A Hybrid Framework for Short-term Irrigation Demand Forecasting

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Abstract

Reliable short-term forecasts of Irrigation Water Demand (IWD) can provide useful information to help water supply system operators with day-to-day operating decisions. Forecasting IWD is a complex task due to different natural (soil, water, crop, and climate interactions) and behavioral (farmers' decision-making) components of the irrigation process. So far, various approaches have been developed to estimate IWD values in different contexts. One common approach is the application of data-driven methods to map the relationship between the main influential factors and IWD. Data-driven approaches often do not consider any conceptual understanding of the system in modeling IWD, which has been found to be effective in improving the predictive performance when considered. In this study, a hybrid framework has been introduced and developed by incorporating existing physical knowledge of the system into a data-driven model to predict IWD. This framework consists of two modules: In the first module, a simple conceptual approach was implemented to model the understood factors leading to crop water needs using observation data. In the second module, a data-driven model was used to capture the remaining relationships between inputs and the output in the irrigation process. The proposed hybrid framework was then applied to estimate daily IWD up to 7 days ahead for an irrigation district in Victoria, Australia. Results show that the integration of physical system understanding into data-driven models can improve the performance of IWD forecasting models, particularly during the high-demand period. In addition, the hybrid framework provides improved system understanding and thus leads to increased capacity to support operational decisions.

Keywords: Irrigation Demand Forecasting, Short-term Water Demand, Hybrid Modeling, Artificial Neural Networks, Lower Murray Water

1. Introduction

Short-term Irrigation Water Demand (IWD) fluctuates due to a wide range of factors, from weather variations (hot periods or rainfall events) to different pressures or opportunities that farmers may face in the real world. Therefore, IWD forecasts can provide helpful insights into daily operational decisions for not only water suppliers but also agricultural businesses (Perera et al., 2016). For example, IWD forecasts will allow decision-makers to distribute water optimally considering variable electricity tariffs and thus minimize energy costs (Perea et al., 2015). IWD forecasts can also be useful in designing new irrigation systems or rehabilitating existing systems (Liao et al., 2021; Peng et al., 2009).

IWD forecasting is a challenging task mainly due to the uncertainty of the climate variables determining the demand for irrigation water, such as evapotranspiration, temperature, and precipitation (Du et al., 2017; Meempatta et al., 2019). Therefore, forecasts of different weather variables have been used as the principal inputs of the IWD forecasting models. Different modeling methods have been utilized to estimate IWD for various applications (Paul et al., 2000; Perea et al., 2019; Prasad et al., 2006; Pulido-Calvo and Gutierrez-Estrada, 2009; Rao et al., 1990). These methods can be classified into two categories: conceptual and data-driven models (Perera et al., 2015).

Conceptual IWD models are developed by modeling key elements of the irrigation process (e.g., soil water content balance or crop water needs) and the relationships between them. These models have been employed for different spatial (from farm to system) and temporal (from lead times of 1–2 days to weeks) scales. Conceptual models estimate the timing and amount of irrigation water by maximizing the production or benefit with different irrigation criteria such as (Broner, 2005; SRINIVASAN, 2006): (1) Farmer's estimates of crop water needs, which results in non-optimal irrigation scheduling (irrigating less or more than crop needs during some crop stages) or, in other words, lower production or benefit (Levidow et al., 2014), (2) Estimates of crop water needs using historical climate data (Perea et al., 2017), (3) Estimates of irrigation water based on climate data and soil water balance (GarcÃ-a et al., 2018; GonzÃ¡lez Perea et al., 2014), (4) Estimates of irrigation water based on soil water data collected from soil moisture sensors (Ramadan et al., 2018; Soulis and Elmaloglou, 2018). A broad spectrum of modeling techniques has been used to calculate daily crop water requirements within the conceptual models, from empirical or functional (Allen et al., 1998; Doorenbos et al., 1979; Doorenbos and Agriculture organization. Rome, 1975) to mechanistic approaches (Van Aelst et al., 1988). Various items such as soil data, crop characteristics, crop patterns, and weather forecasts have been used as the inputs of these models (Cai et al., 2011; Wang et al., 2009).

The primary drawback of the conceptual models is the narrow physical understanding of the system and irrigation process. Therefore, the performance of these models is impacted by the way the irrigation process is represented by the model structure and input data (Cai et al., 2011; Ejieji and Gowing, 2000; Wang et al., 2009; Wilks et al., 1998). Since not all the interactions between system elements are fully understood or can be modeled, the conceptual models mainly consider irrigation water equivalent to crop water needs and do not incorporate any finer details. Calculated water needs do not necessarily provide acceptable estimates of actual water use or, in other words, consumer demand (because other factors like local irrigation practices also affect the demand). In addition, the development of these models is often constrained by limited specific observation data in many irrigation systems.

Increasing data availability, specifically in the last two decades, has led to the emergence of data-driven approaches to simulate complex processes such as IWD (Fernandez Garcia et al., 2020). Data-driven models directly map the relationship between the driving factors of the irrigation water (mainly weather variables) and IWD without requiring any knowledge about the physical processes within the system (Pulido-Calvo and Gutierrez-Estrada, 2009; Ticlavilca et al., 2013; Tikhamarine et al., 2020; Tung and Yaseen, 2020). Data-driven approaches employ a range of different statistical techniques, from artificial intelligence to multivariate time series. Artificial intelligence-based models have been the most popular in the context of short-term IWD forecasting. In some studies, artificial intelligence has been used in combination with tools such as genetic algorithm or fuzzy logic to get better forecasts or address the limitations related to the quality or quantity of input data (Perea et al., 2015; Perea et al., 2019; Pulido-Calvo and Gutierrez-Estrada, 2009).

Although data-driven models have often successfully improved the predictive performance of IWD forecasting, there are some concerns about these models. Because interactions in the system are modeled implicitly, overfitting is a common problem for data-driven models (Wu et al., 2014). In addition, it has been found in some studies that data-driven models perform worse during periods of extreme higher or lower demand (when it would be more beneficial for operators). This is mainly due to the over-generalization of these models when they are developed (Perea et al., 2015; Pulido-Calvo and Gutierrez-Estrada, 2009).

