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INVESTIGATION ON THE CAPABILITY OF ARTIFICIAL NEURAL NETWORK FOR ESTIMATING EVAPOTRANSPIRATION FROM MINIMUM WEATHER DATA

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Preface

Evapotranspiration is one of the most basic components of hydrologic cycle. It affects the water balance from the time water falls upon the land as precipitation until the residual reaches the ocean. Evapotranspiration, which includes evaporation of water from bare soil surface and transpiration by vegetation, continuous to be of foremost importance in water resources planning and management, and in irrigation development. Evapotranspiration data are essential for estimating irrigation water requirements. They also are useful for estimating the municipal and industrial water use, in sizing waster water reuse system, and in estimating water use from mountain watersheds, safe yield of ground water basins, and stream flow prediction is river basins. Numerous formulae have been developed that relate evapotranspiration and climatological data based on experimental data collected by engineers and scientists. However, most of these formulae are more or less empirical, owing to the highly complex non-linear nature of the evapotranspiration process, and require data that are not widely available. The science of estimation of evapotranspiration would benefit, if a model could be developed for computing evapotranspiration using minimum weather data. Such a model can be addressed through system theoretic approach, where the internal physical process need not be explicitly explained. Recent advancements in the field of non-linear system modeling through the use of artificial neural network could be employed for developing such a model. The approach has the advantage of the capability of ANN to reproduce the unknown relationship existing between a set of input-output variables describing the process.

This report '*Investigation on the capability of artificial neural technique for estimating evapotranspiration from minimum weather data*' presents a research study conducted to estimate evapotranspiration through artificial neural network technique. The study has been conducted by Sri. K. P. Sudheer, Scientist 'B' with the assistance of Sri. D. Mohan Rangan, Technician Gr. II under the supervision of Dr. K. S. Ramasastri.

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ABSTRACT

Most of the current hydrologic, water management, and crop growth model require an accurate estimate of evapotranspiration (ET), for reliable applications. A large number of methods for calculation of ET from weather data have been developed and tested for varying geographical and climatological conditions. However, most of these methods require weather data that are not widely available. A recent series of technical papers have discussed the capabilities of ANN to approximate any continuous input-output mapping to an arbitrary degree of accuracy. Accordingly, a research study was conducted to estimate ET from most widely available weather data. Three combinations of input data were considered and three different ANN models were developed. One of the models developed requires only average temperature as input and was estimating daily values of ET with 99% efficiency. The performance of ANN models was evaluated against that of popular ET estimating methods, and was found performing superior to others. The study demonstrated the applicability of ANN technique in accurately estimating ET from minimum weather data.

Chapter 1
Introduction

Evapotranspiration (ET) is a major component of the hydrologic cycle and is involved to some degree in nearly all hydrological studies. It is an especially important factor in planning and developing river basins, water resources and irrigation management. Evapotranspiration forms the foundation for planning and designing of most irrigation projects. It is usually the starting point in determining the surface and subsurface water storage requirements, the capacity of the water delivery system, and general operation practices.

Detailed measurements of ET or collecting data for estimating ET are time consuming and expensive. Some of these measurement methods are soil water depletion (Robins, et. al., 1954; Jensen, 1967; Jensen and Wright, 1978), tanks and lysimeters (Harrold, 1966; Aboukhaled, et. al., 1982). However, these methods are not employed in common owing to their requirement of extensive experimental work. The tremendous and continuing need for evapotranspiration data has resulted in numerous methods for estimating ET. Researchers are required to estimate ET using historical meteorological and cropping conditions or to predict future ET. Both of these involve meteorological data, but predictions are based on expected values of the meteorological and cropping data. Some of these works, which are widely referred to, are of Doorenbos and Pruit (1974), Svehik (1987), Rao et. al. (1971) and Schultz (1971). Doorenbos and Pruit (1974) indicated that modified version of the Penman's formula gives best estimation of ET, but also recommended the radiation, Blaney-Criddle and pan evaporation methods for different climatic conditions. Rao et. al. (1971) and Schultz (1971) recommended both the Penman and Blaney Criddle methods for reliable estimates over India. Hargreaves and Sammani (1985) suggested a simple equation for estimating ET based on temperature and extra terrestrial radiation. Many of these methods consider only a few variables since estimates were often needed where limited meteorological data were available. Also, most of the early applications, as well as some continuing applications, involved the use of long-term mean weather data.

However, most of these methods estimate the reference crop ET as defined by Doorenbros and Pruitt (1974) and requires these values to be converted into actual crop evapotranspiration values by multiplying with the crop factors. The value of crop factors vary from region to region and one need to establish this crop factor values for employing these methods in estimating the crop ET.

Since the process of evapotranspiration is highly complex and non-linear in nature, any attempt to model the actual crop ET would be requiring extensive experimental work and data. Very few research works have been reported that describe a procedure for estimating the actual crop evapotranspiration. One of these methods is the linear time series model, which are employed to generate or forecast the actual crop ET from a historic series of data. Recently, significant progress in the field of non linear pattern recognition and system control theory have been made possible through advances in a branch of non linear system theoretic modeling called artificial neural network (ANN). An ANN is a non-linear mathematical structure, which is capable of representing arbitrarily complex non-linear process that relates inputs and outputs of any system. In the hydrological context, as in many other fields, ANN are increasingly used as black-box simplified models (Bishop, 1994). For hydrological applications, ANN models can take advantage of their capability to reproduce the unknown relationship existing between a set of input variables descriptive of the system.

This reports demonstrates the applicability of ANN approach in developing effective non linear models for estimating evapotranspiration from widely available meteorological data. The model does not explicitly represent the internal process of evapotranspiration. The model has been developed for rice evapotranspiration data. The report also presents the comparison of results from ANN model with those estimated from popular ET estimating methods.

Chapter 2

Artificial neural network: Background and scope

The architecture of ANNs is motivated by models of biological neuron networks, which recognize pattern and learn from their interactions with the environment. The highly sophisticated human brain, which contain more than 100 billion neurons and trillions of interconnections, is able to learn quickly from experience and is generally superior to any existing machine in tasks involving recognition, learning and control. It should be pointed out that the structures of most current ANNs are extremely simple and the capabilities are quite poor when compared to biological neuron network. Nonetheless, since the 1950s, many ANN structures have been proposed and explored.

