A COMPARATIVE EVALUATION OF ARTIFICIAL NEURAL NETWORK MODELS AND EMPIRICAL METHODS IN ACTUAL EVAPOTRANSPIRATION ESTIMATION (CASE STUDY: AMMAMEH REPRESENTATIVE CATCHMENT)

EVALUATION COMPARATIVE DES MODELES DU RESEAU DES NEURONES ARTIFICIELS ET DES METHODES EMPIRIQUES DANS L'EVALUATION ACTUELLE D'EVAPOTRANSPIRATION (ETUDE DE CAS: BASSIN VERSANT D'AMMAMEH)

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ABSTRACT

Actual evapotranspiration (ET) is a basic term in the hydrology cycle and water balance of catchment. In this research an artificial neural network, with multilayer perception structure, and empirical equations Advection–Aridity of Granger and Gray and Combination Equations was adapted and evaluated to model ET by means of conventional climatic data. The estimates of the models are also compared with those of the monthly actual ET of Ammameh catchment obtained through water balance equation. Combination Equation with R^2 of 0.84 and RMSE of 0.46 performed better than the other empirical models.

The best ANN model between 13 different combination and empirical model is ANN5 with minimum, maximum temperature and pan evaporation in the model input and with R^2 of 0.88 and RMSE of 0.32 mm per day.

The ANN1 with Minimum and maximum temperature as model inputs, with R^2 of 0.83 was a poor performer, but the R^2 differed by only 1% when compared to the performance of the

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Combination Equation with eight climate parameter input. The R^2 in ANN14 is 2% better than with combination Equation. Also ANN3 with R^2 of 0.87 and accuracy 0.32 mm per day, with only combination of air temperature and wind speed is an appropriate model due to approximating the superior accuracy of ANN1 and toward ANN5 on account of lesser data requirement. The results of research show that actual evapotranspiration can be estimated successfully with 6% difference in R^2 in comparison with Combination Equation using available climate data.

Key words: *Evapotranspiration, Artificial neural network models, empirical methods, water balance, Jajroud river catchment.*

RESUME ET CONCLUSIONS

L'évapotranspiration réelle (AET) est un terme de base dans le cercle l'hydrologie et le bilan hydrique des bassins versants. Corriger détermine dans le bilan hydrologique, gestion des ressources hydriques, faire des barrages et des eaux de surface est de réglementer problème important pour l'ingénierie de l'eau.

Dans cette recherche d'un réseau de neurones artificiels, avec structure perception multicouche, et des équations empiriques advection-aridité (AA), Granger et Gray (GG) et la combinaison des équations (CE) a été adaptée et évaluée de modéliser cette importante par des procédés classiques de données climatiques record dans les stations climatériques. Les estimations des modèles sont également comparées à ceux de l'évapotranspiration réelle mensuelle du bassin versant Ammameh moyen de l'équation du bilan hydrique. Combinaison équation avec un coefficient de détermination de 0,84 et l'erreur quadratique moyenne 0,46 de meilleurs résultats que les autres modèles empiriques.

Le meilleur modèle ANN entre 13 combinaisons différentes et le modèle empirique est un modèle avec un minimum d'ANN5, température maximale et de l'évaporation dans la casserole d'entrée du modèle et avec un coefficient de détermination de 0,88 et l'erreur quadratique moyenne 0,32 mm dans la journée.

Températures minimale et maximale en entrée du modèle (ANN1), avec 0,83 coefficient de détermination est la plus faible des résultats, mais en combinaison avec l'équation comparer les huit entrées paramètre climatique existe seulement un pour cent déférent entre le coefficient de détermination. Coefficient de détermination dans le modèle ANN14 est de deux pour cent de beter avec la combinaison équation. Également le modèle ANN3 avec un coefficient de détermination de 0,87 et 0,32 mm dans la précision chaque jour, avec la combinaison de la température que l'air et la vitesse du vent est le modèle approprié pour une précision supérieure vers ANN1 modèle et les données exigence Lesser vers ANN5 modèle. Le résultat de la recherche montre que l'évapotranspiration réelle peut être estimée avec succès avec six pour cent du coefficient de détermination comparé avec la combinaison de l'équation au moyen des données climatiques disponibles.

