Forecasting of Karnataka Seasons Rainfall Data Using ANN Approach

Kumudha H R[1*], Kokila Ramesh[2,]

Address[1] Research Scholar, Jain University, Bangalore, Karnataka, India kumudhamayur@gmail.com
Address2 Assistant Professor, Jain University, Bangalore, India r.kokila@jainuniversity.ac.in

Abstract
Monsoon rainfall in India is celebrated as a festival as it plays a crucial role in agricultural production leading to the rise or low of the Indian economy. Hence understanding the rainfall pattern and Modelling and forecasting Indian monsoon rainfall becomes essential. In this paper, an effort has been made to develop a new Artificial Neural Network (ANN) model to study rainfall behaviour for the Indian Meteorological Department (IMD) subdivisions of Karnataka. Karnataka is broadly classified into three subdivisions namely south-interior Karnataka, North-interior Karnataka, and Coastal Karnataka. It is observed that the highest amount of rainfall during the monsoon season is received by Coastal Karnataka. Here the importance has been given to all the seasons around the year as during pre and post-monsoons also some of the crops are ploughed. In the network used, three output nodes comprising pre-monsoon, monsoon, and post-monsoon are considered, to forecast the amount of rainfall during all the seasons. This is achieved by using a backpropagation algorithm. The efficiency of the model, both in the training and testing period is recorded in terms of three measures such as correlation coefficient (CC), performance parameter(PP), and root means square error(RMSE) independently for all the seasons. It is seen that the model explains 98%, 89%, and 93% of pre-monsoon variance, 98%, 89%, and 96% of monsoon variance, and 98%, 94%, and 92% of the post-monsoon variance of Coastal Karnataka (CIK), South Interior Karnataka (SIK) and North Interior Karnataka (NIK) respectively. This model has been extended for forecasting purposes for these seasons of subdivisions of Karnataka.

Keywords: Rainfall, pre-monsoon, monsoon, post-monsoon, ANN, Modelling, Forecasting, Percentage of variance.

1.Introduction

India as a whole is divided into 4 broad regions namely Northeast India, Northwest India, Central India and South Peninsular India by Indian Meteorological Department (IMD). These 4 broad regions are further divided into subdivisions, some of which contribute to individual states. Hence Karnataka is divided into three subdivisions: Coastal Karnataka, North Interior Karnataka and South Interior Karnataka. The seasons in India are majorly divided into four seasons winter season during the January to February amounts to 1% of annual rainfall; pre-monsoon (PRM) season occurs from March to May receives 7% of annual rainfall; Northeast monsoon (NEM) or post-monsoon season from October to December amounts to 12% of annual rainfall and finally 80% of the annual rainfall in the southwest monsoon (SWM) or simply monsoon season happens from June to September. It may be noted that the maximum amount of rainfall is received in monsoon season and becomes important to forecast the same. But, the other seasons cannot be ignored as the important crops such as wheat, barley, mustard sesame peas and so on are grown during these seasons. This made authors to develop a model, which can forecast all three seasons.

There are two models available in the literature survey such as dynamical and statistical models. In particular general circulation models and empirical models. General circulation models use set of partial differential equations with initial and

boundary conditions to model and forecast, which require extensive computations to invoke the physics of atmospheric processes. Empirical models use statistical data of amount of Rainfall and other observable atmospheric variables. The interaction of the other atmospheric variables with rainfall is captured and modelled as regression equation with multiple variables.
The capability of a model to explain the events that have passed in the history can be denoted as descriptive capability. This describes the effectiveness of statistical modeling of arbitrary or extreme events (WMO, 1989). Parthasarathy and Mooley (1978) studied Indian SWM data for the period of 1866- 1970. With the help of Chi-square statistics at 5 significant positions, they showed that the data is typically distributed with the presence of a dominant 2 – 3- time cycle. But as the downfall data is a rigorously positive volume, it's clear that the normal distribution isn't applicable except in some ranges near the mean value. Unless statistical tests are strictly applied one may suppose that normal distribution is sufficient for downfall models. Further continuation of monthly weather review B Parthasarathy and D A Mooley (1978) studied some features of a long homogeneous series of Indian summer monsoon rainfall and the statistical properties of the homogeneous time series have been investigated, also Fisher's and Chi-square statistics are implemented. It's found that power spectrum analysis indicates the presence of a quasi-biennial Oscillation in the time series. It concluded that the monsoon rainfall series is random and normally distributed. There does not appear to be any significant relationship between solar activity and the Indian monsoon rainfall. In durability of the below work Parthasarathy et al (1992) performed statistical analysis on Indian SWM downfall for the period 1871- 1990. It was shown that decadal pars of the Indian SWM downfall indicator were continuously lower than the long- term normal for three decades. J Shukla and D A Mooley (1987) studied Empirical prediction of the summer monsoon rainfall over India and examined 46 years (1939 - 84) of observed data to show the relationships between the summer monsoon rainfall over India, the southern oscillation and the mid tropospheric circulation over India by using statistical and empirical techniques. Singh (1998) used a general power metamorphosis to transfer the data of 50 different stations across India to a near normal distribution, which was used in the estimation of quantiles. Parida (1999) attempted to version the arbitrary geste of summer time season thunderstorm downfall of India with the use of a generalized four- parameter Kappa distribution. Parameters of this distribution were estimated using moment estimation. A comparison was made between the estimated quantiles at a rush interval of 20 times and the thunderstorm downfall values observed at 50 stations across the country and this showed better results in comparison to the results preliminarily attained by Singh (1998). Dietz and Chatterjee (2014) suggested the use of a generalized direct mixed model, specifically the lognormal mixed model, to describe the beginning structure for Indian thunderstorm rush. It was applied to light, moderate and extreme downfall events. Moment estimation system was used to estimate the parameters associated in the distribution function.

M. Rajeevan, V. Thapliyal, S.R. Patil and U.S. De (1998) used the canonical correlation analysis (CCA) approach, to forecast a model for long range forecasts of monsoon (June-September) rainfall of 27 meteorological subdivisions over India were developed. This was developed during the period 1958-1994 and by retaining three significant canonical modes this model showed useful predictive skills. D.S. Pai (2002), A.K. Srivastava, M. Rajeevan and R. Kulkarni (2002) and M. Rajeevan, D.S. Pai and V. Thapliyal (2002) studied teleconnections with global surface air temperature anomalies and teleconnection of OLR and SST anomalies over Atlantic Ocean with Indian Summer Monsoon and the inter-annual variability of Indian summer monsoon rainfall (ISMR) was examined using data for the period 1901-98. In addition to its well understood relationship with SST anomalies over equatorial east & central pacific ISMR showed significant relationship with SST anomalies from tropical and subtropical areas of most of the ocean basins. International satellite cloud climatology project (ISCCP) monthly data of cloud parameters for the monsoon season from June to September for the period 1984-90 have shown the relationship between deep convection and sea surface temperature (SST) over the north Indian Ocean. Also discussed the teleconnection between outgoing long wave radiation (OLR) and sea surface temperature (SST) anomalies over North Atlantic Ocean and the Indian Summer Monsoon Rainfall (ISMR).

