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Research Paper

Assessment of Future Pattern of Rainfall in Different Zones of Kerala Using Incorporation of SARIMA, ANN and Hybrid SARIMA-ANN Models

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ABSTRACT

Agriculture production all over the world is directly influenced by rainfall which is an important weather parameter. The changes in rainfall can cause the failure of crops and even lead to starvation and ruin the economy of a country. The economy of a country becomes inferior due to catastrophic circumstances like floods, drought, and landslides. Thus the prediction of future values with the highest accuracy is very crucial to regulate and avoiding the undesirable influences of instabilities in rainfall. Under current research work, SARIMA, ANN, and hybrid SARIMA-ANN models are applied to identify the future pattern and for availing essential proposals for scheduling agriculture procedures such that variations in rainfall may not affect the economy. The data of monthly rainfall was collected from RARS, Pilicode for the northern zone, RARS, Pattambi for the central zone, and RARS, Vellayani for the southern zone. The results revealed that ANN model predicted future values of rainfall with the highest precision for the northern and central zone, whereas for the southern zone, SARIMA (1,0,1) $(2,0,0)_{12}$ gave anticipated values with more accuracy. The comparison of projected rainfall among different zones indicated that the northern part might receive the highest amount of rainfall, the central zone indicated moderate rainfall, and the southern part of Kerala with the least amount of rainfall. The study also recommended the farmers take necessary safeguards to regulate the adverse influences of fluctuations in rainfall such that it might not affect agricultural production and the economy of the country.

HIGHLIGHTS

- Fluctuations in rainfall affect agricultural production and the economy of the country.
- SARIMA, ANN, and hybrid SARIMA-ANN models are applied to identify the future pattern of rainfall.
- ANN model gave an accurate projection of rainfall in the northern and central zone, whereas SARIMA (1,0,1) $(2,0,0)_{12}$ model gave anticipated values with higher precision in the southern zone.

Keywords: ANN, Economy, Hybrid SARIMA-ANN, RARS, SARIMA

Rainfall is the most important water source for all living organisms in this world. The changes or variations in rainfall can negatively affect the agronomical growth and development of plants and animals. Most of the agricultural crops cultivated in the world are directly influenced by fluctuations in rainfall. The economy of a country can directly be affected by the failure of agricultural crops due to lack of rainfall. The development of the economy of a country is direct gets affected by fluctuations in rainfall and also incidents of disasters like floods, drought, landslides, and even famines. Disasters and famines can lead to the death of a lot of people

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and the destruction of infrastructures. The fast-growing economy gets retarded by the occurrence of calamities and starvation. Thus, the modeling and prediction of rainfall with maximum precision are important for determining future changes in rainfall and also for undertaking necessary precaution measures to minimize the damage caused by changes in rainfall for human beings, crops, livestock, infrastructure, and the economy of the country.

The main crops cultivated in India are rice, wheat, millet, maize, pulses, sugarcane, tea, coffee, rubber, cotton, jute, and various horticultural crops. Most of the cultivated crops in India require a high amount of water, especially rice, sugarcane, cotton, banana, and pineapple. Lack of sufficient water can lead to the failure of crops (Kumar and Parikh 2001; Birthal *et al*. 2014), which require a high amount of water for their growth and development. The failure of crops like rice and wheat leads to famine in India since most of the people in different parts of India consider it as the primary source of a balanced diet. India is a developing country in which agriculture plays a fundamental part in the economic advancement of the country. It is an important fact that almost 60 percent of India's population is working in agriculture and allied sectors. The disturbances in agriculture production due to the absence or deficiency of rainfall can affect the economic growth of the country (Sagar *et al.* 2018). The gross domestic product also falls (GDP) due to failures in agriculture production due to fluctuations in rainfall. Thus, the projection of future rainfall is a fundamental process since it helps in undertaking necessary precautions for decreasing the damage because of changes in rainfall on agriculture production and also to nullify the undesirable impacts on the economy.

