
HYDROLOGICAL MODELLING AND TIME-SERIES STREAMFLOW FORECASTING OF THE KIRI WATERSHED USING SWAT AND ARIMA MODELS

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ABSTRACT

Reliable streamflow estimation and forecasting are essential for sustainable reservoir operation, irrigation planning, flood mitigation, and sustainable water resources management. This study evaluated the hydrological responses of the Kiri Watershed (41,516.46 ha) in Adamawa State, Nigeria, and projected future annual streamflow trends over a 20-year horizon (2023 - 2042). The Soil and Water Assessment Tool (SWAT) was calibrated (70% of the data) and validated (30% of the data) using hydro-meteorological inputs from 2000 to 2022 and daily observed streamflow records from the Tallum Hydrological Station. Spatial analysis revealed a watershed dominated by shrublands (90.40%) and loamy soils (55.22%), organized into 9 sub-basins and 44 Hydrologic Response Units (HRUs). SWAT demonstrated high predictive accuracy during both calibration ($R^2 = 0.83$, $NSE = 0.79$, $RMSE = 0.64 \text{ m}^3/\text{s}$, $MAE = 0.56 \text{ m}^3/\text{s}$, $PBIAS = 2.50\%$) and validation ($R^2 = 0.82$, $NSE = 0.73$, $RMSE = 0.52 \text{ m}^3/\text{s}$, $MAE = 0.51 \text{ m}^3/\text{s}$, $PBIAS = 7.58\%$), indicating close agreement between observed and simulated streamflow. Subsequently, a non-seasonal ARIMA (1,0,0) model was fitted to the aggregated annual streamflow time series. Diagnostic testing via the Ljung-Box test ($Q = 4.9011$, $p = 0.2976$) confirmed that the residuals behaved as white noise. The 20-year projection indicates a stable long-term mean annual discharge of approximately $6.0 \text{ m}^3/\text{s}$, with no significant upward or downward trend. The findings confirm that while average long-term water yield will remain steady, adaptive reservoir management strategies are necessary to mitigate historical inter-annual discharge fluctuations.

Keywords: ARIMA Forecasting; Hydrological Modelling; Streamflow Simulation; SWAT; Water Resources Management

1.0 INTRODUCTION

Reliable streamflow estimation and forecasting are fundamental to sustainable water resources management because they support reservoir operation, irrigation planning, flood forecasting, and equitable water allocation among competing demands (Bodini, 2024; Yifru et al., 2024). The value of streamflow forecasting spans multiple temporal scales. Seasonal forecasts assist water managers in determining irrigation allocations and enable hydropower operators to optimize reservoir drawdown based on anticipated inflows (Ozcan et al., 2025). Long-term forecasts support irrigation development, agricultural water management, and hydropower planning, whereas short-term hourly and daily forecasts facilitate flood preparedness, emergency response, and early warning systems (Kumar et al., 2023). Consequently, reliable streamflow forecasting has become an indispensable component of integrated water resources management.

The benefits of streamflow forecasting have been widely demonstrated in reservoir operation and flood mitigation. Forecast-informed reservoir management using Ensemble Streamflow Prediction (ESP) and optimization techniques has significantly improved reservoir storage and operational efficiency while maintaining downstream flood safety (Anghileri et al., 2016; Delaney et al., 2020). Likewise, probabilistic inflow forecasts generated through Bayesian approaches have enhanced water supply reliability and reduced operational costs compared with deterministic forecasting methods (Guo et al., 2020). Accurate streamflow forecasts also enable reservoir operators to implement controlled pre-releases before major storm events, thereby reducing downstream flood

risks (Delaney et al., 2020; Zarei et al., 2021). Recent advances in machine learning and deep learning have further improved forecasting accuracy, with models such as Long Short-Term Memory (LSTM) achieving high predictive performance for reservoir inflows and flood events (Apaydin et al., 2020; Huang et al., 2025). Hybrid forecasting approaches that integrate physically based hydrological models with machine learning algorithms have demonstrated substantial improvements in prediction accuracy, particularly for extreme hydrological events and data-scarce basins (Bodini, 2024; Jia & Fang, 2025; Liu et al., 2024). Despite these advances, accurately forecasting streamflow under varying hydrological conditions remains a challenge, highlighting the need for approaches that combine physical watershed representation with robust statistical forecasting techniques (Yifru et al., 2024).

