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POTENTIAL EVAPOTRANSPIRATION ESTIMATION FROM PICHE EVAPORIMETER MEASUREMENTS BASED ON ADAPTIVE NEURO FUZZY INFERENCE SYSTEM TECHNIQUE

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ABSTRACT

There are different manners of estimating potential evapotranspiration **(**PET**)**; physical and empirical methods as well as special devices like pan evaporation and Piche evaporimeter. Using Piche evaporimeter data, the aim of this paper is to compare the Adaptive Neuro-Fuzzy Inference System **(**ANFIS**)** technique and empirical equations for good estimation of daily potential evapotranspiration. Piche evaporation, relative humidity and wind speed, have been used as inputs. The values of reference evapotranspiration **(**ETo**)** estimated by the Penman-Monteith equation have been used as outputs. Results showed that the ANFIS models could provide more accurate ETo estimates than empirical methods. Thus, performance criteria of the best ANFIS model are: 0.96, 0.91, 0.78 **(**mm/day**)**, 0.62 **(**mm/day**)** and 8.19 %, respectively for correlation coefficient **(**R**)**, Nash-Sutcliffe efficiency **(**E**)**, root mean squared error **(**RMSE**)**, mean absolute error **(**MAE**)** and mean absolute relative error **(**MARE**)**. This model is more useful when some meteorological parameters as temperature (T) and sunshine duration (I) are not available.

Key words: Adaptive Neuro-Fuzzy Inference System, Empirical methods, Piche evaporimeter, Potential Evapotranspiration.

INTRODUCTION

Evapotranspiration being the major component of hydrological cycle will affect crop water requirement and future planning and management of water resources **(**Goyal *et al.* 2013**)**. Evapotranspiration is a complex process because it depends on several climatic factors, type and growth stage of the crop **(**Trajković and Živković 2009**)**. For these reasons, current irrigation scheduling is based on reference evapotranspiration **(**ETo**)** procedures to estimate crop evapotranspiration **(**Hunsaker *et al.* 2007**)**; thus, improper ET calculation appears to be associated with improper estimations of ETo **(**Kang *et al.* 2009**)**. The relation of evapotranspiration to climatic factors has been studied by many hydrologists and has led to the development of various methods for estimating potential evapotranspiration **(**Paparizos *et al.* 2014**)**. Moreover, evaporation devices as pans and piche evaporimeter are extensively used throughout the world in order to estimate potential evapotranspiration (Van Nghi *et al.* 2008**)**. In this context, some authors have used directly the piche evaporimeter measurements **(**Kadi *et al.* 2014**)**, others have combined these measurements with some meteorological parameters **(**Papaioannou *et al.* 1998**)**.

According to Bei *et al*. (2014), the Piche evaporimeter is widely used in irrigation scheduling in France and other countries. Furthermore, Piche and modified atmometers could be used to estimate the crop evapotranspiration in greenhouse, providing a more exact estimation in relation to the reduced and Class A pans (Blanco and Folegatti, 2004). Anh (1995) mentioned that it is useful to say that the Piche evaporation has long records with dense measurement sites. However, to apply it in hydrological models, a Piche coefficient *Kp*, must be used. Due to the difference on sitting and weather conditions, *Kp* is often expressed as a function of local environmental variables such as wind speed, humidity, upwind fetch, etc. A global equation of *Kp* is still unavailable. Moreover, the observed Piche data show some erroneous results which are difficult to explain (Anh, 1995). Thus, Al Domany *et al*. (2013) reported that until now, there is no instrument fully satisfactory for the direct measurement of evaporation or evapotranspiration. In this context, the conclusion achieved by Van Nghi *et al*. (2008) is that the Penman- Monteith evapotranspiration is more reliable than the Piche method as well as using pan data. Nowadays, a lot of attention is paid to the application of intelligent systems in predicting natural phenomena. Adaptive neuro-fuzzy inference system (ANFIS) is one of these techniques used in this field (Daneshmand *et al.* 2015).ANFIS is a multilayer feed-forward network which uses neural network training algorithms and fuzzy logic to create an input-output correlation for fuzzy decision rules that perform well on any given task. ANFIS is the ability of combining the concepts of linguistic terms of fuzzy systems along with the numerical strength of neural networks (Lafdani *et al.* 2013). This approach has been successfully used for various water resources fields (Kouassi *et al.* 2013). The considered models for related to problems are sufficient tools to reach results within an acceptable error limits.

The main objectives of this study are, first, to apply and investigate some evapotranspiration formulas using the Piche evaporimeter measurements. Second, to investigate the potential of ANFIS for modeling Potential evapotranspiration based on Piche evaporimeter measurements recorded at arid regions of Algeria when some meteorological parameters are not available.