The seasonal autoregressive integrated moving average (SARIMA) model is applied for projecting future values of weather parameters with high precision (Shamsnia *et al.* 2011). The monthly rainfall in Iran was fitted using ARIMA model for accessing the patterns over the years, and the seasonal behavior of rainfall was recognized using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots (Soltani *et al.* 2006). Comparison study was conducted by Jain and Mallick (2017) using ARIMA and Exponential Smoothing (ETS) for predicting different weather parameters, and the evaluation of models was done according to the most negligible value for mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute scale error and root mean square error (RMSE). Murthy *et al.* (2018) applied SARIMA model for projecting future values and determining the configuration of the South-West monsoon in North–East India. The outcomes revealed that the suitable model for projecting the rainfall was SARIMA (0,1,1) $(1,0,1)_4$ and the model also helped in analyzing and forecasting the future rainfall patterns accurately. Box-Jenkins ARIMA model was fitted for precipitation at Jordan (Al Balasmeh *et al.* 2019) for the data of 44 years such that evaluation of the model was undergone using the last 10 years' data (2007-2016), and after completing the evaluation precipitation was projected for the next 10 years (2017-2026). Dimri *et al.* (2020) applied SARIMA model to determine future values of rainfall and maximum and minimum temperatures for the data collected from Uttarakhand for 100 years (1901-2000), and the outcomes disclosed that the best SARIMA model identified for rainfall is SARIMA (0,1,1) $(0,1,1)_{12}$ whereas, for maximum and minimum temperature, it was SARIMA (0,1,0) $(0,1,1)_{12}$ and enhanced water administration decisions based on guidance obtained from the estimated model.

Artificial neural network (ANN) is an important method for undergoing time series forecasting of various phenomena. The rainfall-runoff was predicted by employing ANN with multiple layer perceptron (MLP), and the outcomes are related to other models and results suggested that ANN with MLP gave much more accurate outcomes for a more extended period (Anctil *et al.* (2004)). The anticipated values of rainfall in Thailand were determined with the help of feed-forward ANN by Hung *et al.* (2008), and results using ANN also gave meaningful recommendations for minimizing the harmful effects of the flood. ANN and multiple linear regression (MLR) models were used by El-Shafie *et al.* (2011) for projecting future values of rainfall for also determining the uncertainties in rainfall at Egypt, and a suitable model for prediction was selected based on RMSE, MAE, and coefficient of correlation and bias such that the result concluded that ANN model was much superior in projecting the values. The heavy rainfall in Bangladesh was forecasted using ANN model by Islam *et al.* (2016), and the study concluded that fluctuations in rainfall created problems in determining the pattern. Shamshad *et al.* (2019) applied ANN-MLP, ARIMA, and ETS models to attain future values of weather parameters in Pakistan 30 year monthly data (1987-2016). The outcomes conveyed that ANN-MLP outclassed other models.

Hybrid models are employed for predicting various phenomena because of its ability to consider the linear and non-linear nature of the data. The process of determining future values by considering the linear and non-linear nature of the data enhanced the accuracy of the models. Shi *et al.* (2012) fitted ARIMA-ANN and ARIMA-SVM hybrid models for calculating future values of wind speed to improve the accuracy of prediction, and results revealed that two hybrid models gave better forecasting of wind speed compared to individual ARIMA, ANN, and support vector machine (SVM) models. The precipitation of Iran was predicted by Shafaei *et al.* (2016) with the help of the wavelet SARIMA-ANN model for increasing the precision by addressing the non-linear nature of the data, and the results indicated that wavelet SARIMA-ANN model outpaced wavelet SARIMA and wavelet ANN models. The seasonal variation of the inflow of water in a dam reservoir in Iran was determined by Moeeni and Bonakdari (2017) with the help of the hybrid SARIMA-ANN model, and it was related to individual SARIMA and ANN models, and results suggested that the hybrid model is showing superior performance in predicting future flood runs and the results also advocated to take necessary precaution measures with ultimate stand flood runs. Parviz and Rasouli (2019) applied a hybrid SARIMA-ANN model along with sub-seasonal clustering for calculating the future values of rainfall in different regional stations in Iran, and the application of hybrid methods helped to resolve the problem of temporal and spatial fluctuations of rainfall which improved precision of the hybrid model. The level of water in the reservoir was projected using SARIMA-ANN hybrid model by Azad *et al.* (2022) for accessing the pattern of change in climatic conditions and also for determining the temporal and spatial discrepancies and outcomes of the study indicated that the hybrid model gave projection level of water in the reservoir with more precision.

