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Multiscale Drivers of Rainfall Variability in Wa, Northern Ghana: Relative Roles of Oceanic Teleconnections and Local Atmospheric Controls.

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abstract

Rainfall variability in northern Ghana has significant implications for rain-fed agriculture and climate risk management. This study investigates the multiscale drivers of rainfall variability in Wa over the period 1960-2020, distinguishing between large-scale oceanic teleconnections and local atmospheric controls. A key contribution of this study is the development of a comparative multiscale framework that isolates and quantifies the individual and combined influence of remote oceanic forcing and local atmospheric processes on rainfall variability. Monthly rainfall variability, trends, and interannual fluctuations were first quantified using the coefficient of variation, Mann-Kendall trend analysis, Sen's slope estimator, and change-point detection. To attribute drivers, three regression models were developed: (i) teleconnection indices only, (ii) local ERA5 atmospheric variables only, and (iii) a combined model incorporating both predictor sets. Rainfall exhibited the highest relative variability during the onset and cessation months. It is revealed that interannual variability has significantly declined since 1990, while significant negative trends are confined to March and July. Regression results show that teleconnection indices explain 8.6% of rainfall variance, whereas local atmospheric variables explain 30.2%. The combined model provides the highest explanatory power (41.1%), indicating that large-scale oceanic variability exerts a statistically significant but secondary influence relative to local thermodynamic and cloud-related processes. The findings demonstrate that rainfall variability in Wa is primarily governed by local atmospheric conditions, with large-scale SST anomalies modulating the background monsoon environment. These results highlight the importance of integrating both remote and local predictors to improve seasonal rainfall prediction, climate risk assessment, and agricultural planning in northern Ghana.

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Introduction

Rainfall variability over West Africa is a critical challenge for climate science, water resources management, and climate risk planning, particularly within the semi-arid and sub-humid transition zones of the West African Monsoon (WAM) system (Nicholson, 2013; Nicholson et al., 2018). Northern Ghana, including Wa, lies within this sensitive climatic zone where rainfall exhibits strong variability across seasonal, interannual, and decadal timescales (Nicholson, 2013; Sultan and Gaetani, 2016; Akum et al., 2026). This variability directly affects rain-fed agriculture and food security (Atiah et al., 2022), health, and livelihoods (Wang et al., 2025), making an improved understanding of its drivers both scientifically and societally important. Northern Ghana, especially the Upper West Region, is one of the poorest regions in Ghana and is vulnerable to climate variability and climate change (Osei-Amponsah et al., 2023).

Rainfall over West Africa is primarily governed by the WAM, a coupled ocean-atmosphere system driven by land-sea thermal contrasts (Thorncroft et al., 2011). Superimposed on this regional system are remote oceanic influences arising from sea surface temperature (SST) variability in the tropical Atlantic, Indian, and Pacific Oceans.

Studies have demonstrated that tropical Pacific and Atlantic SST anomalies exert a dominant influence on rainfall variability across the Guinea Coast and Sahel (Rowell, 2001; Giannini et al., 2003). El Niño-Southern Oscillation (ENSO)-related teleconnections, while weaker than in other tropical regions, have been linked to suppressed rainfall during El Niño events and enhanced rainfall during La Niña phases, particularly at the interannual timescales (Janicot et al., 2001; Rowell, 2001).

While these large-scale climate indices provide valuable insights into remote forcing mechanisms, rainfall is ultimately realised through local and regional atmospheric processes. Variables such as near-surface temperature, moisture availability, wind fields, atmospheric instability, cloud cover, and column-integrated water vapour directly influence convective development and precipitation efficiency (Trenberth et al., 2003; Holloway and Neelin, 2009). Reanalysis products, such as the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5th Generation (ERA5), now enable a physically consistent assessment of local atmospheric conditions and their role in shaping rainfall variability at regional scales (Hersbach et al., 2020).

While previous studies have established the importance of large-scale sea surface temperature anomalies and regional atmospheric dynamics in shaping rainfall variability over West Africa, a systematic, quantitative comparison of their relative contributions at the local scale is missing in the region. Many existing analyses either focus on teleconnection patterns as drivers or on regional atmospheric diagnostics without explicitly assessing their combined and independent explanatory power within a unified modelling framework at the local scale. This limitation constrains the ability to distinguish between remote modulation and local realisation of rainfall processes.

Against this background, this current study intends to investigate the drivers of rainfall variability in Wa, northern Ghana, using a regression-based

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framework that explicitly separates and combines large-scale climate indices and local atmospheric variables derived from ERA5. By first assessing the explanatory power of climate indices alone, then local atmospheric variables alone, and finally their combined effects, this study aims to quantify the relative importance of remote versus local controls and to evaluate whether their interaction provides added predictive and physical insights. This approach contributes to a clearer understanding of the multi-scale mechanisms governing rainfall variability in northern Ghana and supports improved climate risk assessment in the region. The study also provides a physically based framework for improving seasonal rainfall assessment and informing climate risk management, agricultural planning, and water resource management in northern Ghana.