Mots clés : *Evapotranspiration, modèles du Réseau des Neurones Artificiels, méthodes empiriques, water balance, bassin versant de Jajroud.*

(Traduction française telle que fournie par les auteurs)

1. INTRODUCTION

Actual evapotranspiration (ET) estimates are necessary for integrated water resources management and modeling studies related to hydrology, agronomy, forestry, irrigation, flood and lake ecosystems (Terzi and Keskin 2005).

Although there is an adequate network of stations at which precipitation is measured, very few measurements of the ET are made in Iran. With respect to ET from a catchment, it is very difficult to measure it directly. Two kinds of indirect methods are used to calculate actual ET from a catchment. The first kind uses water balance of the catchment. The accuracy of actual ET estimates from this method depends on the accuracy of runoff and precipitation data, and represents only an average value for the entire catchment. The other kind uses climatic data. Many of the formula have been used to estimate potential ET using climatic data, and they require the condition that the area in question should have actively transpiring vegetation and an adequate fetch (Penman, 1961). This paper describes three empirical models for estimating actual ET from Ammameh catchment.

Determination of AET is complex and nonlinear phenomenon because it depends on several interacting climatological factors. Artificial neural network (ANN) is a tool that can be used to estimate AET.

In the recent decades, much effort has been made to the use of Artificial Neural Network (ANN) models in various sciences. Research results on water resources show that are shown the ANNs are suitable alternative for such model that predict runoff from rainfall, river flow, entrance flow to the reservoir, sediment load and ET0 (Sudheer et al, 2004; Kisi 2004 and 2005; Trajkovic et al 2003, Coulibaly et al 2000).

Also some studies have shown that ANN models have more accuracy than conventional models (Kumar et al, 2002).

Review related to the use of ANN models for estimating ET show that several models for estimating ET0 has been developed (Trajkovic et al, 2003; Sudheer et al, 2003; Kisi, 2007; Jianbiao,2002). But their use for estimating actual ET is limited to Sudheer's (2003) research. They investigated the ANN model's ability to estimate daily ET by using weather data for rice field. Comparison of their results with those of lysimeter studies, showed that these models have a good accuracy (Sudheer et al, 2003).

This study attempts to evaluate the comparative performance of empirical equations and ANN in determining the actual ET from Ammameh catchment. The estimates of the models are also compared with those of the monthly actual ET of Ammameh catchment that was measured by using water balance equation.

1.1 Study catchment and data base

The Ammameh catchment was selected to demonstrate the methodology and algorithms investigated in this paper. The Ammameh catchment (37.2 km^2) is one of the alpine subcatchments of Jajroud River, in Iran. It is rocky and has steep slopes. The Kamarkhani station at the downstream end of the catchment records daily discharge information. Average annual precipitation is 567 mm. The dominant land use of the catchment is pastures. All the stream flows through the catchment during January to May were attributed to snowmelt during this period, as the area is mountainous with little ground water contribution. The monthly climatic data of three automated weather stations, Ammameh (at the middle of the Catchment) (Latitude 35° 54'N, Longitude 51° 35'W), Rahatabad (Latitude 35° 53'N, Longitude 51° 37'W) and Kalokan Station (Latitude 35° 53'N, Longitude 51° 32'W) are used in the study. The data sample consists of thirty five years (1970–2005) of monthly records of air temperature (T), solar radiation (Rs), wind speed (U2), precipitation (P), humidity (RH) and pan evaporation (E). For each station, 70% of the whole data (348 monthly values) are considered for training and the remaining 30% (72 monthly values) for testing. The location of the Ammameh catchment is shown in Figure 1.