Most of the studies are conducted in agriculture by determining the effect of changes in weather parameters and its influences on specific crops using various models (Mishra *et al.* 2017; Laitonjam *et al.* 2018; Ranjan *et al.* 2020 and Mishra *et al.* 2021). However, in this study, different models are used for forecasting the rainfall for the next 5 years to determine its future changes rather than considering the impacts of the inconsistency of rainfall on a specific crop. The different models employed for forecasting rainfall at different zones were SARIMA, ANN, and a hybrid model incorporating both SARIMA and ANN models (SARIMA-ANN).

Fig. 1: Plot of Area under research for determination of rainfall pattern in northern, central and southern zones of Kerala

MATERIALS AND METHODS

Study Area and Data collection

The ultimate aim of the research work was to determine the rainfall fluctuations with the help of the application of SARIMA, ANN, and hybrid SARIMA-ANN models in various zones of Kerala. The research was conducted to access information about the level of changes in rainfall and also to find the best method for modeling and forecasting the rainfall in different zones of Kerala. The monthly rainfall data is received from three different parts, the northern, central, and southern zones of Kerala.

The data for the northern region is collected from the regional agricultural research station (RARS), Pilicode, Kasaragod district of Kerala. The data was collected for 39 years (1982-2020). The climatic condition of Pilicode, which belongs to the northern region, is humid, with an annual rainfall of 3379mm. The major crops grown in the northern region of Kerala are coconut, coffee, cashew, rice, oil seeds, and pepper.

Monthly rainfall data in central zones of Kerala was received for 39 years (1982-2020) from RARS, Pattambi, which belongs to the Palakkad district of Kerala. The climate of the central zones of Kerala is hot throughout the year and has a total rainfall of 1838. The chief crops cultivated in the central zones of Kerala are rice, coconut, fruits, vegetables, etc.

The data for 36 years (1985-2020) was collected from RARS, Vellayani. Vellayani is part of Trivandrum, the southernmost district of Kerala. The southern zones have a humid and warm climate with an average rainfall of 1704mm. The main crops developed in the southern zones of Kerala are rice, coconut, horticulture crops, etc.

Methodology

Time series analysis is the process of examining a phenomenon by collecting chronological data over a specific period of time. The important point noted is that data from a specific period of time were collected in a sequential order rather than randomly collected from different periods of time. In this study, the different methods, including SARIMA, ANN, and hybrid SARIMA-ANN models, are fitted for rainfall data to understand the variations over the years for the data received from different zones of Kerala.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

Box-Jenkins (1976) developed SARIMA model, which is an extension of ARIMA model, which is symbolized as (p,d,q) $(P,D,Q)_s$. The SARIMA model consists of two components, seasonal and non-seasonal, which are represented as (p,d,q) and $(P,D,Q)_s$ separately. The indication of both seasonal and non-seasonal components is almost the same where autoregressive (p,P), number of differencing to attain stationary (d,D), moving average (q,Q), and periodicity of the data are denoted respectively (S).

The SARIMA model is mathematically expressed as:

$$\phi_p(B)\Phi_P(B^S)\nabla^d\nabla_S^D Y_t = \Theta_Q(B^S)\theta_q(B)\varepsilon_t \quad \ldots(1)$$

Where,

$$\phi_p(B) = 1-\phi_1 B-\ldots-\phi_p B^p, \Phi_p(B) = 1-\Phi_1 B^S-\ldots\Phi_p B^{SP},$$
$$\Theta_Q(B^S) = 1-\Theta_1 B^S-\ldots-\Theta_Q B^{SQ}, \theta_q(B) = 1-\theta_1 B-\ldots\theta_p B^q$$

and the different symbols used in the equations are ε_t for the residual term, Φ and ϕ for representing seasonal and non-seasonal autoregressive terms, Θ and θ indicate the seasonal and non-seasonal moving average terms (Nirmala and Sundaram, 2010).

