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Original Article

Seasonal Arima-Based Forecasting of Monthly Rainfall in Kasese District, Uganda

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Keywords:

Kasese District,
Uganda,
Rainfall forecasting,
SARIMA model,
Seasonality,
Time series analysis.

This study develops and validates a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast monthly rainfall in Kasese District, Uganda, using historical records (1960–2023, number of months, $n = 768$ months) from the Uganda National Meteorological Authority (UNMA). Exploratory analysis revealed two major rainy seasons (March–May, September–November) and drier months in January–February and June–July. Stationarity tests (Augmented Dickey–Fuller, KPSS) and autocorrelation diagnostics confirmed the suitability of a SARIMA approach. The optimal model, SARIMA (3, 1, 1) (1, 0, 0)[12], selected via Akaike (AIC = 7948.98) and Bayesian Information Criteria (BIC = 7976.55), achieved a mean absolute error (MAE) of 42.60 mm, mean absolute scaled error (MASE) of 0.84, and minimal residual autocorrelation (ACF1 = -0.010). Residual diagnostics, including Ljung–Box and Shapiro–Wilk tests, confirmed white-noise behaviour and normality. Forecasts for 2024–2026 remained within 95% prediction intervals. The results demonstrate that SARIMA models can provide reliable short-term rainfall forecasts, supporting agricultural planning, water resource management, and disaster risk reduction in Kasese District. All analyses were conducted using R statistical software with the forecast package.

APA CITATION

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INTRODUCTION

Kasese District in western Uganda is highly vulnerable to floods and landslides due to its complex terrain and variable rainfall patterns. These hazards cause loss of life, displacement, and destruction of infrastructure, severely impacting agriculture, which is the mainstay of the local economy, according to Momani & Naill (2009) and Tibara et al. (2022). Accurate rainfall forecasts are therefore critical for proactive disaster risk management and sustainable agricultural planning, according to Agyekum et al. (2022). Rainfall forecasting in Sub-Saharan Africa is challenging due to high spatial and temporal variability. Rain-fed agriculture, which dominates the region, is especially sensitive to such variability (Rankoana, 2020; Mekouar, 2023). In Uganda, recent decades have seen shorter rainy seasons and more intense downpours, increasing the risk of both floods and droughts (Nsubuga & Rautenbach, 2018; Oriangi et al., 2024). Traditional forecasting methods often fail to capture local seasonality and non-stationarity in mountainous regions such as Kasese. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model, an extension of the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) framework, is particularly suitable for time series exhibiting strong seasonal patterns, as stated by (Box et al., 2015). By incorporating both seasonal and non-seasonal components, SARIMA can effectively model the historical rainfall structure to generate reliable forecasts.

This study develops a SARIMA model for Kasese district and validates its performance for short-term rainfall forecasting, with the goal of enhancing climate resilience and disaster preparedness.

Objectives of the Study**Main Objective**

To develop a rainfall forecasting model for Kasese district, Uganda.