The ANN models have been widely applied in various fields of science and technology involving time series forecasting, pattern recognition and process control. The ANN structure has been mathematically proven to be a universal function approximator that is capable of mapping any complicated non-linear function to an arbitrary degree of accuracy. Since late 1980s, ANN has been successfully used to model a variety of different functions. The network is able to intelligently learn these functions through an automatic training process. However, many issues related to the network architecture are still not well understood. Many researchers seem to view ANN as a black box approach that is unable to provide important and useful insights into underlying nature of the physical processes (Judith, 1990).

An ANN attempts to mimic, in a very simplified way, the human mental and neural structure and functions (Hsieh, 1993). It can be characterized as a massively parallel interconnection of simple neurons that function as a collective system. The network topology consists of a set of nodes (neurons) connected by links and usually organized in a number of layers. Each node in a layer receives and processes weighted inputs from previous layer and transmits its output to nodes in the following layer through links. Each link is assigned a weight, which is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function (typically a sigmoidal function). Most ANNs have three layers or more: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors.

The ability of neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output. In general, the learning process of an ANN will reward a correct response of the system to input by increasing the strength of the current matrix of nodal weights. Therefore, the likelihood of producing similar output when the same inputs are entered in the future will increase. An incorrect response from the system is discouraged by adjusting the nodal weights so that the system will respond differently when it encounters similar inputs in the future (Hsieh, 1993). The learning process may be supervised or unsupervised based on the availability of target output. In supervised learning, inputs proceed through the network and produce an output. The difference between this output and target output represents an error, which is then propagated back through the network to train it. In unsupervised learning, the network automatically detects important features and organizes the input data into classes based on these features. More information about neural networks can be found in Lawrence (1991).

The most widely used and researched structures are multi layer feed forward networks (Rumelhart et. al., 1986), self-organizing feature maps (Kohonen, 1982), Hopefield networks (Hopefield, 1982), counter propagation network (Hecht-Nielsen, 1988) and radial basis function network (Moody and Darken, 1989). Of these, the radial basis function network is addressed in this report.

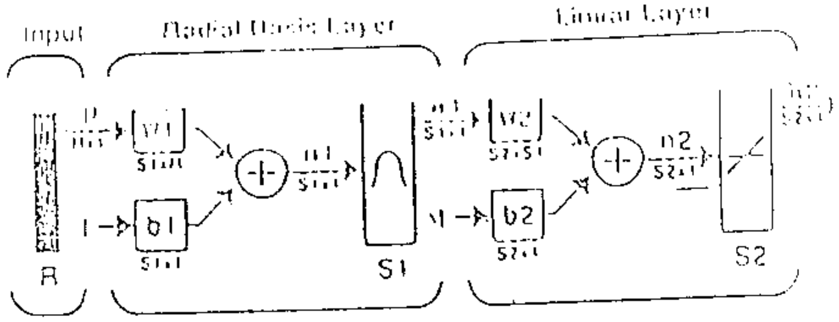
2.1 Radial basis function neural network

The radial basis function network employs combined supervised and unsupervised learning in the same network. The most common idea is to have one layer that learns in an unsupervised way, followed by one (or more) layers trained by back propagation. The network architecture examined by Moody and Darken (1989) has been employed in the present study. The hidden units in the Moody-Darken network are neither linear, nor sigmoidal; instead they have normalized Gaussian activation functions of the form:

$$g_j(\varepsilon) = \frac{\exp[-(\varepsilon - \mu_j)^2 / 2\sigma_j^2]}{\sum_k \exp[-(\varepsilon - \mu_k)^2 / 2\sigma_k^2]} \tag{2.1}$$

where ε is the input vector itself. The Gaussians are a particular example of radial basis functions. Radial basis networks consist of two layers: a hidden radial basis function layer and an output linear neuron layer. The network architecture is presented in Fig 2.1.

The network functions as follows. Suppose a particular input vector ε^μ lies in the middle of the receptive field for unit j, so $\varepsilon^\mu = \mu_j$. If the overlaps between the receptive fields are ignored, only hidden unit j will be activated, making it the only "winner" One could simply



Where

R = number of inputs
S1 = number of radial basis neurons
S2 = number of linear neurons

Fig2.1, Radial basis neural network architecture

choose the output weights leading from that unit to be $w_{ij} = \xi_i^{\varpi}$ (for each i), which will produce the target pattern ξ_i^{μ} at the output assuming linear output units. If another input lies say, between two receptive field centers, then those two hidden units will be appreciably activated and out put will be the weighted average of the corresponding targets. In this way the network is expected to make sensible smooth fit to the desired function.

The unsupervised part of learning is the determination of the receptive field centers μ_j and weights σ_{ij}. Appropriate μ's can be found by any vector quantisation approach including the usual competitive learning algorithm (Hertz et. al., 1991). The σ's are usually determined as ad hoc choice, such as mean distance to the first few nearest neighbor μ's. The performance of the network is not very sensitive to the precise values of the σ's.

Moody and Darken tried their method out on the extrapolation problem for the Mackey-Glass equation and found that the present method, with Gaussian receptive fields, allows one to fit an arbitrary function with just one hidden layer (Hartman, 1990).

Chapter 3
Evapotranspiration Estimation

The network of similar architecture (radial basis), explained earlier has been employed in this study to estimate the daily evapotranspiration for rice crop. The main task in developing any ANN model is identifying the input vector to the network so as to produce the output. A detailed review of the ET estimation technique clearly reveal that ET value is dependent on temperature, humidity, solar radiation and wind speed. Accordingly, these weather parameters have been considered in the present model development.

3.1 Neural network model

The weather parameters considered in this study were temperature, relative humidity, wind speed, sunshine duration and pan evaporation. The daily values of all these parameters have been considered in the study. Various combinations of these parameters were considered as input to the model. The combinations considered were, (i) average temperature, relative humidity, wind speed and sunshine duration [hereinafter referred to as ANN(1)]; (ii) average temperature, wind speed and relative humidity [hereinafter referred to as ANN(2)]; and (iii) average temperature alone [hereinafter referred to as ANN(3)]. Since data was available for only one season, part of the data was used in training the network and balance for validating the model.

