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Estimating potential evapotranspiration from limited weather data over Gangetic West Bengal, India: a neurocomputing approach

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ABSTRACT: This paper reports the development of a neurocomputing-based model for estimating the potential evapotranspiration over Gangetic West Bengal, India during the summer monsoon months of June, July and August. An artificial neural network is implemented in the form of multilayer perceptron to generate the model. Three weather variables, surface temperature, vapour pressure and rainfall are used as the independent variables in generating the model. The performance of the model is judged statistically against non-linear regression in the form of asymptotic regression. The study reveals that an artificial neural network is more efficient than the regression approach to estimate the potential evapotranspiration in the summer monsoon months. Furthermore, it is established that the artificial neural network and non-linear regression have almost equal efficiency in the previously mentioned estimation in the month of June. However, in July and August the higher values of correlation and Willmott's indices, and lower values of estimation error, indicate that the artificial neural network is more reliable than the non-linear regression approach. Since evapotranspiration is one of the basic components of the hydrological cycle and is essential for estimating irrigation water requirement, an efficient estimation procedure may help in agrometeorological modelling and irrigation scheduling in the summer monsoon months, which are of high importance for agriculture in the study zone. Copyright © 2009 Royal Meteorological Society

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1. Introduction

Intricacies in climate and weather related phenomena arise due to the varied degree of correlations among the several processes and parameters associated with them. In a pioneering work, Lorenz (1963) identified the existence of a strange attractor in finite-amplitude convection. Afterwards Grassberger (1986); Henderson and Wells (1988); Tsonis and Elsner (1989); Sharifi *et al.* (1990) studied the chaotic behaviour of meteorological processes and variables. In recent times, the identification of the intrinsic chaos of such processes has drawn the attention of scientists in many disciplines (Weigend and Gershenfeld, 1993; Stehlik, 1999; Varotsos, 2005; Sivakumar *et al.*, 2004; Varotsos *et al.*, 2006). Conventional statistical approaches are not capable of dealing with this complexity efficiently because of their data sensitiveness, and dependence upon prior assumptions regarding the system. In recent times soft computing techniques, which imply a set of flexible computational approaches, has drawn the attention of meteorologists to model complex meteorological processes. The foremost components of soft computing are fuzzy logic, artificial neural networks (ANN), genetic algorithms and rough set theory. Some noteworthy examples towards implementation of such techniques in meteorological modelling are mentioned below. Fuzzy expert systems were applied to predict hazardous weather conditions (Kuciauskas *et al.*, 1998) and a genetic algorithm was employed in prediction of Indian summer monsoon rainfall (Kishtawal *et al.*, 2003). Rough set based rule induction was proved suitable for analysis of environmental data (Berger, 2004) and ANN techniques have been shown to be a potential technique for weather forecasting by several authors, including Silverman and Dracup (2000); Lu *et al.* (2005); Ramírez *et al.* (2005); Lee (2008), and Chattopadhyay and Chattopadhyay (2008). See *et al.* (2007) thoroughly reviewed the application of ANN in various kinds of hydrological modelling.

The present study considers evapotranspiration (ET), which is a combination of evaporation from Earth and canopy surfaces and transpiration from stomata of leaves. Evaporation is the process of conversion of liquid water into water vapour and removal of this vapour from the evaporating surface. Water evaporates from a variety of surfaces, such as lakes, rivers, pavements, soil and wet vegetation. Transpiration consists of the movement and

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vapourization of liquid water contained in plant tissues and then its removal to the atmosphere. Evaporation and transpiration occur simultaneously and there is no easy way of distinguishing between the two processes. Apart from the water availability in the topsoil, the evaporation from a cropped soil is mainly determined by the fraction of the solar radiation reaching the soil surface (Allen *et al*., 1998). The combination of evaporation and transpiration is defined as ET. Potential evapotranspiration (PET) (Zhou *et al*., 2006) is not only the theoretical limitation of actual evapotranspiration but also the basis to evaluate it. PET has been widely used in research related to dry and wet condition analysis of climate, use and assessment of water resources, crop water requirement and production control, and eco-environment research such as desertification (Ge *et al*., 2006).

