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DAILY RAINFALL FORECASTING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (Anfis) MODELS

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ABSTRACT
Climate and rainfall are highly non-linear phenomena in nature. The parameters that are required to predict the rainfall are very complex and subtle so that uncertainty in a prediction using all these parameters is enormous even for a short period. This study aims to forecast the daily rainfall of monsoon period of Junagadh, Gujarat, India. Adaptive neuro-fuzzy inference system (ANFIS) model was used in this study to predict the daily rainfall in the period between June to October in the region. Soft computing is an innovative approach to construct computationally intelligence systems that are supposed to possess humanlike expertise within a specific domain. The statistical data of 1979 to 2011 was obtained from Junagadh Agricultural University, Junagadh from period 1st June to 30th October for training and validation of the developed models. The performance of the models were evaluated using various statistical indices viz. mean square error (MSE), normalized mean square error (NMSE), correlation coefficient (CC), Akaike's information criterion (AIC), percent error (%), minimum description length (MDL), coefficient of efficiency (CE) and volumetric error (EV). The results indicates that the (Gauss, 3) ANFIS model showed higher rainfall forecasting accuracy and low error compared to the other ANFIS models. Furthermore, the rainfall predicted by this technique was closer to the actual data than the other one.

KEYWORDS: Adaptive neuro-fuzzy inference system (ANFIS); Fuzzy sets; Rainfall forecasting; Mean Square Error (MSE); Artificial intelligence

INTRODUCTION
Seasonal rainfall forecasts can have significant value for Water resources planning and management *e.g*., reservoir operations, agricultural practices, town planning and flood emergency responses. To manage and mitigate this, effective planning and management of water resources is very necessary. Rainfed agriculture in India is where crop production is totally dependent upon rainfall. The production of rainfed region, which contributes significantly to the economy of the nation. Rainfall is natural climate phenomena whose prediction is challenging and demanding. In the short term, this requires a good idea of the upcoming rainfall season. In the long term, it needs realistic projections of scenarios of future variability and change (Abraham *et al*., 2001). Understanding the complex physical processes that create rainfall remains a major challenge, and accurate rainfall forecasting remains an important task, with significant implications for food production, securing water supplies for major population centers, urban development and planning and minimizing flood risks. Three-quarters of the state of Queensland, Australia, was declared a disaster zone following torrential rains during the summer of 2010– 2011 (Hurst, 2011). Kararnouz *et al*. (2005) used a model based on fuzzy rules and neural networks using large-scale climatic signals to predict rainfall in the western Iran (the basins of Karoon, Karkheh and the western border). Their results showed that except for the southwest region, where both models had similar errors of above 35%, in the northwest and the western regions, the error of the fuzzy model was 8.4%; that is, 13% lower than that of neural network. Keeping in view the above facts adaptive neuro-fuzzy inference system (ANFIS) is the most efficient rainfall forecasting method. Adaptive Neuro-Fuzzy Inference System (ANFIS) model has become a popular analysis tool due to its ability to evaluate simultaneously spectral and temporal information within the signal. Most of the previous investigations have indicated that ANFIS is an efficient tool for rainfall forecasting and is widely used in different areas of water related research. Tektas (2010) used ANFIS and ARIMA models for weather forecasting and the results were evaluated according to prediction performance, reliability and efficiency. In the field of modeling and classification framework, there are many studies that use the Neuro-Fuzzy Approach (Bacanli 2009 and Tektaş 2010). Jeong *et al*. (2012) developed model for monthly precipitation forecasts using ANFIS. Shiri *et al.* (2013) evaluated neuro-fuzzy models for estimating reference evapo-transpiration using two separate sets of weather data from humid and non-humid regions of Spain and Iran. Sanikhani *et al*. (2012) used two different adaptive neuro-fuzzy inference systems (ANFIS) including grid partitioning (GP) and subtractive clustering (SC), for modeling daily pan evaporation (Epan). Kisi and Tombul (2013) developed model to investigate the ability of fuzzy genetic (FG) approach in estimation of monthly pan evaporation. Present research describes the application of ANFIS models to predict future precipitation in semi arid region of saurashtra of Gujarat in India. The

main purpose is to specify the best type and structure of the ANFIS models and also the most appropriate input variables to have a reliable and accurate prediction of the future rainfall.

