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Solar Radiation Estimation using Temperature-based, Stochastic and Artificial Neural Networks Approaches

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Radiation is a variable that governs many hydrological and phenological processes, but its measurements are not made routinely. To overcome this problem, continuous hydrological models that include evapotranspiration, snowmelt (using solar radiation data) and plant growth modules have applied different strategies to generate daily radiation data. In this paper, artificial neural networks (ANNs), temperature-based (TB) and stochastic (ST) approaches for estimation of solar radiation have been used and compared. These three approaches have been applied to the Ammameh Catchment, an alpine subcatchment of the Jadjroud River, in Iran. Results reveal better performance for ANNs than for TB and ST. However, the TB method because of its capability to generalize results and to be easily linked with hydrological models appears to be a good candidate to be applied in the catchments where the climatological data are limited.

Introduction

Radiation has a significant role in hydrological modelling. Simulation of hydrological processes such as evapotranspiration and snowmelt invariably requires radiation data. For example, the Penman–Monteith and Priestley-Taylor methods, which are well known for estimation of evapotranspiration, require radiation data. For snowmelt also, energy budget and temperature-radiation methods need radiation data. Some recent conceptual hydrological models that embedded plant growth process in their models (*e.g.* EPIC (Williams *et al.* 1984) and SWAT (Arnold *et al.* 1996)) require solar radiation for simulating the above process. Such addition of a plant growth component has helped modelers to transform their models into distributed models, which can be used for planning and the assessment of human impact. However, the availability of data on radiation is limited in developing countries and some limitations in measurements have also been observed in the developed countries (Samani 2000).

Hydrological models have used different strategies to tackle the requirement of radiation data. Some models such as ARNO (Todini 1996) and SVAT (Yang 2000) have postulated that radiation data can be acquired from meteorological stations, whereas models like SWAT (Arnold *et al.* 1996) and SHE (Bathurst and Cooley 1996) generate radiation data from other readily available data. The present study concentrates on various procedures to estimate solar radiation. These procedures include Temperature-Based (TB), Stochastic (ST) and Artificial Neural Networks (ANNs) methods. Another class of methods, which uses cloudiness to compute radiation (Singh 1992; Dozier 2000) has deliberately been ignored, since data on cloudiness are also not widely available.

The performance of the identified approaches during the calibration and validation periods has been evaluated using the correlation statistic (R^2), root mean square error ($RMSE$) and mean absolute error (MAE). The R^2 is used to indicate the relative assessment of the model performance in dimensionless measures, whereas $RMSE$ and MAE give a quantitative indication of the model error in units of the variable. The best performance of the model yields R^2 equal to 1 and in case of $RMSE$ and MAE, zero values confirm a perfect prediction (Liong *et al.* 2000).

Description of the Study Area

To evaluate the performance of the three algorithms in the estimation of solar radiation, the Ammameh Catchment, one of the alpine subcatchments of the Jadjroud River basin in Iran, with an area of 16.1 km^2 has been used. The terrain is mountainous, rocky and with steep slopes. Ammameh station at the downstream end of the catchment records daily meteorological information including solar radiation. The climate of the Ammameh area is temperate with a mean annual temperature of 8.6°C. Winters are relatively cold, and in the month of March, average monthly temperature approaches to –5.8°C. The climate data from 1973 to 1976 were used for this study. The first year data was used for the calibration and the remaining data were used for the validation. Average and standard deviation of daily solar radiation for the study period (1973-76) are 204.8 and 81.4 (W/m^2), respectively.

Description of the Selected Approaches

As has been discussed earlier, three approaches with different bases have been selected for the estimation of solar radiation. A brief description of the approaches is presented as follows:

Temperature Based (TB) Approach

The study carried out by Hargreaves and Samani (1982), who correlated solar radiation (R_s) with temperature and extraterrestrial radiation, has been followed by many researchers. Allen (1997) has referred to a number of such studies. Hargreaves and Samani (1982) calculated R_s as

$$R_s = K_r \ (T_{max} - T_{min})^{0.5} R_a \tag{1}$$

where T_{max} and T_{min} are the mean daily maximum and the minimum air temperature (°C), respectively. R_a is the extraterrestrial radiation; and K_r is an empirical coefficient. This equation is based on the assumption that the difference between daily maximum and minimum temperatures provides a general indication of cloudiness (Allen 1997).

