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# Weather forecasting and modeling using SARIMA, ANN and hybrid model for central zone of Kerala

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**सार** – मौसम संबंधी मापदंडों का पूर्वानुमान लगाना विश्वभर के वैज्ञानिकों के प्रमुख उद्देश्यों में से एक है। मौसम संबंधी मापदंडों का पूर्वानुमान लगाना महत्वपूर्ण है क्योंकि इससे जलवायु परिवर्तन के कारण होने वाली प्राकृतिक आपदाओं के प्रभाव को नियंत्रित करने और हानिकारक प्रभावों को कम करने के लिए एहतियाती उपाय करने में मदद मिलती है। कृषि गतिविधियों में भी मौसम संबंधी मापदंडों का पूर्वानुमान महत्वपूर्ण है क्योंकि विभिन्न फसलें, बुवाई से लेकर कटाई तक, वर्षा, तापमान और सापेक्ष आर्द्रता जैसे कारकों पर निर्भर करती हैं। वर्तमान अध्ययन का मुख्य उद्देश्य केरल के मध्य क्षेत्र के लिए वर्षा, अधिकतम और न्यूनतम तापमान, सापेक्ष आर्द्रता, बादल घनत्व और पवन गति जैसे मौसम संबंधी मापदंडों का सटीक मॉडलिंग और पूर्वानुमान करना था। इस अध्ययन में केरल के पलक्कड़ जिले में स्थित आरएआरएस पट्टाम्बी से प्राप्त मासिक मौसम डेटा (जिसमें वर्षा, अधिकतम और न्यूनतम तापमान शामिल हैं) और उसी स्थान से 39 वर्षों (1982-2020) की अवधि के लिए डेटा एक्सेस व्यूअर का उपयोग करके प्राप्त सापेक्ष आर्द्रता, बादल घनत्व और पवन गति से संबंधित डेटा का उपयोग किया गया। मौसम संबंधी मापदंडों के मॉडलिंग के लिए उपयोग की जाने वाली विधियाँ SARIMA (सीजनल ऑटोरेग्रेसिव इंटीग्रेटेड मूविंग एवरेज), ANN (आर्टिफिशियल न्यूरल नेटवर्क) और हाइब्रिड SARIMA-ANN मॉडल हैं। प्रत्येक मौसम संबंधी मापदंड के लिए उपयुक्त सर्वोत्तम मॉडल की पहचान करने हेतु तुलना माध्य वर्ग त्रुटि (MSE), मूल माध्य वर्ग (RMSE), माध्य निरपेक्ष त्रुटि (MAE) और निर्धारण गुणांक ($R^2$) के आधार पर की गई। त्रुटि का न्यूनतम मान और निर्धारण गुणांक का उच्चतम मान दर्शाने वाले मॉडल को सर्वोत्तम मॉडल के रूप में चुना गया। परिणामों से पता चला कि मौसम संबंधी मापदंडों के लिए विभिन्न मॉडलों का प्रदर्शन सर्वोत्तम रहा। अध्ययन के निष्कर्षों के अनुसार, वर्षा के अनुमानित मानों का पूर्वानुमान लगाने के लिए ANN मॉडल सबसे सटीक मॉडल है। न्यूनतम तापमान और बादल घनत्व के पूर्वानुमान के लिए हाइब्रिड SARIMA-ANN मॉडल को सर्वोत्तम चुना गया, जबकि अधिकतम तापमान, सापेक्ष आर्द्रता और पवन गति के लिए क्रमशः SARIMA, SARIMA और SARIMA मॉडल सर्वोत्तम हैं। सर्वोत्तम रूप से फिट किए गए मॉडल का उपयोग अगले 5 वर्षों के लिए मौसम संबंधी मापदंडों के पूर्वानुमान हेतु किया गया।

**ABSTRACT.** The forecasting of weather parameters is one of the main objectives faced by scientists all over the world. Predicting weather parameters is important because it helps control the effect of natural calamities due to climate change by taking precautionary measures to manage the harmful effects. The forecasting of weather parameters is also important in agriculture activities since various crops, from sowing to till harvesting, clearly depend upon factors like rainfall, temperature and relative humidity. The prime focus of the current study was to undergo modeling and forecasting of weather parameters such as rainfall, maximum and minimum temperature, relative humidity, cloud content and wind speed with maximum accuracy for the central zone of Kerala. The monthly weather data including rainfall, maximum and minimum temperature obtained from RARS Pattambi in Palakkad district of Kerala and data including relative humidity, cloud content and wind speed using data access viewer from the same location over 39 years (1982-2020). The methods for modeling the weather parameter are SARIMA (Seasonal Autoregressive Integrated Moving Average), ANN (Artificial Neural Network) and hybrid SARIMA-ANN models. The comparison for identifying the best model suitable for each weather parameter was selected based on mean square error (MSE), root mean square (RMSE), mean absolute error (MAE) and coefficient of determination (R^2). The model showing the least value for error and the highest value for coefficient of determination was selected as the best model. The results revealed that weather parameter showed the best performance for different models. According to the findings of the study, the ANN model is the most accurate model for projecting anticipated values of rainfall. The best model selected for forecasting minimum temperature and cloud content was the hybrid SARIMA-ANN model whereas, for maximum temperature, relative humidity and wind speed are SARIMA , SARIMA and SARIMA respectively. The best-fitted model was employed for forecasting weather parameters for the next 5 years.

**Key words** – ANN, RARS Pattambi, SARIMA, SARIMA-ANN, Weather parameter.

## 1. Introduction

The climate around the world is unpredictably changing over the years. The weather parameters across the world are showing unexpected behavior due to human-made disturbances. Different parts of the world over the years have shown an uneven distribution of rainfall. Global warming, which is due to greenhouse effects, led to an increase in temperatures over the last decades. Due to climate change, drastic events like floods, droughts, cyclones, tsunamis, etc. frequently occur in many different places of the world. Climate change has led to imbalances in nature and it can have harmful effects on the lives of people all over the globe.

Natural calamities have also occurred in various parts of India. In November 2015, Chennai, Tamil Nadu suffered from a serious flood which led to the loss of more than 300 people and 60 lakh people were displaced. The flood also caused severe damage to infrastructure; the estimated loss was more than 150 billion. The agriculture and allied sectors also suffered due to the food, almost 3.47 lakh hectares of agricultural crops and 35,471 hectares of horticultural crops; roughly 98,000 livestock animals and poultry have died in the states (Yasmoon and Saud, 2017; Seenirajan *et al*., 2017). In August 2018 and 2019, Kerala also suffered from floods for two consecutive years which disturbed the daily livelihoods of different people living in different parts of the state. It was recorded that in the 2018 flood, over all the 14 districts of Kerala, 483 died 140 were missing and over 10 lakh people were evacuated and sheltered in public welfare houses (Mishra and Shah, 2018). According to the Kerala government floods and other related events have directly affected one-sixth of the state's population. It was also considered as the worst flood which occurred in Kerala after the great flood of 19 happened in 1924. Later, the Indian government declared that the Kerala flood of 2018 was a level 3, a calamity of severe nature. The Kerala flood of 2019 also caused severe damage, over 121 people died and more than 2 lakh people were directly influenced and transferred to public relief camps (Ali and George, 2022). The flood mainly affected districts of central and northern Kerala. In May 2020, the Amphan cyclone struck various portions of West Bengal and Orissa, which led to a severe devastating impact on the infrastructure, livelihood of people and many people died and got injured (Chatterjee and Roy, 2022). The Amphan cyclone caused damage of 14 billion and there was a fatality of 98 people throughout India.

The main reasons for natural calamities are due to human activities which disturb the balance of the ecosystem. The emission of greenhouse gases, deforestation, pollution caused by industries and vehicles, and CFCs released by refrigerators caused drastic climate changes which led to uneven rainfall, a rise in global temperature and also the melting of polar ice. Under such circumstances, it is mandatory and crucial to predict the weather parameters with maximum precision. The prediction or forecasting of weather parameters started in the 19$^{th}$ century (Ahmad *et al*., 2013). The forecasting of weather parameters was carried out in such a way that a huge amount of previous data about atmospheric parameters prevailed in the particular place would be collected for a long period and by using this data the future values can be predicted. The rainfall prediction would help to undergo proper precautions to minimize the damage caused by heavy rainfall or scarcity of rainfall. The agriculture sector and the production of various agricultural commodities also directly depend on weather prediction. Many agriculture and allied sectors are affected by changes in rainfall, temperature, relative humidity and solar radiation. The prediction of weather parameters can help farmers take necessary actions to control crop failures (Dash *et al*., 2007). The forecasting of weather parameters was undergone by using different methods like ANN, SARIMA, support vector machine (SVM), exponential smoothing (ETS) and multiple linear regression (MLR). The forecasting of meteorological data for different areas has become more important for researchers in the last decades (Choubin *et al*., 2016).