Test for stationary

The property of stationary is required for undertaking fitting of the SARIMA model for time series data. The time series data consists of constant mean, and variance is termed as stationary, and the absence or presence of this property is identified by applying Augmented Dickey Fuller (ADF) test. The ADF test is described below as:

H_0: Unit roots are present, or stationarity of time series data is absent ($\gamma = 0$)

H_1: Unit roots are absent, or stationarity of time series data is present ($\gamma = 0$)

The test statistic for ADF test is:

$$DF_\tau = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \quad \ldots(2)$$

H_0 is rejected if the DF value is higher than the critical value or else it is accepted.

Criteria of Model Selection

The minimum value of Akaike information criterion (AIC), Akaike information corrected criterion (AICC) and Bayesian information criterion (BIC) are the criterion employed in this study for the selection of suitable SARIMA models for weather parameters at different zones of Kerala.

$$AIC = -2\times \ln(L) + 2\times k \quad \ldots(3)$$

$$BIC = -2\times \ln(L) + 2\times \ln(N)k \quad \ldots(4)$$

$$AICC = -2\times \ln(L) + 2\times k + \frac{2k(k+1)}{N-k-1} \quad \ldots(5)$$

Where L is the likelihood value, N is the number of documented measurements and k is the number of assessed parameters.

Diagnostic Checking of Model

Diagnostic checking of fitted SARIMA models is conducted to ensure the absence of autocorrelation among the residuals. The presence or absence of autocorrelation among residuals is determined using the Ljung-Box test. The absence of autocorrelation between residuals obtained after fitting the SARIMA model ensured the quality of the selected model. The Ljung-Box test is described as the following:

H_0: The autocorrelation is not existed among residuals

H_1: Autocorrelation exists among residuals

The Ljung-Box test is mathematically expressed as:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \quad \ldots(6)$$

The total number of measurements is n, $\hat{\rho}_k$ is the autocorrelation amongst the error terms at lag k and m is the number of tested lags (Roy and Das, 2012).

Artificial Neural Network (ANN)

The ANN is established mainly by undertaking motivation from the working of neural networks controlled by the human brain. The ANN has broad-level applications in various fields, including the processing of speech, prediction of future values, regulation of robotics, the rectification of images, acknowledgment of patterns of any phenomenon, etc. A simple ANN is made up of three important layers, input, hidden, and output layers which are interconnected and also comprise an activation function (Lippmann, 1987). The current research work focuses on applying an ANN model for predicting future rainfall such that input nodes are made up of past rainfall data, hidden layers, and output nodes consist of projected future values of rainfall.

Rumelhart *et al.* (1986) conveyed that a significant progression in the usage of ANN was the implementation of back propagation algorithms, which were created in the initial 1970's and in the early 1980's, it became the most standard neural network. The projection of future values using ANN model for data embraces complex structure and is mainly carried out with multi-layer perceptron (MLP). The ANN model employed in this study consists of a feed forward back propagation (FFBP) algorithm with multi-layer perceptron (MLP) neurons such that input and output sets are related.

ANN with feed-forward MLP neural network is mathematically expressed as:

$$\hat{z}_t = \beta_0 + \sum_{j=1}^{q}\beta_j f\left(\gamma_{0j} + \sum_{i=1}^{p}\gamma_{ij} z_{t-1}\right) + \varepsilon_t \quad \ldots(7)$$

Where, p inputs values are indicated as z_{t-1}, output is expressed as $\hat{z}_t$, β_j $(j = 0,1,2,\ldots,q)$ and specifies connection weights are stipulated as γ_{ij} ($i = 0,1,2,\ldots\ldots,$ p; $j = 0,1,2,\ldots q$) and error terms are represented as ε_t. The p and q is used to designate number of inputs and hidden nodes respectively, β_0 and γ_{ij} are constant terms and the activation function is specified as f (Waciko and Ismail, 2020). The Fig. 2 depicted with ANN with MLP (MLPNN) comprises 23 input nodes, 5 hidden layers and an output.

