Parametric expressions for the adjusted Hargreaves coefficient in Eastern Spain.

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Abstract

The application of simple empirical equations for estimating reference evapotranspiration (ET_o) is the only alternative in many cases to robust approaches with high input requirements, especially at the local scale. In particular, temperature-based approaches present a high potential applicability, among others, because temperature might explain a high amount of ET_o variability, and also because it can be measured easily and is one of the most available climatic inputs. One of the most well-known temperature-based approaches, the Hargreaves (HG) equation, requires a preliminary local calibration that is usually performed through an adjustment of the HG coefficient (AHC). Nevertheless, these calibrations are site-specific, and cannot be extrapolated to other locations. So, they become useless in many situations, because they are derived from already available benchmarks based on more robust methods, *which will be applied in practice. Therefore, the development of accurate equations for estimating AHC at local scale becomes a relevant task. This paper analyses the performance of calibrated and non-calibrated HG equations at 30 stations in Eastern Spain at daily, weekly, fortnightly and monthly scales. Moreover, multiple linear regression was applied for estimating AHC based on different inputs, and the resulting equations yielded higher performance accuracy than the non-calibrated HG estimates. The approach relying on the ratio mean temperature to temperature range did not provide suitable AHC estimations, and was highly improved by splitting it into two independent predictors. Temperature-based equations were improved by incorporating geographical inputs. Finally, the model relying on temperature and geographic inputs was further improved by incorporating wind speed, even just with simple qualitative information about wind category (e.g. poorly vs. highly windy). The accuracy of the calibrated and non-calibrated HG estimates increased for longer time steps (daily < weekly < fortnightly < monthly), although with a decreasing accuracy improvement rate. The variability of goodness-of-fit between AHC models was translated into lower variability of accuracy between the corresponding HG calibrated* ET_o *estimates, because a single AHC was applied per station. The AHC fluctuations throughout the year suggest the convenience of using monthly or, at least, seasonal models.*

Keywords: Reference evapotranspiration, Hargreaves equation, temperature-based, limited inputs

1. Introduction

Sophisticated irrigation water management will be required to optimize water use efficiency and maintain sufficient levels of crop productivity and quality (Ortega-Farias et al., 2009), as well as to mitigate water overutilization and environmental degradation. In order to achieve these targets, accurate assessment of evapotranspiration (ET) can be a viable tool to improve the design and management of irrigation programs. ET is a crucial parameter of the hydrological cycle in agriculture, particularly in irrigated systems. Jensen (1968) introduced the conceptual and widely-extended approach to estimate ET as the product of reference evapotranspiration (ET_o), i.e. ET from a reference surface, and a crop coefficient that accounts for management practices, crop type and development.

The Food and Agriculture Organization (FAO) version of the Penman Monteith equation (Allen et al., 1998), FAO56-PM, has shown in general accurate and sound performance for estimating ET_o in arid and humid climates, and was therefore recommended as the sole standard method for calculating ET_o and validating other equations. However, its application is not possible in many situations, because it relies heavily on weather data that are often not available or reliable, especially in developing countries, where such data are scarce and sparse.

Estimating ET_o with empirical methods is commonly required at the local scale for water resources and irrigation management and planning, because it is not possible to obtain experimental measurements or apply more accurate and robust methods. The application of the FAO56-PM equation by adopting estimated instead of measured values for some variables could lead to errors as shown e.g. by Jabloun and Sahli (2008) and Kwon and Choi (2011). The study and development of temperature-based methods for ET_o estimation is justified for several reasons. First, temperature and solar radiation explain at least 80% of ET_o variability (Priestley and Taylor, 1972; Samani, 2000). Second, several studies indicate that daily temperature range can be related to relative humidity and cloudiness (Samani and Pessarakli, 1986; Shuttleworth, 1993; Di Stefano and Ferro, 1997). Third, advection depends on the interaction between temperature, relative humidity, vapor pressure, and wind speed, and these variables can be related to the temperature range (Vanderlinden et al., 2004). Finally, temperature is the most wide-spread monitored variable among those needed for ET_o estimation (Mendicino and Senatore, 2013).

The well-known Hargreaves (HG) equation (Hargreaves and Samani, 1985) only requires measured mean air temperature and temperature range, in addition to calculated extraterrestrial radiation. Jensen et al. (1997) recommended the HG equation as one of the most simple and accurate empirical methods. According to Allen et al. (1998), the HG equation provides reasonable ET_o estimates with a global validity. Recently, Raziei and Pereira (2013) reported no significant differences in the performance of the HG and the temperature-based FAO56 PM equations in Iran. Although accurate daily estimates have been reported with this equation (Di Stefano and Ferro, 1997), Hargreaves and Allen (2003) stated that the best HG estimates might be expected for five-day or longer periods, because daily estimations are subject to higher variability caused by the movement of weather fronts and by large variations in wind speed and cloud cover. Shuttleworth (1993) even recommended not to use shorter periods than one month. Nevertheless, numerous agricultural and hydrological applications require daily ET_o data.

According to Maestre-Valero et al. (2013), the performance of the original HG equation is strongly influenced by the climatic conditions where it was developed. Several researchers have found over- and underestimation trends in humid and dry scenarios, or under advective conditions (among others, Jensen et al., 1990; Itenfisu et al., 2003; Berengena and Gavilán, 2005; Temesgen et al., 2005; Trajkovic, 2007). Other studies found a tendency to overestimate it at low evapotranspiration rates and vice versa (e.g. Droogers and Allen, 2002; Xu and Singh, 2002). According to Samani (2000), the HG equation should not be extrapolated to different climatic conditions unless it is first calibrated at the local scale. This calibration might be performed using ET_o measurements (e.g. Jensen et al., 1997; López Urrea et al., 2006) or, more commonly, Penman Monteith calculated benchmarks (e.g. Itenfisu et al., 2003; Vanderlinden et al., 2004; Trajkovic, 2005, 2007; Gavilán et al., 2006; Fooladmand and Haghighat, 2007; Ravazzani et al., 2012; Bachour et al., 2013; Mendicino and Senatore, 2013; Berti et al., 2014), considering in most cases an adjusted Hargreaves coefficient (AHC) obtained by regression-based local calibration.

