A parsimonious regional parametric evapotranspiration model based on a simplification of the Penman-Monteith formula

A. Tegos[1*], N. Malamos[2] and D. Koutsoyiannis[1]

[1]*Department of Water Resources and Environmental Engineering, National Technical University of Athens, Heroon Polytechneiou 5, GR-157 80, Zographou, Greece*

[2]*Department of Agricultural Technology, Technological Educational Institute of Western Greece, Amaliada, Greece*

*tegosaris@yahoo.gr

Abstract Evapotranspiration is a key hydrometeorological process and its estimation is important in many fields of hydrological and agricultural sciences. Simplified estimation proves very useful in absence of a complete data set. In this respect, a parametric model based on simplification of the Penman-Monteith formulation is presented. The basic idea of the parametric model is the replacement of some of the variables and constants that are used in the standard Penman-Monteith model by regionally varying parameters, which are estimated through calibration. The model is implemented in various climates on monthly time step (USA, Germany, Spain) and compared on the same basis with four radiation-based methods (Jensen-Haise, McGuiness and Bordne, Hargreaves and Oudin) and two temperature-based (Thornthwaite and Blaney-Criddle). The methodology yields very good results with high efficiency indexes, outperforming the other models. Finally, a spatial analysis including the correlation of parameters with latitude and elevation together with their regionalization through three common spatial interpolation techniques along with a recent approach (Bilinear Surface Smoothing), is performed. Also, the model is validated against Penman-Monteith estimates in eleven stations of the well-known CIMIS network. The total framework which includes the development, the implementation, the comparison and the mapping of parameters illustrates a new parsimonious and high efficiency methodology in the assessment of potential evapotranspiration field.

Key words: Potential evapotranspiration, Penman- Monteith method, Parametric model, Calibration, Spatial analysis

1. Introduction

Accurate estimation of evapotranspiration has gained scientific interest due to high importance in hydrological modelling, irrigation planning and water resources management. According to Farquhar and Roderick (2007), changes in evaporative demand affect fresh water supplies and have impact on agriculture, the biggest consumer of fresh water. Estimating water requirements for irrigation purposes goes back to 1890 in the USA (Jensen and Haise, 1963).

The vast number of scientific attempts to estimate Potential Evapotranspiration (PET) or Reference Evapotranspiration (ETo) depicts the significant role of evapotranspiration in irrigation water management Those attempts yielded about 50 evapotranspiration models (Lu *et al*. 2005, McMahon *et al*. 2013) which can be grouped into seven classes: (i) empirical, (ii) water budget (iii) energy budget, (iv) mass transfer, (v) combination, (vi) radiation and (vii) measurement (Xu and Singh 2000).

The plethora of models and frameworks arises from the complexity of the physical phenomenon, the availability of the necessary hydrometeorological data and the variability of local climatic conditions.

The Penman-Monteith formulation (Monteith 1981) was proposed by FAO as the standard method for computing Potential Evapotranspiration (PET) (Allen *et al*. 1989) and has had numerous successful applications in hydrology and agrometeorology in various hydroclimatic regimes (Wang and Georgakakos 2007).

Basic drawback of the model's applicability is the requirement of several climatic data like temperature, wind speed, relative humidity and radiation. Such measurements are not always easily available or accessible to researchers due to the sparse hydrometeorological stations networks in several regions, e.g. Africa, as well as the instability in the records of radiation and relative humidity (Samani, 2000).

Therefore, the demand of new simplified models in several time scales (Alexandris and Kerkides 2003, Oudin *et al*. 2005, Valiantzas, 2013,) like radiation-based and temperature-based models, is justified. Several publications (Tabari 2010, Samaras *et al*. 2014) demonstrated that radiation-based methods are capable for PET estimation. Additionally, many researchers suggest the need for further model calibration (especially in the energy term of radiation) to improve the overall efficiency (Irmak *et al*. 2003, Zhai L. *et al*. 2010, Azhar and Perera 2010, Thepadia and Martinez 2012, Tabari and Talalee 2011).

This study presents a radiation-based model that introduces an innovative approach in the estimation of potential evapotranspiration. This methodology that requires only temperature data incorporates a new concept concerning local calibration needs and produces a parsimonious expression for the potential evapotranspiration estimation by replacing some of the variables and constants that are used in the standard Penman-Monteith model by regionally varying parameters, which are estimated through calibration. The model is implemented and compared to established radiation and temperature based methods using the available data from 53 hydrometeorological stations of USA, Germany and Spain, representing different climate conditions, both arid and humid. Finally, analyses concerning: (a) the parameters' dependence on latitude and (b) the parameters' spatial variability, was performed based on data from the California Irrigation Management Information

System (CIMIS - Hart *et al.* 2009) programme that was introduced by the California Department of Water Resource and the University of California, Davis, in 1982. For the latter, the calibration procedure incorporates 39 CIMIS stations, while the validation is made against the calculated parameter values from a set of 11 additional stations.

2. Materials and methods

2.1 Penman-Monteith model and radiation-based methods

The classic model of the Penman-Monteith (Monteith 1965) equation to estimate potential evaporation or evapotranspiration is expressed as:

$$\mathrm{PET} = \frac{\mathit{\Delta}}{\mathit{\Delta} + \gamma'}\frac{R_\mathrm{n}}{\lambda} + \frac{\gamma}{\mathit{\Delta} + \gamma'}F(u)\,D\ ,\ \gamma' = \gamma\,(1 + r_\mathrm{s}/r_a) \qquad (1)$$

where PET is potential evaporation or evapotranspiration (mm/d), R_n is net radiation at the surface $\mathit{\Delta}$ is the slope of the saturation vapor pressure curve, γ is psychometric coefficient while r_s and r_a are the surface and aerodynamic resistance factors.

Jensen and Haise (1963) evaluated 3000 observations of ET as determined by soil sampling procedures over a 35-year period, and developed an equation that requires only the average daily temperature and the extraterrestrial radiation, while one decade later, McGuiness and Bordne (1972) using lysimeter data suggested a slight modification to Jensen’s formulation.

Another widely used approach is the Hargreaves model (Hargeaves and Samani 1982) that estimates the reference evapotranspiration at monthly and daily scale. The method has received considerable attention because it can produce very acceptable results under diverse climates using only temperature and radiation measurements (Shahidian *et al.* 2013). According to several researchers (Samani

2000, Xu and Singh 2002) the method performs poorly in extreme humidity and wind conditions.

A recent study (Oudin *et al.* 2005), evaluated a number of evapotranspiration methods, on the basis of precipitation and streamflow data from a large sample of catchments in the USA, France and Australia. After extended analysis with the use of four hydrological models, the researchers modified the Jensen and McGuiness model and proposed a generalized radiation- based equation.

Table 1 summarizes the expressions that estimate PET according to the above-mentioned methodologies:

Table 1

where PET (mm d^{-1}, equivalent to kg m^{-2} d^{-1} of the dimensionally consistent Penman-Monteith equations) is the potential evapotranspiration, R_a (kJ $m^{-2}d^{-1}$) is the extraterrestrial shortwave radiation, T_a (°C) is the air temperature, λ is the latent heat of vaporization (kJ kg^{-1}) and ρ is the water density (kg L^{-1}).

2.2 Temperature-based methods

The Thornthwaite model (Thornthwaite, 1948) is the most simplified method and requires only temperature measurements. The model's form is:

$$\mathrm{PET} = 1.6\, L_d \left(\frac{10\, T_a}{I}\right)^{a} \tag{2}$$

where PET is the potential evapotranspiration (mm/month), L_d is the daytime length, T_a is the mean monthly air temperature (^{o}C), I is the annual heat index and a is an empirically determined parameter which is function of I.

