Forecasting Daily Reference Evapotranspiration for Shepparton, Victoria, Australia using Numerical Weather Prediction outputs

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Abstract: Farmers and irrigation system operators make real-time irrigation decisions based on a range of factors including crop water requirement and short-term weather forecasts of rainfall and air temperature. Forecasts of reference crop evapotranspiration (ET_O) can be calculated from numerical weather prediction (NWP) forecasts and ET_O has the advantage of being more directly relevant to crop water requirements than air temperature. This paper aims to discuss the forecasting ability of ET_O using outputs from the Bureau of Meteorology's operational NWP forecasts derived from the Australian Community Climate and Earth System Simulator – Global (ACCESS-G). The daily ET_O forecasts were evaluated for the Shepparton Irrigation Area in Victoria. Forecast performance for ET_O was quantified using the root mean squared error (RMSE), coefficient of determination (r^2), anomaly correlation coefficient (ACC) and mean square skill score (MSSS). Lead times of daily ET_O forecasts up to 9 days were compared against ET_O calculated using hourly observations from the Shepparton airport automatic weather station. It was found that forecasting daily ET_O was better than using the long-term monthly mean ET_O for lead times up to 6 days and beyond that the long-term monthly mean was better. The average MSSS of ET_O forecasts varied between 64% and 4 % for 1 to 6 day lead times, respectively. The most influential forecast weather variable for daily ET_O forecasts was mean wind speed, air temperature and incoming solar radiation for 1, 2-3 and 4-9 day lead times respectively. Also, it was found that the forecast performance for incoming solar radiation and mean wind speed was relatively poor compared with the air and dew point temperatures.

Keywords: *Reference evapotranspiration, forecasting, Numerical Weather Prediction, FAO56.*

1   INTRODUCTION

Many, if not most real-time irrigation decisions are about supplying the right amount of water at the right time to crops. Predominantly, these decisions can both save water and increase economic benefits. Farmers and irrigation system operators make these real-time irrigation decisions based on a range of factors including crop water requirement and short-term weather forecasts of rainfall and air temperature. To a great extent, these decisions are based on estimates of the near-future crop evapotranspiration. The crop evapotranspiration can be estimated by multiplying reference evapotranspiration (ET_O) with the crop coefficient (K_c), where K_c is expressed as the ratio between crop ET and ET_O (Jensen, 1968). ET_O can be forecasted directly or indirectly. In the direct methods, current and historical data are used to forecast ET_O either by time series methods or by computational/artificial neural networks (CNNs or ANNs). In the indirect method, weather variables needed to calculate ET_O are forecast (often by numerical weather prediction (NWP) models) and then applied empirical or analytical models, such as Hargraves (Hargreaves and Samani, 1985), Penman (Penman, 1948), Penman-Monteith(Allen et al., 1998) models, to forecast ET_O.

The simplest and oldest statistical method of forecasting daily ET_O is to calculate the long-term monthly mean based on historical observations. Time series models such as autoregressive integrated moving average - ARIMA and autoregressive-moving average - ARMA have also been used to forecast daily, weekly or monthly ET_O (Marino et al., 1993, Mohan and Arumugam, 1995, Raghuwanshi and Wallender, 1999). Moreover, CNNs or ANNs have been used to forecast or estimate monthly ET_O based on the historical ET_O data (Tahir, 1998, Kumar et al., 2002, Trajkovic et al., 2003). However, at the beginning of the 21st century, the forecast performance of mesoscale NWP models has improved significantly. Duce et al. (1999) forecasted ET_O 20-70 hours ahead, for six locations in California, United States for a 20 km grid resolution NWP forecast derived from a mesocale atmospheric simulation model. Subsequently, publically available weather forecasts in China have been used to forecast daily ET_O and this work has found that most ET_O forecasts were skilful up to 5 lead days (Cai et al., 2007, Xianghong et al., 2011, Tian and Martinez, 2012). Arca et al. (2003) compared 1 to 3 days lead time ET_O forecasting performance from ARIMA and ANN models with ET_O from the NWP forecasts derived from the limited area model, BOLAM2000 (Arca et al., 2003). They found that ANN performed better than ARIMA, but ET_O forecasts using NWP forecasts provided the best results. These results all suggest that ET_O can be reliably forecasted using NWP forecasts and that the uncertainties of these ET_O forecasts will decline as the performance of the NWP models increases. This would obviously assist farmers and irrigation system operators to reduce the risk embedded in their real-time operational decisions.

