International Journal of Agriculture Sciences
ISSN: 0975-3710 & E-ISSN: 0975-9107, Volume 10, Issue 10, 2018, pp.-6153-6159.
Available online at https://www.bioinfopublication.org/jouarchive.php?opt=&jouid=BPJ0000217

Research Article

RAINFALL FORECASTING USING ARTIFICIAL NEURAL NETWORK (ANN) AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) MODELS

KYADA P.M.[1]*, PRAVENDRA KUMAR[2] AND SOJITRA M.A.[3]
[1]Subject Matter Specialist (Agri. Engg.), Krishi Vigyan Kendra, Lokbharti Gramvidhyapith Trust, Sanosara, Bhavnagar, 364230, Gujarat
[2]Department of Soil & Water Cons. Engineering, G. B. Pant University of Agriculture and Technology, Pantnagar, 263145, Uttarakhand, India
[3]ICAR-Krishi Vigyan Kendra, Targhadia, Rajkot, 360430, Junagadh Agriculture University, Junagadh, 362001, Gujarat, India
*Corresponding Author: Email - pradip.caet.jau@gmail.com

Received: May 09, 2018; Revised: May 26, 2018; Accepted: May 27, 2018; Published: May 30, 2018

Abstract: Accurate rainfall prediction is of great interest for water management in rainfed areas. The occurrence of rainfall as a physical process are uncertain, non-linier and highly complex. The present study investigates the ability of Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for rainfall forecasting of Junagadh region of Gujarat, India. Based on the past observations *i.e.*, vapour pressure, mean temperature, wind velocity and rainfall. ANN model (4-6-4-1) is the best for prediction of rainfall among all the models. ANN models showed better performance than the ANFIS models in rainfall forecasting. The sensitivity analysis revealed that vapour pressure is the most sensitive parameter in rainfall prediction.

Keywords: Artificial Neural Networks (ANN), Adaptive neuro-fuzzy inference system (ANFIS), Rainfall forecasting, Sensitivity Analysis

Citation: Kyada P.M., *et al.*, (2018) Rainfall Forecasting Using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) Models. International Journal of Agriculture Sciences, ISSN: 0975-3710 & E-ISSN: 0975-9107, Volume 10, Issue 10, pp.- 6153-6159.

Introduction

Rainfed agriculture in India is where crop production is totally dependent upon rainfall. Rainfall is natural climate phenomena whose prediction is challenging and demanding. On a world-wide scale, numerous attempts have been made to predict its behavioral patterns using various techniques [1]. The model has evaluated for the applicability of two artificial intelligence techniques including Artificial Neural Networks and Adaptive Neuro Fuzzy Inference Systems in prediction of rainfall amount before its occurrence [2]. In this study, different architectures of ANN and ANFIS models as well as various combinations of meteorological parameters including 3-year rainfall moving average data, mean temperatures, maximum temperatures, mean wind speed, relative humidity, maximum wind direction and evaporation have been selected for inputs of the models. According to the results, the efficiency of TLRN and ANFIS for this application are almost the same, although in different tests with different input patterns the results produced by these two methods are slightly different. In general, it was revealed that both Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System models are efficient tool to model and predict precipitation amounts 12 months in advance. The model has been developed a model of rainfall runoff modelling for the Iguaçu River basin in southern Brazil [3]. The models developed for Artificial Neural Network models to forecast the rainfall in the one of the largest cities of India *i.e.,* Bangalore using Single Neural Network and Ensemble Neural Network models [4]. Artificial Neural Networks have been used for monthly and seasonal rainfall forecasting in Queensland, Australia [5]. It was considered by inputting recognized climate indices, atmospheric temperatures and monthly historical rainfall data into a prototype stand-alone, time-delay, dynamic and recurrent artificial neural network. The model have developed in order to predict rainfall intensity (mm/day) in Athens, Greece, using ANNs models [6]. Two main varieties of artificial intelligence technique which have been widely used to predict natural phenomenon are Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems.