Different scientists have employed various types of methods for modeling weather parameters all over the world. The main aim of researchers was to develop the model and to undergo the forecasting with maximum accuracy since weather data showed high fluctuations. Goswami *et al.* (2017) conducted a study in Dibrugarh in Assam and the results showed that SARIMA $(2,1,1)(0,1,1)_{12}$ was the most effective model for both maximum temperature and minimum temperature. Murthy *et al.*, (2018) investigated minimum and maximum temperatures and concluded that SARIMA $(1,0,0)(0,1,1)_{12}$ was chosen as the top-performing model based on minimum BIC value. Dimri *et al*., (2020)

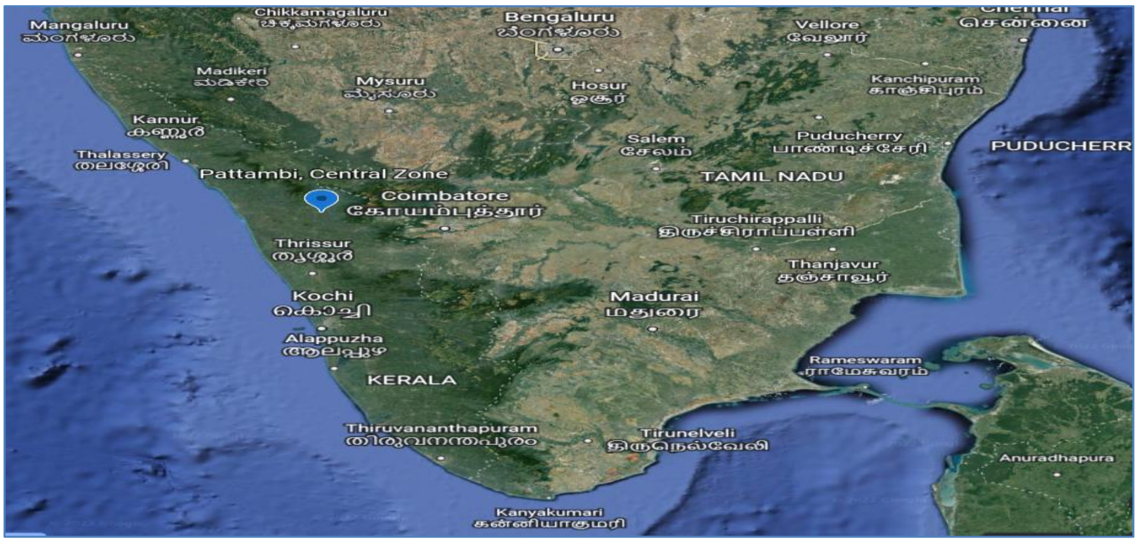



**Fig.** 1. Study Area map indicating Pattambi region of the central zone of Kerala (Source: : NASA. Power Data Access Viewer).

completed a study about weather parameters and showed that the best SARIMA model detected for rainfall, maximum and minimum temperature were SARIMA $(0,1,1)(0,1,1)_{12}$, SARIMA $(0,1,0)\,(0,1,1)_{12}$ and SARIMA$(0,1,0)(0,1,1)_{12}$ respectively.

Hayati and Mohebi (2007) undergo prediction of temperature and results revealed that ANN with MLP forecasting was accurate. Kumar and Jha, (2013) investigated weather forecasting and results based on MSE indicated that ANN with MLP has high precision. Dwivedi *et al.*, (2019) conducted a comparison study between SARIMA and ANN method and results revealed that the ANN outperformed the SARIMA model. Shamshad *et al*. (2019) investigated weather forecasting using ANN with MLP, ARIMA and ETS model and results revealed that ANN with MLP provided better results.

Shi *et al.* (2012) investigated evaluating wind speed by applying a hybrid forecasting approach using ARIMA-ANN and ARIMA-SVM with single models ARIMA, ANN and SVM and the results indicated that hybrid models are more accurate in forecasting wind speed. Mukaram and Yusof (2017) investigated solar forecasting using SARIMA-ANN and according to the outcomes of the study, the hybrid model performed much better than single models. Parviz and Rasouli (2019) conducted a forecasting of rainfall combining SARIMA-ANN with sub-seasonal clustering and the results revealed that the new hybrid model was more accurate.

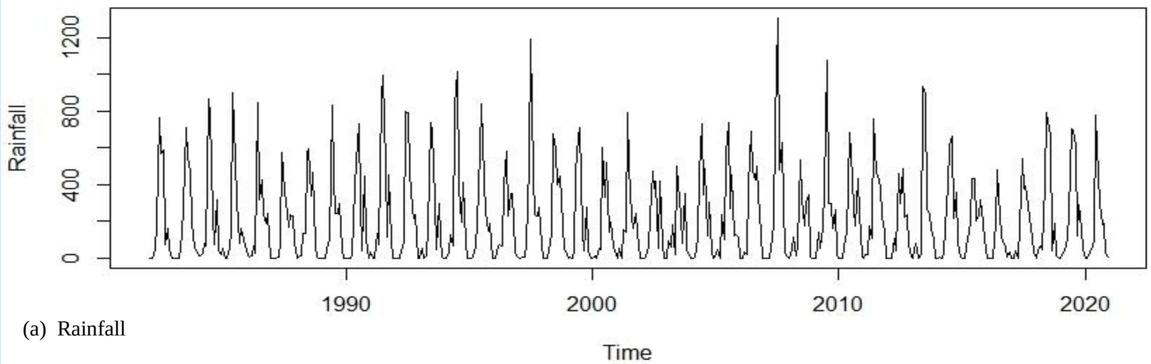
The prime focus of the research was to undergo modeling and forecasting of weather parameters using SARIMA, ANN and hybrid SARIMA-ANN model for the central zone of Kerala and also to identify the best method of modeling suitable for each weather parameter and forecasting the weather parameters using the best-selected model for the next 5 years.

## 2. Data and Methodology

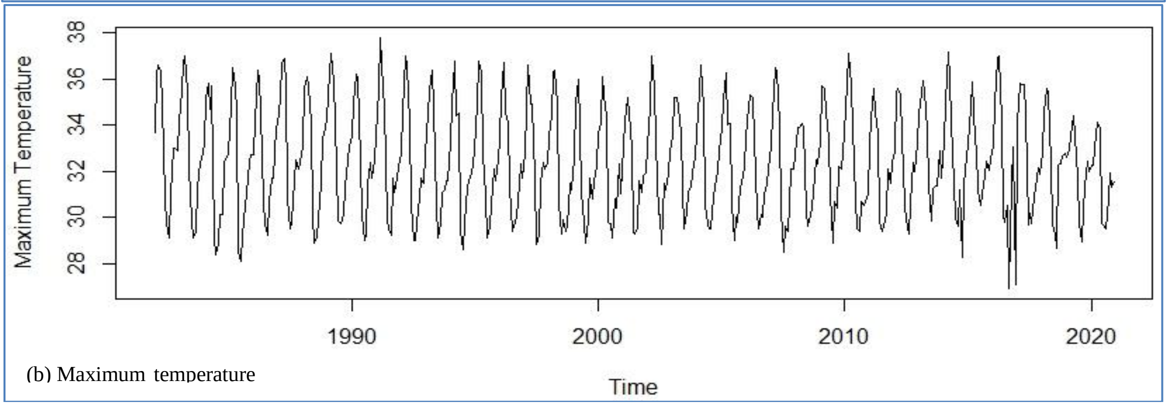
### 2.1. *Study area and data collection*

The monthly data of rainfall, maximum and minimum temperature was collected from the regional agricultural research station (RARS), Pattambi under Kerala Agricultural University whereas the monthly data of relative humidity, cloud content and wind speed were accessed through data access viewer over 39 year (1982-2020Pattambi was once part of the Walluvanad taluk of the British Malabar district, now Pattambi belongs to the Palakkad district of Kerala. Pattambi could be located using the coordinates 10.8057° N and 76.1957° E.

