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Forecasting daily reference evapotranspiration for 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 short-term weather forecasts of rainfall and temperature. The simplest and oldest statistical method for forecasting daily ET_0 is to use the long-term monthly mean ET_0 based on historical observations. Forecasts of reference crop evapotranspiration (ET_0) can be calculated from Numerical Weather Prediction (NWP) outputs and ET_0 has the advantage of being more directly relevant to crop water requirements than temperature. This paper evaluates forecasts of ET_0 made using the Bureau of Meteorology's operational NWP forecasts derived from the Australian Community Climate and Earth System Simulator – Global (ACCESS-G). The forecast performance for ET_0 was quantified using the root mean squared error (RMSE), coefficient of determination (R^2), anomaly correlation coefficient (ACC) and mean square skill score (MSSS). Daily ET_0 forecasts for lead times up to 9 days were compared against ET_0 calculated using hourly observations from the 40 automatic weather stations across Australia.It was found that using NWP forecast daily ET_0 was better than using the long-term monthly mean ET_0 for lead times up to 6 days, beyond which the long-term monthly mean was better. The average MSSS for ET_0 forecasts across all stations varied between 66% and 12% for lead times of 1–6 days, respectively. Further, it was found that forecast performance for daily ET_0 was highest in autumn for tropical climates and lowest in spring for temperate climates. Errors in incoming solar radiation were the most important source of ET_0 forecast error, followed by air temperature, dew point temperature and wind speed, for all lead times. Also, it was found that the forecast performances for incoming solar radiation and mean wind speed were relatively poor compared with the air and dew point temperatures

1. Introduction

Evapotranspiration (ET) and precipitation predictions play a fundamental role in basin scale real-time water resources management decisions by quantifying the prospective spatial and temporal changes of hydrological, agricultural, ecological and climatological processes. These real-time decisions frequently rely on agricultural irrigation water demand predictions, since agriculture is often the dominant water user, consuming 70% of world's fresh water withdrawals (UN-Water, 2006; UNEP, 2007). Real-time irrigation decisions are generally coupled with crop-ET rather than precipitation, because precipitation in most agricultural irrigation areas is fairly low.

Crop water use can be estimated by multiplying reference evapotranspiration (ET_0) with the crop coefficient (K_c), where K_c is expressed as the ratio between crop-ET and ET_0 (Jensen, 1968). Given that ET_0 varies with the weather, forecasts of ET_0 are valuable in real-time irrigation decisions. ET_0 forecasting procedures can be categorized into direct and indirect methods, depending on the methodology used and the input data. In the direct methods, current and historical data is used to forecast ET_0 either using time series methods or using artificial or computational neural networks (ANNs or CNNs). In the indirect method, weather variables needed to calculate ET_0 are forecasted (often by numerical weather prediction (NWP) models) and then empirical or analytical models such as the Hargraves (Hargreaves and Samani, 1985), Penman (Penman, 1948), or Penman–Monteith (Allen et al., 1998) models are applied to forecast ET_0.

The simplest and oldest statistical method for forecasting daily ET_0 is to use the long-term monthly mean ET_0 based on historical observations. More advanced time series models, such as autoregressive moving average (ARMA) or autoregressive

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integrated moving average (ARIMA) models have also been used to forecast monthly, weekly or daily ET_0 (Landeras et al., 2009; Marino et al., 1993; Mohan and Arumugam, 1995; Raghuwanshi and Wallender, 1999) and it has been found that forecast monthly, weekly or daily ET_0 was better than using corresponding long-term averages. Nonlinear system theoretical models such as artificial or computational neural networks (ANNs or CNNs) are an alternative to time series models and (Thirumalaiah and Deo, 2000) stated that they are superior in forecasting than traditional approaches such as auto-regression and multiple-regressions. ANNs have been utilized to forecast numerous hydrological processes including short-term river runoff (Abrahart and See, 2002; Cameron et al., 2002; Pulido-Calvo and Portela, 2007; Thirumalaiah, 1998) and bio-physical factors such as precipitation (French et al., 1992; Kuligowski and Barros, 1998) and temperature (Hayati and Mohebi, 2008). In the context of ET_0, CNNs or ANNs were initially used to estimate monthly (Tahir, 1998) and daily (Kumar et al., 2002) ET_0 using historical observations. Then, ANN models were used to forecast one month ahead, monthly ET_0 for the southeast Europe (Trajkovic et al., 2003; Trajkovic et al., 2005) and for the Mahanadi reservoir project area, India (Chauhan and Shrivastava, 2009) as well as one week ahead, weekly ET_0 for northern Spain (Landeras et al., 2009). These studies found that both monthly and weekly ET_0 forecasts were better than respective historical averages as well as ET_0 forecasts derived from time series models. These studies all intended to forecast weekly or monthly ET_0 and more recently the focus has turned to forecasting daily ET_0.