Most of the previous investigations have indicated that ANN is an efficient tool with superior abilities and is widely used in different water-related research area [7]. In the field of modeling and classification framework, there are many studies that use the Neuro-Fuzzy Approach ([8], [9] and [10]. The models have been developed for monthly precipitation forecasts using ANFIS [11]. The evaluation has been done of ANFIS models for forecasting reference evapotranspiration using two separate sets of climatic data from humid and non-humid regions of Spain and Iran [12]. The developed models used two different adaptive neuro-fuzzy inference systems including subtractive clustering and grid partitioning for modeling daily pan evaporation [13]. The model developed to investigate the ability of fuzzy genetic (FG) approach in estimation of monthly pan evaporation [14].

Present research describes the application of ANN as well as 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 artificial neural networks and adaptive neuro-fuzzy inference system models and also the most appropriate input variables to have a reliable and accurate prediction of the future rainfall.

Materials and Methods

The main objective of this research study is to develop Artificial Neural Networks models and Adaptive Neuro-Fuzzy inference system models for forecasting of monsoon rainfall. This section deals with the location and climate of study area, collection of meteorological data, methodology adopted for rainfall forecasting using artificial neural networks and adaptive Neuro-fuzzy inference system models. Procedure used for calibration and validation of the model and different measures for estimating 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 procurement

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 to train the models. The remaining 4 years data were used for validation of the models.

Artificial neural networks (ANNs)

An ANN is a massively parallel distributed processor that has a natural propensity for loading the experimental knowledge and building it for future use in the field of forecasting. It resembles the human brain whose speed and efficiency has been always attractive to researcher for a quite a long time. Artificial Neural Networks fundamentally involve a non-linear modeling approach that gives a fairly accurate universal approximation to any function. Its power derives from the parallel processing of information from data. A Neural Networks is an information data processing system that is composed of a number of processing elements or artificial neurons similar to biological neurons which is internally connected or weights between these elements that imitate the synaptic strength in a biological nervous system. This approach is based on the human brain and it is faster compared with its conventional compatriots, flexible in the range of problems which models can solve, and highly adaptive to the newer environments. The process of training includes the adjustment of connection between weights and threshold values for each of the nodes. ANNs are methods for empirically mapping inputs to outputs with no specification of the relationship, which leaves them highly sensitive to the composition of the samples used to train them.

The most important attributes of a layered neural network design are choosing the architecture [15]. The number of input nodes is simply determined by the dimension of the input vector to be generalized or associated with a certain output quality. The size of Hidden layer is the most important attention when solving the actual problems by multilayer feed-forward neural networks. The most popular and successful technique for selecting the appropriate number and size of the hidden layer on the basis of trial and error method. A number of networks with one or two hidden layers are trained with different combinations of hidden neurons and a network is selected on the basis of minimum Mean Square Error (MSE) and maximum Correlation Coefficient (CC). It is important that the size of the network should be small as possible. An effective criterion for selecting the best network from these two points of view, *i.e.*, minimum MSE and smallest size, is Akaike's information criterion (AIC).

Architecture of ANN

A neural network is characterized by its architecture that present the pattern of connection between nodes. The architecture of an ANN model is designed by a transfer function to controls the generation of output in a neuron. The architecture of ANN is classified into two types: single hidden layer and multi hidden layer ANN model. The learning process starts with a random set of weights. During the training process, weights are updated through error back-propagation for output and hidden layers. Software NeuroSolutions 5.07 is used for predicting the rainfall of monsoon period. Neurosolutions wizard *viz*., Neural Builder is used for development of a prediction model and Testing Wizard is used for the validation and testing of the developed model.

Single hidden layer ANN model

Neurons in an ANN are organized in groups known as layers which can be single or double hidden layered. The nodes in one layer are connected to those in the next, but not to those in the same layer. A single hidden layer ANN contains one input layer, one hidden layer and one output layer. X1, X2 and X3 are inputs. Each neuron simply computes output of a weighted sum of the inputs to the network. The connection between the neurons, represented by lines, is quantified by their weights, which are shown in the Vji and Wkj, Y is the output from single hidden layer ANN.

Multi hidden layers ANN model

Multi hidden layer ANN is one of the most widely used classes of ANN. Each such ANN consists of an input layer, an output layer and one or more, hidden layer. The most commonly used algorithm for multi hidden layer ANN is the "back-propagation algorithm".

