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Prediction of evapotranspiration in a Mediterranean region using basic meteorological variables

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Abstract

A critical need for farmers, particularly those in arid and semi-arid areas is to have a reliable, accurate and reasonably accessible means of estimating the evapotranspiration rates of their crops in order to optimize their irrigation requirements. Evapotranspiration is a crucial process due to its influence on the precipitation that is returned to the atmosphere. The calculation of this variable often starts from the estimation of reference evapotranspiration, for which a variety of methods have been developed. However, these methods are very complex either theoretically and/or because of the large amount of parameters on which they are based, which makes the development of a simple and reliable methodology for the prediction of this variable important. This research combined three concepts such as cluster analysis, Multiple Linear Regression (MLR) and Voronoi diagrams to achieve that end. Cluster analysis divided the study area into groups based on its weather characteristics, whose locations were then delimited by drawing the Voronoi regions associated with them. Regression equations were built to predict daily reference evapotranspiration in each cluster using basic climate variables produced in forecasts made by meteorological agencies. Finally, the Voronoi diagrams were used again to regionalize the crop coefficients and calculate evapotranspiration from the values of reference evapotranspiration derived from the regression models. These operations were applied to the Valencian Region (Spain), a Mediterranean area which is partly semi-arid and for which evapotranspiration is a critical issue. The results demonstrated the usefulness and accuracy of the methodology to predict the water demands of crops and hence enable farmers to plan their irrigation needs.

Keywords

Cluster analysis; Crop coefficient; Evapotranspiration; Multiple linear regression; Reference evapotranspiration; Voronoi diagrams

1. Introduction

Evapotranspiration (ET) is the sum of two processes whereby water is lost from the soil surface (evaporation) and from the crop (transpiration) (Aytek 2009). As such, it is an important factor in the formation of clouds and the occurrence of rainfall and plays a relevant role in several different water-related fields, including aquifer recharge (Healy and Scanlon 2010), ecosystem water balances (Sun et al. 2011), global circulation models (Dolman 1993), hydrology (Sorooshian et al. 1993), irrigation systems (Allen 2000; Bos et al. 2008), land surface modelling (Chen and Dudhia 2001) and water resource management (Biswas 2004). Despite its importance, ET is still one of the most misunderstood variables in the hydrological cycle and its characterization remains limited (Brutsaert 1982; Naoum and Tsanis 2003).

As a global average, ET is responsible for approximately 60% of the precipitation returned to the atmosphere, a figure that increases to up to 90% in arid and semi-arid regions (Brutsaert 2005). Therefore, its measurement is essential in agricultural terms for estimating crop water demand and managing irrigation systems. The calculation of ET is frequently preceded by the determination of reference evapotranspiration (ET_o) (López-Urrea et al. 2006), which is the rate at which available soil water is lost from a specific crop (Jensen et al. 1990) and which can be estimated using climate data (Xing et al. 2008).

There are many methods developed to determine ET_o based on climate data, but the FAO Penman-Monteith equation (Monteith 1981) has been recommended by the Food and Agriculture Organization (Allen et al. 1998) and the American Society of Civil Engineers

(Allen et al. 2005) as the standard method for this calculation. This equation can be used worldwide without requiring any local adjustment thanks to its physical foundations, validated by the use of lysimeters (Gocic and Trajkovic 2010). In contrast, the main weakness of the FAO Penman-Monteith (PM) method is the large amount of variables it contains, some of which might not be available in many locations, especially developing countries (Martinez and Thepadia 2010).

Several researchers have pointed to the need for simpler methods to estimate ET_o (George et al. 2002; Sabziparvar et al. 2010; Tabari and Talaee 2011). Since the relationships between ET_o and the climate variables on which it depends are nonlinear (Jackson 1985; Kumar et al. 2002; Parasumaran et al. 2007; Wang et al. 2007; Adamala et al. 2014), Artificial Neural Networks (ANNs), Adaptive Neuro Fuzzy Inference Systems (ANFIS) and Genetic Programming (GP) have been the main methods used during the last decades to model it. Kumar et al. (2002) and Adamala et al. (2014) concluded that ANNs outperformed the PM method for reproducing values of ET_o measured with lysimeters, based on the errors yielded by both approaches. Parasuraman et al. (2007), who went one step further and also included GP in the comparison, demonstrated that both this technique and ANNs performed better than the PM method. Similarly, the results achieved by Wang et al. (2008) and Traore et al. (2010) revealed that ANNs could reach higher accuracy than empirical models such as Hargreaves and Blaney-Criddle in the prediction of ET_o.

Despite the nonlinear nature of ET_o, the linear combination of climate variables has been found to provide a simpler and still reliable and accurate alternative to predict it. Hence, the results obtained by Tabari et al. (2012) indicated that the differences between Multiple

Linear Regression (MLR) models and Multiple Nonlinear Regression (MNLR) models were almost negligible, to the extent that MLR outperformed MNLR when the number of predictors used was small. In the same line, the studies carried out by Jain et al. (2008), Mallikarjuna et al. (2013) and Ladlani et al. (2014), who compared the capability of MLR to estimate ET_o with that of nonlinear methods such as ANNs and ANFIS, suggested that the performance of both linear and nonlinear approaches was very similar. The predictive power of the models built by Sanford et al. (2013), which explained around 90% of the proportion of the variance in the ratio of ET over precipitation, also provided evidence of the potential of MLR to estimate this variable.

These previous studies show that although nonlinear methods can be slightly more accurate than MLR, the differences between both approaches might not be significant and the linear combination of climate variables can provide accurate predictions of ET_o. Furthermore, MLR are simpler and easier to understand and interpret than nonlinear techniques, which are frequently used as "black boxes" without having a clear perception of their internal workings. For instance, ANNs, which represent the most widely used nonlinear method to estimate ET_o, require a series of hidden layers to relate inputs and output that are often added arbitrarily to improve the accuracy of the prediction model. This might lead to overfitting of the model and result in misleadingly high-quality estimates. Besides, ANNs do not directly yield equations to estimate future values of ET_o as MLR do. However, former applications of MLR to predict ET_o did not provide solid evidence of their potential for making new estimates. Moreover, they were limited to the prediction of ET_o and did not include any regionalization methodology to group different locations according to their meteorological characteristics, which together with the fact that they were not built according to data availability in weather forecasts precludes the calculation of ET and therefore the design of aprioristic irrigation strategies.

In this context, the aim of this paper was to build linear equations for the prediction of ET based on weather forecasts, so that users can estimate the water requirements of their crops and determine when and how much to irrigate. This was achieved through a methodology which combined three tools such as cluster analysis, MLR models and Voronoi diagrams to enable the estimation and regionalization of ET using basic meteorological variables. These tools were applied to the Valencian Region in Spain, a Mediterranean area with semi-arid climate zones wherein evapotranspiration is an essential factor in optimizing agricultural production.

2. Methodology

2.1. Framework

Evapotranspiration (ET) and reference evapotranspiration (ET_o) can be related through Eq. (1):

$$ET = ET_o \cdot K_c \tag{1}$$

where K_c is the single crop coefficient (dimensionless), which combines the effect of soil evaporation and crop transpiration into a single coefficient and is recommended for irrigation planning, design, management and scheduling (Allen et al. 1998). Since K_c averages evaporation and transpiration, a single crop coefficient is used to determine ET for weekly or longer periods (Allen et al. 1998). Based on findings from several researchers on the temporal scale of K_c for different crops under Mediterranean climate (Ferreira and Carr 2002; Williams et al. 2003; Testi et al. 2004; Amayreh and Al-Abed 2005; Martínez-Cob A. 2008; Villalobos et al. 2009), a monthly period was chosen for the estimation of this coefficient. This is a time horizon that suits the purpose of this research, since it allows the prediction of daily ET for every month.

The FAO PM method is used in Spain for calculating ET_o (Doorenbos and Pruitt 1976). The concept of ET_o was defined by the FAO as the rate of ET from an ideal 12 cm high grass reference crop with a fixed canopy of 70 s·m^{-1} and an albedo of 0.23 (Allen et al. 1998). This reference surface resembles an extensive and well-watered green grass cover of uniform height, actively growing and completely shading the ground (Droogers and Allen 2002). ET_o (mm) can be estimated through Eq. (2), once the aerodynamic and radiation terms derived from the PM equation are combined:

$$ET_o = \frac{0.408 \cdot \Delta \cdot (R_n - G) + \gamma \cdot \frac{900}{T + 273} \cdot U_2 \cdot (e_a - e_d)}{\Delta + \gamma \cdot (1 + 0.34 \cdot U_2)} \qquad (2)$$

where R_n is net radiation at the crop surface (MJ·m^{-2}·d^{-1}), G is soil heat flux (MJ·m^{-2}·d^{-1}), T is mean temperature (ºC), U_2 is mean wind speed at 2 m above the ground (m·s^{-1}), $(e_a - e_d)$ is the difference between the actual (e_a) and saturation (e_d) vapor pressure (kPa), Δ is the slope of the vapour pressure curve (kPa·ºC^{-1}) and γ is the psychrometric constant (kPa·ºC^{-1}), computed as shown in Eq. (3) (Brunt 2011):

$$\gamma = 0.00163 \cdot \frac{P}{\lambda} \tag{3}$$

where P is atmospheric pressure (kPa) and λ is latent heat (MJ·kg^{-1}). Eqs. (2) and (3) reveal the complexity of the PM equation and the great amount of parameters required by it, some of which are not provided by meteorological agencies in their weather forecasts. Therefore, there is a justifiable need to develop alternative models to estimate ET using basic meteorological variables.

2.2. Overview

The Valencian Region is divided into three provinces: Alicante, Castellón and Valencia. Table 1 summarizes their main demographic and climate characteristics and indicates the number of valid agrometeorological stations located in each of them. The Spanish Ministry of Agriculture, Food and Environment (MAGRAMA) provides historical daily values of ET_o for these stations calculated using the FAO PM equation (see Eq. (2)).