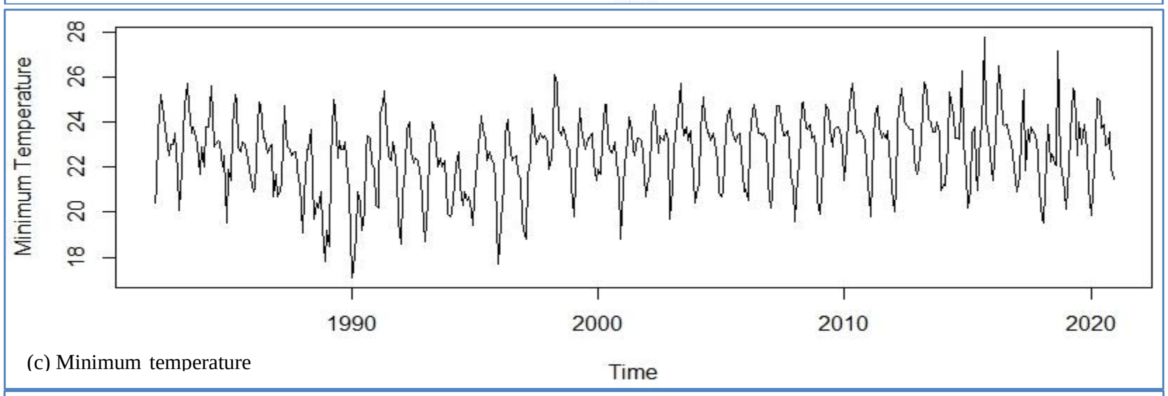
The Pattambi taluk is surrounded by Ottapalamtaluk of Palakkad district to the east, Kunnamkulam taluk of Thrissur district in the south, Tirur and Perinthalmanna taluks of Malappuram district in the north and Ponnani taluk of Malappuram district in the west. The Pattambi taluk always has a tropical wet and dry climate every month except for higher temperatures in the summer season (March-May). The South-West monsoon plays a crucial role in contributing a higher amount of rainfall over the years at the Pattambi. The average annual rainfall in Pattambi region was 1838 mm and July was the month with the maximum rainfall over the years. The main reason for the extreme temperature conditions in Palakkad, district was due to the hot winds coming in from Tamil Nadu. The temperature at different places in



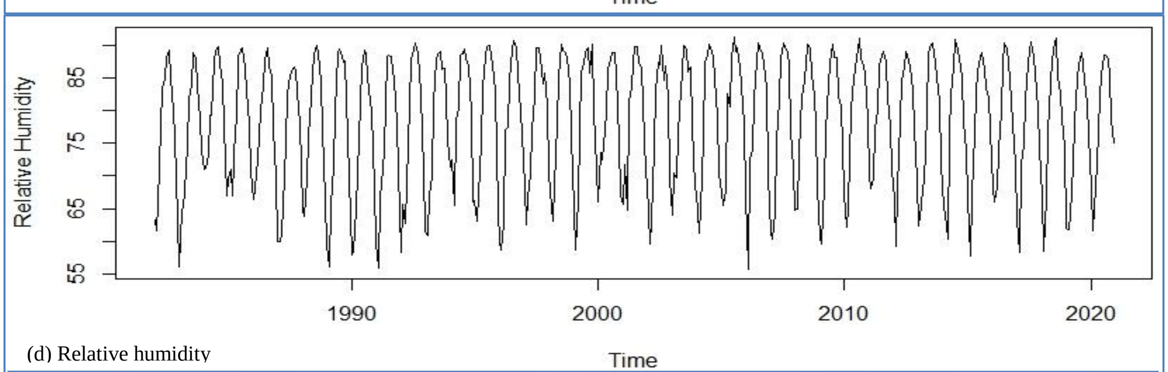

(a) Rainfall



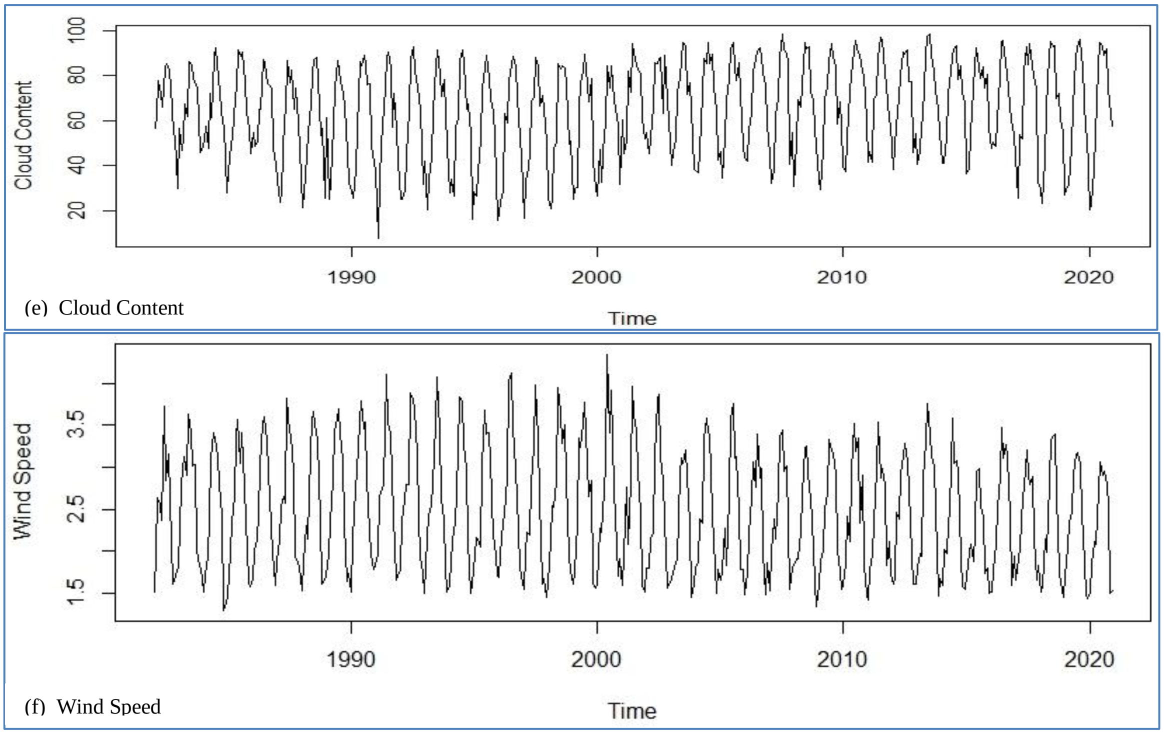

(b) Maximum temperature




(c) Minimum temperature




(d) Relative humidity




**Figs. 2(a-f)**. Pattern of weather parameters (a to c collected from RARS, Pattambi and d to f collected through data access viewer from the same location) over the period of study at Pattambi, central zone of Kerala

Palakkad including Pattambi, reached a maximum of 41℃ in summer and in winter the temperature ranges from 17-28 ℃ which indicates that it is the best time to visit. The Bharathappuzha River, which is the second longest river in Kerala, flows through Pattambi and other parts of Palakkad along with other districts like Thrissur, Malappuram and in some parts of Tamil Nadu and plays a crucial role in agriculture and other related sectors. The modeling and forecasting of weather parameters are done using R software (Chambers, 2008; Crone *et al*., 2010; Dhamo *et al*., 2010; Kourentzes *et al*., 2014; Ord *et al*., 2017). ). The pattern of weather parameters are expressed in Figs. 2(a-f).

2.2. *Methodology*

2.2.1. *Seasonal Autoregressive Integrated Moving Average (SARIMA)*

The SARIMA is an extension of the ARIMA model developed and promoted by Box and Jenkins (1976). The SARIMA model is represented as $(p, d. q)(P, D, Q)_S$ where $(p, d, q)$ represent the non-seasonal part, whereas the $(P, D, Q)_S$ indicated the seasonal part. The non-seasonal part of SARIMA, $p$ represents autoregressive order, $d$ indicates the degree of difference to attain stationarity and $q$ expresses the moving average order. In the seasonal part of the SARIMA model, $P, D, Q$letters indicated the autoregressive, number of differencing to attain stationarity and moving average order respectively and it also consists of an extra symbol '$S$' which indicates the periodicity of the data.

The mathematical representation of the SARIMA model (Ken *et al*., 1998) is expressed as the following:

$$\Phi_P(B^S)\varphi_P(B)\nabla_S^D\nabla^d Y_t = \Theta_Q(B^S)\theta_q(B)e_t + \mu \quad (1)$$

where,$\Phi_P(B^S) = 1 - \Phi_1(B^S) - \Phi_2(B^{2S}) - \ldots - \Phi_P(B^{PS})$ represents the seasonal autoregressive operator of order $P$ $\varphi_p(B) = 1 - \varphi_p(B) - \varphi_p(B^2) - \ldots - \varphi_p(B^p)$ denotes the non-seasonal autoregressive operator of order $p$ $\nabla_S^D = (1 - B^S)^D$ ; $\nabla^d = (1 - B)^d$ ; $B^k\, Y_t = Y_{t-k}$, $\mu$ is the intercept term or mean term.$\Theta_Q(B^S) = 1 - \Theta_1(B^S) - \Theta_2(B^{2S}) - \ldots - \Theta_Q(B^{QS})$ indicates the seasonal moving average operator of order $Q$ $\theta_q(B) = 1 - \theta_1(B) - \theta_2(B^2) - \ldots - \theta_q(B^q)$ represents the non-seasonal moving average operator of order $q$ $e_t$ represented the error terms which are identical and independently distributed with mean zero and variance $\sigma_e^2$, $S$ is a specific time period and $B$ is the back shift operator (Murthy *et al*., 2018).

