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Comparison Study on Modelling and Prediction of Weather Parameters Combining Exponential Smoothing and Artificial Neural Network Models in Different Zones of Kerala

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ABSTRACT

Prediction of weather parameters with maximum precision is the main objective faced by different climatologists all over the world. The researchers devised a number of ways for performing weather parameter predictions. For modelling and prediction of weather parameters, exponential smoothing (ETS), artificial neural networks (ANN) and ETS-ANN hybrid models were employed for the northern, central and southern zones of Kerala. The weather parameters used in the study are relative humidity and wind speed. The monthly data were collected for the northern and central zones, for a period of 39 years (1982-2020), whereas for the southern zone it was for a period of 36 years (1985-2020). The result suggested that the best fitted model for relative humidity was the ANN for the central and southern zones whereas for northern zone it was the ETS model. The accuracy of the model was calculated using MSE, RMSE, MAE, MAPE and R^2 values. The ETS performed best in all three zones of Kerala when it came to wind speed. The study also advocated that traditional model ETS and ANN is performing better compared to the newly developed hybrid model in prediction of weather parameters. The best model chosen for weather parameters of three different zones are used to forecast for the next five years.

Keywords ANN (Artificial Neural Networks), ETS (Exponential Smoothing), ETS-ANN, Northern zone, Central zone, Southern zone.

INTRODUCTION

Prediction of weather parameters with maximum precision is one of the main objectives of climatologists all over the world. The prediction of weather parameters with maximum accuracy can help to reduce the effects of climate change. Necessary precautionary measures have to be taken in order to control the harmful effects of changes in weather parameters. Climate change shows important influence in agriculture and allied sectors, such that prediction of weather parameters is essential to reduce the loss due to adverse weather conditions. Agriculture activities must be adjusted in accordance with the long-term weather forecast for the cultivated area. Thus, pre-

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diction of weather parameters annually, monthly or daily with maximum precision is crucial for undertaking agriculture activities all over the world. India is a tropical country, where most of the population directly or indirectly depends on agriculture and allied sectors. For almost 58% of the Indian population, the main source of income is derived from agriculture and allied sectors. Climate change has been occurring over the years in the form of heavy rainfall, rise in temperature, cyclones, floods, drought and landslides in different parts of India. Determination of patterns of weather parameters with minimum error can help the farmers to undergo necessary steps to overcome the changes in climatic conditions. It should be emphasized that weather conditions have a substantial control on the development of plants. A rise in relative humidity can lead to mould or bacterial growth on plant surfaces, as well as pest assault, which can lead to crop loss. Wind speed contributes to the increase in carbon dioxide intake by plants, which leads to an increase in photosynthesis. Thus fluctuations in weather parameters can affect the flora and fauna directly and indirectly which created huge importance for its prediction with high accuracy (Krishnan *et al.* 2023).

Cadenas *et al.* (2010) underwent a study about forecasting and modeling of wind velocity using a single ETS method in two cities of Mexico and the results indicated that SES method out performed ANN. Affan *et al.* (2019) investigated wind speed using ANN and ETS at Bandung, Indonesia and the results revealed that ANN out performed ETS model. Shamshad *et al.* (2019) investigated weather parameters collected from Lahore, Pakistan using ANN-MLP, ARIMA and ETS models and outcomes of the study revealed that the ANN-MLP model provided better results. Camelo *et al.* (2018) underwent a study about prediction of wind speed using two hybrid models, in first hybrid model ARIMA was combined with ANN whereas in the second hybrid model, Holt-Winters model was combined with ANN and results concluded that both the hybrid models gave accurate results. Huang *et al.* (2021) investigated on wind speed prediction using two hybrid models, first hybrid model is a combination of ARIMA and back propagation neural network (BPNN) whereas in the second hybrid model (ETS) was combined with BPNN and the results suggested that two hybrid models fitted for wind speed showed good performance with high precision. It is to be noted that only few research was carried out on application of ETS technique for prediction of relative humidity and wind speed. Thus, this study is more relevant since the monthly weather data including relative humidity and wind speed were predicted using ETS, ANN, and hybrid ETS-ANN models for the northern, central, and southern zones of Kerala.