K_r has a significant role in Eq. (1) and it is used to adjust the equation for different climatic conditions. Initially K_r was set to 0.17 for arid and semiarid climates. Hargreaves (1994) suggested using $K_r = 0.16$ for interior regions and $K_r = 0.19$ for coastal regions. Allen (1997) has introduced two methods to calculate K_r. The first method, presented in 1995, recommended the following equation to calculate K_r

$$K_r \equiv K_{rs} \left(\frac{P}{P_0}\right)^{0.5} \tag{2}$$

where P is the mean atmospheric pressure at the site in kPa; P_0 is the mean atmospheric pressure at sea level (101.3 kPa); and K_{rs} is an another coefficient whose value is taken as 0.17 for interior regions and 0.20 for coastal regions, respectively. Allen introduced his second procedure to estimate K_r in 1997. He called this procedure a 'self-calibration method' for estimating solar radiation and it has been referred to as the 'Allen method' in this paper.

Estimation of K_r using the Allen Method – Allen (1997) showed that Eq. (1) produces a relationship between R_s/R_a and T_{max}-T_{min}, which is generally consistent throughout the year. The relationship is conservative in the prediction of R_s/R_a, *i.e.* it rarely overestimates R_s values when skies are clear. These characteristics make self-calibration possible by comparing estimates from Eq. (1) with an envelope of R_{so} values expected under entirely clear-sky conditions.

The self-calibration method involves calibration of R_s by applying Eq. (1) on a daily (24-h) basis using daily measurements of T_{max} and T_{min} and an initial value for K_r. The estimates are plotted over time for at least one year and are then overlain by calculated clear sky solar radiation, R_{so} (the R_{so} envelope represents expected R_s when the sky is free of clouds). According to this method, the value of K_r is varied until the highest estimates of R_s approaches the R_{so} values.

There are number of ways to calculate R_{so}. However, there is not much difference between them. A comparison of two of these methods (Majumdar *et al.* 1972; Richardson 1985) is shown in Fig. 1 for our study area. Allen (1996) used the pro-

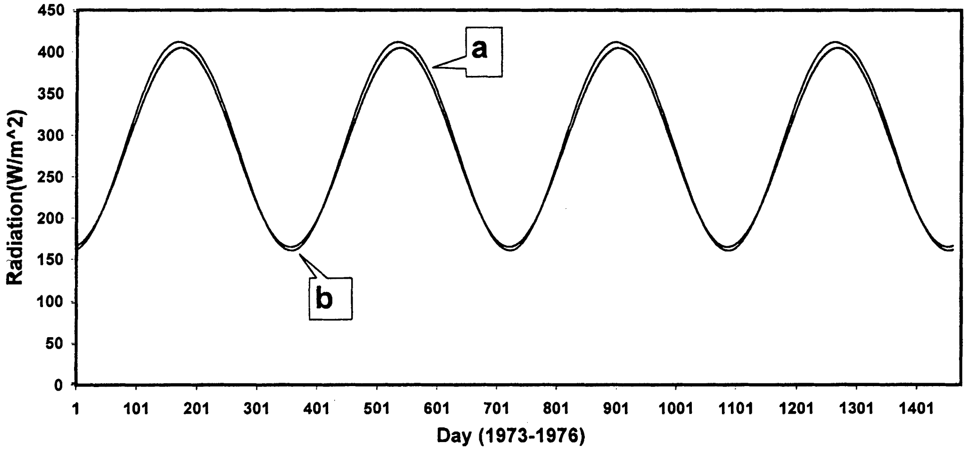


Fig.1. Comparison of Majumdar *et al.* (a) and Richardson (b) methods for calculating of max. incident solar rad. at Ammameh st.

cedure based on Majumdar *et al.* (1972), which expresses the clear sky solar radiation, R_{so} as

$$R_{so} = k_t R_a \tag{3}$$

where $R_a \equiv$ extraterrestrial radiation; and k_t = transmission index. R_a is a function of latitude and day of the year. k_t may range from 0.7 to 0.8, depending on atmospheric clarity (dust, pollution, humidity, *etc.*), elevation and sun angle. More discussion about calculation of k_t is available in Allen (1997). The derivation of R_a has been taken from Duffie and Beckman (1980). Because of very low variation of k_t and total certainty associated with R_a, certainty in computation of R_{so} increases especially for clear atmosphere of mountainous and rural areas.

Estimation of K_r using the Samani Method – Samani (2000) used average monthly temperature and radiation data for a period of 25 years for the continental United States. Using average monthly data for the entire year, from 65 weather stations, the following relationship was developed

$$K_r \equiv 0.00185(T_{max}-T_{min})^2 - 0.0433(T_{max}-T_{min}) + 0.4023 \tag{4}$$

The relation suggests that K_r is a function of the difference between maximum and minimum temperatures. Within the ranges of original data that constituted Eq. (4), the K_r varies between a low value of 0.13 to a high value of 0.24.