The input vector was standardized using the following function (Romesburg, 1984):

$$Z_{ij} = \frac{X_{ij} - C_{minj}}{C_{maxj} - C_{minj}} \tag{3.1}$$

where, Z_{ij} is the standardized value of the input variable X_{ij}; C_{maxj} and C_{minj} are the maximum and the minimum of j^{th} variable in all observations. The main reason for standardizing the data matrix is that the variables are usually measured in different units. By standardizing the variables and recasting them in dimensionless units, the dissimilarity between objects are removed. The daily data for two months were used to train the network and the third month's data was used for validation.

The report evaluates the ANN model developed, by comparing with the results obtained from other models as well as with the actual lysimeter measured data. For the present study, the Penman, radiation Blaney-Criddle, and pan evaporation methods were selected for inter-comparison as well as for comparison with the ANN model. Brief description of the Penman, radiation, Blaney-Criddle pan evaporation and neural network methods are given below.

3.2 Penman method

The climatic data required for the Penman method are mean temperature in ^{0}C, mean relative humidity (in %) or vapour pressure (in mm), total wind speed at 2m height (in km/hour), mean actual sunshine duration (in hours/day) or incoming short-wave radiation (in equivalent evaporation in mm/day), maximum possible sunshine duration (in hours/day), measured or estimated data on maximum relative humidity (in %) and mean day time wind speed at 2 m height (in m/s). The equation for estimating reference evapotranspiration (ET_{pen}) is:

$$ET_{pen} = C_p[wR_n + (1-w).f(u).(e_a - e_d) \quad (3.2)$$

where

e_a = saturation vapor pressure;

e_d = actual vapor pressure in the air;

$$e_d = e_a \ . \ RH/100; \quad (3.3)$$

f(u) is the factor corresponding to the wind speed and is defined as,

$$f(u) = 0.27(1 + U/100) \quad (3.4)$$

R_n = total net solar radiation in mm/day;

u = wind speed at 2 m height

w = temperature and altitude dependant weighting factor; and

C_p = adjustment factor for ratio for U_{day}/U_{night}, RH_{max} and R_s.

A value of 1.5 can be assumed for U_{day}/U_{night} as recommended by Doorenbos and Pruitt (1974) in computing the value of C_p.

3.3 Radiation method

The data required are mean air temperature (T_{mean}), ratio of actual to maximum possible sunshine duration (n/N) or incoming short-wave radiation, mean relative humidity (RH_{mean}) and total wind speed (U_{day}). The estimate of evapotranspiration ET is given by:

$$ET_{rad} = C_r(wR_s) \quad (3.5)$$

where R_s and w have the same meaning as before, and C_r depends on RH_{mean} and U_{day}.

3.4 Blaney -Criddle method

The climatic data required are RH_{min}, U_{day}, n/N, T_{mean} and percentage of daytime hours during the period considered over that of the year (p). Evapotranspiration can be estimated as

$$ET_{BC} = A + B.p(0.46T_{mean} + 8) \quad (3.6)$$

where $A = 0.0043\ RH_{min}\ n/N - 1.41$; and
B = a factor depending on RH_{min}, n/N and U_{day}.

The Blaney criddle formula is believed to underestimate the ET at elevated sites because of the lower air temperature. Doorenbos and Pruit (1974) therefore incorporated an elevation correction in the original equation to give:

$$ET_{BC} = A + B.p(0.46T_{mean} + 8).C_e \quad (3.7)$$

where C_e is the elevation correction factor given by:

$$C_e = 1+0.1 * (\text{Elevation in m})/1000 \quad (3.8)$$

3.5 Pan evaporation method

Doorenbos and Pruitt (1974) relate pan evaporation to ET using empirically derived coefficients (K_p) which take into account the climate, pan environment and crop type. ET can be obtained by:

$$ET_{pan} = K_p.E_{pan} \quad (3.9)$$

where E_{pan} = pan evaporation in mm/day and
K_p = adjustment factor that depends on mean relative humidity, wind speed and ground cover. The value of K_p depends on season too and the reported value is near around 0.8 in summer and 0.6 in winter.

World Meteorological Organization (1966) suggested a correction factor of 1.14 to the observed value of evaporation, where the pans were covered with screen and this was applied in the present study. The values of K_p have been taken from Doorenbros and Pruit (1974) and Frevert et. al. (1983). The value of R_n in equation (3.1) was calculated from the relation:

$$R_n = 0.75\ R_s - R_{nl} \quad (3.10)$$

where R_{nl} is the net long wave radiation. Since measured values of R_s were not available, they were obtained from the equation:

$$R_s = (a+b\ n/N)\ R_z \quad (3.11)$$

where R_a is the extra terrestrial radiation.

The values of 'a' and 'b' were calculated by a regression of published mean monthly values of R against n/N (India meteorological department, 1981; Mohan, 1991). The 'a' and 'b' values differ somewhat from the values of 0.25 and 0.50 respectively when no data is available. R_{nl},

e_d and n/N as well as the values of e_a, R_s, w, C_p and C_r were taken from Doorenbros and Pruitt (1974).

3.6 Data base

The climatic data as well as the actual measurements of ET used in this study were obtained from the agricultural research farm of Kerala Agricultural University, Tavanur (India). Actual evapotranspiration data for rice crop was found from a lysimeter study performed in that area. The lysimeter experiment data from an experiment conducted in the research farm for a short term variety rice crop (Triveni) for a full season (October 1989 to January 1990) has been employed in the study. The climatic data, necessary for calculating reference crop ET using the selected methods, were taken from the agro-meteorological station located inside the research farm. The station is located at $10^0\ 53^{'}\ 30^{''}$ north latitude and 76^0 east longitude. The data was available for a period from October, 1989 to January 1990 and has been used in this study.

The results of study are described and discussed in the next chapter.

Chapter 4
Results and Discussion

The foregoing discussion of neural network approach has been employed to estimate the rice crop evapotranspiration from various combinations of meteorological data. A detailed methodology of the computing technique has been described in the previous chapters. This chapter presents the results pertaining to the results obtained from the study. The results are organized in the following way: evaluating the ANN approach for estimating the rice ET from minimum weather data; comparison of effect of various input combinations to the network in its efficiency; comparison of ANN model with other popular models.

