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Forecasting temperature using Simple exponential Smoothing and Holt's Winter smoothing method in Uttar Pradesh

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Abstract:

Particularly in areas with substantial climate variability, precise temperature forecasting is essential for energy management, agricultural planning, and disaster preparedness. The purpose of this study is to predict Uttar Pradesh's non-monsoon season temperature using two popular time series forecasting methods: Holt's Winter Smoothing Method and Simple Exponential Smoothing (SES). To forecast future temperature changes, the study applies both models to historical temperature data gathered over several years. While Holt's Winter approach incorporates both trend and seasonality in the data, SES is used to capture the underlying trend when seasonality is absent. Metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to assess both models' performance. The results indicate that Holt's Winter approach delivers better accuracy by accounting for seasonal variations, even if SES offers a dependable temperature forecast with less fluctuation. The study's conclusion emphasizes the importance of choosing the right model for precise long-term temperature predictions in areas with complex weather patterns and offers suggestions for the application of these models in climate-related forecasting in Uttar Pradesh, particularly during the non-monsoon season.

Keywords: Temperature, non-monsoon, Simple Exponential Smoothing, Holt's Winter Smoothing

I. Introduction

Climate change and sustainable development are significant challenges that must be addressed as soon as possible.[1] Temperature is one of the important factors for maintaining the sustainability in the region. It has a significant impact on many facets of the ecosystem and human activity. There are notable shifts in temperature trends during the post-monsoon or dry season, which is the time after the monsoon. Energy use, ecology, human health, and agriculture can all be significantly impacted by these temperature fluctuations. Some of temperature in non-monsoon season has directly impact on agriculture.

As in agriculture, Crop productivity and growth are directly impacted by temperature throughout the non-monsoon season. Temperature increases during the dry season are common in tropical and subtropical regions, and this can cause crops to experience water stress. While mild temperatures may be beneficial for certain crops, such as rice and wheat, excessive heat can result in lower yields, especially for heat-sensitive crops like vegetables and maize. Additionally, the greater temperatures during this season accelerate the rate at which plants and soil evaporate, exacerbating drought conditions and decreasing irrigation water supply. Farmers must thus implement suitable techniques, such as using crop cultivars resistant to heat or modifying planting dates.

Temperature has also direct impact on human health and welfare also because variations in temperature during the non-monsoon season have a major effect on people's health as well. The non-monsoon season is marked by high temperatures in many parts of the world, particularly in tropical and dry countries. These high temperatures raise the risk of heat-related disorders such heatstroke, dehydration, and exhaustion. For vulnerable groups including the elderly, children, and people who work outside, this is especially troubling. With higher concentrations of pollutants like ozone and particle matter, rising temperatures can also deteriorate air quality, aggravating respiratory disorders and illnesses like asthma. During this season, it becomes crucial to manage public health resources and awareness programs to prevent excessive heat.

Water Resources also directly affected by changing in the temperature. During the dry season, temperature has a significant impact on the amount of water available. Elevated temperatures cause evaporation rates to rise, which lowers the water levels in lakes, reservoirs, and rivers. Water shortages may result from this, particularly in areas where the water supply is reliant on precipitation and snowmelt. Therefore, to guarantee sustainable water, use during the non-monsoon season, temperature control and conservation measures like water recycling, rainwater collection, and the installation of effective irrigation systems are crucial.

II. EXPERIMENTAL

1. Data (Materials)

In this study we understand the pattern of the temperature in the non-monsoon in Uttar Pradesh. In this paper, we use temperature data from NASA Power Project's data access viewer. This is the **Prediction of Worldwide Energy Resources (POWER)** project. This project was initiated to improve upon the current renewable energy data set and to create new data sets from new satellite systems. In this study, last 41 years data of temperature in monsoon and non-monsoon season is used.

We extract the data as temperature in non-monsoon season. After that, we divide the data into two parts: training data (35 years data) and testing data (6 years data). The data contains the 41 rows and 3 columns(variables) as described below:

Year - represents the Year; Monsoon - represents the temperature in the monsoon season; non-monsoon - represents the rainfall in Non-Monsoon Season. In present study we use only two variables Year and Non-Monsoon.

In this study, we compared the time series forecasting techniques using the statistical programming language 'R.' We also use Microsoft Excel 2021.

2. Background of Forecasting Techniques

In this study, we use four forecasting techniques to forecast the temperature in the non-monsoon season for next seven years. The background of each Forecasting techniques are as follows:

3. Simple Exponential smoothing

Exponential smoothing is a forecasting method that weights the observed time series unequally. Simple Exponential Smoothing is one of simplest method for time series forecasting. In this technique we consider the weighted average of past observations, with more weight assigned to recent data points and diminishing weights as you go back in time. So, the simple exponential smoothing forecast was determined by Eq. (1)

$$\hat{y}_{i+1} = \alpha \times y_i + (1-\alpha)\hat{y}_i \tag{1}$$

Where y_i is the actual, known series value for time period i, $\hat{y}_i$is the forecasted value of the variable Y for time period i, $\hat{y}_{i+1}$ is the forecasted value for time period $i+1$ and $\alpha(0 < \alpha < 1)$ is the smoothing constant [2], representing the weight given to the most recent observation. It determines how quickly the influence of past observations decreases as we move backward in time. A smaller value of α means more past observation is used for forecasting and larger value of α means most recent observation is used for forecasting [3].

