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Analysis And Forecasting Of Monsoonal Rainfall Using Time Series

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Abstract
Time series analysis for forecasting monthly streamflow plays a crucial role in water resources engineering, serving as a fundamental tool in the planning, design, and management of water resource systems. In this study, the Autoregressive Integrated Moving Average (ARIMA) model has been employed to forecast monthly streamflow for five locations: Agra, Cherrapunji, Delhi, Jammu, and Mumbai. The ARIMA model enhances the accuracy of advance information, aiding in the effective planning and maintenance of available water resources.The behavior of streamflow under varying demand levels was analyzed using the ARIMA model, which demonstrated high efficiency in both fitting historical data and making future predictions. A comprehensive dataset spanning 65 years (1950–2015) was utilized for model development and trend analysis. The first 65 years of data were used to develop and calibrate the ARIMA model, while the subsequent two years of data were reserved for model validation. Whenever all of the model variables parameters (p, d, and q, P, D, and Q) have been calculated, the most suitable model is identified. Overall, the forecasting using ARIMA (2,1,1) has better results than forecasting using the other ARIMA input Parameters. Based on the results, the developed model has proven to be a reliable tool for accurate forecasting and effective management of future streamflow resources.
Keywords: *Mansoon, ARIMA, Rainfall, Forecasting and Time series.*

1. INTRODUCTION

The majority of India's economy is centred on agriculture. Water is one of the main factors contributing to its success. Numerous water reservoirs, including rivers, canals, and bore wells, are available for use in agriculture.However, rainwater serves as these reservoirs' primary supply. Owing to geographical and financial constraints, not every farmer can afford a bore well and other raditional systems.

Rainfall is therefore agriculture's largest resource and most important component.Accurately forecasting rainfall is an essential undertaking that will aid a number of industries, including agriculture, pest control, tourism, event planning, water conservation, and the prediction of floods and droughts. India is experiencing numerous catastrophic events that are causing loss of life and property as a result of inaccurate forecasting.

Predicting rainfall with precision is a crucial task that will benefit several businesses, such as agriculture, insect management, tourism, event organising, water preservation, and flood and drought forecasting. Because of poor forecasting, India is seeing a number of catastrophic events that are resulting in the loss of lives and property. Here, we'll use the top four machine learning algorithms to anticipate the amount of rainfall.

In order to predict the inflow of discharge to the Hit station on the Euphrates River in Iraq, Shathir and Saleh (2016) carried out a study. Using a time series autoregressive integrated moving average technique, they created seven distinct models and examined their ability to predict discharge. Using the time series technique, they acquired the actual inflow data from October 1932 to September 1972.

The efficiency of the time series autoregressive integrated moving average model (ARIMA) in stock price prediction was investigated by Mondal et al. (2014). They used a time series data set of 56 firms' stocks to test the model. They measured the statistical model using the Akaike Information Criteria (AIC). They used the data from the same source to confirm the projected value. The accuracy of the program's overall anticipated results, which was around 85%, suggested that the model they created might be used effectively for stock prediction.

The seasonal highway traffic volume was predicted by Mingrong and Hengxin (2008) using a seasonal autoregressive integrated moving average model seasonal (ARIMA). Later, they compared the seasonal ARIMA model's predicted outcome with three seasonal forecasting models—the regression model, the

variable seasonal index forecasting model, and the seasonal regression model—and found that the seasonal ARIMA model performed better and produced more accurate results.
The causes of the Indian summer monsoon rainfall's failure Sun and Koch (2001) examined the cross-correlation between the dynamic regression transfer model and autoregressive integrated moving average ARIMA in order to estimate salinity variations for Apalachicola Bay by analyzing time series data.
(Sal ahi et al. 2016; Dhawal and Mishra 2016; Mahmud et al. 2017; Akinbobola et al. 2018; Buish and Brandsma 2001; Yates et al. 2003; Sharif and Burn 2006; Sumi et al. 2008). Given the aforementioned weather forecasting methods, many scientists have been using the ARIA model extensively in water resources in recent decades, particularly. The finest Bt model for comprehending the climatic variables (temperature and precipitation) is Moving Average (SARIMA). (Sarraf et al. 2011; Sham snia et al. 2011; Abdul-Aziz et al. 2013; Meher and Jha 2013; Bari et al. 2015; Roy and Das 2016; Kaushik and Singh 2008; Tularam and Ilahee 2010).
Afrifa-Yamoah (2015) had applied ARIMA model in Brong Ahafo Region of Ghana for fore casting of monthly averagesurface temperature and found a decreasing trend. Wang et al. (2013) had used seasonal ARIMA model for agricultural irri gation and found that it has good model Btting degree in decision making. Zakaria et al. (2012) had used ARIMAmodelonweeklyrainfalldataandhad found a decreasing trend in it for semi-arid Sinjar District of Iraq.
When Huntra and Keener (2017) used the ARIMA model to anticipate water demand in the Las Vegas Valley, they discovered that the results were quite accurate and useful for tracking the effects of climate change. In a comparison analysis of maximum daily temperature data using ARIMA, exponential smoothing (ETS).
Dimri et al. (2020) discuss the Changes in temperature and precipitation affect the dynamic structure of the climate and can be examined using time series analysis. The Bhagirathi river region, which is located in the Uttrakhand at India , is the subject of this study examination of time series and seasonal analysis of the monthly mean minimum and maximum temperatures and precipitation. The information used spans a century, from 1901 to 2000. Forecasting for the subsequent 20 years (2001-2020) was conducted using the seasonal ARIMA (SARIMA) model. Mishra, A. K., Desai, V. R. (2005) In this research, droughts were predicted based on the model generation process using multiplicative Seasonal Autoregressive Integrated Moving Average (SARIMA) models and linear stochastic ARIMA models. The best models' anticipated outcomes were contrasted with the data actually collected. Mohan and Arumugam (2009) predicted evapotranspiration using the ARIMA model and the Winter's Exponential Smoothing Model, and then compared the results. For the years 1977 through 1992, they gathered daily meteorological data, which included information on the highest and lowest temperatures, the speed of the wind, the highest and lowest relavant humidity, and the vapour pressure. A study was carried out by Karamouz and Zahraie (2004) to provide a technique for enhancing long-term statistical streamflow forecast. They carried out a Salt River Basin case study. They break down the process into three steps. To analyze the combined impact of climatic and hydrological variables, they begin by defining the hydrologic seasons using the relationship between the average snow water equivalent. Subsequently, they employed the ARIMA to generate a seasonal streamflow time series.
The results of the weekly projected evapotranspiration from the ARIMA model and Artificial neural network (ANN) model were compared to those from the weekly averages by Landeras et al. in 2009. They defined the ARIMA and ANN models and produced weekly evapotranspiration time series for the years 1975 to 2003, which was then used for the models' implementation. Mohan and Arumugam (2009) predicted evapotranspiration using the ARIMA model and the Winter's Exponential Smoothing Model, and then compared the results. For the years 1977 through 1992, they gathered daily meteorological data, which included information on the highest and lowest temperatures, the speed of the wind, the highest and lowest relavant humidity, and the vapour pressure.
The streamflow monthly and runoff season in the Rio Grande Headwaters region were predicted by Abudu et al. (2011) using a stochastic TFN model and ANN method combination. They compared to TFN and ANN models that were adjusted specifically for each month of the runoff period for the predicted outcome for one month out.
Alnaa and Ahiakpor (2011) predicted Ghana's inflation using an autoregressive integrated moving average technique. The study used monthly time series values spanning the years 2000 to 2010. The last eight numbers from the available data were fixed for validation purposes. The variable used was the consumer price index. The eight prediction values from the built-in models were then compared to the eight actual