MATERIALS AND METHODS

Study area and location

The main focus of the study was on determining the specific patterns of different weather parameters using ETS, ANN and hybrid ETS-ANN models. In this study, monthly weather data consisting of relative humidity (%) and wind speed (m/s) is collected using data access viewer from northern, central and southern zones of Kerala. The weather data for the northern zone of Kerala was collected from Pilicode situated in Kasaragod district of Kerala over a period of 39 years (1982-2020). Study area is located in between 12.1997^0 N latitude and 75.1633^0 E. The data for the central zone of Kerala was obtained from Pattambi belong to Palakkad district of Kerala for a period of 39 years (1982-2020). The study area lies with in 10.8057^0 N latitude and 76.1957^0 E longitude. Weather data for the southern zone was collected from vellayani located in Trivandrum district of Kerala for a period of 36 years (1985-2020). The geographical location of Vellayani is at 8.4316^0 N latitude and 76.986^0 E longitude. The different places from which data were collected for the northern, central and southern zones of Kerala is depicted in Fig.1.

Methodology

Exponential smoothing (ETS)

The main speciality of ETS method is that it gave more importance to the weighted average of the past observations. The simple ETS method was expanded by Holt (1957) to increase the accuracy of prediction of data showing linear tendency. In order to predict the seasonal component of the data, Winters expanded the Holt model to form the Holt-Winters

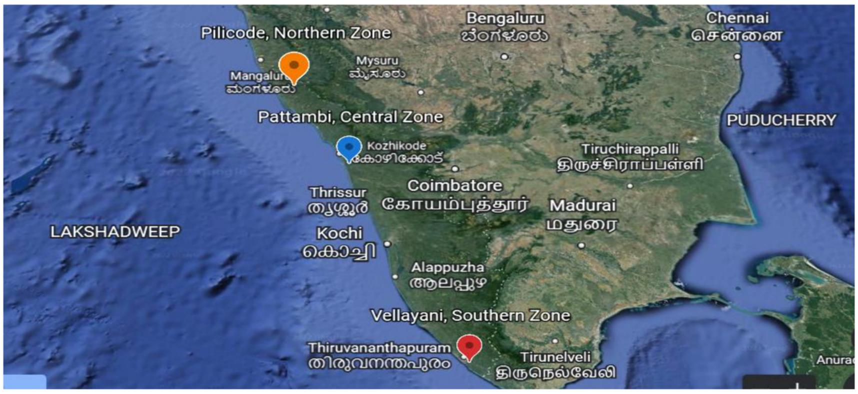


Fig. 1. Study area map for different zones of Kerala (Source: Google Earth).

model (Camelo *et al.* 2018, Winters 1960). The ETS models were developed in the 1950s, such that all the categorization of ETS methods was carried out by Pegels (1969) and the extension of methods was done by Gardener (1985). Hyndman *et al.* (2002) modify and alter developed exponential methods, which are also extended by Taylor (2003). It is important to highlight that trend and seasonal components can be absent, additive, or multiplicative, resulting in new advancements in fifteen models and thirty various exponential models (Hyndman *et al.* 2008). The thirty various exponential models that expressed error, trend, and seasonality components of time series data were represented by triplets, E for error, T for trend and, S for seasonality (E,T,S). The different models are represented using symbols A for additive, N for none and M for multiplicative for error, trend and seasonality of the data.

The generalized ETS model is expressed as:

$$y_{t+h} = (a_t + h.b_t) + S_{(t - p+1+(h-1) \bmod p)} \quad (1)$$

Case-1 ETS model for data with level, trend and additive seasonality.

In this case, a_t denotes the level of series which explained the evolution of time series over time, b_t represents the trend of the data which constitute increasing or decreasing movement of time series for respective time periods, s_t expresses the seasonal component of the data which describes the repetition of variations in time series data in constant time intervals, p is period of seasonality and is the period of forecast.

