An assessment of the potential of remote sensing based irrigation scheduling for sugarcane in Australia

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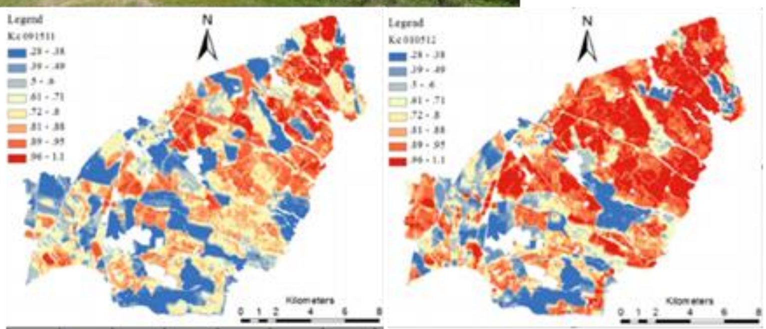

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Executive Summary

There is currently no operational method of managing irrigation in Australia's sugar industry on the basis of systematic, direct monitoring of sugar plant physiology. Satellite remote sensing systems, having come a long way in the past 10 years now offer the potential to apply the current ground-based 'FAO' or 'crop coefficient (K_c)' approach in a way that offers a synoptic view of crop water status across fields. In particular, multi-constellation satellite remote sensing, utilising a combination of freely available Landsat and Sentinel 2 imagery, supplemented by paid-for imagery from other existing satellite systems is capable of providing the necessary spatial resolution and spectral bands and revisit frequency. The significant correlations observed between K_c and spectral vegetation indices (VIs), such as the widely used normalised difference vegetation index (NDVI) in numerous other crops bodes well for the detection and quantification of the spatial difference in evapotranspiration (ET_c) in sugar which is necessary for irrigation scheduling algorithms. Whilst the NDVI may not serve as the appropriate index for sugarcane, given the potential of the NDVI to saturate at the high leaf area index observed in fully developed cane canopies, other VIs such as the Green-NDVI (GNDVI) may provide the response required. In practise, with knowledge of an appropriate K_c-VI relationship, K_c obtained from time-series (weekly) remotely sensed data, integrated with local agrometeorological data to provide ET_o, would provide estimates of ET_c from which site-specific irrigated water requirements (IWR) could be estimated. The use of UAVs equipped with multispectral sensors, even active optical sensors (AOS), to 'fill the gaps' in optical data acquisition due to cloud cover is conceivable. Cross calibration of any passive imaging system, as with the multi-constellation satellite data is essential. The use of radar images (microwave remote sensing) (for example, Sentinel 1&2 C-SAR, 5m) offers all weather, day-and-night capabilities although further work is necessary to understand the link between the radar back scatter, which is responding to surface texture, and evapotranspiration (and K_c). Further R&D in ascertaining the K_c-VI relationships during crop growth is necessary, as is the testing of multi-sensor cross-calibration and the relationship between radar remote sensing and K_c. Existing irrigation advisory delivery systems in Australia such as IrriSAT should be investigated for their applicability to the sugar industry. The estimated season cost to a user for a sugarcane irrigation advisory service in Australia, based on the use of data from existing optical satellite imaging systems and utilising the K_c approach, is likely to be of the order of US$2-3/ha.

Key Recommendations

The realisation of an operational remote sensing-based irrigation scheduling tool for the sugar cane industry requires the following:

1: A investigation of the accuracy and limitations of both model (eg P-M) and empirical (eg Kc-VI) approaches in using remote sensing to quantify the water use/demand of sugarcane crops in key Australian's cane producing regions;

2: Foremost consideration be given to utilising the NDVI –Kc- canopy ground cover (f_c) - sugarcane LAI pathway for predicting sugarcane water demand and crop water productivity.

3: The scoping/specification of an information delivery system, including evaluation of the suitability of existing delivery systems such as IrriSAT, suited to the requirements and data access capabilities of Australian sugarcane growers;

4: An investigation of the use of satellite based radar as a means of augmenting or replacing optical satellite systems for deriving crop water use and irrigation requirements of sugar cane under Australian conditions; and

5: An evaluation of alternative platform such as unmanned autonomous vehicles (UAVs), and sensor payloads (eg active optical sensors- AOS, thermal imaging) to overcome the weather-based limitations of satellite based sensor systems, or for their capacity to operate as a stand-alone irrigation scheduling tools, factoring in outputs from 1-3 above.

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List of Abbreviations

ALEXI	Atmosphere-Land Exchange Inverse
AOS	Active optical sensor
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CWR	Crop water requirement
DSM	Digital Surface model
ET	Evapotranspiration
ET_o	Reference (Grass) evapotranspiration (mm hour^{-1}) or (mm day^{-1})
ET_c	Crop/Sugarcane evapotranspiration
ET_a	Actual Evapotranspiration
ET_p	Potential Evapotranspiration
ET_{adj}	Adjusted Crop evapotranspiration
ET_{max}	Maximum Evapotranspiration
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization (UN)
fPAR	Fraction of Photosynthetically Active Radiation
f_c /V_c	Fraction vegetation cover
G	Soil heat flux
GIS	Geographical Information System
GPS	Global Positioning System
H	flux reflected back to air
IRW	Irrigation water requirement
K_c	Crop/Sugarcane Coefficient
K_{cb}	Basal Crop/Sugarcane Coefficient
$K_{c\text{-}ini}$	Crop Coefficient at initial growth period
$K_{c\text{-}mid}$	Crop Coefficient at mid of growth period
$K_{c\text{-}end}$	Crop Coefficient at end of growth period
K_e	Soil evaporation coefficient
K_s	Water stress coefficient
LAI	Leaf Area Index
METRIC	Mapping EvapoTranspiration with high Resolution and Internalised Calibration
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIR	NIR Infrared
OLI	Operational Land Imager
P-M	Penman-Monteith method
RGB	Red Blue Green composite
Rn	net radiation at the surface
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SEBAL	Surface Energy Balance Algorithm for Land
SEBS	Surface Energy Balance System
SPOT	Satellites Pour l'Observation de la Terre or Earth-observing Satellites
SWB	Soil Water Balance
SWIR	Shortwave infrared
T_a	Air temperature
T_R/T_s	Surface temperature
T_c	Canopy temperature
T_o	Near-surface vertical temperature gradient
TIR	Thermal infrared
UAS	Unmanned Aerial system
UAV	Unmanned Aerial Vehicle
VI	Vegetation Index
VITT	Vegetation Index / Temperature Trapezoid

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1. Introduction

Irrigated agriculture is under pressure not only to improve water use efficiency for sustainable water management, but also to meet an increasing demand to feed an ever growing population (Van Vuuren 2011). Effective irrigation water management assumes a space and time optimization of water inputs across each crop field, and judicious water use requires the water requirement of the crop must be determined at different growing stages (Labbé et al. 2012). Sugarcane is cultivated extensively under irrigation all around the world, however there is continued pressure on the limited water resources available to the sugar industry because of competition with other crops and an increasingly unpredictable climate in growing regions (Jarmain et al. 2014). Even 13 years ago surveys of sugarcane farmers indicated the need for more information on techniques for maximizing water use efficiency (WUE) in utilizing limited water resources and minimizing the loss of production associated with reduced water availability (Olivier and Singels 2004). Despite numerous available tools to assist producers with irrigation scheduling strategies (Culverwell et al. 1999), these are not widely used by producers for various reasons. Past research and practical experience dictates that tools for irrigation management on the farm should be simple, understandable and manageable to be adopted by growers (Santos et al. 2008; Jarmain et al. 2014; Toureiro et al. 2016). This review explores the usefulness of remote sensing (RS) based methods for irrigation water management, and irrigation scheduling for general crops, and in particular for sugarcane crops. The main body of the report focusses directly on operational dimensions of remote sensing for irrigation scheduling for sugarcane. The review then discuss the strategies for RS based sugarcane irrigation scheduling in Australia. A detailed Appendix provides necessary background to the fundamentals of sugar cane growing and biophysical processes and parameters which need to be understood in designing an appropriate scheduling tool.

2. Operational challenges and strategies for RS based sugarcane irrigation scheduling in Australia

Currently in sugarcane growing regions in Australia, sugarcane irrigation scheduling is based on traditional (non-remote-sensing) data sources, where the day-to-day estimates of crop water requirements are performed using the limited available agrometeorological station and field data (Attard et al. 2003**).** The point at which soil water may become limiting to yield accumulation is determined by stalk elongation measurements and atmospheric evaporative demand as measured indirectly using mini-pans (Shannon et al. 1996). In some sugarcane subregions, the irrigation scheduling information is communicated to the end-user in various forms, for example irrigation time or water volume (Attard et al. 2003). The process is not only labour intensive and costly but is time consuming and often unable to cover each field in extended areas at the often necessary short time intervals (Inman-Bamber et al., 2005; Inman-Bamber and Attard, 2005; Watertrack, 2017).

Research in other crops has shown improvements in irrigation scheduling in terms of accurate water-use estimation and more appropriate timing of irrigations when crop coefficient estimates derived from remote sensing (RS) based vegetation index (VI) were incorporated into irrigation-scheduling algorithms (e.g., example, Bausch 1995; Neale et al. 1996; Hunsaker et al. 2003; 2005; Singh et al. 2016; Toureiro et al. 2016). Studies, again in other crops have shown NDVI to be closely related to the water-use and transpiration of the plants (e.g., González-Piqueras, 2006). Therefore, reliable relationships between NDVI and crop coefficients (K_{cb} and K_c), and/or RS/NDVI derived crop parameters (e.g., LAI, f_c) and K_{cb} and K_c, are the most likely candidates for RS based irrigation management and scheduling for sugarcane in Australia, especially given the limited work reported for sugarcane (e.g., Jarmain et al. 2014; Singh et al. 2016). Generally, a correlation equation needs to be defined to relate biophysical crop parameters (LAI, f_c) with NDVI (or other VIs) and K_c/K_{cb}. Time series NDVI can be used to monitor crop growth and to derive crop biophysical parameters for the entire growing season. The crop coefficient maps could be created by dividing the ET_c maps derived from surface energy balance equation (e.g., SEBAL, METRIC, etc) by ET_o. The ET_o maps themselves would be generated by interpolation of weather data located close to the target area. The K_c value is interpolated between each image date to define the temporal evolution of K_c values and to obtain the K_c curves (Santos et al. 2008). The RS based ET_c is then combined with a water balance model to provide accurate irrigation scheduling guidelines for individual fields.

2.1 Scoping sugarcane producer requirements

The precise information on the condition of every pixel of sugarcane field (e.g., water requirement) and irrigation recommendations empowers growers to make smart irrigation decisions. The combined use of up-to-date, high resolution satellite data on field status with local weather conditions and field-tested agronomy models helps irrigation authorities to anticipate their expected irrigation requests by matching irrigation schedules to actual crop water requirements. Getting irrigation just at the right time and amount can make the difference between productive, profitable, consistent and sustainable sugarcane production. The RS based irrigation management system must pay attention to the three basic tenets of market services; namely-

(a) Timely acquisition, or coordination of acquisition with data provider given components of a satellite virtual constellation;

(b) Timely post- processing of data, including inter-satellite calibration, product generation and quality checking; and

(c) Integration into the delivery system and capability of providing timely access to end users (irrigators and farmers).

2.1.1 Spatial and Temporal resolutions of RS data

The RS data required at an operational level must meet the appropriate temporal and spatial resolutions for irrigation scheduling needs. The spatial resolution of imagery must match with the irrigation field sizes, and also the scale at which the imagery be used: farm level, local-regional level. The required spatial resolution must also ensure the presence of a sufficient number of meaningful pixels specific to sugarcane after the internal buffer is applied to each field boundary (edge effect) and also after removal of other adjacent features such as roads, trees, etc. In addition, the desired spatial resolution should also be high enough to detect within field variations and, if required, intra-field variability.

Ultimately, a very high spatial and temporal resolution RS dataset is required to get daily ET_c for soil water balance to determine field-based ET_c demands and subsequent field-scale irrigation schedules. Time series maps of relevant parameters such as crop coefficient will need to be at a spatial resolution of 10–30 metres, and certainly no lower. This resolution allows for identifying sugarcane plots of 1000–10000 m^2, which cover the size ranges most frequently found in irrigated sugarcane fields in Australia. Sub-field spatial resolution is necessary (1-5 m) if the user seeks to identify candidate locations for supporting on-ground infrastructure such as Soil Moisture Probes, Telemetry and other Proximal Sensors. The second component is to provide tools to handle spatial data and distribute irrigation information to the farmers or irrigators. In addition, sugarcane irrigation advisory cycles of 7-10 days are necessary, and at higher frequencies if possible. During the peak growth periods, sugarcane growth and associated changes in crop coefficients can be significant. Therefore time-series RS data at a seven day interval are required to generate weekly irrigation advice. Temporal resolution of 7 days is important, and in cases of poor weather condition or cloud cover that interferes with the image quality, the RS data from other sources such as UAV (Unmanned Aerial Vehicle) or Radar can be used to fill the data gaps. Cloud cover is definitely a limiting factor regarding the availability of multispectral satellite imagery, particularly in northern QLD, where it is possible to go few weeks at a time without having a suitable satellite (Landsat/Sentinel 2) image.

2.1.2 Sugarcane growing season

Across the sugarcane growing regions in Australia, sugarcane planting starts in mid March and continues until late September, while ratooning begins in early June and continues until late November or early December. This suggest that there is always a developing canopy (i.e. crops between 0-4 months of age) in almost every month of the year. This would suggest that the need for regular satellite images is required for almost the entire 12 months of the year.

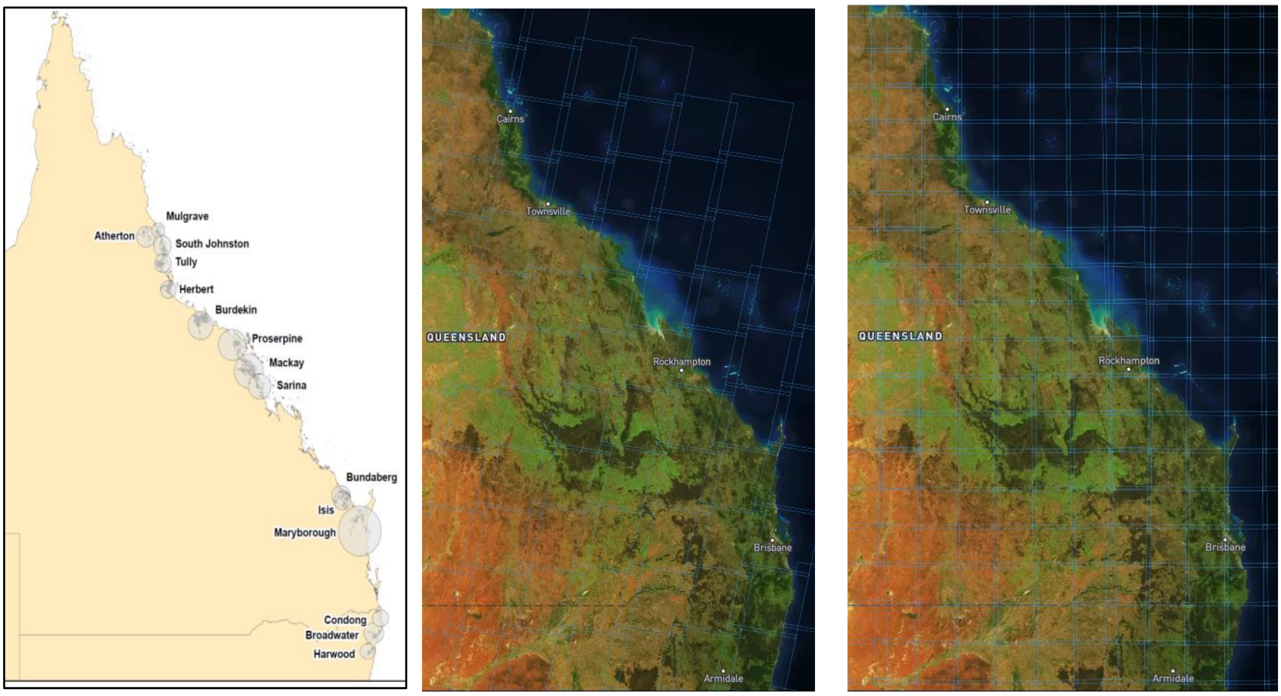
2.2 Remote sensing systems available to provide the required spatial and temporal resolution for sugarcane irrigation scheduling

Table 1 lists currently available, multispectral satellites systems that offer a spatial resolution in the desired range, along with details of coverage, revisit frequency and indicative cost (in US dollars, July 2017). The US Geological Survey allowed open and free access to georeferenced Landsat (30m) and ASTER (15m) data and the European Space Agency similarly offers free access to Sentinel-2 (10m) images (https://earthexplorer.usgs.gov/). A range of commercial sensors offering very high spatial resolution of 1–5m (for example Worldview3/2, QuickBird2, GeoEye1/2, SPOT6/7, RapidEye, PLEIADES) at cost offers the potential of monitoring smaller size fields and within-field spatial variability. The medium resolution satellites DMC and DEIMOS offer very frequent land observations with increasing capabilities with modest data costs (Table 1).

