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RESEARCH ARTICLE

TEMPORAL VARIABILITY AND PREDICTABILITY OF ANNUAL RAINFALL IN CENTRAL PUNJAB, PAKISTAN

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ABSTRACT

In central Punjab, rainfall patterns have been significantly impacted by climate change, leading to anomalies that affect agriculture, water resources, and disaster management. Long-term yearly rainfall data from Multan, Bahawalnagar, and Sargodha are analysed in this work utilising time-series and statistical techniques, such as ARIMA, SARIMA, and L-moment analysis. The findings demonstrate that Sargodha exhibits extremely varied and unpredictable rainfall patterns, Bahawalnagar has the most steady and highest rainfall, and Multan has the least but comparatively consistent rainfall. Forecasts for the years 2017 to 2027 indicate that while Sargodha will continue to have unpredictable rainfall patterns, Bahawalnagar and Multan will continue to have consistent tendencies. The likelihood of severe rainfall occurrences is shown by positive skewness in all three cities. These results highlight how crucial local-scale rainfall studies are for well-informed planning in agriculture, water management, and flood control in the face of climate change. In central Punjab, this study offers unique city-scale evidence of rainfall predictability limits under changing climate conditions.

KEYWORDS

ARIMA, climate change, forecasting, L-moments, Punjab, Pakistan, Rainfall variability, SARIMA.

1. INTRODUCTION

Rainfall patterns are being impacted by climate change worldwide. Farming, water supply, and urban planning can all be significantly impacted by variations in rainfall patterns (Addisu et al., 2015 ; Bhuyan et al., 2018). It is crucial to thoroughly research rainfall because many locations have seen extraordinary rainfall events or protracted dry spells in recent years (Joshi et al., 2019 ; Pastagia and Mehta, 2022). According to recent research, large-scale changes in air circulation have exacerbated rainfall extremes in South Asia due to climate variability.

Rainfall plays a major role in Pakistan's economy and agricultural practices. Punjab, which is regarded as the nation's food basket, is extremely vulnerable to variations in rainfall. Groundwater, agriculture productivity, and flood danger can all be impacted by even slight variations in rainfall (Kumar et al., 2023 ; Mahmood et al., 2019). Over time, the rainfall patterns in cities like Multan, Bahawalnagar, and Sargodha have varied; some have been more consistent, while others have been more erratic (Machiwal et al., 2019 ; Soltani et al., 2007). This makes it difficult to plan for disaster management, flood control, and irrigation (Sohoulande Djebou and Singh, 2016 ; Tarmizi et al., 2019).

The majority of research examines rainfall at the national or regional level, while local studies are more helpful to farmers and urban planners because they display the real trends in a particular city (Ren et al., 2011 ; Soltani et al., 2020). While L-moments show how extreme rainfall events could occur, statistical models like ARIMA and SARIMA are useful for understanding trends and seasonal patterns (Mazvimavi, 2010 ; Soltani et al., 2020). City-scale evaluations of rainfall variability and predictability in central Punjab are still scarce, despite a large number of regional research.

This study focuses on Sargodha, Bahawalnagar, and Multan. Sargodha experiences extremely variable rainfall, Bahawalnagar experiences moderate rainfall, while Multan experiences semi-arid rainfall. This study intends to comprehend rainfall patterns, forecast future rainfall, and assist local authorities in making better plans for agricultural and water management by analyzing long-term rainfall data using ARIMA/SARIMA models and L-moment analysis (Joshi et al., 2019 ; Kumar et al., 2023).

In summary, this study demonstrates how rainfall is fluctuating in various Punjab cities and highlights the significance of city-level research for agricultural planning, water management, and flood control (Mahmood et al., 2019 ; Pastagia and Mehta, 2022).