D. Nagesh Kumar (2004) used Artificial Neural Networks to present temporal disaggregation of rainfall data, and sigmoidal function was used for neuron activation. The training error (RMS error) was measured by squaring the difference between the networks and training pattern desired output and summing over all outputs and all training patterns. In continuation, Radha Gupta (2019) demonstrated New ANN Model for Forecasting Indian Monsoon Rainfall a simple ANN architecture with six nodes at the input layer, a hidden layer with five neurons and an output, is capable of explaining about 80% of the observed inter-annual variability of observed SWM rainfall data This has been demonstrated on six sets of data for the period (1901-2000). Sulochana Gadgil, P.N. Vinayachandran and P.A. Francis (2003) investigated the role of clouds over the Indian ocean, comparison of the evolution of the normal summer monsoon of 2003 with the unanticipated drought of 2002. It shows the role of the deep convection in the atmosphere over the equatorial Indian Ocean. R.H. Kripalani, Ashwini Kulkarni, S.S. Sabade, J.V. Revandekar, S.K. Patwardhan and J.R. Kulkarni (2004) studied intra-seasonal oscillations during Monsoon 2002 and 2003. The discussions carrying intra-seasonal oscillations during the monsoon of 2002, a drought year, and during the monsoon 2003, a normal monsoon year, have been examined by applying the technique of band-pass filter and wavelet analysis. M. Rajeevan, D.S. Pai, S.K. Dikshit and R.R. Kelkar (2004) IMD's New Operational Models for long-range Forecast of South west Monsoon Rainfall over India and Their Verification for 2003and showed the details of new statistical models developed and adopted by IMD for extended rainfall predictions during the southwest monsoon. All these new models proved to be accurate in 2003 in an operational mode and have helped restore the credibility of IMD's forecasts following the drought of 2002. Further, A new approach to reviewing SWM rainfall by breaking down the data series into a finite number of interrelated components called intrinsic mode functions (IMFs) was developed. A.K. Sahai, R. Chattopadhyay and B.N. Goswami (2008) studied sea surface temperature based large multi-model ensemble forecasting system for Indian summer monsoon rainfall. All India summer monsoon rainfall (AIR) due to the seminal role acted by internal fast processes in interannual variability (IAV) of the monsoon and converts a previously used empirical model to construct a large ensemble of models to understand useful probabilistic forecasts of AIR. K. Seetharaman (2009) predicted ARIMA Model for Gangtok (Sikkim). The study carried out between the climatic indices and summer monsoon seasonal rainfalls and climatic ENSO indices chosen. This analysis showed that ARIMA (3,0,3) with initial guess value of 0.1 fits well the data set. Recently, based on the above points into consideration, a new ANN model was developed by Kokila Ramesh and R N Iyengar (2017) including all the seasons variability to forecast 2017 monsoon rainfall for all Indian and its broad regions with optimum number of parameters. A detailed review of various models used to model and forecast Indian monsoon rainfall is captured in the work of Kumudha H R and Dr. Kokila Ramesh 2022.

In view of the work done by Kokila Ramesh and R N Iyengar (2017), a new ANN model is developed in the present paper as an extension. In this work, an effort has been made to model and forecast the three seasons of Karnataka with inter connections.

2. Materials and Methods

The area of state of Karnataka is about 1,91,791 sq. km and located in the south western region of India. Karnataka is meteorologically divided into three subdivisions such as North interior Karnataka (NIK), south interior Karnataka (SIK) and coastal Karnataka (CIK), shown in Fig 1.

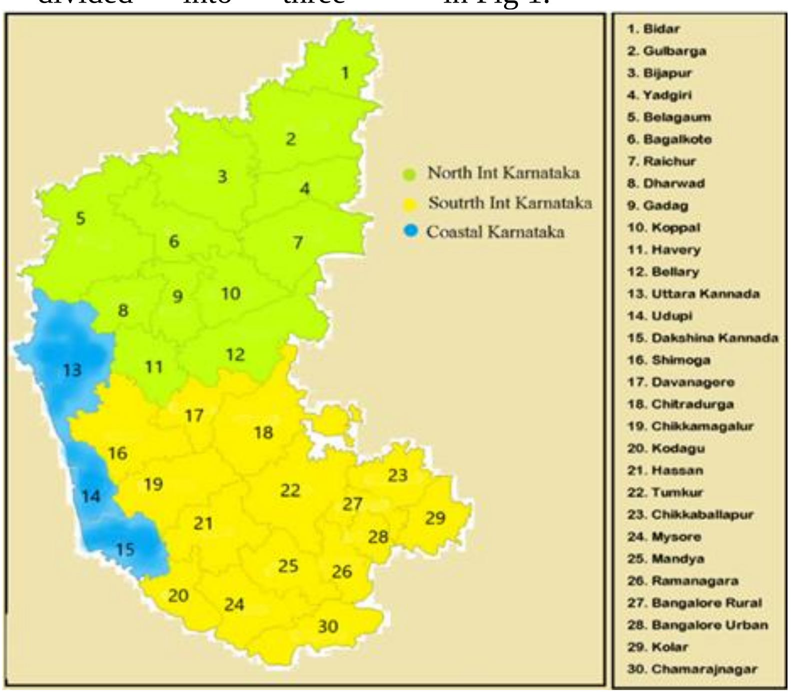


Figure 1: Karnataka map with subdivisions and the regions from Indian Institute of Tropical Meteorology (IITM)

The three subdivisions of Karnataka with respect to three seasons such as PRM, SWM and NEM are considered for the current research work. The rainfall data for these three subdivisions of Karnataka and for 3 seasons for the period of 57 years (from 1960-2016) is collected from the websites of Indian Institute of Tropical Management (IITM) (http://www.tropmet.res.in) and Karnataka State Natural Disaster Monitoring Centre(KSNDMC) (https://www.ksndmc.org). The basic statistics such as long-term average (LTA), long-term deviation (LTD), skewness and kurtosis has been calculated for all the three subdivisions of Karnataka and also for the whole Karnataka and is tabulated in Table 1.