This study tests three hypotheses: (H1) large-scale climate indices (e.g., El Niño-Southern Oscillation, Atlantic and Indian Ocean modes) exert a statistically significant but modest influence on rainfall variability in Wa; (H2) local atmospheric variables derived from ERA5 explain a larger fraction of rainfall variability (than teleconnections do) due to their direct role in rainfall generation; and (H3) a combined model incorporating both large-scale climate indices and local atmospheric variables provides the highest explanatory power (compared to the previous models) by capturing the joint effects of remote climate forcing and local atmospheric processes. These hypotheses are evaluated using multiple linear regression applied to rainfall anomalies, with separate models for climate indices only, local variables only, and their combination. This current framework enables a systematic assessment of the relative and integrated contributions of large-scale and local drivers to rainfall variability in Northern Ghana.

Data and Methods

Study Area and Data

The study focuses on Wa in the Upper West Region of Ghana (Figure 1), located within the Guinea-Savannah ecological zone. The area lies in the transition between the Sudanian and Guinean climatic regimes and is characterised by a unimodal rainfall pattern associated with the West African Monsoon (WAM). Rainfall data for the Wa synoptic station were obtained from the Ghana Meteorological Agency (GMet) from 1960 to 2020. The study also used ERA5 reanalysis data with a spatial resolution of 0.25° × 0.25° (Hersbach et al., 2020). These were extracted over the Wa synoptic station, using the station's longitude and latitude coordinates from the nearest ERA5 grid point. The National Oceanic and Atmospheric Administration's (NOAA) Physical Sciences Laboratory: https://psl.noaa.gov/data/climateindices/list/ contains the climate indices used in this study.

Rainfall Variability Metrics

Rainfall variability was quantified. Interannual variability was assessed using standardised rainfall anomalies. The coefficient of variation (CV) was computed as the ratio of the standard deviation to the mean annual rainfall, expressed as a percentage, to assess relative variability.