Back-propagation training algorithm

In back-propagation algorithm of neural networks, data is treated in the forward direction from the input layer to the hidden layer and then to output layer. The objective of a back-propagation network is to find the weights that approximate target values of output with a particularly higher accuracy. It requires a continuous, differentiable and non-linear function on the ANN to compute output from each neuron. The input data are multiplied by the initial weights, then the weights inputs are added by simple summation to produce the net input to each neuron. In this method, two different combinations prepared as input of the ANN model. The following two cases of the data sets were taken in account for the modeling of ANN for rainfall prediction.

Case I

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 estimated most acceptable rainfall prediction [16]. In this case seven input parameters *i.e.,* the observed time series of vapour pressure, relative humidity, wind velocity, temperature of previous days and previous three, two and one day's rainfall are taken as the input variables (N = 149 days) and one output *i.e.,* current day rainfall as the output variable.

Case II

In this case four input parameters *i.e.,* the observed time series of vapour pressure, relative humidity, wind velocity, temperature and rainfall of previous days are taken as the input variables (N = 152 days) and one output *i.e.* current day rainfall as the output variable.

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 numerical values [17].

Adaptive neuro-fuzzy inference system (ANFIS) model

Fuzzy inference systems models are based on non-liner approaches that describe the input-output relation of a real system using a set of fuzzy IF-THAN rules. 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:

$$Rule\ 1: If\ x\ is\ A_1\ and\ y\ is\ B_1, then\ f_1 = p_1x + q_1y + r_1$$

$$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2, then\ f_2 = p_2x + q_2y + r_2 \ldots \quad (1)$$

A theoretical ANFIS models contains primarily five components: database of inputs and output, 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 methodical procedure for defining 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 [18]. 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 ability of Artificial Neural Networks 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" fuzzy inference system. In a hybrid fuzzy system named as ANFIS, the fuzzy system is configured in parallel fashion based on competitive relationship. 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 of "Takagi-Sugeno" type fuzzy inference system.

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

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

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, O1,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 II, whose output is the product of all incoming signals:

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

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:

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

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:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(\mathrm{p_i x + q_i y + r_i}) \ .... (4)$$

Where, ((w_i)¯) is a normalized firing strength from layer 3 and {pi, qi, ri} 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 labeled Σ that computes the overall output as the summation of all incoming signals:

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

This 5th layer is known as the output nodes in which the single node computes the overall output by summing all the incoming signals and is the last stage of the ANFIS. In this way the input vector was fed through the network layer by layer.

Development of ANFIS model

In this method, only one combination prepared as input of the ANFIS model for reducing error of the model and to make the model simple. The following case of the data sets was taken in account for the modeling of ANFIS for rainfall prediction.

In this case the input variables and the output variable same as point out in ANN Case II.

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 higher the effect observed in the output, the higher is the sensitivity of that particular input parameter.

Results and Discussion

Artificial neural networks models:

The ANN models of single and multi-hidden layer 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) in the both cases, four models were selected for the performance evaluation as shown in Table 1.

Adaptive neuro-fuzzy inference system models:

The ANFIS models of two membership functions *i.e.,* Gaussian and generalized bell which were trained and validated for maximum repetitions of 1000. Based on the performance indices, two models were selected for the performance evaluation.

Performance evaluation of developed models

Qualitative evaluation

The qualitative performance evaluation of models is made by comparing regenerating daily predicted rainfall with observed rainfall. The observed and predicted values for the period (2008-2011) using artificial neural networks are shown in [Fig-1 to Fig-4]. For qualitative performance of ANFIS models, the observed and predicted values of period (2008-2011) are shown in [Fig-5 and Fig-6]. It is observed from the Figs., that there is a close relationship among the predicted and observed rainfall, and overall shape of the plotted graphs of predicted rainfall is correlated to that of the observed rainfall. Therefore, qualitative performance during training has been found satisfactory.

Quantitative evaluation

The performance indices are used for evaluating the quantitative evaluation of ANN and ANFIS models during testing period as shown in Table 1. For better performance evaluation of the model, the predictive effectiveness of ANN model is decided based on of performance indicators. To find batter the predictive capability of the developed model, Correlation Coefficient [19], Mean Square Error (MSE), Normalized Mean Square Error (NMSE) [20], Akaike's Information Criterion (AIC), Coefficient of Efficiency (CE) [21] and Volumetric Error (EV) [22] were employed. Four networks have been selected from the single and double hidden layers of ANN (Case I and II) and two models selected from ANFIS with generalized bell and Gaussian membership functions based on the performance indicators for the rainfall prediction. Thus, the total number of selected models will be six for rainfall forecasting of the Junagadh, Gujatat.