2. STUDY AREA AND DATA

This study examines the rainfall patterns in three cities in Punjab Sargodha, Bahawalnagar, and Multan that reflect different meteorological conditions. This study used rainfall data from the Pakistan Meteorological Department (PMD) for Multan from 1951 to 2016, Bahawalnagar from 1963 to 2016, and Sargodha from 1957 to 2016. Every dataset was examined for consistency and quality before analysis. The three cities show distinct climates: Multan has semi-arid conditions with the least amount of annual rainfall, Bahawalnagar has more consistent rainfall, and Sargodha has extremely variable rainfall.

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Table 1: Details of Rainfall Stations Used in the Study					
Station ID	City	Data Period	Latitude (°N)	Longitude (°E)	Elevation (m)
1	Multan	1951-2016	30.15	71.47	122
2	Bahawalnagar	1963-2016	29.98	73.25	163
3	Sargodha	1957-2016	32.08	72.67	193

3. METHODOLOGY

This study used statistical and time-series approaches to assess rainfall variability and produce short-term projections for Sargodha, Bahawalnagar, and Multan. Preparing the data, monitoring its stability over time, developing models, and assessing forecast accuracy were all part of the technique. The forecast and L-moment packages of R software were used for all statistical studies. ARIMA and SARIMA models were utilized for time-series forecasting to comprehend rainfall patterns and their distribution, and L-moment analysis was used to characterize rainfall features, including extremes (Mazvimavi, 2010 ; Soltani et al., 2020). These techniques aid in capturing rainfall variability and temporal trends, offering trustworthy insights for management and planning.

3.1 Prospective Models

There were two models taken into consideration. Initially, rainfall dynamics were captured using time series models (ARIMA and SARIMA), which efficiently handle autocorrelation, trends, and seasonal patterns. Second, the rainfall statistical distribution was described using L-moments. Because they are less susceptible to outliers and offer accurate measurements of extremes, L-moments are favored over conventional moments. Evaluation of rainfall distributional features and forecasting was made possible by the combination of these methods.

3.2 Performing Stationarity Testing

Before using forecasting models, make sure the rainfall series is stable, which means that neither its variance nor its mean changes over time. For time-series models like ARIMA and SARIMA to be accurate, stationarity is a basic prerequisite (Mazvimavi, 2010 ; Soltani et al., 2020). The Augmented Dickey-Fuller (ADF) test was used to find unit roots under the null hypothesis of non-stationarity.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \Delta y_{t-i}\delta_i + \varepsilon_t$$

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which takes stationarity as the null hypothesis, was also applied

$$y_t = r_t + \beta_t + \varepsilon_t$$

Rainfall stability can be reliably checked by using both methods, and non-stationary series can be differenced for forecasting (Mazvimavi, 2010 ; Soltani et al., 2020).

3.3 ARIMA Model

Rainfall variability was analyzed and forecasted using the Autoregressive Integrated Moving Average (ARIMA) model. Because ARIMA takes trends and autocorrelation into consideration, it is especially well suited for time-series data. The autoregressive (AR) component, the moving average (MA) component, and the differencing component (d) to achieve stationarity are the three main parts of the model. The expression for its broad form is:

$$\phi(B)(1-B)^d X_t = \theta(B)\varepsilon_t$$

The backshift operator is represented by B, the error by ε_t, the moving average term by θ(B), the autoregressive term by (B), and the order of differencing by d. ARIMA can efficiently capture rainfall patterns in non-seasonal data by adjusting its settings (p, d, and q).

3.4 SARIMA Model

The seasonal trends frequently seen in rainfall data were captured using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The seasonal autoregressive (SAR) term, seasonal differencing (SD), and seasonal moving average (SMA) term are three seasonal components that SARIMA adds to the ARIMA framework. Its general shape is as follows:

$$\phi(B)\Phi(B)^s(1-B)^d(1-B^s)^D X_t = \theta(B)\Theta(B_s)\varepsilon_t$$

The seasonal period is denoted by s, the non-seasonal differencing order by d, and the seasonal differencing order by D in this instance. By combining seasonal and non-seasonal elements, SARIMA effectively models changes in rainfall over time.

