Research Article

Journal of Plantation Crops, 2008, 36 (1): 24-29

A fuzzy neural network for coconut yield prediction

C. Palaniswami*, R. Dhanapal, A.K. Upadhyay, C. Manojkumar and K. Samsudeen

Central Plantation Crops Research Institute,
Kasaragod, 671 124, Kerala, India

(Manuscript Received: 28-06-06, Revised: 17-05-07, Accepted: 07-02-08)

Abstract

A fuzzy neural network was developed to predict the coconut yield. The fuzzy membership values of the independent variables (daily mean air temperature, RH, sunshine hours and available soil moisture in the root zone) were used as the input layer for the network. The correlation coefficient between predicted and observed yield was 0.98 with RMS error 11.77 %. The proposed method captured the non-linear relationship between the climate, soil and yield of coconut production system.

Keywords: Artificial neural network, coconut, Fuzzy membership functions, yield prediction

Introduction

Coconut (*Cocos nucifera* L.), an important perennial oil yielding crop of humid tropics, is grown widely in the countries lying in the Indian Ocean and the Pacific Rim. India is the largest producer of coconut and also has the largest acreage under the crop. In India, more than 90 % of the coconut acreage and production lies in the four southern states namely, Kerala, Tamil Nadu, Karnataka and Andhra Pradesh. With the setting up of the WTO and trade liberalization, forecasting crop yield is needed by the Government, agro-industries, traders and agriculturists alike to formulate policies.

Coconut has unique feature among the plantation crops in that it flowers and fruits throughout the year. In general the fruit development in coconut takes 44 months from the time of initiation of inflorescence primordium to full maturity of the nut. Dry spells during ontogeny of coconut inflorescence and growth stages of the developing nut affect the nut yield (Rajagopal *et al.*, 1996). A well managed coconut tree produces at least one leaf and inflorescence a month. Crop yield is a function of both genotype and environment. Amongst the environmental factors, weather plays a crucial role in expressing the yield potential of the crop. The yield of the coconut palm is not only dependent on the current year climatic pattern, but also on the weather pattern of the preceding years.

A crop forecasting model based on the 12 rainfall parameters was used by Abeywardena (1968) and obtained yield predictions close to the observed values (R^2 = 0.81). However, validity of the model for anticipating yields was not tested. In 1983 an empirical statistical model to forecast yields in Sri Lanka was developed based on eight variables (drought indices) for eight different agro ecological regions derived from monthly rainfall figures and taking into consideration the minimum requirement of soil moisture for optimum prediction (Abeywardene, 1983). The errors of the estimated values for some years were very large, but no alternative methods have been developed and the use of drought indices is more meaningful and useful than actual cumulative rainfall. A predictive model (R^2 = 0.91)

*Corresponding author: Senior Scientist, Division of Crop Production, CPCRI, Kasaragod - 671 124, Kerala, India
E-mail: darsanpalaniswami@yahoo.co.uk

with six climatic variables (maximum relative humidity, sunshine duration, vapour pressure and minimum air temperature at different periods) was developed (Vijayakumar *et al.*, 1989). This model could predict the yield for a given year by the middle of May in the year before harvest. These models do not attempt to take into account the non-linear dynamic relationship between the independent variables (weather data) and the dependent variable, the yield.

Artificial neural networks (ANN) are gaining increasing popularity as an alternative to statistical methods for complex modeling. Infact neural network is a series of layers with nodes and weights that represent complex relationships among input and output variable with an objective to obtain optimal weights to give a best value for the nodes of the output layer. Further, for input data to ANN, where the independent variables are attributes and are vaguely formulated and also even though these attributes are precisely defined, however, in practice they retain a strong flavour of qualitative ambiguity. Data mining tools are beginning to show value in analyzing massive data sets from complicated systems and providing high-quality information (Liu *et al.*, 2001). An artificial neural network (ANN) is an attractive alternative for building a knowledge-discovery environment for a crop production system. An ANN can use yield history with measured input factors for automatic learning and automatic generation of a system model. In the past few years, several yield simulation models have been built. Fuzzy sets, however, admit the possibility of partial membership, so they are generalizations of crisp sets to situations where the class boundaries are not or cannot be sharply defined (Burrough, 1989). A fuzzy logic expert system was used to predict corn yields with promising results (Ambuel *et al.*, 1994). The functional relationship using the fuzzy logic expert system was expressed linguistically instead of mathematically. The membership function of fuzzy sets defines how the grade of membership of x in A is determined. The fuzzy membership value of independent variable will be used as input layer for ANN.

