Testing hourly reference evapotranspiration approaches using lysimeter measurements in a semiarid climate

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ABSTRACT

Numerous approaches have been developed for estimating hourly reference evapotranspiration ET_0, most of which require numerous meteorological data. In many areas, the necessary data are lacking and new techniques are required. The objectives of this study are: (1) to develop artificial neural networks for estimating hourly reference evapotranspiration from limited weather data; (2) to evaluate the reliability of obtained artificial neural networks (ANNs) and Food and Agricultural Organization—56 Penman Monteith (FAO-56 PM) equation compared to the lysimeter measurements; (3) to test the performance of the FAO-56 PM equation for hourly daytime periods using $r_c = 70\,\mathrm{s\,m^{-1}}$ (PM70) and using a lower $r_c = 50\,\mathrm{s\,m^{-1}}$ (PM50); and (4) to evaluate the reliability of obtained ANNs compared to the FAO-56 PM equation using an hourly dataset from a variety of locations. The accuracy of two reduced-set artificial neural networks (ANNTR and ANNTHR) and two FAO-56 Penman-Monteith equations with different canopy resistance values (PM50 and PM70) was assessed using hourly lysimeter data from Davis, California. The ANNTR required only two parameters (temperature and radiation) as inputs. Temperature, humidity and $(R_n - G)$ term were used as inputs in the ANNTHR. The ANNTR and PM50 were best at estimating hourly grass ET_0. The ANNTR approach was additionally tested using hourly FAO-56 PM ET_0 data from California Irrigation Management Information System (CIMIS) dataset. The overall results recommended Radial Basis Function (RBF) network for estimating hourly ET_0 from limited weather data. Also, the results support the introduction of new value for canopy resistance ($r_c = 50\,\mathrm{s\,m^{-1}}$) in the hourly FAO-56 PM equation.

Key words | evapotranspiration, lysimeters, net radiation, neural networks, temperature

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INTRODUCTION

Evapotranspiration (ET) is a physical process in which water passes from liquid to gaseous state while moving from the soil to the atmosphere. It refers both to evaporation from soil and vegetative surface and transpiration from plants. These two separate processes (evaporation and transpiration) occur simultaneously and there is no easy way of distinguishing one from the other. Evapotranspiration is one of the major components in the hydrological cycle, and its reliable estimation is essential to water resources planning and management. Reference evapotranspiration (ET_0) is defined in Allen *et al.* (1998) as "the rate of evapotranspiration from hypothetical crop with an assumed crop height (0.12 m) and a fixed canopy resistance ($70\,\mathrm{s\,m^{-1}}$) and albedo (0.23) which would closely resemble evapotranspiration from an extensive surface of green grass cover of uniform height, actively growing, completely shading the ground and not short of water".

Reference evapotranspiration can be measured by lysimeters. However, the use of lysimeters is generally limited to specific research purposes due to difficult and expensive construction; they also require special care for operation and maintenance. These limitations make the

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application of indirect methods to estimate ET_0, based on easy-to-obtain weather data, more attractive. The reference evapotranspiration can be estimated from weather data for several time intervals. The timescale can range from less than 30 min to a month.

Sometimes, the computations of ET_0 that are made using monthly average weather data are not similar to the calculations made using daily average weather data or hourly weather data. Theoretically, this is due to the non-linearities both in the used equation and in the algorithms for computing the weather parameters, such as the vapour pressure and the slope of the saturation vapour pressure curve. When hourly weather data are available and when large changes in vapour pressure, wind speed or cloudiness occur during a day, then the estimation of reference evapotranspiration on an hourly time-step may produce the best results (Ortega-Farias *et al.* 1995). Numerous equations, classified as temperature-based, radiation-based, pan evaporation-based and combination-type have been developed for estimating reference evapotranspiration (ET_0), most of which are complex and require numerous weather parameters. Relationships were often subject to rigorous local calibrations (Trajkovic & Kolakovic 2009) and proved to have limited global validity.

In the past decades, many papers evaluated various equations for calculating the hourly ET_0. The California Irrigation Management Information System (CIMIS) Penman equation was used for estimating hourly ET_0 in several papers (Snyder & Pruitt 1992; Ortega-Farias *et al.* 1995; Ventura *et al.* 1999). The original Penman equation calculates ET_0 for periods not shorter than one week. Pruitt & Doorenbos (1977) have adapted this equation for the calculation of the ET_0 on an hourly basis, through the modification of the wind function. This wind function was locally adjusted by Berengena & Gavilan (2005) under semiarid conditions. The locally adjusted Penman equation performed quite well in a high advection area in Southern Spain (Berengena & Gavilan 2005).

Ventura *et al.* (1999) and Vaughan *et al.* (2007) compared hourly ET_0 estimates by the CIMIS Penman and Penman-Monteith equations to hourly lysimeter observations from Davis and Five Points, California. A comparison shows that Penman-Monteith equation gives better agreement with measured ET_0. Many studies have also indicated the superiority of the Penman-Monteith equation for estimating hourly ET_0 (Lecina *et al.* 2003; Allen *et al.* 2006; Lopez-Urrea *et al.* 2006; Perez *et al.* 2006; Gavilan *et al.* 2007). The Penman-Monteith equation has two advantages over many other equations. First, it can be used globally without any local calibrations due to its physical basis. Secondly, it is a well-documented equation that has been tested using a variety of lysimeters. The FAO-56 Penman-Monteith combination equation (FAO-56 PM) has been recommended by the Food and Agriculture Organization of the United Nations (FAO) as the standard equation for estimating reference evapotranspiration (ET_0). The FAO-56 PM equation requires numerous weather data: air temperature, relative humidity, wind speed, net radiation and soil heat flux.