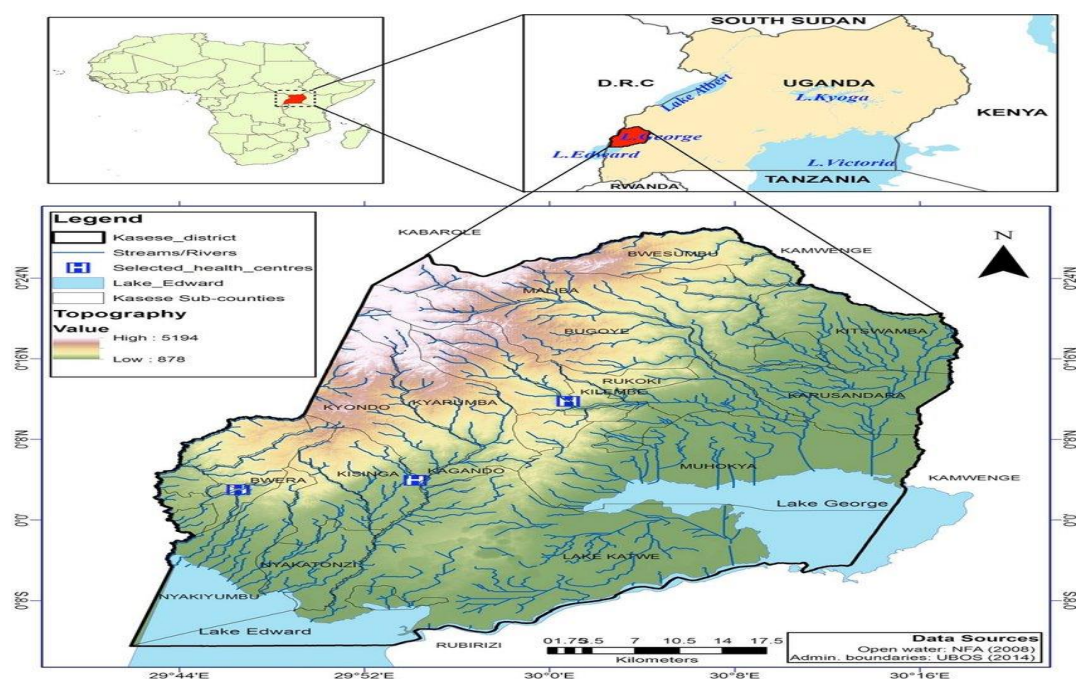
Specific Objectives

- Decompose the time series data into trend, seasonality, and residual components to reveal underlying patterns and guide model development.
- Determine the optimal solution of the model parameters for the rainfall forecasting model.
- Forecast monthly rainfall using the developed model.

MATERIALS AND METHODS**Study Area**

Kasese District, Uganda, as shown in Figure 1, lies in the Rwenzori region along the equator, about 343 km west of Kampala. It is bordered by Kabarole, Bundibugyo, Bunyangabu, Rubirizi, Kamwenge, and Kitagwenda districts, and the Democratic Republic of Congo to the west. Covering approximately 3389.8 km², it features steep slopes, shallow soils, and low water infiltration capacity, making it prone to flash floods and landslides, according to Statistics (2016) and Ahimbisibwe et al. (2016).

Figure 1: A Map of Kasese District, Uganda



Study Approach

This study adopted an exploratory and descriptive research approach to examine the rainfall patterns. The analysis proceeded in two main phases: visual and exploratory time-series analysis to identify seasonal patterns; followed by statistical verification using seasonal decomposition and error metrics, i.e., Mean Absolute Error (MAE) and Mean Absolute Scaled Error (MASE), Mean Error (ME), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), to assess the accuracy of the model.