The terms a_t, b_t and s_t are expressed as:

$$a_t = \alpha(y_t - s_{t-p}) + (1 - \alpha) (\alpha_{t-1} + b_{t-1}) \quad (2)$$

$$b_t = \beta(\alpha_t - \alpha_{t-1}) + (1 - \beta)b_{t-1} \quad (3)$$

$$s_t = \gamma(\gamma_t - a_t) + (1 - \gamma)s_{t-p} \quad (4)$$

Case-2 ETS model for data with level, trend, and multiplicative seasonality

In this case, the terms , and are expressed in a different manner as:

$$a_t = \alpha\left(\frac{\gamma_t}{s_{t-p}}\right) + (1 - \alpha) (\alpha_{t-1} + b_{t-1}) \quad (5)$$

$$b_t = \beta(a_t - a_{t-1}) + (1 - \beta)b_{t-1} \quad (6)$$

$$s_t = \gamma\left(\frac{\gamma_t}{a_t}\right) + (1 - \gamma)s_{t-p} \quad (7)$$

Where b_t and s_t indicated the trend and seasonal component respectively, terms a_t represented the level term, t is the time period and damping constants used are indicated by α, β and γ respectively (Ferreira *et al.* 2019).

Artificial neural network (ANN)

The ANN was developed by Warren McCulloch and Walter Pitts (1943) by taking inspiration from the

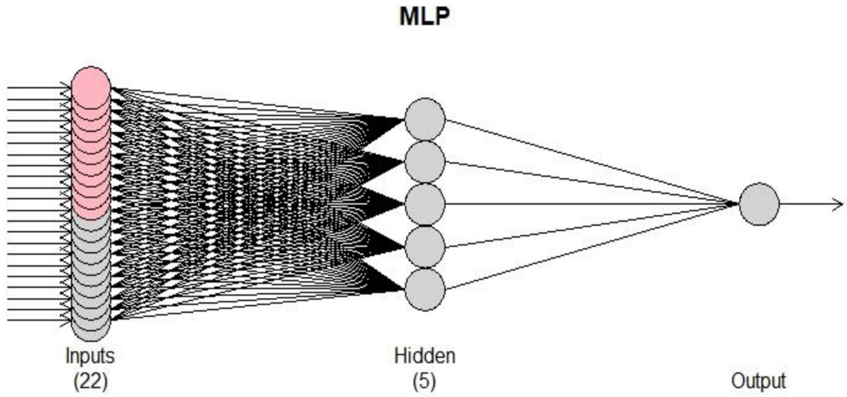


Fig. 2. Architecture of ANN with multi-layer perceptron.

biological neural network controlled by the human brain. An ANN is made up of nodes of input, hidden and output layers which are connected to each other and consist of an activation function that is applied for the determination of specific patterns of datasets (Lippmann 1987). The back propagation technique is the most commonly used estimating strategy in neural networks (Rumelhart *et al.* 1986). Thus, a feed forward back propagation neural network is constituted to form a multi-layer perceptron (MLP) which consists of all the different properties of neural networks (Krishnan *et al.* 2022). ANN with MLP is mathematically expressed as:

$$y_t = w_o + \sum_{j=1}^{\mathcal{Q}} w_j g\,(w_{oj} + \sum_{i=1}^{p} w_{ij}\, y_{t-i}) \qquad (8)$$

Where p and $\mathcal{Q}$ indicates the total number of input nodes and hidden layers respectively, is a constant term, expresses the sigmoid transfer function, (w_j,j = 0,1,2,...,$\mathcal{Q}$ denotes the vector of weights associated among hidden layer and output node w_o and (w_{ij}, i = 1,2,...,P,j = 1,2,...,$\mathcal{Q}$) indicates weights in between input and hidden nodes and w_{oj} denotes the weight given to output from each input and hidden layer (Shi *et al.* 2012). An ANN with a multi-layer perceptron having 22 inputs, 5 hidden layers and an output is shown in Fig.2.

ETS-ANN hybrid model

The ETS and ANN are combined to develop the ETS-ANN hybrid model in such a way that the linear part of the time series data is described by ETS, whereas ANN illustrates the non-linear part (Panigrahi and Behera 2017). ETS-ANN model is mathematically expressed as

$$\hat{y}_t = \hat{c}_t^1 + \hat{c}_t^2 \qquad (9)$$

Where $\hat{y}_t$ indicated the forecasted value of the hybrid model, $\hat{c}_t^1$ described as the predicted value from a_t ETS and $\hat{c}_t^2$ designated as the predicted value from ANN.