The main shortcoming of this equation is that it requires numerous weather data that are not always available for many locations and new techniques are required. A new empirical equation for estimating hourly reference evapotranspiration was proposed in Alexandris & Kerkides (2003). This equation requires solar radiation, air temperature and relative humidity data and does not require wind speed data. The estimation of ET_0 from this new equation gave satisfactory results compared with PM and CIMIS Penman equations.

Artificial neural networks (ANNs) can be used as a new technique for estimating hourly evapotranspiration from limited weather data. The motivation for development of the ANN models was the creation of approaches that could generally be applied to estimate hourly reference evapotranspiration from the limited weather data when an application of the PM approach is not possible. It is interesting to observe that ANNs have not been used for estimating hourly evapotranspiration from limited weather data.

The objectives of this study are: (1) to develop artificial neural networks for estimating hourly reference evapotranspiration from limited weather data; (2) to evaluate the reliability of obtained ANNs and FAO-56 PM equation compared to the lysimeter measurements; (3) to test the performance of the FAO-56 PM equation using $r_c = 70\,\mathrm{s\,m^{-1}}$ (PM70) and using a lower $r_c = 50\,\mathrm{s\,m^{-1}}$ (PM50) and (4) to evaluate the reliability of obtained ANNs compared to the FAO-56 PM equation using an hourly dataset from a variety of locations.

MATERIALS AND METHODS

Study areas and data collection

In this study, two datasets were used. The adaptive artificial neural networks were developed and tested using hourly daytime lysimeter data collected at Davis, CA, USA. The accuracy of two FAO-56 Penman-Monteith equations with different canopy resistance values (PM50 and PM70) was assessed using hourly lysimeter measurements from Davis. The CIMIS dataset with hourly daytime data from four CIMIS stations (Davis, Nicolaus, Modesto, and Oaudale) was used for additional verification of the ANNs.

Davis data set

The Campbell Tract research site in Davis (38°32′ N; 121°46′ W; 18 m above sea level) is characterized by a semiarid Mediterranean climate. Lysimeters in use at Davis consist of the two units. The weighting lysimeter was installed in 1958–59. This lysimeter is circular, 6.1 min diameter and has a depth of 0.91 m. The floating drag-plate lysimeter, identical in size to the earlier one, was installed in 1962. In the period 1959–67 both lysimeters were in grass (perennial ryegrass, 1959–63; alta fescue, 1964–67) and were located about 52 m apart near the middle of 5.2 ha grass field. The soil in and around the lysimeters was disturbed Yolo loam. The grass was maintained under optimal water conditions. The grass was cut every 7–10 days but never to height below 10 cm. The lysimeter was irrigated following a 0.076 m depletion of soil moisture. Data were collected between 24 and 96 h after irrigation depending on the weather (Ventura *et al.* 1999). The ET_0 data were measured in kg of weight loss from the weighting lysimeter and converted to standard units ($1\,kg\,h^{-1} = 0.008554\,mm\,h^{-1}$). Comparison was made for the 1966–67 data with ET from the floating drag-plate lysimeter, and agreement within 2% was usual.

The weather data were taken from smoothed profiles (at heights of 50, 100, 140 and 200 cm) of temperature, humidity and wind. Wet- and dry-bulb thermopile sensors gathered the profile data for temperature and humidity. A separate system measured profiles of absolute humidity using an infrared hydrometer as the sensor. Thornthwaite cup anemometers gathered wind profile data. Net radiation was measured at 2 m above the grass surface with a forced-ventilated radiometer. The soil heat flux density was measured as the mean of three heat flux plates buried at 0.01 m depth in the soil.

The available weather and lysimeter data were collected at half-hour intervals during 1962–63 and 1966–67. A part of these data was also used in Ventura *et al.* (1999) and Todorovic (1999). Twenty-three days of weather and lysimeter data from Davis were used for training and testing RBF networks (Table 1). There were few nighttime data provided, so only data during daylight hours were analyzed. This dataset had a total of 494 records. These data refer to half-hour information for the days covering all of the seasons (9 spring days, 8 summer days, 5 fall days and 1 winter day). The number of days used in this study is similar to the other studies dealing with hourly evapotranspiration. It is higher than the number of days used in Ventura *et al.* (1999), Todorovic (1999) and Berengena & Gavilan (2005) (6, 8 and 21 days, respectively), and slightly lower than the number of days used in Lopez-Urrea *et al.* (2006) (29 days).

A small number of days in all the papers are accounted for by the fact that the hourly reference evapotranspiration is not easy to measure. Data used in Berengena & Gavilan (2005) were taken on days when the crop surface was not wet, at least 24 h after rain or irrigation. During the sampling periods, grass height was always between 10 and 15 cm and there was no free water on the canopy. The hourly data from Davis were collected in a similar way. The average temperature ranged from 13.9 (May 5, 1966) to 29.7°C (August 15, 1963). The average relative humidity was the lowest in October 13, 1966 (23.8%), and it was very high for May 5, 1967, and May 9, 1967 (71.6, and 73.6%, respectively). The average wind speed was the highest in October 13, 1966 (about $8.6\,m\,s^{-1}$) and it was never below $1.2\,m\,s^{-1}$ (August 31, 1962). The average net radiation ranged between 160 (October 13, 1966), and $584\,W\,m^{-2}$ (June 06, 1963). The lysimeter measured ET was the highest in August 15, 1963 ($12.8\,mm\,day^{-1}$) and it was the lowest in March 12, 1963 ($3.3\,mm\,day^{-1}$).