However, these fitted equations are site-specific and cannot be extrapolated to other sites where local ET_o benchmarks are not available for preliminary calibration. Indeed, in weather stations where a local calibration is possible, the FAO56-PM equation would be used in practice, leaving the calibrated HG equation for emergency cases. Accordingly, in addition to local linear calibration, different authors have tackled the parametric calibration of the HG coefficient relying on additional parameters, such as temperature range (Samani, 2000; Mendicino and Senatore, 2013, Maestre-Valero et al., 2013), the ratio of mean temperature to temperature range ($T_{mean}/\Delta T$) (Vanderlinden et al., 2004; Lee, 2010; Thepadia and Martínez, 2012; Mendicino and Senatore, 2013; Maestre-Valero et al., 2013; Berti et al., 2014), wind speed (Jensen et al., 1997; Martínez-Cob and Tejero-Juste, 2004), relative humidity (Hargreaves and Allen, 2003), rainfall (Droogers and Allen, 2002), and altitude (Ravazzani et al., 2012). However, considering a single timescale (commonly the daily or monthly scale) these studies did not provide clear indications on how to calibrate the HG equation at new locations. Therefore, Shahidian et al. (2013) performed an in-depth analysis of the seven most promising additional parameters used for spatial and seasonal calibration of the HG equation by testing those approaches under climatically uniform and non-uniform conditions. They concluded that wind speed appeared as the most important parameter for improving HG estimates in the climatic scenarios under study. By considering wind speed in the HG equation, in addition to the radiative component, also the aerodynamic component of the Penman Monteith equation is taken into account. However, wind speed is usually not available where the HG equation might be useful in practice. Alternative data-driven approaches like artificial neural networks, neuro-fuzzy models or gene expression programming, relying on the same inputs as the HG equation, have been proposed in the last years with promising results (e.g. Zanetti et al., 2007; Martí et al., 2011; Shiri et al., 2013; 2014). Nevertheless, in contrast to the HG equation, the application of such methods requires the implementation of specific software, and the obtained models can generally not be expressed in straightforward simple equations.

The current work aims at evaluating several previously proposed parametric calibration approaches for the AHC in Eastern Spain, relying on daily temperature range (ΔT) and on the ratio $T_{mean}/\Delta T$, and considering four different timescales (day, week, fortnight, and month). The main goal is to improve the performance accuracy of the AHC parametrizations and, as a result, the subsequent calibrated ET_o estimates.

2. Methods

2.1. Data set and study area

Daily measurements of maximum (T_{max}), minimum (T_{min}) and mean (T_{mean}) air temperature at 2 m height (temperature-compact sensor model 110055400 by Thies Clima), relative humidity (RH) at 2 m height (humidity sensor model 110055400 by Thies Clima), solar radiation (R_s), obtained with a pyranometer (sensor model CMP3 by Kipp & Zonen), and wind speed at 2 m height (u_2), obtained with an anemometer (sensor model 4351900000 by Thies clima), were recorded at 30 agro-meteorological stations located along the Mediterranean coast of Spain (Fig. 1) during the period 2000-2007. All the sensors were connected to a CR1000 Campbell Scientific datalogger. Data were provided by the Service of Irrigation Technology from the Valencian Institute of Agricultural Research (http://estaciones.ivia.es). In order to study several timescales, weekly, fortnightly and monthly means of these parameters were computed. The basic geographical data of the 30 stations can be found in Martí and Zarzo (2012). A climatic description of the area under study is provided by Martí and Gasque (2011).

2.2. Approaches to estimate ET_o

2.2.1. FAO56 Penman Monteith equation

Lysimeters were absent at the weather stations considered in this study. Therefore, the FAO56-PM equation was applied to provide the target ET_o values used to calibrate and test the other equations. This equation was validated in the nearby Albacete region against lysimeter measurements, and resulted the most accurate method for calculating average daily ET_o (López Urrea et al., 2006). The FAO56-PM equation is generally considered as the sole standard method for computing ET_o (Allen et al., 1998). It is directly derived from the original Penman-Monteith equation for a reference crop (clipped grass with 0.12 m height) and assuming standard values of surface resistance, aerodynamic resistance, and albedo, and constant values for air density and for the latent heat of water vaporization (Mendicino and Senatore, 2013). The daily FAO56-PM ET_o (mm/day) was calculated as

$$ET_o^{PM} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)}, \qquad (1)$$

where R_n is the net radiation at the crop surface (MJ/m^{2}day); G is the soil heat flux density (MJ/m^{2}day); T is the mean daily air temperature at 2m height (ºC); γ is the psychrometric constant (kPa/ºC); Δ is the slope of vapor pressure curve (kPa/ºC); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa); and u_2 is the wind speed at 2 m height (m/s). All variables were calculated in the present work by applying the equations provided by Allen et al. (1998). G was assumed to be zero for the daily, weekly and fortnightly calculations, and was calculated for the monthly timescale as (Allen et al., 1998)

$$G_{month\ i} = 0.07\ (T_{month\ i+1} - T_{month\ i-1}) \qquad (2)$$

where $G_{month\ i}$ is the soil heat flux in the month i, $T_{month\ i+1}$ is the average mean temperature in the month i+1, while $T_{month\ i-1}$ is the average mean temperature in the month i-1.