Quantification of ET_O forecast performance using outputs from NWP models has been limited to certain geographical areas such the United State, China and Chile (Silva et al., 2010, Cai et al., 2007, Arca et al., 2003) and forecast performance varies between models, lead times, locations and climates. Therefore, this paper aims to quantify the forecasting performance for daily ET_O using the Bureau of Meteorology's operational NWP forecasts derived from the Australian Community Climate and Earth System Simulator – Global model (ACCESS-G). Forecast ET_O for lead times of 1 to 9 days for the Shepparton irrigation area in Victoria, Australia is compared against daily ET_O calculated using the observed weather variables recorded at the Shepparton airport automatic weather station (AWS). Further, we quantified the forecasting performance for ET_O related weather variables, (daily maximum and minimum of air and dew point temperatures, mean daily wind speed and daily incoming solar radiation) and investigated the sensitivity of ET_O forecasts to each weather variable to determine which weather variable contributed most to the ET_O forecast errors.

2   MATERIALS AND METHODS

The study area is Shepparton, Victoria, Australia, which is often referred as the "Food Bowl of Australia" given it produces approximately 25 per cent of Victoria's agricultural production value. Agriculture is dominated by irrigated dairy, pome and stone fruit production, with other agricultural activities related to sheep for wool, beef and dairy cattle. The AWS is located at the Shepparton airport (Figure 1(a)). The latitude, longitude and the elevation are - 36º 25' 44, 145º 23' 41" and 113.9 meters above Australian height datum (AHD), respectively. The climate is temperate with a hot summer (T hot ≥22) but without a dry season (Köppen climate type Cfa) (Peel et al., 2007). The hourly weather variables namely air temperature; relative humidity and wind speed were collected for the period 05 July 1996 to 01 August 2012 to estimate observed daily ET_O. In the absence of measured daily incoming solar radiation or ground heat flux data, satellite imagery based daily incoming solar radiation data was collected from the Bureau of Meteorology, Australia.

The weather variables needed to forecast daily ET_O were collected from the Bureau of Meteorology's operational NWP forecasts, generated using the Australian Community Climate and Earth System Simulator – Global (ACCESS-G). The ACCESS systems are non-hydrostatic, hybrid vertical level structure,

mesoscale, assimilation and forecast systems developed and tested by the Centre for Australian Weather and
Climate Research (CAWCR) (Bureau of Meteorology, 2010). The ACCESS systems were implemented
operationally by the operational development subsection of national weather & oceanographic centre on 17
August 2010 and the spatial resolution of the each NWP ACCESS system is shown in Figure 1(b).
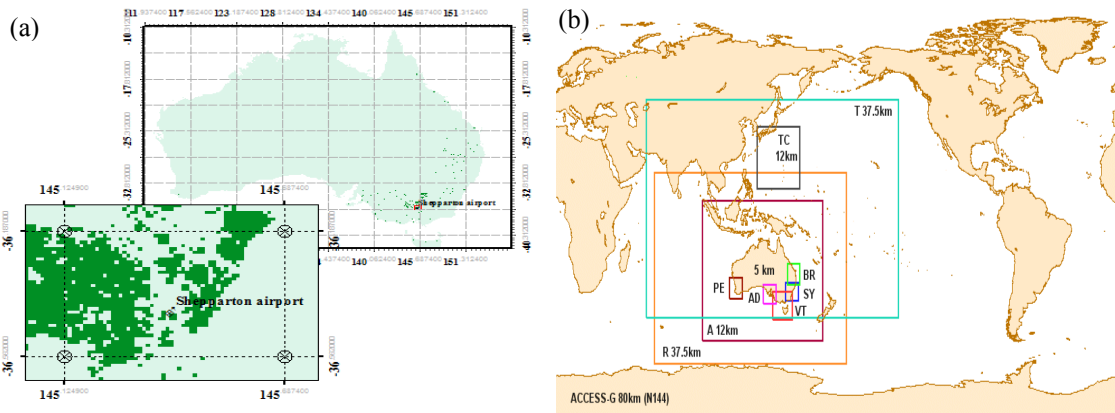
Figure 1. (a) Location of the Shepparton AWS and irrigation agricultural areas as per 2005/06 Australian
land use map and (b) Spatial Resolution of ACCESS Models (Bureau of Meteorology 2010))