Conceptual and data-driven approaches for IWD forecasting have advantages and disadvantages, as explained above. There are potential benefits to combining these two approaches, so they can complement each other and improve the overall modeling performance(Hu et al., 2021; Liu et al., 2020). These benefits have been explored and reported in different areas of water resources management (Hunter et al., 2018; Kraft et al., 2022; Mekonnen et al., 2015). However, in the context of IWD modeling, very few studies have used hybrid approaches to improve the performance of the data-driven models (Perera et al., 2015; Perera et al., 2016), and the majority of existing studies have applied data-driven and conceptual approaches independently.

This study proposes a generic hybrid framework for forecasting irrigation water by combining two conventional modeling approaches and integrating users' understanding of the physical system with data-driven techniques. The hybrid model framework consists of two modules: one conceptual and the other data-driven. In the conceptual module, daily crop needs were estimated using reference crop evapotranspiration, rainfall, and annual cropping pattern and area. In the data-driven module, the remaining residual information (between the previously mentioned conceptual module outputs and the observed pumped volumes) was captured. This framework was then tested on a real-world case study in Red Cliffs irrigation district of Lower Murray Water (LMW) area of operations in Victoria, Australia to predict daily irrigation demand. In addition, the performance of this hybrid modeling framework was compared with a benchmarking model developed using data-driven techniques only. This study demonstrates that the hybrid modeling framework leads to improved performance compared to a data-driven modeling approach on its own. This outcome can bring a new perspective for other researchers working on short-term forecasting of irrigation water.

The remaining sections of this paper are organized as follows: the study area is introduced in the next section, followed by the details of the proposed model in the third section. In section 4, the corresponding results are presented and discussed, and lastly, a summary of the paper and conclusions are provided.

2. Study Area and Data

Red Cliffs irrigation district (with 32 km^2 of irrigated area) is located in Lower Murray Water (LMW) area of operations, Victoria, Australia (Figure 1). Agriculture in this district is dominated by wine grape plantings, table grapes, and dried grapes, with drip irrigation as the most widely used irrigation method. The current irrigation efficiency in the area is approximately 85%. Automated connections of this modernized system provide daily pumped flow values from 1979. The daily value of pumped water to the irrigation district is used as a surrogate for IWD in this study. LMW also provides data on crop types, development of permanent crops, planting trends, irrigation developments, and irrigation methods in the study area from 1997 to 2018 (every three years). However, in this paper, eight years of data from Sep. 2012 to Aug. 2020 were chosen as the study period. This was because the cropping pattern almost remained the same during this time.

Daily values of weather variables were obtained from the Bureau of Meteorology (BOM) for Mildura Airport Station for the study period (Sep. 2012 to Aug. 2020). These variables include daily rainfall (R) [mm], daily maximum and minimum temperatures (T_{max} & T_{min}) [℃], daily relative humidity (RH) [%], bright sunshine hours (SE) in the 24 hours midnight to midnight local time [hr], wind speed (WS) [km hr^{-1}], and daily mean sea level pressure (MSLP) [hPa]. Furthermore, FAO Penman-Monteith method was used to calculate the daily reference evapotranspiration (ET_0) [mm] using air temperature [℃], humidity [%], radiation [MJ m^{-2} day^{-1}], and wind speed data [km hr^{-1}]. ET_0 indicates the evaporating power of the atmosphere at a particular place and time of the year and does not include any crop characteristics and soil factors. Apart from the mentioned cropping data and daily climate variables, seven lags of daily pumped water volumes (PV) [ML] to the irrigation district (prior to the day of prediction) were used as the inputs of the IWD forecasting models in this study as well.

Figure 1 Study area (adapted from Lower Murray Water (2019))

3. Methodology

3.1. Hybrid model development

The hybrid modeling framework, as illustrated in Figure 2, consists of two modules: 1) conceptual and 2) data-driven. Daily crop water needs (CWN) were calculated using the conceptual module based on daily weather variables and annual cropping area in. First, reference evapotranspiration (ET_0) was estimated based on climate variables (such as temperature, humidity, radiation, and wind speed). Then, together with daily rainfall and cropping area, ET_0 values were used to estimate CWN throughout the growing season. Details of the conceptual module are discussed in section 3.1.1. Apart from crop water needs, irrigation demand also depends on a range of other factors such as farmers' irrigation strategies, different interpretations of uncertain weather forecasts, and a degree of randomness that cannot be included in the conceptual module mentioned above. Therefore, an ANN model was used in the data-driven module to capture the remaining information in the irrigation process that the conceptual module could not capture. The details of the ANN-based data-driven module are provided in section 3.1.2.