4.1 Evaluation of ANN models

Visual comparison of lysimeter-measured rice evapotranspiration and ANN model estimates for three models, described earlier, are presented in Fig. 4.1 to 4.3. These figures include daily values for the year 1989-90 (October-January season). Visual evaluation of ANN models reveals that both ANN(1) and ANN(2) models (Fig. 4.1 and 4.2) failed to estimate the peak values of evapotranspiration effectively. This may be because the training range of data did not include the full peak values. At the same time, ANN(3) performed satisfactorily, as is evident from Fig. 4.3. The ANN(3) model, though was trained for the same range of data as for the other two models, it had an additional input of time variable so as to recognize the time series. Normalized day number was added as input to the ANN(3) model. On the contrary, no significant change in evapotranspiration estimates has been observed while the temporal characteristic variable was added to the other two models.

4.1.1 Statistical analysis

Though a visual inspection of the observed and computed evapotranspiration values explains the capability of ANN to represent the ET process in a reasonably accurate manner, the effectiveness of the model is to be understood through statistical analysis of the results. Linear regression analysis was used to test the agreement and variations of neural network estimated evapotranspiration with lysimeter measurements. Two regression equations were evaluated. The first model was of the form:

$$ET_a = a + b(ET_{ann}) \qquad (4.1)$$

where ET_a is lysimeter measured evapotranspiration; and ET_{ann} is the particular evapotranspiration estimated from ANN models.

The second regression model was of the form:

$$ET_a = b(ET_{ann}) \qquad (4.2)$$

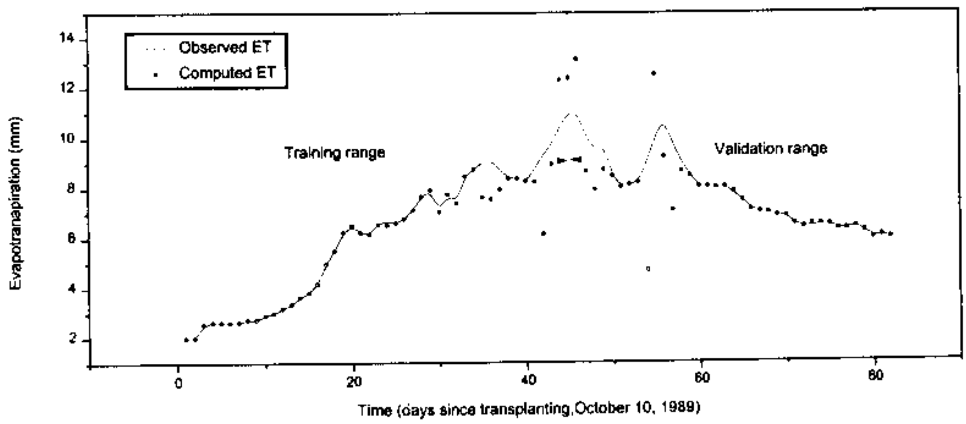


Fig 4.1 Daily ET estimated with ANN(1) model and lysimeter-measured ET

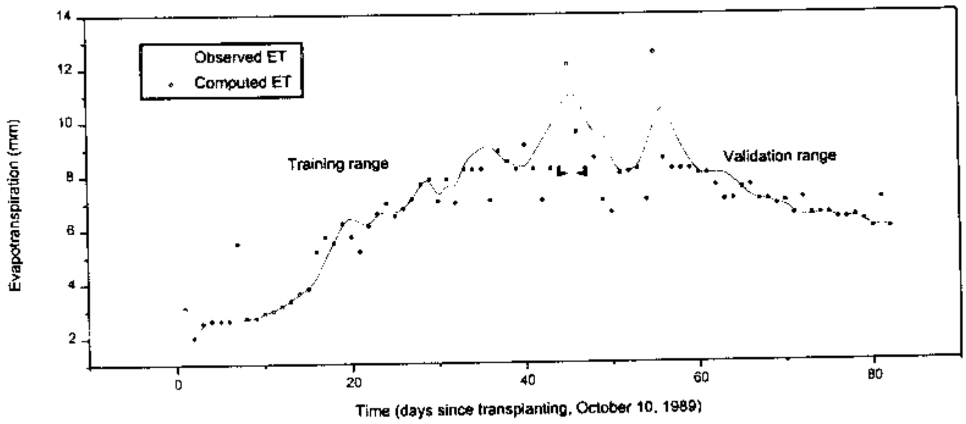


Fig 4.2 Daily ET estimated with ANN(2) model and lysimeter-measured ET

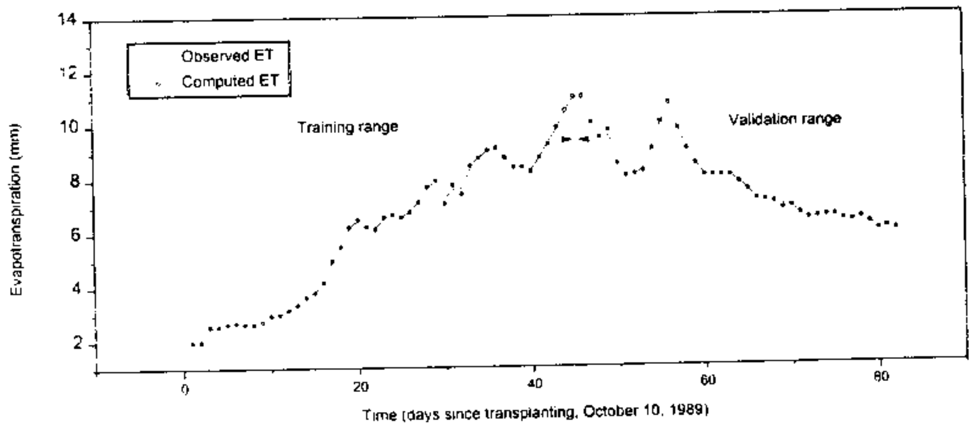


Fig 4.3 Daily ET estimated with ANN(3) model and lysimeter-measured ET

where, the zero intercept was forced through the origin. The value of coefficient 'b' in equation 4.2 could be used to indicate relative conversion ratios.

The hypothesis that the coefficient 'a' in equation 4.1 is significantly different from zero (regression through origin) was tested according to the procedures defined by Steele and Torrie (1960). The values of 'a' was not significantly different from zero for any of the models. Therefore equation 4.2 was used to compare the fit of the various ANN models evaluated.

