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Modeling and forecasting meteorological factors using BATS and TBATS models for the Keonjhar district of Orissa

MONIKA RAY, K. C. SAHOO, MOSTAFA ABOTALEB*, SOUMIK RAY**, P. K. SAHU***, PRADEEP MISHRA*[#], ABDULLAH MOHAMMAD GHAZI AL KHATIB**[#], S. S. DAS*[##], VIKAS JAIN*[#] and RITISHA BALLOO[##]

College of Agriculture, OUAT, Bhubaneswar, India

**Department of System Programming, South Ural State University, Chelyabinsk, Russia*

***Centurion University of Technology and Management, Paralakhemundi, Odisha, India*

****Department of Agricultural Statistics, BCKVV (W.B.), Mohanpur, India*

**[#]College of Agriculture, Powarkheda, J.N.K.V.V., Jabalpur - 482 004, India*

***[#]Department of Banking and Insurance, Faculty of Economics, Damascus University, Damascus, Syria*

**[##]Ranchi Agriculture College, Birsa Agricultural University, Ranchi, India*

[##]Departments of Law and Management, University of Mauritius

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e mail : raysoumik4@gmail.com

सार – अच्छी कृषि के लिए तापमान और आर्द्रता जैसे मौसम कारक आवश्यक हैं। इन मौसम कारकों की स्थिति के के अनुसार सर्वोत्तम-उपयुक्त उत्पादों का चयन किया जा सकता है। इस अध्ययन में भारत में 31 जनवरी 1921 से 31 दिसंबर 2020 तक के अधिकतम तापमान, न्यूनतम तापमान, सुबह की सापेक्षिक आर्द्रता और शाम की सापेक्षिक आर्द्रता आर्द्रता के आंकड़ों का विश्लेषण किया गया है। BATS (एक्सपोनेंशियल स्मूथिंग मेथड + बॉक्स-कॉक्स ट्रांसफॉर्मेशन + अवशिष्ट के लिए ARMA मॉडल) और TBAT (BATS + त्रिकोणमितीय मौसमी) मॉडल के उपयोग पूर्वानुमान प्रक्रियाओं के के लिए किए जाते हैं। कुछ चयनित मानदंडों के अनुसार, सभी मौसम कारकों के लिए सर्वोत्तम मॉडल निर्दिष्ट किए जाते हैं। इस अध्ययन में विस्तृत सारणी और ग्राफिक्स प्रस्तुत किए गए हैं। डेटा श्रृंखला को ट्रेन सेट और परीक्षण सेट में विभाजित किया गया। ट्रेन सेट से प्राप्त परिणाम के अनुसार BATS मॉडल ने सर्वश्रेष्ठ मॉडल के रूप में कार्य किया। परीक्षण डेटा सेट का उपयोग करके त्रुटि के अनुमान के लिए अधिकतम तापमान, सुबह और शाम की सापेक्षिक आर्द्रता के के लिए BATS मॉडल ने अच्छा कार्य किया। दोनों मॉडलों का न्यूनतम तापमान डेटा श्रृंखला में महत्वपूर्ण प्रदर्शनरहा। इस इस अध्ययन में प्राप्त परिणामों और पूर्वानुमानों का उपयोग करते हुए, शोधकर्ता या वैज्ञानिक को मौसम की स्थिति पर विशेष ध्यान देना चाहिए जो कृषि के लिए अधिक संबंधित प्राचल है।

ABSTRACT. Weather factors such as temperature and humidity are indispensable for good agriculture.The best-suitable products can be selected according to the optimal of these weather factors. In this study, data on maximum temperature, minimum temperature, morning relative humidity and evening relative humidity was analyzed from 31st January, 1921 to 31st December, 2020 in India. The BATS (Exponential Smoothing Method + Box-Cox Transformation + ARMA model for residuals) and TBAT (BATS + Trigonometric Seasonal) models are conducted for forecasting procedures. According to some selection criteria, the best models are specified for all weather factors. Extensive tables and graphics are presented in the study. The data series was divided into train set and test set. The result obtained from train set based on goodness of fit, BATS model performed as a best model. For error estimation using testing data set, BATS model performed well for maximum temperature, morning and evening relative humidity. Both models were performed significantly atpar in minimum temperature data series. Using the results and forecasts obtained in this study, the researcher or scientist should be focused on the weather condition which is more concerned parameter for agriculture.

Key words – Weather Factors, BATS, TBATS, Forecasting.

1. Introduction

The primary source of livelihood for about 58% of India's population is agriculture. The major factor affecting Indian agriculture is the weather. In a study to access the potential impact of catastrophic weather on the crop insurance industry, Vergara *et al*., 2008 concluded that 93% of crop loss was directly related to unfavorable weather. Weather includes many variables, such as temperature, rainfall, atmospheric pressure, humidity.The two important factors which have a large effects on crop yield are rainfall and temperature (Runge, 1968; Abbate *et al*., 2004; Calderini *et al*., 1999; Medori *et al*., 2012). Rainfall is considered one of the important factors in crop production programs in dryland areas (Ray and Patro, 2016). Rainfall variability analysis, in agricultural planning, helps in taking farm decisions like sowing time; inter culture operations, fertilizer application and other agricultural operations. In Eastern India, the agricultural operations in the rained agriculture mainly depend upon the onset of South West Monsoon. Huge yield loss may occur if there is a delay in sowing of rained upland crops even by few days (Ahmed *et al*., 2009).

