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Assessment of Pattern of Rainfall in Kerala and its Forecasting using NNAR Model

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SUMMARY

The economy of the state Kerala is dominated by agriculture and the agriculture depends on rainfall. Hence, the study of rainfall is important and its forecasting will aid in crop and hydrological planning. The present study analyzed the pattern of rainfall in Kerala for the period 1991 to 2020 and obtained annual average rainfall as 2906.79 mm. There was no significant trend in annual rainfall. As per monthly rainfall data, month of June receives highest rainfall followed by July. Monthly rainfall had been modelled using Seasonal Autoregressive Moving Average model (SARIMA) and Neural Network Auto Regression (NNAR) model. Comparison of models based on the accuracy measures, revealed NNAR (6,1,4)[12] as the best model for forecasting rainfall in Kerala. Monthly rainfall for 2021 and 2022 was predicted and it showed that rainfall will be high in the month of July.

*Keywords: R*ainfall; Trend; Pattern; SARIMA; NNAR model; Forecasting; Kerala.

1. INTRODUCTION

The state of Kerala (38,863km^2) is situated between the Arabian Sea to the west and the Western Ghats to the east. It lies between 10.85^{0}N latitudes and 76.27^{0}E longitudes. The State of Kerala consists of three natural regions viz., the eastern high lands, the hilly midlands and western low lands. Kerala is the land of monsoon; it is known as “Gateway of monsoon” over India (Gopakumar 2011).The state Kerala is bestowed with abundant rainfall which is about three times the national average (Archana *et al.* 2014). Annual rainfall of the state is 3000 mm. It facilitates agriculture sector into great extent. Hence the economy of the state is dominated by agriculture. Agriculture sector mainly depends on monsoon rains. The monsoon rains are crucial for crops like paddy, oilseeds, coarse cereals, sugarcane and cotton.

According to Economic survey 2020-21, agriculture sector plays vital role in Indian economy and it contributes about 19.9 per cent to the total Gross Domestic Product (GDP) in 2020-21**.** Deviation of rainfall from its periodicity would disrupt the economy of the country. Half of the population in Kerala live in rural areas and are dependent on rural livelihoods such as farming. According to the Kerala Economic review 2021, the share of agriculture and allied sectors in total Gross Value Added (at constant 2011-12 prices) of the State increased from 8.38 per cent in 2019-20 to 9.44 per cent in 2020-21. The annual growth rate of Gross Value Added (at constant 2011-12 prices) of agriculture and allied activities were fluctuating over the years. The sector recorded a positive growth of 2.11 per cent in 2017-18. The growth rate was negative in 2018-19 and 2019-20. Poor return, high labor cost and unexpected climate change in Kerala had forced many farmers to keep away from agriculture and allied sector. The heavy rainfall created negative impact on agriculture sector. It indicates that the study of rainfall is important to crop and hydrological planning.

Rainfall is a common phenomenon but rainfall forecasting is a challenging one. Climate and rainfall are highly nonlinear phenomena in nature giving rise to what is known as the ‘butterfly effect’ (Ninan and Babu, 2001).In the present study monthly average

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rainfall of Kerala in last 30 years (1991-2020) was considered to assess the recent changes in rainfall. Rainfall forecasting is very important factor for flood warning, crop planning, use of water resources and pre-planning of water resources.

Many metrological factors influenced rainfall forecasting. Researchers adopted various techniques to predict rainfall. Precipitation data are highly nonlinear so prediction is very difficult. There are two possible approaches to forecast rainfall. The first approach to forecast rainfall is based on the physical laws. But this approach may not be feasible because rainfall is an end product of a number of complex atmospheric processes. The second approach is based on the pattern recognition. The logic behind this approach is to find out relevant spatial and temporal features in historical rainfall patterns with no consideration of the physics of the rainfall processes (Kin *et al.* 2001).