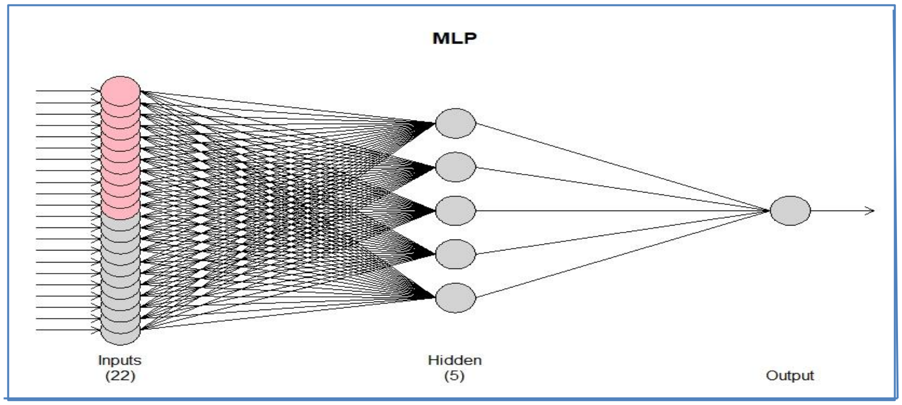



**Fig. 3.** Architecture of an Artificial Neural Network with Multi-layer Perceptrons

The first step before undergoing the modeling of data using the SARIMA method is to determine whether the data is stationary or not. The Augmented Dickey-Fuller (ADF) test is conducted to confirm whether the data is stationary or not. If the data is not stationary, the data should undergo differencing otherwise, it is not required. The test operates under the assumption that data is not stationary (Krishnan *et al*., 2023).

The modeling of time series data is divided into four different iterative stages; they are identification of the model, estimation of the parameters, diagnostic checking and forecasting. The selection of the model was based on the Akaike Information Criterion and the Bayesian Information Criterion (Petrusevich, 2019). The diagnostic checking was done with the help of the Ljung-Box test (Ljung and Box, 1978). This test is used to identify the presence of autocorrelation in the residuals. The test operates under the assumption that there is no autocorrelation present in the residuals. The test statistics are given as the following:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \qquad (2)$$

where $n$ indicated sample size, $\hat{\rho}_k$ represents sample autocorrelation at lag $k$ and $h$ denotes the number of lags tested. The Ljung-Box test operates under a chi-square distribution with $p-q-k$ degrees of freedom. Here $p$ and $q$ indicate autoregressive and moving average order, whereas $k$ denotes the number of orders at which checking of autocorrelation took place.

2.2.2. *Artificial Neural Network (ANN)*

The ANN model was applied to represent intricate data structures consisting of a non-linear nature. To create a relationship between inputs and outputs, it is applied to time series data. The association inputs and outputs of the model were developed without any prior assumptions. The ANN model construction is similar to the human brain, consisting of input, hidden and output layers made up of neurons that are interconnected.

The three layers of ANN are deeply associated; the hidden layer consists of the number of neurons, the relationship between model inputs and hidden layers and the transfer functions carried out, and the close contact between hidden and output layers (Pannakkong *et al*., 2016). ANN has been widely applied for various purposes in modern scientific studies, including complex data structures, image processing, controlling and recognition of specific patterns (Gupta *et al*., 2017). In this study, ANN was employed to model different weather parameters (meteorological data) using multi-layer perceptron neurons along with a feed- forward back propagation algorithm.

The connection among the input layer $\hat{y}_{t-1}, \hat{y}_{t-2}, \ldots, \hat{y}_{t-p}$ and output $\hat{y}_t$ layer of the ANN is mathematically expressed as:

$$\hat{y}_t = w_o + \sum_{h=1}^{q} w_h \times g\left(w_{oh} + \sum_{i=1}^{p} w_{ih} \times \hat{y}_{t-1}\right) + e_t \qquad (3)$$

where $p$ and $q$ are the number of nodes for inputs and hidden layers respectively, $e_t$ represents a small cumulative number depending on the number of input nodes, $w_{ih}$ and $w_h$ indicated the weights associated with the neural network such that $i = 0,1,2,\ldots,p$ and $h = 1,2,\ldots,q$ whereas $g(x)$ indicated non-linear functioning of ANN for the given data (Khashei and Bijari, 2010).

2.2.3. *SARIMA-ANN hybrid model*

Linear and non-linear processes coexist in the time series data from the real world. In the SARIMA-ANN hybrid model developed by Zhang (2003), SARIMA represented the linear part whereas the non-linear part is explained by ANN. It is mathematically expressed as:

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \quad (4)$$

where $\hat{Y}_t$ illustrated the predicted value of the hybrid model, $\hat{L}_t$represented the linear part and $\hat{N}_t$ indicated the non-linear part of the hybrid model. The SARIMA-ANN hybrid model was employed in such a way that the first SARIMA model was applied to the time series data and residuals obtained from the SARIMA models are considered as a non-linear part which was modeled using ANN (Waciko and Ismail, 2020). The sum of forecasted values from both the models is combined and a hybrid model was developed (Krishnan *et al*., 2022).

2.2.4. *Validation and Evaluation of the predicted model*

The model for predicting rainfall was estimated using data from 1982 to 2015 and the validation of the model was done with the help of data from 2016 to 2020 using following error measures given below:

2.2.4.1. *Mean Square Error (MSE)*

The mean of square of discrepancy between observed $y_i$ and forecasted $\hat{y}_i$ values is referred as the mean square error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

2.2.4.2. *Root Mean Square Error (RMSE)*

The RMSE is referred as the square root of MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (6)$$

2.2.4.3. *Mean Absolute Error (MAE)*

The mean of absolute divergence between observed $y_i$ and forecasted $\hat{y}_i$ values is referred as the MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)| \quad (7)$$

2.2.4.4. *Coefficient of determination*

The coefficient of determination describes about the explained variance within the data such that larger the value of $R^2$, better the precision of anticipation using the model. Here, $R^2$ between observed $y_i$ and forecasted $\hat{y}_i$ values are calculated for $n$ observations with average $\bar{y}$.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad (8)$$

These are the most common methods used to evaluate time series models and the best model for forecasting the weather data was deemed to have the lowest error value (Jain and Mallick 2017). The coefficient of determination is also used to determine the best model in such a way that the model with the highest value is selected as the best model.

## 3. Result and discussion

This section compares the results fitting of various models to the relevant weather parameters to choose the best prediction model. However, it is indicated that the prediction of weather parameters is done in a one-to-one manner, such that past values are fitted using SARIMA, ANN and SARIMA-ANN models for predicting future values of the same. The data is divided into training and testing sets to model the meteorological parameters and evaluate the accuracy of the model. The weather data from 1982-2015 is taken as a training set and data from 2016-2020 is considered as a testing set for validating the model. The study mainly focused on establishing the best method for determining future changes in weather parameters using time series models (SARIMA) given in Table 1, a machine language approach by employing the ANN model and also a hybrid model by incorporating SARIMA and ANN.

3.1. *Rainfall*

First, to apply the SARIMA model for rainfall, the stationarity of the data was checked and it was confirmed that the data was stationary. After that by using R software, a suitable model was fitted for the rainfall data. The results showed that SARIMA $(0,0,0)(1,1,0)_{12}$ is the most efficient SARIMA model for projecting future values of rainfall. Next, rainfall was modeled using ANN with a multi-layer perceptron that consists of a back-propagation feed forward program. The ANN model was fitted with 23 input nodes, 5 hidden nodes and 20 repetitions. Lastly, a hybrid model was fitted for rainfall by combining the SARIMA and ANN models. The model validation was done by forecasting the rainfall using SARIMA, ANN and hybrid model and it was compared with the testing data.

3.2. *Maximum Temperature*

Initially SARIMA model was fitted for the maximum temperature using the same way as the model for rainfall. The stationarity of the data was tested using an ADF test and the result indicated that data is stationary such that additional differencing of original data is not required. The best SARIMA model fitted for maximum temperature was SARIMA $(2,0,0)(0,1,1)_{12}$. Later, the

**TABLE 1**

**SARIMA model fitted to weather parameters of Pattambi, central zone of Kerala**

| Weather Parameter | Model | Parameter | Values | AIC | BIC | Ljung-Box value | P value |
|---|---|---|---|---|---|---|---|
| Rainfall | SARIMA $(0,0,0)(1,1,0)_{12}$ | sar1 | -0.59 | 5048.4 | 5056.4 | 2.93 | 0.89 |
| Maximum Temperature | SARIMA $(2,0,0)(0,1,1)_{12}$ | ar1<br>ar2<br>sma1 | 0.28<br>`0.10<br>-0.86 | 868.22 | 884.15 | 17.66 | 0.67 |
| Minimum Temperature | SARIMA $(2,0,2)(1,1,0)_{12}$ | ar1<br>ar2<br>ma1<br>ma2<br>sar1 | 1.58<br>-0.70<br>-1.13<br>0.39<br>-0.53 | 1062.5 | 1090.4 | 59.37 | 0.66 |
| Relative Humidity | SARIMA $(1,0,0)(1,1,0)_{12}$ | ar1<br>sar1 | 0.42<br>-0.53 | 2096.8 | 2112.7 | 80.94 | 0.91 |
| Cloud Content | SARIMA $(1,0,3)(1,1,1)_{12}$ | ar1<br>ma1<br>ma2<br>ma3<br>sar1<br>sma1 | 0.98<br>-0.81<br>0.06<br>-0.19<br>0.01<br>-0.80 | 2828.1 | 2859.9 | 29.06 | 0.33 |
| Wind Speed | SARIMA $(1,0,1)(2,1,1)_{12}$ | ar1<br>ma1<br>sar1<br>sar2<br>sma1 | 0.78<br>-0.60<br>-0.02<br>-0.08<br>-0.86 | 64.98 | 92.85 | 21.33 | 0.26 |