METHODS

Site description

Our study was carried out in the region of Adrar, located in the South-west of Algeria. Latitude: 27° 49′ N and Longitude: 00° 18′ E (Fig. 1). This region is characterized by its extreme meteorological parameters as they are detailed below.

Fig 1 Sketch of the investigation area.

Adrar’s climate is dry throughout the year. The climate is characterized by the extended thermal amplitudes during the year, the month and even the day. The absolute maximum temperature reaches 49.5°C in summer (July and August). On the contrary, ice and frosts are rare in this region. Nevertheless, icy days can cause catastrophic damage, especially to traditional farming. Furthermore, the region has recorded:

- Negligible pluviometry (<25 mm / year).
- Relative humidity often below 50%; dew is very rare.
- A north-east wind blowing almost constantly.
- Completely clear skies with intense brightness.

In this study potential evapotranspiration (PET) has been computed using empirical equations. These equations use Piche evaporation measurements and some meteorological parameters.
On the other hand, ANFIS models were performed using Piche evaporation, relative humidity and wind speed as inputs and the values of reference evapotranspiration (ETo) estimated by the Penman-Monteith equation as outputs. Evaluation of both methods was performed by comparing performance criteria of the obtained results.

Statistics of meteorological variables

In the present investigation, daily data (temperature, relative humidity, wind speed and Piche evaporation) consist of a series of daily values registered throughout the period of 2558 days (From January 2012 to December 2018). The registration of these meteorological statements was performed by the meteorological station located within the experimental site. Using these observed climatic data, daily values of ETo were computed initially using the Penman-Monteith (Eq. 1 given in the next subsection). These computed ETo values were used to train the ANFIS models. The database is divided into three subsets: 70%of data (From January 1, 2012 to November 19, 2016) are used in the training phase. 15 % (From November 20, 2016 to December 8, 2017) in the testing phase the remaining (From December 9, 2017 to December

31, 2018) is reserved for validation. The division of data into three subsets has been performed by several researches as Goyal *et al*. (2014) who they have used 40%of data for training, 30% for validation and the remaining (30%)of the data for testing purposes.

This division has numerous advantages, mainly to avoid the overfitting problem (Laaboudi *et al.* 2013) and the cross validation techniques were used to prove the consistency of the model (Shahbazikhah *et al.* 2011).

In fact, some researchers consider that validation is a kind of test; consequently, they divide their database into two subsets; 80% of total data for training and 20 % of data for testing (Bushara and Abraham, 2015), while others consider that the two phases are different and divide their database into three subsets (Pandorfi *et al.* 2016). In this context, Maier and Dandy (2000) have noted that it is common practice to divide the available data into three subsets: a training, validation and testing sets. Moreover, Bowden *et al*. (2002)have mentioned that the way that available data are divided into training, testing and validation subsets can have a significant influence on the performance of an artificial neural network but it has resulted that the performance is primarily related to the data themselves and note the choice of the ANN's parameters or architecture. As the climatic characteristics of arid zones are important in assessing the applicability of the models in general, the variations in different meteorological parameters in the study area are presented in Table 1. It can be noted that the variability range of meteorological parameters in the study area was very large. For instance, the daily values of temperature ranged between 7.1°Cand 41.6°C; relative humidity between 12.8% and 86.5%, wind speed was between 0.00 and 3.8 ms^{-1} and evaporimeter Piche data were between 2.40 and 33.00 $mm.day^{-1}$.

The statistics of meteorological variables and evapotranspiration in training, test and validation subsets indicate that the properties of all variables are similar in the three data subsets. This shows that the data structures of these three independent subsets for model construction have the same characteristics.

Table1. Statistics of meteorological variables in training, test and validation data subsets

Phases	Statistic parameters	T	RH	W.s	I	Ep Piche	ETo
Training	Min	8.0	19.0	0.0	0.00	2.40	3.34
	Max	41.6	86.5	3.6	12.45	32.00	15.28
	Mean	25.9	40.6	1.6	8.48	16.61	8.36
	Std	8.4	12.8	0.7	2.93	6.84	2.50
Testing	Min	7.1	17.5	0.0	0.00	4.50	3.46
	Max	39.3	87.5	3.8	12.00	31.00	15.28
	Mean	23.9	38.4	1.7	9.11	16.26	8.36
	Std	9.1	14.8	0.7	2.93	6.77	2.64
Validation	Min	8.5	24.0	0.0	0.00	2.60	3.32
	Max	40.8	85.0	3.6	12.30	33.00	14.09
	Mean	23.9	42.0	1.6	9.45	16.29	7.92
	Std	8.7	14.0	0.7	2.57	6.99	2.44

T mean temperature (°C), RH Relative humidity (%), W.s Wind speed ($m.s^{-1}$), and I sunshine duration ($hours.day^{-1}$), Ep.piche Piche evaporation ($mm.day^{-1}$), ETo reference evapotranspiration ($mm.day^{-1}$) and Std Standard deviation

The correlations of all input variables are presented in Table 2. This Table shows that the linear correlations between all parameters **(**except sunshine duration**)** and ETo are very high. Also, the correlation between T, RH and Ep Piche are very satisfactory. They ranged between 0.75 and 0.60 respectively.

