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Short-term forecasting of daily reference evapotranspiration using the Penman-Monteith model and public weather forecasts

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ABSTRACT

Short-term daily reference evapotranspiration (ETo) forecasts are required to facilitate real-time irrigation decision making. We forecasted daily 7-day-ahead ETo using the Penman–Monteith (PM) model and public weather forecasts. Public weather forecast data, including daily maximum and minimum temperatures, weather types and wind scales, for six stations located in a wide range of climate zones of China were collected. Weather types and wind scales were converted to sunshine duration and wind speed to forecast ETo. Meanwhile, daily meteorological data for the same period and locations were collected to calculate ETo, which served as reference standard for evaluating forecasting performance. The results showed that the forecasting performance for the minimum temperature was the best, followed by maximum temperature, sunshine duration and wind speed. Also, it was found that using public weather forecasts and the PM model improved the forecasting performance of daily ETo compared to those obtained when using the HS model with temperature forecasts as the only input data, and this improvement was because the weather type and wind scale forecasts also have positive influence on ETo forecasting. Further, the greatest impact on ETo forecasting error was found to be caused by the errors in sunshine duration and wind speed, followed by maximum and minimum temperature forecasts.

1. Introduction

The process of water loss from soil and crop surfaces to the atmosphere is called evapotranspiration (ET), which is a major component of the hydrological cycle and which impacts crop water resource management, farm irrigation scheduling and environmental assessment (Kisi and Zonemat-Kermani, 2014). Although crop ET can be directly measured, it is laborious, time consuming and costly; therefore, under most conditions, crop water requirements can be computed using reference crop evapotranspiration (ETo) from a standard surface and using an appropriate crop coefficient (K_C) (Eslamian et al., 2012; Rahimikhoob and Hosseinzadeh, 2014). ETo plays an important role in real-time irrigation scheduling and in the management of irrigation systems.

Therefore, some attempts have been made to estimate or predict ETo through observed weather data (Allen et al., 1989, 2005; Droogers and Allen, 2002; Khoob, 2008; Silva et al., 2010). Previous studies have placed particular emphasis on ETo estimation, and ETo forecasts have demonstrated greater utility in real-time irrigation management, as reported in the studies by Snyder et al. (2009), Luo et al. (2014), Lorite et al. (2015), Gavilán et al. (2015) and Traore et al. (2015).

Based on the methodology and the input data, the ETo forecasting procedures can be divided into direct and indirect methods (Perera et al., 2014). In direct methods, two primary and typical procedures, namely, the time series method and artificial neural networks (ANNs), are utilized to forecast medium- or long-term ETo using historical weather data. For the time series method, Tracy et al. (1992) forecasted yearly ETo using an autoregressive integrated moving average (ARIMA) model, and Marino et al. (1993)

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proposed a seasonal ARIMA mode based on the ARIMA model and obtained accurate monthly ETo forecasts. Further, investigators have turned to forecasting daily and weekly ETo, which are more capable of assisting in medium- and short-term irrigation decision making. Mao (1994) analyzed the variation regularity of ETo over a year for North and Southwestern China and presented a modified daily mean model to forecast daily ETo. As the time series method, ANNs were applied for medium- and long-range forecasting and provide high accuracy in the past (Fernando and Jayawardena, 1998; Kumar et al., 2002; Trajkovic et al., 2003; Landeras et al., 2009), then turned to short-term forecasting in recent years (Luo et al., 2015; Ballesteros et al., 2016). Direct methods usually perform well in forecasting medium- or long-term ETo; however, forecasting daily ETo has become a trend because daily ETo forecasts are more useful in short-term irrigation scheduling.

Daily ETo forecasts are restricted by weather conditions to a great extent, and direct methods using historical weather data are not applicable under most circumstances (Xiong et al., 2015). Therefore, indirect methods based on weather forecast data are widely adopted to forecast daily ETo. Recently, numerical weather forecast data have been utilized to forecast daily ETo, and several studies reported that numerical weather prediction models might be more accurate than statistical and time series models if the weather data are accurate (Duce et al., 1999; Arca et al., 2004; Ishak et al., 2010). Arca et al. (2004) forecasted ETo through PM models and weather data from the Agrometeorological Service of Sardinia, Italy, and produced better results in comparison to those obtained by the ARIMA and ANN models. Perera et al. (2014) forecasted daily ETo for lead times of up to 9 days using the PM model and numerical weather prediction (NWP) outputs, and the largest error source of ETo was found to be solar radiation. Although certain studies demonstrated that the utilization of NWP outputs in ETo forecasting could obtain sufficient accuracy (Duce et al., 1999; Perera et al., 2014), complete NWP outputs are still unavailable for the public in China that farmers and irrigation system operators cannot gain these data for practical agricultural production.