Table 1 | Daily micrometeorological and lysimeter data

Day	Time	N	Training/Testing	*T* (°C)	*RH* (%)	R_n(W m^{-2})	U_2 (m s^{-1})	ET_{0_ly} (mm day^{-1})	Advection index I_a
30/07/62	14.00–20.00	12	Training	26.5	38.5	234	4.0	5.11	1.234
31/07/62	06.00–18.30	23	Training	24.2	42.4	382	3.0	11.14	0.859
31/08/62	07.00–19.00	23	Training	26.2	41.6	333	1.2	8.32	0.737
30/10/62	10.00–17.00	15	Training	20.4	65.6	236	1.4	3.70	0.709
12/03/63	12.00–18.30	14	Testing	15.8	30.5	271	7.1	3.27	0.583
06/06/63	10.30–16.30	13	Testing	25.5	30.1	584	5.8	9.94	0.891
14/08/63	06.00–20.00	29	Training	27.1	36.6	290	2.0	11.76	0.949
15/08/63	06.00–19.30	28	Training	29.7	31.1	304	2.4	12.80	1.020
01/06/66	14.30–20.00	12	Testing	18.8	40.9	211	5.7	4.39	1.176
02/06/66	06.00–20.00	29	Training	17.7	43.3	343	2.9	11.60	0.790
03/06/66	06.00–20.00	29	Training	19.3	37.8	326	2.8	11.20	0.804
12/07/66	10.00–20.00	21	Testing	21.1	56.4	354	3.0	9.01	0.822
13/07/66	06.00–20.00	29	Testing	20.9	56.5	324	3.4	12.18	0.878
14/07/66	06.00–20.00	29	Testing	21.0	51.9	324	2.5	11.82	0.852
13/10/66	10.30–20.00	20	Testing	17.9	23.8	160	8.6	7.99	1.699
14/10/66	06.00–12.00	13	Testing	15.1	30.1	179	4.7	3.99	1.164
02/05/67	09.00–19.00	21	Training	18.7	47.4	385	2.6	8.31	0.711
03/05/67	12.30–19.00	14	Testing	19.0	46.4	296	2.5	5.33	0.873
04/05/67	07.00–19.00	25	Training	16.2	65.0	359	3.1	8.70	0.665
05/05/67	06.30–17.00	22	Testing	13.9	71.6	240	3.5	4.87	0.625
09/05/67	06.00–18.00	25	Testing	14.5	73.6	184	5.5	4.94	0.728
28/09/67	10.00–20.00	21	Testing	25.3	51.7	228	4.3	8.22	1.164
29/09/67	06.30–19.30	27	Testing	22.5	60.7	213	3.7	8.79	1.046

CIMIS dataset

The CIMIS is a program developed in 1982 by the California Department of Water Resource and the University of California at Davis to assist California's irrigators to manage their water resources efficiently. The CIMIS manages a network of over 120 automated weather stations in the state of California.

The hourly daytime data of four automated weather stations, Davis (#6, latitude 38°32′09″ N, longitude 121°46′ 32″W, elevation 18 m), Nicolaus (#30, latitude 38°52′16″ N,longitude 121°32′43″ W, elevation 10 m), Modesto (#71, latitude 37°38′43″N, longitude 121°11′ 16″W, elevation 11 m) and Oakdale (#77, latitude 37°43′07″ N, longitude 120°51′03″W, elevation 50 m) operated by the CIMIS were used in the study. Davis is located in Sacramento Valley Region Yolo County (Central District). Nicolaus is located in Sacramento Valley Region Sutter County (Central District). Modesto and Oakdale stations are located in San Joaquin Valley Region Stanislaus County (San Joaquin District). Reference surface for those stations is grass.

The radiation is measured using pyranometers at a height of 2.0 m above the ground. Air temperature is measured at a height of 1.5 m above the ground using a thermistor. The relative humidity sensor is sheltered in the same enclosure with the air temperature sensor at 1.5 m above the ground. Wind speed is measured using three-cup anemometers at 2.0 m above the ground. Hourly net radiation and air temperature data and the ET_0 values estimated using the Penman-Monteith equation for ten days (23/06/2008-02/07/2008) was downloaded from the CIMIS web server.

FAO-56 Penman-Monteith equation

The FAO-56 PM equation for hourly calculations can be expressed as (Allen *et al.* 1998):

$$\mathrm{ET}_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{37}{T+273}U_2(e_a - e_d)}{\Delta + \gamma\left(1 + \frac{r_c}{r_a}\right)}, \tag{1}$$

where ET_0 is reference evapotranspiration (mm h^{-1}); Δ is slope of the saturated vapour pressure curve (kPa°C^{-1}); R_n is net radiation (MJ m^{-2} h^{-1}); G is soil heat flux (MJ m^{-2} h^{-1}); γ is psychrometric constant (kPa°C^{-1}); T is mean air temperature (°C); U_2 is wind speed at a height of 2 m (m s^{-1}); $(e_a - e_d)$ is vapour pressure deficit (kPa); r_a is aerodynamic resistance (s m^{-1}); and r_c is canopy resistance (s m^{-1}).

Allen *et al.* (1998) recommended the use of $r_c = 70$ s m^{-1} for hourly time periods (PM70). However, several recent studies have shown that canopy resistance for daytime hourly periods is less than 70 s m^{-1} (Todorovic 1999; Ventura *et al.* 1999; Lecina *et al.* 2003; Berengena & Gavilan 2005). Based on a national study in the USA and studies by European and American researchers, Allen *et al.* (2006) suggested the use of $r_c = 50$ s m^{-1} for hourly daytime periods (PM50).