In our study an attempt has been made to devise a coconut yield prediction model using fuzzy membership value and ANN.

Materials and Methods

Location of the site

The experimental site is located in the Central Plantation Crops Research Institute, Research Centre at Kidu in Dakshin Kannada district of Karnataka state in India. The experimental site has a gradient of 28° towards east. The mean daily maximum temperature varies between 29.3 and 38.5° C. The average annual rainfall is 2700 mm. The soil is laterite classified as *Oxic haplustults*. The soil characteristics are given in Table 1. The soil moisture content at water holding capacity, permanent wilting point, 0.03 MPa, 0.2 MPa and 1.5 MPa were estimated using pressure plate apparatus. The soil was analysed for its mechanical composition, pH (1:2.5) and organic carbon using standard procedures (Jackson, 1967).

Table 1. Soil characteristics

Sl. No.	Soil characteristics	Values
1	Depth (cm)	125
2	Sand (%)	45
3	Silt (%)	9.95
4	Clay (%)	35
5	pH (1:2.5)	5.45
6	Organic carbon (%)	0.41
7	Soil moisture at 0.03 MPa (% v/v)	29.9
8	Soil moisture at 1.5 MPa (% v/v)	18.2
9	Soil moisture at 0.2 MPa (% v/v)	23.4
10	Soil moisture at permanent wilting point (% v/v)	15.6
11	Water holding capacity (% v/v)	42.9

Description of the model

Coconut is a highly cross pollinated crop. The coefficient of variation for the yield in the population ranges from 20 – 30 %. Year to year fluctuation in coconut is a common feature. In any large population, it is possible to see large number of palms that are biennial in their bearing habits (Jacob Mathew and Jose, 1991). Yield data was collected for eleven consecutive years from 1990-2000 on an individual palm basis, from a coconut plot having 200 West Coast Tall (WCT) palms. Yield variation over years is a function of genetic make up of the palm, field scale soil variability and weather condition prevailing during those years. To over come the variations from the above mentioned factors, the palms were ranked from 1 – 200 every year based on yield. Yield data of only those five palms ranking amongst first 25 ranks in all the years were selected for the study.

Daily climatic variables viz., rainfall, mean air temperature, relative humidity, sunshine hours and open pan evaporation were collected from the class B meteorology observatory of Rubber Research Institute of India, Substation, Kadaba adjacent to the research centre. The data collected were for the period 1990-2000. Missing values were estimated as described in the WEPP weather generator – CLIGEN (Nicks *et al.,* 1995).

The climatic requirements of the crop have been utilized to derive the fuzzy rule.

Soil moisture deficit has been calculated on daily basis as per equation (1) (Bailey and Spackman, 1996):

$$SMD_d = SMD_{d-1} + AE_d - R_d - I_d + D_d + r_d \qquad (1)$$

Where SMD_d = Soil moisture deficit on daily basis; d is the day in question; AE is actual evapotranspiration; R is rainfall; I is irrigation; D is drainage from the root zone and r is runoff. All variables are expressed in millimeters (mm). The actual evapotranspiration (AE) for coconut has been worked out as per the equation (2) (Bailey and Spackman, 1996)

$$AE = kPE \qquad (2)$$

Where PE is potential evapotranspiration (mm) and k is a coefficient dependent on the soil moisture deficit and the potential transpiration rate. Potential evapotranspiration has been calculated as per equation (3):

$$PE = k_c E_o \qquad (3)$$

Where k_c is the crop coefficient (k_c for mature coconut is 0.8). E_o is open pan evaporation in mm. Available soil moisture(ASM) in the root zone of one meter depth was estimated on daily basis as per equation (4).

