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ORIGINAL PAPER

Solar radiation and precipitable water modeling for Turkey using artificial neural networks

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Abstract Artificial neural network (ANN) method was applied for modeling and prediction of mean precipitable water and solar radiation in a given location and given date (month), given altitude, temperature, pressure and humidity in Turkey (26–45°E and 36–42°N) during the period of 2000–2002. Resilient Propagation (RP) learning algorithms and logistic sigmoid transfer function were used in the network. To train the network, meteorological measurements taken by the Turkish State Meteorological Service (TSMS) and Wyoming University for the period from 2000 to 2002 from five stations distributed in Turkey were used as training data. Data from years (2000 and 2001) were used for training, while the year 2002 was used for testing and validating the model. The RP algorithm were first used for determination of the precipitable water and subsequently, computation of the solar radiation, in these stations Root Mean Square Error (RMSE) between the estimated and measured values for monthly mean daily sum for precipitable water and solar radiation values have been found as 0.0062 gr/cm^2 and 0.0603 MJ/m^2 (training cities), 0.5652 gr/cm^2 and 3.2810 MJ/m^2 (testing cities), respectively.

1 Introduction

The amount of solar radiation plays an important role in the design and analysis of energy efficient buildings in different climates. In cold and severely cold regions, passive solar designs and active solar heating systems will help to lower reliance on conventional heating means using fossil fuels (Lam et al. 2006). Energy is essential for the economic and social development, as well as an improved quality of life, in a country. Due to limited energy resources, Turkey has been importing energy and more than half of the national energy requirement is met by imports (Kaygusuz and Sari 2003). Therefore, solar energy is being seriously considered as a resource to meet a significant part of energy demand in Turkey, as it is worldwide (Kaygusuz and Ayhan 1999). Solar energy potential is quite high in Turkey. The yearly average solar radiation is about 3.6 kW h/m^2 days, and the total yearly radiation period is about 2610 h (Tymvios et al. 2005). In recent years, many individual studies have been carried out for solar measurements at different locations in Turkey (Kaygusuz and Ayhan 1999) and in other countries, e.g., in Saudi Arabia (Mohandes et al. 1998, 2000) and in Spain (Lopez et al. 2001; Hontoria et al. 2005). However, they have not been complete studies which cover large areas because of an insufficient number of measuring stations (Bulut 2004). Therefore, predictions about solar radiations at specific locations are still useful for many practical purposes. Several studies have been presented (Şaylan et al. 2003; Dinçer et al. 1996) concerning the prediction of solar radiation in various cities and locations in Turkey. As can easily be seen, solar radiation intercepted at the earth's surface is of paramount importance for various applications in a number of industrial and academic areas, such as in the infrastructure and construction industry, the estimation of crop productivity, environmental and agrometeorological research, atmospheric physics and the practical utilization of renewable energy resources (Tymvios et al. 2005).

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Water vapor is another critical element of the climate system (Chrysoulakis and Cartalis 2002) and is considered to be one of the most significant atmospheric constituents as it contributes substantially to the greenhouse effect. ‘Precipitable Water’ (PW) which is a meteorological term for the total atmospheric water vapor contained in a vertical column of unit area from the earth’s surface to the top of the atmosphere, is an important variable in considerations concerning climate systems, hydrological systems, or terrestrial ecosystems. Some of the major applications of PW are in quantitative precipitation forecasting, determination of moisture flow over an area and in radiation balance studies, since water vapor is one of the greenhouse gasses that can lead to global warming.

Water vapor influences the process of partitioning incoming solar radiation into latent and sensible heat fluxes, through its effect on “stomatal conductance” and “evapotranspiration”, terms important for the Earth’s energy and water budget calculations. In a terrestrial ecosystem modeling, near-surface water vapor is needed to calculate the latent heat flux since the water vapor within and just above the vegetation canopy can limit photosynthesis quite seriously (Czajkowski 2002).