Temperature is another important weather parameter that directly influences the yield and productivity of crops. The air temperature regulates all the biological and chemical processes taking place in the soil, therefore, too-high and too-low temperatures adversely affect the biochemical processes in cells and changes occur which are irreversible. This leads to growth inhibition and the death of crop plants. In temperate crops, if the temperature is high, even for a during short period, the growth of shoots is affected, which in turn reduces the root growth. It was found that there was a decrease of about 17% in the yields of both corn and soybeans for each degree of increase in the temperature during the growing season (Lobell and Asner, 2003). Typically, temperature affects the length of the growing season and rainfall affects plant production (leaf area and the photosynthetic efficiency) (Cantelaube and Terres, 2005; Olesen and Bindi, 2002). Ray *et al*. (2021) developed the SARIMA model to estimate the forecasting behavior of monthly rainfall and temperature in the South Asian countries and draw a conclusion about the variation of global climatic changes. Lama *et al*. (2021) used parametric and non-parametric model to check the future behaviour of monthly rainfall of Sub-Himalayan region of India. ARCH model also used for forecasting of different metrological factor based on error distribution (Mishra *et al*., 2021). Abotaleb *et al*. (2022) estimated the wind speed prediction in England using different time series model. The authors employed that BATS and ARIMA model performed as best model based on error estimation.

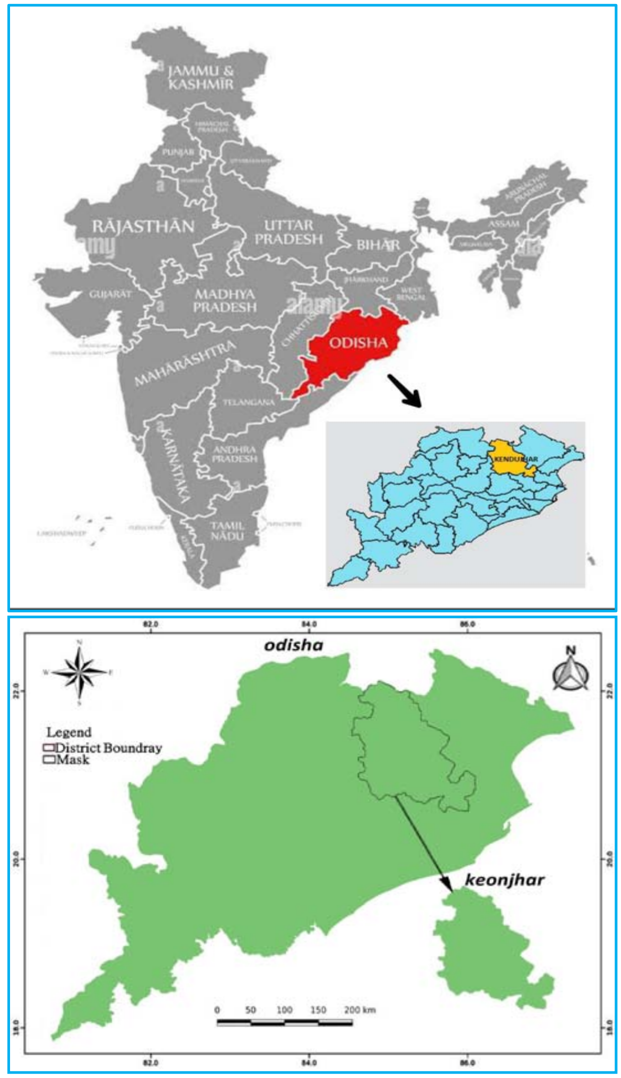

Fig. 1. A geographical area of Keonjhar district

Therefore, detailed knowledge of rainfall and temperature patterns will helps to make a proper planning the cultivation of crops, their varieties, adoption of cultural operations, designing of different storage structures (Ray *et al*., 1987) and harvesting of excess rainwater of any region (Kar, 2002) to fulfil the irrigation requirements during the drought period.

2. Materials and method

The time series data on monthly maximum and minimum temperature, morning and evening relative humidity percent (R.H.) for Keonjhar district of Odisha was analyzed from 31st January, 1921 to 31st December, 2020. Time series data was collected from Gramin Krishi Mausam Seva (GKMS) from ZARS, Keonjhar OUAT. Selecting the map of our study area is depicted in Fig. 1.