The association between ET and climate is well documented in the literature (Shukla and Mintz, 1982; O'Brien, 1996; Koch *et al*., 1997; Willmott *et al*., 2007; Zhou *et al*., 2008). ET plays an important role in changes in the atmospheric boundary layer and cloud formation (Lyons, 2002). The process of ET depends heavily upon several atmospheric parameters. Transpiration rates go up as the temperature increases. As the relative humidity of the air surrounding the plant rises, the transpiration rate falls, as it is easier for water to evaporate into drier air than into more saturated air. Increased movement of the air around a plant will result in a higher transpiration rate (USGS, 2007). Andranistakis *et al*. (1999) studied the significance of the atmospheric stability approach in models for estimating ET and concluded that the actual stability conditions have to be taken into account in the case of estimating the daily ET. Fernandez *et al*. (1996) studied the importance of vegetation properties in estimating the ET in semi-arid areas. The need to apply an ANN for estimation of ET has been noted by agricultural hydro-meteorologists because of its dependence upon several weather factors. PET is recognized as a vital part of the hydrological cycle (Hargreaves and Samani, 1982) and measures the ability of the atmosphere to remove water from the surface through the process of ET assuming that there is no control of the water supply (Pidwirny, 2006). Agrometeorologists over the globe have given much importance to the estimation of PET and its estimation has often been made *via* the Penman-Monteith equation and in recent times in the form of an estimate of reference evapotranspiration (RET). The statistical relationships between PET, RET, leaf area index of vegetation and climate variables have been studied and a strong non-linearity between PET and leaf area index has been identified (Zhou *et al*., 2006).

The purpose of the present paper is to estimate PET over Gangetic West Bengal during the summer monsoon months using an ANN and to compare its performance with a regression approach. Gangetic West Bengal is a highly significant geographical region of India. Both pre-summer monsoon thunderstorms and torrential summer monsoon rainfall strikes this region every year. Evapotranspiration is one of the basic components of the hydrological cycle, a key factor for water balance and for estimating irrigation water requirement (Landeras *et al*., 2008). Thus, an efficient estimation procedure may help in agrometeorological modelling and irrigation scheduling in the summer monsoon months, which are of utmost importance for agricultural practices in the study zone. Moreover, a proper model for evapotranspiration may have some contribution in modelling the rainfall in the season of summer monsoon. To reduce complexity, the present study attempts to estimate PET using only three weather variables: surface temperature, vapour pressure and rainfall amount. Separate predictive models have been generated for each of the three summer monsoon months: June, July and August (Elliott and Angell, 1987). The rest of the paper is organized as follows. Section 2 deals with the methodology and ANN architecture. Estimation ability of the model is assessed statistically in Section 3. The conclusions and future directions are presented in Section 4.

2. Methodology

2.1. Artificial neural networks in evapotranspiration study- a review

The well-known Penman-Monteith (PM) equation is the best method of estimating reference evapotranspiration (ET_o) among the existing methods (Khoob, 2008; Wang *et al*., 2008). If ET_o is considered as PET, then monthly PET is calculated by multiplying the ET_o by the number of days in that month (Ge *et al*., 2006). In the present paper, the similar approach has been adopted. The Penman-Monteith (PM) equation is given by:

$$\mathrm{ET}_0 = \frac{0.408\Delta(R_\mathrm{n} - G) + \dfrac{900}{T + 273}U_2(\mathrm{e}_s - \mathrm{e}_a)}{\Delta + \gamma(1 + 0.34U_2)} \qquad (1)$$

where ET_0 is potential evapotranspiration (mm d^{-1}), R_n is net radiation at reference surface (MJ m^{-2} d^{-1}), G is soil heat flux density (MJ m^{-2} d^{-1}), T represents monthly mean temperature (°C), U_2 is the wind speed at 2 m height (m s^{-1}), e_s is saturation vapour pressure (kPa), e_a is actual vapour pressure (kPa), Δ denotes the slope of vapour pressure curve *versus* temperature (kPa °C^{-1}) and γ is the psychrometric constant (kPa °C^{-1}). Thus, calculation of PET from the PM equation requires eight predictors that are not always available in developing countries such as India. The ANN technique is useful and suitable in estimating the evapotranspiration from limited climatic data over the conventional procedures of estimating evapotranspiration (Sudheer *et al*., 2003; Kisi, 2007; Chauhan and Shrivastava, 2008; Jain *et al*., 2008; Wang *et al*., 2008). Landeras *et al*. (2008) highlighted the necessity of application of an ANN in modelling a non-linear process such as evapotranspiration and, after comparing seven ANN models against various locally calibrated reference evapotranspiration equations, they concluded that ANN-based models were more reliability