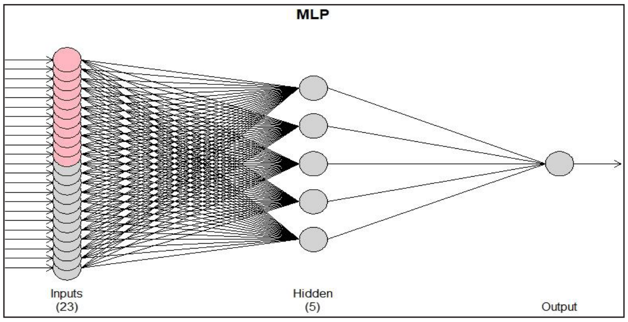


Fig. 2: Architecture of ANN with MLP

SARIMA-ANN hybrid model

The time series data comprises both linear and non-linear parts. The SARIMA-ANN hybrid model is developed so that the SARIMA model illustrates the linear part, whereas the non-linear part is explained by the ANN model (Zhang (2003)).

SARIMA-ANN hybrid model is mathematically expressed as:

$$Y_t = L_t + N_t \qquad \dots(8)$$

Where estimated time series values are symbolized as Y_t, linear part is expressed as L_t the andnon-linear part is indicated as N_t. The estimated values from both SARIMA and ANN models are combined to establish the SARIMA-ANNhybrid model.

Evaluation and Endorsement of the Models

The evaluation of the models used in the study was undertaken by calculating MSE, RMSE, and MAE among the projected $(\hat{y}_i)$ and actual (y_i)values and n number of observations..

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \qquad \dots(9)$$

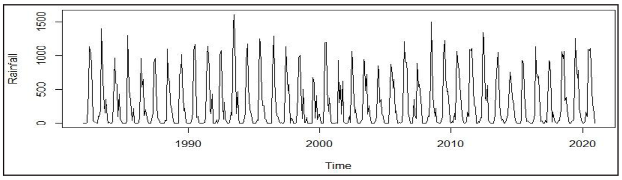
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \qquad \dots(10)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(y_i - \hat{y}_i\right)\right| \qquad \dots(11)$$

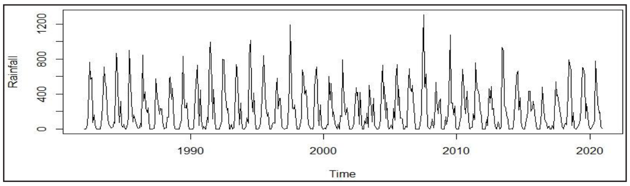
RESULTS AND DISCUSSION

The research work was conducted to determine the pattern of rainfall over the years and also predict the future values of rainfall by fitting SARIMA, ANN, and hybrid SARIMA-ANN models using R software for different zones of Kerala. The trend plots of rainfall in different zones of Kerala are depicted in Fig. 3.

(a) Northern Zone



(b) Central Zone



(c) Southern Zone

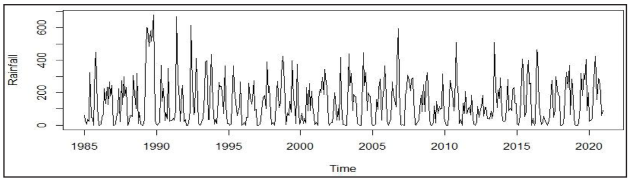


Fig 3: Trend plots for rainfall in various zones of Kerala

The trend plots of rainfall in different zones of Kerala pictured in Fig. 3 indicated seasonal fluctuations over the years. In order to determine the pattern of rainfall and also to estimate the future values with high precision, the whole monthly data is split into two parts, training and testing sets. The training set of the northern and central zones is for 34 years (1982-2015), and for the southern zone, it was for 31 years (1985-2015). The training sets of each zone were for 5 years (2016-2020). The SARIMA model is fitted to time series data only after ensuring that the data is stationary. ADF test was conducted to check whether monthly rainfall data is stationary. The results ofthe ADF test are described in Table 1.

