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Key contributors to uncertainties in irrigation scheduling[1]

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Abstract

Introduction: Irrigation water is an expensive and limited resource. Previous studies show that irrigation scheduling can boost efficiency by 20-60%, while improving the water productivity by at least 10%. A key aspect of irrigation scheduling is accurate estimation of crop water use and soil water status, which often require modelling with good information on soil, crop, climate and field management. However, this input information is often highly uncertain. Our study aims to obtain a comprehensive understanding of uncertainties in irrigation scheduling that arise from individual model inputs, from which identifying the key contributor of uncertainty. Our study aims to understand the uncertainty in model-based irrigation scheduling and the key model inputs that contribute to this uncertainty. To achieve this, we first performed a comprehensive literature review to identify the key sources and the expected ranges of uncertainty in individual model inputs. Secondly, a global sensitivity analysis was conducted to quantify the influence of each model input on the total uncertainty of the modelled irrigation scheduling decision, across 14 climatically different locations in Australia.

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Materials and Methods: To achieve this, we used a global sensitivity analysis to assess the relative importance of the uncertainty in each model input to the total uncertainty in output. This analysis focused on the modelled irrigation scheduling (summarized with irrigation amount per day during an irrigation cycle) with a single-bucket soil water balance model following the Food and Agriculture Organisation (FAO). The key input variables required by the model include weather data, crop parameters (i.e., crop coefficient and root depth), soil parameters (plant available water capacity) and management factors (depletion factor).

Results: To define the uncertainty in each model input, we first performed a comprehensive literature review to summarize the key sources of uncertainty in estimating each of these model inputs, and the expected range of uncertainty in the data of each input. Based on these uncertainty ranges, we ran the global sensitivity analysis with the soil water scheduling model. In this analysis, a large number of random samples were drawn for each input variable within its expected range of uncertainty, to produce ensemble simulations of soil water status and thus irrigation scheduling decisions. The total uncertainty in these scheduling decisions were then analysed with respect to that of each input variable, to establish the relative importance of the uncertainty in individual input variables. The sensitivity analysis was performed at 14 climatically different locations in main irrigation districts across Australia to provide a comprehensive understanding of sensitivity.

Conclusions: Our results highlight the crop coefficient as the most important contributor to the total uncertainty in irrigation scheduling simulation, across different climate zones in Australia. The uncertainty in crop coefficient can be potentially reduced by better representation of its spatial and temporal variation, as well as considering alternative approaches such as remote sensing estimates. Our findings are useful to inform the future direction of research to improve irrigation scheduling in Australia. Further, our modelling approach is transferable to other irrigation regions to better understand the uncertainties associated with irrigation scheduling and the key data sources that lead to these uncertainties.

Keywords: Irrigation scheduling, Soil water balance, Sensitivity analysis, Uncertainity, Water productivity.

1. Introduction

Globally, 70% of freshwater is consumed by irrigation, while about 40% of the worldwide food production is contributed by irrigated agriculture (The World Bank, 2017). Whilst important, irrigation water is expensive and limited. Irrigation scheduling is shown to be able to boost efficiency by 20-60%, while improving the water productivity by at least 10% (Charlesworth, 2005). A key aspect of irrigation scheduling is accurate estimation of crop water use and soil water status. This is often achieved by model-based approaches together with good information on soil, crop, climate and field management, which show good capability for predictions and testing management options, thus illustrate high potential to support on-farm irrigation scheduling as operational tools (George *et al*., 2000, Gu *et al*., 2020).

However, inputs required by the such soil-water based scheduling models are often difficult to measure and/or highly uncertain. For example, the models need future weather to predict the atmospheric evaporative demand, but weather forecasts are often uncertain to inform definite irrigation decisions (Cai *et al*., 2011). Accurate crop information is critical to the modelling of crop water use, which is, however, often difficult to obtain as they are highly variable across different locations, crop types, climatic conditions and growth stages (Guerra *et al*., 2016). Further, the models also require initial soil water content to define the initial condition, while the measurement of soil water is often only practical at point scale, leading to large uncertainty in the measurements to represent the true conditions across space (Paraskevopoulos & Singels, 2014; Grayson & Western, 1998).