The most popular and frequently used time series model is the Autoregressive Integrated Moving Average (ARIMA) by Box and Jenkins (1976). When the data is categorized monthly,additional seasonal terms are included in the ARIMA model which is then called Seasonal ARIMA (SARIMA) model. SARIMA has been used extensively in literature for prediction of rainfall. (Wiredu *et al.*, 2013;Patowary *et al.* 2017; Murthy *et al.* 2018; Lama *et al.* 2022)

Another popular model in timeseries forecasting is neural network autoregressive model. It uses lagged values of timeseries as inputs in neural network. Pal and Mazumdar (2018) and Bhavyashree and Bhattacharryya (2018) compared NNAR (Neural Network Autoregressive) with SARIMA method for monthly rainfall modelling and reported that the accuracy measures were less in case of NNAR than SARIMA. Delna (2021) also used NNAR model for forecasting rainfall of Thrissur district of Kerala. Hence, pattern of precipitation in Kerala was assessed and modelled using SARIMA and NNAR.

2. MATERIALS AND METHODS

2.1 Source of data

In order to analyse the precipitation profile of Kerala in last 30 years (1991-2020), monthly average rainfall data has been collected from https://spb.kerala.gov.in/economic-review-archive (1991-2003), https://www.indiawaterportal.org/articles/district-wise-monthly-rainfall-data-2004-2010-list-raingauge-stations-india-meteorological (2004-2010) and https://datasource.kapsarc.org/explore/dataset/district-wise-rainfall-data-for-india-2014/table/(2011-2020). All the observations were measured in millimeter (mm).

Monthly average rainfalls of Kerala in different years were classified decennially. The pattern and trend of rainfall data were assessed using graphs and simple linear regression. For each period, average of total rainfall in each month was also calculated to study the pattern of rainfall in different months. Seasonal Autoregressive Moving Average (SARIMA) model and Neural Network Auto Regression (NNAR) methodology was used in the present study to model and predict monthly precipitation in Kerala.

2.2 Diagnostic tests

2.2.1 Augmented Dicky Fuller Test (ADF)

The Augmented Dickey Fuller Test (ADF) is unit root test for stationary. Unit roots can cause unpredictable results in time series analysis. This test is a common statistical test used to test whether a given time series is stationary or not. It is one of the most commonly used statistical tests when it comes to analyzing the stationarity of a series.

2.2.2 Jarque-Bera Test

Jarque-Bera test is a goodness of fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The test is named after and .Jarque-Bera test is usually run to confirm normality. The null hypothesis for the test is that the data is normally distributed; the alternate hypothesis is that the data does not come from a normal distribution.

2.2.3 Mann-Kendall Test

Mann–Kendall trend test is one of the widely used non-parametric tests to detect significant trends in time series. The Mann-Kendall trend test, being a function of the ranks of the observations rather than their actual values, is not affected by the actual distribution of the data and is less sensitive to outliers.

2.2.4 White Neural Network Test

White test is based on a neural network model. This test used for neglect nonlinearity in time series. The null is the hypothesis of linearity in mean. This type of test is consistent against arbitrary non linearity in mean. Neural network test can play a valuable role in evaluating model adequacy.

2.3 Models

2.3.1 SARIMA model

The SARIMA model is combination of seasonal and non-seasonal autoregressive, moving average and integrating parameter The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is SARIMA (p, d, q) x (P, D, Q) $_S$, where, (p, d, q) and (P, D, Q) are non-seasonal and seasonal components, respectively with a seasonality 's', p = non-seasonal Auto Regression (AR) of order (p), d = non-seasonal differencing, q = non-seasonal Moving Average (MA) of order (p), P = seasonal AR of order (P), D = seasonal differencing, Q = seasonal MA of order (Q), and s = time span of repeated seasonal pattern. The seasonal components are:

AR: $\Phi(B^s) = 1 - \Phi_1 B^s - ... - \Phi_p B^{sP}$

MA: $\Theta(B^s) = 1 + \Theta_1 B^s + ... + \Theta_Q B^{SQ}$

The non-seasonal components are:

AR: $\varphi(B) = 1 - \varphi_1 B - ... - \varphi_p B_p$

MA: $\theta(B) = 1 + \theta_1 B + ... + \theta_q B_q$

Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of s. With $s = 12$, which may occur with monthly data, a seasonal difference is,

$(1 - B_{12})\, y_t = y_t - y_{t-12}$

The differences (from the previous year) may be about the same for each month of the year giving us a stationary series. Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationary. If trend is present in the data, non-seasonal differencing is also needed. Often a first non-seasonal difference will "de-trend" the data.

