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RESEARCH ARTICLE - HYDROLOGY

Modelling reference evapotranspiration by combining neuro-fuzzy and evolutionary strategies

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Abstract
This study investigates the potential of two evolutionary neuro-fuzzy inference systems, adaptive neuro-fuzzy inference system (ANFIS) with particle swarm optimization (ANFIS–PSO) and genetic algorithm (ANFIS–GA), in modelling reference evapotranspiration (ET_0). The hybrid models were tested using Nash–Sutcliffe efficiency, root mean square errors and determination coefficient (R^2) statistics and compared with classical ANFIS, artificial neural networks (ANNs) and classification and regression tree (CART). Various combinations of monthly weather data of solar radiation, relative humidity, average air temperature and wind speed gotten from two stations, Antalya and Isparta, Turkey, were used as input parameters to the developed models to estimate ET_0. The recommended evolutionary neuro-fuzzy models produced better estimates compared to ANFIS, ANN and CART in modelling monthly ET_0. The ANFIS–PSO and/or ANFIS–GA improved the accuracy of ANFIS, ANN and CART by 40%, 32% and 66% for the Antalya and by 14%, 44% and 67% for the Isparta, respectively.

Keywords Reference evapotranspiration modelling · Evolutionary neuro-fuzzy inference systems · Particle swarm optimization · Genetic algorithm

Introduction

Scarcity of water, increment in pumping costs, complications in water storage and delivery system are the main issues that emphasize on enhancement of the water application efficiency for the operation of large irrigation systems. Irrigation engineers and agricultural managers need to calculate crop water requirement accurately for utilizing the scarce water timely and efficiently. For the efficient water application, evapotranspiration (ET) has a crucial role due to help in the calculation of crop water requirements precisely. Therefore, an accurate estimation of ET is fundamental to improve water application efficiency (Guven et al. 2008). The Food and Agriculture Organization (FAO) introduced the Penman–Monteith equation for modelling ET. This approach has become a commonly used method for calculating ET throughout the world (Allen et al. 2006). Several climatic inputs such as minimum, maximum and average temperature, wind speed, mean relative humidity and sunshine duration are required for ET estimation by the Penman–Monteith equation. These large numbers of climatic data are not always available or reliable. The influence of the mentioned climatic variables on ET makes it a complex nature (Hernandez et al. 2011), and therefore, forecasting ET is one of the most difficult tasks in water resource problems. In such a situation, soft computing (SC) methods that can accurately model complex behaviour between input and output emerge as a better alternative. In recent years, SC methods like ANNs, ANFIS and machine learning (ML) methods have applied for modelling different complex systems in the field of hydrology (Adnan et al. 2018, Adnan et al. 2019a, b; Nair et al. 2018; Muhammad Adnan et al. 2019; Majhi et al. 2019; Wu et al. 2020).

In the literature, ANNs and ANFIS models were applied successfully to predict evapotranspiration (Ladlani et al. 2012, 2014; Kisi et al. 2015; Wen et al. 2015; Luo et al.

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2015; Keshtegar et al. 2018; Abrishami et al. 2019; Walls et al. 2020). Ladlani et al. (2012) compared two ANN models, namely generalized regression artificial neural network (GR-ANN) method and radial basis artificial neural network (RB-ANN), for modelling ET using climatic parameters from Dar El Beida, Algeria. As climatic data, the authors used the data of sunshine duration, average relative humidity, average wind speed, maximum, minimum and average air temperature. They found that the GR-ANN performed better than the RB-ANN in predicting ET. Ladlani et al. (2014) checked the potential of ANFIS and multiple linear regression (MLR) models for forecasting daily ET_0 in the Mediterranean region of Algiers, Algeria. Results obtained from the investigation demonstrated that the ANFIS had better performance compared to the MLR models.

Kisi et al. (2015) compared four soft computing models: (1) MLP-ANN, (2) ANFIS-GP, (3) ANFIS-SC and (4) gene expression programming (GEP) models for predicting monthly ET using the data of 50 climatic stations in Iran. From the obtained results, the authors found the ANFIS-GP as an optimal model. Wen et al. (2015) investigated the prediction accuracy of ANN and empirical methods in comparison with a machine learning method, namely support vector machine (SVM). The selected models were used to predict ET of the arid region of Ejina basin, China, using the minimum temperature and maximum temperature as inputs. Luo et al. (2015) compared four ANN models: (i) multilayer perceptron artificial neural network (MLP-ANN), (2) generalized feed-forward artificial neural network (GFF-ANN), (3) probabilistic neural network (P-ANN) and (4) linear regression artificial neural network (LR-ANN) models for predicting evapotranspiration of Gaoyou climatic station of Jiangsu province in China. The results of this study proved that ANNs can be effectively employed as a reliable ET modelling tool. Keshtegar et al. (2018) applied the ANFIS (ANFIS-FCM) with ANN and M5 model tree models to predict the evapotranspiration of three stations of the Central Anatolian Region of Turkey. They divided data into different training–testing subsets to check ANFIS accuracy for each. They found that the ANFIS model with different subsets performed better than the M5 and ANN models. Abrishami et al. (2019) used the ANN models to predict the ET of Nissouri Creek in Oxford County, Canada. They used two types of activation functions including rectified linear unit (ReLU) and sigmoid. Results showed that ReLU performed better than sigmoid activation function .Walls et al. (2020) applied different ANN structures for modelling the ET of wheat and maize crops and found ANN models suitable for predicting ET of both crops. ANN, ANFIS and ML models have also been successfully used in modelling different hydrological time series due to their ability to capture nonlinear behaviour (Adnan et al. 2017; Kisi et al. 2018; Yuan et al. 2018).