2.2.2. Hargreaves equation

The HG equation for estimating daily reference evapotranspiration (ET_o^{HG}, mm/day) is according to Hargreaves and Samani (1985)

$$ET_o^{HG} = AHC\, R_a\ (T + 17.8)\ \sqrt{\Delta T} \tag{3}$$

where R_a is the water equivalent of extraterrestrial radiation (mm/day); ΔT is the daily temperature range (ºC); T is the mean daily air temperature (ºC), *AHC* is the adjusted Hargreaves coefficient, equal to 0.0023 in the original HG equation. Eq. [3] was developed from

$$ET_o^{HG} = 0.0135\, R_S\ (T + 17.8)\ \text{, and} \tag{4}$$

$$R_S = C\, R_a\ \sqrt{\Delta T} \tag{5}$$

where R_s is the solar radiation (mm/day), and C is an empirical coefficient (C = 0.17 for AHC = 0.0023, i.e. 0.0135×0.17). The historical development of the HG equation can be found in Hargreaves and Allen (2003). Initially, Hargreaves et al. (1985) obtained a value of 0.0022 for *AHC*, after calibrating C using data from four stations in the Senegal river basin in Senegal and Mali, where a value of 0.16 was found. Afterwards, Hargreaves (1994) obtained *AHC*=0.0022 for inland regions, and of 0.0026 for coastal regions. Samani and Pessarakli (1986) obtained C values ranging from 0.119 to 0.212 in the US. A *AHC* value of 0.0023 was accepted for general use (Hargreaves, 1994; Allen et al., 1998). According to Vanderlinden et al. (2004), *AHC* appears to increase in coastal areas, where ΔT decreases due to the sea influence, and decreases in mountainous areas, where air mass movement raises ΔT. Samani (2000) proposed a new formulation based on the analysis of the annual average of monthly temperature range and radiation for a period of 25 years across 65 stations in the US:

$$C = 0.00185\Delta T^2 - 0.0433\,\Delta T + 0.4023, \tag{6}$$

where ΔT is expressed in ºC. Vanderlinden et al. (2004) proposed the following expression for *AHC* based on the analysis of 16 weather stations in Southern Spain for a period of 38 years

$$AHC = k_1 \frac{T_{mean}}{\Delta T} + k_2 \tag{7}$$

where T_{mean} and ΔT correspond to average mean temperature and average temperature range per station (ºC). They proposed k_1=0.0005 and k_2=0.00159, obtaining a good fit (R^2=0.90). The same expression was recalibrated by Lee (2010) in the Korea peninsula using data from 21 weather stations during a period of 10 years, obtaining k_1=0.0004 and k_2=0.0013 (R^2=0.84). The same approach was followed by Thepadia and Martínez (2012) using monthly data from 22 weather stations in Florida during 14 years, obtaining k_1=0.000411 and k_2=0.00132 (R^2=0.97). Similarly, Mendicino and Senatore (2013) recalibrated the same expression in Southern Italy using data from 137 stations and found k_1=0.0006 and k_2=0.00121 (R^2=0.46) considering all stations, and k_1=0.0006 and k_2=0.00097 (R^2=0.83) considering only coastal stations (34). Additionally, they recalibrated the Samani equation based on a quadratic regression:

$$AHC = 1.23057 \cdot 10^{-5}\,\Delta T^2 - 3.9237 \cdot 10^{-4}\,\Delta T + 4.80226 \cdot 10^{-3}\ (\mathrm{R}^2{=}0.77) \tag{8}$$

Given that $AHC = 0.0135 \cdot C$, the following expression is equivalent:

$$C = 0.0009115\,\Delta T^{2} - 0.02906\,\Delta T + 0.3557\,, \qquad (9)$$

where ΔT is expressed in ºC. For clarity, hereafter the term "equation" is used to refer to the specific mathematical expression found by Vanderlinden et al. (2004), with k_1=0.0005 and k_2=0.00159, whereas the term "approach" is used to refer to the same equation type and inputs, but locally fitted in another study area (i.e., k_1 and k_2 obtained by local calibration). The same distinction between "equation" and "approach" is used for the model of Samani (2000). Multiple linear regression (MLR) was applied to estimate the AHC and to assess the approaches of Samani (2000) and Vanderlinden et al. (2004) in the study area. Daily AHCs were obtained by multiplying 0.0023 by the daily ratio of ET_o^{PM} to ET_o^{HG}. An average AHC value was then obtained per station. These "observed" AHC data were considered as the target values for the MLR models.

In a second part, MLR was also used to evaluate new input combinations considering the following parameters as potential input variables: T_{mean}, T_{min}, T_{max}, ΔT, $T_{mean}/\Delta T$, R_a, latitude (τ), longitude (φ), altitude (z), distance to the sea (d_s), and u_2. According to Mendicino and Senatore (2013), more reliable estimates can be achieved by only taking into account a subset of the data (*e.g.* coastal stations). A geographic classification into climatologically homogeneous zones might help to find optimal subregions, although such procedure might lead to inconsistent estimates near the boundaries. The use of geographical inputs might avoid the need for fitting a different model for each homogeneous zone. Geographic data (elevation) were also used by Ravazzani et al. (2012) to correct the HG coefficient in western Alpine river basins. Thus, three other strategies were adopted here aiming at improving the performance of the approaches of Samani (2000) and Vanderlinden et al. (2004) through different input groupings. First, different alternative models relying on temperature data were assessed, considering

T_{mean} and ΔT as independent variables, too. Second, temperature inputs were combined with geographic inputs, and third, temperature, geographic information and wind speed were considered jointly.

In a third part, the model performance was also assessed for estimating annual average cumulative ET_o values, which is of interest for average annual water balance modeling. Due to the presence of data gaps, this analysis was not possible for the individual years. Hence, an average value in 8 years was calculated for each day, week, fortnight and month. For some annual time points, less years were used due to the gaps. Weekly, fortnightly and monthly data were translated into daily values, by assigning the same average value for each week, fortnight and month, respectively. Finally, a cummulative value was calculated for each day of the year.

Step-wise regressions were conducted using the software Statgraphics plus 5.1 (StatPoint Technologies Inc., Warrenton, VA, USA). The rest of calculations were implemented in Matlab.

2.3. Performance evaluation

Several error parameters were calculated to assess the performance accuracy of the obtained predictive models (Willmott, 1982). The relative root mean squared error,

$$RRMSE = \frac{1}{\bar{x}} \cdot \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(x_i - \hat{x}_i \right)^2} \quad (10)$$

and the mean absolute error

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| x_i - \hat{x}_i \right| \qquad (11)$$

were used, being n the total number of used ET_o values, x_i the target value of ET_o obtained by Eq. [1], $\hat{x}_i$ the estimate, and $\bar{x}$ the mean value of the targets. The RRMSE is unitless, while MAE is in mm/day for ET_o, and unitless for AHC.

