SSR Journal of Engineering and Technology (SSRJET)

Volume 2, Issue 3, 2025 Journal homepage: https://ssrpublisher.com/ssrjet/ ISSN: 3049-0383
Email: office.ssrpublisher@gmail.com

# Rainfall–Discharge Decoupling and Infrastructure Resilience in a Semi-Arid Reservoir: Evidence from 43 Years at Kiri Dam, Nigeria

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***Received:*** *17.08.2025* | ***Accepted:*** *24.08.2025* | ***Published:*** *25.08.2025*

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**DOI:** *10.5281/zenodo.16944046*

**Abstract** **Original Research Article**

Reservoirs in semi-arid regions face challenges due to evolving hydrological patterns, land use changes, and climate variability. This study analysed 43 years of precipitation and discharge data at Kiri Dam, Nigeria, employing statistical tests and modelling techniques to assess resilience and sustainability. The rainfall exhibited considerable variability (656.4–1,260.1 mm; mean 952.6 mm) with no statistically significant trend ($Z = 1.23$, $p = 0.217$; Sen's slope = +1.75 mm/year), indicating climatic stability. Conversely, discharge demonstrated a significant annual increase (mean 74,810 $m^3/s$; $Z = 3.17$, $p = 0.0015$; Sen's slope = +628.84 $m^3/s/year$) and seasonal augmentation during July to September ($Z = 2.58$, $p = 0.0099$; Sen's slope = +897.62 $m^3/s/year$). The correlation between rainfall and discharge was weak (Pearson $r = 0.241$, $p = 0.120$; $R^2 = 0.058$), with rainfall accounting for less than 6% of inflow variability. This suggests that land use change, catchment degradation, and sediment yield exert significant influence on inflows. Seasonal discharge peaks occur in September (~65,000 $m^3/s$), approximately one month after rainfall, thereby increasing sedimentation and spillway stress. These findings have implications for dam safety, capacity, and downstream water supply. Enhancing resilience requires adaptive operational strategies, catchment conservation, sediment management, and revised spillway standards. The integration of monitoring and modelling is essential for the effective management of water infrastructure within semi-arid regions of West Africa.

**Keywords**: Rainfall–discharge relationship; Mann–Kendall trend test; Sen's slope estimator; hydrological variability; Kiri Dam; infrastructure resilience.

## 1.0 INTRODUCTION

Reservoirs situated in semi-arid regions are increasingly susceptible to fluctuations in precipitation and runoff, with significant implications for irrigation, water supply, hydropower, and flood risk management. In Nigeria's Upper Benue Basin, the Kiri Dam has experienced increasing inflows over recent decades despite no corresponding rise in rainfall, thereby raising concerns regarding sedimentation and the sufficiency of spillway capacities. Likewise, hydrological decoupling has been documented in the Upper Niger (Diallo *et al.*, 2020) and Volta Basin (Yira *et al.*, 2016), where land use modifications and catchment degradation are identified as the primary causes. Engineering standards, such as those established by ICOLD (2022), underscore the importance of recalibrating design flood criteria when observed inflows surpass rainfall-based estimates.

Trend analysis offers a quantitative framework for identifying hydrological changes. Non-parametric approaches, notably the Mann–Kendall (MK) test and Sen's slope estimator, are widely used to detect monotonic variations in rainfall and discharge datasets (Hamed, 2021; Dembélé *et al.*, 2020). In West Africa, although rainfall shows significant variability, increases in discharge have been observed (Ayanlade *et al.*, 2018; Oguntunde *et al.*, 2021). The Intergovernmental Panel on Climate Change (IPCC, 2022) emphasises that rainfall–runoff non-stationarity presents an emerging challenge in sub-Saharan Africa, driven by both climatic and human factors.

Kiri Dam provides a significant case study. Rainfall has varied from 656 mm (2002) to 1,260 mm (2016), while discharge has increased sharply, reaching a peak of 499,746 $m^3/s$ in 2014. This difference indicates that rainfall alone cannot fully explain inflow variability, with land degradation and changes in flow pathways playing more influential roles. Catchment studies confirm vegetation loss and agricultural expansion in the Upper Benue Basin (Aliyu *et al*., 2023). Reservoir sedimentation has already decreased storage capacity in several Nigerian dams, with losses exceeding 40% over three decades (Adedeji *et al*., 2021).