Among physically based hydrological models, the Soil and Water Assessment Tool (SWAT) is one of the most widely used for watershed-scale streamflow simulation. SWAT is a continuous-time, semi-distributed model that evaluates the impacts of climate, land use, soil characteristics, and management practices on watershed hydrology (Koltsida et al., 2023; Özdoğan-Sarıkoç & Dadaser-Celik, 2024; Saraf & Regulwar, 2024). The model discretizes a watershed into Hydrologic Response Units (HRUs) based on unique combinations of land use, soil type, and slope, enabling spatial simulation of runoff generation, infiltration, evapotranspiration, groundwater flow, and other hydrological processes (Özdoğan-Sarıkoç & Dadaser-Celik, 2024; Saraf & Regulwar, 2024). SWAT has been successfully applied across diverse climatic conditions, including arid, semi-arid, and tropical watersheds, and can effectively utilize remotely sensed climatic inputs where ground observations are limited (Akoko et al., 2021; Quamar et al., 2025).

Numerous studies have demonstrated the robustness of SWAT in streamflow simulation. Daily simulations in the Godavari River Basin achieved NSE values of 0.84 - 0.85 (Saraf & Regulwar, 2024), while studies in Ethiopia, Greece, and the Himalayas also reported satisfactory calibration and validation performance (Andiye & Lohani, 2024; Koltsida et al., 2023; Quamar et al., 2025). Beyond streamflow simulation, SWAT has been widely employed to evaluate climate change impacts, land-use change, watershed management practices, and hydrological responses in both gauged and ungauged basins (Aloui et al., 2022; Janjić & Tadić, 2023; Özdoğan-Sarıkoç & Dadaser-Celik, 2024). However, the model requires extensive hydro-meteorological and spatial datasets, and its calibration is computationally intensive (Janjić & Tadić, 2023; Yuan & Forshay, 2022). In addition, reliance on the Soil Conservation Service Curve Number (SCS-CN) method often introduces bias in low-flow simulations, while calibration procedures that emphasize flood characteristics may reduce predictive performance under low-flow conditions and during extreme events (Islam et al., 2023; Tao et al., 2024).

To complement these limitations, statistical time-series models have increasingly been integrated with physically based hydrological models. The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely applied stochastic forecasting techniques because it effectively captures temporal dependence in hydrological time series. Recent studies have increasingly coupled ARIMA with SWAT outputs to improve forecasting accuracy and extend predictions beyond the simulation period (Khorram & Jehbez, 2024). Such integration combines the physical representation of watershed processes provided by SWAT with the temporal predictive capability of ARIMA, thereby enhancing long-term streamflow forecasting.

The Kiri Watershed in northeastern Nigeria is an important catchment supporting reservoir operation, irrigation development, domestic water supply, and agricultural production. Despite its strategic importance, limited studies have integrated physically based hydrological modelling with statistical time-series forecasting to assess future streamflow behavior within the watershed. This study therefore integrates the SWAT and ARIMA models to simulate watershed hydrology and forecast annual streamflow over 20 years (2023 - 2042). Specifically, the study develops, calibrates, and validates a SWAT model using observed hydro-meteorological data, characterizes the watershed hydrological response, develops an ARIMA model based on the simulated annual streamflow series, and forecasts future streamflow to support adaptive reservoir operation and sustainable water resources management in the Kiri Watershed.

Beyond its hydrological application, the integrated SWAT–ARIMA framework provides an engineering-based decision-support approach for improving the assessment, planning, and sustainable utilization of Nigeria’s water resources. By combining physically based watershed simulation with

statistical streamflow forecasting, the framework can support more informed reservoir operation, irrigation planning, and climate-resilient water resources management. Its application to the Kiri Watershed therefore contributes to the conference theme, “Innovating Tomorrow: Harnessing Engineering to Drive Nigeria’s Growth for Sustainable Development,” particularly the sub-theme of Innovative Resource Utilization and Management, by demonstrating how engineering-based modelling and data-driven forecasting can enhance sustainable and resilient water resources management in Nigeria.

