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ARIMA and Exponential Smoothing Model to Forecast Average Annual Precipitation in Bharatpur, Nepal

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Abstract

Precipitation includes different kinds of moisture that fall from the sky to the Earth's surface, like rain, snow, sleet, hail, or drizzle. In places with flat terrain like Bharatpur, rainfall is the predominant form of precipitation. Therefore, in the plains of Nepal, most of the precipitation comes in the form of rainfall. Rainfall is a natural occurrence known for its unpredictable nature, making it difficult to predict accurately. However, there are statistical methods that can help forecast future rainfall using past data. This research focuses on developing a reliable forecasting model: Auto Regressive Integrated Moving Average and Exponential Smoothing for the prediction of average annual precipitation in Bharatpur, Nepal. The primary objectives are to develop, compare, and identify the superior model between these two approaches. Utilizing average annual adjusted precipitation data (PRECTOTCORR) obtained from the National Aeronautics and Space Administration website for the period 1990 to 2021, both the models were trained and validated using distinct training and test sets. The comparison of these models is based on the minimum Mean Squared Error criterion. The findings reveal that the ARIMA (1, 2, 1) model effectively predicts average annual precipitation in Bharatpur for future periods, outperforming the Exponential Smoothing Model. The results indicate that the time series model for the studied area differs from those of previously examined regions, highlighting the need for a model tailored to the specific characteristics of this region. The research provides valuable insights for stakeholders involved in water management and agricultural planning within the region. Accurate rainfall predictions, as demonstrated by the superior performance of the ARIMA model, can empower decision-making processes related to water resource management and agricultural planning. This, in turn, has the potential to enhance productivity and sustainability outcomes.

Keywords: *ARIMA, exponential smoothing, precipitation, prectotcorr, rainfall forecasting.*

1. Introduction

Precipitation holds a crucial role in various fields such as agriculture, hydrology, meteorology, and ecology. It is a fundamental component of the water cycle and serves as the primary source of water for plants, animals, and human beings (Prakash, 2021). The amount and timing of precipitation are critical in determining the growth of crops, the flow of rivers, and the distribution of freshwater resources. Furthermore, precipitation is a significant concern for the general public as it directly impacts daily life, from commuting to work to leisure activities. Due to its importance and unpredictable nature, accurate forecasting of rainfall patterns is essential for effective decision-making and planning (Ambildhuke & Banik, 2022).

The term precipitation is often used interchangeably with rainfall when measuring the amount of water descending from the atmosphere. Precipitation encompasses any form of moisture that descends from the atmosphere to the Earth's surface, including rain, snow, sleet, hail, or drizzle (Wynne, 2008). Rainfall, in particular, refers to the amount of liquid precipitation that falls to the ground in the form of rain. It is a measure of the amount of rainwater that falls within a particular area over a specific period of time (Petersen & Rutledge, 1998). Thus, while rainfall represents a subtype of precipitation, not all forms of precipitation constitute rainfall. Nonetheless, in flat terrains, precipitation is commonly dominated by rainfall (Palazzi et al., 2013).

'PRECTOTCORR' is a term used in NASA's Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) dataset to refer to the corrected total precipitation. In this dataset, PRECTOTCORR denotes the estimated total amount of precipitation that descends over a specified area during a given time period, which has been adjusted to account for potential biases and errors in the original measurements. The validation and testing process involves comparing the observed precipitation values with model estimates and adjusting the observations to match the model output, thus improving the accuracy and reliability of the data (NASA POWER, 2023). The resulting PRECTOTCORR values can be used to study and monitor precipitation patterns and variability over time Furthermore, they contribute to investigations in fields like climate science, hydrology, and agriculture.