Our study aims to understand the uncertainty in model-based irrigation scheduling and the key model inputs that contribute to this uncertainty. To achieve this, we first performed a comprehensive literature review to identify the key sources and the expected ranges of uncertainty in individual model inputs. Secondly, a global sensitivity analysis was conducted to quantify the influence of each model input on the total uncertainty of the modelled irrigation scheduling decision, across 14 climatically different locations in Australia. We then discuss alternative approaches to estimate the most important model input identified from the sensitivity analysis, along with potential ways to reduce its uncertainty.

2. Methods

The study focuses on irrigation scheduling decisions informed by a simple bucket soil water balance model, and the uncertainties in the modelled decisions contributed by individual model inputs. Here we first provide a brief introduction of the soil water balance model and how it is used to inform irrigation scheduling, followed by an overview of the 14 case study locations. We then introduce the study approach to investigate the contribution of individual model inputs to the total uncertainty in irrigation scheduling.

2-1. Soil water balance model

A simple single-bucket soil water balance model (Allen *et al.*, 1998) was used to inform irrigation scheduling in this study. The model conceptualizes root-zone soil layers as a bucket, taking rainfall and irrigation as water inputs, and evapotranspiration (ET) and deep drainage as water losses. In this study, we assume deep drainage negligible, which makes ET the only way to deplete soil water. The model runs at a daily time step and requires ten main input variables from four categories to estimate the different water balance components, which are listed below and discussed in detail in Section 2.4:

- Daily weather variables include rainfall and other variables required to estimate reference ET (i.e., dew temperature, minimum temperature, maximum temperature, wind speed and solar radiation);
- Crop parameters to modulate the reference ET across the growth cycle of specific crops (i.e., crop coefficient and root depth);
- Soil parameters to define the boundaries of the soil water bucket (i.e., extractable soil water, which is the difference between field capacity and wilting point).
- Irrigation management factor i.e., depletion factor.

The soil water balance model can output both the time and amount of irrigation. For this study, we assumed that the soil water bucket is initially full and ran the simulation until the end of the first irrigation cycle (i.e., when the next irrigation is triggered) only. Both the irrigation amount and timing were then extracted to estimate the average irrigation amount per day across this irrigation cycle. The irrigation amount per day was considered as the model output for which the total uncertainty was to be quantified, for which contributions of individual input variables to be assessed.

2-2. Case study locations

To comprehensively assess the sensitivity of irrigation scheduling to input uncertainties, we included 14 climatically different locations within key irrigation districts across Australia as case study. These study sites are mapped in Figure 1, along with a summary of their key climatic statistics in Table 1. Within these, a key metric to highlight the different climatic conditions of the locations is the Aridity Index, which is defined as the ratio of annual precipitation to annual evapotranspiration, and thus representing the relative dryness. The 14 study locations span across a wide range of aridity from the driest at 0.16 (Station ID 76031) to the wettest at 0.63 (Station ID 32040).

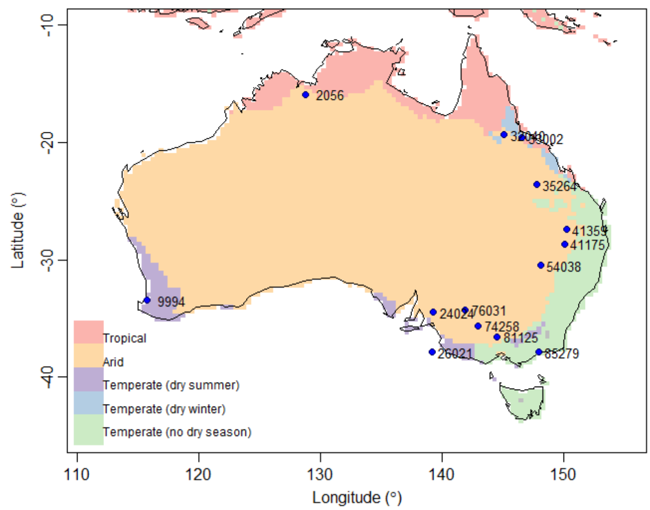

Figure 1. The locations of 14 studied (labelled by weather station ID) in Australia. Background colours show the main climate zones in Australia based on the Köppen classification (Beck *et al*., *2018)*.