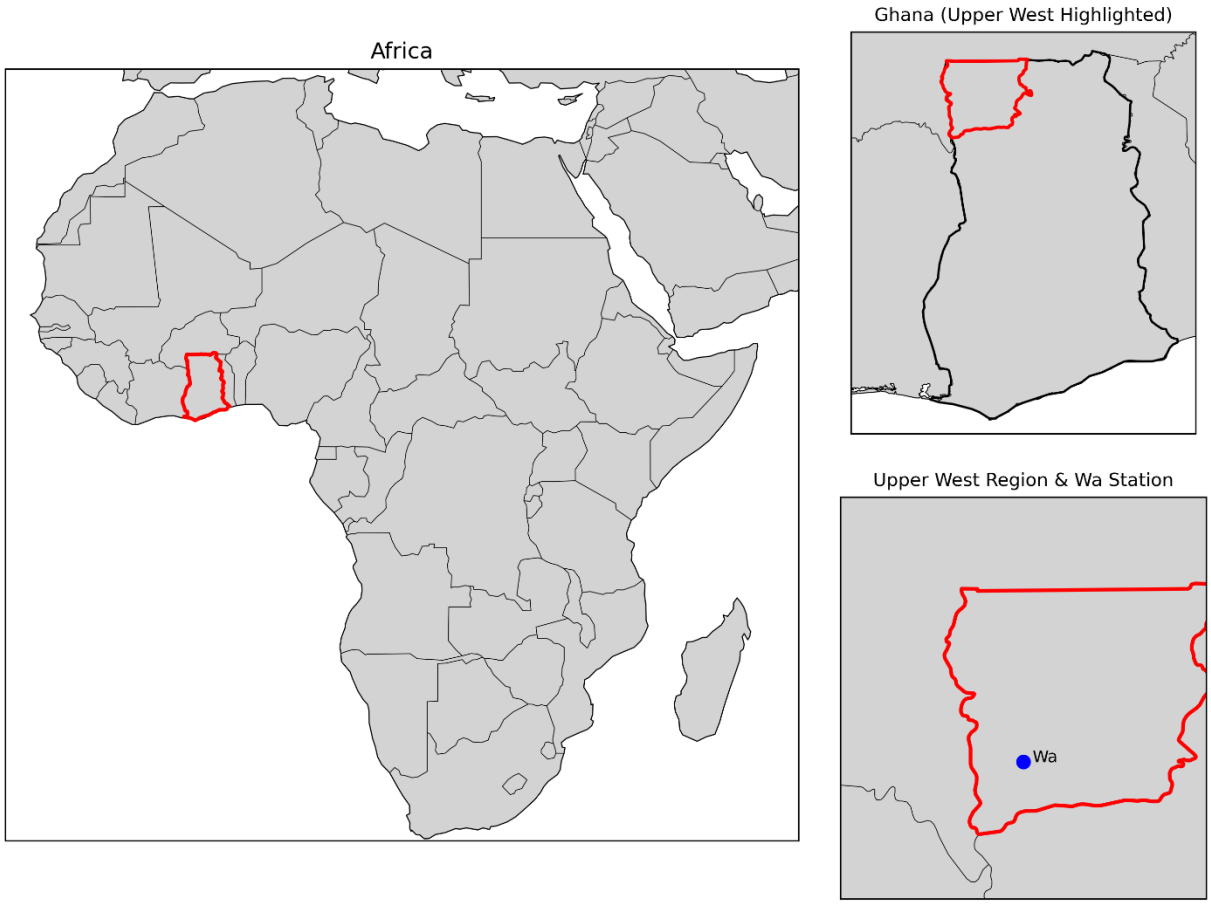


Figure 1: Map of the study area, showing the location of Ghana, the Upper West Region, and the Wa synoptic station.

Trend Analysis

Long-term rainfall trends were evaluated using the nonparametric Mann-Kendall trend test (Mann, 1945; Kendall, 1948), which is robust to non-normal distributions and outliers. Before the trend test, the data was pre-whitened to remove lag-one serial correlation using a technique proposed by Yue et al. (2002). The magnitude of detected trends was estimated using Sen's slope estimator. Statistical significance was assessed at the 95% confidence level.

Regression Analysis

Multiple linear regression was applied to quantify the influence of large-scale climate indices and local atmospheric variables on annual rainfall anomalies in Wa. The Annual teleconnection indices and annual ERA5 atmospheric anomalies were aligned with the corresponding annual rainfall totals for the same year. No lagged relationships were considered. Three regression models were developed: (i) climate indices only, (ii) local atmospheric variables only, and (iii) a combined model incorporating both sets of predictors. Model performance was evaluated using the coefficient of determination (R^2) and the statistical significance of regression coefficients.

To identify the most important drivers of interannual rainfall, candidate predictors were first screened using pairwise correlation ($|r| > 0.70$). Following pairwise correlation screening, stepwise regression guided by the Akaike Information Criterion (AIC; Akaike, 2003) was conducted using the algorithm described by Venables and Ripley (2013). This procedure identified the most informative predictors while minimizing model complexity and reducing the risk of overparameterization. This was done across the three configurations: the climate indices-only model, the ERA5 predictors model, and a final model combining the variables selected from the previous two stages (models). The full list of the predictors on which the bidirectional stepwise regression was applied is in Supplementary Table S1. Residual independence was evaluated using the Durbin-Watson statistic. Model robustness was assessed by employing the nested leave-one-out cross-validation (LOOCV), with predictive performance quantified using root mean square error (RMSE) and mean absolute error (MAE).

To account for multicollinearity, the Variance Inflation Factor (VIF) was computed for the predictors. No predictor with a VIF > 5 was included in the final models. The VIF of all the predictors used in the final models ranges from 1.08 to 2.32.

Results and Discussion

Rainfall Variability and Trend

Rainfall monthly coefficient of variation and interannual variability

The rainfall of Wa is highly seasonal, influenced by the movement of the intertropical convergence zone (ITCZ). The ITCZ is influenced by the intensification of the St Helena high-pressure system (Thiaw et al., 2017) during the rainy season, when intensified, the St Helena high-pressure system supplies moisture to Ghana and Wa. However, during the dry season, Wa is affected by dry northeasterlies (Fink et al., 2017).

To understand the monthly rainfall variability, the coefficient of variation (CV) is calculated for each month, and the results are displayed in Figure 2. The findings demonstrate that rainfall is highly variable in December, January, and February; during these months, the CV values exceed 200%, reflecting near-zero climatological means during the dry season. In such months, small absolute rainfall amounts lead to inflated CV values, indicating statistical instability rather than meaningful hydroclimatic variability. The elevated CV values during the dry-season months do not influence the regression analysis, which was conducted using annual rainfall anomalies. The transition months of October and November, when rainfall ceases, also show high CV values, while the onset transition months of March and April all register CV values above 50%. According to the results, the least variable months are during the rainy season, from May to September, when all recorded CVs are below 50%.

The higher variability recorded in the transition months could have a significant impact on agriculture. Since the onset and cessation months are highly variable, farmers' planting and harvest plans could be affected, which can in turn affect crop yield.