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compared to the locally calibrated equations. In all of the available studies, ANN models were developed using fewer predictors than required by PM equations. In many studies, wind speed, relative humidity, air temperature and solar radiation have been used as predictors in ANN based models for evapotranspiration (Kumar *et al.*, 2002; Trajkovic *et al.*, 2003; Dai *et al.*, 2009; Dogan, 2008; Kisi, 2009).

In another study, only maximum and minimum temperatures were used to generate an ANN-based model for estimating evapotranspiration (Chauhan and Shrivastava, 2008). Kisi and Ozturk (2007) adopted a neuro-fuzzy technique to estimate reference ET and established its suitability over traditional methods.

The present paper attempts to estimate PET using only three weather parameters namely surface temperature, vapour pressure, and rainfall. In this paper, the PET values computed by PM equation have been considered as the actual PET values and the same values have been estimated by ANN using only three readily-available weather parameters instead of the eight parameters required in the PM equation. In the available literature, rainfall has never been used as a predictor. The present study deviates from the studies mentioned above in another aspect, in that only the summer monsoon months (the most important months in agriculture) constitute the study period. No such ANN-based study for the summer monsoon months over Gangetic West Bengal was found in the literature.

2.2. Preparation of the Dataset

The study presented in this paper is based on 50 years data (1951–2000) over Alipur, Kolkata, Howrah, Chandannagore, Barasat, Barakpur, Kalyani, and Srerampur situated in Gangetic West Bengal. The data were collected from the website http://www.indiawaterportal.org/.

In the present study, the data were collected for the summer monsoon months (June–August), when the formation of cloud delivers significant consequences upon human life and agricultural practices. Monthly data pertaining to surface temperature, vapour pressure and rainfall for those three months are considered to estimate monthly PET over the study zone. For each of these four parameters (i.e. surface temperature, vapour pressure, rainfall and PET), time series of length 50 pertaining to June, July and August are available. The predictors are the monthly average temperature, average rainfall, and average air pressure and the predictand is the PET. The descriptive statistics are presented in Table I. The PET has maximum variance in June. All the parameters under study vary significantly from each other with respect to their skewness and kurtosis (Table I). The persistence within the time series pertaining to PET is analyzed using an autocorrelation function (Wilks, 1995) computed up to 16 lags. A high value of autocorrelation coefficient (ACC) at smaller lags reflects persistence within the time series. None of the autocorrelation coefficients is found to be numerically high and they do not exhibit any specific pattern. In Figure 1, the autocorrelation functions are presented for the three months and the low values of the autocorrelation coefficients indicates that no persistence exists within the time series of the predictand variables. Scatterplot matrices are framed to discern how the PET is related to the predictors in the three months (Figure 2(a–c)). From the lowest rows of all the matrices it is discerned that no linear correlation exist for the predictor-predictand pairs. Such observations indicate the necessity of applying an ANN in estimating PET from these weather parameters. To view this numerically, the correlation matrix is presented in Table II. In June, PET has significant correlation with rainfall amount (−0.559) and temperature (0.648). However, the rest of the correlations between predictors and predictands are numerically significantly less than one, which imply significant non-linearity among the predictor-predictand pairs. Before being applied to the ANN model the data have been transformed to values in [0, 1] using:

$$x_{\text{transformed}} = \frac{x - x_{\text{minimum}}}{x_{\text{maximum}} - x_{\text{minimum}}} \qquad (2)$$

2.3. Development of artificial neural network model

Artificial neural networks have enjoyed renewed interest over the last decade, mainly because new learning methods capable of dealing with scalable learning problems were developed. Backpropagation is a very popular method of learning the ANN. In a backpropagation ANN, for a given input vector, the output vector is compared to the targeted result (Rojas, 1996). If the difference is zero, no learning takes place. Otherwise, the weights are adjusted to reduce this difference. In the present paper, the ANN model was constructed with a commercially available computer program (NeuralWare) using a modified cascade method together with an adaptive gradient learning rule (Lundin *et al.*, 1999). The cascade mode of construction involves adding hidden nodes, one or more than one at a time, and always connecting all the previous nodes to the current node. The adaptive gradient learning rule uses back-propagated gradient information to guide an iterative line search algorithm. Hyperbolic

Table I. Descriptive statistics pertaining to the data under study.