By the beginning of the 21st century, the forecasting performance of mesoscale NWP models had improved significantly and this encouraged the use of indirect methods to forecast daily ET_0. Consequently, Duce et al. (1999) forecasted ET_0 20–70 h ahead, for six locations in California, United States. They used 20 km grid resolution hourly NWP forecasts derived from the Mesocale Atmospheric Simulation (MAS) and found that ET_0 forecast under-predicted observed ET_0 by 2–10%. Cai et al. (2007) developed an analytical method to translate publically available weather forecasts in China into weather variables needed to calculate ET_0 and forecast one day ahead daily ET_0. The results for the Willmot index of agreement and coefficient of determination were above 0.96 and 0.91 respectively, for all stations. Subsequently, publically available weather forecasts in China have been coupled with an ANN technique using least-squares support vector machines (LSSVMs) to forecast daily ET_0 (Guo et al., 2011), resulting in successful daily ET_0 forecasts for lead times up to one day, where the root mean square error and mean absolute error were less than 0.5 and 0.4 mm day^{-1} respectively.

Some studies have attempted to forecast ET_0 using coarse-scale NWP model or Global Climate Model (GCM) output together with downscaling techniques. Tian and Martinez (2012a,b) conducted a study in the southeaster United States, to firstly forecast daily ET_0 up to 5 days in advance for at a grid resolution of 2.5° × 2.5° and secondly to compare the performance of two downscaling methods (natural analog and constructed analog) to produce both probabilistic and deterministic downscaled daily ET_0 forecasts at points. NWP forecasts for air temperature, relative humidity and wind speed from the National Centers for Environmental Prediction's (NCEP's) Global Forecast System (GFS) reforecast dataset and, in the absence of GFS reforecast for incoming solar radiation, observed solar radiation from the NCEP–U.S. Department of Energy (DOE) Reanalysis 2 dataset R^2 were used. This work found that most daily ET_0 forecasts were skilful up to 5 lead days and after applying downscaling techniques skilful deterministic results were limited to 3 days lead times. Similarly, Ishak et al., 2010 used the MM5 mesoscale model (developed by National Centre for Atmospheric Research) to downscale European Centre for Medium Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) data to produce hourly weather variables needed to calculate ET_0 in the Brue catchment, southwest England. They found that forecast daily ET_0 was over-predicted by 27–46%. The numerical weather forecasts, derived from MM5 were utilized not only to forecast daily ET_0, but also to estimate the daily ET_0. Silva et al. (2010) also used MM5 outputs and estimated daily ET_0, in the Maipo basin in Chile (Silva et al., 2010). They found that daily ET_0 based on MOS (model output statistics) corrected weather variables reduced the root-mean-squared-error by 10–20% compared to the raw MM5 model output. Similarly, Er-Raki et al. (2010) evaluated the weather forecast data collected from the ALADIN (Aire Limitée, Adaptation Dynamique, développement InterNational) NWP model as an alternative to ground based observations to calculate daily ET_0 in Tensift basin (central of Morocco) and the Yaqui Valley (Northwest Mexico).

These results all suggest that potential for forecast ET_0 using NWP forecasts and that the uncertainties of these ET_0 forecasts will decline as the performance of the NWP models increases or systematic errors are removed from the forecast weather variables. Moreover, reliable ET_0 forecast reduce costs and provide ET_0 data in a more timely fashion by eliminating or reducing the number of automated weather networks that are currently needed to provide near-real time ET_0 data for irrigation scheduling purposes (Duce et al., 2000). However, quantification of ET_0 forecast performance using outputs from NWP models has been limited to a small number of studies in certain geographical areas such United States, Europe, China and Chile and to relatively short lead times (Arca et al., 2003; Cai et al., 2007; Silva et al., 2010) and forecast performance varies depending on NWP model, lead time, location and climate. In addition, seasonal variations in performance have not been assessed.

This paper aims to quantify the forecasting performance for daily ET_0 with lead times up to 9 days using the Australian Bureau of Meteorology's (BoM) operational NWP forecasts derived from the Australian Community Climate and Earth System Simulator – Global model (ACCESS-G). We forecasted ET_0 for lead times of 1–9 days for 40 locations (automatic weather stations), across 23 agricultural irrigation areas from 9 diverse climates zones and assessed the accuracy against daily ET_0 calculated using the observed weather variables recorded at the corresponding automatic weather station (AWS). We also evaluated the temporal and spatial variation of daily ET_0 forecast performances. Further, we quantified the forecasting performance for ET_0 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_0 forecasts to errors in each weather variable to determine which weather variable contributed most to the ET_0 forecast errors.

2. Materials

2.1. Study sites

The study area covers a wide range of irrigation areas as well as various climates across the Australian Continent. The locations of those stations fall between latitudes 15° and 39° south and longitudes 116° and 153° east. We included 23 agricultural irrigation districts in the assessment, based on the 2005/2006 Australian land use map (ABARES, 2010). Fig. 1 shows the locations of 40 Automatic Weather Stations (AWS) in these irrigation districts together with the Köppen climate zones. The stations fall in three main climates, tropical, arid and temperate, and nine sub-climates (Peel et al., 2007). Table 1 provides the characteristic of these AWSs, which are sorted according to the Köppen climate classification (Table 2). The elevation of these stations ranges from 4 m to 871 m in reference to Australian Height Datum (AHD) and precipitation and mean annual temperature ranges from 400 mm to 2400 mm