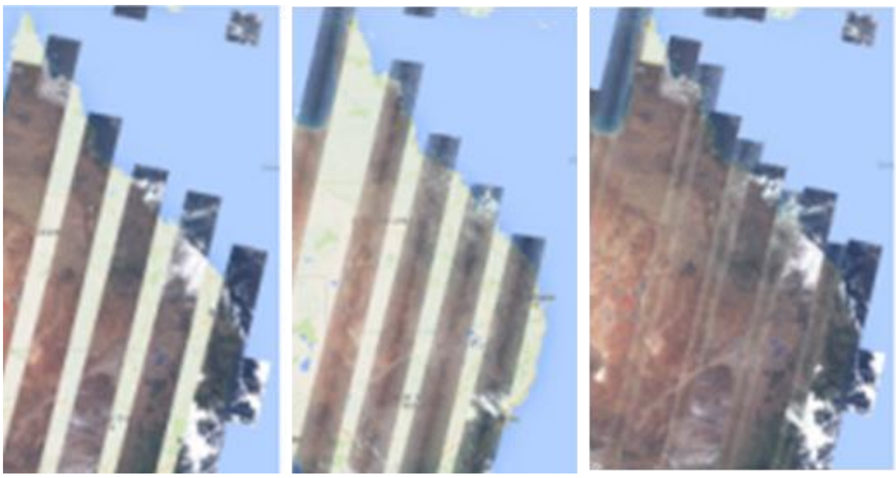
Table 1 Optical remote sensing satellite sampling characteristics in the virtual constellation (cost as of July 2017).

Multispectral (MS) Data					
Satelliete/Sensor	**Spatial Resolution**	**Multipscetral bands (optical, NIR and SWIR)**	**Revist Cycle**	**Swath**	**Cost***
Landsat 8 OLI	30m	B,G,R,NIR,SWIR1,SWIR2	16 days	170km x 185 km	Free
Landsat 7 ETM+	30m	B,G,R,NIR,SWIR1,SWIR2	16 days	185km x 185km	Free
Sentinel-2A	10m	B,G,R,NIR	10 days	290 km x 290km	Free
Aster	15m	G,R,NIR	16 days	60km x 60km	Free
SPOT6/7	6m	B,G,R,NIR	1-5 days	60km x 60km	$1.20/Km2
RapidEye	5m	B,G,R,RedEd,NIR	1 day	77km x 77km	$1.28/Km2
GeoEye1/2	1.8m, 1.24m	B,G,R,NIR	<3 days	15km x 15km	$17.5/Km2
WorldView3	1.24m	B,G,Y,R,RedEd,NIR1,NIR2	<1 day	13km x 13km	$22.5/Km2
WorldView2	2m	B,G,Y,R,RedEd,NIR1,NIR2	1-2 days	16km x 16km	$12/Km2
QuickBird2	2.4m	B,G,R,NIR	1-4 days	16km x 16km	$17.5/Km2
Plaides-1A	2m	B,G,R,NIR	Daily	20km x 20km	$11.6/Km2
Planet	3m	B,G,R,NIR	Daily	20km x 12km	on inquiry
DMC	22m	G,R,NIR	1-2 days	upto 620KM	$0.31/Km2
Deimos1	22m	G,R,NIR	2-3 days	up to 625 km	$0.07/Km2
B=Blue (0.4-0.5μm); G = Green (0.5-0.6μm); R = Red (0.6-0.7μm); NIR=Near Infrared (0.7-1.3μm), NIR1 (0.77-0.89μm), NIR2(0.86-1.04μm); SWIR = Shorwave Infred (1.3-8μm), SWIR1=(1.55-1.75μm), SWIR2(2.09-2.35μm); RedEd = RedEdge (0.70- 0.74μm); Y = Yellow (0.58-0.62μm)					
* tentative cost in USD (source: https://apollomapping.com/)					

The revisit capabilities of the freely available high-resolution satellites (Landsat, ASTER, Sentinel-2) ranges between 10–16 days, and considering the potential presence of clouds on the day of satellite pass, the resulting single-satellite revisit time of any given area would likely be insufficient for operational irrigation scheduling tasks. Meeting an irrigation advisory cycle of 7-10 days requires access to a combination of currently available high-resolution satellites in a virtual constellation. For example, revisit cycles of Landsat 8 (OLI) and Landsat 7 (ETM+) have offset of 8 days from each other, therefore combining two provides full coverage of every 8 days (Figure 1b). For Landsat 7, SLC-off is a problem as it causes striping and therefore it is necessary to combine at least 2-3 overpasses to get a "complete" Landsat 7 image. Table 2 shows the RS and field based derived parameters for sugarcane growth monitoring and irrigation planning, and RS data descriptions (spatial and temporal scale, frequency, cost and coverage) for these measurements.



(a) Sugarcane regions in 2017 Landsat 8 data coverage Sentinel 2 data coverage



(b) Landsat 7 Landsat 8 Combined

(c) Path/Row of Landsat 8 and Scene Id of Sentinel 2 over the sugarcane growing regions

Mill Region	**Landsat 8**	**Sentinel 2 Scene**	**Mill Region**	**Landsat 8**	**Sentinel 2 Scene**
Atherton	96/72	55KCA 55KCB	Isis	90/77	56JMT 56JLT
Broadwater	89/80	56JNN 56JNP	Mackay	93/75 93/74	55KGS 55KFS
Bundaberg	90/77	56JMT 56JLT	Maryborough	90/78	56JMS
Burdekin	94/74	55KET 55KEU	Proserpine	93/74	55KFT
Condong	89/80	56JNP	Sarina	92/75 93/75	55KGS 55KGR
Gordonvale/Mulgrave	95/72	55KCA 55KCB	South Johnston	95/72	55KCA
Harwood	89/80	56JNN	Tully	95/73 95/72	55KCA 55KCV
Herbert	95/73	55KCV 55KDV			

Figure 1 Sugarcane growing regions in Australia in 2017 and coverage area of Landsat 8 and Sentinel2 (a); Combined coverage of 8 days (Landsat 8 &7) (b); and Path/row of Landsat 8 and Sentinel 2 (c).

Table 2 RS based parameters for Sugarcane growth monitoring and irrigation planning

Parameters	RS derived and other products	Spatial Scale, Temporal scale and level of information	Satellite and other Platform RS data (please refer Table 1 for more details)			
			Frequency of use in irrigation studies	**Pre-processed datasets accessible**	**Image data cost w.r.t. field size**	**World Coverage /Historical archive**
Sugarcane Crop Monitoring (Crop Type, Crop Growth Stage, Crop Performance (crop growth against water used), Tracking potential growth, Biomass/Yield Production, Relative performance of field compared to similar field	Vegetation indices (NDVI, GNDVI), Biomass, Yield Forecast, Classified maps	**Pixel/Plot/Regional level** **Daily/weekly/real time** **Field Scale-**Performance Variation, timely identification of problematic area, suggested mitigation measures, spatio-temporal water and nutrient management, Product optimization (accuracy, save time and money) **Regional Scale-** Bird's eye view of cropping area, identification of underperforming area, spatio-temporal water and nutrient management, reduce cost	High (Landsat OLI, ETM+) Medium (Aster/Sentinel/ SPOT/Deimos) Low (RapidEye, Quickbird, Worldview, others) Low UAV, Radar	Yes Yes Yes No/Yes	Free/Low Free/Low/ High High High	Yes Yes/No Yes/No No/Yes
Irrigation Planning (right volume, right time and right location)	Maps for Kc, ETc, Soil Moisture, Crop Water Requirement, Soil stress or Soil water deficit	**Pixel/Plot/Regional level** **Daily/weekly/real time** Determination of extent of crop water need in real time, notification of irrigation requirement to avoid crop damage, generation irrigation advisory for coming week	High (Landsat OLI, ETM+) Medium to Low (others)	Yes	Free to Low	Yes
Field and other information (Weather forecast data, Rainfall, Temperature, Actual irrigation volume, soil type)	ETo, Soil Water Balance (NOAA AVHRR based Eto at regional scale)	**Pixel/Plot/Regional level** **Daily/weekly/real time**	High High (NOAA AHVRR)	Yes Yes	Free to Low Free to Low	Yes Yes

Figure 2 shows the revisit dates of the freely available satellites (Landsat-8 OLI, ETM+ and Sentinel-2A) during the 2015-16 and 2016-17 growing seasons of four major sugarcane growing areas in Australia (e.g., Burdekin, Bundaberg, Maryborough and Isis). An indicative, characteristic crop coefficient (K_c) curve of sugarcane, based on FAO-56, has been superimposed on each plot to illustrate the phenological cycles of sugarcane grown in each respective area. Typically planting-ratooning occurs during August-October, initial growth (25%-50%) between November and December, full plant cover (100%) exists around January to May and senescence/harvest occurs around June-July.

During the 2015-2016 growing season (Nov-Oct), only from Landsat OLI and ETM+ sensors were freely available and there were more gaps (in days) between satellite overpasses to obtain cloud free data for all four growing areas, particularly during initial and mid growing seasons. However, after free online access to Sentinel-2A images became available in November 2015, greater flexibility to acquire cloud-free scenes resulted in fewer gaps at the end of growing season, and also for the beginning of 2016-17 growing season. This is more evident in Burdekin, Bundaberg and Isis regions. However weekly irrigation advisories for the entire growing season (4-8 months) cannot be supported by the freely-available satellite systems on their own; the 2015-16 and 2016-17 (till March 2017) periods do not indicate that degree of temporal coverage is available. In such cases other high resolution satellite data such as SPOT 6/7, RapidEye, DMC, Planet and Deimos1 could be used to fill these gaps in the time series, albeit at cost to the user.

Notwithstanding the issue of revisit frequency and cloud free imagery, the delivery time of images can often be of the order of days, and in some cases weeks, unless particular arrangement are made with data providers for rapid delivery. In the context of a weekly (or better) advisory service, data can, and should, be made available within a few hours after image acquisition time, and the common arrangement is for direct download by means of file transfer protocol (FTP). This is no longer a big 'ask' from providers; ten years ago the DEMETER (DEMonstration of Earth observation TEchnologies in Routine irrigation advisory services) project in Europe was capable of offering Lansdsat 5-TM satellite data acquired at 10:30 GMT on the same day at 15:00 GMT (Belmonte et al. 2005). Rapid access to data may incur a processing fee and it is worth checking with providers.

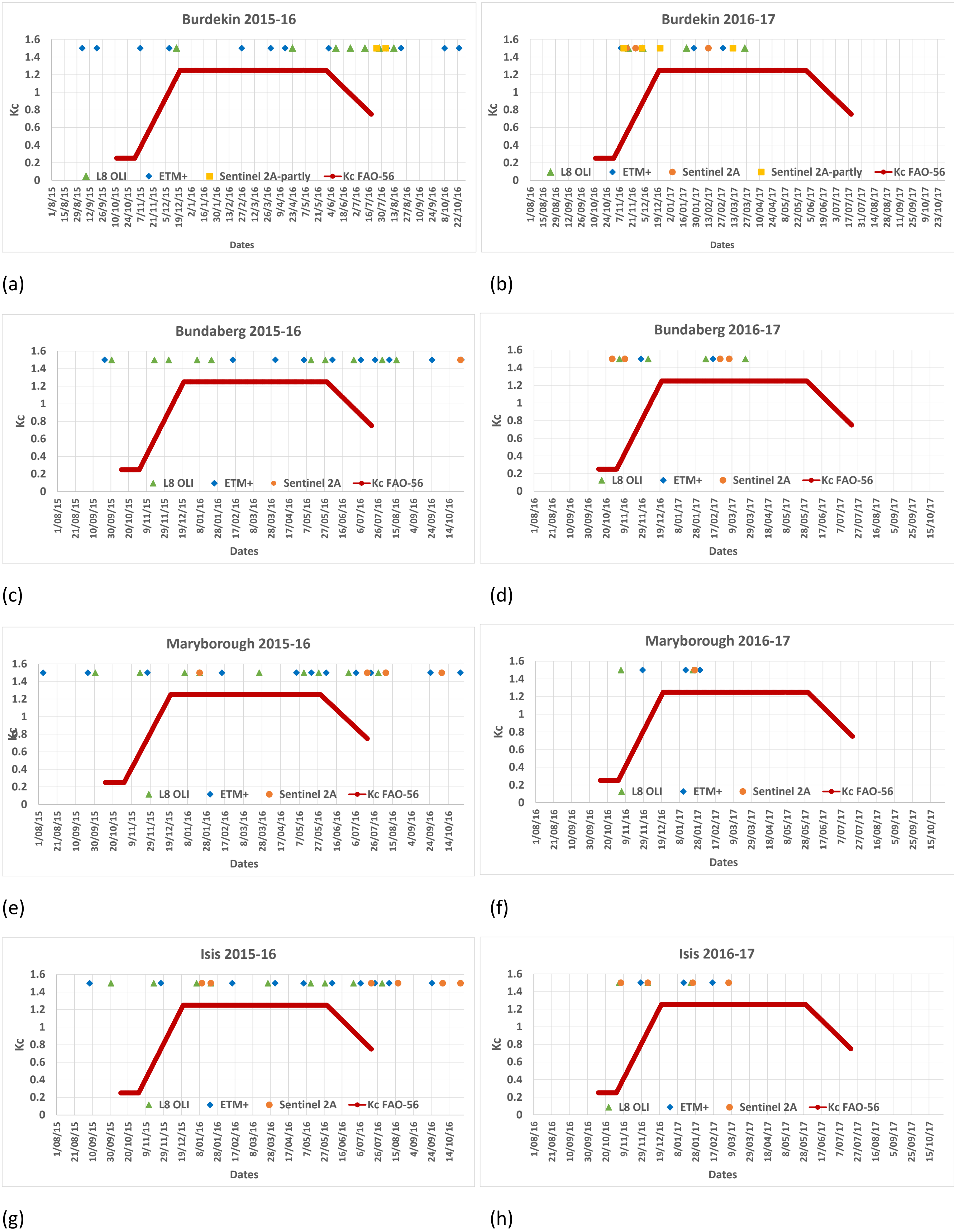


Figure 2 Temporal evolution of sugarcane crop coefficient (K_c) based on FAO-56 and corresponding satellite overpasses for Landsat OLI, ETM+ and Sentinel-2A during 2015-16 and 2016-2017 (till March 2017) growing season (Nov-Oct) in Burdekin, Bundaberg, Maryborough and Isis regions.

2.2.1 Cloud free data from other sources (UAV, Radar)

UAV systems offer the ability to fill the gaps if advisory data is urgently required. If having to use UAVs, unless the instrument is owned and operated by the grower, the costs would be prohibitive on such a short return monitoring interval as 7 days. Also, the use of radar based satellite systems images (microwave remote sensing) as another possibility. Details on this can be found in appendix sections A3.1.2 and A3.1.3 of this document. It must be emphasised that the backscatter signals from radar systems is based on the physical structure of a canopy rather than leaf pigments such as chlorophyll. Radar data from Sentinel 1 is free and has good repeat cover, however it is difficult to interpret in regard to sugarcane due to its high sensitivity to soil moisture. Nevertheless studies have shown sensitivity of radar data to sugarcane growth stages and also similar variation as NDVI change in time-series (for example, Baghdadi et al. 2009). Thus combination of the radar Sentinel-1 and the optical Sentinel-2 (a & b) systems could conceivably be used to create radar-NDVI relationships, and during periods of cloud cover the radar-only platform could then be relied upon to provide a surrogate for the NDVI. More research work is needed to identify and evaluate the links between backscatter and crop coefficients.

2.2.2 Crop Water Use (ET_c)

Crop water requirements (ET_c) can be estimated through reference evapotranspiration (ET_o), and a crop factor called crop coefficient (K_c) as $ET_c = ET_o * K_c$ (more details can be found in appendix section A1.2). For a specific crop in a single location, computing K_c by direct methods (lysimeters, energy balance, and soil water balance) is difficult and expensive. In such situation, generic K_c values are typically used, which often do not match the actual crop water use due to several factors (differences in canopy and agronomic management, row spacings, etc). Indirect methods can be used for this purpose to provide site specific crop coefficients. Studies have shown sugarcane Kc to be closely related to the canopy ground cover fraction (f_c) and LAI which can be estimated from RS-derived NDVI (equation 1, 2 and 3). Thus, RS methodology integrates information from satellite sources (NDVI; K_c) and from on-ground weather stations (ET_o) to estimate site-specific crop water requirements at each individual pixel. The K_c for all pixels are used to determine the crop coefficient for a field by calculating the arithmetic mean of all pixels within its boundary. At plot level, time series K_c maps at an interval of 7-10 days and spatial resolution of 10–30 m are required, and if the estimated K_c or LAI is to be fed into a crop model (e.g., IrrigWeb) then periodic adjustment would be acceptable. The cloud-affected pixels in the satellite image should be identified and removed. The missing pixels can be backfilled with secondary satellite data, to derive blended NDVI. This is used to compute K_c at pixel level and then aggregated for the entire paddock. This spatial algorithm can be reused for time series data processing.

2.3 Algorithm generation, data processing, product generation and validation

The coordinated use of data sourced from different satellite systems in a virtual constellation would require inter-satellite cross-calibration and image co-registration. For this purpose, Calera et al. (2001) has developed a multi-temporal data-synthesising procedure that uses synchronous, or near-synchronous, imagery from different sensors over the same ground footprint. They showed that reflectance and vegetation indices obtained from different spectral bands of different sensors can be compared with high reliability by means of simple correlation procedures. Mart´ınez et al. (2003) demonstrated the joint use of multi-temporal multisensory data with some acceptable spatial degradation. The basic processing comprised of geometric and atmospheric corrections, reflectance estimation, NDVI computation, calculation of K_c maps and other products. This operational procedure assures two points of RS data quality control; detection of cloud cover, and accounting for the values of maximum NDVI for completely green cover and the minimum NDVI value for bare soil. These quality controls enhance the reliability of the image sequence. Table 3 shows an examples of remote sensing based Sugarcane Irrigation studies conducted and types of data product generated in different parts of the world.