Table 1. Main characteristics of the provinces forming the Valencian Region

However, conventional weather stations do not record all the information required to complete the equation, which also cannot be used to predict new values of ET, since it is not compatible with the variables that are presented in the daily Spanish Meteorological

Agency weather forecasts (AEMET 2016). In accordance with the data included in these forecasting models, predictors that are made available include mean temperature (T_{mean}, ºC), maximum temperature (T_{max}, ºC), minimum temperature (T_{min}, ºC), mean relative humidity (RH_{mean}, %), maximum relative humidity (RH_{max}, %), minimum relative humidity (RH_{min}, %) and mean wind speed (WS_{mean}, m·s^{-1}).

The four main steps carried out to develop a methodology capable of predicting ET for a single day in any month using basic meteorological variables are listed below:

- Acquisition of the daily datasets corresponding to the seven predictors for the 49 stations located in the whole region and their subsequent arrangement in months, according to the time horizon of K_c.
- Categorizing the weather stations based on their recorded values in relation to the predictors. Measures of central tendency and variability were used to characterize these stations for clustering.
- Development of regression equations to make predictions of daily ET_o for each month and cluster from the combination of the set of predictors.
- Delimitation of the boundaries associated with both the clusters previously obtained and the values of K_c for each station using Voronoi diagrams.

The fulfilment of these steps enabled daily ET to be determined by multiplying K_c by the regression equation built to estimate ET_o for the month and the cluster corresponding to the coordinates of the study area. The theoretical framework behind the tools on which these last three steps were based is described in the following subsections.

2.3. Cluster analysis

Cluster analysis, a term first introduced by Tryon (1939), is a multivariate data mining technique that uses different algorithms and methods to group objects based on their similarity. As a result, objects within a group are related to one another but unrelated to objects in other groups, so that the distinctness of the clusters increases as the similarity within a group and the difference between groups increase (Tan et al. 2005).

Even though the notion of "cluster" is clear, the definition of the threshold that differentiates two clusters has not been precisely defined. Consequently, many clustering methods have been developed over the years, each of them based on different working principles (Estivill-Castro and Yang 2004). Among them, k-means is one of the most popular algorithms to cluster large datasets in an efficient and simple way (Forgy 1965; MacQueen 1967; Wu et al. 2008).

The k-means algorithm seeks to partition a set of observations n into $k(\leq n)$ clusters by minimising the within-cluster sum of squares ($WCSS$), i.e. the sum of distances of each point in the cluster to its centroid. This algorithm proceeds according to the three following steps (Tan et al. 2005): (1) choose k initial centroids, where k is the number of clusters desired; (2) assign each observation to the closest cluster according to the Euclidean distance between them, i.e. the square root of the sum of their squared differences; and (3) update the centroid of each cluster based on the points assigned to it. The last two steps are repeated until the results converge and there are no point changes in the clusters. In other words, the algorithm stops when the centroids remain the same (Tan et al. 2005).

Two pairs of measures of central tendency and variability were proposed to characterize these variables for each weather station depending on whether they were normally distributed or not: mean ($\bar{x}$) and standard deviation (σ) or median ($\tilde{x}$) and interquartile range (IQR), respectively. The Shapiro-Wilk test (Shapiro and Wilk 1965), which has been found to be more reliable when checking normality than other commonly used tests such as Kolmogorov-Smirnov or Lilliefors (Shapiro et al. 1968), was selected for checking normality.

2.4. Multiple linear regression

Multiple Linear Regression (MLR) aims to model the relationship between two or more predictors (basic meteorological variables) and a predictand (ET_o) by fitting a linear equation to observed data (see Eq. (4)):

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k + \varepsilon \quad (4)$$

where y is the predictand expressed as a linear combination of a set of K predictors x_k, each of which is multiplied by a coefficient β_k that indicates its relative weight in the equation. The equation also includes a constant β_0 and a random component ε (the residuals) which explain everything that cannot be interpreted from the predictors.

The goodness-of-fit of a MLR model is often measured through the coefficient of determination (R^2) (Hirsch et al. 1993). The standard R^2 is useful to determine how well the model fits the original data, but has several limitations that compromise its validity to make predictions. It does not capture the influence of the number of predictors in fitting the model, so that the addition of a predictor always results in an increase in R^2. The adjusted R^2 arose as a modified version of the standard R^2 that compares the explanatory power of regression models built with different numbers of predictors. However, although this coefficient improves the reliability of R^2, it still cannot provide accurate predictions of new data, which is the main goal of this research. Another variant of the coefficient of determination, known as predictive R^2, was used to overcome this drawback by making estimates on new observations according to three steps: (1) remove each observation from the dataset, (2) estimate the regression equation without the removed observation and (3) determine how well the model predicts the removed observation. The goodness-of-fit of the models was also tested through the standard error of the regression (S), which represents the average distance from the observed values to the regression line.

Cook's distance was used to show the influence of each observation on the response values and identify erroneous measurements in the predictors (outliers). According to Eq. (5), an observation with a Cook's distance (D_i) larger than three times the mean Cook's distance is considered as an outlier (Stevens 2009):

$$D_i = \frac{\sum_{j=1}^{n}\left(z_j - z_{j(i)}\right)^2}{p \cdot MSE} \tag{5}$$

where z_j is the jth fitted response values, $z_{j(i)}$ is the jth fitted response value where the fit does not include observation i, p is the number of coefficients of the regression model and MSE is the mean squared error.

MLR is based on four assumptions that must be verified to ensure its validity: linearity, independence, homoscedasticity and normality. Violation to these assumptions was diagnosed through the residual plots and the Durbin-Watson statistic (Osbourne and Waters 2002).

2.5. Voronoi diagrams

The concept of Voronoi diagrams (Voronoi 1908), also known as Dirichlet tessellation (Dirichlet 1850) or Thiessen polygons (Thiessen and Alter 1911), consists of dividing a plane containing a series of points following the nearest-neighbor rule, so that each point belongs to the region of the plane closest to it (Aurenhammer 1991), called a Voronoi cell.

Analytically, if $X = \{x_1, x_2, \ldots, x_n\}$ is a set of point sites in the plane, then the Voronoi cell for a point site x_i ($VC(x_i)$) is defined as the set of points y in the plane that are closer to x_i than any other point site (see Eq. (6)):

$$VC(x_i) = \{y \mid d(x_i, y) < d(x_j, y), \forall j \neq i\} \tag{6}$$

where $d(x, y)$ denotes the Euclidean distance between the points x and y. From a graphical point of view, $VC(x_i)$ can also be defined in terms of the intersection of half-planes. The bisector of x and y is equal to the perpendicular line through the centre of the line segment $\overline{xy}$ and separates the plane into two half-planes. Therefore, the Voronoi diagram of X is the tuple of cells $VC(x_i \in X)$. More details about the properties of Voronoi diagrams can be found in Aurenhammer and Klein (2000).

3. Results and discussion

The study period for this research was between 2008 and 2014, since the former was the first year in which all the agrometeorological stations in the Valencian Region (see Table 1) started to work altogether. Figure 1 shows the location of this region in relation to the geography of Spain and the Mediterranean Sea and its division into the provinces of Alicante, Castellón and Valencia.

Figure 1. Location and provincial division of the Valencian Region

The first step in the methodology was the regionalization of the Valencian Region according to its weather characteristics, which were provided by the values taken by the basic meteorological variables to be used as predictors for building the regression models in the stations. Normality of this set of possible predictors was checked through the Shapiro-Wilk test, which revealed that the null hypothesis was rejected for all of them (p-values < 0.05). Hence, these variables were characterized for clustering through the median ($\tilde{x}$) and interquartile range (IQR) corresponding to each station. As an exploratory inspection of the variations in ET_o across the Valencian Region, Table 2 lists the monthly values of $\tilde{x}$ and IQR obtained after averaging the stations located in each of the three provinces forming it. The general trend of these data suggested that the highest values of ET_o were recorded in Alicante, which is characterised by having a drier climate than either Castellón or Valencia and therefore, higher temperatures coupled with lower humidity. The Köppen Climate Classification for the Iberian Península (Chazarra et al. 2011) confirmed this inference, since Alicante completely belongs to type B (dry), whereas Castellón and Valencia also have some type C areas (temperate).

Table 2. Average median ($\tilde{x}$) and interquartile range (IQR) of ET_o (mm/month) for each province

Many different methods have been developed to optimize the determination of the number of clusters in a dataset, such as the gap statistic, Hartigan's approach or silhouette (Tibshirani et al. 2001). However, since cluster analysis preceded the development of the prediction models, the number of clusters chosen was calculated to maximize the predictive R^2 of subsequent regression equations. The results demonstrated that the optimal number of clusters was 1 in all cases except in May, June, July and August, when it was 2. In other words, the predictive R^2 was maximized for these clusters and then began to decrease its value gradually as the number of clusters increased.

Figure 2 illustrates the Voronoi regions obtained for each of these months from the pair of values $(\tilde{x}, IQR)$ calculated from each station. These were the warmer months of the year and those in which the combination of weather effects resulted in the highest and most varying values of ET (see Table 2), justifying the need to partition the whole workspace into two zones. The clustering patterns were consistent with that premise, since they separated the coastal and interior areas of the region, which were the zones wherein such variability became more accentuated.

Figure 2. Clusters obtained for a) May b) June c) July d) August

From there, multiple linear regression models were built to estimate daily ET_o for each month and cluster by adapting Eq. (4) to the specifics of this research: y = ET_o (mm/day); x_1 = T_{mean} (ºC); x_2 = T_{max} (ºC); x_3 = T_{min} (ºC); x_4 = RH_{mean} (%); x_5 = RH_{max} (%); x_6 = RH_{min} (%); x_7 = WS_{mean} ($m \cdot s^{-1}$). A 95% confidence interval (p-value < 0.05) was set to choose predictors stepwise, whilst Cook's distances were calculated using Eq. (5) to detect and remove influential points. Table 3 shows the regression coefficients and goodness-of-fit measures obtained for the number of days (N) corresponding to each month and cluster (CL) between 2008 and 2014.

