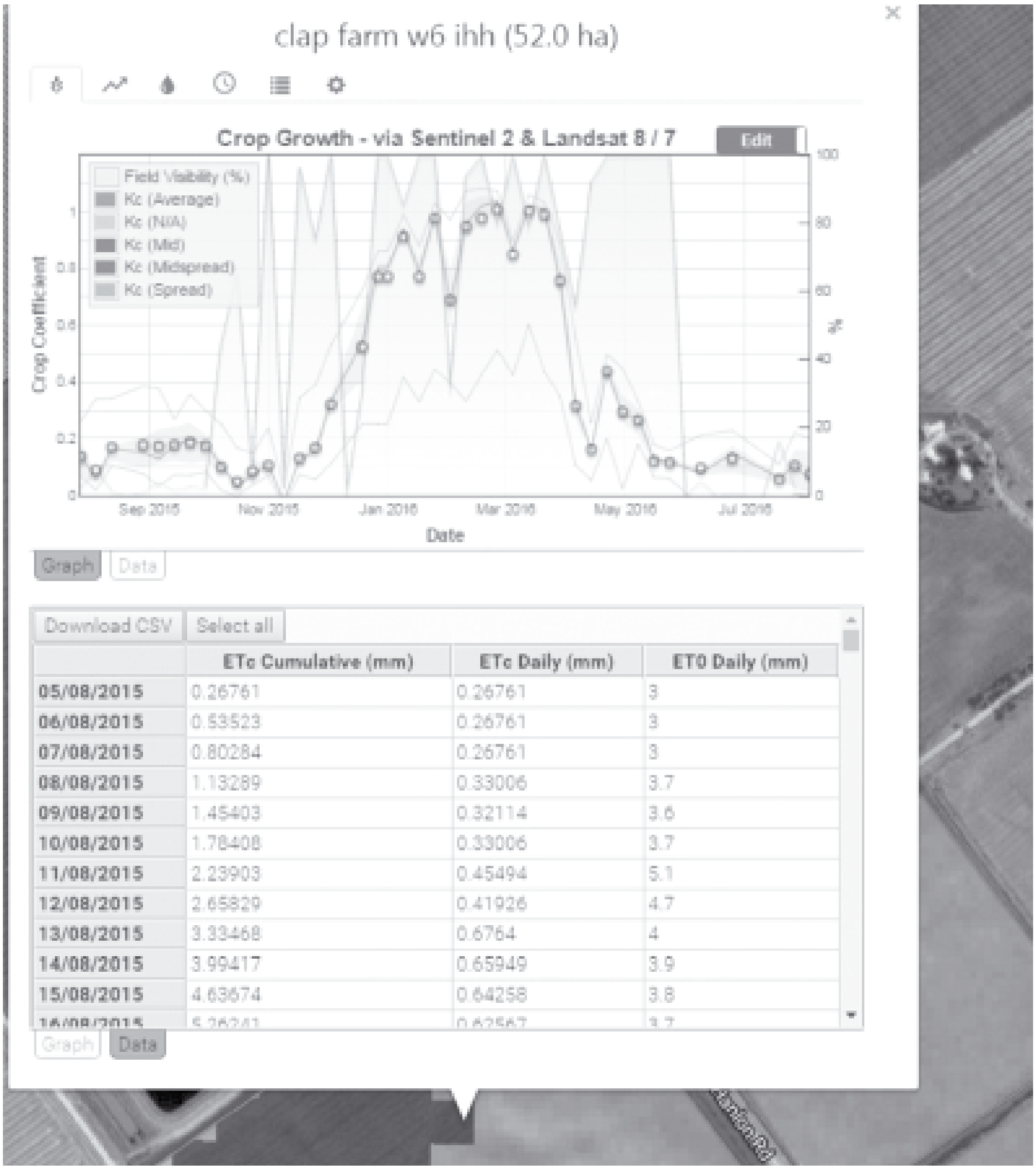

Figure 1. The IrriSAT app interface showing the eight-day time series of Kc in the upper window, and the daily time series of ETo and ETc in the lower window. Polygons of cotton fields can be seen in the background.