Table 1. Summary of 14 studied locations, their climatic statistics and corresponding irrigation area

Weather Station ID	Record Period	Annual rainfall (mm)	Annual Potential ET (mm)	Aridity Index	Irrigation Area
76031	1999-2018	285.4	1783.8	0.16	Sunraysia
24024	1999-2018	256.1	1506.5	0.17	Golden Heights
74258	1999-2018	363.9	1732.9	0.21	Murray
35264	1999-2018	543.2	1873.1	0.29	Nogoa-Mackenzie
54038	2003-2018	569.8	1899.3	0.3	Namoi
81125	1999-2018	436.7	1408.7	0.31	Shepparton
41359	1999-2018	614.7	1707.5	0.36	Logan River
2056	1999-2018	836.1	2039.3	0.41	Ord
9994	2003-2018	927.7	1627.5	0.57	South West

Weather Station ID	Record Period	Annual rainfall (mm)	Annual Potential ET (mm)	Aridity Index	Irrigation Area
85279	1999-2018	644.9	1111.9	0.58	West Gippsland
33002	1999-2018	952.0	1613.6	0.59	Burdekin-Haughton
41175	2000-2018	756.4	1240	0.61	Condamine
26021	1999-2018	777.4	1274.4	0.61	South East
32040	1999-2018	1136	1803.2	0.63	Burdekin-Haughton

2-3. Sensitivity analysis

We performed a Sobol' sensitivity analysis to understand the relative importance of uncertainties in individual input variables for irrigation scheduling. The Sobol' method is a global variance-based approach (Sobol, 1993), which quantifies the contributions of individual model inputs to the uncertainty in the model output by decomposing the total output uncertainty to contributions from individual input variables and their interactions. For each model input, the Sobol' method estimates two key quantities called the sensitivity indices: the main effect and the total effect. The former represents the individual effect of uncertainty in a single input, while the latter represents the combined effects of uncertainty in this specific input together with its interaction with uncertainties in all other inputs. Both the main and the total effect indices are between 0 to 1, indicating no effect to 100% effect on the model output. To perform the variance decomposition and estimate sensitivity indices, the Sobol' method requires generation of a large number of samples for each model input variable within its expected range of uncertainty (Sobol, 2001). In the subsequent section, we describe the comprehensive literature review performed to define these ranges of uncertainty.

2-4. Defining the expected ranges of uncertainty in each model input

As discussed in Section 2.1, we considered ten key input variables to model irrigation scheduling. Thus, the total uncertainty in irrigation scheduling is contributed by individual inputs, which can be due to different sources of uncertainty and thus, consisting of different ranges of uncertainty. We performed a comprehensive literature review to identify the expected source and range of uncertainty for each input. We then identified realistic probabilistic error distributions to generate a large number of representative samples for each input variable within its expected range of uncertainty, these samples were used to understand the sensitivity of irrigation scheduling (Section 2.3). The key references reviewed to understand the uncertainty in each input variable is listed in Table 2.

Table 2. Input factors considered for irrigation scheduling sensitivity analysis and the key literature reviewed to define their uncertainty

Input Variable	Category	Source/Reference on expected uncertainty
Daily dew point temperature (T_{dew})	Weather	BoM automatic weather stations (BoM) (Su *et al.*, 2019; Acharya *et al.*, 2019; Webb, 2010)
Minimum daily temperature (T_{min})		
Maximum daily temperature (T_{max})		
Daily wind speed average (U)		
Daily total solar radiation (R_s)		
Daily rainfall (P)		
Extractable soil water (FC-WP)	Soil	(Veihmeyer & Hendrickson,1928; Zeng *et al.*, 2013; Rab *et al.*, 2011; Ladson *et al.*, 2006; Ratliff *et al.*, 1983; Allen *et al.*, 1998)
Single crop coefficient (K_c)	Crop	(Allen *et al.*,1998; Guerra *et al.*, 2016)
Root depth		(Allen *et al.*, 1998; Canadell *et al.*, 1996)
Depletion factor (ρ)	Management	(Allen *et al.*, 1998)