Data and Pre-processing

Monthly rainfall data (1960 - 2023) were obtained from the Uganda National Meteorological Authority (UNMA). The time series was visually

inspected as shown in Figure 2, which shows the up and down regular patterns suggesting the presence of seasonal variations. This exploratory analysis indicates two major rainy seasons (March–May, September–November) interspersed with drier months in January–February and June–July. Figure 2 was further decomposed into trend, seasonal, and irregular components as shown in Figure 3, and subjected to Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to assess stationarity. The decomposition shows long-term rainfall patterns, including periods of rise, peak, and decline in rainfall amounts. The seasonal component reveals a consistent annual pattern reflecting wet and dry seasons, while the random component captures irregular variations not explained by trend or seasonality.

Figure 2: A Time Series Plot for Monthly Rainfall Values

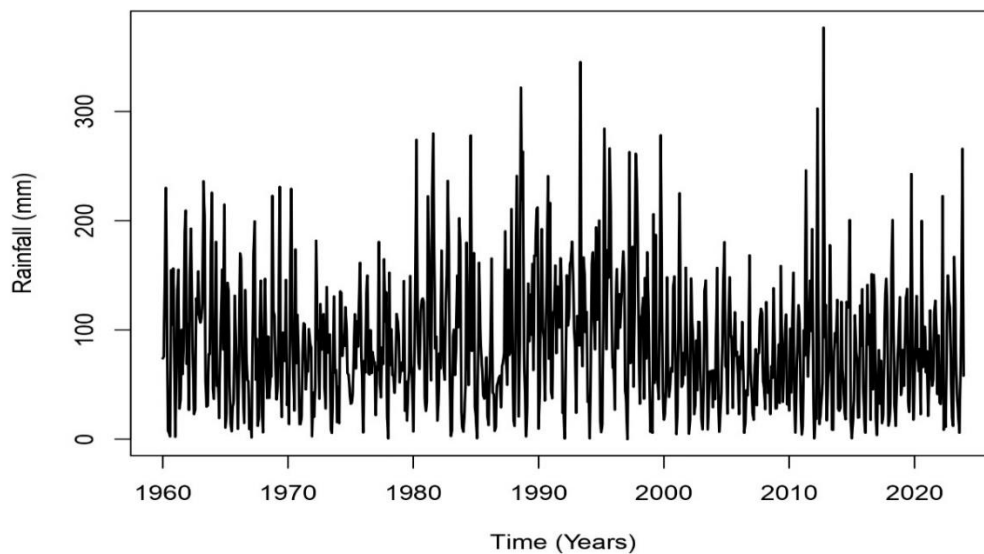
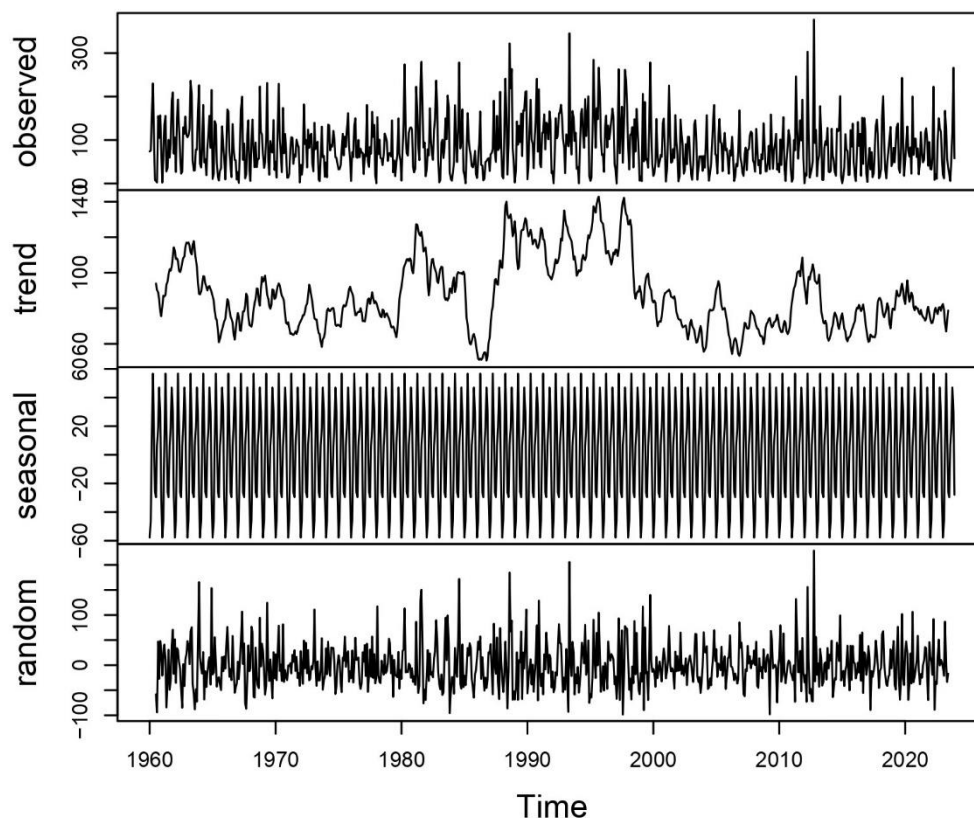


