

An investigation on generalization ability of artificial neural networks and M5 model tree in modeling reference evapotranspiration

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Abstract The generalization ability of artificial neural networks (ANNs) and M5 model tree (M5Tree) in modeling reference evapotranspiration (ET_0) is investigated in this study. Daily climatic data, average temperature, solar radiation, wind speed, and relative humidity from six different stations operated by California Irrigation Management Information System (CIMIS) located in two different regions of the USA were used in the applications. King-City Oasis Rd., Arroyo Seco, and Salinas North stations are located in San Joaquin region, and San Luis Obispo, Santa Monica, and Santa Barbara stations are located in the Southern region. In the first part of the study, the ANN and M5Tree models were used for estimating ET_0 of six stations and results were compared with the empirical methods. The ANN and M5Tree models were found to be better than the empirical models. In the second part of the study, the ANN and M5Tree models obtained from one station were tested using the data from the other two stations for each region. ANN models performed better than the CIMIS Penman, Hargreaves, Ritchie, and Turc models in two stations while the M5Tree models generally showed better accuracy than the corresponding empirical models in all stations. In the third part of the study, the ANN and M5Tree models were calibrated using three stations located in San Joaquin region and tested using the data from the

other three stations located in the Southern region. Four-input ANN and M5Tree models performed better than the CIMIS Penman in only one station while the two-input ANN models were found to be better than the Hargreaves, Ritchie, and Turc models in two stations.

1 Introduction

Evapotranspiration is one of the most important parameters in hydrologic cycle. It is very important for irrigation projects and determination of irrigation regime. Irrigation can be applied with considerable savings by correct estimation of evapotranspiration.

In general, the combination of energy balance/aerodynamic equations provides accurate results because they are based on physics and rational relationships (Jensen et al. 1990). For this reason, the Food and Agricultural Organization of the United Nations (FAO) accepted the FAO Penman-Monteith as the standard equation for estimation of evapotranspiration (Allen et al. 1998; Naoum and Tsanis 2003).

The application of artificial neural networks (ANNs) for reference evapotranspiration (ET_0) modeling has received much attention in recent years (Trajkovic et al. 2003; Trajkovic 2005; Kisi 2006a, b, 2007a; Jain et al. 2008; Kim and Kim 2008; Kumar et al. 2009; Hamid et al. 2011; Kilic 2011; Tabari et al. 2012; Shirin Manesh et al. 2013; Kim et al. 2014; Adamala et al. 2014; Deo and Sahin 2015). Trajkovic et al. (2003) forecasted ET_0 using radial basis neural network (RBNN). Trajkovic (2005) employed temperature-based RBNN models for estimating FAO-56PM ET_0 . Kisi (2006a) investigated the accuracy of ANN method in estimating ET_0 , and he compared ANN results with the Penman and Hargreaves models. He showed that the ANN model performed better than the empirical models. Kisi (2006b)

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modeled ET_0 by using generalized regression neural network (GRNN) models. Kisi (2007a) modeled ET_0 by using multi-layer perceptron and compared test results with the Penman, Hargreaves, and Turc models. The superiority of the multi-layer perceptron to the empirical models was shown in this study. Jain et al. (2008) employed ANN for estimating ET_0 and proposed a procedure to evaluate the effects of input variables on the output using the weight connections of ANN. Kim and Kim (2008) examined the ability of GRNN model for estimating the alfalfa ET_0 . Kumar et al. (2009) employed different ANN models for modeling ET_0 under the arid conditions and compared the results with the FAO-24 Radiation, Turc, and FAO-24 Blaney–Criddle methods. They indicated that the ANN model performed better than the empirical models. Hamid et al. (2011) investigated the ability of ANN in estimating ET_0 . Tabari et al. (2012) compared different data-driven approaches with climate-based models for ET_0 modeling using limited climatic data in a semi-arid highland environment. Shirin Manesh et al. (2013) evaluated the different ANN models to estimate and interpolate the ET_0 in Fars province of Iran. Kim et al. (2014) used two different ANN methods in estimation of ET_0 . Adamala et al. (2014) utilized the second-order ANN method to model the ET_0 in different climatic zones of India. Gocic et al. (2015) forecasted ET_0 data collected during the period 1980–2010 in Serbia using ANN and support vector machine. Deo and Sahin (2015) used ANN for prediction of monthly standardized precipitation and evapotranspiration index using hydrometeorological parameters and climate indices in eastern Australia. The use of M5 model tree (M5Tree) is limited in the hydrology literature (Bhattacharya and Solomatine 2005; Deswal 2008; Pal and Deswal 2009; Singh et al. 2010; Sattari et al. 2013; Rahimikhoob et al. 2013; Rahimikhoob 2014). Bhattacharya and Solomatine (2005) used ANN and M5Tree for modeling water level–discharge relationship. Deswal (2008) investigated the prediction of pan evaporation using M5Tree. Pal and Deswal (2009) investigated the potential of M5Tree to model daily ET_0 using climatic data of Davis station maintained by California Irrigation Management Information System (CIMIS). Singh et al. (2010) explored the potential of ANN and M5Tree to estimate the mean annual flood. Sattari et al. (2013) investigated the potential of M5Tree tree in predicting daily stream flows in the Sohu River located within the municipal borders of Ankara, Turkey. Rahimikhoob et al. (2013) assessed the performance of M5Tree for converting pan evaporation data to ET_0 in semi-arid regions. Rahimikhoob (2014) evaluated the performances of ANN and M5Tree for estimating ET_0 at four meteorological sites in an arid climate. To the best knowledge of the authors, there is not any published work related to investigate the generalization ability of M5Tree in modeling ET_0 .

The main aim of the present study is to examine the ability of ANNs in (i) locally modeling ET_0 of six stations, (ii)

estimating ET_0 of one station using the data from the other two stations, and (iii) estimating ET_0 of three stations located in the Southern region using data of three stations located in San Joaquin region. The performances of the ANN and M5Tree models are compared with the CIMIS Penman, Hargreaves, Ritchie, and Turc empirical models.

2 Artificial neural network

Artificial neural networks (ANNs), inspired from biological nervous system, are massively parallel systems composed of many processing elements. The network consists of layers and each one comprises processing elements, called neurons. Each layer is fully connected to the proceeding layer by interconnection weights. Initial weight values are randomly assigned, and then they are progressively corrected during a training process that compares calculated outputs to known outputs. By this was, the errors are backpropagated to determine the appropriate weight adjustments necessary to minimize the errors (Kisi, 2005).