Assessment of the predicted model

The assessment of the model is done by following methods given below:

Mean square error (MSE)

The average of square of discrepancy among actual y_i and predicted $\hat{y}$ values is termed the mean square error.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (10)$$

Root mean square error (RMSE)

The square root of mean square error is designated as root mean square error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (11)$$

Mean absolute error (MAE)

The average of absolute discrepancy among actual y_i and predicted $\hat{y}_i$ values is known as the mean absolute error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (12)$$

Relative mean absolute percentage error (RMAPE)

The arithmetic average of absolute discrepancy of actual y_i and predicted $\hat{y}_i$ values divided by actual value which is expressed in percentage is termed as the relative mean absolute percentage error.

$$RMAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (13)$$

Coefficient of determination

The coefficient of determination measures the explained variance present in the data such that greater the value of R^2, better the accuracy of prediction using the model. Here, R^2 among actual y_i and predicted $\hat{y}_i$ values are determined for n observations with mean $\bar{y}$.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (14)$$

The model with highest value of R^2 and lowest error is considered as outperforming model.

RESULTS AND DISCUSSION

The foremost intention of the study was to forecast relative humidity and wind speed for northern, central and southern zones of Kerala using combination of ETS and ANN with multi-layer perceptron (MLP) and also to undergo comparison of this model with single ETS and ANN model. In order to undergo the modelling and forecasting of data, R software (Crone and Kourentzes 2010, Hyndman *et al.* 2008, Hyndman and Athanasopoulos 2018, Kourentzes *et al.* 2014, Ord *et al.* 2017) was employed in the study.

Table 1. Descriptive statistics about weather parameters in different zones of Kerala.

Weather parameter	Zone	Maximum	Minimum	Mean	Standard deviation
Relative humidity	Northern	90.620	61.060	78.391	7.385
	Central	91.250	55.750	78.315	9.750
	Southern	92.120	55.440	79.600	8.672
Wind speed	Northern	6.660	2.080	3.836	1.058
	Central	4.340	1.300	2.489	0.712
	Southern	6.700	2.180	4.145	1.124

In Fig. 3 the time series plot for different zones of Kerala is depicted.

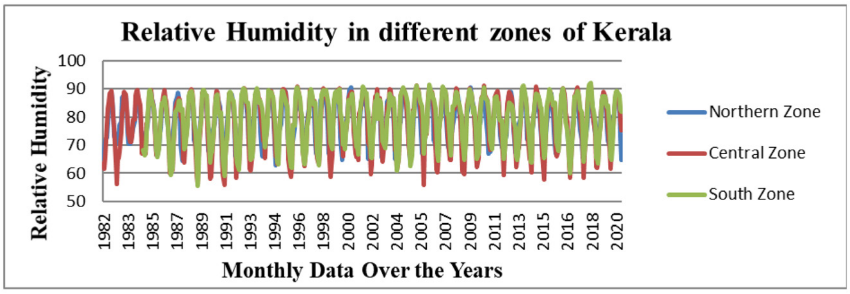
The pattern of weather parameters over the years are illustrated in Fig. 3. The descriptive statistics about the weather parameters in different zones of Kerala is displayed in Table 1. The descriptive statistics given in Table 1 indicated the variations of weather parameters in different zones of Kerala. The whole monthly data divided in to training and testing sets. The training dataset of the northern and central zones of Kerala consists of data from 1982 to 2015 whereas it is 1985 to 2015 for the southern zone of Kerala. The testing set of northern, central and southern Kerala consists of 5 years (2016-2020) data. Next step is fitting of the ETS model for the weather parameters in training set for different zones of Kerala using R software which is presented in Table 2.