Table 1: Basic statistics of Rainfall data of three seasons during 1960 – 2010

Name	**ALL KARNATAKA**			**CIK**			**SIK**			**NIK**		
Season	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**
LTA (m_R cm)	44.51	380.92	58.65	32.72	536.01	48.96	13.52	47.94	18.61	10.66	55.27	13.61
LTD (σ_R cm)	23.16	71.5	17.78	20.97	74.23	15.40	3.91	8.71	6.13	2.1	6.08	3.68
SKEWNESS	1.19	0.55	0.38	1.24	0.65	0.44	0.36	-0.04	0.19	0.55	0.25	0.53
KURTOSIS	3.74	3.06	2.48	3.8	4.28	2.95	2.54	2.28	2.3	2.85	2.07	2.98

The Karnataka subdivisions data considered here consists of three seasons which are given equal importance in modelling. All the seasons data here are in cms and hence to club the same for whole year, the data of pre monsoon (p_i), SWM (s_i) and NWM also known as post monsoon (n_i), $i = 1,2 \dots 57$ is standardized using the relations $P_i = \frac{p_i - m_p}{s_p}$, $S_i = \frac{s_i - m_s}{s_s}$ and $N_i = \frac{n_i - m_n}{s_n}$ respectively. Here (m_p, m_s and m_n) and (s_p, s_s and s_n) are long term average and long term deviations of (p_i, s_i and n_i). The descriptive statistics of the standardized data for 3 seasons are tabulated in table 2.

Table 2: The descriptive statistics of the predicted rainfall data during 1960 – 2010

Subdivisions	**CIK**			**SIK**			**NIK**		
Season	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**
LTA (mR cm)	-0.07	0.03	0.00	-0.04	-0.01	-0.04	-0.09	-0.04	0.00
LTD (σR cm)	0.84	0.86	1.01	0.80	0.89	0.89	0.80	0.95	0.89
SKEWNESS	3.35	3.00	3.01	2.33	2.54	2.36	3.51	2.01	2.59
KURTOSIS	1.10	0.24	0.51	0.35	-0.20	0.11	0.50	0.28	0.54

To decide about the model, one has to check the linearity of the data used. This may be achieved in different ways. In this paper, the tabulated values of skewness and kurtosis depict the fact that the data is non-Gaussian. With this in view a non-Gaussian model is developed here to capture the non-linearity present in seasons data. In the work of Kokila and Iyengar (2017), an ANN model capturing within season variability to forecast the monsoon season of India and its broad regions was developed. Here within seasons variability and inter annual variability is used to model pre-monsoon, SWM and NEM.

As a result, a new ANN network is developed in this paper by considering PRM, SWM and NEM yearly data for the 15 input nodes, followed by 5 hidden neurons and 3 output nodes. It is illustrated in Figure 2. The network employed in the earlier work by the author has been improved by this new network. The input node consisting of 15 input nodes and they are as follows:

$P_{n-5}, S_{n-5}, N_{n-5}, P_{n-4}, S_{n-4}, N_{n-4}, P_{n-3}, S_{n-3}, N_{n-3}, P_{n-2}, S_{n-2}, N_{n-2}, P_{n-1}, S_{n-1}, N_{n-1}$

The number 15 is obtained by trial and error method, to obtain the same, different input nodes starting from 5 input nodes were tested for the network efficiency in training the network and it is found that the efficiency saturates after 15 nodes. This concludes that the network consists of 15 input nodes in the input layer, 5 nodes in the hidden layer and 3 nodes in the output layer. This network is trained using back propagation algorithm using MATLAB software.

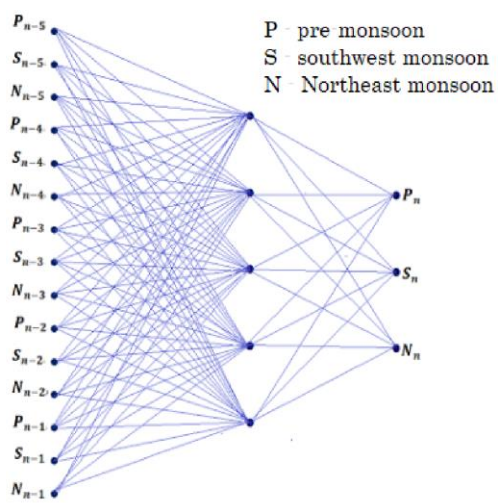


Figure 2: ANN with fifteen input nodes, five neurons in the hidden layer and three outputs.

The total number of parameters used in this network is 98 for the data length of 51 years. It has been made sure that the number of parameters is less than half the size of the data length. The efficiency of the model during training period is measured using three parameters such as (RMSE) root mean square error between the actual data and the model, CC and PP, the correlation between the actual data and simulation and performance parameter (equation to be typed) respectively. These three measures are tabulated in Table 3.

Even though CC is a good measure to find the relation between the observed data and the model, it may not ensure to have an uncorrelated error with the data. Hence PP is considered to be an effective measure to make sure that the model is a best fit. Coefficient correlation (CC) has been computed between the actual data and trained data. As it shows a high coefficient correlation which would be false. CC may not be an incredible marker of the illustrated fitness. On the other hand performance parameter (PP) has been calculated to measure the variance explained by the model for the whole training and testing period. Consequently, for a model to be acknowledged as helpful for forecasting *PP* should be high in both modelling and testing period. The comparisons for both training period and testing period are tabulated in table 3 and table 7 respectively. It is noticed that the new model is able to explain on an average of 83% of the data variance in all the three seasons such as PRM, SWM and NEM with respect to all the three subdivision of the state.