Table 2: Correlation matrix (coefficient of correlation R) between input and output variables

	Temperature	Humidity	Wind speed	Sunshine D.	Ep Piche	ETo
Temperature	1.00					
Humidity	-0.66	1.00				
Wind speed	0.07	-0.06	1.00			
Sunshine D.	0.27	-0.32	0.09	1.00		
EP Piche	0.75	-0.60	0.37	0.32	1.00	
ETo	0.70	-0.69	0.63	0.31	0.61	1.00

All these correlations between variables are linear type but the ETo process is considered to be highly nonlinear.

It should be mentioned that the correlation between different meteorological parameters and ETo may be varied from one period to another. Thus at the same area where the correlation coefficient between mean temperature and ETo is 0.70 (Table 2), it was 0.86 during the period from 2002 to 2007 (Laaboudi et al. 2013). The similar result was obtained by Valipour et al. (2016).

Estimation of reference evapotranspiration

The Penman-Montheith equation used for calculating reference evapotranspiration was proposed by Allen *et al*. **(**1998**)**:

$$\text{ETo} = \frac{0.408\Delta(R_n - G) + \gamma \dfrac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)} \quad (1)$$

Where ETo is the reference evapotranspiration (mm day^{-1}), Rn is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} day^{-1}), T is the mean of daily air temperature at 2 m height (°C), u2 is the wind speed at 2 m height (m s^{-1}), es is the saturation vapor pressure (kPa), ea is the actual vapor pressure (kPa), es - ea is the saturation vapor pressure deficit (kPa), Δ is the slope vapor pressure curve (kPa °C^{-1}), γ is the psychrometric constant (kPa °C^{-1}).

The parameters air temperature, sunshine duration, wind speed and relative humidity are taken directly from the meteorological station and are used to estimate other parameters (Ranjbar and Rahimikhoob, 2015).

Piche Evaporation

Piche Evaporimeter is an old device used in French in most meteorological stations (Aldomany, 2017). It has been described by Angot (1928) (Fig.2**)**.

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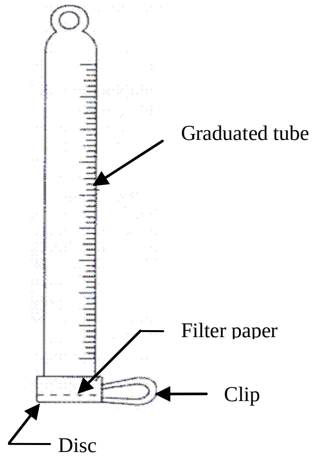

Fig 2 Scheme of Piche Evaporimeter

Use of formulas

To compute potential evapotranspiration using the Piche evaporimeter measurements, many formulas have been developed, For instance: According to Brochet and Gerbbier **(**1968**)**, a formula named“corrected Piche formula”has been developed by Bouchet **(**1963**)(**eq. 2**)**, where it was applied the energy balance method to an evaporating surface **(**filter paper**)**, which led to an expression based on extreme temperatures **(**θ**)**and dew point **(**ʎ**)** measured under shelter **(**Ben Dakhlia, 2004**)**.

1972 Brochet and Gerbier developed a simplified formula **(**eq.3**)** in which the first term depends on global radiation **(**Rg**)**and the second depends on screened Piche evaporation **(**Kumar *et al.* 2013**)**.

Inspiring from the Penman method and making $\frac{\Delta R_n}{\Delta + \gamma} = ETP_r$, Dubost and Dubost (1983) modified Brochet and Gerbier formula (eq. 4).

$$PET_1 = \alpha[1 + \text{ʎ}(\theta)]Ep \quad (2)$$

$$PET_2 = mRg + nE_p \quad (3)$$

$$PET_3 = ETP_r + nE_p \quad (4)$$

Where PET is potential evapotranspiration (mm.day^{-1}), Ep is evaporation measured by the Piche evaporimeter (mm.day^{-1}), α =0.37 for the English shelter, ʎ(θ) is a function of the air and dew point temperatures, Rn is the net radiation at the crop surface (MJ m−2 day^{-1}), Δ is the slope vapor pressure curve (kPa °C^{-1}), γ is the psychrometric constant (kPa °C^{-1}), Rg is the global solar radiation (cal/cm²/day), ETPr is the part of evapotranspiration due to the radiative energy, m and n are tabulated coefficients.

