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Time series analysis and forecasting of Streamflow at Nangbeto dam in Mono Basin using stochastic approaches

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Abstract

Accurate prediction of the streamflow has a significantly importance in water resources management. In this study, two time series models, Autoregressive Moving Average model (ARMA) and Autoregressive Integrated Moving Average model (ARIMA) are used for predicting streamflow based on observed monthly streamflow data from 2000 to 2020. The statistics related to first 16 years were used to train the models and last 5 years (2016-2020) were used to forecast. The accuracy of the models was assessed using statistical metrics such as the Nash efficiency (NE), the Root Mean Square Error (RMSE) and mean absolute percentage error (MAPE). The findings show the following values for the performance criteria: The root mean square error was, 52.525 for ARIMA against 59.273 for ARMA. The mean absolute percentage error was 18.245 for ARIMA against 21.642 for ARMA and the Nash efficiency was 0.848 for ARIMA against 0.839 for ARMA. From these results, it is found that ARIMA model performs better than the ARMA models. The results of this research could assist policymakers in managing water resources, agriculture, and mitigating flood risks in the ORB of West Africa.

Keywords: Streamflow forecasting; Time series models; ARIMA; ARMA**.**

1. Introduction

Regional or local knowledge and understanding of climate and environmental dynamics, have often provided the context and basis on which rural farm households develop valuable adaptation strategies and resilience to climate risks across the west african region. The evolving local knowledge and associated strategies have thrived on the wealth of differing experiences and culturally-embedded understandings of the environment over time (Lamboni et al., 2024a). In this light, resilience and the kind of responses that may be initiated against drought impact and other climatic shocks, are peculiar to every locality and greatly shaped by the varying perceptions of people.

In the Mono River Basin of West Africa, there are competing demands for water use both within of Togo and Benin, riparian countries of the basin. This competition is mainly between industrial demands, particularly for power generation, and for agricultural water supplies, especially for irrigation. This is manifested in dam and reservoir constructed for various purposes including industrial, agricultural and domestic water supplies. Thus, in Togo, there is the largest artificial lake, the Mono Lake, created on the Main Mono River at Nangbeto for hydropower. The Adjarala Hydroelectric Project (Togo-Benin) will constitute the second phase of the hydroelectric development of the Mono River. The dam will be 3700 m long and 48 m high, while the hydropower station will have three 49-MW units (Lamboni et al., 2024b). Paradoxically, the Mono River Basin, spanning Togo and Benin, is a critical area where streamflow

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forecasting plays a pivotal role in water resource planning, flood control, and agricultural management (Lamboni et al., 2024 c).

Unfortunately, existing streamflow series at gauging stations in the Mono Basin are short and full of gaps. In their present form it would be very difficult to extract the necessary information to enable proper assessment of the catchment response to rainfall inputs.

Thus, stream flow simulation in this basin is essential not only as a means of filling in some of these gaps but also for the extension of these series in order to provide adequate information for the water resources management of the basin. In this context, time series models have emerged as essential tools for predicting streamflow, leveraging historical data to uncover temporal dynamics and trends.

Researchers such as, Gebrechorkos et al. (2020) and Oyerinde et al. (2022), Washington et al. (2013) and Niang et al. (2014) have documented the significant influence of climate change on water resources in Africa, highlighting the need for robust forecasting models that can accommodate non-stationarity in hydrological data.

Time series models, with their ability to model temporal dependencies, offer a structured approach to understanding and predicting streamflow dynamics in the context of climate variability. Classical models such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space Models (ETS) have been widely used due to their simplicity and effectiveness in capturing short-term dependencies. In recent years, advanced techniques like Long Short-Term Memory (LSTM) networks have gained attraction for their ability to model complex, nonlinear relationships in data, offering potential improvements in forecasting accuracy. These models have been incorporated into many software packages such as SPSS, MINITAB, STATA, R, Python, Matlab, Mathematica, and with regard to cost-effectiveness, labour planning always opts for the minimum number of workers many others (Comparison of Statistical Packages, 2015). These models are also preferable due to systematic searching at every step (identification, estimation, diagnostic) for a suitable model (Zhang, 2003). These models require long time series data for analysis. At least 50-100 observations are required for a robust result. To analyze a yearly data, this condition will present a problem (Gocheva-Ilieva et al., 2014; Milionis and Davies, 1994). Mostly hydrological time series doesn't have data more than 40-50 years.