a. Weather Variables

Weather data can be obtained from actual observations from weather stations and model-derived reanalysis data. We reviewed literatures from the World Meteorological Organization (WMO, 1996) and the Australian Bureau of Meteorology (BoM) (Webb, 2010) to identify the ranges of measurement errors. To understand the expected ranges of interpolation errors within reanalyse data, we reviewed literature on four commonly used reanalysis weather products in Australia: the BoM's Australian Water Availability Project (AWAP) (Jones *et al.*, 2009) is used, the BoM's Atmospheric high-resolution Regional Reanalysis for Australia (BARRA) (Jakob *et al.*, 2017), the Modern-Era Retrospective analysis for Research and Applications-2 (MERRA-2) (Gelaro *et al.*, 2017) and the European Centre for Medium-Range Weather Forecasts (ECMWF) ReAnalysis Interim (ERA-Interim) (Dee *et al.*, 2011).

Observations from weather stations can be subject to errors due to sensor accuracy, malfunctioning and human errors etc. Reanalysis data are essentially interpolated from observations from nearby weather stations, which are associated with corresponding interpolation errors. In this study, these potential errors were represented in two forms as systematic bias and random noise. Systematic bias represents the situation where the errors in weather data are approximately constant over time, which are mostly seen in observations.

Random noise represents errors which are randomly distributed but centred around zero, which are mostly seen in reanalysis data.

For daily dew temperature (T_{dew}), minimum temperature (T_{min}), maximum temperature (T_{max}), solar radiation (R_s) and wind speed (U), we considered the two types of errors with Eq. 1 as:

$$P_t^{\wedge *} = P_t + \varepsilon_t^{\wedge} + \varepsilon_t^{*} \qquad \textbf{Eq. 1}$$

Where for at time step t, $P_t^{\wedge *}$ is the value of weather input with error, and P_t is the corresponding value without error, $\varepsilon_t^{\wedge}$ and ε_t^{*} are the bias and random errors, respectively.

For rainfall, due to the inclusion of zero values, the measurement errors are often defined differently to the abovementioned weather variables as multiplicative errors, while the random reanalysis errors can still be treated as random noises. This thus leads to Eq.2 which was used to considering rainfall uncertainty:

$$P_t^{\wedge *} = P_t * (1 + \varepsilon_t^{\wedge}) + \varepsilon_t^{*} \qquad \textbf{Eq. 2}$$

To represent the two types of errors in Eq. 1 and 2, $\varepsilon_t^{\wedge}$ and ε_t^{*} were sampled from probabilistic distributions individually defined for each weather input. For bias-only errors, $\varepsilon_t^{\wedge}$ is defined as a non-zero constant and ε_t^{*} is held at zero. The noise-only errors at different time steps are represented by holding $\varepsilon_t^{\wedge}$ at 0, while ε_t^{*} are randomly drawn from a pre-defined error distribution.

b. Soil parameters

The soil water balance model used to inform irrigation scheduling in this study requires extractable soil water as a key soil parameter. The extractable soil water is the difference between field capacity (FC) and the wilting point (WP), which are defined as the upper and lower limits of soil water contents at which drainage and permanent wilting of plant will start, respectively. A common way to estimate the FC and WP is with field measurements of the soil water content at the soil suction pressures of -0.33 and -15 bar (Richards & Weaver, 1944).

We reviewed two seminal field studies which collected a total of 1724 measured soil samples across the United States and measured their water contents at -0.33 and -15 bar pressure (Ratliff *et al*., 1983; Rawls *et al*., 1982). In addition, we reviewed the FAO guidelines on the recommended ranges of extractable soil water for different soil types. Our final estimates of the distribution of extractable soil water were obtained from synthesizing these references.

c. Crop Parameters

The crop coefficient K_c and the root depth are key crop properties used in the soil water balance model used to inform irrigation scheduling. The most widely used approach to estimate K_c is set out in the FAO56 guideline, which provides generalized values of K_c for different crops during different growth stages, for various climates. However, this approach still consists of high level of generalization and simplicity, which can lead to uncertainty in the recommended K_c values under different practical conditions. Considering this, we further reviewed alternative sources of K_c, including a comprehensive review which consists of over 150 field measurements of K_c across multiple crop types (Guerra *et al.*, 2016), along with several other studies which reported measured K_c values (Elliott *et al.*, 1988; Guerra *et al.*, 2015; Pereira *et al.*, 2015; Pôças *et al.*, 2015; Sharma & Irmak, 2017; Peddinti & Kambhammettu, 2019; Wang *et al.*, 2019). We compared these measured K_c with those suggested in the FAO56 guidelines to quantify the potential errors in K_c.