Forecasting precipitation is a complex task due to the non-linear nature of the phenomenon and the rapid changes brought about by climate change. The precision of both short and long-term precipitation forecasts is crucial for various sectors including agriculture, tourism, flood prevention and management, and water body management, which have a direct impact on a country's economy. Precipitation prediction as aligns closely with prediction of rainfall employing a range of tools and techniques. To figure out how much it might rain, scientists have come up with different methods. They've used historical data and radar information along with computer programs. One study created a special computer model using two types of networks, kind of like how our brains work, to predict rainfall. This model was accurate about 82 times out of 100 (Tey *et al*., 2022). Another study compared four different ways to predict rainfall using past data. They found that two of these methods worked well in different parts of Kerala, India (Kabbilawsh *et al*., 2022). Another research project tested various computer programs to predict rainfall called as Bidirectional-LSTM Network (Barrera-Animas *et al*., 2021). Additionally, a study looked at three different computer-based methods to predict rainfall. Among them, the Extreme Gradient Boost method turned out to be the most effective (Chalachew & Haileyesus, 2021). Although the most common method for rainfall prediction involves analyzing radar image data, statistical methods such as ARIMA have proven to be effective for analyzing time series data. ARIMA has been used extensively to predict rainfall trends and for reservoir and river modeling, economics and production, and evapotranspiration studies (Bari *et al.,* 2015). The method has several interesting features that make it desirable for researchers, such as the ability to use a single variable time series or multiple variables for more complex cases. Together with the use of ARIMA model for prediction of amount of rainfall, exponential smoothing can be applied, which is simplex technique for time series prediction (Dhamodharavadhani & Rathipriya, 2018). Both ARIMA and exponential smoothing method use time series data to forecast future value and have been found useful for forecasting in short run as well as long run. ARIMA model development requires an elaborate process that begins with test of stationary and making the time series stationary if required to conform to the assumption of identically independently distributed (IID) normal errors for applying ARIMA models (Shivhare *et al*., 2019). ARIMA models that satisfy stationarity, no autocorrelation, identically independently distribution (IID) normal errors can then can be compared for the selection of the best model based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Exponential Smoothing technique can be applied on the same dataset with fulfilment of ARIMA assumptions, and the results can be compared on the basis of Mean Squared Error (MSE). Model having least MSE is accepted as the better model for future value prediction (Ikpang *et al.*, 2022). There is practice of dividing time series data set into two subsets namely training set and test set. Development of model is done for training set and the model thus developed is tested for test set (Siami-Namini et al., 2018). Best model can be judged based on Coefficient of determination, Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Mean Absolute Deviation (MAD) values (Tseng *et al*., 2001). Many attempts have been made in the past to shed light on the rainfall pattern in Nepal. Chaudhary *et al.* (2023) conducted a study in Biratnagar, Nepal, using statistical methods to assess rainfall variations. Their findings suggested that rainfall patterns in Biratnagar are inconsistent and challenging to predict. On the other hand, Maharjan and Regmi (2015) employed the Weather Research and Forecasting (WRF) Modeling System to study extreme precipitation events in Nepal's Himalayan terrain. While their research successfully captured essential precipitation patterns, it fell short in accurately predicting the actual amount of rainfall, likely due to localized factors. Interestingly, despite these attempts to forecast rainfall, it's noteworthy that the utilization of traditional time series forecasting methods like ARIMA and ESM do not appear to have been explored in these studies. These established techniques, which have proven effective in various contexts, might offer valuable insights into rainfall prediction in Nepal.

The current study is centered to develop best ARIMA model and ESM for future rainfall precipitation based on past time series data of average annual precipitation per month. Secondly it is focused to determine which is best the technique among them.

Findings of this research will be very fruitful to agricultural policy makers, researchers and farmers needing advanced weather predictions.

2. Methods and material

2.1 Data source and study location: The research is based on the secondary data collected from the web site "https://power.larc.nasa.gov" of National Aeronautics and Space Administration (NASA). It is an open access portal that provides metrological time series data. Annual precipitation for Bharatpur area is extracted from the mentioned portal, the latitude and longitude of study point being 27.70' and 83.44' respectively, (as shown in Figure 1). Red point marked in bottom right map is the study point. Yearly data of average precipitation per month from 1991 to 2021 is taken for data analysis. Dataset has PRECTOTCORR variable which is variable name for a corrected or adjusted total precipitation measurement and is measured in millimeter (mm). The data used in this study comes from NASA POWER Data Archives where the data is collected from satellites and radar making it really accurate. More importantly, this data is being checked and improved to fix any mistakes as well. This source operates on an open-access basis, allowing anyone to log in to the site and freely downloadable from the available data.