Application of the TB Approach to the Study Area – For application of the TB approach, both the Allen and the Samani methods for estimation of K_r have been used. The Allen method starts with estimation of a value for K_r (0.15 was used in the present case) and following the procedure explained in the previous section, the optimum value calculated for the study area was 0.2 (Fig. 2). The sinusoidal curve in Fig. 2 shows the estimated incident daily radiation under clear sky (R_{so}). Using Eq. (1) with $K_r = 0.2$ leads to the estimation of R_s values, which are enveloped by the R_{so} curve. Although the value of K_r has been estimated using only observed 1973 data, it shows consistency and appears to be valid for the other years as well. It is obvious that the method to some extent needs engineering judgments, as the enveloping curve of clear sky radiation (R_{so}, sinusoidal curve) passing tangentially through the highest measured solar radiation (R_s, '♦' in Fig. 2) can not solely be the indicator of the optimum enveloping curve. In some cases, measurement errors can provide higher estimation of R_s than R_{so}. So by visualizing the graphs and general status of R_s and R_{so}, the value of K_r can be ascertained.

The Samani (2000) method for evaluation of K_r was also applied in this study. The simulated incident solar radiation by this method has been shown in Fig. 3. The regression coefficient between four years of observed and estimated data is 0.49. The average value of K_r for the entire period (1973-1976) is calculated to be 0.16, whereas by the Allen method it was estimated to be 0.2. Using this method for the study area has resulted in significant under estimation of R_s. It may be concluded that Eq. (4) does not seem to represent a global equation for estimation of K_r. Therefore, the Allen method is recommended for estimation of K_r in the TB based solar radiation estimation.

Stochastic (ST) Approach

Richardson (1981) applied the technique presented by Yevjevich (1972) for simultaneous generation of maximum air temperature, minimum air temperature and solar radiation. This method has been used in weather generation models (USCLIMATE (Hanson *et al.* 1994) and ClimGen (Nelson 1999)) and hydrological models like SWAT (Arnold *et al.* 1996) and EPIC (Williams *et al.* 1984). The approach used in this method considers these meteorological variables to be a continuous multivariate stochastic process with the daily means and standard deviation conditioned on the wet or dry state of the day. According to this technique, the time series of each variable is reduced to a time series of residual elements by removing the periodic mean and standard deviation. These elements are analyzed to determine the time dependence (serial correlation) within the series and the cross correlation between each pair of variable.

The multivariate generation model proposed for generation of a series of residuals of maximum and minimum temperature and solar radiation is the weekly stationary generating process suggested by Matalas (1967). The equation is

$$x_{p,i}(j) = Ax_{p,i}(j) + B\varepsilon_{p,i}(j) \tag{5}$$

where $x_{p,i}(j)$ and $x_{p,i-1}(j)$ are (3×1) matrices for day i-1 of year p whose elements are residuals of maximum temperature (j=2), and solar radiation (j=3); $\varepsilon_{p,i}(j)$ is a (3 $\times$ 1) matrix of independent random components that are normally distributed with a