In the current study, the Levenberg–Marquardt was used for the training of ANN models because this technique is more powerful and faster than the conventional gradient descent technique (Hagan and Menhaj, 1994; Kisi, 2007b). The detailed theoretical information about ANN can be obtained from Haykin (1998).

A difficult task with ANN involves choosing the hidden nodes' number. In the current study, the network with one hidden layer was used and the hidden nodes' number was determined by trial-and-error method. The sigmoid and linear activation functions were used for the hidden and output nodes of the ANN models, respectively. The network training was stopped after 100 epochs since the variation of error was too small after this epoch.

3 M5 model tree

M5 model tree (M5Tree) is first introduced by (Quinlan 1992). In M5Tree, the parameter space is split into subspaces and a local linear regression model is built for each of them. Regression trees have constant values at their leaves. M5Tree, however, has linear regression functions at the leaves and generalizes the concepts of regression trees (Breiman et al. 1984). So, they are similar to piece-wise linear functions. Model trees can adequately learn and succeed in tasks with very high dimensionality. The main advantage of M5Tree compared to regression trees is that it is much smaller than regression trees, the decision strength is clear, and the regression functions do not normally contain numerous variables (Bhattacharya and Solomatine 2005). The splitting criterion for the M5Tree depends on treating the standard deviation of

the class values and calculating the probable reduction in this error in consequence of testing each attribute at that node. Equation (1) is used for calculating the standard deviation reduction (SDR) (Pal and Deswal, 2009):

$$SDR = sd(T) - \sum \frac{|T_i|}{|T|} sd(T_i) \tag{1}$$

where T indicates a set of examples that reaches the node, T_i is the subset of examples that have the i th outcome of the potential set and sd refers the standard deviation (Rahimikhoob et al., 2013; Wang and Witten, 1997). Because of the splitting process, the data in child nodes have less sd in comparison to parent nodes and therefore are purer. Further details of an M5Tree can be attained from Quinlan (1992).

4 Case study

The daily climatic data of King-City Oasis Rd. Station (latitude 36° 07' 17" N, longitude 121° 05' 02" W), Arroyo Seco Station (latitude 36° 21' 32" N, longitude 121° 17' 25" W), Salinas North Station (latitude 36° 43' 00" N, longitude 121° 41' 27" W), San Luis Obispo Station (latitude 35° 18' 22" N, longitude 120° 39' 37" W), Santa Monica Station (latitude 34° 02' 28" N, longitude 118° 28' 34" W), and Santa Barbara Station (latitude 34° 26' 16" N, longitude 119° 44' 10" W) operated by the California Irrigation Management Information System (CIMIS) located in the USA were used in the study. King-City Oasis Rd., Arroyo Seco, and Salinas North stations are located in San Joaquin region while the San Luis Obispo, Santa Monica, and Santa Barbara stations are located in the Southern region (Figs. 1, 2, and 3). Detailed



Fig. 1 The locations of San Joaquin and Southern regions in California

information about data measurements can be obtained from the CIMIS web site (<http://www.cimis.water.ca.gov>). The King-City Oasis Rd., Arroyo Seco, Salinas North, San Luis Obispo, Santa Monica, and Santa Barbara stations are 165, 72, 19, 101, 104, and 76 m below the sea level, respectively.

The data sample covers 16 years (1994–2009) of daily records of air temperature (T), solar radiation (SR), wind speed (U_2), and relative humidity (RH). Before applying ANN models, missing data were removed from the whole data set. First, 8-year (1994–2001) data were used to train the ANN models; second, 4-year (2002–2005) data were used for validation; and the remaining 4-year (2006–2009) data were used for testing. The daily statistical parameters of the climatic data are given in Table 1. In this table, the x_{mean} , Sx , Cv , Csx , x_{max} , and x_{min} denote the mean, standard deviation, variation coefficient, skewness, maximum, and minimum, respectively. The air temperature and solar radiation shows significantly low skewed distribution for the King-City Oasis Rd., Arroyo Seco, and Santa Barbara stations (see Csx values in Table 1). Among the climatic data used in the study, the wind speed data show high skewed distribution especially for the Santa Monica Station. As can be seen from the correlation coefficients in Table 1, the solar radiation has the highest correlation with the ET_0 . Wind speed has the least correlation with ET_0 except for the Santa Barbara Station.

5 Application and results

5.1 Application of ANNs in modeling ET_0

In the present study, the generalization ability of ANNs and M5Tree in modeling ET_0 is investigated. The ET_0 values were calculated using the FAO-56PM method as described in Allen et al. (1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_a - e_d)}{\Delta + \gamma(1 + 0.34U_2)} \tag{1}$$

where ET_0 = reference evapotranspiration ($mm\ day^{-1}$), Δ = slope of the saturation vapor pressure function ($kPa\ ^\circ C^{-1}$), R_n = net radiation ($MJ\ m^{-2}\ day^{-1}$), G = soil heat flux density ($MJ\ m^{-2}\ day^{-1}$), γ = psychrometric constant ($kPa\ ^\circ C^{-1}$), T = mean air temperature ($^\circ C$), U_2 = average 24-h wind speed at 2 m height ($m\ s^{-1}$), e_a = saturation vapor pressure (kPa), and e_d = actual vapor pressure (kPa).

The ANN and M5Tree models were calibrated using the daily climatic inputs, T , SR , U_2 , RH , and output ET_0 values calculated using the FAO-56PM method. Root mean square errors (RMSE), mean absolute errors (MAE), and

Fig. 2 The locations of King-City Oasis Rd. (113), Arroyo Seco (114), and Salinas North (116) stations in San Joaquin region, California