Ignoring clouds, the atmosphere is largely transparent to the incoming solar flux, but opaque to outgoing thermal infrared radiation due to the atmospheric water vapor and other gases absorbing outgoing radiation, in different wavelengths depending upon their spectral properties. The absorbed radiation will be then emitted to the environment causing global warming. More than roughly 60 % of the natural greenhouse effect is attributed to water vapor (Taylor 2005).

PW has been mainly measured by radiosondes (a radiosonde is a complex device that has been especially designed to estimate several atmospheric parameters such as pressure, temperature, relative humidity, wind direction and speed) over and within the atmosphere. However on land, these instruments offer limited opportunities for spatial coverage and continuity measurements of PW (Cuomo et al. 1997).

Specific neural network modeling comes into the picture to remedy this deficiency. They have recently been developed and applied to particular problems in atmospheric and climate sciences, for short- and medium-range forecasting (Pasini et al. 2001; Pasini and Ameli 2003; Pasini et al. 2006).

PW was observed to play a very important role in obtaining highly accurate results, since the construction of a precipitable water database is very useful for solar energy, environmental, agricultural and global climate change purposes, in addition to other applications (Şenkal et al. 2012).

In Turkey (located between longitudes 26°E–45°E and latitudes 36°N–42°N), there are only five radiosonde stations (Adana, Ankara, İstanbul, Samsun and İzmir) with affiant altitude and positions (Fig. 1). Estimations of precipitable water and solar radiation above Turkey are usually based on meteorological and geographical data (pressure, humidity, temperature, month and altitude). Meteorological and geographical data were constantly measured by the Turkish State Meteorological Service (TSMS) for the period from 2000 to 2002. These radiosonde sites throughout Turkey show different characteristic features as seen in Table 1.

In this study, an Artificial Neural Network (ANN), known as Resilient Propagation (RP) is used to estimate precipitable water and solar radiation. The RP networks in this paper are used first for the determination of precipitable water and subsequently, the computation of solar radiation in Turkey (Al-lawati et al. 2003). The monthly mean daily sums was measured and compared during the study period for estimated ANN values.

2 Methodology and data sources

2.1 Precipitable water (PW)

As noted, PW is the total amount of water vapor in a vertical direction between the Earth’s surface (or a surface in a given height) and the top of the atmosphere (Chrysoulakis and Cartalis 2002). It can be expressed as:

$$\mathrm{PW} = \frac{1}{g}\int_{p_s}^{0} M_r dp, \tag{1}$$

where M_r is the mixing ratio, g is the acceleration of gravity over the examined area in m/s^2, p is the pressure at a given altitude, and p_s is the pressure on the surface of the earth in Pascals (Pa = N/m^2) (Iqbal 1983). The above relationship shows that PW has dimensions mass per unit surface (kg/m^2). Thus, PW, which can also be measured in cm as the height of water column above a unit area, is described as the thickness of the liquid, if all water vapor in the zenith direction was condensed at the surface of a unit area.

In each layer, the mixing ratio can be estimated from the relationship (Soden and Bretherton 1993):

$$M_r = \frac{\rho_v}{\rho_d}, \tag{2}$$

where ρ_d is the density of dry air, ρ_v is the water vapor density (absolute humidity).It should be mentioned, that at each pressure level (top or base of the layer), an estimation is made from the relationship:

$$\rho_d = \frac{P}{R_d T}, \tag{3}$$

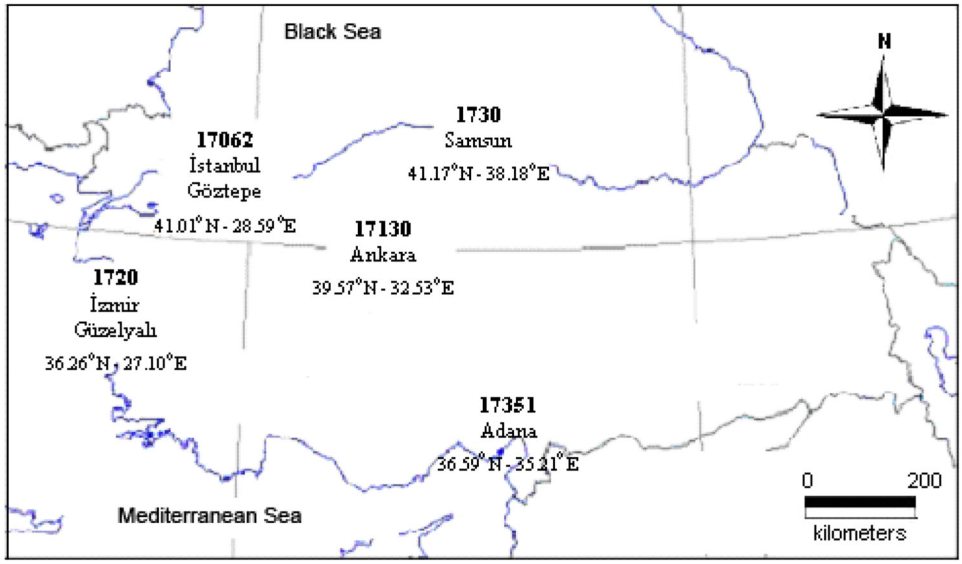

Fig. 1 Radiosonde stations in Turkey

Table 1 Geographical parameters for the stations

Stations	Latitude (°N)	Longitude (°E)	Altitude (m)
Adana	36.59	35.21	27
Ankara	39.57	32.53	891
İstanbul	41.01	28.59	0
İzmir	38.26	27.10	29
Samsun	41.17	36.18	4

where P is partial pressure of the dry air in Pascals (Pa), ρ_d is density of the dry air in kg/m^3, T is absolute temperature in K that the radiosonde measures at that pressure level, and R_d is the Gas constant for the dry air in units of J/kg/K and numerically equal to 287.05 J/kg/K.

Whereas ρ_v is estimated at each pressure level (top or base of the layer) on the basis of the relationship:

$$\rho_v = \frac{e}{R_v T}, \tag{4}$$

where e is partial pressure of the water vapor, or vapor pressure, in Pascals (Pa) which is estimated from the relative humidity radiosonde measurement at each pressure level (top or base of each layer), ρ_v is density of the water vapor in kg/m^3, T is absolute temperature in K that radiosonde measures at each pressure level, and R_v is the gas constant for the water vapor in units of J/kg/K and numerically equal to 461.51 J/kg/K (Cartalis and Chrysoulakis 1997).

As deduced from the daily radiosonde measurements of the Wyoming University database for Turkey, the relative humidity and air temperature vertical profiles as well as the values of surface atmospheric pressure, was used to estimate the daily and monthly mean values of precipitable water at various heights above the surface for the period of time between 2000 and 2002. The integral in Eq. (1) is carried out by a procedure similar to that employed by Soden and Bretherton (1993). The monthly mean for the whole period 2000–2002 was calculated using the radiosonde measurements.

2.2 Solar radiation

Solar radiation data collection starts before sunrise and finishes after sunset. All measurements are referred to in true solar time. Solar radiation data were constantly measured by the Turkish State Meteorological Service (TSMS) for the period from 2000 to 2002.

To collect data from stations, these characteristics are kept in mind:

1. The quality of the measurement stations: synoptic and big stations
2. The availability of data: hourly data
3. Time resolution: 10–15 min (reaction time)
4. The type of instruments: Robitzch-Fuess actinograph
5. The type of corrections applied to the data: Robitzch-Fuess actinography calibrated regarding the Angström Pyroheliometer.