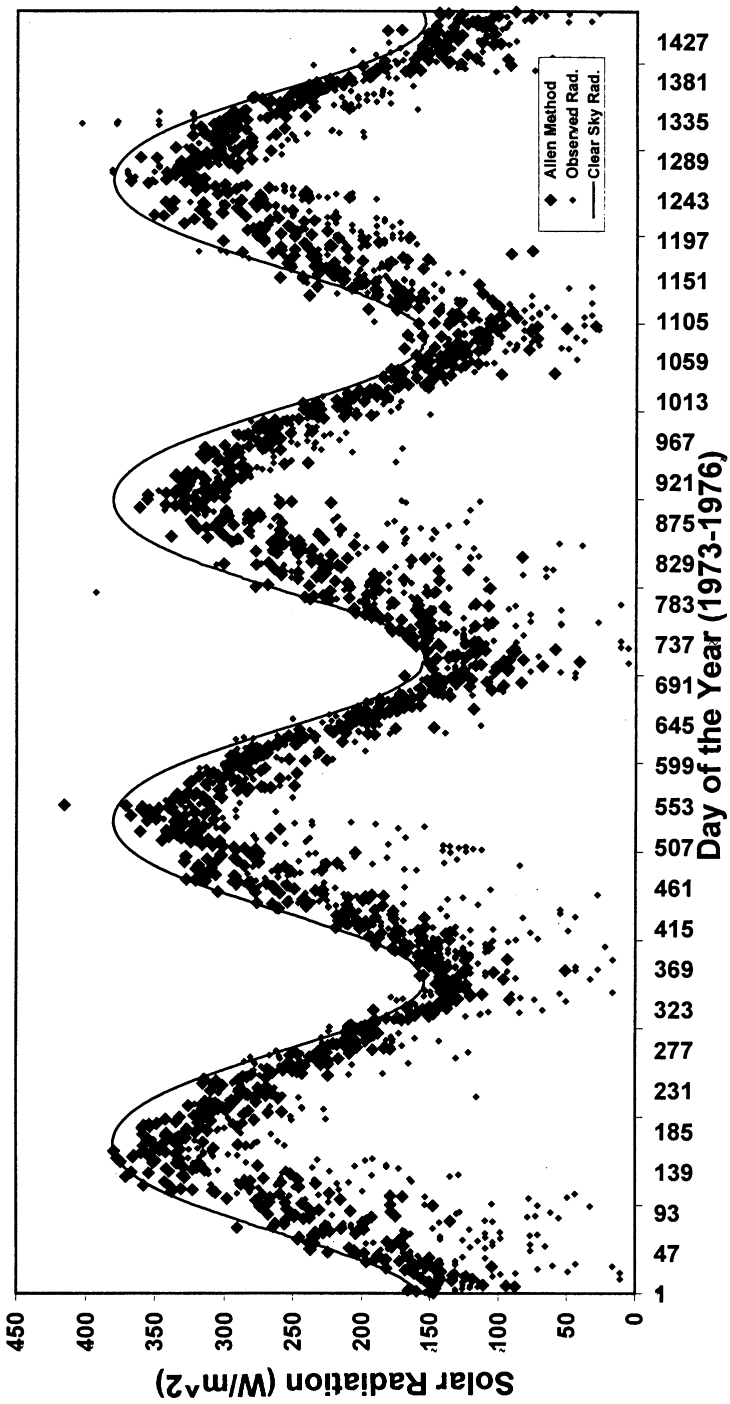


Fig.2. Comparison of incident obs. and est. solar radiation using Allen's Method for Ammameh st.

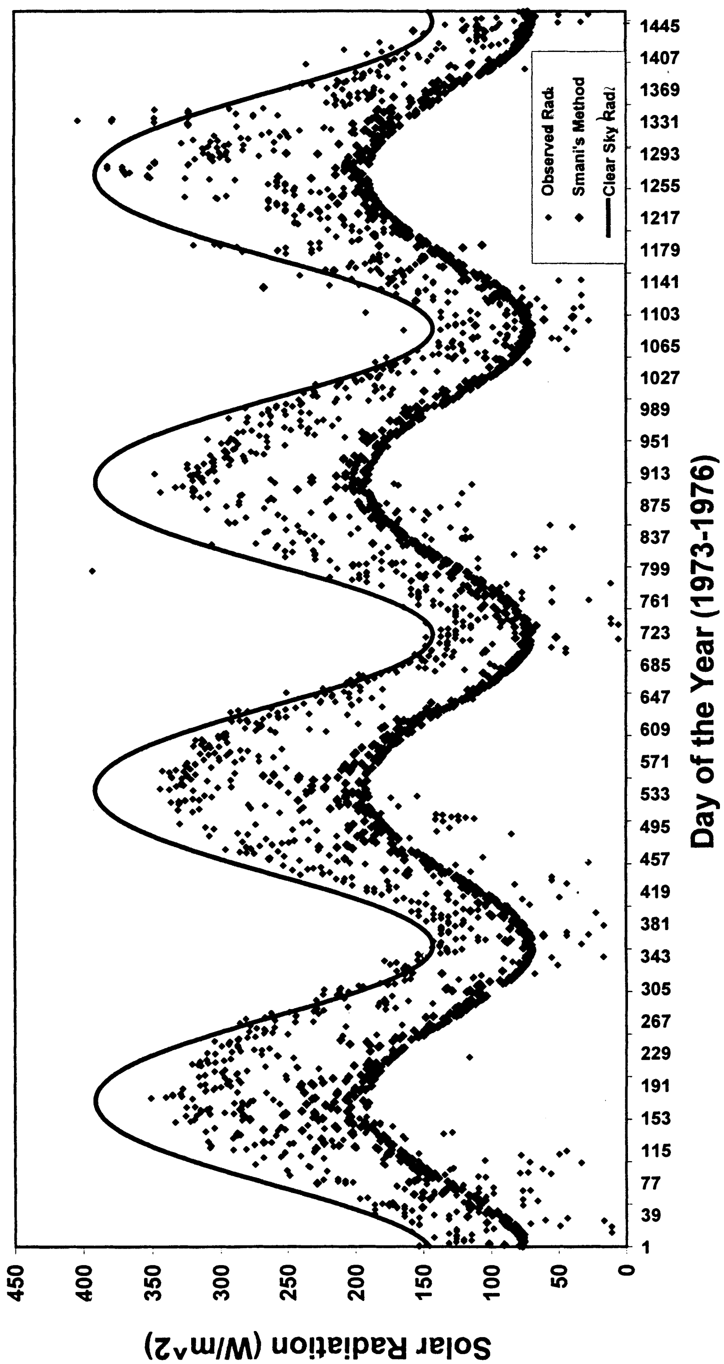


Fig.3. Comparison of incident obs. and est. solar radiation using Samani's Method for Ammameh st.