Table 3. Summary of the regression models to predict ET_o (mm/day) for each month and cluster

The results were 16 regression equations consisting of 5 predictors in each case. Variations in the coefficients associated with the predictors (see Table 3) demonstrated the need to build monthly regression models for the prediction of ET_o, because weather attributes vary over the year (e.g. increased temperature in summer). Although the predictors included in each model varied in some cases depending on the month and cluster, all regression models consisted of two temperature-related variables ('T_{mean} AND T_{min}' OR 'T_{mean} AND T_{max}' OR 'T_{min} AND T_{max}'), two humidity-related variables ('RH_{mean} AND RH_{min}' OR 'RH_{mean} AND RH_{max}' OR 'RH_{min} AND RH_{max}') and WS_{mean}. The most influential predictors were found to be those related to temperature with an average contribution around 50% to estimate ET_o, except for the colder months, in which the combination of relative humidity and wind speed explained up to 80% of the variations in the predictand. The physical relationships between the mean predictors (x_1, x_4 and x_7), which are the most representative ones for each type of variable (temperature, humidity and wind), and the predictand were logical in all cases. The pores of plants in which water is released open if they are surrounded by warmer air, i.e. there is an increase in transpiration (Crawford et al. 2012). In contrast, relative humidity is inversely proportional to evapotranspiration, since the evaporation of water into the air is hindered as this becomes more saturated (Thut 1938). As for wind speed, moving air facilitates the process of evapotranspiration, since it is less saturated than stagnant air and can absorb water vapor more easily (Moore et al. 2003).

The reliability of the regression models for making predictions was guaranteed by the high and low values of predictive R^2 and S reached, respectively. The values of predictive R^2 indicated that these regression models can make estimates for new values of daily ET_o with an accuracy of at least 83% through a linear combination of basic variables related to temperature, humidity and wind. The ratio between S and the average monthly values of $\tilde{x}$ and IQR (see Table 2) was at most 7% and 25%, respectively, which demonstrates that the errors in the regression models were very small in relation to the typical values and spread of ET_o. The relationships between the climate variables used as predictors and ET_o were nonlinear in general. Figure 3 illustrates this circumstance for April, in which the predictand varied nonlinearly in relation to all predictors except RH_{min}, whose relationship to ET_o could be assumed to be linear. Therefore, these results confirmed that the linear combination of climate variables can provide accurate predictions of ET_o, even though their individual correlations are mostly nonlinear.

Figure 3. Relationships between the predictors and the predictand (ET_o) in the regression model for April

Figure 4 shows the histograms and scatterplots of standardized residuals against fitted values for two months representing different weather conditions (April (1 cluster) and June (2 clusters)), which provide graphical diagnose verifying whether the assumptions of normality, linearity and homoscedasticity were violated or not. The symmetrical bell-shape of the histograms, which fitted their corresponding theoretical normal curves with high accuracy, suggested that the normality assumption was true. Moreover, the absence of curvilinear distributions and marked trends (e.g. increasing dispersion as the fitted values increase) in the scatterplots confirmed both the linearity and homoscedasticity of the residuals. Finally, the Durbin-Watson statistics were between 1.5 and 2.5 (Durbin and Watson 1950; Durbin and Watson 1951) in all three cases (1.740 for April and 1.596 (CL1) and 1.591 (CL2) for June), which involved that there was no time trends nor serial correlations in the residuals and their independence could be assumed too. Furthermore, the values of Variance Inflation Factor (VIF) obtained for the predictors, which were always below 10 (Belsley et al. 1980), ensured that they were not highly correlated to each other and multicollinearity was not an issue.

Figure 4. Histograms and scatterplots of standardized residuals against fitted values for a) April b) June - Cluster 1 c) June - Cluster 2

The final step was the regionalization of the Valencian Region according to the crop co-efficients (K_c) in each station, in order to obtain a value for ET from ET_o using Eq. (1). Due to space constraints, this last process was limited to only one crop type: midseason potato. This specific crop was selected because it proved to be variable in terms of both location and time. The daily values of K_c provided by the MAGRAMA through its Agro-climatic Information System for Irrigation (SiAR 2016), which were constant for each month during the years of study, reaffirmed the convenience of choosing a monthly period for the estimation of this coefficient. Therefore, the Voronoi regions were drawn as shown in Figure 5 according to the values of K_c for each station and month of the year. The procedure would be the same for any other crop, with the only difference that the Voronoi regions should be particularized to the monthly values of K_c associated with the specifics of the crop under study.

Figure 5. Monthly crop coefficients (K_c) in the Valencian Region for midseason potato

Knowing the coordinates for where irrigation was planned, the multiplication of crop co-efficients in this area (see Figure 5) by the regression equations summarized in Table 3 enabled an estimation to be made of the water demands of this crop for a single day in any month using basic meteorological variables available from official weather forecasts. For instance, Figure 6 particularizes the procedure for the case of a farmer who planted midseason potatoes in April in the geographic coordinates (39º55'57'' N, 1º04'10'' W) and would like to estimate ET in a day in May. To illustrate the example, the historical average values for May recorded in the closest station to the specified coordinates were taken as the climate variables to be acquired from daily weather forecasts. According to the clusters identified in Figure 6a) and Figure 6b), these coordinates corresponded to

CL1 and a Voronoi region with a value of K_c equal to 0.8. The application of the regression equation in Table 3 for these predictors, month and cluster yielded a value of ET_o of 4.66 mm/day. The multiplication of ET_o by K_c as formulated in Eq. (1) resulted in a final value of ET equal to 3.77 mm/day.

Figure 6. Estimation of ET in May for midseason potato in the coordinates (39º55'57'' N, 1º04'10'' W) a) Cluster b) Monthly crop coefficient (K_c) c) Historical average values for the predictors in the closest station to the coordinates d) Calculation of ET_o (mm/day) e) Determination of ET (mm/day)

4. Conclusions

This paper presents a methodology for the prediction of daily evapotranspiration based on the combination of cluster analysis, multiple linear regression models and Voronoi diagrams. The first was used to partition the study area according to its weather characteristics, so that regression equations to estimate daily reference evapotranspiration could be built for the resultant clusters using basic meteorological variables. Voronoi diagrams enabled regionalization of the workspace in terms of both clusters and crop coefficients associated with it, whose multiplication by reference evapotranspiration yielded the value for real evapotranspiration which was being sought.

Despite the relationships between climate variables and reference evapotranspiration are generally nonlinear, the results proved that the linear combination of the former can provide accurate estimates of the latter. The models obtained using multiple linear regression analysis met the four hypotheses related to their residuals and reached high predictive coefficients of determination, which ensured their reliability and capability to make new estimates from daily weather forecasts. As for cluster analysis and Voronoi diagrams, their combination was found to be a simple and effective method for local application of the predictive regression equations and regionalization of crop coefficients, which enabled determining real evapotranspiration without any need to take into account complex physical considerations.

This methodology is proposed as a tool to be used by farmers for irrigation planning and scheduling based on the estimation of water demands of their crops. The daily value of evapotranspiration corresponding to a given date, coordinates and crop can be determined through the cluster, regression equation and crop coefficient associated with the day and region under study, since they are based on primary weather variables that are available from the daily forecasts made by meteorological agencies. Although the validity of these results is not compromised by the size of the study area, further research should consider the application of this methodology to larger locations, in order to delimit different climate zones and develop regional prediction equations at larger scales.

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Table 1. Main characteristics of the provinces forming the Valencian Region

Province	Population	Surface area (km^2)	Valid stations	Average Annual Precipitation (mm)	Average Annual Max Temperature (ºC)	Average Annual Min Temperature (ºC)
Alicante	1,934,127	5,816	16	311.1	23.3	13.2
Castellón	604,344	6,632	10	467.0	22.3	12.7
Valencia	2,578,719	10,763	23	474.9	23.0	13.8

Table 2. Average median ($\tilde{x}$) and interquartile range (IQR) of ET_o (mm/month) for each province

Province	Measure	Month											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Alicante	$\tilde{x}$	1.18	1.79	2.74	3.65	4.62	5.45	5.70	5.01	3.67	2.36	1.41	1.05
	IQR	0.70	0.85	1.18	1.41	1.17	0.99	0.75	0.94	1.19	0.86	0.71	0.49
Castellón	$\tilde{x}$	1.07	1.69	2.51	3.42	4.32	5.12	5.31	4.59	3.44	2.17	1.30	0.99
	IQR	0.64	0.85	1.06	1.28	1.32	1.02	0.89	1.10	1.19	0.88	0.63	0.48
Valencia	$\tilde{x}$	1.10	1.75	2.68	3.55	4.49	5.30	5.55	4.86	3.55	2.19	1.30	0.98
	IQR	0.81	1.05	1.32	1.47	1.40	1.13	0.77	0.97	1.30	0.94	0.79	0.60

Table 3. Summary of the regression models to predict ET_o (mm/day) for each month and cluster

Month	CL	N	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	S	Pred. R^2
1	1	8309	1.131	-	0.029	0.008	-	-0.007	-0.007	0.464	0.070	96.72
2	1	7473	1.126	-	0.079	-0.006	-	-0.009	-0.009	0.463	0.102	96.96
3	1	8440	1.021	-	0.124	-0.010	-	-0.009	-0.014	0.514	0.174	95.68
4	1	8151	0.881	0.307	-	-0.132	-	-0.007	-0.021	0.553	0.208	95.31
5	1	1027	1.638	-	0.174	-0.035	-0.016	-	-0.020	0.545	0.195	96.19
	2	7070	1.261	0.266	-	-0.114	-0.008	-	-0.016	0.722	0.211	91.45
6	1	967	1.410	0.246	-	-0.069	-	0.002	-0.035	0.616	0.202	95.24
	2	6817	1.969	0.243	-	-0.102	-	-0.007	-0.014	0.673	0.177	89.61
7	1	3092	2.320	0.041	0.077	-	-0.009	-	-0.013	0.830	0.156	93.61
	2	4864	2.751	0.191	-	-0.079	-	-0.007	-0.019	0.692	0.161	86.11
8	1	2467	-0.014	0.038	0.126	-	-0.012	-	-0.009	0.976	0.240	92.64
	2	6175	-0.735	0.353	-	-0.144	-	-0.009	-0.015	0.823	0.237	83.04
9	1	8372	-1.189	0.346	-	-0.149	-	-0.005	-0.018	0.853	0.191	94.53
10	1	8471	-0.452	0.222	-	-0.092	-	0.002	-0.020	0.628	0.168	92.12
11	1	8518	0.568	0.016	0.052	-	-	-0.006	-0.009	0.538	0.082	96.07
12	1	8260	0.755	-	0.028	0.009	-	-0.005	-0.006	0.497	0.043	97.98