MATERIALS & METHODS

The main objective of this study is to develop Adaptive Neuro-Fuzzy models for prediction of monsoon rainfall. This section deals with the location and climate of study area, collection of meteorological data, methodology adopted for rainfall modeling using adaptive neuro-fuzzy inference system models. Procedure used for calibration and validation of the model and various criteria for evaluating performance of the models and sensitivity analysis to identify the most important factor responsible for rainfall occurrence is also discussed here.

Study Area

Junagadh is located on the Kathiawar peninsula in western Gujarat. It is geographically situated between latitude and longitude as 21.5° N and 70.1° E, respectively and at an altitude of 86 m above the mean sea level.

Data Acquisition

The daily meteorological data i.e. vapour pressure, relative humidity, wind velocity, mean temperature and rainfall of 30 years 1979-1981, 1984-1989 and 1991-2011 were collected from meteorological observatory of Krushigadh, JAU, Junagadh. In this study, the first 26 year seasonal data (June to October) were used for model training. The remaining 4 years data were used for verification of the models.

Fuzzy logic

A fuzzy logic model is also known as a fuzzy inference system. The fuzzy logic model adopted in this work composed of two functional components. One is the knowledge based, which contains a number of fuzzy if-than rules and a database to define the membership functions of the fuzzy sets used in the fuzzy rules. Based on the knowledge base, the second component is the fuzzy reasoning of decision making unit to perform the inference operations on the rules. In classical models variables have real number values, the relationship are defined in terms of mathematical functions and the outputs are crip numerical values (Center and Verma, 1998).

Adaptive neuro-fuzzy inference system (ANFIS) model

Fuzzy inference systems are non-linear models that describe the input-output relation of a real system using a set of fuzzy IF-THAN rules. Each fuzzy IF-THAN rule is a proposition of the form: In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output.

The node functions in the same layer are the same as described below:

$$\text{Rule 1: If x is } A_1 \text{ and y is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$
$$\text{Rule 2: If x is } A_2 \text{ and y is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2 \qquad \text{…. (1)}$$

A conceptual ANFIS consists of primarily five components: inputs and output data base, a Fuzzy system generator, a fuzzy inference system and an adaptive neural network. The Fuzzy inference system that we have considered in this model that maps:

- Input characteristics to input membership functions,
- Input membership functions to rules,
- Rules to a set of output characteristics,
- Output characteristics to output membership function, and
- The output membership function to a single valued output, or
- A decision associated with the output.

The neuro adaptive learning technique provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that the best allow the associated fuzzy inference system to track the given input/output data. In fuzzy logic there is no systematic procedure to define the membership function parameters. In this study, three Gaussian membership functions were used for input variable. There are a wide variety of algorithms available for training a network and adjusting its weights. In this study, an adaptive technique called momentum Levenberg-Marquardt based on the generalized delta rule was adapted (Rumelhart *et al*., 1987).ANFIS eliminates the basic problem in fuzzy system design, defining the membership function parameters and design of fuzzy if-then rules, by effectively using the learning capability of ANN for automatic fuzzy rule generation and parameter optimization.

Architecture of ANFIS

Adaptive neuro fuzzy inference system (ANFIS) is a fuzzy mapping algorithm that is based on Takagi-Sugeno-kang (TSK) fuzzy inference system. In a hybrid fuzzy system named as ANFIS, the fuzzy system is configured in parallel fashion based on competitive or co-operative relationship. In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output. The basic structures Takagi-Sugeno type fuzzy inference system as shown in Fig. 3.

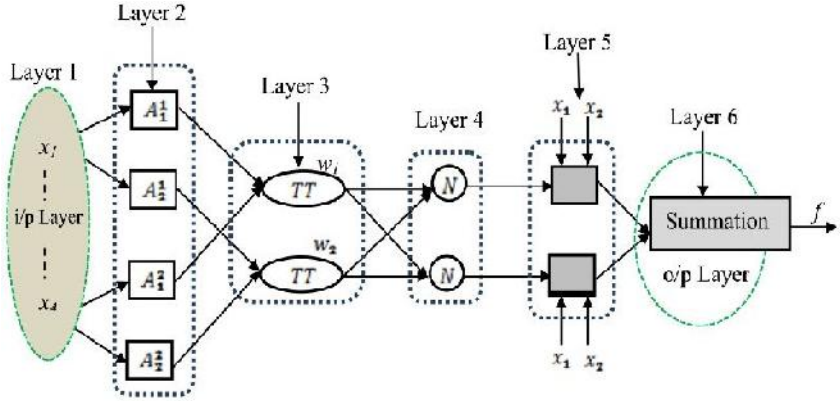

FIGURE 1: Basic structure of first order Sugeno-fuzzy model

Layer 1: Every node i in this layer is a square node with a node function as:

$$O_{1,i} = \mu_{A_1}(x), \ \ for\ i = 1,2$$
$$O_{1,i} = \mu_{B_1-2}(y), \ \ for\ i = 1,2$$

where x is the input to node i, and i A (or i–2 B) is a linguistic label (such as "small" or "large") associated with this node. In other words, $O_{1,i}$is the membership grade of a fuzzy set A and it specifies the degree to which the given input x satisfies the quantifier A . Parameters in this layer are referred to as "premise parameters".

Layer 2: Every node in this layer is a fixed node labeled as Π, whose output is the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \ \ for\ i = 1,2 \qquad (2)$$

Each node output represents the firing strength of a fuzzy rule.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of the rule's firing strength of the sum of all rule's firing strengths:

$$O_{3,i} = w_i = \frac{w_i}{(w_1 - w_2)}, \ \ for\ i = 1,2 \qquad (3)$$

Outputs of this layer are called "normalized firing strengths".

Layer 4: Every node i in this layer is an adaptive node with a node function as:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (4)$$

Where $\overline{w_i}$) is a normalized firing strength from layer 3 and {p_i, q_i, r_i}is the parameter set of this node. Parameters in this layer are referred to as "consequent parameters".

Layer 5: The single node in this layer is a fixed node labeledΣ that computes the overall output as the summation of all incoming signals:

$$overall\ output = O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f}{\sum_i w_i} \qquad (5)$$

This layer is called as the output nodes in which the single node computes the overall output by summing all the incoming signals and is the last step of the ANFIS. In this way the input vector was fed through the network layer by layer.

Development of ANFIS model

In this method, the combination of meteorological parameters *i.e*. vapour pressure, relative humidity, wet bulb temperature, dryness and rainfall at point of forecasting as an input for training of the model was found most satisfactory rainfall prediction, reported by (Hung *et al*., 2008). In this case four input parameters *i.e.* the observed time series of vapour pressure, relative humidity, wind velocity, temperature of previous days are taken as the input variables (N = 149 days) and one output i.e. current day rainfall as the output variable.

Sensitivity Analysis

While training a network, the effect that each of the network inputs has on the network output has studied. This provides feedback as to which input parameters are the most significant. Based on this feedback, it may be decided to prune the input space by removing the significant parameters. This also reduces the size of the network, which in turn reduces the network complexity and the training time. The sensitivity analysis is carried out by removing the each of the parameters in turn from the input parameters used on ANN and ANFIS models and then comparing the performance statistics. The greater the effect observed in the output, the greater is the sensitivity of that particular input parameter.

RESULTS & DISCUSSION

Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS models of two membership functions *i.e.* Gaussian and generalized bell were trained for maximum iterations of 1000. Based on the performance indices Mean Square Error (MSE), Akaike's Information Criterion (AIC) and Correlation Coefficient (CC) (Table 1), two models were selected for the performance evaluation.

Performance evaluation of developed models

Qualitative evaluation

The qualitative assessment of models is made by comparing regenerating daily predicted rainfall with observed rainfall. The observed and predicted values for the period (2008-2011) using ANFIS models are shown (Figs. 2 and 3). It is observed from the Figs., that there is a close agreement between the predicted and observed rainfall, and overall shape of the plot of predicted rainfall is similar to that of the observed rainfall. Therefore, qualitative performance during training has been found satisfactory.