3 Artificial neural networks (ANN)

The use of the ANNs for modeling and prediction purposes has become the recipient of growing interest over the last few decades (Chow et al. 2002). Researchers have been applying the ANN method successfully in various fields including

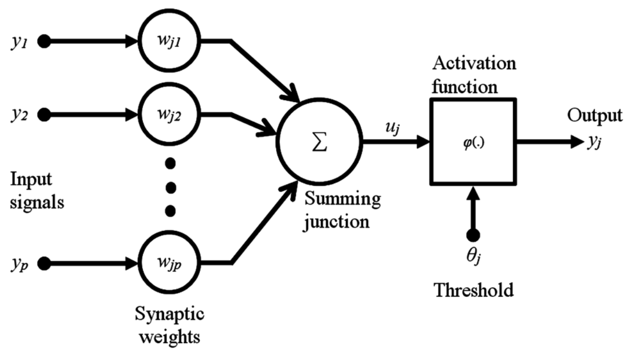

Fig. 2 Non-linear model of a single neuron

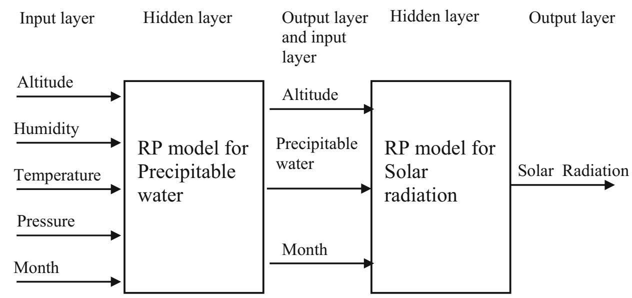

Fig. 3 Block diagram for estimation of monthly daily average precipitable water and solar radiation in Turkey

mathematics and science to engineering, medicine and economics, for example the prediction of mineral exploration sites, electrical and thermal load predictions and adaptive and robotic control applications and a few other specific examples. An ANN has to be trained to overcome the limitations of the conventional approaches to solve complex problems. The method learns from given examples by constructing an input–output matrix of mapping to perform predictions (Mohandes et al. 2004). In other words, it is required to train and test a neural network, for which input data and corresponding output values are necessary (Çam et al. 2005).

The fundamental processing element of a neural network is called a 'neuron'. Each neuron computes a weighted by w_{ij} sum of its p input signals y_i, for $i = 0,1,2,\ldots,n$, hidden layers and then applies a non-linear activation function to produce an output signal u_j. The standard model used for an ANN is shown in Fig. 2.

A neuron j of an ANN may be mathematically described with the following pair of equations (Haykin 1994):

$$u_j = \sum_{i=0}^{p} w_{ji} y_i \tag{5}$$

and

$$y_j = \phi(u_j - \theta_j) \tag{6}$$

The use of the threshold values θ_j has the effect of applying an affine transformation to the output of the linear combiner in the model of Fig. 2 (Haykin 1994; Melesse and Hanley 2005). The sigmoid logistic non-linear function used in the present calculation is described with the following equation (Bilgili et al. 2007):

$$\phi(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

4 Results and discussions

The ANN which consists of two input layers with one hidden layer each and an output layer was used for the determination of precipitable water and the subsequent layer of the second output layer was used for the computation of solar radiation all over Turkey. MATLAB is a commonly used software system which was administered to train and test the ANN on a personal computer. The algorithm used in the study was Resilient Propagation (RP), descripted by the Logistic sigmoid transfer function (named 'logsig'), and the linear transfer function (named 'purelin') was used in the hidden layers and in the output layer of the network as an activation function. For training, ten neurons were used in the first hidden layer for precipitable water and six neurons for the second hidden layer solar radiation. Geographical and meteorological factors have influences on the intensity of incoming solar radiation on the Earth. Thus, the meteorological data provided by the Turkish State Meteorological Service (TSMS) and from the Wyoming University database for Turkey for the period from 2000 to 2002 were used, firstly for training purposes and later as testing data to train the neural network. The data set for the two-year period of 2000–2001 was used for training the network, while another set for (1 year, 2002) was used for testing and validating the RP model. An interesting alternative approach to training, validation and test of ANNs, when dealing with quite limited data sets, is that by Pasini and Modugno (2013). Its application could represent a further development for the present study. The final ANN structure can be followed in Fig. 3.