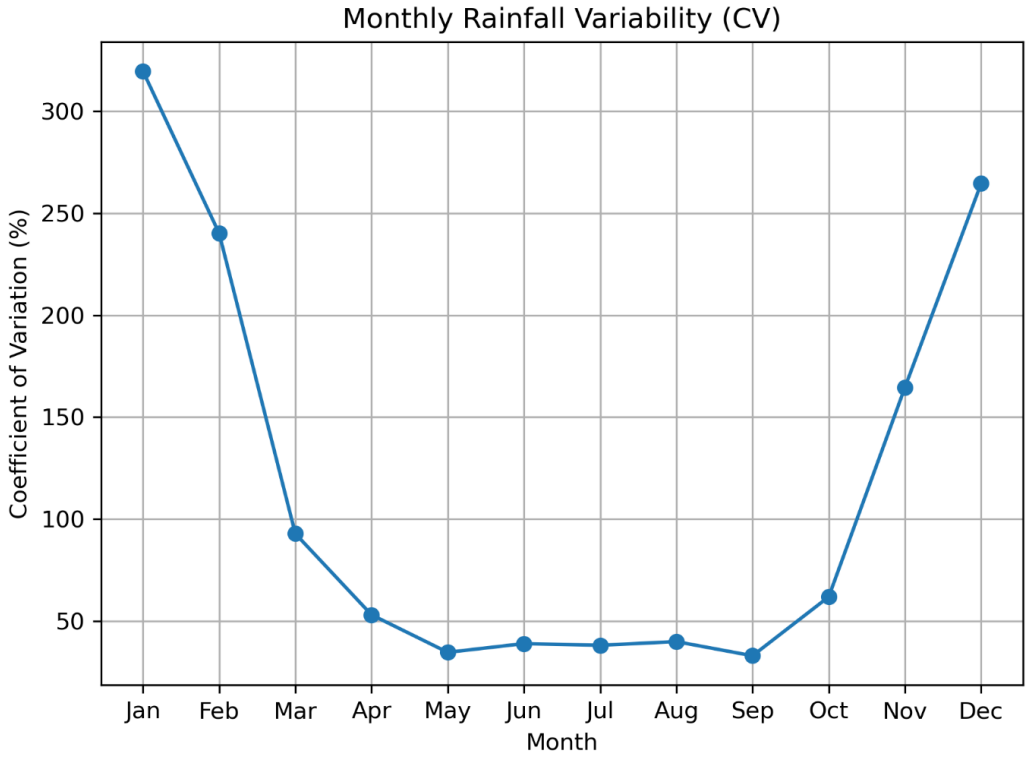


Figure 2: Monthly coefficient of variation (CV) in Wa from 1960-2020.

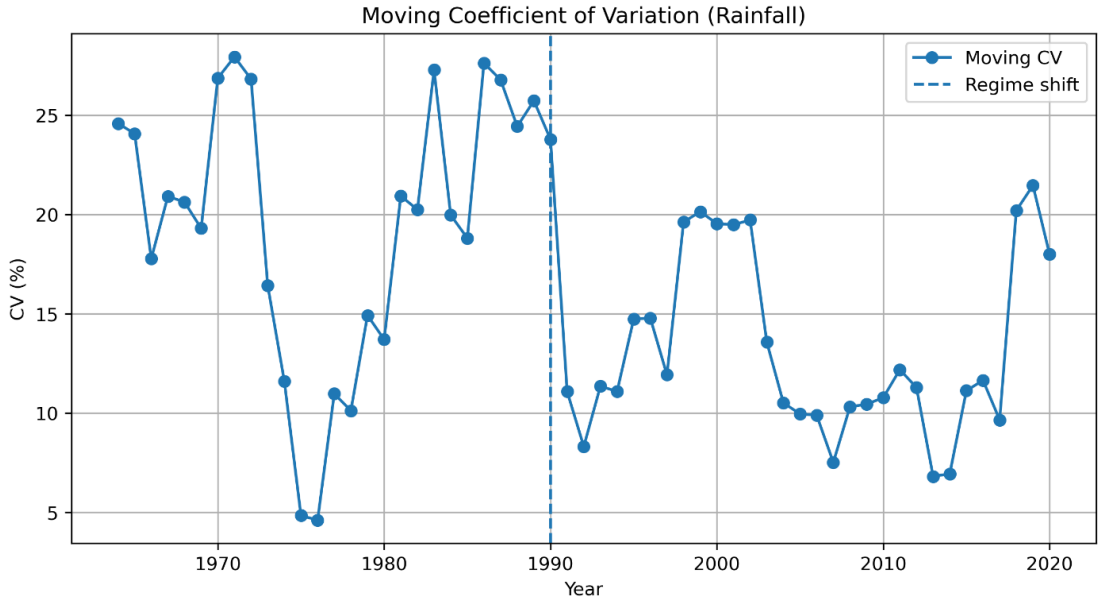


Figure 3: 5-year moving CV of annual rainfall over Wa.