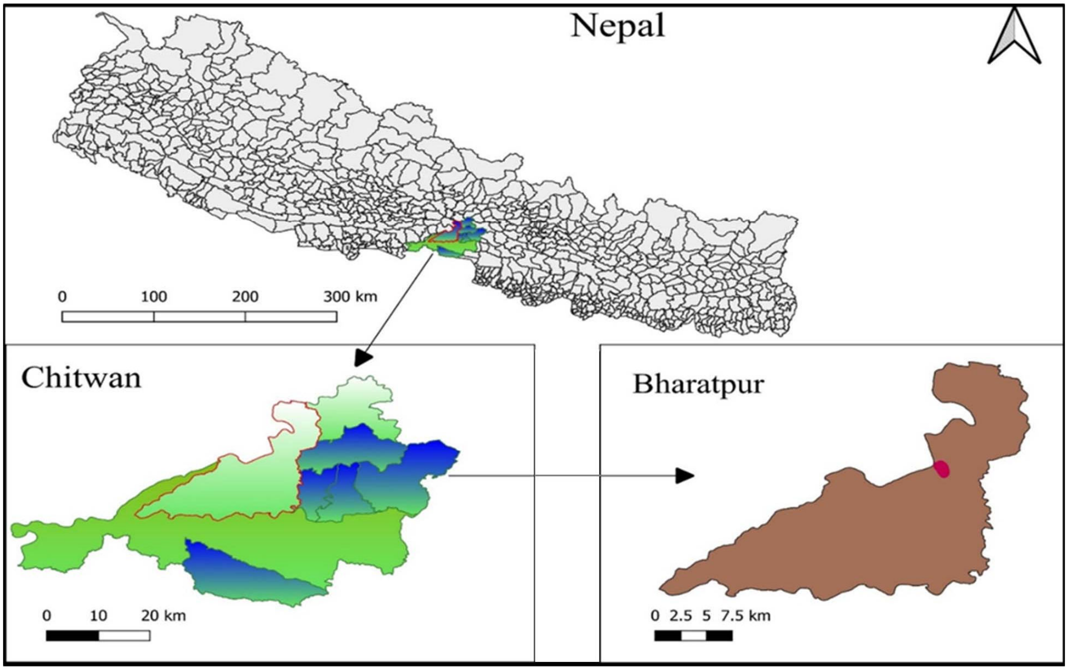

Figure 1. Study location in map

The study employed R-Studio software for data analysis and visualization, focusing on time series data for the purpose of forecasting average annual precipitation per month. The Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) model were fitted for training set and fitted model is used for test set data. Secondly the models are compared on the basis of MSE calculated for training set data.

2.2 Theoretical background

A variety of techniques are available for forecasting time series data, including linear methods like trend lines, moving averages, exponential smoothing, Naive's approach, as well as non-linear techniques such as logarithmic, power, and polynomial trend lines. When the time series data exhibits a linear trend over time, the linear trend line model proves to be effective for forecasting however, when the data doesn't demonstrate linearity across time, adopting non-linear models becomes crucial for achieving accurate forecasts. It's important to note that time series data with trend and non-stationarity need to be transformed into a stationary state before fitting a model. This task is undertaken within the framework of ARIMA model fitting, making it particularly useful for long-term forecasts. Another model within time series analysis, known as ESM, can be applied for prediction purposes as well, provided the data has been rendered stationarity. The transformation of time series data to a stationary state can be accomplished through methods like logarithmic transformation, square root transformation, or differencing (Harvey, 1990).

2.3 ARIMA model

As part of the Box-Jenkins general model, AR and MA parameters, as well as differencing, were formulated in the model. The AR term refers to the autoregression, which describes the dependent relationship between current data and its past values; the 'I' term denotes the number of times differencing has been done to make the stationary; the MA term refers to moving average, which indicates that the forecast of the model is linearly dependent on past values, and that errors in forecasting are linear functions of past errors. In ARIMA model, the future value of a variable is a linear combination of past values and past errors, if a variable value at time t i.e. Y_t follows ARIMA (p, d, q) then the model can be expressed as:

$$\Delta^d Y_t = e_t + \phi_1 \Delta^d Y_{t-1} + \phi_p \Delta^d Y_{t-p} + \theta_1 e_t - \theta_2 e_2 + ---- + \theta_q e_q$$

If the data is stationary and there is no need to make it stationary by differentiating then the model is called Autoregressive Moving Average (ARMA) and can be expressed as:

$$Y_t = e_t + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \theta_1 \mathcal{E}_{t-1} - \theta_2 \mathcal{E}_{t-2\,+} ... + \theta q\, \mathcal{E}_{t-q}$$

Where, Y_t is the estimated value at time t, e_t is the random error at time t, ϕ_i and θ_j are the coefficients of AR and MA processes, respectively (Profillidis & Botzoris, 2019).