Processing the Kc time series

The raw Kc data suffers cloud contamination, which depresses the NDVI and Kc (see top panel of Figure 1). This contamination was removed from the time series of mean Kc values by fitting cubic smoothing splines (Verbyla et al. 1999) and accepting Kc values that lie between the upper 95% confidence interval for the upper quartile and the lower 95% confidence interval of the lower quartile for model fitting. Gompertz 4 parameter growth curves (Equation 1) were then fitted to the left (LHS) and right (RHS) hand sides of the Kc time series using nonlinear least squares regression in the R software package (Bates & Chambers 1992).

$$Kc = A + Ce^{-e^{-B(X-M)}} \quad \text{Constraint}: C<0 \quad \text{Equation 1}$$

Fitting splines and Gompertz (4 parameter) curves

A cubic smoothing spline was fitted to retained mean Kc observations using the asreml-R software package (Butler et al. 2009). The maximum turning point of the mean level spline was determined and the day on which this occurred was used as an initial estimate of when the LHS and RHS joined and was termed the division date. An initial fit of LHS and RHS Gompertz curves was made with upper asymptotes *A* constrained to be equal. Using the initial division date as a starting point, an iterative routine was used to refit the RHS and LHS Gompertz curves. This routine used the day corresponding to the midpoint of the days on which the upper LHS 4th derivative and the upper RHS 4th derivatives of the Gompertz curves were zero as the division date. The routine ran until convergence was achieved, measured by the change in division date of <0.1 days.

Curve fitting

Spline fitting might produce a better estimate of water transpired. However, properties of the Gompertz curve as determined by Calculus can be related to crop phenology, crop management and characteristics of the growing season. As LHS and RHS Gompertz curves were only constrained by the upper asymptote being equal, but otherwise unconstrained, non-symmetrical curves could be fitted to the growing season data to better reflect seasonal change and crop management.

Daily values of Kc were predicted from the curve. Days on which the second, third and fourth derivatives of the curves were equal to zero were calculated. These correspond to the inflexion points (or the day on which there is a maximum rate of change of Kc), the day on which the rate of change of the acceleration is zero, and the day on which the maximum rate of change of the acceleration occurs respectively. These values, along with the curve parameters, were used to characterise and compare Kc curves (see Figure 2).

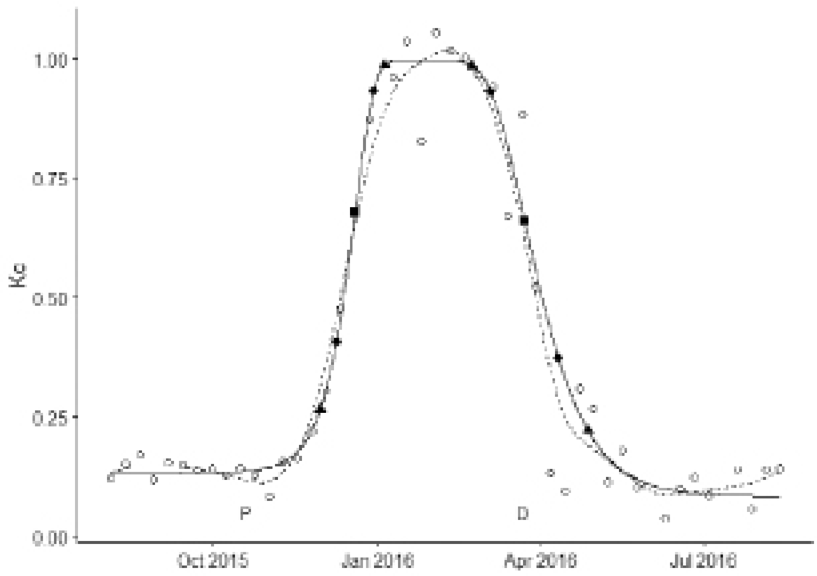

Figure 2. The time series of Kc of one cotton crop. The spline is shown as a dashed line and the fitted curve as a solid line. The curve's inflexion points (■), and where the third (■) and fourth (■) derivatives equal zero are shown, as are the dates when the crop was planted (P) and defoliated (D).