Figure 1

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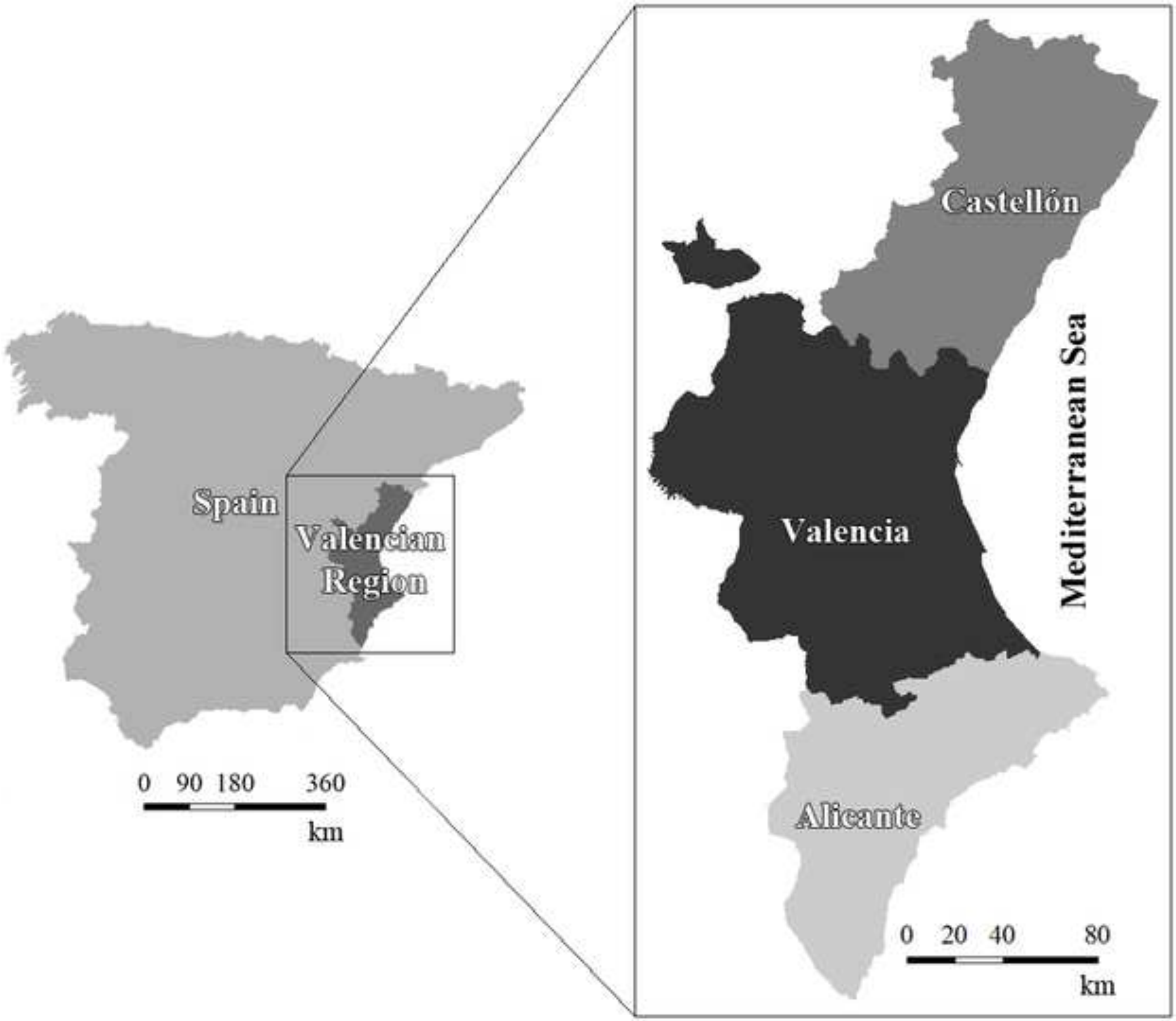

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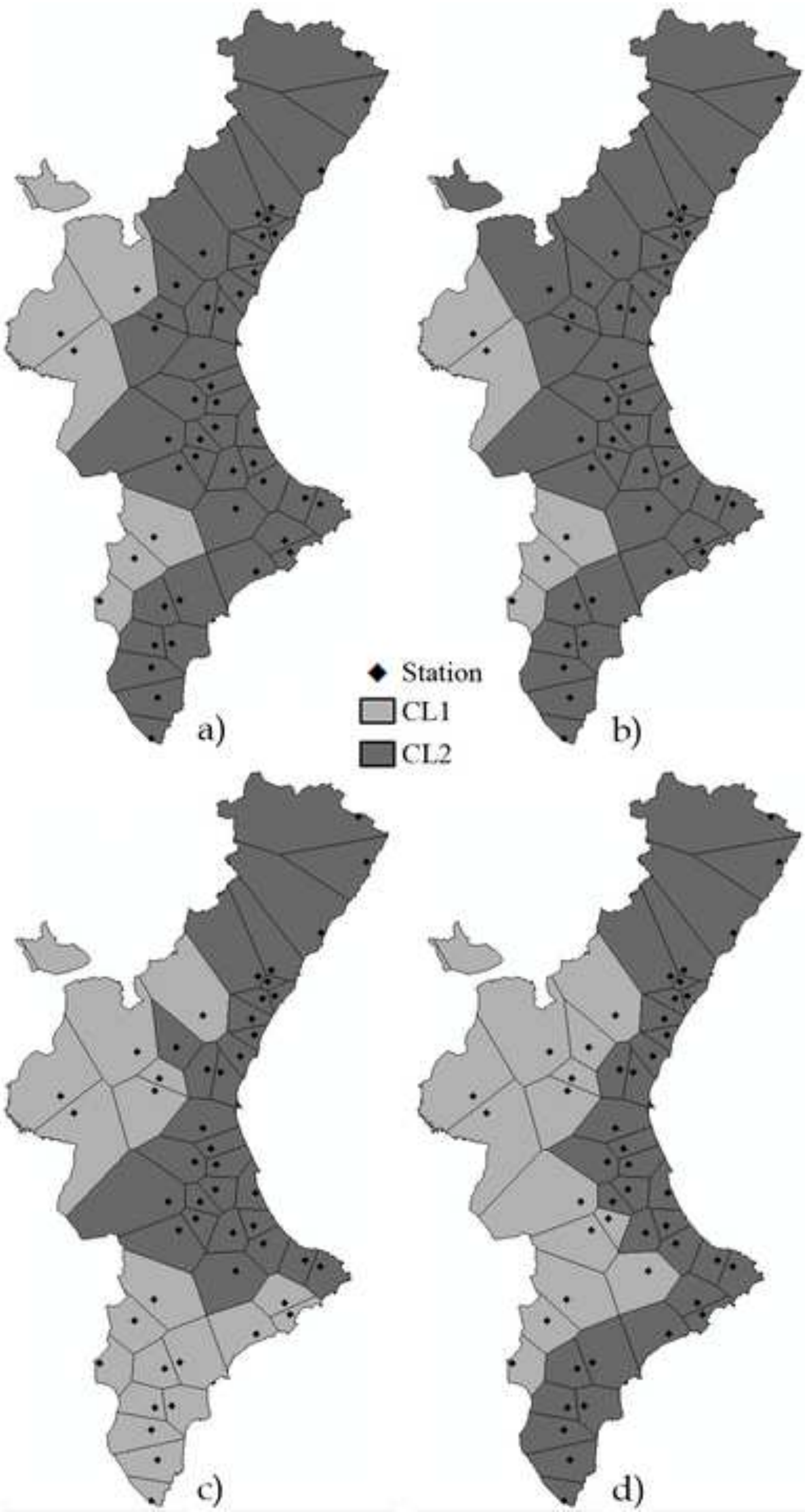

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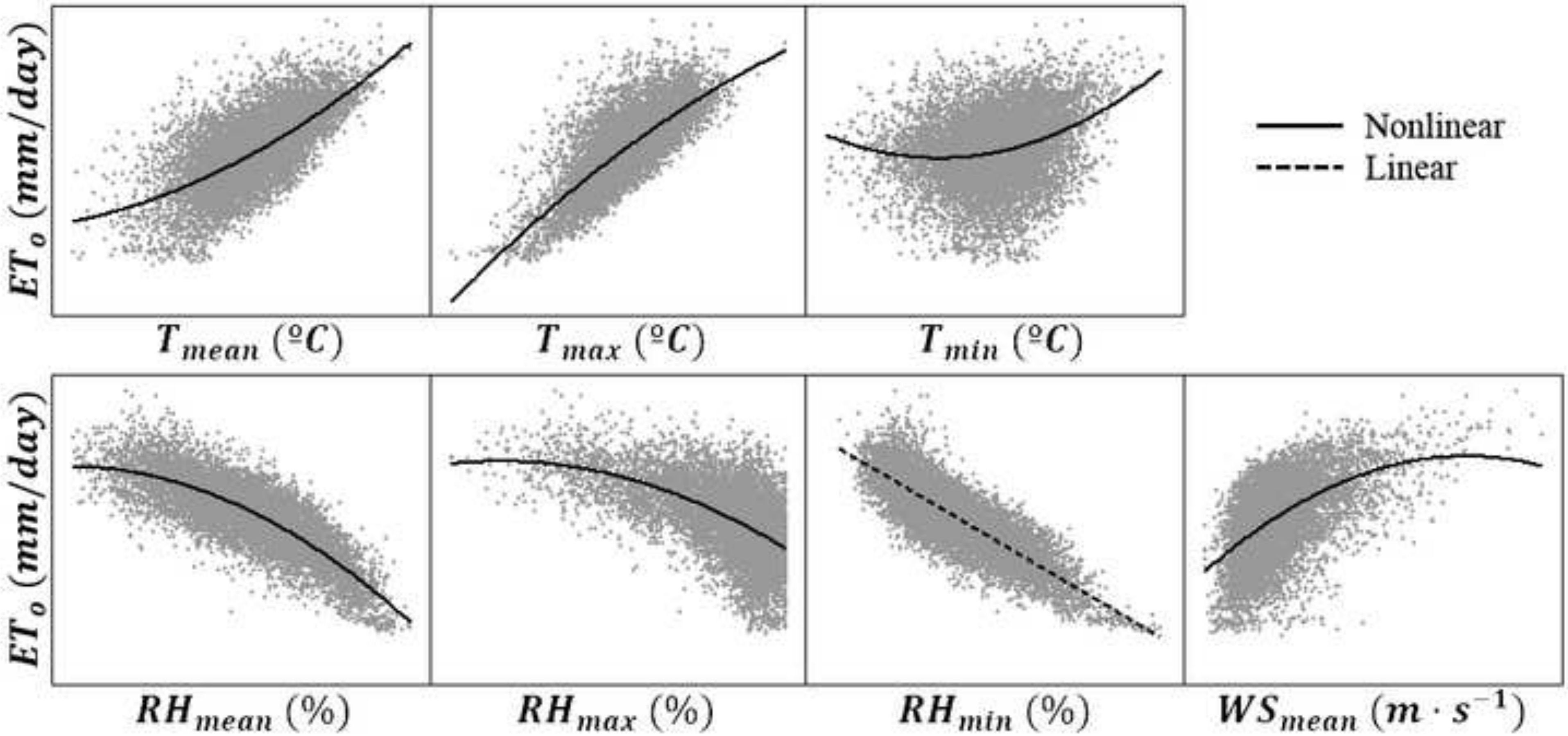