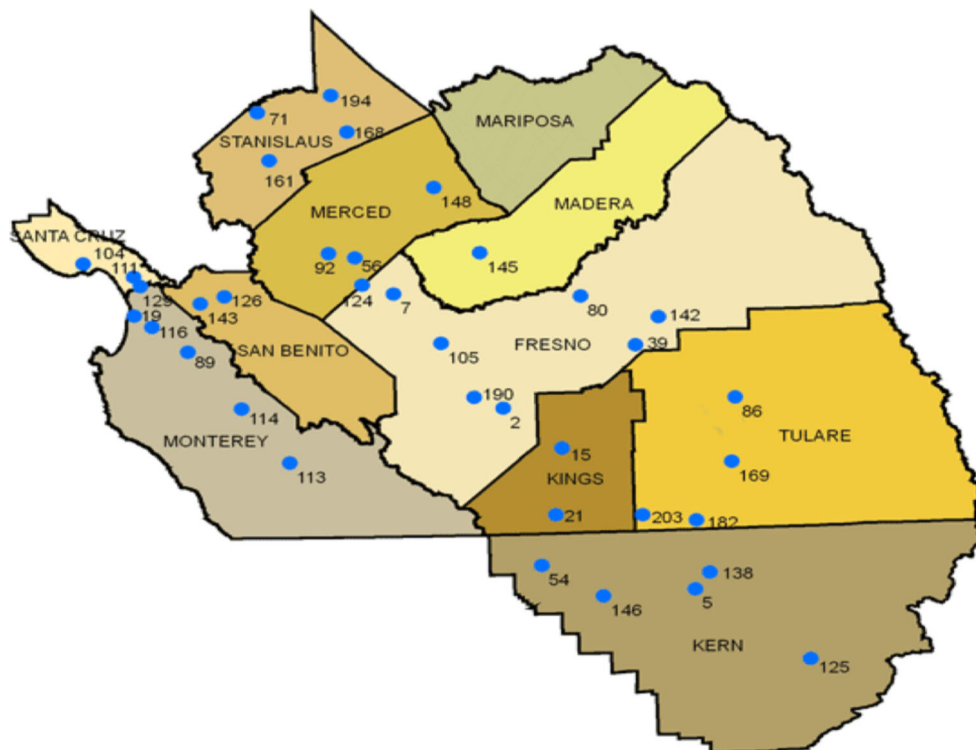


Fig. 3 The locations of San Luis Obispo (52), Santa Monica (99), and Santa Barbara (107) in Southern region, California

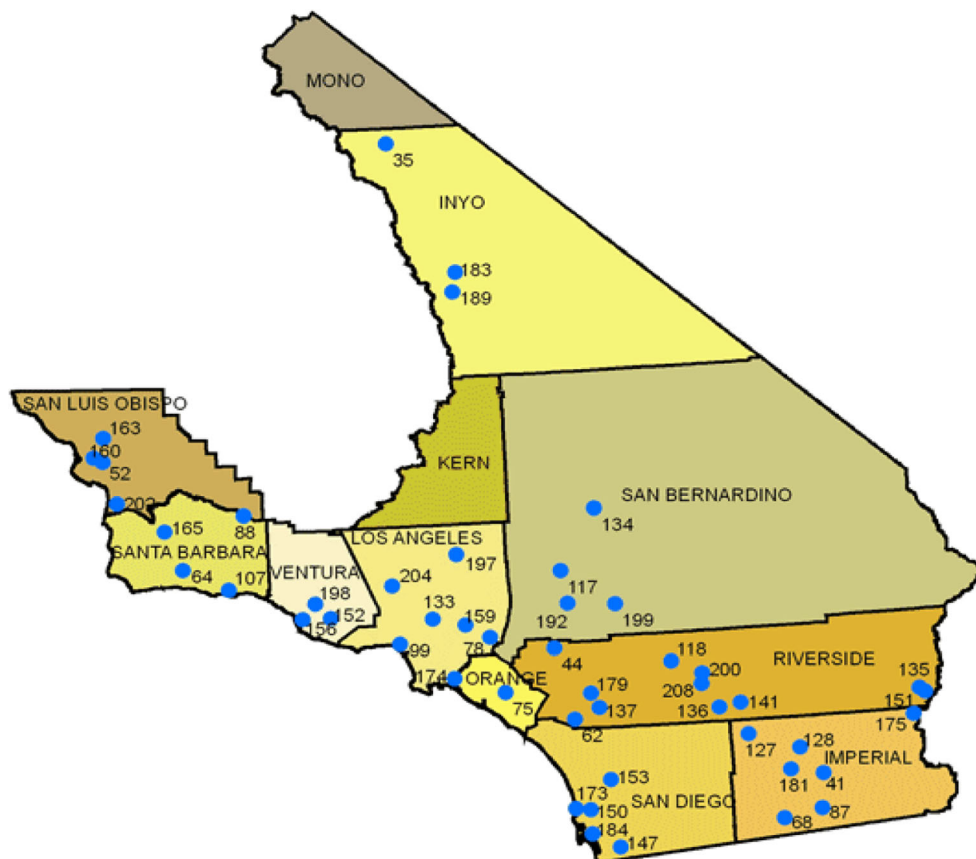


Table 1 The daily statistical parameters of the climatic data used in the study

Station	Data set	Unit	x_{mean}	Sx	Cv (Sx/x_{mean})	Csx	x_{min}	x_{max}	Correlation with E
King-City Oasis Rd.	T	°C	14.8	4.9	0.33	0.010	-0.1	28.8	0.791
	SR	mm	18.3	7.8	0.43	-0.090	0.0	43.2	0.922
	U_2	m/s	2.5	0.8	0.33	0.937	0.4	6.7	0.309
	RH	%	70.3	10.8	0.15	-0.221	29.0	100	-0.638
	E	mm	4.10	2.17	0.53	0.171	-0.27	11.0	1.000
Arroyo Seco	T	°C	14.5	4.1	0.28	-0.086	1.1	27.4	0.730
	SR	mm	17.6	8.0	0.45	-0.045	0.0	41.9	0.910
	U_2	m/s	2.9	0.9	0.33	0.482	0.4	7.6	0.426
	RH	%	72.3	9.3	0.13	-0.553	36.5	99.5	-0.494
	E	mm	3.75	1.87	0.50	0.213	-0.31	10.6	1.000
Salinas North	T	°C	13.1	3.1	0.24	-0.183	2.1	25.8	0.507
	SR	mm	15.2	7.6	0.50	0.219	0.0	37.7	0.866
	U_2	m/s	2.6	0.9	0.34	1.865	0.4	9.7	0.075
	RH	%	81.1	10.0	0.12	-1.374	0.0	100	-0.456
	E	mm	2.55	1.34	0.52	0.374	-0.35	8.19	1.000
San Luis Obispo	T	°C	15.4	4.0	0.26	0.149	3.9	29.5	0.688
	SR	mm	17.7	7.7	0.43	-0.169	0.0	40.9	0.894
	U_2	m/s	1.6	0.6	0.37	3.063	0.4	12.6	0.309
	RH	%	64.3	12.4	0.19	-0.886	16.0	96.0	-0.323
	E	mm	3.60	1.65	0.46	-0.044	-0.27	10.1	1.000
Santa Monica	T	°C	16.6	3.5	0.21	0.122	5.0	28.7	0.593
	SR	mm	17.8	7.2	0.41	-0.066	0.0	41.9	0.857
	U_2	m/s	1.8	0.7	0.41	17.80	0.4	24.9	0.210
	RH	%	73.0	17.0	0.23	-1.381	11.5	100.0	-0.352
	E	mm	3.37	1.47	0.44	-0.042	-0.44	9.45	1.000
Santa Barbara	T	°C	15.7	3.4	0.22	0.052	5.2	26.1	0.621
	SR	mm	17.2	7.5	0.43	-0.044	0.4	33.3	0.946
	U_2	m/s	1.4	0.4	0.31	1.619	0.4	4.2	0.269
	RH	%	71.1	14.4	0.20	-0.680	21.5	100	-0.261
	E	mm	3.20	1.55	0.48	0.039	-0.44	8.37	1.000

determination coefficient (R^2) were used for evaluating the accuracy of the models. The RMSE and MAE can be respectively expressed as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Ei_{\text{observed}} - Ei_{\text{predicted}})^2} \tag{2}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |Ei_{\text{observed}} - Ei_{\text{predicted}}| \tag{3}$$

where N and Ei denote the number of data and ET_0 , respectively.