2.0 MATERIALS AND METHODS

2.1 The Study Area

The Kiri Dam is situated on the floodplain of the lower Gongola River Basin, approximately 25 km upstream of its confluence with the Benue River at Numan, within Shelleng Local Government Area of Adamawa State (Lat. 9°42’N; Long. 12°01’E). Constructed in 1982 on the Gongola River, the dam occupies a rift-related sedimentary depression formed through lithospheric thinning ((Whiteman, 1982)). The area experiences a tropical continental climate characterized by a single rainfall peak, typically in August or September. The wet season extends from April to October, with annual rainfall ranging between 510 and 1,040 mm, while the dry season lasts about seven months. Mean annual temperatures range from a minimum of about 18°C in December to a maximum of 38°C in March. Evapotranspiration rates are high throughout the year, and relative humidity varies seasonally, reaching 60 - 78% during the wet months and declining to 27 - 35% in the dry season. Kiri Dam serves multipurpose functions, including irrigation for a 12,000 hectare sugar estate, support for local agriculture and pilot irrigation schemes, fisheries development through Lake Kiri, domestic water supply to over 70 communities, and partial regulation of seasonal flooding along the Gongola River.

2.2 SWAT Model

The Soil and Water Assessment Tool (SWAT) is a physically based, semi-distributed, continuous-time watershed model widely used for simulating hydrological processes, sediment transport, and water quality under varying land-use, watershed management, and climate change scenarios (Douglas-Mankin et al., 2010; Dwivedi et al., 2024; Gassman et al., 2007). Developed by the United States Department of Agriculture (USDA) in the early 1990s, SWAT has evolved into one of the most extensively applied watershed models worldwide, with thousands of applications supporting hydrological research, watershed assessment, and water resources management (Aloui et al., 2022; Gassman et al., 2007; Janjić & Tadić, 2023).

SWAT simulates the hydrological cycle by dividing a watershed into sub-basins, which are further discretized into Hydrologic Response Units (HRUs) representing unique combinations of land use, soil type, and slope. This spatial discretization enables the model to account for the heterogeneity of watershed characteristics while simulating key hydrological components, including precipitation, surface runoff, infiltration, evapotranspiration, groundwater recharge, lateral flow, and streamflow generation. The model operates on a continuous daily time step, making it suitable for evaluating both short-term hydrological responses and long-term watershed behavior under different environmental and management conditions.

The hydrological simulation in SWAT is based on the principle of water balance, whereby the amount of water stored in the soil is continuously updated as the difference between incoming precipitation and outgoing hydrological fluxes. The soil water balance equation is expressed as:

$$SW_t = SW_0 + \sum_{i=t}^t (R_{day} - Q_{surf} - W_{seep} - E_a - Q_{gw}) \quad (1)$$

Where SW_t is the humidity of the soil (mm), SW_0 is the base humidity of the soil (mm), t is time (days), R_{day} is rainfall volume (mm), Q_{surf} is the value of surface runoff, E_a is the value of evapotranspiration (mm), W_{seep} is the value of seepage of water from the soil into deeper layers, Q_{gw} is the value of underground runoff (mm).

The water balance equation forms the computational foundation of SWAT by quantifying the movement and storage of water within the watershed. Through continuous simulation of these

hydrological processes, the model estimates streamflow at the watershed outlet. Owing to its robust physical basis, spatial representation, and proven performance across a wide range of climatic and physiographic conditions, SWAT was selected in this study to simulate the hydrological behaviour of the Kiri Watershed and generate the streamflow series used for subsequent time-series forecasting.

2.3 Model Setup

2.3.1 SWAT Model Setup

The SWAT model was developed using a 30 m x 30 m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) (Figure 2a), land use/land cover data (Figure 2b), soil map (Figure 2c), and daily meteorological data comprising rainfall, maximum and minimum temperature, relative humidity, wind speed, and sunshine hours for the period 2000 - 2022. The watershed was delineated using the DEM, with the Tallum Hydrological Station defined as the watershed outlet, resulting in nine sub-basins. Hydrologic Response Units (HRUs) were subsequently generated by overlaying the land use, soil, and slope layers, producing a total of 44 HRUs after applying appropriate threshold values to eliminate insignificant land classes. The processed spatial and climatic datasets were integrated within the SWAT environment, and a warm-up period was incorporated to minimize the influence of initial conditions. Observed daily streamflow records from the Tallum Hydrological Station were used to calibrate (70%) and validate (30%) the model, while model performance was evaluated using the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Percent Bias (PBIAS).