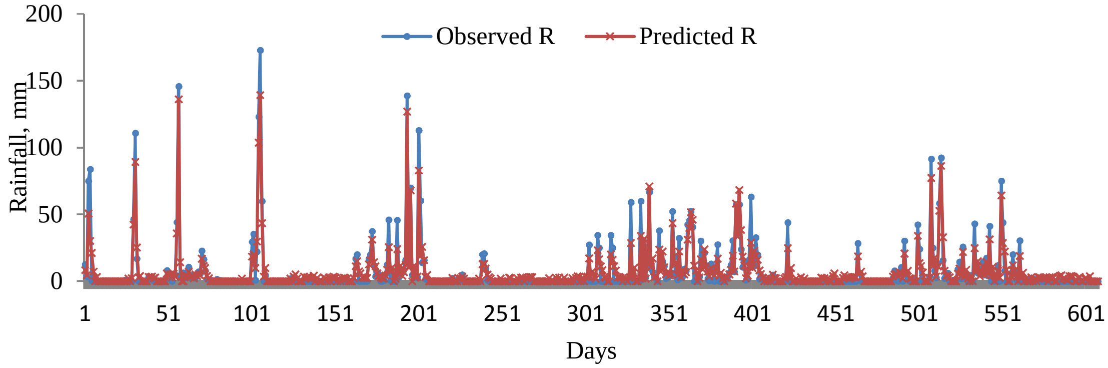

FIGURE 2: Observed and predicted daily rainfall using ANFIS model (Gauss,3) during testing period (2008-2011)

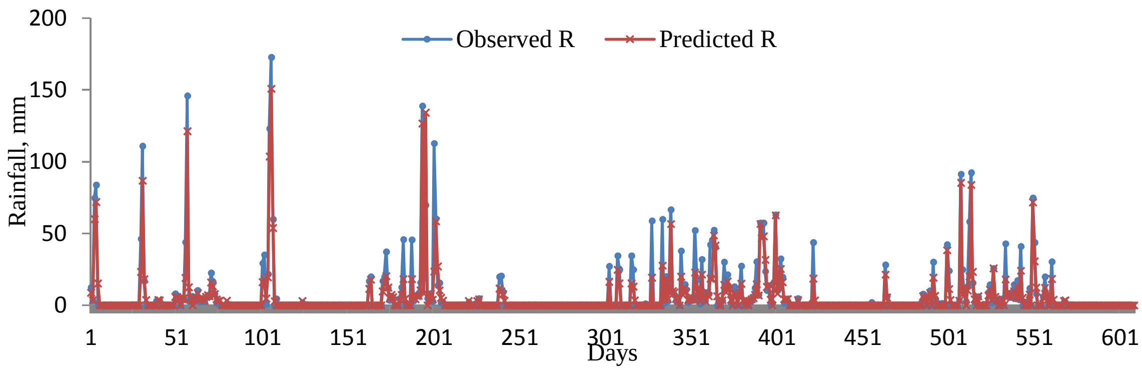

FIGURE 3: Observed and predicted daily rainfall using ANFIS model (Generalized ,5) during testing period (2008-2011)

Quantitative evaluation

The performance indices are used for evaluating the quantitative evaluation of ANFIS models during testing period (Table 1). For better appreciation of the model, the predictive effectiveness of ANFIS model is judged on the basis of performance indicators. To judge the predictive capability of the developed model, Correlation Coefficient (Mutreja, 1992), Mean Square Error (MSE), Normalized Mean Square Error (NMSE) (Wilks, 1995), Akaike's Information Criterion (AIC), Coefficient of Efficiency (CE) (Luchetta *et al.*, 2003) and Volumetric Error (EV) (Kachroo and Natale, 1992) were employed. Two models selected from ANFIS with gaussian and generalized bell membership functions on the basis of the performance indices for the rainfall. Thus, the total number of selected models will be two for rainfall forecasting of the Junagadh (Gujatat) (Table 2).

TABLE 1: Comparison of selected ANFIS models during testing period

	Model ANN				
	No. of Membership functions	No. of Inputs	MSE	CC	AIC
Model AM_{24}	Gauss, 2	4	0.0018	0.73	-3504.56
Model AM_{34}	Gauss, 3	4	0.0012	0.93	-4068.48
Model AM_{44}	Gauss, 4	4	0.0013	0.89	-3870.25
Model AM_{54}	Gauss, 5	4	0.0017	0.68	-3634.45
Model AM_{64}	Gauss, 6	4	0.0018	0.75	-3597.10
Model AM_{24}	Generalized bell, 2	4	0.0021	0.58	-3348.79
Model AM_{34}	Generalized bell, 3	4	0.0014	0.86	-3993.53
Model AM_{44}	Generalized bell, 4	4	0.0018	0.70	-3557.15
Model AM_{54}	Generalized bell, 5	4	0.0013	0.91	-3988.69
Model AM_{64}	Generalized bell, 6	4	0.0017	0.69	-3611.37