	Variance	Skewness	Kurtosis
June-Rainfall	18335.55	1.62	4.32
July-Rainfall	14185.61	0.89	2.20
August-Rainfall	11658.13	0.45	−0.65
June-Vapour pressure	1.26	0.23	2.29
July-Vapour pressure	0.21	−1.41	7.34
August-Vapour pressure	0.15	−2.34	7.87
June-Temperature	0.72	−0.26	0.38
July-Temperature	0.32	−0.14	1.10
August-Temperature	0.19	−0.83	1.04
June-PET	0.13	−0.16	0.12
July-PET	0.06	0.02	−0.26
August-PET	0.05	0.16	0.47

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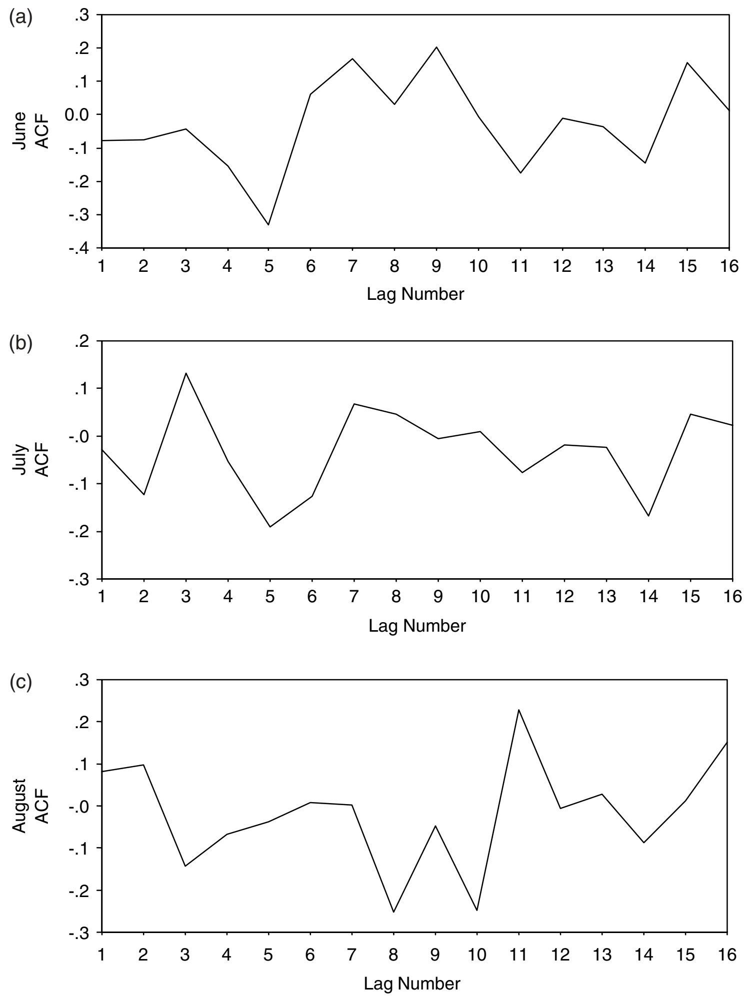

Figure 1. Autocorrelation function (ACF) for the potential evapotranspiration time series pertaining to June (a), July (b), and August (c).

tangent transfer function has been used in the hidden layer and a sigmoid function has been used in the output layer of the ANN model developed in this study (Rojas, 1996).

From the entire dataset under consideration, 70% of the original data have been chosen as training set using the method of the Round Robin (O'Neill and Song, 2003). The Round Robin is an arrangement of choosing all elements in a group equally in some rational order, usually from the top to the bottom of a list and then starting again at the top of the list and so on (O'Neill and Song, 2003). The root mean squared error (RMSE) has been used to evaluate the model. After training, the network has been validated over the entire dataset. It should be mentioned that there is no strict rule to decide the ratio of training and test cases. A survey of the ANN literature found that the ratios 1 : 1 (Chattopadhyay and Chattopadhyay, 2008a), 7 : 3 (Lundin *et al*., 1999) and 3 : 1 (Perez *et al*., 2000) are frequently used in ANN applications. In the present paper an approach similar to that of Lundin *et al*. (1999) has been adopted after examining the other approaches. Each row of the training matrix contains four columns, which correspond to the temperature of the ambient air, vapour pressure of the ambient air, and rainfall as the predictors, and the PET as the predictand. The weight matrix has been generated using a uniform distribution.