**TABLE 2**

**Evaluation and validation of models used for forecasting of weather parameters**

| Weather Parameter | Model | MSE | RMSE | MAE | $R^2$ |
|---|---|---|---|---|---|
| Rainfall | SARIMA | 18600.15 | 136.223 | 94.495 | 0.665 |
| | ANN | **15910.49** | **126.136** | **90.924** | **0.749** |
| | SARIMA-ANN | 23979.94 | 154.854 | 129.878 | 0.643 |
| Maximum Temperature | SARIMA | 1.616 | 1.271 | 0.873 | 0.711 |
| | ANN | 1.628 | 1.276 | 0.868 | 0.720 |
| | SARIMA-ANN | **1.609** | **1.268** | **0.865** | **0.722** |
| Minimum Temperature | SARIMA | **1.607** | **1.267** | **1.048** | **0.428** |
| | ANN | 4.09 | 2.022 | 1.78 | 0.419 |
| | SARIMA-ANN | 6.081 | 2.466 | 2.005 | 0.206 |
| Relative Humidity | SARIMA | **5.268** | **2.295** | **1.789** | **0.945** |
| | ANN | 5.572 | 2.36 | 1.908 | 0.944 |
| | SARIMA-ANN | 6.66 | 2.58 | 2.062 | 0.940 |
| Cloud Content | SARIMA | 106.422 | 10.316 | 7.761 | 0.870 |
| | ANN | 95.647 | 9.779 | 7.674 | 0.871 |
| | SARIMA-ANN | **93.37** | **9.662** | **7.586** | **0.876** |
| Wind Speed | SARIMA | **0.037** | **0.193** | **0.151** | **0.907** |
| | ANN | 0.091 | 0.302 | 0.248 | 0.881 |
| | SARIMA-ANN | 0.06 | 0.245 | 0.193 | 0.888 |

ANN model with MLP was also fitted for the maximum temperature. The result revealed the ANN model consists of 23 input nodes, 5 hidden nodes and 20 repetitions. Finally, the hybrid SARIMA-ANN model was also applied to the maximum temperature data. The models were assessed to determine the best approach for attaining future values of maximum temperature and the results are shown in Table 2.

### 3.3. *Minimum Temperature*

Similar to the preceding portions, the ADF test for stationarity was conducted for the minimum temperature and the result suggested data is stationary and differencing of data is not needed. After the data were fitted with the SARIMA model, SARIMA$(2,0,2)(1,1,0)_{12}$ was chosen as the best model for the minimum temperature. After completing the fitting of the SARIMA model, ANN with MLP model was fitted for minimum temperature. The ANN model for minimum temperature consists of 23 input nodes, 5 hidden nodes and 20 repetitions. Lastly, the SARIMA-ANN hybrid model was also developed for the minimum temperature. The comparison between different models is illustrated in Table 2.

### 3.4. *Relative Humidity*

The first step before fitting the SARIMA model was to check the stationarity of the data. The ADF test was conducted and the results revealed that the data was stationary. The best SARIMA model automatically detected for the relative humidity was SARIMA $(1,0,0)(1,1,0)_{12}$. Later, the ANN model was fitted for the relative humidity. The ANN model fitted for relative humidity consists of 21 input nodes, 5 hidden nodes and 20 repetitions. After fitting the SARIMA and ANN model, a hybrid model combining the SARIMA-ANN model was also developed for the relative humidity. Table 2 lists the criteria for choosing the optimal model for predicting the relative humidity.

### 3.5. *Cloud Content*

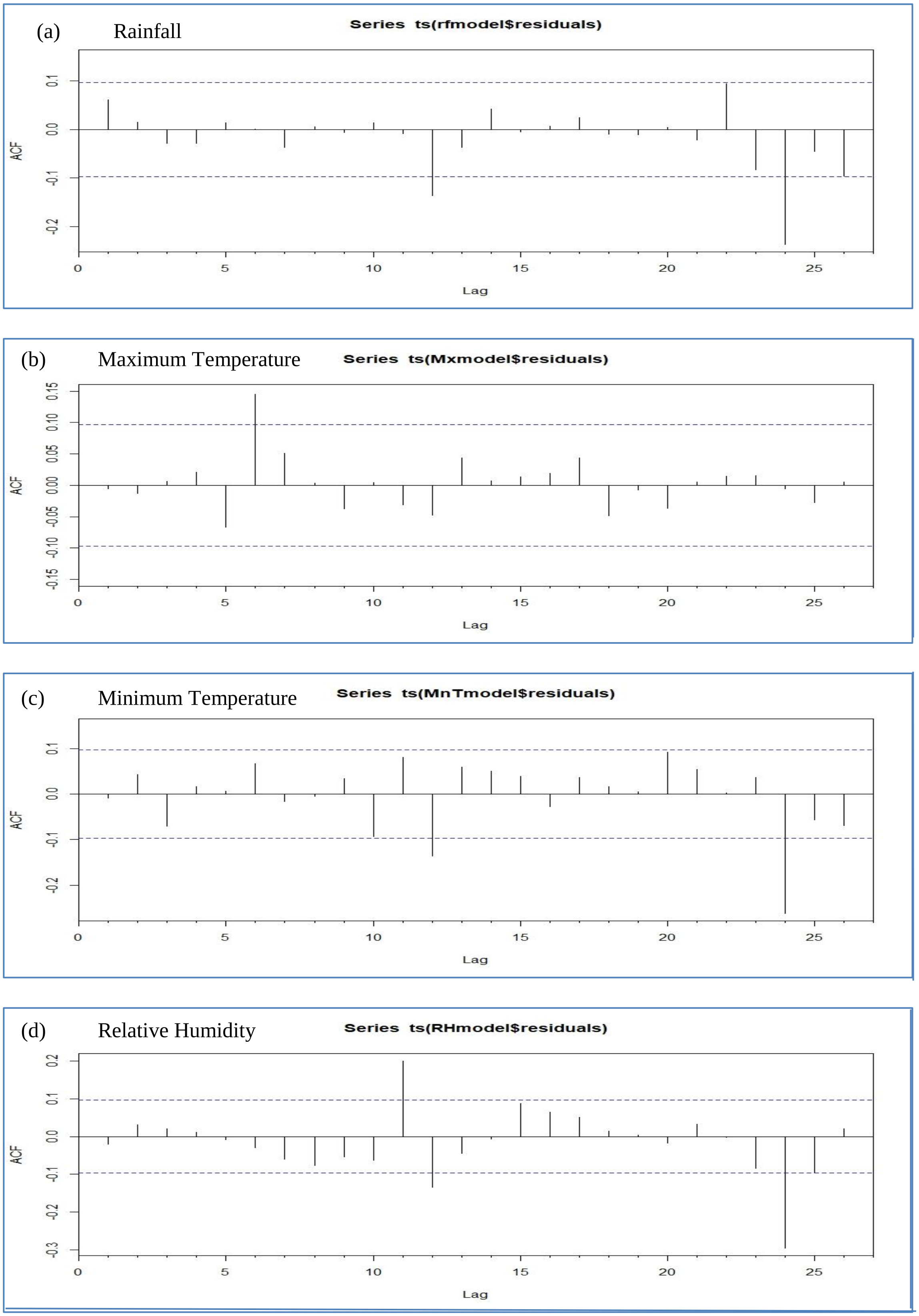
Similar to the previous sections, the SARIMA model was fitted for modeling the cloud content. Before fitting the SARIMA model, the ADF test was conducted to check the stationarity of the data and the result revealed that the data is stationary. The best SARIMA model fitted automatically for the cloud content is SARIMA $(1,0,3)(1,1,1)_{12}$. After fitting the SARIMA model, the next step was to fit the ANN model for the data. The ANN model fitted for cloud content consists of 23 input nodes, 5 hidden nodes and 20 repetitions. Lastly, the hybrid SARIMA-ANN model is also fitted for the cloud content data. The comparison between different models fitted for the cloud content is represented in Table 2.