The Blaney-Criddle method (Blaney and Criddle, 1962) has received worldwide application for the estimation of irrigation demands. The model expression is:

$$\mathrm{PET} = K\,p\,(0.46\,T_\mathrm{a} + 8.13) \tag{3}$$

where PET is the potential evapotranspiration (mm/month), T_a the mean temperature ($^\mathrm{o}$C), K is the monthly consumptive use coefficient and p is the mean daily percentage of annual daytime hours.

2.3 The parametric formula

The need of parsimonious model structure is essential in several fields of water resources sciences (Koutsoyiannis 2009, Koutsoyiannis 2014). This refers both to the model structure and to the input data, which should be easily available. Most of simplified formulas fail to describe the phenomenon of evapotranspiration due to its high complexity and the varying local climate conditions. Thus, the idea of replacing some variables and constants used in the standard Penman-Monteith (PM) formula by a number of parameters which are regionally varying and estimated through calibration from a reference evapotranspiration sample, constitutes a new appealing strategy for evapotranspiration estimation.

Koutsoyiannis and Xanthopoulos (1999), Tegos *et al*. (2009) and Tegos *et al*. (2013) examined the structure and the sensitivity of input data in PM model. They concluded that extraterrestrial radiation and temperature dominate in determining potential evapotranspiration. Furthermore, Mamassis *et al.* (2014) reached to the conclusion that the influence of every meteorological parameter in evaporation is almost linear, with temperature having the greater influence.

By dividing both the numerator and the denominator by $\mathit{\Delta}$, the PM equation can be written in the form:

$$\mathrm{PET} = \frac{1}{\lambda\rho}\,\frac{R_\mathrm{n} + \gamma\,\lambda F(u)\,D}{1 + \gamma'/\mathit{\Delta}} \tag{4}$$

In the above expression, the numerator is the sum of a term related to solar radiation and a term related to the rest of meteorological variables, while the denominator is function of temperature.

Based on the previous analysis, a simplification of the Penman-Monteith formula, where the numerator is approximated by a linear function of extraterrestrial solar radiation, while a linear descending function of temperature approximates the denominator, can be described by the following formula:

$$\mathrm{PET} = \frac{a\,R_a - b}{1 - c\,T_a} \tag{5}$$

where PET (mm) is the potential evapotranspiration, R_a (kJ m^{-2}) is the extraterrestrial shortwave radiation calculated without measurements and T_a (°C) is the air temperature.

Equation (5) contains three parameters, i.e. a (kg kJ^{-1}), b (kg m^{-2}) and c (°C^{-1}), to which a physical interpretation can be assigned. Since extraterrestrial solar radiation is the upper bound of net shortwave radiation, the dimensionless term $a^* = a / \lambda\rho$ represents the average percentage of the energy provided by the sun (in terms of R_a) and, after reaching the Earth's terrain, is transformed to latent heat, thus driving the evapotranspiration process. Parameter b lumps the missing information associated with aerodynamic processes, driven by the wind and the vapour deficit in the atmosphere. Finally, the expression $1 - cT_a$ approximates the term: $1 + \gamma/\Delta$. We recall that γ' is a function of the surface and aerodynamic resistance (equation 1) and Δ is the slope vapour pressure curve, which is a function of T_a.

2.4 Hydrometeorological data and computational tools

For exploration purposes, we use monthly meteorological data from 39 CIMIS stations (Hart *et al.* 2009), available at www.cimis.water.ca.gov, 10 stations from Germany and finally 4 stations from Spain (Table 2). The European data are freely available in the European Climate Assessment data set (Klok and Klein Tank, 2009 - http://eca.knmi.nl/). Stations' latitudes range from N 32.76^{o} to N 53.38^{o} and their altitude varies from 2.74 m to 1342.6 m.

The available data comprise mean temperature, relative humidity, sunshine duration and wind velocity. At all CIMIS stations the data covers the period from October 1992 to September 2012 while the European stations cover the period from January 1948 to December 2013. The choice of the time-periods was based on the simultaneous availability of the four required hydrometeorological variables (temperature, sunshine duration, humidity, wind speed). Additionally, the selection of each station and especially those from the CIMIS network was based on the existence of adequate length time series for the processes involved, i.e. 20 years.

Table 2

The time series processing along for the implementation of the different approaches for potential evapotranspiration estimation, i.e. Penman-Monteith, parametric and Hargreaves, was carried out using the free software application Hydrognomon (Kozanis *et al*. 2010, http://hydrognomon.org/), while the remaining expressions (Jensen, McGuiness and Oudin) were evaluated through spreadsheets.

2.5 **Statistical criteria**

The main statistical criterion used for the evaluation of the methodologies performance against the values computed by the Penman Monteith method (PM) was the coefficient of efficiency (CE), introduced by Nash & Sutcliffe (1970):

$$\mathrm{CE} = 1 - \frac{\sum_{i=1}^{n}(\mathrm{PE}_i - \mathrm{PM}_i)^2}{\sum_{i=1}^{n}(\overline{\mathrm{PM}} - \mathrm{PM}_i)^2} \tag{6}$$

where PM_i and PE_i are the potential evapotranspiration values of month i, computed by the Penman-Monteith method and the other model respectively, $\overline{\mathrm{PM}}$ is the monthly average over the common data period estimated by the Penman-Monteith formula while n is the sample size.

Additionally, we applied several statistical measures, such as the mean bias error:

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{PE}_i - \mathrm{PM}_i) \tag{7}$$

the mean absolute error: $\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\mathrm{PE}_i - \mathrm{PM}_i|$ (8)

and the root mean square error: $\mathrm{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(\mathrm{PE}_i - \mathrm{PM}_i)^2\right]^{1/2}$ (9)

CE ranges between $-\infty$ and 1 (1 inclusive), with CE = 1 being the optimal value. Values between 0 and 1 are generally regarded as acceptable levels of performance, whereas values less than 0 indicate that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance. MBE, MAE and RMSE values of 0 indicate a perfect fit (Moriasi *et al*. 2007).

3. Results

The implementation of the parametric model was accomplished by calculating the three parameters involved at each station, as mentioned above. This procedure is automated via a least square optimization technique, embedded in the Hydrognomon software (Kozanis *et al*. 2010, http://hydrognomon.org/), providing means for acquiring optimized values of *a*, *b* and *c* parameters for the parametric method application.

The calculated monthly Penman-Monteith potential evapotranspiration time series acted as the reference data sets against which the comparisons between the different methodologies took place. Table 3 summarizes the values of the parameters for each of the 53 stations, acquired by the procedure described above.

Table 3

3.1 Comparison with radiation-based methods

Figure 1 presents the mean annual potential evapotranspiration calculated by the Penman-Monteith method for each one of the 39 CIMIS stations against the parametric and the other four methods. It is clear that the parametric, Hargreaves and McGuiness models respect the variation of the over-annual potential evapotranspiration, while the other two models, i.e. Oudin and Jensen-Haise underestimate and overestimate respectively, the potential evapotranspiration values.

Figure 1

The performance indices presented in Table 4 confirm the good performance of the parametric method, which has the highest CE and excellent results in the other statistical indices. The Hargreaves model follows with CE 78.9%, similar MBE and worst MAE and RMSE than the parametric model. The McGuiness method gave moderate results, while the Jensen-Haise and Oudin models totally fail to represent the physical flux.

Table 4

For further comparison of the parametric method against the four radiation-based methods, in terms of the achieved CE distribution from estimating monthly PE, each time series was split into two parts. The first 13 years were used as the calibration data set for the parametric model, while the remaining 7 years were used for validation. Table 5 presents the CE distribution, for the calibration (Cal) and the validation (Val) data set for 39 CIMIS stations, while that of the European stations is presented in Table 6.