3. Assessment of model performance

After training the MLP using the procedure mentioned earlier, the PET estimation power of the ANN model has been judged statistically using the estimated and actual PET values pertaining to the test cases. The statistics used for this purpose are explained below.

1. The measure of error of estimation (EE) is expressed as (Chattopadhyay, 2007):

$$EE = \frac{\langle |y_{\text{estimated}} - y_{\text{actual}}| \rangle}{\langle y_{\text{actual}} \rangle} \tag{3}$$

where, $\langle\ \rangle$ implies the average over the validation cases.

2. Pearson correlation coefficient (Wilks, 1995) ρ is given as:

$$\rho_{xy} = \frac{Cov(x, y)}{\sigma_x \sigma_y} \tag{4}$$

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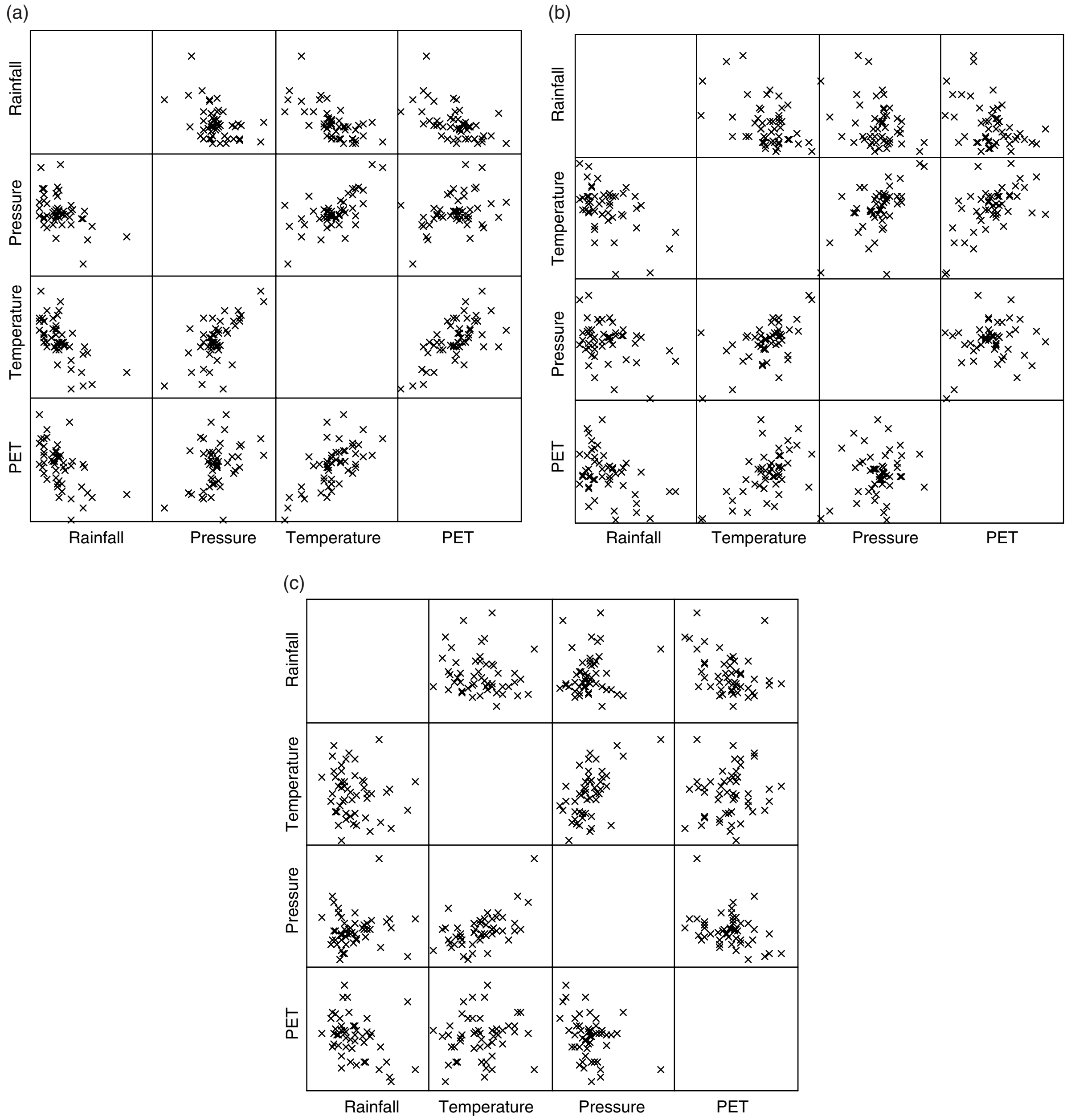