Table 4.1. Regression coefficient and standard errors of estimate for daily evapotranspiration (observed versus computed)

	b	r	SEE	RSEE	Efficiency
ANN(1)	0.973	0.930	0.943	0.905	0.984
ANN(2)	0.954	0.920	1.071	0.945	0.982
ANN(3)	0.990	0.990	0.030	0.030	0.990

The results of the regression analysis using equation 4.2 are presented in Table 4.1. Each set of columns in Table 4.1 are regression coefficient 'b', correlation coefficient 'r', standard error of estimates (SEE), raw standard error of estimates (RSEE) and the efficiency of the model. The standard error of estimates is an estimate of the mean deviation of the regression from observed data. It is defined as:

$$\mathrm{SEE} = \sqrt{\frac{\sum(\mathrm{Y} - \hat{\mathrm{Y}})^2}{(\mathrm{n}-2)}} \tag{4.3}$$

where Y is observed (lysimeter-measured) evapotranspiration; and $\hat{Y}$ is the regression estimated lysimeter evapotranspiration using equation 4.2. The square of the standard error of estimate is an unbiased estimate of the true variance about regression with $(n-2)^0$ freedom (Steele and Torrie, 1960). The fourth column in Table 4.1 is the raw standard error of estimate (RSEE) of the direct comparisons of lysimeter-measured evapotranspiration to ANN estimated evapotranspiration. The RSEE term (Allen, 1987) is an indicative of how well each method estimated with no local or statistical correction (a=0 and b=1).

An evaluation criterion proposed by Nash and Sutcliffe (1970) was also employed to evaluate the performance of each model. The criterion is defining the efficiency of simulation as:

$$\mathrm{Efficiency} = 1.0 - \frac{\sum(\mathrm{ET_a} - \mathrm{ET_{ann}})^2}{\sum(\mathrm{ET_a} - \mathrm{ET_{bar}})^2} \tag{4.4}$$

where ET_a and ET_{ann} are as defined earlier and ET_{bar} is the observed mean during the period. The values of efficiency of computation for each model are presented in Table 4.1.

From Table 4.1, it is apparent that both ANN(1) and ANN(2) models need further refining as can be observed from the high value of standard error of estimate. The ANN(3) model performance was satisfactory and all the evaluation factors agree to this conclusion. Even though the ANN(1) and ANN(2) models compute the evapotranspiration values efficiently (as indicated by high efficiency) their correlation coefficients were considerably low compared to ANN(3) model. This emphasizes the need for various evaluation criteria to test the performance of any model. Table 4.2 depicts the mean weekly observed and computed evapotranspiration values averaged over a period of 7 days since beginning. This table is presented to visualize the model performance when mean values only are considered.

Table 4.2. Mean weekly evapotranspiration values (October 10, 1989 to January 9, 1990)

Lysimeter	ANN(1)		ANN(2)		ANN(3)	
Measured	Computed value	% Error	Computed value	% Error	Computed value	% Error
2.44	2.44	-0.07	3.01	-23.36	2.44	-0.30
3.07	3.07	-0.03	3.07	0.00	3.06	0.21
5.34	5.34	0.01	5.34	0.00	5.34	-0.01
6.80	6.77	0.38	6.83	-0.44	6.79	0.01
8.06	7.86	2.47	7.76	3.62	8.06	0.00
8.70	7.85	9.77	8.15	6.36	8.69	0.12
10.20	10.30	-0.94	8.86	13.21	10.21	-0.11
8.94	8.47	5.27	8.44	5.58	8.94	0.02
8.48	8.05	5.09	7.90	6.83	8.48	-0.04
7.17	7.16	0.06	7.15	0.21	7.15	0.23
6.42	6.44	-0.33	6.53	-1.70	6.44	-0.24
6.12	6.12	-0.03	6.32	-3.23	6.12	0.03

4.2 Comparison of ANN model with other popular models

From the foregoing analysis it is established that an ANN(3) model is very well capable of estimating the crop evapotranspiration from weather data. However, the performance of these ANN models is to be checked over other commonly employed techniques, so as to evaluate the advantage of this approach over existing techniques. This was achieved through comparing the rice evapotranspiration estimated using existing techniques with that estimated from ANN model. These values were compared with the actual measured lysimeter values too and are described below.

The crop factor values of rice to convert the estimated reference crop evapotranspiration values to actual crop evapotranspiration values were not available for the study area. At the same time, lysimeter measured evapotranspiration values were available. Hence in the present study, the values of crop factors were estimated assuming that the Penman's method gives a better estimate of reference crop evapotranspiration. The Penman method was selected as the base since a number of researchers had reported that the method is very efficient (Shouse et. al., 1980; Subrahmanyan and Rao, 1985; Kizer et. al., 1990) in estimating the reference evapotranspiration. Penman's method is probably the most comprehensive approach to estimate ET and takes into account almost all of the factors, which are known to influence ET. The computed reference crop evapotranspiration using the other three methods (radiation, Blaney-Criddle and pan evaporation) were converted to actual crop evapotranspiration (ET_{rice}) using the derived crop factors (Fig 4.4). Since ET estimates using Penman method were used as a reference, a comparison with this method would have no meaning and hence was not carried out. The results of radiation, Blaney-Criddle, pan evaporation and ANN models were compared with Penman estimates and statistically analyzed.

4.3 Comparison of effectiveness of estimation methods

Daily ET_{rice} values from the radiation, Blaney-Criddle, pan evaporation and ANN methods were computed for the period October 1989 to January 1990 from the corresponding climatic records and the crop factors. The daily values of ET_{rice} computed from all the methods considered in this study are presented in Fig 4.5, along with the actual lysimeter measured data.

Visual comparison of the estimates by the different methods reveals that the ANN model was highly efficient to estimate the rice evapotranspiration. The Blaney-Criddle and radiation methods were having the similar trends as that of actual values, but both under estimated the values throughout the period of study. However, the ET_{rice} values estimated from pan evaporation data were not comparable and the model was not performing well, as is evident from Fig 4.5.

The ratios of actual evapotranspiration to the values estimated from these four methods are shown in Fig 4.6. The figure clearly demonstrates the inferiority of pan evaporation method and the superiority of the ANN method for estimating ET_{rice}. The figure also depicts the similarity in seasonal trends of the four models.