observations available. In a 2014 study, Mondal et al. examined how well the time series ARIMA predicted stock prices. They measured the statistical model using the Akaike Information Criteria (AIC). Using information from the same source, they verified the projected value. They constructed a model whose overall anticipated results had an accuracy of roughly 85%, indicating that it might be used well for stock prediction

Temperature and precipitation time series analysis are often used in studies evaluating climate change (Babazadeh and Shamsnia 2014; Balibey and Serpil 2015). Both of these factors are essential in strategic planning for the management of natural disasters like droughts and floods. While trends are long-term rises or declines in the time series, seasonality refers to variations in the data at regular short intervals, such as weekly, monthly, biyearly, quarterly, etc. (Pazvakawambwa and Ogunmokun 2013; Wang et al. 2013). Temperature and precipitation projections are often used to inform basin-scale water management choices.

Another technique is the shared nearest neighbor (SNN) cluster algorithm, which has been used to forecast land temperatures and precipitation in India during monsoon period (June- September). Rajagopalan and Lall in 1999; Buish and Brandsma in 2001; Yates et al. in 2003; Sharif and Burn in 2006; Sumi et al. in 2008; Salahi et al. in 2016; Dhawal and Mishra in 2016; Mahmud et al. in 2017; Sharif and Azhar in 2017; Akinbobola et al. in 2018). The ARIMA model is widely used in the field of water resources by numerous scientists in recent years, and especially in the last few decades, in light of the aforementioned weather forecasting models.

In order to know the climatic variables (precipitation and temperature), they have discovered that ARIMA and Seasonal Auto Regression Integrated Moving Average (SARIMA) are the models that fit the data the best. (Kaushik and Singh 2008; Tularam and Ilahee 2010; Sarraf et al. 2011; Shamsnia et al. 2011; Abdul-Aziz et al. 2013; Meher and In order to forecast the monthly average surface temperature in the Brong Ahafo Region of Ghana, Afrifa-Yamoah (2015) used the ARIMA model and discovered a declining trend. In their analysis of weekly rainfall data using the ARIMA model, Zakaria et al. (2012) discovered a decreasing trend for Iraq's semi-arid Sinjar District. Partheepan et al. (2005) examined the temperature, rainfall, and associated severe event processes in order to investigate the annual climatic trend, evolution, and variability in the Batticaloa District of Sri Lanka. Huntra and Keener (2017) found that the ARIMA model's predictions for the water demand in the Las Vegas Valley were highly accurate and helpful for monitoring the effects of climate change.

2. Study Area

The study's temperature and precipitation data came from the India Water Portal website. The India Water Portal used the information from Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia in Norwich, United Kingdom, which is publicly accessible as the CRU, TS2.1 dataset.

In this study, model forecasts for the years 2001 to 2015 are made using monthly mean data for precipitation and temperatures from the years 1950 to 2000. The SPSS software has been used in examine the correlation between ACF and PACF for past and in addition to this different model parameters has been calculated using the SPSS software.