Figure 2. (a) The scatterplot matrix based on different time series pertaining to June. (b) The scatterplot matrix based on different time series pertaining to July. (c) The scatterplot matrix based on different time series pertaining to August.

where, σ_x, σ_y represent the standard deviations of the variables x and y respectively.

3. Willmott's indices (Comrie, 1997) is:

$$d^{\alpha} = 1 - \left[\sum_i |P_i - O_i|^{\alpha}\right] \times \left[\sum_i \left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^{\alpha}\right]^{-1} \quad (5)$$

where, α has the values 1 and 2, P implies predicted value, and O implies observed value. If α is 1 Willmott's index of order 1(WI 1) and if α is 2 Willmott's index is of order 1(WI 2). Closeness of WI1 and WI2 to 1 imply a good predictive model.

At the outset, the actual and estimated PET values are plotted in line diagrams (Figure 3(a–c)). A close association between actual and estimated values of PET is observed in Figure 3(a–c). Thus, it is perceptible that an ANN in the form of MLP with adaptive gradient learning is suitable for estimating PET from weather parameters as predictor. In the next step, Equations (3), (4), and (5) are used to test the suitability of ANN model for the estimation of PET. The statistical measures corresponding to the validation cases of the proposed ANN model for the monthly estimation of PET over the study zone using the weather parameters are presented in Table III. It is clear from the table that in June the ANN produced significantly high correlation (0.768) between actual and estimated PET values. In July there is a significant

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Table II. Correlation matrix for all the variables** under study.

Variables	June R	July R	August R	June P	July P	August P	June T	July T	August T	June PET	July PET	August PET
June R	1	−0.026	0.170	−0.449	−0.092	0.066	−0.655	−0.057	−0.069	−0.559	−0.265	−0.036
July R	−0.026	1	−0.078	−0.053	−0.155	−0.146	0.085	−0.413	0.139	−0.071	−0.197	0.054
August R	0.170	−0.078	1	−0.090	0.019	−0.078	−0.240	−0.034	−0.458	−0.064	−0.121	−0.315
June P	−0.449	−0.053	−0.090	1	0.071	0.176	0.643	0.128	0.051	0.377	0.104	−0.229
July P	−0.092	−0.155	0.019	0.071	1	0.410	0.139	0.425	0.296	−0.021	−0.108	−0.108
August P	0.066	−0.146	−0.078	0.176	0.410	1	−0.006	0.355	0.365	−0.146	−0.210	−0.164
June T	−0.655	0.085	−0.240	0.643	0.139	−0.006	1	0.208	0.382	0.648	0.389	0.000
July T	−0.057	−0.413	−0.034	0.128	0.425	0.355	0.208	1	0.427	0.313	0.271	−0.100
August T	−0.069	0.139	−0.458	0.051	0.296	0.365	0.382	0.427	1	0.218	0.133	0.203
June PET	−0.559	−0.071	−0.064	0.377	−0.021	−0.146	0.648	0.313	0.218	1	0.699	0.246
July PET	−0.265	−0.197	−0.121	0.104	−0.108	−0.210	0.389	0.271	0.133	0.699	1	0.360
August PET	−0.036	0.054	−0.315	−0.229	−0.108	−0.164	0.000	−0.100	0.203	0.246	0.360	1