This article explores the applicability of various time series models for streamflow forecasting in the Mono River Basin, emphasizing methodological approaches and practical considerations. By examining case studies and incorporating insights from regional climate change research by authors like Conway (2009) and Dike et al. (2018), we aim to demonstrate the effectiveness of these models in capturing streamflow patterns and providing reliable forecasts. Understanding the capabilities and limitations of different time series models enables water resource managers and policymakers to make informed decisions, optimizing water management strategies and enhancing resilience to hydrological and climatic changes in the Mono River Basin.

1.1. Study area

The Mono Basin spans parts of Togo and Benin, with its river flowing through these countries into the Gulf of Guinea. Approximately between 6 ∘ 16 N and 9 ∘ 20 N and ∘ 42 E and 20 ∘ 25 E (Lamboni et al, 2021 d). The Mono River is the primary watercourse, originating in the Atacora Mountains in northern Benin and flowing southward to the Gulf of Guinea (Amoussou et al., 2012). The basin covers an area of about 25,400 square kilometers, encompassing various tributaries and sub-catchments. It houses a dam of hydroelectric power plant called Nangbeto. The region experiences a tropical climate with distinct wet and dry seasons. The annual rainfall varies significantly across the basin. The rainfall annual average ranges from 800 mm to 1,500 mm, with peaks during the rainy season (April to October). The basin supports diverse land uses including agriculture, forestry, and settlements.

1.2. Data Collection and Material

Data is typically collected from hydrological stations located along the Mono River and its tributaries. This includes historical streamflow measurements. Data is collected at daily, monthly, or yearly scale, depending on the available records and the specific requirements of the analysis. The dataset covers a substantial historical period to capture variations and trends. The data used cover the period from January 2000 to December 2020.

In our study, software R (version 4.4) was used to compute all the statistical parameters and graphics. Libraries such as forecast, stats will facilitate data manipulation and model fitting. The dataset will be divided into training and testing subsets. The models will be trained on historical data, and their performance will be evaluated on the testing set. The latest version of the R software for operating system is available from the CRAN archive at the following link: http://www.r-project.org.

1.3. Methodology

Box and Jenkins developed ARIMA stochastic models that describe a wide range of models for forecasting a univariate time series that can be made stationary by applying transformations, primarily differences to address trend and seasonality, and power functions to regulate variance (Box and Jenkins, 1970; Box and Jenkins, 1976; Box et al., 1967). The term "ARIMA" consists of three components: i) AR, ii) I, and iii) MA terms (Rana et al., (2017)). The lags of the differenced time series in the forecasting equations are referred to as the "autoregressive (AR)" term, while the lags of the forecast errors are called the "moving average (MA)" term. A time series that requires differencing to become stationary is termed "Integrated (I)" (Ghafoor and Hanif, 2005).

The AR(p), MA(q), and Autoregressive Moving Average (ARMA(p,q)) models are specific cases of the Box and Jenkins ARIMA model. In this study, ARMA and ARIMA models are used to evaluate the performance of streamflow time series. Time series can be deseasonalized using various methods. In this study, the streamflow time series is deseasonalized using the Seasonal-Trend Decomposition Procedure based on LOESS (STL) (Cleveland et al., 1990). STL offers many advantages for time series deseasonalization, such as the ability to handle seasonal time series with any seasonal period greater than one (Theodosiou, 2011). Additionally, STL can be easily incorporated into statistical software packages. After deseasonalizing the time series, non-seasonal ARIMA and ARMA models can be fitted.