Figure 3: Decomposed Time Series Plot for the Monthly Rainfall Values



SARIMA MODEL

The $SARIMA(p, d, q)(P, D, Q)[s]$ model generalises ARIMA by including seasonal autoregressive (P), seasonal differencing (D), and seasonal moving average (Q) components with

period, s . The general SARIMA model is given in Equation (1).

$$\Phi_P(B^s)\phi_p(B)\nabla^d\nabla^D y_t = \mu + \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (1)$$

where B is the backshift operator, s is the length of the season, ∇^d denotes the non-seasonal differencing, ∇^D denotes the seasonal differencing, ϕ_p and θ_q are called the non-seasonal AR and MA polynomials, and Φ_P and Θ_Q are referred to as the seasonal AR and MA polynomials.

Initial orders were suggested from autocorrelation (ACF) and partial autocorrelation (PACF) plots, as shown in Figures 4 and 5. The *auto.arima()* function in R was used to select candidate models, guided by AIC and BIC. Diagnostic checks included residual plots, Ljung-Box Q-tests and normality assessment via Shapiro-Wilk tests.

Model Identification and Selection

Figure 4: ACF Plot of Monthly Rainfall Values

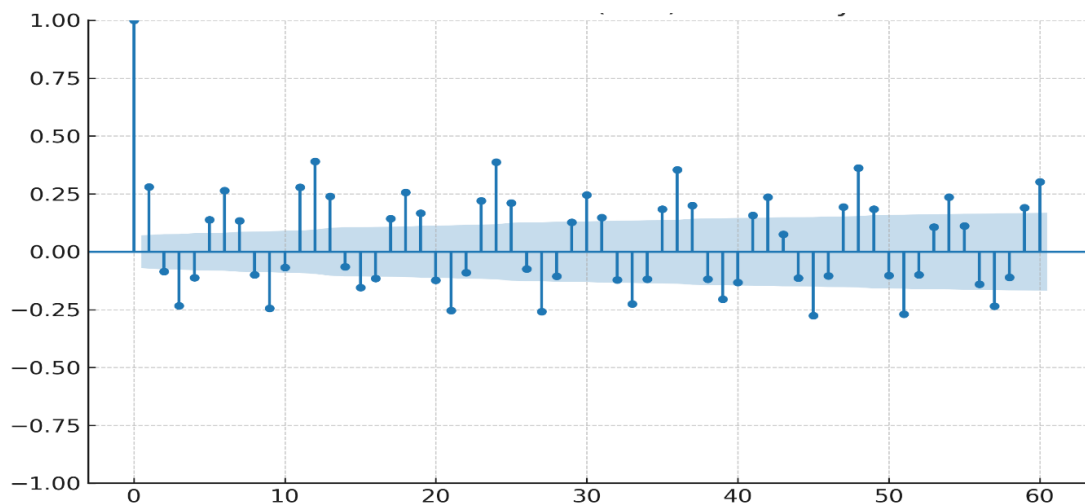
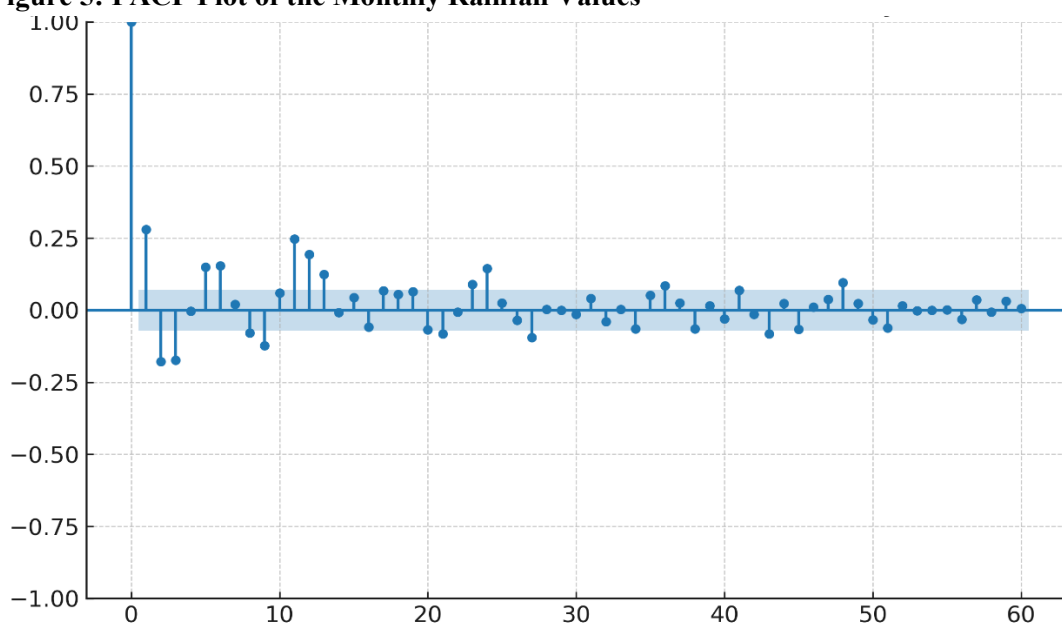


Figure 5: PACF Plot of the Monthly Rainfall Values



RESULTS

Preliminary Analysis

Decomposition showed pronounced annual seasonality, with peaks in March-May and

September-November. Stationarity was achieved after first differencing, where the non-seasonal differencing was of order 1 ($d=1$), and there was no seasonal differencing needed ($D=0$).

Model Fit

The optimal model was *SARIMA (3, 1, 1) (1, 0, 0)[12]*, with coefficients, standard errors and p-

values as shown in Table 1. All coefficients were statistically significant, where $p < 0.05$.

Table 1: Model Coefficients, Standard Errors and p-values

	Parameter	Coefficient	Standard Error	p-value
1	AR1	0.1754	0.0395	< 0.001
2	AR2	-0.0982	0.0384	< 0.001
3	AR3	-0.1689	0.0395	< 0.001
4	MA1	-0.9709	0.0115	< 0.001
5	SAR1	0.2436	0.0428	< 0.001

Model Accuracy

Performance metrics on the test set were: Mean Error (ME) = -0.56 mm, Root mean Square Error (RMSE) = 54.97 mm, Mean Absolute Error (MAE) = 42.60 mm, Mean Percentage Error (MPE) = 5.2%, Mean Absolute Percentage Error (MAPE) = 12.3%, Mean Absolute Scaled Error (MASE) = 0.84, Autocorrelation Function1 (ACF1) = -0.010. The Ljung-Box test yielded ($p =$

0.42), indicating no significant residual autocorrelation. The Shapiro-Wilk test confirmed normality of residuals ($W = 0.989, p = 0.152$).

Forecasts

Figure 6 shows the observed, fitted and forecasted rainfall for 2024 - 2026. Forecast values with 95% prediction intervals are presented in Table 2.