3.5 Identification and Estimation of the Model

Plots of the Autocorrelation Function (ACF) and Partial Autocorrelation Function were used to identify the model and determine the proper autoregressive (AR) and moving average (MA) orders (PACF). The general ARIMA (p, d, q) model's

AR (p) $\quad Y_t = \phi_1 Y_t - 1 + \phi_2 Y_t - 2 + \cdots + \phi_p Y_{t-p} + \epsilon$

MA (q) $\quad Y_t = \epsilon_1 + \epsilon_{t-1}\,\theta_1 + \epsilon_{t-2}\,\theta_2 + \cdots + \epsilon_{t-q}\,\theta_q$

where Y_t is the rainfall series and ε_t is white noise. Maximum Likelihood Estimation (MLE), which yields accurate and trustworthy estimates even for intricate time-series models, was used to estimate model parameters. L-moments were also used to summarize the features of the rainfall distribution. Because they are less impacted by high values and sampling variability than conventional moments, L-moments are thought to be more reliable. This makes them especially useful for hydrological assessments.

3.6 Model Selection Criteria

The model's suitability was assessed using the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) . Additionally, popular error metrics like Mean Absolute Error (MAE) and Root Mean Square Error were used to evaluate forecast performance (RMSE). These metrics offer a thorough assessment of the model's precision and dependability in representing rainfall variations.

$$\mathrm{AIC} = -2ln(\mathrm{L}) + 2\mathrm{k}$$

where n is the sample size, L is the likelihood of the model, and k is the number of estimated parameters.

$$\mathrm{BIC} = -2ln(\mathrm{L}) + \mathrm{k}ln(\mathrm{n})$$

3.7 Examining Diagnoses

After the models were calculated, diagnostic tests were used for validation. Specifically, the residuals have to behave like white noise and have no discernible autocorrelation. To evaluate this, the Ljung-Box Q-statistic **Ljung** and **Box. (1978)** was used

$$\mathrm{Q} = \mathrm{n}(\mathrm{n}+2)\sum_{k=1}^{m} \frac{\hat{p}^2{}_k}{n-k}$$

In this case, ρ_k is the residual autocorrelation at lag k, m is the lag length, and n is the survey size. If the Q value is not significant, the residuals are independent and the model is sufficient. Additionally, randomization was confirmed visually by examining residual plots.

3.8 Forecasting and Accuracy Measures

Rainfall estimates were produced for 2017-2027 using the final models that were chosen. Using common error metrics including Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE), forecast accuracy was assessed :

$$\text{Mean Absolute Error} = \frac{1}{n}\sum_{i=1}^{n}\left|F(x_i) - \hat{F}(x_i)\right|$$

$$\text{Mean Square Error} = \frac{1}{n}\sum_{i=1}^{n}\left(F(x_i) - \hat{F}(x_i)\right)^2$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(F(x_i) - \hat{F}(x_i)\right)^2}$$

By using these criteria, station comparability was guaranteed and predicted performance was clearly evaluated. It should be made clear that annual rainfall time data were used in the forecasting process. However, by dividing the annual totals by twelve, the predicted annual rainfall figures were transformed into mean monthly equivalents for ease of interpretation and comparison. The forecasts' fundamental trend and variability structure are unaffected by this alteration, which is only offered for consistent cross-station comparison.

4. Results And Discussion

4.1 Introduction

The findings of the rainfall frequency analysis for Sargodha, Bahawalnagar, and Multan are shown in this section. Descriptive statistics, stationarity testing, model identification, diagnostic checks, and forecasting are all included in the analysis. Figures and tables are used to provide a clear illustration of the results.

4.2 Descriptive Statistics

The summary statistics of annual rainfall are reported in Table 4.1.