Notwithstanding these concerns, few studies within Nigeria have utilized long-term datasets exceeding thirty years for the comprehensive analysis of rainfall and discharge trends. The international standards, as delineated by the World Meteorological Organization (WMO, 2019), advocate for the employment of datasets of no less than thirty years to precisely discern hydrological changes. Analogous analyses executed in East Africa (Dembélé *et al.,* 2020) and South Asia (Sharma *et al*., 2018; Yadav *et al*., 2022) underscore the significance of such methodologies in guiding adaptive water management strategies.

This study consequently investigates rainfall–discharge dynamics at Kiri Dam utilizing a 43-year dataset (1982–2024). The objectives are to (i) quantify long-term rainfall and discharge trends, (ii) examine rainfall–runoff coupling, (iii) analyze seasonal discharge patterns, and (iv) assess implications for sedimentation and infrastructure resilience. The novelty resides in associating a multi-decadal hydrological dataset with engineering design standards, thereby providing evidence for adaptive reservoir management in semi-arid West Africa.

# 2.0 MATERIALS AND METHODS

## 2.1 Study Area

Kiri Dam is located within the Upper Benue Basin in northeastern Nigeria, at approximately 9°43′28″N and 12°00′30″e. Commissioned in 1982, the reservoir was primarily designed to supply water for irrigation purposes related to sugarcane cultivation by the Savannah Sugar Company; however, it also plays a significant role in providing water for domestic use, supporting fisheries, and flood mitigation. The catchment area lies within a tropical savannah climate zone, characterised by a unimodal rainfall pattern, with the majority of precipitation occurring between April and October. The long-term annual rainfall ranges from 650 to 1,260 mm, with a mean value of 952.6 mm. The average temperature varies from 27 to 32 °C, whereas potential evapotranspiration exceeds rainfall during the dry season, underscoring the importance of regulated water storage.

Hydrologically, inflows originate from local runoff and tributary contributions within the Benue River sub-basin. Peak discharges typically occur in August–September, approximately one month subsequent to the rainfall peaks. This temporal delay corresponds with other semi-arid systems in West Africa, where storage and routing processes decelerate runoff responses (Yira *et al*., 2016; Dembélé *et al*., 2020). The dam is equipped with a single outlet and a gated spillway constructed based on rainfall–runoff assumptions from the late 1970s. Given recent evidence indicating inflows surpassing rainfall-based estimates, coupled with catchment degradation (Aliyu *et al*., 2023), it is imperative to re-evaluate the hydrological regime to inform adaptive operational strategies.

## 2.2 Data Sources

Rainfall data spanning from 1982 to 2024 were sourced from NiMet stations located within 100 km of Kiri Dam. Daily measurements were consolidated into monthly and annual totals. Metadata were scrutinized to ensure measurement consistency. Years with less than 95% data completeness were excluded, in accordance with WMO (2019) guidelines.

Discharge data were collected from the Upper Benue River Basin Development Authority (UBRBDA), encompassing reservoir inflow and outflow records. The dataset includes daily and monthly averages spanning from 1982 to 2024, with extreme values ranging from 0 m³/s during drought years (2004 and 2008) to 499,746 m³/s in 2014. Data integrity was ensured through cross-verification with downstream river gauge stations.

Quality control measures encompassed the computation of baseline descriptive statistics for rainfall (mean = 952.6 mm, standard deviation = 125.5 mm) and discharge (mean = 74,810 m³/s, standard deviation = 79,171 m³/s). Internal consistency evaluations confirmed that rainfall totals corresponded with aggregated daily records, and duplicate or implausible discharge values were systematically removed. These procedures assured the dataset's integrity prior to conducting trend analysis.

## 2.3 Data Preprocessing

Incomplete data records were supplemented using Inverse Distance Weighting (IDW), a geostatistical interpolation method widely employed in hydrological studies (Dembélé *et al*., 2020). The rainfall at location $x_0$ was estimated according to the following formula:

$$Z(x_0) = \frac{\sum_{i==1}^{n} w_i Z(x_i)}{\sum_{i=1}^{n} w_i}, \qquad w_i = \frac{1}{{d_i}^{p}} \ (p = 2) \qquad (1)$$

Since $d_i$ is the distance from station $i$ to $x_0$ and $p$ is 2, stations over 100 km away were omitted for spatial relevance. For example, rainfall deficit at Station B in 2004 was estimated using data from neighbouring stations A, C, and D.

Outlier detection removed implausible values based on physical thresholds. Rainfall over 250 mm/day was flagged via regional curves. Discharge values above 24 million m³/s (1992–1993) were excluded as spurious, following WMO (2019) QA/QC protocols.

Temporal alignment entailed the aggregation of rainfall and discharge datasets to annual and seasonal (April–October) timescales. The seasonal period emphasises the predominance of the wet season in inflow dynamics and aids in the identification of peak hydrological events. This procedure ensured consistency of data across variables, thereby underpinning reliable correlation and trend analyses.