Table 5

The results for both periods and in different climatic regimes are satisfactory for the parametric model, with the average CE values for the calibration period being 94.80% for CIMIS stations and 96.52% for European stations, while for the validation period the corresponding values are 94.34% for CIMIS stations and 90.06% for the European stations. Altogether, the application of the parametric model in 26 stations from the 39 stations achieved CE values between 90 and 95%.

Table 6

The Hargreaves model achieved satisfactory results especially in the case of CIMIS network, where the model has been developed; while in European stations the acquired CE values are lower.

The McGuiness model acquired lower CE values in the CIMIS network than Parametric and Hargreaves with 87.14% in calibration period and 87.76% in the validation period. The Oudin model presented moderate results in the CIMIS network (52.18% in the calibration and 46.82% in the validation period) but considerably better results in European stations (89.37 % calibration and 82.82% validation period). By taking into account the similar results presented by Tegos *et al*. (2013), the Oudin model seems to perform better in humid than in arid climatic conditions.

Finally, the Jensen-Haise model totally failed to produce physically meaningful results, since the achieved CE values were very low (Tables 4, 5, 6).

3.2 Comparison with temperature-based methods

We also compared the performance of the parametric model with two well-known empirical formulas of Thornthwaite and Blaney-Criddle (Tables 7, 8) by implementing the same procedure as in the comparison with the radiation-based methods, i.e. the first 13 years were used as the calibration data set, while the remaining 7 years were used for validation. Both approaches have wide application in data-scarce regions. In the CIMIS network the average CE for the Thornthwaite model was 20.53% for the calibration period and less than zero in the validation period, while in European stations the CE is 84.58% (calibration) and 78.27% (validation). The Blaney-Criddle method achieved average CE 69.99% (calibration), 69.82% (validation) in the CIMIS network and 15.69% (calibration) and <0 (validation) in European stations. Finally, the Thornthwaite model seems to be suitable for use in cold and humid climates (94.84% CE in German stations for the calibration period) and improper in arid regimes, while for the Blaney-Criddle model the opposite occurs.

Table 7

Table 8

3.3 Spatial analysis of the parameters

The key idea of the parametric model is the replacement of some of the variables and constants that are used in standardized Penman-Monteith formula by three parameters, which are regionally varying and estimated through calibration using a reference evapotranspiration data set. Furthermore, knowledge of the spatial variability of the PET is crucial in geosciences and the use of the appropriate interpolation technique is significant (Mancosu *et al.* 2014).

In this context, two applications are implemented. The first is the analysis of the parameters' correlation to latitude and elevation, while the second is their estimation, through spatial interpolation techniques, along an extensive study area such as California, which provides sufficient data to perform the necessary calibration procedures.

3.3.1 Correlation to latitude and elevation

Through regression analysis, we investigated the correlation of every parameter (a, b, c) with latitude φ and elevation. Six scatter plots of Fig. 2, show that parameters a, b are negatively correlated to latitude and elevation, in contrast to parameter c. This is similar to the findings of the previous study over the Greek territory (Tegos *et al*. 2013) for parameter a. There is also noticeable correlation of parameter b with elevation ($R^2 = 0.24$) and insignificant correlation of parameter c with elevation and latitude. Furthermore, Fig. 2 shows that the relation of the three parameters to latitude and elevation, according to findings of the present study, appears to be a non-linear one.

Figure 2

3.3.2 Spatial interpolation over California

Currently, a lot of methods exist which can accomplish spatial interpolation using available computer codes. In the present study, the three parameters' spatial variability was investigated by four different methodologies: (1) Inverse Distance Weighting (IDW); (2) Natural Neighbours (NaN); (3) Ordinary Kriging (OK); and (4) Bilinear Surface Smoothing (BSS).

The first three are well established and commonly used in spatial interpolation of environmental variables (Li and Heap, 2008). The Bilinear Surface Smoothing methodology is a new approach that approximates a surface that may be drawn for the data points with consecutive bilinear surfaces which can be numerically estimated by means of a least squares fitting procedure into a surface regression model with known break points and adjustable weights defined by means of angles formed by those bilinear surfaces. The BSS theory and basic features along with the adjustable parameters estimation methodology which is based on the generalized cross-validation methodology are presented in Malamos and Koutsoyiannis (in review) BSS is implemented by means of a dynamic link library in Object Pascal (Delphi) programming language linked to Microsoft Excel. The obtained optimal values of the four adjustable parameters: the number of intervals according to *x* and *y* directions, i.e. mx, my and the corresponding smoothing parameters $\tau_{\lambda x}$ and $\tau_{\lambda y}$, are presented in Table 9:

Table 9

IDW and NaN were implemented in ESRI's ArcGIS environment using the default settings, while for OK all semivariogram models available in that software were investigated, i.e. circular, exponential, spherical, linear and Gaussian,. In every case, the embedded fitting procedure ensured the minimization of the weighted sum of squares between experimental and model semivariogram values.

Table 10

Table 10 presents the values of the statistical criteria for each one of the implemented semivariogram models, sorted according to the CE criterion for each of the three parameters. It is obvious that the circular semivariogram achieved the best overall performance.

All three parameters of the parametric model were estimated over California by applying the four spatial interpolation methods. The input data set consists of the calculated parameters values at the 39 CIMIS stations (Fig. 3, Table 3).

Figure 3

Table 11 presents the values of the statistical criteria used to assess the performance of the spatial interpolation methods with respect to the input data set. It is apparent that both non-geostatistical methods, according to the statistical criteria used, outperform ordinary kriging and bilinear surface smoothing, which performed similarly. This is not a surprise because both IDW and NaN, from construction, are exact methods of interpolation, so their results respect the data points exactly (Longley *et al.* 2005, Li and Heap 2008).

Table 11

However, the above statistical indices may not be representative with respect to the validity of the interpolation results in other locations, except for those incorporated in the interpolation procedure. In this context, a validation procedure was implemented by means of comparing the reference potential evapotranspiration estimates acquired from the implementation of the parametric method, using the parameter estimates of the four interpolation methods, against those of the eleven additional CIMIS stations with adequate time series length, shown in Table 12 along with the estimated parameter values, in the case of IDW.

Table 12

The performance of each method is presented in Table 13, which summarizes the CE values acquired from the validation procedure. It is apparent that IDW outperforms the other three methods in the majority of the cases. This is an interesting fact, since the IDW method is the effortless of the four methodologies. On the other hand, the BSS performance is analogous or better to that of the input data set, with CE values close to those presented in Table 12. NaN and OK performed similarly, with the first achieving slightly superior outcome, since OK in the case of Borrego Springs resulted in negative CE value.

Table 13

The variation of the three parameters over California produced by the IDW technique is illustrated in Fig. 4. It is apparent that both *a* and *c* present an increasing North to South gradient, while the opposite occurs for parameter *b*. This remark coincides with the previous findings concerning the relation of the three parameters to latitude.

Figure 4

4. Summary and conclusions

The parametric model is a parsimonious radiation-based and physically consistent approach derived from a simplification of the Penman-Monteith equation, which requires three parameters to be calibrated prior to its application. By systematic application of the method the parameters can be eventually provided by maps.

The comparison, on the basis of monthly and annual evapotranspiration data, with commonly used radiation-based models (Hargreaves, McGuiness, Jensen-Haise and Oudin models) and temperature-based models (Thorthwaite and Blaney-Criddle), verified the parametric model's high efficiency in different climatic regimes.

A parameters analysis, through regression techniques, was conducted in order to investigate their correlation to latitude and elevation variation. Moreover, the parameters' spatial estimation was accomplished by implementing interpolation techniques such as: Inverse Distance Weighting (IDW), Natural Neighbours (NaN), Ordinary Kriging (OK) and Bilinear Surface Smoothing (BSS), along an extensive study area such as California. The validation procedure was implemented by comparing the reference potential evapotranspiration estimates acquired from the implementation of the parametric method, using the parameter estimates of the four interpolation methods, against those of the eleven additional CIMIS stations. This combined evaluation of the four different interpolation approaches, indicated that the simple and effortless IDW method performs better than the other three methodologies. Regarding the application of the new methodology, BSS's efficiency to perform interpolation between data points that are interrelated in a complicated manner was confirmed, acquiring high CE values analogous to those of the other three methods.