Table 2: Descriptive statistics for annual total rainfall (mm)

city	N	Mean	S.D	min	max	Cv	skewness	kurtosis
Multan	66	202.2	85	75.9	513.21	42.02	0.94	1.26
Bahawalnagar	60	460.5	143.1	233.9	767.30	31.09	0.36	-0.97
Sargodha	54	233.9	119.1	57.1	523.21	50.93	0.68	-0.34

Table 2 summarizes the locations, elevations, and data periods of the chosen rainfall stations. The highest average rainfall and comparatively little variability are seen in Bahawalnagar, suggesting consistent rainfall patterns. Despite its moderate constancy, Multan has the lowest mean rainfall. Sargodha has the largest coefficient of variation and an intermediate mean rainfall, indicating more irregularity and vulnerability to extreme occurrences.

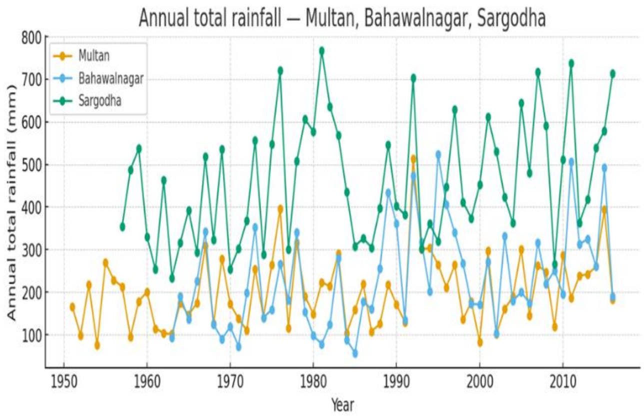


Figure 1: Annual rainfall time series plots for Multan, Bahawalnagar, and Sargodha

Figure 1's time series plots show the three cities' annual rainfall trends. Sargodha has the most interannual variability, Multan receives the least amount of rainfall, while Bahawalnagar constantly receives the most. Sargodha's climate is more variable due to its transition between dry and humid zones, which makes it more vulnerable to changes in the atmosphere and variations in the climate.

4.3 Stationarity Tests

Table 3: Presents the results of the Augmented Dickey-Fuller (ADF) and KPSS stationarity tests.

City	Lag order (ADF)	Dickey-Fuller	Lag order (kpss)	KPSS Statistic	Decision (5%)
Multan	9	-11.60	6	0.3253	Stationary
Bahawalnagar	8	-14.71	6	0.3541	Stationary
Sargodha	8	-11.53	6	0.7139	Non-stationary

Multan and Bahawalnagar's rainfall data are stable, meaning that the mean and variance have remained constant over time. Sargodha, on the other hand, has more variability and irregularity in its rainfall patterns, making it non-stationary and necessitating differencing before using time series models.

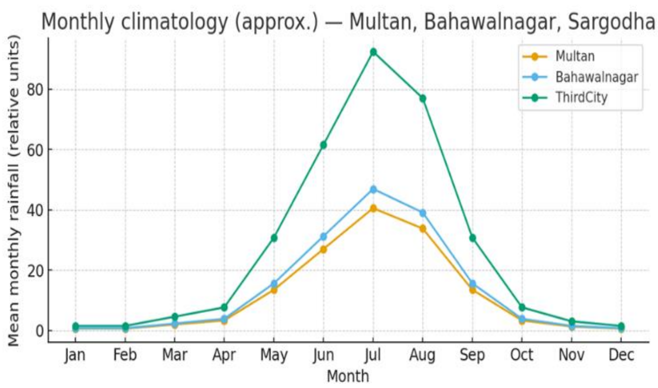


Figure 2: ADF and KPSS test visualization for rainfall series

The ADF and KPSS tests were used to further investigate the stationarity features of the rainfall series Figure 2. Figure 2 displays the results of the ADF and KPSS tests. It is evident that the rainfall series in Multan and Bahawalnagar are stationary, but Sargodha has to be differenced. While the data series from Bahawalnagar and Multan are stable, Sargodha (Third City) needed differencing in order to become stationary, suggesting greater rainfall variability.