Artificial neural networks

An artificial neural network is a mathematical construct whose architecture is essentially analogous to the human brain. Basically, the highly interconnected processing units arranged in layers are similar to the arrangements of neurons in the brain. ANNs are efficient tools to model non-linear processes, which is the case of the evapotranspiration process. ANNs offer a relatively quick and flexible means of modelling and, as a result, application of ANN modelling is widely reported in the evapotranspiration literature (Trajkovic *et al.* 2000; Kumar *et al.* 2002; Kisi 2006, 2007; Landeras *et al.* 2008). Recent papers have reported that ANNs may offer a promising alternative for estimating daily evapotranspiration from limited weather data (Sudheer *et al.* 2003; Trajkovic *et al.* 2005; Zanetti *et al.* 2007; Trajkovic 2009).

In this paper, a sequentially adaptive Radial Basis Function (RBF) network from Trajkovic *et al.* (2003) was applied to estimate hourly ET_0. Sequential adaptation of parameters and structure was achieved using the Extended Kalman filter (EKF). A criterion for network growth is obtained from the Kalman filter consistency test. The adaptive RBF network learns from the data, which arrive continually and are shown in the network only once. The RBF network simultaneously estimates and learns. On the basis of the estimate error on the last sample, the parameters and structure of the RBF network change. The changed network gives the estimate for the next sample, where another error is obtained, which again changes the parameters and the structure of the RBF network. Training is over when all the samples pass through the network. After the training is over, the weights, number of hidden neurons and radial basis functions of the network are frozen. Readers are referred to Trajkovic *et al.* (2003) for a detailed description of this neural network.

The Davis dataset (494 records) was divided into two groups. For the RBF network training, ten randomly chosen days (234 records) were used (Table 1). For verification of the RBF network, obtained in a stage of training, the remaining 13 days (260 records) were used. The sequence of 260 records was scaled between −1 and 1.

The RBF networks were trained with weather data as inputs and ET_0 as output. Two RBF networks with a different number of inputs (ANNTHR and ANNTR) were considered. Air temperature, humidity and $(R_n - G)$ term were used as inputs in the ANNTHR model. Similar to Alexandris & Kerkides (2003), the ANNTHR model did not use the wind speed for the hourly ET_0 calculation. The ANNTR model required only two parameters (air temperature and net radiation) as inputs. The air temperature and net radiation are the most important parameters for driving evapotranspiration. The ANNTR model did not use wind speed, relative humidity and soil heat flux for estimating ET_0.

After the completed training, the ANNTHR model has the following structure. In the input layer, there are three neurons which receive information on air temperature (T_a), humidity (H) and $(R_n - G)$ term. There are four neurons in the hidden layer and there is one neuron yielding the ET_0 value in the output layer. We have:

$$ET_{0,\mathrm{annthr}} = \sum_{i=1}^{4} a_i \exp\left[-\left(\left(\frac{T_a - m_{i1}}{\sigma_{i1}}\right)^2 + \left(\frac{H - m_{i2}}{\sigma_{i2}}\right)^2 + \left(\frac{(R_n - G) - m_{i3}}{\sigma_{i3}}\right)^2\right)\right] + \Theta \quad (2)$$

where a_i is weight of the ith Gaussian basis function; m_{i1} is centre of the ith basis function for first input; σ_{i1} is width of the ith basis function for first input; m_{i2} is centre of the ith basis function for second input; σ_{i2} is width of the ith basis function for second input; m_{i3} is centre of the ith basis function for third input; σ_{i3} is width of the ith basis function for third input; and θ is bias ($\theta = 0.06035$ for the ANNTHR model).

After the completed training, the ANNTR model has the following structure. There are two neurons which receive information on air temperature and net radiation in the input layer. There are five neurons in the hidden layer and, in the output layer, there is one neuron giving the ET_0 value:

$$ET_{0,\mathrm{anntr}} = \sum_{i=1}^{5} a_i \exp\left[-\left(\left(\frac{T_a - m_{i1}}{\sigma_{i1}}\right)^2 + \left(\frac{R_n - m_{i2}}{\sigma_{i2}}\right)^2\right)\right] + 0.4146. \quad (3)$$

Evaluation parameter

In this study, the root mean squared error (RMSE) was used for the evaluation of the ET_0 estimates. Because it is an indication of both bias and variance from the 1:1 line, this evaluation parameter provides a good measure of how closely two independent datasets match. The RMSE was calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ET_{0\_\mathrm{est},i} - ET_{0\_\mathrm{lys},i})^2} \quad (4)$$

where $ET_{0\_\mathrm{est},i}$ is estimated half-hourly ET_0; $ET_{0\_\mathrm{lys},i}$ is half-hourly lysimeter ET_0; and n is number of observations. An RMSE value less than 0.074 mm h^{-1} is acceptable for most practical purposes (Ventura *et al.* 1999).

RESULTS AND DISCUSSION

Davis dataset

Two sequentially adaptive reduced-set RBF networks (ANNTR and ANNTHR) and two Penman-Monteith (PM) equations with different canopy resistance values (PM50 and PM70) were compared against half-hourly daytime lysimeter data from the Davis verification dataset (remaining 13 days). The Davis test dataset contained 260 records.