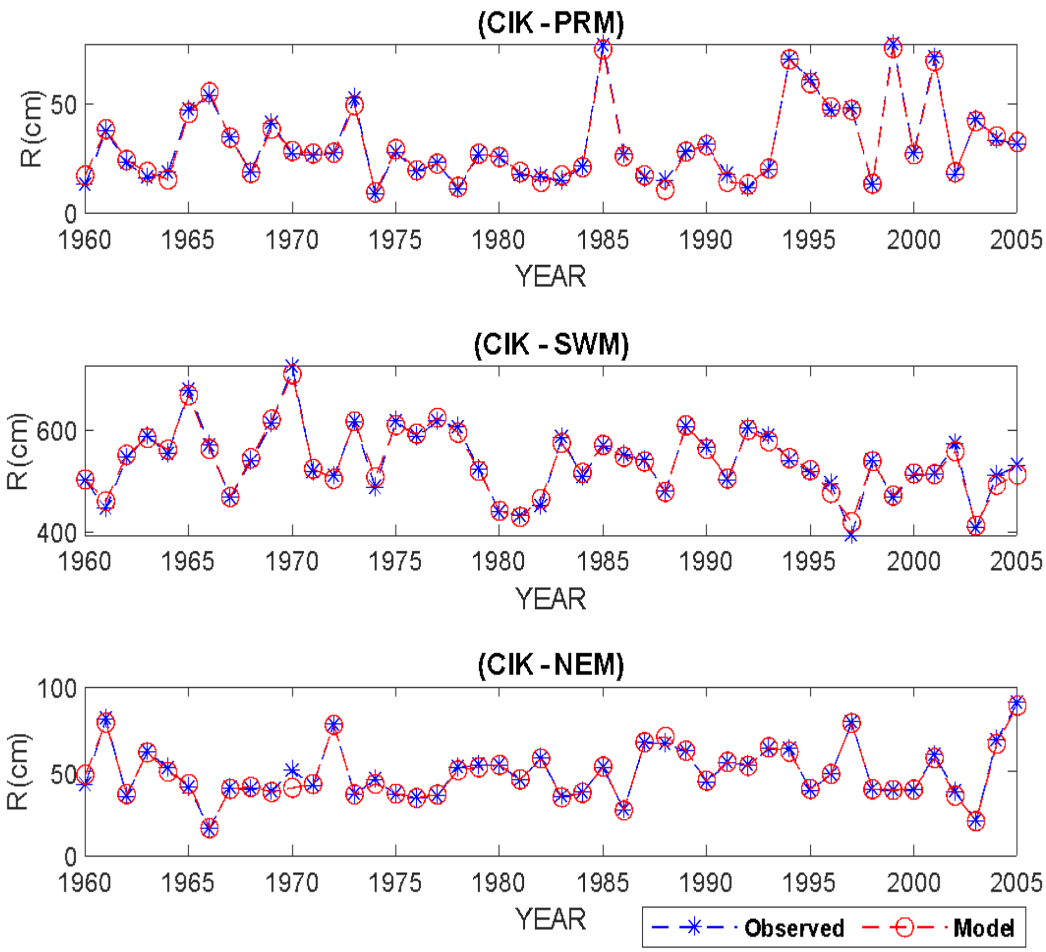


Figure 3: Comparison between the observed data and the model for the region of CIK

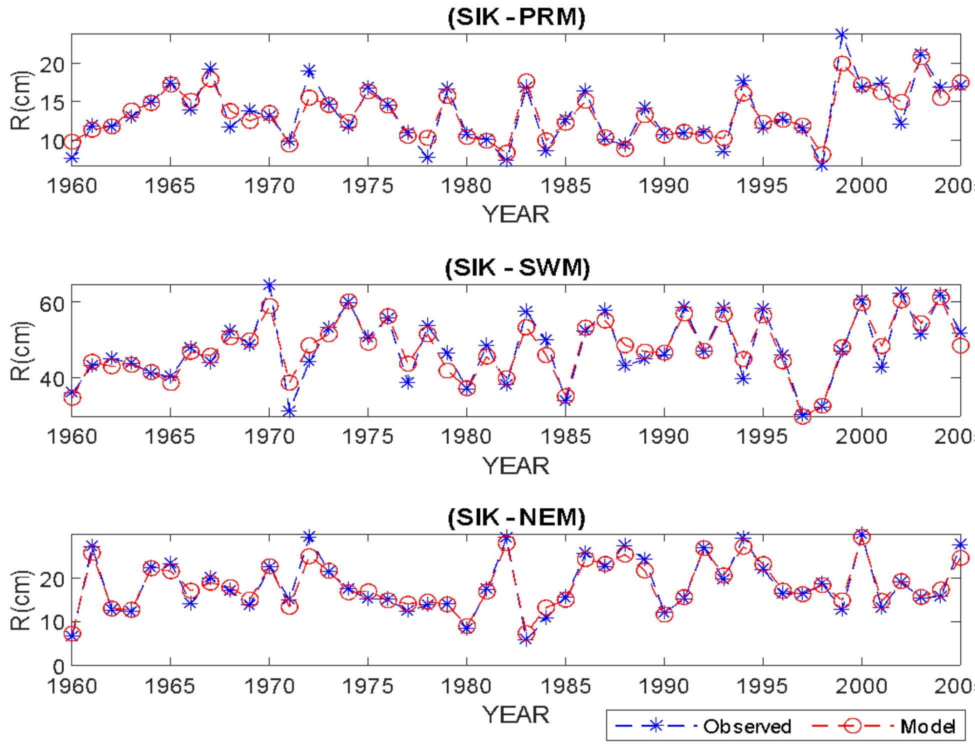


Figure 4: Comparison between the observed data and the model for the region of SIK

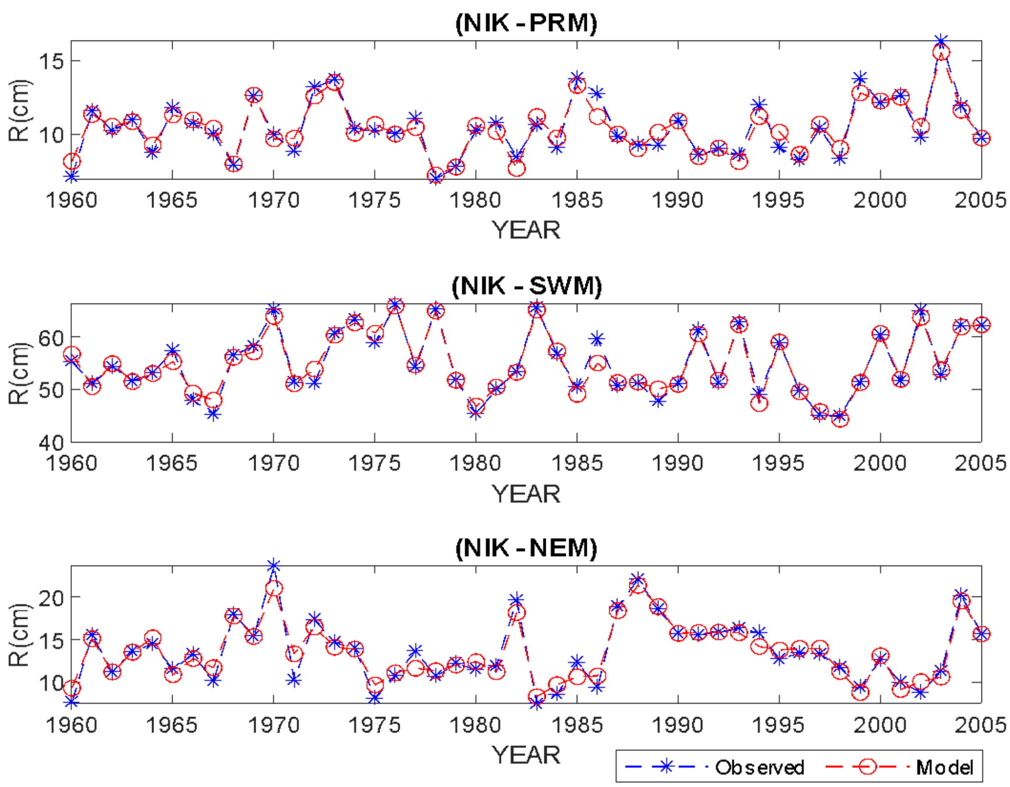


Figure 5: Comparison between the observed data and the model for the region of NIK