In the first part of the study, the ANN and M5Tree models were used for estimating ET_0 of six stations and results were compared with the empirical methods, CIMIS Penman, Hargreaves-Samani, Ritchie, and Turc. The CIMIS Penman equation uses the modified Penman equation (Pruitt and

Doorenbos 1977) with a wind function developed at the University of California, Davis. The method uses hourly average climatic data as an input to calculate hourly ET_0 . The 24-hourly ET_0 values for the day (midnight-to-midnight) are then summed to obtain daily ET_0 . The hourly PM equation that CIMIS uses to estimate hourly PM ET_0 is the Food and Agricultural Organization’s version that is described in Irrigation and Drainage Paper No. 56 (Allen et al. 1998). The CIMIS Penman equation is also described in detail in Hidalgo et al. (2005), (see CIMIS website: <http://www.cimis.water.ca.gov/cimis/infoEtoCimisEquation.jsp>);

$$ET_0 = \left(\frac{\Delta}{\Delta + \gamma} \right) R_n + \left(1 - \frac{\Delta}{\Delta + \gamma} \right) (e_a - e_d) f_U \tag{4}$$

where ET_0 = hourly reference evapotranspiration (mm day^{-1}), Δ = slope of the saturation vapor pressure function ($\text{kPa } ^\circ\text{C}^{-1}$), R_n = mean hourly net radiation (Wm^{-2}),

Table 2 The test statistics of the ANN, M5Tree, and empirical models in the first application

Models	RMSE (mm/day)	MAE (mm/day)	R ²	Models	RMSE (mm/day)	MAE (mm/day)	R ²
King-City Oasis Rd. Station				Arroyo Seco Station			
ANN1(4,9,1)	0.236	0.176	0.989	ANN1(4,7,1)	0.184	0.139	0.988
M5Tree1	0.286	5.84	0.982	M5Tree1	0.281	0.202	0.974
CIMIS Penman	0.622	0.485	0.953	CIMIS Penman	0.475	0.356	0.930
ANN2(2,10,1)	0.707	0.546	0.936	ANN2(2,5,1)	0.520	0.400	0.903
M5Tree2	0.746	0.579	0.922	M5Tree2	0.597	0.454	0.873
Hargreaves	0.995	0.806	0.928	Hargreaves	0.647	0.479	0.890
Ritchie	0.950	0.766	0.933	Ritchie	0.614	0.450	0.898
Turc	3.731	3.309	0.916	Turc	2.877	2.556	0.878
Salinas North Station				San Luis Obispo Station			
ANN1(4,6,1)	0.135	0.100	0.991	ANN1(4,8,1)	0.270	0.186	0.983
M5Tree1	0.188	0.122	0.981	M5Tree1	0.323	0.216	0.979
CIMIS Penman	0.519	0.385	0.852	CIMIS Penman	0.430	0.286	0.940
ANN2(2,6,1)	0.684	0.451	0.777	ANN2(2,7,1)	0.688	0.469	0.835
M5Tree2	0.723	0.482	0.747	M5Tree2	0.728	0.495	0.811
Hargreaves	0.690	0.512	0.740	Hargreaves	0.790	0.534	0.792
Ritchie	0.680	0.508	0.745	Ritchie	0.798	0.526	0.785
Turc	2.032	1.759	0.729	Turc	2.969	2.656	0.804
Santa Monica Station				Santa Barbara Station			
ANN1(4,3,1)	0.117	0.087	0.993	ANN1(4,10,1)	0.088	0.063	0.996
M5Tree1	0.116	0.080	0.993	M5Tree1	0.111	0.077	0.994
CIMIS Penman	0.506	0.349	0.877	CIMIS Penman	0.355	0.222	0.951
ANN2(2,8,1)	0.613	0.448	0.804	ANN2(2,10,1)	0.420	0.327	0.918
M5Tree2	0.700	0.505	0.748	M5Tree2	0.461	0.353	0.901
Hargreaves	0.804	0.676	0.751	Hargreaves	0.497	0.427	0.915
Ritchie	0.748	0.613	0.750	Ritchie	0.449	0.387	0.920
Turc	2.661	2.420	0.751	Turc	2.472	2.198	0.899

γ = psychrometric constant (kPa °C⁻¹), e_a is the saturation vapor pressure (kPa), e_d is the actual vapor pressure (kPa), and the f_U = wind function (m s⁻¹). Daily ET_0 equals to the sum of 24 h ET_0 (mm).

Hargreaves and Samani (1985) equation can be defined as

$$ET_0 = 0.408 \times 0.0023R_a \left(\frac{T_{\max} + T_{\min}}{2} + 17.8 \right) (T_{\max} - T_{\min})^{0.5} \quad (5)$$

where ET_0 is reference evapotranspiration (mm day⁻¹), T_{\max} and T_{\min} are maximum and minimum temperatures (°C), respectively, and R_a is extraterrestrial radiation (MJ m⁻² day⁻¹).

