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Accuracy of reference evapotranspiration (ET_o) estimates under data scarcity scenarios in the Iberian Peninsula

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ABSTRACT

The standard approach for computing reference crop evapotranspiration (ET_o) is the FAO-56 Penman-Monteith (FAO-PM) method, which requires data on air temperature, radiation, air humidity and wind speed. Unlike air temperature the other variables are less frequently available, hindering the application of FAO-PM. A lot of efforts exist to find the best method to estimate FAO-PM ET_o when some variables are not available. The FAO-56 manual recommends to estimate the missing variables based on those currently observed (PM-R), or use the less demanding Hargreaves and Samani method (HS). Additionally, if the missing variables are measured at nearby stations, spatial interpolation can be used to estimate the missing data previous to applying FAO-PM (PM-IC). This paper focuses on the comparison, at the monthly time scale, of the performance of these methods to in the Iberian Peninsula. By using 53 weather stations with all data to calculate FAO-PM, data scarcity scenarios are simulated and the mentioned methods are tested (PM-R, HS, PM-IC)PM-IC yielded consistently the best results according to a number of tests. It yielded the lowest mean absolute error (MAE) at 7.56 mm/month, while PM-R yielded values of 10.15 mm/month and HS 9.36 mm/month and biased results. PM-IC was also best at reproducing the long-term variability and trends in ET_o. A good and unbiased estimation of monthly ET_o time series are required for irrigation planning and crop design.

1. Introduction

Reference crop evapotranspiration (ET_o) is an important variable for agriculture management, hydrological studies and drought monitoring. While at daily and sub-daily time scale its importance is related with irrigation scheduling, at monthly time scale it is crucial for irrigation planning and crop design (Feng et al., 2016). The monthly and annual time scales are also the most relevant if the interest relies on assessing the temporal variability and changes (trends) in ET_o.

The preferred model for calculating ET_o is the Penman-Monteith equation modified by FAO (Allen et al., 1998) (hereinafter FAO-PM). The data required to calculate FAO-PM ET_o include air temperature, solar radiation, vapor pressure deficit and wind speed. The requirement for high levels of data is the main constraint to its generalized application, as some of the variables involved are not widely measured. In addition, the number of stations where all the variables are measured is commonly very limited, especially if large data series are required for regional climatological studies (Chen et al., 2006; Dadaser-Celik et al., 2015; Espadafor et al., 2011; Irmak et al., 2012; McVicar et al., 2007; Thomas, 2000).

Due to the relevance of ET_o lots of efforts have been made in order to develop strategies to estimate ET_o when the FAO-PM method cannot be directly used. In the FAO-56 manual two main recommendations are given. The first one consists in estimating the value of unmeasured variables using data from other variables (PM-R hereinafter). According to this method, the calculation of ET_o is possible even with only temperature data. The second recommendation consists in the use of a less demanding method, such as Hargreaves and Samani (1985) (HS hereinafter). It is an empirical model that requires only data on mean monthly temperature (T) and solar radiation (R_s). Several studies showed that HS performed best compared with other empirical methods applied to diverse climates worldwide (Alexandris et al., 2008; Espadafor et al., 2011; Hargreaves and Allen, 2003; Nandagiri and Kovoor, 2006; Vicente-Serrano et al., 2014a).

Several studies focused on comparing between these two recommendations. Jabloun and Sahli (2008) in Tunisia obtained a

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better performance when using PM with only temperature data than when HS was used, but with a systematic underestimation of ET_o. Todorovic et al. (2013) in a comparison in the Mediterranean area obtained contrasting results depending on the climate.

Besides these two option recommended in the FAO-56 manual, which use only the data available at the site of interest, in some cases data from nearby locations is available and spatial interpolation could be used to estimate the missing variables. Dinpashoh (2006), for instance, used spatial interpolation in Iran to fill gaps in climatic series previous to using the FAO-PM method. Hart et al. (2009) used spatial interpolation in combination with satellite data to obtain all the variables needed to calculate FAO-PM ET_o in California. McVicar et al. (2007) used spline regression to map some of the variables needed for computing FAO-PM ET_o in the Chinese loess plateau. Mardikis et al. (2005) compared two approaches to estimating FAO-PM ET_o in Greece: i) calculation of FAO-PM ET_o followed by interpolation (hereinafter, PM-CI); and ii) interpolation of variables followed by calculation of FAO-PM ET_o (hereinafter, PM-IC). They found no significant difference between these two approaches.

Between these two perspectives (spatial interpolation and the estimation of missing variables using FAO-56 recommendations), only spatial interpolation uses data from the same variable to estimate the missing data. In the other hand, FAO-56 recommendations rely on stationary relationships between variables, a hypothesis that may or not apply.

A good characterization of the inter-annual variability of ET_o and the detection of possible trends are also key for long-term planning. While some studies (Chen et al., 2005; Espadafor et al., 2011; Gocic and Trajkovic, 2014; Vicente-Serrano et al., 2014a) analyzed the ability of HS to detect temporal trends in ET_o, to our knowledge none of the authors who checked the ability of PM-R to estimate FAO-PM ET_o (Jabloun and Sahli, 2008; López-Moreno et al., 2009; Todorovic et al., 2013) focused on its ability to cope with temporal trends.