Overall, the key idea of the parametric model methodology, which is the simplification of the Penman-Monteith formula by introducing three parameters, which are regionally varying and estimated through calibration using a reference evapotranspiration data set, was very successful.

Further research and applications regarding its strengths and weaknesses need to be conducted in future studies towards: (a) the sensitivity analysis of the three parameters and therefore the model's performance against the length of the available time series and (b) the implementation of worldwide climatic databases such as the United Nations Food and Agriculture Organization (UN-FAO) database known as CLIMWAT (Smith 1993), in order to perform regionalization of the parameters in world regions with different climatic regimes.

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References

Azhar, A.H., Perera, B.J.C., 2011. Evaluation of Reference Evapotranspiration Estimation Methods under Southeast Australian Conditions. J. Irrig. Drain. Eng. 137, 268–279.

Alexandris, S., Kerkides, P., 2003. New empirical formula for hourly estimations of reference evapotranspiration. Agric. Water Manag. 60, 157–180.

Allen, R.G., Jensen, M.E., Wright, J.L., Burman, R.D., 1989. Operational Estimates of Reference Evapotranspiration. Agron. J. 81, 650.

Blaney, H.F., Criddle, W.D., 1962. Determining consumptive use and irrigation water requirements (No. 1275). US Department of Agriculture.

Farquhar, G.D., Roderick M.L., 2007. Worldwide changes in evaporative demand, Proceedings of the Pontifical Academy of Sciences, 2005.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating Potential Evapotranspiration. J. Irrig. Drain. Eng. 108, 225–230.

Hart, Q.J., Brugnach, M., Temesgen, B., Rueda, C., Ustin, S.L., Frame, K., 2009. Daily reference evapotranspiration for California using satellite imagery and weather station measurement interpolation. Civ. Eng. Environ. Syst. 26, 19–33.

Jensen, M.E., Haise, H.R., 1963. Estimating evapotranspiration from solar radiation. Proc. Am. Soc. Civ. Eng. J. Irrig. Drain. Div. 89, 15–41.

Klok, E.J., Klein Tank, A.M.G., 2009. Updated and extended European dataset of daily climate observations. Kozanis, S., Christofides, A., Mamassis, N., Efstratiadis, A., Koutsoyiannis D., 2010. Hydrognomon – open source software for the analysis of hydrological data, EGU General Assembly 2010, Geophysical Research Abstracts, Vol. 12, Vienna, 12419.

Koutsoyiannis, D., Xanthopoulos, Th., 1999. Engineering Hydrology, third ed., National Technical University of Athens, Athens.
(http://www.itia.ntua.gr/en/docinfo/115/)

Koutsoyiannis, D., 2009. Seeking parsimony in hydrology and water resources technology (solicited), European Geosciences Union General Assembly 2009, Geophysical Research Abstracts, Vol. 11, Vienna, 11469. (http://www.itia.ntua.gr/en/docinfo/906/)

Koutsoyiannis, D., 2014. Reconciling hydrology with engineering. Hydrol. Res. 45 (1), 2-24.

Li, J., Heap, A.D., 2008. A Review of Spatial Interpolation Methods for Environmental Scientists, Geoscience Australia. Geoscience Australia, GPO Box 378, Canberra, ACT 2601, Australia.

Longley, P.A., Goodchild, M.F., Maguire, D.J., Rhind, D.W., 2005. Geographic information system and Science, second ed, England: John Wiley & Sons, Ltd, West Sussex PO19 8SQ, England, pp. 333–335.

Lu, J., Sun, G., McNulty, S.G., Amatya, D.M., 2005. A comparison of six potential comparison evapotranspiration methods for regional use in the Southeastern United States. J. Am. Water Resour. Assoc. 41, 621–633.

Malamos, N. and Koutsoyiannis, D., in review. Bilinear surface smoothing for spatial interpolation with optional incorporation of an explanatory variable. Part 1: Theory, Hydrol. Sci. J.

Mamassis, N., Panagoulia, D., Novcovic, A., 2014. Sensitivity analysis of Penman evaporation method, Global NEST Journal, Vol.16, No 4, pp. 628-639.

Mancosu, N., Snyder, R.L., Spano, D., 2014. Procedures to Develop a Standardized Reference Evapotranspiration Zone Map. J. Irrig. Drain. Eng. 140, A4014004.

McGuiness J.L, Bordne E.F, 1972. A comparison of lysimeter- derived potential evapotranspiration with computed values, Technical Bulletin 1452, Agricultural Research Service, US Department of Agriculture, Washington, DC

McMahon, T.A., Peel, M.C., Lowe, L., Srikanthan, R., McVicar, T.R., 2013. Estimating actual, potential, reference crop and pan evaporation using standard meteorological data: a pragmatic synthesis. Hydrol. Earth Syst. Sci. 17, 1331–1363.

Monteith, J.L., 1981. Evaporation and environment. Symp. Soc. Exp. Biol. Vol. 19. No. 205-23.

Monteith, J.L., 1981. Evaporation and surface temperature. Q. J. R. Meteorol. Soc. 107, 1–27.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. Trans. ASABE 50, 885–900.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I - A discussion of principles. J. Hydrol. 10, 282–290.

Irmak, S., Allen, R.G., Whitty, E.B., 2003. Daily Grass and Alfalfa-Reference Evapotranspiration Estimates and Alfalfa-to-Grass Evapotranspiration Ratios in Florida. J. Irrig. Drain. Eng. 129, 360–370.

Pereira, A.R., Pruitt, W.O., 2004. Adaptation of the Thornthwaite scheme for estimating daily reference evapotranspiration. Agric. Water Manag. 66, 251–257.

Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andréassian, V., Anctil, F., Loumagne, C., 2005. Which potential evapotranspiration input for a lumped rainfall–runoff model?: Part 2-Towards a simple and efficient potential evapotranspiration model for rainfall–runoff modelling. J. Hydrol. 303, 290–306.

Samani, Z., 2000. Estimating Solar Radiation and Evapotranspiration Using Minimum Climatological Data. J. Irrig. Drain. Eng. 126, 265–267.

Samaras, D.A., Reif, A., Theodoropoulos, K., 2013. Evaluation of Radiation-Based Reference Evapotranspiration Models Under Different Mediterranean Climates in Central Greece. Water Resour. Manag. 28, 207–225.

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

Smith, M., 1993. CLIMWAT for CROPWAT: A climatic database for irrigation planning and management. FAO Irrigation and Drainage Paper No. 49, Rome. (CLIMWAT 2.0), http://www.fao.org/nr/water/infores_databases_climwat.html.

Tabari, H., 2009. Evaluation of Reference Crop Evapotranspiration Equations in Various Climates. Water Resour. Manag. 24, 2311–2337.

Tabari, H., Talaee, P.H., 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, 837–845.

Tegos A., Efstratiadis A., Koutsoyiannis D., 2013. A Parametric Model for Potential Evapotranspiration Estimation Based on a Simplified Formulation of the Penman- Monteith Equation. In: Evapotranspiration-An Overview. S. Alexandris.(Ed.), InTech, pp. 143-165. (http://www.itia.ntua.gr/en/docinfo/1284/)

Tegos, A., Mamassis, N., Koutsoyiannis, D., 2009. Estimation of potential evapotranspiration with minimal data dependence. EGU General Assembly Conference Abstracts. Vol. 11. (http://www.itia.ntua.gr/en/docinfo/905/)

Thepadia, M., Martinez, C.J., 2012. Regional Calibration of Solar Radiation and Reference Evapotranspiration Estimates with Minimal Data in Florida. J. Irrig. Drain. Eng. 138, 111–119.