Models evaluation

The performances of models were evaluated to compare their predictive accuracies based on the following statistical criteria:

The Nash-Sutcliffe efficiency **(**E**)** was proposed by Nash and Sutcliffe **(**1970**)**. It is calculated by formula **(**5**)** according to Krause *et al*. **(**2005**)**, the square value of the correlation coefficient**(**R**)**, the root mean squared error **(**RMSE**)**, the mean absolute error **(**MAE**)** and the mean absolute relative error **(**MARE**)** were calculated as follows:

$$E = 1 - \frac{\sum_{i=1}^{n}(Y_{sim} - Y_{obs})^2}{\sum_{i=1}^{n}(Y_{sim} - \overline{Y}_{obs})^2} \quad (5)$$

$$R = \frac{\sum_{i=1}^{n}(Y_{obs} - \overline{Y}_{obs})(Y_{sim} - \overline{Y}_{sim})}{\sqrt{\sum_{i=1}^{n}(Y_{obs} - \overline{Y}_{obs})}\sqrt{\sum_{i=1}^{n}(Y_{sim} - \overline{Y}_{sim})}} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_{obs} - Y_{sim})^2}{n}} \quad (7)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_{obs} - y_{sim}| \quad (8)$$

$$MARE = \frac{1}{n}\sum_{i=1}^{n} \frac{|Y_{obs} - Y_{sim}|}{|Y_{obs}|} \text{ x } 100 \quad (9)$$

With *E* Nash-Sutcliffe efficiency, Y_{sim} simulated variable, Y_{obs} observed variable, $\overline{Y}_{sim}$ Average of simulated variable, $\overline{Y}_{obs}$ Average of observed variable, *n* number of observations.
These statistical criteria were also used to evaluate the PET formulas applied in this study and to compare their performances with ANFIS models. For the implementation of the ANFIS methods the MATLAB Toolbox was used.

RESULTS AND DISCUSSIONS

Comparison of formulas used

Potential evapotranspiration **(**PET**)** estimated from Piche evaporation tends to follow similar evolution as reference evapotranspiration ETo during the various seasons. PET_1 series is greater than all other series especially during the hot season; PET_2 and PET_3 values are slightly closed to ETo **(**Fig. 3**)**.

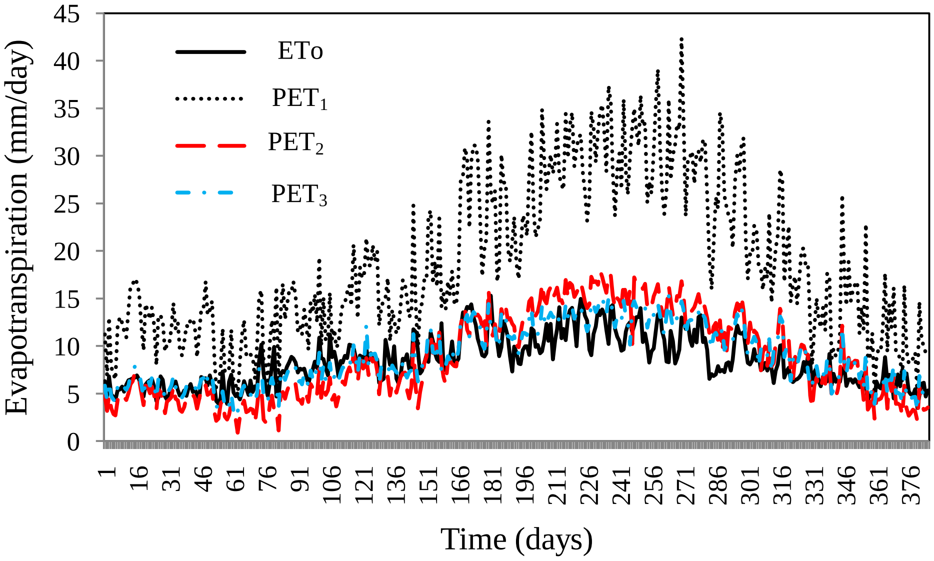

Fig 3 Graphical comparison between ETP_1, ETP_2 and ETP_3

In fact PET_1 formula has been developed in tropical regions, for this reason may be it is invalid in arid zones, so discussion will focus on PET_2 and PET_3.
Regression analysis **(**Fig.4**)** shows a close correlation between PET_3 and ETo where the correlation coefficient is large **(**over 0.84**)**. Between PET_1, PET_2 and ETo, the correlation coefficients are close to each other. They are 0.812 and 0.814 respectively.