Table 3 Examples of Remote Sensing based Sugarcane Irrigation studies conducted in different parts of the world

Method	Algorithm/ Data Used	Derived Parameters	Country	Outcome	Reference
Remote Sensing based surface energy balance (RS-SEB model)	SEBS/ Meteosat (MSG), SPOT-Veg, Terra/MODIS	Actual ET (ETa)	Brazil	Good correlation between ETa-SEBS and ETc (FAO) at maximum sugarcane developing sate (Kc=1.25), overestimation of water use at late sugarcane development stage	Ferreira et al. (2016)
	SEBAL/ MODIS	Daily sugarcane ETc	Rio, Brazil	High correlation ET integrated over 24 hours ET24h (FAO) and ET24h (SEBAL)	Mendonca et al. (2003)
	SEBAL/ DMC (every ten days), TIR/MODIS, SRTM DEM	ETc, Biomass, Yield, Water use efficiency (WUE)	South Africa	WUE information can be applied at operational level	Jermain et al. (2014)
	METRIC/ Landsat 7 Time-series	ETc, Kc, NDVI, f_c	Hawaiian	High correlation (R2 = 0.82) between ETC and Kc	Zhang et al. (2015)
	SEBAL/ DMC, MODIS	Canopy Cover, ETc, Biomass production Biomass Water use Efficiency (BWUE)	South Africa	Satellite based Canopy cover estimate was more accurate than crop model (Canesim), SEBAL data could identify sugarcane area with water deficit, slow growth or low yield at filed, farm and regional scale.	Singles et al. (2014)
	VITT/ Vegetation index-Temp Trapezoid Landsat Time series (TIR band)	ETc, Ts (surface temp), NDVI	Northern NSW, Australia	Consistent negative correlation between Ts and NDVI over sugarcane field, VITT showed potential for evaluating field water availability and assessing the variation on actual ET rate at local level.	Yang et al (1997)
	SEBAL, SSEB/SSEBop Landsat 7 ETM+	Actual ET (ETa)	Ethiopia	Higher ETa values for well-watered sugarcane field in the mid-season growth stage because of grater consumption of wtaer	Genanu et al. (2016)
Remote sensing based Vegetation Index (VI) and or Leaf Area Index (LAI)-crop coefficient relationship (RS-VI (LAI)/Kcb)	VI-Kc/ Landsat 7 Time-series	ETc, Kc (sugarcane), NDVI, f_c	Hawaiian	Very strong relationships between sugarcane NDVI and f_c (R^2 = 0.97) and also f_c and sugarcane K_c (R^2 = 0.89).	Zhang et al. (2015)
	LAI-NDVI/ SPOT4, SPOT 5	LAI, NDVI	Reunion Island	Strong relationship between LAI and NDVI using an exponential function (R^2=0.86) and used NDVI profiles to estimate LAI on a daily basis	Bappel et al. (2005)
	LAI-NDVI/ Landsat7 TM Time-series	LAI, NDVI, hourly variable canopy resistance (r_c), sugarcane water demand and crop water productivity	South Africa (both rain-fed and irrigated fields)	LAI for sugarcane was estimated from NDVI using the empirical relationship defined by Bappel et al. (2005). The study confirmed the sugarcane's ability to regulate and maintain a constant canopy resistance r_c with different LAI under non water-stressed and optimal climatic conditions.	Bastidas-Obando et al. (2017)
	NDVI-Kc/ Landsat-8 Time-series	NDVI, Kc, albedo, Crop water requirement	India	High correlation between ground-based K_c and NDVI and surface albedo. Estimated that with the quality of the data generated could reduce water consumption by 12.5% compared to the 'conventional approach'	Singh et al. (2016)

Please see Appendix A for more details on each method

2.3.1 Sugarcane Crop Coefficient (K_c/K_{cb})

As discussed earlier, the crop coefficient (K_c) provides an insight into water constraints and, in the light of previous work undertaken, K_c can potentially be derived directly from satellite images. The sugarcane K_c curves shown earlier in Figure 2 aid to identify growth periods where high temporal resolution of image data is required (that is prior to or following the plateau in the stage). Here, the simplest approach is to utilise the linear relationship between NDVI (derived from the red and near infrared reflectance) and K_c following Moran et al. (1997). Ratio-based VIs such as the NDVI are well suited to inter-satellite sensor cross-calibration (Calera et al. 2001; Teillet et al. 2001; Steven et al. 2003). Little information is available in the scientific literature concerning the sugarcane K_c-NDVI relationship (most is concerned with yield-NDVI relationship). Work on other crops is certainly encouraging, including corn (Bausch and Neale 1989; Bausch 1993; 1995) and vineyards (Vuolo et al. 2015a).

Recently, Zhang et al (2015) used time-series Landsat-7 to establish the relationships between K_c, canopy ground cover (f_c), and NDVI over two sugarcane fields in Hawaii:

$$f_c \text{ (sugarcane)} = 1.312 * \text{NDVI (sugarcane)} - 0.1921 \qquad (R^2 = 0.97) \qquad (1)$$

$$K_c \text{ (sugarcane)} = 0.7489 * f_c \text{ (sugarcane)} + 0.2776 \qquad (R^2 = 0.89) \qquad (2)$$

The study effectively linked K_c to NDVI via linear relationship. Bappel et al. (2005) determined the exponential relationship between sugarcane LAI and NDVI generated from time-series SPOT 4 & 5 images as:

$$\text{LAI (sugarcane)} = 0.0407 * \text{Exp } (7.0345 * \text{NDVI}) \qquad (R^2 = 0.86) \qquad (3)$$

Using the empirical relationship defined by Bappel et al. (2005), In South Africa, Bastidas-Obando et al. (2017) estimated LAI for sugarcane from NDVI derived from Landsat7 TM time-series to calculate an hourly variable canopy resistance (r_c) value to predict sugarcane water demand and crop water productivity for both rain-fed and irrigated fields. More research is required to confirm the transferability of Equations 1-3 for different region, which includes the robustness of the NDVI at very high LAI values and/or at least the protocol for generating similar local relationships.

Since NDVI values are directly related to f_c, it can be expected that the NDVI values would similarly be low at the initial sugarcane growth period, then peaking at full growth period, and then decreasing at the final stage due to senescence of the crop. This ability of NDVI to detect sugarcane growth pattern including the senescence of the crop is important for irrigation management. It is also important here to notice the duration of the growing phase, because studies have shown deviations from standard FAO reference values (for example Toureiro et al. 2016) will occur as a consequence of variations in planting date and local climatic conditions. For fully established crops, it remains to be seen whether the NDVI is sufficiently responsive enough, or whether, as asserted by Rahman and Robson (2016), alternative indices should be explored.

2.3.2 Local field Validation to establish sugarcane K_c/K_{cb}-VI relationship

Some form of local field validation is likely to be required to establish the K_c or K_{cb}-VI relationship in a given sugarcane growing area for the entire growing cycle. The spectral response can be measured by means of a spectro-radiometer with a range of 0.3-2.3µm. The K_c and K_{cb} would be determined from green plant cover following Allen et al. (1998) for the entire growing period to see the temporal evolution of crop height, biomass, green plant cover, leaf area index (LAI), K_{cb}/K_c and VI. Determining K_c itself is not trivial and detailed evapotranspiration measurements are necessary, either directly using some form of evapotranspiration dome (for example as used by Murphy et al., 2004) or using lysimeters. These ground truth data samples distributed over the entire area (large and statistically significant) would be used to validate and calibrate the method to derive K_c from VI and also for on-going quality control of the RS-derived products.

2.4 Information delivery for irrigation scheduling

The decision whether or not to irrigate can be informed by a tool that utilises remote sensing, but ultimately the decision will also involve other sources of information such as impending rainfall, availability of water and other farm resources (for example staff to manage a cycle). Irrespective of whether other pieces of information need to be specifically included within a single decision advisory tool, the dimension of the tool that utilises the remotely-sensed data must present it in a way that is intuitive and fit for purpose- namely advising on the need to irrigate and how much water to apply. One approach is to simply create digital maps of crop water requirements (CWR) for irrigation scheduling and to distribute that information to the users by different means such as via the internet (for office or mobile smart phone access).

This would require that data be integrated into some form of geographic information system (GIS) to calculate CWR and generate irrigation scheduling information (for example, irrigation water volume or time, etc.) at the appropriate scale, such as plot level. Other information would likely need to include crop phenology data, for example from field based observations, certainly agrometeorological station data, reference climate data, possibly integrating rainfall radar data, last 24 hour rainfall, seasonal accumulated precipitation maps, and short/medium-term weather forecast maps.

2.4.1 The need for ongoing evaluation of sugarcane irrigation advisory products and services

The validation of any sugarcane irrigation advisory system can be carried out at both technical-experimental level and also at users' level (information products, tools and services) using a range of evaluation methods. The modelled soil water balances can routinely be compared with logged soil water monitoring data (e.g., IRES, http://www.naturalresources.sa.gov.au/southeast/water-and-coast/Irrigation-management/Irrigation-scheduling) designed to use irrigation records from growers as a scheduling and water management tool.

The quality of RS-based sugarcane K_c/K_{cb} can be assessed by means of comparison with ground truth data from field data visits (for example, FAO based). The sugarcane K_c/K_{cb} values (averaged for different growth periods) derived from time series VI and the values for $K_{c\text{-}ini}$, $K_{c\text{-}mid}$, $K_{c\text{-}end}$ from FAO-56 can be compared easily enough. With the local calibrations necessary to account for the soil evaporation effects, a benchmark of keeping any variance of K_c within tolerances of, for example ±5% can be achieved using established, long term monitoring plots.

The evaluation of any nascent RS-based irrigation advisory system can be undertaken by established (farmer or agronomic service provider) reference groups at each of the sugarcane growing areas (Burdekin, Bundaberg, Maryborough, Isis, etc.), not only for monitoring the veracity of any algorithms but also the delivery system(s). This approach could be based on the Producer Research Site (PRS) model utilised, with success, by Meat Livestock Australia (MLA).

Belmonte et al. (2005) provides some key ingredients when it comes to delivering an irrigation advisory system, principal of which is the facility/capability to offer personalised delivery layouts. Farmer feedback provided Belmonte et al. (2005) with other presentation ingredients, including incorporating information (RGB image) about spatial distribution of crop status (that is inside a homogenous crop and also crop vigour across each plot) as farmers are quick to develop-situational awareness from a 'synoptic' view, allowing intuitive interpretation of crop growth and water requirement over a given management unit. Also, the spatially resolved RS-based data products can easily be combined with plot boundary or water user group (WUG) data in GIS, which can allow personalization of the irrigation scheduling recommendation, if integrated into a simple text advisory message.

2.5 What is the likely cost for a remote sensing-based sugarcane irrigation advisory service?

The annual cost of RS-based irrigation scheduling services for sugarcane in Australia, based on providing basic products such as K_c maps derived from NDVI, can be estimated based on utilising cloud free (<5%) Landsat, Sentinel 2A and ASTER data (available free of charge), and other satellite data sources at cost to the user (for example SPOT6/7, RapidEye, etc) to fill the temporal gaps in the time series. On average, 36 images (3 images/month x 12 months) would be required for the entire sugarcane growing season (Nov-Oct), including planting/ratooning. The data cost in Table 1 is given in terms of USD/km^2, that is, for each 100ha of irrigated land. The costs (USD) to users for image purchase, personnel cost for data processing and product generation and data transfer for a given area can be computed on the basis size of irrigation area and number of images purchased.

The additional cost of RS based service would have to be evaluated against the potential benefit that is added as compared to existing advisory services (e.g., IrrigWeb or any other crop model). If data from another platform such as UAV or fixed camera is used, there will be added cost in terms of UAV and camera purchase, software and processing costs, obtaining license and training, etc. In addition, for large scale monitoring, a large volume of data and considerable post-processing are required. Not doubting the potential of UAV data in providing very high resolution cloud free data in real time and on demand, its use can be restricted to filling data gaps in time-series to minimize costs and efforts in irrigation management tasks.

For the satellite-based grapevine irrigation advisory service, IrriEye, in the South Australian Murray-Darling Basin, Vuolo et al. (2015a) estimated the cost to be around US$8–11/ha (>

300 ha aggregated area) with 10–11 image acquisitions from DEIMOS-1 satellites during the entire irrigation season. They pointed out that, with the expected reductions of market prices of high resolution satellite images, including the use of freely-available systems, the RS-based irrigation services will become even more cost-effective in the near future. At the present rate of DEIMOS-1 satellites (Table 1), for the same area of 3000 ha with 10-11 images, the RS-based irrigation service cost can be estimated to be US$2-3/ha. Additional cost is also required for necessary ground truthing field work and for the quality-control of the RS-based products, and also for the generation of advanced products (f_c, LAI, fPAR, biomass, irrigation performance indicators, water stress indicator, canopy water content, evaporative fraction). Vuolo et al. (2015b) analysed cost and benefit for different remote sensing data cost scenarios and evaluated the willingness of the farmers to pay for the information generated by the project in Austria. Their results clearly indicated that, the economic benefits could be achieved by reducing irrigation volumes, and farmers in general were willing to pay either directly or via cost sharing, for such a service. They calculated the cost of the service based on different cost scenarios (Variable costs – include the initial farmer's database implementation and a dedicated customer service; and Fixed costs – service coverage/area, satellite data acquisition and processing. For a 20,000 ha regularly irrigated land, they estimated advisory service cost between 2.5 and 4.3 Euro/ha per year depending on the type of satellite data used. They concluded that, with a correct irrigation application, more than 10% of the water and energy could be saved in water-intensive crops, which is equivalent to an economic benefit of 40–100 Euro/ha per year.

2.6 Comparison with other existing products

There is always a need to compare data sources when modelling or even measuring crop water use. Competing forces between cost, accuracy, simplicity, reliability and repeatability all feed into the debate on which technology or method of irrigation scheduling is most appropriate. Sugarcane Research Australia (SRA) has identified interoperability with scheduling tools and big-data platforms to be very important, and hence any newly developed irrigation advisory services (e.g., RS-based) should be compared with the existing ones. This would not only help in evaluating service product accuracy (performance), but also in comparing additional benefits added by the new services and also in filling data gaps in time series. Existing programs and models such as Irrigweb, WaterSched, KMSI, BOM databases, CSIRO soil databases (ASRIS) and many more would/should soon be able to "communicate" with other sources of data for better integration into Decision Support Systems.

Knowles (2015) examined several properties of IrriEye datasets (http://www.irrieye.com) in the Bookpurnong Irrigation District in Riverland of South Australia and compared the results with more commonly used techniques of soil water monitoring and ET_o-driven soil water balances. He found little correlation between the two methods of estimating crop water use as IrriEye data over-estimated the amounts of irrigation compared to the ASCE method of crop water scheduling computation. He pointed out that, although it is difficult to measure true crop water use, a comparison between well-tested methods can give some confidence of validation.

2.6.1 eLEAF

For sugarcane production, eLEAF (http://www.eleaf.com/?page_id=3316) is a Netherlands based developer that applies meteorological and RS based data to quantify crop, water and climate parameters at pixel level. This technology is called Pixel Intelligence Mapping (PiMapping). eLEAF directly measures crop biomass and the water that is actually consumed by the crop in a certain period of time, and differs substantially from conventional RS based methods of using NDVI with historical biomass production time series to estimate a current figure (Bastidas-Obando et al. 2017). For sustainable irrigation management, eLEAF's IrriLook application is an irrigation planner based on the soil water balance that uses specific data on soil properties, satellite data and user-specified ground water level and irrigation inputs. This information is coupled to the weather forecast to provide irrigation advice directly to the farmer for the coming days. IrriLook has been tested and validated extensively in the Netherlands, and subsequently has been successfully implemented in South Africa, Egypt, Ethiopia and Sudan.

2.6.2 IrrigWeb

IrrigWeb (http://www.irrigweb.com/) is a sugarcane irrigation scheduling tool for the sugar industry and provide irrigators with current and local advice on sugarcane crop water use and development. IrrigWeb uses a sugarcane crop model, CANEGRO, to calculate sugarcane crop water use and yield outputs. The tool combines crop water use estimates with user-defined irrigation system constraints and crop cycle inputs to schedule future irrigation events. Meteorological data are obtained daily from Queensland Government's SILO application and local weather stations as inputs for the model.

2.6.3 GoSAT and Goanna Telemetry

For RS based irrigation decision making, Goanna Telemetry (https://www.goannatelemetry.com.au/) provide a combination of tools and technology for water scheduling and crop monitoring based on the IrriSAT technology, Goanna weather stations and their soil moisture probes. The use of IrriSAT technology on the Goanna Soil Total Graph enables more accurate prediction of the irrigation data with the crop ET_c and forecasted daily water use. Goanna provides imagery from two Landsat satellites and one Sentinel2a and NDVI and NDRE imagery are provided regularly from the GoSAT. A part of the GoSAT reporting provides forecasted 10 day rainfall and Min and Max air temperatures and other historical parameters accessible at specific field location.

2.6.4 IrriSAT

IrriSAT is a weather-based irrigation management and benchmarking technology that calculates Kc from relationships with NDVI derived from Landsat and Sentinel data and provides site-specific daily crop water use and a seven day crop water use forecast at low cost and across a large spatial area. Seasonal crop water use is combined with yield data to provide a measure of crop productivity. IrriSAT is moving weather-based scheduling into the future. The free IrriSAT app (https:// irrisat-cloud.appspot.com) automates satellite processing and information delivery of satellite data and provides water management information to assist in irrigation scheduling and crop productivity benchmarking.

2.6.5 IrriEye

IrriEye (http://www.irrieye.com/) is a satellite-based irrigation advisory system funded by the South Australian Murray-Darling Basin Natural Resources, and involves an Italian company (Ariespace s.r.l.) as the service provider. IrriEye provides real-time information on irrigation water needs at various spatial scales (from field and irrigation unit to district and river basin scale) and temporal scales (real time, historical). Irrigation water requirements are estimated using high resolution RS data and standard international methodologies. The information is communicated through Short text (SMS) and maps (email or web access) of irrigation volume expressed in cubic meters or duration of irrigation supply every 7 days.