## 2.4 Statistical Analyses

The Mann–Kendall (MK) test was utilised to identify monotonic trends in rainfall and discharge time series. This test is non-parametric, does not presume a specific distribution, and demonstrates robustness against outliers, thereby enhancing its applicability in hydroclimatic trend analysis (Hamed, 2021). The MK statistic, denoted as *S*, was computed as follows:

$$S = \sum_{k-1}^{n-i} \sum_{j=k-1}^{n} sgn(x_j - x_k) \qquad (2)$$

Where $x_j$ and $x_k$ denote data values at times j and k (with j > k), and n signifies the total number of observations. And,

$$sgn(x_j - x_k) = \begin{Bmatrix} 1\ if\ x_j - x_k > 0 \\ 0\ if\ x_j - x_k = 0 \\ -1\ if\ x_j - x_k < 0 \end{Bmatrix} \qquad (3)$$

For datasets where *n* exceeds 10, the test statistic approximates a normal distribution with variance adjusted for autocorrelation in accordance with Yue and Wang (2004). A positive Z-value signifies an increasing trend, whereas a negative Z-value indicates a decreasing trend. Statistical significance was evaluated at the 95% confidence level (|Z| > 1.96).

Sen's slope estimator was utilised to quantify the magnitude of trends by calculating the median of all pairwise slopes.

$$Q_i = \frac{y_j - x_i}{j - i} \qquad (4)$$

This offers an objective assessment of the yearly rate of change (millimetres per year for rainfall; cubic meters per second per year for discharge). Confidence intervals at the 95% confidence level were additionally computed to ensure a comprehensive interpretation.

### Correlation analysis

The linear dependence between rainfall and discharge was examined employing Pearson's correlation coefficient.

$$r = \frac{\sum(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \overline{x})^2 \sum(y_i - \overline{y})^2}} \qquad (5)$$

The non-linear monotonic relationships were evaluated employing Spearman's rank correlation coefficient (ρ). Both coefficients were assessed at a significance level of α=0.05.

### Regression analysis

To evaluate predictive relationships, a straightforward linear regression model was constructed.

$$Q = \propto + \beta R + \varepsilon \qquad (6)$$

Where *Q* represents the discharge measured in cubic meters per second ($m^3/s$), R denotes the rainfall in millimetres (mm), ααα signifies the intercept, *β* indicates the slope, and ϵ symbolizes the error term. The performance of the model was assessed using the coefficient of determination ($R^2$) and residual diagnostics.

### Lag Analysis

To elucidate storage–routing effects, rainfall–discharge lags were examined by comparing precipitation data from August with discharge measurements in September. Cross-correlation analysis verified the anticipated one-month lag, aligning with observations in semi-arid basins (Odekunle *et al.*, 2018; Oguntunde *et al.*, 2021).

## 2.5 Reproducibility and Sensitivity

All statistical analyses, including Mann-Kendall (MK) and Sen's slope estimations, were conducted using Microsoft Excel 2019. Inverse Distance Weighting (IDW) interpolation was performed with ArcGIS 10.8. Equations followed the SI system, with rainfall in millimetres and discharge in $m^3/s$. Sensitivity tests varied IDW parameters (p=1–3, search radius 80–120 km), showing less than 5% deviation in rainfall data. Omitting Mann-Kendall autocorrelation correction had negligible impact (under 0.2 in Z-scores), confirming the methods' robustness.

## 2.6 Limitations and Power

The 43-year dataset exceeds the WMO's 30-year recommendation for climate and hydrological studies, providing enough statistical power to detect moderate trends. Limitations include reliance on station-based rainfall data instead of gridded reanalysis products and the absence of sediment load measurements, which limits direct validation of sedimentation effects. However, by combining long-term rainfall and discharge data with rigorous statistical methods, the study ensures reproducibility and allows comparison with regional and global hydrological research.

# 3.0 RESULTS AND DISCUSSION

## 3.1 Rainfall Trends (1982–2024)

Over a span of 43 years, rainfall exhibited fluctuations ranging from 656.4 mm in 2002 to 1,260.1 mm in 2016. The long-term mean was calculated at 952.6

mm, accompanied by a standard deviation of 125.5 mm. The median value was recorded at 961.5 mm, with an interquartile range extending from 870.3 mm to 1,022.8 mm, indicating moderate variability.