The value of the monthly mean daily sum of precipitable water and subsequently, the solar radiation over Turkey were determined using the ANN model shown in Fig. 3. The values of performance were correlation coefficient (R^2) 94.64 % and root mean square error (RMSE) 0.0062 g/cm^2 (Fig. 4), R^2 93.35 % and RMSE 0.5652 g/cm^2 (Fig. 5) for precipitable water values (training and testing). In the case of the monthly mean daily sum, the correlation coefficient and RMSE was found to be 98.71 % and 0.0603 MJ/m^2 (Fig. 6), 96.32 % and 3.2810 MJ/m^2 (Fig. 7) for solar radiation values (training and testing). As

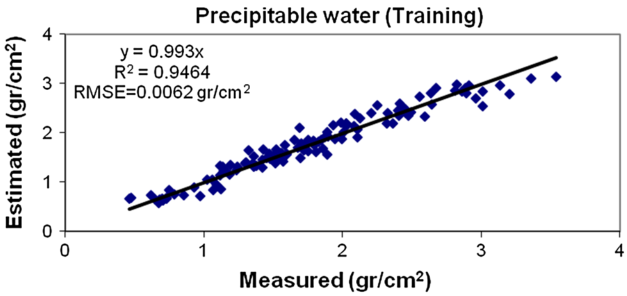

Fig. 4 Comparison of monthly mean daily sum measured and estimated concerning training during the study period for precipitable water

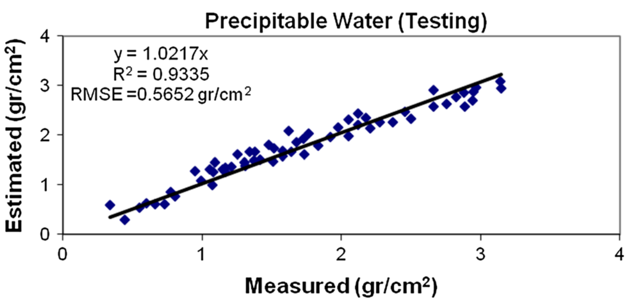

Fig. 5 Comparison of monthly mean daily sum measured and estimated concerning testing during the study period for precipitable water

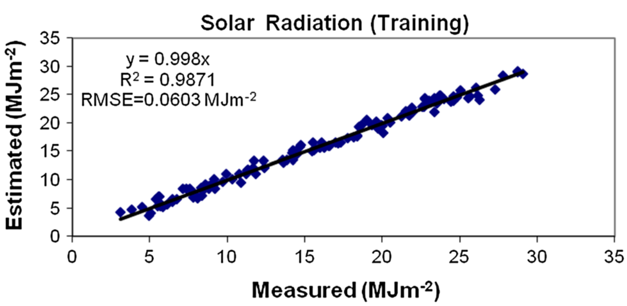

Fig. 6 Comparison of monthly mean daily sum measured and estimated concerning training during the study period for solar radiation

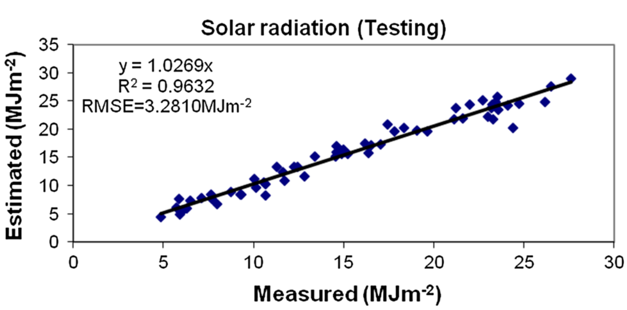

Fig. 7 Comparison of monthly mean daily sum measured and estimated concerning testing during the study period for solar radiation

it has been reported before, R^2 values range from 0.8390 to 0.9464 % (see Table 2) (Şenkal et al. 2012). The 0.9464 R^2 value obtained in this study is higher than the highest existing R^2 data in the literature which is 0.9120 as it is reported by Şenkal et al. (2012).