2.6.6 WATERpak

WATERpak is a field-based guide for irrigation management in cotton and grain farming systems. It provides growers the best available information on water use efficiency and water management based on latest research and provide technical and practical support for the cotton industry's Best Management Practice program myBMP. In its latest version WATERpak can be read electronically on tablets and notebooks, with links to other on-line information sources so further information can be readily accessed.

2.6.7 WaterSched

WaterSched (http://watersched.net.au/default.aspx?ReturnUrl=%2f) is a web-based real-time tool developed by the Queensland Department of Agriculture and Fisheries using FAO56 dual-crop coefficient methodology to model root zone water depletion. It provides guidance for irrigators and consultants on effective irrigation decisions.

2.7 SWOT analysis on use of remote sensing data for Irrigation Scheduling in the Sugarcane Industry

Table 4 shows the descriptive identifying strengths, weaknesses, opportunities and threats (SWOT) related to the use of remote sensing data for irrigation scheduling in the Sugarcane Industry. Australian sugarcane industry earth observation data requirements tend to reflect the best available public good data sources (e.g., Landsat, Sentinel2), and continuing close alignment with other space agencies will help to ensure continuity of supply. Overall, commercial data supply is strong, growing, and diversifying with increasing competition.

Table 4 SWOT analysis on use of remote sensing data for Irrigation Scheduling in the Sugarcane Industry

Remote Sensing data	Strengths	Weaknesses	Opportunities	Threats
Low Resolution (AVHRR, MODIS, MERIS) >80m	▪ High repetitive and global coverage, more suitable for regional studies. ▪ Determine the spatial extent of irrigation at global scales. ▪ Low image data cost and pre-processed datasets accessible. ▪ Cost effective ways of monitoring irrigation in large areas is to use freely	▪ Low spatial resolution ▪ high technical difficulty required to produce maps ▪ Medium to low application in irrigation scheduling. ▪ Imprecise irrigated area estimation, especially in	▪ Continuous observation program ▪ Technical observation challenges solved. ▪ Times-series analysis with other ancillary data. ▪ In combination with medium spatial resolution data such as Landsat to calibrate irrigated area from	▪ Continuity risk as a number of high quality low resolution optical instruments are being developed and also continuity risk with the aging and gradual degradation of

Remote Sensing data	Strengths	Weaknesses	Opportunities	Threats
	available vegetation index data from coarse resolution sensors like AVHRR and MODIS	locations with small cultivated plots and fragmented landscapes. ▪ Cloud free data acquisition is challenging, particularly in sub-tropical region	coarse resolution observations using regression ▪ Determine the spatial extent of irrigation at global scales for accurate estimates of irrigated areas for water use assessments and food security studies. E.g., USGS Global Land Cover Map from 1km AVHRR, European Space Agency (ESA) global land cover product using MERIS data	the instruments (e.g., MODIS) ▪ Latency loss may be the biggest risk ▪ Securing funding for missions has been challenging
Medium Resolution (Landsat 8 OLI, DMC, Deimos1, Sentinel 2 (10-30m)	▪ Determine spatial extent and temporal distribution of crop development and to derive crop ET at field scale with a regional coverage and used widely for irrigation management project. ▪ Worldwide continuous observation program with global coverage and accessibility to pre-processed multi-spectral datasets within less than 24-h of acquisition ▪ Free (Landsat, Sentinel) and low to high data cost for others ▪ Historical achieve (Landsat) can be used to evaluate water conservation plans to determine present and historical irrigation practices. ▪ NDVI and other crop parameters (fc, LAI) derived from Landsat time series used to determine sugarcane water requirement and water use efficiency, distinguishing healthy irrigated lands from	▪ Obtaining cloud free data is challenging and is a limiting factor over irrigated areas, particularly in northern QLD. ▪ In case of Landsat 7, SLC-off is a problem as it causes striping and so even if there is an overpass a lot of area is not covered. It is necessary to combine at least 2-3 overpasses to get a "complete" Landsat 7 image. ▪ Adoption of these technologies and the integration into the day-to-day routine operations of farmers is a complex process and favourable conditions depend on several technical, social, and economic factors	▪ In the world of water resource management, Landsat has played a key role in providing objective and continuous data for the entire world, particularly in the arid region. Water-related benefits of Landsat imagery are also reaped globally to make informed decisions regarding irrigation management and efficient water allocation and use. ▪ Website https://remote pixel.ca/ (Remote pixel) is one way to figure out the cloud problem, by selecting an area and counting the number of sentinel/Landsat images that are cloud free over the areas, and then downloading the cloud free images. ▪ Irrigation advisory service at this scale helps to make better informed decisions on irrigation and studies have shown that farmers in general	▪ Failure of TIRS and loss of thermal data from Landsat-8 is a potential continuity issue as there are no other current or planned thermal data sensors at this spatial resolution. ▪ The emergence of newer actors leveraging advances in small satellite technology (under 500kg, and principally under 100kg) to create dense constellations of 10's or 100's of low cost satellites is expected to create a significant market for high frequency (multiple daily) optical coverage at high and very high resolution.

Remote Sensing data	Strengths	Weaknesses	Opportunities	Threats
	uncultivated and non-productive areas. ▪ Thermal bands of Landsat are used for soil moisture determination		willing to pay, either directly or via cost sharing, for such a service (e.g., Vuolo et al. (2015). ▪ With a correct irrigation application, more than 10% of the water and energy could be saved in water-intensive crops. ▪ Based on DEIMOS-1 and Landsat-8 time series data, Vuolo et al. (2015) estimated the advisory service cost between 2.5 and 4.3 Euro/ha per year for 20,000 ha regularly irrigated lands in Austria	▪ It has been estimated that the new market could account for approximately 50% of total commercial high resolution data sales by 2020. ▪ Rapid revisit and efficient distribution may become as prolific a driver for the development of new satellite data as freely available data streams like MODIS, Landsat, and Sentinel.
High Resolution (Planet, RapidEye, GeoEye, WorldView, Pléiades, SPOT6/7 etc. (1-6m)	▪ Ability to monitor smaller size sugarcane fields and within-field spatial variability, and if required intra-field variability detection ▪ Sub-field spatial resolution is necessary (1-5 m) to identify candidate locations for supporting on-ground infrastructure such as Soil Moisture Probes, Telemetry and other Proximal Sensors ▪ Commercial high resolution data with repeat cover time of 1-5 days, along with freely available data (Landsat/Sentinel) can be a way to increase the number of cloud free images available (i.e. more repeat coverage equals more chance of a cloud free image) to meet temporal resolution of	▪ Low spatial coverage in one scene, high data cost ▪ To acquire image for a given area, in most cases a minimum image area, e.g., 100 sq km restriction is applied. ▪ More research is required to confirm the application of these data in irrigation management. Cost-benefit analysis is required for the integration into the day-to-day routine operations. ▪ Complex process and favourable conditions depend on several technical, social, and economic factors	▪ Daily high-resolution imagery provides unprecedented in-field detail, Global coverage scales with growing operations and solutions. ▪ It does cost money, but satellites like Planet provide API which lends itself to web programing and App development for product deployment. It depends how useful the image bands are too i.e. RGB and NIR. ▪ Seamlessly integrate into user's apps and workflow with Planet APIs to Create dynamic field management zones on user's areas of interest, instantly access data to analyse and act in-season and in-field	▪ Commercial users dictate future priorities and so there is some risk that those priorities are not in alignment with Australian user needs. ▪ Re-tightening of sub-50cm data restrictions by the U.S. Govt- it is open currently and also for the near future. It seems unlikely, however, if the restrictions are reimposed, the very high resolution data supply would be considerably reduced (except

Remote Sensing data	Strengths	Weaknesses	Opportunities	Threats
	about 7–10 days between acquisitions. This would be adequate to monitor the various phases of the sugarcane crop development throughout the growing season		▪ This can support new business models – for example, users could pay a fixed subscription fee for access to a service that provides a steady flow of data over defined areas of interest. ▪ These services will potentially remove the need to order data up front, and in turn may remove a barrier to entry for new users ▪ Irrigation advisory service at this scale helps to real time, more precise decisions on sugarcane irrigations and water use efficiency.	for Pléiades 50cm data). ▪ Source switching between the ranges of high resolution supply options can lead to significant data handling and processing chain changes for users, which can add extra cost.
Radar (Sentinel 1, Radarsat, ALOS-2, SAOCOM)	▪ Can be acquired as frequently as possible without cloud and other atmospheric interference and solar angle variations. ▪ Depending on the wavelength, the radar backscatter signal carries information about the moisture status of vegetated landscapes ▪ Sentinel 1 is free and has good repeat cover ▪ Few studies showed high correlations between the radar backscattering coefficients and NDVI derived from SPOT-4/5 images as a function of sugarcane crop parameters. ▪ The decrease in NDVI for fully mature sugarcane fields due to drying of the sugarcane (water stress) was also observed in the radar signal.	▪ Difficult to interpret in regard to sugarcane due to its sensitivity to soil moisture. ▪ Wet field can look the same as a field with high biomass. ▪ Limited studies on soil moisture estimation with Sentinel 1. There are other radar sensors used for this, but the resolution is generally fairly coarse i.e. SMAP. ▪ More research work is needed to identify and evaluate the links between backscatter and crop coefficients.	▪ Combination of radar data together with optical data has not yet been exploited to its fullest extent. ▪ Radar is useful because of its sensitivity to soil moisture status, even in complex environments. ▪ Furthermore, radar data can be collected in almost all weather conditions, a characteristic that is especially important in areas with frequent cloud cover.	▪ Relatively low Australian civil national heritage and capacity to handle and process SAR data, in particular in application areas where SAR is employed on a routine basis ▪ Development of the Copernicus ground segment and data policy implementation remains may impacts on the supply of Sentinel-1 data, though it is currently available via a rolling Science Archive. ▪ Loss of L-band continuity is a

Remote Sensing data	Strengths	Weaknesses	Opportunities	Threats
				considerable risk with ALOS-2 data.
UAV/ Drone	▪ Ability to collect very high spatial resolution data, from centimetres to even sub-centimetre, and very high positional accuracy (X,Y,Z). ▪ UAV system can operate under cloud, and so long as images are corrected appropriately for varying target illumination associated with cloud cover, they offer unprecedented scheduling flexibility ▪ The UAV systems can carry a large variety of sensors ranging from a low cost commercial RGB cameras to more expensive multispectral, near infrared, thermal and hyperspectral cameras and LiDAR sensors ▪ The major advantages of using UAV systems in the context of tactical crop scouting, including, potentially for irrigation management is cost-effectiveness, especially for small scale operation. ▪ In agriculture, numerous studies have utilised UAV data to compute different plant parameters (LAI, fc) and crop parameters (vigour, quality, yield) measured during the entire growing season, as well as providing information on crop health and nutrient status	▪ Large scale monitoring requires considerable post-processing capability to create mosaic imagery, and this is exacerbated by the difficulties in feature matching on overlapped images in homogenous area, for example within a uniform crop. ▪ It has a serious battery backup issue and frequent battery recharging/replacem -ent is required in between the survey ▪ To use UAVs, unless the instrument is owned and operated by the grower, the costs would be prohibitive on such a short return monitoring interval as 7 days.	▪ The significant and fast-paced technological advancements in small-sized UAVs equipped with GPS and high quality remote sensing devices offer numerous opportunities for irrigation-related management. ▪ Under optimal conditions, the UAV data can serve as a potentially valuable source of very high resolution data in real time and on demand; a particularly useful capability for filling data gaps in any time-critical tool for irrigation management.	▪ UAV/Drones can be shut down mid-flight, injuring bystanders and causing property damage ▪ UAV use in Australia is regulated by the Civil Aviation and Safety Authority (CASA). They understand that for agriculture usage, UAVs are flown low to the ground and hence could be catastrophic. Therefore CASA recognises the requirement that all operators should be appropriately trained and licenced. ▪ The risks increase significantly with the size of the UAV (>3.5kg) and containing batteries that may cause fire, that can cause damage to property or persons on the ground when used incorrectly.

2.8 Conclusion

While our sugar industry has long recognised the need for agile and timely irrigation scheduling tools, the last 10 years has seen significant developments in the field of remote sensing that offer a new window of opportunity for developing and operationalising remote sensing based irrigation management tools. We have seen the launch of new optical as well as radar satellite systems with improved spatial and temporal resolution characteristics, some of which offer free access to data, improvements in the delivery of satellite imagery to clients, the evolution of cloud based computing supported by innovative image processing algorithms (for example object as well as pixel based processing), and of course the enormous improvements in our capabilities to receive data at home, in the office and in the field through the various forms of internet access available, both fixed and mobile. There is a volume of research on irrigation scheduling for different crops (e.g maize, corn, cotton, etc) reliant upon remotely sensed data, and in particular utilising the VI-K_c/K_{cb} approach. While is less work reported on RS based irrigation management and scheduling for sugarcane crops, the basic approaches insofar as developing methodology and algorithms are now well founded and can be readily applied. Moreover there is already experience in the market place in the delivery of irrigation scheduling tools for other crops, and so it may be as simple as extending existing systems to include sugar pending the development of appropriate algorithms.

Appendix A

A1.1 Sugarcane

Sugarcane (*Saccarum officinarum*) is a long duration, tall-growing perennial plant crop that require an abundant supply of water, either in the form of rainfall or irrigation, to achieve maximum productivity. It is cultivated in the tropical and subtropical regions of the world (between latitudes 35°N and 35° S) mainly for sugar production from sucrose stored in the internodes of the stem (Grof and Campbell, 2001), and also for by-products such as bagasse, molasses, fibre cake and cane wax (OGTR, 2004). Countries like Brazil and Reunion also use the crop for fuel ethanol (alcohol) production (Xavier et al. 2006). The favourable climatic condition for sugarcane growth is a long, warm growing season with a high incidence of sunlight (mean daily temperature between 22 and 30°C) and an adequate water supply (moisture), followed by a dry, sunny and cool ripening and harvesting period (mean daily temperature between 20 to 10°C). The most important of these factors is the water availability (Inman-Bamber and Smith, 2005), which is directly related to the amount of cane grown under suitable conditions of temperature and sunlight (Singels et al., 2005). For instance, with each 10 mm of soil water use by the crop, one tonne per hectare of cane is produced. A long growing season is essential for high yields and the normal length varies between 15 to 16 months. Sugarcane does not require a special type of soil and can grow in well aerated soil of 1-5 m depth with the groundwater table 1.5 to 2.0 m below the surface. Sugarcane has high nitrogen and potassium needs and relatively low phosphate requirements, or 100 to 200 kg/ha N, 20 to 90 kg/ha P and 125 to 160 kg/ha K for a yield of 100 ton/ha cane, but application rates are sometimes higher. At maturity, the nitrogen content of the soil must be as low as possible for a good sugar recovery, particularly where the ripening period is moist and warm.

A1.2 Sugarcane and water

Most of the sugarcane growing regions in the world have sub-optimal rainfall for cane production and require some form of irrigation to support sugarcane cultivation (Inman-Bamber 2004; Inman-Bamber and Smith 2005; Jarmain et al. 2014). For example, 60 % of Australia and 40 % of South Africa sugarcane production is dependent on some form of irrigation, while countries like Swaziland and Sudan are completely dependent on irrigation (Inman-Bamber and Smith, 2005). In addition to reducing dependence on rainfall, irrigation enables better planning and flexibility in different farming activities including timing for crop planting. Furthermore it increases the reliability of ratooning and enables more succeeding growth of cane.

For maximum yields it is important to maintain sufficient moisture in the soil throughout the crop growing period as both plant and cane growth is directly related to the water transpired. The crop water requirement refers to the amount of water that needs to be supplied to facilitate crop growth, while crop evapotranspiration refers to the combined amount of water that is lost from the growing 'system' through evaporation and transpiration **(**for example, Inman-Bamber and Smith 2005; Gibson et al. 2013; Zhang et al. 2015). The values for the crop evapotranspiration and the crop water requirement are essentially the same. The crop evapotranspiration under standard conditions (ET_o) (or 'reference ET'**)** is defined as the evapotranspiration from disease free, well-fertilized crop, grown in large fields, under optimum soil water conditions, and achieving full production under the given climatic condition 'FAO56' (Allen et al. 1998). Effectively the crop water requirement is therefore the amount of water required to compensate the evapotranspiration loss from the cropped field. The quantity of irrigation water required represents the difference between the crop water requirement and effective precipitation, the latter referring to the rainfall-derived water available for uptake by the sugar plant. The irrigation water requirement, therefore includes additional water for leaching of salts and to compensate for non-uniformity of plant water demand. In the sugarcane sector, the water use efficiency (WUE) (or water productivity) is used as a measure of overall effectiveness of water use (either rainfall, or irrigation, or both) for cane production (via plant evapotranspiration) (Zwart and Bastiaanssen, 2004). The irrigation water use efficiency (IWUE) can be defined as the cane yield in response to unit of irrigation water applied (Inman-Bamber et al. 1999).