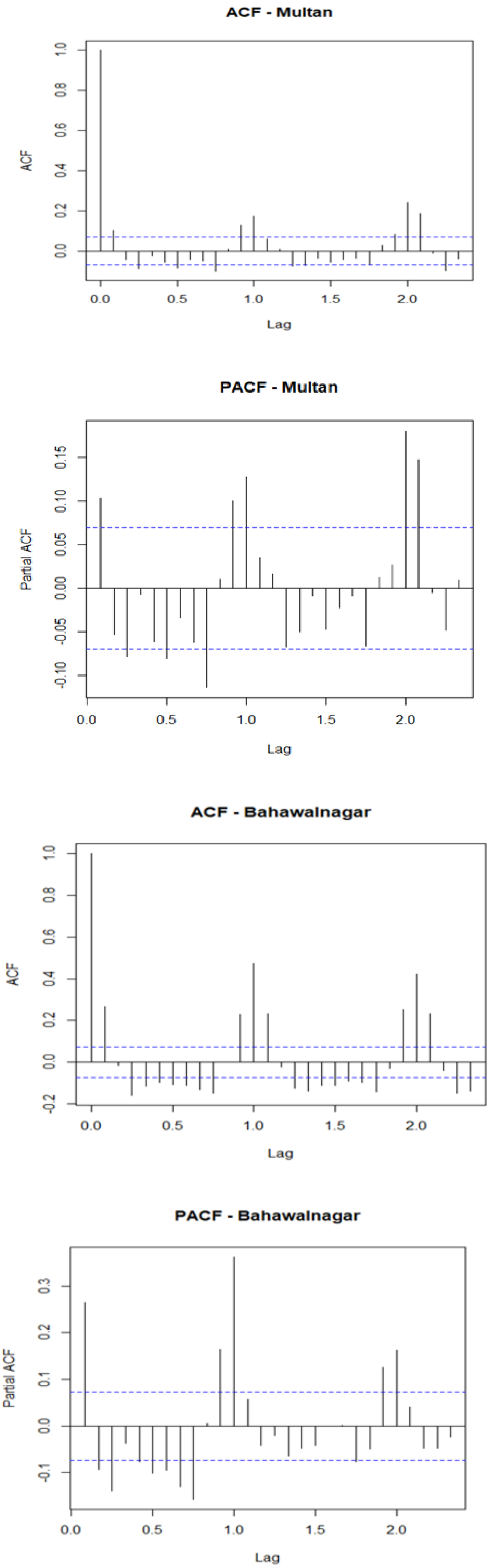
4.4 Model Identification

The best-fit ARIMA/SARIMA models selected using AIC and BIC values are summarized in Table 4.3.

Table 4: Selected ARIMA models and information criteria.

City	Selected ARIMA Model	Residual Var(σ^2)	Log Likelihood	AIC	BIC
Multan	ARIMA(1,0,2)(0,0,2)[12]	840.7	-3788.0	7589.99	7622.7
Bahawalnagar	ARIMA(0,0,1)(2,0,0)[12]	1995.0	-3757.29	7524.58	7547.5
Sargodha	ARIMA(5,1,0)(2,0,0)[12]	1332.0	-3243.20	6504.40	6544.7

The chosen models for Multan and Bahawalnagar offer a decent fit with comparatively reduced AIC, BIC, and residual variance, as Table 4.3 demonstrates. Sargodha's non-stationarity necessitated differencing (d=1), and its higher information criteria indicate a less dependable model fit and increased rainfall variability.