1.3.1. ARIMA Model

A non-seasonal ARIMA model is represented by ARIMA (p, d, q), where "p" indicates the number of non-seasonal autoregressive terms, "q" denotes the number of non-seasonal moving average terms, and "d" specifies the number of non-seasonal differences applied to the time series. The general form of a non-seasonal ARIMA (p, d, q) model can be expressed as follows (Theodosiou, 2011).:

$$S_t = c + \Phi_1 s_{t-1} + \Phi_2 s_{t-2} + \ldots\ldots + \Phi_p s_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots\ldots - \theta_q e_{t-q} \quad (1)$$

Or in backshift notation:

$$\left(1 - \Phi_1 B - \Phi_2 B^2 - \ldots\ldots - \Phi_p B^p\right) S_t = c + \left(1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots - \theta_q B^q\right) e^t \quad (2)$$

Where c=constant term (called intercept), Φ_i = i^{th} autoregressive parameter, θj= j^{th} moving average parameter e^t=the error term at time *t*.

1.3.2. ARMA Model

The auto-regressive moving average (ARMA) model ARMA (p, q) can be expressed as (Theodosiou, 2011):

$$S_t = c + \sum_{i=1}^{p} \Phi_i s_t - 1 + \sum_{j=1}^{q} \theta_j e_{t-j} + e_t \quad (3)$$

Where c is the constant term of the ARMA model, Φ_i indicates the i^{th} auto-regressive coefficient, θ_j is the j^{th} moving average coefficient, e_t shows the error term at time period t, and St refers the value of forecasted streamflow at time period t.

1.3.3. Time Series Models Building Procedure

During the estimation stage, several models are tentatively selected, and the Akaike Information Criterion corrected (AICc) (Hurvich and Tsai, 1989) and/or the Bayesian Information Criterion (BIC) suggested by Schwarz (1978) are computed. The model structure with the lowest AICc and BIC values is chosen as the best model among the candidates. Equation (4) shows the formula for calculating AIC_c, while equation (5) provides the formula for *BIC*:

$$AIC_c = -2\ln(Max.Likelihood) + \frac{2T_p}{n - T_p - 1} \quad (4)$$

$$BIC = -2\ln(Max.Likelihood) + T_p \ln(n), \quad (5)$$

with T_p the number of AR, I and MA parameters.

After selecting the best model, the third stage involves conducting a diagnostic check. This stage allows the modeler to assess the goodness of fit of the selected model. Researchers typically use two tests for this purpose. The first test involves examining the residuals using ACF and PACF graphs. If the model is appropriate, the residuals should exhibit white noise, indicating no remaining correlation. The second test is the Ljung-Box test (1978). If the p-values from this test are greater than 5%, it suggests that the residuals do not significantly deviate from white noise. If the residuals are large or the model fails the Ljung-Box test, the modeler should return to select an alternative model and repeat the process until satisfactory results are obtained.

1.3.4. Data Distribution and Data Preprocessing

In this study, two time series models, ARIMA and ARIMA models used for forecasting monthly flow of Nangbéto Station in Mono Basin. Rana et al., (2017) have used the similar methods for forecasting monthly flow of Doyian station. The implantation period covered the data values from 2000 to 2020 and used for building of ARIMA and ARMA models. The testing period covers the streamflow data values from 2015 to 2020 and has been used to Evaluate the performance of both selected models. In order to select the best model between the ARMA and ARIMA models, root mean square error (RMSE), mean absolute percentage error (MAPE) and Nash efficiency (NE) indexes are used in this study. RMSE is one of the most used statistical index for measuring error in the Prediction with respect to original data (Lin et al., 2006). It is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum(s_o - s_f)} \qquad (6)$$

MAPE is statistical indexes used for measuring the error in the predicting time series value. It is defined as:

$$MAPE = \frac{1}{N}\sum\left|\frac{(S_o - S_f)}{S_o}\right| \qquad (7)$$

The Nash efficiency (NE) is a model evaluation criterion suggested by Nash and Sutcliffe (McCuen et al., 2006). A model efficiency of 90 % represents satisfactory performance whereas a value in range of 80 to 90 % represents fairly good performance. This statistical index helps in determining how much the predicted data match the original data. It has been used for streamflow time series forecasting evaluation (McCuen et al., 2006). It can be calculated as:

$$\mathrm{NE} = 1 - \frac{\Sigma(s_o - s_f)^2}{\Sigma(s_o - s_m)^2} \qquad (8)$$

Where N is the total number of observations, S_o is observed flow, S_f is forecasted streamflow, S_m is average of streamflow and S_f is average forecasted flow.