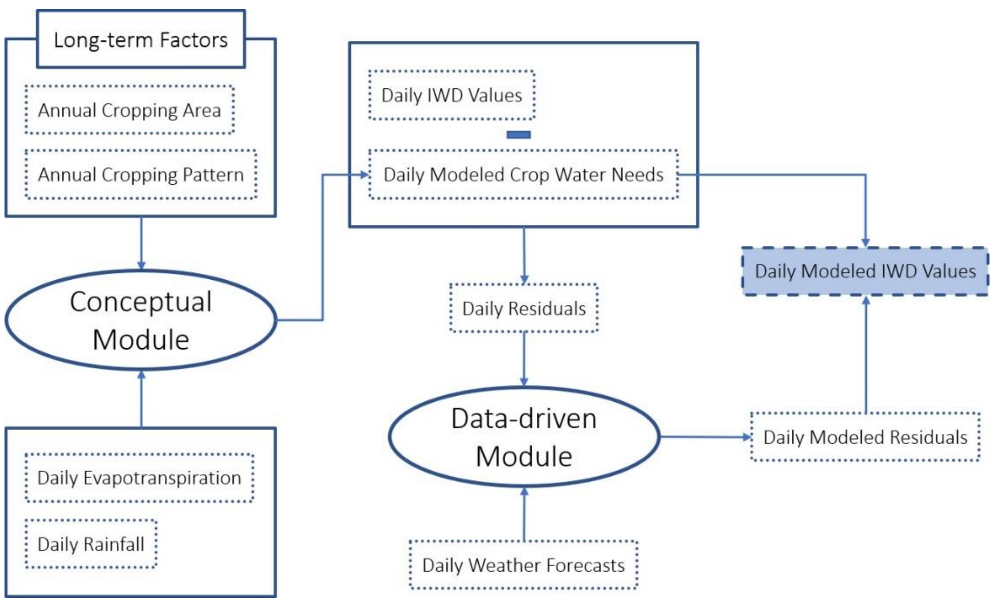


Figure 2 Flowchart of the hybrid model

3.1.1. Conceptual module

In the conceptual module, daily crop water needs (CWNs) were estimated. CWNs are mainly driven by weather conditions throughout the growing season (considered in reference evapotranspiration and rainfall) and cropping area and pattern in the study area. The most important factor affecting crop water needs (in a unit of area) is reference evapotranspiration (ET_0), which was estimated based on Penman-Monteith equation recommended by FAO 56 paper (Allen et al., 1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{3}$$

where:

ET_0 reference evapotranspiration [mm day^{-1}]

R_n net radiation at the crop surface [MJ m^{-2} day^{-1}]
G soil heat flux density [MJ m^{-2} day^{-1}]
T air temperature at 2m height [°C]
u_2 wind speed at 2m height [m s^{-1}]
e_s saturation vapor pressure [kPa]
e_a actual vapor pressure [kPa]
$e_s - e_a$ saturation vapor pressure deficit [kPa]
Δ slope vapor pressure curve [kPa °C^{-1}]
γ psychrometric constant [kPa °C^{-1}]

In addition, rainfall can act as irrigation water and hence decreases IWD. However, the relationship between IWD and rainfall is more complex. Heavy rainfalls after soil saturation (often represented using a rainfall threshold) can lead to runoff and deep percolation (Allen et al., 1998). Therefore, a rainfall threshold has been defined to simulate runoff generation in reaction to rainfall in the conceptual module. In other words, only when rainfall reaches the threshold value runoff will be generated. The equations below represent the formulation of the conceptual module:

$$CWN_i = \alpha_s \times ET_{0_i} \times A_y - \beta_s \times R_i \times A_y + \delta_s \quad if\ R_i < T \tag{1}$$

$$CWN_i = \alpha_s \times ET_{0_i} \times A_y - \gamma_s \times R_i \times A_y + \theta_s \quad if\ R_i \geq T \tag{2}$$

i: day counter
s: season counter
y: year counter
CWN_i: crop water needs of the ith day (ML),
ET_{0_i}: reference crop evapotranspiration (mm)
A_y: annual cropping area of the yth year (ha),
R_i: rainfall of the ith day (mm),
α_s: ET_0 coefficient of the sth season,
T: rainfall threshold (mm),
β_s & γ_s: rainfall coefficients of the sth season
δ_s & θ_s: seasonal intercepts.
(s=1,2 & 3 for spring, summer & non-growing period)

The parameters of the conceptual module were calibrated by minimizing the Mean Squared Error (MSE) between the estimated CWNs, and the observed pumped volumes, knowing there would be relatively large errors since not all the factors affecting IWD are represented in the conceptual module. However, this error will be corrected by the data-driven module, as explained above. To avoid getting stuck in local minimum points, “patternsearch” was employed from the Global Optimization Toolbox in MATLAB. Unlike more traditional optimization algorithms, this method does not require any information about the gradient of the objective function.

3.1.2 Data-driven module

In the data-driven module, an ANN was utilized to correct the error between CWNs and pumped water values. An extensive range of variables can influence short-term IWD directly or indirectly. Based on the interview with the farmers in the study area, soil moisture levels (a result of irrigation during past days) and weather forecasts for the next days are the two substantial factors affecting water ordering decisions. Since farmers can order water from 1 to 7 day(s) prior to irrigation (within certain volumetric limits due to equitable access to water), seven lags of all the prospective inputs variables (reference evapotranspiration (ET_0), precipitation (R), maximum temperature (Tmax), solar exposure (SE), wind speed (WS), mean sea level pressure (MSLP)) and the output variable (the pumped volumes (PV)) were considered as input candidates. Furthermore, forecasts of the mentioned weather variables over the next seven days have been included as candidate inputs given that farmers consider weather forecasts before placing an order. In this study, the "perfect weather forecast" assumption has been made by adopting observation values of the weather variables. This way, weather uncertainties can be avoided in the modeling process.

Input and model structure selection are the main stages of data-driven module development. Two stages of the input selection are: (1) ranking inputs (based on the degree of numerical association with daily demand values) and (2) determining the optimum number of inputs. The partial correlation value quantifies the degree of association between two variables considering the effect of a set of controlling variables removed. Quantifying the numerical relationship between two variables based on the (normal) correlation coefficient could lead to misleading results if a third variable is numerically related to both variables. Therefore, PV_{t-1}, the first input variable of the conceptual module (of the hybrid framework) was selected based on the correlation coefficient. Table below lists the first thirty ranked variables for the data-driven module inputs based on the partial correlation analysis.

Table 1 List of the first thirty inputs of the data-driven module of the hybrid model

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PV_{t-1}	ET_{0t}	PV_{t-7}	ET_{0t-7}	PV_{t-2}	R_{t-2}	PV_{t-3}	PV_{t-4}	R_{t-4}	ET_{0t+1}	R_{t-1}	SE_{t-7}	R_{t-3}	R_{t-5}	ET_{0t-1}
16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
ET_{0t-6}	WS_{t-1}	R_{t+1}	PV_{t-6}	PV_{t-5}	R_{t+7}	WS_{t-4}	R_{t+3}	SE_{t+1}	SE_{t-6}	ET_{0t+3}	R_{t-6}	SE_{t+2}	WS_{t-2}	SE_{t+4}

As mentioned earlier, it is possible to improve the performance by adding more inputs when fitting a model. This may, however, result in redundancy, noise and therefore overfitting and BIC reflects this by introducing a penalty term for the number of inputs in the model. In the figure below, BIC values are presented for the calibration period of the models fitted with different numbers of inputs. In total, 11 variables, including PV_{t-1}, ET_{0t}, PV_{t-7}, ET_{0t-7}, PV_{t-2}, R_{t-2}, PV_{t-3}, PV_{t-4}, R_{t-4}, ET_{0t+1}, and R_{t-1} are selected as the final set of predictors for the data-driven module based on partial correlation analyses and the Bayesian Information Criterion (BIC). It should be noted that t-i shows the ith lag of the variable where i ranges from -7 to -1. Similarly, t+i shows the forecast of ith day after the current time step where i ranges from 1 to 7.