In ARIMA, *p, d* and *q* are parameters of model, where the parameter *p* refers to the number of lag observations or autoregressive terms, *d* indicates the degree of differencing required to make the data stationary and *q* specifies the order of the moving average process. To determine the appropriate values of *p* and *q* in an ARIMA model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots can be used. The ACF plot shows the correlation of a time series with its past values at different lags, while the PACF plot shows the correlation between a time series and its lagged values after adjusting for the effects of the intervening lags.

To determine the value of *p*, significant spikes in the PACF plot is lookup. A significant spike at lag k indicates that lag k can be used to predict the value at the current time period. The order of the AR component (p) can be determined by identifying the last lag with a significant spike in the PACF. Whereas, the lag up to which ACF plot has significant spike is considered as value of *q* (Alghamdi *et al.,* 2019). A significant spike at lag k suggests that the value at lag k can be used to predict the value at the current time period. The order of the MA component (q) can be determined by identifying the last lag with a significant spike in the ACF plot.

By using these techniques to determine the appropriate values of *p* and *q*, ARIMA model can build up that accurately captures the underlying patterns in the time series data and produces reliable forecasts.

2.4 Exponential smoothing

Exponential smoothing is a time series forecasting method that uses a weighted mean of the past observations to make predictions about future values (Hyndman, 2008). It is based on the principle that recent observations are more relevant in predicting future values than older observations, and therefore should be given greater weight in the forecast.

The basic idea behind exponential smoothing is to calculate a weighted average of the previous observations, where the weights decrease exponentially as the observations get older. This can be represented by the following formula:

$$F_t = \alpha Y_t + (1-\alpha)F_{\{t-1\}}$$

Where, F_t = forecast for time period t

Y_t = actual observation at time period t

$F_{\{t-1\}}$ = forecast for the previous time period t-1

α = smoothing parameter

The value of alpha is between 0 and 1 that determines the weight given to the most recent observation. The closer α is to 1, the more weight is given to the most recent observation, while the closer α is to 0, the more weight is given to the previous forecast. The initial forecast F_0 can be set to the first observation in the time series or to the average of the first few observations. Exponential smoothing is a simple and flexible forecasting method that can be applied to a wide range of time series data. However, it does have some limitations, such as the fact that it assumes a constant level of trend and seasonality in the data, and it may not perform well for time series with irregular or extreme fluctuations (Hyndman, 2008).

2.5 Model adequacy

To obtain a good ARIMA model, the time series data need to make stationary and then have to identify best ARIMA model based on AIC, BIC criteria. Also, the model having highest Coefficient of Determination and minimum RMSE, MAPE, MAD is selected as the best model (Tseng *et al*., 2001). However, the model needs to satisfy some other requirements of error terms. Requirements for error terms are:

- Errors are not autocorrelated
- Errors have zero mean over the time

- Errors are Normally distributed

The original set of data is first divided into two subsets using the 80:20 method. The first subset is the training set, and the second subset is the test set. Both the ARIMA and exponential smoothing models are fitted based on data of the training set, and the performance of each model is evaluated on separate test set data. The evaluation is done based on the MSE criteria, which is a measure of the average squared difference between the predicted values and the actual values. The model that has the lowest MSE is declared as the best model for predicting future precipitation in the study area.

3. Results and discussion

The study utilizes time series data of average monthly precipitation measured in millimeters as the dependent variable and time as independent variable. The data shows that the maximum average monthly precipitation was record high in 2021 at 7.38 mm per month while the minimum was recorded in 2002 at 1.29 mm per month. The trend of precipitation is illustrated in the first chart in Figure 2.

The dotted line marked horizontally parallel to x axis is the mean line. In the first figure, the original data set is plotted and shows that it does not have same mean and variance over the time implying it is not stationary over the time. At first the data set does not show any stationarity of data over the time which is shown in the second figure of first row in Figure 2. To make data stationary, natural log transformation is carried and then differencing is done until stationary is obtained in the data series. To check stationary of data Dickey Fuller test is applied. The null hypothesis of this test assumes that the time series is non-stationary and has a unit root. Figure-2 below shows the trend of time series data used in this study after different stages for achieving stationary.