$$ASM_d = ASM_{d-1} - SMD_d \qquad (4)$$

A fuzzy set is most commonly used for classifications of objects or phenomena in continuous values, where the classes do not have sharply defined boundaries. It deals with a class with a continuum of grades of memberships (Zadeh, 1965). A fuzzy set A may be defined as follows in the equation (5).

$$A = \{x, \mu_A(x)\}\ x \in X \qquad (5)$$

Where X = {x} is a finite set (or space) of objects or phenomena, μ_A (x) is a membership function of X for subset A. Therefore, a fuzzy subset is defined by the membership function (MF) that defines the membership grades of fuzzy objects or phenomena in the ordered pairs, consisting of the objects and their membership grades. The MF of a fuzzy subset determines the degree of membership of x in A (Burrough, 1989). There are several ways to generate a fuzzy membership function. For environmental applications, there are two different but complementary approaches to grouping individuals into fuzzy sets or classes (McBratney and Odeh, 1997). The first is the Similarity Relation model (SR), and the second is based on the Semantic Import model (SI). This SI model approach is adopted in this study. The SI model (see Burrough, 1989) is comparatively simple to use, because it utilizes an *a priori* membership function (MF) for individual variables under consideration (Burrough, 1989). Examples can be seen in Burrough (1989), Burrough *et al.* (1992), and Davidson *et al*. (1994). With this approach, the attribute values considered are converted to common membership grades (from 0 to 1.0), according to the class limits specified by the analysts based on experience or conventionally imposed definitions (McBratney and Odeh, 1997). If MF(x) represents individual MF values for property x, then, the basic SI model function can be defined as fuzzy membership function has been worked out for sunshine hours, relative humidity, available soil moisture and mean air temperature as per the equation (6) (Burrough, 1989).

$$F(x) = \frac{1}{1 + \frac{(a-x)^2}{c}} \qquad (6)$$

Where F (*x*) is the fuzzy membership value of x; a defines the value of x at the central concept or optimum for the coconut, and c is parameter governing the shape of the function.

The fuzzy membership values derived are used as input layer for the ANN. The description of ANN models are available elsewhere (Gautam *et al.*, 2000; Grönroos, 1998; Sajikumar and Thandaveswara, 1999; Šima, 1998). Multi-layer feed forward neural network has been used for the coconut yield prediction by providing input-output training sets and minimizing the objective function (error function). Sixty per cent of the data set is used for training and 20 % each for the test and evaluation. The back propagation network simulator was implemented in the Visual C++ as per the algorithm described by Rumelhart *et al.* (1986). Input data are normalized in the range of 0.1-0.9. The output data are also normalized in the range of 0.1-0.9 since logistic activation function is used.

The accuracy of the trained ANN was evaluated by calculating an individual modeling error for each of the examples reserved for testing. Individual prediction errors were calculated as:

$$\text{Prediction error} = \frac{\text{Predicted yield} - \text{Observed yield}}{\text{Observed yield}} \times 100\,\% \qquad (7)$$

Using equation 8, positive errors indicate over-predictions, while negative errors indicate under-predictions. To obtain an overall accuracy measure for the 60 test examples, the RMS error was calculated:

$$\text{RMS error} = \sqrt{\frac{\sum^{N} prediction\ error^{2}}{N}} \qquad (8)$$