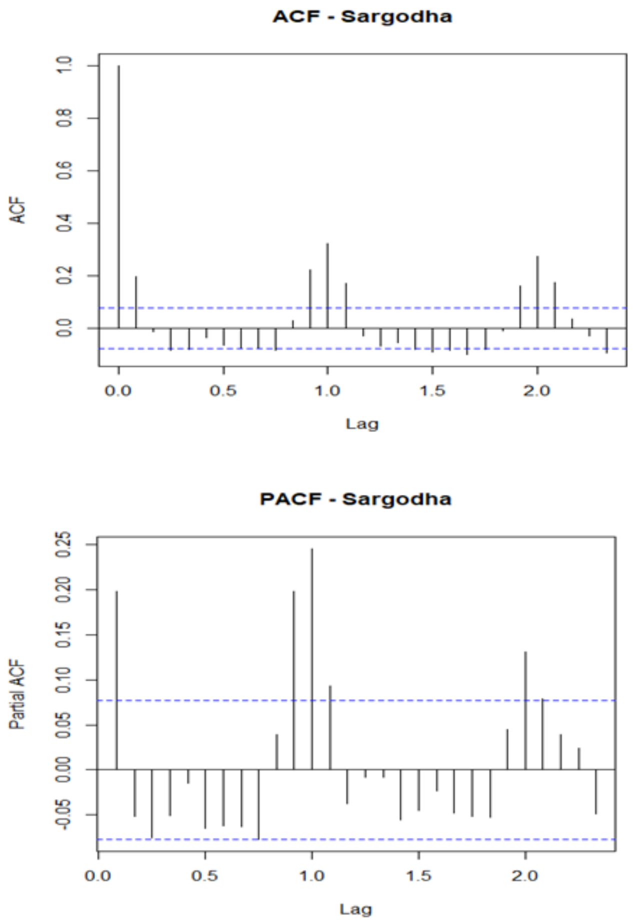


Figure 3: ACF and PACF plots for each city

Model identification was carried out using ACF and PACF plots Figure 4.3. Figure 4.3 displays the ACF and PACF graphs used to identify the ARIMA/SARIMA models for each city. According to the residual diagnostic tests, the Sargodha model was unable to fully reflect the variability in rainfall dynamics, but the Multan and Bahawalnagar models did significant residual autocorrelation.

4.5 L-Moments

The LM describing the distributional properties of annual rainfall are presented in Table 4.4.

Table 5: Approximate L-moments for annual totals

L-moment	Multan	Bahawalnagar	Sargodha
L-mean	16.8470076	38.3724306	19.4899383
L-scale	12.3500190	24.2462705	14.6202457
L-skewness	0.5637702	0.4600078	0.5899246
L-kurtosis	0.2890642	0.2398512	0.3188085

Positive skewness is seen in all three cities, indicating a propensity for intense rainfall occurrences.

4.6 Diagnostic Checking

Diagnostic results based on the Ljung-Box test are provided in Table 4.5.

Table 6: Ljung-Box test results for residual independence				
City	**Residuals from ARIMA Model**	**(χ^2)**	Q-statistic	**Decision (α = 0.05)**
Multan	ARIMA(1,0,2)(0,0,2)[12]	19.9	20.1	Residuals are independent
Bahawalnagar	ARIMA(0,0,1)(2,0,0)[12]	15.4	29.7	Residuals are independent
Sargodha	ARIMA(5,1,0)(2,0,0)[12]	59.6	73.5	Residuals are NOT independent

Table 4.5 displays the results of the Ljung-Box test for residual independence of the fitted ARIMA/SARIMA models. The lack of considerable autocorrelation in the residuals indicates that the models accurately reflect the underlying rainfall patterns for Multan and Bahawalnagar. However, the residuals for Sargodha show a high connection, suggesting that the rainfall dynamics at this site are not sufficiently explained by the fitted model. This suggests that Sargodha has greater model uncertainty and variability. The increased climatic irregularity and non-linear climate variability linked to Sargodha's transitional climate setting are reflected in the incapacity of linear ARIMA models to accurately depict rainfall dynamics.