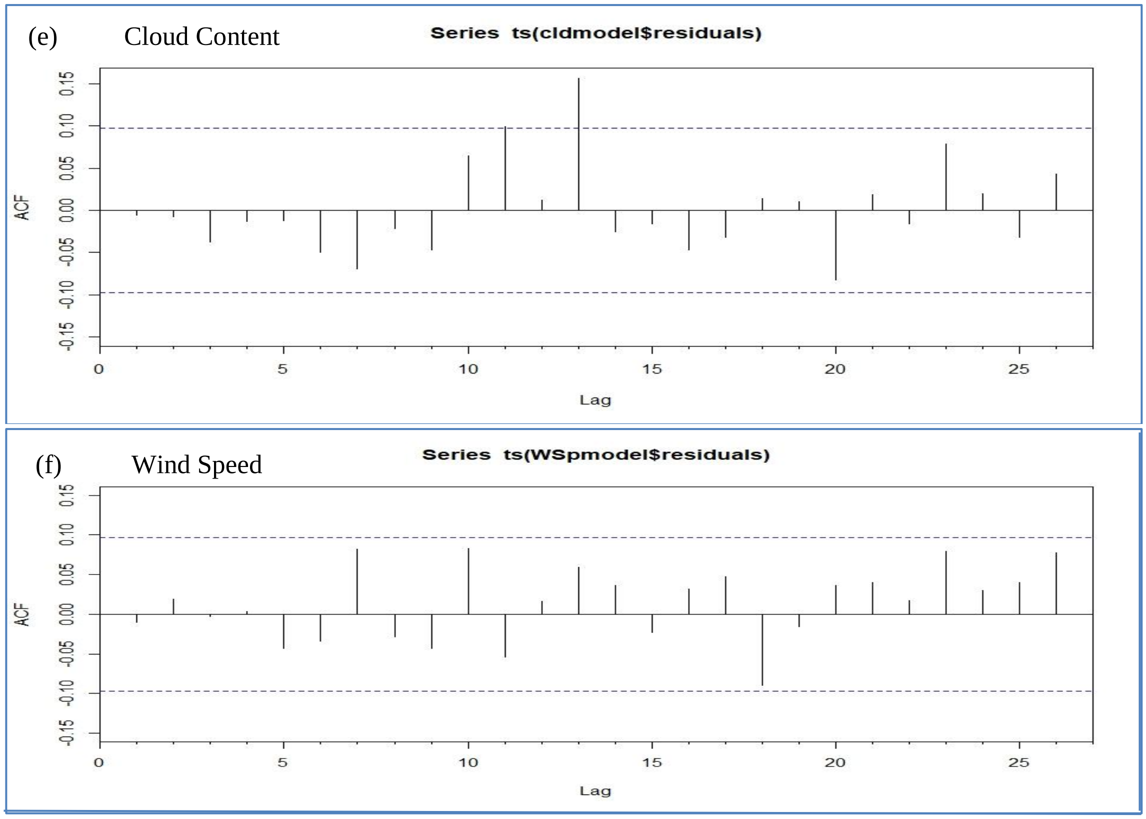
### 3.6. *Wind Speed*

Initially, the SARIMA model was fitted for the wind speed data. Before undergoing fitting of the SARIMA model, the ADF test was conducted to ensure the stationarity of the data. The results indicated that the data is stationary. After that the SARIMA model was fitted and the result showed that SARIMA $(1,0,1)(2,1,1)_{12}$ is the top choice SARIMA model for wind speed. The next step was fitting the ANN model for wind speed. The ANN model fitted for wind speed consists of 23 input nodes, 5 hidden nodes and 20 repetitions. After fitting the ANNmodel, the hybrid SARIMA-ANN model was also fitted for the wind speed data at Pattambi. The comparison between the models fitted for wind speed data is described in Table 2.

From Figs.4(a-f), it is noted that the standard residuals do not have any specific patterns and also the residual ACF plot for all the weather parameters shows stationary since most of the residual versus lag values lie within the confidence limit. The ACF plot expresses some significant spikes at different lag values but it may not seriously affect the prediction of weather parameters. However, this indicated that by only applying the SARIMA model, results with maximum accuracy are not possible such that the ANN model was also employed for better apprehension of information from weather data and residuals of the SARIMA model. The comparison of error values obtained from fitting SARIMA, ANN and hybrid SARIMA-ANN models for each weather parameter is given in Table 2.

The results from Table 2 reveal that ANN is the best method for forecasting rainfall with the least MSE, RMSE and MAE values, and the coefficient of determination between predicted and observed values is highest for the same model. Correspondingly, for maximum temperature, the best model for forecasting with maximum accuracy is the hybrid SARIMA-ANN model compared to SARIMA and ANN models since error values showed was least. Likewise, for minimum temperature, results indicated that SARIMA $(2,0,2)(1,1,0)_{12}$ is the best model for prediction compared to the ANN and SARIMA-ANN models. Equivalently, results depicted in Table 2 suggested that SARIMA $(1,0,0)(1,1,0)_{12}$ has more precision in forecasting the relative humidity compared to the ANN and the hybrid SARIMA-ANN models. The result presented in Table 2 also revealed that the hybrid SARIMA-ANN model is the most accurate model for attaining future values of the cloud content in the central zone of Kerala compared to single SARIMA and ANN models since the error value is minimum for the hybrid model. Additionally, the coefficient of determination indicated the hybrid model to have the highest value, which confirms that the hybrid SARIMA-ANN model is the most effective model for analyzing and predicting cloud content. Similarly, the study also concluded that SARIMA$(1,0,1)(2,1,1)_{12}$is the best-selected model for fitting wind speed data in the central zone of Kerala. The error values described in Table 2 indicated that the SARIMA model showed the minimum values compared to the ANN and the hybrid SARIMA-ANN model. The coefficient of determination was also given a higher value for the SARIMA model. However, the study concluded that even though we are applying more advanced hybrid SARIMA-ANN model, only for maximum temperature and cloud content it was selected as the best-performing


(a) Rainfall
Series ts(rfmodel$residuals)
ACF
Lag
(b) Maximum Temperature
Series ts(Mxmodel$residuals)
ACF
Lag
(c) Minimum Temperature
Series ts(MnTmodel$residuals)
ACF
Lag
(d) Relative Humidity
Series ts(RHmodel$residuals)
ACF
Lag




**Figs.4(a-f)**. Residual ACF plot for SARIMA models of each weather parameters (a-b collected from RARS, Pattambi and d-f collected through data access viewer from the same location)

model. For maximum temperature, relative humidity and wind speed the outperforming model was SARIMA whereas for rainfall it was ANN model which may considered as a limitation of the study. The study revealed that even though the highly developed machine language method or hybrid model combining both time series model and machine language was used for modeling and predicting weather parameters, the time series model SARIMA gave the most accurate performance in predicting future weather condition of central Kerala.

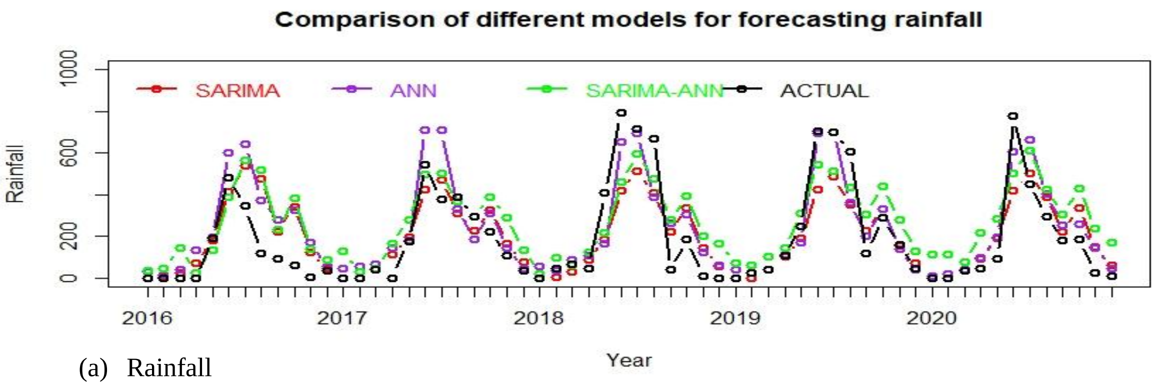
From Figs.5(a-f), a comparison between models used in the study for forecasting and actual values of each weather parameter are presented using different colors in such a way that red (SARIMA), purple (ANN), green (hybrid SARIMA-ANN) and black (Actual) respectively. The patterns for each model selected for forecasting different weather parameters show almost similar behavior. However, Figs.5(a-f) helps to understand and select the best-performing model for each weather parameter.

The weather parameters forecasted for the next 5 years using their respective outperformed models are illustrated below.