Results and Discussion

Fuzzy membership function

It is generally assumed that the optimum temperature for coconut is about 27° C, and the mean diurnal variation between 5-7° C. Normally, an absolute low temperature of 0° C for a short spell will not kill a palm. One cold spell with temperatures below 15°C lasting 57-75 days had seriously damaged coconuts and losses of upto 90 per cent of the nuts occurred during two consecutive years. Relative humidity is one of the factors determining the transpiration rate and, consequently, the water and nutrient uptake by the palm. Even in the case of sufficient water supply from the soil, low relative humidity of the air may induce stomatal closure in the palm, reducing its photosynthetic capacity. It was observed that coconut reduces its stomata opening when relative humidity drops below 60%, even if soil is close to field capacity (Ohler,1999). It is observed that when RH is more than 85% for three or more consecutive days outbreak of pest and disease occurred causing yield reduction. It is generally accepted that the coconut palm requires at least 2,000 hours of sunshine per year to exploit its production potential fully estimated to be 120 hours of sunshine per month would be favourable for coconut. Coconut can tolerate six months or more of drought, yields are seriously affected when the water deficit amounts to more than 300 mm per year. In general crop is affected when available soil moisture reduces below 50 % (Ohler, 1999). Based on these optimum climate and soil conditions fuzzy rule set were framed for the membership function and given in Table 2.

Table 2. Rule set for fuzzy membership function

Membership function	Description of criteria
Temperature	< 15ºC affects fruit setting adversely
Relative humidity	< 60 % - affects stomata opening > 95 % - crop affected by pest and diseases
Sunshine hours	< 4 hours - affects the coconut growth
Available soil moisture	< 50 % of available soil moisture content affects nutrient uptake