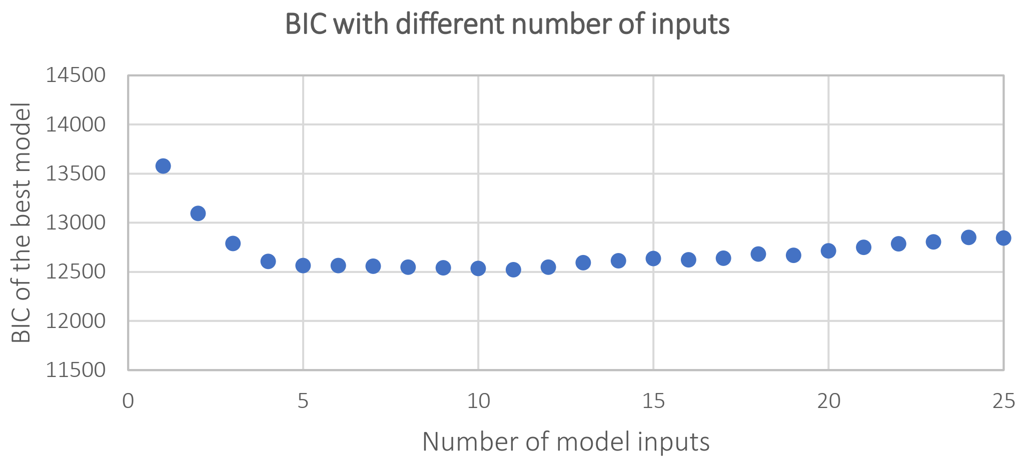


Figure 3 BIC values for different number of inputs for the data-driven module of the hybrid model

Artificial Neural Network Toolbox of MATLAB was employed to generate the data-driven module following the steps of the ANN model development process outlined in Wu et al. (2014). A Multi-Layer Perceptron (MLP) with one hidden layer was used in this study. This is because MLP is one of the most widely used network architectures for water resources management and it has been proven to be effective in modeling most environmental systems (Wu et al., 2014). Model structure selection has two stages: selecting the transfer functions and the number of nodes for the hidden layer. Since the number of nodes for the hidden layer affects the number of model parameters, it is optimized using BIC. The training algorithm and transfer function were finalized by evaluating different combinations of training algorithms, transfer functions, and the number of hidden nodes based on the averaged Mean Squared Error across 20 random seeds. The training algorithms tested include Levenberg-Marquardt, BFGS Quasi-Newton, Resilient Backpropagation, Scaled Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts, Fletcher-Powell Conjugate Gradient, Polak-Ribiére Conjugate Gradient, One Step Secant, and Variable Learning Rate Backpropagation. The tested transfer functions for the hidden layer include Log-sigmoid, Hyperbolic tangent sigmoid, and Linear. The numbers tested for the hidden layer nodes range from 5 to 20. The network weights and biases are initialized randomly based on specified distributions (Foresee and Hagan, 1997). The learning rate and momentum used are 0.01 and 0.9. The final model structure includes one hidden layer with five nodes and Log-sigmoid as the transfer function. Finally, like any data-driven model, an MLP model can overfit the calibration data. To avoid overfitting, 75% of the calibration data was used for training, and the remaining 25% was used as the testing data for early stopping.

3.2. ANN benchmarking model development

For the benchmarking model, the same data-driven method as the hybrid model was used to map the candidate inputs to daily IWD values (to evaluate the predictive performance of the hybrid model). All the benchmarking model development details are the same as the data-driven module of the hybrid model. However, there are two main differences:

- The data-driven module of the hybrid model was trained to produce residuals between the conceptual model (not pumped volume values) and observations, as mentioned earlier.

- Because ET_0 and precipitation variables had already been used in the conceptual part of the model, they were not included in the potential input set of the data-driven module.

Because crop need (translated through ET_0) and rainfall of the day to be predicted are the most important information that farmers use for making irrigation decisions, these two variables were preselected as input variables in the benchmarking model. For the rest of the candidate inputs, partial correlation analysis has been done to determine the level of association of each variable with other predictors. Table below lists the first thirty inputs of the benchmarking model. Finally, seven variables were selected as the optimum number of inputs for the data-driven benchmarking model because of the lowest BIC value (Figure 4). These variables are ET_{0t}, R_t, PV_{t-1}, PV_{t-7}, ET_{0t-7}, PV_{t-2}, and PV_{t-3}. Also, Log-sigmoid transfer function, five neurons in the hidden layer, and Levenberg-Marquardt training algorithm were selected.

Table 2 List of the first thirty inputs of the data-driven benchmarking model

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ET_{0t}	R_t	PV_{t-1}	PV_{t-7}	ET_{0t-7}	PV_{t-2}	PV_{t-3}	R_{t-2}	PV_{t-4}	ET_{0t+1}	R_{t-1}	R_{t-4}	PV_{t-6}	PV_{t-5}	R_{t-5}
16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
R_{t-3}	ET_{0t-1}	R_{t+1}	SE_{t-7}	ET_{0t-6}	WS_{t-7}	T_{maxt-1}	SE_{t+4}	R_{t+3}	SE_{t+2}	ET_{0t+3}	SE_{t-6}	R_{t+7}	$MSLP_{t+3}$	R_{t-6}