The adaptive neuro-fuzzy inference system (ANFIS) model AM_{34} has better performance than the model AM_{54} because of lower value of MSE, NMSE and volumetric error and higher value of correlation coefficient, EC and AIC (Table 2). Therefore, the model AM_{34} is chosen for rainfall prediction of the study area. According to the overall performance of the ANFIS models, the model AM_{34} has better accuracy than other models. Therefore the ANFIS model AM_{34} was selected for rainfall forecasting for study area.

TABLE 2: Performance evaluations of developed ANN and ANFIS models during testing period for the best chosen network

Performance indies	ANFIS	
	AM_{34}	AM_{54}
MSE	0.0012	0.0013
NMSE	0.37	0.45
CC	0.93	0.91
AIC	-4068.48	-3988.68
CE	84.70	83.91
EV	20.75	24.45

Sensitivity Analysis

The sensitivity analysis has been done by utilizing the performance indices (Fig. 4) for ANFIS model AM_{34} because of higher correlation coefficient and the lowest error between observed and predicted rainfall. Here WVP, WRH, WWS, and WMT are indicating as without vapour pressure, without relative humidity, without wind velocity and without mean temperature respectively. The sensitivity analysis of ANFIS model revealed that the rainfall is the most sensitive with vapour pressure followed by the relative humidity, mean temperature and wind speed respectively. The results show that by removing vapour pressure, relative humidity, wind velocity and mean temperature the models have higher error and lower correlation between observed and predicted rainfall respectively (Fig. 4). It indicates that the most significant parameter for rainfall forecasting is vapour pressure followed by the relative humidity, mean temperature and wind velocity using ANFIS model.