The Ritchie method can be given as (Jones and Ritchie, 1990)

$$ET_0 = \alpha_1 \cdot [3.87 \times 10^{-3} \cdot R_s \cdot (0.6T_{\max} + 0.4T_{\min} + 29)] \quad (6)$$

where ET_0 = reference evapotranspiration (mm day⁻¹), T_{\max} and T_{\min} = maximum and minimum temperature (°C), and R_s = solar radiation (MJ m⁻² day⁻¹).

where

$$\begin{aligned} 5 < T_{\max} \leq 35^\circ C & \quad \alpha_1 = 1.1 \\ T_{\max} > 35^\circ C & \quad \alpha_1 = 1.1 + 0.05(T_{\max} - 35) \\ T_{\max} < 5^\circ C & \quad \alpha_1 = 0.01 \cdot \exp[0.18(T_{\max} + 20)] \end{aligned} \quad (7)$$

Turc (1961) formula with reduced wind data is also a common method for calculating ET_0

$$ET_0 = (23.89R_s + 50) \frac{0.013T}{T + 15} [1 - W_{RH}(0.71 - 1.43RH/100)] \quad (8)$$

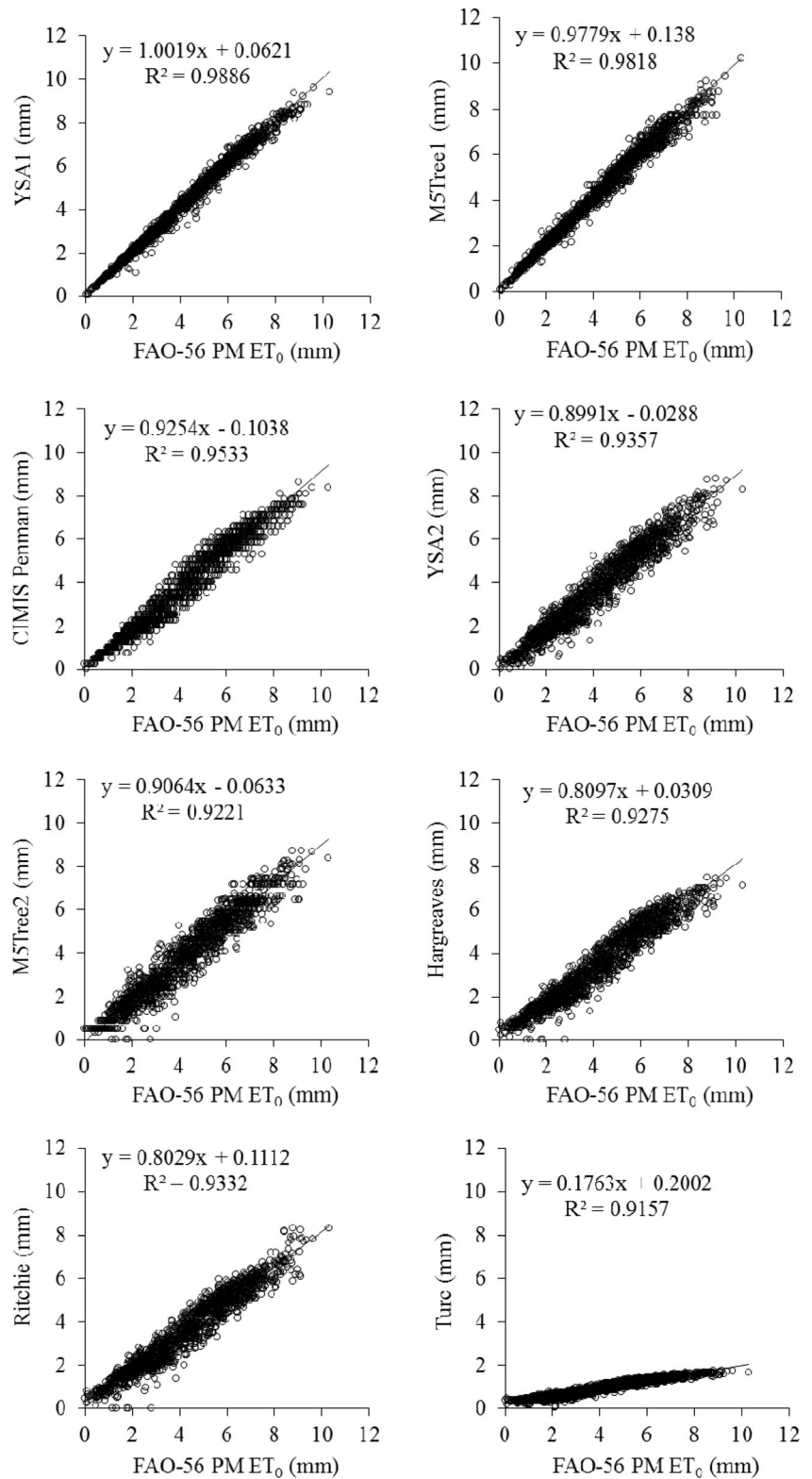
where $W_{RH} = 1$ when $RH < 50\%$ and $W_{RH} = 0$ when $RH > 50\%$.

Two different ANN and M5Tree models were developed in the study. ANN1 and M5Tree1 models have four inputs comprising whole climatic variables. The ANN2 and M5Tree2 models with two inputs, T and SR , were also developed for the valid comparison with

two-parameter Hargreaves-Samani, Ritchie, and Turc methods. For the ANN models, the optimal hidden node numbers were determined by using trial-and-

error method. The optimal ANN and M5Tree models are compared with empirical methods in Table 2. It is clear from the table that the four-input ANN1 and

Fig. 4 The FAO-56PM and estimated ET₀ values by the ANN, M5Tree, and empirical models in test period—King-City Oasis Rd. Station



M5Tree1 models perform better than the CIMIS Penman models for all stations. In five stations out of six, two-input ANN2 and M5Tree2 models showed better accuracy than the Hargreaves, Ritchie, and Turc models. In the Salinas North Station, Ritchie model has slightly better accuracy than the ANN2 model. M5Tree2 model performs worse than the Hargreaves and Ritchie models in this station. The ANN models generally performs better than the M5Tree models in local ET_0 estimation. In the Santa Monica Station, the M5Tree1 model has a slightly better accuracy than the ANN1 model. As an example, the estimates of the ANN, M5Tree, and empirical models are compared in Fig. 4 for the King-City Oasis Rd. Station. As seen from the scatterplots, the ANN and M5Tree models have less scattered estimates than those of the corresponding empirical models.