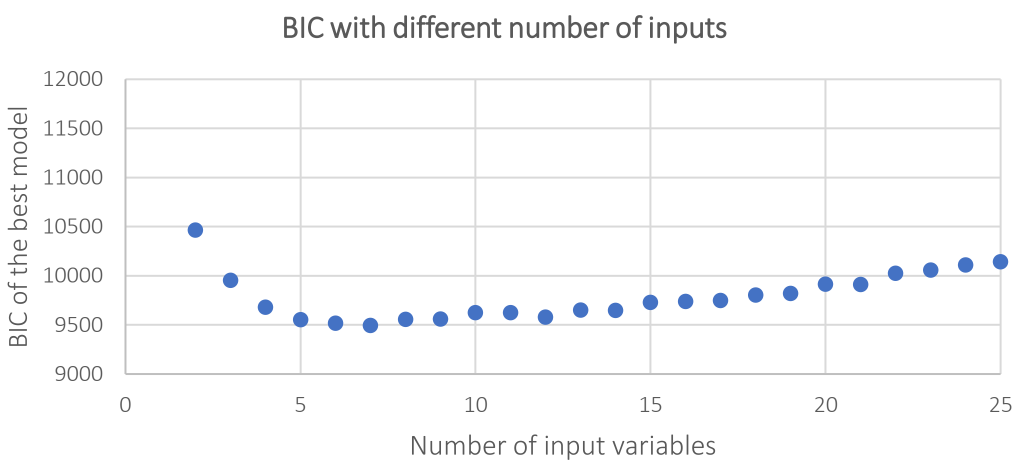


Figure 4 BIC values for different number of inputs for the data-driven benchmarking model

3.3. Model Evaluation

The most important aspect of a forecasting model is the predictive ability during an independent testing period. Hence, a leave-one-year-out cross-validation (LOOCV) technique was applied. In this way, available data was split into eight one-year periods, with one year being omitted from the calibration in turn and the omitted year used to evaluate the estimations. Re-calibrating the model, step by step, gave the entire data a chance to be reflected in the independent validation periods. In this study, four different measures of Root Mean Squared Error (RMSE), Nash-Sutcliffe Efficiency (NSE), Anomaly Correlation Coefficient (ACC), and Mean Square Skill Score (MSSS) were applied to quantify the predictive performance.

RMSE aggregates the magnitudes of errors (difference between modeled values and observations) for several data points into a single measure. RMSE measures accuracy by comparing different models for a particular dataset (not between datasets, as it is scale-dependent). NSE, equivalent to the coefficient of determination (R2), is used to assess the predictive skill of hydrological models. NSE values closer to 1 suggest a model with more predictive skill. ACC is used to estimate the sharpness of forecasting or, in better words, the ability to forecast extreme values. Moreover, MSSS shows the forecast skill in another way by quantifying accuracy relative to the long-term monthly averaged irrigation demand. In the equations below, M_i and O_i are model output and observation of the ith day, while $\bar{C}$ is long-term mean monthly observation (2012-2020) and n is the number of observations.

$$RMSE = \sqrt{\frac{\sum(M_i - O_i)^2}{n}} \tag{4}$$

$$NSE = 1 - \frac{\sum(M_i - O_i)^2}{\sum(O_i - \bar{O}_i)^2} \tag{5}$$

$$ACC = \frac{\sum(M_i - \bar{C})(O_i - \bar{C})}{\sqrt{\sum(M_i - \bar{C})^2 \sum(O_i - \bar{C})^2}} \tag{6}$$

$$MSSS = 1 - \frac{\sum(M_i - \bar{C})^2}{(\frac{n}{n-1})^2 \sum(O_i - \bar{C})^2} \tag{7}$$

3.4. Application of the models to produce IWD forecasts

The hybrid and benchmarking models introduced above were applied one time step at a time over n (n =1, 2…,7) days into the future to produce IWD forecasts up to 7 days ahead, as shown in Figure 3. This means forecasts of IWD for the next days were generated using modeled values from the previous time steps. The process of predicting the first three lead times of the data-driven benchmarking model has been depicted in Figure 3. As we go forward in time, because there is no observation for the pumped volume values after day t-1, the outputs of the previous lead days are used for the coming days (as shown below).

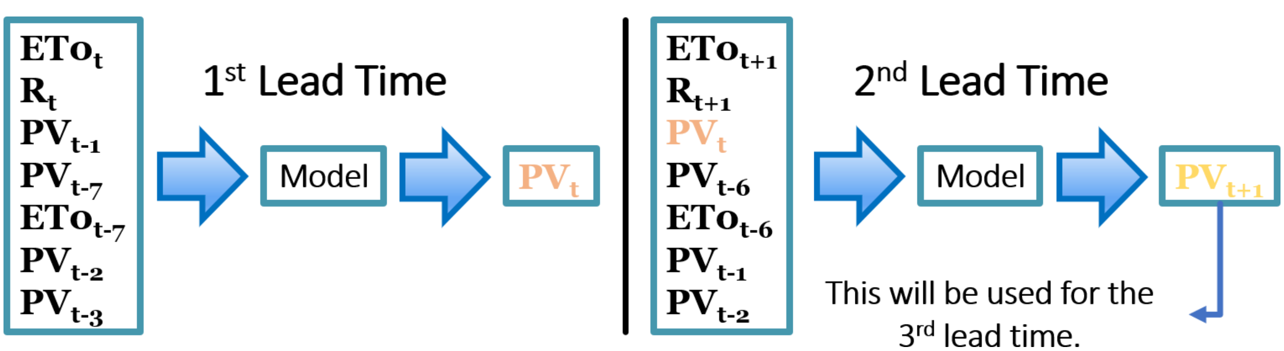


Figure 5 Process of calculating different lead times as we go forward in time

4. Results and Discussion

4.1. Calibration of the conceptual module

Calibrated values of the conceptual module parameters were summarized in the table below.

Table 3. Calibrated Parameters of the conceptual model

α_1	β_1	δ_1	α_2	β_2	δ_2	α_3	β_3	δ_3	T(mm)
0.687	0.065	0.049	0.727	0.279	0.022	0.721	0.018	0.015	6.1

α and β values are the evapotranspiration and rainfall coefficients for early-season (Sep. to Nov. or stage 1, which is spring in Victoria), mid-season (Dec. to Feb. or stage 2), and non-growing season(Mar. to Aug. or stage 3), respectively. As can be seen, α has its highest value during the mid-season period (summer). This was, more or less, expected because α acts like crop coefficients in a way that has its maximum value in the summer for the study area based on Chalmers (2012). Also, rainfall plays a more significant role in compensating for irrigation water during the summer. This is because soil moisture drops quicker during higher air temperatures. In Figure 4, the number of rainy days with different magnitudes of rainfall and optimized rainfall threshold are shown. According to calibration results, rainfalls heavier than 6.1 mm had the same effect as this threshold in reducing irrigation demand.