In the recent past years, the literature study has exposed that the hybrid soft computing models provide better ET prediction accuracy in comparison with stand-alone soft computing methods. The primary consideration of the researchers is towards combining several novel heuristic search algorithms with soft computing methods for optimizing their control parameters and enhancement of their forecasting accuracy. Patil and Deka (2017) applied the hybrid of wavelet transform with ANN and ANFIS methods for the modelling of evapotranspiration in the arid regions of India. The results confirmed that the hybrid models had better performance than the stand-alone soft computing models in predicting ET. Araghi et al. (2018) also demonstrated the benefits of WT (wavelet transform) combined with the ANFIS (WT–ANFIS), ANN (WT–ANN) and MLR (WT–MLR) models for ET forecasting of three climatic stations chosen from three different climates of Iran. Using daily weather data of selected stations, the authors found that the WT–ANN outperformed the other wavelet-based hybrid models (i.e. WT–ANFIS and WT–MLR). Gocić et al. (2015) combined the firefly algorithm with SVM (SVM–FFA) for predicting ET in Serbia. The authors compared the proposed SVM–FFA model with WT–SVM, SVM and ANN. They found that the SVM–FFA and WT–SVM models provided better prediction results in comparison with stand-alone ANN and SVM computational methods. Shamshirband et al. (2016) applied a novel heuristic method called cuckoo search algorithm (CSA) for optimizing the ANN and ANFIS methods in estimation of ET at 12 climatic stations in Serbia. The prediction results of designed hybrid methods (ANN–CSA and ANFIS–CSA) are compared with stand-alone ANN and ANFIS models. Also, the authors compared the proposed methods with the Hargreaves and Priestley–Taylor empirical models.

Available literature indicates that hybrid heuristic soft computing methods generally provided better prediction accuracy compared to stand-alone soft computing models. The literature surveys point out that the application of new hybrid soft computing methods is vital to improve prediction accuracy and minimize the method's error. For this reason, evolutionary neuro-fuzzy systems are proposed in this research for an effective evapotranspiration modelling. Genetic algorithm (GA) and particle swarm optimization (PSO) heuristic algorithms are used to optimize the parameters of ANFIS models and to develop hybrid soft computing methods, ANFIS–PSO and ANFIS–GA. Also, ET modelling using classification and regression tree (CART) model is very scarce, and this study looks to be the first that compares the accuracy of CART with the ANFIS–PSO, ANFIS–GA, ANFIS and ANN models in ET prediction.

Materials and methods

Used data

The study uses monthly weather data, solar radiation, relative humidity, air temperature and wind speed, from two automated climatic stations, Antalya (long. of 30°44′00″E, lat. of 36°42′00″N and altitude of 64) and Isparta (long. of 30°34′00″E, lat. of 37°47′00″N and altitude of 997) operated by the TMO (Turkish Meteorological Organization). The study area and stations' location are illustrated in Fig. 1. The stations are situated in the Mediterranean region having a Mediterranean climate (dry summers and mellow to cold, wet winters). The temperature in winter has its highest value as 24 °C, and in summer season, it can increase to 40 °C.

In the study, data (25-year monthly values for the period of 1982–2006) were divided into two parts as training (80% of the aggregate data) and testing (20% remaining part). The brief statistical properties of the used data are summed up in Table 1. It is evident from the average statistics that the Antalya has a higher temperature, solar radiation, wind speed and reference evapotranspiration compared to Isparta.

Used methods

Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS interface represents a multilayer model initially proposed by Jang (1993) that trains input and output variables and affords estimations agreement between input and output in the most efficient way. There are several fuzzy interfaces system (FIS) reported in the literature, which has different performance and as results in significant differences in the results among them. The FIS is categorized into three main groups: Mamdani's interface system (Mamdani and Assilian 1975), which consists of a system that considered inputs and outputs as a fuzzy set. This system is the most often applied; Tsukamoto's system (Tsukamoto 1979), which is not very commonly used; finally, Sugeno's FIS, which considers the input data as a fuzzy set, while the outputs as a constant coefficient of a linear function (Takagi and Sugeno 1985). The fact of being compact and very efficient in terms of computational time makes the Sugeno's system very commonly used also (Nourani et al. 2014; Zhu et al. 2019; Adnan et al. 2019c; Alizamir et al. 2020a). ANFIS applied in this study consists of a network structure which uses Sugeno inference system (S-FIS) and supported from the artificial neural network (ANN) in the training phase of the input data (Fig. 2).

The ANFIS interface is composed of several nodes connected through directional links. Indeed, the combination of the fuzzy-based rules systems with the high performance regarding the learning capability of the ANN has made the ANFIS interface more robust and popular in modelling different problems (Tabari et al. 2012). ANFIS is more commonly used in solving complicated problems characterized by significantly high nonlinearity (Rezakazemi et al. 2017). Training of the data sets is done based on the fundamental learning rule backpropagation approach, which tends to minimize the error computation of the input data set (Cobaner 2011). In addition to the binary variables, a set of linguistic variables were used to design the fuzzy system. Afterwards, several IF/THEN rules were used to characterize the relationship between fuzzy variables (Nourani et al. 2014). In the case of the Sugeno's system, which is the system used in this study, the conditional rules IF/THEN can be expressed as follows (Sayed et al. 2003):

Fig. 1 The study area and stations' location (adapted from d-maps.com)

Table 1 Brief statistics for the climatic data of Antalya and Isparta stations

Station		Data set	Unit	Avr.	Min.	Max.	SD	Skewness
Antalya	Training data	T	°C	19.52	7.3	32.25	7.33	0.03
		SR	cal/cm^2	412	120	679.2	154	−0.09
		RH	%	57.0	47.5	68.5	3.81	0.25
		WS	m/s	2.64	0.9	4.9	0.69	0.008
		ET$_0$	mm day^{-1}	5.64	1.16	10.4	2.1	0.16
	Testing data	T	°C	20.1	9.7	31.85	7.27	0.1
		SR	cal/cm^2	361	1268	595.6	145	−0.08
		RH	%	52.9	45.5	67	4.16	0.93
		WS	m/s	2.63	1.8	4.9	0.49	1.87
		ET$_0$	mm day^{-1}	5.54	2.67	9.28	1.82	0.15
Isparta	Training data	T	°C	12.3	−2.3	25	7.71	−0.12
		SR	cal/cm^2	318	112	657	117	0.02
		RH	%	60.0	46	72	5.08	−0.31
		WS	m/s	1.84	0.6	3.6	0.5	0.42
		ET$_0$	mm day^{-1}	3.53	0.69	6.79	1.51	−0.02
	Testing data	T	°C	12.6	−0.9	25.2	8.04	−0.05
		SR	cal/cm^2	355	148	638	141	0.21
		RH	%	63.4	52.5	72.5	2.57	0.006
		WS	m/s	1.43	0.8	2.5	0.42	0.68
		ET$_0$	mm day^{-1}	3.43	1.03	6.43	1.54	0.11