4. Holt and Winter's Forecasting Method

It is also known as the triple exponential smoothing method. It is used when data shows trend and seasonality. It is developed by Charles Holt and Peter Winters.

It comprises three components: Level, Trend and Seasonality. The three main variations of this method are: -

Simple Exponential Smoothing (SES): This method models only the level component without considering trend or seasonality. The forecast is a weighted average of past observations.

Double Exponential Smoothing: In this method, we use another smoothing constant β which measures trend in the data. There are two types of trend multiplicative trend, used for exponential trend analysis and additive trend, used for linear trend analysis.

Triple Exponential Smoothing: In this method, we also study seasonality γ apart from α and β. It is useful method when we examine the changing pattern of trend, level, and seasonality by using either additive or multiplicative seasonality [4].

The statistical formula for Holt and Winter's Smoothing is defined as:

$$S_t = \alpha \frac{y_t}{I_t - L} + (1-\alpha)(S_{t-1} + b_{t-1}) \tag{2}$$

Eq. (2) represents the Overall smoothing equation.

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \tag{3}$$

Eq. (3) represents the Smoothing by trend equation.

$$I_t = \beta \frac{y_t}{S_t} + (1-\beta)I_{t-L} \tag{4}$$

Eq. (4) represents the Smoothing seasonal parameter equation.

$$F_{t+m} = (S_t + mb_t)I_{t-L+m} \quad (5)$$

Eq. (5) represents the forecast equation. Where α, β *and* γ is the smoothing factor for the level, trend, and seasonality; y and S are actual and smoothed observation; b is the trend factor; I is the seasonal index; F is the forecast at m steps ahead, L is cycle length and t is a period. The value of α, β *and* γ and are to be chosen very carefully so that the error is minimized [5].

5. Measures use for comparing the performance of the testing data

We use two measures MAPE and RMSE to check the performance of the testing data.

MAPE measure represents the percentage of average absolute error occurred. It is independent of the scale of measurement, but affected by data transformation. It does not show the direction of error.

The formula for calculating the MAPE is represented in Eq. (7) [6,7]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| \times 100 \quad (7)$$

The RMSE has been used as a standard statistical metric to measure model performance in meteorology and climate research studies. RMSE is nothing but square root of calculated MSE.RMSE is used for measuring the accuracy of time series forecasting models. The formula for calculating the RMSE is represented in Eq. (8) [6,8]:

III. RESULTS AND DISCUSSION

1. Performance Evaluation of Forecasting Techniques through Residuals, ACF and Histogram of Residuals

Residuals are helpful in checking whether a model has sufficiently captured the information in the data. It has the following properties:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \quad (8)$$

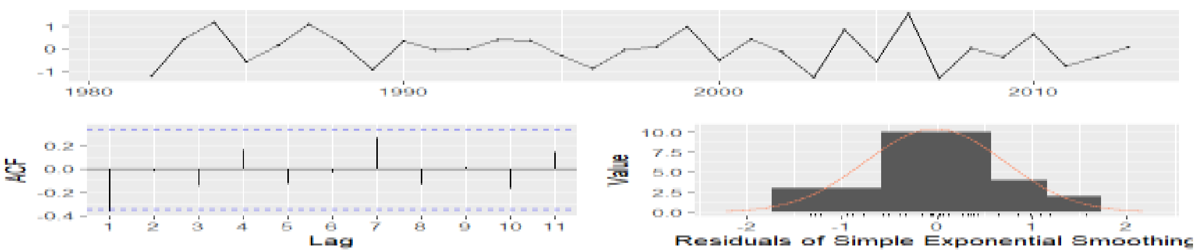
1. The residuals are uncorrelated. If there are correlations between residuals, then there is information left in the residuals which should be used in computing forecasts.
2. The residuals have zero mean. If the residuals have a mean other than zero, then the forecasts are biased [9].

The horizontal lines on the graphs of the sample ACF are the bounds ±1.96/ √n. If the data constitute a large sample from an independent white noise sequence, approximately 95% of the sample autocorrelations should lie between these bounds [10].

To validate existing forecasting techniques, we use first 35 years temperature data of non-monsoon season in Uttar Pradesh (1981-2015) as a training data and 6 years data (2016-2021) as a testing data. We first forecast this 6-year (2016-2021) temperature non-monsoon season data by existing forecasting techniques and compare with the actual value.