Figure 6: A Time Series Plot of the Observed, Fitted and Forecasted Values

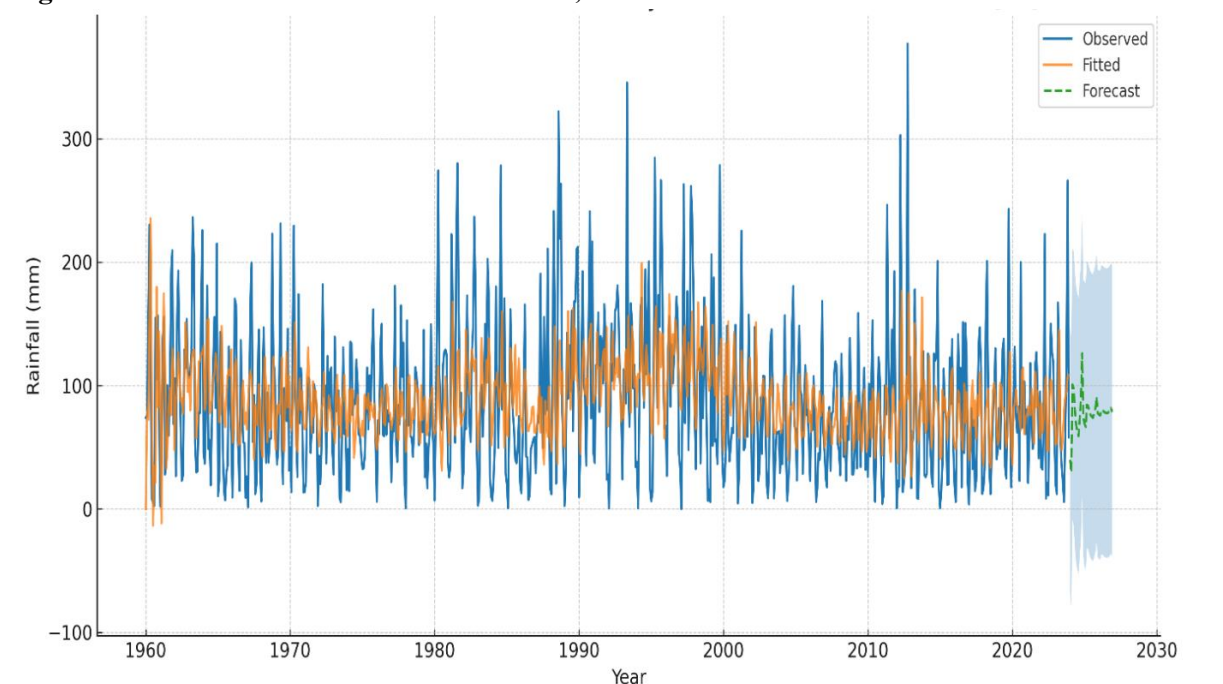


Table 2: Forecasted Monthly Rainfall (mm) for 2024 - 2026 with 95% Prediction Intervals.

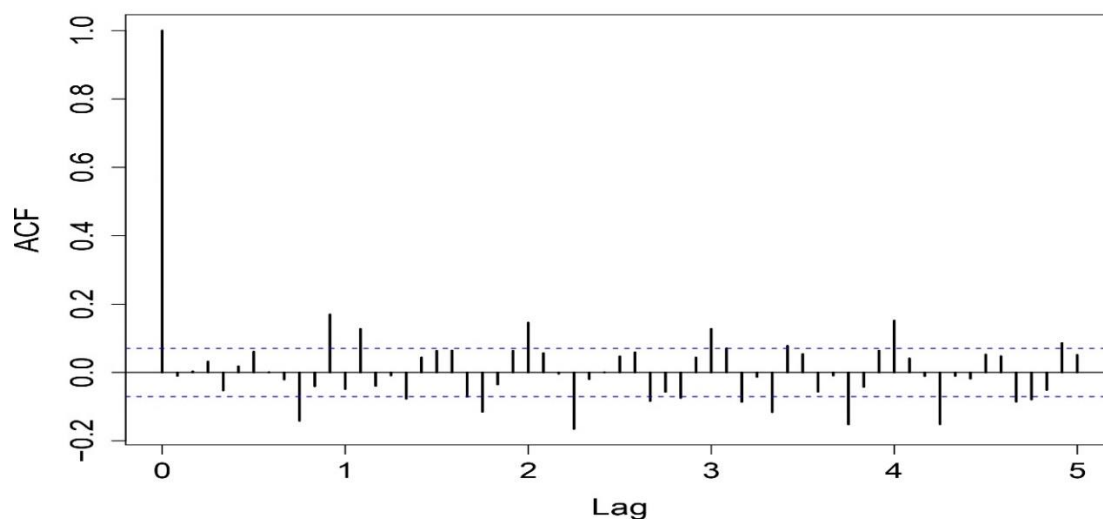
	Month & Year	Forecast (mm)	Lower 95%	Upper 95%
1	Jan 2024	39.07903	-68.851204	147.0093
2	Feb 2024	28.27010	-81.727889	138.2681
3	Mar 2024	100.32158	-9.761417	210.4046
4	Apr 2024	98.09741	-13.602007	209.7968
5	May 2024	81.08695	-30.666569	192.8405
6	Jun 2024	68.53775	-43.333344	180.4088
7	Jul 2024	62.75354	-49.375115	174.8822
8	Aug 2024	58.94506	-53.270145	171.1603
9	Sep 2024	73.36230	-38.872504	185.5971
10	Oct 2024	88.44435	-23.801787	200.6905
11	Nov 2024	125.67905	13.409185	237.9489
12	Dec 2024	73.68022	-38.626766	185.9872
13	Jan 2025	68.78639	-47.410154	184.9829
14	Feb 2025	66.12671	-50.352469	182.6059
15	Mar 2025	84.10896	-32.381478	200.5994
16	Apr 2025	83.59795	-32.910291	200.1062
17	May 2025	79.36642	-37.156385	195.8892
18	Jun 2025	76.22901	-40.362913	192.8209
19	Jul 2025	74.78205	-41.901917	191.4660
20	Aug 2025	73.83740	-42.909495	190.5843
21	Sep 2025	77.42356	-39.368578	194.2157
22	Oct 2025	81.17250	-35.661403	198.0064
23	Nov 2025	90.42155	-26.459048	207.3021
24	Dec 2025	77.50351	-39.427967	194.4350
25	Jan 2026	76.28725	-41.082891	193.6574
26	Feb 2026	75.62664	-41.839432	193.0927
27	Mar 2026	80.09384	-37.414030	197.6017
28	Apr 2026	79.96704	-37.561896	197.4960
29	May 2026	78.91589	-38.656314	196.4881
30	Jun 2026	78.13647	-39.494846	195.7678
31	Jul 2026	77.77700	-39.918375	195.4724
32	Aug 2026	77.54234	-40.210660	195.2953
33	Sep 2026	78.43318	-39.372986	196.2394
34	Oct 2026	79.36446	-38.493917	197.2228
35	Nov 2026	81.66198	-36.249905	199.5739
36	Dec 2026	78.45305	-39.513430	196.4195