The reference evapotranspiration (ET_o) can be calculated from meteorological data using the standard FAO Penman-Monteith method (Allen et al. 1998). The FAO Penman-Monteith method requires data on solar radiation (photosyntethically-active radiation- PAR), air temperature, air humidity and wind speed. Allen et al. (1998) recommends the use of a standard hypothetical crop, namely grass having a plant height of 0.12 m, a surface resistance of 70 sm^{-1} and an albedo of 0.23 for ET_o calculation. The crop evapotranspiration (ET_c) is determined by multiplying ET_o by a crop coefficient (K_c) according to :

$$ET_c = K_c \times ET_o \qquad \text{(A1)}$$

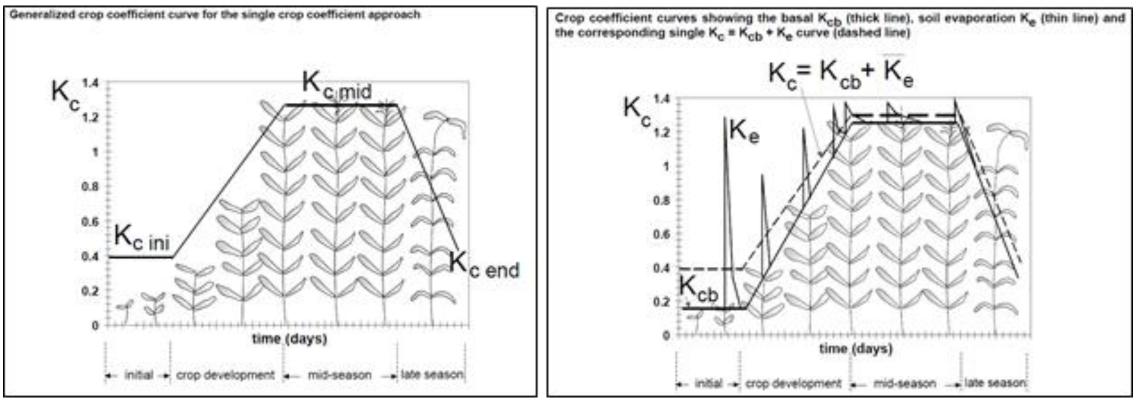
The crop coefficient (K_c) integrates the departures of actualy field crops at different stages of growth from the ET_o reference surface. In what is referred to as the “dual” crop coefficient approach the value of K_c can be separated into two coefficients: a basal crop coefficient (K_{cb}) and a soil evaporation coefficient (K_e) (Allen et al. 1998; Allen and Pereira 2009) according to:

$$K_c = K_{cb} + K_e \qquad \text{(A2)}$$

Therefore,

$$ET_c = (K_{cb} + K_e) * ET_o \qquad \text{(A3)}$$

The basal crop coefficient (K_{cb}) represents the plant-only transpiration component of ET_c. The soil evaporation coefficient (K_e) represents the evaporation from just the soil, after wetting by precipitation or irrigation. When the soil surface is dry but plant transpiration occurs without water limitation then $K_e = 0$ and from Eq. A3 K_{cb} can be calculated by the ratio of the crop evapotranspiration (ET_c) to the reference evapotranspiration (ET_o).
On selection of the calculation approach (single or dual crop coefficients), the lengths of the crop growth stages and the corresponding crop coefficients are used to construct a crop coefficient curve. The curve represents the changes in the K_c over the length of the growing season and the shape of the curve represents the changes in the vegetation and ground cover during plant development and maturation (Allen et al. 1998). From suchs curve, the K_c and ET_c can be derived for any period within the growing season. Examples of generalised, seasonal crop coefficient curves based on both single crop and dual crop coefficients are given in Figure A1.



(a) (b)

Figure A1 Generalised seasonal crop coefficient curves based on single crop and dual crop coefficients (source: Allen et al., 1998).

At the time of planting, and during the initial plant development stages, the value for K_c is typically small, and this increases rapidly with the plant development and reaches a maximum value, $K_{c\text{-}mid}$. During the late season period, K_c decreases to a value at the end of the growing period equal to $K_{c\text{-}end}$. The values for $K_{c\text{-}ini}$ and $K_{c\text{-}end}$ can vary considerably on a daily basis, as transpiration is dependent on plant available water. Bearing in mind that fact that K_c includes the effects of evaporation from the soil. the values of the basal crop coefficient, K_{cb}, lies below the K_c values (Figure A1b). The difference between K_c and K_{cb} is more pronounced during the initial growth stages where significant evaporation from the exposed soil occurs. At the mid-stage of plant development, the crop canopy obscures more, if not all, of the soil and soil evaporation is minimal. The value of K_{cb} then approaches the value of K_c. Depending on the frequency with which the crop is irrigated during the late season stage, K_{cb} will either be similar to K_c if irrigation adequately meets the plant water demand, or will less than the K_c value if the plant water demand is not met. In Figure 1b, the 'spikes' in K_e are associated irrigation or rainfall events, where strong evaporation occurs from the wetted soil surface. Note that such spikes reduce in amplitude with ongoing crop development as less of the soil surface is exposed. At the same time, if water is limiting, then K_{cb} may also exhibit spikes due to the increase in plant evapotranspiration associated with increased plant function. Both, of course, contribute to spikes in K_c.

Allen et al. (1998) describe criteria for the use of single and dual crop coefficient approaches. As the single K_c coefficient integrates both soil evaporation and plant transpiration, ET_c is often computed for weekly or longer time periods, although calculations may proceed on a daily time step. The time-averaged single coefficient K_c is used for scoping studies and irrigation system design where the averaged effects of soil wetting are acceptable and relevant. This is often the case for surface irrigation and set sprinkler systems where the time interval between successive irrigation is of several days, often ten days or more. In other words, for typical irrigation management, the time-averaged, single K_c is valid.

The dual coefficient approach requires more detailed site information and can support more complex numerical calculations. For example, the dual coefficient procedure is appropriate for real time irrigation scheduling, especially for soil water balance computations where knowledge of variations in soil surface wetness and the resulting impacts on daily ET_c, the soil water profile, and deep percolation fluxes are important. This is potentially important information in the case for high frequency irrigation with micro-irrigation systems or lateral move systems such as centre pivots and linear move systems.

In any discussion of ET_c, what is important is water available to the plant rather than water in (or on) the soil. For example, low soil water availability reduces plant transpiration (T) while mulches decrease soil evaporation (E) (Allen et al. 1998). In such conditions, ET_c is adjusted ($ET_{c\text{-}adj}$) either, by introducing a 'water stress coefficient' (K_s) as a penalty to the non-stress related value of K_c in the single coefficient approach:

$$ET_{c\text{-}adj} = K_s * K_c * ET_o; \qquad (A4)$$

or by introducing a penalty term to the basal crop coefficient component in the dual coefficient approach:

$$ET_{c\text{-}adj} = (K_s * K_{cb} + K_e) * ET_o \qquad (A5)$$

Allen et al. (1998) provides guidelines for adjustment of soil evaporation and crop coefficients under various climatic, environmental and crop management conditions. The value of K_s describes the effect of water stress on crop transpiration. Since K_s has more impact on crop transpiration, rather than evaporation from soil, the application of K_s in the dual crop coefficient equation considered more appropriate.

A1.3 Sugarcane irrigation scheduling

The aim of an irrigation scheduling tool is to provide information about the correct time and quantity of water application necessary to optimize crop yield, maximize water use efficiency and ensure minimum damage to the soil and crop (Mulla, 2013). In other words, irrigation scheduling is a process that helps in making decision on when and how much water needs to be applied to a cropped field to maintain the soil moisture to the desired level. The decision on when, where and how much to irrigate can be a complex task for growers/managers. Monitoring the crop, weather and soil are essential requirements of any irrigation scheduling process (Gibsen et al. 2013). Three basic approaches are used, either on their own or in combination:

- Calculating crop water requirements, for example evapotranspiration (ET_c) based observations of third-party parameters (for example ET_o via data extracted from nearby weather stations), not necessarily directly connected with the crop itself;
- Directly monitoring soil moisture levels in the crop root zone; and/or
- Directly monitoring the crop plants themselves

For sugarcane, the frequency of application and volume of water required varies with the climatic conditions, environmental conditions (soil moisture) and cane growth phase (for example, Robertson et al. 1999; Inman-Bamber 2004; Inman-Bamber and Smith 2005; Zhang et al. 2015). A consideration of the physiological characteristics of the sugar cane at different growing stages is important. Figure A2 shows the relationships between relative yield decrease (1-Y_a/Y_m) and relative evapotranspiration deficit (1-ET_a/ET_m) for the individual growth periods (IWM, 2017; Robertson et al. 1999; Inman-Bamber and Smith, 2005). Here ET_a is the actual evapotranspiration, ET_m is the maximum evapotranspiration, Y_a the actual yield (kg/ha), Y_m the maximum yield (kg/ha), and K_y is the yield response factor (crop specific and vary over the growing season according to growth stages). During the initial germination, emergence and establishment of young seedlings the crop requires less water and hence light and frequent irrigation applications are preferred to just keep the soil moist with adequate aeration. Infrequent and less water application at this stage can lead to lower and delayed germination, while over irrigation can cause bud rotting (due to lack of aeration), fungal attack and lower soil temperature. Thus both under- and over-irrigation are unfavourable conditions for germination which can result in low stalk population per unit area (Robertson et al. 1999; Jarmain et al. 2014**).**

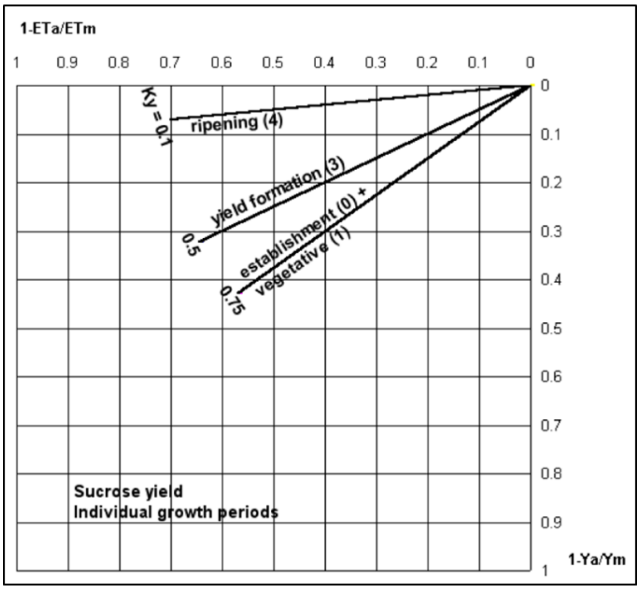


Figure A2 Relationships between relative yield decrease (1-Y_a/Y_m) and relative evapotranspiration deficit (1-ET_a/ET_m) for the individual growth periods (FAO 1998). (Source: IWM 2017).

During the early vegetative period the tillering is direct proportion to the frequency of irrigation application. However, excess use of water is not suitable as it hinders active root development process by blocking nutrient uptake due to poor oxygen diffusion. The stem elongation and early yield formation is the most critical period for moisture supply in sugarcane because the actual stalk growth and production of sugar storage tissues takes place in this period. The crop reaches its peak water requirement in this stage and the stalk elongation is directly related to the water use. Adequate water supply during this period ensures active growth and the formation of long internodes. Therefore the irrigation interval can be extended but the depth of water should be increased to maintain a moisture content of 84-85% in the leaf sheaths, the production of longest internodes with more girth (thick cane) and the greater total cane weight.

In India, the tillering/early yield formation period coincides with the hot weather period (March-June) when high evapotranspiration results in more crop water needs. In such conditions, the management of irrigation water supplies to meet the large water requirement is crucial to obtaining optimum sugarcane yields. In the ripening period, a restricted water supply or mild water deficit (sheath moisture content of 74-75%) is necessary to bring the crop to maturity by reducing the rate of vegetative growth, dehydrating the cane and forcing the conversion of total sugars to recoverable sucrose. With the checking of vegetative growth, the ratio between dry matter stored as sucrose and that used for new growth also increases.

Based on the FAO Irrigation and Drainage Paper No. 24 (FAO 1992), the indicative duration of each of the four distinct growth stages of sugarcane and the total growing period for various types of climate and location is given in Table A1. Depending on the climatic conditions, cultivation method and length of the cropping cycle, the water requirements (ET_c) for sugarcane ranges from 1500 to 2500 mm, more or less evenly distributed throughout the growing season. The transpiration coefficient of sugarcane is around 400. This means 400 m^3 of water is required to produce one ton of dry matter. The amounts of water required to produce 1kg of cane, dry matter and sugar are 50-60, 135-150 and 1000-2000g, respectively. Table 1 shows the single (time-averaged) crop coefficients, K_c, and basal crop coefficients, K_{cb} for non-stressed, well-managed crops in sub-humid climates (FAO 1998; Allen et al. 1998). Table A2 summarises the sugarcane crop coefficient (K_c) values, relating ET_c to reference evapotranspiration (ET_o) for the different growth stages.

Table A1 Single crop coefficients, K_c, and basal crop coefficients, K_{cb} for non-stressed, well-managed crops in subhumid climates (FAO-56; Source: Allen et al. 1998)

Crop Coefficients	Initial/ Beginning of growing season	Mid of growing season	End of growing season
K_c	0.40	1.25	0.75
K_{cb}	0.15	1.2	0.7

Table A2 Summary of sugarcane crop coefficient (K_c) values, reference evapotranspiration (ET_o) for the different growth stages.

Development stages	Days	K_c
Planting to 25% of full canopy	30-60	0.45-0.6
25% to 50% of full canopy	30-60	0.45-0.6
50% to 75% of full canopy	15-25	0.90-1.00
90%-100% of full canopy	45-55	1.00-1.20
peak use	180-330	1.05-1.30
early senescence	30-150	0.80-1.05
Ripening	30-60	0.60-0.75
K_c values depend on minimum relative humidity and wind velocity (FAO Irrigation and Drainage Paper No. 24) (FAO 1992)		

The single K_c value of sugarcane ranges from 0.4–1.25 for the initial (low canopy) and mid (full canopy) periods of crop development, to 0.75 for the end (harvest) of development (Allen et al. 1998). Inman-Bamber and McGlinchey (2003) confirmed the values for the initial and mid periods of development, but they reported a higher K_c of 1.25 for the final stage, when water was not limiting. They found measured ET_c to rarely exceed 8 mm/day in Australia and 7 mm/day in Swaziland. Allen et al. (1998) stated that ‘Class A’ pan evaporation can also be used as another reference for ET_c in many crops, including sugarcane. Inman-Bamber and Smith (2005) reviewed the findings for the ET_c and pan factor and found 7.8 mm/day (pan factor 0.66-0.95) in Australia (and the pan factor for drip irrigated sugarcane in Hawaii to be 0.88). Win et al. (2014) determined water requirement and K_c of sugarcane at different crop growth stages in Myanmar using a lysimeter.

A1.4 Soil water balance and water deficit (stress)

Soil water balance is used to control the quantity and availability of soil moisture to a crop by modelling the quantitative water dynamics within the soil. In soil water balance, the inputs of water to the soil are in the form of irrigation, rainfall, subsurface inflow and capillary rise, while outputs that remove water from the soil include evaporation, transpiration, runoff and, percolation. In its simplest form, the RS-based water balance model aims to track the water deficit in the soil root zone over time by quantifying the evapotranspiration (ET_c) (removal of water from the soil root zone) and amount of water supply through irrigation and rainfall (adding water to the soil root zone) as:

Rain + Irrigation – Crop Water Use (ET_c) = 0 (Soil Water balance)

or

Change in soil water Storage = Rain + Irrigation – Crop Water Use (ET_c)

The soil moisture deficit can be calculated on a daily basis to indicate when the amount of water in the root zone is insufficient, and hence timing for irrigation application (Wigginton et al. 2012).

Deficit (today) = Deficit (yesterday) – irrigation – rainfall +ET_c

Where: Deficit = soil moisture deficit (amount of available water in the root zone below field capacity); ET_c = Crop evapotranspiration (crop water use)

Excess of water supply can cause inefficient plant growth, while too little results in restricted plant growth. This is very important in water-limited regions of Australia, where the main issue is to determine the trigger point for irrigation; with scarcity of water supply, determination of exact timing and amount of irrigation is vital so as not to irrigate too early (and in excess) or too late (and too little). Seasonal K_c datasets derived from time-series RS data give a guide for when sugarcane crops are active for a season, to be supported by ground inspections. This really depends on crop, irrigation system and management preference. Thus, irrigation-related decisions are made based on ground-based information with support from RS data inputs. Both the crop water stress and scheduling irrigations can use RS technology but it is so important to ground truth models thoroughly with reality.

For irrigation scheduling management, knowledge of the basic soil states (saturation, field capacity, permanent wilting point, and readily available water) within the soil root zone are required (Wigginton et al. 2012). Saturation in soils occurs after heavy rain, or over-irrigation, when larger soil pores are filled with water resulting in no air for the plant roots and stress in plants. Field capacity (full point) occurs after large soil pores (macropores) have drained due to gravity but the soil is still wet, but not saturated. The soil water deficit is 0 mm at field capacity. Permanent Wilting Point (PWP) of soil is the point at which the plant cannot extract moisture from soil due to very low water content and the plant starts dying. The water between field capacity and PWP is available to the plant, and to improve water-use efficiency, irrigators aim to maintain the soil water in the range that can be readily used the plant. This range is called the Readily Available Water (RAW) (mm/m) and indicates the depth of water (mm) held in every metre (m) of soil that can be readily removed by the plant (Hornbuckle et al. 2016). To achieve high production and to avoid waterlogging or excess drainage, the RAW for each crop and field/block (soil type, texture etc.) should be known.

A1.5 Time of irrigation (Refill point)

Once RAW has been used, the plant roots struggle to extract water from the soil and growth is affected. At this point refilling of water (refill point) is done in the form of irrigation. More water is required for drier soil to bring it to its field capacity (Hornbuckle et al. 2016) (Figure A2).