The ETS model selected for weather parameters in different zones of Kerala using R software along with its parameters are shown in Table 2. ETS (A,N,A) model showed that error is additive, trend is absent and seasonality is additive whereas ETS (M,N,M) model indicated that error is multiplicative, trend is absent and seasonality is multiplicative. The optimal ETS model was chosen based on the lowest values for Akaike information criterion (AIC), modified Akaike information criterion (AICc) and Bayesian information criterion (BIC) and it is also presented in Table 2. After completing, modelling of weather parameters using ETS, next step is to undergo fitting of weather parameters and residuals obtained from ETS models using ANN. The architecture of ANN model fitted using R software is shown in Table 3.

Table 2. ETS model with parameters and model selection criteria for relative humidity and wind speed.

Weather parameter	Zone	ETS model	Alpha	Gamma	AIC	AICc	BIC
Relative humidity	Northern zone	ETS (A,N,A)	0.0174	0.000	3080.516	3081.741	3140.685
	Central zone	ETS (A,N,A)	0.3557	0.000	3377.202	3378.426	3437.371
	Southern zone	ETS (A,N,A)	0.5805	0.000	2986.149	2987.497	3044.932
Wind speed	Northern zone	ETS (M,N,M)	0.0469	0.000	1686.387	1687.612	1746.556
	Central zone	ETS (M,N,M)	0.0706	0.000	1316.764	1317.989	1376.933
	Southern zone	ETS (A,N,A)	0.0857	0.000	1611.024	1612.373	1669.808

a) Relative Humidity



b) Wind Speed

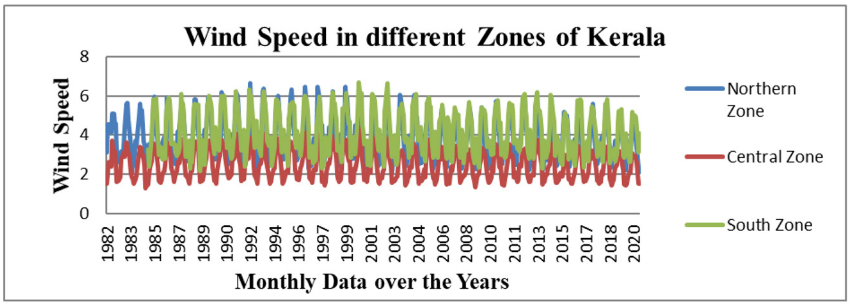


Fig. 3. Time series plots for relative humidity (a) and wind speed (b) for different zones of Kerala.

The suitable architecture for each weather parameter and its residuals in different zones of Kerala are presented in Table 3. After completing the fitting of hybrid models for weather parameters in different zones of Kerala, the next step is evaluation and validation of models in order to determine which model showed superior performance related to other models. The model is evaluated by forecasting weather parameters for next 5 years (2016-2020) using ETS, ANN, and hybrid ETS-ANN models, as well as evaluated by comparing predicted values with and actual ob-

Table 3. ANN Architecture for weather parameters and residuals of ETS models fitted for weather parameters in different zones of Kerala.

Weather Parameter	Zone	Architecture	ANN Architecture
Relative humidity	Northern zone	22-5-1	11-5-1
	Central zone	21-5-1	12-5-1
	Southern zone	23-5-1	12-5-1
Wind speed	Northern zone	23-5-1	9-5-1
	Central zone	23-5-1	12-5-1
	Southern zone	22-5-1	12-5-1