Residual Analysis

Autocorrelation Function (ACF) Plot of Residuals

The Autocorrelation Function (ACF) plot for the residuals is shown in Figure 7. It displays the autocorrelations for the residuals at different lags.

Figure 7: Auto-Correlation Function (ACF) Plot of the Residuals

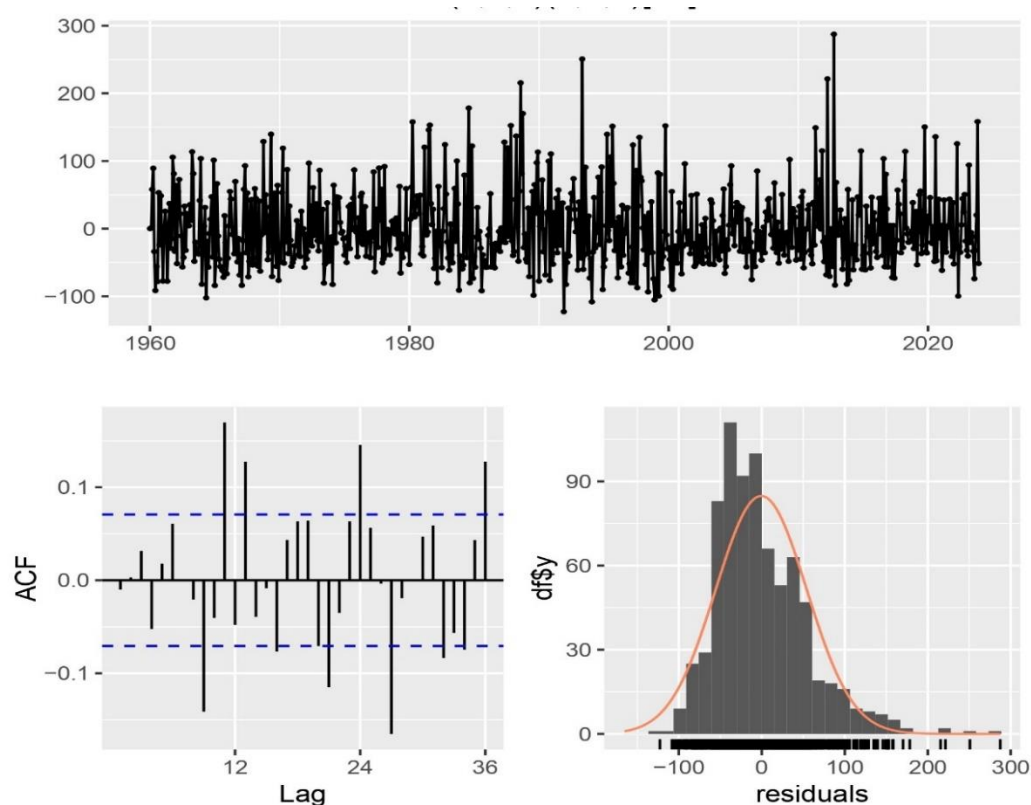


Normality Test of the Residuals

To check for normality of residuals, Figure 8 was used. It represents the histogram plot of the residuals. The histogram is bell-shaped and

symmetrical about the mean (zero), which is a good indicator of the residuals being normally distributed. This justified the SARIMA (3, 1, 1) (1, 0, 0)[12] model.