Table 1 – Solar radiation simulation errors and goodness of fit using different approaches

Approach	Calibration (1 year)			Validation (3 year)		
Criteria	R^2	RMSE	MAE	R^2	RMSE	MAE
TB	0.62	57.1	46.1	0.57	56.9	47.4
ST	0.58	71.8	59.6	0.53	72.4	61.6
ANNs	0.70	42.1	32.7	0.64	49.9	36.8

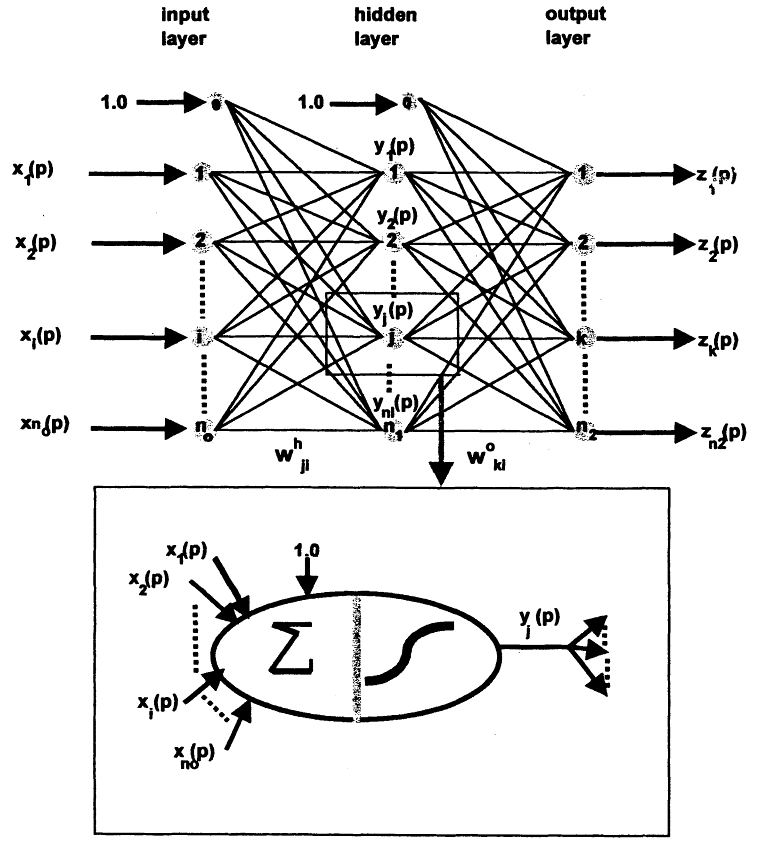
mean of zero and variance of unity; and A and B are (3 × 3) matrices whose elements are defined such that the new sequences have the desired serial correlation and cross-correlation coefficients. The multivariate generation model (Eq. (5)) implies that the residuals of solar radiation (as well as temperature) are normally distributed and the serial correlation of each variable may be described by a first-order autoregressive model. More details are available in Richardson (1981; 1985) and Hanson *et al.* (1994).

Application of ST Approach to the Study Area – In this method, monthly long term average values of incoming radiation and air temperature as well as the probability of wet day following a dry day and the probability of a dry day following a wet day for each month are separately needed as inputs. These long term statistics were available for the Ammameh Station. There is no specific parameter in the method to be calibrated. Fig. 5b shows a comparison of estimated and calibrated solar radiation for the study area. Statistical criteria of the model performance are shown in Table 1.

Artificial Neural Networks Approach

Since the early nineties, ANNs have been successfully applied for different hydrological applications such as rainfall-runoff process, snowmelt-runoff process, water quality, climate change and ground water remediation. The major advantages of ANNs that have made them suitable for hydrological applications are their simplicity and ability to extract the relationship between the inputs and outputs of the process without considering the physics explicitly. Even if the data is noisy, of short duration and involving errors, ANNs have been known to identify the complex nonlinear relationships between input and output data (Dawson and Wilby 1998; ASCE I 2000).

Mathematical Aspects of Artificial Neural Networks – ANN is a massively parallel-distribution information processing system that is composed of a number of elements called neurons (or nodes, cells, units). As the name implies, ANNs designs are based on the structure and operation of the brain. In ANN architecture, the neurons are arranged in groups called layers and are interconnected (Fig. 4). A network can be constructed of one or several layers. The basic structure of a network that is



A Processing Element

Fig.4. Typical three-layer feed forward artificial neural network (Hsu *et al.* 1995).

common in hydrological applications consists of three layers namely: input layer (where data are introduced to the network), hidden layers (where data are processed) and output layer (where the results for the given inputs are produced). The ANNs can be categorized based on the direction of information flow and processing. The most popular ANN for hydrological purposes is feed-forward (Coulibaly *et al.* 2000). In this network, output of a node in a layer is only dependent on the inputs it receives from previous layers and the corresponding weights.