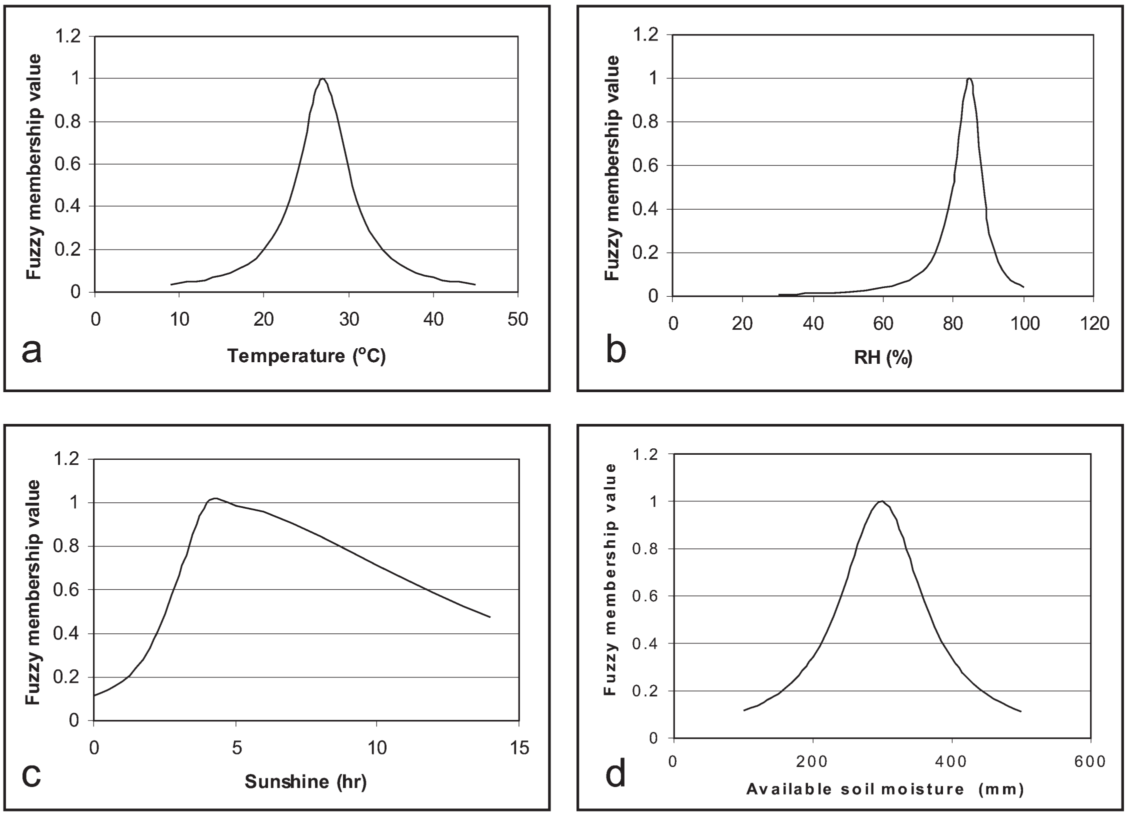

Fig. 1. Membership functions of selected parametrs: Mean air temperature (a), Relative humidity (b), Sunshine hours (c), and Available soil moisture (d)

The coefficients ‘a’ and ‘c’ for the different fuzzy membership functions have been derived using the rule set as shown in Table 2. The coefficient values are given in Table 3. The fuzzy membership functions are given in Figure 1.

Table 3. Coefficient values for fuzzy membership functions

Membership function	Coefficient a	Coefficient c
Temperature	27	12
Relative humidity (<= 85 %)	85	25
Relative humidity (> 85 %)	85	10
Sunshine hours (<= 4 hours)	4	2
Sunshine hours (> 4 hours)	4	90
Available soil moisture	299.2	5140.89

The fuzzy membership value (F(x)) obtained on daily basis were cumulated to monthly as per the equation (9). The cumulative fuzzy membership values will be unity, if that particular parameter is optimum for all the days in the month.

$$CF(x) = \frac{\sum_{1}^{n} F(x)}{n} \tag{9}$$

Where CF(x) is cumulative fuzzy membership value on monthly basis and n is number of days in the month.

Neural network

The input layer consists of cumulative fuzzy membership values (CF(x)) of each parameter for varying periods. Further, to include the alternate bearing habit of coconut, modulus 4 of the reporting year divided by 3 is used. The cumulative fuzzy membership values range from 0-1 for climatic variables so, to have the value of modulus 4 in the range of 0-1, it is divided by 3. To avoid overfitting, the termination of the learning process is controlled by the stopped training method.

Multilayer FNN was run for 10 epochs for the training set for different FNN topology, as 10 epochs gave the least root mean prediction error with 200 iterations. The final topology, which gave the least mean square error (0.21) has 145 nodes in the input layer (previous 36 months CF(x) values for the selected variables viz. RH, temperature, available soil moisture in the root zone and sunshine hours and alternate bearing habit of coconut), two hidden layers with 180 and 60 nodes and output layer with five nodes. The predicted output layers under all the years of study are given in Figure 2. The nut yield, both observed and predicted are given in Figure. 3. The FNN model during the evaluation stage predicted the coconut yield adequately in the year 1999 compared to the observed values. The overall root mean square error for the simulation of entire data set is 0.21 in the output layer. The coconut yield was predicted to a higher degree (R^2 =0.98) by this model where even the non-linear relationship between the input and output were taken into account. As shown in Figure 4, a histogram of the yield prediction errors, the RMS error was 11.77%. The RMS error is the result of inter year variation in the yield, since the random selection of the initial weights had some influence on the RMS error. As expected, the histogram approached a normal distribution, except that there was one very large over-prediction of yield. However, in the year 2000, the model gave an overestimate of the nut yield for the palm numbers P4 and P5. This may be because only 10 years data was taken for the study. Taking more number of years of data set might improve the FNN model for better yield prediction.