3. Results and Discussion

Existing approaches

The linear approach proposed by Vanderlinden et al. (2004) based on the ratio $T_{mean}/\Delta T$ (Eq. 7) has been widely applied in recent years for estimating AHC in different climatic contexts even without fitting the slope (k_1) and intercept (k_2) to the local conditions. Fig. 2 represents the observed AHCs vs. the ratio $T_{mean}/\Delta T$ for the 30 stations, as well as the linear relationships found by Vanderlinden et al. (2004) in Southern Spain, Lee (2010) in Korea, Thepadia and Martínez (2012) in the US, and Mendicino and Senatore (2013) in Southern Italy. Despite the relatively similar climatic conditions of some of these studies, the relationships cannot be extrapolated to other locations and require local recalibration. Maestre-Valero et al. (2013) assessed the approach of Vanderlinden et al. (2004) in South-Eastern Spain and concluded that the regional functions of the AHC cannot be extrapolated to other regions, even in their vicinity. Moreover, Fig. 2 also represents the local linear fit for the 30 stations according to the approach of Vanderlinden et al. (2004) with R^2=0.17, a considerably worse fit than found in the cited studies. Nevertheless, when applied only to coastal stations R^2 increased to 0.77. A similar performance of the Vanderlinden approach was found by Mendicino and Senatore (2013) in Southern Italy, although with higher coefficients of determination (0.46 and 0.83 for all stations and for coastal stations, respectively).

The relationship between *C* of the original Samani equation (Eq. 6) (computed as observed AHC per station / 0.0135) and ΔT is represented in Fig. 3. It must be noted that all timescales lead to the same average AHC values per station, in agreement with Mendicino and Senatore (2013), who obtained very similar AHC values for monthly and daily ET_o estimates (results not shown). The original Samani quadratic equation (Eq. 6) yielded a poor fit for this study area (R^2=0.09), though R^2 increased when this approach was fitted to local data (R^2=0.35). Similarly, Mendicino and Senatore (2013) already reported that the approach of Samani (2000) provided a higher goodness-of-fit (R^2=0.77) than that of Vanderlinden et al. (2004) (R^2=0.46), although a lower R^2 was obtained here. Fig. 3 also represents C = AHC / 0.0135, with AHC calculated using the locally fitted Vanderlinden approach (model 1 in Table 1, as explained below). As stated by Vanderlinden et al. (2004) and later confirmed by Mendicino and Senatore (2013), the Samani curve reaches a relative minimum and, hence, assumes an increasing *C* for higher values of ΔT, which was not observed neither in Southern Spain nor in Southern Italy, and neither in this study. Therefore, also a power function was fitted ($C=0.5352\cdot\Delta T^{-0.4785}$, R^2=0.35) according to Vanderlinden et al. (2004). The coefficients of determination of the fitted curves are considerably lower than those obtained in the cited studies. As a result, none of these approaches provided accurate estimates of *C* and AHC in this study, as further discussed below, and are therefore not suitable for this region.

Alternative methods for estimating AHC

The new parametric expressions for AHC based on MLR are presented in Table 1, grouped into models relying on temperature data (models 1 to 5), temperature data combined with geographic information (model 6), temperature data combined with geographic information and wind speed (models 7, 9 and 10), and geographic inputs combined with wind speed (models 11 to 14). The equations shown in Table 1 (except model 5) contain only statistically significant variables, selected according to step-wise multiple regression.

Focusing on temperature-based approaches, models 1 and 5 correspond to the local versions of the Vanderlinden et al. (2004) and Samani (2000) approaches, respectively. The latter approach yields a slightly higher goodness-of-fit in this region (R^2 of 0.35 vs. 0.17), although the accuracy is very poor in both cases. The quadratic effect incorporated by Samani (2000) in his model was not statistically significant in this study (model 2). Finally, if the ratio T_{mean} / ΔT (Vanderlinden et al., 2004) is split up as two independent predictors (model 3), a noteworthy increase of the model accuracy was achieved (R^2 of 0.64 vs. 0.17), reducing the RRMSE from 10.7% to 7%. A relevant quadratic effect was found for this model, which leads to equation 4, with a slight performance improvement. If geographical inputs are incorporated, which are easily available for any station, the performance of the temperature-based models increased (model 6). It was found that only the effect of ΔT, longitude and altitude was statistically significant. Compared with the optimal temperature-based model (model 4), R^2 increased from 0.71 to 0.90, while RRMSE decreased from 6.2% to 3.7%, and MAE was reduced from 0.000115 to 0.000070. For the third strategy (models 7-10 in Table 1), in addition, wind inputs were considered. According to the results of Shahidian et al.

(2013), wind speed is the most important parameter for improving the precision of HG estimates, especially for correcting the bias and calibration slope. By incorporating wind speed into the original HG equation, in additon to the radiative component, also the aerodynamic component of the PM equation is taken into account. Accordingly, model 7 provided improved AHC estimates, with R^2 = 0.97 and a RRMSE reduction from 3.7% to 1.9% as compared to model 6. Nevertheless, it must be noted that wind speed is usually not available or reliable at many stations, and this model would not be strictly applicable when the HG models should be useful in practice. In order to overcome this drawback, an extra model was fitted for estimating u_2 based on temperature and geographical information (model 8). Taking advantage of model 8, model 7 might be applied in stations were wind speed is not available. Under these conditions, model 6 (without u_2) provided similar accuracy than model 7. Note that in Table 1 the indicators of model 8 are obtained using model 7 for AHC and model 8 for u_2.