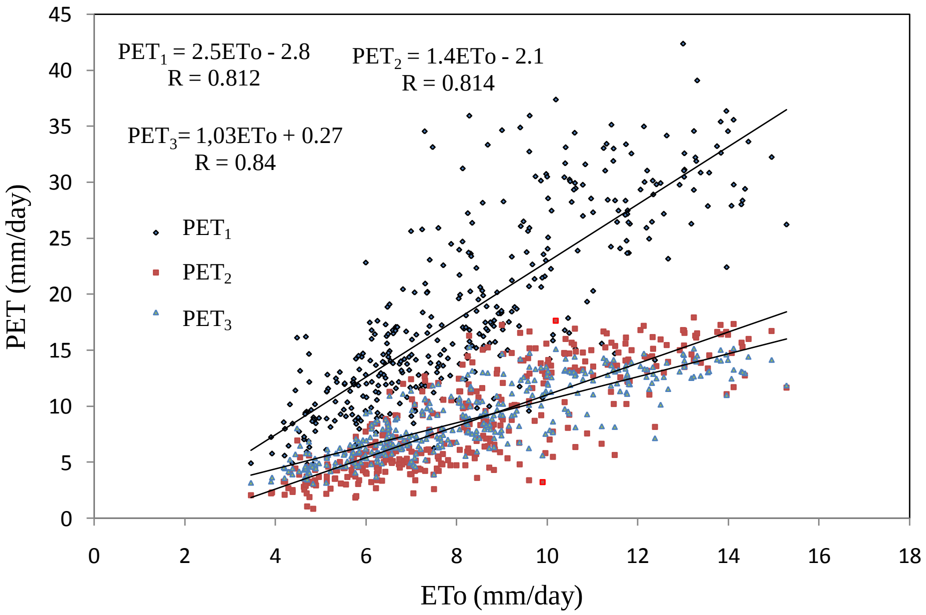

Fig 4 Correlation between PET_1, PET_2, PET_3 and ETo

Adaptive Neuro-Fuzzy Inference System

Due to the nonlinear and fuzzy behavior of evapotranspiration process, it is difficult to simulate the desired potential evapotranspiration using physically based model. According to Babuška and Verbrunggen (2003) most processes in industry and in other fields are characterized by nonlinear and time-varying behavior. Nonlinear system identification is becoming an important tool which can be used to improve control performance and achieve robust fault-tolerant behavior. Among the different nonlinear identification techniques, methods based on neuro-fuzzy models are becoming established not only in the academia but also in many application techniques. In this context, comparing between ANFIS and empirical methods for evapotranspiration estimation, Tabatabaee *et al*. (2014) have showed that accurate with ability method is ANFIS and also is more precise than empirical models.

To find out the best model in among the all ANFIS models 50 and 100 epochs, 2 and 4 number of membership functions were tried for each model, Here, an ANFIS (2, gbellmf, linear) indicates a model having 2 generalized bell membership functions for each input and the output is linear (Table 3). Result shows that the ANFIS (2, gbellmf, linear) model (model 4) performed better than the other models with 2 membership functions (RMSE= 0.772 in training phase). Model 5; ANFIS (2, gauss2mf, linear) is the best one in testing phase (RMSE = 0.775).

Table 3: R and RMSE values of the ANFIS models in training and testing phases

Models	MF	Number of MF	Training phase		Testing phase	
			R	RMSE	R	RMSE
Model 1	Trimf	2	0.951	0.777	0.954	0.795
Model 2	Trapmf	2	0.951	0.774	0.956	0.781
Model 3	Psigmf	2	0.951	0.777	0.956	0.776
Model 4	Gbellmf	2	0.951	0.772	0.956	0.776
Model 5	gauss2mf	2	0.951	0.774	0.956	0.775
Model 6	gauss2mf	3	0.956	0.739	0.948	0.845
Model 7	gauss2mf	4	0.962	0.687	0.729	2.264

Mf membership function, R Correlation coefficient, RMSE root mean squared error($mm.day^{-1}$), tri Triangular, trap Trapezoidal psig Product of two sigmoidally, gbell Generalized bell, gauss2mf Gaussian combination.