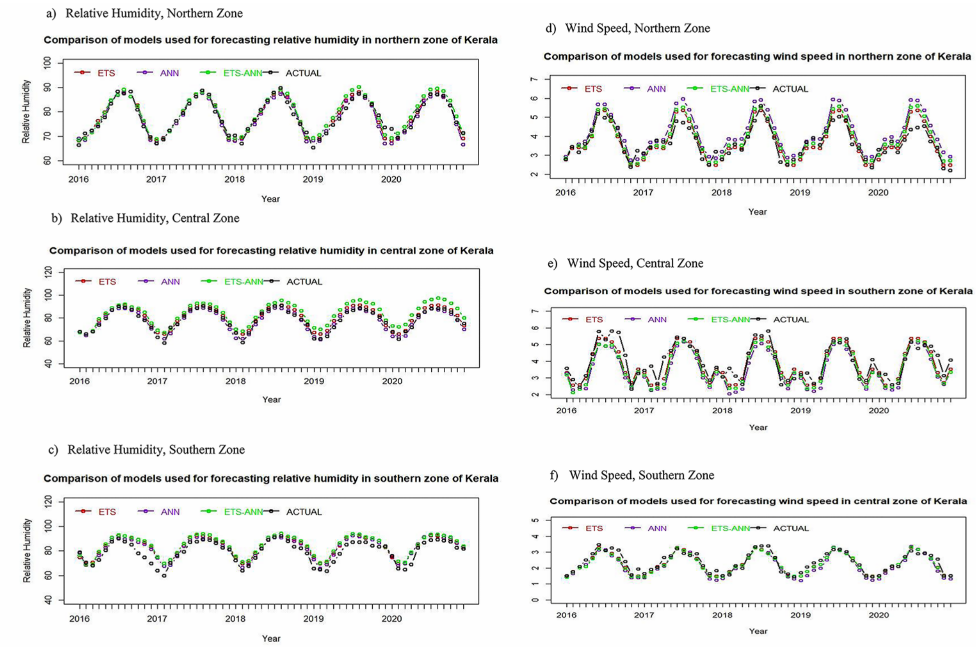
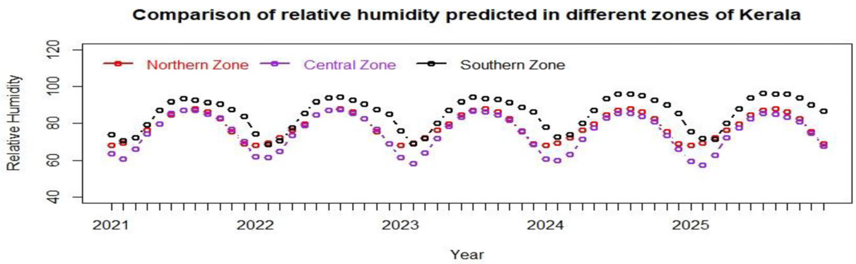


Fig. 4. Comparison of forecasting of relative humidity (a-c) and wind speed (d-f) with actual observations using ETS, ANN and hybrid ETS-ANN.

Table 4. Evaluation and validation of models fitted for weather parameters.

Weather parameter	Zone	Model	MSE	RMSE	MAE	RMAPE	R^2
Relative humidity	Northern zone	ETS	**3.19**	**1.78**	**1.39**	**1.82**	**0.939**
		ANN	4.30	2.07	1.54	2.02	0.923
		ETS-ANN	4.51	2.12	1.75	2.27	0.933
	Central zone	ETS	9.77	3.12	2.58	3.47	0.943
		ANN	**5.57**	**2.36**	**1.91**	**2.53**	**0.944**
		ETS-ANN	39.92	6.31	5.61	7.37	0.900
	Southern zone	ETS	27.03	5.19	4.33	5.74	0.867
		ANN	**19.29**	**4.39**	**3.41**	**4.49**	**0.875**
		ETS-ANN	36.30	6.02	5.21	6.85	0.860
Wind speed	Northern zone	ETS	**0.12**	**0.35**	**0.28**	**7.89**	**0.867**
		ANN	0.38	0.62	0.50	13.95	0.843
		ETS-ANN	0.17	0.41	0.32	9.03	0.853
	Central zone	ETS	**0.04**	**0.21**	**0.16**	**6.90**	**0.905**
		ANN	0.09	0.30	0.24	11.01	0.881
		ETS-ANN	0.05	0.23	0.18	7.78	0.895
	Southern zone	ETS	**0.23**	**0.48**	**0.36**	**9.54**	**0.817**
		ANN	0.47	0.68	0.54	13.81	0.799
		ETS-ANN	0.35	0.59	0.45	11.74	0.798

a) Relative Humidity



b) Wind Speed

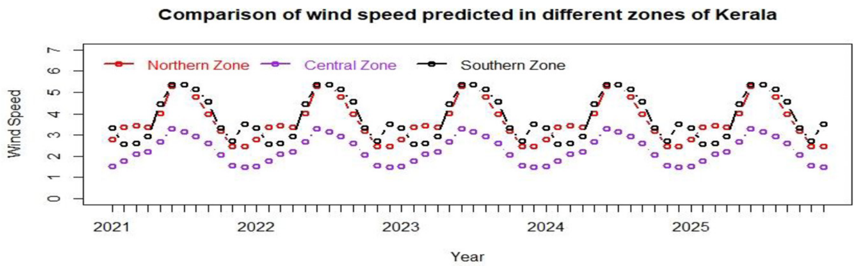


Fig. 5. Comparison of forecasted values using outperformed model for relative humidity (a) and wind speed (b) for northern, central and southern zones of Kerala.