The root depth determines the depth of soil layers where the crop extracts water from, which thus influences the extractable soil storage capacity. However, root depth is difficult to measure due to its variation with crop growth stage, soil type, irrigation management and weather conditions. Due to the lack of literature, the uncertainty in the root depth was assumed in this study as a multiplicative error of 30%. Specifically, errors in root depth were sampled from a normal distribution of mean zero and standard deviation of 30%. These errors were applied to the maximum root depth during the middle growth stage of individual crops, as suggested by the FAO guidelines.

d. Management factors

The depletion factor represents the maximum soil water depletion allowed by an irrigator before applying the next irrigation. This parameter represents the relative level of risk that irrigators can tolerate. The FAO guidelines provided typical depletion factors, which we considered to construct this uncertainty.

3. Results and Discussions

3-1. Expected ranges of uncertainty in each model input

a. Weather Variables

From literature, we summarized the expected range of errors for each weather input as in Table 3. Based on these recommendations, we formulated the error distribution for the sensitivity analysis as detailed subsequently.

Table 3. Observation and interpolation and errors in various sources of weather data

Parameters	Observation Errors	Reanalysis Errors		
		RMSE	Mean bias	SD
T_{dew} (°C)	±0.3	1.7[a] 1 - 3.75[b]	0[a] -4 - 2.5 with mean of -0.75[b]	1.7[a] 2.8[b]
T_{min} (°C)	±0.3			
T_{max} (°C)	±0.3			
R_s (MJ/kg.m^2)	7% for clear and 20% for cloudy sky[a]			
U (m/s)	2.5 or 30% (whichever greater)	0.8 - 4.5[b]	3.5 - 4.5 with mean of 4[b]	2.83[b]
P (mm)	6%	3.1[a]	0[a]	3.1[a]
References	(WMO, 2018; Webb, 2010)	[a](Jones *et al*., 2009) [b](BARRA & ERA-Interim & MERRA2) (Su *et al*., 2019)		

For daily maximum, minimum and dew point temperature, systematic bias errors ($\varepsilon_t^{\wedge}$ in Eq. 1) were sampled from a truncated normal distribution with mean value of zero, standard deviation of 0.1 within the limits of ±0.3. The interpolation random errors (ε_t^{*} in Eq. 1) were sampled from a normal distribution with mean and standard deviation defined by the recommendations from the reanalysis datasets of BARRA, ERA-Interim and MERRA-2 (Table 3), which consists of the larger range of errors within literature reviewed.

Bias and random errors in solar radiation and wind speed were also sampled from probabilistic distributions based on Table 3, with an additional constraint to allow only positive values after the error has been added, considering their physical plausibility. The bias and random errors for solar radiation were treated together with a truncated normal distribution with a mean of 0 and a standard deviation of 7% of the value and limited within 20% of the value itself. The bias errors for wind speed were sampled from a truncated normal distribution with a mean of 0 and a standard deviation of 10% and limited within the greater value between 30% of the measured wind speed or 2.5 m/s. For interpolation random errors of wind speed, the error distribution was defined by the mean bias and standard deviation suggested by from the reanalysis datasets of BARRA, ERA-Interim and MERRA-2 (Table 2).

To represent systematic errors in rainfall, the multiplicative error factor ($\varepsilon_t^{\wedge}$ in Eq. 2) was selected from a log-normal distribution with mean value of one, standard deviation of 2% and limited within 6% of the measured value, based on Table 3. To estimate the random errors in rainfall (ε_t^{*} in Eq. 2), we took a different approach to other weather variables. Here we defined the random errors in rainfall based on a previous study (Acharya *et al*., 2019) which investigated the performance of the AWAP, BARRA and ERA-Interim modelled rainfall against observed values across different climate zones in Australia. The three key performance metrics reported were the correlation between modelled and observed values (ρ), the bias ratio (β) and the variability ratio (γ, ratio of coefficient of variation of modelled rainfall to observed values), as summarized in Table 4. The random errors for rainfall were then sampled from a probability distribution, with a mean defined by the bias ratio β, and the standard deviation defined by the variability ratio γ.