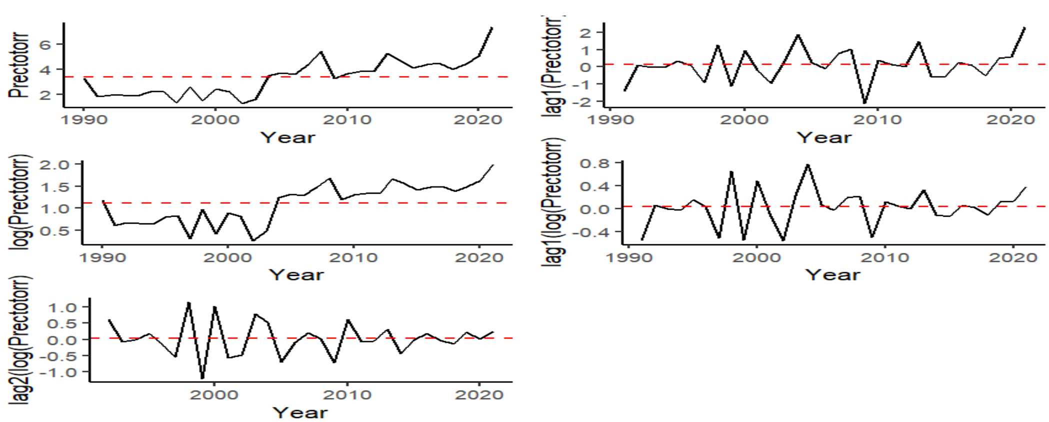

Figure 2. Trend of average Pretotorr per month over the study period.
(Data source: NASA Power, 2023)

Line charts in Figure 2 displays trend of data at original stage and after differencing, log transformation, first order differencing of log of original data and second order differencing of log of original data from left to right and top to bottom respectively. Stationary is obtained in the data set after second order differencing of log transformed data, where the test statistics of Augmented Dickey-Fuller was 4.0071 with p-value 0.02208, this shows that thus obtained data series is stationary.

ARIMA model

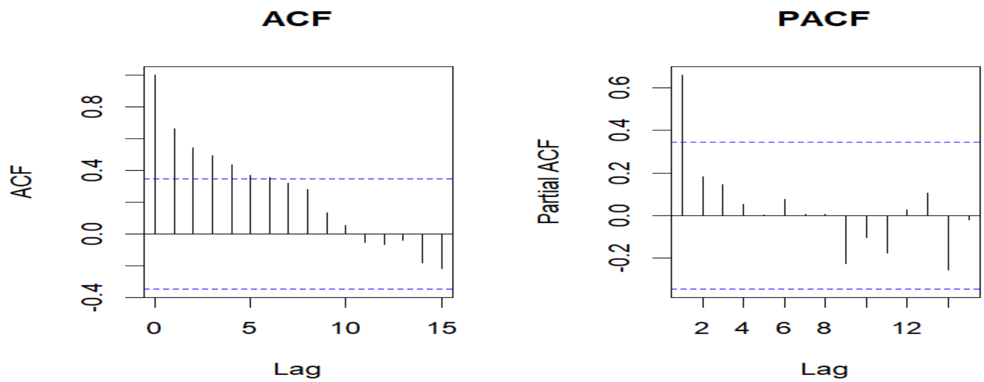

Figure 3. ACF and PACF plot. (Data source: NASA POWER, 2023)

In Figure 3 there are significant spikes up to 6 lags in the ACF and significant spike up to one lag in the PACF, so the figure suggests that an ARIMA (6, 2, 0) model may be appropriate. However, this is just a general guideline, and the choice of ARIMA order should also consider other factors such as the model fit, AIC and BIC values. In this study AIC criteria is being used to select the best ARIMA model because this approach is used by, Paul et al. (2013), Dhaheri et al. (2017), Wahyudi (2017) and Gao (2021).

The data set is divided in to two data sets namely training data set and test data sets on the basis of 80:20. The model development is done on training set and is tested in to test set. The data of training set found stationary (P-value >0.05) as it has p-value 0.4579 for Augmented Dickey Fuller test. The ACF and PACF chart for training set is displayed as in figure 4.