2. Results

To assess the prediction accuracy of these time series models, the first step is to identify the appropriate ARMA and ARIMA model structures based on the AICc and BIC criteria, following the Box and Jenkins model selection procedure. The process for selecting suitable ARMA and ARIMA structures is outlined below:

2.1. Selecting Suitable ARIMA and ARMA Models

Monthly streamflow data (Fig. 1) exhibit seasonal variation with a periodicity of 12 months. To fit a non-seasonal ARIMA model, the data were first deseasonalized using the STL decomposition method. The deseasonalized monthly streamflow time series (Fig. 1) reveals no distinct seasonal or trend components but still demonstrates non-stationary behavior. To address this, a non-seasonal difference was applied to the time series to achieve stationarity.

Figures 2 show the plots of ACF, PACF, and the deseasonalized time series after applying the non-seasonal difference. These plots were analyzed to determine the appropriate model structure (Rana et al., 2017). Based on the correlation plots, the suggested ARMA model is (1, 3), as the PACF plot indicates an AR(3) term and the ACF plot suggests an MA(1) term. For selecting the ARIMA model, various ARIMA model structures were estimated to identify the best model.

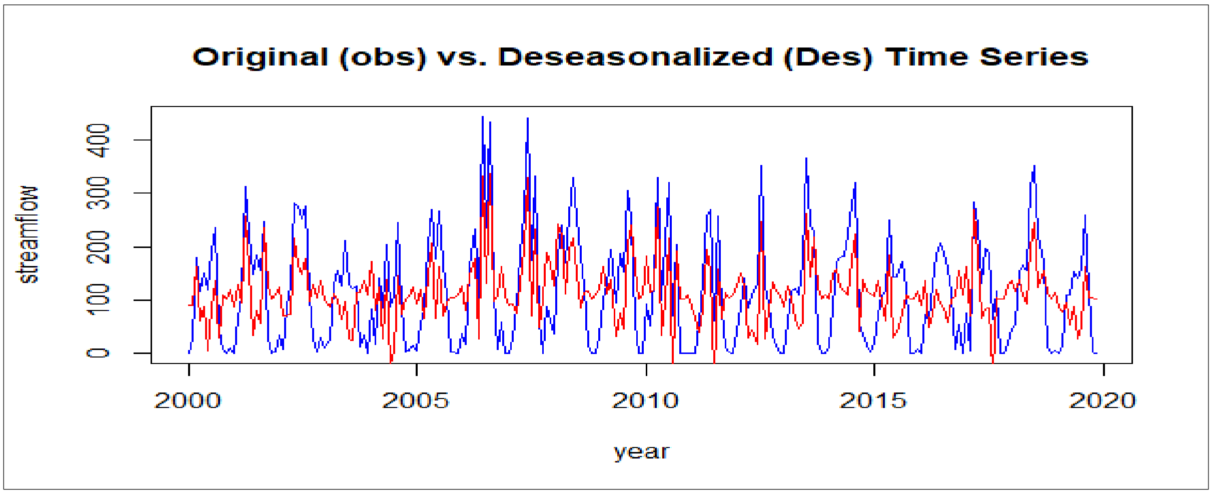

Figure 1 Original streamflow time series (line blue) and Deseasonalized time series (line red) plot (Nangbeto-dame)