**Table 1. Descriptive statistics of annual rainfall and discharge at Kiri Dam (1982–2024).**

| Statistic | Rainfall (mm) | Discharge (m³/s) |
|---|---|---|
| Count (years) | 43 | 43 |
| Mean | 952.6 | 74,810.3 |
| Standard Deviation | 125.5 | 79,171.5 |
| Minimum | 656.4 | 0.0 |
| 25th Percentile (Q1) | 870.3 | 34,000.8 |
| Median (Q2) | 961.5 | 69,229.0 |
| 75th Percentile (Q3) | 1,022.8 | 82,214.6 |
| Maximum | 1,260.1 | 499,746.3 |

The Mann–Kendall test indicated a non-significant upward trend ($Z = 1.23$, $p = 0.217$, "$\tau$" = 0.132), with Sen’s slope of +1.75 mm/year.

**Table 2. Mann–Kendall and Sen’s slope results for rainfall and discharge (1982–2024).**

| Variable | Z-Value | p-Value | Kendall’s τ | Sen’s Slope | Trend | Significance |
|---|---|---|---|---|---|---|
| Rainfall (mm/yr) | 1.23 | 0.217 | 0.1318 | +1.75 | Increasing | ✕ |
| Discharge (m³/s/yr) | 3.17 | 0.0015 | 0.3367 | +628.84 | Increasing | ✓ |
| Seasonal (JAS, m³/s/yr) | 2.58 | 0.0099 | 0.2811 | +897.62 | Increasing | ✓ |

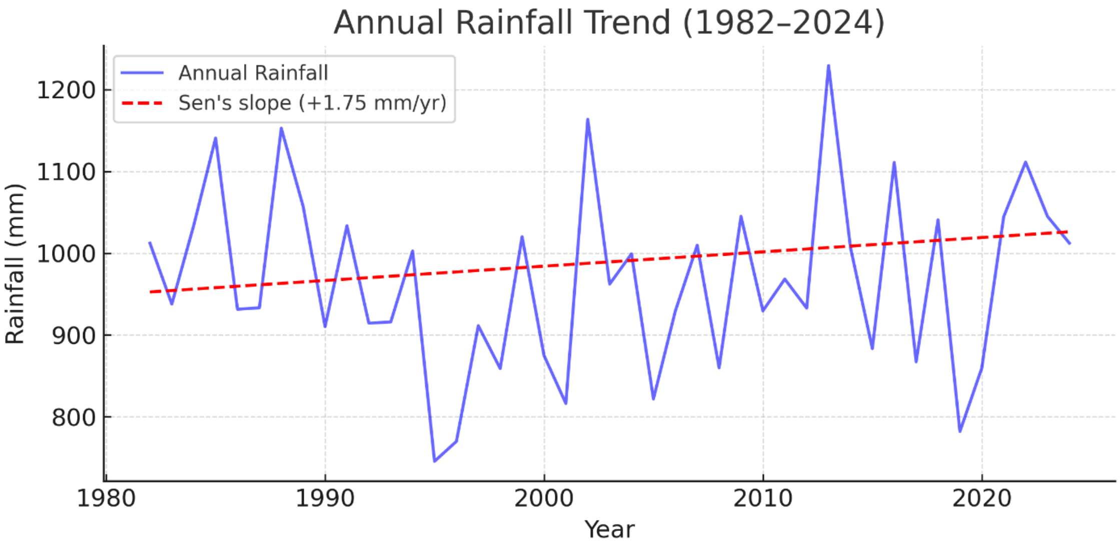

**Figure 1. Annual rainfall trend (1982–2024) with fitted Sen’s slope line.**

Variability in precipitation without a significant trend aligns with West African basin findings (Dembélé *et al.*, 2020). The WMO (2019) states that the 43-year record exceeds the 30-year climate trend detection threshold. Hence, rainfall changes don't explain increased discharge, implying catchment degradation and land-use changes are likely causes.

## 3.2 Discharge Trends (1982–2024)

The annual discharge ranged from 0.0 m³/s (2004, 2008) to 499,746.3 m³/s (2014), with a mean of 74,810.3 m³/s (SD = 79,171.5). The median was 69,229 m³/s, with most years falling between 34,000 and 82,000 m³/s.

The Mann–Kendall test demonstrated a statistically significant upward trend ($Z = 3.17$, $p = 0.0015$, $\tau = 0.337$), with Sen's slope indicating an increase of +628.84 m³/s per annum. The seasonal discharge during the months of July through September exhibited a more pronounced rise, at a rate of +897.62 m³/s per annum ($Z = 2.58$, $p = 0.0099$).