** R ⇒ Rainfall, P ⇒ Vapour pressure, T ⇒ Temperature, PET ⇒ Potential evapotranspiration.

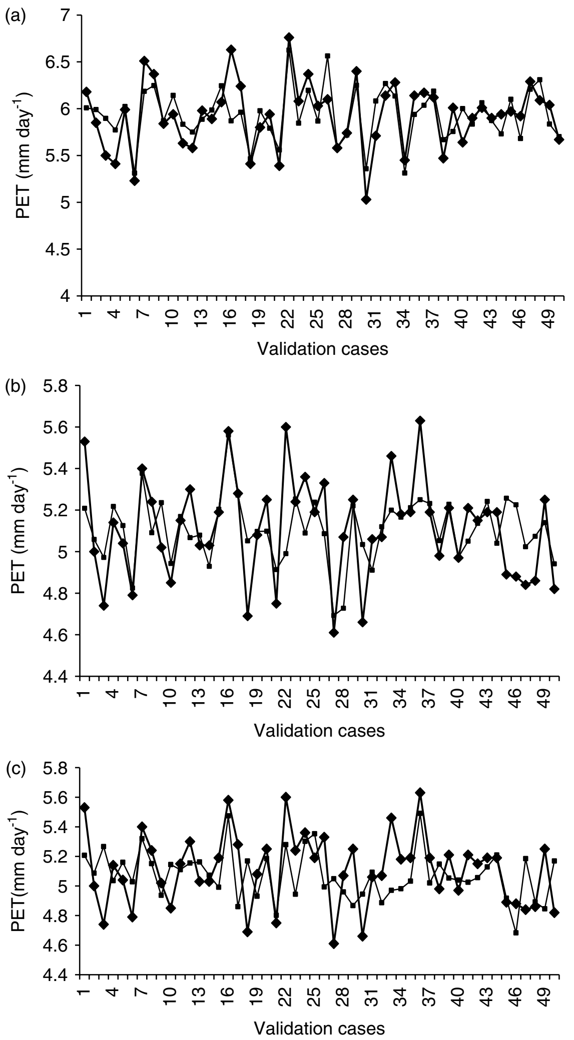

Figure 3. (a) The observed (bold line) and the artificial neural network (ANN) estimated (thin line) PET (mm day^{-1}) over the study zone in the validation years for June. (b) The observed (bold line) and the artificial neural network (ANN) estimated (thin line) PET (mm day^{-1}) over the study zone in the validation years for July. (c) The observed (bold line) and the artificial neural network (ANN) estimated (thin line) PET (mm day^{-1}) over the study zone in the validation years for August.

Table III. The statistical measures of suitability of the proposed models in estimating the monthly potential evapotranspiration.

Month (Model)	CORREL	EE	WI1	WI2
June (ANN)	0.768	0.029	0.652	0.873
June (NLR)	0.674	0.025	0.632	0.868
July (ANN)	0.585	0.030	0.498	0.683
July (NLR)	0.393	0.031	0.426	0.576
August (ANN)	0.381	0.040	0.353	0.567
August (NLR)	0.294	0.079	0.304	0.424

ANN ⇒ artificial neural network, NLR ⇒ nonlinear regression, CORREL ⇒ Pearson correlation, EE ⇒ Estimation error, WI1 ⇒ Willmott's index of order 1, and WI2 ⇒ Willmott's index of order 2.

correlation (0.585) between the actual and estimated values of PET but it is obvious from the magnitudes of the correlation that in July the association between actual and estimated PET is not strongly linear as it is in June. In the month of August, the association is much less linear as implied by the lower magnitude (0.381) of the correlation. It is further apparent in the same table that ANN produced the minimum estimation error in June. Willmott's indices of order 1 and 2, which are highly acceptable measures of goodness of fit (Willmott, 1982; Chattopadhyay and Chattopadhyay, 2008a) in meteorological modelling, are given in Table III. It is revealed that the maximum values of Willmott's indices of order 1 and 2 are produced in June and the values 0.657 (for order 1) and 0.873 (for order 2) are considerably high in this case. In July, there are significant values of Willmott's indices but they are notably less than the values corresponding to June. In August, the values are much less than those corresponding to June and July. Thus, the ANN provides the best fit for June with respect to PET estimation based on weather data.