Table 1: Results of ADF test statistics on rainfall in different zones of Kerala

Weather Parameter	Zone	Test Statistic	P value
	Northern	-15.66	0.01
Rainfall	Central	-14.49	0.01
	Southern	-8.69	0.01

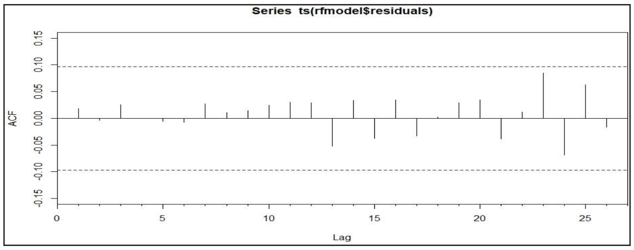
The ADF test results displayed in Table 1 confirmed that monthly data of rainfall from different zones of Kerala is stationary. After confirming that rainfall data is stationary, the next step is fitting of the SARIMA model. The assortment of SARIMA models suitable for rainfall data is based on least value for AIC, AICC, and BIC. The selected SARIMA model and parameters, along with model selection criteria, are illustrated in Table 2.

Table 2: Best SARIMA model selected based on criteria of selection along with its parameters for rainfall in different zones of Kerala

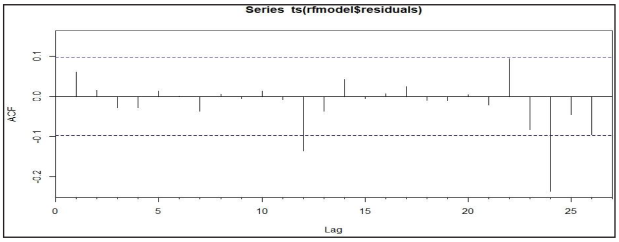
Zone	Model	Parameters	AIC	AICC	BIC
Northern	SARIMA (0,0,0) $(2,1,0)_{12}$	sar1 -0.7509 sar2 -0.3121	5263.49	5263.55	5275.43
Central	SARIMA (0,0,0) $(1,1,0)_{12}$	sar1 -0.5949	5048.43	5048.46	5056.39
Southern	SARIMA (1,0,1) $(2,0,0)_{12}$	ar1 0.5995 ma1 -0.3053 sar1 0.3154 sar2 0.2782	4585.21	4585.44	4608.72

The results placed on Table 2 consist of the best performing SARIMA model with the least value for various criteria for the selection of the model. Next step is checking the performance of the SARIMA model fitted by determining ACF plots for residuals. The ACF plots of residuals for different zones of Kerala are depicted in Fig. 4.

(a) Northern Zone



(b) Central Zone



(c) Southern Zone

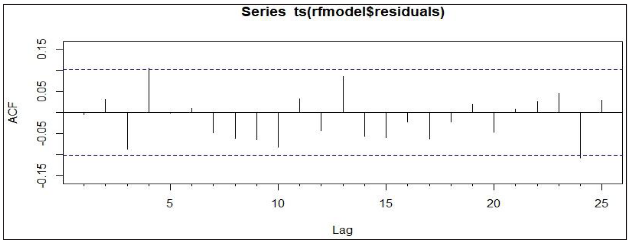


Fig. 4: Residual ACF plots for rainfall in different zones of Kerala

The residual ACF plots indicated in Fig. 4 suggested that there is a non-appearance of autocorrelation between error terms. The Ljung-Box test was also undertaken to confirm the absence of autocorrelation among error terms and results are depicted in Table 3.

Table 3: Ljung-Box test results for different rainfall zones of Kerala

Weather Parameter	Zone	Q Statistic	P value
Rainfall	Northern	11.87	0.96
	Central	29.32	0.89
	Southern	30.27	0.30

The results displayed in Table 3 clearly established that autocorrelation is absent among the residuals. After completing the SARIMA model, the next step is the application of the ANN model for projecting the rainfall. The R software was again applied for fitting ANN with MLP neural network model for the rainfall in different zones of Kerala, and the results are illustrated in Table 4.