The performance values for all stations, such as MBE (Mean Bias Error) and RMSE for training, testing precipitable water and solar radiation values are given in Table 3. The maximum MBE was found to be 0.0693 (precipitable water) and 0.3718 (solar radiation) values, while the minimum MBE was found as −0.1429 (precipitable water) and −0.9017 (solar radiation) values. The RMSE values of precipitable water and solar radiation, ranging from 0.0489 to 0.4950 % and 0.1421 to 3.1234 %, differ from the actual value for all stations. The maximum RMSE was found to be 0.4950 % (precipitable water) for İstanbul station and 3.1234 % (solar radiation) for İzmir station in the testing values, while the best result was found to be 0.0489 % (precipitable water) and 0.1421 % (solar radiation) for Ankara station in the training values. Another significant point in this table is that the performance values of the training by ANN method are generally better than the performance values of the testing. Figures 8 and 9 shows a comparison between measured and ANN (precipitable water and solar radiation) values for the five stations (training and testing stations). There are two main reasons causing the differences in the RMSE values between all stations; firstly, the calculation of precipitable water is based on the integration of radiosonde data (relative humidity, pressure and temperature) over the whole atmosphere; secondly, the ANN results are based on satellite over pass time, meteorology stations measurement time and seasonal variability of Earth's surface incoming sun radiation. The errors in the RMSE values of other methods, which are used by many researchers for the computation of the solar radiation, are more than the errors in this study which includes five stations located in five cities in Turkey. The performance values for all stations are given in Table 4.

The results of our own study confirm the ability of the ANN method to predict precipitable water values for every pixel of the study area, throughout Turkey, where data from only five upper air radiosonde observation station are used. In addition, meteorological radiosonde observations are held on large TSMS climate stations, having a minimum distance of 250 km distance from each other. The small scale climate stations were unable to make radiosonde observation, so they were not able to calculate PW values for the regions where they are located. Using the ANN, PW values can be calculated for each such station, where pressure, humidity and temperature (for months with altitudes) are measured, and subsequently, the solar radiation can be computed at that location. Therefore, this method (the ANN technique) is very useful and presents a

Table 2 Comparison with other ANN methods using different input parameters

Study	Input data	Algorithm	Correlation coefficient
Current study	Geographical and meteorological	ANN/RP	0.9464
Şenkal et al. (2012)	Geographical and meteorological	ANN/LM	0.9120
Mattioli et al. (2010)	Satellite data	ANN/MLP	0.8570
Basili et al. (2010)	Satellite data	ANN/MLP	0.8140
Wang et al. (2006)	Satellite data	ANN/MLP	0.8390

Table 3 Error values of the solar radiation and precipitable water method approach

Stations	Training procedure				Testing procedure			
	Precipitable water		Solar radiation		Precipitable water		Solar radiation	
	MBE	RMSE	MBE	RMSE	MBE	RMSE	MBE	RMSE
Adana	0.0693	0.3393	0.0589	0.2883	−0.0302	0.1044	−0.7762	2.6888
İstanbul	−0.0860	0.4212	0.3110	1.5235	−0.1429	0.4950	0.3718	1.2878
İzmir	−0.0146	0.0714	−0.1158	0.5674	−0.1111	0.3850	−0.9017	3.1234
Samsun	0.0440	0.2154	−0.2858	0.9747	−0.0163	0.0557	−0.2929	1.0147
Ankara	−0.0099	0.0489	0.0290	0.1421	−0.0646	0.2236	−0.4614	1.5982