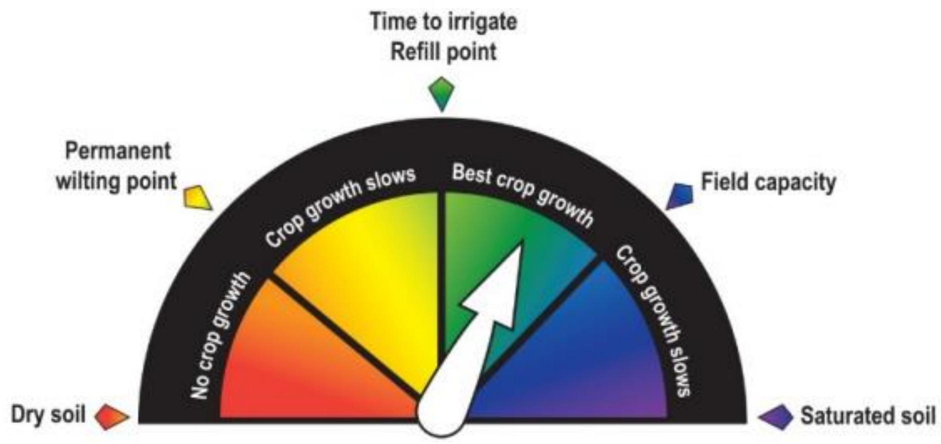


Figure A2 Soil water fuel gauge (Wigginton et al. 2012; Hornbuckle et al. 2016).

While determining the refill point, three factors namely soil type (water holding capacity of clay vs sandy soil), crop rooting depth and type of irrigation system (sprinkler, drip, surface), should be taken into account. Factors like crop root depth may change over time, hence the refill point may also change throughout the season. Similarly, knowing the irrigation system limitations can help in setting the refill point and guide on irrigation decisions. The refill point values do not affect the water balance deficit but simply indicate that the soil moisture profile has reached a value that is going to be stressful for the crop and irrigation is needed to maintain a comfortable root zone environment for plant growth (Hornbuckle et al. 2016).

A2. Remote sensing based irrigation scheduling

For effective implementation of different irrigation scheduling strategies, measurements of plant, environmental and climate parameters are required. The irrigation water requirements (IWR); water that must be supplied by irrigation to satisfy evapotranspiration, leaching, and other plant water needs for optimal plant growth and yield other than precipitation (Jensen et al. 1990), is computed based on crop water requirements (CWR) and soil water balance (CWB). Crop evapotranspiration (ET_c) is a primary component. Several methods and guidelines have been developed to estimate ET_c, CWR and IWR for different crops grown under different geographic and climatic conditions, for example FAO24 (Doorenbos et al. 1977) and FAO56 (Allen et al. 1998). Numerous field based methods and models have been developed to provide information on crop water use (or water losses through ET), crop irrigation requirements, biomass and yield production and water use efficiency for sugarcane growers (for example, Savage et al. 2004; Annandale et al. 2005; Ehlers et al. 2007; Van Heerden et al. 2008; Jarmain et al. 2009). All of these standard methods are 'spatially integrative', insofar that unless specifically configured for the purpose, that is configured whereby certain input parameters are spatially registered, they won't factor in spatial patterns or variations in crop water use across an agricultural field. Put simple, input parameters are simply average values expected to apply to a given spatial scale, or region, of interest.

The application of remote sensing (RS) based irrigation management involve accurate assessment of spatial and temporal patterns of ET_c, or a surrogate indicator of ET_c to help in designing irrigation schedules and to match water placement with actual crop water needs at the appropriate spatial scale. Recent advances in RS technology, namely through platforms that offer appropriate spatial and temporal characteristics offer the opportunity to spatially estimate the ET_c, crop water use, biomass and yield production, and water use efficiency (WUE) (Barnes et al. 2003; Pinter et al. 2003). Moreover, recent open data initiatives such as the USGC data policy of providing open and free access to georeferenced Landsat images in near real-time have greatly increased activity in the market place (and R&D community) in developing RS-based tools for on farm management decisions including irrigation (https://earthexplorer.usgs.gov/). A similar open data policy of the European Space Agency allows free and open access to the 10m Sentinel-2 data. Furthermore, an increasing number of commercial sensors providing very high spatial resolution, for example 1–6 m (for example, SPOT6/7, RapidEye, Digital Globe, WorldView2, PLEIADES) provide frequent land observations with increasing revisit capabilities (https://scihub.copernicus.eu/dhus/). Non-sugar examples include Zwart et al. (2010), who used RS data for WUE assessment for all mono-culture wheat areas in the world, which was subsequently extended to rice and corn, and also for grapes in the Western Cape (Klaasse et al. 2011; Jarmain et al. 2010).

An accurate determination of seasonal crop evapotranspiration (ET_c) is essential for irrigation scheduling and the data derived from remote sensing has been found to be useful in calculation of spatially distributed actual ET (ET_a) (for example, Chen et al. 2014). Numerous RS-based ET_c computation algorithms have been developed (detailed review can be found in Verstraeten et al. 2008). Depending on the variables measured from the RS data (K_c, K_{cb}, K_e, K_s), three RS-based ET_c estimation approaches have been used: (a) parameterisation of the surface energy balance using RS based reflectance and surface temperatures, along with ground-based meteorological data; (b) estimation of the basal crop coefficient (K_{cb}) from the spectral characteristics of crop leaves using single or multiple wavelength, including spectral reflectance index, relationships; and (iii) a direct application of RS-based parameters into the Penman-Monteith (PM) formulation. Such RS based ET_c computation methods are found well suited for estimating crop water use or ET_c (Allen et al. 1998) and also in determining the spatial pattern of ET_c over time. Figure A3 shows a schematic framework of the integration of RS based models for the assessment of CWR and IWR. These will be discussed in the following sections.

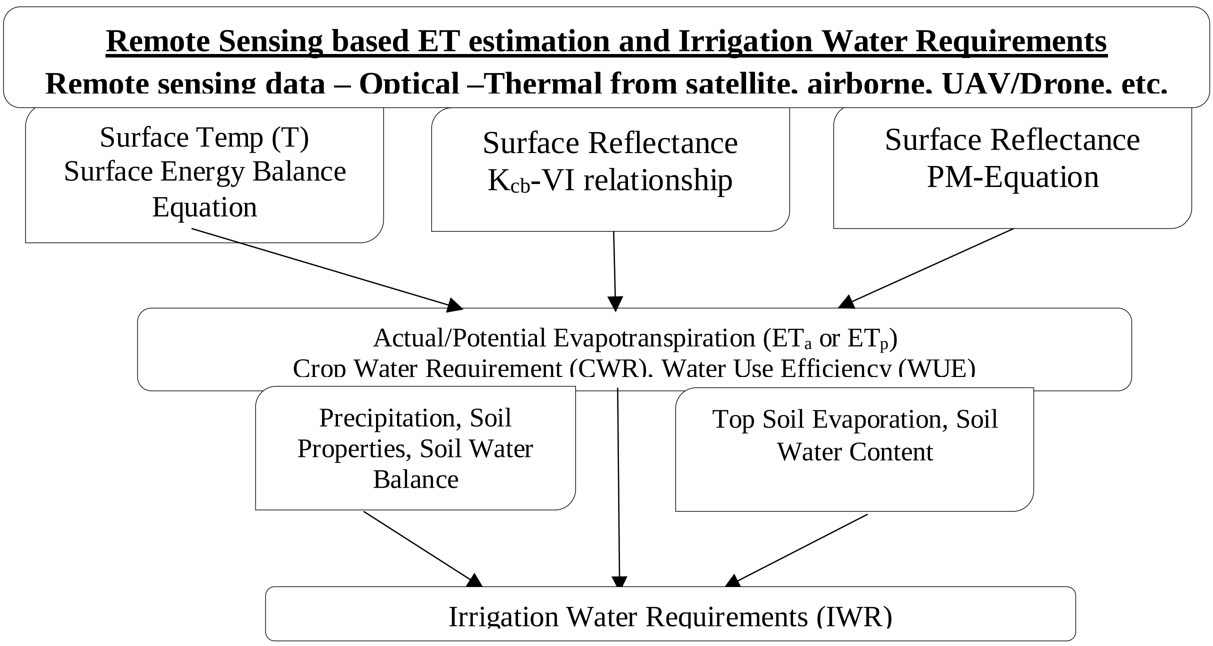


Figure A3 Schematic framework of the integration of RS based different models for the assessment of CWR and IWR

A2.1 Remote sensing based Surface Energy Balance (RS-SEB)

A number of surface energy balance models have been developed to estimate actual ET (ET_a) using an energy balance equation, surface temperature and water use efficiency relationship. These include the Surface Energy Balance Algorithm for Land (SEBAL) model (Bastiaanssen et al. 1998), Mapping EvapoTranspiration with high Resolution and Internalised Calibration (METRIC) model (Allen et al. 2007), Surface Energy Balance System (SEBS) model (Su, 2002), Vegetation Index / Temperature Trapezoid (VITT) model (Moran et al. 1994), Two Source Energy Balance (TSEB) model (Norman et al. 1995), the Atmosphere-Land Exchange Inverse (ALEXI) model (Anderson et al. 2007). While there are actually more, this review will focus on these owing to their potentnial (or actual) relevance to remote sensing based approaches.

A2.1.1 SEBAL

The SEBAL model uses RS images recorded in visible, infrared and thermal bands instantaneously from satellites such as Landsat, ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), MODIS (Moderate Resolution Imaging Spectroradiometer), NOAA AVHRR (Advanced Very High Resolution Radiometer) to estimate pixel-based actual ET (ET_a)-amount of water used crops; crop potential ET (ET_p)- the amount of water that could be evaporated and transpired if sufficient water was available; ET deficit (ET_d) or water deficit- the difference between the ET_p and ET_a as an indicator of plant water stress; biomass growth- ground dry matter production; biomass water use efficiency (WUE)- total biomass produced (kg/ha) per unit of water used; and soil moisture. The basis of SEBAL is computation of residual energy from the classical energy balance equation:

$$\lambda ET = R_n – G – H \tag{A6}$$

where λET is energy used for evapotranspiration (latent heat flux), R_n is net radiation at the surface, G is soil heat flux and H is flux reflected back to air (space) (also known as sensible heat flux) (all fluxes measured in $W/m^2/day$). The ET (mm/day) is calculated from the λET by dividing it by the latent heat of water vaporization (λ) (J/kg). Land surface characteristics such as surface albedo, leaf area index (LAI), the vegetation index (VI) and surface temperature (T_R) are derived from satellite imagery. In addition to satellite images, the SEBAL model requires some meteorological data, such as wind speed, humidity, solar radiation and air temperature. The SEBAL model uses the energy balance, and not the water balance, therefore no data on land cover, soil type or hydrological conditions are required. Since the ET and biomass production are key indicators for water management and irrigation performance, SEBAL map these key indicators in time and space for days, weeks or years and applied and validated in different parts of the world (for example Teixeira et al. 2009). The SEBAL is based on assumptions of a linear relationship between near-surface vertical temperature gradient (T_o) and land surface temperature (T_R). The relationship is obtained by selection of two extreme hydrological pixels- extreme wet/cold and extreme dry/hot pixels. Although SEBAL has been applied in more than 30 countries worldwide with considerable accuracy (Bastiaansssen, 2000; Bastiaansssen et al. 2005), there are still some deficiencies, including the requirement of selection of extreme "cold" and "hot" pixels throughout the image scene, which is subjective and user dependent.

A2.1.2 METRIC

To overcome the difficulty of manual selection of cold and hot pixels with SEBAL, Allen et al. (2007) proposed METRIC model; a satellite-based image processing procedure for calculating actual ET efficiently and accurately from irrigated lands throughout growing seasons. The METRIC model differs from the SEBAL model in its use of weather-based reference ET to establish energy balance conditions at a "cold" pixel. An alfalfa crop-based reference ET (ET_R) value of 1.05, estimated by a standardized ASCE Penman-Monteith equation, is considered to be ET_a of the "cold" pixel. In addition, METRIC considers the effects of complicated topography. However, METRIC still needs to include a "representative cold pixel" from the satellite scene, which has biophysical characteristics similar to the reference crop (alfalfa). According to Allen et al. (2007), the actual ET_a, calculated by METRIC has very high correlation with ET as measured by on-ground lysimeters.

A2.1.3 SEBS

The SEBS model is an energy balance approach (Su 2002) that estimates daily actual ET from RS and meteorological data by calculating the energy required for water to change phase from liquid to gas. The SEBS model estimates the evaporative fraction based on energy balance of dry/wet limiting cases. At the wet-limit, ET takes place at its potential rate, while at the dry-limit point the sensible heat flux reaches its maximum value ($R_n - G$) for each pixel. SEBS does not require the existence and the selection of extreme pixels, but it needs many required parameters and a relatively complex solution of the turbulent heat fluxes which may introduce considerable uncertainty when *a priori* knowledge about the target crop area is insufficient. The SEBS model has been widely used in a range of agriculture environments for the computation of actual ET (for example Su, 2002; Jia et al. 2003; Su et al. 2005; Timmermans et al. 2005; Hailegiorgis, 2006; Lin, 2006; McCabe et al. 2008). However, the accuracy of the SEBS model results is difficult to assess as no standard method has been followed for presenting the results and validation methods, and also the associated accuracies were found to be dependent on the given study area, with little information provided to ascertain transferability. In most cases, the SEBS model results have been validated with a variety of field and/or complementary methodologies such as lysimeters (for example, Lin 2006), Bowen ratio (Su 2002; Timmermans et al. 2005; McCabe et al. 2008; Badola 2009), scintillometers (Jia et al. 2003), hydro-meteorological equations (Hailegiorgis 2006; Gebreyesus 2009) and the water balance equations (Su and Roerink 2004; Pan et al. 2008).

A2.1.4 VITT

The VITT model developed by Moran et al. (1994) is based on the hypothesis that the plot between measured surface minus air temperatures ($T_s - T_a$), and fractional vegetation cover (V_c) which has values ranging between 0 to 1 (where 0 and 1 represent bare soil and full vegetation cover, respectively), would have a trapezoidal shape. The vertices of the ($T_s - T_a$) vs V_c trapezoid are defined as well-watered vegetation, water-stressed vegetation, saturated bare soil, and dry bare soil. By using the physical energy balance equation (measured T_a, R_n and G), the values of the four vertices of the trapezoid can be computed for a specific time, day and crop. However, large deviations of R_n (up to 20%) and G values between bare soil and vegetation may distort the trapezoidal space significantly. In addition, $T_s - T_a$ measurements for the four extreme vertices of the trapezoid are not necessarily available directly. To overcome this, Wang et al. (2011) suggested a pixel-based T_s vs vegetation index (VI) trapezoidal model using an iterative procedure to consider the interaction process between T_s with R_n and the difference of G at different vertices.

A2.1.5 TSEB

The TSEB model, described by Norman et al. (1995), estimates evaporation (E), transpiration (T), and ET of vegetated surfaces based on soil (T_s) and canopy (Tc) surface temperatures. Most annual crops including sugarcane contain partial canopy cover starting from the early part of the growing season, therefore the composite surface temperature (T_R) contains both canopy (Tc) and soil (T_s), particularly for deficit-irrigated crops in dryland with limited water supply. Usually only composite surface temperature (T_R) measurements are available at a single view angle, the T_s and T_C are derived from single T_R using simple linear mixing. The meteorological variables normally used to calculate ET (air temperature, vapour pressure deficit, wind speed, and solar irradiance), and ancillary information about the vegetation are estimated for common crops (LAI, crop height, row spacing, etc.). Quantification and management of ET and its components, E and T) are found useful to increase crop water use efficiency (WUE) and also in water resources management for irrigated crops. Though few studies have estimated T_c and T_s from multiple view angles of T_R (Pinter et al. 2003) the estimations were found sensitive to errors in T_R measurements (for example, Chehbouni et al. 2001 and Merlin and Chehbouni 2004).

A2.1.6 ALEXI

The ALEXI model, proposed by Anderson et al. (2007) as an improvement of a two-source scheme, is a multi-sensor thermal approach to map ET by reducing the need for ancillary data input over a large area. The model deals with the errors in T_R remote estimation by using the rate of change in T_R observations (Anderson et al. 2010). The model estimates surface changes of heat and water vapour at scales of 5-10 km primarily from weather satellites, surface temperature derived from GOES (Geostationary Satellite Server) data, and vegetation indices from AVHRR satellite data on a daily basis. The model output used for regional hydrologic analyses, water stress assessment, agricultural decision-making and yield forecasting.

A2.1.7 CWSI

Plant water stress is very important indicator to evaluate the causes of variability in crop yields and development of water stress management strategies for optimal yield productions (Moran et al. 1997). The crop water stress index (CWSI) is an indicator for monitoring and quantifying crop water stress as well as for irrigation scheduling. The CWSI is based on the relationship between difference between air and canopy temperature (T_c–T_a) (Jackson et al. 1980) and the atmospheric vapour pressure deficiency (AVPD) to develop a non-stressed baseline equation for the growing season, which can be used to monitor water status and planning irrigation scheduling. There are only a few studies that have reported on using ground based measurements to compute CWSI to measure the water status of the sugarcane crop for irrigation scheduling in humid (for example Lebourgeois et al. 2010) and in arid regions (for example Boroomand-Nasab et al. 2005) in spite of the fact that sugarcane crop covers the soil during approximately two thirds of its growing cycle. For example, in humid regions of Reunion Island, Lebourgeois et al. (2010) tested the use of a TIR derived CWSI as an in situ measurement of the water status of sugarcane. They used ground based measurements for crop surface temperature, soil moisture and drainage to derive the ratio between actual and maximum evapotranspiration (ET_a/ET_{max}) values. Their results showed significant correlation between AET/MET and CWSI which indicated the effectiveness of the CWSI to measure the water status of the sugarcane crops. Silva et al. (2008) and Holanda et al. (2015) also utilized CWSI to evaluate water stress in sugarcane.