4.3.1 Statistical evaluation of results from various models

As stated earlier, the visual inspection may have a subjective effect in the conclusion and hence to overcome this effect, statistical evaluation of the results were carried out. Comparing the computed results with actual measurements in the same area can test the suitability of each of the above methods in estimating evapotranspiration. Such comparison can be reached through evaluation criteria based on specific statistical parameters. The evaluation criteria used in this work have included the procedure adopted by Jensen (1974), Burman et. al. (1975), Hargreaves and Samani (1982), and Salih and Sendil (1984). At least two of the

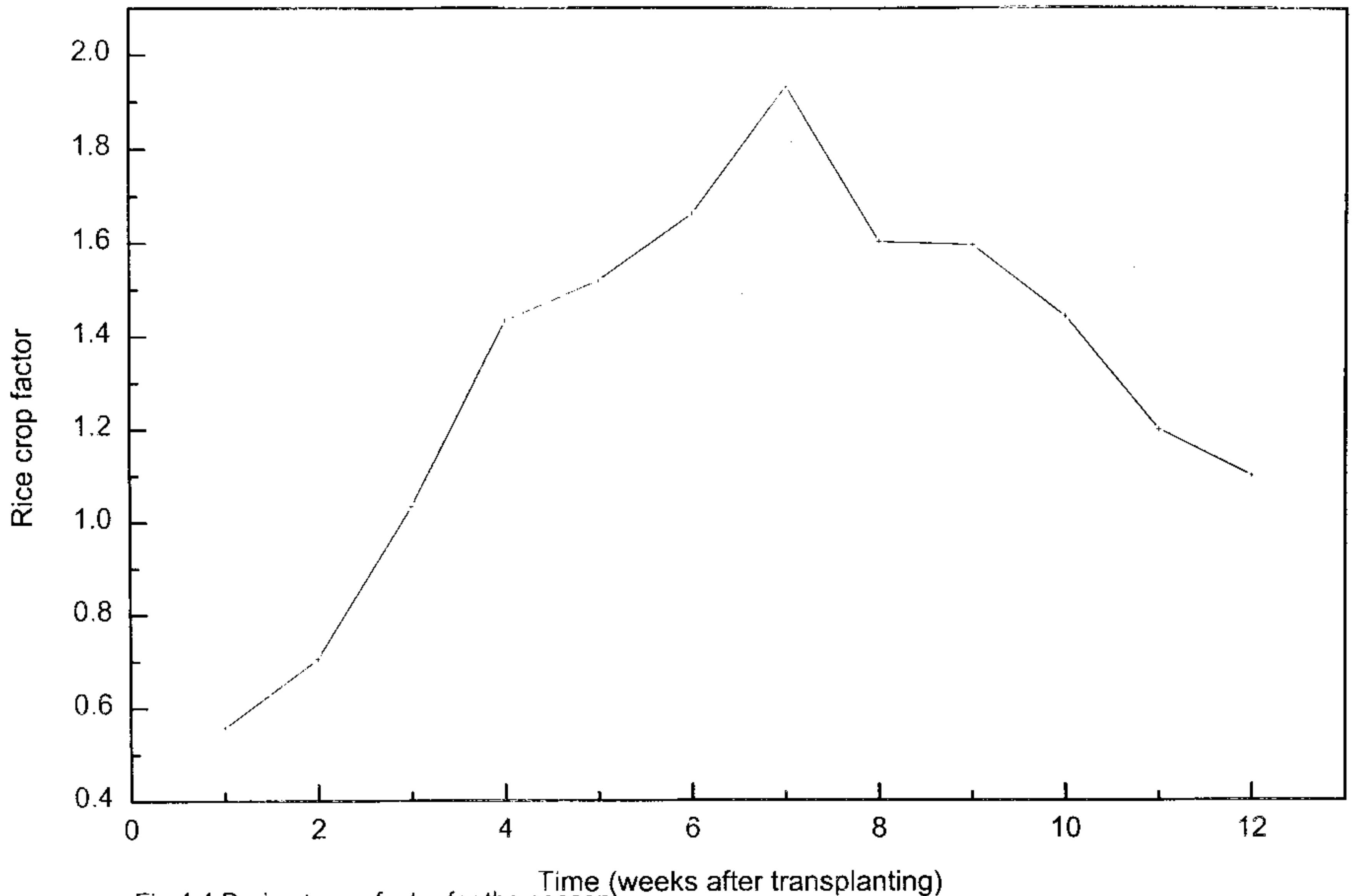


Fig 4.4 Derived crop factor for the season

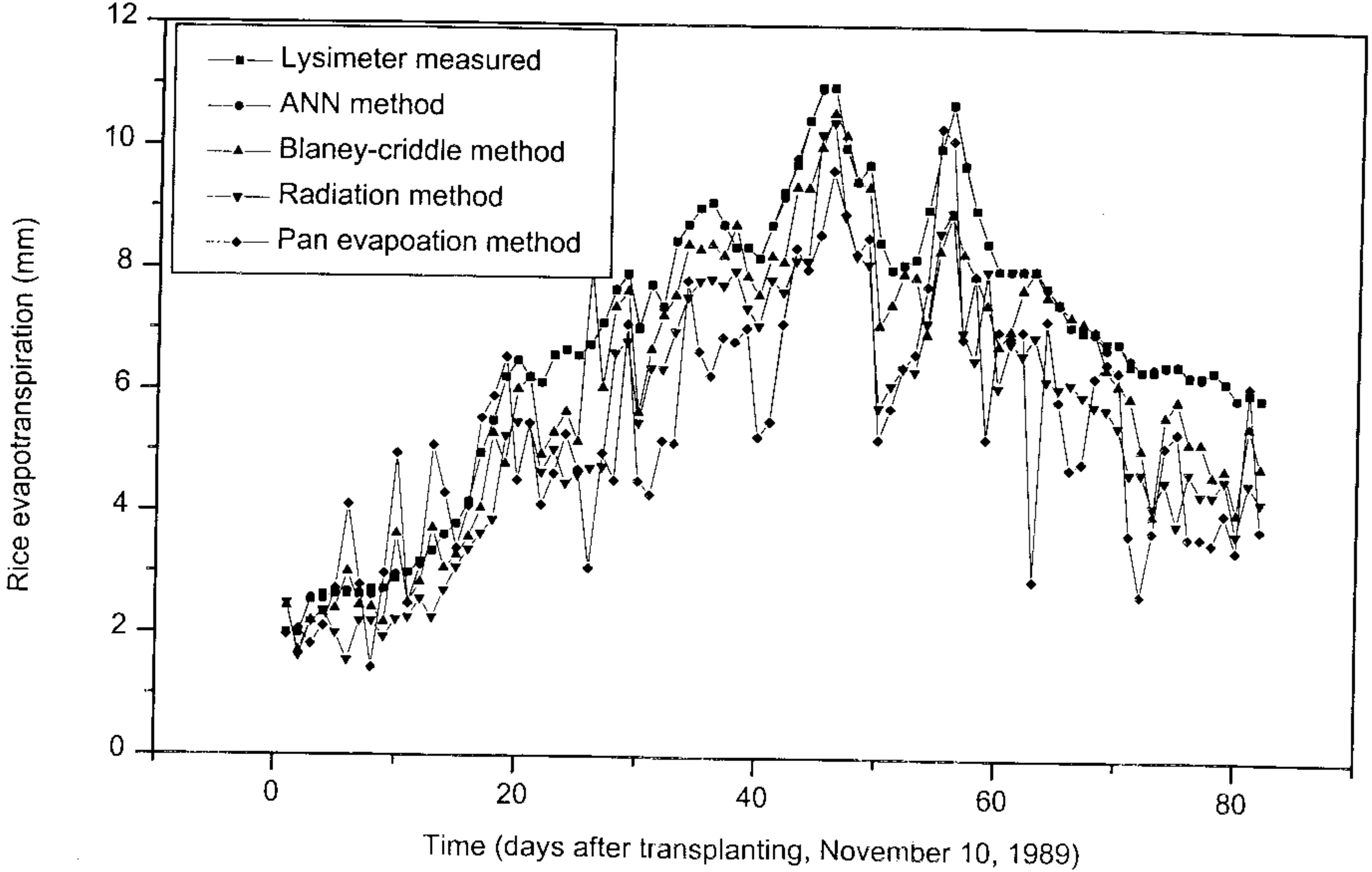


Fig 4.5 Daily value of rice evapotranspiration

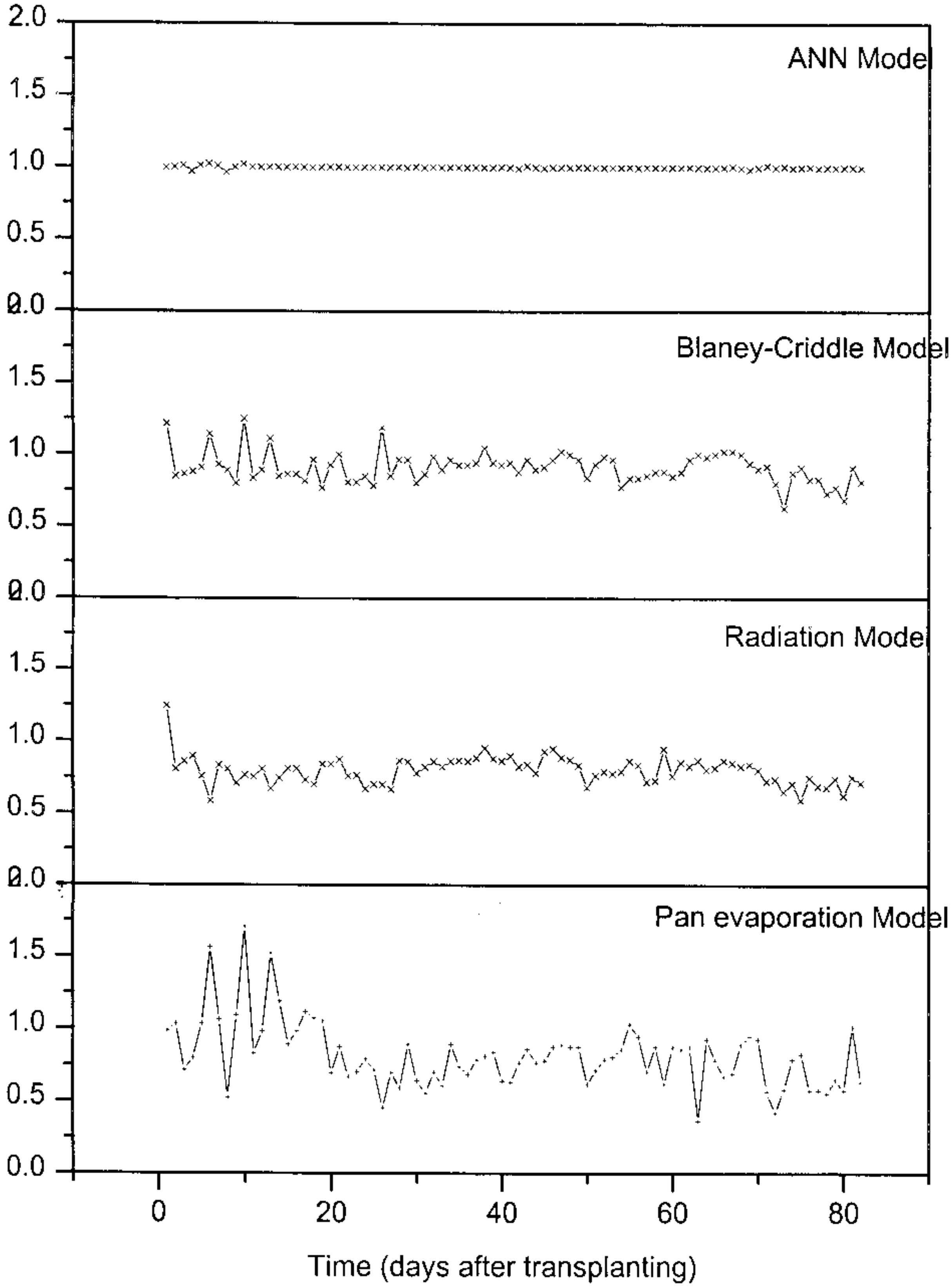


Fig 4.6 Ratio of actual to estimated evapotranspiration

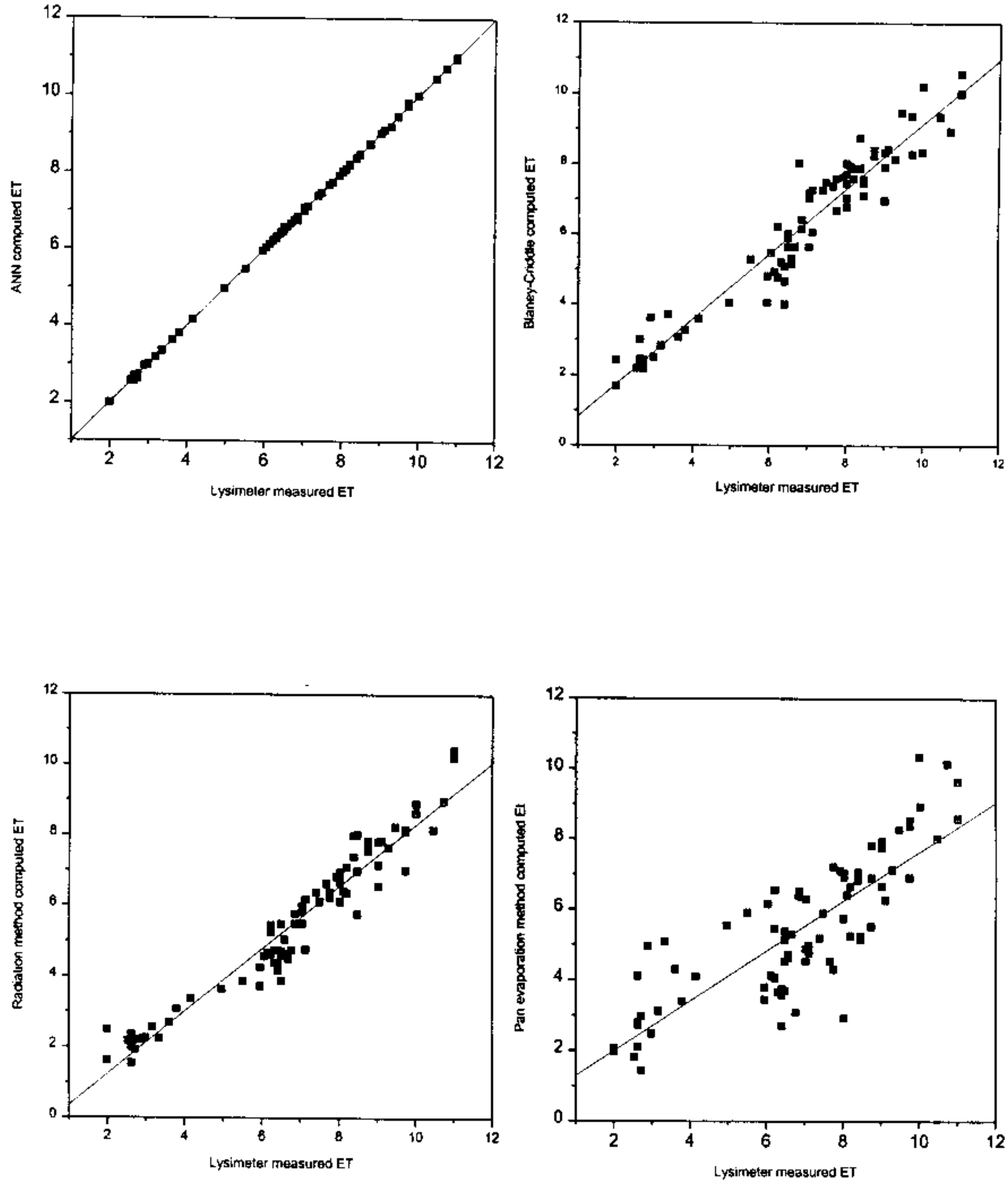


Fig 4.7 Scatter diagram of observed Vs computed rice ET

following parameters have been used in evaluating the models: the accuracy of seasonal estimate (ET %); the root mean square of the difference between the measured and estimated values (RMS); the smallness of the intercept (A) of the correlation line; the coefficient of regression (R) of the measured versus estimated values; and the standard deviation of the ratios of measured to estimated value. Efficiency of the method for estimating the evapotranspiration was computed using the equation suggested by Nash and Sutcliffe (1970).