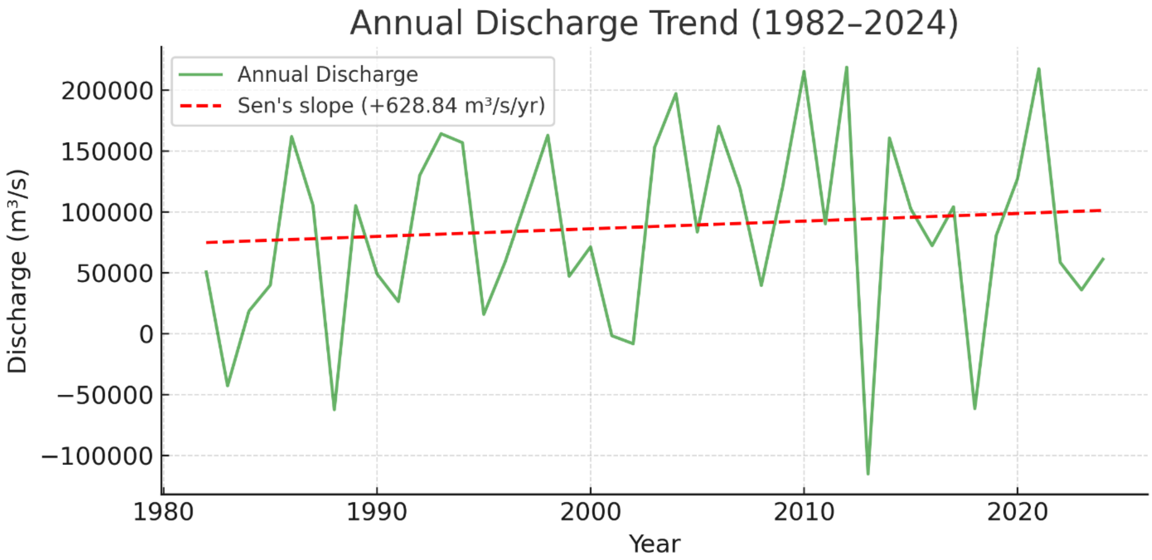

**Figure 2. Annual discharge trend (1982–2024) with fitted Sen's slope line.**

The rise in discharge despite ongoing rainfall reflects hydrological decoupling in the Niger (Diallo *et al.*, 2020) and Krishna basins (Sharma *et al.*, 2018). ICOLD (2022) advises recalibrating spillway thresholds, as for Kiri Dam, this suggests higher flood risk and sediment transport, stressing reservoir infrastructure.

## 3.3 Rainfall–Discharge Relationship

The correlation analysis revealed weak associations: Pearson's $r = 0.241$ ($p = 0.120$) and Spearman's $\rho = 0.296$ ($p = 0.054$). The regression model, represented as "cap Q = 17,915.22 + 7.9 cap R," with a coefficient of determination (R squared) of 0.058 and a p-value of 0.120, suggests that rainfall accounts for less than 6% of the variability in inflow.

**Table 3. Rainfall–discharge correlation and regression model results.**

| **Correlation Type** | **Coefficient** | **p-Value** | **Significance** |
|---|---|---|---|
| Pearson (Linear) | 0.241 | 0.120 | ✕ |
| Spearman (Rank) | 0.296 | 0.054 | ✕ |