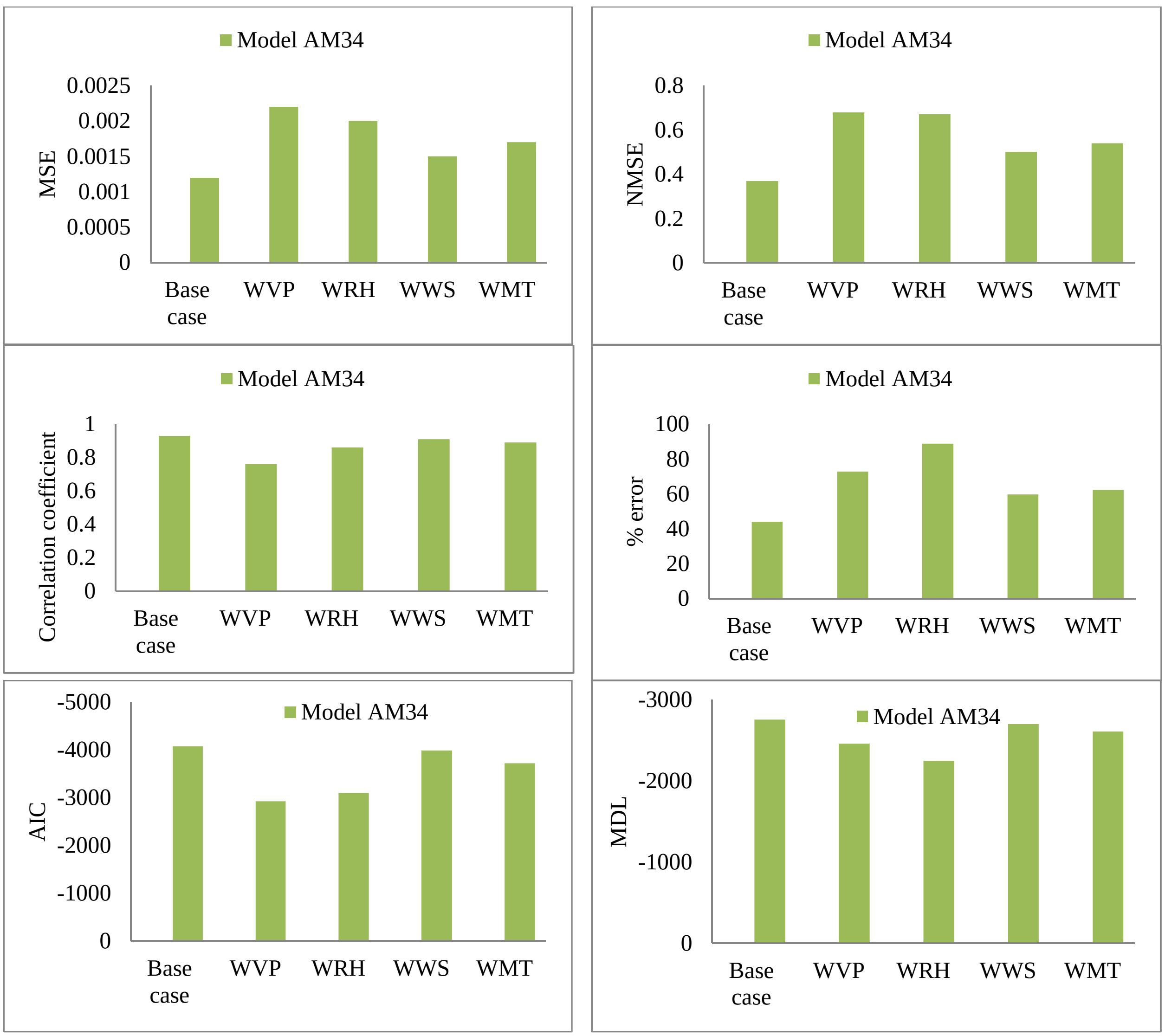

FIGURE 4: Performance of ANN and ANFIS models for sensitivity analysis

CONCLUSION

In this study, we attempted to predict the daily rainfall based on adaptive neuro-fuzzy inference system (ANFIS) techniques for Junagadh of kathiawar region. Daily weather data were collected from the meteorological observatory of Junagadh Agricultural University, Junagadh. The qualitative performances, based on the observed and predicted values of rainfall during training and testing periods using developed models show satisfactory results. It is found that the ANFIS model gives the more accurate results as compared to the other ANFIS models. Therefore the ANFIS model AM_{34} is the best accurate model for rainfall prediction of study area. The sensitivity analysis of ANFIS model AM_{34} show that the vapour pressure the highest sensitive parameter for rainfall prediction as compared to relative humidity, mean temperature and wind speed.

REFERENCES

Abraham, A., Philip, N. and Joseph, B. (2001) 'Viii We Have a Wet Summer'? Soft Computing Models for Long Term Rainfall Forecasting. In: 15th European Simulation Multi conference (ESM, August/September 2001), Modeling and Simulation 2000, Kerckhoffs, EJ.H. and M. Snorek (Eds.). Czech Republic, Prague., pp: 1044-1048.

Aldrian, E. & Djamil, Y.S. (2008) Application of Multivariate ANFIS for Daily Rainfall Prediction: Influences of Training Data size, MAKARA, SAINS, 13:7-14.

Bacanli, U. G., Firat, M. & Dikbas, F. (2009) Adaptive Neuro-Fuzzy Inference System for Drought Forecasting. *Stochastic Environmental Research and Risk Assessment*, 23:1143-1154.

Center, B. & Verma, B.P. (1998) Fuzzy logic for biological and agricultural systems. *Artif. Intell. Rev.* 12:213-225.

Chen, S. H., Lin, Y.H., Chang, L.C. and Chang, F.J. (2006) The strategy of building a flood forecast model by neuro-fuzzy network. *Hydrological Processes*. 20:1525–1540.

Dastorani, M.T., Moghadamnia, A., Piri, J. & Rico-Ramirez, M. (2009) Application of ANN and ANFIS models for reconstructing missing flow data. *Environmental Monitoring Assess*, DOI: 10.1007/s1066-1009-1012-8.

El-Shaffie, A., Jaafr, O. and Akrami, S. A. (2011) Adaptive neuro-fuzzy inference system based model for rainfall forecasting in Klang River, Malaysia, *International Journal of the Physical Sciences*, 6(12):2875-2888.