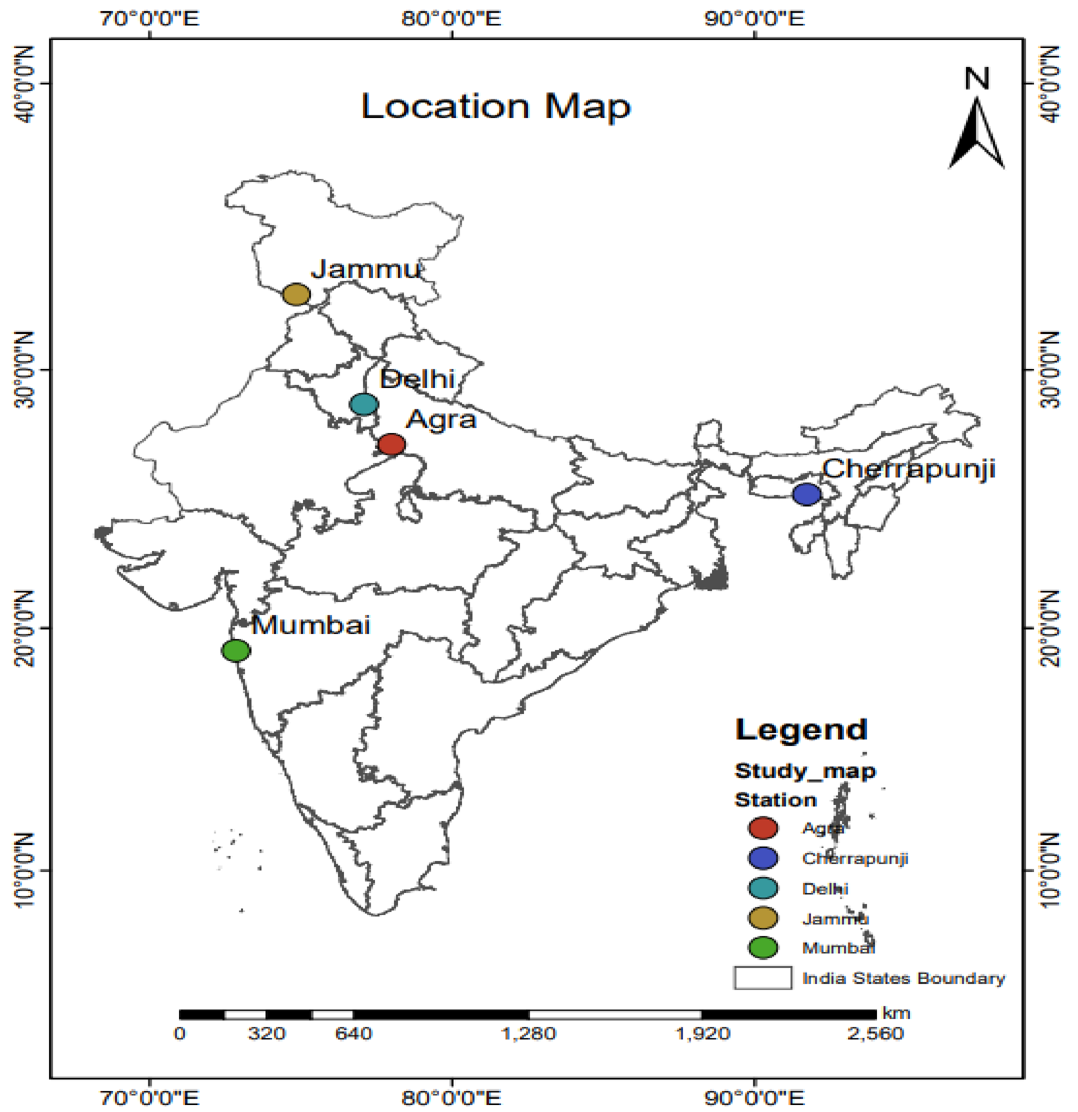


Figure 1 Geographical locations of rainfall stations

3. Model Description

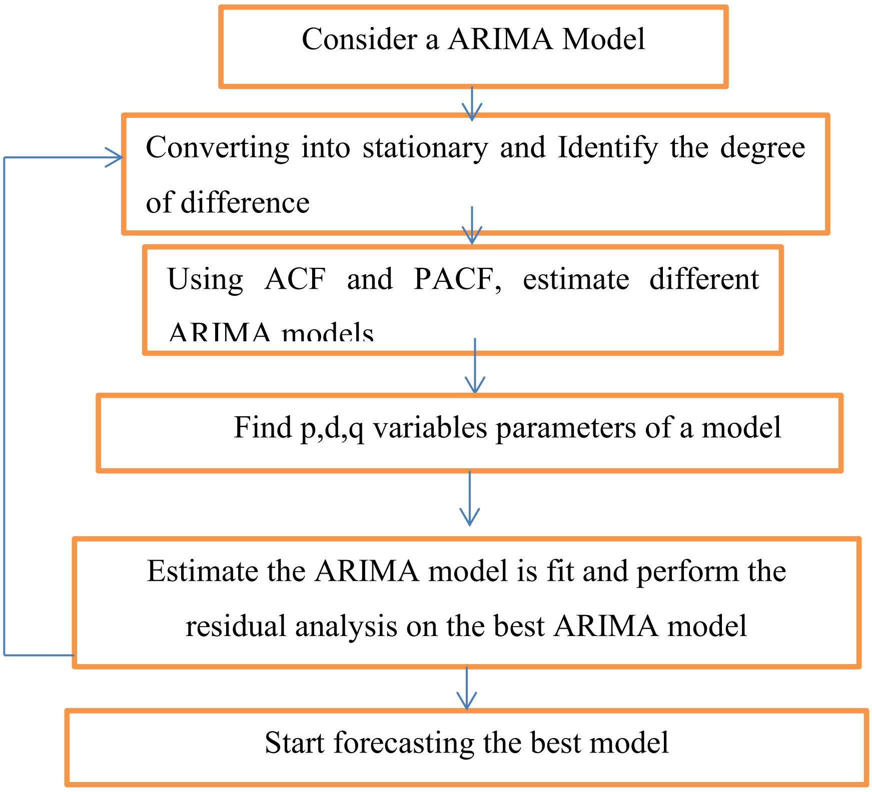
The ARIMA model is used in time series analysis to better comprehensive the data and for future forecasting. The fundamental principle behind the ARIMA model is to transform a non-stationary series into a stationary series by removing the pattern of the series via differencing.

The first portion displays how frequently differencing has been done.The goal of finding an appropriate AR and MR term is to make the model as data-driven as possible. The model implies that the data are non-seasonal series that must first be de-seasonalized. ARIMA(p, d, q), where p is the lag order, d is the order of differencing, and q is the order of moving average, is the standard notation for a non-seasonal ARIMA model.