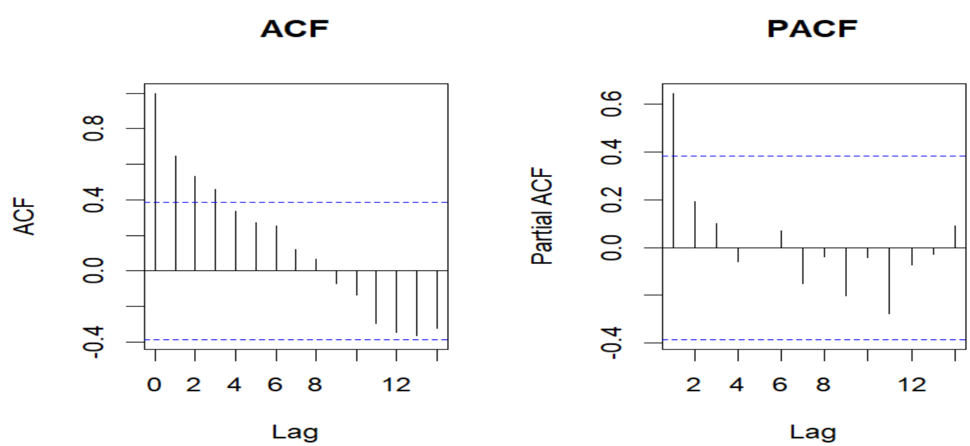

Figure 4. ACF and PACF chart for training set. (Data source: NASA POWER, 2023)

Figure 4 suggests that the ARIMA (4,2,0) model because there are significant spikes up to lag 4 in ACF and significant spikes up to lag 1 in PACF. However, the model will be decided based on AIC criteria. Table 1 is for selection of ARIMA model based on AIC.

Table 1. Different ARIMA models with AIC value

Model No.	Model Name	AIC	Model No.	Model Name	AIC	Model No.	Model Name	AIC
1	ARIMA(1,1,0)	18.62	9	ARIMA(3,1,2)	24.80	17	ARIMA(2,2,1)	25.31
2	ARIMA(1,1,1)	19.06	10	ARIMA(4,1,0)	22.84	18	ARIMA(2,2,2)	27.31
3	ARIMA(1,1,2)	20.99	11	ARIMA(4,1,1)	24.74	19	ARIMA(3,2,0)	29.95
4	ARIMA(2,1,0)	18.94	12	ARIMA(4,1,2)	25.74	20	ARIMA(3,2,1)	27.31
5	ARIMA(2,1,1)	20.93	13	ARIMA(1,2,0)	35.09	21	ARIMA(3,2,2)	28.47
6	ARIMA(2,1,2)	22.87	14	ARIMA(1,2,1)	24.71	22	ARIMA(4,2,0)	31.29
7	ARIMA(3,1,0)	20.93	15	ARIMA(1,2,2)	25.51	23	ARIMA(4,2,1)	29.25
8	ARIMA(3,1,1)	22.84	16	ARIMA(2,2,0)	30.00	24	ARIMA(4,2,2)	31.18

(Data source: NASA POWER, 2023)

Table 1 shows different twenty four models fitted for the training set data. Although, the model ARIMA (1,1,0) has least AIC but the data is not stationary at first order difference so this model is rejected and the model having second order difference (d =2) having least AIC is ARIMA(1,2,1). So, this model is selected as best ARIMA model.

Errors from the model ARIMA (1,2,1) are normally distributed as shown in figure 6, also Shapiro test for normality of errors has p-value 0.5712 so, the errors are IID normal.

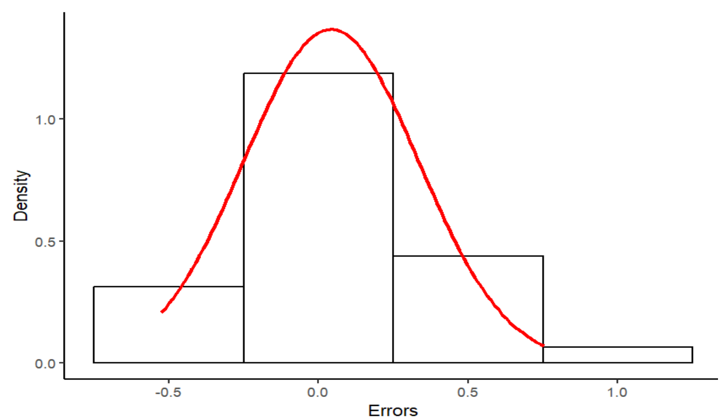

Figure 5. *Histogram of Errors. (*Data Source: NASA POWER, 2023)