Table 1: Trend analysis results of Wa's monthly rainfall from 1960-2020. Included in the table are the lower and upper confidence intervals (CI).

Month	Trend	Lower CI	Upper CI
January	0.000	0.000	0.000
February	0.003	-0.014	0.068
March	-0.418*	-0.847	-0.112
April	0.053	-0.621	0.763
May	0.264	-0.398	0.967
June	-0.114	-1.002	0.862
July	-0.979*	-1.947	-0.111
August	0.601	-0.687	1.892
September	0.037	-0.923	1.056
October	0.442	-0.215	1.097
November	-0.067	-0.157	0.000
December	0.000	-0.009	0.000

* Trend is significant at $\alpha = 0.05$.

Interannual rainfall variability was quantified using a 5-year moving CV of annual rainfall totals, and the results are presented in Figure 3. The highest 11 CVs were recorded before or in 1990. Using the Pettitt change-point test, a statistically significant change point was detected in 1990. Therefore, there is a statistically significant regime shift in the 5-year moving CV of interannual rainfall in Wa (p-value < 0.01). The trend of the CV results over the study period also shows a significant reduction of -0.17 (p-value < 0.01). Thus, interannual rainfall variability (CV) has significantly decreased over time, implying interannual rainfall is becoming more stable. This stabilisation may reflect partial recovery from the severe Sahel drought era of the 1970s-1980s, widely attributed to Atlantic and global SST anomalies (Giannini et al., 2003; Nicholson, 2013). The reduction in variability suggests that rainfall totals have become more stable, although stability does not imply the absence of monthly-scale fluctuations or extreme-event risk.

The monthly trend results are shown in Table 1. Throughout the study period, there have been no significant changes in rainfall in 10 months. Only March (-0.418 mm month^{-1}) and July (-0.979 mm month^{-1}) recorded a significant decrease in rainfall during the period. The observed decline in monthly rainfall in March and July could significantly affect agriculture, especially that of July. In July, the rainy season in Wa has started, and farmers depend heavily on this rainfall for crop production. A consistent decline in rainfall in July will therefore reduce the water available for rain-fed agriculture in Wa.

Drivers of Rainfall Variability

Teleconnection and Local Drivers of Rainfall

Table 2: Regression results of teleconnection indices on Wa rainfall, showing the regression coefficients. These were the selected indices using the bidirectional stepwise regression. The Adjusted R-squared for the regression model is 0.086.

Climate Driver	Abbreviation	Regression Coefficient
Pacific North America	PNA	-0.185
North Atlantic Oscillation	NAO	-0.340*

* Coefficient is significant at $\alpha = 0.05$

The teleconnection-only regression model (Table 2) explains 8.6% of rainfall variance (Adjusted $R^2 = 0.086$).

The only significant climate index predictor is the North Atlantic Oscillation (negative). When NAO is in the positive phase, the Azores high-pressure system is unusually high (Hurrell et al., 2003; Fiedler et al., 2015). High values of the Azores high-pressure system will result in an intensification of the Harmattan winds (Fiedler et al., 2015). Dry Harmattan winds will reduce moisture inflow and suppress convection over West Africa. Thus, convection in the Sahel region of West Africa has been reported to correlate negatively with the Azores (Gaetani et al., 2011). Therefore, the negative regression coefficient of NAO in Table 2 is consistent with the findings of previous studies.

These findings support Hypothesis 1: teleconnections exert a statistically significant but modest influence on rainfall in northern Ghana on their own (8.6%). They act as "boundary conditions" rather than direct triggers.

Table 3: Regression results of local ERA5 drivers on Wa rainfall, showing the regression coefficients. These were the selected ERA5 predictors using the bidirectional stepwise regression. The Adjusted R-squared for the regression model is 0.302.

Climate Driver	Abbreviation	Regression Coefficient
2 m temperature	T2M	-0.514*
Total column cloud ice water	TCIW	0.540*
2 m dewpoint temperature	D2M	0.412*
Medium cloud cover	MCC	-0.408*
Convective available potential energy	CAPE	-0.499*

* Coefficient is significant at α = 0.05

The results of the ERA5 local drivers of rainfall in Wa are presented in Table 3. The ERA5-based regression explains 30.2% of rainfall variance (Adjusted R^2 = 0.302), indicating a substantial explanatory power from local thermodynamic and cloud-related variables. All five (5) retained predictors recorded significant coefficients. T2M (2-m temperature) is negatively associated with rainfall. The negative T2M (-0.514) coefficient indicates that thermal forcing without moisture is unproductive for Wa. On a yearly scale, a "hot" year is synonymous with a "dry" year because the natural cooling mechanisms of rainfall and clouds were absent. TCIW (total column cloud ice water) shows a positive coefficient. The positive coefficient of TCIW (0.540) indicates that interannual "wet" years are driven by the successful conversion of moisture into deep, ice-bearing convection. D2M (2 m dew-point temperature) recorded a positive regression coefficient (0.412) with the interannual rainfall anomaly; elevated dew-point temperature near the surface increases moisture availability for condensation and sustained convective rainfall. The negative association of medium cloud cover (MCC) with interannual rainfall anomaly (-0.408) shows that MCC is not a dominant characteristic of wet years; but that wet years in West Africa are rather often associated with deep convection (Maranan et al., 2018). The negative association of convective available potential energy (CAPE) with the interannual rainfall anomalies (-0.499) indicates that high CAPE years may represent accumulated convective energy that is not efficiently converted into rainfall; thus, the high CAPE results from warmer and clearer conditions.