Thornthwaite, C.W., 1948. An approach toward a rational classification of climate. Geographical Review, 55-94.

Xu, C.Y., Singh, V.P., 2001. Evaluation and generalization of temperature-based methods for calculating evaporation. Hydrol. Process. 15, 305–319.

Xu, C.Y., Singh, V.P., 2002. Cross comparison of empirical equations for calculating potential evapotranspiration with data from Switzerland. Water Resour. Manag. 16, 197–219.

Wang, J., Georgakakos, K.P., 2007. Estimation of potential evapotranspiration in the mountainous Panama Canal watershed. Hydrol. Process. 21, 1901–1917.

Valiantzas, J.D., 2013. Simplified forms for the standardized FAO-56 Penman–Monteith reference evapotranspiration using limited weather data. J. Hydrol. 505, 13–23.

Table 1 Radiation-based methods for potential evapotranspiration estimation

Method	Jensen and Haise	Mcguiness and Bordne	Hargreaves	Oudin
PET expression	$\frac{R_a T_a}{40\,\lambda\,\rho}$	$\frac{R_a (T_a + 5)}{68\,\lambda\,\rho}$	$0.0023\frac{R_a}{\lambda}(T_a + 17.8)(T_{max} - T_{min})^{0.5}$	$\frac{R_a (T_a + 5)}{100\,\lambda\,\rho}$

Table 2 Meteorological stations used for the evaluation of the potential evapotranspiration methods

No.	Station name, Location	No.	Station name, Location	No.	Station name, Location
1	Five Points, U.S.A.	19	Buntigville, U.S.A.	37	De Laveaga, U.S.A.
2	Davis, U.S.A.	20	Temecula, U.S.A.	38	Westlands, U.S.A.
3	Firebaugh Teles, U.S.A.	21	Santa Ynez, U.S.A.	39	Sanel Valley, U.S.A.
4	Gerber, U.S.A.	22	Seeley, U.S.A.	40	Aachen, Germany
5	Durham, U.S.A.	23	Manteca, U.S.A.	41	Angermunde, Germany
6	Carmino, U.S.A.	24	Modesto, U.S.A.	42	Bremen-Seefahrtshule, Germany
7	Stratford, U.S.A.	25	Irvine, U.S.A.	43	Dresden-Klotzsche, Germany
8	Castorville, U.S.A.	26	Oakville, U.S.A.	44	Dusseldorf, Germany
9	Kettleman, U.S.A.	27	Pomona, U.S.A.	45	Frankfurt, Germany
10	Bishop, U.S.A.	28	Frenso State, U.S.A.	46	Hamburg Fuhlsbuettel, Germany
11	Parlier, U.S.A.	29	Santa Rosa, U.S.A.	47	Karlsrhue, Germany
12	Calipatria, U.S.A.	30	Browns Valley, U.S.A.	48	Muenchen-Flughafen, Germany
13	Mc Arthur, U.S.A.	31	Lindcove, U.S.A.	49	Stuggart-Schnarreberg, Germany
14	UC Riverside, U.S.A.	32	Meloland, U.S.A.	50	Alicante, Spain
15	Brentwood, U.S.A.	33	Alturas, U.S.A.	51	Badajoz Televera, Spain
16	San Luis Obispo, U.S.A.	34	Cuyama, U.S.A.	52	Valencia, Spain
17	Blackwells Corner, U.S.A.	35	Tulelake, U.S.A.	53	Zaragoza Aeropuerto, Spain
18	Los Banos, U.S.A.	36	Windsor, U.S.A.		

Table 3 Meteorological stations numbers and corresponding parameter values for the parametric method

Station No.	*a* (kg kJ^{-1})	*b* (kg m^{-2})	*c* (°C^{-1})	Station No.	*a* (kg kJ^{-1})	*b* (kg m^{-2})	*c* (°C^{-1})
1	1.47 10^{-4}	1.49	1.58 10^{-2}	28	1.29 10^{-4}	1.3	1.73 10^{-2}
2	1.04 10^{-4}	6.51 10^{-1}	2.15 10^{-2}	29	8.88 10^{-5}	6.09 10^{-1}	2.63 10^{-2}

3	$1.46\ 10^{-4}$	1.48	$1.47\ 10^{-2}$	30	$8.95\ 10^{-5}$	$4.07\ 10^{-1}$	$2.11\ 10^{-2}$
4	$1.02\ 10^{-4}$	$4.97\ 10^{-1}$	$1.93\ 10^{-2}$	31	$1.12\ 10^{-4}$	1.04	$1.74\ 10^{-2}$
5	$1.97\ 10^{-4}$	2.07	$-2.70\ 10^{-4}$	32	$2.12\ 10^{-4}$	2	$4.94\ 10^{-3}$
6	$8.82\ 10^{-5}$	$2.49\ 10^{-1}$	$2.34\ 10^{-2}$	33	$7.92\ 10^{-5}$	$-2.20\ 10^{-1}$	$2.44\ 10^{-2}$
7	$1.12\ 10^{-4}$	$-2.50\ 10^{-1}$	$1.44\ 10^{-2}$	34	$1.08\ 10^{-4}$	$4.03\ 10^{-1}$	$1.97\ 10^{-2}$
8	$1.68\ 10^{-4}$	1.06	$-3.60\ 10^{-2}$	35	$9.28\ 10^{-5}$	$5.20\ 10^{-2}$	$2.12\ 10^{-2}$
9	$1.34\ 10^{-4}$	1.23	$1.62\ 10^{-2}$	36	$8.65\ 10^{-5}$	$5.66\ 10^{-1}$	$2.60\ 10^{-2}$
10	$1.43\ 10^{-4}$	$7.39\ 10^{-1}$	$1.05\ 10^{-2}$	37	$1.02\ 10^{-4}$	$5.82\ 10^{-1}$	$1.24\ 10^{-2}$
11	$1.29\ 10^{-4}$	1.32	$1.61\ 10^{-2}$	38	$1.40\ 10^{-4}$	1.33	$1.67\ 10^{-2}$
12	$1.69\ 10^{-4}$	1.32	$8.86\ 10^{-3}$	39	$9.88\ 10^{-5}$	$6.54\ 10^{-1}$	$2.37\ 10^{-2}$
13	$9.75\ 10^{-5}$	$4.26\ 10^{-1}$	$2.36\ 10^{-2}$	40	$3.96\ 10^{-5}$	$-2.46\ 10^{-1}$	$2.62\ 10^{-2}$
14	$8.68\ 10^{-5}$	$5.10\ 10^{-2}$	$1.78\ 10^{-2}$	41	$3.96\ 10^{-5}$	$-2.58\ 10^{-1}$	$2.73\ 10^{-2}$
15	$1.11\ 10^{-4}$	$9.00\ 10^{-1}$	$2.09\ 10^{-2}$	42	$4.28\ 10^{-5}$	$-1.64\ 10^{-1}$	$2.68\ 10^{-2}$
16	$8.10\ 10^{-5}$	$1.60\ 10^{-1}$	$2.28\ 10^{-2}$	43	$3.67\ 10^{-5}$	$-3.45\ 10^{-1}$	$2.81\ 10^{-2}$
17	$1.21\ 10^{-4}$	1.02	$1.89\ 10^{-2}$	44	$4.12\ 10^{-5}$	$-3.02\ 10^{-1}$	$2.64\ 10^{-2}$
18	$1.31\ 10^{-4}$	1.31	$1.81\ 10^{-2}$	45	$4.75\ 10^{-5}$	$-8.8\ 10^{-2}$	$2.62\ 10^{-2}$
19	$9.29\ 10^{-5}$	$-1.10\ 10^{-1}$	$2.11\ 10^{-2}$	46	$4.18\ 10^{-5}$	$-1.66\ 10^{-1}$	$2.66\ 10^{-2}$
20	$6.66\ 10^{-5}$	$-2.80\ 10^{-1}$	$2.10\ 10^{-2}$	47	$4.64\ 10^{-5}$	$-6.6\ 10^{-2}$	$2.58\ 10^{-2}$
21	$9.44\ 10^{-5}$	$4.91\ 10^{-1}$	$2.06\ 10^{-2}$	48	$4.69\ 10^{-5}$	$-8.8\ 10^{-2}$	$2.51\ 10^{-2}$
22	$2.50\ 10^{-4}$	2.58	$7.52\ 10^{-4}$	49	$4.53\ 10^{-5}$	$-1.64\ 10^{-1}$	$2.52\ 10^{-2}$
23	$1.13\ 10^{-4}$	1.02	$2.03\ 10^{-2}$	50	$5.89\ 10^{-5}$	$-4.67\ 10^{-1}$	$1.84\ 10^{-2}$
24	$1.17\ 10^{-4}$	1.08	$2.00\ 10^{-2}$	51	$6.24\ 10^{-5}$	$1.72\ 10^{-1}$	$2.35\ 10^{-2}$
25	$6.64\ 10^{-5}$	$-4.40\ 10^{-2}$	$2.28\ 10^{-2}$	52	$5.34\ 10^{-5}$	$-1.93\ 10^{-1}$	$1.96\ 10^{-2}$
26	$8.42\ 10^{-5}$	$4.29\ 10^{-1}$	$2.54\ 10^{-2}$	53	$7.00\ 10^{-5}$	$-2.2\ 10^{-2}$	$2.39\ 10^{-2}$
27	$1.13\ 10^{-4}$	1.25	$2.00\ 10^{-2}$				