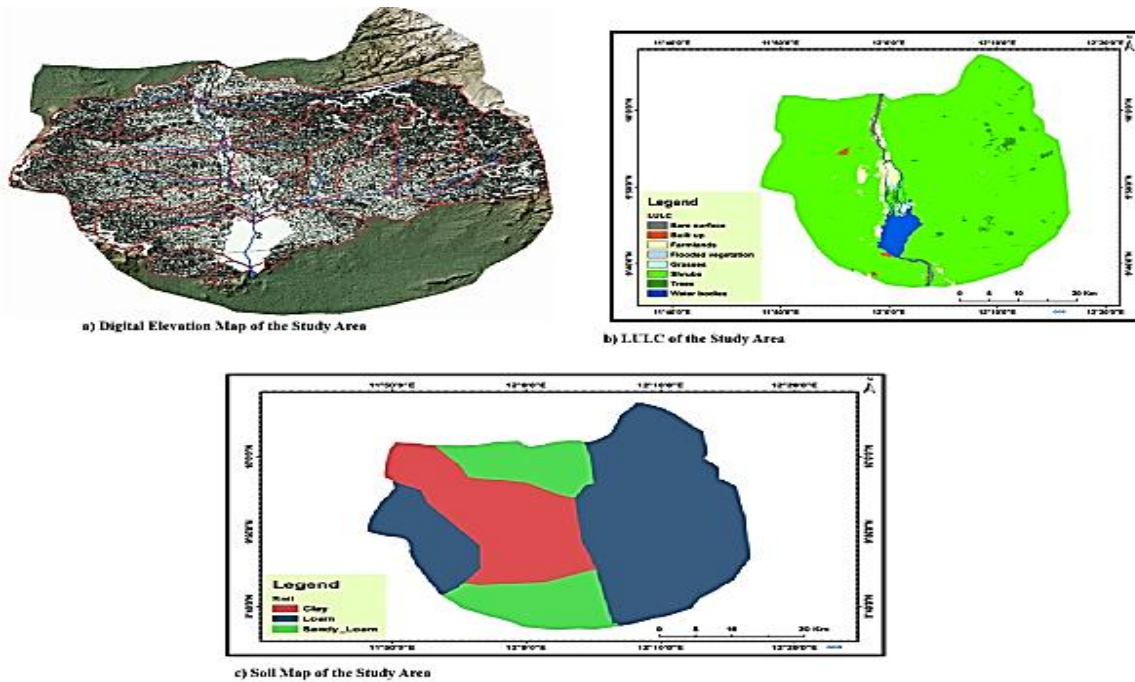


Figure 2: The Digital Elevation, Land Cover, and Soil Maps of the Study Area

2.3.2 ARIMA Model Setup

The daily streamflow data were aggregated into annual values to develop a long-term streamflow forecasting model for the 20-year planning horizon (2023–2042). Annual aggregation reduces the influence of short-term and intra-annual variability and provides a consistent temporal scale for assessing long-term changes in overall water availability. However, this aggregation also results in the loss of monthly and seasonal information, including within-year variations that may be important for operational applications such as irrigation scheduling and reservoir management.

A non-seasonal ARIMA model was therefore fitted to the annual streamflow series. The approach was intended primarily to characterize and forecast long-term annual water availability rather than to reproduce seasonal flow dynamics. The potential loss of intra-annual information is recognized as a limitation of the present approach. A Seasonal ARIMA (SARIMA) model based on monthly streamflow data could provide additional information on seasonal patterns and would be

particularly useful for future studies focusing on seasonal irrigation planning, reservoir operation, and flood management.

3.0 RESULTS AND DISCUSSION

3.1 Watershed Characteristics

The SWAT model successfully delineated the Kiri Watershed into nine (9) sub-basins with a total drainage area of 41,516.46 ha. The delineated stream network adequately represented the natural drainage pattern and provided the spatial framework for hydrological simulation. The watershed was further discretized into 44 Hydrologic Response Units (HRUs) by integrating land-use, soil, and slope data, enabling detailed representation of its spatial heterogeneity.

The land-use analysis (Table 1) revealed that the watershed is predominantly covered by shrubland (90.40%), followed by water bodies (3.30%) and farmland (2.61%). The extensive shrubland cover is expected to enhance infiltration and reduce surface runoff, while agricultural areas may locally influence runoff generation and sediment transport. Similarly, the dominant soil type is loam (55.22%), followed by clay (24.60%) and sandy loam (20.19%), indicating generally favorable infiltration and moderate water-holding capacity across the watershed (Table 1).