Results from Table 3 support Hypothesis 2: Local ERA5 predictors more than tripled the explanatory power of the teleconnection drivers (30.2% vs 8.6%).

3.2.2 Combined effect of teleconnections and local drivers

Table 4: Regression results of both local ERA5 and teleconnection indices on Wa rainfall, showing the regression coefficients. These were the selected predictors using the bidirectional stepwise regression. The Adjusted R-squared for the regression model is 0.411.

Climate Driver	Abbreviation	Regression Coefficient
Atlantic Multi-decadal Oscillation	AMO	0.520*
Indian Ocean Dipole	IOD	0.258*
North Atlantic Oscillation	NAO	-0.164
Total column cloud ice water	TCIW	0.385*
2 m temperature	T2M	-0.635*

* Coefficient is significant at α = 0.05.

The combined model (Table 4; using a combination of the selected predictors in the climate indices-only model and the ERA5 predictors-only model) increased the explanatory power to 41% (Adjusted R^2 = 0.411). The Atlantic Multi-decadal Oscillation (AMO) records a significant positive coefficient (0.520). A positive phase of the AMO has been reported to strengthen the Sahara heat low (Martin and Thorncroft, 2014). An intensified Sahara heat low will strengthen the flow of moist winds from the Atlantic Ocean into northern Ghana and hence enhance rainfall. The Indian Ocean Dipole (IOD) records a positive coefficient. A positive phase of the IOD occurs when the western Indian Ocean (near Africa) is warm (Saji et al., 1999). This association is consistent with documented, though spatially and directionally variable, IOD-West African rainfall teleconnections. For example, Ezedigboh et al. (2018) found a significant relationship between the IOD Mode Index and Nigerian rainfall that was strongest over the Sahelian north, though its sign varied across years, indicating that the physical mechanism linking IOD variability to rainfall at Wa is not yet established and warrants further investigation. The improvement over the local-only model (30.2%) indicates that large-scale SST anomalies modulate the background atmospheric state upon which local convective processes act. The results show that rainfall in Wa is modulated by convective success (TCIW) and the global position of the ITCZ (driven by AMO).

More broadly, the results reinforce the multiscale nature of rainfall variability over West Africa. Large-scale climate modes influence the background state of the atmosphere by modulating moisture transport, the position of the intertropical convergence zone, and the strength of the monsoon circulation. However, rainfall occurrence at the local scale ultimately depends on the ability of the atmosphere to initiate and sustain convection under these broader conditions. This establishes a clear hierarchy in the rainfall generation process: remote oceanic forcing provides the boundary conditions within which the regional climate system operates, while local thermodynamic and cloud processes determine whether rainfall is actually realised. The improvement in explanatory power in the combined model, therefore, reflects the interaction between these scales.

The results support Hypothesis 3: the joint model (Table 4) achieved the highest predictive performance of R^2 = 0.411. This model successfully bridges the remote-local gap. It shows that AMO (0.520) is likely one of the major drivers of moisture flux in Wa, while TCIW (0.385) determines whether that moisture is successfully converted into rainfall. Local processes explain more variance, but remote forcing enhances predictive skill.

The summary statistics of model diagnostics and validation are presented in Table 5. The robustness of each model was assessed using nested leave-one-out cross-validation (LOOCV). Also, residual independence was evaluated using the Durbin-Watson statistic; there was no strong evidence of autocorrelation, as the values range from 1.746 to 1.965. The combined model also recorded the lowest LOOCV MAE of 0.708; however, the local ERA5-only model recorded the lowest LOOCV RMSE of 1.001.

Table 5. Summary of model diagnostics and validation.

Model	Adjusted R^2	Max VIF	Durbin–Watson	LOOCV RMSE	LOOCV MAE
Teleconnections only	0.086	1.08	1.965	1.100	0.898
Local ERA5 only	0.302	2.32	1.851	1.001	0.763
Combined model	0.411	1.96	1.746	1.002	0.708

Conclusions

This study examined rainfall variability in Wa (1960-2020) and quantified the relative contributions of large-scale climate indices and local atmospheric conditions using a structured regression framework.