The mathematical formulation of a SARIMA (p, d, q) x (P, D, Q) $_S$ model in terms of lag polynomials is given below.

$$\Phi_P(B^s)\varphi_p(B)(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t,$$

After identifying suitable order for SARIMA (p, d, q) (P, D, Q) s, attempt is made to find precise estimates of parameters of the model using least squares as described by Box and Jenkins. The parameters are obtained by maximum likelihood which is asymptotically correct for time series. Estimators are usually sufficient, efficient and consistent for Gaussian distributions and are asymptotically normal and efficient for several non-Gaussian distribution families.

2.3.2 Neural Network Auto Regression (NNAR)

Neural network time series prediction goes through a dynamic filtering, in which past values of the time series are used to predict future values. Artificial neural network (ANN) is a convincing data modeling technique that is able to represent complex input/output relationship. ANN is considered as a powerful and highly automatic approach to nonlinear forecasting. In the recent past, the ANN has been applied to model large data with large dimensionality. The roots of all work on neural networks are in neurobiological studies that date back to about a century ago. The first model of a neuron was developed by McCulloch and Pitts (1943). Most of the ANN studies spoke to the problem allied with pattern recognition, forecasting and comparison of the neural network with other traditional approaches in ecological and atmospheric sciences.

Neural networks are number of parallel operating processors, termed neurons, connected into some circuit (Bodri and Cermak 2000). The ANN model has three layers, the first layer connecting to the input variables is called the input layer. The last layer connecting to the output variables is called the output layer. Layers between the input and output layers are called hidden layers;there can be more than one hidden layer(Kin *et al.* 2001). Information is passed forward only;this type of network is called a feedforward network, or multilayer feedforward network (MLFN).

Once an intermediate layer is added with hidden neurons, the neural network becomes nonlinear. In Multilayer Feed-Forward Network, each layer of nodes receives inputs from the previous layers. The outputs of the nodes in one layer are inputs to the next layer. The inputs to each node are combined using a weighted linear combination. The result is then modified by a nonlinear function before being output. When using a feed-forward neural network in forecasting a time series, the inputs can be previous observed values of the time series y_t. This is known as Neural Network Auto Regression (NNAR). In the hidden layer, an activation function is applied to the hidden nodes. The activation function is a nonlinear function such as a sigmoid function,

$$F(x) = \frac{1}{1+e^{-x}}$$

One benefits of the sigmoid function is that it reduces the effects of extreme input values, thus providing some degree of robustness to the work. The main parameters of the MLFN are the connection weights. The estimation of parameters is known as "training" in which optimal connection weights are determined by minimizing an objective function.

In general, form of neural network model with seasonal input is NNAR (p, P, k) [m] where p is the number of input nodes or number of non-seasonal lags, the value of P, which is the number of seasonal lags is taken as one and k neurons in the hidden layer (Soumen and Debasis 2018). The inputs are represented by (y_{t-1}, y_{t-2}….y_{t-p}, y_{t-m}, y_{t-2m},….y_{t-Pm}) y_t. The 'nnetar' function in the forecast package for R fits a NNAR (p,P,k)[m] model to a time series with lagged values of the time series as inputs. If we do not specify a choice for the number of hidden nodes k, the nnetar function will use k= (p+P+1)/2 rounded to the nearest integer.

2.4 Forecast accuracy measures

An accuracy measure is often defined in terms of the forecasting error which is the difference between the actual and the predicted value. There are a number of measures of accuracy in the forecasting literature and each has their own properties. In each of the following definitions, y_t is the actual value, f_t is the forecasted value $e_t = y_t - f_t$ is the forecast error and n is the size of the test set. The important performance measures are:

i. **Mean Error (ME)**

It measures the average of forecasted values from original ones.

$$\text{ME} = \frac{1}{n}\sum_{i=1}^{n} e_t$$

ii. **Mean Absolute Error (MAE)**

It measures the average absolute deviation of forecasted values from original ones. It is also termed as the Mean Absolute Deviation (MAD). In MAE, the effects of positive and negative errors do not cancel out.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_t|$$

iii. **Mean Squared Error (MSE)**

The mean squared error is a measure of accuracy computed by squaring the individual error for each item in a data set and then finding the average or mean value of the sum of these squares. It gives more weight to large errors than to small errors because the errors are squared before being summed. Lower mean squared values are better and zero means no error.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_t^2$$

iv. **Root Mean Squared Error (RMSE)**

RMSE is nothing but the square root of calculated MSE

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_t^2}$$

v. **Mean Absolute Scaled Error (MASE)**

The mean absolute scaled error is a scale-free error metric that gives each error as a ratio compared to a baseline's average error.

$$\text{MASE} = \frac{\mathbf{e_t}}{\frac{1}{\mathbf{n}-1}\sum_{\mathbf{t}=1}^{\mathbf{n}} |\mathbf{y_t} - \mathbf{y_{t-1}}|}$$

The analysis was done using R.