Table 4 Values of performance indices used to evaluate the parametric method, in the estimation of mean annual potential evapotranspiration for the 39 CIMIS stations, against the other four models

Method	CE (%)	MBE (mm)	MAE (mm)	RMSE (mm)
Parametric	99.1	4	6	17
Hargreaves	78.9	2	60	82
Jensen-Haise	< 0	417	452	493
McGuiness	30.1	19	111	149
Oudin	< 0	-393	393	411

Table 5 Distribution of CE values of radiation-based approaches in CIMIS network

CE (%)	Parametric	Hargreaves	Jensen-Haise	McGuiness	Oudin

	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val
95-100	26	26	26	23	0	7	16	15	0	0
90-95	11	5	10	7	0	2	6	7	0	0
80-90	2	8	3	9	1	2	10	10	1	0
70-80	0	0	0	0	6	3	3	3	3	5
60-70	0	0	0	0	1	6	2	3	7	4
50-60	0	0	0	0	3	4	1	1	12	6
0-50	0	0	0	0	16	9	1	0	16	24
<0	0	0	0	0	12	6	0	0	0	0

Table 6 Distribution of CE values of radiation-based approaches in European stations

CE	Parametric		Hargreaves		Jensen-Haise		Mcguiness		Oudin	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val
95-100	10	9	6	0	0	0	0	0	9	1
90-95	4	4	4	6	0	0	0	0	2	8
80-90	0	0	3	7	0	0	0	0	0	2
70-80	0	0	1	1	0	0	7	1	1	1
60-70	0	0	0	0	0	0	3	1	1	1
50-60	0	0	0	0	0	0	3	1	1	0
0-50	0	1	0	0	5	1	2	9	0	1
<0	0	0	0	0	9	13	1	2	0	0

Table **7** Distribution of CE values of temperature-based approaches in CIMIS network

CE	Thornthwaite		Blaney-Criddle	
	Cal	Val	Cal	Val
95-100	0	0	0	0
90-95	0	0	0	0
80-90	0	0	10	16
70-80	0	0	18	12
60-70	1	0	5	5
50-60	4	3	2	1
0-50	24	21	3	4
<0	10	15	1	1

Table 8 Distribution of CE values of temperature-based approaches in European stations

CE	Thornthwaite		Blaney-Criddle	
	Cal	Val	Cal	Val
95-100	5	0	0	0

90-95	5	1	0	0
80-90	0	9	0	0
70-80	2	1	1	1
60-70	0	1	0	0
50-60	1	1	0	1
0-50	1	1	12	1
<0	0	0	1	11

Table 9 BSS parameters optimal values, for the California application

Parameter	mx	my	$\tau_{\lambda x}$	$\tau_{\lambda y}$
a (kg kJ^{-1})	3	8	0.082	0.001
b (kg m^{-2})	3	28	0.001	0.01
c (°C^{-1})	3	8	0.001	0.001

Table 10 Values of the statistical criteria used to assess the performance of the different kriging semivariogram models

Parameter	kriging semivariogram	CE (%)	MBE	MAE	RMSE
a (kg kJ^{-1})	circular	99.9	$1.03\ 10^{-8}$	$5.18\ 10^{-7}$	$8.93\ 10^{-7}$
	exponential	99.9	$1.03\ 10^{-8}$	$5.18\ 10^{-7}$	$8.93\ 10^{-7}$
	spherical	99.9	$1.03\ 10^{-8}$	$5.18\ 10^{-7}$	$8.93\ 10^{-7}$
	linear	99.9	$1.03\ 10^{-8}$	$5.18\ 10^{-7}$	$8.93\ 10^{-7}$
	gaussian	44.6	$1.24\ 10^{-6}$	$1.86\ 10^{-5}$	$2.88\ 10^{-5}$
b (kg m^{-2})	circular	68.6	$4.24\ 10^{-3}$	$2.71\ 10^{-1}$	$3.68\ 10^{-1}$
	exponential	72.8	$3.12\ 10^{-3}$	$2.50\ 10^{-1}$	$3.43\ 10^{-1}$
	spherical	67.4	$5.46\ 10^{-3}$	$2.77\ 10^{-1}$	$3.76\ 10^{-1}$
	linear	66.6	$6.00\ 10^{-3}$	$2.81\ 10^{-1}$	$3.80\ 10^{-1}$
	gaussian	29.7	$4.09\ 10^{-2}$	$4.07\ 10^{-1}$	$5.51\ 10^{-1}$
c (°C^{-1})	circular	39.3	$3.56\ 10^{-4}$	$4.62\ 10^{-3}$	$8.19\ 10^{-3}$
	exponential	11.0	$4.67\ 10^{-4}$	$5.62\ 10^{-3}$	$9.92\ 10^{-3}$
	spherical	11.7	$4.64\ 10^{-4}$	$5.60\ 10^{-3}$	$9.88\ 10^{-3}$
	linear	11.0	$4.67\ 10^{-4}$	$5.62\ 10^{-3}$	$9.92\ 10^{-3}$
	gaussian	11.0	$4.67\ 10^{-4}$	$5.62\ 10^{-3}$	$9.92\ 10^{-3}$

Table 11 Values of the statistical criteria used to assess the performance of the spatial interpolation methods with respect to the input data set