Hung, N.Q., Babel, M.S., Weesakul, S. and Tripathi, N.K. (2009) An artificial neural network model for rainfall forecasting in Bangkok,Thailand. *Hydrological Earth Syst. Sci. Discuss.*, 5:183–218.

Hurst, D., (2011) Three-quarters of Queensland a disaster zone. Brisbane Times, Fairfax Media. [Available online at http://www.brisbanetimes.com.au/environment/weather/th reequarters-of-queensland-adisaster-zone2011011119 mf8. html].

Jacquin, A.P. and Shamseldin, A.Y. (2008) Sensitivity analysis of Takagi-sugeno-kang rainfall runoff fuzzy models. *Hydrology and Earth System Sciences Discussions*, 5:1967-2003.

Jeong, C., Shin, J., Kim, T. and Heo, J.H. (2012) Monthly Precipitation Forecasting with a Neuro-Fuzzy Model. *Water Resource Management*, Doi: 10.1007/s11269-012-0157-3.

Kachroo, R.K. & Natale, L. (1992) Non-linear modeling of the rainfall-runoff transformation. *J. Hydrology*, 135:341-369.

Karamouz, M., Zahraie, B. and Eghdamirad, S. (2005) Seasonal rainfall forecasting using meteorological signals. Proceedings of the 1st Conference of Iran Water Sources Management, Nov. 15-16, Technological Faculty, Tehran University, pp: 60-72.

Karimi, S., Kisi, O., Shiri, J. and Makarynskyy, O. (2012) Neuro-fuzzy and neural network techniques for forecasting sea level in Darwin Harbor, Australia. *Computers & Geosciences*, http://dx.doi.org/10.1016/ j.cageo.2012.09.015.

Kim, J. & Kasabov, N. (1999) HyFIS: Adaptive Neuro-Fuzzy Inference Systems and their applications to nonlinear dynamical systems. *Neural Networks*, 12:1301-1319.

Kisi, O. & Tombul, M. (2013) Modeling monthly pan evaporations using fuzzy genetic approach. *Journal of Hydrology*. 477:203-212.

Kurian, C.P., George, J., Bhut, I.J. and Aithal, R.S. (2006) ANFIS model for the time series prediction of interior daylight luminance. *AIML Journal*, 6:35-40.

Lohani, A.K., Kumar, R. & Singh, R.D. (2012) Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive technique. *Journal of Hydrology*. 442-443:23-35.

Luchetta, A. & Manetti, S. (2003) A real time hydrological forecasting system using artificial fuzzy clustering approach. *Computers and Geosciences*, 29:1111-1117.

Mutreja, K.N. (1992) Applied Hydrology. New Delhi, Tata McGraw-Hill, Pub. Co. Ltd.

Rank, H.D. (2006) Effects of irrigation systems and moisture designs an physiological response function of the cotton crop. Unpublished Ph.D. Thesis submitted to JAU, Junagadh.

Rumelhart, D.E., Hinton, G.E. and Williams, R.I., (1987) Learning Internal Representations by Error Propagation. In: Parallel Distributing Processing, Rumelhart, D.E., and G.B. Hintonand RI. Williams (Eds.). MIT Press, Cambridge, MA, pp: 318-362.

Sanikhani, H. and Kisi, O. (2012) River Flow Estimation and Forecasting by using Two Different Adaptive Neuro-FuzzyInference Approches. *Water Resource Management*. 26:1715-1729.

Shiri, J., Nazemi, A.H., Sadraddini, A A., Landeras, G., Kisi, O., Fard, A.F. & Murti, P. (2013) Global cross-station assessment of neuro-fuzzy models for estimating daily reference evapotranspiration. *Journal of Hydrology*. 480:46-57.

Sumithira, T.R. and Kumar, A.N. (2012) Prediction of Monthly Global Solar Radiation Using Adaptive neuro-Fuzzy Inference System (ANFIS) Technique Over the State of Tamilnadu (India): a Comparative Study. *Applied Solar Energy*. 48:140-145.

Tektas, M. (2010) Weather Forecasting Using ANFIS and ARIMA Models. *Environmental Research, Engineering and Management*, 51:5-10.

Wilks, D.S. (1995) Statistical methods in the atmospheric sciences: An introduction. Academic press, San Diego, C.A., pp.457.