3. RESULTS

3.1 Trends in annual rainfall

Total rainfall of Kerala in last 30 years (1991-2020) was classified decennially to study the trend and pattern of rainfall. The annual rainfall in Kerala was derived from the monthly average rainfall from all Districts. During this period annual average rainfall in Kerala was 2906.79 mm with a standard deviation 377.71 mm and a coefficient of variation (CV) of 12.99 percent. Thirty years of data was classified decennially and is shown in Fig.1.Therewas no significant ($p>0.05$) trend in annual rainfall for decennial years and for thirty years. The highest and lowest rainfall in Kerala in the decennially years is shown in Table 1.

Table 1. Highest and lowest rainfall (mm) in Kerala in the decennially years

	1991-2000		2001-2010		2011-2020	
	Year	**Rainfall**	**Year**	**Rainfall**	**Year**	**Rainfall**
Highest	1994	3471.66	2007	3545.49	2018	3433.81
Lowest	2000	2464.8	2003	2379.714	2016	1885.44

3.2 Pattern in annual rainfall per month

Average monthly rainfall in Kerala calculated for the period 1991 to 2000 is shown in Fig. 2. The highest monthly rainfall for the period 1991-2020 was

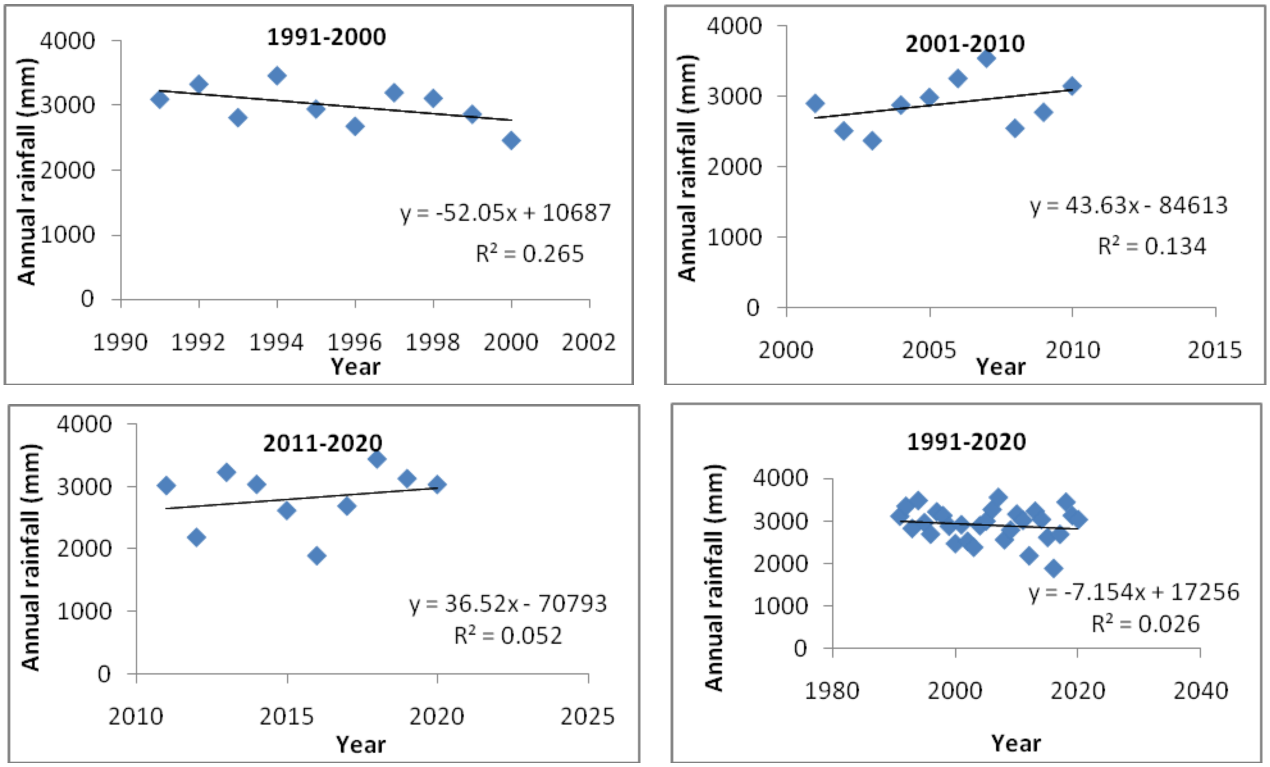

Fig. 1. Rainfall trend in decennially years in Kerala

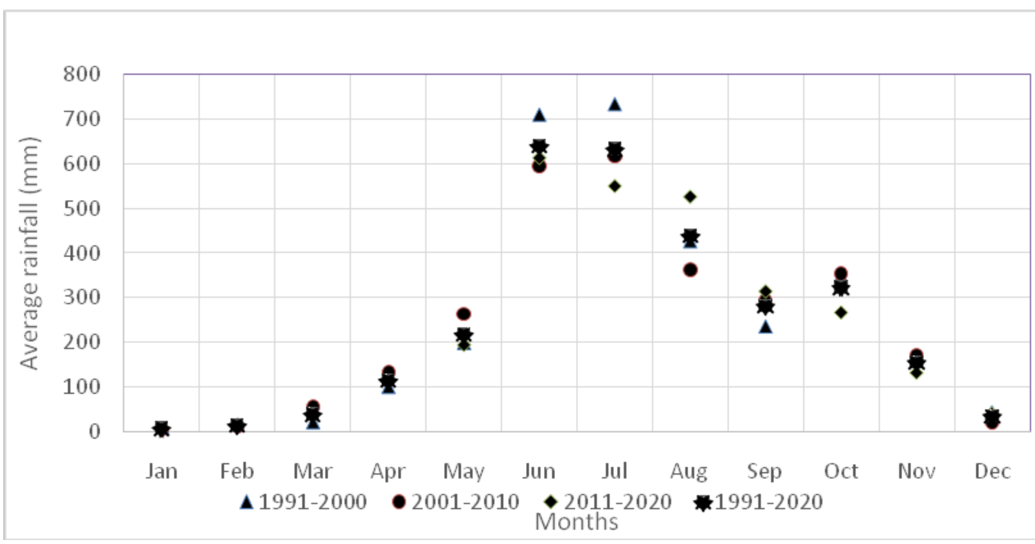