2. Residuals, ACF and Histogram of Residuals of SES Method of temperature in non-monsoon season

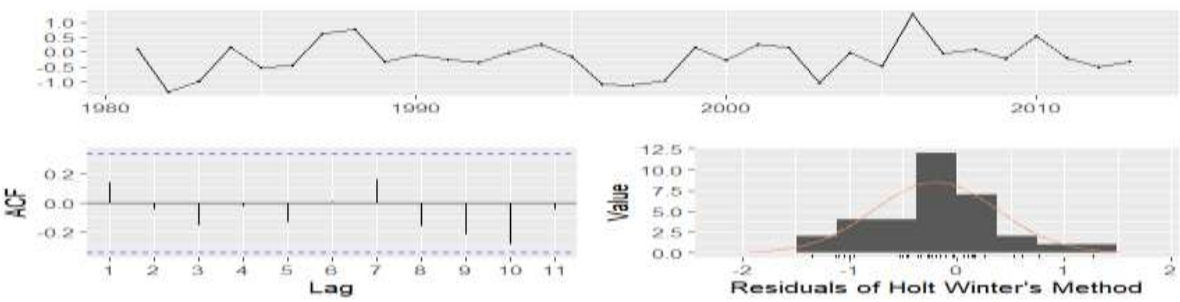
Fig. S1



In Fig. S1, first is the time plot of residuals of **Temperature data in non-monsoon season** through SES Method there is more sudden changes in temperature in non-monsoon season during 2002-2008. There is more stable pattern during 1989-2002. The Autocorrelation function graph does not have any spike, all values are within the limits. The histogram of residuals is nearly bell-shaped.

3. Residuals, ACF and Histogram of Residuals of Holt Winter's Method of temperature in non-monsoon season

Fig. S2



In Fig. S2, first is the time plot of residuals of **Temperature data in non-monsoon season** through Holt's Winter Method there is more sudden changes in temperature in non-monsoon season during 2005-2007. There is more stable pattern during 1987-2005. The Autocorrelation function graph does not have any spike, all values are within the limits. The histogram of residuals is almost bell-shaped.

4. Comparison of forecasted values to actual values of training data by three forecasting methods of temperature in non-monsoon season

Table S1

Temperature in the Non-Monsoon Season			
Year	Actual Value	Simple Exponential Smoothing	Holt's Trend Method
2014	22.48	22.045	22.321
2015	23.375	22.380	22.199
2016	24.175	22.845	22.076
2017	24.125	22.345	21.954
2018	23.25	22.845	21.842
2019	22.466	22.145	21.710
2020	22.347	22.145	21.687
2021	22.986	22.045	21.485

From Table S1, SES performs better for forecasting the temperature in non-monsoon season for upcoming years.

5. Evaluating performance of forecasted model through MAPE and RMSE

Table S2

Forecasting method	Temperature in the Non-Monsoon Season	
	MAPE	RMSE
Simple Exponential Smoothing	3.452039	1.084221
Holt's Trend Smoothing	5.490592	1.464552

Above table shows that, SES has lowest MAPE and RMSE among other forecasting techniques. So, SES performs better for forecasting the temperature in non-monsoon season for upcoming years.

6. Comparison of Actual Forecasted Values and their Confidence Interval by all Forecasting Methods of temperature in the Non-Monsoon Season

	Temperature forecast in non-monsoon Season	
Year	Simple Exponential Smoothing (95%C I)	Holt's trend Method (95%C I)
2022	22.86041(21.50927 ,24.21155)	22.86483(21.47765, 24.25200)
2023	22.86041(21.37019, 24.35063)	22.87622 (21.31646, 24.43599)
2024	22.86041(21.24303, 24.47780)	22.88762 (21.17249, 24.60275)
2025	22.86041(21.12516, 24.59567)	22.89902 (21.04142, 24.75662)
2026	22.86041(21.01480, 24.70602)	22.91041 (20.92047, 24.90036)
2027	22.86041(20.91068, 24.81014)	22.92181 (20.80774, 25.03588)
2028	22.86041(20.81184, 24.90898)	22.93321 (20.70187, 25.16455)

We find that SES is better forecasting technique among other existing forecasting techniques for predicting the temperature in non-monsoon season for upcoming years. because it has lowest MAPE and RMSE among other forecasting techniques and it has shortest 95% confidence interval for predicting the temperature in non-monsoon season for upcoming years.

IV. **Conclusions**:

Generally, there is a time lag between awareness of an impending event or occurrence of that event. This leads to main reason for forecasting [11]. Since temperature forecast in non-monsoon season becomes very difficult in Uttar Pradesh due to its random pattern of observation. However, predication is necessary for proper planning of future events. In this paper, we compare existing forecasting technique such as SES, Holt's Winter Method, and SES method for temperature in non-monsoon season. In this paper, MAPE and RMSE is used to check the performance of the fitted model. SES emerge as a best forecasting method among others. It is MAPE is (3.45) and RMSE is (1.084221). Based on these forecasting techniques, we forecast and calculate 95% Confidence Interval of the temperature in non-monsoon season for upcoming 7 years. This gives an idea that how much variation in temperature is possible in non -monsoon season for upcoming years. SES method has lowest 95% confidence interval. So, we say that for proper management and planning is necessary for upcoming temperature in non-monsoon season in Uttar Pradesh we would use SES method for forecasting.

V. **References**

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