servations in the testing set. The relationship among anticipated and observed values in the testing set for relative humidity and wind speed is shown in Fig. 4.

Comparison between predicted values using different models and actual values depicted in Fig.4 clearly indicated that all models are performing well. In order to determine which model is showing maximum accuracy, evaluation and validation of models are done using MSE, RMSE, MAE, MAPE and R^2 values. In each of the cases stated in Table 4, the model showing lowest inaccuracy measure is considered as outperforming model.

The results described on Table 4 suggested that for forecasting of relative humidity, ANN model outperformed other models in both the central and the southern zones, but for the northern zone of Kerala, ETS model showed maximum accuracy. ETS model outperformed other models for prediction of wind speed, in the northern, central and southern zones of Kerala. The RMAPE values are less than 20% and high R^2 value indicated that accuracy of all best selected models for each weather parameters in different zones of Kerala are very high. After identifying the best suitable model for weather parameters in different zones of Kerala, the selected model was used for forecasting weather parameters for next 5 years in different zones of Kerala which is depicted in Fig. 5.

The forecasted values of relative humidity and wind speed for next 5 years for the northern, the central and the southern zones of Kerala is illustrated in Fig. 5. The relative humidity was predicted highest in the southern zone and least amount was predicted in the central zone whereas in the northern zone of Kerala, humidity was moderate for next 5 years (2021-2025). The wind speed prediction for next 5 years suggested that the southern zone of Kerala may have the highest wind speed and it may be almost par with the northern zone of Kerala whereas for the central zone of Kerala predicted wind speed is comparatively smaller.

CONCLUSION

The foremost attention of the current study was to obtain the future projection of weather parameters with high precision. The ETS, ANN and a hybrid model combining ETS and ANN was used in this study for forecasting weather parameters with maximum accuracy. The weather parameters including relative humidity and wind speed of the northern, central and southern zone were collected using data access viewer. The data were collected for a period of 39 years (1982-2020) for the northern and central zones whereas for southern zone data were collected for a period of 36 (1985-2020) years. In order to undergo fitting and evaluation of weather data, the data were separated into training and testing sets. The training set for northern and central zones consists of data from 1982 to 2015 whereas for the southern zone it was from 1985 to 2015. The testing set for the different zones consists of data for the last 5 years (2016-2020). The best suited model for relative humidity was ANN for the central and southern zones, whereas for the northern zone it was the ETS model. For wind speed, the ETS model indicated high accuracy in all three zones of Kerala. The high precision of all the best selected models is indicated by RMAPE values less than 20% and high values. The research suggested that even though most novel hybrid model ETS-ANN was applied, the traditional method of modelling ETS and neural network ANN was giving more précised prediction of weather parameters in different zones of Kerala. The outperformed model for each weather parameter for different zones of Kerala was used for forecasting the next 5 (2021-2025) years. The prediction suggested that relative humidity will increase in the southern zone and decrease in the central zone whereas similar behavior in the northern zone whereas the anticipated values of wind speed suggested declining nature in different zones of Kerala. The study suggested that within a single state at different zones, climate is behaving very differently. The changes in weather parameters are very important since it can affect the growth and development of flora and fauna by increasing pest and disease incidence, disturbances in pollination, uneven rainfall etc. The prediction of weather parameters must be done with more accuracy and least error such that more methods of modelling must be developed by scientific community which indicate less error values in validation.

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REFERENCES

Affan MF, Abdullah AG, Surya W (2019) Forecasting of wind speed using exponential smoothing and artificial neural networks (ANN). *J Phys Conf Ser* 1402(3): 033-082.