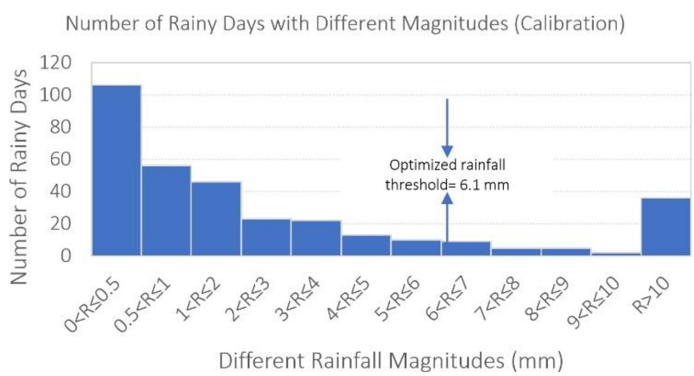


Figure 6 Number of rainy days with different rainfall magnitudes

4.2. Hybrid Model Performance

4.2.1. Overall model performance

Predictive ability during an independent testing period is the most important feature of a model. That is why validation results provide more reliable knowledge about the model's predictive capacity. Figure 5 summarizes the calculated values of the four evaluation measures for seven lead times during validation. These graphs show almost similar performance of the data-driven and hybrid models in the first two lead times. However, this changes after the third lead time, and the hybrid model starts to perform slightly better than the data-driven model across all metrics. The most interesting point is that the difference between the performance of the two models constantly grows with increasing lead times until 7 days, when the performance of the hybrid model deteriorates and the difference in modelling error between the hybrid and the benchmarking model becomes smaller. This diminishing benefits of the hybrid model at a long lead time of 7 days is most likely due to the fact that after a few days, the benefits from including additional knowledge of the physical system represented by the conceptual module is no longer significant. Therefore, the performance of the hybrid and benchmarking models become similar.

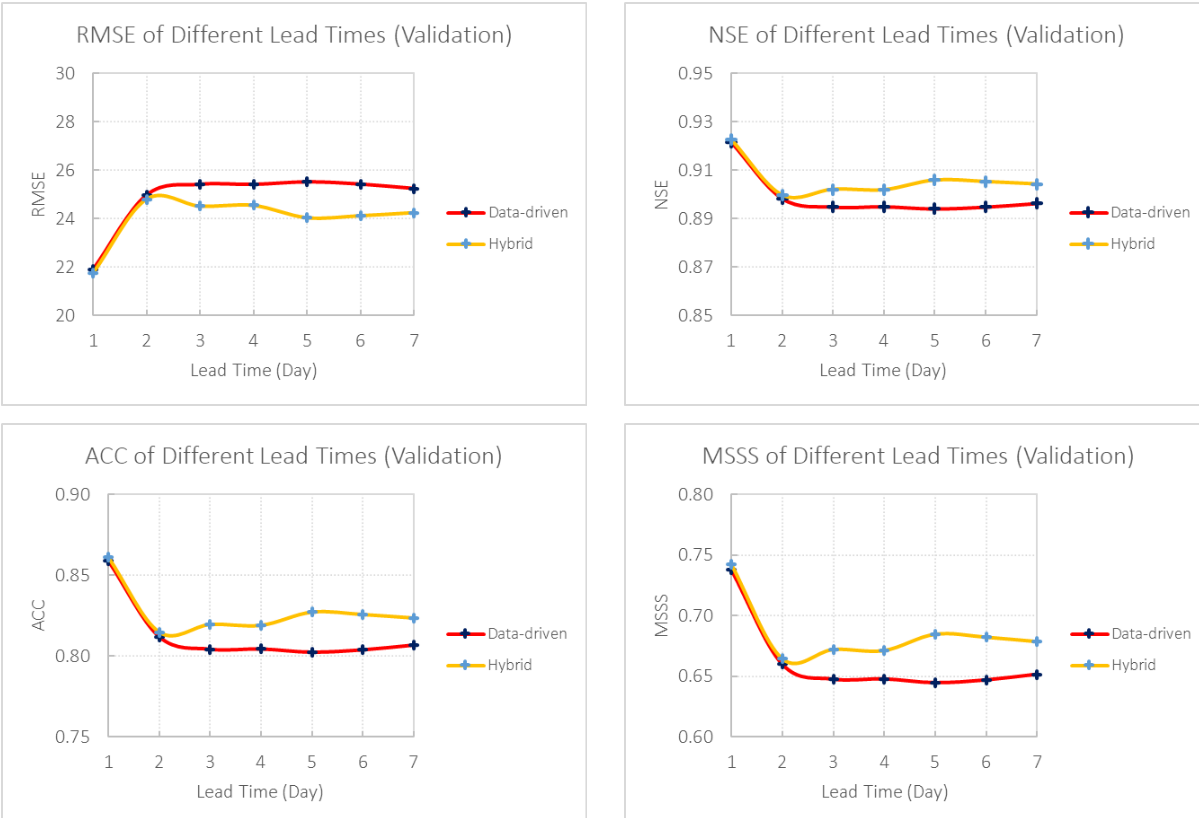


Figure 5 Validation predictive performance of the hybrid and data-driven models (Lead times: 1 to 7 day(s))

4.2.2. Model performance for the high demand period

To explore the capacity of the two approaches in forecasting high demand values, another analysis has been done on the top 10% demand values of the validation period (Figure 6). It shows consistent results with the findings on overall performance and slightly better forecasts of the hybrid model compared to the data-driven model for the high season period. This implies that the ability of the data-driven model depends to a degree on the similarity of the input data to the training data. Therefore, including even a small amount of system understanding could add to the reliability of the IWD forecasting models.