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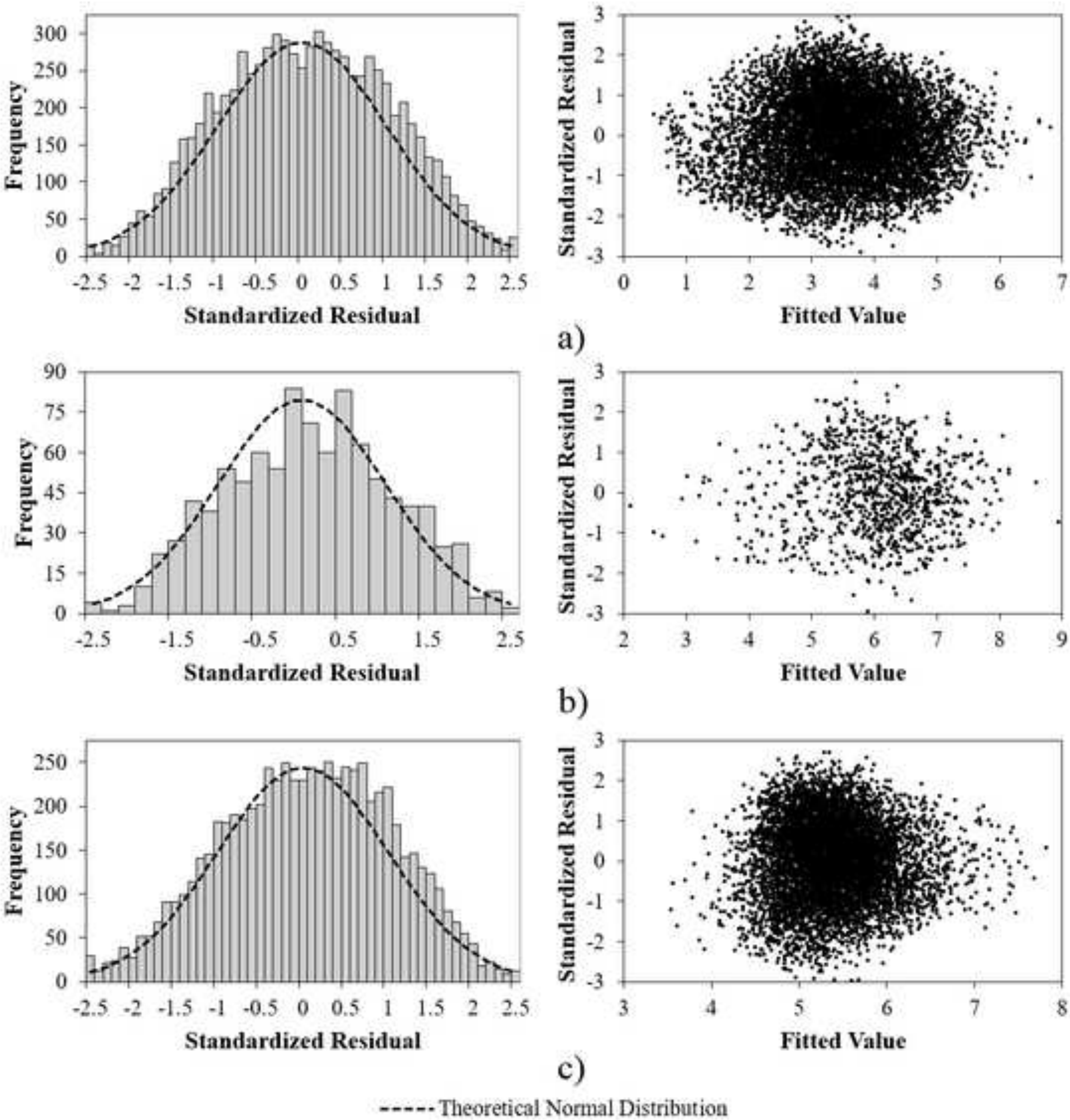

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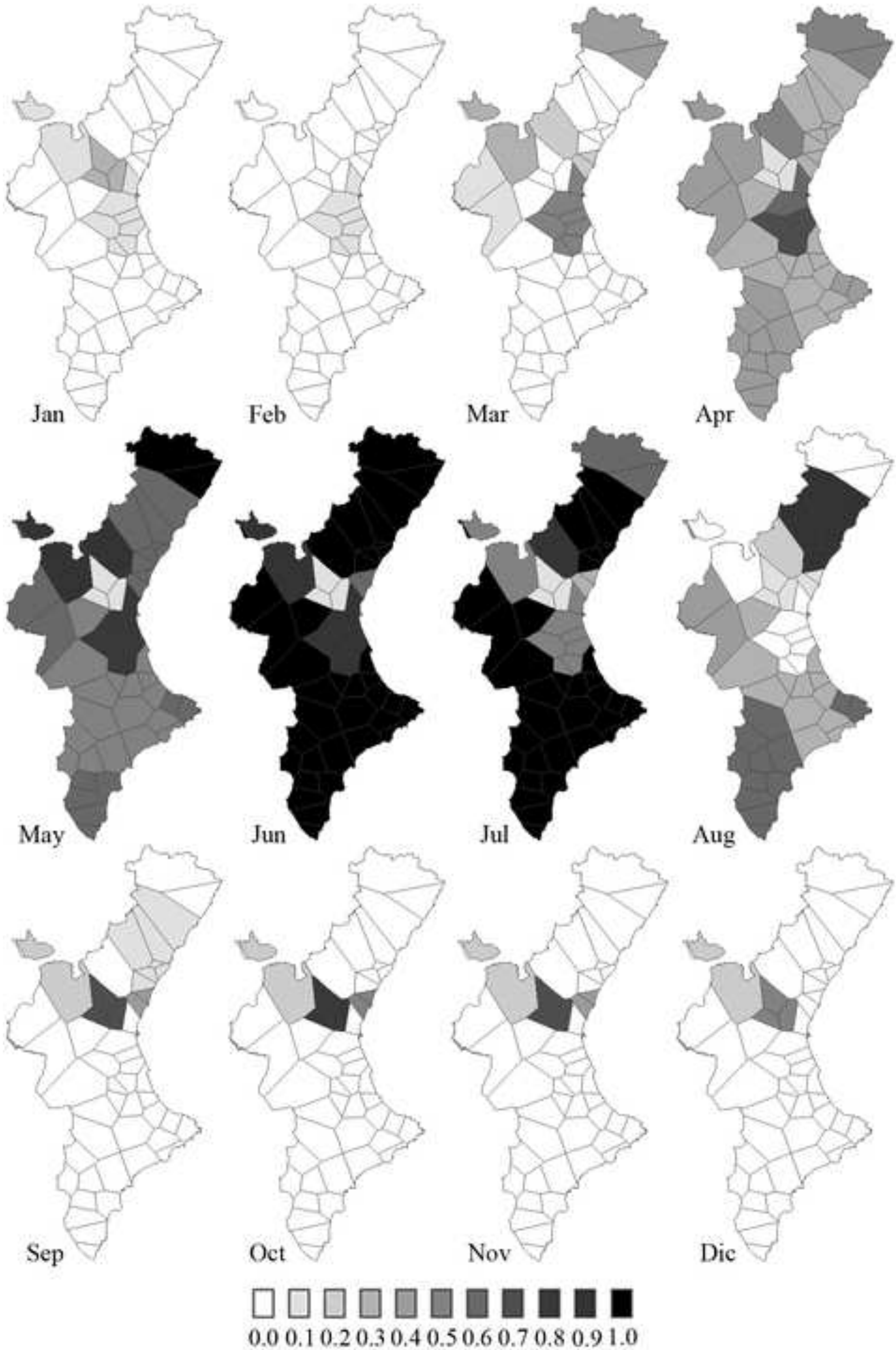