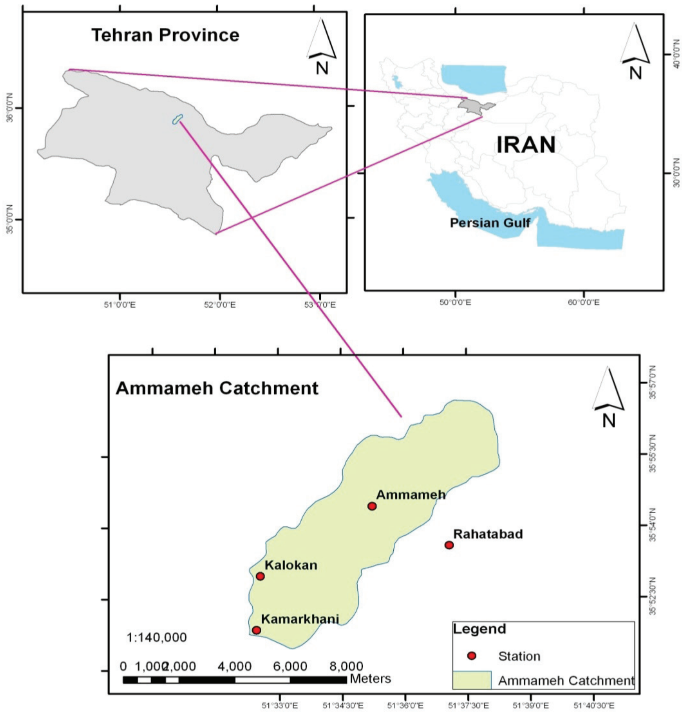

Fig. 1. Location of the catchment and climatological stations (Situation des bassins versants en Iran et en stations climatologique étudiées région)

2. THEORY AND METHODS OF DATA ANALYSIS

2.1 Water balance analysis

Water balance checks in the catchment showed that it was watertight, which is a condition to be satisfied to make water balance equation useful for estimation of AET, within the accuracy of other hydrological measurements.

Streamfow data were organized in chronological order and daily hydrographs were drawn (Figure 2). The hydrographs displayed a number of troughs and crests from which identical recession limbs were used to discern the time interval over which a water balance equation was applied in a simple form. From the hydrograph, two points with equal discharges (say 1 and 2 as shown in Fig. 2) were chosen, each on recession limbs. The water balance equation between points 1 and 2 is:

$$P_t = R_t + AET_t \pm \Delta S_t \quad (1)$$

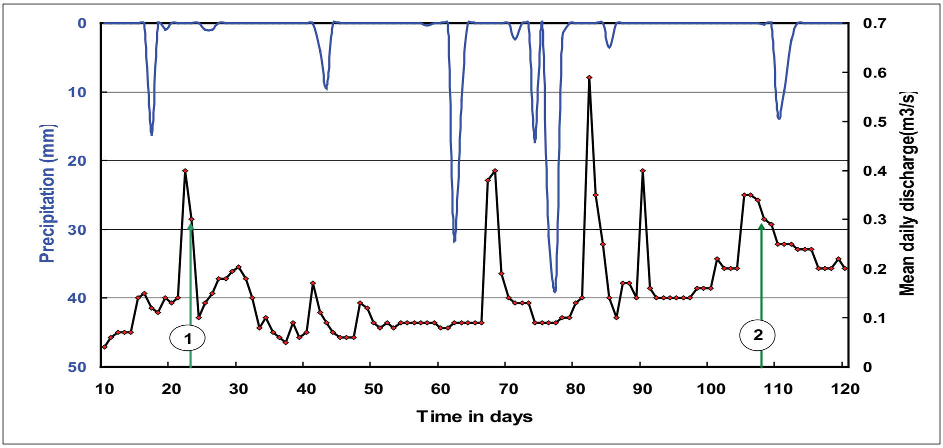

Fig. 2. Mean daily discharge hydrograph for Ammameh catchment (Hydrogramme moyenne quotidienne de rejet pour le captage ammameh)

where t is the time interval between points 1 and 2 in days, and AETt , Pt , Rt and ΔSt represent actual ET, rainfall, runof and change in storage, respectively, in depth units (mm) over time interval t.

The catchment was assumed to obey the linear law (S = Kq), where S is the storage (m^3), K is the storage parameter (days) and q is the discharge (m^3/s). Therefore, for points 1 and 2 showing the same discharge, ΔSt = 0 and Equation (1) becomes:

$$AET_t = P_t - R_t \quad (2)$$

The value of runof was obtained as the area of the shaded region, whereas Pt was obtained as the sum of daily rainfall between points 1 and 2. Taking the hydrograph of one of the catchments given in Figure 2 as an example (1970-1971: October, November, December and January), the rainfall between points 1 and 2 (99 days) was 170.9 mm, while the runoff was 33.8 mm.

$$AET\ (99\ days) = 170.9 - 33.8 = 137\ mm, \quad \therefore AET = \frac{137}{99} = 1.4 mm/day \quad (3)$$

The other segments, as indicated by the vertical lines, were also used to estimate AET over corresponding time intervals. The AET for a given month was evaluated as the average of all the segments that could be isolated in that given month.