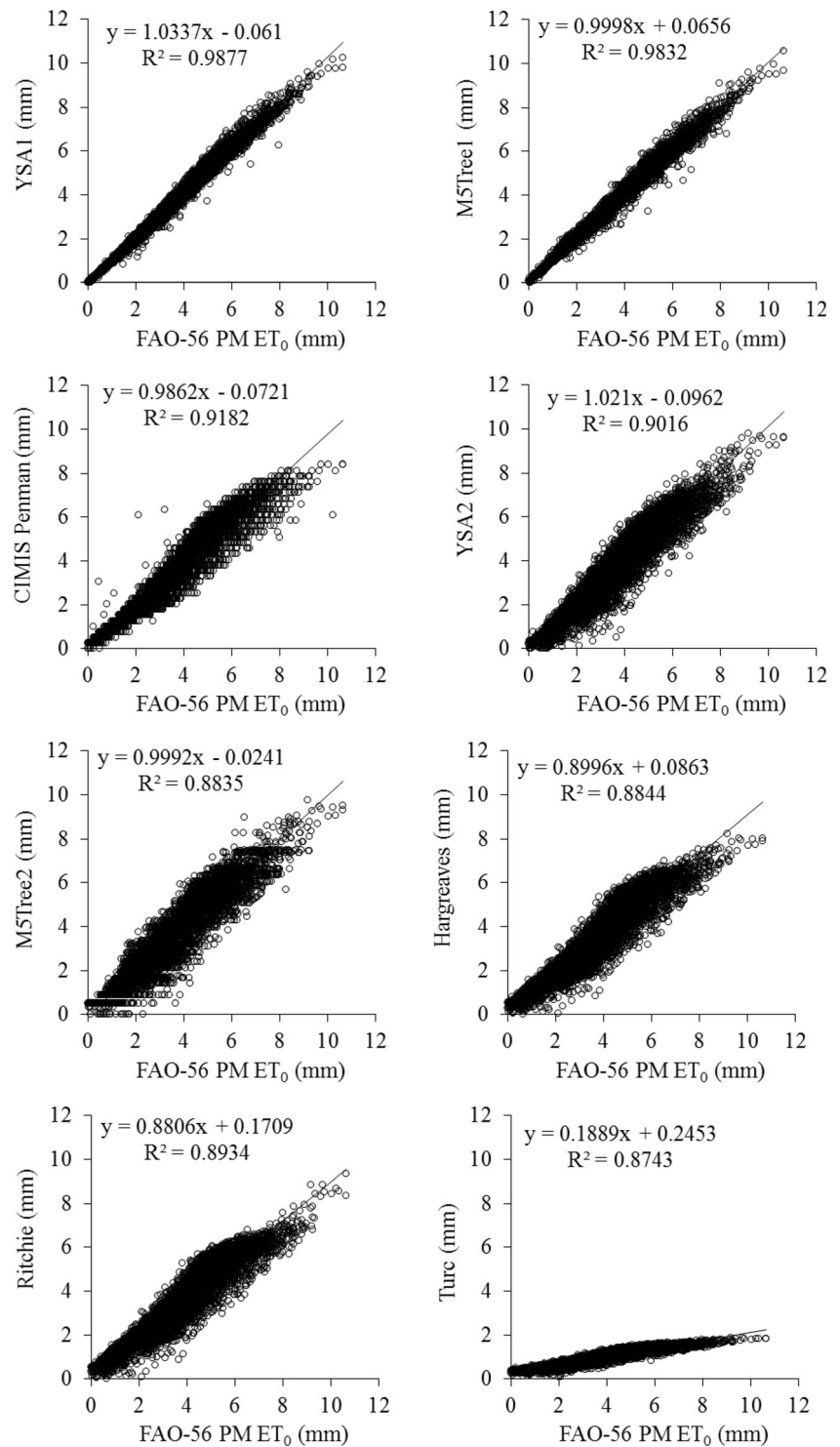
In the second part of the study, the four- and two-input ANN and M5Tree models obtained from one station in the previous application were tested using the data from other two stations for each region. In the San Joaquin region, the optimal ANN and M5Tree models obtained for the King-City Oasis Rd. Station in the previous application were tested using the data of Arroyo Seco and Salinas North stations. In the Southern region, the optimal ANN and M5Tree models obtained for the San Luis Obispo Station were tested by the data of Santa Monica and Santa Barbara stations. Test results of the ANN, M5Tree, and empirical models

are given in Table 3 for each station. In Arroyo Seco and Santa Monica stations, the four-input ANN1 model performs better than the CIMIS Penman model. In Salinas North and Santa Barbara stations, however, CIMIS Penman shows better accuracy than the ANN1 model. The main reason of this maybe the fact that the statistical properties of the data of the stations (King-City Oasis Rd. and San Luis Obispo) used in the calibration of ANN models are different with those of the stations used for testing (see Table 1). M5Tree1 models, however, perform better than the CIMIS Penman in all stations. In Arroyo Seco Station, the ANN1 model has better ET_0 estimates than the M5Tree1. Comparison of the two-parameter models indicates that the ANN2 model is better than the Hargreaves, Ritchie, and Turc methods in Salinas North and Santa Monica stations while the Ritchie model performs better than the ANN2 model in Arroyo Seco and Santa Barbara stations. Two-parameter M5Tree2 models generally provide inferior results compared to Hargreaves and Ritchie models. Among the two-input models, the Hargreaves is ranked as the second best in Santa Barbara Station. As an example for each region, the estimates obtained by ANN, M5Tree, and empirical models for the Arroyo Seco and Santa Barbara stations are shown in Figs. 5 and 6. It is clear from the figures that the four-input models give less scattered estimates than the two-input models. The superior accuracy of M5Tree model to the ANN in Santa Barbara Station can be clearly seen from

Table 3 The test statistics of the ANN, M5Tree, and empirical models in the second application

Models	RMSE (mm/day)	MAE (mm/day)	R^2	Models	RMSE (mm/day)	MAE (mm/day)	R^2
Arroyo Seco Station				Salinas North Station			
ANN1(4,9,1)	0.234	0.166	0.988	ANN1(4,9,1)	0.863	0.784	0.954
M5Tree1	0.252	0.182	0.983	M5Tree1	0.209	0.149	0.982
CIMIS Penman	0.475	0.356	0.918	CIMIS Penman	0.522	0.387	0.877
ANN2(2,10,1)	0.632	0.499	0.902	ANN2(2,10,1)	0.658	0.492	0.804
M5Tree2	0.678	0.529	0.884	M5Tree2	0.901	0.728	0.786
Hargreaves	0.647	0.479	0.884	Hargreaves	0.694	0.516	0.788
Ritchie	0.614	0.450	0.893	Ritchie	0.683	0.512	0.795
Turc	0.877	2.556	0.874	Turc	2.047	1.777	0.769
Santa Monica Station				Santa Barbara Station			
ANN1(4,8,1)	0.464	0.324	0.945	ANN1(4,8,1)	0.931	0.795	0.978
M5Tree1	0.253	0.169	0.971	M5Tree1	0.172	0.118	0.988
CIMIS Penman	0.505	0.347	0.897	CIMIS Penman	0.355	0.221	0.957
ANN2(2,7,1)	0.670	0.535	0.809	ANN2(2,7,1)	0.876	0.704	0.906
M5Tree2	0.784	0.659	0.785	M5Tree2	0.591	0.489	0.893
Hargreaves	0.801	0.675	0.786	Hargreaves	0.499	0.428	0.914
Ritchie	0.744	0.610	0.788	Ritchie	0.450	0.389	0.922
Turc	2.665	2.426	0.782	Turc	2.481	2.210	0.896