Table 3: Performance of the new ANN model in the training period

Region	Training Period during 1960 – 2010								
	R_i			CC			PP		
	PRM	SWM	NEM	PRM	SWM	NEM	PRM	SWM	NEM
CIK	2.69	9.36	2.16	0.99	0.99	0.99	0.98	0.98	0.98
SIK	1.30	2.83	1.45	0.95	0.95	0.98	0.89	0.89	0.94
NIK	0.55	1.25	1.05	0.96	0.98	0.96	0.93	0.96	0.92

The rainfall data during 2011 – 2016 is considered for the testing period. By using the above ANN architecture multi-step ahead forecasting is demonstrated for the all three seasons. Every year the monsoon phenomenon occurs. It is noticed that about 81% - 89% of the variance in all the three seasons data over the course of 51 years may be explained by using the above network. To forecast the upcoming years rainfall previous rainfall is important as the model parameters are to be updated every year. The preceding training session did not use the testing data. By using the previous 5 years seasonal data, one year ahead predictions have been done; likewise, 6 step ahead predictions had been taken up for the period 2011 - 2016. Data non-stationary can be successfully dealt with by using the above model. The descriptive statistics of all the subdivisions and with respect to all the three seasons are tabulated in Table 4, Table 5 and Table6. The observed data and forecasted data are tabulated in Table 8, Table 9 and Table 10. The comparison data for the observed data and forecasted data plot is shown in Figure 6, Figure 7 and Figure 8 respectively.

Table 4: The descriptive statistics of Coastal Karnataka - rainfall data during 2011 – 2016

Subdivision	**Coastal Karnataka (CIK)**					
Season	**PRM**		**SWM**		**NEM**	
	Observed	**Forecast**	**Observed**	**Forecast**	**Observed**	**Forecast**
Rainfall mean (mR cm)	13.65	13.65	284.73	275.22	23.24	21.54
Standard deviation (σR cm)	4.75	3.24	41.94	34.21	7.44	7.31
SKEWNESS	0.29	-0.63	-0.44	0.22	-1.07	0.2
KURTOSIS	2.19	2.71	1.7	1.5	2.82	2.26

Table 5: The descriptive statistics of South Interior Karnataka - rainfall data during 2011 – 2016

Subdivision	**South Interior Karnataka (SIK)**					
Season	**PRM**		**SWM**		**NEM**	
	Observed	**Forecast**	**Observed**	**Forecast**	**Observed**	**Forecast**
Rainfall mean (mR cm)	11.16	18.58	52.45	47.3	8.88	15.76

Standard deviation (σR cm)	5.15	4.78	10.51	10.49	3.97	6.39
SKEWNESS	0.58	0.3	-0.11	0.5	-0.43	0.14
KURTOSIS	2.36	1.44	1.19	1.62	1.77	2

Table 6: The descriptive statistics of North Interior Karnataka - rainfall data during 2011 – 2016

Subdivision	**North Interior Karnataka (NIK)**					
Season	**PRM**		**SWM**		**NEM**	
	Observed	**Forecast**	**Observed**	**Forecast**	**Observed**	**Forecast**
Rainfall mean (mR cm)	18.69	18.58	47.19	47.3	14.83	15.76
Standard deviation (σR cm)	6.53	3.07	12.68	6.55	4.52	2.84
SKEWNESS	0.09	1.29	0.39	0.33	-0.36	-0.66
KURTOSIS	1.53	3.44	1.55	1.74	1.78	1.84

Table 7: Performance of the new ANN model in the testing period

Region	**Testing Period during 2010 - 2016**								
	R_i			**CC**			**PP**		
	PRM	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**	**PRM**	**SWM**	**NEM**
CIK	2.41	20.72	3.46	0.85	0.88	0.90	0.74	0.76	0.78
SIK	2.69	4.43	1.89	0.91	0.93	0.95	0.73	0.82	0.77
NIK	2.49	6.21	2.29	0.90	0.87	0.92	0.85	0.76	0.74

Table 8: Comparison of forecast with independent data in cm for coastal Karnataka (CIK)

Region	**Coastal Karnataka**					
Year	**PRM**		**SWM**		**NEM**	
	Observed data (cm)	**Forecast data (cm)**	**Observed data (cm)**	**Forecast data (cm)**	**Observed data (cm)**	**Forecast data (cm)**
2011	7.47	8.19	325.87	310.89	25.74	21.11
2012	12.76	13.08	289.75	248.50	25.86	19.95
2013	14.24	12.92	325.44	319.12	19.87	17.86
2014	16.23	15.32	297.87	279.70	30.15	32.65
2015	21.04	17.74	223.59	234.82	28.04	26.36
2016	10.16	14.74	245.87	258.31	9.77	11.32