As the fitted model ARIMA (1,2,1) satisfyies all the requirements for ARIMA model so it can be used for forecasting future values. Also, the mathematical expression for this model is found from the findings suggested as

$$Y_t = -0.3513\ Y_{t-1} - e_{t-1}$$

Exponential smoothing

Exponential smoothing is carried on the training set and the model with alfa 0.4772 and initial value 0.8992 is obtained, thus the mathematical expression model is as

$$F_t = 0.4772\ Y_t + (1-0.4772)\ F_{\{t-1\}}$$

Model comparison between ARIMA and exponential smoothing

Both the models fitted for training set are used to forecast value for test data set, the forecast values are shown in Table 2. Mean Square Error (MSE) for ARIMA (1,2,1) was found to be 0.036 and that for Exponential smoothing was 0.051, thus the ARIMA (1,2,1) model is found best among these two models because of having minimum MSE.

Table 2. *Mean Square Error (MSE) for test data set using ARIMA (1, 2, 1) and ESM model*

Year	Actual Value	Forecast Value	
		ARIMA(1,2,1)	Exponential Smoothing
2016	4.39	4.44031	4.3683
2017	4.49	4.43425	4.3683
2018	3.99	4.54065	4.3683
2019	4.47	4.60882	4.3683
2020	5.06	4.69252	4.3683
2021	7.38	4.77254	4.3683

(Data Source: NASA POWER, 2023)

The study investigated the performance of ARIMA and ETS models in forecasting annual average precipitation in the study area. The ARIMA (1,2,1) model was found the best among other ARIMA models, and it was found superior to the ETS model. These findings are consistent with previous researches, which have generally found ARIMA models to be superior to ETS models in precipitation forecasting. However, the ARIMA model determined in this study is quite different from those determined for other regions. For instance, other researchers have determined different ARIMA and SARIMA models for rainfall prediction in different regions of the world. Shivhare et al. (2019) determined ARIMA(2,0,2) model for daily rainfall prediction in Banarashi. Ikpang et al. (2022) found a SARIMA (1,0,2) $(1,1,2)_{12}$ for monthly rainfall prediction, also, Aborass et al. (2022) concluded seasonal ARIMA model (11.0.2) x (11.0.2) was the best model to forecast monthly rainfall in Berzine, Palestine, Bari et al. (2015) detected SARIMA(0, 0, 1) $(1,1, 1)_{12}$ as the best SARIMA model for monthly precipitation Sylhet, Bangladesh also Nyatuame and Agodzo (2018) concluded ARIMA(3,0,3) and ARIMA(3,1,3) for Kpetoe and Tordzinu respectively to predict annual rainfall, Dhamodharavadhani and Rathipriya (2018) concluded that Holt-Winter's Exponential Smoothing provided the better accuracy for monthly rainfall prediction. There are a number of researchers who completed their research to forecast rainfall, precipitation or PRECTOTORR annually, seasonally, monthly or daily, the researches were for different regions of the globe, thus models are not matching for place to place due to random nature of rainfall in random places. Thus, result of this research is also found different from other researches. This highlights the random nature of rainfall in different places and the need to develop region-specific models for accurate precipitation forecasting. The results of this study thus provide valuable insights into precipitation forecasting in the study area, but caution should be taken when extrapolating these findings to other regions.

4. Conclusion

After conducting an analysis on the average annual precipitation data in Bharatpur, Nepal using annual data, it has been determined that the ARIMA (1,2,1) model is the best fit for forecasting purposes. This model is found superior to the Exponential Smoothing Model using MSE approach, indicating that the ARIMA model is more suitable for this type of data. This research suggests that the ARIMA(1,2,1) model can be used effectively to forecast precipitation patterns in Bharatpur, Nepal. These findings have important implications for stakeholders, including government agencies, farmers, and other organizations that rely on precipitation data for planning and decision-making. Also this research will be very helpful to the scholar willing to do research for forecasting rainfall using ARIMA and ESM in Nepal. At last, this study contributes to understanding of forecasting models for precipitation and highlights the importance of selecting the appropriate model for accurate predictions.

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