Table 4.3. Values of evaluation parameters considered

	Actual	ANN	Blaney-Criddle	Radiation	Pan Evaporation
Mean	6.828	6.829	6.196	5.500	5.396
Standard Deviation	2.344	2.344	2.253	2.146	2.020
R square		0.999	0.923	0.933	0.673
R value		0.999	0.960	0.965	0.821
Efficiency		1.000	0.850	0.605	0.294
Covariance		5.428	5.013	4.799	3.838
RMS value of error		0.030	0.903	1.464	1.958
Y-intercept		0.001	-0.110	-0.537	0.568
Standard deviation of ratios		0.007	0.106	0.095	0.229

Table 4.3 presents the values of the above evaluation parameters. All the statistical parameters in the table agree to the efficiency of the ANN model to estimate evapotranspiration. From Table 4.3, it is very clear that the pan evaporation method failed to estimate the ET_{rice} efficiently, as can be observed by the low efficiency (29.4%) and high RMS value of error (1.958). The coefficient of correlation for all the methods were acceptable and this fact leads to the need for considering other statistical parameters also to assess the performance of any model. The results of regression analysis are shown in Fig 4.7, in a dispersion diagram. The covariance value of the actual and predicted values are used to check whether large values of one set are associated with large values of the other (positive covariance), whether small values of one set are associated with large values of the other (negative covariance), or whether values in both sets are unrelated (covariance near zero). The covariance analysis in the present study leads to reject the pan evaporation method for computing rice crop evapotranspiration.

Chapter 5
Summary and Conclusions

A neural network model was developed and analyzed to estimate the daily values of rice crop evapotranspiration from minimum meteorological data. A radial basis function network was employed in the study. Three combinations of weather data were considered as input to the ANN structure. These combinations were selected based on a detailed review of research work in this area of study. The results from each of these models were compared with actual lysimeter observations and it was found that the ANN model with temperature as sole input neuron estimated the lysimeter measured crop ET effectively.

The study attempted to estimate the actual crop evapotranspiration from minimum weather data and resulted in an ANN model, which makes use of only average temperature data alone to estimate the actual ET. The effectiveness of this model was evaluated using various statistical indices. The results of this model were compared with various existing techniques. The analysis led to the conclusion that the ANN models were performing superior to all existing techniques for computing the actual evapotranspiration. However, the study was based on a single season lysimeter data and more research woık may be required to reinforce this conclusion.

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