Increasing number of membership functions more than 2,enhances the model performance in training phase but decreases it in testing and validation phases, Thus, ANFIS (2, gauss2mf,linear) is better than ANFIS (3, gauss2mf, linear) and ANFIS (4, gauss2mf, linear), in testing phase. The R values are 0.956. 0,948 and 0.729 respectively for 2, 3 and 4 membership functions. These values are higher than values of R = 0.67 and R = 0.93 obtained by Dinesh *et al*. (2011) and by Areerachakul (2012) respectively, but they are much closed to 0.956 obtained by Kumar *et al*. (2012) in testing phase. The ANFIS structure used for this study with three inputs and one output is presented in Fig.5.

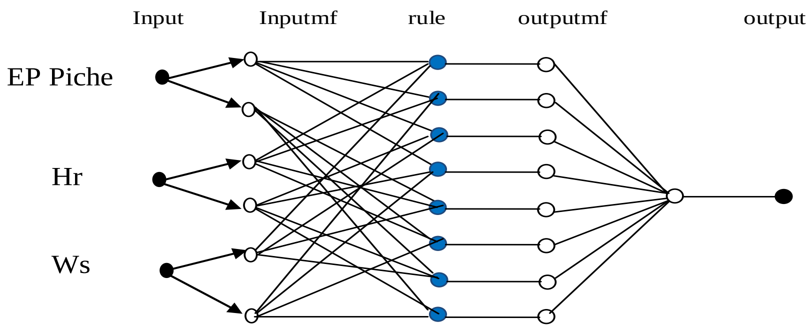

Fig 5 ANFIS structure used for this study with three inputs and one output

In order to apprehend the potential input variables affecting the ETo process, several input combinations have been performed (Table 4). This may help to understand the weather influence on ETo. The results showed that sunshine duration parameter has a slight effect on ETo. Thus, the statistical test showed that the difference between the PET with and without sunshine duration was no significant (F= 0.999 with 384 and 384 degrees of freedom for the F test, T= 0.0038 with 384 degrees of freedom for the T test, α =0.05).

Moreover, the presence of EP Piche as input into model reduces the temperature effect on ETo. We have noted that with additional of inputs, the results could be less than satisfactory. This is due probably to the complexity of ANFIS structure. In this context Goyal *et al*. (2014) have found that ANFIS model provided the best validation and testing performance when using 3 input variables instead of 5 input variables. Thus, it is possible to perform an accurate model without these two climatic parameters. The combination; EP Piche, relative humidity and wind speed **(**model 7**)**, shows some very satisfactory results **(**Table 4**)**.

Table 4: ANFIS input data structure in testing phase

Models	Inputs	R	E	RMSE	MAE	MARE
Model (1)	EP	0.841	0.465	1.447	1.124	13.902
Model (2)	EP,T	0.824	0.489	1.499	1.171	14.350
Model (3)	EP, I	0.848	0.587	1.411	1.100	13.290
Model (4)	EP, Rh	0.858	0.617	1.358	1.062	12.796
Model (5)	EP, T, Rh	0.859	0.621	1.353	1.050	12.636
Model (6)	EP, Ws	0.900	0.756	1.153	0.920	12.190
Model (7)	EP, Rh, Ws	0.956	0.908	0.776	0.622	8.189
Model (8)	EP, T, Rh, Ws, I	0.962	0.923	0.733	0.524	6.964
Model (9)	EP, T, Rh, Ws	0.964	0.924	0.704	0.534	7.176

EP evaporation of Piche (mm.day^{-1}), R correlation coefficient, E The Nash-Sutcliffe efficiency, RMSE root mean squared error (mm.day^{-1}), MAE mean absolute error (mm.day^{-1}), MARE mean absolute relative error (%), T mean temperature (°C), Rh Relative humidity (%), Ws Wind speed (m.s^{-1}), and I sunshine duration (hours.day^{-1}).

The observed and simulated values of evapotranspiration are shown in Figure 6 for testing period with the best ANFIS model. Visual inspection of figure shows that, there is a fairly good agreement between the estimated and the observed values of evapotranspiration, and overall shape of the plot of estimated evapotranspiration is similar to that of the observed evapotranspiration.