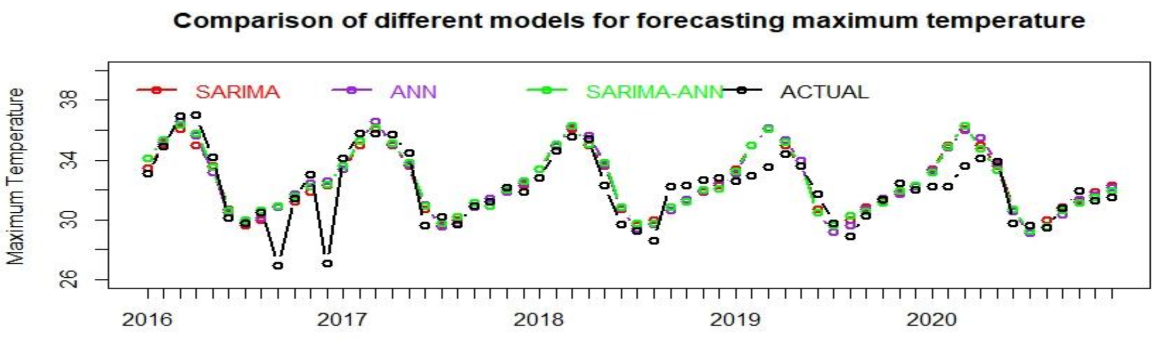
The rainfall predicted using the ANN model for the next 5 years (2021-2025) is presented in Table 3. The maximum amount of rainfall is predicted in June and July, whereas the least rainfall is predicted in January and February. As we know rainfall produces maximum fluctuations compared to other weather parameters, over the years, the predicted rainfall has shown uneven behaviour such that it shows an increase for the first 2 years and then decline for the next 3 years.

Table 4 indicates the monthly maximum temperature predicted for the next 5 years (2021-2025) using the SARIMA-ANN model. The highest value of maximum temperature was predicted in March and April, whereas the lowest value for maximum temperature was attained in July and August due to heavy rainfall. The forecasted values of maximum temperature showed a decreasing trend over the years.

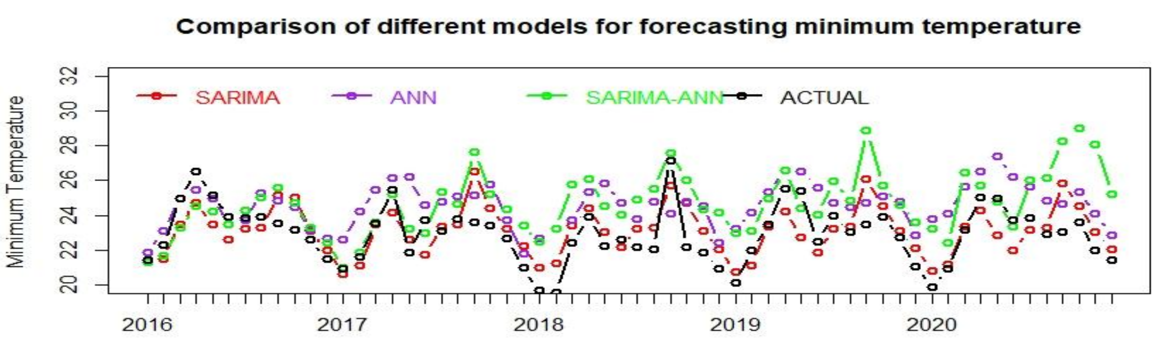
The forecasted minimum temperature for 5 years (2021-2025) is depicted in Table 5 using the SARIMA-ANN model. The monthly minimum temperature showed the highest value in September and October and the lowest value in January and February. The predicted minimum temperature revealed a decreasing trend over the years.



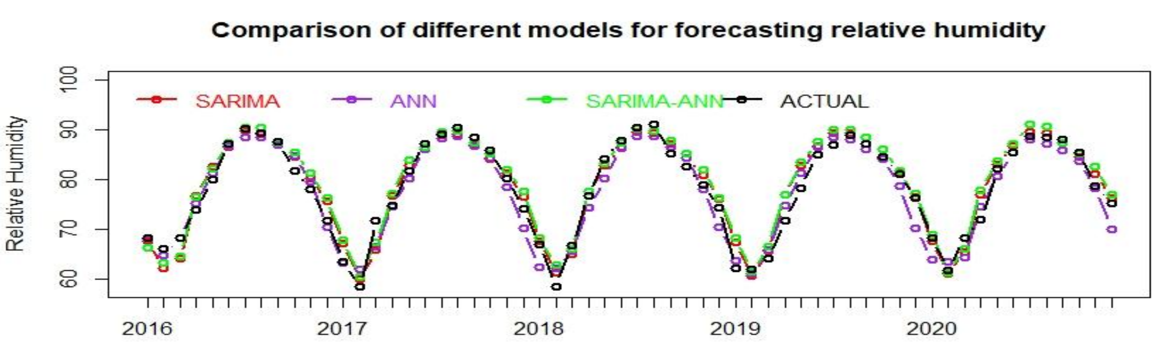

(a) Rainfall



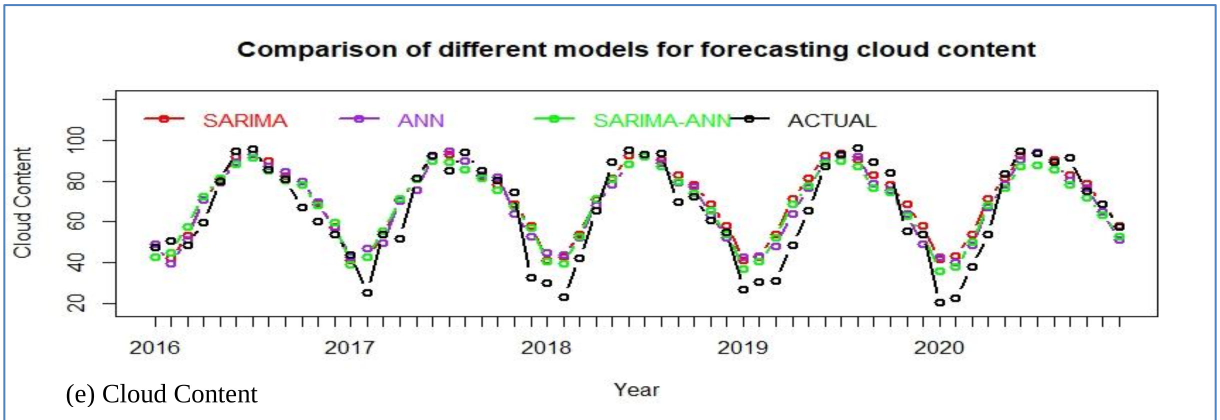

(b) Maximum Temperature



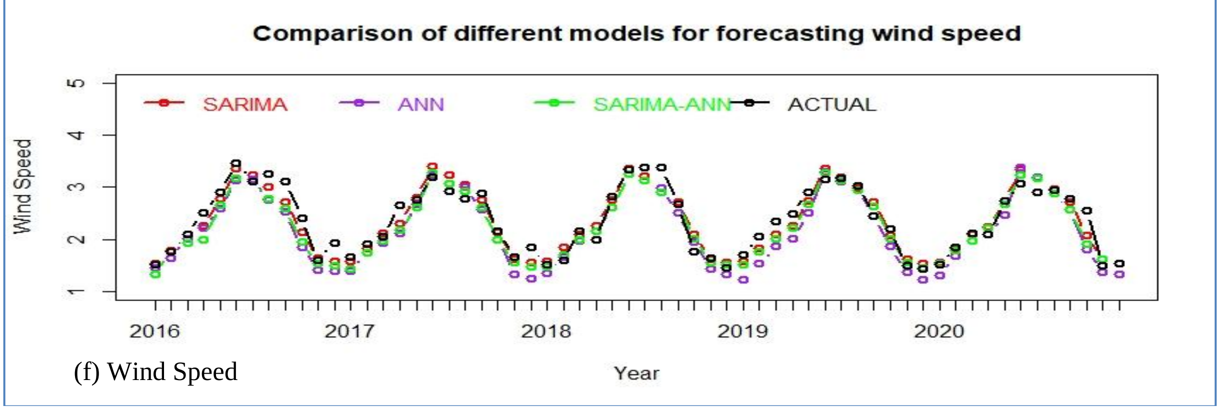

(c) Minimum Temperature




(d) Relative Humidity




(e) Cloud Content




(f) Wind Speed

**Figs. 5(a-f)**. Comparison of forecasting of weather parameters (a-b collected from RARS, Pattambi and d-f collected through data access viewer from the same location)with actual observations using SARIMA, ANN and SARIMA-ANN model

**TABLE 3**

**Predicted rainfall (mm) using the ANN model for central Kerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 20.8 | 13.8 | 53.5 | 109 | 149 | 634 | 618 | 338 | 178.8 | 315.6 | 154.3 | 40.66 |
| 2022 | 35.3 | 37.4 | 47.9 | 70.4 | 182 | 639 | 631 | 411 | 231.4 | 322.1 | 97.87 | 26.28 |
| 2023 | 5.75 | 5.37 | 40.6 | 102 | 198 | 703 | 593 | 316 | 169.8 | 327.2 | 67.75 | 43.98 |
| 2024 | 4.34 | 46.9 | 9.08 | 77.5 | 126 | 724 | 614 | 358 | 169.1 | 315.7 | 9.023 | 99.61 |
| 2025 | 21.5 | 62.1 | 21.5 | 31.9 | 133 | 540 | 561 | 286 | 141.9 | 240.7 | 8.476 | 51.32 |