Rainfall recorded the highest relative variability during onset and cessation months and lower variability during peak monsoon months. Interannual variability has declined significantly since approximately 1990, indicating a shift toward greater annual rainfall stability. Trend analysis shows that only March and July experienced significant declines, suggesting that long-term changes are seasonally localised rather than uniform across the year.

Regression analysis provides quantitative attribution of rainfall drivers. The teleconnection-only model explains 8.6% of rainfall variance, confirming that large-scale climate modes exert statistically significant but modest influence. The local atmospheric model explains 30.2% of the variance, demonstrating that rainfall realisation is more strongly governed by local processes. The combined model yields the highest explanatory power (41.1%), indicating that remote oceanic forcing provides additional but secondary information beyond local atmospheric conditions.

The emergent predictive power of the combined model ($R^2 = 0.411$) exceeds the additive contribution of the individual climate indices and local ERA5 models (combined contribution of $R^2 = 0.386$). The higher explanatory power of the combined model reflects the complementary contributions of teleconnection indices and local atmospheric variables, indicating that large-scale climate variability modulates local atmospheric conditions that collectively influence annual rainfall. Where the AMO acts as a primary moisture regulator, with its influence fully realised when local atmospheric conditions allow for deep convection (TCIW). Indicating that rainfall in Wa is not driven by a single scale. No interaction terms were included in the regression models.

Overall, the results show that rainfall variability in Wa is controlled more by local atmospheric processes than by teleconnection indices, while large-scale SST variability modulates the broader dynamical environment. Rainfall therefore emerges from multiscale interaction: remote oceanic anomalies influence circulation patterns, but precipitation is ultimately realised through local moisture, instability, and cloud processes.

Despite the improvement in explanatory power achieved by the combined model, a substantial proportion of rainfall variability remains unexplained, indicating the influence of additional processes not captured within the current framework. These may include mesoscale convective systems, land–atmosphere feedbacks, and stochastic variability inherent in convective processes. This highlights an inherent limit to the predictability at the local scale, particularly in regions where rainfall is dominated by highly nonlinear and transient atmospheric dynamics.

From an applied perspective, the findings suggest that predictive frameworks based solely on large-scale climate indices are insufficient for capturing rainfall variability at local scales. Instead, improved prediction and climate risk assessment require the integration of both remote oceanic indicators and local atmospheric diagnostics. Such hybrid approaches are more likely to capture the combined effects of large-scale modulation and local convective processes, thereby providing more reliable guidance for climate-sensitive sectors.

These findings have two implications. First, predictive frameworks focusing solely on climate indices will underestimate rainfall variability at local scales. Second, improved seasonal outlooks require integrating large-scale teleconnections with local atmospheric diagnostics to capture both background modulation and convective realization mechanisms.

Data and Code Availability

The Wa data used in this study were obtained from the Ghana Meteorological Agency. Climate indices used in the study were all from the Netherlands Meteorological Institute (KNMI) climate explorer and can be accessed on this website: https://climexp.knmi.nl/selectfield_obs2.cgi?id=someone@somewhere, however, some of the climate indices were taken from the National Oceanic and Atmospheric Administration's physical sciences laboratory: https://psl.noaa.gov/data/climateindices/list/. The ERA5 reanalysis data were taken from: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download.

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Competing Interests

The author has no competing interests to declare.

Supporting Information

The following are the supporting information:

Table S1. List of all predictors used in this work. The table provides the full and corresponding abbreviation for each large-scale climate index, surface and atmospheric variables used as input features in the Linear regression models.

References

Akaike, H. (2003). A new look at the statistical model identification. *IEEE transactions on automatic control*, *19*(6), 716-723.

Akum, R. A., Lischeid, G., Oguntunde, P. G., & Balogun, R. A. (2026). Thunderstorm drivers and trends in Ghana, West Africa: an interpretable machine learning study. *Meteorology and Atmospheric Physics*, *138*(3), 38.

Atiah, W. A., Amekudzi, L. K., Akum, R. A., Quansah, E., Antwi-Agyei, P., & Danuor, S. K. (2022). Climate variability and impacts on maize (Zea mays) yield in Ghana, West Africa. *Quarterly Journal of the Royal Meteorological Society*, *148*(742), 185-198.

Ezedigboh, U. O., Usman, M. T., Suleiman, M. Y., Bello, E., Orisakwe, I. C., & Aganbi, B. (2018). Possible Teleconnection Between the Indian Ocean Dipole and the Rainfall Distribution Over Nigeria.

Fiedler, S., Kaplan, M. L., & Knippertz, P. (2015). The importance of Harmattan surges for the emission of North African dust aerosol. *Geophysical Research Letters*, *42*(21), 9495-9504.