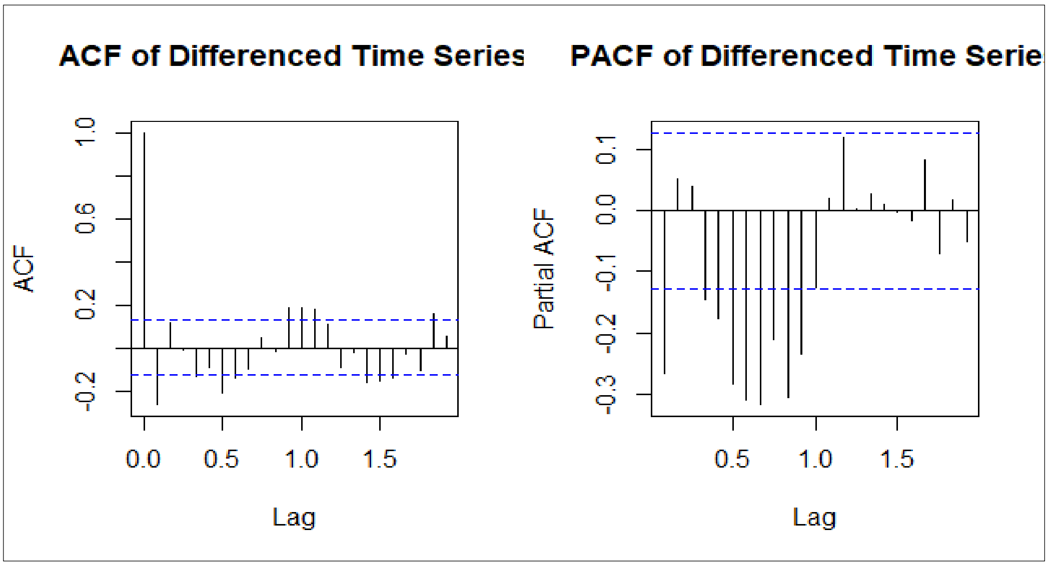

Figure 2 ACF, PACF graphs after non seasonal difference (Nangbeto-dam)

Table 1 presents the AICc and BIC values for the different ARIMA models. The initially suggested model structure, which shows the lowest AICc and BIC values, has been selected as the best model for the deseasonalized streamflow time series. This model also passed both diagnostic tests.

Figures 3 display the ACF and PACF plots for the residuals, and Table 2 provides a summary of the Ljung-Box test for the deseasonalized ARIMA model.

Table 1 AICc and BIC values for different ARIMA model (Nangbeto-dam).

Model	**Order**	**AIC**	**BIC**
ARIMA(0,1,0)	p=0, d=1, q=0	299.212963	303.126466
ARIMA(1,0,0)	p=1, d=0, q=0	299.690326	311.438932
ARIMA(0,1,3)	p=0, d=1, q=3	210.312752	225.966764
ARIMA(3,1,3)	p=3, d=1, q=3	196.85964	224.254161
ARIMA(3,1,1)	p=3, d=1, q=1	193.447732	213.015247

ARIMA(3,1,2)	p=3, d=1, q=2	195.244901	218.725919
ARIMA(3,1,0)	p=3, d=1, q=0	208.254934	223.908946
ARIMA(1,1,1)	p=1, d=1, q=1	213.227333	224.967842
ARIMA(1,1,2)	p=1, d=1, q=2	209.094277	224.748289
ARIMA(1,1,3)	p=1, d=1, q=3	210.991483	230.558998
ARIMA(2,1,1)	p=2, d=1, q=1	210.589646	226.243658
ARIMA(2,1,2)	p=2, d=1, q=2	210.853733	230.421248
ARIMA(2,1,3)	p=2, d=1, q=3	212.853035	236.334053

The results of both tests suggest that the residuals are white noise. From Eq. (1), in back shift notation, the ARIMA(3, 1, 1) model can be written as:

$$(1-B)^d s_t = \left(1-\Phi_{INMA}(B)-\Phi 2_{NMA}\left(B^2\right)-\Phi_{3NMA}\left(B^3\right)\right)e_t \qquad (9)$$

By substituting the coefficients, one obtains the model

$$S_t - S_{t-1} = e_t - 0.56997634e_{t-1} - 0.07632119e_{t-2} - 0.35369072e_{t-3} \qquad (10)$$

2.2. Evaluation of Best Predicting Model

To assess model performance, forecasts were made one month ahead for the testing period spanning from January 2004 to December 2010. Table 3 presents a comparison of the two time series models based on various statistical indices. Figure 4 displays the hydrograph comparing the original and forecasted streamflow for both ARMA and ARIMA models. The analysis in Table 3 and Figure 4 indicates that the ARIMA model performs better than the ARMA models. Specifically, the ARIMA model demonstrates lower error values, higher Nash efficiency, and a superior fit with the observed data.