The information processing that is done by neurons is shown in Fig. 4. Each of the inputs ($x_1, x_2, \ldots, x_n$) is multiplied by a corresponding weight ($w_{1j}, w_{2j}, \ldots, w_{nj}$) and all the weighted inputs are then summed to indicate effective incoming signal (S_j) to the neuron j. This weight represents its connection strength. The mathematical form of the said explanation is as follows

$$S_j = x_1 w_{1j} + x_2 w_{2j} + \ldots + x_n w_{nj} + w_{0j} \tag{6}$$

In Eq. (6) an additional term, w_{0j}, has been included, which is called a *bias* or *threshold*. In ANN parlance, the *bias* of the neuron must be exceeded before it can be activated. The effective incoming signal, (S_j), is subjected to a nonlinear transformation through an activation function (*f*) to determine the active level of the neuron at output. The most popular activation function is the sigmoid function, which varies between 0 and 1.

$$f(S_j) = \frac{1}{1+e^{-S_j}} \tag{7}$$

The most interesting characteristic of an ANN is its ability to learn from the examples. Through the learning process, the ANN will find the optimum values of weights. Different training algorithms have been formulated. The back-propagation training method (Rumelhart *et al.* 1986) is the most widely used for hydrological applications of ANNs (Coulibaly *et al.* 2000). In any training algorithm, the aim is to minimize the global error, *E*, defined as

$$E = \sum_{p=1}^{P} \sum_{i=0}^{N} (S_i - T_i)^2 \tag{8}$$

where *P* is total number of training patterns; N is total number of output neurons ; S_i is network output at the *i*th output node; T_i is target output at node *i*, and *E* is error for training pattern, *p*. In the back-propagation scheme, network weights and biases are adjusted by moving them along the negative gradient of the error function during each iteration until the convergence is reached (Thirumalaiah and Deo 2000).

The ANN inputs require to be standardized. There are many equations available for standardization and one such equation implemented in the present study (Dawson and Wilby 1998) is as follows

$$N_i = \frac{R_i - \mathrm{Min}_i}{\mathrm{Max}_i - \mathrm{Min}_i} \tag{9}$$

where R_i is the real value applied to node i; N_i is the subsequent standardized value calculated for node *i*; Max_i and Min_i are the maximum and the minimum of all values applied to node *i*, respectively. N_i in Eq. (8) always has positive value (0-1), even if the input data are negative (*e.g.* daily air temperature values of the study area). So it confines standardized data within the range of the sigmoid function.

Application of the ANN Approach to the Study Area – The inputs used for the ANN model were observed daily minimum and maximum air temperature, and extraterrestrial solar radiation, which was calculated with the method of Duffie and Beckman (1980), thus making it a three neurons input layer ANN model. This data set is the same as that for the input to the TB approach. In this case also, the first year of observed data was used for training and the remaining three years for testing the ANN model.

Table 2 – Performance of different ANN models architecture (R^2)

Type of neural network	Calibration	Validation
3-3-1	0.68	0.67
3-4-1	0.70	0.64
3-5-1	0.73	0.63
3-8-1	0.76	0.59
3-10-1	0.77	0.54
3-5-5-1	0.81	0.40
3-10-10-1	0.94	0.22

Unfortunately, there are no fixed rules to indicate how many neurons or layers should be included in the hidden layer. Networks that are too small can lead to underfitting and a network that is too complex tends to overfit the training patterns. For the present study, different networks have been explored in which various combinations of hidden layers and neurons have been tested for various learning methodologies. The multilayer feedforward, training with standard backpropagation algorithm was found to be more suitable for solar radiation estimation. Some of the results of applying different networks architecture are presented in Table 2. It is evident from this table that as number of layers and neurons increase, ANN performance improves during the training period (higher values of R_2), but deteriorates during the testing period (decline in R_2). An ANN model with (3-4-1) (refer to Table 2) architecture was selected for this study because of its quite good performance and model robustness. Results of statistical evaluation of the model are presented in Table 2.

Analysis of Results

Using the selected criteria of comparison, the various models can be arranged with respect to the descending order of performance as ANN, TB and ST, respectively. This trend is true for all the criteria as well as the period of simulation *i.e.* calibration and validation periods. The best results have been obtained using the ANN, both in calibration and validation periods. The model has been able to successfully predict the daily incident solar radiation. It has been observed that the ANN has been able to map the highly nonlinear function through its complex structure of interconnected layers, using even one year of observed solar radiation in addition to the maximum and the minimum temperatures.