Cadenas E, Jaramillo OA, Rivera W (2010) Analysis and forecasting of wind velocity in chetumal, quintana roo, using the single exponential smoothing method. *Renew Energ* 35(5): 925-930.

Camelo H, Lucio PS, Junior JBVL, de Carvalho PCM, dos Santos DVG (2018) Innovative hybrid models for forecasting time series applied in wind generation based on the combination of time series models with artificial neural networks. *Energy* 151: 347-357.

Crone SF, Kourentzes N (2010) Feature selection for time series prediction – A combined filter and wrapper approach for neural networks. *Neurocomputing* 73(10): 1923-1936.

Ferreira M, Santos A, Lucio P (2019) Short-term forecast of wind speed through mathematical models. *Energy Reports* 5: 1172-1184.

Gardener JrES (1985) Exponential smoothing: The state of the art. *J Forecast* 4: 1–28.

Google Earth. https://www.google.com/intl/en_in/earth/ (accessed on 30th March 2022).

Holt CC (1957) Forecasting seasonals and trends by exponentially weighted moving averages; ONR Research Memorandum, Carnegie Institute of Technology, Reprint, pp52.

Huang X, Wang J, Huang B (2021) Two novel hybrid linear and nonlinear models for wind speed forecasting. *Energy Convers Manag* 238: 114-162.

Hyndman RJ, Athanasopoulos (2018) Forecasting: Principles and practice; 2nd edn. OTexts: Melbourne, Australia.

Hyndman RJ, Koehler AB, Ord JK, Snyder RD (2008) Forecasting with exponential smoothing: The state space approach. Springer-Verlag: New York.

Hyndman RJ, Koehler AB, Snyder RD, Grose S (2002) A state space framework for automatic forecasting using exponential smoothing methods. *Int J Forecast* 18(3): 439–454.

Kourentzes N, Barrow BK, Crone SF (2014) Neural network ensemble operators for time series forecasting. *Expert Syst Appl* 41(9): 4235-4244.

Krishnan GKB, Mehta V, Rai VN (2023) Stochastic modelling and forecasting of relative humidity and wind speed for different zones of Kerala. *Mausam* 74(04): 1053-1064.

Krishnan GKB, Mehta V, Yadav RS (2022) Assessment of future pattern of rainfall in different zones of Kerala using incorporation of SARIMA, ANN and Hybrid SARIMA-ANN models. *Econ Aff* 67(05): 823-832.

Lippmann R (1987) An introduction to computing with neural nets. *IEEE ASSP Magazine* 4(2): 4-22.

McCulloch WS, Pitts W (1943) A logical calculus of the ideas immanent in nervous activity. *Bull Math Biophys* 5: 115-133.

NASA (2022) Power Data Access Viewer. Available online: https://power.larc.nasa.gov/data-access-viewer/ (accessed on 20th January 2022).

Ord K, Fildes R, Kourentzes N (2017) Principles of Business Forecasting 2e; Wessex Press Publishing Co, Chapter, pp 10.

Panigrahi S, Behera HS (2017) A hybrid ETS–ANN model for time series forecasting. *Eng Appl Artif Intell* 66: 49-59.

Pegels CC (1969) Exponential forecasting: Some new variations. *Manage Sci* 15(5): 311–315.

Rumelhart DE, Hinton GE, Williams RJ (1986) Learning representations by back-propagating errors. *Nature* 323(1): 533–536.

Shamshad B, Khan MZ, Omar Z (2019) Modeling and forecasting weather parameters using ANN-MLP, ARIMA and ETS model: A case study for Lahore, Pakistan. *J Appl Stat* 5: 388.

Shi J, Guo J, Zheng S (2012) Evaluation of hybrid forecasting approaches for wind speed and power generation time series. *Renew Sust Energy Rev* 16(5): 3471-3480.

Taylor JW (2003) Exponential smoothing with a damped multiplicative trend. *Int J Forecast* 19: 715–725.

Winters PR (1960) Forecasting sales by exponentially weighted moving averages. *Manage Sci* 6(3): 324–342.