Based on the performance indicators, among artificial neural networks (ANNs) single hidden layer models the model AH14 has better performance than model AH17 due to lower value of MSE, NMSE and volumetric error and higher value of correlation coefficient, EC and AIC for prediction of rainfall as presented in Table 2. Performance of double hidden layered ANN model AH24 is better than the model AH27 due to lower value of error and higher value of correlation coefficient. Further these two models AH24 and AH14 were compared using performance indices and the result shows that the model AH24 is more accurate than the model AH14 for the rainfall prediction. Therefore, the ANN model AH24 is selected.

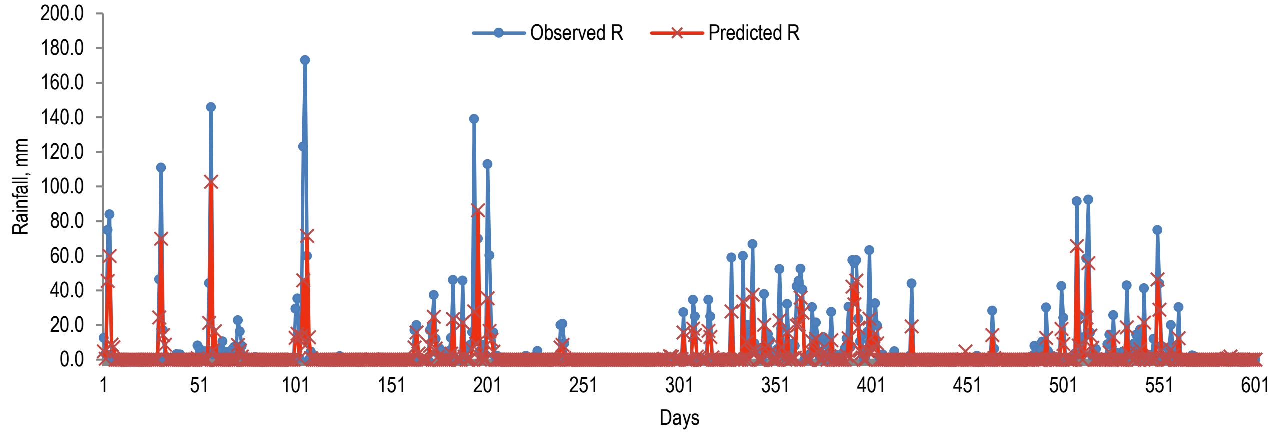

Fig-1 Observed and Predicted daily rainfall using ANN Single Hidden Layer with 7 inputs during testing period (2008-2011)