Other approaches (models 9 and 10) considered qualitative wind information instead of measured u_2. Stations were grouped according to their average wind speed as high, intermediate or low windy (model 9), assigning the values 1 for the low, 2 for the intermediate, and 3 for the highest speed category. Model 10 uses only two wind classes (high or low), assigning 1 for windy stations and 0 for the others. These classes were determined considering the u_2 variability among the 30 stations. Given the relevance of wind for HG estimates, users might provide additional information about the local wind conditions without the need of requiring local experimental measurements. As can be observed in Table 1, replacing quantitative wind speed data by qualitative information has only a small effect on the model accuracy, even when taking into account only two wind classes (model 10). In this case, when comparing with model 6 (thermal and geographic information), the R^2 increased from 0.90 to 0.94 (to 0.97 using three wind classes), and the RRMSE decreased from 3.7% to 2.8% (to 2% using three classes). Hence, considering a station as windy or not should be sufficient to apply the model and to improve the accuracy of the AHC estimates considerably. Considering more than three wind classes would complicate the application of such models in practice, or even decrease their performance due to the risk of choosing the wrong wind class. Therefore, model 10 would be preferable to ensure a proper class selection. Finally, a fourth strategy was examined by considering jointly geographical and wind inputs (models 11-14). Nevertheless, these models did not improve substantially the performance as compared with models of category 2 which, besides, can be applied easier. Caution is warranted when extrapolating the proposed expressions since they rely on a rather short 8-year data set. The main goal was to suggest new alternative procedures for improving the AHC prediction taking advantage of additional available information when the HG equation is supposed to be useful in practice, e.g. geographical information and, eventually, qualitative wind speed information.

AHCs per station and average HG accuracy at different timescales

The AHCs per station are compared in Fig. 4. Here, observed AHCs (target values) and the locally fitted values according to the approaches of Samani (2000) and Vanderlinden et al. (2004) are shown (models 5 and 1, respectively). Moreover, two of the new optimal models are represented as well, namely model 6 relying on temperature and geographic inputs, and model 9, which also incorporates qualitative $u_{1\text{-}3}$ wind speed. Despite its higher accuracy, model 7 was not considered here, since it requires local measurements of wind speed, in contrast to models 9 or 10. As stated above, it presents the drawback of requiring local measurements of u_2. The original HG coefficient 0.0023 is also plotted as a reference.

No clear over-/underestimation trend of the observed AHC could be found between inland and coastal stations. Neither the inland stations nor the coastal stations showed consistently AHCs over or under 0.0023, in contrast to the results of Vanderlinden et al. (2004). Despite being located near the sea, the location of some coastal stations might present particularities, which could justify those AHC values under 0.0023. The estimates of the new models (red circles) are clearly closer to the observed AHCs than the existing models (blue squares). Moreover, the differences in AHC between the different approaches are station-dependent, with small differences (*e.g.* stations 3, 5, 9 or 22) and large differences (*e.g.* stations 21 or 27).

The values of the observed AHC ranges were also assessed for the different timescales (results not shown). For each timescale point (day, week, fortnight, month), an AHC value was calculated as the quotient between FAO56-PM and HG ET_o estimates. As expected, the AHC variability increased for smaller timescales, *i.e.* the deviation ranges between HG and FAO56-PM estimates decreased from daily to monthly timescales. Although this decreasing variability might be a result of the smaller variability of ET_o for longer timescales, it must be noted that the input variables for the HG and FAO56-PM equations were averaged, but not the ET_o values. These differences between timescales suggest the need for applying different AHC coefficients throughout the year, and not a single AHC per station. Also Vanderlinden et al. (2004) suggested the possibility of providing monthly AHCs.

The average performance accuracy of the non-calibrated HG equation for the different timescales at the 30 stations is shown in Table 2. Also the average performance indicadors of the calibrated HG equation using the AHC models of Table 1 are included, in addition to the indicators obtained for the observed AHC (locally fitted target values). Focusing on the non-calibrated HG estimates, it can be observed that the error measures decreased when the timescale increases (RRMSE values of 0.223, 0.168, 0.145, and 0.141 for daily, weekly, fortnightly and monthly timescales, respectively). The increment in accuracy was more significant from daily to weekly than from weekly to fortnightly timescales (5.5% vs. 2.3%), and higher from weekly to fortnightly than from fortnightly to monthly timescales (0.4%). These results seem to be in agreement with Hargreaves and Allen (2003), who found optimal accuracies for five-day or longer timescales.

The reduction in RRMSE for the calibrated HG estimates (using the observed AHCs) with respect to the non-calibrated HG estimates was higher for the weekly (from 16.8% to 13.3%), fortnightly (from 14.5% to 10.4%) and monthly (from 14.1% to 9.5%) timescales than for the daily (from 22.3% to 19.7%) timescales. ET_o estimates using AHC model 6 (relying on temperature and geographic information) as well as models 7, 9, and 10 (relying additionally on wind information) showed similar accuracies as compared with the estimates calculated using the observed AHCs. The performance differences between the AHC models in Table 1 are translated into smaller performance differences between the corresponding calibrated ET_o estimates, because one single AHC is used for all time points at a given station, and the ET_o ranges are larger than the AHC ranges. Even the locally fitted AHC approaches of Samani (2000) and Vanderlinden et al. (2004) provide small accuracy improvements. Nevertheless, these average error parameters should be split up per station to properly assess the differences between approaches. Finally, all ET_o estimations corresponding to the same timescale presented the same coefficient of determination. Although they were calculated with different AHC models, a single AHC is applied per station, and the different calibrated HG alternatives are proportional to the non-calibrated HG.

HG accuracy per station and average cumulative ET_o estimation

Fig. 5 presents the RRMSE of the calibrated and non-calibrated HG estimations per station for daily timescales. The same approaches as in Fig. 4 were represented here, except for model 9, which was replaced by model 10 (two wind classes instead of three), because the corresponding RRMSE values were very similar and because model 10 can be applied more easily (the probability of selecting correctly the wind class is higher). The general trend observed in Fig. 5, as expected from the average results, is that the non-calibrated HG errors were consistently higher than the calibrated HG errors, and that the new AHC models incorporating geographic and qualitative wind speed information provided ET_o estimates with lower errors than those calculated using the approaches of Samani (2000) and Vanderlinden et al. (2004). This can be clearly observed for example at stations 8 and 18. At some stations (*e.g*. 9, 10, 19, 22), all approaches presented a very similar performance, including the non-calibrated HG estimates. In other cases, the new AHC approaches led to ET_o estimates with slightly higher RRMSE than the temperature-based models (*e.g*. stations 11, 23, 24). Finally, in other stations (*e.g*. 24, 28), the non-calibrated HG estimates presented even slighly lower RRMSE than the calibrated HG estimates, in accordance with the findings of Mendicino and Senatore (2013) at some of their stations. Again, this might be due to the consideration of a single AHC value per station, i.e. the same AHC was applied for all daily HG estimates per station. This is an important simplification, because the daily actual AHC might fluctuate significantly throughout the year. Therefore, a single coefficient might not be suitable for correcting the HG estimates throughout the considered period.