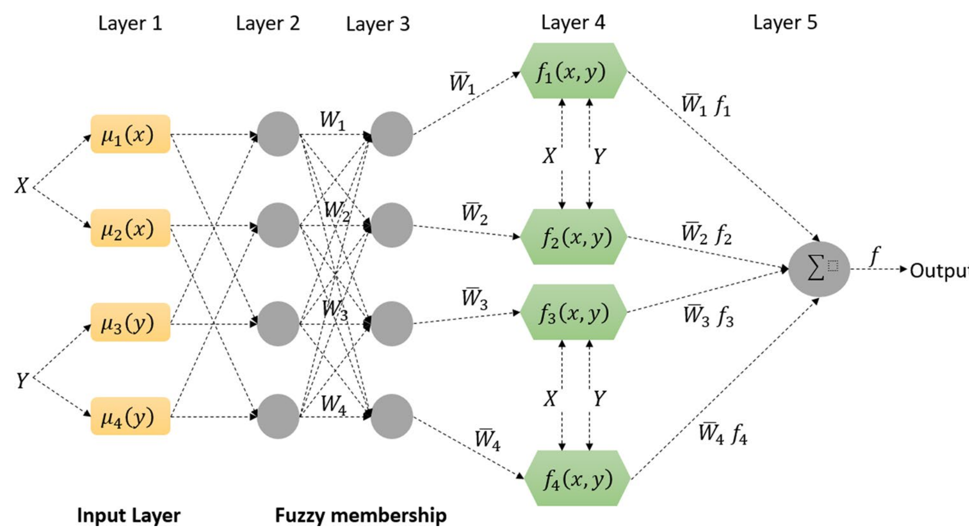

Fig. 2 The fundamental structure of the ANFIS interface

$$\text{Rule1}: \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } z_1 = p_1x + q_1y + r_1 \quad (1)$$

$$\text{Rule2: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } z_2 = p_2x + q_2y + r_2 \quad (2)$$

where A_1 and B_1 represent the fuzzy sets in the originator, and p_i, q_i and r_i are the design parameters defined during the training process of the data set. As shown in Fig. 2, the architecture of the ANFIS was designed considering five layers, and detailed explanation for each layer and the equations used can be found in the literature (Tabari et al. 2012). The hybrid learning algorithm used in the ANFIS architecture applies a combination of gradient descent, in order to identify the proposition parameters, while the least-squares method is applied to allocate the linear consequent parameters. The training algorithm makes the ANFIS outputs with the lowest error (Jang 1993; Nourani et al. 2014).

ANFIS–PSO In this ANFIS model, a particle swarm optimization (PSO) was used. This optimization algorithm is very efficient in case of discrete data type (Nourani et al. 2014). This combination may be considered as a surrogate approach. So, after determining the design variables, the objective function and constraints, ANFIS was mainly used to search the space, while PSO approach as an optimization algorithm can be employed to establish the efficient way to find the best salutation (Kennedy and Eberhart 1995). PSO is a stochastic optimization method which consists of selecting a specific population or particles in given space completely in a random way while subsequently looking for the optimal solution (Rezakazemi et al. 2017). There are several applications of ANFIS–PSO. Basser et al. (2015) used ANFIS–PSO to predict the optimal parameters to mitigate scouring depth in existing spur dykes, while Djavareshkian and Esmaeili (2014) applied ANFIS–PSO to optimize the operation of the submerged hydrofoil. ANFIS–PSO interface is also used to solve nonlinear problems related to the nanomaterial's components (Rezakazemi et al. 2017).

ANFIS–GA In ANFIS–GA model, genetic optimization algorithm (GA) is incorporated. The GA consists of the inset of chromosome combinations, which evaluates the results obtained in each computational step by seeking the optimal solution possible (Termeh et al. 2018). Differently, from PSO, GA can provide relatively large solution spaces since it utilizes a probabilistic transition and not deterministic rules (Rezakazemi et al. 2017). The GA interface uses variables that represent real values or binary coding. The GA optimization procedure is associated with several processes as follows: population initialization, selection, crossover and mutation (Rezakazemi et al. 2017). GA has become a prevalent optimization method in different areas. Termeh et al. (2018) applied GA in flood susceptibility mapping; they found that this algorithm among the other advantages reveals high accuracy. Rezakazemi et al. (2017) used GA to assess the hydrogen mixed matrix membrane considering several operating conditions. While Khosravi et al. (2018) applied GA to predict potential solar radiation to support solar-based energy systems, all the studies above found that the GA interface poses the ability to provide efficient computation time and high accuracy.

Artificial neural network (ANN)

Artificial neural network (ANN) consists of imitating the biological nervous system, although much of the biological details are neglected. ANNs are composed of several massively processing elements organized in parallel systems connected by using variable weights. Each layer is connected to the other layers through interconnection weights, W. The methodology applied for tuning the weights based on backpropagation process (Rumelhart et al. 1986). The backpropagation network is by far the most commonly used paradigms in ANNs (Nourani et al. 2014; Kisi et al. 2017; Alizamir et al. 2018; Kisi and Alizamir 2018). The processing elements that composed the ANNs are called neurons. The basic structure of the ANN interface is shown in Fig. 3. The neural network layers i, j and k are interconnected with weights W_{ij} and W_{jk} between layers of neurons. Further details and explanation about the training process of the input data may be found at Kisi and Öztürk (2007).

Classification and regression tree (CART)

Classification and regression tree (CART) is based on a set of decision trees on the predictor variables which grew by repeatedly stratifying the data set into consecutively smaller subgroups (Breiman 1984). CART is a predictive tree model based on the recursive approach in data mining models that constructs the structure of the given data set which generates