Fink, A.H., Engel, T., Ermert, V., van der Linden, R., Schneidewind, M., Redl, R., Afiesimama, E., Thiaw, W.M., Yorke, C. & Evans, M. (2017) 'Mean climate and seasonal cycle', in Parker, D.J. & Diop-Kane, M. (eds.) *Meteorology of Tropical West Africa: The Forecasters' Handbook*. Chichester: John Wiley & Sons, pp. 37-95.

Gaetani, M., Pohl, B., Douville, H., & Fontaine, B. (2011). West African Monsoon influence on the summer Euro-Atlantic circulation. *Geophysical Research Letters*, *38*(9).

Giannini, A., Saravanan, R., & Chang, P. (2003). Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. *Science*, *302*(5647), 1027-1030.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., ... & Thépaut, J. N. (2020). The ERA5 global reanalysis. *Quarterly journal of the royal meteorological society*, *146*(730), 1999-2049.

Holloway, C. E., & Neelin, J. D. (2009). Moisture vertical structure, column water vapor, and tropical deep convection. *Journal of the atmospheric sciences*, *66*(6), 1665-1683.

Hurrell, J. W., Kushnir, Y., Ottersen, G., & Visbeck, M. (2003). An overview of the North Atlantic oscillation. *Geophysical Monograph-American Geophysical Union*, *134*, 1-36.

Janicot, S., Trzaska, S., & Poccard, I. (2001). Summer Sahel-ENSO teleconnection and decadal time scale SST variations. *Climate Dynamics*, *18*(3), 303-320.

Kendall, M.G. (1948) *Rank correlation methods*. London: Charles Griffin.

Mann, H.B. (1945) 'Nonparametric tests against trend', *Econometrica: Journal of the Econometric Society*, 13(3), pp. 245-259.

Maranan, M., Fink, A.H. & Knippertz, P. (2018) 'Rainfall types over southern West Africa: Objective identification, climatology and synoptic environment', *Quarterly Journal of the Royal Meteorological Society*, 144(714), pp. 1628-1648.

Martin, E. R., & Thorncroft, C. D. (2014). The impact of the AMO on the West African monsoon annual cycle. Quarterly Journal of the Royal Meteorological Society, 140(678), 31-46.

Nicholson, S. E. (2013). The West African Sahel: A review of recent studies on the rainfall regime and its interannual variability. *International Scholarly Research Notices*, *2013*(1), 453521.

Nicholson, S. E., Fink, A. H., & Funk, C. (2018). Assessing recovery and change in West Africa's rainfall regime from a 161-year record. *International Journal of Climatology*, *38*(10), 3770-3786.

Osei-Amponsah, C., Quarmine, W., & Wahabu, E. (2023). The place of social transformation analysis in vulnerability assessment for climate adaptation planning in Upper West Region, Ghana: A review synthesis. *Climate Resilience and Sustainability*, *2*(3), e251.

Rowell, D. P. (2001). Teleconnections between the tropical Pacific and the Sahel. *Quarterly Journal of the Royal Meteorological Society*, *127*(575), 1683-1706.

Saji, N. H., Goswami, B. N., Vinayachandran, P. N., & Yamagata, T. (1999). A dipole mode in the tropical Indian Ocean. *Nature*, *401*(6751), 360-363.

Sultan, B., & Gaetani, M. (2016). Agriculture in West Africa in the twenty-first century: climate change and impacts scenarios, and potential for adaptation. *Frontiers in plant science*, *7*, 1262.

Thiaw, W.M., Janicot, S., Bekele, E., Cook, K.H., Fontaine, B., Mekonnen, A., Ndiaye, O., Tamo, P.H.K. & Vizy, E.K. (2017) 'Subseasonal forecasting', in Parker, D.J. & Diop-Kane, M. (eds.) *Meteorology of Tropical West Africa: The Forecasters' Handbook*. Chichester: John Wiley & Sons, pp. 255-277.

Thorncroft, C. D., Nguyen, H., Zhang, C., & Peyrillé, P. (2011). Annual cycle of the West African monsoon: regional circulations and associated water vapour transport. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 129-147.

Trenberth, K. E., Dai, A., Rasmussen, R. M., & Parsons, D. B. (2003). The changing character of precipitation. *Bulletin of the American Meteorological Society*, *84*(9), 1205-1218.

Venables, W. N., & Ripley, B. D. (2013). *Modern applied statistics with S*. Springer Science & Business Media.

Wang, P., Rogne, T., Warren, J. L., Asare, E. O., Akum, R. A., Toure, N. D. E., ... & Chen, K. (2025). Long-term drought and risk of infant mortality in Africa: A cross-sectional study. *PLoS medicine*, *22*(1), e1004516.

Yue, S., Pilon, P., Phinney, B., & Cavadias, G. (2002). The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological processes*, *16*(9), 1807-1829.