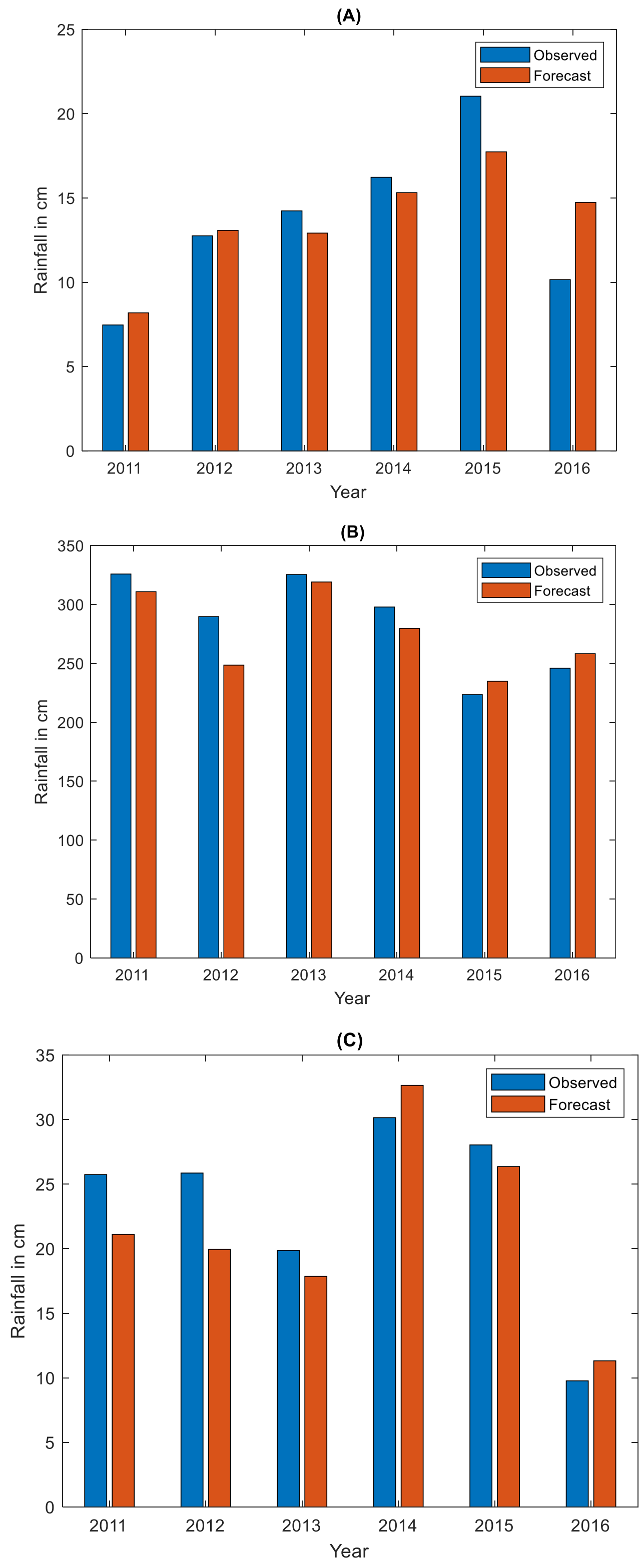
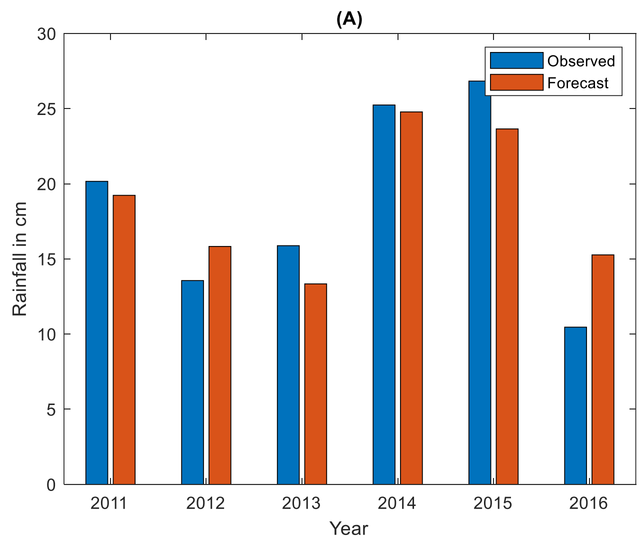
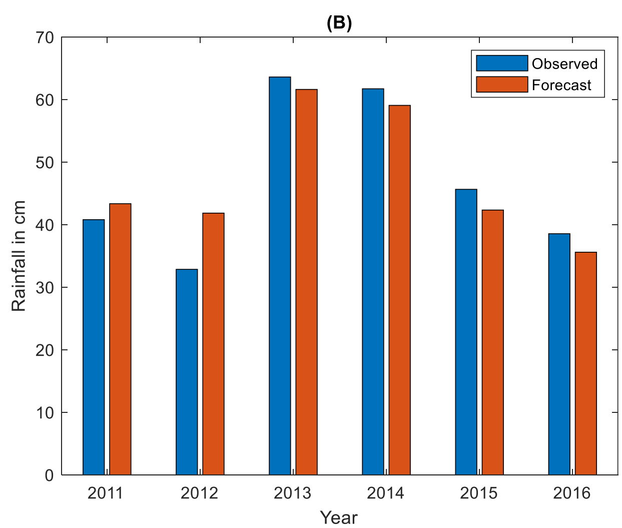


Figure 6: Comparison between the actual data and the forecast data for the period of 6 years (2011:2016) for (A) PRM, (B) SWM and (C) NEM for CIK

Table 9: Comparison of forecast with independent data in cm for the south interior Karnataka (SIK)

Region	**South Interior Karnataka**					
Year	**PRM**		**SWM**		**NEM**	
	Observed data (cm)	**Forecast data (cm)**	**Observed data (cm)**	**Forecast data (cm)**	**Observed data (cm)**	**Forecast data (cm)**
2011	20.16	19.23	40.79	43.34	21.79	25.24
2012	13.56	15.83	32.85	41.84	16.52	15.23
2013	15.88	13.34	63.60	61.61	9.56	10.23
2014	25.24	24.78	61.71	59.06	21.01	19.45
2015	26.83	23.65	45.64	42.33	16.90	16.89
2016	10.46	15.27	38.54	35.59	5.27	7.49





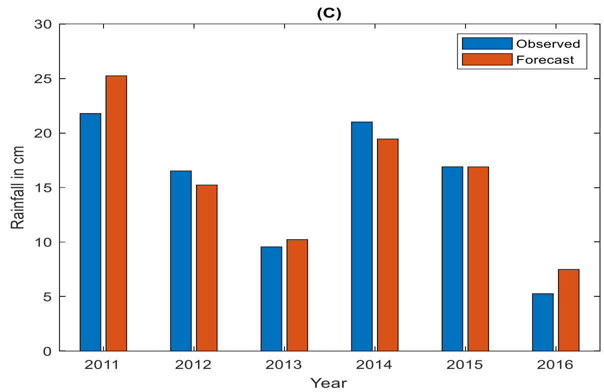
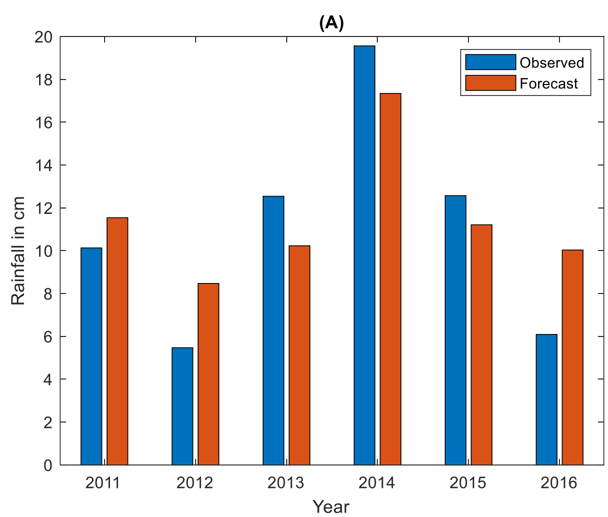


Figure 7: Comparison between the actual data and the forecast data for the period of 6 years (2011:2016) for (A) PRM, (B) SWM and (C) NEM for SIK

Table 10: Comparison of forecast with independent data in cm for the north interior Karnataka (NIK)

Region	North Interior Karnataka					
Year	PRM		SWM		NEM	
	Observed data (cm)	Forecast data (cm)	Observed data (cm)	Forecast data (cm)	Observed data (cm)	Forecast data (cm)
2011	10.13	11.54	46.96	48.32	14.52	10.36
2012	5.47	8.47	39.85	52.27	12.64	10.86
2013	12.54	10.23	62.88	65.38	6.93	8.63
2014	19.56	17.34	60.14	57.60	12.48	10.10
2015	12.57	11.21	42.54	50.14	6.94	5.81
2016	6.09	10.03	62.33	60.18	2.78	3.84