ACCESS-G assimilates and forecasts twice a day at 0000 and 1200 UTC (i.e. 10.00 AM and 10.00 PM local
time) and NWP forecasts are available at 03.50 PM and next day 3.50 AM respectively(Bureau of
Meteorology, 2010). We selected NWP forecasts generated for 10.00 AM local time run by considering the
local time of NWP forecasts availability. For the study period (17 Aug. 2010 - 01 Aug. 2012), we extracted
three hourly NWP forecasts of incoming solar radiation, air temperature, dew point temperature and wind
speed corresponding to the four grid points (Figure 1(a)) surrounding the station and linearly interpolated to
the AWS location. We note that small-scale spatial variation is likely to be relatively low in this flat
landscape.

All daily ET_O calculations were made using the FAO56 Penman-Monteith (FAO56-PM) daily ET_O equations
(Allen et al., 1998). This method has been recommended as the standard method of computing daily ET_O
(Allen et al., 1998) and numerous studies have demonstrated the superior performances of the FAO56-PM
equations compared with other ET_O equations (Allen et al., 1989; Chiew et al., 1995; Chen 2005).Net
radiation is the difference between the incoming net shortwave radiation and the outgoing net longwave
radiation (Allen et al., 1998). Incoming net shortwave radiation was calculated using the collected incoming
shortwave solar radiation and albedo of 0.23. Outgoing net longwave radiation was estimated from the daily
maximum and minimum air temperature and relative shortwave radiation, calculated using the collected
incoming shortwave solar radiation and calculated clear-sky radiation (Allen et al., 1998).

The performance of daily ET_O forecasts were quantified using the root mean squared error (RMSE),
correlation coefficient (^{2}), anomaly correlation coefficient (ACC) (Miyakoda et al., 1972) and mean square
skill score (MSSS) (Murphy, 1988). These statistical indices were used to evaluate the performance of ET_O
forecasts with 1 to 9 days lead times against the daily ET_O calculated using observed weather data. These
statistical indices are as follows.

(a) The root mean squared error, RMSE is:

$$RMSE = (\sum(P_i - O_i)^2/n)^{1/2} \quad (1)$$

(b) The Anomaly Correlation Coefficient (ACC) is:

$$ACC = \frac{\sum(P_i - \bar{C})(O_i - \bar{C})}{(\sum(P_i - \bar{C})^2 \sum(O_i - \bar{C})^2)^{1/2}} \quad (2)$$

(c) The Mean Square Skill Score (MSSS) is:

$$MSSS = 1 - \frac{\sum(P_i - O_i)^2}{(n/(n-1))^2 \sum(O_i - \bar{C})^2} \quad (3)$$

In equations 1-3, P_i and O_i are the ith predicted and observed values respectively, n is the number of
observations and $\bar{c}$ is the climatological or long-term mean monthly observation.