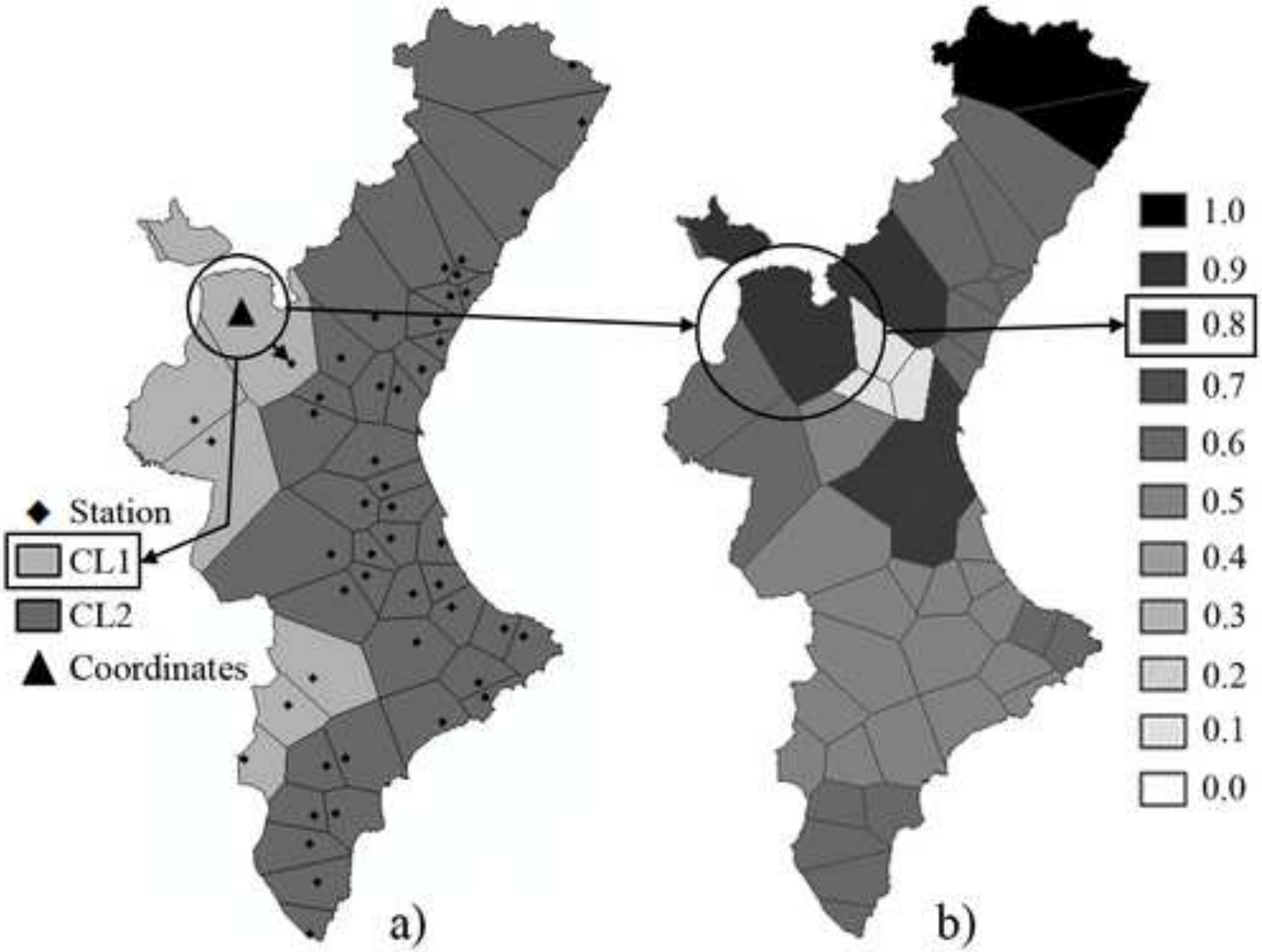

Month	T_{max} (°C)	T_{min} (°C)	RH_{mean} (%)	RH_{min} (%)	WS_{mean} ($m \cdot s^{-1}$)
May	23.84	11.23	61.62	32.45	1.66

c)

$$ET_o = 1.638 + 0.174 \cdot T_{max} - 0.035 \cdot T_{min} - 0.016 \cdot RH_{mean} - 0.020 \cdot RH_{min} + 0.545 \cdot WS_{mean} = 4.66\ mm/day$$

d)

$$ET = ET_o \cdot K_c = 3.73\ mm/day$$

e)

Figure Caption List

Figure 1. Location and provincial division of the Valencian Region

Figure 2. Clusters obtained for a) May b) June c) July d) August

Figure 3. Relationships between the predictors and the predictand (ET_o) in the regression model for April

Figure 4. Histograms and scatterplots of standardized residuals against fitted values for a) April b) June - Cluster 1 c) June - Cluster 2

Figure 5. Monthly crop coefficients (K_c) in the Valencian Region for midseason potato

Figure 6. Estimation of ET in May for midseason potato in the coordinates (39º55’57’’ N, 1º04’10’’ W) a) Cluster b) Monthly crop coefficient (K_c) c) Historical average values for the predictors in the closest station to the coordinates d) Calculation of ET_o (mm/day) e) Determination of ET (mm/day)

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Cover Letter

Dear Editor,

We are sending the revised version of the research paper entitled **"Prediction of evapotranspiration in a Mediterranean region using basic meteorological variables"**, for your consideration to be published in **Journal of Hydrologic Engineering**.

Point-to-point responses to every comment made by the four reviewers and the associate editor are attached in five separate WORD files. We have made a great effort to address all the concerns posed by them, since we are very interested in publishing in HEENG. Thanks to their helpful suggestions, we believe that the quality of the manuscript has substantially improved, so we hope you continue considering our work for publication.

We look forward to receiving your opinion.

Yours sincerely,

Daniel Jato-Espino
Susanne M. Charlesworth
Sara Perales-Momparler
Ignacio Andrés-Doménech

The authors.

Response to the Associate Editor

Dear Sir or Madam,

Thank you for your comments on our manuscript. The detailed response to them are given below.

GENERAL COMMENTS

*The manuscript has been evaluated by four referees. Reviewers agree that the contribution fits well to the scope of our journal and second version should be significantly improved by considering review comments. The authors should expand the literature section and clearly explain the contribution of their study. Why the authors use linear equations instead of GP or GEP for modeling non-linear ET process? The results section should also be expanded by explaining findings of the study. Based on the reviewer comments, my recommendation is "Revise for Re-*Review *(Technical Paper). The review comments should be carefully taken into account while preparing the revised version.*

The literature review has been extended as suggested by Reviewer #3, in order to give more details about former similar studies (see lines 80-105). A new paragraph has also been included in the Introduction to highlight the contributions of our study in relation to these former similar works (see lines 107-122).

Although the relationships between climate variables and *ETo* are nonlinear, as proved in current Figure 3, the linear combination of the former can provide accurate predictions on the latter (see lines 94-95). We agree that nonlinear techniques can be slightly more accurate than MLR, but these differences might not be significant, as demonstrated in the studies described in lines 94-105. In particular, we are presenting average results of pred. R^2 (equivalent to the R^2 obtained in the validation phase in ANNs) of more than 90% (see current Table 3), which speak for themselves. In addition, MLR are simpler and easier to understand and interpret than nonlinear methods such as ANNs, in which hidden layers are often added without really knowing why to improve the quality of the model and obtain higher values of R^2. Actually, including too many hidden layers might lead to overfitting of the model and result in misleadingly high values of R^2.

We have extended and strengthened the discussion about the results obtained through the application of the proposed methodology (see lines 369-377, lines 387-399, lines 414-417 or lines 441-450, to cite some examples).

Reviewer #1

Dear Sir or Madam,

Thank you for your useful suggestions on our manuscript, they have led us to improve the quality of our paper substantially. The detailed responses to your comments are listed below point by point.

GENERAL COMMENTS

The paper is well organized and well written. It offers excellent and sufficient, if not exhaustive, literature review that provides a clear justification for the reported research. The authors discuss the complexity of the FAO- and ASCE-recommended Penman-Monteith equation for estimating the reference evapotranspiration, ETo, that is crucial (along with crop coefficients) for estimating irrigation needs. They correctly note that often there is not enough data to use this equation for estimating the local irrigation needs.

The authors resolve this problem by developing a simpler model with smaller number of input requirements. The price for the relative simplicity is the local nature of the model: as opposed to the Penman-Monteith equation that is valid for arbitrary location, the developed model is valid only locally for the Valencian Region--the overview of this region is well done. Although the proposed model is local, the methodology developed to specify its parameters can be applied to other regions.

In the development of their model, the authors combine skilfully cluster analysis, multiple linear regression, and Voronoi diagrams to basically derive separate submodels for the subregions of the Valencian Region. The subregions are defined by means of Voronoi tessellations.

Advancing applied knowledge, the paper is novel and should be of interest to hydrologists, soil physicists, agronomists, and irrigation engineers, as well as farmers planning their irrigation schedules.

PARTICULAR COMMENTS

Comment #1

Table 1: provide units to the numbers (or columns) for precipitation and temperature.

Table 1 has been modified to include units for precipitation (mm) and temperature (ºC) (see line 182).

Comment #2

Table 3: ETo (mm) ... ETo is a rate, so it has to be measured in L^3/TIME or L^3/TIME/L^2 = L/TIME. Specify the time unit you imply here (your Tables 4 suggests that your time unit is a day).

Current Table 2 (former Table 3) has been modified to specify the time unit of *ETo*, which in this case was mm/month (see line 334), since the exploratory analysis associated with this table was done according to the same time horizon used for the calculation of the crop coefficient *Kc*, as explained in subsection 2.1 (see lines 145-150).

Comment #3

Expand their skimpy discussion of Figure 3, which contains the meat of their results. Expand the discussion of what these six plots tell you and the reader: spell it out; don't imply it.

The discussion of current Figure 4 (former Figure 3) has been expanded as you suggested, including more details about the quality of the regression models and the fulfilment of the assumptions on which they are based (see lines 403-417). Also a new paragraph (see lines 387-399) and a new figure (current Figure 3) have been added to provide more details about the quality of the prediction models determined.

Comment #4

Compare their new model's performance to that of the Penman-Monteith equation with the characteristic literature values assumed for the unmeasured parameters. Which model is better? Which one is more reliable?