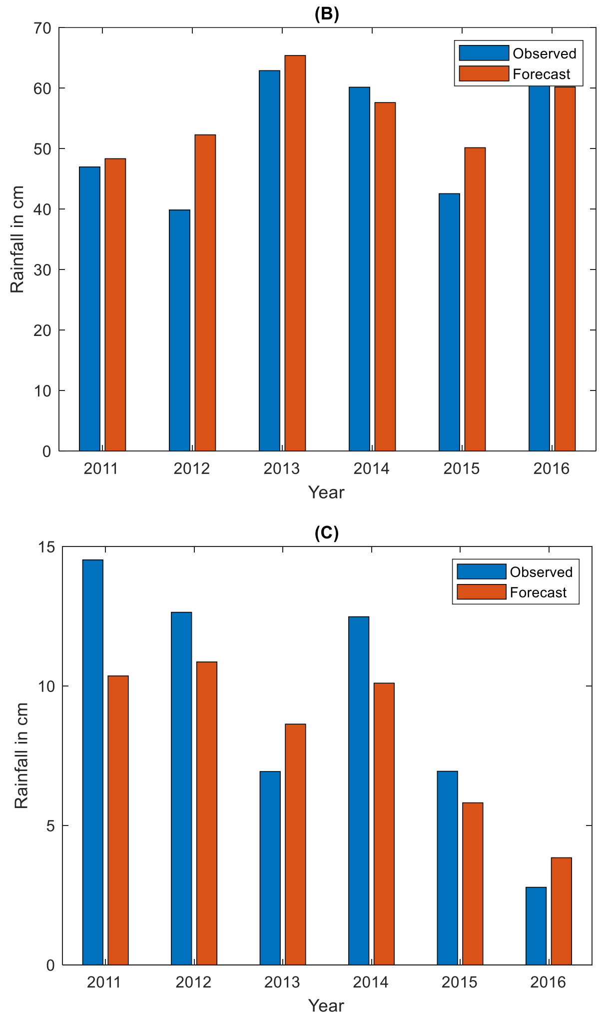


Figure 8: Comparison between the actual data and the forecast data for the period of 6 years (2011:2016) for (A) PRM, (B) SWM and (C) NEM for NIK

3.Discussion and Results

Rainfall time series is highly non-stationary. This is due to the fact that the moving average and moving standard deviation of the time series is not going to a constant value as data length increases with time (Kokila Ramesh and R N Iyengar 2017). The network used here is an improved version of the work carried out by the authors Kokila Ramesh and R N Iyengar for the subdivisions of Karnataka. The considered monthly time series data during 1960 – 2016 is broadly classified into three seasons namely PRM, SWM, and NEM. The data from 1960 – 2010 is considered as the training period and the rest of the data from 2011 – 2016 is considered for testing data. The data shows the nonlinearity pattern with very less correlation observed between seasons to season. It also takes into consideration seasonal or intra-annual fluctuation. This method has been chosen because ANN methodology has the adaptability to handle such unstructured nonlinear relations. It has been observed that the rainfall time series data used in the past is mostly on the broad regions of India and its subdivisions. Vamsidhar et al. (2010) proposed backpropogation neural a network model for predicting precipitation based on humidity, Dew point and atmospheric pressure in India. or Neural network architecture used for prediction 3:7:1 (input node: hidden node: output node). precipitation data Data extracted from the period 1901-2000. Two-thirds of the data was used for training and one-third for testing. The number of samples for training and testing is 250 training and 120 tests. In the end he scored 99% accuracy in training and 94% in testing. Experiments by J. Litta et al. (2013) performed using an ANN model to predict severe rainfall over Kolkata (22.52∘N, 88.37∘E) using thunderstorm-affected meteorological parameters. Compare the performance of his six learning algorithms: Step (STP), Momentum (MOM), Conjugate Gradient (CG), Quick Propagation (QKP), Levenberg-Marquardt (LM), and Delta-Bar-Delta (DBD) increase. Hourly surface temperature and relative humidity predicted for those thunderstorm days. Prediction accuracy is assessed using the correlation coefficient (CC), mean squared error (RMSE), mean absolute error (MAE), and percent correctness (PC) between measured and predicted values, and this the overall accuracy is 74% for one year ahead forecast. Piyush Joshi et al (2021) an attempt was made to predict precipitation at six stations in the western Himalayas using grayscale values extracted from IR and WV imagery. Pixel values extracted at a location are trained against the corresponding precipitation at that location. An artificial neural network (ANN) model is used for qualitative and quantitative precipitation forecasting. The overall performance of qualitative forecasting ranges from 61% to 84%. The mean squared errors for the various sites surveyed ranged from 5.81 to 8.7. The work of Kokila Ramesh and Iyengar (2017), where they have developed ANN model which included intra seasonal variability and inter annual variability by using back propagation algorithm. It's a new method that is typically used to model and estimate the total amount of precipitation in India during the monsoon season. In the model a simple ANN architecture is demonstrated with 10 input nodes in detail 2 nodes of PRM, 2 nodes of NEM and 6 nodes of SWM, hidden layers of five neurons and an output layer. About 94% of the reported inter-annual variability of the observed SWM rainfall data can be explained by the model. This has been illustrated in four sets of information for the period of 1901-2000.

4.Conclusion and Future Work

In the present study, the same model has to be developed for the subdivisions of Karnataka. Initially, the data has been standardized for the considered dataset and then data pre-processing concluded accordingly. The number of input layers has been considered based on the root mean squared error (RMSE) value with respect to different input nodes. Firstly the model started with 9 input nodes and it went up to 20 input nodes by considering 5 hidden nodes in the hidden layer and 3 output nodes in the output layer. The model has been taken into consideration before looking at the saturation level of the RMSE value. In the present paper ANN architecture is demonstrated with 15 input neurons with 5 nodes each of PRM, SWM and NEM, 5 hidden nodes in the hidden layer and 3 output nodes in the output layer. The seasons have been added to the network to serve as a model as result for all the three seasons. The above model is capable of explaining 85% - 89% of the observed inter-annual variability of observed PRM, SWM and NEM for the testing period rainfall data.

It is observed that the rainfall data at the temporal scale considered for the present study is highly unstructured. Such unstructured nonlinear relationship of the time series data is handled using Artificial Neural Network (ANN) model. The network used here consists of 15 input nodes in the input layer having 3 seasons data, 5 hidden neurons to capture the non-linear relation between the present and the past seasons rainfall data and 3 output nodes in the output layer having prediction of pre-monsoon, monsoon and post-monsoon seasons rainfall. In this model all the three seasons namely pre-monsoon, monsoon and post-monsoon rainfall data in the training period of 50 years have been utilized to construct the network. This network uses the inter annual and inter seasonal variability to predict all seasons rainfall. Model has captured 85-95% variance of the observed seasonal rainfall time series. With this in view the same network model has been used to predict in the testing period of 6 years from 2011 to 2016 to validate the model. It may be seen that this model has explained 74 to 85% of the actual data variance of all the seasons in this testing period. Further, this model is used to forecast for the period of 4 years consisting of 3 seasons. In this study the concentration was only on forecasting Karnataka seasons rainfall data. This work can be extended to the other states of India, hence in our future study; the work will be forecasting rainfall time series for other state subdivisions of India.