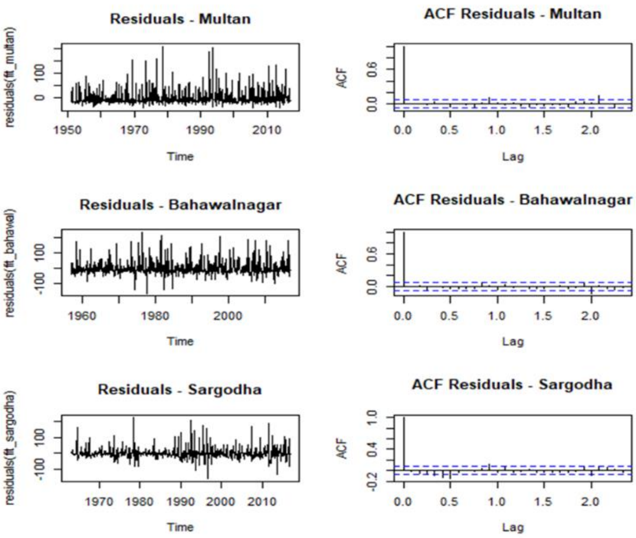


Figure 4: Residual diagnostic plots for the fitted ARIMA/SARIMA models

Model adequacy was evaluated using residual diagnostic plots Figure 4.4.Figure 4.4 displays residual diagnostic plots for the fitted ARIMA/SARIMA models, showing sufficient model performance for Multan and Bahawalnagar but residual autocorrelation for Sargodha .While Sargodha's residuals exhibit some association, the results for Multan and Bahawalnagar reveal that the residuals are independent. The fitted ARIMA model, however, does not adequately represent the underlying rainfall dynamics for Sargodha, as evidenced by the residuals' notable autocorrelation.

4.7 Forecasting

Forecast accuracy measures are reported in Table 4.6, and projected rainfall values for 2017-2027 are given in Table 4.7.

Table 7: Training Set Accuracy Measures of ARIMA Models				
City	**RMSE**	**MAE**	**MASE**	**Decision**
Multan	28.8853	18.4538	0.8849	Adequate (Model accepted)
Bahawalnagar	44.5407	29.0894	0.8787	Adequate (Model accepted)
Sargodha	36.2403	22.3893	0.9973	Not Adequate (Residuals not white)

The models for Multan and Bahawalnagar have sufficient forecasting ability, as seen by the comparatively low RMSE, MAE, and MASE values in Table 4.6. In contrast, the Sargodha model exhibits residual autocorrelation and MASE near 1, indicating decreased reliability and requiring cautious interpretation.

Table 8: Forecasted mean monthly rainfall equivalents (mm) derived from annual rainfall series			
Year	**Multan**	**Bahawalnagar**	**Sargodha**
2017	15.39	18.43	20.61
2018	15.95	18.12	21.00
2019	16.91	19.54	21.32
2020	16.86	19.62	21.55
2021	16.86	19.62	21.55
2022	16.86	19.62	21.55
2023	16.86	19.62	21.55
2024	16.86	19.62	21.55
2025	19.34	20.35	22.11
2026	16.23	19.07	21.44
2027	16.90	19.75	21.86

Rainfall forecasts for Sargodha should be carefully examined. This restriction shows that complicated and perhaps non-linear meteorological factors control rainfall variability in Sargodha. Even when the ARIMA model provides suggestive trends, diagnostic results revealed residual autocorrelation, indicating higher forecast uncertainty. Sargodha's highly complex and diverse rainfall behaviour, which is likely influenced by its transitional climate, is reflected in this constraint.