2.2 Artificial neural network (ANN)

In this study, an ANN of the multilayer perceptron (MLP) type with one-input layer, one-hidden layer and one -output layer was used. The transfer function in the networks was SigmoidAxon (SI) and TanhAxon (TH). Backpropagation (BP) algorithm was employed to train the MLP neural network. Conjugate-Gradient (CG) and Levenberg-Marquardt (LM) algorithm was used with an early stopping criterion to improve the network training speed and efficiency. For the criterion, all the data were divided into three sets (Coulibaly et al. 2000). The first set is the training set for determining the weights and biases of the network. The second set is the validation set for evaluating the weights and biases and for deciding when to stop training. The last data set is for validating the weights and biases to verify the effectiveness of the stopping criterion and to estimate the expected network operation on new data sets. In this study, for training the network, the data were divided into two parts: The first part (228 patterns) was used for network training and the second part (72 patterns) was used for testing the trained network. Seventy percent of the training set was reserved for training the ANN and 30% were used to validate the training.

Since the purpose of this study was the estimation of AET, the ANN has only one output variable. The measured monthly AET (by means of Water balance analysis) values were employed for output values. The number of hidden nodes in the ANN is determined empirically by trial and error, considering the need to derive reasonable results. In order to suit the consistency of the model, all source data are firstly normalized in the range [0.0, 1.0] and then returned to original values after the simulation using equation 3:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

where X_{norm} is the normalized value; X is the original value; X_{min} and X_{max} are the maximum and minimum of original values. Twelve input structures of the climatic data are shown in Table 1.

Table 1. The models climatic inputs data in artificial neural network (Les modèles climatiques les données entrées dans le réseau de neurones artificiels)

Model	Inputs parameters	Model	Inputs parameters
ANN1	Tmin,Tmax	ANN7	Tmin,Tmax,Ra
ANN2	Tmean,RS	ANN8	Tmin,Tmax,Epan,RH
ANN3	Tmean,U2	ANN9	Tmean,RS,RH,U2
ANN4	Tmean,RH	ANN10	Tmin,Tmax,Ra,RH
ANN5	Tmin,Tmax,Epan	ANN11	Tmin,Tmax,Epan,RH,U2
ANN6	Tmean,RS,RH	ANN12	Tmin,Tmax, Ra,RH,U2
		ANN13	Tmin,Tmax, RS,RH,U2

2.3 Empirical equations

2.3.1 CE model

The Penman equation is widely known as the combined equation model for estimating evaporation. It was developed originally to estimate the potential evaporation of water and saturated land surfaces and is usually expressed as

$$E_{pen} = \frac{\Delta}{\Delta+\gamma}\frac{R_n}{L} + \frac{\gamma}{\Delta+\gamma} f(u)(e_{sa} - e_a) \quad (5)$$

in which Epen (mm day^{-1}) is the potential evaporation, Rn (W m^{-2}) is the net radiation, L is the latent heat of vaporization, Δ (mbar ºC^{-1}) is the ratio of change of vapour pressure with respect to temperature, e_{sa}(mbar) is the saturation vapour pressure of the air, e_a (mbar) is the vapour pressure of the air, and f(u) is the function of wind speed at 2 m above the ground. The spatially distributed net radiation Rn and wind function f(u) may be estimated by the following equations,

$$R_n = (1-\alpha)I_H(0.18 + .55\frac{n}{N}) - \sigma(T_a + 273)^4(0.56 - .092\sqrt{e_a})(0.1 + 0.9\frac{n}{N}) \quad (6)$$

$$f(U) = 0.35(1 + 0.54U_2) \quad (7)$$

in which I_H is the incident global radiation (Wm^{-2}); n(h) is the sunshine duration, N(h) is the maximum possible sunshine duration, σ is the Stefan–Boltzmann constant = (5.67 x 10^{-8}) Wm^{-2} K^{-4}, T_a ºC is the air temperature, and α is albedo, a measure of surface reflectivity and dependent on the nature of surface, the water content of the soil, solar altitude, and the atmospheric conditions. In Equation (5), the first term represents a lower limit on the evaporation from moist surfaces; the second term represents the effects of large-scale advection (Hobbins et al., 2001a). In order to convert the potential ET to the actual ET, a conversion factor φ with a value of 0.6–0.8 was proposed by Penman (1948) as follows:

$$E_a^{CE} = \varphi E_{Pen} \quad (8)$$

With the combination of the actual ET data measured by a weighing lysimeter, with both diameter and length of 2 m, as well as other related meteorological data, the following equation was proposed by Kotoda (1986):

$$\varphi = 0.468 + \frac{(0.5P + 21.9T - 23.6U)}{1000} \quad (9)$$

in which P (mm month^{-1}) is the precipitation, T (ºC) is the air temperature, and u(ms^{-1}) the wind speed 1.6 m above the ground. The effect from rooting depth and interception losses is partly covered by the inclusion of precipitation in Equation (9).

2.3.2 AA model

In the AA model (Brutsaert and Stricker, 1979), the ETp is calculated by combining information from the energy budget and water vapour transfer in the Penman (1948) equation:

$$ETp = \frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda} + \frac{\gamma}{\Delta+\gamma}E_a \qquad (10)$$

where Rn is the net radiation near the surface, Δ is the slope of the saturation vapour pressure curve at the air temperature, γ is the psychrometric constant, λ is the latent heat, and Ea is the drying power of the air, which in general can be written as

$$E_a = f(U_Z)(e_S - e_a) \qquad (11)$$

where $f(U_z)$ is a function of the mean wind speed U_z at a reference level z above the ground, and e_a and e_s are the vapor pressure of the air and the saturation vapor pressure at the air temperature respectively. In this study, the empirical linear approximation for $f(U_z)$ originally suggested by Penman (1948) is used:

$$f(U_Z) = 0.0026(1+0.54U_2) \qquad (12)$$

which, for wind speed at 2 m elevation in ms^{-1} and vapor pressure in Pascal, yields Ea in mm day^{-1}. This formulation of f(U2) was first proposed by Brutsaert and Stricker (1979) for use in the AA model operating at a time scale of a few days. Substituting Equation (11) and the wind function Equation (12) into Equation (10) yields the expression for ETp used by Brutsaert and Stricker (1979) in the original AA model:

$$ET_P^{AA} = \frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda} + \frac{\gamma}{\Delta+\gamma}f(Uz)(e_S - e_a) \qquad (13)$$

The AA model calculates ETw (Brutsaert and Stricker, 1979) using the Priestley and Taylor (1972) partial equilibrium ET equation:

$$ET_W^{AA} = \alpha\frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda} \qquad (14)$$

where α =.1.26. Different values for α have been reported in the literature; the original value is tested in this study. Substitution of Equations (13) and (14) into Equation (15) results in the expression for ETa in the AA model:

$$ET_a^{AA} = (2\alpha-1)\frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda} - \frac{\gamma}{\Delta+\gamma}\left[f(U_2)\right](e_S - e_a) \qquad (15)$$

2.3.3 GG model

Granger (1989) showed that an equation similar to Penman's could also be derived following the approach of Bouchet's (1963) complementary relationship. Granger and Gray (1989) derived a modified form of Penman's equation for estimating the actual evapotranspiration from different non-saturated land covers:

$$ET_a^{GG} = \frac{\Delta G}{\Delta G + \gamma}\frac{R_n}{\lambda} + \frac{\gamma G}{\Delta G + \gamma} Ea \tag{16}$$

where G is a dimensionless relative evapotranspiration parameter. Granger and Gray (1989) showed that the relative evapotranspiration, the ratio of actual to potential evapotranspiration, G = ETa/ETp is a unique parameter for each set of atmospheric and surface conditions. Based on daily estimated values of actual evapotranspiration from water balance, Granger and Gray (1989) showed that there exists a unique relationship between G and a parameter that they called the relative drying power D, given as:

$$D = \frac{E_a}{E_a + R_n} \tag{17}$$

$$G = \frac{1}{1 + 0.028 e^{8.045 D}} \tag{18}$$

And later, Granger (1998) to modified Eq. (14)

$$G = \frac{1}{0.793 + 0.20 e^{4.9002 D}} + 0.006 D \tag{19}$$

2.4 Criteria of evaluation

The performances of the models developed in this study were evaluated using R^2 and RMSE criteria, which are calculated as:

$$R^2 = \frac{\left[\sum (Y_i - \overline{Y})(X_i - \overline{X})\right]^2}{\sum (Y_i - \overline{Y})^2 (X_i - \overline{X})^2} \tag{20}$$

$$RMSE = \sqrt{\frac{\sum (Y_i - X_i)}{N}} \tag{21}$$

In the above, N is the number of measured, Yi is the estimated AET (using the ANN methods), Xi is the measured AET (calculated with Water balance analysis), $\overline{X}$ and $\overline{Y}$ are the average value for Xi and Yi. The RMSE is a measure of the residual standard deviation and should be as small as possible (optimally 0).

3. CONCLUSIONS AND RECOMMENDATIONS

In this study, the ability of artificial neural network models and empirical relations for estimating actual monthly evapotranspiration were assessed. Due to careful analysis of appropriate water balance in calculating the actual evapotranspiration, results of water balance as a base for comparison were used in this study (Karongo et al, 1977; Sharma, 1988; Kotoda, 1989; Morton, 1983; Chun, 1989).

The results of simulation show the superiority of neural network models in comparison with the empirical relationships. According to the results of Table (2), the combined equation (CE) has higher accuracy and its R^2 is about 6% higher as compared with the two empirical equations.

Various neural network models to estimate real evapotranspiration were developed by a hidden layer and their results are presented in Table 2. As may be seen, the 52 neural network models with different input parameters, Levenberg-Marquardt training algorithm, Marquardt (LM) and Conjugate-Gradient (CG) and two types of stimulation sigmoid function (SI) and TanhAxon (TH) were constructed. Number of neurons in middle layer of these models was determined by trial and error method. Thus every model was trained 30 times with the number of neurons 0 to 30 in hidden layer, and then tested using the RMSE and R^2 criteria.

Lowest RMSE for each model with the desired profile was considered to select the best number of neurons in the middle layer. It can be seen the R^2 between 0.82-0.88 and RMSE between 0.31-0.48 mm/day could be obtained depending on the model type, neural network training method and transfer function. The highest performing models are ANN8 and ANN11. In either of them, the accuracy is 0.31 m/day. The R^2 for these two models indicate that 88 percent of the variation in actual ET is accounted for due to the variation in meteorological data.

Minimum accuracy of the model is in ANN1 because of the least input data used. The R^2 of this model that is about 0.82, which indicates that the maxima and minima data of air temperature changes alone account for 82% of the variation in the estimated actual ET. This result is useful for the stations where only temperatures are measured.

According to the results of Table 3, the relative importance of meteorological parameters to estimate actual ET could be observed. By including the evaporation pan data with data of air temperature and relative humidity as input to the ANN model, the R^2 and the RMSE improves a lot (RMSE = 0.45, R^2 = 0.98).

According to Table 3, training algorithm Levenberg-Marquardt (LM) and Conjugate-Gradient (CG) provides almost identical results and therefore estimates of ET by using either of the two an used. But between the transition functions used in this study (sigmoid and tangent hyperbolic) hyperbolic tangent function gives better results.

Table 2. Statistical performance evaluation criteria for empirical equations(Des critères statistiques d'évaluation des performances pour les equations empiriques)

RMSE, (mmd^{-1})	R^2	Empirical equations
0.51	0.81	Combination Equation (CE)
0.51	0.77	Advection–Aridity (AA)
0.92	0.78	Granger and Gray (GG)

Table 3. Statistical performance evaluation criteria for each ANN models(Des reporting criteria Statistiques d'évaluation des performances des versez Modèles Every ANN)