Currently, public weather forecasts can be obtained freely from public channels in China, which released by China Meteorological Administration (CMA) through Weather China (http://www.weather.com.cn/). The public weather forecast data are based on a model called Global and Regional Assimilation and Prediction System (GRAPES), which is the new generation NWP system in China established by CMA, and these weather forecast data are also modified by weather forecasters in order to minimize the forecast error from NWP system error (Xue, 2005). Additionally, public weather forecasts contained enough parameters for daily ETo forecasting, including maximum and minimum temperature, weather type and wind scale. In this context, previous studies confirmed that the public weather forecasts were reasonable for ETo forecasting (Cai et al., 2007; Guo et al., 2011; Luo et al., 2014). Guo et al. (2011) proposed the Least squares support vector machine (LSSVM) model using public weather forecasts to forecast ETo, and the forecasted values exhibited a good fit with values calculated from meteorological data; however, this model lacked a physical basis. Although public weather forecast data include temperature, weather type and wind scale forecasts, temperature is the most influential and accurately forecasted variable; hence, several studies have used temperature-based models for forecasting ETo. Luo et al. (2014) proposed a method for short-term 7-day-ahead ETo forecasting using the Hargreaves-Samani (HS) model and temperature forecasts. Similarly, the Blaney-Criddle HS and ANN models and forecasted temperature data were adopted to forecast daily ETo in East China (Xiong et al., 2015; Ballesteros et al., 2016). All the models obtained ideal results and also showed that the major error in ETo forecasts resulted from the fact that the wind speed and humidity were not considered in the relevant method. Regarding the above studies, although the temperature-based models can provide reasonable results, weather type and wind scale are also contained in public weather forecasts. Weather type and wind scale forecasts are original forecast data that cannot be directly applied as inputs to the PM model and they are also unable to be evaluated in a quantitative manner; however, through the analytical method (AM) proposed by Cai et al. (2007), weather type and wind scale can be respectively converted into sunshine duration and wind speed, which needed in ETo calculations and their forecasting performance can be measured through quantitative method. If the weather type and wind scale are accurately forecasted, considering these two variables might improve the forecasting performance of ETo because of the comprehensive consideration; however, if the errors of these two variables are high, a larger error can be introduced and lead to decreased ETo forecasting performance.

Thus, the objectives of this work are twofold: (1) to verify whether the forecasting performance of ETo will improve when weather type and wind scale forecasts are adopted as the input weather variables and (2) to quantify the impact on ETo forecasting accuracy by each weather variable, including daily maximum and minimum temperature, sunshine duration and wind speed.

2. Materials and methods

2.1. Study area and data collection

Public weather forecast data with a 7-day lead time for the period of 2012–2014 collected at six stations in China were obtained from Weather China (http://www.weather.com.cn), and daily observed meteorological data for the same period and stations were gathered from the China Meteorological Data Sharing Service System (http://data.cma.gov.cn). Forecasting performance of daily ETo and weather variables vary spatially with the change of climate to a certain extent (Perera et al., 2014). Therefore, the stations used in this study fall in typical climates, including humid, sub-humid and sub-arid regions, which distribute in a wide range of China according to different latitudes and longitudes. The characteristic of these six stations are shown in Fig. 1 and are described in Table 1. The meteorological data and public weather forecast data collected at these stations were obtained for the same period (May 24, 2012–May 24, 2014). Mean air pressure, daily minimum and maximum temperature, average temperature, average wind speed, sunshine duration and mean relative humidity were included in the observed daily meteorological data. Moreover, the corresponding public weather forecast data set for 7-day-ahead forecasting included daily minimum and maximum temperatures, weather type and wind scale.

2.2. Penman-Monteith model

The FAO recommended the PM method (Allen et al., 1998) as the universal standard for ETo calculation; thus, we used the ETo calculated from the PM model to evaluate the forecasted ETo. The FAO-PM model (Allen et al., 1998) is

$$\mathrm{ETo}_{,\mathrm{PM}} = \frac{0.408\Delta(R_n - G) + \gamma[900/(T+273)]u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where $\mathrm{ETo}_{,\mathrm{PM}}$ is the daily ETo calculated from the PM model, in mm day $^{-1}$; R_n is the net radiation at the crop surface, in MJ m^{-2} day^{-1}; G is the soil heat flux density, in MJ m^{-2} day^{-1}; T is the air temperature at a height of 2 m, in °C; u_2 is the wind speed at a height of 2 m, in m s $^{-1}$; e_s is the vapor pressure of the air at saturation, in kPa; e_a is the actual vapor pressure, in kPa; Δ is the slope of the vapor pressure curve, in kPa °C^{-1}; and γ is the psychrometric constant, in kPa °C^{-1}.