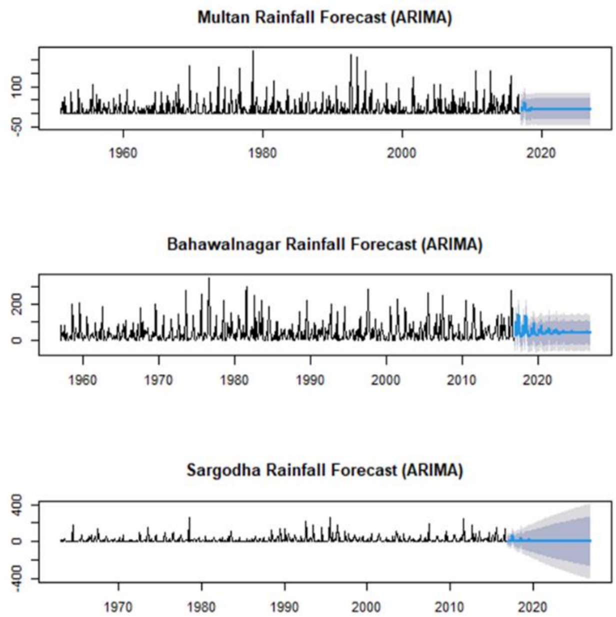


Figure 5: Forecast plots of annual rainfall for 2017-2027

Forecasted rainfall trends for 2017-2027 are illustrated in Figure 4.5.Figure 4.5 shows the predicted rainfall trends for the years 2017-2027, with Sargodha showing more uncertainty than Multan and Bahawalnagar. According to the projections, rainfall in Sargodha exhibits greater variability than in Multan and Bahawalnagar, which is in line with previous findings.

The general conclusions can be summed up as follows Bahawalnagar has consistent forecasts and the greatest average rainfall. Though the trend is steady, Multan has the least amount of rainfall. The model performance of Sargodha is the least dependable and most variable. Forecasts show that while Sargodha is still unpredictable, Multan and Bahawalnagar are experiencing steady rainfall trends.

5. Conclusion

This study used long-term data, time series models (ARIMA/SARIMA), and L-moment analysis to investigate the yearly rainfall patterns in Multan, Bahawalnagar, and Sargodha, Punjab. Understanding rainfall variability and producing projections for 2017-2027 were the goals.

The findings indicate that the three cities differ significantly. Bahawalnagar is stable for planning because it receives the greatest rainfall and does it consistently. Although Multan has the least amount of rainfall, it is nevertheless quite consistent. However, Sargodha exhibits significant fluctuation and erratic rainfall patterns, which reduces the accuracy of projections. All cities have positive skewness, which suggests that extreme rainfall events could occur.

Sargodha is expected to stay unpredictable, while Bahawalnagar and Multan are expected to maintain consistent trends. These results demonstrate the necessity of planning at the city level, particularly with regard to irrigation, water management, and disaster preparedness. Sargodha in particular might need more sophisticated modelling or adaptive tactics because of its unpredictable environment. In general, improved planning and management in central Punjab depend on localised rainfall analysis. Policymakers and farmers can use these insights to make well-informed decisions that lower the risks associated with extreme rainfall events and climate variability. These results imply that in order to more accurately depict rainfall dynamics in climatically transitional areas, future research should include non-linear or climate-informed modelling frameworks.

Funding Statement

There is no funding for this research study.

Conflict Of Interest

There are no pertinent financial or non-financial interests that the authors would want to declare. The writers affirm that they have no competing interests.

Data Availability

The Pakistan Meteorological Department provided the annual rainfall data utilized in this study for Multan (1951-2016), Bahawalnagar (1963-2016), and Sargodha (1957-2016). PMD is able to disclose the information upon reasonable request.

Code Availability

The authors' own custom R scripts were used for all analyses. If a legitimate request is made, the R codes can be shared.

Ethics Approval

There are no trials involving either humans or animals in this study. Consequently, official ethics approval is not necessary.

Consent To Participate

Since there are no human volunteers in the study, it is not applicable.

Consent For Publication

Since there are no human participants in the study, it is not applicable.

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