5.References

[1] Parthasarathy, B., & Mooley, D. (1978). Some Features of a Long Homogeneous Series of Indian Summer Monsoon Rainfall. *Monthly Weather Review*, *106*(6), 771-781.

[2] Shukla, J., & Mooley, D. (1987). Empirical Prediction of the Summer Monsoon Rainfall over India. *American Meteorological Society Monthly Weather Review*, *115*, 695 – 704.

[3] Singh, S., Datar, S., & Srivastava, H. (1998). Long range forecasting parameters vis-a-vis sub-divisional summer rainfall over India. *Mausam*, *44*(2), 185–190.

[4] Parida, B. (1999). Modelling of Indian summer monsoon rainfall using a four-parameter Kappa distribution. *International Journal Of Climatology*, *19*(12), 1389-1398. Retrieved 22 August 2022.

[5] RAJEEVAN, R., THAPLIYAL, V., PATIL, S., & DE, U. (1998). Canonical correlation analysis (CAA) model for long-range forecasts of sub-divisional monsoon rainfall over India. *MAUSAM*, *50*(2), 145-152.

[6] PAI, D. (2003). Interannual variation in the sea surface temperature threshold for the deep convection over north Indian ocean. *MAUSAM*, *54*(3), 595-604.

[7] PAI, D. (2003). Teleconnections of Indian summer monsoon with global surface air temperature anomalies. *MAUSAM*, *54*(2), 407-418.

[8] NAGESH KUMAR, D., & SRINIVASA RAJU, K. (2000). Temporal disaggregation of rainfall data using artificial neural networks. *Proceedings Of International Conference On Integrated Water Resources Management For Sustainable Development*, *19*(21), 788-795. Retrieved 22 August 2022.

[9] Kokila Ramesh, Anita Chaturvedi, & Radha Gupta. (2019). New ANN model for forecasting Indian monsoon rainfall. *Journal of Engineering Mathematics & Statistics*, *3*(1), 1–12.

[10] Sulochana Gadgil, Vinayachandran, P. N. P., Francis, A & Pavanathara, P. N.

(2003). Droughts of the Indian summer monsoon: Role of clouds over the Indian ocean. *Current Science*, *85*(12), 1713–1719.

[11] Kripalani, R., Kulkarni, A., Sabade, S., Revadekar, J., Patwardhan, S., & Kulkarni, J. (2004). Intra-seasonal oscillations during monsoon 2002 and 2003. *Current Science*, *87*(3), 325-332. Retrieved 22 August 2022.

[12] Rajeevan, M., Pai, D., Dikshit, S., & Kelkar, R. (2004). IMD's new operational models for long-range forecast of southwest monsoon rainfall over India and their verification for 2003. *CURRENT SCIENCE*, *86*(3), 422-431. Retrieved 22 August 2022.

[13] Sahai, A., Chattopadhyay, R., & Goswami, B. (2008). A SST based large multi-model ensemble forecasting system for Indian summer monsoon rainfall. *Geophysical Research Letters*, *35*(19).

[14] Seetharam, K. (2009). Arima model for rainfall prediction at gangtok (Sikkim). *Mausam*, *60(3*), 361–367.

[15] Iyengar, R., & Raghukanth, S. (2004). Intrinsic mode functions and a strategy for forecasting Indian monsoon rainfall. *Meteorology And Atmospheric Physics*, *90*, 17-36. Retrieved 22 August 2022.

[16] Enireddy. Vamsidhar, K.V.S.R.P. Varma , P Sankara Rao, Ravikanth satapati, 2010, "Prediction of Rainfall Using *Back propagation Neural Network Model"*, International Journal on Computer Science and Engineering, Vol. 02, No. 04, pp. 1119-1121.

[17] A. J. Litta, Sumam Mary Idicula, and U. C. Mohanty (2013) "Artificial Neural Network Model in Prediction of Meteorological Parameters during Premonsoon Thunderstorms", *Hindawi Publishing Corporation International Journal of Atmospheric Sciences Volume 2013, Article ID 525383.*

[18] P. JOSHI, M. SHEKHAR, A. KUMAR, and J. QUAMARA, "Artificial neural network model for precipitation forecast over Western Himalaya using satellite images", *MAUSAM, vol. 73, no. 1, pp. 83–90, Mar. 2022.*

[19] Kokila Ramesh, & Iyengar, R. N. (2017). Forecasting indian monsoon rainfall including within year seasonal variability. *International Journal of Civil Engineering and Technology (IJCIET)*, *8*(2), 390–399.

[20] Bawiskar, S., Awade, S., & Singh, S. (1989). Harmonic analysis of summer mean wind at 200 mbar level during contrasting monsoon years over India. *Journal Of Earth System Science*, *98*(4), 365-373.

[21] Kokila Ramesh, & Kumudha, H. R. (2019). A review on forecasting Indian monsoon rainfall. = *International Journal of Innovative Science and Research Technology*, *Special Issue*(AAM 2019), 9–14.

[22] Kulkarni, A., Kripalani, R., Sabade, S., & Rajeevan, M. (2011). Role of intra-seasonal oscillations in modulating Indian summer monsoon rainfall. *Climate Dynamics*, *36*(5-6), 1005-1021.

[23] Kumar, K., Pant, G., Parthasarathy, B., & Sontakke, N. (1992). Spatial and subseasonal patterns of the long-term trends of Indian summer monsoon rainfall. *International Journal Of Climatology*, *12*(3), 257-268.

[24] RAJEEVAN, M., PAI, D., & THAPLIYAL, V. (2002). Predictive relationships between Indian Ocean sea surface temperatures and Indian summer

monsoon rainfall. *MAUSAM*, *53*(3), 337-348.

[25] Rajeevan, M., Pai, D., Anil Kumar, R., & Lal, B. (2006). New statistical models for long-range forecasting of southwest monsoon rainfall over India. *Climate Dynamics*, *28*(7-8), 813-828.

[26] Srivastava, H. N., & Singh, S. S. (1993). Empirical orthogonal functions associated with parameters used in long range forecasting of Indian summer monsoon. *Mausam*, *44*(1), 29–34.

[27] Srivastava, A. K., Rajeevan, M., & Kulkarni, R. (2002). Teleconnection of OLR and SST anomalies over Atlantic Ocean with Indian summer monsoon. *Geophysical Research Letters*, *29*(8), 125–1.