3.2 SWAT Model Performance

The SWAT model demonstrated satisfactory to good predictive performance during calibration and validation (Table 2). During calibration, the model achieved $R^2 = 0.83$, $NSE = 0.79$, $RMSE = 0.64 \text{ m}^3/\text{s}$, $MAE = 0.56 \text{ m}^3/\text{s}$, and $PBIAS = 2.50\%$, while validation produced $R^2 = 0.82$, $NSE = 0.73$, $RMSE = 0.52 \text{ m}^3/\text{s}$, $MAE = 0.51 \text{ m}^3/\text{s}$, and $PBIAS = 7.58\%$. According to the performance evaluation criteria of (Moriassi et al., 2007), NSE values greater than 0.75 indicate very good performance, while values between 0.65 and 0.75 indicate good performance. Similarly, $PBIAS$ values within $\pm 10\%$ indicate very good model performance for streamflow simulations. The obtained NSE and $PBIAS$ values therefore indicate very good performance during calibration and good to very good performance during validation. The relatively low MAE values (0.56 and $0.51 \text{ m}^3/\text{s}$) further indicate relatively small average absolute differences between observed and simulated streamflow. Overall, the performance statistics demonstrate that the calibrated SWAT model adequately reproduces the observed hydrological response of the Kiri Watershed.

Table 1: Land Use/Land Cover and Soil Distribution of the Kiri Watershed

Land Use/Land Cover	
LULC Class	%
Water bodies	3.3
Trees	1.59
Grasses	0.1
Flooded vegetation	0.29
Farmlands	2.61
Shrubs	90.4
Built up	0.29
Bare surface	1.41
Total	100
Soil Type	
Soil Type	%
Loam	55.22
Clay	24.6
Sandy Loam	20.19
Total	100

Table 2: SWAT Calibration and Validation Performance Statistics

Performance Indicator	Calibration	Validation
R ²	0.83	0.82
NSE	0.79	0.73
RMSE (m ³ /s)	0.64	0.52
MAE (m ³ /s)	0.56	0.51
PBIAS (%)	2.50	7.58

The comparison between observed and simulated annual streamflow further demonstrated that the model successfully reproduced the temporal variability of streamflow throughout the study period. The simulated hydrograph closely followed the observed pattern, including the high-flow event recorded in 2019. Although minor underestimation and overestimation occurred in a few years, the overall agreement remained satisfactory, indicating that the calibrated model reliably represents the watershed hydrology. Regression analysis also confirmed strong linear relationships between observed and simulated streamflow during both calibration and validation, consistent with the high coefficients of determination obtained.

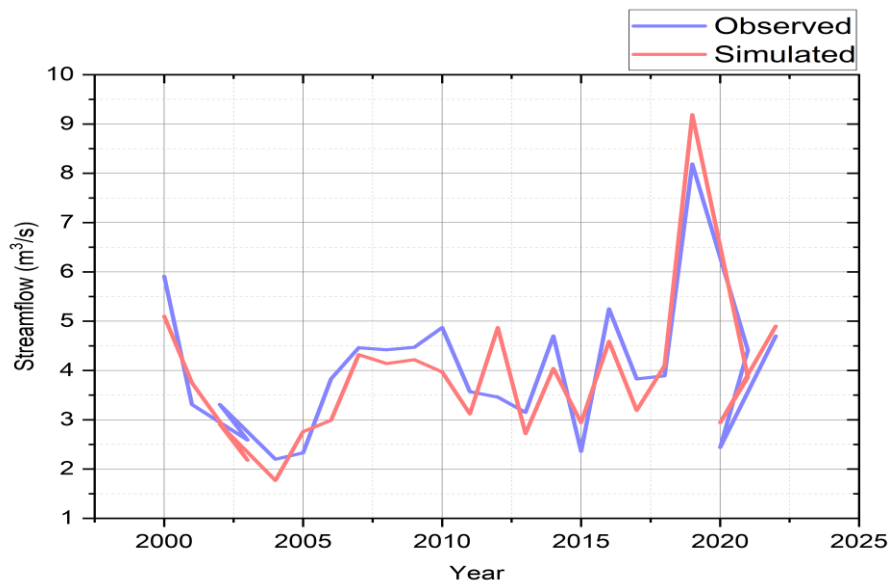


Figure 3: Observed and Simulated Annual Streamflow (2000 - 2022)