In addition, the diminishing benefits of the hybrid model compared to the data driven benchmarking model at a long-lead time of 7 days is more pronounced for the high demand periods. This implies that high demand is not only driven by theoretical crop water needs represented by the conceptual module. High irrigation demand is also likely driven by other factors that cannot be represented using a conceptual crop water need models, e.g farmers' irrigation decision-making behavior. For example, farmers are likely to water significantly more than what the crops actually needs when a hot and dry day is expected. This highlights the importance to consider other including factors other than crop water needs in irrigation water demand forecast, and further demonstrates the potential benefits of the hybrid model.

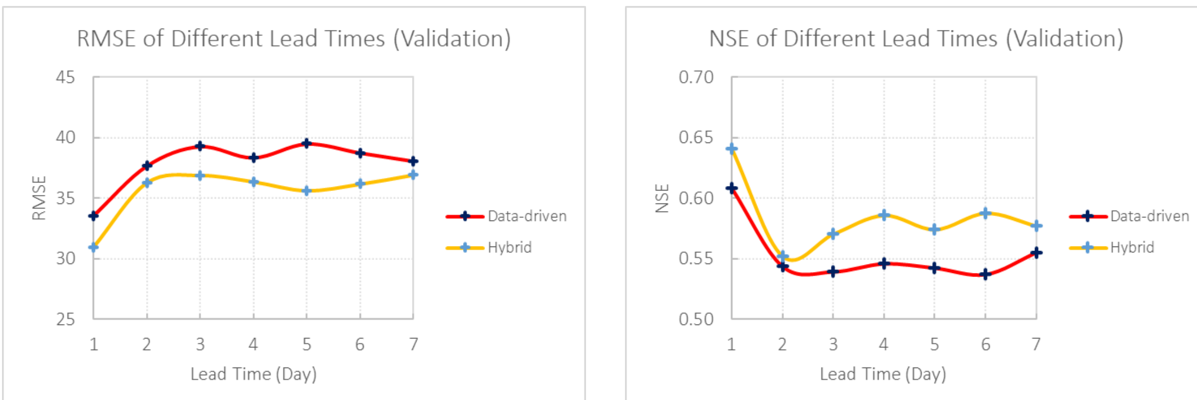
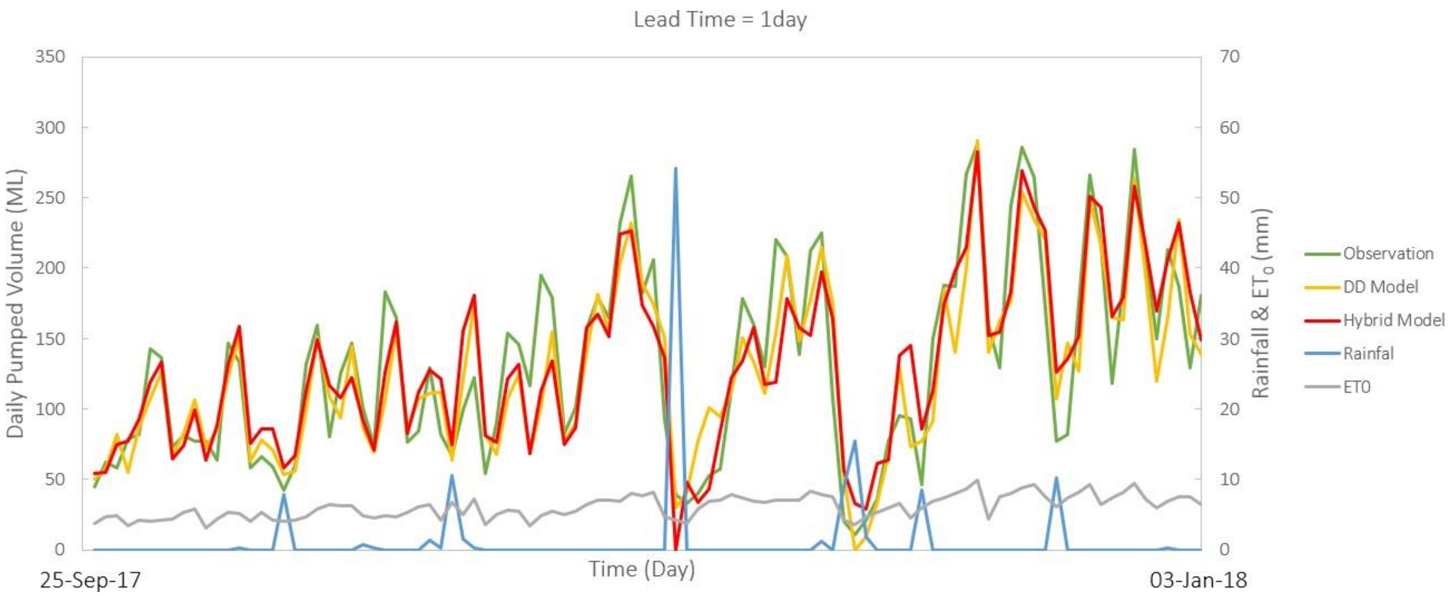


Figure 6 Validation predictive performance of the hybrid and data-driven models for the top 10% of demands (Lead times: 1 to 7 day(s))

4.2.3. Model performance for the high rainfall days

Daily observed pumped volumes clearly show seasonality in demand behavior. In the early season days, demand starts to grow, and during summer, demand reaches its highest value, where the role of modeling becomes more critical in informing system operators. Figure 7 shows how the hybrid and data-driven benchmarking models perform during a high-demand period (100 days of the validation period from Oct 2017 to Dec 2018), specifically when the system faces fluctuations in demand due to rainfall events. According to this figure, both models could produce demand variations during rainfall events to an acceptable degree. The data-driven benchmarking model sometimes has underestimated part of the rainfall compensating for irrigation water. In contrast, the hybrid model has overestimated this part during heavy rainfall events. This kind of underestimation of high and overestimation of low values of observations is typical of models (not just water demand models!) that rely on data fitting using objective functions that minimizes, say, sum squared errors. This issue can potentially be addressed by using some other objective functions, such as the Kling-Gupta efficiency (KEG). In addition, the conceptual model, data driven model and hybrid model are all simplified representations of the real system. It is assumed that the system is stationary in input and output relationships, but this assumption may not be valid for the data period.