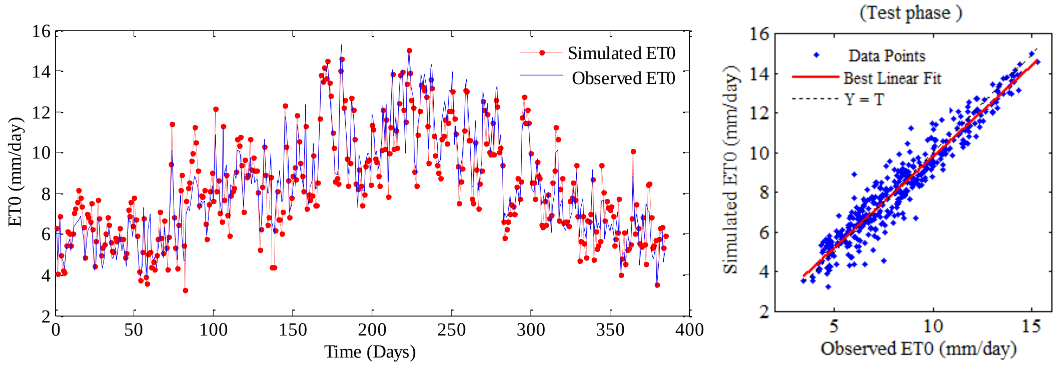

Fig 6 Graphical comparison of observed and simulated ETo series and scatter plot for the best fit ANFIS model in testing phase

Its corresponding scatter plot for the best fit ANFIS model to represent study of evapotranspiration clearly give the information of the best fit modeling for the study location with R value = 0.956.

When we compared the performance criteria of testing phase with those of PET_2 and PET_3, we found that the performance criteria of ANFIS model were more interesting. All statistical parameters used showed that the ANFIS model is better than the empirical models **(**Table 5**)**.

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Table 5: Comparison of performance criteria values for ANFIS and empirical models in testing phase

Performance criteria	PET_2	PET_3	ANFIS
R	0.81	0.84	0.956
E	0.61	0.69	0.908
MSE (mm/day)²	8.15	3.35	0.602
RMSE (mm/day)	2.86	1.83	0.776
MAE (mm/day)	2.36	1.38	0.622
MARE (%)	29.00	16.84	8.189

PET_2 potential evapotranspiration form equation 2, PET_3 potential evapotranspiration form equation 3, MSE mean squared error (mm/day)²

The MARE **(%)**, i.e., the percentage of recorded errors between real and simulated values of ETo indicates the higher performance of the ANFIS technique over empirical methods. MARE value (8.189 %) obtained by ANFIS method in this study is lower than 16.43 % and 17.50 % obtained by both ANFIS techniques used by Zakhrouf et al. (2019).

Figure7 demonstrates the observed values of ETo compared with the estimated values from the PET formulas and adaptive neuro-fuzzy inference system model.

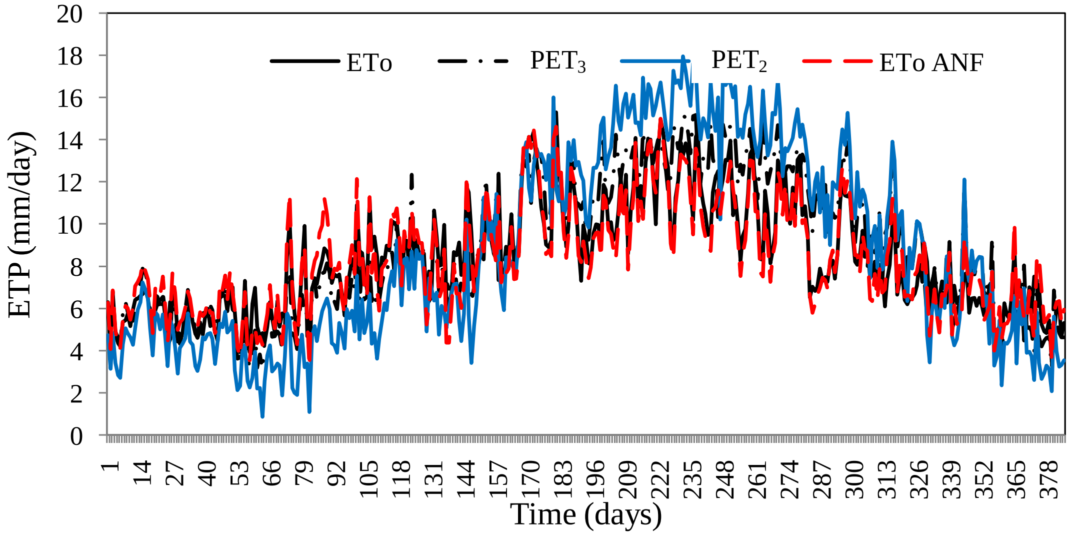

Fig 7 Comparison between evapotranspiration values; P-M (ETo), ANFIS (EToANF) and empirical models (PET_2, PET_3) in testing phase

The graph illustrates that predicted values from ANFIS is closer to the observed values than those computed from PET formulas.

In order to evaluate the correlation between the observed values of the ETo and the simulated values of both training and validation phases, we plotted them in graphs as shown in Figure 8.