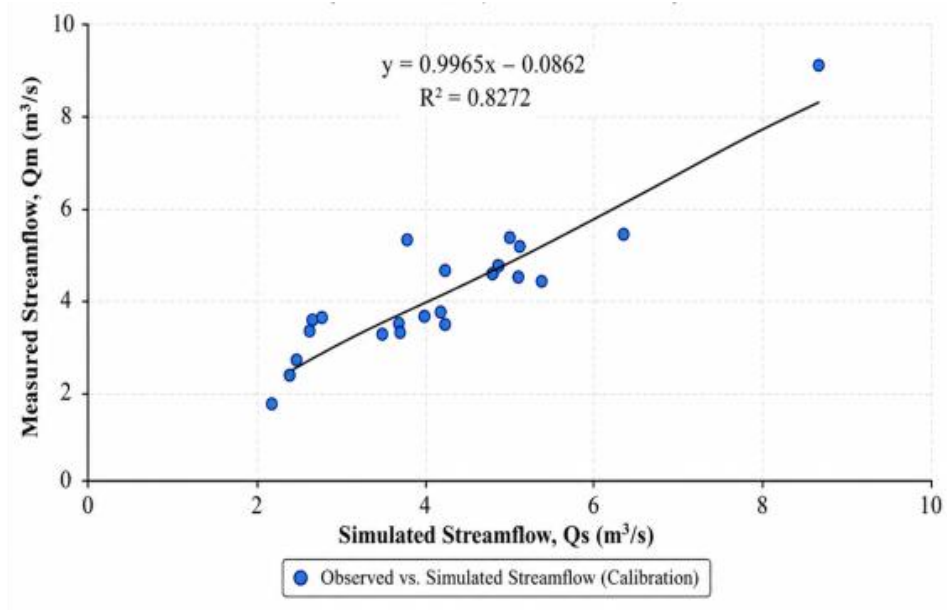


Figure 4: Calibration Scatter Plot of Measured and Simulated Streamflow

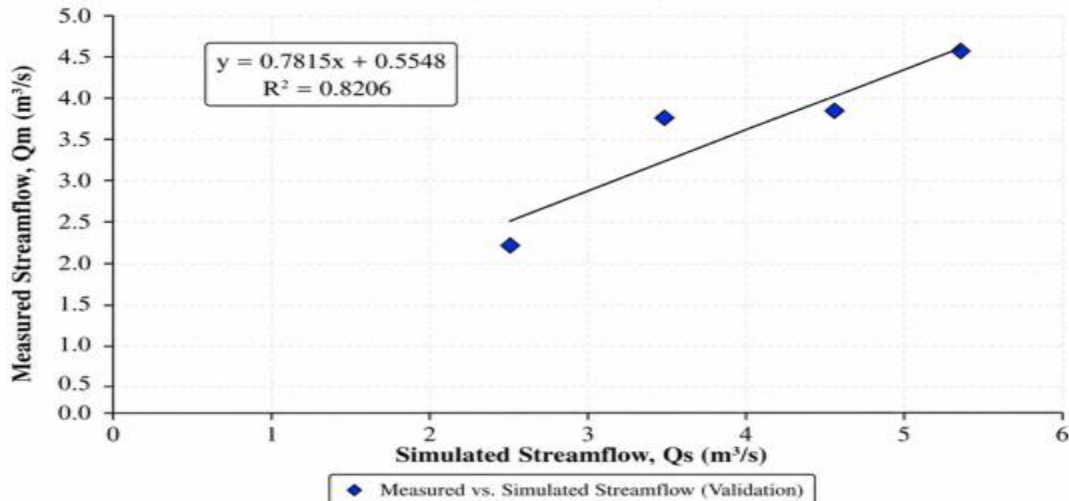


Figure 5: Validation Scatter Plot of Measured and Simulated Streamflow

3.3 ARIMA Streamflow Forecasting

The annual streamflow series for 2000–2022 was analysed using non-seasonal ARIMA models. Candidate models, including ARIMA(0,0,0), ARIMA(1,0,0), ARIMA(1,0,1), and ARIMA(2,0,1), were fitted and compared using the Akaike Information Criterion (AIC), corrected AIC (AICc), Bayesian Information Criterion (BIC), and forecast accuracy measures. Forecast performance was assessed using time-series cross-validation based on rolling forecast origins to provide an out-of-sample assessment of predictive accuracy.