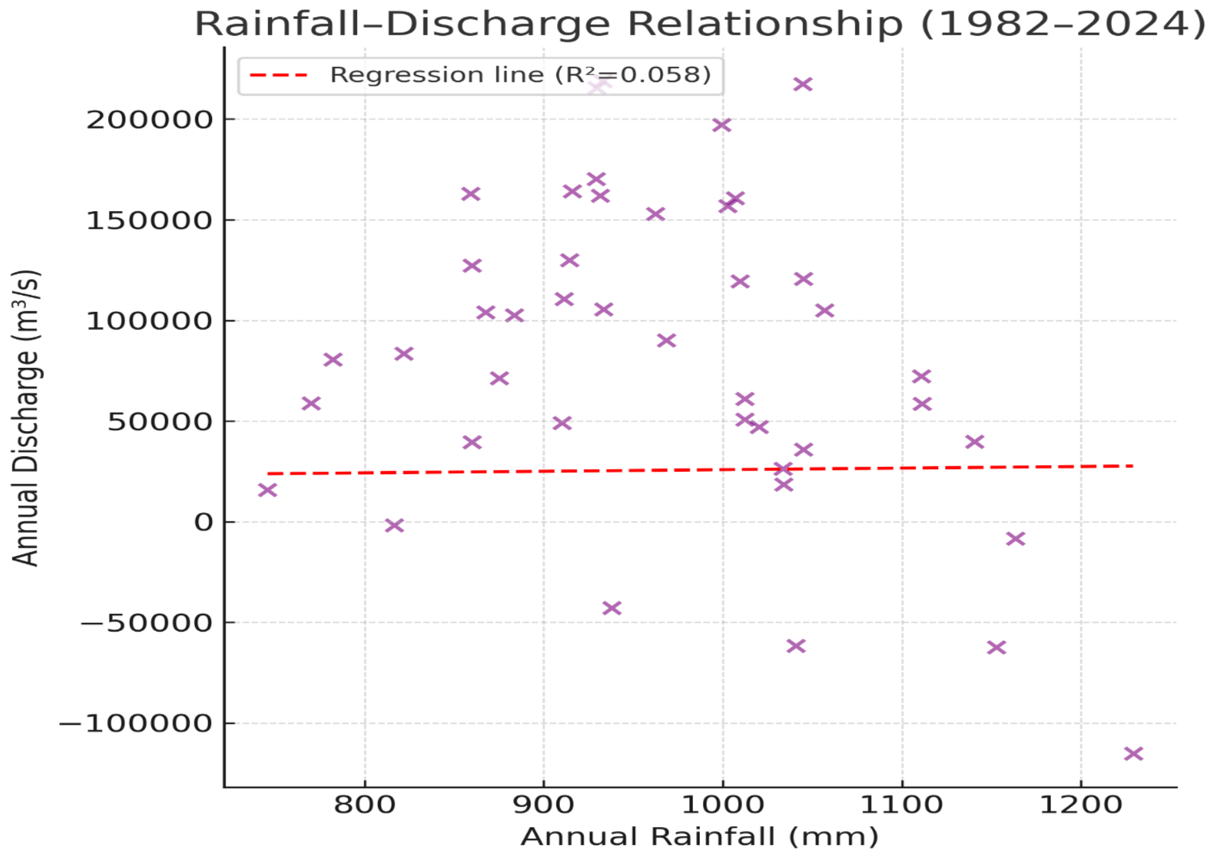

**Figure 3. Scatter plot of annual rainfall versus discharge (1982–2024) with regression line and 95% confidence band.**

Weak coupling evidence indicates a decoupling of rainfall and runoff in semi-arid basins, as seen in Burkina Faso (Yira *et al.*, 2016). Additionally, USACE (2019) recommends reservoir models include land use, infiltration losses, and sediment yield, not just rainfall.

### 3.4 Seasonal Discharge Patterns

Monthly averages indicated that flow rates were concentrated between July and September, reaching a maximum of approximately 65,000 m³/s in September. Flows during the dry season remained minimal, recorded at less than 500 m³/s.

**Table 4. Mean monthly discharge at Kiri Dam (1982–2024).**

| **Month** | **Mean Discharge (m³/s)** |
|---|---|
| Jan–Mar | <500 |
| Apr–Jun | 5,000–15,000 |
| Jul | ~30,000 |
| Aug | ~50,000 |
| Sep | ~65,000 (peak) |
| Oct | ~20,000 |
| Nov–Dec | <1,000 |