3   RESULTS AND DISCUSSION

The long-term observed mean monthly ET_O and corresponding box plots of daily ET_O for the Shepparton
irrigation area are shown in Figure 2. In each box plot represents the lower (25th), middle (50th) and upper (
75th) percentile and the bottom and top whiskers represents 5th and 95th percentiles respectively. Long-term
monthly mean ET_O varies from 1.12 mm day^{-1} during mid-winter (July) to 7.30 mm day^{-1} during mid-summer
(January). This strong seasonality results from the variability in solar radiation and air temperature due to the
latitude of the Shepparton area. The highest absolute variability in daily ET_O occurs during the summer,

followed by spring and autumn and the lowest is during winter. These inter- and intra-monthly variations in ET_O result from the input weather variables (air temperature, dew point temperature, wind speed and incoming solar radiation). Therefore, first we report the forecast performance for these weather variables. Then we report the performance of 1 to 9 day lead time daily ET_O forecasts. Finally, the sensitivity of each the ET_O forecasts to errors in each weather variable is assessed by substituting one observed weather variable at a time in the ET_O forecast, thereby eliminating the forecast error for that variable. While ACCESS-G provides a 240 hour lead time, the lead time of this report was limited to 9 lead days by excluding the 1st partial day and last partial days from the NWP results (the NWP output does not start at 00:00 local time).
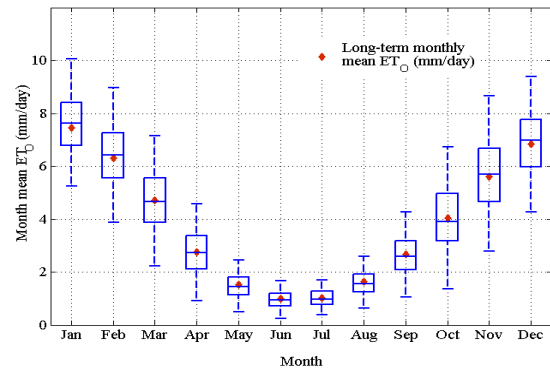

Figure 2. Seasonal variation of ET_O in Shepparton irrigation area

3.1 Forecasting ability of weather variables

The statistical indices for the forecast performance for daily maximum and minimum air temperature (T_{max} and T_{min}), daily maximum and minimum dew point temperature ($Dewpt_{max}$ and $Dewpt_{min}$), daily mean wind speed and incoming shortwave solar radiation (R_s) are shown in Figure 3. The forecast performance declines with increasing lead time. Uncertainties in observed weather variables were significantly lower than uncertainty of corresponding forecast variables for all lead time. T_{max} and T_{min} forecasts had 95% confidence intervals of ±2.99 and ±3.34 °C (one day lead) against ±0.3°C for the observation. Similarly, uncertainty for the satellite based "observed" R_s values was ±1.5MJm^{-2} during summer (Bureau of Meteorology, 2005) against the forecast uncertainty forecast of ±9.55 MJm^{-2} for R_s.

The RMSE values for the weather variables considered approximately doubles as the lead time increases from 1 to 9 days, with the exception of the daily mean wind speed. The RMSE values of T_{max} were higher than those for T_{min} for the first two days, but it reversed later. The RMSE values of $Dewpt_{min}$ were always more than $Dewpt_{max}$. Therefore, here the ACCESS-G forecast performance for maximum air and dew point temperatures is higher than for the corresponding minimums. In terms of daily mean wind speed and R_s, the RMSE values ranged between 3.84 and 4.42 kmh^{-1} and between 3.16 and 6.32 MJm^{-2}day^{-1}, respectively.