The methodology proposed in the paper does not aim to outperform the results provided by the Penman-Monteith method, but rather replicate them using more accessible variables, in order to facilitate the calculation of *ETo* from daily weather forecasts which do not include several variables considered in the Penman-Monteith equation. Actually, we state that the Penman-Monteith method is recommended by several organizations, such as FAO and ASCE, as a reliable and worldwide applicable approach for the estimation of

ETo (see lines 70-73). In fact, we specify in lines 178-180 that the historical daily values of *ETo* used in the paper to build the regression models were originally calculated through the Penman-Monteith equation.

Reviewer #2

Dear Sir or Madam,

Thank you for your useful suggestions on our manuscript, they have led us to improve the quality of our paper substantially. The detailed responses to your comments are listed below point by point.

Authors have developed a methodology to estimate evapotranspiration (ET) using limited meteorological data in Spain. Initially, they have grouped the weather stations based on their characteristics (central tendency and variability). Then for each group, a monthly regression model has been developed for each month to predict the reference evapotranspiration (ET_0). Finally, the ET was estimated by multiplying the crop coefficient (Kc) of that region, which is obtained using Voronoi diagrams. In general, the manuscript is well written. However, the methodology section deserves some more explanation for clarity and better understanding. The detailed comments are as follows:

Comment #1

Line 87: Recently, many researchers have derived equations (extracted the knowledge (weights and bias) gained during training) from ANN models, and used for future prediction. Other techniques like genetic programming (GP) and gene expression programming (GEP) will directly yield equations. Many studies have been reported using these techniques to predict ET.

We have reworded those lines to clarify that we mean that ANNs do not provide direct equations as MLR do (see lines 115-116).

Comment #2

Line 97: Why linear equations? ET is a non-linear process. A non-linear equation may result in much better prediction. Why MLR is chosen for prediction? Many recent techniques have been proved to be better than MLR.

We have added some explanations about this issue (see lines 94-95 and lines 107-109 and lines 397-399). Although the relationships between climate variables and *ETo* are nonlinear, as proved in current Figure 3, the linear combination of the former can provide accurate predictions on the latter. We agree that nonlinear techniques can be slightly more accurate than MLR, but these differences might not be significant, as demonstrated in the studies described in lines 94-105. In particular, we are presenting average results of pred. R^2 (equivalent to the R^2 obtained in the validation phase in ANNs) of more than 90% (see current Table 3), which speak for themselves. In addition, MLR are simpler and easier to understand and interpret than nonlinear methods such as ANNs, in which hidden layers are often added without really knowing why to improve the quality of the model and obtain higher values of R^2. Actually, including too many hidden layers might lead to over-fitting of the model and result in misleadingly high values of R^2. We have added a new paragraph to justify the choice of MLR (see lines 107-122).

Comment #3

Line 121: The value of Kc varies for different stages of crop growth. Does this monthly time period is in agreement with crop growth stages?

Yes, the values of *Kc* vary according to the month, which in turn depends on the growth stages of the crop.

Comment #4

Line 171-173: How the daily data of each variable were arranged monthly? For example, the January month data of each year was separated and arranged (January month alone) chronologically? Explain in detail.

As we explain in lines 145-150, since a monthly period was chosen for the estimation of *Kc*, the models for the prediction of daily *ET* were also built according to such a time horizon. Therefore, we extracted the daily values for the seven predictors for each month of all the years available in each station located in the Valencian Region. The chronological order is not relevant for the application of the methodology, since the aim is to predict *ET* for a single (and random) future day in a month (January, for example). This "arrangement" is just a division of the whole dataset in each station, which consists of several years of daily data (the exact number of years depends on the station), in months.

Comment #5

It is also not clearly explained why a separate regression models/equations is required for each month. Instead you can have a single equation for all the months with different Kc values for each month.

This can be explained through current Table 3 (former Table 4). The coefficients associated with the predictors and their values vary according to the month, which is consistent with the fact that the weather characteristics change throughout a year (e.g. increased temperature in summer months, etc.). We have added some lines to highlight this (see lines 366-369).

Comment #6

Line 215: I think clustering is done only for ET (based on properties of ET). However, it is not clearly mentioned in the text. What is i, j and p? 'ip' and 'jp' are confusing. Are you finding the euclidean distance between two points or between the centroid of cluster and a point? In line 318-318, it mentioned that regionalisation was done based according to the weather characteristics. However, it is not clearly mentioned whether it is based on only ET or all the parameters used in this study.

As a result of the suggestions made by other reviewer, we have shortened some explanations in section 2, including the equation related to the Euclidean distance (former Eq. (4)). As specified in lines 231-232, the Euclidean distance is calculated between each point and the centroids of the clusters identified, in order to assign each station to the closest cluster.

Regionalisation (e.g. cluster analysis) was carried out according to the weather characteristics of the stations in terms of the values they recorded for the set of predictors used. The aim of the paper is to provide a methodology for the prediction of *ET* using only basic meteorological variables, so the clustering of the study area must be done according to these parameters. We have reworded that sentence you mention to clarify it (see lines 318-321).

Comment #7

Line 213: Is 'k' subjective/ arbitrary? Have done sensitivity analyses on 'k'. How to fix 'k'? It is mentioned in line 336-338, that 'the number of clusters chosen was calculated to maximise the predictive 2.' How? Do you have any separate method/algorithm for this? How this is done within cluster analysis?

Although k was not set arbitrarily, we did not develop any algorithm to automate the optimization of the number of clusters. As explained in lines 338-342, we built the regression models with different numbers of the clusters and calculated their corresponding pred. R^2, in order to select the number of clusters that maximised it. We found out that pred. R^2 was maximised for 1 cluster in all cases and then started to gradually decrease as the number of clusters increased (2, 3, 4…), except for May, June, July and August, where pred. R^2 was maximised for 2 clusters and then started to gradually decrease as the number of clusters increased (3, 4, 5…). We have included an additional sentence to clarify this (see lines 342-343).

Comment #8

Line 236: Xi and x are the smallest value and mean of clusters or whole sample? What is 'n' in Eq 5. Is it number of points in cluster or sample size?

xi and *x* are the smallest value and mean value of the whole sample used to test normality. Consequently, *n* was the number of points in such a sample. However, as a result of the suggestions made by other reviewer, we have shortened some explanations in section 2, including these equations related to the Shapiro-Wilk test.

Comment #9

Multiple linear regression model: Change the variable notations. The manuscript is not consistent with notations. Same notations are used at different places.

Since we have removed the equations corresponding to the Shapiro-Wilk test, *xi* and *x* are now only used for MLR. We have changed the notation in the equation for the Cook's distance (current Eq. (5)), which now includes *zj* and *zj(i)* instead of *yj* and *yj(i)* (*y* was also the response in the regression equation).

Comment #10

There are lot of uncertainties associated with the meteorological variable, which is not properly addressed in this study. Table 4: The random component (ε) is missing, without which how will you estimate the future predictions?

ε refers to the residuals, i.e. the distances from the fitted values to the hyperplane defined by the multiple linear regression models. In other words, they indicate the error of prediction in the regression models, so that $\varepsilon = 0$ if $R^2 = 100\%$. Although $\varepsilon \neq 0$ in our models, the errors are very small because the values of pred. R^2 are around 90% on average, which demonstrates their predictive potential. Furthermore, we have analysed in great detail the characteristics of the residuals (see lines 403-417 and current Figure 4) and guaranteed they met all the hypotheses required to validate multiple linear regression analysis, so we believe we have thoroughly demonstrated the reliability of our models and their capability to make future predictions.

Lines 441-450 and current Figure 6 have been added to clarify and demonstrate the applicability of the regression models.

Comment #11

The predictive R2 needs much clear explanation. How it overcomes the drawbacks of standard R2. Give equation for estimating predictive R2.

We have added some lines to highlight the benefits provided by the predictive R^2 in relation to the standard R^2 and the adjusted R^2 (see lines 259-265). The explanation of how it overcomes the inability of the two other coefficients was already explained in the previous version of the manuscript according to three steps: (1) remove each observation from the dataset, (2) estimate the regression equation without the removed observation and (3) determine how well the model predicts the removed observation. Thus, this process includes the estimation of new data in the calculation of the regression models and their corresponding pred. R^2, which ensures their capability to predict future values. It uses the same equation than the standard R^2, so that what changes is related to the inclusion of the abovementioned three-step process. That equation is widely known among engineers, so we believe it is not necessary to specify it, unless the Editor considers it is really necessary. Instead, we have added a reference which can be consulted in case anyone wants more details about the R^2 coefficient (see line 258).

Comment #12

Is your Kc value varies based on clusters or weather stations?

Kc varies depending on the station, as explained in line 423 and line 430.

Comment #13

Some stations have two clusters for summer months, especially the stations in coastal regions. Therefore, there will be two equations for these months and only for these stations. However, the Table 4 doesn't show like this. Are the equations same for all the stations? Also, among two equations, which one has to used and for which station?

Some months (not stations) have two clusters for summer. The purpose for clustering is precisely to group the set of stations according to the similarity in the values they recorded for the predictors. Figure 2 illustrates this pretty well: the polygons are the Voronoi regions associated with the set of stations, whereas the clusters are identified according to the shades of grey (light grey: Cluster 1; dark grey: Cluster 2). Therefore, the equation summarised in the row for the 5th month and the 2nd cluster in current Table 3 (former Table 4) is to be applied in any location enclosed by the dark grey areas in Figure 2a).

The remaining months had only one cluster, which means that all the stations under consideration belonged to the same cluster (the values they recorded for the basic meteorological variables used as predictors were similar enough as to assume that).

Comment #14

Table 4: Why the number of days varies for each cluster in May, June, July and August? How the number of days is obtained for each month?

The number of days in each month depends on data availability in the stations, e.g. one station might have started to work in July and, therefore, it wouldn't include data about May and June of that year. Besides, outliers or influential points were removed from the datasets associated with each month using the Cook's distance. The number of points discarded can also slightly vary depending on the month. In any case, the number of days is about 8,000 in all cases.

Comment #15

Line 363: Why only 5 predictors for each month? What about other two predictors? This also varies for different months? Authors have to do impact analysis of each input variable in their model.