Normally, an ARIMA model that is not seasonal is written as ARIMA(p, d, q), where p denotes the lag order, d the differencing order, and q the order of moving average. The acronym for a seasonal ARIMA model is ARIMA(p, d, q) (P, D, Q)m, where m is the number of time periods in each season and the uppercase letters P, D, and Q stand for the autoregressive (AR), differencing (I), and moving average (MR) terms, respectively, for the seasonal part of the ARIMA model.

4. METHODOLOGY

The monthly means for of the precipitation data for the 1950 – 2015 has been used as the input to the ARIMA model. We attempted to fit various SARIMA models to the time series of precipitation with the intent to determine the best fit model. The methodology for the determination of best fit ARIMA model is shown in



Flow diagram of ARIMA Model

a. Ensuring stationarity (d)

The first and most important step is to choose the sequence in which the series' stationaries should be differentiated (d).The standard deviation is minimized by choosing the differencing order (d) in this manner. In order to do this, numerous ARIMA models with varying orders of differencing are fitted, but a constant coefficient is chosen. When AR terms ($p \geq 1$) and MA terms ($q \geq 1$) are included in the forecasting formula, auto-correlated errors that were present in a differenced series that has since become a stationery series can be eliminated. The model is expanded with AR terms to account for any minor "under-differencing," and expanded with MA terms to account for any minor "over-differencing."

b. Identification of AR(p) and MR(q) parts

When data values are produced by an ARMA(p, 0) model or by an ARMA(0, q) model, the sample ACF and PACF plots are used to choose the order of an ARMA model. This suggests that d is bigger than zero, i.e., differencing should be performed, if the ACF and PACF have large values (positive) that decline extremely slowly over time.For choosing p, d, and q, one can use the autocorrelation function ACF and partial autocorrelation function (PACF). A sharp cutoff in the differenced series's PACF indicates an AR term should be included to the model if the differenced series exhibits modest under-differencing. If the differenced series' ACF has a sharp cutoff and exhibits mild "over-differenced," an MA term is included to the model.

c. Remove seasonality

The ARIMA models are estimated for values of p, d, q which are given best suitable residuals.The seasonality in the datasets is removed by calculating the data values of P, D, Q for m = 12 on similar lines as the p, d, q were estimated.

d. Selecting best SARIMA model

The calculated SARIMA residuals are tested for white noise, and the model with the best residual behavior is chosen.The forecasting period is 15 years, from 2001 to 2015. The capacity of the chosen SARIMA model to assess the relavant quality of statistical model for a given dataset is examined using AIC and BIC criteria for precipitation and temperature .The Akaike Information Criterion (AIC) measures the relative distance between the fitted likelihood function of the model and the unknown true likelihood function of the data; the smaller the AIC, the closer the model is thought to be to the truth. The model with the lowest Bayesian Information Criterion (BIC) is preferred when selecting a model from a subset of models. Based on probability, it is similar to the Akaike information criterion (AIC) in many ways (Rahman and Hasan 2017; Wali et al. 2017).

5. RESULTS AND DISCUSSIONS

Time Series: A collection of a variable's values that vary over time is called time series data. A time series may have different intervals between observations. Nonetheless, the intervals' range daily, weekly, monthly, yearly etc.should remain constant during the course of the monitored time. In empirical work based on time series, the time series is typically believed to be stationary. The values for each parameter (p, d, q) are: (0,0,0), (0,0,1), (0,1,1), (1,0,0), (1,0,1), (1,1,1), (2,1,1) and (2,0,3).