Crop transpiration

The quantity of water transpired each day was calculated as the product of the Kc value predicted by the curves and the daily ETo extracted from the SILO gridded data (Jeffrey et al. 2001) by the IrriSAT app. These values were summed to obtain an estimate of the total amount of transpiration over various time periods during the crop season.

Field data

Fields were targeted where agronomic and irrigation data were being collected. These field data were provided by:

- Cotton Seeds Distributors (CSD) from their ambassador program for the 2014–15 and 2015–16 seasons
- two commercial cotton consultants for some of their clients for the 2015–16 growing season
- Gwydir Valley Irrigators Association (GVIA) from a trial of four irrigation methods that were tested over four seasons between 2009–10 and 2015–16 on one farm.

Key agronomic data are:

- the dates of planting
- first flower

- 'cutout'
- defoliation and picking
- crop yield
- any hail or chemical damage.

Key hydrologic data are:

- quantities of irrigation
- in-season rainfall
- effective rainfall.

Not all data was available for all fields, the CSD data set was the most comprehensive.

Results

Ability to predict key agronomic events

The CSD data measured all the key agronomic and hydrologic parameters. They were able to predict key agronomic events with an accuracy of ±7 days (Table 1). This is a remarkable result given that the satellite data can be observed at any time within an eight-day window.

Table 1. The ability of fitted curve parameters to predict agronomic events, measured by the R^2 of the linear model between the predictor and the event and the standard error of the mean (SEM) of the prediction, the accuracy with which the mean of the event is predicted.

Event	2014–15			2015–16		
	Predictor	R^2	SEM	Predictor	R^2	SEM
First flower	Inflexion Pt LHS	63.3	7.37	3rd derivative (= 0) Upper LHS	71.7	7.07
Cutout	Divide	54.4	7.88	Divide	65.4	8.82
Defoliation	3rd derivative (= 0) Lower RHS	82.5	6.34	Inflexion point RHS	76.6	7.20
Picking	4th derivative (= 0) Lower RHS	75.0	10.20	4th derivative (= 0) Lower RHS	24.3	18.70

Benchmarking

Productivity variation

A large range in crop water use and yield was observed over five cotton seasons (Figure 3). The yield for a given amount of water used varied greatly and, at the extreme, the range in yield could be as wide as 12 bales/ha. This variation was present within the given years, with the 2015–16 season being the most variable (Table 2).

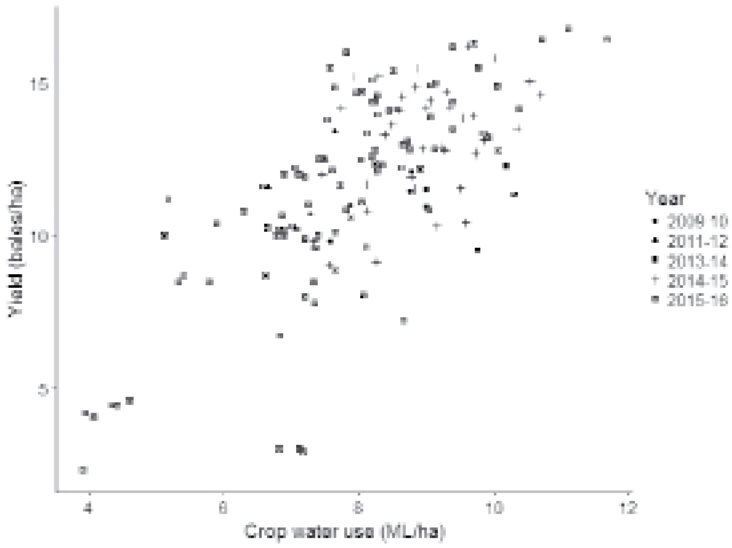

Figure 3. The variation in yield and crop water use over five cotton seasons.

Irrigation & climate

Table 2. The mean and coefficient of variation (CV) yield and crop water use in six different seasons.