The comparison of candidate models is presented in Table 3. Although ARIMA(0,0,0) produced the lowest AIC, the ARIMA(1,0,0) model provided a better balance between model parsimony and predictive performance, as indicated by its comparatively lower out-of-sample forecast errors. The ARIMA(1,0,0) model produced an RMSE of 1.320 m³/s, MAE of 0.980 m³/s, and MAPE of 27.18%. The model was therefore selected for forecasting based on its combined forecasting performance, information criteria, and diagnostic adequacy.

Table 3: Comparison of candidate ARIMA models

Candidate model	AIC	AICc	BIC	RMSE (m ³ /s)	MAE (m ³ /s)	MAPE (%)	Decision
ARIMA (0,0,0)	82.36	82.96	83.58	1.48	1.13	31.42	Rejected
ARIMA (1,0,0)	82.72	83.36	84.04	1.32	0.98	27.18	Selected
ARIMA (1,0,1)	83.91	85.18	85.52	1.39	1.04	28.76	Rejected
ARIMA (2,0,1)	85.21	87.43	87.02	1.44	1.09	30.15	Rejected

The selected ARIMA(1,0,0) model was subsequently subjected to residual diagnostic testing. The residual autocorrelation function and Ljung–Box test (Figure 6) were used to confirm that no significant serial dependence remained in the residuals before generating forecasts for 2023–2042.

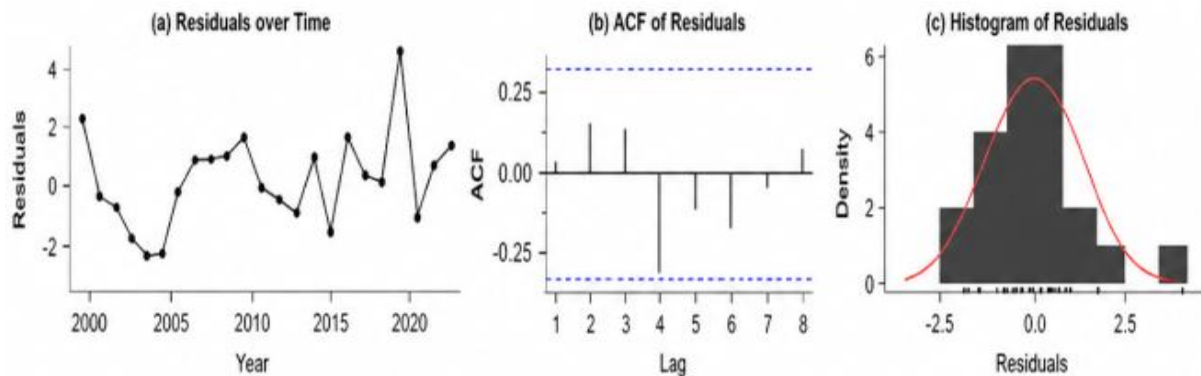


Figure 6: The residual time series, autocorrelation function (ACF) of the residuals, and the residual histogram

The validated ARIMA (1,0,0) model was subsequently used to forecast annual streamflow for the period 2023–2042 (Figure 7). The forecasts indicate that annual discharge is expected to remain relatively stable, with a long-term mean of approximately 6.0 m³/s and no statistically significant increasing or decreasing trend over the forecast horizon. As expected, the 80% and 95% prediction intervals widen progressively with time, reflecting increasing uncertainty associated with long-term forecasting. While the long-term mean streamflow is projected to remain stable, the historical record suggests that inter-annual variability is likely to persist, implying that individual years may still experience above- or below-average flows.