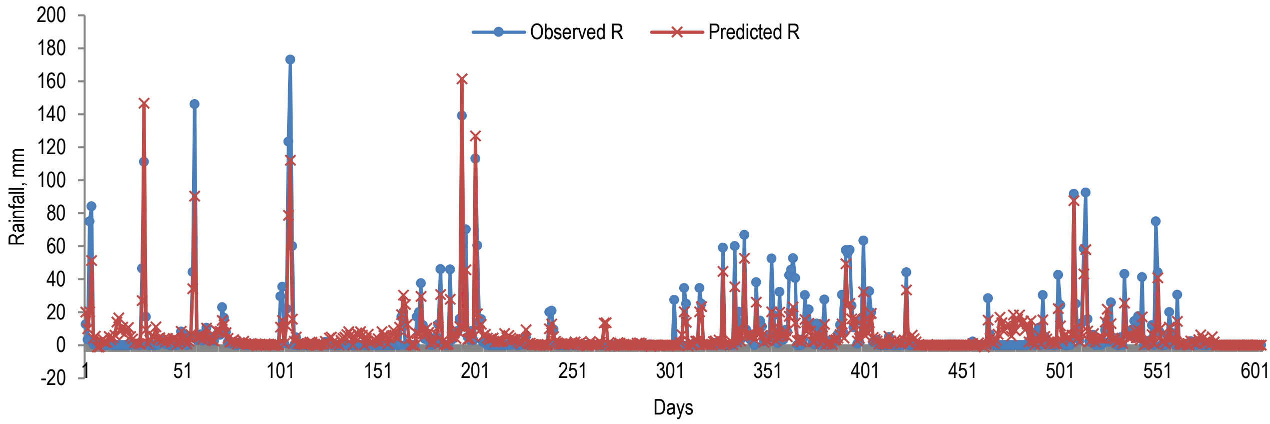

Fig-2 Observed and predicted daily rainfall using ANN Single Hidden Layer with 4 inputs during testing period (2008-2011)

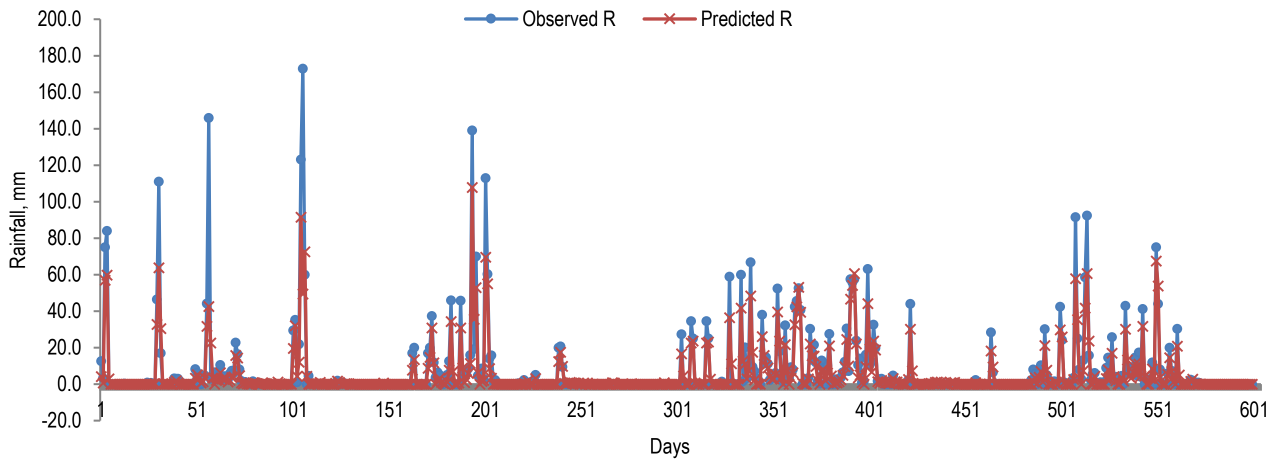

Fig-2 Observed and predicted daily rainfall using ANN Double Hidden Layer with 7 inputs during testing period (2008-2011)

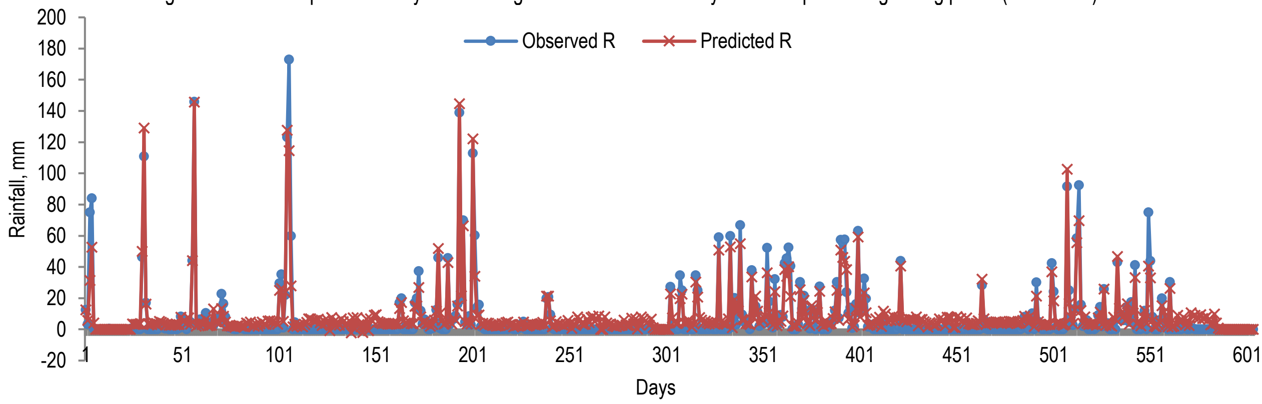

Fig-4 Observed and predicted daily rainfall using ANN Double Hidden Layer with 4 inputs during testing period (2008-2011)