Parameter	Interpolation Method	CE (%)	MBE	MAE	RMSE
a ($kg\ kJ^{-1}$)	IDW	100	$3.59\ 10^{-8}$	$1.08\ 10^{-7}$	$1.97\ 10^{-7}$
	NaN	100	$-1.03\ 10^{-7}$	$4.77\ 10^{-7}$	$8.95\ 10^{-7}$
	OK	99.9	$1.03\ 10^{-8}$	$5.18\ 10^{-7}$	$8.93\ 10^{-7}$
	BSS	73.2	$4.36\ 10^{-8}$	$1.35\ 10^{-5}$	$2.01\ 10^{-5}$
b ($kg\ m^{-2}$)	IDW	100	$2.95\ 10^{-4}$	$1.72\ 10^{-3}$	$3.06\ 10^{-3}$
	NaN	99.9	$-9.48\ 10^{-4}$	$1.16\ 10^{-2}$	$2.12\ 10^{-2}$
	OK	68.6	$4.24\ 10^{-3}$	$2.71\ 10^{-1}$	$3.68\ 10^{-1}$
	BSS	65.2	$1.97\ 10^{-4}$	$2.68\ 10^{-1}$	$3.88\ 10^{-1}$
c ($°C^{-1}$)	IDW	100	$2.56\ 10^{-7}$	$8.82\ 10^{-6}$	$1.52\ 10^{-5}$
	NaN	99.9	$1.54\ 10^{-6}$	$1.50\ 10^{-4}$	$3.10\ 10^{-4}$
	OK	39.3	$3.56\ 10^{-4}$	$4.62\ 10^{-3}$	$8.19\ 10^{-3}$
	BSS	68.9	$-2.57\ 10^{-7}$	$3.25\ 10^{-3}$	$5.87\ 10^{-3}$

Table 12 CIMIS Stations used for validation purposes and estimated parameters values in the case of IDW

Station	*a* ($kg\ kJ^{-1}$)	*b* ($kg\ m^{-2}$)	*c* ($°C^{-1}$)
Arroyo Seco	$1.38\ 10^{-4}$	1.06	$1.20\ 10^{-3}$
Carneros	$9.10\ 10^{-5}$	$5.48\ 10^{-1}$	$2.42\ 10^{-2}$
Green Valey Road	$1.16\ 10^{-4}$	$7.75\ 10^{-1}$	$7.26\ 10^{-3}$
King City Oasis	$1.34\ 10^{-4}$	1.09	$9.53\ 10^{-3}$
Santa Barbara	$1.03\ 10^{-4}$	$5.56\ 10^{-1}$	$1.98\ 10^{-2}$
Alpaugh	$1.23\ 10^{-4}$	$8.27\ 10^{-1}$	$1.67\ 10^{-2}$
Auburn	$1.04\ 10^{-4}$	$6.20\ 10^{-1}$	$1.99\ 10^{-2}$
Borrego Springs	$1.73\ 10^{-4}$	1.44	$9.33\ 10^{-3}$
Lodi West	$1.10\ 10^{-4}$	$8.54\ 10^{-1}$	$2.05\ 10^{-2}$
Merced	$1.30\ 10^{-4}$	1.20	$1.73\ 10^{-2}$
Palmdale	$1.01\ 10^{-4}$	$7.86\ 10^{-1}$	$2.00\ 10^{-2}$

Table 13 CE values for every interpolation method in validation procedure stations

Station	IDW	NaN	OK	BSS
Arroyo Seco	77.7	78.9*	76.8	66.8
Carneros	96.1	96.2*	83.6	95.9
Green Valey Road	71.6*	69.5	70.2	65.7
King City Oasis	85.1	60.3	93.6*	64.3
Santa Barbara	47.9	72.4	78.2*	23.4
Alpaugh	95.7	95.5	96.0*	95.9
Auburn	94.4*	93.6	94.3	85.8
Borrego Springs	85.3*	81.3	<0	70.1
Lodi West	94.0*	93.7	92.9	92.3
Merced	96.9	97.1*	96.9	89.5
Palmdale	69.6	70.3	91.1*	56.0

* denotes each station's highest CE value

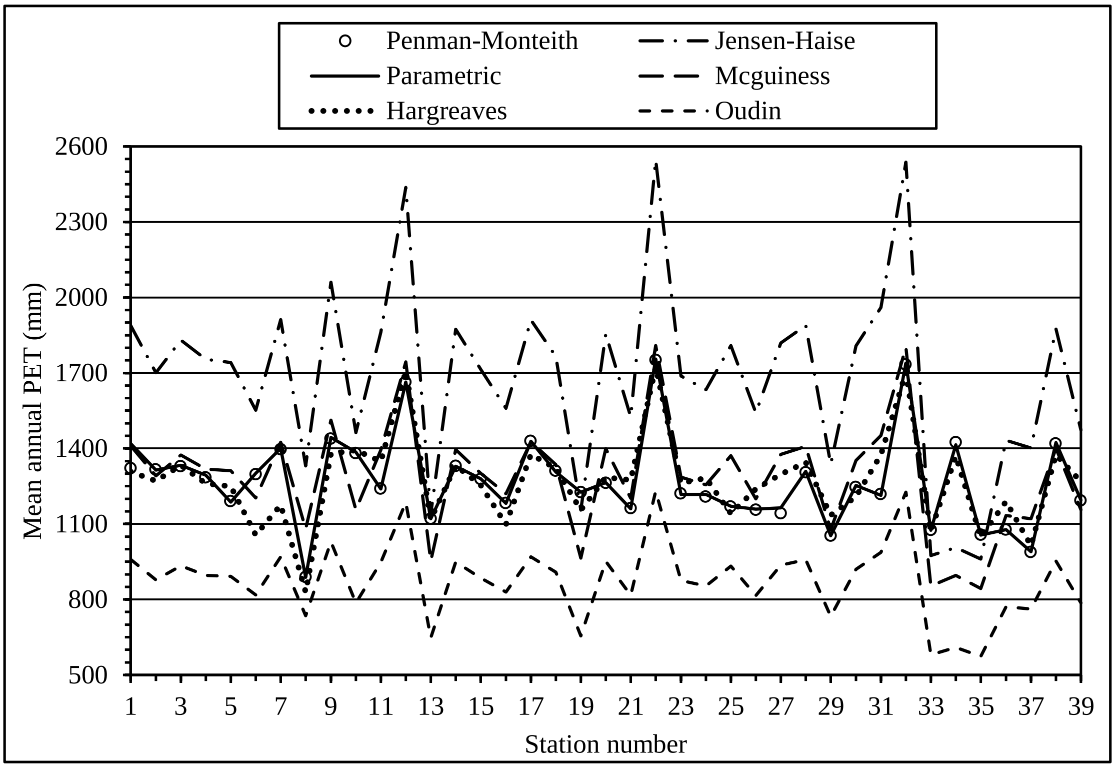

Fig. 1 Mean annual Penman-Monteith potential evapotranspiration (symbols) for the 39 CIMIS stations against the parametric model and the other four methods