Fig. 2. Monthly rainfall for the period 1991-2020 in Kerala

recorded in the month of June (638.64 mm) followed by July (632.41) whereas the lowest in January (8.52 mm) followed by February (15.83mm). The highest monthly rainfall was recorded in the month of July for the period 1991-2000 (731.91)and 2001-2020 (614.98), in June for 2011-2020 (613.16).

3.3 Forecasting rainfall in Kerala

The rainfall data collected from January 1991 to December 2020 were used to forecast the monthly rainfall in the year 2021and 2022. The time series plot along with decomposition of monthly rainfall from January 1991 to December 2020 is shown in Fig.3.

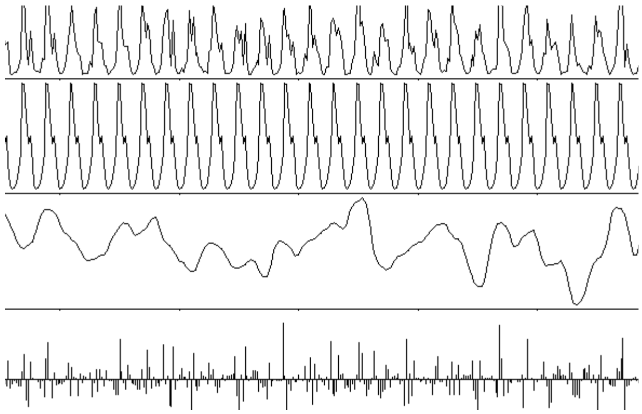

Fig. 3. Decomposed monthly rainfall of Kerala from 1991 to 2020

The time series plot of monthly rainfall for 1991-2020 did not show any increasing or decreasing trend. The normality assumption of the data set was examined using Jarque-Bera test and it showed that the data set does not follow a normal distribution ($p<0.001$). The data showed a nonlinear pattern as per White neural network test ($p=0.001$). In addition, the Mann-Kendall test suggested that the data doesn't show any trend ($p=0.77$). Further, stationarity assumption of data set assessed through ADF test showed the data set as stationary ($p<0.01$).