The results of comparison are presented in Table 2. Figures 1–3 present the comparison between estimated and measured hourly ET_0. The ANNTHR model performed reasonably well for most days. This approach underestimated hourly ET for the second half of 1 June 1966, midday of 13 October 1966 and 28 September 1967, and overestimated the second half of 12 March 1963. The daily ratio of estimated ET_0 to lysimeter ET data ($ET_{0\_\mathrm{est}}/ET_{0\_\mathrm{lys}}$) was 0.860, 0.865, 0.889 and 1.482, respectively. RMSE values were within an acceptable range, excluding 12 March 1963 (RMSE = 0.120 mm h^{-1}), 13 October 1966 (RMSE = 0.115 mm h^{-1}), 28 September 1967 (RMSE = 0.095 mm h^{-1}) and 29 September 1967 (RMSE = 0.079 mm h^{-1}). On average, the ANNTHR model underestimated hourly ET_{0_lys} by about 3% with RMSE value equal 0.073 mm h^{-1}.

Estimates by ANNTR were in closest agreement with the grass ET for most days. The ANNTR model underestimated hourly ET for the second half of June 1, 1966, midday of October 13, 1966 and the first half of October 14, 1966 and overestimated the second half of March 12, 1963 and first half of September 29, 1967 with $ET_{0\_\mathrm{est}}/ET_{0\_\mathrm{lys}}$ ratios of 0.827, 0.601, 0.737, 1.236 and 1.096, respectively. RMSE values were within an acceptable range for the majority of days excluding March 12, 1963 (RMSE = 0.090 mm h^{-1}), October 13, 1966 (RMSE = 0.165 mm h^{-1}), October 14, 1966 (RMSE = 0.092 mm h^{-1}) and September 28, 1967 (RMSE = 0.080 mm h^{-1}). On average, this approach slightly overestimated ET_{0_lys} by 3.2% with RMSE value equal to 0.071 mm h^{-1}.

The deviation of ANNTHR and ANNTR on June 1, 1966, September 28, 1967, and September 29, 1967 may be partly due to high wind speed (average wind speed was 5.7, 4.3 and 3.7 m s^{-1}, respectively) and low net radiation (average net radiation was 211, 228 and

Table 2 | Statistical summary of hourly ET_0 estimates for Davis dataset

Date	Parameters	ANNTHR	ANNTR	PM70	PM50
12/03/63	ET_{0_est} (mm day^{-1})	4.840	4.036	4.832	5.614
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	1.482	1.236	1.478	1.719
3.265 mm day^{-1}	RMSE (mm h^{-1})	0.120	0.090	0.123	0.186
06/06/63	ET_{0_est} (mm day^{-1})	9.671	9.226	8.793	9.730
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.973	0.928	0.885	0.979
9.940 mm day^{-1}	RMSE (mm h^{-1})	0.026	0.063	0.091	0.033
01/06/66	ET_{0_est} (mm day^{-1})	3.774	3.629	3.618	3.995
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.860	0.827	0.825	0.911
4.387 mm day^{-1}	RMSE (mm h^{-1})	0.062	0.071	0.075	0.040
12/07/66	ET_{0_est} (mm day^{-1})	8.744	9.311	7.616	8.139
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.971	1.033	0.845	0.903
9.010 mm day^{-1}	RMSE (mm h^{-1})	0.039	0.037	0.086	0.060
13/07/66	ET_{0_est} (mm day^{-1})	11.510	12.320	10.591	11.380
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.945	1.011	0.869	0.934
12.182 mm day^{-1}	RMSE (mm h^{-1})	0.064	0.051	0.081	0.051
14/07/66	ET_{0_est} (mm day^{-1})	11.783	12.245	10.510	11.122
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.997	1.036	0.889	0.941
11.817 mm day^{-1}	RMSE (mm h^{-1})	0.040	0.033	0.068	0.046
03/05/67	ET_{0_est} (mm day^{-1})	5.006	5.129	4.298	4.564
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.946	0.963	0.806	0.857
5.328 mm day^{-1}	RMSE (mm h^{-1})	0.052	0.041	0.096	0.081
05/05/67	ET_{0_est} (mm day^{-1})	4.816	5.014	4.224	4.677
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.990	1.030	0.872	0.961
4.866 mm day^{-1}	RMSE (mm h^{-1})	0.024	0.026	0.044	0.028
09/05/67	ET_{0_est} (mm day^{-1})	4.913	4.975	4.084	4.642
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.994	1.007	0.826	0.939
4.941 mm day^{-1}	RMSE (mm h^{-1})	0.028	0.032	0.051	0.034
28/09/67	ET_{0_est} (mm day^{-1})	7.306	8.483	7.314	7.853
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.889	1.033	0.890	0.956
8.215 mm day^{-1}	RMSE (mm h^{-1})	0.095	0.080	0.073	0.051
29/09/67	ET_{0_est} (mm day^{-1})	8.921	9.651	7.438	8.061
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	1.013	1.096	0.845	0.913
8.806 mm day^{-1}	RMSE (mm h^{-1})	0.079	0.061	0.073	0.047
13/10/66	ET_{0_est} (mm day^{-1})	6.914	4.806	7.374	8.602
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.865	0.601	0.922	1.076
7.993 mm day^{-1}	RMSE (mm h^{-1})	0.115	0.165	0.091	0.071
14/10/66	ET_{0_est} (mm day^{-1})	3.827	2.900	3.714	4.119
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.960	0.737	0.931	1.039
3.988 mm day^{-1}	RMSE (mm h^{-1})	0.042	0.092	0.033	0.021
Average	ET_{0_est} (mm day^{-1})	7.070	7.056	6.495	7.136
ET_{0_lys} =	ET_{0_est}/ET_{0_lys} (%/100)	0.970	0.968	0.891	0.979
7.289 mm day^{-1}	RMSE (mm h^{-1})	0.073	0.071	0.077	0.064