Fig. 3 The ANN interface used for the ET_0 estimation

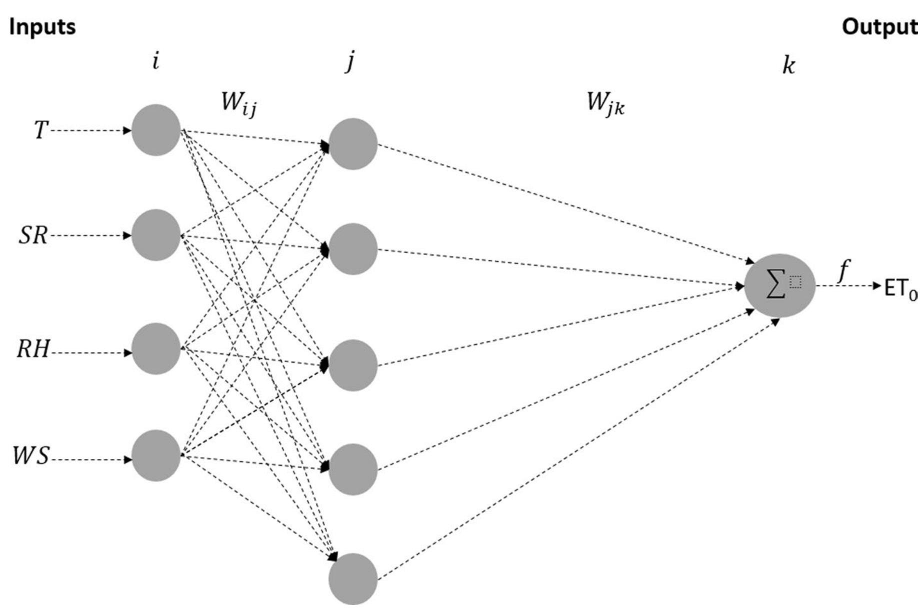

Table 2 The test statistics of the ANFIS–PSO, ANFIS–GA, ANFIS, ANN and CART models in estimating ET_0 of Antalya Station

Input combination	RMSE					NSE					R^2				
	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART
(i)															
T	**0.742**	**0.730**	**0.762**	**0.758**	1.230	**0.831**	**0.837**	**0.822**	**0.824**	0.537	**0.844**	**0.847**	**0.848**	**0.84**	0.618
SR	1.023	0.952	1.033	1.474	**1.179**	0.679	0.722	0.673	0.335	**0.574**	0.819	0.835	0.819	0.793	**0.774**
RH	2.058	2.090	2.129	1.785	2.170	−0.295	−0.335	−0.386	0.025	−0.439	0.001	0.003	0.023	0.151	0.024
WS	1.829	1.837	1.848	1.835	1.858	−0.023	−0.031	−0.043	−0.029	−0.056	0.047	0.046	0.036	0.041	0.071
(ii)															
T, SR	0.780	0.718	0.871	1.717	0.904	0.814	0.842	0.768	0.098	0.750	0.889	0.887	0.853	0.149	0.865
T, RH	0.831	0.833	0.963	0.763	1.807	0.788	0.787	0.716	0.822	0.001	0.863	0.813	0.734	0.858	0.223
T, WS	0.639	0.617	**0.681**	0.652	0.887	0.875	0.883	**0.858**	0.869	0.759	0.905	0.898	**0.885**	0.901	0.792
SR, RH	**0.502**	**0.593**	0.779	**0.58**	**0.861**	**0.922**	**0.892**	0.814	**0.896**	**0.773**	**0.935**	**0.915**	0.906	**0.922**	**0.869**
SR, WS	0.898	0.880	0.776	1.424	1.109	0.753	0.763	0.815	0.379	0.623	0.833	0.856	0.872	0.802	0.808
(iii)															
T, SR, RH	0.588	**0.402**	0.908	0.437	0.868	0.894	**0.950**	0.747	0.941	0.769	0.910	**0.953**	0.857	0.954	0.875
T, SR, WS	**0.453**	0.441	**0.555**	**0.399**	**0.774**	**0.937**	0.940	**0.905**	**0.951**	**0.816**	**0.949**	0.957	**0.937**	**0.958**	**0.912**
iv															
T, SR, RH, WS	**0.248**	**0.253**	**0.424**	**0.371**	**0.746**	**0.981**	**0.980**	**0.945**	**0.957**	**0.829**	**0.986**	**0.983**	**0.950**	**0.975**	**0.918**