Table 4: MLPNN architecture for rainfall in different zones of Kerala

Zone	Model	Architecture
Northern	ANN	22-5-1
Central	ANN	23-5-1
Southern	ANN	23-5-1

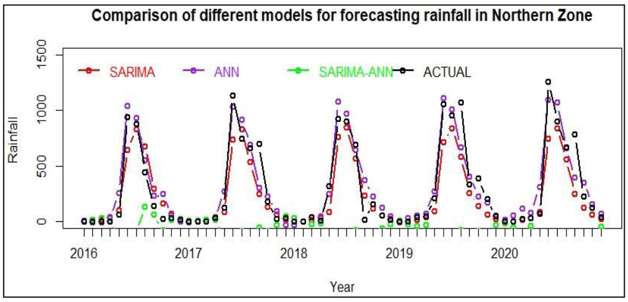
The architecture of ANN model for rainfall in different zones of Kerala is depicted in Table 4. After completing the fitting of ANN and obtaining the architecture of the model, the next step is the fitting of the SARIMA-ANN model. The hybrid model is applied in such a way that the residuals obtained from SARIMA model is fitted with ANN model. The architecture of the MLPNN model fitted for residuals is illustrated in Table 5.

Table 5: MLPNN architecture for residuals obtained from SARIMA model for rainfall in different zones of Kerala

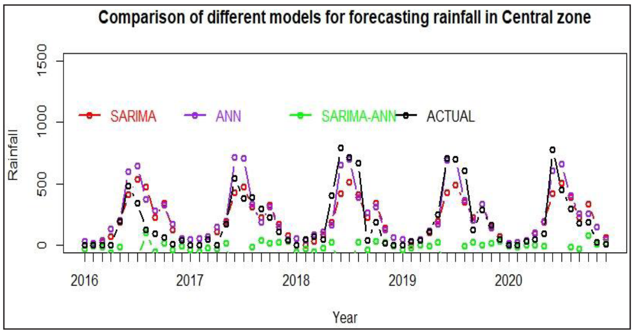
Zone	Model	Architecture
Northern	ANN	11-5-1
Central	ANN	11-5-1
Southern	ANN	23-5-1

The architecture of ANN for residuals obtained from SARIMA is portrayed in Table 5. After completing the fitting of the SARIMA, ANN, and hybrid SARIMA-ANN model, the next step is plotting the projected values and comparing it with the actual values in the testing set for a period of 5 years (2016-2020) and depicted in Fig. 5.

(a) Northern Zone



(b) Central Zone



(c) Southern Zone

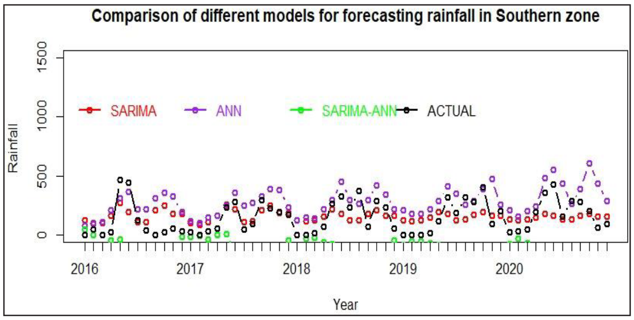


Fig. 5: Comparison of actual and projected rainfall in different zones of Kerala

The comparison plots depicted in Fig. 5 clearly suggest that in the northern (a) and central (b) zone ANN is showing values almost near to the actual values, whereas in the southern (c) zone SARIMA model is almost colliding with the actual values. In order to confirm the suggestions from the plot among projected values and actual values, evaluation of the models by calculating MSE, RMSE, and MAE was undergone and displayed in Table 6.

Table 6: Evaluation of models fitted for rainfall for each zones of Kerala

Zone	Model	MSE	RMSE	MAE
Northern	SARIMA	29697.804	172.330	102.312
	ANN	**17004.85**	**130.40**	**84.76**
	SARIMA-ANN	31580.64	177.71	110.91
Central	SARIMA	18612.328	136.427	94.495
	ANN	**15910.49**	**126.13**	**90.92**
	SARIMA-ANN	23979.94	154.85	129.87
Southern	**SARIMA**	**14783.950**	**121.589**	**105.466**
	ANN	29273.07	171.09	145.58
	SARIMA-ANN	20565..4	143.40	120.15

The performance authentication of the models recommended that ANN is outperforming the model in projecting future values of rainfall in northern and central zones, whereas in the southern zone, SARIMA is designated as the most accurate model. The rainfall is projected for next five years (2021-2025) in different zones of Kerala using the respective best-selected models, and it is depicted in Fig. 6.