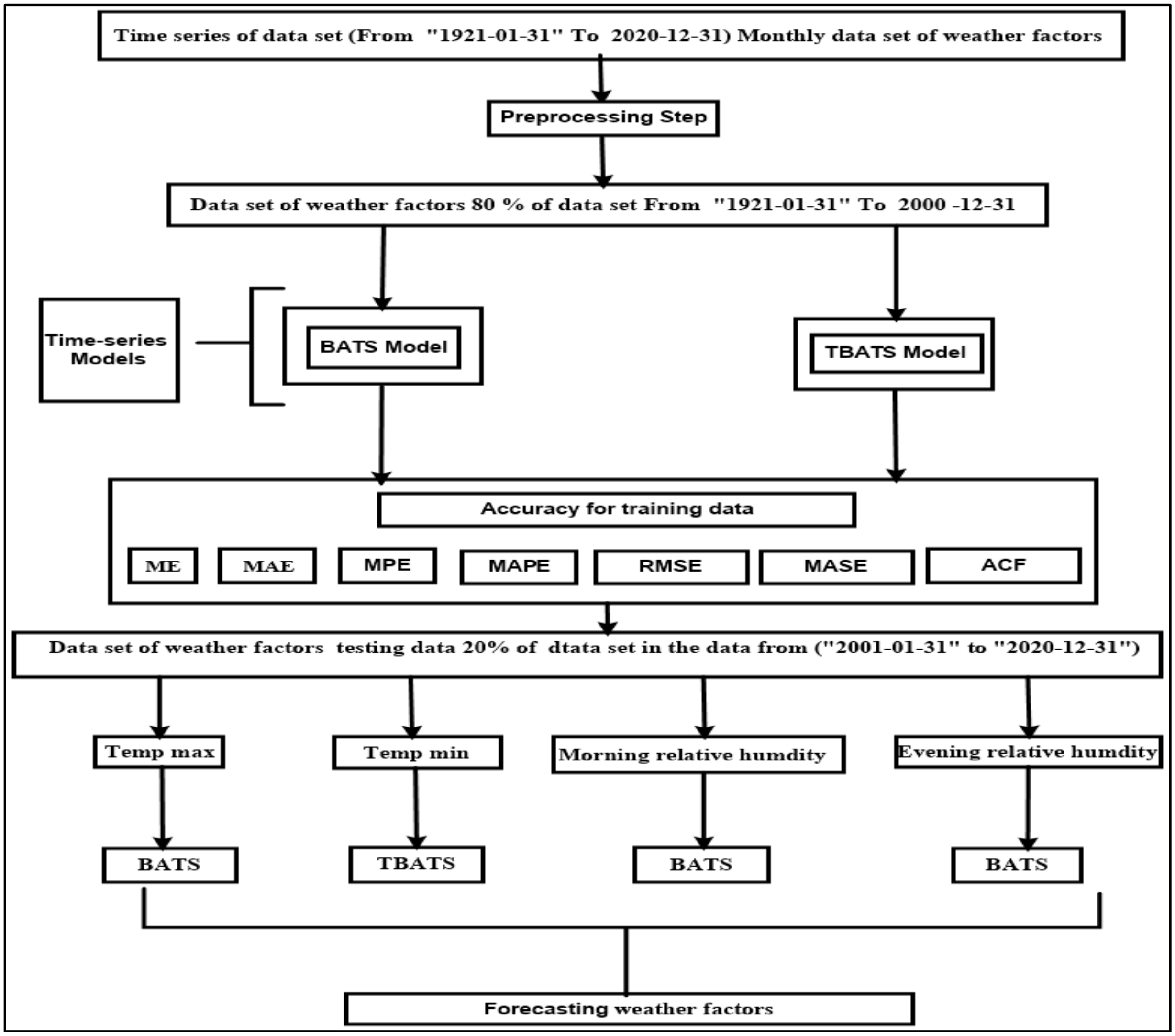

Fig. 2. Schema for the best model for forecasting

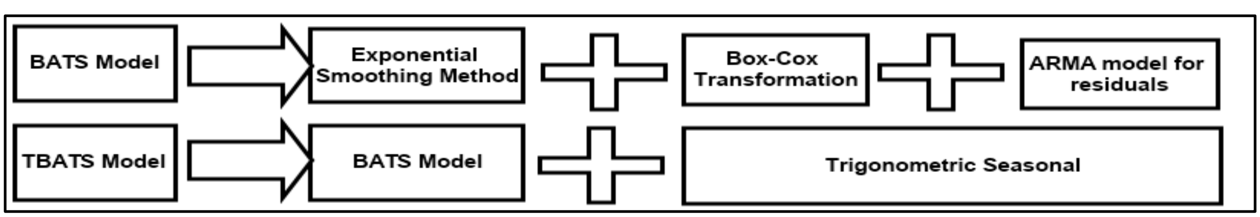

Fig. 3. BATS and TBATS model

2.1. *BATS and TBATS Models*

BATS model is Exponential Smoothing Method + Box-Cox Transformation + ARMA model for residuals. The Box-Cox Transformation here is for dealing with non-linear data and ARMA model for residuals can de-correlated the time series data. BATS model can improve the prediction performance compared to the simple Sate Space Model. (Mishra *et al*., 2021).TBATS is an improvement modification of BATS that allows multiple seasonal incorrect cycles. TBATS has the following equation (De Livera, 2011) from Fig. 3 that represents the BATS and TBATS model.