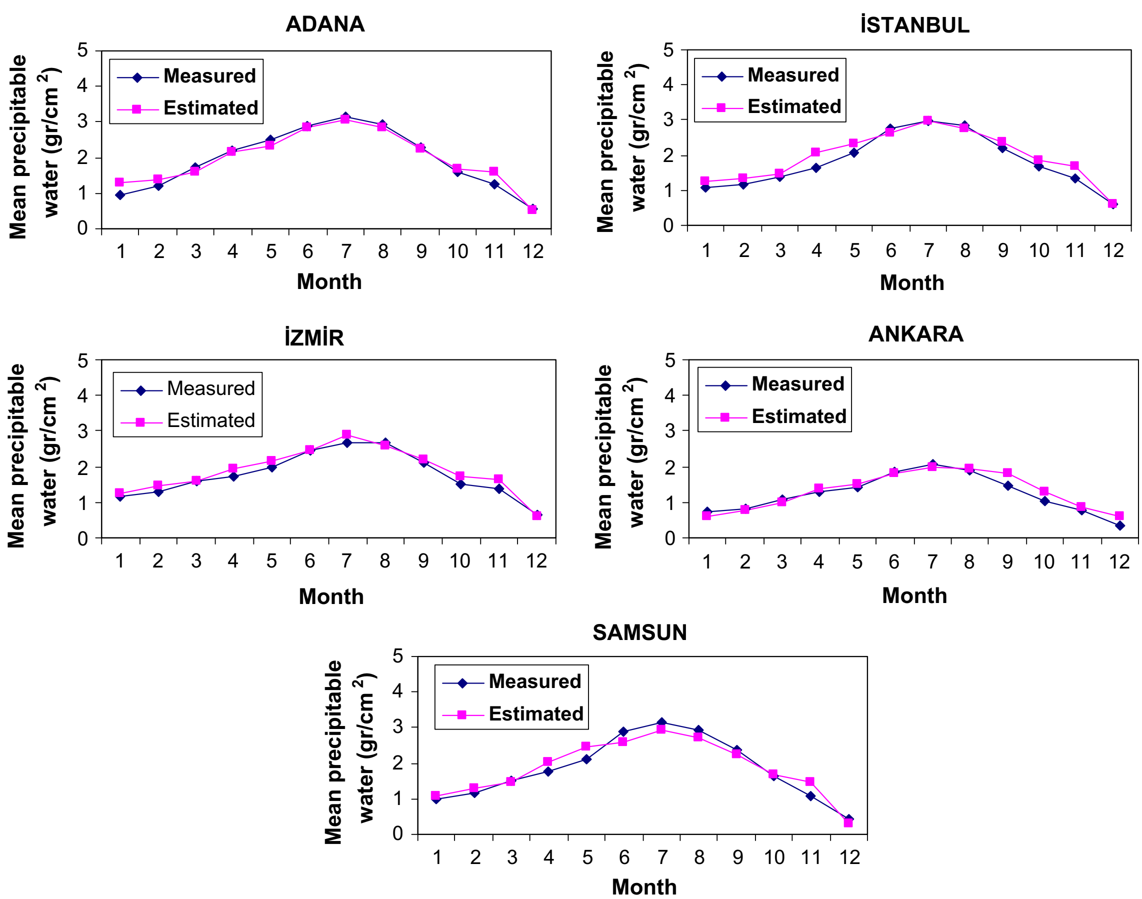

Fig. 8 Comparison between measured and estimated monthly mean daily global precipitable water for 2002