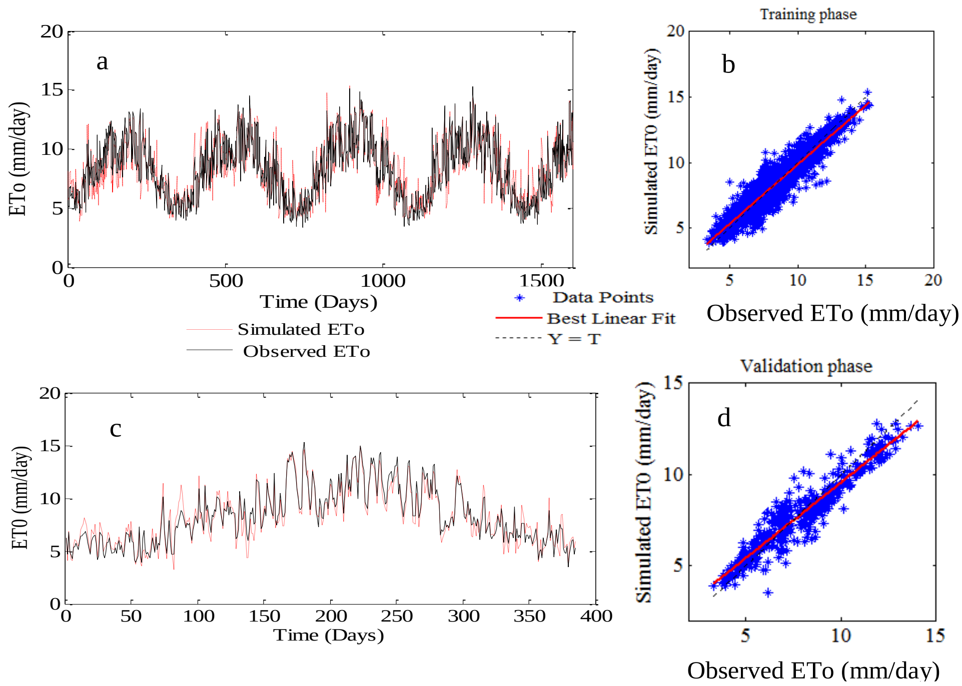

Fig 8 Evolution of observed series and simulated series of ETo and their corresponding scatter plots in training (a, b) and validation (b, c) phases

The result reveals a high resemblance between the observed and simulated series of ETo values and shows scattered points distributed statistically around the line y = x. This shows a very good agreement that explains a high correlation coefficient between the training and validation phases. We mentioned that most of the values predicted with ANFIS lie near the y = x line. Further, this study concludes that a combination of EP Piche evaporation, mean relative humidity and wind speed provides better performance in predicting ETo when T and I are not available.

It was noticed that R^2 for modeled with ANFIS has reached highest value in testing phase. Also lowest values of error **(**RMSE, MAE and MARE**)** were obtained in this method.
According to values of statistical indicators, first method modeled using ANFIS has best performance among the studied methods. Also, by visual observation it is concluded that ANFIS model is better than empirical methods for potential evapotranspiration estimation.
Overall, the ANFIS model provided the best ETo estimates among the potential evapotranspiration formulas using Piche evaporation measurements.
Finally, it is inessential to make periodic estimates of ETo using a high-performance method because, according to Seung and Truong (2019), under the effect of climate change, the water requirement of crops were increased.

In the end, it is useful to say that, it is essential to make periodic estimates of ETo using a high-performance method because, according to Seung and Truong (2019) under the effect of climate change, the water needs of crops were increased.

CONCLUSIONS

In this study has been made to analyze and compare evapotranspiration formulas using the Piche evaporation measurements, adaptive neuro fuzzy inference system **(**ANFIS**)** to well estimate reference evapotranspiration.

The results of prediction ETo indicated that the measured correlation between predicted and observed data using empirical methods were overall non satisfactory.

With a suitable architecture, the ANFIS model for prediction of ETo revealed the most reliable prediction because the performance indices between predicted and experimental data showed higher accuracy comparing with PET formulas. These results are quite encouraging and suggest the usefulness of ANFIS based modeling techniques for accurate prediction of evapotranspiration as an alternative to empirical methods. Furthermore, the results obtained confirm that ANFIS technique have become powerful tools for modeling in many varied fields of research. Accuracy and the user's required qualities justify the choice of this approach. Using ANFIS in the prediction can result in satisfactory findings. Moreover, Piche evaporimeter measurements could replace some parameters as temperature and sunshine duration in area study conditions. The main disadvantage of ANFIS technique is the complexity of implementation with additional of inputs or membership functions. This task required more time and the results could be less than satisfactory. As a whole, the findings of this study revealed that the ANFIS model can be employed successfully in reference evapotranspiration estimation using Piche evaporation measurements.

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