The r^2 between forecast and observed weather variables was more than 0.60 up to 7 days lead time, with the exception of $Dewpt_{min}$ and daily mean wind speed. T_{max} yielded the best r^2 values for all lead times and even at 9 lead days it was 0.73. The worst r^2 values were found for the daily mean wind speed which ranged between 0.02 and 0.33, followed by the $Dewpt_{min}$ which ranged from 0.27 to 0.81. The ACC measures correlation between the anomalies of the forecast and observed weather variables from the corresponding long-term monthly mean (climatology). If ACC is close to 1, it implies that there is a strong linear relationship between the temporal pattern of the forecast and observed anomalies. The best ACC values were found for T_{max} and the other variables were in the following descending order $Dewpt_{max}$, $Dewpt_{min}$, R_s, T_{min} and daily mean wind speed as shown in Figure 3(c).
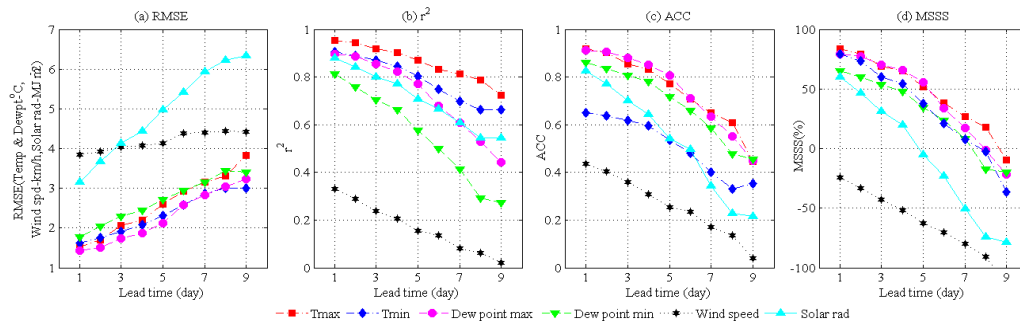
Figure 3. Forecast performance as indicated by (a) RMSE, (b) r^2, (c) ACC and (d) MSSS of forecasted vs. observed T_{max}, T_{min}, $Dewpt_{max}$, $Dewpt_{min}$, daily mean wind speed and R_s at Shepparton airport.

The MSSS is based on anomalies from the monthly mean and measures ACCESS-G ability to forecast the short-term variations in weather variables. A value of 1 (100%) indicates a perfect forecast and a value less than zero indicates that monthly climatology is a better predictor than the NWP. The MSSS values for

different weather variables were calculated and highest MSSS values were obtained for T_{max}. Other weather variables were in the following descending order $Dewpt_{max}$, T_{min}, $Dewpt_{min}$, R_s and daily mean wind speed throughout the lead time as shown in Figure 3(d). For the one day lead time, the MSSS for all the weather variables considered was more than 60%, with the exception of daily mean wind speed. It then gradually declines and falls below zero for lead times between 5 and 9 days, with the exception of daily mean wind speed. However, MSSS for daily mean wind speed was below zero for all lead times. Notably, for lead times up to 3 days, four out of six forecast variables were 50% better than the reference forecasts. These results indicate that ACCESS-G provides good forecasts of ET_O related weather variables up to 3 lead days and that it is better than monthly climatology for lead times of up to a week.

## 3.2 Forecasting performance for ET_O

The FAO56-PM daily equation and the NWP forecasts were used to forecast ET_O up to 9 days lead time. Daily forecasted ET_O was then compared against "observed" ET_O calculated using the observed hourly weather data at the Shepparton airport AWS and a satellite based measurement of global radiation. Figure 4 shows scatter plots of the 1, 3, 5 and 7 day lead time forecasts vs. observed daily ET_O values for the 0000 UTC ACCESS-G run. The increase in scatter between forecast and observed daily ET_O values with the lead time was as a result of the weakened forecasting performance of the weather variables as discussed previously. To quantify the forecast performance for daily ET_O the statistical performance indices were calculate (Table 1) and are plotted in Figure 5. As for the weather variables, forecast performance for ET_O gradually declines with increased lead. The regression lines in Figure 4 shown that for small daily ET_O, the forecast very slightly over-predicted ET_O whereas at the relatively high daily ET_O values forecast under-predicted ET_O. This trend tended increase with lead time. On average, the forecast under-predicted ET_O by 2% to 0 % for lead times between 1 and 6 days and then over-predicted ET_O by 0% to 4%, for lead times between 7 and 9 days. These biases are small from a practical perspective.