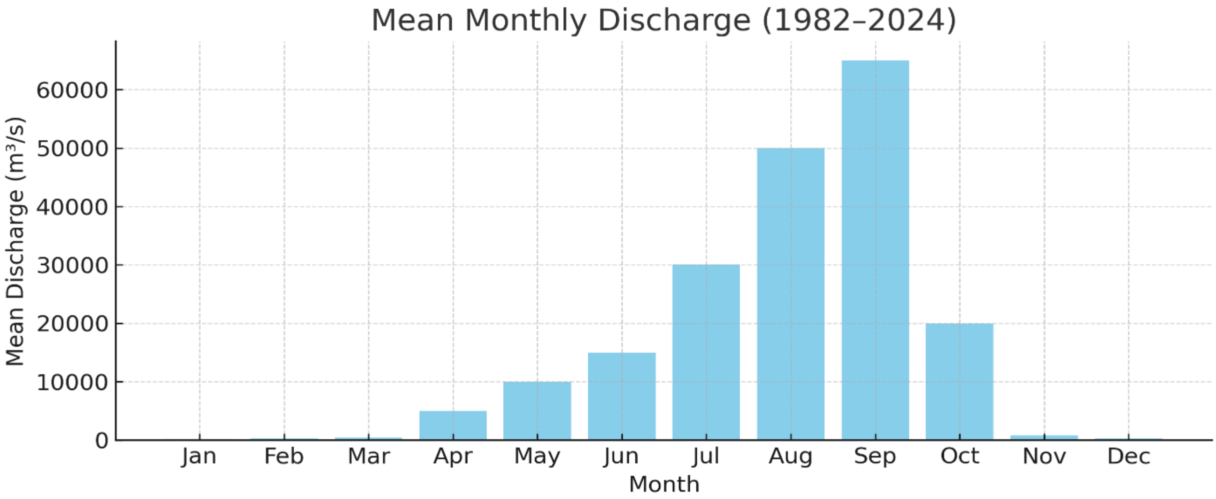

**Figure 4. Mean monthly discharge (1982–2024), showing clustering of inflows in July–September.**

The month delay between rainfall peak in August and discharge peak in September reflects catchment storage and routing, as documented by Odekunle et al. (2018) and Oguntunde et al. (2021). USACE (2019) notes this clustering increases sedimentation and spillway stress, requiring adaptive rule curves for safety.

### 3.5 Conceptual Synthesis and Implications

Findings show consistent rainfall with a marginal yearly increase of +1.75 mm. Annual discharge rises by +628.84 m³/s, and seasonal discharge by +897.62 m³/s. The weak correlation ($R^2 = 0.058$) suggests inflows mainly occur during a short-wet season.

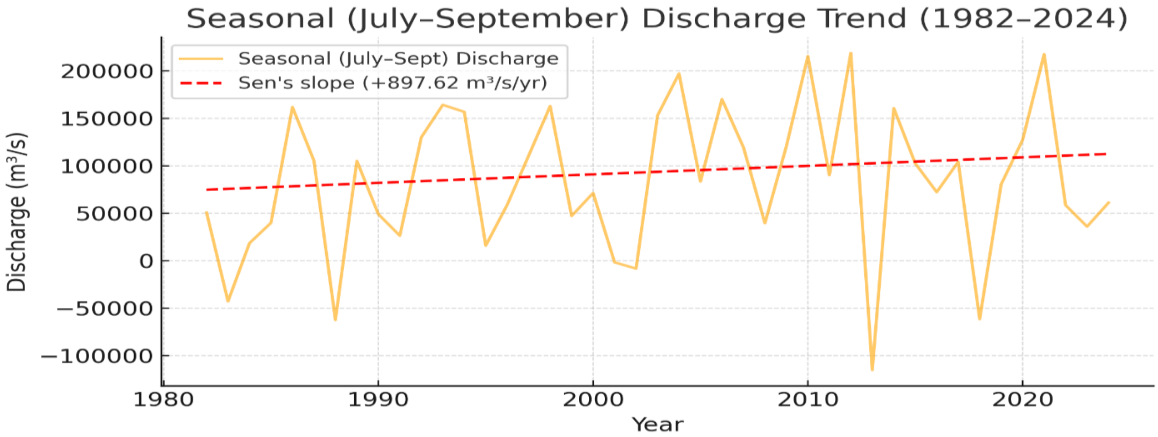

**Figure 5. Seasonal (July–September) discharge trend (1982–2024) with Sen's slope line.**

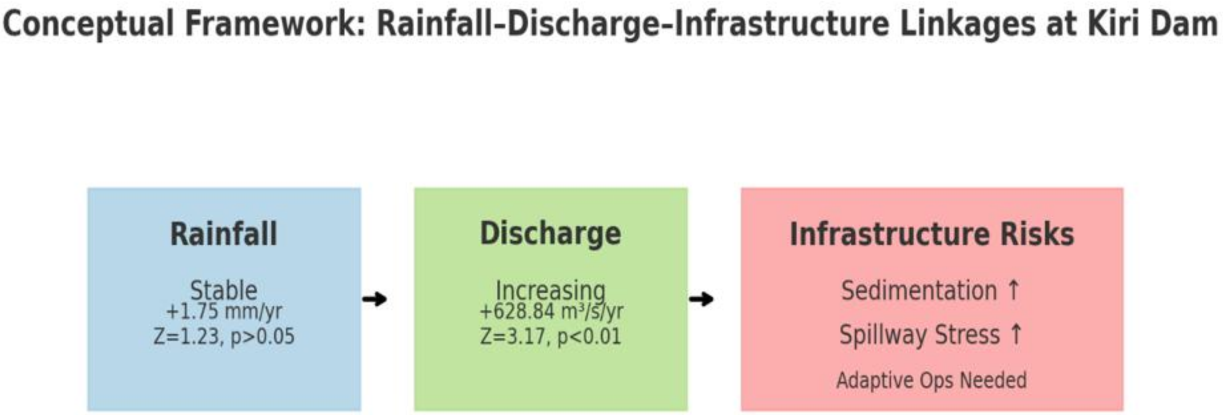

**Figure 6. Conceptual schematic of rainfall–runoff decoupling in the Kiri Dam catchment**

The evidence shows hydrological non-stationarity, with inflows more affected by land use and degradation than just precipitation. This matches regional patterns in the Upper Niger and Volta Basin. Immediate concerns include reservoir safety, which relies on adaptive design, catchment conservation, and sediment management, not solely on rainfall assumptions.