The first Equation (1) is a Box-Cox transformation, error modeled by ARMA (Mishra *et al.*, 2020).

$$Y_t^{(\eta)} = \begin{cases} \dfrac{Y_t^{(\eta)} - 1}{\eta} \eta \neq 0 \\ \log y_t \eta = 0 \end{cases} \quad (1)$$

The second Equation (2) represents the seasonal *M* pattern.

$$Y_t^{(\mu)} = l_{t-1} + \xi Z_{t-1} + \sum_{i=1}^{T} s_{t-\rho_i}^{(i)} + d_t \quad (2)$$

global trends and local trends are Equations (3),(4) and (5).

$$l_t = l_{t-1} + \xi Z_{t-1} + \alpha d_t \quad (3)$$

$$b_t = \xi b_{t-1} + \beta d_t \quad (4)$$

$$s_t^{(i)} = s_{t-\rho_i}^{(i)} + \gamma_i d_t \quad (5)$$

Equation (6) error can be modeled by ARMA.

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_{t'} \quad (6)$$

From $\rho_1, \ldots$ to ρ_T denote the seasonal period, level and trend of components of the time series can be denoted by l_t and Z_t at time t. The seasonal component can be denoted by$s_t^{(i)}$ at time t, d_t represents to ARMA (p, q) component and ε_t is white noise process (Mishra *et al*., 2021; Rahman *et al.,* 2022).

The smoothing parameters are given by α, β, γ_i for $i = 1\ldots T$ and ξ is the dampening parameter, which gives more control over trend extrapolation when the trend component is damped (Taylor, 2003). For seasonal data, the following equations representing Trigonometric exponential smoothing models.

$$s_t^{(i)} = \sum_{j=1}^{k_i} a_{j,t}^{(i)} \cos\left[\psi_j^{(i)} t\right] \quad (7)$$

$$a_{j,t}^{(i)} = a_{j,t-1}^{(i)} + k_1^{(i)} d_t \quad (8)$$

$$\beta_{j,t}^{(i)} = \beta_{j,t-1}^{(i)} + k_2^{(i)} d_t \quad (9)$$

The smoothing parameters are $k_1^{(i)}$ and $k_2^{(i)}$.

$\psi_j^{(i)} = 2\pi j / \rho_i$. This is an extended, modified single source of error version of single seasonal multiple sources of error representation suggested by (Hannan, 1970) (Harvey, 1990) and (Durbin, 2012).

$$a_{j,t}^{(i)} = s_{j,t}^{(i)} \cos\left[\psi_j^{(i)} t\right] - s_{jt}^{*(i)} \sin\left[\psi_j^{(i)} t\right] \quad (10)$$

$$\beta_{j,t}^{(i)} = s_{j,t}^{(i)} \sin\left[\psi_j^{(i)} t\right] - s_{jt}^{*(i)} \cos\left[\psi_j^{(i)} t\right] \quad (11)$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t'}^{(i)} \quad (12)$$

where,

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin \psi_j^{(i)} + \left\{ k_1^{(i)} \cos\left[\psi_j^{(i)} t\right] + k_2^{(i)} \sin\left[\psi_j^{(i)} t\right] d_t \right\} \quad (13)$$

$$s_{j,t}^{(i)} = -s_{j,t-1} \sin \psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos \psi_j^{(i)} + \left\{ k_2^{(i)} \cos\left[\psi_j t\right] - k_1^{(i)} \sin\left[\psi_j t\right] d_t \right\} \quad (14)$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t'}^{(i)} \quad (15)$$

Equations (16) and (17) are seasonal patterns modeled by the Fourier model.

$$s_{j,t}^{(i)} = -s_{j,t-1}^{(i)} \cos \psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin \psi_j^{(i)} + \gamma_1^{(i)} dt \quad (16)$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} \sin \psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos \psi_j^{(i)} + \gamma_2^{(i)} dt' \quad (17)$$

The notation of TBATS [p, q, (ρ_1, k_1), (ρ_2, k_2), …, (ρ_T, k_T)] is used for these trigonometric models. The total frame work of model building is represented in Fig. 2 (Devi *et al*., 2021). The statistical software R (version 4.0.0) (https://www.r-project.org) were used for the whole analysis according to the objective of the study (https://cran.r-project.org).