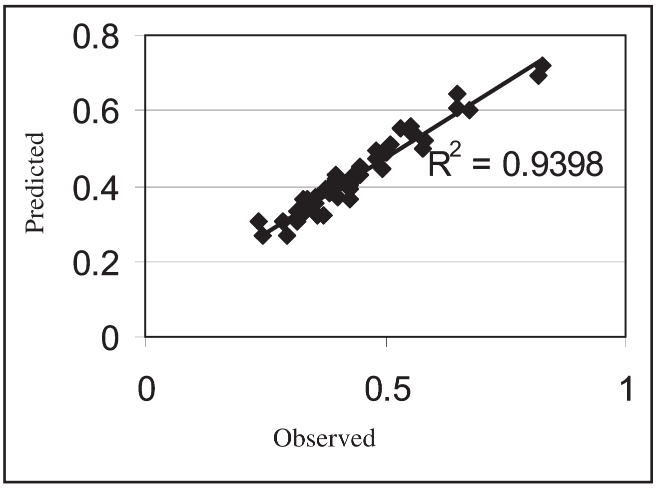

Fig. 2. Observed and predicted output layers

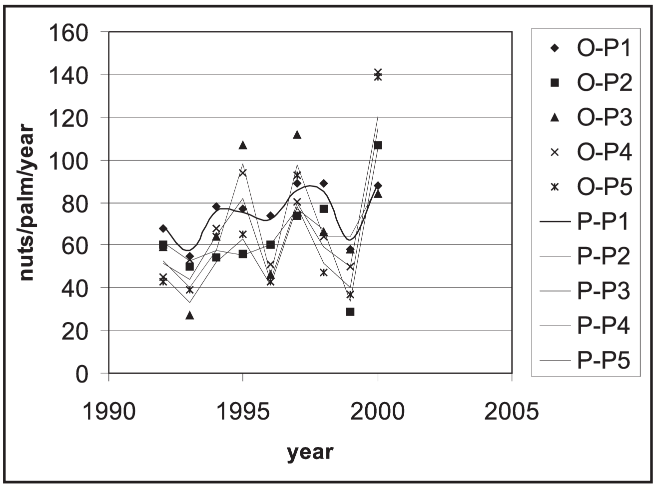

Fig. 3. Fuzzy – neuro system predicted coconut yield (Observed (O) and predicted (P) nut yield

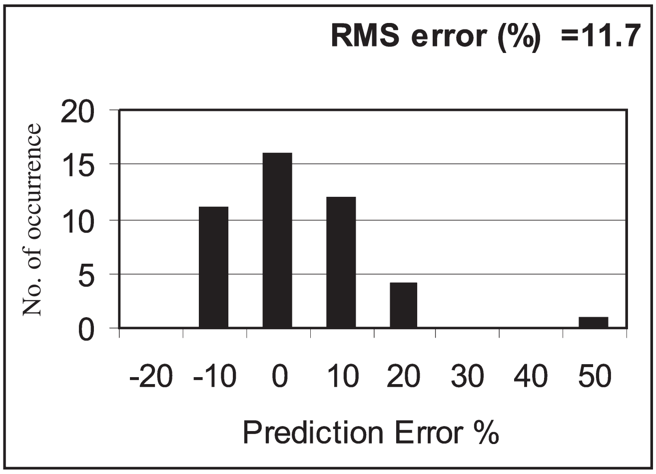

Fig. 4. Error histogram for the FNN model

Conclusion

The coconut yield can be predicted to a higher degree of accuracy by using neural network and fuzzy membership functions, because non linear relationship between independent (climatic and irregular bearing habit) and dependent(nut yield) variables is mapped. The studies have also established that previous 36 months of prevailing weather data influences the coconut yield. This shows that, by using this approach we can simulate the impact of different factors (climate and soil and water conservation practices) on coconut yield, however, the model developed has to be validated. This approach can also be extended to different varieties under different management practices for predicting the yield. Further, coconut grown in different situations/ conditions (like monocrop, mixed / inter crop and mixed farming) and their yield predictions with different input variables can be taken up in the future to have a clear understanding of the effect of differential input variables.

Acknowledgement

The authors are thankful to Director, C.P.C.R.I., Kasaragod for his constant encouragement in the project work. The necessary budgetary support provided through the National Agricultural Technology Project is also acknowledged. We also sincerely acknowledge with thanks the Scientist Incharge, Rubber Research Institute, Substation, Kadaba for providing the weather data.

References

Abeywardena, V. 1968. Forecasting coconut crops using rainfall data – a preliminary study. *Ceylon Coconut Quarterly* **19**: 161-176.