The TB method although has not performed as well as the ANN, although its performance is not very far from that of the ANN. Moreover, the TB has performed significantly better than the ST. The main advantage of the TB is that it has a single parameter, K_r, which is very robust and can be easily obtained from as little as one year of observed solar radiation data. In the event of even such a length of data also being not available for calibration of K_r, it can be reasonably assumed from nearby similar

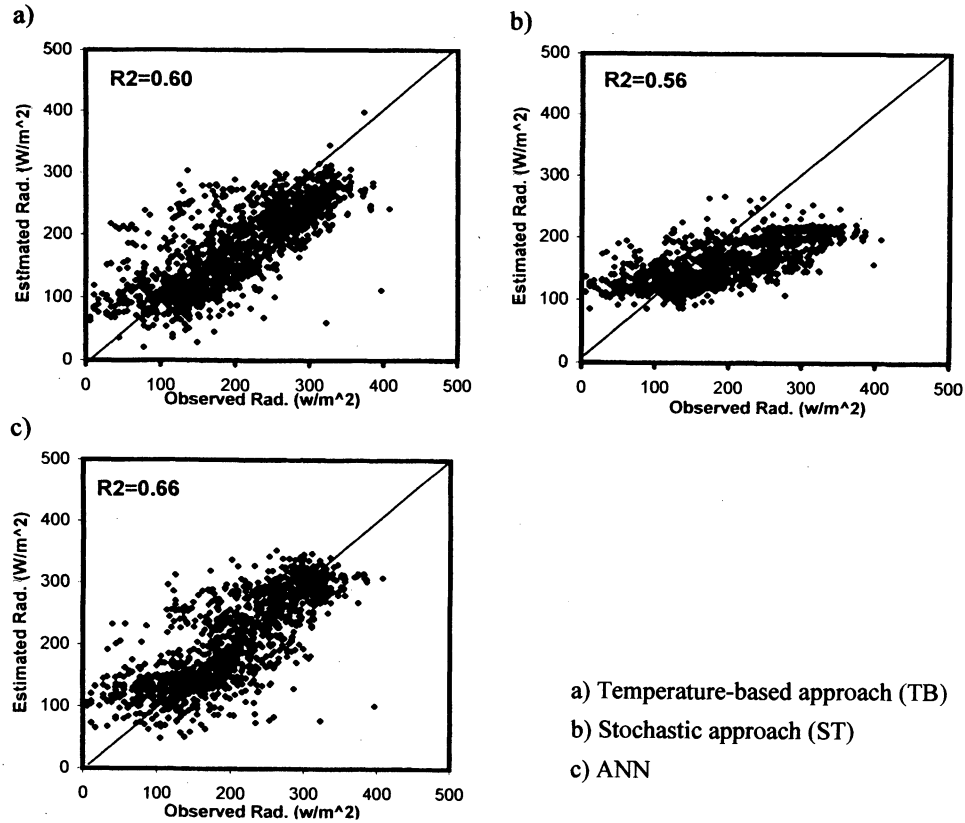


Fig.5. Scatterplots comparing simulated and observed daily values of solar radiation at Ammameh st. (1973, calibration period and 1974 to 1976, validation period).

areas or obtained from the available literature. Further, if spatial variation of solar radiation is desired (as in the case of predicting snow cover area in mountainous catchments), it can be easily incorporated into the TB method by correlating temperature with the elevation and thus estimating radiation at respective elevation. This is not the straightforward in case of the ANN method. Therefore, the TB method may be more confidently proposed for linkage with hydrological models, requiring the estimation of solar radiation under the situation of low level of data availability.

Conclusions

The application of the three different approaches for estimation of solar radiation, viz. the ST, the TB and the ANN was studied for the Ammameh catchment, an alpine subcatchment of the Jadjroud River basin in Iran. The assessment of model performance was carried out using regression coefficient R^2, *RMSE* and *MAE* criteria with four years of observed radiation data. The best results have been obtained using the ANN. However, the ANN method may be used for only those sites, which have been gauged and where observed solar radiation data are available for training, although this method can give satisfactory results with even short length of observed data. The performance of the TB method follows closely that of the ANN method. It is relatively simpler, robust and is more suitable to catchments with inadequate data. Further, spatial variation of radiation can be easily obtained in case of the TB method. It is recommended on account of the relative ease in implementation as the major parameter, K_r, can be estimated even in the event of observed data on solar radiation are not available.

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References

Allen, R.G. (1996) Assessing Integrity of Weather Data for Reference Evapotranspiration Estimation, *J. Irrigation and Drainage Eng. ASCE, Vol. 122 (2),* pp. 97-106.

Allen, R.G. (1997) Self-Calibration Method for Estimating Solar Radiation from Air Temperature, *J. Hydrol., Vol. 2 (2),* pp. 56-67.