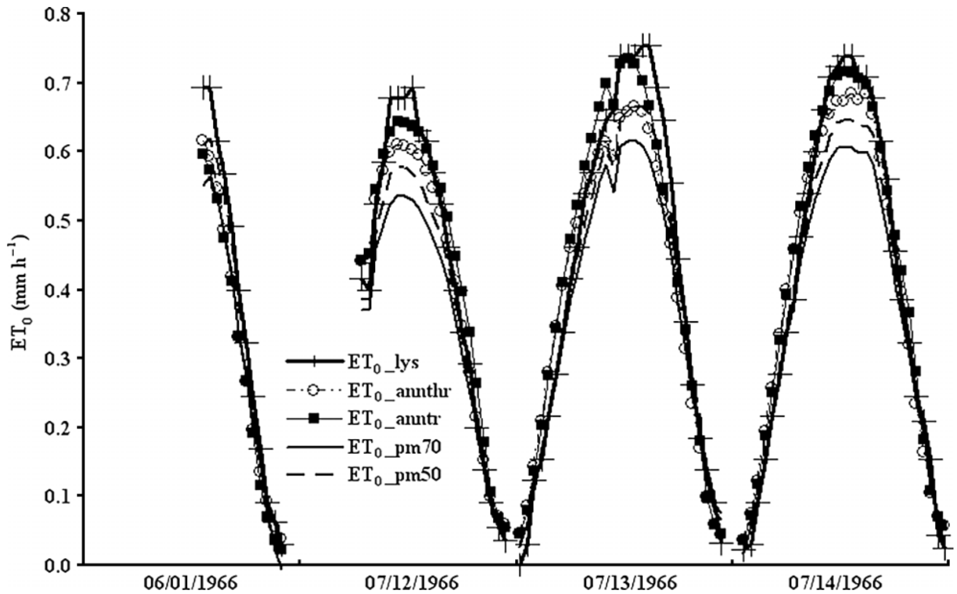

Figure 1 | Lysimeter measured and estimated hourly ET_0 during days of 1966.

213 W m^{-2}, respectively). The average wind speed only in one of ten training days exceeded 3.1 m s^{-1}, and the average net radiation was not less than 234 W m^{-2} in any training day.

The data from October 13, 1966 come from a strong advection situation with data collected at a site with an upwind fetch of grass of only 100 m, yielding extreme values of weather data (the lowest relative humidity, the lowest net radiation and highest wind speed). According to RMSE statistics, all equations were poor in estimating of ET_{0_lys} for October 13, 1966. The deviation of ANNTR model on October 13, 1966 and October 14, 1966 may be partly due to very low net radiation (average net radiation was 160 and 179 W m^{-2}, respectively). The poor performance of the ANNTR model is expected as this approach is the only method which does not require measurements of humidity. It is not possible to calculate the hourly ET without the humidity data during the strong advection days.

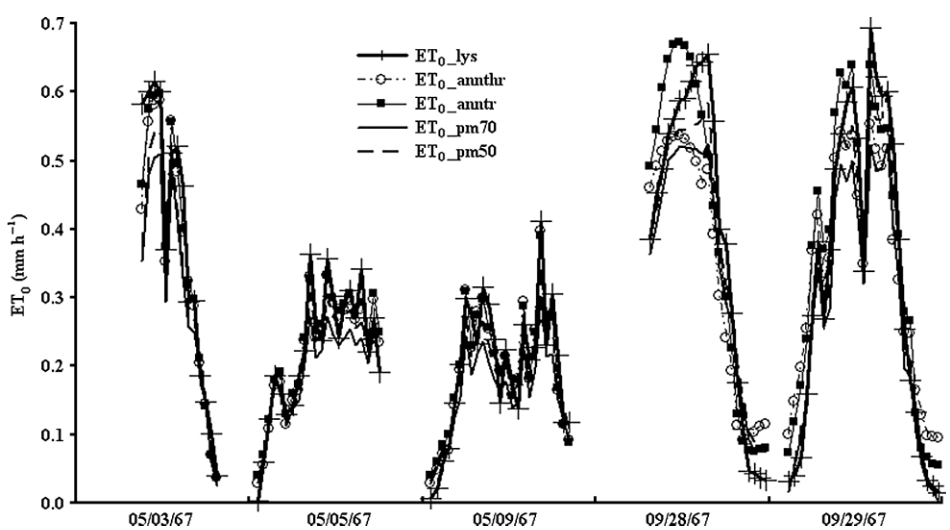

Figure 2 | Lysimeter measured and estimated hourly ET_0 during days of 1967.