Attending to the intra-annual trend of station 28 (results not shown), although the non-calibrated HG estimations present a lower average error than the calibrated estimates (Fig. 5), this pattern is month-dependent. Although the calibrated estimates are more accurate at a larger number of months (september to march), the errors of the calibrated estimates between April and August were considerably higher than for the rest of the year. Thus, where the non-calibrated HG equation already provided accurate estimates, the application of a single AHC might worsen the estimation performance, especially when ET_o increases (summer). Fig. 6 shows the intra-annual patterns of daily and monthly ET_o estimates at Ondara (station 7) and Vila-Joiosa (station 3), according to the FAO56-PM and HG equations, as well as using the AHC model 10 for the HG calibrated version. Apart from the over- (Ondara) and underestimation (Vila-Joiosa) trend of the non-calibrated HG estimates, a further important difference could be observed with respect to the calibrated HG estimates, especially for the monthly estimates. While in Ondara (upper plot) the monthly HG estimates presented a rather homogeneous and constant deviation from the FAO56-PM estimates throughout the year (except in August), this was not the case in Vila-Joiosa. The calibrated HG equation presented a tendency to overestimate from February to August, while it underestimated from September to January. In addition, the deviation from the FAO56-PM estimates was considerably different from month to month, even for months with similar ET_o rates, *e.g.* November vs February, July vs August, May vs September, etc.). Thus, while a single AHC per station might provide suitable estimates in station 7 for the whole year due to a homogeneous annual deviation pattern of the HG estimates, by contrast, the application of different AHCs throughout the year might be required in station 3 for a suitable fit of the HG trend.

The assessment of the model performance for estimating annual average cumulative ET_o values is presented in Table 3. The average performance indicators of such estimates in the 30 stations are presented here for the daily timescale. As can be observed, the error parameters are considerably lower in comparison to Table 2. This can be linked to the variability reduction due to the use of averaged values. The performance parameters were very similar for the different timescales (results not shown), where the RRMSE fluctuates between 0.11 (non-calibrated HG) and 0.03 (optimum calibrated HG). By averaging the inputs for the weekly, fortnightly and monthly timescales and applying the HG and FAO56-PM, similar results were obtained as compared to averaging directly daily ET_o estimates for the different timescales (results not shown). Therefore, a model provided very similar daily accumulated estimates for the different timescales. Coastal station 1 (Pilar de la Horadada, mean ΔT=9.2ºC) and inland station 18 (Carcaixent, mean ΔT=13.6ºC) were selected to show the evolution of the accumulated ET_o during an average year based on daily estimates (Fig. 7). The mean ΔT ranged from 8.8ºC to 14.4ºC among the 30 stations. In this case, model 6 (relying on temperature and geographic information) was used instead of models 9 and 10, in order to provide a more conservative comparison, and because it can be applied with less uncertainty than the AHC models relying additionally on wind speed class. The estimates derived from using the observed AHC were not shown since model 6 already provided very accurate estimates, as can be observed in Fig. 7. The annual FAO56-PM ET_o in station 1 was approximately 200 mm higher than in station 18. At station 1, the HG and the temperature-based approaches underestimated ET_o, with a total annual error of -150 mm (HG), -75 mm (Vanderlinden et al., 2004), and -50 mm (Samani, 2000). These errors are noteworthy bearing in mind that the average annual precipitation at this station is 353 mm. The proposed AHC model provided very accurate mean cumulative estimates, and eliminated the error almost completely. Station 18, with an average annual precipitation of 583 mm, showed higher and positive errors, ranging from 280 to 120 mm, corresponding to overestimations by the non-calibrated and calibrated HG estimates, with the exception of the proposed AHC model. In both cases, a higher error is accumulated at the end of the year, when actual evapotranspiration is rather controlled by the available soil moisture and soil physical properties than by the atmospheric demand (Vanderlinden et al., 2004). Moreover, as stated by Mendicino and Senatore (2013), the summertime provided the highest increments in the accumulated error (steeper slopes), because T and ET_o are higher during this period.

Further research should assess the encountered relationships in other climatic and geographic scenarios. Moreover, the presented conclusions should also be confirmed using experimental benchmarks, according to Martí et al. (2015).

4. Conclusions

This paper evaluates the performance of the calibrated and non-calibrated versions of the Hargreaves equation in Eastern Spain at daily, weekly, fortnightly and monthly scales. This study assesses previous parametric calibrations of the AHC coefficient and provides new procedures to improve their performance accuracy considering additional available inputs.

The accuracy of the calibrated and non-calibrated HG estimates increased for longer timescales, with decreasing accuracy improvements. The average accuracy improvement rate of the calibrated HG estimates is similar for all timescales.

The locally fitted approaches relying, respectively, on average temperature range (Samani, 2000), and the ratio $T_{mean}/\Delta T$ (Vanderlinden et al. 2004) did not perform satisfactory in this region at the considered stations.

Three strategies were adopted to improve the performance of the parametric AHC equations. First, the mentioned ratio was split into two independent inputs, namely mean temperature and mean temperature range. Second, temperature-based inputs were combined with additional geographic inputs. Third, temperature-based and geographic inputs were combined with additional qualitative wind inputs (wind classes).