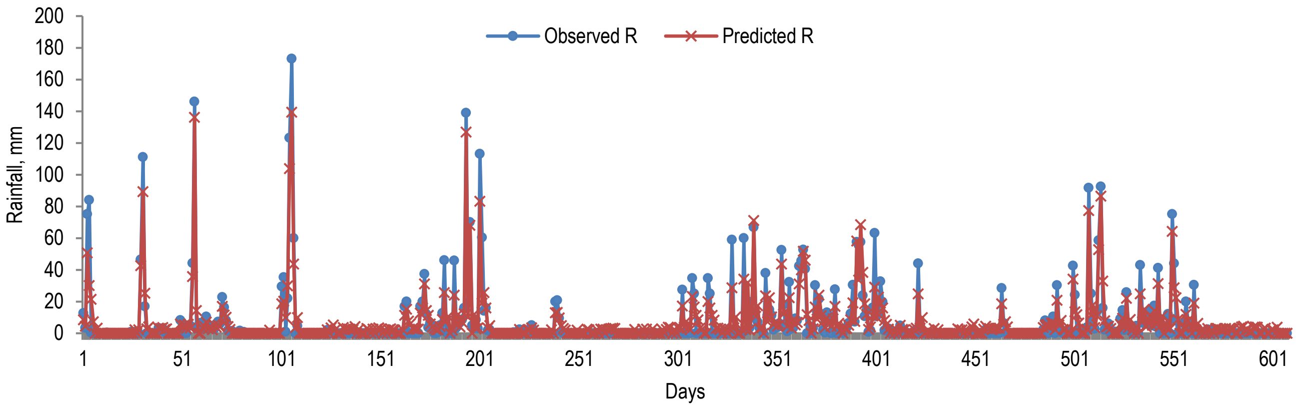

Fig-5 Observed and predicted daily rainfall using ANFIS model (Gauss,3) during testing period (2008-2011)

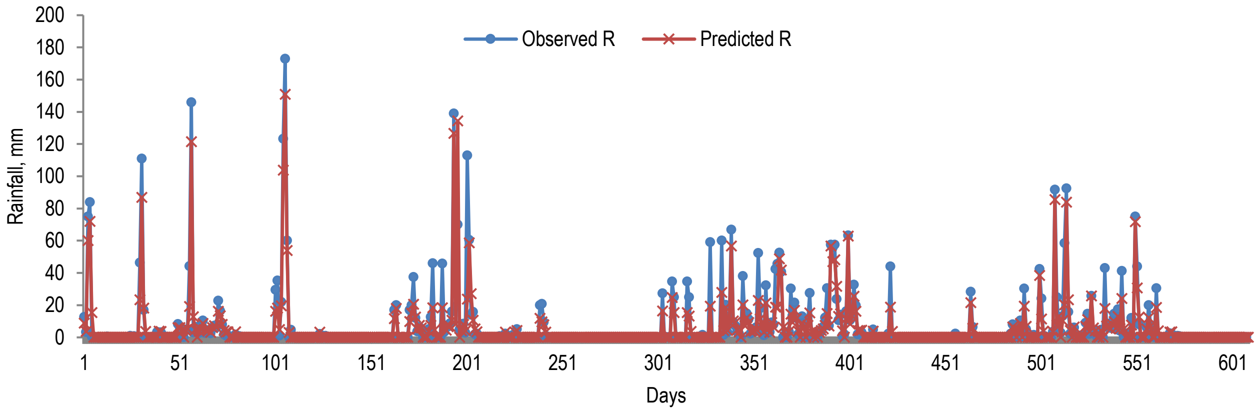

Fig-6 Observed and predicted daily rainfall using ANFIS model (Generalized ,5) during testing period (2008-2011) of ANN and ANFIS models for sensitivity analysis