Table 1. Statistical indices of forecasted vs. observed ET_O at Shepparton airport

Lead time (days)	RMSE (mm. day^{-1})	r^2	ACC	MSSS (%)
1	0.65	0.91	0.79	63.87
2	0.72	0.89	0.77	56.17
3	0.82	0.86	0.70	43.74
4	0.85	0.85	0.67	39.63
5	0.97	0.80	0.59	20.42
6	1.01	0.79	0.57	14.12
7	1.14	0.75	0.45	-04.43
8	1.17	0.73	0.40	-12.25
9	1.26	0.69	0.31	-30.4
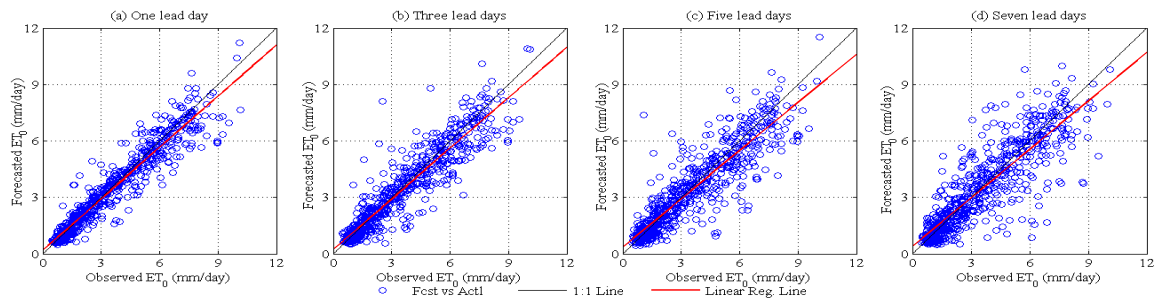
Figure 4. Daily ET_O forecasted (NWP forecasts driven from ACCESS-G) vs. observed at the Shepparton airport: (a) One lead day, (b) Three lead days,(c) Five lead days and (d) Seven lead days
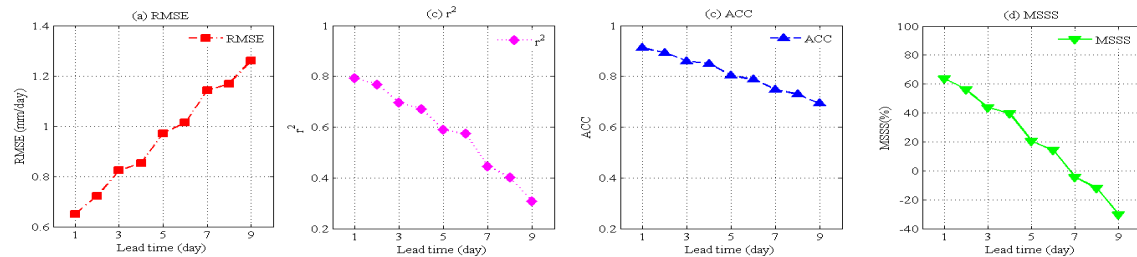
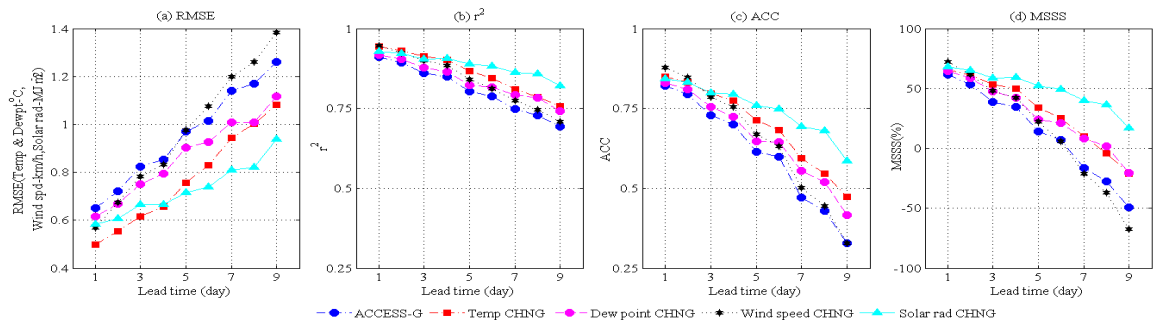
Figure 5. Statistical indices, (a) RMSE, (b) r^2, (c) ACC and (d) MSSS of forecasted and estimated daily ET_O at Shepparton airport