Table 2 Summary of Ljung Box test for deseasonalized ARIMA Model (Nangbeto-dam)

lag	Lag 10	Lag 12	Lag 24	Lag 48
Chi square	1.7523	14.955	42.724	51.511
Df	10	12	24	48
p-value	0.9847	0.8199	0.1395	0.2596

Table 3 Evaluation of model performance for testing period on basis of statistical indexes (Nangbeto-dam)

Statistical Index	ARIMA ((3,1,1)	ARMA (1,3)
MAPE	18.245	21.642
RMSE	52.525	59.273
NE	0.848	0.839

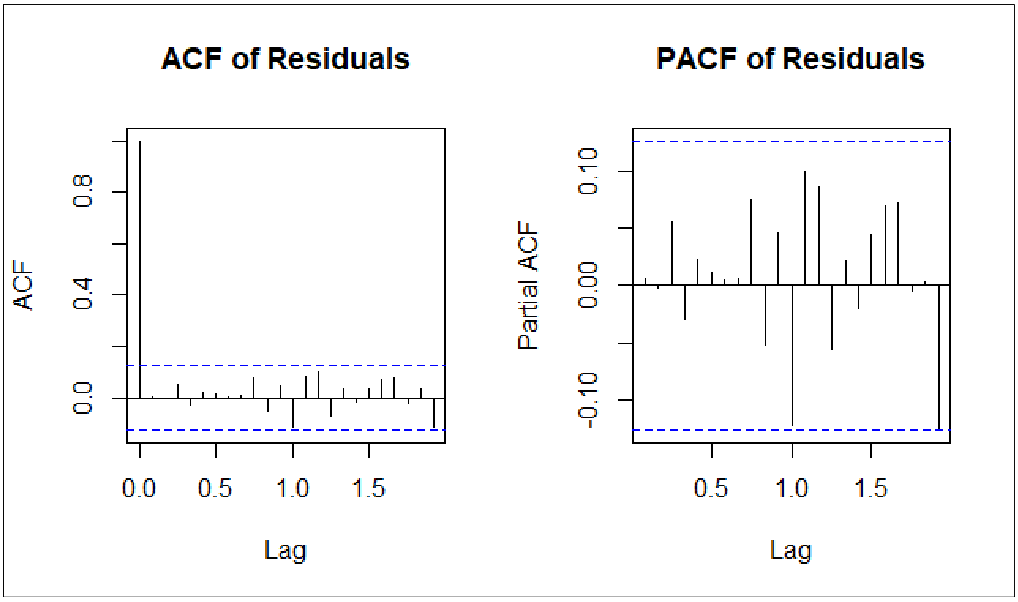

Figure 3 Residual graphs of ACF, PACF of ARIMA model(Nangbeto-dam)