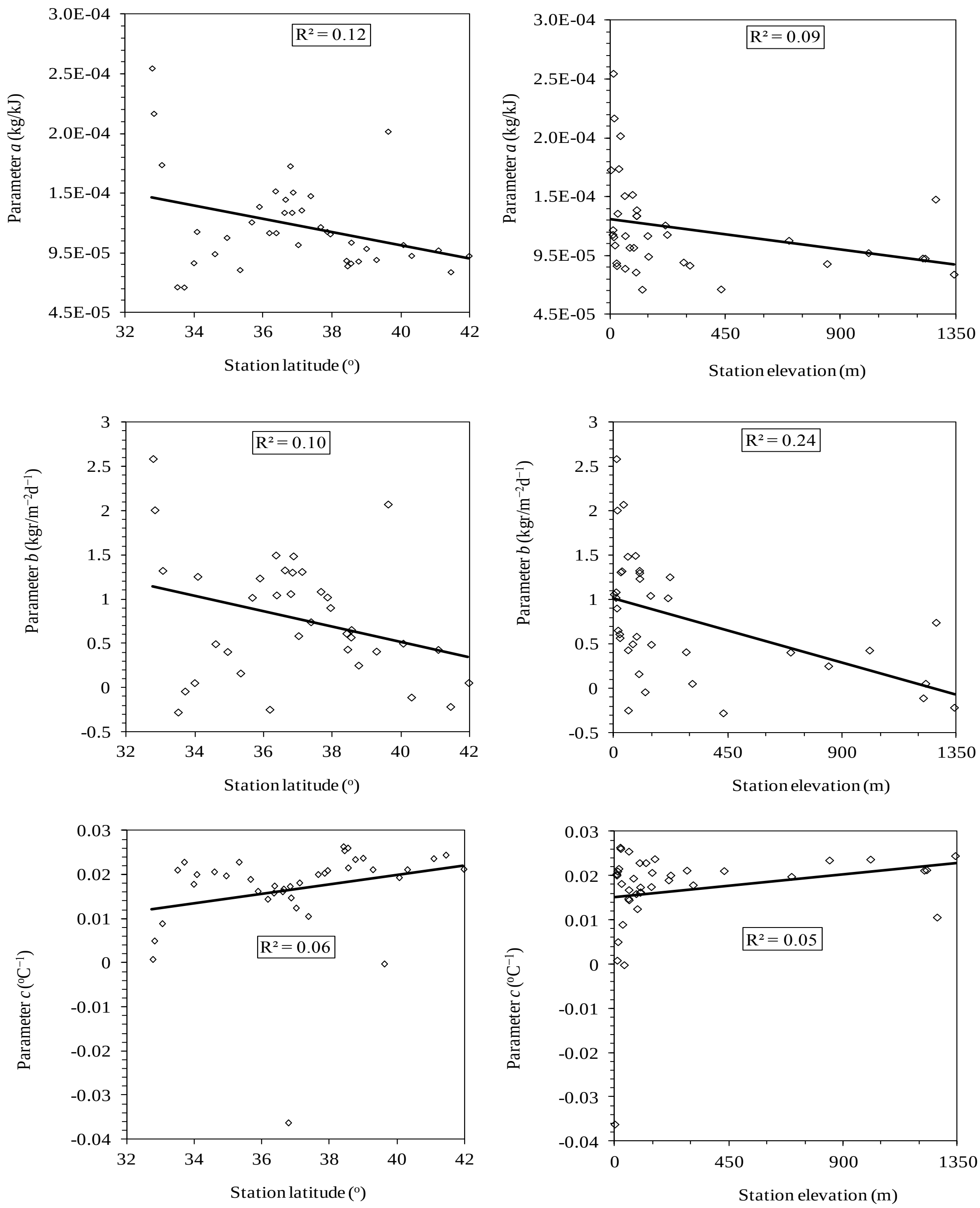

Fig. 2 Scatter plots of parameters against latitude and elevation

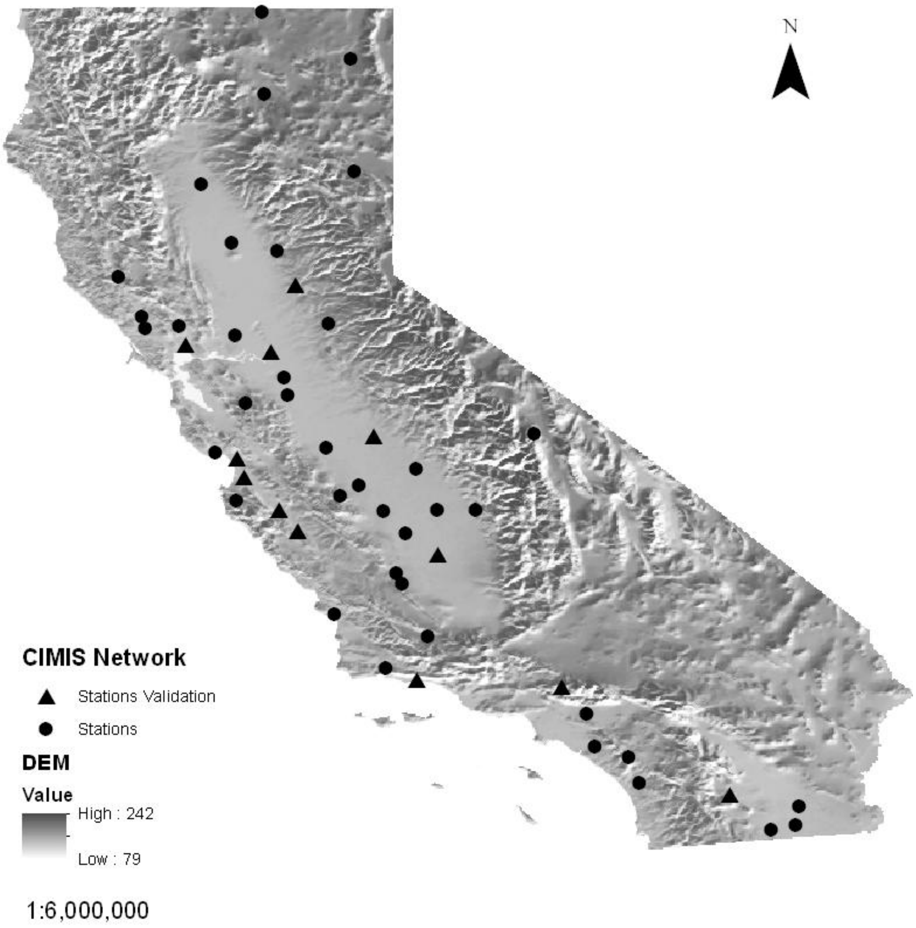

Fig. 3 Study area and the CIMIS Stations used for spatial analysis

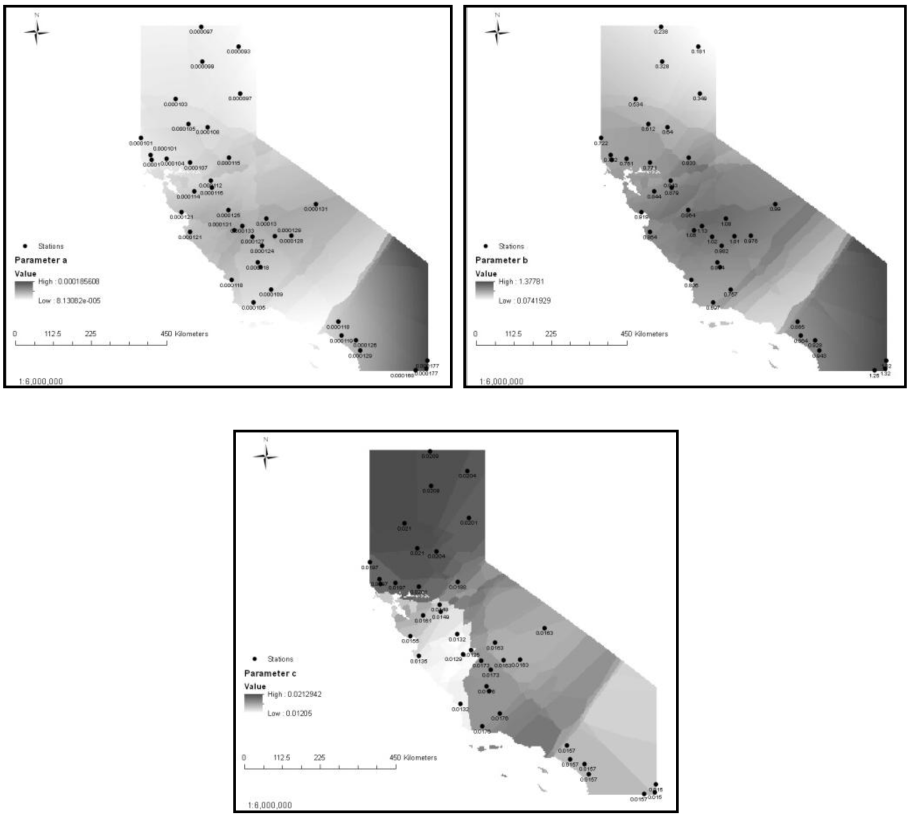

Fig. 4 Parameters maps produced by the IDW method, for the California region