Table-1 Performance of Selected ANN and ANFIS Models during Testing Period

Model ANN						
	No. of Hidden layers	No of Neurons	No. of Inputs	MSE	CC	AIC
Model AH17	1	30	7	0.0015	0.80	-3275.82
Model AH14	1	12	4	0.0006	0.89	-4250.5
Model AH27	2	13	7	0.0008	0.89	-3472.79
Model AH24	2	1	4	0.0003	0.95	-4691.61
Model ANFIS						
	No. of Membership functions		No. of Inputs	MSE	CC	AIC
Model AM34	Gauss, 3		4	0.0012	0.93	-4068.48
Model AM54	Generalized bell, 5		4	0.0013	0.91	-3988.68

Table-2 Performance Evaluations of Developed ANN and ANFIS Models during Testing Period for the Best Chosen Network

Performance indies	Single and Double Hidden Layer of ANN				ANFIS	
	AH17	AH14	AH27	AH24	AM34	AM54
MSE	0.0015	0.0006	0.0008	0.0003	0.0012	0.0013
NMSE	0.43	0.37	0.40	0.29	0.37	0.45
CC	0.80	0.89	0.89	0.95	0.93	0.91
AIC	-3275.82	-4250.50	-3472.79	-4691.61	-4068.48	-3988.68
CE	69.71	83.48	82.5	87.1	84.70	83.91
EV	32.14	17.34	14.70	13.54	20.75	24.45

Table-3 Performance Indices of ANN Model and ANFIS Model for Sensitivity Analysis during Testing Period

Performance Indies	Base case Model (with all input parameters ANN model AH24	WVP	WRH	WWS	WMT
MSE	0.0003	0.0028	0.0025	0.0007	0.0013
NMSE	0.29	0.99	0.88	0.42	0.65
r	0.95	0.4	0.63	0.83	0.72
% error	34.47	52.78	44.35	39.52	37.13
AIC	-4691.61	-3365.55	-3492.75	-4108.87	-3735.81
MDL	-4035.3	-3258.59	-3328.85	-3685.8	-3983.89
	Base case Model ANFIS model AM34	WVP	WRH	WWS	WMT
MSE	0.0012	0.0022	0.002	0.0015	0.0017
NMSE	0.37	0.68	0.67	0.5	0.54
r	0.93	0.76	0.86	0.91	0.89
% error	44.12	72.71	88.73	59.82	62.29
AIC	-4068.48	-2922.81	-3091.77	-3979.56	-3716.91
MDL	-2756.14	-2459.89	-2245.26	-2699.44	-2612.37

The ANFIS model AM34 has better performance than the model AM54 because of lower value of MSE, NMSE and volumetric error and higher value of correlation coefficient, EC and AIC (Table 2). Therefore, the model AM34 is chosen for rainfall prediction of the study area. The ANN model AH24 is compared with the ANFIS model AM34. It is concluded from the performance evaluation that the ANN model provides the more accurate results as compared to the ANFIS model due to lower value of error and higher correlation efficient. According to the overall performance of the ANN models, the model AH24 has superior accuracy than other selected models. Therefore, the ANN model AH24 was selected for rainfall forecasting for study area.

Sensitivity Analysis

The sensitivity analysis has been done by utilizing the performance indices for ANN model AH24 and ANFIS model AM34 because of higher correlation coefficient and the lowest error between observed and predicted rainfall as shown in Table 3. 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 ANN and ANFIS models 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 as described in Table 3. It indicates that the most significant parameter for rainfall forecasting is vapour pressure followed by the relative humidity, mean temperature and wind velocity using both ANNs and ANFIS models.

Conclusion

In this study, we attempted to forecast the daily rainfall on the basis of artificial neural networks and adaptive neuro-fuzzy inference system 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 discovered that the ANN model gives the more accurate forecasting as compared to the ANFIS model. Therefore, the ANN model AH14 is the greatest accurate model for rainfall forecasting of study area. The sensitivity analysis of ANN model AH24 and ANFIS model AM34 show that the vapour pressure the highest sensitive parameter for rainfall prediction as compared to relative humidity, mean temperature and wind speed.