Fig. 5 The FAO-56PM and estimated ET₀ values by the ANN, M5Tree and empirical models in test period—Arroyo Seco Station

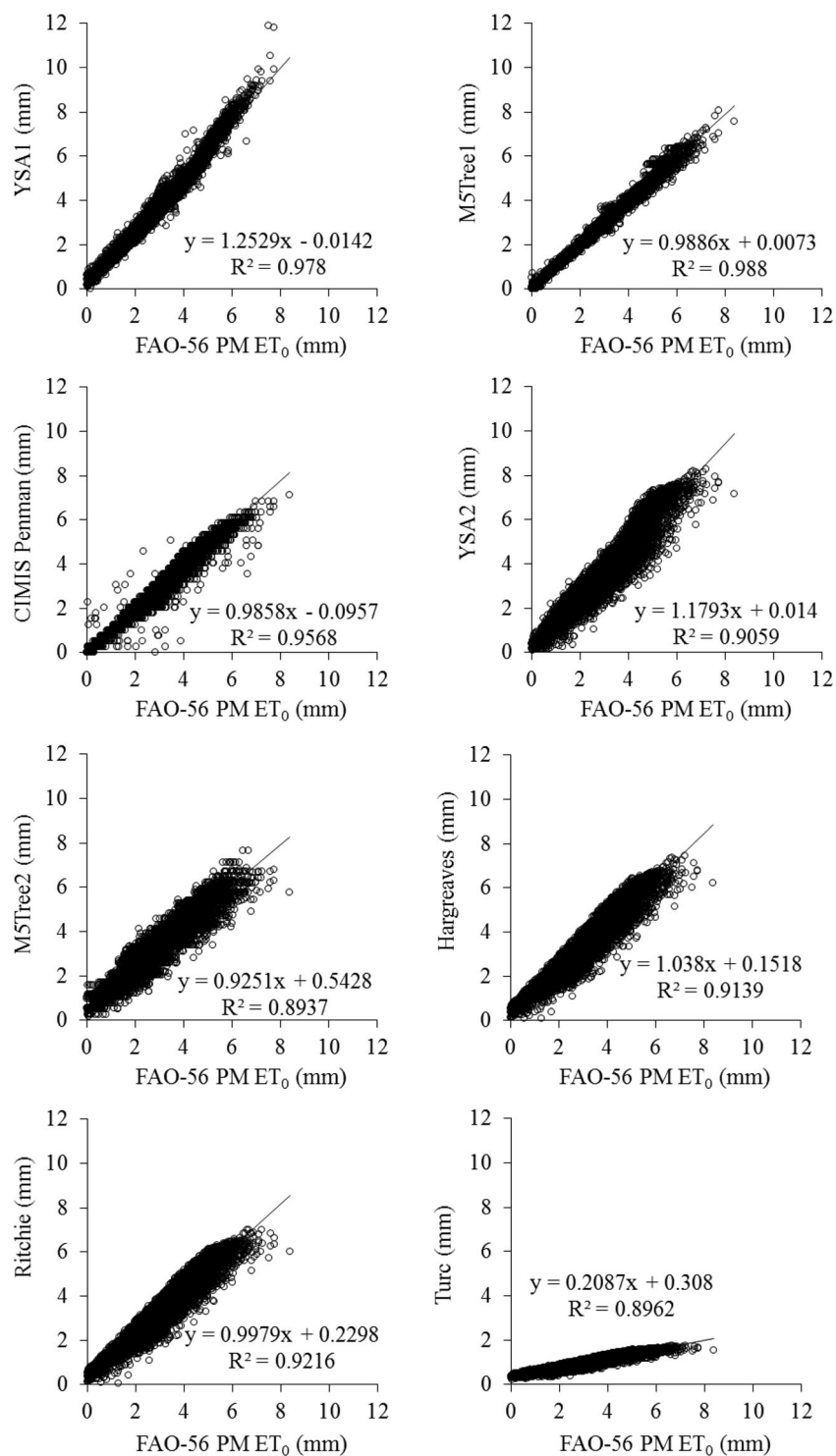


the scatterplots. Turc model gives inaccurate estimates for both stations.

In the third part of the study, the ANN and M5Tree models were calibrated using the data of three stations located in San Joaquin region and obtained models were

tested using the data from other three stations located in the Southern region. Test results of the ANN, M5Tree, and empirical models for each station are provided in Table 4. It is apparent from the table that four-input ANN1 and M5Tree models show better accuracy than

Fig. 6 The FAO-56PM and estimated ET_0 values by the ANN, M5Tree, and empirical models in test period—Santa Barbara Station



the CIMIS Penman in San Luis Obispo and Santa Monica stations, respectively. The M5Tree1 models perform better than the ANN1 models in Santa Monica and

Santa Barbara stations. On the other hand, two-input ANN2 model performs better than the Hargreaves, Ritchie, and Turc models in San Luis Obispo and Santa

Table 4 The test statistics of the ANN, M5Tree, and empirical models in the third application

Models	RMSE (mm/day)	MAE (mm/day)	R^2	Models	RMSE (mm/day)	MAE (mm/day)	R^2
San Luis Obispo Station				Santa Monica Station			
ANN1(4,7,1)	0.339	0.249	0.967	ANN1(4,7,1)	0.641	0.572	0.961
M5Tree1	0.707	0.589	0.967	M5Tree1	0.494	0.361	0.963
CIMIS Penman	0.432	0.287	0.949	CIMIS Penman	0.505	0.347	0.897
ANN2(2,3,1)	0.589	0.408	0.890	ANN2(2,3,1)	0.727	0.505	0.795
M5Tree2	0.674	0.505	0.870	M5Tree2	1.056	0.862	0.766
Hargreaves	0.795	0.537	0.881	Hargreaves	0.801	0.675	0.786
Ritchie	0.803	0.529	0.876	Ritchie	0.744	0.610	0.788
Turc	2.990	2.682	0.881	Turc	2.665	2.426	0.782
Santa Barbara Station							
ANN1(4,7,1)	0.695	0.540	0.950				
M5Tree1	0.577	0.444	0.962				
CIMIS Penman	0.355	0.221	0.957				
ANN2(2,3,1)	0.733	0.568	0.878				
M5Tree2	0.823	0.656	0.865				
Hargreaves	0.499	0.428	0.914				
Ritchie	0.450	0.389	0.922				
Turc	2.481	2.210	0.896				