Table 4. Performance metrics of AWAP (A), BARRA (B) and ERA-Interim (E) modelled rainfall compared to observations (Acharya *et al.*, 2019)

	Tropical			**Arid**			**Temperate**		
	A	**B**	**E**	**A**	**B**	**E**	**A**	**B**	**E**
Correlation (ρ)	0.88	0.42	0.55	0.91	0.6	0.65	0.93	0.72	0.71
Bias Ratio (β)	1.24	1.28	0.97	1.22	1.35	1.01	1.2	1.22	1.06
Variability Ratio (γ)	0.87	1.15	0.61	0.9	0.85	0.86	0.91	0.93	0.79

b. Soil Parameters

Based on the FAO guidelines, the average extractable soil water for light, medium and heavy soils are 6.25%, 13.75% and 21.25% with standard deviations of 1.25%, 3% and 3%, correspondingly. These were compared with the estimated mean and standard deviations of extractable soil water from the other two key references (Table 5, based on Rawls *et al.*, 1982; Ratliff *et al.*, 1983). We found that within the three soil types, the medium soil has the estimated mean and standard deviation closer to the those suggested by the FAO guidelines. Therefore, we focused on the uncertainty range of extractable soil water for the medium soil for this study.

Table 5. The mean and standard deviation of extractable soil water extracted from Rawls *et al.* 1982 and Ratliff *et al.* 1983.

FAO Class	**Texture Class**	**Rawls *et al.* 1982**			**Ratliff *et al.* 1983**		
		Sample size	**Mean**	**SD**	**Sample size**	**Mean**	**SD**
Light	Sand	762	6%	6%	76	6%	2%
	Loamy Sand	338	7%	5%	7	12%	4%
Medium	Sandy Loam	666	11%	6%	31	11%	5%
	Loam	383	15%	5%	51	11%	4%
	Silt Loam	1206	20%	5%	83	19%	4%
	Sandy Clay Loam	198	11%	5%	24	11%	3%
	Clay Loam	366	12%	4%	41	14%	4%
	Silty Clay Loam	689	16%	4%	53	14%	3%

FAO Class	Texture Class	Rawls *et al.* 1982			Ratliff *et al.* 1983		
		Sample size	Mean	SD	Sample size	Mean	SD
Heavy	Sandy Clay	45	10%	9%	0	-	-
	Silty Clay	127	14%	3%	31	13%	5%
	Clay	291	13%	6%	3	12%	1%

c. Crop Parameters

Figure 2 shows the difference between the field-measured K_c values and the recommended values from FAO56 for different crop types. A two-way Analysis of Variance (ANOVA) test was applied on crop type and crop growth stage (initial, middle and end), and found a statistically significant (P=0.01%) difference of crop coefficient errors across different crop types, but no significant different across different growth stages (P=9%). However, the maximum number of reported K_c values we found for a crop type is only 13. Considering the small number of studies on assessing K_c values for each crop type, we decided to poll the K_c errors across for all crop types over all growth stages to define a single error distribution of K_c in this study. This led to a normal distribution with mean of 0.04 ad standard deviation of 0.22, from which the errors in K_c were drawn from.

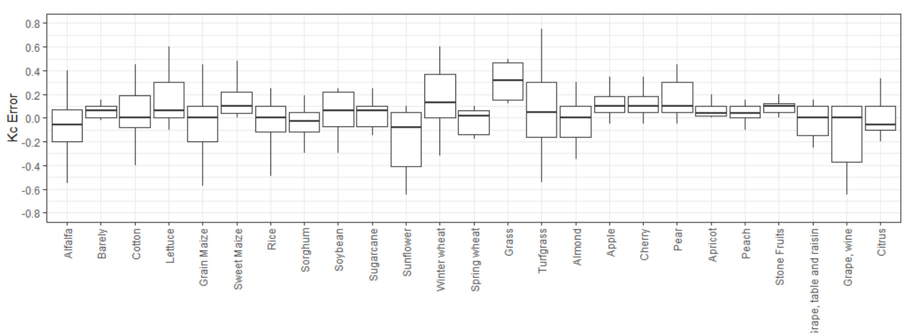

Figure 1. Distribution of K_c errors for 25 crop types, which were calculated as the difference between measured K_c values in literature and FAO K_c.

d. Management factors

FAO56 suggested that the depletion factor is typically associated with an uncertainty of 5%. Thus, errors in the depletion factor were drawn from a normal distribution with a zero mean and a standard deviation of 5%. The FAO suggested value for depletion factors was considered as the nominal value where no error presents.