Moreover, the performance of the two models is worse in general for the lead time of 7 days. This is mainly due to the way the data-driven module or benchmarking model is structured to produce irrigation demand forecast for a forecast period of 7 days. Because a traditional MLP model can only produce one point prediction at a time, a recursive process (as shown in Figure 3) is used to produce predictions up to 7 days ahead. In other words, the prediction of day 7 will be based on predictions of day 6 as one of the input variables, and prediction of day 6 will be based on predictions from day 5, etc. Therefore, the modeling error of each lead time can accumulate and become larger as the lead time becomes longer. This is one of the limitations of using a traditional ANN model structure such as MLP. This limitation can be addressed when more data are available for the development of more complicated data-driven models, such as recurrent neural networks, that can better handle time series data.



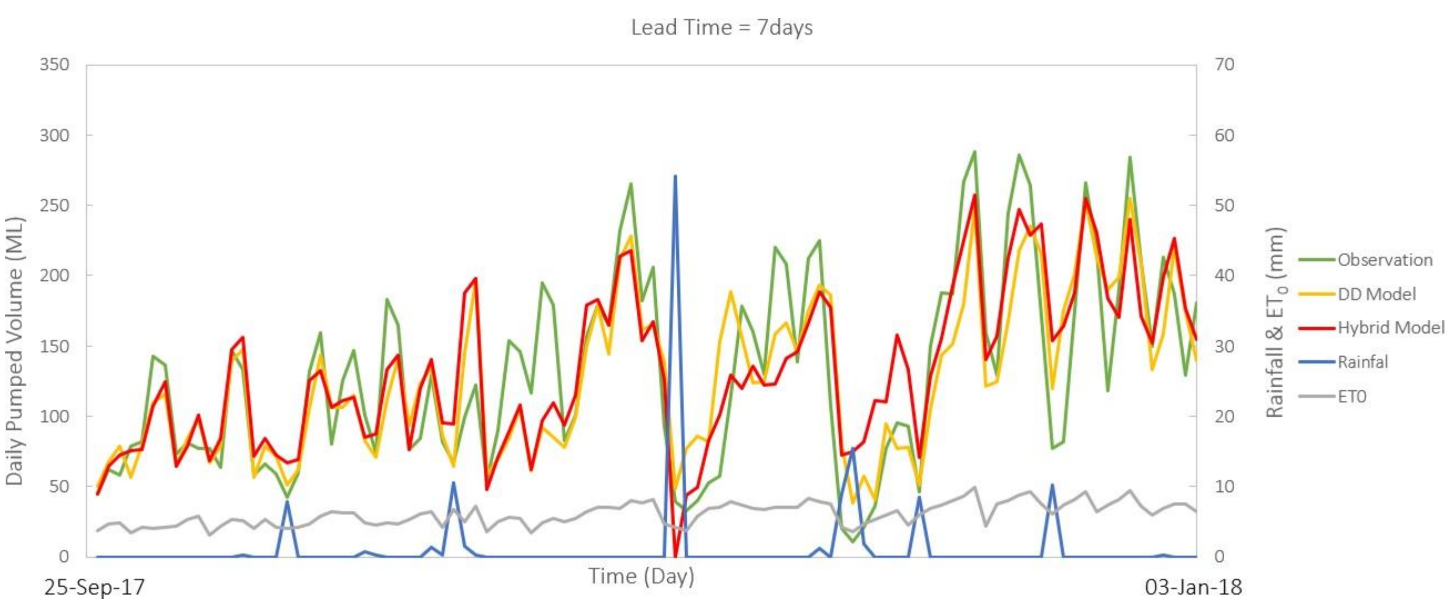


Figure 7 Daily observed v modeled pumped volumes v daily ET_0 and rainfall for the validation period covering Sep 2017 to Jan 2018

5. Summary

Short-term Irrigation Water Demand (IWD) forecasts with high levels of accuracy can be very helpful in operational decisions of water supply systems. IWD forecasting is challenging because of the biophysical and behavioral complexities involved in the irrigation process. Early studies have conceptualized the irrigation process (based on underlying causes leading to water demand) to model IWD. However, many recent studies have applied data-driven techniques to map the relationship between these factors and water demand (considering weather variables as the main influential factors of IWD to simplify the modeling process). Conceptual and data-driven approaches have their advantages and disadvantages.

In this study, a hybrid model was developed by combining the system understanding with data-driven methods of forecasting short-term irrigation demand. The hybrid model consists of two modules, one conceptual and the other data-driven. In the conceptual module, daily crop needs were estimated using reference crop evapotranspiration, rainfall, and annual cropping pattern and area. Then, in the data-driven module, residuals (between the previously mentioned conceptual module outputs and the observed pumped volumes) were trained to capture the remaining information between the inputs and the output. The performance of the hybrid model was evaluated against that of a benchmarking model based on data-driven technique only for an irrigation district in Victoria, Australia. The performance of these models was evaluated under the assumption of “perfect weather forecasts” for lead times 1 to 7 days ahead.

It has been found in this study that the hybrid model provided better outcomes for the validation period than the data-driven benchmarking model. An interesting finding was that the difference between the performance of the two models constantly grew with increasing lead times. This implies that the ability of the data-driven model depends to a degree on the similarity of the input set to training data. Therefore, including even a basic amount of system understanding could improve the performance of IWD forecasts.

6 Conclusions

This paper demonstrates the potential of improving short-term irrigation demand forecasting by combining the system understanding with data-driven methods. In this study, uncertainty associated with weather variables has not included. One future research direction is to study how the uncertainty in weather forecasts will impact the performance of the hybrid model. In many real-world cases, there is not often such a rich record of daily irrigation demand available, which limit the type of data driven methods that can be used in the hybrid model. With improved data collection practice, more data will become available, when more complicated data driven techniques that can better handle time series data can be investigated for the development of the hybrid model. In addition, given that the reliability of these models is highly dependent on data availability, another future direction can be to evaluate the modeling results under different calibration time periods (to examine how sensitive the outcomes are to data availability).

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