The bold numbers show the best model in each input combination

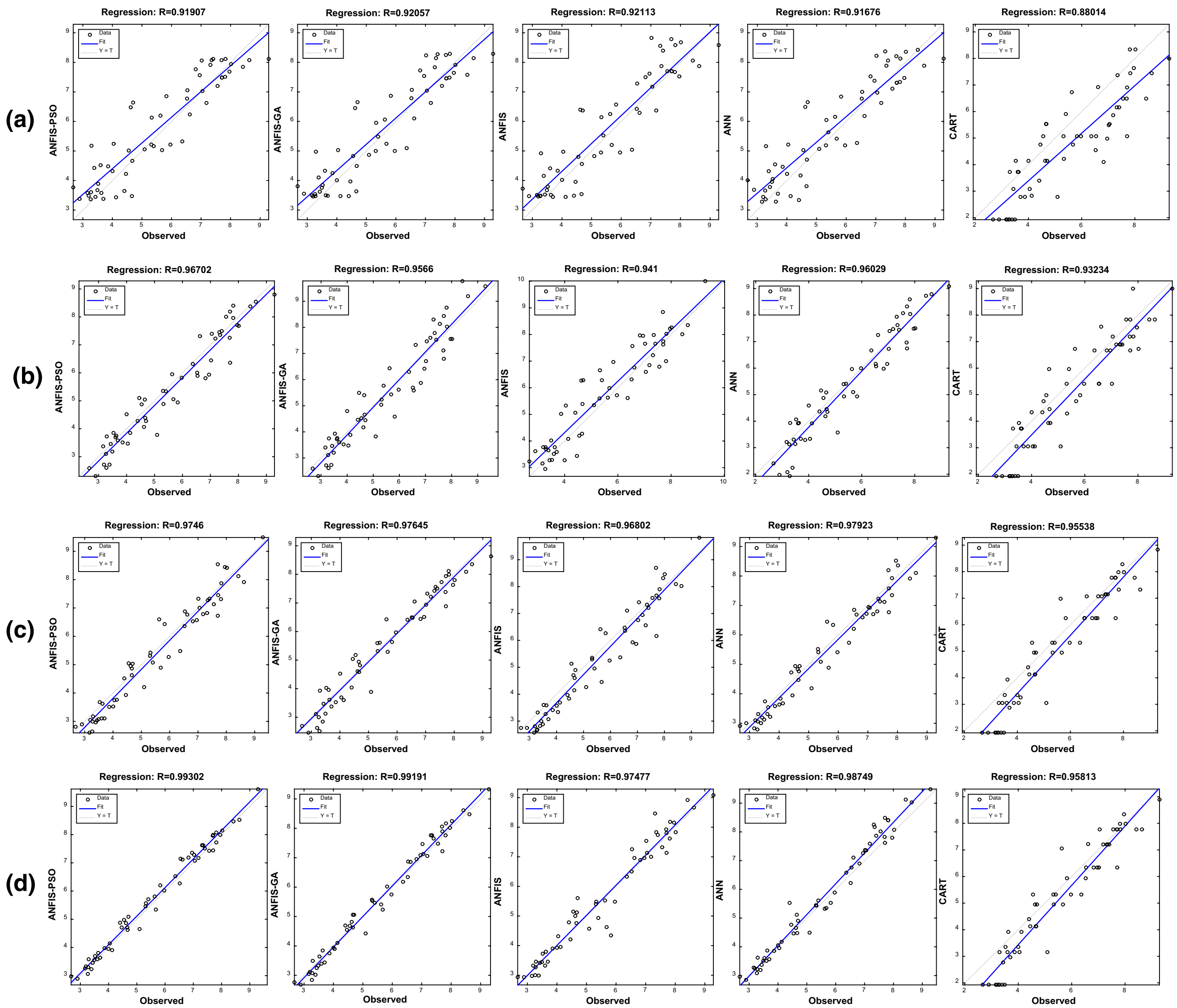

Fig. 4 The observed and estimated ET_0 values by the best models in the test period of Antalya Station: **a** input combination (i), **b** input combination (ii), **c** input combination (iii) and **d** input combination (iv)

decision rules for predicting a categorical variable (Choubin et al. 2018; Kisi et al. 2020; Alizamir et al. 2020a, b). Considering the principle of homogenization or less variability among the nods, the splitting procedure of the variables is made until the best split is reached (Breiman 1984).

CART algorithm has also become commonly applied in different fields. Choubin et al. (2018) have applied CART to predict sediment transport in alpine rivers; they found that CART has relatively high accuracy. Ebrahimy and Azadbakht (2019) have applied CART to predict land surface temperature over several different areas. Also, Juntakut et al. (2019) have used CART to predict the long-term contamination of the groundwater in Nebraska State. They concluded that CART was capable of differentiating the weight of several physical factors in the water contamination.

Application and results

The ability of two evolutionary neuro-fuzzy systems: ANFIS–PSO and ANFIS–GA, are investigated in modelling reference evapotranspiration (ET_0) using various input combinations of climatic data and compared with the classic ANFIS, ANN and CART methods. For the control parameters, different values were tried for each method. For the ANFIS–PSO, 500 iterations were used, and population, inertia weight, personal learning coefficient and global learning coefficient were set to 45, 1, 1 and 2, respectively. For the ANFIS–GA, number of iterations, population, mutation and crossover percentages were set to 400, 55, 0.7 and 0.4, respectively. For the ANFIS, subtractive clustering with 150 iterations and 0.35 radii was used. For the ANN, Bayesian

Table 3 The test statistics of the ANFIS–PSO, ANFIS–GA, ANFIS, ANN and CART models in estimating ET_0 of Isparta Station

Input combination	RMSE					NSE					R^2				
	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART	ANFIS–PSO	ANFIS–GA	ANFIS	ANN	CART
(i)															
T	0.683	0.686	0.694	**0.697**	0.829	0.800	0.799	0.794	**0.792**	0.706	0.808	0.805	0.799	**0.801**	0.711
SR	**0.632**	**0.631**	**0.638**	1.306	**0.748**	**0.829**	**0.829**	**0.825**	0.271	**0.761**	**0.931**	**0.931**	**0.931**	0.850	**0.899**
RH	1.494	1.480	1.502	1.514	1.456	0.047	0.065	0.036	0.021	0.095	0.271	0.273	0.268	0.270	0.262
WS	1.542	1.524	1.546	1.557	1.608	−0.015	0.007	−0.02	−0.034	−0.104	0.001	0.014	0.001	0.006	0.002
(ii)															
T, SR	0.492	0.515	0.492	1.317	0.627	0.896	0.886	0.896	0.259	0.832	0.961	0.960	0.964	0.724	0.906
T, RH	0.750	0.706	0.790	0.702	0.777	0.760	0.786	0.733	0.789	0.742	0.800	0.811	0.791	0.816	0.783
T, WS	0.678	0.669	0.774	0.675	0.804	0.803	0.809	0.743	0.805	0.723	0.852	0.844	0.786	0.848	0.745
SR, RH	**0.422**	**0.386**	**0.441**	**0.380**	**0.600**	**0.923**	**0.936**	**0.916**	**0.938**	**0.846**	**0.926**	**0.940**	**0.924**	**0.946**	**0.855**
SR, WS	0.525	0.511	0.545	1.472	0.651	0.882	0.888	0.873	0.074	0.818	0.912	0.911	0.899	0.811	0.844
(iii)															
T, SR, RH	0.333	0.338	0.319	**0.329**	0.599	0.952	0.951	0.956	**0.953**	0.846	0.953	0.956	0.959	**0.963**	0.859
T, SR, WS	**0.210**	**0.212**	**0.215**	1.302	**0.430**	**0.981**	**0.980**	**0.980**	0.270	**0.921**	**0.981**	**0.985**	**0.980**	0.863	**0.944**
iv															
T, SR, RH, WS	**0.201**	**0.191**	**0.221**	**0.339**	**0.577**	**0.982**	**0.984**	**0.979**	**0.950**	**0.857**	**0.984**	**0.984**	**0.979**	**0.960**	**0.862**