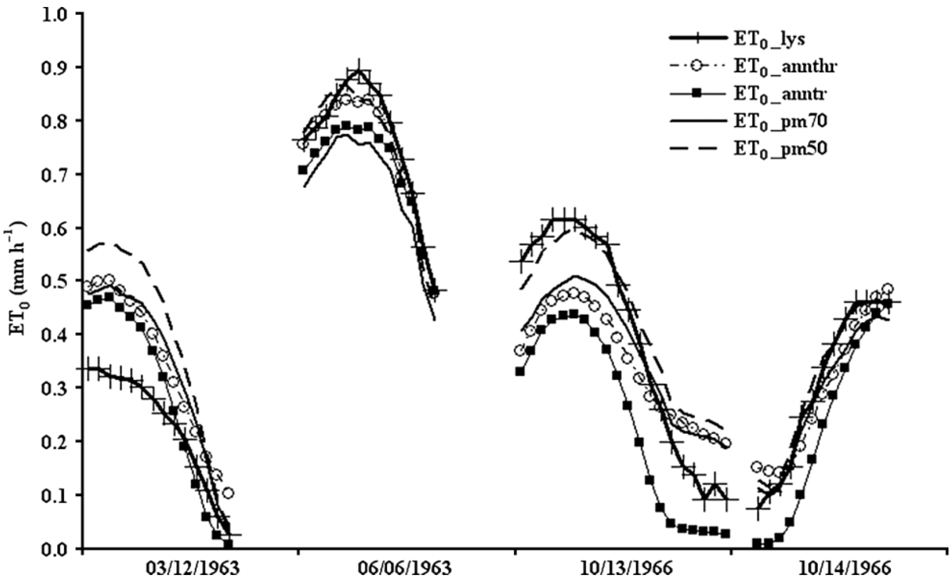

Figure 3 | Lysimeter measured and estimated hourly ET_0 during days of 1963 and advection days of 1966.

The ANNTHR and the ANNTR models were especially successful on May 5, 1967 and May 09, 1967. These days had extreme values of weather data (the lowest air temperature, the highest relative humidity, very low net radiation and high wind speed). The ANNTHR and the ANNTR models had the negligible departures from the ET_{0_lys}, even although the existence of the cloudiness produced high variations of the grass evapotranspiration during the day. The success is even greater, if it is emphasized that during the training days there were no days with such extreme values of the weather data.

The FAO-56 Penman-Monteith equation using the canopy resistance $r_c = 70\,\mathrm{s\,m^{-1}}$ (PM70) was the poorest in estimating ET_0 of all equations evaluated. The PM70 consistently underestimated hourly ET_{0_lys} for all days except March 12, 1963 by about 11%. The RMSE values varied from 0.044 (May 5, 1967) to $0.123\,\mathrm{mm\,h^{-1}}$ (March 12, 1963). These results strongly support the introduction of a new value for canopy resistance for the daytime periods in the FAO-56 PM equation recommended by Allen *et al.* (2006).

The PM50 yielded the acceptable estimate of the grass ET for the most days. This equation underestimated ET_{0_lys} during June 01, 1966, July 12, 1966, May 3, 1967 and September 29, 1966 and overestimated $ET0_{\_lys}$ during March 12, 1963 and October 13, 1966 with ET_{0_est}/ET_{0_lys} ratios of 0.911, 0.903, 0.857, 0.913, 1.719 and 1.076, respectively. RMSE values were within an acceptable range for most days excluding the March 12, 1963 (RMSE $= 0.186\,\mathrm{mm\,h^{-1}}$) and May 3, 1967 (RMSE $= 0.081\,\mathrm{mm\,h^{-1}}$). On average, this equation underestimated ET_{0_lys} by 2% with an RMSE value equal to $0.064\,\mathrm{mm\,h^{-1}}$.

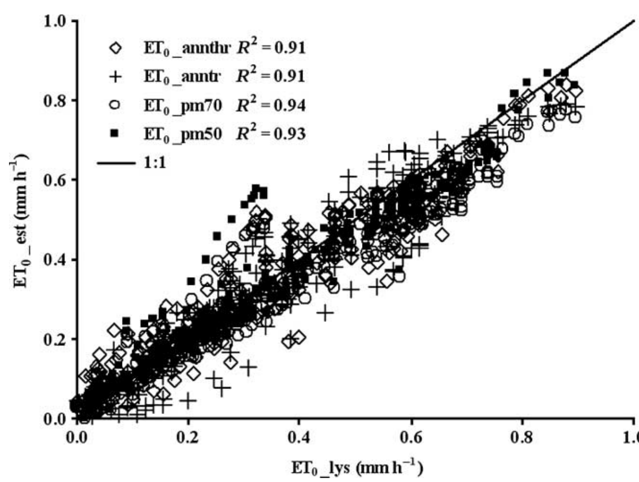

Figure 4 | Hourly ET_0 estimates (ET_{0_est}) versus lysimeter ET_0 (ET_{0_ly}).

Table 3 | Statistical summary of hourly ET_0 ANNTR estimates for CIMIS dataset

06/23/2008–07/02/2008 (10 days)		
Davis	ET_{0_anntr} (mm day^{-1})	6.401
ET_{0_pm50} =	ET_{0_anntr}/ET_{0_pm} (%/100)	1.040
6.158 mm day^{-1}	RMSE (mm h^{-1})	0.076
Nicolaus	ET_{0_anntr} (mm day^{-1})	6.518
ET_{0_pm50} =	ET_{0_anntr}/ET_{0_pm50} (%/100)	1.074
6.069 mm day^{-1}	RMSE (mm h^{-}1)	0.078
Modesto	ET_{0_anntr} (mm day^{-1})	6.382
ET_{0_pm50} =	ET_{0_anntr}/ET_{0_pm50} (%/100)	1.130
5.648 mm day^{-1}	RMSE (mm h^{-1})	0.071
Oaudale	ET_{0_anntr} (mm day^{-1})	6.634
ET_{0_pm50} =	ET_{0_anntr}/ET_{0_pm50} (%/100)	1.064
6.230 mm day^{-}1	RMSE (mm h^{-1})	0.065
03/12/1963–10/14/1967 (13 days)		
Davis	ET_{0_anntr} (mm day^{-1})	7.056
ET_{0_pm50} =	ET_{0_anntr}/ET_{0_pm50} (%/100)	0.989
7.136 mm day^{-1}	RMSE (mm h^{-1})	0.080

The ET_0 estimates (ET_{0_est}) were plotted against lysimeter measurements (ET_{0_ly}) in Figure 4. Locations of points evenly distributed about the 1:1 line indicate remarkable agreement between ANNTR estimates and lysimeter measurements. The PM70 and PM50 points are mostly distributed below the 1:1 line.