The aim of our study is to compare the performance of these two approaches, the FAO-56 manual recommendations and spatial interpolation, using a dataset comprising 53 complete weather stations covering the Iberian Peninsula for the period 1961–2011. These data allows us computing ET_o time series using the complete FAO-PM method. We then generate missing data scenarios by removing one or several variables at the time, and we compare the performance of different approaches in estimating FAO-PM ET_o. Our hypothesis is that using measured data at nearby stations to estimate the missing variables, even at a relatively low spatial density as it is our case, is a better option than using stationary relationships between variables as recommended by FAO-56. To extend our analysis to the whole range of FAO-56 recommendations, the HS method is also tested. Besides obtaining common statistics comparing computed FAO-PM ET_o using all the variables with estimations when one or more variables are missing such as the mean absolute error (MAE) or the coefficient of determination (R^2), we are also interested in the ability of the estimation methods to capture the temporal evolution of ET_o. Comparison of methods is highly data-dependent. However, important conclusions can be drawn that will help others select the most appropriate approach for their particular datasets.

2. Data and methods

2.1. ET_o methods

2.1.1. FAO Penman-Monteith (FAO-PM) and FAO-56 recommendations (PM-R)

The FAO-PM method was defined by Allen et al. (1998) for calculating the reference evapotranspiration of a hypothetical crop having a height of 0.12 m, a surface resistance of 70 s m^{-1} and an albedo of 0.23:

$$\text{FAO-PMET}_o = \frac{0.408 \cdot \Delta \cdot (R_n\text{-}G) + \gamma \cdot \frac{900}{T+273} \cdot u_2 \cdot (e_s\text{-}e_a)}{\Delta + \gamma \cdot (1 + 0.34u_2)} \tag{1}$$

where R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), T is the mean air temperature at 2 m (°C), u_2 is the wind speed at 2 m (m s^{-1}), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), e_s-e_a is the saturation vapor pressure deficit (kPa), Δ is the slope of the vapor pressure curve (kPa °C^{-1}) and γ is the psychrometric constant (kPa °C^{-1}). The value 0.408 is used to convert from MJ m^{-2} day^{-1} units to kg m^{-2} day^{-1} (alternatively: mm day^{-1}).

The FAO-56 manual includes recommendations on how to estimate the value of unmeasured variables at the site of interest (PM-R). This makes it theoretically possible to use the PM method based on temperature data alone.

Where no air humidity data are available, FAO-56 recommends estimating the dew point temperature by equating it to the minimum temperature. Where there are no wind speed data, the regional wind speed or a constant 2 m s^{-1} wind speed can be used. In the absence of radiation data, it can be derived from air temperature according to the equation of Hargreaves et al. (1985):

$$R_s = a \cdot R_a \cdot \sqrt{T_{max}\text{-}T_{min}} + b \tag{2}$$

where a and b are empirical coefficients. There is no way to replace air temperature data when it is missing, so minimum and maximum temperatures are the minimum data requirements for using PM-R.

2.1.2. Hargreaves and Samani (HS)

Hargreaves and Samani (1985) developed a temperature-based method to estimate ET_o in the absence of other variables:

$$\text{HSET}_o = 0.408 \cdot k_g \cdot R_s \cdot (T + 17.8) \tag{3}$$

Although R_s is rarely available, it is possible to estimate it with considerable accuracy using the extraterrestrial radiation (R_a, easily derived from the latitude and the day of the year) and the maximum and minimum temperature. The most commonly used HS equation, and the one used in the study, is thus:

$$\text{HSET}_o = 0.408 \cdot k_g \cdot k_{RS} \cdot R_a \cdot (T_R)^{\beta} \cdot (T + 17.8) \tag{4}$$

where T_R is the temperature range, computed as the difference between maximum and minimum temperature. When this equation was developed at Davis, California, the term $k_g \cdot k_{RS}$ (also termed c_h) was empirically determined to have a value of 0.0023, while the value of the parameter β was fixed at 0.5.

2.2. Dataset

Monthly data from 53 first-order weather stations in the Iberian Peninsula for the period 1961–2011 were used (Fig. 1). Unfortunately, the spatial distribution of these weather stations, in terms of the availability of complete and homogeneous weather data, is quite variable, with some areas having few stations meeting that criterion and other areas having a high spatial density of suitable stations. The same dataset was used by Vicente-Serrano et al. (2014b), who aggregated data from the Spanish (AEMET) and Portuguese (IPMA) national weather services (45 and 8 stations, respectively).

The variables used in this study were maximum and minimum air temperature, wind speed, relative air humidity, atmospheric pressure and sunshine duration. Details of the quality control and homogenization of the Spanish data have been described elsewhere (Azorin-Molina et al., 2014; González-Hidalgo et al., 2011;