Model	Learning rule	Transfer function	Processing Elements	R^2	RMSE mmd^{-1}	Model	Learning rule	Transfer function	Processing Elements	R^2	RMSE mmd^{-1}
ANN 1	CG	SI	2	82	0.37	ANN 7	LM	SI	7	86	0.36
ANN 1	CG	TH	21	82	0.36	ANN 7	LM	TH	1	86	0.33
ANN 1	LM	SI	20	82	0.37	ANN 8	CG	SI	1	85	0.33
ANN 1	LM	TH	15	82	0.38	ANN 8	CG	TH	8	88	0.31
ANN 2	CG	SI	8	84	0.35	ANN 8	LM	SI	26	87	0.35
ANN 2	CG	TH	18	85	0.34	ANN 8	LM	TH	5	87	0.35
ANN 2	LM	SI	15	85	0.34	ANN 9	CG	SI	6	82	0.37
ANN 2	LM	TH	3	85	0.34	ANN 9	CG	TH	25	87	0.42
ANN 3	CG	SI	12	86	0.32	ANN 9	LM	SI	2	85	0.34
ANN 3	CG	TH	29	87	0.32	ANN 9	LM	TH	4	87	0.33
ANN 3	LM	SI	22	87	0.35	ANN 10	CG	SI	29	82	0.37
ANN 3	LM	TH	7	87	0.32	ANN 10	CG	TH	24	84	0.35
ANN 4	CG	SI	2	84	0.37	ANN 10	LM	SI	30	84	0.36
ANN 4	CG	TH	10	86	0.46	ANN 10	LM	TH	6	84	0.35
ANN 4	LM	SI	27	85	0.34	ANN 11	CG	SI	1	85	0.34
ANN 4	LM	TH	22	85	0.34	ANN 11	CG	TH	28	87	0.36
ANN 5	CG	SI	7	87	0.32	ANN 11	LM	SI	29	87	0.33
ANN 5	CG	TH	3	87	0.32	ANN 11	LM	TH	21	88	0.31
ANN 5	LM	SI	10	87	0.34	ANN 12	CG	SI	12	85	0.35
ANN 5	LM	TH	8	87	0.32	ANN 12	CG	TH	9	84	0.34
ANN 6	CG	SI	8	80	0.39	ANN 12	LM	SI	8	86	0.34
ANN 6	CG	TH	7	86	0.33	ANN 12	LM	TH	6	85	0.48
ANN 6	LM	SI	2	84	0.35	ANN 13	CG	SI	23	81	0.38
ANN 6	LM	TH	26	85	0.37	ANN 13	CG	TH	11	86	0.33
ANN 7	CG	SI	10	85	0.34	ANN 13	LM	SI	6	86	0.39
ANN 7	CG	TH	23	85	0.33	ANN 13	LM	TH	4	86	0.37

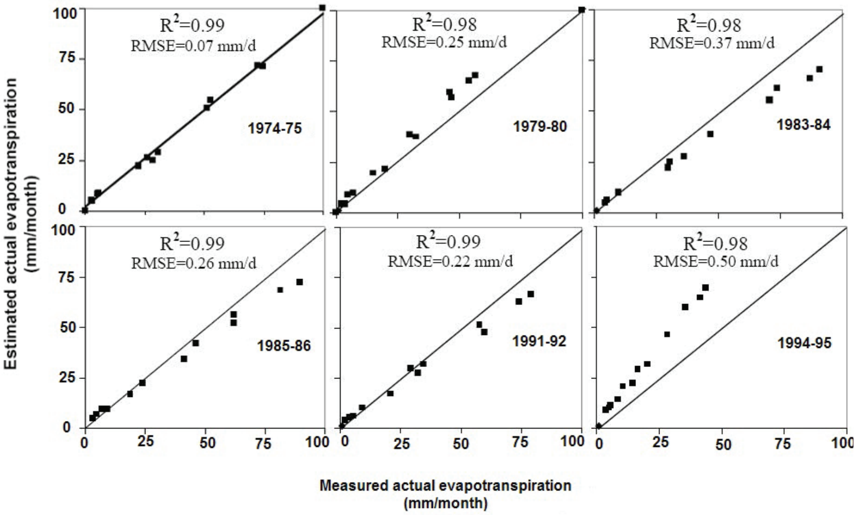

Fig. 3. Comparaison of the AET estimated by ANN 8 and measured values by water balance analysis in test years (Comparaison de l'AET estimée par ANN 8 et les valeurs mesurées par l'analyse du bilan de l'eau au cours des années d'essai)

Based on the accuracy of the results for six years, the ANN8 model was selected as the optimal and its results are presented in Figure 3. It can be seen that R^2 for all years is greater than 0.98 and precision (RMSE) is in the range of 0.07-0.5 mm/day. The output data for all the six years are evenly distributed around the 1:1 line. In general, the results identify the suitable ANN model to estimate the actual ET from the Ammameh watershed.

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