Season	Yield (bales/ha)		Crop water use (ML/ha)	
	Mean	CV	Mean	CV
2009–10	11.09	8.8	8.250	7.5
2011–12	12.05	9.7	7.270	6.0
2013–14	11.05	10.5	9.498	6.1
2014–15	13.07	14.9	8.965	9.5
2015–16	11.34	30.1	7.737	20.2

Industry patterns

The group of CSD fields are assumed to represent the range of productivity present in the Australian cotton industry. There were no statistical differences in the productivity or water use between 2014–15 and 2015–16. There were trends to lower production and less water use in 2015–16, however, this lower production occurred at marginally higher water use efficiency (Table 3).

Table 3. The median productivity and coefficient of variation (CV) of the CSD sites.

Season	Yield (bales/ha)		Crop water use (ML/ha)		Water use efficiency (bales/ML)	
	Med	CV	Med	CV	Med	CV
2014–15	13.52	14.9	8.97	9.5	1.437	14.21
2015–16	12.98	19.7	8.64	14.9	1.489	15.02

Regional patterns

None of the differences observed in the water use efficiency between 2014–15 and 2015–16 were statistically significant. There was a trend to increased water use efficiency in all regions during the 2015–16 season, except in Central Queensland (CQ) (Figure 4).

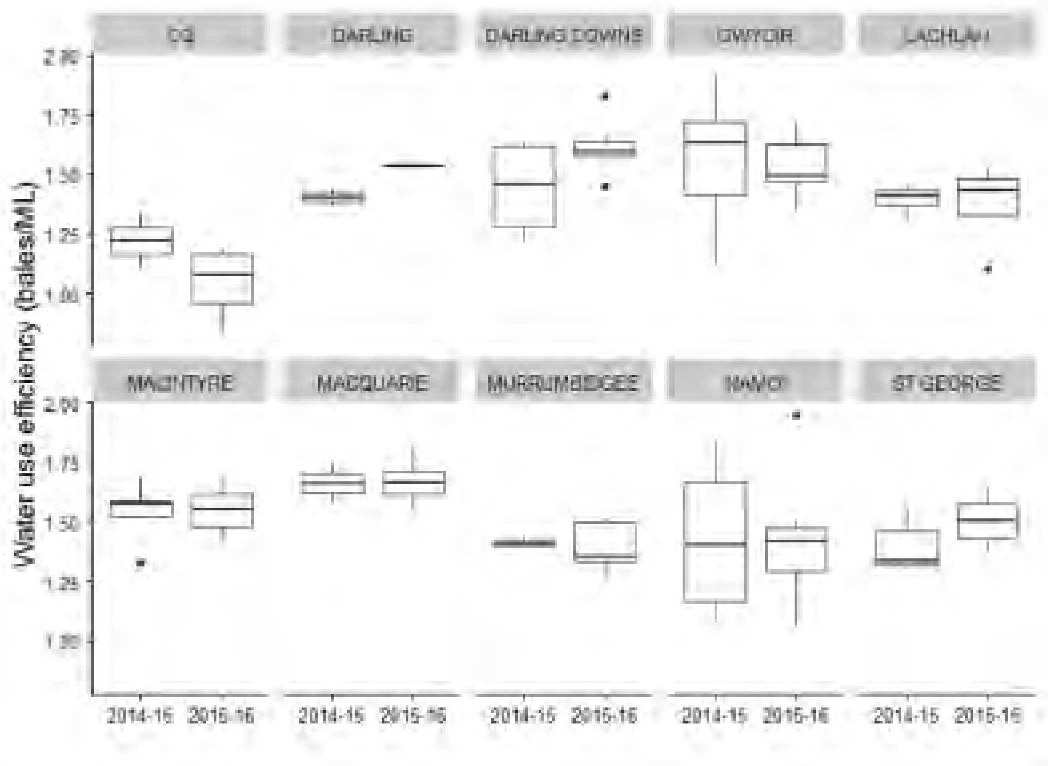

Figure 4. Regional water use efficiency over two seasons of CSD data in ten regions.

Water use efficiency of different groups on the Darling Downs

Irrigated cotton crops in the 2015–16 cotton season from the CSD data base, along with those of the clients of a consultant were compared. Only fields that did not suffer hail or herbicide damage were used in this comparison (Figure 5). The water use efficiency of the CSD fields was in the highest quantile of the whole CSD data set and had low variability. The water use efficiency of the consultant's client's fields was statistically similar, but had a wider range than the CSD fields. The consultant group contained both the most and least water-efficient crops.