The whole data set of the period January 1991 to December 2020 (360 data points) was divided into training set and test set. Training set included data from January 1991 to December 2018 (336 data points i.e.93 per cent of data). Test set included data from January 2019 to December 2020 (24 data points i.e.7 per cent of data). Using R software, as per ACF and PACF of the data, different SARIMA models were fitted. The best fitted model was SARIMA $(1,0,1)(0,1,1,)_{12}$ as per the accuracy measures (Table 6). The coefficients of the model along with its standard error is given in Table 7. L-Jung Box test was conducted for examining independence of residuals and it showed that the residuals were uncorrelated ($p=0.9629$). Some of the points in residual ACF chart were lying outside the control limits.

NNAR (p, P, k) [m] models were fitted to the train data set. As it is a seasonal time series; the value of P, which is the number of seasonal lags is taken as one. Accuracy measures for fitted models are shown in Table 8.

Comparing the accuracy measures for test data and trained data the model NNAR (6,1,4)[12] had been chosen as the best model among fitted NNAR

Table 6. Accuracy measures for fitted SARIMA models

		Train data set				Test data set			
Sl.no	SARIMA	RMSE	ME	MAE	MASEE	RMSE	ME	MAE	MASE
1	$(1,0,1)(0,1,1)_{12}$	110.27	-5.85	72.24	0.49	151.58	20.02	90.08	0.63
2	$(0,0,1)(1,1,1)_{12}$	110.40	-4.94	72.85	0.49	153.91	25.81	88.5	0.62
3	$(1,0,1)(1,1,1)_{12}$	110.41	-4.62	72.93	0.49	154.33	26.31	88.53	0.62
4	$(0,0,1)(1,1,0)_{12}$	120.20	0.07	82.6	0.56	159.28	-3.60	103.57	0.72
5	$(0,0,0)(1,1,1)_{12}$	110.68	-5.37	72.92	0.49	153.75	25.57	88.50	0.62

Table 7. The parameters and coefficients of SARIMA$(1,0,1)(0,1,1)_{12}$

	AR1	MA1	Seasonal MA1
Coefficient	0.0355	0.0375	-0.8794
Standard error	0.6049	0.6034	0.0487

Table 8. Accuracy measures for fitted NNAR models

		Train data set				Test data set			
Sl.no	NNAR	RMSE	ME	MAE	MASE	RMSE	ME	MAE	MASE
1	(6,1,4)[12]	94.14	-0.171	64.62	0.64	149.07	14.31	97.14	0.68
2	(8,1,5)[12]	82.41	0.109	55.49	0.55	151.60	10.01	101.16	0.71
3	(5,1,4)[12]	101.80	0.138	68.47	0.68	154.10	14.75	96.21	0.68
4	(14,1,8)[12]	44.22	0.017	29.37	0.29	160.05	13.33	105.29	0.74
5	(13,1,8)[12]	44.86	0.063	30.09	0.31	165.69	8.76	110.37	0.78

models. As per the RMSE of selected SARIMA and NNAR models, NNAR model showed less RMSE for train data and test data. Hence NNAR (6,1,4)[12] was selected for forecasting. L-Jung Box test was conducted for examining independence of residuals intime series data and it showed that the residuals were uncorrelated (p=0.9816). The plot of residuals along with autocorrelation graph and histogram is given Fig.4. Residual ACF graph indicated that residuals were uncorrelated because lag values for residuals lies within the control limit.