3-2. Relative importance of input uncertainties for irrigation scheduling

The Sobol' sensitivity indices for each input variable to the soil water balance model is shown in Figure 3, with two panels showing the results with uncertain in the weather variables considered as bias or random noises, respectively. Comparing across the two types of errors, representing weather uncertainty as noises has generally reduced the contributions of all the weather variables to the total uncertainty in irrigation scheduling. This is expected as the bias represents a constant error, while random noises are more likely averaged over time. In general, the crop coefficient K_c is the most important variable amongst all inputs to the soil water balance model, and this is consistent regardless of when weather uncertainty is considered as bias or random errors.

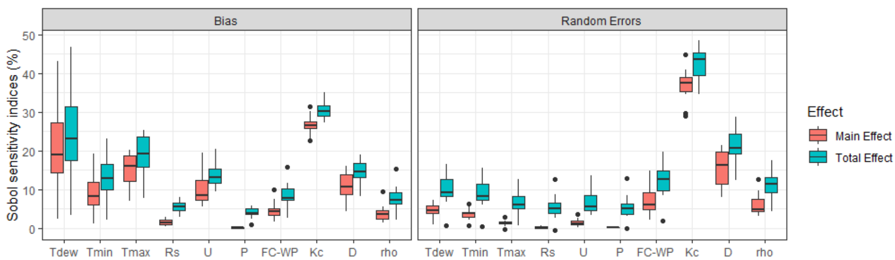

Figure 3. Sobol sensitivity indices for the main and total effects of each input factor with a) bias in weather data and b) random errors in weather data. Boxes represent the range of each sensitivity index of each input across individual study sites.

The least important input is rainfall. Specifically, the main effects of rainfall uncertainty are negligible with both the bias and random errors, while its total effects are notable but generally smaller than those of all other weather variables. A possible explanation for this result is that, the systematic bias in rainfall is assumed as multiplicative errors that can only appear with rainfall events (where rainfall>0)–which was based on previous assessments of weather station data quality (see *Section 2.4–Weather Variables*). The multiplicative errors also mean that greater uncertainty is often associated with more intense rainfall events. On the other hand, if rain falls during an irrigation cycle, the time to the next irrigation generally increases, leading to a decrease in the irrigation amount per day (i.e., the model output of interest in this study) compared to dry days. Linking these with the mechanisms of the Sobol' sensitivity analysis, it is expected that for a wetter condition the modelled irrigation per day is lower, while the uncertainty in rainfall is generally high. In contrast, for a dryer condition when the modelled irrigation per day is higher, there will be lower or no uncertainty in rainfall. Meanwhile, the effect of uncertainties in all other weather variables are not affected by neither the occurrence nor the intensity of rain events. Consequently, we can expect the relative importance of other weather variables to be higher than rainfall as they have more influences on situations with higher irrigation amount per day.

4. Conclusions

This study aims to assess the sensitivity in irrigation scheduling to the uncertainties in individual inputs of the soil water balance model which is used to inform scheduling. A global sensitivity analysis was used to assess the relative importance of the uncertainty in each model input to the total uncertainty in output. We performed a comprehensive literature review to define the range of uncertainty in each input variable. Our results highlight the crop coefficient K_c as the most important contributor to the total uncertainty in modelled irrigation scheduling. Using FAO56-based values for K_c may induce a maximum error of ±0.8 for a single crop type, due to the high variation in K_c across different locations and crop growth stages. Therefore, alternative approaches to estimate K_c should be considered in addition to FAO56, with particular focus on representing field-specific K_c while accurately capturing its temporal dynamic across the cropping season. Near-time or real-time satellite-based K_c, such as the *IrriSat* product which used satellite-based NDVI to derive K_c, has popular uptake amongst irrigators in Australia and New Zealand (Montgomery *et al*., 2015). Other satellite data on ground cover and crop conditions along with field data can be used to adjust further improve the accuracy of K_c values (Yang *et al*., 2020; Yang *et al*., 2022).

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