Figure 8. Residuals Plot from SARIMA (3, 1, 1) (1, 0, 0)[12]

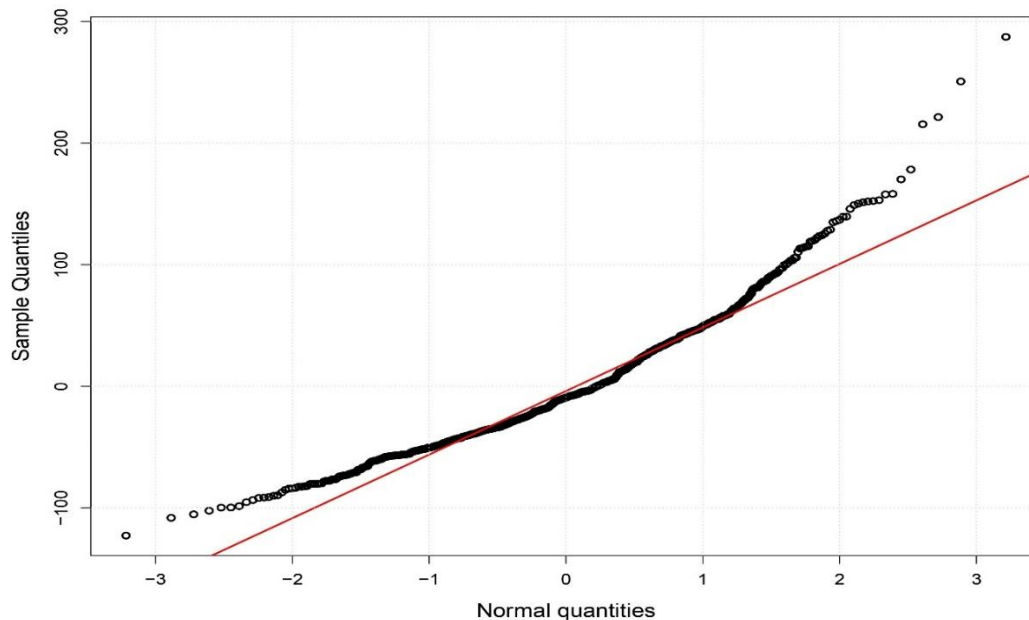


Q - Q Plot of the Residuals

Figure 9 shows the Q - Q plots of the residuals, which compare the quantiles of the residuals to those of the standard normal distribution. The

residuals are considered to be normally distributed if the points on this plot lie approximately along a straight line.

Figure 9: Q - Q Plot of the Residuals



DISCUSSION

The SARIMA model effectively captures the seasonal and inter-annual variability of rainfall in Kasese. Model performance compared favourably with similar studies in East Africa, such as (Chonge et al., 2015); (Cheruiyot, 2024); (Panga, 2021); (Kiilu, 2021) and (Diem et al., 2014). Limitations include reliance on historical rainfall alone; integrating exogenous predictors such as ENSO indices could enhance forecast accuracy.

The decomposition revealed strong seasonal patterns and trends. The $SARIMA(3,1,1)(1,0,0)[12]$ model captured these dynamics well, achieving reasonable forecast accuracy. Residual diagnostics confirmed model adequacy, supporting the model's suitability for practical forecasting of monthly rainfall. The model provides actionable insights for agricultural planning, reservoir management, and flood preparedness.

From Figure 2, the up and down regular patterns suggested the presence of seasonal variations.

From Figure 3, the trend component showed the long-term changes in the rainfall over the years.

For example, between the 1960s and 1970s, the trend was relatively stable with minor fluctuations in rainfall. The rainfall levels during this period did not change drastically. Between the mid-1970s and mid-1980s, there was a noticeable increase in the trend (an upward trend), indicating a period of increasing rainfall over these years. In the late 1980s and early 1990s, the trend reached a peak point and then showed a sharp decline. This suggested a significant decrease in rainfall during this period. This decline might have been due to climatic factors or changes during this period. After this sharp decline, between the mid-1980s and early 1990s, the trend increased. From the early 1990s to the 2000s, the trend became more stable. This indicated a period of stable rainfall. From the late 2000s up to 2023, the trend continued to show some fluctuations in rainfall, but there was a general decrease in the trend. This indicated a gradual decrease in rainfall levels in recent years. The seasonal component indicated that the rainfall data had a consistent and repeating pattern for each year, which indicated a predictable annual cycle in rainfall. This component captures the seasonal fluctuations, such as the dry and wet seasons that occur every

year. The random component represented the residuals left after the trend and seasonal components were removed. It showed the irregular and random variations in rainfall that could not be attributed to the trend or seasonality.