On average, the RMSE approximately doubled from 0.65 to 1.26 mm day^{-1}, as the lead time increased from 1 to 9 days. The correlation between forecast and observed ET_O was very good for all lead times, with r^2 values ranging from 0.91 (1 day lead time) to 0.69 (9 day lead time). This in part reflects the strong seasonality in ET_O. The ACC values ranged from 0.79 to 0.31 for 1 day to 9 day lead times. The MSSS progressively

declined from 1 to 9 lead days, ranging from 64% to -30%. The MSSS becomes negative after a lead time of 6 days. Therefore, for up to a lead time of 6 days, daily ET_O forecasts made using NWP weather variable forecasts was better than using the long-term monthly mean ET_O. The declining performance of the ET_O forecast is directly due to the declining forecast performance for the weather variables such as wind speed and solar radiation (George et al., 1985, Duce et al., 1999). Therefore, in the next section, we evaluate which forecast weather variable has the highest impact on the forecasting error of daily ET_O.

3.3   Impact of weather variables forecasts to daily ET_O forecasts

In this section, four daily ET_O forecasts were made by replacing one forecast weather variable (air temperature, dew point temperature, incoming solar radiation, daily mean wind speed) with the equivalent observation. The statistical indices computed using these forecasts are shown in Figure 6. All four performance indices show some improvement when the observations are used; however the differences for wind speed are marginal. The important point here for interpretation is that the larger the improvement (or sensitivity) gained by using corresponding observed weather variable the more important forecast errors in that variable are in terms of forecast errors in ET_O.

Figure 6. Statistical indices, (a) RMSE, (b) r^2, (c) ACC and (d) MSSS of estimated and forecasted daily ET_O by swapping observed variable one at a time at Shepparton airport

The largest improvements in RMSE were obtained by substituting observed air temperature during the first 4 lead days and by substituting observed global radiation after that. The patterns of improvement in r^2 and ACC were very similar to each other. During a lead time up to 2 days, the greatest improvement in r^2 and ACC values were obtained by substituting observed daily mean wind speed. After a lead time of 2 days, using observed R_s provided greatest improvement. In terms of MSSS, for one lead day, wind speed lead to the greatest improvement, followed by R_s. For longer lead times, using observed R_s provided the best improvement followed by observed air temperature, daily mean wind speed and then dew point temperature. The impact of weather variables forecasts on the daily ET_O forecast vary with the lead time, with greater improvements at longer lead times. The result suggests that improvements in incoming solar radiation forecasts would lead to the greatest gains in ET_O forecasts.

4   CONCLUSION

Short-term ET_O forecasts would be useful in making short-term real-time irrigation decisions. There is an opportunity to forecast daily ET_O from the mesoscale NWP systems like ACCESS-G. This paper quantifies the forecast performance for ET_O using weather variables from the Bureau of Meteorology's operational NWP forecasts derived from ACCESS-G for the Shepparton irrigation area.

Daily ET_O was forecast for lead times up to 9 days and evaluated against "observed" ET_O calculated using observed weather data from the Shepparton automatic weather station. The results showed that ACEESS-G is capable of generating skilful weather variables forecasts up to 3 days ahead and that for lead times up to 7 days ACCESS-G's NWP forecasts are better than the monthly mean climatology. Moreover, daily ET_O forecasts calculated using NWP weather variable forecasts were better than the long-term monthly mean ET_O for lead times up to 6 days, after which the long-term monthly mean ET_O provided a better forecast. Furthermore, it was found that the largest source of error between forecast and observed ET_O was the forecasting performance of incoming solar radiation, except for a lead time of one day where wind speed was slightly more important. This agrees with the forecast performance of the input weather variables where radiation and wind speed actually showed the lowest skill. In practice, farmers and irrigation system operators can rely on daily ET_O forecasts computed using NWP forecasts derived from ACCESS-G for lead times of up to 6 days.

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ACKNOWLEDGEMENT

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