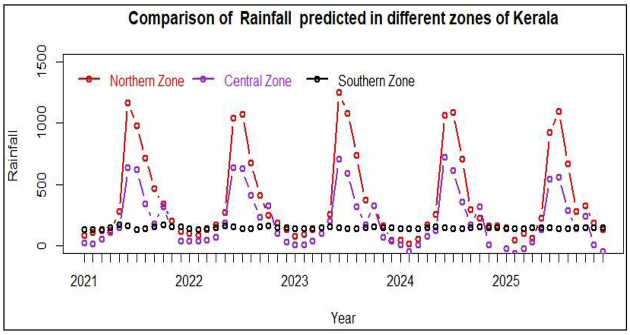


Fig. 6: Projection of future rainfall among different zones of Kerala

The anticipated rainfall using the ANN model in the northern and central zone, along with values of rainfall in the southern zone using SARIMA is related and displayed in Fig. 6. The plot suggested that severe rainfall will occur in the northern zone compared to the central and southern zone. The central zone is predicted to moderate rainfall, whereas in the southern zone, comparatively smaller rainfall is forecasted for next 5 years. The plot also suggested that the southern zone of Kerala will have constant rainfall all over the years without much variation. The farmers undergoing cultivation in the northern part of Kerala must take necessary actions to limit the damages due to heavy rainfall predicted for the northern zone of Kerala.

The central zone will have moderate rainfall which shows a decreasing nature in the final years; the farmers must ensure that there is no lack of rainfall for proper conduction of agricultural production. The rainfall in the southern zone is anticipated with smaller rainfall over the years, such that water must be stored properly using canals and check dams to maintain water requirements in the field. The agricultural practices are highly dependent on rainfall for undertaking production, and if there is fluctuations in rainfall, it can lead to the failure of crops and can affect the economy of the country. The study suggested that even though a hybrid model was applied for modeling the rainfall, single models like ANN and SARIMA gave more accurate results. The study also encourages the application of more models such that the prediction of rainfall is possible with the least amount of error values and much better accuracy. Forecasting with more precision helps to take necessary precautions to control the fluctuations in rainfall and not affect the agriculture production and economy of the country.

CONCLUSION

Rainfall is an important weather parameter that influences agriculture production all over the world. The fluctuations or variations in rainfall can lead to the failure of crops and even lead to famines and the destruction of the economy of a country. The disastrous situations like floods, drought, and landslides can make the economy of a country even worse. Thus projection of future values with maximum efficiency is very essential to control and prevent the negative impacts of fluctuations in rainfall. Under this research work, SARIMA, ANN, and hybrid SARIMA-ANN models are applied to determine the future pattern and to avail necessary suggestions for planning future agriculture operations such that fluctuations in rainfall may not affect the economy. The rainfall data were collected from RARS, Pilicode for the northern zone, RARS, Pattambi for the central zone, and RARS, Vellayani for the southern zone. The monthly data was collected for a period of 39 years (1982-2020) for the northern and central zone, whereas for the southern zone, data was collected for 36 years (1985-2020). The results advocated that for the northern and central zone, ANN model projected future values with the highest precision, and for the southern zone, SARIMA (1,0,1) $(2,0,0)_{12}$ gave forecasting with more accuracy. The comparison of projected rainfall among different zones indicated that the northern part would receive the highest amount of rainfall, the central zone indicates moderate rainfall, and the southern part of Kerala will receive the least amount of rainfall. The study also suggested that farmers should take necessary safeguards to control the negative impacts of fluctuations in rainfall such that it might not affect agricultural production and the economy of the country. The study also encourages the researchers to include other weather parameters for the study and also use various other single and hybrid models for understanding the pattern and determination of future values with higher precision.

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