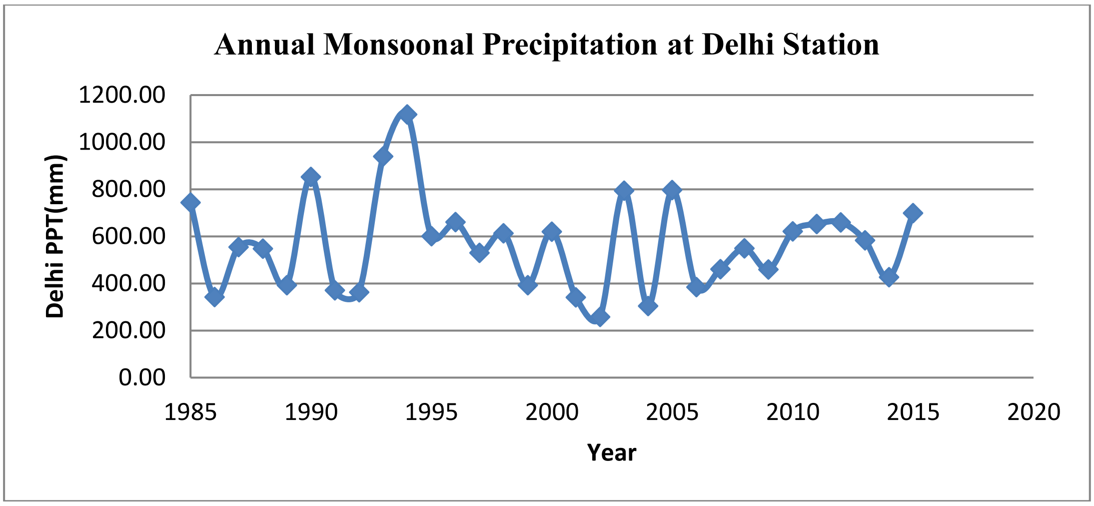


Figure 2 Annual Monsoonal Precipitation at Delhi Station

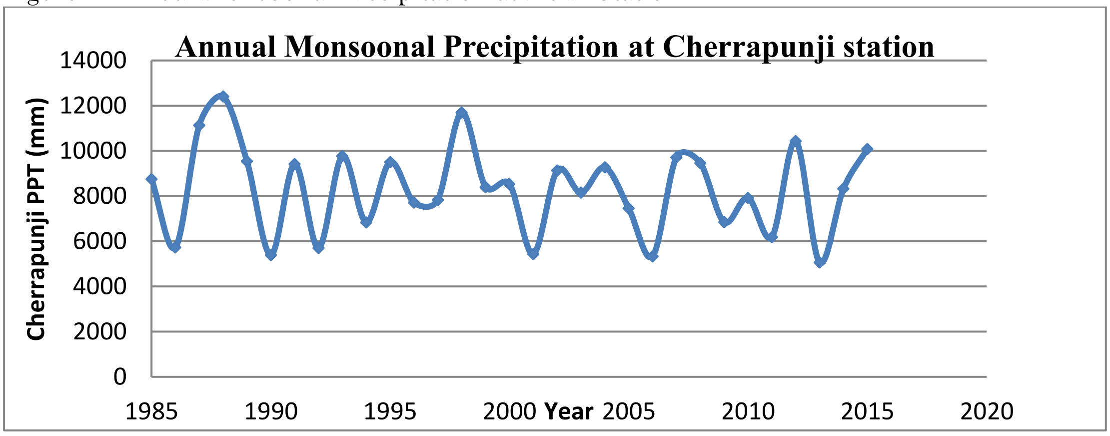


Figure 3 Annual Monsoonal Precipitation at Cherrapunji station

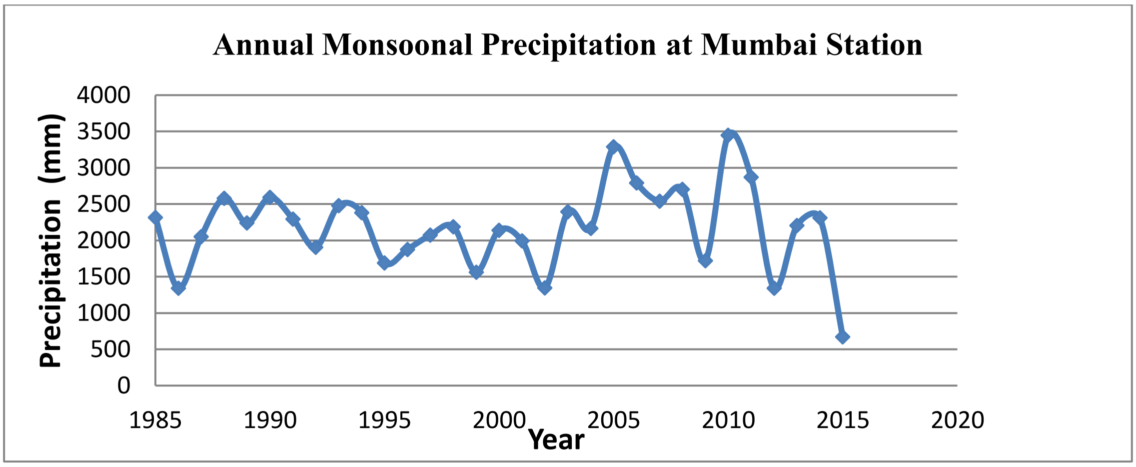


Figure 4 Annual Monsoonal Precipitation at Mumbai Station