The RS based detecting of CWSI is through the measurement of a crop's surface temperature. The RS-based canopy temperature measurements is based on the fact that the water stress cause decrease in the transpiration rate (process responsible for cooling the plants) which results in increase in canopy temperature. However, crop temperature is sensitive to other variables, such as air temperature, relative humidity, wind speed, and incoming irradiance. The CWSI minimizes the effect of these environmental variables by normalizing the temperature differences between the plant and the air. The value of CWSI ranges from 0 to 1, representing no water-stressed through to water stressed (non-transpiring) conditions, respectively. Numerous studies have used CWSI for the assessment of crop water status and irrigation scheduling (Alderfasi and Nielsen 2001; Gontia et al. 2008; Oapos et al. 2011), however, they have not been used to predict the exact time and amount of irrigation needed to maintain the crop under optimum conditions. Remote sensing data from the NOAA AVHRR, LANDSAT TM, ASTER, and MODIS satellites collect information in thermal infrared (TIR) which can be used to determine surface temperature and to estimate CWSI. For example, Khomarudin and Sofan (2006) estimated CWSI using MODIS for paddy fields in eastern Java and obtained significant correlations between CWSI, NDVI and soil moisture storage.

A2.1.8 Remote sensing based Surface Water Balance

The remote sensing based surface water balance (RS-SWB) modelling approach estimates soil water content, cumulative ET and IWR (Neale et al. 2012). However, for an accurate estimation of these components the model requires information such as water inputs via precipitation and irrigation, as well as soil moisture properties such as the amount of soil water storage in the root zone. Accurate values of soil water content are necessary in the model and can be estimated on the basis of water balance maintained for long periods.

However, uncertainties on the spatial variability of the water inputs (mainly rainfall) can result in a bias in the water balance estimation, although this may not necessarily be a problem if sub-field scale management is required (assuming rainfall is evenly distributed over the spatial scale in question). What is likely of more concern is the dearth of information concerning those soil properties related to water retention, field capacity, and wilting point which may limit the practical operation of these models.

Remote sensing based estimations of root zone water storage capacity are generally based on field observations and look up tables (Schuurmans et al. 2003; Sanchez et al. 2010; Sanchez et al. 2012). A few recent studies proposed the optimization-calibration and inverse modelling approaches for soil root zone moisture estimation. Others use a combination of SWB models to estimate water stress from canopy temperature (Colaizzi et al. 2003) or ET estimates based on SEB models (Anderson et al. 2007; Crow et al. 2008) to calibrate the fraction of water depleted derived from the SWB model (Hain et al. 2009; Campos et al. 2016). The rationale of all of these approaches is that any plant water stress must be equivalent to the soil water stress, a stress index that can be determined by the parametrization of the soil properties. With proper initialization and maintenance of a SWB model, the two approaches of determining water stress can result in similar values. However, no information is available on the use of such approaches as the basis of irrigation scheduling.

A2.2 RS-SEB for Sugarcane

Remote sensing surface energy balance models have been applied for field scale irrigation water management in sugar cane. In Brazil, Ferreira et al. (2016) evaluated the water consumption of irrigated sugarcane using SEBS driven products derived from Meteosat Second Generation (MSG), SPOT/VEGETATION, Terra/MODIS satellite data and meteorological observations data. They compared the ET_a derived from the SEBS (ET_a-SEBS) with standard ET_c obtained under standard conditions using ET_o and the FAO based K_c. Their results showed good correlations between ET_a-SEBS and ET_c (FAO) when sugarcane was at maximum development stage with $K_c = 1.25$. The ET_a-SEBS values was found to overestimate the water use during the late sugarcane development stage as compared to FAO K_c value of 0.7. The results of Ferreira et a. (2016) were found to be consistent with those of Inman-Bamber and Mcglinchey (2003) for irrigated sugarcane in Australia and Swaziland, who also reported a higher K_c of 1.25 for the final growth stage. In another study in Brazil, Mendonça et al. (2012) used the SEBAL algorithm and MODIS satellite images to estimate daily sugarcane ET_c in North Fluminense Region, Rio de Janeiro State. They found a high correlation between values of ET integrated over 24 hours (ET24h) as estimated with the method FAO (PM-FAO56) and the values of ET24h estimated by SEBAL. In South Africa, Jarmain et al. (2014) used data from the Disaster Monitoring Constellation (DMC) sensor (G, R and IR) every ten days over their study period, and TIR data from MODIS (1km), both resampled to 30m spatial resolution. They included local meteorological and SRTM-DEM data in SEBAL to estimate evapotranspiration (ET), biomass, yield production and WUE. From the results, they demonstrated how spatial WUE information can be applied at operational level in South Africa. For Hawaiian sugarcane, Zhang et al. (2015) used the METRIC model to obtain the spatial distribution of ET_c and Kc from Landsat7 time-series data. They found a high correlation (0.82) between METRIC derived ET_c and K_c with the satellite derived K_c using canopy ground cover measurements. In Ethiopia, Genanu et al. (2016) compared SEBAL, SSEB and the Operational Simplified Surface Energy Balance (SSEBop) to estimate and map actual evapotranspiration (ET_a) of the Wonji Shoa Sugarcane Estate using Landsat7 ETM+ images. These results showed higher ET_a values for well-watered sugarcane fields in the mid-season growth stage, ostensibly confirming the greater consumption of water during this period of active development. In northern NSW Australia, Yang et al. (1997) estimated ET using Landsat TM data for a sugarcane field based on the concept of a vegetation index / temperature trapezoid (VITT). They used TIR band to extract surface temperature (T_s) and the Red and NIR to derive NDVI. Their result showed a consistent negative correlation between T_s and NDVI over the sugarcane field and they confirmed that the VITT concept showed potential for evaluating field water availability and assessing the variation on actual ET rate at a local scale, even without the need to invoke complex atmospheric corrections to the image data.

A2.3 The use of remotely-sensed vegetation indices and basal crop coefficient

The general K_{cb} curves constructed using the FAO-56 method describes ET_c for standard crop under optimum conditions. However, simple use of the time-based curves such as those depicted in Figure 1 may not adequately represent the actual crop development and water use conditions at a given time. Many different factors can cause deviations from the ideal curves, including local weather conditions, plant and soil nutrient status and soil water content. Soil moisture is not the only constraint to plant growth. In recognition of the realities of crop growth and development, FAO-56 recommends adjustments to the K_{cb} curve to estimate

ET_c. But tis is easier said than done; time-based K_{cb} curve adjustment is operationally difficult and requires considerable skills, time, and effort to achieve with any degree of accuracy.

Optical, multispectral vegetation indices (VIs) computed from crop canopy reflectance characteristics, particularly those such as the normalized difference vegetation index (NDVI) or soil adjusted vegetation index (SAVI) that focus on the red and near-infrared wavelength bands, may provide useful additional information in relation to K_c or K_{cb}. Such VIs, for example NDVI and SAVI have been used as surrogates for basal crop coefficients (K_{cb}) to detect and quantify the spatial difference in evapotranspiration and crop growth stages, useful for irrigation scheduling algorithms (for example Bausch and Neale 1987; Singh et al. 2013). More recently, Rahman and Robson (2016) demonstrated the potential of the Green NDVI (GNDVI) for yield prediction on the basis that the NDVI is prone to saturation at high LAI typical of established sugarcane canopies. Numerous studies have observed statistically significant, and in most cases simple linear relationships between the K_{cb} and a vegetation index (VI) derived from multispectral satellite images (Neale et al. 1989). The basis of these K_{cb}-VI relationships is the direct relationship between K_{cb} and the fraction of photosynthetic active radiation absorbed by the canopy (fPAR); the latter which is related with the particular VI. Although a few early studies have shown the relationships between K_{cb}-VI and fPAR for herbaceous crops such as wheat and corn (for example Asrar et al. 1992; Baret and Guyot 1991; Pinter et al. 1993), other workers have undertaken direct measurements of crop ET using lysimeters and Bowen ratio techniques for the development of empirical K_{cb}-VI relationships for different crops. Examples include the K_{cb}-VI relationship for potato (Jayanthi et al. 2007), cotton (Hunsaker et al. 2005), sugar beets (Gonzalez-Dugo and Mateos 2008) and vegetable crops including beans (Jayanthi et al. 2001) as well as garlic, bell pepper, broccoli, and lettuce (Johnson et al. 2012). The K_{cb}-VI relationship has been recognized for almost every crop, but the relationship was found very important for fruit trees, with large variations in local cropping practice conditions (planting densities, plant architecture and the management of the crop understory). These localized variables have great influence on the actual crop coefficient values and studies have shown that values of K_{cb} derived from local VIs to be able to take care of many of these variations. Examples include pecan trees (Samani et al. 2009) and vineyards (Campos et al. 2010; Er-Raki et al. 2013). Only a few studies have used fractional canopy ground cover (f_c) as a factor to estimate crop water use with reasonable success (for example Grattan et al. 1998). Remotely

sensed spectral indices such as NDVI have been found to be highly correlated to f_c of many crops (for example Trout et al. 2008), and f_c can be used for accurate estimation of K_{cb} (Allen et al. 1998; Allen and Pereira 2009). With the NDVI/f_c/K_{cb} relationships, Johnson and Trout (2012) used a time series of NDVI data to monitor vegetative crop ET in California. Their results suggested the application of RS based technique in timely estimation of crop water use, which can be useful for irrigation scheduling or water resource management.
Other workers have investigated the relationships between VI data and ET based on thermal remote sensing data (Rafn et al. 2008; Sing and Irmak,2009). These methods allow for a determination of latent heat fluxes, hence the actual ET of crops. When these methods are applied over irrigated areas (where in most cases evapotranspiration can be considered under standard conditions) they result in a massive calibration of the single K_c-VIs relationships without the necessity of cumbersome and expensive field campaigns measuring ET.

A2.3.1 Remotely sensed vegetation indices and K_{cb} for sugarcane

The relationships between remote sensing derived vegetation indices such as NDVI and SAVI and the fractional canopy ground cover (f_c), and between f_c and K_c have been investigated for sugar cane. For example, Zhang et al. (2015) used time-series Landsat 7 to measure canopy ground cover (f_c) and spectral reflectance over two sugarcane fields in Hawaii. They found a very strong relationships between sugarcane NDVI and f_c ($R^2 = 0.97$) and also f_c and sugarcane crop coefficient (K_c) ($R^2 = 0.89$). The K_c was calculated from ET_o based on nearby weather station network data, and sugarcane crop evapotranspiration (ET_c) based on ground-based measurements. Regression analyses was used to convert the satellite NDVI to K_c maps, which in turn was used to create satellite-based ET_c maps using a ET_o map created by spatial interpolation of nearby weather network data. In an another study, Bappel et al. (2005) determined the relationship between LAI and NDVI generated from time-series SPOT4 and SPOT5 satellite images for a sugarcane crop in Reunion Island. They found a strong relationship between LAI and NDVI using an exponential function (R^2=0.86) and used NDVI profiles to estimate LAI on a daily basis. Figure A4 shows the relationship between sugarcane LAI and SPOT derived NDVI (Bappel et al. 2005). It can be seen that NDVI increases rapidly until a LAI of 2, and then in typical fashion associated with NDVI and LAI as the number of leaf layers impede penetration of the radiation into the deeper parts of the overlayed canopy, the NDVI-LAI response curve begins to saturate.

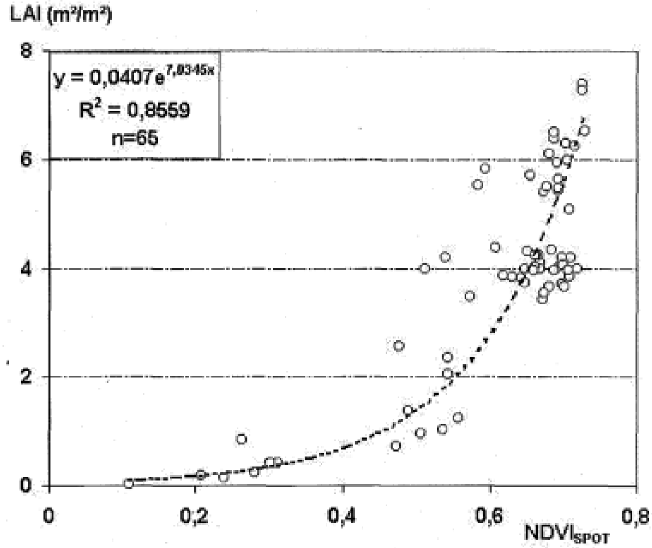


Figure A4 The relationship between sugarcane LAI and SPOT derived NDVI from Bappel et al (2005).

Singh et al. (2016) computed K_c, T_s and albedo from time-series NDVI data derived from Landsat-8 to estimate sugarcane crop water requirement in India. They found high correlation between ground-based K_c and NDVI and surface albedo. They estimated that the quality of the data generated in this approach could reduce water consumption by 12.5% compared to the ‘conventional approach’. In South Africa, Bastidas-Obando et al. (2017) combined environmental stress functions and LAI to calculate an hourly variable canopy resistance (r_c) value to predict sugarcane water demand and crop water productivity for both rain-fed and irrigated fields. The LAI for sugarcane was estimated NDVI derived from Landsat7 TM time-series using the empirical relationship defined earlier by Bappel et al. (2005). Their study confirmed the sugarcane’s ability to regulate and maintain a constant canopy resistance r_c with different LAI under non water-stressed and optimal climatic conditions. However, they suggested the need for more experimental data and longer time series from other countries to validate their stress functions parameters.

It is important to note that any K_c - NDVI relationship can vary due to evaporation from the soil, especially during the initial sugarcane growth stages when f_c is small. It has been recommended that is situations where K_{cb} is less stable than K_c, the K_c should be computed on a weekly basis to smooth out possible daily fluctuations (Calera-Belmonte et al. 2005).

A2.3.2 Remote sensing based Penman-Monteith direct method (RS-PM)

As discussed earlier, the Penman-Monteith (P-M) equation is used to estimate the evaporation from soil (E) and transpiration from plant leaves (T) from the canopy parameters related to the surface properties such as the surface and canopy resistances and the net radiation (R_n). These parameters are related to RS derived leaf area index (LAI), crop height (h_c), and the surface albedo (r). The variable canopy resistance is found to be inversely related to the photosynthetically active LAI, an index that actively contributes to the surface heat and vapour transfer (Allen et al. 1998). The maximum resistance of a single leaf is crop-specific and differs among crop varieties and crop management (Allen et al. 1998), but a fixed value of 100 m/s can be considered in 'operational' approaches (D'Urso et al. 1999). The canopy height is used to estimate r_c, The P-M formulation varies with climatic conditions, however for well-watered agricultural fields no correction is needed. Several studies have determined canopy parameters such as surface albedo and LAI from VIS-NIR observations, either using empirical relationships between VIs or physical radiative transfer models (Myneni 1997; Shi et al. 2016). The P-M method forms the basis of the MOD16 global ET product (Mu et al. 2011), ET estimates and irrigation management and for and irrigation advisory service presently operational in Italy, Austria, and Australia (Vuolo et al. 2015a).

A2.3.3 Calculation of Crop Water Requirement (CWR) for sugarcane irrigation scheduling

The standard FAO approach can be used to calculate CWR and that can be adapted to remote sensing data. The pixel-based CWR map can be transformed into a vector map by taking plot boundary or water user group boundary layers in GIS. The resulting irrigation advice for a generic plot (*i*) is then calculated from a simple water balance equation for any given day (*j*) as shown in Eq.(A7) (Vuolo et al. 2015a) as.

$$d_{i,j} = d_{i,j-1} + \frac{IRR_{i,j-1}}{\eta_i} - CWR_{i,j-1} \qquad \text{(A7)}$$

where, $IRR_{i,j-1}$ represents irrigation depth in plot *i* on the previous day; $d_{i,j}$ is soil water depletion from a given initial value of day 0; and η_i is the on-farm irrigation efficiency. The irrigation water volume is then computed by multiplying $IRR_{i,j}$ with the plot area.

A3. Operational use of RS data for irrigation water management

A3.1 Monitoring crop development at an appropriate spatial and temporal scale

For practical irrigation management, RS data must be available at key stages of crop development as well as at key time intervals at which irrigation intervention is likely to be necessary. Henceforth, temporal resolution of any source data is a key consideration, coupled with turn-around times of any source data. There is little point in having an appropriate revisit capability available if the data cannot be provisioned to the end user in a timely way. Revisit time is only part of the challenge. Ground visibility constrained by cloud cover and haze (eg smoke) is possibly the biggest constraint to temporal resolution faced by users of satellite image data.

The RS data should also be of sufficient spatial resolution ('granularity') to resolve field-scale variability in plant characteristics, or at least be able to provide information on spatial variability at a scale at which the irrigation is to be managed. Spatial resolution versus management scale is an important consideration. Having source data at a spatial resolution which exceeds the subsequent management scale allows for appropriate 'averaging' or spatial integration of key parameters to achieve the required spatial management scale by the user of the particular model. This is often more desirable than having a source that integrates potentially important variability indicators, unseen, before ingestion by an analyst into calculations or predictive tools.

A3.1.1 Optical satellite remote sensing systems

The combination of both planned and existing satellites into 'virtual constellations' can help to overcome the temporal resolution limitation by combining all available observations from different sensors (Wulder et al. 2015). For example, for reflectance-based VI models that use visible and NIR data, the spectral bands can be available at spatial resolutions (pixel size) ranging from 5 to 30 m from a variety of commercially available sensors, for example World View (2.5 m), Rapid Eye (5 m), DMC (22m), and Deimos, IKONOS, Digital Globe) as well as freely available from the Landsat-8 and Sentinel-2A. Currently, Landsat-8 and Sentinel-2A together provide data with a time resolution of around one image per 10-16 days, although this may not be considered sufficient for adequately monitoring of crop development. The time series information of both sensors can be accessible through USGS (http://glovis.usgs.gov/) and Copernicus (https://cophub.copernicus.eu/) websites. In addition, companies like Amazon S3 (https://aws.amazon.com/es/public-datasets/landsat/) and Google Earth Engine (https://earthengine.google.com/) provide time catalogues of image data available from the two sensors.