The bold numbers show the best model in each input combination

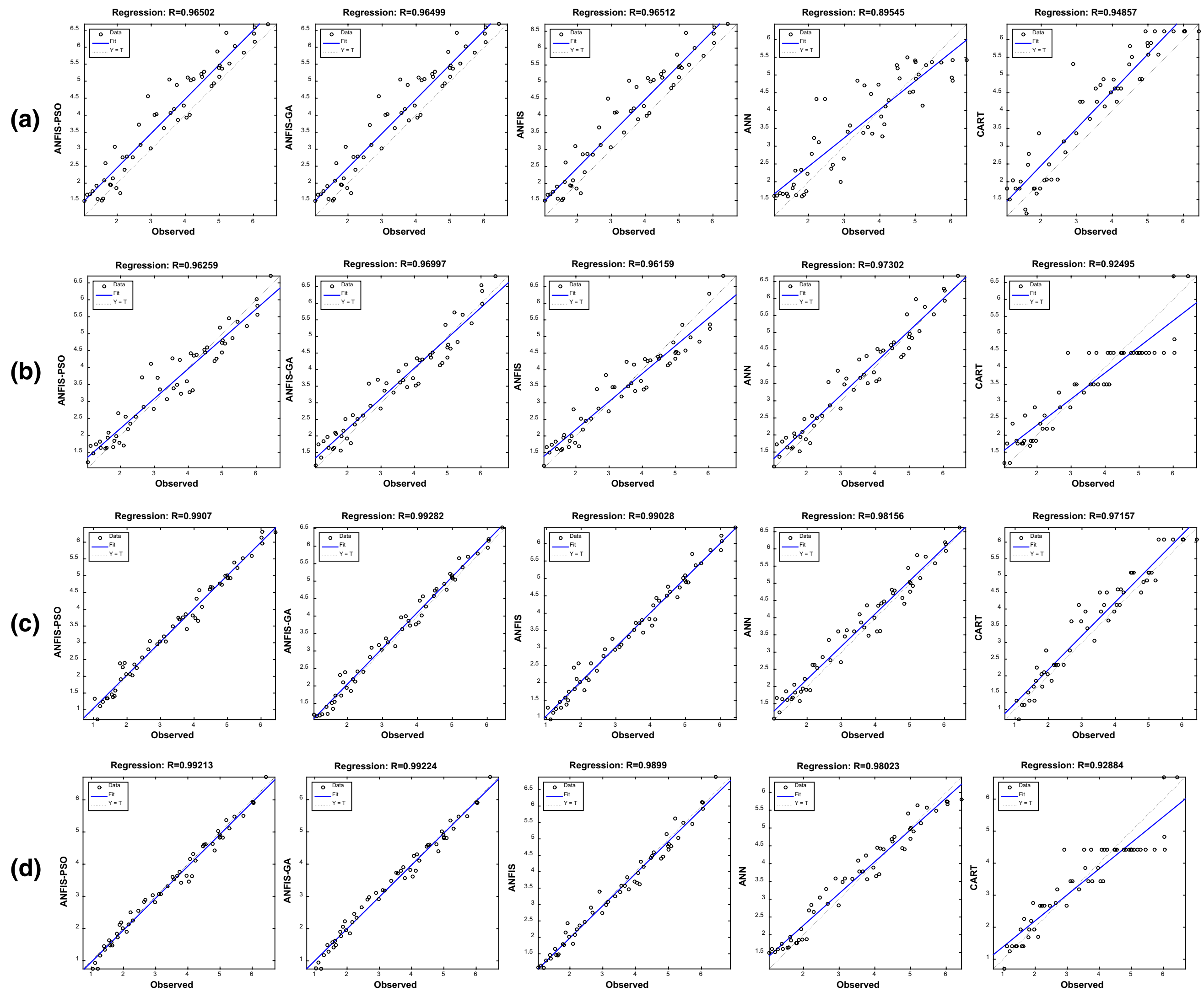

Fig. 5 The observed and estimated ET_0 values by the best models in the test period of Isparta Station: **a** input combination (i), **b** input combination (ii), **c** input combination (iii) and **d** input combination (iv)

regulation was used, and the optimal number of neurons in the hidden layer (HL) was found to be 10. The following evaluation metrics are used to select the best models:

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{N}\left(\mathrm{ET}_{im} - \mathrm{ET}_{ip}\right)^2}{N}} \tag{3}$$

$$\text{Nash} - \text{Sutcliffe efficiency (NSE)} = 1 - \frac{\sum_{i=1}^{N}\left(\mathrm{ET}_{im} - \mathrm{ET}_{ip}\right)^2}{\sum_{i=1}^{N}\left(\mathrm{ET}_{im} - \overline{\mathrm{ET}}_{m}\right)^2} \tag{4}$$

where N = number of data, $\overline{ET}_m$ = mean FAO 56 PM ET_0, ET_{ip} = predicted ET_0, and ET_{im} = FAO 56 PM ET_0.

Table 2 compares the test statistics of the ANFIS–PSO, ANFIS–GA, ANFIS, ANN and CART models for different input combinations of Antalya Station. Among the one input combinations, T variable provided the best statistics for all methods. Out of two-input models, the model with SR and RH inputs had the lowest RMSE and the highest NSE and R^2 for the ANFIS–PSO, ANFIS–GA, ANN and CART methods. Three-input ANFIS–PSO, ANFIS, ANN and CART models with T, SR and WS variables performed better than the corresponding models with T, SR and RH variables. It is apparent from Table 2 that the models with whole input variables (T, SR, RH and WS) outperformed the other models for all methods. The ANFIS–PSO and ANFIS–GA with full climatic inputs have almost the same accuracy, and they have better statistics than the other models. The relative RMSE differences between the ANFIS–PSO and ANFIS, ANN, CART are 40%, 32% and 66%, respectively.