The overall results indicate that the ANNTR, ANNTHR and PM50 models give acceptable estimates of daytime hourly grass ET. The ANNTR and PM50 models were slightly better than ANNTHR model at matching ET_{0_lys}. It is interesting to note that the ANNTR model provided better results compared to FAO-56 Penman-Monteith with $r_c = 70\,s\,m^{-1}$ (PM70), although it only required measurements of two weather parameters.

CIMIS dataset

The ANNTR model was additionally tested using daytime hourly FAO-56 PM ET_0 data from the CIMIS dataset, which contained 600 records. The comparison results are presented in Table 3. Estimates by the ANNTR model are in closest agreement with the FAO-56 PM estimates for all locations. The RMSE values varied from 0.065 (Oakdale) to 0.078 mm h^{-1} (Nicolaus). The ET_{0_anntr}/ET_{0_pm50} ratio varied from 1.04 for Davis to 1.13 for Modesto. The hourly ET_0 values as estimated by ANNTR (ET_{0_anntr}) and FAO-56 PM equation (ET_{0_pm50}) for Oakdale data are plotted in Figure 5. The ANNTR ET_0 estimates matched ET_{0_pm50} fairly well. The results suggest that the hourly ET_0 for CIMIS stations could be computed from air temperature and net radiation using the ANNTR model developed from Davis lysimeter measurements.

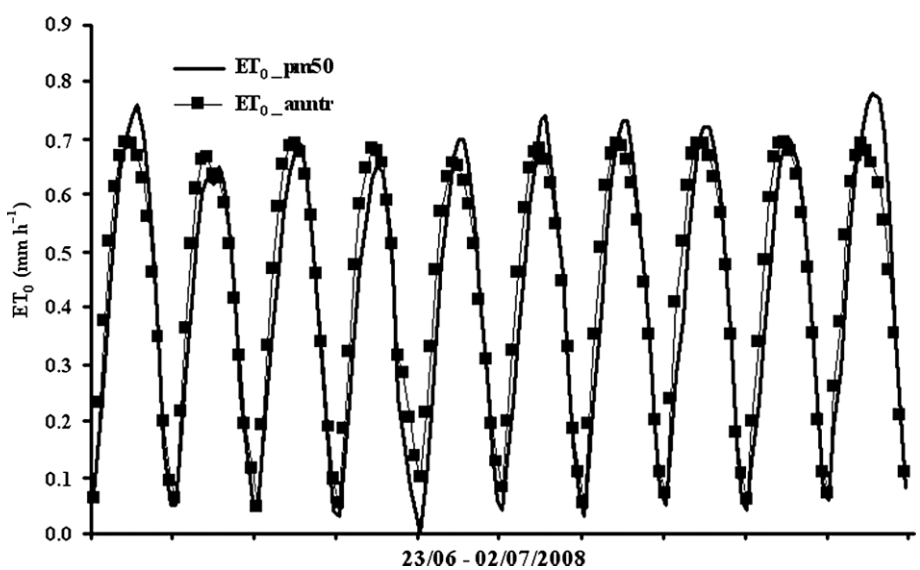

Figure 5 | Comparison of hourly ET_0 calculated for ten summer days at Oakdale, CA, USA using FAO-56 PM equation (ET_0_pm50) and RBF network (ET_0_anntr).

CONCLUSIONS

In this paper, two sequentially adaptive reduced-set RBF networks (ANNTR and ANNTHR) and two Penman-Monteith equations with different canopy resistance values (PM50 and PM70) were compared to hourly lysimeter observations from Davis, California, USA. The obtained results demonstrate that RBF networks are a successful alternative to the FAO-56 Penman-Monteith equation for estimating hourly reference evapotranspiration under those climatic conditions.

The ANNTR model required only two parameters (temperature and radiation) as inputs. Temperature, humidity and $(R_n - G)$ term were used as inputs in the ANNTHR model. PM equations use temperature, humidity, wind speed, net radiation and soil heat flux as inputs.

The FAO-56 Penman-Monteith equation using the canopy resistance $r_c = 70\,\mathrm{s\,m^{-1}}$ (PM70) was the poorest at estimating ET_0. The results reveal that the ANNTR and PM50 models were generally the best in estimating hourly grass ET. The ANNTHR model performed less well, but the results were acceptable for estimating grass ET. It is interesting to observe that the ANNTR model provided better results for the Davis dataset compared to the FAO-56 Penman-Monteith with $r_c = 70\,\mathrm{s\,m^{-1}}$ (PM70), although it required measurements of only two weather parameters. However, it is possible that accuracy problems for these approaches could occur under strong advection conditions.

This study indicates that, using limited weather data, artificial neural networks were able to reliably estimate hourly reference evapotranspiration under different atmospheric conditions. The adaptive RBF network is recommended for estimating hourly ET_0 from limited weather data. Also, the results strongly support the introduction of a new value for canopy resistance ($r_c = 50\,\mathrm{s\,m^{-1}}$) in the hourly FAO-56 PM equation. The use of the RBF network is very simple and does not require any knowledge of ANNs. Users only require code (RBF network), air temperature data and corresponding R_n data. The code can be obtained from the author.

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