It could be presumed that the need for irrigation water management and the implementation of operational services around irrigation management would be heightened in regions of low rainfall and high atmospheric demand; in other words in regions that experience comparatively infrequent cloud cover. However the tropic and sub-tropical regions where sugar is typically grown, even when experiencing significant periods of little rain, may nonetheless experience extended periods of cloud cover.

The recently-launched Sentinel-2b satellite (https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2) will add further flexibility to the provision of optical data. Remotely-sensed SEB based ET products rely upon TIR data sources and the thermal bands limit the spatial resolution of derived products, in many instances to a size not appropriate for small agricultural fields (Allen et al. 2011). Such medium resolution ET maps contain mixed pixels of crops and other vegetation (for example shelter belts and pasture), which results in mixed surface temperature signals and makes the ET retrievals difficult to interpret. The thermal band pixel size ranges from 100m for Landsat-8 to 1000m for MODIS-AQUA, MODIS-TERRA and Sentinel-3, and therefore additional data sources and downscaling algorithms are required to improve the temporal and spatial resolution. The strength of any RS-SEB model is the assessment of surface ET which is used as an indicators of water stress and irrigation performance, and the measurements of canopy temperatures from thermal data provide addition information for irrigation management. Research targeting disaggregation techniques is underway to increase the effective spatial resolution of the thermal data to be comparable to the optical wavebands utilised (Semmens et al. 2015). In addition, use of the airborne thermal cameras has improved the spatial resolution up to 2–5m and produced high resolution temperature maps (Berni et al. 2009), although airborne systems have their own operational challenges and opportunities insofar as flexibility and cost. Some of these will be discussed later.

A3.1.2 Radar remote sensing

The use of radar images (microwave remote sensing) is an alternative solution to dealing with the limitations of optical images and cloud cover. Sentinel-1, a two satellite constellation carries an advanced radar instrument (synthetic aperture radar, SAR) operating in C-band (C-SAR) to provide an all-weather, day-and-night imaging capability of multiple spatial resolutions in different scanning modes (Strip Map Mode: 80 km Swath, 5m; Interferometric Wide Swath: 250 km Swath, 5x20 m, etc.), with a revisit cycles of 6 days (combined) and 12 days (single). The SAR data acquisition strategy results in inhomogeneous data archives with image products differing in the spatial resolution, revisit frequency, and radiometric accuracy. Therefore the choice of the data set for a particular application is a trade-off between those three properties. Several studies have used Sentinel-1 data for soil moisture monitoring (for example Hornacek et al. 2012; Gruber et al. 2013). Baghdadi et al. (2009) used TerraSAR-X, PALSAR/ALOS and ASAR/ENVISAT over Reunion Island to determine the sensitivity of different radar parameters (wavelength, incidence angles, and polarization) to sugarcane growth stages. They found high correlations between the radar backscattering coefficients and NDVI derived from SPOT-4/5 images as a function of sugarcane crop parameters. They also noted that the decrease in NDVI for fully mature sugarcane fields due to drying of the sugarcane (water stress) was also observed in the radar signal.

A3.1.3 UAV Systems

The significant and fast-paced technological advancements in small-sized, unmanned aerial vehicles (UAVs) equipped with GPS and high quality remote sensing devices offer numerous opportunities for irrigation-related management among other (for example Ballesteros et al. 2015; Candiago et al. 2015). The major advantages of using UAV systems in the context of tactical crop scouting, including, potentially for irrigation management is cost-effectiveness, especially for small scale operation, the ability to collect very high spatial resolution data, from centimetres to even sub-centimetre, and very high positional accuracy (X,Y,Z).
Like any form of low-level airborne sensing including low-level conventional manned aircraft, the most important benefit of using UAV system is that they can operate under cloud, and so long as images are corrected appropriately for varying target illumination associated with cloud cover, they offer unprecedented scheduling flexibility (Padua et. al. 2017), bearing in mind the limited weather conditions (wind speeds, actual precipitation) and regulatory conditions (altitude, visible line of sight, proximity to populated areas and events) under which flights can be undertaken.

The UAV systems can carry a large variety of sensors ranging from a low cost commercial RGB cameras to more expensive multispectral, near infrared, thermal and hyperspectral cameras and LiDAR sensors (Klemas 2015). Different camera sensors (single or in combination) are used for different applications and the resultant photos/images are processed to generate orthophotographs (Turner et al. 2012), or to build digital surface models (DSMs) (Nex and Remondino 2013). In agriculture, numerous studies have utilised UAV data to compute different plant parameters (LAI, f_c) and crop parameters (vigour, quality, yield) measured during the entire growing season (for example Ballesteros et al. 2015), as well as providing information on crop health and nutrient status (Candiago et al. 2015). Navia et al. (2016) used UAV-based multispectral data to compute NDVI to assist farmers in their assessment and monitoring of plant health. Bendig et al. (2014) used RGB data with VIs and plant height to determine biomass of barley. They found optical images to be highly suitable for deriving plant height from Crop Surface Model for biomass estimation. In sugarcane, UAV data has been used to detect stalk growth and infer soil moisture for irrigation scheduling. Luna and Lobo (2016) used UAV data to map crop planting quality of sugarcane in Nicaragua, while De Souza et al. (2017) used UAV and other proximal data for managing spatial variability.

Bellvert et al. (2013) demonstrated the feasibility of using high-resolution thermal imagery for irrigation management across vineyards. They found the best time to acquire thermal images is around noon, because of less shadow effects and also higher sensitiveness for the identification of water stress problems. Baluja et al. (2012) used both multispectral and thermal UAV data to determine water status variability in vineyards for better irrigation management at the fruit parcel scale. Zarco-Tejada et al. (2012) used UAV- a micro-hyperspectral and a thermal camera to detect of water stress in a citrus orchard.

A potential limitation of these platforms is the fact that large scale monitoring requires considerable post-processing capability to create mosaic imagery, and this is exacerbated by the difficulties in feature matching on overlapped images in homogenous area, for example within a uniform crop. However it is acknowledged that developments in cloud-based data processing is going to be key in meeting this particular set of challenges.

Despite these limitations, when used under optimal conditions, the UAV data can serve as a potentially valuable source of very high resolution data in real time and on demand; a particularly useful capability for filling data gaps in any time-critical tool for irrigation management.

A3.1.4 Filling the 'time gap' in RS-based irrigation scheduling

As discussed previously, crop canopy reflectance measured from multispectral, time series remote sensing data can be used to infer and map K_{cb}, or related variables, to describe the potential crop water use. This is done either through K_{cb}-VI relationships, or using more complex models. The use of 'gap filling' techniques reliant upon images taken at close time intervals can be used to fill the gaps in missing data owing to, for example, cloud cover.

A3.1.5 The need for soil moisture/evaporation measurements

For adequate determination of irrigation water requirement (IWR), both VI-based K_{cb} and remote sensing P-M models require the assessment of soil water content (Sanchez et al. 2012). Following the FAO56 procedures, the RS-based IWR can be calculated under water stress condition such as controlled deficit irrigation or supplementary irrigation. For this, the knowledge of the degree of desired water stress is required to calibrate the methodology. The model computes soil evaporation separately by applying a soil water balance at the top soil layer as proposed by Allen et al. (1998) and with some modifications by (Torres and Calera, 2010). This approach requires the information on the irrigation timing and amount and can be known from irrigation assessment scenarios. In absence of field data, as an alternative, synthetic crop coefficients (Mateos et al. 2013) can be used to estimate mean soil evaporation derived from canopy cover estimates. Microwave RS data could provide insight on the bare soil evaporation, however spatial resolutions of the current sensors SMAP and SMOS (20 km) are very coarse for the agriculture scale applications (Merlin et al. 2012).

A4. Examples of other remote sensing-based irrigation advisory services in Australia and other countries

Quite a few remote sensing based irrigation management services are operational worldwide to assist in different farm management activities. Those in operation over Australia include IrriSAT (https://irrisat-cloud.appspot.com; Deakin University), IriSatSMS (CSIRO, Australia) and IRRiEYE (http://www.irrieye.com). Others include IRRISAT (the Italian On-line Satellite Irrigation Advisory Service) and EO4Water (http://eo4water.com) in Austria. These operate based on the P-M method (Vuolo et al. 2015a) and NDVI-K_c relationships. The LAI is calculated from the crop surface reflectance, and the local climatic data are used to compute crop ET and suggested irrigation depth (pixel and plot scale). The RS data from different platforms such as Landsat-8, Sentinel-2, and DEIMOS are used to derive crop parameters (LAI and surface albedo) on a weekly basis. The information is delivered to end-users through a webGIS tool developed in an open-source software environment suiting to each area based on the requirements of the local users. Figure A5 depicts a schematic of the data integration.

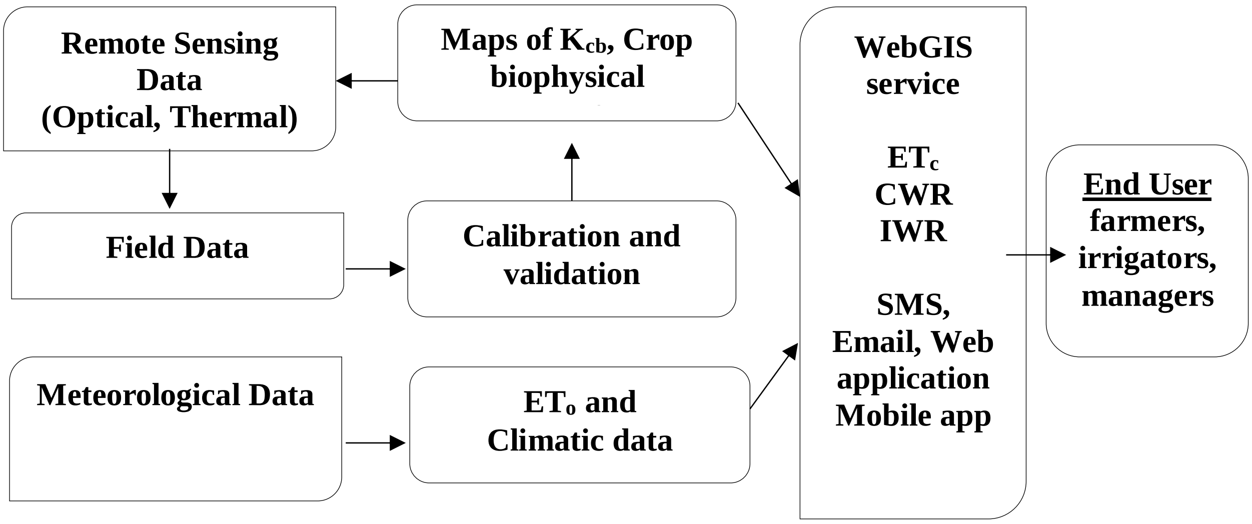


Figure A5. RS and weather observations integration into a webGIS to provide irrigation scheduling information to users.

The cloud-based IrriSAT app automates satellite processing and information delivery of Landsat and Sentinel data, including NDVI, and provides water management information across a range of scales. The IrriSAT app calculates the seasonal daily crop water use for the field by automatically retrieving the time series K_c values and linking them with the nearest weather station time series data. Similarly, the IRRISAT service aims to provide real time information on agricultural water needs to farmers and managers. Irrigation needs are estimated using high resolution data from satellites and FAO methodology for the calculation of crop water requirements at various spatial scales (field, catchment) and temporal scales (real time, historical series). The information is distributed in near-real time to the users through SMS, email, and also provide access to web-mapping applications. Accordingly, IRRISAT has been deemed a “best practice” for agricultural applications by EURISY (http://www.eurisy.org/good-practice-campania-encouraging-the-sustainable-use-of-irrigationwater-in-the-region_85) and by the International Selection Committee of the call for “Best Sustainable Practices on Food Security” for EXPO 2015 in Milan (Italy). In terms of cost-benefit analysis, IRRISAT demonstrated water savings of about 18% without loss of yield production.

IrriSatSMS system is an approach developed by CSIRO Australia based on the NDVI-K_{cb} relationship (Car et al. 2012) that uses satellite data, mobile phones, and webGIS tools for information delivery. The system was originally applied for vineyards in the Murrumbidgee Irrigation Area, but now covers the entire Australian. The IrriSatSMS system simplifies input data collection requirements and reduce both costs and complexity of information output (Hornbuckle, 2009). The system comprises a server that acts as a data collection portal for various data feeds and as a processing engine to convert these data into usable irrigation management information. The latest version of IrrSatSMS uses the Google Earth Engine for the image processing and algorithm implementation. Initially, the system delivered information through the SMS interface directly to the irrigators' mobile phones, but more recently a web-interface (https://irrisat-cloud.appspot.com/) has been developed that allows user to define the target field boundaries to get the information contained in the system. Information about the crop type, management, growing cycle, and soil properties are required to complete the water balance.

The Satellite Irrigation Management Support (SIMS) project integrates NASA's Terrestrial Observation and Prediction System (TOPS), Landsat and MODIS satellite imagery, to map indicators of crop irrigation demand and develop information products to support irrigation management and other water use decisions. The system provides a capability for mapping fractional cover, associated K_{cb}, and ET_c for farmland in California's Central Valley. A generalized NDVI-K_{cb} relationship is used for near real time mapping K_{cb} and ET_c. A web-based user interface provides access to visualizations of TOPS-SIMS (http://ec2-54-197-48-121.compute-1.amazonaws.com/dgw/sims/).

In southern Spain, time series Landsat5 images have used to obtain K_{cb} curves based on NDVI temporal changes and a web-GIS based open-source software called SPIDER was used to display the information (http://maps.spiderwebgis.org/webgis; University of Castilla-La Mancha). Currently, the system provides time series Sentinel-2a and Landsat-8 imagery and derived products for the entire Iberian Peninsula of Spain and Portugal. The products include ET_o maps, NDVI, K_{cb} and CWR values, 24 hours after the image delivery. A mobile app version of SPIDER webGIS (Agrisat App) was released in 2016.

A5. Pros and cons of the RS-based models for irrigation assessment

For crop irrigation management, the estimation of potential ET_c from the development of time-series RS-based K_{cb} and local ET_o values is the main strength of spectral reflectance-based models. The VI-based K_{cb} estimation for irrigation assessment has several advantages (Allen et al. 2011), including (a) algorithm simplicity and (b) geographical scaleability and application at varying spatial resolutions. However, the main weakness of K_{cb}-VIs for crop ET assessment are (a) the uncertainty in estimating the baseline soil evaporation, (b) under acute water shortage, it tends to overestimate transpiration; and (c) the K_{cb}-VI relationships vary within and between vegetation types. Moreover, discrepancies in the source VI values for a given location can arise be due to differences in sensors' spectral and radiometric resolutions (Martinez-Beltran et al. 2009), differences in the acquisition angle, atmospheric correction and calibration process (Fensholt et al. 2004). These sources of uncertainty can be minimized by applying cross-calibration approaches and ensuring the compatibility of the data-sources (Martinez-Beltran et al. 2009). Additional differences might be attributed to the variable sensitivities of VIs to variation in stomatal response for K_{cb} assessment. In the absence of known K_{cb}-VI relationships for sugar, those relationships reported in scientific literature for different crops have proven potentially transferable to other crops; Hornbuckle (2014), for example concluded that the relationships developed for multitude of different crops are potentially valid for the assessment of vineyard ET in Australia (Trout and Johnson, 2007). Similarly, Odi-Lara et al. (2016) and Campos et al. (2013) found that the relationship described by Campos et al. (2010) in row vineyards was adequate for ET assessment in apple trees and Mediterranean holm oak savanna.

The remotely sensed P-M methods have similar strength and weakness to the reflectance-based K_{cb} models. The P-M model approach also gets around the problem of estimating the resistances in the P-M formulation for well-watered canopy. The parameters are found strongly related with RS data (LAI, albedo and h_c) that describe smooth-continuous functions, easily interpolated over time. The uncertain crop-specific LAI-VI and h_c-VI relationships, difficulty in assessing the effect of the water stress in the ET process and the role of the soil evaporation are the main weaknesses. Anderson et al. (2004) concluded that the LAI-VI relationships to be relatively stable for corn and soybean using determinate VIs. In another study, Vuolo et al. (2013) concluded that the models and calibration parameters used to estimate LAI from VIs can be transferred across different environments, management practices, and for multiple crops. In addition, the availability of sensors with improved spectral and spatial resolution (such as, for example Sentinel-2) and also the application of improved methods (for example inversion) in canopy radiation transfer models to estimate crop biophysical parameters, can add more reliability in LAI estimation. Freely available packages, such as SNAP, developed by the ESA exist to estimate LAI, f_c, etc from Sentinel-2 data (https://sentinel.esa.int/web/sentinel/toolboxes/sentinel-2).

The main shortcoming of RS-SEB models is the applicability of the ET estimates over time because they provide the ET estimation at the time of image acquisition (Calera et al. 2016)**,** which must then be extrapolated in time based on crop physiology and crop coefficient (Allen et al. 2007). The time gaps between estimates of ET for all satellite systems may bias daily-to-seasonal estimates. Furthermore, the effects of rain or irrigation events occurring between satellite overpasses may result in underestimation of seasonal ET. The use of images in interpolation close to recent rainfall events could lead to overestimation of the seasonal values of ET. For the estimation of the net irrigation water requite (NIWR), another issue is the use of ET data obtained under water stress conditions. Since the NIWR is the amount of water that should be applied to maintain the crop transpiring at its potential rate, the use of water stress ET data could lead to an underestimation of NIWR. Finally, the limited availability of thermal sensors in terms of spatial and temporal resolution restricts the development of operational applications of surface energy balance from remote sensing.

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