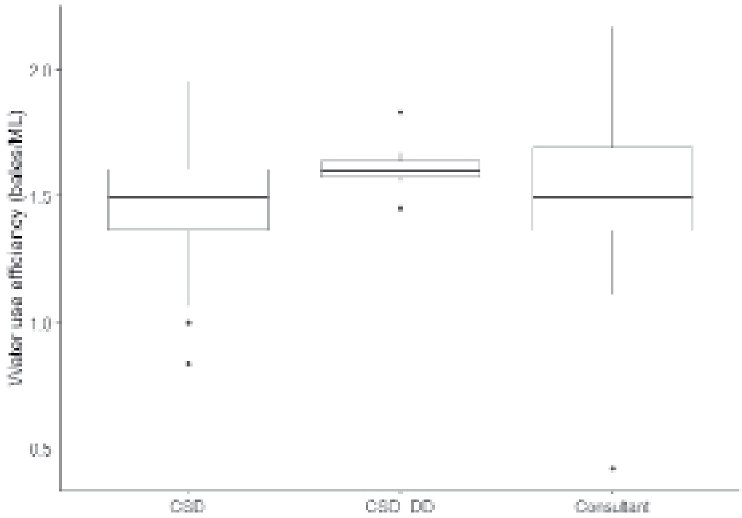

Figure 5. Water use efficiency on the Darling Downs during the 2015–16 cotton season. The range in water use efficiency of CSD ambassador fields in all regions (CSD), a subset of CSD Ambassador fields on the Darling Downs (CSD_DD) and those of a private consultant are shown.

Irrigation systems trial

There were significant differences between the water use efficiency in different years; 2011–12 and 2015–16 were more efficient than 2009–10 and 2013–14 (Figure 6). The irrigation systems had no measurable effect on the water use efficiency in a given year.

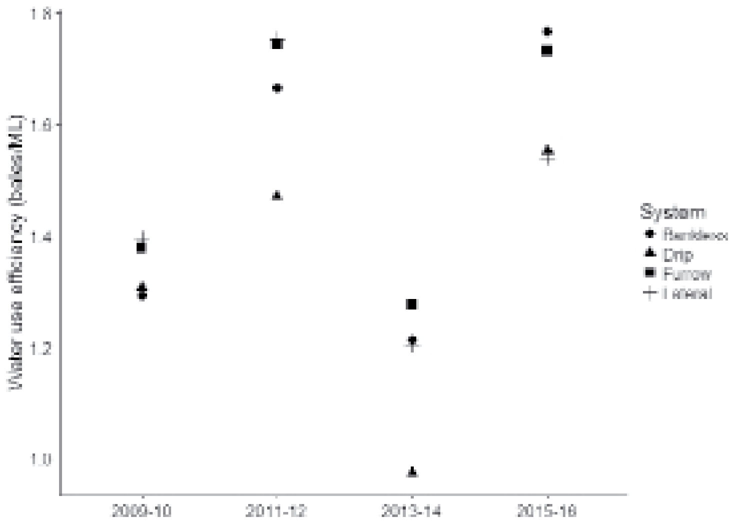

Figure 6. The water use efficiency of four irrigation systems over four irrigation seasons. These were tested on one farm in the Namoi Valley.

Summary

This study highlighted the efficiency with which data can be collected using modern, cloud-based technology, (IrriSAT 2017).

Our methods identify typical crop coefficient (Kc) curves for different regions and years. It might be possible to anchor these curves to different agronomic events (first flower, cutout and defoliation) and so allow the operational prediction of Kc and water use late in the season where irrigation management decisions are crucial and difficult.

The data sets we analysed are small, but highlight the potential of these new methods to produce metrics that allow comparative analysis both within years and between years. The most striking finding of this study was that cotton water productivity could be six bales/ha below its potential.

The work reported here shows the potential of these benchmark metrics. A time series of data for the extent of the cotton growing regions over a number of seasons is required to realise this potential. An extensive water productivity benchmarking system will need to engage on-ground collectors and custodians of agronomic data; agronomic consultants and cotton gins are the most likely candidates.

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