The most accurate AHC model relied on temperature range, longitude, altitude and three qualitative wind speed classes (low, intermediate, high). When considering two wind classes (highly vs. poorly windy) only a slight accuracy decrease was observed. Nevertheless, the accuracy of the AHC estimates might increase in practice, because increasing the number of wind classes complicates the application of such models or might even worsen their performance because of choosing the wrong station class. The model relying on temperature range, longitude and altitude only involves a slight accuracy decrease in comparison to models incorporating wind class, while its application is easier and more reliable.

The differences in accuracy between the AHC models were translated into smaller differences in the accuracy of the corresponding ET_o estimates, because a single AHC is considered per station. The error parameters decreased when the models were used to provide average cumulative annual values. Further, the performance parameters were very similar for the different timescales, because they provided very similar cumulative values.

The AHC fluctuation throughout the year might recommend the calibration of monthly or at least seasonal models for estimating AHC. The relationships encountered might only be valid for the studied locations. However, the new methodological strategies for improving the local parametric calibration of AHC might also be applied elsewhere, trying to take advantage of additional inputs which might be available under conditions where the HG equation might be the only alternative.

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References

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration. Guidelines for computing water requirements. FAO Irrigation and Drainage, Paper 56. FAO, Rome.

Bachour, R., Walker, W.R., Torres-Rua, A.F., McKee, M., 2013. Assessment of reference evapotranspiration by the Hargreaves methods in the Bekaa valley, Lebanon. J. Irrig. Drain. Eng., 139(11), 933-938.

Berengena, J., Gavilán, P., 2005. Reference evapotranspiration estimation in a highly advective semiarid environment. J. Irrig. Drain. Eng., 131(2), 147-163.

Berti, A., Tardivo, G., Chiaudani, A., Rech, F., Borin, M., 2014. Assessing reference evapotranspiration by the Hargreaves methods in north-eastern Italy. Agric. Water Manage., 140(7), 20-25.

Di Stefano, C., Ferro, V., 1997. Estimation of evapotranspiration by Hargreaves formula and remote sensed data in semi-arid Mediterranean areas. J. Agric. Eng. Res., 68, 189–199.

Droogers, P., Allen, R.G. 2002. Estimating reference evapotranspiration under inaccurate data conditions. Irrig. Drain. Syst., 16(1),33-45.

Fooladmand, H.R. Haghighat, M. 2007. Spatial and temporal calibration of Hargreaves equation for calculating monthly ETo based on Penman-Monteith method. Irrig. Drain., 56(4), 439-449.

Gavilán, P., Lorite, I.J., Tornero, S., Berengena, J., 2006. Regional calibration of Hargreaves equation for estimating reference ET in a semi arid environment. Agric. Water Manage., 81, 257–281.

Hargreaves, G.H., 1994. Defining and using reference evapotranspiration. J. Irrig. Drain. Eng., 120(6),1132-1139.

Hargreaves, G.H., Allen, R.G. 2003. History and evaluation of Hargreaves evapotranspiration equation. J. Irrig. Drain. Eng., 129(1), 53-63.

Hargreaves, G.L., Hargreaves, G.H., Riley, J.P., 1985. Irrigation water requirements for Senegal river basin. J. Irrig. Drain. Eng., 129(1), 265-275.

Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from ambient air temperature. Appl. Eng. Agric. 1 (2), 96–99.

Itenfisu, D., Elliott, R.L., Allen, R.G., Walter, I.A., 2003. Comparison of ET_o calculation as part of the ASCE standardization effort. J. Irrig. Drain. Eng., 129(6), 440-448.

Jabloun, M., Sahli, A., 2008. Evaluation of FAO-56 methodology for estimating ETo using limited climatic data application to Tunisia. Agric. Water Manage., 95(6), 707-715.

Jensen, M.E., 1968. Water consumption by agricultural plants. In: Water deficits and plant growth, Vol. 2. Academic Press Inc, New York.

Jensen, M.E., Burman, R.D., Allen, R.G.,1990. Evapotranspiration and irrigation water requirements. ASCE Manual and Report on Engineering Practice No. 70, ASCE, New York.

Jensen, D.T., Hargreaves, G.H., Temesgen, B., Allen, R.G., 1997. Computation of ET_o under non ideal conditions. J. Irrig. Drain. Eng, 123(5), 394-400.

Kwon, H., Choi, M., 2011. Error assessment of climate variables for FAO-56 reference evapotranspiration. Meteorol. Atmos. Phys., 112(1-2), 81-90.

Lee, K.H. 2010. Relative comparison of the local recalibration of the temperature-based equation for the Korea Peninsula. J. Irrig. Drain. Eng., 136(9), 585-594.

López-Urrea, R., Martín de Santa Olalla, F., Fabeiro, C., Moratalla, A., (2006) Testing evapotranspiration equations using lysimeter observations in a semiarid climate. Agric. Water. Manage., 85(1-2), 15–26.

Maestre-Valero, J.F., Martínez-Álvarez, V., González-Real, M.M., 2013. Regionalization of the Hargreaves coefficient to estimate long-term reference evapotranspiration series in SE Spain. Span. J. Agric. Res., 11(4), 1137-1152.

Martí, P., Manzano, J, Royuela, A., 2011. Assessment of a 4-input artificial neural network for ET_o estimation through data set scanning procedures. Irrig. Sci., 29(3), 181-195.

Martí, P., Gasque, M., 2011. Improvement of temperature-based ANN models for solar radiation estimation through exogenous data assistance. Energ. Convers. Manage., 52(2), 990-1003.

Martí, P., Zarzo, M., 2012. Multivariate statistical monitoring of ET_o. A new approach for estimation in nearby locations using geographical inputs. Agr. Forest. Meteorol., 152(1), 125-134.

Martí, P., González-Altozano, P., López-Urrea, R., Mancha, L.A., Shiri, J., 2015. Modeling reference evapotranspiration with calculated targets. Assessment and Implications. Agric. Water Manage., 149(2), 81-90.

Martínez-Cob, A., Tejero Juste, M., 2004. A wind-based qualitative calibration of the Hargreaves ET_o estimation equation in semiarid regions. Agric. Water Manage., 64(3), 251-264.