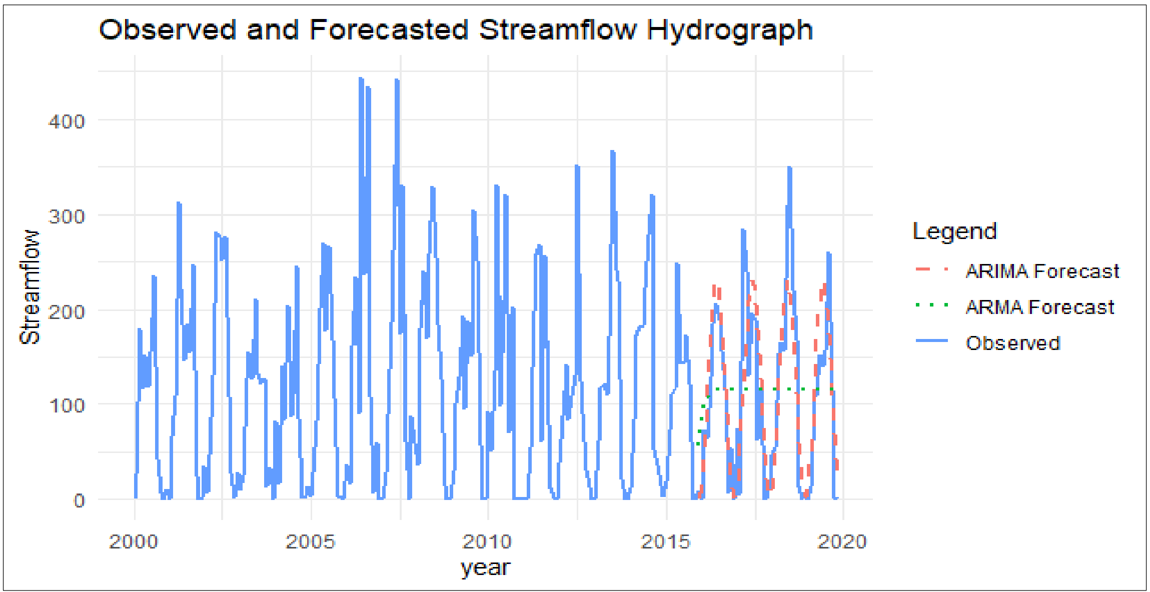

Figure 4 Observed and forecasted streamflow hydrograph using ARIMA and ARMA models for testing period

3. Discussion

This study demonstrates the effectiveness of ARIMA models over ARMA models in forecasting streamflow at the Nangbeto site in the Mono Basin. The ARIMA model's ability to handle non-stationary time series through differencing provides a significant advantage over the ARMA model, which assumes stationarity in the time series data. Recent studies have highlighted how climate change exacerbates the variability in streamflow, making accurate forecasting even more crucial. For instance, Lamboni et al. (2024) examined the impacts of climate variability on hydrological systems in the Mono Basin, emphasizing the need for robust models that can adapt to changing climatic conditions. Their research supports the use of ARIMA models for capturing complex, non-stationary behaviors in streamflow data. The use of more sophisticated model selection criteria has been a focus in recent research. Oyerinde et al. (2022) explored advanced techniques in model selection for time series forecasting in West Africa. Their work aligns with the findings of this study by reinforcing the importance of selecting models based on criteria like AICc and BIC, which are critical for distinguishing between ARIMA and ARMA models.

The process of deseasonalizing time series data using methods such as STL decomposition has been validated in recent research. Gocheva-Ilieva et al. (2014) demonstrated how seasonal-trend decomposition can improve the performance of forecasting models. Their findings suggest that properly deseasonalized data, as used in this study, enhances the accuracy of ARIMA models, particularly in regions with significant seasonal variations. Recent research by Conway (2009) has shown that ARIMA models are effective in managing hydrological forecasting challenges in various regions, including Africa. Conway's study reinforces the conclusion that ARIMA models can effectively handle the stochastic nature of streamflow, particularly in contexts similar to the Mono Basin. The performance of ARIMA models has been compared with other advanced models in recent studies. For example, Washington et al. (2013) explored various time series models for forecasting climate variables and found that ARIMA models often outperformed simpler models like ARMA in terms of accuracy and reliability. This supports the findings of our study regarding the superiority of ARIMA models.

4. Conclusions

In this research, the stochastic nature of streamflow is analyzed with deseasonalized ARIMA and ARMA stochastic models. The ARIMA model has a better performance than ARMA model because it makes time series stationary, in both training and forecasting. The values of mean absolute percentage error and root mean square error of ARIMA model was less than ARMA model. This indicated the superiority of ARIMA models to the ARMA models. it can be concluded that the ARIMA model could be used for forecasting one month ahead streamflow at the Nangbéto site in Mono basin. The superior performance of the ARIMA model suggests its potential application in water resource management. Policymakers can use this model to forecast streamflow more accurately, which is crucial for planning and managing water resources effectively, especially in regions prone to variability in water availability. Future research could focus on integrating climate change scenarios into the ARIMA model to assess the impact of climate change on streamflow patterns. This integration could provide valuable insights for long-term water resource planning and management in the Mono basin.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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