3. Empirical results

3.1. *Data visualisation*

All the data series considered in this study is visualized in Fig. 4. Some descriptive statistics such as mean, minimum, maximum, standard deviation, skewness and kurtosis for maximum temperature, minimum temperature, morning relative humidity and evening relative humidity in Table 1. The mean (standard

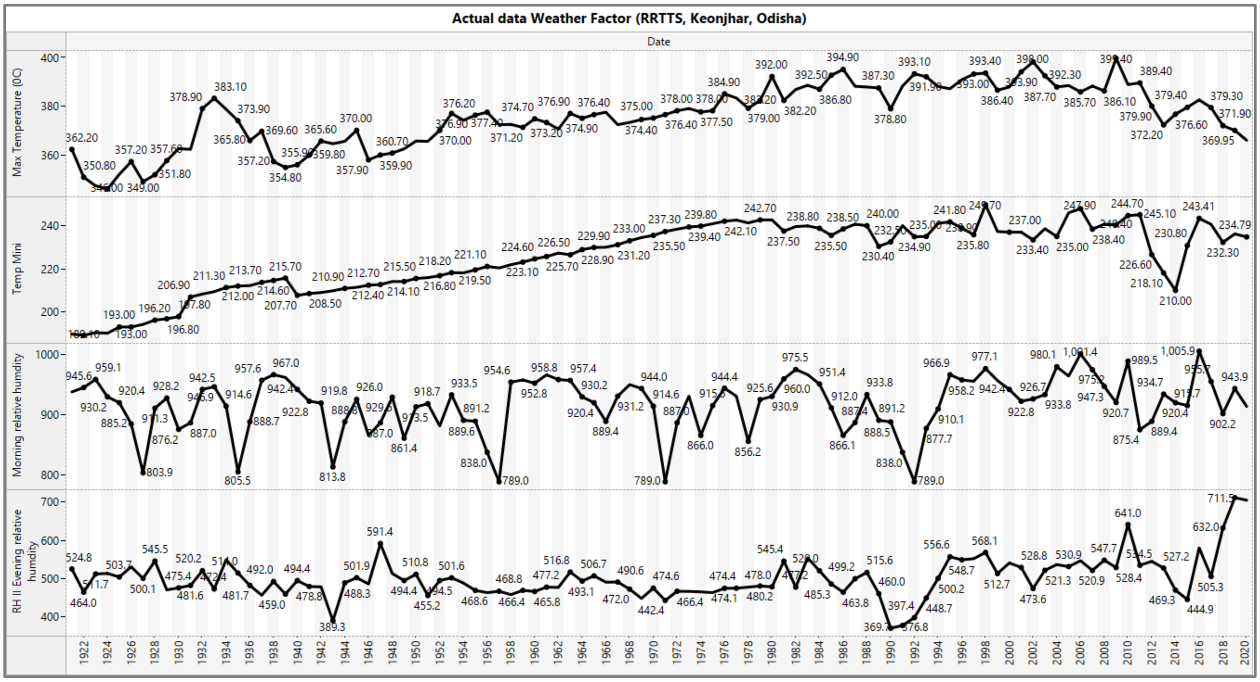

Fig. 4. Actual Data presentation of weather factor

TABLE 1

Descriptive statistics of weather factors

Cases	Mean	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis
Temp max	31.320	23.900	41.000	3.445	0.613	2.683
Temp min	18.800	8.700	26.800	4.330	-0.415	2.246
Morning relative humidity	76.510	39.470	95.600	10.883	-0.819	2.968
Evening relative humidity	41.730	14.000	86.000	15.102	0.387	2.217

deviation) for maximum temperature, minimum temperature, morning relative humidity and evening relative humidity are given, respectively, 31.32(3.44), 18.80(4.33), 76.51(10.88) and 41.73(15.10).

The minimum (maximum) for maximum temperature, minimum temperature, morning relative humidity and evening relative humidity are given, respectively, 23.90(41.00), 8.70(26.80), 39.47(95.60) and 14.00(86.00). The weather factor maximum temperature, evening relative humidity follows positive skewness and minimum temperature, morning relative humidity follows negative skewness. From the values of skewness, one can consider all the data series followsa symmetrical distribution (Ray and Bhattacharyya, 2020). It is also concluded from the coefficient of kurtosis in Table 1 that all weather factors have a leptokurtic distribution which shows fatter.

3.2. *Decomposition of data*

Before developing time series model for all the data series, it was required to decompose the data set to check irregular, trend and seasonality behaviour (Ray *et al*., 2021). Decomposition process done using BATS and TBATS model, because the models have a special feature to extract complex trends and seasonality from data series (Fig. 5). An interesting part could be observed that decomposition using the TBATS model was more adoptable than the BATS model. BATS model separated two components, whereas the TBATS model additionally separated the complex seasonal component using trigonometric seasonal expression. So, it was required to build these two models to estimate the component effect of all the data series. All the data series is split into training set (80%) and testing set (20%) for model building and validation purposes respectively.