Application of research: The study has been done to develop a model which can predict an accurate rainfall. This model will be used for the short-term rainfall forecasting. In Agriculture, accurate rainfall forecasting will help to save the agriculture crops from Climate hazards *i.e.,* Heavy storm, cyclone, Droughts *etc.*

Research Category: Rainfall forecasting

Abbreviations

AIC - Akaike's information criterion
ANFIS - Adaptive Neuro-Fuzzy Inference System
ANN - Artificial Neural Networks
CC - Correlation Coefficient
CE - Coefficient of Efficiency
EV - Volumetric Error
JAU - Junagadh Agricultural University
mm - millimetre
MSE - Mean Square Error
NMSE - Normalized Mean Square Error
TLRN - Time Lag Recurrent Neural Networks

Acknowledgement / Funding: Author thankful to G. B. Pant University of Agriculture and Technology, Pantnagar, 263145, Uttarakhand, India

***Research Guide: Professor Dr Pravendra Kumar**
University: G.B. Pant University of Agriculture and Technology, Pantnagar, 263145
Research project name or number: 'Comparative Study of Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for Rainfall Forecasting of Monsoon Season'.

Author Contributions: All author equally contributed
Author statement: All authors read, reviewed, agree and approved the final manuscript

Conflict of Interest: None declared
Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Somvanishi V.K., Panday O.P., Agrawal P.K., Kalanker N.V., Ravi Prakash M. and Chand R. (2006) Journal of Indian Geophysical Union, 10:2 , 141-151.
[2] Dastorani M. T., Afkhami H., Sharifidaran, H. and Dastorani M. (2010) Journal of Applied Sciences, 10:20, 2387-2394.
[3] Evsukoff A. G., Lima B. S. L. P. and Ebecken N. F. F. (2011) Water Resource Management, 25,963-985.
[4] Gadgay B., Kulkarni S. and Chandrashekhar B. (2011) World Journal of Science and Technology, 1,2231-2587.
[5] Abbot J., and Marohasy J. (2012) Advance in Atmospheric sciences, 29,717–730.
[6] Nastos P. T., Moustris K. P., Larissi I. K. and Paliatsos A. G. (2013) Atmospheric Research, 199,153-160.
[7] Dastorani M. T., Moghadamnia A., Piri J. and Rico-Ramirez M. (2009) Environmental Monitoring Assess, 166(1-4), 421-434.

[8] Aldrian E. and Djamil Y. S. (2008) *Makara Journal of Science*, 13,7-14.
[9] Bacanli U.G., Firat M. and Dikbas F. (2009) *Stochastic Environmental Research and Risk Assessment*, 23,1143-1154.
[10] Tektas M. (2010) *Environmental Research Engineering and Management*, 51,5-10.
[11] Jeong C., Shin J., Kim T. and Heo J.H. (2012) *Water Resource Management*, 26(15),4467-4483.
[12] Shiri J., Nazemi A. H., Sadraddini A. A., Landeras G., Kisi O., Fard A. F. and Murti P. (2013) *Journal of Hydrology*, 480,46-57.
[13] Sanikhani H., Kisi O., Nikpour M.R. and Dinpashos Y. (2012) *Water Resource Management*, 26(15), 4347-4365.
[14] Kisi O. and Tombul M. (2013) *Journal of Hydrology*, 477,203-212.
[15] Zurada M.Z. (1992) *St. Paul New York, West Pub. Co*.
[16] Hung N.Q., Babel M.S., Weesakul S. and Tripathi N.K. (2009) *Hydrology and Earth System Science*, 5,183–218.
[17] Center B. and Verma B.P. (1998) *Artificial Intelligence Review*, 12,213-225.
[18] Rumelhart D.E., Hinton G.E. and Williams R.I. (1987) *MIT Press, Cambridge, MA*, 318-362, (1987).
[19] Mutreja K.N. (1992*) Tata Mc Graw-Hill, Pub.Co.Ltd*.
[20] Wiliks D. S. (1998) *Journal of Hydrology*, 210,178-191.
[21] Luchetta A. and Manetti S.A. (2003) *Computers and Geosciences*, 29,1111-1117.
[22] Kachroo R.K. and Natale L. (1992) *Journal of Hydrology*, 135,341-369.