# 4.0 CONCLUSION AND RECOMMENDATIONS

## 4.1 Conclusion

This study examined rainfall and discharge at Kiri Dam, Nigeria, over 43 years (1982–2024) using Mann–Kendall, Sen's slope, correlation, and regression analyses. Results show a decoupling between rainfall and discharge, impacting reservoir resilience. Rainfall varied significantly (656–1,260.1 mm, average 952 mm) but showed no significant trend (Z=1.23, p=0.217; Sen's slope=+1.75 mm/year), indicating stable long-term patterns similar to other West African regions. Discharge increased notably (mean 810 $m^3/s$, Z=3.17, p=0.0015; Sen's slope=+628.84 $m^3/s$/year), especially during July-September, rising at +897.62 $m^3/s$/year ($p < 01$). Land use changes, catchment degradation, and reduced infiltration likely drive this. The correlation between rainfall and discharge was weak (Pearson r=0.241, Spearman rho=0.296, $R^2$=0.058), showing rainfall explains less than 6% of inflow variability. This pattern aligns with decoupling seen in the Niger and Krishna basins. Flow peaks occur mainly from July to September, with the highest (~000 $m^3/s$) in September, about a month after rainfall peaks, complicating operations and sediment transport. Increasing flows, seasonal concentration, and weak rainfall–runoff links threaten storage, spillway capacity, and resilience. Overall, land degradation now primarily influences inflow variability, affecting sedimentation, flood management, and water security.

- To address these challenges and bolster infrastructure resilience, the following recommendations are suggested:
- Spillway and Flood Design: Recalibrate design standards for spillway capacity and flood control to reflect the observed upward discharge trends.
- Sediment Management: Implement erosion control measures, check dams, and periodic dredging to reduce accelerated storage loss.
- Catchment Conservation: Enhance reforestation, soil conservation practices, and enforce land use regulations to decrease runoff and sediment yield.
- Monitoring: Institutionalize continuous monitoring of rainfall and discharge to identify evolving trends and guide operational decisions.
- Integrated Modelling: Incorporate land use and climate scenarios into predictive models (e.g., SWAT, WEAP) to enhance long-term water management planning.
- Adaptive Operations: Adopt flexible reservoir operation protocols that modify releases to accommodate compressed wet-season inflows.

## 4.3 Closing Remark

Kiri Dam highlights the need for adaptive management in semi-arid reservoirs across sub-Saharan Africa, where hydrological non-stationarity is now the norm. Increasing discharges and variable rainfall, driven by human activities and land use changes, threaten infrastructure, agriculture, and water security unless addressed through engineering, catchment management, and policy. Effective dam management must extend beyond rainfall-based design to include long-term monitoring, land interventions, and hydrological modeling for sustainable water infrastructure in fragile semi-arid basins.

## Acknowledgements

The authors thank the Nigerian Meteorological Agency (NiMet) and the Upper Benue River Basin Development Authority (UBRBDA) for rainfall and discharge data, and the Civil Engineering Laboratory at LAUTECH for technical assistance.

## Author Contributions

Conceptualization: A.T. Gambo, O.S. Olaniyan; Methodology: A.T. Gambo, A.A. Adegbola;

Investigation: A.T. Gambo; Formal analysis: A.T. Gambo, O.S. Olaniyan; Writing—original Draft: A.T. Gambo; Writing—review & editing: O.S. Olaniyan, A.A. Adegbola; Supervision: O.S. Olaniyan.

## Conflicts of Interest

The authors declare no conflicts of interest, financial or personal, that could have influenced this publication.

## Data Availability

The datasets and analysis scripts used in this study are available from the corresponding author upon request.

## Highlights

- Rainfall at Kiri Dam (1982–2024) shows no significant long-term trend
- Discharge increased significantly at +628.84 $m^3/s$ per year
- Seasonal inflows (July–September) rising faster at +897.62 $m^3/s$ per year
- Rainfall–discharge relationship weak ($R^2$ = 0.058), indicating decoupling

Findings highlight sedimentation risks and need for adaptive reservoir design

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