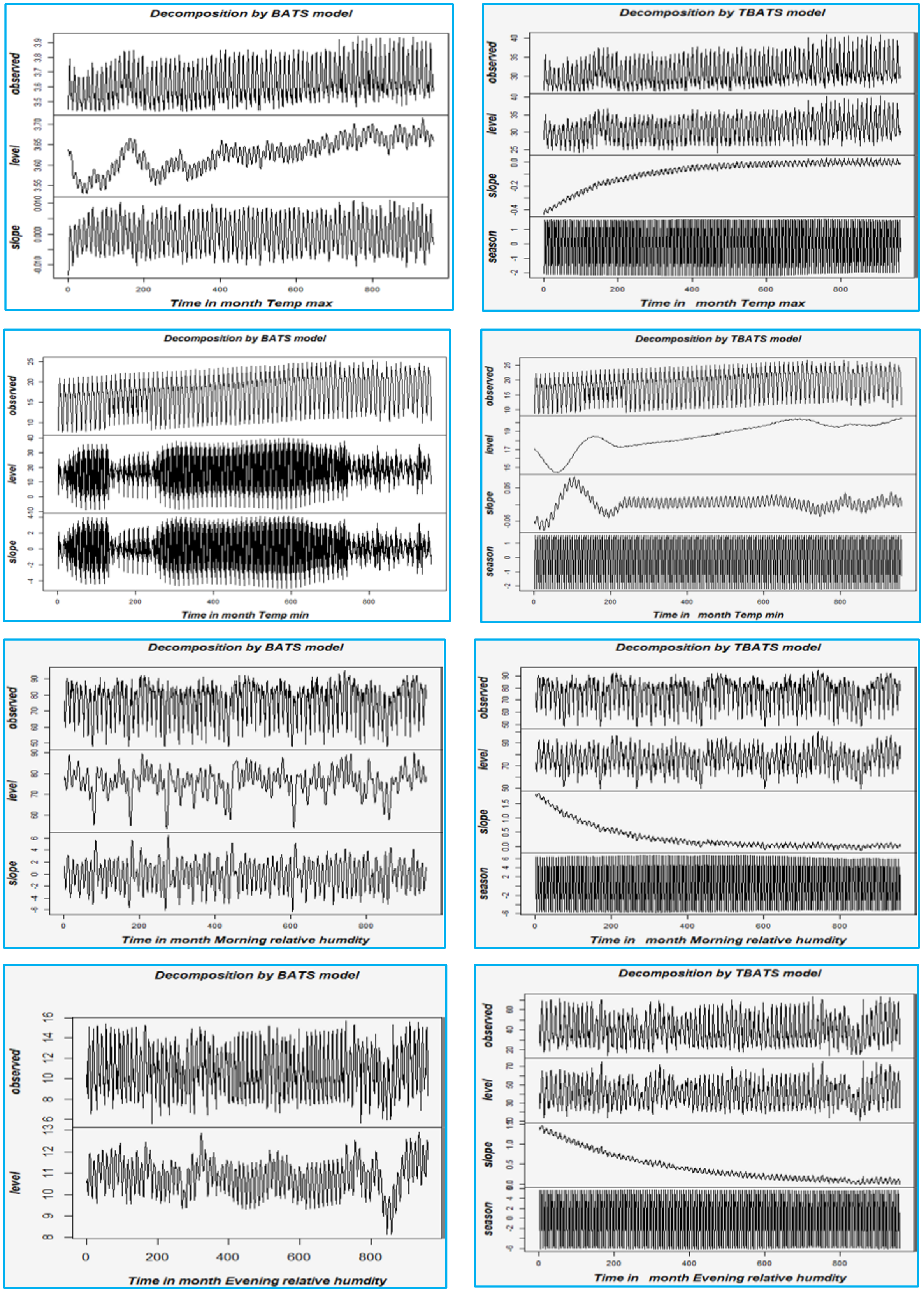

Fig. 5. Decomposition of data series with BATS and TBATS model

TABLE 2

BATS Model fitted weather factors training data for 80% of data set

Cases	Model	*Box-Cox transformation (Lambda)	Smoothing parameter		Damping Parameter For trend	ARMA Coefficients		Prediction error	
			Alpha	Beta		AR coefficients	MA Coefficients	Sigma	AIC
Temp max	BATS (0.032, {3,2}, 0.8, -)	0.032	0.052	0.023	0.8	1.208 -0.317 -0.29	-0.456 -0.392 -	0.059	7567.615
Temp min	BATS (0.992, {3,3}, 0.979, -)	0.992	1.796	0.317	0.979	0.611 0.685 -0.884	-1.926 0.891 0.037	1.805	7805.489
Morning relative humidity	BATS (1, {3,2}, 0.949, -)	1	0.057	0.084	0.949	0.612 0.757 -0.821	0.004 -0.944 -	7.176	10405.98
Evening relative humidity	BATS (0.511, {4,3}, -, -)	0.511	0.149	-	-	-0.139 0.874 0.098 -0.827	0.75 -0.526 -0.812 -	1.352	10624.72

*Box-cox transformation (Lambda) equals to 1, that means no transformation is required

TABLE 3

TBATSModel fitted for Weather factors training data for 80% of data set (From 1921-01-31 to 2000-12-31)