The stepwise process mentioned in lines 358-359 demonstrated that 5 was the optimal number of predictors for each month to maximize the accuracy of the regression models (i.e. the values of pred. R^2) without having problems of multicollinearity (see lines 414-417). This means that including one more predictor resulted in problems of multicollinearity (VIF values above 10), whilst excluding one more predictor resulted in a loss of precision (decrease in R^2). Hence, the process for selecting the number of predictors was accomplished very carefully based on statistical considerations. Although the selected predictors varied for some months, they always consisted of two temperature-related variables (mean and min, mean and max or min and max), two humidity-related variables (mean and min, mean and max or min and max) and mean wind speed.

We have also added some lines about the contribution of the predictors to the estimation of the predictand (see lines 369-377). The most influential predictors were those related to temperature in general, with the exception of the colder months, wherein relative humidity and wind speed proved to be the greatest contributors for the estimation of *ETo*.

Comment #16

Line 366-371: These statements are general. Give reference to these sentences?

We have added references to those statements according to your suggestion (see lines 381-385).

Comment #17

References are not according to the style of ASCE. For all web pages in the references, give the date of access.

We have modified both the references in text and the list of references (see lines 496-673) according to the style of ASCE. We have also included the date of access for webpages (see line 500 and lines 623-624).

Reviewer #3

Dear Sir or Madam,

Thank you for your useful suggestions on our manuscript, they have led us to improve the quality of our paper substantially. The detailed responses to your comments are listed below point by point.

The paper presents a methodology for the prediction of evapotranspiration based on weather forecasts. In addition, the authors applied this method to the Valencian region in Spain. The methodology was explained clearly but the following comments need to be addressed:

Comment #1

In Introduction section, literature review should be expanded.

The literature review has been extended as you suggested, in order to give more details about former similar studies (see lines 80-105).

Comment #2

Study area section should be added and explained in detail by using a map which shows the selected area in Spain.

A new figure (current Figure 1) has been added to show the study area in relation to the Map of Spain (see line 316).

Comment #3

The authors should give a brief explanation for the terms of e_a and e_d which are given in Eq.2 on page 6.

The definition of the term $(e_a - e_d)$ has been rewritten, so now it reads: "$(e_a - e_d)$ is the difference between the actual (e_a) and saturation (e_d) vapor pressure (kPa)" (see line 163).

Comment #4

On page 6, Equation 3 is incorrect. The correct form is given on web page of FAO as […].

Psychrometric Constant

Reference: Brunt (1952)

$$\gamma = \frac{c_p P}{\varepsilon \lambda} \times 10^{-3} = 0.00163 \frac{P}{\lambda}$$

Yes, there was a typo error in Eq. (3) (we "forgot" one zero). It has been modified according to your comment (see lines 166-167).

Comment #5

On page 8, Figure 1 should be more understandable.

Former Figure 1 has been removed as a result of one of the comments made by other reviewer, since the detailed description provided in lines 193-210 is enough to understand the main steps carried out to develop the proposed methodology.

Comment #6

On page 10, Equation 4 is incorrect, as well. It should be corrected.

The Euclidean distance between two points is the square root of the sum of their squared differences, which is what former Eq. (4) represented. In any case, as a result of the comments made by other reviewer, we have shortened some descriptions in section 2, including the equation for the Euclidean distance (former Eq. (4)).

Comment #7

There is no need to write the full name of MAGRAMA on page 17 as it is already given on page 7.

The full meaning of MAGRAMA has been removed from that page (see line 426).

Reviewer #4

Dear Sir or Madam,

Thank you for your useful suggestions on our manuscript, they have led us to improve the quality of our paper substantially. The detailed responses to your comments are listed below point by point.

The paper adresses the prediction of evapotranspiration rates from crops, which is an interesting and very useful study. I therefore find the authors approach interesting and relevant, but I also have some difficulties with the current manuscript. Unfortunately, there are little details on the findings and discussion of the results from the study and very little evaluation if the approach taken is working. I think the paper needs to be tightened up and more focus should be on the results and their application. So my main suggestions are as follows.

Comment #1

You do not need both figure 1 and the detailed description from line 171->. My suggestion would be to remove the figure.

Former Figure 1 has been removed according to your suggestion.

Comment #2

Much of 2.3 – 2.5 contain basic text book information that could be left in the referenced literature. These sections could be reduced to cover only info critical for your use of the methods. E.g. table 2 could be removed since this covers just basic requirements for the regression application. Similar goes for the Cooks distance, the formula is shown but I can´t find any results in the paper computed from this formula (except it is used to remove points if necessary – was it necessary?). The Voroni chapter is too long, I think most hydrologists would understand if you just stated you used Thiessen polygons for the cluster boundaries.

We have reduced subsections 2.3, 2.4 and 2.5 as you suggested. The detailed changes are listed below:

- **2.3. Cluster analysis**: removal of bullet points (see lines 230-233) and shortening of the explanation about the Shapiro-Wilk test (see lines 240-243).
- **2.4. Multiple linear regression**: removal of former Table 2 and shortening of the explanation about the assumptions of MLR (see lines 283-286).
- **2.5. Voronoi diagrams**: removal of former Eqs. (7) and (8) and their associated descriptions in text (see lines 304-305).

The equation of the Cook's distance was used to detect and remove influential points (outliers) as specified in lines 359-360.

Comment #3

I am not sure why the Penman-Monteith equation is shown, is it to illustrate the data needs? But on the other hand it is interesting to see the equation since it is an adaptation to the standard version on the P-M equation found in text books.

The Penman-Monteith is shown for two reasons. First, to highlight the great amount of parameters it requires and the need to develop alternative and simpler methods to estimate *ETo*. And second, because the historical daily values of *ETo* used in the paper to build the regression models were originally calculated through the Penman-Monteith equation. So we are actually trying to replicate them using more accessible variables, in order to facilitate the calculation of *ETo* from daily weather forecasts.

Comment #4

I miss a discussion of the accuracy of the method, e.g. by leaving some stations out of the analysis and then testing the prediction of the simplified method on these data. This would strengthen the understanding of the goodness of the method which is important. Now the output is figure 4 with little discussion on it´s content and if the values are reasonable.

We precisely used the predictive R^2 as a goodness-of-fit statistic because it is based on that principle you mentioned, as we explain in lines 267-269: "(1) remove each observation from the dataset, (2) estimate the regression equation without the removed observation and (3) determine how well the model predicts the removed observation". So the results we are presenting in Table 3 included these considerations already. To further clarify it, we have extended and strengthened the discussion about the statistical accuracy of the models summarized in current Table 3 (see lines 387-399).

Comment #5

You state (l.366) that the relationships were generally logical. Were there cases where they were not, and if so when and why?

They were logical in all cases. According to the values of the Beta coefficients in current Table 3, the mean values of temperature, relative humidity and wind follow the physical relationships explained in lines 379-385 in all cases (for every month and cluster). We have reworded that sentence to make it clear (see line 379).

Comment #6

Did you consider methods to evaluate the significance of the regression variables with the purpose of reducing the number of variables? Is the difference in results between a model of all predictors and a model of e.g. mean predictors large?

The variables included in current Table 3 as predictors were all statistically significant (p-values < 0.05) (see line 358). The differences between choosing more or less predictors were not high. The number of predictors was selected with the aim of both reaching the highest possible value of R^2 and avoiding multicollinearity (see lines 414-417).

Comment #7

You tested for normality (line 320). You could state that more clearly on line 379 which now states that the graphs suggest that the assumption of normality is ok.

The discussion about Figure 2 has been enhanced, including more details about the fulfilment of the assumption of normality (see lines 403-417).

Comment #8

Space constraints (l.390) limited the study to one crop type. If you can reduce the introductory material could you get space for more crop types, or do I misunderstand this statement?

Yes, you understood it well. Unfortunately, although we have reduced Section 2 and 4, Section 1 and 3 were actually extended as a result of the comments made by the remaining reviewers, so the situation has even worsened in this sense. Anyway, we understand that limiting the paper to one crop type (as an example) does not limit the scope of our research as both methodology and results are directly replicable for every crop type.

Comment #9

L.402 – 408 is not very clear to me. You talk about water demands and combined regression results with crop factors, but no specific results are shown and no conclusions are drawn from this except that it is possible to do it. Does it produce useful results and based on your results is this a method ready for practical use? This is potentially a central component of the paper that needs more detail.

Lines 441-450 and current Figure 6 have been added to clarify and demonstrate the applicability of this part of the results.

Comment #10

You discuss data availability in more general terms in the intro. Have you considered the application of measured evapotranspiration over reference crops a potential future source? Much work is going into e.g. the fluxnet cooperation. Similarly, many forecasts today provide humidity and basics for radiation estimations, could this combined with reanalysis data be a potential for the future?

Yes, measured evapotranspiration from FLUXNET might be a source from which to build prediction models to estimate *ET*, as we did in this paper with the values of measured *ETo* provided by the Spanish Ministry of Agriculture, Food and Environment. Humidity (relative humidity) is already included in the models we are presenting in this paper. As for radiation, it might be estimated as you say and included in the prediction models, but that would involve adding more error in the eventual prediction of *ET*. Besides, very accurate models can be obtained without requiring radiation-related variables, as we prove in the results of this paper.

Comment #11

The conclusion is long and in parts more of a discussion. It should be shorter anf more concise, and the elements of discussion or summaries of the work belongs in the results – discussion section.

The conclusions section is 325 words long, which seems quite reasonable from our perspective. In our opinion, a potential reader can get an overview of the whole article with these conclusions, since paragraph 1 summarises it, paragraph 2 provides evidence of the technical performance of the methods used and paragraph 3 describes the potential uses of the research behind the paper. We have reworded the second paragraph according to your comment (see lines 467-476), in order to avoid giving specific details which might be more characteristic of the results & discussion section.

Comment #12

Line 62: The value of 60% is the global average and the text should state this. E.g. in northern latitudes the percentage is significantly lower than this.

We have modified that sentence according to your comment (see line 62).

Comment #13

I miss a small map of Spain inserted into fig 2 to show where your region is, and as an aid to see inland and coastal areas.

We have added a new figure (current Figure 1) to show the study area in relation to the Map of Spain, including the location of the Mediterranean Sea (see line 316).