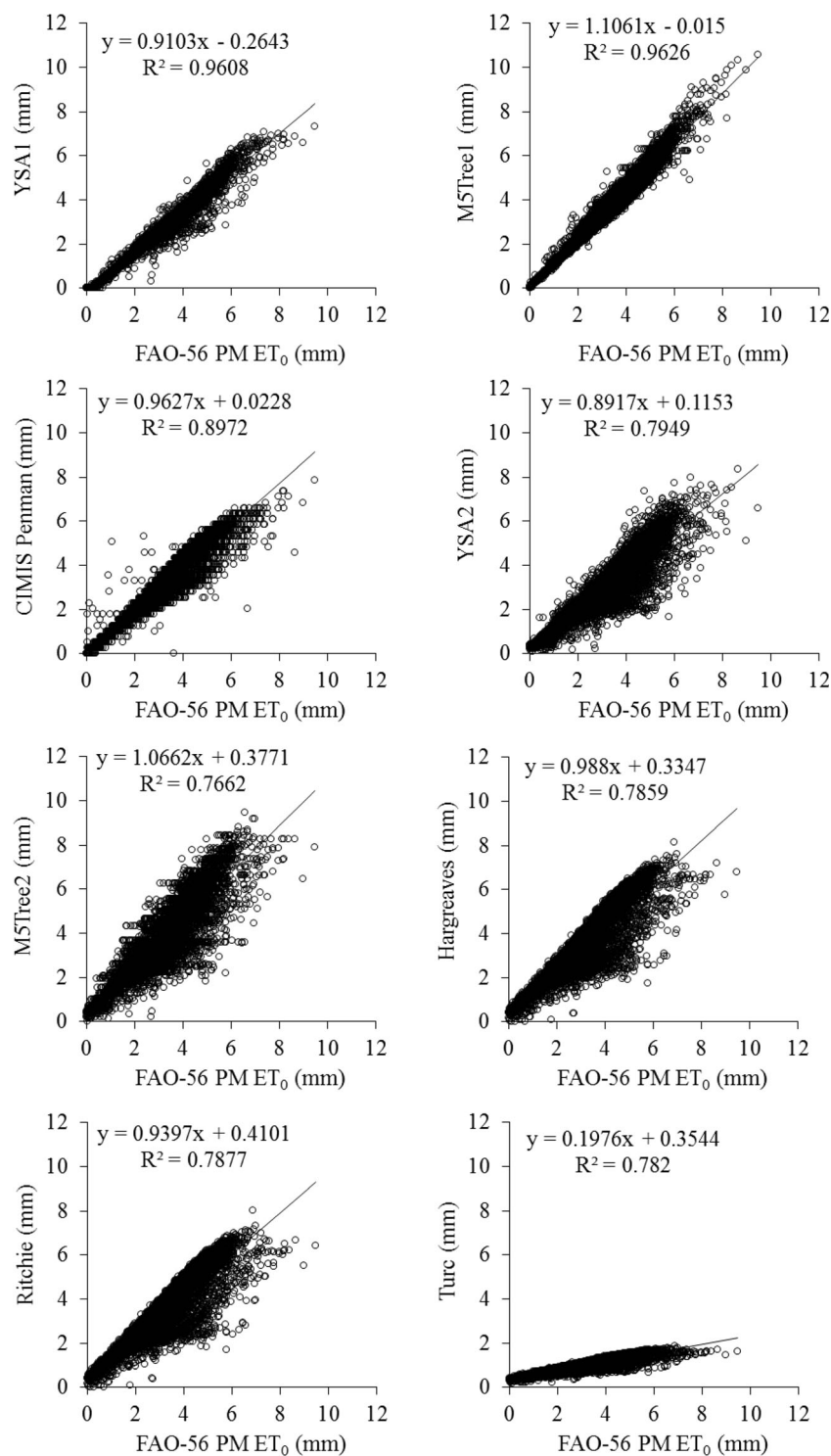
Monica stations while the M5Tree2 model provides worse accuracy than the Hargreaves and Ritchie models in Santa Monica and Santa Barbara stations. The main reason of the poor generalization ability of the ANN and M5Tree models is maybe the fact that the stations located in San Joaquin region have different statistical properties than those of the tested stations located in the Southern region (see Table 1). As an example, the estimates of the ANN, M5Tree, and empirical models are compared in Fig. 7 for the Santa Monica Station. It is clear from the figure that the M5Tree1 has less scattered estimates than the ANN1 and empirical models. All these results indicate that the ANN and M5Tree models should be carefully used without local calibration. M5Tree1 model may be a better alternative to ANN1 model in case of a lack of local climatic data.

6 Concluding remarks

The generalization ability of ANN and M5Tree in modeling ET_0 has been investigated in this study. The daily climatic data from King-City Oasis Rd., Arroyo Seco, and Salinas North stations located in San Joaquin region and San Luis Obispo, Santa Monica, and Santa Barbara stations located in the Southern

region were used as inputs to the ANN and M5Tree models for estimating ET_0 obtained using the standard FAO-56 Penman–Monteith equation. Three different applications were employed in the study. In the first application, the ANN and M5Tree models were tested using each station's data and results were compared with the empirical methods. The comparison results revealed that the ANN and M5Tree models performed better than the empirical models. In the second application, the ANN and M5Tree models were calibrated using climatic data of one station and tested by using the data of the other two stations for each region. Four-input ANN1 model performed better than the CIMIS Penman model in Arroyo Seco and Santa Monica stations while the M5Tree1 model provided better accuracy than the CIMIS Penman in all stations. The Hargreaves, Ritchie, and Turc models showed better accuracy than the two-input ANN2 model in Arroyo Seco and Santa Barbara stations. M5Tree2 model generally provided inferior results in ET_0 estimation compared to Hargreaves and Ritchie models. In the third application, three stations located in San Joaquin region were used for calibration of ANN and M5Tree models and obtained models were tested by the data of other three stations located in Southern region. Four-input ANN1 and M5Tree1 models were found to be better than the

Fig. 7 The FAO-56PM and estimated ET_0 values by the ANN, M5Tree, and empirical models in test period—Santa Monica Station



CIMIS Penman in San Luis Obispo and Santa Monica stations, respectively. Two-input ANN2 model performed better than the Hargreaves, Ritchie, and Turc models in San Luis Obispo and Santa Monica stations while the M5Tree2 model provided worse accuracy than the Hargreaves and Ritchie models in Santa Monica and

Santa Barbara stations. The study indicated that the ANN and M5Tree models calibrated without local climatic data can give poor estimates in some cases and should be carefully employed in modeling ET_0 . M5Tree1 can be used as a better alternative to ANN1 in the case without input and output data.

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