Arnold, J.G., Williams, J. R., Srinivasan, R., and King, K.W. (1996) SWAT-Soil and Water Assessment Tool, User's Manual, USDA-ARS, Temple, Texas.

ASCE-I (2000) Task Committee on application of ANNs in hydrology (2000) Artificial Neural Networks In Hydrology, I: Preliminary Concepts, *J. Hydrol. Eng.-ASCE, Vol. 5(2),* pp. 115-123.

Bathurst, J.C., and Cooley, K.R. (1996) Use of the SHE hydrological modeling system to investigate basin response to snowmelt at Reynolds Creek, Idaho, *J. Hydrol., Vol. 175*, pp. 181-211.

Coulibaly, P., Anctil, F., and Bobee, B. (2000) Daily reservoir inflow forecasting using artificial neural networks with stopped training approach, *J. Hydrol., Vol. 230*, pp. 244-257.

Dawson, Ch., and Wilby, R. (1998) An artificial neural network approach to rainfall-runoff modelling, *Hydrol. Sci. J., Vol. 43(1),* pp. 47-66.

Dozier, J. (2000) Personal communication, Dept. of Geography and Center for Remote Sensing and Environmental Optics, Univ. of California, Santa Barbara.

Duffie, J. A., and Beckman, W. E. (1980) *Solar Engineering of Thermal Processes*, John Wiley publication, New York, pp. 3-45.

Hargreaves, G. H., and Samani, Z. A. (1982) Estimating potential evapotranspiration, *J. Irrigation and Drainage Eng., ASCE, Vol. 108(3),* pp. 25-230.

Hargreaves, G.H. (1994) Simplified coefficients for estimating monthly solar radiation in North America and Europe, Dept. Paper, Dept. Biol. and Irrig. Engrg., Utah State Univ., Logan, Utah.

Hanson, C.L., Cumming, K.A., Woolhiser, D.A., and Richardson, C.W. (1994) Microcomputer Program for Daily Weather Simulation in the Contiguous United States, Model's Overview, ARS-USDA, USA.

Hsu, K., Gupta, H.V., and Sorooshian, S. (1995) Artificial neural network of the rainfall-runoff process, *W. Resour. Res., Vol. 31(10),* pp. 2517-2530.

Liong, Sh.Y., Lim, W.H. and Paudyal, G.N. (2000) River stage forecasting in Bangladesh: neural network approach, *J. Computing in Civ. Eng., ASCE, Vol. 14(1),* pp. 1-8.

Luk, K.C., Ball, J.E., and Sharma, A. (2000) A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting, *J. Hydrol., Vol. 227,* pp. 56-65.

Majumdar, N. C., Mathur, B. L., and Kaushik, S. B. (1972) Prediction of Direct Solar Radiation From Low Atmospheric Turbidity, *Solar Energy, Vol. 13,* pp. 383-394.

Matalas, N. C. (1967) Mathematical assessment of synthetic hydrology, *Water Resour. Res. 3(4),* pp. 937-945

Nelson, R. (1999) URL: http://www.bsyse.wsu.edu/cligen/manual/manual.htm

Richardson, C. W. (1981) Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation, *Water Resour. Res., Vol. 17(1),* pp. 182-190.

Richardson, C. W. (1985) Weather Simulation for Crop Coefficient, *J. Irrigation and Drainage Div., ASCE, Vol. 108 (2),* pp. 57-74.

Rumelhart, D.E., and MaClelland, J.L., Editors (1986) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition,* Vol. 1. MIT Press, Cambridge, MA, pp. 318-362.

Samani, Z. (2000) Estimating Solar Radiation and Evapotranspiration Using Minimum Climatological Data, *J. Irrigation and Drainage Eng., ASCE, Vol. 126(4),* pp. 265-267.

Singh, V. P. (1992) *Elementary Hydrology,* Prentic-Hall of India, New Delhi, pp. 364.

Thirumalaiah, K., and Doe, M.C. (2000) Hydrological Forecasting using Neural Networks, *J. Hydrol. Eng. ASCE, Vol 5 (2),* pp. 180-189.

Todini, E. (1996) The ARNO rainfall-runoff model, *J. Hydrol., Vol. 175,* pp. 339-382.

Williams, J.R., Jones, C.A., and Dyke, P.T. (1984) A modeling approach to determining the relationship between erosion and soil productivity, *Trans. ASAE Vol. 27(1),* pp 129-144.

Yang, Z.L. (2000) Personal communication, Dept of Hydrology and Water Resources, University of Arizona.

Yevjevich, V. (1972) Structural Analysis of Hydrology Time series, *Hydrol. Paper, Vol.* 56, Colorado State Univ., Fort Collins, pp 59.

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