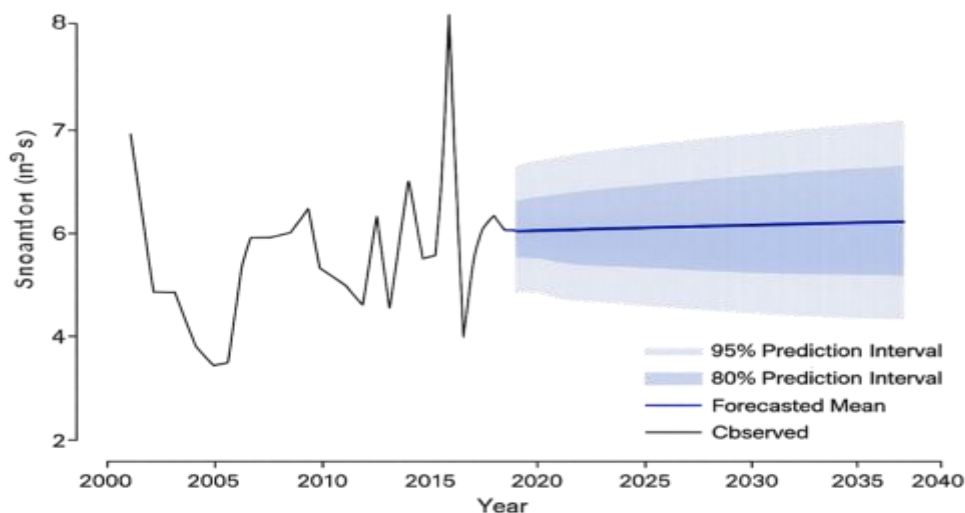


Figure 7: Forecasted Annual Streamflow Using ARIMA

3.4 Implications for Water Resources Management

The combined SWAT and ARIMA modelling framework provide valuable information for long-term water resources planning in the Kiri Watershed. The projected stability in average annual streamflow suggests that current water availability is likely to remain adequate for reservoir operation and irrigation planning under prevailing climatic conditions. However, the continued occurrence of inter-annual variability highlights the need for adaptive reservoir operation and flexible irrigation scheduling to accommodate periods of relatively high and low streamflow. Regular updating of forecasting models using newly observed hydrological data will further improve forecast reliability and support sustainable water resources management within the watershed.

It is important to note that the forecasts developed in this study are based on annual streamflow and therefore describe long-term changes in overall water availability rather than intra-annual flow dynamics. Consequently, the results should be interpreted primarily as information for strategic water resources planning rather than as a direct basis for monthly irrigation scheduling or short-term reservoir operation. Future research should incorporate monthly streamflow data and evaluate Seasonal ARIMA (SARIMA) or other seasonal/hybrid forecasting approaches to capture within-year variability and provide more operationally relevant forecasts.

4.0 CONCLUSION

This study integrated the Soil and Water Assessment Tool (SWAT) and the Autoregressive Integrated Moving Average (ARIMA) model to simulate the hydrological behavior of the Kiri Watershed and forecast annual streamflow over the period 2023–2042. The SWAT model successfully represented the watershed hydrological processes, with satisfactory calibration and validation performance ($R^2 = 0.83$ and 0.82 ; $NSE = 0.79$ and 0.73 , respectively), demonstrating its suitability for streamflow simulation within the study area. The watershed characterization further showed that the catchment is dominated by shrubland and loamy soils, which significantly influence runoff generation and infiltration processes.

The ARIMA (1,0,0) model adequately captured the temporal characteristics of the annual streamflow series, with residual diagnostics confirming the statistical adequacy of the model. Forecast results indicate that the Kiri Watershed is likely to maintain a relatively stable mean annual discharge of approximately $6.0 \text{ m}^3/\text{s}$ over the next two decades, with no significant long-term increasing or decreasing trend. However, the historical inter-annual variability suggests that fluctuations in annual streamflow are likely to persist despite the overall stability in average water availability.

The integrated SWAT–ARIMA framework demonstrated in this study provides a practical approach for combining physically based hydrological simulation with statistical time-series forecasting to support long-term water resources planning. The findings provide useful information

for adaptive reservoir operation, irrigation water allocation, and sustainable watershed management within the Kiri Watershed. Future studies should investigate the combined effects of climate change and land-use change on streamflow dynamics and evaluate advanced hybrid forecasting approaches, including machine learning techniques, to further improve long-term predictive accuracy.

The study also demonstrates the relevance of integrated hydrological and statistical modelling to Nigeria's sustainable development agenda. The SWAT-ARIMA framework provides an engineering-based decision-support tool for improving water availability assessment, reservoir management, and irrigation planning, thereby contributing to innovative resource utilization and management. Its application to the Kiri Watershed demonstrates how engineering innovation and data-driven modelling can support more resilient and sustainable water resources management in Nigeria, consistent with the conference theme, "Innovating Tomorrow: Harnessing Engineering to Drive Nigeria's Growth for Sustainable Development."

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