Cases	Model	*Box-Cox transformation (Lambda)	Smoothing parameter				Damping Parameter For trend	Prediction error	
			Alpha	Beta	Gamma-1 Values	Gamma-2 Values		Sigma	AIC
Temp max	TBATS (1, {0,0}, 1, {<6,2>})	1	1.212	0.006	-0.001	-0.002	1	1.882	7826.695
Temp min	TBATS (1, {0,0}, 1, {<6,2>})	1	0.004	0.002	0	0	1	3.825	9187.855
Morning relative humidity	TBATS (1, {0,0}, 1, {<6,2>})	1	0.935	0.006	-0.002	0.002	1	7.614	10509.91
Evening relative humidity	TBATS (1, {0,0}, 1, {<6,2>})	1	1.007	0.003	-0.001	0	1	10.103	11052.81

*Box-cox transformation (Lambda) equals to 1, that means no transformation is required

TABLE 4

BATS and TBATS Models fitted withweather factors training data for 80% of data set (From "1921-01-31" to 2000-12-31)

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
				Temp max			
BATS	0.069	1.637	1.326	-0.061	4.299	0.690	-0.019
TBATS	0.066	1.882	1.548	0.111	5.046	0.805	0.047
				Temp min			
BATS	0.024	1.845	1.427	-1.312	8.754	0.575	-0.057
TBATS	0.023	3.825	3.314	-4.949	20.047	1.336	0.790
				Morning relative humidity			
BATS	-0.133	7.176	5.663	-1.175	8.016	0.837	-0.075
TBATS	-0.342	7.614	6.156	-1.070	8.387	0.910	-0.017
				Evening relative humidity			
BATS	0.443	8.074	6.429	-3.370	17.839	0.780	-0.107
TBATS	-0.452	10.103	7.933	-4.012	21.367	0.963	-0.002