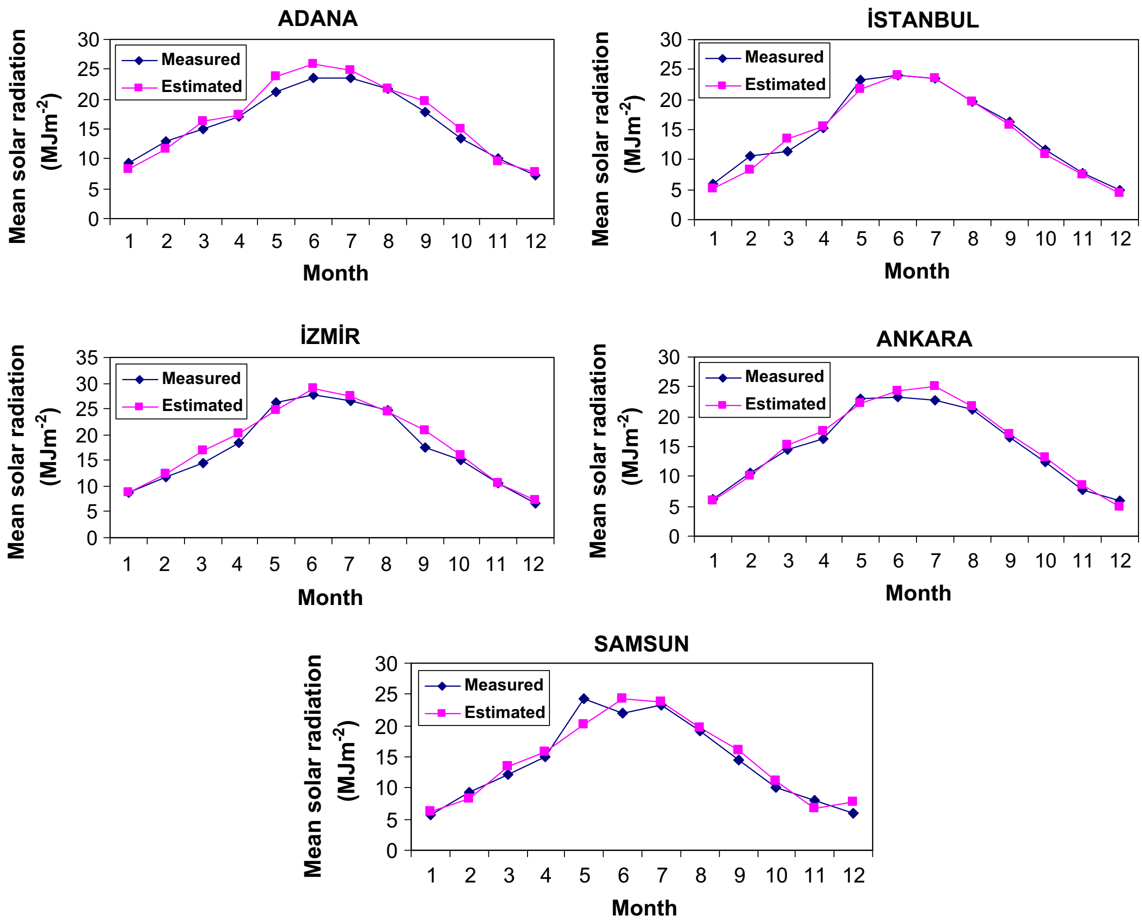

Fig. 9 Comparison between measured and estimated monthly mean daily global solar radiation for 2002

Table 4 Comparison of error values in current study and the other studies; Levenberge Marquardt (LM), Scaled conjugate gradient (SCG), Pola–Ribiere conjugate gradient (CGP), and Resilient propagation (RP)

Sözen et al. (2004)				Şenkal and Kuleli (2009)			Current study		
Stations	Input data	Algorithm	RMSE (MJ/m^2)	Input data	Algorithm	RMSE (MJ/m^2)	Input data	Algorithm	RMSE (MJ/m^2)
Adana	Geographical and meteorological data	ANN/LM SCG, CGP	2.00	Geographical and satellite data	ANN/RP, SCG	0.49	Geographical and meteorological data	ANN/RP	0.29
İstanbul			2.42			0.03			1.52
İzmir			1.60			4.91			0.57
Samsun			1.14			0.33			0.98
Ankara			1.00			0.86			0.14

less costly method than using the classical direct observations carried out in some meteorology stations in this country.

5 Conclusion

In this study, a method was proposed to calculate PW through an ANN system, within and over a large area (Turkey) using only a limited number of high atmosphere reading solar station data. PW is known to play an important role in obtaining highly accurate solar energy values over the same large area. Both PW and solar energy are important inputs in energy, environmental and agricultural areas as well as having other applications. The results for Turkey also revealed that correlation values indicate a relatively good agreement between the observed values and the ANN-calculated precipitable water and solar radiation values. Thus, it is suggested that the cheaper and faster method of ANN, when compared to metrological methods in the estimation of precipitable water and solar radiation values, has large economic benefits for a country like Turkey with regard to the measurement of both sets of values.

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