The task is now to see whether the ANN in the form of MLP performs better than regression-based estimation. The ANN is a non-linear model and thus it is logical to perform the comparison with a non-linear regression

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instead of a linear regression. An asymptotic regression equation (Chattopadhyay and Chattopadhyay, 2008b) is chosen as:

$$y_{\text{estimated}} = b_1 + b_2 \exp(b_3 x) + b_4 \exp(b_5 y) + b_6 \exp(b_7 z) \quad (6)$$

The regression parameters are estimated using the Levenberg-Marquardt algorithm. The parameters b_3, b_5 and b_7 are initialized at 0.001 and the rest of the parameters are initialized at 0.01. Such choices of the initial values of the regression parameters and constant have been made to scale the available PET values to a range suitable for exponentiation. The values of the statistics (Equations (3), (4), and (5)) produced over the validation cases (same as the ANN) by the non-linear regression Equation (6) are also presented in Table III. It is observed that in June the non-linear regression equation produces significantly high correlation value (0.674). However, the correlation is much smaller in July and August. Moreover, in all of the three months the correlations are less than those produced by the ANN models. While considering the error of estimation (EE), it is found that the minimum and maximum EE values are produced in June and August respectively. In June and July, the EE values from the non-linear regression are very close to the EE values produced by the ANN. However, in August the EE from non-linear regression is much greater than that from the ANN. In the case of Willmott's indices, it is found that in June both order 1 and order 2 of the indices are significantly high and are very close to those produced by the ANN model. In July, both of the indices attain significant values, but they are notably less than those produced by the ANN model. The least values of the indices are available in August and the values are significantly less than those produced by the ANN in this month. It is, therefore, evident from the Table III that in June, the ANN and non-linear regression are estimating PET with almost equal efficiency. However, in July and August, the ANN produces significantly better estimation than non-linear regression.

Having explained the estimation capability of the ANN and non-linear regression models over the entire validation set for the three summer monsoon months, the individual validation cases require discussion with respect to the estimation capability of the models. Choosing 5% error as an acceptable error of estimation it is found that in the month of June 86% of the validation cases show an error below 5% when the ANN is applied (Table IV). In July, it is 82% and in August it is 70%. In the case of non-linear regression, the maximum of this percentage (76%) is available in June. Thus, it is significantly lower than 86% as obtained by the ANN. Thus, is spite of almost equal estimation efficiency with respect to the entire validation set, the efficiency of the ANN is significantly higher if individual patterns are considered in June. The better estimation yield is also available for July and August.

Table IV. Validation cases (in %) where the magnitudes of estimation errors are below 5%.

Month (Model)	Validation cases (%)
June(ANN)	86
June(NLR)	76
July(ANN)	82
July(NLR)	70
August(ANN)	70
August(NLR)	24

ANN ⇒ artificial neural network, NLR ⇒ nonlinear regression.

4. Conclusions

The present study has reported the possibility of modelling monthly potential evapotranspiration over Gangetic West Bengal of India in the summer monsoon months using an artificial neural network. This modelling technique has depended only upon three weather variables, surface temperature, vapour pressure and rainfall, as independent weather variables. Before generating the model, the temporal structures of the time series under study have been explored and it has been revealed that they do not exhibit any significant persistence over time. The descriptive statistical parameters have been calculated for all of them and it has been found that none of the time series exhibits any specific pattern. Finally, an artificial neural network in the form of multilayer perceptron with adaptive gradient learning has been implemented in estimating the monthly potential evapotranspiration over Gangetic West Bengal in the summer monsoon months, June, July and August. A separate model has been generated for each of the three months and the correlation coefficients, errors of estimation, and Willmott's indices have been computed for each of them. Asymptotic regression equations have been fitted to all of those three months using the same data as in the neural network models and the above-mentioned statistics have been measured over the same validation cases as in the neural network models. After the statistical comparison it has been proved that the artificial neural network performs better the non-linear regression approach adopted in the form of asymptotic regression. However, in June the asymptotic regression performs almost equally efficiently to the neural network. Thus, in this month, asymptotic regression can be used as an alternative estimation procedure. On the other hand, in July and August the regression technique produced significantly higher estimation error and lower values of correlation and Willmott's indices than artificial neural network. Thus, in July and August the artificial neural network would be a more potent model than regression in estimating potential evapotranspiration over the study zone. In future, other neural networks such as a modular neural network, a radial basis function network, and generalized neural networks can be adopted to increase the degree of accuracy in the estimation of potential evapotranspiration.

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