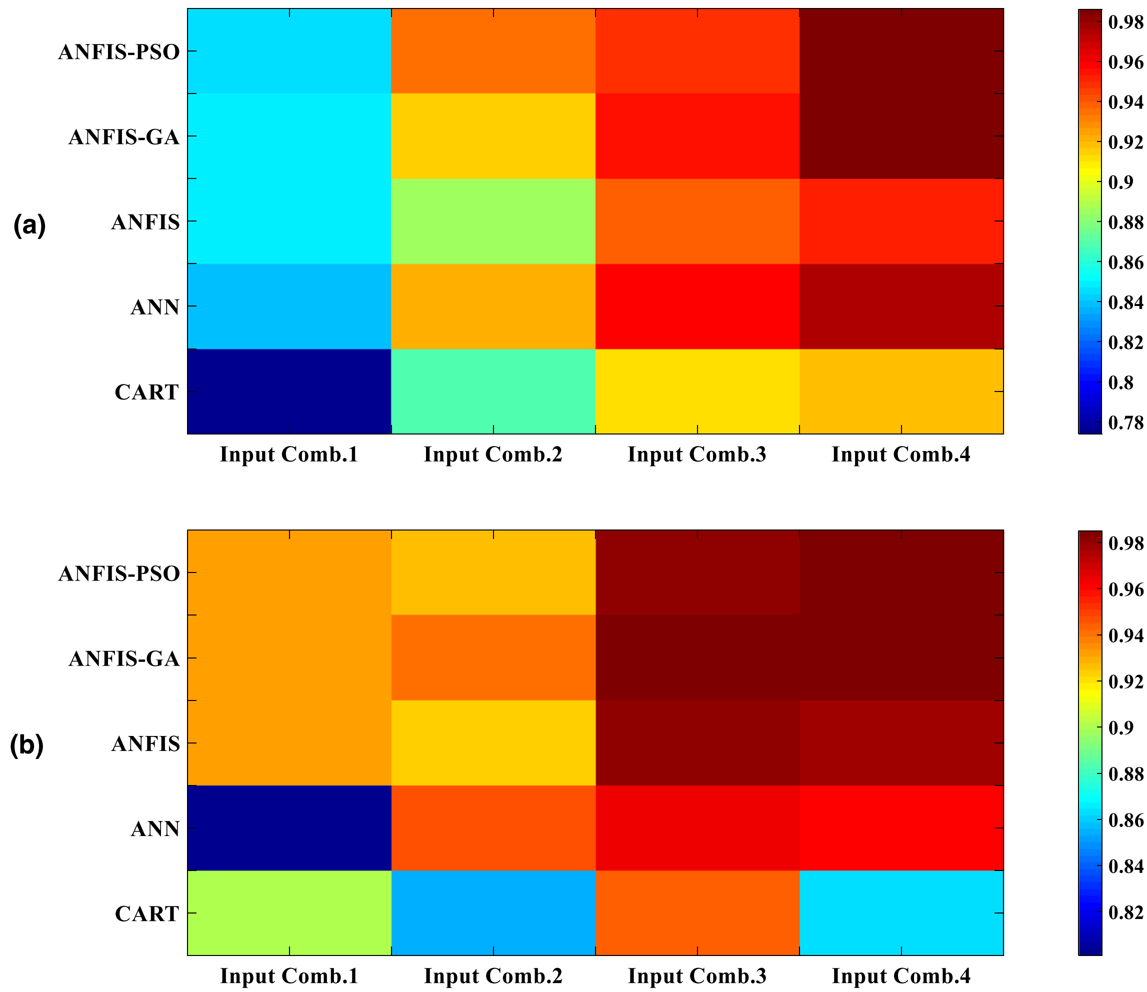

Fig. 6 R^2 values of the best models for different input combinations: **a** Antalya Station, **b** Isparta Station

Figure 4 illustrates the observed and estimated ET_0 values by the best models in the test period for the Antalya Station. It is clearly observed that the ANFIS–PSO and/or ANFIS–GA models generally have less scattered estimates compared to other models. It is also apparent from the scatter graphs that all the methods produce less scattered estimates by increasing the number of input variables.

Test results of the employed methods are summed up in Table 3 for estimating ET_0 of Isparta Station utilizing various climatic input variables. In this station, the models with SR variable have the best statistics among the one input combinations. Similar to the Antalya Station, here also the SR, RH and T, SR, WS combinations generally provided the most accurate estimates for two- and three-input models, respectively. Among all input combinations, the models with full climatic input variables performed the best. The best ANFIS–GA model outperformed the ANFIS–PSO, ANFIS, ANN and CART with respect to RMSE, NSE and R^2. The relative RMSE differences between the ANFIS–GA and ANFIS–PSO, ANFIS, ANN, CART are 5%, 14%, 44% and 67%, respectively. It is clear from Tables 2 and 3 that the evolutionary algorithms, PSO and GA, improve the classical ANFIS model in both stations, improvement in RMSE by about 40% and 14% for the Antalya and Isparta stations. In Isparta Station, SR seems to be more effective on ET_0 compared to Antalya. The RH and WS variables produce worse results compared to Isparta. One reason for this may be the fact that these variables have higher skewed distribution in Antalya than the Isparta (see skewness values of the SR and RH data in Table 1).

The test results of the employed models are graphically compared in Fig. 5 for the Isparta Station. Here also, the better estimates are obtained by increasing input numbers, and the models with full inputs (T, SR, RH and WS) have the best estimates among the input combinations tried. Both ANFIS–PSO and ANFIS–GA have less scattered