Mendicino, G., Senatore, A., 2013. Regionalization of the Hargreaves coefficient for the assessment of distributed reference evapotranspiration in Southern Italy. J. Irrig. Drain. Eng., 139(5),349-362.

Ortega Farias, S., Irmank, E., Cuenca, R.H., 2009. Special issue on evapotranspiration measurement and modeling. Irrig. Sci., 28(1),1–3.

Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large scale parameters monitoring. Weather Rev., 100(2), 81-92.

Ravazzani, G., Corbari, C., Morella, S., Gianoli, P., Mancini, M., 2012. Modified Hargreaves-Samani equation for the assessment of reference evapotranspiration in Alpine River Basins. J. Irrig. Drain. Eng., 138(7), 592-599.

Raziei, T., Pereira, L.S., 2013. Estimation of ETo with Hargreaves-Samani and FAO-PM temperature methods for a wide range of climates in Iran. Agric. Water Manage., 121(4), 1-18.

Samani, Z., 2000. Estimating solar radiation and evapotranspiration using minimum climatological data. J. Irrig. Drain. Eng., 126(4), 265-267.

Samani, Z.A., Pessarakli, M. 1986. Estimating potential crop evapotranspiration with minimum data in Arizona. Trans. ASAE 29, 522-524.

Shahidian, R., Serralheiro, P., Serrano, J., Teixeira, J.L., 2013. Parametric calibration of the Hargreaves-Samani equation for use at new locations. Hydrol. Process., 27(4), 605-616.

Shiri, J., Nazemi, A.H., Sadraddini, A.A., Landeras, G., Kisi, O, Fakheri Fard, Martí, P., 2013. Global cross-station assessment of neuro-fuzzy models for estimating daily reference evapotranspiration. J. Hydrol., 480(2), 46-57.

Shiri, J., Nazemi, A.H., Sadraddini, A.A., Landeras, G., Kisi, O, Fakheri Fard, Martí, P., 2014. Comparison of heuristic and empirical approaches for estimating reference evapotranspiration from limited inputs in Iran. Computers and Electron., 108(10), 230-241.

Shuttleworth, W.J., 1993. Evaporation. Handbook of Hydrology, D.R. Maidment, ed., McGraw-Hill, New York.

Tabari, H., Hosseinzadeh Talaee, P., 2011. Local Calibration of the Hargreaves and Priestley-Taylor Equations for Estimating Reference Evapotranspiration in Arid and Cold Climates of Iran Based on the Penman-Monteith Model. J. Hydrol. Eng., 16(10):837-845.

Temesgen, B., Eching, S., Davidoff, B., Frame, K., 2005. Comparison of some reference evapotranspiration equations for California. J. Irrig. Drain. Eng., 131(1),73-84.

Thepadia, M., Martínez, C.J., 2012. Regional calibration of solar radiation and reference evapotranspiration estimates with minimal data in Florida. J. Irrig. Drain. Eng., 138(2),111-119.

Trajkovic, S., 2005. Temperature-based approaches for estimating reference evapotranspiration. J. Irrig. Drain. Eng., 131(4),316-323.

Trajkovic, S., 2007. Hargreaves versus Penman-Monteith under humid conditions. J. Irrig. Drain. Eng., 133(1), 38-42.

Vanderlinden, K., Giraldez, J. V., and Van Meirvenne, M., 2004. Assessing reference evapotranspiration by the Hargreaves method in Southern Spain. J. Irrig. Drain. Eng., 130(3), 184–191.

Willmott, C.J., 1982. Some comments on the evaluation of model performance. Bulletin American Meteorological Society 63(11), 1309-1313.

Xu, C.Y., Singh, V.P., 2002. Cross comparison of empirical equations for calculating potential evapotranspiration with data from Switzerland. Water Resour. Manage., 16(3), 197-219.

Yrisarry, J.J.B., Naveso F.S., 2000. Use of weighing lysimeter and Bowen-Ratio Energy-Balance for reference and actual crop evapotranspiration measurements. Acta Horticulturae, 537:143–150.

Zanetti S.S., Sousa E.F., Oliveira V.P.S., Almeida F.T., Bernardo S., 2007. Estimating evapotranspiration using artificial neural network and minimum climatological data. J. Irrig. Drain. Eng., 133 (2), 83-89.

Figure captions.

Fig.1. Location of studied stations (c coastal, i inland). Codes as in Figs. 4 and 5.

Fig.2. Relationships between AHC and $T_{mean}/\Delta T$.

Fig.3. Relationships between C and ΔT.

Fig.4. Comparison of the estimated AHCs per station according to different models in Table 1. The horizontal line represents the original AHC of 0.0023

Fig.5. RRMSE of calibrated (HG_c) and non-calibrated HG estimates per station at daily timescale, according to different models in Table 1. (-) means unitless

Fig.6. Annual evolution of daily and monthly ET_o estimates in two weather stations according to FAO56-PM, HG and HG_c (model 10).

Fig.7. Cumulative mean annual pattern of ET_o daily estimates in two weather stations according to FAO56-PM, HG, and calibrated HG based on model 1 (Vanderlinden et al., 2004), 5 (Samani, 2000), and 6. The lower plots indicate the deviations with respect to the FAO56-PM curve.

Footnote Table 1:

AHC: adjusted Hargreaves coefficient, T_{mean}: average mean temperature, ΔT: average daily temperature range, φ: latitude; τ: longitude, z: altitude (m), u_2: wind speed at 2 m height (m/s), u_{2c}: calculated wind speed at 2 m height, $u_{1\text{-}3}$: qualitative wind speed (1 low, 2 medium, 3 high), $u_{0\text{-}1}$: qualitative wind speed (0 low, 1 high), d_s: distance to the sea (km).

Table captions.

Table 1. Proposed AHC models and associated statistical parameters

Table 2. Average performance indicators of calibrated and non-calibrated HG estimates for the different timescales considered. Model codes as in Table 1.

Table 3. Average performance indicators of the mean daily cumulative calibrated and non-calibrated HG estimates for the daily timescale.