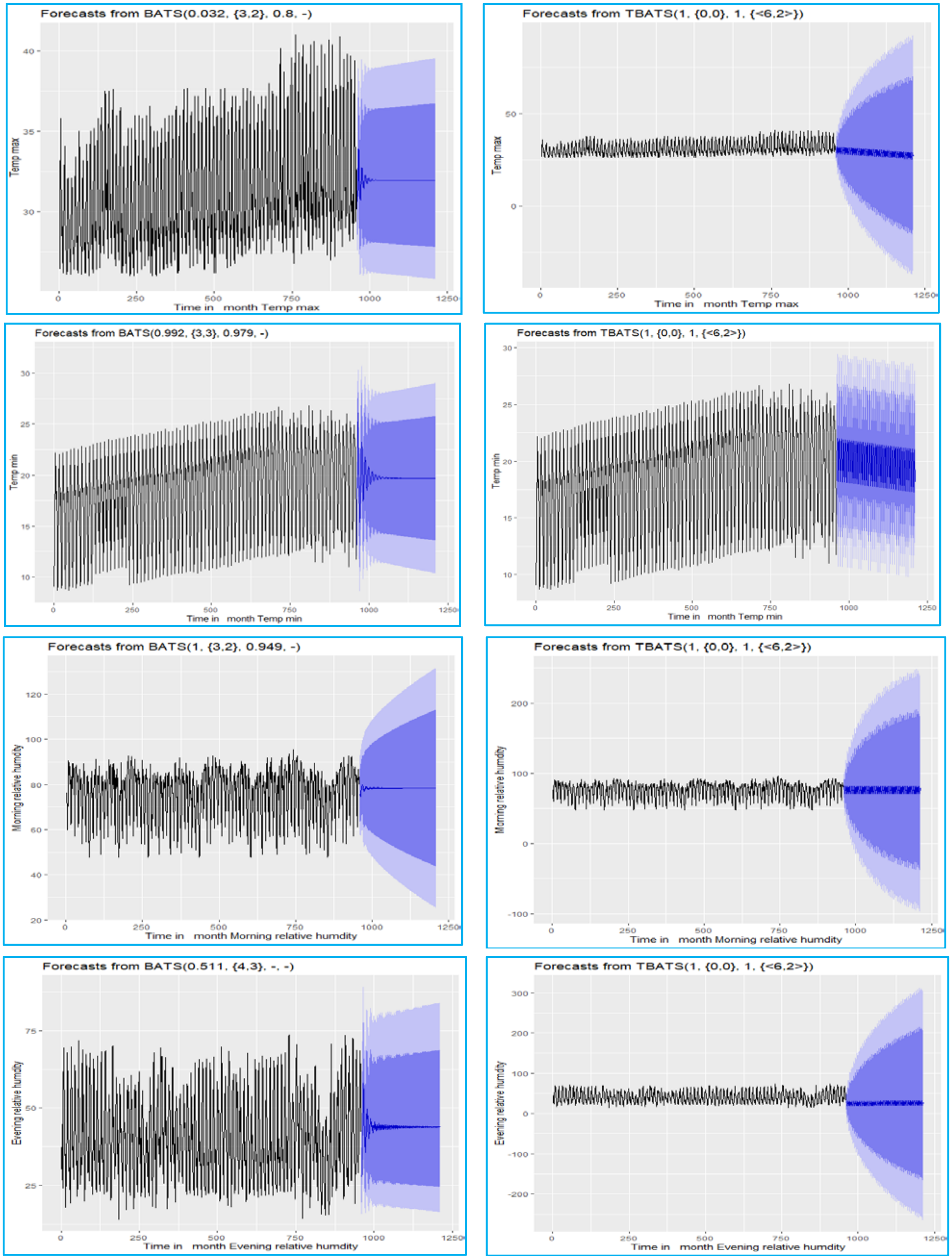

Fig. 6. Forecast from BATS and TBATS models for all data series

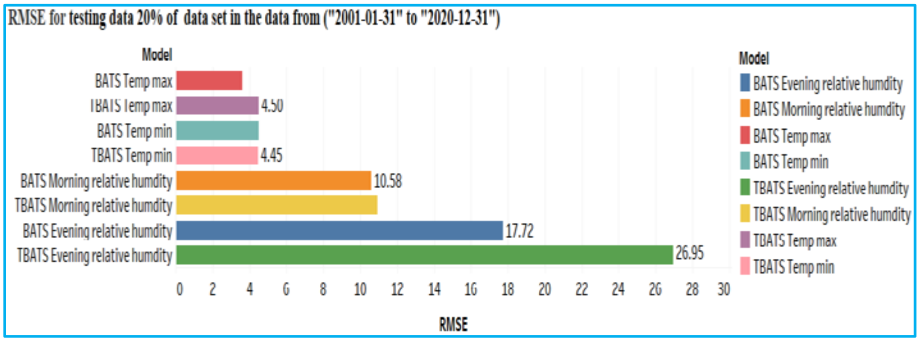

Fig. 7. BATS and TBATS models in different weather parameters RMSE

TABLE 5

RMSE for BATS, TBATS Models for Weather factors testing data 20% of data set in the data from ("2001-01-31" to "2020-12-31")

Model	RMSE
Temp max	
BATS	3.599922
TBATS	4.49846
Temp min	
BATS	4.495816
TBATS	4.445661
Morning relative humidity	
BATS	10.5791
TBATS	10.92716
Evening relative humidity	
BATS	17.71902
TBATS	26.9484

3.3. *Model building and forecasting*

The BATS models for weather factors are examined in Table 2 for training data. The best-suited BATS models maximum temperature, minimum temperature, morning relative humidity and evening relative humidity are given respectively: BATS (0.032, {3,2}, 0.8, -), BATS (0.992, {3,3}, 0.979, -), BATS(1, {3,2}, 0.949, -) and BATS (0.511, {4,3}, -, -). The TBATS models for weather factors are examined in Table 3 for training data. The best-suited TBATS models maximum temperature, minimum temperature, morning relative humidity and evening relative humidity are given respectively: TBATS (1, {0,0}, 1, {<6,2>}), TBATS (1, {0,0}, 1, {<6,2>}), TBATS (1, {0,0}, 1, {<6,2>}) and TBATS (1, {0,0}, 1, {<6,2>}). The lowest values of the RMSE, MAE and MAPE are shown as the best model. The comparisons of BATS and TBATS models are given in Table 4 for training data. According to Table 4, the BATS model acts as the best model for all weather factors data series. From the graphical representation in Fig. 6, one can find all the information about forecasting from BATS and TBATS models. The blue colour line indicates the forecast values, lies within the confidence limit of upper and lower 95% level, confirms that the good prediction of selected models. An interesting part has that the forecast obtained from BATS model is not performed well, whereas the forecast from the TBATS model performed quite good. So, advanced statistical models, neural network models can be used to estimate the best forecasting behavior of these weather factors data series.

Besides, the comparisons of BATS and TBATS models for testing data based on the RMSE are given in Table 5 and Fig. 7. According to this table and figure, BATS, TBATS, BATS and BATS models are selected respectively for maximum temperature, minimum temperature, morning relative humidity and evening relative humidity.

4. Conclusions

In this study the climatic weather factors like maximum and minimum temperature, morning and evening relative humidity in Keonjhar district of Odisha has been modelled using the BATS and TBATS for developing the forecasting model. In this study, all the data series decomposed by BATS and TBATS model to extract the time series component to find the trending behaviour. After developing BATS and TBATS models, we compared both models best on goodness of fit, confirmed that BATS model for all the series performed well based on the training set. But the forecasting behaviour from the TBATS model performed better than the BATS model. The comparison with a testing data set, BATS model acts as the best for maximum temperature, morning and evening relative humidity data series. For the minimum temperature data series, both BATS and TBATS models performed significantly at per. Finally in this study, the BATS model considered as best model comparatively to the TBATS model based on the error estimation. Also in the present scenario advanced machine learning techniques can be used to develop a model for climatic weather factors. We strongly believe that this work has contributed to the vast and rapidly growing literature of forecasting models on different climatic factors to help policy makers and researcher.

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Conflict of Interest : On behalf of all authors, the corresponding author states that there is noconflict of interest.

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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