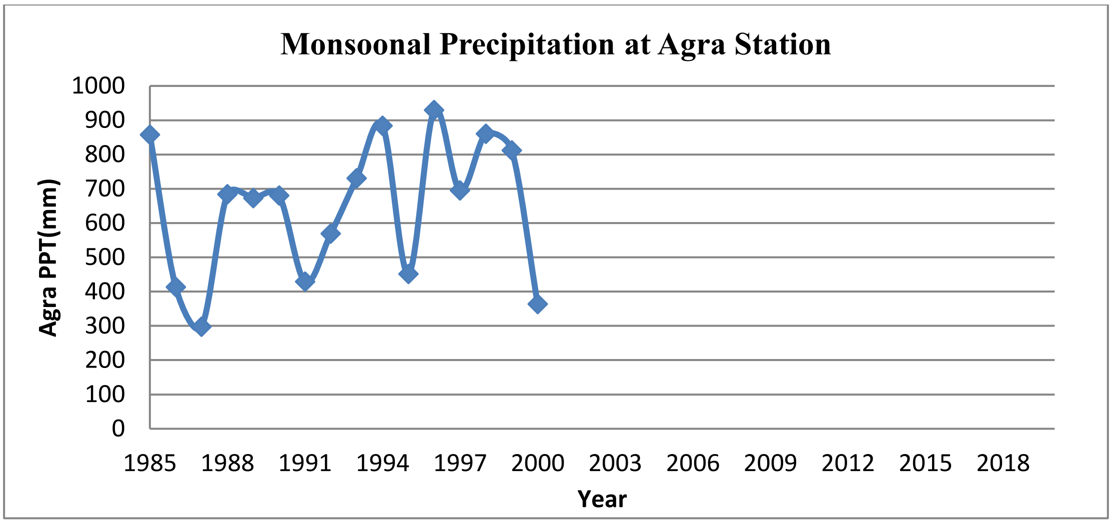


Figure 5 Monsoonal Precipitation at Agra Station

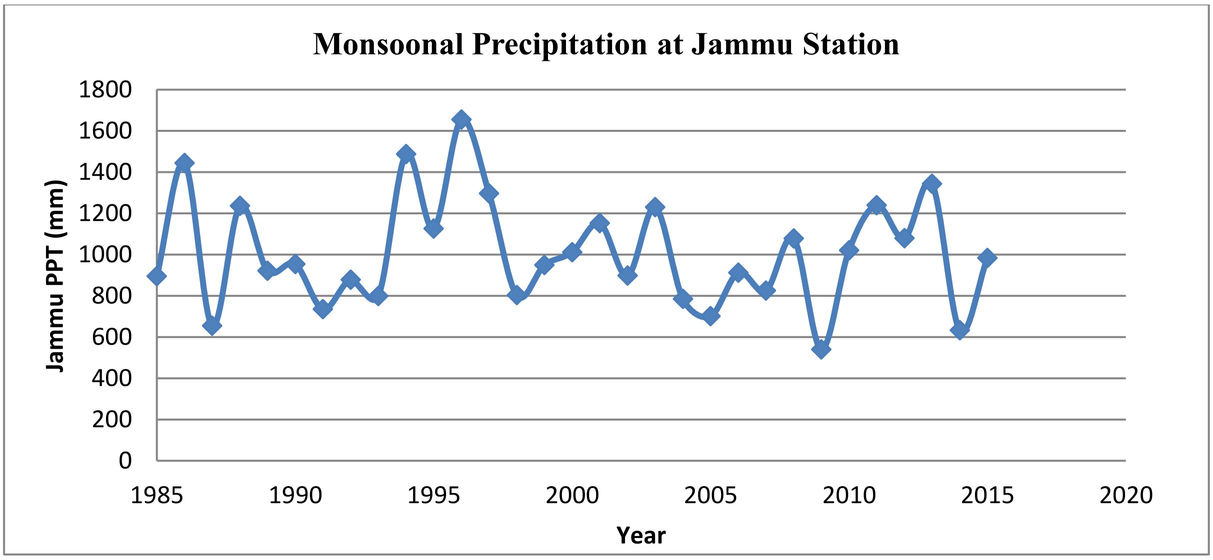


Figure 6 Monsoonal Precipitation at Jammu Station

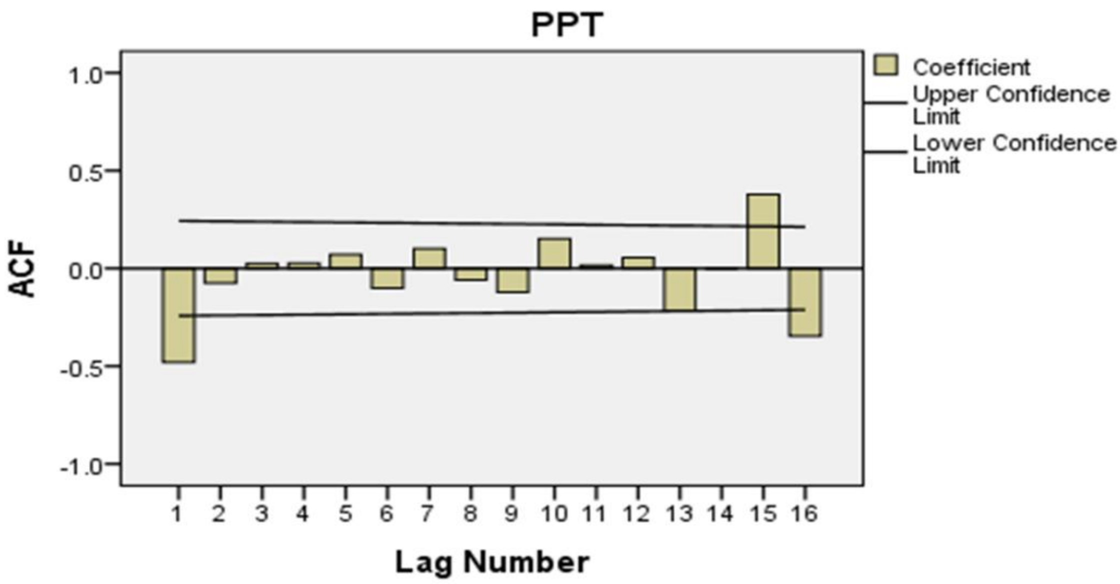


Figure 7 Autocorrelation Function(ACF)