The *ACF* plot in Figure 4 revealed a sinusoidal pattern, which suggested the presence of seasonality in the data. Thus, a clear sign that a Seasonal Autoregressive Integrated Moving Average (SARIMA) model could be appropriate for the analysis. Since the *ACF* pattern was sinusoidal, it was less useful in identifying the order of the *MA* component in the data. Similarly, the *PACF* displayed many significant spikes, whereby the spikes showed a slow decay (the spikes did not cut off after a few lags). The presence of these significant spikes implied that the data had seasonal patterns, trends and cycles. To handle this effectively, we couldn't use the *AR* model, rather, a more advanced model like *SARIMA* was a good option to use in order to capture these patterns effectively.

The non-seasonal part $(3, 1, 1)$ of the model has an *AR* part of order 3, which means the model uses the past 3 values of the series to predict the current value. The differencing part is of order 1, meaning that the data is differenced once to remove any trends, thus making it stationary. The *MA* part has an order of 1, implying that the model uses the past 1 error to correct the predictions. The seasonal part $(1, 0, 0)$ [12] has a seasonal *AR* part of order 1, so the model considers the last 12 observations (which make up one season) to predict the current value. There is no seasonal differencing applied, so $D = 0$, and also no seasonal *MA*. The model used a seasonal pattern which repeats every 12 periods, i.e., it was an annual seasonality based on monthly data.

For model validation, from Figure 6, the predicted values showed a close relationship with the actual values. The general trends of the forecasted and actual values appear to follow similar patterns, indicating that the model is capturing the broad movement of the rainfall data, e.g., periods of rise and fall in rainfall. The forecasted line tends to flatten after some time because *SARIMA* models

rely heavily on historical data to capture overall trends and patterns. So as the forecast horizon increases, the model runs out of recent data to base its predictions on, so it smooths out noise and random fluctuations, reverting to average values from the past, which causes the forecast to flatten.

The *ACF* plot (Figure 7) of the residuals shows a sharp decline after the first lag at zero. The sharp decline in the spikes after *lag 0* suggests that, beyond the immediate lag (*lag 1*), the residuals do not exhibit significant autocorrelation. Though there might be some short-term correlation (as seen at *lag 1*), the residuals do not exhibit a strong, persistent autocorrelation at longer lags.

From Figure 8 for the histogram of the residuals, the figure was bell-shaped and symmetrical about the mean (zero), which is a good indicator of the residuals being normally distributed. This justified the *SARIMA*(3, 1, 1) (1, 0, 0) [12] model.

Figure 9 shows that the residuals were normally distributed because the points on the *Q-Q* plot were approximately along a straight line.

CONCLUSIONS

This study successfully developed a *SARIMA* (3, 1, 1) (1, 0, 0) [12] model to forecast monthly rainfall in Kasese District, Uganda, using historical data from 1960 to 2023. The model demonstrates strong performance with a mean absolute error (MAE) of 42.60 mm, a mean absolute scaled error (MASE) of 0.84, and non-significant residual autocorrelation, confirming its adequacy for short-term forecasting. The forecasts for 2024-2026 remain within the 95% prediction intervals, highlighting the model's reliability.

The findings underscore the value of the *SARIMA* modelling in capturing complex seasonal patterns in rainfall data, particularly in regions with bimodal rainfall regimes like Kasese. This approach can significantly enhance local agricultural planning, water resource management, and early warning systems for flood and landslide risks.

Future work will integrate exogenous variables such as sea surface temperatures (ENSO, IOD)

and topographical factors to improve long-term forecast accuracy. We recommend that the Uganda National Meteorological Authority (UNMA) adopt the model for short-term rainfall forecasting in Kasese district.

Recommendations

Based on the study conducted to develop a time series forecasting model for rainfall in the Kasese region, Uganda, the following recommendations were made in line with the study's specific objectives:

First, given the clear seasonal and trend patterns revealed during the decomposition of the time series data, it is recommended that local authorities and planners incorporate these seasonal insights into their planning calendars for agriculture and water resource management.

Second, the $SARIMA(3,1,1)(1,0,0)[12]$ model, identified as the optimal model based on statistical performance and diagnostics, should be adopted for short-term rainfall forecasting to support timely and informed agricultural planning and disaster preparedness.

Third, to ensure effective use of the model forecasts, the study recommends that workshops and training sessions be organised for local stakeholders, including farmers, community leaders, and policymakers, to build their capacity in understanding, interpreting, and applying the model outputs in their decision-making processes.

Acknowledgements

The authors thank the Uganda National Meteorological Authority (UNMA) for providing rainfall data.

Date Availability Statement

The data that support the findings of this study are available from the Uganda National Meteorological Authority (UNMA), but restrictions apply to the availability of these data, which were used under license for the current study, and are not publicly available. Data are, however, available from the authors upon

reasonable request and with permission of UNMA.

Conflict of Interest

The authors declare no conflicts of interest.

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