**TABLE 4**

**Predicted maximum temperature (℃) using SARIMA-ANN model for centralKerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 33.32 | 34.69 | 35.47 | 35.06 | 33.08 | 30.02 | 29.22 | 29.65 | 30.32 | 30.83 | 31.29 | 31.91 |
| 2022 | 32.69 | 34.30 | 35.34 | 34.47 | 33.22 | 30.25 | 28.89 | 29.30 | 30.51 | 30.73 | 31.23 | 31.92 |
| 2023 | 32.55 | 34.38 | 35.27 | 34.24 | 32.83 | 29.97 | 28.93 | 29.18 | 30.03 | 30.55 | 30.99 | 31.56 |
| 2024 | 32.71 | 34.26 | 35.20 | 34.17 | 32.60 | 29.92 | 28.64 | 29.20 | 29.89 | 30.31 | 31.37 | 31.48 |
| 2025 | 32.30 | 34.13 | 34.99 | 33.94 | 32.84 | 29.73 | 28.65 | 29.00 | 29.69 | 30.18 | 30.73 | 31.50 |

**TABLE 5**

**Predicted minimum temperature (℃) using SARIMA-ANN model for central Kerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 20.72 | 21.09 | 23.32 | 24.21 | 22.74 | 21.87 | 23.15 | 23.27 | 25.95 | 24.48 | 23.02 | 22.03 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2022 | 20.72 | 21.07 | 23.28 | 24.2 | 22.75 | 21.87 | 23.11 | 23.23 | 25.85 | 24.48 | 22.99 | 21.98 |
| 2023 | 20.67 | 21.03 | 23.25 | 24.16 | 22.7 | 21.82 | 23.08 | 23.2 | 25.85 | 24.43 | 22.96 | 21.96 |
| 2024 | 20.65 | 21.01 | 23.22 | 24.13 | 22.68 | 21.8 | 23.05 | 23.17 | 25.8 | 24.41 | 22.92 | 21.92 |
| 2025 | 20.61 | 20.97 | 23.19 | 24.1 | 22.64 | 21.76 | 23.02 | 23.14 | 25.78 | 24.37 | 22.89 | 21.89 |

**TABLE 6**

**Predicted relative humidity (%) using SARIMA model for central Kerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 67.56 | 60.94 | 65.55 | 76.99 | 83.02 | 86.77 | 89.53 | 89.47 | 87.31 | 84.52 | 81.31 | 76.5 |
| 2022 | 67.67 | 61.12 | 65.55 | 77.07 | 83.1 | 86.85 | 89.64 | 89.55 | 87.41 | 84.61 | 81.34 | 76.54 |
| 2023 | 67.73 | 61.14 | 65.67 | 77.14 | 83.17 | 86.93 | 89.7 | 89.63 | 87.48 | 84.68 | 81.44 | 76.64 |
| 2024 | 67.81 | 61.24 | 65.72 | 77.22 | 83.25 | 87 | 89.78 | 89.71 | 87.56 | 84.76 | 81.5 | 76.7 |
| 2025 | 67.88 | 61.3 | 65.81 | 77.3 | 83.32 | 87.08 | 89.85 | 89.78 | 87.63 | 84.83 | 81.59 | 76.78 |

**TABLE 7**

**Predicted cloud content (%) using SARIMA-ANN model for central Kerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 33.57 | 36.8 | 48.98 | 62.97 | 73.29 | 84.73 | 86.3 | 86.26 | 75.68 | 72.21 | 61.15 | 51.21 |
| 2022 | 31.85 | 36.63 | 47.09 | 64.78 | 74.32 | 82.69 | 85.24 | 82.92 | 75.31 | 71.6 | 60.87 | 49.52 |
| 2023 | 31.23 | 34.36 | 45.59 | 62.87 | 72.94 | 82.22 | 84.38 | 82.14 | 74.4 | 69.81 | 60.03 | 49.49 |
| 2024 | 28.62 | 35.21 | 41.41 | 61.47 | 69.68 | 84.54 | 78.98 | 81.87 | 72.45 | 70.84 | 55.66 | 50.82 |
| 2025 | 28.46 | 29.45 | 41.08 | 59.24 | 67.39 | 85.05 | 79.62 | 81.46 | 69.4 | 70.46 | 53.7 | 49.19 |

**TABLE 8**

**Predicted wind speed (m/s) using SARIMA model for central Kerala (2021-2025)**

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 1.55 | 1.81 | 2.08 | 2.24 | 2.73 | 3.34 | 3.19 | 2.97 | 2.7 | 2.07 | 1.6 | 1.53 |
| 2022 | 1.55 | 1.81 | 2.07 | 2.24 | 2.73 | 3.33 | 3.18 | 2.96 | 2.7 | 2.07 | 1.6 | 1.53 |
| 2023 | 1.54 | 1.80 | 2.07 | 2.23 | 2.72 | 3.33 | 3.17 | 2.96 | 2.69 | 2.06 | 1.59 | 1.52 |
| 2024 | 1.53 | 1.79 | 2.06 | 2.22 | 2.71 | 3.32 | 3.17 | 2.95 | 2.68 | 2.05 | 1.58 | 1.51 |
| 2025 | 1.53 | 1.79 | 2.05 | 2.22 | 2.71 | 3.31 | 3.16 | 2.94 | 2.68 | 2.05 | 1.58 | 1.51 |

values of maximum temperature showed a decreasing trend over the years.

The forecasted minimum temperature for 5 years (2021-2025) is depicted in Table 5 using the SARIMA-ANN model. The monthly minimum temperature showed the highest value in September and October and the lowest value in January and February. The predicted minimum temperature revealed a decreasing trend over the years.

The relative humidity forecasted using the SARIMA model for 5 years (2021-2025) is presented in Table 6. The highest relative humidity is recorded in July & August, whereas the lowest is in January & February. The relative humidity showed an increasing trend over the years.

The cloud content forecasted using the SARIMA-ANN model for 5 years (2021-2025) presented in Table 7. The highest cloud content is recorded in July and August, whereas the lowest is in the months of January and February. The cloud content over the years showed a decreasing trend.

The forecasted wind speed for 5 years (2021-2025) is depicted in Table 8 using the SARIMA model. The monthly wind speed showed the highest value in June and July and the lowest value in December and January. The predicted wind speed revealed a decreasing trend over the years.

## 4. Conclusions

The forecasting of weather parameters was carried out in central zone of Kerala for which monthly data of rainfall, maximum and minimum temperature was collected from the regional agricultural research station (RARS), Pattambi under Kerala Agricultural University whereas the monthly data of relative humidity, cloud content and wind speed was accessed through data access viewer over 39 year (1982-2020). Scientists have employed various methods for forecasting weather parameters with maximum precision. The time series model named SARIMA, the machine language method of ANN and the hybrid model made up of incorporation of both SARIMA and ANN were utilized in this study for forecasting monthly rainfall, maximum and minimum temperature, relative humidity, cloud content and wind speed. The comparison of weather forecasting was done by calculating MSE, RMSE, MAE and coefficient of determination.

The result suggested that for each parameter a different model gave maximum accuracy. The most efficient model for forecasting maximum temperature and cloud content was determined to be the hybrid SARIMA-ANN model. The ANN model showed maximum accuracy for forecasting rainfall. The best models attained for forecasting minimum temperature, relative humidity and wind speed are SARIMA $(2,0,2)(1,1,0)_{12}$, SARIMA $(1,0,0)(1,1,0)_{12}$ and SARIMA $(1,0,1)(2,1,1)_{12}$ respectively. Even though a more advanced ANN or hybrid model was employed in the study, for most of the parameters SARIMA was selected as the most accurate model which can considered as a limitation of the study. For rainfall ANN model showed better performance compared to the hybrid model which suggested that that hybrid model does not need to always show a more accurate prediction of future values compared to single models. The research study mainly focused on determining whether there is an improvement in weather forecasting using the hybrid SARIMA-ANN model compared to the SARIMA and ANN models. Compared with other Machine learning/Deep Learning Models are outside the scope of the current study and they can be incorporated as a future line of work. The weather parameters were forecasted for the next 5 years (2021-2025) such that maximum and minimum temperature, cloud content and wind speed showed a decreasing nature whereas relative humidity indicated an increasing trend. The rainfall predicted showed an uneven distribution without a continuous increasing or decreasing trend.

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*Data Availability*

The monthly data of rainfall, maximum and minimum temperature was collected from the regional agricultural research station (RARS), Pattambi under Kerala Agricultural University, Thrissur whereas the monthly data of relative humidity, cloud content and wind speed was accessed through data access viewer over 39 year (1982-2020).

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*Disclaimer*

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