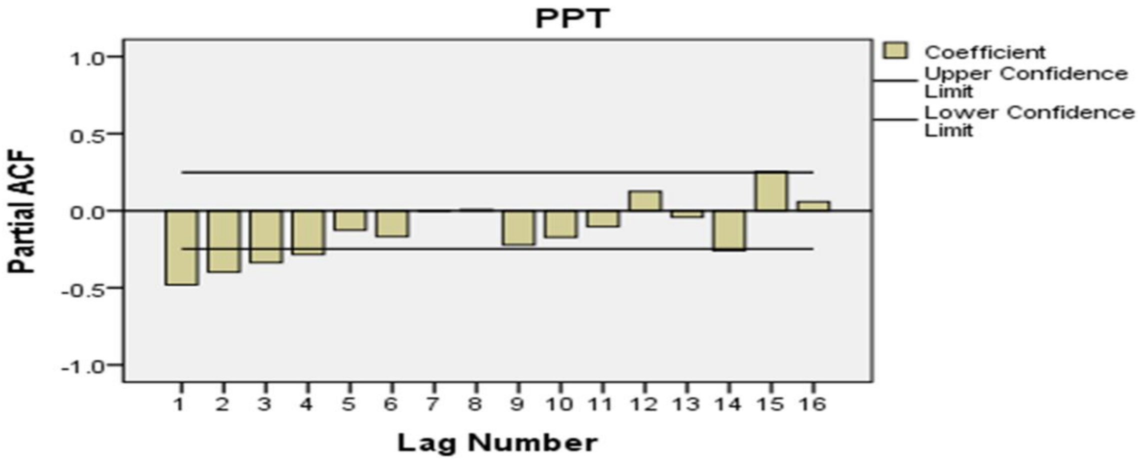


Figure 8 Partial ACF

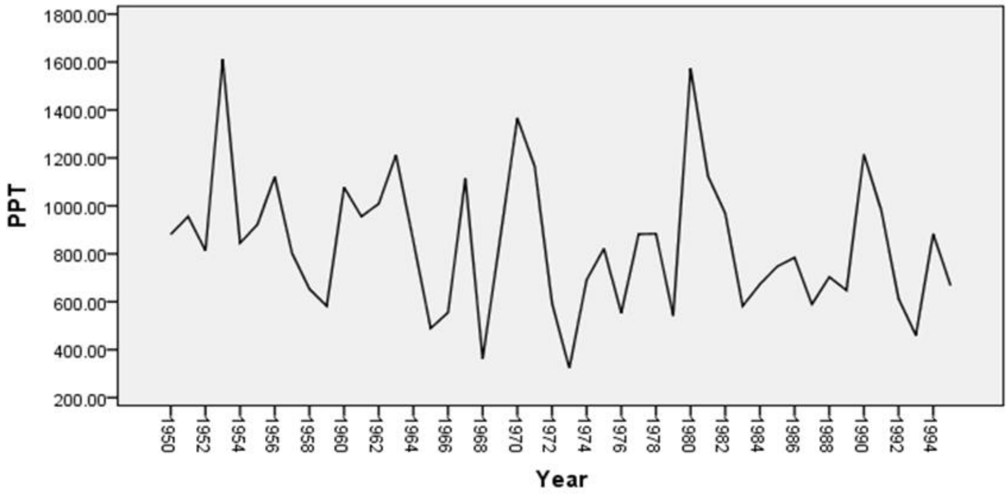


Figure 9 Annual precipitation variation at Agra station

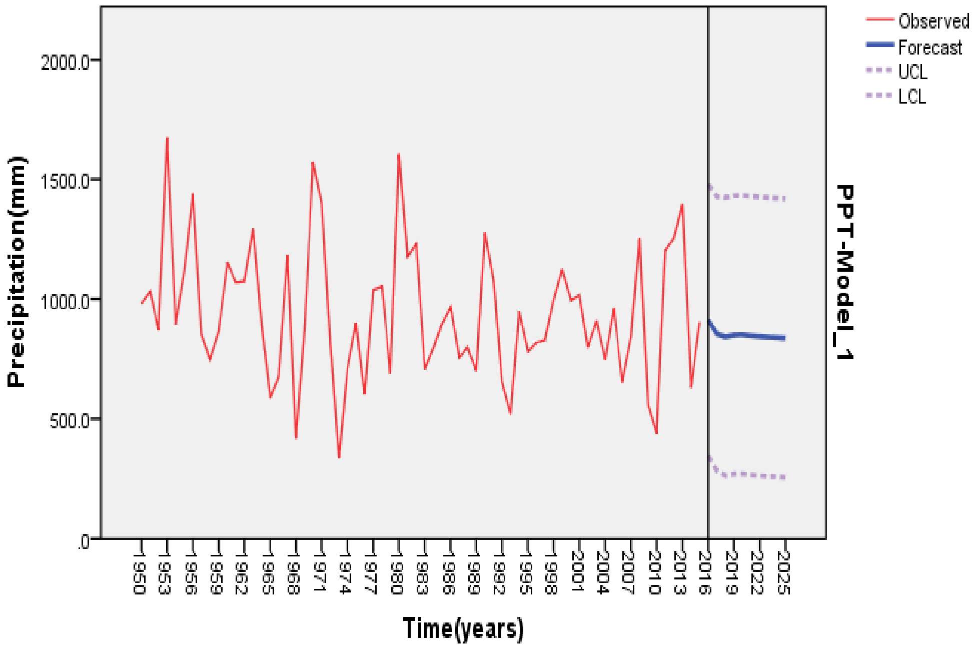


Figure 10 Plot Agra Station

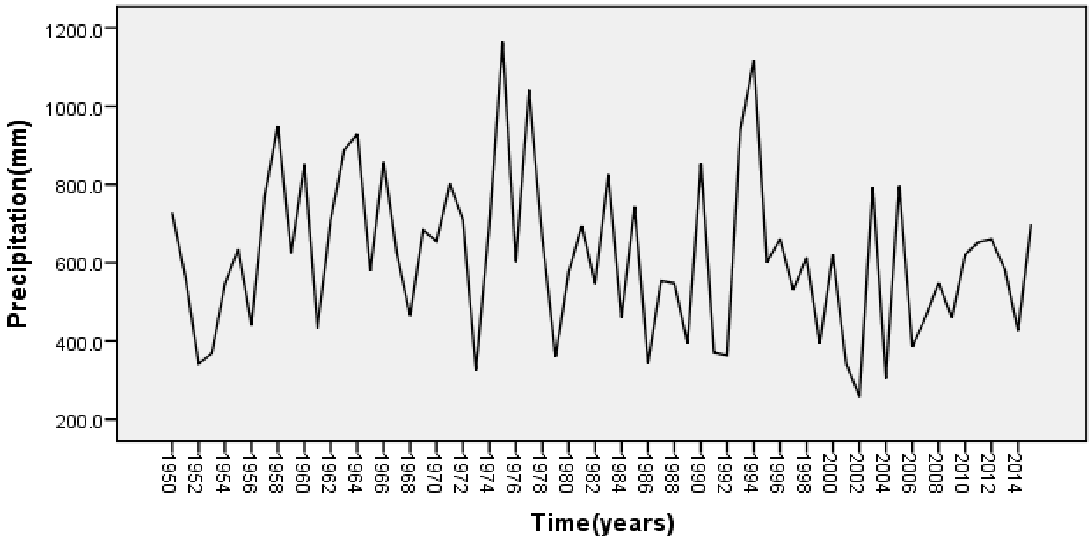


Figure 11Annual precipitation variation at Delhi station

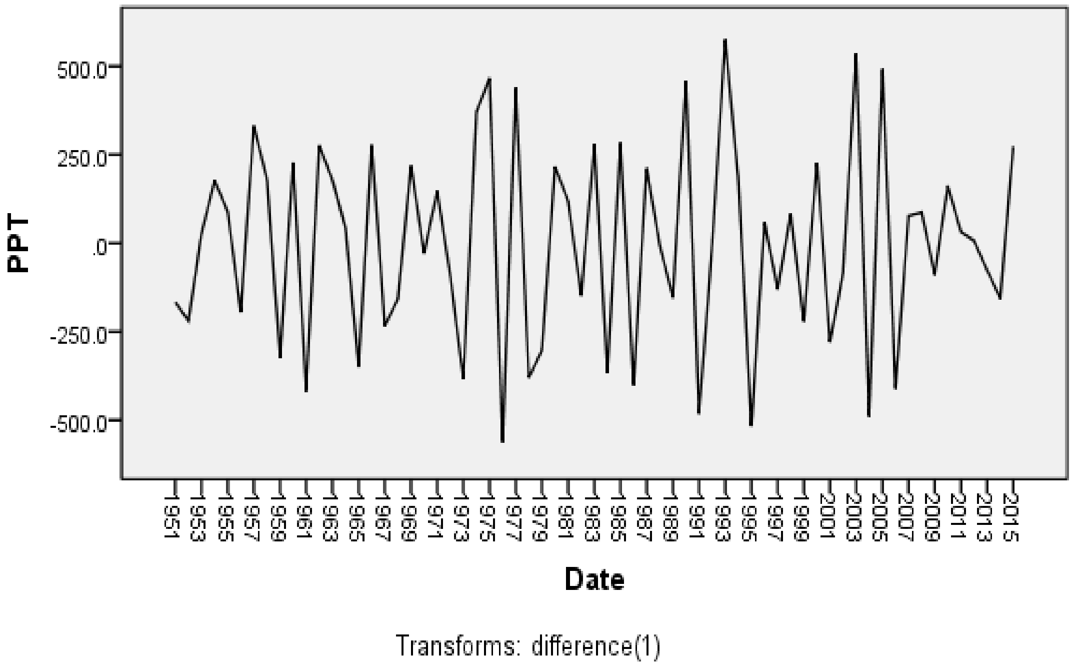


Figure 12 Annual precipitation seasonal variation at Delhi station

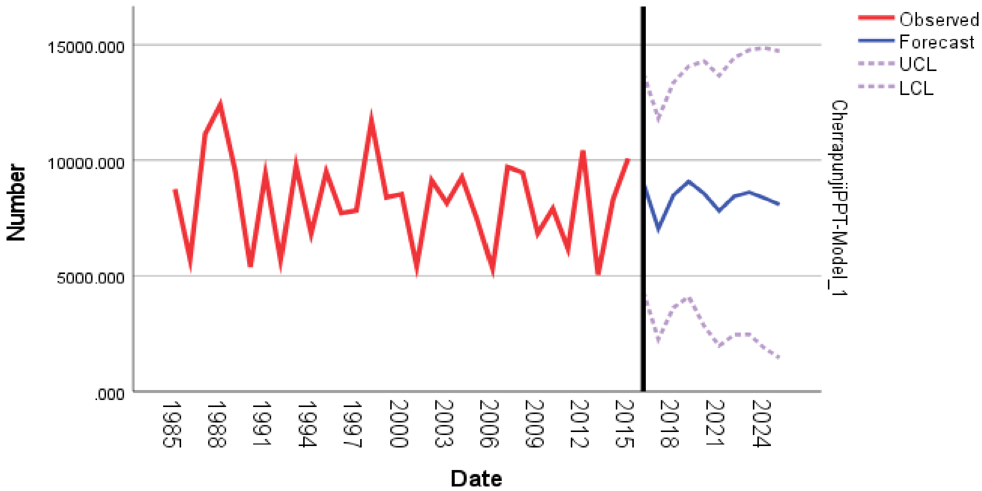


Figure 13 Plot Delhi Station

Table 1 Fit statistic at Delhi station

Fit Statistic	Mean	Min	Max	Percentile						
				5	10	25	50	75	90	95
Stationary R-squared	.477	.477	.477	.477	.477	.477	.477	.477	.477	.477
R-squared	-.034	-.034	-.034	-.034	-.034	-.034	-.034	-.034	-.034	-.034
Normalized BIC	10.98	10.98	10.98	10.98	10.98	10.98	10.98	10.98	10.98	10.98

Table 2 Rainfall forecast at Delhi station

Model	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Delhi PPT Forecast	548.9	557.3	548.9	547.4	545.2	543.3	541.3	539.4	537.5	535.5
Model_1 UCL	967.3	975.8	968.1	966.6	964.4	962.4	960.5	958.6	956.6	954.7
LCL	130.6	138.9	129.8	128.2	126.0	124.1	122.1	120.2	118.3	116.4

6. CONCLUSIONS

In the present study, the ARIMA model was fitted after the removal of seasonality, and forecasting was done using the same model. The values for each parameter (p, d, q) are: (0,0,0), (0,0,1), (0,1,1), (1,0,0), (1,0,1), (1,1,1), (2,1,1) and (2,0,3). Overall, the forecasting using ARIMA (2,1,1) has better results than forecasting using the other ARIMA input Parameters. The time series variation of precipitation for Delhi station, cherrapunji station, Mumbai station, Agra station and Jammu station for last 30 years are shown in below slides respectively.The precipitation data shows that the maximum rainfall occurs in Delhi during the years of 1994 is1118.30 mm and minimum rainfall during the years of 2002 is 257.90 mm.The precipitation data shows that the maximum rainfall occurs in cherrapunji during the years of 1988 is12403.90 mm and minimum rainfall during the years of 2013 is 5060.50 mm.The precipitation data shows that the maximum rainfall occurs in Mumbai during the years of 2010 is 3446.80 mm and minimum rainfall during the years of 2015 is 671.50 mm.The precipitation data shows that the maximum rainfall occurs in Agra during the years of 1996 is 929.00 mm and minimum rainfall during the years of 1987 is 297.70 mm.The precipitation data shows that the maximum rainfall occurs in Jammu during the years of 1996 is 1654.60 mm and minimum rainfall during the years of 2009 is 539.90 mm. Precipitation and temperature are the main factors governing the dynamic structure of climate resulting in climate change. The SARIMA model developed herein has the potential to assist scientists and decision makers develop policies for efficient flood management, urban planning, and environmental planning.

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