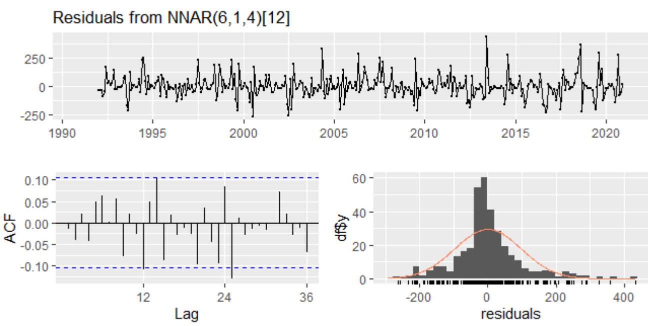

Fig. 4. Residuals plot from NNAR model

Monthly rainfall forecasting for the year 2021 and 2022 with 95 per cent confidence limit are given in Table 9 and Fig.5. During these periods the highest rainfalls in Kerala is predicted in July and lowest in February.

Table 9. Forecasted values of Rainfall in Kerala for 2021 and 2022

	2021			2022		
Month	**Lower limit**	**Forecast**	**Upper limit**	**Lower limit**	**Forecast**	**Upper limit**
January	0*	27.07	241.58	0*	26.68	272.91
February	0*	26.55	263.06	0*	26.50	292.24
March	0*	33.27	379.22	0*	33.11	425.17
April	0*	104.41	500.31	0*	102.65	630.66
May	0*	194.99	743.17	0*	199.82	824.71
June	58.71	634.17	875.02	37.47	636.04	886.28
July	133.91	655.70	873.71	81.04	651.78	862.11
August	94.14	421.85	783.52	69.89	421.61	769.12
September	20.15	299.86	637.60	0*	300.22	668.47
October	0*	301.75	538.52	0*	301.12	534.53
November	0*	223.40	459.83	0*	225.58	464.71
December	0*	28.43	386.83	0*	28.45	395.22

*The value obtained was negative, but as amount of rainfall cannot be less than zero, represented as zero.

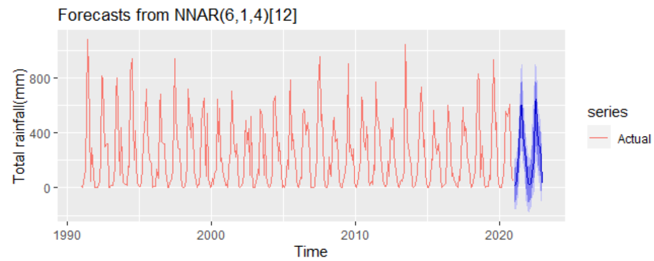

Fig. 5. Monthly rainfall forecastingusing NNARmodel in Kerala

4. CONCLUSION

During the period from 1991 to 2020, the annual average rainfall in Kerala was 2906.79 mm with a standard deviation 377.71 mm and a coefficient of variation (CV) of 12.99 percent. Krishnakumar *et al.* (2009) reported annual average rainfall for the period 1871 to 2005 as 2817mm with a standard deviation of 406 mm. They also reported insignificant trend in rainfall during 1871 to 2005 and commented that a significant declining trend was observed when rainfall data was considered from 1951 to 2005. No significant trend was observed in annual rainfall during 1991 to 2020. The annual average rainfall obtained for 1991 to 2020 was greater than annual average rainfall of 1871to 2005.The highest annual rainfall in Kerala was recorded in the year 2007 (3545.49 mm) and the lowest rainfall was recorded in the year 2016 (1885.44).

Pattern of monthly rainfall in Kerala revealed that the highest monthly rainfall was recorded in the month of June (638.64 mm) followed by July(632.41) whereas the lowest in January (8.52 mm). Similarly Krishnakumar *et al.* (2009) also reported highest rainfall in June (684mm) followed by July (632) and least in January(12mm).

Lama *et al.* (2022) modelled and forecasted rainfall of Sub-Himalayan West Bengal and Sikkim using SARIMA$(1,0,1)(0,1,1,)_{12}$. The SARIMA model of same order with different parameters were obtained as suitable SARIMA model for rainfall series of Kerala. Comparison of SARIMA with Neural Network Autoregressive (NNAR) model revealed that NNAR(6,1,4)[12] was more appropriate than SARIMA model to forecast rainfall as per the accuracy measures obtained. Similarly Pal and Mazumdar (2018) and Bhavyashree and Bhattacharryya (2018) reported NNAR as better than SARIMA for forecasting rainfall. This study recommends use of NNAR model for prediction of rainfall in Kerala. This in turn will help policy makers and farmers for planning agriculture activities and efficient use of water resources.

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