Abeywardena, V.1983. Effect of moisture stress and irrigation on yield of coconut in Sri Lanka. pp. 98-106. In: Nayar, N.M.(Eds), Coconut Research Development.

Ambuel, J. R., Colvin, T. S. and Karlen. D. L. 1994. A fuzzy logic yield simulator for prescription farming. *Trans. ASAE.* **7**: 1999-2009.

Bailey, R.J. and Spackman, E. 1996. A model for estimating soil moisture changes as an aid to irrigation scheduling and crop water-use studies: I. Operational details and description. *Soil Use and Management* **12**: 122-128.

Burrough, P.A. 1989. Fuzzy mathematical methods for soil survey and land evaluation. *Journal of Soil Science* **40**: 477-492.

Burrough, P.A., MacMillan, R. A. and van Deursen, W. 1992 "Fuzzy classification methods for determining land suitability from soil profile observations and topography." *Journal of Soil Science* **43** (2): 193-210.

Davidson, D.A., Theocharopoulos, S.P. and Bloksma, R.J. 1994. A land evaluation project in Greece using GIS and based on Boolean and fuzzy set methodologies. *International Journal of Geographic Information Systems* **8** (4): 369-384.

Gautam, M.R. Watanabe, K. and Saegusa, H. 2000. Runoff analysis in humid forest catchment with artificial neural network. *Journal of Hydrology* **235**: 117-136.

Grönroos, M.A. 1998. Evolutionary design of neural networks. Master of Science Thesis, Computer Science, Department of Mathematical Sciences, University of Turku, pp 1-80.

Jackson, M.L. 1967. Soil Chemical Analysis. Prentice Hall of India Pvt. Ltd., New Delhi, India.

Jacob Mathew and Jose, C. T. 1991. Measurement of bienniality in coconut. *J. Plantn. Crops* **18** (supp.) 364-368.

Liu J., Goering C. E. and Tian L. 2001. A Neural Network for Setting Target Corn Yields. *Trans. ASAE* **44**: 705-713.

McBratney, A.B. and Odeh, I.O.A. 1997. Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurements and fuzzy decisions. *Geoderma* **77**: 85-113.

Nicks, A.D., Lane, L.J. and Gander, G.A. 1995. Weather Generator. In: Flanagan, D.C., Nearing, M.A. (Eds.) (1995). WEPP USDA – Water Erosion Prediction Project. NSERL Rep. 10. National Soil Erosion Lab., U.S. Dep. Of Agric., Laffayette, Indiana, pp. 2.1 – 2.22.

Ohler, J. G. 1999. Climate and soils. pp. 35-53. In: Ohler, J.G. (Ed.). Modern coconut management – palam cutivation and proproducts. Intermediate Publications Private Limited, 103-105 Southampton Row, London WC1B 1HH, UK.

Rajagopal, V., Shivashankar, S. and Jacob Mathew. 1996. Impact of dry spells on the ontogeny of coconut fruits and its relation to yield. *Plantation Research and Development* **3**: 251-255.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. 1986. Learning Internal representation by error propagation. pp. 318-362. In: Rumelhart, D.E., McClelland, J.L. (Eds) Parallel distributed processing, Volume 1 MIT press, Cambridge, MA.

Sajikumar, N. and Thandaveswara, B.S. 1999. A non-linear rainfall-runoff model using an artificial neural network. *Journal of Hydrology* **216**: 32-55.

Šíma, J. 1998. Introduction to neural networks. Technical report No. V-755, Institute of Computer Science, Academy of Sciences of Czech Republic, Prague, Czech Republic, 1998.

Vijayakumar,K., Nambiar, P.T.N., Jacob Mathew, Amarnath, C.H. and Balakrishnan, T.K. 1989. Forecasting of yield in coconut by using weather variables. *Journal of Plantn. Crops* **16**: 463-468.

Zadeh, L.A. 1965. Fuzzy sets. *Information and Control* **8** (6): 338-353.