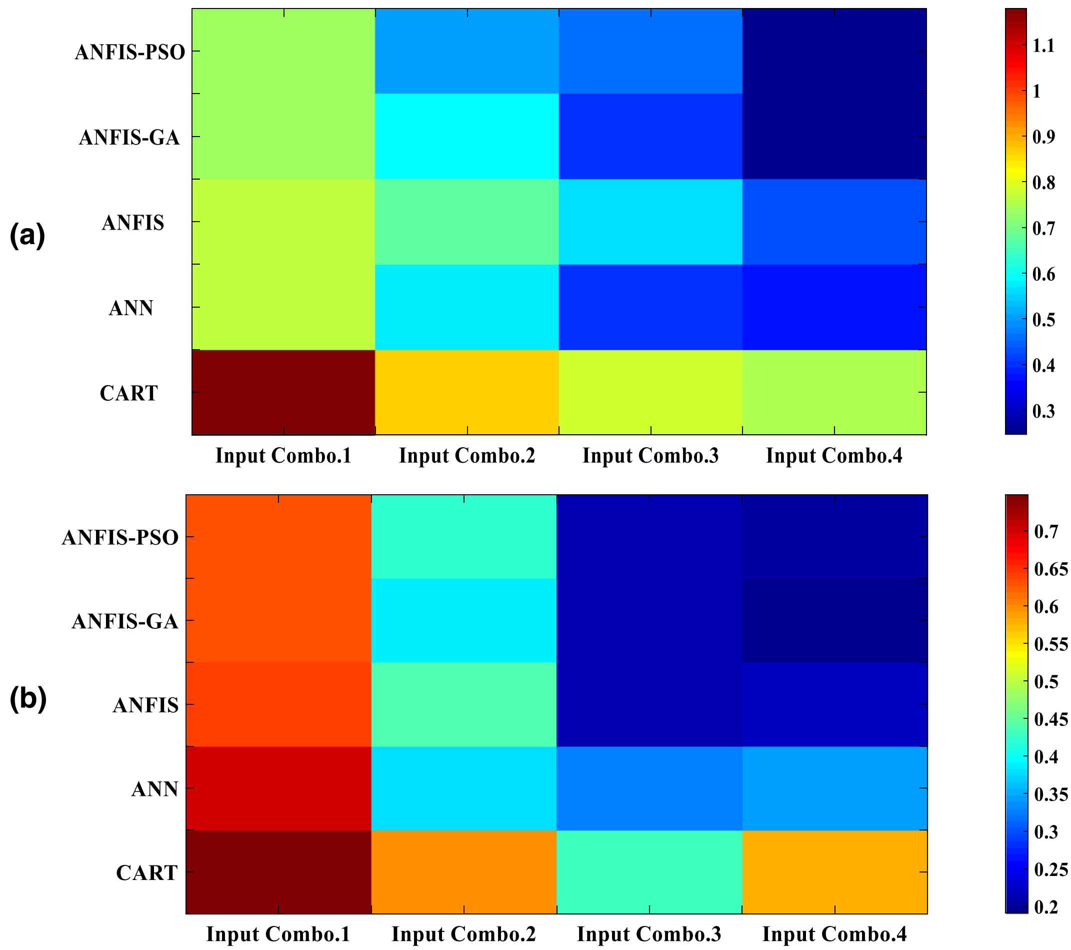

Fig. 7 RMSE values of the best models for different input combinations: **a** Antalya Station, **b** Isparta Station

estimates than the ANFIS, ANN and CART models. CART model has the worst estimates among the models applied. Figures 6, 7 and 8 compare the R^2, RMSE and NSE values of the five optimal models with different input combinations for the Antalya and Isparta stations, respectively. It is clearly observed that the ANFIS–PSO and/or ANFIS–GA generally have the highest R^2 and NSE and the lowest RMSE compared to other three methods.

Overall, the ANFIS–PSO and ANFIS–GA models perform superior to the other models in estimating monthly ET_0. PSO and GA are heuristic methods and have some advantages compared to classical training algorithms such as gradient descent and least square. These belong to a class of search methods so that they have a notable balance between exploitation of the optimal solutions and reconnaissance of the search space. Stochastic search and directed search are combined in such methods. Therefore, they are more robust compared to directed search techniques and capable of finding global optimum without local optima problem (Mantoglou et al. 2004; Karterakis et al. 2007).

Conclusion

The accuracy of two evolutionary neuro-fuzzy methods was investigated in the presented study in modelling reference evapotranspiration. Their results were compared with the classic ANFIS, ANN and CART models. Various input combinations of climatic data obtained from two stations; Turkey were utilized for the employed models. Evolutionary ANFIS–PSO and/or ANFIS–GA produced better ET_0 estimates than the ANFIS, ANN and CART models with the relative RMSE differences of 40%, 32% and 66% for one station (Antalya) and 14%, 44% and 67% for the other station (Isparta), respectively.

Comparison of various climatic inputs revealed that the estimation accuracy of the applied models increases by including more input variables and four inputs (average temperature, solar radiation, relative humidity and wind speed) produced the best estimates for each method. The comparison also indicated that solar radiation has more influence on ET_0 in Isparta, while including relative humidity and wind speed in inputs makes models less accurate in Antalya.

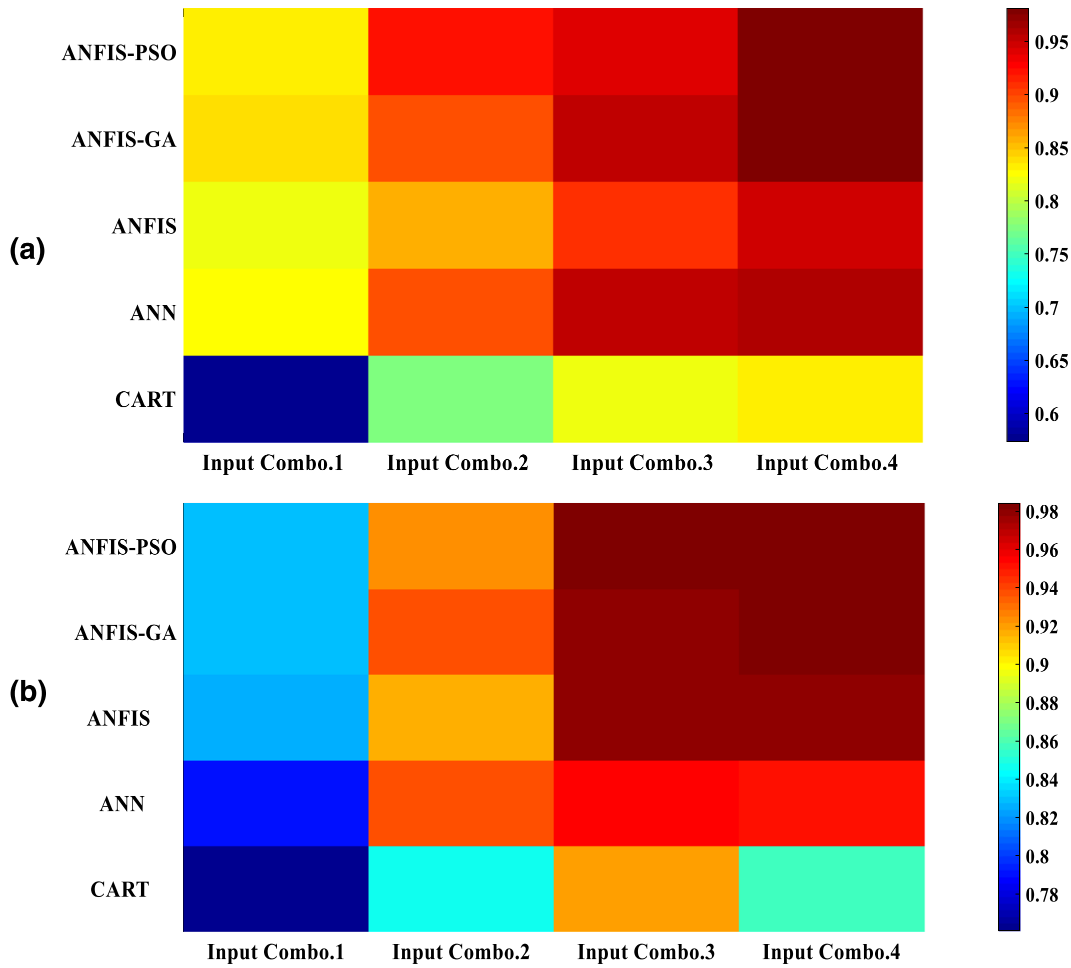

Fig. 8 NSE values of the best models for different input combinations: **a** Antalya Station, **b** Isparta Station

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Compliance with ethical standards

Conflict of interest There is not any conflict of interest in this study.

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